

A tripartite study on Bayesian estimation of photosynthetically active radiation, impacts of future climate, and adaptation strategies on crop production: a spatial model framework for the Eastern Kansas River Basin

by

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Abstract

Climate change impacts and adaptation strategies on rainfed and irrigated cropping systems in the Eastern Kansas River Basin (EKSRB; a historically wetter portion of the Great Plains) have not been well-reported. While there are regional-to-global scale climate impact analyses, they rarely provide insights into management and adaptation strategies needed to tackle climate risk impacts on crop production in the EKSRB. As climate warms with its negative impacts, producers in the region continually look out for the latest management and adaptation options to optimize crop production, while saving resources. Traditional methods for quantifying climate change impacts and studies done in the western part of the Great Plains have relied on point-scale process-based crop modeling analysis to generalize regional insights. However, a comprehensive outlook to provide specific solutions and insights into climate change impacts and adaptation options will require a spatially explicit approach, treating each field in the region as an independent landscape capable of providing location-specific insight on crop productivity and water use management. More so, improvement in process-based crop model inputs such as photosynthetically active radiation (PAR) is essential to enhance model accuracy, while also documenting new estimation methods.

The ultimate goal of this dissertation is to develop climate change adaptation strategies for rainfed and irrigated maize production in EKSRB using a combination of county-level and fine-scale spatial protocols. We quantified location-specific impacts under heterogeneous responses to environmental variability and different water management techniques using process-based crop models. In addition, this dissertation also developed a Bayesian regression framework to improve the estimation of PAR, which is required to enhance process-based crop model accuracy. The specific research objectives are: (1) assess the impacts of future climate conditions and root

proliferation adaptation strategy on rainfed maize production; (2) develop a fine-scale spatial protocol for quantifying climate change impacts on maize productivity under different irrigation management strategies; (3) improve irrigated maize productivity based on genotype-specific and agronomic adaptation strategies under climate change; and (4) develop a Bayesian regression framework to improve estimation of PAR for crop yield prediction in EKS RB.

A county-level CERES-Maize crop model was calibrated and validated in the EKS RB to study the impacts of late century (2071-2100) future climate scenarios under the SSP245 emission pathway using the CMIP6 climate models. A novel root proliferation adaptation strategy was tested to assess the impact of these climate change signals on regional rainfed maize yield and rainfall productivity relative to baseline climate conditions (1985–2014). Results showed that baseline yield values ranged from 6,522 to 12,849 kg ha⁻¹, with a regional average value of 9,270 kg ha⁻¹. Projections for the late century scenario indicate a substantial decline in maize yield (36% to 50%) and rainfall productivity (25% to 42%). Introducing a hypothetical maize cultivar by employing root proliferation as an adaptation strategy resulted in a 27% increase in regional maize yield, and a 28% increase in rainfall productivity compared to the reference cultivar without adaptation. These findings offer valuable insights for the US Great Plains maize growers and breeders, guiding strategic decisions to adapt rainfed maize production to the region's impending challenges posed by climate change.

To assess the location-specific response of irrigated maize production to future climate conditions, a fine-scale spatial protocol was developed. This protocol was tested using Shawnee County of the EKS RB as a case study for a comprehensive assessment of climate change impacts under different future representative concentration pathways (RCPs) of CO₂ emission and irrigation management techniques. Simulation results showed that future irrigated maize yield

decline may have occurred due to shortened growing season length, with values ranging from 21% to 38% (early and late century, respectively) under RCP 4.5, and from 22% to 70% (early and late century, respectively) under RCP 8.5. Despite the yield declines, irrigation water use under full allocation increased by 9% to 23%, with a significant reduction in average farmers' net returns ranging from 53% to 80% (RCPs 4.5 and 8.5, respectively), and a significant decline in irrigation water productivity. Assessing the impacts of deficit irrigation resulted in water savings ranging from 3 to 15% without further diminishing overall maize productivity. Our results indicate that climate-smart irrigation management strategies implemented at a fine-scale spatial resolution could help save water despite negative climate impacts on future maize production in the region. The future of maize production in the region necessitates integrating yield-advancing cultivars and proper agronomic management with improved water management in order to meet the expected grain demand over the next decades.

Impacts of *in silico* genotype-specific adaptation for selected maize genotype-specific parameters, treated as quantitative traits (improve canopy photosynthesis for radiation use efficiency [RUE], light extinction [KCAN], and heat tolerance [HEAT]), and agronomic management (shifting planting window [PD1 & PD2], and non-limiting nutrient allocation [NNL]) on yield and irrigation water use were assessed. Results showed that incorporating individual levels of either genotype-specific or agronomic adaptation strategies resulted in significant yield and water savings improvements relative to no adaptation scenario under future climate conditions. However, an integrated adaptation strategy linked to improved RUE, HEAT, KCAN, NNL, and PD2, resulted in the early 21st century (2025-2049) yield gain of 0.6 to 3% (RCPs 4.5 and 8.5, respectively), with water savings of 10 to 13% (RCPs 4.5 and 8.5, respectively), relative to historical condition (1991-2015). Going forward into the 21st century, marginal yield deviations

were observed (especially under RCP 4.5) with further increase in water savings. The overall findings emphasize the transformative potential of all-inclusive integrated adaptation strategies in mitigating the impacts of climate change on irrigated maize production in the Great Plains.

Finally, a practical Bayesian regression framework for PAR estimation was developed for the EKS RB. Results revealed that daily PAR values generated from the posterior predictive distribution using the Gibbs sampler algorithm outperformed the PAR estimates from the traditional linear modeling approach. In addition, soybean yield estimates using PAR from the Bayesian framework as inputs, captured the year-to-year variability in observed yield better than using PAR estimates from the traditional linear modeling approach. The results of this study support the use of the Bayesian regression framework for robust estimation of PAR inputs to crop models.

This dissertation underscores the utility of climate-smart strategies for the EKS RB maize production by assessing climate impacts, adaptive irrigation, and climate adaptation strategies, and in addition, enhancing crop model accuracy using Bayesian-estimated PAR. In general, it offers location-specific solutions to improve maize productivity and resilience under climate change.

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“The only true wisdom is in knowing you know nothing.” — Socrates (470 – 399 BCE)

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Dedication

I dedicate this work to:

God, who showed me mercy and made all things possible.

my wife (Chidimma Onyekwelu), who supported me tirelessly and suffered the most during my

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my lovely daughters (Adannia and Akuabata), for their meek undying love and in whose smiles, I

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Preface

In writing this dissertation, I have carefully followed the format made available by Kansas State University Graduate School. The arrangement of the dissertation is presented in manuscript format and chapterized following the university guidelines. The dissertation consists of six chapters, each serving a unique purpose in presenting my research findings.

Chapter 1 is an introduction to the topic which documents review of literature on global climate change and impacts on agriculture systems. It went further to describe the Eastern Kansas River Basin (EKSRB) of the US Great Plains and the 100th Meridian more broadly. This chapter also discussed the importance of process-based crop models for assessing agroecosystem productivity and input constraints challenges. Finally, it discussed the utility and need for spatial model frameworks for assessing climate and adaptation impacts on agricultural systems. The four subsequent chapters consist of manuscripts prepared according to specific guidelines for different academic journals.

Chapter 2, *Root proliferation adaptation strategy improved maize productivity in the US Great Plains: insights from crop simulation model under future climate change*, has been published in the Science of the Total Environment journal in 2024. This research represents impacts of future climate and root proliferation adaptation strategy on rainfed maize productivity in EKSRB of the US Great Plains. The research offers valuable insights for the US Great Plains maize growers and breeders, guiding strategic decisions to adapt rainfed maize production to the region's impending challenges posed by climate change.

Chapter 3, *Quantifying climate change impacts on maize productivity under different irrigation management strategies: a high-resolution spatial analysis in the U.S. Great Plains* is currently under review in Agricultural Water Management journal. This research developed a

spatial protocol for a comprehensive location-specific assessment of future climate impacts on maize production in EKS RB under different climate scenarios and irrigation management strategies. The research is essential for identifying location-specific proactive water management strategies that, when combined with agricultural adaptation techniques, will help farming communities manage emerging climate risks linked to drier future conditions.

Chapter 4, *in-silico evidence for improving irrigated maize productivity based on genotype-specific adaptation and agronomic management under climate change* has been prepared for submission to Computer and Electronics in Agriculture journal. This research presents location-specific insights on maize yield and irrigation water use under future climate conditions, deficit irrigation management, and different adaptation strategies. This research offers optimism for improving maize yield, while saving water resources under future climate conditions in EKS RB.

Chapter 5, *A Bayesian regression approach for estimating photosynthetically active radiation using satellite data: implications for soybean yield prediction using the CROPGRO model*, has been published in Earth Systems and Environment journal in 2024. This research offers a practical and novel approach for estimating photosynthetically active radiation (PAR) using Bayesian regression framework. The improved PAR estimates led to improvement in crop yield simulation in EKS RB.

Finally, Chapter 6 summarizes the research findings, creating a link between overall outcome and agricultural implications of the research. It also offered recommendations for future research and directions, creating a continuum for advancing climate impact research on agroecosystem of the US Great Plains.

Chapter 1 - Introduction

1.1 Global climate change and impacts on agricultural systems.

Global climate change, which is driven by natural variability and human activities, entails the change in the mean state of the earth climate system, usually at decadal timescales (IPCC, 2023a, 2023b; Porinchu, 2017). These changes in mean state of the earth climate system include changes in temperature, precipitation, and atmospheric circulation patterns (Porinchu, 2017). While variability in natural systems contribute to global climate change, reports from different scientific fronts, especially the Intergovernmental Panel on Climate Change (IPCC), affirms that human activities, mainly through industrial emissions of greenhouse gases (GHGs) such as CO₂ and methane (CH₄), have unambiguously caused global warming, with record value of global surface temperature reaching 1.1 °C above the mid-19th century (1850-1900) in 2011–2020 (IPCC, 2023a, 2023b; C. Lyon et al., 2022; L. M. Lyon et al., 2022). With further increase in global GHG emissions due to unequal and ongoing contributions arising from unsustainable energy use, land-use changes, and consumption and production patterns, the Paris Agreement through the United Nations, pursues efforts to limit global warming to 1.5 °C (Brown et al., 2018; United Nations, 2015). The multifaceted impacts of this effort may involve cutting down on GHG emissions through sustainable practices, integrating land-use practices that encourage sustainable management of land resources, and so on. However, with the current rate of GHG emissions, coupled with adverse anthropogenic actions like massive deforestation of the Amazon rainforest (one of the largest carbon sinks on Earth), the Paris Agreement is not on track to limit global temperature increases to 1.5 °C above pre-industrial levels (das Neves et al., 2021; IPCC, 2023a; Staal et al., 2015, 2020; Zaman, 2022).

Recent quantitative changes in GHGs emissions such as those of CO₂ and CH₄ have been reported in the literature. For example, atmospheric CO₂ concentration reached 410 parts per million (ppm) in 2019, significantly increasing from the 360 ppm during the mid-1990s (IPCC, 2023a, 2023b). CH₄ concentration on the other hand, reached 1866 parts per billion (ppb), with the current levels suggesting an unprecedented increase seen in at least 800,000 years. (IPCC, 2023a). The record changes in GHG emissions are an indication of future warming and variability in precipitation patterns (IPCC 2023a).

Coupled ocean-atmospheric global climate models (GCMs) are used to simulate the Earth's climate system to study the sensitivity of the climate system to various forcings, and to project changes in temperature and precipitation under various future scenarios (Porinchu, 2017). Representative Concentration Pathways (RCPs) are the scenarios that guide global climate projections presented in IPCC reports (Porinchu, 2017). Different greenhouse gas emission pathways are represented by four RCPs: RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5. Each RCP corresponds to a different level of radiative forcing measured in watts per square meter (W/m²). For example, the RCP 2.6 scenario based on 2.6 Wm⁻² radiative forcing characterizes future climate in which strong reductions are seen in GHG emissions, with radiative forcing peaking in the mid-21st century and subsequently declining towards the end of the 21st century (2100). The RCP 8.5 on the other hand, represent a future where GHG emissions continue to increase unabated throughout the 21st century (IPCC, 2023a, 2023b; C. Lyon et al., 2022; Porinchu, 2017). It is important to note that the choice of RCP influences the magnitude of climate impacts and projected changes in temperature and precipitation. For instance, using multi-model projections under RCP 8.5, the surface temperature is expected to exceed 5 °C in North America through the end of the 21st century, relative to 1985-2005 (Figure 1.1; IPCC, 2023a; Pachauri et al., 2014; Porinchu,

2017). Precipitation on the other hand is expected to show greater spatial variability, with a sharp distinction between wet and dry seasons and wet and dry regions increasing during the 21st century (Figure 1.1; Almazroui et al., 2021; Porinchu, 2017).

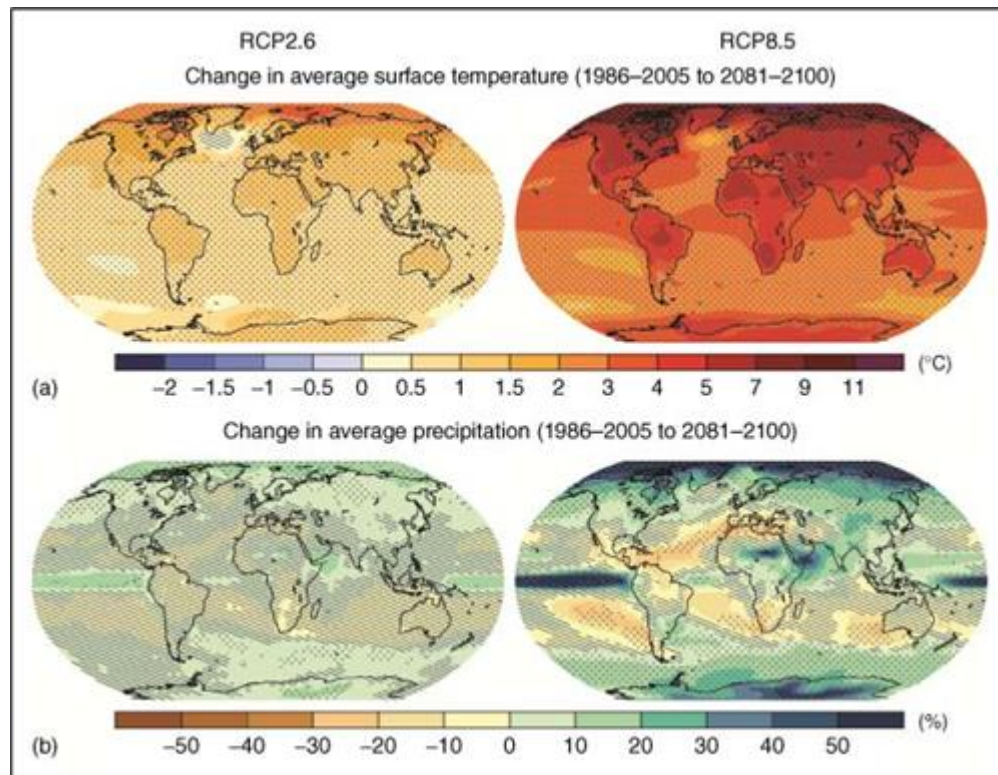


Figure 1.1. Multi-model mean projections of global surface temperature and precipitation under RCP 2.6 and RCP 8.5 (IPCC, 2013; 2023a)

With increasing temperature and uncertain variability in precipitation due to climate change (Figure 1.1), global agricultural system may suffer yield shock and increased atmospheric evaporative demand (Araya et al., 2015; Ayankojo et al., 2020; Getachew et al., 2021; Godfray et al., 2010; IPCC, 2023a, 2023b; Onyekwelu & Sharda, 2024b; Rosenzweig et al., 2008; 2013; 2014). For global mean temperature increase ranging from 1.6 to 6.0 °C, coupled with changes in precipitation, humidity, solar radiation, and CO₂, projected climate change impacts on maize biophysical responses ranges from -15% to > -35% in the higher latitudes (Figure 1.2), respectively (IPCC, 2023a, 2023b). At regional scale, Yang & Wang (2023) reported that heat stress due to

climate change will jeopardize crop production in the US Corn Belt. They found that yield declines of 40% and 22% are projected for rainfed maize and soybean by late century, respectively.

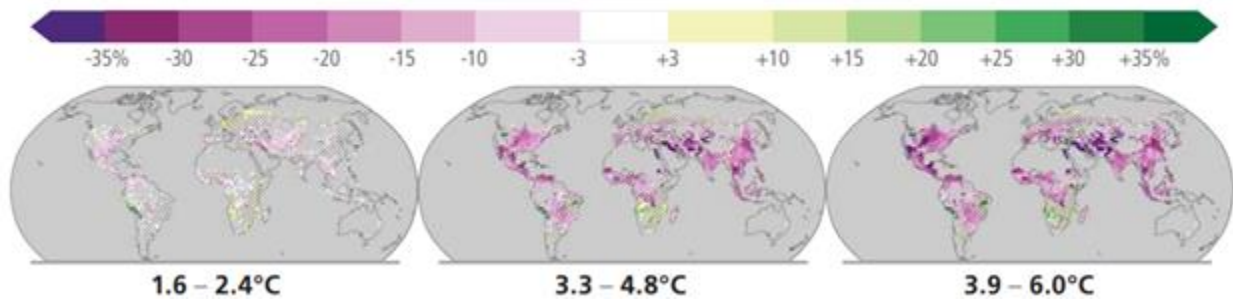


Figure 1.2. Projected changes in maize yield due to changes in temperature, coupled with changes in precipitation, humidity, solar radiation, and CO₂ (IPCC, 2023b, 2023a)

Increased atmospheric evaporative demand due to climate change has severe implications for agricultural water use and management. For example, Albano et al. (2022) found that evapotranspiration (ET) has increased in the current climate and will further increase under future climate conditions. Increases in ET in the contiguous US were found to be strongly impacted by temperature change, with highest increase centered on the Rio Grande region (Albano et al., 2022). The ET increase in the contiguous US points towards potential increase in freshwater withdrawals for agricultural use. A study in the contiguous US (Figure 1.3) shows that projected changes in freshwater withdrawals may increase by 50% in the Great Plains (Brown et al., 2013). Overall, studies have shown the potential adverse effects of climate change on crop biophysical responses and water withdrawal. However, the need for more in-depth and localized studies have been the subject of intense discussion, especially with respect to prioritizing climate transition pathways and adaptation strategies to ensure food security and resource management.

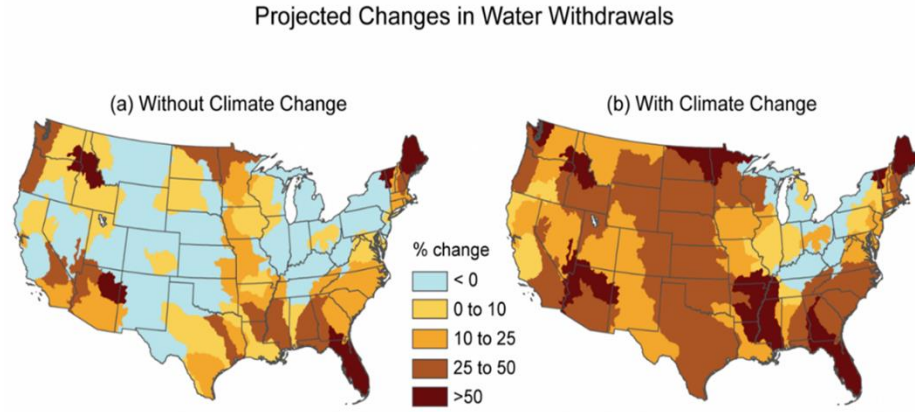


Figure 1.3. Projected changes in freshwater withdrawal with and without climate change (Brown et al., 2013).

1.2 The 100th Meridian and the Eastern Kansas River Basin

As first noted by John Wesley Powell (Powell, 1879; Seager, et al., 2018), there is a significant difference between precipitation (rainfall) in the west and the east of the United States. John Powell introduced the idea that the 100th Meridian west (Figure 1.4; line of longitude) partitions the United States into arid western and humid eastern regions, creating an east-west aridity gradient (Figure 1.4; Seager, et al., 2018). The nation's agricultural patterns follow this east-to-west gradient of increasing aridity, which also shapes its hydrology, vegetation, human settlements, and land use practices. For example, Seager et al. (2018) reported that moving from east to west of the country reveals that farms are fewer but larger in the west, reflecting low land productivity and water as a potential limiting factor.

While the 100th Meridian represents a real arid-humid divide in the physical climate and landscape (Figure 1.4), scientists have shown that the hydroclimatic conditions that characterize this line have been shifting eastwards, thereby creating drier conditions (sometimes termed a ‘new 100th meridian’) to the east (Figure 1.4; Krajick, 2018; Seager et al., 2018). The implications of

this eastward migration of aridity on crop production and water use remain uncertain, as further eastward migration is expected over the next decades (Krajick, 2018; Seager et al., 2018).



Figure 1.4. The 100th meridian west (solid black line), with potential eastward shift in the line (dotted line) due to climate change (Krajick, 2018).

The “new 100th Meridian” encroaches into the Eastern Kansas River Basin (Figure 1.5; EKSRB; a very important crop-producing region and historically wetter portion of the Great Plains), with a higher tendency to create warmer conditions in the region under future climate projections (Figure 1.5). The EKSRB represents a socially and economically important region and includes some of the Kansas’s major population centers, including the seat of the state government. It represents the watershed of the Kansas River, spanning from the confluence of the Smoky Hill and Republican rivers in the west, to its terminus at the Missouri river in Kansas City (Onyekwelu & Sharda, 2024a, 2024b; Sen et al., 2023, 2024).

Historically, most agricultural research in the Kansas River watershed has occurred in its major upstream tributaries such as the Smoky Hill Rivers (Araya et al., 2017; Kisekka et al., 2016, 2017). As a result, little is known about climate risks or adaptation options in the EKSRB, or more broadly along the new 100th Meridian. The EKSRB is a useful analog for the eastern Great Plains spanning Texas, Oklahoma, Kansas, Nebraska, and South Dakota that may be exposed to increasing aridity in the 21st century (Figure 1.5).

Crop production in EKS RB includes a mix of rainfed and irrigated croplands, with irrigation particularly common for crops that are water-demanding, like maize and soybean (Onyekwelu & Sharda, 2024b, 2024a). Irrigation in the EKS RB is predominantly sourced from groundwater, with surface water use in some counties on the eastern edge of the basin (Kansas Department of Agriculture, 2012). Irrigation in the region is highly sensitive to interannual rainfall variability (Figure 1.6); consequently, representing the water use sector with the greatest potential sensitivity to climate change. Increasing groundwater pumping to enhance crop yield has been reported to result in the depletion of groundwater and surface water resources (Scanlon et al., 2012; Steward et al., 2013). Declining water levels in the High Plains aquifer have necessitated the need to find alternative irrigation water management strategies to sustain crop production and improve aquifer recovery. This is because producers need irrigation recommendations that can optimize overall farm profit, especially under depleting water resources and future climate conditions.

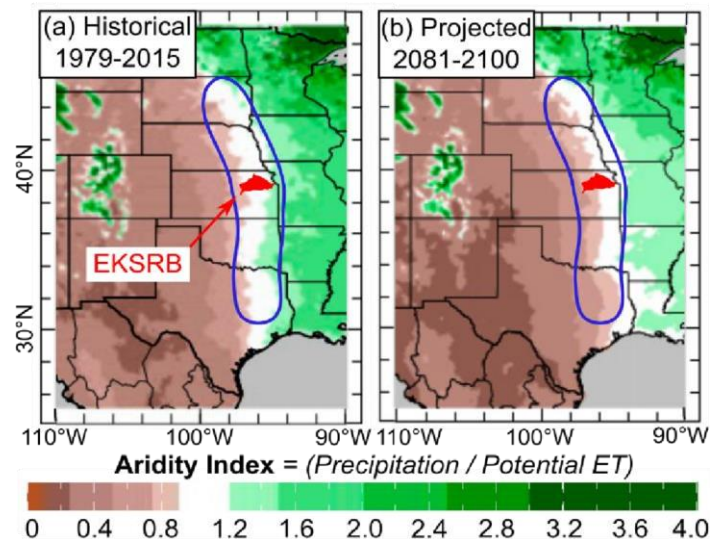


Figure 1.5. Aridity index for (a) historical mean and (b) projected future conditions. An aridity index of 1.0 indicates that annual precipitation is equal to annual potential evapotranspiration. The EKS RB is shown in red. The blue outline indicates the agricultural region similarly positioned with respect to the aridity gradient (Seager et al., 2018).

With consequences of groundwater depletion in the Great Plains due to over-pumping for irrigation (McGuire, 2012; Scanlon et al., 2012; Steward et al., 2013), the EKS RB stand a chance to learn from experience and enshrine management strategies that can sustain the region's water resources. Much of the EKS RB is underlain by the alluvial aquifer, which has maintained stable water levels mainly attributed to regional rainfall (Compare et al., 2021). Sustainable use of water resources for irrigation requires developing water management strategies that promote water conservation, enhance farm profitability, and support other water-dependent sectors. This is especially important to avert similar water decline issues faced by Western Kansas and major upstream tributaries of the Kansas River. Therefore, there is a critical need to understand potential climate change and impacts on crop productivity and water use along the new 100th Meridian and the EKS RB.

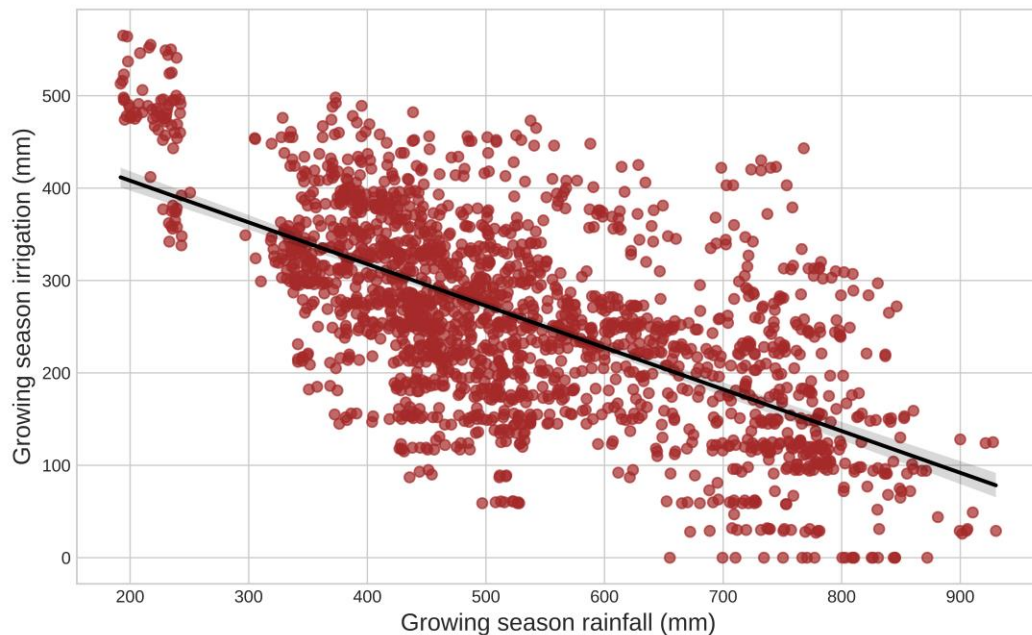


Figure 1.6. Maize irrigation sensitivity to rainfall in the EKS RB. Black line represents linear model with shaded 95% confidence interval (not prediction interval) around the mean. Datasets generated from regional gridded crop modeling analysis.

1.3 Process-based crop models and input requirement constraints.

Process-based crop models are essential tools for studying agricultural systems because they provide a robust framework for evaluating "what-if" scenarios and exploring complex genotype-by-environment-by-management (GxE_M) interactions (Hoogenboom et al., 2019; Jones et al., 2003; Liang et al., 2023; Zhao et al., 2019). Traditional field experiments are constrained by time, resources, and environmental variability; limiting the ability to test numerous treatments or anticipate responses under future conditions. Crop models bridge this gap by simulating crop growth and development in diverse conditions based on mechanistic understanding of crop physiology, integrating crop genotypes, soils, environmental variables, and management conditions. When the corresponding genotype-specific parameters (cultivar parameters) are properly calibrated and validated with field observations (Figure 1.7), process-based crop models can be used to simulate a wide range of environmental and management scenarios. For instance, researchers have evaluated the impact of different planting dates (Getachew et al., 2021), irrigation regimes (Araya et al., 2017b; Kisekka et al., 2017), fertilizer strategies (Liang et al., 2023), or climate change (Araya et al., 2021; Onyekwelu & Sharda, 2024b; Sen et al., 2023, 2024) without the logistical challenges and costs of setting up corresponding field trials. By capturing interactions among genetic traits (Guarin et al., 2022, 2023; Poudel et al., 2023), environmental variables, and management practices, crop models can be used to provide insights into optimal strategies for specific cultivars or environments.

Process-based crop models such as DSSAT (Hoogenboom et al., 2019), RZWQM (Ahuja et al., 2000), and SPACSYS (Wu et al., 2007) have been used extensively to quantify the impacts of different field-management practices under different climate conditions. However, the input requirements of these crop models are intensive, and in some cases, a predefined data conversion

routine is used to achieve a set of desired inputs. For example, it is well-reported in the literature that photosynthetically active radiation (PAR) is half of solar radiation (SRAD), and most crop models use this conversion to arrive at PAR input for simulating leaf photosynthesis and aboveground biomass. While this relationship is straightforward and intuitive, many authors have argued that PAR depends on other meteorological variables than just SRAD alone (Aguiar et al., 2012; Alados et al., 1996; Ferrera-Cobos et al., 2020; Mazorra Aguiar et al., 2019; Mizoguchi et al., 2014). According to Ferrera-Cobos et al. (2020b), all PAR models face the difficulty of dependence on local atmospheric conditions, making it impossible to have a good fit extrapolating a model developed under some atmospheric conditions to a place with a different atmospheric condition. More so, the use of half of SRAD as PAR conversion negates the recognition of uncertainty in the input generation process; thus, a stochastic estimation of PAR using the Bayesian modeling framework may be optimum for modeling a random varying cropping system. In addition, it is not always easy to have PAR measurements in an arbitrary location due to difficulties in procuring quantum sensors (Ferrera-Cobos et al., 2020). This is particularly true for some developing countries where meteorological monitoring stations are inadequate (Emeka et al., 2021). Even for developed countries, Su et al. (2007) reported that the United States Surface Radiation Budget Network (SURFRAD) which was established in 1993 to support continuous and long-term measurements of PAR and solar fluxes, has only seven stations operating in climatologically diverse regions. In addition, there are no standards for calibrating PAR sensors; thus, creating shortfalls of PAR datasets in locations where they are needed (Ferrera-Cobos et al., 2020). With every sensor having different limits of uncertainty, concerns also exist about the accuracy of uncalibrated PAR sensors (Ferrera-Cobos et al., 2020b; Mizoguchi et al., 2010; Su et al., 2007). Therefore, with increasing demands for accurate PAR measurements to drive process-

based crop models and future climate research, there is a need for location-specific estimates of PAR to make up for PAR data unavailability.

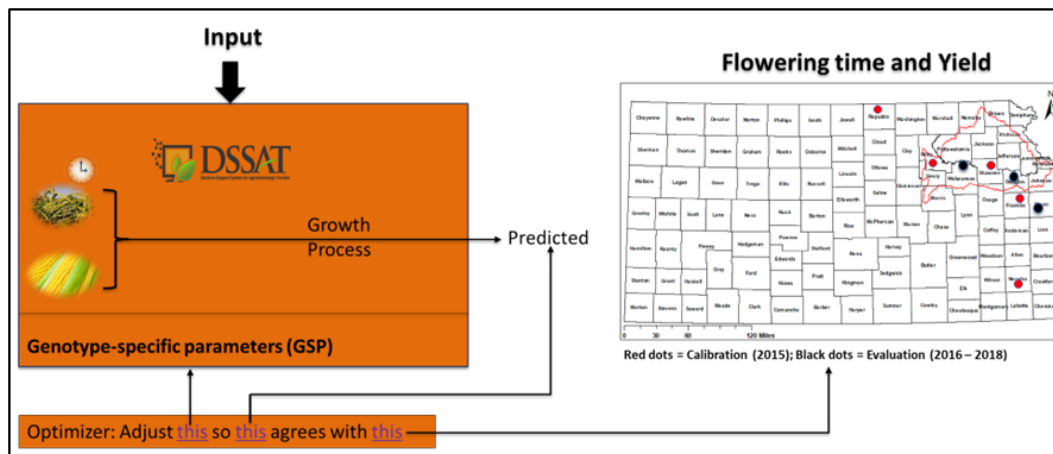


Figure 1.7. Process-based crop modeling framework for calibration and validation. Map is showing locations of maize field trials in Northeast Kansas, United States.

1.4 Spatial crop modeling, climate impacts and adaptation assessment

Although process-based agroecosystem/crop models such as DSSAT (Hoogenboom et al., 2019), RZWQM (Ahuja et al., 2000), and SPACSYS (Wu et al., 2007) have been used extensively to quantify the impacts of different field-management practices under different climate conditions, they are designed to run at point-scale to simulate a homogenous unit, such as a field, which has limitations when considering spatial heterogeneity of environmental conditions (e.g., soil and climate) at a regional scale. While climate impacts are likely to be spatially variable with a heterogeneous response to environmental variability and different water management techniques, transitioning these process-based crop models from field to regional scales is still challenging (Zhang et al., 2020).

Integrating point-scale process-based crop models with geographic information system (GIS) is a perfect illustration of regional crop model applications (Liang et al., 2023; Manivasagam & Rozenstein, 2020; Thorp et al., 2008; Thorp & Bronson, 2013; Zhang et al., 2020). For example,

spatial simulations provide location-specific impacts (Figure 1.8), which can be used to target the allocation of input resources (e.g., irrigation, fertilizer, etc.) for profit maximization, and to assess co-benefits and trade-offs among different ecosystem services (Qiu et al., 2018, 2019). In addition, gridded outputs of regional crop models mapped to their corresponding unique fields can be combined with spatial soil distribution and growing season climate variables to understand key landscape and atmospheric controls on yield, irrigation water use, irrigation water productivity, and farmers' net returns (Onyekwelu et al., 2025). Spatial simulations can provide location-specific insights, which can be used to target the combination of high-yielding and low water use locations under different management and adaptation strategies, especially under future climate condition. Therefore, incorporating a spatial framework into point-scale crop models enables the treatment of each field within a region as an independent landscape (Figure 1.8). This approach facilitates the generation of location-specific insights on crop productivity or water use management (Figure 1.8), thereby supporting sustainable decision-making aimed at mitigating climate impacts and enhancing adaptation potentials.

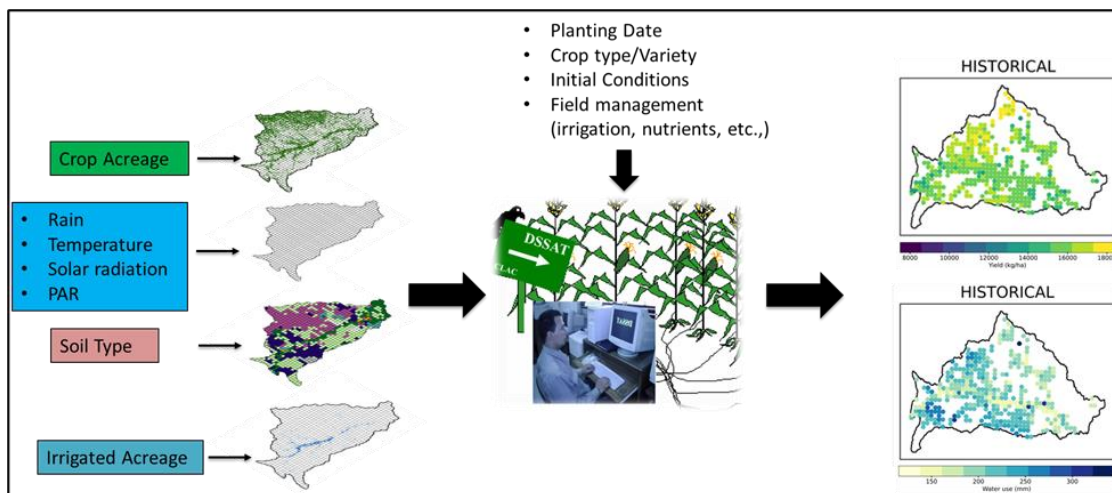


Figure 1.8. Spatial process-based crop modeling framework showing spatial input assimilation to DSSAT crop model and mapping of gridded yield and water use outputs. Example is shown for irrigated maize production in EKS RB.

1.5 Research needs and objectives

Climate change impacts and adaptation strategies on rainfed and irrigated cropping systems in the Eastern Kansas River Basin have not been well-reported. While there are regional-to-global scale climate impact analyses, they rarely provide insights into management and adaptation strategies needed to tackle climate risk impacts on crop production in the EKSRB. As climate warms with its negative impacts, producers in the region continually look out for the latest management and adaptation options to optimize crop production, while saving resources. Traditional methods for quantifying climate change impacts and studies done in the western part of the Great Plains have relied on point-scale process-based crop modeling analysis to generalize regional insights. However, a comprehensive outlook to provide specific solutions and insights into climate change impacts and adaptation options will require a spatially explicit approach, treating each field in the region as an independent landscape capable of providing location-specific insight on crop productivity and water use management. More so, improvement in process-based crop model inputs such as photosynthetically active radiation (PAR) is essential to enhance model accuracy, while also documenting new estimation methods.

The overall goal of this dissertation is to assess climate change impacts and adaptation strategies on rainfed and irrigated maize production in EKSRB using a combination of county-level and fine-scale spatial protocols to quantify location-specific impacts under heterogeneous responses to environmental variability and different water management techniques. We used process-based crop models configured to run in spatial mode to provide location-specific solutions and insights. In addition, the dissertation also developed a Bayesian regression framework to improve the estimation of PAR, which is required to enhance process-based crop model accuracy.

A case study assessing the performance of Bayesian PAR input was tested using the CROPGRO crop model for soybean yield prediction. The specific research objectives of this dissertation are:

1. Assess the impacts of future climate conditions and root proliferation adaptation strategy on rainfed maize production.
2. Develop a fine-scale spatial protocol for quantifying climate change impacts on maize productivity under different irrigation management strategies.
3. Improve irrigated maize productivity based on genotype-specific and agronomic adaptation strategies under climate change.
4. Develop a Bayesian regression framework to improve estimation of PAR for improve crop yield prediction in EKS RB.

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Chapter 2 - Root proliferation adaptation strategy improved maize productivity in the US Great Plains: insights from crop simulation model under future climate change

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2.1 Abstract

Adaptation measures are essential for reducing the impact of future climate risks on agricultural production systems. The present study focuses on implementing an adaptation strategy to mitigate the impact of future climate change on rainfed maize production in the Eastern Kansas River Basin (EKSRB), an important rainfed maize-producing region in the US Great Plains, which faces potential challenges of future climate risks due to a significant east-to-west aridity gradient. We used a calibrated CERES-Maize crop model to evaluate the impacts of baseline climate conditions (1985–2014), late-term future climate scenarios (under the SSP245 emission pathway and CMIP6 models), and a novel root proliferation adaptation strategy on regional maize yield and rainfall productivity. Changes in the plant root system by increasing the root density could lead to yield benefits, especially under drought conditions. Therefore, we modified the governing equation of soil root growth in the CERES-Maize model to reflect the genetic influence of a maize cultivar to improve root density by proliferation. Under baseline conditions, maize yield values ranged from 6,522 to 12,849 kg ha^{-1} , with a regional average value of 9,270 kg ha^{-1} . Projections for the late-term scenario indicate a substantial decline in maize yield (36% to 50%) and rainfall

productivity (25% to 42%). Introducing a hypothetical maize cultivar by employing root proliferation as an adaptation strategy resulted in a 27% increase in regional maize yield, and a 28% increase in rainfall productivity compared to the reference cultivar without adaptation. We observed an indication of spatial dependency of maize yield and rainfall productivity on the regional precipitation gradient, with counties towards the east having an implicit advantage over those in the west. These findings offer valuable insights for the US Great Plains maize growers and breeders, guiding strategic decisions to adapt rainfed maize production to the region's impending challenges posed by climate change.

Keyword: CMIP6, root proliferation, DSSAT CERES-Maize model, EKSRB, rainfed maize yield, rainfall productivity, climate change adaptation.

2.2 Introduction

Agriculture remains the sole foundation for fighting against global malnutrition and hunger (FAO et al., 2020), and in addition, plays a very important role in enhancing regional economy (Wang et al., 2014). The United States, being the world's leading maize producer, accounts for up to 37% of global maize production, with about 14% of this production exported to other countries (Ortiz-Bobea et al., 2019; Yang & Wang, 2023). Major maize-producing regions in the United States lie in the Midwest and the Great Plains, accounting for up to 86% of non-irrigated maize production (Ortiz-Bobea et al., 2019). However, maize requires intensive management optimization for maintaining yields while sustaining global food security and feeding the growing population (Wang et al., 2022). Maize sensitivity to climate change has been reported in form of low yield, alteration in phenology, and shortened photosynthesis (Jones & Thornton, 2003; Lobell & Field, 2007; Ureta et al., 2016; Wang et al., 2022). In addition, it has also been reported that during grain filling of maize, drought stress results in premature death of leaf tissues, lodging, shortened grain filling periods, fewer number of kernels and low kernel weight (K-State Extension, 2007). With variability in the current climate, drought stress impacts have worsened under rainfed production, and may get even worst as precipitation declines under future climate change (Jin et al., 2016). With the proposition that rainfed maize production may suffer severe yield decline in the future, irrigation may close yield loss gaps of explicit disadvantage of drought stress on rainfed production. However, increasing water scarcity due to low well capacities is gradually making irrigation an unsustainable strategy to buffer against future climate change impacts. For example, the Ogallala Aquifer in the Great Plains of the US, which is the major source of irrigation water is declining without sufficient recharge due to over-pumping (Araya, et al., 2017b; McGuire, 2012). Therefore, research efforts need to be channeled towards adapting rainfed maize production to

maximize the benefits of growing season precipitation and improve uptake of deep soil water, especially under limiting and future climate change conditions.

Much like the rest of the agricultural producing areas of the Midwest and the Great Plains, the state of Kansas is one of the largest maize-producing states in the US, with about 700 million bushels produced per year (K-State Extension, 2022) and is ranked 6th in the US for maize production (K-State Extension, 2022; US Corn Production, 2022). Rainfed production dominates the eastern portion of the state, where precipitation is marginally higher than evapotranspiration, with a significant increase in precipitation towards the east, and a rapid decline westward (Lin & Brunsell, 2013; Seager et al., 2018). Increasing temperatures and decline in precipitation are expected to impact the thriving rainfed maize production in the region. Mean surface temperature at global scale has gone up by approximately 0.6 °C during the 20th century (Kothari et al., 2020), and is expected to hit 3.7 °C by the end of 21st century (Pachauri et al., 2014). Tubiello et al. (2002) reported that climate change could potentially affect rainfed maize production in the Great Plains, with yield decline in the range of 30 to 40%. Yang & Wang (2023) found that under CMIP5 climate projections, heat stress is likely to jeopardize rainfed maize production in the Midwest and the Great Plains, with a potential yield reduction of 40% on average. An important study from India, shows that rainfed maize production decline in the future may reach up to 80% in selected districts of the country (Rao et al., 2022). Using statistical models, Chen et al. (2017) found that all the villages in Hubei Province of China may suffer maize yield loss under future climate change. The future climate projections indicate a future characterized by elevated temperatures and reduced precipitation, potentially posing adverse effects on maize production (Kothari et al., 2022). This observation is consistent across various studies employing diverse methodologies,

including multiple regression (Lobell and Field, 2007) and process-based crop simulation models (Chen et al., 2019; Kothari et al., 2022).

As climate changes with anticipated negative impacts on rainfed production, adaptation measures become essential. One way to adapt to these changes is by developing cultivars with modified morphology, genetic, and physiological properties (Battisti et al., 2017; Sinclair et al., 2010; Singh et al., 2017). Cultivar genetic characteristics such as root proliferation traits can be used to develop crop cultivars adapted to climate change and drought stress (Battisti et al., 2017; Carretero et al., 2014; Kothari et al., 2020; Sinclair et al., 2010; Singh et al., 2014). According to Coudert et al. (2010), a more extensive root growth deep into the soil profile will be crucial for good crop growth under adverse soil conditions, enabling crops to extract more soil water and nutrients. However, because root system is not directly accessible, and as a result, poses difficulty to study, it remains a strong target for breeders to improve the ability of crops to exploit soil water resources (Coudert et al., 2010). Developing root architecture through breeding requires the identification of the genetic factors that influence root proliferation and development (Pantuwan et al., 2002; Coudert et al., 2010). A more thorough understanding of the fundamental genes governing root proliferation and development is expected to enable breeders select cultivars that possess improved root system (Coudert et al., 2010; Hochholdinger et al., 2018). Testing campaigns for cultivars with improved root system involve assessing the performance of the cultivars under resource use and limiting conditions. However, the time between the breeding and identifying the performance of the traits (e.g., root proliferation and development traits) in crop cultivars and their application may be long, and in some cases, field experiments may not be readily feasible to test this due to intensive resource and labor requirements (Battisti et al., 2017; Sinclair et al., 2010; Singh et al., 2017). Crop simulation models are powerful tools that allow multiple

scenario runs under vast climates and environments and can facilitate testing of modified cultivar traits and evaluate how these traits can impact crop yield for a specific region (Battisti et al., 2017; Sinclair et al., 2010). Further, studying the modified traits via crop models may help address new questions that are difficult to answer; for instance: Does root proliferation improve rainfed crop yield under future climate change conditions? Does crop cultivars with high root density/proliferation traits utilize growing season precipitation effectively? If yes, does this effective utilization of growing season precipitation vary with soil textures and the amount of water in the soil profile? And finally, what will be the role of crop simulation models in helping breeders to efficiently combine functional genomics and genetic approaches to identify genes involved in adaptive root development to improve crop tolerance to limited soil resources (Coudert et al., 2010)?

Crop models are valuable tools for simulating genotype, management, and environmental interactions on crop productivity (Challinor et al., 2013) and several studies have used process-based crop models to evaluate different climates and root proliferation adaptation strategy on crop production. Kothari et al. (2019) assessed the benefits of different adaptation strategies for rainfed production of winter-wheat under climate change in the High Plains of Texas and found that root proliferation strategy produced desirable results. In Argentine Pampas, Carretero et al. (2014) tested the impact of root proliferation on maize yield under current climate by modifying the soil root growth function (SRGF) using the CERES-Maize model and found yield gains reaching up to 12%. Using the CSM-CERES-Sorghum, Singh et al. (2014) quantified the possible advantages of increasing root growth at depth for climate change adaptation at two sites, each in India and Mali. They found that under climate change, increasing root growth increased yield by 8%.

Overall, these studies showed that increasing the potential for root growth to mimic root proliferation system increased yield.

Producers in the Midwest and the Great Plains continually look out for latest management options to optimize crop production under climate variability and potential future climate change. However, studies contributing knowledge on the ways to hasten cultivar breeding programs by genetically adapting rainfed maize production to future climate change using crop simulation models are lacking. Even if they exist, most study frameworks have been conducted at point scale without exploring spatially varying regional soils and climate (Kothari et al., 2019, 2022). Therefore, the aim of this study was to assess the potential benefits of adapting maize cultivar to root proliferation under future climate change in Eastern Kansas River Basin (EKSRB) of the US Great Plains, considering county-level dominant soils and climate variability. Specific objectives were to: (1) calibrate and evaluate the DSSAT-CERES-Maize model for regional rainfed maize production and assess the impacts of baseline regional climate and environmental variability on yield. (2) assess future climate change impacts on yield and rainfall productivity and identify the potential benefits of root proliferation adaptation strategy in the region. (3) map the yield and rainfall productivity variabilities in the region. In addition, this study was spurred by the fact that in the state of Kansas, most of the research to study the impact of climate change on maize production has been done for locations in western Kansas, which is a heavily irrigated part of the state (Araya et al., 2017a; Araya et al., 2017b). However, for eastern Kansas, which is an important rainfed maize producing region in the state and the US Great Plains, information on climate change impacts on maize production is lacking, with no studies that have focused on adapting rainfed maize production to future climate change in the state and the region.

2.3 Materials and Methods

2.3.1 Study Area

The current study was carried out in EKSRB, located in the northeast region of Kansas State (KS, hereafter, Figure. 2.1), US. The basin is an exemplar region exposed to challenges of possible increase in aridity which may undermine rainfed production under future climate (Seager et al., 2018). EKSRB is defined as the Kansas River watershed, between its beginning at the convergence of the Smoky Hill and Republican rivers located near Junction city, KS and its outflow at the confluence of the Missouri River in Kansas City, KS (Sinnathamby et al., 2018) (Figure. 2.1). The western edge of EKSRB lies close to the 100th meridian, which is a zone of moisture transition where precipitation is approximately equal to potential evapotranspiration (Seager et al., 2018). The basin consists of 17 counties (Figure. 2.1) covering an area of 15,100 km² and includes some of the major areas of native prairies left in the US (Sinnathamby et al., 2018), with maize, soybean, and winter wheat being the major crops grown in the basin.

Future shifts in land use for crop production are expected with increasing population and climate change. Kansas has a unique east to west precipitation (prcp) gradient, with mean annual precipitation varying between 635 mm in the west and a little over a 1000 mm in the east (Lin & Brunsell, 2013; Seager et al., 2018; Sinnathamby et al., 2018). However, growing season precipitation in EKSRB varies from 470 mm in the west and 520 mm in the east (Figure. 2.2). In addition to this precipitation gradient, spatial variability in factors like land use, and soils exists and can cause variations in crop productivity (Seager et al., 2018; Sinnathamby et al., 2018) with soils playing a specially critical part (Sharda et al., 2017; Sen et al., 2023) (see Table 2.1).

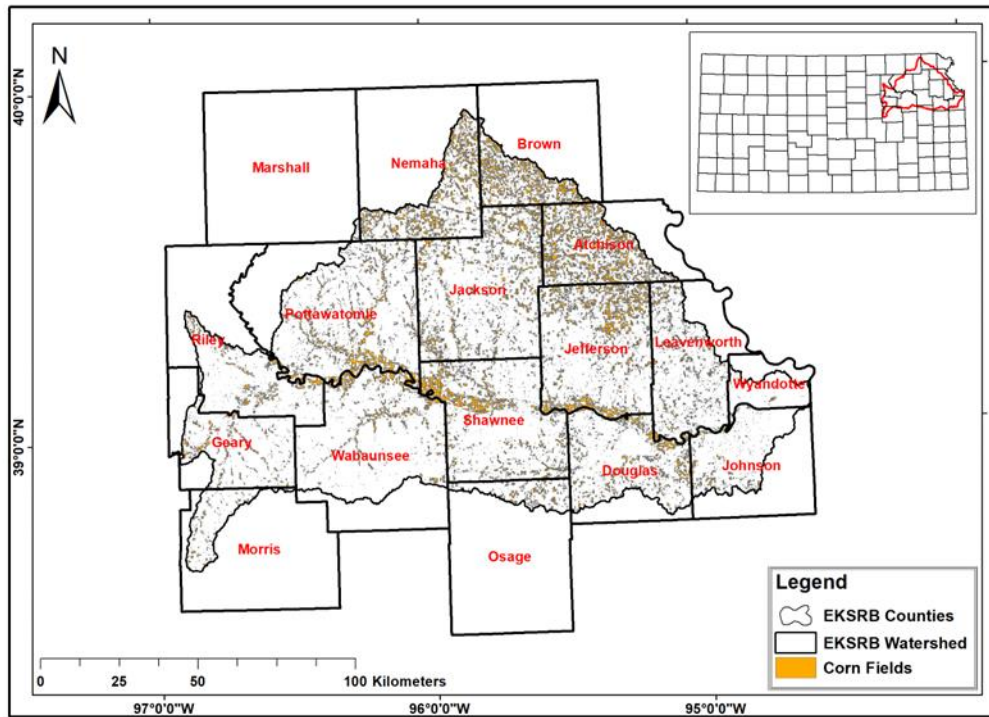


Figure 2.1. Map of EKS RB showing counties, inset map of Kansas state is shown in the upper right. (Maize and corn refer to the same crop in this paper).

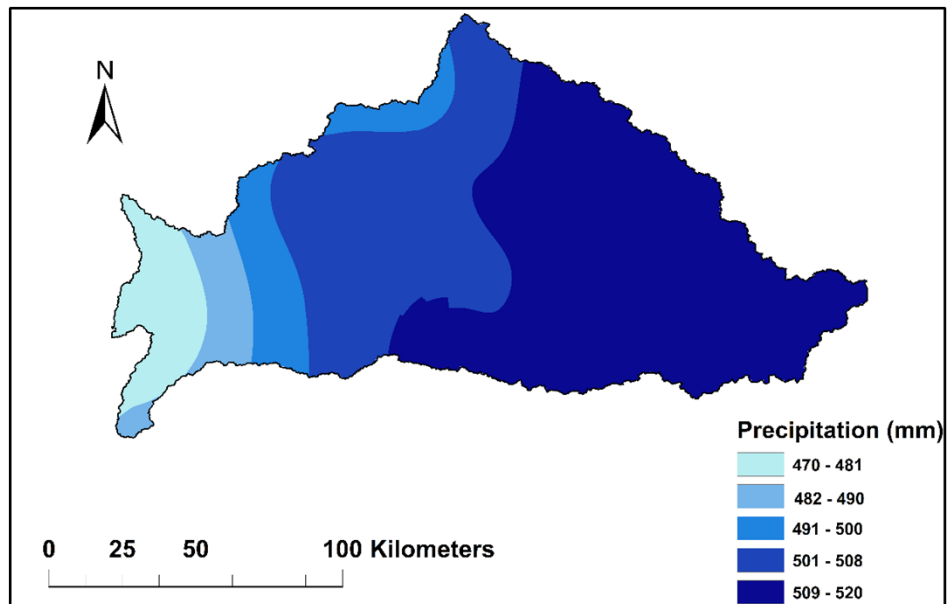


Figure 2.2. EKS RB growing season precipitation gradient map.

Table 2.1. Dominant soil type by county in EKS RB

S/N	Counties	Dominant Soil Series	Runoff Curve Number
1	Atchison	Wymore SCL	81
2	Brown	Grundy SCL	81
3	Douglas	Martin SCL	81
4	Geary	Benfield SL	87
5	Jackson	Pawnee CL	76
6	Jefferson	Grundy SCL	81
7	Johnson	Woodson SL	81
8	Leavenworth	Kennebec SL	81
9	Marshall	Pawnee CL	76
10	Morris	Labette SCL	84
11	Nemaha	Pawnee CL	76
12	Osage	Kenoma SL	81
13	Pottawatomie	Kennebec SL	81
14	Riley	Wymore SCL	81
15	Shawnee	Ladysmith SCL	84
16	Wabaunsee	Benfield SL	87
17	Wyandotte	Ladoga SL	91

Notes: SCL = silty clay loam, SL = silty loam, CL = clay loam

2.3.2 DSSAT-CSM-CERES-Maize Model

The CERES-Maize module (Jones et al., 1986; Jones et al., 2003; Ritchie et al., 1998) within the Decision Support Systems and Agrotechnology Transfer v 4.7.5 (DSSAT, hereafter) (Hoogenboom et al., 2019) was used in this study. DSSAT is a process-based modular crop modeling system that simulates crop growth and development at point scale taking into account crop management (water, planting conditions, and nutrients), weather/climate, and soils (Araya et al., 2017a; Jones et al., 2003). Minimum climate datasets required to run DSSAT include daily maximum and minimum air temperatures, solar radiation, and precipitation.

The CERES-Maize module used in this study simulates phenological stages of maize growth with respect to biomass partitioning to root, stem, kernels and leaves, and grain yield. The simulation is based on daily weather inputs, crop management inputs such as irrigation and nutrient, soil properties, cultivar characteristics represented as genetic coefficients, and initial

conditions at planting. More details on the CERES-Maize module can be found in Hoogenboom et al. (2019) and Araya et al. (2017a).

2.3.3 Model Inputs

As described previously, the CERES-Maize model within the DSSAT, requires minimum dataset to initiate model run and scenario analysis. DSSAT requires information on soil properties such as soil layer including depth to root zone, bulk density, texture, hydraulic conductivity, and surface information such as drainage coefficient, soil fertility and mineralization factors, runoff curve number, and albedo. Soil data at 30 m resolution were retrieved from the Natural Resource Conservation Service (NRCS) Gridded Soil Survey Geographic (gSSURGO) database for Kansas (Soil Survey Staff, 2022), and the dominant soil series for each county in the study area (Table 2.1) were extracted using the method described by Sharda et al. (2017). The dominant soil types of the study area are presented in Table 2.1. Data not available to meet the minimum soil requirements were calculated using the function in the DSSAT Soil Build (SBUILD) and methods provided by Gijsman et al. (2002).

Baseline weather information (daily minimum and maximum air temperatures, precipitation, and solar radiation for the seventeen (17) counties of the EKSRL (shown in Table 2.1) were downloaded for a 30-year period between 1985 and 2014 from the National Aeronautics and Space Administration (NASA) Langley Research Center (LaRC) Prediction of Worldwide Energy Resource (POWER) Project funded through the NASA Earth Science/Applied Science Program. NASA POWER data has been used by several studies around the world to obtain weather data required for DSSAT and other related studies at regional scale (Shelia et al., 2019; Singh et al., 2014; Jha et al. 2021; Emeka et al. 2021; Ndulue et al. 2019; Onyekwelu et al., 2023; Onyekwelu & Sharda 2023a, b). Precipitation data measured at county level weather stations were

used to replace precipitation datasets downloaded from NASA POWER. This was done in discussion with DSSAT developers who suggested that NASA POWER precipitation datasets could only serve as alternative when station level datasets are missing. These datasets were converted to daily weather file format of the DSSAT (*.WTH) for each county.

Crop management information for model simulation were selected based on recommendations of Kansas State Research and Extension (KSRE) of Kansas State University (K-State Extension, 2007). Rainfed experiments in DSSAT were set up based on 2015 regional variety trial datasets provided by the KSRE (Lingenfelser et al., 2015) for five (5) maize-growing counties within and outside the EKS RB (Table 2.2; Figure. 2.3). Variety trial experiments are used to evaluate crop varieties for performance using datasets generated from multi-environmental trials (Sharda et al., 2021; Smith et al., 2005). Several studies have used variety trial datasets for CERES-Maize model parameterization in the absence of in-season field observations (Bao et al., 2017; Sharda et al., 2021). Weather data measured from trial stations as obtained from High Plain Regional Climate Center (HPRCC, University of Nebraska) in addition to input management data reported in Table 2.2, were used for rainfed maize simulation set up and calibration.

Table 2.2. Location-specific input management data for initial model set up and calibration.

County/Farm	Distance from EKS RB	Soil type	Planting date	Planting population (plants/m ²)	Row spacing (cm)	N-Fertilizer (lb/ac)	Cultivar type	Drought tolerance?
Riley/Agronomy North Farm	Within	Reading silt loam	04/28/2015	6	76	180	Midland-656 PR	Yes
Franklin/East Central Farm	< 10 km	Crete silt loam	04/17/2015	6	76	180	Midland-656 PR	Yes
Shawnee/River Valley Exp. Station	Within	Reading silt loam	04/22/2015	6.5	76	180	Midland-656 PR	Yes

Neosho/Private Farm	< 100 km	Dennis silt loam	04/28/2015	8	76	225	Midland-656 PR	Yes
Republic/Central Exp. Farm	< 50 km	Crete silt loam	06/17/2015	6	76	180	Midland-656 PR	Yes

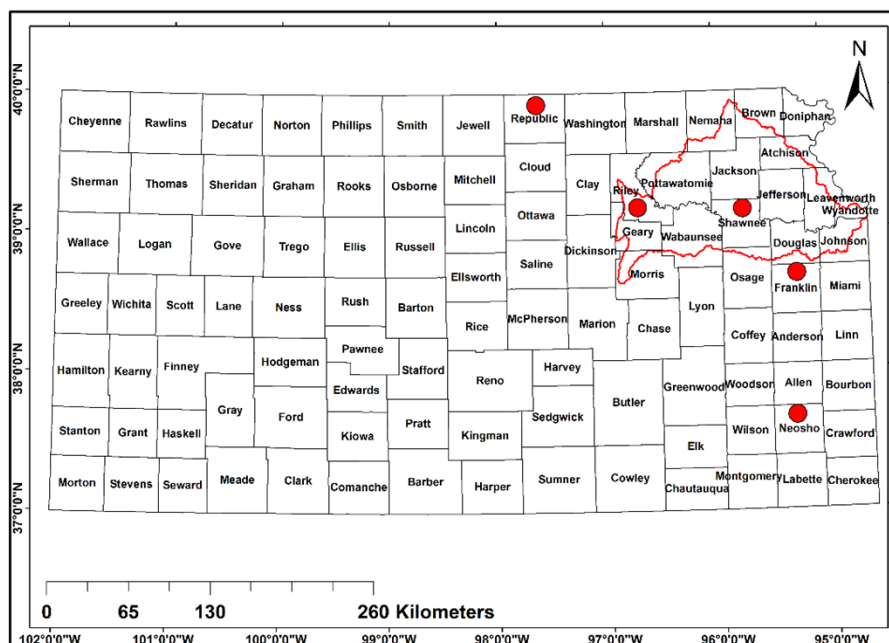


Figure 2.3. Map of Kansas State showing rainfed trial stations in red dots, inset map of the EKSRB shown in the upper right.

2.3.4 Model Calibration and Evaluation

Model calibration of any kind is the optimization of an objective function. Phenology and yield estimates using the CERES-Maize model are determined by six genetic coefficients. The objective of calibration is to obtain reasonable or matching estimates of genetic coefficients by successively comparing the simulated results with field observations (Sharda et al., 2021). The method described by Sharda et al. (2021) was used to systematically calibrate the CERES-Maize model. 2015 maize yield and days to anthesis from the regional variety trials were obtained for the trial stations (Figure 2.3) (Lingenfelser et al., 2015) and were used in the calibration process. Cultivar selection from regional variety trial reports is a rigorous process and decisions were made based on expert opinion and the following assumptions and criteria: 1. Cultivar represents farmers'

choice in the region, 2. Cultivar grain yield was reported in the top five of the trial, and 3. Cultivar was tested in different agroclimatic locations and has extensive yield and days to anthesis observations for model calibration and evaluation. After conducting this exercise, the Midland-656 PR was selected as the best choice cultivar for the regional model calibration considered in the present study (Table 2.2). The GENCALC calibration program, which was used in the calibration process, iteratively compares the field observation to the simulated data using genetic coefficients from a generic cultivar or initial guess in the DSSAT.CUL file. For this study, default Pioneer 3489 maize cultivar was used to initiate the regional model calibration process. Coefficient adjustments were made using the GENCALC calibration tool within the DSSAT, starting with a set of cultivar coefficients as recommended by Hunt et al. (1993). It is noteworthy that since only yield and days to anthesis data were available for model calibration, the calibration rule was set to iterate over days to anthesis (ADAP) first, and subsequently for yield (HWAM). After obtaining the initial set of coefficients, the cultivar coefficients of the variety trial cultivar were adjusted until a reasonable error tolerance was achieved.

For model evaluation, Midland-656 PR cultivar trial datasets (end of season maize yield and days to anthesis) from the regional variety trial stations conducted in 2016 through 2018 were used. Model evaluation/validation was performed by comparing the model-simulated maize yield and days to anthesis with the observed data without changing the calibrated coefficients described previously. Indicators for assessing model accuracy for the proposed application included goodness of fit (d-statistic, (Willmott, 1982)), normalized root mean square error (NRMSE) (Araya et al., 2017a), and test (p-value) statistics. The NRMSE was calculated as the ratio of RMSE (Eq. (2.2)) and the observed mean of the response variable (yield, and days to anthesis) multiplied by 100.

$$NRMSE = \frac{RMSE}{Observed\ mean} \times 100 \quad (2.1)$$

$$RMSE = \left(\frac{\sum (p_i - o_i)^2}{N} \right)^{0.5} \quad (2.2)$$

where p_i is the predicted value, o_i is the measured field observation, and N is the total number of field observations.

Soler et al. (2007) classified NRMSE values for meeting model accuracy with 0-10% being excellent and more than 30% as a poor model. In a similar way, Willmott (1982) classified d-statistic (Eq. (2.3)) values as follows: < 0.7 as poor, 0.7-0.8 as moderate, 0.8-0.9 as good, and 0.9-1 as excellent.

$$d = 1 - \left[\frac{\sum_{i=1}^N (P_i - O_i)^2}{\sum_{i=1}^N (|P'_i| + |O'_i|)^2} \right] \quad (2.3)$$

P_i is the predicted value, O_i is the measured observation, and N is the total number of field observations.

$|P'_i| = |P_i - M|$, and $|O'_i| = |O_i - M|$. M is the mean of observed field variables (maize yields and day to anthesis).

A novel approach was employed to assess how accurately the model simulations matched the observed variabilities in field observations using the coefficient of variation (CV) metrics. This was done to increase regional model calibration accuracy and perhaps, lower model uncertainty. This was accomplished by successively examining different model assessment metrics and the CV values between simulated and observed data. The closer the simulated CV to the observed CV, the more robust the model.

2.3.5 Crop Management Data for Baseline and Future Simulations

To conduct baseline and future simulations, single management information for maize production in the region was adopted. This approach has been adopted by several studies, especially under regional simulation (Araya et al., 2017a; Kothari et al., 2019; Sharda et al., 2021). Maize was independently planted in the 17 counties on April 28th at a seeding rate of 6 seeds/m², planting depth of 5 cm, and row spacing of 76 cm. This information is widely used in eastern Kansas and was reported by Kansas State University research and extension for the region (K-State Extension, 2007; Kiniry et al., 1997). Initial moisture condition assumed the dominant soil profiles to be at field capacity at planting, and the initial soil nitrogen was set to 25 kg Nha⁻¹ assuming 1% soil organic matter. These assumptions are within the values reported for rainfed maize production and other cereal crops in Kansas and the Great Plains (Kothari et al., 2019; K-State Extension, 2007). In addition, fertilizer applications in the model were set according to regional recommendations (K-State Extension 2007) and applied as 12% (30 kg Nha⁻¹) of total nitrogen at planting and 88% (227 kg Nha⁻¹) 30 days after planting (DAP) (Araya et al., 2017a).

2.3.6 Crop Water Productivity Indicator

Crop water productivity defined as rainfall productivity in this study was determined as proposed by Fernandez et al. (2020) using equation (2.4) below. Rainfall productivity, which refers to the amount of maize yield produced per mm of growing season rainfall, is a key determinant factor of effective rainfall utilization during the growing season, especially under rainfed production. Under long term simulation, rainfall productivity was computed for baseline and under future climate change conditions.

$$WP_r = \frac{\text{Maize Yield}}{RWU} \quad (2.4)$$

where WP_r is the rainfall water productivity (rainfall productivity, $\text{kg ha}^{-1}\text{mm}^{-1}$), and RWU is the rainfall water used in millimeters (mm).

2.3.7 Climate Change Scenarios

Climate change scenario impact on rainfed maize production was simulated for each of the seventeen (17) counties of the EKS RB. The scenario was selected based on late term period (2071-2100), one trajectory of greenhouse gas (GHG) emissions, and one Shared Socio-economic Pathway (SSP245) of the latest Coupled Model Intercomparison Project 6 (CMIP6) (Böttinger & Kasang, 2020; O’neill et al., 2016). SSP245 is the climate scenario with midway challenges to mitigation and adaptation, in which income growth and development proceeds unequally amongst countries, with environmental systems experiencing degradation (O’neill et al., 2016; Riahi et al., 2017). This scenario was selected as it has been reported to represent a more plausible trajectory to make better policy push needed to keep global temperature rise below $1.5\text{ }^{\circ}\text{C}$ (Hausfather & Peters, 2020), and represents the pathway of the projected radiative forcing of 4.5 Wm^{-2} until the end of the century. Climate variables (solar radiation, minimum and maximum temperatures, and precipitation) were obtained for five CMIP6 (Table 2.3) Global Climate Models (GCMs) from the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP3b) repository (Lange, 2021). The ISIMIP3b datasets contain statistically downscaled and bias-adjusted climate projections for a set of complete GCMs at 50 km and have been used by several studies for climate impact assessment (Liersch et al., 2023; Schroder et al., 2024; Xu et al., 2023).

To ensure robust model simulation in each county, the five GCMs were selected based on their performance in the simulation of baseline climate and completeness of climate variables needed for this study (Table 2.3). The five basic models, according to Lange (2021), are a wise option since they provide simulations of both low and high climate sensitivities. After model

simulation, maize yield and rainfall productivity values for the five selected GCMs were averaged per county to get ensemble averages and then compared to the baseline period.

Table 2.3. List of selected CMIP6 GCMs

GCMs	Country	Group	Member	Climate sensitivity
GFDL-ESM4	USA	primary	r1i1p1f1	Medium
IPSL-CM6A-LR	France	primary	r1i1p1f1	Low
MPI-ESM1-2-HR	Germany	primary	r1i1p1f1	Medium
MRI-ESM2-0	Japan	primary	r1i1p1f1	Low/Medium
UKESM1-0-LL	UK	primary	r1i1p1f2	High

2.3.8 Climate Change Adaptation Strategy

One of the aims of this study was to simulate future climate change impact on rainfed maize production by adapting in silico genetically modified root proliferation of a hypothetical/virtual cultivar in the region. Changes in plant root system could lead to yield benefits, especially under drought conditions (Coudert et al., 2010; Hochholdinger et al., 2018; Kothari et al., 2019, 2022). Root proliferation in soil layers is assumed to depend on crop genetic tendency to distribute roots in the soil (Jones et al., 1986). According to Jones et al. (1986), rooting fronts descend from the depth of planting at germination to an ultimate depth that is dependent on genotype and the rooting environment. In this study, two maize cultivars differing in root growth structure and architecture were used: a reference cultivar with no root modification (no adaptation) and a virtual/hypothetical cultivar with root modification (adaptation), i.e., higher root density partitioned in all dominant soil layers than the reference cultivar.

Differences in root distribution of the two cultivars were simulated by modifying the DSSAT SRGF (soil root growth factor) model from $e^{-0.02 \times Z}$ for all dominant soils in the region to $(1 - \frac{Z}{300})^Y$ (Carretero et al., 2014; Jones et al., 1986). Where Z is the depth to the middle of the soil layer in cm, and Y is a genotype specific factor. SRGF determines the ability of different soil layers for root growth (Carretero et al., 2014). This strategy was similar to the approach used by

Carretero et al. (2014) and Kothari et al. (2019) for their maize and winter wheat simulation studies, respectively. Carretero et al. (2014) and Jones et al. (1986) observed that if a crop cultivar genetically inclines to distribute equal root density in all soil layers, $Y = 0$ should be used. Y values ranging from 1.0 to 3.0 were reported by Jones et al. (1986) to provide estimates of fairly linear decrease in root density in layers of soil profiles for different crop genotypes, with $Y = 1.0$ for deep rooting/denser root crops like sunflower, and 2.0 for maize and soybean, and 3.0 for sorghum. However, in this study, $Y = 1.0$ was used in order to adapt the hypothetical maize cultivar to sunflower rooting density. In addition, maize and sunflower have been found to grow at an approximately similar depth (Ransom, 2017).

Adaptation is defined to mean an activity that is impacting-reducing in a way that it reduces the negative climate change impacts while enhancing its positive impacts Lobell (2014). In this study, SRGF in the CERES-Maize model was modified as described previously to capture more roots in the layers of the soil profiles than the reference cultivar. Following the adaptation strategy, maize yield and rainfall productivity were simulated as percent increase or decrease in production under hypothetical cultivar (adaptation) relative to reference cultivar (no adaptation). This simulation analysis was conducted for the seventeen (17) counties in the region using the five GCMs per county as outlined previously.

2.3.9 Spatial Response of Yield and Rainfall Productivity

To study the spatial variability of maize yield and rainfall productivity under baseline and future climate conditions, spatial maps were generated using ordinary kriging by spatial interpolation based on spherical variogram model in ArcMap 10.7 (Esri, 2022). Ordinary kriging interpolation is the choice for representing spatial variation in crop productivity with varying climate and environment (Battisti et al., 2017). The configuration of the observed data and the

variogram, where the error variance is minimized, is the basis of ordinary kriging (Yamamoto, 2005). The spatial maps were produced to represent the mean variations in maize yield and rainfall productivity in the region.

2.4 Results and Discussion

2.4.1 Model Calibration and Evaluation

The genetic coefficients P1, P2, P5, G2, G3, and PHINT (Table 2.4) were adjusted to 247.50, 0.48, 980,965, 11.68, and 46.20 respectively, which are similar to those reported by Araya et al. (2017b) for western KS. The results showed that adjustment of coefficients related to crop phenology and development, resulted in a close match of the simulated and observed days to anthesis (Figure 2.4b).

Table 2.4. Genetic coefficients adjusted during CERES-Maize regional model calibration.

Coefficients	Description	Initial value	Calibrated value
P1	Thermal time from seedling emergence to the end of the juvenile phase (degree days)	225.0	247.50
P2	Extent to which development is delayed for each hour increase in photoperiod (days)	0.600	0.48
P5	Thermal time from silking to physiological maturity (degree days).	895.0	980.0
G2	Maximum number of kernels per plant.	875.0	965.0
G3	Kernel filling rate during the linear grain filling stage (mg/day).	8.80	11.68
PHINT	Phyllochron interval between successive leaf tip appearances (degree days).	48.00	46.20

Simulated days to anthesis was 75 DAP (days after planting) as compared to an observed value of 70 DAP. Overestimation of days to anthesis may have occurred due to water stress underestimation and model not accounting for pests and diseases and has also been reported by Araya et al. (2017b) for maize simulation in western KS using the CERES-Maize model.

Simulated and observed days to anthesis were compared after calibration with NRMSE = 8% (RMSE = 5.8 days), d-statistics = 0.73, p-value = 0.33, and simulated and observed CV of 4% and 9%, respectively. During model evaluation periods (2016 to 2018, Figure 2.4d), simulated and observed mean days to anthesis were 74 and 71 DAP, respectively. NRMSE during evaluation was observed to be 6% (RMSE = 3.9 days), d-statistics = 0.94, p-value = 0.94, and simulated and observed CV of 10% and 12%, respectively. The model performance for days to anthesis was determined to range between good to excellent (Soler et al., 2007; Willmott, 1982); consequently, demonstrating confidence in using the model for the proposed application.

End of season maize yield calibration, similar to days to anthesis calibration, was performed across different range of climate, soils, and management conditions in the region (Figure 2.4a). Model performance was very satisfactory after calibration with NRSME = 11% (1208 kg ha^{-1}), d-statistics = 0.92, p-value = 0.69, and simulated and observed CV of 19% and 18%, respectively. After calibration, average simulated and observed maize yield were found to be 12,141 and 11,487 kg ha^{-1} , respectively. The overestimation of end of season yield could be due to underestimation of water stress; similar to results obtained by Kothari et al. (2019). During model evaluation for end of season maize yield, the observed and simulated yield matched closely (Figure. 2.4c) as indicated by NRMSE = 16% (RMSE = 1724 kg ha^{-1}), d-statistics = 0.86, p-value = 0.5, and simulated and observed CV of 23% and 21%, respectively. Simulated and observed end of season maize yield values during evaluation were 11,353 kg ha^{-1} and 10,524 kg ha^{-1} , respectively. Overall, the CERES-Maize model was able to satisfactorily reproduce observe yield and days to anthesis with minimal error tolerance and variability.

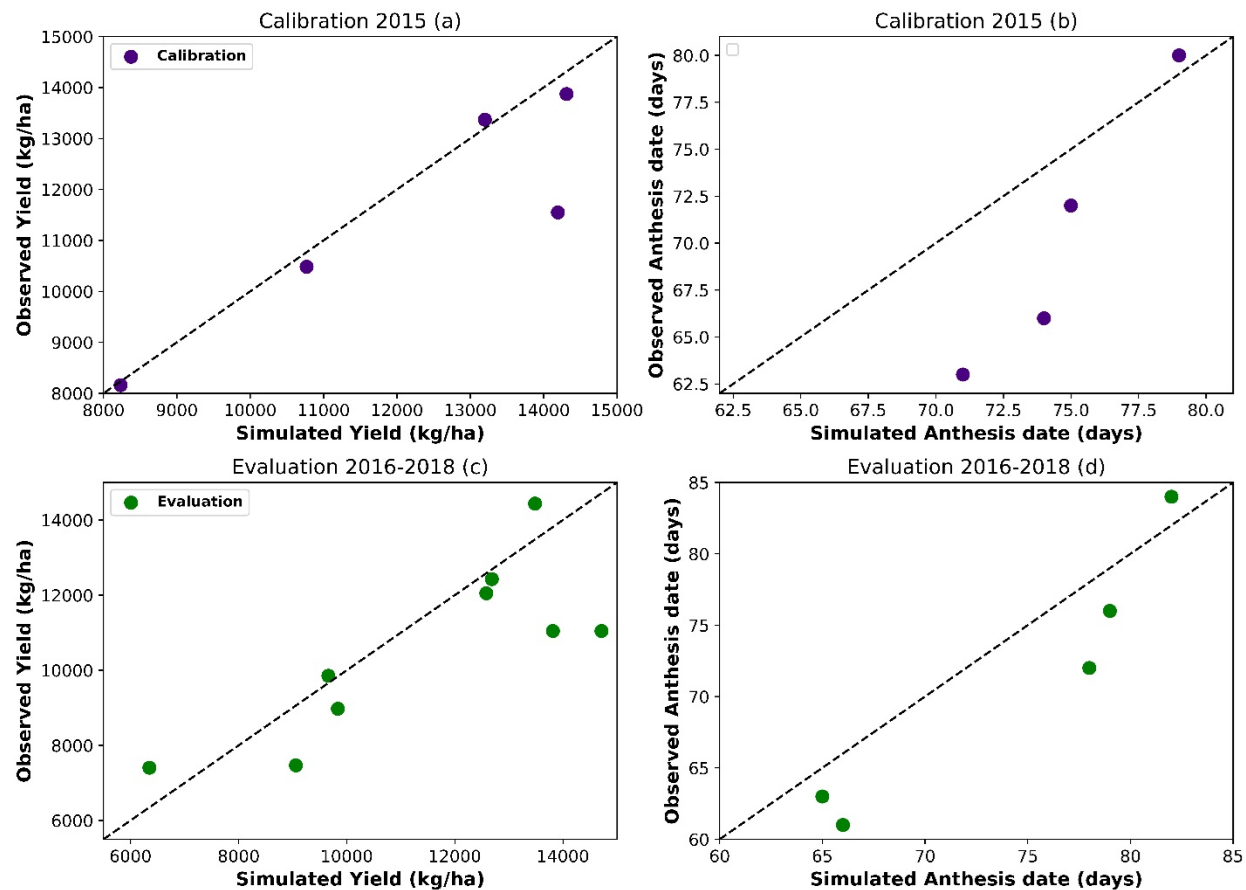


Figure 2.4. Observed and simulated maize yield and days to anthesis (DAT) comparison. Black dash lines represent 1:1 line.

2.4.2 Baseline Climate and Environmental Variability Impact on Rainfed Yield

Table 5 below shows the growing season average climate outlook from 1985 to 2014 by county in EKS RB.

Table 2.5. County-level growing season average climate outlook (1985-2014)

S/N	Counties	Tmax °C	Tmin °C	SRAD (MJ/m ² /d)	Prpc (mm)
1	Atchison	28.6	16.6	21.5	513.0
2	Brown	28.5	16.4	21.5	513.9
3	Douglas	28.7	17.1	21.7	515.7
4	Geary	29.5	17.5	22.0	472.2
5	Jackson	28.6	16.7	21.6	508.7
6	Jefferson	28.9	17.1	21.6	509.6
7	Johnson	28.7	17.1	21.5	516.0
8	Leavenworth	28.7	17.1	21.6	516.5
9	Marshall	28.6	16.3	21.8	498.4

10	Morris	29.4	17.4	22.2	481.3
11	Nemaha	28.6	16.3	21.8	494.9
12	Osage	28.7	17.2	21.7	516.5
13	Pottawatomie	28.8	16.7	21.8	505.2
14	Riley	29.3	17.0	21.9	479.2
15	Shawnee	28.9	17.1	21.6	506.6
16	Wabaunsee	29.0	17.2	22.1	504.2
17	Wyandotte	28.7	17.1	21.3	515.1

Notes: regional average Tmax = 28.9 °C; Tmin = 16.9 °C; SRAD = 21.7 MJ/m²/d; Prcp = 504.1 mm (precipitation). S/N refers to county serial numbers in alphabetical order.

Variabilities in county-level climate (Table 2.5) and soil (Table 2.1) impacted baseline yield in the region (Figure 2.5a). Average yield over the 30-year baseline period (1985-2014) per county ranged from 6,522 kg ha⁻¹ to 12,849 kg ha⁻¹ for Geary and Pottawatomie counties, respectively, with coefficient of variation (CV) values ranging from 41% to 68% (Pottawatomie and Geary, respectively, Figure 2.5b). Average regional yield of 9,270 kg ha⁻¹ was found in this study, with average CV value of 54% (Figure 2.5b). The variability in baseline yield per county correlated with CV values, with high-yielding counties showing low variability, while characteristic low-yielding counties show high variability (Figure. 2.5a, b). In a study by Araya et al. (2020), CV values for inter-seasonal yield comparison were grouped into three classes as follows: 0-30% (low), 31-60% (high), and 61-90% (extremely high). Based on the above classification, we observed that most counties in EKS RB were within the low to high variability class, with the exception of Geary, Morris, Shawnee, and Wabaunsee counties, which fall within the extremely high variability class (Figure 2.5b). Counties with low average yield and extremely high variability may have been impacted by a combination of soil type, high Tmax and Tmin (maximum and minimum temperatures), and low precipitation (prcp). For example, in Geary County where we observed the lowest average yield and highest variability, Tmax and Tmin were highest (Table 2.5), with lowest average prcp (Table 2.5). In addition, the dominant soil type in Geary County was characterized as shallow, with rooting depth reaching up to 100 cm (not shown),

while in Pottawatomie County where the highest average yield and lowest yield variability were observed, Tmax and Tmin were very close to the minimum values, while prcp was very close to the maximum value (not shown), with dominant soil rooting depth reaching up to 200 cm (not shown). These results are similar to those reported by Tubiello et al. (2002) and Ye et al. (2017) in the key maize-producing regions of the US. In addition, we observed a systematic spatial variability in yield and CV values, with increasing yield trend from west to east of the region (MO to WY, west and east bound counties, Figure 2.5a) and decreasing CV trend from west to east of the region (MO to WY, west and east bound counties, Figure 2.5b). This indicates that the increasing and decreasing yield and CV values, respectively, west to east of the region, follow the region's precipitation gradient presented in Figure 2.2, and equally shows that adequate precipitation remains a strong environmental determinant for boosting rainfed maize production and maintain yield stability.

Figure 2.5c shows the regional baseline yield by different soil textures. We found that soil texture plays a significant role in determining the outcome of an agricultural production. Our result showed that soils of silt loam (SL) texture in the region proved more productive than soils of silt clay loam (SCL), and clay loam (CL) in that order, with average yield of 9,656 kg ha⁻¹ found for SL, 9,093 kg ha⁻¹ for SCL, and 8,782 kg ha⁻¹ observed for CL (Figure 2.5c). The reason behind the better productivity of SL soils in the region was due to the presence of more macropores compared to SCL and CL textures, and readily plant available water. While SCL soils may have higher or comparable soil water tension as compared to SL, it is generally considered to have more available water than SL but are locked in the mesopores and micropores of the soils; thus, making soil water unavailable for crop use. CL soils generally have higher soil available water than SL and SCL, but are characterized by more micropores than mesopores, explaining the reason behind the low

productivity of such soil texture as observed in the region. Kothari et al. (2020) reported similar trend in crop productivity by different soil textures, with SL soils being the most favorable under optimum condition.

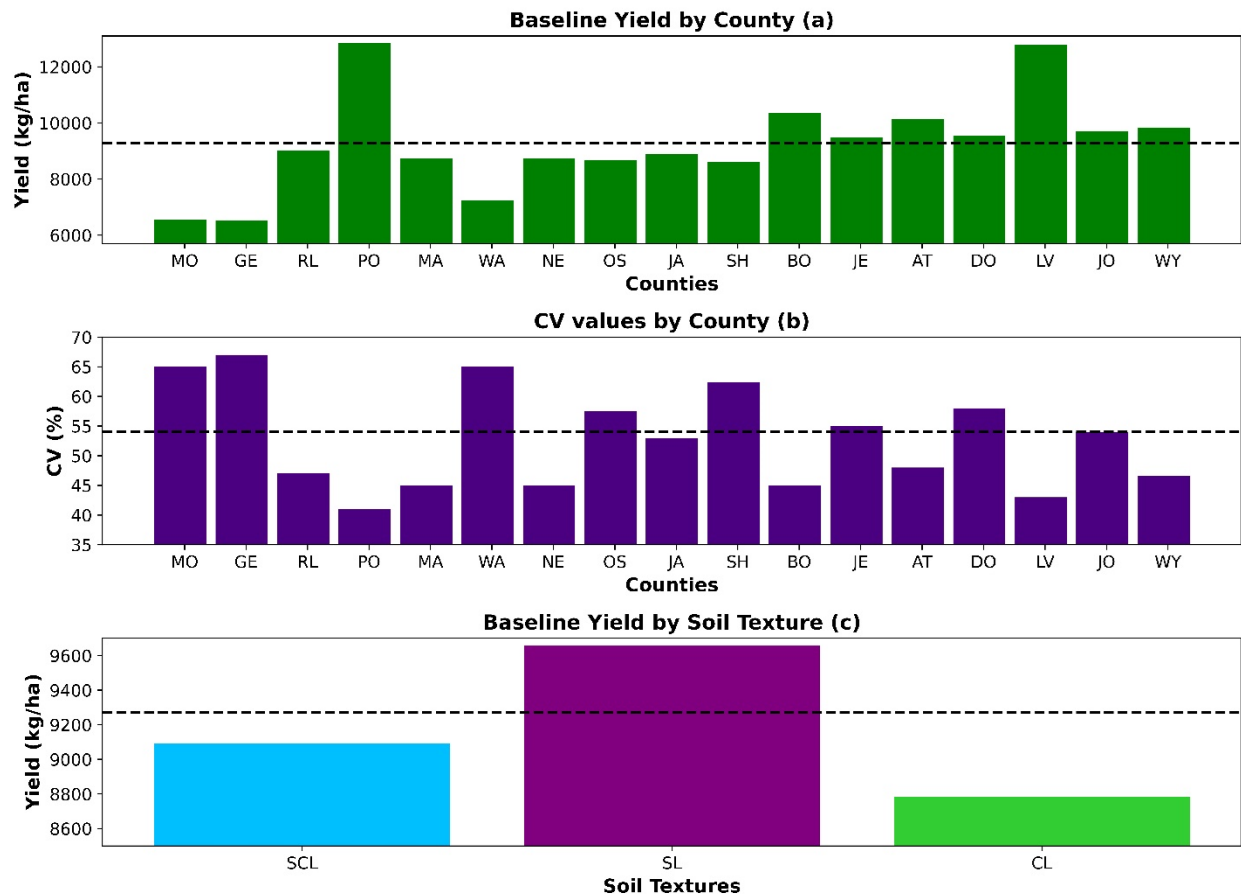


Figure 2.5. a) County-level yield under baseline condition. (b) County-level yield variability under baseline condition. (c) Mean regional yield by soil texture. The black dash lines represent the regional averages. Counties are ordered from west to east of increasing precipitation in the region. MO = Morris, GE = Geary, RL = Riley, PO = Pottawatomie, MA = Marshall, WA = Wabaunsee, NE = Nemaha, OS = Osage, JA = Jackson, SH = Shawnee, BO = Brown, JE = Jefferson, AT = Atchison, DO = Douglas, LV = Leavenworth, JO = Johnson, WY = Wyandotte.

Figure 2.6(a-d) further explains the yield trend dependency on climatic variables in the region. County-level values of rainfed yield were regressed against growing season climatic variables. We observed that rainfed yield has negative correlations with growing season Tmax,

Tmin, and SRAD (solar radiation), while having a positive correlation with growing season prcp (Figure 2.6a-d). Statistically significant yield loss trend in EKSRB due to Tmin and Tmax was found to be 2,916 kgha⁻¹°C⁻¹ and 2,123 kgha⁻¹°C⁻¹, respectively. With the observed trends, it is evident that increase in Tmin has more severe impacts than increase in Tmax in the region. Lin et al. (2017) observed that over the last 121 years in Kansas, warming of Tmin has greatly surpassed that of Tmax. In their study, warming of Tmax showed no statistically significant trend in the last 121 years but Tmin showed a significant warming trend of 0.078 ± 0.03 °C per decade. However, they argued that in regions where Tmax is warming more than Tmin, impact of Tmax on yield and yield-components is more severe compared to that of Tmin. Our results suggest that under rainfed maize production in the region, the optimum Tmin and Tmax to achieve yield values above 10,000 kgha⁻¹ ranges from 14 to 18 °C (Figure 2.6a), and 24 to 30 °C (Figure 2.6b), respectively. However, crop yield performance under rainfed production is not solely dependent on optimum Tmin and Tmax, but also limited by water availability and high heat during critical vegetative and reproductive stages. In addition, increase and decrease in growing season Tmin and Tmax, has direct impacts on other meteorological variables like diurnal temperature range (DTR) and potential evapotranspiration (ETo), which ultimately affects rainfed crop production (Onyekwelu et al., 2023a).

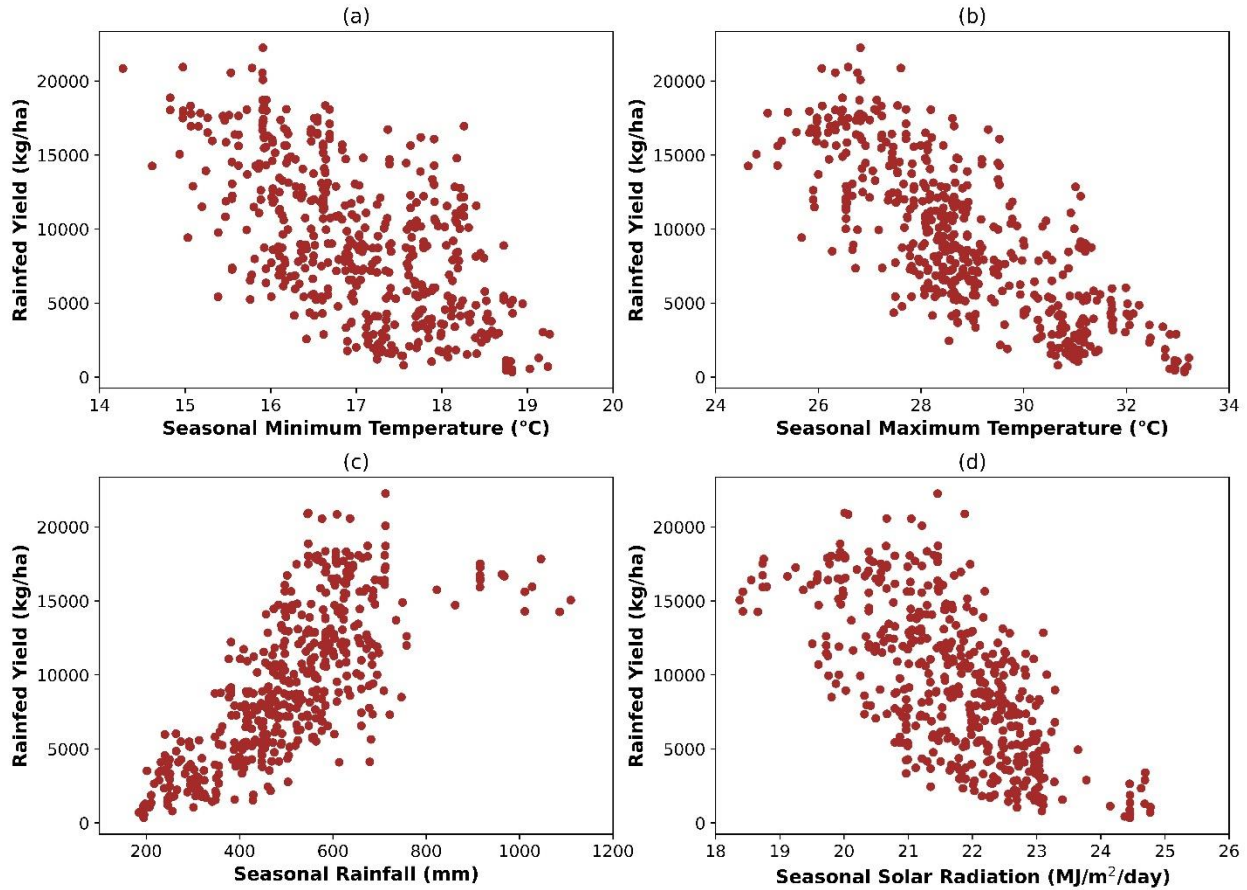


Figure 2.6. Rainfed yield response to regional climatic variables.

A significant increasing yield trend at 23.4 kg ha^{-1} per mm of growing season prcp was observed in the region. We further observed that the relationship between maize yield and growing season prcp appeared fairly nonlinear, with marginal yield decline at very high growing season prcp (Figure 2.6c). From Figure 2.6c, it is evident that under rainfed maize production in the region, the optimum growing season prcp to achieve yield values above $10,000 \text{ kg ha}^{-1}$ ranges from 700 to 1000 mm. It is important to note that the presence of variable soils in the region may result in different patterns of soil moisture retention, and may in turn, result in yield and growing season precipitation exhibiting variable trends. However, the present trend analysis did not factor in the interaction effects of growing season prcp and soil moisture variables based on individual counties on yield. Rahmani et al. (2016) reported statewide increase in extreme prcp events, with high

increase in the EKSRB area. This may result in increased soil wetting, thereby reducing yield when coincided with maize growing season. Our results on growing season prcp increase with maize yield also agree with the results of Ye et al. (2017).

The uneven distribution of SRAD has been reported as one of the reasons for variations in yield (Yang et al., 2021). We observed maize yield loss trend at $2,893 \text{ kg ha}^{-1}$ per MJ m^{-2} increase in growing season SRAD. It is important to note that the yield loss trend observed due to growing season SRAD may not be a reflection of an actual causal effect relationship but may be due to limited water availability and high heat under rainfed production. For example, low crop yield occurs during drought years, with high heat overlapping with drought due to high growing season SRAD and limited water availability. However, available water through irrigation reduces high heat due to growing season SRAD and drought stress (Zhang et al., 2015). This is one explicit disadvantage of rainfed production under limited water resources. From Figure 2.6d, our result suggests that under rainfed maize production in the region, the optimum growing season SRAD to achieve yield values above $10,000 \text{ kg ha}^{-1}$ ranges from 18 to 22 MJ m^{-2} .

Overall, putting things into perspective, our result shows that under rainfed maize production in the region, the optimum environmental conditions to achieve rainfed maize yield values above $10,000 \text{ kg ha}^{-1}$ ranges from 14 to 18°C and 24 to 30°C for $T_{\min}$ and $T_{\max}$, respectively, 700 to 1000 mm for precipitation, and 18 to 22 MJ m^{-2} for SRAD.

2.4.3 Climate Change Impact on Rainfed Maize Yield

Results of county-level future climate outlook under late term (2071-2100) SSP245 scenario, expressed as ensemble average of five CMIP6 GCMs indicate increased warming of growing season $T_{\min}$ and $T_{\max}$, decline in growing season prcp, and increase in growing season incident SRAD (Table 2.6). Deviations in growing season $T_{\max}$ and $T_{\min}$ from baseline climate

ranges from 3.2 °C to 4.9 °C, and 2.3 °C to 3.7 °C, respectively (Table 2.6). Growing season SRAD and prcp deviations ranges from 0.3 MJm⁻² to 1.7 MJm⁻², and -59.9 mm to -102.1 mm, respectively. Regional average growing season Tmin, Tmax, Tmean (mean temperature), prcp, and SRAD deviations were 3.4 °C, 4.2 °C, 3.8 °C, -84 mm, and 1.4 MJm⁻², respectively. These results are similar to those reported by Almazroui et al. (2021) who found that for CMIP6 GCMs under SSP245 scenario, there was up to 4 to 4.5 °C increase in annual mean temperature for late term in some parts of the Midwestern US. In addition, they reported that annual decline in prcp towards the end of the century (late term) has large uncertainty and exhibit somewhat a meridional dipole-like pattern. Since the above conditions are generally higher than the baseline climate and the optimum environmental conditions for achieving yield values above 10,000 kg ha⁻¹ reported in Table 2.5 and the previous section, respectively, growing rainfed maize under these climate conditions without adaptation would expose maize to heat stress and limited growing season water availability.

Table 2.6. County-level growing season average future climate outlook (2071-2100) under SSP245 scenario.

S/N	Counties	Tmax °C	Tmin °C	SRAD (MJ/m ² /d)	Prcp (mm)	Dev. Tmax °C	Dev. Tmin °C	Dev. SRAD (MJ/m ² /d)	Dev. Prcp (mm)
1	Atchison	32.9	20.1	23.1	435.6	4.3	3.5	1.6	-77.4
2	Brown	33.5	19.9	23.2	429.6	4.9	3.5	1.7	-84.3
3	Douglas	33.4	20.7	22.9	417.6	4.7	3.6	1.3	-98.1
4	Geary	33.4	20.5	23.4	388.2	4.0	3.0	1.4	-84.0
5	Jackson	32.7	20.2	23.2	428.1	4.2	3.5	1.6	-80.6
6	Jefferson	33.0	20.8	23.0	440.3	4.1	3.7	1.5	-69.3
7	Johnson	32.8	20.7	23.1	437.2	4.1	3.6	1.6	-78.8
8	Leavenworth	33.0	20.8	23.0	440.3	4.3	3.7	1.5	-76.2
9	Marshall	33.1	19.8	23.4	396.3	4.6	3.5	1.6	-102.1
10	Morris	33.4	20.4	23.4	404.0	4.0	3.0	1.2	-77.3
11	Nemaha	33.3	19.8	23.2	414.9	4.7	3.7	1.4	-80.0
12	Osage	33.0	20.3	23.1	426.1	4.4	3.1	1.4	-90.4
13	Pottawatomie	33.2	20.4	23.2	407.1	4.4	3.7	1.4	-98.1
14	Riley	33.5	20.5	23.4	388.2	4.2	3.5	1.5	-91.0
15	Shawnee	33.2	20.3	23.1	424.5	4.2	3.2	1.5	-82.1
16	Wabaunsee	32.1	19.4	22.4	406.3	3.2	2.3	0.3	-97.9

17	Wyandotte	32.4	20.9	22.9	455.2	3.7	3.8	1.6	-59.9
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Dev. was calculated as deviation from county level baseline averages. Refer to table 5 above. S/N refers to county serial numbers in alphabetical order.

The future rainfed maize yield change calculated as ensemble average based on the five GCMs decreased in all the counties relative to baseline period (Figure 2.7a). With respect to individual GCM projections, rainfed yield change varied from -41% to -56% under GFDL-ESM4, -14% to -30% under IPSL-CM6A-LR, -30% to -51% under MPI-ESM1-2-HR, -24% to -44% under MRI-ESM2-0, and -71% to -85% under UKESM1-0-LL. Our results captured the sensitivities of each GCM as reported in Table 2.3. IPSL-CM6A-LR and UKESM1-0-LL simulated extreme cases of low and high sensitivities, given bad and worst case scenarios, respectively, while GFDL-ESM4, MPI-ESM1-2-HR, and MRI-ESM2-0 models simulated intermediate cases of low climate change effect and sensitivity under SSP245 late term scenario. Araya et al. (2017a) simulated similar sensitivities using the CMIP5 parent models of the CMIP6 models reported above under deficit and full irrigated maize production in western Kansas.

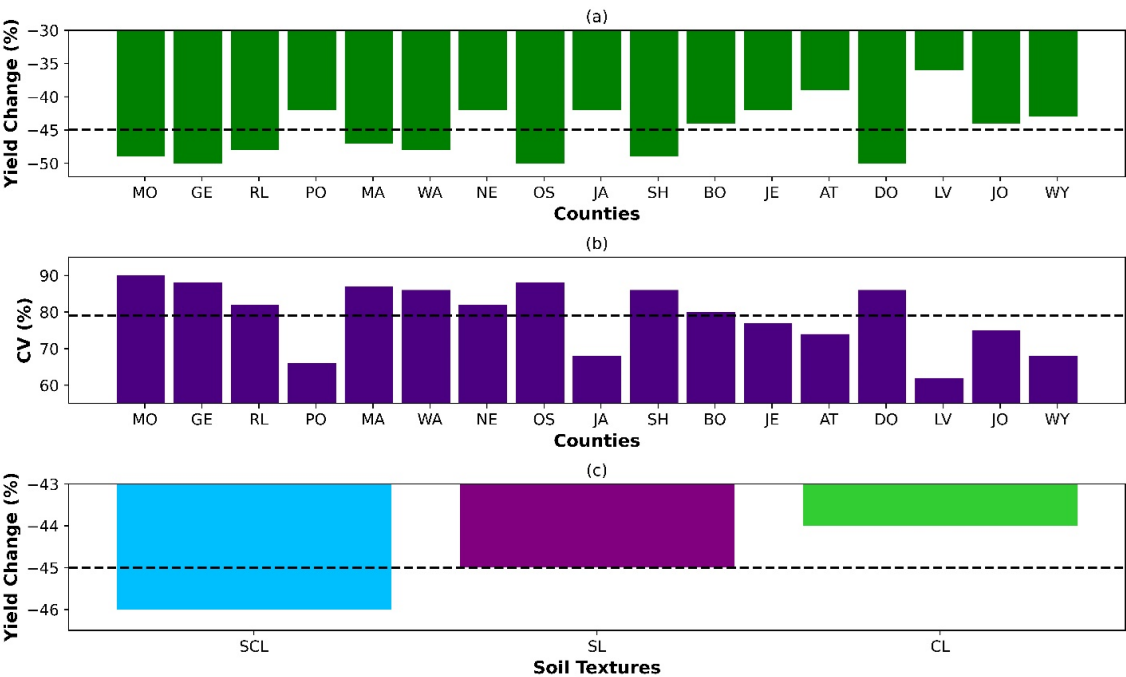


Figure 2.7. (a) Percent change in county-level rainfed maize yield relative to baseline period. (b) Percent change in CV relative to baseline period. (c) Percent change in rainfed

maize yield by soil texture relative to baseline period. The black dash lines represent the regional average decline and variability. Counties are ordered from west to east of increasing precipitation in the region (see Figure 2). MO = Morris, GE = Geary, RL = Riley, PO = Pottawatomie, MA = Marshall, WA = Wabaunsee, NE = Nemaha, OS = Osage, JA = Jackson, SH = Shawnee, BO = Brown, JE = Jefferson, AT = Atchison, DO = Douglas, LV = Leavenworth, JO = Johnson, WY = Wyandotte.

Ensemble changes in rainfed yield ranges from -36% to -50%, with regional average decline of 45% (regional average value, 5148 kg ha⁻¹) (Figure 2.7a). The highest reduction in yield was observed for Geary County where high growing season SRAD and shallow soils of high curve number were observed, while the lowest reduction was observed for Leavenworth County where deep silt loam texture and low curve number, and high seasonal precipitation were observed (Figure 2.7a). However, the overall results indicate that the reasons behind maize yield decline under future climate change were due to heat stress and limited water availability induced by increases in growing season temperature and solar radiation and decline in growing season precipitation in the region. This result is consistent with the findings of Tubiello et al. (2002) who found that the future decrease in precipitation and increase in temperature in Kansas resulted in yield reduction ranging from -30 to -40%, as well as high yield variability. Yield variability observed in this study under future climate change varied from 62% to 90%, with regional average variability of 79% (Figure 2.7b). Our results agree with several studies that have been conducted within the US (Lobell et al., 2013) as well as around the world. For example, using the DSSAT CERES-Maize model under mid-century, Araya et al. (2020) projected that maize yield of an early maturing variety will be changed by -13% to -8% in Ethiopia. The anticipated rainfed maize yield in 2055 in central Illinois is expected to go down by 23% to 34%, with the likelihood that yield may not reach 50% of the potential yield (Cai et al., 2009). In a more recent study conducted in the US Corn Belt, Yang & Wang (2023) found that 40% decline in rainfed maize yield in the region resulted due to heat stress. In Malawi, Msowoya et al. (2016) projected that rainfed maize yield

may decline by 14% by mid-century (mid-term), and 33% by late century (late term). There are indications of 30% decline in regional rainfed maize yield in Mexico (Murray-Tortarolo et al., 2018). Overall, our results show consistency with the findings reported in literature and suggest significant future climate change impacts on rainfed maize production in the region.

As previously observed, we also observed a systematic spatial variability in yield change and CV values, with decreasing yield decline (Figure 2.7a) and decreasing CV (Figure 2.7b) trends from west to east of the region (MO to WY, west and east bound counties), suggesting that future climate change on rainfed maize may have lesser impacts moving from west to east of the region. This trend is also true for climate change shift impacts and variation in aridity and precipitation gradients in the Midwest (Seager et al., 2018; Yang & Wang, 2023). Our results agree with the results of Yang & Wang (2023) who found that future climate change on rainfed maize may have less impacts moving from west to east of the region. As stated earlier, precipitation gradient in the US Midwest increases from west to east, which attenuates the impacts of high heat on maize production in the east, while maize production in the west may suffer severe loss without irrigation (Araya et al., 2017a).

Figure 2.7c shows the regional yield change by different soil textures. We found that there is deviation in maize productivity from what was previously reported. Results showed that, given the fact that soil texture plays a significant role in determining the outcome of an agricultural production, productivity decline was observed to be lower in soils of CL texture (44%), followed by SL (45%), and then SCL (46%) textures. The difference in yield decline observed under different soil textures were not statistically significant, indicating that all soil textures in the region may have equal productivity performance under future climate change. Bird et al. (2016) found that rainfed wheat yield under future climate change will be 64% less on CL soils. In another study,

Nouri et al. (2016) found that yield loss will likely be higher in finer-textured soils. Overall, there is no clear consistency as to which soil texture will be better suited for crop production under future climate change in the region. However, what is clear is that climate change will change the course of rainfed maize production under variable soil textures and limited water availability, exacerbated by heat stress due to high temperatures and solar radiation, and decline in growing season precipitation in the region.

2.4.4 Climate Change Impact on Rainfall Productivity

Changes in rainfall productivity, expressed as rainfall utilization potential in the region is shown in Figure 2.8a. Under future climate change, rainfall productivity varied from -25% to -42% (ensemble average of five models for Jackson and Wabaunsee counties, upper and lower bounds, respectively) with regional average value of -37%. Putting this into perspective, we observed that rainfall productivity is likely to decline by 37% at regional level. Decline in rainfall productivity may have occurred due to observed decline in growing season prcp, heat stress and limited soil moisture. With reduced growing season prcp and increased warming, rainfed maize may struggle with utilization of available soil-water due to reduced transpiration. In addition, variability and depletion of soil moisture may have worsened the observed decline in rainfall productivity found in the region. Coefficient of correlation between maize yield decline and changes in rainfall productivity was 0.68, suggesting that rainfall productivity decline may likely impact overall maize yield in the region. Khongdee et al. (2022) reported that maize water productivity is significantly correlated with yield. Our result further suggests that the reduced growing season prcp, which further reduced the rainfall productivity, impacted maize yield, given the strong positive correlation observed in this study.

Figure 2.8b shows the regional rainfall productivity decline by different soil textures. Rainfall productivity decline follow similar trend observed for yield change under different soil textures, with rainfall productivity decline observed to be lower in soils of CL texture (33%), followed by SL (36%), and then SCL (39%). Contrary to yield decline findings under different soil textures in the region, there is significant difference among rainfall productivity declines found under different soil textures, indicating that all soil textures in the region may not have equal growing season prcp utilization potential under future climate change.

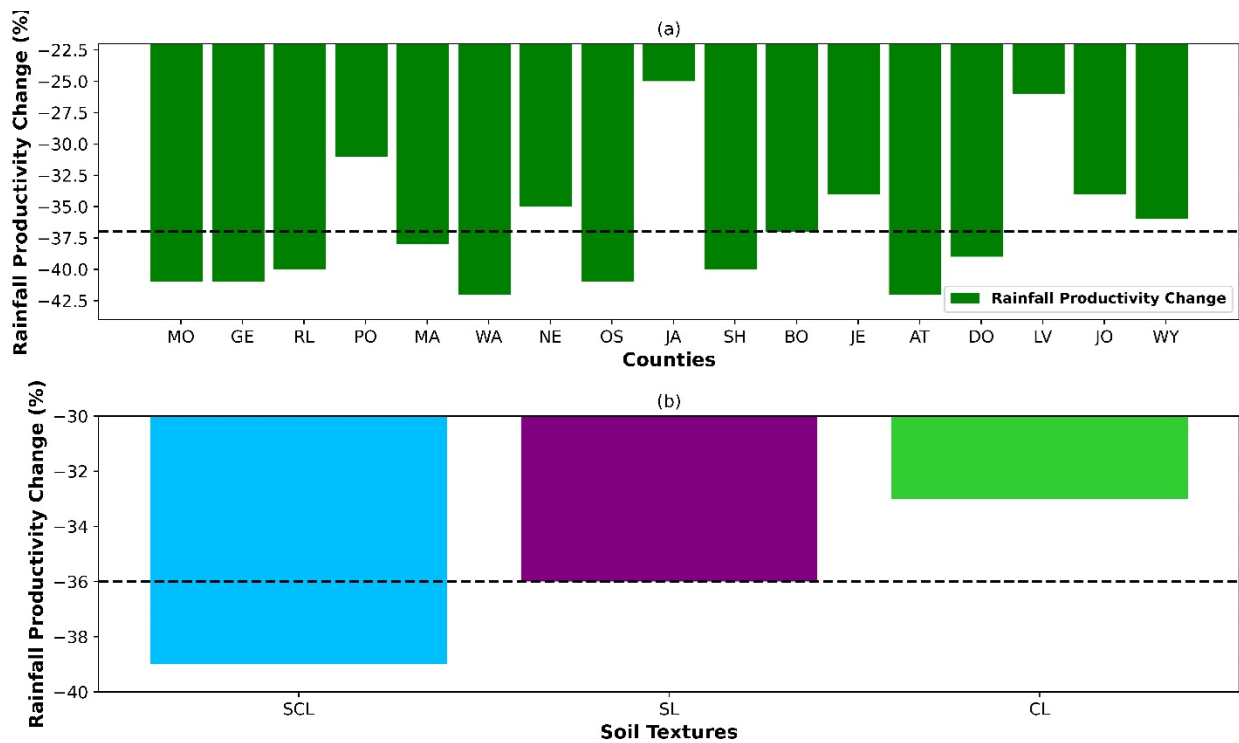


Figure 2.8. (a) Percent change in county-level rainfall productivity relative to baseline period. (b) Percent change in rainfall productivity by soil texture relative to baseline period. The black dash lines represent the regional average decline. Counties are ordered from west to east of increasing precipitation in the region (see Figure 2). MO = Morris, GE = Geary, RL = Riley, PO = Pottawatomie, MA = Marshall, WA = Wabaunsee, NE = Nemaha, OS = Osage, JA = Jackson, SH = Shawnee, BO = Brown, JE = Jefferson, AT = Atchison, DO = Douglas, LV = Leavenworth, JO = Johnson, WY = Wyandotte.

There is little or no literature contributing knowledge to other reasons behind rainfall productivity decline under future climate change using the CERES-Maize model. Given the

aforementioned, therefore, there is need to optimize the productivity of available growing season rainfall under future climate change, which requires smart adaptation strategy to sustain rainfed maize production in the region.

2.4.5 Climate Change Adaptation

2.4.5.1 Impact of Adaptation on Yield

Simulated changes in rainfed maize yield between hypothetical (adaptation) and reference (no adaptation) cultivars under future climate change are presented per county in Figure 2.9a below.

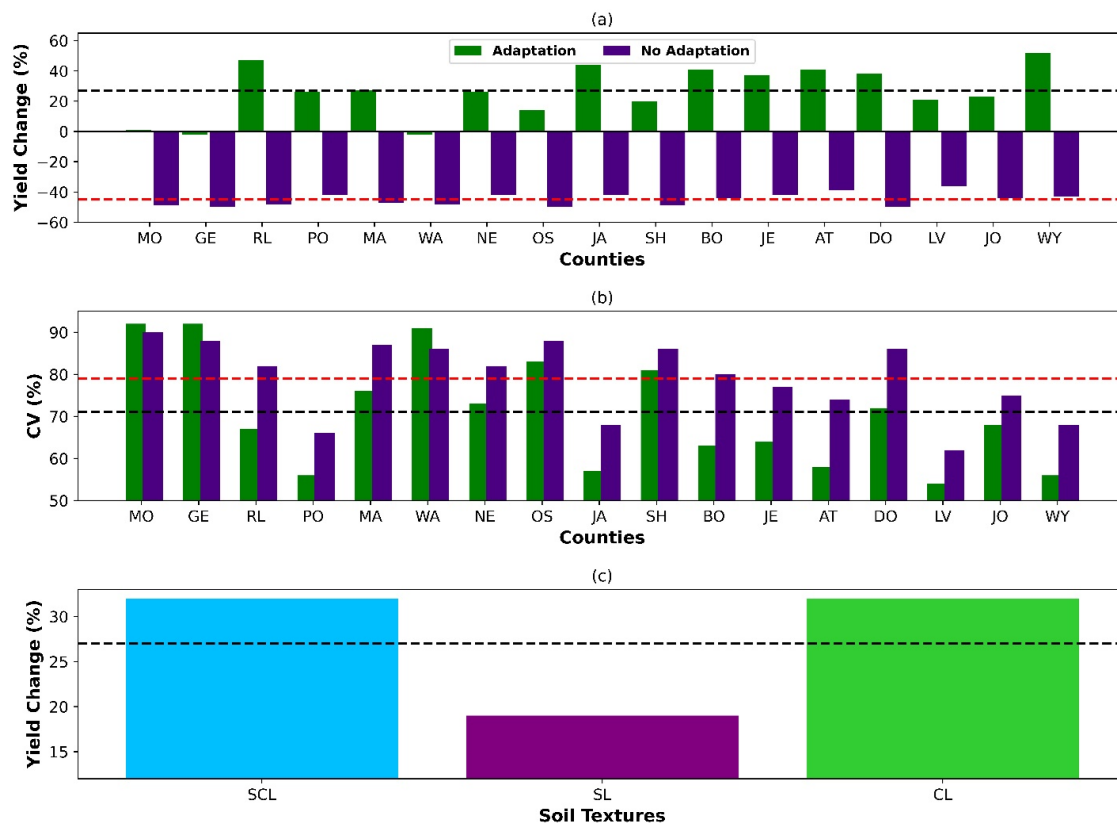


Figure 2.9. (a) Percent change in county-level rainfed maize yield under adaptation and no adaptation. (b) Percent change in CV values under adaptation and no adaptation. (c) Percent change in rainfed maize yield by soil texture under adaptation. The black and red dash lines represent the regional average changes under adaptation and no adaptation, respectively. Counties are ordered from west to east of increasing precipitation in the region (see Figure 2). MO = Morris, GE = Geary, RL = Riley, PO = Pottawatomie, MA = Marshall, WA = Wabaunsee, NE = Nemaha, OS = Osage, JA = Jackson, SH = Shawnee,

BO = Brown, JE = Jefferson, AT = Atchison, DO = Douglas, LV = Leavenworth, JO = Johnson, WY = Wyandotte.

Yield gain varied from -2% to 52% (Geary and Wyandotte counties, respectively), with regional average gain of 27%. Ensemble regional average rainfed maize yield obtained under hypothetical cultivar with adaptation was 7063 kg ha⁻¹. Our results indicate that root proliferation strategy improved rainfed yield in over 85% of the counties, with the exception of Geary and Wabaunsee counties, having 2% further yield decline. The reason behind this further decline was attributed to soil type found in the counties. Shallow soils of SL textures were observed in the two counties, indicating that root proliferation strategy may not be effective in shallow soils. Yield gain of 52% observed in Wyandotte county was attributed to possible soil rooting depth, proper utilization of plant available water and relatively favorable environment for crop production. For example, we observed that the Ladoga silt loam dominant soil found in Wyandotte county is deep, and the location of the county is found in the eastern extreme of the region where precipitation decline is lowest (Table 2.6, Figures 2.1 and 2.2).

With the hypothetical cultivar adaptation, regional maize yield variability reduced to 71%; thus, reducing climate change variability risk by 8%. As previously observed, variability in maize yield coincided with yield gain trajectory, with low variability indicating higher yield gain and high variability indicating lower yield gain (Figure 2.9b). In addition, we observed a systematic spatial variability in yield gain and CV values, with increasing yield gain trend from west to east of the region (MO to WY, west and east bound counties, Figure 2.9a), and decreasing CV trend from west to east of the region (MO to WY, west and east bound counties, Figure 2.9b). CV values were reduced in 85% of the counties in the region, except for Morris, Geary, and Wabaunsee counties where the CV values were 2%, 4%, and 5% higher, respectively. We found that the modified root architecture of the hypothetical cultivar would make a good strategy to improve

drought tolerance under rainfed production if the amount of deep soil water holding capacity is high. This could be the reason behind the high yield gain in Wyandotte county. These results agree with the findings of Carretero et al. (2014) who found similar observation in their maize simulation study of improving drought tolerance using the CERES-Maize model under current climate. They reported 11.7% and 4.7% rainfed maize yield gain for Pergamino and Pilar in the Argentine Pampas, respectively, and that the performance of a hypothetical cultivar under water stressed conditions depends on the availability of water in the deep soil layers and climate. By modifying the root architecture model governing root proliferation, Battisti et al. (2017) observed soybean yield gain above 300 kg ha⁻¹ in southern Brazil. It is important to note that yield gain in this study under hypothetical cultivar was more for soils of SCL and CL textures than observed for soils of SL texture (Figure 2.9c). As previously reported, soils of SCL and CL are generally considered to have more available water holding capacity than SL but are locked in the mesopores and micropores of the soils; thus, making soil water unavailable for crop use under normal condition. With root proliferation adaptation strategy, more roots may branch into soil layers where water and nutrients are available; thus, harnessing the benefits of deep soil water and nutrients. This could be the reason behind the high yield gain observed for soils of SCL and CL in this study. Our findings emphasized the importance of cultivar adaptation to drought stress conditions in the face of future climate risk.

2.4.5.2 Impact of Adaptation on Rainfall Productivity

Changes reported as rainfall productivity gains under hypothetical cultivar (adaptation), relative to reference cultivar (no adaptation) are shown in Figure 2.10a. Under hypothetical cultivar, rainfall productivity gains varied from -2% to 56% (ensemble average of five models, Geary, and Wyandotte counties, upper and lower bounds, respectively) with regional average value

of 28%. Similar to maize yield gain, high rainfall productivity gains observed in Wyandotte county were attributed to soil type, possible proper utilization of plant available water and effective rainfall, and relatively favorable environment. As previously reported, the location of Wyandotte County is found in the eastern extreme of the region where precipitation decline is lowest (Table 2.6, Figures 2.1 and 2.2). Furthermore, we noted a consistent spatial variation in rainfall productivity gains, revealing an increasing trend from the western to the eastern part of the region (including MO to WY, west and east bound counties, Figure 2.10a).

Similar to findings reported above, rainfall productivity gains in this study under hypothetical cultivar was more for soils of SCL and CL textures than observed for soils of SL texture (Figure 2.10b). Carretero et al. (2014) reported that in addition to distribution and availability of water throughout the soil profile, the benefits of enhanced root system depend on the total amount of water available in the soil profile, especially deeper in the profile.

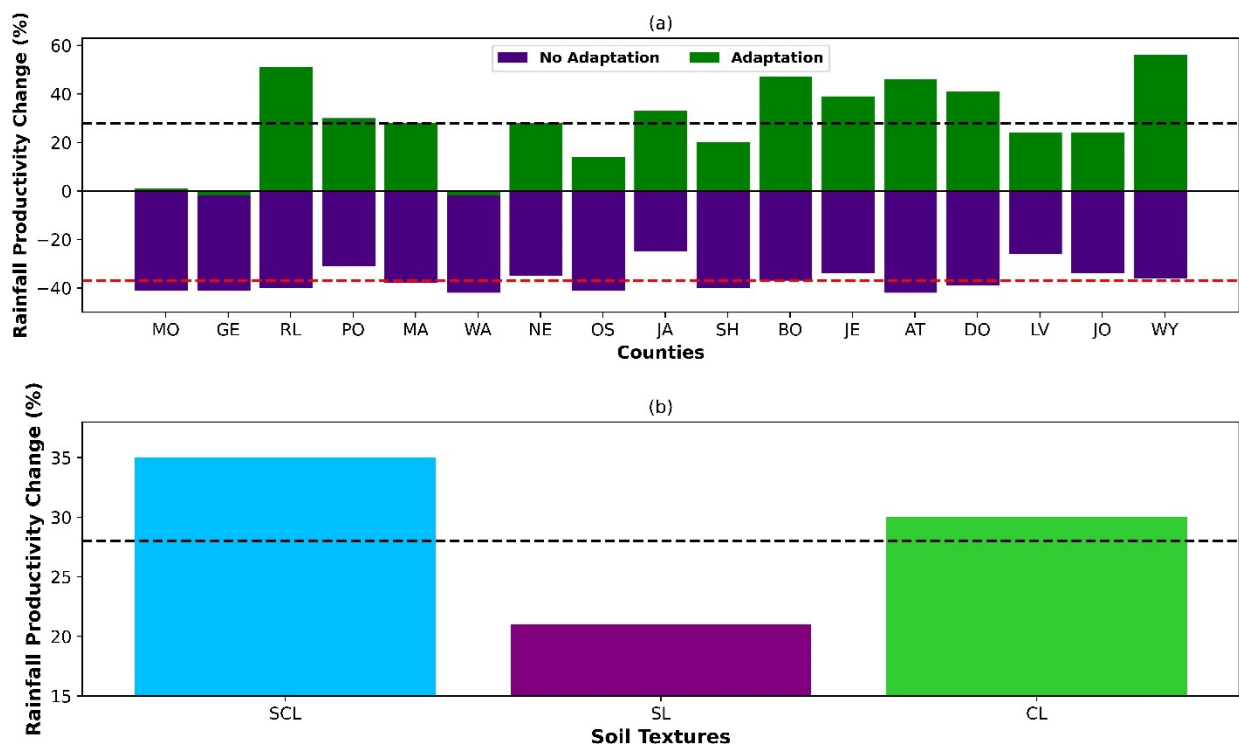


Figure 2.10. (a) Percent change in county-level rainfall productivity under adaptation and no adaptation. (b) Percent change in rainfall productivity by soil texture under adaptation.

The black and red dash lines represent the regional average changes under adaptation and no adaptation, respectively. Counties are ordered from west to east of increasing precipitation in the region (see Figure 2). MO = Morris, GE = Geary, RL = Riley, PO = Pottawatomie, MA = Marshall, WA = Wabaunsee, NE = Nemaha, OS = Osage, JA = Jackson, SH = Shawnee, BO = Brown, JE = Jefferson, AT = Atchison, DO = Douglas, LV = Leavenworth, JO = Johnson, WY = Wyandotte.

In another similar study, Hammer et al. (2009) indicated that soils with lower amounts of stored water typically have less water in the deeper soil layers; consequently, limiting the gains of root proliferation. Between improved maize yield and rainfall productivity under hypothetical cultivar, a significant strong positive correlation exists, with correlation coefficient of 0.99. Our results indicate that improving the root architecture function governing root proliferation by switching from exponential to a fairly linear root growth was found to be desirable towards effective utilization of growing season rainfall in the region. This attribute of making the rooting front and root proliferation either exponential or fairly linear is dependent on cultivar genotype and rooting environment (Jones et al., 1986).

2.4.6 Spatial Variability of Maize Yield and Rainfall Productivity

Figures 2.11 and 2.12 show the spatial variability of maize yield and rainfall productivity responses to future climate change (with and without adaptation) in comparison to baseline condition. Yield and rainfall productivity variations in the region show a clear indication of the impact of variable soils and climate. Under baseline conditions, higher yield responses were simulated than under future climate adaptation and no adaptation scenarios, respectively. (Figure 2.11). Similar variations were observed for rainfall productivity presented in Figure 2.12. This indicates that yield and rainfall productivity responses were higher under baseline due to favorable crop, soil, and climate interactions in the region. Under no adaptation in the future, there is a clear spatial yield variation ranging from 0 - 8,000 kg ha^{-1} . However, cultivar adaptation under future climate change improved yield ranges from 0 - 11,000 kg ha^{-1} . Similar response was observed for

rainfall productivity, where productivity values range from 0 – 17 kg $\text{ha}^{-1}\text{mm}^{-1}$ (under no adaptation) to 0 - 23 kg $\text{ha}^{-1}\text{mm}^{-1}$ (under adaptation) (Figure 2.12).

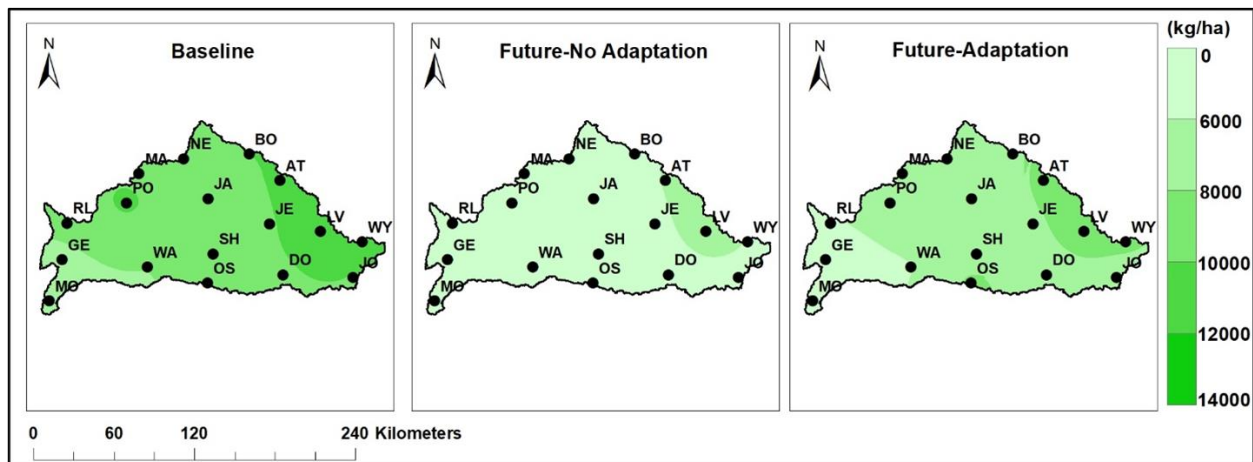


Figure 2.11. Yield response to climate change in comparison to baseline condition. AT = Atchison, BO = Brown, DO = Douglas, GE = Geary, JA = Jackson, JE = Jefferson, JO = Johnson, LV = Leavenworth, MA = Marshall, MO = Morris, NE = Nemaha, OS = Osage, PO = Pottawatomie, RL = Riley, SH = Shawnee, WA = Wabaunsee, WY = Wyandotte.

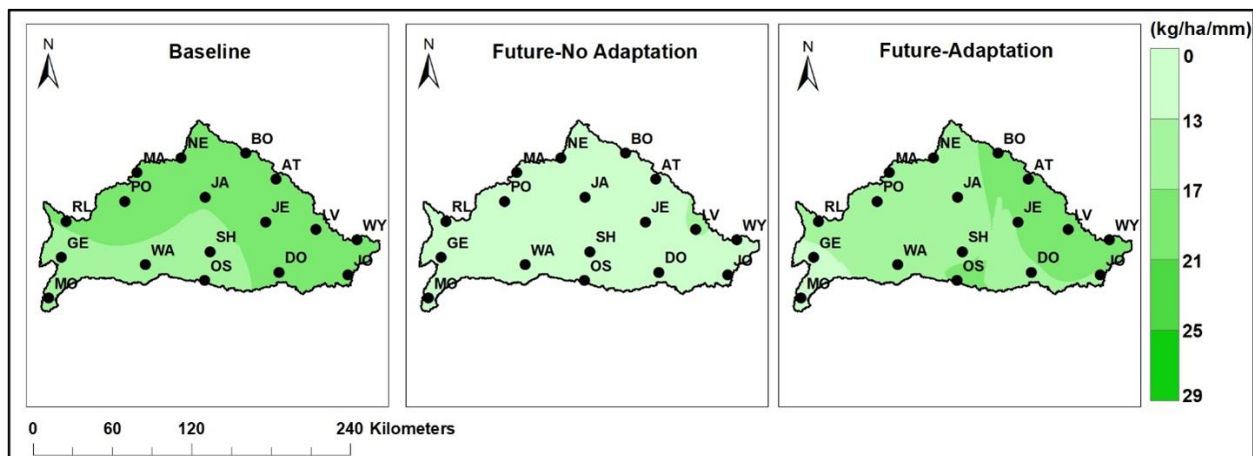


Figure 2.12. Rainfall productivity response to climate change in comparison to baseline condition. AT = Atchison, BO = Brown, DO = Douglas, GE = Geary, JA = Jackson, JE = Jefferson, JO = Johnson, LV = Leavenworth, MA = Marshall, MO = Morris, NE = Nemaha, OS = Osage, PO = Pottawatomie, RL = Riley, SH = Shawnee, WA = Wabaunsee, WY = Wyandotte.

It is important to note that rainfall plays a huge role in yield variation in the region. A clear indication of consistent spatial variation in yield and rainfall productivity was observed, revealing an increasing trend from the western to the eastern part of the region (including MO to WY, west

and east bound counties, Figures 2.11 and 2.12, respectively). This trend coincided with the spatial rainfall gradient in the region as shown in Figure 2.2. Areas of high rainfall were observed to have higher yield both under baseline condition and future climate with adaptation. It is also important to note that based on spatial visualization of our observation as shown in Figures 2.11 and 2.12, root proliferation adaptation strategy explored in this study improved maize productivity in the region. In general, climate change adaptation based on root proliferation assessed in this study, may approximate rainfed yield and rainfall productivity values close to baseline conditions.

2.4.7 Limitations of the Study

The primary focus of our study was to quantify the baseline yield conditions of rainfed maize and to assess the impacts of future climate change and root proliferation adaptation strategy under variable soils and climate in EKS RB of the US Great Plains. To achieve this, our study made some important assumptions. Firstly, the CERES-Maize model simulations did not account for disease and pest losses, hence, may have resulted in slight overestimation of maize yield and days to anthesis observed during calibration in this study. A good and sound assumption is to accept that the system is well controlled and free from significant pest and disease losses (Tesfaye et al., 2018). This assumption was also reported in the variety trial report used for cultivar selection (Lingenfelser et al., 2015). Secondly, future climate projections from the ISIMIP3b CMIP6 GCMs were at 50 km by 50 km spatial resolution. While the ISIMIP3b datasets are robust and have been used by several studies (Liersch et al., 2023; Schroder et al., 2024; Xu et al., 2023), these studies may not have considered the spatial mismatch of multiple smaller areas overlapping in one grid. For our case, we observed that at maximum two counties in our region were found collapsing in one grid; thus, we made a reasonable assumption that the overlapping counties share the same climate. This is true for very small counties with spatially independent administrative boundaries.

However, to provide variability and county-level independence, no two counties have the same dominant soil properties, especially with the levels of upper and lower limits of soil moisture. Thirdly, the study did not include other genetic and agronomic adaptation strategies other than root proliferation through modifying the root growth function to optimize deep soil water uptake. The adaptation in this case assumed that maize may grow at a similar depth as sunflower and was supported by findings reported in literature. This assumption influenced the choice of the genetic-specific factor used to parameterize the root growth function model, which determines the ability of different soil layers for root growth (Carretero et al., 2014). Nevertheless, the scope and the selection of the hypothetical cultivar are reasonable and provide opportunities for future studies on the impacts of stacked genetic adaptation strategies on yield and rainfall productivity due to future climate change.

2.5 Conclusion

Future rainfed maize production under baseline and future climate change conditions were studied for the first time in the EKS RB of the US Great Plains. Using a well-calibrated CERES-Maize model, regional baseline yield was found to range from 6,522 to 12,849 kg ha⁻¹, with a regional average value of 9,270 kg ha⁻¹. Future maize yield and rainfall productivity were projected to suffer substantially from climate change, with productivity decreases reaching up to 45% and 37%, respectively. The projected losses in yield and rainfall productivity were majorly due to heat stress and limited water availability induced by high growing season temperatures and solar radiation, and a decline in growing season precipitation. Climate change may shift the most productive soil from silt loam to silt clay loam; however, this shift is not significant across all dominant soils found in the study region.

As climate warms, adaptation strategies become very essential for reducing the negative impacts of future climate risks on rainfed production systems. Changing the plant root system as a potential adaptation strategy by increasing the root density (root proliferation) could lead to yield benefits, especially under drought and climate change conditions. Root proliferation of a hypothetical maize cultivar resulted in a 27% increase in regional maize yield and a 28% increase in rainfall productivity compared to the reference cultivar without adaptation. Root proliferation adaptation strategy is likely to shift the most productive soil from soils of silt loam texture to soils of silt clay loam and clay loam textures. This is due partly to more soil water in the profiles of silt clay loam and clay loam than in silt loam soils, and that more roots may branch into soil layers where water is available; thus, harnessing the benefits of deep soil water.

In general, we observed a clear indication of consistent spatial variation in yield and rainfall productivity, revealing an increasing trend from the western to the eastern part of the region; a trend coinciding with the regional precipitation gradient. The results highlight the importance of maize cultivar adaptation to root proliferation to maximize uptake of deep soil water storage to boost rainfed maize production under a changing climate and limiting conditions. We infer that a combination of adaptation strategies, in addition to root proliferation assessed in this study, may further improve maize yield and rainfall productivity in the region.

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Chapter 3 - Quantifying future climate impacts on maize productivity under different irrigation management strategies: a high-resolution spatial analysis in the U.S. Great Plains

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3.1 Abstract

A comprehensive assessment of climate change impacts on irrigated maize production has not been well-reported for the U.S. Great Plains. Producers east of the 100th meridian, a historically wetter portion of the Great Plains, face uncertainties regarding climate change effects on yield, irrigation water use, irrigation water productivity, and farmers' net returns. Additionally, climate impacts are likely to be spatially variable with a heterogeneous response to environmental variability and different water management techniques. Therefore, the present study addresses climate change impacts on irrigated maize productivity in the Eastern Kansas River Basin of the Great Plains using Shawnee County, Kansas as a case study. Our approach incorporated spatially variable soils coupled with grid-level historical and future climate scenarios under different irrigation water management strategies using the CERES-Maize model within the Decision Support System for Agrotechnology Transfer (DSSAT) modeling system. Our model simulations matched observed yield and irrigation water use data closely, with the index of agreement values greater than 0.9 and 0.85, respectively. We simulated two Representative Concentration Pathways

(RCPs) of the future climate (RCPs 4.5 and 8.5) over three 25-year periods (2025-2049, 2050-2074, and 2075-2099) relative to historical climate (1991–2015) condition for each irrigated maize-growing grid cell. We found that future irrigated maize yield decline occurred as a result of shortened growing season length due to increases in growing season minimum and maximum temperatures, with values ranging from 21% to 38% (early and late century, respectively) under RCP 4.5, and from 22% to 70% (early and late century, respectively) under RCP 8.5. Irrigation water use under full allocation increased by 9% to 23%, with a significant reduction in average net returns ranging from 53% to 80% (RCPs 4.5 and 8.5, respectively), and a significant decline in irrigation water productivity. Assessing the impacts of deficit irrigation resulted in water savings ranging from 3 to 15% without further diminishing maize productivity. Our results indicate that climate-smart irrigation management strategies implemented at a fine spatial resolution could help save water despite negative climate impacts on future maize production in the region. The future of maize production in the region necessitates integrating yield-advancing cultivars and proper agronomic management with improved water management found in this study in order to meet the required grain demand over the next decades.

Keywords: Irrigated maize yield, climate change, irrigation water use, spatial crop model, CERES-Maize model, net return, water productivity, Great Plains

3.2 Introduction

Fewer than 15 crops provide nearly 90% of the calories consumed globally by humans (Kastner et al., 2012; Stewart & Lal, 2018), with just three crops - wheat, rice, and maize - accounting for about two-thirds of that total (Stewart & Lal, 2018). Both climate change (IPCC, 2023) and population growth (FAO, 2023a, 2023b), independently, are expected to cause significant disruptions to food security within the next two to three decades. Maize, for example, is sensitive to heat stress (Onyekwelu & Sharda, 2024b; Yang & Wang, 2023), with numerous studies reporting yield shock and alteration in phenology due to climate change (Lobell, 2007; Lobell & Field, 2007; Ureta et al., 2016) and a high yield sensitivity to drought conditions (Zipper et al., 2016). The US Great Plains and broader Midwest region is one of the world's leading maize producers, but irrigation has led to the depletion of the Ogallala Aquifer, which is the largest aquifer in the US and the Great Plains (Araya et al., 2017; McGuire, 2012; Scanlon et al., 2012). As a result, understanding the potential impacts of climate change on future maize yield and irrigation water is crucial to identify potential water management strategies to sustain water resources and crop productivity across the Great Plains.

As early as 1879, John Powell highlighted the west-east precipitation gradient across the US and the Great Plains, indicating the need for more irrigation water use in the west than in the east (Powell, 1879). He noted that in the midst of this precipitation gradient lies the 100th meridian, which is the hydroclimatic dividing line between the moist eastern part of the United States and the drier western plains, and where precipitation is approximately equal to potential evapotranspiration (Seager et al., 2018a). However, recent studies have shown that the hydroclimatic conditions that characterize this line are shifting eastwards, thereby creating drier conditions (sometimes termed a 'new 100th meridian') to the east of the 100th meridian (Krajick,

2018; Seager et al., 2018a; Seager et al., 2018b). The implications of this eastward migration of aridity on total irrigated maize productivity remain uncertain in the region, and further eastward migration is expected over the next decades (Krajick, 2018; Seager et al., 2018a; Seager et al., 2018b).

While drier future conditions are expected east of the 100th meridian (Seager et al., 2018b), opportunities for managing water resources and assessing the impacts of future climate change on maize yield, water use, water productivity, and farmers' net returns have not been studied. Irrigation is a common crop adaptation to buffer rainfed production response to drought and climate variability (Zipper et al., 2016). However, the solution to understanding climate change impacts on irrigated maize productivity in the Great Plains requires a spatially explicit modeling approach that accounts for heterogeneity in environmental conditions and agricultural management practices. This approach is essential for testing different irrigation management strategies needed to maintain or improve crop productivity without impairing water resources.

Process-based crop simulation models are extensively used to quantify the impact of genotype by environment by management (GxExM) interactions on yield and yield components (Onyekwelu & Sharda, 2022, 2024a, 2024b, 2024c). They are also used to explore best management practices for cropland ecosystems managing limited resources (Liang et al., 2023). Given the constraints that global climate change is projected to induce on crop productivity, several studies have used crop models such as the Decision Support System for Agrotechnology Transfer (DSSAT) to quantify climate change impacts on crop productivity (Ayankoyo et al., 2020; Jha et al., 2021; Kothari et al., 2019a, 2019b; Mauget et al., 2020; Sen et al., 2023, 2024). However, most crop models run at point-scale to simulate a homogenous unit, such as a field, which has limitations when considering spatial heterogeneity of environmental conditions (e.g., soil and climate) at a

regional scale. Adapting point-scale crop models for spatial simulation of crop productivity offers many advantages. For example, spatial simulations provide location-specific impacts, which can be used to target input resources (e.g., irrigation, fertilizer, etc.) for profit maximization, and to assess co-benefits and trade-offs among different ecosystem services (Qiu et al., 2018, 2019). In addition, gridded outputs of regional crop models mapped to their corresponding unique fields can be combined with spatial soil distribution and growing season climate variables to understand key landscape and atmospheric controls on yield, irrigation water use, irrigation water productivity, and farmers' net returns. This allows an improved understanding of regional crop productivity and aid in formulating efficient management strategies for crop sustainability.

Due to these factors, producers east of the Great Plains' 100th meridian do not know what potential climate change impacts on yield, irrigation water use, irrigation water productivity, and net returns to expect. Here, we address this for a case study region in the eastern Great Plains (Shawnee County KS in the Eastern Kansas River Basin) via the following objectives: 1) develop a protocol for adapting point-scale crop model for spatial maize productivity simulation, 2) quantify historical irrigated maize productivity at 4 km grid scale of unique soils and climate variables, and 3) quantify future maize productivity under different irrigation management strategies and future climate scenarios across three 25-year time periods (2025–2049, 2050–2074, and 2075–2099) relative to historical conditions (1991–2015). In doing so, we account for environmental heterogeneity to quantify location-specific impacts of future climate and in doing so provide a useful reference for other regions in the Great Plains battling climate change uncertainty and advancing management zone delineation for irrigated maize production. By adopting the spatial protocol described in this study, climate impacts of locations experiencing

similar aridity in the Great Plains and other regions can be quantified, guiding the implementation of location-specific proactive measures to improve irrigated maize production.

3.3 Materials and Methods

3.3.1 Study Area

This study was conducted in Shawnee County, which is the county seat of the state of Kansas (Figure 3.1) and is in the central part of the Eastern Kansas River Basin (EKSRB, hereafter) of the US Great Plains. The EKSRB spans from the confluence of the Smoky Hill and Republican rivers in the west to the confluence with the Missouri River in Kansas City, including parts of 17 counties (Onyekwelu & Sharda, 2024a, 2024b; Sinnathamby et al., 2018). The ‘new 100th meridian’ lies at the western edge of the EKSRB and is projected to cross the EKSRB during the 21st century (Seager et al., 2018a, 2018b), making it an ideal setting to develop generalizable insights for adaptation to climate change for the broader agricultural system of the eastern Great Plains.

Crop production in Shawnee County and the rest of the EKSRB include a mixture of rainfed and irrigated cropland, with irrigation particularly common for crops that are water-demanding like maize and soybean. There are over 600 irrigated maize fields in Shawnee County (Figures 3.2 and A.3), resulting in over 13,000 acres (Figure A.2). Most irrigated cropland is located in the alluvial river valley of the Kansas River (Figure 3.2). There are 14 unique dominant agricultural soils in the county (Figures A.1 and A.5), with variable distributions of clay loam, silty loam, and silty clay loam textures. Most irrigated cropland is on silty loam soils, with a smaller fraction on clay loam and silty clay loam (Figure 3.2).

The average growing season (between April and September) rainfall (precipitation) in Shawnee County is 507 mm, with growing season average daily temperatures (minimum and

maximum) ranging from 17 to 29 °C, and average solar radiation value of 21.6 MJ m⁻²d⁻¹ (Onyekwelu & Sharda, 2024a, 2024b). Recent studies have shown that climate change could lead to rainfall declines of up to 16%, temperature increases by 3.2 to 4.2 °C, and average solar radiation increase of 1.5 MJ m⁻² (Onyekwelu & Sharda, 2024b). More information on the regional climate outlook and trajectory is shown in Figure 3.3, with monotonically increasing trends observed for minimum and maximum temperatures (Figures 3.3a, b) up until the end of the 21st century. However, growing season precipitation shows no trend, with values largely deviating around the mean values of the historical precipitation (Figure 3.3c).

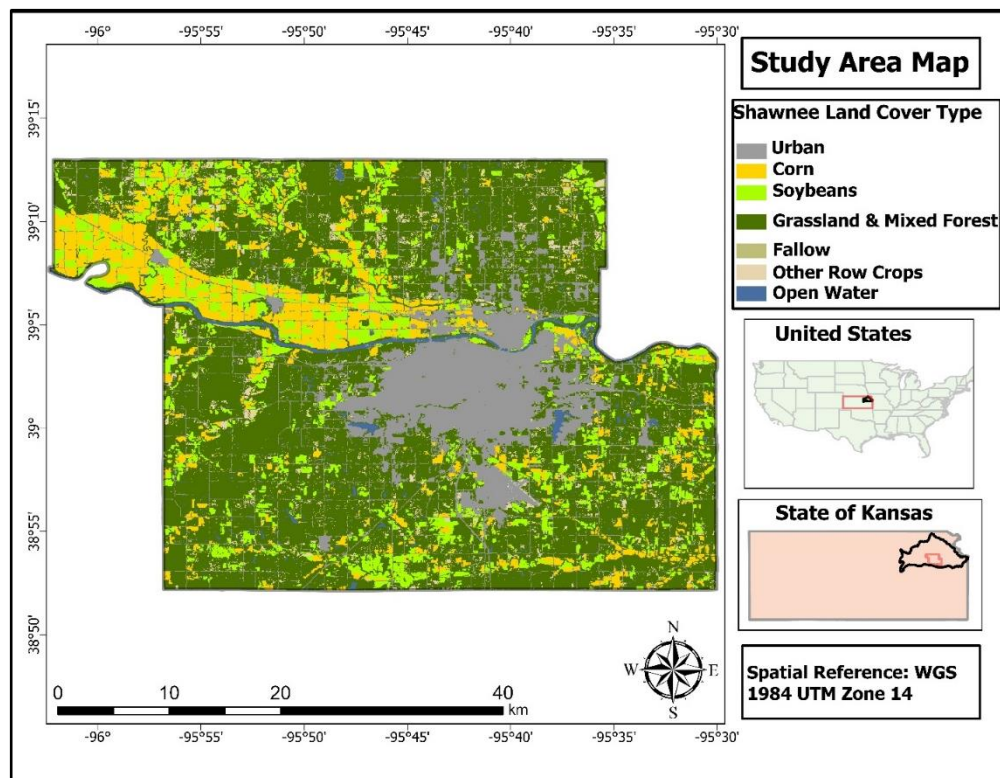


Figure 3.1. Inset map of the study area (Shawnee County in red outline in the State of Kansas map) with land cover types. EKS RB boundary is shown in black watershed outline in the state of Kansas map. Adapted from (Onyekwelu & Sharda, 2024b).

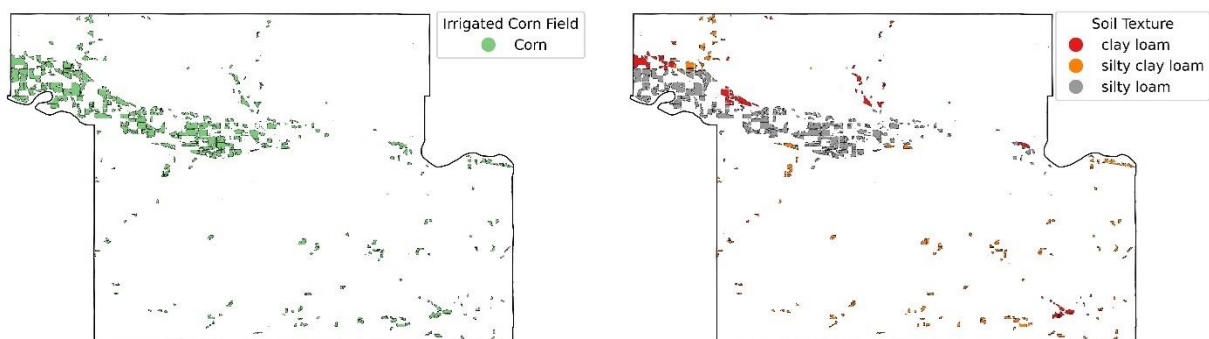


Figure 3.2. Shawnee County irrigated maize croplands and spatial distribution of soil texture.

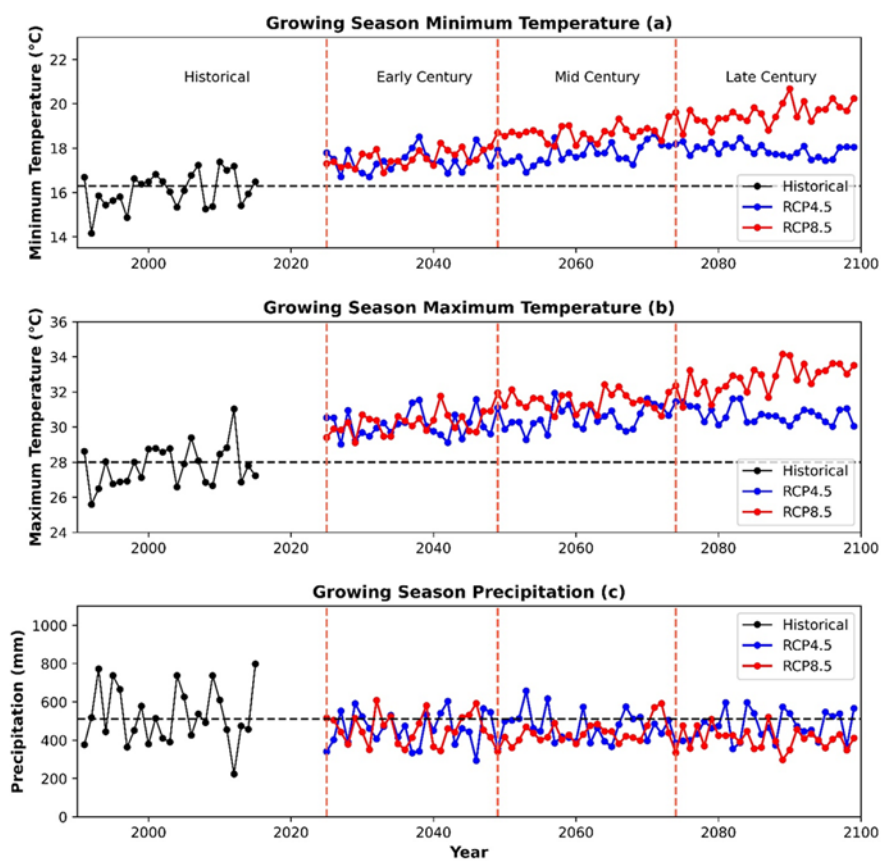


Figure 3.3. (a) Growing season minimum temperature trajectory, (b) Growing season maximum temperature trajectory, (c) Growing season precipitation trajectory. Black dash line represents historical (baseline) mean values.

3.3.2 CERES Maize Model: Spatial Implementation Framework

We used the CERES-Maize model, which is the maize simulation module within the Decision Support System for Agrotechnology Transfer (DSSAT version 4.7.5, hereafter), for simulating maize growth and irrigation practices (Jones et al., 2003; Ritchie et al., 1998). DSSAT is an application software program that comprises crop simulation modules for over 40 crops. Minimum climate datasets required to run the model include daily minimum and maximum air temperatures, precipitation (rainfall), and solar radiation. The model also accounts for soil information/properties, crop management data (water, nutrients, and planting conditions), initial conditions at planting, and cultivar characteristics represented as genotype-specific coefficients (Jones et al., 2003; Onyekwelu & Sharda, 2024b). More details on the recent updates on the model and set up can be found in Hoogenboom et al. (2019) and Onyekwelu & Sharda (2024b).

Although the DSSAT and its crop simulation models have been used extensively for a variety of studies, the model is designed as a point-based model meant to represent a homogeneous management unit (such as a field) and therefore lacks any spatial-oriented user interface designed for simulating cropping systems over large spatial areas such as counties. As a result, we used the model's *.GSX spatial execution file (Hoogenboom et al., 2019) and expanded its application by linking spatially varying grid-level inputs (soil and climate variables) to generate sets of grid-level outputs (yield, irrigation water use, water productivity, and net return) in order to aid farmers in spatiotemporal decision-making (Figure 3.4). To design the spatial model framework, a top-down design approach was used, where the region was first divided into regular 4 km grids to simulate irrigated maize productivity at the finest scale possible and matching the resolution of the meteorological input data, resulting in 130 unique grids (Figure 3.4). Next, we used the grid information to query areas in the region where irrigated maize grows

(<https://nassgeodata.gmu.edu/CropScape/>; USDA NASS 2017; Han et al., 2012) to adapt the point-scale model to regional simulation. To assign maize-growing grids, a combination of the soil map, land use map, and irrigation map were used. For soils, we used the gSSURGO (Gridded Soil Survey Geographic) detailed soil map at 30 m (Soil Survey Staff, 2022), while the 2017 USDA's CropScape - Crop Data Layer (<https://nassgeodata.gmu.edu/CropScape/>; USDA NASS 2017) for all land use was used (Han et al., 2012). Irrigation maps at 30 m resolution (Xie et al., 2021; Xie & Lark, 2021) for the contiguous United States were used to distinguish irrigated and rainfed fields. The irrigation map reported datasets for all irrigated crops within a particular region in the contiguous United States. Geoprocessing tools available in ArcMap 10.7 (Esri Inc, 2022) were used to extract maize fields (irrigated and rainfed) from the USDA CropScape - Crop Data Layer. Since the extracted maize fields consist of both irrigated and rainfed areas and the irrigation map (Xie et al., 2021; Xie & Lark, 2021) contains irrigated areas for all possible crops in the region, a geoprocessing operation in ArcMap 10.7 was carried out to compute the geometric intersection of fields that overlap in both layers (extracted maize fields and irrigation map). The resultant maize fields (irrigated fields) (Figure 3.2) were linked with the regional soil map and the initial 130 unique grids using the Zonal Statistics Tool in ArcMap to assign irrigated maize grids and dominant soil type for each grid (Figure 3.4). The final unique grid count was updated from 130 to 78 (Figure 3.4), representing the total units for running our model. The updated grid information was used to obtain weather variables and crop management data for the model, which will be discussed in the subsequent sections. Model outputs were merged into GIS layers by mapping grid-based simulations to their corresponding fields using a unique identifier for each grid. All mapping analysis were done in Python program environment using GeoPandas, Pandas, and Matplotlib packages (Jordahl et al., 2021; Hunter, 2007).

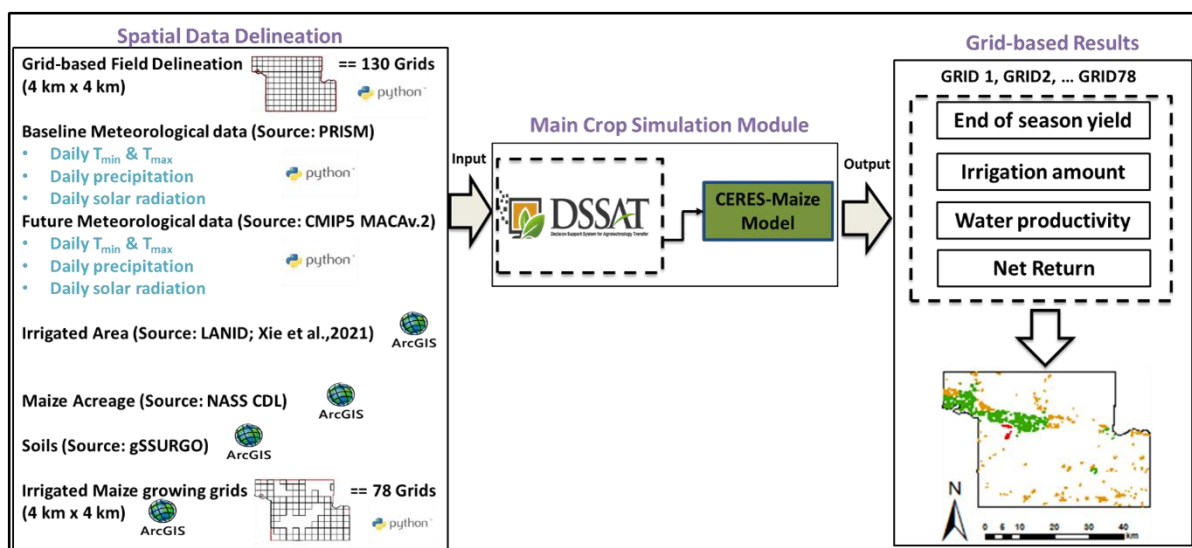


Figure 3.4. Workflow for spatially distributed maize simulation using the DSSAT CERES-Maize Model by integrating grid-based inputs to generate grid-specific simulation results (yield, irrigation amount, water productivity, and net return), visualized as field-specific spatial output maps.

3.3.3 Model Calibration and Validation

Model calibration involves systematically comparing the simulated and observed data based on an objective function to derive reliable estimates of the model parameters. Phenology and yield estimates using the CERES-Maize model are determined by six (6) genetic coefficients. Model calibration was performed following the approach reported by Onyekwelu & Sharda (2024b) and Araya et al. (2017). When conducting the model calibration, all management data (including nitrogen fertilizer, plant population, irrigation amount, planting dates and row spacing), soil type and characteristics, and climate information were acquired for locations reported in Table 3.1. Irrigated maize yield trials conducted in 2015 to 2017 were used for the calibration and were obtained from three counties in the EKS RB region, making nine (9) site-years of data (Table 3.1). Cultivar selection from variety trial reports was based on the approach reported by Onyekwelu & Sharda (2024b). Adjustments of model coefficients were made using the Genetic Calculator (GENCALC) tool to initiate a range of possible cultivar coefficients (Hoogenboom et al., 2019;

Hunt et al., 1993). By using the genetic coefficients of a default cultivar or initial guess in the DSSAT.CUL file, GENCALC iteratively compares the observed to the simulated data. Once a range of cultivar coefficients were obtained, the genetic coefficients of the trial maize cultivar were adjusted until reasonable yield estimates were achieved.

It is important to note that depending on the data used in calibration, several CERES-Maize model parameters have been demonstrated to suffer from equifinality (Lamsal et al., 2018). This is because different sets of parameter estimates will produce identical model predictions and, therefore, identical goodness-of-fit function values (Lamsal et al., 2018). This undermines genetic unique information of crop cultivars or varieties needed to advance breeding, as the parameter values themselves are treated as quantitative traits to infer underpinning genetics. However, since our interest is prediction and assessing climate impacts on yield and resource use, equifinality is not a concern (Lamsal et al., 2018). In addition to optimizing the cultivar genetic coefficients, parameters related to irrigation water use were simultaneously adjusted to improve irrigation simulation results. The Priestly-Taylor/Ritchie and the Suleiman-Ritchie methods in the model were selected for calculating reference evapotranspiration and soil evaporation, respectively. Initial water condition at planting was set at field capacity (FC), while irrigation application was set using the automatic routine in the model and refills the soil profile to FC at 50% management allowable depletion (MAD). All irrigation application was by sprinkler and the application efficiency was adjusted to 90%, assuming low-elevation spray application (LESA) systems, which are generally used in the Great Plains (Kisekka et al., 2016).

Table 3.1. Location-specific management data for model set up and calibration.

County/Year	Distance from EKS RB	Soil type	Planting date	Climate information	Plants/m ²	Row spacing (cm)	Nitrogen (lb/ac)	Cultivar type
Riley/2015	Within	Wymore silty clay loam	04/23/2015	Kansas Mesonet	7	76	180	Midland-656 PR
Riley/2016	Within	Wymore silty clay loam	05/05/2016	Kansas Mesonet	6	76	180	Midland-656 PR
Riley/2017	Within	Wymore silty clay loam	04/11/2017	Kansas Mesonet	7	76	230	Midland-656 PR
Shawnee/ 2015	Within	Reading silt loam	04/21/2015	Kansas Mesonet	11	76	180	Midland-656 PR
Shawnee/ 2016	Within	Reading silt loam	04/11/2016	Kansas Mesonet	11	76	194	Midland-656 PR
Shawnee/ 2017	Within	Reading silt loam	04/12/2017	Kansas Mesonet	7	76	180	Midland-656 PR
Republic/ 2015	< 50 km	Crete silty clay loam	04/29/2015	Kansas Mesonet	9	76	194	Midland-656 PR
Republic/ 2016	< 50 km	Crete silty clay loam	04/29/2016	Kansas Mesonet	6	76	160	Midland-656 PR
Republic/ 2017	< 50 km	Crete silty clay loam	06/08/2017	Kansas Mesonet	7	76	160	Midland-656 PR

Kansas Mesonet: <https://mesonet.k-state.edu/>

Model validation for yield was done using the field experiments reported in Table 3.2. This was achieved by comparing the simulated yield without changing the calibrated coefficients described earlier. For irrigation water use, we used ten (10) years (2010-2019) of irrigation withdrawal data from 92 wells (Figure A.4) reported by the Water Information Management and Analysis System (WIMAS; <https://geohydro.kgs.ku.edu/geohydro/wimas/>) database and have been used by different studies for assessing irrigation dynamics in the state of Kansas (Gardner & Sampson, 2024; Lin et al., 2024; Whittemore et al., 2023; Zipper et al., 2024). This database includes mandatory annual water use reports for all non-domestic wells in the state (Orduna Alegria et al., 2024) and is maintained by the Kansas Department of Agriculture – Division of Water Resources and the Kansas Geological Survey. Withdrawal data are at points of diversion (PD) resolution which are defined as either surface water diversions or groundwater wells (Zipper et al., 2024), and includes a reported crop type associated with each irrigation water use.

Table 3.2. Location specific management data for model evaluation.

County/Year	Distance from EKS RB	Soil type	Planting date	Climate Information	Plants/m ²	Row spacing (cm)	Nitrogen (lb/ac)	Cultivar type
Riley/2018	Within	Wymore silty clay loam	05/03/2018	Kansas Mesonet	8.5	76	265	Midland-656 PR
Shawnee/2018	Within	Reading silt loam	04/23/2018	Kansas Mesonet	7	76	194	Midland-656 PR
Republic/2018	< 50 km	Crete silty clay loam	05/07/2018	Kansas Mesonet	7	76	200	Midland-656 PR
Republic/2019	< 50 km	Crete silty clay loam	05/17/2019	Kansas Mesonet	6	76	160	Midland-656 PR

Kansas Mesonet: <https://mesonet.k-state.edu/>

Model validation accuracy was quantified using goodness of fit (index of agreement, d-statistic (Willmott, 1982)) and test statistics (p-value), root mean squared error (RMSE), and normalize root mean square error (NRMSE) (Araya et al., 2017; Onyekwelu & Sharda, 2024b). We calculated NRMSE as RMSE (Eq. 3.1) divided by observed mean value (yield and irrigation water use) multiplied by 100 (Eq. 3.2).

$$RMSE = \left(\frac{\sum (S_i - O_i)^2}{N} \right)^{0.5} \quad (3.1)$$

N is the number of observations, S_i is the predicted value, O_i is the measured observation.

$$NRMSE = \left(\frac{RMSE}{Observed\ Mean\ Value} \right) \times 100 \quad (3.2)$$

$$d = 1 - \left[\frac{\sum_{i=1}^n (P_i - O_i)^2}{\sum_{i=1}^n (|P_i'| + |O_i'|)^2} \right] \quad (3.3)$$

n is the number of observations, P_i is the predicted value, O_i is the measured observation, $|P_i'| = |P_i - M|$, and $|O_i'| = |O_i - M|$. M is the mean of the observed variables (yield and irrigation water use).

We used the coefficient of variation (CV) to evaluate the degree to which the model captured the variability in the observed yield and irrigation water use. This was in order to improve regional model calibration and lower model uncertainty. We verified this approach by comparing various test and fitness statistics alongside the CV of simulated and observed data. The calibrated and validated regional model is better and more reliable the closer the simulated CV is to the observed CV (Onyekwelu & Sharda, 2024b).

3.3.4 Plant Available Water and Irrigation Threshold Design

For the present study, the calibrated model was then used with an irrigation management experimental design to simulate the impacts of different irrigation strategies on maize productivity. The irrigation management design was based on four thresholds using the plant available water (PAW, Figure 3.5) scheme (Kisekka et al., 2016).

PAW thresholds represent different limits of soil water depletion required to trigger irrigation to FC or by a constrained application depth in the absence of sufficient growing season precipitation. Based on this approach, we used two full irrigation treatments (50% PAW and 75% PAW), which refilled soil profile to FC without any constraints, and two deficit irrigation treatments (50%* PAW and 25% PAW) as shown in Figure 3.5. The 50%* PAW represents a modified irrigation strategy for the region, where irrigation was triggered at 50% of plant available water (PAW), with the application depth limited to 15 mm per event and an application efficiency of 95%. The 25% PAW on the other hand, allowed a depletion of soil water by 75% before the next irrigation event returned it to FC. Details on how these thresholds were coupled with grid-level simulations are discussed in the subsequent sections.

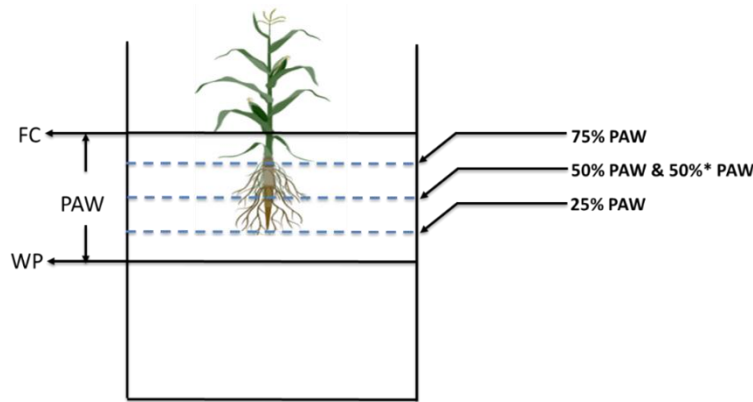


Figure 3.5. Irrigation threshold design and plant available water description. FC = field capacity; WP = wilting point; PAW = plant available water.

3.3.5 Historical Model Input Preparation and Long-term Spatial Simulation

A set of Python scripts was written for retrieving and translating the grid-level weather and soil datasets into DSSAT formats (*.WTH and *.SOL, respectively). Soil data retrieved from the gSSURGO at 30 m were regridded to 4 km as mentioned in section 3.3.2. Similarly, historical climate information at 4 km was retrieved from the PRISM (Parameter-elevation Regressions on Independent Slopes Model) (PRISM Climate Group, 2014) group for a period of 25 years (1991 – 2015).

To conduct long-term and future simulations, a single management practice for maize production in the county was assumed (Araya et al., 2021; Onyekwelu & Sharda, 2024b). Maize was planted in each grid on April 15th at a seeding rate of 10 plants/m², row spacing of 76 cm, and planting depth of 5 cm (K-State Extension, 2022; Lingenfelser et al., 2015; Onyekwelu & Sharda, 2024b; Sassenrath et al., 2021). Since each grid in the model is a unique combination of soil and climate, no two grids share the same input (climate and soil). This allows us to map location-specific impacts of climate change and irrigation management for proper decision-making. Initial moisture conditions assumed the grid-level soil profiles to be at field capacity at planting, and the initial soil nitrogen was set to 25 kg Nha⁻¹, assuming 1% soil organic matter (Onyekwelu & Sharda,

2024b). In-season fertilizer applications were set according to regional recommendations (K-State Extension, 2007, 2022) and as per the variety trial reports (Lingenfelser et al., 2015; Sassenrath et al., 2021). Each unique grid was allocated all four levels of irrigation based on the thresholds defined in section 3.3.4. To accurately capture the effect of CO₂ fertilization on biomass accumulation, dynamic CO₂ values were used.

To assess the historical and future climate impacts on maize productivity, the model was run for the period ranging from 1991 to 2099; driven by historical climate information and future climate data from the CMIP5 model family. Details on the future climate scenarios and the global climate models (GCMs) used are presented in section 3.3.6.

3.3.6 Future Climate Scenarios

Future climate change scenario impacts on irrigated maize production were simulated for each of the 78 unique grids in the region. We selected the scenarios based on RCPs 4.5 and 8.5, divided into three time slices: 2030s (early century), 2060s (mid-century), and 2090s (late century). RCP 4.5 is described as an intermediate scenario with midway challenges to mitigation, and RCP 8.5 is a high-emission scenario with unabated and rising greenhouse gases until the end of the century (Pachauri et al., 2014). Climate variables (solar radiation, minimum and maximum temperatures, and precipitation) were obtained for CMIP5 GCMs available from the MACA-2 database (Abatzoglou, 2013; Abatzoglou & Brown, 2012). The MACA-2 datasets are available at 4 km resolution and cover the entire contiguous United States. The datasets contain statistically downscaled and bias-adjusted climate projections using the Multivariate Adaptive Constructed Analogs (MACA v2) method. Details on the MACA v2 method can be found in Abatzoglou (2013) and Abatzoglou & Brown (2012). The resulting MACA-2 product has been found to be robust and has been used by several studies (Kothari et al., 2020, 2021; Yang & Wang, 2023; Sen et al., 2024).

Although the CMIP6 climate models represent the current update in future atmospheric climate simulations, recent studies have used CMIP5 climate models for climate impact studies and have shown comparable results to CMIP6 (Dahri et al., 2024; Dehghan Moroozeh et al., 2024; Hamlet et al., 2024; Jha et al., 2024; Xu et al., 2024; Zhou et al., 2024). For example, Jha et al. (2024) evaluated the consistency of CMIP5 and CMIP6 in evaluating biofixes and generation of three different pests in California. They found that by the end of the 21st century, 0.5-0.6 and 1.2-1.4 additional generations of the three pests considered are projected to occur under RCP 4.5/SSP 2-4.5 and RCP 8.5/SSP 5-8.5, respectively. Try et al. (2022) reported that while two different GCMs from the same institution can be different in terms of representation of different physical processes, GCMs from the same institutions in CMIP5 and CMIP6 have similar patterns than GCMs from other institutions. Recent crop modeling studies by the AgMIP group (Guarin et al., 2022, 2023; Liu et al., 2023; Stella et al., 2023) also used CMIP5 GCMs with great results. Furthermore, Trancoso et al. (2024) assessed global drying and wetting agreement across multiple CMIP5 and CMIP6 GCMs. They found that CMIP5 and CMIP6 GCMs across various calendar seasons and emission scenarios showed significant overlap in the hotspots where wetting and drying patterns agreed, with up to 100% agreement in some cases among the entire ensemble of 146 GCMs analyzed. Overall, these various studies suggest that our selection of CMIP5 instead of CMIP6 likely does not have a substantial impact on our findings.

To ensure robust model simulation and to account for GCM-related uncertainty, we selected 5 GCMs that span the full range of climate sensitivities based on the sensitivity labeling reported by Yang & Wang (2023), including two low-sensitivity models (BCC-CSM1-1, GFDL-ESM2M), one medium sensitivity model (CCSM4), and two high sensitivity models (CanESM2, CNRM-CM5). For the possible impact of CO₂ fertilization, we used dynamic CO₂ values for the

two RCPs from 2025 to 2099. After model simulation, maize productivity (yield, irrigation water use, water productivity, and net returns) for the five selected GCMs were averaged per grid across different time slices and RCPs to get ensemble averages and then compared to the historical period (1991-2015).

3.3.7 Crop Water Productivity Indicator

In this study, crop water productivity, defined as irrigation water productivity, was determined following the method proposed by Onyekwelu & Sharda (2024b) using equation 3.4 below. Irrigation water productivity, which measures the maize yield produced per millimeter of irrigation water use, is a key factor for tracking effective utilization of irrigation water during the growing season. Long-term simulations were conducted to compute irrigation water productivity for both historical conditions and future climate change scenarios.

$$WP_{i,j} = \left[\frac{Maize\ Yield_{i,j}}{IWU_{i,j}} \right] \quad (3.4)$$

where $WP_{i,j}$ is the irrigation water productivity (irrigation productivity, $\text{kg ha}^{-1} \text{mm}^{-1}$) for i^{th} grid in j^{th} year, and $IWU_{i,j}$ is the irrigation water used in millimeters (mm) for i^{th} grid in j^{th} year.

3.3.8 Economic and ANCOVA Analysis

Economic analyses reported as net returns (NR) were computed based on the difference between the total revenues, irrigation cost and other production costs as shown in equation 3.5 below.

$$NR_{i,j} = Yield_{i,j} \times Price - \sum \left(Irrigation_{cost_{i,j}} + Other_{production_{cost}} \right) \quad (3.5)$$

where $NR_{i,j}$ is the farmer's net return ($\text{\$ ha}^{-1}$) for i^{th} grid in j^{th} year, $Price$ is maize market price in $\text{\$ kg}^{-1}$, $Yield_{i,j}$ is the simulated maize yield (kg ha^{-1}) for i^{th} grid in j^{th} year, $Total\ Irrigation_cost_{i,j}$ ($\text{\$ ha}^{-1}$) is the irrigation cost for i^{th} grid in j^{th} year. We used the mean of

range of maize market prices (\$0.10, \$0.14, \$0.18, and \$0.26 kg⁻¹) in Kansas, documented in Kisekka et al. (2016) to compute the gross profit. Irrigation water cost per m³ was considered as \$0.029 (Kisekka et al., 2016). To account for other production costs (fertilizer, herbicides, insecticides, seeds) for irrigated maize production as shown in equation (5), we used the input costs survey for irrigated maize production reported by Tsoodle & Li (2023) for central and eastern Kansas as shown in Table 3. Other base production costs like land charges and machinery expenses were included as part of other production costs following Kisekka et al. (2016).

Table 3.3. Average regional input costs for irrigated maize in Central Kansas

Commodity	Cost in \$/acre	Cost in \$/ha
Fertilizer	190.13	469.80
Herbicides	83.00	205.10
Insecticides	15.00	37.10
Seeds	98.70	243.88

We conducted analysis of covariance (ANCOVA) at 5% significance level to understand the spatial controls of irrigated maize productivity. ANCOVA combines the features of ANOVA and multiple linear regression to understand to what extent the categorical factor impacts the target variable in the presence of quantitative variables (covariates) (Heil & Schmidhalter, 2017). According to Heil & Schmidhalter (2017), the covariates are included to reduce error term variance and enhance the precision of measuring the effects of categorical factor (treatment effects).

In this study, the unique soil for each grid was treated as a categorical factor, while the grid-level growing season climate variables (minimum and maximum temperatures, solar radiation, and precipitation) were treated as covariates. Equation 3.6 below was used for the ANCOVA procedure and programmed in Python program environment.

$$Y_{i,j} = \mu_{i,j} + factor(soil)_j + precipitation_{i,j} + solar\ radition_{i,j} + T_{max_{i,j}} + T_{min_{i,j}} + \varepsilon_{i,j} \quad (3.6)$$

where $Y_{i,j}$ is the productivity component of interest (yield, water use, water productivity, and net returns) for i^{th} grid in j^{th} year, $\mu_{i,j}$ is the overall mean of the productivity component of interest for i^{th} grid in j^{th} year, $factor(soil)$ represent the soil impact on the productivity component of interest in i^{th} grid, given minimum and maximum temperatures (T_{min} and T_{max}), solar radiation, and precipitation for i^{th} grid in j^{th} year, and ε is the error term for i^{th} grid in j^{th} year.

3.4 Results and Discussion

3.4.1 Model Calibration and Validation

Table 3.4 below shows the maize cultivar coefficients (genetic coefficients) P1, P2, P5, G2, G3, and PHINT. These values were adjusted to 249, 0.48, 970, 692.5, 11.28, and 45.20, respectively, which are similar to earlier studies reported in the region (Araya et al., 2017; Onyekwelu & Sharda, 2024b, Sen et al., 2024). As shown in Figure 3.6a, the adjustment of coefficients related to crop growth, phenology, and development resulted in a close match between simulated and observed yield.

Table 3.4. Genetic coefficients adjusted during model calibration.

Coefficients	Description	Initial estimates	Calibrated value
P1	Thermal time from seedling emergence to the end of the juvenile phase (degree days)	225.0	249.0
P2	Extent to which development is delayed for each hour increase in photoperiod (days)	0.600	0.48
P5	Thermal time from silking to physiological maturity (degree days).	895.0	970.0
G2	Maximum number of kernels per plant.	875.0	692.5
G3	Kernel filling rate during the linear grain filling stage (mg/day).	8.80	11.28
PHINT	Phyllochron interval between successive leaf tip appearances (degree days).	48.00	45.20

Yield calibration results showed satisfactory performance across different range of climate, soils, and management conditions (Figure 3.6); with NRSME = 3% (RMSE = 421 kg ha⁻¹), d-statistics = 0.97, p-value = 0.94, and simulated and observed CV of 8% and 9%, respectively. Model performance was determined to range between good to excellent (Soler et al., 2007; Willmott, 1982), and therefore the model was considered suitable for the intended application. The average simulated and observed yields during calibration were found to be 14,299 and 14,255 kg ha⁻¹, respectively. The slight mean yield overestimation could be due to process simplification and underestimation of water stress, which has been reported by Onyekwelu & Sharda (2024b). During model validation, observed and simulated yield values matched closely, with mean values reported as 13,778 and 15,296 kg ha⁻¹, respectively. Test statistics also showed satisfactory performance as indicated by NRMSE = 12% (RMSE = 1706 kg ha⁻¹), d-statistics = 0.73, p-value = 0.3, and simulated and observed CV of 10% and 10%, respectively. Yield was generally overestimated during validation, which may have occurred due to process-related reasons that were not captured in the calibration, including water stress underestimation, model simplification, and year-to-year climate variability. For example, we infer that prolonged drought during the 2018 growing season, followed by intermittent wetness in 2019, may have contributed to model overestimation of yield and underestimation of water stress (Figure A.5, Table A.1). This is true since each growing season is treated independently and therefore soil moisture limitations from 2018 were not captured in the 2019 simulations. In addition, our model does not account for pest and disease infestations that may have contributed to the slight overestimation of yield. Overall, model performance during validation ranges from moderate to excellent based on standard statistical classifications (Soler et al., 2007; Willmott, 1982).

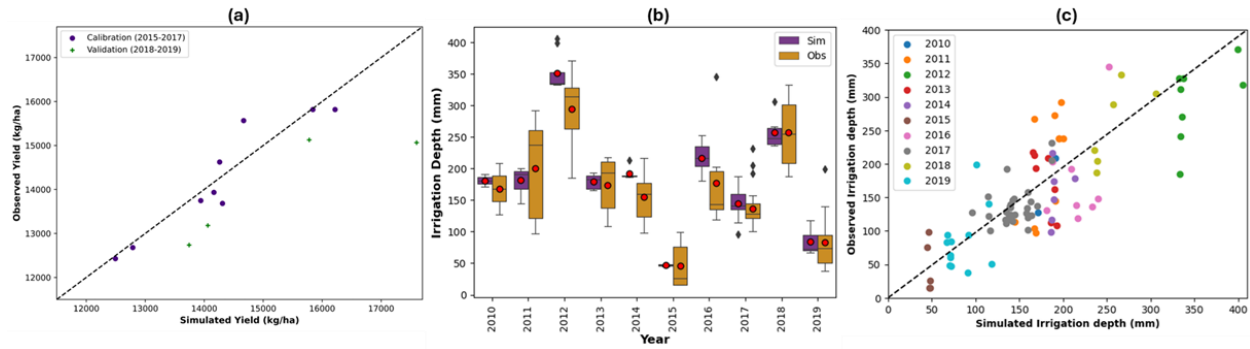


Figure 3.6. Observed and simulated yield, (b) observed and simulated irrigation depth distribution, (c) observed and simulated irrigation depth by year. In (a) and (c), the black dashed line shows 1:1 agreement and the red dots in (b) represent mean values.

Figures 3.6b and c show the validation of irrigation depth for different years and 1:1 comparison between observed and simulated irrigation depth, respectively. We found that our model satisfactorily reproduced observed irrigation depths in the 92 wells over the ten (10) year period, with test statistics values indicated as NRMSE = 28%, d-statistics = 0.89, p-value = 0.3, and simulated and observed CV of 45% and 50%, respectively. The satisfactory performance of the model in reproducing irrigation depths was consistent in both dry and wet years as shown in Figure 3.6b. For example, irrigation depth distributions were reasonably reproduced for 2012 and 2018 growing seasons, which were considered as dry years (Table A.1, Figure 3.6b) in the region. Similarly, for wet growing seasons (2015 and 2019), our model was consistent in reproducing irrigation depth distributions with reasonable mean values (Table A.1, Figure 3.6b). In addition, irrigation depth distributions and mean values were consistent during normal growing seasons classified as 2010, 2011, 2014, and 2017 (Table A.1, Figure 3.6b). In summary, our model performance in reproducing both yield and irrigation depth were satisfactory, indicating its reliability for our historical and future climate applications.

3.4.2 Historical Maize Productivity and Drivers

Figure 3.7a-d shows the historical maize spatial productivity with respect to yield, irrigation water use, irrigation water productivity, and farmer's net returns, respectively. Variability in yield values was closely associated with soil texture variations (Figure 3.2) in the region, with areas under silt loam and silty clay loam soils typically having considerably higher yield values than areas under clay loam (Figure 3.7a). Interestingly, we found that a few areas under silty clay loam soils had low yield values (below 12,000 kg ha⁻¹), which may be due to shallow soil depth and possible variations in soil particle distribution below 100 cm. Zhang et al., (2024) found for Jilin Province in China that increasing topsoil depths significantly increased maize yield. In another study by Calviño et al., (2003), they found that shallow soils generally had lower yield than deep soils across different rainfall regimes. The decreases in yield in shallow soils might be due to changes in the water stored at field capacity and wilting point, with lower soil water availability in shallowed soils.

To further ascertain the possible cause-and-effect of spatially varying soils and growing season climate variables (maximum and minimum temperatures, precipitation, and solar radiation) on yield, we performed ANCOVA at 5% significance level as shown in Table A.2. We observed that regional spatial soil variability has a highly significant effect on yield (Table A.2), substantiating our interpretations of the mapped simulation results. The impacts of spatial soil variability on crop yield are consistent with past studies. Sharda et al. (2017) showed using the CERES-Maize crop model that spatial soil variability impacted rainfed maize yield in Alabama, resulting in significant yield improvement compared to adopting a single dominant soil type. In Wisconsin, Zipper et al. (2015) found substantially different soil hydrological dynamics and resulting impacts on yield as a function of soil texture using both field observations and the Agro-

IBIS crop model. In a recent study by Onyekwelu & Sharda (2024b) in the EKSRB, it was found that soils of silt loam and silty clay loam textures had significantly higher yields than soils of clay loam texture under rainfed condition. It is important to note that the range of yield values observed in this study were generally within the values reported by similar studies (Kisekka et al., 2016; Araya et al., 2017).

Minimum and maximum temperatures (T_{min} and T_{max} , respectively), and solar radiation had significant effects on yield, with T_{min} having the strongest influence, followed by solar radiation and T_{max} (Table A.2). Previous studies have explained the probable reason behind the strong influence of T_{min} more than T_{max} and solar radiation on crop production in the region. Lin et al. (2017) reported that trends and changes in T_{min} has been increasing significantly in the last 121 years compared to trends and changes in T_{max} ; consequently, this trend may have influenced the magnitude of diurnal temperature range (Onyekwelu et al., 2023). By assessing the impacts of historical climate variability on rainfed maize yield in EKSRB, Onyekwelu & Sharda (2024b) reported that the yield loss caused by 1 °C rise in temperature or 1 MJ m⁻² rise in solar radiation increases is most sensitive to changes in T_{min} , followed by increases in solar radiation and T_{max} . As expected, the impact of growing season precipitation on yield was not significant (Table A.2), due to the yield stability provided by irrigation water applications.

Irrigation water use (Figure 3.7b) revealed a consistent inverse relationship with yield. We found that areas associated with silt loam soils have lower water use and higher yields compared to areas dominated by silty clay loam and clay loam soils (Figures 3.2, 3.7a-b). These findings agree with studies reported in the literature which showed that better maize yield productivity in silt loam soils is due to the presence of well-connected pore spaces, and greater readily plant available water compared to silty clay loam and clay loam soils (Onyekwelu & Sharda, 2024b). It

is important to note that the range of maize irrigation water use observed in this study were generally lower than values reported for more arid regions in western Kansas (Kisekka et al., 2016; Araya et al., 2017), and the Western United States (Lamsal & Marston, 2024). This is because of the strong precipitation gradient in the state of Kansas, where growing season precipitation increases from west to east (Onyekwelu & Sharda, 2024a, 2024b; Seager et al., 2018a), leading to lower irrigation requirements in the eastern portion of the state where our study is focused.

In addition, soil properties and types play an important role in determining the amount of seasonal water use (Araya et al., 2021; Sharda et al., 2017). ANCOVA analysis at 5% significance level further revealed the significant impacts of spatially varying soils and growing season climate variables (T_{min} , T_{max} , precipitation, and solar radiation) on irrigation water use (Table A.3). We observed that spatial soil variability plays a significant role in determining the amount of irrigation water use in each field during the growing season. This finding further improved our understanding of the need to prioritize crop landscapes by different soil types for effective water management, especially under climate change. Our results also revealed that growing season T_{min} has no significant impact on irrigation water use in the historical condition. This finding agrees with results in the literature, substantiating the fact that daytime crop water demand is not driven by T_{min} , but largely influenced by T_{max} and solar radiation (Emeka et al., 2021; Ndulue et al., 2019). As expected, the influence of growing season precipitation on irrigation water use was found to be highly statistically significant, outweighing the significant effects of T_{max} and solar radiation combined (Table A.3).

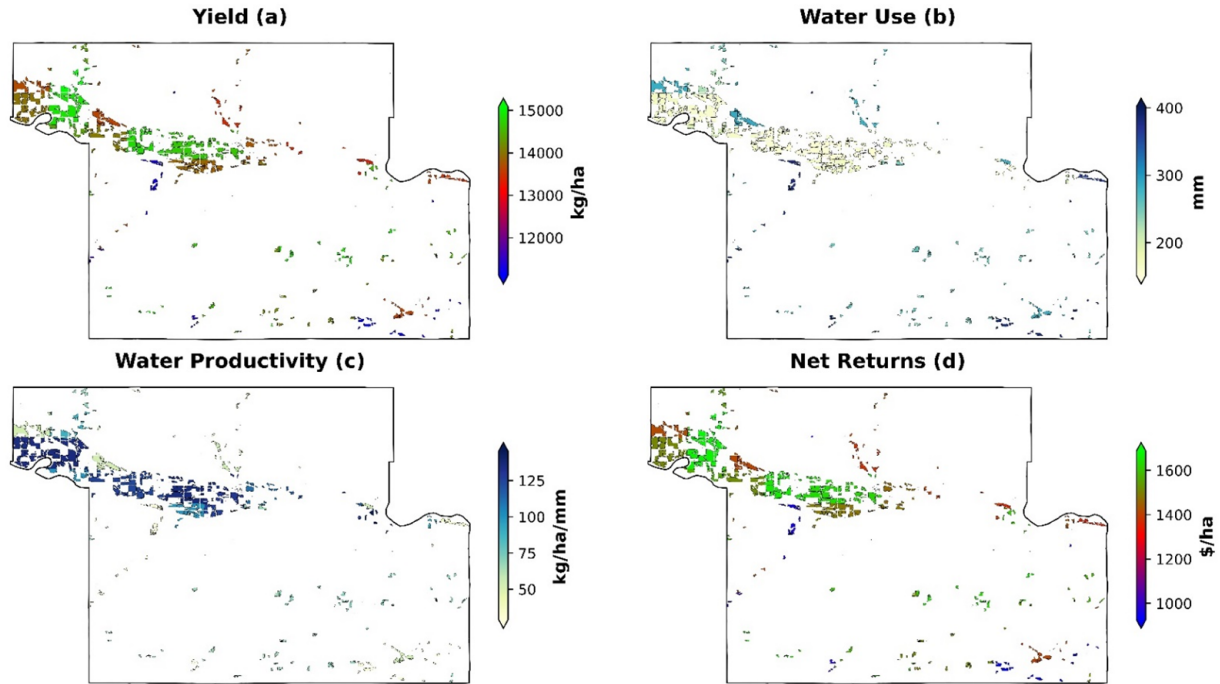


Figure 3.7. Historical maize spatial productivity (1991-2015) (a) Yield (kg ha⁻¹); (b) Irrigation water use (mm); (c) Irrigation water productivity (kg ha⁻¹ mm⁻¹); (d) Farmer's net returns (\$ ha⁻¹).

These results reveal a soil-mediated spatial correlation between yield, water productivity, and irrigation water use (Figure 3.7a-c). Maize croplands dominated by silt loam soils with associated high yield values and low water use were observed to have higher water productivity compared to areas under silty clay loam and clay loam soils (Figure 3.7a-c). ANCOVA analysis at 5% significance level further revealed the significant impacts of spatially varying soils and growing season climate variables on water productivity (Table A.4). We observed that significant levels of environmental impact on water productivity were in the order precipitation>Tmin>soil>solar radiation, with no significant effect of Tmax on water productivity. Since irrigation water applications sustain transpiration and photosynthesis, this may mitigate the temporal effects of elevated Tmax on yield, especially during the reproductive stage.

Net return (Figure 3.7d) has a similar spatial distribution to yield (Figure 3.7a), indicating that yield values driven by spatially varying soils and climate control the farmer's net returns based on the simplified economic model used in this study. In addition, we found that areas with high net returns were more productive, with low irrigation water use and higher water productivity. The individual impacts of soil and growing season climate on net returns were assessed as shown in the ANCOVA table (Table A.5). We found that significant impacts on net returns were in the order $T_{min} > \text{soil} > \text{solar radiation} > T_{max} > \text{precipitation}$. This shows the complex feedback of different environmental conditions on farm economics. For example, it is well-established that T_{min} largely influences crop growth duration, while soil maintains water and nutrient balance, and solar radiation drives photosynthesis. The lesser impact of T_{max} and precipitation are likely caused by the stabilizing impact of irrigation on yield as previously discussed. The range of net return values observed in this study were generally within the values reported by similar studies (Kisekka et al., 2016). Overall, our results highlighted significant and complex interactions between spatially varying soils and climate on irrigated maize productivity.

3.4.3 Future Climate Impacts on Irrigated Maize Productivity

Figure 3.8a-d shows the average climate change impacts on maize productivity under two emission pathways (RCPs 4.5 and 8.5) and four irrigation treatments, and a tabular summary of climate change impacts on irrigated maize productivity is presented in Table A.6. The projection of climate change impacts was based on an ensemble of five GCMs of varying climate sensitivity. Going forward, we observed that growing season T_{min} and T_{max} will generally increase monotonically in both RCPs, with stronger trends observed under RCP 8.5 (Figure 3.3a-b). In contrast, growing season precipitation revealed non-monotonically declining trends but largely varies around the mean value of the historical precipitation (Figure 3.3c), with higher deviation

observed under RCP 8.5. Therefore, based on the environmental consequences of increasing growing season Tmin and Tmax, and slightly declining precipitation in the region, we found that irrigated maize yield, water productivity, and net returns are projected to decline under both RCPs and all four irrigation treatments simulated, with increasing declines later in the 21st century (Figure 3.8a, c, d). The projected decline in productivity is likely caused by shortened growing season length, mediated by rapid accumulation of growing degree days and warming-induced high temperatures, and consistent with past studies (Araya et al., 2017; Onyekwelu & Sharda, 2024b; Yang & Wang, 2023). We found in this study that growing season length shortened in the range between 10 to 18 days under RCP 4.5, and 10 to 28 days under RCP 8.5.

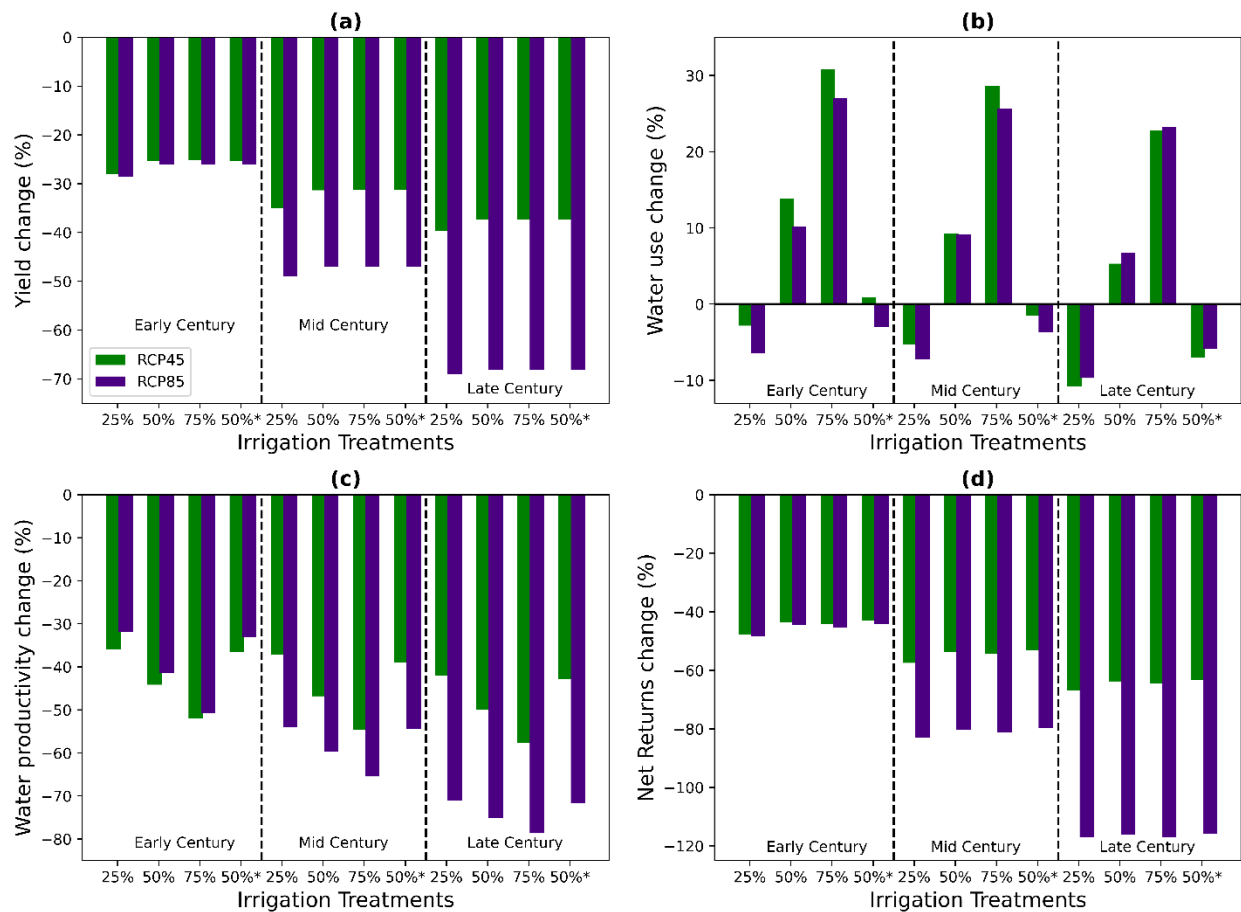


Figure 3.8. Future climate impacts on irrigated maize productivity under different irrigation water treatments (a) % change in yield; (b) % change in irrigation water use; (c)

% change in irrigation water productivity; (d) % change in farmer's net returns. All percent changes are expressed relative to the mean of the historical period.

Productivity declines with respect to yield, water productivity, and net returns during the early century were similar under both RCPs and all irrigation treatments, with slight differences in water productivity (Figure 3.8 a,c,d). Yield and net returns declined during the early century under RCP 4.5 by less than 30% and 45%, respectively, in all irrigation treatments. During the mid-century, we observed consistent declines in yield and net returns in all irrigation treatments under RCP 4.5, with values up to 35% and 55%, respectively. Similarly, during the late century, yield decline under RCP 4.5 was up to 40%, while net returns declined by up to 65%.

While similar decline values were observed under both RCPs for yield and net returns during the early century, high-temperature impact under RCP 8.5, coupled with increasing greenhouse gases, resulted in more drastic yield and net returns decline during the mid and late-century time periods. We found yield declines up to 50% in all irrigation treatments, and up to 80% for net returns during the mid-century. During the late century, less than 70% yield decline was observed in all irrigation treatments, with net returns decline reaching up to 120%. Our results suggest that yield and net returns decline under irrigated conditions may largely be due to warming-induced stress (leading to shortened growing season length) than water stress, since consistent declines were observed in all irrigation treatments. While there are limited studies quantifying the impacts of climate change on net returns under different irrigation treatments, we found that our results agree with other studies with respect to yield decline. For example, in western Kansas, Araya et al. (2017) found that maize yield decline ranged from 10% to 60% and 5% to 80% (RCPs 4.5 and 8.5, respectively) under deficit irrigation, and 10% to 58% and 5% to 77% (RCPs 4.5 and 8.5, respectively) under full irrigation. They argued that using the same crop

cultivars under future climate resulted in 18–24 days reduction in growing season length, which is similar to values observed in this study.

We observed that the water productivity decline was variable, with greater declines observed under RCP 4.5 than in 8.5 during the early century, especially under full irrigation treatments (Figure 3.8c). The higher decline in water productivity observed under full irrigation may have resulted from the inability of irrigation to compensate for yield reductions due to climate change. This agrees with the findings in the literature, arguing that increasing irrigation to compensate for yield reductions decreased overall water use efficiency (Yang et al., 2017). As the 21st century progressed, water productivity declined more under RCP 8.5 in the mid and late century time periods (Figure 3.8c). This further substantiated our claim that maize productivity decline may largely be due to warming-induced stress than water stress. Due to its C4 pathway, maize productivity (including water productivity) during the early century may have benefitted slightly from the higher CO₂ concentration under RCP 8.5 (Figure 3.8a,c,d), consistent with findings reported in literature (Yang & Wang, 2023). The benefit of CO₂ fertilization was largely counteracted by the mid and late century time periods, as maize productivity drastically declines, especially under RCP 8.5 (Figure 3.8a,c,d) due to the increase in other stressors.

Despite productivity declines as reported above, we found that irrigation water use under full irrigation (50% and 75% PAW) increased under both RCPs, with values ranging from 10% to 32% during the early century, 9% to 30% during the mid-century, and 5% to 23% during the late century (Figure 3.8b). Brown et al. (2013) reported that future climate change is likely to significantly increase water withdrawals in the Great Plains. We also observed generally higher irrigation water use under full irrigation, with the largest water use increase under RCP 4.5 in the 75% PAW irrigation treatment. This may be additional evidence that higher CO₂ concentrations

in RCP 8.5 resulted in leaf stomatal closure and reduced transpiration and therefore lower water requirements (Kirschbaum & McMillan, 2018; Li et al., 2019; Mengis et al., 2015; Serna, 2022; Tubiello & Ewert, 2002). This indicates that full irrigation under climate change is not able to tap the benefits of CO₂ fertilization without adaptation (Yang et al., 2017). Additionally, full irrigation under climate change may lead to increased water withdrawal without maintaining productivity increase (Figure 3.8a-d). In the western Great Plains, Steward et al., (2013) reported that 30% of groundwater in the High Plains Aquifer (Ogallala Aquifer) has been pumped and another 39% will be depleted over the next 50 years, with potentially devastating economic impacts for the region (Deines et al., 2020).

Our results, however, showed that deficit irrigation (25% and 50%*) took advantage of CO₂ fertilization without further diminishing productivity (Figure 3.8a-d), with water savings ranging from 2% to 6% during the early century, 2% to 7% during the mid-century, and 5% to 12% during the late century (Figure 3.8b). Interestingly, we observed more water savings during the early and mid-century time periods under RCP 8.5 than in RCP 4.5 (Figure 3.8b). In addition, we observed similar water savings under both scenarios during the late century, suggesting similar landscape and climate controls on water use. While the overall maize productivity under 25% and 50%* irrigation treatments show similar results, the 25% scenario shows generally higher water savings, but overall maize productivity under 50%* matches more closely to the full irrigation treatments (Figure 3.8a-d, Table A.6), and in some cases resulted in lower reductions in productivity (Figure 3.8a-d, Table A.6). Overall, our results suggest a widespread and dramatic decrease in overall productivity. Nonetheless, there might be opportunities to couple water-saving deficit irrigation strategies evaluated in this study with other agronomic management and yield-advancing varieties for yield improvement under climate change. In the subsequent section, which

focused on spatial patterns of productivity, we showed only the 50%* irrigation treatment since it represents the greatest potential for improved water management for balancing hydrologic and agronomic tradeoffs under climate change.

3.4.4 Spatial Maize Productivity in the early, mid, and late 21st Century

Figures 3.9 through 3.11 illustrate the spatial distribution of future maize productivity in the 2030s (early century), 2060s (mid-century), and 2090s (late century), respectively. In addition, we included boxplots (Figure 3.12) to map changes split out by different soil textures. By the 2030s, we found that the most productive maize fields are projected to shift from soils of silt loam texture to soils of silty clay loam and clay loam textures in both RCPs (Figure 3.9 and Figure 3.12a-b). We do not observe a noticeable longitudinal or latitudinal variation in yield change, suggesting the dominant influence of soils in controlling yield rather than hydroclimatic factors that vary spatially. The shift of the most productive fields from soils of silt loam texture to soils of silty clay loam and clay loam textures is likely driven by differences in soil water holding capacity and moisture availability under future climate change. While silt loam soils were the most productive under historical conditions, as future water requirements increase due to climate change, silty clay loam and clay loam soils are able to better meet plant water needs. This agrees with findings reported in the literature, arguing that the productivity shift from silty loam to silty clay loam and clay loam soils is due to soil moisture depletion in silty loam soils (Nouri et al., 2016; Onyekwelu & Sharda, 2024b). It is important to note that yield losses in the 2030s are similar between the two emission scenarios (Figure 3.9a-b) but differ greatly by the 2060s (Figure 3.10a-b) and 2090s (Figure 3.10a-b). This is additional evidence that higher CO₂ concentrations under moderate RCP 8.5 warming resulted in some minor CO₂ fertilization benefits, but the increased

warming (RCP 8.5 > RCP 4.5) later in the century forced drastic yield declines irrespective of soil type and available water condition under the RCP 8.5 conditions.

While productivity with respect to yield may shift from areas dominated by soils of silt loam to silty clay loam and clay soil textures, the spatial distribution of irrigation water use did not always follow the same patterns (Figures 3.9c-d, 3.10c-d, 3.11c-d). We found that under RCP 4.5, areas dominated by silt loam soils had increased water use, with median value reaching up to 3% in 2030s, and 2% in 2060s. However, during the 2090s, we observed a median water savings of 6%. This is an indication that increased evapotranspiration with marginal CO₂ fertilization under RCP 4.5 resulted in rapid soil moisture loss for soils of higher porosity ratios such as silt loam in 2030s and 2060s. However, with higher stomatal closure by 2090s, improved water savings was observed. On the other hand, the spatial change under RCP 8.5 for areas dominated by silt loam soils revealed slightly significant water use decrease and remained consistent until the end of century (Figure 3.9c-d, 3.10c-d). This is also evident in Figure 3.12c-d, where the average water use change in silt loam soils is negative and remained consistency until the end of century. Interestingly, areas dominated by silty clay loam and clay loam soil textures under both RCPs could obtain water savings up to 15% without further diminishing productivity (Figures 3.9c-d, 3.10c-d, 3.12). There are no spatial correlations between water use in 2030s and 2060s under both RCPs, suggesting different climate controls on water use under both scenarios and time periods. However, we observed spatial correlations of irrigation water use in 2090s under both scenarios, reflecting potential similar climate controls on water use under both scenarios. These findings are consistent with evidence reported in the previous section (Figures 3.8b, 3.12c-d, and Table A.6).

Figures 3.9e-f, 3.10e-f, and 3.11e-f show the spatial water productivity during the 2030s, 2060s, and 2090s, respectively. Changes in spatial water productivity are controlled by changes in

yield and irrigation water use and, therefore, show a blending of the patterns discussed in the preceding paragraphs for these two variables. We observed that spatial water productivity is projected to shift from soils of silt loam texture to soils of silty clay loam and clay loam textures, indicating that soils of silt loam will significantly reduce water productivity more than soils of clay loam and silty clay loam combined. This is true for all future trajectories and emission pathways and consistent with findings described for yield and water use in this study. There is a spatial correlation of water productivity change in the 2030s between the two emission scenarios, suggesting the possibility of similar climate control in both scenarios and evidence that higher CO₂ concentration under moderate RCP 8.5 warming resulted in CO₂ fertilization benefits (Figure 3.9e-f). However, water productivity changes in the 2060s (Figure 3.10e-f) and 2090s (Figure 3.11e-f) revealed no spatial correlation between the two scenarios, an additional indication that increased warming later in the century caused more severe spatial water productivity declines in RCP 8.5 than RCP 4.5. In addition, this is an indication that water productivity may be more strongly controlled by yield outcomes than irrigation water use in the conditions simulated and was substantiated by findings presented in Figure 3.12a-b and Figure 3.12e-f.

In analyzing maize productivity in the 2030s with a focus on spatial net returns (Figure 3.9g-h), we observed similar evidence as reported for yield, with the greatest losses in net returns for soils of silt loam texture compared to those of silty clay loam and clay loam textures. In addition, we observed a spatial correlation in net return losses between the RCPs 4.5 and 8.5 emission scenarios in the 2030s (Figure 3.9g-h). This is an indication that the higher CO₂ concentrations under moderate warming of RCP 8.5, compared to RCP 4.5 for the same time period, provided fertilization benefits and led to similar spatial pattern. We observed similar correspondence between the two scenarios for yield during the same period. This suggests that

spatial yield variability may largely control net returns, reflecting the need to prioritize high-yielding zones with less input resources for increasing profit in the region. Comparisons of net return losses in the 2060s (Figure 3.10g-h) and 2090s (Figure 3.11g-h) showed no such spatial correlation, indicating that more intense warming in the mid and late century time periods under RCP 8.5, compared to RCP 4.5, resulted in significant net return declines regardless of soil type or water availability. In contrast, we found that net return losses were slightly lower in silt loam soil textures than in soils of clay loam and silty clay loam textures (Figure 3.12g-h) under all RCPs; an indication that net returns reflect a balance between yield outcomes and water resources utilization. Wang et al., (2014) reported that climate change will hurt farmers net revenue in North and South China, arguing that each farmer wishes to maximize revenue subject to the exogenous conditions of their farm. It is evident from our results that farms in the present study region will suffer severe climate shock unless adaptation measures are taken, requiring out-of-the-box solutions to improve farm productivity.

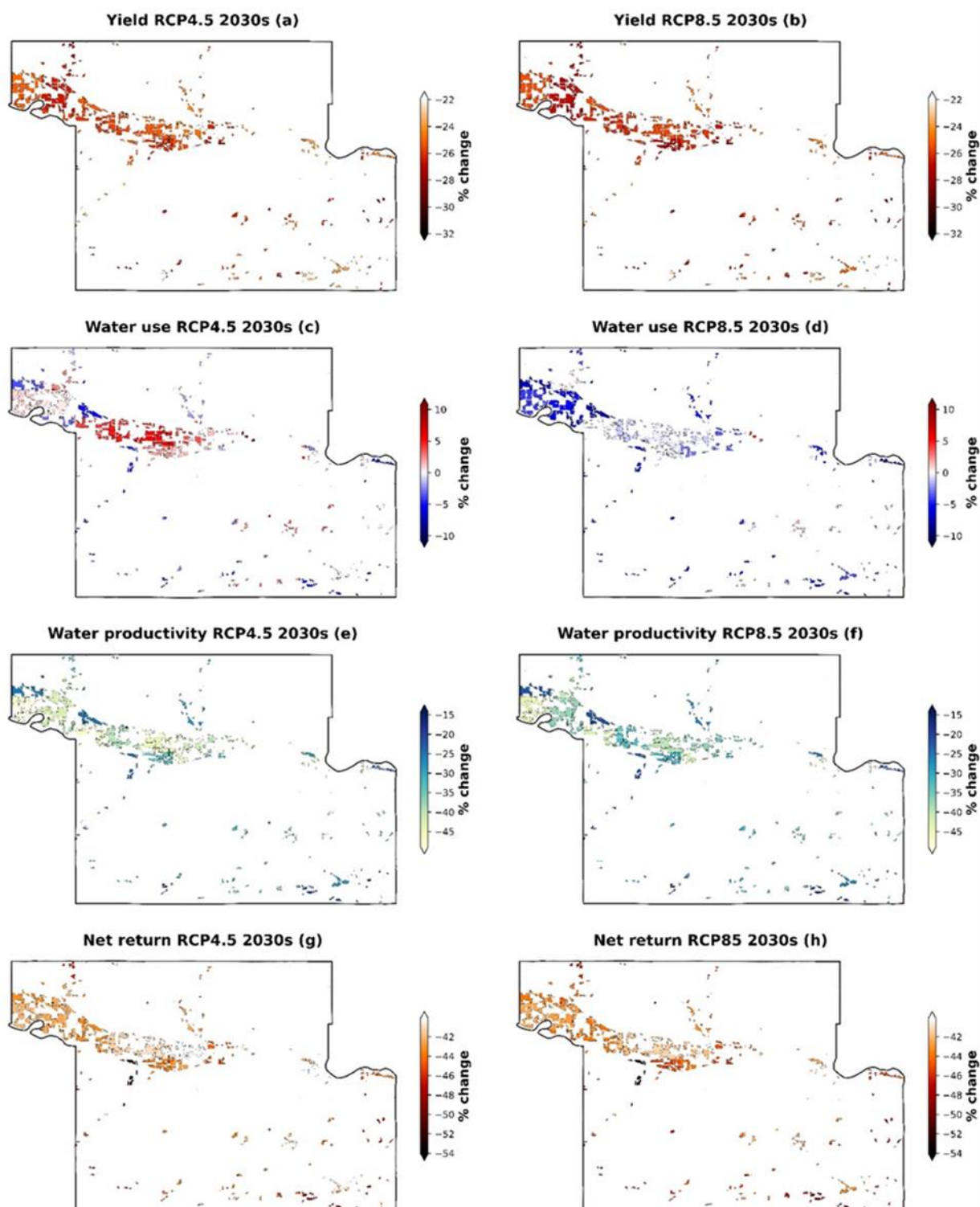


Figure 3.9. Spatial maize productivity in 2030s (late century – 50%*).

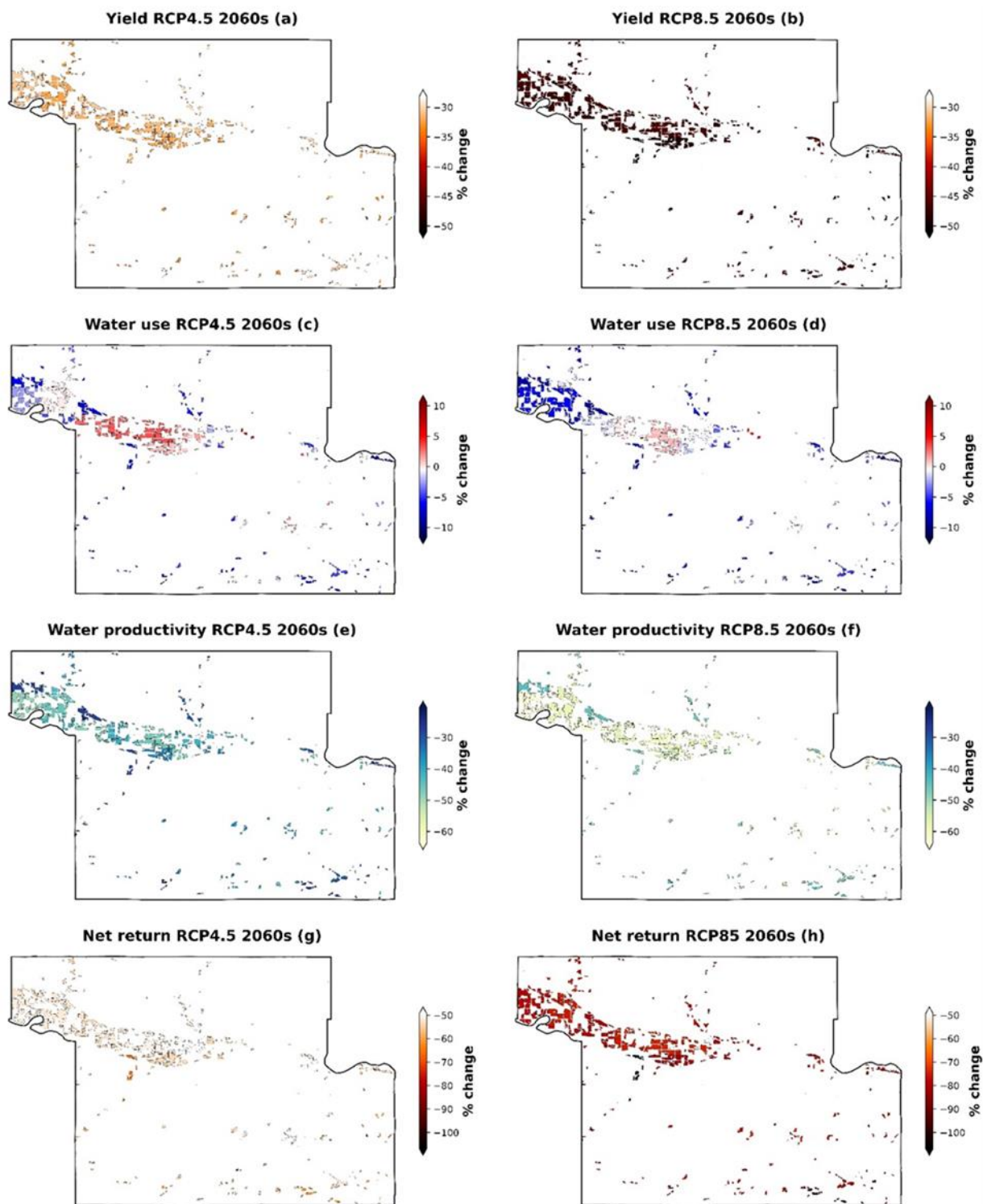


Figure 3.10. Spatial maize productivity in 2060s (late century – 50%*)

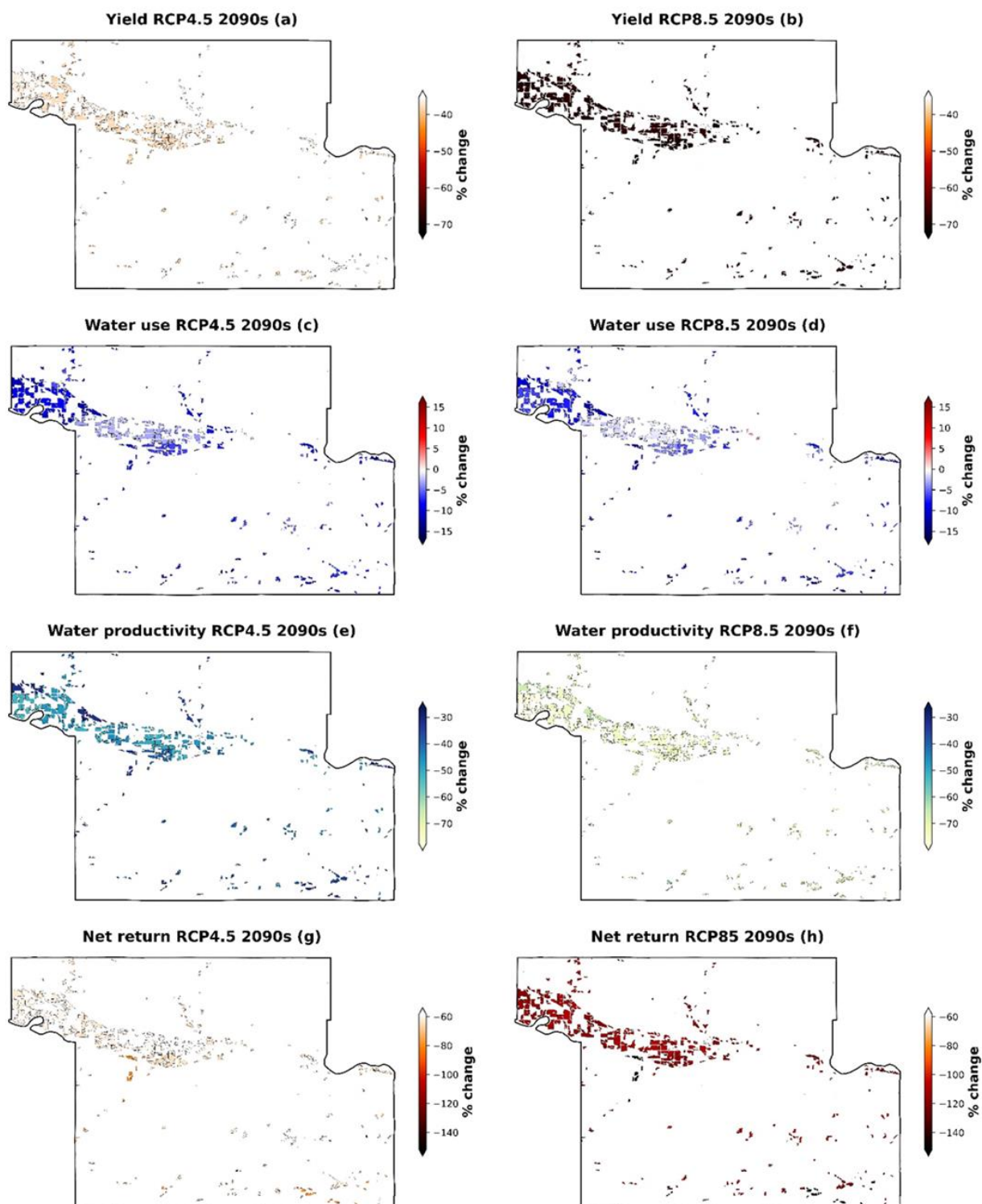


Figure 3.11. Spatial maize productivity in 2090s (late century – 50%*)

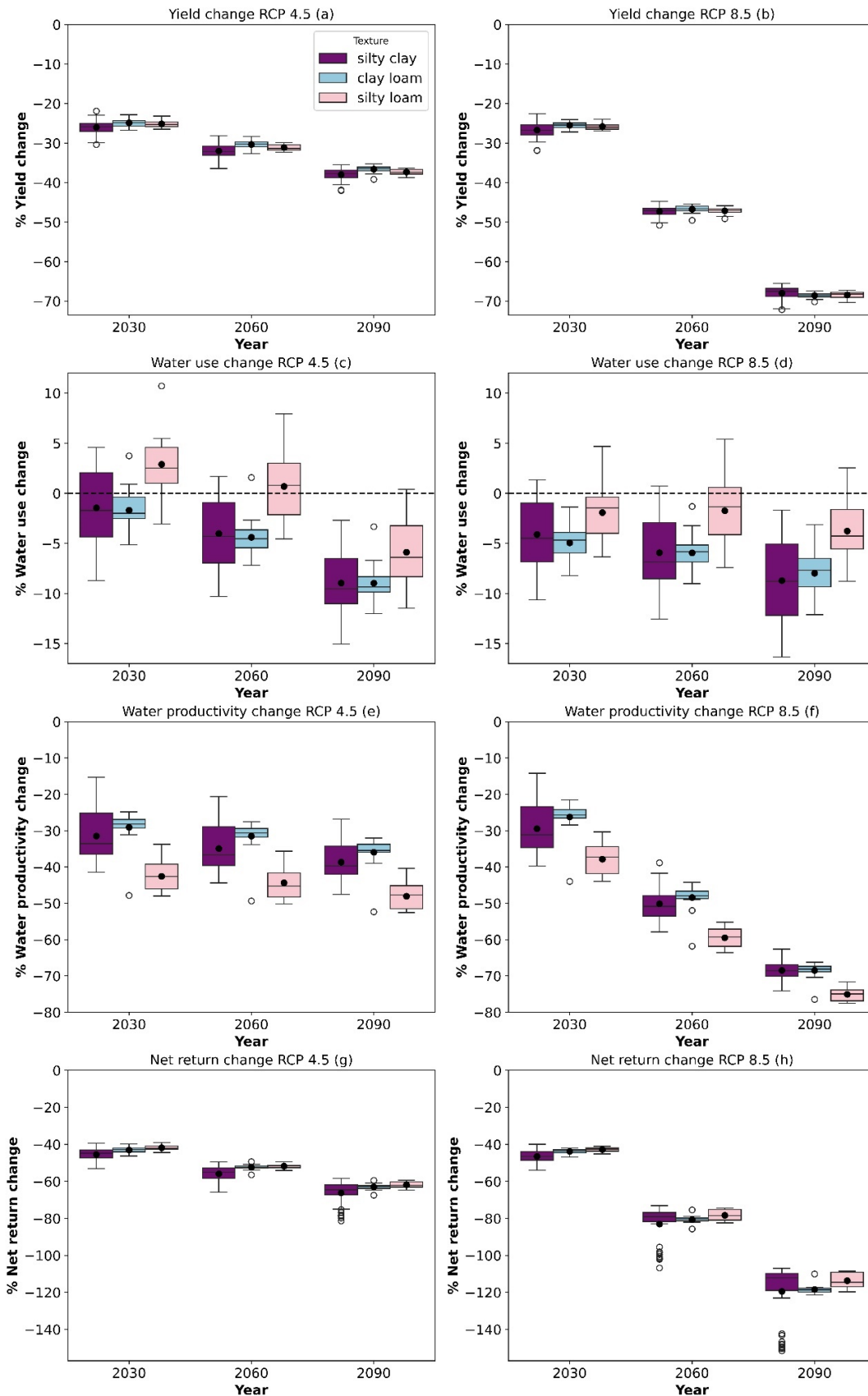


Figure 3.12. Boxplots of changes in overall productivity under deficit irrigation 50%* split out by soil texture with mean values shown as black dots. Black dashed line in (c) and (d) represent the absolute zero line.

3.4.5 Limitations of the Study

This study quantified spatial patterns of irrigated maize productivity under different irrigation management strategies and climate change scenarios in the eastern Great Plains. Given the nature of the study and the need to design a spatial protocol for simulating irrigated maize productivity, a number of reasonable assumptions were made.

First, the dynamic crop model (CERES-Model) used in this study did not account for pest and disease losses, hence, may have resulted in slight overestimation of maize yield observed during calibration and evaluation. A reasonable assumption is that the system is well-managed and largely free from significant pest and disease losses as noted by Onyekwelu & Sharda, (2024b) and Tesfaye et al. (2018). This assumption was also reflected in the variety trial report used for cultivar selection (Lingenfelser et al., 2015; Sassenrath et al., 2021).

Second, there was also uncertainty regarding matching field/cropland to each irrigation well in the region, which was necessary for our model evaluation (Figure 3.6c). While the irrigation withdrawal datasets from WIMAS are robust, they are reported at the resolutions of points of diversion (PD) such as pumping wells, and therefore it can be challenging to link them to specific fields simulated in DSSAT (Zipper et al., 2024). However, we observed strong grid-resolution (Figure 3.6c) and aggregated (Figure 3.6b) agreement between simulated and observed irrigation, suggesting this is not a substantial issue.

Third, although crop models are robust tools for understanding GxExM interactions, a limitation of most process-based crop models (including the CERES-Maize model) is not accounting for temporal improvement in genetics (Wang et al., 2019; White & Hoogenboom, 2003), which may impact parameter values related to cardinal growth temperatures and stress

response capabilities. While accounting for temporal yield improvement due to genetics is unambiguous in statistical models, process-based and dynamic models require extensive biophysical and marker data (often collected under trial experiments and genotyping) to benchmark temporal changes in genotype-specific parameters and cardinal growth temperatures. For example, Zhao et al., (2022) used a linear mixed-effects model to examine the impact of climate indices on yield by accounting for county-specific weather, time-invariant spatial controls like coordinates, and yield improvement term due to genetics. In contrast, White & Hoogenboom, (2003) argued that for process-based models, genetic information plays the most significant role in understanding temporal and tissue-level variations in the genetic regulation of specific processes and, for enhancing the representation of cultivar differences. Along those lines, the present study did not account for potential improvements in maize hybrids and genetics to deal with future climate conditions, which have the potential to alleviate the observed productivity decline. Nevertheless, our model calibration and validation were performed using 13 site-years of biophysical data, making our model fit for climate impact analysis.

Finally, model parameter equifinality is rarely discussed among crop model users. Most crop model genotype-specific parameters suffer from non-unique solution referred to as equifinality (unidentifiability) in mathematical modeling. This is because different combinations of genotype-specific parameter values may give exact same result, thereby undermining genetic uniqueness of crop cultivars or varieties. The present study did not account for mathematical equifinality of model parameters. However, since our interest is prediction and assessing climate impacts on yield and resource use, equifinality is not a concern (Lamsal et al., 2018). In addition, to deal with reducing model uncertainty and regression dilution of comparing observed versus simulated datasets, our model calibration exercise added a layer of robustness by iteratively

checking how variance in the observed datasets were reproduced in our model simulations. A future study will require testing our spatial protocol with simple standalone dynamic models programmed in Python or R, which will allow easy model parts decoupling for rigorous testing of equifinality (Welch et al., 2024).

3.5 Conclusion

This study developed a spatial protocol for adapting point-scale dynamic crop model for regional simulation of irrigated maize productivity under historical and future climate conditions in the US Great Plains. By integrating grid-level soil and climate variables, the modeling analysis enabled a comprehensive assessment of climate change impacts on irrigated maize productivity (yield, water use, water productivity, and net returns) under different irrigation management strategies and climate change scenarios in the Eastern Kansas River Basin. Historical maize productivity revealed strong spatial control of different soil textures and climate variables, with higher productivity and low water resource use observed for areas dominated by silt loam soils than areas dominated by silty clay loam and clay loam soil textures. However, going forward into the future, we found that the greatest maize productivity will likely shift from soils of silt loam to silty clay loam and clay loam soil textures; evidence that soils of higher porosity ratios such as silt loam may have rapid moisture rapid loss under warming-induced heat stress, leading to increased water use and low productivity. In addition, irrigated maize productivity will substantially decline under both RCPs 4.5 and 8.5, despite 9 – 23% increases in water use under full irrigation. However, assessing the impacts of deficit irrigation strategies (25% PAW or 50%* PAW) resulted in water savings ranging from 3 to 15% without further diminishing maize productivity. These findings suggest that climate-smart irrigation management strategies implemented at a fine spatial resolution, combined with yield-advancing varieties, could hold the key to sustainable future maize

production and balance hydrologic and agronomic tradeoffs under climate change. This research is essential for identifying proactive water management strategies that, when combined with agricultural adaptation techniques, will help farming communities manage emerging climate risks linked to drier future conditions.

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Chapter 4 - *In-silico* evidence for improving irrigated maize productivity in the Great Plains: a high-resolution spatial simulation approach

*A modified version of this chapter is ready for submission to a journal.

4.1 Abstract

Food security and the depletion of water resources have become the two main concerns for the future of agricultural sustainability. Climate change on the other hand challenges global agricultural productivity, making target agricultural zones less productive. However, increasing yield potential through adaptation is crucial for improving global agricultural production. In this study, an approach for studying the impacts of future climate conditions and adaptation strategies on yield and water use dynamics of maize in the Eastern Kansas River Basin (EKSRB) of the US Great Plains, based on different future climate scenarios and deficit irrigation water management at a 4 km spatial resolution was presented. Using spatially adapted CERES-Maize model, the combination of impacts of in silico genotype-specific adaptations for selected genotype-specific parameters, treated as quantitative traits (improved canopy photosynthesis for radiation use efficiency [RUE], light extinction [KCAN], and heat tolerance [HEAT]), and agronomic management (shifting planting window [PD1 & PD2], and non-limiting nutrient allocation [NNL]) on yield and irrigation water use were explored. In addition, we assessed the integration of the individual genotype-specific and agronomic adaptations to understand the co-benefits and trade-offs on yield improvement and water savings. Future climate scenarios for the region were created for two Representative Concentration Pathways (RCPs) (4.5 and 8.5) over three 25-year future periods (2025-2100) and compared to historical climate (1991-2015). Results showed that future

maize yield declined by approximately 34% to 43% (early and late century time periods, respectively) under RCP 4.5, and 33% to 68% (early and late century time periods, respectively) under RCP 8.5. Despite the yield declines, we found water use savings ranging from 9% to 20% (early and late century time periods, respectively) under RCP 4.5, and 13% to 18% (early and late century time periods, respectively) under RCP 8.5. We observed that integrated adaptation strategy linked to improved RUE, HEAT, KCAN, NNL, and PD2 (INT-NNL-PD2; Int 4), resulted in the early 21st century yield gain of 0.6 to 3% (RCPs 4.5 and 8.5, respectively), with water savings of 10 to 13% (RCPs 4.5 and 8.5, respectively), relative to historical condition. However, going forward into the 21st century, we found marginal yield deviation (especially under RCP 4.5) with further increase in water savings; more than observed under no adaptation scenario, suggesting the need to re-examine and re-design these adaptation strategies for the co-benefits of further yield gain and improvement, while leveraging the benefits of water savings under future climate conditions. The overall results indicate that climate-smart irrigation management strategies implemented at a fine spatial resolution, along with cultivar genetic improvement and smart agronomic management, could hold the key to sustainable maize production in the future. Our findings emphasize the transformative potential of all-inclusive integrated adaptation strategies in mitigating the impacts of climate change on irrigated maize production in the Great Plains.

Keywords: Genotype-specific adaptation, agronomic adaptation and management, irrigated maize yield and water use, irrigation water savings and yield gain, climate change, spatial crop model, Great Plains, CERES-Maize model.

4.2 Introduction

The projected increases in growing season climate variables (minimum and maximum temperatures, rainfall and solar radiation) due to climate change (IPCC, 2023; Kothari et al., 2019; Onyekwelu & Sharda, 2024b; Onyekwelu et al., 2025; Stella et al., 2023), challenges the future of three key crops – maize, wheat, and rice - which supply nearly two-thirds of 90% of the global human calorie consumption (Kastner et al., 2012; Stewart & Lal, 2018). Projected increase in future population, on the other hand, challenges food security in major regions of the world, stretching the need to intensify food production in target/high-yield regions (FAO, 2023a, 2023b). Maize, for example, will suffer severe yield shock due to future climate change, with majority of studies recommending adaptation as one of the key strategies for yield improvement in high-yielding regions (Onyekwelu & Sharda, 2024b; Onyekwelu et al., 2025; Sen et al., 2024; Yang & Wang, 2023). The US Great Plains and broader Midwest region as one of the world's high-yielding regions and leading maize producers, face significant challenges as irrigation practices deplete the High Plains Aquifer (Ogallala Aquifer), which is the largest aquifer in the US and the Great Plains (Araya et al., 2017; McGuire, 2012; Scanlon et al., 2012). Studies have shown that irrigation demand for maize in the Great Plains will increase amid uncertain rainfall conditions; consequently, leading to further depletion of the High Plains Aquifer. For example, Onyekwelu et al. (2025) has shown that maize irrigation water use in the early 21st century climate conditions under current farmers' choice will increase by 30 to 32%, without yield improvement. In the same study, they found that deficit irrigation may offer benefits of water savings reaching up to 15% without further diminishing productivity, while maintaining water resources needed to improve aquifer recovery. However, the solutions for implementing maize adaptation to future climate

conditions that are aimed at improving spatiotemporal yield and maintaining irrigation water savings under these climate conditions are still lacking.

While the US Great Plains and broader Midwest region remains one of the world's high-yielding and leading maize-producing regions, John Powell as early as 1879 (Powell, 1879), defined the east-west aridity gradient that characterize the region's agriculture and water use. He noted that amid the east-west aridity gradient lies the 100th meridian, which is the symbolic hydroclimatic dividing line between the moist eastern part of the United States and the drier western plains (Seager et al., 2018), and where precipitation is approximately equal to potential evapotranspiration (Seager et al., 2018). However, recent studies have shown that the hydroclimatic conditions that characterize this line are shifting eastwards, thereby creating drier conditions (sometimes termed a 'new 100th meridian') to the east of the 100th meridian (Krajick, 2018; Seager et al., 2018). The implications of this eastward migration of aridity on irrigated maize response to different climate scenarios and adaptation strategies remain uncertain in the region, as further eastward migration is expected over the next decades (Krajick, 2018; Seager et al., 2018).

As climate changes with anticipated negative consequences (Onyekwelu & Sharda, 2024b), it is widely agreed that agricultural crop production will not be on track to meet the production doubling needed by 2050 for humanity to avoid major food security disruption (Godfray et al., 2010). Researchers have recognized climate adaptation strategies to include accelerating genetic gains through breeding and employing improved in-field production methods and agronomic management such as adjusting planting dates, managing nutrient application and allocation of biologicals, and precision agriculture (Guarin et al., 2022, 2023; Kothari et al., 2019, 2020; Martre et al., 2024; Onyekwelu & Sharda, 2024b; Poudel et al., 2023; Stella et al., 2023). While accelerating genetic gains through breeding and agronomic management are essential

adaptation strategies for improving crop production, the time horizon between identifying high-performance traits in crop genotypes or cultivars and stable agronomic management practices for yield improvement and water use savings may be long under field or laboratory experiments, and in some cases, field or laboratory experiments may not be readily feasible to test these strategies due to intensive financial investment and labor requirements (Battisti et al., 2017; Onyekwelu & Sharda, 2024b; Sinclair et al., 2010). In addition, field or laboratory experiments lack the advance time horizon and regional scalability needed to achieve agricultural sustainability and assess location-specific impacts of these strategies under different future climate scenarios and soil variability.

Process-based crop models are powerful tools that allow multiple scenario analysis under different climates and environmental conditions and can facilitate testing of modified cultivar traits and agronomic management practices, and evaluate how they can impact crop production, especially under climate change (Battisti et al., 2017; Onyekwelu & Sharda, 2024b; Sinclair et al., 2010). For example, Guarin et al. (2022) tested the best performing doubled haploid crosses of wheat with improved RUE, KCAN, fruiting efficiency, grain filling duration, and grain size using a multi-model ensemble of process-based wheat models in 34 global locations. They found that global wheat production is projected to increase by 37%/year without cropland expansion. In another study, Tesfaye et al. (2018) assessed the potential benefits of drought and heat tolerance traits of maize cultivars using the CERES-Maize model. They reported that incorporating drought and heat tolerance traits into benchmark maize cultivars increased maize yield under future climate conditions. By adjusting planting dates as an adaptation strategy, Getachew et al. (2021) found that early planting of sorghum resulted in better yield compared to the baseline planting dates

based on simulated results from two sites in Ethiopia. Overall, these studies concluded that adaptation is key to sustaining agricultural crop production under future climate conditions.

Given that numerous studies have tested different adaptation strategies for improving crop productivity under future climate conditions using process-based crop models, studies testing individual adaptation levels (genotype-specific traits or agronomic management practices), alongside integration of genotype-specific and agronomic adaptation strategies on irrigated maize production are still lacking. In addition, the scale of most climate impact and adaptation studies has remained point-based, given that most process-based crop models run at point-scale to simulate a homogenous unit, such as a field (Onyekwelu et al., 2025). This has limitations when considering spatial heterogeneity of environmental conditions (e.g., soil and climate) and how different adaptation strategies respond to different landscape conditions at a regional scale. More so, spatial information on irrigation water use of maize and response under different adaptation strategies is lacking. Adapting point-scale crop models for spatial simulation of crop productivity offers many advantages (Onyekwelu et al., 2025). For instance, spatial simulations provide location-specific impacts, which can be used to target the combination of high-yielding and low water use locations under different adaptation strategies for resource management. In addition, spatial simulation of crop productivity can be used to manage input resources (e.g., irrigation, fertilizer, etc.) for profit maximization (Onyekwelu et al., 2025), and to assess co-benefits and trade-offs among different ecosystem services (Qiu et al., 2018, 2019). By integrating gridded outputs from regional crop models with spatial soil distributions and seasonal climate data under different adaptation strategies, valuable insights into the key factors influencing crop yield and irrigation water use can be drawn to improve agricultural management zones (Onyekwelu et al., 2025). This approach enhances the understanding of how landscape and atmospheric conditions shape regional

agricultural productivity. It also supports the development of effective adaptation and management strategies aimed at improving crop sustainability and resource efficiency (Onyekwelu et al., 2025).

In our previous study, we developed a spatial protocol for adapting a point-scale crop model for spatial simulation of irrigated maize productivity (yield, water use, water productivity, and farmers' net returns) under different climate scenarios, using the Shawnee County in EKS RB of the Great Plains as a case study (Onyekwelu et al., 2025). Based on the spatial protocol, a novel crop modeling study was developed and evaluated for the entire EKS RB (comprising of 17 counties) in order to understand the impacts of different climate change scenarios and adaptation strategies on irrigated maize yield and water use. Thus, the objectives of this study were to: (1) investigate the spatial and temporal patterns of irrigated maize yield and water use responses to future climate changes and deficit irrigation in the EKS RB; (2) assess the combination of impacts of *in silico* genotype-specific adaptations for selected genotype-specific parameters, treated as quantitative traits (improve canopy photosynthesis for radiation use efficiency [RUE], light extinction [KCAN], and heat tolerance [HEAT]), and agronomic management (shifting planting window [PD1 & PD2], and non-limiting nutrient allocation [NNL]) on yield and irrigation water use. In addition, we assessed the integration of the genotype-specific and agronomic adaptation strategies to understand the co-benefits and trade-offs on yield improvement and water savings. By accounting for spatial heterogeneity, we quantified location-specific impacts of climate change and adaptation strategies, offering valuable insights for other regions in the Great Plains facing climate change uncertainty.

4.3 Materials and Methods

4.3.1 Study Area

This study was carried out in the Eastern Kansas River Basin (Figure 4.1; EKS RB, hereafter), which represent the watershed of the Kansas River, spanning from the confluence of the Smoky Hill and Republican rivers in the west, to its terminus at the Missouri river in Kansas City (Onyekwelu & Sharda, 2024a, 2024b; Sen et al., 2023, 2024). The basin represents an exemplar region in the Great Plains exposed to potential impacts of aridity increase due to climate change on crop production and ecosystem function. With the 100th meridian (Powell, 1879) lying adjacent to its western edge, projected aridity increases (Seager et al., 2018) are expected to encroach into the basin; continuing eastwards, thus, making the region a perfect location to develop sustainable solutions for the climate impact mitigation and adaptation strategies for the broader Great Plains agricultural system.

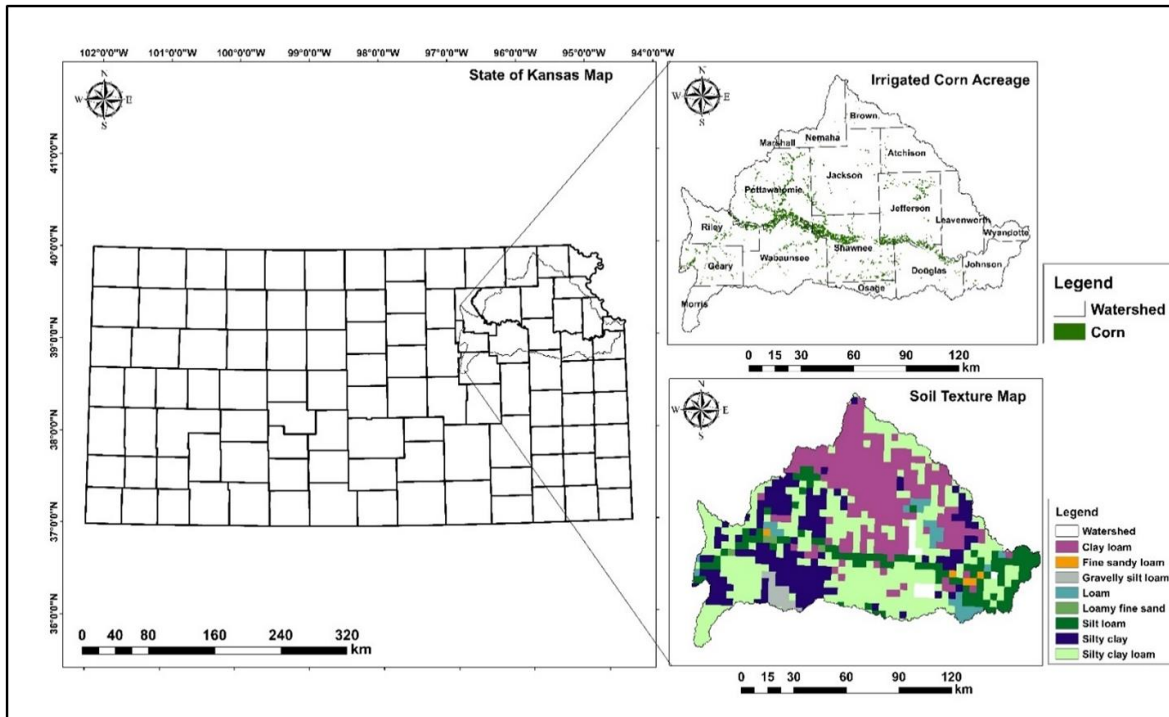


Figure 4.1. Inset map of the study area (EKS RB in the State of Kansas map) with irrigated maize acreage and spatial soil textures shown in the upper and lower rights, respectively.

There are seventeen counties in EKSRB (Figure 4.1), with the basin covering an area of over two million acres (Figure 4.1; larger than the State of Connecticut in the United States). Crop production in EKSRB comprises a mixture of rainfed and irrigated cropland, with irrigation playing crucial role in growing water-demanding crops like maize and soybean. There over 2,900 irrigated maize fields in EKSRB, resulting in over 55,000 acres. It is important to note that majority of the large, irrigated fields are located in the alluvial river of the Kansas River (Figure 4.1; Onyekwelu et al., 2025). There are over 100 unique dominant soil types, with variable distribution of different textures as shown in Figure 4.1.

The average growing season rainfall (between April and September) in EKSRB ranges from 472 mm in the west and 520 mm in the east, showing an increasing trend from west to east (Onyekwelu & Sharda, 2024b). Growing season temperatures (T_{min} and T_{max}) increases from east to west, with values ranging from 16 to 17.5 °C, and 28.5 to 30 °C, respectively. Solar radiation (SRAD) on the other hand is fairly stable, with an average value of 22.2 MJ m⁻²d⁻¹ in the west, and 21.3 MJ m⁻²d⁻¹ in the east (Onyekwelu & Sharda, 2024b). More details on the location-specific or county-level growing season climate outlook will be discussed in the subsequent sections.

4.3.2 CERES Maize Model: Spatial Implementation Framework

The present study used the CERES-Maize model within the Decision Support System for Agrotechnology Transfer (DSSAT version 4.7.5, hereafter), for simulating maize yield and irrigation water use under different climate scenarios and adaptation strategies (Jones et al., 2003; Onyekwelu & Sharda, 2024b; Ritchie et al., 1998). As it is quite common for this class of model, it assumes a homogeneous unit of land for simulating crop growth and development, taking into account different management practices and weather variables (Jones et al., 2003). The DSSAT

application software currently comprises over 40 crop simulation models, with new modules being developed for handling different processes such as yield forecasting (Hoogenboom et al., 2019). The minimum climate datasets required to run the CERES-Maize model include daily minimum and maximum air temperatures, rainfall, and SRAD. The model also accounts for soil information, management data (irrigation, nutrients, and planting conditions), initial condition at planting, and cultivar characteristics represented as genotype coefficients (Onyekwelu & Sharda, 2024b; Onyekwelu et al., 2025). Thus, it is possible to use this model for evaluating the effects of various genotype-specific traits and agronomic management on irrigated maize yield and water use, and for designing maize ideotypes for climate change mitigation (Onyekwelu & Sharda, 2024b).

While the DSSAT and its suites of crop simulation models have been used extensively for a wide range of studies, they are designed to run as point-based models for representing a homogeneous agricultural unit and as such, lacks any spatially distributed or spatial-oriented user interface for location-specific simulation of cropping systems. In addition, given that climate change impacts are likely to be spatially-variable, understanding how different locations respond to different management and atmospheric conditions is necessary for designing strategic adaptation for climate impact mitigation. As a result, the spatial execution file (*.GSX) of the DSSAT was used by linking grid-level soil and climate inputs in order to simulate grid-level specific impacts. A top-down spatial protocol designed by Onyekwelu et al. (2025) was used for spatial simulation of irrigated maize productivity in EKS RB. The region was first divided into 4 km grids, representing the finest resolution possible for matching the input meteorological datasets required to run the model (Figure 4.2). This approach resulted in 1024 grids in the region, with unique soil and atmospheric conditions (Figure 4.2). The grid information were then used to access areas in the region where irrigated maize grows using a combination of the USDA CropScape

Crop Data Layer (<https://nassgeodata.gmu.edu/CropScape>; Han et al., 2012) for total maize (rainfed and irrigated) acreage, gSSURGO (Gridded Soil Survey Geographic) for detailed spatial soil distribution (Soil Survey Staff, 2022), and Landsat-based irrigation dataset (LANID) for cropland irrigation in the contiguous United States (Xie et al., 2021; Xie & Lark, 2021). To filter irrigated maize fields in the region, a geoprocessing operation in ArcMap 10.7 was carried out to compute geometric intersections of maize fields that overlays with irrigation map (LANID) with attendant soil information. In order to assign maize-growing grids, the resultant irrigated fields were linked with the initial 1024 grids using Zonal Statistics Tool in ArcMap 10.7 (Onyekwelu et al., 2025). The final result was a total of 402 grid counts, representing unique locations where irrigated maize grows for the model simulation run in the region (Figure 4.2). More details about the workflow can be found in Onyekwelu et al. (2025).

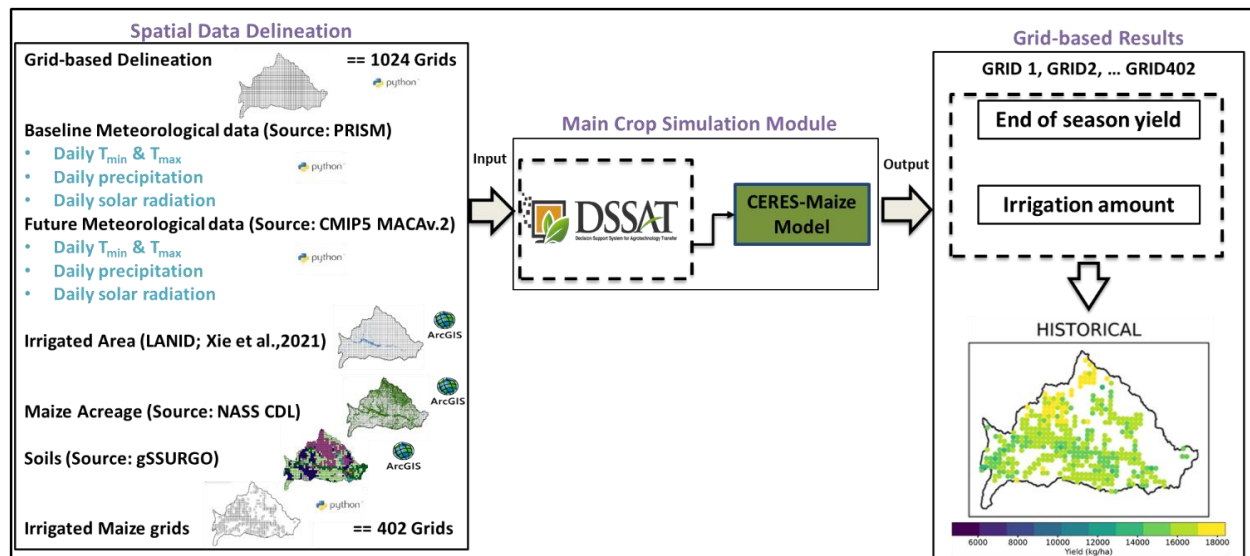


Figure 4.2. Workflow for spatially distributed maize simulation using the DSSAT CERES-Maize model by integrating grid-based inputs to generate grid-specific simulation results (yield, and irrigation water use), visualized as grid-specific spatial output maps. Adapted from Onyekwelu et al. (2025).

The updated spatial grids information was used to retrieve weather variables and crop management inputs required for model simulation. Model outputs were spatially integrated to each

unique grid location using the corresponding grid centroids. All spatial mapping and analytical procedures were conducted within the Python programming environment, leveraging the GeoPandas, Pandas, and Matplotlib libraries (Jordahl et al., 2021; Matplotlib, 2022).

4.3.3 Model Input Preparation and Long-term Spatial Simulation

A set of Python scripts was developed for retrieving and converting the grid-level weather and soil datasets into DSSAT-compatible formats (*.WTH and *.SOL, respectively). Soil data retrieved from the gSSURGO at 30 m were regridded to 4 km as mentioned in previously. Similarly, historical climate information at 4 km were retrieved from the PRISM (Parameter-elevation Regressions on Independent Slopes Model) (PRISM Climate Group, 2014) group for a period of 25 years (1991 – 2015).

Previously calibrated and validated regional CERES-Maize model using 13 site-years of maize yield data and 10 years of irrigation water use data in 92 wells was used (Onyekwelu et al., 2025). As it has been observed for the CERES class models in DSSAT, the issue of equifinality of genotype-specific parameters was reported by Onyekwelu et al. (2025) and as documented by Lamsal et al. (2018). However, since the interest of this study focuses on assessing in-silico climate impacts and adaptation strategies on yield and resource use without inferring the resultant genotype-specific parameters to any underpinning genetics for breeding, the impact of equifinality is not a concern (Lamsal et al., 2018). In addition, several other studies have explored the in-silico adaptation methods to provide insights into potential yield improvements and resource maximization under climate change (Kothari et al., 2019, 2020; Onyekwelu & Sharda, 2024b; Singh et al., 2014).

To conduct long-term and future simulations, spatial-dependent (county-scale) management practices for maize production in the region were implemented based on the

information reported in Table 4.1 (K-State Extension 2022). According to K-State Extension (2022), there are two planting zones (zone 2 and 3) in the region, with planting dates ranging from 15th April to 10th May for zone 2, and 1st April to 5th May for zone 3 (Table 4.1). Maize was planted in each grid at a seeding rate of 9 plants/m², row spacing of 76 cm, and planting depth of 5 cm (Table 4.1, K-State Extension, 2022; Lingenfelser et al., 2015; Onyekwelu & Sharda, 2024b; Sassenrath et al., 2021). Since each grid in the model is a unique combination of soil and climate, no two grids share the same input; therefore, treated as spatially independent. Initial soil moisture conditions assumed the grid-level soil profiles to be at field capacity at planting. In addition, the initial soil nitrogen was set to 25 kg N/ha⁻¹, assuming 1% soil organic matter (Onyekwelu & Sharda, 2024b). In-season fertilizer applications were set according to regional recommendations (K-State Extension, 2007, 2022) and as per the variety trial reports (Lingenfelser et al., 2015; Sassenrath et al., 2021). Under historical condition, irrigation allocation in each grid was managed at 50% management allowable depletion (MAD), which represent the farmers' choice water management regime required to fill soil profile to field capacity (FC) in the region. However, deficit irrigation approach was adopted under future climate based on our previous study in the region reporting substantial irrigation increase (up to 32%) under full irrigation without yield improvement (Onyekwelu et al., 2025). This was achieved by managing irrigation allocation in each grid at 75% MAD, allowing 25% of soil water before the next irrigation event returned it to FC (Onyekwelu et al., 2025). This strategy represents the greatest potential for improved water management for balancing hydrologic and agronomic tradeoffs under climate change (Onyekwelu et al., 2025).

In order to accurately capture the effect of CO₂ on seasonal biomass accumulation and transpiration, dynamic CO₂ values were used. To evaluate the historical and future climate impacts on maize productivity, the model was run for the period ranging from 1991 to 2099; driven by

historical information and future climate data from the CMIP5 model family. Details on the future climate scenarios and the global climate models (GCMs) used are presented in the following section.

Table 4.1. County-level planting conditions.

County	Zone	Planting start	Planting end	Plant pop (plants/m ²)	Row spacing (cm)	Planting depth (cm)
AT	2	15-Apr	10-May	9	76	5
BO	2	15-Apr	10-May	9	76	5
DO	3	01-Apr	05-May	9	76	5
GE	3	01-Apr	05-May	9	76	5
JA	2	15-Apr	10-May	9	76	5
JE	3	01-Apr	05-May	9	76	5
JO	3	01-Apr	05-May	9	76	5
LV	3	01-Apr	05-May	9	76	5
MA	2	15-Apr	10-May	9	76	5
MO	3	01-Apr	05-May	9	76	5
NE	2	15-Apr	10-May	9	76	5
OS	3	01-Apr	05-May	9	76	5
PO	2	15-Apr	10-May	9	76	5
RL	2	15-Apr	10-May	9	76	5
SH	3	01-Apr	05-May	9	76	5
WA	3	01-Apr	05-May	9	76	5
WY	3	01-Apr	05-May	9	76	5

4.3.4 Future Climate Scenarios

Future climate change scenario impacts on irrigated maize production were simulated for each of the 402 unique grids in the region. We selected the scenarios based on RCPs 4.5 and 8.5, divided into three time slices: 2030s (early century), 2060s (mid-century), and 2090s (late century). Details on the RCPs (4.5 and 8.5) have been clearly reported in our previous study (Onyekwelu et al., 2025). Daily weather variables (SRAD, rainfall, Tmin, and Tmax) were obtained for CMIP5 GCMs available from the MACA-2 database at https://climate.northwestknowledge.net/MACA/data_portal.php (Abatzoglou, 2013; Abatzoglou & Brown, 2012). These datasets are available at 4 km resolution and cover the entire conterminous

United States. In addition, the resolution of this dataset accurately matches the resolution of our modeling unit. The datasets have been statistically downscaled and bias-adjusted using the Multivariate Adaptive Constructed Analogs (MACA v2) method (Abatzoglou, 2013; Abatzoglou & Brown, 2012), and have been used by several studies (Onyekwelu et al., 2024; Kothari et al., 2020, 2021; Yang & Wang, 2023; Sen et al., 2024).

While the CMIP6 climate models represent the current update in future atmospheric climate simulations, recent studies have used CMIP5 climate models for climate impact studies and have shown comparable results to CMIP6 (Dahri et al., 2024; Dehghan Moroozeh et al., 2024; Guarin et al., 2022, 2023; Hamlet et al., 2024; Jha et al., 2024; Stella et al., 2023; Trancoso et al., 2024; Try et al., 2022; Onyekwelu et al., 2025). The results from these studies suggest that the selection of CMIP5 in this study instead of CMIP6 likely does not have any substantial impact on the findings. However, to ensure robust model simulation and to account for GCM-related uncertainty, five GCMs spanning full range of climate sensitivities were used. This was based on sensitivity labeling reported by Onyekwelu et al. (2025) and Yang & Wang (2023), and as shown in Table 4.2 below. CO₂ impacts on biophysical processes was captured using dynamic CO₂ values for the two RCPs from 2025 to 2099. After model simulation, maize productivity (yield, and irrigation water use) for the five selected GCMs were averaged per grid across different time slices and RCPs to get ensemble averages and then compared to the historical period (1991-2015).

Table 4.2. List of selected CMIP5 GCMs.

GCMs	Country	Group	Climate sensitivity	Ensemble member	Native Resolution (deg. lon x deg. lat)	Downscaled Resolution (km x km)	Reference
BCC-CSM1-1	China	Primary	Low	r1i1p1f1	2.8 x 2.8	4 x 4	(Abatzoglou, 2013)
GFDL-ESM2M	USA	Primary	Low	r1i1p1f1	2.5 x 2.0	4 x 4	(Abatzoglou, 2013)

CanESM2	Canada	Primary	High	r1i1p1f1	2.8 x 2.8	4 x 4	(Abatzoglou, 2013)
CNRM-CM5	France	Primary	High	r1i1p1f1	1.4 x 1.4	4 x 4	(Abatzoglou, 2013)
CCSM4	USA	Primary	Medium	r6i1p1f1	1.25 x 0.94	4 x 4	(Abatzoglou, 2013)

4.3.5 Climate Change Adaptation Strategies

According to Lobell (2014), adaptation is any agricultural practice or activity that is impact-reducing in a way that it reduces the negative climate impact while enhancing its positive impacts (Onyekwelu & Sharda, 2024b). Based on this definition, one of the objectives of this study was recalled by assessing the impacts of different in silico adaptation strategies on maize yield and irrigation water use under future climate conditions. Model simulations was first conducted under no adaptation strategy in order to benchmark the impacts of future climate on yield and irrigation water use in the region. A set of adaptation strategies were implemented under three categories (Figure 4.3): genotype-specific adaptations (Ge), agronomic adaptations (Ag), and integrated adaptations (Int). These adaptation strategies were implemented based on evidence found in the literature, preliminary analysis, and the need to meet the expected grain demand to feed the growing population (Ciampitti & Lemaire, 2022; Getachew et al., 2021; Guarin et al., 2022, 2023; Liu et al., 2013; Martre et al., 2024; Stella et al., 2023; Tesfaye et al., 2017, 2018). A total of 10 climate change adaptation strategies that are aimed at improving crop yield and maintaining irrigation water savings were assessed. Each adaptation strategy simulation was executed based on five GCMs, two RCP scenarios, 402 maize-growing grids, one irrigation scenario, and 75 years of simulation in the future: thus, making a total of 301,500 runs per adaptation. Details of different adaptation categories are presented below (Figure 4.3).

4.3.5.1 Genotype-specific Adaptation Strategies (Ge)

The cultivar, species, and ecotype parameters in DSSAT are jointly referred to as genotype parameters (Hoogenboom et al., 2019). The genotype-specific adaptations were termed “ideotypes” to refer to combinations of ideal traits needed to achieve yield improvement and water savings under future climate (Mi et al., 2016). These genotype-specific adaptation strategies were based on evidence reported for improved maize varieties, with improved canopy photosynthesis (radiation use efficiency; RUE), improved light extinction (KCAN), and heat tolerance under extreme air temperatures (Guarin et al., 2022, 2023; Martre et al., 2024; Mi et al., 2016; Stella et al., 2023; Tesfaye et al., 2017).

4.3.5.1.1 Ideotype I – Radiation Use Efficiency (RUE)

An ideotype with improved canopy photosynthesis was created by increasing the benchmark RUE value of the reference cultivar by 20%. This approach is consistent with findings found in the literature for high-yielding maize cultivars around the globe. For example, studies in the US have shown that recent advances in maize genetics have seen RUE values ranging from 3 to 5.5 g MJ⁻¹ (Shi et al., 2022). According to Shi et al. (2022), RUE values obtained from different field experiments around the world ranges from 1.05 to 5.74 g MJ⁻¹. Loomis & Amthor (1999) has indicated that the maximum RUE value of a closed maize canopy is about 5.5 g MJ⁻¹. The benchmark values for RUE of reference cultivars in the DSSAT CERES-Maize model ranges from 2.0 to 4.5 g MJ⁻¹, with a mean value of 4.1 g MJ⁻¹ after calibration (Hoogenboom et al., 2019). This value was increased to 4.92 g MJ⁻¹ (20% increase) and was within the limits RUE estimated from field experiments (Shi et al., 2022; Wei et al., 2017).

4.3.5.1.2 Ideotype II – Light Extinction Coefficient (KCAN)

Studies in different fronts have shown that recent advances in breeding have improved KCAN (Guarin et al., 2022, 2023; Martre et al., 2024; Stella et al., 2023). According to Guarin et al. (2022), the advances in doubled haploid wheat varieties relative to traditional varieties has seen KCAN increased by 10%; thus, supporting evidence for increasing wheat yield potential especially under climate change. Successful modeling of plant growth relies on adequate description of KCAN for intercepted photosynthetically active radiation distribution (Wei et al., 2017). The benchmark value for KCAN within the CERES-Maize model is 0.85 after calibration. An ideotype with improved KCAN was created by increasing the benchmark value by 9%.

4.3.5.1.3 Ideotype III – Heat Tolerance (HEAT)

Although maize is a summer crop, it is very sensitive to high daily temperatures during the growing season (Tesfaye et al., 2018). With increasing temperature under climate change scenarios, optimal temperatures for growing maize may fluctuate between day and night, as well as over the growing season. The sensitivity of maize to high temperatures affects grain-filling rate and duration. Therefore, a heat tolerant ideotype was created by modifying the optimum and maximum temperature parameters (T_{opt} and T_{max} , respectively) that affect relative grain-filling rate (RGFIL). In the CERES-Maize model, the RGFIL is a daily timestep temperature function (Hoogenboom et al., 2019) with values ranging from 0 to 1 (for limiting and non-limiting conditions, respectively). Accordingly, the heat tolerant ideotype was created by increasing the T_{opt} and T_{max} values of the reference cultivar by 2 °C. This is similar to the methods used by Singh et al. (2014) and Tesfaye et al. (2018) in CERES-Sorghum and CERES-Maize models, respectively.

4.3.5.2 Agronomic Adaptation Strategies (Ag)

The agronomic adaptation strategies came from the awareness of risk-averse farming system and were implemented to explore changes in management practices that could lead to yield improvements and water savings under future climate conditions. Details of the individual implementations are found below.

4.3.5.2.1 Planting dates – PD1 and PD2

Early planting of maize has been shown to ameliorate yield loss due to climate change. In a study conducted in Ethiopia, they found that early planting dates of sorghum resulted in better yield compared to the baseline planting dates (Getachew et al., 2021). In this study, two early planting strategies were created as follows: PD1 and PD2 (Figure 4.3, planting dates 1 and 2, respectively) implemented by shifting the baseline county-level planting dates presented in Table 4.1 by one week and two weeks (7 and 14 days), respectively.

4.3.5.2.1 Non-limiting Nutrient – NNL

Non-limiting nutrient condition was implemented by turning off the nutrient balance and simulation routine in DSSAT to ensure potential nutrient allocation throughout the growing season, while still strategically allocating nutrient as at when and how much plant needs. Studies have shown that nutrient management and needs will increase for some crops, especially under future climate condition. For example, Martre et al. (2024) reported that global nitrogen fertilizer needs for wheat yield improvement will increase under climate change. In another study, Liu et al. (2016) reported that maize yield gap of up to 40% could be reduced by improving local agronomic management (fertilizer input and selecting high-yielding cultivars). Overall, the choice of implementing NNL as an adaptation strategy represents a true opportunity to maximize maize production given climate risk constraints.

4.3.5.3 Integrated Adaptation Strategies (Int)

The genotype-specific and agronomic adaptation strategies were linked to develop different levels of integrated adaptation strategies (Figure 4.3). The strategies were implemented to ensure that targeting yield improvement and water savings may not be realized in isolation or through a single farming practice. Based on that, four levels of integrated adaptation strategies (Int) as follows: Ge + Ag (Int 1; NL + Default PD), Ge + Ag (Int 2; NNL + Default PD), Ge + Ag (Int 3; NNL + PD1), and Ge + Ag (Int 4; NNL + PD4). Int 1 (NL + Default PD) integrated all levels of genotype-specific adaptation with limiting nutrient (NL) condition and county-level baseline planting dates (Default PD) to assess its impact on yield and water use. Similarly, Int 2 (NNL + Default PD) combined all levels of genotype-specific adaptation with non-limiting nutrient (NNL) condition and county-level baseline planting dates (Default PD). Int 3 and Int 4 (NNL + PD1 and NNL + PD2, respectively) linked all genotype-specific and NNL adaptation strategies, but with county-level baseline planting dates shifted by 7 and 14 days, respectively.

It is important to note that the level of adaptation strategies, coupled with spatially distributed modeling approach presented here is the first of its kind in the Great Plains.

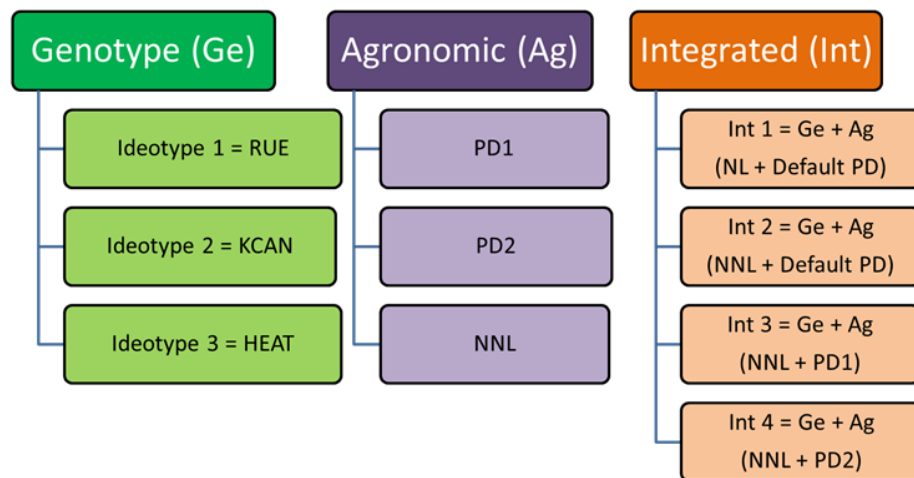


Figure 4.3. Different adaptation strategies based on genotype designed as ideotypes, agronomic management, and integrated designed by linking genotype-specific adaptations with agronomic managements.

4.4 Results & Discussion

4.4.1 Growing Season Future Climate Deviations in EKSRB

Figures 4.4 to 4.6 show the growing season climate deviations from the historical conditions with respect to T_{min} , T_{max} , and rainfall, respectively. Climate deviations are shown for both RCPs 4.5 and 8.5 over three future time periods (2030s, 2060s, and 2090s). The spatial distribution of T_{min} deviation under RCP 4.5 ranges from 0.9 to 1.5 °C under 2030s, 1 to 2 °C under 2060s, and 1.5 to 2.5 °C under 2090s time periods (Figure 4.4). These deviations, except under 2090s, are consistent with the Paris Agreement (United Nations, 2015), which aims for temperature stabilization to well below 2 °C. The Paris Agreement pursues efforts to limit the temperature increase to 1.5 °C (Brown et al., 2018; United Nations, 2015); however, studies have shown impacts of temperature increase at 1 to 1.5 °C on cropping systems without adaptation. For instance, Onyekwelu & Sharda (2024b) showed that for a 1 °C rise in T_{min} , a 2,916 kg ha⁻¹ maize yield loss was observed in eastern Great Plains under rainfed condition. T_{min} deviation under RCP 8.5 (Fig. 4) ranges from 0.9 to 1.7 °C in 2030s, 2.0 to 3.2 °C in 2060s, and 3.2 to 4.0 °C in 2090s. These deviations are far from Paris Agreement below 2.0 °C stabilization, especially in the 2060s and 2090s. The gradual increase in deviation observed under RCP 4.5 was absent in RCP 8.5, suggesting strong atmospheric forcing present under high emission pathway of 8.5. It is important to note that T_{min} deviations increases from east to west, a trend consistent with the regional aridity gradient of the Great Plains (Onyekwelu & Sharda, 2024b; Seager et al., 2018).

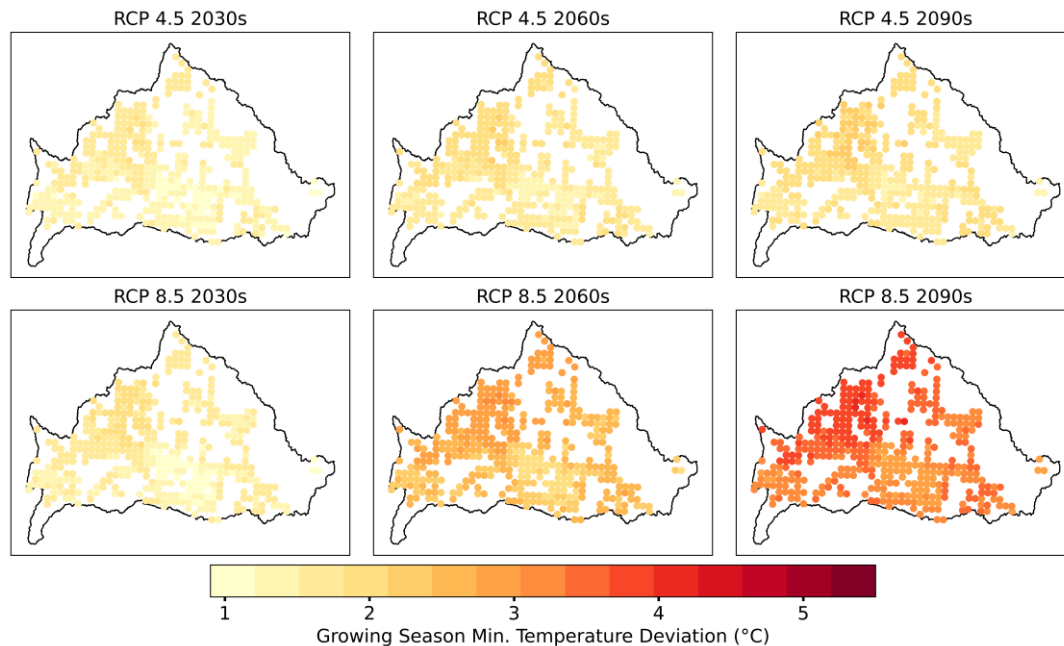


Figure 4.4. Growing season minimum temperature deviation for RCPs 4.5 and 8.5 over three future time periods (2030s, 2060s, and 2090s).

Figure 4.5 shows the Tmax spatial deviations under RCPs 4.5 and 8.5, with values ranging from 0.9 to 1.5 °C under 2030s (both 4.5 and 8.5), 1.2 to 2 °C and 2 to 3.2 °C under 2060s (4.5 and 8.5, respectively), and 2 to 2.5 °C and 3.2 to > 5.0 °C under 2090s (4.5 and 8.5, respectively) time periods (Figure 4.5). The deviations observed for Tmax follow similar patterns found in Tmin, especially under RCP 4.5, but largely deviates under RCP 8.5. this suggests that atmospheric forcings mediating Tmin and Tmax changes under RCP 4.5 might be similar, however, due to higher greenhouse gas emission under RCP 8.5, the separation of these forcings mediation effects became distinct and pronounced in the region. It is important to note that, similar to Tmin under RCP 4.5, the deviations found in Tmax under RCP 4.5 are consistent with the Paris Agreement (United Nations, 2015), which aims for temperature stabilization to well below 2 °C. However, the impact of a 1 °C rise in Tmax has been found to result in maize yield loss reaching up to 2,123 kg ha^{-1} (Onyekwelu & Sharda, 2024b).

While the spatial distribution of Tmax deviation under all RCPs increases from east to west, the gradual increase observed under RCP 4.5 was absent in RCP 8.5, indicating significant atmospheric forcing present under high-emission scenarios of 8.5. Previous studies have shown similar results as observed in this study. For example, Ruosteenoja et al. (2016) found that climate change projections for Finland during the next few decades are fairly similar under all RCP forcing scenarios. However, in the second half of the century, they reported that the evolution of climate in the region is highly dependent on greenhouse gas emissions. They also found that summer warming deviation ranges from 1 to 4 °C; equivalent of growing season Tmax deviation found in this study.

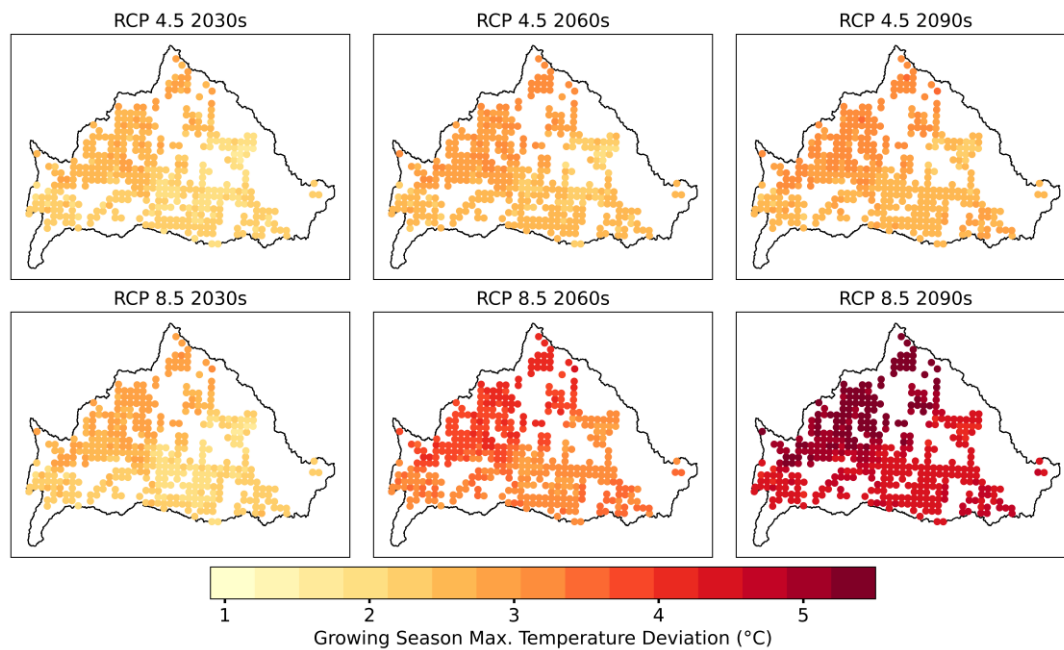


Figure 4.5. Growing season maximum temperature deviation for RCPs 4.5 and 8.5 over three future time periods (2030s, 2060s, and 2090s).

The spatial deviation of growing season rainfall from the historical conditions shows declining values in all RCPs and the three time periods in the future (Figure 4.6). Results revealed that deviation values decreased going into the future under RCP 4.5, with deviation range in the 2090s potentially close to the historical (-60 mm to -15 mm) growing season rainfall than in the

2060s (-75 mm to -20 mm) and 2030s (-100 mm to -30 mm; Figure 4.6). This pattern of rainfall deviation can be attributed to several mechanisms, driven by climate dynamics, atmospheric composition, and regional feedback. For instance, under RCP 4.5 greenhouse gas concentrations continue to rise until mid-century before stabilizing (IPCC, 2023). Based on the atmospheric feedback, the warming atmosphere can hold more water vapor due to the Clausius-Clapeyron relationship, which increases the atmospheric moisture content by approximately 7% per °C of warming (Trenberth, 2011). This could be the reason behind the lesser decline in growing season rainfall found later in the 21st century under RCP 4.5 in this study. Conversely, the pattern of growing season rainfall deviation under RCP 8.5 display further decreasing spatial trend in future time periods (2030s to 2090s; Figure 4.6). Bhatta et al. (2019) reported that under RCP 8.5 during the late 21st century, rainfall is projected to decrease by 4.5%. Since RCP 8.5 represent a high-emission scenario leading to significant global warming, intensified warming under this scenario may disrupt atmospheric circulation systems, leading to drastic decline in rainfall (Trenberth & Asrar, 2014; Trenberth, 2011). It is important to note that rainfall deviation increases from east to west, a spatial trend consistent with the regional rainfall gradient of the Great Plains (Onyekwelu & Sharda, 2024b; Seager et al., 2018).

With temperature and rainfall deviations from the historical reaching up to 5 °C and -140 mm, growing irrigated maize under these climate conditions without adaptation may result in yield failure and reduced irrigation water productivity. Therefore, implementing adaptation strategies that are aimed at improving maize yield and maintaining irrigation water savings under these climate conditions are essential for meeting the expected the grain demand, while also saving water resources in order to ensure gradual improvement in aquifer recovery.

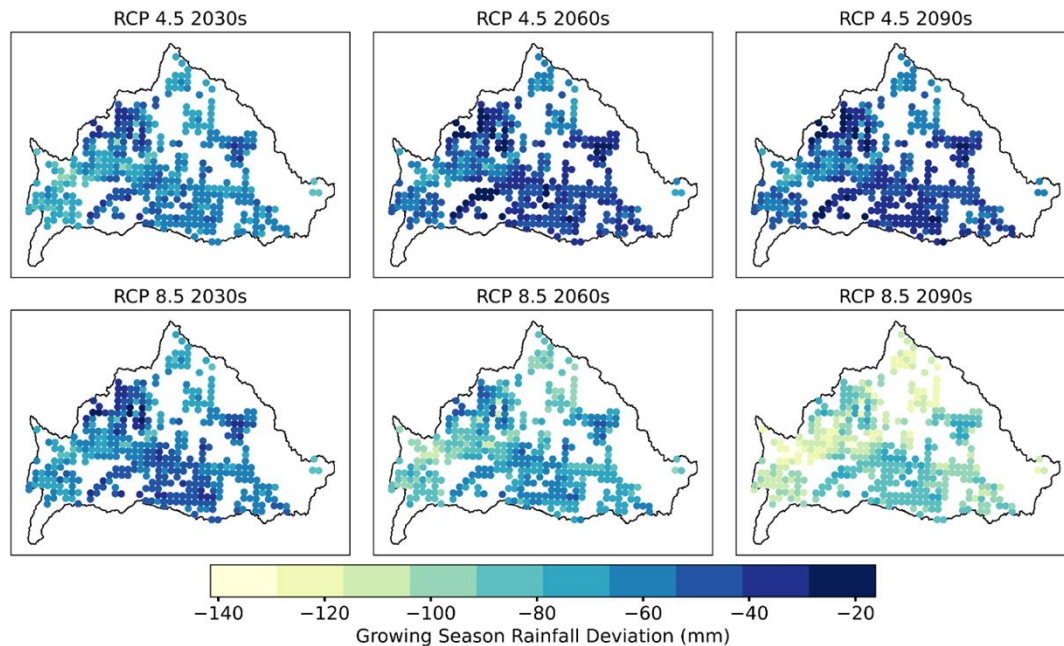


Figure 4.6. Growing season rainfall deviation for RCPs 4.5 and 8.5 over three future time periods (2030s, 2060s, and 2090s).

4.4.2 Yield and Irrigation Sensitivities to Future Climate Conditions and Adaptation Strategies in the early 21st century (2030s)

Figures 4.7 and 4.8 display maize yield sensitivity to historical and future climate conditions, and different adaptation strategies under RCPs 4.5 and 8.5. We observed no spatial pattern in historical (HISTORICAL) yield distribution; however, we found that high yield values dominated the northern parts of the region. This suggest that irrigated yield distribution under historical condition might be controlled by a myriad of factors, including spatial soil textures and climate variables, county-level planting conditions, irrigation, and so on. Previous studies have shown that irrigated yield in the region is primarily controlled by soil type, T_{min}, T_{max}, and SRAD (Onyekwelu et al., 2025).

We found that maize yield in the early 21st century declined (relative to historical yield) by -34% under RCP 4.5 (Figure 4.7, Table 4.3) and -33% under RCP 8.5 (Figure 4.8, Table 4.3).

Yield decline may have occurred primarily due to warming-induced stresses and shortened growing season length (GSL). We observed in this study that GSL shortened by 12 to 18 days under RCP 4.5, and 12 to 20 days under RCP 8.5. Interestingly, our further analysis using linear modeling approach revealed that a one day shortening of GSL may result in about 243 kg ha^{-1} yield loss under RCP 4.5, and 321 kg ha^{-1} under RCP 8.5 (Figure 4.9). These results agree with findings reported in literature. For example, Araya et al. (2017) found that maize yield decline in Western Kansas ranged from 10% to 60% and 5% to 80% (RCPs 4.5 and 8.5, respectively). In addition, they observed that shortened GSL in the range 18-24 days may have triggered yield loss under future climate condition.

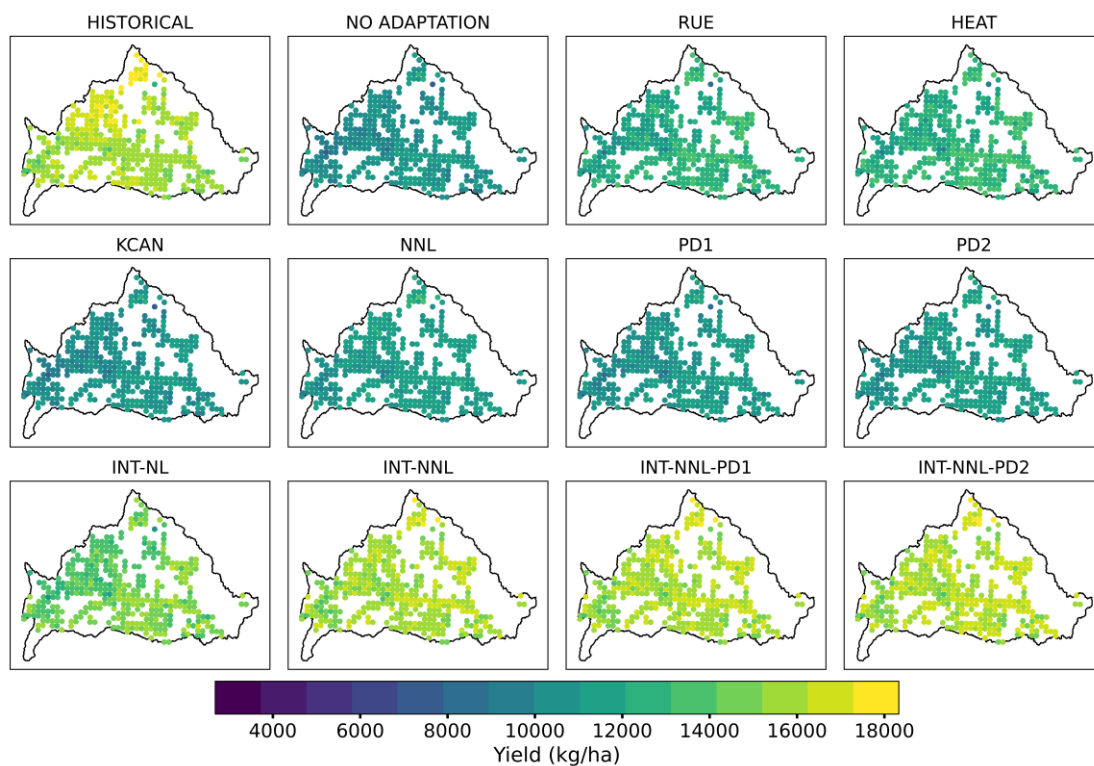


Figure 4.7. Yield sensitivity under RCP 4.5 (2030s). Without adaptation = NO ADAPTATION; Radiation use efficiency = RUE; light extinction coefficient = KCAN; heat tolerance = HEAT; non-limiting nutrient = NNL; planting date 1 = PD1; planting date 2 = PD2; Int 1 = INT-NL; Int 2 = INT-NNL; Int 3 = INT-NNL-PD1; Int 4 = INT-NNL-PD2.

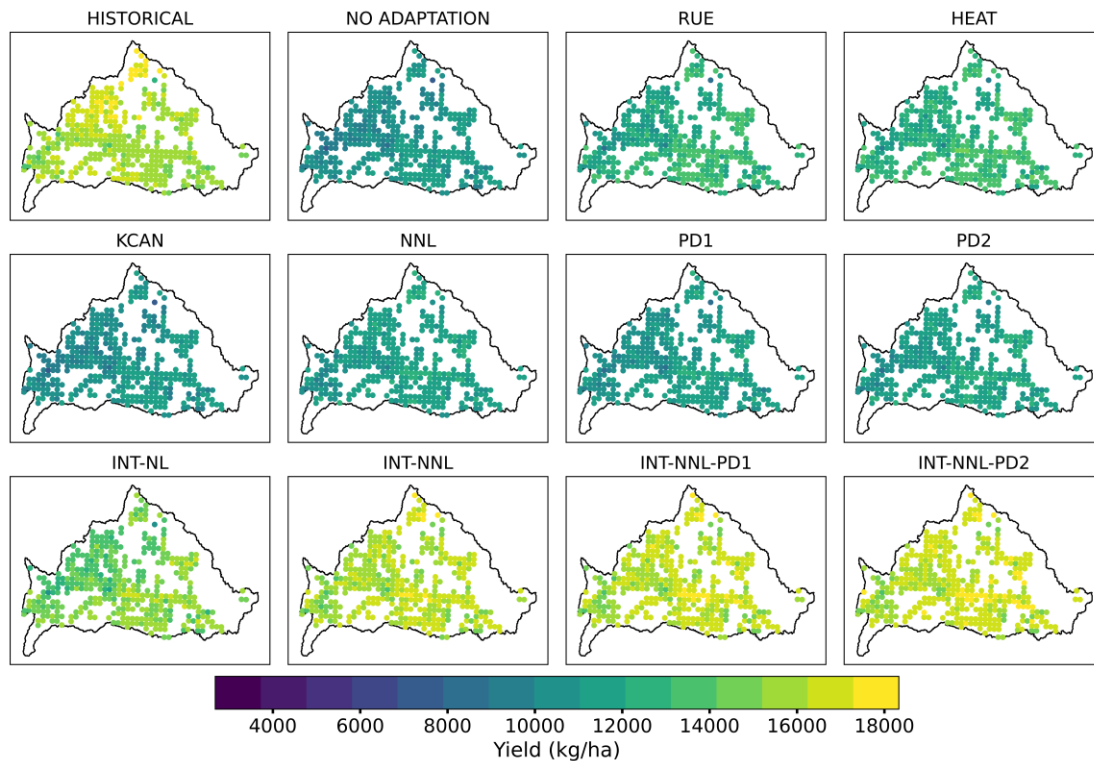


Figure 4.8. Yield sensitivity under RCP 8.5 (2030s). Without adaptation = NO ADAPTATION; Radiation use efficiency = RUE; light extinction coefficient = KCAN; heat tolerance = HEAT; non-limiting nutrient = NNL; planting date 1 = PD1; planting date 2 = PD2; Int 1 = INT-NL; Int 2 = INT-NNL; Int 3 = INT-NNL-PD1; Int 4 = INT-NNL-PD2.

The similar decline responses found between RCPs 4.5 and 8.5 suggest comparable climatic controls in the region under both RCPs. For example, our findings in this study revealed that growing season Tmin and Tmax distributions show similar pattern in the region (Figures 4.4 and 4.5). The 1% marginal gain under RCP 8.5 may be due to CO₂ fertilization effects (Tubiello & Ewert, 2002; Onyekwelu et al., 2025), resulting partly due to higher CO₂ emission in RCP 8.5, although having similar temperature range with RCP 4.5 (Figures 4.4 and 4.5). Relative to the historical yield distribution (Figures 4.7 and 4.8), there are obvious patterns of west to east gradient of yield decline, with lower yield values towards the western side of the region under both RCPs, suggesting potential temperature-mediated impacts. These findings agree with the region's temperature gradient observed previously.

By integrating adaptation strategies, we found significant improvements in yield relative to no adaptation scenario (NO ADAPTATION; under RCPs 4.5 and 8.5), with highest individual improvement reported for heat tolerant ideotype (Table 4.3, Figures 4.7 and 4.8; HEAT) under genotype-specific adaptation, non-limiting nutrient condition (Table 4.3, Figures 4.7 and 4.8; NNL) under agronomic adaptation, and Int 4 (Table 4.3, Figures 4.7 and 4.8; INT-NNL-PD2) under integrated adaptation strategies. While there are significant yield improvements for the individual adaptation under different categories relative to historical condition (Table 4.3), KCAN as an adaptation strategy showed no yield improvement under both RCPs, suggesting possible light extinction saturation at peak KCAN values, which is consistent with previous studies. For example, Stella et al. (2023) found in their in-silico study of wheat response to doubled haploid traits modification under climate change that altered KCAN values had the least effect on yield levels, with no effect under rainfed condition.

Interestingly, we found that all the integrated adaptation strategies (INT-NNL [Int 2], INT-NNL-PD1 [Int 3], and INT-NNL-PD2 [Int 4]), with the exception of Int 1 (INT-NL), resulted in optimal yield improvements, which is either higher than or substantial relative to historical yield distribution (Table 4.3, Figures 4.7 and 4.8). However, a global optimum for the integrated adaptation was found corresponding to the combination of RUE, HEAT, KCAN, NNL, and PD2, regarded as INT-NNL-PD2 (Int 4, Figures 4.7 and 4.8) under both RCPs. This strategy resulted in mean yield gain of 0.6% under RCP 4.5, and 3% significant gain under RCP 8.5, relative to historical yield distribution. The higher yield gain under RCP 8.5 is evidence of CO₂ fertilization benefits in the early 21st century (2030s). Interestingly, we found that yield values under this adaptation increase from west to east, possibly mediated by the two weeks (PD2) early planting window coupled in the adaptation, resulting in expanding the range of optimum temperatures early

on in the growing season; thus, giving more room for proper utilization of nutrients, and for the HEAT and RUE traits to dominate for yield improvement. Studies have shown that early planting and improved nutrient management towards non-limiting condition, are great agronomic adaptations for managing cropping systems (Getachew et al., 2021; Martre et al., 2024). The consistency of this adaptation strategy on yield improvement in the region, especially under RCP 8.5, indicates that the combination could be a successful strategy for developing resilient cultivars and agronomic management for yield improvement.

Table 4.3. Simulated mean changes (%) in yield and irrigation water use in EKS RB under different climate scenarios and adaptation strategies with respect to historical condition.

		Grain yield changes (%)						Irrigation water use changes (%)					
		2030s		2060s		2090s		2030s		2060s		2090s	
Adaptation Strategies	RCP Scenarios	4.5	8.5	4.5	8.5	4.5	8.5	4.5	8.5	4.5	8.5	4.5	8.5
	No Adaptation	-34	-33	-38	-51	-43	-68	-9	-13	-13	-15	-20	-18
Genotype	Ideotype 1 (RUE)	-23	-22	-28	-43	-33	-64	-11	-15	-15	-17	-22	-20
	Ideotype 2 (KCAN)	-34	-33	-39	-51	-42	-69	-8	-11	-12	-13	-19	-16
	Ideotype 3 (HEAT)	-21	-20	-25	-36	-28	-55	-7	-11	-12	-11	-16	-10
Agronomic	PD1	-32	-30	-36	-48	-40	-65	-10	-12	-13	-15	-20	-17
	PD2	-30	-28	-34	-45	-37	-62	-9	-12	-13	-15	-20	-16
	NNL	-29	-29	-34	-46	-38	-64	-9	-13	-13	-13	-19	-14
Integrated	Int 1 (INT-NL)	-9	-8	-13	-26	-17	-48	-8	-12	-12	-12	-16	-10
	Int 2 (INT>NNL)	-0.9	0.6	-5	-17	-9	-39	-7	-11	-11	-10	-15	-6
	Int 3 (INT>NNL-PD1)	-0.2	1.8	-3	-15	-7	-36	-9	-12	-13	-12	-16	-8
	Int 4 (INT>NNL-PD2)	0.6	3	-2	-13	-6	-33	-10	-13	-14	-13	-18	-10

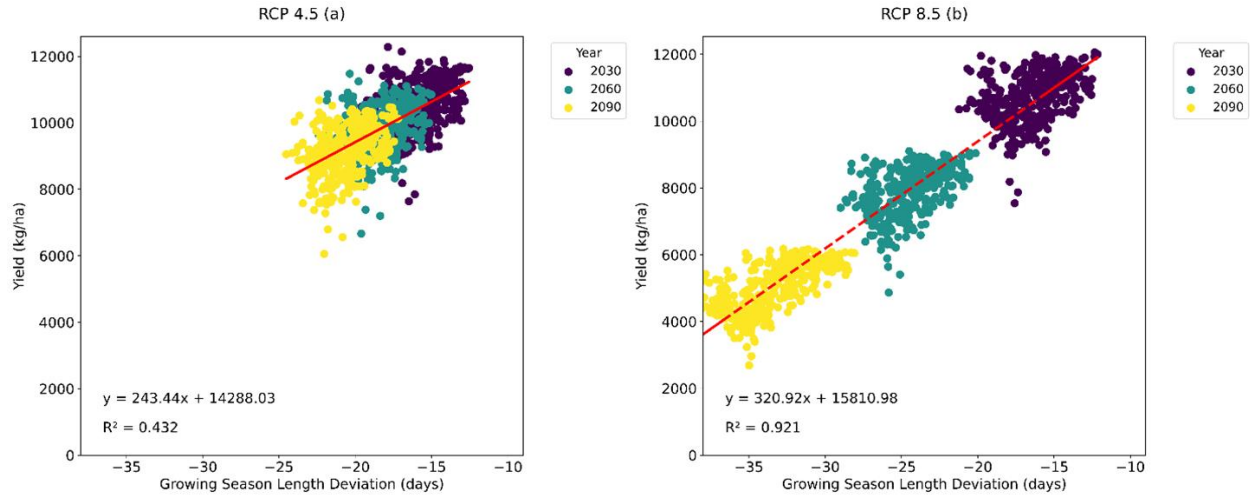


Figure 4.9. Regression analyses between yield (kg/ha) and growing season length deviations (GSL, days) under RCPs 4.5 (a) and 8.5 (b).

Irrigation sensitivity to historical and future climate conditions, and different adaptation strategies are presented in Figures 4.10 and 4.11. Irrigation water use under historical and future climate conditions follow similar spatial gradient observed for rainfall deviation (Figure 4.6) in this study, with more water use in the west than in the eastern part of the region. Similarly, we found comparable irrigation water use patterns under future climate without adaptation and with adaptation strategies (Figures 4.10 and 4.11). Under future climate without adaptation, irrigation water use declined relative to historical condition, with average savings of -9% under RCP 4.5, and -13% under RCP 8.5. Our previous study reported that full irrigation under future climate resulted in increased water use by 32% without improving productivity. The decline in irrigation water use observed under deficit irrigation (75% MAD) likely provides additional evidence that higher CO₂ concentrations, especially under RCP 8.5 in the early 21st century, drives physiological changes in plants, including stomatal closure, which reduces transpiration rates. Stomatal closure occurs as plants optimize their water use efficiency (WUE) in response to increased CO₂ availability for photosynthesis. Reduced transpiration leads to lower water requirements for

maintaining plant growth as documented in previous studies (Kirschbaum & McMillan, 2018; Serna, 2022; Tubiello & Ewert, 2002).

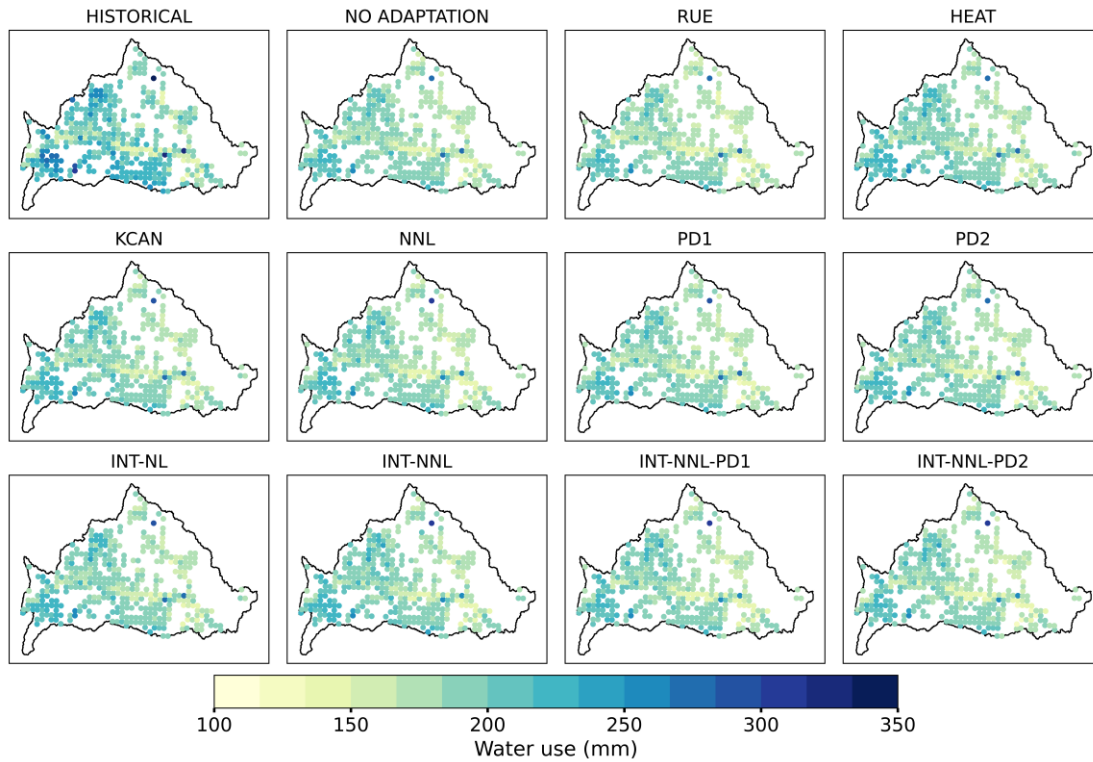


Figure 4.10. Irrigation sensitivity under RCP 4.5 (2030s). Without adaptation = NO ADAPTATION; Radiation use efficiency = RUE; light extinction coefficient = KCAN; heat tolerance = HEAT; non-limiting nutrient = NNL; planting date 1 = PD1; planting date 2 = PD2; Int 1 = INT-NL; Int 2 = INT-NNL; Int 3 = INT-NNL-PD1; Int 4 = INT-NNL-PD2.

Under adaptation strategies, we found that irrigation water use increases from east to west; similar to our observation under historical and future climate (without adaptation) conditions (Figures 4.10 and 4.11). Individual adaptation strategies under future climate (RCPs 4.5 and 8.5) reduced irrigation water use relative to the historical, with highest water savings for RUE under genotype-specific adaptation, PD1 under agronomic adaptation, and Int 4 (INT-NNL-PD2) under integrated adaptation (Table 4.3, Figures 4.10 and 4.11). While there are significant water savings under all adaptation strategies relative to historical water use, we found that adaptation strategies such as KCAN, HEAT, and Int 2 (INT-NNL) increased water use by 2% relative to no adaptation scenario (NO ADAPTATION). With respect to HEAT ideotype, this might be due to cooling effect

of irrigation under high temperature scenario, thereby increasing irrigation water use. Overall, achieving a 0.6 to 3% yield increase and water savings of 10 to 13% relative to historical condition in the early 21st century climate condition, requires integrated adaptation approach corresponding to the combination of RUE, HEAT, KCAN, NNL, and PD2 (INT-NNL-PD2; Int 4).

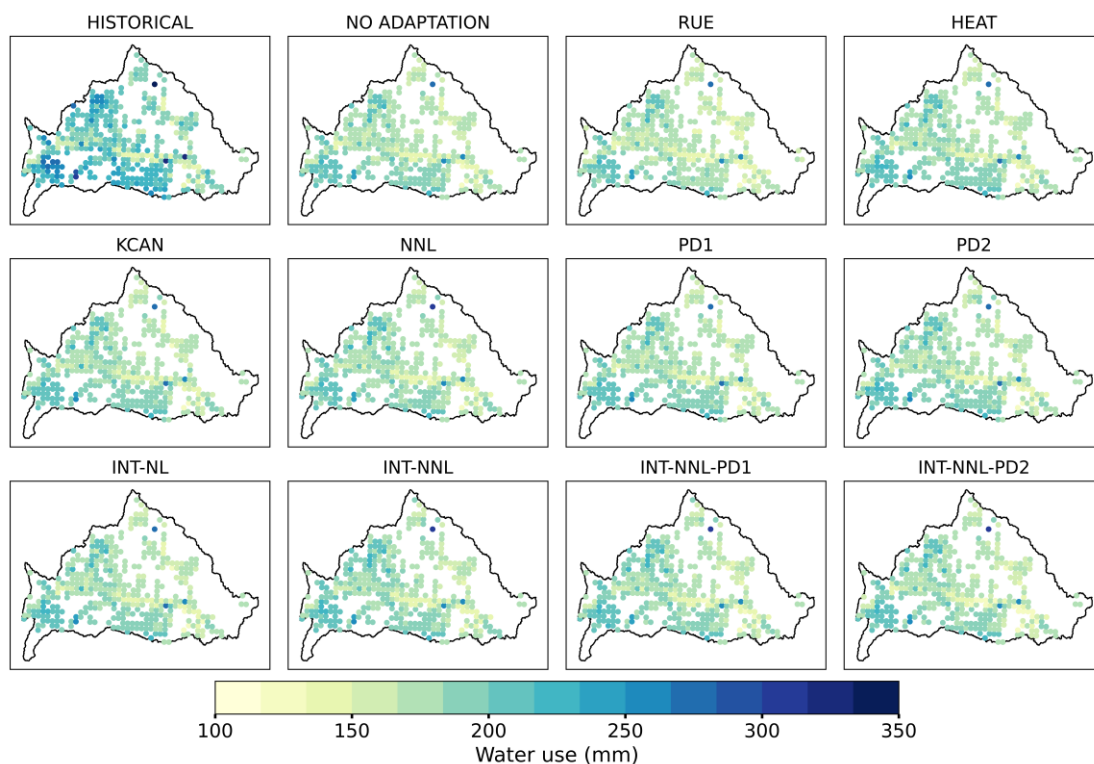


Figure 4.11. Irrigation sensitivity under RCP 8.5 (2030s). Without adaptation = NO ADAPTATION; Radiation use efficiency = RUE; light extinction coefficient = KCAN; heat tolerance = HEAT; non-limiting nutrient = NNL; planting date 1 = PD1; planting date 2 = PD2; Int 1 = INT-NL; Int 2 = INT-NNL; Int 3 = INT-NNL-PD1; Int 4 = INT-NNL-PD2.

4.4.3 Yield and Irrigation Sensitivities to Future Climate Conditions and Adaptation Strategies in the mid-21st century (2060s)

Yield sensitivities to different climate scenarios and adaptation strategies in the mid-21st century are presented in Figures 4.12 and 4.13 below. We found that maize yield under no adaptation in the mid-21st century further declined (relative to historical yield) than previously reported in the early 21st century, with mean values ranging from -38% under RCP 4.5, and -51%

under RCP 8.5 (Figures 4.12 and 4.13, Table 4.3). As previously reported, we inferred that the yield decline in the mid-21st century might be linked to shortened GSL and warming-induced stresses. Under the mid-21st century climate condition, we found that GSL reduced by 15 to 25 days under RCP 4.5, and 17 to 30 days under RCP 8.5, and agrees with previous studies (Araya et al., 2017).

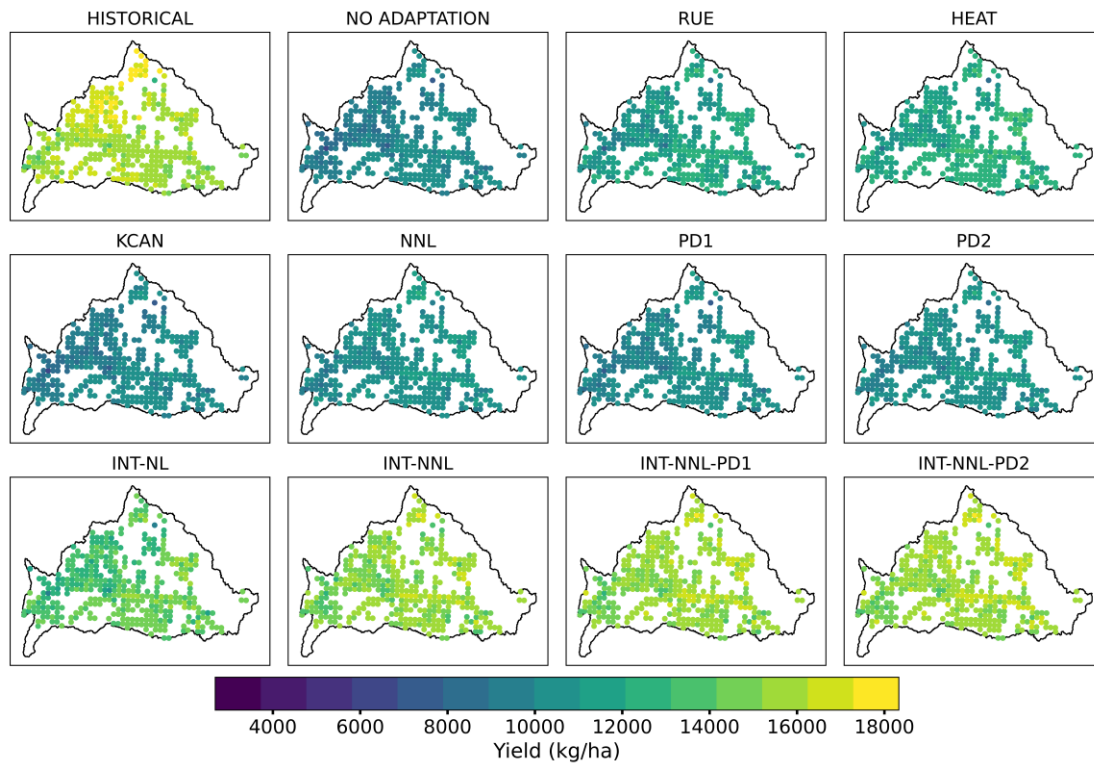


Figure 4.12. Yield sensitivity under RCP 4.5 (2060s). Without adaptation = NO ADAPTATION; Radiation use efficiency = RUE; light extinction coefficient = KCAN; heat tolerance = HEAT; non-limiting nutrient = NNL; planting date 1 = PD1; planting date 2 = PD2; Int 1 = INT-NL; Int 2 = INT-NNL; Int 3 = INT-NNL-PD1; Int 4 = INT-NNL-PD2.

The dissimilar decline responses found between RCPs 4.5 and 8.5 suggest divergent climatic controls under both RCPs in the region. We recall that growing season Tmin and Tmax deviations under both scenarios show disparate patterns in the region (Figures 4.4 and 4.5). In addition, the increasing Tmin and Tmax under RCP 8.5 more than in RCP 4.5, may have resulted in such wide margin. Furthermore, there are obvious patterns of yield decline increasing from east

to west under both RCPs, suggesting temperature-mediated effects, which agrees with the already established temperature gradient in the region.

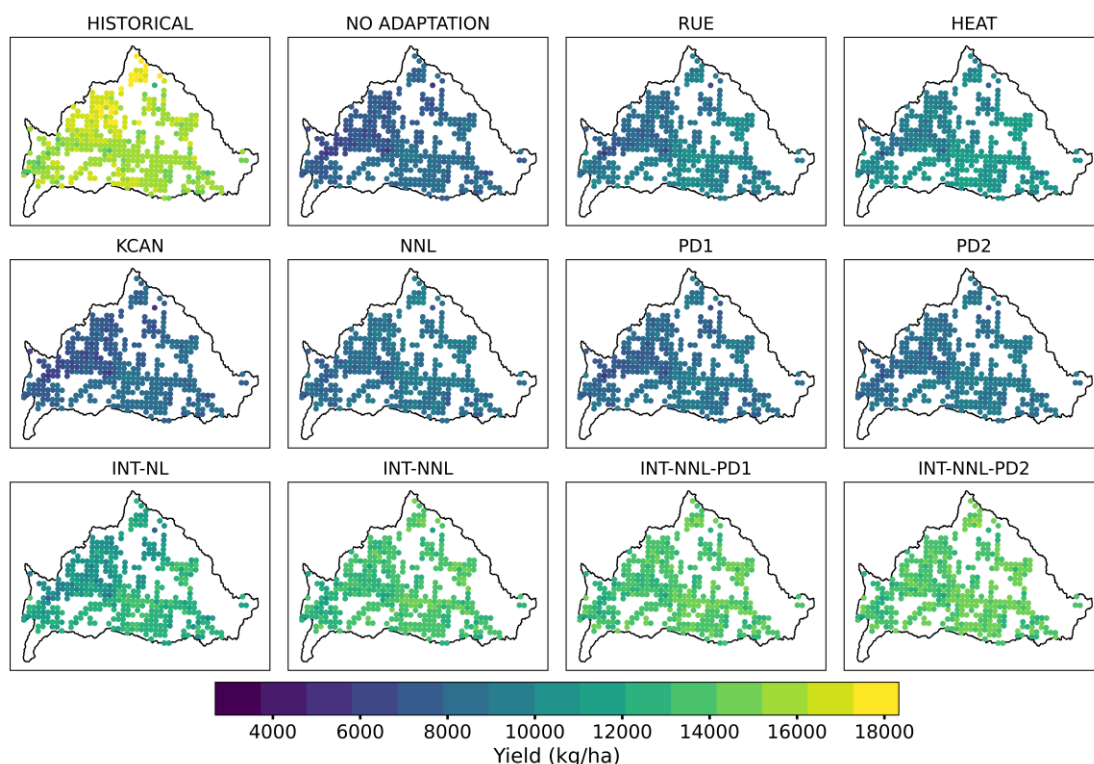


Figure 4.13. Yield sensitivity under RCP 8.5 (2060s). Without adaptation = NO ADAPTATION; Radiation use efficiency = RUE; light extinction coefficient = KCAN; heat tolerance = HEAT; non-limiting nutrient = NNL; planting date 1 = PD1; planting date 2 = PD2; Int 1 = INT-NL; Int 2 = INT-NNL; Int 3 = INT-NNL-PD1; Int 4 = INT-NNL-PD2.

Incorporating different levels of adaptation strategies resulted in significant yield improvement relative to no adaptation scenario (NO ADAPTATION, Figures 4.12 and 4.13). However, KCAN under genotype-specific adaptation resulted in increasing the yield decline by 1% (Table 4.3). This is similar to earlier stated reasons, which might be linked to light extinction saturation at peak KCAN values, especially under high temperatures. Similar results have been reported by Stella et al. (2023). Similar to our observation in the early 21st century simulations, we found that the global optimum adaptation in the mid-century for improving yield matches the combination of RUE, HEAT, KCAN, NNL, and PD2 (INT-NNL-PD2; Int 4); however, there were substantial yield improvements, especially under RCP 4.5, with a marginal mean deviation of -2%

under RCP 4.5, and -13% under RCP 8.5 (Table 4.3). Interestingly, under RCP 4.5, we found significant yield improvement towards the eastern portion of the region, suggesting possible effect of early planting (PD2) coupled in the adaptation (Figure 4.12). The climate mitigation effect of this adaptation strategy was gradually masked out under RCP 8.5 in the region (Figure 4.13), indicating high temperature impacts and less interconvertibility of CO₂ fertilization benefits.

Irrigation sensitivities to future climate conditions and different adaptation strategies are presented in Figures 4.14 and 4.15 below. Similar to our findings in the early 21st century, we found that irrigation water use savings increase from west to east both under future climate without and with adaptation strategies. In general, significant water savings under no adaptation was observed relative to historical condition, with an average value of -13% under RCP 4.5, and -15% under RCP 8.5. The higher water savings under RCP 8.5 might have been due to previously documented reasons, including stomatal closure, which reduces transpiration rates, especially under high CO₂ emission scenario (Kirschbaum & McMillan, 2018; Serna, 2022; Tubiello & Ewert, 2002). It is important to note that water savings increased through time, with higher savings observed in the mid-21st century than in the early 21st century. We found that individual adaptation strategies showed further savings in irrigation water use compared to historical levels. The greatest water savings were observed for strategies focused on RUE under genotype-specific adaptation, planting date adjustments (PD1 and PD2) under agronomic adaptation, and integrated approach combining multiple strategies (INT-NNL-PD2; Int 4), see Table 4.3. Although all adaptation strategies resulted in significant water savings relative to historical use, some strategies, such as KCAN, HEAT, Int 1 (INT-NL), Int 2 (INT-NNL), and Int 3 (INT-NNL-PD1) slightly increased water use by 1 to 2% compared to no adaptation scenario under both RCPs (Table 4.3). This might be linked to increasing temperature in the mid-21st century, in combination with light extinction

saturation due to KCAN, and shifts in planting dates to further expand the optimum growing season length. In summary, achieving yield improvement in the mid-21st century climate with a marginal deviation of -2% under RCP 4.5, and significant deviation of -13% under RCP 8.5, may result in significant water savings of -13 to -14% relative to historical conditions. This will require an integrated adaptation approach corresponding to the combination of RUE, HEAT, KCAN, NNL, and PD2 (INT-NNL-PD2; Int 4).

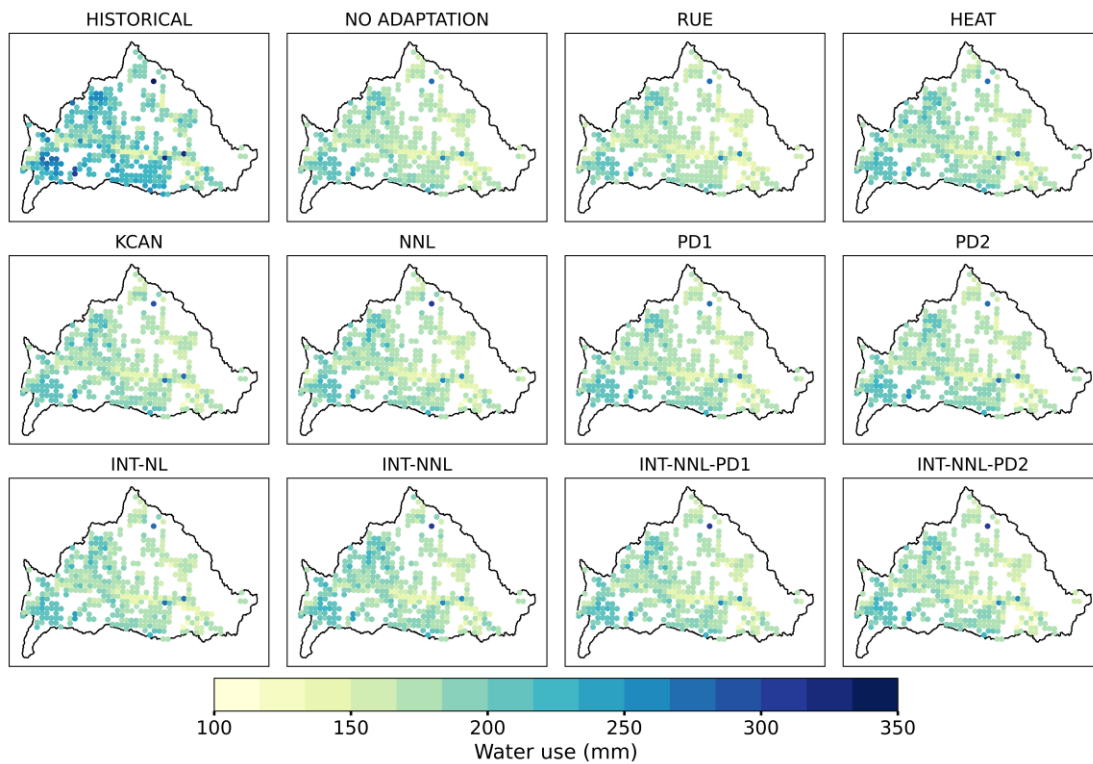


Figure 4.14. Irrigation sensitivity under RCP 4.5 (2060s). Without adaptation = NO ADAPTATION; Radiation use efficiency = RUE; light extinction coefficient = KCAN; heat tolerance = HEAT; non-limiting nutrient = NNL; planting date 1 = PD1; planting date 2 = PD2; Int 1 = INT-NL; Int 2 = INT-NNL; Int 3 = INT-NNL-PD1; Int 4 = INT-NNL-PD2.

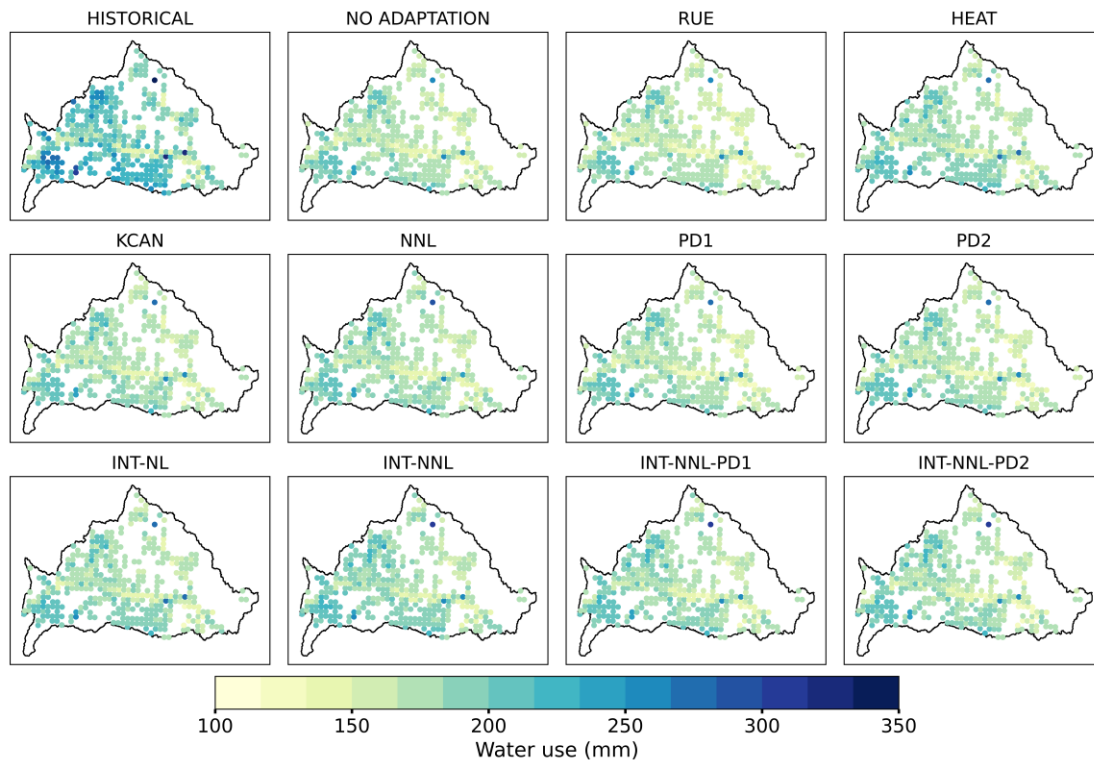


Figure 4.15. Irrigation sensitivity under RCP 8.5 (2060s). Without adaptation = NO ADAPTATION; Radiation use efficiency = RUE; light extinction coefficient = KCAN; heat tolerance = HEAT; non-limiting nutrient = NNL; planting date 1 = PD1; planting date 2 = PD2; Int 1 = INT-NL; Int 2 = INT-NNL; Int 3 = INT-NNL-PD1; Int 4 = INT-NNL-PD2.

4.4.4 Yield and Irrigation Sensitivities to Future Climate Conditions and Adaptation Strategies in the Late 21st century (2090s)

Future yield distribution under adaptation and no adaptation are shown in the Figures 4.16 and 4.17 for RCPs 4.5 and 8.5, respectively. Yield decline under no adaptation shows strong consistency through time, with further decline observed in the late century. We found decline values ranging from -43% under RCP 4.5 to -68% under RCP 8.5. As expected, GSL deviation was higher under RCP 8.5 than in RCP 4.5, with values ranging from 32 to 40 days, and 20 to 28 days, respectively. The noticeable decline increasing from east from west, suggest the strong mediation effects of temperature changes, especially under RCP 8.5 (Figure 4.17).

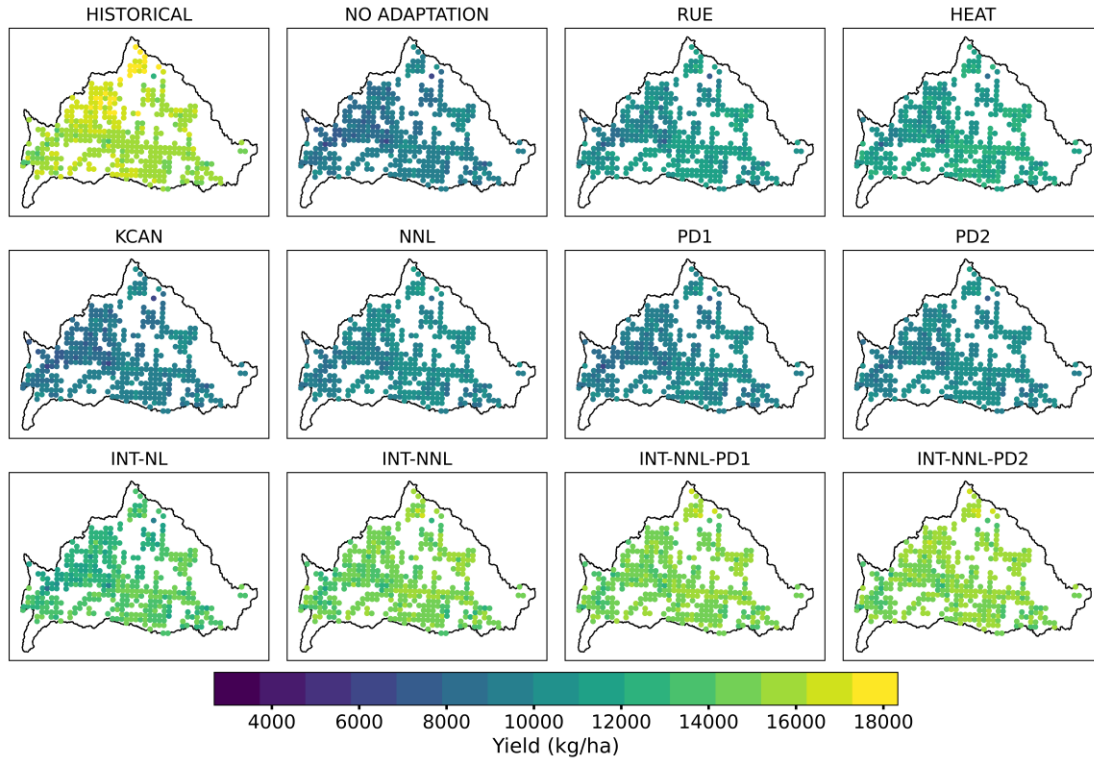


Figure 4.16. Yield sensitivity under RCP 4.5 (2090s). Without adaptation = NO ADAPTATION; Radiation use efficiency = RUE; light extinction coefficient = KCAN; heat tolerance = HEAT; non-limiting nutrient = NNL; planting date 1 = PD1; planting date 2 = PD2; Int 1 = INT-NL; Int 2 = INT-NNL; Int 3 = INT-NNL-PD1; Int 4 = INT-NNL-PD2.

While adaptation may offer solutions to reduce drastic yield decline and shock caused by future climate conditions in the late 21st century, we found that under the present condition being tested, individual adaptation strategies targeted towards increasing canopy photosynthesis (RUE), improving light extinction (KCAN), and shifting planting dates (PD1 and PD2) may no longer be beneficial for yield improvement, especially under RCP 8.5 (Figures 4.16 and 4.17, Table 4.3). Interestingly, we observed that the HEAT ideotype (HEAT) significantly outperformed all other genotype-specific and agronomic adaptations, with deviations from historical condition ranging from -28% (RCP 4.5) to -55% (RCP 8.5). However, integrated adaptation strategies, especially the combination of RUE, HEAT, KCAN, NNL, and PD2 (INT-NNL-PD2; Int 4) may be useful for significant yield improvement relative to no adaptation scenario, with a marginal deviation of -6% relative to historical condition (Table 4.3). This is only true for RCP 4.5 scenario, in which changes

in atmospheric conditions are more gradual than under RCP 8.5. Under RCP 8.5, we found yield deviation of -33% relative to historical condition, indicating that a suitable adaptation strategy under RCP 8.5 scenario might be one which is more adaptable to high temperatures. It is important to note that while we tested the combination of RUE, HEAT, KCAN, NNL, and PD2 to be the best strategy, we infer that given the present results and evidence, a combination of HEAT ideotype, NNL, and PD2 will make a great strategy for improving yield, especially under RCP 8.5 scenario. Therefore, advance heat-tolerant cultivars beyond what was tested in this study, coupled with optimum nutrient allocation under non-limiting condition and two weeks early planting may adapt well to RCP 8.5 forcings in the late 21st century.

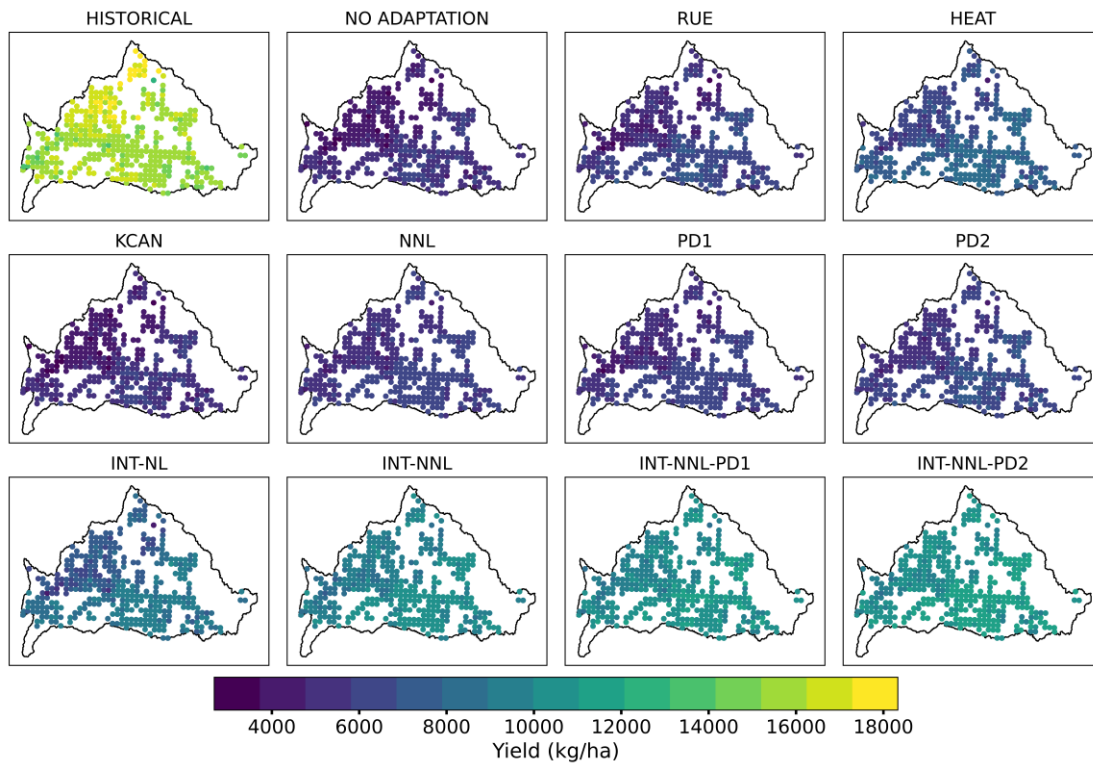


Figure 4.17. Yield sensitivity under RCP 8.5 (2090s). Without adaptation = NO ADAPTATION; Radiation use efficiency = RUE; light extinction coefficient = KCAN; heat tolerance = HEAT; non-limiting nutrient = NNL; planting date 1 = PD1; planting date 2 = PD2; Int 1 = INT-NL; Int 2 = INT-NNL; Int 3 = INT-NNL-PD1; Int 4 = INT-NNL-PD2.

While drastic yield decline was observed under the late century climate condition without adaptation, we found further increment in water savings under both RCP scenarios, with water savings increasing from west to east (Figure 4.18 and 4.19). Under no adaptation, average savings relative to historical condition range from -20% and -18% (RCPs 4.5 and 8.5, respectively). The higher water savings under RCP 4.5 more than in RCP 8.5 indicates the benefits of gradual warming conditions and relatively high CO₂ without quickly hitting the saturation level of maize CO₂ assimilation for photosynthesis. Studies have shown that CO₂ saturation of maize ranges from 400 to 500 ppm (Leakey et al., 2006). Under elevated and ambient CO₂ using Free-Air Concentration Enrichment technology (FACE), Leakey et al. (2006) found that elevated CO₂ beyond 550 ppm does affect photosynthesis, productivity, and yield of maize. In addition, they observed that stomatal conductance was lower by -34%, with high soil moisture reaching up to 31%; hence, reduced crop water use. This implies that the increasing CO₂ levels under RCP 8.5 may not deliver the full benefits to the Great Plains maize production expected in the late 21st century. Individual adaptation strategies showed further water savings compared to historical levels. Similar to previous results in the early and mid-21st century time periods, we found the highest water savings with strategies focused on RUE under genotype-specific adaptation, planting date adjustments (PD1 and PD2) under agronomic adaptation, and integrated approach combining multiple strategies (INT-NNL-PD2; Int 4), see Table 4.3. Adaptation strategies, such as HEAT, Int 1 (INT-NL), Int 2 (INT-NNL), and Int 3 (INT-NNL-PD1) further increased water use by 5 to 12% (RCPs 4.5 and 8.5, respectively) compared to no adaptation scenario (Table 4.3).

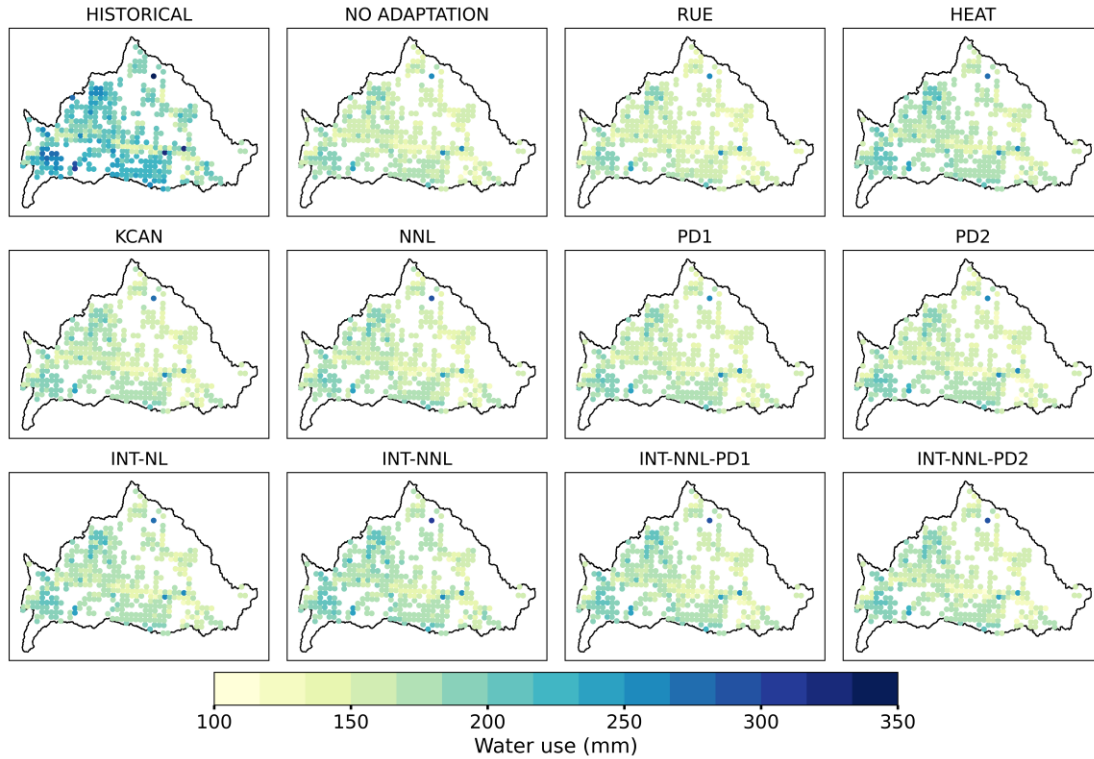


Figure 4.18. Irrigation sensitivity under RCP 4.5 (2090s). Without adaptation = NO ADAPTATION; Radiation use efficiency = RUE; light extinction coefficient = KCAN; heat tolerance = HEAT; non-limiting nutrient = NNL; planting date 1 = PD1; planting date 2 = PD2; Int 1 = INT-NL; Int 2 = INT-NNL; Int 3 = INT-NNL-PD1; Int 4 = INT-NNL-PD2.

This indicates that adaptation strategies linked to heat tolerance in the late century, might increase water use beyond the limits found under no adaptation scenario. In conclusion, achieving yield improvement in the late 21st century climate may require re-examining the current adaptation implementation for potential improvement, especially under RCP 8.5. However, we found under the current conditions simulated marginal yield deviation of -6% from the historical condition under RCP 4.5, resulting in water savings of -18%. This will require an integrated adaptation approach corresponding to the combination of RUE, HEAT, KCAN, NNL, and PD2 (INT-NNL-PD2; Int 4).

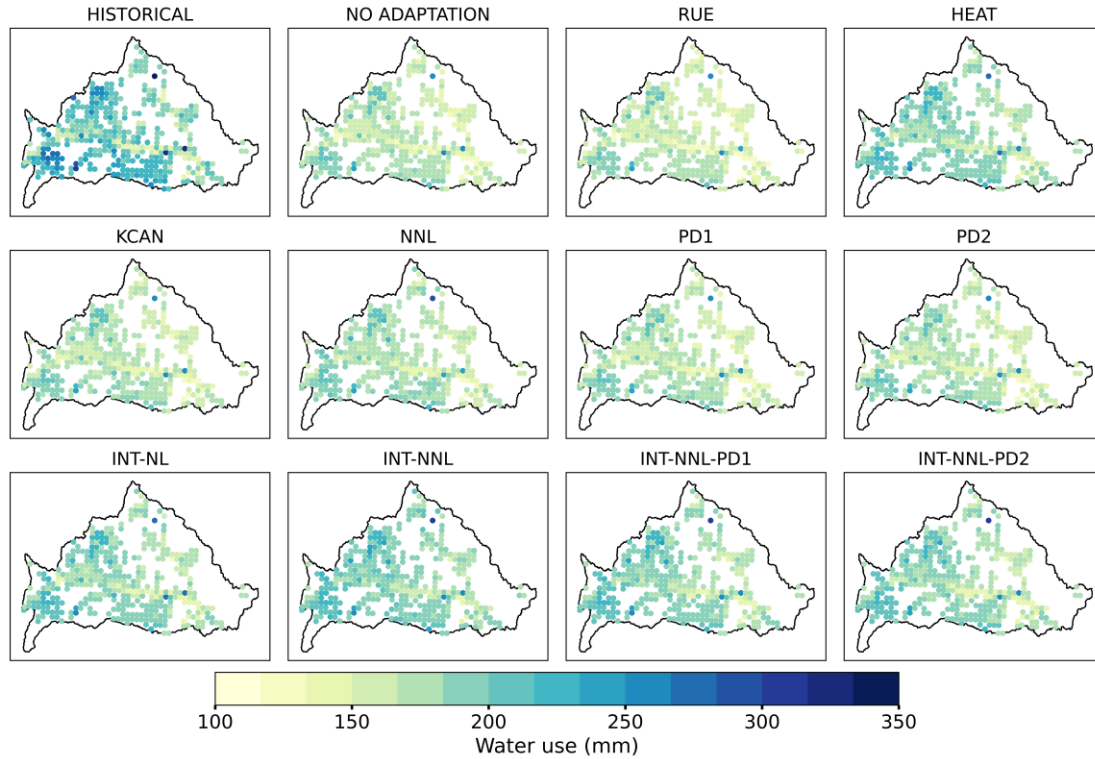


Figure 4.19. Irrigation sensitivity under RCP 8.5 (2090s). Without adaptation = NO ADAPTATION; Radiation use efficiency = RUE; light extinction coefficient = KCAN; heat tolerance = HEAT; non-limiting nutrient = NNL; planting date 1 = PD1; planting date 2 = PD2; Int 1 = INT-NL; Int 2 = INT-NNL; Int 3 = INT-NNL-PD1; Int 4 = INT-NNL-PD2.

4.4.5 Limitations of the Study

This study assessed the spatiotemporal pattern of irrigated maize productivity under different future climate scenarios and adaptation strategies in the Great Plains. Given that the present study is an extension of our previous study (Onyekwelu et al., 2025) in the region, it shared similar assumptions which were substantially addressed in the previous study. However, an important assumption which was not included, and was not part of the previous study was selection of early planting dates and adjustment. We selected early planting date adjustments as one of the adaptation strategies under agronomic management scenario. The adjustments were purely based on literature and plausible benefits of early planting to ameliorate yield loss due to climate change (Getachew et al., 2021). However, due to the scale and scope of this study, the potential impacts

of spring freeze due to low soil temperature below maize base temperature of 10 °C was not considered. Typical planting dates in the region ranges from April 1 to May 15. A baseline planting date selection of April 1 for example, and adjusted to occur one or two weeks earlier, will see maize planted around March 25th or 18th, respectively.

While this is plausible to escape potential heat stress during reproductive stages (Waqas et al., 2021), the chilling stress due to potential low temperature may have impact on the plant cell or tissue (Waqas et al., 2021). However, a three-year study in the region showed that yield values remained either stable or increased when planting was done in late March compared to planting in mid-to-late April and early-to-mid May (Adee et al., 2024). In addition, we selected early planting as an adaptation because of the probable benefits of moderate climate-induced warming, potentially expanding the range of optimum temperatures early on in the growing season. Nonetheless, there are biological solutions for seed treatment, especially for risk-averse farmers to protect seeds against uncertain soil conditions during the critical early growth period, pests, and disease (Corteva Agriscience, personal communication). In addition, incorporating early vigor traits in maize hybrids could lead to significant agronomic and yield benefits (Capo et al., 2023; Dadrasi et al., 2024).

4.5 Conclusion

This study offers a first-time comprehensive solution through a fine-scale spatial analysis of the impacts of future climate scenarios and adaptation strategies on irrigated maize production in the Great Plains. Under future climate without adaptation, maize yield declined by 34% and 43% (2030s and 2090s, respectively) under RCP 4.5, and between 33% and 68% (2030s and 2090s, respectively) under RCP 8.5. The decline in yield under future climate conditions were primarily due to shortened growing season length and warming-induced stresses due to high growing season temperatures. Despite the yield declines, we found water use savings ranging from 9% to 20% (early and late century time periods, respectively) under RCP 4.5, and 13% to 18% (early and late century time periods, respectively) under RCP 8.5. By integrating agronomic and genotype-specific adaptations, our findings underscore the critical role of tailored adaptation strategies in mitigating the adverse effects of climate change on irrigated maize production system in the Great Plains. We found that individual adaptation categories, such as the genotype-specific or the agronomic modifications, demonstrated significant maize yield improvements when compared to a no adaptation scenario. However, the incorporation of integrated adaptation strategies resulted in significantly greater benefits, indicating that an all-inclusive approach is more effective in addressing the complex challenges posed by climate change in the Great Plains. These integrated strategies not only enhanced crop productivity but also contributed to substantial water savings—a critical factor for sustaining the region's water resources and ensuring long-term agricultural viability. In quantitative terms, we found that the integrated adaptation strategy linked to improved RUE, HEAT, KCAN, NNL, and PD2 (INT-NNL-PD2; Int 4) resulted in the early 21st century yield gain of 0.6 to 3% (RCPs 4.5 and 8.5, respectively), with water savings of -10 to -13% (RCPs 4.5 and 8.5, respectively), relative to historical condition. However, going forward into the 21st

century, we observed marginal yield deviation and further increase in water savings; more than observed under no adaptation scenarios, suggesting the need to re-examine and re-design these adaptation strategies for the co-benefits of further yield gain and improvement, while leveraging the benefits of water savings under future climate conditions.

Our study further highlights the dual importance of productivity and sustainability in the Great Plains. While yield improvements are vital to meet food security needs, the water savings achieved through adaptation strategies underscore the necessity of water resource conservation to support aquifer recovery. This balance between adaptation and resource management is essential for promoting resilience in agricultural systems under future climate uncertainties. In addition, the insights drawn from this study have important implications for farmers, breeders, and policymakers. For farmers, our findings provide actionable guidance on selecting and implementing effective adaptation strategies tailored to specific environmental and agronomic management, given our spatial model framework. For breeders, the study underscores the value of developing climate-resilient genotypes that complement broader adaptation frameworks. Policymakers can use these insights to develop targeted interventions and support systems that promote sustainable agricultural practices in the face of climate risks. Our findings emphasize the transformative potential of integrated adaptation strategies in mitigating the impacts of climate change on irrigated maize production in the Great Plains. This work serves as a crucial step toward building resilient agricultural systems capable of thriving under future climate conditions, offering a useful analog to other regions in the Great Plains and around the globe facing similar threats to food security and water resources.

4.6 Acknowledgements

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4.7 References

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Chapter 5 - A Bayesian regression approach for estimating photosynthetically active radiation using satellite data: implications for soybean yield prediction using the CROPGRO model

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5.1 Abstract

Accurate estimates of photosynthetically active radiation (PAR) are important in crop simulation models for predicting the productivity of a crop. However, the lack of data from radiometric stations has resulted in the use of PAR estimated as half of solar radiation, negating the recognition of uncertainty in the data generation process, and consequently impairing inference. In this study, the Bayesian regression framework was used with the Clouds and the Earth's Radiation Energy System (CERES) PAR datasets, to estimate PAR parameters for stochastic prediction of daily PAR values. By using the linear modeling approach as a proxy for model selection, twelve regression models of different combinations of climate variables were trained for a soybean-growing county in eastern Kansas. Daily PAR values and climate inputs from 1986 to 2000 were used for training the models, and then the validation was done with daily inputs from 2001 to 2005. After this, the best-performing model was selected for Bayesian regression framework implementation. Results revealed that the regression model consisting of clearness index (Kt), solar radiation (SRAD), and maximum temperature (Tmax) as predictors was

the best model, with the highest R^2 and lowest root mean squared error values. Sampling 4000 samples of PAR predictive parameters from the posterior distributions using the Gibbs sampler, daily PAR estimates were derived using the mean quantile composition sampling of four quantiles (0.25, 0.5, 0.75, and > 0.75) from 2006 to 2022 for incorporation into the CROPGRO Soybean model. Results showed that PAR estimates from the Bayesian regression framework outperformed the PAR estimates from the best linear model and the default PAR conversion in the CROPGRO model. In addition, soybean yield estimates using the mean quantile composition samples of PAR from the Bayesian framework as inputs, captured the year-to-year variability in yield better than soybean yield estimates obtained using the default PAR values and the best linear model developed in this study. Hence, the results of this study strongly support the use of input combinations consisting of SRAD, Kt, and Tmax under Bayesian regression framework for robust estimation of PAR inputs to crop models for long-term climate research.

Keywords: Bayesian regression, linear model, photosynthetically active radiation, DSSAT, CROPGRO-Soybean model, Crop model

5.2 Introduction

Photosynthetically active radiation (PAR) is the component of shortwave irradiance in the visible light spectrum (400-700 nm) which is the driver of plant growth and biomass production. Most terrestrial ecological and dynamic crop models require daily PAR values for dynamic process simulation of leaf photosynthesis and plant biomass (Aguiar et al., 2012), but only instantaneous PAR values are directly retrieved from remotely sensed data (Zheng & Liang, 2011). In addition, it is not always easy to have PAR measurements in an arbitrary location due to difficulties in procuring quantum sensors (Ferrera-Cobos et al., 2020b). This is particularly true for some developing countries where meteorological monitoring stations are inadequate (Emeka et al., 2021). Even for developed countries, Su et al. (2007) reported that the United States Surface Radiation Budget Network (SURFRAD) which was established in 1993 to support continuous and long-term measurements of PAR, has currently only seven (7) stations operating in climatologically diverse regions. In addition, there are no standards for calibrating PAR sensors; thus, creating shortfalls of PAR datasets in locations where they are needed (Ferrera-Cobos et al., 2020b). With every sensor having different limits of uncertainty, concerns also exist about the accuracy of uncalibrated PAR sensors (Ferrera-Cobos et al., 2020b; Mizoguchi et al., 2010; Su et al., 2007). Therefore, with increasing demands for accurate PAR measurements to drive dynamic crop models and future climate change research, there is a need for location-specific estimates of PAR to make up for shortfalls of PAR data unavailability.

To fill these gaps, empirical models have been used by researchers across the globe to obtain PAR estimates. Most of the empirical methods rely on the deterministic linear regression type models, and in some cases, machine learning models for modeling PAR using regularly measured meteorological variables. For example, Aguiar et al. (2012) used clearness index (Kt),

vapor pressure, and solar radiation (SRAD) to develop daily and hourly models for ecosystem-specific PAR estimates. In Spain, Alados et al. (1996) modeled PAR using solar elevation angle, dew point temperature, K_t , and skylight brightness variables as inputs. Ferrera-Cobos et al. (2020b) modeled PAR in oceanic and Mediterranean climates using eleven multilinear regression models and eleven Artificial Neural Network models by incorporating different combinations of climate variables such as temperature, and relative humidity, and global extraterrestrial irradiance. In another study published by García-Rodríguez et al. (2021), PAR was modeled in Burgos, Spain following different approaches: multilinear regression and Artificial Neural Networks. A similar study in Japan modeled PAR in five (5) sites using already existing linear models (Mizoguchi et al., 2014). Yu et al. (2015) developed ten regression models for estimating PAR at 7 locations of the US SURFRAD stations using K_t , dew point temperature, cosine of solar zenith angle, and skylight brightness.

While the choice of modeling approach for estimating PAR has remained the use of traditional linear regression and machine learning models in some cases, studies using Bayesian methods and analyses are still lacking. Since automatic linear regression and machine learning models are deterministic in nature, PAR models fitted using the automatic linear regression and machine learning are incapable of recognizing uncertainty inherent in random variables (Zheng & Liang, 2011). Bayesian applications to modeling studies implement the concept of uncertainty in the data generation process, which is negated by deterministic linear regression approaches. Consequently, Bayesian approach tends to improve inference confidence and prediction by stochastic process, bearing in mind the noisy nature of the real world (Poudel et al., 2022).

Crop models are vital tools for simulating genotype, management, and environmental interactions on crop productivity (Challinor et al., 2013). However, the input requirements of most

crop models are intensive, and in some cases, a predefined data conversion routine is used to achieve a set of desired inputs. For example, it is well-reported in the literature that PAR is half of SRAD, and most crop models use this conversion to arrive at PAR input for simulating leaf photosynthesis and aboveground biomass. While this relationship is straightforward and intuitive, many authors have argued that PAR depends on other meteorological variables than just SRAD alone (Aguiar et al., 2012; Alados et al., 1996; Ferrera-Cobos et al., 2020b; Mazorra Aguiar et al., 2019; Mizoguchi et al., 2014). According to Ferrera-Cobos et al. (2020b), all PAR models face the difficulty of dependence on the local atmospheric conditions, making it impossible to have a good fit extrapolating a model developed under some atmospheric conditions to a place with a different atmospheric condition. More so, the use of half of SRAD as PAR conversion negates the recognition of uncertainty in the input generation process; thus, a stochastic implementation of PAR modeling may be optimum for modeling a random varying cropping system.

Therefore, the main goal of this study was to implement multilinear regression model for estimating PAR within a Bayesian framework to make stochastic inferences on model-generated parameters and ultimately compare results with traditional linear modeling approach. The linear modeling approach was used as a proxy for model selection towards Bayesian modeling. The best resultant linear model was used to implement the Bayesian framework to estimate PAR inputs for use in the DSSAT-CROPGRO-Soybean model for estimating county-level soybean yield in the Eastern Kansas River Basin (EKRSB) of the US Great Plains. Yield comparison was established for different PAR inputs relative to observed USDA NASS (National Agricultural Statistical Services) yield as follows: 1) using the default PAR generating routine (half of solar radiation) in the CROPGRO-Soybean model, and 2) using the mean quantile PAR samples from the posterior

distribution of the Bayesian framework and PAR values from the best linear regression model implemented in this study.

5.3 Materials and Methods

5.3.1 Study Area and Data Acquisition

The present study was carried out in Shawnee County (with longitude 95.76 W, and latitude 39.04 N, Figure 5.1), located in the Eastern Kansas River Basin (EKSRB) of the US Great Plains. The EKSRB, which covers an area of approximately 14,700 km² is defined as the watershed of the Kansas River, with its beginning at the confluence of Smoky Hill and Republican rivers and its terminus at the confluence of the Missouri River in Kansas City (Sinnathamby et al., 2018). Crop production systems in Shawnee County and the rest of the basin are mostly rainfed, which offers a great opportunity for groundwater conservation in the face of changing climate. However, irrigation still plays a major role in the region in supplementing crop water demands unmet by effective rainfall, especially for water-thirsty crops like maize (corn) and soybeans.

Typically, in the US Great Plains, there are few or no decentralized stations monitoring PAR variables, with only about seven Surface Radiation Budget Network (SURFRAD) stations present in the country; hence, making in situ PAR incorporation into crop models and other independent eco-physiological models very challenging. Therefore, measurements of PAR under all sky conditions, which were treated as observed records in this study were obtained from the Clouds and the Earth's Radiation Energy System (CERES); hosted by National Aeronautics and Space Administration (NASA) Langley Research Center (LaRC) Prediction of Worldwide Energy Resource (POWER) Project, funded through the NASA Earth Science/Applied Science Program. PAR products from CERES have been validated with LI-COR PAR measurements at seven

SURFRAD sites in the US, with mean CERES PAR and mean LI-COR measurements of 256 Wm^{-2} and 245 Wm^{-2} , respectively, and a regression slope of 1.03 (Su et al., 2007). Su et al. (2007) reported that given the substantial uncertainty quoted for LI-COR PAR sensors used in the SURFRAD stations, the errors between CERES PAR and the LI-COR PAR measurements are within each instrument's uncertainty; indicating that CERES PAR products can alternatively be used as observed inputs in net primary production models (Su et al., 2007). PAR datasets and other meteorological variables (minimum, maximum, and dew point temperatures, clearness index, relative humidity, solar radiation) were collected at daily time step from January 1986 to December 2005. These datasets are downloadable at NASA POWER website (<https://power.larc.nasa.gov/data-access-viewer/>) and have been used by several studies around world for parameterization of ecophysiology models and long-term climate research (Emeka et al., 2021; Jha et al., 2021; Ndulue et al., 2019; Singh et al., 2014; Nwokolo et al., 2022; Junior et al. 2022; Onyekwelu et al., 2023; Onyekwelu & Sharda 2023a, 2023b). Downloaded meteorological variables mentioned above were screened for continuity, inconsistency, and error following the recommendations of Emeka et al. (2021).

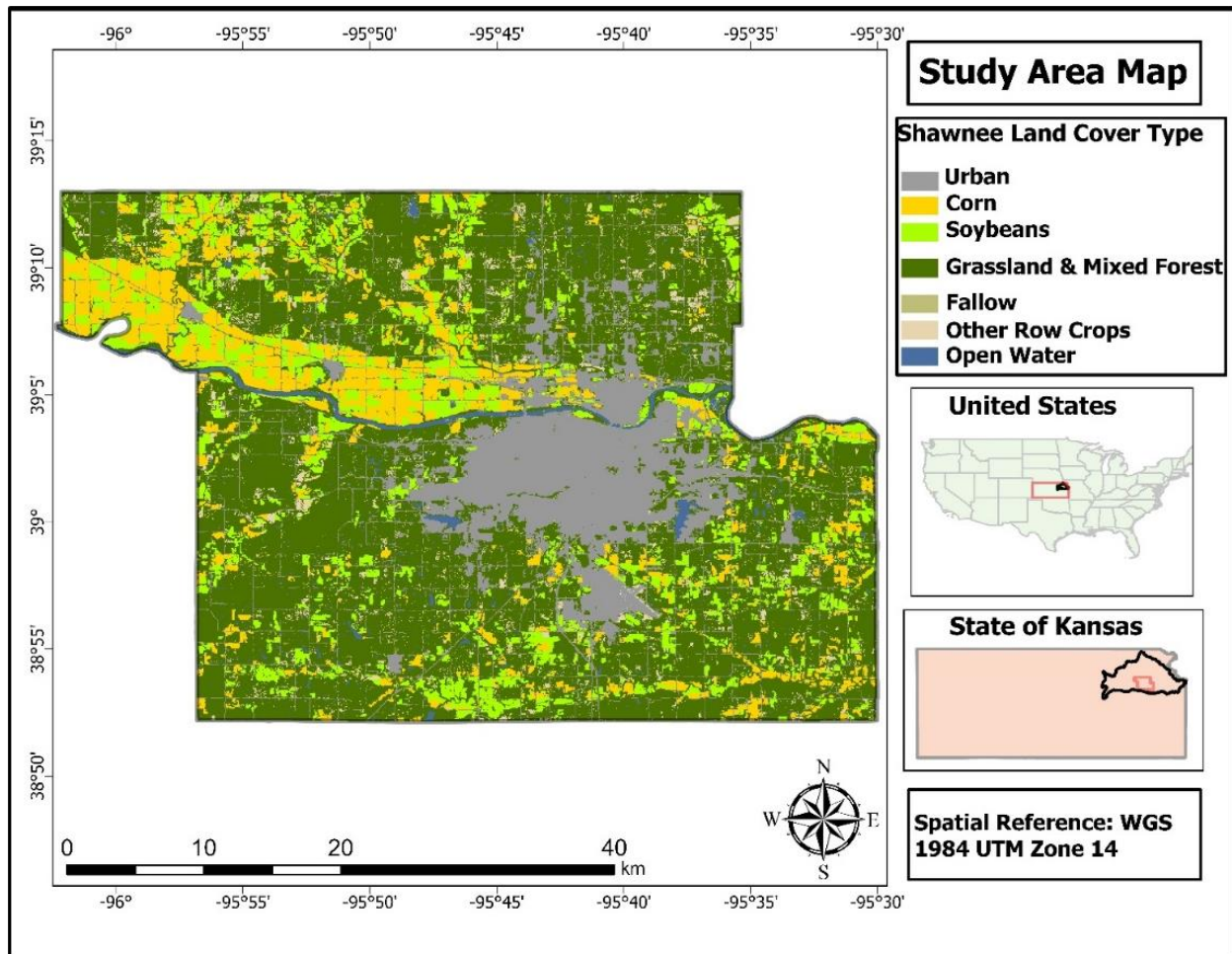


Figure 5.1. Inset map of the study area (Shawnee County in red outline in the State of Kansas map) with land cover types. EKS RB boundary is shown in black outline in the state of Kansas map.

5.3.2 Linear Model Development

Twelve regression models were formulated to estimate PAR based on variables regularly measured in weather stations. The choice of variable combinations was selected based on their influence on PAR, works previously demonstrated in literature, and information retrieved from the multicollinearity test of variables using correlation matrix and variance inflation factor. For example, Alados et al. (1996) suggested the use of clearness index (kt), dew point temperature, and solar radiation for PAR estimation and modeling. Similarly, Aguiar et al. (2012) used solar radiation, kt, and water vapor variable combinations for PAR modeling in Southwest Amazonia

under all sky conditions. In this study, we used the correlation and variance inflation factor functions in R programming (R Core Team, 2023, 2024) to examine the correlation of variables and variance inflation of parameters to avoid common model overfitting issues and excessive multicollinearity of variables. Variables with significant correlations with each other were not included in the same model. Variables were also weighed against their correlations with the response variable (PAR) and preference were given to variables with the most direct correlations. Based on the aforementioned assessments, the following models were developed based on different combinations of meteorological variables.

Model 1: The model was expressed as PAR response dependent on solar radiation plus some intercept term and random error as:

$$PAR = \beta_0 + \beta_1 * SRAD + \varepsilon \quad (5.1)$$

Model 2: The model was expressed as PAR response dependent on solar radiation and minimum temperature plus some intercept term and random error:

$$PAR = \beta_0 + \beta_1 * SRAD + \beta_2 * T_{min} + \varepsilon \quad (5.2)$$

Model 3: The model was expressed as PAR response dependent on solar radiation and maximum temperature plus some intercept term and random error:

$$PAR = \beta_0 + \beta_1 * SRAD + \beta_3 * T_{max} + \varepsilon \quad (5.3)$$

Model 4: The model was expressed as PAR response dependent on solar radiation and dew point temperature plus some intercept term and random error:

$$PAR = \beta_0 + \beta_1 * SRAD + \beta_4 * T_{dew} + \varepsilon \quad (5.4)$$

Model 5: The model was expressed as PAR response dependent on solar radiation and relative humidity plus some intercept term and random error:

$$PAR = \beta_0 + \beta_1 * SRAD + \beta_5 * RHUM + \varepsilon \quad (5.5)$$

Model 6: The model was expressed as PAR response dependent on solar radiation, maximum temperature, and relative humidity plus some random error:

$$PAR = \beta_1 * SRAD + \beta_3 * T_{max} + \beta_5 * RHUM + \varepsilon \quad (5.6)$$

Model 7: The model was expressed as PAR response dependent on solar radiation, maximum temperature, and relative humidity plus some intercept term and random error:

$$PAR = \beta_0 + \beta_1 * SRAD + \beta_3 * T_{max} + \beta_5 * RHUM + \varepsilon \quad (5.7)$$

Model 8: The model was expressed as PAR response dependent on solar radiation, maximum temperature, and clearness index plus some random error:

$$PAR = \beta_1 * SRAD + \beta_3 * T_{max} + \beta_6 * Kt + \varepsilon \quad (5.8)$$

Model 9: The model was expressed as PAR response dependent on solar radiation, maximum temperature, relative humidity, and square root of clearness index plus some random error:

$$PAR = \beta_1 * SRAD + \beta_3 * T_{max} + \beta_5 * RHUM + \beta_6 * \sqrt{Kt} + \varepsilon \quad (5.9)$$

Model 10: The model was expressed as PAR response dependent on solar radiation plus some random error as:

$$PAR = \beta_1 * SRAD + \varepsilon \quad (5.10)$$

This model is the present format for PAR conversion from solar radiation in most crop models.

Model 11: The model was expressed as PAR response dependent on solar radiation and clearness index plus some intercept term and random error:

$$PAR = \beta_0 + \beta_1 * SRAD + \beta_6 * Kt + \varepsilon \quad (5.11)$$

Model 12: The model was expressed as PAR response dependent on solar radiation and clearness index plus some random error only:

$$PAR = \beta_1 * SRAD + \beta_6 * Kt + \varepsilon \quad (5.12)$$

where $SRAD$ is solar radiation (MJ m^{-2}), T_{min} is the minimum temperature ($^{\circ}\text{C}$), T_{max} is the maximum temperature ($^{\circ}\text{C}$), T_{dew} is the dew point temperature ($^{\circ}\text{C}$), $RHUM$ is the relative humidity (%), and Kt is the clearness index (ratio of $SRAD$ to extraterrestrial radiation). The PAR unit was converted from W m^{-2} to MJ m^{-2} . The coefficients $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5$, and β_6 are associated with intercepts and model variables listed previously, respectively, and were determined using regression analysis. ε is the error term, which was assumed to follow a normal distribution given zero expected value and some standard deviation as follows.

$$\varepsilon \sim N(0, \sigma^2)$$

Each model was developed using daily weather observations from 1986 to 2000, and then validated with independent daily datasets from 2001 to 2005. The deterministic part of the linear models was modeled assuming the response (PAR) follows a normal distribution with some expected value of $X\beta$ ($X[SRAD, T_{min}, T_{max}, T_{dew}, RHUM, \text{and } Kt,]$), and identity matrix of standard deviation $\sigma^2 \mathbf{I}$:

$$PAR \sim N(X\beta, \sigma^2 \mathbf{I})$$

All model development was performed using the linear model function in R programming (R Core Team, 2023).

5.3.3 Bayesian Framework Specification

The concept of Bayesian statistics is based on Thomas Bayes rule which dates back to 1763; such that $[\beta, \sigma_{\varepsilon}^2 | PAR] \propto [PAR | \beta, \sigma_{\varepsilon}^2] * [\beta, \sigma_{\varepsilon}^2]$; where $[\beta, \sigma_{\varepsilon}^2 | PAR]$ refers to the target distribution of the posterior (regarded as the posterior distribution of the unknown system parameters β , and error variance σ_{ε}^2 given PAR observations). The target posterior distribution can be expressed as being proportional to the product of the data likelihood $[PAR | \beta, \sigma_{\varepsilon}^2]$ (sampling

distribution of PAR) and the previous knowledge of the parameter(s) β , and error variance σ_{ε}^2 known as the prior distributions $[\beta, \sigma_{\varepsilon}^2]$ (Gelman et al., 2013; Poudel et al., 2022). According to Poudel et al. (2022), the prior distribution of parameters implies prior knowledge about the system generating the parameters and can in some cases be informative, vague, or diffused. Informative priors for a system that has been extensively modeled can be sourced from existing literature or expert knowledge. However, diffused priors have a low level of informativeness and can be used to convey vague knowledge of a system that is not well studied (van de Schoot et al., 2021; Poudel et al., 2022). In this study, the prior distribution specifications related to β , error variance σ_{ε}^2 , and variance of the parameters (σ_{β}^2) were specified based on the underlying assumptions of the linear model, such that:

$$[\beta] \equiv N(0, \sigma_{\beta}^2 \mathbf{I}); \text{ and that the error variance distribution } [\sigma_{\varepsilon}^2] \equiv IVG(q, r)$$

Where IVG = inverse gamma distribution, $q = 2.01$ and $r = 1$ are hyperparameters for tuning the error variance distribution following expert opinion (Trevor Hefley, personal communication). Prior specifications for all parameters are presented in Table 5.1 below.

Table 5.1. Prior specification for the model parameters

Parameter	Description	Expected value	Variance	Probability distribution	Source
β	Model parameters	0	10^6	Normal	Expert opinion
σ_{ε}^2	Error variance	$1/(r * (q - 1))$	$1/(r^2 * (q - 1^2) * (q - 2))$	Inverse gamma	Expert opinion

The present study implemented a Bayesian hierarchical framework to provide a building block for data and parameter dependence. Bayesian hierarchical framework allows for multiple levels of variability when the goal is to estimate parameters at different levels of the hierarchy (Jonsen et al., 2006). As a result, a set of order was defined to establish the distribution of the data

(data model), the model underlying process given some parameters (process model), and the prior information (parameter model) as follows: 1). The data model was defined such that the observed PAR datasets mimic some true observation without measurement error, such that $PAR_i = Z_i$, where Z_i is the i^{th} true observation without measurement error. 2). The process model accounts for the data generation process given some prior parameter values, such that $[PAR|\beta, \sigma_\varepsilon^2] = [Z|\beta, \sigma_\varepsilon^2] \equiv N(X\beta, \sigma_\varepsilon^2 I)$, and 3). The prior or parameter model elicits the prior information of the Bayesian framework such that $[\beta] \sim N(0, 10^6 I)$ and the distribution of the error variance $[\sigma_\varepsilon^2] \sim IVG(2.01, 1)$.

5.3.4 Full Conditional Gibbs Sampling

The full conditional Gibbs sampling was employed as an approach to obtain the posterior distributions of the parameters given PAR datasets and parameter prior information as described in the previous section. Gibbs sampling is a very useful approach for multiparameter Bayesian models as in the present study (Hooten & Hefley, 2019). The Gibbs sampling approach is a Monte Carlo Markov Chain (MCMC) simulation, constructed for sequential block update of multiparameter conditioned on the existence of the data and prior models. In practice, it is difficult to find the close-form solutions of the marginal posterior ($[\beta|PAR]$ and $[\sigma_\varepsilon^2|PAR]$) distributions of the parameters given the data. However, it has become increasingly easy to find the close-form solutions for the full conditional posterior distributions of $[\beta|\sigma_\varepsilon^2, PAR]$ and $[\sigma_\varepsilon^2|\beta, PAR]$ (Hooten & Hefley, 2019). The full conditional distribution is the probability distribution of the parameter of interest assuming everything else in the model is known. In practice, using the Gibbs sampling MCMC algorithm, samples of each parameter were sequentially drawn from their full conditionals, giving each parameter in the model an equal chance to influence each other (Hooten & Hefley,

2019). In this study, the Gibbs sampling MCMC algorithm as reported in Hooten & Hefley (2019) was implemented as follows:

- Assigning initial value for $\sigma_{\varepsilon}^{2(0)}$.
- Setting initial value for $n = 1$.
- Sample for β . The sample for β was made from its full conditional distribution, such that β depends on the previous value of σ_{ε}^2 : $\beta^{(n)} \sim [\beta | \cdot] \equiv [\beta | PAR, \sigma_{\varepsilon}^{2(n-1)}]$.
- Then sample for σ_{ε}^2 . The sample for σ_{ε}^2 was made from its full conditional distribution, such that σ_{ε}^2 depends on the latest value of β : $\sigma_{\varepsilon}^{2(n)} \sim [\sigma_{\varepsilon}^2 | \cdot] \equiv [\sigma_{\varepsilon}^2 | PAR, \beta^{(n)}]$.
- Setting $n = n + 1$, the MCMC sampling was repeated from bullet point 3 until the MCMC samples were large enough or converged to the target/posterior distribution.

Sampling the full conditionals of β , the R package 'mvnfast' (Fast Multivariate Normal and Student's t Methods) was used to draw $[\beta | \sigma_{\varepsilon}^2, PAR] \equiv MVN \left((X'X + \frac{1}{\sigma_{\beta}^2})^{-1} X'PAR, \sigma_{\varepsilon}^2 (X'X + \frac{1}{\sigma_{\beta}^2} I)^{-1} \right)$ from a multivariate normal distribution, alongside the Gibbs sampling algorithm (Hooten & Hefley, 2019; Salmon et al., 2011; R Core Team, 2023). Similarly, the full conditionals of σ_{ε}^2 were drawn from an inverse gamma distribution such that $[\sigma_{\varepsilon}^2 | \beta, PAR] \equiv IVG \left(q + \frac{N}{2}, (r + \frac{1}{2} (PAR - X\beta)' (PAR - X\beta))^{-1} \right)$;

where X is the variable ($SRAD, Tmin, Tmax, Tdew, RHUM, and Kt$), and N is the number of observation (PAR). A total of 5000 MCMC samples were drawn for each β and σ_{ε}^2 from the posterior distributions, after which, 4000 MCMC samples were retained and the first 1000 samples

discarded. The discarded samples were regarded as the burn-in interval. The burn-in interval refers to the period in the MCMC simulation during which the chain has not yet converged to its target stationary distribution (Dunson & Stanford, 2005; Hooten & Hefley, 2019). It is important to note that β was used in this setting to represent all model parameters as outlined in the linear model building section. Daily PAR datasets from 1986 to 2000 were used for model fitting. Independent sets of daily PAR samples (from 2006 to 2022) were created from the posterior predictive parameter distributions after the Gibbs update using the mean quantile composition sampling to draw samples from the posterior predictive distribution. The essence of the mean quantile sampling is to obtain a representative/random subset of PAR, since the MCMC simulation returned 4000 values of PAR for each day, making the values intractable for the intended use. The representative subsets were selected based on their position relative to four quantile distributions of the MCMC samples. The following quantiles were used to divide the daily PAR datasets into four equal parts: 0.25 quantile (which are samples less than or equal to the first quartile or 25% of the population when arranged in increasing order [PAR25]), 0.5 quantile (which are samples greater than 25% of the population but less than or equal to the median or 50% of the population when arranged in increasing order [PAR50]), 0.75 quantile (which are samples greater than 50% of the population but less than or equal to the third quartile or 75% of the population when arranged in increasing order [PAR75]), and > 0.75 quantile (which are samples greater than 75% of the population when arranged in increasing order [PAR100]). The mean of each quantile created the basis for assessing daily PAR impacts for the intended application as will be discussed in the subsequent sections.

5.3.5 DSSAT-CROPGRO Soybean Model: Calibration, Validation, and Long-Term Simulation

The CROPGRO-Soybean module (Jones et al., 1986; Jones et al., 2003; Ritchie et al., 1998) within the Decision Support Systems and Agrotechnology Transfer v 4.7.5 (DSSAT, hereafter) (Hoogenboom et al., 2019) was used in this study. DSSAT is a process-based crop modeling system that simulates crop growth and development at a point scale considering crop management, weather/climate, and soils (Araya et al., 2017; Jones et al., 2003). Minimum climate datasets required to run DSSAT include daily maximum and minimum air temperatures, solar radiation, and precipitation. These variables were obtained for the period 2006 to 2022 from the NASA POWER website as described previously.

Daily PAR values are treated as optional input since the model by default estimates PAR as half of solar radiation. However, PAR inputs can be supplied if they are available from radiometric stations or through other estimation means. The present study modeled PAR using the Bayesian regression approach. Mean quantile composition sampling was used to create daily PAR sensitivity of low and high possible values. PAR values in $\text{MJ m}^{-2}\text{day}^{-1}$ were converted to $\text{moles m}^{-2}\text{day}^{-1}$ for incorporation into the DSSAT crop model (K. J. Boote & F. A. Antunes De Oliveira, personal communication). This was in line with the concept of the moles of light that plants receive from total radiation which PAR represents.

The CROPGRO-Soybean module used in this study simulates phenological stages of soybean growth with respect to biomass partitioning to root, stem, seed, and leaves, and final yield. In addition to daily weather inputs, the simulation is based on crop management inputs such as seed/ m^2 , row spacing, planting date, and depth, soil properties, cultivar characteristics represented as genetic coefficients, and initial conditions at planting (Araya et al., 2017). Information on

county-level dominant soil (Ladysmith silt loam) properties such as soil layer including depth to the subsurface, texture, bulk density, hydraulic conductivity, runoff curve number, albedo, etc., were retrieved from Soil Survey Geographic (SSURGO) (Soil Survey Staff, 2022). Information not available to meet the soil minimum requirements were calculated using the function in the DSSAT Soil Build (SBuild) and methods provided by Gijsman et al. (2002).

Model calibration was systematically performed following the approach reported by (Battisti et al., 2017). Phenology and yield estimates using the CROPGRO-Soybean model are determined by eighteen (18) genetic coefficients. The purpose of calibration is to obtain reasonable estimates of these coefficients by sequentially comparing the simulated results with the observed data (Sharda et al., 2021). Yield trial experiments conducted in 2020 were used for calibration and were obtained from six counties in the EKSRB region. Adjustments of coefficients were made using the GENCALC tool to initiate a range of cultivar coefficients (Hunt et al., 1993). GENCALC uses genetic coefficients of a default cultivar in the DSSAT.CUL file and iteratively compares the observed to the simulated data. It is important to note that since only yield data were available for model calibration, the GENCALC.RUL file for the CROPGRO-Soybean model was fixed to iterate for only yield (HWAM). Once a range of cultivar coefficients were obtained from the GENCALC output file, the genetic coefficients of the trial soybean cultivar were adjusted until reasonable estimates were achieved.

For model evaluation, 2021 variety trial datasets, obtained in four counties in the region were used. Model evaluation was done by comparing the simulated end-of-season yield without modifying the calibrated coefficients described earlier. Test (p-value) and goodness of fit (index of agreement, d-statistic (Willmott, 1982)) statistics, normalize root mean square error (NRMSE))

(Araya et al., 2017) were used as indicators to assess model accuracy for the intended application. The NRMSE is the RMSE (Eq. (5.14)) divided by observed mean multiplied by 100 (Eq. (5.13)).

$$NRMSE = \frac{RMSE}{\text{observed mean}} \times 100 \quad (5.13)$$

$$RMSE = \left(\frac{\sum (s_i - o_i)^2}{n} \right)^{0.5} \quad (5.14)$$

where n is the number of observations, s_i is the predicted value, o_i is the measured observation.

NRMSE values for model evaluation as described by (Soler et al., 2007) are classified as 0-10% excellent; 10-20% good; 20-30% fair, and > 30% poor. In a similar way, (Willmott, 1982) classified d-statistic (Eq. (15)) values as < 0.7 (poor), 0.7-0.8 (moderate), 0.8-0.9 (good) and 0.9-1 (excellent).

$$d = 1 - \left[\frac{\sum_{i=1}^n (P_i - O_i)^2}{\sum_{i=1}^n (|P'_i| + |O'_i|)^2} \right] \quad (5.15)$$

where n is the number of observations, P_i is the predicted value, O_i is the measured observation,

$|P'_i| = |P_i - M|$, and $|O'_i| = |O_i - M|$. M is the mean of the observed variable (end of season yield).

To enhance regional model calibration and reduce model uncertainty, an approach was adopted to assess how well the model simulated the variability in the observed end-of-season yield using coefficient of variation (CV). This was ensured by checking the CV match of simulated and observed data alongside other test and fitness statistics. The closer the simulated CV is to the observed CV, the better and more confident the calibrated and evaluated regional model.

Long-term simulation was conducted from 2006 to 2022 having successfully calibrated and evaluated the CROPGRO-Soybean model and fitted the PAR Bayesian model with daily

inputs. For the long-term simulation, single management information for soybean production in the region was adopted. Soybean was planted in the county on April 17th at a seeding rate of 30 seeds/m², planting depth of 5 cm, and row spacing of 76 cm. This information is widely used in Kansas and was reported by Kansas State University research and extension services for the region (Kiniry et al., 1997; K-State Extension, 2007). Initial moisture condition for the soil assumed the profiles to be at field capacity at planting and initial soil nitrogen assuming 1% soil organic matter was set to 25 kg N/ha¹. These assumptions are within the values reported for rainfed crop production in the Great Plains (Kothari et al., 2019). In addition, nitrogen (N) applications in the model were set according to regional recommendations assuming there is no history of nodule-forming bacteria in the soil and were applied as 22 kg-N/ha¹ of total nitrogen 30 days after planting and 45 kg N/ha¹ 60 days after planting (DAP).

The predictive ability of different PAR inputs was used to create a case study simulation of soybean yield in Shawnee County of the EKS RB using the CROPGRO-Soybean model in DSSAT. First, PAR inputs from the Bayesian posterior distribution were created using the mean quantile sampling method as described previously. In the second step, default PAR input regarded as DEFAULT in the subsequent sections was created within the CROPGRO-Soybean model in DSSAT using the Weatherman utility. The CROPGRO model uses half of the solar radiation input as default to arrive at PAR inputs for the model, and then convert the PAR values from MJ m⁻²day⁻¹ to moles-m⁻²day⁻¹. The third step used PAR input estimated from the best linear regression model developed in this study. Finally, an ensemble model was created by averaging the yield estimates derived from using the mean quantile PAR samples (PAR25, PAR50, PAR75, and PAR100) as inputs. Yield estimates resulting from different PAR inputs were compared to observed USDA NASS yield from 2006 to 2022.

5.3.6 Model Checking and Accuracy

The linear modeling approach was used as a proxy in this study for model selection toward Bayesian framework implementation. The best-performing linear model with the lowest RMSE and high coefficient of determination while being parsimonious enough was selected. Linear model checking and accuracy were carried out based on the model evaluation metrics discussed above. The overall aim was to determine how well the models performed relative to observed PAR datasets and equally identify any potential issue that may be affecting model accuracy.

5.4 Results and Discussion

5.4.1 CROPGRO Model Calibration and Validation

The adjusted coefficients during the CROPCGRO-Soybean model calibration for the region are presented in Table 2 below.

Table 5.2. Genotype coefficients adjusted during the CROPGRO-Soybean regional model calibration.

Coefficients	Definitions	Calibrated values	Default values
CSDL	Critical Short-Day Length below which reproductive development progresses with no daylength effect (for short-day plants) (hour)	14.14	13.40
PPSEN	Slope of the relative response of development to photoperiod with time (positive for short-day plants) (1/hour)	0.340	0.294
EM-FL	Time between plant emergence and flower appearance (R1) (photothermal days)	22.50	19.4
FL-SH	Time between first flower and first pod (R3) (photothermal days)	9.0	7.0
FL-SD	Time between first flower and first seed (R5) (photothermal days)	10.0	14.0

SD-PM	Time between first seed (R5) and physiological maturity (R7) (photothermal days)	38.60	35.0
FL-LF	Time between first flower (R1) and end of leaf expansion (photothermal days)	27.0	26.0
LFMAX	Maximum leaf photosynthesis rate at 30 C, 350 vpm CO ₂ , and high light (mg CO ₂ /m ² -s)	1.25	1.03
SLAVR	Specific leaf area of cultivar under standard growth conditions (cm ² /g)	375	375
SIZLF	Maximum size of full leaf (three leaflets) (cm ²)	180	180
XFRT	Maximum fraction of daily growth that is partitioned to seed + shell	1.00	1.00
WTPSD	Maximum weight per seed (g)	0.195	0.19
SFDUR	Seed filling duration for pod cohort at standard growth conditions (photothermal days)	29.0	23.0
SDPDV	Average seed per pod under standard growing conditions (#/pod)	2.20	2.20
PODUR	Time required for cultivar to reach final pod load under optimal conditions (photothermal days)	13.0	10.0
THRSH	Threshing percentage. The maximum ratio of (seed/(seed+shell)) at maturity. Causes seeds to stop growing as their dry weight increases until shells are filled in a cohort.	79.0	77.0
SDPRO	Fraction protein in seeds (g(protein)/g(seed))	0.405	0.405
SDLIP	Fraction oil in seeds (g(oil)/g(seed))	0.205	0.205

The adjustment of the 18 CROPGRO-Soybean coefficients (Table 5.2) related to phenology and crop development resulted in close agreement between simulated and observed yield values. End-of-season yield calibration was performed across different ranges of climate, soil, and management conditions in the region. Model performance was highly satisfactory during calibration with NRMSE = 8% (334 kg ha⁻¹), p-value = 0.62, d-statistics = 0.88, and a CV value of 12% for both observed and simulated end-of-season yield. Mean simulated and observed end-of-

season yield values during calibration were found to be 4,158 and 3,999 kg ha^{-1} , respectively. End-of-season yield overestimation found in this study may have resulted due to underestimation of water stress. Model structure simplification could be another factor accounting for the overestimation. However, model performance based on yield calibration ranges from good to excellent following the recommendations of (Soler et al., 2007; Willmott, 1982); thus, confirming the fitness of our model for the intended use.

During the model evaluation, observed and simulated end-of-season yields matched closely (Figure 5.2) as indicated by NRMSE = 11% ($\text{RMSE} = 480 \text{ kg ha}^{-1}$), $p\text{-value} = 0.78$, $d\text{-statistics} = 0.75$, and observed and simulated CV of 14% and 9%, respectively. Simulated and observed mean yield values during evaluation were 4,308 kg ha^{-1} and 4,432 kg ha^{-1} , respectively. Overall, variety trial datasets employed in this study for model calibration and evaluation proved very satisfactory and should be recommended in the absence of detailed in-season data.

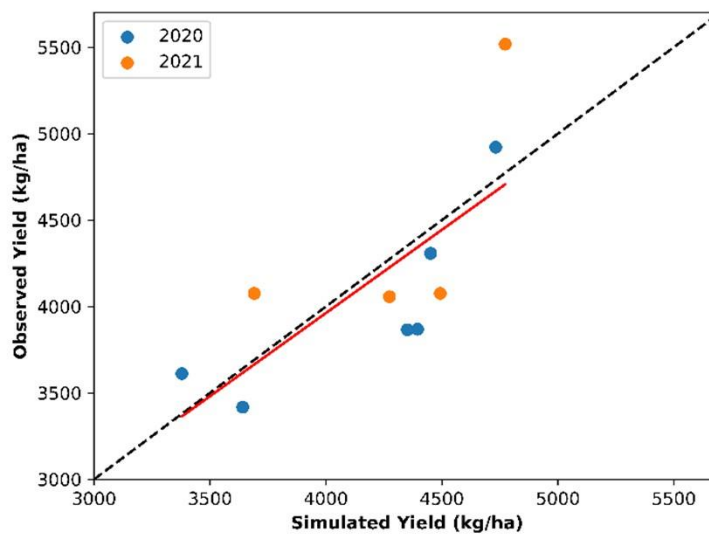


Figure 5.2. CROPGRO model calibration (2020) and validation (2021). Black dash and red lines are 1:1 line and regression line, respectively.

5.4.2 Correlations and Multicollinearity of Climate Variables: Linear Model Fitting and Validation

Figure 5.3 below shows the correlation matrix of the collinearity of variables. The collinearity test examines the strength and association of two or more variables. Usually, in a regression-type problem, collinearity refers to the non-independence of predictor variables and can pose a problem in parameter estimation, partly due to variance inflation of model parameters (Dormann et al., 2012; Vu et al., 2015). Based on result shown in Figure 5.3, variable correlations with PAR are in the order SRAD>Tmax>Tmin>Tdew>Kt>RHUM, with highest absolute correlation coefficient of 0.94, and least correlation coefficient of -0.36 (SRAD and RHUM, respectively). The high correlation between SRAD and PAR (Figure 5.3) supports the results found in other studies, indicating that SRAD is a robust input for fitting a model to observed PAR data (Aguiar et al., 2012; Ferrera-Cobos et al., 2020b). Kt has a relatively strong positive correlation with PAR, with RHUM showing weak negative correlation. This result indicates that a reduction in relative atmospheric moisture may result in clear sky conditions, leading to high clearness index (Kt) and vice versa. Further, on very clear days, high PAR values may occur as a result of relatively low atmospheric moisture. Aguiar et al. (2012) reported similar result of correlation between PAR and vapor pressure, which is a function of RHUM, indicating that increased vapor pressure ultimately leads to build up in relative atmospheric moisture, leading to low PAR values. We observed in this study where Kt has a negative correlation with RHUM (Figure 5.3). The negative correlation between Kt and RHUM observed in this study may have occurred due to atmospheric dynamics between RHUM, Kt, and air temperature. Relatively strong correlation coefficients ranging from 0.57 to 0.72 were observed between PAR and Tdew, Tmin, and Tmax.

To address multicollinearity, we assessed correlation matrix to identify variables with high interdependent correlations. We found that Tmax, Tmin, and Tdew have high positive interdependent correlations, with correlation coefficients ranging from 0.91 to 0.95; hence, the three variables did not appear in the same model fitting equations. Similar approach of using correlation matrix to examine multicollinearity has been reported by Kyriazos & Poga (2023). Weak correlations exist among Tdew, RHUM, and Kt; Tmax, RHUM, and Kt; and finally, Tmin, RHUM, and Kt; thus, making good variable combinations for model building and selection. To consolidate the values of the correlation coefficients for making judgement for model building and selection, we tested for the variance inflation of an all-encompassing model (model of PAR as a function of all predictor variables) with parameters linking each variable using the variance inflation factor function in R (R Core Team, 2024). The variance inflation results due to correlation of a variable with other predictor variables in a model. Our result showed that variance inflation factor for the model parameters ranges from 2.36 to 23.57 for RHUM and Tdew predictor variables, respectively, with the highest variance inflation factors found for Tdew, Tmax, and Tmin (23.57, 16.69, and 13.31, respectively), while the least variance inflation factors were observed for SRAD, Kt, and RHUM (3.22, 2.89, and 2.36, respectively). Studies have shown that variance inflation factor ranging from 1 to 5 is the acceptable limit for specifying variables of moderate correlation with each other in a model (Shrestha, 2020; Kyriazos & Poga, 2023), with values greater than 10 representing high collinearity. The high variance inflation factors observed for Tdew, Tmax, Tmin further confirm the interdependency of the variables and high correlation coefficients previously reported for the three variables (Figure 5.3). However, O'brien (2007) suggested that variance inflation factor values such as 10, 20, 40, or even higher should not automatically lead to the dismissal of regression analysis results, prompt the removal of

independent variables, recommend the adoption of ridge regression, or necessitate the merging of independent variables into a singular index.

Linear relationship between few independent climate variables and one dependent variable can represent the characteristics of the dependent variable. Hence, adding too many independent variables to fit the dependent variable may add no new information to the model (Vu et al., 2015). Therefore, to guarantee that model results are precise and trustworthy, it is crucial to test for collinearity before fitting any regression-type model.

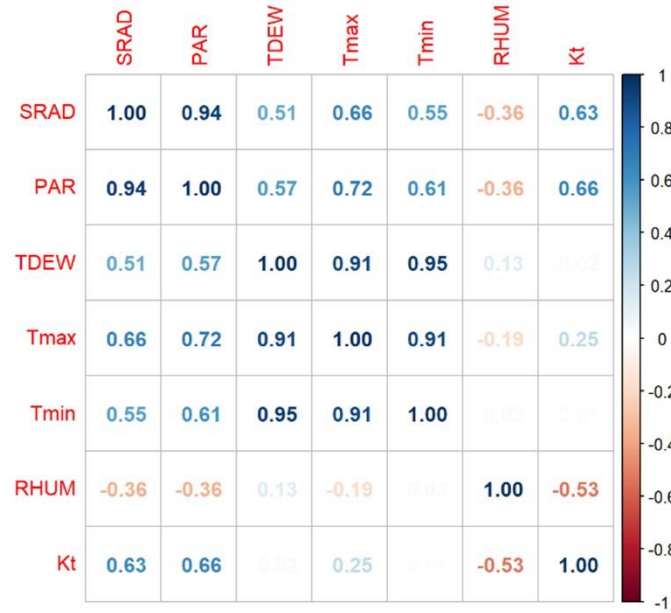


Figure 5.3. Correlation matrix of variable collinearity.

The present study employed the linear modeling approach as a proxy for model selection for implementing the Bayesian regression framework. Figures 5.4 and 5.5 show all model results versus the observed PAR products for fitting and validation, respectively. Model selection was based on the availability of the predictor variables, low RMSE, and high coefficient of determination (R^2) values (Table 5.3). All models showed the need to include SRAD as a predictor variable to obtain accurate estimates of PAR as suggested by (Ferrera-Cobos et al., 2020b). Results

revealed that “Model 8” with SRAD, Tmax, and Kt as predictor variables has the highest R^2 and lowest RMSE values (Table 5.3, Figure 5.4 and 5.5) while being input parsimonious.

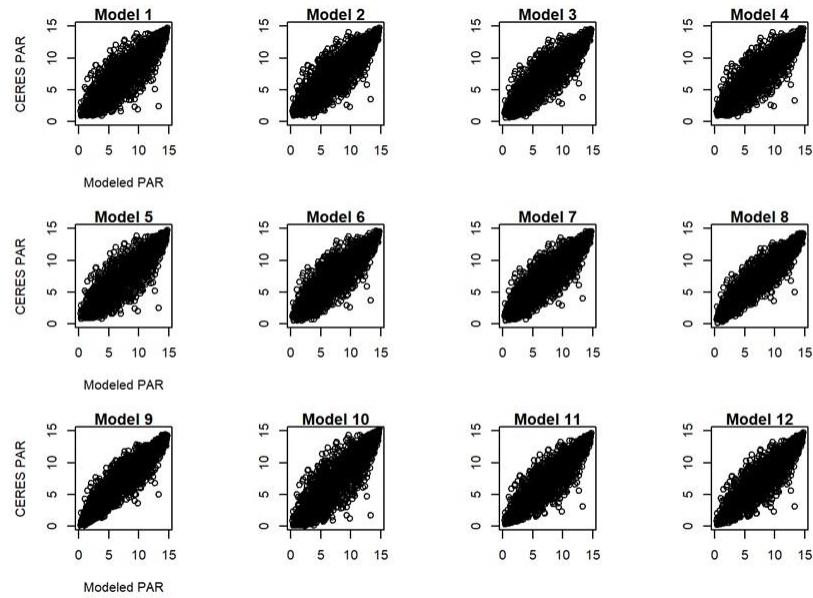


Figure 5.4. Model fitting results for the 12 models (1986-2000). Unit of PAR ($\text{MJ m}^{-2}\text{day}^{-1}$).

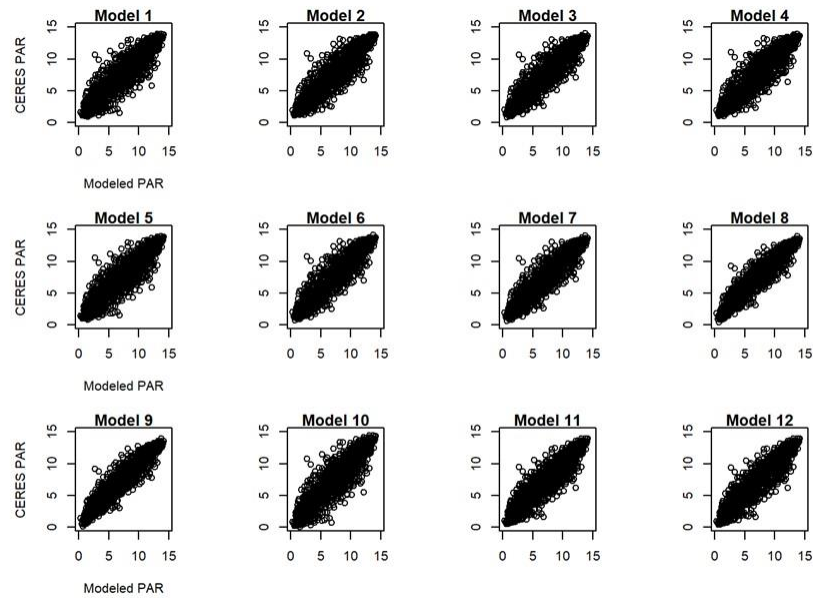


Figure 5.5. Model validation results for the 12 models (2001-2005). Unit of PAR ($\text{MJ m}^{-2}\text{day}^{-1}$).

Aguiar et al. (2012) used similar input combinations but replaced Tmax with vapor pressure. Parsimonious models focus on the most relevant predictor variables, making them more robust and easier to understand (Aguiar et al., 2012). It is also important to emphasize that the best model physically makes sense with the inclusion of Kt, SRAD, and Tmax as PAR predictors. For example, the clearness index provides information on the transparency of the atmosphere and the presence of atmospheric and surface factors that affect the intercepted PAR and solar radiation (Aguiar et al., 2012; Ferrera-Cobos et al., 2020b). Our result (Table 5.3) showed that the linear modeling approach can be used for PAR estimation with high statistical accuracy and has been used by many studies in the past (Aguiar et al., 2012; Alados et al., 1996; Ferrera-Cobos et al., 2020b, 2020a, 2021; Foyo-Moreno et al., 2017). However, there is a need to explore methods that allow for disambiguation in the estimation parameters of PAR by combining prior information with data likelihood to make stochastic inference for a variable whose observation is random in nature. The sections that follow outlined our results for the Bayesian framework, compared Bayesian PAR samples with the traditional linear model estimates and the observed values, and the application of PAR estimates as inputs for soybean yield estimation using the CROPGRO model.

Table 5.3. Linear model parameters with model performance statistics

Models	Parameters							Model Performance		
	β_0	β_1	β_2	β_3	β_4	β_5	β_6	R ² Fit	R ² Val	RMSE Val
1	0.845	0.44						0.891	0.863	1.37
2	1.017	0.42	0.04					0.902	0.876	1.30
3	0.567	0.39		0.05				0.907	0.888	1.25
4	0.951	0.42			0.04			0.902	0.875	1.31
5	1.270	0.44				-0.005		0.891	0.865	1.35
6		0.40		0.06		0.005		0.980	0.885	1.27
7	1.133	0.39		0.06		-0.007		0.908	0.892	1.23
8		0.33		0.06			2.5	0.984	0.913	1.12
9		0.34		0.06		-0.010	2.7	0.983	0.911	1.13
10		0.49						0.974	0.863	1.41
11	0.0148	0.41					2.2	0.900	0.879	1.29
12		0.41					2.5	0.978	0.882	1.29

Notes: The model highlighted in **bold** signifies the best model; Val = model validation, Fit = model fitting. RMSE (MJ m⁻²d⁻¹).

5.4.3 Bayesian Model and PAR Comparison

The Bayesian posterior distribution of model parameters is shown in Figure 5.6 below. The Bayesian posterior distribution of model parameters is specified for “Model 8” only since this model performed the best in the list of linear models in this study. The results show the random normal distributions for all model parameters and error variance and suggest that the posterior predictive parameters were well-drawn from their corresponding normal distributions. Estimates of the parameter credible intervals as seen in Figure 5.6 indicate that the parameter estimates for “Model 8” using the traditional linear regression approach were within their corresponding probability distributions under the Bayesian model, showing that the Bayesian algorithm converged to its true mean values for all parameters.

The Bayesian modeling framework explored in this study enabled incorporation of uncertainty in parameter estimation process and subsequent composition sampling of PAR values. For our Bayesian model based on the linear modeling approach, the parameters of interest related to SRAD, Tmax, and Kt variables and error variance are β_1 , β_3 , β_6 , and σ_ε^2 respectively. These parameters convey direct implications regarding the dynamics and interactions of atmospheric variables towards PAR prediction. As seen in Figure 5.6, posterior inference on β_1 resulted in posterior median value of 0.337 and 95% high-density interval (HDI) of [0.327, 0.345]. As a result, we may quantify the contributory effect of SRAD on PAR within the 95% credible interval, keeping in mind that the true effect of SRAD is contained within the HDI. This is a unique aspect of Bayesian models, and a similar approach has been reported by Poudel et al. (2022) for winter wheat crop modeling study using dynamic ordinary differential equation. Similarly, the posterior median values for β_3 and β_6 were 0.063 and 2.5, with 95% HDI of [0.059, 0.068] and [2.30, 2.65], respectively. This indicates that we may quantify the contributory effects of Tmax and Kt on PAR within the 95% credible intervals, keeping in mind that the true effects of both variables are contained within their respective HDIs. Further, error variance represented as σ_ε^2 resulted in posterior median value of 1.12 and 95% HDI of [1.05, 1.15]. In summary, posterior inference on the model parameters β_1 , β_3 , β_6 , and σ_ε^2 helped us understand the daily random evolution of PAR based on the prevailing atmospheric condition. For example, low values of the parameters may predict low PAR values, provided that the prevailing atmospheric condition is cloudy (Kt) with low air temperature (Tmax) and of high relative humidity (RHUM). Similarly, high values of the model parameters may capture high PAR values on the days when the prevailing atmospheric condition is clear and sunny (Kt) with high temperature (Tmax) and of low relative humidity

(RHUM). Therefore, accurate estimate of model parameters under Bayesian framework is key to understanding the underlying mechanisms of PAR variability and prediction.

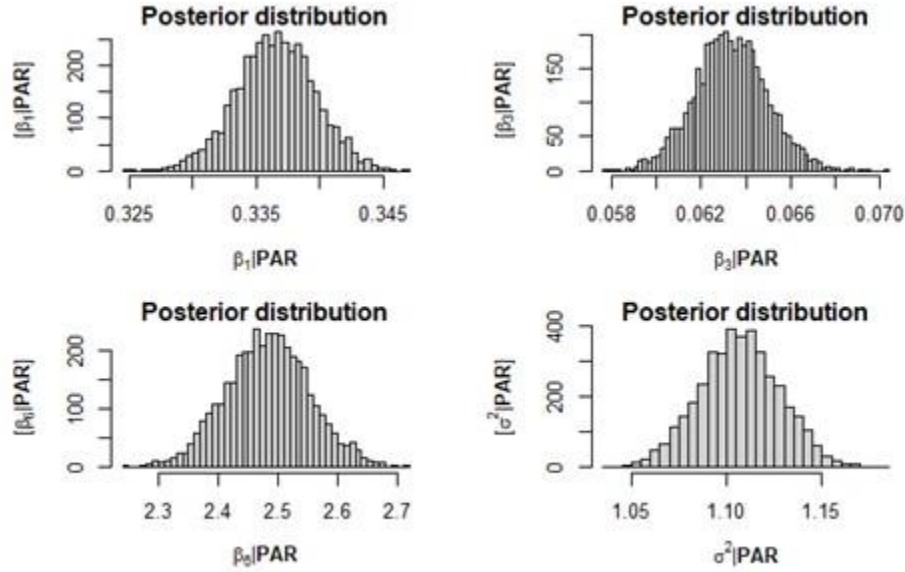


Figure 5.6. Posterior distributions of model parameters.

Table 5.4 shows the PAR sample comparison for different quantiles, the default PAR (DEFAULT) and Model 8 relative to observed PAR values. Results showed that the true PAR records based on point estimates, lie within the median (PAR50, 0.5 quantile) of the distribution (Table 5.4, Figure 5.7b), with NRMSE of 7% and d-statistics of 0.99. This comparison was made using daily averages of PAR samples over the course of 17 years (2006 – 2022) (Figure 5.7a-b). This is also apparent in Figure 5.7b, where the mean values of PAR50 and CERES PAR (observed values) boxplots closely align. The first quantile of the distribution, which signifies the lower 25%, captured similar range of results found for the median PAR records, with NRMSE of 10% and d-statistics of 0.98, but was outperformed by PAR50. PAR75, which is the third quantile signifying the upper 25% of the distribution had a high NRMSE value as well as high d-statistics value (Table 5.4).

Table 5.4. PAR performance relative to observed record (CERES PAR; 2006 to 2022).

Samples	NRMSE	d-statistics
PAR25	10%	0.984
PAR50	7%	0.991
PAR75	16%	0.958
PAR100	30%	0.870
MODEL 8	10%	0.983
DEFAULT	11%	0.983

Notes: PAR25 = first quantile PAR samples; PAR50 = second quantile PAR samples; PAR75 = third quantile PAR samples; PAR100 = greater than third quantile PAR samples.

Interestingly, for PAR samples greater than the upper 25% (PAR100), the NRMSE and d-statistics were 30% and 0.87, respectively (Table 5.4). Overall, the results suggest that for point prediction of daily PAR values, PAR50 resulted in a very close match with the observed CERES records; however, observation of such environmental variables like PAR is very random and requires stochastic estimation.

Comparison of mean values and distribution of PAR75, MODEL 8, and DEFAULT (Table 5.4, Figure 5.7b) are similar, with their prediction statistics within the same order of magnitude. This indicates the possibility of utilizing the traditional linear modeling approach for estimating point PAR values in situations where Bayesian frameworks are not available. However, PAR75 results showed evidence of lower d-statistics and NRMSE of 0.958 and 16%, respectively, compared to the DEFAULT and MODEL 8. There is no difference between the DEFAULT PAR estimates and MODEL 8 as seen from Figure 5.7b and Table 5.4. However, based on Figure 5.7b, it can be concluded that the DEFAULT approach has more variability than MODEL 8. This may be due to the fact that the DEFAULT approach predicts PAR as a function of SRAD alone without accounting for the effects of other variables.

Given the fact that the Bayesian models may track the evolution of PAR based on atmospheric composition and weather variables, and adjust daily PAR values accordingly, we

consider the Bayesian models superior to traditional linear modeling approach for estimating a variable whose response is random. For example, low values of daily PAR were captured better by PAR25 as compared to other PAR samples, while high values were captured by PAR50 and PAR75 (Figure 5.7b). Nevertheless, the daily variabilities of PAR results for the traditional linear models (MODEL 8 and DEFAULT), compares to that of PAR50, however, slightly different as seen in Figure 5.7a. PAR100 serves as the extreme PAR estimation for catching outliers or extreme values (Figure 5.7a-b). Therefore, the approach of using Bayesian framework for estimating PAR will facilitate tracking of daily PAR trajectory, hence, improve prediction accuracy.

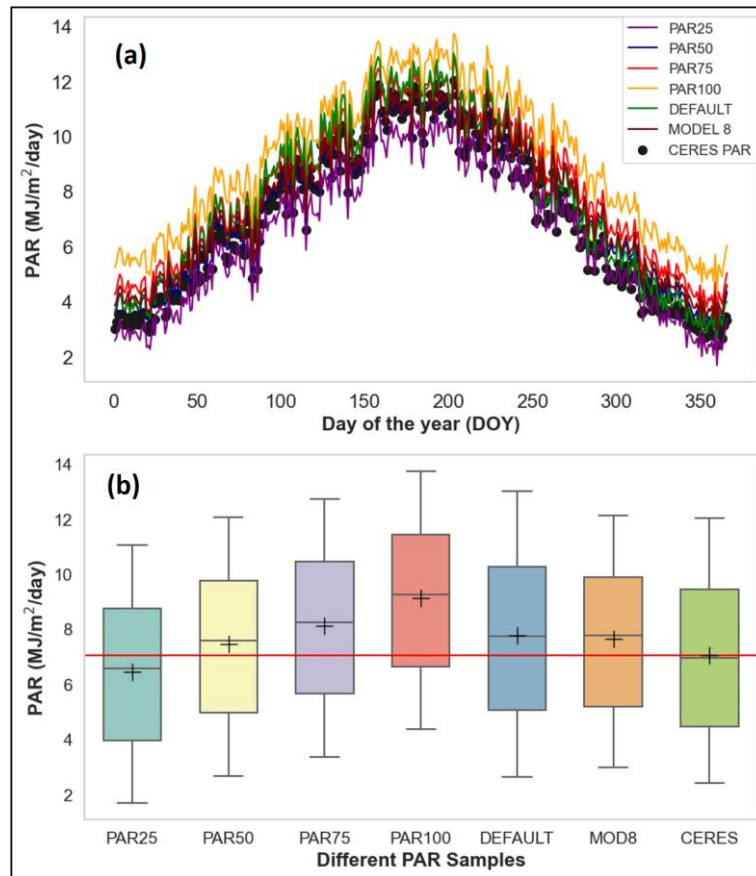


Figure 5.7. (a) Daily averages of different PAR samples compared to observed values. (b) PAR distribution compared to observed values. Plus signs and the red line in (b) represent mean values of different PAR samples and observed mean value, respectively. MOD8 = Model 8; CERES = observed values.

5.4.4 Crop Yield Simulation Case Study

Figure 5.8a-b below show year-to-year variability in soybean yield with respect to different PAR inputs and the mean values relative to observed USDA NASS yield records. It was observed that yield estimates using PAR inputs from the Bayesian posterior mean quantile composition sampling captured the year-to-year variability in the observed USDA NASS yield records better than using the default PAR input (DEFAULT) (Figure 5.8a). This result was further statistically reiterated by the statistics presented in Table 5.5. It was found that soybean yield simulated with PAR25 as input demonstrated the lowest RMSE and NRMSE, and relatively high d-statistics, while PAR100 had the highest RMSE and NRMSE, and lowest d-statistics. Using PAR25 as input, the dynamics of low and relatively high soybean yield values were closely captured in some years (Figure 5.8a). On the other hand, using PAR100 as input, very low yield values were closely captured, while high yield values were overestimated (Figure 5.8a). However, using PAR50 and PAR75 as inputs captured both low and high soybean yields reasonably, thus, providing yield estimation uncertainty bounds, which characterize the random nature of agricultural harvest yields (Figure 5.8a). As expected with point estimates of random variables, using default PAR input (DEFAULT) resulted in high RMSE and NRMSE, and low d-statistics. In addition, yield estimates using PAR values from MODEL 8 (MOD8) as input, captured range of values similar to PAR50. Overall, these results suggest the use of the predictor combinations found in this study for estimating PAR under a hierarchical Bayesian framework.

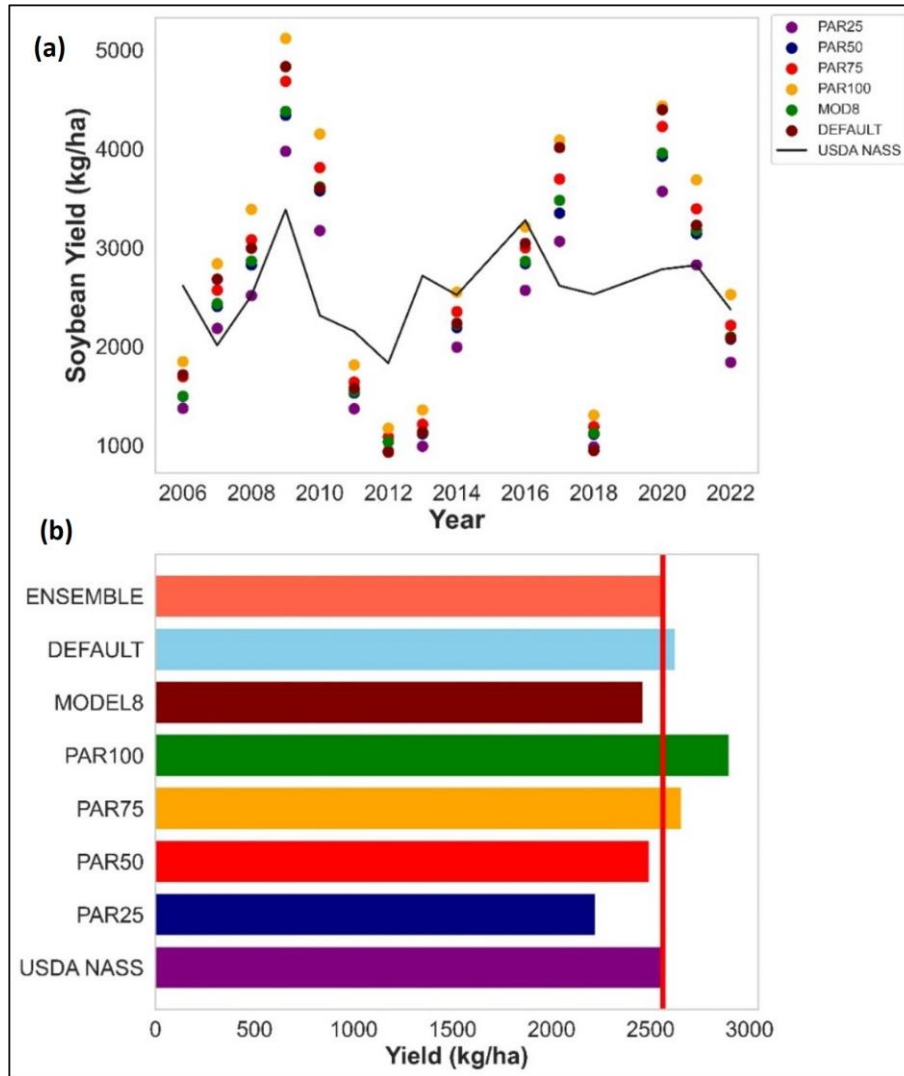


Figure 5.8. (a) Year-to-year yield variability with respect to different PAR inputs. (b) Mean yield sensitivity to different PAR inputs relative to USDA NASS yield. The red line is the mean USDA NASS yield.

Ensemble model was created by taking the mean of yield estimates of PAR25, PAR50, PAR75, and PAR100. Results showed that the ensemble model resulted in the best mean yield approximation relative to observed USDA NASS yield (Figure 5.8b), with lowest mean yield difference of -3 kg ha^{-1} (Table 5.5). This indicates that the stochastic process embedded in the PAR generation process under the Bayesian framework, improved county-level yield simulation. Mean yield difference using other PAR inputs ranged from -339 to 336 kg ha^{-1} (PAR25 and PAR100,

respectively) (Table 5.5). There are no studies contributing information on the impacts of stochastic generation of PAR inputs on soybean yield estimates. However, the present study has set the basis for modeling PAR inputs with a combination of SRAD, Tmax, and Kt as predictors using the Bayesian framework; consequently, improving the results of biophysical model simulations.

Table 5.5. Yield performance statistics for different PAR inputs relative to USDA NASS yield.

Samples	RMSE (kg ha ⁻¹)	NRMSE	d-statistics	Mean yield difference (kg ha ⁻¹)
PAR25	868	34%	0.56	-339
PAR50	893	35%	0.57	-100
PAR75	966	38%	0.55	93
PAR100	1095	43%	0.51	336
DEFAULT	1044	41%	0.53	64
MODEL 8	906	35%	0.56	-68
Ensemble	921	36%	0.56	-3

5.4.5 Limitations of the Study

This study assessed the improvement of daily PAR values by comparing traditional linear modeling approaches and Bayesian regression method. In addition, we assessed the sensitivity of soybean yield to different PAR inputs using the CROPGRO model. In order to achieve the objectives of the study, reasonable assumptions were made.

First, the CROPGRO model used for modeling soybean growth and development did not account for pest infestation, which may have resulted in the overestimation of yield variability observed during yield sensitivity to different PAR inputs shown in Figure 5.8a. Model of any kind is a simplification of reality. As such, some processes are trivialized in order to reduce model complexity. In addition, other trivialized processes other than pest infestation may have

contributed to model overestimation of soybean yield in the region. However, the limits of uncertainty in the estimated soybean yield values were bounded by the distributional regime of the Bayesian PAR inputs (Figures 5.7a, 5.8a), thereby creating the room to model temporal yield values as random variables and not just treating the mean values as sufficient.

Second, the use of CERES PAR datasets hosted by NASA POWER as observed values may have introduced marginal bias in the model parameters. As of this writing, there are only seven SURFRAD stations in seven climatologically distinct zones of the United States <https://gml.noaa.gov/grad/surfrad/sitepage.html>. While the SURFRAD stations provide robust solar flux datasets for atmospheric research, it lacks location-specific datasets for field scale research. Su et al. (2007) reported that PAR products from CERES have been validated with LI-COR PAR measurements at seven SURFRAD sites in the US, with mean CERES PAR and mean LI-COR measurements of 256 W m^{-2} and 245 W m^{-2} , respectively, and a regression slope of 1.03 (Su et al., 2007). In addition, they reported that given the substantial uncertainty quoted for LI-COR PAR sensors used in the SURFRAD stations, the errors between CERES PAR and the LI-COR PAR measurements are within each instrument's uncertainty; indicating that CERES PAR products can alternatively be used as observed inputs in net primary production models. Therefore, the need for PAR datasets in local meteorological stations to drive dynamic crop models and crop physiological research requires urgent attention to address PAR data paucity.

5.5 Conclusion

The present study has set the basis for modeling PAR using a Bayesian regression framework, with a case study assessing performance of different PAR inputs on soybean yield sensitivity and estimates using the CROPGRO-Soybean model. By using the linear modeling approach as a proxy for model selection, the Bayesian framework enabled the estimation of PAR

predictive parameters that support incorporation of uncertainty in the parameter generation process. Results showed that the linear model consisting of Kt, Tmax, and SRAD performed as the best model for estimating PAR under all sky conditions. Implementing the Bayesian framework using the best linear model, PAR estimates were improved compared to the traditional linear modeling approach. Quantifying soybean yield sensitivity using the mean quantile composition sampling of PAR provided flexibility for making stochastic inferences on yield. Results further suggest that yield estimates using the PAR inputs created from the Bayesian posterior mean quantile composition sampling, closely captured the year-to-year variability in the observed yield records than using the default PAR values from SRAD inputs and the best linear model (Model 8). Interestingly, the ensemble yield values created as mean yield estimates of PAR25, PAR50, PAR75, and PAR100, resulted in the best approximation of the observed USDA NASS yield records, with mean yield difference of -3 kg ha^{-1} . The present study being the first to estimate PAR using the CERES PAR products in the region, has set the basis for improving PAR variables and input to dynamic crop models. The findings of this study recommend the use of input combinations that include SRAD, Kt, and Tmax within a Bayesian regression framework for reliable estimation of PAR inputs to crop models and long-term studies. PAR models fitted using the Bayesian framework as seen in this study, may be a valid substitute for stochastic generation of PAR inputs rather than direct conversion of SRAD to PAR using a constant fraction, which may impair inference and increase model uncertainty. However, in situations where Bayesian frameworks are not available, the best linear model found in this study or the default PAR conversion from SRAD may be used, as their predictive accuracies are within the same order of magnitude.

5.6 Acknowledgements

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Chapter 6 - Conclusions and implications

6.1 Conclusions

This chapter includes a summary of key conclusions and recommendations for future research directions.

This dissertation assessed climate change impacts and adaptation strategies on rainfed and irrigated maize production in EKS RB using a combination of county-level and fine-scale spatial protocols to quantify location-specific impacts under heterogeneous responses to environmental variability and different water management techniques. We used process-based crop models configured to run in spatial mode to provide location-specific solutions and insights. In addition, the dissertation also developed a Bayesian regression framework to improve the estimation of PAR, which is required to enhance process-based crop model accuracy. A case study assessing the performance of Bayesian PAR input was tested using the CROPGRO crop model for soybean yield simulation. The research objectives of this dissertation are:

1. Assess the impacts of future climate conditions and root proliferation adaptation strategy on rainfed maize production.
2. Develop a fine-scale spatial protocol for quantifying climate change impacts on maize productivity under different irrigation management strategies.
3. Improve irrigated maize productivity based on genotype-specific and agronomic adaptation strategies under climate change.
4. Develop a Bayesian regression framework to improve estimation of PAR for crop yield prediction in EKS RB.

6.1.1 Key Conclusions

6.1.1.1 Key Conclusions and Agricultural Implications for Research Objective 1

In Objective 1, we focused on the impacts of future climate conditions and root proliferation adaptation strategy on rainfed maize yield and rainfall productivity. This study was published in *Science of the Total Environment*, 2024. Through our county-level process-based modeling analysis using the CERES-Maize crop model, our study reported that under historical climate conditions, yield values in the region range from 6,500 kg ha^{-1} in the west to about 12,800 kg ha^{-1} in the east. The west-east rainfall gradient in the region significantly impacted yield outcomes, with counties in the east having an implicit advantage. Our further analysis revealed the underpinning impacts of environmental variability on yield outcomes in the region. For instance, we found that for a 1 °C rise in minimum and maximum temperatures beyond the optimal maize growth temperature, yield loss could reach up to 2,916 and 2,123 kg ha^{-1} , respectively. In addition, county-level soil distribution drives yield outcomes and utilization of growing season rainfall. Soils of silt loam textures showed tendencies for higher yields and growing season rainfall utilization than clay loam and silt clay loam soil textures. This is true because of the high porosity and well-connected pores in silt loam soils, thereby making soil water freely available to plants.

The vulnerability of rainfed maize production to climate change requires urgent adaptation to ensure maize sustainability in EKSRB and the Great Plains. In quantitative terms, the increasing temperatures and declining growing season rainfall in the future, caused yield and rainfall productivity declines in the range of 36 to 50%, and 25 to 42%, respectively. This dramatic decline increased yield and rainfall productivity variability, making rainfed maize production in EKSRB uncertain under future climate conditions. However, improving maize productivity requires strategic adaptation to reduce yield shock caused by climate change. Changing the plant root

system as a potential adaptation strategy by increasing the root density (root proliferation) could lead to yield and deep soil water utilization benefits, especially under drought and climate change conditions. Root proliferation of a hypothetical maize cultivar resulted in a 27% increase in regional maize yield and a 28% increase in rainfall productivity compared to the reference cultivar without adaptation. In addition, the root proliferation adaptation strategy is likely to shift the most productive soil from soils of silt loam texture to soils of silt clay loam and clay loam textures. This is due partly to slow release of soil water in the profiles of silt clay loam and clay loam than in silt loam soils and that more roots may branch into soil layers where water is available, thus harnessing the benefits of deeper soil water. The findings from our study offer valuable insights for the US Great Plains maize growers and breeders, guiding strategic decisions to adapt rainfed maize production to the region's impending challenges posed by climate change. We recommend testing a combination of other adaptation strategies, in addition to the root proliferation assessed in this study. An all-inclusive adaptation approach may further improve maize yield and rainfall productivity in the region.

6.1.1.2 Key Conclusions and Agricultural Implications for Research Objective 2

In the second objective, we focused on developing a spatial protocol for adapting point-scale CERES-Maize process-based crop model for regional simulation of irrigated maize productivity under different irrigation water management techniques and future climate conditions. This study is under review in *Agricultural Water Management*, 2024. While some studies in the Great Plains have provided climate impacts analysis of maize under future climate conditions, the rarity of studies comprehensively quantifying location-specific climate impacts on irrigated maize productivity (yield, water use, water productivity, and farmers' net returns) at fine scale resolution, speak to the reason why this objective was born. We understood a great deal that

producers east of the 100th Meridian and EKSRB, a historically wetter portion of the Great Plains, face uncertainties regarding climate change effects on yield, irrigation water use, irrigation water productivity, and farmers' net returns. In addition, climate impacts are likely to be spatially variable, with a heterogeneous response to environmental variability and different water management techniques. Our spatial model implementation resulted in a 4 km grid resolution of unique soil and climate per grid, allowing us to treat each cropland as an independent landscape. Our future climate scenarios were divided into three time slices under two RCPs (4.5 and 8.5), given room to peer into spatiotemporal dynamics of climate impacts under different water management regimes. Irrigation water management scenarios were designed to account for two full irrigation and two deficit irrigation scenarios. Historical maize productivity revealed strong spatial control of different soil textures and climate variables, with higher productivity and low water resource use observed for areas dominated by silt loam soils than areas dominated by silty clay loam and clay loam soil textures. This result is essential to prioritize management zones for maximizing inputs.

It was clear from our findings that irrigated maize yield will be vulnerable to future climate conditions, suggesting that irrigation may not substantially mitigate climate risk impacts on existing irrigated maize cropping systems. For example, we found that irrigated maize yield under future climate conditions declined due to shortened growing season length, with values ranging from 21% to 38% (early and late century, respectively) under RCP 4.5, and from 22% to 70% (early and late century, respectively) under RCP 8.5. While we anticipated that water use may not be impacted significantly, it was observed that amid the yield declines, irrigation water use under full allocation substantially increased by 9 to 23%. This resulted in substantial decrease in water productivity. In addition, average net returns declined by 53% to 80% (RCPs 4.5 and 8.5,

respectively). Conversely, deficit irrigation resulted in water savings ranging from 3 to 15% without further diminishing maize productivity, with locations under clay loam and silt clay loam significantly saving water, while locations under silt loam increased water used. The result of this study is essential for identifying proactive water management strategies that, when combined with agricultural adaptation techniques, will help farming communities manage emerging climate risks linked to drier future conditions.

6.1.1.3 Key Conclusions and Agricultural Implications for Research Objective 3

Objective three leveraged the utility of fine-scale spatial protocol developed in objective two to assess the impacts of future climate conditions and adaptation strategies on irrigated maize yield and water use under deficit irrigation management. We assessed a combination of impacts of *in silico* genotype-specific adaptation for selected maize genotype-specific parameters, treated as quantitative traits (improve canopy photosynthesis for radiation use efficiency [RUE], light extinction [KCAN], and heat tolerance [HEAT]), and agronomic management (shifting planting window [PD1 & PD2], and non-limiting nutrient allocation [NNL]) on yield and irrigation water use were assessed. An extension of our investigation results revealed that a one day shortening of growing season length may result in about 243 kg ha⁻¹ yield loss under RCP 4.5, and 321 kg ha⁻¹ under RCP 8.5. In order to close the yield loss gap, we found that incorporating the individual genotype-specific traits in newer maize hybrids or singly making effective adjustments to agronomic management practices resulted in significant yield and water savings improvements relative to no adaptation scenarios under future climate. Interestingly, our study realized that climate impact adaptation of irrigated maize production in the Great Plains requires an all-inclusive approach for effective mitigation. For example, we found that an integrated adaptation strategy linked to a combination of improved RUE, HEAT, KCAN, NNL, and PD2, resulted in the early

21st-century yield gain of 0.6 to 3% (RCPs 4.5 and 8.5, respectively), with water savings of 10 to 13% (RCPs 4.5 and 8.5, respectively), relative to historical condition. In addition, increasing yield gain and water savings pattern was observed to be likely more beneficial to producers in the eastern part of the region, indicating the plausibility of sustainable intensification within that portion of the region. Going forward into the 21st century, marginal yield gain was observed (especially under RCP 8.5) with a further increase in water savings. While our findings offer optimism regarding the potential of breeding and improved agronomic management practices to offer co-benefits of yield gain and water savings, they also underscore the urgent need for a directed breeding pace to counter potential yield reductions resulting from climate change. The overall findings emphasize the transformative potential of all-inclusive integrated adaptation strategies in mitigating the impacts of climate change on irrigated maize production in the Great Plains.

6.1.1.4 Key Conclusions and Agricultural Implications for Research Objective 4

In our final objective, we developed a Bayesian regression framework for stochastic estimation of daily PAR values needed as input to simulate crop photosynthesis and biomass accumulation process. This study was published in *Earth Systems and Environment*, 2024. Improvement in process-based crop model inputs such as PAR is essential to enhance model accuracy, while also documenting new estimation methods. We demonstrated that sourcing PAR as half of solar radiation (SRAD) may negate the recognition of uncertainty in data generation process, consequently impairing inference. Based on the Clouds and the Earth's Radiation Energy System (CERES) PAR datasets and Bayesian regression analysis using the Gibbs sampling algorithm, we found that daily PAR values from the posterior predictive distribution, outperformed the PAR estimates using the traditional linear modeling approach. In addition, we tested our framework by assimilating PAR input into the CROPGRO model for soybean yield prediction.

Results showed that using PAR from the Bayesian framework as inputs captured the year-to-year variability in observed yield better than using PAR estimates from the traditional linear modeling approach. While our new method offers confidence for accurately estimating PAR distribution, the choice of using our Bayesian framework is dependent on whether the system to be modeled requires accounting for its random behavior or whether the mean behavior of the system is sufficient. Given the preceding prelude, we additionally observed that the median PAR values from the posterior predictive distribution lie within the same order of magnitude as the PAR values estimated using the traditional linear modeling approach. However, our overall results support the use of the Bayesian regression framework for robust estimation of PAR inputs to crop models.

6.1.2 Future Directions

The following future directions have been itemized in order to further advance climate change and agroecosystem sustainability research in the Great Plains.

- Future studies will seek to couple the gridded outputs obtained in this research with machine models towards building tailored prediction models for on-the-fly application in the region. In addition, the gridded output may be linked with remote sensing products at pixel level in order to provide real-time predictions.
- Creating an “AgExplorer” dashboard to enable producers and stakeholders to visualize climate and adaptation impacts on crop productivity in the EKS RB.
- There is a need to update hybrid-specific temperature, radiation use efficiency, and drought-related parameters to study temporal genetic gain related insights.
- An improved economic model will make a difference to improve estimation of farmers’ net returns. The output of our model can be post-processed and leveraged to build strong economic model for the region.

- Testing more adaptation strategies is essential for improving cropping system resilience and identifying tailored strategies for different emission scenarios in the region.

Appendix A - Supplementary Information for Chapter 3

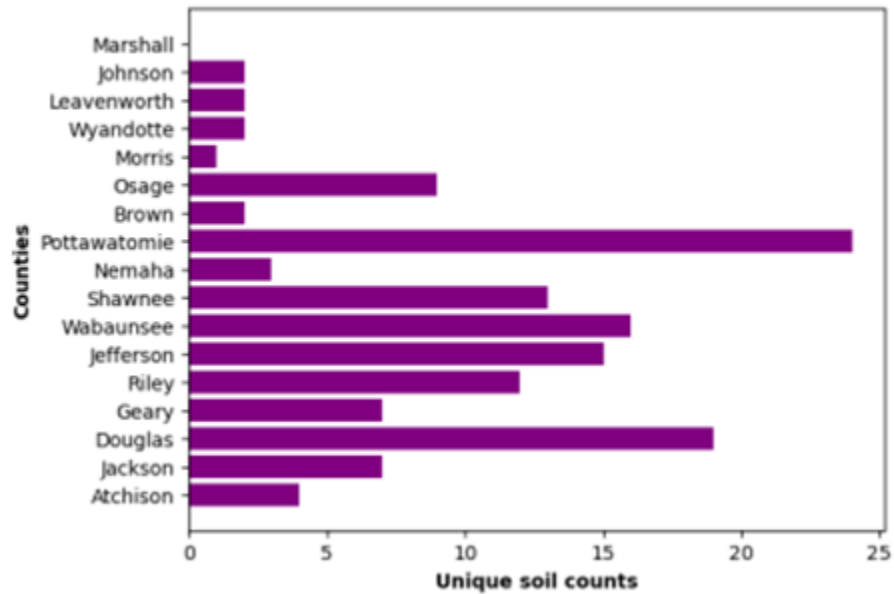


Figure A.1. Unique soil count per county in EKS RB of the US Great Plains.

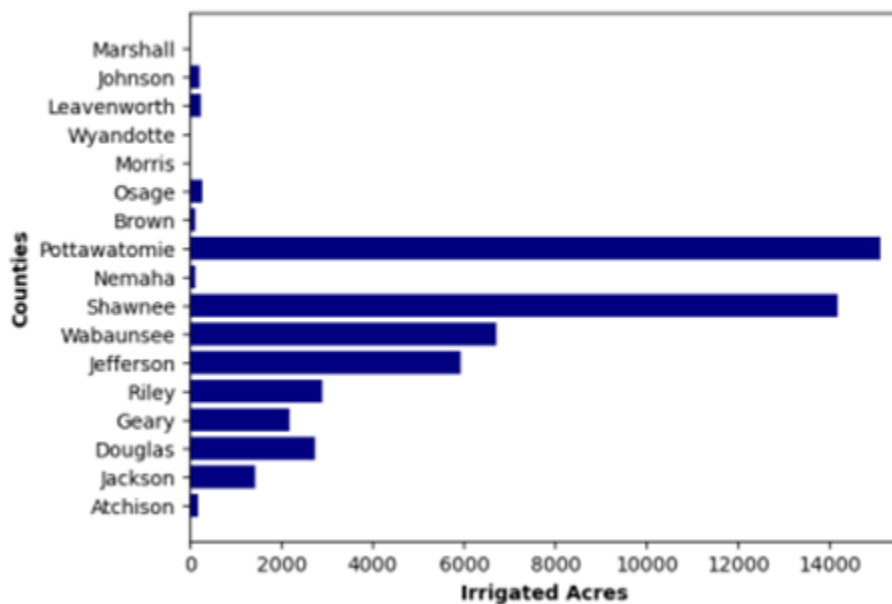


Figure A.2. Irrigated acres per county in EKS RB of the US Great Plains.

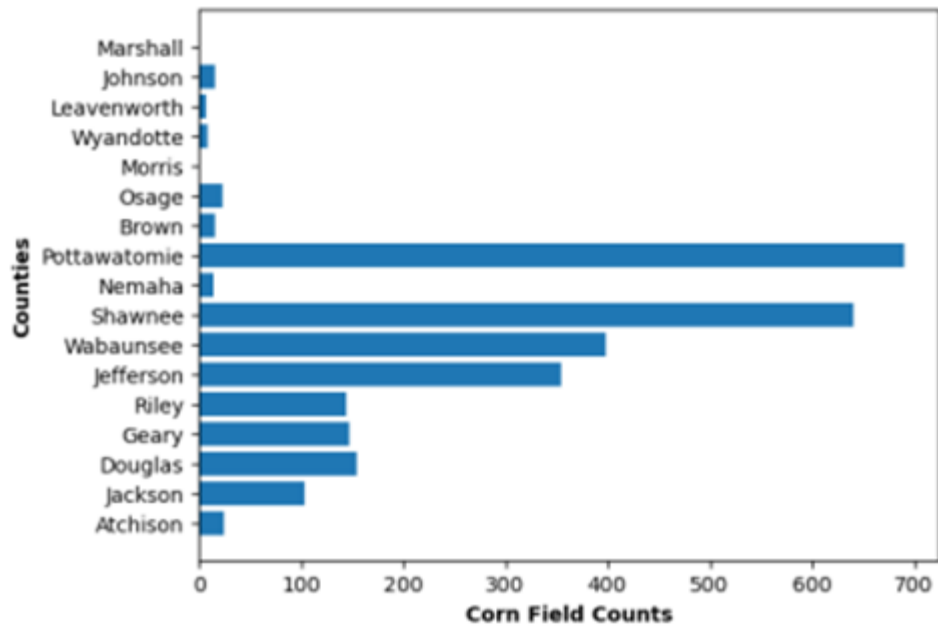


Figure A.3. Irrigated maize field count per county in EKS RB of the US Great Plains.

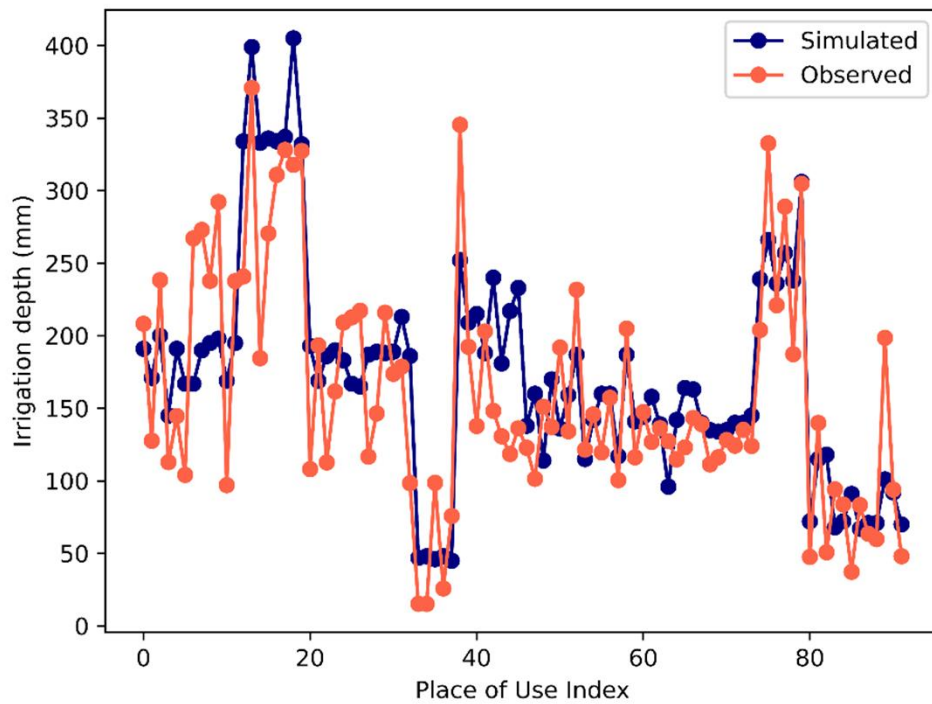


Figure A.4. Point of diversion irrigation withdrawal versus model simulation.

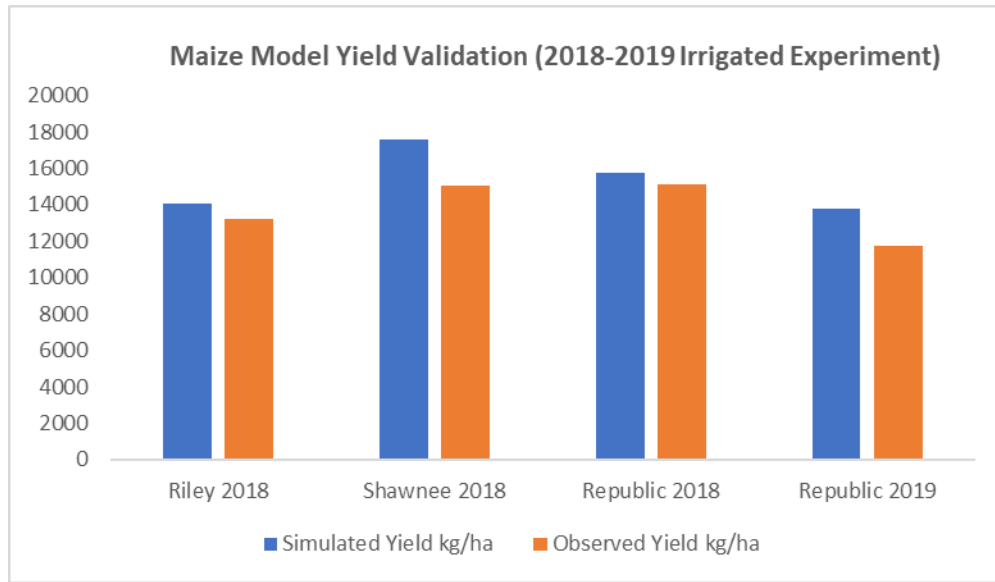


Figure A.5. County-year observed and simulated maize yield comparison during model validation.

The classification of dry, wet, and normal agronomic years was done following the drought index (DI) equation reported by (Wang et al., 2023) as follows:

$$DI = \frac{(P - M)}{\sigma}$$

where P is the annual/growing season precipitation (mm), M is the average annual/growing season precipitation over the period 1991-2020 (mm), and σ is the standard deviation (mm). Based on this, wet years were ascribed when $DI > 0.70$, normal years when $-0.70 \leq DI \leq 0.70$, and dry years when $DI < -0.70$. There were 14 years defined as normal years, 7 years defined as wet years, and 9 years defined as dry years (Table A.1).

Table A.1. Meteorological condition classification

PRCP (mm)	Year	Class
316.9	1991	Dry
491.6	1992	Normal
761.5	1993	Wet
428.9	1994	Normal
649.1	1995	Normal
779.4	1996	Wet
443.4	1997	Normal
419.5	1998	Normal
443.6	1999	Normal
279.0	2000	Dry
479.6	2001	Normal
320.6	2002	Dry
284.7	2003	Dry
738.3	2004	Wet
696.2	2005	Wet
365.1	2006	Dry
544.9	2007	Normal
633.7	2008	Normal
713.1	2009	Wet
562.4	2010	Normal
416.3	2011	Normal
188.6	2012	Dry
374.5	2013	Dry
487.3	2014	Normal
775.8	2015	Wet
729.9	2016	Wet
603.0	2017	Normal
310.7	2018	Dry
984.3	2019	Wet
591.6	2020	Normal

Notes: PRCP is growing season precipitation

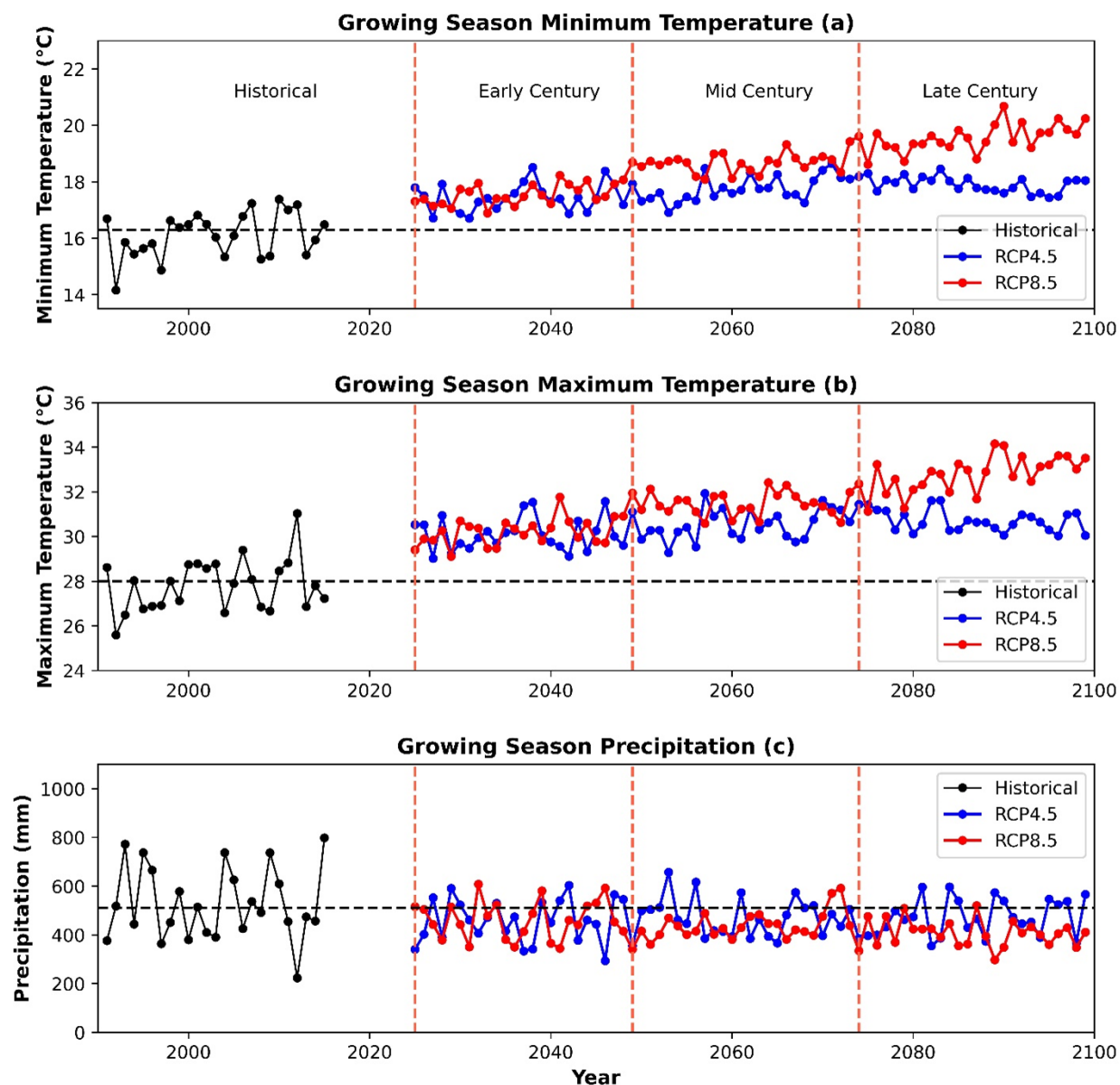


Figure A.6. (a) Growing season minimum temperature trajectory, (b) Growing season maximum temperature trajectory, (c) Growing season precipitation trajectory. Black dash line represents historical (baseline) mean values.

Table A.2. ANCOVA table showing environmental impact on yield.

	Sum_sq	F	PR(>F)
C(SOIL_ID)	2.32E+09	157.2054	2.90E-275*
TMAXA	83251847	67.69548	3.46E-16*
TMINA	4.72E+08	383.7097	4.39E-78*
SRADA	1.41E+08	114.8591	4.49E-26*
PRCP	1112355	0.904501	0.341697
Residual	2.38E+09		

Notes: PR(>F) with * are statistically significant.

1. Sum of Squares (sum_sq): This shows how much variation each factor explains in the dependent variable (yield). Larger values indicate more explanation of variance.

2. F-statistic (F): This is the ratio of the variance explained by each factor to the unexplained variance. Higher F-values suggest a stronger effect of the factor.

3. p-value (PR(>F)): This indicates the statistical significance of each factor. Lower p-values (typically < 0.05) suggest strong evidence against the null hypothesis of no effect.

Table A.3. ANCOVA table showing environmental impact on irrigation water use.

	Sum_sq	F	PR(>F)
C(SOIL_ID)	286858.236	293.29763	0*
TMAXA	1263.875	15.506962	0.0000851*
TMINA	18.333	0.2249352	0.6353585
SRADA	338.868	4.1577043	0.0415813*
PRCP	6037.933	74.081679	1.526332E-17*
Residual	157465.217		

Notes: PR(>F) with * are statistically significant.

1. Sum of Squares (sum_sq): This shows how much variation each factor explains in the dependent variable (irrigation water use). Larger values indicate more explanation of variance.

2. F-statistic (F): This is the ratio of the variance explained by each factor to the unexplained variance. Higher F-values suggest a stronger effect of the factor.

3. p-value (PR(>F)): This indicates the statistical significance of each factor. Lower p-values (typically < 0.05) suggest strong evidence against the null hypothesis of no effect.

Table A.4. ANCOVA table showing environmental impact on irrigation water productivity.

	sum_sq	F	PR(>F)
C(SOIL_ID)	1382993	38.69581	8.54E-82*
TMAXA	430.8812	0.144671	0.703722
TMINA	134714.2	45.23128	2.30E-11*
SRADA	15775.94	5.296885	0.021469*
PRCP	514065.6	172.6012	7.93E-38*
Residual	5757137		

Notes: PR(>F) with * are statistically significant.

1. Sum of Squares (sum_sq): This shows how much variation each factor explains in the dependent variable (irrigation water productivity). Larger values indicate more explanation of variance.

2. F-statistic (F): This is the ratio of the variance explained by each factor to the unexplained variance. Higher F-values suggest a stronger effect of the factor.

3. p-value (PR(>F)): This indicates the statistical significance of each factor. Lower p-values (typically < 0.05) suggest strong evidence against the null hypothesis of no effect.

Table A.5. ANCOVA table showing environmental impact on net returns.

	sum_sq	F	PR(>F)
C(SOIL_ID)	87356543	181.2542	1.09E-305*
TMAXA	3492004	86.94581	2.95E-20*
TMINA	14347569	357.2335	3.02E-73*
SRADA	4484621	111.6605	2.06E-25*
PRCP	231315.3	5.759412	0.016495*
Residual	77635074		

Notes: PR(>F) with * are statistically significant.

1. Sum of Squares (sum_sq): This shows how much variation each factor explains in the dependent variable (net returns). Larger values indicate more explanation of variance.

2. F-statistic (F): This is the ratio of the variance explained by each factor to the unexplained variance. Higher F-values suggest a stronger effect of the factor.

3. p-value (PR(>F)): This indicates the statistical significance of each factor. Lower p-values (typically < 0.05) suggest strong evidence against the null hypothesis of no effect.

Table A.6. Tabular summary of climate change impacts on maize productivity

Yield components	RCP45 (%)	RCP85 (%)
Yield_25%	-34	-49
Yield_50%	-31	-47
Yield_75%	-31	-47
Yield_50%*	-31	-47
Water_use_25%	-6	-8
Water_use_50%	9	9
Water_use_75%	27	25
Water_use_50%*	-3	-4
WP_25%	-38	-52
WP_50%	-47	-59

WP_75%	-55	-65
WP_50%*	-39	-53
NR_25%	-57	-83
NR_50%	-54	-80
NR_75%	-54	-81
NR_50%*	-53	-80

Table A.7. ANCOVA table showing environmental impact on maize productivity under RCP 4.5.

	sum_sq	F	PR(>F)
C(SOIL_ID)	790484056.2771	61.4025	1.4838E-125*
TMAXA	65080584.2087	60.6632	0*
TMINA	147922533.2489	137.8823	9.0616E-31*
SRADA	15381980.2977	14.3379	0.0001575*
PRCP	21239510.9943	19.7978	0.000009115*
Residual	2.0E+10		

Notes: PR(>F) with * are statistically significant.

Table A.7. ANCOVA table showing environmental impact on maize productivity under RCP 8.5.

	sum_sq	F	PR(>F)
C(SOIL_ID)	8.23E+08	71.33905	1.75E-143*
TMAXA	6.96E+08	723.9558	4.79E-135*
TMINA	58137932	60.46195	1.23E-14*
SRADA	68707491	71.45401	5.63E-17*
PRCP	2043304	2.124984	0.145082
Residual	1.8E+09		

Notes: PR(>F) with * are statistically significant.

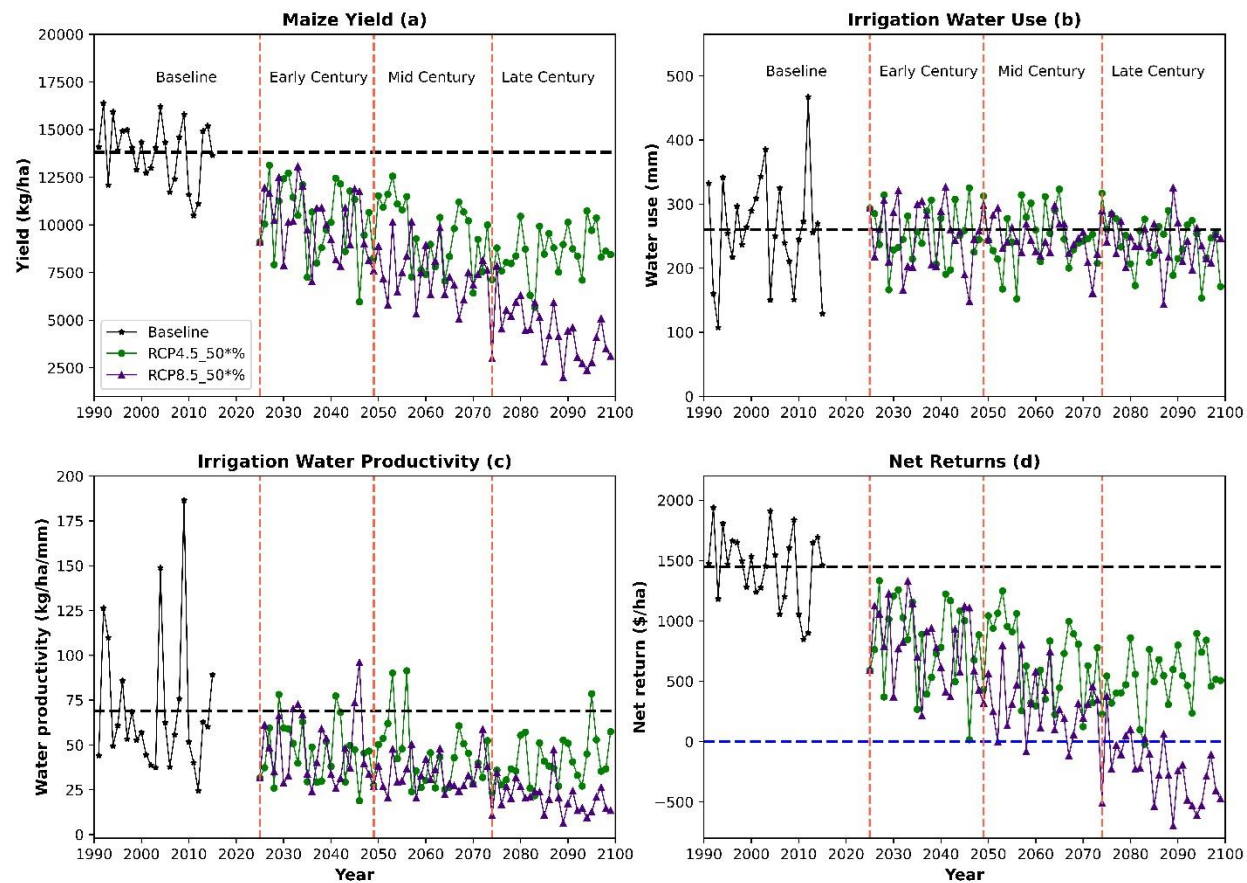


Figure A.7. Temporal variability of irrigated maize productivity under deficit irrigation (50%*) Black and blue dash lines represent historical (baseline) mean values and absolute zero mark.

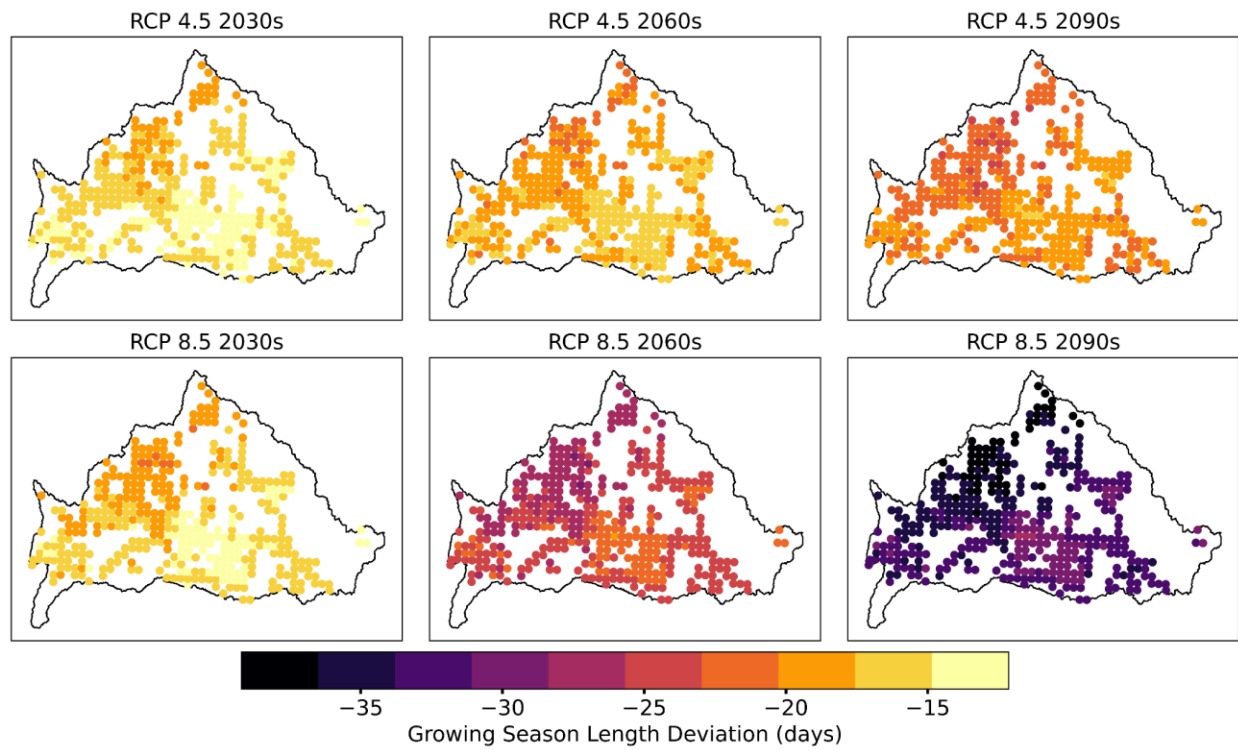


Figure A.8. Spatiotemporal variability of growing season length (GSL) under two RCP scenarios

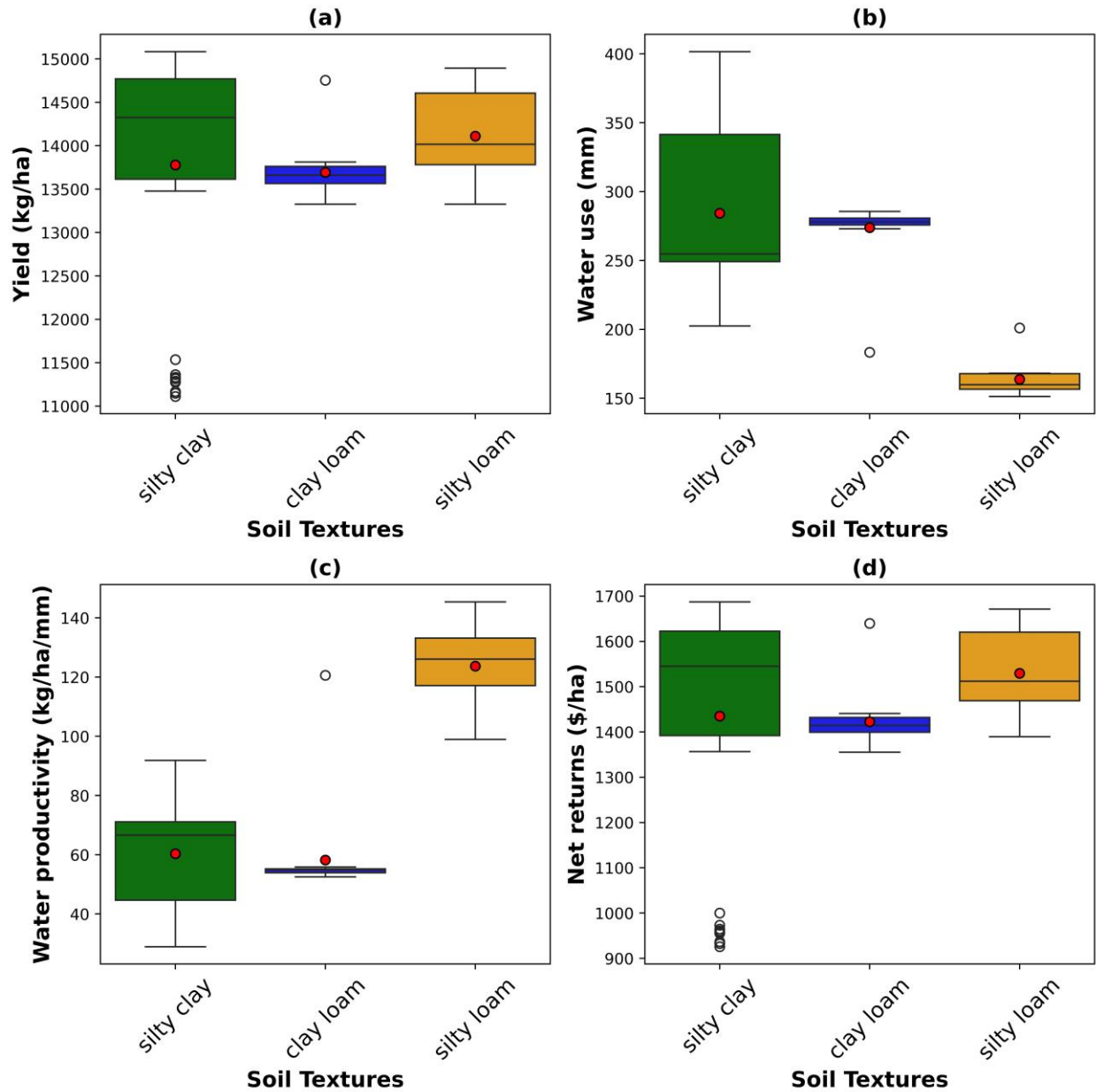


Figure A.9. Boxplots showing (a) yield, (b) water use, (c) water productivity, and (d) net returns distributions among different soil textures under historical condition. Red dots represent the mean values. Result is shown for Shawnee County case study linked to Chapter 3.

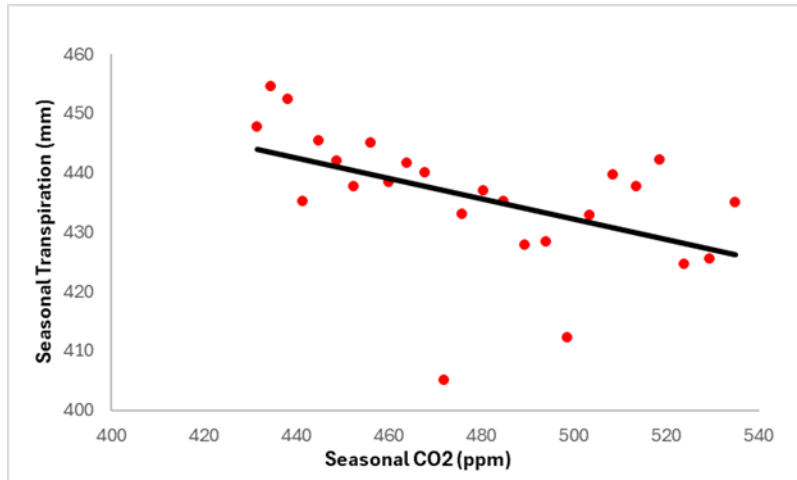


Figure A.10. Relationship between seasonal transpiration and seasonal CO₂ under future climate condition.