

Remote sensing-based assessment of crop yield and water dynamics in the southern Great Plains
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by

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Abstract

Remote sensing has emerged as a crucial tool for estimating and understanding yield variability and water management in diverse cropping systems. This is particularly important in water-limited areas, such as the southern Great Plains, where water is the key to sustaining agricultural production. Therefore, the present research integrated remote sensing with weather variables and machine learning (ML) to predict crop yields, identify key variables affecting crop yields, and enhance overall water use efficiency.

The study began by highlighting the significance of satellite remote sensing in predicting soybean yield, utilizing various inputs that can impact soybean yield metrics. We evaluated different ML models to predict soybean yield and identify key variables, utilizing agronomic management factors such as planting dates, seeding rates, and maturity groups, with weather variables and remote sensing vegetation indices. Our findings showed that variability is accurately captured by the Random Forest and Adaptive Boosting models (R^2 : 0.77-0.79). The accuracy was higher during the late vegetative and late reproductive stages when crops require more water. Furthermore, it was found that crop evapotranspiration (ET_c) was the most significant feature affecting the performance of the ML model among the various meteorological variables. The importance score was 0.73. These findings demonstrate that high-resolution satellite data can support early-season yield prediction and identify the key meteorological variable (ET_c) under adaptive management practices.

Based on the knowledge that ET_c was a key factor in measuring crop yields, the second chapter of the research compared and evaluated different precision irrigation systems using ET_c. The overarching goal was to identify field-scale crop water stress and irrigation scheduling. Therefore, we have utilized and quantified satellite-derived ET_c to evaluate different irrigation

systems that can save irrigation water. In this chapter, we have compared a precision irrigation method (AI-integrated Ground Penetrating Radar; AI-Radar) with the conventional subsurface drip irrigation (SDI) system using spatial water stress maps. High-resolution satellite imagery, combined with meteorological data, was utilized to generate spatial water stress maps (Water Deficit Index; WDI), where lower WDI values indicate less crop water stress. This index is a key indicator of crop water stress. Results showed that fields irrigated with AI-Radar maintained considerably lower WDI values (0.15-0.16) than SDI fields (0.20-0.24) during critical reproductive stages, with 31-34% less irrigation water from SDI. These findings demonstrate the potential of the AI-Radar irrigation system for effective irrigation management, which can help to conserve irrigation water while maintaining crop productivity.

In the third chapter, we have expanded this study by moving from spatial water maps to field-scale water use efficiency (WUE_f), which accounts for actual evapotranspiration (ET_a) as a water variable and crop yield. Here, we have moved from satellite-scale monitoring to finer, field-scale observation using UAV-based measurements. At this stage, high-resolution UAV imagery was combined with OpenET satellite estimates to capture more accurate spatial variation in ET and its relationship to yield. Based on our results, fields irrigated with the AI-Radar irrigation system showed higher WUE_f ($6.7-7.17 \text{ kg ha}^{-1} \text{ mm}^{-1}$) and a 30.8% increase in yield compared to SDI.

The three chapters of this study demonstrate a clear progression from identifying ET_c as an important factor influencing crop yield variability to estimating ET_c for irrigation assessment using satellite data, followed by a UAV-based field-scale evaluation. Using satellite and UAV remote sensing together with machine learning provides a scalable method for linking yield

prediction and water use efficiency. This framework supports efficient irrigation planning and improved productivity with reduced irrigation use in the Southern Great Plains.

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Dedication

I would like to dedicate my master's journey to my parents, whose endless love, sacrifices, and unwavering belief in me have been my greatest strength, and to my sister, whose encouragement and warmth have been a constant source of support. Their faith has carried me through every challenge and made this journey possible.

Chapter 1 - Evaluating the Effect of Planting Dates on Soybean Yield Using Remote Sensing and Weather Data

Abbreviations

AdaBoost, Adaptive Boosting; ET_c, Crop Evapotranspiration; GDD, Growing Degree Days; KNN, K-Nearest Neighbor Regression; LAI, Leaf Area Index; LASSO, Least Absolute Shrinkage and Selection Operator; MG, Maturity Group; NDRE, Normalized Difference Red Edge Index; NDVI, Normalized Difference Vegetation Index; RF, Random Forest; UAV, Unoccupied Aerial Vehicle; WDRVI, Wide Dynamic Range Vegetation Index.

Abstract

Soybean yield is influenced by fluctuations in meteorological factors throughout the growing season and across planting windows. Therefore, for growers, predicting soybean yield early in the season and addressing yield variability is essential for strategic decisions, including crop insurance, crop storage demand, and resource utilization. The objective of our study was to capture soybean yield variability under three different planting dates (early, mid, and late), for two seeding rates (Low~247,100 and High~370,650 seeds ha⁻¹) and two maturity groups (MG 3 and 4), and use machine learning (ML) models to predict soybean yield. Agronomic and meteorological data from the Kansas Mesonet, along with high-resolution (3m) PlanetScope satellite imagery, were utilized to predict and address soybean yield variability. Results showed that early-planted soybeans demonstrated a higher mean yield potential with a higher coefficient of variation (CV) than mid- and late-planted soybeans. Therefore, to model this variability, four ML models, including random forest (RF), Adaptive Boosting (AdaBoost), K-Nearest Neighbor (KNN), and Least Absolute Shrinkage and Selection Operator (LASSO), were evaluated. The RF and AdaBoost algorithms performed comparatively better (R²: 0.78-0.80). Moreover, we have

observed that the accuracy percentage (with a 10% error threshold) and R-squared (R^2) values increased as the crop growth progressed, with the highest values occurring during the late vegetative and reproductive stages. This highlights the importance of in-season monitoring of the resources and market planning. The study would help soybean growers assess yields under variable weather conditions and make informed crop management decisions using readily available and cost-effective high-resolution satellite data.

Keywords: Early planting, random forest, Maturity group, satellite timing, soybean yield variability

1. Introduction

1.1. Importance of Soybean

According to the United Nations, the world population is projected to reach 9.6 billion by 2050 (United Nations, 2024). This increasing population growth highlights the importance of food security in the strategic plans of developed and developing nations. In the United States, soybeans (*Glycine max* L. Moench) are one of the most important crops known for their nutritional aspects. Soybean has a nutritional composition of 35% carbohydrates (including 17% dietary fiber), 19% oil, 36% protein, 5% minerals, and various vitamins (Liu, 1997). Soybeans are also crucial as a crop that can contribute to the global economy and agricultural sustainability. Soybeans are leguminous crops that enhance soil fertility by utilizing rhizobia to fix nitrogen from the air. This reduces nitrogen fertilizer application in the soil, thereby lowering cultivation costs (Salvagiotti et al., 2008). Additionally, this ecological process also improves the soil. Additionally, soybean oil is used as a biodiesel, which can be a form of renewable energy for sustainable growth (Hill et al., 2006). Soybeans have become a major crop in the US as expected to bring in \$124 billion for the US economy in 2022 (Checkoff, 2023). Soybeans are an

important crop in the Midwest and High Plains, particularly in Kansas. In Kansas, 97% of soybean meal is used for livestock feed (Checkoff, 2023).

1.2. Importance of Yield Prediction for Soybeans Under Different Management Practices

In agriculture, soybean crop yields are affected by different meteorological variables, including temperature, precipitation, and extreme weather events (Hamed et al., 2021). These fluctuations in meteorological factors influence yield variability over the growing season and across the planting dates. In Kansas, soybeans are shown after corn (*Zea mays* L.), with a sowing window ranging from mid-April to July (Ciampitti et al., 2022). Therefore, varying planting dates can result in varying yields of soybeans. According to Ciampitti et al. (2022) Early-planted soybeans resulted in higher yields with greater variability. In the literature review, different planting dates of soybean were investigated for increasing soybean yield according to the agroclimatic zone and management practices (Vossenkemper et al., 2015). Therefore, in order to maximize resource utilization, such as water, fertilizer, and pesticides, there is a need for early-season yield prediction in order to make well-informed decisions (van Klompenburg et al., 2020). Additionally, accurate yield prediction also helps food security by informing policymakers and growers about the potential crop failures early in the season (Horie et al., 1992). However, in agricultural practices, yield prediction is complex as it is affected by different factors such as genotypes, crop management, environments, and their interactions (Khaki & Wang, 2019; W. Lu et al., 2022). Additionally, traditional crop growth models often lack information about key management practices, including crop variety details, seed rates, fertilizer doses, and irrigation scheduling. This can make it sometimes impractical for yield prediction, especially with historical data (F. Li et al., 2022). Thus, crop yield estimation using remote sensing and machine learning models is important.

1.3. A component of satellite remote sensing used for yield prediction

Among the several systems of remote sensing used in agriculture, satellites have emerged as an efficient instrument for estimating agricultural production, such as Sentinel 2 (Perich et al., 2023), MODIS satellite (Johnson, 2016; Medina et al., 2021), Landsat-8 satellite (Newton et al., 2018), and PlanetScope satellites (F. Li et al., 2022). Generally speaking, satellite data contains spectral bands that can be utilized to compute various vegetation indices (VIs), which are essential for yield prediction and other forecasting models in agriculture (Haboudane et al., 2004; Ji et al., 2021; Panda et al., 2010; Satir & Berberoglu, 2016). Among the different satellites used in agriculture, PlanetScope has great potential. This is due to its easy availability, high accuracy rate (both spatially and temporally), and cost-effectiveness. These satellites have a spatial resolution of three to five meters and a daily temporal resolution (Planet Labs, 2022). This is useful for agricultural applications, as we require time-series data. The PlanetScope satellite has different wavelength bands, as listed in Table 1.2. Spectral bands can be used to collect crop and soil data for yield prediction (Haboudane et al., 2004; Ji et al., 2021; Panda et al., 2010; Satir & Berberoglu, 2016). Different VIs, for example, Normalized Difference Vegetation Index (NDVI), are used to assess the crop health (Shrestha et al., 2023; Walsh et al., 2023). NDVI is the ratio of near-infrared (NIR) (780–900 nm) to red reflectance (630–690 nm). NDVI values range from -1 to 1, with healthy crops having higher values. This indicates higher chlorophyll content, which reflects more NIR and absorbs more Red light (Stamford et al., 2023). Higher NDVI values between 0.6 and 0.9 indicate dense and healthy vegetation due to NIR reflectance and red absorption (Johnson, 2016; Walsh et al., 2023). Some essential pigments, including chlorophyll, carotenoids, and anthocyanins, influence the absorption and reflection of light at specific wavelengths. Therefore, NDVI can be used to indirectly measure crop health and make

accurate predictions of crop yield. However, NDVI approaches saturation asymptotically quickly in the presence of moderate to high above-ground dense biomass. This is due to the reflectance in the red region, which exhibits a nearly flat response once the leaf area index (LAI) exceeds 2 (Gitelson, 2004). Additionally, the theory of wavelength dependence on atmospheric scattering is known as Rayleigh scattering. Due to Rayleigh scattering, radiance in shorter wavelengths (red region, 630 – 690 nm) is three times greater than in longer wavelengths (NIR region, 780 – 900 nm), and it is also sensitive to soil, atmosphere, and other materials (Huang et al., 2021; Imran et al., 2020). Other indices, such as the Normalized Difference Red Edge Index (NDRE), can be used to accurately predict yield. It is designed specifically to penetrate thick vegetation canopies and provide precise assessments of plant health, especially in later growth stages when the canopy has developed and is completely covered (Stone et al., 2000; Su et al., 2023). NDRE is the ratio of NIR (780 – 900 nm) and red edge (705 – 745 nm) spectral bands. The red edge spectral band, which is between the red band and the NIR band, is more sensitive to small changes in the chlorophyll concentration of the plant than the standard red band (630–690 nm) (F. Li et al., 2014). In the red edge region, the spectral reflectance of green vegetation increases rapidly, which is closely associated with the pigment state and the physical and chemical characteristics of the crop (Kang et al., 2021). According literature review, quantitative analysis showed that NDRE has higher correlation coefficients (R^2) than 0.70 for estimating the biomass and yield of rice (Su et al., 2023), Corn (Saravia et al., 2022), Wheat (K. Wang et al., 2019), and Soybean. This capability to detect deep canopy conditions makes NDRE an invaluable tool for managing crop health and optimizing agricultural output. Another vegetation index, the Wide Dynamic Range Vegetation Index, improves the correlation with vegetation fraction by linearizing the relationship for crop canopies, with a weighting coefficient of 0.1-0.2 (Gitelson,

2004). The WDRVI is approximately three times more sensitive than the NDVI to moderate-to-high LAI (between 2 and 6) (Gitelson, 2004). WDRVI enables a more reliable assessment of crop physiological and phenological characteristics by increasing the dynamic range while maintaining the same bands (Gitelson, 2004).

1.4. Advancement in yield prediction with machine learning

Traditional crop modeling is unable to accurately represent detailed and nonlinear interactions among agroclimatic variables. Thus, advancements in computational approaches such as remote sensing, in addition to machine learning (ML) models, are effective in understanding sub-field and regional yield predictions and crop yield variability (Al-Gaadi et al., 2016; Ilyas & Ahmad, 2020; Marshall et al., 2022; L. Zhao et al., 2024). ML is classified as a subset of artificial intelligence, which is an ensemble form of mathematical equations used to develop an adaptive system that can learn and train with minimal human intervention. In our study, we had both quantitative data and qualitative data. Therefore, ML was selected because it can handle both data types (Morales & Villalobos, 2023). As machine learning (ML) can identify complex correlations and patterns among variables, it is mainly utilized in yield predictions (Crusiol et al., 2021; Gajula et al., 2021; Iniyan et al., 2023; Prasad et al., 2021a). ML algorithms are used to reduce overfitting resulting from non-linearity in agricultural datasets (Schwalbert et al., 2020). ML can also be used for estimating planting dates (Elbasi et al., 2023; Gümüüşcü et al., 2020), nutrient management (Gayathiri et al., 2023; Liben et al., 2024), and agricultural commodity prices (Thapaswini & Gunasekaran, 2022). ML focuses on real-world applications that can produce predictions with an accuracy of over 90% based on patterns and correlations in large data sets (Elbasi et al., 2023; Prasath et al., 2023a; van Klompenburg et al., 2020). Training the model requires datasets that represent outcomes based on correlations (van Klompenburg et

al., 2020). After training the datasets, models were tested and validated for performance evaluations. Based on the literature review, some of the most used machine learning algorithms for accurately predicting crop yield are Random Forest (RF) (Marques Ramos et al., 2020; Prasath et al., 2023b), adaptive boosting (AdaBoost) (Mishra et al., 2020), Least Absolute Shrinkage and Selection Operator (LASSO) (Singh et al., 2019), and K-nearest neighbor regression (KNN) (Gajula et al., 2021). Therefore, the application of advanced ML algorithms to address this interaction has gained popularity among growers due to their computational efficiency, growing availability of data, and the broader range of tools.

Therefore, understanding the interaction between meteorological factors, agronomic practices, and remote sensing variables is important for accurately predicting soybean yield and optimizing agricultural profits. The present study integrates ML models to predict and address soybean yield variability across the different planting dates. The objectives of our study were: (i) to analyze the soybean seasonal and temporal yield variability in the north-central region of Kansas, (ii) to identify the most suitable machine learning algorithm for accurate in-season yield prediction based on planting dates, weather, and satellite data, and (iii) to determine the optimal timing for accurate in-season yield prediction.

2. Materials and Methodology

2.1. Study area

The research was carried out in the north-central region of Kansas (North Central Research Station, Scandia, Kansas, USA) over three growing seasons: 2021 (field coordinates: 39°49'45.07"N, 97°50'50.38"W), 2022 (field coordinates: 39°49'49.78"N, 97°50'20.98"W), and 2023 (field coordinates: 39°49'47.41"N, 97°50'21.24"W) (Figure 1.1). This area mostly comes under the central and northern part of the soybean-growing area in Kansas, with similarity in

planting dates (Ciampitti et al., 2024). According to the Köppen climate classification, this region falls under the category "*Dfa*", signifying hot summers and harsh winters typical of such climates. The soil texture in this area is silty loam (up to 15 cm), slope is 1 to 3 %, with moderately well drainage, medium runoff, non-saline to very slightly saline (0.0 to 2.0 mmhos/cm) with 5 % calcium carbonate (Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture). The elevation of this location ranges from approximately 400 to 500 meters (Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture). Annual mean temperature ranges from approximately 9°C (USA mean: 5.7 °C) in January to 32°C (USA mean: 29.8 °C) in July. Precipitation is approximately 731.5 mm of rain (USA mean: 967.7 mm) and 421.6 mm of snow (USA mean: 706.1 mm) annually.

2.2. Experimental plan

In this study, a split-split-plot design with four blocks (replications) arranged within a random complete block design (RCBD) was implemented. The primary factor in the main plot was planting date, with three levels: early (March 20 to April 7), mid (April 20 to April 30), and late (May 15 to May 26). For all three planting dates, planting date had a subplot factor for seeding rate, ranging from low ($\sim 247,100$ seeds ha^{-1}) to high ($\sim 370,650$ seeds ha^{-1}). Within each seeding rate subplot, two soybean cultivars were used as sub-subplots, representing maturity groups 3 and 4. There were 48 plots per year (3 planting dates $\times$ 2 seeding rates $\times$ 2 varieties $\times$ 4 blocks), representing each treatment combination once. Plot dimensions were 3 meters $\times$ 10 meters in 2021 and 3 meters $\times$ 15 meters in 2022 and 2023 (Table 1.1). This study determined that late March or early April was the optimal early planting date because higher air temperatures and longer daylight durations contributed to soil drying and reduced the soil chilling effect. The

mid-planting date (late April) has been selected, as most regional growers follow this pattern. A late planting (late May) date was selected, one month after the mid-planting date, as recommended for this zone (Zone 2), where the sowing window extends up to June 1 (Ciampitti et al., 2022). Maturity groups 3 and 4 were selected because they are commonly recommended for the central and northern regions of Kansas, which have improved yield potential and agronomic adaptability in these environments. The low seeding rate (247,101 seeds ha⁻¹) corresponds to the optimum plant density for medium-to-high-yield environments in this region (Ciampitti, 2020). The higher seeding rate (370,650 seeds ha⁻¹) was selected as a precaution, especially during early planting, against reduced emergence when cooler soil temperatures may lower seed emergence. Additionally, many growers in Kansas have been planting between 345,800 and 395,400 seeds ha⁻¹ (140,000 to 160,000 seeds ac⁻¹). Soil testing was conducted every three years in each field, and fertilization was applied accordingly to maintain or improve soil fertility as needed. Crop yield data were collected from the middle two rows of each plot for every growing season (2021, 2022, and 2023). The crop was rainfed in 2021 to establish rainfed agriculture without irrigation. In 2022 and 2023, irrigation was provided using a linear travel irrigation system. The soybean was not fertilized during the three growing seasons, as it was planted after the corn. All the necessary fertilizer had already been applied to the previous corn crop.

2.3. Meteorological data

Meteorological information was obtained from the Kansas Mesonet located at 0.13 kilometers from the Scandia experimental station (39°49'41.60"N, 97°50'22.07" W). The elevation of this station was 457.2 m with a three-meter tripod-type station. Daily weather collected included: air temperature (°C) (using *HMP60 sensor, Vaisala, Helsinki, Uusimaa*,

Finland), soil temperature (2 inches) ($^{\circ}\text{C}$), solar radiation (kWhm^{-2}) (*Apogee CS301*, *Apogee Instruments, Inc., Logan, Utah, USA.*), crop evapotranspiration (ETc) (mm) (calculated by multiplying the crop coefficient value of 1.0 to 1.05 collected from during the reproductive time (Doorenbos & Pruitt, 1975) and overall precipitation (mm) (TB3H-LP, Delta-T Devices, Cambridge, Cambridgeshire, United Kingdom) and growing degree days (GDD) (calculated using daily maximum and minimum temperatures and the crop base temperature, $(T_{\max} + T_{\min})/T_{\text{base}}$). For each growth stage, the daily weather data were summarized by calculating the mean values for all variables except precipitation, which was calculated as the total. This information was used as input for ML models (discussed below) to determine the relative importance of meteorological features impacting the soybean yield.

2.4. High-resolution satellite data

In our research, satellite imagery comes from the PlanetScope constellation and has an average temporal interval of three to seven days and less than 10% cloud cover (Planet Labs, 2022). PlanetScope satellite operates a constellation of more than 200 small Earth observation satellites in low Earth orbit (LEO). This includes Dove, SkySat, and RapidEye satellites (Planet Labs, 2022). For this study, all satellite imagery was collected from SuperDove sensors. These satellites provide daily imagery with a spatial resolution of three to five meters on the ground. The PlanetScope satellite contains different wavelength-based bands, which are listed in Table 1.2 (Planet Labs, 2022). DOS and radiative transfer models based on Advanced atmospheric correction techniques improve image spatial accuracy. It reduces haze and pollutants to improve imagery. For each year, images were taken at a range of 3 to 7 days to capture the growth stages from early to late-planted soybeans. For our research, we utilized spatial reflectance data to

calculate three indicative indices: NDVI (Eq. 1), NDRE (Eq. 2), and WDRVI (Eq. 3), in addition to agronomic and meteorological data, to predict crop yield.

$$\text{NDVI} = (\rho\text{NIR} - \rho\text{red}) / (\rho\text{NIR} + \rho\text{red}) \quad (1)$$

$$\text{NDRE} = (\rho\text{NIR} - \rho\text{re}) / (\rho\text{NIR} + \rho\text{re}) \quad (2)$$

$$\text{WDRVI} = (a * \rho\text{NIR} - \rho\text{red}) / (a * \rho\text{NIR} + \rho\text{red}) \quad (3)$$

(The weighting coefficient (a) ranges between 0.1 and 0.2)

In the above Equation, ρ (rho) represents surface reflectance values. NIR = Near Infrared (865 nm), red = Red (665 nm), and re = Red edge (705 nm).

We have collected satellite data from March 31 (2021, 2022, and 2023) to October 8 with a mean temporal interval of 5 to 7 days (depending on satellite overpass and cloud cover; <10%). For the 2021 growing season, three data points (i.e., pixels) were extracted per plot. For 2022 and 2023, five data points per plot were extracted to predict soybean yield. Due to the plot size and pixel resolution, we included pixels that predominantly fall within the plot boundary to represent the values for each plot using the *Zonal statistic as table* function, which automatically considers only the pixels whose center lies within the defined plot boundary (ArcGIS Pro; v3.2.2). These pixel values represent reflectance-derived vegetation indices (VIs) within each plot. For interpretation, we grouped the growth stages into Early Vegetative (V1–V3), Late Vegetative (V4–V6), Early Reproductive (R1–R3), and Late Reproductive (R6–R7) stages to assist soybean growers in identifying optimal timing for yield prediction.

2.5. Statistical analysis and applied machine learning models

The model framework depicted in Figure 1.2 demonstrates the ML model development and data preparation process. Input data, including agronomic, meteorological, and satellite data, are presented in Table 1.3 for reference. A mixed-effects ANOVA was conducted in Python

(v3.11.12) using *pandas*, *numpy*, and *statsmodels* to evaluate the effects of planting date (main plot), seeding rates (subplot), and maturity group (sub-subplot) on soybean yield in a split-split-plot design with four blocks. In our study, planting dates, seeding rates, and maturity groups were treated as fixed effects. The blocks were treated as a random effect in the model. For our study, the model was fitted using *the mixedlm() function*, and *interaction effects were assessed accordingly for the other factors, including agronomic, meteorological, and remote sensing*. Tukey's Honest Significant Difference (HSD) test was performed using the *statsmodels* and *scipy* libraries (v3.11.12) to investigate significant differences in yield and meteorological variables across different planting dates, seeding rates, and MG. To determine the important agronomic, meteorological, and satellite data affecting crop yield, a Random Forest regressor was implemented using *sklearn.ensemble* (v3.11.12). In our study, we have selected four better-performed ML models for soybean yield prediction, including RF (from *sklearn.ensemble*), AdaBoost (from *sklearn.ensemble*), KNN (from *sklearn.neighbors*), and Least Absolute Shrinkage and Selection Operator (LASSO) (from *sklearn.linear_model*) (Aravind et al., 2022; Peerlinck et al., 2019; Prasad et al., 2021a; Sharifi, 2018; Suresh et al., 2021a). All packages were used in Python (version 3.11.12). The *train_test_split* function from *sklearn.model_selection* (Python v3.11.12) was used to assess model performance after the dataset was split into training (70%, n = 100) and testing (30%, n = 44). This function randomly shuffles the data before splitting (by default) to ensure no ordering bias and splits the dataset into mutually exclusive subsets for training and testing. The testing set remained independent from the training process to ensure an unbiased performance assessment. Proper hyperparameter tuning was done to deploy the optimal parameter settings for each model (Table 1.3). We observed two missing data points from Kansas Mesonet weather data during the 2022 growing

season (September 21, 2022, to September 22, 2022) and six for soil temperature during the 2023 growing season (April 28 to May 5, 2023). Due to the limited quantity of the missing data set, these calendar days were omitted from our dataset. The datasets were structured and cleaned using the *Pandas* and *NumPy* libraries (version 3.11.12), with categorical variables converted into binary form via One-hot encoding. All features were normalized using Min-Max scaling from the *scikit-learn.preprocessing* package (version 3.11.12).

2.5.1. Random forest (RF)

The Random Forest (RF) algorithm is a popular and extensively used method for predicting crop yields, as it detects and captures complex patterns and relationships in large datasets, such as agronomic and meteorological datasets (Pang et al., 2022; Raza et al., 2023). Therefore, in our study, we have used this RF algorithm. This algorithm improves the prediction accuracy of the model by combining multiple decision trees. In our study, for the RF model, input variables, such as agronomic, meteorological, and remote sensing data (as listed in Table 1.3), were used in each decision tree that was trained on a random dataset. After training each decision tree, averaging the predictions from all decision trees resulted in the final yield prediction ($\hat{Y}$) (Breiman, 2001; Prasath et al., 2023a). *n_estimators* determines the RF model and forest trees. In general, more trees improve stability but increase computation time. The *max_depth* parameter determines the maximum tree level based on the root node of the RF model. The deeper tree can create more splits and can catch more detailed information about the yield. The chances of overfitting decrease when the depths are smaller, as this makes the model less complex. The *min_samples_leaf* parameter defines the minimum number of samples that exist in a leaf node after the split. Higher values help reduce overfitting and smooth the model. The *min_samples_split* specifies the minimum number of data samples required in each node for

prediction. We tested the hyperparameters and selected the best values based on the error matrices, which are listed in Table 1.3. Therefore, the RF model combines the predictions from each decision tree and produces a stable and accurate crop yield prediction. The equation used for the RF model is

$$\hat{Y} = \frac{1}{N} \sum_{i=1}^N T_i(X)$$

$\hat{Y}$ is the final predicted yield

N is the number of decision trees in the RF model, controlled by `n_estimators`.

$T_i(X)$ is a prediction estimated by the i^{th} decision tree, which was trained using a random subset of the data.

X is the input features used in the model, as listed in Table 1.3

2.5.2. Adaptive Boosting (ADABOOST)

Adaptive Boosting (AdaBoost) was used in our research, which is capable of simulating intricate interactions between the input features and crop yield. This model employs a method of iteration and educates several learners who are not particularly strong (Seireg et al., 2022). The weak learners are shallow decision trees with limited depth, calculated using the input variables, including agronomic, meteorological, and remote sensing variables listed in Table 1.3. AdaBoost gives greater emphasis on previously mis-predicted samples by adjusting the weights of individual samples. Iterative reweighting progressively reduces prediction error and improves the final yield prediction $\hat{Y}(x)$ (Freund & Schapire, 1997). In the AdaBoost model, `n_estimators` indicates the number of weak learners (trees) combined sequentially. Also, the `learning_rate` controls the contribution of each tree to the overall model, which balances bias and variance. The

loss parameter specifies the loss function guiding model updates (Table 1.3). The final yield prediction using AdaBoost is:

$$\hat{Y}(x) = \sum_{n=1}^N \alpha_n T_n(x)$$

$$\alpha_n = \ln\left(\frac{1 - \varepsilon_n}{\varepsilon_n}\right)$$

$$\varepsilon_n = \frac{\sum_{i=1}^n w_i 1(y_i \neq T_n(x_i))}{\sum_{i=1}^n w_i}$$

$\hat{Y}(x)$ is the final predicted soybean yield for a given location or observation

N is the number of decision trees in the forest, controlled by the hyperparameter `n_estimators`.

$T_n(x)$ prediction from the n^{th} weak learner (a shallow decision tree).

α_n is the weight assigned to the n^{th} learner, based on its accuracy during training.

ε_n is the weighted error of the n^{th} learner.

w_i is the sample weight of observation i , updated after each iteration.

$(y_i \neq T_n(x_i))$ is an indicator function (1 if wrong prediction, 0 if correct).

2.5.3. K-Nearest Neighbors (KNN)

In our study, we have also used the k-Nearest Neighbors (KNN) algorithm. This is a non-parametric and instance-based model used in agricultural yield prediction because of its simplicity and ability to capture local patterns (Altman, 1992; Patrick & Fischer, 1970). In general, KNN relies on the “*Euclidean distance*” metric in feature space, which includes different input variables as listed in Table 1.3. This measures the distances in the feature space to identify similar instances and clusters. Yield prediction is then made by averaging the observed yields of the most similar data points. In KNN, we used $k=15$ and the Euclidean distance metric ($p=2$) to determine how similar the two data points appeared. In the new sample, the mean yield

of the 15 nearest neighbors in the training dataset was employed to make the final yield prediction. In KNN, $n_neighbors$ sets the number of *nearest neighbors* used for prediction, which affects model smoothness and complexity. For the KNN model, *Weights* assign equal importance to neighbors, while *leaf_size* affects nearest neighbor search speed. p parameter defines Euclidean distance metric, which affects neighbor measurement. The equation was

$$\hat{Y}(x) = \frac{1}{k} \sum_{i \in N_k(x)} y_i$$

$$d(x, x_i) = \sqrt{\sum_{j=1}^n (x_j - x_{ij})^2}$$

$\hat{Y}(x)$ is the predicted soybean yield for the new observation x

k number of nearest neighbors (here, $k=15$)

$N_k(x)$ the set of the k nearest training samples to x , based on the distance metric

y_i observed yield of the i^{th} neighbor.

$d(x, x_i)$ is distance between the new sample x and the i^{th} training sample

n number of input features (agronomic, meteorological, and remote sensing variables) as listed in Table 3.

x_j and x_{ij} values of the j^{th} feature for the new sample and the i^{th} training sample, respectively

2.5.4. Least Absolute Shrinkage and Selection Operator (LASSO)

The Least Absolute Shrinkage and Selection Operator (LASSO) algorithm primarily uses modified linear regression models. Due to the large datasets in our study, the multicollinearity problem exists in simple linear regression (Slinker & Glantz, 1985). In the context of soybean

yield prediction, where large datasets were used, LASSO regression uses regularization (a well-tuned penalty term) that keeps all the variables but reduces the magnitude of their coefficients in prediction. Additionally, it reduced the number of predictors in the regression model. It identified the important variables among the datasets used in our study, which includes meteorological parameters, satellite-derived indices, and agronomic factors that significantly impact soybean yield (Lockhart et al., 2014). For LASSO, *alpha* is the regularization parameter that controls the strength of the penalty on coefficients. The factor shrinks the less important factors toward zero to simplify the model and avoid overfitting. In the model, the *max_iter* feature limits the number of optimization iterations, and *selection* determines the coordinate descent approach used during fitting (Table 1.3).

2.6. Performance Metrics for Machine Learning Model

The predicted crop yield data from four ML models were compared against actual crop yield data for all three 3-fold cross-validation. The coefficient of determination (R^2) (Eq. 4), root mean square error (RMSE) (Eq. 5), mean absolute error (MAE) (Eq. 6), mean squared error (MSE) (Eq. 7), and mean absolute percentage error (MAPE) (Eq. 8) were used to compare the actual and predicted yield. All the error metrics for model performance were calculated using functions from *sklearn.metrics* package in Python (Version: 3.11.12).

$$R^2 = 1 - \frac{\sum_{i=1}^n (x_i - y_i)^2}{\sum_{i=1}^n (\bar{y} - y_i)^2} \quad (\text{Eq. 4})$$

(Least performed = 0; best performed = 1)

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (x_i - y_i)^2}{n}} \quad (\text{Eq. 5})$$

(Best performed = 0; Least performed = $+\infty$)

$$\text{MAE} = \frac{\sum_{i=1}^n |x_i - y_i|}{n} \quad (\text{Eq. 6})$$

(Best performed = 0; Least performed = + ∞)

$$MSE = \frac{\sum_{i=1}^n (x_i - y_i)^2}{n} \quad (\text{Eq. 7})$$

(Best performed = 0; Least performed = + ∞)

$$MAPE = \frac{\sum_{i=1}^n |x_i - y_i|}{n} \times 100\% \quad (\text{Eq. 8})$$

(Best performed = 0%; Least performed = 100%)

Where y represents the observed value for the i^{th} data, $\bar{y}$ represents the mean value of y , x represents the predicted value for the i^{th} data, and n represents the total number of validation data. Furthermore, we used an accuracy percentage and R^2 metric to evaluate the performance of the RF model at each growth stage. This metric quantifies the proportion of the prediction that falls within $\pm 10\%$ (Eq. 9) of the corresponding observed yield values. This index was selected for its lower sensitivity to outliers and simpler interpretation for growers.

$$\text{Accuracy Percentage} = \frac{\sum_{i=1}^n |\hat{y}_i - y_i| \leq \epsilon \times y_i}{n} \times 100\% \quad (\text{Eq. 9})$$

Where: $\hat{y}_i$ is the predicted yield for observation i , y_i is observed yield for observation i , ϵ = error tolerance level (0.01 for $\pm 10\%$), n is the total number of observations.

3. Results and Discussion

3.1. Seasonal Variability in Soybean Yield in North Central Kansas

To observe the seasonal yield variability, we investigated soybean yield from 2021 to 2023. The non-irrigated 2021 season had the lowest soybean yield potential, with a mean yield of 3.20 to 3.30 Mg/ha, a CV of 8.02 to 13.1%, and an SD of 0.26 to 0.42 Mg/ha (Table 1.4). In contrast, during the transition from rainfed to irrigated agriculture in north central Kansas, the 2022 growing season had a higher yield potential, with a mean yield of 4.62 to 5.24 Mg/ha and lower CV (7.39 to 9.97%) than the previous two years (Table 1.4). The average yield for the

2023 season was lower than the 2022 season, with values ranges from 3.36 Mg/ha to 3.49 Mg/ha and a higher CV (14.5 to 15.5%) (Table 1.4).

Based on the RF model, water-related factors within the meteorological variables were identified as major drivers of seasonal yield variation in north central Kansas (Figure 1.3). For the 2021 growing season, crop evapotranspiration (ET_c) was a key factor (Feature importance of 0.49) impacting soybean yield (Figure 1.3a). During the reproductive stage (flowering to pod filling), the mean ET_c varied from 4.10 to 4.91 mm per day (Table 1.4), which was below the optimal amount of 5.08 mm to 7.62 mm of water per day (Montoya et al., 2017). Mean precipitation was 25.19% and 39.34% lower than in 2022 and 2023 (Table 1.4; Figure 1.4), resulting in water stress and yield reductions. A similar study by Montoya et al (2017) observed that, in rainfed situations, soybeans produced 35% less yield compared to irrigated conditions. This reduction in soybean crop yield is due to inadequate water availability, which directly caused water stress in the soybean. The response of soybeans to water stress has been reported by various studies (Foroud et al., 1993; Karam et al., 2005; Korte et al., 1983; Momen et al., 1979). According to the literature review, water stress in soybeans, specifically in the reproductive stage, significantly reduces crop biomass and seed yield. This is due to a pronounced reduction in the number of pods and biomass, resulting in a 40% decrease in dry matter accumulation (Karam et al., 2005). Additionally, the lack of water availability has exacerbated crop water stress and indirectly affected dry matter accumulation by limiting evapotranspiration (ET_c). Moisture stress during seed filling lowers ET_c, reducing crop dry matter (Boamah et al., 2024). Furthermore, Karam et al. (2005) found that 65% of soybean evapotranspiration occurred during seed filling (R3 to R5), so moisture stress during seed filling reduces ET_c and crop dry matter accumulation. Soybean response to moisture stress also alters in

different growth stages. As reported by Foroud et al. (1993) and Karam et al. (2005), no significant reduction in soybean yield was observed during flowering (R2) if moisture stress occurred, which reflects an effective compensatory mechanism of the crop. However, moisture stress at the seed enlargement stage (R5) might cause a significant reduction of seed yield due to a reduction in pod number (Karam et al., 2005).

For the irrigated seasons (2022 and 2023), precipitation was the key factor affecting soybean yield (Figure 1.4b), with a feature importance of 0.64. During July 2022, the mean precipitation was 12.64% higher than the 60-year mean precipitation (Figure 1.4), which has positively impacted reproductive growth by increasing the number of pods and flower bud differentiation in soybeans (Hollinger & Changnon, 1994; Wang et al., 2020). Additionally, in July, the soybean plant entered a period of reproductive growth, during which effective rainfall was beneficial for flower bud differentiation in soybeans (Wang et al., 2020). This increased and evenly distributed precipitation in 2022 allowed the soybean crop to have consistent dry matter accumulation, resulting in higher yields across the region (Shaxson & Barber, 2003). However, in 2023, the soybean crop experienced a sharp decline in July mean precipitation (43.16% lower than the 60-year mean), followed by excessive rainfall in August (48.26% above the 60-year mean) (Figure 1.4). Excessive precipitation during August in the 2023 growing season resulted in pod shattering, unfavorable seed germination, lodging, and contamination. In fact, excess precipitation for more than seven days causes 17 to 43 % damage in the soybean root system (Wang et al., 2020). This temporal imbalance in water availability during the critical growth stages can suppress the soybean yield, despite supplemental irrigation. It is projected that excess precipitation in August can lead to increased insurance losses of \$0.593/ha (\$0.24/acre) to \$0.741/ha (\$0.30/acre) in soybean (Wang et al., 2020). Additionally, based on the Palmer

Drought Severity Index (PDSI), the central and eastern part of Kansas tends to be wetter (Lin et al., 2017). This increased precipitation would result in a 0.63 Mg/ha (9.43 bu/acre) soybean yield reduction in the RCP4.5 scenario (lower emission) to a 0.92 Mg/ha (13.7 bu/acre) yield reduction in the RCP8.5 scenario (higher emission) by 2050 (Wang et al., 2020).

3.2. Temporal Variability in Soybean Yield in North Central Kansas

Our study also found temporal variation across planting dates. The mean yield of early planted soybeans was significantly higher (5.24 Mg/ha) compared to mid (4.86 Mg/ha) and late (4.62 Mg/ha) planted soybeans during the transition from rainfed to irrigated agriculture in 2022 (Table 1.4). This yield was significantly higher than the yield of late-planted soybeans (4.62 Mg/ha). However, yield differences among planting dates were not statistically significant in 2021 ($p = 0.67$) and 2023 ($p = 0.75$). Despite the non-significant results, descriptive statistics demonstrated an important trend: in 2021 and 2022, the minimum yield potential decreased progressively from early to late planting dates, whereas in 2023, the maximum yield potential also declined across the planting dates (Table 1.4). Additionally, across seasons, early planted soybeans have resulted in higher mean yields (3.75 to 4.32 Mg/ha) than mid-planted (3.74 to 4.15 Mg/ha) and late planted (3.64 to 3.93 Mg/ha) soybeans (Figure 1.5c). This can be attributed to the meteorological variables, which have a negative impact on mid- and late-planted soybeans.

For example, in 2022, the amount and distribution of rain varied greatly across three planting dates (Table 1.4) (p -value = 0.05). Early planted soybeans received 12.10% and 27.95% more precipitation than crops than mid and late planted soybeans, respectively (Table 1.4). Additionally, there was a significant decrease in ET_c from early and planted crops to late-planted crops, which indicates water stress during the reproductive stage (p -value = 0.05) (Table 1.4). Late and mid-planted soybeans accounted for 10.68 % to 4.74 % less ET_c than early planted

soybeans, respectively. It leads to a reduction in yield from early to mid- and late planting dates (Table 1.4) with high CV, SD, and ranges (Table 1.4) as there is a linear relationship between ETc and dry matter accumulated in the crop. According to previous studies, drought stress during the reproductive stage of soybeans can have a major effect on crop yield by lowering flower and pod abortions (Poudel et al., 2023; Westgate & Peterson, 1993). Drought stress imposed at R3, R5, and R6 soybean stages might contribute to significant yield reduction compared (Meghraoui et al., 2024). Specifically, water stress during the R5 stage causes a significant reduction in plant height by approximately 7%, the number of pod-bearing nodes by 13%, and the number of seeds and total dry matter by 20% and 23%, respectively (Foroud et al., 1993). Water stress increases the levels of reactive oxygen species (ROS) in plants, which causes oxidative stress. This damages cells, causes ions to leak outside, and ultimately destroys the cells (Ahanger et al., 2017). Additionally, water stress decreases the absorption and translocation of mineral nutrients in the plants. An interesting study conducted by Jin et al. (2006) revealed that, due to water stress, Phosphorus (P) translocation is limited to the seed, which contributes to decreased grain yield.

Furthermore, we found that the air temperature for mid- and late-planted soybeans was higher (~1.6 to 3.2 °C) than for early planted soybeans. This increase in temperature is crucial, as Lobell & Asner (2003) suggested that a 1°C increase in temperature decreases mean soybean yield by 17%. Quantitatively, soybean crops are more susceptible to higher cumulative heat units. A three-degree Celsius increase in maximum temperature reduced soybean production by 50%. (Lal et al., 1999). Another finding by Sharma et al. (2022) suggested that a 1°C increase in minimum temperature and maximum temperature decreases soybean yield by 31.6% 5 and 25.6 % respectively. So, early planting is always suggested to cope with the water stress during the

growing season in this region. Furthermore, ongoing observations in 2024 indicate that late-planted soybeans are subjected to lodging effects due to high wind and precipitation during the late reproductive stage, which may lead to pod-shattering, unfavorable seed germination, lodging, and contamination (Figure 1.7). Along with that, if we plant early, it enables growers to utilize inherent soil moisture and nutrients from the previous crop (corn for this study) (Bongiovanni & Lowenberg-Deboer, 2004; Subedi & Ma, 2011). These findings suggest that early planting has the potential to maximize yield potential. This aligns with the results from (Ciampitti et al., 2022). who estimated a yield loss of 0.02 Mg/ha (0.3 bu/acre) per day as planting dates shift later in the season.

3.3. Interaction Between Maturity Group, Seeding Rate, and Planting Dates in Soybean

For each of the three growing seasons, we have also evaluated the maturity group (MG) performance and seeding rate. MG 4 performed better than maturity group 3 during the 2023 season ($p\text{-value} < 0.05$) (Figure 1.5a). MG 4 has also outperformed the maturity group 3 for the 2021 and 2022 growing season, as shown in Figure 1.5a with a higher mean yield (3.33 to 3.72 Mg/ha) than MG 3 (3.10 to 3.19 Mg/ha). We have observed no significant differences in yield between low and high seeding rates for all three growing seasons. In contrast, the 2021 and 2022 growing seasons with low seeding rates had higher CV and SD and more yield variability. (Figure 1.5b). Early planted soybeans with MG 4 and a low seeding rate (E_Low_MG4) have shown a higher mean yield (4.32 Mg/ha) due to the interaction between the treatments (Figure 1.5c). However, the combination E_High_MG4 has also demonstrated a comparatively higher mean yield (4.05 Mg/ha). This demonstrated the adaptability of MG 4 with early planting with minimal effect of seeding rates. While early planted soybeans have contributed to higher yields, they have also introduced a greater risk due to increased yield variability and unpredictability,

primarily because of the alterations in meteorological factors. As demonstrated in our research, early planted soybeans exhibited a higher coefficient of variation (23.2 to 27.5%) than mid (14.0 to 25.7%) and late (14.6 to 25.3%) planting dates (Figure 1.5c). Therefore, incorporating a multi-planting date strategy tailored to local meteorological variables using ML models can enhance yield stability, specifically in Kansas, where the growers are shifting their planting dates earlier.

3.4. Evaluation of Machine Learning Models for Yield Prediction in North Central Kansas

Seasonal and temporal variability can be addressed by advanced ML algorithms. The use of advanced ML algorithms is gaining popularity among growers and farmers for three main reasons: their computational simplicity, increasing data availability, and a wider selection of tools. To address the variability in soybean yield, specifically during early growth stages, we incorporated ML models into our study. Among the four ML models used in our study (RF, AdaBoost, KNN and LASSO), RF and AdaBoost models comparatively outperformed the others in terms of accuracy, with R^2 values (0.79 to 0.80), RMSE values (0.38 to 0.39 Mg/ha), MAE value (0.31Mg/ha), MSE values (0.14 to 0.15 Mg/ha), and MAPE values (0.08%) in the testing datasets (Figure 1.6). It suggests that, for this specific site (North Central Part of Kansas), the RF and AdaBoost models were suitable for data types related to soybean yield prediction.

Among the well-performing models in this study (RF and AdaBoost), RF has performed slightly better in yield prediction in terms of R^2 value (0.80), RMSE (0.38 Mg/ha), MSE (0.14 Mg/ha), MAE (0.31 Mg/ha), and MAPE (0.08%) (Figure 1.6a). The RF model is a supervised regression algorithm that creates multiple decision trees using the selected dataset at each split. Earlier research has demonstrated the effectiveness of the RF model for crop yield prediction under field crops, such as corn (Jeong et al., 2016), wheat (Pang et al., 2022), potato (Jeong et al., 2016), and soybean (Sakamoto, 2020), with climate and biophysical parameters at a global

and regional scale. The reason for the performance of the RF model is due to its ensemble-based approach (Suresh et al., 2021b), which builds multiple decision trees from subsets of the datasets and aggregates their outputs to improve accuracy. This structure makes the model more robust and less prone to overfitting, which is frequently observed with agricultural datasets that have noise and variability in the environment. This finding is consistent with other researchers (Geetha et al., 2020; Kiran Moraye et al., 2021; Prasad et al., 2021b; Suresh et al., 2021b; Suruliandi et al., 2021; Yamparla et al., 2022). Our results showed that the accuracy of the predictive RF model changes with optimized use of hyperparameters. For example, we noticed in our study that the RF model with 100 as $n_estimators$ performed better (R^2 : 0.80) than the RF model with 300, 600, and 1200 as $n_estimators$ (R^2 : 0.78). This result is consistent with the result found by Santos et al (2024).

AdaBoost also performed well with R^2 value (0.79), RMSE (0.39 Mg/ha), MSE (0.15 Mg/ha), MAE (0.31 Mg/ha), and MAPE (0.08%) (Figure 1.6b). AdaBoost is an ensemble-type algorithm (Cao et al., 2013) that has the adaptive reweighting mechanism to handle complex datasets. This algorithm creates a sequential model based on modified datasets in our research. The following model performs better than the previous model for yield prediction, and it assigns higher weights to the error that was associated with the previous iterations. A study conducted by Nagesh et al (2024) concluded that the performance of the AdaBoost model is more accurate for crop yield prediction, with 98% accuracy and a 99% Recall rate. Furthermore, the KNN model performed comparably regarding error metrics (Figure 1.6c), due to its non-parametric nature and simplicity in capturing local patterns in complex agricultural datasets (Srisuradetchai & Suksrikran, 2024). This model predicts outcomes based on the average response of the nearest

neighbors in the feature space, therefore being more effective when similar variables, such as planting date, weather, or vegetation indices, provide similar results.

The LASSO model did not perform better than other ML models in our study. The R^2 , RMSE, MAE, MSE, and MAPE values were 0.57, 0.55 Mg/ha, 0.47 Mg/ha, 0.30 Mg/ha, and 0.12%, respectively (Figure 1.6d). The LASSO algorithm normally presumes a linear relationship between features and target variables (Tibshirani et al., 2012). For soybean yield prediction, a complex nonlinear relationship exists among agronomic, meteorological, and environmental variables. The LASSO regression is well known for its feature selection and interpretability. The performance of LASSO may be limited when dealing with high-dimensional nonlinear datasets in soybean yield prediction (Friedman et al., 2010). Additionally, LASSO-based methods may have difficulty differentiating between predictors when the predictors are highly correlated (Zou & Hastie, 2005). In yield prediction, meteorological variables such as ETc, air temperature, and precipitation are highly correlated, which can create some error in the LASSO model in the appropriate variable selection. This result aligns with prior research (Cai et al., 2019; Leroux et al., 2020), indicating that nonlinear models outperformed linear models (LASSO).

Among the remote sensing factors for all years, NDRE was the most important feature, with an Importance score of 0.41 (using the RF regressor). Additionally, regarding meteorological factors for all the years, ETc was the most important feature influencing the ML performance of ML model, with an importance score of 0.73. This high sensitivity indicates that ETc and NDRE were important in determining soybean yield and model performance. However, it is important to consider the interplay between ETc and other meteorological variables (especially air, soil temperature, and precipitation) to ensure model performance, as ETc is

governed mainly by these factors. Overall, our findings highlight the importance of using advanced ML techniques, specifically AdaBoost and RF models for North Central Kansas, which represents Zone 2, to establish data-driven plans for efficient resource allocation, food distribution, and price stabilization.

3.5. Selecting The Best Time for Collecting Satellite Imagery for Soybean Yield Prediction

In our study, based on the satellite data collection, we observed that the accuracy percentage of soybean yield has increased from the early vegetative (V1) stage to the physiological maturity stage (R7). The accuracy percentage has increased from 68.19 to 80.97 % (10% error percentage), with R^2 increased from 0.566 to 0.720 (Table 1.5). During the initial stages of the vegetative stage (V1-V3), the accuracy percentage and R^2 were relatively low at 68.89% and 0.587, respectively. Early in crop production, accurate measurements were low due to reflections from undesirable surroundings or background reflectance errors from rocks, soil, and weeds. This has reduced the accuracy of satellite image collection (Roznik et al., 2022). Additionally, the residues from previously harvested crops affected by biotic and abiotic stressors might reduce the accuracy percentage. This is consistent with a study conducted by Joshi et al (2024). According to the research, after soybean emergence (VE), all the VIs were poorly correlated with soybean crop yield (Joshi et al., 2024). We have observed that, accuracy percentage started improving from the early to the late vegetative stage (V4-V6) with an accuracy percentage of 73.61 % and R^2 of 0.629. This is because, as the plant started growing and covering the canopy, the accuracy percentage began to improve, which discards the other particles, previous season residues, and other vegetation. A higher accuracy percentage helps producers regulate input for reproductive growth stages, which require considerable amounts of input. This information can help farmers to plan for the market and mitigate risks for the in-

season or coming growing season. According to Bai et al (2022), soybean yield, particularly grain number per plant, had a weaker correlation before emergence than at the trifoliate stage, with yield prediction increasing from the third trifoliate stage to the late vegetative stage (V6).

During reproductive stages, the accuracy percentage was relatively higher with complete flowering and initial pod development stage (R2-R3), complete pod and beginning of seed stage (R4-R5), and whole seed and physiological maturity stage (R6-R7). The accuracy percentage ranged from 71.39% to 80.97% and the R^2 values ranged from 0.697 to 0.720, respectively (Table 1.5). Similar observations were observed for coefficients of determination (R^2) with soybean yield during the physiological maturity stage (R6/R7) were reported by Joshi et al (2024). Another study by Khaki et al (2021) mentioned that the collection time for satellite images is important for soybean yield prediction. Satellite images collected during the month of August have higher accuracy for soybean yield prediction (Khaki et al., 2021). A comparatively higher R^2 value (0.697 to 0.720) in the R4-R5 stage (Table 1.5) was also observed during that time. This result is consistent with other reports (Ma et al., 2001; Stepanov et al., 2020). Our study found that both the late vegetative and reproductive stages performed well in terms of accuracy percentage; however, higher accuracy percentages in the late vegetative stage are more important for input resource management, market planning, and risk mitigation. The differences found among various authors regarding the optimal stage for yield predictions can be attributed to differences in varieties, soil type, and climatic conditions. So, from the production perspective in the North Central part of Kansas, satellite imagery collection during the late reproductive stage near the physiological maturity stage is valuable for yield prediction and economic evaluation.

4. Conclusions

Soybean production in north-central Kansas is affected by seasonal and temporal variability. This is primarily due to changing environmental conditions throughout the season and the associated planting dates. In our study, we found that early-planted soybeans and maturity group 4 (MG4) had a higher mean yield (4.05 to 4.32 Mg/ha) (E_Low/High_MG4). This highlights the significance of determining maturity groups based on location, as MG 4 performed better with early-planted soybeans. However, early-season planting also introduced a higher degree of yield variability and unpredictability under variable meteorological conditions, with a coefficient of variation (CV) ranging from 23.2% to 27.5%.

Therefore, data-driven, machine learning models that incorporate planting dates as an input, adapted to regional meteorological conditions, may enhance yield stability. In our research, Random Forest and AdaBoost models accurately predicted soybean yield ($R^2 = 0.79$ to 0.80). These models utilized high-resolution remote sensing and meteorological variables to account for variability in planting dates. This finding is significant for Kansas farmers, as a growing number of farmers in Kansas are planting early. These insights also help farmers make informed decisions about soybean planting management. This can be achieved by using proper agronomic input strategies, such as identifying the best planting dates and crop varieties.

Our findings also showed that yield accuracy increased as the crop matured from emergence to reproductive stages. The late vegetative and reproductive stages had the highest accuracy and R^2 . It highlights the importance of timing in satellite data collection for remote sensing monitoring. This is also beneficial for decision-making related to input applications, market planning, and risk mitigation. The current study incorporated high-resolution satellite imagery (PlanetScope) to support yield prediction at a plot level. Future research will expand this

work to a large scale and integrate UAV-based approaches with more data layers. This includes soil data for more detailed yield and grain quality prediction.

Building on these findings, Chapter 2 extends the focus from yield prediction to the underlying climatic and hydrological processes that affect yield variability. Since ET emerged as the most important weather factor affecting crop yield, the next chapter explores how remote sensing-based ET estimation can be used to quantify crop water use, identify periods of water stress, and evaluate irrigation systems. This shift from yield modeling to water dynamics establishes the link between predictive modeling and on-farm water management in Kansas irrigated farms.

References

- Ahanger, M. A., Tomar, N. S., Tittal, M., Argal, S., & Agarwal, R. M. (2017). Plant growth under water/salt stress: ROS production; antioxidants and significance of added potassium under such conditions. *Physiology and Molecular Biology of Plants*, 23(4), 731–744. <https://doi.org/10.1007/s12298-017-0462-7>
- Al-Gaadi, K. A., Hassaballa, A. A., Tola, E., Kayad, A. G., Madugundu, R., Alblewi, B., & Assiri, F. (2016). Prediction of Potato Crop Yield Using Precision Agriculture Techniques. *PLOS ONE*, 11(9), e0162219. <https://doi.org/10.1371/journal.pone.0162219>
- Altman, N. S. (1992). An Introduction to Kernel and Nearest-Neighbor Nonparametric Regression. *The American Statistician*, 46(3), 175–185. <https://doi.org/10.1080/00031305.1992.10475879>
- Aravind, K. S., Vashisth, A., Krishanan, P., & B.DAS. (2022). Wheat yield prediction based on weather parameters using multiple linear, neural network and penalised regression

- models. *Journal of Agrometeorology*, 24(1), Article 1.
<https://doi.org/10.54386/jam.v24i1.1002>
- Bai, D., Li, D., Zhao, C., Wang, Z., Shao, M., Guo, B., Liu, Y., Wang, Q., Li, J., Guo, S., Wang, R., Li, Y., Qiu, L., & Jin, X. (2022). Estimation of soybean yield parameters under lodging conditions using RGB information from unmanned aerial vehicles. *Frontiers in Plant Science*, 13, 1012293. <https://doi.org/10.3389/fpls.2022.1012293>
- Boamah, P. O., Onumah, J., Apam, B., Salifu, T., Abunkudugu, A. A., & Alabil, S. A. (2024). Climate variability impact on crop evapotranspiration in the upper East region of Ghana. *Environmental Challenges*, 14, 100828. <https://doi.org/10.1016/j.envc.2023.100828>
- Bongiovanni, R., & Lowenberg-Deboer, J. (2004). Precision Agriculture and Sustainability. *Precision Agriculture*, 5(4), 359–387.
<https://doi.org/10.1023/B:PRAG.00000040806.39604.aa>
- Breiman, L. (2001). Random Forests. *Machine Learning*, 45(1), 5–32.
<https://doi.org/10.1023/A:1010933404324>
- Cai, Y., Guan, K., Lobell, D., Potgieter, A. B., Wang, S., Peng, J., Xu, T., Asseng, S., Zhang, Y., You, L., & Peng, B. (2019). Integrating satellite and climate data to predict wheat yield in Australia using machine learning approaches. *Agricultural and Forest Meteorology*, 274, 144–159. <https://doi.org/10.1016/j.agrformet.2019.03.010>
- Cao, Y., Miao, Q.-G., Liu, J.-C., & Gao, L. (2013). Advance and Prospects of AdaBoost Algorithm. *Acta Automatica Sinica*, 39(6), 745–758. [https://doi.org/10.1016/S1874-1029\(13\)60052-X](https://doi.org/10.1016/S1874-1029(13)60052-X)
- Checkoff, S. (2023, August 29). New Study Finds U.S. Soybean Industry Has \$124 Billion Impact on the United States Economy. *United Soybean Board*.

- <https://unitedsoybean.org/hopper/new-study-finds-u-s-soybean-industry-has-124-billion-impact-on-the-united-states-economy/>
- Ciampitti, I. (2020). *Agronomy eUpdate April 24th, 2020: Issue 796*.
- https://eupdate.agronomy.ksu.edu/article_new/soybean-seeding-rates-and-optimum-plant-populations-384-6
- Ciampitti, I., Correndo, A., & Versendaal, E. (2022). *Agronomy eUpdate April 14th, 2022: Issue 902*. https://eupdate.agronomy.ksu.edu/article_new/soybean-planting-date-and-maturity-group-selection-490
- Crusiol, L. G. T., Nanni, M. R., Furlanetto, R. H., Sibaldelli, R. N. R., Cezar, E., Sun, L., Foloni, J. S. S., Mertz-Henning, L. M., Nepomuceno, A. L., Neumaier, N., & Farias, J. R. B. (2021). Yield Prediction in Soybean Crop Grown under Different Levels of Water Availability Using Reflectance Spectroscopy and Partial Least Squares Regression. *Remote Sensing*, 13(5), Article 5. <https://doi.org/10.3390/rs13050977>
- Doorenbos, J., & Pruitt, W. O. (1975). Guidelines for predicting crop water requirements. *Irrigation and Drainage Paper (FAO)*, 24.
- <https://agris.fao.org/search/en/providers/122621/records/64711cc89dd8810bf64b2e0f>
- Elbasi, E., Zaki, C., Topcu, A. E., Abdelbaki, W., Zreikat, A. I., Cina, E., Shdefat, A., & Saker, L. (2023). Crop Prediction Model Using Machine Learning Algorithms. *Applied Sciences*, 13(16), Article 16. <https://doi.org/10.3390/app13169288>
- Foroud, N., Mündel, H.-H., Saindon, G., & Entz, T. (1993). Effect of level and timing of moisture stress on soybean plant development and yield components. *Irrigation Science*, 13(4), 149–155. <https://doi.org/10.1007/BF00190029>

- Freund, Y., & Schapire, R. E. (1997). A Decision-Theoretic Generalization of On-Line Learning and an Application to Boosting. *Journal of Computer and System Sciences*, 55(1), 119–139. <https://doi.org/10.1006/jcss.1997.1504>
- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–22.
- Gajula, A. K., Singamsetty, J., Dodda, V. C., & Kuruguntla, L. (2021). Prediction of crop and yield in agriculture using machine learning technique. *2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, 1–5. <https://doi.org/10.1109/ICCCNT51525.2021.9579843>
- Gayathiri, B., Brindha, P., Karthika, I., Saranya, E., Rajeshkumar, G., & Rajesh Kanna, P. (2023). Machine Learning based Crop Suitability Prediction and Fertiliser Recommendation System. *2023 4th International Conference on Electronics and Sustainable Communication Systems (ICESC)*, 1023–1028. <https://doi.org/10.1109/ICESC57686.2023.10193542>
- Geetha, V., Punitha, A., Abarna, M., Akshaya, M., Illakiya, S., & Janani, A. P. (2020). An Effective Crop Prediction Using Random Forest Algorithm. *2020 International Conference on System, Computation, Automation and Networking (ICSCAN)*, 1–5. <https://doi.org/10.1109/ICSCAN49426.2020.9262311>
- Gitelson, A. A. (2004). Wide Dynamic Range Vegetation Index for Remote Quantification of Biophysical Characteristics of Vegetation. *Journal of Plant Physiology*, 161(2), 165–173. <https://doi.org/10.1078/0176-1617-01176>

- Gümüşçü, A., Tenekeci, M. E., & Bilgili, A. V. (2020). Estimation of wheat planting date using machine learning algorithms based on available climate data. *Sustainable Computing: Informatics and Systems*, 28, 100308. <https://doi.org/10.1016/j.suscom.2019.01.010>
- Haboudane, D., Miller, J. R., Pattey, E., Zarco-Tejada, P. J., & Strachan, I. B. (2004). Hyperspectral vegetation indices and novel algorithms for predicting green LAI of crop canopies: Modeling and validation in the context of precision agriculture. *Remote Sensing of Environment*, 90(3), 337–352. <https://doi.org/10.1016/j.rse.2003.12.013>
- Hamed, R., Van Loon, A. F., Aerts, J., & Coumou, D. (2021). Impacts of compound hot–dry extremes on US soybean yields. *Earth System Dynamics*, 12(4), 1371–1391. <https://doi.org/10.5194/esd-12-1371-2021>
- Hill, J., Nelson, E., Tilman, D., Polasky, S., & Tiffany, D. (2006). Environmental, economic, and energetic costs and benefits of biodiesel and ethanol biofuels. *Proceedings of the National Academy of Sciences*, 103(30), 11206–11210. <https://doi.org/10.1073/pnas.0604600103>
- Hollinger, S. E., & Changnon, S. A. (n.d.). *Response of Corn and Soybean Yields to Precipitation Augmentation, and Implications for Weather Modification in Illinois*.
- Horie, T., Yajima, M., & Nakagawa, H. (1992). Yield forecasting. *Agricultural Systems*, 40(1), 211–236. [https://doi.org/10.1016/0308-521X\(92\)90022-G](https://doi.org/10.1016/0308-521X(92)90022-G)
- Huang, S., Tang, L., Hupy, J. P., Wang, Y., & Shao, G. (2021). A commentary review on the use of normalized difference vegetation index (NDVI) in the era of popular remote sensing. *Journal of Forestry Research*, 32(1), 1–6. <https://doi.org/10.1007/s11676-020-01155-1>

- Ilyas, Q. M., & Ahmad, M. (2020). Smart Farming: An Enhanced Pursuit of Sustainable Remote Livestock Tracking and Geofencing Using IoT and GPRS. *Wireless Communications and Mobile Computing*, 2020, e6660733. <https://doi.org/10.1155/2020/6660733>
- Imran, H. A., Gianelle, D., Rocchini, D., Dalponte, M., Martín, M. P., Sakowska, K., Wohlfahrt, G., & Vescovo, L. (2020). VIS-NIR, Red-Edge and NIR-Shoulder Based Normalized Vegetation Indices Response to Co-Varying Leaf and Canopy Structural Traits in Heterogeneous Grasslands. *Remote Sensing*, 12(14), Article 14. <https://doi.org/10.3390/rs12142254>
- Iniyar, S., Akhil Varma, V., & Teja Naidu, C. (2023). Crop yield prediction using machine learning techniques. *Advances in Engineering Software*, 175, 103326. <https://doi.org/10.1016/j.advengsoft.2022.103326>
- Jeong, J. H., Resop, J. P., Mueller, N. D., Fleisher, D. H., Yun, K., Butler, E. E., Timlin, D. J., Shim, K.-M., Gerber, J. S., Reddy, V. R., & Kim, S.-H. (2016). Random Forests for Global and Regional Crop Yield Predictions. *PLOS ONE*, 11(6), e0156571. <https://doi.org/10.1371/journal.pone.0156571>
- Ji, Z., Pan, Y., Zhu, X., Wang, J., & Li, Q. (2021). Prediction of Crop Yield Using Phenological Information Extracted from Remote Sensing Vegetation Index. *Sensors*, 21(4), Article 4. <https://doi.org/10.3390/s21041406>
- Jin, J., Wang, G., Liu, X., Pan, X., Herbert, S. J., & Tang, C. (2006). Interaction Between Phosphorus Nutrition and Drought on Grain Yield, and Assimilation of Phosphorus and Nitrogen in Two Soybean Cultivars Differing in Protein Concentration in Grains. *Journal of Plant Nutrition*, 29(8), 1433–1449. <https://doi.org/10.1080/019041606000837089>

- Johnson, D. M. (2016). A comprehensive assessment of the correlations between field crop yields and commonly used MODIS products. *International Journal of Applied Earth Observation and Geoinformation*, 52, 65–81. <https://doi.org/10.1016/j.jag.2016.05.010>
- Joshi, D. R., Clay, S. A., Sharma, P., Rekabdarkolaee, H. M., Kharel, T., Rizzo, D. M., Thapa, R., & Clay, D. E. (2024). Artificial intelligence and satellite-based remote sensing can be used to predict soybean (*Glycine max*) yield. *Agronomy Journal*, 116(3), 917–930. <https://doi.org/10.1002/agj2.21473>
- K, R., & V, B. (2024). Optimizing Crop Yield Prediction through Multiple Models: An Ensemble Stacking Approach. *International Journal of Data Informatics and Intelligent Computing*, 3(2), Article 2. <https://doi.org/10.59461/ijdiic.v3i2.120>
- Kang, Y., Meng, Q., Liu, M., Zou, Y., & Wang, X. (2021). Crop Classification Based on Red Edge Features Analysis of GF-6 WFV Data. *Sensors (Basel, Switzerland)*, 21(13), 4328. <https://doi.org/10.3390/s21134328>
- Karam, F., Masaad, R., Sfeir, T., Mounzer, O., & Rouphael, Y. (2005). Evapotranspiration and seed yield of field grown soybean under deficit irrigation conditions. *Agricultural Water Management*, 75(3), 226–244. <https://doi.org/10.1016/j.agwat.2004.12.015>
- Khaki, S., Pham, H., & Wang, L. (2021). Simultaneous corn and soybean yield prediction from remote sensing data using deep transfer learning. *Scientific Reports*, 11(1), 11132. <https://doi.org/10.1038/s41598-021-89779-z>
- Khaki, S., & Wang, L. (2019). Crop Yield Prediction Using Deep Neural Networks. *Frontiers in Plant Science*, 10, 621. <https://doi.org/10.3389/fpls.2019.00621>

- Kiran Moraye, Pavate, A., Suyog Nikam, & Smit Thakkar. (2021). *Crop Yield Prediction Using Random Forest Algorithm for Major Cities in Maharashtra State* (SSRN Scholarly Paper No. 3832826). <https://papers.ssrn.com/abstract=3832826>
- Korte, L. L., Specht, J. E., Williams, J. H., & Sorensen, R. C. (1983). Irrigation of Soybean Genotypes During Reproductive Ontogeny II. Yield Component Responses. *Crop Science*, 23(3), crops1983.0011183X002300030020x. <https://doi.org/10.2135/crops1983.0011183X002300030020x>
- Lal, M., Singh, K. K., Srinivasan, G., Rathore, L. S., Naidu, D., & Tripathi, C. N. (1999). Growth and yield responses of soybean in Madhya Pradesh, India to climate variability and change. *Agricultural and Forest Meteorology*, 93(1), 53–70. [https://doi.org/10.1016/S0168-1923\(98\)00105-1](https://doi.org/10.1016/S0168-1923(98)00105-1)
- Leroux, L., Falconnier, G. N., Diouf, A. A., Ndao, B., Gbodjo, J. E., Tall, L., Balde, A. A., Clermont-Dauphin, C., Bégué, A., Affholder, F., & Roupsard, O. (2020). Using remote sensing to assess the effect of trees on millet yield in complex parklands of Central Senegal. *Agricultural Systems*, 184, 102918. <https://doi.org/10.1016/j.agsy.2020.102918>
- Li, F., Miao, Y., Chen, X., Sun, Z., Stueve, K., & Yuan, F. (2022). In-Season Prediction of Corn Grain Yield through PlanetScope and Sentinel-2 Images. *Agronomy*, 12(12), Article 12. <https://doi.org/10.3390/agronomy12123176>
- Li, F., Mistele, B., Hu, Y., Chen, X., & Schmidhalter, U. (2014). Reflectance estimation of canopy nitrogen content in winter wheat using optimised hyperspectral spectral indices and partial least squares regression. *European Journal of Agronomy*, 52, 198–209. <https://doi.org/10.1016/j.eja.2013.09.006>

- Liben, F., Abera, W., Chernet, M. T., Ebrahim, M., Tilaye, A., Erkossa, T., Degefie, D. T., Mponela, P., Kihara, J., & Tamene, L. (2024). Site-specific fertilizer recommendation using data driven machine learning enhanced wheat productivity and resource use efficiency. *Field Crops Research*, 313, 109413. <https://doi.org/10.1016/j.fcr.2024.109413>
- Lin, X., Harrington, J., Ciampitti, I., Gowda, P., Brown, D., & Kisekka, I. (2017). Kansas Trends and Changes in Temperature, Precipitation, Drought, and Frost-Free Days from the 1890s to 2015. *Journal of Contemporary Water Research & Education*, 162(1), 18–30. <https://doi.org/10.1111/j.1936-704X.2017.03257.x>
- Liu, K. (1997). Chemistry and Nutritional Value of Soybean Components. In K. Liu (Ed.), *Soybeans: Chemistry, Technology, and Utilization* (pp. 25–113). Springer US. https://doi.org/10.1007/978-1-4615-1763-4_2
- Lobell, D. B., & Asner, G. P. (2003). Climate and Management Contributions to Recent Trends in U.S. Agricultural Yields. *Science*, 299(5609), 1032–1032. <https://doi.org/10.1126/science.1078475>
- Lockhart, R., Taylor, J., Tibshirani, R. J., & Tibshirani, R. (2014). A SIGNIFICANCE TEST FOR THE LASSO. *Annals of Statistics*, 42(2), 413–468. <https://doi.org/10.1214/13-AOS1175>
- Lu, W., Du, R., Niu, P., Xing, G., Luo, H., Deng, Y., & Shu, L. (2022). Soybean Yield Preharvest Prediction Based on Bean Pods and Leaves Image Recognition Using Deep Learning Neural Network Combined With GRNN. *Frontiers in Plant Science*, 12. <https://doi.org/10.3389/fpls.2021.791256>

- Ma, B. L., Dwyer, L. M., Costa, C., Cober, E. R., & Morrison, M. J. (2001). Early Prediction of Soybean Yield from Canopy Reflectance Measurements. *Agronomy Journal*, 93(6), 1227–1234. <https://doi.org/10.2134/agronj2001.1227>
- Marques Ramos, A. P., Prado Osco, L., Elis Garcia Furuya, D., Nunes Gonçalves, W., Cordeiro Santana, D., Pereira Ribeiro Teodoro, L., Antonio da Silva Junior, C., Fernando Capristo-Silva, G., Li, J., Henrique Rojo Baio, F., Marcato Junior, J., Eduardo Teodoro, P., & Pistori, H. (2020). A random forest ranking approach to predict yield in maize with uav-based vegetation spectral indices. *Computers and Electronics in Agriculture*, 178, 105791. <https://doi.org/10.1016/j.compag.2020.105791>
- Marshall, M., Belgiu, M., Boschetti, M., Pepe, M., Stein, A., & Nelson, A. (2022). Field-level crop yield estimation with PRISMA and Sentinel-2. *ISPRS Journal of Photogrammetry and Remote Sensing*, 187, 191–210. <https://doi.org/10.1016/j.isprsjprs.2022.03.008>
- Medina, H., Tian, D., & Abebe, A. (2021). On optimizing a MODIS-based framework for in-season corn yield forecast. *International Journal of Applied Earth Observation and Geoinformation*, 95, 102258. <https://doi.org/10.1016/j.jag.2020.102258>
- Meghraoui, K., Sebari, I., Pilz, J., Ait El Kadi, K., & Bensiali, S. (2024). Applied Deep Learning-Based Crop Yield Prediction: A Systematic Analysis of Current Developments and Potential Challenges. *Technologies*, 12(4), Article 4. <https://doi.org/10.3390/technologies12040043>
- Mishra, S., Mishra, D., & Santra, G. H. (2020). Adaptive boosting of weak regressors for forecasting of crop production considering climatic variability: An empirical assessment. *Journal of King Saud University - Computer and Information Sciences*, 32(8), 949–964. <https://doi.org/10.1016/j.jksuci.2017.12.004>

- Momen, N. N., Carlson, R. E., Shaw, R. H., & Arjmand, O. (1979). Moisture-Stress Effects on the Yield Components of Two Soybean Cultivars. *Agronomy Journal*, 71(1), 86–90.
<https://doi.org/10.2134/agronj1979.00021962007100010022x>
- Montoya, F., García, C., Pintos, F., & Otero, A. (2017). Effects of irrigation regime on the growth and yield of irrigated soybean in temperate humid climatic conditions. *Agricultural Water Management*, 193, 30–45.
<https://doi.org/10.1016/j.agwat.2017.08.001>
- Morales, A., & Villalobos, F. J. (2023). Using machine learning for crop yield prediction in the past or the future. *Frontiers in Plant Science*, 14.
<https://doi.org/10.3389/fpls.2023.1128388>
- Nagesh, O. S., Budaraju, R. R., Kulkarni, S. S., Vinay, M., Ajibade, S.-S. M., Chopra, M., Jawarneh, M., & Kaliyaperumal, K. (2024). Boosting enabled efficient machine learning technique for accurate prediction of crop yield towards precision agriculture. *Discover Sustainability*, 5(1), 78. <https://doi.org/10.1007/s43621-024-00254-x>
- Newton, I. H., Tariqul Islam, A. F. M., Saiful Islam, A. K. M., Tarekul Islam, G. M., Tahsin, A., & Razzaque, S. (2018). Yield Prediction Model for Potato Using Landsat Time Series Images Driven Vegetation Indices. *Remote Sensing in Earth Systems Sciences*, 1(1), 29–38. <https://doi.org/10.1007/s41976-018-0006-0>
- Panda, S. S., Ames, D. P., & Panigrahi, S. (2010). Application of Vegetation Indices for Agricultural Crop Yield Prediction Using Neural Network Techniques. *Remote Sensing*, 2(3), Article 3. <https://doi.org/10.3390/rs2030673>

- Pang, A., Chang, M. W. L., & Chen, Y. (2022). Evaluation of Random Forests (RF) for Regional and Local-Scale Wheat Yield Prediction in Southeast Australia. *Sensors (Basel, Switzerland)*, 22(3), 717. <https://doi.org/10.3390/s22030717>
- Patrick, E. A., & Fischer, F. P. (1970). A generalized k -nearest neighbor rule. *Information and Control*, 16(2), 128–152. [https://doi.org/10.1016/S0019-9958\(70\)90081-1](https://doi.org/10.1016/S0019-9958(70)90081-1)
- Patrignani, A., Knapp, M., Redmond, C., & Santos, E. (2020). *Technical Overview of the Kansas Mesonet*. <https://doi.org/10.1175/JTECH-D-19-0214.1>
- Peerlinck, A., Sheppard, J., & Senecal, J. (2019). AdaBoost with Neural Networks for Yield and Protein Prediction in Precision Agriculture. *2019 International Joint Conference on Neural Networks (IJCNN)*, 1–8. <https://doi.org/10.1109/IJCNN.2019.8851976>
- Perich, G., Turkoglu, M. O., Graf, L. V., Wegner, J. D., Aasen, H., Walter, A., & Liebisch, F. (2023). Pixel-based yield mapping and prediction from Sentinel-2 using spectral indices and neural networks. *Field Crops Research*, 292, 108824. <https://doi.org/10.1016/j.fcr.2023.108824>
- Planet Labs. (2022). <https://docs.planet.com/>
- Poudel, S., Vennam, R. R., Shrestha, A., Reddy, K. R., Wijewardane, N. K., Reddy, K. N., & Bheemanahalli, R. (2023). Resilience of soybean cultivars to drought stress during flowering and early-seed setting stages. *Scientific Reports*, 13(1), 1277. <https://doi.org/10.1038/s41598-023-28354-0>
- Prasad, N. R., Patel, N. R., & Danodia, A. (2021a). Crop yield prediction in cotton for regional level using random forest approach. *Spatial Information Research*, 29(2), 195–206. <https://doi.org/10.1007/s41324-020-00346-6>

- Prasad, N. R., Patel, N. R., & Danodia, A. (2021b). Crop yield prediction in cotton for regional level using random forest approach. *Spatial Information Research*, 29(2), 195–206.
<https://doi.org/10.1007/s41324-020-00346-6>
- Prasath, N., Sreemathy, J., Krishnaraj, N., & Vigneshwaran, P. (2023a). Analysis of Crop Yield Prediction Using Random Forest Regression Model. In C. So-In, N. D. Londhe, N. Bhatt, & M. Kitsing (Eds.), *Information Systems for Intelligent Systems* (pp. 239–249). Springer Nature. https://doi.org/10.1007/978-981-19-7447-2_22
- Prasath, N., Sreemathy, J., Krishnaraj, N., & Vigneshwaran, P. (2023b). Analysis of Crop Yield Prediction Using Random Forest Regression Model. In C. So-In, N. D. Londhe, N. Bhatt, & M. Kitsing (Eds.), *Information Systems for Intelligent Systems* (pp. 239–249). Springer Nature. https://doi.org/10.1007/978-981-19-7447-2_22
- Raza, A., Munir, K., Almutairi, M. S., & Sehar, R. (2023). Novel Class Probability Features for Optimizing Network Attack Detection With Machine Learning. *IEEE Access*, 11, 98685–98694. IEEE Access. <https://doi.org/10.1109/ACCESS.2023.3313596>
- Roznik, M., Boyd, M., & Porth, L. (2022). Improving crop yield estimation by applying higher resolution satellite NDVI imagery and high-resolution cropland masks. *Remote Sensing Applications: Society and Environment*, 25, 100693.
<https://doi.org/10.1016/j.rsase.2022.100693>
- Sakamoto, T. (2020). Incorporating environmental variables into a MODIS-based crop yield estimation method for United States corn and soybeans through the use of a random forest regression algorithm. *ISPRS Journal of Photogrammetry and Remote Sensing*, 160, 208–228. <https://doi.org/10.1016/j.isprsjprs.2019.12.012>

- Salvagiotti, F., Cassman, K. G., Specht, J. E., Walters, D. T., Weiss, A., & Dobermann, A. (2008). Nitrogen uptake, fixation and response to fertilizer N in soybeans: A review. *Field Crops Research*, 108(1), 1–13. <https://doi.org/10.1016/j.fcr.2008.03.001>
- Santos, L. B., Gentry, D., Tryforos, A., Fultz, L., Beasley, J., & Gentimis, T. (2024). Soybean yield prediction using machine learning algorithms under a cover crop management system. *Smart Agricultural Technology*, 8, 100442. <https://doi.org/10.1016/j.atech.2024.100442>
- Saravia, D., Salazar, W., Valqui-Valqui, L., Quille-Mamani, J., Porras-Jorge, R., Corredor, F.-A., Barboza, E., Vásquez, H. V., Casas Diaz, A. V., & Arbizu, C. I. (2022). Yield Predictions of Four Hybrids of Maize (*Zea mays*) Using Multispectral Images Obtained from UAV in the Coast of Peru. *Agronomy*, 12(11), Article 11. <https://doi.org/10.3390/agronomy12112630>
- Satir, O., & Berberoglu, S. (2016). Crop yield prediction under soil salinity using satellite derived vegetation indices. *Field Crops Research*, 192, 134–143. <https://doi.org/10.1016/j.fcr.2016.04.028>
- Schwalbert, R., Amado, T., Nieto, L., Corassa, G., Rice, C., Peralta, N., Schauburger, B., Gornott, C., & Ciampitti, I. (2020). Mid-season county-level corn yield forecast for US Corn Belt integrating satellite imagery and weather variables. *Crop Science*, 60(2), 739–750. <https://doi.org/10.1002/csc2.20053>
- Seireg, H. R., Omar, Y. M. K., El-Samie, F. E. A., El-Fishawy, A. S., & Elmahalawy, A. (2022). Ensemble Machine Learning Techniques Using Computer Simulation Data for Wild Blueberry Yield Prediction. *IEEE Access*, 10, 64671–64687. IEEE Access. <https://doi.org/10.1109/ACCESS.2022.3181970>

- Sharifi, A. (2018). Estimation of biophysical parameters in wheat crops in Golestan province using ultra-high resolution images. *Remote Sensing Letters*, 9(6), 559–568.
<https://doi.org/10.1080/2150704X.2018.1452058>
- Sharma, R. K., Kumar, S., Vatta, K., Dhillon, J., & Reddy, K. N. (2022). Impact of recent climate change on cotton and soybean yields in the southeastern United States. *Journal of Agriculture and Food Research*, 9, 100348. <https://doi.org/10.1016/j.jafr.2022.100348>
- Shaxson, T. F., & Barber, R. G. (2003). *Optimizing Soil Moisture for Plant Production: The Significance of Soil Porosity*. Food & Agriculture Org.
- Shrestha, A., Bheemanahalli, R., Adeli, A., Samiappan, S., Reddy, K. R., & Moorhead, R. (2023). Phenological stage and vegetation index for predicting corn yield under rainfed environments. *Frontiers in Plant Science*, 14. <https://doi.org/10.3389/fpls.2023.1168732>
- Singh, K. N., Singh, K. K., Kumar, S., Panwar, S., & Gurung, B. (2019). Forecasting crop yield through weather indices through LASSO. *The Indian Journal of Agricultural Sciences*, 89(3). <https://doi.org/10.56093/ijas.v89i3.87602>
- Slinker, B. K., & Glantz, S. A. (1985). Multiple regression for physiological data analysis: The problem of multicollinearity. *American Journal of Physiology-Regulatory, Integrative and Comparative Physiology*, 249(1), R1–R12.
<https://doi.org/10.1152/ajpregu.1985.249.1.R1>
- Srisuradetchai, P., & Suksrikan, K. (2024). Random kernel k-nearest neighbors regression. *Frontiers in Big Data*, 7. <https://doi.org/10.3389/fdata.2024.1402384>
- Stamford, J. D., Viallet-Chabrand, S., Cameron, I., & Lawson, T. (2023). Development of an accurate low cost NDVI imaging system for assessing plant health. *Plant Methods*, 19(1), 9. <https://doi.org/10.1186/s13007-023-00981-8>

- Stepanov, A., Dubrovin, K., Sorokin, A., & Aseeva, T. (2020). Predicting Soybean Yield at the Regional Scale Using Remote Sensing and Climatic Data. *Remote Sensing*, 12(12), 1936. <https://doi.org/10.3390/rs12121936>
- Stone, C., Coops, N., & Culvenor, D. (2000). Conceptual Development of a Eucalypt Canopy Condition Index Using High Resolution Spatial and Spectral Remote Sensing Imagery. *Journal of Sustainable Forestry*, 11(4), 23–45. https://doi.org/10.1300/J091v11n04_02
- Su, X., Wang, J., Ding, L., Lu, J., Zhang, J., Yao, X., Cheng, T., Zhu, Y., Cao, W., & Tian, Y. (2023). Grain yield prediction using multi-temporal UAV-based multispectral vegetation indices and endmember abundance in rice. *Field Crops Research*, 299, 108992. <https://doi.org/10.1016/j.fcr.2023.108992>
- Subedi, K., & Ma, B. (2011). In: *Corn Crop Production Growth, Fertilization and Yield CORN CROP PRODUCTION: GROWTH, FERTILIZATION AND YIELD* (pp. 1–85). <https://doi.org/10.13140/2.1.3515.9040>
- Suresh, N., Ramesh, N. V. K., Inthiyaz, S., Priya, P. P., Nagasowmika, K., Kumar, Kota. V. N. H., Shaik, M., & Reddy, B. N. K. (2021a). Crop Yield Prediction Using Random Forest Algorithm. *2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS)*, 1, 279–282. <https://doi.org/10.1109/ICACCS51430.2021.9441871>
- Suresh, N., Ramesh, N. V. K., Inthiyaz, S., Priya, P. P., Nagasowmika, K., Kumar, Kota. V. N. H., Shaik, M., & Reddy, B. N. K. (2021b). Crop Yield Prediction Using Random Forest Algorithm. *2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS)*, 1, 279–282. <https://doi.org/10.1109/ICACCS51430.2021.9441871>

- Suruliandi, A., Mariammal, G., & Raja, S. P. (2021). Crop prediction based on soil and environmental characteristics using feature selection techniques. *Mathematical and Computer Modelling of Dynamical Systems*, 27(1), 117–140.
<https://doi.org/10.1080/13873954.2021.1882505>
- Thapaswini, G., & Gunasekaran, M. (2022). A Methodology for Crop Price Prediction Using Machine Learning. *2022 IEEE 2nd International Conference on Mobile Networks and Wireless Communications (ICMNWC)*, 1–7.
<https://doi.org/10.1109/ICMNWC56175.2022.10031852>
- Tibshirani, R., Bien, J., Friedman, J., Hastie, T., Simon, N., Taylor, J., & Tibshirani, R. J. (2012). Strong Rules for Discarding Predictors in Lasso-Type Problems. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 74(2), 245–266.
<https://doi.org/10.1111/j.1467-9868.2011.01004.x>
- United Nations. (2024). *Population*. United Nations; United Nations.
<https://www.un.org/en/global-issues/population>
- van Klompenburg, T., Kassahun, A., & Catal, C. (2020). Crop yield prediction using machine learning: A systematic literature review. *Computers and Electronics in Agriculture*, 177, 105709. <https://doi.org/10.1016/j.compag.2020.105709>
- Vossenkemper, J. P., Nafziger, E. D., Wessel, J. R., Maughan, M. W., Rupert, M. E., & Schmidt, J. P. (2015). Early Planting, Full-season Cultivars, and Seed Treatments Maximize Soybean Yield Potential. *Crop, Forage & Turfgrass Management*, 1(1), cftm2015.0166.
<https://doi.org/10.2134/cftm2015.0166>
- Walsh, O. S., Marshall, J. M., Nambi, E., Jackson, C. A., Ansah, E. O., Lamichhane, R., McClintick-Chess, J., & Bautista, F. (2023). Wheat Yield and Protein Estimation with

- Handheld and Unmanned Aerial Vehicle-Mounted Sensors. *Agronomy*, 13(1), Article 1.
<https://doi.org/10.3390/agronomy13010207>
- Wang, K., Huggins, D. R., & Tao, H. (2019). Rapid mapping of winter wheat yield, protein, and nitrogen uptake using remote and proximal sensing. *International Journal of Applied Earth Observation and Geoinformation*, 82, 101921.
<https://doi.org/10.1016/j.jag.2019.101921>
- Wang, K., Patrawala, A., Xin, T., & Wang, H. (n.d.). *Weather Impact on Soybean Yield and Insurance Loss in Brown County, South Dakota*. Retrieved August 14, 2024, from
<https://www.mtfchallenge.org/wp-content/uploads/2022/02/Math-Modeling.pdf>
- Westgate, M. E., & Peterson, C. M. (1993). Flower and Pod Development in Water-Deficient Soybeans (*Glycine max* L. Merr.)¹. *Journal of Experimental Botany*, 44(1), 109–117.
<https://doi.org/10.1093/jxb/44.1.109>
- Yamparla, R., Shaik, H. S., Guntaka, N. S. P., Marri, P., & Nallamotheu, S. (2022). Crop Yield Prediction using Random Forest Algorithm. *2022 7th International Conference on Communication and Electronics Systems (ICCES)*, 1538–1543.
<https://doi.org/10.1109/ICCES54183.2022.9835756>
- Zhao, L., Um, D., Nowka, K., Landivar-Scott, J. L., Landivar, J., & Bhandari, M. (2024). Cotton yield prediction utilizing unmanned aerial vehicles (UAV) and Bayesian neural networks. *Computers and Electronics in Agriculture*, 226, 109415.
<https://doi.org/10.1016/j.compag.2024.109415>
- Zou, H., & Hastie, T. (2005). Regularization and Variable Selection Via the Elastic Net. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 67(2), 301–320.
<https://doi.org/10.1111/j.1467-9868.2005.00503.x>

Tables

Table 1.1. Details of soybean planting dates, seeding rates, and cultivars (maturity groups, MG) used for each planting window during the 2021–2023 growing seasons in Kansas

Growing Season	Early Planting Date	Mid-Planting Date	Late Planting Date	Seeding rate (seeds ha ⁻¹)	Golden Harvest Soybean Cultivars
2021	March 21	April 27	May 24	247,100 and 370,650	GH3442XF (MG: 3.4) and GH4452XFS (MG: 4.4)
2022	April 6	April 27	May 17	247,100 and 370,650	GH3442XF (MG: 3.4) and GH4222XF (MG: 4.2)
2023	April 5	April 24	May 17	247,100 and 370,650	GH3442X (MG: 3.4) and GH4392XF (MG: 4.3)

Table 1.2. Spectral band configuration of PlanetScope multispectral imagery showing wavelength range, central wavelength, and corresponding spectral region applied for vegetation index computation and crop biophysical analysis

Band	Spectral Range (nm)	Central Wavelength (nm)	Description
Band 1	450 – 510	490	Blue
Band 2	510 – 580	565	Green
Band 3	630 – 690	665	Red
Band 4	705 – 745	705	Red Edge
Band 5	780 – 900	865	Near-Infrared (NIR)
Band 6	570 – 590	610	Yellow
Band 7	400 – 700	—	Visible (Broadband)

Table 1.3. Optimized hyperparameter configurations and model inputs for the four machine learning algorithms applied in soybean yield prediction

ML models	Hyperparameters	Model Inputs
Random Forest (RF)	n_estimators: 100 random_state: 42 max_depth: 3 min_samples_leaf: 1 min_samples_split: 2	'Planting_Date', 'Variety', 'Maturity_Group', Seeding_Rate, 'Maturity_time', 'Air_Temperature', 'GDD', 'Precipitation (mm)', 'Soil_Temperature', 'Solar_Radiation', 'ETc', 'Moisture', 'Test_Weight', 'NDVI', 'NDRE', 'WDRVI
Adaptive Boosting (AdaBoost)	n_estimators = 100 learning_rate: 0.1 random_state: 42 loss: linear	
k-Nearest Neighbors (KNN)	n_neighbors: 15 weights: uniform leaf_size: 30 p: 2	
Least Absolute Shrinkage and Selection Operator (LASSO)	random_state: 42 alpha: 0.2 selection: cyclic max_iter: 1000	

Table 1.4. Summary of mean temperature, mean precipitation, mean soil temperature, ETc for Early, Mid, and Late planting dates during 2021, 2022, and 2023 (Calculated from Kansas Mesonet, mesonet.k-state.edu)

Growing season and Planting dates	Mean Air Temperature over the growing season (°C)*	Mean Precipitation over the growing season (mm)*	Mean Soil Temperature over the growing season (Profile Depth: 15cm, °C)*	ETc during reproductive stage (mm)*	Mean Soybean Yield (Mg/ha)					
					Mean (Mg/ha)*	Min (Mg/ha)	Max (Mg/ha)	Range (Mg/ha)	SD (Mg/ha)	CV (%)
2021										
Early	19.30a	295.39a	22.05a	4.91a	3.30a	2.74	3.73	0.99	0.26	8.02
Mid	20.95b	259.83b	23.90b	4.47b	3.28a	2.57	4.09	1.52	0.42	13.1
Late	22.05c	228.59b	25.15c	4.10c	3.20a	2.38	3.69	1.32	0.33	10.3
2022										
Early	19.20a	391.91a	23.10a	5.08a	5.24a	4.63	5.80	1.16	0.38	7.39
Mid	21.25b	349.62b	24.40b	4.85b	4.86b	4.42	5.35	0.92	0.28	5.76
Late	23.85c	306.31b	25.40c	4.59c	4.62b	3.67	5.41	1.74	0.46	9.97
2023										
Early	20.95a	455.67a	24.50a	5.37a	3.36a	2.42	4.21	1.79	0.48	14.5
Mid	21.95b	442.96a	24.55b	5.02b	3.49a	2.02	4.32	2.30	0.53	15.5
Late	23.00c	393.44b	24.08c	4.98c	3.38a	2.55	4.35	1.80	0.52	15.5

*Numbers followed by different lowercase letters are significantly different at $\alpha = 0.05$

Table 1.5. The accuracy percentage and R^2 values of each growing season are presented in percentage based on the Random Forest regressor

Growth Stage Category	Stages	Error Percentage of 10%			Mean of three growing seasons	R-squared value			Mean of three growing seasons
		2021	2022	2023		2021	2022	2023	
Early Vegetative	V1	68.75	73.33	62.50	68.19	0.562	0.609	0.526	0.566
	V2	72.92	73.33	64.58	70.28	0.515	0.655	0.539	0.570
	V3	70.83	71.25	62.50	68.19	0.579	0.679	0.615	0.624
					68.89%				0.587
Late Vegetative	V4	68.75	83.33	66.67	72.92	0.571	0.715	0.619	0.635
	V5	68.75	85.42	64.58	72.92	0.473	0.707	0.700	0.627
	V6	72.92	85.42	66.67	75.00	0.530	0.726	0.622	0.626
					73.61%				0.629
Early Reproductive	R1	64.58	85.42	62.50	70.83	0.536	0.729	0.602	0.622
	R2	68.75	83.33	64.58	72.22	0.492	0.704	0.604	0.600
	R3	64.58	85.42	62.50	70.83	0.529	0.717	0.682	0.643
					71.30%				0.622
Late Reproductive	R4	78.75	85.42	60.42	74.86	0.675	0.752	0.666	0.697
	R5	76.67	87.50	66.67	76.95	0.608	0.794	0.692	0.698
	R6	62.50	85.42	66.25	71.39	0.621	0.741	0.798	0.720
	R7	77.08	87.50	78.33	80.97	0.616	0.784	0.690	0.697
					75.21%				0.702

Figures

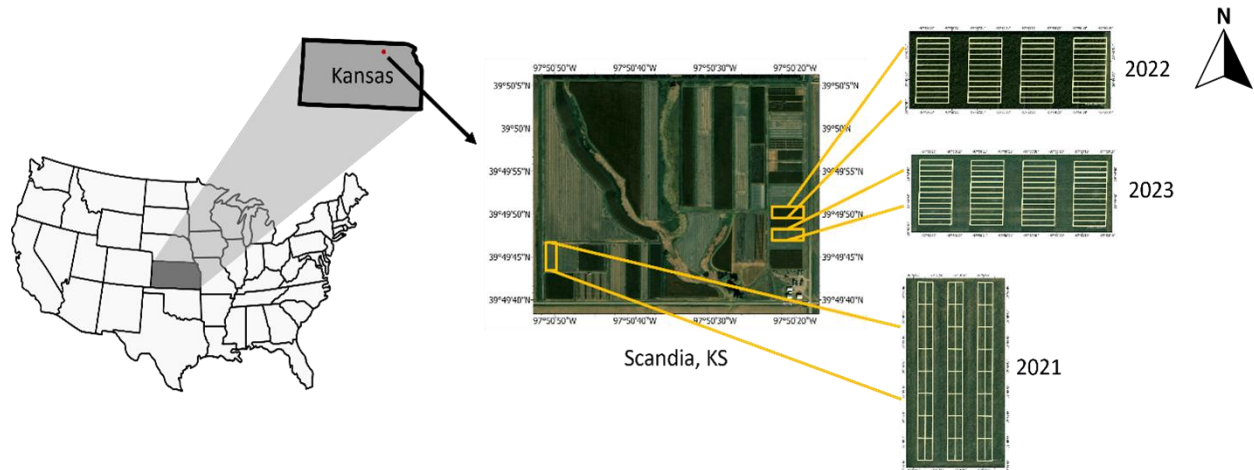


Figure 1.1. Study location in the north-central region of Kansas showing three designated experimental fields used for data collection and analysis

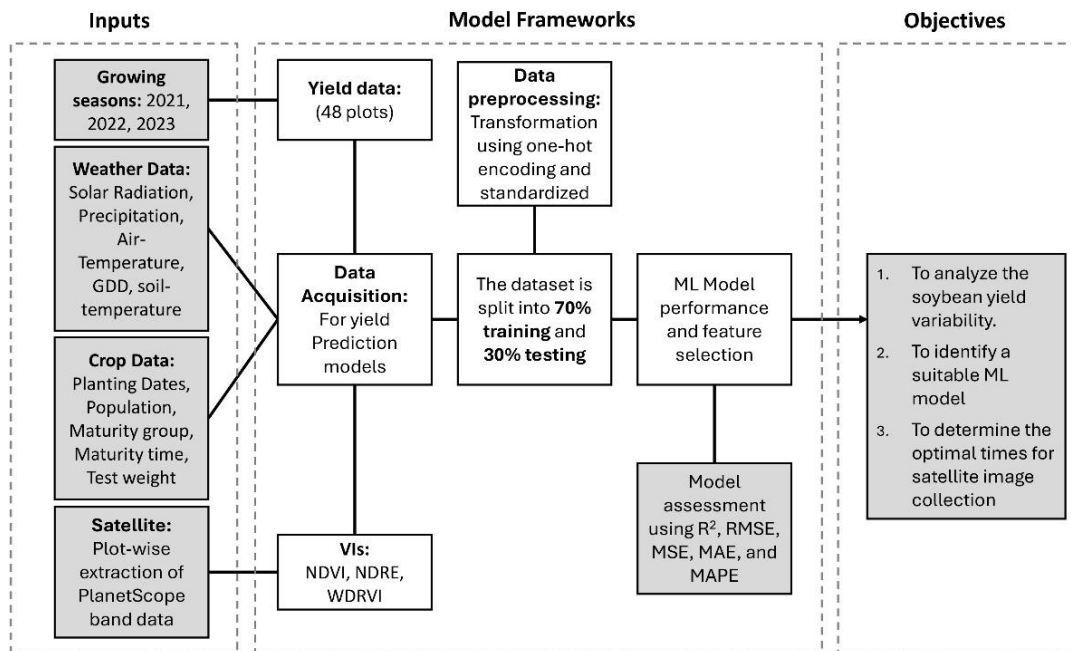


Figure 1.2. Conceptual framework illustrating the implementation of machine learning algorithms, data preprocessing pipeline, and performance evaluation metrics used to achieve the study objectives

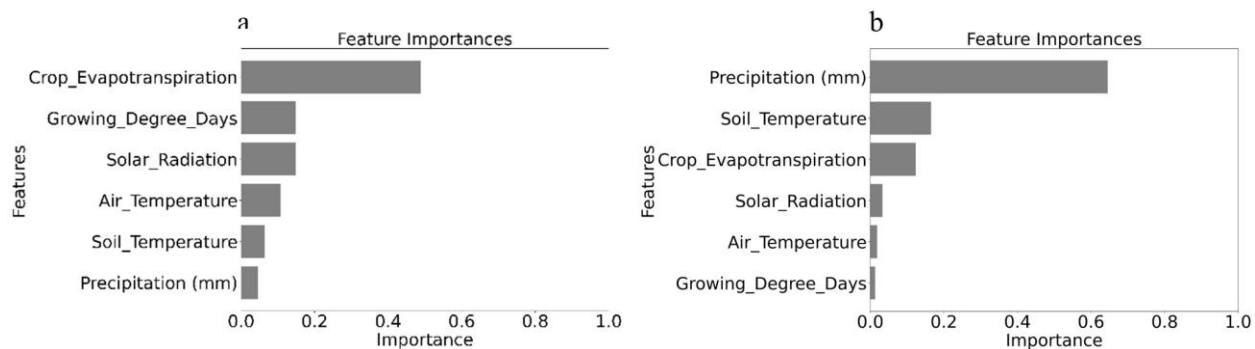


Figure 1.4. Feature importance analysis from the Random Forest model illustrating key agronomic, meteorological, and spectral predictors influencing yield during (a) rainfed and (b) irrigated growing seasons

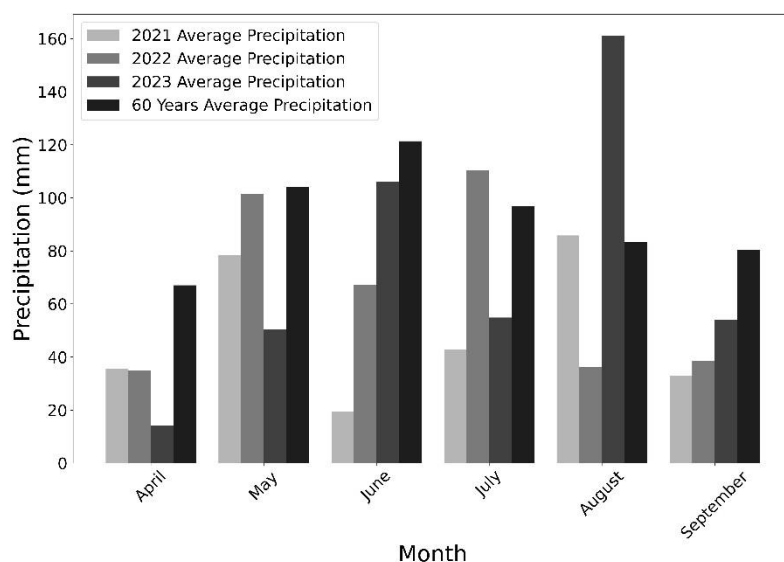


Figure 1.3. Temporal distribution of monthly rainfall across the three soybean growing seasons (2021–2023) based on data from the Kansas Mesonet (mesonet.k-state.edu) and Western Regional Climate Centre (WRCC).

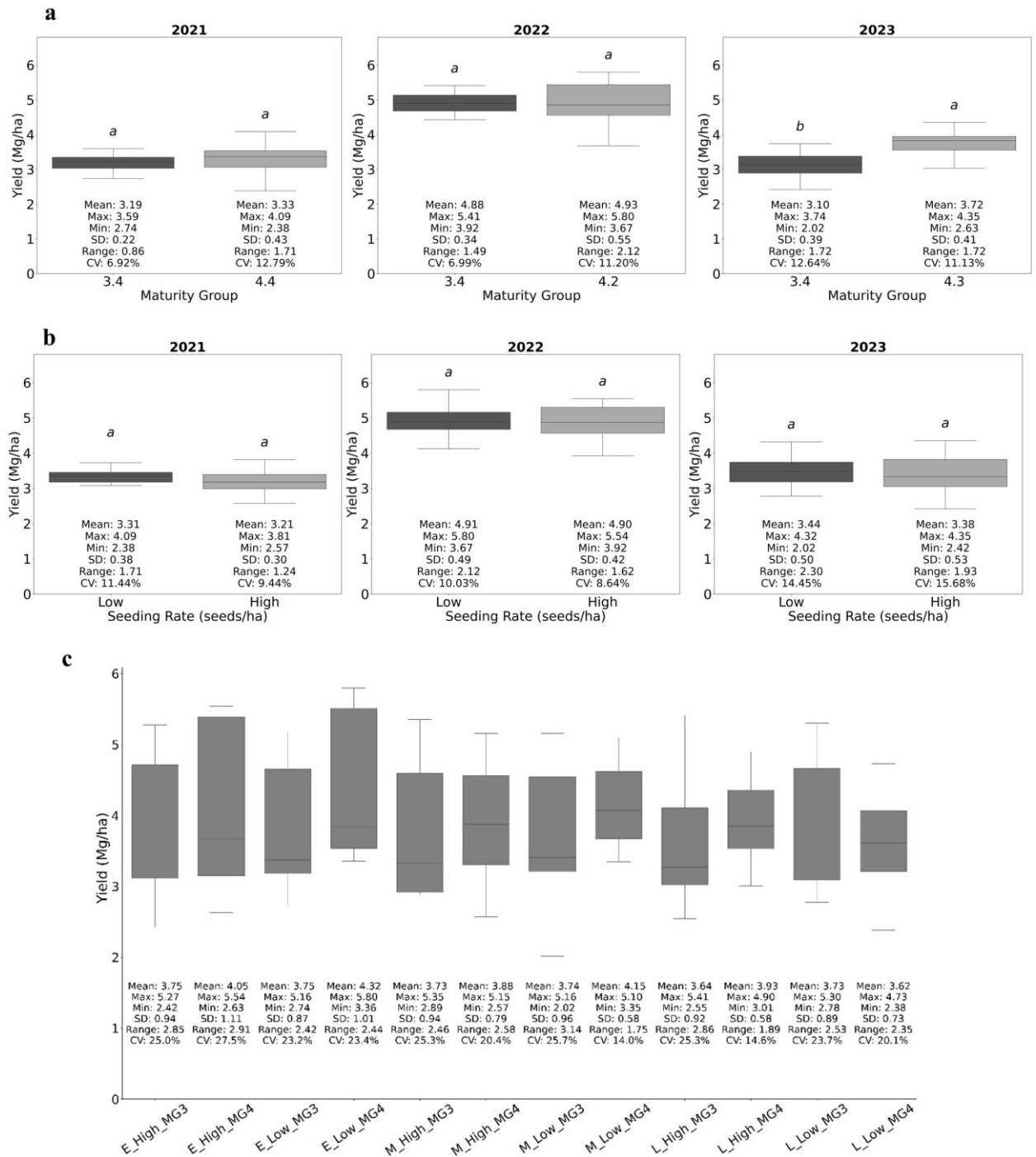


Figure 1.5. Descriptive statistics between Maturity Groups (MG 3.4, 4.2, 4.3, 4.4), Seeding rate (high and low) and their interaction with Crop Yield in 2021, 2022, and 2023 growing seasons (E: Early, M: Mid, L: Late)

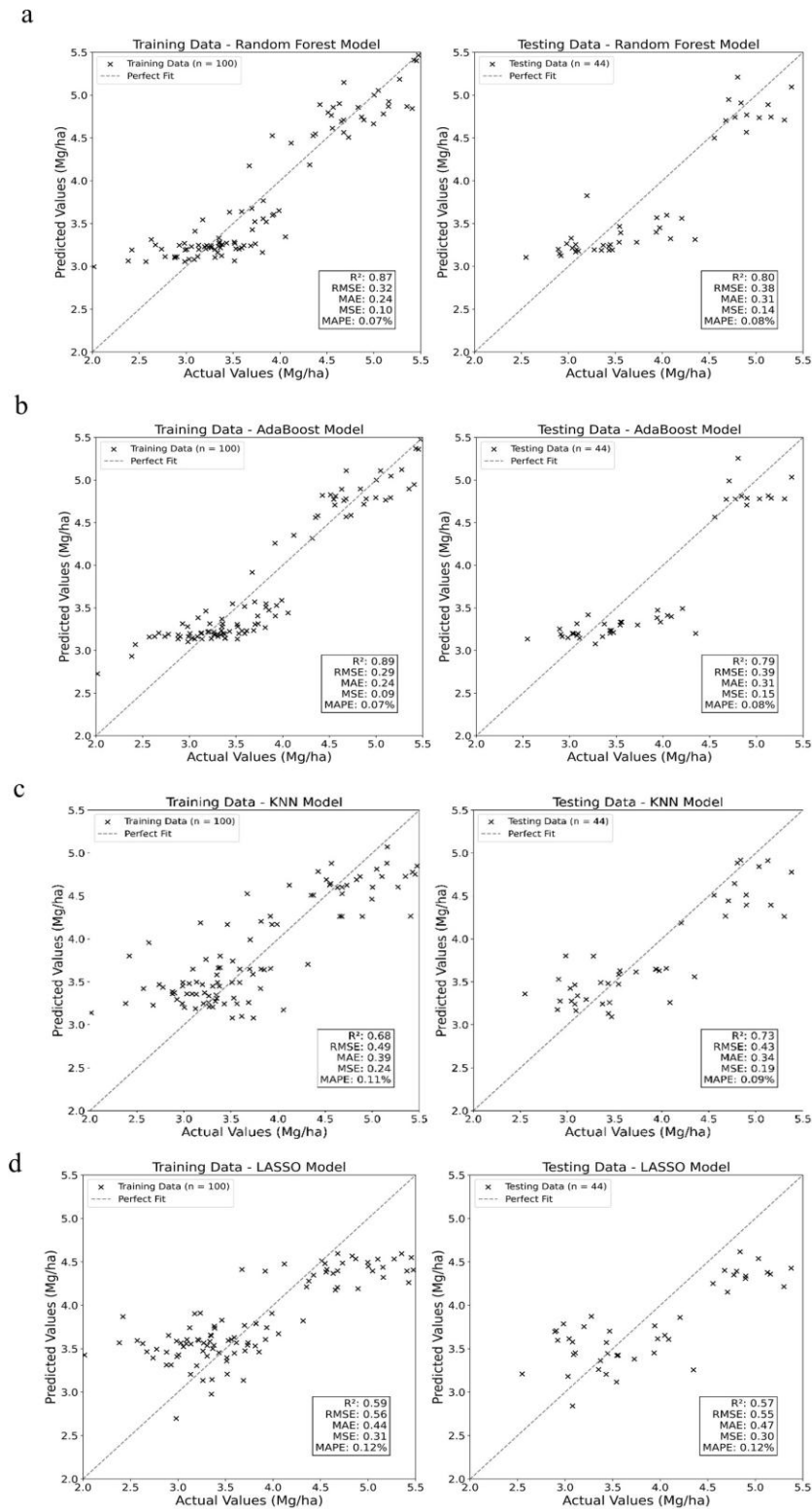


Figure 1.6. The performance of four ML models in predicting soybean yield (late reproductive stage), as indicated by R^2 , RMSE, MSE, MAE, and MAPE error (a) RF model; (b) AdaBoost; (c) KNN; (d) LASSO



Figure 1.7. Condition during the late growing stage of the early-planted crop (left side) and the lodged late-planted crop (right side). The research is being continued, and the picture was taken by the author during the 2024 growing season

Chapter 2 - Precision Irrigation with AI-Integrated Ground Penetrating Radar Reduces Water Stress in Kansas Corn

Abbreviations

AI: Artificial Intelligence; AI-Radar: Artificial Intelligence-Integrated Ground Penetrating Radar Irrigation System; ASL: Above Sea Level; AWHC: Available Water Holding Capacity; CNN: Convolutional Neural Network; ET_a: Actual Evapotranspiration; ET_c: Crop Evapotranspiration; ET_o: Reference Evapotranspiration (from grass surface); GMD: Groundwater Management District; GPR: Ground Penetrating Radar; K_e: Soil Evaporation Coefficient; K_{cb}: Basal Crop Coefficient; K_{c-act}: Actual Crop Coefficient; K_s: Soil Water Stress Coefficient; MAD: Maximum Allowable Depletion; NDVI: Normalized Difference Vegetation Index; PET: Potential Evapotranspiration (from alfalfa surface); RMSE: Root Mean Square Error; SDI: Subsurface Drip Irrigation; WDI: Water Deficit Index; WGS84: World Geodetic System 1984.

Abstract

Water management is becoming increasingly vital in the Southern Great Plains due to declining levels of the Ogallala Aquifer and the increasing drought conditions. As water scarcity intensifies, precision irrigation technologies, such as AI-integrated Ground Penetrating Radar (AI-Radar), can be a promising solution for optimizing water use at the field scale in crop production systems. This on-farm trial compares the AI-Radar irrigation system to a conventional irrigation system (subsurface drip irrigation, SDI) in central Kansas. Spatial analysis of the Water Deficit Index (WDI) determined using high-resolution satellite imagery revealed significantly reduced values of this index under AI-Radar-based irrigation (0.15-0.16) compared to SDI (0.20-0.24) ($p < 0.07$) during the critical tasseling to dough (VT-R4) growth

stages. Lower WDI indicates more efficient spatial water distribution with minimal crop water stress. The AI-Radar system applied 31 to 34% less irrigation water than the SDI system while maintaining lower crop water stress. Therefore, this case study demonstrates that adopting AI-radar-based irrigation could support groundwater conservation and regulatory compliance in the Southern Great Plains region.

Keywords: Satellite Remote Sensing, Southern Great Plains, Spatial Water Management, Water Deficit Index

1. Introduction

1.1. Importance of Water Resources in Kansas

Water is one of the most essential resources in Kansas agriculture, with 80 to 85% of water allocated for irrigation (Kansas State University Foundation, 2025). Declining groundwater availability, reduced irrigation water supply, and increasing drought have placed pressure on water resources in Kansas (Kansas State Water Office, 2022). Climate change is exacerbating water scarcity in Kansas by altering temperature and precipitation patterns, which impact the regional variability in irrigation scheduling and the extent of farming in Kansas (Suttles et al., 2024). Kansas will be severely affected by a water shortage due to the unsustainable use of groundwater and climate change. In 2023, an average of 55.7% of Kansas was under severe drought and 36.1% under Extreme Drought (Drought.Gov, 2025). On the other hand, the Ogallala aquifer supports the majority of irrigated crops in Kansas, particularly in western Kansas, but demand has outpaced recharge rates, resulting in aquifer depletion (McGuire, 2011). According to the United States Geological Survey, in Kansas, the average water level declined by 57.6 cm (22.7 in) in 2022 (Kansas Geological Survey, 2023).

Furthermore, between 2007 and 2050, the volume of surface water reservoirs is expected to decrease by 50% due to a decline in precipitation and high evaporative losses (Brikowski, 2008).

As water scarcity grows more severe, farmers might be unable to manage crop productivity and profitability. The depletion of the aquifer also affects energy costs for pumping water from lower levels. Therefore, water scarcity and less water availability can impact crop yield. For example, corn and soybean yields are expected to drop by 25.4% and 43.4%, respectively (Economic Research Service, 2024). To achieve this long-term objective of adapting to climate change and promoting equity in water distribution, precise irrigation management is required. This aligns with the United Nations Sustainable Development Goals for access to clean water, sanitation, and climate action. Therefore, to address these challenges, precision water management and conservation planning, including improved irrigation efficiency through the use of precision irrigation technology, are necessary.

1.2. Precision Irrigation Technology Over Traditional Irrigation

Traditional irrigation techniques can reduce crop productivity, resulting in over-irrigation, water scarcity, and uneven water distribution. On the other hand, precision irrigation responds to field variability through variable-rate irrigation. Using instruments such as soil moisture sensors, this approach can also address micro-water needs in the field (Soulis et al., 2015), radar (Q. Lu et al., 2023), and advanced computer vision (Oudah et al., 2024). Among them, ground-penetrating radar has recently been utilized to assess soil moisture in radar-based irrigation systems, enabling real-time monitoring and precise water application, thereby reducing water waste and enhancing crop health (Dwevedi et al., 2017). The presence of water in the soil affects the dielectric permittivity of the soil, which can be detected using GPR based on travel time. According to one study, ground-penetrating radar (GPR) reflection travel time data can be

used to estimate changes in soil water content throughout the growing season. The GPR reflection method has an RMS error of $0.018 \text{ m}^3 \text{ m}^{-3}$, making it suitable for estimating average water content in natural conditions with borehole control and adequate reflection strength (Lunt et al., 2005). On the other hand, artificial intelligence-based, high-resolution images can be used to make more informed decisions about irrigation schedules, water distribution, and crop management. According to Goyal et al (2023), water stress in corn can be detected by using the deep learning-based custom convolutional neural network model with an accuracy of 98.71% for the training set and 98.53% for the test set. GPR only provides information on soil water status, but it does not indicate crop water stress. This is important because crop roots might have some root disease that can prevent them from uptake water from the soil. Despite the soil having enough water, this can hinder crop growth by reducing the water uptake. AI-Radar utilizes real-time data and weather forecasts to determine the precise amount of water crops require and when to apply it. Therefore, combining GPR with AI and weather (AI-Radar) could be a potential solution for providing site-specific irrigation. This innovative system uses real-time data on soil, crops, and weather to predict crop water needs and optimize irrigation schedules for a specific time and location within a field (*Autonomous Pivot Product Guide*, 2024). However, its effectiveness in quantifying crop water stress has not yet been thoroughly evaluated. To our knowledge, this is the first field-scale study to compare the performance of an AI-Radar irrigation system, which integrates ground-penetrating radar, crop imaging, and weather data, with a subsurface drip irrigation (SDI) system. This comparison uses satellite-derived crop water stress indices. Therefore, the objective of this study was to assess the effectiveness of the AI-Radar irrigation system in comparison to SDI based on spatial assessment of water stress using high-resolution satellite data.

2. Materials and Methods

2.1. Study Area and Experimental Plan

Our study was conducted as an on-farm study during the 2021 and 2023 growing seasons in two adjacent corn fields in central Kansas. Field A (~11 ha) (38°12'04.9"N 97°34'10.7" W) was irrigated by AI-Radar irrigation, and Field B (~7 ha) (38°12'05.4"N 97°33'59.4" W) was under SDI irrigation (Figure 2.1). Both fields come under GMD 2 at an elevation of 447m (1466 ft) above sea level. The region depends on groundwater from the Equus Beds Aquifer (saturated thickness varies between 22.86m (75 ft) and 76.20 m (250 ft). A total of 69% of the water is used for irrigation (Wilson et al., 2020). The depth to the water table exceeds 20 m, with moderately well-drained and medium runoff. This region is classified under “cfa” in the Köppen climate classification, indicating humid subtropical with hot summers and mild winters, high evapotranspiration, and irregular precipitation rates (Kotték et al., 2006). During the crop growth period, the average (10 years) temperature ranged from 18.8 to 29.6 °C with an average precipitation of 117.8 mm (highest during May, 168 mm) and average precipitation days of 7.4 (highest during May, 10 days). Soil texture in this area (Field A and Field B) was mainly silty loam (up to 15 cm) to silty clay loam (less than 15cm). The slope was around 1 to 3%. Given the proximity of the two fields and a similar type of soil, soil variability was considered minimal in influencing crop evapotranspiration (Web Soil Survey, 2024). Corn (*Zea mays* L.) was planted in mid-April to May and harvested in mid-September to early October for both fields in both growing seasons. The plant population was 80,000 per hectare, with a row spacing of 75 cm.

2.2. Technical overview of the SDI and AI-Radar irrigation system

2.2.1. Subsurface drip irrigation (SDI)

In our study, there were two different irrigation systems used, one was SDI, and the one was an AI-Radar-based system. The information about the SDI irrigation was documented from the farmers' records. SDI comes under micro irrigation, which supplies water directly to the crop root zone below the soil surface through a network of plastic tubes with small emitters. SDI can conserve water by applying the irrigation water directly to the crop root zone, which can also minimize evaporation (Rogers et al., 2020). In SDI, emitters are installed below or between rows of crops. According to Rogers et al (2020). The irrigation rates are based on the crop water requirement. This configuration helps to prevent losses due to evaporation and reduces water runoff by delivering water directly to the root zone of the crop (DripWorks, 2025). Previous research has shown that this SDI-based water management can result in yield increases by up to ten percent (G. Zhao et al., 2024). SDI can maintain higher soil moisture retention at root depth, which can increase crop root development (G. Zhao et al., 2024). The efficiency of SDI depends on soil type, irrigation timing, and management practices (Western Kansas Research-Extension Center, 2025). Proper system design and maintenance are crucial for minimizing emitter clogging and ensuring uniform water distribution.

The zone receives 200 gallons per minute at the manifold, with drip tapes installed at 35 to 45 cm (14 to 18 inches) below the surface, with a lateral space of 1.02 m (40 inches). The distance between the emitters was 0.56 to 0.91 m (22 to 36 inches). The irrigation scheduling was a fixed type. Growers typically irrigate every 2 to 3 days for corn years (2021 and 2023). The system was usually on for eight hours for each of the 28 irrigation applications, which happened from planting in mid-April to the R3 growth stage in early August. According to the

grower, the length of time for each irrigation application (15 applications) was cut down to 4 to 6 hours after R3 to R6. For each irrigation event, the operator targeted to apply 6.35 to 8.38 mm (0.25 to 0.30 in). Therefore, the total irrigation water depth ranged from 273 to 360 mm (10.7 to 14.2 in) (Figure 2.2).

2.2.2. AI-Radar

To determine the level of moisture in the soil, the AI-Radar system includes a ground penetrating radar (GPR) sensor that operates at an electromagnetic wavelength ranging from 400 to 1200 megahertz (Autonomous Pivot Product Guide, 2024). As the irrigation system moves over the field, for every thirty minutes, the GPR component records about 300 soil moisture datapoints (%) (Figure 2.3). These percentages show the amount of water in the soil in relation to the field capacity (100%) and permanent wilting point (0%) readings. The process begins with determining the water content at FC and PWP per slice using soil type data (user-provided texture data based on prior soil testing) for the effective root zone (Autonomous Pivot Product Guide, 2024). Using this data, the system divides the field into eight equal 45° zones based on available water holding capacity ($AWHC = FC - PWP$) (Figure 2.3). AWHC for each segment was calculated separately. AWHC values are derived from soil texture, while crop data (crop type and growth stages), soil type, and irrigation strategies were used to determine the maximum allowable depletion (MAD) for irrigation recommendations (Autonomous Pivot Product Guide, 2024). Crop root depth was provided by the grower, as this was an on-farm trial. The MAD threshold ranged from 50% to 85% depending on the corn growth stage and soil type. From VE to V4 (early vegetative stage), MAD was 50 to 60%; from V5 to V7 (mid vegetative stage), it was 60 to 70%; from V7 to R2 (late vegetative to early reproductive stage), it was 75 to 80%; and after R2 (mid to late reproductive stage), MAD was maintained below 65% (Autonomous

Pivot Product Guide, 2024). In addition to the GPR, the AI-Radar system includes an AI-powered imaging camera that uses a convolutional neural network (CNN) to detect crop growth stages and crop coverage every 30 minutes during in-season pivot rotation (Figure 2.3). Based on this coverage, the system internally calculates the crop coefficient (K_c) and crop evapotranspiration (ET_c) using integrated web-based weather data for irrigation scheduling. The NDVI-based K_{c-act} values presented later in the paper were used only for comparison between the two irrigation systems.

In Field A, an AI-Radar irrigation system was installed on the center pivot irrigation system (Figure 2.3). The sensor was installed 3 m laterally and 2.5 m vertically from the tower of the center-pivot irrigation system to ensure adequate coverage at varying radial distances. Irrigation application depth was accounted for using a pressure sensor installed with the pivot. For the 2021 and 2023 growing seasons, the mean irrigation depth was 237 mm and 242 mm, respectively, over the eight segments.

2.3. Spatial Water Indices for Evaluation

Spatial water indices are essential for assessing crop water status and scheduling irrigation in precision agriculture. Among the several spatial water indices, the Crop Water Stress Index (CWSI) is a widely used indicator that quantifies plant water stress by comparing canopy temperature to air temperature under varying environmental conditions (Jackson et al., 1981). To accurately reflect relative transpiration rates, this index incorporates meteorological data, such as the vapor pressure deficit of the atmosphere. It is important to note that CWSI is only applicable to the entire crop canopy and may be susceptible to partial soil exposure. To address these limitations, the Water Deficit Index (WDI) was introduced by Moran (1994). Combination measurement of surface temperature with normalized vegetation indices (like the

NDVI), the WDI considers the effects of both the soil background and the vegetation cover to determine the WDI. The Water Deficit Index (WDI) formula includes a range of values, from zero (no stress) to one (maximum water deficit). This enables more precise stress estimates across a variety of vegetation and soil types. (Tanriverdi et al., 2017). Moreover, WDI correlates strongly with physiological indicators such as stomatal conductance and crop water status, providing a precise proxy for irrigation scheduling and drought stress monitoring (Antoniuk et al., 2021). Advances in remote sensing and data analytics continue to improve these spatial water indices for sustainable water management in agriculture.

2.4. Vegetation Indices (VIs) Based on Crop Coefficient for Spatial Water Stress

Assessment

To improve and maximize crop growth and yield, it is essential to understand the water status of the crop and the agricultural system. Lack of soil moisture and water limits crop biomass development, photosynthetic activity, and stomatal conductance, which can indirectly lower crop yield and economic profitability (Tavares et al., 2022). Therefore, accurately assessing water stress is crucial for more precise yield estimation in relation to water stress (Velazquez-Chavez et al., 2024). Traditional ground-based measurements are labor-intensive, time-consuming, and limited in spatial coverage (Tavares et al., 2022). These methods are not reliable for large agricultural land because they give point data (Tavares et al., 2022). This can be addressed by remote which provides a higher spatial scale and regular data that support precision agriculture practices (French et al., 2020). Based on the literature review, vegetation indices (VIs) can be used to detect crop health and crop water status (Abbasi et al., 2021; Nagler et al., 2013). These indices are derived from multispectral remote sensing data, which can serve as proxies for crop physiological conditions such as water usage and stress (Abbasi et al., 2021;

Nagler et al., 2013). Among these, we have employed the Normalized Difference Vegetation Index (NDVI) because of its strong correlation with leaf area index, chlorophyll content, and overall crop health (Kamble et al., 2013). NDVI-based crop coefficients (K_c) can be used to estimate crop evapotranspiration and water demand, reflecting the dynamic patterns of crop water use (Glenn et al., 2011). We have used NDVI-based actual K_c estimation during the critical growth stages of soybeans to determine the spatial water index.

2.5. Calculation and Assumptions for Spatial Water Indices

For spatial assessment, actual crop evapotranspiration (ET_a) and potential evapotranspiration (PET) were used to estimate the Water Deficit Index (WDI) for both fields (Antoniuk et al., 2021; El-Shirbeny et al., 2015; Feiziasl et al., 2022). The PET was calculated using the Penman-Monteith equation from the Kansas Mesonet data with a 0.5m Alfalfa surface (Patrignani et al., 2020). The ET_a was computed by multiplying reference evapotranspiration (ET_o) by the actual crop coefficient (K_{cact}), which is composed of the basal crop coefficient (K_{cb}), the soil water stress coefficient (K_s), and the soil evaporation coefficient (K_e) ($K_{c-act} = K_{cb} \times K_s + K_e$) (Allen et al., 2005). However, direct measurement of field-scale ET_a is logistically complex and often cost-prohibitive in large, heterogeneous agricultural systems. Particularly in on-farm trials, instrumentation like lysimeters or an eddy covariance tower is impractical. To estimate the $K_{cb} \times K_s$ components, we used remote sensing-based methods, which demonstrate the actual vegetation cover conditions and can be used to compute the product of $K_{cb} \times K_s$ (Abbasi et al., 2021; Nagler et al., 2013; Pôças et al., 2015). Additionally, canopy reflectance and ET_a estimation were conducted during periods of high canopy coverage (from the eighth leaf to the dough stage, V8-R4) for the corn crop with a fractional vegetation cover (FVC) above 0.79

(Figure 2.4). As a result, the contribution of the K_e was assumed to be minimal. This approach was also followed by Tang et al (2019) for mapping corn ET_a .

Therefore, satellite reflectance data were used to calculate the normalized difference vegetation index (NDVI) (Eq. 1), which was then used to estimate the time series of K_{c-act} through a linear regression model (Eq. 2), proposed by Kamble et al (2013). This approach was selected due to its demonstrated application in field-scale crop water-use modeling. Kamble et al (2013) reported a strong linear relationship between the NDVI-estimated and the measured crop coefficient, with r-squared values of 0.90-0.91 and a root-mean-square error of 0.16-0.19. Although the original approach by Kamble et al (2013) was developed using the MODIS datasets (250 m); this study applied the method to PlanetScope imagery (3 m). We are assuming that the finer spatial resolution of provides greater potential for estimating ground-based K_{c-act} by reducing mixed-pixel effects. Following the derivation of K_{c-act} , WDI (Eq. 3) was calculated using ET_o and PET data obtained from the Kansas Mesonet located 15m away from the fields (Figure 2.5). The WDI ranges from zero, indicating no water stress, to one, which is maximum water stress (Colaizzi et al., 2003; El-Shirbeny et al., 2015; Feiziasl et al., 2022; Moran, 1994).

$$NDVI = \frac{(\rho_{nir} - \rho_{red})}{(\rho_{nir} + \rho_{red})} \quad (\text{Eq. 1})$$

$$K_{c-act} NDVI = 1.457 \times NDVI - 0.1725 \quad (\text{Eq. 2})$$

$$WDI = 1 - \frac{(K_{c-act} \times ET_o)}{PET} \quad (\text{Eq. 3})$$

In the above equations, ρ_{nir} = Near Infra-red (865 nm), ρ_{red} = Red (665 nm), K_{c-act} = actual crop coefficient, ET_o = Reference evapotranspiration (from grass surface), and PET = Potential evapotranspiration (from Alfalfa surface).

2.6. Satellite Data Acquisition and Statistical Analysis

In our research, satellite imagery comes from the PlanetScope constellation and has an average temporal interval of three to seven days and less than 10% cloud cover (Planet Labs, 2022). PlanetScope satellite operates a constellation of more than 200 small Earth observation satellites in low Earth orbit (LEO). This includes Dove, SkySat, and RapidEye satellites (Planet Labs, 2022). For this study, all satellite imagery was collected from SuperDove sensors. These satellites provide daily imagery with a spatial resolution of three to five meters on the ground. The PlanetScope satellite contains different wavelength-based bands, which are listed in Table 1.2 (Planet Labs, 2022). DOS and radiative transfer models based on Advanced atmospheric correction techniques improve image spatial accuracy. It reduces haze and pollutants to improve imagery. For each year, images were taken at a range of 3 to 7 days to capture the growth stages from early to late-planted soybeans. For our research, we used spatial reflectance data to calculate NDVI for the estimation of the actual crop coefficient. To minimize the effects of soil evaporation (K_e) on water stress assessment, we collected data during periods of high canopy coverage in the crop. This was indicated by fractional vegetation cover (FVC). In our study, FVC refers to the percentage of an area that is covered by vegetation growing above ground. A high FVC indicates that the canopy covers a significant portion of the soil, which can reduce soil evaporation. Therefore, satellite images were collected during higher FVC stages with values exceeding 0.79 (Figure 2.4). This includes the important stages in corn, such as the late vegetative phase (V8–V11) and the reproductive phases from tasseling to dough (VT–R4), which correspond to having high FVC. The canopy was sufficiently mature at this to cover the soil effectively and reduce the impact of soil evaporation.

To capture the key growth stages, such as the late vegetative stage and the period from mid-July to late August covering tasseling to dough stages, imagery was acquired from mid-June

to mid-July. ArcGIS Pro software (v3.2.2) was employed using the World Geodetic System 1984 (WGS84) for spatial data processing and analysis (Esri, Redlands, CA, USA). We used Python (version 3.13.3) to apply Welch's t-test at $\alpha = 0.10$ for statistical comparison and analyzing group differences. The Welch t-test was selected because of its reliability in handling unequal sample sizes and variances. Therefore, this provides a reliable estimate of water stress differences across space (Welch, 1947).

3. Results and Discussions

3.1. Interpretation of Water Deficit Index (WDI) Between Irrigation Systems

The AI-Radar-based precision irrigation system in Field A consistently resulted in significantly lower WDI values than the conventional irrigation system (SDI; Field B) during critical corn growth stages of corn for both seasons. Based on our results, Field A (AI-Radar) had significantly lower WDI values than Field B (SDI), particularly during the late vegetative stage (V8-V11; except in 2023) and tasseling to dough stage (VT-R4) ($p < 0.07$; Figure 2.7, Table 2.1). In 2021, during the V8-V11 stage, Field A showed a lower mean WDI of 0.16 (min: 0.02, max: 0.43) than Field B (mean: 0.28, min: 0.04, max: 0.46) ($p = 0.01$; Figure 2.7, Table 2.1). In 2023, this trend was inconsistent, with Field A recorded a slightly higher WDI (0.11) than Field B (0.09) ($p = 0.3$). At the reproductive growth stages (VT-R4) for corn, Field A had significantly lower WDI values for both years (2021 and 2023). The mean WDI under Field A has ranged from 0.15-0.16 (min: 0.01-0.05, max: 0.26-0.34). Field B exhibited higher values with a mean of 0.20-0.24 (min: 0.08-0.13, max: 0.32-0.57) ($p < 0.07$; Figure 2.7, Table 2.1).

Under Field A, a low WDI value (0.15-0.16) indicated that the corn ET_a was closely related to PET for the system. This reflects a negligible water deficit to satisfy crop water demand in the AI-Radar irrigation system-based irrigation. During the critical growth stages, this

reflects a more balanced water status as well as a reduction in water stress by increasing stomatal conductance (Fereres & Soriano, 2006). A higher stomatal conductance, as reflected by higher ET_a , defines a positive correlation with corn yield by reducing leaf surface temperature and plant respiration. As indicated by high NDVI values (Table 1), a low WDI values indicate less water stress and improved crop health (Antoniuk et al., 2021). Additionally, the spatial uniformity of the low WDI values (Figure 2.7) suggests that Field A further supports the idea that irrigation was aligned with the spatial crop water demand. In contrast, the higher WDI values (0.20-0.24) in Field B reflect a reduced ET_a and a water-limited condition for corn, which affects crop growth. In corn, water stress has a significant impact on yield (Kunrath et al., 2020; Main et al., 2023; Sah et al., 2020). According to Li et al (2023), water stress occurring during the early reproductive stage and grain filling can reduce final yield by 36-99% and 22-39%, respectively.

3.2. Relationship Between WDI, NDVI, and ET_a

According to our research, the NDVI values under Field A were higher (NDVI: 0.82 to 0.84) than Field B (NDVI: 0.77 to 0.78). This occurred during the critical growth stages (VT-R4) for corn in 2021 and 2023 ($p < 0.07$; Table 2.1). High NDVI values during pre-silking and silking indicate greater canopy coverage (Maresma et al., 2020; R. Wang et al., 2016). Furthermore, a positive correlation exists between biomass and corn yield potential, as well as a higher NDVI (Maresma et al., 2020; R. Wang et al., 2016). Additionally, we have found that ET_a under Field A was higher than that under Field B. According to the quantitative studies, corn ET_a has a strong correlation with corn yield (Corn Water Use and Evapotranspiration, 2017; Ko & Piccinni, 2009). There is a positive correlation between higher corn yield and higher ET_a . For example, corn yield can increase by approximately 1.1 Mg per ha (17 bushels per acre) with an

additional 25.4 millimeters (1 inch) of evapotranspiration from the system (Corn Water Use and Evapotranspiration, 2017).

3.3. Comparison of Irrigation Depth and Spatial Variability for Irrigation Systems

Additionally, in terms of irrigation depth, the results highlight a clear contrast between Field A (AI-Radar) and Field B (SDI). The SDI system applied a total depth of 273 to 360 mm (10.7 to 14.2 in), which was consistently greater (31 to 34% in 2021 and 2023, respectively) than the seasonal depths recorded for the AI-Radar system. Based on pivot pressure-sensor records, the AI-Radar system applied an average of 237 mm (9.33 in) in 2021 and 242 mm (9.51 in) in 2023 across the eight pivot segments. The AI-Radar system showed clear spatial variation in irrigation depth for each segment. In 2021, segment-wise irrigation water ranged from 193 mm (7.60 in) in Segment E to 286 mm (11.26 in) in Segment A. In 2023, the range was 222 mm (8.74 in) in Segment G to 264 mm (10.39 in) in Segment D. This represents that irrigation water was distributed according to the spatial crop need and soil variability. Independent studies have substantiated the use of GPR and advanced computer vision in irrigation scheduling. Namdari et al (2025) demonstrated that GPR can accurately determine soil water content with a high R^2 (0.89) and reduced RMSE (<2.9%). Similarly, Fernández-Pacheco et al (2014) found a strong correlation between crop coefficient and crop coverage percentage, with high predictive accuracy ($R\text{-squared} > 0.90$), suggesting the strength of estimating crop coefficient from mean canopy cover percentage.

3.4. Evaluation of the SDI System with Adaptive Scheduling Systems of AI-Radar

SDI is widely recognized as an efficient method of irrigation that delivers water directly to the root zone. The accuracy ranged from 35 to 55% in water savings compared to surface irrigation systems in Kansas (Lamm & Trooien, 2003). In our study, SDI was operated on a fixed

schedule. Therefore, there was no consideration for soil water status and crop water status, which are crucial for meeting the dynamic water demands of corn throughout its phenological stages. Furthermore, it is also possible that deeper placement of drip lines can delay the availability of water in the upper soil profile (Lamm et al., 2012). In SDI, this can limit water uptake compared with sensor-driven approaches such as AI-Radar. On the other hand, the AI-Radar irrigation system improved the water status of crops during critical reproductive growth stages (VT-R4) by simultaneously assessing soil and crop water stress before each irrigation event. For instance, the GPR estimated the AWHC at a depth of 0 to 15 cm to be 22% for segments A, D, and H, and 15% for segments B, C, E, F, and G, which informed variable-rate irrigation decisions. As a result, for 2021, irrigation recommendations were made based on the AWHC as 213.86 to 286.0 mm (8.42 to 11.26 in) and 193.0 to 282.70 mm (7.60 to 11.13 in) for segments A, D, H, and segments B, C, E, F, and G, respectively. Similarly, irrigation recommendations for 2023 were made based on the AWHC as 241.5 to 263.9 mm (9.51 to 10.39 in) and 221.9 to 246.12 mm (8.74 to 9.69 in) for segments A, D, and H, as well as segments B, C, E, F, and G. This adaptive scheduling approach effectively reduced excess application in some segments while allocating greater amounts in others, which reflects the ability of the system to manage irrigation based on localized field conditions.

Future studies are required to incorporate field-based actual evapotranspiration measurements. The current study was based on the measurement of WDI based on the NDVI-K_{c-act} model performance and accuracy.

4. Implications of this study

Future studies are required to incorporate field-based actual evapotranspiration measurements. The current study measured WDI using the NDVI-K_{c-act} model performance and

accuracy. This novel system has great potential for Kansas agriculture. About 96% of irrigation water in Kansas comes from groundwater (Lanning-Rush, 2016). Given this scenario, understanding the spatial and temporal distribution of water based on the actual crop needs is important for rational water resource allocation without reducing crop yield (Zhang et al., 2022). Furthermore, Ineffective use can result in overuse, decreased crop productivity, economic loss, and negative environmental consequences (Rogers & Aguilar, 2023). Therefore, this retrofitted AI-Radar sensor, combined with a center pivot irrigation system, can significantly enhance irrigation management and promote sustainable agricultural practices in Kansas and similar semi-arid regions.

5. Conclusion

To establish a baseline evaluation of the AI-Radar irrigation system, the current study utilizes satellite imagery-derived Water Distribution Index (WDI) to quantify water spatial distribution in central Kansas for two growing seasons, 2021 and 2023. The findings showed that during critical growth stages, the AI-Radar irrigation system continuously maintained higher NDVI values (0.82 to 0.84; $p < 0.07$), which led to lower WDI values (0.15 to 0.16; $p < 0.07$) across a 3 m spatial scale during the corn tasseling to dough stages. The consistently low WDI value, resulting from high actual evapotranspiration relative to potential evapotranspiration, indicates optimal stomatal conductance and signifies the ability of AI-Radar irrigation systems to maintain optimal crop watering, especially during the tasseling-to-dough stage (VT-R4) for the corn crop. This case study demonstrates that the AI-Radar system outperformed the current SDI setup in terms of the water deficit index. However, additional research is needed to validate this work.

Building on these results, Chapter 3 moves from satellite-based irrigation assessment to finer, field-scale analysis using UAV-derived measurements. By combining high-resolution (UAV) imagery with OpenET data, the next study assesses the accuracy of the AI-Radar irrigation system based on field-scale water use efficiency. This would help growers to understand how AI-Radar irrigation influences the spatial water use efficiency of the crop.

References

- Abbasi, N., Nouri, H., Didan, K., Barreto-Muñoz, A., Chavoshi Borujeni, S., Salemi, H., Opp, C., Siebert, S., & Nagler, P. (2021). Estimating Actual Evapotranspiration over Croplands Using Vegetation Index Methods and Dynamic Harvested Area. *Remote Sensing*, 13(24), 5167. <https://doi.org/10.3390/rs13245167>
- Allen, R. G., Pereira, L. S., Smith, M., Raes, D., & Wright, J. L. (2005). *FAO-56 Dual Crop Coefficient Method for Estimating Evaporation from Soil and Application Extensions. Journal of Irrigation and Drainage Engineering*, 131(1), 2–13. [https://doi.org/10.1061/\(ASCE\)0733-9437\(2005\)131:1\(2\)](https://doi.org/10.1061/(ASCE)0733-9437(2005)131:1(2))
- Antoniuk, V., Manevski, K., Kørup, K., Larsen, R., Sandholt, I., Zhang, X., & Andersen, M. N. (2021). Diurnal and Seasonal Mapping of Water Deficit Index and Evapotranspiration by an Unmanned Aerial System: A Case Study for Winter Wheat in Denmark. *Remote Sensing*, 13(15), 2998. <https://doi.org/10.3390/rs13152998>
- Autonomous Pivot Product Guide*. (2024). Google Docs. https://drive.google.com/file/d/1FTyVn84TR-SdivONN4tEPxxy8dSpsjcW/view?usp=sharing&usp=embed_facebook

- Brikowski, T. H. (2008). Doomed reservoirs in Kansas, USA? Climate change and groundwater mining on the Great Plains lead to unsustainable surface water storage. *Journal of Hydrology*, 354(1), 90–101. <https://doi.org/10.1016/j.jhydrol.2008.02.020>
- Colaizzi, P. D., Barnes, E. M., Clarke, T. R., Choi, C. Y., Waller, P. M., Haberland, J., & Kostrzewski, M. (2003). Water Stress Detection Under High Frequency Sprinkler Irrigation with Water Deficit Index. *Journal of Irrigation and Drainage Engineering*, 129(1), 36–43. [https://doi.org/10.1061/\(ASCE\)0733-9437\(2003\)129:1\(36\)](https://doi.org/10.1061/(ASCE)0733-9437(2003)129:1(36))
- Corn Water Use and Evapotranspiration*. (2017). Integrated Crop Management. <https://crops.extension.iastate.edu/cropnews/2017/06/corn-water-use-and-evapotranspiration>
- DripWorks*. (2025). <https://www.dripworks.com/blog/subsurface-drip-irrigation-the-most-sustainable-way-to-water>
- Drought.gov*. (2025). <https://www.drought.gov/>
- Dwevedi, A., Kumar, P., Kumar, P., Kumar, Y., Sharma, Y. K., & Kayastha, A. M. (2017). 15 - Soil sensors: Detailed insight into research updates, significance, and future prospects. In A. M. Grumezescu (Ed.), *New Pesticides and Soil Sensors* (pp. 561–594). Academic Press. <https://doi.org/10.1016/B978-0-12-804299-1.00016-3>
- Economic Research Service*. (2024). https://www.ers.usda.gov/amber-waves/2024/march/ers-research-models-future-effects-of-climate-change-on-corn-and-soybean-yields-production-and-exports?utm_source=chatgpt.com
- El-Shirbeny, M. A., Ali, A. M., Rashash, A., & Badr, M. A. (2015). Wheat Yield Response to Water Deficit under Central Pivot Irrigation System Using Remote Sensing Techniques.

World Journal of Engineering and Technology, 3(3), 65–72.

<https://doi.org/10.4236/wjet.2015.33B011>

F. R. Lamm, J. P. Bordovsky, L. J. Schwankl, G. L. Grabow, J. Enciso-Medina, R. T. Peters, P. D. Colaizzi, T. P. Trooien, & D. O. Porter. (2012). Subsurface Drip Irrigation: Status of the Technology in 2010. *Transactions of the ASABE*, 55(2), 483–491.

<https://doi.org/10.13031/2013.41387>

Feiziasl, V., Jafarzadeh, J., Sadeghzadeh, B., & Mousavi Shalmani, M. A. (2022). Water deficit index to evaluate water stress status and drought tolerance of rainfed barley genotypes in cold semi-arid area of Iran. *Agricultural Water Management*, 262, 107395.

<https://doi.org/10.1016/j.agwat.2021.107395>

Fereres, E., & Soriano, M. A. (2006). Deficit irrigation for reducing agricultural water use.

Journal of Experimental Botany, 58(2), 147–159. <https://doi.org/10.1093/jxb/erl165>

Fernández-Pacheco, D. G., Escarabajal-Henarejos, D., Ruiz-Canales, A., Conesa, J., & Molina-Martínez, J. M. (2014). A digital image-processing-based method for determining the crop coefficient of lettuce crops in the southeast of Spain. *Biosystems Engineering*, 117, 23–34. <https://doi.org/10.1016/j.biosystemseng.2013.07.014>

French, A. N., Hunsaker, D. J., Sanchez, C. A., Saber, M., Gonzalez, J. R., & Anderson, R. (2020). Satellite-based NDVI crop coefficients and evapotranspiration with eddy covariance validation for multiple durum wheat fields in the US Southwest. *Agricultural Water Management*, 239, 106266. <https://doi.org/10.1016/j.agwat.2020.106266>

Glenn, E. P., Neale, C. M. U., Hunsaker, D. J., & Nagler, P. L. (2011). Vegetation index-based crop coefficients to estimate evapotranspiration by remote sensing in agricultural and

- natural ecosystems. *Hydrological Processes*, 25(26), 4050–4062.
<https://doi.org/10.1002/hyp.8392>
- Goyal, P., Sharda, R., Saini, M., & Siag, M. (2023). A deep learning approach for early detection of drought stress in maize using proximal scale digital images. *Neural Computing and Applications*, 36, 1–15. <https://doi.org/10.1007/s00521-023-09219-z>
- Jackson, R. D., Idso, S. B., Reginato, R. J., & Pinter Jr., P. J. (1981). Canopy temperature as a crop water stress indicator. *Water Resources Research*, 17(4), 1133–1138.
<https://doi.org/10.1029/WR017i004p01133>
- Kamble, B., Kilic, A., & Hubbard, K. (2013). Estimating Crop Coefficients Using Remote Sensing-Based Vegetation Index. *Remote Sensing*, 5(4), Article 4.
<https://doi.org/10.3390/rs5041588>
- Kansas Geological Survey. (2023). <https://kgs.ku.edu/news/article/2023/03/10/groundwater-levels-fall-across-western-and-south-central-kansas>
- Kansas State University Foundation. (2025). <https://ksufoundation.org/impact/good-for-k-state/the-last-drop/>
- Kansas State Water Office. (2022). <https://www.kwo.ks.gov/water-plan/water-plan>
- Ko, J., & Piccinni, G. (2009). Corn yield responses under crop evapotranspiration-based irrigation management. *Agricultural Water Management*, 96(5), 799–808.
<https://doi.org/10.1016/j.agwat.2008.10.010>
- Kottek, M., Grieser, J., Beck, C., Rudolf, B., & Rubel, F. (2006). World Map of the Köppen-Geiger climate classification updated. *Meteorologische Zeitschrift*, 15(3), 259–263.
<https://doi.org/10.1127/0941-2948/2006/0130>

- Kunrath, T. R., Lemaire, G., Teixeira, E., Brown, H., Ciampitti, I. A., & Sadras, V. (2020). Allometric relationships between nitrogen uptake and transpiration to untangle interactions between nitrogen supply and drought in maize and sorghum. *European Journal of Agronomy*, 120. <https://doi.org/10.1016/j.eja.2020.126145>
- Lamm, F. R., & Trooien, T. P. (2003). Subsurface drip irrigation for corn production: A review of 10years of research in Kansas. *Irrigation Science*, 22(3–4), 195–200. <https://doi.org/10.1007/s00271-003-0085-3>
- Lanning-Rush, J. L. (2016). *Irrigation Water Use in Kansas* (Data Series) [Data Series]. U.S. Geological Survey Data Series. <https://pubs.usgs.gov/ds/0981/ds981.pdf>
- Li, Y., Zhang, P., Sheng, W., Zhang, Z., Rose, R. J., & Song, Y. (2023). Securing maize reproductive success under drought stress by harnessing CO₂ fertilization for greater productivity. *Frontiers in Plant Science*, 14, 1221095. <https://doi.org/10.3389/fpls.2023.1221095>
- Lu, Q., Liu, K., Zeng, Z., Liu, S., Li, R., Xia, L., Guo, S., & Li, Z. (2023). Estimation of the Soil Water Content Using the Early Time Signal of Ground-Penetrating Radar in Heterogeneous Soil. *Remote Sensing*, 15(12), 3026. <https://doi.org/10.3390/rs15123026>
- Lunt, I. A., Hubbard, S. S., & Rubin, Y. (2005). Soil moisture content estimation using ground-penetrating radar reflection data. *Journal of Hydrology*, 307(1), 254–269. <https://doi.org/10.1016/j.jhydrol.2004.10.014>
- Main, O., Jacquemot, M.-P., Griveau, Y., Guillaume, S., Demonceaux, C., Lopez-Marnet, P.-L., Rey, S., Fargier, S., Sartre, P., Montagnier, C., Uijttewaal, A., Mangel, N., Meunier, F., Reymond, M., Méchin, V., & Coursol, S. (2023). Precise control of water stress in the

- field reveals different response thresholds for forage yield and digestibility of maize hybrids. *Frontiers in Plant Science*, 14. <https://doi.org/10.3389/fpls.2023.1142462>
- Maresma, A., Chamberlain, L., Tagarakis, A., Kharel, T., Godwin, G., Czymmek, K. J., Shields, E., & Ketterings, Q. M. (2020). Accuracy of NDVI-derived corn yield predictions is impacted by time of sensing. *Comput. Electron. Agric.*, 169(C). <https://doi.org/10.1016/j.compag.2020.105236>
- McGuire, V. L. (2011). *Water-level changes in the High Plains aquifer, predevelopment to 2009, 2007–08, and 2008–09, and change in water in storage, predevelopment to 2009.* <https://digitalcommons.unl.edu/usgspubs/105/>
- Moran, M. S. (1994). Irrigation management in Arizona using satellites and airplanes. *Irrigation Science*, 15(1), 35–44. <https://doi.org/10.1007/BF00187793>
- Nagler, P., Glenn, E., Nguyen, U., Scott, R., & Doody, T. (2013). Estimating Riparian and Agricultural Actual Evapotranspiration by Reference Evapotranspiration and MODIS Enhanced Vegetation Index. *Remote Sensing*, 5(8), 3849–3871. <https://doi.org/10.3390/rs5083849>
- Namdari, H., Moradikia, M., Zekavat, S., Askari, R., Mangoubi, O., & Petkie, D. (2025). Advancing Precision Agriculture: Machine Learning-Enhanced GPR Analysis for Root-Zone Soil Moisture Assessment in Mega Farms. *IEEE Transactions on AgriFood Electronics*, 3(1), 98–109. <https://doi.org/10.1109/TAFE.2024.3455238>
- Oudah, M., Al-Naji, A., AL-Janabi, T. Y., Namaa, D. S., & Chahl, J. (2024). Automatic Irrigation System Based on Computer Vision and an Artificial Intelligence Technique Using Raspberry Pi. *Automation*, 5(2), Article 2. <https://doi.org/10.3390/automation5020007>

- Patrignani, A., Knapp, M., Redmond, C., & Santos, E. (2020). *Technical Overview of the Kansas Mesonet*. <https://doi.org/10.1175/JTECH-D-19-0214.1>
- Planet Labs. (2022). <https://docs.planet.com/>
- Pôças, I., Paço, T., Paredes, P., Cunha, M., & Pereira, L. (2015). Estimation of Actual Crop Coefficients Using Remotely Sensed Vegetation Indices and Soil Water Balance Modelled Data. *Remote Sensing*, 7(3), 2373–2400. <https://doi.org/10.3390/rs70302373>
- Rogers, D. H., & Aguilar, J. (2023). *Kansas Irrigation Trends*. K-State Research and Extension. https://bookstore.ksre.ksu.edu/download/kansas-irrigation-trends_MF2849.pdf
- Rogers, D. H., Lamm, F. R., & Aguilar, J. (2020). *K-State Research and Extension, 2020*.
- Sah, R. P., Chakraborty, M., Prasad, K., Pandit, M., Tudu, V. K., Chakravarty, M. K., Narayan, S. C., Rana, M., & Moharana, D. (2020). Impact of water deficit stress in maize: Phenology and yield components. *Scientific Reports*, 10(1), 2944. <https://doi.org/10.1038/s41598-020-59689-7>
- Soulis, K. X., Elmaloglou, S., & Dercas, N. (2015). Investigating the effects of soil moisture sensors positioning and accuracy on soil moisture based drip irrigation scheduling systems. *Agricultural Water Management*, 148, 258–268. <https://doi.org/10.1016/j.agwat.2014.10.015>
- Suttles, K. M., Smoliak, B. V., Ranade, A. P., Potter, S. F., Jaeger, M., & McLellan, E. L. (2024). Kansas agriculture in 2050: A pathway for climate-resilient crop production. *Frontiers in Sustainable Food Systems*, 8. <https://doi.org/10.3389/fsufs.2024.1404315>
- Tang, J., Han, W., & Zhang, L. (2019). UAV Multispectral Imagery Combined with the FAO-56 Dual Approach for Maize Evapotranspiration Mapping in the North China Plain. *Remote Sensing*, 11(21), 2519. <https://doi.org/10.3390/rs11212519>

- Tanriverdi, C., Atilgan, A., Degirmenci, H., & Akyuz, A. (2017). COMPARASION OF CROP WATER STRESS INDEX (CWSI) AND WATER DEFICIT INDEX (WDI) BY USING REMOTE SENSING (RS). *Infrastruktura i Ekologia Terenów Wiejskich / Infrastructure and Ecology of Rural Areas, III/1*, 879–894.
<https://doi.org/10.14597/infraeco.2017.3.1.068>
- Tavares, C. J., Ribeiro Junior, W. Q., Ramos, M. L. G., Pereira, L. F., Casari, R. A. das C. N., Pereira, A. F., de Sousa, C. A. F., da Silva, A. R., Neto, S. P. da S., & Mertz-Henning, L. M. (2022). Water Stress Alters Morphophysiological, Grain Quality and Vegetation Indices of Soybean Cultivars. *Plants, 11*(4), 559. <https://doi.org/10.3390/plants11040559>
- Velazquez-Chavez, L. J., Daccache, A., Mohamed, A. Z., & Centritto, M. (2024). Plant-based and remote sensing for water status monitoring of orchard crops: Systematic review and meta-analysis. *Agricultural Water Management, 303*, 109051.
<https://doi.org/10.1016/j.agwat.2024.109051>
- Wang, R., Cherkauer, K., & Bowling, L. (2016). Corn Response to Climate Stress Detected with Satellite-Based NDVI Time Series. *Remote Sensing, 8*(4), 269.
<https://doi.org/10.3390/rs8040269>
- Web Soil Survey*. (2024). <https://websoilsurvey.nrcs.usda.gov/app/>
- Welch, B. L. (1947). The Generalization Of ‘Student’s’ Problem When Several Different Population Variances Are Involved. *Biometrika, 34*(1–2), 28–35.
<https://doi.org/10.1093/biomet/34.1-2.28>
- Western Kansas Research-Extension Center*. (2025).
https://www.wkrec.org/programs/irrigation_engineering/subsurface_drip/news/pros-cons.html

- Wilson, B., G, L., G.C, B., & J.J, B. (2020). *Groundwater Flow Model: High Plains Aquifer Modeling Maintenance Project* (Nos. 2020–1). Kansas Geological Survey.
<https://www.kgs.ku.edu/Publications/OFR/2020/OFR2020-1.pdf>
- Zhang, P., Ma, W., Hou, L., Liu, F., & Zhang, Q. (2022). Study on the Spatial and Temporal Distribution of Irrigation Water Requirements for Major Crops in Shandong Province. *Water*, 14(7), Article 7. <https://doi.org/10.3390/w14071051>
- Zhao, G., Luo, X., Wang, Z., Sheng, G., Liu, W., & Wang, Y. (2024). Effects of subsurface drip fertigation on potato growth, yield, and soil moisture dynamics. *Frontiers in Sustainable Food Systems*, 8. <https://doi.org/10.3389/fsufs.2024.1485377>

Table

Table 2.1. Summary statistics of NDVI, ET_a, and WDI for AI-Radar (Field A) and SDI (Field B) irrigation systems across major corn growth stages (V8–V11 and VT–R4) during the 2021 and 2023 growing seasons

Year	Growth Stages	NDVI		ET _a		WDI							
		Field A	Field B	Field A	Field B	Field A				Field B			
						WDI	WDI _{max}	WDI _{min}	WDI _{sd}	WDI	WDI _{max}	WDI _{min}	WDI _{sd}
2021	V8-V11	0.80*	0.73	5.08	4.97	0.16*	0.43	0.02	0.15	0.28	0.46	0.04	0.13
	VT-R4	0.82*	0.78	4.69	4.39	0.15*	0.26	0.05	0.05	0.20	0.32	0.13	0.06
2023	V8-V11	0.86	0.86	6.24	5.81	0.11	0.17	0.05	0.03	0.09	0.23	0.03	0.05
	VT-R4	0.84*	0.77	5.68	5.15	0.16*	0.34	0.01	0.09	0.24	0.57	0.08	0.13

Figures

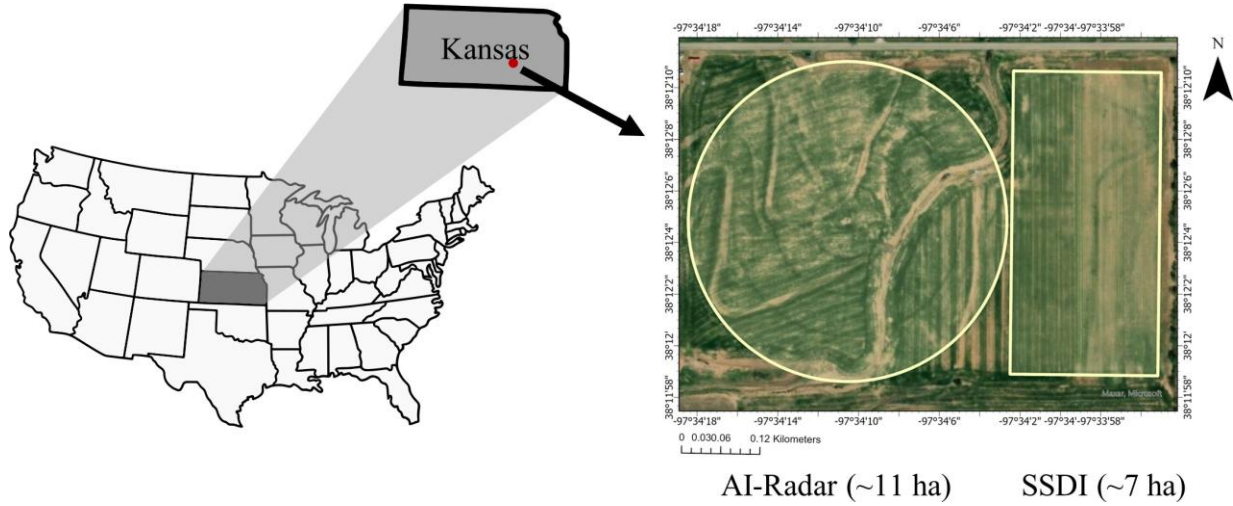


Figure 2.1. Study location in Central part of Kansas with two designated fields (AI-Radar and SSDI)

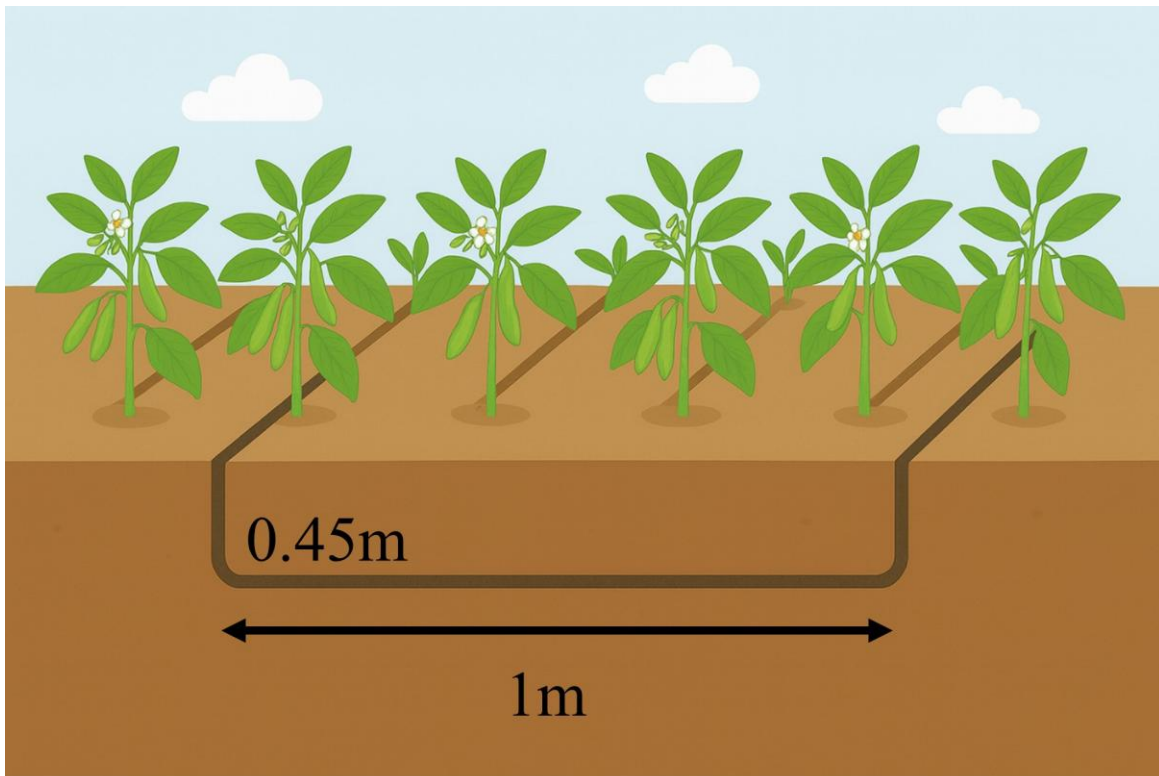


Figure 2.2. Layout of the subsurface drip irrigation (SDI) system showing the distribution network

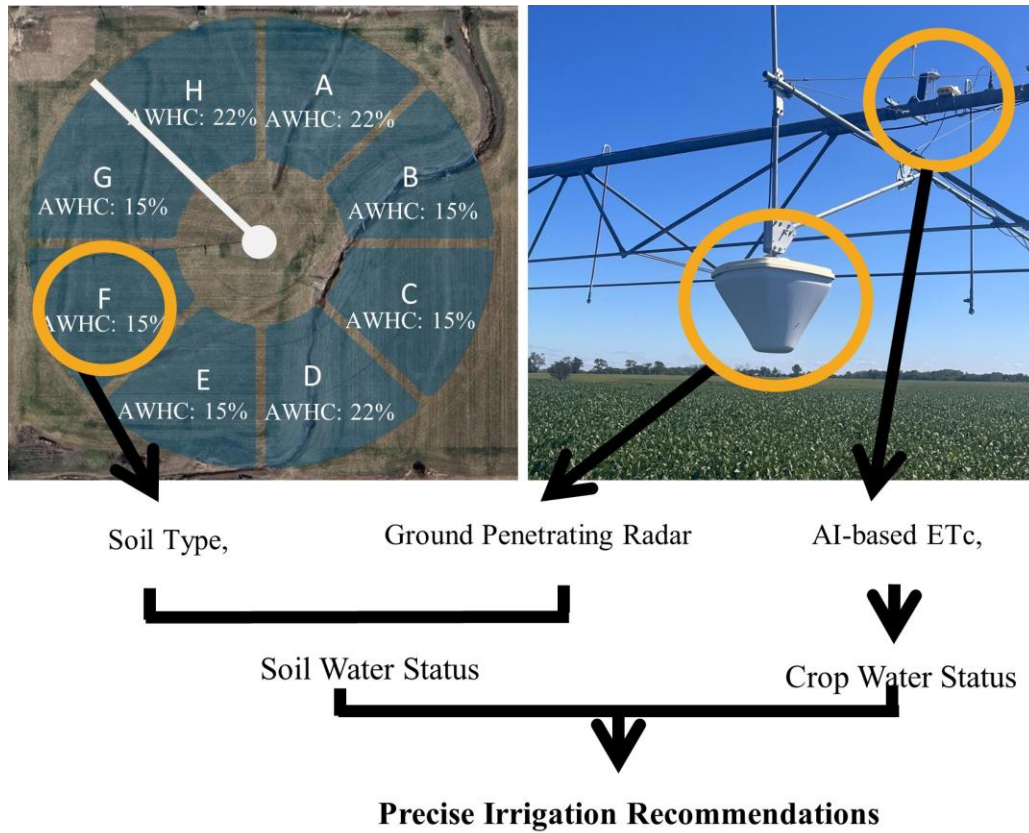


Figure 2.3. Detailed description of the AI-Radar irrigation system showing integration of ground-penetrating radar (GPR), soil moisture sensing, and AI-based decision algorithms for variable-rate irrigation scheduling.

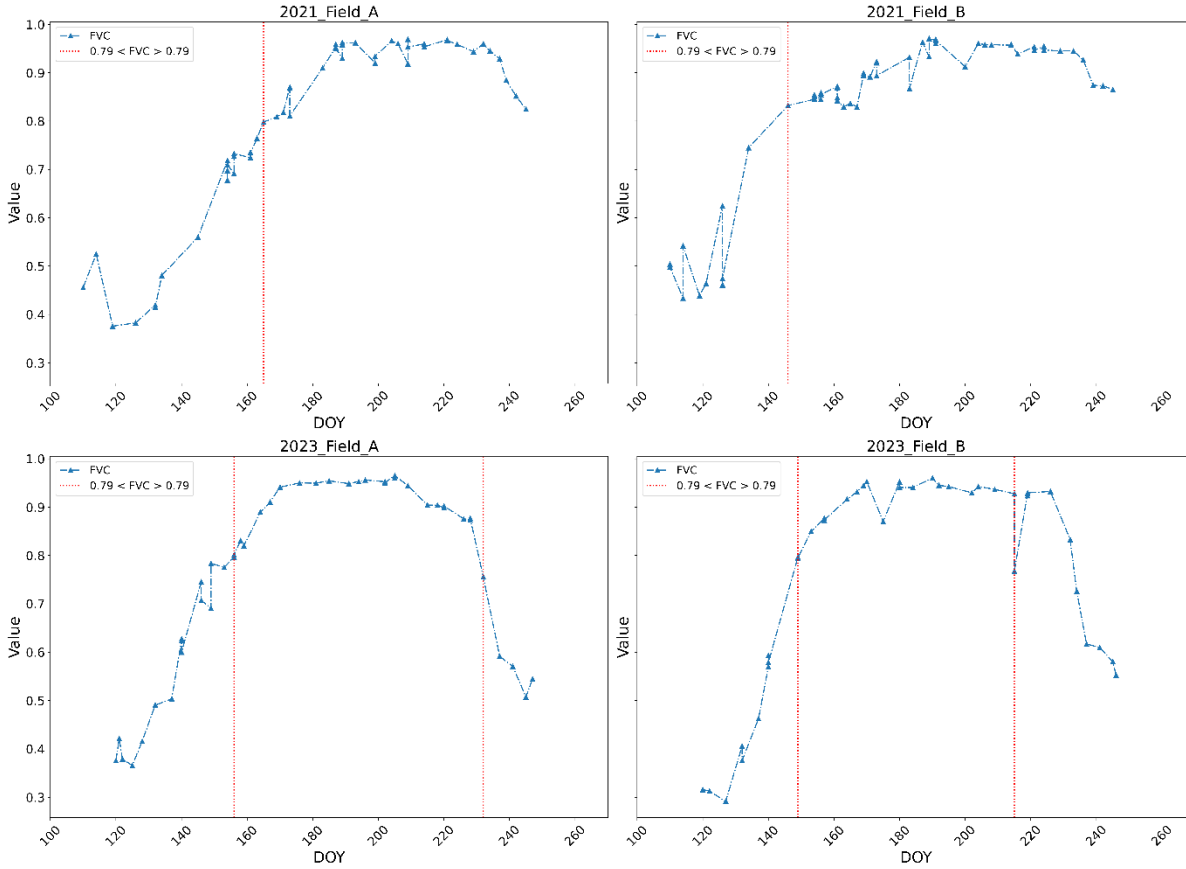


Figure 2.4. Canopy Coverage Thresholds ($FVC > 0.79$) and Distributions Across Corn Growth Stages (The stages of ET estimation were conducted during periods of high canopy coverage, defined as a fraction of vegetation cover (FVC) more than 0.79, estimated from NDVI)

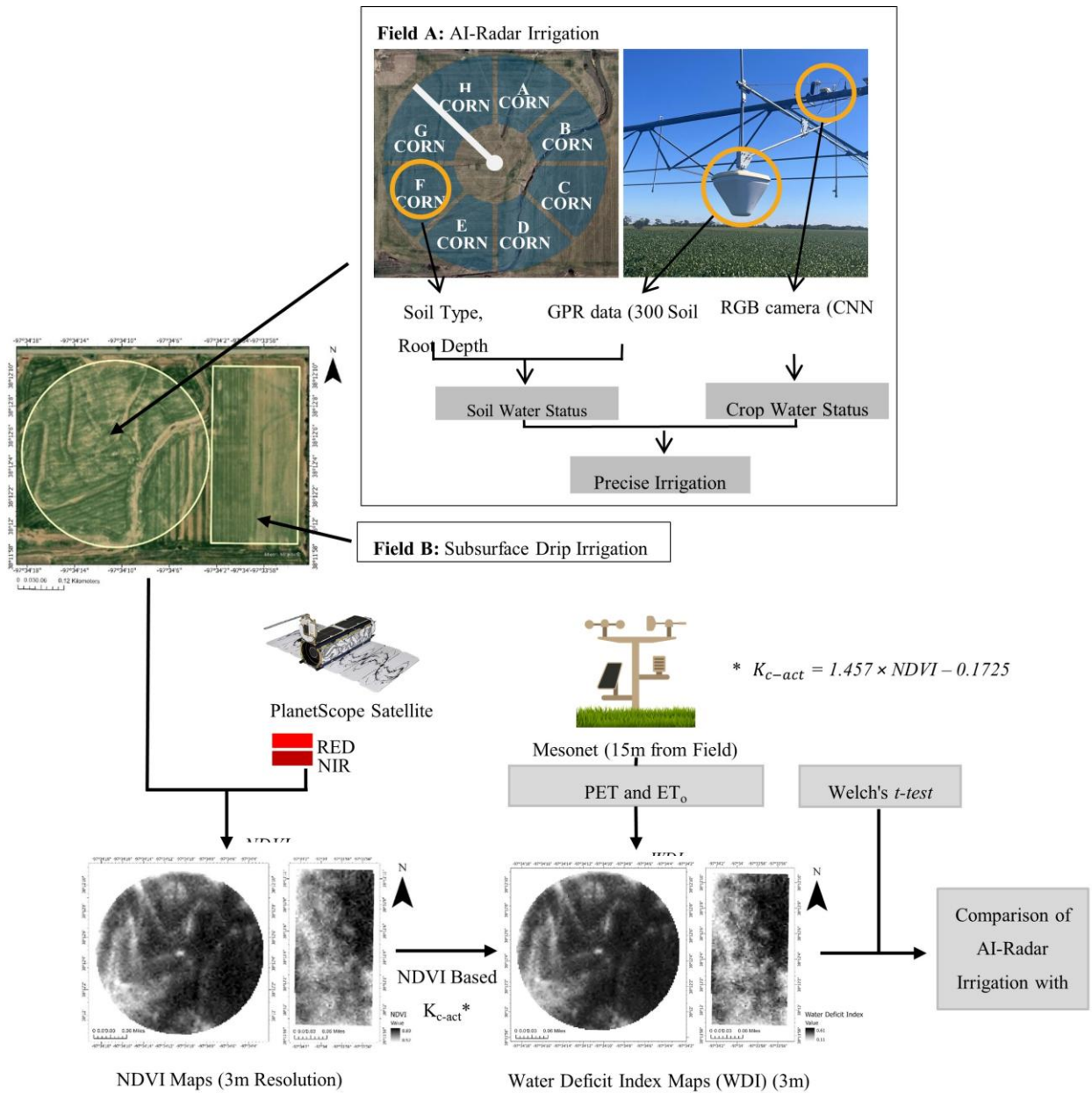


Figure 2.5. Workflow for evaluating the performance of AI-Radar and subsurface drip irrigation (SDI) systems using the Water Deficit Index (WDI) derived from remote sensing data.

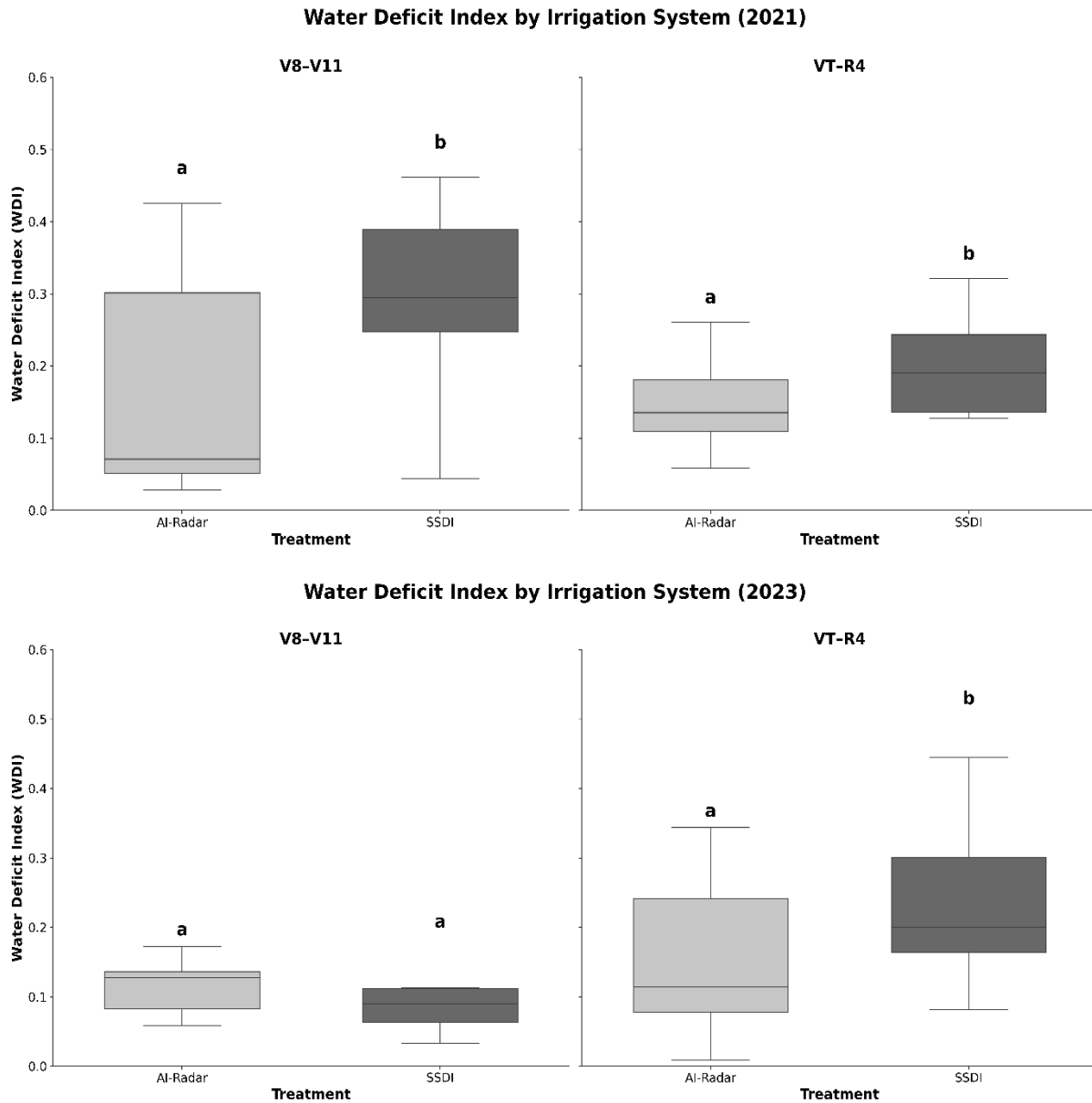


Figure 2.6. Boxplot of Water Deficit Index (WDI) for AI-Radar and SDI systems across corn growth stages (V8–V11, VT–R4) in 2021 and 2023.

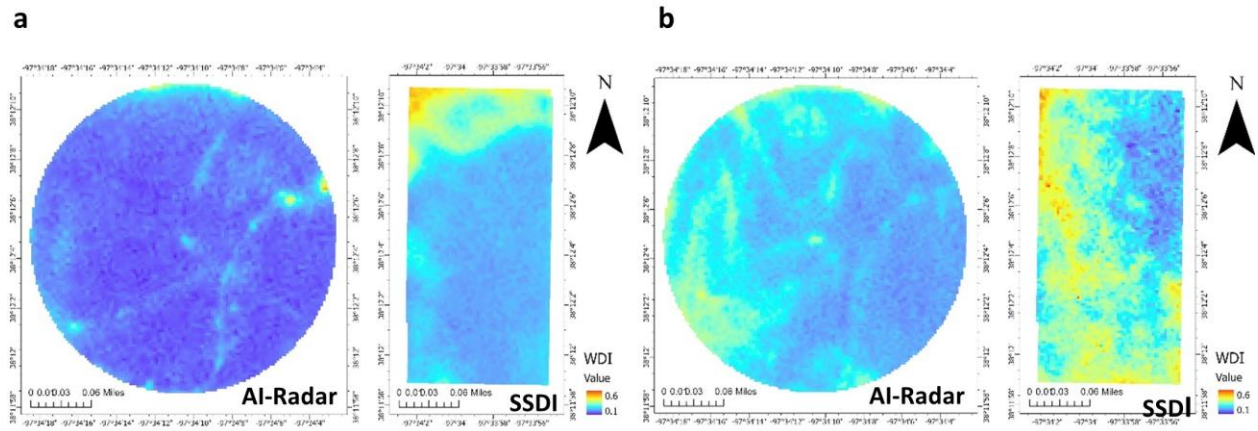


Figure 2.7. Spatial Maps of Water Deficit Index (WDI) for Fields A and B Under AI-Radar and SDI. For both the growing seasons (2021 and 2023), WDI under AI-Radar fields was significantly low during the critical growth stages (more blueish in color).

Chapter 3 - Quantifying Field-Scale Water Use Efficiency in AI-Radar Irrigation System Using Unoccupied Aerial Vehicle (UAV)

Observations and OpenET-Derived Spatiotemporal ET

Abbreviations

AI: Artificial Intelligence; AI-Radar: Artificial Intelligence-Integrated Ground Penetrating Radar Irrigation System; AWHC: Available Water Holding Capacity; CNN: Convolutional Neural Network; CST: Crop Surface Temperature; CV: Coefficient of Variation; DN: Digital Number; DOY: Day of Year; ET_a: Actual Evapotranspiration; ET_c: Crop Evapotranspiration; ET_o: Reference Evapotranspiration (from grass surface); FC: Field Capacity; FOV: Field of View; G: Soil Heat Flux; GMD: Groundwater Management District; GPR: Ground Penetrating Radar; HRMET: High-Resolution Mapping of Evapotranspiration; K_c: Crop Coefficient; LAI: Leaf Area Index; LWIR: Longwave Infrared; MAD: Maximum Allowable Depletion; MBE: Mean Bias Error; MG: Maturity Group; MS: Multispectral; NDVI: Normalized Difference Vegetation Index; NRMSE: Normalized Root Mean Square Error; OpenET: Open Evapotranspiration Consortium Platform; pa: Atmospheric Pressure; PWP: Permanent Wilting Point; RMSE: Root Mean Square Error; R_n: Net Radiation; RTK: Real-Time Kinematic; SD: Standard Deviation; SDI: Subsurface Drip Irrigation; S_{Win}: Incoming Solar Radiation; T_a: Air Temperature; TIR: Thermal Infrared; UAV: Unoccupied Aerial Vehicle; u: Wind Speed; WUE_f: Field-Scale Water Use Efficiency.

Abstract

Water management in the Southern Great Plains is critical due to erratic climate variability and declining levels of the Ogallala Aquifer. As water scarcity intensifies, farmers are

now facing challenges in maintaining high crop productivity and profitability. Therefore, precision irrigation technologies offer potential for sustainable water use by integrating soil variability, crop growth dynamics, and weather patterns. Our study evaluated two on-farm field locations in central Kansas under soybean (*Glycine max* L.) cultivation for the 2024 growing season: Field A was equipped with an AI-Radar irrigation system, and Field B was irrigated using a subsurface drip irrigation system (SDI) using field-scale water use efficiency (WUE_f). WUE_f was calculated using crop yield and seasonal evapotranspiration (seasonal ET_a ; comparatively computed using UAV and OpenET, separately). Results showed that WUE_f was significantly (p -value < 0.05) improved under AI-Radar (UAV: $7.17 \pm 2.41 \text{ kg ha}^{-1} \text{ mm}^{-1}$; OpenET: $6.66 \pm 2.24 \text{ kg ha}^{-1} \text{ mm}^{-1}$) than SDI (UAV: $5.70 \pm 2.13 \text{ kg ha}^{-1} \text{ mm}^{-1}$; OpenET: $5.06 \pm 1.89 \text{ kg ha}^{-1} \text{ mm}^{-1}$), with total applied irrigation depth being 15 to 27% less than the SDI. The mean yield under AI-Radar (3189.04 kg/ha) was 30.8% higher than SDI (2207.83 kg/ha) (p < 0.05), with a lower coefficient of variation (9.96%), indicating higher yield potential in Field A. The mean seasonal ET_a was also higher for AI-Radar (UAV-based: 444.44 mm; satellite-based (NASA OpenET): 478.8 mm) than for SDI (UAV: 386.66 mm and OpenET: 436.2 mm), indicating reduced water stress in Field A. In addition, agreement analysis between the UAV and OpenET for estimating seasonal ET_a showed comparatively strong agreement ($R^2 = 0.65$ to 0.69 , $RMSE = 0.77$ to 0.90 mm day^{-1} ; $NRMSE = 21.8$ to 23.4% ; $MBE = -0.28$ to $-0.42 \text{ mm day}^{-1}$), indicating OpenET as an alternative open-sourced tool for estimating seasonal ET_a . These findings suggest that adopting radar-based precision irrigation systems integrated with AI can help farmers to produce more grain yield per drop of water in irrigated agriculture.

Keywords: AI-Radar Irrigation, Ogallala Aquifer, OpenET, Southern Great Plains, Water Use Efficiency

1. Introduction

1.1. Importance of Precision Irrigation

Water is essential for sustaining life, ecosystems, and agriculture. Agriculture is responsible for more than 70% of the freshwater withdrawal globally (Aivazidou et al., 2016). In recent years (2018-2022), drought-affected areas have expanded by 74% compared to 1981 to 2017 (Gebrechorkos et al., 2025). The high-resolution standardized precipitation evapotranspiration index shows a drying trend, with the drought area growing by $0.36 \pm 0.03\%$ annually from 1981 to 2022 (Gebrechorkos et al., 2025). Particularly in Kansas, the unsustainable use of groundwater and changing weather patterns will exacerbate water shortages. For example, in 2023, 55.7% of Kansas experienced severe drought, and 36.1% extreme drought (*Drought.Gov*, 2025).

In Kansas, soybeans are one of the most important crops, with planted areas of 5.53 million acres (*NASS, USDA, 2024*). Historically, the percentage of irrigated soybean acres has been low (around 9.5%) (Kansas Soybean Association, 2025). In central Kansas, most of this irrigation water comes from the Ogallala aquifer. Meanwhile, Kansas's heavy reliance on the Ogallala aquifer for irrigation has led to depletion, as water extraction far exceeds natural recharge rates. (McGuire, 2011). According to the United States Geological Survey, in Kansas, the average water level declined by 57.6 cm (1.89 ft) in 2022 (Kansas Geological Survey, 2023). Furthermore, between 2007 and 2050, the volume of surface water reservoirs is expected to decrease by 50% due to a decline in precipitation and high evaporative losses (Brikowski, 2008). Due to this cumulative effect, major crop yields such as corn and soybean yields are projected to decline by up to 25.4% and 43.4%, respectively (Economic Research Service, 2024).

The use of traditional irrigation methods often results in overwatering, water shortages, and uneven water distribution (Ahmed et al., 2023; Levidow et al., 2014). This uneven distribution can also lower crop productivity. Therefore, precision irrigation methods apply variable rate irrigation to handle variable field water needs, utilizing tools such as soil moisture sensors (Soulis et al., 2015), ground penetrating radar (GPR) (Lunt et al., 2005), and artificial intelligence (AI) (Oudah et al., 2024). Among them, AI-Radar is an innovative system that utilizes soil data, weather data, artificial intelligence (AI), and ground penetrating radar (GPR) to provide irrigation recommendations. This system accounts for field-wide soil and crop variability. AI-Radar is a retrofitted sensor that can be installed on any type of irrigation system, making it compatible with various irrigation systems (*Autonomous Pivot Product Guide*, 2024). Details of the AI-Radar irrigation settings have been discussed in the methodology section. We believe that this system could be a potential solution to conserve water resources and improve yields by addressing field variability. However, before high-scale recommendations are made to farmers, rigorous evaluation is needed against established irrigation practices, such as subsurface drip irrigation (SSDI) in this study.

1.2. Evapotranspiration as an Indicator for Water Stress

Evapotranspiration is the process by which liquid water is converted to water vapor (vaporization) and removed from the evaporating surface (vapor removal), particularly the Soil surface (Evaporation), and the plant surface (transpiration) (Allen et al., 1998). The evapotranspiration rate is expressed in millimeters (mm) per unit time. The driving force for evapotranspiration is the difference between the water vapour pressure at the evaporating surface and the surrounding atmosphere (Allen et al., 1998). Evapotranspiration can be divided into reference evapotranspiration (ET_o), crop evapotranspiration (ET_c), and actual evapotranspiration

(ETa). ETo, denoted as the maximum evapotranspiration rate from a reference surface. The reference surface is a hypothetical grass reference crop with specific characteristics. According to the FAO Expert Consultation on Revision of FAO Methodologies for Crop Water, ETo derivation was standardized from a hypothetical reference crop (grass) with a crop height of 0.12 m, a fixed surface resistance of 70 s m^{-1} , and an albedo of 0.23 (Allen et al., 1998). ETo determines the atmospheric evaporative demand regardless of crop type, development, or management. Therefore, ETo depends solely on climatic parameters and can be derived from weather variables at a specific location and time of year. On the other hand, ETc represents the water demand for the particular crop surface. The ETc differs from the ETo in that it accounts for crop height, ground cover, canopy properties, evaporation from the soil, and the aerodynamic resistance of the crop (Allen et al., 1998). Therefore, crop characteristics that distinguish field crops from grass are integrated into the crop coefficient (Kc). In the single crop coefficient approach, ETc can be derived by multiplying ETo by Kc to derive ETc. The Kc incorporates crop characteristics and the averaged effects of evaporation from the soil. These approaches for determining ETo and ETc were under standard conditions where water stress or other environmental stresses were not present (Allen et al., 1998). However, in field conditions, these factors differ in terms of waterlogging, drought, salt stress, and other environmental factors. Therefore, estimating ETa is essential, as it combines the actual field conditions of water loss. The ETa can be derived by separating the Kc into the basal crop coefficient (Kcb), the soil evaporation coefficient (Ke), and the soil stress coefficient (Ks). Other methods of determining ETa include mass transfer methods and energy balance methods. The mass transfer method depends on the vertical movement of water vapor and heat from the surface to the atmosphere. Therefore, the use of wind speed and vapor pressure gradient to quantify ETa. On the other hand,

the energy balance method quantifies the actual evapotranspiration by tracking the incoming energy as net radiation. Net radiation is distributed into sensible heat, latent heat, and soil heat flux. This method uses surface temperature and radiative energy to quantify the ET_a . In this study, we have utilized the energy balance method, derived using a UAV. The rationale behind using ET_a was that it represents the actual surface condition, and the actual water availability within the crop-soil system. Additionally, ET_a captures the integrated response of canopy NDVI, canopy temperature, and net radiation, providing an actual indicator of crop water status. The utilization of ET_a as a water variable offers distinct advantages because it is directly linked to crop health and reflects the actual physiological water loss from the crop canopy and soil storage (Liu et al., 2022). In addition, ET_a is a key component of the global balance of water and energy, making it an important measure for connecting crop production (Hussain et al., 2019). Also, remote sensing-based spatial ET_a estimation primarily represents water lost to the atmosphere or flux from the systems as the canopy covers the ground across the field. This component is important for us as we want to understand the overall water status from the systems, and as indicated by actual ET. Therefore, ET_a was used in our study to determine the water use efficiency of the field scale.

1.3. Water Use Efficiency

Water use efficiency (WUE) has emerged as a key indicator in water management studies, particularly in relation to crop yield (Hirwa et al., 2022). The term Initially, the water use efficiency was first introduced by Vites in 1965 (Wang et al., 2024a) and defined as the ratio of crop yield and evaporation (Wang et al., 2024a). As research continues, the revised definition of WUE is the ratio of crop biomass accumulation (including CO_2 assimilation, crop biomass, and grain yield) to water consumption (including transpiration, evapotranspiration, and total

water input) throughout the entire growing season (Kang et al., 2002; Sinclair et al., 1984). Despite the simplicity of the WUE, many indicators have been used to quantify WUE in agricultural ecosystems (Hoover et al., 2023). Understanding crop production and water consumption is a necessary component to understand WUE in the crop field. To calculate WUE, two variables are required: crop yield as the *production variable* and crop water use as the *water variable*. The WUE evaluation indicators include three levels in cropping systems: leaf level (the leaf photosynthesis rate relative to the transpiration rate, WUE_L), whole plant level (the ratio of total dry mass to water usage, WUE_p), and yield level (the crop grain yield per unit area relative to transpiration, WUE_y) (Ali & Talukder, 2008; Cao et al., 2007; Wang et al., 2024b). WUE_y is closest to the actual production and is regarded as the final result of WUE_L and WUE_p (Angus & van Herwaarden, 2001). In terms of water use, various variables include physiological scale (transpiration), biomass (precipitation irrigation, evapotranspiration), ecosystem scale (precipitation, evapotranspiration), regional scale (gridded precipitation, modeled evapotranspiration), and supply chain (water footprint) (Hoover et al., 2023). For the field-scale water use efficiency (WUE_f), crop economic yield is used as a production variable, while actual ET (ET_a) is used as a water variable (Hoover et al., 2023). The ET_a represents the combined water loss through transpiration and evaporation (Hoover et al., 2023). Therefore, to evaluate both irrigation systems (AI-Radar and Subsurface drip) and understand the field-scale water use status, we have used WUE_f . Previous studies have explored this index for evaluation purposes (Liu & Song, 2020; Liao et al., 2019; Leghari et al., 2021). For instance, Liu & Song (2020) conducted a comprehensive study to evaluate the WUE of different crops. On the other hand, Liao et al. (2019) evaluated that the micro irrigation system has significantly higher WUE.

Additionally, as stated by Wang et al (2024a), the unoccupied aerial vehicle (UAV) platform is rarely used for fine-scale farmland WUE.

1.4. Spatial Evapotranspiration Estimation

Conventional ET_a methods like flux measurements using eddy covariance methods and lysimeters rely on single-point and high-density (hourly or daily) data. These methodologies can produce datasets for a singular data point. They are also costly, primarily research-grade, and time-consuming for installation and maintenance (Attalah et al., 2024). Remote sensing offers a cost-effective alternative for mapping ET_a across space and time during the growing season, which also accounts for stable (due to soil properties) and dynamic (due to canopy growth and weather) variability. In our study, UAV based and satellite-based (NASA Earth Observation Product *OpenET*) were used to estimate spatial scale ET_a . The rationale behind selecting UAV-based ET_a is that multispectral and thermal cameras mounted on UAVs can capture ultra-high spatial (3 cm in this study) resolution data. This enables estimation of components of energy balance, namely net radiation (R_n ; Wm^{-2}), soil heat flux (G ; Wm^{-2}), and sensible heat flux (H ; Wm^{-2}) to estimate ET_a [or latent heat flux (λET ; Wm^{-2})] (Ortega-Farias et al., 2025; Fuentes et al., 2024). High-resolution UAVs can accurately estimate ET_a using energy balance components (Ramírez-Cuesta et al., 2023; Wei et al., 2023), crop water status estimation (Ramírez-Cuesta et al., 2025; Santesteban et al., 2017), and water deficit index (Ndlovu et al., 2024). For example, Ramírez-Cuesta et al. (2023) used a UAV-based energy balance method to estimate ET_a to compare different soil management practices. Additionally, UAV-based indices and spatial estimates can also be used to provide real-time irrigation scheduling, which improves WUE and economic productivity (Mokari et al., 2022; Hoffmann et al., 2016; H. Jaafar & H. Sujud, 2025). On the other hand, OpenET, a combined product of NASA and Google Earth Engine, provides

satellite-based estimates of spatial evapotranspiration (link: <https://etdata.org/>). OpenET provides ET_a data from multiple satellite-derived models and also calculates single ensemble values for all models. The majority of the models included in the OpenET are based on simplified implementations of surface energy balance modelling. This is an emerging source for spatial ET_a (30-m spatial resolution, daily temporal resolution) over the field (Melton et al., 2022). This provided data with daily temporal resolution. The rationale behind selecting OpenET because of its high temporal resolution (1 day). It also showed a strong agreement with ground-based flux tower and lysimeter measurements (Volk et al., 2024; Tawalbeh et al., 2024; Attalah et al., 2024; Nassar et al., 2025; Knipper et al., 2024). For example, Volk et al. (2024), compare OpenET estimates with 152 in-situ ground stations. They have observed that the mean absolute error for the OpenET ensemble value is 15.8 mm per month with an R-squared value of 0.9. They have observed that cropland has higher accuracy than shrubland and forest land. The results highlight the potential of OpenET in estimating field-scale ET_a compared to UAV-derived ET_a. These spatial estimates of ET_a can be used to estimate WUE_f for evaluating the AI-Radar irrigation system in comparison with the SDI system. In Kansas, farmers have widely adopted SDI. The novelty of our study lies in assessing the AI-Radar system, which integrates soil, crops, and weather variability over the field using an AI-driven decision support system. However, their performance at the field scale has not been explored against existing precision irrigation systems. Therefore, the hypothesis of our study was that AI-Radar irrigation enhances field-scale water use efficiency (WUE_f) than Sub-Surface Drip Irrigation (SDI). The objective of this study was to comparative evaluation of the AI-Radar system against widely used and adopted SDI irrigation system using UAV-based and OpenET-based WUE_f.

2. Materials and Methods

2.1. Site description and crop management

An on-farm research experiment was carried out during the 2024 growing season in Flickner Innovation Farm (Link: https://www.kcare.k-state.edu/wrip/flickner/Flickner_Farm.html), Central Kansas (38°12'04.9"N 97°34'10.7" W) with two distinctive fields: Field A (2.5 ha) and Field B (6 ha) (Figure 3.1). Field A was irrigated using an AI-Radar irrigation system (Autonomous Pivot Inc., Wichita, USA), and Field B was irrigated using SDI. According to the Köppen-Geiger climate classification, this region falls under the category "*cfa*", indicating a humid subtropical climate with hot summers and mild winters (Kottek et al., 2006). Air temperature during the growing season (June to October) in the year 2024 averaged 23.9 °C, which was 0.7 °C higher than the 10-year average, with a mean daily minimum temperature of 16.6 °C (-0.7 °C from the 10-year average), and a maximum temperature of 31.3 °C (+1.5 °C from the 10-year average). The highest average temperature was for July (26.4 °C), followed by August (25.7 °C). The seasonal precipitation was 283.4 mm, which was 34.18% (147 mm) less than the average (430 mm; June to October), with July becoming the driest month (40.4 mm) and August being the wettest month (108.9 mm). The reference evapotranspiration (ET_o) for the 2024 growing season (June to October) was 694.46 mm (+150.86 mm than 5-year mean), with an average daily ET_o of 4.53 mm day⁻¹ (+0.34 mm day⁻¹ than 5-year mean) and July being the highest (165.3 mm) followed by August (140.7 mm) (Patrignani et al., 2020).

The soil texture in this area ranged from loam (23.1% of area) (up to 15 cm) and silty loam (72.9% of area) (below 15 cm), with a 1 to 3 % slope. The depth to the water table is more than 20 m, with moderately well-drained soil, medium runoff, and non-saline to very slightly

saline (0.0 to 2.0 mmhos/cm) water, with 5% calcium carbonate (*Web Soil Survey*, 2024). The crop for the 2024 growing season was soybeans. The planting date was around mid-June (June 15) and the harvest occurred around the first Third week of October (October 17). The soybean variety was PIONEER 42A84ENLIST, with a row spacing of 40 cm. This seed is resistant to Soybean Cyst Nematode. The seeding rate was 296,520 seeds/ha (120,000 seeds/acre). For both fields, crop management practices were the same, including herbicides (Roundup PowerMax, 2.27 liters ha⁻¹) and fertilizer applications (solution of 10-34-0, 54.25 liters ha⁻¹), except for irrigation management.

2.2. Data Collection

2.2.1. Image Acquisition Framework using Unoccupied Aerial Vehicle System (UAV)

In this study, a DJI Matrice 350 RTK (*DJI Innovation Technology Co., Ltd., Shenzhen, China*) was used as the remote sensing platform, offering centimeter-level (± 10 cm vertically and horizontally) real-time kinematic accuracy. Altum PT (*MicaSense, Inc., Seattle, WA, USA*), is a multispectral and thermal imaging system designed for high-resolution agricultural and environmental monitoring. It integrates five narrow multispectral bands (Table 3.1), with a radiometrically calibrated thermal infrared (TIR) band centered at approximately 11 μm (Table 3.1). The sensor operates at a capture rate of 2 Hz (two images per second) and features an integrated global shutter, enabling simultaneous capture across all bands and minimizing image misalignment caused by motion (sensor resolution of 2064x1544 pixels with a pixel size of 3.45 μm paired with an 8 mm focal length) (Figure 3.2a).

Four flights were conducted over both fields (Field A and Field B) to capture early vegetative growth, late vegetative growth, early reproductive growth, and late reproductive growth, thereby covering the entire season. For our study, the growth stages were selected as

second trifoliate to third trifoliate (V2-V3), sixth trifoliate to flower initiation (V6-R1), full bloom to pod initiation (R2-R3), and full pod to seed initiation (R4-R5) for our study. These stages were identified as they represent critical transitions in crop physiology and are sensitive to weather fluctuations and water management. The UAV captured the images primarily between 11:00 and 15:00 local time (CST) when atmospheric conditions were optimal in terms of cloud cover <10% and low wind speeds ($<5 \text{ m s}^{-1}$) for radiometric consistency and image stability. MS and TIR were acquired at 80% frontal and side overlap at an altitude of 60 m above the take-off point and a flight speed of 3.5 ms^{-1} . For each campaign, flights were executed using a predefined and fixed mission plan for spatiotemporal consistency across all acquisitions. Each flight lasts approximately 30 minutes, depending on environmental conditions. All thermal images were captured simultaneously with the multispectral bands using isochronous triggering, which provides accurate temporal and spatial alignment. This configuration minimizes parallax errors and supports the accurate fusion of multisensory data for analysis.

2.2.2. Multispectral and thermal imaging data processing

The MS images (500-650 images per flight per field) were imported into Pix4D Mapper (*Pix4D SA, Prilly, Switzerland*) and processed using the *Ag Multispectral* template. This workflow performed radiometric calibration (using MicaSense calibration panel), geometric correction, and image orthogonalizing to obtain spectral reflectance image mosaics for each band. The Ag Multispectral pipeline is specifically optimized for aerial nadir imagery from sensors and produces output that includes surface reflectance and various vegetation indices. In this study, processed output includes band-specific surface reflectance (0-1) and vegetation indices layer, such as the normalized difference vegetation index (NDVI; -1 to 1). For TIR (100-150 images per flight per field), the sensor features an internal non-uniform calibration

mechanism that automatically calibrates itself every five minutes or upon temperature changes of 2°C to mitigate sensor drift and maintain thermal accuracy during flights. All the TIR images were generated as digital number values from the software and converted to degrees Celsius using the manufacturer-provided conversion formula ($DN/100 - 272.15$). The combined corrected MS and TIR images were then imported into ArcGIS Pro software (*ESRI, Inc., Redlands, CA, USA*) for resolution resampling and delineation to our area of interest. All the images were resampled to a resolution of 3 cm and georeferenced using local ground control points. Additionally, a manual correction was made to remove noise from the metal body of the center pivot irrigation system located at Field A using the Extract by Mask and Erase tool in ArcGIS Pro. This correction ensured that only soil and crop pixels were retained for subsequent ET_a calculation.

2.2.3. Meteorological data, Leaf area index (LAI), and grain yield

Hourly meteorological data included atmospheric parameters, such as incoming solar radiation (SW_{in}), wind speed (u), air temperature (T_{air}), wind speed measurement height (Z_u), and air temperature measurement height (Z_t) (Table 3.2). All this data was collected from the nearby Mesonet station (Station name: Flickner Tech Farm, Latitude: 38.203; Longitude: -97.572; Elevation: 446.83 m), which is 15 m away from the field (Patrignani et al., 2020). Additionally, the Arable Mark 3 ground sensor (*Arable Labs, Inc., Princeton, New Jersey, United States*) was used to gather hourly atmospheric pressure (pa) and actual vapor pressure (ea) data. The meteorological variables served as essential inputs for quantifying net radiation, aerodynamic resistance, and sensible heat flux, enabling the estimation of ET_a within the energy balance framework. .

AccuPAR LP-80 Plant Canopy Analyzer (*METER Group, Pullman, WA, USA*) was used to estimate the LAI in each field. Three to five measurements were taken from each field at each stage of soybean growth, resulting in a total of approximately 15 to 20 LAI samples per field. Then, these ground measurements were compared to the NDVI values from nearby image pixels to derive a regression equation (Eq. 1; $r = 0.81$; $p < 0.001$) between LAI and NDVI for spatial mapping of LAI across the field (Figure 3.2b).

$$LAI = 0.006 \times e^{7.234 \times NDVI} \quad \text{Eq. 1}$$

Grain yield was harvested in October 2024 using a georeferenced John Deere (*Deere & Company, Moline, IL, USA*) combine harvester (*equipment ID: 1H0S660SKF0775528*). The onboard mass flow sensor recorded yield data and saved it as yield monitor files that were georeferenced. The yield datapoints were corrected using QGIS software (*QGIS Development Team, Beaverton, Oregon, USA*) by removing spurious yield datapoints resulting from uneven combine harvester speed, swath width, and overlap, as well as grain flow delay. Outlier points were identified and excluded based on spatial and statistical thresholds. Additionally, a 15% moisture correction was applied to the data. Following this correction, the ordinary *kriging* in QGIS was applied to fill in the gaps between the corrected yield points and create a continuous yield map for each field. The resulting yield maps captured the spatial information on within-field yield variability (Figure 3.2c).

2.3. Operational Specifications of SDI and AI-Radar Irrigation System

. Under the Subsurface Drip Irrigation (SDI) system, soybeans were irrigated for 8 to 10 hours per application from planting (June 15) to harvesting (October 17). The SDI system delivered water directly to the crop root zone through buried drip lines, allowing for precise and uniform soil moisture regulation while minimizing surface evaporation losses. The SDI system

had drip tapes installed at 35 to 45 cm (14-18 inches) below the soil surface, with a lateral space of 1.02 m (40 inches) between adjacent lines. The distance between the emitters was 0.56 to 0.91 m (22-36 inches) intervals along each tape. Each pressure-compensating dripper provided 0.66 liters per hour (0.159 gallons per hour). The growers typically watered the soybeans every two to three days, following a fixed irrigation schedule. The irrigation system was usually run for 8 to 10 hours for each irrigation application from planting to the R6 growth stage. The targeted water supply was 6.35 to 8.38 mm (0.25 to 0.30 inches) per irrigation event. The total amount of water was between 229 and 305 mm (9 and 12 inches) for irrigation during the growing season.

The AI-Radar system incorporates a GPR sensor that operates at an electromagnetic wavelength of 400-1200 MHz to determine soil moisture levels (*Autonomous Pivot Product Guide*, 2024). The GPR part of the irrigation system records approximately 300 soil moisture data points (%) every 30 minutes as it traverses the field. These percentages indicate the relative percentage of soil moisture in relation to the permanent wilting point (0%) and the field capacity (100%). Using soil type data (texture data from the user by previous soil testing) for the effective root zone, calculate the water content at FC and PWP per slice (*Autonomous Pivot Product Guide*, 2024). Using this data, the system divides the field into eight equal 45° zones based on available water holding capacity ($AWHC = FC - PWP$). AWHC for each segment was calculated separately and derived from soil texture. Crop data (crop type and growth stages), soil type, and irrigation strategies were used to determine the maximum allowable depletion (MAD) for irrigation recommendations (*Autonomous Pivot Product Guide*, 2024). Since this was an on-farm trial, the crop root depth information was provided directly by the grower to parameterize the irrigation management model. The MAD threshold varied between 50% and 85%, depending on the corn growth stage and soil type. From the VE to the R1 stage, MAD was 50 to 60%; from the

R2 to R3 stage, it was 60 to 70%; from the R3 to the R7 stage, it was 70 to 80% (*Autonomous Pivot Product Guide*, 2024).

In addition to the GPR, the AI-Radar system features an AI-powered imaging unit that utilizes a convolutional neural network (CNN) to detect crop growth stages and assess crop coverage every 30 minutes during in-season pivot rotation. Based on this coverage, the system internally calculates the crop coefficient (K_c) and crop evapotranspiration (ET_c) using integrated web-based weather data for irrigation scheduling. The NDVI-based K_{c-act} values presented later in the manuscript were used only for comparison between the two irrigation systems. In Field A, an AI-Radar irrigation system was installed on the center pivot irrigation system. The sensor was installed 3 m laterally and 2.5 m vertically from the center-pivot irrigation system tower to ensure adequate coverage at varying radial distances. Irrigation application depth was monitored using a pressure transducer installed on the pivot line, allowing for the accurate estimation of the applied water volume for each irrigation event. Across the soybean growing season, the mean cumulative irrigation depth ranged from 167.64 to 260.86 mm (6.6 to 10.27 inches) across the eight segments.

2.4. Framework for estimation of seasonal ET_a

2.4.1. UAV-based high-resolution ET_a using the surface energy balance model

In this study, a High-resolution Mapping of Evapotranspiration (HRMET) model was employed to estimate ET_a at high spatial resolution using the principle of physical energy balance principles and empirical parameterizations for computing at sub-meter scales (Figure 3.2d) (Zipper & Loheide II, 2014). Traditional energy balance models often depend on the manual selection of ‘dry’ and ‘wet’ pixels to define the range of latent and sensible heat fluxes, which limits their ability to map at very high spatial resolutions (<1 m) (Zipper & Loheide II,

2014). HRMET calculates net radiation (Rn) and soil heat flux (G) using physical and empirical formulas, employing an iterative process (Eq. 3) to derive the sensible heat flux (H), which is part of surface balance modeling (Eq. 2, Figure 3.2d). For each point, HRMET is iterate 100 times and produces 100 ET estimates using unique input parameters, and is used to calculate the final mean ET and standard deviation for each pixel (Zipper & Loheide Ii, 2014). To estimate H, the model first computes the zero-plane displacement height (d; m), as well as the roughness lengths for momentum (z0M; m) and heat (z0H; m) transfer (Raupach, 1994). These parameters were then used to derive initial estimates of H and boundary layer stability factor (ζ). Based on ζ , the model determines diabatic correction factor for momentum (Ψ_M) (Eq. 3) and heat flux (Ψ_H) (Eq. 4). Subsequently, the friction velocity (u_* ; ms^{-1}) (Eq. 4), the aerodynamic resistance to heat transport (r_{ha} ; sm^{-1}) (Eq. 6) and the excess resistance to heat transport (r_{ex} ; sm^{-1}) (Eq. 7) were calculated. Using these values, the model recalculated iteratively H (Eq. 8) and the ζ (Eq. 9) until convergence for H ($\leq 0.1\%$ change) is achieved (Zipper & Loheide Ii, 2014). The final converged H is then used in the surface energy balance to solve for λET .

$$R_n - G = H + \lambda ET \quad \text{Eq. 2}$$

$$\Psi_M = 6 \log(1 + \zeta); \quad \Psi_M + \Psi_M \text{ when } \zeta < 0 \quad \text{Eq. 3}$$

$$\Psi_M = -2 \log \left(1 + (1 - 16\zeta) \right)^{0.5}; \quad \Psi_H + 0.6\Psi_M \text{ when } \zeta > 0 \quad \text{Eq. 4}$$

$$u_* = \frac{uk}{\log \frac{z_u - d}{z_{0M}} + \Psi_M} \quad \text{Eq. 5}$$

$$r_{ex} = \frac{\log \frac{z_{0M}}{z_{0H}}}{\rho_a k u_*} \quad \text{Eq. 6}$$

$$r_{ha} = \frac{\left[\left(\log \frac{z_u - d}{z_{0M}} \right) + \Psi_M \right] \left[\left(\log \frac{z_T - d}{z_{0H}} \right) + \Psi_M \right]}{k^2 \rho_a u} \quad \text{Eq. 7}$$

$$H = \frac{\rho_a C_p (T_s - T_a)}{r_{ha} + r_{ex}} \quad \text{Eq. 8}$$

$$\zeta = \frac{-9.8kz_u H}{\rho_a c_p T_{air,k}(u_*^3)} \quad \text{Eq. 9}$$

where R_n is net radiation [Wm^{-2}], G is soil heat flux [Wm^{-2}], H is sensible heat flux [Wm^{-2}], and λET is latent heat flux [Wm^{-2}]. Air density is ρ_a [$kg\ m^{-3}$], the specific heat of air is C_p [$Jkg^{-1}\ K^{-1}$], surface temperature is T_s [K], and the air temperature is T_a [$^{\circ}C$]. Wind speed is u [ms^{-1}], friction velocity is u_* [ms^{-1}]. The heights of wind speed and air temperature measurements were Z_u and Z_T [m], respectively. Zero-plane displacement height is d [m], roughness lengths for momentum and heat transfer are Z_{0M} and Z_{0H} [m], aerodynamic resistance to heat transport is r_{ha} [sm^{-1}], and excess resistance is r_{ex} [sm^{-1}], k is the von Kármán constant (≈ 0.41), the stability parameter is ζ , and the stability correction functions for momentum and heat are ψ_M and ψ_H .

For four flying dates over both fields (Field A and Field B), the HRMET model required hourly meteorological inputs, which are listed in Table 3.2. Additionally, spatially variable inputs include crop surface temperature (CST), leaf area index (LAI), and crop height. In this study, CST and LAI were derived from UAV images (Figures 3.2a and 3.2b) (detailed method discussed in. Direct crop height measurements were not undertaken during the 2024 growing season because the study design prioritized spatially continuous, high-resolution canopy characterization across large experimental fields. Instead, UAV-derived multispectral and thermal metrics were used as quantitative proxies for canopy structure and vigor. Numerous studies have demonstrated that spectral indices are strongly correlated with plant height, leaf area index, and biomass under comparable agronomic conditions (Liu et al., 2021; Shammi et al., 2025). Each field was distributed across variable microtopography, making manual canopy-height sampling impractical and time-consuming during UAV flight operations. Therefore, to

parameterize the HRMET model, crop height data were obtained from a recent soybean study conducted under comparable environmental conditions, growth stages, the same season, and maturity group (4.2) (Table 3.2). For consistency, crop height was assumed to be uniform across both fields. This assumption minimizes structural bias in the energy-balance inputs. As a result, the effective spatially variable inputs for our analysis were CST and LAI. HRMET generates instantaneous ET_a (mm hr^{-1}), which were then converted to daily ET_a (mm day^{-1}) (Figure 3.2e) using the ET fraction method, using the hourly and daily ET_o for that day from Mesonet as described by Zhang et al (2017) and Jiang et al (2022). Seasonal ET_a was subsequently calculated for the entire crop growth period from planting (June 15) to harvest (October 17) as described by Hussain et al (2019). Since the first and last UAV flights were conducted 20-25 days before and after the planting and harvesting dates, we have incorporated the FAO-56-based crop coefficient (K_c) to extend the ET_a values, anchored by initial K_c and late-season K_c values of 0.35 and 0.50, respectively. We assumed that no major ET spikes occurred between the UAV flight dates, and therefore we estimated the seasonal ET_a using anchored FAO-56 based K_c values.

2.4.2. OpenET-based high temporal seasonal ET_a

OpenET data were obtained by delineating the study area (Fields A and B) boundary using a polygon feature in the web platform (<https://explore.etdata.org/#14/38.2031/-97.5721>). OpenET consisted of six satellite-based models (ALEXI/DisALEXI, eeMETRIC, geeSEBAL, PT-JPL, SIMS, and SSEBop) with their ensemble products. Most of the included models are based on the surface energy balance approach using the Landsat satellite, except for SIMS, which relies on the dual crop coefficient approach that utilizes canopy density and crop type information to estimate ET. The single crop coefficient (K_c) can be estimated by dividing crop

evapotranspiration by reference evapotranspiration, which assumes no water stress in the field. However, in field conditions, these factors differ in terms of waterlogging, drought, salt stress, and other environmental factors. Therefore, estimating the dual crop coefficient is essential, as it combines the actual field conditions of water loss. It can be derived by separating the K_c into the basal crop coefficient (K_{cb}), the soil evaporation coefficient (K_e), and the soil stress coefficient (K_s) ($K_c = K_{cb} \times K_s + K_e$). OpenET calculates the per-pixel ET fraction (the ratio of satellite-derived ET to reference ET) at the Landsat overpass time (12:30 PM in our study area) and interpolates it over the whole day (Melton et al., 2022). The final ensemble ET datasets represent the simple arithmetic mean of all individual model outputs, after outlier removal using the median absolute deviation factor. (Melton et al., 2022). In this study, ensemble ET datasets were used from planting (June 15) to harvesting (October 17) in accordance with the UAV-derived seasonal ET_a model.

2.5. Estimation of WUE_f and statistical analysis

WUE_f for each field was determined by the ratio of spatial crop yield (section 2.2.3) and seasonal ET (section 2.4). Grain yield was collected using a combine harvester equipped with a calibrated yield monitor, and the resulting point data were spatially interpolated using kriging (detailed method discussed under section 2.2.3). Seasonal ET_a was obtained by interpolating daily ET_a values derived from UAV data between the crop growth period (detailed method discussed in Section 2.4). Pixel-wise WUE_f was calculated by dividing yield ($kg\ ha^{-1}$) by seasonal ET_a (mm) with final output as $kg\ ha^{-1}\ mm^{-1}$ (Figure 3.2e). Descriptive statistics (mean, minimum, maximum, standard deviation (SD), and coefficient of variation (CV) were used to characterize WUE_f distribution for each Field (Field A and Field B). For estimating WUE_f based

on OpenET, grain yield (mean, minimum, maximum) was divided by seasonal ET_a (mm), resulting in the final output as kg ha⁻¹ mm⁻¹.

For evaluation between the WUE_f derived from UAV of two fields, one-sided Welch's t-test (Welch-1947) ($\alpha=0.05$) was used, which considers the unequal sample size as there are two different sizes of fields with different shapes of arrays for UAV-derived ET_a. All data processing and statistical analysis were carried out in Python (v3.13.3). Descriptive statistics and statistical computation were conducted with NumPy, Pandas, SciPy, Sklearn, and the math module in Python (v3.13.3). To evaluate the agreement between UAV-based ET_a and OpenET-derived seasonal ET_a, we have compared the seasonal estimates from June 15 to October 17 ($n = 124$). Statistical performances were assessed using root mean square error (RMSE), normalized root mean square error (NRMSE), and mean bias error (MBE). We used the Python packages (v3.13.3) *rasterio*, *geopandas*, and *fiona* for the geospatial operations and raster handling. Additionally, the *icecream* package (Python: v3.13.3) was used for efficient debugging and code validation throughout the analysis.

3. Results

3.1. Evaluation of AI-Radar and SDI Irrigation Systems

3.1.1. Yield and WUE_f comparison

Soybean grain yield under AI-Radar was significantly ($p\text{-value} < 0.05$) higher ($3189.04 \pm 317.75 \text{ Kg ha}^{-1}$) compared to the SDI irrigation system ($2207.83 \pm 393.05 \text{ Kg ha}^{-1}$). The coefficient of variation (CV) indicated a more uniform yield distribution under AI-Radar (CV: 9.96%) compared to SDI (CV: 17.80%) ($p < 0.05$), suggesting improved spatial consistency in the crop's performance (Table 3.4). The field-scale water use efficiency (WUE_f) under the AI-Radar was also significantly higher than that of the SDI irrigation system for both the UAV and

the OpenET-derived estimates. Based on UAV-derived ETa, mean WUE_f under AI-Radar has a higher value ($7.17 \pm 2.41 \text{ kg ha}^{-1} \text{ mm}^{-1}$) than SDI ($5.70 \pm 2.13 \text{ kg ha}^{-1} \text{ mm}^{-1}$) ($p < 0.05$). This improves field-wide water distribution and efficiency (Table 3.4). Additionally, the variability under AI-Radar (CV: 33.6%) was lower than under SDI (CV: 37.4%) (Table 3.4). Similarly, the OpenET-derived WUE_f trend was similar to the HRMET-derived WUE_f trend. AI-Radar has a higher mean WUE_f ($6.66 \pm 2.24 \text{ kg ha}^{-1} \text{ mm}^{-1}$) compared to SDI ($5.06 \pm 1.89 \text{ kg ha}^{-1} \text{ mm}^{-1}$). Additionally, the variability under AI-Radar (CV: 33.7%) was lower than under SDI (CV: 37.3%).

3.1.2. Seasonal ETa comparison

Based on the UAV-derived seasonal ETa distribution from the HRMET Model, the AI-Radar irrigation system exhibited a significantly higher mean seasonal ETa ($444.44(?) \pm 43.91 \text{ mm}$) compared to SDI ($386.66 \pm 62.54 \text{ mm}$) ($p < 0.05$). Additionally, the variability under AI-Radar (CV: 9.88%) was also lower than that under SSDI (CV: 16.17%), indicating a more uniform water distribution and crop water uptake (Figure 3.3e). A similar pattern was observed in OpenET-based seasonal ETa estimates, where the AI-Radar recorded a higher mean seasonal ETa (478.88 mm) compared to SDI (436.22 mm) (Figure 3.4b). Seasonal ETa derived from UAV estimates represented the cumulative product of growth stage-specific ETa for soybeans. During the early and late vegetative growth stages (second to third trifoliate stage; V2-V3 and sixth trifoliate to flower initiation; V6-R1), ETa under AI-Radar was significantly higher ($p < 0.05$) with ranged from 2.77 ± 0.48 to $3.33 \pm 1.07 \text{ mm day}^{-1}$ (CV: 17.32 to 32.01 %) compared to SDI (2.11 ± 0.46 to $2.77 \pm 0.98 \text{ mm day}^{-1}$; CV: 21.99 to 35.49 %) (Figure 3.3a, 3b; Table 3.3). Specifically, during the early reproductive growth stages (full bloom to pod initiation; R2-R3), ETa under AI-Radar was significantly higher ($p < 0.05$) with a range of $5.33 \pm$

0.55 (CV: 10.57 %) compared to SDI (4.21 ± 1.31 mm day⁻¹; CV: 31.16 %). Similar trends have been observed during the late reproductive growth stage (from full pod to seed formation; R4-R5) (Figures 3.3c and 3.3d; Table 3.3). Particularly, during the full bloom to pod initiation stage (R2-R3), Field A (AI-Radar) recorded higher ET_a (Figures 3c; Table 3.3), higher NDVI (0.85 ± 0.10) and lower CST (33.53 ± 0.87) than Field B (SDI; lower ET_a; NDVI: 0.75 ± 0.19 ; high CST: 37.96 ± 2.66) (Table 3.5 and 3.6).

3.2. Agreement between UAV and OpenET-derived seasonal ET_a

For the AI-Radar field, the seasonal ET_a ET_a estimated from the UAV-derived HRMET model was 444.44 mm, while the corresponding OpenET-based estimate was 478.88 mm., Both methods exhibited higher agreement between planting (June 15; DOY 167) to harvesting (October 17; DOY 291) as directed by less MBE (-0.28 mm), RMSE (0.90 mm day⁻¹), and NRMSE (23.4%) and moderate R² (0.65) (Figure 3.4a). From the scatter plot between the UAV-derived ET_a and OpenET-based ET_a, it was found that lower ET_a levels (1.5 to 2.5 mm), OpenET has underestimated the UAV for the AI-Radar field (Figure 3.4b). However, during higher ET_a (>5.5 mm), OpenET estimates were lower than UAV-derived (Figure 3.4a). For the SDI field, the seasonal ET_a was 386.66 mm UAV-derived HRMET and 436.2 mm from OpenET, with both methods showing higher agreement between planting (June 15; DOY 167) to harvesting (October 17; DOY 291) with less MBE (-0.42 mm), RMSE (0.77 mm day⁻¹), and NRMSE (21.8%) and moderate R² (0.69) (Figure 3.4a).

Analysis of the scatter plot relationship between the UAV-derived ET_a and OpenET-based ET_a estimates revealed that during higher ET_a (4.5 to 5.5 mm), OpenET estimates were lower than UAV-derived measurements (Figure 3.4a). In general, both systems effectively captured the temporal dynamics and magnitude of soybean water use throughout the season.

However, the UAV-derived HRMET model slightly overestimated during early emergence or bare soil stage (DOY: 170 to 180) (Figure 4b) under Field A (AI-Radar). Furthermore, OpenET has slightly overestimated during the R1 reproductive stage (DOY 205-220) and the mid-reproductive stage (R2-R3: DOY 225-240) (Figure 4b). Overall, the scatter plot indicates that each system effectively captures the key fluctuations in crop water use for soybeans.

4. Discussion

4.1. Maintaining higher WUE_f and yield potential under AI-Radar irrigation

In Field A, the AI-Radar irrigation system maintained a higher WUE_f , which corresponds with greater yield and higher ET_a . The consistently elevated seasonal ET_a and growth stage-specific ET_a in the soybean indicate reduced water stress and more balanced plant-soil water status compared with Field B (SDI) (Figure 3.3a to 3.3e). This physiological advantage was complemented by higher NDVI and a lower CST in Field A (Tables 3.5 and 3.6). A higher NDVI during this stage under Field A is related to higher yield, healthier canopy development, and soil cover fraction, which is directly correlated with higher soybean yield (Farias et al., 2023) as reported in our study (30.85% higher yield under Field A than Field B; Table 3.4). Additionally, lower CST represents greater stomatal opening, which enables more carbon dioxide intake and higher photosynthetic activity (Poudel et al., 2023), ultimately supporting higher yield formation in soybeans (Table 3.4). On the other hand, Field B (SDI), which recorded less ET_a with higher CST and lower NDVI (Table 3.5 and 3.6) during full bloom to pod stage (R2-R3), can be attributed to lower yield (Table 3.4) due to shortening of the flowering period, reducing the pollen germination, number of seeds, and seed weight. According to Poudel et al. (2023) and Anderson (2020) moisture stress and higher CST during full bloom to pod infection stage (R2-R3) can shorten the flowering period, reduce pollen germination by 17 %,

number of seeds by 45 % and seed weight by 35 % and ultimately reduce yield potential (Poudel et al., 2023; Anderson, 2020). Specifically, during stage R3, temperatures above 35 °C (95 °F), as observed under Field B (SSDI), have been shown to significantly decrease pod settings in soybeans (Anderson, 2020). This represents water stress, resulting in lower biomass yield for Field B under SSDI, which leads to a lower yield and ultimately lower WUE_f (Table 3.4).

4.2. Addressing spatial variability in a heterogeneous field by AI-Radar irrigation

At our study site, the agricultural fields were heterogeneous in nature, with variable organic matter, cation exchange capacity, and other nutrients across the field, as indicated in the soil analysis report. Therefore, variation in topography and crop cover results in spatial and temporal variability in soil moisture over the large field (Lunt et al., 2005). AI-Radar could improve the irrigation scheduling primarily by utilizing present soil and crop data (*Autonomous Pivot Product Guide*, 2024). This is attributed to the combined use of a GPR and an AI-integrated RGB camera, which can simultaneously detect soil water status and crop water status, respectively, before each irrigation and every thirty minutes during the irrigation event (*Autonomous Pivot Product Guide*, 2024). For example, in 2024, the GPR estimated the total available water of 62.48 mm at a depth of 0 to 30 cm for segment A and H; 67.0 mm for segment D, and 45.72 mm for segments B, C, E, F, and G, which informed variable-rate irrigation decisions (Table 3.7). Consequently, irrigation recommendations were made based on the available water per segment. Therefore, segment D received less irrigation water (167.64 mm) than segments A and H (259.84 to 260.86 mm), followed by other segments (B, C, E, F, G; 194.06 to 211.58 mm) (Table 3.7). Notably, segment D exhibits elevated available soil water due to the cumulative input from both the SDI and AI-Radar irrigation systems operating within that field zone. Additionally, the applied irrigation water was 15 to 27% lower in Field A (AI-Radar;

167.6-260.9 mm) compared with Field B (SDI; 229-305 mm). Therefore, the AI-Radar system adjusted irrigation amounts in response to spatial soil variability and real-time moisture conditions, resulting in more appropriate water application across the field. This is also evident from the ETa map over the field at different growth stages in Field A (Figures 3.3a-3.3d). The CV was always lower under Field A (6.05 to 31.82%) than under SDI (6.95 to 35.45%), which represents site-specific irrigation under AI-Radar, compared to SDI, which uses a fixed scheduling method for irrigating the soybeans. Additionally, the integrated high-resolution camera system and AI algorithm enabled a precise assessment of the mean canopy cover percentage to detect crop coefficients and water stress, supporting targeted irrigation decisions (Figure 3.5).

Independent research has demonstrated the value of integrating GPR and AI-based computer vision for irrigation scheduling. GPR has the potential for higher accuracy in estimating soil moisture over large areas with varying hydrological conditions. Its capacity to sense changes in soil dielectric permittivity allows accurate estimation of volumetric water content even under variable texture, bulk density, and moisture gradients (Lunt et al., 2005; Lu et al., 2017). Additionally, Zhou et al. (2019) showed that GPR can accurately measure the amount of water in the soil with a high R^2 (0.89) and a low RMSE (<2.9%). Similarly, Fernández-Pacheco et al. (2014) found a strong correlation between crop coefficient and crop coverage percentage, with high predictive accuracy ($R^2 > 0.90$). This suggests the strength of estimating the crop coefficient from the mean canopy cover percentage. Therefore, combining these two approaches together with AI-Radar has greater potential for variable rate irrigation management over heterogeneous fields and could provide advantages over the current settings of the SDI system in the farm.

4.3. OpenET as an alternative for estimating Seasonal ET_a and WUE_f

In this study, both UAV-derived ET_a and OpenET ensemble ET_a produced comparable estimations of soybean WUE_f as indicated by the close agreement (UAV: 5.70 to 7.17 kg ha⁻¹ mm⁻¹; OpenET: 5.06 to 6.66 kg ha⁻¹ mm⁻¹) using seasonal ET_a estimates between the two approaches. The proximity of these estimates demonstrated that both approaches effectively captured the relationships between water and yield at the field level. Broadly, there may be errors in both OpenET and UAV-derived ET_a due to climatic factors and some assumptions. Although uncertainties exist in both approaches due to methodological constraints, the overall alignment highlights the quantitative strength of seasonal ET_a estimation from both UAV-HRMET and OpenET. Under low ET_a ranges (primarily during the early stages with bare soil and vegetative emergence; DOY 170 to 180), the deviation could be explained by the misinterpretation of soil heat flux under the HRMET model, particularly with irrigation scheduling practices in Field A. In UAV-derived HRMET, the G was calculated as a function of R_n and fractional vegetation cover. Thereby, during the early stage, a lower fractional vegetation cover caused a larger share of R_n to be allocated as G . Additionally, in Field A, the soil was relatively drier than in Field B, as the first irrigation was applied on July 13 (10.16 mm), whereas in SDI, irrigation was given at a three-day interval. Therefore, HRMET might have overestimated ET_a by assigning more R_n to evaporation even though less water was available. However, this disappearance was not present in SDI because of frequent irrigation with more soil water.

Under higher ET_a ranges (primarily during R1 reproductive stage; DOY: 205 to 220 and mid reproductive stage; R2-R3; DOY: 225 to 240) (Figure 3.4b), the deviation could be explained by overestimation of OpenET during peak summer temperature and higher atmospheric demand (Nassar et al., 2025). These periods coincided with peak summer conditions

in late July to early August and late August, characterized by higher temperatures ($T_{\max}$: 33.1-36.1 °C; T_{mean} : 25.9-27.9 °C), increased atmospheric demand (ET_o : 98 to 141.36 mm), and lower precipitation (10.67 to 22.10 mm). Under these situations, OpenET has been shown to systematically estimate higher ET_a (Nassar et al., 2025). Additionally, it is evident that OpenET has a lower accuracy level in regions with higher atmospheric demand and lower water availability (Reitz et al., 2025). A further source of discrepancy may be linked to the fact that OpenET relies on coarse 4-km grid scale ET_o (Reitz et al., 2025). Such coarse reference values can exaggerate ET under hot and dry conditions, whereas locally measured ET_o from a nearby weather station (15 meters from the field) better captures the variability of the microclimate under the UAV-derived HRMET model.

Despite these deviations, the overall agreement between OpenET and UAV-derived HRMET at different stages highlighted the reliability in measuring seasonal ET_a and WUE_f . This consistency suggests that OpenET, which is also open-sourced, could be used as a promising tool for estimating seasonal crop water dynamics and their relations with the yield by farmers. This is consistently supported by the demonstrated accuracy of ground-based flux tower and lysimeter measurements. For example, according to (Attalah et al., 2024; Knipper et al., 2024), the OpenET-based ensemble approach significantly lowered the biases and prediction error with a high R^2 (>0.70) and MAE of 0.95 mm day⁻¹.

5. Limitations and Future Scopes

As an on-farm study designed to evaluate irrigation performance under real production conditions, a few practical constraints were unavoidable. Precise quantification of irrigation volumes was limited by the absence of inline flow meters on SDI systems. However, all comparisons were made consistently across fields, ensuring that relative differences remain

valid. Additionally, the study was limited by the absence of crop height measurements, which could have provided additional insights for canopy development. The UAV flying was also limited by the restricted number of flights, which may not capture the short-term variability in the field. Future work should incorporate more UAV-based measurements with ground-based data, utilizing water meters and flux towers for enhanced validation. Furthermore, future work should also focus on validating OpenET across a broader range of agroecological regions, including drought-prone and well-irrigated systems, to better understand potential discrepancies under varying water availability conditions.

6. Conclusions

This study provides an initial field-scale evaluation of the AI-Radar irrigation system by quantifying field-scale water use efficiency (WUE_f) and irrigation depth for soybeans in central Kansas. Results demonstrated that, under Field A, the AI-Radar irrigation system had higher WUE_f (UAV: $7.17 \pm 2.41 \text{ kg ha}^{-1} \text{ mm}^{-1}$; OpenET: $6.66 \pm 2.24 \text{ kg ha}^{-1} \text{ mm}^{-1}$) and a higher seasonal ET_a (UAV: 444.44 mm; OpenET: 478.88 mm) than Field B (SDI). The consistently higher WUE_f value, resulting from higher seasonal ET_a and higher grain yield, indicates better utilization of water to produce higher soybean yield (*“more crop per drop”*) under field conditions with optimal stomatal conductance. Additionally for AI-Radar system, the total irrigation depth was 15 to 27% less than the SDI. This signifies the improved ability of the AI-Radar irrigation system to maintain optimal crop water management, especially during the critical growth stage for soybeans. The agreement between OpenET and UAV (MBE: -0.28 to -0.42 mm; RMSE: 0.77-0.90 mm day⁻¹; NRMSE: 21.8-23.4 %; R²: 0.65 to 0.69) also showed that OpenET, which is open-source, could be a useful tool for farmers to use to derive the WUE_f under field conditions. Overall, these results highlight the ability of the AI-Radar system to

distribute water more efficiently, particularly in areas with declining aquifer levels and increased water scarcity in the Southern Great Plains (USA).

References

- Ahmed, Z., Gui, D., Murtaza, G., Yunfei, L., & Ali, S. (2023). An Overview of Smart Irrigation Management for Improving Water Productivity under Climate Change in Drylands. *Agronomy*, 13(8), Article 8. <https://doi.org/10.3390/agronomy13082113>
- Aivazidou, E., Tsolakis, N., Iakovou, E., & Vlachos, D. (2016). The emerging role of water footprint in supply chain management: A critical literature synthesis and a hierarchical decision-making framework. *Journal of Cleaner Production*, 137, 1018–1037. <https://doi.org/10.1016/j.jclepro.2016.07.210>
- Ali, M. H., & Talukder, M. S. U. (2008). Increasing water productivity in crop production—A synthesis. *Agricultural Water Management*, 95(11), 1201–1213. <https://doi.org/10.1016/j.agwat.2008.06.008>
- Allen, R. G., Pereira, L. S., Raes, D., & Smith, M. (1998). Crop evapotranspiration-Guidelines for computing crop water requirements-FAO Irrigation and drainage paper 56. Fao, Rome, 300(9), D05109.
- Anderson, E. (2020, July 9). *Moisture stress and high temperature effects on soybean yields*. Michigan State University Extension. https://www.canr.msu.edu/news/moisture_stress_and_high_temperature_effects_on_soybean_yields
- Angus, J. F., & van Herwaarden, A. F. (2001). Increasing Water Use and Water Use Efficiency in Dryland Wheat. *Agronomy Journal*, 93(2), 290–298. <https://doi.org/10.2134/agronj2001.932290x>

Attalah, S., Elsadek, E. A., Waller, P., Hunsaker, D., Thorp, K., Bautista, E., Williams, C., Wall, G., Orr, E., & Elshikha, D. E. (2024). Evaluating the Performance of OpenET Models for Alfalfa in Arizona. *2024 Anaheim, California July 28-31, 2024*. 2024 Anaheim, California July 28-31, 2024. <https://doi.org/10.13031/aim.202400041>

Autonomous Pivot Product Guide. (2024). Google Docs.
https://drive.google.com/file/d/1FTyVn84TR-SdivONN4tEPxy8dSpsjcW/view?usp=sharing&usp=embed_facebook

Brikowski, T. H. (2008). Doomed reservoirs in Kansas, USA? Climate change and groundwater mining on the Great Plains lead to unsustainable surface water storage. *Journal of Hydrology*, 354(1), 90–101. <https://doi.org/10.1016/j.jhydrol.2008.02.020>

Cao, H.-X., Zhang, Z.-B., Xu, P., Chu, L.-Y., Shao, H.-B., Lu, Z.-H., & Liu, J.-H. (2007). Mutual physiological genetic mechanism of plant high water use efficiency and nutrition use efficiency. *Colloids and Surfaces B: Biointerfaces*, 57(1), 1–7.
<https://doi.org/10.1016/j.colsurfb.2006.11.036>

Drought.gov. (2025). <https://www.drought.gov/>

Economic Research Service. (2024). https://www.ers.usda.gov/amber-waves/2024/march/ers-research-models-future-effects-of-climate-change-on-corn-and-soybean-yields-production-and-exports?utm_source=chatgpt.com

Farias, G. D., Bremm, C., Bredemeier, C., de Lima Menezes, J., Alves, L. A., Tiecher, T., Martins, A. P., Fioravanço, G. P., da Silva, G. P., & de Faccio Carvalho, P. C. (2023). Normalized Difference Vegetation Index (NDVI) for soybean biomass and nutrient uptake estimation in response to production systems and fertilization strategies. *Frontiers in Sustainable Food Systems*, 6. <https://doi.org/10.3389/fsufs.2022.959681>

Kansas Soybean Association. (2025). *Kansas Soybean Association*.

<https://kansassoybeans.org/news/faq/>

NASS, USDA, 2024. (n.d.). Retrieved November 16, 2025, from

https://data.nass.usda.gov/Statistics_by_State/Kansas/Publications/Crops_Releases/Annual_Summary/2025/KS-cropsum2501.pdf

Fernández-Pacheco, D. G., Escarabajal-Henarejos, D., Ruiz-Canales, A., Conesa, J., & Molina-Martínez, J. M. (2014). A digital image-processing-based method for determining the crop coefficient of lettuce crops in the southeast of Spain. *Biosystems Engineering*, 117, 23–34. <https://doi.org/10.1016/j.biosystemseng.2013.07.014>

Fuentes, S., Ortega-Farías, S., Carrasco-Benavides, M., Tongson, E., & Gonzalez Viejo, C. (2024). Actual evapotranspiration and energy balance estimation from vineyards using micro-meteorological data and machine learning modeling. *Agricultural Water Management*, 297, 108834. <https://doi.org/10.1016/j.agwat.2024.108834>

Gebrechorkos, S. H., Sheffield, J., Vicente-Serrano, S. M., Funk, C., Miralles, D. G., Peng, J., Dyer, E., Talib, J., Beck, H. E., Singer, M. B., & Dadson, S. J. (2025). Warming accelerates global drought severity. *Nature*, 642(8068), 628–635. <https://doi.org/10.1038/s41586-025-09047-2>

H. Jaafar, H., & H. Sujud, L. (2025). High resolution evapotranspiration from UAV multispectral thermal imagery: Validation and comparison with EC, Landsat, and fused S2-MODIS HSEB ET. *International Journal of Applied Earth Observation and Geoinformation*, 136, 104359. <https://doi.org/10.1016/j.jag.2025.104359>

Hirwa, H., Zhang, Q., Li, F., Qiao, Y., Measho, S., Muhirwa, F., Xu, N., Tian, C., Cheng, H., Chen, G., Ngwijabagabo, H., Turyasingura, B., & Itangishaka, A. C. (2022). Water

- Accounting and Productivity Analysis to Improve Water Savings of Nile River Basin, East Africa: From Accountability to Sustainability. *Agronomy*, 12(4), 818.
<https://doi.org/10.3390/agronomy12040818>
- Hoffmann, H., Jensen, R., Thomsen, A., Nieto, H., Rasmussen, J., & Friberg, T. (2016). Crop water stress maps for an entire growing season from visible and thermal UAV imagery. *Biogeosciences*, 13(24), 6545–6563. <https://doi.org/10.5194/bg-13-6545-2016>
- Hoover, D. L., Abendroth, L. J., Browning, D. M., Saha, A., Snyder, K., Wagle, P., Witthaus, L., Baffaut, C., Biederman, J. A., Bosch, D. D., Bracho, R., Busch, D., Clark, P., Ellsworth, P., Fay, P. A., Flerchinger, G., Kearney, S., Levers, L., Saliendra, N., ... Scott, R. L. (2023). Indicators of water use efficiency across diverse agroecosystems and spatiotemporal scales. *Science of The Total Environment*, 864, 160992.
<https://doi.org/10.1016/j.scitotenv.2022.160992>
- Hussain, M. Z., Hamilton, S. K., Bhardwaj, A. K., Basso, B., Thelen, K. D., & Robertson, G. P. (2019). Evapotranspiration and water use efficiency of continuous maize and maize and soybean in rotation in the upper Midwest U.S. *Agricultural Water Management*, 221, 92–98. <https://doi.org/10.1016/j.agwat.2019.02.049>
- Jiang, Y., Wang, J., & Wang, Y. (2022). Daily Evapotranspiration Estimations by Direct Calculation and Temporal Upscaling Based on Field and MODIS Data. *Remote Sensing*, 14(16), 4094. <https://doi.org/10.3390/rs14164094>
- Kang, S., Zhang, L., Liang, Y., Hu, X., Cai, H., & Gu, B. (2002). Effects of limited irrigation on yield and water use efficiency of winter wheat in the Loess Plateau of China. *Agricultural Water Management*, 55(3), 203–216. [https://doi.org/10.1016/S0378-3774\(01\)00180-9](https://doi.org/10.1016/S0378-3774(01)00180-9)

Kansas Geological Survey. (2023). <https://kgs.ku.edu/news/article/2023/03/10/groundwater-levels-fall-across-western-and-south-central-kansas>

- Knipper, K., Anderson, M., Bambach, N., Melton, F., Ellis, Z., Yang, Y., Volk, J., McElrone, A. J., Kustas, W., Roby, M., Carrara, W., Castro, S., Kilic, A., Fisher, J. B., Ruhoff, A., Senay, G. B., Morton, C., Saa, S., & Allen, R. G. (2024). A comparative analysis of OpenET for evaluating evapotranspiration in California almond orchards. *Agricultural and Forest Meteorology*, 355, 110146. <https://doi.org/10.1016/j.agrformet.2024.110146>
- Kottek, M., Grieser, J., Beck, C., Rudolf, B., & Rubel, F. (2006). World Map of the Köppen-Geiger climate classification updated. *Meteorologische Zeitschrift*, 15(3), 259–263. <https://doi.org/10.1127/0941-2948/2006/0130>
- Leghari, S. J., Hu, K., Wei, Y., Wang, T., Bhutto, T. A., & Buriro, M. (2021). Modelling water consumption, N fates and maize yield under different water-saving management practices in China and Pakistan. *Agricultural Water Management*, 255, 107033. <https://doi.org/10.1016/j.agwat.2021.107033>
- Levidow, L., Zaccaria, D., Maia, R., Vivas, E., Todorovic, M., & Scardigno, A. (2014). Improving water-efficient irrigation: Prospects and difficulties of innovative practices. *Agricultural Water Management*, 146, 84–94. <https://doi.org/10.1016/j.agwat.2014.07.012>
- Liao, R., Wu, W., Hu, Y., Xu, D., Huang, Q., & Wang, S. (2019). Micro-irrigation strategies to improve water-use efficiency of cherry trees in Northern China. *Agricultural Water Management*, 221, 388–396. <https://doi.org/10.1016/j.agwat.2019.05.017>
- Liu, Y., Jiang, Q., Wang, Q., Jin, Y., Yue, Q., Yu, J., Zheng, Y., Jiang, W., & Yao, X. (2022). The divergence between potential and actual evapotranspiration: An insight from climate,

- water, and vegetation change. *Science of The Total Environment*, 807, 150648.
<https://doi.org/10.1016/j.scitotenv.2021.150648>
- Liu, Y., & Song, W. (2020). Modelling crop yield, water consumption, and water use efficiency for sustainable agroecosystem management. *Journal of Cleaner Production*, 253, 119940. <https://doi.org/10.1016/j.jclepro.2019.119940>
- Lu, Y., Song, W., Lu, J., Wang, X., & Tan, Y. (2017). An Examination of Soil Moisture Estimation Using Ground Penetrating Radar in Desert Steppe. *Water*, 9(7), 521.
<https://doi.org/10.3390/w9070521>
- Lunt, I. A., Hubbard, S. S., & Rubin, Y. (2005). Soil moisture content estimation using ground-penetrating radar reflection data. *Journal of Hydrology*, 307(1), 254–269.
<https://doi.org/10.1016/j.jhydrol.2004.10.014>
- McGuire, V. L. (2011). *Water-level changes in the High Plains aquifer, predevelopment to 2009, 2007–08, and 2008–09, and change in water in storage, predevelopment to 2009*.
<https://digitalcommons.unl.edu/usgspubs/105/>
- Melton, F. S., Huntington, J., Grimm, R., Herring, J., Hall, M., Rollison, D., Erickson, T., Allen, R., Anderson, M., Fisher, J. B., Kilic, A., Senay, G. B., Volk, J., Hain, C., Johnson, L., Ruhoff, A., Blankenau, P., Bromley, M., Carrara, W., ... Anderson, R. G. (2022). OpenET: Filling a Critical Data Gap in Water Management for the Western United States. *JAWRA Journal of the American Water Resources Association*, 58(6), 971–994.
<https://doi.org/10.1111/1752-1688.12956>
- Mokari, E., Samani, Z., Heerema, R., Dehghan-Niri, E., DuBois, D., Ward, F., & Pierce, C. (2022). Development of a new UAV-thermal imaging based model for estimating pecan

- evapotranspiration. *Computers and Electronics in Agriculture*, 194, 106752.
<https://doi.org/10.1016/j.compag.2022.106752>
- Nassar, A., Tarboton, D., Anderson, M., Yang, Y., Fisher, J. B., Purdy, A. J., Baig, F., He, C., Gochis, D., Melton, F., & Volk, J. (2025). Intercomparison of the U.S. National Water Model with OpenET over the Bear River Basin, U.S. *Journal of Hydrology*, 656, 132826.
<https://doi.org/10.1016/j.jhydrol.2025.132826>
- Ndlovu, H. S., Odindi, J., Sibanda, M., & Mutanga, O. (2024). A systematic review on the application of UAV-based thermal remote sensing for assessing and monitoring crop water status in crop farming systems. *International Journal of Remote Sensing*, 45(15), 4923–4960. <https://doi.org/10.1080/01431161.2024.2368933>
- Ortega-Farias, S., Ramírez-Cuesta, J. M., & Nieto, H. (2025). Recent advances on water management using UAV-based technologies. *Irrigation Science*, 43(1), 1–3.
<https://doi.org/10.1007/s00271-025-01002-3>
- Oudah, M., Al-Naji, A., AL-Janabi, T. Y., Namaa, D. S., & Chahl, J. (2024). Automatic Irrigation System Based on Computer Vision and an Artificial Intelligence Technique Using Raspberry Pi. *Automation*, 5(2), Article 2.
<https://doi.org/10.3390/automation5020007>
- Patrignani, A., Knapp, M., Redmond, C., & Santos, E. (2020). *Technical Overview of the Kansas Mesonet*. <https://doi.org/10.1175/JTECH-D-19-0214.1>
- Poudel, S., Vennam, R. R., Shrestha, A., Reddy, K. R., Wijewardane, N. K., Reddy, K. N., & Bheemanahalli, R. (2023). Resilience of soybean cultivars to drought stress during flowering and early-seed setting stages. *Scientific Reports*, 13(1), 1277.
<https://doi.org/10.1038/s41598-023-28354-0>

- Ramírez-Cuesta, J. M., Intrigliolo, D. S., Lorite, I. J., Moreno, M. A., Vanella, D., Ballesteros, R., Hernández-López, D., & Buesa, I. (2023). Determining grapevine water use under different sustainable agronomic practices using METRIC-UAV surface energy balance model. *Agricultural Water Management*, 281, 108247. <https://doi.org/10.1016/j.agwat.2023.108247>
- Ramírez-Cuesta, J. M., Martínez-Gimeno, M. A., Badal, E., Tasa, M., Bonet, L., & Pérez-Pérez, J. G. (2025). UAV-based multispectral and thermal indexes for estimating crop water status and yield on super-high-density olive orchards under deficit irrigation conditions. *Precision Agriculture*, 26(3), 47. <https://doi.org/10.1007/s11119-025-10240-6>
- Raupach, M. R. (1994). Simplified expressions for vegetation roughness length and zero-plane displacement as functions of canopy height and area index. *Boundary-Layer Meteorology*, 71(1), 211–216. <https://doi.org/10.1007/BF00709229>
- Reitz, M., Volk, J. M., Ott, T., Anderson, M., Senay, G. B., Melton, F., Kilic, A., Allen, R., Fisher, J. B., Ruhoff, A., Purdy, A. J., & Huntington, J. (2025). *Performance Mapping and Weighting for the Evapotranspiration Models of the OpenET Ensemble*. <https://doi.org/10.1029/2024WR038899>
- Santesteban, L. G., Di Gennaro, S. F., Herrero-Langreo, A., Miranda, C., Royo, J. B., & Matese, A. (2017). High-resolution UAV-based thermal imaging to estimate the instantaneous and seasonal variability of plant water status within a vineyard. *Agricultural Water Management*, 183, 49–59. <https://doi.org/10.1016/j.agwat.2016.08.026>
- Sinclair, T. R., Tanner, C. B., & Bennett, J. M. (1984). Water-Use Efficiency in Crop Production. *BioScience*, 34(1), 36–40. <https://doi.org/10.2307/1309424>

- Soulis, K. X., Elmaloglou, S., & Dercas, N. (2015). Investigating the effects of soil moisture sensors positioning and accuracy on soil moisture based drip irrigation scheduling systems. *Agricultural Water Management*, 148, 258–268.
<https://doi.org/10.1016/j.agwat.2014.10.015>
- Tawalbeh, Z. M., Bawazir, A. S., Fernald, A., Sabie, R., & Heerema, R. J. (2024). Assessing Satellite-Derived OpenET Platform Evapotranspiration of Mature Pecan Orchard in the Mesilla Valley, New Mexico. *Remote Sensing*, 16(8), 1429.
<https://doi.org/10.3390/rs16081429>
- Volk, J. M., Huntington, J. L., Melton, F. S., Allen, R., Anderson, M., Fisher, J. B., Kilic, A., Ruhoff, A., Senay, G. B., Minor, B., Morton, C., Ott, T., Johnson, L., Comini de Andrade, B., Carrara, W., Doherty, C. T., Dunkerly, C., Friedrichs, M., Guzman, A., ... Yang, Y. (2024). Assessing the accuracy of OpenET satellite-based evapotranspiration data to support water resource and land management applications. *Nature Water*, 2(2), 193–205. <https://doi.org/10.1038/s44221-023-00181-7>
- Wang, T., Sun, S., Yin, Y., Zhao, J., Tang, Y., Wang, Y., Gao, F., & Luan, X. (2024a). Status of crop water use efficiency evaluation methods: A review. *Agricultural and Forest Meteorology*, 349, 109961. <https://doi.org/10.1016/j.agrformet.2024.109961>
- Wang, T., Sun, S., Yin, Y., Zhao, J., Tang, Y., Wang, Y., Gao, F., & Luan, X. (2024b). Status of crop water use efficiency evaluation methods: A review. *Agricultural and Forest Meteorology*, 349, 109961. <https://doi.org/10.1016/j.agrformet.2024.109961>
- Web Soil Survey*. (2024). <https://websoilsurvey.nrcs.usda.gov/app/>
- Wei, J., Dong, W., Liu, S., Song, L., Zhou, J., Xu, Z., Wang, Z., Xu, T., He, X., & Sun, J. (2023). Mapping super high resolution evapotranspiration in oasis-desert areas using

UAV multi-sensor data. *Agricultural Water Management*, 287, 108466.

<https://doi.org/10.1016/j.agwat.2023.108466>

Zhang, B., Chen, H., Xu, D., & Li, F. (2017). Methods to estimate daily evapotranspiration from hourly evapotranspiration. *Biosystems Engineering*, 153, 129–139.

<https://doi.org/10.1016/j.biosystemseng.2016.11.008>

Zhou, L., Yu, D., Wang, Z., & Wang, X. (2019). Soil Water Content Estimation Using High-Frequency Ground Penetrating Radar. *Water*, 11(5), Article 5.

<https://doi.org/10.3390/w11051036>

Zipper, S. C., & Loheide II, S. P. (2014). Using evapotranspiration to assess drought sensitivity on a subfield scale with HRMET, a high resolution surface energy balance model.

Agricultural and Forest Meteorology, 197, 91–102.

<https://doi.org/10.1016/j.agrformet.2014.06.009>

Tables

Table 3.1. Technical specifications of UAV-mounted multispectral sensors used for crop monitoring, including spectral bands and resolution.

Sensors and Instruments	Parameter	Details
Multispectral (MS)	Sensor resolution	2064×1544 pixel
	Pixel size	3.45 μm
	Sensor size	7.12×5.33 mm (8.9 mm diagonal)
	Focal length	8 mm
	Field of view (FOV)	48° (H)×36.8° (V)
	Ground sampling distance (GSD) at 60 m	≈ 2.64 cm/pixel
	Blue, Green, Red, Red edge, Near infrared	Band center (band width): 475 nm (32nm), 560 nm (27nm), 668 nm (16 nm),

		717 nm (12nm), 842 nm (57nm)
Thermal (TIR)	Detector type	Uncooled microbolometer (Altum-PT integrated TIR)
	Resolution	320×256 pixel
	Band center (band width)	10.5 μm (6 μm)
	Focal length	4 mm
	FOV	$\approx 48^\circ$ (H)× 39° (V)
	Wavelength range	8-14 μm (LWIR)
	Thermal GSD at 60m	≈ 16.8 cm/pixel
GPS Platform	Positioning	RTK-enabled; cm-level horizontal/vertical accuracy under RTK (M350 RTK)

Table 3.2. Summary of crop height and meteorological measurements in Field A (AI-Radar) and Field B (SDI) during 2024 UAV flight dates

Date (2024)	Local time (CST)	Growth stages	Field A (AI-Radar)						
			CH (m)	T _a (°C)	u (ms ⁻¹)	SW _{in} (Wm ⁻²)	RH (%)	pa (kPa)	ea (kPa)
July 6 (DOY 190)	11.30 – 12.30 pm	V2-V3	0.75	28.2	1.0	819.5	47.4	96.6	1.813
August 8 (DOY 219)	1.30 – 2.30 pm	V6-R1	0.90	30.6	2.1	835.7	46.9	96.8	2.061
August 27 (DOY 240)	12.30 – 1.30 pm	R2-R3	1.05	32.9	3.2	826.2	46.1	97	2.313
September 23 (DOY 267)	1.30 – 2.30 pm	R4-R5	1.10	20.3	2.3	738.6	47.1	96	1.193
Date (2024)	Local time (CST)	Growth stages	Field B (SDI)						
			CH (m)	T _a (°C)	u (ms ⁻¹)	SW _{in} (Wm ⁻²)	RH (%)	pa (kPa)	ea (kPa)
July 6 (DOY 190)	12.00 – 1.00 pm	V2-V3	0.75	29.0	1.0	774.3	45	96.6	1.803
August 8 (DOY 219)	2.00– 3.00 pm	V6-R1	0.90	31.4	2.0	765.2	43.5	96.7	2.001
August 27 (DOY 240)	1.00 – 2.00 pm	R2-R3	1.05	34.2	3.3	856.3	39.2	96.9	2.001
September 23 (DOY 267)	2.30 – 3.30 pm	R4-R5	1.10	21.6	2.2	673.7	44.8	96	1.156

Table 3.3. Growth stage-wise descriptive statistics of daily ETa based on UAV-derived HRMET model

Growth Stages	System	Mean (mm day ⁻¹)	Min (mm day ⁻¹)	Max (mm day ⁻¹)	SD (mm day ⁻¹)	Range	CV (%)
V2-V3	SDI	2.11	0.00	3.82	0.46	3.81	21.99
	AI-Radar	2.77*	0.00	3.97	0.48	3.97	17.32
V6-R1	SDI	2.77	0.00	6.87	0.98	6.87	35.49
	AI-Radar	3.33*	0.00	7.82	1.07	7.82	32.01
R2-R3	SDI	4.21	0.00	8.47	1.31	8.47	31.16
	AI-Radar	5.17*	0.18	6.66	0.55	6.48	10.57
R4-R5	SDI	3.81	0.87	4.89	0.28	4.02	7.28
	AI-Radar	3.92*	0.00	4.72	0.37	4.72	9.44

Bold with asterisk () represents significantly higher ($p < 0.05$)*

Table 3.4. Descriptive statistics for yield and WUE_f under AI-Radar and SDI irrigation system

Parameter	System	Mean	Min	Max	SD	Range	CV (%)
Yield (kg ha⁻¹)	SDI	2207.83	1021.74	3032.84	393.05	2011.10	17.8
	AI-Radar	3189.04*	1835.08	4463.78	317.75	2628.70	9.9
UAV-based WUE (kg ha⁻¹ mm⁻¹)	SDI	5.70	2.64	7.84	2.13	5.20	37.4
	AI-Radar	7.17*	4.12	10.04	2.41	5.91	33.6
OpenET-based WUE (kg ha⁻¹ mm⁻¹)	SDI	5.06	2.34	6.95	1.89	4.61	37.3
	AI-Radar	6.66	3.83	9.32	2.24	5.48	33.7

Table 3.5. Histogram-based statistics of NDVI for soybean at different growth stages (V2-V3, V6-R1, R2-R3, and R4-R5) under AI-Radar and SDI irrigation systems.

Stage	System	Mean	Min	Max	Median	SD	Range	CV (%)
V2-V3	SDI	0.23	0.05	0.83	0.19	0.11	0.78	48.66
	AI-Radar	0.22	0.00	0.84	0.18	0.11	0.84	49.26
V6-R1	SDI	0.46	0.04	0.92	0.37	0.24	0.88	51.97
	AI-Radar	0.51	0.04	0.91	0.47	0.24	0.87	46.78
R2-R3	SDI	0.75	0.15	0.95	0.86	0.19	0.81	25.57
	AI-Radar	0.85	0.00	0.96	0.90	0.10	0.96	12.18
R4-R5	SDI	0.86	0.16	0.96	0.88	0.05	0.80	6.18
	AI-Radar	0.90	0.08	0.97	0.92	0.06	0.89	6.83

Table 3.6. Histogram-based statistics of crop surface temperature (CST) for soybean at different growth stages (V2–V3, V6–R1, R2–R3, and R4–R5) under AI-Radar and SDI irrigation systems.

Stage	System	Mean (°C)	Min (°C)	Max (°C)	Median (°C)	SD	Range	CV (%)
V2-V3	SDI	47.90	31.27	59.72	47.92	2.11	28.46	4.40
	AI-Radar	46.14	36.45	55.30	46.16	1.88	18.85	4.07
V6-R1	SDI	43.65	32.52	56.69	43.67	2.63	24.16	6.04
	AI-Radar	41.07	27.96	54.74	41.07	2.27	26.78	5.53
R2-R3	SDI	37.96	25.40	52.27	37.85	2.66	26.87	7.00
	AI-Radar	33.53	28.89	43.39	33.43	0.87	14.50	2.58
R4-R5	SDI	21.25	15.68	31.90	21.15	0.93	16.22	4.39
	AI-Radar	20.84	17.17	35.04	20.69	0.98	17.87	4.70

Table 3.7. Summary of irrigation and water balance for soybean segments, highlighting segment-wise differences in available water holding capacity (AWAC), total water bank, effective rainfall, and optimal irrigation

Slice	Crop	AWAC (0 to 15cm)	AWAC (15 to 30cm)	Water Bank (0 to 30cm)	Total Optimal Irrigation	Total Effective Rain
A	Soybean	5.59	4.83	62.48	259.84	106.68
B		3.81	3.81	45.72	194.06	95.5
C		3.81	3.81	45.72	194.82	102.87
D		5.59	5.59	67.06	167.64	101.6
E		3.81	3.81	45.72	211.58	103.12
F		3.81	3.81	45.72	199.64	90.68
G		3.81	3.81	45.72	203.71	86.87
H		5.59	4.83	62.48	260.86	110.74

(AWAC: Available water holding capacity (% Field capacity - % permanent wilting point))

Figures

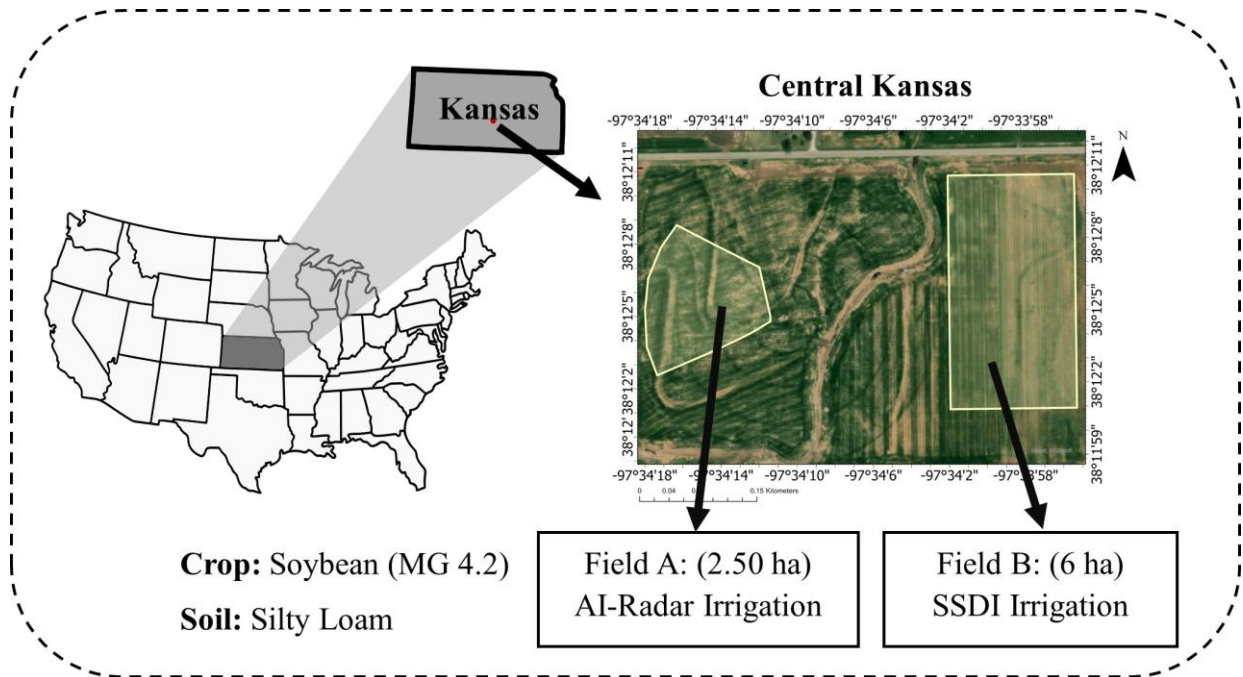


Figure 3.1. Geographic location and field layout of the on-farm soybean trial in central Kansas. The study compared AI-Radar irrigation (Field A, 2.5 ha) with subsurface drip irrigation (SDI; Field B, 6 ha)

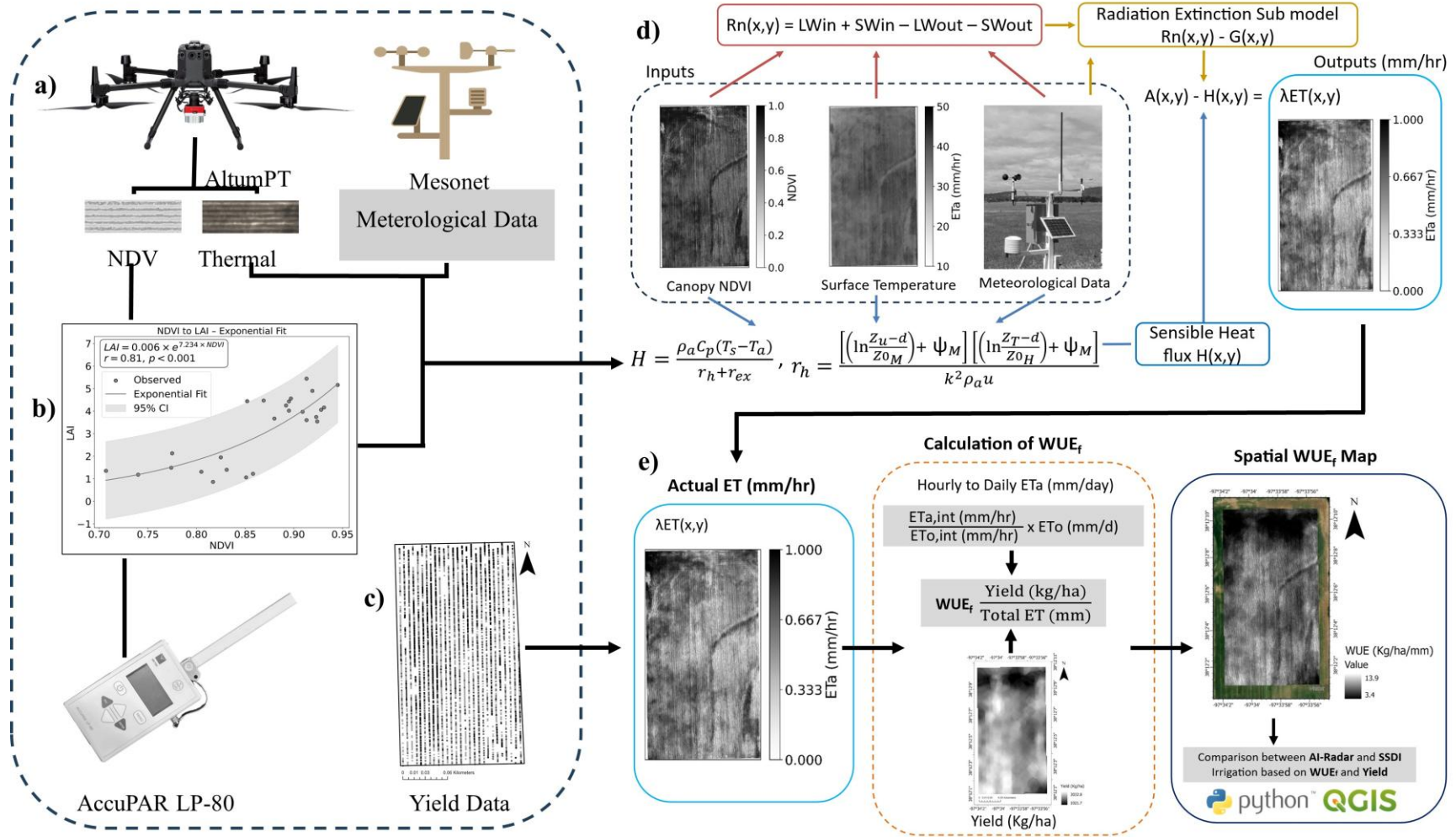


Figure 3.2. Workflow for estimating WUE_f. a) UAV-based multispectral and thermal data acquisition integrated with meteorological data. b) Regression between NDVI and LAI using an exponential fit equation Eq. 1; $r = 0.81$, $p < 0.001$). c) Yield data collection using

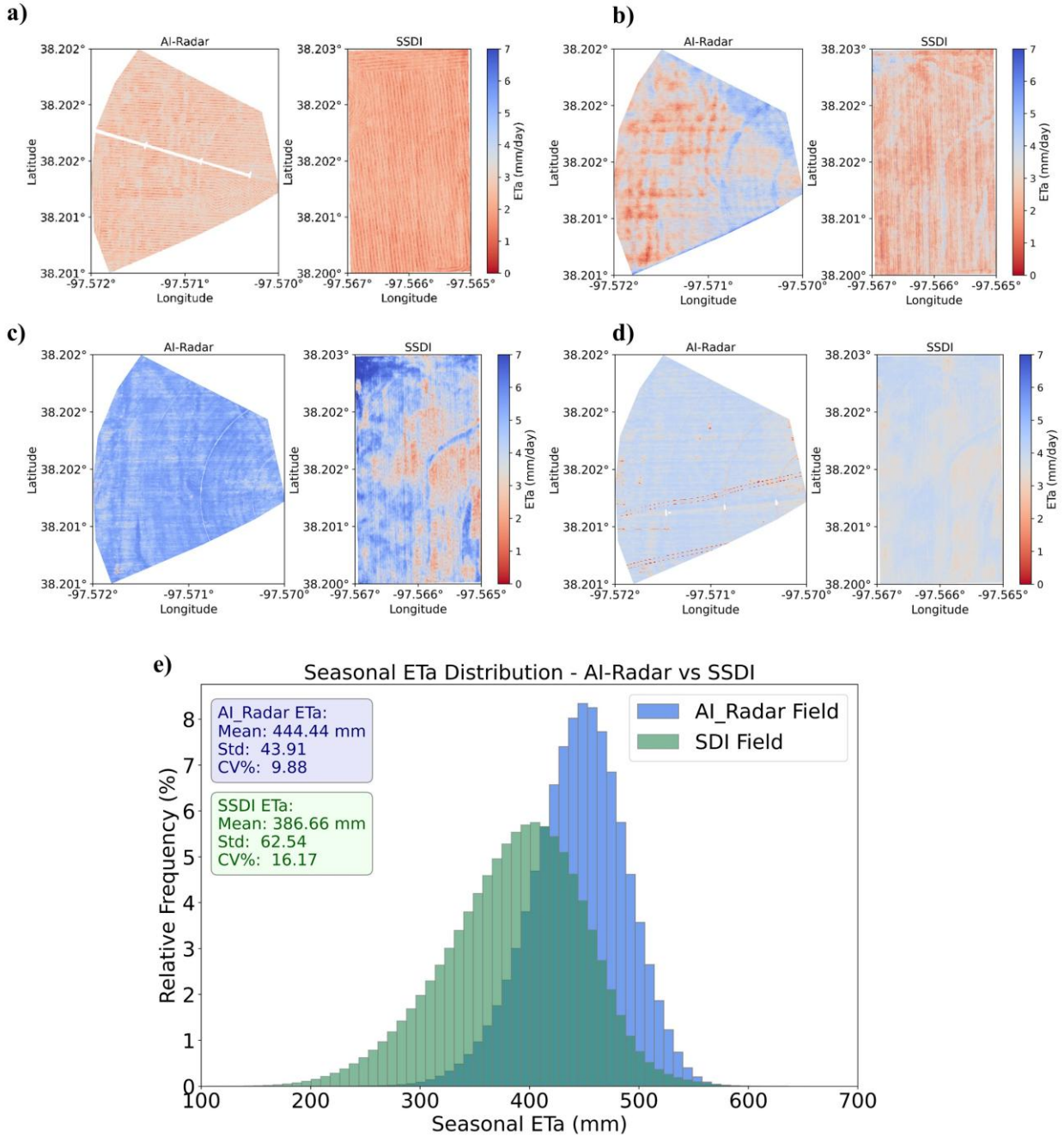


Figure 3.3. Growth stage wise UAV derived spatial ETa (a: V2-V3; b: V6-R1; c: R2-R3; d: R4-R5) and e) Spatial Distribution of seasonal ETa

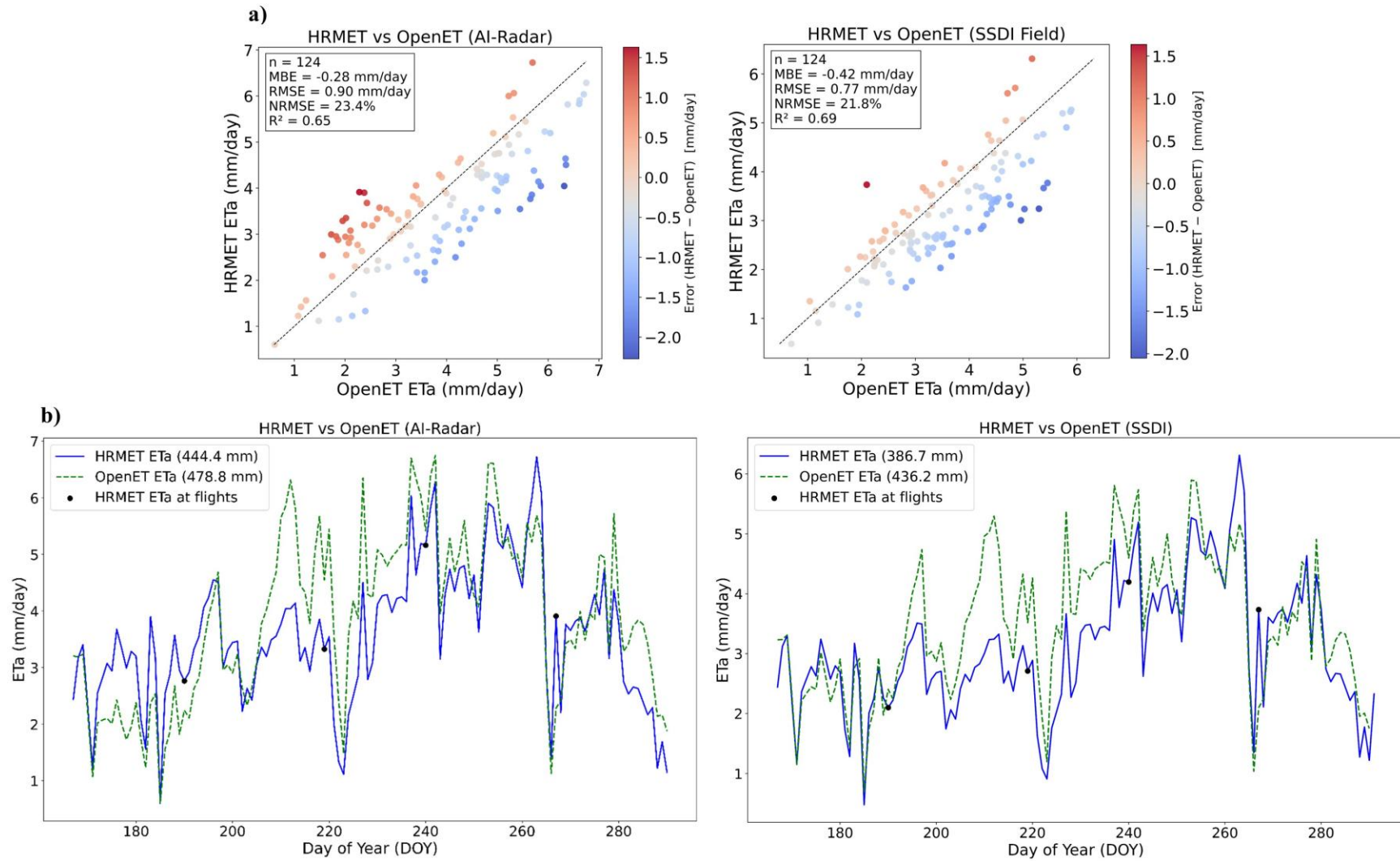


Figure 3.4. a) Scatterplot between UAV and OpenET-derived seasonal ETa; b) Temporal dynamics over the season with total seasonal ETa (The first plot belongs to the AI-Radar field, followed by SDI for both the graphs)

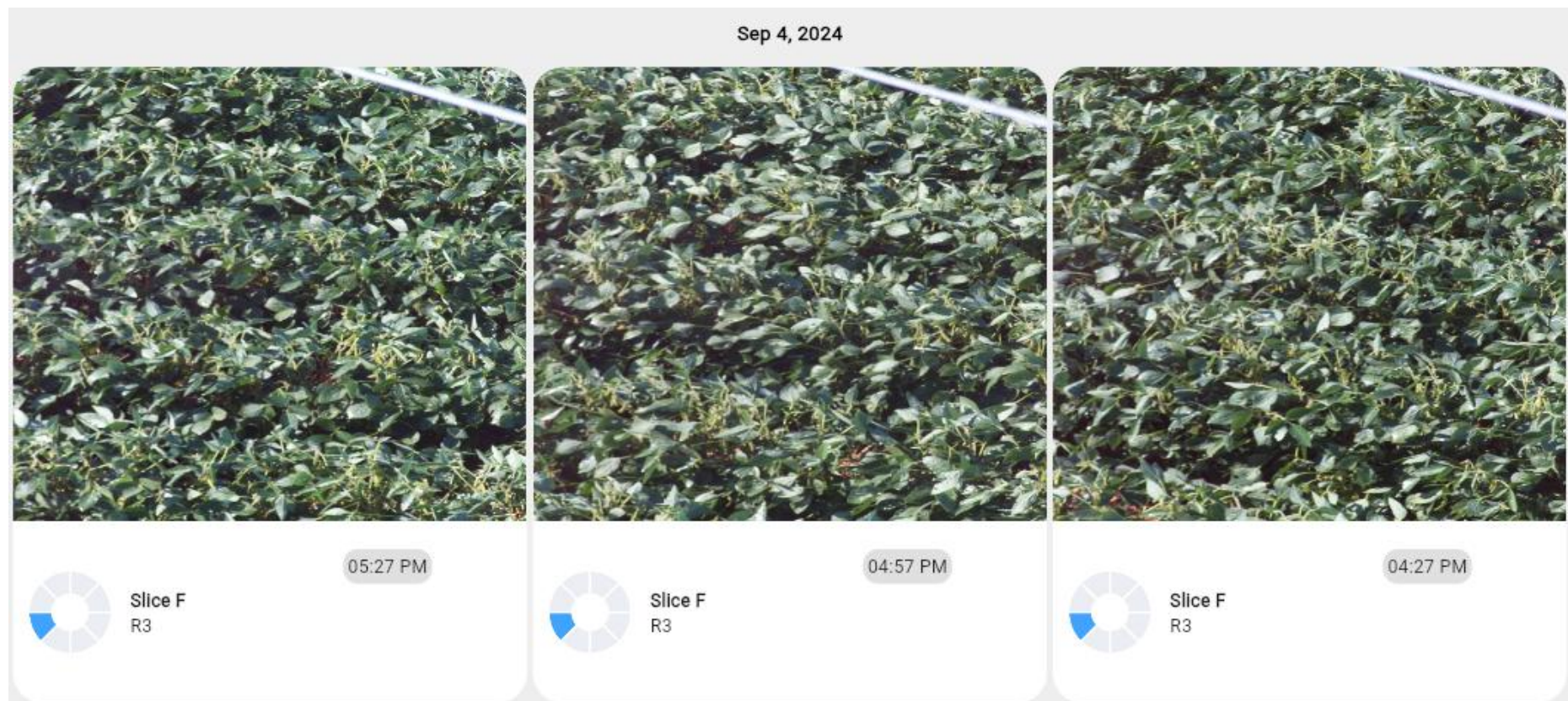


Figure 3.5. CNN-based growth stage detection (R3, beginning pod) on September 4, 2024, showing consistent identification under varying light conditions.

Chapter 4 - Thesis Summary and Future Research

1. Thesis Summary

The research studies in chapters 1-3 were designed to enhance the understanding of the dynamics of crop yield and water use, which utilize remote sensing, meteorological data, and agronomic data. In recent years, remote sensing has emerged as a crucial tool for estimating and observing yield variability and water management in diverse cropping systems. This research has focused on both satellite remote sensing and unoccupied aerial vehicle (UAV)-based remote sensing (UAV). These tools were selected due to the spatial coverage across the field, which is beneficial for understanding variability across the field than single-point data. Additionally, satellite remote sensing offers higher temporal resolution and reduced dependency on weather conditions like clouds or wind. On the other hand, UAV has the benefit of higher spatial resolution for the field. These tools were used to assess crop water use, predict crop yields, and evaluate spatial crop water stress indices. Addressing these key factors has significant importance for sustaining agricultural production in the southern Great Plains, where water is one of the most important resources for agricultural production. Therefore, the studies presented in chapters 1-3 integrated satellite and UAV-based imagery with weather data to predict crop yields using classical statistics and machine learning approaches.

In the first study (Chapter 1), it was found that soybean yield varies across different planting dates and agronomic practices. Specifically, Soybean yield is influenced by fluctuations in meteorological factors throughout the growing season and across planting windows. Therefore, for Kansas growers, predicting soybean yield early in the season and addressing yield variability are essential for making strategic decisions, including crop insurance, crop storage demand, and resource allocation. So, this study assessed the impact of different planting dates on

soybean yield prediction using high-resolution PlanetScope imagery and weather variables under various agronomic practices. The study began by highlighting the significance of satellite remote sensing in predicting soybean yield, utilizing various input variables that can impact soybean yield metrics. The study evaluated different ML models to predict soybean yield and identify key variables, utilizing agronomic management factors such as planting dates, seeding rates, and maturity groups, with weather variables and remote sensing vegetation indices. The findings showed that variability is accurately captured by the Random Forest and Adaptive Boosting models (R^2 : 0.77-0.79). Prediction accuracy was higher during the late vegetative and reproductive stages when crops needed more water. This highlights the importance of in-season monitoring of the resources and market planning. It was also found that crop evapotranspiration (ETc) was the most significant feature affecting the performance of the ML model among the various meteorological variables. The importance score was 0.73, which means a higher impact on yield by ETc. Therefore, high-resolution satellite data can support early-season yield prediction and identify the key meteorological variable (ETc) under adaptive management practices. The study would help soybean growers assess yields under variable weather conditions and make informed crop management decisions using readily available and cost-effective high-resolution satellite data.

In the first study, ETc was the key meteorological factor in estimating crop yields. Building on that insight, the second chapter shifted from yield modeling to irrigation performance, using ETc as the central metric to compare and evaluate different precision irrigation systems. In this chapter, the overarching goal was to identify crop water stress and optimize irrigation scheduling. This is important due to the rising water-related issues in the Southern Great Plains, which are exacerbated by declining levels of the Ogallala Aquifer and

increasing drought conditions. As water scarcity intensifies, precision irrigation technologies, such as AI-integrated Ground Penetrating Radar (AI-Radar), could be a promising solution for optimizing water use at the field scale in crop production systems. Therefore, the study has utilized and quantified ET_c using satellite-based observations to evaluate different irrigation systems that can save irrigation water. The study compared a precision irrigation method (AI-Radar) with the conventional subsurface drip irrigation (SDI) system using spatial water use maps in an on-farm trial. For evaluation, the study utilized high-resolution satellite imagery, along with meteorological data, to derive spatial water stress maps (Water Deficit Index; WDI). This is a key indicator of crop water stress. Results showed that Field A, irrigated with AI-Radar, maintained considerably lower WDI values (0.15-0.16) than SDI fields (0.20-0.24) during critical reproductive stages. Field A also recorded 31 to 34% less irrigation water compared to Field B (SDI). These findings evaluated the potential of the AI-Radar irrigation system for effective irrigation scheduling, which can conserve groundwater while maintaining crop productivity.

Increasing the spatial resolution in the field allows us to capture a large amount of data that accurately captures field variability (at the soil and crop levels). This can also reduce the mix pixel effect, where pure pixels accurately reflect specific on-the-ground conditions for more precise characterization of field variability. With Chapter 2 demonstrating how precision irrigation systems differ in their ability to meet ET_c-driven crop water needs, Chapter 3 extends this framework by using ultra-high-resolution UAV imagery and cross-validating it with OpenET to evaluate how these differences translate into fine-scale WUE_f patterns and yield outcomes. Based on our results, fields irrigated with the AI-Radar irrigation system showed higher WUE_f (6.7-7.17 kg ha⁻¹ mm⁻¹) and a 30.8% increase in yield compared to SDI ($p < 0.05$).

Additionally, total irrigation water depth was 31-34% less than SDI. The mean seasonal ET_a was also higher for AI-Radar (444.44 - 478.8 mm) than for SDI (386.66 - 436.2 mm), indicating reduced water stress in Field A. These findings suggest that adopting AI-Radar-based irrigation can help Southern Great Plains farmers to produce more grain yield per drop of water.

The three chapters of this study demonstrated clear progression from identifying ET_c as an important factor influencing crop yield variability to estimating ET_c for irrigation assessment using satellite data and UAVs. Overall, this research reveals that precision irrigation (AI-Radar) can save more than 15% of irrigation water compared to conventional subsurface drip irrigation. This promotes sustainability through reduced water use and increased yield potential. Furthermore, using satellite and UAV remote sensing together with machine learning provides a scalable method for yield prediction. This framework supports efficient irrigation planning and improved productivity, resulting in reduced irrigation use in the Southern Great Plains.

2. Future Research

This study can be extended in two ways: first, by focusing on a regional framework that integrates medium (10–30 m; Sentinel 1-2, Landsat 8/9) to high (3-5 m; PlanetScope) spatial resolution satellite data. At this scale, yield variability is driven by $G \times E \times M$ interactions across diverse management zones. Therefore, next-generation regional models should incorporate (1) spatially explicit maturity group distributions, (2) planting date clusters derived from crop calendars and remote sensing, (3) seeding rate gradients, (4) soil functional traits, including organic carbon, CEC, texture (% sand, silt, clay), bulk density, soil depth, plant-available water, and baseline fertility. Research has shown that soil characteristics are crucial for explaining structural yield variation across landscapes. Incorporating features such as soil organic matter, cation exchange capacity, texture, and nutrient content with satellite and weather data can

improve regional yield prediction accuracy. Furthermore, for the plot-level yield prediction, the study can also be extended by utilizing a UAV, which offers much higher spatial resolution and can aid in using crop metrics like (1) canopy height model (2) crop structural variables or biophysical measurements (3) 3D point cloud features for biomass proxies, and (4) time series of crop growth for early stress detection. A valuable extension is to embed yield prediction within a crop rotation context, such as the *corn–wheat–soybean* system common in the U.S. Central Plains. Modelling across rotations can allow for the evaluation of carry-over effects (soil moisture legacy, nitrogen mineralization, residue cover), the quantification of multi-year yield stability indices, and the assessment of inter-season ET_c patterns and water debt accumulation. Additionally, another area for future work might be modeling crop quality attributes, such as determining plant protein and oil content based on planting dates.

Regarding the second study, a future study could extend this by developing a site-specific, locally calibrated vegetation index-based evapotranspiration (ET_c) model using high-resolution satellite data. This can be achieved using a ground-based ET sensor, which provides us with daily actual ET data. Additionally, rather than focusing on NDVI (saturates at later growth stages (LAI>2)), the future study can explore other biophysical parameters that can correlate with the crop water stress. Therefore, analysis of other various biophysical parameters, such as the Normalized Difference Red Edge (NDRE), Enhanced Vegetation Index (EVI), and Wide Dynamic Range Vegetation Index (WDRVI) at different crop growth stages, would help identify the most reliable spectral indicators for water stress and biomass accumulation during each phenological phase.

The third chapter focused on estimating field-scale water use efficiency. Future research can include other metrics of water use efficiency, specifically, CO₂ flux and transpiration, which

can be calculated using eddy covariance and sap flow techniques. This would provide a more comprehensive picture of plant water uptake and yield, as well as photosynthesis and production, under advanced precision irrigation technologies. Further enhancements can be achieved by integrating detailed water balance components, including actual irrigation volumes, precipitation inputs, changes in soil moisture storage, and percolation losses. Accounting for these variables would enable a more complete assessment of field-level hydrology. This can provide a more comprehensive picture of the field-water balance under both irrigation systems.

Ultimately, future research should aim to develop a modelling framework that integrates datasets from satellites, UAVs, and ground-based measurements to create real-time predictive models for yield, water status, and crop quality. Furthermore, the prediction model and irrigation system should be tested across all agroclimatic regions to assess their site-specific efficiency. Advancing toward this integrated and regionally adaptable framework would provide Kansas growers with more practical decision-support tools and enhance resilience under variable climate conditions.