Modeling agricultural crop water demands and sustainable water management under extreme climate conditions in Western Kansas

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Abstract

Prevalent extreme climate conditions, as well as depleting water resources in semi-arid regions continue to underscore the need for adopting efficient and data-driven management practices to ensure the long-term viability of agriculture. Crop evapotranspiration (ET) data—an indication of the water requirement of crops—varies significantly in response to these prevailing extreme climate conditions. Understanding the primary indicators responsible for the observed variability in crop ET, among the indices chosen to represent these events, as well as the degree to which these events may have an impact on crop ET in the future, is vital. Additionally, it is necessary to investigate water conservation strategies that can assist agricultural producers to become better prepared for the effects of these conditions by increasing the resilience of the maize crop to these extreme conditions, without compromising on the yield output or water use and productivity. The predictive power of a random forest machine-learning algorithm was employed to identify climate extreme indices that most influences crop ET, and to quantify their potential impacts in future climate change scenarios. The Decision Support System for Agrotechnology Transfer-Crop Environment REsource Synthesis (DSSAT-CERES) Maize model was further used to develop and evaluate diverse irrigation strategies based on crop ET data. The aim was to assess their effectiveness in enhancing maize crop's resilience to extreme climate conditions while minimizing the overuse of limited water resources. Our study revealed that crop evapotranspiration (ET) was primarily influenced by two key indices: the maximum number of consecutive dry days, and the maximum temperature. Model predictions further indicate that these indices have the potential to increase crop ET by 0.4, 3.1 and 3.8% under low greenhouse gas emission scenario, and by 1.7, 5.9 and 9.6% under high greenhouse gas emission scenario in the near, mid and end

century, respectively. A comprehensive 30-year simulation utilizing the DSSAT model revealed that in comparison to the commonly practiced full irrigation treatment, an irrigation strategy based on crop evapotranspiration (ET) – specifically, applying 75% of the ET requirement– demonstrated superior effectiveness. Applying 75% of the required ET amount when it reached a 30mm threshold, optimized yield, water usage, and productivity. Yield loss was limited to ~6%, with irrigation water savings of up to 19%, and water productivity decline was limited to a level below 5%, when the maximum temperature or the maximum consecutive dry days increased by up to 2^{o}C or 1 day, respectively. The decline in yield, as well as the losses in irrigation water and productivity, however, were significantly exacerbated when temperatures increased by up to 4^{o}C, thereby highlighting the importance of managing heat stress in order to preserve crop yields and significantly minimize water use in agriculture. Overall, these findings show that the ET-based deficit irrigation strategy adapts well to extreme heat and water stress, bearing important implications for irrigation management decisions in the future.

Table of Contents

List of Figures

List of Tables

List of Equations

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Dedication

This research is dedicated to the broader agricultural engineering community, whose commitment to advancing the frontiers of scientific knowledge plays a pivotal role in securing the sustainability of global food production for the benefit of all.

Preface

This master's thesis is the outcome of years of learning and personal development. I present this work with gratitude and a sense of accomplishment, hoping that as I do so, the findings and information contained within it will eventually prove to be beneficial contributions to the ongoing advancement of agricultural knowledge for the sustainability of global food production.

At the time of this thesis writing, the third chapter had already been published in a peer-reviewed journal, while the manuscript for the fourth chapter is currently being prepared.

Chapter 1 - Introduction

1.1 Problem Statement

Globally, arid and semi-arid regions are often faced with the challenge of limited water resources. The annual precipitation in these regions is often insufficient to meet the demands of agricultural production, thereby, exerting significant stress on surface and groundwater reservoirs, which serve as the primary sources of water for agricultural activities. Irrigation activities, especially for crop production account for a substantial proportion of the of yearly water consumption. Irrigation supports about 40% of the world’s food production (Mrad et al., 2020). In the United States, groundwater resources account for 60% of the water supplied to irrigated areas (Fienen & Arshad, 2016). However, these groundwater resources are unreliable, thereby, endangering the prospects of sustained agricultural production (Lopez et al., 2022). Therefore, it is crucial to ensure that these water sources can continue to support agricultural production in the future, and that requires a sufficient understanding of the conditions of climate, as well as the implementation of effective management practices, especially in arid and semi-arid regions. Crop evapotranspiration (ET) data—an estimate of the maximum amount of water required by crops at any given time—help producers to reduce excess withdrawals of the groundwater resource, by applying only the needed amount of water per time, during irrigation operations. However, the increasingly erratic climate patterns, characterized by extreme weather conditions during growing seasons, may create a significant variation in the amount of water used for irrigation (Islam et al., 2012), and the amount of water resource recharged through precipitation, compared to historical times. For example, rising temperatures have the potential to increase crop evapotranspiration, which, if not met adequately, can lead to water stress rising beyond the threshold which plants can handle, and ultimately impacting on crop yields (Çakir, 2004; Yilmaz et al., 2010). This situation necessitates a meticulous examination of the factors influencing evapotranspiration variability in regions like Western Kansas, which are particularly vulnerable to climate extremes (Lin et al., 2017; Rammig & Mahecha, 2015).

Western Kansas, situated in the U.S high plains depends on the Ogallala aquifer for as much as 90% of its irrigation needs (Mrad et al., 2020). The region is relatively dry, as the mean annual rainfall during growing season is about 350mm, accounting for only about 30% of the seasonal evapotranspiration (Araya et al., 2017). Additionally, the high plains are prone to extreme climate conditions with a long-term study showing that temperatures are gradually increasing, as the number of frost days have increased by 5.2 days relative to historic times (Lin et al., 2017). To cushion the effects of these extreme conditions, producers are forced to apply more irrigation, which implies an accelerated depletion of the water reserves (Kenny & Juracek, 2013). Under current observed trends, studies (McGuire, 2014; Scanlon et al., 2012; Steward et al., 2013; Steward & Allen, 2016) project a higher depletion of the groundwater reserve in the future, relative to the predevelopment period of the aquifer—often considered to be before the year 1950. This implies that the continuous withdrawal of the limited water resources without adequate recharge can cause the water resource to be depleted to the point where they may not be able to sustain agricultural activities, and even human needs in the future. In fact, in a recent study (Obembe et al., 2023), the overall groundwater withdrawal from the high plains aquifer within Kansas alone, is projected to increase further by mid-century. Under the representative concentration pathway (RCP) 4.5 scenario, which anticipates coordinated efforts to mitigate greenhouse gas emissions in the future, the study projects a notable increase of 5.9% in groundwater withdrawals. The trend becomes even more pronounced under the RCP8.5 scenario, where greenhouse gas emissions continue to rise due to inadequate intervention efforts, with a projected increase of up to 7.6%.

Conversely, future projections based on the sixth assessment report of the working groups of the Intergovernmental Panel on Climate Change (IPCC) (Seneviratne et al., 2021), indicate an expected increase in the intensity and frequency of climate extreme conditions, due to increased CO_2 emissions. This poses an imminent and increased threat to agricultural sustainability, further underscoring the critical importance of investigating the factors driving ET variability in the region, as well as estimating the potential change in crop ET under future climate change scenarios. It is also imperative to evaluate what irrigation management practices may be well adapted to mitigate against the impacts of these extreme conditions, as study shows that the peak grain production might decline by as much as 60%, under the current management practices employed in the region (Cotterman et al., 2018).

To help address these outlined challenges, the strengths of a machine learning statistical model and a robust process-based crop model were separately employed in this study. Machine-learning models have shown to be very effective at capturing both linear and non-linear interactions, which are often a common occurrence in climate-related phenomena (Kadkhodazadeh et al., 2022; Konduri et al., 2020). Their adeptness at discerning random patterns that may be present weather-influenced datasets makes them invaluable (Roberts et al., 2017a). Consequently, a random forest (RF) machine learning model was employed to investigate the climate extreme conditions driving ET in Finney County, Western Kansas.

Consequently, process-based models are extremely helpful for illustrating the physiological mechanism underlying crop yield and yield components. The Decision Support System for Agrotechnology Transfer (DSSAT) cropping system model (Jones et al., 2003) was therefore deployed to identify and assess efficient irrigation management practices tailored to the study area. Establishing effective management strategies is critical to avoid further depletion of the already limited groundwater supply, particularly because the current management practices are ineffective. This investigation not only considered strategies that improved or maintained crop yield at a satisfactory level, but also prioritized minimizing excessive water resource demand, both under normal and extreme climatic situations.

1.2 Statement of objectives

The specific objectives of this study were aimed at: (i) evaluating the impacts of seasonal climate extremes on crop evapotranspiration and quantifying the expected change in crop evapotranspiration of maize under future climate change scenarios, using a machine learning algorithm; and (ii) investigating sustainable water management strategies for improving crop adaptation to extreme climate conditions in western Kansas, using the DSSAT model.

Chapter 2 - Literature Review

2.1 Estimating potential crop water demands

The crop evapotranspiration (ET) estimation is crucial for understanding and managing crop water demands. To accurately estimate crop ET, various direct and indirect methods have been explored in literature. Crop ET is often modeled as a function of the environmental and crop characteristics. The former is mostly contained in the reference evapotranspiration (ET_o) component, which is the amount of water that can be lost from a reference surface like grass or alfalfa, and is usually estimated from weather variables. The latter, however, is captured by a factor known as the crop coefficient. The crop coefficient may be estimated by considering specific crop characteristics such as the crop type, crop height and leaf area index, as well as using indices such as the normalized difference vegetation index, which can be estimated from satellite data (Igwe et al., 2023), and also from data collected using unmanned aerial vehicles (Wiederstein et al., 2022). Standardized values of the crop coefficient for various crops, including maize are reported in the FAO 56 irrigation and drainage paper (Allen & Pereira, 1998) along with various other approaches reported in literature for estimating the ET_o. The most commonly used, and widely accepted methods are the Priestly-Taylor (Priestley & Taylor, 1972) and the FAO-Penman Monteith (Allen & Pereira, 1998) methods. While the application of these models are largely limited to the specific regions (Valipour et al., 2017), machine learning models have however, been reported to be robust in accurately estimating ET_o and its associated climatic impacts, under various vegetation types (Dou & Yang, 2018), climatic regions (Huang et al., 2019; Wei et al., 2022; Wu & Fan, 2019), and even under limited data (Mostafa et al., 2023; Torres et al., 2011). For example, in Midwestern U.S., a Random Forest machine learning model was reported to show good potential for estimating ET_o with satisfactory accuracy (Talib et al., 2021).

2.2 Climate-driven variation in seasonal crop water demands

Crop water demand, represented by evapotranspiration often vary seasonally due to several factors (Zhang et al., 2023) with climate driven factors being the major contributors to this variation (Basso et al., 2021). Several climatic components which have been reported to dominantly influence reference ET (ET_o) vary extensively by location (Feng et al., 2020). In the south, central and northwestern regions of Iraq, for instance (Al-Hasani & Shahid, 2022), and in the Mediterranean region (Gorguner & Kavvas, 2020), the air temperature was found as the pre-dominant variable affecting ET_o. Conversely, in Northeastern China, relative humidity was found to dominantly influence ET at high altitudes, while windspeed exerts the greatest impact at low altitudes (Liu et al., 2022). Meanwhile, precipitation is reported to be the major driver of ET_o in most humid regions (Feng et al., 2020; Zhou et al., 2015). Seasonal crop variability is also affected by extreme weather events that are primarily a result of climate change. Unusual conditions of climate, especially those derived from temperatures and precipitation tend to influence ET_o rates more abruptly (Sadok et al., 2021). These unusual conditions referred to as climate extremes can lead to severe water stress which may likely increase crop water demand, and consequently, the irrigation water use. In the united states, high correlation between potential ET_o and summer precipitation, were reported in the northeastern regions, while the southern regions showed higher correlation with temperature indices than with precipitation indices (Nie et al., 2021; Vadeboncoeur et al., 2018). In other comparable research, the expected magnitude of change in ET_o due to the climate-induced shift in the patterns and occurrence of these climatic variables, relative to historical period, was evaluated and quantified. In a study conducted in Ethiopia, it was found ET_o will likely increase under Representative Concentration Pathways (RCP4.5) and (RCP8.5) scenarios by 14.3 to 15.3%, and 19 to 28.5%, respectively (Gurara et al., 2021).

Similarly, in a study carried out in Iran, an increase in ET_o ranging between 1.3% and 7.3% was predicted, with the biggest increase predicted under the RCP 8.5 scenario (Lotfi et al., 2020). In the United States, several studies indicate an overall increasing trend in ET rates (Basso et al., 2021; Condon et al., 2020; Walter et al., 2004). This trend is not only temporal but also exhibits a spatial shift, with rates generally increasing from west to east, as indicated by the shift in imaginary 100th meridian line separating western arid parts US from the eastern humid parts (Seager et al., 2018). The Midwestern regions of the U.S. are particularly vulnerable to these shifts in evapotranspiration dynamics, majorly because a substantial portion of cultivated areas in the region rely predominantly on rainfed agriculture (Ao et al., 2021; Basso et al., 2021). As a result, these areas are more exposed to extreme temperatures which have been reported to influence evapotranspiration (Igwe et al., 2023; Roderick et al., 2015), and consequently reductions in crop production (Lobell et al., 2013, 2014; C. Zhao et al., 2017). These findings suggest the need for improving crop adaptation to climate impacts, especially under limited water resources which is prevalent in semi-arid regions like western Kansas.

2.3 Agricultural sustainability under deficit irrigation management

Irrigation is very useful for mitigating against the impacts of climate extremes on crop productivity (Sadok et al., 2021; Schauberger et al., 2017; Troy et al., 2015). This is because, in addition to meeting crop water needs, irrigation helps to reduce crop heat stress by cooling the crop through evaporative effect (Li et al., 2020), giving an advantage in yield production compared to rainfed agriculture in areas with limited rainfall. However, because irrigating in response to extreme climate conditions would likely necessitate increased groundwater withdrawals, it is therefore essential that a well-adapted deficit irrigation management be implemented to maximize water savings without yield penalty. Deficit irrigation management strategies may be based on an allowable percentage depletion of the plant available soil water, indices representing crop water stress, or based on crop evapotranspiration data (Ma et al., 2017). Also, when additional resource constraints, such as a limit on pumping capacity, render it difficult to meet peak crop water demands, growth-stage based irrigation management can be used as an alternative to full irrigation (Rudnick et al., 2019). In general, no single irrigation management strategy is well-adapted for all regions. This is largely because in addition to the irrigation scheduling techniques (Attia et al., 2021), crop and water productivity response varies, depending on the crop type (Li & Troy, 2018), soil type (Araya et al., 2021), climate condition (Araya et al., 2017), and the water supply available (Xiang et al., 2020), among others. Therefore, the optimum irrigation technique for a given area can be chosen based on how well it preserves the region's scarce resources without negatively affecting agricultural output. Due to the limitation of water resources in western Kansas, the most effective irrigation scheduling technique is often determined by its ability to reduce water use while increasing output and water use efficiency under various conditions (Rudnick et al., 2019). Field experimental designs can be used to assess the capabilities of these irrigation scheduling techniques (Ko & Piccinni, 2009), but these experiments are usually cost and labor intensive. As an alternative approach, researchers are increasingly adopting process-based cropping system models, such as the Decision Support System for Agrotechnology Transfer (DSSAT) model. Due to its robust modeling framework, the DSSAT model has gained wide acceptance, since it offers an advantage of simulating crop growth processes given the weather, soil, crop and management information. The model has the capability of setting up automatic and controlled irrigation scheduling treatments based on soil water depletion, evapotranspiration accumulation or target growth stages. For example, the DSSAT model was used to assess the performance of varying levels of plant available soil water, controlled by irrigation frequencies (Araya et al., 2021) on the maize crop and water productivity in western Kansas. Similarly, several other studies (Araya et al., 2017; Attia et al., 2021; Lone et al., 2020) have applied the DSSAT model assess crop response under varying climatic conditions. Therefore, the DSSAT model proves to be a useful tool for gaining insightful knowledge about how to best optimize water resources, and boost crop output while mitigating against the adverse effects of climate-induced conditions.

Chapter 3 - Evaluating the Impact of Future Seasonal Climate Extremes on Crop Evapotranspiration of Maize in Western Kansas Using a Machine Learning Approach

Abstract

Data-driven technologies are employed in agriculture to optimize the use of limited resources. Crop evapotranspiration (ET) estimates the actual amount of water crops require at different growth stages, thereby proving to be the essential information needed for precision irrigation. Crop ET is essential in areas like the U.S. high plains, where farmers rely on groundwater for irrigation. The sustainability of irrigated agriculture in the region is threatened by diminishing groundwater levels and the increasing frequency of extreme events caused by climate change further exacerbates the situation. These conditions can significantly affect crop ET rates, leading to water stress which adversely affects crop yields. In this study, we analyzed historical climate data using a machine learning model to determine which climate extreme indices that most influenced crop ET. Crop ET was estimated using reference ET derived using the FAO-Penman-Monteith equation which was multiplied with crop coefficient data estimated from remotely-sensed normalized difference vegetation index (NDVI). We found that climate extreme indices of consecutive dry days and mean weekly maximum temperatures most influenced crop ET. It was found that temperature-derived indices influenced crop ET more than precipitation-derived indices. Under the future climate scenarios, we predict that crop ET would in-crease by 0.4% and 1.7% in the near term, by 3.1% and 5.9% in the mid-term, and by 3.8% and 9.6% at the end-of-century, under low greenhouse gas emission and high greenhouse gas emission scenarios

respectively. These predicted changes in seasonal crop ET can help agricultural producers to make well-informed decisions to optimize groundwater resources.

Keywords: extreme weather events; crop evapotranspiration; climate change; machine learning

3.1 Introduction

Crop evapotranspiration (ET), when estimated accurately, can enable agricultural producers to make effective irrigation management decisions. In areas such as the High Plains region, agricultural production relies heavily on groundwater resources (Dennehy et al., 2002). However, due to the declining amount of yearly precipitation, groundwater withdrawals have greatly surpassed recharge, posing a threat to the sustainability of agriculture in the future (Cotterman et al., 2018; Deines et al., 2019; Haacker et al., 2016). Since crop ET is the estimate of the actual amount of water required by the crops at any given time during growing season, effective use of crop ET information can help mitigate this problem. Therefore, when incorporated into irrigation scheduling, crop ET data can help optimize the use of limited groundwater resources and ensure its sustainability by reducing the rate of groundwater pumping while also meeting crop water needs (Ajaz et al., 2020; Brauer et al., 2017).

Crop ET rates and amounts, however, are affected by the variability of growing-season weather conditions. More specifically, the increased frequency and intensity of the occurrence of extreme climate events caused by climate change, influences in-season variation in the crop water requirement (Condon et al., 2020). Climate extremes are instances of harsh weather conditions, such as heat waves and highly variable precipitation. They have become a global concern to agricultural researchers and producers, especially due to the extent of the effect they can have on the hydrological cycle, and on crop productivity (Vogel et al., 2019). Many studies have assessed the impact of climate extremes on the end-of-season yield of crops, and have discovered that relationships exist between climate extremes and crop yields (Powell & Reinhard, 2016; Troy et al., 2015; Wilson et al., 2022). For example, researchers (Lobell et al., 2013; Lobell & Asner, 2003) report that extreme heat occurrences, which are conditions where the maximum temperature during the growing season exceeds 30°C, have a negative effect on maize yield. This is because prolonged exposure to high temperatures induces water stress by increasing the rate of soil evaporation and plant transpiration; as plants are then forced to close their stomata in order to prevent desiccation (Schauberger et al., 2017). A decreased yield at the end of the growing season is therefore likely, if sufficient water is not provided to relieve the water stress brought on by these extreme temperature conditions. These extreme weather conditions may even have more devastating effects on crop productivity, particularly if they occur at growth stages where the crops are most vulnerable to water stress (Comas et al., 2019). In an experimental study, (Hatfield & Prueger, 2015) reported that the reproductive stage of maize is most sensitive to warmer temperatures, and when com-pared to maize growth under normal temperatures, these warmer temperatures can re-duce the end-of-season yield by as much as 80% to 90%. A similar study (Suárez et al., 2019) also reported that with the exposure of crops to climate extremes, like 24 hours under temperatures above 33°C, the biomass yield reduces by up to 3%. Maize is highly susceptible to water stress (Lobell et al., 2014), and it needs more adequate watering during its vegetative and tasseling stages, in order to prevent significant yield decline at the end of its growing season (Yilmaz et al., 2010). However, under well-managed conditions, maize responds well to irrigation in terms of production; yielding 673Kg/ha to 1009Kg/ha for every 25 mm of water applied. This makes maize the most heavily irrigated crop in Kansas; covering over half of the state's three million acres of maize-producing land. Rogers et al., (2012) reports that the full-season variety types of maize need between 500mm and 800mm of water, often at a rate of 9mm to 13mm per day, depending on the weather during the growing season.

Variability in in-season weather conditions will likely impact on maize's average crop water needs. Rising annual and seasonal temperatures resulting from increased greenhouse gas emissions due to human activities (Hayhoe et al., 2009), are already being reported in the Midwest (Seneviratne et al., 2021) and other parts of the world (Smith, 2011). These observed changes are expected, given that future climate estimates from global climate models (GCMs) show an upward trajectory in global warming and aridity in the future (Alexander et al., 2006). GCMs are models developed based on the knowledge of the earth's system and how its components interact. Using historically observed data, and scenarios that depict the levels of greenhouse gas emissions from human activities, these GCMs generate data for various climate parameters like temperature, precipitation, humidity, etc. at various regional and temporal scales. Four gas emission scenarios referred to as representative concentration pathways (RCPs) were developed and standardized by the intergovernmental panel on climate change (IPCC) in the IPCC fifth assessment report (*IPCC*, 2014). Two of these scenarios commonly used in studies are the RCP4.5 scenario—a future in which mitigation efforts are implemented to reduce greenhouse gas emissions—and the RCP8.5 scenario, which depicts a future in which greenhouse gas emissions continue to rise all through the twenty-first century. The scenarios serve as input data to over twenty GCMs that have been developed by the coupled model inter-comparison project (CMIP). The predictions from the GCMs are usually compared with historically observed data to estimate the severity of climate change to be anticipated in the future. The changes projected by these GCMs pose a significant threat to the sustainability of agriculture in semi-arid regions like the U.S. high plains region. Particularly, since the current limitation in groundwater resources might not be adequate to satisfy a change in the growing season water requirement of maize in the future. Further-more, (Seneviratne et al., 2021) reported a likely increase, globally, in the frequency and severity of extreme weather events.

The US high plains—a portion of the great plains—comprises of eight states which include South Dakota, Nebraska, eastern Colorado, southern Wyoming, western Kansas, northwestern Texas, eastern New Mexico, and northwestern Oklahoma. Together, these states produce more than 50 million tons of grain annually (Mrad et al., 2020). Agricultural production in the region depends heavily on irrigation activities, which accounts for approximately 90% of the yearly water use. Irrigation significantly lowers heat stress on maize, which is brought on by extreme climatic conditions during the growing season (Siebert et al., 2017). Research shows that irrigation increases the overall seasonal biomass yield of crops in the region by 51% (Mrad et al., 2020), approximately $3 billion today. However, irrigation induces a strain on water re-sources, as it further depletes the limited groundwater resources available (Rosa et al., 2018). A related study shows that the current groundwater management conditions in the high plains' region are inadequate, and may lead to a decrease in maize production by acreage, by as much as 60%, if no further adaptation strategies are implemented (Cotterman et al., 2018). Furthermore, a long-term trend analysis of climate in Western Kansas, which is a part of the high plains' region, revealed that the annual number of frost-free days has increased by 5.2 days (Lin et al., 2017). With this rate of warming, future moisture loss from evapotranspiration could rise, which would lead to a corresponding increase in the amount of water needed to irrigate the maize crop. This can eventually impact on the crop yield, as the limited amount of groundwater might not be adequate to support the irrigation demand which is deter-mined by the crop evapotranspiration estimates.

Crop evapotranspiration is often modeled as a function of the reference evapotranspiration (ET_o) which accounts for most of the environmental influences like temperature, solar radiation, and wind, and the crop coefficients (Kc) which account for the effects of crop characteristics like crop height, albedo, canopy resistance and even evaporation from the soil (Allen & Pereira, 1998). ET_o estimation models may be broadly classified into: (1) fully physically-based models such as the widely accepted Penman-Monteith equation, and the Surface Energy Balance System (SEBS) (Su, 2002) that incorporate mass and energy conservation principles; (2) semi-physically-based models like Surface Energy Balance Algorithm for Land (SEBAL), the Mapping Evapotranspiration at high resolution with internalized Calibration (METRIC) model, and the Variable-Infiltration Capacity Model —often applied in spatiotemporal studies using remote sensing—which both combine empirical adjustments with either mass or energy conservation principles (Li et al., 2009; Liou & Kar, 2014; Srivastava et al., 2017); and (3) black-box or machine learning models based on artificial neural networks (Elbeltagi et al., 2022; Kumar et al., 2011), adaptive neuro fuzzy computing (Kişi & Öztürk, 2007), and genetic algorithms (Yin et al., 2016),which estimates ET_o by learning patters and relationships from a given set of input data. Physically-based models are computationally demanding as they require a lot of data, and as a result, they can be cost intensive. In contrast, semi-physically based models (Li et al., 2009) offer less expensive options, especially when carrying out studies over larger areas.

However, due to recent advances in technologies and processing capabilities, machine learning (ML) models are becoming popular in estimating ET_o, and also in studying its associated climatic impacts. This is largely because machine learning models are more effective than other methods at predicting both linear and non-linear relationships, as is often the case for climate-related phenomena (Kadkhodazadeh et al., 2022; Konduri et al., 2020). ML models such as random forests (RF), support vector machine, artificial neural networks (ANN) and many more have been applied in predicting crop water demands, and crop water stress (Granata, 2019), for various vegetation types (Dou & Yang, 2018), and under limited climatic data (Mostafa et al., 2023; Torres et al., 2011). For example, a comparative study in China (Fan et al., 2018) evaluated the performance of simple tree-based machine learning models like random forests (RF), extreme gradient boosting (XGBoost), and M5 model in comparison to other related machine learning models like support vector machines (SVM). The result indicated that based on determining factors like complexity level, prediction accuracy, stability and computational costs, the RF model generally provided satisfactory estimates of ET_o (R2 > 0.9) in the temperate continental, mountain plateau and temperate monsoon zones of China. In a similar study (Huang et al., 2019), the same determining factors were used to compare RF, SVM, and gradient boosting on decision trees with support for categorical features (Catboost), and it was revealed that in humid regions, the SVM generally exhibited more levels of accuracy and stability (R2 > 0.98) for ET_o estimation under limited climatic data, although, it is worth noting that in the study, the RF model also demonstrated strong performance during the model's training phase, suggesting a potential robustness across different climatic zones. Furthermore, in a comprehensive comparison of eight machine learning models conducted across multiple climatic regions in China (Wu & Fan, 2019), the SVM model demonstrated strong prediction capability. The study categorized the models into different types, including neuron-based models such as Generalized Regression Neural Network (GRNN), Multilayer Perceptron Neural Networks (MLP), and Adaptive Neuro-Fuzzy Inference System (ANFIS); kernel-based models like Support Vector Machine (SVM) and Kernel-based Nonlinear Extension of Arps Decline Model (KNEA); tree-based models like M5 model tree (M5Tree) and XGBoost, as well as a curve-based model called Multivariate Adaptive Regression Spline

(MARS). Among these models, the SVM model consistently performed well and exhibited strong predictive capabilities across the evaluated regions in China.

In semi-arid regions like the high plains' region of the United States, ML models have also demonstrated their effectiveness in accurately estimating evapotranspiration. In Kansas, the RF model was observed to effectively capture the temporal and spatial variability of irrigation amounts with a satisfactory accuracy ($R2$ = 0.82) using hydrometeorological and remote sensing products (Wei et al., 2022). Similarly, in Texas, a comparative study between a linear regression model and two more advanced ML models—the artificial neural net-works (ANNs) and the Gaussian process models (GPs)—was conducted to predict daily reference ET. The findings indicated that the GP machine learning model yielded the highest estimation accuracy (R2 = 0.95) (Holman et al., 2013.). These results highlight the effectiveness of ML models in accurately estimating ET in semi-arid regions, therefore showcasing the potential of capturing the complex relationships associated with ET estimation. However, most of these studies have been done using mean meteorological variables, and considering only the impacts of mean climate change conditions. The seasonal interactions of extreme climate conditions with crop evapotranspiration, which is a crucial component in determining crop yield, have not yet been extensively studied.

To ensure well-informed decision-making with regard to irrigation, it is therefore necessary to study the impacts of these climate extremes on crop ET, especially in the face of climate change. There is also a need to quantify how much change in seasonal crop water requirements of a water-intense crop like maize is likely to occur in the future given the likelihood of an increase in the intensity and duration of extreme climate occurrences. The objectives of this study, therefore, are: i) to analyze historical weather data to deter-mine which climate extremes most influence crop ET and; ii) to use a machine learning-based model to quantify the seasonal change in crop ET for future climate change scenarios.

3.2 Data and Methods

3.2.1 Study Area

The Southwest portion of Kansas is semi-arid. Its annual minimum and maximum temperatures are averaged at 4°C and 20°C respectively (Steward et al., 2013). Also, the mean annual precipitation is less than 500 mm, with a positive trend of only about 2.54 mm per decade (Araya et al., 2017). Finney County (Latitude = 38.0625°N, Longitude = 100.8903°W, elevation of 867m), which is located in the southwestern part of Kansas, was selected as the area of focus for this study. During the growing season–usually from May to October—Finney County experiences an average precipitation of 349 mm, a maximum temperature of 28.3°C, and a minimum temperature of 12.3°C, respectively (Araya et al., 2017). Furthermore, only approximately 35% of the reference evapotranspiration is met by the yearly precipitation and during the growing season, the percentage usually falls between 29 - 48% (Araya et al., 2017). The arid condition in the region can be seen in the 30-year time series plot of annual cumulative precipitation and evapotranspiration shown in figure 3.1 below. This makes groundwater supplies a crucial resource for agricultural productivity in the study area. There are 1,629 wells used for irrigation, however, the water table in some of the wells has dropped by 15 meters since 1950 (Xiang et al., 2020), due to excess pumping.

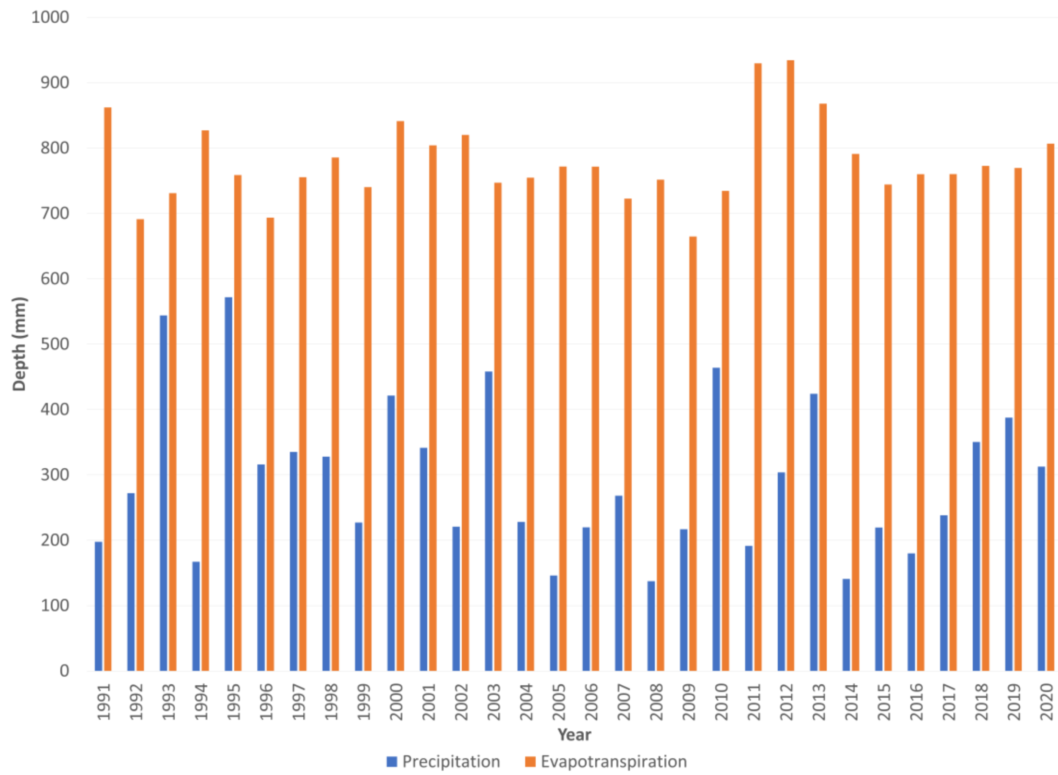


Figure 3.1: A 30-year time series plot of annual cumulative precipitation and evapotranspiration in Finney County, Kansas.

Maize is the second most widely grown crop in Finney County, after winter wheat. According to the 2020 USDA national crop data layer (National Agricultural Statistics Service (NASS) & Development Division (RDD) Geospatial Information Branch (GIB), 2020), it covers approximately 50,000 hectares (49,320 hectares) of cultivated land. The three most widely grown crops in Finney County, Kansas, as measured by the area of land cultivated, are shown on the typical county map in figure 3.2 below

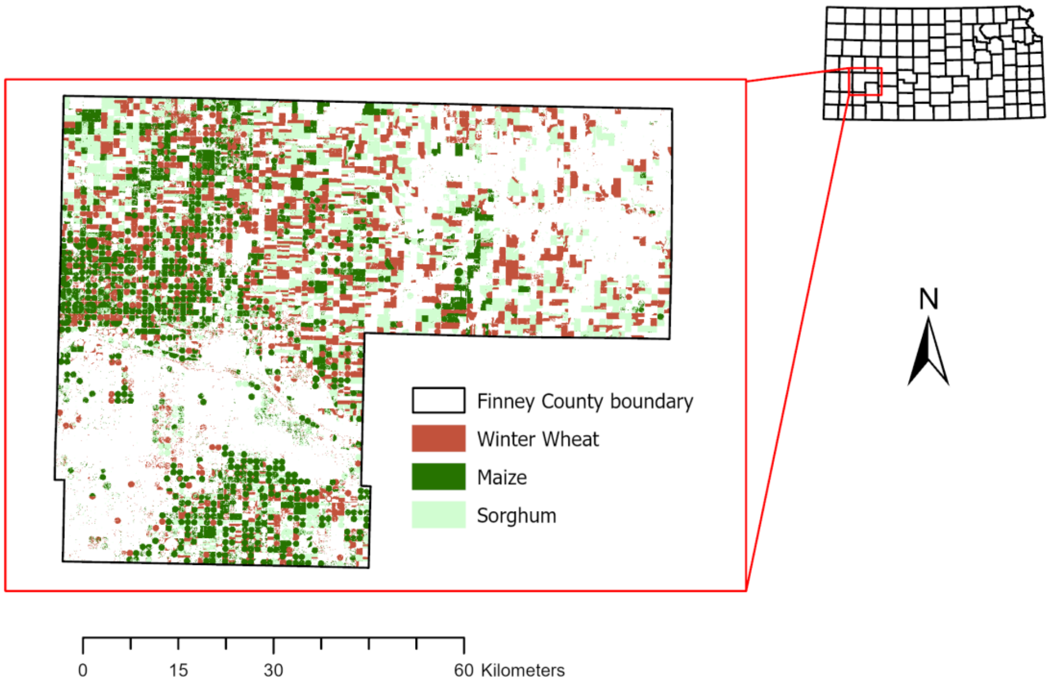


Figure 3.2: Finney County, Kansas showing most cultivated crops by acreage.

3.2.2 Data and Data Sources

3.2.2.1 Historic climate extremes

Weather data comprising of daily maximum and minimum temperature, and daily precipitation were extracted for Finney County from the High Plains Regional Climate Center (HPRCC), for a 30-year historical time period (from 1991 to 2020). Eleven indices (Table 3.1) representing agriculturally relevant climate extremes (Zhang et al., 2011) were calculated from HPRCC temperature and precipitation datasets following the procedure recommended by the expert team on climate change detection and indices (ETCCDI) (Karl et al., 1999; Zhang et al., 2005). To represent moderate climate extreme indicators, a core set of 27 indices was first created by the ETCCDI. The initial set of indices developed, however, could not be used in many specialized disciplines, such as agriculture. The indices were then revised by the expert team on sector-specific climate indices (ET-SCI) to make them useful for specific industries like agriculture. Therefore, the indices chosen for this study were those that were considered to be pertinent to agricultural crop production, particularly for growing maize. These indices were also selected based on their capability to be aggregated at a weekly temporal resolution, unlike other indices published by the ETCCDI, which were commonly aggregated at a monthly or an annual temporal scale. The calculated indices were aggregated to a weekly temporal scale for the maize growing period, to ensure the homogeneity of their temporal resolution with that of the crop ET data. Indices derived from precipitation and temperatures data were categorized as precipitation-based indices and temperature-based indices, respectively. Indices of temperature expressed in percentages—which are commonly called warm spells—were further classified as percentile-based indices. The maize growing season length that was defined in this study for Finney County, spanned between May 5th and October 7th as recommended by Araya et al., (2017).

Table 3.1: Agriculturally relevant climate extremes adapted from Zhang et al., (2011)

Extreme indices	Description	unit
	Precipitation-based indices	
Consecutive dry days (CDD)	Maximum length of dry spell: Maximum number of consecutive days with RR < 1mm	day
Consecutive Wet Days (CWD)	Maximum number of consecutive days with precipitation > 1mm	day
Total precipitation (PRPtot)	Weekly total precipitation on wet days (PRPtot)	mm
	Temperature-based indices	
Daily temperature range (DTR)	Daily Temperature Range; difference between maximum and minimum temperature	^oC
TM below 10 °C (Tmlt10)	Weekly number of days when TM < 10 ^oC	day
TX of at least 30 °C (TXge30)	Weekly number of days when TX > 30 ^oC	day
Mean TX (TX_avg)	Mean daily maximum temperature	^oC
Mean TN (TN_avg)	Mean daily minimum temperature	^oC
Tropical nights (TR)	Number of days when TN > 20 °C	day
	Percentile-based indices	
Amount of hot days (TX90p)	Percentage of days when TX > 90th percentile	%
Amount of warm nights (TN90p)	Percentage of days when TN > 90th percentile	%

**TN = Minimum Temperature, TX = Maximum Temperature, TM = Mean Temperature*

3.2.2.2 Estimation of crop evapotranspiration

The crop evapotranspiration (ET_c) was estimated from two variables: the reference evapotranspiration (ET_o), which was calculated from weather data extracted from the high plains regional climate center (HPRCC); and crop coefficient (K_c) data (Equation 3.1) using:

Equation 3.1: Crop Evapotranspiration:

$$ET_c = K_c \; x \; ET_o.$$

Where, ET_c is the crop evapotranspiration in mmday^{-1}; K_c is the crop coefficient; and ET_o is the reference evapotranspiration in mmday^{-1}.

This crop coefficient approach in Equation 1 above is recommended by the Food and Agriculture Organization (FAO) for estimating ET_c more accurately from weather datasets when field measurements are not readily available (Allen et al., 2005). The step-by-step procedure applied is similar to one reported by Reyes-González et al. (Reyes-González et al., 2018), as shown in figure 3.3. The ET_o was estimated using the FAO Penman-Monteith equation (Equation 3.2) (Allen et al., 2004), from weather datasets extracted for Finney County from the HPRCC using:

Equation 3.2: Reference Evapotranspiration:

$$ET_o = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T + 273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)}.$$

Where ET_o is the reference evapotranspiration in mmday^{-1}; R_n is the net radiation at the crop surface in MJm-2day^{-1}; T is the average daily temperature at 2m height in ^oC; u_2 is the wind speed at 2m height in ms^{-1}; (e_s-e_a) represent the saturation vapor pressure deficit in kPa; and Δ is the slope vapor pressure curve in kPaoC^{-1}; γ is the psychometric constant (kPa^{o}C^{-1}); and G is the Soil heat flux in MJm^{-2}day^{-1}, which was considered to be equal to zero in accordance with recommendations by Allen et al. (Allen et al., 2004), for calculating ET_o at daily time steps using a hypothetical reference crop with height of 0.12m, albedo of 0.23 and a fixed surface resistance of 70sm^{-1} was assumed for well-watered condition.

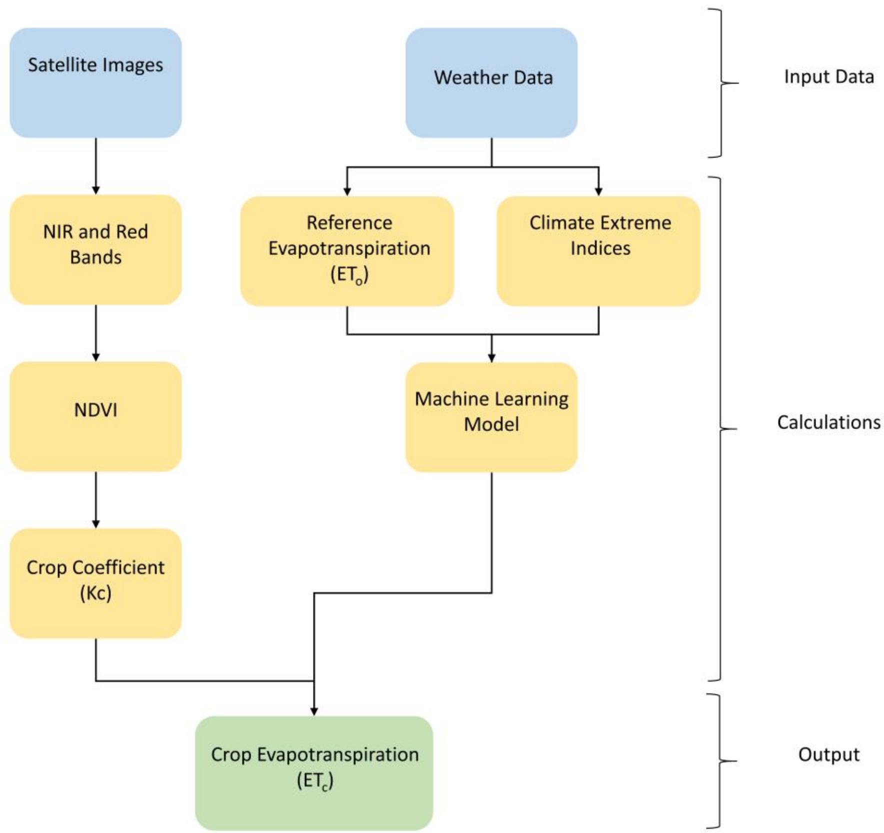


Figure 3.3: Flowchart showing procedure for modeling crop ET from crop coefficient and climate extreme indices. Adapted from Reyes-González et al. (2018)

Crop coefficient (Kc) of maize crop was estimated from remotely sensed normalized difference vegetation index (NDVI). The FAO's irrigation and drainage paper 56 (Allen & Pereira, 1998) pro-vides Kc values for maize at the early, midseason, and late season phases of growth. However, these values do not take into consideration the daily and weekly variations of Kc values throughout the course of the full growing season. Several studies (Bausch, 1993; Campos et al., 2017; Kamble et al., 2013; Neale et al., 1990) have reported that a linear relationship exists between the single Kc, and the NDVI. (Wiederstein et al., 2022) compared Kc values of maize estimated from several of these empirical relationships reported by researchers, using NDVI raster images extracted from the Landsat 7 satellite, and also from aerial images captured from un-manned aircraft. He found that the (Kamble et al., 2013) empirical model for Kc produced the best results in Finney County. We therefore applied the (Kamble et al., 2013) empirical model in this study to determine Kc values for maize, using NDVI data. Surface reflectance images were extracted from both the Landsat 5 satellite for the period of 1991 to 2000; and the Landsat 7 satellite, for the years 2001 to 2020. NDVI was computed using the surface reflectance values in near-infrared (NIR) and red region of the electromagnetic spectrum, in the widely applied NDVI index (Equation 3.3) (Kriegler et al., 1969)

Equation 3.3: Normalized Difference Vegetation Index (NDVI):

$$NDVI = \frac{NIR - RED}{NIR + RED}.$$

Where NDVI is Normalized Difference Vegetation Index; NIR is Percent reflectance of light in the near-infrared region of the electromagnetic spectrum; RED is Percent reflectance of light in the red region of the electromagnetic spectrum.

The Images obtained by the Landsat satellite sensors are often subject to various influences, including atmospheric effects, and bidirectional reflectance distribution function (BRDF) which result from the sun's position, sensor view angle, and the nature of the terrain (F. Li et al., 2010). Due to the combination of atmospheric influences with these BRDF effects, remote sensing techniques might be particularly challenging, especially in mountainous regions with steep slopes. Although the study area chosen for this research is a relatively flat area with an average slope of less than 2% and an elevation of 867 meters above sea level (Araya et al., 2017), the potential errors that may arise from variations in the elevation and slope, as well as potential atmospheric effects on the quality of the images, were taken into consideration. To address potential errors that may occur due to the BRDF effects, the Landsat satellite surface reflectance products have been pre-processed (Masek et al., 2006), by using approximated BRDF parameters which are derived from complex algorithms (Li et al., 2012). To further eliminate atmospheric effects, the Landsat surface reflectance images underwent additional processing within in the google earth engine (GEE) code editor platform. This process involved filtering out only the days with no cloud cover (i.e. cloud cover = 0%). The filtered images were then clipped to a raster mask of maize-cultivated fields in Finney County using ESRI's ArcGIS pro software. The raster mask containing pixels for maize growing areas was extracted from the cropland data layer (CDL) of the USDA (NASS, 2020). The clipped images of NDVI were then imported into GEE platform for additional processing. Since the NDVI data were only available for every 16 days because of the Landsat 5 and Landsat 7 thematic mapper satellites' 16-day revisit cycle, further data processing was required in order to provide daily time series for NDVI. Several researchers have adopted statistical smoothing techniques such as the weighted least-squares linear regression method, Kernel, and Gaussian smoothing techniques to increase the data quality of time series NDVI (Cai et al., 2017; Cao et al., 2018; Shao et al., 2016). The Gaussian technique was applied to the NDVI curve using the 'gam' function in R (Hastie & Tibshirani, 2014), in order to extract the NDVI data at daily time steps. The power of polynomial (k=300) was found to produce the best approximation of the seasonal and temporal pattern of the estimated NDVI data. The smoothened daily NDVI values were then aggregated to weekly time steps to homogenize with the temporal resolution of the climatic extreme indices and the evapotranspiration data. The selected NDVI-based Kc model (Equation 3.4) (Kamble et al., 2013) was then used to estimate crop coefficient values from the 30-year historical NDVI data.

Equation 3.4: Crop coefficient (K_c)

$$K_c = 1.4571 * NDVI - 0.1725.$$

The obtained values of Kc were then multiplied with the FAO Penman-Monteith reference ET to obtain the potential crop ET of maize, using Equation 1. The estimated crop coefficients were kept constant in historical and future time periods, because the effects of various weather conditions on crop evapotranspiration are largely accounted for by the reference evapotranspiration estimate (Allen & Pereira, 1998), while the crop-specific characteristics are integrated into the crop coefficient, which is primarily influenced by physiological development stages of the crop, irrigation management, and soil conditions.

3.2.2.3 Future climate data and extreme indices

Future climate data for Finney County were retrieved from twenty global climate models (GCMs) (Table 3.2), for a 75-year time period, which were divided into the near-term period (2025-2049), the mid-century period (2050-2074), and the end-of-century period (2075-2099). GCMs are chosen based on how well they perform in capturing the dynamics of various climate phenomena, including precipitation, the pacific oscillations, the dynamics of the El Nino-Southern Oscillation (ENSO), and robust simulations of future cli-mate scenarios. The ability of each GCM to model a particular climate process, however, varies because of the complexity of climate processes (Pierce et al., 2009). As a result, an ensemble of GCMs is frequently used in climate change research in order to account for the numerous errors and biases that may be present in the individual models. The Coupled Model Inter-comparison Project Phase 5 (CMIP5) output of daily statistically downscaled data (Abatzoglou, 2013), has been pre-processed to extract daily future temperature and precipitation data for the 20 GCMs available, by the University of Idaho at a 1/24-degree spatial resolution. The data was downscaled using the multivariate adaptative constructed analogs (MACA) method, and was bias-corrected using a quantile mapping approach. The method has also been validated for the Western regions of the United States (Abatzoglou & Brown, 2012). In this study, two representative concentration pathways (RCPs) developed by the intergovernmental panel on climate change were taken into account: the RCP4.5 scenario, which projects that reduced greenhouse gas emissions stabilize radiative forcing at about 4.5 Wm^{-2}, and the RCP8.5 scenario, which projects that greenhouse gas emissions increase radiative forcing above 8.5 Wm^{-2} by the end of the century., implying much higher warming in the future under RCP8.5 than under RCP4.5 scenario. These data were used to calculate the same set of climate extreme indices that had been previously calculated using historical weather data. The calculated indices were then used as input data to predict reference evapotranspiration for each GCM and for both the RCP4.5 and RCP8.5 scenarios.

Table 3.2: Statistically downscaled Global Climate Models; adapted from (Abatzoglou & Brown, 2012; Taylor et al., 2012).

S/N	Model Name	Model Agency	Atmosphere Resolution (Lon x Lat)
1.	bcc-csm1-1_r1i1p1	Beijing Climate Center, China Meteorological Administration	2.8 deg x 2.8 deg
2.	CanESM2_r1i1p1	Canadian Centre for Climate Modeling and Analysis	2.8 deg x 2.8 deg
3.	CSIRO-Mk3-6-0_r1i1p1	Commonwealth Scientific and Industrial Research Organization/Queensland Climate Change Centre of Excellence, Australia	1.8 deg x 1.8 deg
4.	HadGEM2-CC365_r1i1p1	Met Office Hadley Center, UK	1.88 deg x 1.25 deg

5.	IPSL-CM5A-LR_r1i1p1	Institut Pierre Simon Laplace, France	3.75 deg x 1.8 deg
6.	MIROC-ESM_r1i1p1	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies	2.8 deg x 2.8 deg
7.	bcc-csm1-1-m_r1i1p1	Beijing Climate Center, China Meteorological Administration	1.12 deg x 1.12 deg
8.	GFDL-ESM2G_r1i1p1	NOAA Geophysical Fluid Dynamics Laboratory, USA	2.5 deg x 2.0 deg
9.	HadGEM2-ES365_r1i1p1	Met Office Hadley Center, UK	1.88 deg x 1.25 deg
10.	IPSL-CM5A-MR_r1i1p1	Institut Pierre Simon Laplace, France	
11.	MIROC5_r1i1p1	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology	1.4 deg x 1.4 deg
12.	MRI-CGCM3_r1i1p1	Meteorological Research Institute, Japan	1.1 deg x 1.1 deg

13.	BNU-ESM_r1i1p1	College of Global Change and Earth System Science, Beijing Normal University, China	2.8 deg x 2.8 deg
14.	CNRM-CM5_r1i1p1	National Centre of Meteorological Research, France	1.4 deg x 1.4 deg
15.	GFDL-ESM2M_r1i1p1	NOAA Geophysical Fluid Dynamics Laboratory, USA	2.5 deg x 2.0 deg
16.	inmcm4_r1i1p1	Institute for Numerical Mathematics, Russia	2.0 deg x 1.5 deg
17.	IPSL-CM5B-LR_r1i1p1	Institut Pierre Simon Laplace, France	
18	MIROC-ESM-CHEM_r1i1p1	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies	2.8 deg x 2.8 deg
19.	NorESM1-M_r1i1p1	Norwegian Climate Center, Norway	2.5 deg x 1.9 deg
20.	CCSM4_r6i1p1	National Center of Atmospheric Research, USA	

3.2.3 Development of Machine Learning Model and Performance Evaluation

The random forest (RF) regression model (Breiman, 2001; Hastie et al., 2009) was used to model the association be-tween climate extremes and crop ET. Studies show that when compared to linear and generalized additive models, the random forest machine learning (ML) model performed better in estimating linear and non-linear relationships involving climate change parameters with minimal errors(Khanal et al., 2021; Konduri et al., 2020). RFs are regression-type ML techniques that are devised for creating a prediction ensemble utilizing numerous decision trees that are randomly trained on a subset of the input data (Breiman, 2001). Each decision tree is produced by randomly resampling the input data, using bootstrapping approach. The same sample of predictors may be chosen for splitting at each node, and the trees run independently of one another (Biau & Fr, 2012). The RF model was validated by splitting the dataset containing the eleven climate extreme indices into two parts; an initial 70% of the data, which was used to train the model, and then, the remaining 30% of the data which was used to test the model. To improve the RF model's performance, the model parameters were adjusted through a process known as "tuning." The parameters tuned for optimum performance were the number of trees (*ntree*), which specifies the number of trees that can be generated, and the *mtry* parameter which randomly distributes the variables that are used as candidates at each split to form the datasets on which the trees are formed (Probst et al., 2019). Using the 70% of the data for the parameter tuning resulted in the optimal RF Model parameters being the number of variables randomly sampled at each split (*mtry* = 4) and the number of regression trees to build (*ntree* = 500). The coefficient of determination (R2), root mean squared error (RMSE), and mean ab-solute error (MAE) statistics, were used to assess the model's performance accuracy on both the training and the test data. The coefficient of determination given by (Equation 5) quantifies the percentage of variance in the response variable that can be explained by the predictor variables (Draper & Smith, 2014). Therefore, it indicates how well the data fits the model. Similarly, when comparing predicted values to actual values in a dataset, the root mean squared error (Equation 6) reveals the square root of the average squared difference between them. The lower the RMSE, the better the model fits the data (Hyndman & Koehler, 2006). Additionally, the mean absolute error (Equation 7) is a measure of the average deviation of the predicted values of a model from the actual values (Willmott & Matsuura, 2005). These statistical metrics defined above were utilized to assess the RF model's effectiveness on both the test and training period data:

Equation 3.5: Coefficient of determination

$$R^2 = 1 - \frac{\sum_{i=1}^{m}(X_i - Y_i)^2}{\sum_{i=1}^{m}(\bar{Y} - Y_i)^2},$$

Equation 3.6: Root mean squared error

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(X_i - Y_i)^2} \; ,$$

Equation 3.7: Mean absolute error

$$MAE = \frac{1}{m}\sum_{i=1}^{m}|X_i - Y_i|.$$

where X_i is the predicted value; Y_i is the actual value; $\bar{Y}$ is the mean of the actual values; m is the number of samples in the equations above.

The influence of each climate extreme indices on crop ET was determined using a variable importance plot. The variable importance plot in a RF model illustrates how the elimination of each variable affects the mean squared error (MSE) of the model. Therefore, variables that have a greater influence on the MSE of the model will have a negative impact on evapotranspiration. Additionally, the variable importance plot is very useful for reducing the complexity of machine learning models, since it identifies and selects the most crucial predictors (Chen et al., 2020). As a result, it can be used to eliminate variables that have the least impact on the accuracy of the model, further simplifying the model. This process is commonly referred to as feature selection.

3.2.4 Future Prediction of Crop Evapotranspiration

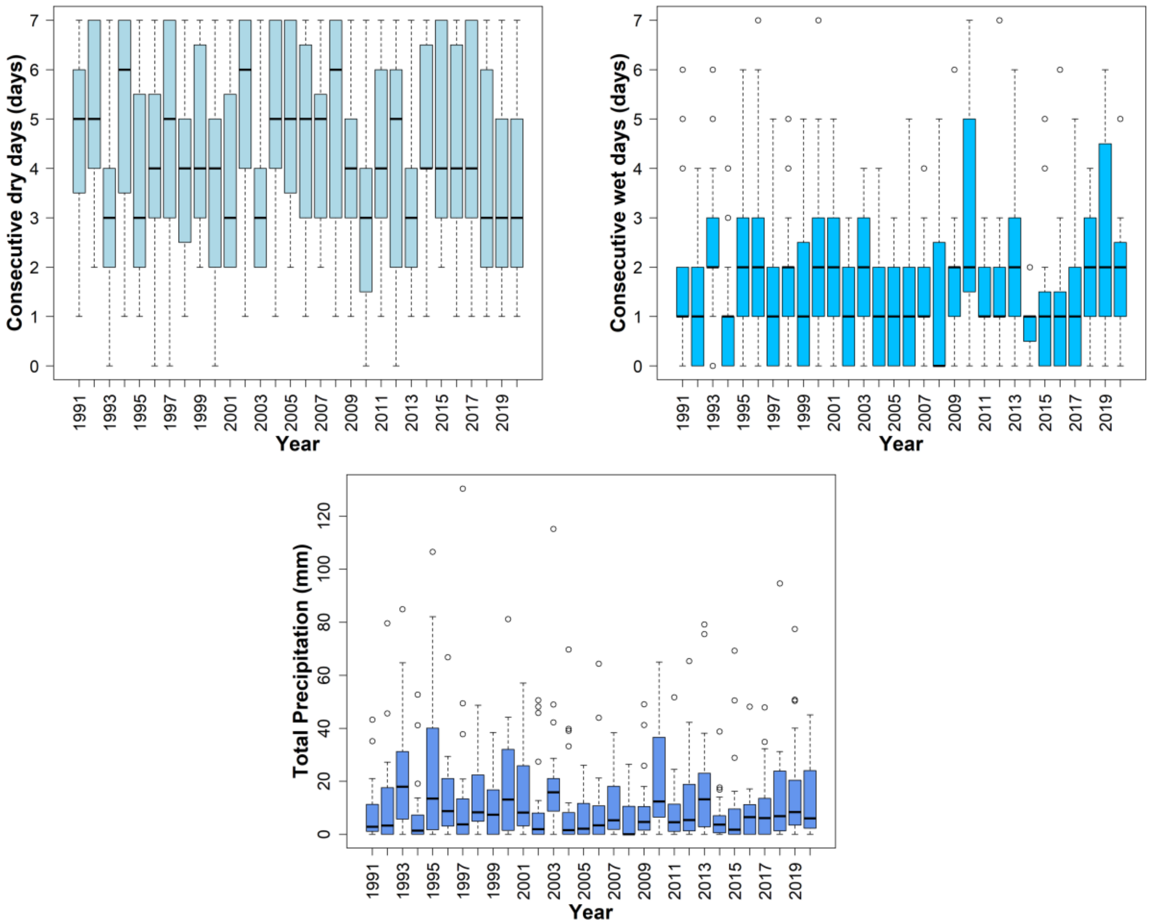
Future prediction of weekly crop ET_o were estimated with the RF model, using cli-mate extreme variables which were extracted from 20 GCMs each, under the two gas emission scenarios considered in the study, and for three future time periods; the near-term (2025–2049), mid-century (2050–2074), and the end-of-century (2075–2099). The confidence in the model predictions rely on the performance of the already developed RF model (Chambers & Hastie, 2018), which was assessed using statistical metrics. We computed the average ensemble of the ET_o forecasts from the 20 selected GCMs for each scenario and time period. The ensemble of ET_o forecasts were then multiplied with the crop coefficient values to estimate ET_c. An analysis of variance (ANOVA) test (Girden, 1992) was performed at a 95% confidence level to determine if the forecasted mean crop ET values for all the future scenarios were significantly different from the historic time period, and from each other. Since an ANOVA test does not provide information about which of the future time periods show significant differences in means from each other, and from the historical time period, we further per-formed Dunnett's test (Dunnett, 1955) on the forecasted crop ET values for the three time periods, using the historical crop ET values as the control group, and then compared each forecasted crop ET values with the crop ET determined from historical weather data, so as to quantify the expected percentage change in crop ET in the future.

3.3 Results and Discussions

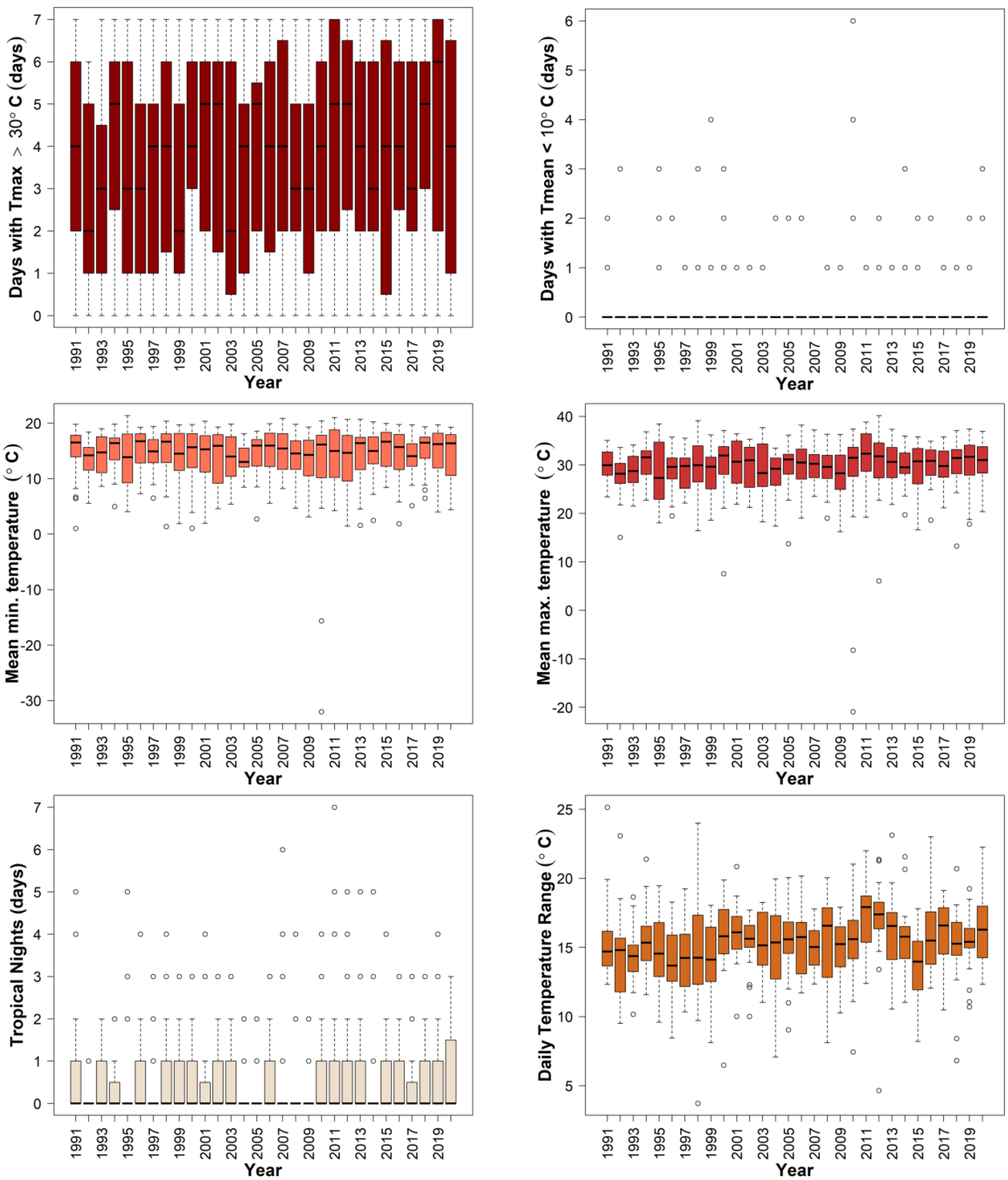
3.3.1 Summary statistics for historic climate extreme indices

Occurrences of unusually extreme weather conditions during the growing season, pose a threat to the sustainability of maize production in the high plains' region. This is because they affect crop evapotranspiration rates, which may have an effect on the region's limited water resources. Climate extreme indices, which represent instances of extreme weather, and are thought to affect the evapotranspiration rate of maize, were selected and used as input variables in a random forest model, in order to estimate reference evapotranspiration from which to determine the actual crop water requirement. Figure 3.4 below is a boxplot summary statistic showing the weekly variations in the occurrences of these eleven selected climate extreme indices during the maize growing season. Figure 3.4a shows the boxplot summary of indices derived from precipitation data, figure 3.4b represents summary of in-dices derived from temperature data, and figure 3.4c is a summary of indices of temperature expressed in percentages, represented here as percentile-based indices. The mean weekly maximum number of consecutive dry days (CDD) over a 30-year period was 4.2 days, with a standard deviation of 2.1 days. Although the CDD showed less variability, as indicated by its coefficient of variation of 48.6%, the upper quartile (75th percentile) of the data revealed that there were instances of up to six consecutive days in the week being completely dry or having weekly rainfall amount of less than 1mm. Similarly, the mean weekly total precipitation was 12.8mm, with a SD of 17.6mm, while the mean of the consecutive wet days was 1.7 days, with SD of 1.6 days. The observed significant deviations from their mean explains their high coefficient of variations of about 137.7% and 92.8% respectively. A similar analysis of the distribution of rainfall in western Kansas (Rahmani & Harrington, 2019) showed that there is significant variability in the precipitation patterns due to the climate, with an overall tendency of drier conditions.

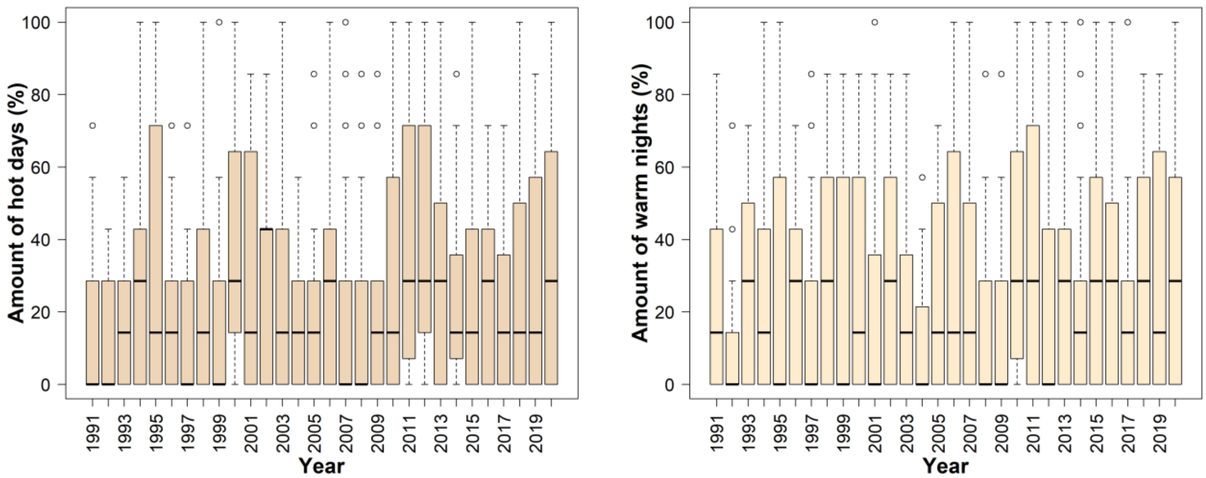
Our analysis also showed high variations in the warm spells, which comprises of the weekly percentage of days with minimum temperature (Tmin) greater than the 90th per-centile (Mean = 26.2%, SD = 29.3%), and the weekly percentage of days with maximum temperature (Tmax) greater than the 90th percentile (Mean = 26.2%, SD = 29.3%). Both displayed CVs of 116.3% and 111.9%, respectively. We observed up to 42.2% days in a week where temperature was greater than the 90th percentile. This is similar to the study by (Anandhi et al., 2016), reported that for Kansas, the annual warm spells typically last up to 4 days on average (i.e., up to 60% of days in a week), especially in the summer months. Similarly, other temperature-derived indices such as the mean weekly minimum temperature (Mean = 14.2^{o}C, SD = 4.8^{o}C), the mean weekly maximum temperature (Mean = 29.5^{o}C, SD = 5.3^{o}C), the weekly number of days with Tmax greater than 30^{o}C (Mean = 3.7 days, SD = 2.4 days), the daily temperature range (Mean =15.3^{o}C, SD = 2.7^{o}C) in a week, all showed less seasonal variation than the precipitation-based indices. Their CVs of 33.6%, 18.1%, 65.7%, 17.8%, and 92.8% respectively, implied that their individual weekly variations remained relatively constant throughout the entire growing season from year to year. Meanwhile, much higher variations surpassing those of all the other indices were observed in the weekly number of days with mean temperature less than 10^{o}C (Mean = 0.1 days, SD = 0.5) and in the tropical nights (Mean = 0.6 and SD = 1.1); as indicated by the high coefficient of variation (CV) of 401.7%, and 188.4% respectively. These extremely high values were expected, however. This is due to the fact that their mean values were very close to zero, making the CV to become very sensitive to changes in the mean. However, the boxplot summary of the weekly number of days with mean temperature less than 10^{o}C was skewed to the right with unusually high frequency of outliers, indicating multiple occurrences of cold temperatures with significantly higher magnitudes than the mean observations.


Consecutive dry days (days)
Year
Consecutive wet days (days)
Year
Total Precipitation (mm)
Year

(a)


Days with Tmax > 30° C (days)
Year
Days with Tmean < 10° C (days)
Year
Mean min. temperature (° C)
Year
Mean max. temperature (° C)
Year
Tropical Nights (days)
Year
Daily Temperature Range (° C)
Year

(b)



(c)

Figure 3.4: Boxplots showing statistical summary of the selected climate extreme indices: (a) Precipitation-based indices; (b) Temperature-based indices; and (c) Percentile-based indices.

3.3.2 Estimated crop coefficient from maize pixels

Using the (Kamble et al., 2013) linear regression model, the values of the average weekly crop coefficient (Kc) for the pixels of maize were determined from Landsat NDVI images. The estimated Kc curve (Figure 3.5) follows a similar trend with the maize crop coefficient curve reported in the FAO's irrigation and drainage paper 56 (Allen & Pereira, 1998). The Kc curve typically starts out with low values at the initial growth stage of maize, and gradually increases over the first 4 weeks (0–30 days) after planting. It reaches its apex at the mid-season stage, when the canopy ground cover is between 25% and 60%, before declining to a constant value at the end stage, which typically occurs 12 to 24 weeks (50 to 170 days) after planting. During the early stage of growth, the estimated minimum Kc value was 0.46 while the maximum value observed was 0.65. The observed mean value for the early growth season which was averaged over the 30-year historic time period was 0.55, indicating higher values than the Kc value of 0.35, which was reported by the FAO for the initial growth stage. This variation in the values can be attributed to the differing field conditions and management practices of the corn fields in Finney County, compared to the conditions on which the FAO Kc values were developed. The FAO provides Kc values based on standard climate conditions involving a sub-humid climate with average minimum relative humidity of 45% and moderate windspeed of 2 ms-1. However, field conditions often differ significantly from that of the FAO, as also seen in a similar study by (Singh & Irmak, 2009), performed in southcentral Nebraska, and also by (Abedinpour, 2015) in New Delhi, India. Similarly, during the mid-season growth stage, where the crop reaches its peak, the values of Kc ranged between 0.55 and 0.99; with peak estimated values of up to 1.06. Meanwhile, the mean peak value of Kc for the 30-year period was 0.90, thus, showing slight under-estimation when compared to the typical FAO value of 1.2. This difference is likely due to the normalization of peak values of Kc, resulting from the averaging of all the Landsat NDVI values from pixels of maize-growing areas to produce a single value of NDVI for each day. During the late season, the Kc values ranged between 0.19 and 0.30. The mean value was estimated at 0.24. The FAO value for this phase typically ranges be-tween 0.60 and 0.35 depending on whether the crop was harvested fresh or dried, respectively. These findings suggest that the Kc values for maize are influenced by site-specific variables and therefore, underscores the importance of site-specific calibration of Kc values for accurate crop ET calculations. For semi-arid areas like Finney County in western Kansas, the FAO irrigation and drainage paper offers adjustment steps including considering the frequency of growing season irrigation events, to adjust the Kc values appropriately before they are used to calculate the actual crop ET.

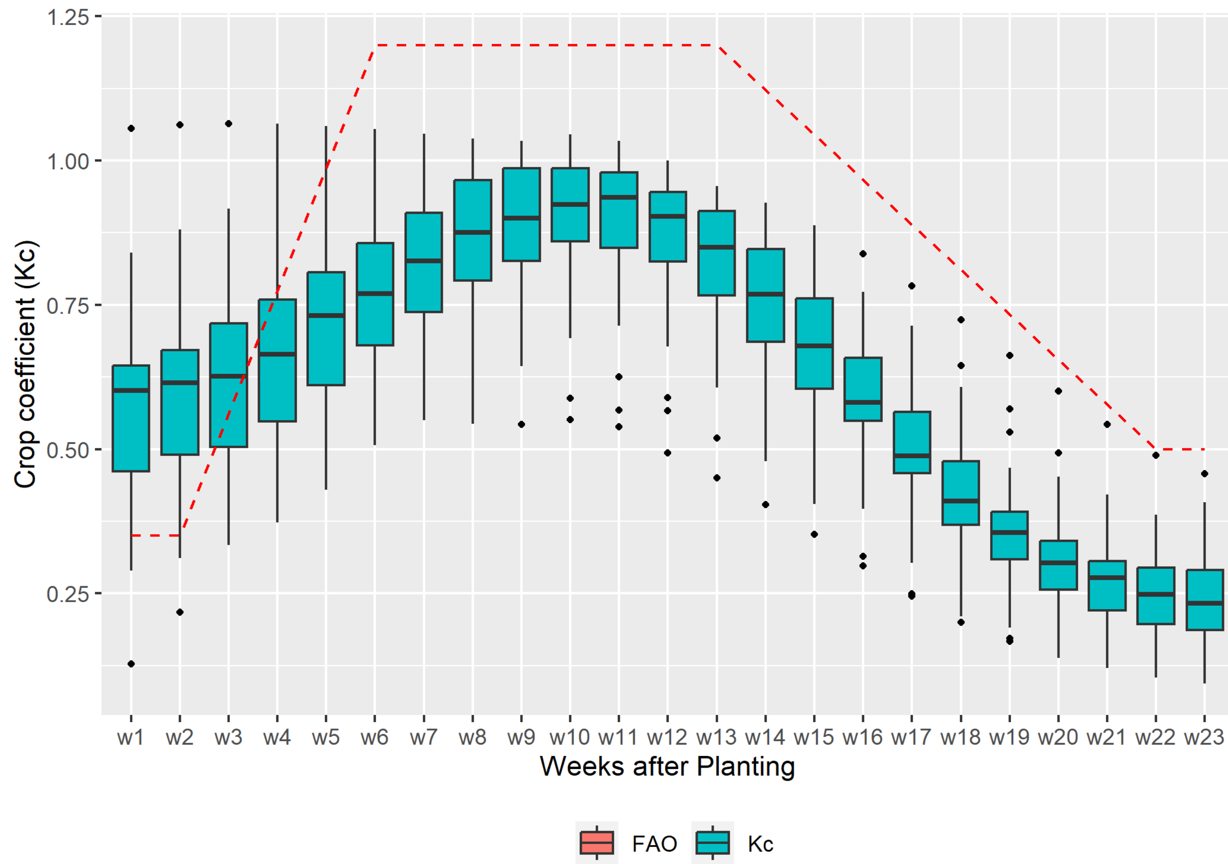


Figure 3.5: Comparison of crop coefficients (Kc) estimated from Landsat NDVI using a linear model with the standardized Kc values of FAO

3.3.3 RF Model Performance Evaluation

After training the RF ML model with 70% of the entire data and testing on the remaining 30% of the data, our analysis showed that these selected climate extreme indices explained up to 70% variability (R2 = 0.70) in crop ET on the training data and up to 71% variability (R2 = 0.71) on test data (Figure 3.6); implying a satisfactorily robust model. How-ever, we observed that the R2 also increased to about 80% when more variables of mean weather conditions such as the solar radiation and wind speed were added as inputs to the model. It was therefore evident that the R2 is not always a good metric for evaluating the accuracy of the model, even though it has been recommended and widely accepted by researchers as a metric for evaluating machine learning models (Chicco et al., 2021). The training set's RMSE and MAE values were observed to be

5.73mm and 4.41mm, respectively. While on the test data, the RMSE and MAE values were 5.35mm and 4.30mm respectively. A comparison between the observed evapotranspiration from the test data and the predicted evapotranspiration revealed that both very low and large levels of ET were underestimated by the model. This is probably because RF averages values at each node's end when building decision trees, causing extremely high values to be averaged with low values. This was observed in a similar study by (Khanal et al., 2021).

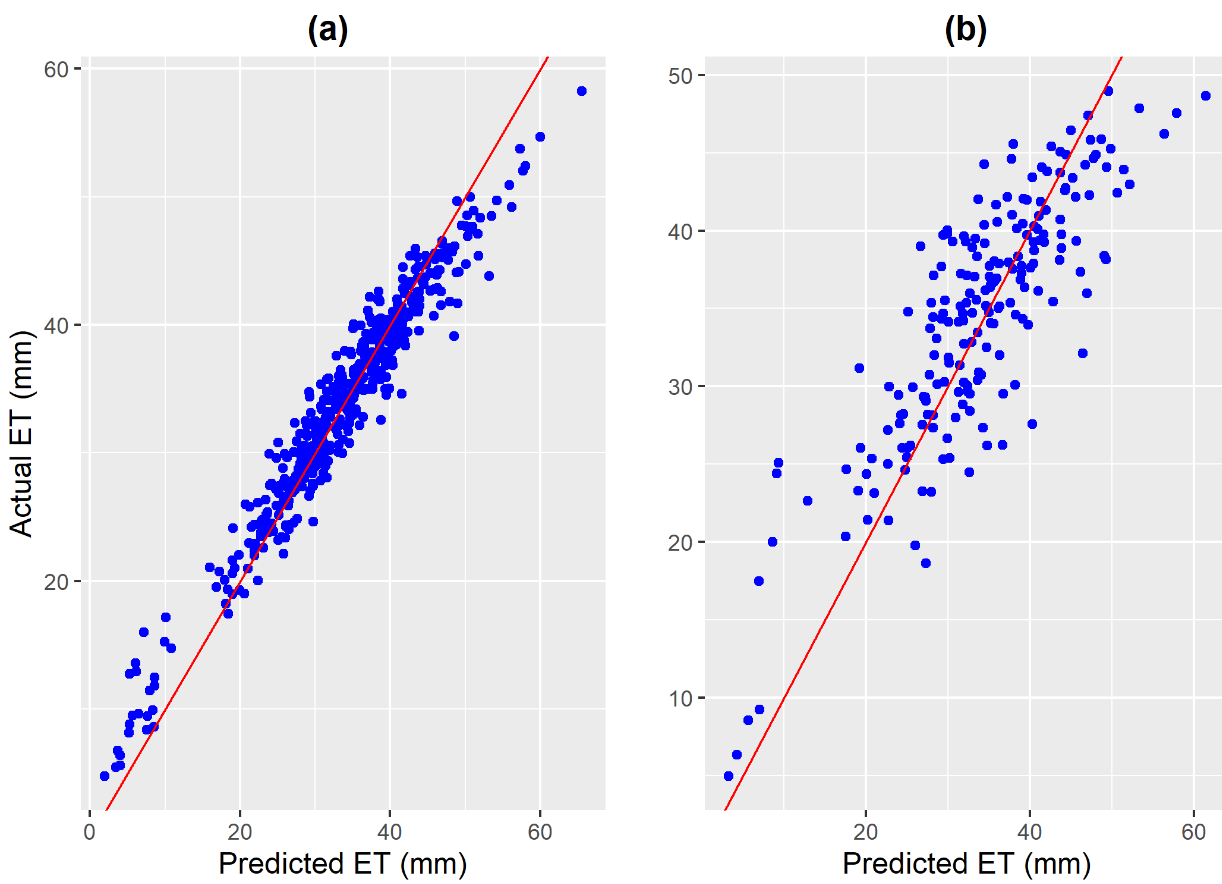


Figure 3.6: Plot of actual evapotranspiration against predicted evapotranspiration: (a) training data; and (b) test data

3.3.4 Climate extreme indices influencing crop evapotranspiration

Figure 3.7 is a variable importance plot that shows the influence of each climate extreme indices on reference evapotranspiration. The indices were ranked based on their individual influences on the mean squared error (MSE) of the random forest (RF) model. We found that by removing the index representing maximum number of consecutive dry days (CDD), the MSE of the RF model increased by 29.7%, making it the variable with the greatest influence (Figure 3.7). This is expected because, without rainfall events over a significant number of days, the amount of water loss by evapotranspiration will continue to increase. And because there is no recharge of lost moisture through the soil and plants through precipitation, this situation can lead to yield loss, especially if it occurs at growth stages where the maize crop is most sensitive to water stress. Also, we found that the average weekly maximum temperature (tx_avg), when removed from the model, increased the MSE of the model by 27.2%, while, the daily temperature range (DTR) increased the model's MSE by 21.3% when eliminated from the model, making the former to be the second most influential variable and the latter to be the third most influential variable in the model. Climate extreme indices such as the average weekly minimum temperature (tn_avg), the amount of hot days (tx90p), the total weekly precipitation (prp_tot), and the weekly number of days with maximum temperature more than 30^{o}C (txge30), were found to influence the MSE of the model by a percentage ranging between 15% and 20%. When these indices removed individually from the model, the MSE increased by 19.1%, 18.7%, 17.8%, and 17.3% respectively. Meanwhile, other variables when removed from the model only affected the model's MSE by 15% or less; the consecutive wet days (CWD) by 14.2%, the amount of warm nights (tn90p) by 10.5% and the tropical nights (tr) by 7.6%. The number of days with a mean temperature less than 10^{o}C (tmlt10) had the least influence on evapotranspiration; increasing the MSE only by 3.5%.

Although, the maximum number of consecutive dry days, which we found to be the single most influential variable, was derived from precipitation data alone, most of the other derived indices which had the most significant influence on crop ET were observed to be those relating to increasing temperatures. These outcomes are anticipated because temperature continues to be a key driver of ET. This is because, more energy becomes available to turn water into vapor as the temperature rises. Therefore, prolonged periods of high temperature will eventually result in a great loss by evapotranspiration. However, similar studies performed under various climate types in Nigeria (Emeka et al., 2021), and in Iran, south-west Asia (Tabari & Talaee, 2014), showed that significant predictors of ET vary depending on the location, and field management conditions. In his study conducted for agricultural lands in the mid-western US regions, (Talib et al., 2021) observed that the key evapotranspiration predictors differed based on whether the fields were rainfed or irrigated. Furthermore, it is also important to note that the variable importance plot also pos-es some level of uncertainties as it tends be biased for large number of input variables (van der Laan, 2006), especially when the variables are correlated (Strobl et al., 2008).

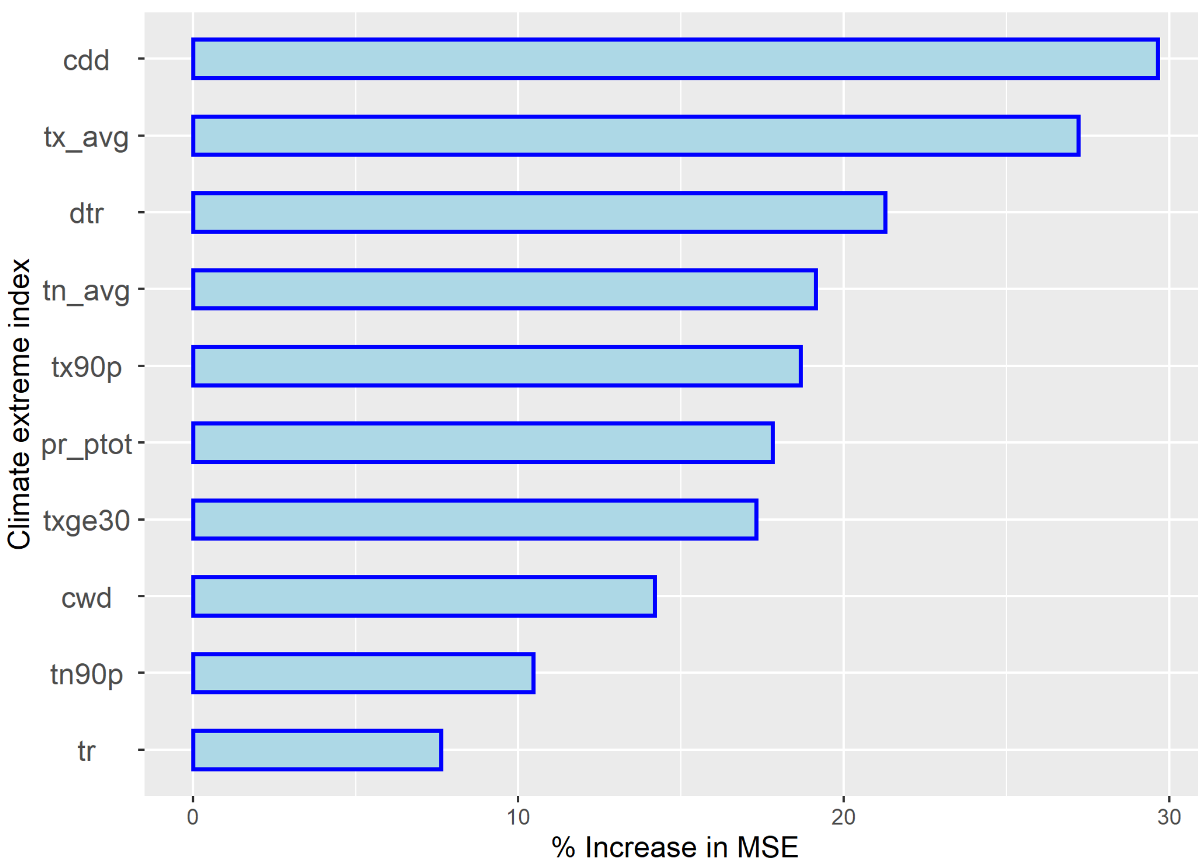


Figure 3.7: Variable importance plot showing influence of each variable on RF model accuracy

In figure 3.7 above, cdd represents the consecutive wet days, tx_avg is the weekly maximum temperature, dtr is the daily temperature range, tn_avg is the average weekly minimum temperature, tx90p is the amount of hot days, prp_tot is the total weekly precipitation, txge30 represents the weekly number of days with maximum temperature more than 30oC, cwd represents the consecutive wet days, tn90p represents the amount of warm nights, and tr represents the tropical nights.

3.3.5 Projections of evapotranspiration in the future

The ensemble of model predictions of crop ET from 20 GCMs were computed and averaged for both RCP4.5 and RCP8.5 future climate scenarios, for the near-term (2025-2049), mid-century (2050-2074) and end-of-century (2075-2099). The interquartile ranges of forecasted weekly Crop ET under RCP4.5 (Figure 3.8) were between 13.4mm and 31.0mm in the near term; 13.5mm and 31.7mm in the mid-term; and 14.3mm and 31.8mm towards the end of century period. The boxplots for each scenario were slightly skewed to the right, as indicated by the upper whiskers being slightly longer than the lower whiskers. The mean weekly crop ET values were 21.9mm, 22.6mm and 22.9mm in the near-term, mid-term, and end-of-century, respectively.

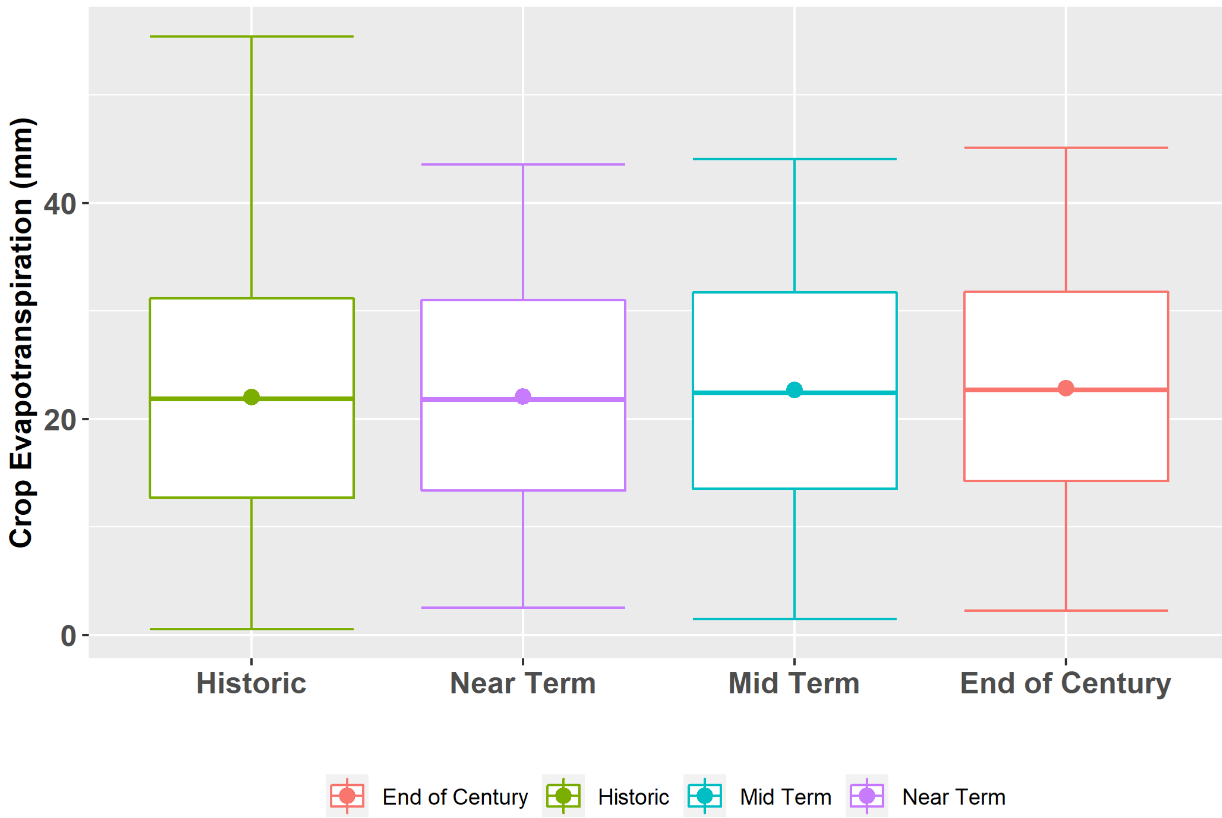


Figure 3.8: Boxplots summary of Crop ET predictions under RCP4.5 Scenarios

Similarly, under RCP8.5 scenario (Figure 3.9), the interquartile ranges of the predicted crop ET values were observed to fall between 13.5mm and 31.5mm in the near term; 14.1mm and 32.3mm in the mid-term; and 15.3mm and 33.1mm in the end of century period. Although the mean crop ET values gradually increased periodically in the near-term, mid-term and end of the century periods, under both RCP4.5 and RCP8.5 scenarios, the peak estimated value of crop ET (ETc = 55.4mm) was higher in the historical time period than the values in each of the future scenarios. This decline in peak values in the future scenario is likely because all the 20 GCMs were ensembled and averaged to get a representative value for each scenario. And as such, all predicted crop ET values were normalized over the individual GCMs. The overall results show an increment in mean crop ET under both RCP4.5 and RCP8.5 scenarios, but higher increments in crop ET were predict-ed in the mid-term and end of century periods than in the near-term period of both RCP4.5 and RCP8.5 climate scenarios. Also, the wider interquartile ranges of the boxplots during the mid-term and end of century periods indicate a higher variability in crop ET values in both periods, than in the near term.

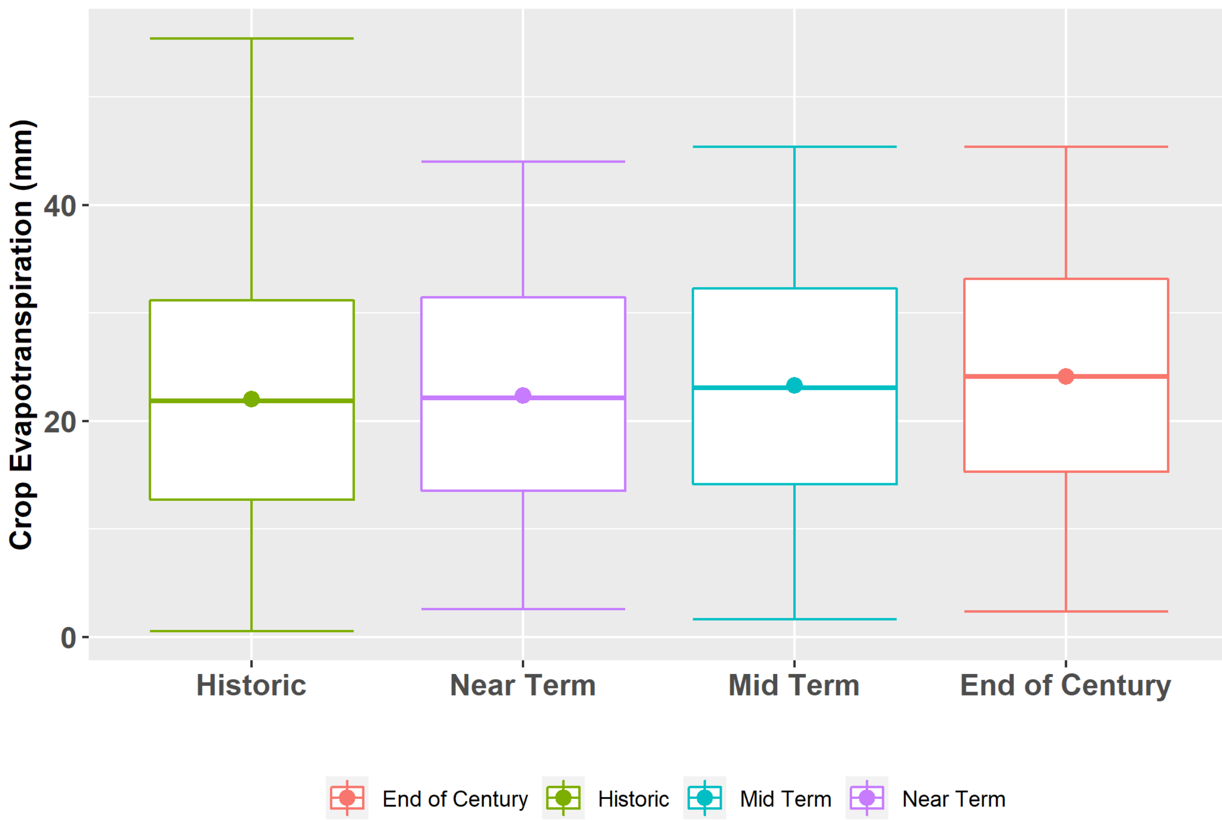


Figure 3.9: Boxplots summary of Crop ET predictions under RCP8.5 Scenarios.

The results of the ANOVA test at a 95% confidence level, indicated that there was no statistical difference in the mean values of crop ET (p-value > 0.05) under the RCP4.5 scenario. However, an ANOVA test under RCP8.5 scenario indicated that there were statistically significant differences (p-value < 0.05) in the means of the predicted ET values. But since an ANOVA test does not provide information about which of the future time periods under RCP8.5 showed significant differences in means from each other, and from the historical time period, we further performed Dunnett's test on the crop ET values for the three time periods, using the historical crop ET values as the control group. We found that the end of century crop ET values was significantly different from the near-term period but not significantly different (p-value > 0.05) from the mid-term period. The plot below (Figure 3.10) shows the weekly crop ET values averaged over 25-year period for the historic period and the predicted crop ET values for the 75-year future time periods, for both RCP4.5 and RCP8.5 scenarios.

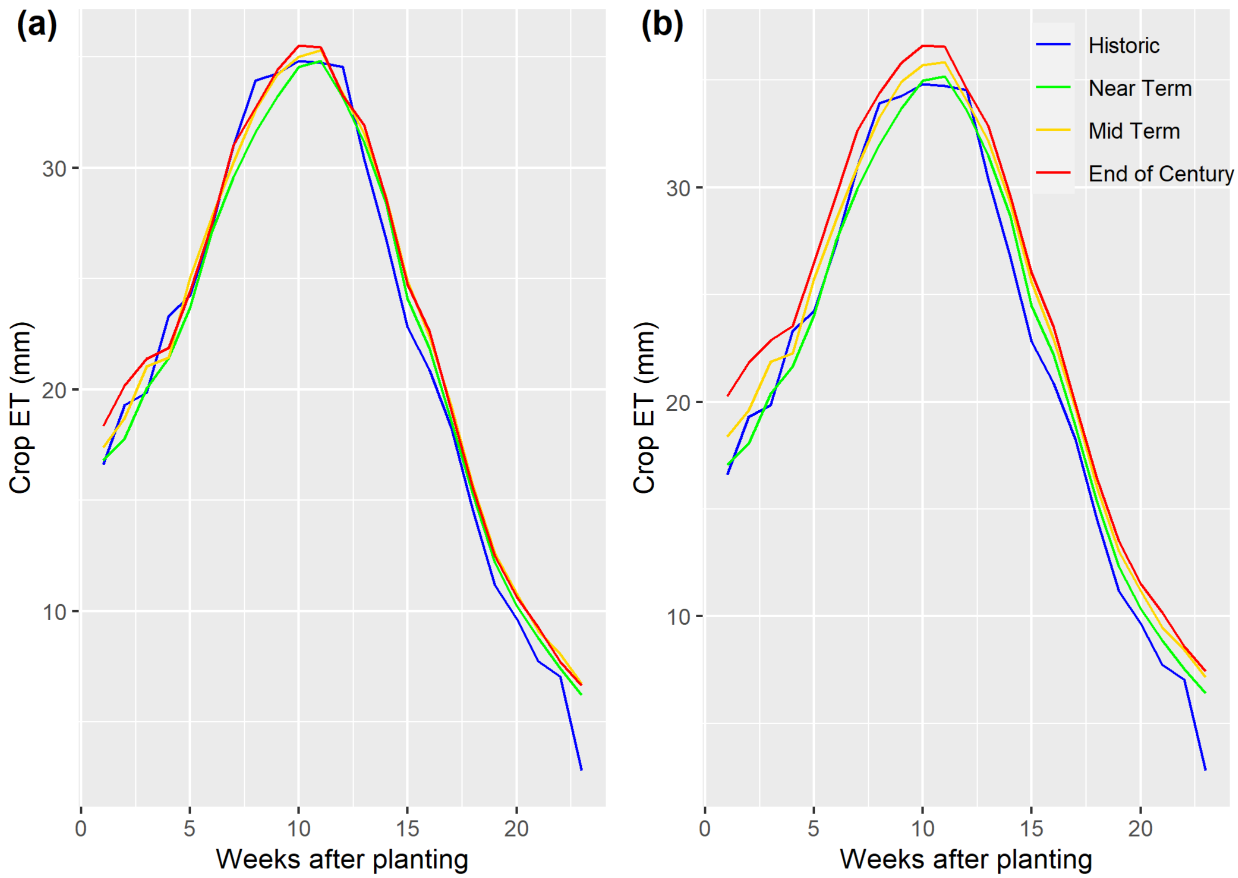


Figure 3.10: Predicted average weekly crop ET values for (a) RCP4.5 and (b)RCP8.5 scenarios

Overall, when compared with historical data (Figure 3.11), the results of ET predictions under RCP4.5 showed a 0.4% increase (Mean = 22.1mm) in the weekly ET in the Near Term; a 3.1% increase (Mean = 22.7mm) in the Mid Century; and 3.8% increase (Mean = 22.8mm) at the End of Century. While under RCP8.5, the results of predicted ET showed a 1.7% increase (Mean

= 22.4mm) in the weekly ET in the Near Term; 5.9% increase (Mean = 23.3mm) in the Mid Century; and 9.6% increase (Mean = 24.1mm) at the End of Century. The observed higher increase in crop ET under RCP8.5 scenario aligns with similar pre-dictions of ET under global temperature rise, caused by to high greenhouse gas emissions, leading to greater loss by evapotranspiration (Koukouli et al., 2019). Using an ensemble of three GCMs at three locations in Ethiopia, (Gurara et al., 2021) projected that by the end of the 21st century, there would be an increase in potential evapotranspiration by an amount between the range of 21.1% to 41% compared to historical time period, under the RCP8.5 scenario.

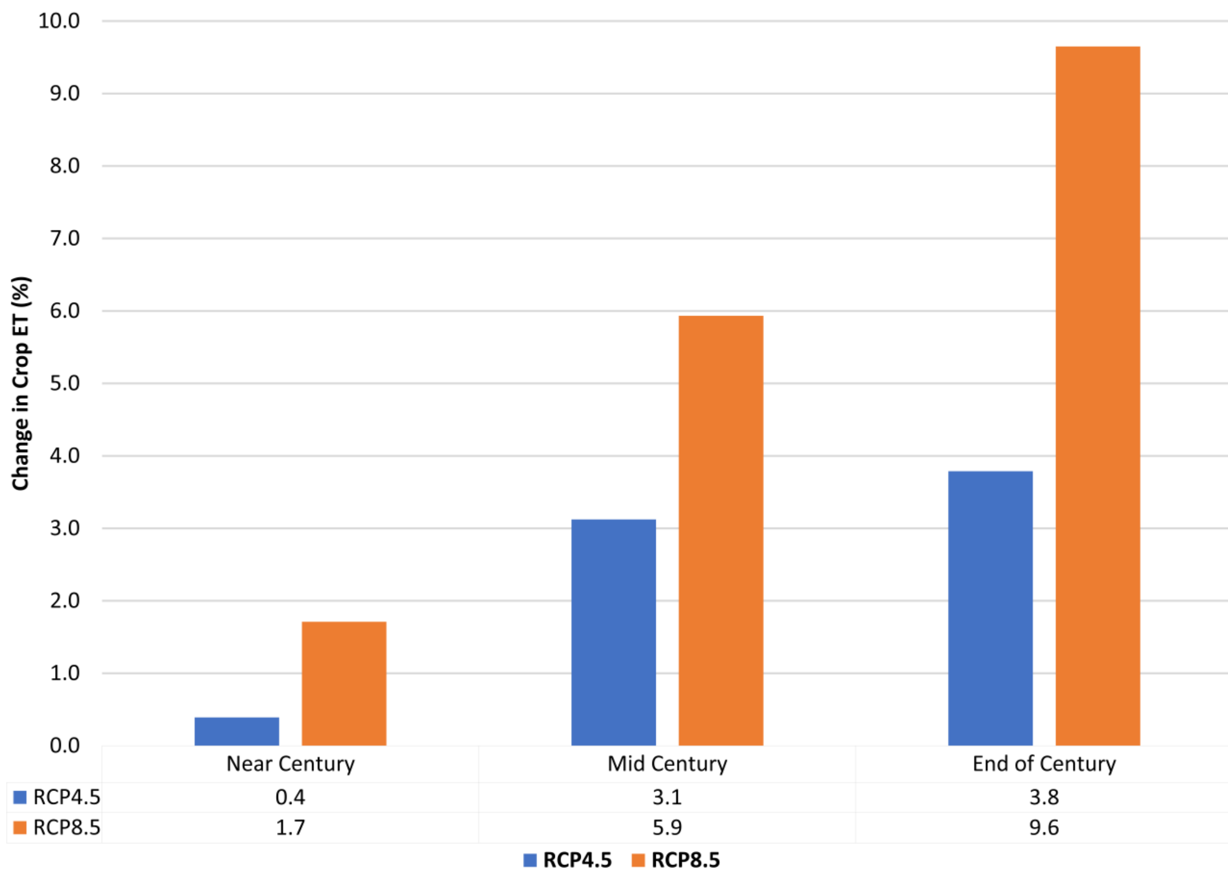


Figure 3.11: Percentage change in Crop Evapotranspiration under both RCP4.5 and RCP8.5 Scenarios

3.4 Conclusions and Recommendations

This study analyzed historical data using a random forest model to determine which climate extreme indices most influenced crop evapotranspiration (crop ET) during the growing -season. We found that crop ET was most influenced by the maximum number of consecutive dry days and mean weekly maximum temperatures. Our analysis demonstrated that climate extremes can have a substantial effect on agricultural crop water de-mand. Given the current limitation of water resources in western Kansas, the persistence of these extreme conditions might lead to inability to meet the crop water demands of the maize crop. This has critical implications as inadequate water supply might impact crop productivity, and ultimately, food security. Although crop ET, have been reported to vary greatly based on a number of other factors such as the planting date and the irrigation management (Wu & Fan, 2019), it is advised that robust frameworks be put in place to monitor growing season climate extremes, and understand their likely impacts, so as to develop adaptation and mitigation strategies against the impacts.

Furthermore, this study provided future projections of crop ET under two representative concentration pathway scenarios; RCP4.5 and RCP8.5. The projections, based on the ensemble of 20 downscaled GCMs, revealed that crop ET would increase significantly under both scenarios in the near-century, mid-century, and end-of-century timeframes. More significant increases where predicted under the RCP8.5 scenario, emphasizing the necessity of reducing greenhouse gas emissions to lessen the effects of climate change on agriculture. In comparison to the historical time period, an average ensemble of the models under RCP4.5 indicated an increase in weekly ET by 0.4% in the near-term, 3.1% in the mid-century, and 3.8% by the end of the century, while predictions under RCP8.5 scenario indicated an increase in weekly ET by 1.7% in the near-term, 5.9% in the mid-century, and 9.6% by the end of the century. The overall results of this study imply a steady potential increase in crop water requirement in the future. With the aid of these predicted crop ET data, and anticipated changes in crop ET during the growing season, agricultural producers can be better informed in developing strategies to optimize their use of the limited water resources, particularly where limited water rights are allotted to producers. Some of the strategies may include adopting more efficient irrigation techniques, cultivating maize cultivars which are more drought-tolerant, and other precision agriculture techniques that could be relevant to increasing crop productivity while reducing groundwater pumping. Additionally, it is imperative to assess the current management practices in the region to evaluate their adapt-ability to extreme climatic conditions. By identifying areas for improvement and implementing more efficient technologies, farmers and stakeholders can optimize production while reducing the vulnerability to climate extremes and ensuring the long-term sustain-ability of agriculture.

The effects of these extremes on evapotranspiration, however, were examined by considering the individual influence of each extreme indices. However, some of these extreme conditions frequently take place in quick succession or all at once (Tavakol et al., 2020). These situations are frequently referred to as compound extremes. Recent studies (Bloomfield et al., 2019; Li et al., 2009) have reported that the combined effects of dry periods and warming on the evaporative demand are likely responsible for changes in groundwater levels. Therefore, studying these compound extremes might therefore prove to be valuable since their combined effects could have a greater impact on crop ET and eventually, the end of season crop yield. Also, some indices such as the Combined Terrestrial Evapotranspiration Index (CTEI) (Elbeltagi et al., 2021), Evaporative Demand Drought Index (EDDI), and the Standardized Precipitation Evapotranspiration Index (SPEI), uses anomalies in atmospheric evaporative demand and precipitation to establish a relationship with climate extreme conditions, especially drought. These indices might better estimate the nature of relationships be-tween climate extremes and crop water needs.

Chapter 4 - Investigating sustainable water management strategies for improving crop adaptation to extreme climate conditions in Western Kansas

Abstract

Semi-arid regions are often confronted with the challenge of depleting water resources, and optimal irrigation strategies play a pivotal role in minimizing excessive use of limited water resources while enhancing or maintaining agricultural productivity in these regions. The persistence of extreme climate conditions driven by climate change, exacerbates the challenge of depleting water reserves, as conditions such as increased temperatures during the crop growing season may affect the crop water demand, thereby threatening the long-term viability of agriculture in these regions. It is therefore pertinent to identify and implement deficit irrigation management strategies that are well-adapted to mitigate the potential impacts of extreme weather conditions on crop yield and water resources. In this study, the DSSAT model was used to evaluate the adaptability of evapotranspiration-based (ET-based) irrigation scheduling to extreme growing season weather conditions. A 30-year simulation was executed on twelve distinctive irrigation treatments, consisting of four ET accumulation thresholds (15mm, 20mm, 25mm and 30mm) at three deficit ET replacement levels (50%, 75%, 100%), and compared with a baseline scenario where irrigation is automatically triggered when plant available water in the soil falls below 50% (usually referred to as the farmers choice). The best performing treatment was selected based on its capability to minimize yield loss, optimize water savings, and water productivity. Overall results indicated that increasing the percentage levels of ET applied improves yield much higher than decreasing the accumulated ET threshold. When compared to the farmers' choice, it was

found that applying a 75% deficit of the required ET amount when it reached the 30mm threshold proved to be a superior strategy. In this treatment, yield loss was limited to 6%, water savings increased up to 19%, and the water productivity improved by up to 6%, under normal weather conditions, as well as under increased maximum temperature and the duration of dry periods by up to 2°C and 1 day, respectively. Notably, when maximum temperature increased by up to 4°C, yield decline doubled, compared to normal conditions and mild temperature increases of 1 and 2°C, indicating a threshold-like response of Maize to extreme heat stress. Overall, these findings show that the ET-based deficit irrigation strategy adapts well to extreme heat and water stress, bearing important implications for irrigation management decisions in the future.

Keywords: Extreme weather events, Deficit irrigation, DSSAT crop model, water productivity

4.1 Introduction

Irrigation, while essential, exerts substantial pressure on water reserves, accounting for over 70% of worldwide water consumption (Malik & Dechmi, 2019), and approximately 40% of annual freshwater withdrawals (Nie et al., 2021; Scanlon et al., 2012). In the United States, there are growing concerns about the sustainability of agriculture, especially in the arid and semi-arid regions. This is because agricultural production relies heavily on groundwater resources that are depleting due to excessive withdrawal for irrigation. Groundwater resources account for 60% of the water supplied to irrigated areas nationwide, while in the semi-arid regions of the nation, such as the eight states underlain by the high plains' aquifer, 90% of ground water supply is being used agricultural production (Mrad et al., 2020). In the Western U.S. Corn Belt, maize cultivation occupies a substantial 70% of the total cropland area, with approximately 43% of these maize-growing regions relying on irrigation practices to support their annual production. Additionally, these irrigated areas contribute substantially to the region's maize output, accounting for roughly

58% of the total maize production in the Western U.S., as reported by Grassini et al., (2009). Therefore, improved irrigation management strategies are crucial in these regions to ensure the sustainability of agriculture.

Groundwater depletion and its associated challenges are further compounded by prevalence of conditions of extreme climate during the crop growing seasons which have been reported in recent studies (Anandhi et al., 2016; Igwe et al., 2023; Lin et al., 2017; Rahmani & Harrington, 2019). This is because extreme conditions such as increased heat stress induced by increased temperature, as well as prolonged dryness have the potential to increase crop water demands (Tack et al., 2017). When these heightened demands are unmet, it may have significant adverse impact on crop yield. In a recent study conducted in Western Kansas, it was found that climate extreme conditions, especially increased maximum temperatures and prolonged duration of consecutive dry days may increase crop water demands of maize by approximately 10% by the end of the 21st century, potentially impacting on maize productivity (Igwe et al., 2023). Irrigation however, has notably proven to be useful in shielding crops from the adverse effects of persistent extreme conditions during crop growing seasons (Thiery et al., 2017, 2020). This is because irrigation not only provides the crop with the water it needs, but also cools the crop through evaporation to lessen crop heat stress. This cooling effect is responsible for 16% of the improvement in yield over rainfed maize, with the remaining 84% going towards meeting crop water need and other processes (Li et al., 2020). This makes it particularly useful in regions experiencing extreme climate conditions caused either by climate change or climate variability.

However, irrigating in response to extreme weather events may imply increase in groundwater withdrawals. It therefore becomes imperative to implement more advanced water conservation methods that help to enhance crop adaptability to climate impacts (Ahmad et al., 2020), without compromising on the overall crop yield, as well as the use of water resources

Although, it has been shown that, under the current practices, groundwater resources may not be sufficient to support the U.S high plains region's agricultural production in the future (Mrad et al., 2020), several strategies have been employed by researchers, in a bid to determine the best management practices that reduces excess withdrawal of groundwater resources. Some of these studies consider varying management operations such as planting dates (Araya, et al., 2017a), adopting alternative cropping systems (Araya, et al., 2017b), or implementing deficit irrigation approaches (Rudnick et al., 2019). Commonly utilized irrigation scheduling methods are broadly classified into those based on soil moisture depletion (Gu et al., 2020), evapotranspiration (Olberz et al., 2018), or plant physiological response to water stress (Jones, 2004). Scheduling irrigation based on soil moisture can increase water savings by 7.2 to 37%, while irrigation based on evapotranspiration data can increase water savings by 10 to 33% with higher water savings in wet seasons and lower savings in dry seasons (Zhao et al., 2023). However, most of the studies conducted evaluate the performance of irrigation scheduling methods under mean climate conditions without considering the conditions of extreme heat and water stresses on the crop that are caused due to increased temperatures and prolonged dryness, respectively. In this study, we aim to fill this gap by evaluating irrigation management practices that are adapted to mitigate the impacts of climate extreme conditions on the maize production.

Due to the complex nature of crop growth and its interactions with the environment, process-based models (Holzworth et al., 2014; Jones et al., 2003; Raes et al., 2009; Stöckle et al., 2003) are often used to study crop growth in response to environmental and management processes. For example, the root zone water quality model (RZWQM) was used to assess the response of maize to ET-based irrigation scheduling (Ma et al., 2017) and the DSSAT model was used to assess optimal irrigation strategies for maize (Kisekka et al., 2016). These process-based models have also been used in combination with statistical (Roberts et al., 2017b), remote sensing (H. Zhao et al., 2023), or machine learning algorithms (Alibabaei et al., 2022), to improve the model performance. The DSSAT-CERES Maize model has also been used for climate impact investigations such as impact of increased temperatures, extended period of dryness, and CO_2 increase on maize production (Ahmad et al., 2020).

The outputs of these models help researchers to understand complex underlying relationships and how they impact on crop and water, as well as nutrient productivities. Within the DSSAT ecosystem, irrigation application and management may be configured based on soil moisture's minimum allowable depletion levels, or accumulated evapotranspiration threshold. The management operations may further involve varying the irrigation frequencies, depths and stages of irrigation application (Lopez et al., 2017). In this study, the ET-based routine of the DSSAT was used to assess best irrigation management practices for the study region under extreme climate conditions. The specific objectives of the study were to: (i) identify optimum evapotranspiration-based irrigation scheduling treatment for maize, using a calibrated DSSAT-CERES Maize model; and (ii) assess crop yield and water productivity response under increased temperature and prolonged dryness.

4.2 Data and Methods

4.2.1 Study area

The southwest research and extension center (SWREC), which is in Finney county and is in the southwest part of Kansas, was chosen as the study location for this study (Figure 4.1). This area is geographically located between the latitudes of and longitudes of 38.0625^{o}N and

100.8903°W. The elevation of the study area ranges from 746.8 to 941.8 m above sea level with climate categorized as semiarid (Klocke et al., 2011). The region's reported mean annual maximum and lowest temperatures are 12.3°C and 28.3°C, respectively. The long term average rainfall and evapotranspiration recorded during the growing season are approximately 349mm and 962mm, respectively (Araya et al., 2017), while the annual number of frost-free days amounts to 170 days (Klocke et al., 2012). However, a recent long-term trend analysis of climate data shows that the number of frost-free days has increased by 5.2 days in the region (Lin et al., 2017). The dominant soil type is Ulysses silt loam which is made up of organic matter content of 1.5% and is slightly alkaline with a pH of 8.1 (Klocke et al., 2011).

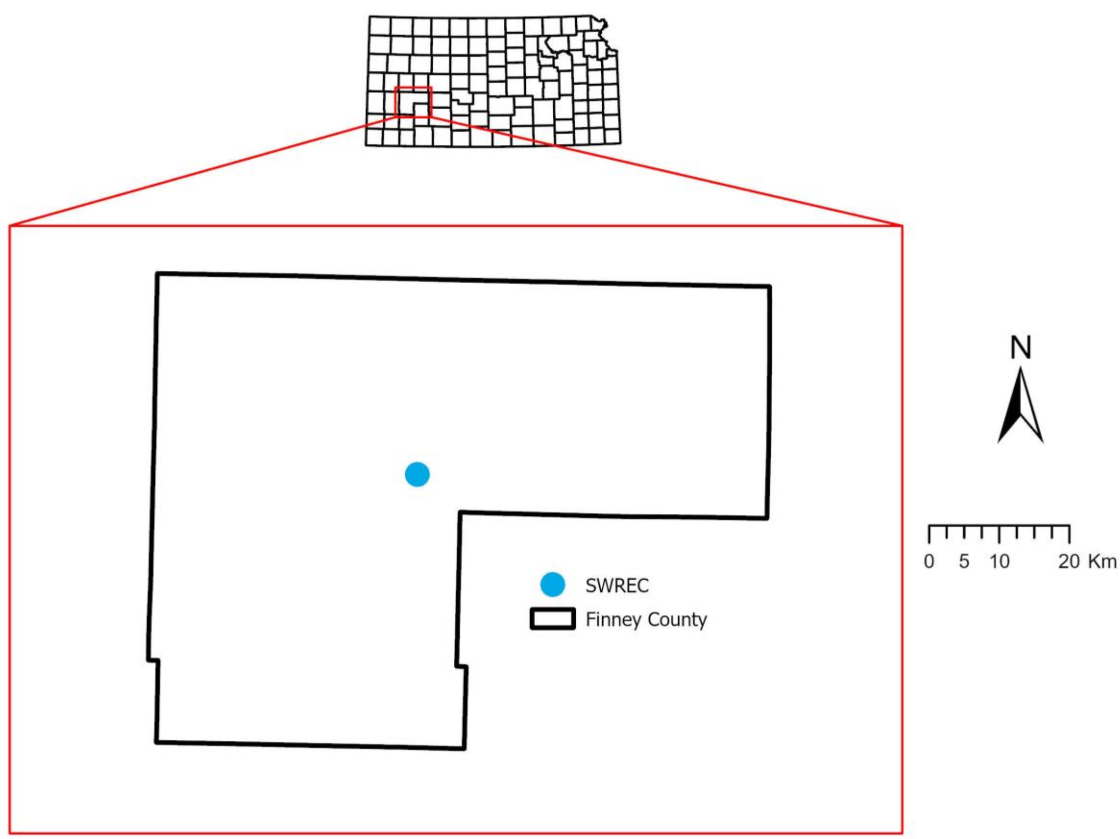


Figure 4.1: Map of Finney County, Kansas showing southwest research and extension center (SWREC)

4.2.2 DSSAT model description

The Decision Support System for Agrotechnology Transfer Cropping System Model (DSSAT-CSM) model (Jones et al., 2003) is a system that integrates weather, soil, crop and management data to simulate and analyze water, nitrogen and carbon processes, in addition to crop phenology and yield. Five different modules in the DSSAT are used to import data which are used to simulate these processes. The weather module or weatherman accepts or generates a minimum weather data input containing temperature, precipitation, and solar radiation or sunshine hours which are required to simulate the process of photosynthesis and potential transpiration. The soil module simulates dynamics such as soil water, inorganic soil nitrogen (N), phosphorus (P) and potassium (K). It also contains sub-modules for simulating soil organic matter, and the SBuild tool within the DSSAT is used to import information that describes the characteristics of the soil profile for the different soil horizons where plant roots can grow. The Soil-Plant-Atmosphere module (SPAM) performs the soil water balance routine soil where rainfall and irrigation are inflows into the system, evapotranspiration (soil evapotranspiration and plant transpiration), as well as drainage and surface runoff are outflows from the system. Rainfall is partitioned into infiltration and surface runoff using the SCS curve number method, while the drainage is modeled using a one-directional "Tipping bucket" approach (Ritchie, 1998). Depending on the availability of data, the evapotranspiration itself can be estimated using the Priestly-Taylor (Priestley & Taylor, 1972), FAO-56 (Allen & Pereira, 1998), or ASCE (Allen et al., 2005) standard methods. The plant module contains various sub-modules that simulate the growth and development process of various crop types. It contains models capable of simulating the growth and development process of over forty crops. The version 4.8 of the DSSAT-CERES Maize module, which is one of these sub-modules, simulates maize yield and yield components, as well as the phenological development and the nutrient and water processes, from planting period to harvest. Finally, the management module models field operations such as planting event, irrigation application, fertilizer application, tillage event, organic matter and chemical application along with the harvest operation. For example, treatments can be setup to assess how different irrigation management operations such as varying irrigation depth, frequency, application timing and efficiency, etc. can affect crop output and the utilization of water resources. The XBuild tool in DSSAT is used to create or modify these operations in an experimental file commonly called the FileX. Simulations can be run for a single growing-season period or a seasonal analysis can be performed, where the year to year variation in crop productivity is simulated.

4.2.3 DSSAT Model setup

Climatic data comprising of minimum and maximum temperature, precipitation, solar radiation over a 30-year period from 1991 to 2020 were extracted from the Kansas Mesonet (Kansas Mesonet, 2023) weather station located in Garden city, Kansas. Soil physical and chemical properties, along with their engineering characteristics at each soil depth were obtained from the Gridded Soil Survey Geographic (gSSURGO) database (gSSURGO, 2023) and were imported into the model using the SBuild tool of the DSSAT. The Ulysses silt loam soil type was used as it is the dominant soil type in the study area (Araya, et al., 2017). The planting date was set at May 15 which is common for the study region (Araya et al., 2021) and was fixed for each growing season over the entire 30-year period of simulations. The Priestly-Taylor approach and the Suleiman-Ritchie method were used to estimate soil evaporation and evapotranspiration, respectively, to calibrate and validate a maize model for the research site (Araya, et al., 2017). The crop management practices include uniform apply Urea fertilizer of 10 Kg N on the day of planting and at one month after planting. The seeds were planted 5 cm deep with a planting density of 7.6

plants/m2 and a row spacing of 76 cm, respectively. The selected cultivar applied in the study, as well as its genetic coefficients are presented in Araya et al., (2017).

4.2.4 Irrigation management scenarios

4.2.4.1 Baseline automatic irrigation scenario (Farmers' choice)

To represent the historically common irrigation management strategy for the study area, an automatic irrigation application with an irrigation depth of 1.2m was specified in accordance with the reported root zone depth of maize (Allen & Pereira, 1998). The initial soil moisture content was assumed to be at 60% of the field capacity. The field capacity and permanent wilting point have been reported to be 33% and 15% volumetric water content, respectively (Klocke et al., 2011). Based on prevalent practice—commonly called "farmers' choice"—in the study area (Araya et al., 2021), the model was set to trigger an irrigation event when the depth of water in the upper 30cm depth of soil reaches the 50% threshold of the plant available soil water (PASW). The model was setup to apply 25mm of water per irrigation event, thereby always keeping the water in the soil above the 50% PASW threshold and avoiding potential water stress. The routine was set to apply 25mm of water per irrigation event with application efficiency assumed to be 80%.

4.2.4.2 Evapotranspiration-based irrigation scenario

The evapotranspiration-based automatic irrigation routine in the DSSAT accumulates daily potential evapotranspiration (plant transpiration and soil evaporation), then subtracts infiltration (Rain – Runoff) to obtain an amount of evapotranspiration (ET) to be applied through irrigation. This is represented mathematically in the DSSAT irrigation subroutine as:

Equation 4.1: Daily accumulated evapotranspiration (daily potential ET demand)

$$ET\_ACCUM = ET\_ACCUM + (EOP + EVAP) - (RAIN - RUNOFF)$$

Where the ET_ACCUM is the daily potential ET demand or accumulated ET in mm/day; The EOP represents the plant transpiration, while the EVAP represents the soil evaporation. Both are summed up to obtain the potential ET for a given day. The RAIN represents rainfall amount; while RUNOFF represents water lost through runoff. Since this potential ET value ET_ACCUM is accumulated daily, it also represents the initial accumulated ET from the previous day(s), as shown in equation (1). The reference evapotranspiration is calculated using the Priestly-Taylor approach which was specified during the setup of the DSSAT CERES Maize model, and is then adjusted by the static crop coefficient for maize (equation 4.2) defined based on the leaf area index (LAI), in the DSSAT model (DeJonge et al., 2012). The resulting value then represents the potential evapotranspiration, as illustrated in equation 4.3, so that:

Equation 4.2: Static crop coefficient

$$K_{cs} = 1.0 + (K_{c\,max} - 1.0) \times \frac{LAI}{6.0}.$$

Equation 4.3: Potential evapotranspiration

$$E_o = K_{cs} \times ET_o.$$

Where K_{cs} is the static crop coefficient of maize; $K_{c\,max}$ is the maximum K_{cs} at LAI value of 6.0; LAI is the leaf area index; E_o is the potential evapotranspiration; and ET_o is the reference evapotranspiration. The water infiltration through the soil is obtained, using the soil conservation service (SCS) approach (Mishra & Singh, 2003). In the SCS method, the rainfall is split into runoff and infiltration based on a curve number which is derived by considering soil properties such as slope, texture and tillage. The SCS method was also further improved (Williams et al., 1984) to account for the antecedent soil moisture content at the time of the rainfall event, by adding any irrigation amount applied prior to the rainfall event. Therefore, the rainfall value used in the SCS method to isolate infiltration, is a combination of both natural precipitation and any irrigation that may have been previously applied. A threshold value for accumulated ET (ET_ACCUM) in equation (1) was set such that when the set threshold was surpassed, the routine would trigger an irrigation event. This was done by modifying the IMDEP variable under the simulations control within the experimental file (hereafter referred to as "FILE X") in DSSAT. Furthermore, the ITHRU variable was modified to constrain the model to apply only a percentage proportion of the accumulated ET amount. These modifications are performed within the raw experiment file, as the X-Build user interface for entering experimental data in the DSSAT version 4.8 model used in this study did not yet possess the capability to handle the input variables. Four thresholds for ET accumulation were defined; three distinctive treatments having ET amounts increased consecutively by 5mm, starting at 20mm; and a fourth treatment having an ET amount that was 5mm lower than the starting ET amount. These thresholds were selected in line with a prior study by (Igwe et al., 2023), where he predicted that the average weekly crop evapotranspiration of maize during the growing season would significantly increase by up to 10% towards the end of the 21st century, relative to a historical average of 21mm. The irrigation routine was further programmed to replace different percentages (50, 75, and 100%) of the required potential evapotranspiration, making up a total of twelve distinctive treatments.

4.2.5 Statistical Analysis and irrigation performance assessment criteria

Yield, irrigation amount and water productivity were used as criteria for assessing the performance of each irrigation treatment. Water savings were calculated in percentages as the reduction in the amount of water consumed during the growing season, relative to the baseline condition, while water losses were represented as the increase in the amount of water consumed relative to the baseline. The water productivity (Li et al., 2016; Molden, 1997) was defined in this study as the amount of yield obtained per unit depth of irrigation water applied. Research shows that is a useful indicator of the level of management of irrigation and the crop (Kijne et al., 2004), as well as the limitations associated with crop production (Grassini et al., 2011).

Although, the nature of relationship of maize with full and deficit irrigation has been debated (Comas et al., 2019; Trout & DeJonge, 2017), water productivity in this study was considered linear following the widely accepted practice in literature (Farré & Faci, 2006; Payero et al., 2006; Yilmaz et al., 2010). Therefore, an increase in the amount of water used, without corresponding increase in the yield, would imply a decline in the water productivity, as shown in the equation 4.4 below:

Equation 4.4: Water productivity:

$$Water\ Productivity = \frac{Yield\ [Kg/ha]}{Irrigation\ [mm]}$$

Where water productivity is measured in [(Kg/ha)/mm], yield is in Kg/ha, and irrigation amount is in mm.

Following acceptable guidelines of hypothesis testing, an analysis of variance (ANOVA) (Girden, 1992) was performed along with post-hoc tests, particularly the Tukey's Honestly Significant Difference (TukeyHSD) test (Tukey, 1949), or the Dunnett’s test (Dunnett, 1955), where appropriate. The objective of these tests, performed at a 95% confidence level, were to ascertain if there were any statistically significant differences between the results produced under the various treatment scenarios, and when compared with the baseline which was represented by the automatic full irrigation scenario serving as the control. The null hypothesis, which was a crucial part of the analytical framework, proposed that there were no statistically significant differences between the different treatment outcomes when compared to one another or to the baseline. The alternative hypothesis, on the other hand, argued that there were statistically significant differences between the results obtained. This strategy ensured a strong and methodologically sound evaluation, allowing us to make significant inferences about the impacts of the treatments and their relative differences from the control situation.

4.2.6 Extreme conditions through environmental modification

To induce extreme environmental conditions during the crop growing season, we altered/changed specific variables within the DSSAT weather file. The variables chosen were those that have been shown to significantly affect the variability of evapotranspiration (ET) in an previous study by Igwe et al., (2023). These factors were determined to be the maximum temperature, which was represented as heat stress, and the maximum number of consecutive dry days, which was represented as water stress. In addition, as described by Igwe et al., (2023), the extent to which these stressors were forced was also based on the projected change in the future, in comparison to a 30-year historical period which ranged from the year 1991 to 2020, as shown in table 1 below. The projections were obtained from twenty global climate models (GCMs), and represented in three time slices as near-century (2025-2049), mid-century (2050-2074), and end-century (2075-2099). As a result, the maximum temperature was raised by 1°C, 2°C, and 4°C to symbolize heat stress. Similar to this, the maximum number of consecutive dry days at the tasseling phase indicated by a month—which was identified by calculating the growing degree days corresponding to the tasseling stage for the selected Maize cultivar—was increased by 1 day over a 30-year period in the weather file, to represent water stress. The sensitive stage of corn growth such as the tasseling stage was chosen, since the grain producing capability of the plant is determined during this stage, as reported in the Kansas Corn Production Handbook and by Jiang et al., (2016). As a result, forcing water stress during this stage of crop growth results in a larger loss of maize yield (Çakir, 2004; Mansouri-Far et al., 2010). The model was then independently run under these novel circumstances, and the outcomes were compared to the conventional farmers' choice scenario.

Table 4.1: Projected future changes in Finney County climate extremes relative to historical time period

Future Period	Change in Tmax (oC)	Change in CDD (day)
	RCP4.5	
Near-Century	+0.9	+0.71
Mid-Century	+2.13	+0.73
End-Century	+2.65	+0.72
	RCP8.5	
Near-Century	+1.14	+0.73
Mid-Century	+3.01	+0.74
End-Century	+5.39	+0.77

4.3 Results and Discussions

4.3.1 Maize yield, water use and water productivity under normal climate conditions

The farmer's choice irrigation strategy consisted of an automatic irrigation schedule which triggered irrigation to apply 25mm irrigation per event. This was done to minimize water stress by maintaining the depth of water in the upper 30cm soil depth above 50% of the plant available water. Over the 30-year simulation period, the observed maize yield ranged from 10,871 to 11,915 kg/ha, with a mean yield of 11,435 kg/ha. The irrigation amount applied varied between 379 to 514mm, resulting in water productivity ranging from 21.6 to 29.1 Kg/ha/mm. The mean irrigation amount and water productivity were 456mm and 28.3 Kg/ha/mm, respectively.

Alternatively, employing ET-based irrigation produced yields which were comparable to the farmer's choice. Statistical analysis showed that there was no significant difference (p-value > 0.05) between the yields obtained under the ET-based strategy and the farmers' choice. An exception was that yields produced at the 50% ET replacement level under the ET-based strategy. At this level, yield was significantly lower, which was expected since applying only 50% of the ET requirement at the specified ET requirement thresholds ranging from 15 to 30mm resulted in inadequate water supply, leading to increased water stress. The water supply was therefore, much lower than the farmer's choice, where its 25mm per irrigation event, aimed at maintaining the soil water content above 50% of plant available capacity was more likely to meet the crop water demands.

Notably, yield slightly exceeded the farmer's choice when 100% of the ET requirement was replaced across the four ET thresholds of 15, 20, 25, and 30mm, as shown in figure 4.2(a). This is because ET-based irrigation at this level not only estimated the crop's actual water requirements, but fully applied it, gaining an advantage over the farmer's method which relied on a fixed 50% threshold of plant available water that might potentially not meet the crop water needs more accurately. However, it is essential to note that although, the 100% ET replacement treatment produced higher yield than the famers' choice, the strategy may not be sustainable due to its higher water demand, as the irrigation amount at the 100% ET replacement treatment was observed to be substantially higher (p-value < 0.05) than the amount applied under the farmers' choice, as indicated by figure 4.2(b). Consequently, since yield did not increase substantially with increase in irrigation amount, the water productivity at the 100% ET replacement level also significantly declined (p-value <0.05) compared to the 50% and 75% replacement levels, as shown in figure 4.2(c).

Irrigating at 75% ET replacement level presents a potentially more efficient strategy. This is because despite producing marginally lower yield compared to the conventional famers' choice, statistical analysis reveals that the mean yields obtained from both the 75% ET replacement treatment and the famers' choice were not significantly different from each other. This result implies that rather than applying the full 100% of ET requirement, applying 75% of the ET replacement can be used instead without substantially reducing the yield. This finding aligns with a similar study (Lamm & Trooien, 2003), which demonstrated that increasing percentage ET replacement beyond 75% of the required amount did not significantly increase maize yield. Mean yields obtained at the 75% ET replacement level ranged from 10,861.7 to 11,042.5 kg/ha across the various ET requirement thresholds. The highest mean yield of 11,042.5 Kg/ha was obtained at the 25mm ET requirement, indicating a 3.4% decline in yield compared to the farmer's choice, while the lowest mean yield of 10,861.7 Kg/ha was obtained at the 15mm ET threshold, which implied a 5% decline compared to the farmer's choice. In a similar study (Ko & Piccinni, 2009), it was found that applying 75% of the ET amount helped maintain yield losses below 10%. Furthermore, less water was used by the 75% ET replacement treatment, conserving water by up to 14% and 19% at the 25mm and 30mm ET thresholds, respectively. Therefore, due to the reduced water use without significant decline in yield, the water productivity at both thresholds also increased by 0.2% and 6.2%, respectively. Therefore, implying that a 30mm ET threshold may be more effective in improving water productivity.

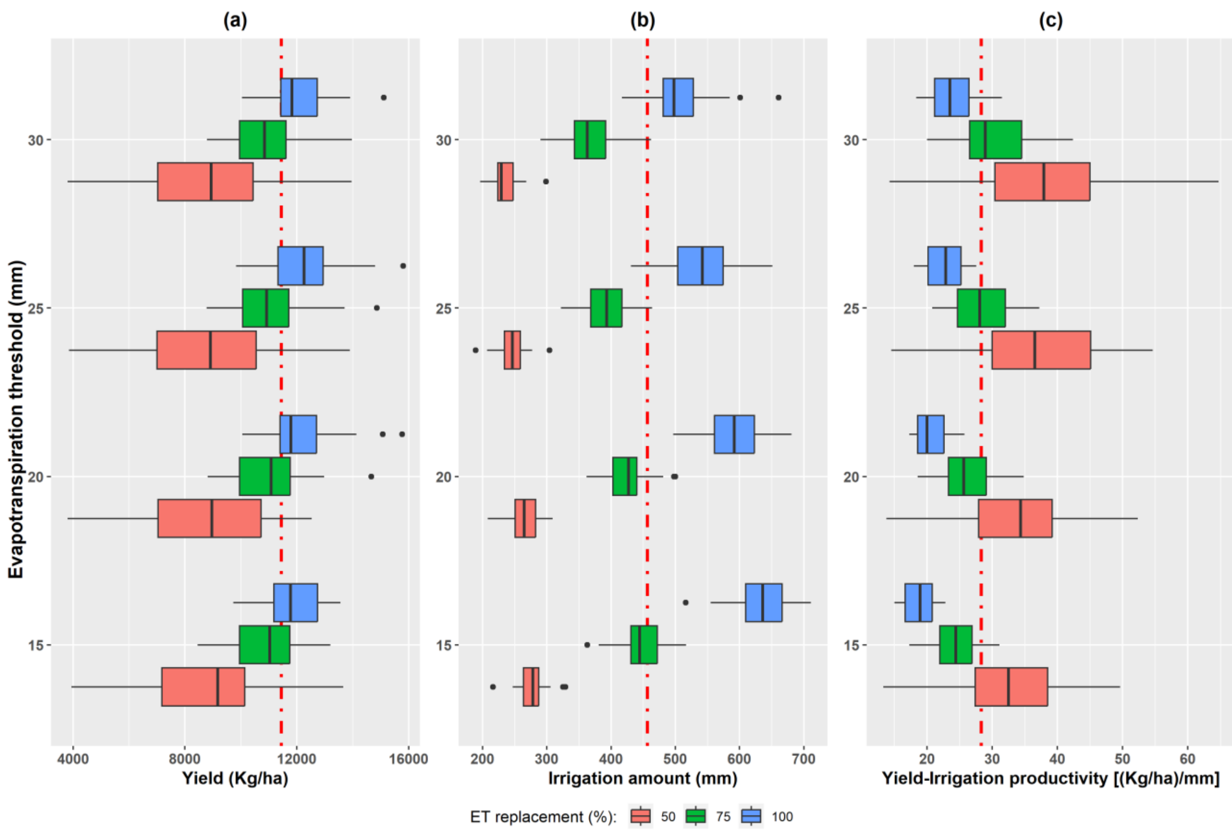


Figure 4.2: (a) Maize yield, (b) Irrigation amount, and (c) Yield-irrigation distribution for ET-based irrigation under normal conditions

The overall results revealed a consistent linear pattern of increasing yield, as the percentage of crop ET replaced increased from 50% to 100%, as shown in figure 4.3(A). The finding is consistent with the study by Kresović et al., (2016), as well as Greaves & Wang, (2017), where they both demonstrated a linear increase in yield with greater crop ET and irrigation amounts, under temperate climate. Therefore, the observed pattern is likely due to the reduction in water stress that results from applying more water leading up to the required irrigation amount. Interestingly, the maize yield relationship with the ET requirement threshold, however, was not linear but rather exhibited a threshold-like relationship. This fact holds true, as the yield initially increased as the ET requirement increased from 15 to 20mm. It then peaked at the 25mm ET requirement, and finally declined at the 30mm ET requirement, as shown in figure 4.3 (A). This threshold-like relationship suggests that maize can endure water stress until a certain threshold. A higher ET requirement threshold implies that it will take a longer duration before an irrigation event is triggered. As a result, a decrease in yield might therefore, likely be the result of greater water stress. This pattern was however not the same at the 50% ET replacement level, as the yield was observed to vary erratically at this level. In his study, Hokam et al., (2011) demonstrated that at deficiency rates, maize yield rises with more frequent irrigation events. However, that might not apply in all cases, as excess water may result from irrigating at a low ET threshold, and study (Ahmad et al., 2020) shows that this can lead to loss in yield due to the leaching of available nutrient in the soil. Excess application of water has also been reported to account for an average reduction in maize yield (Liu et al., 2022), even by up to 17% (Li et al., 2019). Conversely, the irrigation amount increased gradually with increase in the ET percentage replacement and decreased with increase in the ET requirement threshold, as shown in figure 4.3(B) and figure 4.4(B), respectively. In contrast, water productivity decreased with increase in ET percentage replacement (figure 4.3C) and increased linearly with increase in ET requirement threshold (figure

4.4 C). This result agrees with a similar study (Nasseri, 2021) which argued that under semi-arid conditions, limited water supply could be practiced to enhance water productivity in Maize.

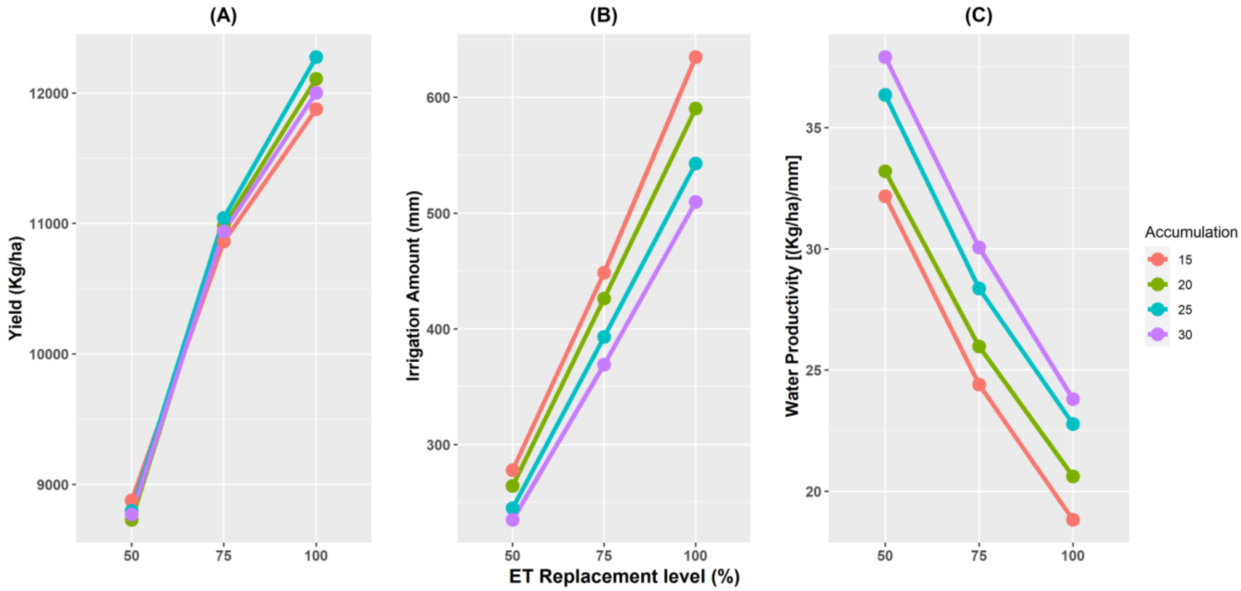


Figure 4.3: Relationship between (A) Yield, (B) Irrigation amount, and (C) Water productivity and ET percentage replacement level

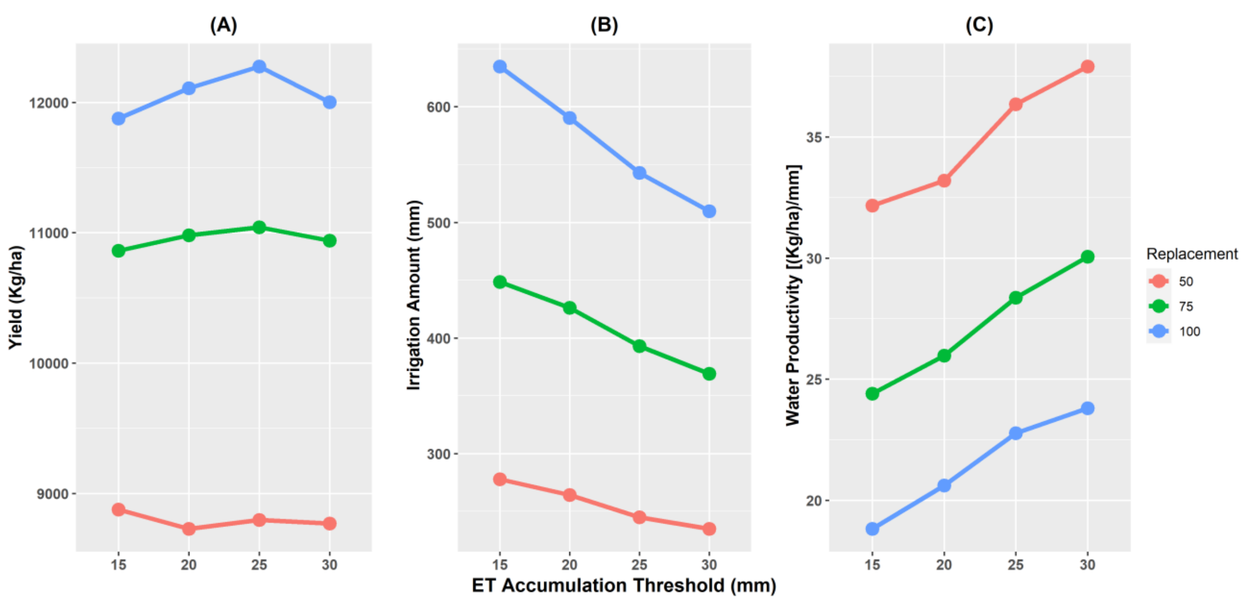


Figure 4.4: Relationship between (A) Yield, (B) Irrigation amount, and (C) Water productivity and ET requirement threshold

4.3.2 Maize yield and water productivity response to extreme temperatures

The observed trend in maize yield, irrigation amount and water productivity with respect to changes in the percentage ET replacements, as well as with respect to ET thresholds, were similar to that depicted under normal climate conditions, as shown in figures 4.3 and figure 4.4, respectively.

When subjected to a 1^{o}C increase in the maximum temperature, the yield slightly declined in comparison to the yields obtained under the normal climate conditions. This was expected as increasing temperatures often tend to decrease yield by shortening the growing season length (Bassu et al., 2014). When compared to the farmers' choice, however, yields slightly declined under the ET replacement levels of 50 and 75%, but increased under the 100% ET replacement level (figure 4.5), as was previously observed for this treatment under normal climate condition. More interestingly, statistical analysis showed that the yield gains and losses at both the 100% and 75% ET replacement levels, respectively, were not significantly different from the farmers' choice, thereby suggesting that the 75% deficit irrigation might remain a more viable strategy. even under heat stress represented by a 1°C rise in temperature. This hypothesis was further supported by the fact that the 100% ET replacement level when compared to the farmers' choice, required significantly higher amounts of irrigation water ranging from 38 to 47%, to produce the observed yields (as shown in figure 4.6). Moreover, since there was no significant increase in yield with increased water usage, the water productivity at the 100% ET replacement level declined significantly from the farmers' choice by percentages ranging from 17 to 34%, as shown in figure 4.7.

In contrast, the 75% ET replacement treatment demonstrated superiority, conserving irrigation water by amounts ranging from 1 to 17%, across the various ET requirement thresholds when compared to the farmers' choice. At the 75% replacement level, an overall minimum yield loss of 3.4% (figure 4.5) was observed at the 25mm ET threshold, indicating its potential superior performance over other ET requirement thresholds. However, higher water savings and water productivity were observed at the 30mm ET requirement threshold, than at the 25mm ET threshold. Statistically significant water savings of 12% and 17% were obtained at the 25 and 30mm ET thresholds, respectively, as displayed in figure 4.6. Meanwhile, the water productivity decreased by 2.8% at the 25mm threshold, but increased by 2.7% at the 30mm ET thresholds, as shown in figure 4.7. Notably, the changes in water productivity at both thresholds were not significantly different from each other, and from the farmers' choice. These findings suggest that both threshold treatments could exhibit resilience to temperature increase of 1^{o}C, depending on what component among yield, water use and water productivity is of priority to the producer. Although, this research has not applied a weighting factor to these variables that were used to assess the performance of the irrigation treatments, studies (Ali et al., 2007; Geerts & Raes, 2009) demonstrated that in cases where the most production-limiting factor is water, it might be best to maximize the water productivity more than yield. This approach allows more water to be allocated to irrigate other plots, potentially compensating for the initial yield loss.

When examining the impact of a 2^{o}C increase in temperature, it was interesting to find that yield variability was very minimal, fluctuating only by approximately 1%, across all the twelve treatment combinations in comparison to the yields obtained from treatments under temperature increases of 1^{o}C. Similar to the trends observed under a 1°C temperature rise, yield decline relative to the farmers' choice, were observed at both the 50% and 75% ET replacement, while yield remained slightly higher under the 100% ET replacement. Importantly, statistical analysis reaffirmed that the yield changes observed at both the 100% and 75% ET replacement levels were not significantly different from the farmers' choice, even under the 2°C temperature increase. Again, the 75% ET replacement treatments also proved to be a potentially robust strategy for improving crop adaptiveness to mild changes in temperature. This is because, in addition to maintaining the mean yield decline below 6% (figure 4.5), especially at the 25 and 30mm ET thresholds, water savings also increased significantly by 10.5% and 14.8% (figure 4.6), respectively when compared to the farmers' choice. Whereas, the 100% ET replacement levels showed higher water usage, as indicated by increasing percentages ranging from 16% at 30mm threshold to 43.4% at 15mm ET threshold (figure 4.6). The decline in water productivity was also significantly higher at 100% ET replacement when compared to the farmers' choice than at the 75% ET replacement level, which only exhibited non-significant decline in water productivity by 5.1 and 0.7% at the 25mm and 30mm ET threshold levels, respectively (as demonstrated in figure 4.7).

In contrast to the relatively gradual yield responses to mild temperature increases of 1°C and 2°C, yield variability was greater across all the ET replacement levels when maximum temperature was increased to 4^{o}C. Although, yield did not vary significantly across the ET requirement thresholds of each ET replacement level, indicating a weak relationship between yield and ET threshold, similar to what was previously observed under normal climate conditions (as depicted in figure 4.3 and 4.4). Yield drastically declined at across all the ET replacement levels. The decline in yields at the 75% and 100% ET replacement levels—although not significantly different from the farmers' choice except at the 30mm ET threshold at 75% ET replacement level—were particularly pronounced, approximately doubling the magnitude of yield loss when compared to the milder temperature increases of 1°C and 2°C (figure 4.5). These findings align with similar studies (Ahmad et al., 2020; Lone et al., 2020) which have reported a percentage loss in yield approximately twice as high when temperatures were increased from 2°C to 4°C. This underscores the heightened sensitivity of maize yield to extreme temperature increases and further emphasizes the need for adaptive strategies. The treatments at the 100% ET replacement level showed superior resilience by maintaining yield losses at approximately 3%, performing better than the treatments at the 75% ET replacement level which incurred yield losses of approximately 12% across all ET thresholds (Figure 4.5). The result of the latter aligns with a similar study by (Ma et al., 2017), which demonstrated a 14% yield decline under temperature increases greater than 4^{o}C. Other related studies indicate greater effect of extreme temperatures on maize grain yield, demonstrating that by increasing temperatures by greater than 3^{o}C relative to the normal conditions, grain yield loss can increase by over 50% (Hatfield & Prueger, 2015; Jerry L. Hatfield & Christian Dold, 2018; Schlenker & Roberts, 2009).

The superiority of the treatment at the 100% ET replacement level was tempered by its higher water usage, which increased significantly by percentages ranging from 23% to 49% across all ET thresholds (figure 4.6), and lower water productivity, with declines ranging from 29% to 42% (Figure 4.7). Conversely, the 75% ET replacement level exhibited lower water usage, conserving significant amounts of water by 3% and 9% at the 25mm and 30mm ET thresholds, respectively (figure 4.6), as well as limiting the decline in water productivity to 17% and 12% at both thresholds, respectively (as shown in figure 4.7). Overall, these findings underscore the importance of adopting an irrigation strategy which applies a deficit 75% of the ET requirement, particularly at the 25mm and 30mm ET thresholds, to maintain both maize yield and water productivity under extreme temperature conditions.

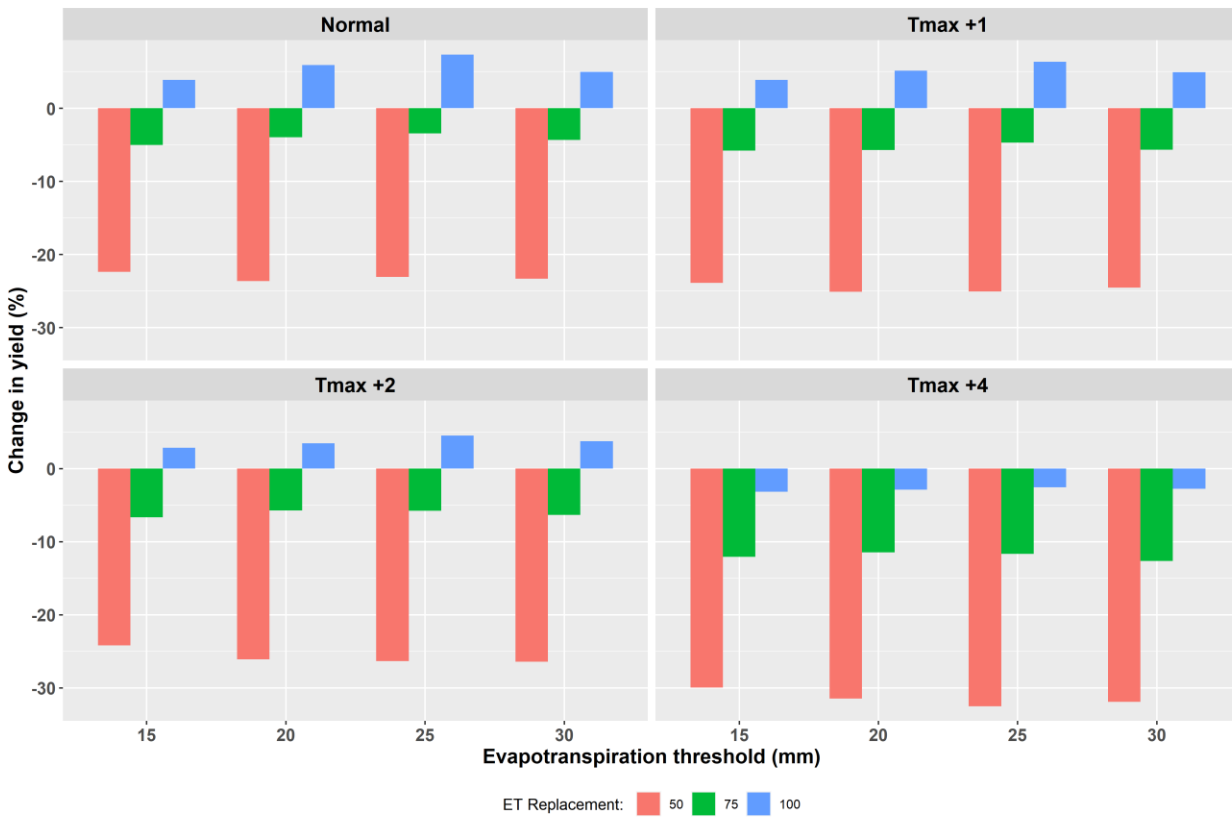


Figure 4.5: Percentage change in yield under increased maximum temperatures

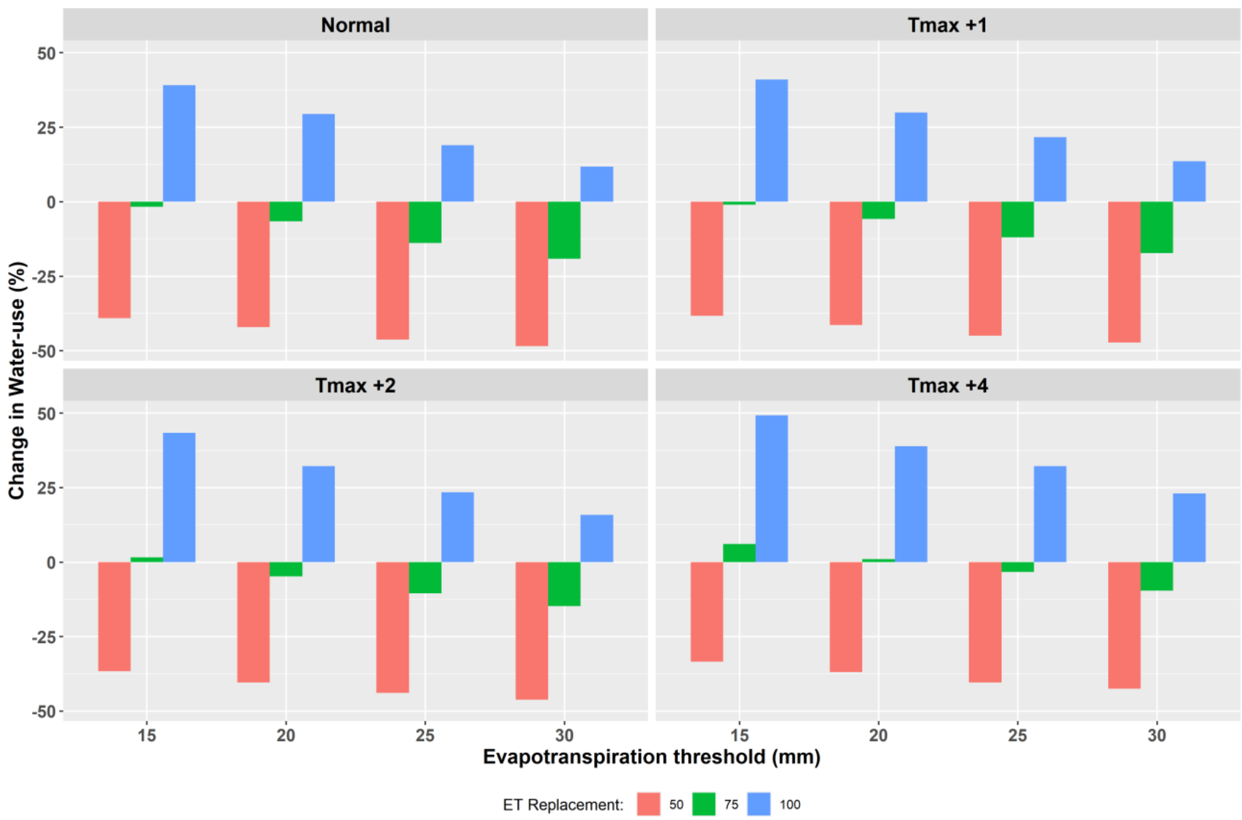


Figure 4.6: Percentage change in irrigation water use under increased maximum temperatures

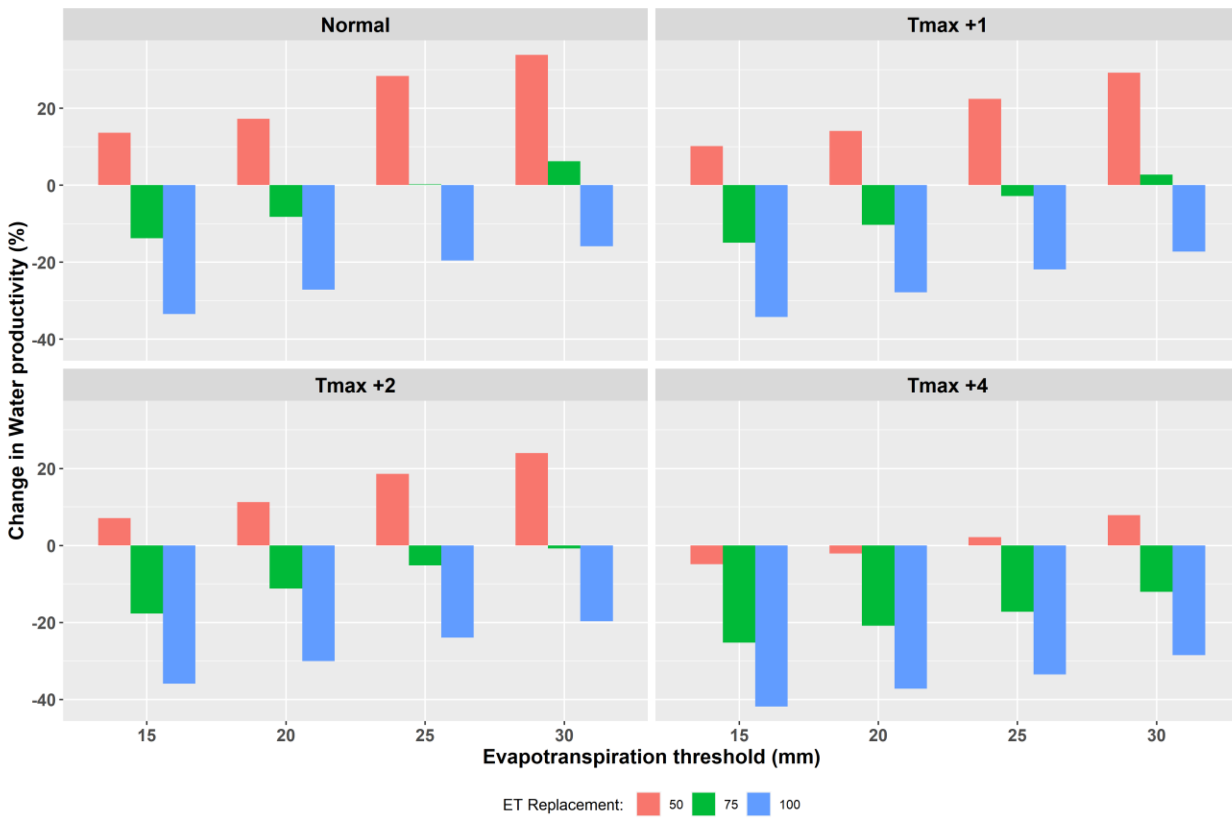


Figure 4.7: Percentage change in water productivity under increased maximum temperatures

4.3.3 Maize productivity response to increased maximum number of consecutive dry days

Introducing an additional consecutive dry day during the critical tasseling stage of maize development resulted in a mean yield decline relative to the conventional farmer's choice. The yield decline was similar to what was observed under a 1oC temperature increase.

Notably, significant yield declines were only observed at the 50% ET replacement level, while the 100% ET replacement level exhibited a degree of resilience to water stress, modestly outperforming the farmer's choice by percentages ranging from 3% to 7%. However, the 100% ET replacement treatment, despite its resilience, was hindered by its significantly higher water usage and lower water productivity, making it a less favorable option for mitigating water stress.

Conversely, treatments at the 75% ET replacement level showcased remarkable resilience by maintaining yield losses below 6% across all ET accumulation thresholds. Particularly noteworthy was the performance of the 25mm ET threshold, which incurred the lowest yield loss of 4.3% compared to the farmer's choice, as illustrated in Figure 4.8. However, the 30mm ET threshold, when compared to the farmer's choice, conserved 18% more water (as depicted in Figure 4.9) and increased water productivity by 5% (as shown in Figure 4.10), thus surpassing the 25mm ET threshold treatment in overall effectiveness.

Although the water productivity declines remained statistically insignificant under both heat and water stresses, represented by 1^{o}C and 1 day increase in maximum temperature and number of consecutive dry days, respectively, the percentage decline in water productivity under increased water stress was much lower than observed under increased heat stress. This finding also implied that more water savings were observed under water stress than under heat stress, suggesting that temperature-associated impacts were more pronounced on maize yield than water-limited impacts. This suggests the possibility of a more intricate interplay in the response of maize to heat and water stress at various growth stages, warranting further in-depth investigation.

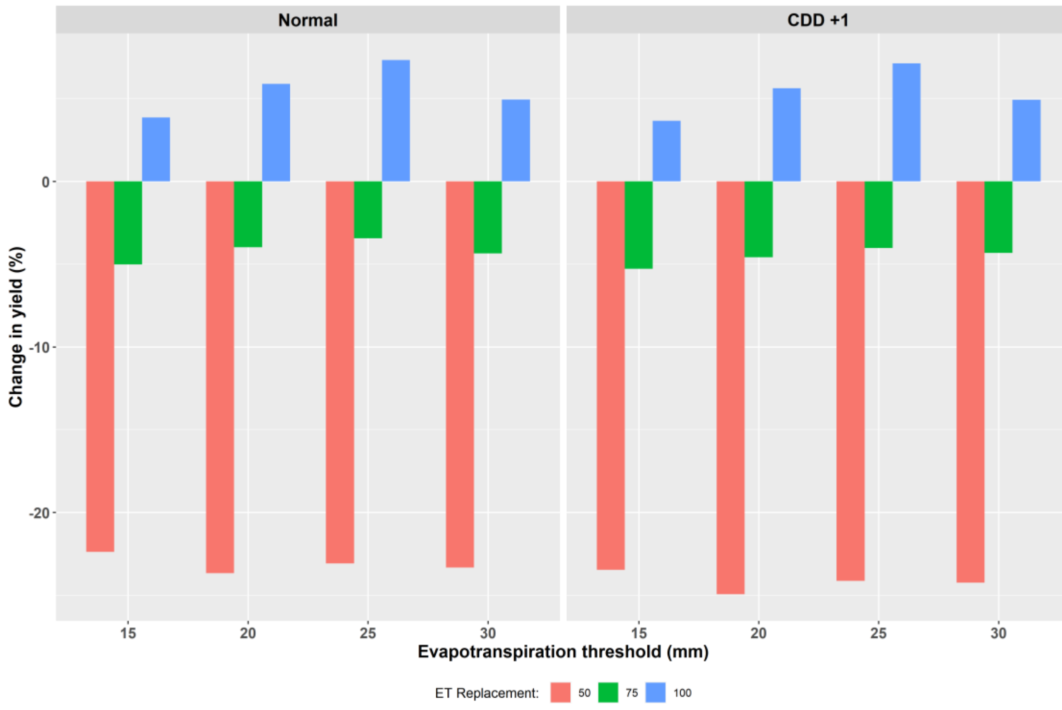


Figure 4.8: Percentage change in yield under increased number of consecutive dry days

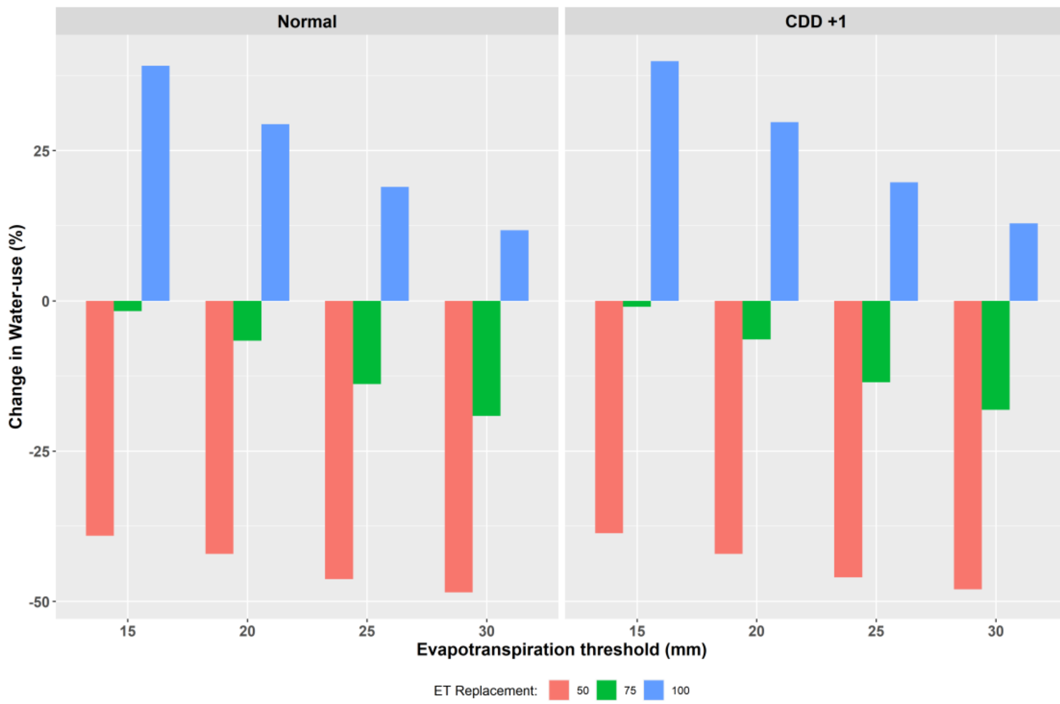


Figure 4.9: Percentage change in irrigation amount under increased number of consecutive dry days

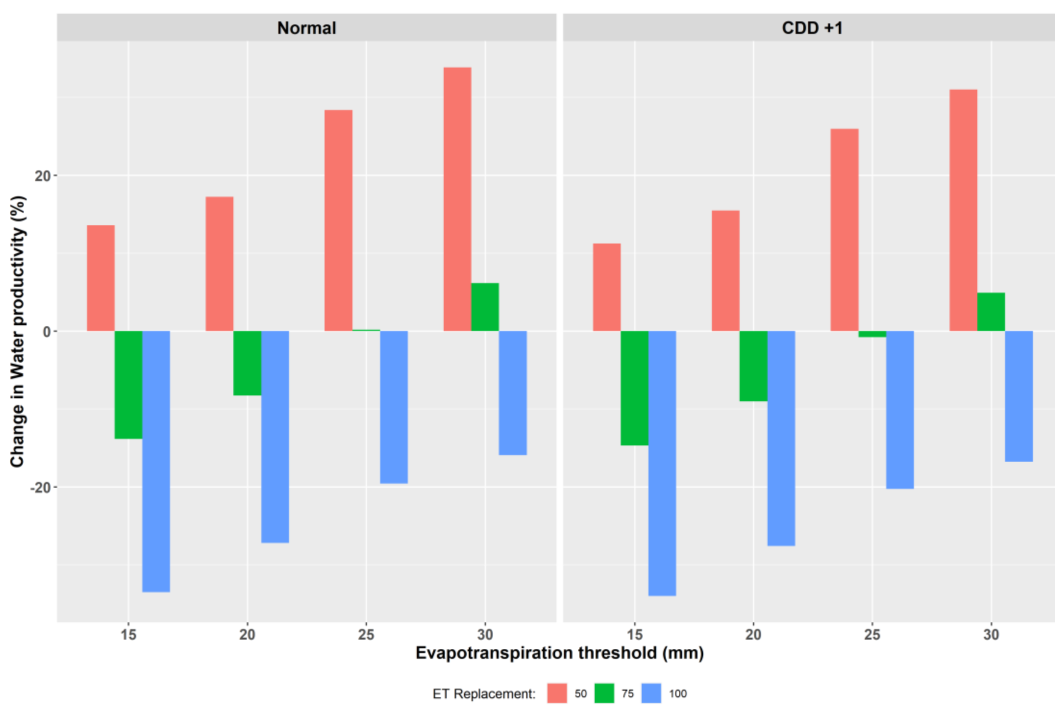


Figure 4.10: Percentage change in water productivity under increased number of consecutive dry days

4.4 Conclusion and Recommendations

In summary, the overall findings of this study underscore important implications for sustainable agriculture. As temperature continues to increase due to climate change, deficit ET replacement, especially at a 75% threshold level may be a viable adaptation strategy for reducing the negative effects of heat stress on maize and water productivity. This relationship holds regardless of the fact that increasing the percentage of ET application have more pronounced impact on yield compared to variations in the accumulated ET threshold. The study further emphasizes the significance of considering both ET replacement levels and ET thresholds as important factors when optimizing crop yield and reducing water use under normal and extreme temperatures.

The ET accumulation threshold of 25mm was observed to optimize yield production, while the 30mm ET threshold better optimized water savings and productivity. Both strategies are critical for improving crop adaptation to typical climate and under extreme conditions. Under normal conditions, and under both mild temperatures increase and increase in dryness by one day, the 75% Et replacement treatment at 25mm and 30mm ET thresholds limited yield loss to approximately 6%. However, when the maximum temperature was substantially increased by up to 4^{o}C, the yield loss doubled to approximately 12%. It is important to note that the yield losses were however, not statistically significant from the baseline, for all scenarios. Concurrently, the water savings increased up to 13% and 19%, under the 25 and 30mm ET threshold treatments, respectively. While the water productivity decline was less than 5% under both treatments, except under high temperature of 4^{o}C where the reduction was significantly higher by up to 17%. Therefore, while noting that these results provide insights into the response of maize crops to a 4°C temperature increase, it's vital to consider that in semi-arid regions, temperature increases are often higher, and global climate models project potential temperature increases of up to 4°C by the end of the 21st century (Ahmad et al., 2020; Condon et al., 2020; Ma et al., 2017b). Therefore, the performance of irrigation strategies under such conditions warrants profound attention and further investigation in the context of climate change adaptation strategies.

Also, the variable among yield and water use or productivity, which an agricultural producer prefers to optimize plays an important role in determining the best performing irrigation strategies. As demonstrated in other studies (Ali et al., 2007; Geerts & Raes, 2009), the variable to be optimized is dependent on knowledge of the most production-limiting factor in the area. For example, research (Ao et al., 2021) shows that expanding a small irrigated farmland (usually between 0–80 hectares) by up to double its initial size, can save up to 1.2% in groundwater use, compared to the amount used individually by the initial farm sizes. Although, this was done assuming that there would be no changes in the technology and crop management, irrigation strategy would be considered to perform satisfactorily if it optimizes water productivity, such that water savings can be used to increase area of irrigated land.

Like many other studies, this investigation has only considered extreme conditions applied here to be occurring independently. However, the conditions may happen concurrently (Haqiqi et al., 2020). Therefore, further assessments considering the impact of compound extremes may prove resourceful in better understanding crop responses under deficit irrigation management. Additionally, incorporating other metrics such as irrigation water use efficiency (Zou et al., 2021) might be useful to consider in future studies. In his study, (Ko & Piccinni, 2009) found that applying 75% of the ET amount increased water use efficiency by 1.6 gm-2mm-1 with an irrigation amount of 456mm of water, while (Kresović et al., 2016), also found that at 75% irrigation, the grain yield was satisfactory, and water use efficiency increased. Finally, assessing the response of other strategies like crop growth stage irrigation management (Comas et al., 2019), or even choice of irrigation technology (Frisvold & Bai, 2016), can help to increase crop adaptiveness to climate impacts.

Chapter 5 - Summary and Conclusions

5.1 Summary and Conclusions

The first objective of this study was to evaluate the impact of climate extremes on seasonal crop water demands in Finney County, Western Kansas, using a machine learning model. The maximum number of consecutive dry days (CDD) and the weekly mean maximum temperatures were found to be the most common indices of climate extremes affecting crop evapotranspiration in the region, according to our research. While the mean maximum temperature accounted for 27.2% variability in ET_o, the CDD accounted for about 29% of its variability. Altogether, the eleven indices that were used to represent climate extreme conditions, explained up to 70% variability in ET_o. Overall, indices derived from temperature data were more highly correlated with ET that those derived from precipitation data. Furthermore, an ensemble prediction from twenty global climate models (GCMs) under two representative concentration pathways (RCPs) all project potential increases in crop ET in the future starting from the near century to the end of 21st century, which was defined in 25-year time periods from the year 2025 to 2099. Under the RCP4.5 scenario, crop ET was projected to increase by 0.4, 3.1 and 5.9% by the near, mid and end century, respectively. While under the RCP8.5 scenario, crop ET was projected to increase by 1.7, 5.9 and 9.6% in the near, mid and end century, respectively. However, statistical analysis indicate that these increases are statistically significant under the RCP 8.5 scenario, compared to historical time period.

The second objective aimed to investigate sustainable water management strategies for improving crop adaptation to extreme climate conditions in Finney County in Western Kansas. According to our research, implementing deficit evapotranspiration replacement, particularly at the 75% threshold level, shows promise as a successful adaptation method to lessen the negative effects of heat stress on maize crop yield and water productivity. The obtained results demonstrate the need of simultaneously considering both ET replacement levels and ET accumulation thresholds as crucial elements when optimizing crop output and managing water resources, especially under both normal and high temperature circumstances.

5.2 Future Work

In this study, the Priestly-Taylor method was chosen as the preferred method for estimating reference evapotranspiration, during the DSSAT model development. This is because the same method was initially used to calibrate the DSSAT model. However, since reference evapotranspiration which is a major component of the crop evapotranspiration is influenced by several factors, depending on the location, it is important to consider the influence of the most dominant factors in the study areas when selecting the method for estimating evapotranspiration.

Furthermore, it is also important to explore alternative methods of irrigation application such as the drip irrigation system, within the framework of the DSSAT model. This is useful to comparatively evaluate the application efficiency of each method, as it plays a pivotal role in optimizing crop yield, conserving water resources, and enhancing agricultural productivity.

Finally, alternative irrigation scheduling strategies such as one that synchronizes irrigation events with specific growth stages where the crop is less resistant to water stress may be explored. A comprehensive assessment of these strategies might prove to be instrumental in contributing to sustainable and more climate-resilient agricultural practices.

References

A. Islam, L. R. Ahuja, L. A. Garcia, L. Ma, & A. S. Saseendran. (2012). Modeling the Effect of Elevated CO2 and Climate Change on Reference Evapotranspiration in the Semi-Arid Central Great Plains. *Transactions of the ASABE*, *55*(6), 2135–2146. https://doi.org/10.13031/2013.42505

Abatzoglou, J. T. (2013). Development of gridded surface meteorological data for ecological applications and modelling. *International Journal of Climatology*, *33*(1), 121–131. https://doi.org/10.1002/JOC.3413

Abatzoglou, J. T., & Brown, T. J. (2012). A comparison of statistical downscaling methods suited for wildfire applications. *International Journal of Climatology*, *32*(5), 772–780. https://doi.org/10.1002/JOC.2312

Abedinpour, M. (2015). Evaluation of growth-stage-specific crop coefficients of maize using weighing lysimeter. *Soil and Water Research*, *10*(2), 99–104. https://doi.org/10.17221/63/2014-SWR

Ahmad, I., Ahmad, B., Boote, K., & Hoogenboom, G. (2020). Adaptation strategies for maize production under climate change for semi-arid environments. *European Journal of Agronomy*, *115*, 126040. https://doi.org/10.1016/j.eja.2020.126040

Ajaz, A., Datta, S., & Stoodley, S. (2020). High plains aquifer-state of affairs of irrigated agriculture and role of irrigation in the sustainability paradigm. *Sustainability (Switzerland)*, *12*(9). https://doi.org/10.3390/SU12093714

Alexander, L. V., Zhang, X., Peterson, T. C., Caesar, J., Gleason, B., Tank, A. M. G. K., Haylock, M., Collins, D., Trewin, B., Rahimzadeh, F., Tagipour, A., Kumar, K. R., Revadekar, J., Griffiths, G., Vincent, L., Stephenson, D. B., Burn, J., Aguilar, E., Brunet, M., … Vazquez-Aguirre, J. L. (2006). Global observed changes in daily climate extremes of temperature and precipitation. *Journal of Geophysical Research: Atmospheres*, *111*(D5), 5109. https://doi.org/10.1029/2005JD006290

Al-Hasani, A. A. J., & Shahid, S. (2022). Spatial distribution of the trends in potential evapotranspiration and its influencing climatic factors in Iraq. *Theoretical and Applied Climatology*, *150*(1), 677–696. https://doi.org/10.1007/s00704-022-04184-4

Ali, M. H., Hoque, M. R., Hassan, A. A., & Khair, A. (2007). Effects of deficit irrigation on yield, water productivity, and economic returns of wheat. *Agricultural Water Management*, *92*(3), 151–161. https://doi.org/10.1016/j.agwat.2007.05.010

Alibabaei, K., Gaspar, P. D., Assunção, E., Alirezazadeh, S., & Lima, T. M. (2022). Irrigation optimization with a deep reinforcement learning model: Case study on a site in Portugal. *Agricultural Water Management*, *263*, 107480. https://doi.org/10.1016/j.agwat.2022.107480

Allen, R. G., Asce, M., Luis, ;, Pereira, S., Smith, ; Martin, 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)

Allen, R. G., null, Walter, I. A., Elliott, R. L., Howell, T. A., Itenfisu, D., Jensen, M. E., & Snyder, R. L. (2005). *The ASCE Standardized Reference Evapotranspiration Equation*. American Society of Civil Engineers. https://doi.org/10.1061/9780784408056

Allen, R. G., & Pereira. (1998). Crop evapotranspiration: Guidelines for computing crop water requirements,FAO Irrigation and drainage paper No. 56. *Food and Agriculture Organization of the United Nations, Rome*.

Allen, R. G., Smith, M., Pereira, L. S., Raes, D., & Wright, J. L. (2004). Revised FAO Procedures for Calculating Evapotranspiration: Irrigation and Drainage Paper No. 56 with Testing in Idaho. *Watershed Management and Operations Management 2000*, *105*, 1–10. https://doi.org/10.1061/40499(2000)125

Anandhi, A., Hutchinson, S., Harrington, J., Rahmani, V., Kirkham, M. B., & Rice, C. W. (2016). Changes in spatial and temporal trends in wet, dry, warm and cold spell length or duration indices in Kansas, USA. *International Journal of Climatology*, *36*(12), 4085–4101. https://doi.org/10.1002/JOC.4619

Ao, Y. Z., Hendricks, N. P., & Marston, L. T. (2021). Growing farms and groundwater depletion in the Kansas High Plains. *Environmental Research Letters*, *16*(8), 084065. https://doi.org/10.1088/1748-9326/ac1816

Araya, A., Kisekka, I., Gowda, P. H., & Prasad, P. V. V. (2017). Evaluation of water-limited cropping systems in a semi-arid climate using DSSAT-CSM. *Agricultural Systems*, *150*, 86–98. https://doi.org/10.1016/j.agsy.2016.10.007

Araya, A., Kisekka, I., Lin, X., Vara Prasad, P. V., Gowda, P. H., Rice, C., & Andales, A. (2017). Evaluating the impact of future climate change on irrigated maize production in Kansas. *Climate Risk Management*, *17*, 139–154. https://doi.org/10.1016/J.CRM.2017.08.001

Araya, A., Prasad, P. V. V., Gowda, P. H., Sharda, V., Rice, C. W., & Ciampitti, I. A. (2021). Evaluating optimal irrigation strategies for maize in Western Kansas. *Agricultural Water Management*, *246*, 106677. https://doi.org/10.1016/J.AGWAT.2020.106677

Attia, A., El-Hendawy, S., Al-Suhaibani, N., Alotaibi, M., Tahir, M. U., & Kamal, K. Y. (2021). Evaluating deficit irrigation scheduling strategies to improve yield and water productivity of maize in arid environment using simulation. *Agricultural Water Management*, *249*, 106812. https://doi.org/10.1016/j.agwat.2021.106812

Basso, B., Martinez-Feria, R. A., Rill, L., & Ritchie, J. T. (2021). Contrasting long-term temperature trends reveal minor changes in projected potential evapotranspiration in the US Midwest. *Nature Communications*, *12*(1), Article 1. https://doi.org/10.1038/s41467-021-21763-7

Bassu, S., Brisson, N., Durand, J.-L., Boote, K., Lizaso, J., Jones, J. W., Rosenzweig, C., Ruane, A. C., Adam, M., Baron, C., Basso, B., Biernath, C., Boogaard, H., Conijn, S., Corbeels, M., Deryng, D., De Sanctis, G., Gayler, S., Grassini, P., … Waha, K. (2014). How do various maize crop models vary in their responses to climate change factors? *Global Change Biology*, *20*(7), 2301–2320. https://doi.org/10.1111/gcb.12520

Bausch, W. C. (1993). Soil background effects on reflectance-based crop coefficients for corn. *Remote Sensing of Environment*, *46*(2), 213–222. https://doi.org/10.1016/0034-4257(93)90096-G

Biau, G., & Fr, G. B. (2012). Analysis of a Random Forests Model. *Journal of Machine Learning Research*, *13*, 1063–1095.

Bloomfield, J. P., Marchant, B. P., & McKenzie, A. A. (2019). Changes in groundwater drought associated with anthropogenic warming. *Hydrology and Earth System Sciences*, *23*(3), 1393–1408. https://doi.org/10.5194/HESS-23-1393-2019

Brauer, D., Devlin, D., Wagner, K., Ballou, M., Hawkins, D., & Lascano, R. (2017). Ogallala Aquifer Program: A Catalyst for Research and Education to Sustain the Ogallala Aquifer on the Southern High Plains (2003–2017). *Journal of Contemporary Water Research & Education*, *162*(1), 4–17. https://doi.org/10.1111/J.1936-704X.2017.03256.X

Breiman, L. (2001). Random forests. *Machine Learning*, *45*(1), 5–32. https://doi.org/10.1023/A:1010933404324/METRICS

Cai, Z., Jönsson, P., Jin, H., & Eklundh, L. (2017). Performance of Smoothing Methods for Reconstructing NDVI Time-Series and Estimating Vegetation Phenology from MODIS Data. *Remote Sensing 2017, Vol. 9, Page 1271*, *9*(12), 1271. https://doi.org/10.3390/RS9121271

Çakir, R. (2004). Effect of water stress at different development stages on vegetative and reproductive growth of corn. *Field Crops Research*, *89*(1), 1–16. https://doi.org/10.1016/J.FCR.2004.01.005

Campos, I., Neale, C. M. U., Suyker, A. E., Arkebauer, T. J., & Gonçalves, I. Z. (2017). Reflectance-based crop coefficients REDUX: For operational evapotranspiration estimates in the age of high producing hybrid varieties. *Agricultural Water Management*, *187*, 140–153. https://doi.org/10.1016/J.AGWAT.2017.03.022

Cao, R., Chen, Y., Shen, M., Chen, J., Zhou, J., Wang, C., & Yang, W. (2018). A simple method to improve the quality of NDVI time-series data by integrating spatiotemporal information with the Savitzky-Golay filter. *Remote Sensing of Environment*, *217*, 244–257. https://doi.org/10.1016/J.RSE.2018.08.022

Chambers, J. M., & Hastie, T. J. (2018). Statistical Models. *Statistical Models in S*, 13–44. https://doi.org/10.1201/9780203738535-2/STATISTICAL-MODELS-JOHN-CHAMBERS-TREVOR-HASTIE

Chen, R. C., Dewi, C., Huang, S. W., & Caraka, R. E. (2020). Selecting critical features for data classification based on machine learning methods. *Journal of Big Data*, *7*(1), 1–26. https://doi.org/10.1186/S40537-020-00327-4/FIGURES/13

Chicco, D., Warrens, M. J., & Jurman, G. (2021). The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation. *PeerJ Computer Science*, *7*, 1–24. https://doi.org/10.7717/PEERJ-CS.623/SUPP-1

Comas, L. H., Trout, T. J., DeJonge, K. C., Zhang, H., & Gleason, S. M. (2019). Water productivity under strategic growth stage-based deficit irrigation in maize. *Agricultural Water Management*, *212*, 433–440. https://doi.org/10.1016/J.AGWAT.2018.07.015

Condon, L. E., Atchley, A. L., & Maxwell, R. M. (2020). Evapotranspiration depletes groundwater under warming over the contiguous United States. *Nature Communications 2020 11:1*, *11*(1), 1–8. https://doi.org/10.1038/s41467-020-14688-0

Cotterman, K. A., Kendall, A. D., Basso, B., & Hyndman, D. W. (2018). Groundwater depletion and climate change: Future prospects of crop production in the Central High Plains Aquifer. *Climatic Change*, *146*(1–2), 187–200. https://doi.org/10.1007/S10584-017-1947-7/FIGURES/4

Deines, J. M., Kendall, A. D., Butler, J. J., & Hyndman, D. W. (2019). Quantifying irrigation adaptation strategies in response to stakeholder-driven groundwater management in the US High Plains Aquifer. *Environmental Research Letters*, *14*(4), 44014. https://doi.org/10.1088/1748-9326/AAFE39

DeJonge, K. C., Ascough, J. C., Andales, A. A., Hansen, N. C., Garcia, L. A., & Arabi, M. (2012). Improving evapotranspiration simulations in the CERES-Maize model under limited irrigation. *Agricultural Water Management*, *115*, 92–103. https://doi.org/10.1016/j.agwat.2012.08.013

Dennehy, K. F., Litke, D. W., & McMahon, P. B. (2002). The High Plains Aquifer, USA: Groundwater development and sustainability. *Geological Society Special Publication*, *193*, 99–119. https://doi.org/10.1144/GSL.SP.2002.193.01.09

Dou, X., & Yang, Y. (2018). Evapotranspiration estimation using four different machine learning approaches in different terrestrial ecosystems. *Computers and Electronics in Agriculture*, *148*, 95–106. https://doi.org/10.1016/j.compag.2018.03.010

Draper, N. R., & Smith, H. (2014). Applied regression analysis. *Applied Regression Analysis*, 1–716. https://doi.org/10.1002/9781118625590

Dunnett, C. W. (1955). A Multiple Comparison Procedure for Comparing Several Treatments with a Control. *Journal of the American Statistical Association*, *50*(272), 1096–1121. https://doi.org/10.1080/01621459.1955.10501294

Elbeltagi, A., Kumari, N., Dharpure, J. K., Mokhtar, A., Alsafadi, K., Kumar, M., Mehdinejadiani, B., Ramezani Etedali, H., Brouziyne, Y., Towfiqul Islam, A. R. M., & Kuriqi, A. (2021). Prediction of Combined Terrestrial Evapotranspiration Index (CTEI) over Large River Basin Based on Machine Learning Approaches. *Water*, *13*(4), Article 4. https://doi.org/10.3390/w13040547

Elbeltagi, A., Nagy, A., Mohammed, S., Pande, C. B., Kumar, M., Bhat, S. A., Zsembeli, J., Huzsvai, L., Tamás, J., Kovács, E., Harsányi, E., & Juhász, C. (2022). Combination of Limited Meteorological Data for Predicting Reference Crop Evapotranspiration Using Artificial Neural Network Method. *Agronomy*, *12*(2), Article 2. https://doi.org/10.3390/agronomy12020516

Emeka, N., Ikenna, O., Okechukwu, M., Chinenye, A., & Emmanuel, E. (2021). Sensitivity of FAO Penman–Monteith reference evapotranspiration (ETo) to climatic variables under different climate types in Nigeria. *Journal of Water and Climate Change*, *12*(3), 858–878. https://doi.org/10.2166/WCC.2020.200

Fan, J., Yue, W., Wu, L., Zhang, F., Cai, H., Wang, X., Lu, X., & Xiang, Y. (2018). Evaluation of SVM, ELM and four tree-based ensemble models for predicting daily reference evapotranspiration using limited meteorological data in different climates of China. *Agricultural and Forest Meteorology*, *263*, 225–241. https://doi.org/10.1016/j.agrformet.2018.08.019

Farré, I., & Faci, J. M. (2006). Comparative response of maize (Zea mays L.) and sorghum (Sorghum bicolor L. Moench) to deficit irrigation in a Mediterranean environment. *Agricultural Water Management*, *83*(1–2), 135–143. Scopus. https://doi.org/10.1016/j.agwat.2005.11.001

Feng, S., Liu, J., Zhang, Q., Zhang, Y., Singh, V. P., Gu, X., & Sun, P. (2020). A global quantitation of factors affecting evapotranspiration variability. *Journal of Hydrology*, *584*, 124688. https://doi.org/10.1016/j.jhydrol.2020.124688

Fienen, M. N., & Arshad, M. (2016). The International Scale of the Groundwater Issue. In A. J. Jakeman, O. Barreteau, R. J. Hunt, J.-D. Rinaudo, & A. Ross (Eds.), *Integrated Groundwater Management: Concepts, Approaches and Challenges* (pp. 21–48). Springer International Publishing. https://doi.org/10.1007/978-3-319-23576-9_2

Frisvold, G., & Bai, T. (2016). Irrigation Technology Choice as Adaptation to Climate Change in the Western United States. *Journal of Contemporary Water Research & Education*, *158*(1), 62–77. https://doi.org/10.1111/j.1936-704X.2016.03219.x

Geerts, S., & Raes, D. (2009). Deficit irrigation as an on-farm strategy to maximize crop water productivity in dry areas. *Agricultural Water Management*, *96*(9), 1275–1284. https://doi.org/10.1016/j.agwat.2009.04.009

Girden, E. (1992). *ANOVA*. https://doi.org/10.4135/9781412983419

Gorguner, M., & Kavvas, M. L. (2020). Modeling impacts of future climate change on reservoir storages and irrigation water demands in a Mediterranean basin. *Science of The Total Environment*, *748*, 141246. https://doi.org/10.1016/j.scitotenv.2020.141246

Granata, F. (2019). Evapotranspiration evaluation models based on machine learning algorithms—A comparative study. *Agricultural Water Management*, *217*, 303–315. https://doi.org/10.1016/j.agwat.2019.03.015

Grassini, P., Yang, H., & Cassman, K. (2009). Limits to maize productivity in Western Corn-Belt: A simulation analysis for fully irrigated and rainfed conditions. *Agricultural and Forest Meteorology*, *149*, 1254–1265. https://doi.org/10.1016/j.agrformet.2009.02.012

Grassini, P., Yang, H., Irmak, S., Thorburn, J., Burr, C., & Cassman, K. G. (2011). High-yield irrigated maize in the Western U.S. Corn Belt: II. Irrigation management and crop water productivity. *Field Crops Research*, *120*(1), 133–141. https://doi.org/10.1016/j.fcr.2010.09.013

Greaves, G. E., & Wang, Y.-M. (2017). Yield response, water productivity, and seasonal water production functions for maize under deficit irrigation water management in southern Taiwan. *Plant Production Science*, *20*(4), 353–365. https://doi.org/10.1080/1343943X.2017.1365613

gSSURGO. (2023). *Soil Survey Staff. Gridded Soil Survey Geographic (gSSURGO) Database for State name. United States Department of Agriculture, Natural Resources*

Conservation Service. Available online at https://gdg.sc.egov.usda.gov/. Accessed 06 November 2023. https://gdg.sc.egov.usda.gov/

Gu, Z., Qi, Z., Burghate, R., Yuan, S., Jiao, X., & Xu, J. (2020). Irrigation Scheduling Approaches and Applications: A Review. *Journal of Irrigation and Drainage Engineering*, *146*(6), 04020007. https://doi.org/10.1061/(ASCE)IR.1943-4774.0001464

Gurara, M. A., Jilo, N. B., & Tolche, A. D. (2021). Impact of climate change on potential evapotranspiration and crop water requirement in Upper Wabe Bridge watershed, Wabe Shebele River Basin, Ethiopia. *Journal of African Earth Sciences*, *180*, 104223. https://doi.org/10.1016/J.JAFREARSCI.2021.104223

Haacker, E. M. K., Kendall, A. D., & Hyndman, D. W. (2016). Water Level Declines in the High Plains Aquifer: Predevelopment to Resource Senescence. *Groundwater*, *54*(2), 231–242. https://doi.org/10.1111/GWAT.12350

Haqiqi, I., Grogan, D. S., Hertel, T. W., & Schlenker, W. (2020). *Quantifying the Impacts of Compound Extremes on Agriculture and Irrigation Water Demand* [Preprint]. Water Resources Management/Theory development. https://doi.org/10.5194/hess-2020-275

Hastie, T., & Tibshirani, R. (2014). Generalized Additive Models. *Wiley StatsRef: Statistics Reference Online*. https://doi.org/10.1002/9781118445112.STAT03141

Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The Elements of Statistical Learning*. https://doi.org/10.1007/978-0-387-84858-7

Hatfield, J. L., & Prueger, J. H. (2015). Temperature extremes: Effect on plant growth and development. *Weather and Climate Extremes*, *10*, 4–10. https://doi.org/10.1016/J.WACE.2015.08.001

Hayhoe, K., Vandorn, J., Naik, V., & Wuebbles, D. (n.d.). *Climate Change in the Midwest Projections of Future Temperature and Precipitation*.

Hokam, E. M., El-Hendawy, S. E., & Schmidhalter, U. (2011). Drip Irrigation Frequency: The Effects and Their Interaction with Nitrogen Fertilization on Maize Growth and Nitrogen Use Efficiency under Arid Conditions. *Journal of Agronomy and Crop Science*, *197*(3), 186–201. Scopus. https://doi.org/10.1111/j.1439-037X.2010.00460.x

Holman, D., Sridharan, M., Gowda, P., Porter, D., Marek, T., Howell, T., & Moorhead, J. (n.d.). *Estimating Reference Evapotranspiration for Irrigation Management in the Texas High Plains*.

Holzworth, D. P., Huth, N. I., deVoil, P. G., Zurcher, E. J., Herrmann, N. I., McLean, G., Chenu, K., van Oosterom, E. J., Snow, V., Murphy, C., Moore, A. D., Brown, H., Whish, J. P. M., Verrall, S., Fainges, J., Bell, L. W., Peake, A. S., Poulton, P. L., Hochman, Z., … Keating, B. A. (2014). APSIM – Evolution towards a new generation of agricultural systems simulation. *Environmental Modelling & Software*, *62*, 327–350. https://doi.org/10.1016/j.envsoft.2014.07.009

Huang, G., Wu, L., Ma, X., Zhang, W., Fan, J., Yu, X., Zeng, W., & Zhou, H. (2019). Evaluation of CatBoost method for prediction of reference evapotranspiration in humid regions. *Journal of Hydrology*, *574*, 1029–1041. https://doi.org/10.1016/j.jhydrol.2019.04.085

Hyndman, R. J., & Koehler, A. B. (2006). Another look at measures of forecast accuracy. *International Journal of Forecasting*, *22*(4), 679–688. https://doi.org/10.1016/J.IJFORECAST.2006.03.001

Igwe, K., Sharda, V., & Hefley, T. (2023). Evaluating the Impact of Future Seasonal Climate Extremes on Crop Evapotranspiration of Maize in Western Kansas Using a Machine Learning Approach. *Land*, *12*(8), Article 8. https://doi.org/10.3390/land12081500

IPCC Fifth Assessment Report: Climate Change 2014 (AR5) — European Environment Agency. (n.d.). [Rationale Reference]. Retrieved May 24, 2023, from https://www.eea.europa.eu/data-and-maps/indicators/greenhouse-gas-emission-trends-5/ipcc-fifth-assessment-report-climate

Jerry L. Hatfield & Christian Dold. (2018). Climate Change Impacts on Corn Phenology and Productivity. In Amanullah & Shah Fahad (Eds.), *Corn* (p. Ch. 6). IntechOpen. https://doi.org/10.5772/intechopen.76933

Jiang, Y., Zhang, L., Zhang, B., He, C., Jin, X., & Bai, X. (2016). Modeling irrigation management for water conservation by DSSAT-maize model in arid northwestern China. *Agricultural Water Management*, *177*, 37–45. https://doi.org/10.1016/j.agwat.2016.06.014

Jones, H. G. (2004). Irrigation scheduling: Advantages and pitfalls of plant-based methods. *Journal of Experimental Botany*, *55*(407), 2427–2436. https://doi.org/10.1093/jxb/erh213

Jones, J. W., Hoogenboom, G., Porter, C. H., Boote, K. J., Batchelor, W. D., Hunt, L. A., Wilkens, P. W., Singh, U., Gijsman, A. J., & Ritchie, J. T. (2003). The DSSAT cropping system model. *European Journal of Agronomy*, *18*(3), 235–265. https://doi.org/10.1016/S1161-0301(02)00107-7

Kadkhodazadeh, M., Anaraki, M. V., Morshed-Bozorgdel, A., & Farzin, S. (2022). A New Methodology for Reference Evapotranspiration Prediction and Uncertainty Analysis under Climate Change Conditions Based on Machine Learning, Multi Criteria Decision

Making and Monte Carlo Methods. *Sustainability 2022, Vol. 14, Page 2601*, *14*(5), 2601. https://doi.org/10.3390/SU14052601

Kamble, B., Kilic, A., & Hubbard, K. (2013). Estimating Crop Coefficients Using Remote Sensing-Based Vegetation Index. *Remote Sensing 2013, Vol. 5, Pages 1588-1602*, *5*(4), 1588–1602. https://doi.org/10.3390/RS5041588

Kansas Mesonet. (2023). *Kansas Mesonet · Historical Weather. Accessed 06 November 2023*. https://mesonet.k-state.edu/weather/historical/

Karl, T. R., Nicholls, N., & Ghazi, A. (1999). CLIVAR/GCOS/WMO Workshop on Indices and Indicators for Climate Extremes Workshop Summary. *Weather and Climate Extremes*, 3–7. https://doi.org/10.1007/978-94-015-9265-9_2

Kenny, J. F., & Juracek, K. E. (2013). *Irrigation trends in Kansas, 1991–2011: U.S. Geological Survey Fact Sheet 2013–3094, 4 p., https://pubs.usgs.gov/fs/2013/3094/.* https://pubs.usgs.gov/fs/2013/3094/

Khanal, R., Dhungel, S., Brewer, S. C., & Barber, M. E. (2021). Statistical Modeling to Predict Climate Change Effects on Watershed Scale Evapotranspiration. *Atmosphere 2021, Vol. 12, Page 1565*, *12*(12), 1565. https://doi.org/10.3390/ATMOS12121565

Kijne, J., Barker, R., & Molden, D. (2004). *Water productivity in agriculture: Limits and opportunities for improvement*. https://doi.org/10.1079/9780851996691.0000

Kisekka, I., P. Aguilar, J., H. Rogers, D., Holman, J., M. O'Brien, D., & Klocke, N. (2016). Assessing Deficit Irrigation Strategies for Corn Using Simulation. *Transactions of the ASABE*, *59*(1), 303–317. https://doi.org/10.13031/trans.59.11206

Kişi, Ö., & Öztürk, Ö. (2007). Adaptive Neurofuzzy Computing Technique for Evapotranspiration Estimation. *Journal of Irrigation and Drainage Engineering*, *133*(4), 368–379. https://doi.org/10.1061/(ASCE)0733-9437(2007)133:4(368)

Klocke, N. L., Currie, R. S., Tomsicek, D. J., & Koehn, J. (2011). Corn yield response to deficit irrigation. *Transactions of the ASABE*, *54*(3), 931–940. Scopus.

Klocke, N. L., Currie, R. S., Tomsicek, D. J., & Koehn, J. W. (2012). Sorghum yield response to deficit irrigation. *Transactions of the ASABE*, *55*(3), 947–955. Scopus.

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

Konduri, V. S., Vandal, T. J., Ganguly, S., & Ganguly, A. R. (2020). Data Science for Weather Impacts on Crop Yield. *Frontiers in Sustainable Food Systems*, *4*, 52. https://doi.org/10.3389/FSUFS.2020.00052/BIBTEX

Koukouli, P., Georgiou, P. E., & Karpouzos, D. K. (2019). Evaluation of climate change impacts on reference evapotranspiration under RCPs scenarios in northern Greece. *Global Nest Journal*, *21*(4), 519–529. https://doi.org/10.30955/GNJ.002998

Kresović, B., Tapanarova, A., Tomić, Z., Životić, L., Vujović, D., Sredojević, Z., & Gajić, B. (2016). Grain yield and water use efficiency of maize as influenced by different irrigation regimes through sprinkler irrigation under temperate climate. *Agricultural Water Management*, *169*, 34–43. https://doi.org/10.1016/j.agwat.2016.01.023

Kriegler, F. J., Malila, W. A., Nalepka, R. F., & Richardson, W. (1969). Preprocessing Transformations and Their Effects on Multispectral Recognition. *Rse*, 97.

Kumar, M., Raghuwanshi, N. S., & Singh, R. (2011). Artificial neural networks approach in evapotranspiration modeling: A review. *Irrigation Science*, *29*(1), 11–25. https://doi.org/10.1007/s00271-010-0230-8

Lamm, F. R., & Trooien, T. P. (2003). Subsurface drip irrigation for corn production: A review of 10 years of research in Kansas. *Irrigation Science*, *22*(3), 195–200. https://doi.org/10.1007/s00271-003-0085-3

Li, F., Jupp, D. L. B., Reddy, S., Lymburner, L., Mueller, N., Tan, P., & Islam, A. (2010). An Evaluation of the Use of Atmospheric and BRDF Correction to Standardize Landsat Data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *3*(3), 257–270. https://doi.org/10.1109/JSTARS.2010.2042281

Li, F., Jupp, D. L. B., Thankappan, M., Lymburner, L., Mueller, N., Lewis, A., & Held, A. (2012). A physics-based atmospheric and BRDF correction for Landsat data over mountainous terrain. *Remote Sensing of Environment*, *124*, 756–770. https://doi.org/10.1016/j.rse.2012.06.018

Li, X., & Troy, T. J. (2018). Changes in rainfed and irrigated crop yield response to climate in the western US. *Environmental Research Letters*, *13*(6), 064031. https://doi.org/10.1088/1748-9326/aac4b1

Li, X., Zhang, X., Niu, J., Tong, L., Kang, S., Du, T., Li, S., & Ding, R. (2016). Irrigation water productivity is more influenced by agronomic practice factors than by climatic factors in Hexi Corridor, Northwest China. *Scientific Reports*, *6*(1), Article 1. https://doi.org/10.1038/srep37971

Li, Y., Guan, K., Peng, B., Franz, T. E., Wardlow, B., & Pan, M. (2020). Quantifying irrigation cooling benefits to maize yield in the US Midwest. *Global Change Biology*, *26*(5), 3065–3078. https://doi.org/10.1111/gcb.15002

Li, Y., Guan, K., Schnitkey, G. D., DeLucia, E., & Peng, B. (2019). Excessive rainfall leads to maize yield loss of a comparable magnitude to extreme drought in the United States. *Global Change Biology*, *25*(7), 2325–2337. https://doi.org/10.1111/gcb.14628

Li, Z.-L., Tang, R., Wan, Z., Bi, Y., Zhou, C., Tang, B., Yan, G., & Zhang, X. (2009). A Review of Current Methodologies for Regional Evapotranspiration Estimation from Remotely Sensed Data. *Sensors*, *9*(5), Article 5. https://doi.org/10.3390/s90503801

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

Liou, Y.-A., & Kar, S. K. (2014). Evapotranspiration Estimation with Remote Sensing and Various Surface Energy Balance Algorithms—A Review. *Energies*, *7*(5), Article 5. https://doi.org/10.3390/en7052821

Liu, W., Li, Z., Li, Y., Ye, T., Chen, S., & Liu, Y. (2022). Heterogeneous impacts of excessive wetness on maize yields in China: Evidence from statistical yields and process-based crop models. *Agricultural and Forest Meteorology*, *327*, 109205. https://doi.org/10.1016/j.agrformet.2022.109205

Liu, X., Liu, C., Liu, X., Li, C., Cai, L., & Dong, M. (2022). Spatial and Temporal Variation in Reference Evapotranspiration and Its Climatic Drivers in Northeast China. *Water*, *14*(23), Article 23. https://doi.org/10.3390/w14233911

Lobell, D. B., & Asner, G. P. (2003). Climate and Management Contributions to Recent Trends in U.S. Agricultural Yields. *Science*, *299*(5609), 1032. https://doi.org/10.1126/SCIENCE.1078475

Lobell, D. B., Hammer, G. L., McLean, G., Messina, C., Roberts, M. J., & Schlenker, W. (2013). The critical role of extreme heat for maize production in the United States. *Nature Climate Change 2013 3:5*, *3*(5), 497–501. https://doi.org/10.1038/nclimate1832

Lobell, D. B., Roberts, M. J., Schlenker, W., Braun, N., Little, B. B., Rejesus, R. M., & Hammer, G. L. (2014). Greater sensitivity to drought accompanies maize yield increase in the U.S. Midwest. *Science*, *344*(6183), 516–519. https://doi.org/10.1126/SCIENCE.1251423/SUPPL_FILE/LOBELLETAL.DATABASES1.ZIP

Lone, B. A., Fayaz, A., Qayoom, S., Dar, N. A., Dar, Z. A., Singh, P., Kumar, S., Rasool, F., Andrabi, N., & Mushtaq, N. (2020). Studying Yield and Water Productivity of Maize at Enhanced Level of Temperature Using DSSAT 4.7.5. *Current Journal of Applied Science and Technology*, 93–104. https://doi.org/10.9734/cjast/2020/v39i2630909

Lopez, J. R., Winter, J. M., Elliott, J., Ruane, A. C., Porter, C., & Hoogenboom, G. (2017). Integrating growth stage deficit irrigation into a process based crop model. *Agricultural and Forest Meteorology*, *243*, 84–92. https://doi.org/10.1016/j.agrformet.2017.05.001

Lopez, J. R., Winter, J. M., Elliott, J., Ruane, A. C., Porter, C., Hoogenboom, G., Anderson, M., & Hain, C. (2022). Sustainable Use of Groundwater May Dramatically Reduce Irrigated Production of Maize, Soybean, and Wheat. *Earth's Future*, *10*(1), e2021EF002018. https://doi.org/10.1029/2021EF002018

Lotfi, M., Kamali, G. A., Meshkatee, A. H., & Varshavian, V. (2020). Study on the impact of climate change on evapotranspiration in west of Iran. *Arabian Journal of Geosciences*, *13*(15), 722. https://doi.org/10.1007/s12517-020-05715-x

Ma, L., Ahuja, L. R., Islam, A., Trout, T. J., Saseendran, S. A., & Malone, R. W. (2017b). Modeling yield and biomass responses of maize cultivars to climate change under full and deficit irrigation. *Agricultural Water Management*, *180*, 88–98. https://doi.org/10.1016/j.agwat.2016.11.007

Ma, L., Qi, Z., Shen, Y., He, L., Xu, S., Kisekka, I., Sima, M., Malone, R. W., Yu, Q., & Fang, Q. (2017). Optimizing Et-Based Irrigation Scheduling for Wheat and Maize with Water Constraints. *Transactions of the ASABE*, *60*(6), 2053–2065. https://doi.org/10.13031/trans.12363

Malik, W., & Dechmi, F. (2019). DSSAT modelling for best irrigation management practices assessment under Mediterranean conditions. *Agricultural Water Management*, *216*, 27–43. https://doi.org/10.1016/j.agwat.2019.01.017

Mansouri-Far, C., Modarres Sanavy, S. A. M., & Saberali, S. F. (2010). Maize yield response to deficit irrigation during low-sensitive growth stages and nitrogen rate under semi-arid climatic conditions. *Agricultural Water Management*, *97*(1), 12–22. https://doi.org/10.1016/j.agwat.2009.08.003

Masek, J. G., Vermote, E. F., Saleous, N. E., Wolfe, R., Hall, F. G., Huemmrich, K. F., Gao, F., Kutler, J., & Lim, T.-K. (2006). A Landsat surface reflectance dataset for North America, 1990-2000. *IEEE Geoscience and Remote Sensing Letters*, *3*(1), 68–72. https://doi.org/10.1109/LGRS.2005.857030

McGuire, V. L. (2014). *Water-level changes and change in water in storage in the High Plains aquifer, predevelopment to 2013 and 2011-13* (Report 2014–5218; Scientific Investigations Report, p. 24). USGS Publications Warehouse. https://doi.org/10.3133/sir20145218

Mishra, S. K., & Singh, V. P. (2003). SCS-CN Method. In *Soil Conservation Service Curve Number (SCS-CN) Methodology* (pp. 84–146). Springer Netherlands. https://doi.org/10.1007/978-94-017-0147-1_2

Molden, D. J. (1997). *Accounting for water use and productivity*. https://api.semanticscholar.org/CorpusID:109299257

Mostafa, R. R., Kisi, O., Adnan, R. M., Sadeghifar, T., & Kuriqi, A. (2023). Modeling Potential Evapotranspiration by Improved Machine Learning Methods Using Limited Climatic Data. *Water*, *15*(3), Article 3. https://doi.org/10.3390/w15030486

Mrad, A., Katul, G. G., Levia, D. F., Guswa, A. J., Boyer, E. W., Bruen, M., Carlyle-Moses, D. E., Coyte, R., Creed, I. F., Giesen, N. V. D., Grasso, D., Hannah, D. M., Hudson, J. E., Humphrey, V., Iida, S., Jackson, R. B., Kumagai, T., Llorens, P., Michalzik, B., … Scanlon, B. R. (2020). Peak grain forecasts for the US High Plains amid withering waters. *Proceedings of the National Academy of Sciences of the United States of America*, *117*(42), 26145–26150. https://doi.org/10.1073/PNAS.2008383117/SUPPL_FILE/PNAS.2008383117.SAPP.PDF

Nasseri, A. (2021). Long-term Water Productivity of Maize (Zea mays L.) From Limited Irrigation Conditions under Moderate Semi-arid Environment. *Tekirdağ Ziraat Fakültesi Dergisi*, *18*(3), Article 3. https://doi.org/10.33462/jotaf.702148

National Agricultural Statistics Service (NASS), R., & Development Division (RDD) Geospatial Information Branch (GIB), S. A. R. S. (SARS) U. S. D. of A. (USDA). (2020). USDA, National Agricultural Statistics Service, 2019 Crop Frequency Layers. *2019 Crop Frequency Layer*. https://doi.org/10.1109/AGRO-GEOINFORMATICS.2014.6910657

Neale, C. M. U., Bausch, W. C., Heermann, D. F., Member, A., Member, A. A., & Asae, A. M. (1990). Development of Reflectance-Based Crop Coefficients for Corn. *Transactions of the ASAE, 32*(6), 1891–1900. https://doi.org/10.13031/2013.31240

Nie, W., Zaitchik, B. F., Rodell, M., Kumar, S. V., Arsenault, K. R., & Badr, H. S. (2021). Irrigation Water Demand Sensitivity to Climate Variability Across the Contiguous United States. *Water Resources Research*, *57*(3), 2020WR027738. https://doi.org/10.1029/2020WR027738

Obembe, O. S., Hendricks, N. P., & Jagadish, S. V. K. (2023). Changes in groundwater irrigation withdrawals due to climate change in Kansas. *Environmental Research Letters*, *18*(9), 094041. https://doi.org/10.1088/1748-9326/acf147

Olberz, M., Kahlen, K., & Zinkernagel, J. (2018). Assessing the Impact of Reference Evapotranspiration Models on Decision Support Systems for Irrigation. *Horticulturae*, *4*(4), Article 4. https://doi.org/10.3390/horticulturae4040049

Payero, J. O., Melvin, S. R., Irmak, S., & Tarkalson, D. (2006). Yield response of corn to deficit irrigation in a semiarid climate. *Agricultural Water Management*, *84*(1–2), 101–112. Scopus. https://doi.org/10.1016/j.agwat.2006.01.009

Pierce, D. W., Barnett, T. P., Santer, B. D., & Gleckler, P. J. (2009). Selecting global climate models for regional climate change studies. *Proceedings of the National Academy of Sciences*, *106*(21), 8441–8446. https://doi.org/10.1073/pnas.0900094106

Powell, J. P., & Reinhard, S. (2016). Measuring the effects of extreme weather events on yields. *Weather and Climate Extremes*, *12*, 69–79. https://doi.org/10.1016/J.WACE.2016.02.003

Priestley, C. H. B., & Taylor, R. J. (1972). On the Assessment of Surface Heat Flux and Evaporation Using Large-Scale Parameters. *Monthly Weather Review*, *100*(2), 81–92. https://doi.org/10.1175/1520-0493(1972)100<0081:OTAOSH>2.3.CO;2

Probst, P., Wright, M. N., & Boulesteix, A. L. (2019). Hyperparameters and tuning strategies for random forest. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *9*(3), e1301. https://doi.org/10.1002/WIDM.1301

Raes, D., Steduto, P., Hsiao, T. C., & Fereres, E. (2009). AquaCrop—The FAO Crop Model to Simulate Yield Response to Water: II. Main Algorithms and Software Description. *Agronomy Journal*, *101*(3), 438–447. https://doi.org/10.2134/agronj2008.0140s

Rahmani, V., & Harrington, J. (2019). Assessment of climate change for extreme precipitation indices: A case study from the central United States. *International Journal of Climatology*, *39*(2), 1013–1025. https://doi.org/10.1002/JOC.5858

Rammig, A., & Mahecha, M. D. (2015). Ecosystem responses to climate extremes. *Nature*, *527*(7578), Article 7578. https://doi.org/10.1038/527315a

Reyes-González, A., Kjaersgaard, J., Trooien, T., Hay, C., & Ahiablame, L. (2018). Estimation of Crop Evapotranspiration Using Satellite Remote Sensing-Based Vegetation Index. *Advances in Meteorology*, *2018*. https://doi.org/10.1155/2018/4525021

Ritchie, J. T. (1998). Soil water balance and plant water stress. In G. Y. Tsuji, G. Hoogenboom, & P. K. Thornton (Eds.), *Understanding Options for Agricultural Production* (pp. 41–54). Springer Netherlands. https://doi.org/10.1007/978-94-017-3624-4_3

Roberts, M. J., Braun, N. O., Sinclair, T. R., Lobell, D. B., & Schlenker, W. (2017a). Comparing and combining process-based crop models and statistical models with some implications for climate change. *Environmental Research Letters*, *12*(9), 095010. https://doi.org/10.1088/1748-9326/AA7F33

Roberts, M. J., Braun, N. O., Sinclair, T. R., Lobell, D. B., & Schlenker, W. (2017b). Comparing and combining process-based crop models and statistical models with some implications for climate change. *Environmental Research Letters*, *12*(9), 095010. https://doi.org/10.1088/1748-9326/aa7f33

Roderick, M. L., Greve, P., & Farquhar, G. D. (2015). On the assessment of aridity with changes in atmospheric CO2. *Water Resources Research*, *51*(7), 5450–5463. https://doi.org/10.1002/2015WR017031

Rogers, D. H., Aguilar, J., Agricultural, R., Barnes, P. L., & Lamm, F. R. (n.d.). *AGRICULTURAL CROP WATER USE Isaya Kisekka*.

Rosa, L., Rulli, M. C., Davis, K. F., Li, X., & Troy, T. J. (2018). Changes in rainfed and irrigated crop yield response to climate in the western US. *Environmental Research Letters*, *13*(6), 64031. https://doi.org/10.1088/1748-9326/AAC4B1

Rudnick, D. R., Irmak, S., West, C., Chávez, J. L., Kisekka, I., Marek, T. H., Schneekloth, J. P., McCallister, D. M., Sharma, V., Djaman, K., Aguilar, J., Schipanski, M. E., Rogers, D. H., & Schlegel, A. (2019). Deficit Irrigation Management of Maize in the High Plains Aquifer Region: A Review. *Journal of the American Water Resources Association*, *55*(1), 38–55. https://doi.org/10.1111/1752-1688.12723

Sadok, W., Lopez, J. R., & Smith, K. P. (2021). Transpiration increases under high-temperature stress: Potential mechanisms, trade-offs and prospects for crop resilience in a warming world. *Plant, Cell & Environment*, *44*(7), 2102–2116. https://doi.org/10.1111/pce.13970

Scanlon, B. R., Faunt, C. C., Longuevergne, L., Reedy, R. C., Alley, W. M., McGuire, V. L., & McMahon, P. B. (2012). Groundwater depletion and sustainability of irrigation in the US High Plains and Central Valley. *Proceedings of the National Academy of Sciences of the United States of America*, *109*(24), 9320–9325. https://doi.org/10.1073/PNAS.1200311109/SUPPL_FILE/PNAS.201200311SI.PDF

Schauberger, B., Archontoulis, S., Arneth, A., Balkovic, J., Ciais, P., Deryng, D., Elliott, J., Folberth, C., Khabarov, N., Müller, C., Pugh, T. A. M., Rolinski, S., Schaphoff, S., Schmid, E., Wang, X., Schlenker, W., & Frieler, K. (2017). Consistent negative response of US crops to high temperatures in observations and crop models. *Nature Communications 2017 8:1*, *8*(1), 1–9. https://doi.org/10.1038/ncomms13931

Schlenker, W., & Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proceedings of the National Academy of Sciences of the United States of America*, *106*(37), 15594–15598. https://doi.org/10.1073/PNAS.0906865106

Seager, R., Lis, N., Feldman, J., Ting, M., Williams, A. P., Nakamura, J., Liu, H., & Henderson, N. (2018). Whither the 100th Meridian? The Once and Future Physical and Human Geography of America's Arid–Humid Divide. Part I: The Story So Far. *Earth Interactions*, *22*(5), 1–22. https://doi.org/10.1175/EI-D-17-0011.1

Seneviratne, S. I., Zhang, X., Adnan, M., Badi, W., Dereczynski, C., Luca, A. D., Ghosh, S., Iskandar, I., Kossin, J., Lewis, S., Otto, F., Pinto, I., Satoh, M., Vicente-Serrano, S. M., Wehner, M., & Zhou, B. (2021). Weather and Climate Extreme Events in a Changing Climate. *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, 1513–1766. https://doi.org/10.1017/9781009157896.013

Shao, Y., Lunetta, R. S., Wheeler, B., Iiames, J. S., & Campbell, J. B. (2016). An evaluation of time-series smoothing algorithms for land-cover classifications using MODIS-NDVI multi-temporal data. *Remote Sensing of Environment*, *174*, 258–265. https://doi.org/10.1016/J.RSE.2015.12.023

Siebert, S., Webber, H., Zhao, G., & Ewert, F. (2017). Heat stress is overestimated in climate impact studies for irrigated agriculture. *Environmental Research Letters*, *12*(5), 54023. https://doi.org/10.1088/1748-9326/AA702F

Singh, R. K., & Irmak, A. (2009). Estimation of Crop Coefficients Using Satellite Remote Sensing. *Journal of Irrigation and Drainage Engineering*, *135*(5), 597–608. https://doi.org/10.1061/(ASCE)IR.1943-4774.0000052

Smith, M. D. (2011). An ecological perspective on extreme climatic events: A synthetic definition and framework to guide future research. *Journal of Ecology*, *99*(3), 656–663. https://doi.org/10.1111/J.1365-2745.2011.01798.X

Srivastava, A., Sahoo, B., Raghuwanshi, N. S., & Singh, R. (2017). Evaluation of Variable-Infiltration Capacity Model and MODIS-Terra Satellite-Derived Grid-Scale Evapotranspiration Estimates in a River Basin with Tropical Monsoon-Type Climatology. *Journal of Irrigation and Drainage Engineering*, *143*(8), 04017028. https://doi.org/10.1061/(ASCE)IR.1943-4774.0001199

Steward, D. R., & Allen, A. J. (2016). Peak groundwater depletion in the High Plains Aquifer, projections from 1930 to 2110. *Agricultural Water Management*, *170*, 36–48. https://doi.org/10.1016/j.agwat.2015.10.003

Steward, D. R., Bruss, P. J., Yang, X., Staggenborg, S. A., Welch, S. M., & Apley, M. D. (2013). Tapping unsustainable groundwater stores for agricultural production in the High Plains Aquifer of Kansas, projections to 2110. *Proceedings of the National Academy of Sciences of the United States of America*, *110*(37), E3477–E3486. https://doi.org/10.1073/PNAS.1220351110/SUPPL_FILE/PNAS.201220351SI.PDF

Stöckle, C. O., Donatelli, M., & Nelson, R. (2003). CropSyst, a cropping systems simulation model. *European Journal of Agronomy*, *18*(3), 289–307. https://doi.org/10.1016/S1161-0301(02)00109-0

Strobl, C., Boulesteix, A. L., Kneib, T., Augustin, T., & Zeileis, A. (2008). Conditional variable importance for random forests. *BMC Bioinformatics*, *9*(1), 1–11. https://doi.org/10.1186/1471-2105-9-307/FIGURES/4

Su, Z. (2002). The Surface Energy Balance System (SEBS) for estimation of turbulent heat fluxes. *Hydrology and Earth System Sciences*, *6*(1), 85–99. Scopus. https://doi.org/10.5194/hess-6-85-2002

Suárez, F. G., Fulginiti, L. E., & Perrin, R. K. (2019). What Is the Use Value of Irrigation Water from the High Plains Aquifer? *American Journal of Agricultural Economics*, *101*(2), 455–466. https://doi.org/10.1093/AJAE/AAY062

Tabari, H., & Talaee, P. H. (2014). Sensitivity of evapotranspiration to climatic change in different climates. *Global and Planetary Change*, *115*, 16–23. https://doi.org/10.1016/J.GLOPLACHA.2014.01.006

Tack, J., Barkley, A., & Hendricks, N. (2017). Irrigation offsets wheat yield reductions from warming temperatures. *Environmental Research Letters*, *12*(11), 114027. https://doi.org/10.1088/1748-9326/aa8d27

Talib, A., Desai, A. R., Huang, J., Griffis, T. J., Reed, D. E., & Chen, J. (2021). Evaluation of prediction and forecasting models for evapotranspiration of agricultural lands in the Midwest U.S. *Journal of Hydrology*, *600*, 126579. https://doi.org/10.1016/J.JHYDROL.2021.126579

Tavakol, A., Rahmani, V., & Harrington, J. (2020). Probability of compound climate extremes in a changing climate: A copula-based study of hot, dry, and windy events in the central United States. *Environmental Research Letters*, *15*(10), 104058. https://doi.org/10.1088/1748-9326/ABB1EF

Thiery, W., Davin, E. L., Lawrence, D. M., Hirsch, A. L., Hauser, M., & Seneviratne, S. I. (2017). Present-day irrigation mitigates heat extremes. *Journal of Geophysical Research: Atmospheres*, *122*(3), 1403–1422. https://doi.org/10.1002/2016JD025740

Thiery, W., Visser, A. J., Fischer, E. M., Hauser, M., Hirsch, A. L., Lawrence, D. M., Lejeune, Q., Davin, E. L., & Seneviratne, S. I. (2020). Warming of hot extremes alleviated by expanding irrigation. *Nature Communications*, *11*(1), Article 1. https://doi.org/10.1038/s41467-019-14075-4

Torres, A. F., Walker, W. R., & McKee, M. (2011). Forecasting daily potential evapotranspiration using machine learning and limited climatic data. *Agricultural Water Management*, *98*(4), 553–562. https://doi.org/10.1016/j.agwat.2010.10.012

Trout, T. J., & DeJonge, K. C. (2017). Water productivity of maize in the US high plains. *Irrigation Science*, *35*(3), 251–266. Scopus. https://doi.org/10.1007/s00271-017-0540-1

Troy, T. J., Kipgen, C., & Pal, I. (2015). The impact of climate extremes and irrigation on US crop yields. *Environmental Research Letters*, *10*(5), 54013. https://doi.org/10.1088/1748-9326/10/5/054013

Tukey, J. W. (1949). Comparing Individual Means in the Analysis of Variance. *Biometrics*, *5*(2), 99–114. JSTOR. https://doi.org/10.2307/3001913

Vadeboncoeur, M. A., Green, M. B., Asbjornsen, H., Campbell, J. L., Adams, M. B., Boyer, E. W., Burns, D. A., Fernandez, I. J., Mitchell, M. J., & Shanley, J. B. (2018). Systematic variation in evapotranspiration trends and drivers across the Northeastern United States. *Hydrological Processes*, *32*(23), 3547–3560. https://doi.org/10.1002/hyp.13278

Valipour, M., Gholami Sefidkouhi, M. A., & Raeini−Sarjaz, M. (2017). Selecting the best model to estimate potential evapotranspiration with respect to climate change and magnitudes of extreme events. *Agricultural Water Management*, *180*, 50–60. https://doi.org/10.1016/j.agwat.2016.08.025

van der Laan, M. J. (2006). Statistical inference for variable importance. *International Journal of Biostatistics*, *2*(1). https://doi.org/10.2202/1557-4679.1008/MACHINEREADABLECITATION/RIS

Vogel, E., Donat, M. G., Alexander, L. V., Meinshausen, M., Ray, D. K., Karoly, D., Meinshausen, N., & Frieler, K. (2019). The effects of climate extremes on global agricultural yields. *Environmental Research Letters*, *14*(5), 54010. https://doi.org/10.1088/1748-9326/AB154B

Walter, M. T., Wilks, D. S., Parlange, J.-Y., & Schneider, R. L. (2004). Increasing Evapotranspiration from the Conterminous United States. *Journal of Hydrometeorology*, *5*(3), 405–408. https://doi.org/10.1175/1525-7541(2004)005<0405:IEFTCU>2.0.CO;2

Wei, S., Xu, T., Niu, G.-Y., & Zeng, R. (2022). Estimating Irrigation Water Consumption Using Machine Learning and Remote Sensing Data in Kansas High Plains. *Remote Sensing*, *14*(13), Article 13. https://doi.org/10.3390/rs14133004

Wiederstein, T., Sharda, V., Aguilar, J., Hefley, T., Ciampitti, I. A., Sharda, A., & Igwe, K. (2022). Evaluating spatial and temporal variations in sub-field level crop water demands. *Frontiers in Agronomy*, *0*, 98. https://doi.org/10.3389/FAGRO.2022.983244

Williams, J. R., Jones, C. A., & Dyke, P. T. (1984). A modelling approach to determining the relationship between erosion and soil productivity. *Transactions - American Society of Agricultural Engineers*, *27*(1), 129–144. Scopus.

Willmott, C. J., & Matsuura, K. (2005). Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. *Climate Research*, *30*(1), 79–82. https://doi.org/10.3354/CR030079

Wilson, A. B., Avila-Diaz, A., Oliveira, L. F., Zuluaga, C. F., & Mark, B. (2022). Climate extremes and their impacts on agriculture across the Eastern Corn Belt Region of the U.S. *Weather and Climate Extremes*, *37*, 100467. https://doi.org/10.1016/J.WACE.2022.100467

Wu, L., & Fan, J. (2019). Comparison of neuron-based, kernel-based, tree-based and curve-based machine learning models for predicting daily reference evapotranspiration. *PLOS ONE*, *14*(5), e0217520. https://doi.org/10.1371/journal.pone.0217520

Xiang, Z., Bailey, R. T., Nozari, S., Husain, Z., Kisekka, I., Sharda, V., & Gowda, P. (2020). DSSAT-MODFLOW: A new modeling framework for exploring groundwater conservation strategies in irrigated areas. *Agricultural Water Management*, *232*, 106033. https://doi.org/10.1016/j.agwat.2020.106033

Yilmaz, E., Akçay, S., Gürbüz, T., Dagdelen, N., & Sezgin, F. (2010). Effect of different water stress on the yield and yield components of second crop corn in semiarid climate. *Journal of Food, Agriculture and Environment*, *8*(3-4 PART 1), 415–421.

Yin, Z., Wen, X., Feng, Q., He, Z., Zou, S., & Yang, L. (2016). Integrating genetic algorithm and support vector machine for modeling daily reference evapotranspiration in a semi-arid mountain area. *Hydrology Research*, *48*(5), 1177–1191. https://doi.org/10.2166/nh.2016.205

Zhang, J., Zhou, X., Yang, S., & Ao, Y. (2023). Spatiotemporal Variations in Evapotranspiration and Their Driving Factors in Southwest China between 2003 and 2020. *Remote Sensing*, *15*(18), Article 18. https://doi.org/10.3390/rs15184418

Zhang, X., Alexander, L., Hegerl, G. C., Jones, P., Tank, A. K., Peterson, T. C., Trewin, B., & Zwiers, F. W. (2011). Indices for monitoring changes in extremes based on daily temperature and precipitation data. *Wiley Interdisciplinary Reviews: Climate Change*, *2*(6), 851–870. https://doi.org/10.1002/WCC.147

Zhang, X., Hegerl, G., Zwiers, F. W., & Kenyon, J. (2005). Avoiding Inhomogeneity in Percentile-Based Indices of Temperature Extremes. *Journal of Climate*, *18*(11), 1641–1651. https://doi.org/10.1175/JCLI3366.1

Zhao, C., Liu, B., Piao, S., Wang, X., Lobell, D. B., Huang, Y., Huang, M., Yao, Y., Bassu, S., Ciais, P., Durand, J. L., Elliott, J., Ewert, F., Janssens, I. A., Li, T., Lin, E., Liu, Q., Martre, P., Müller, C., … Asseng, S. (2017). Temperature increase reduces global yields of major crops in four independent estimates. *Proceedings of the National Academy of Sciences of the United States of America*, *114*(35), 9326–9331. https://doi.org/10.1073/PNAS.1701762114/SUPPL_FILE/PNAS.1701762114.SAPP.PDF

Zhao, H., Di, L., Guo, L., Zhang, C., & Lin, L. (2023). An Automated Data-Driven Irrigation Scheduling Approach Using Model Simulated Soil Moisture and Evapotranspiration. *Sustainability*, *15*(17), Article 17. https://doi.org/10.3390/su151712908

Zhou, G., Wei, X., Chen, X., Zhou, P., Liu, X., Xiao, Y., Sun, G., Scott, D. F., Zhou, S., Han, L., & Su, Y. (2015). Global pattern for the effect of climate and land cover on water yield. *Nature Communications*, *6*(1), Article 1. https://doi.org/10.1038/ncomms6918

Zou, Y., Saddique, Q., Ali, A., Xu, J., Khan, M. I., Qing, M., Azmat, M., Cai, H., & Siddique, K. H. M. (2021). Deficit irrigation improves maize yield and water use efficiency in a semi-arid environment. *Agricultural Water Management*, *243*, 106483. https://doi.org/10.1016/j.agwat.2020.106483