

Impact of climate change on the suitability of major crops in the eastern Kansas River basin

by

Rintu Sen

B.S., Hajee Mohammad Danesh Science and Technology University, 2014

M.S., Bangladesh Agricultural University, 2016

A THESIS

submitted in partial fulfillment of the requirements for the degree

MASTER OF SCIENCE

Carl and Melinda Helwig Department of Biological and Agricultural Engineering
Carl R. Ice College of Engineering

KANSAS STATE UNIVERSITY

Manhattan, Kansas

2023

Approved by:
Major Professor
Dr. Vaishali Sharda

Copyright

© Rintu Sen 2023.

Abstract

Climate change will have a considerable impact on agricultural production and its associated processes all around the world, along with an increase in the frequency and intensity of extreme events (like floods and droughts), introducing uncertainty and vulnerability into the agricultural systems. Rainfed crop production system is especially more vulnerable to these extreme effects of climate change. Though the focus area of this study, Eastern Kansas River Basin (EKSRB), lies in the humid northeastern part of Kansas; and is also expected to experience increasing aridity. Keeping this in mind, this study was undertaken to assess the suitability of growing primary cash crops in the region under a changing climate. The crop simulation model, Decision Support System for Agrotechnology Transfer (DSSAT), was used to simulate maize and soybean yields under baseline (1990-2019) and future (2006-2099) climate scenarios. CERES-Maize and CROPGRO-Soybean models in DSSAT were calibrated and validated using observed yield data from USDA NASS with long-term historical weather data, soils data from gSSURGO to account for spatial variability of soils in the study area. The eighteen downscaled Global Climate Models (GCMs) under two Representative Concentration Pathways (RCP4.5 and RCP8.5) were used for projecting future yields. Finally, yield gap percentage ($YG_{\text{percentage}}$) was used to determine future crop-suitable growing areas in the EKSRB. The highest yield loss observed for maize and soybean was 45% and 30% under RCP8.5 at the end of the century. The increasing yield gap trend for both crops under both RCPs points towards the reduction of the suitability of growing maize and soybean in the EKSRB under future climate change scenarios. The results showed that soybean could be a more robust crop under future climate change conditions.

Table of Contents

List of Figures	vi
List of Tables	viii
List of Equations	ix
Acknowledgements.....	x
Chapter 1 - Introduction.....	1
1.1 Problem Statement.....	1
1.2 Objectives	3
Chapter 2 - Literature Review	4
2.1 Foreword.....	4
2.2 Impacts of Climate Change on Agriculture	5
2.3 Use of Crop Simulation Models in Climate Change Studies.....	6
2.4 Crop Suitability Analysis under Changing Climate	8
Chapter 3 - Impact of Spatial Soil Variability on Rainfed Maize Yield under a Changing Climate	9
Abstract.....	9
3.1 Introduction.....	10
3.2. Materials and Methods.....	13
3.2.1 Study area.....	13
3.2.2 DSSAT CERES-Maize Cropping System Model.....	14
3.2.2.1 Model Description	14
3.2.2.2 Model Inputs	16
3.2.2.2.1 Climate Data	16
3.2.3.2.2 Soils Data	18
3.2.3.2.3 Crop Management Data	19
3.2.3 Cultivar Calibration	19
3.2.4 Model Evaluation and Statistical Analysis	20
3.3 Results and Discussion	22
3.3.1 DSSAT Performance	22
3.3.2 Impact of Soil Variability on Maize Yield	23

3.3.3 Projected Changes in Temperature and Precipitation	28
3.3.4 Climate Change Impact on Maize Yield.....	29
3.4 Summary and Conclusions	33
Chapter 4 - Impact of Climate Change on Suitability of Major Crops in the Eastern Kansas River Basin	36
Abstract.....	36
4.1 Introduction.....	37
4.2. Materials and Methods.....	39
4.2.1 Study Area	39
4.2.2 Crop Model Inputs	40
4.2.2.1 Climate Data	40
4.2.2.2 Soil and Crop Management Data.....	41
4.2.3 Database Preparation for the DSSAT Model Run	42
4.2.4 Calibration and Evaluation of Crop Models	43
4.2.5 Suitability Analysis	45
4.3. Results and discussion	46
4.3.1 Calibration and Evaluation of DSSAT Models	46
4.3.2 Impacts of Climate Change on Yield Variability in the EKS RB.....	48
4.3.3 Consequences of Climate Change on the County Level Maize and Soybean	50
4.3.4 Yield Gap Trend under Changing Climate	52
4.3.5 Crop Area Suitability for Growing Maize and Soybean under Future Climate	54
4.4. Conclusions.....	57
Chapter 5 - Conclusions.....	59
References.....	61

List of Figures

Figure 2.1. Eastern Kansas River Basin (EKSRB).....	4
Figure 3.1. Map shows our study area, which consists of ten rainfed maize-producing counties in northeastern Kansas. Green color showed the maize growing area in our study region (USDA CDL, 2019)	14
Figure 3.2. A flowchart illustrating the simulation and projection made by the DSSAT CERES-Maize model based on spatial soil variability and climate data.....	16
Figure 3.3. DSSAT CERES-Maize model a) calibrated for 2000- 2006 and b) validated for 2015 - 2019 for the ten maize producing counties of northeastern Kansas.	23
Figure 3.4. Spatially distributed soils in the study area	24
Figure 3.5. Comparison between DSSAT-CERES simulated and observed yields for the baseline study period (1990-2019) in the top ten maize-producing counties of eastern Kansas while using 1 most dominant soil, 3 most dominant soils, and spatially distributed gSSURGO soils for each county.	26
Figure 3.6. Variation of maize yield due to the spatial distribution of soils in the ten rainfed maize-producing counties of northeastern Kansas (dark green areas on the map indicate higher simulated maize yields whereas red color shows areas with extremely low yields). 27	
Figure 3.7. Spatial distribution of a) annual mean temperature (°C) and b) precipitation (mm) obtained from the ensemble mean of 18 GCMs for near-century (2010-2039), mid-century (2040-2069), and end-century (2070-2099) under RCP 4.5 and RCP 8.5 emission scenarios in comparison to the baseline (1990-2019) study period for ten rainfed maize producing counties in northeast Kansas.	29
Figure 3.8. Pearson correlation coefficient heatmap of maize yield with temperature, precipitation, and CO ₂ concentration under baseline, near, mid and end century (RCP4.5 and RCP8.5) scenarios.	31
Figure 3.9. Pearson correlation coefficient heatmap of maize yield with temperature, precipitation, and CO ₂ concentration under baseline, near, mid and end century (RCP4.5 and RCP8.5) scenarios.	32

Figure 3.10. Yield variation under changing climate in ten maize-producing counties in northeastern Kansas under three study periods (near, mid, and end-century) for RCP4.5 and RCP8.5. The red color stands for low-yielding and the green for the high-yielding region.	33
Figure 4.1. Map showing the study area Eastern Kansas River Basin (EKSRB) with their associated maize and soybean growing area from the USDA Cropland data layer (2019).	40
Figure 4.2. Flowchart showing yield simulation from the DSSAT model and yield gap assessment.....	43
Figure 4.3. Comparison of a) maize and b) soybean yield variation under present and future climate change scenarios under RCP4.5 and RCP8.5. The study period was divided into baseline (1990-2019), near-century (2010-2039), mid-century (2040-2069), and end-century (2070-2099). Horizontal dashed lines indicate the average yield in the EKSRB under the baseline study period.....	50
Figure 4.4. Projected yield change (maize and soybean) for seventeen counties under RCP4.5 and RCP8.5 compared to the baseline study period. The number depicted the seventeen counties of the EKSRB in sequence 1. Atchison, 2. Brown, 3. Nemaha, 4. Douglas, 5. Geary, 6. Jackson, 7. Jefferson, 8. Johnson, 9. Leavenworth, 10. Marshall, 11. Morris, 12. Osage, 13. Pottawatomie, 14. Riley, 15. Shawnee, 16. Wabaunsee, and 17. Wyandotte....	51
Figure 4.5. Simulated average maize and soybean potential (Y_w) and actual (Y_a) yield based on the weather, soil properties, and management conditions for the EKSRB. Each bar represents an individual year of the study period (1990-2099).	53
Figure 4.6. Temporal evaluation of average yield gap percentage trend for maize and soybean in the EKSRB under climate change scenarios (RCP4.5 and RCP8.5). The green color for the baseline, blue for RCP4.5, red for RCP8.5, and the dashed line for National Average Yield Gap (NAYG) for maize (26%) and soybean (22%).....	54
Figure 4.7. Area suitable for growing maize in the EKSRB under baseline (1990-2019), near-century (2010-2039), mid-century (2040-2069), and end-century (2070-2099) under the two representative concentration pathway scenarios (RCP4.5 and RCP8.5).	55
Figure 4.8. Area suitable for growing soybean in the EKSRB under baseline (1990-2019), near-century (2010-2039), mid-century (2040-2069), and end-century (2070-2099) under the two representative concentration pathway scenarios (RCP4.5 and RCP8.5).	56

List of Tables

Table 3.1. List of global climate models and their source	17
Table 3.2. Cultivar coefficients for the CERES-Maize model	20
Table 3.3. Average observed and simulated maize yield with d-stat and RMSE, for ten counties and various soil types.....	25
Table 3.4. Summarized average climatic parameters along with average yield under different climate change scenarios during the maize growing season (May-September)	30
Table 4.1. Crop management recommended practices for the EKS RB.....	41
Table 4.2. Genotype coefficients adjusted during CROPGRO-Soybean regional model calibration	46

List of Equations

Equation 3.1. Root Mean Square Error.....	20
Equation 3.2. Index of Agreement.....	20
Equation 3.3. Coefficient of Determination.....	21
Equation 3.4. Pearson's Correlation Coefficient	21
Equation 4.1. Normalize Root Mean Square Error.....	44
Equation 4.2. Root Mean Square Error.....	44
Equation 4.3. Index of Agreement.....	45
Equation 4.4. Yield Gap Percentage	46

Acknowledgements

I would like to express my most profound appreciation to my major professor, Dr. Vaishali Sharda, for her support, suggestions, encouragement, and guidance during the past two years. Dr. Sharda provided me with knowledge and expertise in DSSAT modeling, climate change, data analysis, and paper writing, and also offered me the chance to present my research on different platforms, which added precious experiences that are valuable for my career. I would like to thank my committee members, Dr. Xiaomao Lin and Dr. Katherine S Nelson, for their co-operations and suggestions during my master's program. This project was funded by the Global Food Systems Seed Grant program of Kansas State University, and special thanks to them for their support.

I am grateful to the faculty members and staff of Carl and Melinda Helwig, Department of Biological and Agricultural Engineering, Kansas State University. I am also thankful to Dr. Zachary Zambreski for providing the downscaled future climate data (GCMs); without this help, this work could not have been completed. I would also like to thank Meenakshi for our incredible friendship and my other lab mates at K-State, for their company and support during the past two years.

At last, I want to thank my parents and my sister for giving me unconditional love, trust, continuous support, and encouragement throughout my life. I am proud of having the best parents in the world. I truly appreciate my husband, Arnob Saha, who always cares for me and gives good advice for my study. His endless patience, love, and support over the last two years helped keep me grounded through the storm and achieve my goals.

Chapter 1 - Introduction

1.1 Problem Statement

Climate change is a transition in the state of the climate that can be recognized by the differences in mean and variability of its properties (temperature, precipitation, solar radiation etc), which lasts for a considerable amount of time, typically decades or longer (IPCC, 2021). The two main factors that drive climate change are natural processes (biogeographical) and human activities (anthropogenic). Human activities like industrialization, burning of fossil fuels, gas flaring, urbanization, and agriculture that emit large amounts of greenhouse gases into the atmosphere have been identified as the main reason for the ongoing unequivocal global warming. The Intergovernmental Panel on Climate Change (IPCC) sixth assessment report (AR6) provides evidence that global temperatures are predicted to rise by 1.5–5 °C over the next century, and therefore, the precipitation and wind patterns may also be altered (IPCC, 2021).

Kansas is a part of the U.S. Corn Belt known for its high maize and soybean production. According to the USDA (2020), Kansas ranked 8th and 6th in the nation for maize and soybean production, respectively. The East to west precipitation gradient prevalent in Kansas makes eastern Kansas ideal for growing crops under rainfed conditions. Rainfed agricultural production is generally governed by the prevailing climate, the quality of the soil, and crop management factors (Lal, 2000; Laux et al., 2010). In the past decade, Kansas has been impacted by several droughts and floods that have been tied to the increased frequency of extreme events under climate change (Brunsell et al., 2010). These extreme events put increasing pressure on agricultural production systems in the region, with rainfed agriculture being more susceptible to these events. Several studies have demonstrated that climate change impacts crop production, mainly due to growing

season high temperatures and changing precipitation patterns, resulting in a higher rainfed crop yield loss (McGrath et al., 2015; Jin et al., 2017; Luan et al., 2021; Zhou et al., 2021). Overall, climate change has introduced a high level of uncertainty in maize and soybean production, especially under the rainfed agricultural system; therefore, it is crucial to find suitable areas to produce these crops in the future under a changing climate to sustain rainfed crop production.

In addition to the changing climate, soil properties and the variability within spatial distribution of soils in a region are essential to determine yield levels (Hansen et al., 2000; Olesen et al., 2000; Xiong et al., 2008). Soil properties such as soil texture, pH, nutrient levels, and water-holding capacity can vary significantly across a field, and these differences can affect the growth and development of crops (Batchelor et al., 2002).

For this study, we considered the spatial distribution of soils under present and future climate change scenarios to identify the yield variabilities associated with soil types and find the future suitability of corn and soybean rainfed production in northeastern Kansas River Basin. The spatial distribution of soils is reflected in yield variability across space whereas extreme climate change alters cropping patterns over time. The degradation of arable agricultural land (loss of topsoil and lowered soil nutrient concentrations) with a reduced crop-growing suitable area has been observed under the changing climate (Kates et al., 2001; Shukla et al., 2019), therefore, to ensure future crop-suitable growing areas and to develop strategies to overcome food insecurity, it is essential to analyze the suitability of growing crops on a regional scale. Regional scale analysis of the impact of climate change on food production is essential because it allows for a localized understanding of how changes in temperature, precipitation, and extreme weather events are likely to affect crop yields, water availability, and soil health (Southworth et al., 2002).

Crop simulation models have been widely used in agricultural research, and are a valuable tool for analyzing the impact of climate change and other environmental factors on crop yield and growth (Beebe et al., 2011; Jarvis, 2011; Laderach et al., 2013; Estes et al., 2013; Ramirez-Villegas et al., 2020). The Decision Support System for Agrotechnology Transfer (DSSAT) (Hoogenboom et al., 2021) is one of the most widely used crop simulation models for evaluating agricultural management options (Thorp et al., 2008) and simulating crop water use and yield along with the development of management strategies for different soil and climate conditions (McNider et al., 2015) for a suite of agricultural crops. Therefore, this study used the DSSAT model to assess the impact of spatial soil variability and climate change on rainfed maize and soybean yield in northeastern Kansas. Furthermore, a regional scale crop suitability analysis will be conducted to identify areas most vulnerable to these impacts and to inform the prioritization of resources for adaptation and mitigation efforts.

1.2 Objectives

The goal of this study was to determine the future suitability of production of the major crops (maize and soybean) grown in a rainfed eastern Kansas River Basin (EKSRB) region. We used DSSAT-CERES-Maize (Jones & Kiniry, 1986) and CROPGRO-Soybean (Hoogenboom et al., 1992) models to simulate or project maize and soybean yields, respectively. Therefore, this study aims to assess: 1) the impact of spatial soil variability on rainfed maize yield under a changing climate and 2) the impact of climate change on the suitability of major crops in the EKSRB.

Chapter 2 - Literature Review

2.1 Foreword

Climate change is associated with an increase in the frequency and intensity of extreme events like drought, floods (IPCC, 2021) and is expected to introduce uncertainty and vulnerability into the crop production systems (Steiner et al., 2018). Significant climate variability has been observed across Kansas; the increasing trend of temperature and changing precipitation patterns strain the state's rainfed agricultural system. Though eastern Kansas has a favorable climate to grow crops under rainfed conditions, under a changing climate, it is getting warmer (Lin et al., 2017). This, in turn, makes the rainfed crop-growing areas in the eastern Kansas River Basin (EKSRB) (Fig.2.1) vulnerable to higher temperatures and lower cumulative precipitation amounts. Therefore, it is crucial to assess this impact and determine what areas in the region will remain suitable for growing crops in the EKSRB under future climate change scenarios.

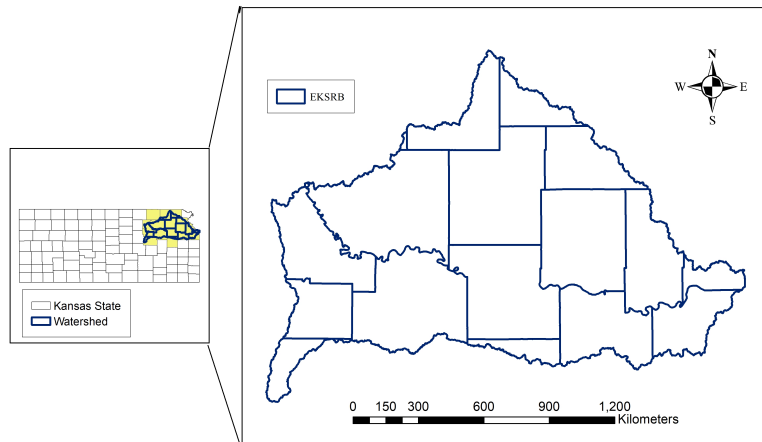


Figure 2.1. Eastern Kansas River Basin (EKSRB)

2.2 Impacts of Climate Change on Agriculture

Increasing temperatures, altering precipitation patterns, and increasing atmospheric CO₂ concentrations are all reasonable possibilities under climate change. Since the annual temperature has increased by 0.7-1.0 °C over the past 35 years, it has negatively impacted crop production systems around the world (USGCRP, 2017). Elias et al., 2019 studied climate impact on agricultural production in the southwest United States and by evaluating the fluctuations in climatic parameters, found that temperature was the main reason for exacerbating pressure on agriculture, resulting in the reduction of crop production. Several studies found that increasing trends of temperatures and extreme events impair crop yields in the Midwest U.S. (Tubiello et al., 2008; Lobell & Asseng, 2017; Sabagh et al., 2020). In addition, lower average crop yields with greater yield variability were observed due to climatic uncertainty in the Midwest United States (Asseng et al., 2013; Challinor et al., 2014; Lobell et al., 2014).

Maize and soybean are two dominant crops in the U.S. and have contributed 40% and 35% of global annual production, respectively (Gaupp et al., 2019). These two crops are vulnerable to the impacts of climate change, such as changes in temperature and precipitation patterns, which can affect crop growth and productivity (Yu et al., 2021). Kucharik et al., 2008 studied the long-term climate change impact on Wisconsin's maize and soybean and found that for each additional degree (°C) of future warming during summer months, maize and soybean yields could potentially decrease by 13% and 16%, respectively. Goldblum, 2009 studied the future climate impact on maize and soybean yields in Illinois and found that the yield loss was a result of high-temperature days during the growing season. Several studies conducted on a global scale climate change impact on crops, and they found that high concentrations of CO₂ and other greenhouse gases in the atmosphere could lead to decreased crop yields and productivity (Hasegawa et al., 2018; Wang et

al., 2018; Ray et al., 2019). Several country-level (USA, China, Brazil, and South Africa) studies found that extreme climate change would reduce maize and soybean yields by 2050, indicating the urgent need for adaptation measures to minimize the impact of climate change on agricultural production (Kucharik et al., 2008). Wang et al., 2018 conducted a global scale study, which emphasized that climate change would lead to a decline in maize and soybean yields in most countries, mainly tropical regions. The study also projected that by 2050, maize yields could decline by up to 20% and soybean yields by up to 40% due to climate change. Most of the studies in the literature focused on a global, country, and state scale reported a wide range of yield loss associated with changing climate, so, there remains a need for regional-scale studies to understand the future climate change impact on maize and soybean production in order to develop region-specific agricultural strategies to overcome the negative impacts of changing climate on agricultural production systems.

2.3 Use of Crop Simulation Models in Climate Change Studies

Computer-based crop simulation models have been widely used in a large number of studies to evaluate the relationship between crop yields and climate change (Basak et al., 2010; Challinor et al., 2009; White et al., 2011). Climate change impacts on crop production are viewed as positive under increasing carbon dioxide (CO₂) (Kellogg, 2019). However, extremely high CO₂ concentrations with increasing temperatures and variable precipitation timing and amounts negatively impact crop yields (Hatfield et al., 2011). Since crop simulation models are a valuable tool for simulating crops' growth and development under different climate conditions, the use of crop simulation models has increased in projecting future climate change impacts on crop yields (Battisti et al., 2018). APSIM, DSSAT, EPIC, and AquaCrop are widely known crop simulation models, and they are used to predict the impact of climate change and other environmental factors

on crop production and evaluate the effectiveness of different management practices and adaptation strategies (Keating et al., 2003; Steduto et al., 2009; Hoogenboom et al., 2021). The Decision Support System for Agrotechnology Transfer (DSSAT) is a computer software with crop simulation models for more than 42 crops (Version 4.8) that is considered an important and powerful tool to assess the impact of climate change on production levels (Hoogenboom et al., 2021). The DSSAT model can predict crop growth and yield using daily weather data, local soil conditions, crop management, and genetics as input. The North American Regional Climate Change Assessment Program (NARCCAP) Phase I multi-model regional climate models were used as a driver in the CSM-DSSAT crop models to project the yields of three crops (maize, peanuts, and cotton) for the years 1981–2003 in order to evaluate the effects of climate on agricultural production in the southeast United States (Shin et al., 2020). Phetheet et al., 2021 studied the historical (2008-2017) and two RCP climate scenarios (2018-2098) at a site in the Midwest of the US, using the DSSAT model, which provided an initial quantification of increased agricultural hurdles due to climate change, such as decreased crop yields and increased financial losses. Sharda et al., 2017 used the DSSAT's CERES-Maize model to take into consideration the spatial soil variabilities at a regional scale to simulate maize yield under fluctuations caused by climate variability signal ENSO (El Niño-Southern Oscillation) in Alabama. The results showed that a significant maize yield variability is associated with the spatial distribution of soils. Since spatial soil variability plays a vital role in determining crop performance, it is essential to consider soil properties when determining crop production changes under future climate change scenarios. Overall, based on the literature reviewed, it can be said that the DSSAT is a powerful tool that can be used to explore the impacts of climate change on crop production and inform decision-making related to adapting to climate change in the agriculture sector.

2.4 Crop Suitability Analysis under Changing Climate

Crop suitability analysis is the process of assessing the suitability of growing a particular crop in a specific location, and it is essential to evaluate the suitability of growing crops under different climate change scenarios for sustainable crop production. Several studies revealed that crop suitability analysis is crucial to reduce the effects of climate change by providing a strategy for adopting the right crops over time for higher agricultural production (Pereira et al., 2017; Aggarwal et al., 2019; Abd-Elmabod et al., 2020). Different approaches have been used to determine the suitability of growing a particular crop in a specific location (Estes et al., 2013; Rodcha et al., 2019; Mugiyo et al., 2021). In agricultural research, processed-based crop simulation models are frequently used to assess crop-climate suitability and productivity (Ramirez-Villegas et al., 2020). The processed-based crop simulation model DSSAT was used to determine crop suitability in South Africa; the study suggested this model's accuracy over other empirical and mechanistic models (Estes et al., 2013). In addition, the DSSAT model is used in several studies to project crop growth and yield changes based on the projected changes in temperatures, precipitations, and other climatic factors (Alexandrov et al., 2000; Basak et al., 2010; Knox et al., 2010). The DSSAT model was used by Etizinger et al., 2017 to classify high-impact soybean growing regions in the Central US under future climate. The study predicted a 10–38% decline in yield compared to the baseline study period. Therefore, using the DSSAT model can provide detailed and accurate information about the suitability of different locations for growing a particular crop and can be helpful for crop planning, land-use management, and conservation efforts.

Chapter 3 - Impact of Spatial Soil Variability on Rainfed Maize

Yield under a Changing Climate

Abstract

As the climate changes, there is a growing demand to identify and manage spatial variation in crop yield to ensure food security for a growing global population. Soils are an important environmental component that can significantly impact crop growth performance, and this effect is more pronounced under rainfed conditions. This study is designed to assess spatial soil variability and its impact on maize yield under future climate in eastern Kansas's top ten maize-producing counties. The cropping system model CERES-Maize of Decision Support System for Agrotechnology Transfer (DSSAT) was calibrated using observed maize yield. To assess the impact of future climate change on rainfed maize yield, the DSSAT-CSM was run for a historic baseline study period and for the future using 18 downscaled Global Climate Models (GCMs) from the Coupled Model Intercomparison Project Phase5 (CMIP5) under two Representative Concentration Pathways (RCP4.5 and RCP8.5). The results showed that the future projected increase in temperatures and lower precipitation patterns during the maize growing season in northeastern Kansas resulted in a higher yield loss. It was found that climate change impacts on yield loss were more pronounced than the effect of spatial variability of soils. Climate change scenarios projected 28% and 45% lower yield under RCP4.5 and RCP8.5 at the end of the century, respectively, as compared to the baseline (historic) study period. The results indicated that production of maize under rainfed conditions would not be commercially viable in our study region under the changing climate, emphasizing the need for developing strategies to sustain maize in the region.

Keywords: Crop Simulation, DSSAT, yield change, Global Climate Models, Emission Scenarios

3.1 Introduction

Climate change impacts agriculture both positively and negatively. Increased levels of carbon dioxide (CO₂) concentration caused by the changing climate are beneficial for plant growth (Reilly et al., 2007; Leakey, 2009; Rogers et al., 2009); however, according to some studies (Gornall et al., 2010; Hatfield et al., 2011; Deryng et al., 2014, Sakurai et al., 2014), the projected rise in temperature and precipitation uncertainty may potentially wipe out the beneficial effects of higher CO₂ on agricultural productivity. Since increasing CO₂ induces high temperatures (Kellogg, 2019), and maize plants are sensitive to heat stress (temperatures >30 °C), pollen viability and silk receptivity during different maize growth stages can be restricted, significantly reducing seed setting and grain yield (Shin et al., 2020). The Intergovernmental Panel on Climate Change (IPCC) sixth assessment report (AR6) provides evidence that global temperatures are predicted to rise by 1.5-4 °C over the next century (IPCC, 2021). Therefore, heat stress and temperature fluctuation have the potential to be a source of variability and decline in maize production (Southworth et al., 2000; Kucharik & Serbin, 2008; Wang et al., 2018; Sabagh et al., 2020).

Maize (*Zea mays* L.), is the most abundant crop grown in the United States (USDA NASS, 2020) and is a major contributor to the economy of the country due to its wide range of uses (Ranum et al., 2014). Kansas is a part of the U.S. Corn Belt, it contributes approximately 5% of the total U.S. maize production (USDA NASS, 2020). The east to west precipitation gradient in Kansas makes eastern Kansas ideal for growing crops under rainfed conditions and maize is one of the major cereal crops grown in northeast Kansas. Since, under changing climate, the severity of extreme events (heat waves and changing precipitation patterns) has increased in Kansas (Lin

et al., 2017) rainfed crop-growing areas have become more susceptible to yield disruptions (Anderson et al., 2016) making these areas growing rainfed maize vulnerable.

Several climate changes studies (Challinor et al., 2014; Lobell et al., 2014; Asseng et al., 2015) focus on a large spatial scale (country or continent) impact analysis and do not consider soil variability as a significant factor in agricultural yield analyses. Since crop growth is sensitive to both spatial (soil properties) and temporal (precipitation and temperature) factors (Armstrong et al., 2009), crop performance can be significantly influenced by soil variability, particularly in dry situations when spatial variability in soil texture can drive the influence of moisture scarcity, affecting plant growth (Milewski et al., 2022). Several studies analyzed soil-dependent responses of US crop yields under changing climate (Huang et al., 2020), and concluded that apart from precipitation and temperature, crop yields are also highly dependent on soil properties such as soil texture (Butcher et al., 2018), nutrient availability (Liu et al., 2018), and soil water storage (Schyns et al., 2019). Since soil variability can be very high even at a fine spatial scale (0.1 to 10 km) (Rounsevell et al., 2003), in order to develop adaptation strategies and sustainable production systems, it is crucial to understand how future climate change interacts with spatial soil variability to impact crop yield at a regional scale.

Crop simulation models are valuable tools for analyzing the impact of climate change and other environmental factors on crop yield and growth (Asseng et al., 2014). The Cropping System Model (CSM) of the Decision Support System for Agrotechnology Transfer (DSSAT) can simulate crop growth, development, and yield in response to variations in weather, soil properties, and management practices (Jones et al., 2003; Amin et al., 2017; Hoogenboom et al., 2021). The DSSAT CSM is a point scale model that can account for factors; like cultivar genetics, soil water, soil carbon and nitrogen, and crop management practices for single-season or multiple

seasons/crop rotation simulations at any location. Researchers worldwide have used the DSSAT CSM extensively for various applications (Pathak et al., 2007, Thorp et al., 2014) and several studies in the past have used the DSSAT model to simulate crop water use and production and evaluate management strategies under different environmental conditions (Sarkar et al., 2006; Boote et al., 2017; Boonwichai et al., 2018). DSSAT has also been employed at various temporal and spatial scales to model climate change impacts on crop production (Carbone et al., 2003; Tubiello et al., 2008) and to forecast yield (Soler et al., 2007; Yakoub et al., 2017; Anar et al., 2019).

Crop Estimation through Resources and Environmental Synthesis (CERES) Maize (Jones & Kiniry, 1986) model in DSSAT can simulate crop growth and water and nitrogen balance at a daily time step by simulating processes of soil water, nutrient, and plant growth, along with options to simulate and analyze management strategies for yield components and end of season crop yield. The DSSAT CERES-Maize model has been used to study the impact of spatial soil variability and climate variability signals on maize yield in Southeast United States (Sharda et al., 2017), and it was found that the maize yield was significantly affected by the spatial distribution of soils. The DSSAT CERES-Maize model under future climate reported yield loss in Midwest USA (Southworth et al., 2002) and indicated the need for adaptations to climate change to increase the maize yield. Araya et al., 2017 used the DSSAT CERES-Maize model to evaluate the impact of future climate change on irrigated maize production in western Kansas and found that a decrease in yield may be primarily due to a shortening of the growth season (9–18% less time till maturity), which is caused by high temperatures and consequently, the authors developed irrigation strategies for the region for future climate scenarios (Araya et al., 2021).

It is becoming increasingly important to understand the impact of climate change on regional future crop yield and investigate the effects of spatial soil variability on yield to adapt to feeding a growing world population. Most of the past studies have focused on the climate change impact on irrigated maize yield and its adaptation strategies. However, no past studies have evaluated the use of DSSAT-CERES-MAIZE model for rainfed maize yield projection while considering the impact of spatial soil variability. This study focuses on investigating the impacts of the spatial distribution of soil on rainfed maize yield under future climate change scenarios. The specific objectives addressed in this study are i) to determine the impact of the spatial distribution of soils on rainfed maize yield at a regional scale and ii) to determine spatial maize yield change under future climate change scenarios.

3.2. Materials and Methods

3.2.1 Study area

Our study domain consists of ten rainfed maize-producing counties in Kansas: Brown, Nemaha, Jackson, Jefferson, Atchison, Pottawatomie, Marshall, Shawnee, Riley, and Geary (Fig. 3.1). The study region is situated in northeastern Kansas between latitudes 39° 0' and 40° 0' and longitudes 95° 0' to 97° 0'. The elevation of the study area is between 340-376 m above sea level, with the climate categorized as humid (Howard et al., 2016). The long-term average growing season precipitation, maximum and minimum daily temperatures (May to October) are nearly 676 mm, 21.2°, and 12.3° C, respectively.

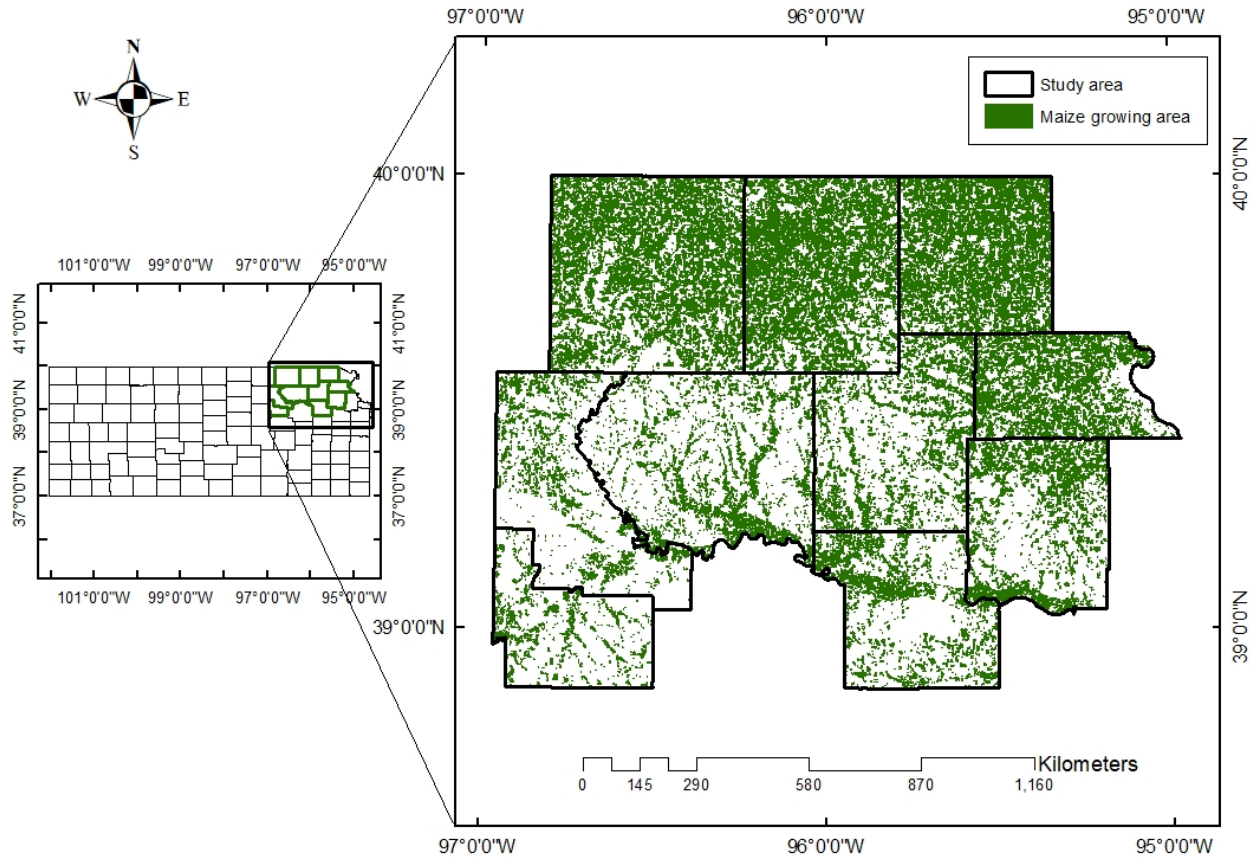


Figure 3.1. Map shows our study area, which consists of ten rainfed maize-producing counties in northeastern Kansas. Green color showed the maize growing area in our study region (USDA CDL, 2019)

3.2.2 DSSAT CERES-Maize Cropping System Model

3.2.2.1 Model Description

The DSSAT CERES-Maize Model v4.8 (Hoogenboom et al., 2021) was used to simulate maize growth in response to the soil, genotype, management, and baseline (1990-2019) and future climate change conditions across the study area. The model requires a variety of soil parameters, including bulk density, organic carbon content, hydraulic conductivity, slope, albedo, color, drainage, the drained upper limit (DUL), lower limit (LL), saturated water content (SAT), and soil

texture. Additionally, the model needs inputs for information on cultivars, the environment, and crop management (Jones et al., 2003). The planting date and method, seedling depth, plant population, row spacing, cultivar characteristics, tillage type, tillage depth, irrigation method, irrigation amounts and dates, fertilizer application method, fertilizer amount and dates, and harvesting date and method are all necessary crop management parameters. Environmental variables such as daily maximum and minimum temperature, incoming solar radiation, and precipitation are also required as inputs, while dew point temperature and wind speed are optional. A flowchart of steps undertaken to simulate historic and future maize yields are shown in Fig 3.2.

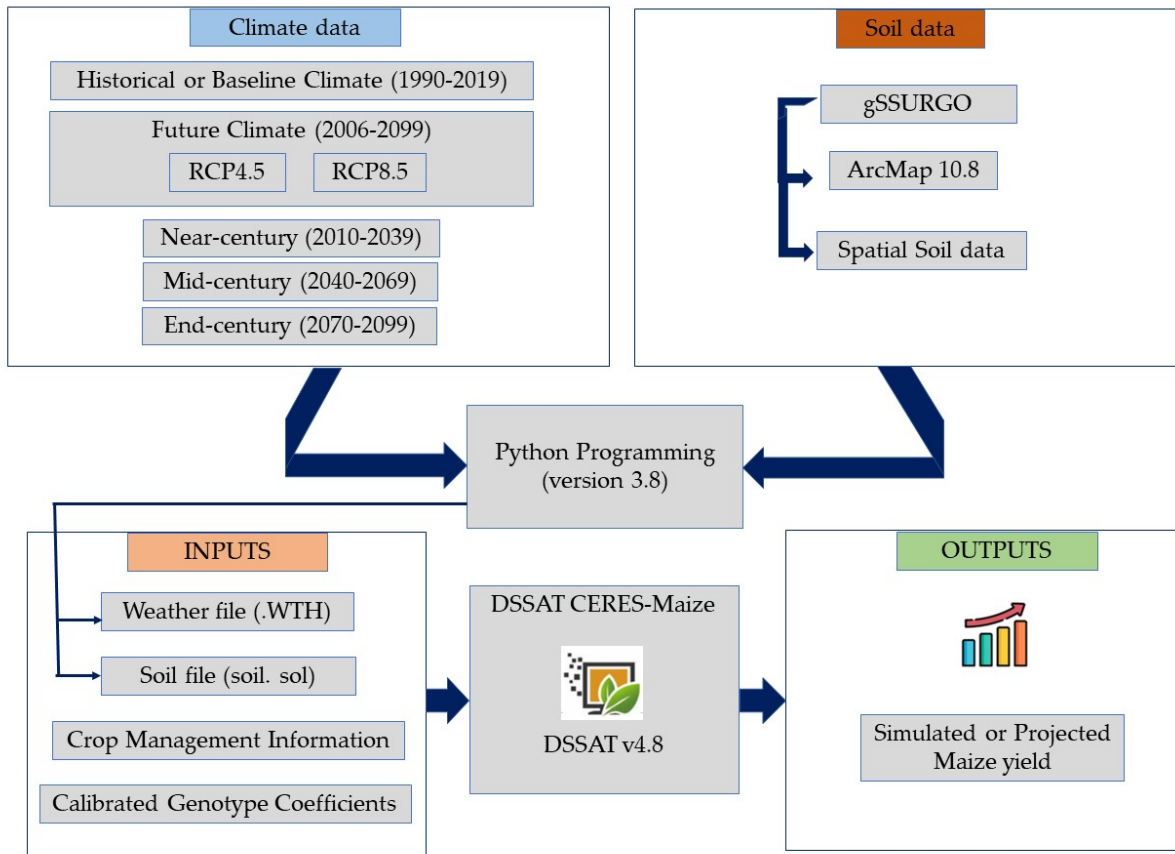


Figure 3.2. A flowchart illustrating the simulation and projection made by the DSSAT CERES-Maize model based on spatial soil variability and climate data.

3.2.2.2 Model Inputs

3.2.2.2.1 Climate Data

For this study, the baseline (historic) climate data, such as daily maximum and minimum temperatures, precipitation, solar radiation, wind speed, and relative humidity, were obtained from the Gridded Surface Meteorological (gridMET) dataset (Abatzoglou, 2012) for 30 years (1990-2019). The future climate data was the output from 18 GCMs (Table 3.1) from CMIP5 was

extracted and statistically downscaled using the Multivariate Adaptive Constructed Analogs (MACAv2) methodology (Abatzoglou, 2012). Each model and experiment aggregated daily maximum and minimum temperature, wind speed, precipitation, relative humidity, and solar radiation from the 4 km downscaled resolution to the county level between 2006 and 2099. The data was formatted in an annual time scale, and three 30-year periods were calculated to represent a near (2010-2039), mid (2040-2069), and end (2070-2099) century climate projections. Data were generated for two representative concentration pathways (RCPs) RCP4.5 and RCP8.5 for each GCM. These data were used as weather inputs in the DSSAT model, creating a multi-model ensemble of 18 models per experiment for each DSSAT treatment. Additionally, mean temperature and precipitation accumulation were calculated under each RCP scenario (near, mid and end century) and ArcGIS 10.8 was used to map the severity (ESRI,2020), to indicate the changes in temperature and precipitation patterns in the study region.

Table 3.1. List of global climate models and their source

Models	Source
BCC_CSM1.1	Beijing Climate Center, China Meteorological Administration, China
BCC_CSM1.1-m	Beijing Climate Center, China Meteorological Administration, China
BNU-ESM	Beijing Normal University, China
CanESM2	Canadian Centre for Climate Modelling and Analysis, Canada
CNRM-CM5	National Centre for Meteorological Research, France
CSIRO-Mk3.6.0	The Commonwealth Scientific and Industrial Research Organization, Australia
GFDL-ESM2G	Geophysical Fluid Dynamic Laboratory, USA
GFDL-ESM2M	Geophysical Fluid Dynamic Laboratory, USA
HadGEM2-CC365	Met Office Hadley Center, UK
HadGEM2-ES365	Met Office Hadley Center, UK
inmcm4	Institute of Numerical Mathematics, Russian Academy of Sciences

IPSL-CM5A-LR	Institute Pierre-Simon Laplace, France
IPSL-CM5A-MR	Institute Pierre-Simon Laplace, France
IPSL-CM5B-LR	Institute Pierre-Simon Laplace, France
MIROC5	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (University of Tokyo Japan)
MIROC-ESM	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (University of Tokyo Japan)
MIROC-ESM-CHEM	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (University of Tokyo Japan)
MRI-CGCM3	Meteorological Research Institute of Japan

3.2.3.2.2 Soils Data

Gridded Soil Survey Geographic (gSSURGO) database was used to account for the spatial soil variability (USDA NRCS, 2016) in the study area. The gSSURGO dataset was created for national, regional, and statewide resource planning and analysis of soil data, provides soil data for all counties of the conterminous U.S., and contains all the soil properties required for DSSAT, such as sand, silt, and clay percentages, organic carbon content, pH, color, cation exchange capacity, drainage rate, etc. Soil data development toolbox in ArcMap 10.8 (ESRI, 2020) was used to extract the soil information and create the attribute table containing all the required information from various soil depths. The desired soil properties were then exported from the database to Microsoft Excel, which was used as the input for Python (Python 3.8, 2009) that was built to convert these profiles into a DSSAT-compatible soil (soil. sol) file.

The USDA NASS Cropland Data Layer (CDL) (USDA NASS, 2019) was used to get the rainfed maize mask for ten selected counties in our study area. We ran the DSSAT model for each soil present in the maize growing area of each county and created the yield maps in ArcMap 10.8 by assigning yield values for each soil.

3.2.3.2.3 Crop Management Data

The crop management practices for the DSSAT model simulations were based on recommendations from the Kansas State University's Research and Extension (Ciampitti et al., 2023). Rainfed practices were simulated for planting dates ranging from April 1 to May 20, depending on the location of the county. The plant population was set to 7.6 plants/m², row spacing was 0.51 m, and 170 kg/ha of nitrogen fertilizer was applied as Urea equally divided over two, in-season applications. To isolate the crop model's reaction to weather and soil type, only soil and weather variables were allowed to vary from simulation to simulation (Fig.3.2).

3.2.3 Cultivar Calibration

In the DSSAT CERES-Maize model, yield and phenology are determined by six genetic coefficients (Table 3.2), and the calibration process attempts to get accurate estimates of these coefficients by comparing simulated and observed data. The model calibration was performed using rainfed crop yield data that was obtained using USDA's Quickstat 2.0 database (USDA NASS, 2016). The first step to calibrate the DSSAT model was to adjust the soil fertility factor (SLPF). The soil fertility factor (SLPF), a parameter input linked to variations in soil fertility and soil-based pests, affects the overall growth rate of simulated total biomass by altering daily canopy photosynthesis, and ranges from 0.7 to 1. The default value of SLPF for this study was set to 1, and the value was adjusted manually by checking for the Root Mean Squared Error (RMSE) that gave the least difference between the simulated and observed maize yields. Genotype Coefficient Calculator (GENCALC) was used to calibrate the cultivar parameters with corresponding observations and manually adjusted the remainder of the coefficients (Bao et al., 2016; Hunt et al., 1993; Adnan et al., 2019). GENCALC automatically calibrated the cultivar genetic coefficients

G2 and G3, and the cultivar phenological coefficients P1, P2, P5, and PHINT were adjusted manually by a certain percentage.

Table 3.2. Cultivar coefficients for the CERES-Maize model

Coefficient	Definition	Units	Min.	Max.	Calibrated Value
P1	Thermal time from seedling emergence to end of juvenile phase.	°C days	5.0	450.0	270.0
P2	Extent to which development is delayed for each hour increase in photoperiod above the longest photoperiod at which development proceeds at a maximum rate.	day h ⁻¹	0.0	2.0	0.660
P5	Thermal time from silking to physiological maturity.	°C days	580.0	999.0	895.0
G2	Maximum possible number of kernels per plant.	kernel plant ⁻¹	248.0	990.0	875.0
G3	Kernel filling rate during the linear grain filling state and under optimum conditions	mg d ⁻¹	5.0	16.50	8.80
PHINT	Interval in thermal time between successive leaf tip appearances.	°C days	38.0	75.0	48

3.2.4 Model Evaluation and Statistical Analysis

We selected widely used statistical parameters to assess crop model performance (Anothai et al., 2008; Yang et al., 2015; Soler et al., 2007). The following criteria were used to compare simulated, and observed data for both calibration and evaluation: RMSE and index of agreement (d) or d-stat (Willmott et al., 2012), given by following equations:

Equation 3.1. Root Mean Square Error

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

Equation 3.2. Index of Agreement

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

The lower the RMSE value is and the closer the value of d-stat is to 1, the better the simulation. In addition, the coefficient of determination (R^2) was also calculated to evaluate the goodness of fit for the model calibration (i.e., the observed and simulated yield for gSSURGO soils). The coefficient of determination (R^2) is considered the most commonly used method for describing the variance between simulated and observed values (equation 3.3). It ranges from 0 to 1, where higher values represent a good model performance, and an $R^2 > 0.5$ is generally considered satisfactory (Golmohamadi, 2014).

Equation 3.3. Coefficient of Determination

$$R^2 = \left[\frac{\sum_{i=1}^n (O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^n (O_i - \bar{O})^2 (P_i - \bar{P})^2}} \right]^2$$

Where n is the number of observations, P_i is the simulated value for the i th measurement, O_i is the observed value for the i th measurement, and $P_i' = P_i - \bar{P}$ and $O_i' = O_i - \bar{O}$, where $\bar{O}$ is the mean of all observations.

The Pearson correlation coefficient (r) was calculated to assess (linear) associations between yields and climatic parameters (temperature, precipitation, and CO_2 concentration) under climate change scenarios. This correlation coefficient analysis was conducted to determine the strength and direction of the linear relationship between two continuous variables, and it ranged between -1 to 1 (Swinscow & Campbell, 2002). The formula adopted for calculating Pearson's correlation coefficient is given by the following equation,

Equation 3.4. Pearson's Correlation Coefficient

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{[\sum_{i=1}^n (x_i - \bar{x})^2][\sum_{i=1}^n (y_i - \bar{y})^2]}}$$

Where x_i and y_i are the values of x and y for the i th individual.

3.3 Results and Discussion

3.3.1 DSSAT Performance

The DSSAT–CERES-Maize model assessment showed high accuracy with an RMSE of 1309 kg/ha and d-statistic of 0.88 (Fig.3.3). The differences between simulated and observed grain yield were no more than 10% of the observations for the calibration period. The model performance during calibration based on end-of-yield followed other studies (Liu et al., 2018; Malik et al.,2019; Sharda et al.,2021) and showed high d-stat values with low RMSE errors between the observed and simulated yield, thus, confirming the fitness of the model for the intended use.

During the model evaluation period, observed and simulated end-of-season yields matched closely (Fig.3.3), with an RMSE of 1472 kg/ha and d-statistics of 0.86. Simulated and observed mean yield values during the evaluation were 8,896kg/ha and 8,299kg/ha, respectively. The difference between the simulated and observed yield was less than 12% during evaluation period. The DSSAT CERES-Maize model overestimated maize yield for almost all simulations, which was expected because the observed yield from the field is limited by weeds, insects, etc., which were not considered during the model simulation.

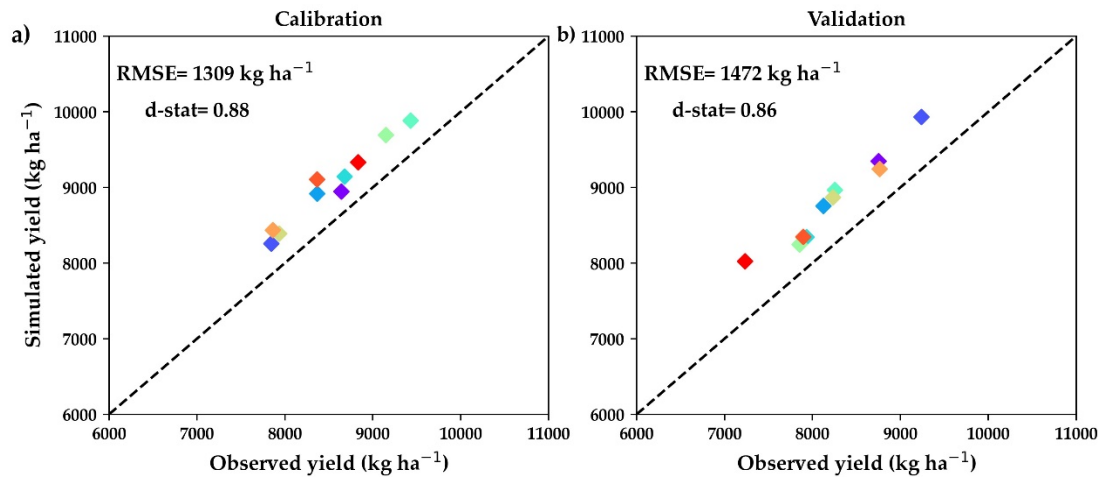


Figure 3.3. DSSAT CERES-Maize model a) calibrated for 2000- 2006 and b) validated for 2015 - 2019 for the ten maize producing counties of northeastern Kansas.

3.3.2 Impact of Soil Variability on Maize Yield

The number of soils (gSSURGO) underlying the USDA NASS maize crop mask in each county ranged between 12 to 51 soils with the largest spatial soil variability in Riley and Pottawatomie County and the lowest in Jackson County (Fig.3.4). It was found that Pawnee clay loam, Wymore silty clay loam, and Kennebec silt loam were the three most commonly found soils in the region.

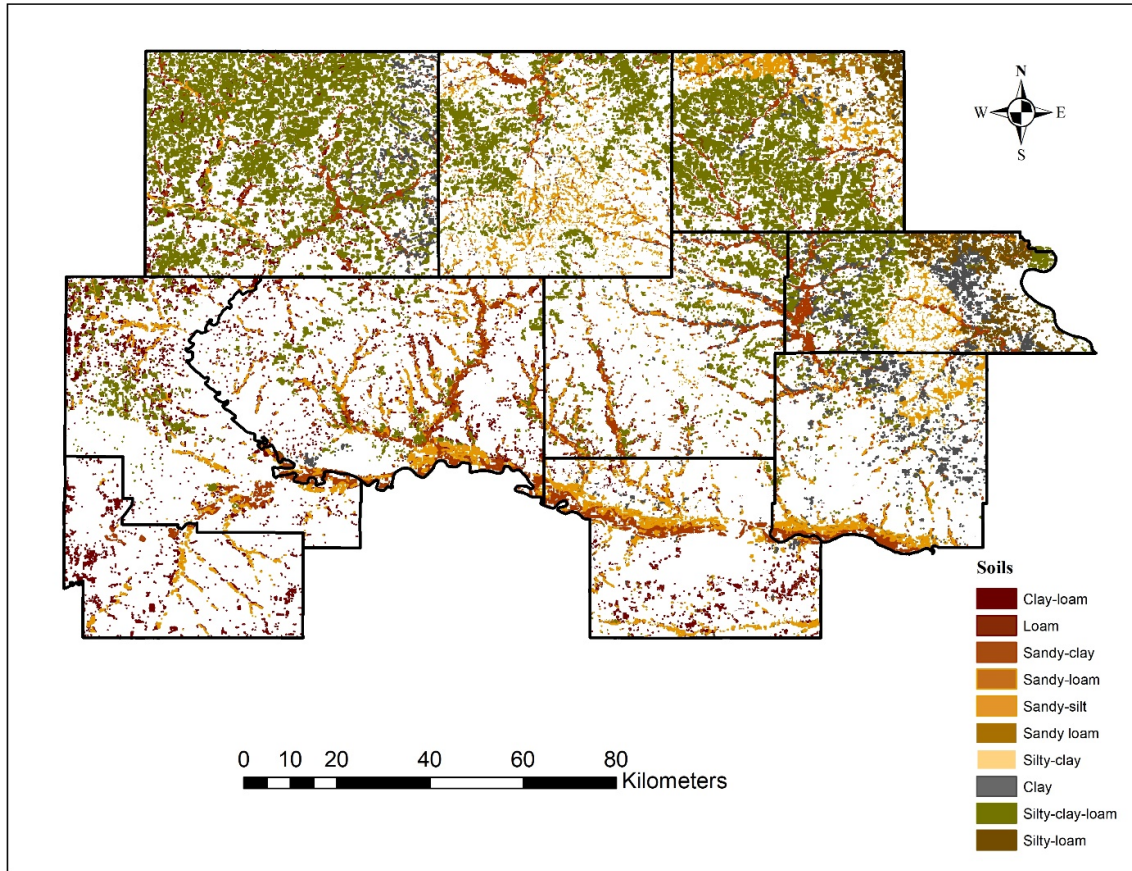


Figure 3.4. Spatially distributed soils in the study area

Table 3.3 shows simulated maize yields that were compared with observed yields for the study region to assess the impact difference in model performance when using 1 most common soil of each county, 3 dominant soils per county and spatially distributed soils. Under the baseline study period, Brown County had the highest rainfed maize-producing county (9,692 kg/ha) whereas Geary County had the lowest simulated yield (5,777 kg/ha). The average annual yield varied significantly ($p < 0.05$) and the result reflected that the average of simulated yields when using spatially distributed gSSURGO soils were the closest to observed yields in the region as compared to simulated yields when using one or three dominant soils for each county. The d-stat for gSSURGO simulations ranged from 0.81 to 0.92, demonstrating the model's strong capacity to simulate yield under the given. Results of correlation analysis showed that the R^2 value ranged

between 0.79 to 0.85 indicating that, for the spatially distributed gSSURGO soils, the model performed well, and closely mimicked the observed yield (Fig. 3.5).

Table 3.3. Average observed and simulated maize yield with d-stat and RMSE, for ten counties and various soil types

County	Observed Yield (Kg/ha)	Simulated Yield (kg/ha)			d-stat			RMSE		
		1	3 soils	SSU- RGO soils	1	3	SSU- RGO soils	1	3	SSU- RGO soils
		soil			soil	soils		soil	soils	
Brown	9692	8765	8852	9084	0.79	0.85	0.92	2199	1689	731
Nemaha	7717	8836	8683	8168	0.86	0.86	0.89	1939	1384	976
Jackson	7609	8624	8201	7794	0.82	0.85	0.87	1734	1534	1326
Jefferson	7946	9243	8851	8247	0.81	0.84	0.85	2059	1512	1116
Atchison	8890	7643	9545	9326	0.76	0.87	0.91	2612	1513	876
Pottawatomie	7368	8468	8310	8173	0.87	0.87	0.89	1801	1741	982
Marshall	7534	8079	7817	7586	0.87	0.89	0.87	1746	1187	1233
Shawnee	7645	8167	8136	7966	0.86	0.89	0.90	1959	1439	1079
Riley	7906	8681	8467	8277	0.88	0.89	0.92	1309	1396	909
Geary	5777	7825	7184	6830	0.71	0.82	0.81	1898	1885	1612

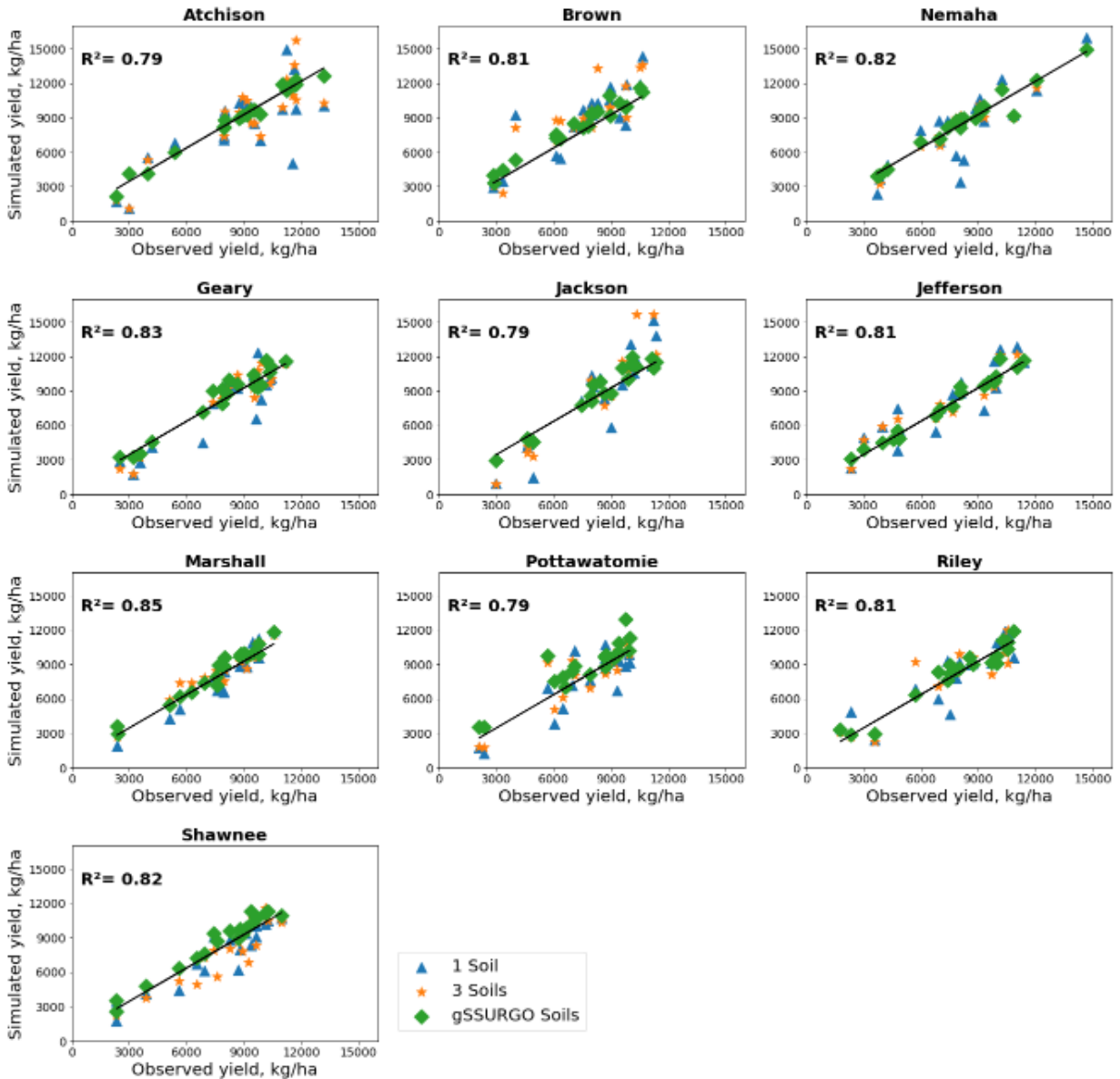


Figure 3.5. Comparison between DSSAT-CERES simulated and observed yields for the baseline study period (1990-2019) in the top ten maize-producing counties of eastern Kansas while using 1 most dominant soil, 3 most dominant soils, and spatially distributed gSSURGO soils for each county.

Maize yields ranged from 4222 kg/ha to 12261 kg/ha, with a regional average of 8745 kg/ha across soils. The high-yielding and low-yielding areas were identified in the northeast and

southwest part of the study area, respectively (Fig.3.6). However, there was a large yield variability within the study region due to the spatial distribution of soils. Since soil type, texture, structure, and soil physical, chemical and engineering properties like pH, moisture content, and drainage capacity can highly influence crop yields across a field (Plant, 2001; Quine, 2002; Huang et al., 2007); there was a significant yield variation observed around the study area even when all other crop management practices remained the same.

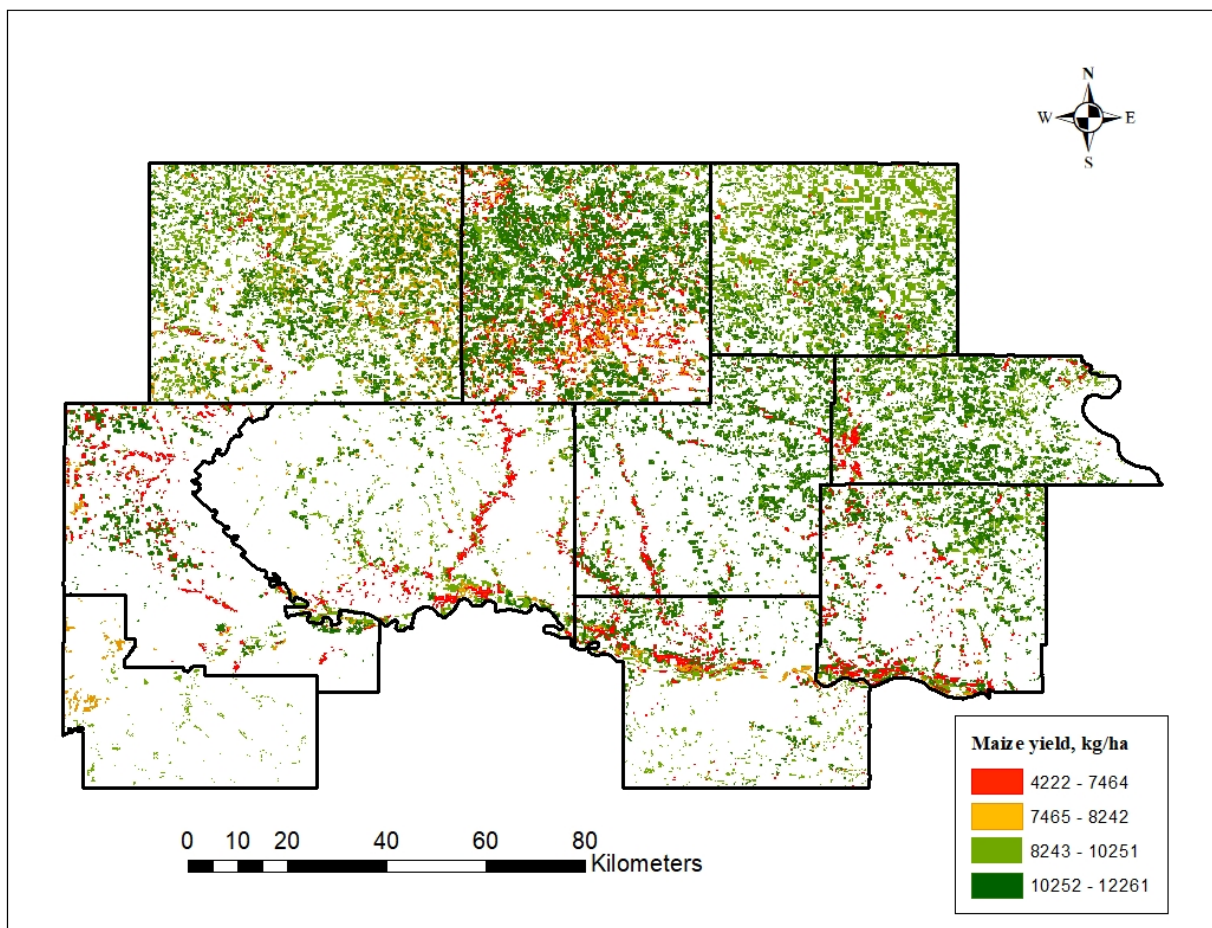
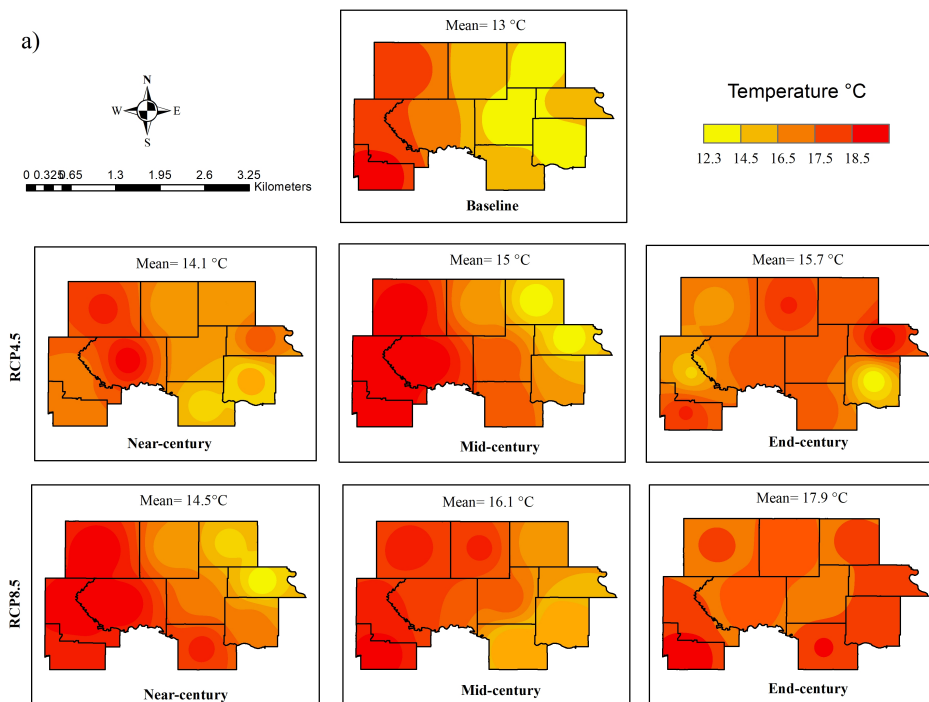


Figure 3.6. Variation of maize yield due to the spatial distribution of soils in the ten rainfed maize-producing counties of northeastern Kansas (dark green areas on the map indicate higher simulated maize yields whereas red color shows areas with extremely low yields).

3.3.3 Projected Changes in Temperature and Precipitation

Based on the analysis of temperature and precipitation data generated by the 18 GCMs for two RCP scenarios, it was observed that there is an increasing trend in mean temperature with increasing CO₂ concentration (Fig. 3.7) whereas the future precipitation values did not follow any specific pattern over the study area. The highest mean temperature recorded at the end of the century under RCP8.5 was 5°C higher than the 30 years baseline study period (1990-2019). Future precipitation analysis also showed that as compared to the baseline period, the study area received less precipitation as compared to historic values and became dryer at the end of the century under both RCP scenarios. These results are consistent with other studies that have focused on changes in climate of the future (Amin et al., 2017; Herring et al., 2018). This trend of lower precipitation in the region can probably be attributed to extreme heat occurrence as reported in some past studies conducted in the United States (Almazroui et al., 2021; Yue et al., 2021).



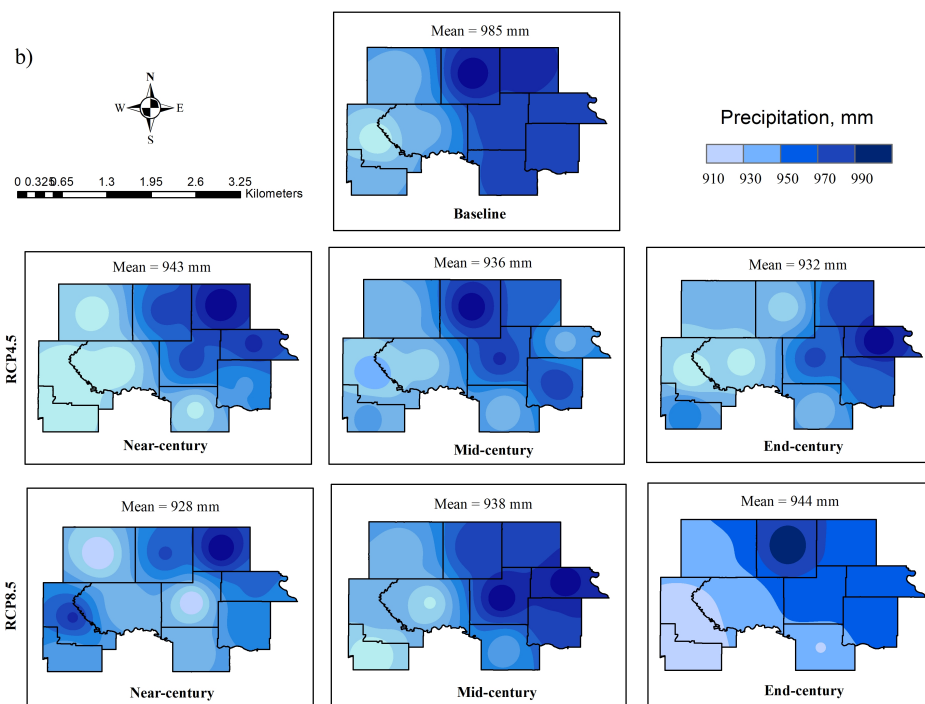


Figure 3.7. Spatial distribution of a) annual mean temperature ($^{\circ}\text{C}$) and b) precipitation (mm) obtained from the ensemble mean of 18 GCMs for near-century (2010-2039), mid-century (2040-2069), and end-century (2070-2099) under RCP 4.5 and RCP 8.5 emission scenarios in comparison to the baseline (1990-2019) study period for ten rainfed maize producing counties in northeast Kansas.

3.3.4 Climate Change Impact on Maize Yield

The impact of changes (with respect to baseline period) in average maximum temperature and total precipitation during the maize growing season in the near, mid, and end of century under both RCP scenarios impacted yield simulations for all future conditions with the highest yield simulated during near century (2010-2039) under RCP 4.5 scenario and the lowest yield simulated under RCP8.5 at the end of the century (2070-2099) (Table 3.4).

Table 3.4. Summarized average climatic parameters along with average yield under different climate change scenarios during the maize growing season (May-September)

Scenarios	Time	Maximum Temperature, °C	Total Precipitation, mm	CO ₂ Concentration, ppm	Yield, Kg/ha
Base Period	1991-2019	21.92	676	412	8546
	2010-2039	23.32	640	458	7741
RCP4.5	2040-2069	24.52	632	523	6514
	2070-2099	25.02	623	538	6225
RCP8.5	2010-2039	23.62	589	485	7658
	2040-2069	25.32	612	750	6164
	2070-2099	27.42	636	927	3304

The correlation analysis showed a strong negative correlation between maize yield and temperature (0.96), followed by the CO₂ concentration (0.93) (Fig.3.8) which implies that higher temperature and CO₂ concentration tend to adversely impact yields. However, there was a positive correlation between precipitation and maize yield, and the Pearson coefficient was 0.46. So, contrary to the effect of increase in temperature and CO₂ concentration, an increase in precipitation is related to an increase in maize yield. One issue that should be noted is that increased precipitation is connected with yields up to a limit where excessive precipitation might cause water logging or flooding, which can lower yields. These findings confirm a study by Lobell et al., 2014 that suggested that high-temperature days with low precipitation conditions during the critical growth stages of maize significantly reduced yield in the United States.

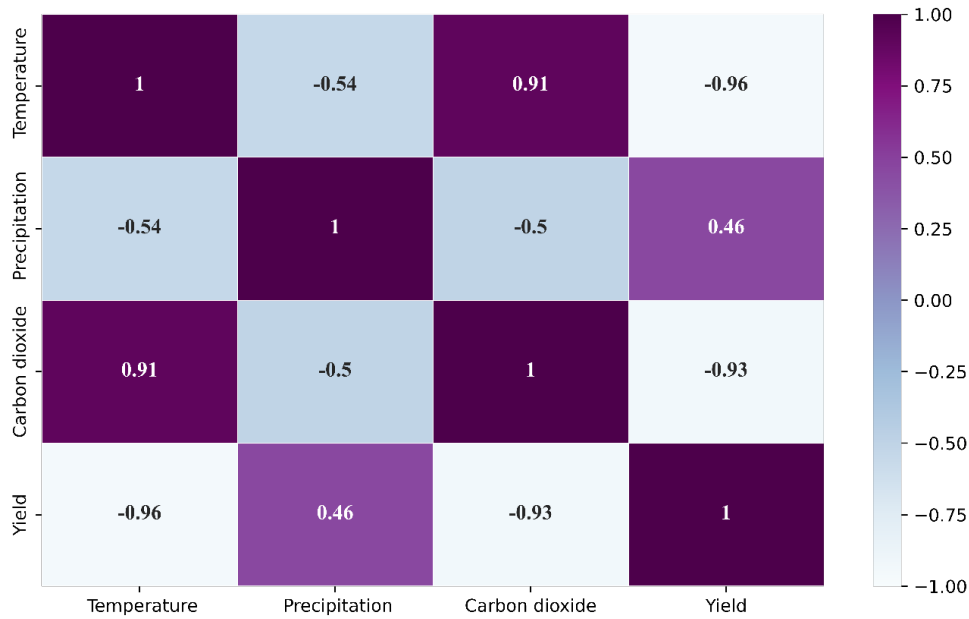


Figure 3.8. Pearson correlation coefficient heatmap of maize yield with temperature, precipitation, and CO₂ concentration under baseline, near, mid and end century (RCP4.5 and RCP8.5) scenarios.

Fig. 3.9 shows the changes in yield for ten counties of northeastern Kansas by comparing the future projected maize yields to the baseline yields in terms of percent difference. A yield loss was observed for the future climate under both RCP4.5 and RCP8.5 scenarios. All ten counties observed simulated yield loss with the losses ranging from 4-12%, 12-18%, and 22-34%, for RCP 4.5 and 12-19%, 23-27%, and 39-57% under RCP8.5 in the near, mid, and end-century, respectively.

It must be noted that higher yield loss was observed under RCP8.5 as compared to RCP4.5 which can most likely be explained by high-temperature days, high CO₂ concentration levels, and relatively smaller change in precipitation values under RCP 8.5 emission scenario. High yield producing counties during the baseline period - Atchison, Brown, and Nemaha - exhibited lower yield loss than other counties in the study region under all climate change scenarios. This county-

scale yield analysis explored the magnitude of yield loss over time and highlighted counties that were relatively less affected by climate change. According to Srivastava et al. (2018), the effects of climate change on maize yield depend on how changes in temperature and precipitation amounts combine to bring about shifts in the onset and length of future growing seasons. Therefore, the decline in precipitation and high-temperature days under future climate tends to lower yields under all climate change scenarios. A finding of a comprehensive study conducted in Africa by Dale et al. (2017) also mentioned that the leading causes of maize yield loss were the high temperatures and changes in precipitation patterns.

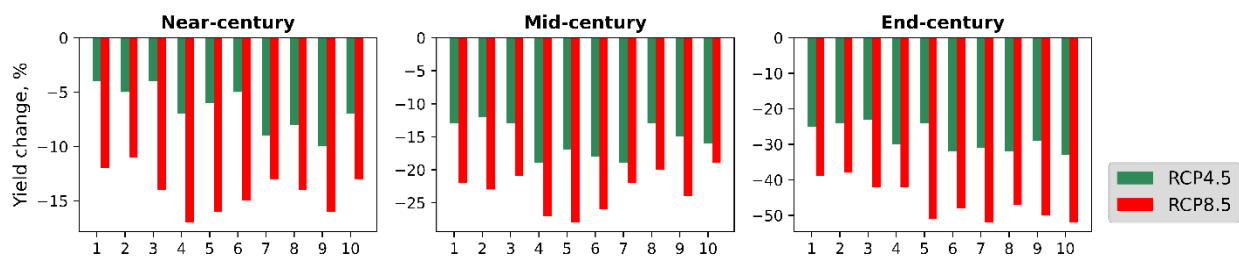


Figure 3.9. Pearson correlation coefficient heatmap of maize yield with temperature, precipitation, and CO₂ concentration under baseline, near, mid and end century (RCP4.5 and RCP8.5) scenarios.

3.3.5 Mapping Future Rainfed Maize Yield Variability

Under RCP4.5, in the near, mid, and end centuries, the regional average yield was 7865 Kg/ha, 6776 kg/ha, and 6198 kg/ha, respectively. Similarly, under RCP8.5, it was 6985kg/ha, 5678kg/ha, and 4744 kg/ha, respectively. The average yield loss for the entire region under RCP4.5 and RCP8.5 in the near, mid, and end centuries was 7, 16, 28%, and 14, 23, 45%, respectively. The climate change impact was less in the northeastern part of the study region under RCP4.5 for all the study periods (Fig. 3.10). However, under RCP8.5, no specific pattern of yield loss was identified but the entire region observed higher yield loss when compared to the RCP4.5 scenarios.

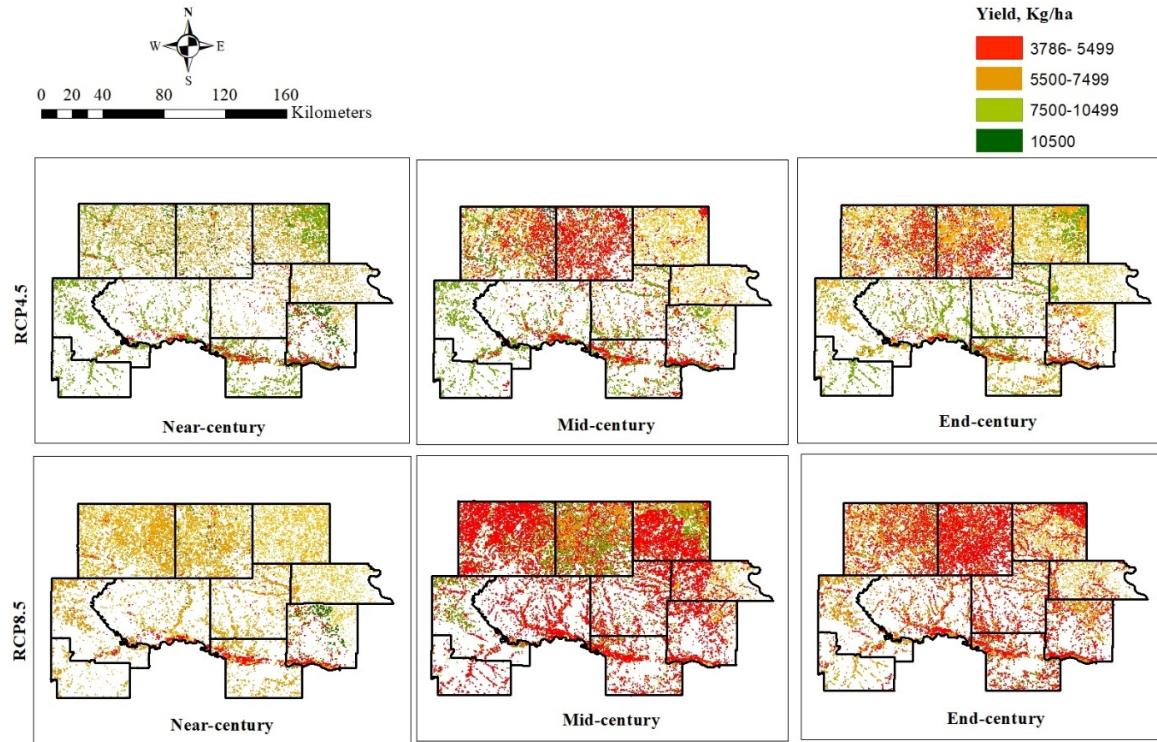


Figure 3.10. Yield variation under changing climate in ten maize-producing counties in northeastern Kansas under three study periods (near, mid, and end-century) for RCP4.5 and RCP8.5. The red color stands for low-yielding and the green for the high-yielding region.

3.4 Summary and Conclusions

This study used calibrated and validated DSSAT CERES-Maize model in ten rainfed maize-producing counties in northeastern Kansas. The seasonal analysis feature of DSSAT was used to simulate maize yields for the 30-year baseline study period and for future climate scenarios using forecasted climate from 18 GCMs and under two CO₂ emission scenarios RCP 4.5 and RCP 8.5 to determine how yields are impacted by changing temperature and precipitation along with studying the impact of spatial soil variability in the region. Since the differences between simulated and observed yield were at most 10% for calibration and less than 12% for evaluation period selected, the model performance was considered satisfactory based on the statistics calculated. Although the model generally overestimated maize yields for all counties and soil conditions. The

effect of climate change on maize yield agreed with previous studies that have been conducted in the region and that have demonstrated the effects of changing forecasted temperature and precipitation values on crop production in the Midwestern U.S. (Southworth et al.,2002; O’Neal et al.,2005; Basche et al.,2016; Jin et al.,2018). The study emphasized how the spatial distribution of soils influenced yield variation under the same climate. Maps created by overlapping soil type, maize mask, and yield simulations illustrated the spatial variability in maize yield attributable to soil variability. The future yield distribution maps under changing climate also show the variation of yield due to changing climate. These maps allow us to examine yield variation under different climate change scenarios and emphasize that soils are essential in considering yield variation in climate change studies. The impacts of future climate change on maize yields in our study area also suggest that using GCM forecasts to predict maize yields could enhance maize production in the Midwestern U.S. Since most of the area used in this study is rainfed, these results also highlight the relationship between maize yield and soil conditions.

Soil variability in the study strongly affected the spatial variability yields simulated by the calibrated validated DSSAT model for the 30-year baseline study period (1990-2019). Using spatially distributed gSSURGO soils as input to simulate maize yield was statistically better for almost all counties as compared to using the most dominant soil or using the top three soils for each county, which resulted in higher overestimations of yield. There is large spatial soil variation in the region and mapping yield variation under different climate change scenarios allows stakeholders and farmers to manage areas that may need specific or targeted management strategies (for e.g., water and nutrient).

The DSSAT model projected maize yield loss substantially higher under RCP8.5 as compared to RCP4.5. At the end of the century, under RCP8.5, the highest yield loss was observed, and an average of 45% reduced maize yield was recorded for the study region. Furthermore, the correlation analysis found a strong negative correlation between maize yield with temperature and CO₂ and a moderate positive relation with the precipitation pattern of the study area. Hence, it can be concluded that the study area could observe a higher maize yield loss under the future climate due to the high temperature and low precipitation pattern as compared to the baseline study period.

Overall, it can be concluded that this well-calibrated and validated DSSAT CERES-Maize model can be used to quantify the impacts of climate change and spatial soil variability on maize yields under different synthetic scenarios. The key findings of this study include that spatial soil variability can impact maize yield and that using spatially distributed soils produce better simulation of yield as compared to using the most dominant soil in a county. This study found that, under future climate change conditions, the ten top rainfed maize producing counties of northeastern Kansas would lose substantial maize productivity. More importantly, this study identifies the vulnerable part of this region under changing climate, which could be a valuable input to develop region-specific adaptation strategies based on quantifying the impact of climate and spatial soil variability on maize yield. The results of this study will be used as a basis of a future study that will include crop suitability analysis and this methodology could be adopted to assess climate change's impact on other crops across the world.

Chapter 4 - Impact of Climate Change on Suitability of Major Crops in the Eastern Kansas River Basin

Abstract

Climate change impacts are a serious threat to food security and the economy. The increasing heat and drought under the changing climate have made maize and soybean production unstable in regions under rainfed agriculture. Thus, assessing the suitability and yield reduction of major crops under climate change is crucial for sustainable agricultural production. In this study, the DSSAT crop simulation model was used to identify suitability of maize and soybeans by determining the yield gap percentage ($YG_{percentage}$) under baseline (1990-2019) and future (2006-2099) climate change scenarios (RCP4.5 and RCP8.5) for 17 counties of the Eastern Kansas River Basin (EKSRB). The results showed higher yield loss associated with RCP8.5 scenarios as compared to RCP4.5. The increasing yield gap trend under both RCPs points out the reduction of the suitability of growing maize and soybean under future climate change scenarios in EKSRB. The study found less suitable maize-growing areas than soybean under both RCPs, where the highest yield gap percentage for maize and soybean was 52% and 43%, respectively. The result concluded that the projected suitable crop-growing areas in the EKSRB will shift with a significant yield loss, where soybean could be a more suitable crop in the future. This study helps to provide insights into how climate change is affecting the conditions for growing crops, which could be helpful for farmers and policymakers to choose crops that would be resilient to climate change conditions, and plan for sustainable agriculture.

Keywords: DSSAT model, agriculture, maize, soybean, yield gap, emission scenarios

4.1 Introduction

The increasing heat and drought under the changing climate have made maize and soybean production unstable in the Eastern Kansas River Basin (Zipper et al., 2016). Climate change increases the frequency and intensity of extreme events, considerably impacting agricultural production and introducing vulnerability to global food security (Joos et al., 2001; Steiner et al., 2018). The Intergovernmental Panel on Climate Change (IPCC) sixth assessment report (AR6) provides evidence that global temperatures are predicted to rise by 1.5-4 °C over the next century (IPCC, 2021). Several studies have found that the elevated atmospheric carbon dioxide (CO₂) concentration, increased temperature, and changing precipitation patterns during the growing season directly affect the rainfed crop production system (Flores López et al., 2014; Luo et al., 2019; Zheng et al., 2021). Since agriculture is highly susceptible to climate change, this uncertainty in climate has placed an enormous strain on global food security (Asseng et al., 2015; Yang et al., 2015) and recent studies suggest that climate change impacts will intensify during crop growing seasons in areas such as the Midwestern United States (Southworth et al., 2002; O’Neal et al., 2005; Basche et al., 2016).

Production of maize and soybean has reduced due to the increasing growing season temperatures in the US (Kucharik & Serbin, 2008; Ainsworth & Ort, 2010; Avnery et al., 2011), indicating the sensitivity of growing crops under a changing climate. A study analyzed the drought sensitivity of US maize and soybean production from 1958 to 2007 and reported a 13% yield loss occurred due to extreme hot days during the growing season (Zipper et al., 2016). Kansas is one of the largest producers of maize and soybean in the US (USDA, 2020) covering 30% of the total cultivable land (UDA CDL, 2019). An increasing number of heat waves and increasing heat wave severity have been observed in Kansas (Feddema et al., 2008), significantly impacting the rainfed

crop production system (Layzell & Evans, 2012). Therefore, it is important to determine the suitability of crops at a regional scale to understand the shifting pattern of growing crops and to develop a region-specific agricultural strategy to ensure future food security.

The Decision Support System for Agrotechnology Transfer (DSSAT) model has been used in many studies to study the climate change impacts on yield gap under rainfed or irrigated field conditions (Southworth et al., 2000; Basak et al., 2010; Shin et al., 2020). The DSSAT model was used in South Africa and Central US for projecting the crop suitability of maize and dry bean, and the result evaluated that the DSSAT model performance was higher compared to other mechanistic models; the projection performance was assessed from their baseline suitability results which mimic the real suitability scenarios (Estes et al., 2013; Eitzinger et al., 2016).

The ability to accurately predict crop suitability under present and future climate is an important tool that could help decide the right crop choice under the climate transition to achieve sustainable crop production intensification. Conventional crop suitability assessments are usually based on yield gap analyses (Fischer et al., 2002), which compare the actual yield to its potential yield to assess the suitability of the crop growing according to climatic factors. Since most of the past studies for suitability analysis have been done on large spatial scales (Asseng et al., 2013; Challinor et al., 2014; Lobell et al., 2014) several gaps remain at local and regional scales. There is a need to do regional scale suitability analyses to understand the vulnerability associated with climate change at finer spatial scales and provide more specific solutions.

In this study, DSSAT model was applied in the Eastern Kansas River Basin (EKSRB) with two specific objectives: (a) to assess the impact of future climate change on maize and soybean yields under two representative concentration pathways, RCP4.5 and RCP8.5, for near (2010-2039), mid (2040-2069), and end (2070-2099) of century; and (b) provide a regional assessment

of maize and soybean growing suitability under baseline (1990-2019) and future (2006-2099) climate change scenarios by quantifying the yield gap. These findings could provide a foundation for identifying the future suitability of maize and soybean under a changing climate and a guide for agricultural policymakers to make adaptive plans and management practices.

4.2. Materials and Methods

4.2.1 Study Area

The region of this study is the Eastern Kansas River Basin (EKSRB) (Fig. 4.1), which is the watershed of the Kansas River between the confluence of the Smoky Hill and Republican rivers at Junction City and its terminus at the point where its confluence with Missouri. This region, between 39°N~40°N and 95°W~97°W, is majority rainfed crop-growing area in Kansas, which consists of seventeen counties, with a total maize and soybean cultivation area of 1425 Km² and 1659 Km², respectively (USDA CDL, 2019). The region mainly has a humid climate, with long-term annual average precipitation is 676 mm (1990-2019), and the maximum and minimum daily temperatures during the growing season (May to October) are 21.2°, and 12.3° C, respectively.

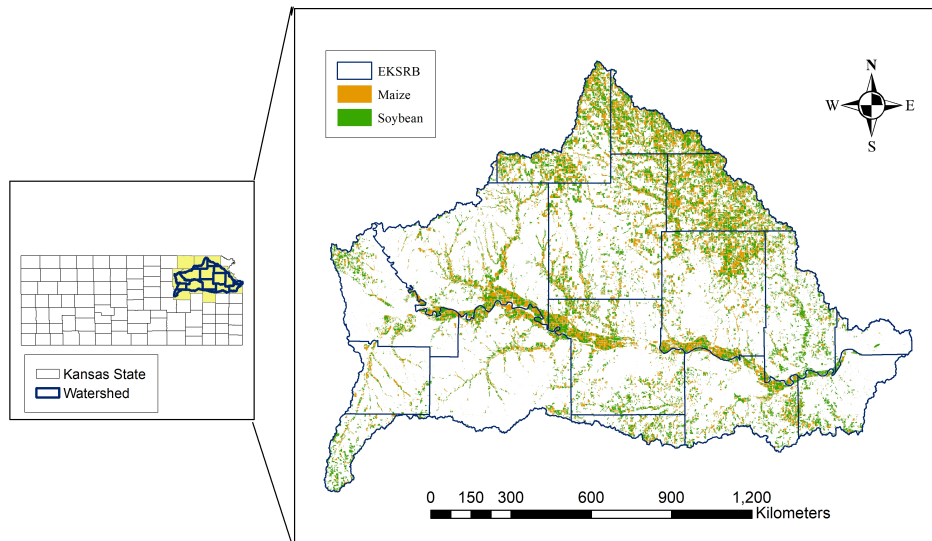


Figure 4.1. Map showing the study area Eastern Kansas River Basin (EKSRB) with their associated maize and soybean growing area from the USDA Cropland data layer (2019).

4.2.2 Crop Model Inputs

4.2.2.1 Climate Data

The daily observed weather data, such as daily maximum and minimum temperatures, precipitation, solar radiation, wind speed, and relative humidity for the baseline period of 1990-2019 were obtained from the Gridded Surface Meteorological (gridMET) dataset (Abatzoglou, 2012). The Coupled Model Intercomparison Project Phase 5 (CMIP5) report (Abatzoglou, 2012) stated that climate models are used to comprehend the past and quantify the future uncertainty in the climate system. Moreover, to avoid uncertainty in climate projections and, consequently, in projected crop yields, a large ensemble of climate models must be used in impact assessments. Therefore, to extract the future climate data (2006-2099), we used the Multivariate Adaptive Constructed Analogs (MACAv2) methodology to statistically downscale the output from 18 global

circulation models (GCM) from CMIP5. The baseline and future climate from each GCM were converted to DSSAT weather file format to be used in the model to assess climate change's impact on crop production in the EKS RB. Two representative concentration pathways (RCP4.5 and RCP8.5) were taken into consideration to assess the impacts of climate change on crop production in the EKS RB and to compare the changes with the baseline study period (1990-2019); the future study period was divided into near-future (2010-2039), mid-future (2040-2069), and end-future (2070-2099).

4.2.2.2 Soil and Crop Management Data

The DSSAT model requires detailed information on soil properties, including soil layer information -depth and thickness, texture, bulk density saturated hydraulic conductivity, etc., and soil surface information- albedo, runoff curve number, soil fertility factor, and drainage coefficient (Hoogenboom et al., 2021). To account for the spatial soil variability impact in the EKS RB, Gridded Soil Survey Geographic (gSSURGO) soil dataset (NRCS, 2021) was used. The procedure for making DSSAT-compatible soil files was described in the chapter 3.

The DSSAT crop management data, such as plant population, row spacing, and fertilizer application, were collected (Table 4.1) from the Kansas State Research and Extension of Kansas State University (Ciampitti et al., 2022). For the study area, the planting dates for maize and soybean were set to April 20 and May 5, respectively.

Table 4.1. Crop management recommended practices for the EKS RB

Crops	Plant population, plants m⁻²	Row spacing, m	Fertilizer (Urea), Kg/ha	Fertilizer application
Maize	7.6	0.51	170	Broadcasted
Soybean	37	0.76	60	Broadcasted

4.2.3 Database Preparation for the DSSAT Model Run

Python (Python 3.8, 2009), a high-level programming language was used to convert historic and future climate and soils datasets to DSSAT input files format. For the baseline study period, the python programming code was used to a) prepare the weather (.WTH) and soil.sol input file for the EKS RB, b) run the DSSAT model to simulate yields by linking all files, and c) organize the output files of the model run (. OSU, .OOV, and warning .OUT) for data analysis. The same process was used future climate scenario runs where the DSSAT model was run for each soil type of the region and for each of the 18 GCMs for simulating yield, and the ensemble mean yield of 18 GCMs for each soil type was used for further analyses.

The potential and actual yield differences were used to calculate the yield gap percentage for each soil in the EKS RB under baseline and future scenarios. Various steps involved in the DSSAT model simulation and projection are reflected in Fig. 4.2.

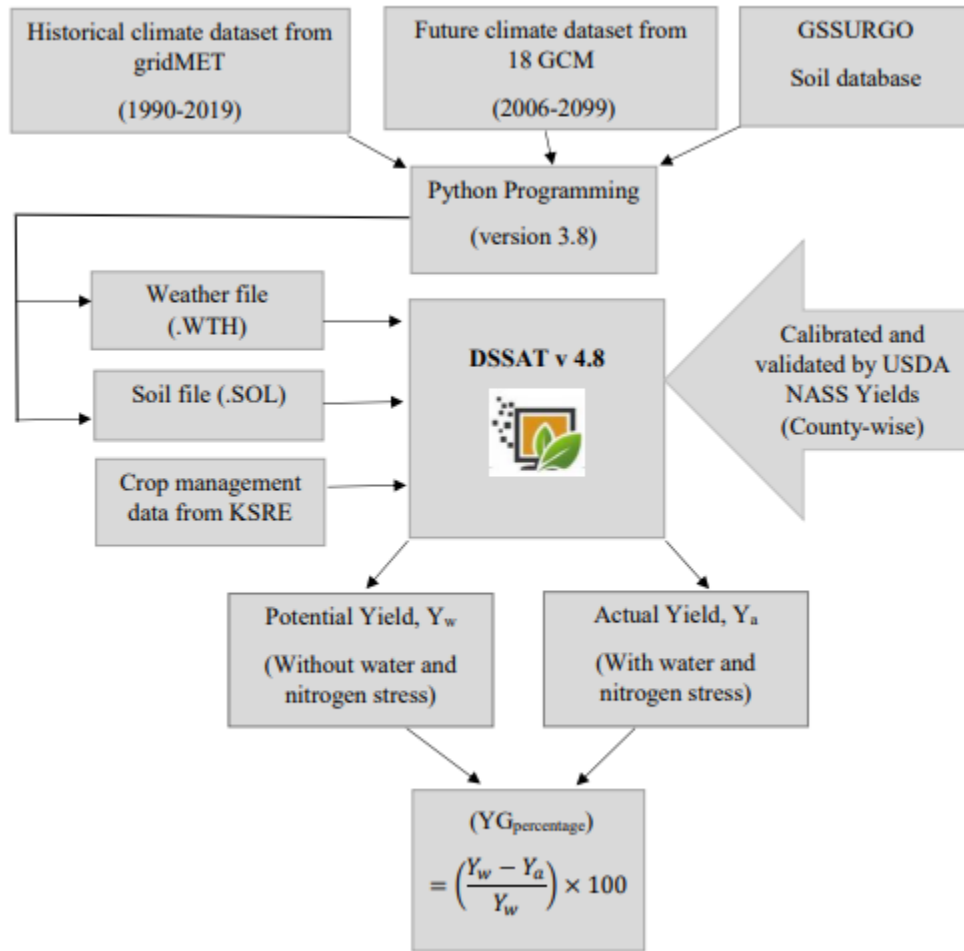


Figure 4.2. Flowchart showing yield simulation from the DSSAT model and yield gap assessment

4.2.4 Calibration and Evaluation of Crop Models

The DSSAT-CSM CERES-Maize (Jones & Kiniry, 1986) and CROPGRO-Soybean (Wilkerson et al., 1983) models were calibrated for the study area. The calibration procedure for CERES-Maize model was described in chapter 3.

For soybeans, the CROPGRO-Soybean model was calibrated systematically following the approach reported by (Battisti et al., 2018). In CROPGRO-Soybean model eighteen genetic coefficients determine phenology and yield estimates. 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). The 2020 yield trial dataset used for calibration was obtained from 6 counties in the region: Riley, Republic, Franklin, Shawnee, Saline, and Pottawatomie, made available by Kansas State Research and Extension Service (Ciampitti et al., 2022). The genetic coefficients were adjusted using GENCALC to initiate a range of cultivar coefficients (Hunt et al., 1993). GENCALC uses genetic coefficients of the default cultivar in the DSSAT.CUL file and iteratively compares the observed to the simulated data. Since only yield data were available for model calibration, it is essential to note that the GENCALC.RUL file for the CROPGRO-Soybean model was conditioned to iterate for only yield (HWAM). Once a range of cultivar coefficients was obtained from the GENCALC output file, the genetic coefficients of the trial soybean cultivar were manually adjusted until reasonable estimates were achieved.

For model evaluation, 2021 variety trial datasets obtained for Riley, Franklin, Shawnee, and Pottawatomie 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-statistics (Willmott, 1982)), 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. 4.2) multiplied by 100% (Eq. 4.1).

Equation 4.1. Normalize Root Mean Square Error

$$NRMSE = \frac{RMSE}{Observed\ mean} \times 100$$

Equation 4.2. Root Mean Square Error

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

Where n is the number of observations, s_i is the predicted value, and 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. Similarly, d-statistic (Eq. 4.3) values as < 0.7 (poor), 0.7-0.8 (moderate), 0.8-0.9 (good), and 0.9-1 (excellent).

Equation 4.3. Index of Agreement

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

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).

A new approach adopted in this study to enhance regional model calibration and evaluation accuracy and possibly reduce model uncertainty was to assess how well our model simulated the variability in the observed end-of-season yield using the 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.

4.2.5 Suitability Analysis

To assess crop suitability in the EKS RB region, yield gap percentage ($YG_{\text{percentage}}$) was calculated as described in Equation 4.4. $YG_{\text{percentage}}$ is calculated as the percentage difference between the potential and actual yield, simulated by the DSSAT model where potential yield (Y_w) is the yield achievable with optimal water and nutrient levels, i.e., the crop experiences no nitrogen or water stress. Potential and actual yield (Y_a) (i.e., rainfed yield considering water and nitrogen-limited conditions) was simulated for maize and soybean using DSSAT-CSM CERES-Maize and CROPGRO-Soybean models, respectively under baseline and future climate change scenarios. The national average yield gap percentage (NAYG) was used as a threshold value to classify the suitability of growing maize and soybean in the EKS RB. The national average yield gap

percentage (NAYG) for rainfed maize is 26% (Van Wart et al., 2013; Grassini et al., 2015), and for rainfed soybean is 22% (Edreira et al., 2017). Values lower than the national average indicated that the actual yield was closer to its potential level and the areas where those yields were simulated are highly suitable for growing that particular crop whereas, values of yield gap percentage higher than the national average indicated that the areas are unsuitable.

Equation 4.4. Yield Gap Percentage

$$YG_{\text{percentage}} = \left(\frac{Y_w - Y_a}{Y_w} \right) \times 100$$

Therefore, we used the NAYG to divide our study area suitability into three groups: suitable, moderately suitable, and unsuitable, under baseline and future climate change scenarios.

4.3. Results and discussion

4.3.1 Calibration and Evaluation of DSSAT Models

Results of calibration and evaluation of CERES-Maize DSSAT model were discussed in Chapter 3. The genotype coefficients adjusted during the CROPCGRO-Soybean model calibration for the EKS RB region are presented in Table below.

Table 4.2. Genotype coefficients adjusted during CROPGRO-Soybean regional model calibration

Coefficients	Definitions	Calibrated values
CSDL	Critical Short-Day Length below which reproductive development progresses with no day length effect (for short-day plants) (hour)	14.14
PPSEN	Slope of the relative response of development to photoperiod with time (positive for short-day plants) (1/hour)	0.340
EM-FL	Time between plant emergence and flower appearance (R1) (photothermal days)	22.50
FL-SH	Time between first flower and first pod (R3) (photothermal days)	9.0
FL-SD	Time between first flower and first seed (R5) (photothermal days)	10.0
SD-PM	Time between the first seed (R5) and physiological maturity (R7) (photothermal days)	38.60

FL-LF	Time between first flower (R1) and end of leaf expansion (photothermal days)	27.0
LFMAX	Maximum leaf photosynthesis rate at 30 C, 350 ppm CO ₂ , and high light (mg CO ₂ /m ² -s)	1.35
SLAVR	Specific leaf area of cultivar under standard growth conditions (cm ² /g)	375
SIZLF	Maximum size of the full leaf (three leaflets) (cm ²)	180
XFRT	Maximum fraction of daily growth that is partitioned to seed + shell	1.00
WTPSD	Maximum weight per seed (g)	0.195
SFDUR	Seed filling duration for pod cohort at standard growth conditions (photothermal days)	29.90
SDPDV	Average seed per pod under standard growing conditions (#/pod)	2.20
PODUR	Time required for cultivar to reach final pod load under optimal conditions (photothermal days)	13.0
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
SDPRO	Fraction protein in seeds (g(protein)/g(seed))	0.405
SDLIP	Fraction oil in seeds (g(oil)/g(seed))	0.205

The adjustment of 18 CROPGRO-Soybean coefficients (Table 4.2) related to phenology and crop development resulted in a close agreement between simulated and observed yield values. Model performance was highly satisfactory during calibration with NRSME = 8% (334 kg/ha), p-value = 0.62, d-statistics = 0.88, and observed and simulated CV of 12%, respectively. Mean simulated and observed end-of-season yield during calibration were found to be 3,999 and 4,158 kg/ha, respectively. End-of-season yield overestimation in this study may have resulted from an underestimation of water stress. According to Kothari et al. (2019), the overestimation of dryland wheat yield in Texas High Plains using the CERES-Wheat model resulted from an underestimation of water stress. Model structure simplification could be another factor accounting for the overestimation. However, model performance based on end-of-yield calibration ranges from good

to excellent following the recommendations of (Soler et al., 2007), thus, confirming the fitness of our model for the intended use.

During the model evaluation, observed and simulated end-of-season yields matched closely (Fig.4.3) as indicated by NRMSE = 11% (RMSE = 480 kg/ha), p-value = 0.78, d-statistics = 0.75, and observed and simulated CV of 14% and 9%, respectively. Simulated and observed mean yield values during the evaluation were 4,308 kg/ha and 4,432 kg/ha, respectively. Overall, the variety of 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.

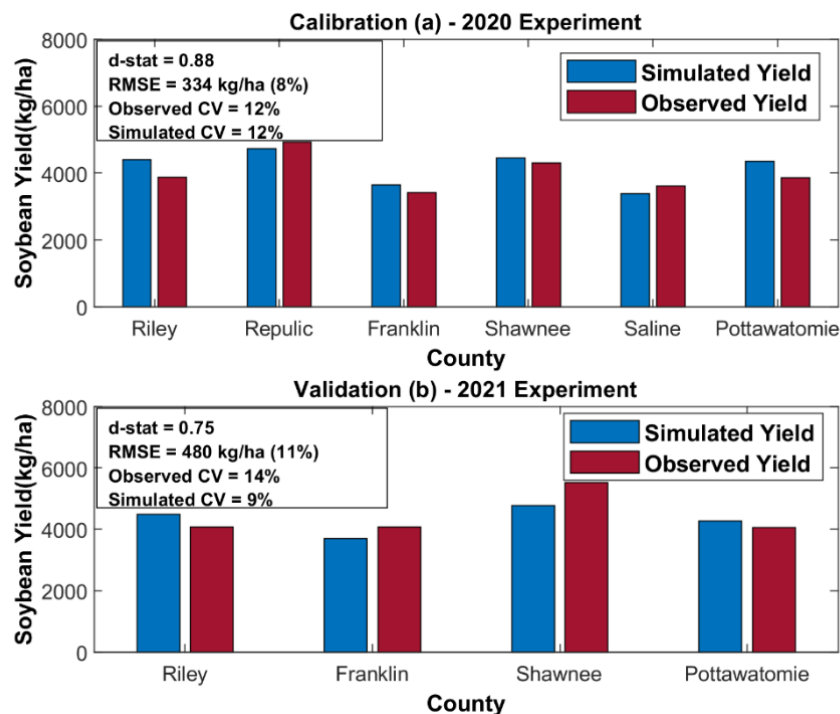


Figure 4.3. DSSAT CROPGROW-Soybean Model calibration and validation for the EKS RB

4.3.2 Impacts of Climate Change on Yield Variability in the EKS RB

The changes in the mean crop yields and inter-annual variability (CV) for maize and soybean were calculated for the two long-term climate change emission scenarios (RCP4.5 and

RCP8.5) (Fig. 4.4). Maize yield loss was observed under both RCPs with an increasing inter-annual yield variability (CV). Under the baseline study period (1990-2019), the mean yield for the entire EKS RB was 8978 kg/ha with an inter-annual variability (CV) of 35%. Under RCP4.5 and RCP8.5, the mean yield for near, mid, and end-century was 7995 kg/ha (CV = 36%), 6532 kg/ha (CV = 39%), 5092 kg/ha (CV = 37%), and 6874 kg/ha (37%), 5665 kg/ha (37%), 3834 kg/ha (36%), respectively (Fig. 4(a)). Similarly, under the baseline study period for soybean, the mean yield was 3712 kg/ha with a CV of 32%. Unlike maize, soybean yield under RCP4.5 (near-century) was 3917 kg/ha (CV= 34%) which was 6% higher than the baseline yield although under RCP4.5, the projected mean yield for the mid and end-century was 3248 kg/ha (CV=38%) and 2504 kg/ha (34%), respectively (Fig 4.4(b)).

On the other hand, the projected soybean yield loss was recorded under RCP8.5, the mean yield for the near, mid, and end centuries was 3002 kg/ha, 2044 kg/ha, and 1831 kg/ha, with a CV of 35%, 36%, and 34%, respectively. The results showed that changes in average climate conditions cause alterations in crop yield levels and variability. Several studies found that the sensitivity of growing crops under future climate change scenarios reduced the maize and soybean yields in the US Midwest (Cai et al., 2009; Lobell & Asseng, 2017; Zhou et al., 2021) due to increased CO₂ concentration induced heat extremes, and the changing precipitation patterns. Higher maize yield loss was observed as compared to soybean in the study area under each RCP scenarios which could be attributed to the fact that maize production is more sensitive to extremely high temperatures than soybean due to a higher sowing density in maize (Lobell et al., 2014) and growth behavior (Deryng et al., 2014; Mera et al., 2015; Petersen, 2019). These results show that under projected climate change scenarios, maize and soybean yield loss will increase along with increased inter-annual variability in yield in the EKS RB region.

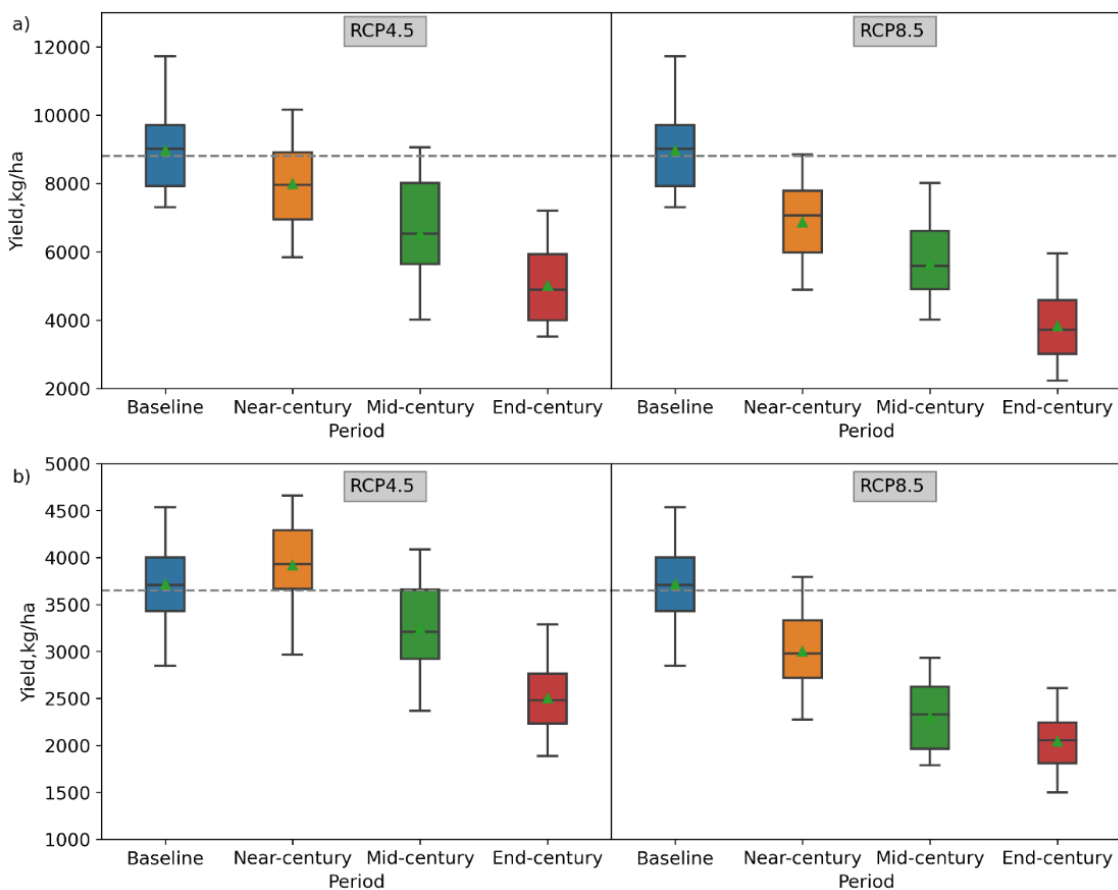


Figure 4.3. Comparison of a) maize and b) soybean yield variation under present and future climate change scenarios under RCP4.5 and RCP8.5. The study period was divided into baseline (1990-2019), near-century (2010-2039), mid-century (2040-2069), and end-century (2070-2099). Horizontal dashed lines indicate the average yield in the EKS RB under the baseline study period.

4.3.3 Consequences of Climate Change on the County Level Maize and Soybean

The results of change in yield, expressed as percent difference, for seventeen counties of EKS RB calculated by comparing the future projected maize and soybean yields to the baseline yields are shown in Fig. 4.5. The maize yield loss under RCP4.5 and RCP8.5 in the near, mid, and end-century ranged between 4-11%, 11-22%, and 23-34%, and 12-20%, 22-38%, and 36-57%, respectively. Soybean yield increased under RCP4.5 in the near century by 6% whereas in the mid and end-century the yield loss ranged from 11-22% and 20-25%, respectively. Under RCP8.5, in

the near, mid, and end-century, the soybean yield loss was recorded as 3-8%, 16-22%, and 24-36%, respectively.

It must be noted that the maize yield loss was higher as compared to soybean under all climate change scenarios explored. It is also important to note that under the baseline study period, Atchison, Brown, and Nemaha counties were the higher maize and soybean-producing counties in the EKS RB and these three counties exhibited less yield loss than other counties under future scenarios.

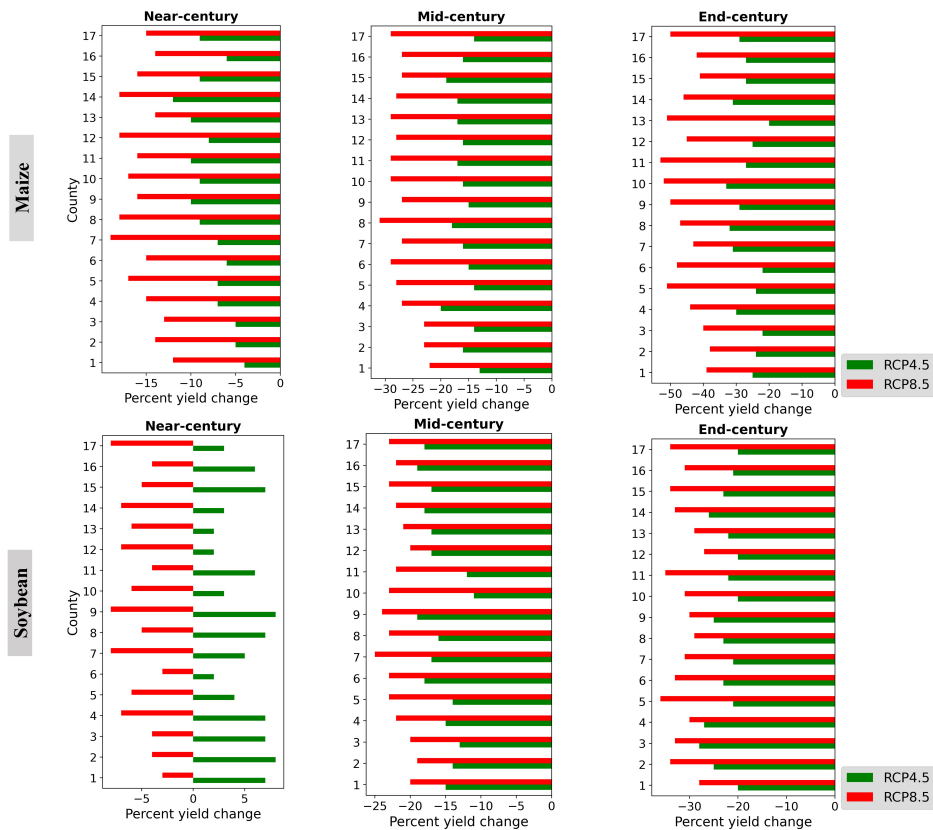


Figure 4.4. Projected yield change (maize and soybean) for seventeen counties under RCP4.5 and RCP8.5 compared to the baseline study period. The number depicted the seventeen counties of the EKS RB in sequence 1. Atchison, 2. Brown, 3. Nemaha, 4. Douglas, 5. Geary, 6. Jackson, 7.

Jefferson, 8. Johnson, 9. Leavenworth, 10. Marshall, 11. Morris, 12. Osage, 13. Pottawatomie, 14. Riley, 15. Shawnee, 16. Wabaunsee, and 17. Wyandotte.

4.3.4 Yield Gap Trend under Changing Climate

According to the temporal analysis of yield, under the projected future climatic conditions, Y_a and Y_w dropped significantly (30-70%) as compared to the baseline average Y_a and Y_w (Fig. 4.6). As a result, the projected yield gap increased for both crops over the study period under both the future climate scenarios (RCP4.5 and RCP8.5). These results are in agreement with the study by O'Brien et al. (2021), the study stated that future climate change exacerbates the yield gap and has indirect impact on deteriorating soil quality due to interactions between climate and management, which could be an important implication for this study area as well. It can be said that climate change results in unfavorable growing conditions for certain crops and causes uncertainties in production levels, especially under rainfed management conditions.

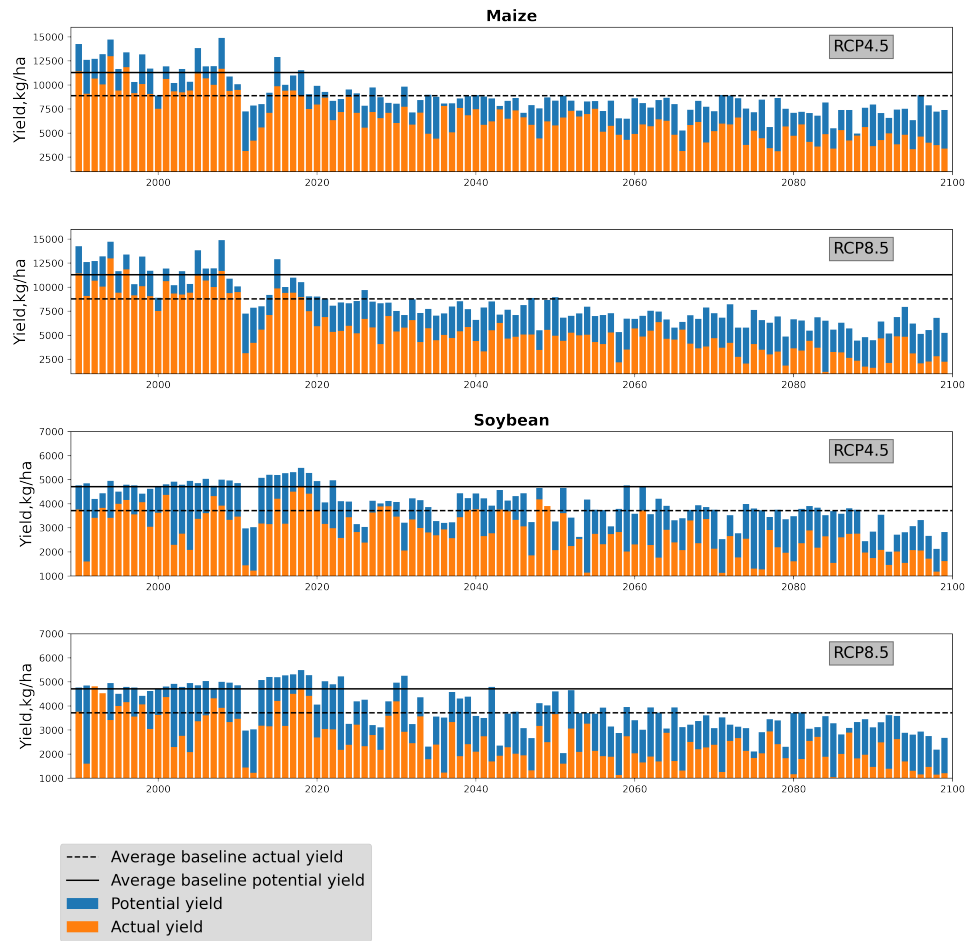


Figure 4.5. Simulated average maize and soybean potential (Y_w) and actual (Y_a) yield based on the weather, soil properties, and management conditions for the EKS RB. Each bar represents an individual year of the study period (1990-2099).

The long-term yield gap trend analysis for maize and soybean under baseline and future climate change scenarios (RCP4.5 and RCP8.5) (Fig. 4.7) was conducted and an increasing yield gap trend was observed in both crops. In particular, a higher yield gap percentage trend was observed under RCP8.5 as compared to RCP4.5. During the baseline period, the highest yield gap for maize was recorded as 30% while on the other hand, under RCP4.5 and RCP8.5, it was 43% and 52%, respectively. Similarly, the highest yield gap in soybean was observed at 27% under the

baseline study period; however, under RCP4.5 and RCP8.5, it increased to 29% and 36%, respectively.

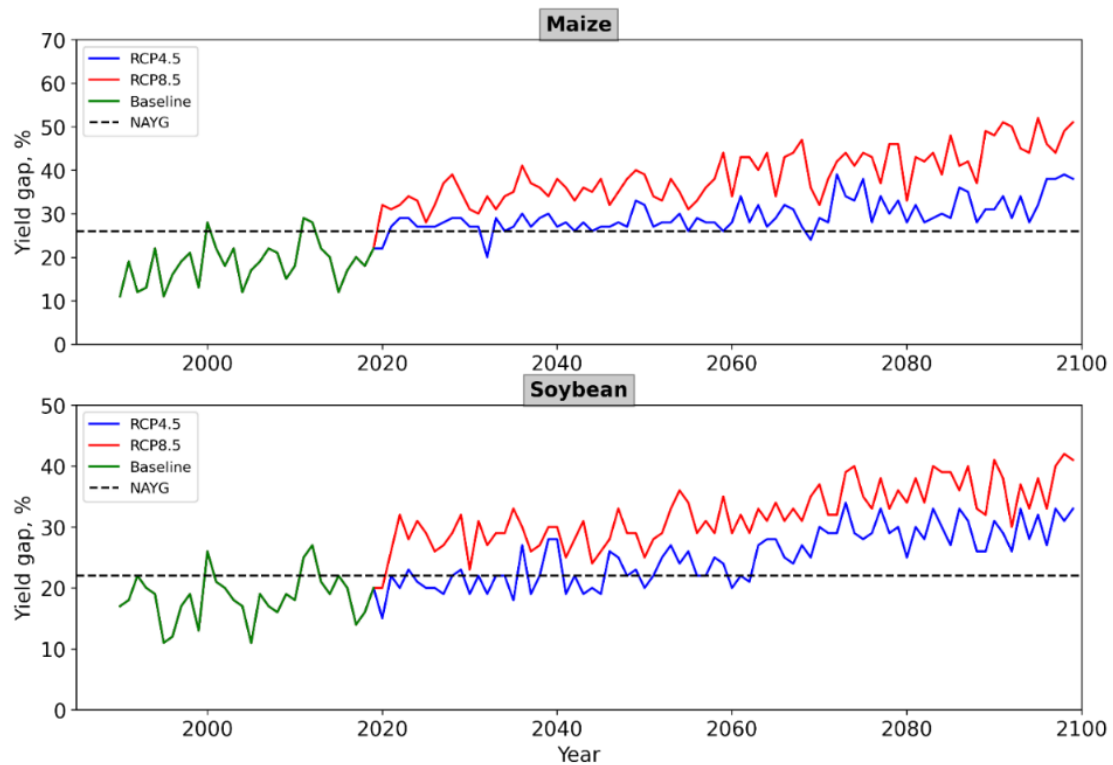


Figure 4.6. Temporal evaluation of average yield gap percentage trend for maize and soybean in the EKS RB under climate change scenarios (RCP4.5 and RCP8.5). The green color for the baseline, blue for RCP4.5, red for RCP8.5, and the dashed line for National Average Yield Gap (NAYG) for maize (26%) and soybean (22%).

4.3.5 Crop Area Suitability for Growing Maize and Soybean under Future Climate

The shifting pattern of the areas suitable for growing maize under climate change scenarios in the EKS RB are given in Fig. 4.8. Under the baseline study period, 92% of the land was considered suitable for growing maize with the area suitable for growing maize concentrated in a zone stretching from the northeast to the central part of the EKS RB and along the river. Under

RCP4.5 scenario, in the near, mid, and end-centuries, suitable maize areas were reduced to 90%, 58%, and 40%, respectively.

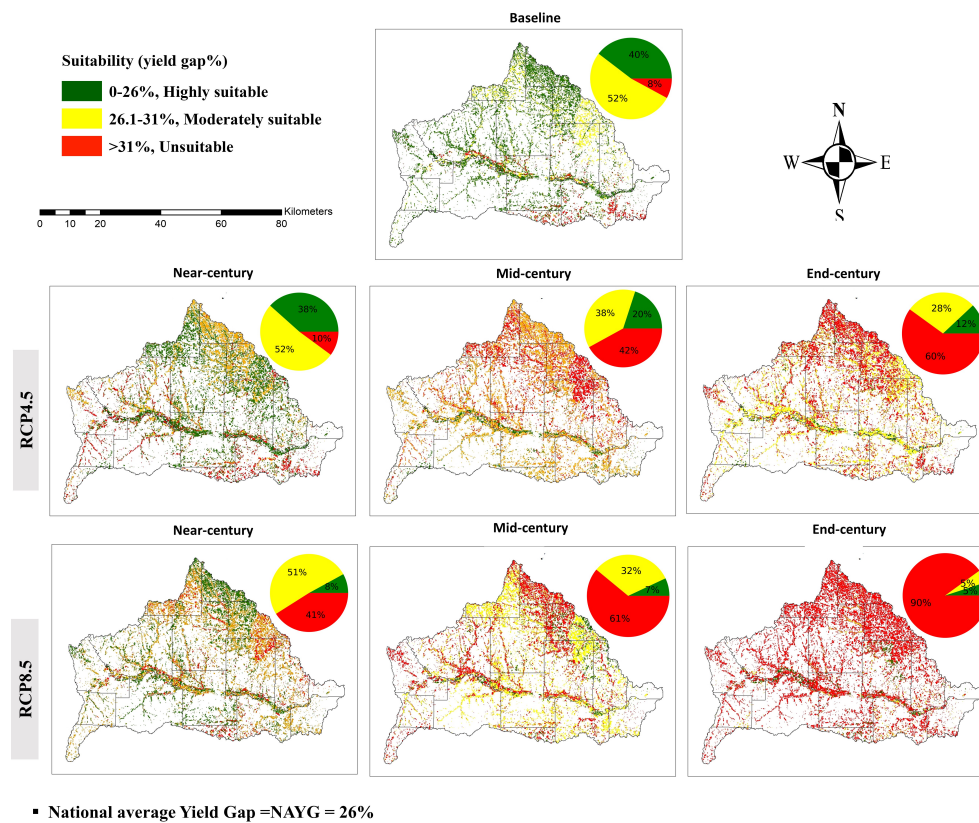


Figure 4.7. Area suitable for growing maize in the EKS RB under baseline (1990-2019), near-century (2010-2039), mid-century (2040-2069), and end-century (2070-2099) under the two representative concentration pathway scenarios (RCP4.5 and RCP8.5).

Similarly, under the RCP8.5, near-century, the area suitable for growing maize was mainly concentrated in the northeastern EKS RB and the suitable area decreased in the near, mid, and end-century to 59%, 39%, and 10%, respectively from the baseline maize-growing area. The comparison between the RCP scenarios showed a lower maize-suitable growing area with a higher yield gap percentage under RCP8.5 as compared to RCP4.5 scenarios.

In case of soybeans, the suitable area under the baseline study period was 91% (Fig. 4.9). Most counties were found suitable for growing soybean except for three southwest counties (Wabaunsee, Geary, and Riley).

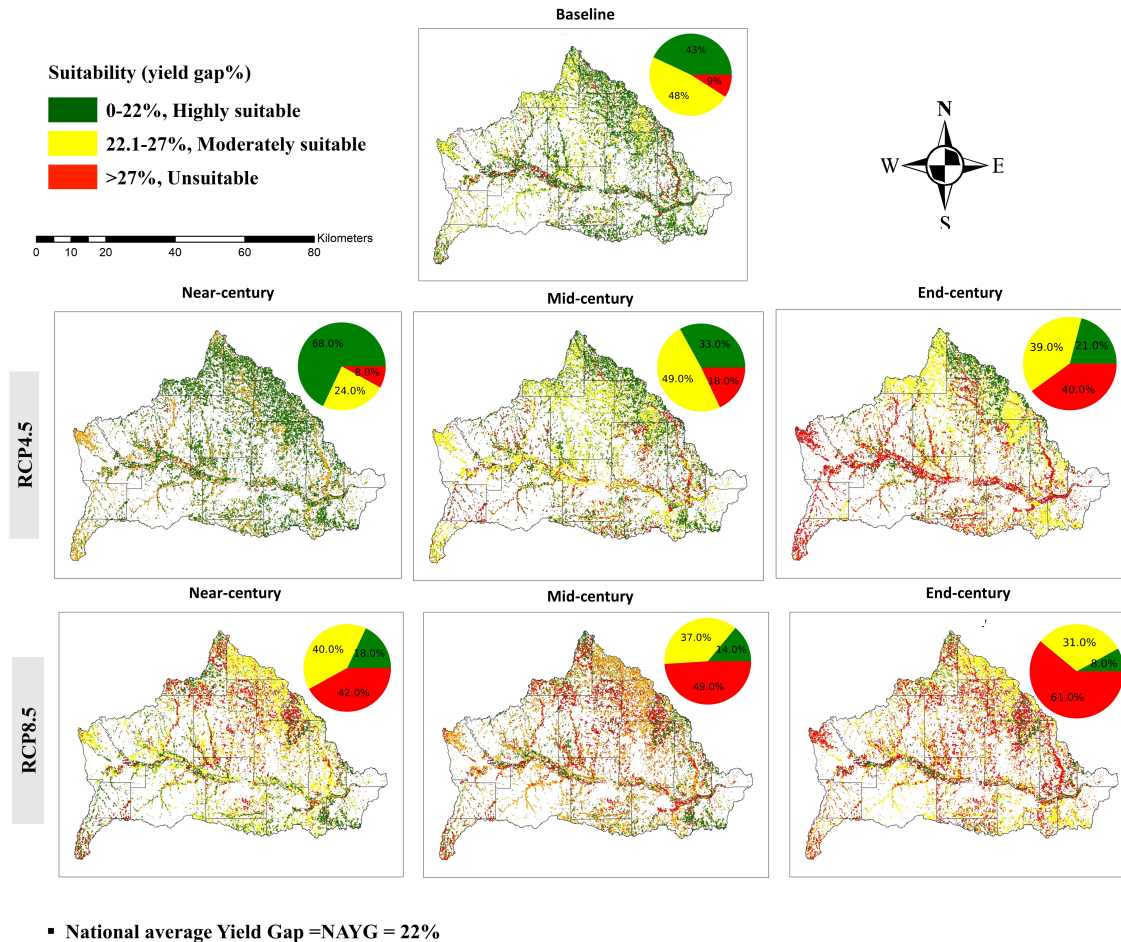


Figure 4.8. Area suitable for growing soybean in the EKS RB under baseline (1990-2019), near-century (2010-2039), mid-century (2040-2069), and end-century (2070-2099) under the two representative concentration pathway scenarios (RCP4.5 and RCP8.5).

The soybean-suitable growing area under RCP4.5 in the near, mid, and end-century was 92%, 82%, and 60%, respectively. Similarly, under RCP8.5, the suitable soybean-growing area

was concentrated on the northeast side of the EKSRB and were found to be 58%, 51%, and 38% in the near, mid, and end-century, respectively.

The outcome from two climate change scenarios showed less suitable areas existed for soybean at the end of the century under the RCP4.5 and RCP8.5 compared to the baseline study period. However, based on the overall suitability analysis of the two crops, it can be concluded that relatively more areas would be suitable for growing soybeans than maize in the EKSRB under future climate scenarios studied.

4.4. Conclusions

The suitability of growing maize and soybean in the EKSRB under future climate change scenarios was assessed by determining the yield gap percentage using DSSAT simulated historic and future yields. However, due to regional heterogeneity in climate, several southwestern counties in the EKSRB showed lower suitability for growing maize and soybean under future scenarios. An increasing yield gap trend was observed for maize and soybean under RCP4.5 and RCP8.5, indicating the projected suitability for growing maize and soybean reduced over time possibly due to the high temperature and changing lower precipitation patterns compared to the baseline study period.

The highest yield gap was recorded for both crops (maize= 52% and soybean=38%) under RCP8.5 at the end of the century (2070-2099), at 1.5 to 2 times higher than the current national average yield gap percentage (maize=26% and soybean=22%). The percent of yield changes was also determined under the changing climate compared to the baseline study period; under RCP4.5, it was -15 to -46% for maize, whereas for soybean, it was +6 to -38%. Similarly, under RCP8.5, maize and soybean yield changed between -24 to -59% and -19 to -50%, respectively.

It was found that more soybean suitable growing area existed than maize throughout the study period in the EKS RB. The study concluded from the suitability analysis that higher yield loss and a lower suitable growing area were observed for maize than soybean; hence soybean could be a more robust rainfed crop choice in the EKS RB under the future climate change scenarios.

The study identified the regions with the highest chance of meeting projected crop production demands or where modified strategies may be required to sustain crop production. It can be concluded that this study can enable policymakers to understand the likely patterns of future crop suitability and help to facilitate agricultural policy planning and the selection of mitigation strategies for vulnerable regions. The study also has the potential to be translated for other parts of the world and for crops to develop adaptation strategies to reduce the crop yield gap to improve regional and global food security.

Chapter 5 - Conclusions

This study investigated the impact of spatial distributions of the soil on crop yield under the changing climate and determined suitability of growing maize and soybeans in the EKSRB. The DSSAT CERES-Maize and CROPGRO-Soybean models were successfully calibrated and validated and were then used to simulate yields under future climate scenarios. Historic (baseline) and future climate data from 18 downscaled GCMs under two RCP scenarios (RCP4.5 and 8.5) were used in combination with spatially distributed gSSURGO soils data and crop management data to simulate historic and future yields for maize and soybean in the region.

From the results, it can be concluded that higher yield loss was observed for both maize and soybean across the study area under RCP8.5 at the end of the century as compared to RCP 4.5 due to the high CO₂ concentration, increasing temperature, and low precipitation patterns. Yield gap percentage analysis conducted using the DSSAT model identified the regions with the highest yield loss under future climate indicating what areas in the future would require management strategies to sustain crop production. It was found that several southwestern counties in the EKSRB lost suitability for growing maize and soybean under future scenarios. An increasing yield gap trend indicated that the projected suitability for growing maize and soybean reduced over time for all future climate scenarios. More soybean growing areas were recorded than maize throughout the study period indicating that soybean could be a more robust crop choice in the EKSRB under future climate change scenarios.

Overall, this study demonstrates a loss of suitability of crop growing areas for maize and soybean under future climatic conditions and can help guide stakeholders and policymakers to understand the patterns of future crop suitability and help to facilitate selection of mitigation strategies for vulnerable regions. The study also has the potential to be translated for other parts of

the world and for crops to develop adaptation strategies to reduce the crop yield gap to improve regional and global food security.

References

- Abatzoglou J.T. & Brown T.J. (2012). A comparison of statistical downscaling methods suited for wildfire applications, *International Journal of Climatology*, 32, 772-780.
- Abd-Elmabod, S. K., Muñoz-Rojas, M., Jordán, A., Anaya-Romero, M., Phillips, J. D., Jones, L., & de la Rosa, D. (2020). Climate change impacts on agricultural suitability and yield reduction in a Mediterranean region. *Geoderma*, 374, 114453.
- Aggarwal, P., Vyas, S., Thornton, P., Campbell, B. M., & Kropff, M. (2019). Importance of considering technology growth in impact assessments of climate change on agriculture. *Global Food Security*, 23, 41-48.
- Ainsworth, E. A., & Ort, D. R. (2010). How do we improve crop production in a warming world? *Plant Physiology*, 154(2), 526-530.
- Alexandrov, V. A., & Hoogenboom, G. (2000). The impact of climate variability and change on crop yield in Bulgaria. *Agricultural and forest meteorology*, 104(4), 315-327.
- Almazroui, M., Islam, M. N., Saeed, F., Saeed, S., Ismail, M., Ehsan, M. A., & Barlow, M. (2021). Projected changes in temperature and precipitation over the United States, Central America, and the Caribbean in CMIP6 GCMs. *Earth Systems and Environment*, 5, 1-24.
- Amin, A., Nasim, W., Mubeen, M., Nadeem, M., Ali, L., Hammad, H. M., & Fathi, A. (2017). Optimizing the phosphorus use in cotton by using CSM-CROPGRO-cotton model for semi-arid climate of Vehari-Punjab, Pakistan. *Environmental Science and Pollution Research*, 24(6), 5811-5823.
- Anar, M. J., Lin, Z., Hoogenboom, G., Shelia, V., Batchelor, W. D., Teboh, J. M., & Khan, M. (2019). Modeling growth, development and yield of Sugarbeet using DSSAT. *Agricultural Systems*, 169, 58-70.

- Anderson, T. R., Hawkins, E., & Jones, P. D. (2016). CO₂, the greenhouse effect and global warming: from the pioneering work of Arrhenius and Callendar to today's Earth System Models. *Endeavour*, 40(3), 178-187.
- Anothai, J., Patanothai, A., Jogloy, S., Pannangpetch, K., Boote, K. J., & Hoogenboom, G. (2008). A sequential approach for determining the cultivar coefficients of peanut lines using end-of-season data of crop performance trials. *Field Crops Research*, 108(2), 169-178.
- Araya, A., Kisekka, I., Gowda, P. H., & Prasad, P. V. (2017). Evaluation of water-limited cropping systems in a semi-arid climate using DSSAT-CSM. *Agricultural Systems*, 150, 86-98.
- Araya, A., Prasad, P. V. V., Gowda, P. H., Sharda, V., Rice, C. W., & Ciampitti, I. A. (2021). Evaluating optimal irrigation strategies for maize in Western Kansas. *Agricultural Water Management*, 246, 106677.
- Armstrong, R. D., Fitzpatrick, J., Rab, M. A., Abuzar, M., Fisher, P. D., & O'Leary, G. J. (2009). Advances in precision agriculture in south-eastern Australia. III. Interactions between soil properties and water use help explain spatial variability of crop production in the Victorian Mallee. *Crop and Pasture Science*, 60(9), 870-884.
- Asseng, S., Ewert, F., Martre, P., Rötter, R. P., Lobell, D. B., Cammarano, D., & Zhu, Y. (2015). Rising temperatures reduce global wheat production. *Nature Climate Change*, 5(2), 143-147.
- Asseng, S., Zhu, Y., Basso, B., Wilson, T., & Cammarano, D. (2014). Simulation Modeling: Applications in Cropping Systems. In N. K. Van Alfen (Ed.), *Encyclopedia of Agriculture and Food Systems* (pp. 102–112). Academic Press. <https://doi.org/10.1016/B978-0-444-52512-3.00233-3>.

- Avnery, S., Mauzerall, D. L., Liu, J., & Horowitz, L. W. (2011). Global crop yield reductions due to surface ozone exposure: 2. The Year 2030 potential crop production losses and economic damage under two scenarios of O₃ pollution. *Atmospheric Environment*, 45(13), 2297-2309.
- Basak, J. K., Ali, M. A., Islam, M. N., & Rashid, M. A. (2010). Assessment of the effect of climate change on boro rice production in Bangladesh using DSSAT model. *Journal of Civil Engineering (IEB)*, 38(2), 95-108.
- Basche, A. D., Archontoulis, S. V., Kaspar, T. C., Jaynes, D. B., Parkin, T. B., & Miguez, F. E. (2016). Simulating long-term impacts of cover crops and climate change on crop production and environmental outcomes in the Midwestern United States. *Agriculture, Ecosystems & Environment*, 218, 95-106.
- Batchelor, W. D., Basso, B., & Paz, J. O. (2002). Examples of strategies to analyze spatial and temporal yield variability using crop models. *European Journal of Agronomy*, 18(1-2), 141-158.
- Battisti, R., Sentelhas, P. C., Parker, P. S., Nendel, C., Gil, M. D. S., Farias, J. R., & Basso, C. J. (2018). Assessment of crop-management strategies to improve soybean resilience to climate change in Southern Brazil. *Crop and Pasture Science*, 69(2), 154-162.
- Beazley, D. M. (2009). *Python essential reference*. Addison-Wesley Professional.
- Beebe, S., Ramirez, J., Jarvis, A., Rao, I. M., Mosquera, G., Bueno, J. M., & Blair, M. W. (2011). Genetic improvement of common beans and the challenges of climate change. *Crop adaptation to climate change*, 356-369.
- Boonwichai, S., Shrestha, S., Babel, M. S., Weesakul, S., & Datta, A. (2018). Climate change impacts on irrigation water requirement, crop water productivity and rice yield in the Songkhram River Basin, Thailand. *Journal of Cleaner Production*, 198, 1157-1164.

- Boote, K. J., Dimes, J., Hargreaves, J., Thorburn, P. J., Porter, C., Jones, J. W., & McDermid, S. (2017). Interpreting Apsim and DSSAT Maize Model Responses to Carbon Dioxide, Temperature, Water, and Nitrogen Under Degraded Soil Conditions. ASA, CSSA and SSSA International Annual (2017).
- Brunsell, N. A., Jones, A. R., Jackson, T. L., & Feddema, J. J. (2010). Seasonal trends in air temperature and precipitation in IPCC AR4 GCM output for Kansas, USA: evaluation and implications. *International Journal of Climatology*, 30(8), 1178-1193.
- Butcher, K., Wick, A. F., DeSutter, T., Chatterjee, A., & Harmon, J. (2018). Corn and soybean yield response to salinity influenced by soil texture. *Agronomy Journal*, 110(4), 1243-1253.
- Cai, X., Wang, D., & Laurent, R. (2009). Impact of climate change on crop yield: A case study of rainfed corn in central Illinois. *Journal of Applied Meteorology and Climatology*, 48(9), 1868-1881.
- Carbone, G. J., Kiechle, W., Locke, C., Mearns, L. O., McDaniel, L., & Downton, M. W. (2003). Response of soybean and sorghum to varying spatial scales of climate change scenarios in the southeastern United States. In *Issues in the Impacts of Climate Variability and Change on Agriculture* (pp. 73-98). Springer, Dordrecht.
- Challinor, A. J., Ewert, F., Arnold, S., Simelton, E., & Fraser, E. (2009). Crops and climate change: progress, trends, and challenges in simulating impacts and informing adaptation. *Journal of experimental botany*, 60(10), 2775-2789.
- Ciampitti, I. A., Correndo A., Lancaster S., Diaz D.R., Aguilar J., Sharda A., Onofre R., McCornack B. (2023). *Kansas Corn Management 2023*, Kansas State University.
- Ciampitti, I. A., Diaz, D.R.; Onofre R. B.; Lancaster S.; Whitworth R.J.; Aguilar J. (2022). *Kansas Soybean Management 2022*, Kansas State University.

- Dale, A., Fant, C., Strzepek, K., Lickley, M., & Solomon, S. (2017). Climate model uncertainty in impact assessments for agriculture: A multi-ensemble case study on maize in sub-Saharan Africa. *Earth's Future*, 5(3), 337-353.
- Deryng, D., Conway, D., Ramankutty, N., Price, J., & Warren, R. (2014). Global crop yield response to extreme heat stress under multiple climate change futures. *Environmental Research Letters*, 9(3), 034011.
- Edreira, J. I. R., Mourtzinis, S., Conley, S. P., Roth, A. C., Ciampitti, I. A., Licht, M. A., & Grassini, P. (2017). Assessing causes of yield gaps in agricultural areas with diversity in climate and soils. *Agricultural and forest meteorology*, 247, 170-180.
- Eitzinger, A., Läderach, P., Rodriguez, B., Fisher, M., Beebe, S., Sonder, K., & Schmidt, A. (2017). Assessing high-impact spots of climate change: spatial yield simulations with Decision Support System for Agrotechnology Transfer (DSSAT) model. *Mitigation and adaptation strategies for global change*, 22(5), 743-760.
- Elias, E. H., Flynn, R., Idowu, O. J., Reyes, J., Sanogo, S., Schutte, B. J., & Sutherland, C. (2019). Crop vulnerability to weather and climate risk: Analysis of interacting systems and adaptation efficacy for sustainable crop production. *Sustainability*, 11(23), 6619.
- ESRI (2020). ArcGIS Desktop: Release 10.8. Redlands, CA: Environmental Systems Research Institute.
- Estes, L. D., Bradley, B. A., Beukes, H., Hole, D. G., Lau, M., Oppenheimer, M. G., & Turner, W. R. (2013). Comparing mechanistic and empirical model projections of crop suitability and productivity: implications for ecological forecasting. *Global Ecology and Biogeography*, 22(8), 1007-1018.

- Feddema, J., Brunsell, N., Jackson, T., & Jones, A. (2008). Climate change in Kansas. Prepared for the Climate and Energy Project of the Land Institute, Department of Geography, University of Kansas, 1-10.
- Fischer, G., Van Velthuisen, H. T., Shah, M. M., & Nachtergaele, F. O. (2002). Global agro-ecological assessment for agriculture in the 21st century: methodology and results.
- Flores López, H. E., Ruíz Corral, J. A., Mora Orozco, C. D. L., Zarazúa-Villaseñor, P., Chávez Durán, Á. A., Ramírez Vega, H., & Velásquez Valle, M. A. (2014). Applying the EPIC model to assess the impact of climate change and management practices on grain yield in rainfed maize. *Mexican Journal of Agricultural Sciences*, 5 (SPE10), 2007-2020.
- Gaupp, F., Hall, J., Mitchell, D., & Dadson, S. (2019). Increasing risks of multiple breadbasket failure under 1.5 and 2 C global warming. *Agricultural Systems*, 175, 34-45.
- Goldblum, D. (2009). Sensitivity of corn and soybean yield in Illinois to air temperature and precipitation: the potential impact of future climate change. *Physical Geography*, 30(1), 27-42.
- Golmohammadi, G. (2014). Development and evaluation of SWATDRAIN, a new model to simulate the hydrology of agricultural tile-drained watersheds.
- Gornall, J., Betts, R., Burke, E., Clark, R., Camp, J., Willett, K., & Wiltshire, A. (2010). Implications of climate change for agricultural productivity in the early twenty-first century. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 365(1554), 2973-2989.
- Grassini, P., van Bussel, L. G., Van Wart, J., Wolf, J., Claessens, L., Yang, H., & Cassman, K. G. (2015). How good is good enough? Data requirements for reliable crop yield simulations and yield-gap analysis. *Field Crops Research*, 177, 49-63.

- Hansen, J. W., & Jones, J. W. (2000). Scaling-up crop models for climate variability applications. *Agricultural Systems*, 65(1), 43-72.
- Hasegawa, T., Fujimori, S., Havlík, P., Valin, H., Boudry, B. L., Doelman, J. C., & Witzke, P. (2018). Risk of increased food insecurity under stringent global climate change mitigation policy. *Nature Climate Change*, 8(8), 699-703.
- Hatfield, J. L., Boote, K. J., Kimball, B. A., Ziska, L. H., Izaurralde, R. C., Ort, D., & Wolfe, D. (2011). Climate impacts on agriculture: implications for crop production. *Agronomy journal*, 103(2), 351-370.
- Herring, S. C., Christidis, N., Hoell, A., Kossin, J. P., Schreck III, C. J., & Stott, P. A. (2018). Explaining extreme events of 2016 from a climate perspective. *Bulletin of the American Meteorological Society*, 99(1), S1-S157.
- Hoogenboom, G. J. W. Jones, & K. J. Boote. 1992. Modeling growth, development and yield of grain legumes using SOYGRO, PNUTGRO, and BEANGRO: A Review. *Transactions of the ASAE* 35(6):2043-2056.
- Hoogenboom, G., C.H. Porter, V. Shelia, K.J. Boote, U. Singh, J.W. White, W. Pavan, F.A.A. Oliveira, L.P. Moreno-Chain, J.I. Lizaso, S. Asseng, D.N.L. Small, B.A. Kimball, P.D. Alderman, K.R. Thorp, M.R. Jones, S.V. Square, M.S. Vianna, F.J. Villalobos, T.B. Ferreira, W.D. Batchelor, J., L.A. Hunt, and J.W. Jones. (2021). Decision Support System for Agrotechnology Transfer (DSSAT) Version 4.8 (DSSAT.net). DSSAT Foundation, Gainesville, Florida, USA.
- Huang, B., Sun, W., Zhao, Y., Zhu, J., Yang, R., Zou, Z., & Su, J. (2007). Temporal and spatial variability of soil organic matter and total nitrogen in an agricultural ecosystem as affected by farming practices. *Geoderma*, 139(3-4), 336-345.

- Hunt, L. A., Pararajasingham, S., Jones, J. W., Hoogenboom, G., Imamura, D. T., & Ogoshi, R. M. (1993). GENCALC: Software to facilitate the use of crop models for analyzing field experiments. *Agronomy Journal*, 85(5), 1090-1094.
- IPCC, 2021: Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Masson-Delmotte, V., P.
- Jarvis, N. J. (2011). Simple physics-based models of compensatory plant water uptake: Concepts and eco-hydrological consequences. *Hydrology and Earth System Sciences*, 15(11), 3431-3446.
- Jin, Z., Ainsworth, E. A., Leakey, A. D., & Lobell, D. B. (2018). Increasing drought and diminishing benefits of elevated carbon dioxide for soybean yields across the US Midwest. *Global change biology*, 24(2), e522-e533.
- Jin, Z., Zhuang, Q., Wang, J., Archontoulis, S. V., Zobel, Z., & Kotamarthi, V. R. (2017). The combined and separate impacts of climate extremes on the current and future US rainfed maize and soybean production under elevated CO₂. *Global change biology*, 23(7), 2687-2704.
- Jones, C.A., & J.R. Kiniry (Eds.). (1986). CERES-Maize: A simulation model of maize growth and development. Texas A&M Univ. Press, College Station.
- Jones, J. W., Hoogenboom, G., Porter, C. H., Boote, K. J., Batchelor, W. D., Hunt, L. A., & Ritchie, J. T. (2003). The DSSAT cropping system model. *European journal of agronomy*, 18(3-4), 235-265.
- Kates, R. W., Clark, W. C., Corell, R., Hall, J. M., Jaeger, C. C., Lowe, I., & Svedin, U. (2001). Sustainability science. *Science*, 292(5517), 641-642.

- Keating, B. A., Carberry, P. S., Hammer, G. L., Probert, M. E., Robertson, M. J., Holzworth, D., .
& Smith, C. J. (2003). An overview of APSIM, a model designed for farming systems
simulation. *European journal of agronomy*, 18(3-4), 267-288.
- Kellogg, W. W. (2019). *Climate change and society: consequences of increasing atmospheric
carbon dioxide*. Routledge.
- Kimm, H., Guan, K., Gentine, P., Wu, J., Bernacchi, C. J., Sulman, B. N., & Lin, C. (2020).
Redefining droughts for the US Corn Belt: The dominant role of atmospheric vapor pressure
deficit over soil moisture in regulating stomatal behavior of Maize and Soybean.
Agricultural and Forest Meteorology, 287, 107930.
- Knox, J. W., Díaz, J. R., Nixon, D. J., & Mkhwanazi, M. (2010). A preliminary assessment of
climate change impacts on sugarcane in Swaziland. *Agricultural systems*, 103(2), 63-72.
- Kucharik, C. J., & Serbin, S. P. (2008). Impacts of recent climate change on Wisconsin corn and
soybean yield trends. *Environmental Research Letters*, 3(3), 034003.
- Läderach, P., Martinez-Valle, A., Schroth, G., & Castro, N. (2013). Predicting the future climatic
suitability for cocoa farming of the world's leading producer countries, Ghana and Côte
d'Ivoire. *Climatic change*, 119(3), 841-854.
- Lal, R. (2000). Physical management of soils of the tropics: priorities for the 21st century. *Soil
science*, 165(3), 191-207.
- Laux, P., Jäckel, G., Tingem, R. M., & Kunstmann, H. (2010). Impact of climate change on
agricultural productivity under rainfed conditions in Cameroon—A method to improve
attainable crop yields by planting date adaptations. *Agricultural and Forest Meteorology*,
150(9), 1258-1271.

- Layzell, A. L., & Evans, C. S. (2012). A thousand years of drought and climatic variability in Kansas—Implications for water resources management. Kansas Geological Survey, Open-File Report, 23 p.
- Leakey, A. D. (2009). Rising atmospheric carbon dioxide concentration and the future of C4 crops for food and fuel. *Proceedings of the Royal Society B: Biological Sciences*, 276(1666), 2333-2343.
- Lin, X., Harrington, J., Ciampitti, I., Gowda, P., Brown, D., & Kisekka, I. (2017). Kansas trends and changes in temperature, precipitation, drought, and frost-free days from the 1890s to 2015. *Journal of Contemporary Water Research & Education*, 162(1), 18-30.
- Liu, L., Tan, Z., Gong, H., & Huang, Q. (2018). Migration and transformation mechanisms of nutrient elements (N, P, K) within biochar in straw–biochar–soil–plant systems: a review. *ACS Sustainable Chemistry & Engineering*, 7(1), 22-32.
- Lobell, D. B., & Asseng, S. (2017). Comparing estimates of climate change impacts from process-based and statistical crop models. *Environmental Research Letters*, 12(1), 015001.
- Lobell, D. B., Roberts, M. J., Schlenker, W., Braun, N., Little, B. B., Rejesus, R. M., & Hammer, G. L. (2014). Greater sensitivity to drought accompanies maize yield increase in the US Midwest. *Science*, 344(6183), 516-519.
- Luan, X., Bommarco, R., Scaini, A., & Vico, G. (2021). Combined heat and drought suppress rainfed maize and soybean yields and modify irrigation benefits in the USA. *Environmental Research Letters*, 16(6), 064023.
- Luo, X., Hou, E., Zang, X., Zhang, L., Yi, Y., & Wen, D. (2019). Effects of elevated atmospheric CO₂ and nitrogen deposition on leaf litter and soil carbon degrading enzyme activities in a

- Cd-contaminated environment: a mesocosm study. *Science of the Total Environment*, 671, 157-164.
- Malik, W., Isla, R., & Dechmi, F. (2019). DSSAT-CERES-maize modelling to improve irrigation and nitrogen management practices under Mediterranean conditions. *Agricultural Water Management*, 213, 298-308.
- McGrath, J. M., Betzelberger, A. M., Wang, S., Shook, E., Zhu, X. G., Long, S. P., & Ainsworth, E. A. (2015). An analysis of ozone damage to historical maize and soybean yields in the United States. *Proceedings of the National Academy of Sciences*, 112(46), 14390-14395.
- McNider, R. T., Handyside, C., Doty, K., Ellenburg, W. L., Cruise, J. F., Christy, J. R., & Caldwell, P. (2015). An integrated crop and hydrologic modeling system to estimate hydrologic impacts of crop irrigation demands. *Environmental Modelling & Software*, 72, 341-355.
- Mera, R., Massey, N., Rupp, D. E., Mote, P., Allen, M., & Frumhoff, P. C. (2015). Climate change, climate justice and the application of probabilistic event attribution to summer heat extremes in the California Central Valley. *Climatic Change*, 133(3), 427-438.
- Milewski, R., Schmid, T., Chabrillat, S., Jiménez, M., Escribano, P., Pelayo, M., & Ben-Dor, E. (2022). Analyses of the Impact of Soil Conditions and Soil Degradation on Vegetation Vitality and Crop Productivity Based on Airborne Hyperspectral VNIR–SWIR–TIR Data in a Semi-Arid Rainfed Agricultural Area (Camarena, Central Spain). *Remote Sensing*, 14(20), 5131.
- Mugiyo, H., Chimonyo, V. G., Sibanda, M., Kunz, R., Masemola, C. R., Modi, A. T., & Mabhaudhi, T. (2021). Evaluation of land suitability methods with reference to neglected and underutilised crop species: A scoping review. *Land*, 10(2), 125.

- O'Brien, P., Kral-O'Brien, K., & Hatfield, J. L. (2021). Agronomic approach to understanding climate change and food security. *Agronomy Journal*, 113(6), 4616-4626.
- Olesen, J. E., Bøcher, P. K., & Jensen, T. (2000). Comparison of scales of climate and soil data for aggregating simulated yields of winter wheat in Denmark. *Agriculture, ecosystems & environment*, 82(1-3), 213-228.
- O'Neal, M. R., Nearing, M. A., Vining, R. C., Southworth, J., & Pfeifer, R. A. (2005). Climate change impacts on soil erosion in Midwest United States with changes in crop management. *Catena*, 61(2-3), 165-184.
- Pathak, T. B., Fraisse, C. W., Jones, J. W., Messina, C. D., & Hoogenboom, G. (2007). Use of global sensitivity analysis for CROPGRO cotton model development. *Transactions of the ASABE*, 50(6), 2295-2302.
- Pereira, V. R., Blain, G. C., Avila, A. M. H. D., Pires, R. C. D. M., & Pinto, H. S. (2017). Impacts of climate change on drought: changes to drier conditions at the beginning of the crop growing season in southern Brazil. *Bragantia*, 77, 201-211.
- Petersen, L. K. (2019). Impact of climate change on twenty-first-century crop yields in the US. *Climate*, 7(3), 40.
- Phetheet, J., Hill, M. C., Barron, R. W., Rossi, M. W., Amanor-Boadu, V., Wu, H., & Kisekka, I. (2021). Consequences of climate change on food-energy-water systems in arid regions without agricultural adaptation, analyzed using FEWCalc and DSSAT. *Resources, Conservation and Recycling*, 168, 105309.
- Plant, R. E. (2001). Site-specific management: the application of information technology to crop production. *Computers and electronics in agriculture*, 30(1-3), 9-29.

- Quine, T. A., & Zhang, Y. (2002). An investigation of spatial variation in soil erosion, soil properties, and crop production within an agricultural field in Devon, United Kingdom. *Journal of Soil and Water Conservation*, 57(1), 55-65.
- Ramirez-Villegas, J., Molero Milan, A., Alexandrov, N., Asseng, S., Challinor, A. J., Crossa, J., & Reynolds, M. (2020). CGIAR modeling approaches for resource-constrained scenarios: I. Accelerating crop breeding for a changing climate. *Crop Science*, 60(2), 547-567.
- Ranum, P., Rock-Roses, J. P., & Garcia-Casal, M. N. (2014). Global maize production, utilization, and consumption. *Annals of the New York Academy of Sciences*, 1312(1), 105-112.
- Ray, D. K., Gerber, J. S., MacDonald, G. K., & West, P. C. (2015). Climate variation explains a third of global crop yield variability. *Nature communications*, 6(1), 5989.
- Ray, D. K., West, P. C., Clark, M., Gerber, J. S., Prishchepov, A. V., & Chatterjee, S. (2019). Climate change has likely already affected global food production. *PloS one*, 14(5), e0217148.
- Reilly, J., Paltsev, S., Felzer, B., Wang, X., Kicklighter, D., Melillo, J., & Wang, C. (2007). Global economic effects of changes in crops, pasture, and forests due to changing climate, carbon dioxide, and ozone. *Energy Policy*, 35(11), 5370-5383.
- Rodcha, R., Tripathi, N. K., & Prasad Shrestha, R. (2019). Comparison of cash crop suitability assessment using parametric, AHP, and FAHP methods. *Land*, 8(5), 79.
- Rogers, A., Ainsworth, E. A., & Leakey, A. D. (2009). Will elevated carbon dioxide concentration amplify the benefits of nitrogen fixation in legumes? *Plant Physiology*, 151(3), 1009-1016.
- Rounsevell, M. D. A., Annetts, J. E., Audsley, E., Mayr, T., & Reginster, I. (2003). Modelling the spatial distribution of agricultural land use at the regional scale. *Agriculture, Ecosystems & Environment*, 95(2-3), 465-479.

- Sabagh, A. E., Hossain, A., Iqbal, M. A., Barutçular, C., Islam, M. S., Çiğ, F., & Saneoka, H. (2020). Maize adaptability to heat stress under changing climate. In *Plant stress physiology*. IntechOpen.
- Sakurai, G., Iizumi, T., Nishimori, M., & Yokozawa, M. (2014). How much has the increase in atmospheric CO₂ directly affected past soybean production? *Scientific Reports*, 4(1), 1-5.
- Sarkar, R., & Kar, S. (2006). Evaluation of management strategies for sustainable rice–wheat cropping system, using DSSAT seasonal analysis. *The Journal of Agricultural Science*, 144(5), 421-434.
- Schyns, J. F., Hoekstra, A. Y., Booij, M. J., Hogeboom, R. J., & Mekonnen, M. M. (2019). Limits to the world's green water resources for food, feed, fiber, timber, and bioenergy. *Proceedings of the National Academy of Sciences*, 116(11), 4893-4898.
- Sharda, V., Handyside, C., Chaves, B., McNider, R. T., & Hoogenboom, G. (2017). The impact of spatial soil variability on simulation of regional maize yield. *Transactions of the ASABE*, 60(6), 2137-2148.
- Sharda, V., Mekonnen, M. M., Ray, C., & Gowda, P. H. (2021). Use of Multiple Environment Variety Trials Data to Simulate Maize Yields in the Ogallala Aquifer Region: A Two Model Approach. *JAWRA Journal of the American Water Resources Association*, 57(2), 281-295.
- Shin, D. W., Cocke, S., Baigorria, G. A., Romero, C. C., Kim, B. M., & Kim, K. Y. (2020). Future Crop Yield Projections Using a Multi-model Set of Regional Climate Models and a Plausible Adaptation Practice in the Southeast United States. *Atmosphere*, 11(12), 1300.
- Shukla, P. R., Skeg, J., Buendia, E. C., Masson-Delmotte, V., Pörtner, H. O., Roberts, D. C., & Malley, J. (2019). *Climate Change and Land: an IPCC special report on climate change,*

desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems.

Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture (2019). Web Soil Survey. Available online at <http://websoilsurvey.nrcs.usda.gov/> accessed [08/05/2021].

Soler, C. M. T., Sentelhas, P. C., & Hoogenboom, G. (2007). Application of the CSM-CERES-Maize model for planting date evaluation and yield forecasting for maize grown off-season in a subtropical environment. *European Journal of Agronomy*, 27(2-4), 165-177.

Southworth, J., Pfeifer, R. A., Habeck, M., Randolph, J. C., Doering, O. C., Johnston, J. J., & Rao, D. G. (2002). Changes in soybean yields in the midwestern United States as a result of future changes in climate, climate variability, and CO₂ fertilization. *Climatic Change*, 53, 447-475.

Southworth, J., Randolph, J. C., Habeck, M., Doering, O. C., Pfeifer, R. A., Rao, D. G., & Johnston, J. J. (2000). Consequences of future climate change and changing climate variability on maize yields in the midwestern United States. *Agriculture, Ecosystems & Environment*, 82(1-3), 139-158.

Srivastava, A. K., Mboh, C. M., Zhao, G., Gaiser, T., & Ewert, F. (2018). Climate change impact under alternate realizations of climate scenarios on maize yield and biomass in Ghana. *Agricultural Systems*, 159, 157-174.

Steduto, P., Hsiao, T. C., Raes, D., & Fereres, E. (2009). AquaCrop—The FAO crop model to simulate yield response to water: I. Concepts and underlying principles. *Agronomy Journal*, 101(3), 426-437.

- Steiner, J. L., Briske, D. D., Brown, D. P., & Rottler, C. M. (2018). Vulnerability of Southern Plains agriculture to climate change. *Climatic change*, 146, 201-218.
- Swinscow, T. D. V., & Campbell, M. J. (2002). *Statistics at square one* (pp. 111-25). London: Bmj.
- Thorp, K. R., Barnes, E. M., Hunsaker, D. J., Kimball, B. A., White, J. W., Nazareth, V. J., & Hoogenboom, G. (2014). Evaluation of CSM-CROPGRO-Cotton for simulating effects of management and climate change on cotton growth and evapotranspiration in an arid environment. *Trans. ASABE*, 57(6), 1627-1642. <https://doi.org/10.13031/trans.57.10612>.
- Thorp, K. R., DeJonge, K. C., Kaleita, A. L., Batchelor, W. D., & Paz, J. O. (2008). Methodology for the use of DSSAT models for precision agriculture decision support. *computers and electronics in agriculture*, 64(2), 276-285.
- Tubiello, F., Schmidhuber, J., Howden, M., Neofotis, P. G., Park, S., Fernandes, E., & Thapa, D. (2008). Climate change response strategies for agriculture: challenges and opportunities for the 21st century. *Agriculture and rural development discussion paper*, 42.
- Urban, D., Roberts, M. J., Schlenker, W., & Lobell, D. B. (2012). Projected temperature changes indicate significant increase in interannual variability of US maize yields: A Letter. *Climatic change*, 112, 525-533.
- USDA National Agricultural Statistics Service Cropland Data Layer. (2019). Published crop-specific data layer [Online].
- USDA National Agricultural Statistics Service, (2016). Quickstats 2.0. Washington, DC: USDA National Agricultural Statistics Service. http://www.nass.usda.gov/Quick_Stats/.
- USDA National Agricultural Statistics Service, (2020). Census of Agriculture. Complete data is available at www.nass.usda.gov/AgCensus.

- USGCRP, 2017: *Climate Science Special Report: Fourth National Climate Assessment*. Vol. I. D. J. Wuebbles et al., Eds., U.S. Global Change Research Program, 470 pp., <https://doi.org/10.7930/J0J964J6>.
- Wang, J., Vanga, S. K., Saxena, R., Orsat, V., & Raghavan, V. (2018). Effect of climate change on the yield of cereal crops: a review. *Climate*, 6(2), 41.
- White, J. W., Hoogenboom, G., Kimball, B. A., & Wall, G. W. (2011). Methodologies for simulating impacts of climate change on crop production. *Field Crops Research*, 124(3), 357-368.
- Williams, J. R., Jones, C. A., Kiniry, J. R., & Spanel, D. A. (1989). The EPIC crop growth model. *Transactions of the ASAE*, 32(2), 497-0511.
- Willmott CJ. 1982. Some comments on the evaluation of model performance. *Bulltein of Amer. Met.Soc.*63.1309-1369.
- Xiong, W., Holman, I., Conway, D., Lin, E., & Li, Y. (2008). A crop model cross-calibration for use in regional climate impacts studies. *Ecological Modelling*, 213(3-4), 365-380.
- Yakoub, A., Lloveras, J., Biau, A., Lindquist, J. L., & Lizaso, J. I. (2017). Testing and improving the maize models in DSSAT: Development, growth, yield, and N uptake. *Field Crops Research*, 212, 95-106.
- Yang, X., Chen, F., Lin, X., Liu, Z., Zhang, H., Zhao, J., & Tang, H. (2015). Potential benefits of climate change for crop productivity in China. *Agricultural and Forest Meteorology*, 208, 76-84.
- Yu, C., Miao, R., & Khanna, M. (2021). Maladaptation of US corn and soybeans to a changing climate. *Scientific reports*, 11(1), 1-12.

- Yue, Y., Yan, D., Yue, Q., Ji, G., & Wang, Z. (2021). Future changes in precipitation and temperature over the Yangtze River Basin in China based on CMIP6 GCMs. *Atmospheric Research*, 264, 105828.
- Zheng, J., Fan, J., Zhang, F., Guo, J., Yan, S., Zhuang, Q & Guo, L. (2021). Interactive effects of mulching practice and nitrogen rate on grain yield, water productivity, and fertilizer use efficiency and greenhouse gas emissions of rainfed summer maize in northwest China. *Agricultural Water Management*, 248, 106778.
- Zhou, W., Guan, K., Peng, B., Wang, Z., Fu, R., Li, B., & Chen, Z. (2021). A generic risk assessment framework to evaluate the historical and future climate-induced risk for rainfed corn and soybean yield in the US Midwest. *Weather and Climate Extremes*, 33, 100369.
- Zipper, S. C., Qiu, J., & Kucharik, C. J. (2016). Drought effects on US maize and soybean production: spatiotemporal patterns and historical changes. *Environmental Research Letters*, 11(9), 094021.