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Crop Circles in the Corn Belt: A Farm-Scale Model to Curb Future Crop Yield Loss with Blended Policy-Structural Adaptations

Daniel Ress

CROP CIRCLES IN THE CORN BELT: A FARM-SCALE MODEL TO CURB FUTURE CROP YIELD LOSS WITH BLENDED POLICY-STRUCTURAL ADAPTATIONS

THESIS

Daniel Ress, Captain, USAF

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Abstract

In today's rainfed agricultural regions, such as the Midwestern United States, farmers reliably produce marketable yields without the need for irrigation technology or specific planting policies. However, climate change is expected to challenge global food security. Future climate change projections, namely wholesale temperature rise and temporal shifts in the peak precipitation seasons, might reduce crop yields and alter spatial crop suitability. As a result, farmers might seek adaptation strategies to continue current productivity and profitability, rather than make costly changes associated with planting different crop types. This research investigates the spatiotemporal suitability of blended policy-structural adaptations to reduce yield losses without crop type and planting pattern changes in Greene County, Ohio. Using CMIP5 predictions of precipitation and temperature and soil profile data from NRCS, a crop-water model is used to generate field-scale yield predictions and water-deficit estimates by alternating emission scenario, crop type, planting date, irrigation level, and soil type. Field-level yield predictions and water deficits are mapped at the county-scale throughout this century to illustrate the efficacy of planting policy interventions. Structural adaptation, in the form of center pivot-type irrigation technology, is applied where water deficits generate persistent yield losses. An economic model is used to determine the efficient investment strategy required to purchase, operate, and maintain irrigation infrastructure at the farm-scale. Implementing a planting policy and irrigation could help avoid a 5.5% annual corn yield loss by the end of the century. The policy suggests farmers should plant corn 18 days earlier and soybeans 15 days earlier by end-of-century. The irrigation

requirement to sustain stress-free plant growth decreases by 16.7% for corn and 19.2% for soybeans by end-of-century. The economic analysis results show that a corn farmer with a 160-acre Silt Loam field should implement a center-pivot irrigation system by 2060 to maintain profitable revenue under the worst-case emission scenario but should avoid it entirely under an intermediate emission scenario. A farmer planting soybeans on the same field should install a center-pivot irrigation system as soon as financially feasible to seek profitable gains. The resultant framework holds the potential to inform farmer and county-level decision making under future climate uncertainty, and it illustrates the tradeoffs between adaptation cost and yield security.

Acknowledgments

Before I thank the many people who have assisted me in this process, I would like to express my primary and eternal gratitude to my Savior, Jesus Christ. He has directed my journey of becoming a new father and lit the path that was dimmed by a tough year of a global pandemic. Without Christ's love, patience, and grace, focusing on my work while maintaining my relationships would have been impossible. I would like to give a big thank you to Maj Justin Delorit, advisor and committee chair, for guiding me with wisdom and understanding. Through the ease at which you exemplify it, you have motivated me to become a better student, leader, and family man. Your mentorship, as well as your friendship, has pushed me forward towards each arising goal. I would like to recognize the abundance of insight and inspiration given to me by my committee members, Lt Col Steven Schuldt and Dr. Christopher Chini. Additionally, I can't help but give a big shout out to the 21M graduating class for the accountability, companionship, and laughter they have blessed me with this past year. Finally, I would like to thank my family, especially my wife, for her motivation and guidance. It is her that has continuously, if not daily, reminded me of who I am and what I am capable of accomplishing. I am forever grateful to have a partner who grounds me and encourages me.

Daniel Ress

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CROP CIRCLES IN THE CORN BELT: A FARM-SCALE MODEL TO CURB FUTURE CROP YIELD LOSS WITH BLENDED POLICY-STRUCTURAL ADAPTATIONS

I. Introduction

1.1 Background

The planet is continuously changing due to a mixture of natural and anthropogenic influences. Only recently have these changes been a cause for existential concern. Changes to the earth are nonlinear and interconnected. The global average surface air temperature has increased by about 1°C over the last 115 years (USGCRP, 2017). The extra heat has been absorbed by the ocean, increasing sea surface temperature, which largely defines global climate patterns (Levitus et al., 2017). Arctic sea ice and glaciers are shrinking, and mountains have decreased snow cover (Velicogna et al., 2020; Robinson et al., 2014). This melting ice combined with ocean swell contributes to sea level rise that puts coastal populations in jeopardy (Nerem et al., 2018). Extreme weather events occur at an unprecedented rate and magnitude, causing severe terrestrial destruction (USGCRP, 2017). The reason for these changes is primarily attributed to the increase in the atmospheric concentration of carbon dioxide from burning fossil fuels, which is trapping more of the earth's radiated heat, causing a greenhouse effect (IPCC, 2014). The higher temperatures will cause heat stress to people and the planet. In drought conditions, wildfires will start and spread more easily (IPCC, 2014). More intense

hurricanes will cause dangerous flooding. Sea level rise will force a large portion of the world population to relocate (IPCC, 2014). The imminent threat of climate change is clear.

Longer-term threats, due to the graduality aspect of climate change, are expected to have socioeconomic effects. One looming crisis surrounds the interconnected global agricultural system, which is expected to become less stable as global temperature rises, and precipitation becomes increasingly variable (USGCRP, 2018). Food production uncertainty could cause various issues, stemming from starvation, the spread of disease, and conflict (IPCC, 2014). Clearly, the focus should be given to adapting agricultural production systems such that they are robust to a variety of climate-induced stresses.

1.2 Problem Statement

Climate change is expected to impact agriculture in numerous ways. Studies show that an increase in air temperature will shorten the growing season due to the impact on the soil water balance leading to increased soil evaporation and plant transpiration (Kang et al., 2009). Precipitation patterns are expected to shift due to water abundance in the winter and spring and scarcity in the summer (USGCRP, 2018). Furthermore, winter precipitation that historically fell as snow, and served as pseudo-storage until spring melting, is expected to fall as rain (Mearns et al., 2013). An increase in extreme temperature and precipitation occurrence will cause more flooding and periods of drought, creating interannual crop yield variability, and potentially, failures. Higher levels of atmospheric carbon dioxide can stimulate plant growth (Gamage et al., 2018). However, rising carbon dioxide concentrations create a reduction in nutritional value,

which decreases food quality (Dong et al., 2018). The change in temperature and precipitation will likely increase the prevalence of weeds and pests among crops, forcing increases in expensive and potentially dangerous chemical mitigation strategies (Peters et al., 2014).

The cumulative effects of these uncertainties and threats are widely believed to result in future decreases in crop yields, which will threaten food security (Kang et al., 2009). This threat is magnified by a growing world population and increases in life expectancy (Tripathi et al., 2019). The problem with this threat is that different parts of the world will be impacted differently by climate change. The uncertainty of this impact spatially warrants investigation into one of the largest crop-producing regions in the world, the corn belt. The decrease in crop yields due to climate change could negatively impact the profits of farmers working within this region (USGCRP, 2018). With the threat of growing and harvesting seasons changing, it is essential for farmers to adapt techniques to continuously reap a plentiful supply. Additionally, it is necessary for each farmer to consider the location and size of their farms to adopt the best techniques for their crop yield.

1.3 Research Objectives

Given the clear globality of the threat that climate change imposes on agricultural and human survival, identifying adaptation strategies to stabilize yields and ensure sustainable system profitability is imperative. As such, the questions addressed in this research are designed to provide hard and soft adaptation strategies for agricultural

producers to ensure future food security under increasing water stress induced by climate change. The study will address the following research questions:

1. What is the effect of climate change on farm-scale yield production through 2100?
2. Can a blend of hard and soft adaptation policies be used to offset yield loss?
3. Which blend of policies provides farmers with a least-cost approach to ensuring yield production and profitability?

1.4 Research Focus

The United States is the largest producer of corn and soybeans in the world, and production is most dense in the midwestern “Corn Belt” states (Schlenker & Roberts, 2009). Conditions in the Corn Belt are ideal for agricultural production and include deep, rich, well-drained soils occurring on mostly level land (Green et al., 2018). Combining that with warm temperatures and peak precipitation to produce a well-aligned growing season, corn has become a reliable cash crop for farmers. The current climate in this region allows for much of the corn and soybean production to be achieved without the need for irrigation (Green et al., 2018). The concern lies in the fact that, even though rainfed agricultural production is less expensive than irrigation-supported operations, it is susceptible to greater losses during drought (Kimm et al., 2020). With much of the world relying on stable crop yields from this region, and existing evidence of climate change affecting yield, various mitigation strategies have already been developed. Most notably, genetically modified crop varieties have been on the rise over the past few last decades. Herbicide-tolerant (HT) and insect-resistant (Bt) corn have steadily increased since 1996

(McFadden et al., 2019). Drought-tolerant (DT) corn has become available more recently between 2011 and 2013 (McFadden et al., 2019). Although yields have seen marginal improvements from these genetically modified crops, the data is lacking to determine the long-term effects. This strategy will decrease biodiversity and soil fertility and potentially have additional negative consequences by the end of the century (Schütte et al., 2017).

Different levels of intervention exist that the farmer can choose to utilize considering land size to protect against water soil imbalances. First, an optimized planting policy based on temperature can be developed for a specific crop for a given region. With warmer temperatures, farmers will be able to plant crops earlier in the year to maximize yields. However, they should be sure not to plant too early when the soil is still frozen. Additionally, an irrigation system can be implemented to offset precipitation deficits. Water deficit creates water stress in crops and can also exacerbate temperature stress-related yield loss (Jumrani & Bhatia, 2018). Utilizing high-capacity wells to supply center-pivot sprinkler systems, farmers can make use of groundwater resources to augment crops (Grassini et al., 2011). While each of these changes could be implemented separately, they can be used together to achieve greater yield stability. This study determines the timing and feasibility of implementing these adaptations.

1.5 Preview

The chapters that follow will include a literature review of the impact climate change has on agriculture as well as various crop modeling software to predict future yield. The case study chapter will outline the climate, soil, and crop details of Greene County, Ohio, used for this research and provide a justification for its selection. The

methodology chapter will describe the calibration of AquaCrop and running simulations. The results chapter will show the outcome of simulations temporally and spatially. Finally, the conclusions chapter will offer implications of the research along with limitations and recommendations for future research.

II. Literature Review

2.1 Chapter Overview

This chapter provides a review of the literature published on the impact climate change will have on agriculture. It illustrates how world population change will affect food demand as a means of motivating the work. Studies are reviewed that use various crop modeling software to predict changes in yield. Finally, a review of various adaptation strategies to mitigate yield loss is shown to illustrate the future value of curbing yield loss today. The impact that a blended approach to adaptions will have on yield loss at a farm-scale will be revealed as a gap in the literature.

2.2 Climate Change Impact on Agriculture

The impact of climate change on crop production around the world is spatially variable and crop-dependent. A combination of studies found that the number and severity of decreased future crop yield scenarios were more common than increased yield scenarios, which mostly came from high latitude areas (IPCC, 2014). The projected future yields depended on crop type, region, and adaptation selected. With a global temperature increase of 2°C, major crops such as wheat, rice, and corn throughout tropical and temperate regions were projected to have a loss in future yields, with the risk becoming more severe after 2050 (IPCC, 2014). The uncertainty of the impact to crops due to climate change has been found to be more impacted by uncertainty in temperature rather than precipitation (Lobell and Burke, 2008). One adaptation study argues the integration of climate change-related issues with other risk factors is required to achieve a comprehensive and dynamic policy approach (Howden et al., 2007).

The impact of climate change at a regional level is unique to the United States. Corn and soybeans make up two of the four largest sources of caloric energy, and since the United States produces 41% of the world's corn and 38% of the world's soybeans, shifts in agricultural productivity may have implications for global food security (Schlenker and Roberts, 2009). With the world population expected to continue to 9 billion by 2050, the increase in global food demand will make it even more challenging to feed the world population (Godfray et al., 2010). Optimum temperatures have been reached for crops in North American, so continued regional warming could decrease end-of-century yield by 63–82% under the most rapid warming scenario (Schlenker and Roberts, 2009). It has been observed that the grain production in the Corn Belt may be limited due to a degradation of the soil caused by severe weather events (Hatfield et al., 2013). One model showed negligible changes for crop growth in 10 southeastern US counties when warming was moderate but increased severity as warming increased (Paudel and Hatch, 2012). Crop yields have been found to have a negative sensitivity to extreme temperatures around 30°C, with each day over 30°C diminishing US corn and soybean yields by up to 6% under rainfed conditions (Schauberger et al., 2017).

The Midwestern United States will be impacted by climate change as well, and they act as a major producer of a wide range of food and animal feed. It has been reported that the agricultural productivity of this region will be set back to that of the 1980s due to climate change if major technological advances are not implemented (USGCRP, 2018). The United States will see a national increase in temperature, but the Midwest will see a greater increase than any other region (USGCRP, 2017). Within the region, there can be a large variance of projected yield. One study showed that midcentury yield loss was

greater than 25% of the baseline for corn in some parts of the Midwest but also showed a yield gain greater than 25% of the baseline for soybeans in the northern part of the Midwest (Takle et al., 2013). Temperature and precipitation were found to account for 70% of the variations in US agriculture productivity, but the largest contributor to the climate penalty was the projected increase in summer temperature over the Midwest (Liang et al., 2017). One simulation suggests that drought will be the largest threat to US rainfed soybean production, but high temperature and heat stress will become the dominant stress on corn production under an RCP8.5 emission scenario (Jin et al., 2017).

2.3 Crop Modelling Software

Crop simulation software can assist in the prediction of future crop yields. Numerous software packages exist, such as Aquacrop, CropSyst, DSSAT, and SWAT. CropSyst is a cropping system simulation model developed to serve as an analytical tool that simulates the soil water and nitrogen budgets, crop growth and development, crop yield, residue production and decomposition, soil erosion by water, and salinity (Stöckle et al., 2003). CropSyst and Aqaucrop were compared simulating the growth of barley in Southern Italy, but AquaCrop seemed to be easier to calibrate when available crop growth data was limited (Abi Saab et al., 2015). The Decision Support System for Agrotechnology Transfer (DSSAT) utilizes different modules with one each for soil, crop type, and weather, as well as a module for dealing with competition for light and water among the soil, plants, and atmosphere (Jones et al., 2003). DSSAT has also been compared to Aquacrop for soybean production in Southern Brazil, showing that multiple completely calibrated models had the best performance (Battisti et al., 2017).

The crop growth model used for this research was AquaCrop, which was developed by the Land and Water Division of the Food and Agriculture Organization of the United Nations (FAO, 2021). It was chosen over other crop modeling software because it uses a relatively small number of parameters and attempts to balance simplicity, accuracy, and robustness (Steduto et al., 2009). It is a menu-driven program with a well-developed user interface requiring simple inputs of weather data, crop characteristics, and soil and management characteristics that define the crop development environment (Raes et al., 2009). The first crop tested with AquaCrop was corn in Davis, California, and it simulated the final aboveground biomass within 10% of the observed value for 8 of the 13 treatments (Hsiao et al., 2009). The largest deviation between the simulated and measured values was 24% for grain yield and 22% for biomass, which could have been the result of simplifications in the model or inaccuracies in measurements (Hsiao et al., 2009). AquaCrop was validated using corn in three different locations where it was able to simulate the crop water use (ET) under very high ET and wind conditions (Heng et al., 2009). It performed satisfactorily for the growth of aboveground biomass, grain yield, and canopy cover (CC) in the non-water-stress treatments and mild stress conditions and less than satisfactory in simulating severe water-stress treatments (Heng et al., 2009). Five years after it was released, it was well-received and had been validated and applied by the scientific community at the field and regional scale (Vanuytrecht et al., 2014). One study found that modeled yields were within +19% to −30% of observed yields of rainfed corn in Nigeria (Akumaga et al., 2017). Greaves & Wang (2016) found that AquaCrop simulated crop evapotranspiration

and water use efficiency values were within the range of 9.5% to 22.2% and 6.0% to 32.2%, respectively, for corn growth in Taiwan.

Crop growth models have frequently been used to predict crop yield in a climate-changed induced environment. A meta-analysis reviewed over 1700 publications to find that crop yield losses were expected for wheat, rice, and corn with a 2°C level of warming, but adaptions increased simulated yields by 7-15% (Challinor et al., 2014). One study found the damages to corn and soybeans in the US to be very harmful when their maximum temperatures were exceeded (Schlenker & Roberts, 2009). Bhattarai et al. (2017) used the Environmental Policy Integrated Climate (EPIC) growth model along with soil properties and cropland data layers to project an increase in corn and soybean yields under low and medium carbon emission scenarios but a decrease in yields under high carbon emission scenarios in the Racoon Watershed in Iowa.

2.4 Adaptation Strategies

Strategies to offset the impact of climate change have been researched. The optimal planting date for corn in the Corn Belt was shown to advance 0.13 days earlier per year from 1980 to 2015 with an economic analysis of potential revenue loss (Baum et al., 2020). To determine the effectiveness of various adaptation strategies, technology has advanced to use publicly available remote sensing and meteorological data to better estimate county-level corn yields (Jiang et al., 2020). Crop insurance has been used to hedge against the implications of climate change (Falco et al., 2014). Laux et al. (2010) created a model to compare an optimal planting date against a traditional planting date and found a 15% increase in corn yield in Cameroon. One study showed a blended

approach to adaption indicated an earlier planting date combined with decreased irrigation intervals caused higher yield for corn in Iran (Moradi et al., 2013). Crop modeling has been used to evaluate the integrated effects of genetically modified corn hybrids to produce superior yields for drought-prone areas in the Corn Belt. (Cooper et al., 2014).

2.5 Summary

Climate change has a clear impact on agriculture across the globe. Specifically, the midwestern United States, a major producer of the world's corn and soybeans, is expected to experience a loss in agriculture productivity, making it more challenging to provide food security for a growing population. Various crop modeling software exists to predict future yield under different climate scenarios. Adaptations exist to offset the yield loss due to climate change, but the benefit of a blended strategy approach needs to be evaluated using a crop growth model in AquaCrop.

III. Case Study Data

3.1 Chapter Overview

This chapter provides a description and justification for selecting Greene County, Ohio, as the case study for this research. It describes the location and includes current and future climate projections, soil types used for agriculture, crop planting history, and their economic value.

3.2 Location

Greene County is located in the southwestern corner of Ohio with coordinates of 39°41'N and 83°53'W. It has a land area of 414 square miles with a population of 168,937 as of 2019 (US Census Bureau, 2019).

Figure 1. Location of Greene County in Ohio, USA

3.3 Climate Data

The climate data used came from the fifth phase of the Coupled Model Intercomparison Project (CMIP5), which started at a 2008 meeting of 20 climate modeling groups from around the world agreeing on a set of coordinated climate model

experiments (Taylor et al., 2012). It was requested from the Lawrence Livermore National Laboratory (LLNL) Green Data Oasis (LLNL, 2021). Data was requested for five separate coordinate locations, seen in Figure 2 below, from January 2000 to December 2099. Daily climate projections of precipitation rate and minimum and maximum surface air temperature projected using the 1/8-degree bias-correction, and constructed analogs (BCCA) model were analyzed. Five locations were used to determine if the effect of climate change was temporally homogenous throughout the county. An ANOVA test was used to determine if there was a significant statistical difference between the five coordinates sampled. There was not enough evidence to reject the null hypothesis that the population means were equal. Therefore, only the climatic values from the center point were used in this research.

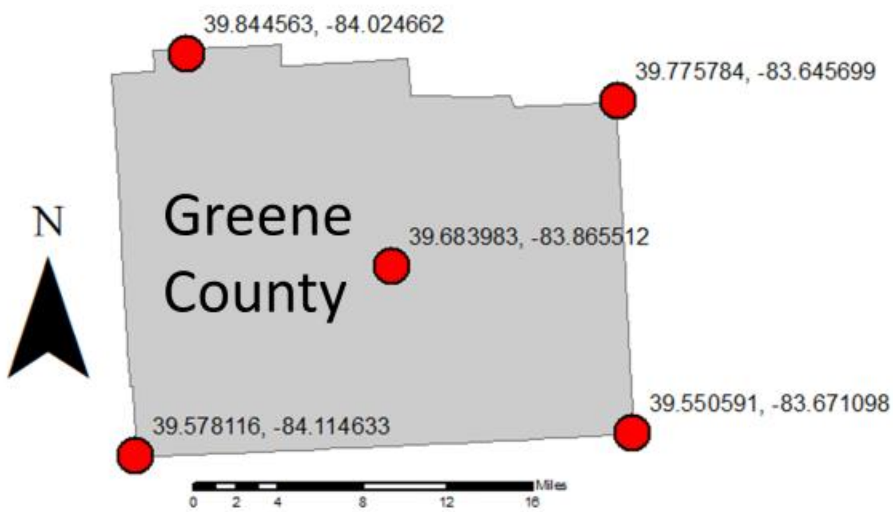


Figure 2. Coordinates used for climate data download

Based on the decision to treat the county as climatologically homogenous, all climate models were downloaded for two emission scenarios, RCP4.5 and RCP8.5. Across all

models for RCP4.5 and RCP8.5, the median value for each of the three climate variables was selected for every day from January 1, 2000, to December 31, 2099.

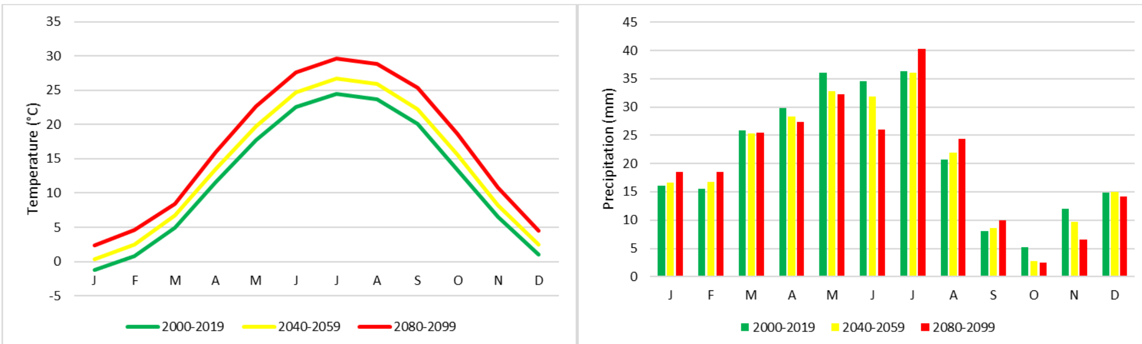
A climate profile in AquaCrop requires four sets of information: minimum and maximum air temperature, rainfall, evapotranspiration (ET_o), and atmospheric CO_2 concentrations. The first two were provided in the climate data downloaded from LLNL. There is a CO_2 concentrations file built into AquaCrop for each RCP as recorded by the Mauna Loa Observatory in Hawaii. The last dataset left to create is ET_o. AquaCrop has a built-in ET_o calculator that uses the Penman-Monteith equation. This requires further climatic variables such as air humidity and wind speed, which could not be obtained from LLNL. Therefore, the Modified Hargreaves equation (1) was used to calculate daily ET_o:

$$ET_O = 0.0023(0.408)(RA)\left(T_{avg} + 17.8\right)(TD)^{0.5} \qquad (1)$$

where RA is the extraterrestrial radiation obtained from tables (Hargreaves, 1994; Droogers and Allen, 2002) and is multiplied by the constant 0.408 to convert to millimeters, T_{avg} is the average mean daily temperature in degrees Celsius, and TD is the daily temperature range. With these four sets of information loaded into AquaCrop, bidecadal bins were used to split the century into five 20-year sections: 2000-2019, 2020-2039, 2040-2059, 2060-2079, and 2080-2099. The median value was used for each day of the year from each 20-year section creating an average climate variable for each bidecadal bin.

A summary of current and future climatology for Greene County can be seen in Figure **3**, below. Future projections of temperature, in terms of climatological patterning, remain consistent, though temperatures rise roughly proportionally across each month. Historically, July is the warmest month, with an average temperature of 24.5°C and the

coldest month is January with an average temperature of -1.2°C. Those temperatures shift up by the end of the century, with July ending at 29.6°C and January being 2.3°C. In terms of precipitation, future projections show less rain in Spring but more in Winter and late Summer. Historically, the most precipitation accumulates in May, June, and July, with around 35 mm of rain per month.



(a) (b)

Figure 3. Greene County, Ohio average monthly climate: a) temperature; b) precipitation

3.4 Soil

Soil is an important and necessary input to the crop growth model because it impacts observed yields and required irrigation. Greene County consists mainly of Silt Loam and Silty Clay Loam soils. With 164,046 acres, the Silt Loam soils are found mostly in the central and western urban areas. The Silty Clay Loam soil is located on the eastern side of the county, with 63,843 acres consisting mostly of farmland. Smaller strips of Loam and Clay Loam soils can be found in the central region but only make up 17,412 acres combined.

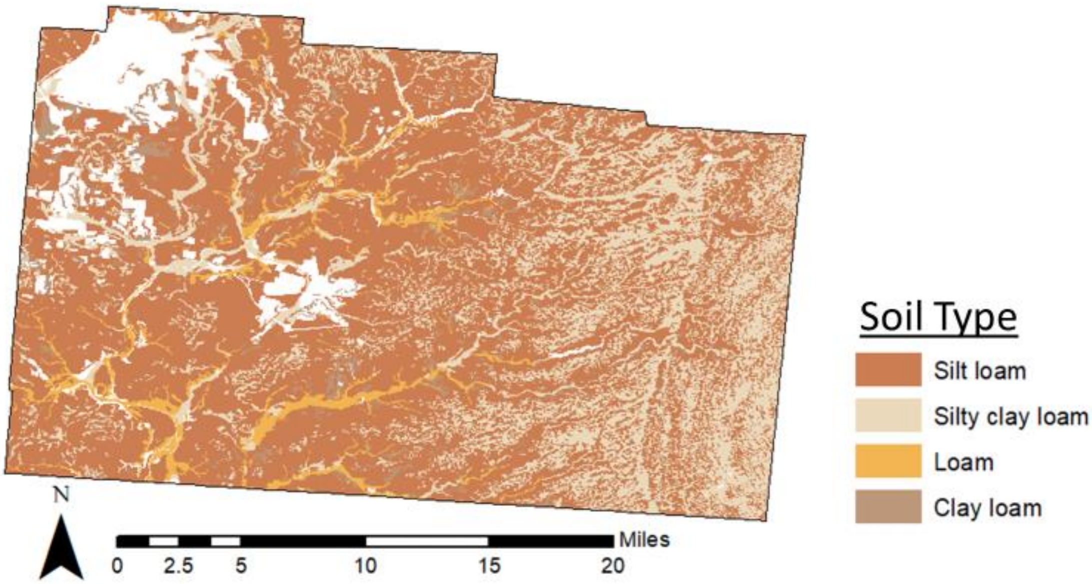


Figure 4. Simplified Soil Map of Greene County

Soil data for Greene County was downloaded from the Web Soil Survey (WSS) website, which is operated by the United States Department of Agriculture (USDA) Natural Resources Conservation Service (NRCS) (WSS, 2021). The area of interest was set to Greene County, which included a recent soil survey with tabular data from June 2020 and spatial data from September 2019, which revealed 113 unique soil profiles. Each soil profile is made up of layers of different soil types. For example, the most common soil profile in Greene County, making up 10% of the area, is called Ragsdale Silty Clay Loam. This profile consists of 50 inches of Silty Clay Loam on top with 29 inches of Silt Loam underneath. Only the surface texture was used to simplify the 113 soil types. This information was readily available from the WSS using the Soil Data Explorer under Soil Properties and Qualities. The surface texture table classified all 113 soil profiles into one of 12 USDA soil texture classifications, which is determined based on the percentage of Clay, Silt, and sand found in a given sample. Most of the county, 94

of the 113 soil types containing 91.8% of the county, was classified as either Clay Loam, Loam, Silt Loam, or Silty Clay Loam, making the county relatively homogenous. The remaining land area was either urban development, water, or an infertile soil type such as Muck or Gravelly Loam. These areas were not considered in the spatial analysis. Only the four USDA soil textures found were used for simulation runs in AquaCrop. This soil simplification step was essential to the model because AquaCrop only has the 12 USDA soil textures loaded. A table of the original soil profiles and their topsoil textures that were used in AquaCrop can be found in Appendix A.

3.5 Agriculture

The United States produced 13.6B bushels of corn and 3.55B bushels of soybeans in 2019 (USDA NASS, 2021). The geographic distribution of that production can be seen in Figure **5** below, with most of the corn and soybeans grown in the United States coming from the Corn Belt in the midwestern US.

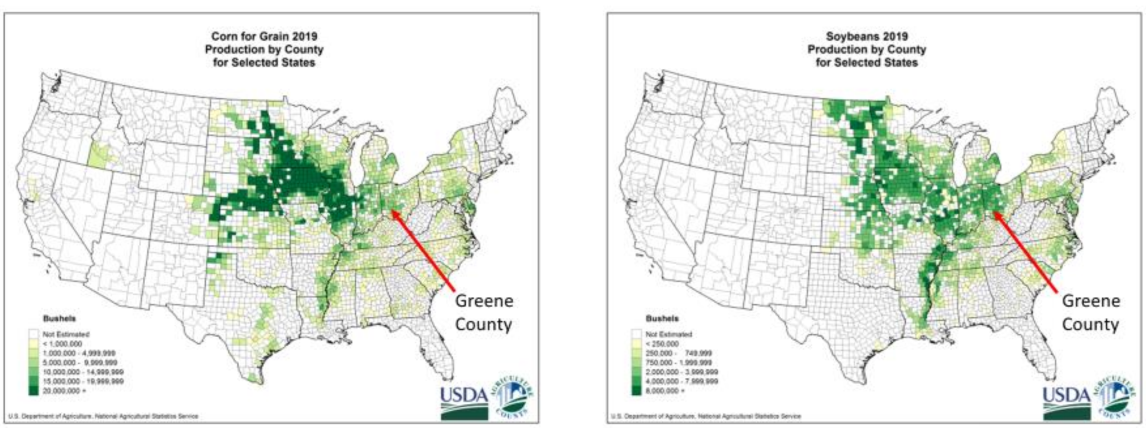


Figure 5. Corn and Soybeans Production by County for 2019 (USDA NASS, 2021)

Ohio was the tenth largest producer of corn (421M bushels) and the seventh-largest producer of soybeans (209M bushels) in 2019. Greene County produced 2.5% and 1.53%

of Ohio's corn and soybeans, respectively, in 2019. According to the 2017 Census of Agriculture, there were 817 farms in Greene County planted on 167,701, and only 395 acres were irrigated (USDA NASS, 2017). The total market value of agriculture was $97M, with $88.1M coming from crops.

The last piece of data needed was the land usage in the county to determine which fields had planted corn and soybeans. The USDA National Agricultural Statistics Service (NASS) provides cropland data layers through a geospatial interface called CropScape. These data layers present a map of how cropland was used for a given year. The cropland data layers for the previous three years can be seen in Figure **6** below. Nearly half of all land use in the county is cropland for corn and soybeans. The farmers will frequently alternate crops each planting season. The 2019 cropland data layer for Greene County was used in this research. For that year, corn was planted on 61,473 acres while soybeans were planted on 62,322 acres, which accounts for 76% of all agricultural land in Greene County. This makes the county a strong candidate for this analysis because most of the crops planted in the county were evenly split between corn and soybeans. The crop map was downloaded as a TIF file so it could be used in GIS. This allowed for the overlay of the crop map with the soil map to reveal which crop was planted on a certain soil type.

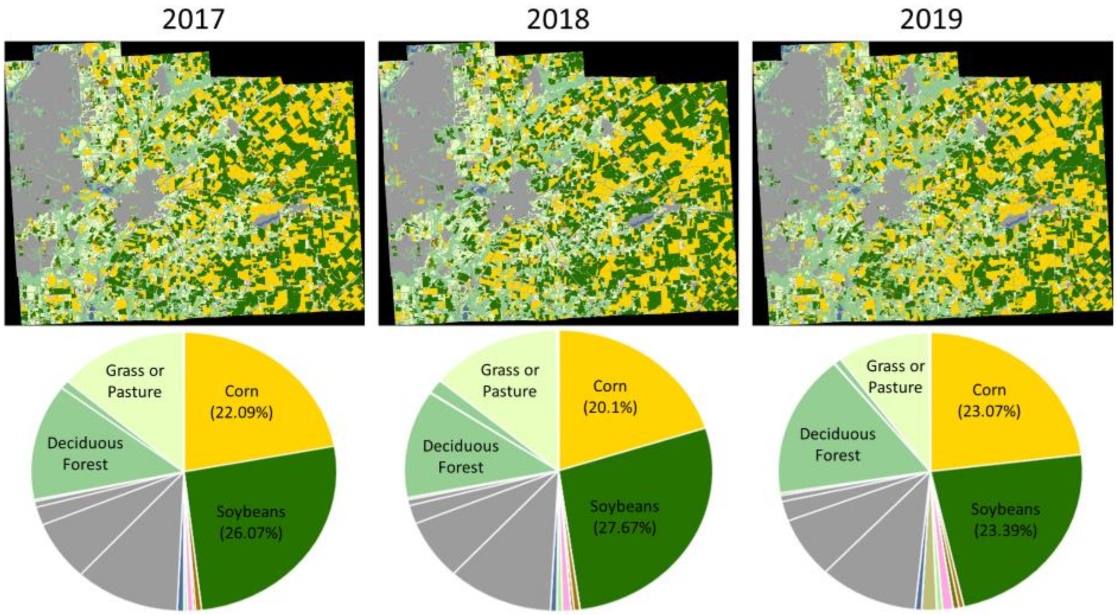


Figure 6. Cropland Data Layer for Greene County (USDA NASS CropScape, 2021)

IV. Methodology

4.1 Chapter Overview

The methodical approach used to meet the objectives of this research downloaded climate, soil, and crop data from Greene County, Ohio, to inform a crop growth model called AquaCrop to project future yields under varied scenarios. The results were visualized temporally to show yield trends to the end of the century. The temporal outputs were utilized in a spatial model by joining the future yields to a soil map of Greene County and filtered by a cropland data layer. This chapter will provide an overview of the methods used to include data collection and analysis. The flow diagram below shows the overall flow of the research.

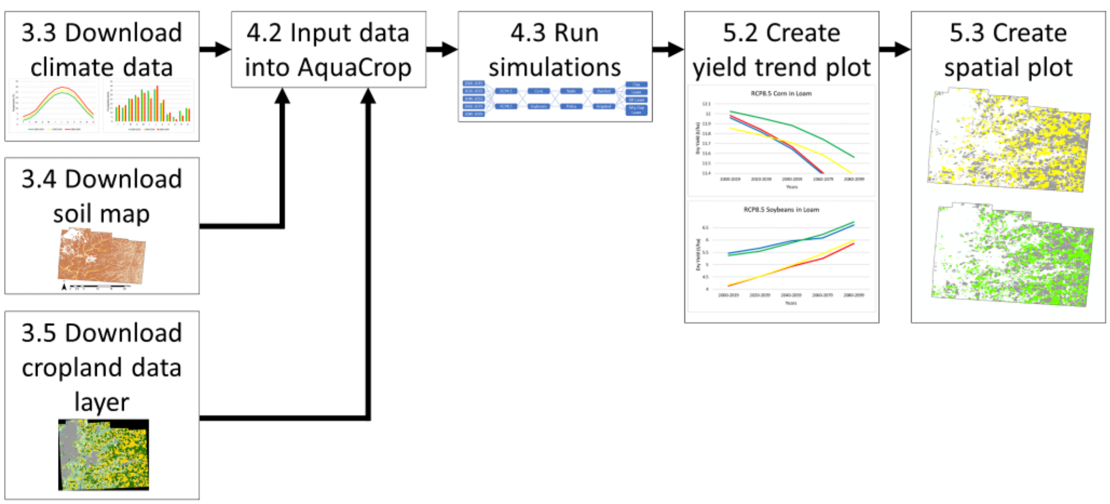


Figure 7. Model Flow Diagram showing climate data (3.3), soil data (3.4), and cropland data (3.5) being used to run simulations (4.3) to project future yield temporally (5.2) and spatially (5.3)

4.2 Input Data into AquaCrop

The crop growth model used for this research was AquaCrop, which is an open-source application created by the Land and Water Division of the Food and Agriculture Organization of the United Nations (FAO) to address food security and assess the effect of the environment and management on crop production (FAO, 2021). The inputs required for simulating crop yield are divided into four categories: 1) climate conditions, 2) crop characteristics, 3) management practices, and 4) soil characteristics.

First, the climate conditions are read into the program using climate files, which reference four daily data files: 1) precipitation ($mm\ day^{-1}$); 2) maximum and minimum temperature (C°); 3) evapotranspiration ($mm\ day^{-1}$); 4) atmospheric carbon dioxide (ppm). A set of climate inputs was used for RCPs 4.5 and 8.5. The precipitation and temperature data were acquired from LLNL. The ET_o was calculated using the Modified Hargreaves equation, which is based on temperature. The CO_2 file was endogenous to AquaCrop and based on RCP4.5 and 8.5 projections.

Second, a crop file is read into the program that contains crop parameters such as the number of growing degree days in a season and the minimum temperature required for crop growth. Fortunately, AquaCrop includes crop files for a wide variety of crops, including corn and soybeans. They were used for the simulations in this analysis. A user has the option to set the planting date in this input section. A criterion can be used to specify a planting date manually or as triggered by a temperature or precipitation threshold value.

Third, a user can specify if the crop will be rainfed or irrigated in the management section. Custom irrigation schedules or system-generated schedules can be implemented.

Field management and soil fertility can be calibrated using local crop characteristics of a stressed field. No field-level data is available to calibrate the model, and as such, it is assumed that farmers act to maximize yield through typical field management practices, e.g., apply fertilizer to limit weeds and pests. Soil fertility was assumed to be non-limiting for all simulation runs. Users have the option to add mulches, but none were used for this research based on practices typical in the Corn Belt. Also, weed management is assumed to be perfect. An additional benefit of this approach is that by holding field management constant, the effect of climate change is isolated. The management of field conditions through moisture and fertilizer management is a well-explored topic, and advances in precision agriculture make the assumption that perfect management of field conditions realistic. Still, this assumption does not account for the role that climate change may drive variability in crop growth, which may require holistic shifts in management regimes.

Lastly, AquaCrop allows users to create custom soil profiles with up to five different layers at varying depths. These custom soils are saved as files and read into the program. AquaCrop includes prebuilt soil files for each of the 12 USDA soil textures. The soil data downloaded for this research was not downloaded in this format. It included more information than AquaCrop could process, so the data was simplified down to only include topsoil textures, as shown in the Appendix. Only the four soil types found in the county were used for this analysis. No custom soil profiles were created because they are unknown. Soil samples would need to be taken in the region to gain this information. The soil parameter section also includes an opportunity to add a groundwater table. No shallow groundwater was assumed to be present for all simulation runs.

4.3 Simulating Results

After preparing the data and creating the necessary input files, simulations in AquaCrop are possible. The rotating inputs that drove multiple scenarios included the RCP, bidecadal bin, crop type, soil type, irrigation, and planting policy. They can be visualized in the process chart below.

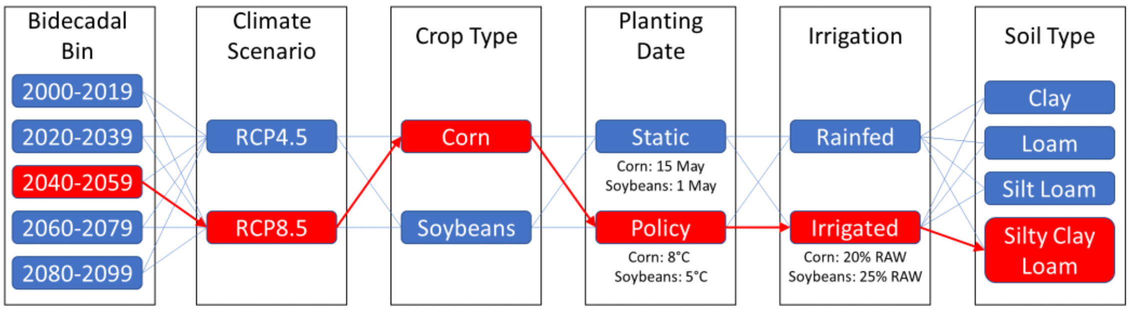


Figure 8. Simulation Process Flow Diagram. Represents 17 independent variable inputs from 6 categories. Example combination shown in red. 320 total scenarios producing yield outcomes.

The two climate scenarios used for simulations were RCP4.5 and RCP8.5. This strategy provides the worst-case scenario (RCP8.5), under which no changes being made to mitigate climate change. It also provides an intermediate scenario with some changes (RCP4.5). The comparison will reveal the effect climate change will have on the yield. Along with the two RCPs, the climate conditions will cycle through the five bidecadal bins from 2000 to 2100. The first bin (2000-2020) is projected climate data instead of historical to stay consistent, and the simulation of this bin was used as a basis of comparison for the subsequent bins referred to as the baseline. All simulations were run for both corn and soybeans. AquaCrop includes the crop files for both crops using calendar days and growing degree days (GDD). Using calendar days, the crop files have a built-in schedule to progress through their growth cycle with a predetermined number of

days. Using GDD, the crop advances through its growth cycle based on the temperature of each calendar day. This research utilized the GDD crop type to allow the growing season schedule to change with temperature. Simulations are conducted for each of the four soil types found in Greene County: Clay Loam, Loam, Silt Loam, or Silty Clay Loam.

The basic parameterization described above is the equivalent of a static production policy or status quo with crops that are rainfed with no irrigation. Ultimately, this scenario is representative of a farmer that has made no effort to offset the decline in yield due to climate change. Alternative scenarios are climate-smart and assume farmers follow a planting policy or an irrigation strategy and a blend of both.

The planting policy implemented here is flexible. Planting occurs on the first calendar year day, where the 3-day minimum temperature was at least as high as the crop's base temperature. The base temperature is a parameter listed in the crop files that indicates the lowest possible temperature that still allows for crop growth when calculating growing degree days. The base temperature for corn is 8°C and 5°C for soybeans. This policy follows the theory that the growing season will occur earlier in the year and that farmers could easily adapt to the changing temperature conditions. A precipitation-based threshold was also possible, though given the stochasticity of precipitation, following a trigger depth results in highly variable planting dates.

The final parameter that was cycled was irrigation. In AquaCrop, an irrigation schedule can be utilized that is either created by the user or system-generated based on specified threshold criteria. To simplify and standardize the process, the net irrigation requirement option was used as an alternative to the irrigation schedule. This option

allows the user to specify a maximum allowable root zone depletion before the crop is watered. This is set using a percentage from 0% to 100% of the readily available soil water (RAW) in the root zone. Field capacity is represented as 0% RAW, while 100% RAW represents the threshold for stomatal closure, which is a common response under drought conditions. Within those boundaries, each crop type in AquaCrop has a threshold for leaf expansion growth. For corn, 20% RAW is specified, while soybeans are slightly higher at 25% RAW. To determine the water required to ensure stress-free crop development, the simulations for this research used the net irrigation requirement and set the maximum allowable root zone deletion equal to the crop's threshold for leaf expansion growth. Using this setting ensured the best possible crop yield without any regard to how much water was used for irrigation. The limitation to this approach does not factor in the cost of water into the scenario. Water is assumed to be a free and limitless resource for these simulations.

In summary, the simulations were run using two RCP conditions, five bidecadal bins, two crop types, four soil types, with and without a planting policy, with and without irrigation, creating a total of 320 simulation runs. Again, these simulations were run as a single crop growing season even though each yielded result represents a 20-year period. Each simulation output included production values for biomass and dry yield recorded in tons per hectare ($T\ ha^{-1}$). Only the dry yield results were kept for analysis. For the 160 simulations that included irrigation, the annual net irrigation requirement was recorded in millimeters of water as well as the daily irrigation values throughout the growing season.

4.4 Calibrating ArcMap

The final and most valuable aspect of this research was adding the spatial component to the variable yield loss trends across Greene County. This was accomplished using the program ArcMap, included in the ArcGIS package. First, a shapefile of the soil map was added to the GIS project that included 12,720 polygons of the 113 various types of soil profiles found in Greene County. A tabular join was used to add the topsoil texture classification to each polygon. From this, a map of only the four soil texture classifications could be shown after filtering out the 8% of the county that was either urban, water, or infertile. Next, the cropland data layer was added to the GIS project using a raster to polygon conversion tool. This read in the TIF picture file containing the various crop types into GIS and converted every grouping of same-colored pixels into its own polygon. Fortunately, a grid code ID that represented each crop type was attached to each polygon. The cornfields and soybean fields were each saved to their own separate shapefiles. Some very small polygons were kept that made it seem as if a smaller corn field was planted within a much larger soybean field and vice versa. This was obviously an error in the pixel conversion, so a minimum size threshold was set to filter out the smallest fields of each crop. Finally, an extraction tool was used called Clip to show only the parts of the soil map that had a cornfield or a soybean field planted on top of it. The final product was a soil texture map of Greene County that included only the plots of land used to plant corn or soybeans in 2019. Using this map, the results from AquaCrop were added to the map using another tabular join linking each soil and crop type to the respective dry yield. The values added to the spatial plots were converted to a yield change from the baseline, which was the status quo yield, that is, no policy and no

irrigation from the first bidecadal bin, for each soil type. Those yield changes were then converted to bushels per hectare ($bu\ ha^{-1}$) using a bushel-per-ton conversion factor of 39.368 for corn and 36.7437 for soybeans. Converting the spatial plot values to bushels will provide more value from an economic perspective since market prices are shown in dollars per bushel. Knowing the change in bushels per hectare, a farmer will have a better perspective of the change in dollar value of that field.

4.5 Summary

Climate data was downloaded for the case study region and used to calibrate AquaCrop. Simulations were run by cycling the parameters to produce projected yield plots. Soil maps and cropland data layers were downloaded and coupled with simulation results to produce spatial analysis plots.

V. Analysis and Results

5.1 Chapter Overview

The results section presents the simulation outputs in a series of time series plots as well as the spatial plots showing the change in yield based on soil type. The effect of the temperature planting policy is represented by a planting date ridge plot that shows the change in planting date over time. Finally, the net irrigation requirement shows the daily water requirement in a growing season throughout the century.

5.2 Yield Change

The yield plots are shown below (Figure 9 corn and Figure 10, soybeans). These figures represent the temporal analysis of yield trends with each of the five bidecadal bins shown on the horizontal axis. The vertical axis represents the dry yield from each simulation, which remains consistent across all simulations of a given crop type. The four main soil types are placed above and below one another to visualize a comparison across soil types. RCP4.5 is shown on the left, and RCP8.5 is shown on the right of the same soil type to show the change in yield with a greater climate change effect. The four colored lines represent the four different scenarios a farmer could choose with the status quo shown in blue and the blended approach shown in gold.

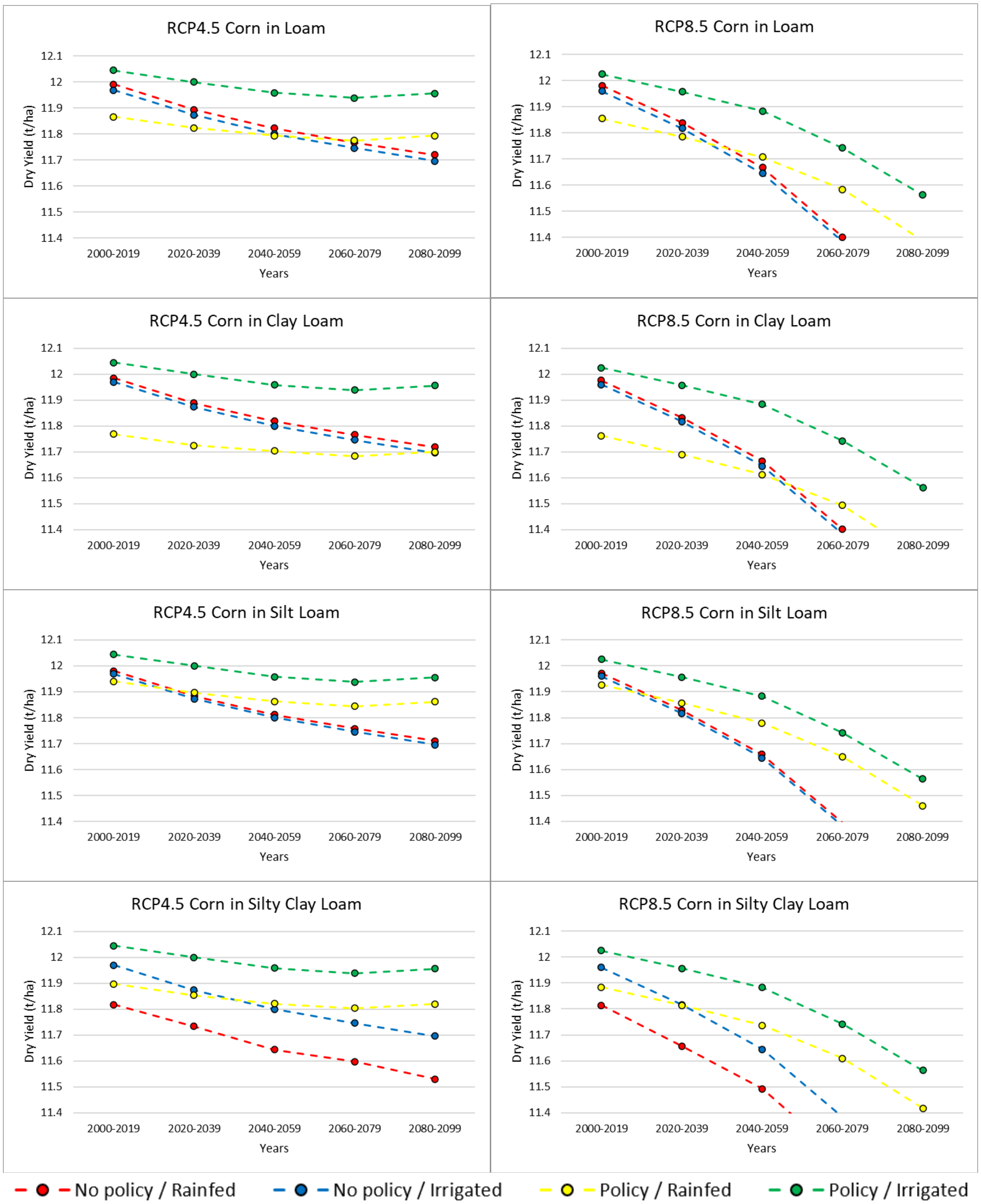


Figure 9. Corn Yield under two emission scenarios with four soil types

The results for corn show that the blended approach implementing a temperature-based planting policy coupled with an irrigation system provides the greatest amount of yield security across all soil types. Variation exists between soil types for all scenarios except the blended approach. With the policy and irrigation, yield results were identical across soils, meaning that a farmer will get the same yield result if they apply the same policy and 20% RAW irrigation to any soil. The amount of irrigation required will vary, but only slightly. Given the yield results for each soil are the same in the blended approach, the effect of climate change can be assessed. The yield loss is more significant under RCP8.5 conditions than RCP4.5. The yield started at 12.044 $T\ ha^{-1}$ for RCP4.5 and moved to 11.956 $T\ ha^{-1}$, creating only a 0.7% decrease, while RCP8.5 yield started at 12.025 $T\ ha^{-1}$ and moved to 11.563 $T\ ha^{-1}$ creating a 3.8% decrease, meaning climate change had a negative impact on yield. The yield results varied greatly across soils when implementing the policy or irrigation separately. Irrigation without the policy seemed to have no effect on Loam, Clay Loam, or Silt Loam but improved the yield results of Silty Clay Loam greatly. A farmer with Silty Clay Loam soil would benefit the most from installing an irrigation system. When utilizing the policy without irrigation, the yield results surpassed the status quo at different time periods for each soil. In Clay Loam soils, the status quo outperformed the policy for nearly the entire century under RCP4.5 conditions encouraging a farmer to keep the planting date the same. Conversely, the policy outperformed the status quo almost immediately in Silt Loam soil, suggesting a farmer with that kind of soil should change their planting date as soon as possible.

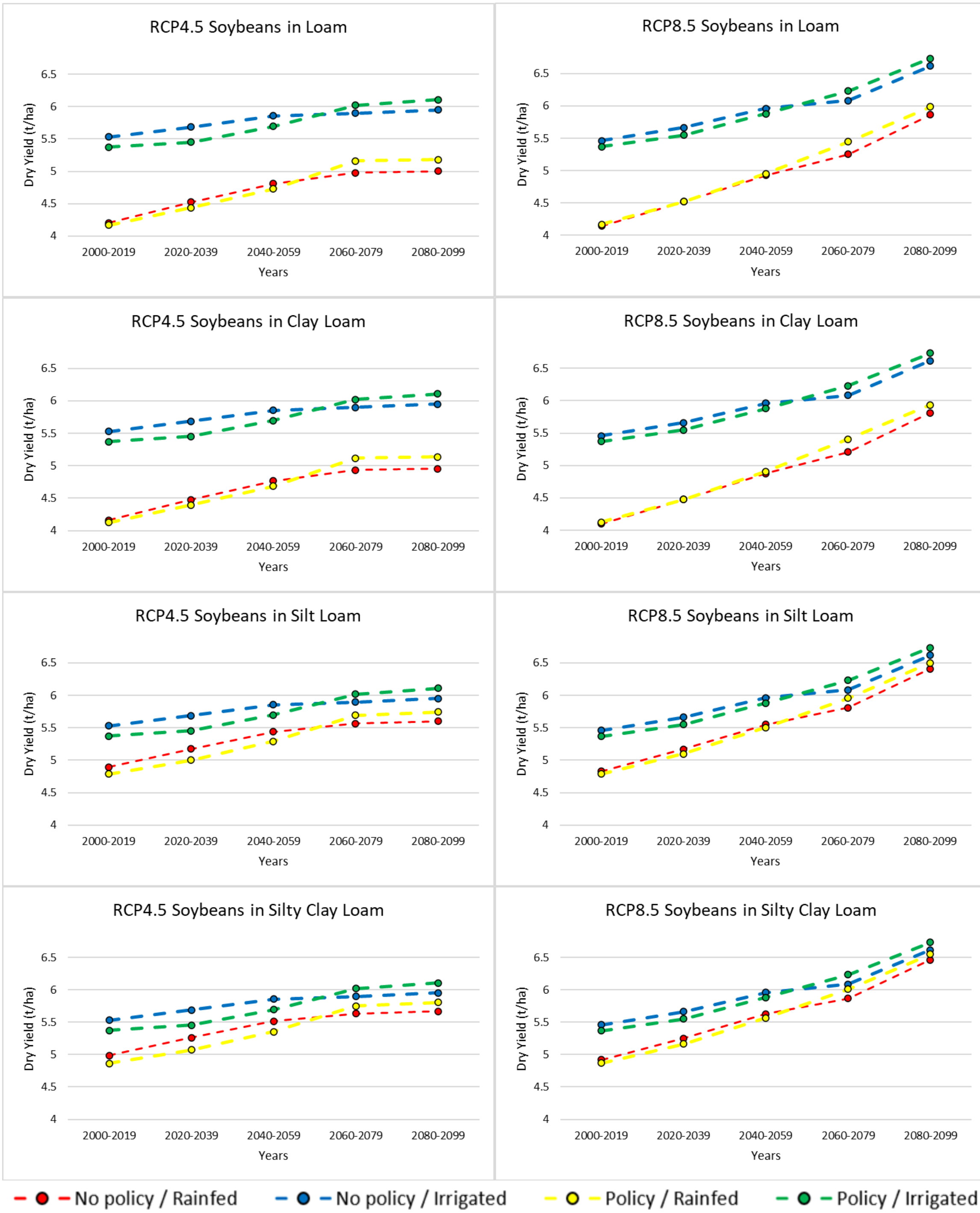


Figure 10. Soybeans Yield under two emission scenarios with four soil types

The results for soybeans show distinctly different results. The yield results increase over time, under all scenarios, with an even higher yield under RCP8.5, meaning

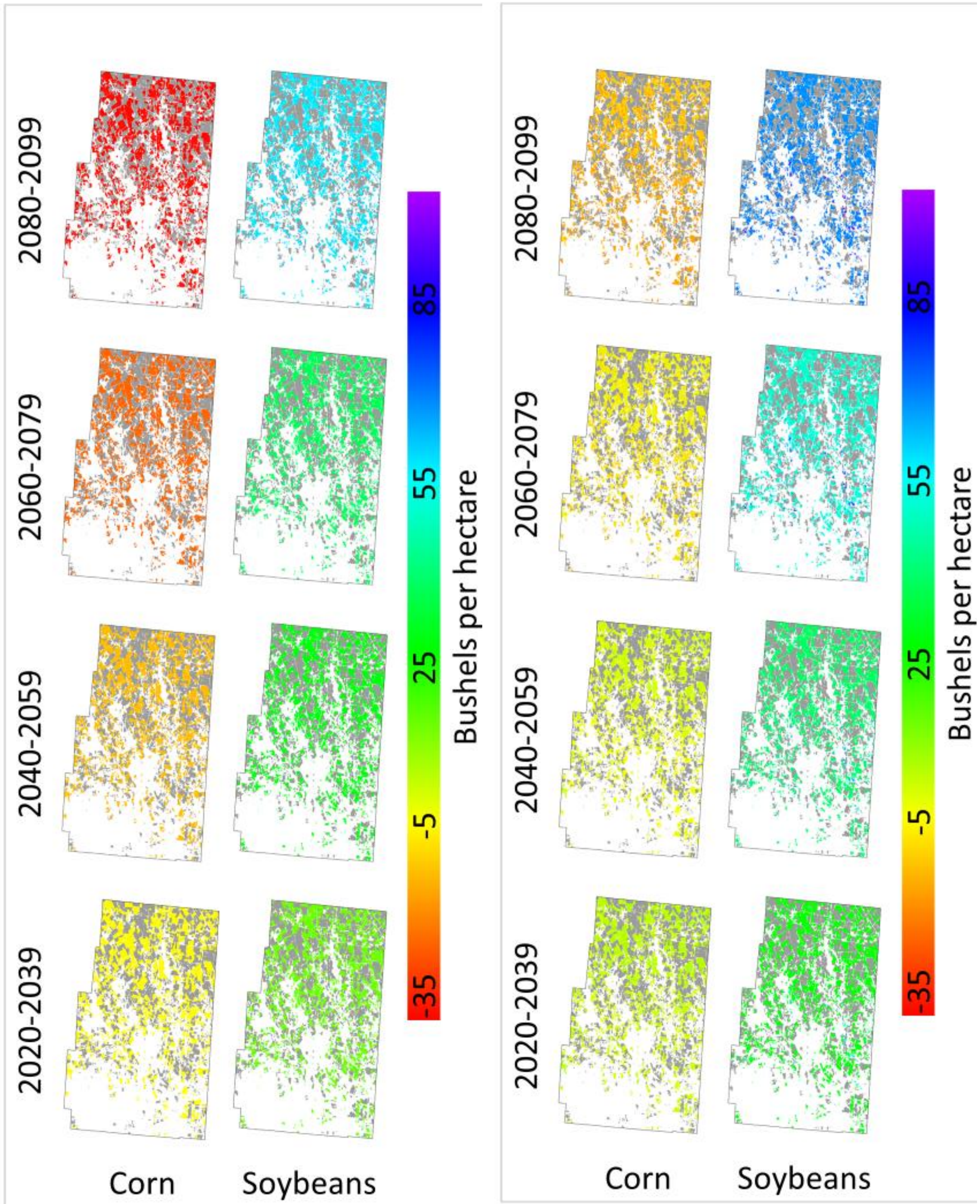
climate change actually improves soybean yield. The item that remains the same between corn and soybeans is that the blended approach still provides the best yield results by the end of the century. However, with soybeans, the improvement is not as great, with the blended approach only becoming the best performer after the year 2060. Focusing on the policy and irrigation separately, irrigation proves to be much more valuable than the planting policy. The irrigation without policy strategy is the top performer for the first three bidecadal bins and nearly the top performer for the last two, only slighted bested by the blended approach. This top performance comes at a higher cost in terms of water requirements. For soybeans in Loam under RCP8.5 conditions at the beginning of the century, 386 mm of water is required annually to maintain 25% RAW. This amounts to a 1.313 $T\ ha^{-1}$ or 31.7% increase from the status quo yield results meaning 12.2 mm of water is required to see a 1% increase in soybean yield. Depending on the price of water and soybeans at the time, this may be worth it to the farmer to see that improvement. That increase is more costly in Silty Clay Loam at 34.5 mm of water required for a 1% increase in yield. The policy without irrigation strategy, on the other hand, does very poorly, essentially matching the status quo for the entire century, meaning that the planting date is not as important for soybeans as it is for corn. The farmer that would benefit the most from installing an irrigation system would be a soybean farmer with Loam and Clay Loam soils. A significant improvement would be realized immediately without a need to ever change the planting date. Modifying the planting date near the end of the century would provide the greatest benefit. A soybean farmer with Silt Loam or Silty Clay Loam soils would gain the smallest benefit from any change in strategy,

particularly because the starting yield production is already high compared to the other soil types.

Climate change clearly affects corn and soybeans differently. A farmer will need to take the benefits of each crop type into account since most farmers will likely rotate these crops year after year. For corn, the policy performs the best in Silt Loam soil, while irrigation is only beneficial for Silty Clay Loam soil. For soybeans, the policy does not affect yield in any soil type, while irrigation is beneficial for all soil types, particularly Loam soil. An irrigation system would benefit a farmer that primarily plants soybeans, while the policy could greatly improve a corn farmer's yield.

5.3 Spatial Analysis

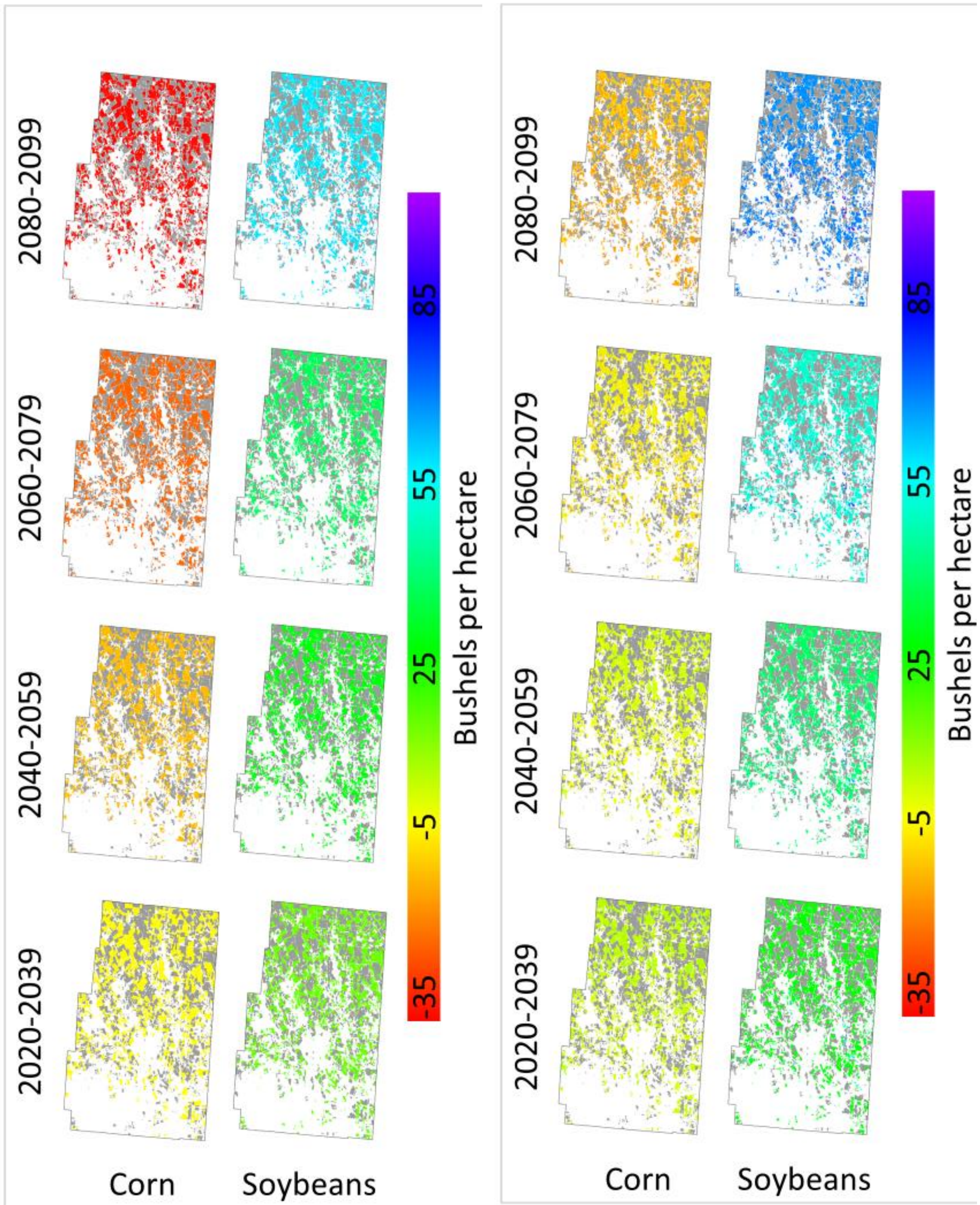
The temporal yield trends can be visualized spatially on the plots seen in



(a) (b)

Figure 11. Spatial Plots: a) No policy and no irrigation; b) With policy and irrigation

. Instead of simply showing the dry yield output, the change in yield is displayed compared to the baseline scenario of no policy and no irrigation in the first bidecadal bin. For that reason, the 2000 to 2019 bin is not shown in this figure. Also, the focus is set on the status quo scenario for the eight plots on the top compared to that of the blended policy approach with the eight plots on the bottom. The other two strategies, with policy but no irrigation and with irrigation but no policy, are ignored in this figure to show the greatest impact that could be made. The color scale shows a negative yield change as red or yellow and a positive yield change as green or blue.



(a) (b)

Figure 11. Spatial Plots: a) No policy and no irrigation; b) With policy and irrigation

The spatial plots reveal the same overall trend as the time series plots, and corn yield decreases over the course of the century while soybean yield increases in both scenarios. However, the spatial plots reveal the extent of change moving from the status quo to the blended approach. With no policy and no irrigation, corn yield deviation from the baseline shifts from a range of -6.2 to -5.6 $bu\ ha^{-1}$ to a range of -35.1 to -33.5 $bu\ ha^{-1}$. With policy and with irrigation, it shifts from a range of -0.9 to 5.6 $bu\ ha^{-1}$ to a range of -16.5 to -9.9 $bu\ ha^{-1}$. Silty Clay Loam was the only soil to show a net positive yield change from 2020 to 2039 and from 2040 to 2059. The final bidecadal bin for corn under the blended strategy looks much like the second bin in the status quo scenario, meaning the blended strategy is extending the yield security 40 years further into the century. For soybeans, yield increases are not as dramatic, with the blended policy shifting the yield security further by a single bidecadal bin. The lack of variation shows a spatial homogeneity across soil types for both corn and soybeans. This shows the limitation in this research that the crop yield results vary only a small amount across climate scenarios and soil textures. With these spatial plots, a county-level analysis can be conducted to determine the value of implementing the blended approach strategy. At a farm scale, a farmer would be able to tell the number of bushels gained or lost depending on the crop type planted and a given soil type.

By subtracting the values of Figure 11a from Figure 11b, the impact of the blended approach can be realized across crop type and soil type. The yield increase observed for corn shows a positive linear relationship starting the century with a 5 $bu\ ha^{-1}$ increase and ending the century with a 17 $bu\ ha^{-1}$ increase for all soils except Silty Clay Loam, which performed much better starting a 12 $bu\ ha^{-1}$increase and ending

at a 25 $bu\ ha^{-1}$ increase. The blended approach for corn improves with time for all soils, and it improves the yield of Silty Clay Loam more than other soil types. The yield increase for soybeans had a slightly negative trend over time, with Loam and Clay Loam outperforming all soil types of corn while Silt Loam and Silty Clay Loam underperformed all soil types of corn. Loam and Clay Loam soils produced a yield increase of 38 $bu\ ha^{-1}$ for soybeans at the start of the century and ended with a yield increase of 32 $bu\ ha^{-1}$. Silt Loam and Silty Clay Loam started the century at 12 $bu\ ha^{-1}$ and ended at 11 $bu\ ha^{-1}$. This shows that soybeans had a mixed result of yield increase based on soil type but had an overall negative drift over time. A farmer planting soybeans in Loam and Clay Loam soils would see a greater benefit from adopting the blended approach than a farmer with Silt Loam or Silty Clay Loam soils.

The spatial plots can also be used to reveal the net irrigation requirement, as seen in Figure 12. Both crops are included in a single county map using the blended approach under RCP8.5 conditions. The color scale from light blue to dark blue was used to show the annual net irrigation requirement for stress-free crop development. The crop fields can easily be differentiated because soybeans required much more water. Soybeans start the century with an annual water requirement range of 374 to 388 mm per year and end with a range of 323 to 337 mm per year. Corn starts with a range of 217 to 232 mm per year and ends with a range of 200 to 215 mm per year.

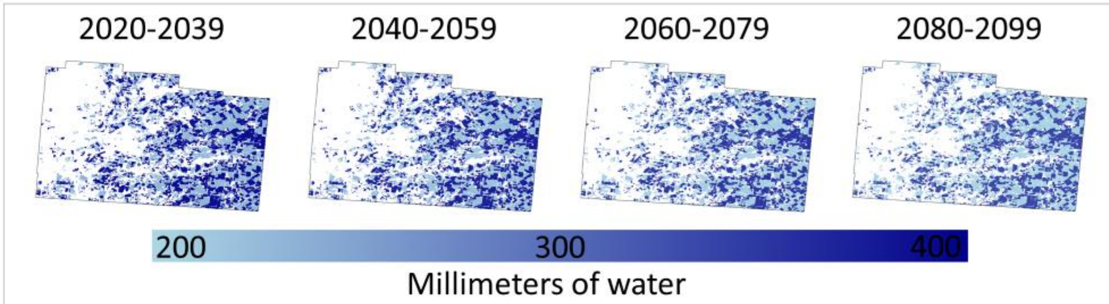


Figure 12. Seasonal net irrigation requirement for both crops with a blended approach

The soil map shows a slight variation for water requirement among soil types, but the overall trend remains the same. The county net irrigation requirement plots would be a valuable tool when factoring in the cost of water. It may be more beneficial to forego the added yield increase from soybeans by not installing an irrigation system or switching to a less water-intensive crop such as corn. At a field scale, a farm could use both the yield map and the irrigation maps to determine if their specific field would benefit more from planting corn or soybeans and if installing an irrigation system would be necessary.

5.4 Daily Irrigation Requirement

The daily irrigation requirement can be seen below in Figure 13. This simulation was only a sample scenario with both crops planted in Silt Loam soil under RCP8.5 conditions. There was no variation across soil types with respect to the seasonal requirement or growing season length. The only exception was a slight variation in the amount of water required on the first day of watering. All plots have consistent axes with the growing season on the horizontal axis and the daily water requirement on the vertical axis. This value is represented in millimeters of water required to maintain stress-free crop development. The area under each curve would represent the total seasonal requirement. Three bidecadal bins were selected to display the beginning, middle, and

end of the century results. The two plots on the top display a static planting date of May 15 for corn and May 1 for soybeans for all three scenarios. The two plots on the bottom display a changing planting date based on the temperature policy moving from May 3 to April 15 for corn and April 19 to April 4 for soybeans.

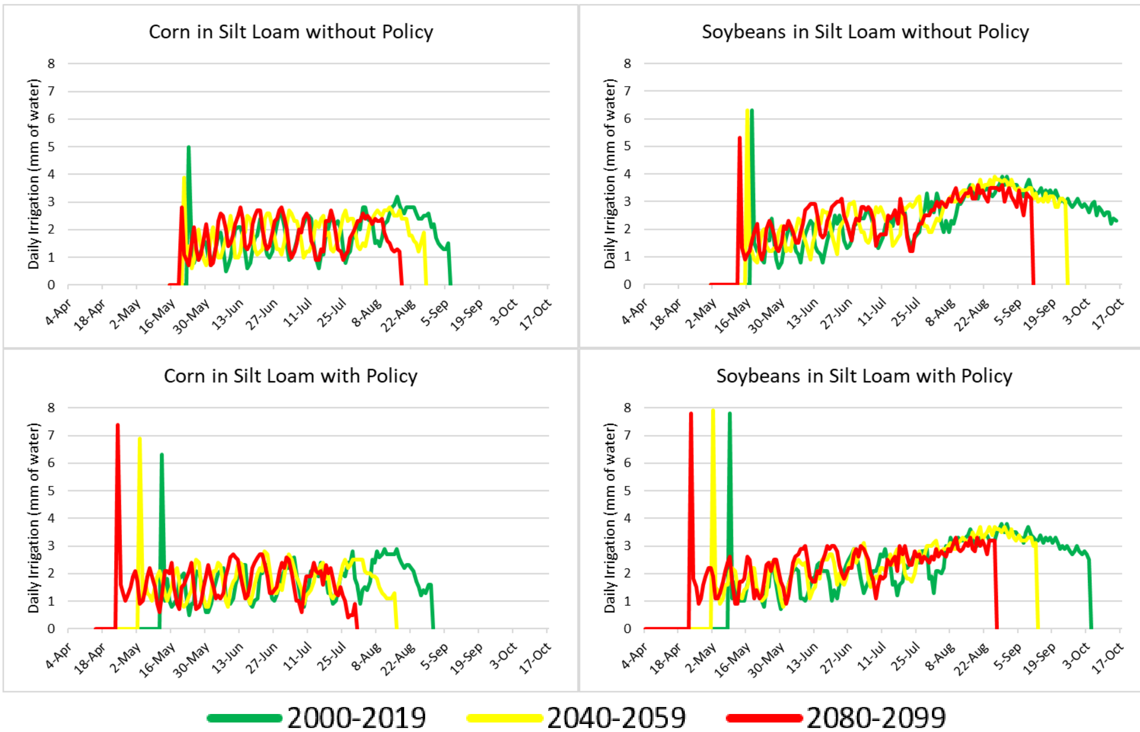


Figure 13. Daily Irrigation Requirement for both crops under RCP8.5 conditions

The daily irrigation results show that soybeans require nearly twice as much water in any given scenario. The situation that demanded the highest seasonal requirement from both crops was the earliest bin without policy. Corn required only 196.8 mm, while soybeans required 375.8 mm, 90% more than corn. That percentage drops to 75% in the latest bin with a policy scenario where corn required 168.5 mm and soybeans required 295.6 mm. The change observed over the course of the century was consistent across all four plots. The growing season was shorter later in the century, reducing the corn season

by 20 days without the policy and 13 days with the policy, while the soybean growing season was shortened by 34 days without the policy and 24 days with the policy. The seasonal water requirement was reduced as well, showing a 15% reduction for corn and a 19% reduction for soybeans comparing the first bin to the last bin. The policy had variable effects on each crop. In the last bin, the policy would lengthen the growing season for both crops by 12 days. Even though the crops are planted earlier in the season, 31 days for corn and 28 days for soybeans, the crops require more time to develop. However, the policy changed the seasonal water requirement for corn to be 2.4% higher, whereas the policy for soybeans lowered the seasonal water requirement by 2.4%. Nevertheless, the policy shifted the average daily irrigation requirement from 1.7 $mm\ day^{-1}$ to 1.55 $mm\ day^{-1}$ for corn and 2.26 $mm\ day^{-1}$ to 2.02 $mm\ day^{-1}$ for soybeans.

5.5 Optimal Planting Date

To determine the impact of the temperature policy, simulations were run at various planting dates, and the resulting yield is shown in Figure 14. These simulations planted corn and soybeans in a Silt Loam soil under RCP8.5 conditions. Other soil types produced similar results. The crops were rainfed used all five bidecadal bins. Irrigation was not used to solely investigate the impact the planting date had on yield.

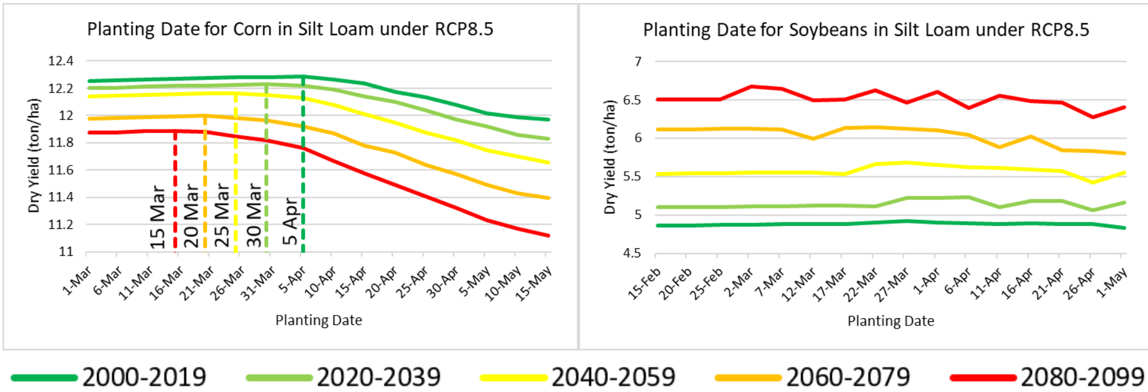


Figure 14. Yield based on optimal planting date

The results show the expected results of corn yield decreasing and soybean yield increasing over the course of the century. However, the planting date has a different effect on each crop. For corn, there is a clear maximum and minimum yield for each curve that represents the most optimal and least optimal planting date, respectively. Those dates drift further apart as time goes on. At the beginning of the century, the highest yield producing day is around April 5, while the lowest producing day is around May 15. By the end of the century, those dates spread apart to March 15 and May 30. The results support the use of a temperature-based planting policy to encourage earlier planting dates as time goes on to maximize yields. The policy implemented in this analysis resulted in a planting date of April 15 for corn in the final bidecadal bin. Although this produced better results than the static planting date of May 15, the policy could have used a lower temperature encouraging an even earlier planting date to improve the overall yield.

The support for a planting policy for soybeans is not as well seen from the plot above. Regardless of planting date, the yields stay relatively the same for each bin with a general negative drift. Opposite from the corn plot, the yields increase as it goes later into

the century, but there is no optimal planting date. The yields are more consistent earlier in the planting season for each bin and earlier in the century overall. By the end of the century, there was more variability in the yield throughout the entire growing season. From this data, moving to an earlier planting date could not prove to obtain higher yields meaning soybeans are less sensitive to planting date. This coincides with the data seen in the yield plots in **Error! Reference source not found.** when the rainfed soybeans with policy produced nearly the same yield as the rainfed soybeans without policy.

5.6 Investigative Questions Answered

The results showed that corn yield is expected to be negatively impacted by the effects of climate change in Greene County, Ohio, through the end of the century. Conversely, the soybean yield is expected to see improvements. These effects can be mitigated by implementing an irrigation system or utilizing a temperature-based planting policy. When combined, the yield for both crops will be the highest. However, the decision for a farmer to implement either of these strategies will come down to cost. Changing the planting date is a free option that should be used by all farmers. Installing a center pivot high capacity well irrigation system is expensive and should only be done after conducting an economic analysis. An example of this economic analysis is provided below.

5.7 Economic Analysis

The following economic analysis is adapted from USDA (USDA NRCS, 2021). The ownership costs consist of the purchase price, interest, repairs, taxes, and insurance, while the operating costs consist of power and labor. Combining the two over the lifetime

of the system, a farmer can see how much a center pivot irrigation system will cost per acre of irrigated crop. This cost can be compared to the value produced by the irrigation to determine if it is worth it. For example, a 160-acre field could be irrigated with a center pivot system to cover 132 acres of cropland since the corners cannot be reached. If the pivot costs $48,000 with a $15,000 salvage value after 10 years of use, the annual price would be $3,300 per year. If the well cost $30,000 with a $10,000 salvage value after 20 years of use, the annual price would be $1,000. Annual interest and insurance can be added as 9.5% and 0.5%, respectively, of the average investment value-adding $5,150 to the annual cost totaling $9,450. Assuming no additional tax and an annual repair charge of 3% for the pivot and 2% for the well adds $2,040, creating a total annual ownership cost of $11,490. When calculating operating costs, the actual power and labor bills at the end of the growing season would be best to use. For this example, a value estimation for acre-inches of gross water applied is be used. For power, the annual cost of irrigating 132 acres with 6 inches of water using a $3.50 per acre inch would cost $2,772. For labor, the annual cost of maintaining 6 inches of water spread over 132 acres at a rate of $1.00 per acre inch would cost $792, creating an annual total of $3,564 for operation costs. The grand total of ownership and operating costs would be $15,054, or $114.05 per 6 inches of water, per acre. This price per acre would increase if fewer acres were irrigated with the same system or if more water was used. For example, every additional inch of water used would cost an additional $4.50 per acre.

With the cost of an irrigation system considered, the focus shifts to calculating the benefits of the higher yield. For example, if a farmer were to plant corn in a Silt Loam soil on May 15, 2020, and allow it to be rainfed, a yield of 11.83 $T\ ha^{-1}$ could be

expected under RCP8.5 conditions. Applying the same strategy in 2040 would produce 11.658 $T\ ha^{-1}$, while implementing a blended approach would produce 11.883 t/ha, creating a differential equal to about 21.89 bushels per acre between the two planting years. The average closing price for corn in 2020 was $3.6393 per bushel. Therefore, the blended strategy would allow a farmer to obtain a net profit increase of $79.66 per acre irrigated.

With the cost of implementing an irrigation system being higher than the additional revenue added, a farmer should not choose to purchase the irrigation system in this example. However, there are many variables to consider, including the fact that yield loss potential increases throughout the century. In the next bidecadal bin from 2060-2079, the yield difference is 33.76 bushels per acre, equaling an additional $122.85 profit per acre, making the irrigation cost-effective at this point. By the end of the century, the yield differential from status quo to blended approach increases to 43.29 bushels per acre, creating an additional $157.54 per acre, making the system highly profitable. The maximum profit afforded under RCP4.5 comes in the last bidecadal bin at $87.09 per acre irrigated, which is lower than the $114.05 required to be profitable. Therefore, the farmer would not need to adopt irrigation under RCP4.5 but should consider adoption between 2060-2079 under RCP8.5.

Assuming the same farmer rotates their fields with soybeans every year, the same economic analysis can be done for soybeans. Under RCP8.5, soybeans planted in Silt Loam would increase by 0.382 $T\ ha^{-1}$ or 34.68 bushels per acre. Using $9.5344 as the average closing price of soybeans in 2020, a farmer would benefit from $330 per acre by

implementing an irrigation system. Even under RCP4.5, the farmer would still profit $239 per acre, so irrigation could be valuable by adopting it early in the century.

The net gain per acre for corn and soybeans planted in a 160-acre Silt Loam field are shown in Table 1 below under both RCP4.5 and RCP8.5. Corn under RCP4.5 conditions shows a negative net gain, so it would not be worth it to implement an irrigation system here. Under RCP8.5, however, the net gain becomes positive in 2060 and continues on an upward trend, so implementing this would be profitable for the foreseeable future. Net gains for all soybean scenarios are positive. Therefore, it would be worth installing an irrigation system immediately, especially assuming RCP4.5 conditions where the profit margin continues on an upward trend.

Table 1. Economic Analysis Net Gain per Acre for 160-Acre Silt Loam Farmer

		2020-2039	2040-2059	2060-2079	2080-2099
Corn	RCP4.5	-$72.98	-$62.36	-$50.33	-$26.96
	RCP8.5	-$69.09	-$34.39	$8.80	$43.49
Soybeans	RCP4.5	$124.87	$109.29	$281.56	$325.71
	RCP8.5	$216.63	$169.89	$252.99	$167.29

This example assumes a static, per-bushel price of corn. Recently, corn prices have been on the rise, with a current price of $5.3425 per bushel as of January 14, 2021. Applying this to the 21.89 bushels per acre differential expected in the near term, the additional revenue would be $116.94, making the benefits outweigh the costs of the irrigation system. Using the crop yield predictions from this model coupled with accurate crop market prices and irrigation system prices, a farmer can make the most financially informed decision.

5.8 Discussion

Corn yield is shown to decrease, and soybean yield is shown to increase over the course of the century with the implementation of the policy and irrigation adaptations. The blended approach provided the best yield outcomes for both crops but will require significant amounts of water. For that reason, and in the interest of conservation of water resources, it is advisable that the State of Ohio regulate the installation and use of high-capacity irrigation systems. There are a variety of long-standing regulatory frameworks from which the state could borrow to construct its own. The Department of Natural Resources of Wisconsin, for example, recently added a new list of environmentally conscious criteria to high-capacity well applications (Connatser, 2020). This was done in order to protect groundwater as a valuable resource, which will become a similar issue in Ohio if regulation is not put in place.

The policy on its own is a reliable, free, and simple option to improve yields without purchasing an expensive center pivot irrigation system. The policy can also be adapted from year to year. The value of the 3-day average minimum temperature policy proved to be beneficial in this research; however, other policies should be tested to determine the similarity in results. The minimum temperature was set at the crop's base temperature, but this could be adjusted depending on the sensitivity of the crop. Precipitation policies should be tested as well to determine if the variability in precipitation has a negative effect. If the policy implemented by a farmer has proven successful, the farmer can plant based on that policy the following year. If the policy is not providing profitable yields, the policy should be adjusted.

Slight variations of yield change across soil types can be seen in the spatial analysis. The homogeneity of soils and climate within Greene County limits the robustness of this research. Adding more variables to the model, including other soil types and climatic variables, could produce more meaningful results. If the case study region included all 12 USDA soil textures, a greater variance in the results would be observed. From that, a more guided adaption strategy could be implemented for that given region. Nevertheless, the results still provide valuable information to farmers in Greene County that can aid in their decision to maintaining crop yields.

Climate uncertainty in the model was not accounted for by only using the median climatic values for each bidecadal bin. Using the interquartile range estimates for climate variables would capture an expected output range of crop yield. This uncertainty would factor into the decision to implement an irrigation system by accounting for the risk. If a minimum threshold crop yield was not guaranteed within a given confidence range to produce a profitable yield, a farmer might elect not to purchase the expensive system by deeming it too risky.

This research focused on an unlimited supply of irrigation water, but there are unintended consequences of extracting groundwater. If enough farmers in a given area begin to adopt irrigation systems at the same time, groundwater may be extracted at an unsustainable right. For that reason, a cost to extract groundwater may need to be enforced through the use of water rights. By factoring in the cost of using this water, it will change the economic analysis of implementing this irrigation system. In 1984, the Ohio Supreme Court revised a water ownership law from 1861 adding that an owner

must have a “reasonable use” for the water they own underneath their property (Hall, n.d.). The current groundwater legislature in Ohio would not be adequate for conversion.

VI. Conclusions and Recommendations

6.1 Chapter Overview

This chapter summarizes the conclusions and significance of this research. It also provides an accounting of the limitations encountered during the research, either discovered as part of the research or created through assumptions. Finally, a discussion of recommendations for future research is provided.

6.2 Conclusions of Research

The objectives of this research investigated the effect climate change had on a farm-scale model. It also determined the impact of implementing individual hard and soft adaptations to offset yield loss. Finally, the research pursued the least-cost approach a farmer could take to guarantee a level of yield production and profitability. The research was accomplished by utilizing the AquaCrop program to simulate future yield projections for corn and soybeans under RCP4.5 and RCP8.5 conditions. The results of those simulations showed that the current crop yields in 2020 could not be maintained to the year 2100 without adaption. Irrigation alone was not able to recover lost yield for corn. An economic analysis would need to be accomplished for each farmer to determine the necessity of an irrigation system. A blended approach produced the best yield security by irrigating the crop to allow for stress-free growth and planting the crop based on a 3-day minimum temperature threshold policy. The results proposed here are median expectations in bidecadal bins. The decrease or loss in yield is small such that a sensitivity analysis would be required to determine if adaptation is required.

6.3 Significance of Research

This research shows the value of combining two separate mitigation strategies into a blended approach that produces better results together. Offering a variety of least-cost solutions to farmers will allow them to choose the best solution for crop type, field size, and topsoil texture. Overlaying the results spatially provides a yield loss hazard map that can be used at the farm or county level. This is obviously valuable for farmers in the region, but it could also be used by researchers or policymakers to improve crop yield around the world to improve food security for a growing population. By separating the soft and hard adaptations of the blended approach, the policy can act as a hedge against future uncertainty. Avoiding the expensive cost of an irrigation system, the policy by itself allows for a wait-and-see strategy to offer farmers a simple and cost-effective solution upfront. After seeing a yield increase from the policy, a farmer can then decide if the expensive irrigation system will still be worth it.

6.4 Limitations and Assumptions

A primary limitation to this research was the soil data used for the simulation runs. By simplifying the complexity of the soil types down to one of four textures, much of the variability in yield results were lost. The transition from 113 soil types to only four could have a significant impact on the results. Creating a custom soil profile could lead to more diverse results but AquaCrop does not specialize as a crop-soil model. A different program would need to be used that accounts for soil variation. Field management within Aquacrop is also assumed to be perfect, which removes everything the farmer controls

from the simulation. Soil fertility is assumed to be non-limiting, but that will rarely be the case.

The blended approach is not the only solution to this problem. An alternate strategy exists that utilized the effects of climate change to the farmer's benefit. Instead of implementing an expensive irrigation system to minimize the crop yield loss of corn, the farmer could instead plant more soybeans. Most of the farm fields in Greene County are already rotating between corn and soybeans on a regular basis. To minimize their revenue losses, it may be best for a farmer to switch to planting soybeans as a monoculture crop to reap the most reward from a climate change-induced environment. It would be a demand-driven decision. If soybeans are not as desired as corn by the end of the century, the farmer will need to adapt to offset their yield loss in corn. However, if we are able to transition to soybeans as a replacement for corn, the farmer will see yield improvements regardless of the strategy they implement.

6.5 Recommendations for Future Research

This research can be expanding by conducting a more robust analysis using soil samples. Creating custom soil profiles could provide more specific results to a given field, creating a more valuable spatial plot. More simulation runs would be required, so it would be beneficial to use batch runs in MATLAB with AquaCrop OS. Different software that focuses on other aspects of the crop-environment interface could be used entirely to validate the model.

Applying this model to a different spatial scale could prove to be valuable. This research, conducted at a county level, can be expanded to visualize the results at a state

level. With state-level results, Ohio would be able to implement a blended approach to improve the overall market value of state agriculture. Expanded to a national level, the United States could analyze the impact climate change would have on a wide variety of crops and soil types to better prepare for an uncertain agricultural future.

Appendix A. Simplified Soil Classification

Map unit symbol	Map unit name	Rating	Acres in AOI	Percent of AOI
Ag	Algiers Silt Loam	Silt Loam	2,080.0	0.8%
BbB	Birkbeck Silt Loam, 1 to 4 percent slopes	Silt Loam	2,011.8	0.8%
BcB	Birkbeck Silt Loam, 2 to 6 percent slopes	Silt Loam	9.8	0.0%
Bs	Brookston Silty Clay Loam, fine texture, 0 to 2 percent slopes	Silty Clay Loam	17,750.5	6.7%
Bt	Brookston-Urban land complex	Silty Clay Loam	189.9	0.1%
CaE2	Casco Silt Loam, 18 to 50 percent slopes, eroded	Silt Loam	0.4	0.0%
CbD2	Casco gravelly Loam, 12 to 20 percent slopes, eroded	Gravelly Loam	12.5	0.0%
CcD2	Casco-Eldean Loams, 12 to 18 percent slopes, moderately eroded	Loam	1,289.5	0.5%
CdE2	Casco-Rodman Loams, 18 to 50 percent slopes, moderately eroded	Loam	2,242.3	0.8%
CeA	Celina Silt Loam, 0 to 2 percent slopes	Silt Loam	1,813.9	0.7%
CeB	Celina Silt Loam, 2 to 6 percent slopes	Silt Loam	7,491.5	2.8%
CfB	Celina-Losantville Silt Loams, 2 to 6 percent slopes	Silt Loam	32.0	0.0%
ChB	Celina-Strawn complex, 2 to 6 percent slopes	Silt Loam	35.9	0.0%
CrA	Crosby Silt Loam, Southern Ohio Till Plain, 0 to 2 percent slopes	Silt Loam	4,168.9	1.6%
CrB	Crosby Silt Loam, Southern Ohio Till Plain, 2 to 6 percent slopes	Silt Loam	213.9	0.1%
CsA	Crosby-Lewisburg Silt Loams, 0 to 2 percent slopes	Silt Loam	35.1	0.0%

Map unit symbol	Map unit name	Rating	Acres in AOI	Percent of AOI
CsB	Crosby-Lewisburg Silt Loams, 2 to 6 percent slopes	Silt Loam	18.5	0.0%
CtA	Crosby-Celina Silt Loams, 0 to 2 percent slopes	Silt Loam	2.6	0.0%
CtB	Crosby-Celina Silt Loams, 2 to 4 percent slopes	Silt Loam	6.2	0.0%
Du	Dumps		5.2	0.0%
EdB	Edenton Silt Loam, 2 to 6 percent slopes	Silt Loam	86.0	0.0%
EdC2	Edenton Silt Loam, 6 to 12 percent slopes, moderately eroded	Silt Loam	78.6	0.0%
EdD2	Edenton Silt Loam, 12 to 18 percent slopes, moderately eroded	Silt Loam	169.9	0.1%
Ee	Eel Loam	Loam	1,306.8	0.5%
EmA	Eldean Silt Loam, 0 to 2 percent slopes	Silt Loam	1,070.6	0.4%
EmB	Eldean Silt Loam, 2 to 6 percent slopes	Silt Loam	3,530.5	1.3%
EmB2	Eldean Silt Loam, 2 to 6 percent slopes, moderately eroded	Silt Loam	1,135.4	0.4%
EmC2	Eldean Silt Loam, 6 to 12 percent slopes, moderately eroded	Silt Loam	3,047.7	1.1%
EnC3	Eldean Clay Loam, 6 to 12 percent slopes, severely eroded	Clay Loam	258.8	0.1%
EoC2	Eldean-Miamian complex, 6 to 12 percent slopes, eroded	Silt Loam	53.1	0.0%
EoD2	Eldean-Miamian complex, 12 to 18 percent slopes, eroded	Silt Loam	5.5	0.0%
EpC	Eldean-Urban land complex, rolling	Silt Loam	190.0	0.1%
Etn6F2	Edenton flaggy Silty Clay Loam, 25 to 50 percent slopes, eroded	Flaggy Silty Clay Loam	555.9	0.2%
FnA	Fincastle Silt Loam, southern Ohio till plain, 0 to 2 percent slopes	Silt Loam	5,728.3	2.2%

Map unit symbol	Map unit name	Rating	Acres in AOI	Percent of AOI
Gn	Genesee Loam	Loam	1,706.3	0.6%
Ko	Kokomo Silty Clay Loam, 0 to 2 percent slopes	Silty Clay Loam	2,493.7	0.9%
Lh	Linwood mucky Silt Loam, drained	Mucky Silt Loam	10.1	0.0%
Ln	Linwood muck	Muck	1,047.2	0.4%
LuF2	Lumberton Silt Loam, 25 to 50 percent slopes, eroded	Silt Loam	1.9	0.0%
MhA	Miamian Silt Loam, 0 to 2 percent slopes	Silt Loam	464.3	0.2%
MhB	Miamian Silt Loam, 2 to 6 percent slopes	Silt Loam	17,663.5	6.6%
MhB2	Miamian Silt Loam, 2 to 6 percent slopes, eroded	Silt Loam	11,420.4	4.3%
MhC2	Miamian Silt Loam, 6 to 12 percent slopes, moderately eroded	Silt Loam	18,835.5	7.1%
MhD2	Miamian Silt Loam, 12 to 18 percent slopes, eroded	Silt Loam	4,210.8	1.6%
MlB3	Miamian Clay Loam, 2 to 6 percent slopes, severely eroded	Clay Loam	262.7	0.1%
MlC3	Miamian Clay Loam, 6 to 12 percent slopes, severely eroded	Clay Loam	2,727.6	1.0%
MlD3	Miamian Clay Loam, shallow to dense till substratum, 12 to 18 percent slopes, severely eroded	Clay Loam	1,196.7	0.4%
MmD2	Miamian-Casco complex, 12 to 18 percent slopes, moderately eroded	Silt Loam	767.1	0.3%
MmE2	Miamian-Casco complex, 18 to 35 percent slopes, moderately eroded	Silt Loam	1,454.6	0.5%
MoB2	Miamian-Eldean Silt Loams, 2 to 6 percent slopes, moderately eroded	Silt Loam	525.0	0.2%
MoC2	Miamian-Eldean Silt Loams, 6 to 12 percent slopes, moderately eroded	Silt Loam	1,631.0	0.6%

Map unit symbol	Map unit name	Rating	Acres in AOI	Percent of AOI
MpE	Miamian and Hennepin soils, 18 to 25 percent slopes	Silt Loam	1,785.2	0.7%
MpF	Miamian and Hennepin soils, 25 to 50 percent slopes	Silt Loam	1,805.6	0.7%
MqE2	Miamian-Thrifton complex, 18 to 25 percent slopes, eroded	Silt Loam	20.4	0.0%
MqF2	Miamian-Thrifton complex, 25 to 50 percent slopes, eroded	Silt Loam	31.2	0.0%
MrB	Miamian-Urban land complex, undulating		7,097.9	2.7%
MrC	Miamian-Urban land complex, rolling	Clay Loam	2,212.8	0.8%
Ms	Millsdale Silty Clay Loam, 0 to 2 percent slopes	Silty Clay Loam	538.6	0.2%
MtA	Milton Silt Loam, 0 to 2 percent slopes	Silt Loam	323.1	0.1%
MtB	Milton Silt Loam, 2 to 6 percent slopes	Silt Loam	2,019.5	0.8%
MtC2	Milton Silt Loam, 6 to 12 percent slopes, moderately eroded	Silt Loam	603.9	0.2%
MUF	Milton soils, channery variant, 25 to 50 percent slopes	Very channery Silt Loam	747.2	0.3%
OcA	Ockley Silt Loam, Southern Ohio Till Plain, 0 to 2 percent slopes	Silt Loam	2,498.3	0.9%
OcB	Ockley Silt Loam, Southern Ohio Till Plain, 2 to 6 percent slopes	Silt Loam	4,351.5	1.6%
OcB2	Ockley Silt Loam, 2 to 6 percent slopes, moderately eroded	Silt Loam	423.1	0.2%
OdB	Ockley-Urban land complex, undulating		2,024.3	0.8%
OeB	Odell Silt Loam, 2 to 6 percent slopes	Silt Loam	179.0	0.1%
Pa	Patton Silty Clay Loam, 0 to 2 percent slopes	Silty Clay Loam	376.0	0.1%

Map unit symbol	Map unit name	Rating	Acres in AOI	Percent of AOI
Pg	Pits, gravel		970.7	0.4%
Pu	Pits, quarry		1,210.9	0.5%
Ra	Ragsdale Silty Clay Loam, 0 to 2 percent slopes	Silty Clay Loam	27,892.2	10.5%
RbA	Randolph Silt Loam, 0 to 2 percent slopes	Silt Loam	174.4	0.1%
RdA	Raub Silt Loam, 0 to 2 percent slopes	Silt Loam	225.7	0.1%
RdB	Raub Silt Loam, 2 to 6 percent slopes	Silt Loam	1,358.5	0.5%
ReA	Reesville Silt Loam, 0 to 2 percent slopes	Silt Loam	15,767.8	5.9%
RhB	Ritchey Silt Loam, 2 to 6 percent slopes	Silt Loam	272.3	0.1%
RhC	Ritchey Silt Loam, 6 to 12 percent slopes	Silt Loam	226.5	0.1%
RhD	Ritchey Silt Loam, 12 to 18 percent slopes	Silt Loam	399.4	0.2%
RhE2	Ritchey Silt Loam, 18 to 25 percent slopes, moderately eroded	Silt Loam	205.8	0.1%
RkE	Rodman gravelly Loam, 18 to 35 percent slopes	Gravelly Loam	49.9	0.0%
RpA	Ross Loam, 0 to 1 percent slopes, occasionally flooded	Loam	233.5	0.1%
RqA	Ross Silt Loam, 0 to 2 percent slopes, frequently flooded	Silt Loam	16.3	0.0%
Rs	Ross Loam, 0 to 2 percent slopes, occasionally flooded	Loam	3,771.5	1.4%
RtA	Rush Silt Loam, 0 to 2 percent slopes	Silt Loam	1,986.0	0.7%
RtB	Rush Silt Loam, 2 to 6 percent slopes	Silt Loam	2,292.8	0.9%
RuA	Russell Silt Loam, 0 to 2 percent slopes	Silt Loam	115.0	0.0%
RvB	Russell-Miamian Silt Loams, 2 to 6 percent slopes	Silt Loam	14,984.6	5.6%

Map unit symbol	Map unit name	Rating	Acres in AOI	Percent of AOI
RvB2	Russell-Miamian Silt Loams, 2 to 6 percent slopes, moderately eroded	Silt Loam	3,286.5	1.2%
RwB2	Russell-Xenia Silt Loams, 2 to 6 percent slopes, eroded	Silt Loam	77.6	0.0%
SkA	Sligo Silt Loam, 0 to 1 percent slopes, occasionally flooded	Loam	18.4	0.0%
SlA	Sleeth Silt Loam, Southern Ohio Till Plain, 0 to 2 percent slopes	Silt Loam	545.8	0.2%
Sn	Sloan Silt Loam, sandy substratum, occasionally flooded	Silt Loam	779.5	0.3%
So	Sloan Silty Clay Loam	Silty Clay Loam	8,344.1	3.1%
Sp	Sloan-Fill land complex		1,254.0	0.5%
Sr	Sloan-Urban land complex		506.5	0.2%
SuA	Strawn-Crosby complex, 0 to 2 percent slopes	Silt Loam	22.3	0.0%
ThA	Thackery Silt Loam, 0 to 2 percent slopes	Silt Loam	891.5	0.3%
ThB	Thackery Silt Loam, 2 to 6 percent slopes	Silt Loam	367.6	0.1%
Ts	Tremont Silt Loam, occasionally flooded	Silt Loam	3.8	0.0%
TtA	Treaty Silty Clay Loam, 0 to 1 percent slopes	Silty Clay Loam	365.8	0.1%
Ud	Udorthents		945.3	0.4%
Ur	Urban land		90.4	0.0%
W	Water		877.7	0.3%
WaA	Warsaw Loam, 0 to 2 percent slopes	Loam	144.2	0.1%
WbA	Warsaw-Fill land complex, nearly level		1,346.9	0.5%
WcA	Warsaw-Urban land complex, nearly level		1,517.2	0.6%

Map unit symbol	Map unit name	Rating	Acres in AOI	Percent of AOI
WeB	Wea Silt Loam, 0 to 2 percent slopes	Silt Loam	1,128.5	0.4%
WpC3	Wapahani-Miamian Clay Loams, 6 to 12 percent slopes, severely eroded	Clay Loam	39.8	0.0%
WpD3	Wapahani-Miamian Clay Loams, 12 to 18 percent slopes, severely eroded	Clay Loam	1.3	0.0%
Ws	Westland Silty Clay Loam, Southern Ohio Till Plain, 0 to 2 percent slopes	Silty Clay Loam	5,891.8	2.2%
Wt	Westland-Urban land complex		701.0	0.3%
XeA	Xenia Silt Loam, Southern Ohio Till Plain, 0 to 2 percent slopes	Silt Loam	2,406.9	0.9%
XeB	Xenia Silt Loam, Southern Ohio Till Plain, 2 to 6 percent slopes	Silt Loam	12,479.8	4.7%
Totals for Area of Interest			**266,271.6**	**100.0%**

Bibliography

Abi Saab, M. T., Todorovic, M., & Albrizio, R. (2015). Comparing AquaCrop and CropSyst models in simulating barley growth and yield under different water and nitrogen regimes. Does calibration year influence the performance of crop growth models? *Agricultural Water Management*, *147*, 21–33. https://doi.org/10.1016/j.agwat.2014.08.001

Akumaga, U., Tarhule, A., & Yusuf, A. A. (2017). Validation and testing of the FAO AquaCrop model under different levels of nitrogen fertilizer on rainfed maize in Nigeria, West Africa. *Agricultural and Forest Meteorology*, *232*, 225–234. https://doi.org/10.1016/j.agrformet.2016.08.011

Battisti, R., Sentelhas, P. C., & Boote, K. J. (2017). Inter-comparison of performance of soybean crop simulation models and their ensemble in southern Brazil. *Field Crops Research*, *200*, 28–37. https://doi.org/10.1016/j.fcr.2016.10.004

Baum, M. E., Licht, M. A., Huber, I., & Archontoulis, S. V. (2020). Impacts of climate change on the optimum planting date of different maize cultivars in the central US Corn Belt. *European Journal of Agronomy*, *119*, 126101. https://doi.org/10.1016/j.eja.2020.126101

Bhattarai, M. D., Secchi, S., & Schoof, J. (2017). Projecting corn and soybeans yields under climate change in a Corn Belt watershed. *Agricultural Systems*, *152*, 90–99. https://doi.org/10.1016/j.agsy.2016.12.013

Challinor, A. J., Watson, J., Lobell, D. B., Howden, S. M., Smith, D. R., & Chhetri, N. (2014). A meta-analysis of crop yield under climate change and adaptation. *Nature Climate Change*, *4*(4), 287–291. https://doi.org/10.1038/nclimate2153

Connatser, G. (2020, June 25). Changes eyed for high-capacity well application process after Kaul opinion reversal. *Wisconsin State Farmer*. https://www.wisfarmer.com/story/news/2020/06/25/environmental-regulations-tighten-high-capacity-wells-wisconsin/3156048001/

Cooper, M., Gho, C., Leafgren, R., Tang, T., & Messina, C. (2014). Breeding drought-tolerant maize hybrids for the US corn-belt: discovery to product. *Journal of Experimental Botany*, *65*(21), 6191–6204. https://doi.org/10.1093/jxb/eru064

Dong, J., Gruda, N., Lam, S. K., Li, X., & Duan, Z. (2018). Effects of Elevated CO2 on Nutritional Quality of Vegetables: A Review. *Frontiers in Plant Science*, *9*, 924. https://doi.org/10.3389/fpls.2018.00924

Droogers, P., & Allen, R. G. (2002). Estimating Reference Evapotranspiration Under Inaccurate Data Conditions. *Irrigation and Drainage Systems*, *16*(1), 33–45. https://doi.org/10.1023/A:1015508322413

Falco, S. D., Adinolfi, F., Bozzola, M., & Capitanio, F. (2014). Crop Insurance as a Strategy for Adapting to Climate Change. *Journal of Agricultural Economics*, *65*(2), 485–504. https://doi.org/10.1111/1477-9552.12053

FAO. (2021). *AquaCrop | Food and Agriculture Organization of the United Nations*. http://www.fao.org/aquacrop/en/

Gamage, D., Thompson, M., Sutherland, M., Hirotsu, N., Makino, A., & Seneweera, S. (2018). New insights into the cellular mechanisms of plant growth at elevated atmospheric carbon dioxide concentrations: Elevated CO_2 effect on plant growth and development. *Plant, Cell & Environment*, *41*(6), 1233–1246. https://doi.org/10.1111/pce.13206

Godfray, H. C. J., Beddington, J. R., Crute, I. R., Haddad, L., Lawrence, D., Muir, J. F., Pretty, J., Robinson, S., Thomas, S. M., & Toulmin, C. (2010). Food Security: The Challenge of Feeding 9 Billion People. *Science, 327*(5967), 812–818. https://doi.org/10.1126/science.1185383

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

Greaves, G., & Wang, Y.-M. (2016). Assessment of FAO AquaCrop Model for Simulating Maize Growth and Productivity under Deficit Irrigation in a Tropical Environment. *Water, 8*(12), 557. https://doi.org/10.3390/w8120557

Green, T. R., Kipka, H., David, O., & McMaster, G. S. (2018). Where is the USA Corn Belt, and how is it changing? *Science of The Total Environment, 618*, 1613–1618. https://doi.org/10.1016/j.scitotenv.2017.09.325

Hall, P. K. (n.d.). *Understanding Water Rights in Ohio*. OSU Agricultural & Resource Law Program. https://farmoffice.osu.edu/sites/aglaw/files/site-library/Understanding%20Water%20Rights%20in%20Ohio.pdf

Hargreaves, G. H. (1994). Defining and Using Reference Evapotranspiration. *Journal of Irrigation and Drainage Engineering, 120*(6), 1132–1139. https://doi.org/10.1061/(ASCE)0733-9437(1994)120:6(1132)

Hatfield, J. L., Cruse, R. M., & Tomer, M. D. (2013). Convergence of agricultural intensification and climate change in the Midwestern United States: implications for soil

and water conservation. *Marine and Freshwater Research*, *64*(5), 423. https://doi.org/10.1071/MF12164

Heng, L. K., Hsiao, T., Evett, S., Howell, T., & Steduto, P. (2009). Validating the FAO AquaCrop Model for Irrigated and Water Deficient Field Maize. *Agronomy Journal*, *101*(3), 488–498. https://doi.org/10.2134/agronj2008.0029xs

Howden, S. M., Soussana, J.-F., Tubiello, F. N., Chhetri, N., Dunlop, M., & Meinke, H. (2007). Adapting agriculture to climate change. *Proceedings of the National Academy of Sciences*, *104*(50), 19691–19696. https://doi.org/10.1073/pnas.0701890104

Hsiao, T. C., Heng, L., Steduto, P., Rojas-Lara, B., Raes, D., & Fereres, E. (2009). AquaCrop-The FAO Crop Model to Simulate Yield Response to Water: III. Parameterization and Testing for Maize. *Agronomy Journal*, *101*(3), 448–459. https://doi.org/10.2134/agronj2008.0218s

IPCC, Pachauri, R. K., & Mayer, L. (2014). *Climate change 2014: synthesis report*. Intergovernmental Panel on Climate Change.

Jiang, H., Hu, H., Zhong, R., Xu, J., Xu, J., Huang, J., Wang, S., Ying, Y., & Lin, T. (2020). A deep learning approach to conflating heterogeneous geospatial data for corn yield estimation: A case study of the US Corn Belt at the county level. *Global Change Biology*, *26*(3), 1754–1766. https://doi.org/10.1111/gcb.14885

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. https://doi.org/https://doi.org/10.1111/gcb.13617

Jones, J. W., Hoogenboom, G., Porter, C. H., Boote, K. J., Batchelor, W. D., Hunt, L. A., Wilkens, P. W., Singh, U., Gijsman, A. J., & Ritchie, J. T. (2003). The DSSAT cropping system model. *European Journal of Agronomy*, *18*(3–4), 235–265. https://doi.org/10.1016/S1161-0301(02)00107-7

Jumrani, K., & Bhatia, V. S. (2018). Impact of combined stress of high temperature and water deficit on growth and seed yield of soybean. *Physiology and Molecular Biology of Plants*, *24*(1), 37–50. https://doi.org/10.1007/s12298-017-0480-5

Kang, Y., Khan, S., & Ma, X. (2009). Climate change impacts on crop yield, crop water productivity and food security – A review. *Progress in Natural Science*, *19*(12), 1665–1674. https://doi.org/10.1016/j.pnsc.2009.08.001

Kimm, H., Guan, K., Gentine, P., Wu, J., Bernacchi, C. J., Sulman, B. N., Griffis, T. J., & Lin, C. (2020). Redefining droughts for the U.S. 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. https://doi.org/10.1016/j.agrformet.2020.107930

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. https://doi.org/10.1016/j.agrformet.2010.05.008

Levitus, S., Antonov, J. I., Boyer, T. P., Baranova, O. K., Garcia, H. E., Locarnini, R. A., Mishonov, A. V., Reagan, J. R., Seidov, D., Yarosh, E., & Zweng, M. M. (2017). *NCEI ocean heat content, temperature anomalies, salinity anomalies, thermosteric sea level anomalies, halosteric sea level anomalies, and total steric sea level anomalies from 1955*

to present calculated from in situ oceanographic subsurface profile data (NCEI Accession 0164586) [Data set]. NOAA National Centers for Environmental Information. https://doi.org/10.7289/V53F4MVP

Liang, X.-Z., Wu, Y., Chambers, R. G., Schmoldt, D. L., Gao, W., Liu, C., Liu, Y.-A., Sun, C., & Kennedy, J. A. (2017). Determining climate effects on US total agricultural productivity. *Proceedings of the National Academy of Sciences*, *114*(12), E2285–E2292. https://doi.org/10.1073/pnas.1615922114

LLNL. (2021). *Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections*. https://gdo-dcp.ucllnl.org/downscaled_cmip_projections/dcpInterface.html

Lobell, D. B., & Burke, M. B. (2008). Why are agricultural impacts of climate change so uncertain? The importance of temperature relative to precipitation. *Environmental Research Letters*, *3*(3), 034007. https://doi.org/10.1088/1748-9326/3/3/034007

McFadden, J., Smith, D., Wechsler, S., & Wallander, S. (2019). *Development, Adoption, and Management of Drought-Tolerant Corn in the United States* (EIB-204). U.S. Department of Agriculture, Economic Research Service.

Mearns, L. O., Sain, S., Leung, L. R., Bukovsky, M. S., McGinnis, S., Biner, S., Caya, D., Arritt, R. W., Gutowski, W., Takle, E., Snyder, M., Jones, R. G., Nunes, A. M. B., Tucker, S., Herzmann, D., McDaniel, L., & Sloan, L. (2013). Climate change projections of the North American Regional Climate Change Assessment Program (NARCCAP). *Climatic Change*, *120*(4), 965–975. https://doi.org/10.1007/s10584-013-0831-3

Moradi, R., Koocheki, A., Nassiri Mahallati, M., & Mansoori, H. (2013). Adaptation strategies for maize cultivation under climate change in Iran: irrigation and planting date

management. *Mitigation and Adaptation Strategies for Global Change*, *18*(2), 265–284. https://doi.org/10.1007/s11027-012-9410-6

Nerem, R. S., Beckley, B. D., Fasullo, J. T., Hamlington, B. D., Masters, D., & Mitchum, G. T. (2018). Climate-change–driven accelerated sea-level rise detected in the altimeter era. *Proceedings of the National Academy of Sciences*, *115*(9), 2022–2025. https://doi.org/10.1073/pnas.1717312115

Paudel, K. P., & Hatch, L. U. (2012). GLOBAL WARMING, IMPACT ON AGRICULTURE AND ADAPTATION STRATEGY: GLOBAL WARMING AND AGRICULTURE. *Natural Resource Modeling*, *25*(3), 456–481. https://doi.org/10.1111/j.1939-7445.2012.00127.x

Peters, K., Breitsameter, L., & Gerowitt, B. (2014). Impact of climate change on weeds in agriculture: a review. *Agronomy for Sustainable Development*, *34*(4), 707–721. https://doi.org/10.1007/s13593-014-0245-2

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

Robinson, D. A., & Et Al. (2014). *MEaSUREs Northern Hemisphere Terrestrial Snow Cover Extent Daily 25km EASE-Grid 2.0* [Data set]. NASA National Snow and Ice Data Center DAAC. https://doi.org/10.5067/MEASURES/CRYOSPHERE/NSIDC-0530.001

Schauberger, B., Archontoulis, S., Arneth, A., Balkovic, J., Ciais, P., Deryng, D., Elliott, J., Folberth, C., Khabarov, N., Müller, C., Pugh, T. A. M., Rolinski, S., Schaphoff, S., Schmid, E., Wang, X., Schlenker, W., & Frieler, K. (2017). Consistent negative response

of US crops to high temperatures in observations and crop models. *Nature Communications*, *8*(1), 13931. https://doi.org/10.1038/ncomms13931

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

Schütte, G., Eckerstorfer, M., Rastelli, V., Reichenbecher, W., Restrepo-Vassalli, S., Ruohonen-Lehto, M., Saucy, A.-G. W., & Mertens, M. (2017). Herbicide resistance and biodiversity: agronomic and environmental aspects of genetically modified herbicide-resistant plants. *Environmental Sciences Europe*, *29*(1), 5. https://doi.org/10.1186/s12302-016-0100-y

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. https://doi.org/10.2134/agronj2008.0139s

Stöckle, C. O., Donatelli, M., & Nelson, R. (2003). CropSyst, a cropping systems simulation model. *European Journal of Agronomy*, *18*(3–4), 289–307. https://doi.org/10.1016/S1161-0301(02)00109-0

Takle, E. S., Gustafson, D., Beachy, R., Nelson, G. C., Mason-D'Croz, D., & Palazzo, A. (2013). US Food Security and Climate Change: Agricultural Futures. *Economics: The Open-Access, Open-Assessment E-Journal*, *7*(2013–34), 1. https://doi.org/10.5018/economics-ejournal.ja.2013-34

Taylor, K. E., Stouffer, R. J., & Meehl, G. A. (2012). An Overview of CMIP5 and the Experiment Design. *Bulletin of the American Meteorological Society*, *93*(4), 485–498. https://doi.org/10.1175/BAMS-D-11-00094.1

Tripathi, A. D., Mishra, R., Maurya, K. K., Singh, R. B., & Wilson, D. W. (2019). Estimates for World Population and Global Food Availability for Global Health. In *The Role of Functional Food Security in Global Health* (pp. 3–24). Elsevier. https://doi.org/10.1016/B978-0-12-813148-0.00001-3

US Census Bureau. (2019). *U.S. Census Bureau QuickFacts: Greene County, Ohio*. https://www.census.gov/quickfacts/fact/table/greenecountyohio/INC110219

USDA NASS. (2017). *USDA - National Agricultural Statistics Service - Census of Agriculture*. https://www.nass.usda.gov/AgCensus/index.php

USDA NASS. (2021). *USDA - National Agricultural Statistics Service - Charts and Maps - County Maps*. https://www.nass.usda.gov/Charts_and_Maps/Crops_County/index.php

USDA NASS CropScape. (2021). *CropScape - NASS CDL Program*. https://nassgeodata.gmu.edu/CropScape/

USGCRP, Reidmiller, D. R., Avery, C. W., Easterling, D. R., Kunkel, K. E., Lewis, K. L. M., Maycock, T. K., & Stewart, B. C. (2018). *Impacts, Risks, and Adapation in the United States: Fourth National Climate Assessment, Volume II*. U.S. Global Change Research Program.

USGCRP, Wuebbles, D. J., Fahey, D. W., Hibbard, K. A., DeAngelo, B., Doherty, S., Hayhoe, K., Horton, R., Kossin, J. P., Taylor, P. C., Waple, A. M., & Yohe, C. P. (2017). *Climate Science Special Report: Fourth National Climate Assessment, Volume I*. U.S. Global Change Research Program. https://doi.org/10.7930/J0DJ5CTG

Vanuytrecht, E., Raes, D., Steduto, P., Hsiao, T. C., Fereres, E., Heng, L. K., Garcia Vila, M., & Mejias Moreno, P. (2014). AquaCrop: FAO's crop water productivity and yield

response model. *Environmental Modelling & Software*, *62*, 351–360. https://doi.org/10.1016/j.envsoft.2014.08.005

Velicogna, I., Mohajerani, Y., A, G., Landerer, F., Mouginot, J., Noel, B., Rignot, E., Sutterley, T., Broeke, M., Wessem, M., & Wiese, D. (2020). Continuity of Ice Sheet Mass Loss in Greenland and Antarctica From the GRACE and GRACE Follow-On Missions. *Geophysical Research Letters*, *47*(8). https://doi.org/10.1029/2020GL087291

WSS. (2021). *Web Soil Survey*. https://websoilsurvey.sc.egov.usda.gov/App/WebSoilSurvey.aspx

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14. ABSTRACT
In today's rainfed agricultural regions farmers reliably produce marketable yields without the need for irrigation technology or specific planting policies. However, climate change is expected to challenge global food security. As a result, farmers might seek adaptation strategies. This research investigates the spatiotemporal suitability of blended policy-structural adaptations to reduce yield losses in Greene County, Ohio. A crop-water model is used to calibrate and generate field-scale yield predictions. The resultant framework holds the potential to inform farmer and county-level decision making under future climate uncertainty, and it illustrates the tradeoffs between adaptation cost and yield security.

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