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ABSTRACT

Assessment of Potential Changes in Crop Yields in the Central United States under Climate Change Regimes

by

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Climate change is one of the great challenges facing agriculture in the 21st century. The goal of this study was to produce projections of crop yields for the central United States in the 2030s, 2060s, and 2090s based on the statistical relationship between weather and yield from historical crop yields from 1980 to 2010. These projections were made on a county to county basis, across 16 states in the U.S., from Louisiana in the south to Minnesota in the north. They include projections for maize, soybeans, cotton, spring wheat, and winter wheat.

Simulated weather variables based on three climate scenarios, which correspond to different carbon dioxide concentrations, were used to project future crop yields. In addition, factors of soil characteristics, topography, and fertilizer application were used in the crop production models. Multivariable Fractional Polynomials (MFP) were used to generate a regression model which predicted crop yields based on variables of weather (temperature and precipitation) and variables of soil, topography and fertilization. Two
technology scenarios were used: one simulating a future in which crop technology continues to improve and the other a future in which crop technology remains similar to where it is today.

Results showed future crop yields to be responsive to both the different climate scenarios and the different technology scenarios. The effects of a changing climate regime on crop yields varied both geographically throughout the study area and from crop to crop. One broad geographic trend was greater potential for crop yield losses in the south and greater potential for gains in the north.

Whether or not new technologies enable crop yields to continue to increase as the climate becomes less favorable is a major factor in agricultural production in the coming century. Results of this study indicate the degree to which society relies on these new technologies will be largely dependent on the degree of the warming that occurs.
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Whether or not new technologies enable crop yields to continue to increase as the climate becomes less favorable is a major factor in agricultural production in the coming
century. Results of this study indicate the degree to which society relies on these new
technologies will be largely dependent on the degree of the warming that occurs.

Continued research into the potential negative impacts of climate change on the
current crop system in the United States is needed to mitigate the widespread losses in
crop productivity that could result. In addition to study of negative impacts, study should
be undertaken with an interest to determine any potential new opportunities for crop
development with the onset of higher temperatures as a result of climate change. Studies
like this one with a broad geographic range should be complemented by studies of
narrower scope that can manipulate climatic variables under controlled conditions.
Investment into these types of agricultural studies will give the agricultural sector in the
United States greater tools with which they can mitigate the disruptive effects of a
changing climate.
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Projected proportion of mean winter wheat yield in each county under six climate scenarios when compared to historical yield in the decade between 2000 and 2009.
INTRODUCTION

The central United States is the one of the most agriculturally productive regions of the world. In 2014 the U.S. produced 38% of the world’s maize (USDA-FAS 2017) and 35% of the world’s soybeans (FAOSTAT 2017). Most of this production occurred in the central United States, the agricultural heart of the country. How will productivity, in terms of crop yields of four major crops (maize, wheat, soybeans, and cotton), be affected by climate change in this region? Many studies have investigated broad trends in crop production in response to climate change but most of them have used projections of wide-scale climate shifts like weekly or monthly mean temperatures. This study looks at cumulative effects of daily weather projections over the growing season. This should enable county-level crop yield projections to reflect changes in aggregated daily weather patterns. The combination of daily temporal resolution, crop-specific models, and a large study area (16 states in the central United States) distinguish this study from most previous studies of the effect of climate change on agricultural yields.
In the developed world, impacts from climate change on agriculture are often overlooked because of agriculture’s relatively modest contribution to GDP. The importance of agriculture in developed economies, however, is often greater than its proportion of economic output. In less developed countries, agriculture is often a central component of the economy, and the main sector through which climate change is expected to diminish food security (FAO 2016). Impacts of climate change on yields may not have consequences on livelihoods and food security as substantial in more developed countries, but yields may still decline. Modeling how much these yields will change in different regions can provide information to facilitate adaptation.

Increasing concentrations of carbon dioxide in the atmosphere have numerous effects on crop yields. One of the most important of these effects is increasing temperatures. Determining the effect on soybean yields of a 1- or 2-degree shift in temperature in a particular county, however, can be difficult because the relationship between temperature and crop yields is nonlinear (Schlenker and Roberts 2009). This means crop yields are affected differently by a change in temperature depending on where the crop is in its thermal tolerance zone. On the lower end of a plant’s tolerance zone, yields increase with temperature. As temperatures increase to the higher end of the tolerance zone and beyond, however, yield increases slow, stop, and then turn into yield decreases. This results in a parabolic curve as shown in Figure 1. According to one global study from Lobell et al. (2014), climate change has slowed rates of yield increase over
The purpose of this study is to quantify potential impacts of climate for each crop of interest in each county of the study area.

Precipitation or, more precisely, plant-available water, which is a function of precipitation and evapotranspiration, also has a nonlinear relationship with crop yields. More precipitation tends to increase crop yields to a degree until the amount of water is too much to be beneficial for the plants (Lobell et al. 2011). This results in a crop productivity “sweet spot” where the amount of water available is just right for the given
plant. It follows that the relationship between soil moisture and crop yields is, similar to
temperature, a bell-shaped, parabolic curve (Fig. 1).

The relationship between the crop yields and the percent slope of the land is more
straightforward: as the slope increases the yields decrease. It is also a nonlinear
relationship, however, because when the slope is low, a small increase causes major
losses in productivity. As the slope increases, incremental changes have less of an effect
because productivity is very close to zero. A point of “diminishing losses” is reached, as
shown in Figure 1. This is principally because higher slopes result in more erosion, which
has a negative effect on crop yields (Crist et al. 1995). The single curve in the figure is a
simplification: in reality we expect the row crops, maize, soybeans, and cotton, to drop
off in productivity more rapidly than the field crop wheat in response to increasing slope.

The curve of the relationship between soil fertility (and fertilizer application) and
crop yields follows an inverse pattern to that of slope. With relatively infertile soil, small
increases in fertility can greatly increase crop yields. As the soil becomes more fertile (or
more fertilizer is applied), an incremental increase has less of a positive impact on crop
yields. The soil fertility or fertilizer application reaches a point of “diminishing returns,”
as can be seen in Figure 1. This relationship in fertilizer application has been observed in
studies where nitrogen use efficiency decreases rapidly as more fertilizer is applied than
is needed to achieve maximum yields (Raun and Johnson 1999). This is our
understanding of how each variable nonlinearly affects crop yields. In order to be able to
project how a different temperature regime will affect crop yields, it is important to
understand how a crop’s physiological processes are influenced by temperature. One way
higher temperatures influence plant development is by increasing the rate of crop growth
(Lobell and Gourdji 2012). When crops grow faster, this means a shorter time to maturity, which often results in lower yields. Higher temperatures also increase rates of photosynthesis, respiration, and grain filling (Lobell and Gourdji 2012). These increased rates can result in higher yields. This could mean a net positive or negative effect on yields depending on how each of these processes are influenced. This collection of factors influencing yields, each of varying magnitude, contributes to the nonlinear relationship demonstrated between temperature and yield (Schlenker and Roberts 2009).

Because of the distinct level of sensitivity to heat in each part of a plant’s development, it is not long-term yearly or monthly average temperatures affecting yields. Short-term hot or cold periods have acute effects on crop development that have disproportionate influence on seasonal yields. This provides the motivation to use a daily weather generator to translate larger climatic trends into simulations of daily weather.

In addition to higher average temperatures, it is predicted climate change will include more severe weather, including longer heat waves and more variable temperature patterns in some regions (Lobell and Gourdji 2012). These more extreme weather events could have severe impacts if they occur during sensitive parts of the plant growing cycle. A few days of warmer than average temperatures could be especially harmful if they occur during seed formation or flowering (Easterling et al. 2007). Even apart from sensitive parts of the growing season, there are numerous direct and indirect effects of heat above 30 °C on cotton, maize, and soybeans including increasing water stress, reducing gas exchange efficiency, and causing tissue damage (Schauberger et al. 2017). Issues of heat stress may become substantial throughout our study area in the coming century. Although it is conventionally accepted that agriculture in tropical regions will be
harmed more severely than temperate regions, the heat stress resulting from climate change may acutely damage agricultural production in temperate and sub-tropical regions as well (Teixeira et al. 2013).

The other important climatic factor affecting crop yields is overall precipitation trends. Precipitation is naturally highly variable so isolating any of the effects of climate change as opposed to yearly variations is difficult (NCA 2015). That being the case, it is projected precipitation trends in the United States are changing in a systematic way; the northern part of the country is getting wetter in the winter and spring with the south and southwest of the country getting drier during the spring and summer. This follows a general climate trend across the world that has many wet places becoming wetter and dry places becoming drier (NCA 2015). The climate projections for the central United States indicate a potential positive impact because of an increase in precipitation in the spring while also showing a potential negative impact of reduced precipitation in the summer during the middle of the growing season. Much of the cultivation in the central United States is rain-fed, making it vulnerable to changes in precipitation.

Climate models are more consistent in projections of temperature changes than in projections of precipitation changes. This means there is high confidence in the prediction of increased heat stress due to higher temperatures. However, precipitation is an important piece of the climate regime—and uncertainty in precipitation projections consequently leads to uncertainty in yield projections. One of the reasons uncertainty in precipitation projections presents a problem in projecting crop yields is because inter-annual variation in yields tends to be more affected by variable precipitation than by variations in temperature (Lobell et al. 2011). So, uncertainty in precipitation projections
is a major problem in projecting yields in the 21st century because how much rain falls is an essential factor in how well crops do in a given year. There is evidence, however, that even with uncertainty in precipitation, there are still conclusions that can be drawn about future crop yields just looking at temperature shifts. According to a study using the CERES model in projecting corn yields in Africa: as temperature increases become more severe, temperature will have a greater impact on crop yields than precipitation (Lobell and Burke 2010). This runs counter to conventional wisdom because we tend to see higher year-to-year fluctuations in precipitation than in temperature. It appears precipitation is the more influential factor. This may not always be the case. This study hints at the idea that there are potential climates where heat stress becomes so severe that no amount of precipitation can make up for it.

Concerns about climate affecting future crop yields are well-founded in historical crop yield data: variability in weather has been shown to explain greater than 60% of variability in crop yields in some regions of the world (Ray et al. 2015). The observed effects vary from crop to crop, however, and from region to region. For example, the correlation between climate and yields is higher for wheat than it is for soybeans in the central United States (Ray et al. 2015). Predicting how the climate will change and how these changes will impact agriculture is an essential area of research to enable adaptation to the consequences of a changing climate.

The main consequence of a changing regime of precipitation is changing soil moisture. This affects the water available to crops in that soil. A more basic question in regard to soil is whether the composition will be changed with a changing climate. Because of the uncertainty in how soils will change as climate changes, this study treats
soil as temporally invariate. It is an important component in determining crop yields, but we are unable to say exactly how it is going to change so we will assume it will stay the same. There are reasons this is not a great assumption. Organic carbon content of soils has been shown to be affected by changes in temperature and precipitation regimes (Manning et al. 2015). Furthermore, soil erosion is a major issue because the amount of soil lost is greater than the replacement rate in much of the central United States (Amundson et al. 2015). This rate of soil loss is unsustainable as the productive layer of earth used to grow crops becomes thinner and thinner over time. Soil fertility is a complex issue, however, that requires its own model to describe. Since this study is principally focused on the effects of climate, we will make assumptions that soil composition and fertility will not change even though both very well may. It is because of these potential negative impacts of change in soil composition not taken into account that any projections of climate-induced changes in yields should be viewed as conservative.

Technological innovation is another important determinant of crop yield. The new technologies adopted during the Green Revolution enabled increased crop yields from the 1940s onward. A key innovation of the Green Revolution was the use of nitrogen fertilizer. Use of fertilizer allowed major increases in yield from the 1940s until around 1980. At this point, increasing fertilizer application reached a point of diminishing returns and rates of application consequently stopped increasing (USDA-ERS 2015). From the 1980s until 2005, crop yields continued to increase but at a lower rate (Egli 2008). These increases were driven by other technological advances: mainly crop management techniques and development of new genetic hybrids (Warren 1998). The historical influence of technology on crop yields can be understood in (at least) two ways:
(1) Even though the level of fertilizer application stopped increasing over 30 years ago, crop yields have continued to improve because of technological advances. There is no reason to think technology will not continue to enable yield increases.

(2) The diminished increases in yields as a result of reaching the maximum fertilizer applications are an indication of future diminishing returns in technological advances. Yield improvements will continue to slow down or stop altogether as the maximum impacts of other technological improvements are reached.

We must make an assumption about the influence of new crop technologies on yields during the 21st century. In our “optimistic” technology scenario, we will use year as a proxy for technological innovation. This assumes crop technology will continue to advance at the linear pace of the last 30+ years. This is a major assumption. In order for the historical increases to continue, there will need to be new technologies continually developed. There is no roadmap to developing these innovations or any way to guarantee that any amount of investment will enable a continuation of this level of improvement in crop yields. In our “pessimistic” technology scenario, we will assume technology has reached its peak and will not add to yield potential in the future. This is not a great reflection of what we expect reality to be either. There is a lot of investment into developing new technologies that will allow increased crop yields. It would not be surprising to see some new disruptive technologies produced from this investment. The two technology scenarios are extreme ends of the spectrum of potential changes to yields in the future. These are scenarios that represent what the worst case could be and what
the best case could be, but the reality of future crop yields is expected to be somewhere in between these two extremes.

Although fertilizer use has reached a maximum in the study region, it is still an important component contributing to crop yields. Fertilizer application rates are included in the model to control for the important effect fertilizer has on crops. We expect the rates of fertilization do vary from place to place according to local conditions and these differences may contribute to differences in crop yields.

The large-scale farming techniques used in the central U.S. allow consistently high yields but are reliant on a relatively narrow range of a number of controlled factors. Among these is nutrient availability, which is augmented by fertilizer use. Also of importance is the gradient of the land. In the land use study in the same region, the crops of interest were most likely to be planted on land in the range of 0 to 10% slope (Stoebner and Lant 2014). This is because the agricultural practices used in this region are designed for flat to mildly sloping land to avoid soil erosion and facilitate the use of large equipment. Crop productivity in row crops (cotton, maize, soybeans) is lower on land with higher slope gradients (Al-Kaisi 2001). Farmers are able to grow wheat on steeper slopes than the row crops, but the gradient does reduce productivity at a point for wheat as well. Because of its importance in crop yields, slope will be included as a predictor variable.

This project is informed by earlier work exploring the geographic determinants of land use in the same 16 state area (Stoebner and Lant 2014). That study found land use could change with climatic factors as determinants of topography and soil composition stayed the same. The prediction from this previous study is that as growing season
temperatures increase throughout the study area, the ideal region for growing each crop will shift northward. Our study seeks to further investigate the relationship between climate and yields that would result in this northward shift. Will expected yields of corn in the southern area of the range in which it is grown decrease? Will expected yields of soybeans north of their current range increase as summer temperatures become warmer? Will yields of particular crops be lower or more unpredictable in areas with more short-term heat waves because of the changing temperature regime? How important will water deficit/surplus and available water capacity be in predicting future yields? Will the changes in yield potential follow the expected changes in land use determined by the earlier Stoebner and Lant study? These are a sample of the research questions we are seeking to answer with this study.

Temperature is the principle variable in the study. It has been shown that temperature is the greatest predictor of yields over the entire course of the growing season. Precipitation is an important factor at certain times during the growing season, however, and must also be considered a major predictor. Water availability is particularly important early in the growing season, so precipitation is expected to be positively correlated with yields in the months of May and June. Higher temperatures later in the summer have a strong effect on water stress in July and August. Precipitation consequently is expected to be positively correlated with yields in July and August as well. Immediately before harvest in September or October, however, dry conditions can produce better yields. For this reason, the relationship between seasonal precipitation and crop yield is not expected to be straightforward. There may be overall trends in total seasonal precipitation, however, that can be effective predictors of crop yields.
METHODS

The study area includes 16 states in the central United States, incorporating the agricultural heart of the country, including the Corn Belt. This area was the focus because of its agricultural significance following a land cover study in the same 16 state region (Stoebner and Lant 2014). We focus on the major crops in this region, including cotton, maize, soybeans, and spring and winter wheat. These are the crops most widely grown and constitute the major agricultural components of the economy in this region.

To focus the analysis on only the section of the study area concerning crops of interest to us, we used the Cropland Data Layer (CDL) available from the USDA National Agricultural Statistics Service (USDA/NASS) to assess the crop-relevant areas of these 16 states. The CDL consists of a raster file at a spatial resolution of 30 m that correctly identifies land covers 88% of the time (USDA/NASS 2016). We used the CDL to identify the portion of the study area with the crops of interest and used this area to confine each county-based soil and topography variable to only the area relevant to our study, which we refer to as the crop-relevant area (Fig. 2).

In order to model the relationship in terms of characteristics of climate, soil, and topography data we used data from multiple sources. Once we focused the study on the crop-relevant area, we were able to investigate the relationships between the different environmental variables (Table I).

We obtained historical daily weather data referred to as the NOAA global summary of the day (GSOD) from the National Centers for Environmental Information (NCEI) for 119 weather stations within the study area. Available daily historical weather
Fig. 2  Crop relevant portion of study area. Portion of study area where crops of interest have historically been grown. This is the portion of each county over which soil and topography variables were aggregated.

data from these stations includes maximum temperature (Tmax), minimum temperature (Tmin), dew point (Tdew), solar radiation (SR), and amount of precipitation (Precip). We then used a weather generator in combination with future climate projections based on ten different Atmosphere-Ocean General Circulation Models (AOGCMs) and three representative concentration pathways (RCPs) to simulate daily weather for the same locations as the historical data. Representative Concentration Pathways (RCPs) are
Table 1  Data used by variable type, source, spatial resolution, and format

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<thead>
<tr>
<th>Variable type</th>
<th>Data source</th>
<th>Spatial Res.</th>
<th>Data format</th>
</tr>
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<td>County-level</td>
<td>Tables formatted in ArcGIS (.dbf)</td>
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<tr>
<td>Climate (GDDs)</td>
<td>NOAA Global Summary of the Day (GSOD) dataset, available through National Centers for Environmental Information (NCEI). Projected daily weather courtesy of Dr. Justin Schoof</td>
<td>119 stations throughout study area</td>
<td>Text file (.txt)</td>
</tr>
<tr>
<td>Climate (PET)</td>
<td>Similar to GDD data, these data are derived from the GSOD dataset available through NCEI</td>
<td>119 stations throughout study area</td>
<td>Text file (.txt)</td>
</tr>
<tr>
<td>Climate (PET) correction data</td>
<td>Climate Research Unit (CRU) gridded dataset from Center for Environmental Data Analysis</td>
<td>0.5 degree grid</td>
<td>Gridded text file (.dat or NetCDF)</td>
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<td>Fertilizer (USDA-NASS)</td>
<td>USDA National Agricultural Statistics Service (USDA-NASS) application estimates for each crop</td>
<td>State-level</td>
<td>Excel spreadsheets (.xlsx)</td>
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<tr>
<td>Crop yield</td>
<td>USDA National Agricultural Statistics Service (USDA-NASS) dataset</td>
<td>County-level</td>
<td>Spreadsheets (.xlsx, .csv)</td>
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climate “forcings” that represent different degrees of climate change. These degrees of climate change correspond to different levels of carbon dioxide concentrations, or different radiative forcing levels that correspond with the carbon dioxide concentrations.

The three RCPs we are using are termed RCP 2.6, 4.5, and 8.5. Although these forcings can be referred to in short-hand as low, medium and high, the differences between these forcings varies as the 21st century progresses (Fig. 3). Under RCP 2.6, greenhouse gas concentrations in the atmosphere peak between 2040 and 2050 and decline later in the century. Climate change could have a larger impact on crop yields in the 2060s than in the 2090s under this scenario. Under RCP 4.5, the rate of increase of greenhouse gas
Fig. 3  Representative Concentration Pathways and their total anthropogenic radiative forcings (Wm$^{-2}$) throughout the 21st century (Stocker 2014)

concentrations begin to diminish in the 2060s. Concentrations in the atmosphere stabilize near the end of the 21st century. Under this scenario, there is not a large difference in the greenhouse gas concentrations between the 2060s and the 2090s. In the highest forcing scenario, RCP 8.5, the concentration of climate-influencing gases increases throughout the 21st century. Representative concentration pathway 6.0 is another climate forcing modeled by the Intergovernmental Panel on Climate Change (IPCC 2007), but not used in the climate projections in this study. AOGCMs are global climate models that combine simulations from atmospheric and oceanic science. These take into account global patterns and are meant to be interpreted at large scales (regional or continental trends). These are coarse-scale future climate projections. Since our study is concerned with county-level climatic factors, these models had to be downscaled to provide projections for each of the stations in our study area. We downscaled these projections by identifying
a statistical relationship between coarse-scale historical climate data and fine-scale historical climate data. We then applied this relationship to the coarse-scale future projections to reach fine-scale future projections. The weather generator produced daily values for the same variables available historically (Tmax, Tmin, Tdew, SR, Precip). The daily precipitation values were determined using a stochastic model defined by two parameters: $p_{01}$ (probability a wet day follows a dry day) and $p_{11}$ (probability a wet day follows a wet day). These parameters differ according to the calendar month. For more details on this process, refer to Schoof (2015). The daily temperature values were determined using a different stochastic weather generator that incorporated numerous atmospheric predictor variables as parameters (Schoof et al. 2007). This produced 28 different daily outputs for each of the variables depending on the climate scenario, defined by RCP, AOGCM model, and time period.

We then used the historical climate data (along with soil, slope, and fertilizer data) along with historical crop yield totals to build models for crop yields for the station-containing counties in the study area. Since we have climate data for 119 stations, this enabled the model to initially be fixed based on data only in these counties. These data were used to build preliminary crop models. This dataset proved to be too small, however, particularly for cotton and spring wheat, which have limited geographical distributions. The historical weather variables were then interpolated across all the counties. From this larger dataset, the crop models were calibrated to their final forms.

We are interested principally in the relationship between weather and crop yields. For this reason, we limited the study to areas of rain-fed agriculture. To do this, we
excluded the portion of the study area overlying the Ogallala aquifer because of the widespread use of irrigation.

One predictive measure of crop development and productivity derived from temperature is growing degree days (GDDs). GDDs are calculated by finding the degrees above a certain threshold up to a higher maximum temperature above which growth rate stops increasing. These threshold temperatures vary by crop (Table 2).

Accumulated GDDs can be used to predict at what point in the growing season a plant goes through each phenological stage (Miller et al. 2001). GDDs are measured from planting until harvest. This makes it simple to determine when a certain number of GDDs is reached during or after a growing season, but difficult to predict when those thresholds are reached when projecting potential future growing seasons. Planting dates, for instance, are often determined by calendar as a proxy for environmental conditions (Corn Planting Guide 2001). Planting dates are likely to change as the climate warms and the growing season becomes longer. One approach to estimating planting dates found to be effective is to calculate mean air temperature over a period of 20 years and assume planting will occur when the temperature crosses a particular threshold, 16 °C in the case of maize (Bondeau et al. 2007; Sacks et al. 2010). We determined this method is not responsive enough to current weather and environmental conditions such as soil temperature, which are the real determinants of planting date.

This temperature-determined planting date idea was adapted to take into account recent weather. The 20-year mean method was incorporated into a heating degree day method. Up until the time of planting, degrees above the growing threshold were referred to as heating degree days (HDDs). The theory was that a certain number of HDDs would
correspond to the date of planting as determined by the 20-year mean temperature threshold. The threshold number of HDDs would then be used to determine planting date. After the planting date, GDDs would begin to be accumulated. This methodology did not end up working. A predictive number of HDDs for each crop that closely correlated with historical planting dates could not be found. It is likely that this is because there are numerous factors other than temperature that contribute to when a crop is planted. It turned out that predicting planting date based on early season weather may have needed to incorporate a lot of other factors like precipitation and farm operations. Since the purpose of this study was not to build a crop planting date model, the method for defining the start of the growing season had to be simplified.

Each crop has a different growing season because of its unique characteristics. Growing seasons were defined separately in each state as the period between the point when 50% of that crop had been planted and the point when 50% of the crop had been harvested. These time points were determined by 20 years of historical crop estimates (USDA/NASS 2010). This definition allowed us to capture the weather when most of the plants were in the ground. Defining growing season in this way works well when looking at the relationship between historical weather and historical crop yields. It did become a limitation in future yield projections since there is no way to account for a change in

<table>
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<tr>
<th>Crop</th>
<th>Cotton</th>
<th>Maize</th>
<th>Soybeans</th>
<th>Spring Wheat</th>
<th>Winter Wheat</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Lower</strong></td>
<td>15.6</td>
<td>10</td>
<td>10</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td><strong>Upper</strong></td>
<td>37.8</td>
<td>30</td>
<td>30</td>
<td>35</td>
<td>30</td>
</tr>
</tbody>
</table>

(Mesonet 2017; NDAWN 2017)
growing season as a management response to a changing climate. This adds an assumption to our crop yield projections that the growing season of the future will start and end around the same time as the growing season of today.

In addition to growing degree days, we used a related measure of accumulated temperature we call stress degree days (SDDs). Stress degree days are defined as the accumulated total of maximum temperature degrees above the GDD maximum threshold. This definition closely follows a study showing that both maize and soybeans are strongly negatively impacted by temperatures above 30 °C (Schauberger et al. 2017). This, as its name indicates, is meant to be a measure of the amount of heat stress a plant is exposed to during the growing season. Just as each crop has a distinct growing degree day range, each crop also has a distinct SDD threshold temperature, above which stress degree days accumulate. Although the temperature threshold for SDDs is the same as the top temperature for the range of GDDs, this was not pre-determined. Several thresholds were tested for SDDs and the one that showed the strongest relationship with crop yields was selected.

The precipitation variables were similarly defined by the growing season between 50% planted and 50% harvested. Effective precipitation is an estimation of the amount of rain that contributes positively to plant growth. There is a variable quantity of rain in a day that stops helping a plant to grow because it runs off the surface (Dastane 1974). Although this interaction is known, the amount of rainfall that is effective is not constant and depends largely on the plant, its stage of development, and the characteristics of the soil (particularly infiltration rate and available water capacity) (Dastane 1974). Because this quantity is not known exactly, we approximated its value statistically by comparing
several threshold measurements at which daily rainfall would no longer be added. We
determined that for our study area, a good estimate of maximum effective rainfall was 20
mm. This estimation was done by testing correlations between effective rainfall and yield
to determine what threshold produced the measure with the strongest relationship. Any
day that had rainfall above 20 mm, had an effective precipitation value of 20 mm. It is
important to have some estimation of effective rainfall instead of simply incorporating
total precipitation because higher intensity rainfall events, where much of the
precipitation may not be beneficial to crop growth, are likely to occur more often in some
locations under future climate regimes (Walthall et al. 2013). The extra rainfall that fell
on each of those days where total precipitation was above 20 mm was counted as the last
weather variable, excess precipitation. This was defined as:

\[
Excess\ Precipitation = Growing\ Season\ Precipitation - Growing\ Season\ Effective\ Precipitation
\]

Weather variables were selected to summarize seasonal fluctuations, while taking
into account daily weather variations. Stress degree days and excess precipitation in
particular are two variables that were generated to capture daily weather events and
summarize them into growing season length variables.

In coordination with weather variables, water availability is also a key
determinant of crop yields. In order to determine how much water was available to the
crops in the study area, we calculated water surplus/deficit based on precipitation and
\(ETO\), reference evapotranspiration. Determining \(ETO\) involved using the Turc equation,
which is based principally on temperature and solar radiation. The preferred method is to
use the Penman-Monteith equation which incorporates more of the factors that affect
evapotranspiration (Allen et al. 1998). Unfortunately, the climate data available at the level of spatial resolution in which we are working does not enable use of the Penman-Monteith equation. Consequently, we used the Turc equation to determine ET₀. Since the Turc equation does not take into account all of the important factors of reference evapotranspiration, it can underestimate ET₀ under some climatic conditions (Trajkovic and Kolakovic 2009). We determined this was the case in our calculations by comparing our ET₀ totals to those typically recorded in similar areas.

Water available to a crop is determined by three factors: (1) available water capacity (AWC), which is a measure of how much water the soil can hold and varies with soil composition and depth; (2) precipitation, how much water is added to the field; and (3) evapotranspiration, how much water is lost due to evaporation and transpiration, which are a function of several climatic factors. A helpful analogy is to think of an agricultural system as a container with a set size (AWC), how much is added to the container each day (precipitation), and how much is subtracted from it each day (evapotranspiration).

Our soil composition and topography data are from the USDA-NRCS (2016) STATSGO2 database. Soil composition variables include soil pH, AWC, cation exchange capacity (CEC), and percent organic matter. Topography data from the same source are limited to percent slope. We used ArcGIS to aggregate and summarize these datasets into county-level variables.

Fertilizer application rates are another important factor in projecting crop yields. The fertilizer input we would have liked for our study is the mean (by county) amount of
fertilizer applied on each acre of farmland for each crop in each year. In order to
determine this, we would need to know how much fertilizer is used for each crop and
how many acres are planted to each crop. There are data available from USDA/NASS on
the total area of land planted to each crop in each county. Unfortunately, the data
available for how much fertilizer is used for each crop is only at the state level at its finest
resolution from USDA/NASS. We used this dataset (USDA/NASS 2010), assuming that
in a given year the amount of fertilizer applied to each crop within a state does not vary
widely.

The datasets addressed so far include variables of climate, soil, topography, and
fertilization. These are predictor variables in the model. The response variable is county-
level crop yields in each year. The model was calibrated using historical crop yields from
USDA/NASS that are given in bushels (or pounds for cotton) per acre per year, historical
daily weather data from the NOAA Global Summary of the Day (GSOD) dataset, and the
soil, topography, and fertilization values from the other datasets. This model enabled
projections of yield given changing climate variables with static soil, topography, and
fertilization variables.

**Modeling approach**

This study used a multiple regression framework designed to incorporate climatic,
edaphic, topographic, and fertilization factors as predictors of crop yields in the study
area. We used multivariable fractional polynomial regression (MFP) in order to model
the nonlinear pattern of these relationships (see Fig. 1).
Results include estimates using these MFP regressions for each crop, for each county, for each of the climate scenario/RCP combinations. Each result utilizes two technology scenarios: no change and continued annual linear improvement in yields. These results are mapped on a county basis per crop per scenario.

Using daily weather data to build a model predicting crop yields presented the challenge to summarize the daily data over a longer period of time without losing benefits of using daily data. Variables used in our analysis consist of three types: soil and land characteristics, a single fertilizer variable, and weather variables. Soil and land characteristic variables include slope, available water capacity (AWC), and pH. Organic matter and cation exchange capacity were not significant once these variables were included. The fertilizer component of the study was limited to a summary variable of the total of nitrogen, phosphate, and potassium. This was done to prevent multicollinearity among fertilizer variables since application rates are highly correlated with one another.

Weather variables include growing season accumulated growing degree days (GDDs), growing season accumulated stress degree days (SDDs), growing season effective precipitation, and growing season excess precipitation.

Crop yield datasets were obtained from USDA/NASS online quickstats tool. Data were available at a county level and derived from annual crop surveys carried out by the National Agricultural Statistics Service (NASS). Maize, soybeans, spring and winter wheat were measured in bushels per acre. Cotton was reported in pounds per acre and was later converted to bushels per acre at a rate of 32 pounds per bushel, as is the reported rate (Murphy 2017). This conversion was done to allow cotton yield curves to be
easily compared to the yield curves of the other crops. However, the cotton-specific yield maps will still be presented in pounds per acre.

**Model building**

The statistical model is built using multivariable fractional polynomials (MFP). Unlike standard multiple regression, it allows various levels of interaction between a predictor variable and the response variable. The power terms of the fractional polynomials are restricted to a small, predetermined set of values, which can be both integers and non-integers (Royston and Altman 1994). This allows models to produce a wide array of curve shapes without the necessity of calculating or estimating powers.

The MFP models were built using the R package “mfp.” This interface allowed the inclusion of all variables of interest and a great deal of control over the relationship between each variable of interest and the response variable. There were three levels of fractional polynomial that could be specified for each variable using this package. The default fractional polynomial \((df = 4)\) allows as many terms as can fit the model. The second option \((df = 2)\) limits the number of terms to two, preventing overly complex relationships from entering the model. The third option \((df = 1)\) limits the number of terms to one, and this term is always linear. Most variables were started with \(df = 4\), and then reduced if the model appeared to be overfitting the relationship based on the MFP curves shown below. Another factor in determining whether a certain variable would be constrained in MFP was to compare the relationships with yield produced by the model with those hypothesized (Fig. 1).
Variable interpolation

There are numerous methods of spatial interpolation, including natural neighbor analysis, thin plate spline analysis, inverse distance weighting, and several types of kriging analysis. Each of these has advantages and disadvantages, making some methods of interpolation more suitable for particular types of variables. We utilized the method of thin plate spline (TPS) analysis.

This type of interpolation is geared toward generating a smooth surface over closely following each observation. It is generally used for variables that change regularly throughout space like temperature (Li and Heap 2011). It is less widely used to interpolate variables that vary irregularly like precipitation. However, because the precipitation variables we used are growing season aggregations, they do not vary as much across space as daily or weekly precipitation does. TPS has been used to interpolate seasonal precipitation with acceptable error levels (Hutchinson 1995).

Two different samples were used in the interpolation process: one in model-building and the other in crop yield projection. In building the model, we used the 119 weather stations that are within the study area. This restricted the data upon which we built the model to only calculations from weather stations in the study area. We used all 214 weather stations available to us to interpolate the future scenario weather variables. Since the weather data going into predicting future yields was not influencing the nature of the model, we saw no problem in using it to improve the interpolated weather data to the edges of the study area.
**Future yield projections**

Each of the four weather variables were calculated for future climate scenarios. There are several permutations of future scenarios based on representative concentration pathways (RCPs) and climate models. The climate scenario for which the seasonal weather variables were generated was an ensemble of three different Atmosphere-Ocean General Circulation Models (AOGCMs). These are the L’Institut Pierre-Simon Laplace Coupled Model, Version 5 (IPSL-CM5-LR), Meteorological Research Institute Coupled Atmosphere–Ocean General Circulation Model, Version 3 (MRI-CGCM3), and the Norwegian Earth System Model, Version 1 (NORESM-1 M). These three models capture a cross-section of the variety of climate modeling techniques, and therefore represent a good cross-section of the variation in climate models (Knutti et al. 2013). The seasonal weather variables were calculated based on daily weather generated from each of these models at 3 concentration pathways (RCPs 2.6, 4.5, and 8.5). These seasonal weather variables, which include growing degree days (GDDs), stress degree days (SDDs), effective precipitation, and excess precipitation were averaged across the models and within each concentration pathway. The resulting dataset includes GDDs, SDDs, effective precipitation, and excess precipitation for the ensemble weather model at each concentration pathway 2.6, 4.5, and 8.5.

These weather variables were then put into the model built from historical weather observations to project future crop yields based on two technology scenarios. The crop yield models were built with year as a predictor variable. This stood as a proxy for technological advances which allowed increased crop yields. The first technology scenario allows year to increase as a predictor variable, simulating a future where crop
yields would continue to increase due to development and adoption of new crop technologies. The second technology scenario keeps year constant at 2010 to simulate a future where crop yields do not increase further because technology does not advance crop intensification possibilities significantly.
RESULTS

Models were produced for each of the crops using the historical weather and yield data (Table 3).

All crops had somewhat similar models in terms of which predictors were included. There are some important differences, however, between crops in which variables were found to be significant predictors of yield (Table 3). Stress degree days were not included in the winter wheat model though they were included in the rest of the crop models. Another predictor variable left out of the winter wheat model was pH. The cotton model did not have fertilizer as a predictor variable. Maize, soybeans, and spring wheat all have models that include all nine of the predictor variables.

The coefficients and MFP transformations give some idea of the relationship between each predictor variable and crop yields. The different transformations make these model outputs difficult to interpret. For this reason, below are included MFP curves of each predictor variable for each of the crops studied.

MFP model curves

The curves in Figure 4 show the response of yield to one variable at a time as all other variables are held at their mean values. This is not a perfect representation of these relationships because many of the variables are closely related to one another. For instance, as available water capacity changes, so too does soil pH.

Expected yields vary by crop. Maize generally has higher yields than any of the other crops because it naturally has higher yield potential. These curves are not meant to
<table>
<thead>
<tr>
<th>Yield Determinant</th>
<th>MFP Transformation</th>
<th>Maize</th>
<th>Soybeans</th>
<th>Cotton</th>
<th>Spring Wheat</th>
<th>Winter Wheat</th>
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</thead>
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<tr>
<td>Intercept</td>
<td></td>
<td>-3206</td>
<td>-805.4</td>
<td>-23210</td>
<td>-1230</td>
<td>-1261</td>
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<td>Year</td>
<td></td>
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<td>0.4014</td>
<td>10.92</td>
<td>0.6032</td>
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</tr>
<tr>
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<td>x/100</td>
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<td>x^-2</td>
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<td></td>
<td>(x/10)^-0.5</td>
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<td>Available Water Capacity</td>
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<tr>
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<td>(x/10)^-0.5</td>
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<td></td>
<td>(x/10)^-2 * log(x/10)</td>
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<td>Growing degree days</td>
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<td></td>
<td>log(x/1000)</td>
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<td>(x/1000)^-2</td>
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<td>(x/1000)^-1</td>
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<td>254.9</td>
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<td></td>
<td>(x/1000)^3</td>
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<td>-283.4</td>
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<td></td>
<td>log(x/1000)</td>
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<tr>
<td></td>
<td>x/1000</td>
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<td></td>
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<td></td>
<td>462.9</td>
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<td>Stress degree days</td>
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<tr>
<td></td>
<td>(x/100)^0.5</td>
<td></td>
<td></td>
<td></td>
<td>-8.318</td>
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<tr>
<td></td>
<td>((x+0.1)/10)^0.5</td>
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<td>-151.3</td>
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<td>Effective precipitation</td>
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<td>-91.81</td>
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<td></td>
<td>(x/1000)^0.5</td>
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<td></td>
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<td></td>
<td>(x/1000)^2</td>
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<td></td>
<td>log(x/1000)</td>
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<td>93.46*</td>
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<tr>
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<td>x/100</td>
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<td></td>
<td>(x/100) * log(x/100)</td>
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<tr>
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<td>(x/1000)^-1</td>
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<td>-9.036</td>
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Table 3 continued

<table>
<thead>
<tr>
<th>Excess precipitation</th>
<th>((x+0.1)/100)^2</th>
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<tr>
<td></td>
<td>(\log((x + 0.1)/100))</td>
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<td>((x + 0.1)/100)</td>
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</tr>
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<td>((x + 0.1)/100)^{0.5})</td>
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<td>-67.22</td>
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<td>-9.910</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-16.05</td>
</tr>
</tbody>
</table>

Model performance

| \(R^2\) | 0.552 | 0.624 | 0.527 | 0.649 | 0.552 |

*Only significant at 0.1 level. All others are significant at 0.01 level.

compare yields between crops but to observe similarities and differences between the shapes of the curves of the five crops studied.

Again, each of the variables was aggregated to the county level. Consequently, each of these curves represents the relationship between a particular variable in a county and the yield in that county.

Year was used as a predictor variable to represent technological changes that have enabled increased crop yields. Our model shows as the years advanced from 1980 to 2013, crop yields increased linearly in response (Fig. 4a). This reflects the impact of technological improvements in crop yields over this period.

Four of the crops had a positive relationship between total fertilizer applied and crop yields. There was not a statistically significant relationship between fertilizer application and yields in cotton. The MFP model produced a linear curve for soybeans and both wheat models. It produced a logistic curve for maize yields, reflecting a decrease in the benefit of each additional unit of fertilizer applied above a certain point – or diminishing marginal returns (Fig. 4a).

Fertilizer applications were separated into nitrogen, phosphate, and potassium. Each of these was entered into the model separately for each crop. The statistically
Fig. 4a  Nonlinear response curves from multivariable fractional polynomials (MFP) for each of the five crops studied to the temporal, management, and environmental determinants
significant effects of each individual fertilizer varied from crop to crop but each crop model had a similar problem: multicollinearity. Application of each type of fertilizer was highly correlated with application of each other type of fertilizer within each crop. For this reason, all fertilizer application was aggregated into a single number of total nitrogen, phosphate, and potassium application. The components of each fertilizer vary depending on the crop.

The response curve for percent slope shows crop yields to be highest at very low slopes. As slopes increase, yields decrease. The effect of slope on yields flattened out for maize, soybeans, and cotton above around 5%. Spring wheat showed a continuously negative linear relationship with slope. The negative effect on winter wheat decreased at higher slopes but the curve still shows a negative relationship at higher slopes, unlike maize, soybeans, and cotton.

All five crops showed a positive relationship between available water capacity (AWC) and yields.

Soil pH had a statistically significant relationship with crop yield for 4 out of the 5 crops. Winter wheat yields did not show a relationship with soil pH. Soybeans and spring wheat were shown to be positively correlated with higher pH up to around 7.5. Maize yields increased with pH in the same range but to a diminishing extent as pH became higher. Cotton yields peaked around a pH of 5.5 to 6. The curves only extend to a pH of 7.5 because there were no counties in the study area with even moderately alkaline soil (above pH of 8).

Growing season growing degree days (GDDs) were a strong predictor of yields in all 5 crops. In analyzing the GDD curve, it is important to keep in mind that GDDs are
Defined differently in this study depending on the crop. Maize and soybeans are calculated between thresholds of 10 and 30 °C (NDAWN 2017). Winter wheat is calculated between thresholds of 0 and 30 °C (Mesonet 2017). Cotton GDDs were calculated between thresholds of 15.6 °C and 37.8 °C (Mesonet 2017). Spring wheat GDDs were calculated between thresholds of 0 and 35 °C (NDAWN 2017). These ranges were determined by the thermal ranges of each plant. This is the reason winter wheat generally accumulates more growing degree days than cotton even though cotton is grown in warmer regions over a hotter portion of the year.

Four out of the five crops showed peaks in the response of yield to growing degree days (Fig. 4b). These peaks correspond to what we observe to be the ideal thermal range of each crop. Spring wheat did not show a peak in its GDD curve, but instead a negative linear response to an increasing number of growing degree days.

Growing season stress degree days were a significant predictor of yields in all crops except winter wheat. Stress degree days (SDDs) were defined as degrees above the high threshold for growing degree days. Consequently, the definition varies with crop depending on its thermal range.

All four of these crops showed a negative relationship between accumulated SDDs and crop yields. A negative linear effect was shown in spring wheat. Maize, soybeans, and cotton showed an effect that diminished as the number of SDDs increased. Growing season effective precipitation, which is defined as total precipitation over the growing season below a daily threshold of 20 mm, was a highly significant (p < 0.001) predictor of yields in four out of five crops and close to statistical significance in cotton (p = 0.056). There was a positive effect on yields from increasing effective
Nonlinear response curves from multivariable fractional polynomials (MFP) for each of the five crops studied to the climatic determinants precipitation up to a certain point in maize, soybeans, spring wheat, and winter wheat. Each of these curves reached a point where more precipitation no longer corresponded with increasing yields.

Accumulated excess precipitation, which is defined as the total precipitation above a daily threshold of 20 mm over the course of the growing season, was a highly significant predictor of yields (p < 0.001) in all five crops. All crops show similar
relationships where the highest yields are seen at low values of excess precipitation and yields tend to diminish as excess precipitation increases.

**Study area yield projections**

Figure 5 depicts the mean yields for the entire study area throughout the 21st century. Means were calculated for the periods 2030–2039, 2060–2069, and 2090–2099 for three representative concentration pathways (RCPs 2.6, 4.5, and 8.5), which represent different carbon dioxide concentration scenarios.

Each emission scenario was projected under two technology scenarios - the first where technology enables continual advances in crop yields and the second where technology would enable crop yields similar to those in 2010 if the climate was not considered.

Assuming continual technological adaptation resulted in higher crop yields in all emission scenarios for all crops. In most instances, crop yields are projected highest at the lowest emissions scenario (RCP 2.6), second highest in the middle emissions scenario (RCP 4.5), and lowest in the highest emissions scenario (RCP 8.5). In some instances there is little difference between RCP 2.6 and 4.5, and in a few instances there is little difference between the three emissions scenarios.

**County-level yield projections**

The projections that span the entire study area give a general picture of what our model shows about future crop yields. This section deals with projections for each
Fig. 5  Mean decadal yield projections (in bushels per acre) for each crop under three representative concentration pathways (or RCPs) and two technology scenarios. Yield is shown on each y axis and is measured in bushels per acre. Solid black lines represent historical trend from MFP model. For each crop the two technology scenarios are visibly separate and are labeled on each plot. Each point plotted represents the decadal mean for either 2030–2039, 2060–2069, and 2090–2099, each corresponding to its placement on the x axis. Error bars for each point show standard deviation of projections within that decade.
county, showing where in the study area yields are expected to increase or decrease and the magnitude of those changes under each emissions/technology scenario.

The top map in Figure 6 depicts the historical mean maize yields for each county in the study area during the period from 2000 to 2009. White counties in the study area had no historical yield data. There are consequently more counties included in the future projections than in past observations because future projections were not limited by where yield observations were recorded.

In the static technology scenario, the highest yields projected are between 146 and 180 bushels per acre. In the historical data from the 2000s, counties with yields in this range were mostly grouped in the central corn belt across the states of Illinois, Iowa, Indiana and into southern Minnesota. There are a few more of these high-yielding counties in Ohio and along the southern portion of the Mississippi River in Missouri and Arkansas. Under the static technology scenario for RCP 2.6 in the 2030s, there is an expansion of the corn belt both to the north and to south, with high-yielding counties expanding in both directions. Under RCP 4.5 in the 2060s, there is northward movement of the high-yielding corn belt and less productivity in Missouri, southern Illinois, and southern Indiana than under RCP 2.6 in the 2030s. Also under RCP 4.5 in the 2060s, most counties in the southern half of the study area become less productive, with the higher-yielding southern counties observed under RCP 2.6 in the 2030s disappearing almost entirely. Under RCP 8.5 in the 2090s, the highest yielding counties are in northern portions of the study area in the states of Michigan, Wisconsin, and Minnesota. The counties in Illinois, Iowa, and Indiana that were historically high-yielding are all projected to have lower yields (111–145 bushels per acre in most cases).
Fig. 6  Historical and projected decadal mean maize yields (bushels per acre) by county. The top map shows the historical mean in the 2000s. The left column shows projected yields under RCP 2.6, 4.5 and 8.5 in the 2030s, 2060s, and 2090s with the assumption of crop technology staying at 2010 levels. The right column shows projected yields under RCP 2.6, 4.5, and 8.5 in the 2030s, 2060s, and 2090s with the assumption of crop technology advancing linearly with year according to model fit. The Ogallala aquifer has been removed from the study area to prevent irrigated yields from influencing the model.
The inclusion of year as a predictor of linear increase in crop yields produced large increases in maize yields under all climate change scenarios. Although climate factors were shown to decrease yield projections over time under the static technology scenario, the negative influence of climate is not seen in overall yield projection maps under the “optimistic,” continually improving technology scenario. Higher yields are projected throughout the study area under RCP 2.6 in the 2030s. The highest yields are projected for the traditional corn belt and areas just to the east of it. Even higher yields are projected for RCP 4.5 in the 2060s. The distribution of high yields under RCP 4.5 is similar in both technology scenarios. The highest yields are observed in the historical corn belt with an expansion northward and eastward. Though the difference in the technology factor results in these yield projections being very different in magnitude. The starkest difference in comparing maps between static and improving technology is in RCP 8.5 in the 2090s. Despite climate factors being most harmful to maize yields in the 2090s under RCP 8.5, this scenario shows larger yields than any of the other emissions/year permutations mapped under the improving technology scenario. The static technology scenario resulted in projections of the historical maximums being confined to northern counties with counties in the south showing all around lower yields.

Figure 7, depicting percentage of historical yields, shows a similar story to total change in yields. Any counties that did not have historical data could not be included in the mapping of percent change. These maps consequently do not include as many counties as the yield projection maps.

Under static technology, the yields in the central corn belt of Iowa and Illinois are decreased under all emissions/time instances. It is mostly the high-yielding counties that
Fig. 7  Projected change in maize yields from historical yields. The left column shows the change in yields in comparison to the mean for the decade from 2000 to 2009 under RCP 2.6, 4.5, and 8.5 in the 2030s, 2060s, and 2090s with the assumption of crop technology staying at 2010 levels. The right column shows the change in yields in comparison to the mean for the decade from 2000 to 2009 under RCP 2.6, 4.5, and 8.5 in the 2030s, 2060s, and 2090s with the assumption that crop technology will advance linearly with year according to model fit.
show decreases in RCP 2.6 in the 2030s, although they are modest decreases. There are numerous counties that gain yields in RCP 2.6 in the 2030s in the northern part of the study area, as well as in the south. In fact, yields look to increase most places except the central corn belt and the Mississippi valley. There is a similar pattern of gains and losses of yields under RCP 4.5 in the 2060s. In the southern part of the study area, however, the “losing counties” show more severe losses and there are more counties whose gains are minimal instead of moderate. In the northern part of the study area under RCP 4.5 in the 2060s there are more counties with moderate and substantial gains as opposed to the minimal gains many showed under RCP 2.6 in the 2030s. The yield losses are most noticeable under RCP 8.5 in the 2090s. The southern portion of the study area shows numerous counties with substantial yield losses. The mid-latitude portion of the study area shows most counties with minimal to moderate yield losses. The northern portion of the study area shows most counties with minimal to substantial yield gains, with the western parts of North and South Dakota showing the widest and most substantial gains. Under the improving technology scenario, percent yield change is positive virtually everywhere in the study area under all greenhouse gas concentration scenarios. The percentage increases were more modest in the central corn belt where yields have historically been the highest in the study area. The percentage increases in yield are higher later in the 21st century throughout the study area, following the general pattern observed in study area mean yields, as shown in Figure 5.

The top map in Figure 8 depicts the historical mean soybean yields for each county in the study area during the period from 2000 to 2009. White counties in the study area had no historical yield data. There are consequently more counties included in the
Fig. 8  Historical and projected decadal mean soybean yields (bushels per acre) by county. The top map shows historical mean yields in the 2000s. The left column shows projected yields under RCP 2.6, 4.5 and 8.5 in the 2030s, 2060s, and 2090s with the assumption of crop technology staying at 2010 levels. The right column shows projected yields under RCP 2.6, 4.5, and 8.5 in the 2030s, 2060s, and 2090s with the assumption of crop technology advancing linearly with year according to model fit.
future projections than in past observations because future projections were not limited by where yield observations were recorded.

The highest yields projected for a broad area in the static technology scenarios was between 46 and 55 bushels per acre. In the historical yields map, this highest-yielding area is observed in the central portion of the study area across the states of Iowa, Illinois, Indiana, and Ohio. There are moderately high-yielding counties (between 36 and 45 bushels per acre) spread throughout the study area from Mississippi to Minnesota. In the 2030s under RCP 2.6, the highest-yielding portion is projected to expand north and south from this central area, but still be confined to the middle-to-high latitudes of the study area. In the 2060s under RCP 4.5, the highest-yielding portion is in a similar region but has shifted northward, with more high-yielding counties in Wisconsin, Minnesota, and Michigan. In the 2090s under RCP 8.5, there are very few high-yielding counties in the study area. These counties are confined to far northern parts of the region. Although the highest yielding counties are greatly reduced in number under this scenario, the moderately high-yielding counties cover the northern half of the study area. Many of the counties in the southern end of the study area show a large reduction in projected yield from the yields observed historically. Also noticeable in the 2090s under RCP 8.5 are fairly marked lines between yield levels along lines of latitude.

In the improving technology scenario, yields were higher overall. Growth in yields continue throughout the 21st century regardless of climate scenario. Under RCP 2.6 in the 2030s, the historically high-yielding corn/soy belt shows improved yields (56–65 bushels per acre) and expands into most of the center part of the study area. This area of high yields in the 2030s makes way for even higher yields (66–75 bushels per acre) in
the 2060s under RCP 4.5. This high-yielding area expands further in the 2090s under RCP 8.5 and even higher yields (76–91 bushels per acre) are projected in some northern counties. Similar to maize, this is the CO₂ scenario in which the greatest contrast can be seen between the static and improving technology scenarios. Although the effects of climate change under RCP 8.5 are shown to greatly diminish yields in much of the country when technology is static, the effect of climate does not show up in the high yields produced under RCP 8.5 when technology is assumed to continue progressing.

This is the highest yielding scenario mapped.

Figure 9, depicting proportion of projected future yields to historical yields, shows what direction yields moved in each of the counties for each scenario. In the static technology scenario, the majority of the study area showed positive changes from historical yields under RCP 2.6 in the 2030s. Exceptions to this are some counties around the periphery of the study area and a number of counties in the central soy belt. There was variation in the extent of the losses in the peripheral counties but all of the losses in the central soy belt were minimal (0–12%). A similar trend was seen in RCP 4.5 in the 2060s, though the magnitude and scope of the yield losses increased. Many of the highest yielding counties in the central soy belt showed minimal losses. Higher losses were observed in the southern part of the study area, particularly in the lower Mississippi valley. The majority of the study area shows projected gains in soybean yields under this scenario. Under RCP 8.5 in the 2090s, yield losses become greater and expand through a higher percentage of the study area. A large portion of the southern half of the study area shows substantial yield losses (> 25%) in this scenario. Yield losses have moved from minimal under RCP 4.5 in the 2060s to moderate (12–25%) under RCP 8.5 in the 2090s.
Fig. 9  Projected proportion of mean soybean yield in each county under six climate scenarios when compared to historical yield in the decade between 2000 and 2009. The left column shows the proportion (in percent) of projected yield to the historical mean under RCP 2.6, 4.5, and 8.5 in the 2030s, 2060s, and 2090s under the assumption that crop technology will stay at 2010 levels. The right column shows the proportion of projected yield to the historical mean under RCP 2.6, 4.5, and 8.5 in the 2030s, 2060s, and 2090s under the assumption that crop technology advances linearly with year according to model fit. Both columns are on the same scale.
The northern quarter of the study area still shows minimal to moderate yield gains under this high CO₂, late century instance.

In the improving technology scenarios, the projected crop yields are improvements over historical crop yields throughout the study area across all greenhouse gas concentration scenarios. Soybean yields increased the least amount in the central soy belt where yields have historically been the highest. Proportion to historical yields is higher in the later part of the 21st century throughout the study area, with many counties in the north projected to produce yields of greater than 200% of historical yields.

The top map in Figure 10 depicts the historical mean cotton yields for each county in the study area during the period from 2000 to 2009. White counties in the study area had no historical yield data. There are consequently more counties included in the future projections than in past observations because future projections were not limited by where yield observations were recorded.

The counties with the highest cotton yields have been in the lower Mississippi valley. Under the static technology scenario, the highest yields (901–1100 lbs per acre) in RCP 2.6 in the 2030s are observed in the counties along the Mississippi River, similar to the historically highest yielding counties. Under this scenario, high yields extend south into Louisiana. There is a similar geographic area showing high yields (901–1100 lbs per acre) under RCP 4.5 in the 2060s. There is also an extension of this area northward and some high-yielding counties in north-central Mississippi. There is a loss of high-yielding counties under RCP 8.5 in the 2090s. The area of moderately high-yielding (701–900 lbs per acre) counties has shifted to the north into central Missouri and Kansas and the southern parts of Illinois and Indiana. Most of Oklahoma and portions of Arkansas and
Fig. 10  Historical and projected decadal mean cotton yields (pounds per acre) by county. The top map shows historical mean yields in the 2000s. The left column shows projected yields under RCP 2.6, 4.5 and 8.5 in the 2030s, 2060s, and 2090s with the assumption of crop technology staying at 2010 levels. The right column shows projected yields under RCP 2.6, 4.5, and 8.5 in the 2030s, 2060s, and 2090s with the assumption of crop technology advancing linearly with year according to model fit.
Louisiana are shown to yield much lower totals in this scenario than in RCP 2.6 or 4.5 earlier in the 21st century.

The improving technology scenario shows a similar pattern of geographic distribution, but with higher yields all around the study area. In RCP 2.6 in the 2030s, numerous counties are projected to have yields higher (1101–1300 lbs per acre) than almost all historical observations. These counties are seen throughout the lower Mississippi valley. This area is projected to still be the highest producing region in the 2060s under RCP 4.5, with almost universally higher yields throughout the study area than in the 2030s under RCP 2.6. The distribution of high-yielding counties changes dramatically in the 2090s under RCP 8.5. The most productive region of the study area is now the northern portions of southern states like Mississippi and Arkansas and the southern portions of northern states like Illinois and Indiana. These counties are projected to have very high yields (1601–1900 lbs per acre) in comparison to historic levels.

Proportion of projected cotton yields to historical cotton yields, depicted in Figure 11, shows the direction yields are expected to move according to each scenario. A relatively small number of counties in the study area had historical cotton yield data available. This limited the number of counties for which proportions of future yields to historical yields could be calculated.

In the static technology scenario, the effect of a changing climatic regime on crop yields varied depending on the year and carbon concentration in the projection. In the 2030s under RCP 2.6, much of the cotton-producing counties showed positive responses in comparison to observed yields in the 2000s. There are also positive responses in much
Fig. 11  Projected proportion of mean cotton yield in each county under six climate scenarios when compared to historical yield in the decade between 2000 and 2009. The left column shows the proportion (in percent) of projected yield to the historical mean under RCP 2.6, 4.5, and 8.5 in the 2030s, 2060s, and 2090s under the assumption that crop technology will stay at 2010 levels. The right column shows the proportion of projected yield to the historical mean under RCP 2.6, 4.5, and 8.5 in the 2030s, 2060s, and 2090s under the assumption that crop technology advances linearly with year according to model fit. Both columns are on the same scale.
of the area in the 2060s under RCP 4.5. In the 2090s under RCP 8.5, most of the cotton-producing counties showed negative responses. Those negative responses were particularly severe in Oklahoma and areas of Louisiana. There were moderately high losses in much of Mississippi, Arkansas, and the remainder of Louisiana.

In the improving technology scenario, yield projections increased throughout the 21st century regardless of the greenhouse gas concentration scenario. Under RCP 2.6 in the 2030s, the vast majority of counties showed a minimal, moderate, or substantial increase in yields. Only a small number of counties showed a minimal decrease in yields. Under RCP 4.5 in the 2060s, no counties showed decreases in yields in comparison to yields of the 2000s decade. Most counties showed moderate or substantial increases in yields with a smaller number showing minimal increases in yields. Similar to RCP 4.5 in the 2060s, under RCP 8.5 in the 2090s most counties showed moderate or substantial increases in yields. It is not visually apparent whether most counties have improved more or less than in RCP 4.5 in the 2060s.

The top map in Figure 12 depicts the historical mean spring wheat yields for each county in the study area during the period from 2000 to 2009. White counties in the study area had no historical yield data.

In the static technology scenarios, projected spring wheat yields are influenced by carbon concentration. In the historical dataset, the highest spring wheat yields were observed in the eastern portion of the 3 state study area. Yields generally decreased the further west a county was in this area. Under RCP 2.6 in the 2030s, the highest yielding region expanded and moved slightly west into the central portion of the study area. There were not as many low-yielding counties in RCP 2.6 in the 2030s as there were in the
Fig. 12  Historical and projected decadal mean spring wheat yields (bushels per acre) by county. The top map shows historical mean yields in the 2000s. The left column shows projected yields under RCP 2.6, 4.5 and 8.5 in the 2030s, 2060s, and 2090s with the assumption of crop technology staying at 2010 levels. The right column shows projected yields under RCP 2.6, 4.5, and 8.5 in the 2030s, 2060s, and 2090s with the assumption of crop technology advancing linearly with year according to model fit. The only states included in this map are North Dakota, South Dakota, and Minnesota because they are the only states that have historically been significant producers of spring wheat.
historical yield data from the 2000s. The number of high-yielding (51–60 bushels per acre) counties was lower under RCP 4.5 in the 2060s compared to RCP 2.6 in the 2030s. It was more similar to the number of high-yielding counties in the 2000s historical yield data. Many of the other counties outside the central high-yielding area show decreasing yield trends in RCP 4.5 in the 2060s. In the 2090s under RCP 8.5, the decreases in yields are clear with the highest yielding counties projected to produce between 43 and 50 bushels per acre.

Under the improving technology scenarios, projected spring wheat yields increase throughout the 21st century without noticeable negative effects from atmospheric carbon concentrations. Under RCP 2.6 in the 2030s, the geographic distribution of the highest yielding counties is similar to the same time period and RCP under the static technology scenario. The magnitude is just greater in the improving technology scenario. Under RCP 4.5 in the 2060s, the central portion of the 3 state study area continues to produce the highest yields, but the maximum yields are higher than under RCP 2.6 in the 2030s. Under RCP 8.5 in the 2090s, the highest yielding (81–95 bushels per acre) areas expand through most of the 3 state study area. There is no apparent regional shift in high-yielding areas under static or improving technology for any of the carbon concentration scenarios.

Figure 13 shows the proportion of projected spring wheat yield to historical spring wheat yield. These maps indicate the direction yields are expected to move under each scenario. White counties did not have data for proportions to be calculated, which means either historical data were not available or future weather data were not available. In the static technology scenarios, different regions of the three state study area were impacted in different ways by the various climate scenarios. In the 2030s under RCP 2.6,
Fig. 13  Projected proportion of mean spring wheat yield in each county under six climate scenarios when compared to historical yield in the decade between 2000 and 2009. The left column shows the proportion (in percent) of projected yield to the historical mean under RCP 2.6, 4.5, and 8.5 in the 2030s, 2060s, and 2090s under the assumption that crop technology will stay at 2010 levels. The right column shows the proportion of projected yield to the historical mean under RCP 2.6, 4.5, and 8.5 in the 2030s, 2060s, and 2090s under the assumption that crop technology advances linearly with year according to model fit. Both columns are on the same scale.
the central part of the study area showed some minimal negative effects on yields. The western part of the study area showed mostly minimal to moderate positive effects on yields. Under RCP 4.5 in the 2060s the central-eastern part of the study area showed expanded minimal negative effects from RCP 2.6 in the 2030s and some moderate negative effects. The western part of the study area showed positive effects, but more of these were of a smaller magnitude. In the 2090s under RCP 8.5, the eastern half of the study area all showed negative effects of mostly substantial magnitude. The western part of the study area showed minimal to moderate positive effects.

All counties in the three state study area are projected to increase spring wheat yields under all sub-scenarios within the improving technology scenario. Under RCP 2.6 in the 2030s, most of the historically high-yielding counties in the eastern part of the study area (Fig. 12) showed minimal increases in yields (Fig. 13). The historically low-yielding counties in the western part of the study area showed substantial increases (> 200%) in yields. Under RCP 4.5 in the 2060s, this geographic pattern of unequal yield increases persisted, though with higher magnitudes throughout: moderate increases from the 2000s yields in the east and more counties in the west with substantial yield increases from the 2000s. There was some expansion of the substantial yield increasing counties under RCP 8.5 in the 2090s, though the distribution of increases is very similar to that of RCP 4.5 in the 2060s.

The top map in Figure 14 depicts the historical mean winter wheat yields for each county in the study area during the period from 2000 to 2009. White counties in the study area had no historical yield data. There are consequently more counties included in the
Fig. 14  Historical and projected decadal mean winter wheat yields (bushels per acre) by county. The top map shows historical mean yields in the 2000s. The left column shows projected yields under RCP 2.6, 4.5 and 8.5 in the 2030s, 2060s, and 2090s with the assumption of crop technology staying at 2010 levels. The right column shows projected yields under RCP 2.6, 4.5, and 8.5 in the 2030s, 2060s, and 2090s with the assumption of crop technology advancing linearly with year according to model fit.
future projections than in past observations because future projections were not limited
by where yield observations were recorded.

Historically, winter wheat yields were highest in the northeastern portion of the
study area in the states of Illinois, Indiana, Ohio, Michigan, and Wisconsin. There were
moderately high yielding (59–67 bushels per acre) counties observed throughout the
study area. Under the static technology scenario in RCP 2.6 during the 2030s, this
historically high-yield region becomes less important, making way for high yields (68–78
bushels per acre) in the northwestern region of the study area in the states of North
Dakota, South Dakota, and Minnesota. Much of the study area shows potential for
moderately high yields under this scenario. In the 2060s under RCP 4.5, the bands of
high-yielding counties become smaller, though the geographic distribution of
productivity is similar to that of RCP 2.6 in the 2030s. Under RCP 8.5 in the 2090s, the
moderately high-yielding counties are confined to the northern half of the study area.
There are only a small number of the highest yielding counties observed in the northern
parts of Minnesota and North Dakota.

Under the improving technology scenarios, the potential yields of winter wheat
increase all the way through the 2090s, regardless of atmospheric carbon concentration.
Under RCP 2.6 in the 2030s, the highest yielding counties are all in northern states. There
are moderately high yields (68–78 bushels per acre) projected for most of the study area.
These projected yields are similar to the maximums projected in the static technology
scenarios. Under RCP 4.5 in the 2060s, the same region shows the highest yields, though
the maximum yields have increased (to 91–110 bushels per acre for most of the study
area). In the 2090s, the high yields (91–110) have extended throughout the study area,
with even higher yields (111–130 bushels per acre) projected for areas in the northeast and northwest.

Proportion of projected winter wheat yield to historical spring wheat yield is shown in Figure 15. This gives an indication of the direction yields are expected to move in each scenario. White counties did not have data for proportions to be calculated. This was largely limited by a lack of historical data in a large number of counties in the central part of the study area.

Across all the static technology scenarios, an east-west divide of the impacts on yield can be seen. In the 2030s under RCP 2.6, yield losses of varying magnitudes are projected across the eastern part of the study area, with most losses being minimal to moderate. In the same scenario, moderate to substantial yield gains are projected across much of the western part of the study area. A similar geographic distribution can be observed in the 2060s under RCP 4.5. In the 2090s under RCP 8.5, yield losses in the east are more severe than in either of the other two carbon concentration scenarios. The number of counties showing losses in the east is also larger. Throughout the western part of the study area, many of the counties show projections of minimal to moderate gains in yield. A smaller number of counties in the northwest part of the study area still show substantial yield gains under RCP 8.5 in the 2090s compared to historical yields from the 2000s.

In the improving technology scenarios, most counties are projected to gain winter wheat yields under all carbon concentration scenarios. In the 2030s under RCP 2.6, most counties in the eastern part of the study area are projected to show minimal to moderate
Fig. 15  Projected proportion of mean winter wheat yield in each county under six climate scenarios when compared to historical yield in the decade between 2000 and 2009. The left column shows the proportion (in percent) of projected yield to the historical mean under RCP 2.6, 4.5, and 8.5 in the 2030s, 2060s, and 2090s under the assumption that crop technology will stay at 2010 levels. The right column shows the proportion of projected yield to the historical mean under RCP 2.6, 4.5, and 8.5 in the 2030s, 2060s, and 2090s under the assumption that crop technology advances linearly with year according to model fit. Both columns are on the same scale.
improvements in yields over the historical yields from the 2000s. Only a small number of counties are projected to show yield losses under this scenario. The western part of the study area shows projections of moderate to substantial yield gains for most counties. Under RCP 4.5 in the 2060s, more of the western counties show substantial yield gains while much of the eastern counties now show moderate gains over the yields in the 2000s. In the 2090s under RCP 8.5, much of the study area shows substantial gains in yields. A smaller area shows moderate gains in yields. A small number of counties in the northeastern part of the study area show only minimal gains in yields from the decadal means of the 2000s.
DISCUSSION

The purpose of this study was to answer questions about potential yield changes under various climate change scenarios. In addition, it was to determine if the potential yield changes would correspond to changes in spatial distribution of crops projected in previous work (Lant et al. 2016). Crop yields in the United States have been negatively impacted by climate change in the recent past (Lobell et al. 2011) and are expected to be negatively impacted by climate change in the future (Schlenker and Roberts 2009). The suitability of land for particular crops is also expected to change in response to climate (Lant et al. 2016).

The models built indicate that under future climate scenarios, there will be changes in both crop yield potential and what the most productive regions for particular crops are. This varies to a degree by crop and is largely dependent on the climate scenario. The overarching pattern is decreasing yields in the south with static or increasing yields in the north of the study area.

**Crop model unexpected findings**

The crop models and the individual MFP curves based on them generally showed what we expected the relationships to be between each predictor variable and crop yields. There were some unexpected findings in terms of which variables were found to be significant predictors in each model.

Winter wheat in particular had two potential predictor variables found insignificant in its model. One of those variables was stress degree days. The growing season for winter wheat spans from early to late fall through the winter and into the
following spring or early summer. It makes sense that stress degree days were not found to be an important predictor of crop yields given this growing season. The high temperature stress part of the year is during the summer when crops grown in the conventional growing season are in the ground. It is possible that there will be a greater amount of heat stress at the beginning and end of the winter wheat growing season under future climate regimes. Because that stress has historically not been a factor in winter wheat growth, however, the model built for winter wheat was unable to capture any stress degree day effects.

The other predictor variable left out of the winter wheat model was pH. This was more surprising. It was expected that since pH is an important soil characteristic, it would be a good predictor of crop yields. It is possible the range of pH’s was not large enough in winter wheat for an effect on yields to be evident. As shown in Figure 4, the range does not expand far from around neutral so perhaps the range of counties we observed for winter wheat did not include particularly low or high pH values. It makes sense that the areas where crops have been planted historically are well-suited to crops. If this is the case, the question may be what the difference is between winter wheat and the other crops that makes it not quite as sensitive to small differences in pH.

The cotton model did not include fertilizer as a predictor variable. This finding was less surprising since fertilizer data were aggregated to a state level. It may be that the assumption that fertilizer does not vary highly within a state was not good for cotton. Perhaps there is greater variability within some of the cotton states on how much fertilizer is used than for some of the other crops. If this is the case, the methodology used would not have picked up that variability within each state.
MFP curves explanations and unexpected findings

The MFP curves produced generally followed expectations. This can be observed in the resemblance between these curves and the hypothesized relationships in Figure 1. The different predictor variables and their modeled relationships with crop yields are addressed below.

Four of the crops show a similar pattern in the response to percent slope. It is a negative relationship, with the effect diminishing at higher slopes. This conforms to expectations that row crops (maize, soybeans, and cotton) show lower yields when slopes are steeper (Al-Kaisi 2001). However, we would expect a decrease in potential yields to continue as slopes get steeper. This may be explained in much of the land dedicated to cultivation of these crops (particularly maize, soybeans, and cotton) being fairly flat. In fact, there are not much data at higher slopes for these crops so the negative effect on high slopes is not seen in the models. Winter wheat does show a continuous, although gradual, decline in yield in response to percent slope. Spring wheat is the crop that does not fit this pattern. There is a steady decline in yield in response to increasing slope for spring wheat. This may be a reflection of more spring wheat being grown in areas of higher slope where other crops do not do well.

The available water capacity MFP response curves showed a positive relationship: higher AWC is linked with higher yields in all crops. This fits with earlier findings that available water capacity is a strong predictor of crop yields (Lant et al. 2016).

The MFP response curves for pH did not fit what the expectation of a pH response curve to be. The expectation was to see yields highest in neutral soils with
declines in both directions as soil was more acidic or basic. What is seen in the MFP response curves are largely positive relationships between pH and yields. Cotton was the exception that did show a peak pH value just below 6.0 for optimum yields. The curves for maize, soybeans, and spring wheat show yields increasing with increasing pH up to the end of the curve around a pH of 7.5. Although if this curve were continued up to a pH of 12, that would predict high yields in some very basic soil. We expect that this is due to a limited range of data. There are not many counties in the study area with overall basic pH values. In fact, the highest pH is below 8.0. If there were more counties with highly basic soil, we expect the yields in those counties would be low and the pH response curves would show peaks around neutral soil.

Growing season growing degree days (GDDs) were an important predictor of yields in all 5 crops. Four out the five crops studied showed a peak GDD value. It is worth repeating that GDDs were calculated differently for each crop: both the growing season over which they were calculated and the thresholds by which they were calculated are dependent on crop. Since cotton GDDs are generally calculated between April and October and winter wheat GDDs are generally calculated between September and May, the total GDDs for these crops are in ranges that are distinct from one another. The importance of GDDs fits with other findings that each crop has an optimum range in terms of growing degree days (Lant et al. 2016). Outside of that range yields are expected to be lower. Although the effect of GDD was seen in all crops, the shapes of the curves are variable. Maize shows a very strong effect with steep drop-offs on either side of its optimum range. Soybeans have a steep drop-off when GDDs are lower than the optimum range but a gradual decline in yields with GDDs higher than the optimum range. The
steep drop in maize yields at higher GDD totals may be related to genetic advances and
more intensive management practices that have been shown to make maize more
sensitive to drought (Lobell et al. 2014). Or it could simply be that maize naturally has a
more rigid, narrowly defined thermal range than other crops. Spring wheat does not have
a peak GDD value but shows a negative response to a higher number of growing degree
days. This crop is adapted to cooler areas, so it is not entirely unexpected that more
thermal energy throughout the growing season has a negative linear relationship with
crop yields.

Stress degree days (SDDs), as expected, have a negative relationship with yields. This was most pronounced with maize, fitting with the hypothesis that maize is more
sensitive to stresses because it is managed to produce very high yields. Cotton and spring
wheat have short SDD curves. For cotton, this is largely because the threshold for cotton
to be under stress is quite high (37.8 °C). With such a high threshold, there are not a lot
of days where SDDs are accumulated for cotton. For spring wheat, it is a combination of
a fairly high threshold temperature (35 °C) and a colder growing region than the other
crops.

Effective precipitation showed a mostly positive relationship with crop yields, as
expected. Four of the five crops showed a peak effective rainfall range, after which yields
are expected to decline. This may be capturing the effects of particularly wet seasons.
Higher precipitation can lead to later planting in the spring, shortening the growing
season. More rainfall also corresponds with colder days and less solar radiation which
both slow photosynthetic rates. For these reasons, the findings that yields are expected to
decline at higher effective precipitation totals are not unexpected.
Growing season excess precipitation showed a mostly negative relationship with crop yields. This is not necessarily interpreted as a causal relationship. After all, a little more rain than can be absorbed by the soil is not necessarily a bad thing. It is only when the amount of rain corresponds with loss of soil or flooding that leads to crop loss. These occurrences of plant-harming soil loss may be captured by this excess precipitation measure, producing overall negative trends. If this is the case, the measure of excess precipitation can be considered a stand-in for rainfall intensity. It does not indicate how many events of a certain intensity occurred, though it does provide an accumulated total precipitation above a certain level of intensity based on daily precipitation totals. It is expected precipitation regimes will change in the future, leading to more heavy rain events in some locations (Walthall et al. 2013). If this is the case, and the excess precipitation variable is capturing rainfall intensity, it is expected projections of future yields in the crop models will be lower in the future in response to more intense rainfall.

**Study area mean yields explanations**

The study area mean yields under each scenario confirmed expectations. Technology was a major factor in how yields will change according to our model. This was expected since year (which was used as a proxy for technological adaptation) was one of the strongest predictors of yield in the model. Although the effects of climate can be observed to lower the rate at which yields increase, there is no instance in these crop yield models where climate has a great enough effect on yields to lower output as time passes. The models were calibrated using the period from 1980 to 2010. In the central United States this was an era of enormous yield improvements. There is of course no
guarantee that past improvements will allow future improvements. If technological adaptation continues to occur at the rate it has for the past 30 years, the negative effects of climate change are not expected to stop yield improvements, but will slow them down, according to these crop models. These findings indicate it is not only the rate of climate change, but the rate of adaptation to it, that will be important in determining future crop yields in this region.

Higher emissions generally led to lower yields. Emissions scenario RCP 8.5 had lower yields for all crops in the 2090s under both technology scenarios. The only case where RCP 8.5 did not have the lowest projected yields was with spring wheat in the 2030s. There is not as much divergence in emission levels between the scenarios by the 2030s, so this finding is surprising but not troubling.

In a number of cases there are very few differences in yields between the different emissions scenarios. In the case of cotton, it is difficult to discern between the three scenarios until the 2090s. This can be explained in cotton having a higher heat tolerance than the other crops. As a result of this higher tolerance for hot weather, the effects of a changing climate do not seem to affect yield projections until later in the 21st century. It could be a reflection of the physiology of the cotton plant itself. It could also be that the crop model built was not able to pick up damaging heat effects until it reached a higher threshold because of low sensitivity to those effects. This lack of sensitivity could also explain the lack of differentiation between RCP 2.6 and RCP 4.5 in the cotton model.

However, there may be something else going on because there is very little differentiation between RCP 2.6 and RCP 4.5 for all the other crops, excepting spring wheat. The total anthropogenic radiative forcing for each RCP 2.6 and RCP 4.5 level off
before the second half of the 21st century (Fig. 2). Although they are at different magnitudes, it is possible that the difference between these levels of warming is not enough to cause a noticeable difference in yields in the models. It is only in RCP 8.5, where radiative forcing continues to increase throughout the century, that the deleterious effects of climate on yields can be observed in these models.

The degree to which the different representative concentration pathways affected crop yields varied by crop. In comparing across concentration scenarios, the lowest magnitude decreases in crop yields in the 2090s are observed in winter wheat. There are still negative effects of high carbon dioxide concentrations, but not to the same degree. It is worth noting again here that winter wheat is the only crop for which stress degree days was not found to be a significant predictor of crop yields and was consequently left out of the winter wheat crop model. Both of these results can be understood as functions of the winter wheat growing season. Climate change will not make the winters in the study area too hot for winter wheat to grow. In fact, there may be parts of the season where warmer weather is beneficial to wheat and allows it to grow faster. Most of the potentially damaging effects of climate change have been limited to the beginning and end of the winter wheat growing season, particularly in the spring (Tack et al. 2015).

**Overall crops yield discussion**

Many of the counties in the study area show positive effects on yield for one or multiple crops from the changing climate regimes, even under the static technology scenario. This is particularly the case for RCP 2.6 in the 2030s and RCP 4.5 in the 2060s. This could be the model showing the positive effects higher temperatures can have when
it causes higher rates of photosynthesis, respiration, and grain filling. Then in most cases, counties show lower yields under RCP 8.5 in the 2090s. This conforms with the nonlinear effects of heat shown by Lobell and Gourdji (2012).

**Maize yield projections**

The expansion of high-yielding counties both northward and southward from the historical corn belt under RCPs 2.6 and 4.5 even in the static technology scenario may be evidence that these lower emission scenarios will not immediately cause declines in yields for maize. The movement and reduction in size and of the high-yielding area could prove disastrous for maize yields under RCP 8.5 in the 2090s. In the improving technology scenario, yields do not decline anywhere but there is a clear implication that cropland in the north will be better suited to getting the highest yields possible.

**Soybean yield projection**

The noticeable lines between yield levels in the static technology future projections (particularly RCP 8.5 in the 2090s) may represent the limits heat stress has on soybean yields in more southern locations. Unexpectedly, in the static technology scenario under RCP 8.5 in the 2090s, the northern portion of the study area shows mostly modest yields. We would have expected to see more variation in yields from county to county due to variation in natural suitability for soybeans because of soil characteristics and topography. The fact that this area shows a lack of variation may indicate the model is more responsive to weather than it is to the environmental suitability variables.

Although much of the study area shows improvements in yields in the static technology scenario under RCP 2.6 and 4.5, it is not clear that this would produce a net
positive national soybean yield. Most of the counties showing negative effects on soybean yield are some of the most productive in the country. Since the soybean model predicts yield in bushels per acre, not total county yield, it is difficult to say whether the improvements in yield in historically less productive counties outweigh the losses in yield in more productive counties. This same principle is important in assessing counties where yield gains are observed. Many of the counties with substantial gains under the improving technology scenario may not have large soybean crops. Consequently, these gains may not have a great positive effect on national soybean yields.

**Cotton yield projections**

Cotton yields are projected to improve in areas on the northern end of the historic range of cotton in response to climatic shifts. This finding follows what was observed in maize and soybeans, with northern areas showing improved yields and southern areas showing decreasing yields and corroborates earlier land use change findings (Lant et al. 2016).

The manner in which weather variables were calculated was a limiting factor in predicting future yields in areas where a crop has not historically been planted. This was a greater issue for cotton than any of the other crops. Because the weather variables were aggregated at a seasonal level, they were defined by the growing season for each crop in each individual state. This worked well for maize, soybeans, and winter wheat in which most states had recorded start and end dates for the growing season (USDA/NASS 2010). For cotton, the model projections show good conditions for states that have not historically grown much of this crop. Particularly Illinois and Indiana seem to benefit
from future climate scenarios in terms of cotton growing conditions. Since they do not have a defined growing season for cotton, the weather variables were not calculated for these states. The projections shown are based upon calculations from neighboring states. This is a limiting factor in making yield projections outside of the historic range using this methodology.

**Spring wheat yield projection discussion**

Spring wheat unexpectedly showed an overall increase in yield projections under RCP 2.6 in the 2030s under the static technology scenario. This could be the positive portion of a nonlinear temperature response curve shown in multiple crops in an earlier study (Schlenker and Roberts 2009). The negative response to hotter temperatures may not be evident until later in the century or in more severe climate scenarios.

There are fewer counties with data in the future yield projection maps than in the historical yield maps because the climate data interpolation was limited by what areas have historically grown wheat. The only states in the study area with growing season beginning and end dates for spring wheat were North Dakota, South Dakota, and Minnesota. These were consequently the only states with weather stations for which seasonal totals in the four weather variables could be calculated. As a result, the spline interpolation of these weather variables cut off the outside counties of these states because they were outside the area for which weather station data could be interpolated.

**Winter wheat yield projection discussion**

The exclusion of the Ogallala aquifer from the study area may have resulted in a large loss of counties for which winter wheat is an important crop. Most of Nebraska and
much of Kansas were excluded because they overlay this aquifer. These two states historically had large areas planted to winter wheat (USDA 2015).

The east-west divide in yield changes was more clear in winter wheat than in any of the other crops. Under static technology and severe change in climate due to high carbon emissions (RCP 8.5 in 2090s), the westernmost counties showed improved winter wheat yields while the easternmost counties showed severely reduced winter wheat yields. This does not conform to the more typical pattern of gains/losses along a north-south line in other widely-ranging crops like maize, soybeans, and cotton. This could reflect winter wheat being more strongly affected by precipitation than by temperature. There are numerous factors that are expected to have some effect on winter wheat yields, water availability and precipitation among them (Walthall et al., 2013). The westward growth in yields of winter wheat is possibly a response to wetter conditions projected in the western great plains.

**Known limitations**

The reason we built a model to predict crop yields at a county level is because that is the level at which historical yield totals are available from USDA-NASS. Counties in the central United States are defined by a mix of natural and man-made borders and do not necessarily constitute an agriculturally consistent region. The size of counties varies from state to state and within states. The eastern half of hypothetical county A may be much more similar to the western portion of county B than it is to its own other half. Although counties are typically small enough in this portion of the country that a single value representing the weather in a county over a growing season is not necessarily
problematic, using the county level to assess crop yields was limiting for the other variables.

Soil characteristics were aggregated to a county level. This involved averaging soil values from across a county to arrive at one number that is representative of the county. The problem with this methodology is counties are highly variable in soil characteristics. In fact, soil characteristics can vary to some degree from field to field on one farm (Cambardella et al. 1994). Although our methodology did capture overall soil characteristics of each county, these variables contributed a limited amount to the model because they did not accurately reflect the highly varying nature of soil characteristics within each county.

The proportion of each county that is suitable to cultivation is highly variable throughout the study area. This was the reason for the process to isolate the “crop relevant layer,” so that the summary soil characteristics for each county would reflect soil characteristics only in areas where the crops of interest had been grown in the past. This was successful in limiting soil variables to only the area relevant to agriculture. The maps produced from this analysis may be misleading, however, in representing all counties with equal amounts of color that reflect yield potential in that county. It may be more accurate to only show the crop-relevant area of a county colored to show where the yield potential actually is (and how much of the county is important with respect to these crops). However, maps of this type would be harder to read with only a fraction of each county having color. It is important to keep the variable crop suitabilities of the counties in mind when considering yield potentials. Although for some crops, under some climate scenarios, projections may show yield gains in northern Minnesota, Wisconsin, and
Michigan, these are areas with small amounts of suitable cropland due to soil characteristics. So, although it is plausible that in 50 years a county in northern Wisconsin will have the climatic characteristics that would allow huge improvements in maize yields, there may be only 60 acres in that county where maize can be grown because of the nature of the land.

Fertilizer applications, unlike the other variables which summarized at the county level, were aggregated at a state level. There is no county-level database reflecting fertilizer application for the central United States. We made the assumption that fertilizer applications would be consistent enough across each state in a given year that they would be a good predictor of crop yields. The fertilizer application data being restricted to the state level is one of the reasons fertilizer was not a good predictor of yields for cotton. Another reason fertilizer applications were not always a good predictor of crop yields is fertilizer application is often related to soil fertility. Application recommendations are dependent on characteristics determined by soil tests (Kaiser et al. 2017; Staton 2017). Farmers put more fertilizer on their field if they have low-fertility soil. So, we did not see a straightforward relationship between fertilizer application and crop yields. We did see the overall trend of increasing fertilizer leading to increasing yields until a point of diminishing returns in the other four crops studied. That is consistent with trends in agriculture where farmers have increased fertilization rates on a large scale to increase yields. The model was able to capture the macro-trend of increasing fertilization and the resultant increasing yields, but not able to capture the micro-tuning of varying fertilizer applications from county to county, farm to farm, and field to field. This is a successful outcome for a model covering a 16 state area.
The 16 state study area allowed the production of parsimonious crop models for a wide range of geographic zones. It was successful in showing the wide-ranging importance of the variables used in predicting crop yields. It did require some simplification of these relationships, however, in order to make one model for each crop that fit such a large geographic area. Having one soybean model for the entire area is, we believe, the best way to draw wide conclusions about soybeans in the entire area. However, there are numerous cultivars of soybeans (and the other crops) grown throughout the study area. One reason all these varieties of each crop were developed was to adapt the plants to the various climatic conditions present across this area. The parsimonious, though admittedly overly simplistic, models developed to map future crop yields fail to take into account the variation of plants throughout the study area. Since a proposed strategy for adapting to the changing climatic regime is to switch varieties to those that are more adapted to warmer weather (Challinor et al. 2014), it is important to note that the methods used in this analysis are not able to account for that possibility.

The decision to define the growing season as the historic mean growing season for each state was a limiting factor in the analysis. Although it was necessary to make an assumption since the “heating degree days” method did not prove to be an effective predictor of planting date, this assumption presented some problems. The first way this assumption limited the analysis was the inability to allow planting dates to change with the climate. Sacks and Kucharik (2011) found that planting dates from 1981 to 2005 have shifted 10 days earlier for maize and 12 days earlier for soybeans. Since our analysis did not have a way to predict changing planting dates, it did not pick up any effects a longer or shifted future growing season may have on crop yields. The other main way this
definition of growing seasons was a limiting factor was in only enabling yield projections in states with historic growing seasons for each crop. For example, the reason future cotton projections are not made in Iowa is that there is no historic growing season for cotton in Iowa. The weather variables upon which the projections are made were consequently not calculated because there was no growing season window in which to calculate them. This methodology prevented the corroboration of a far more northern distribution of cotton under some severe climate scenarios from a previous study (Lant et al. 2016).

Our findings project crop yield potentials and do not take into account the likelihood that a crop will be planted in any given location. The decisions farmers make to plant certain crops are complex and difficult to predict, taking into account not only weather but other factors such as labor and equipment availabilities, as well as varying economic incentives for each crop. This is well represented by the historic distribution of winter wheat in comparison to its highest yielding counties. Although the counties that produce the most winter wheat per acre in the study area are in Illinois, Indiana, Ohio, and Michigan, these states are not the major producers of winter wheat. The main producers of winter wheat in the study area are Oklahoma, Kansas, and Nebraska (USDA/NASS 2016). The counties in Illinois, Indiana, Ohio, and Michigan likely do not grow a lot of winter wheat because farmers there choose to grow maize or soybeans because of the greater economic benefit of these crops. For these economic reasons, it cannot be concluded that because a county shows high yield potential for a particular crop that it will result in a lot of that crop being produced there.
**Major findings and implications**

The use of growing degree days to build this model confirmed that this commonly used measure of accumulated thermal energy is a good predictor of yield. Stress degree days, effective precipitation, and excess precipitation are variables that are less often used but may prove to be good predictors of crop yields in many applications.

The findings of the study confirm the effectiveness of stress degree days as an important predictor of yields shown for maize, spring wheat, and soybeans demonstrated by Schaubberger et al. (2017). Furthermore, this study successfully expanded the use of this metric to predict cotton yields. Our model fitting indicated the best threshold from which to calculate stress degree days was the top of the range in which growing degree days were calculated. This made sense intuitively as once a plant is above its growth-promoting thermal range, it is likely experiencing stress. This threshold was determined empirically by model fit but, in the future, could be integrated with agronomic findings on what conditions lead to stress in particular plants.

The inclusion of precipitation as a predictor in the crop model was logical. The separation of precipitation into effective and excess categories is where this study can contribute to possible future studies. Since the level at which precipitation is no longer beneficial to crops is not universal, it had to be determined by model fitting in this study. The positive relationship between effective precipitation and crop yields confirmed expectations. The negative relationship between excess precipitation and crop yields exceeded expectations. This finding indicates excess precipitation is a measure of a harmful level of precipitation throughout the growing season. This could mean excess precipitation is a good measure for intense rainfall. This is a promising finding and
indicates the need for more research into how much rain is too much and at what time-scales.

The models built in this study corroborate earlier findings that the effects of climate on yield are nonlinear (Schlenker and Roberts 2009). Within the static technology scenario in the 2030s and 2060s, under representative concentration pathways (RCPs) 2.6 and 4.5, yields were in many cases not drastically reduced despite the different climate. Severe losses in yields were observed in most cases under RCP 8.5, especially in the 2090s. It is possible that climate change has to reach a certain degree of severity before crop yields are significantly reduced. This is a particularly troubling finding as climate change is not an easily reversible process. Crop productivity could reach a point in the future where yields start to drop off rapidly because this tipping point has been crossed but the options for adapting to the new climate regime are limited.

The results of this study indicate climate change could be a problem for the entire study area, though of differing severity depending on the region and what happens in crop technology. Some areas, particularly in the south, will feel impacts more strongly than other areas. However, the study area overall shows significant vulnerability to the impacts of climate change. In the south, under severe climate change and static technology, some crops show yields essentially collapsing. This scenario in this location would probably make cultivation of some historically significant crops economically untenable. In the north, under moderate climate change and improving technology, some crops show yields increasing at a less rapid pace. The impacts of this diminished return on investment in crop improvements may not be large enough to change what is grown at all.
Regardless of which technology scenario will end up being closer to reality, this analysis indicates potentially disruptive changes in yield potentials throughout the study area. Whether yields increase dramatically due to innovation or decrease with technological stagnation, these findings indicate a strong incentive to adapt to future climatic changes. The areas with the highest yields today for maize will not be the areas with the highest yield potential for maize in the 2090s. This indicates a geographic shift in where maize is grown is possible, as previously shown (Lant et al. 2016). This potential shift will be limited by the agricultural suitability of each county in terms of soil and topographic factors, which this analysis did not address directly. It is expected that counties in the central northern plains with suitable soil characteristics will stand to gain relative to more southern counties in response to climate change. This includes many counties in North and South Dakota, as well as Minnesota. This will likely continue a trend of expansion of maize and soybeans into the northern plains that has already begun (Johnston 2014).
SUMMARY AND CONCLUSIONS

This study demonstrates a methodology for summarizing daily weather data into growing season-length variables that can be used as predictors of yearly crop yields. It resulted in 5 parsimonious crop models that could be used to predict yields over a large, highly variable study area. It provides an effective example of use of a daily weather generator to project future crop yields under several climate change scenarios.

The projections from this study showed nonlinear yield effects from changes in the climate regime. In many places yields were not strongly affected under low to moderate climate forcings but showed drastic declines under severe climate forcings. This confirms findings from an earlier study (Schlenker and Roberts 2009).

Projections generally showed the highest yielding counties moving from south to north under more severe climate change scenarios. Spring and winter wheat future projections were an exception to this trend. Although this is expected under the changes in climate projected, it is also expected that in reality this trend will be limited by crop suitability in each county.

Technology is a major factor in what crop yields will look like in the central United States during the 21st century. If technological innovation is able to keep improving yields at the rate it has historically, the negative effects of climate on crop yields may be able to largely be mitigated in this part of the world.
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