SPATIAL SMOOTHING OF CORN YIELD TRENDS AND ROBUSTNESS OF THE IMPACT OF CLIMATE CHANGE ON U.S. CORN YIELDS

By

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Abstract: In evaluating plans to mitigate climate change, policy makers require estimates of the cost of climate change. One potential cost of climate change is the negative effect that an increase in temperature would have on agricultural yields. We begin with a model suggested by Schlenker and Roberts (2009) and we are largely successful in replicating their results. We then modify the model to determine its robustness as we change assumption. These changes include (i) using long-term average data for temperature and precipitation variables instead of yearly data, (ii) temperature and precipitation data from different periods of the growing season, with an emphasis on critical corn growth periods, (iii) using a different method for estimating temperature exposure times, (iv) using two-knot time trends instead of quadratic time trends, (v) adding Corn Belt dummy variables, and (vi) removing data from the 1950s and 1960s. We make predictions of the impact of climate change under two warming scenarios (RCP4.5 and RCP8.5) of three General Circulation Models, and in each we make predictions with and without adaptation. The assumption change to which yield change predictions are most sensitive is the use of long-term average data instead of yearly data; predicted yield decreases based on models that use long-term average data are smaller by 18.0 percentage points compared to predictions based on models that use yearly data.

In the second chapter, Bayesian Kriging is used for spatial smoothing of yield density parameters, including time trends. There is a paucity of useful historical yield data for counties, but properly using other counties' information in the estimation of a county's yield density alleviates the problem of not having enough observations. Yield density parameters are assumed to be spatially correlated, through a Gaussian spatial process. The Bayesian Kriging model can handle unbalanced panel data. The forecast accuracy of our model is similar to that of Bayesian Model Averaging (BMA) that assumes a normal distribution, but our approach is the only one that provides the spatial smoothing desired by the Risk Management Agency.

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CHAPTER I

ROBUSTNESS OF THE IMPACT OF CLIMATE CHANGE ON U.S. CORN YIELDS

Abstract

In evaluating plans to mitigate climate change, policy makers require estimates of the cost of climate change. One potential cost of climate change is the negative effect that an increase in temperature would have on agricultural yields. We begin with a model suggested by Schlenker and Roberts (2009) and we are largely successful in replicating their results. We then modify the model to determine its robustness as we change assumption. These changes include (i) using long-term average data for temperature and precipitation variables instead of yearly data, (ii) temperature and precipitation data from different periods of the growing season, with an emphasis on critical corn growth periods, (iii) using a different method for estimating temperature exposure times, (iv) using two-knot time trends instead of quadratic time trends, (v) adding Corn Belt dummy variables, and (vi) removing data from the 1950s and 1960s. We make predictions of the impact of climate change under two warming scenarios (RCP4.5 and RCP8.5) of three General Circulation Models, and in each we make predictions with and without adaptation. The assumption change to which yield change predictions are most sensitive is the use of long-term average data instead of yearly data; predicted yield decreases based on models that use long-term average data are smaller by 18.0 percentage points compared to predictions based on models that use yearly data. Using a model that changes all six assumptions, including the use of July-August long-term average data, and assuming adaptation, the average prediction under the three

circulation models is a 14.1 percent corn yield decrease under the RCP4.5 scenario and a 26.4 percent yield decrease under the RCP8.5 scenario.

Keywords: corn yield, temperature, climate change, adaptation, Corn Belt, RCP4.5, RCP8.5, CCSM4, GFDL-ESM2G, GFDL-ESM2M

1. Introduction

Most climate scientists predict increasing carbon dioxide and other greenhouse gas emissions will cause temperatures to increase. In evaluating plans to mitigate climate change, world leaders and policy makers need estimates of the cost of climate change. One potential cost of climate change is the effect of increased temperature on agricultural yields. Corn is a major source of calories for much of the world, and the United States is the leading producer and exporter of corn. The impact of climate change on U.S. corn yields is a good measure of the impact on corn production and a good proxy for the impact on food security. Climate change will also have an adverse impact on coastal areas (due to sea level rise), human health, other vulnerable market sectors (e.g., changes in energy use), and human settlements and ecosystems (Federal Interagency Working Group 2010, USGCRP 2018).

As Hendricks and Peterson (2014) explain, higher temperatures reduce crop yields through heat stress. Schlenker and Roberts (2009) analyze the yields of corn, soybeans, and cotton, and find that for all three crops the yields increase with temperature up to an optimal level (29°C for corn) and that after this temperature yields decrease sharply. Previous research predicts the impact of climate change on agriculture. However, there is no consensus about the magnitude of this impact. World food security would be threatened by dramatic drops in yield predicted by estimates such as Schlenker and Roberts (2009). They predict that by the end of the twenty-first century average corn, soybeans, and cotton yields will drop by 30-46% under the slowest warming scenario (B1) of the Hadley III climate model (Hadley Centre Coupled Model, version

3) and by 63-82% under the most rapid scenario (A1F1). Peng et al. (2004) find that for each 1°C increase in minimum temperature (which is generally at night), rice yields decrease by 10%; interestingly, they do not find a significant relationship between yield and maximum temperature.

Other studies such as Deschênes and Greenstone (2007), Brown and Rosenberg (1999) and Mendelsohn, Nordhaus, and Shaw (1994) find less severe effects of climate change on agricultural yields. Deschênes and Greenstone (2007) predict that agricultural profits will increase under climate change. They also argue that although an increase in temperature has a negative effect on crop yields, the predicted increase in precipitation has a positive effect on yields, which results in an overall small negative effect of climate change on the main crops in the U.S., such as corn and soybeans. Deschênes and Greenstone (2007) also find considerable heterogeneity in the predicted impact across states. Spatial heterogeneity is corroborated by other studies such as Thornton et al. (2009). Kaiser et al. (1993) report that with a 2.5℃ temperature increase, corn yields will decrease by less than 5%. They also find that adapting to climate change is feasible.

Studies have used different approaches to predict the effects of climate change on the agricultural sector. These approaches can be classified into (i) agronomic research characterized by process-based models and (ii) empirical approaches using regression-based analysis. The agronomic approach emphasizes plant growth physiology. Studies that follow this approach include those based on experiments (e.g., Houghton et al. 2001, Long et al. 2004, Long et al. 2006), and studies based on simulations. Examples of simulation models are the Erosion Productivity Impact Calculator (EPIC) used by Brown and Rosenberg (1999), the Agricultural Production Systems Simulator (APSIM) used by Lobell et al. (2013), the CERES-Maize model (e.g., Thornton et al. 2009), and the Agricultural Policy/Environmental eXtender Model (APEX) model (e.g., Williams and Izaurralde 2000, Osei and Jafri 2017). In these studies, models simulate yields based on inputs such as daily weather, initial soil characteristics, and fertilizer applications. An advantage of agronomic studies is the simulation of realistic conditions under which plants are expected to grow. Carbon fertilization, for example, can be simulated in these studies. Agronomic field experiments or trials are costly and can only be conducted at a small scale in greenhouses or other controlled environments; generalizations beyond agronomic experiments are therefore difficult. The disadvantage of agronomic simulations is their complexity. In addition, this simulation approach does not account for farmer decision making and only focuses on plant growth physiology.

There is currently no consensus on the extent of carbon fertilization. Brown and Rosenberg (1999) attribute to CO2 fertilization the alleviation of the decline in yields under climate change. They use three General Circulation Models (GCMs) to measure the impact of climate change on the potential production of dryland winter wheat and corn for primary U.S. regions that grow each crop, with global mean temperature changes of 1.0, 2.5 and 5°C and levels of atmospheric CO2 concentration of 365 (no CO2fertilization), 560, and 750 ppm. The least impact in this study is that of a reduction in potential production by 6% for corn and by 7% for wheat with a global mean temperature of 2.5°C and no CO2 fertilization. Other studies claim that higher CO2 levels will improve wheat yield and predict yield gains under most climate change scenarios. However, according to Long et al. (2006), this positive effect of CO2 levels on crop yields is not large enough to offset the negative effect of expected higher temperature. Long et al. (2006) claim that studies overestimating the effect of CO2 fertilization were based on experiments conducted in enclosed areas. Their study uses free-air concentration (FACE) technology to conduct experiments on the effect of CO2 in open-air fields. The increase in crop yields due to CO2 fertilization is 50% lower than previously predicted by enclosure studies.

Recently, the Agricultural Model Intercomparison and Improvement Project (AgMIP) was established, assembling researchers from various disciplines to compare yield responses to changes in temperature and CO_2 concentration in 23 different models. The objective of the AgMIP study was not to make large-scale predictions about the impact of climate change on corn yields but, instead, it was to compare yield responses at the site level. Sites chosen for this intercomparison were Ames (Iowa, USA), Lusignan (France), Rio Verde (Brazil), and Morogoro (Tanzania). Bassu et al. (2014) report considerable differences in yield simulation and the ability of an ensemble of models to accurately simulate yields at the four sites.

Empirical approaches typically use a regression framework. The hedonic —or Ricardian— approach uses reduced-form linear regression models to measure directly the effect of climate on land values. In such studies, land values are regressed against weather or climate variables. Studies that have used this approach include Mendelsohn, Nordhaus, and Shaw (1994), Schlenker, Hanemann, and Fisher (2006), and Hendricks and Peterson (2014).The underlying assumption of the hedonic approach is that land prices are the discounted infinite sum of land rents. One advantage of this approach is that it accounts for adaptation. Another advantage of the hedonic approach is that it studies the effect of climate on the agricultural sector as a whole instead of singling out one crop. The hedonic approach uses long-term average data collected over several years instead of using yearly data. Deschênes and Greenstone (2007) modify the hedonic approach by associating land values to year-to-year weather variations and by using county fixed-effects. Deschênes and Greenstone (2007) predict increases in agricultural profits and land values under climate change.

Our study is empirical and follows the approach outlined by Schlenker and Roberts (2009). It uses a panel of yields and weather variables. This approach combines strengths from various approaches. Similar to the hedonic approach, it takes advantage of the flexibility of regression models. But like the simulation approach, our approach also uses daily weather information. A disadvantage of our approach is the difficulty of incorporating farmers' adaptation to climate.

In reaching a rational decision about mitigation policies, it is important to provide accurate estimates of the effect of increased temperatures on crop yields. It is also important to have estimates for different warming scenarios and to test the sensitivity of such estimates to certain assumptions. The objective of this study is to conduct a fragility test of Schlenker and Roberts (2009). Their results have received much attention, evidenced by the 1733 citations recorded by Google Scholar as of June 2019. They also estimate a much higher cost of climate change than other methods. Before using their results to guide policy, it is important to carefully evaluate the sensitivity of their results to changes of assumptions. This study's approach is to begin with Schlenker and Roberts' (2009) model and to modify it to see how their conclusions hold up or fall apart as certain assumptions are changed. The changes include: (i) using a varying time trend as is common in the crop insurance literature; (ii) using data from different periods of the growing season with an emphasis on critical corn growth periods; (iii) using long-term data for temperature and precipitation variables instead of yearly data; (iv) including dummy variables for the Corn Belt region, (v) changing the type of sinusoidal function used to estimate daily temperature distributions; (vi) removing data from the 1950s and 1960s; (vii) allowing adaptation; and (ix) using different GCMs. This study considers two different Representative Concentration Pathways (RCP); these are greenhouse gas concentration scenarios.

The climate change literature is recent relative to the crop insurance literature; research on climate change could borrow models—or features of models—developed in the crop insurance literature. The crop insurance literature has documented time trend variables that influence crop yields (e.g., Harri et al. 2011). Another major difference with current climate change literature and previous yield models is the inclusion of weather or climate variables spanning the entire growing season. Yield prediction models typically use weather or climate measurements at crops' specific growth stages. In the case of corn, yield is sensitive to weather conditions during the pollination and grain-filling stages. Weather in this growth stage is expected to be a better predictor of yield than conditions over the entire growing season.

Predictions have been made based on various climate change scenarios. A simplistic scenario would be a uniform temperature increase by, say, 2°C or 4°C. However, climatologists compute more realistic scenarios based on several climate models. In this study we use projections from the CCSM4 model[1], the GFDL-ESM2G model[2], and the GFDL-ESM2M model[3]. For each of the three climate models, we consider two warming scenarios.

The three aforementioned climate models are some of the atmospheric General Circulation Models (GCMs) created in the last decade. Schlenker and Roberts (2009) use four scenarios of the Hadley III climate model. Other GCMs used in previous research include the Goddard Institute for Space Studies (GISS) model (e.g., Brown and Rosenberg 1999, Kittel et al. 1995) and different GFDL models (e.g., Kittel et al. 1995). Kaiser et al. (1993) simulate yields based on four scenarios for Southern Minnesota: (i) a base scenario with no climate change, (ii) a scenario with 2.5℃ increase in temperature and a 10% increase in precipitation in the year 2060, (iii) a scenario with 2.5℃ temperature increase but with a 10% reduction in precipitation in the year 2060, and (iv) a scenario with 4.2℃ temperature increase and a 20% decrease in 2060.

The rest of the paper proceeds as follows. In section 2 we describe how data were obtained and transformed (subsection 2.1), explain the base model (subsection 2.2) and the different components of our sensitivity analysis. Subsection 2.3 describes the sensitivity analysis of assumptions made in the estimation of regression models, while subsection 2.4 explains the

[1] CCSM4: the fourth version of the Community Climate System Model
[2] GFDL-ESM2G: Earth System Model (ESM) that uses Generalized Ocean Layer Dynamics; constructed by the Geophysical Fluid Dynamics Laboratory
[3] GFDL-ESM2M: Earth System Model (ESM) that uses the Modular Ocean Model version 4.1; constructed by the Geophysical Fluid Dynamics Laboratory

sensitivity analysis of assumptions made in estimating expected yield changes. In section 3 we present and discuss the results. Finally in section 4 we conclude.

2. Materials and Methods

2.1. Data

We analyze the relationship between weather variables and corn yield in the United States. Following Schlenker and Roberts (2009), we use counties east of the 100° meridian because western states have considerable irrigation. Counties in Florida are also excluded. We use yearly corn yield data by county from the National Agricultural Statistics Service (NASS) of the United States Department of Agriculture (USDA) for the period 1950-2016. The yield is calculated as the total production in the county divided by the total number of harvested acres. The natural logarithm of the yield is also computed.

Daily weather was obtained for 1950-2016 from Schlenker (2016). The data contains estimates for daily precipitation, daily maximum temperature, and daily minimum temperature for 4km x 4km grid cells of the contiguous United States. Schlenker and Roberts (2009) made these estimates based on monthly estimates for the 4km x 4km grid cells provided by the PRISM[4] Climate Group at Oregon State University. Schlenker and Roberts also make available a meta-file that links each grid cell to a county. Similar to their work, in each county we only select cells containing cropland. We assume that land used for farming has not changed much over the last few decades.

From the minimum and maximum temperatures, we estimate the distribution of temperature throughout the day like Schlenker and Roberts (2009), using a sinusoidal curve suggested by Baskerville and Emin (1969) and later used by Snyder (1985). This curve allows

[4] PRISM: Parameter-elevation Regressions on Independent Slopes Model

estimating the time in each day spent within each one-degree interval for each grid cell. These exposure times are then averaged for each county and aggregated for the growing season. Other temperature-related variables discussed later in the text are derived from these exposure times; the details of these derivations are in the appendix. Similarly, precipitation is averaged in each county and aggregated for the desired period of the growing season. We obtain soil characteristics data, including water holding capacity and soil slope, from Yun and Gramig (2017). The data is available for years 1992, 2001, 2006, and 2011. Soil characteristics data for other years are computed by linear interpolation.

In addition to these yearly temperature and precipitation variables, corresponding long-term averages for the years 1950-20116 are also computed. The calculation of the long-term average precipitation for each county is a simple average of the precipitations recorded in all years. Average temperature exposure times in each county are first calculated before the derivation of subsequent temperature variables.

Data for climate projections were obtained from the University of Idaho's Northwest Knowledge Network (2018), who computed the data using the second version of Multivariate Adaptive Constructed Analogs (MACA), a statistical downscaling method that facilitates the removal of biases from global climate models. We use 4-km gridded data for the years 2070-2099 from three GCMs: CCSM4, GFDL-ESM2G, and GFDL-ESM2M. The estimation of temperature times and the aggregation of exposure times and precipitation are performed in a similar fashion as for the historical data. To aid in the visualization of the temperature changes from current future conditions, Figures I-4 and I-5 are maps of the average total time spend above 32°C under the current climate and the RCP4.5 scenario of the CCSM4 circulation model, respectively. Variables are first computed at the grid level before being averaged over each county, aggregated over each year, and averaged over the 30-year period; additionally, different climate models and scenarios are considered, and two different methods of computing temperature variables are used.

These computations were performed on the Pistol Pete supercomputer housed in the High Performance Computing Center (HPCC) at Oklahoma State University.

2.2. Base Model

The concern of this study is to determine how the expected temperature increase under climate change will influence yields. Although corn is adaptable and grows in a variety of climates, extended periods of higher temperature are harmful to corn growth, and extreme temperatures can directly damage plant cells (Lobell and Gourdji 2012; Hendricks and Peterson 2014).

Corn yields are harmed by temperatures above a threshold. This threshold is commonly regarded in the agronomy literature to be 30℃ (e.g., McMaster, Gregory and Wilhelm 1997), but Schlenker and Roberts (2009) suggested a threshold of 29℃. The base model for our study follows Schlenker and Roberts (2009). The model assumes temperature effects on yields are cumulative over the growing season (March-August for corn). In this model, the natural logarithm of yield for county *i* in year *t* is

$$y_{it} = \int_{\underline{h}}^{\overline{h}} g(h)\varphi_{it}(h)dh + \beta_1 P_{it} + \beta_2 P_{it}^2 + \tau_{i1} t + \tau_{i2} t^2 + C_i + \varepsilon_{it}, \quad (1)$$

where y_{it} is the natural logarithm of corn yield for county *i* in year *t*, *h* represents the temperature, $\overline{h}$ and $\underline{h}$ are the highest and lowest observed temperatures, $g(h)$ is a nonlinear plant growth function, $\varphi_{it}(h)$ is the time distribution of heat over the growing season, P_{it} is the season total precipitation for county *i* in year *t*, C_i is the fixed effect for county *i*, the terms $\tau_{i1} t$ and $\tau_{i2} t^2$ are state-specific time trends, and $\varepsilon_{it} \sim N(0, \sigma^2)$ is a random error term. We do not make the error term spatially autocorrelated; changes we make in the sensitivity analysis would substantially increase the estimation time if the spatial autocorrelation of the error term was included. The specification of the covariance matrix only affects the standard errors, estimates remain unbiased and consistent. Since this paper's main goal is forecasting, the omission of spatial autocorrelation does not affect our work.

Schlenker and Roberts (2009) use three specifications for the function $g(h)$ that lead to similar results in their study. In this study, we only use a piecewise linear function. County fixed effects control for heterogeneous characteristics of counties, such as soil quality. The time trends capture yield improvements resulting from better production technology such as planting earlier and improvements in genetics; perhaps these time trends also capture yield increases resulting from increases in CO_2, reductions in ozone, and could be net of reductions due to any global warming that has already taken place.

The integral in equation (1) is approximated numerically and equation (1) becomes

$$(2) \quad y_{it} = \sum_{-5}^{49} g(h+0.5)[\Phi_{it}(h+1) - \Phi_{it}(h)] + \beta_1 P_{it} + \beta_2 P_{it}^2 + \tau_{i1} t + \tau_{i2} t^2 + C_i + \varepsilon_{it}$$

where $\Phi_{it}(h)$ is the cumulative distribution function of heat in county *i* and year *t*.

The piecewise linear function $g(h)$ has a break point at 29°C. The shape of the function is similar to that in Figure I-1. This function has two slopes. In light of the impact of higher temperatures, we are interested in the magnitude of the second slope, i.e., the slope associated with an accumulation of temperatures above 29°C. The appendix details the calculation of temperature exposure times, based on daily maximum and minimum temperatures. Because temperatures below zero or above 39°C are rare during the growing season, the exposure times for all negative temperatures are grouped into the [-1, 0] interval, while the exposure times for all temperatures above 39°C are grouped into the [39, 40] interval. The appendix also provides an expansion of the first term of the right-hand side of equation (2) and the derivation of two key temperature variables: a weighted accumulation of temperatures below the 29°C threshold and a weighted accumulation of temperatures above the threshold. These two variables, hereafter referred to as *Temperature Sum 1* and *Temperature Sum 2*, respectively, are directly used in the estimation of equation (2).

The impact of climate change on corn yields is computed as follows. First, each county's expected yield under future conditions is predicted using the parameters estimated in equation (2) and the county's projected average temperature and precipitation variables for the years 2070-2099. The averages are computed in a similar manner as the long-term averages for historical data mentioned above. The county's expected yield under current conditions is predicted using the same parameters and the county's long-term historical (1950-2016) temperature and precipitation variables. In the prediction of yields under both current and future conditions, time trend effects are assumed to end in the year 2016. For each county, a percentage change in yield from current to future conditions is calculated. An average yield change for the Eastern United States is then calculated, weighted by average acres planted in the last 10 years of the study. Instead of using 2016 temperature and precipitation variables in the prediction of current yields, long-term historical averages were used because 2016 weather is only a random occurrence. A fortiori, observed yields in 2016 should not be used in the comparison.

Our regression assumes that the natural logarithm y of yield follows a normal distribution, i.e., the yield X follows a lognormal distribution. The mean of the logarithm of yield is computed using the predictors and their corresponding coefficients in equation (2) or its modifications. If X_1 is the yield under current conditions and X_2 is the yield under a future climate, then

$$\log(X_1) \sim N\ (\mu_1, \sigma_1^2),$$

$$\log(X_2) \sim N\ (\mu_2, \sigma_2^2),$$

$$E[X_1] = \exp\left[\mu_1 + \frac{1}{2}\sigma_1^2\right]$$

$$E[X_2] = \exp\left[\mu_2 + \frac{1}{2}\sigma_2^2\right]$$

The expected value of $\frac{X_2}{X_1}$ is $E\left[\frac{X_2}{X_1}\right] = \exp\left[\mu_2 - \mu_1 + \frac{1}{2}(\sigma_2^2 - \sigma_1^2)\right]$.

The expected change in yield is $E\left[\frac{X_2}{X_1} - 1\right] = \exp\left[\mu_2 - \mu_1 + \frac{1}{2}(\sigma_2^2 - \sigma_1^2)\right] - 1$

In addition, our model assumes that the errors are the same for the prediction of both current and future yields. This implies that the variance of the logarithm of yield is the same under the current climate and under future conditions, that is, $\sigma_1^2 = \sigma_2^2$. Therefore, the expected change in yield is

$$E\left[\frac{X_2}{X_1} - 1\right] = \exp[\mu_2 - \mu_1] - 1.$$

2.3. Sensitivity Analysis of Model Estimation

We now explain the changes that constitute this robustness study of the base model. Our approach is to first replicate Schlenker and Roberts' (2009) model described previously as the base model and then see how results change as the assumptions change. The base model is replicated using data from the same period Schlenker and Roberts (2009) used, i.e., from 1950-2005. We then add more recent data (2006-2016) and see how results change. This addition of recent data is maintained throughout the sensitivity analysis. For the assumption changes described below, we build models corresponding to their implied specifications. Assumptions are changed according to the following categories: (i) the type of data used (weather vs. climate); (ii) the period of the growing season included; (iii) the method of calculating temperature exposure times; (iv) the type of time trend utilized; (v) the inclusion or exclusion of Corn Belt dummy variables; and (vi) the inclusion or exclusion of data from the 1950s and 1960s. We refer to the following characteristics as the assumptions of the base model: the base model uses March-August yearly data, estimates temperature exposure times in a similar manner as Schlenker and Roberts (2009), uses quadratic time trends, does not have Corn Belt dummy variables, and does not exclude data from the 1950s and 1960s.

The first change to the base model is the use of long-term average for temperature and precipitation variables, rather than yearly data. Our study includes the use of long-term average data because: (i) the end goal is to predict average yields over a period of several years, not a particular year, and (ii) using long-term averages partially considers potential adaptations. Even currently, farmers in the South have adapted to different temperature patterns by planting earlier than farmers in the North and by growing different varieties. Schlenker and Roberts (2009) implicitly use unexpected annual deviations rather than long-term averages. By including county fixed effects in the models that use annual temperature and precipitation data, one is adjusting for long-term averages and only obtains the effects of annual fluctuations; furthermore, this practice does not consider the variation of temperature and precipitation across space.

It is important to restate here that long-term averages are calculated by computing simple averages of weather variables. Specifically, the temperature exposures in each degree interval for all years of the study period are averaged; yearly precipitations in the study period are averaged for each county. In the resulting equation, the yield and time variables of a county change each year, but the long-term average temperature and precipitation variables remain the same throughout the study period. Equation (2) is then transformed to:

(3) $$y_{it} = \sum_{-5}^{49} g(h+0.5)[\Phi_{it}(h+1) - \Phi_{it}(h)] + \beta_1 P_{it} + \beta_2 P_{it}^2 + \tau_{i1} t + \tau_{i2} t^2 + \boldsymbol{S}_{it} + G_i + \varepsilon_{it},$$

where $\boldsymbol{S}_{it}$ represents the county's soil characteristics, and G_i is the logarithm of the average number of acres planted in the county in the 1950s.

Due to collinearity, when long-term average data are used, county fixed effects would not be appropriate. In their stead, soil characteristics, such as water holding capacity and soil slope, and the average corn acreage in the 1950s are used. The latter variable is a proxy for the level of corn farming technology in the county. We expect these characteristics to have a positive effect on corn yield. There are therefore two changes in equation (3) compared to equation (2): the different type of data used and the replacement of county fixed effects. To ensure that the full difference between equations (2) and (3) is not wrongly attributed to the different data used, another equation with annual temperature and precipitation but without county fixed effects is estimated:

(4) $$y_{it} = \sum_{-5}^{49} g(h+0.5)[\Phi_i(h+1) - \Phi_i(h)] + \beta_1 P_i + \beta_2 P_i^2 + \tau_{i1} t + \tau_{i2} t^2 + \boldsymbol{S}_{it} + G_i + \varepsilon_{it}.$$

The results of equations (4) and (2) are similar, thus in the rest of the text only equations (2) and (3) will be compared.

The second assumption whose robustness is included in our study is the period of the growing season included in the data. Planting and harvesting dates for corn vary across the country (NASS, USDA 1997), but most planting takes place in March and April and most corn is harvested in October. However, corn yields are particularly sensitive to weather conditions during the pollination stage (Nielson 2002). It is at this stage that pollen grains are transferred by wind or gravity from the tassel (male flower) to the silks of the corn ear (female flower). Another period where corn yield is sensitive to weather conditions, though less so, is the grain-filling stage, hence the addition of September and October data in some of the models. We use weather or long-term average data from the following subsets of the growing season: March through August, March through September, March through October, July through August, July through September, and July through October.

The third element of our sensitivity analysis is the use of two methods for the estimation of temperature exposure. The first method is to use the curve directly, in a similar way it is used in the calculation of growing degree days (GDD). The sinusoid has a domain of $[0, 2\pi]$, a period of 2π representing one day, and an amplitude equal to half of the difference between the maximum and minimum temperatures. The second method, used by Schlenker and Roberts (2009) and Yun and Gramig (2017) in estimating time exposures to 1-degree intervals, transforms the sinusoid to have a period of 2π but only a domain of $[0, \pi]$; one day is represented by a time equal to π. The appendix provides details about the two methods, and Figure I-3 provides a graphical comparison of the two methods.

The difference in the two methods lies in the concavity of the functions used to estimate the exposure time. Compared to the first method, the second method estimates a higher exposure time near the maximum temperature. Compared to the second method, the first method estimates a higher exposure time near the minimum temperature. In a hypothetical day with a maximum temperature of 20.3°C and a minimum temperature of 9.6°C, the first method estimates that 2.57 hours are spent in the 20°C -21°C interval and 2.97 hours are spent in the 9°C -10°C interval, while the second method estimates that 3.63 hours are spent in the 20°C -21°C interval and 0.57 hours are spent in the 9°C -10°C interval.

The specification of time trends in corn yields constitutes the fourth element of the sensitivity analysis. The base model uses state-specific quadratic time trends. The alternative specification is the use of two-knot time trends instead of quadratic trends. This assumption is borrowed from the crop insurance literature, which has been in existence longer than the climate change literature (e.g., Harri et al. 2011; Skees and Reed 1986). With a two-knot time trend, equations (2) becomes:

$$(5) \quad y_{it} = \sum_{-5}^{49} g(h+0.5)[\Phi_{it}(h+1) - \Phi_{it}(h)] + \beta_1 P_{it} + \beta_2 P_{it}^2 + \gamma_{i1} \min(t, knot_1) + \gamma_{i2} d_1[\min(t, knot_2) - knot_1] + \gamma_{i3} d_2(t - knot_2) + C_i + \varepsilon_{it}.$$

In equation (5), $knot_1$ and $knot_2$ are the time trend knots, d_1 is 1 if $t \geq knot_1$ and 0 otherwise, and d_2 is 1 if $t \geq knot_2$ and 0 otherwise. The knots are the years when the time trend takes a new slope. $knot_1$ and $knot_2$ are therefore discrete variables, and they are selected by estimating the equations with several different knots and selecting the knot combination that yields the highest log likelihood. It is because of this number of times the model is estimated here that we opted not to include spatial autocorrelation of the error term. The standard errors from these models and the resulting statistical inference are therefore conditional. However, this does not pose an issue since prediction is this paper's main purpose.

Corn Belt dummy variables are the subject of the fifth part of the sensitivity analysis. Corn is grown in a variety of climates within the U.S. and in warmer climates such as Mexico. However, the Corn Belt is a key production region for corn in the United States. By including Corn Belt dummy variables, we avoid using data from other regions to predict corn yields in the Corn Belt. We include both intercept dummies and dummies for the coefficients of temperature and precipitation variables. The Corn Belt has had a comparative advantage in growing corn, in part due to fertile soils and favorable climate. A different response may be due to soil characteristics or to other climatological properties not reflected in temperature and precipitation measurements. The Corn Belt states are Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, Ohio, and Wisconsin. In this study Corn Belt counties are those in Corn Belt states where at least 20% of the land area is planted with corn. These counties are highlighted in Figure I-2.

The sixth part of the sensitivity analysis is the inclusion or exclusion of data from the 1950s and 1960s. Some of these years were marked by severe droughts and with technological change they may not be representative of corn yields today.

2.4. Sensitivity Analysis of Prediction

The next components of this sensitivity are on the assumptions about future conditions and predicted corn yields under these conditions. We use three different climate models: the CCSM4 model, the GFDL-ESM2G model, and the GDDL-ESM2M model. Although it is generally recommended to use more climate models, for the scope of the current work, these three were selected because they were developed in area. For each of these climate models, we consider two warming scenarios, known as Representative Concentration Pathways (RCPs). The milder scenario, RCP4.5, assumes that at the end of the twenty-first century radiative forcing[5] will be 4.5 watts per meter squared (W/m^2) higher than radiative forcing before industrialization. The more severe scenario, RCP8.5, now considered more likely, assumes a radiative forcing higher by 8.5 W/m^2 at the end of the twenty-first century relative to before industrialization. The two scenarios are from three different climate models. The sensitivity regarding climate scenarios is common among climate change impact studies.

The last element of the sensitivity analysis is adaptation. Most projections of the impacts of climate change do not consider farmer's ability to adapt to the new climate, due to the difficulty of incorporating such an assumption. Adapting to climate change will reduce the potential losses caused by higher temperatures. Kaiser et al. (1993) suggest that adaptation is feasible by changing planting and harvesting dates, and by making other farm-level decisions. In

[5] Radiative forcing is the difference between energy absorbed by the Earth and energy radiated back to space. Greenhouse gases contribute to the absorption of energy.

this study we examine how shifting the planting date to a month earlier affects the predicted impacts of climate change on corn yields. For example, when using a model estimated using July and August data, we make predictions based on future weather conditions in June and July. The point of this exercise is for avoid the hottest month of the year, August.

For each of the 192 models resulting from different combinations of model assumptions we perform 6 predictions of the impact of climate change. We consider two warming scenarios (RCP4.5 and RCP8.5) of three climate models (CCSM4, GDFL-ESM2G, and GFDL-ESM2M). An additional 6 predictions are performed assuming adaptation, when July-August data is used. This results in 1344 different predictions of the percentage yield change from current to future conditions. We summarize the results and conduct a sensitivity analysis using linear regression, where the dependent variable is the predicted percentage yield change corresponding to each combination of assumptions and climate scenarios, while the explanatory variables are categorical variables indicating the assumptions made in the prediction. The reference categories are the absence of adaptation, the RCP4.5 scenario, the CCSM4 climate model, and the assumptions corresponding to the base model. The first regression equation we estimated is:

(6) $$YieldChange_j = \alpha_0 + \alpha_1 LongTermAverageData_j + \alpha_2 MarSept_j + \alpha_3 MarOct_j + \alpha_4 JulAug_j + \alpha_5 JulAug\_Adaptation_j + \alpha_6 JulSept_j + \alpha_7 JulOct_j + \alpha_8 ChangeTempExposureMethod_j + \alpha_9 TwoKnotTrend_j + \alpha_{10} CornBeltDummies_j + \alpha_{11} Remove1950sAnd1960s_j + \alpha_{12} ESM2G_j + \alpha_{13} ESM2M_j + \alpha_{14} Adaptation_j + \alpha_{15} RCP85_j + e_j,$$

where $YieldChange_j$ is the j^{th} prediction of the percentage change in yield from current to future conditions; $ClimateData_j$ is 1 if the j^{th} prediction is based on a model that uses long-term average data and 0 if it is based on a model that uses yearly data; $MarSept_j$, $MarOct_j$, $JulAug_j$, $JulSept_j$, and $JulOct_j$ are dummy variables that take the value of 1 if the j^{th} prediction is based on a model that uses March-September data, March-October data, July-August data, July-September data, and July-October data, respectively; $JulAug\_Adaptation_j$ is 1 if the j^{th} prediction uses July-August data and assumes adaptation, (i.e., the model is estimated using July-August data, but the prediction is performed using a June-July under future conditions); $ChangeTempExposureMethod_j$ is 1 if the j^{th} prediction is based on a model that uses a different sinusoidal function than the base model to estimate temperature exposure times; $TwoKnotTrend_j$ is 1 if the j^{th} prediction is based on a model that uses two-knot time trends and 0 if it is based on a model that uses quadratic time trends; $CornBeltDummies_j$ is 1 if the j^{th} prediction is based on a model that includes Corn Belt dummy variables and 0 otherwise; $Remove1950sAnd1960s_j$ is 1 if the j^{th} prediction is based on a model that removes data from the 1950s and 1960s and 0 otherwise; $ESM2G_j$ and $ESM2M_j$ are dummy variables that take the value of 1 if the j^{th} prediction uses the GFDL-ESM2G and GFDL-ESM2M climate models, respectively; $Adaptation_j$ is 1 if the j^{th} prediction assumes adaptation and 0 otherwise; and $RCP85_j$ is 1 if the j^{th} prediction assumes the RCP8.5 warming scenario and 0 if it assumes the RCP4.5 scenario.

3. Results and Discussion

3.1. Regression Results.

We first replicate the Schlenker and Roberts (2009) model, using 1950-2005 data. Table I-A1 in the appendix partially presents the model's regression results and Figure I-1 is a graph of the $g(h)$ function corresponding to this replication. The replication is successful. Schlenker and Roberts do not explicitly reveal their estimated coefficients, but the shape of the relationship between temperature and the logarithm of corn yield is consistent with their findings. The success of the replication is discussed again later, with respect to predictions of the impact of climate on yields. The downward slope of -0.00471 representing the decrease in log yield due to temperatures above the 29°C threshold is much steeper than the upward slope of 0.000224 depicting the effect of a temperature increase from suboptimal levels. In this model and all models, we scale the precipitation variable by dividing it by 100 to simplify the interpretability of results. In this and subsequent tables, results for time trends will only be presented for Illinois and Iowa, the top two crop-producing states. County fixed effects results will only be presented for Adams County in Iowa. The reference county is Wood County in Iowa.

The results of the replication of the base model that includes recent data are partially presented in Table I-A2. The results are largely the same as those obtained without including recent data. The coefficients of all parameters are of the same signs and of comparable magnitudes. In particular, the upward slope of the piecewise function representing the relationship between temperature and log yield is 0.00019, while the downward slope is -0.0046. In both models the amount of precipitation throughout the growing season positively influences corn yields. This effect is demonstrated by a quadratic where the coefficient of the linear term in precipitation is positive and the coefficient of the quadratic term is negative, signifying that the marginal effect of precipitation on corn yield diminishes as precipitation increases. The magnitude of the coefficient of the quadratic term is smaller than the coefficient of the linear term by a factor of approximately 7, so the diminution of the positive effect of precipitation is slow. Quadratic state-specific time trends are similar in shape to the effect of precipitation; the coefficients for time are positive while the coefficients for the square of time are negative. In the rest of the paper, this replication that is estimated 1950-2016 data is referred to as the base model.

We now present models that contain only one change of assumption relative to the base model. Regression results for the model that uses the exposure calculation method with a domain of $[0, 2\pi]$ are partially presented in Table I-A3. While the upward temperature slope does not change, the downward temperature slope of -0.00632 is 34 percent steeper than in the base model. However, the intercept is greater in the model where temperature exposure calculation is changed. Table I-A4 presents regression results for the model that excludes data from the 1950s but keeps all other assumptions of the base model. The downward slope representing the harmful effect of higher temperatures on corn yields is similar to that estimated in the base model. The upward slope representing the positive effect of temperature increases below 29°C is shallower than that estimated in the base model by 21 percent; however, the intercept of the new model is 10 percent greater than in the base model. The regression results for the model that includes Corn Belt dummy variables but keeps all other assumptions of the base model are presented in Table I-A5. The relationship between temperature and log yield for non-Corn Belt counties, represented by an upward slope of 0.00019 and a downward slope of -0.0045, is comparable to that estimated in the base model. However, the slopes are steeper in Corn Belt counties by 21 percent and 13 percent, respectively. These findings suggest that the yields are more sensitive to temperature changes in the Corn Belt than in other regions.

Table I-A6 shows regression results from the model that uses a two-knot time trend but keeps all other assumptions of the base model. The two slopes representing the effect of temperature are similar to those estimated in the base model. Both coefficients representing the effect of precipitation are shallower in this new model compared to the base model. The years 1971 and 1990 are identified as the time trend knots. In both Iowa and Illinois, corn yields grew faster in the period from 1950 to 1971 compared to later years. Although the time trend slopes are state-specific, the knots are forced to be the same to allow timely estimation of the model. In Illinois the yearly increases in the 1971-1990 period were on average similar to the yearly yield increases in the 1990-2016 period; but in Iowa the average yearly yield increased faster in the 1990-2016 period than in the 1971-1990 period. Table I-A7 displays the knots for all the models that use two-knot time trends. Partial regression results for a model that uses July-August data but keeps the other assumptions of the base model are partially displayed in Table I-A8.

The temperature coefficients in models that use different subsets of the growing season should not be compared directly because the corresponding temperature variables are not of similar dimensions. For example, the temperature variables in a model that uses March-August data are larger than temperature variables in a model that uses July-August data, because there are 184 days in March-August and only 62 days in July-August. For a similar temperature effect, the coefficients in the model that uses July-August data but maintains the base model's assumptions should be smaller in magnitude. Since the temperature coefficients in the new model are of similar magnitude as in the base model, the estimated effects of temperature are larger in the new model. Similarly, the estimated effects of precipitation are larger. These results suggest that corn yields are more sensitive to temperature in the months of July and August compared to the rest of the growing season. A caveat here is that the temperature variables are not directly proportional to the number of days included, because of the nonlinear computation of these variables and the fact that months do not have identical distributions of temperature. Details of the computation of these variables are provided in the appendix.

To see how the results change when assumptions are changed simultaneously, we present in Table I-A9 the results of a model that uses yearly data, but changes the other five assumptions of the base model. The model in Table I-A9 uses a different method of calculating temperature exposure times, a different specification for time trends, includes Corn Belt dummy variables, removes data from the 1950s and 1960s, and uses only data from the months of July and August. For Corn Belt counties, the upward temperature slope is similar to that estimated in the base model, but for other counties this slope is insignificant. The downward temperature slope is steeper for Corn Belt counties than for non-Corn Belt counties. In all counties, downward temperature slope is steeper than the slope estimated in the base model. The results also indicate an additional sensitivity of corn yields to precipitation in the Corn Belt relative to other parts of the Eastern United States. However, the intercept in the new model is larger than in the base model, and the number of the days in the considered period of the year, so the relative magnitudes are not directly interpretable.

Table I-A10 partially shows the regression results of the model that uses long-term average data but maintains all other assumptions of the base model. The change in assumption alters the regression results considerably. Compared to the coefficient in the base model, the second temperature slope is 70 percent shallower. Interestingly, the first temperature slope is negative, albeit with a magnitude equal to only half of the magnitude of the first temperature slope in the base model. The first-degree coefficients of the quadratic time trends for both Illinois and Iowa are around 66 percent greater than in the base model, while the second-degree coefficients are twice greater than in the base model. County fixed effects are not included in models that use long-term average data. Water holding capacity, soil type, and average corn acreage in the 1950s are the county-specific characteristics that remain relatively constant through the study period. The coefficients for water holding capacity and soil type are positive, as expected. Surprisingly, the coefficient on the logarithm of average corn acreage in the 1950s is negative, which may reflect technological improvements being greater in marginal corn producing areas.

3.2. Impact of Climate Change

We compute the average percentage corn yield change between current yield levels and predicted yields in the last thirty years of the twenty-first century. We first calculate for each county the expected percentage change from predicted corn yield under current climate to predicted corn yield under future climate. An average is then computed for the Eastern United States, weighted by the average acres of corn planted in the years 2007-2016 in the counties.

Our replication of Schlenker and Roberts (2009) using 1950-2005 data in the regression estimation predicts that a 2°C uniform temperature increase would decrease yields by 15.89

percent on average, while a 4°C uniform temperature increase would decrease yields by 37.42 percent. These projected changes are comparable to those estimated by Schlenker and Roberts under these two scenarios: a 14.87 percent yield reduction for a 2°C temperature increase and a 35.30 percent reduction for a 4°C temperature increase. The impact does not change when we predict using the replication of Schlenker and Roberts (2009) that includes recent data in the regression estimation. This replication predicts a 16.28 percent average yield decrease under a 2°C uniform temperature increase and a 37.84 percent average yield decrease under a 4°C uniform temperature increase.

The results presented hereafter are based on more realistic climate scenarios rather than uniform temperature increases. Table I-1 presents the impacts of climate change on corn yield predicted by the base model (first row) and by models where only one assumption of the base model is changed. For example, under the RCP4.5 scenario of the CCSM4 climate model, the base model predicts a 44.6 percent yield decrease relative to current yields.

Table I-1. Predictions of the Impact of Climate Change on Corn Yields Using the Base Model and Its Modifications.

	Scenario					
Model	CCSM4 RCP4.5	GFDL-ESM2G RCP4.5	GFDL-ESM2M RCP4.5	CCSM4 RCP8.5	GFDL-ESM2G RCP8.5	GFDL-ESM2M RCP8.5
Base model	-44.6%	-27.8%	-23.3%	-63.8%	-46.0%	-44.9%
Use of two-knot time trends	-44.9%	-28.2%	-23.6%	-64.1%	-46.4%	-45.3%
Use of July-August data	-40.8%	-24.7%	-17.7%	-56.0%	-41.0%	-39.5%
Use of long-term average data	-22.2%	-14.9%	-13.3%	-33.7%	-25.4%	-24.0%
Addition of Corn Belt dummy variables	-47.8%	-31.6%	-27.7%	-67.0%	-50.2%	-49.3%
Change the temperature exposure time estimation method	-44.9%	-28.0%	-23.6%	-64.6%	-46.4%	-45.4%
Exclusion of data from the 1950s and 1960s	-45.5%	-28.6%	-24.1%	-64.6%	-47.1%	-45.8%
Assume adaptation (with July-August data)	-32.5%	-17.0%	-12.8%	-50.2%	-32.0%	-29.8%

This predicted yield decrease only changes slightly if one of the following model assumption changes is made: the replacement of quadratic time trends by two-knot time trends, the addition of Corn Belt dummy variables, the estimation of temperature exposure times using a sinusoid with a domain $[0, 2\pi]$ in lieu of the sinusoid with a domain of $[0, \pi]$, and the exclusion of data from the 1950s and 1960s. The use of July-August data instead of March-August data leads to a smaller yield decrease of 40.8% under the RCP4.5 scenario of the CCSM4 climate model. When July-August data are used and adaptation is assumed, a 32.5% yield decrease is predicted. The model that uses long-term average temperature and precipitation data instead of yearly data predicts a 22.2 percent yield decrease under the same scenario. This assumption change leads to the largest change in the prediction of the effect of climate change on corn yields.

The details of the predictions from the models corresponding to all combinations of assumptions are presented in Tables I-A17 through I-A24 in the appendix. The linear regression presented in equation (6) is used to summarize these predictions and conduct a sensitivity analysis to determine how changes in assumptions affect the predictions. Coefficients obtained by estimating equation (6) indicate that the prediction of the impact of climate change on corn yields is most sensitive to whether yearly temperature and precipitation data or long-term data are used. On average the yield decrease is 18.0 percentage points smaller when long-term average data are used than when yearly data are used. The source of this considerable difference is in the regression coefficients. The second temperature slope is less steep in models that use long-term average data compared to models that use yearly data; thus predicted yields are less sensitive to an increased prevalence of high temperatures. Additionally, a look at the residuals from the regressions show that residuals are larger when long-term average data are used; for example, the base model has a r-square of 0.854, while the r-square for the model that uses long-term average data but keeps all other assumptions of the base model is 0.641.

We modify equation (6) to include interactions between the indicator variables, where the most pronounced are interactions involving $LongTermAverageData$. For simplicity these are the only interactions we keep in the final results. For a better visualization, however, the results are presented as two separate regressions: one for predictions based on models that use yearly data, and another for predictions based on models that use long-term average data.

Table I-2 presents the sensitivity analysis of the predicted yield change based on models that use yearly data. The table shows that the assumption to which the yield decrease prediction is most sensitive is the warming scenario.

Table I-2. Predicted Percentage Yield change as a Function of Model and Prediction Assumptions: Models That Use Yearly Data

		Estimate	Standard Error
Intercept		-43.28*	0.28
Period of season			
	March-September	-0.93*	0.28
	March-October	-2.36*	0.28
	July-August	6.93*	0.28
	July-August (with Adaptation)	15.15*	0.28
	July-September	7.40*	0.28
	July-October	7.70*	0.28
Change Temperature exposure method		-0.43*	0.15
Two-knot trend		-0.29	0.15
Corn Belt Dummies		-4.01*	0.15
Remove 1950s and 1960s data		-1.29*	0.15
Climate model			
	GFDL-ESM2G	15.42*	0.18
	GFDL-ESM2M	18.44*	0.18
Warming scenario			
	RCP8.5	-19.38*	0.15

*: significant at the .01 level, N=672 R^2= 0.987

On average the predicted yield decrease is larger by 19.3 percentage points when the RCP8.5 scenario is assumed compared to when the RCP4.5 scenario is assumed. The direction of this effect is expected due to the higher prevalence of hot days under RCP8.5. The next most important assumption in the prediction of yield change is the climate model. Relative the CCSM4 climate model, using the GFDL-ESM2G and GFDL-ESM2M climate models leads to yield decreases that are smaller by 15.42 and 18.44 percentage points, respectively. This is caused by lower temperature levels under the two GFDL climate models.

The period of the growing season used is also important in the prediction of corn yield changes. Including the latter months of the corn growing season leads to more slightly pessimistic predictions. Relative to predictions based on models that use March-August data, yield decreases predicted based on models that use March-September and March-October data are larger by 0.93 and 2.36 percentage points, respectively. In contrast, restricting data only to the periods corresponding to the most sensitive phases of corn growth generally leads to more optimistic yield predictions. Relative to predictions based on models that use March-August data, yield decreases predicted based on models that use July-August data, July-September data, and July-October data are smaller by 6.93, 7.40, and 7.70 percentage points, respectively. When July-August data are used and adaptation is assumed, predicted yield decreases are smaller by 15.15 percentage points compared to when March-August data are used.

Yield decreases predicted based on models that include Corn Belt dummy variables are larger by 4.01 percentage points compared to predictions based on models that do not include the dummies. The use of a different sinusoid in the estimation of temperature exposure times, the replacement of quadratic time trends with two-knot trends, and the removal of data from the 1950s and 1960s only have small effects on the prediction of the impact of climate change on corn yields, on average.

Table I-3 presents the sensitivity analysis of the predicted yield change based on models that use long-term average data. The assumption change with the greatest effect on the predicted impact of climate change on corn yield is the inclusion of Corn Belt dummy variables. Predicted yield decreases based on models that include Corn Belt dummy variables are greater by 16.82 percentage points compared to predictions based on models that do not include such dummy variables. This is in contrast to the modest change in prediction resulting from the inclusion of Corn Belt dummy variables in models that use yearly data.

Table I-3. Predicted Percentage Yield change as a Function of Model and Prediction Assumptions: Models that Use Long-Term Data

	Estimate	Standard Error
Intercept	-21.49*	0.53
Period of season		
March-September	-1.67*	0.53
March-October	-3.26*	0.53
July-August	4.60*	0.53
July-August (with Adaptation)	9.64*	0.53
July-September	5.20*	0.53
July-October	4.82*	0.53
Change Temperature exposure method	-0.19	0.28
Two-knot trend	2.05*	0.28
Corn Belt Dummies	-16.82*	0.28
Remove 1950s and 1960s data	6.24*	0.28
Climate model		
GFDL-ESM2G	8.68*	0.34
GFDL-ESM2M	10.19*	0.34
Warming scenario		
RCP8.5	-11.20*	0.28

*: significant at the .01 level, N=672 R^2= 0.946

The other assumption changes whose effects are more perceptible in models that use climate change are the exclusion of data from the 1950s and 1960s and the use of two-knot time trends. Predicted yield decreases are smaller by 6.24 percentage points when data from the 1950s and 1960s are not included in the model estimation compared to when these data are included. Predicted yield decreases are larger by 2.05 percentage points when two-knot time trends are used compared to when quadratic time trends are used. Similarly to models that use yearly data, yield decrease predictions do not change significantly when a different method of estimating temperature exposure times is used.

The rest of the effects of assumption changes on yield change predictions among models that use long-term data are of the same directions and of comparable magnitudes as those observed among models that use yearly data. Relative to predictions based on models that use March-August data, predicted yield decreases based on models that use March-September data and March-October data are larger by 1.67 and 3.26 percentage points, respectively, while yield decreases based on July-August data, July-September, and July-October data are smaller by 4.60, 5.20, and 4.82 percentage points, respectively. When July-August data are used and adaptation is assumed, predicted yield decreases are smaller by 9.64 percentage points compared to when March-August data is used and adaptation is not considered. Predicted yield decreases are larger by 11.20 percentage points when the RCP8.5 scenario is assumed compared to when the RCP4.5 scenario is assumed. In addition, yield decreases under the GFDL-ESM2G and GFDL-ESM2M climate models are smaller by 8.68 and 10.19 percentage points, respectively, compared to yield decreases under the CCSM4 climate model.

In some models, all six assumptions of the base model are changed. One such model uses long-term average July-August data, estimates temperature exposure times using a sinusoid of domain [0,2π], uses state-specific two-knot time trends, includes Corn Belt dummy variables, and does not exclude data from the 1950s and the 1960s. Under the RCP4.5 scenario and assuming adaptation, the average predicted yield change using the three circulation models is a 14.1 percent decrease. Under the RCP8.5 scenario, the average prediction is a 26.4 yield decrease.

All predicted impacts of climate change presented thus far are weighted averages of all counties in the study. The impacts, however, are not uniform throughout the counties. Figures I-6 through I-14 present maps of predictions by different models under different climate scenarios. The maps were created with the same color coding, with red representing the largest yield reductions and green representing the largest yield increases. A recurring observation is that effects of climate change are predicted to be less severe in northern counties compared to southern counties. This heterogeneity in predicted yield changes is a consequence of the manner in which temperatures are expected to change. Northern counties are cooler than southern counties under the current climate. This disparity is expected to increase under future climates.

Figure I-4 is a map the average time spent above 32°C in each county in the months of July and August under the current climate. This time is not the average count of the days in which a temperature above 32°C was experienced; it is rather an average the accumulation of shorter times where the temperature is above 32°C. In figure I-5 the same measure is mapped for the RCP4.5 scenario of the CCSM4 model. The higher occurrence of warm temperatures in southern counties lead to larger yield decreases. Understanding the heterogeneity of the impact of climate on corn yields is useful for policy. For example, policy makers can create incentives for increasing farmland in the North and reducing it in the South. Results show that the effect of adaptation is also heterogeneous. As a consequence, the decision to change farming practices is expected to vary by region. For example, contrasting Figures I-9 and I-10 shows that counties in the south would gain more from adaptation than northern counties.

4. Summary and Conclusions

The results of this study show that the expected temperature increases will lead to yield decreases, on average, in the Eastern United States. Positive effects from expected precipitation increases are too small to offset the deleterious effects of temperature increases. We conduct a sensitivity analysis of the predicted impact of climate change on corn yields in United States. This robustness study consists in determining how predictions of the impact of climate change are affected by changes in assumptions of the estimation of the relationship between corn yields and weather variables and by changes in assumption. The base model is a replication of the Schlenker and Roberts (2009) model. The six changes of model assumptions that we consider are the use of long-term average temperature and precipitation data instead of yearly data, the use of different periods of the growing season, the use of a different method of estimating temperature exposure times, the modeling of time trends as two-knot functions instead of quadratic functions, the inclusion of Corn Belt dummy variables, and the exclusion of data from the 1950s and 1960s.

The assumption change to which yield change predictions are most sensitive is the use of long-term average data instead of yearly data. On average, predicted yield decreases based on models estimated using long-term average data are greater by 18 percentage points compared to predictions based on models that use yearly data. This means that roughly half of the predicted yield losses go away when long-term average data are used. The addition of Corn Belt dummy variables leads to larger predicted yield decreases, while the restriction of data only to months in the growing season corresponding to the most sensitive phases of corn growth generally leads to smaller yield decreases. The Schlenker and Roberts (2009) findings are not fragile from using two-knot time trends instead of quadratic trends, the use of a different method of estimating temperature exposure times, and the exclusion of data from the 1950s and 1960s. However, among models that use long-term average data, the removal of 1950s and 1950s data leads to smaller yield decreases.

The yield change predictions are sensitive to assumptions made about future conditions: the General Circulation Model (GCM) and the warming scenario. Predictions made using the GFDL-ESM2G and GFDL-ESM2M circulation models are more optimistic than those that use the CCSM4 circulation model. As expected, predictions that use the more severe warming scenario (RCP8.5) are more pessimistic compared to predictions that use the milder scenario (RCP4.5). Changes in weather patterns will likely compel farmers to alter their farming practices. One possible form of adaptation is to change planting dates so as to allow plants to grow under optimal conditions (Bassu et al. 2014). The present study implements this strategy by shifting planting data, and hence all the stages of the growing season, to one month earlier. The critical period for corn growth that currently occurs around July-August would then take place around June-July under future conditions. Predicted yield decreases are smaller when adaptation is assumed compared to when adaptation is not assumed. Farmers could also adapt by irrigating to compensate for evapotranspiration and by altering how they use fertilizer. It is worth noting that there is spatial heterogeneity in the predictions of the impact of climate change on corn yields.

Yield losses are expected to be larger in southern counties than in northern counties. This suggests increasing corn acreage in the North and reducing it in the South as a collective form of adaptation to expected future conditions.

Using a model that changes all model assumptions, including the use of July-August long-term average data, and assuming adaptation, the average prediction under the three circulation models is a 14.1 percent corn yield decrease under the RCP4.5 scenario and a 26.4 percent yield decrease under the RCP8.5. The yield loss predictions from all models in this study are larger than they would be if the effects of time trends were assumed to continue. These conservative predictions ignore the possibility of innovations such as heat-resistant corn varieties or varieties with shorter growing cycles. For perspective, average corn yields in Iowa increased by roughly 50% between the early 1980s and the early 2010s. When time trends are allowed to continue, large yield increases are predicted. In particular, models that use long-term average data have steeper time trends, and allowing the trends to continue for a few decades would not be appropriate. Policy makers need estimates such as those presented in the current study. Given the importance of U.S.-produced corn as a source of calories in the world and yield decreases predicted in this study, especially under the RCP8.5 scenario, policy makers need to regulate the emission of greenhouse gases. Furthermore, research aiming at the invention of new varieties of corn needs to be undertaken.

The predicted yield changes are spatially heterogeneous. But the predicted average change is computed as a weighted average, where the weights are the average acres of corn planted in the 2007-2016 period. In addition, the regression models assume temperature and precipitation responses are similar in all regions. The results are therefore disproportionately influenced by counties with marginal corn acreage. The inclusion of Corn Belt dummy variables partially resolves this concern. Other possible approaches for estimating different responses for different regions are the geographically weighted regression (Brunsdon et al. 2004) and Bayesian Kriging (Niyibizi et al. 2018).

The long-term averages directly measure climate differences whereas Schlenker and Roberts measure unexpected deviations in weather. So the long-term averages capture the adaption that already exists with respect to climate differences. While the results largely confirm Schlenker and Roberts (2009), they do show that the yield losses are not likely to be as catastrophic as predicted by Schlenker and Roberts.

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CHAPTER II

USING BAYESIAN KRIGING FOR SPATIAL SMOOTHING OF TRENDS IN THE MEANS AND VARIANCES OF CROP YIELD DENSITIES

Abstract

Crop yield forecasts are useful for several purposes such as rating crop insurance and government budget predictions, and allocation of barges and railcars. We use Bayesian Kriging for spatial smoothing of yield density parameters, including time trends. There is a paucity of useful historical yield data for counties, but properly using other counties' information in the estimation of a county's yield density alleviates the problem of not having enough observations. Yield density parameters are assumed to be spatially correlated, through a Gaussian spatial process. We spatially smooth multiple parameters, including time trends. The Bayesian Kriging model can handle unbalanced panel data. Using corn yield data from Illinois and Iowa, we find that the yield mean has increased faster in northern counties, but that the yield variance has increased faster in southern counties. The forecast accuracy of our model is similar to that of Bayesian Model Averaging (BMA) that assumes a normal distribution, but our approach is the only one that provides the spatial smoothing desired by the Risk Management Agency.

Key words: Spatial econometrics, Bayesian Kriging, Bayesian hierarchical modelling, Bayesian spatial smoothing, yield density, corn yield, density forecasting.

1. Introduction

Crop yield forecasts are useful for several purposes. Farmers can use yield forecasts in making decisions such as entering commodity contracts, buying crop insurance, or determining land values. The Risk Management Agency (RMA) of the USDA calculates area yield crop insurance premiums based on forecasted county yields. With the emergence of the need for risk management, density forecasts have become attractive rather than point forecasts. There is uncertainty in forecasting, and relative to point forecasts, density forecasts provide more information. In crop insurance, accurate rating of an insurance program is crucial. For the RMA, inaccurate rates could lead to substantial losses that would result from insurance indemnities considerably exceeding collected premiums. As Harri et al. (2011) remark, if an insurance policy is not actuarially fair, producers with high knowledge of yield risk may arbitrage the program or select against it.

Yield density forecasts are generally made before the beginning of a crop's growing season and therefore cannot use yield-determining information observed during the season such as weather or production inputs. In addition, the yield forecast for a county is traditionally based largely on a density estimated from that county's past yield observations. However, the time series of county yields are usually short. In addition, there is a concern that structural changes in crop genetics, weather patterns, and farming practices may imply that current yield observations are from very different distributions than observations from several decades ago, making yield time series even shorter.

To surmount this problem, spatial data can be useful in estimating crop yield densities. Due to similarities in climate, soil type, and shared information, the assumption that there are similarities in densities of neighboring counties is plausible. In spatial econometrics, the traditional spatial error model of Cliff and Ord (1972), popularized by Anselin (1988) treats spatial correlation as being in the error term and restricts all locations to have the same model parameters.

However, there have been efforts to incorporate spatial data at the parameter level. For example, Harri et al. (2011) estimate parameters of yield densities at the county level but the parameters have restrictions determined at the district level. Ker, Tolhurst, and Liu (2016) estimate the yield density of a county by first estimating a posterior density using the county's own data and then finding a weighted average of posterior densities from all counties, based on the Bayesian Information Criterion (BIC).

Ker, Tolhurst, and Liu (2016) assume yield density similarities, but they make no assumptions about the source of the similarities. The time trend used in these models is likely the most important parameter in making density forecasts. Yet, their time trend is smoothed in the same way as the other distribution parameters. Park et al. (2016, 2018) and Harri et al. (2011) used two-step methods where the trend was estimated separately from the other parameters.

The objective of this study is to develop a general Bayesian Kriging approach for spatial smoothing of yield density parameters. The similarity in yields is assumed to come from the correlation between parameters that define yield densities. This technique allows the smoothing of parameters and gives the ability to estimate yield densities even for counties with missing observations. Previous applications of Bayesian Kriging in the agricultural economics literature (e.g., Ozaki et al. 2008) perform spatial smoothing of the intercept, while Park et al. (2016, 2018) use it for spatial smoothing of two distributional parameters. This paper contribute to the spatial econometrics literature by extending Bayesian Kriging to the general heteroscedastic error regression problem. This work is the second paper, after Reich (2012), to extend Bayesian Kriging to the slope parameters in the linear regression problem rather than just the intercept as in Ozaki et al. (2008). While the paper assume that yields are normally distributed, its general approach can be extended to nonnormal distributions.

Forecasts of expected yield densities are based on past yield observations. But there are counties that lack yield records for certain years. Ker, Tolhurst, and Liu's (2016) approach can only accommodate balanced data. Using interpolation techniques, the Bayesian Kriging approach makes it possible to include counties without a full yield history during estimation and for making predictions.

2. Methods

Suppose there are *N* counties for which yield densities have to be estimated in year *t* (*t*=1,…,*T*). In this study, each county's yield is assumed to have a normal density. It is common practice in yield forecasts to assume time trends in the yield densities. Examples of what time trends capture include advances in production technology and improvements in seed genetics. Unlike previous research, we assume a linear time trend rather than a spline because a short time period (1984-2015) is included in the study; there is no need to assume a change in the trend during that period. We assume that there are time trends in both the mean and variance. The yield Y_{it} in year *t* for county *i* is:

$$Y_{it} = \alpha_i + \beta_i t + \varepsilon_{it}, \qquad i = 1,2,\ldots,201, \qquad t = 1,2,\ldots,31 \tag{1}$$

where α_i and β_i are the parameters that determine the mean of the yield, and ε_{it} is a random error term with mean zero and variance σ_{it}^2. As noted above, we assume heteroskedasticity through a time trend in the variance equation. The yield variance σ_{it}^2 is:

$$\sigma_{it}^2 = \gamma_i + \delta_i t + \nu_{it}, \tag{2}$$

where γ_i is the intercept, δ_i is the slope or time trend, and $\nu_{it}$is a random error term with mean zero. This assumption is different from assumptions made in previous research such as Harri et al. (2011), where the variance is assumed to be proportional to a power of predicted yields.

Note that there are four parameters that define the mean and variance equations for county i's yield densities. For convenience of notation we will sometimes collectively refer to the parameters as $\boldsymbol{\theta_i}$, that is, $\boldsymbol{\theta_i} = (\alpha_i, \beta_i, \gamma_i, \delta_i)$. Equation (1) is then written as:

$$Y_{it} \sim p_1(Y_{it}|\boldsymbol{\theta_i}). \quad (3)$$

Equation (3) can further be written in matrix form as:

$$\boldsymbol{Y} \sim p_1(\boldsymbol{Y}|\boldsymbol{\theta}), \quad (4)$$

where $\boldsymbol{Y}$ is the N×T matrix of yields from all counties and all years and $\boldsymbol{\theta}$ is the N×4 matrix of yield density parameters for all counties. In the remainder of the paper, a mention of parameters without more details refers to $\boldsymbol{\theta}$.

The Bayesian approach to inference assumes that model parameters are random variables. This is in contrast to the frequentist approach that assumes that the observed data are random but that the model parameters are fixed. The parameters $\boldsymbol{\theta}$ follow a density

$$\boldsymbol{\theta} \sim p_2(\boldsymbol{\theta}|\boldsymbol{\lambda}). \quad (5)$$

The prior distributions of parameters represent prior beliefs about the parameters before observing the data. The parameters of the prior distributions are called hyperparameters ($\boldsymbol{\lambda}$ in this case). The hyperparameters comprise the parameters that determine the parameters $\boldsymbol{\theta}$, including the Kriging parameters (sill and range) that define the spatial similarities among parameters of counties' yield densities based on distance. The prior distribution for the Kriging approach is a Gaussian spatial process. Bayesian inference is based on the posterior distribution of the parameters. The posterior is proportional to the product of the likelihood $p_1(\boldsymbol{Y}|\boldsymbol{\theta})$ and the prior $p_2(\boldsymbol{\theta}|\boldsymbol{\lambda})$.

Our Kriging approach uses Bayesian hierarchical modelling, where hyperparameters have prior distributions of their own, called hyperpriors:

(6) $$\boldsymbol{\lambda} \sim p_3(\boldsymbol{\lambda}).$$

In the Bayesian hierarchical modelling for this paper, the determination of yield densities is based on the posterior distribution of the parameters. The joint posterior distribution of the parameters is proportional to the product of: (i) the likelihood, (ii) the prior, and (iii) the hyperprior,

(7) $$p(\boldsymbol{\theta}, \boldsymbol{\lambda}|\boldsymbol{Y}) \propto p_1(\boldsymbol{Y}|\boldsymbol{\theta}, \boldsymbol{\lambda}) p_2(\boldsymbol{\theta}|\boldsymbol{\lambda}) p_3(\boldsymbol{\lambda}),$$

and is expressed mathematically as:

(8) $$p(\boldsymbol{\theta}, \boldsymbol{\lambda}|\boldsymbol{Y}) = \frac{p_1(\boldsymbol{Y}|\boldsymbol{\theta},\boldsymbol{\lambda}) p_2(\boldsymbol{\theta}|\boldsymbol{\lambda}) p_3(\boldsymbol{\lambda})}{\iint p_1(\boldsymbol{Y}|\boldsymbol{\theta},\boldsymbol{\lambda}) p_2(\boldsymbol{\theta}|\boldsymbol{\lambda}) p_3(\boldsymbol{\lambda})} .$$

Note that the likelihood notations $p_1(\boldsymbol{Y}|\boldsymbol{\theta}, \boldsymbol{\lambda})$ in equations (7) and (8) and $p_1(\boldsymbol{Y}|\boldsymbol{\theta})$ in equation (4) are equivalent, as the likelihood of $\boldsymbol{Y}$ depends on $\boldsymbol{\lambda}$ only through $\boldsymbol{\theta}$.

As mentioned above, we assume that yields are normally distributed. The likelihood function for our data is

(9) $$p_1(\boldsymbol{Y}|\boldsymbol{\theta}, \boldsymbol{\lambda}) = \prod_{i=1}^{N} \prod_{t=1}^{T} \frac{1}{\sqrt{2\pi(\gamma_i + \delta_i t)}} \exp\left\{-\frac{[Y_{it} - (\alpha_i + \beta_i t)]^2}{2(\gamma_i + \delta_i t)}\right\}.$$

Perhaps the most important aspect of our Bayesian hierarchical modelling is the Gaussian spatial process. It is at this stage that we model the spatial processes of each parameter. The spatial processes of each parameter are assumed to be independent. For brevity, here we only present the spatial process of the intercept of the mean equation.

(10) $$\boldsymbol{\alpha} = MVGP(\boldsymbol{\mu}, \Sigma_{\alpha}),$$

$$\alpha_i = \mu_i + u_i,$$

$$u_i \sim MVN(0, \Lambda),$$

$$\Sigma_{\boldsymbol{\alpha}} = \psi\left(d_{ij}, \rho_{\boldsymbol{\alpha}}, \Phi_{\boldsymbol{\alpha}}\right),$$

where $\boldsymbol{\alpha} = \alpha_1, \dots, \alpha_N$ is the vector of intercept parameters for all counties, and is assumed to follow a multivariate Gaussian process (MVGP), $\boldsymbol{\mu}$ is the deterministic part of the Gaussian process, $\Sigma_{\boldsymbol{\alpha}}$ is the covariance matrix of the Gaussian process, d_{ij} is the distance between counties *i* and *j* measured from longitude and latitude coordinates, $\rho_{\boldsymbol{\alpha}}$ is the sill parameter, and $\Phi_{\boldsymbol{\alpha}}$ is the range parameter. Note that the spatial correlation is captured in the stochastic parameters of the MVGP. The approach assumes that there is no spatial correlation in the error term.

The covariance between two counties is a function of the distance separating them and the Kriging parameters (sill and range). There are different possible specifications for this function; we use the exponential:

(11) $$\psi\left(d_{ij}, \rho_{\boldsymbol{\alpha}}, \Phi_{\boldsymbol{\alpha}}\right) = \rho_{\boldsymbol{\alpha}} e^{-\frac{d_{ij}}{\Phi_{\boldsymbol{\alpha}}}}.$$

As noted before, the hyperprior is the prior for the vector of hyperparameters. We assume that each hyperprior is independent from the others.

3. Data

Historical county corn yields from 1984 to 2015 are obtained from the National Agricultural Statistics Service (NASS). Only yields from the states of Illinois and Iowa are used. County with incomplete yield histories are not excluded. When comparing the predictive performance of the Bayesian Kriging approach that the Bayesian Model Averaging (BMA) approach, all counties are used for the Bayesian Kriging approach but only counties with full yield histories are used for

BMA. Illinois and Iowa are the two leading producers of corn in the country. Due to the computational needs of the algorithm used in this study, only data from these two states are used. The distance between counties is measured using the longitude and latitude coordinates of the county centroids.

4. Procedures

Our approach estimates the mean and variance of yield densities together. Yield densities have usually been estimated in two stages. The first stage is to regress a county's historical yield against a trend. The second stage—the determination of the variance of the yield densities— uses the estimated residuals from the first stage. There are different functional forms used by researchers for the mean yield. The trend is usually deterministic. The common approaches are a simple linear trend and a trend modeled through a spline with knots (e.g. Harri et al. 2011). This paper uses a simple linear trend. One slope suffices because we use a limited time period.

Similarly, in the crop insurance literature, different assumptions have been made about the structure of the variance of yield. Some researchers have assumed a constant coefficient of variation, with changes in the yield standard deviation proportional to the yield mean (e.g. Ker, Tolhurst, and Liu 2016; Deng, Barnett, and Vedenov 2007; Ker and Coble 2003; Miranda and Glauber 1997; Skees, Black and Barnett 1997). Other researchers have assumed homoskedasticity (Coble, Heifner, and Zuniga 2000; Mahul 1999; Miranda 1991). Our model assumes a linear trend in the variance equation.

There have been different specifications for yield densities. This study uses the normal density. In addition to the normal, other specifications that have been used are the gamma (Gallagher 1987), the logistic (e.g., Atwood, Shaik, and Watts 2003), the mixture of normals (e.g. Ker, Tolhurst, and Liu 2016), and the lognormal (e.g., Sherrick et al. 2004), among others.

Ker, Tolhurst, and Liu (2016) use BMA, a technique where a weighted average of a set of models is computed. They first estimate each county's conditional yield density using its own historical yield data. To obtain the BMA estimate for county *i*, they compute the Bayesian Information Criterion (BIC) of each estimated model using county *i*'s yield data. County *i*'s BMA estimate is the weighted average of all models, where the weights are derived from the BIC of each model given the data in county *i*. Like the BMA approach, our approach improves estimation efficiency by using data from all counties in the estimation of each county's yield density. Unlike the BMA approach, our Bayesian Kriging approach assumes that the similarity in yield density results from proximity in space.

The computation of integrals such as the one in equation (8) generally does not have closed-form solutions. To obtain the marginal posterior distributions of the parameters $\boldsymbol{\theta}$, Markov Chain Monte Carlo (MCMC) simulations are used. Specifically, the Metropolis-Hastings algorithm is used within a Gibbs sampler. Metropolis-Hastings algorithm, random parameter values are drawn from a candidate density and then accepted or rejected; the accepted values are included in the posterior density.

We impose hyperpriors as follows. For the hyperparameters corresponding to prior means of the parameters $\boldsymbol{\theta}$, we impose normal hyperprior distributions derived from maximum likelihood estimates of the following pooled model, estimated using 1950-1983 data with year random effects

(12) $$Y_{it} = a + bt + +\xi_t + e_{it}, t = 0,1,2,\dots 33$$

The hyperprior means for trend parameters β_i and δ_i are as estimated in equation (12). The hyperprior means for intercept parameters α_i and γ_i are the values predicted by equation (12) for the year 1983. The hyperprior variances of parameters $\boldsymbol{\theta}$ computed by multiplying the corresponding variances in equation (12) by the total number of counties. This serves to weaken the priors and to account for the fact that standard errors are smaller when pooled data.

The posterior distributions obtained from the MCMC are given as samples of values from the posterior distributions. The samples are generated by a Markov Chain whose stationary distribution is the same as the posterior. We assume that the marginal distributions of the simulated values are close to the target distributions of the parameters.

The MCMC is used to sample from the posterior distribution. The total number of iterations is 30,000, but the first 10,000 are discarded (i.e., the burn-in is 10,000). Discarding the early iterations diminishes the influence of the starting values. To perform a diagnosis of the convergence of the MCM simulations, we the Gelman-Rubin test is conducted. The procedure for this test follows the outline in Gelman et al. (2014). Two sequences are simulated, each with 10,000 iterations after burn-in. Then each of the sequences is split into two sequences of length 5,000, and we end up with *m*=4 sequences of *n*=5000 iterations each. Convergence is judged based on the following scale reduction factor:

(11) $$\hat{R} = \sqrt{\frac{n-1}{n} + \frac{1}{n}\frac{B}{W}}$$

where *B* and *W* are the between-and within-sequence variances. The MCMC is said to converge if the value of $\hat{R}$ is close to 1.

We compare the predictive performance of our approach to that of the BMA model (Ker, Tolhurst, and Liu 2016), using the root mean squared error of prediction (RMSEP). For a reasonable comparison, however, we use the BMA approach under normality rather than the mixture of normal distributions. We first estimate posterior densities using 1984-2008 data and predict 2009 yield means. We then estimate posterior densities using 1984-2009 data to predict

2010 yield means. The same process is repeated until we use 1984-2014 data to predict 2015 yields. All these predictions are compared to actual observed yields, and the RMSEP is computed.

5. Results

Parameters of corn yield densities are estimated using Bayesian Kriging. The MCMC provides four parameters for each of the 201 counties in Illinois and Iowa. Because there are many counties in this study, we present the posterior means using maps (Figures II-1 through II-6). All results presented in these maps are from the estimation that uses 1984-2014 data. Figures II-1 through II-4 contain results from the Bayesian Kriging approach, while figures II-5 and II-6 have results from the BMA model.

Figure II-1 is a map of the intercept parameter of the mean of yield density. The posterior mean of the intercept is highest in central Illinois and in northern Iowa. The map in Figure II-2 shows the posterior mean of the trend parameter of the mean of yield density. The map shows that yields have grown faster in northern counties for both states. An explanation is perhaps that due to the cooler climate in the north, improvements in production technology have resulted in larger yield increases in the north. Tannura et al. (2008) argue that increased yields are a result of earlier planting and this earlier planting may be more important in northern areas.

Figure II-3 shows the posterior mean of the intercept of the variance of yield density, and figure II-4 shows the posterior mean of the trend of the variance of yield density. As seen in these figures, the variance intercept is highest and in the counties of eastern Illinois, while the variance trends is highest in northwest Iowa. These results are interesting since the variance did not increase faster in the counties where the mean increased faster. However, a close look at the legend in both figures show that the variance only varied little across space.

Figure II-5 shows the posterior mean of the intercept of the mean of yield density, computed using BMA. Figure I-6 is a map of the posterior mean of the trend of the mean of yield density. In contrasting figures II-5 and II-6 with figures II-1 and II-2, respectively, two key differences are observed. First, the blanks in figures II-5 and II-6 reflect the inability of BMA to estimate yield densities for counties without a complete yield history. Second, the transition from clusters with higher values to clusters with lower values is smoother in figures II-1 and II-2.

To test the convergence of the MCMC chains, the Gelman-Rubin diagnostic is used. In this test, values close to 1 are desired for the scale reduction factor. Overall, the test was not satisfied. Of the 201 counties for which four parameters were estimated, the Gelman-Rubin test was satisfied in 26 counties for the intercept of the mean equation, in 35 counties for the trend of the mean equation, and in 19 counties for trend of the variance of the mean equation. This lack of convergence is due to the high number of parameters to sample, and significantly increasing the number of iterations could improve convergence. However, future research needs to improve the sampling strategy.

We now compare the predictive performance of our approach to that of BMA. Although we make this comparison, we note that the BMA model only uses counties with a full yield history, while our model uses all 201 counties. Because Bayesian Kriging is an interpolation technique, it has the advantage of handling missing values. A major similarity between the BMA approach and our approach is that data from all counties are candidates for use in the estimation of each county's yield density.

The RMSEP for our Bayesian Kriging model is 29.70 bushels/acre, while the RMSEP of BMA is 30.07 bushels/acre. These values are similar, but our model is the only one that has predictions for all counties and provides the spatial smoothing desired by the Risk Management Agency. Both RMSEP values are high, because both models' predictions of 2012 corn yields were poor. Corn yields were atypically low in 2012, due to the 100-year flood that took place. We compute separate RMSEP's to evaluate how the models performed in each individual year. Our model outperforms BMA in 2010, 2013, 2014, and 2015, while BMA outperforms our model in 2009, 2011, and 2012. These results are summarized in table II-1.

Table II-1. Root Mean Squared Error of Prediction (bu/acre) Comparison between BMA and Bayesian Kriging Models

	BMA	Bayesian Kriging
2009	13.51	14.10
2010	26.35	25.53
2011	16.61	18.08
2012	60.88	61.79
2013	18.78	16.15
2014	28.91	14.64
2015	16.85	15.50
2009-2015	30.07	29.70

6. Conclusion

Forecasts of yield densities are important for crop insurance rating. The RMA needs accurate forecasts to make actuarially fair premiums for insurance policies. Producers and agricultural businesses also need accurate yield forecasts for land valuation and for their own planning. We introduce a new approach for the estimation of yield densities. We use Bayesian Kriging for spatial smoothing of all parameters of counties' yield densities. The intercept and trend parameters are spatially smoothed in both the mean equation and the variance equation. Our Bayesian Kriging approach assumes that the stochastic parameters are spatially correlated. The spatial autocorrelation in the data is captured by the spatial correlation in parameters rather than spatial correlation in error. A county's estimated yield density is derived not only from its own historical yield observations, but also from other counties.

This paper extends Bayesian Kriging to the general heteroskedastic error regression model. The approach can be used even when yields are not assumed to be normally distributed, but that increases computational time considerably. This paper has two main contributions to the crop insurance literature. The first is the ability to spatially smooth multiple parameters of yield densities, including trend parameters. The second is the ability to use unbalanced data in the estimation. There are counties whose yield is not recorded in all years; previous approaches that only use balanced data cannot be used directly in forecasting yield densities for such counties. A drawback of the Bayesian Kriging approach is that it is computationally expensive. It takes approximately 3.5 days to estimate one model on a regular office computer. However, with increases in computers' performance, this problem is expected to lessen. Also, we are using the R software package, which is notorious for being computationally burdensome. Convergence is currently not fully satisfied. The Gelman-Rubin convergence test is satisfied for 26 of 201 intercept parameters of yield mean equations in Illinois and Iowa counties, 35 of 201 trend parameters of yield mean equations, and 19 of 201 trend parameters of yield variance equations. A possible future improvement to this work is to sample the posterior distribution using Hamiltonian Monte Carlo.

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APPENDICES

APPENDIX FOR CHAPTER I

1. Estimating Temperature Exposure Time

Following Snyder (1985) and D'Agostino and Schlenker (2016), we approximate the temperature distribution by the following sinusoidal:

(A1) $$h = \frac{h_{max}+h_{min}}{2} - \frac{h_{max}-h_{min}}{2}\cos(s)$$

where *h* is the temperature and $s \in [0,2\pi]$ is the time. This distribution is graphed in the left panel of figure I-3.

For each temperature level h, the corresponding *s* values on the time axis are:

$s = \text{acos}\left(\frac{h_{max}+h_{min}-h}{h_{max}-h_{min}}\right)$ and $s = 2\pi - \text{acos}\left(\frac{h_{max}+h_{min}-h}{h_{max}-h_{min}}\right)$

The time spent between two temperatures h_1 and h_2 , where $h_2 > h_1$ can be estimated as:

$$time = \frac{1}{2\pi} * \left\{\left[\text{acos}\left(\frac{h_{max}+h_{min}-2h_2}{h_{max}-h_{min}}\right) - \text{acos}\left(\frac{h_{max}+h_{min}-2h_1}{h_{max}-h_{min}}\right)\right]\right.$$
$$\left. + \left[\left[2\pi - \text{acos}\left(\frac{h_{max}+h_{min}-2h_1}{h_{max}-h_{min}}\right)\right] - \left[2\pi - \text{acos}\left(\frac{h_{max}+h_{min}-2h_2}{h_{max}-h_{min}}\right)\right]\right]\right\}$$
$$= 2 * \frac{1}{2\pi} * \left[\text{acos}\left(\frac{h_{max}+h_{min}-2h_2}{h_{max}-h_{min}}\right) - \text{acos}\left(\frac{h_{max}+h_{min}-2h_1}{h_{max}-h_{min}}\right)\right].$$

Specifically, the time spent within a 1C temperature interval [*h*, *h*+1] is

$$time = 2 * \frac{1}{2\pi} * \left[\text{acos}\left(\frac{h_{max}+h_{min}-2(h+1)}{h_{max}-h_{min}}\right) - \text{acos}\left(\frac{h_{max}+h_{min}-2h}{h_{max}-h_{min}}\right)\right].$$

The multiplication by $\frac{1}{2\pi}$ serves to convert the unit of time to days. When calculating the exposure time for an interval with a lower bound below the minimum temperature, the term $\text{acos}\left(\frac{h_{max}+h_{min}-2h_1}{h_{max}-h_{min}}\right)$ is replaced by 0. Similarly, when calculating the exposure time for an interval whose upper bound exceeds the maximum temperature, the term $\text{acos}\left(\frac{h_{max}+h_{min}-2h_2}{h_{max}-h_{min}}\right)$ is replaced by π.

The alternative method of estimating the temperature exposure time is to use the following sinusoidal function, used by Schlenker and Roberts (2009) and Yun and Gramig (2017):

$$h = h_{min} + (h_{max} - h_{min})\sin(s)$$

where $s \in [0,\pi]$ is the time representing one day.

The time spent within two temperatures h_1 and h_2, where $h_2 > h_1$ is estimated as:

$$time = 2 * \frac{1}{\pi} * \left[\text{asin}\left(\frac{h_2 - h_{min}}{h_{max} - h_{min}}\right) - \text{asin}\left(\frac{h_1 - h_{min}}{h_{max} - h_{min}}\right)\right].$$

This method of computing temperature exposure times is graphed in the right panel of Figure I-3.

2. Computing Temperature variables

Assuming a piecewise linear corn growth function

$$g(h) = \begin{cases} a + bh, & h \leq 29 \\ a + bh + c(h - 29), & h > 29, \end{cases}$$

the first term of the right-hand side of equation (2), after grouping all negative temperatures into the [-1,0] interval and all temperatures above 39℃ into the [39,40] interval ,is computed as follows.

$$\sum_{-1}^{39} g(h+0.5)[\Phi_{it}(h+1)-\Phi_{it}(h)]$$

$$= g(-0.5)[\Phi_{it}(0)-\Phi_{it}(-1)] + g(0.5)[\Phi_{it}(1)-\Phi_{it}(0)] + \cdots$$

$$+ g(28.5)[\Phi_{it}(29)-\Phi_{it}(28)] + g(29.05)[\Phi_{it}(30)-\Phi_{it}(29)] + \cdots$$

$$+ g(39.5)[\Phi_{it}(40)-\Phi_{it}(39)]$$

$$= [a+b(-0.5)][\Phi_{it}(1)-\Phi_{it}(0)] + [a+b(0.5)][\Phi_{it}(1)-\Phi_{it}(0)] + \cdots$$

$$+ [a+b(28.5)][\Phi_{it}(29)-\Phi_{it}(28)]$$

$$+ [a+b(29)+c(0.5)][\Phi_{it}(30)-\Phi_{it}(29)] + \cdots$$

$$+ [a+b(29)+c(10.5)][\Phi_{it}(40)-\Phi_{it}(39)]$$

$$= a\sum_{-1}^{39}[\Phi_{it}(h+1)-\Phi_{it}(h)]$$

$$+ b\left[\sum_{-1}^{28}(h+0.5)[\Phi_{it}(h+1)-\Phi_{it}(h)] + 29\sum_{29}^{39}[\Phi_{it}(h+1)-\Phi_{it}(h)]\right]$$

$$+ c\sum_{29}^{39}(h+0.5-29)[\Phi_{it}(h+1)-\Phi_{it}(h)].$$

The sum $\sum_{0}^{39}[\Phi_{it}(h+1)-\Phi_{it}(h)]$ is the same for all counties and is simply the total number of days in the period of the growing season included in the estimation (e.g., 184 days for March-August). We do not estimate the coefficient *a*; we instead keep it as part of the overall intercept.

In the text *Temperature Sum 1* refers to the sum $[\sum_{-1}^{28}(h+0.5)[\Phi_{it}(h+1)-\Phi_{it}(h)] + 29\sum_{29}^{39}[\Phi_{it}(h+1)-\Phi_{it}(h)]]$, while *Temperature Sum 2* is the sum $\sum_{29}^{39}(h+0.5-29)[\Phi_{it}(h+1)-\Phi_{it}(h)]$. Their corresponding coefficients, *b* and *c*, are referred to as the upward temperature slope and the downward temperature slope, respectively.

3. Tables for Chapter I

Table I-A1. Regression of Log Yield Using the Base Model and 1950-2005 Data

	Estimate	Standard Error
Intercept	3.14358*	0.03602
Temperature Sum 1	0.00022*	6.5E-06
Temperature Sum 2	-0.0047*	2.4E-05
Precipitation [100mm]	0.06435*	0.00285
Squared precipitation[10000mm^2]	-0.0087*	0.0003
Illinois time [year]	0.03021*	0.0007
Illinois time^2[years^2]	-0.0002*	1.2E-05
Iowa time[year]	0.0317*	0.00071
Iowa time^2[years^2]	-0.0002*	1.3E-05
Adams County, Illinois (17001)	0.17972*	0.04319

*: significant at the .01 level

Table I-A2. Regression of Log Yield Using the Base Model and 1950-2016 Data

	Estimate	Standard Error
Intercept	3.23805*	0.03291
Temperature Sum 1	0.00019*	5.8E-06
Temperature Sum 2	-0.0046*	2.3E-05
Precipitation	0.06199*	0.00266
Squared Precipitation	-0.0081*	0.00028
Illinois time	0.02757*	0.00054
Illinois time^2	-0.0002*	8E-06
Iowa time	0.02894*	0.00055
Iowa time^2	-0.0002*	8.1E-06
Adams County, Illinois (17001)	0.1878*	0.03973

*: significant at the .01 level, N=122378 R^2= 0.0.854

Table I-A3. Regression of Log Yield: Model with a Different Method of Calculating Temperature Exposure Times

	Estimate	Standard Error
Intercept	3.28187*	0.03233
Temperature Sum 1	0.0002*	6E-06
Temperature Sum 2	-0.00632*	3.1E-05
Precipitation[100mm]	0.05947*	0.00265
Squared Precipitation[$100mm^2$]	-0.00798*	0.00028
Illinois time[years]	0.02761*	0.00054
Illinois $time^2$[$years^2$]	-0.00016*	8E-06
Iowa time[years]	0.02898*	0.00055
Iowa $time^2$[$years^2$]	-0.00017*	8.1E-06
Adams County, Illinois (17001)	0.17821*	0.03977

*: significant at the .01 level

Table I-A4. Regression of Log Yield: Model that Removes Data from the 1950s and 1960s

	Estimate	Standard Error
Intercept	3.55649*	0.05606
Temperature Sum 1	0.00015*	6.6E-06
Temperature Sum 2	-0.0046*	2.7E-05
Precipitation[100mm]	0.0545*	0.003
Squared Precipitation[100mm^2]	-0.0073*	0.00031
Illinois time[years]	0.02476*	0.00168
Illinois time^2[years^2]	-0.0001*	1.9E-05
Iowa time[years]	0.00761*	0.00168
Iowa time^2[years^2]	7.2E-05*	1.9E-05
Adams County, Illinois (17001)	0.05453	0.06996

*: significant at the .01 level

Table I-A5. Regression of Log Yield: Model that Includes Corn Belt Dummies

	Estimate	Standard Error
Intercept	3.22622*	0.034575
Temperature Sum 1	0.00019*	6.82E-06
Corn Belt * Temperature Sum 1	4.2E-05*	1.29E-05
Temperature Sum 2	-0.0045*	2.42E-05
Corn Belt * Temperature Sum 2	-0.0007*	7.08E-05
Precipitation [100mm]	0.07232*	0.002975
Corn Belt * Precipitation	0.02176*	0.00797
Squared Precipitation	-0.0087*	0.000304
Corn Belt * Squared Precipitation	-0.0065*	0.000959
Illinois time [year]	0.02719*	0.000545
Illinois time^2[years^2]	-0.0002	8.03E-06
Iowa time[year]	0.02859*	0.00055
Iowa time^2[years^2]	-0.0002*	8.07E-06
Adams County, Illinois (17001)	0.09966	0.059639

*: significant at the .01 level

Table I-A6. Regression of Corn Log Yield: Model that Uses Two- Knot Time Trends

	Estimate	Standard Error
Intercept	3.25237*	0.032789
Temperature Sum 1	0.00018*	5.71E-06
Temperature Sum 2	-0.00461*	2.28E-05
Precipitation	0.05702*	0.002632
Squared Precipitation	-0.00772*	0.000277
Illinois time trend 1	0.02738*	0.000586
Illinois time trend 2	0.01401*	0.000528
Illinois time trend 3	0.013*	0.000453
Iowa time trend 1	0.03315*	0.000595
Iowa time trend 2	0.00961*	0.000534
Iowa time trend 3	0.01627*	0.00045
Adams County, Illinois (17001)	0.20073*	0.039622

*: significant at the .01 level

Time trend knots: 1971 and 1990

Table I-A7. Knots for Models that Use Two-Knot Time Trends

Model	Knot 1 Year	Knot 2 Year
5	1971	1990
6	1982	1999
7	1971	1990
8	1982	1999
13	1971	1990
14	1982	1999
15	1971	1990
16	1982	1999
21	1971	1990
22	1982	1999
23	1963	1980
24	1982	1999
29	1971	1990
30	1982	1999
31	1971	1990
32	1982	1999
37	1971	1990
38	1982	1999
39	1971	1990
40	1982	1999
45	1971	1990
46	1982	1999
47	1971	1990
48	1982	1999
53	1971	1990
54	1982	1999
55	1971	1990
56	1982	1999
61	1971	1990
62	1982	1999
63	1971	1990
64	1982	1999
69	1971	1990
70	1982	2000
71	1971	1990
72	1982	1999
77	1971	1990
78	1982	2000
79	1971	1990

Table I-A7 (continued).

80	1982	1999
85	1971	1990
86	1982	2000
87	1971	1990
88	1982	1999
93	1971	1990
94	1982	2000
95	1971	1990
96	1982	1999
101	1966	1990
102	1980	1998
103	1966	1990
104	1980	1998
109	1966	1990
110	1980	1998
111	1966	1990
112	1980	1998
117	1966	1990
118	1980	1998
119	1966	1990
120	1980	1998
125	1966	1990
126	1980	1998
127	1966	1990
128	1980	1998
133	1966	1990
134	1980	1998
135	1966	1990
136	1980	1998
141	1966	1990
142	1980	1998
143	1966	1990
144	1980	1998
149	1966	1990
150	1980	1998
151	1966	1990
152	1980	1998
157	1966	1990
158	1980	1998
159	1966	1990
160	1980	1998
165	1966	1990

Table I-A7 (continued).

166	1980	1998
167	1966	1990
168	1980	1998
173	1966	1990
174	1980	1998
175	1966	1990
176	1980	1998
181	1966	1990
182	1980	1998
183	1966	1990
184	1980	1998
189	1966	1990
190	1980	1998
191	1966	1990
192	1980	1998

Table I-A8. Regression of Corn Log Yield: Using July-August Data instead of March-August Data

	Estimate	Standard Error
Intercept	3.46495*	0.037997
Temperature Sum 1	0.0002*	1.85E-05
Temperature Sum 2	-0.00503*	3.62E-05
Precipitation	0.11095*	0.003622
Squared Precipitation	-0.02048*	0.000716
Illinois time	0.02976*	0.000556
Illinois time^2	-0.00019*	8.2E-06
Iowa time	0.03032*	0.000561
Iowa time^2	-0.00019*	8.22E-06
Adams County, Illinois (17001)	0.22886*	0.040484

*: significant at the .01 level

Table I-A9. Regression of Corn Log Yield: Using July-August Yearly Data and Changing Other Assumptions of the Base Model

	Estimate	Standard Error
Intercept	3.85175*	0.06171
Temperature Sum 1	3.9E-05	2.5E-05
Corn Belt * Temperature Sum 1	0.00022*	4.7E-05
Temperature Sum 2	-0.0067*	6.4E-05
Corn Belt * Temperature Sum 2	-0.0014*	0.00018
Precipitation	0.06051*	0.00473
Corn Belt * Precipitation	0.17987*	0.01005
Squared Precipitation	-0.0105*	0.00092
Corn Belt * Squared Precipitation	-0.0387*	0.00201
Illinois time trend 1	0.02742*	0.00126
Illinois time trend 2	0.00966*	0.00071
Illinois time trend 3	0.01494*	0.00082
Iowa time trend 1	0.01399*	0.00128
Iowa time trend 2	0.01229*	0.00072
Iowa time trend 3	0.01691*	0.00081
Adams County, Illinois (17001)	-0.4059*	0.09573

*: significant at the .01 level

Time trend knots: 1982 and 1999

Table I-A10. Regression Corn Log Yield: Using Long-Term Average Data and Keeping Other Assumptions of the Base Model

	Estimate	Standard Error
Intercept	3.42544*	0.01631
Temperature Sum 1	-4.7E-05*	4.5E-06
Temperature Sum 2	-0.00139*	2.5E-05
Precipitation	0.00961*	0.00337
Squared Precipitation	-0.00292*	0.00035
Water holding capacity	0.01324*	0.00022
Soil slope	0.00066*	3.8E-05
Log of average corn acres in the 1950s	-0.00834*	0.00051
Illinois time	0.04576*	0.00049
Illinois time^2	-0.00037*	8.7E-06
Iowa time	0.04877*	0.00053
Iowa time^2	-0.0004*	9.1E-06

*: significant at the .01 level, N=152558 R^2= 0.641

Table I-A11. Regression of Corn Log Yield: Changing All Six Assumptions of the Base Model (July-August Data)

	Estimate	Standard Error
Intercept	3.29549*	0.0306
Corn Belt	-0.6466*	0.06897
Temperature Sum 1	-0.0002*	2.1E-05
Corn Belt * Temperature Sum 1	0.00053*	5.2E-05
Temperature Sum 2	-0.0005*	6.3E-05
Corn Belt * Temperature Sum 2	-0.0071*	0.00024
Precipitation	0.05548*	0.00525
Corn Belt * Precipitation	0.17394*	0.01412
Squared Precipitation	-0.0094*	0.001
Corn Belt * Squared Precipitation	-0.037*	0.00283
Water holding capacity	0.01252*	0.00026
Soil slope	0.00088*	4.3E-05
Log of average corn acres in the 1950s	0.04235*	0.00104
Illinois time trend 1	0.03952*	0.00062
Illinois time trend 2	0.00852*	0.00087
Illinois time trend 3	0.01529*	0.00104
Iowa time trend 1	0.02078*	0.00067
Iowa time trend 2	0.01102*	0.00088
Iowa time trend 3	0.01747*	0.00105

*: significant at the .01 level

Time trend knots: 1980 and 1998

Table I-A12. Regression of Corn Log Yield: Using March-September Data instead of March-August Data

	Estimate	Standard Error
Intercept	3.12885*	0.03405
Temperature Sum 1	0.00019*	5.4E-06
Temperature Sum 2	-0.00397*	2E-05
Precipitation	0.07443*	0.00268
Squared Precipitation	-0.00885*	0.00028
Illinois time	0.02711*	0.00055
Illinois time^2	-0.00016*	8.1E-06
Iowa time	0.02879*	0.00055
Iowa time^2	-0.00017*	8.1E-06
Adams County, Illinois (17001)	0.15697*	0.04015

*: significant at the .01 level

Table I-A13. Regression of Corn Log Yield: Using March-October Data instead of March-August Data

	Estimate	Standard Error
Intercept	3.01581*	0.03412
Temperature Sum 1	0.0002*	4.9E-06
Temperature Sum 2	-0.0039*	2E-05
Precipitation	0.07562*	0.00267
Squared Precipitation	-0.009*	0.00028
Illinois time	0.02757*	0.00055
Illinois time^2	-0.0002*	8.1E-06
Iowa time	0.02926*	0.00055
Iowa time^2	-0.0002*	8.1E-06
Adams County, Illinois (17001)	0.11855*	0.04016

*: significant at the .01 level

Table I-A14. Regression of Corn Log Yield: Using July-September Data instead of March-August Data

	Estimate	Standard Error
Intercept	3.26116*	0.037522
Temperature Sum 1	0.00026*	1.3E-05
Temperature Sum 2	-0.00429*	3.07E-05
Precipitation	0.10839*	0.003676
Squared Precipitation	-0.01965*	0.000725
Illinois time	0.02892*	0.000561
Illinois time^2	-0.00018*	8.28E-06
Iowa time	0.02992*	0.000566
Iowa time^2	-0.00018*	8.29E-06
Adams County, Illinois (17001)	0.18397*	0.04091

*: significant at the .01 level

Table I-A15. Regression of Corn Log Yield: Using July-October Data instead of March-August Data

	Estimate	Standard Error
Intercept	3.16737*	0.035163
Temperature Sum 1	0.00026*	8.99E-06
Temperature Sum 2	-0.00418*	2.72E-05
Precipitation	0.10925*	0.00367
Squared Precipitation	-0.01967*	0.000724
Illinois time	0.02949*	0.000562
Illinois time^2	-0.00018*	8.28E-06
Iowa time	0.03058*	0.000566
Iowa time^2	-0.00019*	8.29E-06
Adams County, Illinois (17001)	0.14799*	0.040886

*: significant at the .01 level

Table I-A16. Regression of Corn Log Yield: Changing All Six Assumptions of the Base Model (July-October Data)

	Estimate	Standard Error
Intercept	2.94685*	0.02578
Corn Belt	-0.5586*	0.04695
Temperature Sum 1	7.3E-06*	9.3E-06
Corn Belt * Temperature Sum 1	0.0003*	2.1E-05
Temperature Sum 2	-0.0005*	4.9E-05
Corn Belt * Temperature Sum 2	-0.0066*	0.00018
Precipitation	0.06048*	0.00531
Corn Belt * Precipitation	0.15092*	0.01428
Squared Precipitation	-0.0102*	0.001
Corn Belt * Squared Precipitation	-0.0332*	0.00286
Water holding capacity	0.01187*	0.00026
Soil slope	0.00084*	4.3E-05
Log of average corn acres in the 1950s	0.0397*	0.00104
Illinois time trend 1	0.03898*	0.00063
Illinois time trend 2	0.00876*	0.00087
Illinois time trend 3	0.01487*	0.00104
Iowa time trend 1	0.02235*	0.00068
Iowa time trend 2	0.01105*	0.00088
Iowa time trend 3	0.01686*	0.00105

*: significant at the .01 level

Time trend knots: 1980 and 1998

Table I-A17. Impact of Climate Change under the RCP4.5 Scenario Based on Models that Use Yearly Data

Model number	CCSM 4	GFDL-ESM2G	GFDL-ESM2M	Period of Season	Temperature Exposure Method[6]	Type of Time Trend[7]	Corn Belt Dummies	Remove 1950s and 1960s
1	-44.9%	-28.0%	-23.6%	March-August	1	1	No	No
2	-45.6%	-28.8%	-24.3%	March-August	1	1	No	Yes
3	-48.2%	-32.0%	-28.1%	March-August	1	1	Yes	No
4	-49.9%	-33.0%	-28.7%	March-August	1	1	Yes	Yes
5	-45.1%	-28.3%	-23.9%	March-August	1	2	No	No
6	-46.8%	-29.7%	-25.1%	March-August	1	2	No	Yes
7	-48.2%	-32.0%	-28.1%	March-August	1	2	Yes	No
8	-50.7%	-33.6%	-29.3%	March-August	1	2	Yes	Yes
9	-44.6%	-27.8%	-23.3%	March-August	2	1	No	No
10	-45.5%	-28.6%	-24.1%	March-August	2	1	No	Yes
11	-47.8%	-31.6%	-27.7%	March-August	2	1	Yes	No
12	-49.5%	-32.6%	-28.3%	March-August	2	1	Yes	Yes
13	-44.9%	-28.2%	-23.6%	March-August	2	2	No	No
14	-46.6%	-29.5%	-24.9%	March-August	2	2	No	Yes
15	-47.7%	-31.6%	-27.7%	March-August	2	2	Yes	No
16	-50.2%	-33.2%	-28.9%	March-August	2	2	Yes	Yes
17	-43.3%	-27.9%	-24.2%	March-September	1	1	No	No
18	-43.7%	-28.2%	-24.4%	March-September	1	1	No	Yes
19	-49.1%	-34.4%	-31.5%	March-September	1	1	Yes	No
20	-50.4%	-34.7%	-31.2%	March-September	1	1	Yes	Yes
21	-43.6%	-28.2%	-24.5%	March-September	1	2	No	No
22	-44.7%	-29.0%	-25.1%	March-September	1	2	No	Yes
23	-48.9%	-34.3%	-31.4%	March-September	1	2	Yes	No
24	-51.1%	-35.2%	-31.6%	March-September	1	2	Yes	Yes
25	-43.0%	-27.6%	-23.8%	March-September	2	1	No	No
26	-43.6%	-28.0%	-24.2%	March-September	2	1	No	Yes
27	-48.7%	-34.0%	-31.1%	March-September	2	1	Yes	No
28	-50.1%	-34.4%	-30.9%	March-September	2	1	Yes	Yes
29	-43.3%	-27.9%	-24.2%	March-September	2	2	No	No
30	-44.6%	-28.9%	-24.9%	March-September	2	2	No	Yes
31	-48.6%	-34.0%	-31.0%	March-September	2	2	Yes	No
32	-50.7%	-34.9%	-31.3%	March-September	2	2	Yes	Yes
33	-43.6%	-29.4%	-26.1%	March-October	1	1	No	No
34	-44.3%	-29.8%	-26.4%	March-October	1	1	No	Yes
35	-50.4%	-37.4%	-35.0%	March-October	1	1	Yes	No
36	-51.6%	-37.3%	-34.1%	March-October	1	1	Yes	Yes
37	-43.9%	-29.7%	-26.4%	March-October	1	2	No	No

[6] Method 1 uses a sinusoid with a domain of $[0, 2\pi]$, and method 2 uses a sinusoid with a domain of $[0, \pi]$.
[7] Type 1 is the quadratic time trend; type 2 is the two-knot time trend.

Table I-A17 (continued).

38	-45.3%	-30.6%	-27.0%	March-October	1	2	No	Yes
39	-50.3%	-37.3%	-34.8%	March-October	1	2	Yes	No
40	-52.2%	-37.7%	-34.4%	March-October	1	2	Yes	Yes
41	-43.3%	-29.1%	-25.7%	March-October	2	1	No	No
42	-44.1%	-29.7%	-26.1%	March-October	2	1	No	Yes
43	-50.1%	-37.0%	-34.6%	March-October	2	1	Yes	No
44	-51.3%	-37.0%	-33.8%	March-October	2	1	Yes	Yes
45	-43.6%	-29.4%	-26.0%	March-October	2	2	No	No
46	-45.1%	-30.4%	-26.7%	March-October	2	2	No	Yes
47	-50.0%	-36.9%	-34.4%	March-October	2	2	Yes	No
48	-51.9%	-37.4%	-34.1%	March-October	2	2	Yes	Yes
49	-41.0%	-24.8%	-17.9%	July-August	1	1	No	No
50	-41.3%	-25.1%	-18.1%	July-August	1	1	No	Yes
51	-42.5%	-25.4%	-18.2%	July-August	1	1	Yes	No
52	-43.5%	-26.1%	-18.7%	July-August	1	1	Yes	Yes
53	-40.6%	-24.4%	-17.6%	July-August	1	2	No	No
54	-42.3%	-25.9%	-18.7%	July-August	1	2	No	Yes
55	-41.8%	-24.8%	-17.7%	July-August	1	2	Yes	No
56	-44.5%	-26.9%	-19.4%	July-August	1	2	Yes	Yes
57	-40.8%	-24.7%	-17.7%	July-August	2	1	No	No
58	-41.1%	-25.0%	-17.9%	July-August	2	1	No	Yes
59	-42.3%	-25.2%	-18.0%	July-August	2	1	Yes	No
60	-43.2%	-25.9%	-18.4%	July-August	2	1	Yes	Yes
61	-40.4%	-24.3%	-17.3%	July-August	2	2	No	No
62	-42.2%	-25.8%	-18.5%	July-August	2	2	No	Yes
63	-41.6%	-24.6%	-17.4%	July-August	2	2	Yes	No
64	-44.3%	-26.7%	-19.1%	July-August	2	2	Yes	Yes
65	-37.6%	-22.5%	-16.4%	July-September	1	1	No	No
66	-37.7%	-22.6%	-16.4%	July-September	1	1	No	Yes
67	-41.4%	-25.3%	-19.0%	July-September	1	1	Yes	No
68	-42.6%	-26.0%	-19.4%	July-September	1	1	Yes	Yes
69	-37.1%	-22.0%	-15.9%	July-September	1	2	No	No
70	-38.8%	-23.4%	-17.2%	July-September	1	2	No	Yes
71	-40.4%	-24.3%	-18.1%	July-September	1	2	Yes	No
72	-43.7%	-26.9%	-20.3%	July-September	1	2	Yes	Yes
73	-37.4%	-22.3%	-16.2%	July-September	2	1	No	No
74	-37.6%	-22.5%	-16.2%	July-September	2	1	No	Yes
75	-41.2%	-25.0%	-18.7%	July-September	2	1	Yes	No
76	-42.4%	-25.7%	-19.1%	July-September	2	1	Yes	Yes
77	-36.9%	-21.8%	-15.6%	July-September	2	2	No	No
78	-38.7%	-23.3%	-17.0%	July-September	2	2	No	Yes
79	-40.2%	-24.0%	-17.8%	July-September	2	2	Yes	No
80	-43.5%	-26.6%	-20.0%	July-September	2	2	Yes	Yes
81	-36.4%	-22.4%	-17.0%	July-October	1	1	No	No
82	-36.6%	-22.5%	-16.9%	July-October	1	1	No	Yes
83	-40.4%	-26.0%	-20.9%	July-October	1	1	Yes	No

Table I-A17 (continued).

84	-41.5%	-26.5%	-21.0%	July-October	1	1	Yes	Yes
85	-35.9%	-21.9%	-16.5%	July-October	1	2	No	No
86	-37.8%	-23.5%	-17.8%	July-October	1	2	No	Yes
87	-39.3%	-25.0%	-19.9%	July-October	1	2	Yes	No
88	-42.7%	-27.5%	-21.9%	July-October	1	2	Yes	Yes
89	-36.1%	-22.1%	-16.6%	July-October	2	1	No	No
90	-36.5%	-22.4%	-16.6%	July-October	2	1	No	Yes
91	-39.9%	-25.6%	-20.4%	July-October	2	1	Yes	No
92	-41.1%	-26.1%	-20.6%	July-October	2	1	Yes	Yes
93	-35.6%	-21.6%	-16.1%	July-October	2	2	No	No
94	-37.7%	-23.4%	-17.6%	July-October	2	2	No	Yes
95	-38.8%	-24.5%	-19.5%	July-October	2	2	Yes	No
96	-42.3%	-27.1%	-21.5%	July-October	2	2	Yes	Yes

Table I-A18. Impact of Climate Change with Adaptation under the RCP4.5 Scenario Based on Models that Use Yearly Data

Model number	CCSM 4	GFDL-ESM2G	GFDL-ESM2M	Period of Season	Temperature Exposure Method[8]	Type of Time Trend[9]	Corn Belt Dummies	Remove 1950s and 1960s
49	-32.5%	-17.0%	-12.8%	July-August	1	1	No	No
50	-32.7%	-17.1%	-12.8%	July-August	1	1	No	Yes
51	-33.6%	-17.2%	-12.8%	July-August	1	1	Yes	No
52	-34.5%	-17.6%	-13.0%	July-August	1	1	Yes	Yes
53	-32.0%	-16.6%	-12.4%	July-August	1	2	No	No
54	-33.7%	-17.7%	-13.3%	July-August	1	2	No	Yes
55	-32.9%	-16.6%	-12.3%	July-August	1	2	Yes	No
56	-35.4%	-18.3%	-13.6%	July-August	1	2	Yes	Yes
57	-32.3%	-16.8%	-12.5%	July-August	2	1	No	No
58	-32.6%	-17.0%	-12.5%	July-August	2	1	No	Yes
59	-33.4%	-17.0%	-12.6%	July-August	2	1	Yes	No
60	-34.2%	-17.4%	-12.7%	July-August	2	1	Yes	Yes
61	-31.9%	-16.5%	-12.2%	July-August	2	2	No	No
62	-33.5%	-17.6%	-13.1%	July-August	2	2	No	Yes
63	-32.6%	-16.4%	-12.0%	July-August	2	2	Yes	No
64	-35.1%	-18.0%	-13.3%	July-August	2	2	Yes	Yes

[8] Method 1 uses a sinusoid with a domain of $[0, 2\pi]$, and method 2 uses a sinusoid with a domain of $[0, \pi]$.
[9] Type 1 is the quadratic time trend; type 2 is the two-knot time trend.

Table I-A19. Impact of Climate Change under the RCP8.5 Scenario Based on Models that Use Yearly Data

Model number	CCSM 4	GFDL-ESM2G	GFDL-ESM2M	Period of Season	Temperature Exposure Method[10]	Type of Time Trend[11]	Corn Belt Dummies	Remove 1950s and 1960s
1	-64.6%	-46.4%	-45.4%	March-August	1	1	No	No
2	-65.2%	-47.5%	-46.2%	March-August	1	1	No	Yes
3	-67.9%	-50.8%	-49.9%	March-August	1	1	Yes	No
4	-69.5%	-52.3%	-51.2%	March-August	1	1	Yes	Yes
5	-64.8%	-46.8%	-45.7%	March-August	1	2	No	No
6	-66.4%	-48.7%	-47.4%	March-August	1	2	No	Yes
7	-67.8%	-50.8%	-49.8%	March-August	1	2	Yes	No
8	-70.2%	-53.1%	-51.9%	March-August	1	2	Yes	Yes
9	-63.8%	-46.0%	-44.9%	March-August	2	1	No	No
10	-64.6%	-47.1%	-45.8%	March-August	2	1	No	Yes
11	-67.0%	-50.2%	-49.3%	March-August	2	1	Yes	No
12	-68.6%	-51.7%	-50.6%	March-August	2	1	Yes	Yes
13	-64.1%	-46.4%	-45.3%	March-August	2	2	No	No
14	-65.8%	-48.3%	-47.0%	March-August	2	2	No	Yes
15	-66.9%	-50.2%	-49.3%	March-August	2	2	Yes	No
16	-69.4%	-52.5%	-51.3%	March-August	2	2	Yes	Yes
17	-63.0%	-47.4%	-46.6%	March-September	1	1	No	No
18	-63.4%	-48.1%	-47.1%	March-September	1	1	No	Yes
19	-68.6%	-54.2%	-53.6%	March-September	1	1	Yes	No
20	-69.9%	-55.2%	-54.4%	March-September	1	1	Yes	Yes
21	-63.3%	-47.8%	-46.9%	March-September	1	2	No	No
22	-64.5%	-49.1%	-48.1%	March-September	1	2	No	Yes
23	-68.4%	-54.1%	-53.4%	March-September	1	2	Yes	No
24	-70.6%	-55.8%	-55.0%	March-September	1	2	Yes	Yes
25	-62.4%	-47.0%	-46.2%	March-September	2	1	No	No
26	-62.9%	-47.9%	-46.8%	March-September	2	1	No	Yes
27	-67.9%	-53.7%	-53.1%	March-September	2	1	Yes	No
28	-69.2%	-54.8%	-54.0%	March-September	2	1	Yes	Yes
29	-62.7%	-47.4%	-46.6%	March-September	2	2	No	No
30	-64.0%	-48.9%	-47.8%	March-September	2	2	No	Yes
31	-67.7%	-53.6%	-53.0%	March-September	2	2	Yes	No
32	-69.9%	-55.4%	-54.6%	March-September	2	2	Yes	Yes
33	-63.1%	-47.8%	-47.7%	March-October	1	1	No	No
34	-63.8%	-48.9%	-48.4%	March-October	1	1	No	Yes
35	-69.3%	-55.6%	-55.7%	March-October	1	1	Yes	No
36	-70.7%	-56.6%	-56.3%	March-October	1	1	Yes	Yes
37	-63.4%	-48.3%	-48.0%	March-October	1	2	No	No

[10] Method 1 uses a sinusoid with a domain of [0, 2π], and method 2 uses a sinusoid with a domain of [0, π].
[11] Type 1 is the quadratic time trend; type 2 is the two-knot time trend.

Table I-A19 (continued).

38	-64.8%	-49.8%	-49.3%	March-October	1	2	No	Yes
39	-69.2%	-55.6%	-55.6%	March-October	1	2	Yes	No
40	-71.3%	-57.1%	-56.8%	March-October	1	2	Yes	Yes
41	-62.4%	-47.4%	-47.2%	March-October	2	1	No	No
42	-63.2%	-48.6%	-48.1%	March-October	2	1	No	Yes
43	-68.7%	-55.1%	-55.3%	March-October	2	1	Yes	No
44	-70.0%	-56.2%	-55.9%	March-October	2	1	Yes	Yes
45	-62.7%	-47.8%	-47.6%	March-October	2	2	No	No
46	-64.3%	-49.6%	-49.1%	March-October	2	2	No	Yes
47	-68.5%	-55.1%	-55.1%	March-October	2	2	Yes	No
48	-70.6%	-56.7%	-56.4%	March-October	2	2	Yes	Yes
49	-56.9%	-41.5%	-40.1%	July-August	1	1	No	No
50	-56.9%	-42.1%	-40.6%	July-August	1	1	No	Yes
51	-58.6%	-42.7%	-41.4%	July-August	1	1	Yes	No
52	-59.6%	-43.9%	-42.5%	July-August	1	1	Yes	Yes
53	-56.4%	-41.0%	-39.6%	July-August	1	2	No	No
54	-58.2%	-43.2%	-41.6%	July-August	1	2	No	Yes
55	-57.8%	-41.9%	-40.6%	July-August	1	2	Yes	No
56	-60.8%	-44.9%	-43.5%	July-August	1	2	Yes	Yes
57	-56.0%	-41.0%	-39.5%	July-August	2	1	No	No
58	-56.0%	-41.6%	-40.0%	July-August	2	1	No	Yes
59	-57.8%	-42.1%	-40.7%	July-August	2	1	Yes	No
60	-58.6%	-43.2%	-41.7%	July-August	2	1	Yes	Yes
61	-55.5%	-40.5%	-39.1%	July-August	2	2	No	No
62	-57.4%	-42.7%	-41.1%	July-August	2	2	No	Yes
63	-56.9%	-41.3%	-39.9%	July-August	2	2	Yes	No
64	-59.8%	-44.2%	-42.8%	July-August	2	2	Yes	Yes
65	-54.5%	-41.2%	-39.9%	July-September	1	1	No	No
66	-54.3%	-41.5%	-40.2%	July-September	1	1	No	Yes
67	-59.1%	-45.0%	-43.9%	July-September	1	1	Yes	No
68	-60.4%	-46.4%	-45.2%	July-September	1	1	Yes	Yes
69	-53.8%	-40.6%	-39.3%	July-September	1	2	No	No
70	-55.7%	-42.6%	-41.3%	July-September	1	2	No	Yes
71	-58.0%	-43.9%	-42.8%	July-September	1	2	Yes	No
72	-61.6%	-47.5%	-46.3%	July-September	1	2	Yes	Yes
73	-53.7%	-40.6%	-39.4%	July-September	2	1	No	No
74	-53.7%	-41.2%	-39.8%	July-September	2	1	No	Yes
75	-58.4%	-44.5%	-43.3%	July-September	2	1	Yes	No
76	-59.6%	-45.9%	-44.6%	July-September	2	1	Yes	Yes
77	-53.1%	-40.0%	-38.8%	July-September	2	2	No	No
78	-55.0%	-42.2%	-40.9%	July-September	2	2	No	Yes
79	-57.3%	-43.4%	-42.2%	July-September	2	2	Yes	No
80	-60.9%	-47.0%	-45.7%	July-September	2	2	Yes	Yes
81	-53.2%	-40.3%	-39.4%	July-October	1	1	No	No
82	-53.4%	-40.9%	-39.9%	July-October	1	1	No	Yes
83	-57.9%	-44.7%	-44.0%	July-October	1	1	Yes	No

Table I-A19 (continued).

84	-59.2%	-46.0%	-45.2%	July-October	1	1	Yes	Yes
85	-52.7%	-39.8%	-39.0%	July-October	1	2	No	No
86	-54.8%	-42.0%	-41.1%	July-October	1	2	No	Yes
87	-56.8%	-43.6%	-42.9%	July-October	1	2	Yes	No
88	-60.5%	-47.1%	-46.4%	July-October	1	2	Yes	Yes
89	-52.4%	-39.6%	-38.8%	July-October	2	1	No	No
90	-52.8%	-40.4%	-39.4%	July-October	2	1	No	Yes
91	-56.9%	-43.9%	-43.2%	July-October	2	1	Yes	No
92	-58.3%	-45.3%	-44.5%	July-October	2	1	Yes	Yes
93	-51.8%	-39.1%	-38.3%	July-October	2	2	No	No
94	-54.2%	-41.6%	-40.6%	July-October	2	2	No	Yes
95	-55.8%	-42.8%	-42.0%	July-October	2	2	Yes	No
96	-59.6%	-46.4%	-45.7%	July-October	2	2	Yes	Yes

Table I-A20. Impact of Climate Change with Adaptation under the RCP8.5 Scenario Based on Models that Use Yearly Data

Model number	CCSM 4	GFDL-ESM2G	GFDL-ESM2M	Period of Season	Temperature Exposure Method[12]	Type of Time Trend[13]	Corn Belt Dummies	Remove 1950s and 1960s
49	-50.2%	-32.0%	-29.8%	July-August	1	1	No	No
50	-50.2%	-32.6%	-30.3%	July-August	1	1	No	Yes
51	-51.9%	-32.9%	-30.6%	July-August	1	1	Yes	No
52	-52.8%	-33.9%	-31.6%	July-August	1	1	Yes	Yes
53	-49.7%	-31.5%	-29.3%	July-August	1	2	No	No
54	-51.5%	-33.6%	-31.3%	July-August	1	2	No	Yes
55	-51.0%	-32.1%	-29.9%	July-August	1	2	Yes	No
56	-54.0%	-34.8%	-32.5%	July-August	1	2	Yes	Yes
57	-49.4%	-31.5%	-29.4%	July-August	2	1	No	No
58	-49.4%	-32.1%	-29.9%	July-August	2	1	No	Yes
59	-51.1%	-32.3%	-30.1%	July-August	2	1	Yes	No
60	-51.9%	-33.2%	-31.0%	July-August	2	1	Yes	Yes
61	-48.9%	-31.0%	-29.0%	July-August	2	2	No	No
62	-50.7%	-33.1%	-30.9%	July-August	2	2	No	Yes
63	-50.2%	-31.5%	-29.4%	July-August	2	2	Yes	No
64	-53.1%	-34.2%	-31.9%	July-August	2	2	Yes	Yes

[12] Method 1 uses a sinusoid with a domain of $[0, 2\pi]$, and method 2 uses a sinusoid with a domain of $[0, \pi]$.
[13] Type 1 is the quadratic time trend; type 2 is the two-knot time trend.

Table I-A21. Impact of Climate Change under the RCP4.5 Scenario Based on Models that Use Long-Term Average Data

Model number	CCSM4	GFDL-ESM2G	GFDL-ESM2M	Period of Season	Temperature Exposure Method[14]	Type of Time Trend[15]	Corn Belt Dummies	Remove 1950s and 1960s
97	-22.3%	-14.9%	-13.3%	March-August	1	1	No	No
98	-12.3%	-8.5%	-7.7%	March-August	1	1	No	Yes
99	-38.1%	-25.7%	-23.6%	March-August	1	1	Yes	No
100	-34.6%	-22.3%	-19.9%	March-August	1	1	Yes	Yes
101	-18.7%	-12.4%	-11.0%	March-August	1	2	No	No
102	-10.9%	-7.4%	-6.6%	March-August	1	2	No	Yes
103	-35.5%	-23.7%	-21.7%	March-August	1	2	Yes	No
104	-34.2%	-21.7%	-19.2%	March-August	1	2	Yes	Yes
105	-22.2%	-14.9%	-13.3%	March-August	2	1	No	No
106	-12.5%	-8.6%	-7.9%	March-August	2	1	No	Yes
107	-37.7%	-25.4%	-23.3%	March-August	2	1	Yes	No
108	-34.3%	-22.0%	-19.6%	March-August	2	1	Yes	Yes
109	-18.6%	-12.4%	-11.0%	March-August	2	2	No	No
110	-11.1%	-7.5%	-6.8%	March-August	2	2	No	Yes
111	-35.1%	-23.4%	-21.3%	March-August	2	2	Yes	No
112	-33.8%	-21.4%	-18.9%	March-August	2	2	Yes	Yes
113	-22.5%	-15.7%	-14.7%	March-September	1	1	No	No
114	-12.1%	-8.8%	-8.5%	March-September	1	1	No	Yes
115	-40.1%	-29.4%	-28.1%	March-September	1	1	Yes	No
116	-36.1%	-24.9%	-23.1%	March-September	1	1	Yes	Yes
117	-18.7%	-13.1%	-12.2%	March-September	1	2	No	No
118	-10.4%	-7.4%	-7.1%	March-September	1	2	No	Yes
119	-37.4%	-27.1%	-25.9%	March-September	1	2	Yes	No
120	-35.4%	-24.0%	-21.9%	March-September	1	2	Yes	Yes
121	-22.4%	-15.7%	-14.7%	March-September	2	1	No	No
122	-12.2%	-9.0%	-8.7%	March-September	2	1	No	Yes
123	-39.8%	-29.1%	-27.8%	March-September	2	1	Yes	No
124	-35.8%	-24.6%	-22.8%	March-September	2	1	Yes	Yes
125	-18.7%	-13.1%	-12.2%	March-September	2	2	No	No
126	-10.6%	-7.6%	-7.2%	March-September	2	2	No	Yes
127	-37.1%	-26.8%	-25.6%	March-September	2	2	Yes	No
128	-35.1%	-23.7%	-21.5%	March-September	2	2	Yes	Yes
129	-23.7%	-17.3%	-16.2%	March-October	1	1	No	No
130	-12.7%	-9.8%	-9.5%	March-October	1	1	No	Yes
131	-42.5%	-32.9%	-32.0%	March-October	1	1	Yes	No
132	-37.4%	-27.3%	-25.7%	March-October	1	1	Yes	Yes
133	-19.8%	-14.4%	-13.6%	March-October	1	2	No	No

[14] Method 1 uses a sinusoid with a domain of $[0, 2\pi]$, and method 2 uses a sinusoid with a domain of $[0, \pi]$.
[15] Type 1 is the quadratic time trend; type 2 is the two-knot time trend.

Table I-A21 (continued).

134	-10.8%	-8.1%	-7.8%	March-October	1	2	No	Yes
135	-39.5%	-30.4%	-29.6%	March-October	1	2	Yes	No
136	-36.4%	-25.9%	-24.1%	March-October	1	2	Yes	Yes
137	-23.7%	-17.3%	-16.2%	March-October	2	1	No	No
138	-12.9%	-9.9%	-9.6%	March-October	2	1	No	Yes
139	-42.3%	-32.7%	-31.7%	March-October	2	1	Yes	No
140	-37.2%	-27.0%	-25.4%	March-October	2	1	Yes	Yes
141	-19.8%	-14.4%	-13.6%	March-October	2	2	No	No
142	-10.9%	-8.2%	-7.8%	March-October	2	2	No	Yes
143	-39.3%	-30.2%	-29.3%	March-October	2	2	Yes	No
144	-36.1%	-25.7%	-23.7%	March-October	2	2	Yes	Yes
145	-21.3%	-12.4%	-8.5%	July-August	1	1	No	No
146	-11.5%	-6.2%	-3.5%	July-August	1	1	No	Yes
147	-34.1%	-19.4%	-13.8%	July-August	1	1	Yes	No
148	-29.9%	-16.5%	-11.4%	July-August	1	1	Yes	Yes
149	-17.5%	-9.8%	-6.4%	July-August	1	2	No	No
150	-10.9%	-5.8%	-3.3%	July-August	1	2	No	Yes
151	-31.6%	-17.6%	-12.3%	July-August	1	2	Yes	No
152	-30.4%	-16.8%	-11.8%	July-August	1	2	Yes	Yes
153	-21.3%	-12.4%	-8.4%	July-August	2	1	No	No
154	-11.6%	-6.2%	-3.5%	July-August	2	1	No	Yes
155	-34.1%	-19.4%	-13.7%	July-August	2	1	Yes	No
156	-29.8%	-16.4%	-11.3%	July-August	2	1	Yes	Yes
157	-17.5%	-9.8%	-6.3%	July-August	2	2	No	No
158	-11.0%	-5.9%	-3.2%	July-August	2	2	No	Yes
159	-31.4%	-17.4%	-12.1%	July-August	2	2	Yes	No
160	-30.2%	-16.7%	-11.6%	July-August	2	2	Yes	Yes
161	-19.4%	-11.4%	-8.5%	July-September	1	1	No	No
162	-7.5%	-3.3%	-1.8%	July-September	1	1	No	Yes
163	-33.7%	-20.1%	-15.4%	July-September	1	1	Yes	No
164	-29.1%	-16.4%	-12.2%	July-September	1	1	Yes	Yes
165	-14.7%	-8.0%	-5.6%	July-September	1	2	No	No
166	-6.8%	-2.8%	-1.5%	July-September	1	2	No	Yes
167	-30.2%	-17.3%	-13.0%	July-September	1	2	Yes	No
168	-29.6%	-16.9%	-12.7%	July-September	1	2	Yes	Yes
169	-19.4%	-11.4%	-8.4%	July-September	2	1	No	No
170	-7.7%	-3.4%	-1.9%	July-September	2	1	No	Yes
171	-33.7%	-20.0%	-15.3%	July-September	2	1	Yes	No
172	-29.1%	-16.3%	-12.1%	July-September	2	1	Yes	Yes
173	-14.8%	-8.1%	-5.6%	July-September	2	2	No	No
174	-7.0%	-3.0%	-1.6%	July-September	2	2	No	Yes
175	-30.3%	-17.3%	-12.9%	July-September	2	2	Yes	No
176	-29.5%	-16.7%	-12.5%	July-September	2	2	Yes	Yes
177	-19.8%	-12.4%	-9.8%	July-October	1	1	No	No
178	-6.9%	-3.4%	-2.6%	July-October	1	1	No	Yes
179	-34.0%	-21.8%	-18.1%	July-October	1	1	Yes	No

Table I-A21 (continued).

180	-28.3%	-17.0%	-13.9%	July-October	1	1	Yes	Yes
181	-14.7%	-8.6%	-6.6%	July-October	1	2	No	No
182	-6.1%	-2.9%	-2.2%	July-October	1	2	No	Yes
183	-30.0%	-18.6%	-15.3%	July-October	1	2	Yes	No
184	-28.9%	-17.7%	-14.6%	July-October	1	2	Yes	Yes
185	-19.9%	-12.4%	-9.8%	July-October	2	1	No	No
186	-7.1%	-3.5%	-2.6%	July-October	2	1	No	Yes
187	-33.8%	-21.6%	-17.8%	July-October	2	1	Yes	No
188	-28.1%	-16.9%	-13.7%	July-October	2	1	Yes	Yes
189	-14.8%	-8.6%	-6.6%	July-October	2	2	No	No
190	-6.3%	-3.0%	-2.3%	July-October	2	2	No	Yes
191	-29.9%	-18.4%	-15.1%	July-October	2	2	Yes	No
192	-28.7%	-17.4%	-14.3%	July-October	2	2	Yes	Yes

Table I-A22. Impact of Climate Change with Adaptation under the RCP4.5 Scenario Based on Models that Use Long-Term Average Data

Model number	CCSM 4	GFDL-ESM2G	GFDL-ESM2M	Period of Season	Temperature Exposure Method[16]	Type of Time Trend[17]	Corn Belt Dummies	Remove 1950s and 1960s
145	-16.2%	-8.0%	-5.8%	July-August	1	1	No	No
146	-8.0%	-3.2%	-1.7%	July-August	1	1	No	Yes
147	-26.8%	-12.8%	-9.3%	July-August	1	1	Yes	No
148	-23.3%	-10.4%	-7.3%	July-August	1	1	Yes	Yes
149	-12.9%	-6.0%	-4.1%	July-August	1	2	No	No
150	-7.5%	-2.9%	-1.5%	July-August	1	2	No	Yes
151	-24.6%	-11.3%	-8.1%	July-August	1	2	Yes	No
152	-23.9%	-10.8%	-7.7%	July-August	1	2	Yes	Yes
153	-16.2%	-7.9%	-5.6%	July-August	2	1	No	No
154	-8.1%	-3.2%	-1.6%	July-August	2	1	No	Yes
155	-26.8%	-12.7%	-9.2%	July-August	2	1	Yes	No
156	-23.2%	-10.3%	-7.1%	July-August	2	1	Yes	Yes
157	-12.9%	-6.0%	-4.0%	July-August	2	2	No	No
158	-7.7%	-2.9%	-1.4%	July-August	2	2	No	Yes
159	-24.5%	-11.2%	-7.9%	July-August	2	2	Yes	No
160	-23.7%	-10.7%	-7.4%	July-August	2	2	Yes	Yes

[16] Method 1 uses a sinusoid with a domain of $[0, 2\pi]$, and method 2 uses a sinusoid with a domain of $[0, \pi]$.
[17] Type 1 is the quadratic time trend; type 2 is the two-knot time trend.

Table I-A23. Impact of Climate Change under the RCP8.5 Scenario Based on Models that Use Long-Term Average Data

Model number	CCSM 4	GFDL-ESM2G	GFDL-ESM2M	Period of Season	Temperature Exposure Method[18]	Type of Time Trend[19]	Corn Belt Dummies	Remove 1950s and 1960s
97	-34.2%	-25.7%	-24.3%	March-August	1	1	No	No
98	-19.6%	-14.5%	-13.9%	March-August	1	1	No	Yes
99	-54.0%	-41.3%	-40.6%	March-August	1	1	Yes	No
100	-48.6%	-36.0%	-35.7%	March-August	1	1	Yes	Yes
101	-29.2%	-21.5%	-20.4%	March-August	1	2	No	No
102	-17.5%	-12.7%	-12.2%	March-August	1	2	No	Yes
103	-50.8%	-38.4%	-37.8%	March-August	1	2	Yes	No
104	-47.8%	-35.1%	-34.9%	March-August	1	2	Yes	Yes
105	-33.7%	-25.4%	-24.0%	March-August	2	1	No	No
106	-19.5%	-14.7%	-14.0%	March-August	2	1	No	Yes
107	-53.2%	-40.8%	-40.0%	March-August	2	1	Yes	No
108	-47.9%	-35.5%	-35.2%	March-August	2	1	Yes	Yes
109	-28.8%	-21.4%	-20.2%	March-August	2	2	No	No
110	-17.4%	-12.9%	-12.3%	March-August	2	2	No	Yes
111	-50.0%	-37.9%	-37.2%	March-August	2	2	Yes	No
112	-47.1%	-34.7%	-34.4%	March-August	2	2	Yes	Yes
113	-34.2%	-27.1%	-25.9%	March-September	1	1	No	No
114	-18.8%	-14.9%	-14.3%	March-September	1	1	No	Yes
115	-55.7%	-45.6%	-45.1%	March-September	1	1	Yes	No
116	-49.8%	-39.4%	-39.3%	March-September	1	1	Yes	Yes
117	-29.0%	-22.7%	-21.7%	March-September	1	2	No	No
118	-16.4%	-12.8%	-12.3%	March-September	1	2	No	Yes
119	-52.4%	-42.5%	-42.1%	March-September	1	2	Yes	No
120	-48.8%	-38.3%	-38.2%	March-September	1	2	Yes	Yes
121	-33.8%	-26.9%	-25.6%	March-September	2	1	No	No
122	-18.8%	-15.1%	-14.5%	March-September	2	1	No	Yes
123	-55.1%	-45.2%	-44.6%	March-September	2	1	Yes	No
124	-49.2%	-39.1%	-38.9%	March-September	2	1	Yes	Yes
125	-28.7%	-22.6%	-21.6%	March-September	2	2	No	No
126	-16.5%	-13.0%	-12.4%	March-September	2	2	No	Yes
127	-51.7%	-42.1%	-41.6%	March-September	2	2	Yes	No
128	-48.2%	-37.9%	-37.8%	March-September	2	2	Yes	Yes
129	-35.5%	-28.5%	-27.5%	March-October	1	1	No	No
130	-19.5%	-15.4%	-15.2%	March-October	1	1	No	Yes
131	-57.6%	-48.1%	-48.2%	March-October	1	1	Yes	No
132	-50.7%	-40.9%	-41.2%	March-October	1	1	Yes	Yes
133	-30.2%	-23.9%	-23.2%	March-October	1	2	No	No

[18] Method 1 uses a sinusoid with a domain of $[0, 2\pi]$, and method 2 uses a sinusoid with a domain of $[0, \pi]$.
[19] Type 1 is the quadratic time trend; type 2 is the two-knot time trend.

Table I-A23 (continued).

134	-16.7%	-12.9%	-12.8%	March-October	1	2	No	Yes
135	-54.1%	-44.8%	-45.0%	March-October	1	2	Yes	No
136	-49.4%	-39.4%	-39.8%	March-October	1	2	Yes	Yes
137	-35.1%	-28.3%	-27.3%	March-October	2	1	No	No
138	-19.5%	-15.6%	-15.3%	March-October	2	1	No	Yes
139	-57.1%	-47.7%	-47.8%	March-October	2	1	Yes	No
140	-50.3%	-40.6%	-40.9%	March-October	2	1	Yes	Yes
141	-29.8%	-23.8%	-23.0%	March-October	2	2	No	No
142	-16.7%	-13.1%	-12.9%	March-October	2	2	No	Yes
143	-53.6%	-44.4%	-44.6%	March-October	2	2	Yes	No
144	-48.9%	-39.1%	-39.4%	March-October	2	2	Yes	Yes
145	-31.2%	-22.5%	-21.3%	July-August	1	1	No	No
146	-16.5%	-12.0%	-11.1%	July-August	1	1	No	Yes
147	-47.2%	-33.8%	-32.9%	July-August	1	1	Yes	No
148	-40.8%	-28.9%	-28.2%	July-August	1	1	Yes	Yes
149	-25.7%	-18.2%	-17.2%	July-August	1	2	No	No
150	-15.6%	-11.3%	-10.5%	July-August	1	2	No	Yes
151	-43.8%	-30.9%	-30.1%	July-August	1	2	Yes	No
152	-41.3%	-29.3%	-28.7%	July-August	1	2	Yes	Yes
153	-30.6%	-22.2%	-21.0%	July-August	2	1	No	No
154	-16.3%	-11.9%	-11.0%	July-August	2	1	No	Yes
155	-46.6%	-33.4%	-32.4%	July-August	2	1	Yes	No
156	-40.2%	-28.4%	-27.7%	July-August	2	1	Yes	Yes
157	-25.2%	-18.0%	-16.9%	July-August	2	2	No	No
158	-15.4%	-11.3%	-10.5%	July-August	2	2	No	Yes
159	-43.1%	-30.4%	-29.6%	July-August	2	2	Yes	No
160	-40.6%	-28.8%	-28.2%	July-August	2	2	Yes	Yes
161	-29.6%	-22.5%	-21.4%	July-September	1	1	No	No
162	-12.4%	-8.9%	-8.3%	July-September	1	1	No	Yes
163	-48.2%	-36.7%	-35.8%	July-September	1	1	Yes	No
164	-41.4%	-30.8%	-30.4%	July-September	1	1	Yes	Yes
165	-23.2%	-17.1%	-16.2%	July-September	1	2	No	No
166	-11.3%	-8.1%	-7.5%	July-September	1	2	No	Yes
167	-43.8%	-32.7%	-32.0%	July-September	1	2	Yes	No
168	-41.7%	-31.2%	-30.8%	July-September	1	2	Yes	Yes
169	-29.2%	-22.3%	-21.1%	July-September	2	1	No	No
170	-12.4%	-9.1%	-8.4%	July-September	2	1	No	Yes
171	-47.8%	-36.4%	-35.5%	July-September	2	1	Yes	No
172	-41.0%	-30.6%	-30.1%	July-September	2	1	Yes	Yes
173	-22.9%	-17.0%	-16.0%	July-September	2	2	No	No
174	-11.4%	-8.3%	-7.6%	July-September	2	2	No	Yes
175	-43.4%	-32.5%	-31.7%	July-September	2	2	Yes	No
176	-41.3%	-30.9%	-30.5%	July-September	2	2	Yes	Yes
177	-30.4%	-23.4%	-22.4%	July-October	1	1	No	No
178	-12.1%	-8.4%	-8.0%	July-October	1	1	No	Yes
179	-48.5%	-37.6%	-37.1%	July-October	1	1	Yes	No

Table I-A23 (continued).

180	-40.7%	-30.6%	-30.5%	July-October	1	1	Yes	Yes
181	-23.5%	-17.5%	-16.7%	July-October	1	2	No	No
182	-10.9%	-7.4%	-7.1%	July-October	1	2	No	Yes
183	-43.7%	-33.3%	-32.9%	July-October	1	2	Yes	No
184	-41.0%	-31.0%	-31.0%	July-October	1	2	Yes	Yes
185	-30.0%	-23.2%	-22.2%	July-October	2	1	No	No
186	-12.1%	-8.5%	-8.1%	July-October	2	1	No	Yes
187	-47.9%	-37.1%	-36.6%	July-October	2	1	Yes	No
188	-40.1%	-30.2%	-30.1%	July-October	2	1	Yes	Yes
189	-23.2%	-17.4%	-16.6%	July-October	2	2	No	No
190	-10.9%	-7.5%	-7.1%	July-October	2	2	No	Yes
191	-43.1%	-32.8%	-32.4%	July-October	2	2	Yes	No
192	-40.5%	-30.6%	-30.6%	July-October	2	2	Yes	Yes

Table I-A24. Impact of Climate Change with Adaptation under the RCP8.5 Scenario Based on Models that Use Long-Term Average Data

Model number	CCSM4	GFDL-ESM2G	GFDL-ESM2M	Period of Season	Temperature Exposure Method[20]	Type of Time Trend[21]	Corn Belt Dummies	Remove 1950s and 1960s
145	-26.6%	-16.9%	-15.6%	July-August	1	1	No	No
146	-13.6%	-8.3%	-7.5%	July-August	1	1	No	Yes
147	-41.6%	-25.7%	-23.9%	July-August	1	1	Yes	No
148	-36.1%	-21.6%	-20.0%	July-August	1	1	Yes	Yes
149	-21.6%	-13.3%	-12.2%	July-August	1	2	No	No
150	-12.8%	-7.9%	-7.1%	July-August	1	2	No	Yes
151	-38.5%	-23.1%	-21.5%	July-August	1	2	Yes	No
152	-36.6%	-22.1%	-20.5%	July-August	1	2	Yes	Yes
153	-26.2%	-16.7%	-15.4%	July-August	2	1	No	No
154	-13.4%	-8.3%	-7.5%	July-August	2	1	No	Yes
155	-41.2%	-25.3%	-23.6%	July-August	2	1	Yes	No
156	-35.5%	-21.3%	-19.7%	July-August	2	1	Yes	Yes
157	-21.3%	-13.1%	-12.0%	July-August	2	2	No	No
158	-12.7%	-7.8%	-7.0%	July-August	2	2	No	Yes
159	-37.9%	-22.7%	-21.1%	July-August	2	2	Yes	No
160	-36.0%	-21.7%	-20.1%	July-August	2	2	Yes	Yes

[20] Method 1 uses a sinusoid with a domain of $[0, 2\pi]$, and method 2 uses a sinusoid with a domain of $[0, \pi]$.
[21] Type 1 is the quadratic time trend; type 2 is the two-knot time trend.

4. Figures for Chapter I

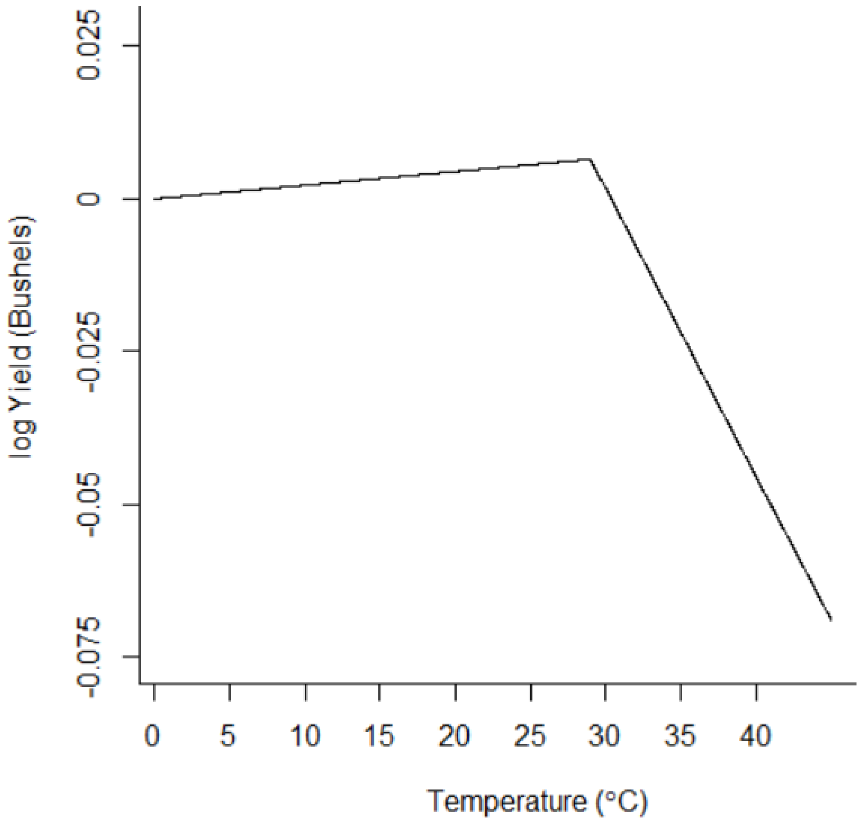


Figure I-1. Effect of Temperature on Log Yield in the Base Model (using 1950-2005 Data)

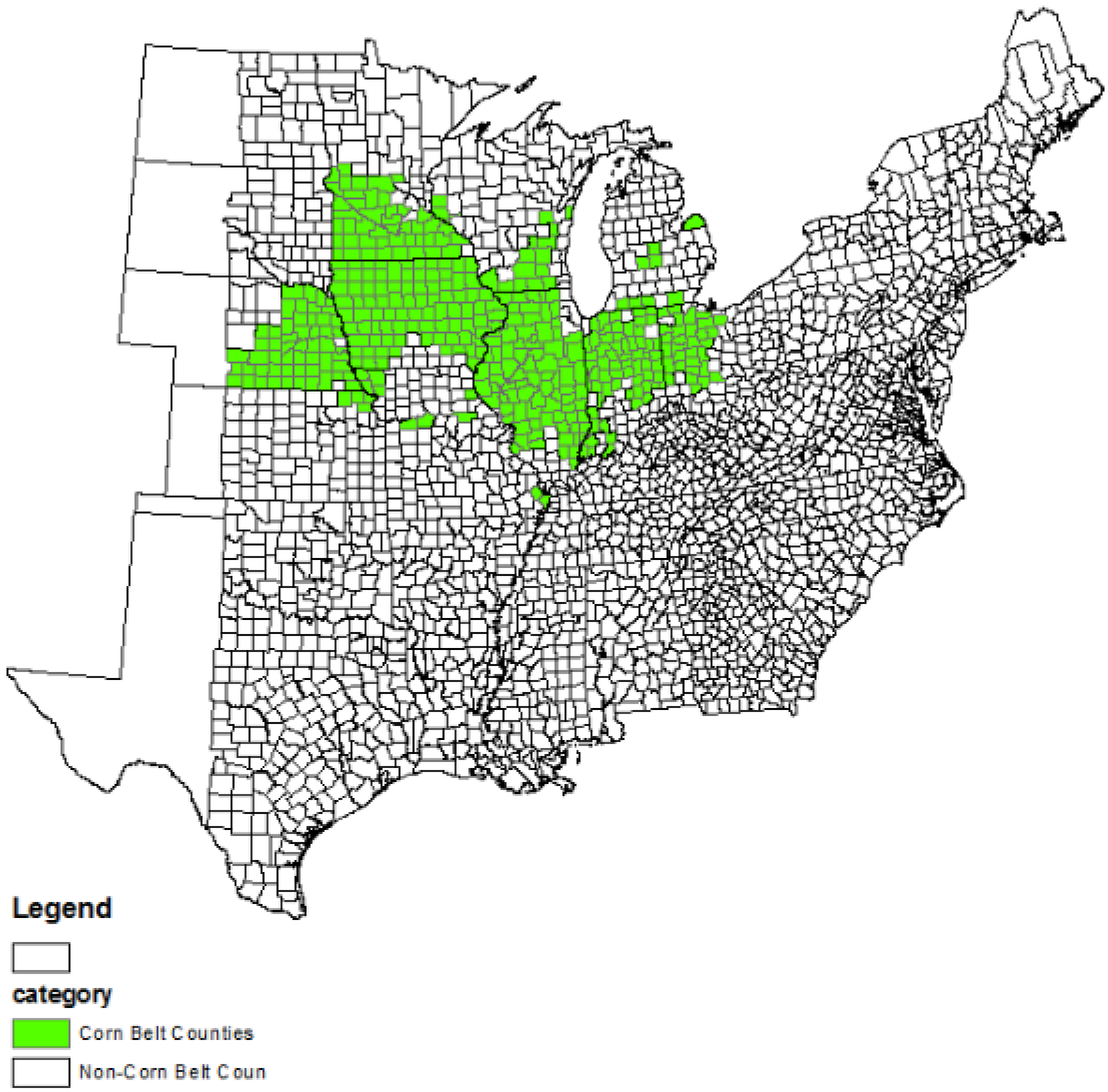
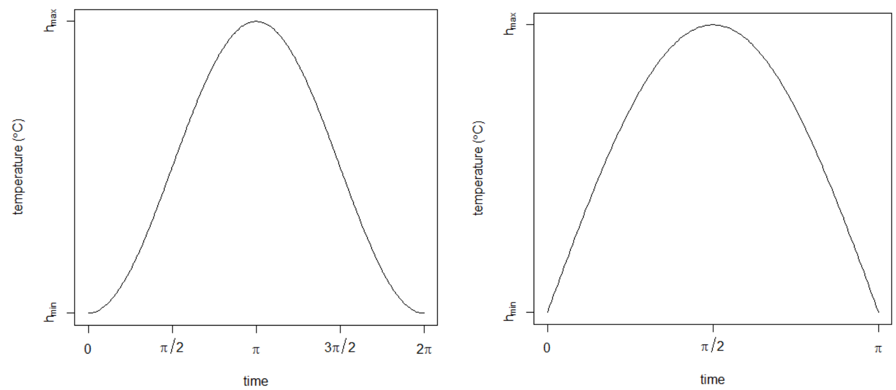


Figure I-2. Corn Belt Region in the United States



Left: $h = \frac{h_{max}+h_{min}}{2} - \frac{h_{max}-h_{min}}{2}\cos(s)$

Right: $h = h_{min} + (h_{max} - h_{min})\sin(s)$

Figure I-3. Two Methods of Calculating Temperature Exposure Times

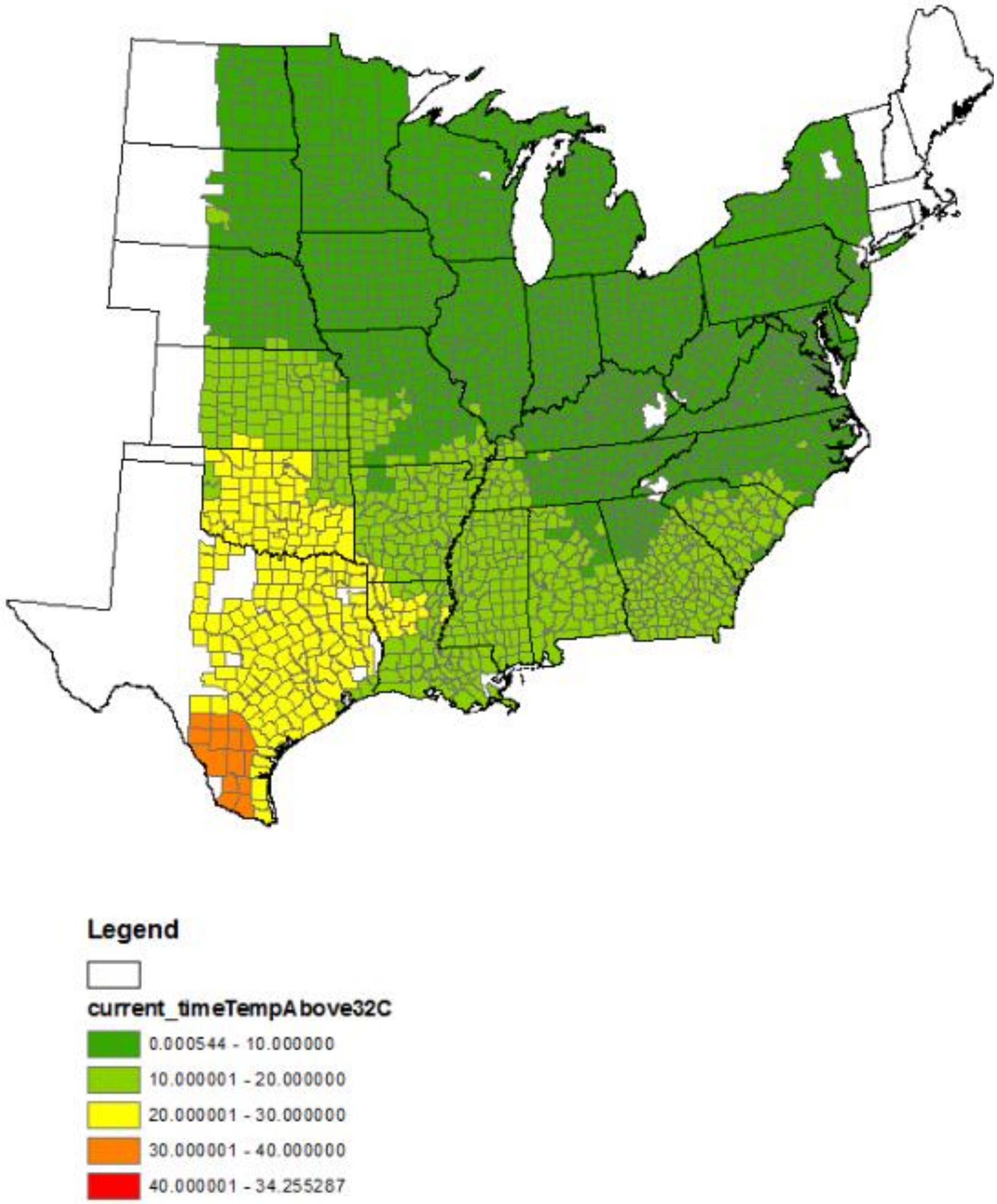


Figure I-4. Average Time with Temperature above 32°C in July-August under the Current Climate

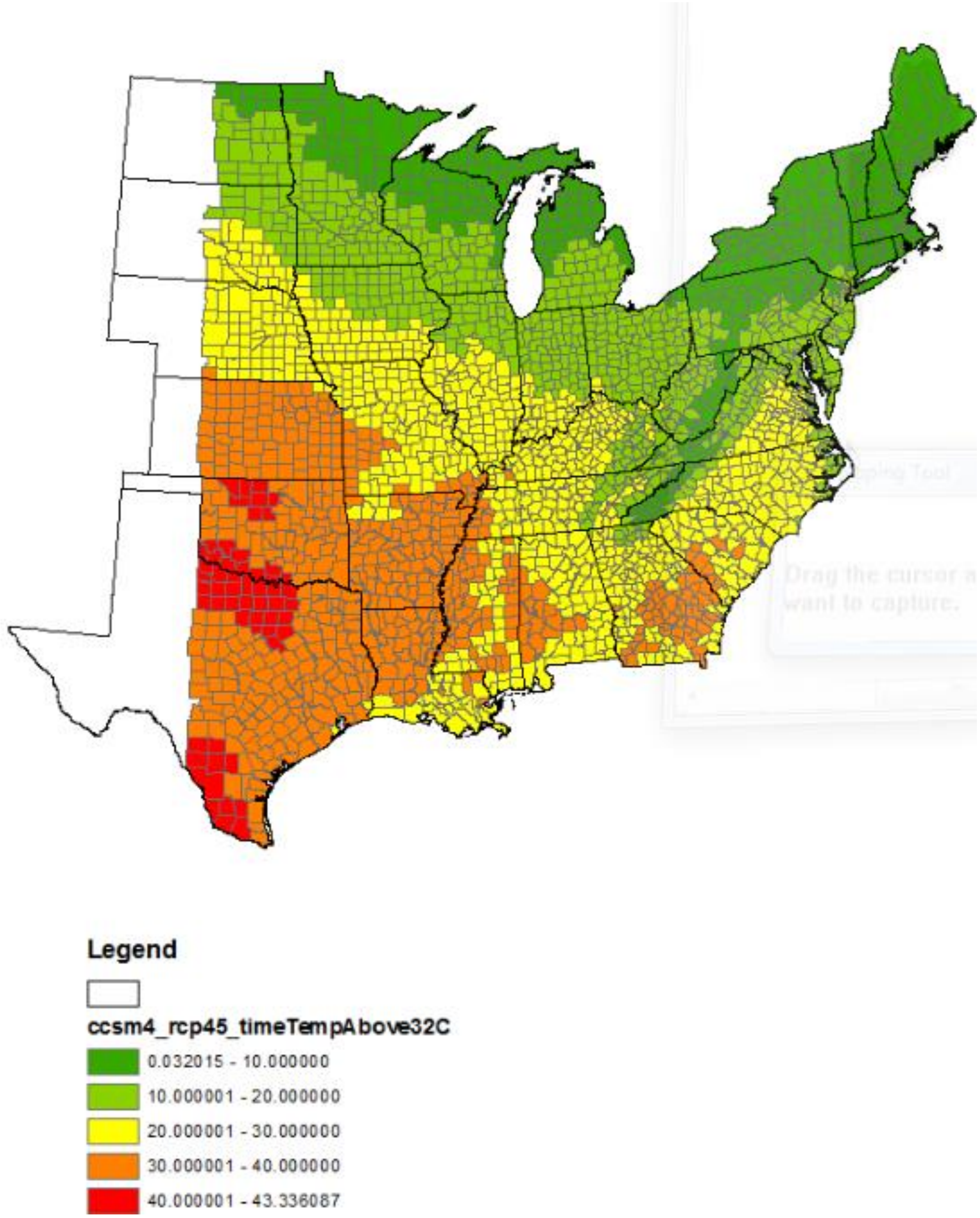


Figure I-5. Average Time with Temperature above 32°C in July-August under the RCP4.5 Scenario of the CCSM4 Climate Model

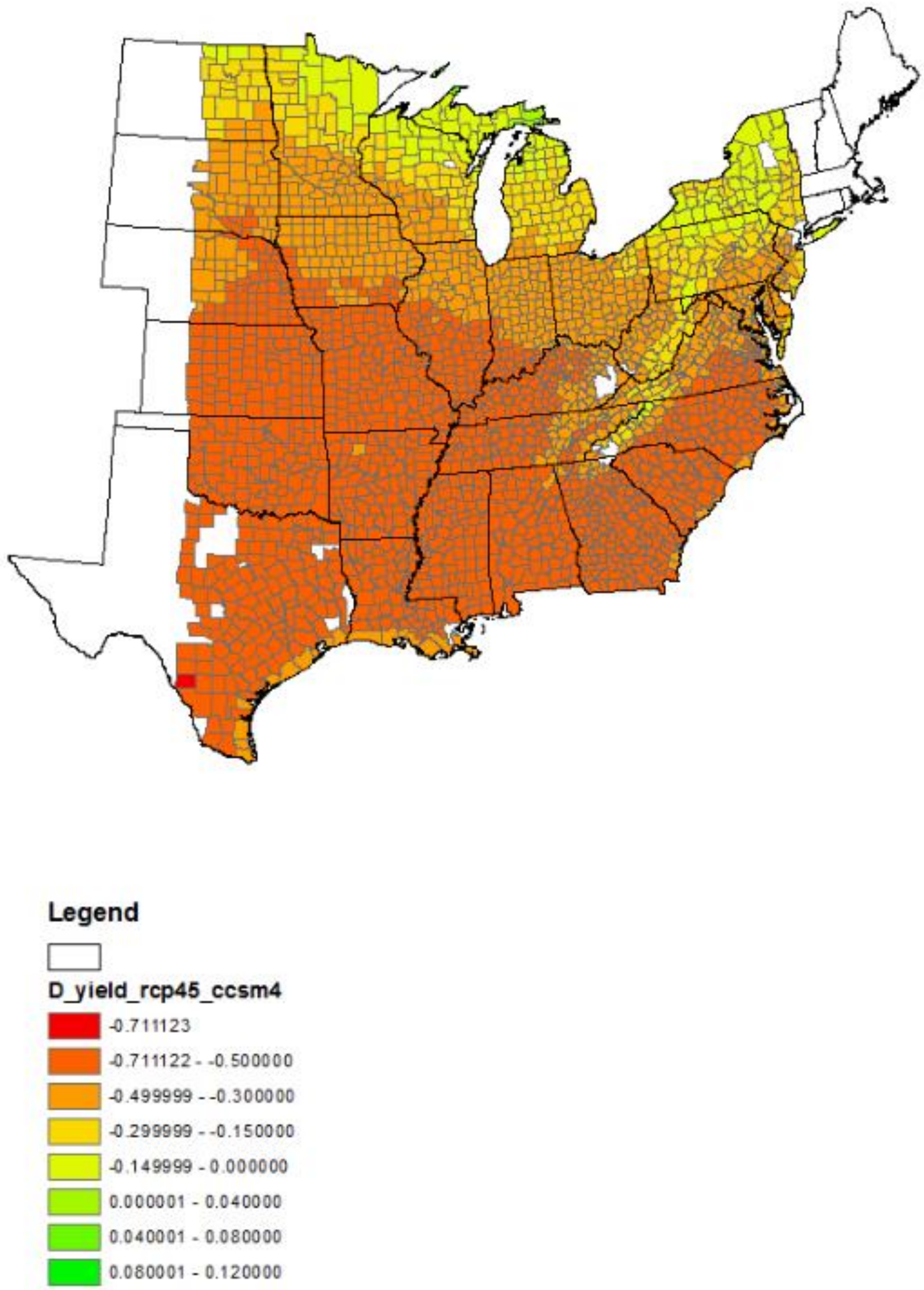


Figure I-6. Using the Base Model to Predict Corn Yield Changes under the RCP4.5 Scenario of the CCSM4 Climate Model

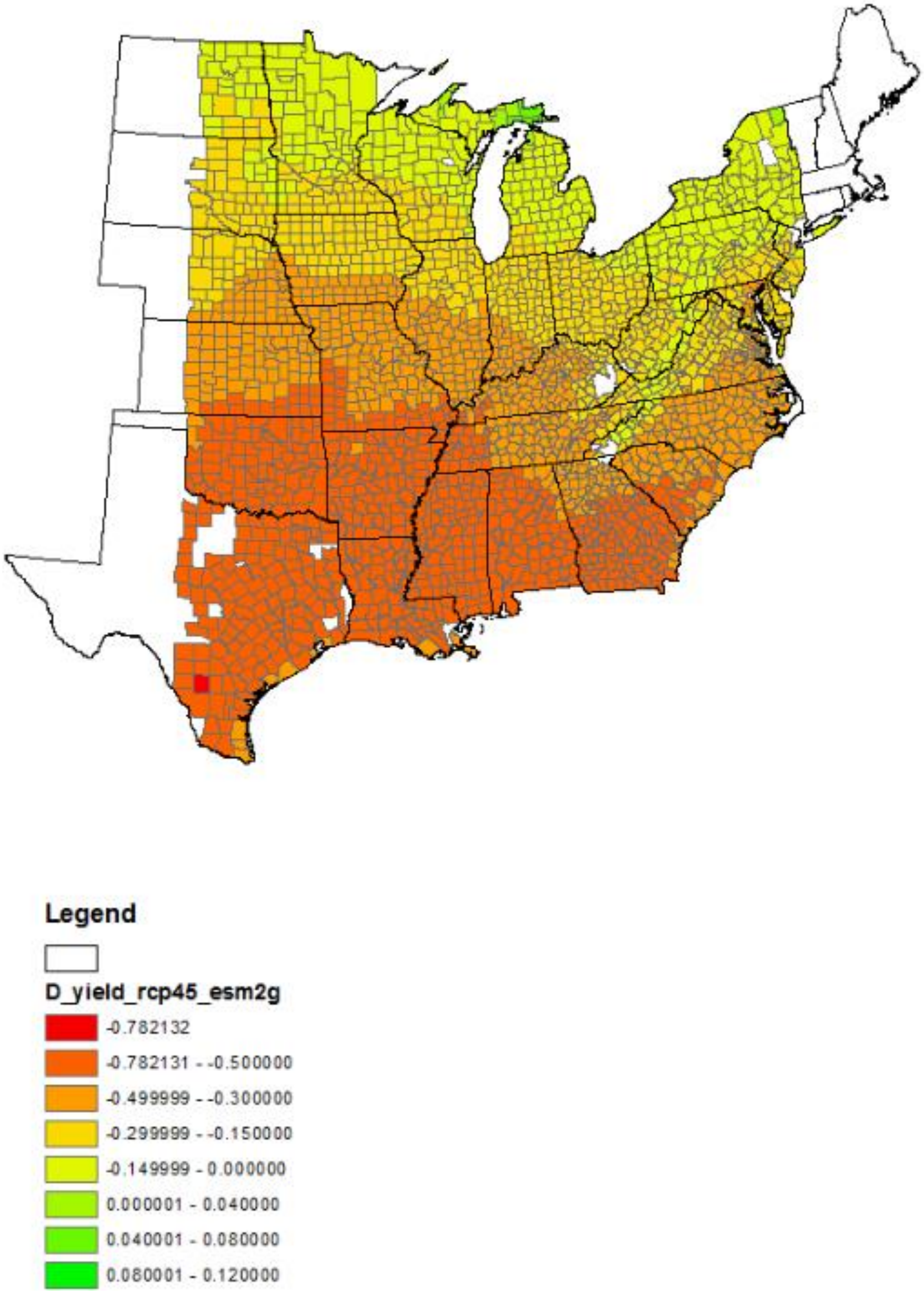


Figure I-7. Using the Base Model to Predict Corn Yield Changes under the RCP4.5 Scenario of the GFDL-ESM2G Climate Model

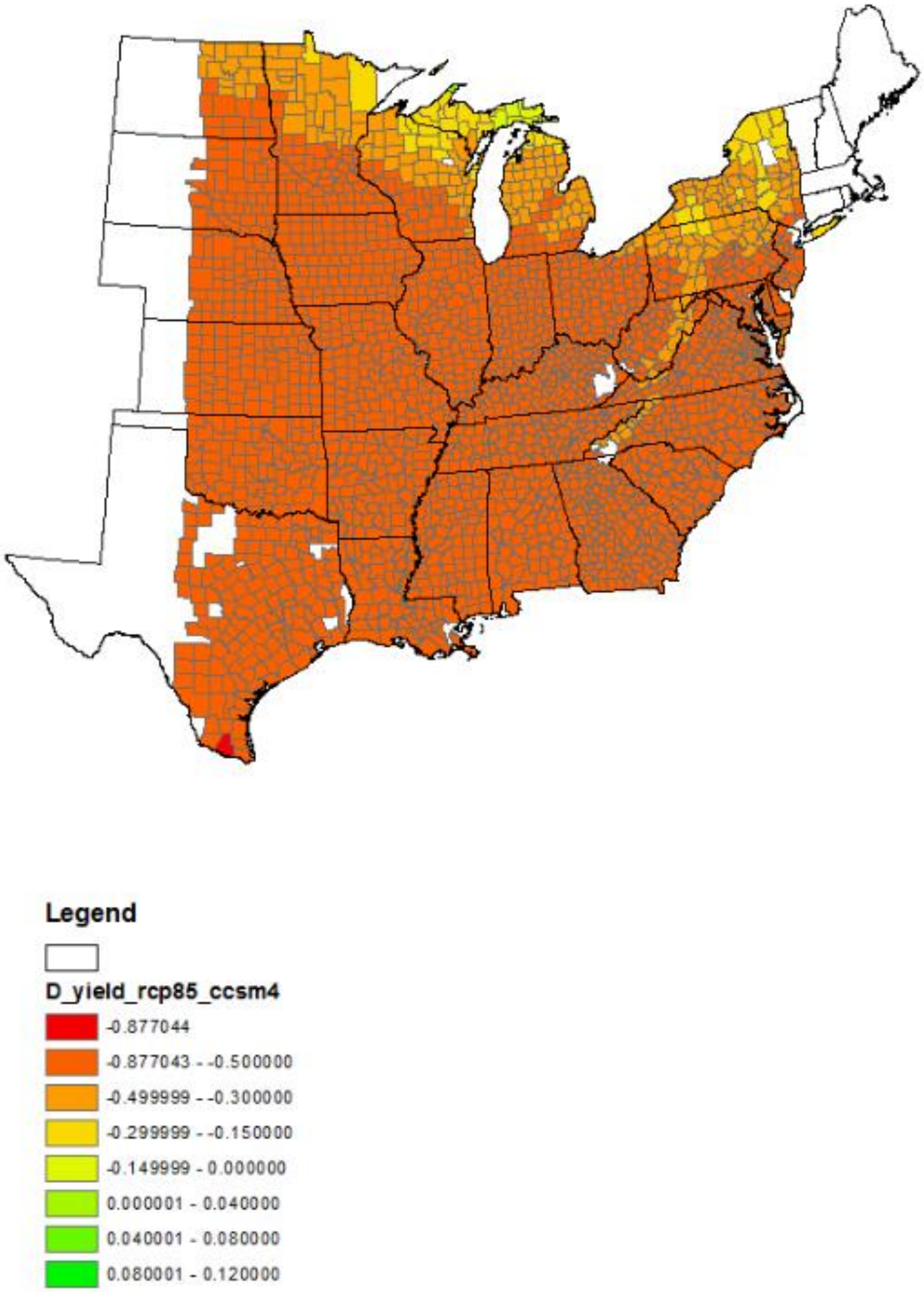


Figure I-8. Using the Base Model to Predict Corn Yield Changes under the RCP8.5 Scenario of the CCSM4 Climate Model

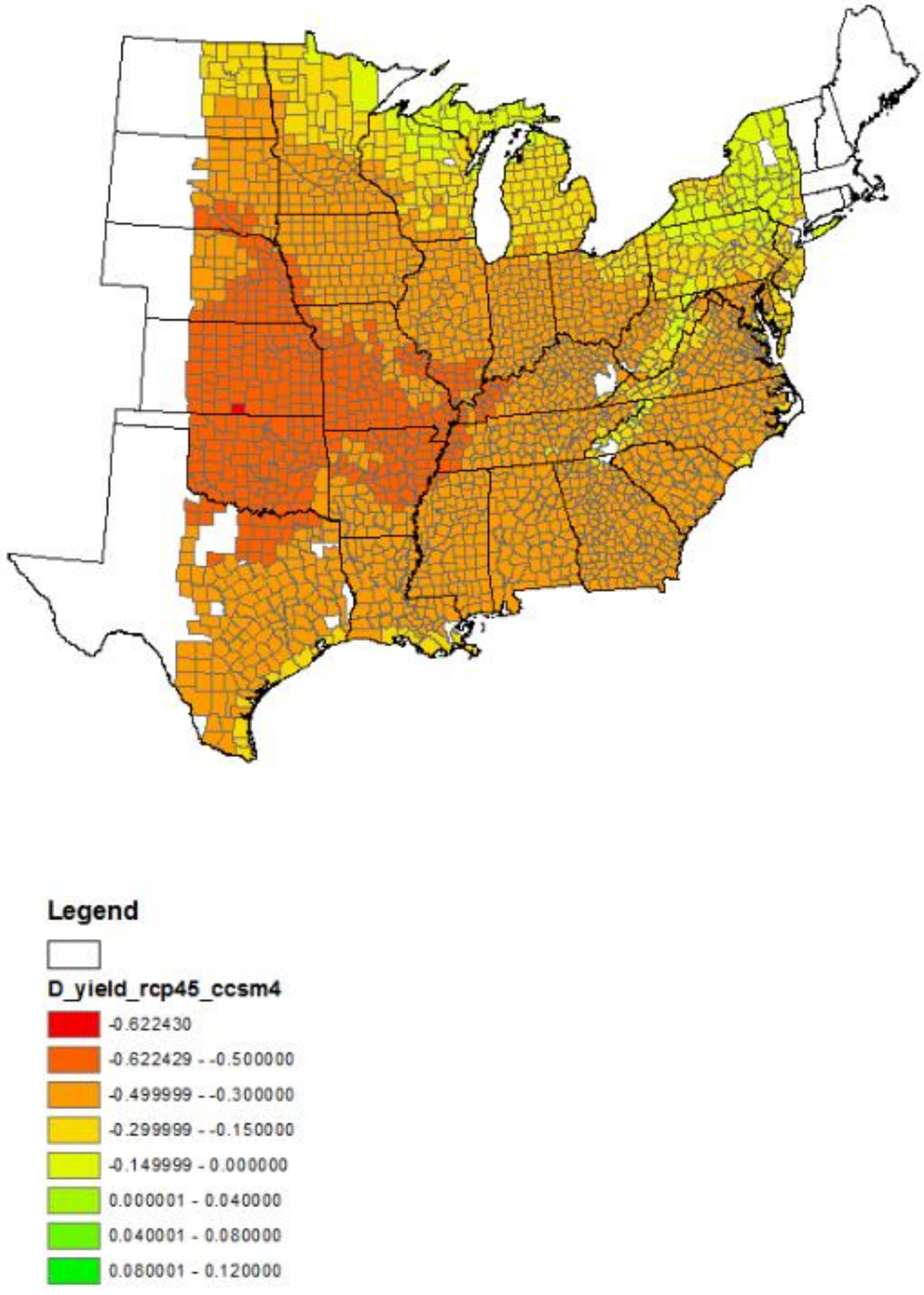


Figure I-9. Using the Model that Uses July-August Data to Predict Corn Yield Changes under the RCP4.5 Scenario of the CCSM4 Climate Model

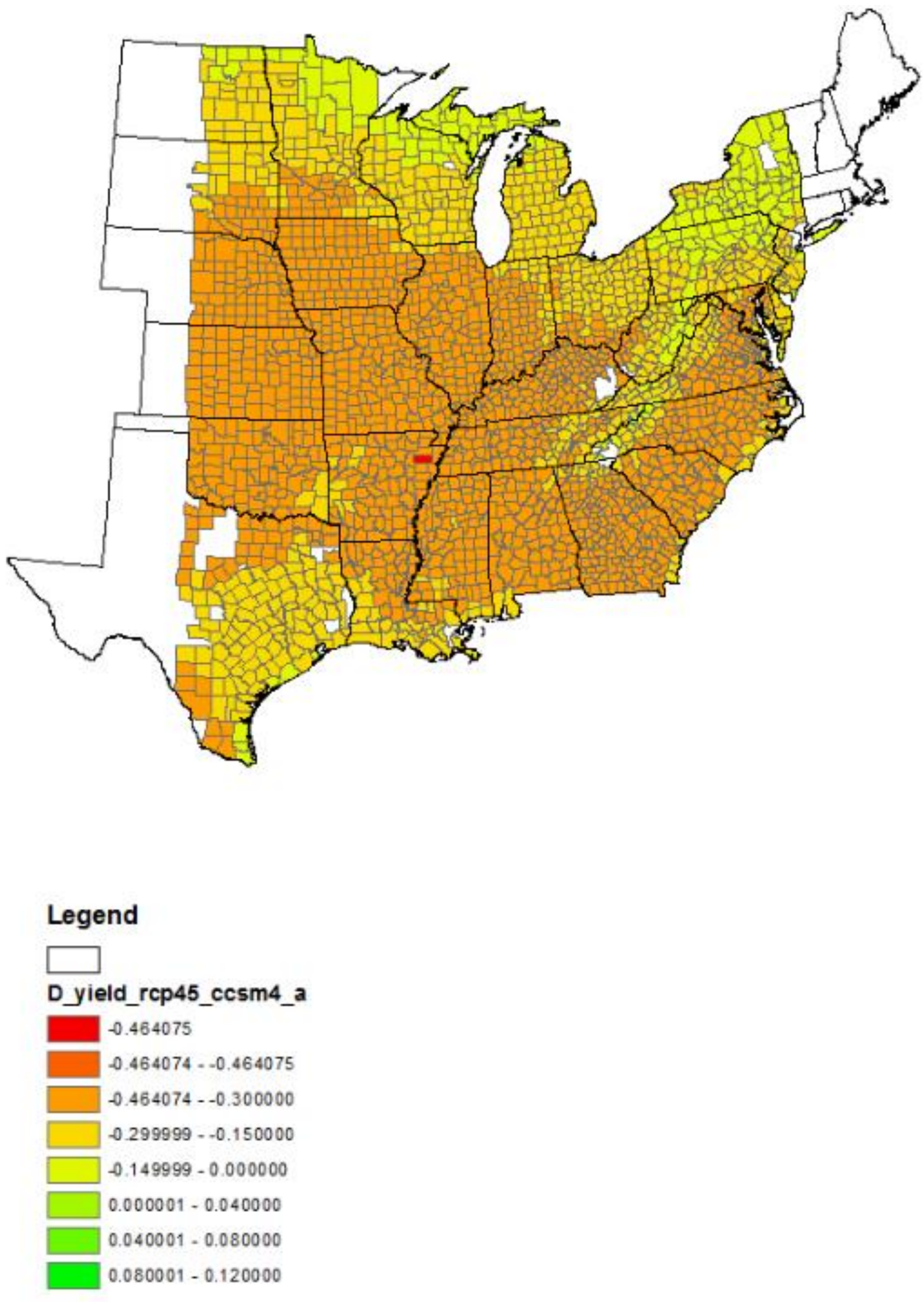


Figure I-10. Using the Model that Uses July-August Data to Predict Corn Yield Changes under the RCP4.5 Scenario of the CCSM4 Climate Model Assuming Adaptation

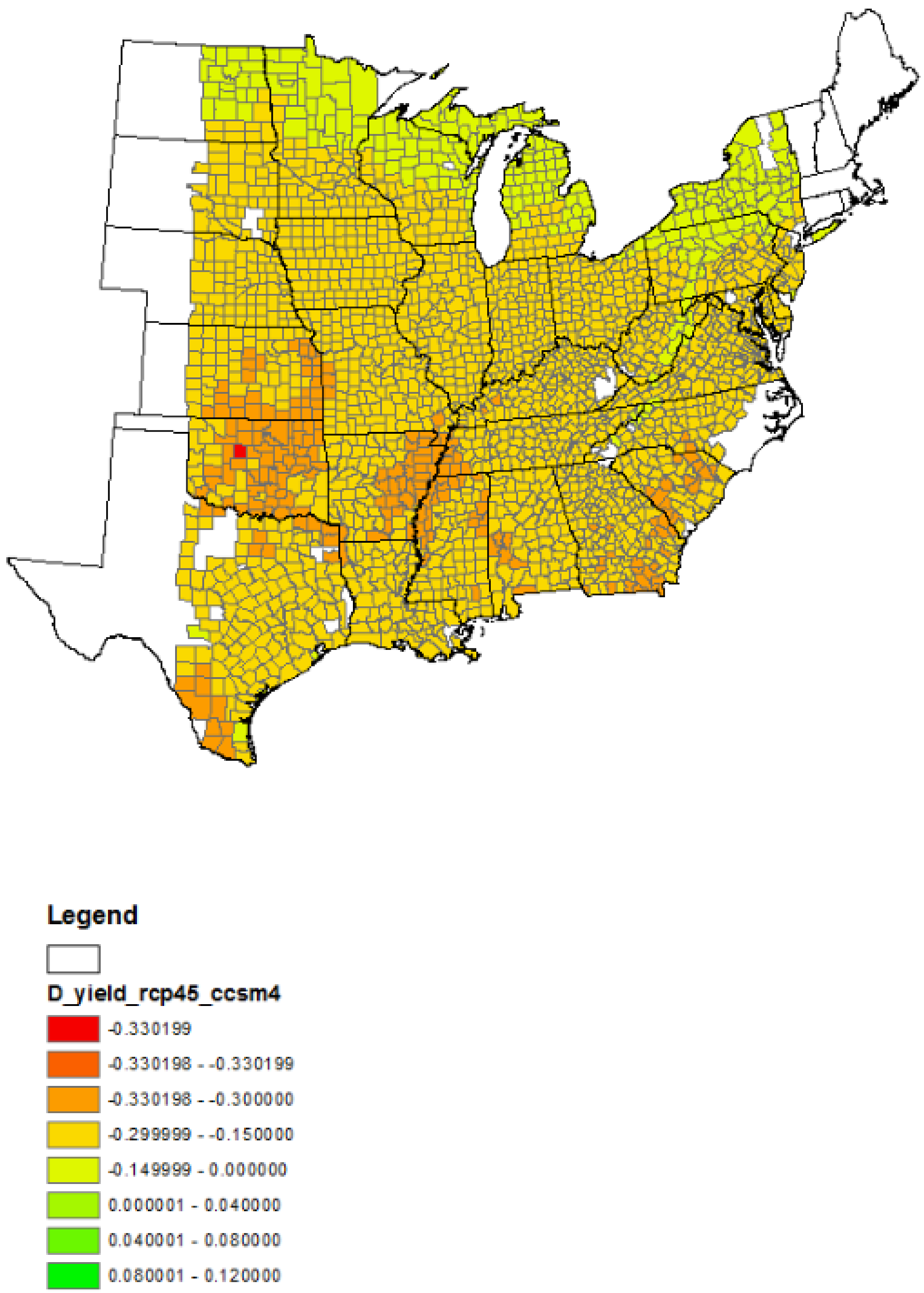


Figure I-11. Corn Yield Changes under the RCP4.5 Scenario of the CCSM4 Climate Model: Predictions from the Model that Uses Long-Term Average Data

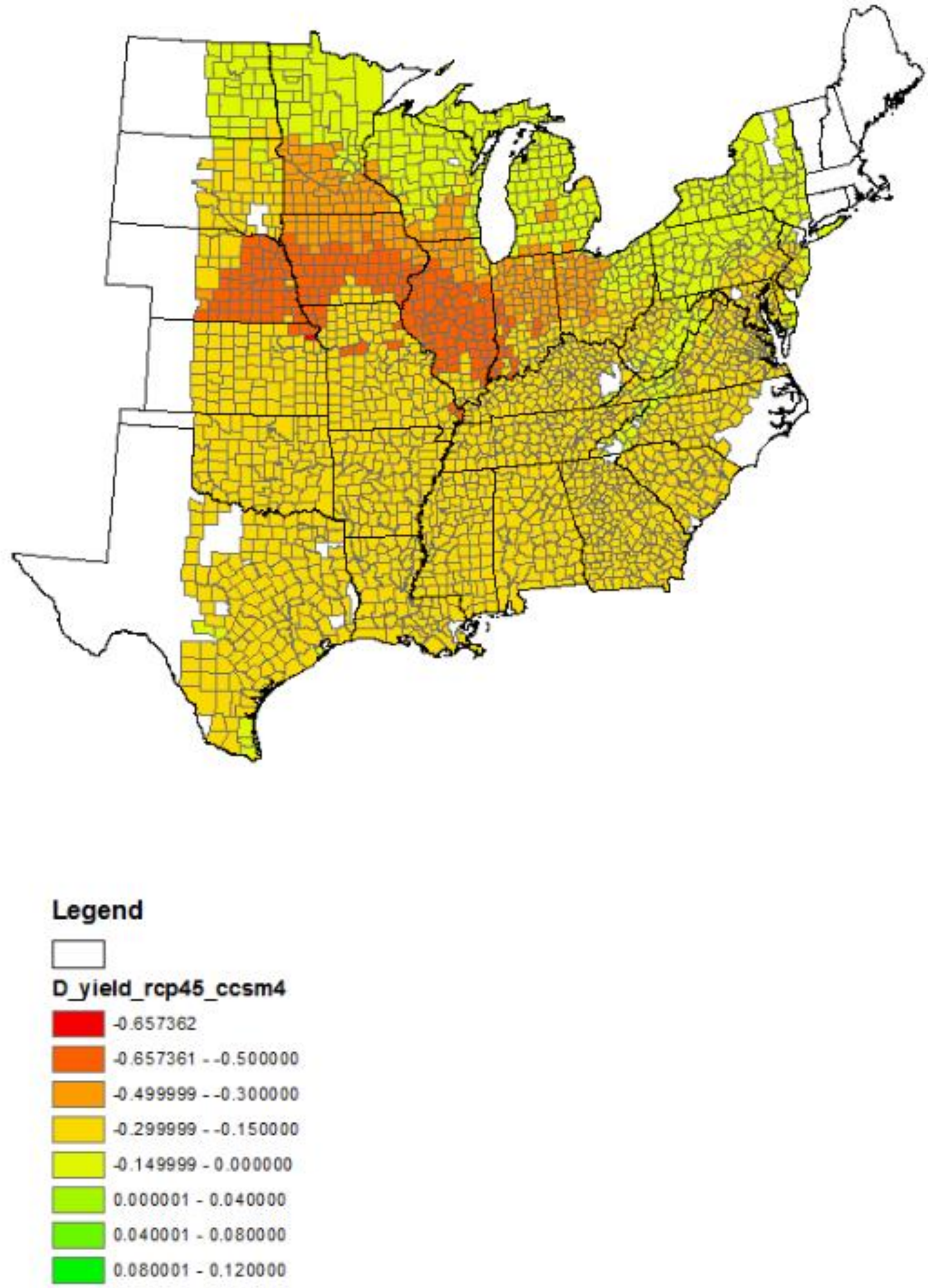


Figure I-12. Corn Yield Changes under the RCP4.5 Scenario of the CCSM4 Climate Model: Predictions from the Model that Uses Long-Term Average Data and Includes Corn Belt Dummies

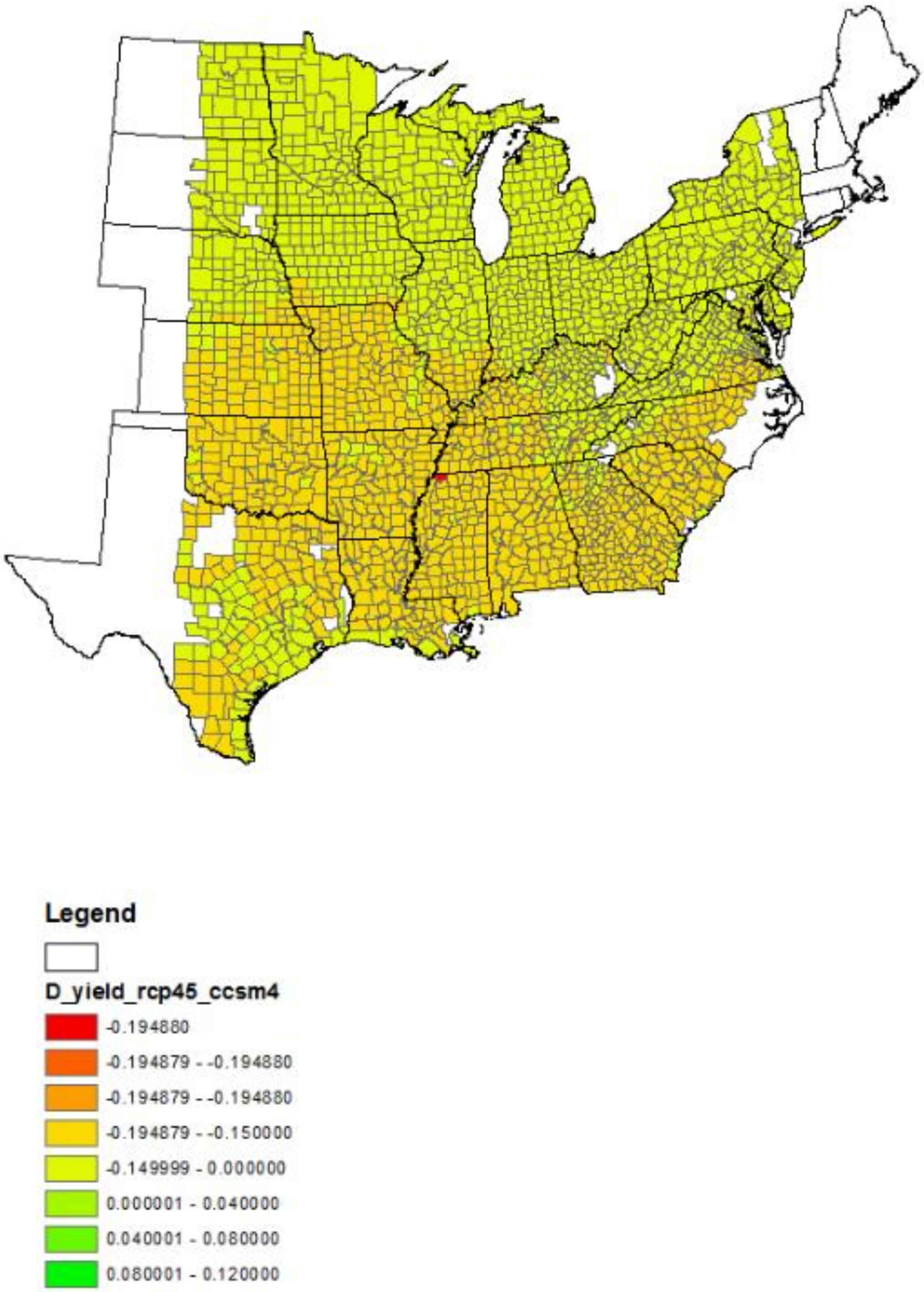


Figure I-13. Corn Yield Changes under the RCP4.5 Scenario of the CCSM4 Climate Model: Predictions from the Model that Uses Long-Term Average Data and Excludes Data from the 1950s and 1960s

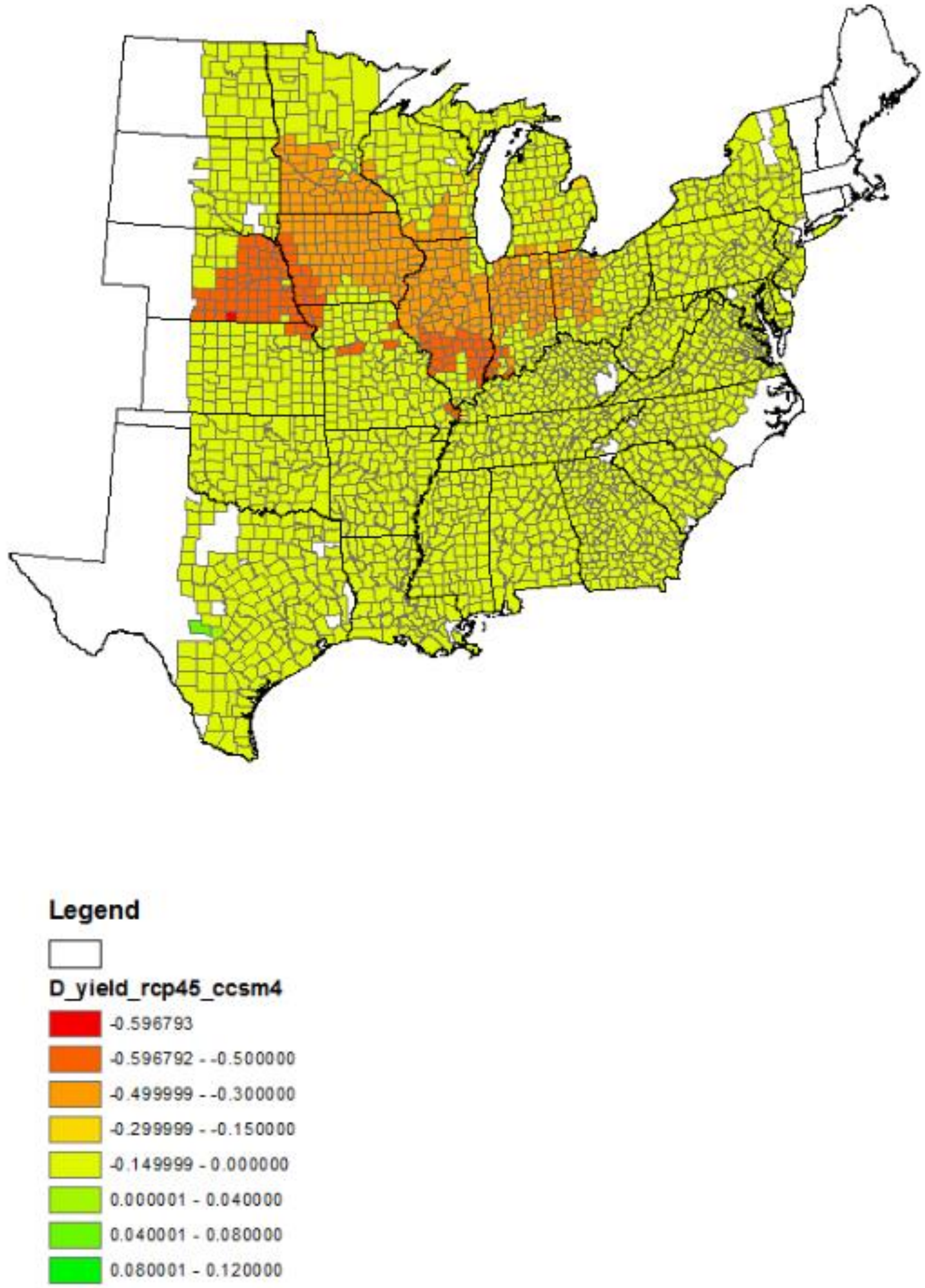


Figure I-14. Corn Yield Changes under the RCP4.5 Scenario of the CCSM4 Climate Model: Predictions from the Model that Uses July-August Long-Term Average Data and Changes All Assumption of the Base Model

APPENDIX FOR CHAPTER II

1. **Figures**

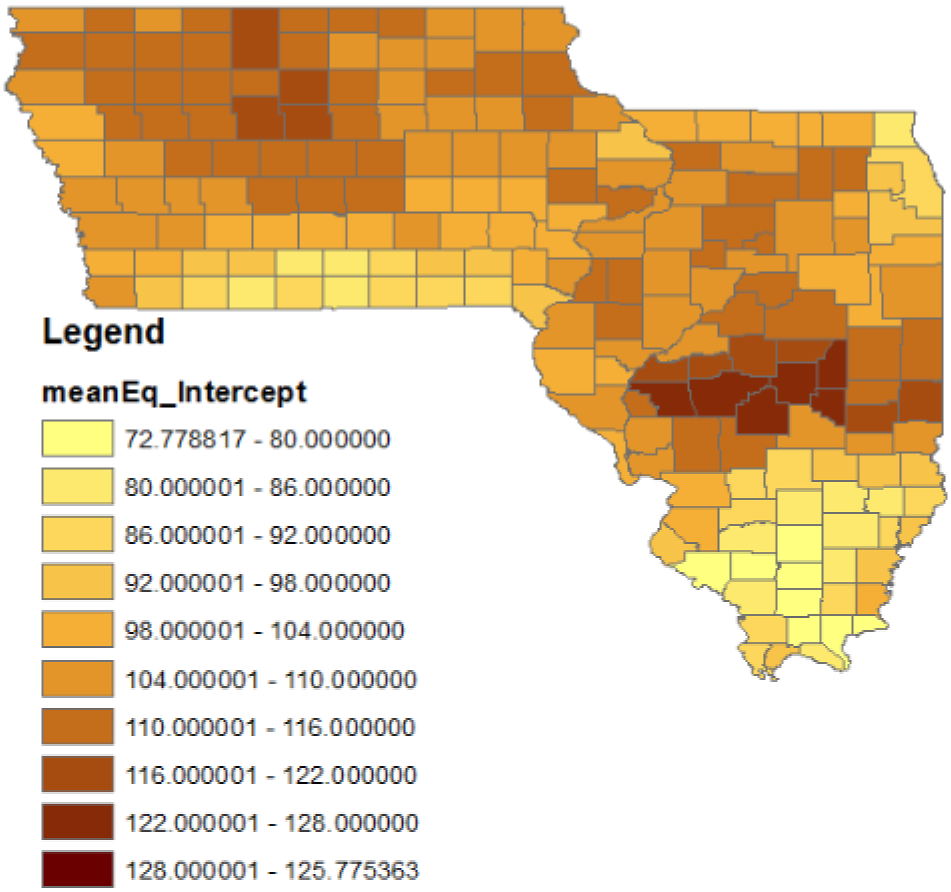


Figure II-1. Intercept of Mean Equation for County Yield Density (Bayesian Kriging)

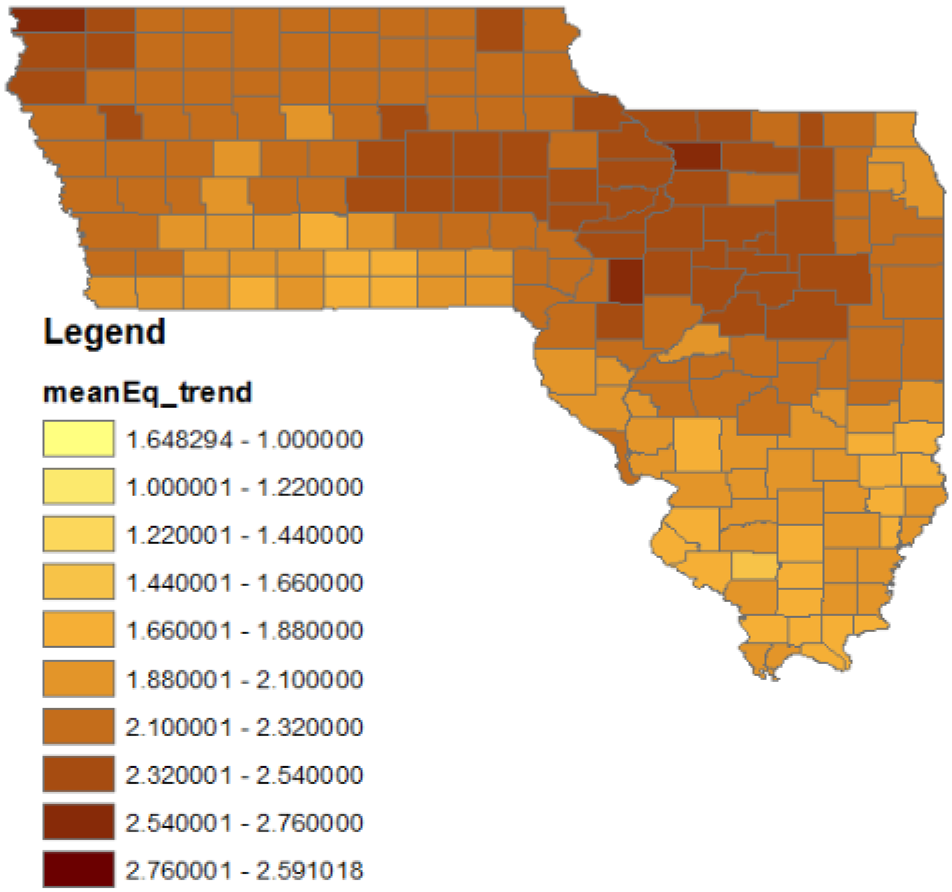


Figure II-2. Trend of Mean Equation for County Yield Density (Bayesian Kriging)

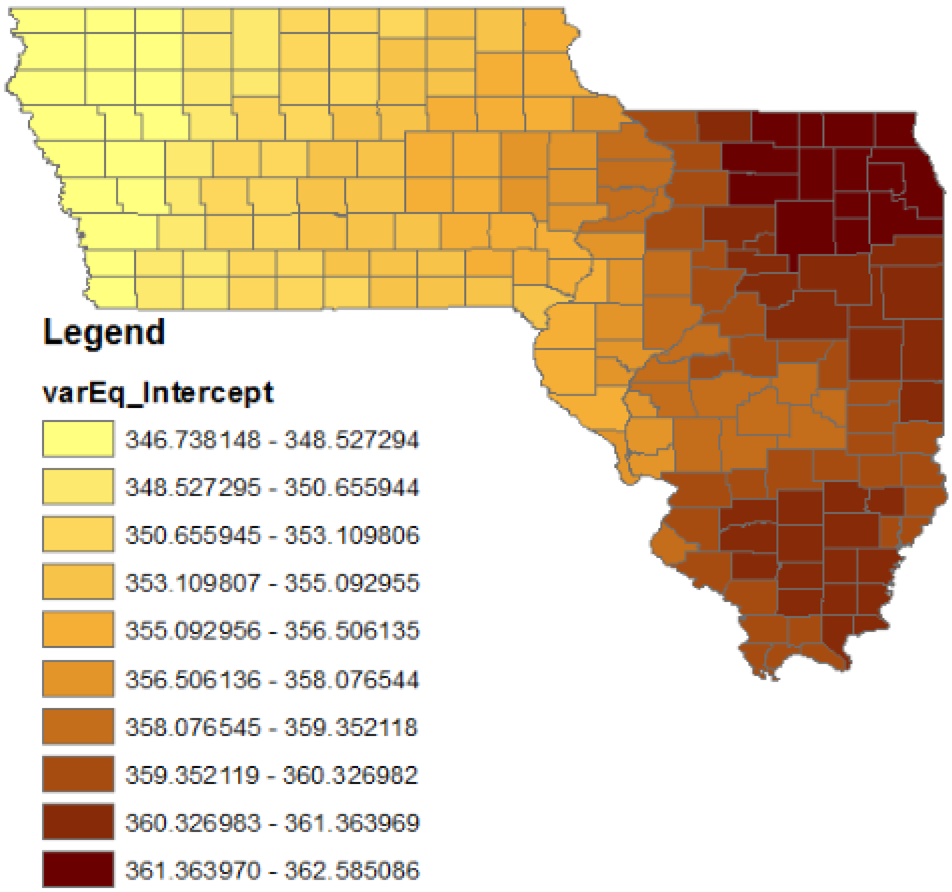


Figure II-3. Intercept of Variance Equation for County Yield Density (Bayesian Kriging)

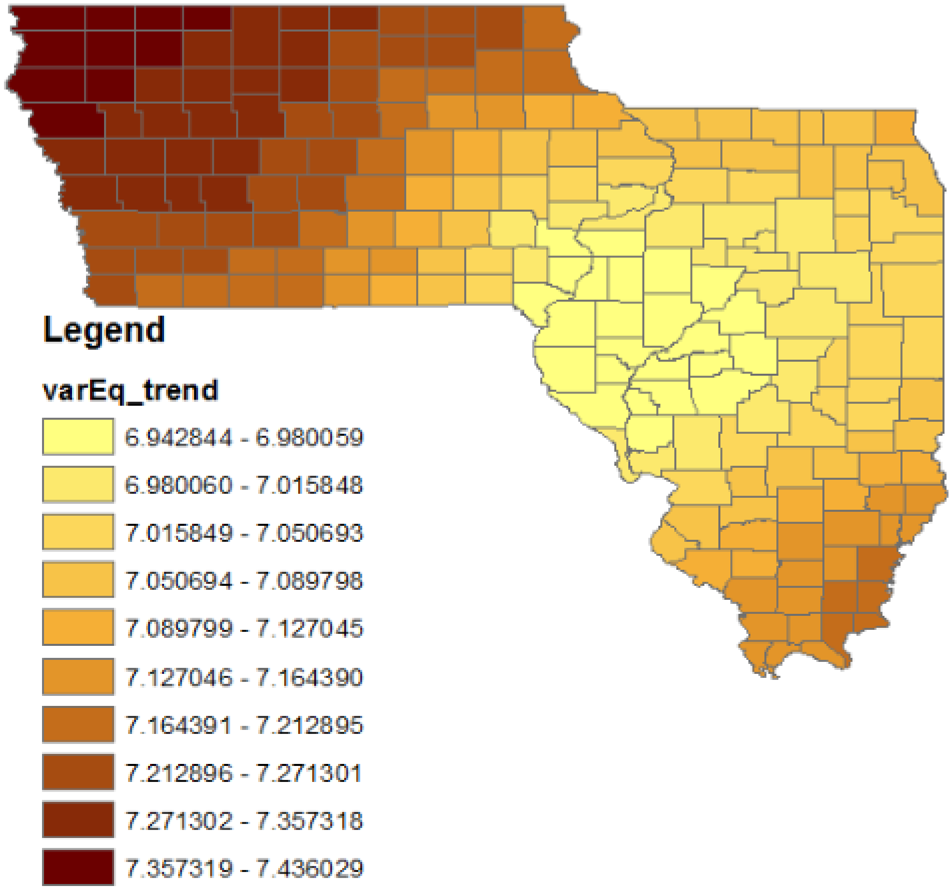


Figure II-4. Trend of Variance Equation for County Yield Density

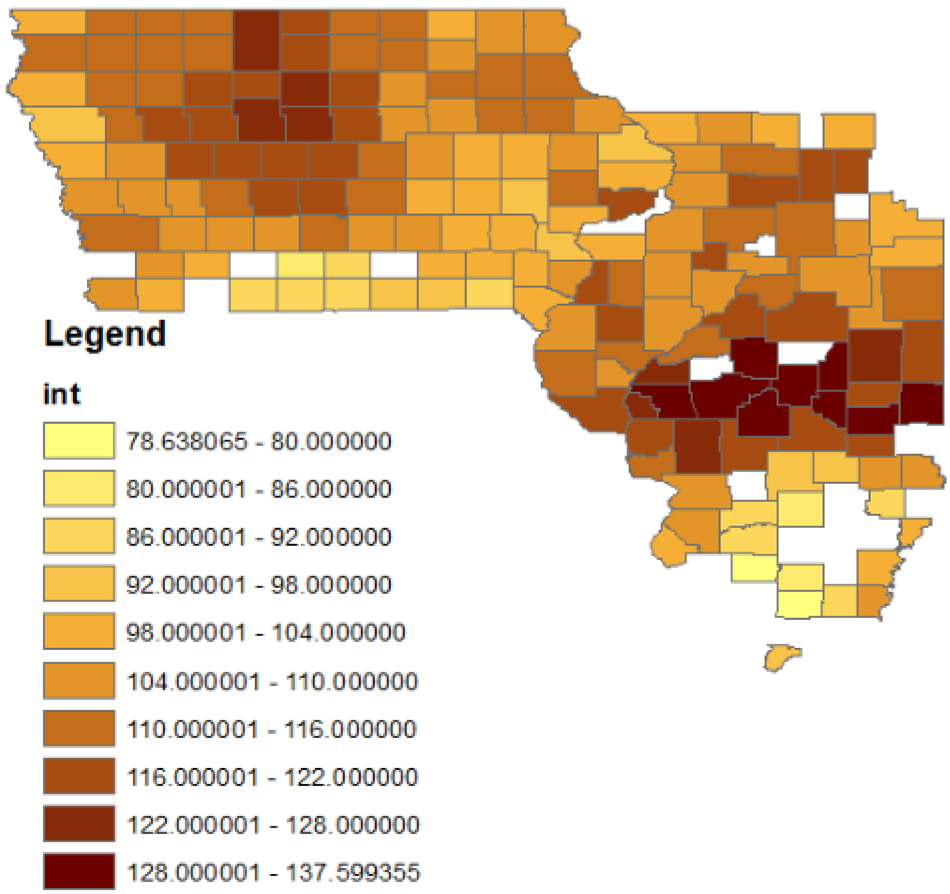


Figure II-5. Intercept of Mean Equation for County Yield Density (BMA)

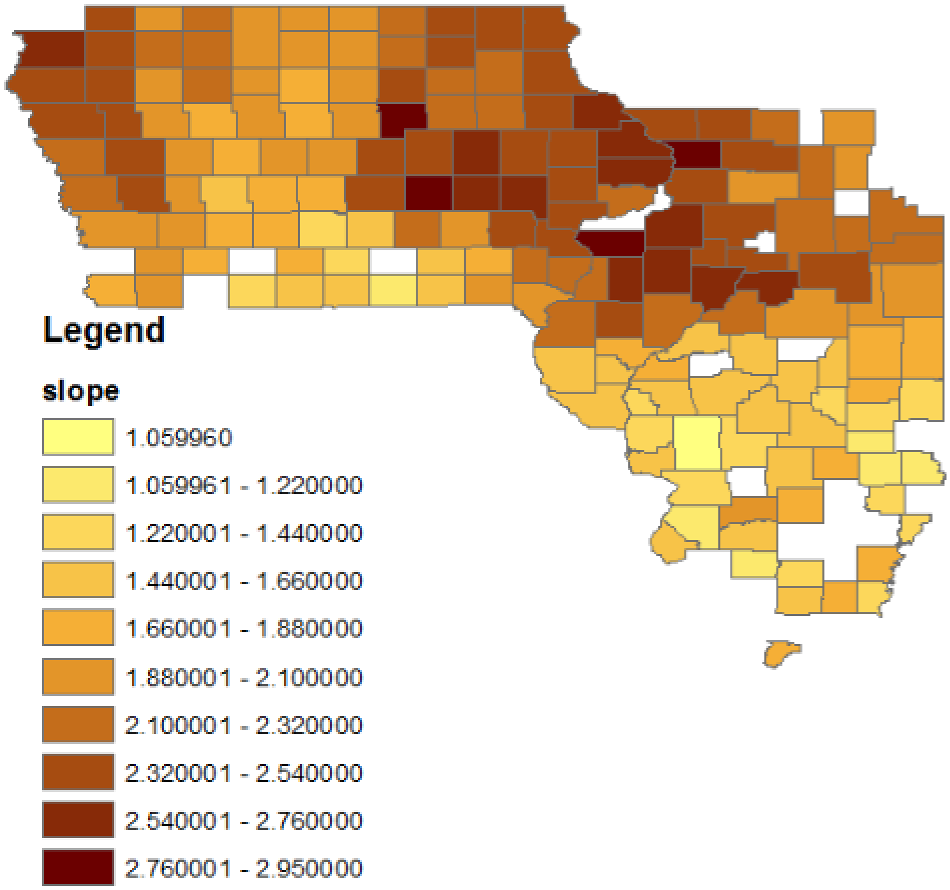


Figure II-6. Trend of Mean Equation for County Yield Density (BMA)

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