Estimating the impact of climate change on crop yields: The importance of non-linear temperature effects

Wolfram Schlenker
Michael J. Roberts

Discussion Paper No.: 0607-01

Department of Economics
Columbia University
New York, NY 10027

September 2006

Estimating the impact of climate change on crop yields: The importance of non-linear temperature effects

Wolfram Schlenker♣ and Michael J. Roberts♠

September 2006

Abstract

There has been an active debate whether global warming will result in a net gain or net loss for United States agriculture. With mounting evidence that climate is warming, we show that such warming will have substantial impacts on agricultural yields by the end of the century: yields of three major crops in the United States are predicted to decrease by 60 to 79% under the most rapid warming scenario. We use a 55-year panel of crop yields in the United States and pair it with a unique fine-scale weather data set that incorporates the whole distribution of temperatures between the minimum and maximum within each day and across all days in the growing season. The key contribution of our study is in identifying a highly non-linear and asymmetric relationship between temperature and yields. Yields increase in temperature until about $29°C$ for corn and soybeans and $33°C$ for cotton, but temperatures above these thresholds quickly become very harmful, and the slope of the decline above the optimum is significantly steeper than the incline below it. Previous studies average temperatures over a season, month, or day and thereby dilute this highly non-linear relationship. We use encompassing tests to compare our model with others in the literature and find its out-of-sample forecasts are significantly better. The stability of the estimated relationship across regions, crops, and time suggests it may be transferable to other crops and countries.

Keywords: Agriculture, Nonlinear temperature effects, Climate change.
JEL code: Q54, C23

♣ Department of Economics and School of International and Public Affairs, Columbia University, 420 West 118th Street, Room. 1308, MC 3323, New York, NY 10027. Email: ws2162@columbia.edu. Phone: (212) 854-1806.

♠ Economic Research Service, United States Department of Agriculture. 1800 M Street NW, Washington, DC 20036. Email: mroberts@ers.usda.gov. Phone (202) 694-5557.

Views expressed are the authors', not necessarily those of the U.S. Department of Agriculture.

1 Introduction

With accumulating evidence that greenhouse gas concentrations are warming the world's climate, research increasingly focuses on impacts likely to occur under different warming scenarios. Agriculture is a key focus due to its obvious links to weather and climate, as well as the inelastic demand for staple food commodities. Although there is some consensus that warming will likely be harmful to agriculture in tropic and sub-tropic zones, active debate continues about whether warming will be a net gain or loss for agriculture in the more temperate United States and Europe (Mendelsohn et al. 1994, Darwin 1999, Schlenker et al. 2006, Kelly et al. 2005, Timmins 2006, Ashenfelter and Storchmann 2006, Deschenes and Greenstone 2006).

This paper develops novel estimates of the link between weather and yields for several prevalent crops grown in the United States: corn, soybeans, and cotton. Corn and soybeans are the nation's most prevalent crops and are the predominant source of feed grains in cattle, dairy, poultry, and hog production. Cotton is next largest crop in the U.S. and more suitable to warmer climates than corn and soybeans. We pair yield data for these crops with a newly constructed fine-scale weather data set to develop a large panel that spans most U.S. counties from 1950 to 2004. The new weather data includes daily precipitation and the time a crop is exposed to each 1-degree Celsius temperature interval. We estimate these data for the specific locations where crops are grown in every county. These data are combined with publicly-available yield data from the U.S. Department of Agriculture's National Agricultural Statistical Service (USDA-NASS).

The new fine-scale weather data facilitates estimation of a flexible model in order to identify nonlinearities and breakpoints in the effect of temperature on yield. If temperatures are averaged over time or space, and the true underlying relationship is nonlinear (e.g., increasing and then decreasing in temperature), standard regression techniques dilute the true underlying curvature in the relationship. Accurate estimation of non-linear effects is particularly important when predicting effects on non-marginal changes in temperatures, as is expected under climate change.

Unraveling the nonlinear relationship between weather and agricultural output has implications beyond climate change impacts. Many empirical studies use weather as an instrument as it is arguably exogenous. However, the standard instrumental variables (IV) approach assumes that the marginal effect is constant, which we show to be a bad assumption for temperatures. Second, total liabilities of crop insurance in the United States totaled 47 billion in 2004, with a subsidy of 2.5 billion. Identifying a stronger link between weather and crop yields may facilitate the creation of financial instruments to spread crop yield risk in a way that is not subject to moral hazard.

We find a robust nonlinear relationship between weather and yields that is consistent across space, time, and crops: plant growth increases approximately linearly in temperature up to a point where additional heat quickly becomes harmful. The non-linear relationship is starkly asymmetric, with the slope of the decline above the peak being much steeper than the slope of the incline below it. Despite significant technological progress over our 55-year sample period, we find no evidence that crops have become significantly better at withstanding extreme heat above the upper threshold. Moreover, hotter southern states exhibit the same threshold as cooler states in the north, suggesting that there is limited potential for adaptations.

Encompassing tests show our nonlinear model predicts yields out-of-sample significantly better than other approaches in the literature. While our model is better at predicting actual yields, the sharp asymmetry where temperatures above a critical threshold quickly become harmful also implies that if climate change shifts the temperature distribution above such a threshold, the impacts would be significant.

We use our estimated model to forecast yields under several climate change scenarios. Global warming shifts the temperature distribution upward enough that damaging heat waves are observed more frequently. As a result, yields at the end of the century are predicted to decrease by 44% for corn, 33-34% for soybeans, and 26-31% for cotton under a slow warming scenario (B1) and 79-80%, 71-72%, and 60-78%, respectively, under a quick warming scenario (A1). These predictions are highly significant and consistent across alternative model specifications.

The next section reviews past literature and motivates our new approach. Section 3 provides a description of our model. In Section 4 we describe the construction of the fine-scale weather estimates and yield data. Section 5 reports a detailed empirical analysis of crop yields before Section 6 presents robustness checks, and Section 7 compares the model's out-of-sample predictions with other approaches found in the literature. Section 8 reports predictions under several of the latest climate change scenarios. We conclude in Section 9.

2 Background and Motivation

Many studies link weather and climate to outcomes such as yields, land values, and farm profits. These studies span several disciplines and methods. Agronomists sometimes estimate simple regressions but usually link weather and nutrient inputs to yields using crop simulation models. Economists have linked climate (average weather) to land values in cross-sectional hedonic studies. They have also linked weather to crop yields and profits using simple regressions and more complex structural models, and sometimes have used agronomists' simulation models. The different approaches have different strengths and weaknesses. We briefly review these approaches here to help motivate our new approach, which combines strengths from each one.

2.1 Agronomic Simulation Models

Agronomic studies emphasize the dynamic physiological process of plant growth and seed formation. This process is understood to be quite complex and dynamic in nature and thus not easily molded into a simple regression framework. Instead, these studies use a rich theoretical model to simulate yields given daily weather inputs, nutrient applications, and initial soil conditions. Models specific to each crop take inputs as exogenous, without economic or behavioral considerations. Economists may think of these models as complex production functions. Micro-parameters embedded in these models are taken as "reasonable assumptions" or taken one-at-a-time from experimental studies. In some cases, simulated yields are compared to observed yields with some success. But we are not aware of any study that has tested a simulation model using data besides that used to calibrate it. Current versions of models developed for many crops are maintained by the Decision Support System for Agrotechnology Transfer (http://www.icasa.net/dssat/).

At the heart these models is a state-dependent plant growth function. Plant growth potential is linked to temperature (available energy) while an absence of other factors (moisture and nutrients) may limit growth below this potential. The agronomic concept of "growing degree days," a highly nonlinear function of temperature, can be linked to the basic concept of growth potential. The shape of this function has been estimated rather imprecisely due to the relatively few observations available from experimental field trials.

A key strength of this growth function, and simulation models generally, is they way they incorporate the whole distribution of weather outcomes realized over the growing season. This differs from standard regression approaches, discussed below, which generally use average weather outcomes or averages from particular months. While our model is far simpler than crop simulation models, we show how it incorporates the whole distribution of weather outcomes and generalizes the concept of growing degree days.

There are two general problems with crop simulation models. First, there is considerable uncertainty about physiological process (functional form) and the many parameters in these highly non-linear models. Given the complex dynamic and non-linear nature of the models, it is not possible to estimate them statistically (Wallach et al. 2001). If it were possible, many agronomists would be skeptical about the physiological interpretation of these estimates and there are worries about possible misspecification and omitted variables biases (Sinclair and Seligman 2000, Long et al. 2005). The second critical problem is the assumption of exogenous production systems and nutrient applications: there is no account for behavioral response on behalf of farmers.

In some circles, there seems to be an understandable skepticism about how these models should be calibrated and how one model can be empirically compared to another (Sinclair and Seligman 1996, Sinclair and Seligman 2000). Nevertheless, these models are the predominant tool used to evaluate likely effects from climate change on crop yields. Examples include Black and Thompson (1978) and Adams et al. (1995), but there are many others.

2.2 Hedonic and Other Cross-Sectional Studies

The most widely received economic studies use hedonic models to link land values to land characteristics, including climate, using relatively simple reduced-form linear regression models (e.g., Mendelsohn et al. (1994); Schlenker et al. (2006); Ashenfelter and Storchmann (2006)). For evaluation of impacts from climate change, the strength of the approach is that it can account for a large degree of behavioral response. Cooler areas are likely to become more like warmer areas, with crops choice, management, and land values changing in accordance with climate changes. Analysis of yields, particularly using simulation models which take both crop choice and management practices as exogenous, cannot capture these adaptive changes.

Some changes, however, cannot be evaluated, even with a hedonic model. To the extent that global warming changes the overall production capacity of crops, relative commodity prices will change, which in turn will affect land values, and thus induce feedback effects on crop choice and management practices (earlier studies argue price effects will be small). Nor can hedonic models account for passive or induced technological change.

Perhaps a greater concern with the hedonic approach is possible confounding from omitted variables or model misspecification. Climate variables (e.g., average temperature) and other critical variables, such as soil types, distance to cities, and irrigation, are all spatially correlated. If critical variables correlated with climate are omitted from the regression model, or the functional form the regression model is incorrect, the climate variables may pick up effects of variables besides climate and lead to biased estimates and predictions. Indeed, earlier work shows how omission of irrigation critically influences predicted climate impacts (Schlenker et al. 2005). Hedonic studies become more credible when findings are robust to many alternative specifications (Schlenker et al. 2006). Timmins (2006) relies on a cross-section of farmland values and shows how under certain assumptions about the error-term structure, use-specific error terms can be recovered.

2.3 Time-Series and Panel Studies

Omitted variables bias has been a concern since the early part of the last century, when Ronald Fisher wrote "Studies in Crop Variation I-VI." The ostensible purpose of the papers was to discern the influences of nutrient applications and soil types on crop yields. The challenge was to discern the effects of these factors given considerable confounding, particularly from weather, which, like nutrient applications and soil types, were strongly spatially correlated. Fisher used this setting to motivate development of modern experimental methods, including random assignment of treatment levels and split-plot designs, as well as formal statistical concepts, including maximum likelihood and analysis of variance. Fisher's experimental designs and subsequent refinement of them would later help to facilitate rapid growth in agricultural productivity through the rest of the century, and more broadly, statistical assessment of experimental outcomes in all scientific disciplines.

Studies employing panel data attempt to mitigate confounding using a richer set of control variables and location and/or year fixed effects. Recent studies include Kaylen et al. (1992) who link yield to weather outcomes and find that yield variability has increased partly due to an increase in weather variability. Kelly et al. (2005) use a panel data set of county-level profits for midwestern states to discern the influence of climate (weather averages) from yearly weather shocks, i.e., the authors include both historic mean climate and variability (standard deviation between years) as well as yearly weather shocks. Since the authors include climate averages (which are constant in the cross-section), they can not include county fixed effects because they would be perfectly collinear with climate. Deschenes and Greenstone (2006) link profits and yields to weather fluctuations for the entire U.S. using county fixed effects to capture all time-invariant factors like soil quality. They assume remaining year-to-year variation in weather is random.

3 A New Model and Approach

Our objective is to discern the effect of weather, particularly heat, on crop yields using a new and rich data set and a novel approach that allows us to estimate nonlinear effects of heat over the growing season. By using the whole distribution of temperature outcomes (which is critical for estimating non-linear effects), we depart from earlier cross-sectional and panel data studies and share a common thread with the agronomic literature that employs crop simulation models. Unlike agronomic literature, we incorporate our model into a statistical regression framework. We focus on yields because yields are linked to the year a plant is grown (unlike profits which can be affected by storage), avoid potentially confounding influences of price changes, and because many observations are available for each county and crop. Here we describe our model and discuss exogeneity assumptions and Identification.

3.1 Statistical Model

Following the spirit of the agronomic literature we postulate that the effect of heat on relative plant growth is cumulative over time, so yield is the integral of plant growth over the growing season. In other words, we assume the effect of temperature is perfectly substitutable over time. In extreme cases, this assumption is implausible. For example, if frost or extreme heat were to kill the plant it would obviously affect future growth. Specifically, plant growth $g(h)$ depends nonlinearly on heat h and log yield, y_{it}, in county i and year t is

$$y_{it} = \int_{\underline{h}}^{\overline{h}} g(h)\phi_{it}(h)dh + \mathbf{z}_{it}\boldsymbol{\delta} + c_i + \epsilon_{it} \tag{1}$$

where $\phi_{it}(h)$ is the time distribution of heat over the growing season in county i and year t. We fix the growing season to months March through August for corn and soybeans and the months April through October for cotton. Fixing it exogenously makes it robust to farmers' decisions like planting dates. Observed temperatures during this time period range between the lower bound $\underline{h}$ and the upper bound $\overline{h}$. Other factors, such as precipitation and technological change, are denoted $\mathbf{z}_{it}$, and c_i is a time-invariant county fixed effect to control for time-invariant heterogeneity.

While time separability is rooted in agronomic experiments, we implicitly validate this assumption by showing a statistically significant relationship between the cumulative distribution of temperatures and yields. We would not observe this if time separability were not appropriate, because random pairing of various temperatures over a season and between years would not provide clear identification. In the empirical section we split the six-month growing season into two three-months intervals and find comparable estimates for both subintervals, i.e., temperature effects in the early and later states of the plant cycle are similar. Earlier studies using quadratic specifications in average temperature for various months find this quadratic relationship to vary by month of the year. More specifically, July temperatures, the hottest month, usually peak at a very low level (around 22°C), while higher April temperatures are always beneficial. However, if the true underlying relationship is asymmetric, the quadratic functional form might be restrictive. Since *average* temperatures in April and July are correlated, the former will pick up the beneficial effects of moderate heat, while the latter will pick up the effects of harmful extreme heat. Hence, the difference in coefficients between months does not necessarily imply that the effects vary by season, but might be a result of an inappropriate implicit assumption that the relationship is symmetric.

A special case of time-separable growth is the concept of growing degree days, typically defined as the sum of truncated degrees between two bounds. For example, Ritchie and NeSmith (1991) suggests bounds of 8°C and 32°C for "beneficial heat". For example, a day of 9°C contributes 1 degree day, a day of 10°C contributes 2 degree days, up to a temperature of 32°C, which contributes 24 degree days. All temperatures above 32°C also contribute 24 degree days. Degree days are then summed over the entire season. Temperatures above $34°C$ are included as a separate variable and speculated to be harmful. These particular bounds have been implemented in a cross-sectional analysis by Schlenker et al. (2006). Thus, growing degree days are the special case of our model where (using the above bounds as an example)

$$g(h) = \begin{cases} 0 & \text{if } h \leq 8 \\ h - 8 & \text{if } 8 < h < 32 \\ 24 & \text{if } 32 \leq h \end{cases}$$

The exact degree day bounds are still debated, partly because earlier studies use a limited number of observations from field experiments to identify them. There is also uncertainty about temperature effects above the upper bound. While some speculate that high temperatures are harmful, the critical temperature and severity of damages remain uncertain. We use a flexible functional form allows us to identify effects of extreme heat.

In the data section we explain how we derive the amount of time a plant is exposed to each 1-degree Celsius interval. With these data, we approximate the integral over temperature with

$$y_{it} = \sum_{h=-5}^{49} g(h + 0.5)[\Phi_{it}(h + 1) - \Phi_{it}(h)] + \mathbf{z}_{it}\boldsymbol{\delta} + c_i + \epsilon_{it} \qquad (2)$$

where $\Phi_{it}(h)$ is the cumulative distribution function of heat in county i and year t. We consider two specifications of this model.

First we model $g(h)$ as a m-th order Chebychev polynomial of the form $g(h) = \sum_{j=1}^{m} \gamma_j T_j(h)$, where $T_j()$ is the $j-th$ order Chebyshev polynomial. We rely on Chebyshev polynomials because each term is orthogonal which makes least-squares estimates numerically more stable. By interchanging the sum we obtain

$$
\begin{aligned}
y_{it} &= \sum_{h=-5}^{49} \sum_{j=1}^{m} \gamma_j T_j \left(h+0.5\right) \left[\Phi_{it}\left(h+1\right) - \Phi_{it}\left(h\right)\right] + \mathbf{z}_{it}\boldsymbol{\delta} + c_i + \epsilon_{it} \\
&= \sum_{j=1}^{m} \gamma_j \underbrace{\sum_{h=-5}^{49} T_j \left(h+0.5\right) \left[\Phi_{it}\left(h+1\right) - \Phi_{it}\left(h\right)\right]}_{x_{it,j}} + \mathbf{z}_{it}\boldsymbol{\delta} + c_i + \epsilon_{it}
\end{aligned} \tag{3}
$$

where $x_{ij,t}$ is the exogenous variable obtained by summing the $j-th$ Chebyshev polynomial evaluated at each temperature interval midpoint, multiplied by the time spent in each temperature interval. We successively use higher-order polynomials until our estimated relationship appears stable

The polynomial regressions are parsimonious and easy to interpret. As a more flexible alternative model, we use dummy variables for each one-degree interval. The dummy-variable model, spelled out in detail below, effectively regresses yield on season-total time within each degree interval. Note that standard non-parametric methods, such as local regression or cubic splines, are not possible, because each yield outcome is associated with a whole temperature distribution.

Because temperatures rarely exceed 39°C (102 degrees Fahrenheit) in counties where corn and soybeans are grown, we lump all the time a plant is exposed to a temperature above 39°C into one category. (Temperature intervals above 39°C have a frequency of less than one hour during the growing season for soybeans and corn. For cotton the analogous cutoff is 42°C). The model becomes (where $\Phi_{it}(40)$ is set to 1 for corn and soybeans).

$$
y_{it} = \sum_{j=-5}^{39} \gamma_j \underbrace{\left[\Phi_{it}(h+1) - \Phi_{it}(h)\right]}_{x_{it,j}} + \mathbf{z}_{it}\boldsymbol{\delta} + c_i + \epsilon_{it} \tag{4}
$$

Note that county fixed effects c_i capture the additive influence of time-invariant factors in the cross-section. The error terms, however, remain spatially correlated within each year. We therefore use the non-parametric routine by Conley (1999) to adjust the variance-covariance matrix for spatial correlation. We also use bootstrap simulations where we resample entire years with replacement, as weather between years is plausibly i.i.d., but error terms within a year are spatially correlated.

While equations (3) and (4) specify our main two models, the concept of degree days is a special case where the function $g(h)$ is piecewise linear. In a sensitivity check we therefore estimate a piecewise-linear model, i.e., growth is forced to increase linearly in temperature up to an endogenous plateau, and then forced to decrease linearly above an endogenous upper bound. Since our data is aggregated by 1-degree Celsius intervals, we loop over possible combinations of bounds and pick the ones with the least sum of squared residuals.

3.2 Exogeneity and Identification

Because we use observational data, confounding is the pervasive concern. In this case, however, observational data are the only choice. The main reason is that with observational data we can estimate the consummate effects of the weather on yields, which may differ from effects of weather *ceteris paribus*. The consummate effects of the weather depend on weather itself and on farmers' management practices, which may also be influenced by weather. The experimental plot designs developed by Fisher and refined over the years by statisticians and agronomists cannot measure these effects because the designs were constructed to measure the effects of practices, not weather. The behavioral element was deliberately controlled. While greenhouses may be used to experimentally vary temperature and moisture, such a design cannot mimic naturally occurring behavioral response. We therefore embrace a focus on observed, and arguably random, year-to-year variation in weather. We use county fixed effects to limit identification from cross-sectional variation in climate, which would be more susceptible to confounding from omitted variables.

Fixed-effects models are often described as within estimators because identification comes from deviations from within-group averages. However, when fixed effects are used in conjunction with a non-linear specification of other covariates, identification of the curvature stems in part from between-group variation, which may be more subject to confounding. Fixed effects only shift the intercept. Thus, a key assumption is that non-linearity in the cross-section is exogenous and behaves similarly to non-linear effects over time. We test this assumption below by examining many different subgroups that limit time-series and/or cross-sectional variation.

4 Data

4.1 Dependent Variable

Our dependent variable consists of publicly-available yield data for corn, soybean and cotton for the years 1950-2004. The U.S. Department of Agriculture's National Agricultural Statistical Service (USDA-NASS) reports yields as total production per acres harvested. There is hence a potential selection bias as during extremely bad years farmers might decide it does not pay to harvest, making the harvested area endogenous. We therefore also obtained the area planted for roughly 80% of our data, and conducted a sensitivity check by deriving yields as total production divided by acres planted. The results do not change. Since the area planted is not reported in all areas and years, we focus in our analysis on yields per acres harvested.

4.2 Weather Variables

Earlier studies have examined average temperatures over a longer time horizon (e.g., an entire season, month, or day), which can hide extreme events like maximum temperatures that occur during a fraction of the day. The construction of our fine-scale weather aids identification of non-linear weather effects that are diluted with courser data or if weather outcomes are averaged over time or space. We hence first develop *daily* predictions of minimum and maximum temperature on a 2.5x2.5mile grid for the entire U.S. before we derive the time a crop is exposed to each 1 degree Celsius interval in each grid cell. We then match those predictions with the cropland area in each 2.5x2.5 miles grid cell, and aggregate the whole distribution of outcomes for all days in the growing season in each county. Since our study emphasizes non-linearities, we stress that we first derive the time a plant is exposed to each 1 degree Celsius interval before we average the grid cells in a county, and not vice versa. (Data development is briefly described here and in more detail in Schlenker and Roberts (2006).)

Thom (1966) developed a method to predict the distribution of daily temperatures from the distribution of average monthly temperatures. This method appears appropriate for predicting the *average* probability that a certain weather outcome will be realized, but less appropriate in predicting a *specific* weather outcome in a particular year. As a result, these methods work well in a forward-looking cross-sectional analysis where the dependent variable is tied to weather *expectations* (for example, the link between land values and climate), but less well in our analysis where the dependent variable (yield) linked to specific weather outcomes. Directly obtaining daily values on a small scale requires a spatial smoothing procedure to approximate daily weather outcomes between individual weather stations.

The "Parameter-elevation Regressions on Independent Slopes Model" (PRISM) is widely regarded as one of the best interpolation procedures (http://www.ocs.orst.edu/prism/). It accounts for elevation and prevailing winds to predict weather outcomes on 2.5x2.5 mile grid across the contiguous United States. However, the PRISM data are on a *monthly* time scale. We therefore combine the advantages of the PRISM model (good spatial interpolation) with better temporal coverage of individual weather stations (daily instead of monthly values). We pair each of the 259,287 PRISM grids that cover agricultural area in a LandSat satellite scan with the closest seven weather stations having a continuous record of daily observations. We then regress monthly averages at each PRISM cell against monthly averages at each of the seven closest stations, plus fixed effects for each month. (Linking monthly PRISM averages to averages at individual weather stations approximates the spatial smoothing procedure in the PRISM model. The R-squares are usually in excess of 0.999). The derived relationship between *monthly* PRISM grid averages and *monthly* averages at each of the seven closest stations is then used to predict *daily* records at each PRISM grid from the *daily* records at the seven closest weather stations.

We use a cross-validation exercise to test whether the results from monthly regressions can be used to predict daily outcomes. Specifically, we construct a daily weather record at each PRISM cell that harbors a weather station without using that weather station in the interpolation. We then compare predicted daily outcomes at the PRISM cell with a weather station to actual outcomes recorded at the weather station in the grid cell. The mean absolute error is $1.36°C$ for minimum temperature and $1.49°C$ for maximum temperature, while the average standard deviations are 9.37 and 10.56, respectively.

We approximate the distribution of temperatures within a day with a sinusoidal curve between minimum and maximum temperatures. In a sensitivity check we instead use a linear interpolation between minimum and maximum temperature. Both methods give similar results. We derive the time spent in each $1°C$-degree temperature interval between $-5°C$ and $+50°C$. Finally, we construct the area-weighted averages over all PRISM grid cells in a county. Note that we first derive the weather variables and then average over the agricultural area, not vice versa, which is important for our exploration of non-linear effects. The agricultural area in each cell was obtained from LandSat satellite images. Vince Breneman and Shawn Bucholtz at the Economic Research Service were kind enough to provide us with the agricultural area in each PRISM grid cell. Since we use the LandSat scan of a given year, we are not able to pick up shifts in growing regions.

Descriptive statistics for temperature, precipitation, and yields of corn (for grain), soybeans, and upland cotton are reported in Table 1. Note that some yields appear artificially low. These few outliers are very infrequent. If we drop them, the results do not change, but the cutoff point becomes somewhat arbitrary (The outliers have little influence because we use log yield, so they have small errors). The weather variables are summed over the six-months period from March through August for corn and soybeans, and the seven-months period April through October for cotton. As noted above, exogenously fixing this time period allows for an endogenous choice of the growing season within this time frame.

We divide the United States into several regions as shown in Figure 1. The default data set for corn and soybeans is the union of northern, interior, and southern states–what we label eastern counties. We exclude the Western United States east of the 100 degree meridian and Florida because agricultural production in these area relies on heavily subsidized access to irrigation water. Since the access to subsidized water rights is correlated with climate, omitting these variables, which vary on the sub-county level of irrigation districts, will result in biased coefficient estimates on the climatic variables (Schlenker et al. 2005). Cotton is predominantly grown in the south and west, and we include all states in the analysis to obtain a larger sample of counties.

4.3 Climate Change Scenarios

We forecast the impact of a changing climate using the latest climate change predictions from the Hadley 3 model (http://www.metoffice.com/research/hadleycentre/). This is a major climate change model that will form the basis for the next report by the Intergovernmental Panel on Climate Change (IPCC). We obtained monthly model output for both minimum and maximum temperatures under four major emissions scenarios (A1, A2, B1, and B2) for the years 1960-2099. Each scenario rests on a different assumption about population growth and availability of alternative fuels, among other factors (Nakicenovic, ed 2000).

Climate changes are estimated as follows. At each of 216 Hadley grid nodes covering the United States, we find the predicted difference in monthly mean temperature for 2020-2049 (medium-term), 2070-2099 (long-term), and historic averages (1960-1989). Next, the predicted change in monthly minimum and maximum temperature at each 2.5x2.5 mile PRISM grid is calculated as the weighted average of the monthly mean change in the four surrounding Hadley grid points, where the weights are proportional to the inverse squared distance and forced to sum to one. In a final step, we add the predicted changes in monthly minimum and maximum temperatures at each PRISM grid to *observed daily* time series from 1960 to 1989. In other words, we leave the variability constant but shift the mean. We use an analogous approach for precipitation, except that we rely on the ratio of future rainfall compared to historic rainfall instead of absolute changes. Each county's weather outcomes in a climate scenario are the area-weighted averages of all PRISM grids that cover farmland. Predicted changes for the B2-scenario (which assumes a intermediate growth in CO_2 concentrations) is listed in Table 2.

5 Estimation Results

This section presents our main empirical results. We first present an analysis for corn, a relatively high-value crop that comprises more acreage than any other cash crop in the United States. After presenting results for three specifications for corn, we briefly report similar results for soybeans and cotton. Like corn, soybeans, the second largest commodity crop in the U.S, are grown over an extensive geographic area. The extensive geographic spread of corn and soybean production aids empirical analysis because it provides more data and more variation in weather outcomes within years. Cotton, a higher-value crop with less acreage, is predominantly found in warmer-weather areas of the western and southern United States. We include cotton, a warm-weather crop, to check whether warming is less damaging or beneficial for a crop that thrives in warmer climates. In Section 6 we conduct specification checks before we compare results with other approaches in the literature in Section 7.

5.1 Corn

We first estimate the model using Chebyshev polynomials as outlined in equation (3) above. Since previous studies relied on linear and quadratic models, we start with a linear model and then add additional polynomials up to degree six. In a later step, we abandon the polynomials and rely on a non-parametric dummy-variables approach instead.

5.1.1 Chebyshev Polynomials

Our dependent variable is log corn yield, which we link to the product between the time spent in each 1°C interval in the months March-August and the j^{th}-order Chebyshev polynomial evaluated at the midpoint of the interval. Other control variables includes a linear and quadratic term for total precipitation in the growing season March-August and quadratic time trends estimated separately for each state. County fixed effects c_i capture all time-invariant factors, such as soil characteristics and proximity to markets. Our standard errors are adjusted to account for a spatial correlation of errors ϵ_{it} within years but not across years.

A regression with county fixed effects and quadratic time trends for each state has an R-square of 0.66, so two-thirds of the variance in corn yields is explained by time-invariant factors and an almost threefold increase in yields in our 55-year study period.

Table 3 presents regression results for the full data set including all northern, southern, and interior counties as shown in Figure 1. The six columns use Chebyshev polynomials of degree 1 through degree 6. The first six rows give the coefficient estimates on the Chebyshev polynomials and associated t-values, corrected for spatial correlation of the errors, are in parentheses Conley (1999). Conley (1999) is an application of Newey and West (1987). We use a Barlett window in both the longitude and latitude dimension and a cutoff value of 5 decimal degrees, or approximately 350 miles. Accounting for the spatial correlation of the contemporaneous error terms lowers t-values by a factor of 6, on average, as compared to standard OLS estimates.

Because coefficients on Chebyshev polynomials are difficult to interpret, we display the fitted curves on the relevant temperature range $[5°C, 40°C]$ in Figure 2 as a solid line. County fixed effects shift the curve up and down. To facilitate comparison between specifications, we normalize all plots for a specific crop relative to a baseline temperatures. We use baseline temperatures from agronomic experiments, when plant growth was found to start, i.e., 8°C for corn and soybeans and 12°C for cotton. Because we are ultimately interested in the effects of *changes* in the temperature distribution, levels drop out, so this normalization has no influence on the predicted changes in yields. The 95% confidence band, adjusted for the spatial correlation of the error, is added as dashed lines. The figure shows how misleading a simple linear or even quadratic functional form can be – the negative slope above 29°C is much steeper than the positive slope at more temperate and cool temperatures. Once we add polynomials of fifth order or higher, the relationship becomes relatively stable.

Results obtained using fifth-order Chebyshev polynomials support the concept of degree days: yields increase roughly linearly in temperature between 8°C up to 25°C, before they level off and start decreasing sharply above 29°C. We define the breakpoint between "good" yield-enhancing increases in temperatures to "bad" yield-decreasing temperatures where the slope changes from positive to negative. This finding is a key contribution of this paper: to estimate this breakpoint more precisely. Since Chebyshev polynomials are by design smooth, it is difficult to depict the exact breakpoint from the graph, and we rely on dummy variables in a second step to pinpoint the breakpoint at $29°C$.

Precipitation exhibits an inverted U-shaped relationship. The optimal precipitation level hence is the coefficient on the linear term divided by twice the negative coefficient on the quadratic term. The optimal precipitation level ranges from 25-31 inches, which is comparable to the optimum obtained from agronomic experiments. Peak precipitation levels in the six columns of Table 3 are 31.4, 29.0, 28.5 26.7, 24.7, and 24.9 inches. (Note that precipitation is measured in cm). Because the specification regresses *log* corn yields on temperature and precipitation variables, the marginal effect of temperature depends on rainfall. Below, we show how precipitation mitigates the harmful effects of heat. At the same time, daily records show that the correlation between temperatures and precipitation are rather low, so our model identifies the correct average effect of each temperature, even if the log-linear specification does not fully capture all interactions between temperature and precipitation.

County fixed-effects capture all time-invariant effects, including soil-quality and even average climates to which a farmer can adapt. Thus, while our model implicitly captures short-run adaptations to current and impending and forecastable weather events, it cannot capture longer-run adaptations. This limitation exists in all studies, though perhaps less so in hedonic analyses. Hedonic studies, however, may be more susceptible to omitted variables bias. The fixed effects are displayed in Figure 3. The largest fixed effect (best average growing conditions) are found in the traditional "corn belt" states, while counties further north and south tend to have lower fixed effects.

5.1.2 Dummy variables

The advantage of the fifth-order Chebyshev polynomial is that it reduces the data to five parameters that are easy to interpret and display, yet the functional form might still be too restrictive. We hence replicate the analysis using 50 dummy variables for each 1°C interval between -5°C and 39°C as well as a dummy for temperatures above 39°C for a total of 45 variables. The point estimates as well as confidence intervals over the relevant range are presented in the top middle panel of Figure 4. Note that only weather deviations from county means enter the identification in this linear functional form. The use of fixed effects jointly demeans both the dependent and independent variables; however, the demeaned squared term is different from the square of the demeaned term, and hence the identification also rests on weather averages (climate) for nonlinear functional forms. The estimated relationship is similar to the ones we obtained using Chebyshev polynomials. Harmful effects of temperatures in excess of $29°C$ are clearly visible, as the point estimates of dummies start to drop. There is some noise for lower temperatures as time in these categories change little from year to year. Similarly, confidence intervals for temperatures above $39°C$ become larger as these temperatures are observed less frequently in corn-growing counties.

5.1.3 Piecewise Linear

The Chebyshev polynomial and dummy variable approach are our preferred model estimates, the former because it reduced the data to a few parsimonious parameters that are easy to interpret, the latter because it is more flexible. However, in a third regression we would like to contrast our results to the concept of degree days, which by assumption is piecewise linear. The right panel of Figure 4 displays estimates of such piecewise linear function.

As described in the previous paragraph, the amount of time in each 1-degree has little year-to-year variance for lower and moderate temperature intervals, which makes the likelihood function extremely flat with respect to the lower bound. We therefore fix the lower bound to be 8°C for corn, but allow the linearly increasing part to end anywhere between $20-34°C$, where it could start to plateau. The downward sloping portion is allowed to start at $20 - 34°C$ and plateau anywhere between $20°C$ and $45°C$. We fixed the lower bound at various other levels and consistently get the same breakpoints where temperatures become harmful. The piecewise linear function shows how "good" yield-enhancing temperatures suddenly switch and become harmful once temperatures exceed $29°C$. To maximize yields, a farmer would like constant temperatures of $29°C$. The damaging effects of hotter temperatures are much larger in relative magnitude than the reductions in yields if temperatures fall short of $29°C$. Hence even a limited number of heat waves will severely reduce yields. Due to space constraints we do not report climate change impacts using the piecewise linear function, but they are comparable for corn and soybeans, and deviate slightly for cotton, suggesting that the concept of degree days is appropriate for the former two but maybe not the latter.

5.2 Soybeans and Cotton

We replicated similar analyses for soybeans using all counties in states in Figure 1 that lie east of the 100 degree meridian. We end up with 80854 observations in 2075 counties. The regression results are comparable to those for corn. Precipitation effects peak at 27.4 inches, again close to optimum observed in field experiments.

The middle row of Figure 4 reports the results for soybeans. The left panel shows the fifth-order Chebyshev polynomial which is added in grey for comparison in the remaining two panels: the one using 1°C dummy variables (middle) and the one using a piecewise linear function (right panel). The results are similar to those for corn: the threshold when temperatures become harmful is at 29°C.

Corn and Soybeans are grown in a wide geographic range and are the top two commodity crops in acreage in the U.S. accounting for 32% of crop acreage. We consider cotton next, a crop that is grown predominantly in warmer climates. In order to obtain a larger spatial coverage we pool cotton yields from irrigated West and parts of Texas with cotton yields from non-irrigated southern states. An analysis using only counties in the south gives comparable results but has much larger standard errors. The relationship between temperature and log yields is displayed in the last row of Figure 4. The left panel shows the estimated 5-th order Chebychev polynomial, which, for comparison, is plotted in grey in the remaining two panels. The middle panel uses dummies for each $1°C$ degree interval and the right panel estimates the piecewise-linear function with the lowest sum of squared errors. For the piecewise-linear model, we f ix the lower bound at $12°C$, the lower bound found in the agronomic literature. Cotton is a warm weather crop, and hence the threshold when temperatures become harmful increases to 33°C. The confidence interval increases significantly as well. This might be partly due to fact that the sample frame is much smaller (980 counties with cotton yields, while we had 2075 counties with soybeans yields and 2275 with corn yields). However, as we will show below, the impacts of climate change are statistically significant.

6 Sensitivity Checks

The last section reported basic regression results for all three crops. In this section we consider a series of specification checks for our corn yield models. We focus on corn for brevity (results for soybeans and corn are similar) and because it is the largest and most prevalent crop grown the United States. In the next section we compare our model with others in the literature.

6.1 Geographic Subregions - Potential for Adaptation

In a first sensitivity analysis we examine whether the regression results are comparable for various climatic subregions. We replicate the analysis for northern, interior, and southern counties using the preferred 5^{th}-order Chebyshev polynomial and dummy variables approach.

The regression results for the Chebyshev-polynomials are listed in the first three columns of Table 4, and the Chebyshev polynomials are shown in the top row of Figure 5. All three subsets show similar point estimates for the relationship between temperature and yields, suggesting that there is only limited potential for adaptation to higher average temperatures. If adaptation potential were present, hotter southern counties would exhibit a different functional relationship between yields and temperature. At the same time, confidence intervals increase significantly for southern counties, likely due to the fact that the growing season is shorter in the south and hence warm temperatures are observed after the crop is harvested. Since weather is fairly uncorrelated between months, this will not induce bias but noise. By pooling geographic regions we are measuring the average marginal effect, and it appears interesting to examine whether the marginal effect varies systematically across states. We hence compare the pooled results for eastern to the results from regressions using one state at a time for the 24 states that are not intersected by the 100 degree meridian. Again, the results appear stable across states, but the confidence intervals sometimes increase significantly due to reduced sample sizes. Due to space constraints, the results are available in an additional appendix.

While the results on the Chebyshev polynomials give graphical evidence that the relationship is stable across various subregions, we can also test this conjecture formally with the help of the less restrictive dummy variables approach. The ultimate question is how well farmers could adapt to a warmer climate by switching to other corn varieties. To answer this question, we estimate the area-weighted impacts on all eastern counties using *all observations* in the estimation of the coefficients and compare it to the impacts we would obtain if we only used *southern counties* in the estimation of the coefficients. The rationale for the latter is that in the warmer south farmers supposedly adapted to hotter temperatures by growing the appropriate variety of corn. We do this for both the medium-term (2020-2049) and long-term (2070-2099) for all four emissions scenarios (A1, A2, B1, and B2). Out of the eight estimates, none is statistically different.

6.2 Technological Change

Due to technological progress, corn yields have increased 2.6-fold between the 1950s and 1990s. The quadratic time trends show slowing technological progress, i.e. average growth rates have risen fastest in the 1950s and have since slowed. One possible question is whether technological change not only increased average yields but also the ability of corn to withstand extreme heat above $29°C$. We examine this issue by estimating the model for two subsets of data spanning the years 1950-1977 and 1978-2004.

We start again with the fifth-order Chebyshev polynomial as it offers a clear graphical representation of the fitted curve. The last two columns of Table 4 report the regression results and the first two columns of the middle row of Figure 5 plot the estimated relationship between temperature and yields for each time span. Note how the effect of yield trends is reflected in the R-square. The first subset, years 1950-1977, is the period with the largest average increase in yields. Accordingly the yield trends pick up a significant portion of the variation of the dependent variable, and hence the regression has a higher R-square. The estimated relationship shows little difference between the later and earlier time periods. This suggest that while there was an almost threefold increase in average yields in our sample period, technological progress did not make plants more resistant to extreme heat. The threefold increase in yields in our study might be disguised by changes in cropping areas. For example, if over the years more marginal land was included in the sample, the estimated increase in yields would be downward biased. However, the number is comparable to other estimates that keep the planting area fixed. Also, the total amount of cropland in the U.S. has changed little since 1950.

In a second step we replicate the analysis using our dummy variables approach. Similar to the previous section where we tested for adaptation possibilities by restricting the data set to southern counties in the estimation, we now restrict the data set to the last subperiod 1987-2004 and test whether predicted climate change impacts are significantly different. If heat tolerance of plants had increased over time, one would expect the revised model to give lower damage estimates. However, none of our eight comparison gives significantly different results, suggesting that technological progress has not made plants significantly more heat resistant. The results are given in the climate impact section below.

In this section we have broken the analysis into two subperiods of about 27 years each and gotten similar results. One might wonder what sample size is required for the identification of our model as other variables, like profits, are only available for the Census years 1987, 1992, 1997, 2002. We replicate the analysis using county-fixed with only four observations per county for these four Census years in the bottom right panel of Figure 5. Not only do the confidence intervals increase significantly, but the point estimate for the harmful effects of extreme heat are no longer observable. With this limited data set, we no longer find a statistically significant relationship between temperatures and yields.

6.3 Interaction with Water Availability

One issue is how water availability, either through precipitation or irrigation, mitigates the harmful effects of heat. Many plants can withstand heat better if sufficient water is applied. If irrigation is a perfect substitute for precipitation, then irrigated counties should depend less on precipitation. Yet precipitation peaks at comparable levels for subgroups of states that rely to various degrees on irrigation. (The optimal precipitation levels of the five regressions in Table 4 are 21.9, 24.9, 25.1, 25.7, and 23.7 inches, respectively). However, none of our counties relies on heavily subsidized irrigation water.

Because precipitation and temperatures have a surprisingly low correlation of 0.09, the current approach will correctly predict the average impact of heat. The importance of water (i.e., precipitation in non-irrigated areas) is illustrated in Figure 6, which breaks the data set of all eastern counties into quartiles by total precipitation for the months of June and July. Consecutively higher quartiles include all years and counties with more rainfall during the hottest months. Figure 6 clearly shows how harmful effects of heat are mitigated by more precipitation. Note that precipitation is random enough that most quartiles include observations from almost all counties.

6.4 Length of Growing Season and Time Separability

Here we consider several definitions of the growing season: The starting month is set to be March, April, and May, while the growing season is allowed to end in either August or September. The results are given in the first two rows of Figure 7. Point estimates remain stable across specifications, but confidence intervals increase for later starting months. Such behavior is consistent with the assumed time separability of temperatures. Using a start date of May omits temperatures in earlier parts of the seasons, and widens the confidence band over the lower range of temperatures. At the same time, weather is arguably random, so omitting part of the season does not introduce bias.

Finally, the last rows of Figure 7 splits the six-months growing season into two three-months periods, and the overall shape still remains fairly constant suggesting that time separability is appropriate.

6.5 Other Issues

First, the top left panel of Figure 4 uses year-fixed effects instead of quadratic time trends by state. Although the use of year-fixed effects avoids assumptions regarding the form of the trend, it has a potential drawback: If weather is highly spatially correlated, the year fixed effects may remove most year-to-year variance in weather, severely limiting our source of identification. Our results, however, do not bear this out. The estimated effects of temperature on yield are insensitive to how we model the time trend.

Second, the top left panel of Figure 4 also includes two confidence intervals: one constructed using Conley's technique (black dashed line) and one using a bootstrap technique (black solid line) where we resample years with replacement. In each of the 10000 runs we randomly pick 55 years with replacement and pool all data from these years. Because weather is random between years, but error terms might be spatially correlated within years, such a procedure gives consistent estimates of the variance-covariance matrix of parameter estimates. The confidence bands increase slightly compared to the nonparametric approach by Conley.

Third, the data by the National Agricultural Statistical Service reports yields by acre harvested. There is hence a potential selection problem during extremely bad years when yields are close to zero and farmers choose not to harvest. The yield measure may therefore underestimate of the harmful effects of heat waves. However, when we divide total production quantity by acres planted instead of acres harvested, we obtain similar results which are available in an appendix. Because data on planted acres is missing for 20% of our data, we use production per harvested acre in the body of the paper.

Fourth, we test the sensitivity of our results to the chosen sinusoidal interpolation between minimum and maximum temperature by replicating the analysis using a linear interpolation instead. The results are again similar to our initial estimates and available in an appendix.

7 Comparisons with Other Models in the Literature

Table 5 reports statistical tests that use out-of-sample predictions to compare our models (dummy variables as well as the fifth-order Chebyshev polynomial) to other approaches in the literature. Models are listed in order of best out-of-sample fit. We first motivate our tests and then discuss results.

We estimate each model using 85% of the data and use the estimates to predict the remaining 15%. We reset the random sampler in MATLAB to state 0 for each run so the same in-sample and out-of-sample observations are used for each model. The rationale behind such a test is straight forward: The ultimate goal of this paper is to predict how yields relate to weather. We examine how well a model performs by examining how well it can predict out-of-sample yields. The model that consistently results in the lowest forecast errors can arguably be called the best model. Column 1 of Table 5 hence reports the root mean squared prediction error of each model (RMS) of the out-of-sample forecast. It is important to compare out-of-sample predictions as one wants to rule out "over-fitted" or mispecified models. It is unlikely that a spurious relationship will extend out-of-sample. An example might illustrate this point: Someone discovered that before 2006, Germany had won the world cup if and only if the final was played on a single-digit day in July. The model with the best (perfect) in-sample prediction whether Germany would win the world cup hence examined on what day the final was to take place. The organizer had scheduled the final for July 8th, 2006, but to the big dismay of one of the authors, the out-of sample prediction was inaccurate, as Italy won the world cup.

The RMS examines which model is individually best at forecasting yields. Granger extended the analysis and examined what convex combination of two forecasts will give the best prediction. Intuitively, if the best forecast gives both model 1 and model 2 an equal weight of 0.5, the models "contribute" approximately the same to the optimal forecast. On the other extreme, if one model were to receive a weight of 1, while the other model receives a weight of zero, the latter would not "add" anything to the forecast of the former. Columns 2 and 3 of Table 5 report the Granger weights when the 1-degree dummy variables and the fifth-order Chebyshev polynomial, respectively, are compared to all other models.

While models might give different RMS errors, one might wonder whether the differences are due to chance or whether they are statistically significant. The Morgan-Granger-Newbold statistic examines the Null-hypothesis whether both models have equal forecast accuracy (Diebold and Mariano 1995). The test statistic is approximately standard normal. These statistics are reported in columns 4 and 5, for comparisons with the dummy-variable and Chebychev models, respectively.

We compare our two models, the 1-degree Celsius dummy variable approach as well as the 5th-order Chebyshev polynomial to the following alternatives:

1. Mendelsohn et al. (1994) use a quadratic specification in average temperature and total precipitation for the months January, April, July, and October. (As mentioned above, in a cross-sectional analysis of farmland values, a similar Morgan-Granger-Newbold test favored Thom's formula over monthly averages. The cross-sectional analysis uses expectation of the average climate and not weather outcomes in a particular year, and the interpolation works better for averages than for a single year).

2. Schlenker et al. (2006) include a quadratic functional form in degree days 8-32°C as well as the square root of degree days above 34°C, which are obtained with help of an interpolation method (Thom's formula) from *monthly* data. (The interpolation method is necessary as the concept of degree days is based on daily observations and not monthly observations, yet many data sets only give monthly observations. Thom's formula relates monthly variance of temperatures to the daily variance of temperatures).

3. This paper argues the appropriate bounds for corn are degree days 8-29°C and above 29°C. We hence replicates Thom's formula using these bounds as well as the bounds under point (2).

4. Deschenes and Greenstone (2006) first derive the *average* daily temperature in a county by taking the mean between daily minimum and maximum temperature of all stations in a county. Since *average* temperatures hardly ever exceed 32°C, the authors do not include any category above 32°C. (Deschenes and Greenstone (2006) simply average all minimum and maximum temperature readings in a county, while we construct minimum and maximum temperatures *over the farmland area* in a county with the help of satellite imagines. We use the weather data over all farmland in the tests below to make it comparable to other implementations in this paper, but obtain comparable results if we average all stations in a county.)

5. In this paper we use a quadratic specification using both the original bounds of Deschenes and Greenstone (2006) as well as the best bounds found in this paper, i.e., degree days 8-29°C.

Kelly et al. (2005), briefly described above, use a panel data set of county-level profits for midwestern states to discern the influence of climate (weather averages) from yearly weather shocks, i.e., the authors include both historic mean climate and variability (standard deviation between years). Since climate does not change over time, they cannot include county fixed effects. In our replications we focus on models that use county-fixed effects.

The first column of Table 5 reveals that both the 1-degree Celsius dummy variable approach as well as the fifth-order Chebyshev polynomial clearly dominate all other models in terms of root mean squared error. For comparison, a model with county fixed effects and quadratic yield trends by state, but *no* weather variables, gives a RMS of 0.270. Difference in RMS are statistically significant as the Morgan-Granger-Newbold tests reveal in the last two columns. The Null-hypothesis of equal forecasting accuracy is rejected in all comparisions.

Finally, the optimal Granger weight in the best combined forecast between one of our models (as defined in columns 2 and 3) is always higher on our model compared to inferior models listed in the rows. We report the weight on the model in the column, and the weight on the model in the row is simply one minus the weight on the model in the column. Moreover, degree days models that do not include a category for harmful heat above an upper threshold (the last two rows) perform far worse when compared to any model that accounts for damaging heat. The quadratic functional in 8-32°C outperforms the one using 8-29°C, even though the latter are the appropriate bounds. This is, however, not surprising as the concave quadratic 8-32°C is better at picking up some of the harmful effects of extreme heat, which are omitted as a separate category. This reinforces our point about the importance of the nonlinear relationship between temperature and crop growth: once temperatures exceed an upper threshold, they quickly become very harmful. Our nonparametric approach utilizing the distribution of temperatures within a day is best at picking up this nonlinear relationship.

While we have established the validity of our models compared to others, one might wonder whether they give significantly different climate impacts. We examine this question in the next section.

8 Climate Change Impacts

This section predicts impacts of various climate change scenarios on crop yields. In the previous section we presented two models of the relationship between temperature and yields: (i) a fifth-order Chebyshev polynomial; (ii) a model using dummy variables for each $1°C$ degree Celsius interval. The regression results from each of these models is used to evaluate the effects of climate change on crop yields.

Climate change scenarios are taken from the Hadley HCM3 model that will underly the next report of the Intergovernmental Panel on Climate Change. Emissions scenarios are outlined in Nakicenovic, ed (2000). These scenarios give predicted changes for both minimum and maximum temperatures , and we use both to construct the predicted changes in the distribution of daily temperatures as well as predicted changes for precipitation. The model run B1 assumes the slowest rate of warming over the next century, while model run A1 assumes continued use of fossil fuels, which results in the largest increase in CO_2-concentrations and temperatures. Model B2's warming scenario falls in the middle. We choose the first two scenarios, A1 and B1, to derive the range of possible climate change scenarios and display the spatial extent of the predicted damages for the intermediate B2 scenario. In an appendix available upon request, we also simulate the effects of uniform temperature increases, which might be easier to interpret. Construction of the forecast data was described in section 4. Predicted changes in the temperature distribution under the B2 scenario are given in Table 2. The table reports predictions over both the medium term (2020-2049) and long-term (2070-2099) for the 2275 eastern counties with corn yield data.

8.1 Impact on Corn Yields

Predicted impacts under the B1 scenario are given in the top of Table 6. We examine the range of predicted impacts on the 2275 eastern counties in our sample under both specifications. The first four columns give the mean, minimum, maximum, and standard deviation of the predicted impacts among the 2275 counties for the average weather outcome in the medium-term (2020-2049). The last four columns give the range of predictions in the long-term (2070-2099). For each specification we separate the impacts into changes attributable to temperature and precipitation and give the total impact in the third row. The first three rows use the fifth-order Chebyshev polynomial from the fifth panel of Figure 2, while the next set of estimates uses the 1°C-dummy specification displayed in the top middle panel of Figure 4.

Several results are noteworthy: First, the estimates imply a sharp decline in corn yields, ranging from 29% in the short term to 46% in the long-term, even under the slower warming trend B1. Second, changes in temperatures are more important than the accompanying changes in precipitation. This is partly due the fact that we allow for highly nonlinear effects in temperatures but lump all precipitation in the growing season together. As noted above, temperatures have a low correlation with precipitation, and this procedure hence gives correct average effect of temperature changes. Third, the maximum impact of temperature increases is positive, i.e., there are some northern counties that benefit from warming. Finally, the results are comparable across specifications, indicating they do not follow from assumptions about the exact functional form. The less restrictive 1°C-dummy variables approach gives comparable results to the fifth-order Chebyshev polynomial.

The last four rows of Table 6 give aggregate estimates of all counties. The first column gives the area-weighted change in yields, which is slightly lower than the unweighted average of all counties. The high t-values suggest that these changes are highly statistically significant, even after adjusting for the spatial correlation of the error terms. We also list the number of counties (out of 2275) with statistically significant gains in yields, and how many have statistically significant losses. Counties with significant losses far outnumber the ones with gains, especially towards the end of the century when increases in temperatures have resulted in a significant increase in harmful temperatures above $29°C$. Due to the sharp asymmetry, the harmful effects of temperatures above 29°C outweigh the beneficial effects of more temperatures in the 25-29°C period (see Table 2).

Predicted impacts are larger under the A1-scenario. By the end of the century, predicted yields would decline by up to 80%. Comparing results for the B1-scenario to the ones for the A1-scenario illustrates the benefits of slower warming under the B1-scenario compared to the A1-scenario. The latter implies average area-weighted impacts of approximately 29% in the medium-term and 79-80% in the long-term, while the former implies area-weighted reductions of 22-23% in the medium-term and approximately 44% in the long-term.

The spatial distribution of impacts under the B2-scenario is shown in Figure 8. The B2-scenario predicts warming that lies in the range of the band spanned by the B1 and A1 scenarios. As expected, counties in the south are hit hardest as warming would significantly increase the time temperatures exceed the critical threshold of 29°C. Nevertheless, few northern counties show gains. (Gains are displayed in cross-haired pattern).

In Sections 6.1 and 6.2 we have addressed whether adaptation or technological change might mitigate these large damages. The area-weighted point estimates for the A1, A2, B1 and B2 models when using all counties in the estimation are given in the top row of Table 7 for both the medium-term (2020-2049) and long-term (2070-2099). We first rerun our analysis and only include southern counties in the estimation of the coefficients (as these hotter counties should have adapted to hotter temperatures) but evaluate the impacts for all eastern counties. The point-estimates in the top row of Table 7 change by 3.08, 8.99, 1.83, 7.77, 2.25, 4.37, 1.90, and 4.95, respectively. The associated t-statistic whether the impacts are different are 1.05, 0.86, 0.73, 1.00, 0.91, 1.00, 0.83, and 1.14 respectively, i.e., none of the changes is statistically significant. In a second step we only use the years 1987-2004 in the estimation of the coefficients (to test whether heat tolerance has increased for the last subperiod). The point-estimates in the top row of Table 7 change by 0.54, 9.23, 0.32, 7.64, 0.18, 2.99, 0.08, and 3.3, respectively. The associated t-statistic whether the impacts are different are 0.26, 0.93, 0.18, 1.04, 0.11, 0.85, 0.05, and 0.89, respectively, i.e., again none of the changes is statistically significant.

8.2 Comparison of Impacts on Corn Yields to Other Models

Table 5 has shown that our model is far better at predicting yields out of sample than other approaches in the literature. For comparison, we replicate other approaches found in the literature and predict the potential effects of an increase in temperatures in Table 7.

In a first step we calculate aggregated impacts (weighted by the farmland area in a county) under each model in the first seven rows of Table 7. Differences in predictions can exceed 30 percentage points as the highly non-linear and asymmetrical relationship os inadequately modeled by some of the other approaches.

Second, the aggregate impact might disguise that a model is systematically over- or underpredicting impacts for certain geographic regions. For example, a quadratic functional form led to peak temperature levels of 22°C as it was picking up the sharp asymmetry. This would lead to overestimated damages for counties that usually have temperatures between 220° and 29°C, and overestimate them for counties with very high temperatures. Accordingly, we calculate the mean absolute prediction error compared to our least restrictive model, the 1°C dummy variable model in the last six rows of Table 7. In each county, the predicted change in yields is calculated for both the preferred and the comparison model, and we then average over the absolute differences in all counties included in our data set. Note that even though monthly averages outperformed Thom's formula when predicting yearly yields in Table 7, the latter now performs better as the average absolute prediction error is lower. This is not surprising as climate impacts are evaluated over a 30-year period, and as mentioned above, while Thom's formula is bad at predicting weather (heat waves) in a given year, it fares much better at predicting the average occurrence of harmful heat waves. On the other hand, models that only include one degree days category for beneficial degree days, but not for the harmful effects of extreme heat, perform the worst and give large prediction errors.

Because we examine year-to-year fluctuations to establish the link between temperatures and yields, a farmer cannot switch crops in response to higher average weather outcomes as the seeds are planted before the weather is realized. In this sense our study will provide a lower bound of impacts. At the same time, corn is grown over an extensive geographic region, and the harmful effects are consistent across space and time. If adaptation possibilities were readily available, one might wonder why farmers in warmer, southern parts of the country currently grow corn having no more heat tolerance than corn grown further north. To put our estimates in perspective, we can contrast them in Figure 8 with predicted changes in farmland values from the cross-sectional analysis that incorporate adaptation possibilities for the same climate change scenario in Figure 1 of Schlenker et al. (2006). While the estimates impacts on corn yields are higher than the ones obtained from a cross-section, the geographic distribution of impacts is similar.

8.3 Impacts on Soybeans Yields

The predicted impacts of global warming on soybeans yields are shown in Table 8. In the medium-term, area-weighted yields are predicted to decrease by 16-21%, while, depending on the climate scenario chosen, they are predicted to decline between 33-34% (B1) and 71-72% (A1) by the end of the century. These effects are large, highly significant, and consistent between both models.

8.4 Impact on Cotton Yields

Table 9 reports predicted impacts from climate change on cotton yields. The predicted area-weighted impacts range from 18-19% in the medium term (2020-2049) to 25-31% in the long-term under the B1-scenario and 60-78% under the A1-scenario.

9 Conclusions

An extensive literature relates weather outcomes to crop yields. Traders of corn futures, risk management agencies interested in designing improved crop insurance contracts, as well as regulators assessing the effects of climate change all require an accurate relationship between temperature and yields. Previous empirical studies mostly utilize aggregated weather data or crop simulation models. Reduced-form estimates based on aggregated data obscures non-linear effects. Simulation methods embed strong assumptions in complex dynamic models that rely on calibration methods for a small geographic scale and a limited number of observations, which makes identification difficult. Hence, the exact bounds for various regions of nonlinear growth are still debated.

In this paper we use a unique fine-scale data set of daily weather records and link the entire distribution of temperatures within each day to corn, soybeans, and cotton yields on a large geographic scale for the 55-year time period from 1950 to 2004. This large data set is crucial: for comparison, a panel consisting only of the last four Census years used in other studies does not give any significant results as the sample size is too small.

We find a robust and significant nonlinear relationship between temperature and yields that is in line with the concept of degree days, i.e., yields are linearly increasing in temperature for moderate temperatures, but become quickly harmful once temperatures exceed $29°C$ for corn and soybeans, and $33°C$ for cotton. This relationship is highly significant even after allowing for the spatial correlation of the error terms, which reduce average t-values by a factor of 6.

Encompassing tests show that our new estimate is significantly better at predicting yields than other approaches found in the literature. Our flexible functional form reveals that growth is highly nonlinear and asymmetric in temperature, yet most of the previous studies use a quadratic functional form and thereby impose symmetry, i.e., assume that temperature deviations below and above the optimal growing temperature give equivalent reductions in yield. This is assumed symmetry gives counterintuitive results (optimal growing temperatures sometimes peak at 22°C, which seem to low, and hence give biased estimates of the an increase in temperatures as shown in Table 7. The crucial component in an accurate prediction of yields is the frequency with which the upper threshold is crossed, when temperatures quickly become very harmful. Accordingly, models that do not include a separate category for harmful heat waves perform worst and lead to average absolute prediction errors of up to 30% compared to our preferred model.

Because we use year-to-year fluctuations in weather, farmers are incapable of adapting to any random weather shock by switching crops as the weather shocks are only realized after the crops are planted. A permanent shift to higher average temperatures might induce farmers to grow different crops, and our estimates might therefore overestimate true losses. At the same time, corn is currently grown in many geographic areas, and counties in the hotter southern regions show comparable harmful effects of extreme heat. If adaptation possibilities were cheaply available, one might wonder why these farmers are currently growing corn or why they are not capable to adapting to these higher average temperatures. Moreover, we find no evidence that technological progress increased heat tolerance over the last 55 years: while average yields have gone up almost threefold, the breakpoint where temperatures become harmful is the same in later time periods as it is in earlier periods.

The relationship between temperatures and crop yields is used to derive the effects of changes in average weather on crop yields. The estimated damages are large, highly significant, and robust to various model specifications. Under our preferred model using 1°C degree dummy variables, impacts for corn, soybeans, and cotton imply a 79%, 71%, and 60% reductions in yields, respectively, under the rapid warming scenario (A1) and a 44%, 33%, and 25% under the slower warming scenario (B1). As mentioned above, our analysis will not be able to pick up changes in cropping patterns as a response to climate change. We therefore compare our results to estimates obtained from a cross-sectional analysis using farmland values that incorporate adaptations, which also give large negative impacts, albeit at a lower magnitude.

It should be noted that our analysis focuses on yield responses. How these yield responses translate into welfare change depends on world food supply. Rosenzweig and Hillel (1998) predict significant shifts in production regions, but limited effects on world food supply and price. For example, the main corn growing region would shift north into Canada. In such a cases farmers bear all consequences of predicted reductions in yields, while consumers are not impacted at all. If, on the other hand, world food supplies were dropping, prices for agricultural goods would rise, especially given the inelastic demand of agricultural goods. Rising food prices shift the burden from farmers to consumers. Farmers will fare comparatively better as reductions in harvest quantities are offset by rising prices per unit harvested. Consumers, on the other hand, would face higher food expenditures.

Important caveats are that our analysis does not incorporate technological progress that may be induced by warmer temperatures and large yields losses. Yet, as pointed out above, plants have not become more heat tolerant over the last 55 years even though average yields increased almost threefold. And corn grown in the warmer southern region shows no more heat tolerance than the cooler north. A second caveat pertains to the fact that we are unable to account for effects stemming from CO_2-fertilization. Plants use CO_2 as an input in the photosynthesis process and increasing CO_2 levels might hence spur plant growth. While CO_2-fertilization may significantly offset impacts predicted in this study, the magnitude of the effect is still debated. At present possible CO_2 effects associated with climate change are not sufficiently understood. Long et al. (2005) recently stressed that existing laboratory studies as well as field experiments might overestimate this effect.

References

Adams, Richard M., Ronald A. Flemming, Ching-Chang Chang, Bruce A. McCarl, and Cynthia Rosenzweig, "A Reassessment of the Economic Effects of Global Climate Change on U.S. Agriculture," *Climatic Change*, June 1995, *30* (2), 147–167.

Ashenfelter, Orley and Karl Storchmann, "Using a Hedonic Model of Solar Radiation to Assess the Economic Effect of Climate Change: The Case of Mosel Valley Vineyards," *NBER Working Paper 12380*, July 2006.

Black, J. Roy and Stanley R. Thompson, "Some Evidence on Weather-Crop-Yield Interaction," *American Journal of Agricultural Economics*, August 1978, *60* (3).

Conley, Timothy G., "GMM Estimation with Cross Sectional Dependence," *Journal of Econometrics*, September 1999, *92* (1), 1–45.

Darwin, Roy, "A Farmers view of the ricardian approach to measuring agricultural effects of climate change," *Climatic Change*, March-April 1999, *41*, 371–411.

Deschenes, Olivier and Michael Greenstone, "The Economic Impacts of Climate Change: Evidence from Agricultural Profits and Random Fluctuations in Weather," *Center for the Study of Energy Markets Working Paper 158*, August 2006.

Diebold, Francis X. and Roberto S. Mariano, "Comparing Predictive Accuracy," *Journal of Business and Economic Statistics*, July 1995, *13* (3), 253–263.

Kaylen, Michael S., John W. Wade, and Deon B. Frank, "Stochastic trend, weather and US corn yield variability," *Applied Economics*, May 1992, *24* (5), 513–518.

Kelly, David L., Charles D. Kolstad, and Glenn T. Mitchell, "Adjustment costs from environmental change," *Journal of Environmental Economics and Management*, November 2005, *50* (3), 468–495.

Long, Stephen P., Elizabeth A. Ainsworth, Andrew D.B. Leakey, and Patrick B. Morgan, "Global food insecurity. Treatment of major food crops with elevated carbon dioxide or ozone under large-scale fully open-airconditins suggests recent models may have overestimated future yields.," *Philosophical Transaction of the Royal Society B*, 2005, *360*, 2011–2020.

Mendelsohn, Robert, William D. Nordhaus, and Daigee Shaw, "The Impact of Global Warming on Agriculture: A Ricardian Analysis," *American Economic Review*, September 1994, *84* (4), 753–771.

Nakicenovic, Nebojsa, ed., *Special Report on Emissions Scenarios*, Cambridge University Press, 2000.

Newey, Whitney K. and Kenneth D. West, "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica*, May 1987, *3* (3), 703–708.

Ritchie, J. T. and D. S. NeSmith, "Temperature and Crop Development," in John Hanks and J. T. Richie, eds., *Modeling Plant and Soil Systems. Agronomy 31*, American Society of Agronomy Madison, WI 1991, pp. 5–29.

Rosenzweig, Cynthia and Daniel Hillel, *Climate Change and the Global Harvest*, New York: Oxford University Press, 1998.

Schlenker, Wolfram and Michael Roberts, "Non-linear Effects of Weather on Corn Yields," *Review of Agricultural Economics (Proceedings of the American Agricultural Economics Association Sessions at the 2006 Allied Social Science Associations Meeting, Boston, MA)*, 2006, *28* (3), 391–398.

___ **, W. Michael Hanemann, and Anthony C. Fisher**, "Will U.S. Agriculture Really Benefit From Global Warming? Accounting for Irrigation in the Hedonic Approach.," *American Economic Review*, March 2005, *95* (1), 395–406.

___ **,** ___ **, and** ___ , "The Impact of Global Warming on U.S. Agriculture: An Econometric Analysis of Optimal Growing Conditions," *Review of Economics and Statistics*, February 2006, *88* (1), 113–125.

Sinclair, Thomas R. and Noam G. Seligman, "Crop modeling: from infancy to maturity," *Agronomy Journal*, September-October 1996, *88* (5), 698–704.

___ **and Noam Seligman**, "Criteria for publishing papers on crop modeling," *Field Crops Research*, November 2000, *68* (3), 165–172.

Thom, H. C. S., "Normal Degree Days Above Any Base by the Universal Truncation Coefficient," *Monthly Weather Review*, July 1966, *94* (7), 461–465.

Timmins, Christopher, "Endogenous Land Use and the Ricardian Valuation of Climate Change," *Environmental and Resource Economics*, January 2006, *33* (1), 119–142.

Wallach, Daniel, Bruno Goffinet, Jacques-Eric Bergeza, Philippe Debaekea, Delphine Leenhardta, and Jean-Nol Aubertotc, "Parameter Estimation for Crop Models: A New Approach and Application to a Corn Model," *Agronomy Journal*, July-August 2001, *93* (4), 757–766.

Table 1: Descriptive Statistics

	Corn / Soybeans Counties					Cotton Counties				
Variable	**Mean**	**Min**	**Max**	σ	σ_{years}	**Mean**	**Min**	**Max**	σ	σ_{years}
Yield Data										
log Corn Yield	4.19	-3.19	5.32	0.54	0.42					
log Soybeans Yield	3.23	0.59	5.52	0.37	0.27					
log Cotton Yield						5.97	2.08	8.14	0.54	0.37
Weather Data - Temperature Data are Days in each 1-degree Celsius Interval										
Temp in [-5°C,-4°C)	0.77	0.00	4.40	0.75	0.30	0.01	0.00	0.58	0.03	0.02
Temp in [-4°C,-3°C)	0.97	0.00	5.08	0.87	0.34	0.01	0.00	0.79	0.05	0.03
Temp in [-3°C,-2°C)	1.21	0.00	5.45	0.99	0.37	0.03	0.00	1.45	0.08	0.05
Temp in [-2°C,-1°C)	1.48	0.00	6.50	1.11	0.41	0.06	0.00	1.72	0.12	0.08
Temp in [-1°C,0°C)	1.76	0.00	6.72	1.24	0.46	0.12	0.00	1.67	0.18	0.11
Temp in [0°C,1°C)	2.02	0.00	7.27	1.30	0.49	0.20	0.00	2.20	0.24	0.15
Temp in [1°C,2°C)	2.21	0.00	7.48	1.30	0.50	0.31	0.00	2.62	0.31	0.18
Temp in [2°C,3°C)	2.38	0.00	7.33	1.26	0.49	0.45	0.00	3.07	0.39	0.22
Temp in [3°C,4°C)	2.54	0.00	7.25	1.22	0.50	0.63	0.00	3.54	0.47	0.26
Temp in [4°C,5°C)	2.72	0.00	7.13	1.18	0.50	0.85	0.00	4.26	0.56	0.31
Temp in [5°C,6°C)	2.90	0.00	6.87	1.14	0.52	1.10	0.00	5.01	0.64	0.34
Temp in [6°C,7°C)	3.10	0.00	7.30	1.11	0.53	1.39	0.00	6.22	0.73	0.37
Temp in [7°C,8°C)	3.31	0.00	7.39	1.09	0.54	1.70	0.00	8.13	0.81	0.41
Temp in [8°C,9°C)	3.53	0.00	8.14	1.09	0.55	2.05	0.00	9.50	0.90	0.44
Temp in [9°C,10°C)	3.79	0.00	8.38	1.11	0.57	2.43	0.00	10.59	0.99	0.47
Temp in [10°C,11°C)	4.10	0.14	8.59	1.15	0.59	2.86	0.00	11.80	1.08	0.51
Temp in [11°C,12°C)	4.44	0.25	9.35	1.19	0.62	3.35	0.01	11.62	1.17	0.55
Temp in [12°C,13°C)	4.83	0.50	10.34	1.25	0.66	3.89	0.07	11.68	1.26	0.59
Temp in [13°C,14°C)	5.24	0.54	11.51	1.30	0.69	4.48	0.12	12.35	1.35	0.64
Temp in [14°C,15°C)	5.68	0.53	12.98	1.34	0.73	5.14	0.19	11.83	1.44	0.69
Temp in [15°C,16°C)	6.16	0.86	13.35	1.35	0.77	5.90	0.30	11.68	1.53	0.75
Temp in [16°C,17°C)	6.64	1.30	13.24	1.33	0.80	6.76	0.78	12.75	1.63	0.83
Temp in [17°C,18°C)	7.14	1.54	13.12	1.27	0.82	7.74	1.34	14.19	1.72	0.91
Temp in [18°C,19°C)	7.61	2.35	13.96	1.24	0.84	8.85	1.96	15.61	1.83	1.01
Temp in [19°C,20°C)	8.06	2.51	14.15	1.32	0.87	10.17	2.56	17.63	1.98	1.14
Temp in [20°C,21°C)	8.46	2.88	16.04	1.57	0.88	11.70	3.39	18.48	2.07	1.21
Temp in [21°C,22°C)	8.61	3.53	16.88	1.90	0.82	12.76	4.56	19.21	2.10	1.12
Temp in [22°C,23°C)	8.41	2.76	17.67	2.05	0.75	12.77	5.82	22.38	2.03	0.98
Temp in [23°C,24°C)	7.95	2.46	19.32	1.98	0.68	12.10	6.35	20.53	1.94	0.81
Temp in [24°C,25°C)	7.43	1.52	19.18	1.80	0.64	11.31	5.96	22.05	1.77	0.72
Temp in [25°C,26°C)	6.97	0.79	19.55	1.66	0.65	10.67	5.48	22.21	1.57	0.70
Temp in [26°C,27°C)	6.56	0.00	17.12	1.66	0.68	10.21	4.94	22.05	1.47	0.71
Temp in [27°C,28°C)	6.12	0.00	14.26	1.77	0.73	9.80	4.27	18.85	1.45	0.75
Temp in [28°C,29°C)	5.61	0.00	12.93	1.94	0.78	9.37	3.92	17.82	1.48	0.79
Temp in [29°C,30°C)	4.99	0.00	12.93	2.11	0.81	8.81	3.06	16.84	1.56	0.86
Temp in [30°C,31°C)	4.28	0.00	12.56	2.22	0.83	8.10	1.45	15.43	1.66	0.90
Temp in [31°C,32°C)	3.52	0.00	11.34	2.23	0.81	7.21	0.25	14.87	1.80	0.96
Temp in [32°C,33°C)	2.74	0.00	11.08	2.10	0.81	6.03	0.04	14.49	1.94	1.08
Temp in [33°C,34°C)	1.95	0.00	10.35	1.82	0.79	4.63	0.00	13.20	2.03	1.23
Temp in [34°C,35°C)	1.25	0.00	9.46	1.44	0.74	3.19	0.00	11.47	2.02	1.28
Temp in [35°C,36°C)	0.73	0.00	9.08	1.10	0.61	2.02	0.00	10.93	1.84	1.14
Temp in [36°C,37°C)	0.41	0.00	8.22	0.82	0.47	1.22	0.00	9.44	1.56	0.91
Temp in [37°C,38°C)	0.22	0.00	8.08	0.57	0.32	0.71	0.00	8.63	1.24	0.65
Temp in [38°C,39°C)	0.10	0.00	7.17	0.36	0.19	0.40	0.00	8.42	0.95	0.42
Temp in [39°C,40°C)	0.05	0.00	6.93	0.21	0.10	0.22	0.00	8.83	0.73	0.24
Temp in [40°C,41°C)	0.02	0.00	3.42	0.12	0.05	0.12	0.00	8.10	0.57	0.12
Temp in [41°C,42°C)	0.01	0.00	2.27	0.06	0.02	0.07	0.00	7.17	0.44	0.06
Temp in [42°C,43°C)	0.00	0.00	1.53	0.03	0.01	0.04	0.00	6.10	0.31	0.03
Temp in [43°C,44°C)	0.00	0.00	0.83	0.02	0.00	0.02	0.00	4.88	0.20	0.02
Temp in [44°C,45°C)	0.00	0.00	0.48	0.01	0.00	0.01	0.00	3.23	0.12	0.01
Temp in [45°C,46°C)	0.00	0.00	0.33	0.00	0.00	0.00	0.00	2.06	0.06	0.00
Temp in [46°C,47°C)	0.00	0.00	0.18	0.00	0.00	0.00	0.00	1.63	0.03	0.00
Temp in [47°C,48°C)	0.00	0.00	0.07	0.00	0.00	0.00	0.00	0.76	0.01	0.00
Temp in [48°C,49°C)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.52	0.01	0.00
Temp in [49°C,oo)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.24	0.00	0.00
Precipitation (cm)	59.20	5.78	143.33	15.68	12.10	65.80	0.08	175.75	22.01	14.22
Counties	2277					980				
Observations	108746					31075				

Notes: Table lists descriptive statistics. The first five columns use counties east of the 100 degree meridian, where aggregated weather variables for the months March through August are averaged over counties that either have corn or soybeans yields. The last five columns use all counties in the United States that have cotton yields (which is mainly grown in the southwest) and aggregates variables for the months April through October. In each set, the first four columns give the mean, minimum, maximum, and standard deviation of each variable in the years 1950-2004. The fifth column gives the average *within-county* year-to-year standard deviation.

Table 2: Predicted Changes in Climatic Variables Under the B2 Scenario

	Time Period 2020-2049				Time Period 2070-2099			
Variable	**Mean**	**Min**	**Max**	σ	**Mean**	**Min**	**Max**	σ
Temp in [-5°C,-4°C)	-0.12	-0.60	0.07	0.14	-0.32	-0.84	0.00	0.24
Temp in [-4°C,-3°C)	-0.16	-0.76	0.06	0.17	-0.40	-1.05	0.00	0.28
Temp in [-3°C,-2°C)	-0.20	-0.78	0.09	0.20	-0.48	-1.19	0.00	0.31
Temp in [-2°C,-1°C)	-0.25	-0.98	0.10	0.23	-0.57	-1.35	-0.00	0.35
Temp in [-1°C,0°C)	-0.29	-1.07	0.12	0.25	-0.66	-1.61	-0.00	0.38
Temp in [0°C,1°C)	-0.28	-1.11	0.08	0.19	-0.67	-1.73	-0.01	0.34
Temp in [1°C,2°C)	-0.24	-0.72	0.09	0.14	-0.60	-1.51	-0.01	0.25
Temp in [2°C,3°C)	-0.24	-0.69	0.22	0.15	-0.50	-1.09	0.15	0.21
Temp in [3°C,4°C)	-0.26	-0.73	0.19	0.15	-0.47	-1.18	0.33	0.23
Temp in [4°C,5°C)	-0.30	-0.79	0.12	0.15	-0.49	-1.15	0.37	0.24
Temp in [5°C,6°C)	-0.33	-0.92	0.05	0.15	-0.53	-1.16	0.31	0.22
Temp in [6°C,7°C)	-0.37	-0.95	-0.01	0.15	-0.59	-1.45	0.09	0.20
Temp in [7°C,8°C)	-0.42	-1.03	-0.10	0.16	-0.65	-1.70	0.02	0.20
Temp in [8°C,9°C)	-0.45	-1.05	-0.11	0.18	-0.73	-1.87	-0.00	0.22
Temp in [9°C,10°C)	-0.52	-1.19	-0.13	0.19	-0.82	-1.87	-0.26	0.27
Temp in [10°C,11°C)	-0.61	-1.38	-0.22	0.21	-0.96	-2.14	-0.42	0.31
Temp in [11°C,12°C)	-0.70	-1.73	-0.24	0.23	-1.13	-2.33	-0.53	0.35
Temp in [12°C,13°C)	-0.79	-2.15	-0.23	0.25	-1.30	-2.97	-0.50	0.38
Temp in [13°C,14°C)	-0.87	-2.91	-0.15	0.27	-1.46	-3.97	-0.62	0.42
Temp in [14°C,15°C)	-0.96	-3.31	0.05	0.31	-1.62	-4.86	-0.31	0.44
Temp in [15°C,16°C)	-1.05	-3.09	0.24	0.38	-1.79	-4.50	0.01	0.48
Temp in [16°C,17°C)	-1.14	-3.53	0.69	0.49	-1.96	-4.54	0.26	0.57
Temp in [17°C,18°C)	-1.21	-3.79	1.28	0.65	-2.09	-5.02	0.85	0.74
Temp in [18°C,19°C)	-1.25	-3.84	1.54	0.89	-2.19	-5.11	1.38	1.01
Temp in [19°C,20°C)	-1.25	-4.57	1.59	1.18	-2.22	-5.61	2.10	1.38
Temp in [20°C,21°C)	-1.23	-4.93	1.78	1.56	-2.20	-6.01	2.12	1.86
Temp in [21°C,22°C)	-1.03	-5.40	1.76	1.85	-1.93	-6.84	2.23	2.26
Temp in [22°C,23°C)	-0.52	-6.38	1.98	1.78	-1.37	-7.85	2.46	2.37
Temp in [23°C,24°C)	0.09	-6.84	2.24	1.47	-0.59	-8.83	2.49	2.18
Temp in [24°C,25°C)	0.51	-7.43	2.44	0.91	0.22	-9.47	2.67	1.69
Temp in [25°C,26°C)	0.64	-5.88	3.29	0.53	0.80	-9.35	3.98	1.18
Temp in [26°C,27°C)	0.62	-1.74	3.71	0.51	1.06	-6.64	5.26	0.78
Temp in [27°C,28°C)	0.59	-0.52	3.43	0.54	1.15	-2.35	5.51	0.75
Temp in [28°C,29°C)	0.66	-0.45	3.45	0.63	1.21	-0.22	5.32	0.87
Temp in [29°C,30°C)	0.85	-0.49	3.62	0.71	1.36	-0.15	5.59	0.97
Temp in [30°C,31°C)	1.09	-0.68	3.57	0.78	1.66	-0.21	5.31	1.10
Temp in [31°C,32°C)	1.32	-0.53	3.53	0.81	2.03	-0.29	5.27	1.20
Temp in [32°C,33°C)	1.54	-0.22	3.60	0.76	2.43	-0.17	5.22	1.18
Temp in [33°C,34°C)	1.70	-0.00	5.01	0.80	2.81	-0.32	5.67	1.09
Temp in [34°C,35°C)	1.77	0.00	6.40	1.07	3.07	-0.33	7.27	1.13
Temp in [35°C,36°C)	1.69	0.00	6.48	1.30	3.07	-0.27	7.52	1.32
Temp in [36°C,37°C)	1.43	0.00	6.35	1.28	2.85	0.01	7.59	1.48
Temp in [37°C,38°C)	1.10	0.00	5.41	1.11	2.48	0.00	7.03	1.55
Temp in [38°C,39°C)	0.77	0.00	4.70	0.94	2.02	0.00	6.70	1.52
Temp in [39°C,40°C)	0.51	0.00	4.21	0.77	1.53	0.00	6.10	1.37
Temp in [40°C,41°C)	0.32	0.00	4.00	0.59	1.07	0.00	5.85	1.18
Temp in [41°C,42°C)	0.18	0.00	3.43	0.39	0.72	0.00	5.67	0.97
Temp in [42°C,43°C)	0.09	0.00	2.34	0.21	0.46	0.00	4.77	0.74
Temp in [43°C,44°C)	0.04	0.00	1.10	0.10	0.28	0.00	3.79	0.52
Temp in [44°C,45°C)	0.01	0.00	0.53	0.04	0.15	0.00	2.80	0.31
Temp in [45°C,46°C)	0.00	0.00	0.24	0.02	0.07	0.00	1.43	0.16
Temp in [46°C,47°C)	0.00	0.00	0.12	0.01	0.03	0.00	0.72	0.08
Temp in [47°C,48°C)	0.00	0.00	0.04	0.00	0.01	0.00	0.34	0.03
Temp in [48°C,49°C)	0.00	0.00	0.01	0.00	0.00	0.00	0.14	0.01
Temp in [49°C,oo)	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.01
Precipitation (cm)	-0.13	-14.65	8.82	3.60	1.70	-14.22	11.36	4.10

Notes: The Table lists predicted changes in the temperature distribution for 2275 eastern counties with corn yields under the B2-scenario. The first four columns list predicted changes for 2020-2049 compared to the 1960-1989 baseline period, while the last four columns list longer term changes for 2070-2099 compared to 1960-1989.

Table 3: Polynomial Regression Results for Corn

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Temperature (1st-order)	-1.09E-02	-2.10E-02	-5.72E-02	-4.06E-02	2.48E-03	-1.91E-03
	(7.87)	(13.06)	(13.24)	(11.23)	(0.67)	(0.48)
Temperature (2nd-order)		-1.66E-02	-3.20E-02	-1.09E-02	9.84E-03	1.47E-02
		(13.23)	(14.50)	(5.24)	(4.30)	(5.61)
Temperature (3rd-order)			-1.72E-02	-7.93E-03	2.73E-02	3.00E-02
			(10.08)	(5.23)	(9.49)	(9.75)
Temperature (4th-order)				1.15E-02	2.16E-02	3.19E-02
				(13.10)	(16.60)	(8.62)
Temperature (5th-order)					1.71E-02	2.12E-02
					(11.65)	(9.59)
Temperature (6th-order)						7.24E-03
						(3.27)
Precipitation	1.99E-02	1.59E-02	1.49E-02	1.21E-02	1.04E-02	1.02E-02
	(10.78)	(9.28)	(9.07)	(7.91)	(6.87)	(6.79)
Precipitation Squared	-1.25E-04	-1.08E-04	-1.03E-04	-8.96E-05	-8.25E-05	-8.09E-05
	(8.88)	(8.49)	(8.44)	(7.79)	(7.27)	(7.21)
R^2	0.69	0.72	0.73	0.75	0.76	0.76
Number of Observations	104307	104307	104307	104307	104307	104307
Number of Counties	2275	2275	2275	2275	2275	2275
County Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
State Yield Trend	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports coefficient estimates and t-values (in parentheses) for six regressions with temperature polynomials of order one to six. (We use Chebyshev polynomials instead of regular polynomials as the former are more flexible and orthogonal). The dependent variable is the natural log of corn yields for a pooled sample of 2275 counties and years 1950 to 2004. Only counties east of the 100th meridian are included in the sample to focus on non-irrigated cropland. The model is given in equation (3). Each column reports results from one regression. T-values are adjusted for spatial correlation of contemporaneous errors following Conley (1999).

Table 4: Regression Results Using Various Geographic and Temporal Subsets

Variable	**North**	**Interior**	**South**	**1950-1977**	**1978-2004**
Temperature (1st-order)	8.98E-04	-2.43E-03	4.88E-02	-6.87E-03	1.36E-02
	(0.23)	(0.27)	(1.75)	(1.36)	(2.68)
Temperature (2nd-order)	9.30E-03	6.91E-03	3.85E-02	4.29E-03	1.66E-02
	(3.59)	(1.39)	(2.19)	(1.43)	(5.15)
Temperature (3rd-order)	2.63E-02	2.87E-02	5.57E-02	2.24E-02	3.24E-02
	(7.95)	(4.68)	(3.27)	(5.57)	(9.04)
Temperature (4th-order)	2.30E-02	2.30E-02	2.94E-02	1.97E-02	2.52E-02
	(12.30)	(8.73)	(4.92)	(10.05)	(15.54)
Temperature (5th-order)	1.64E-02	2.05E-02	2.61E-02	1.63E-02	1.74E-02
	(9.39)	(6.21)	(4.88)	(7.58)	(10.59)
Precipitation	2.39E-02	1.48E-02	5.53E-03	1.14E-02	8.94E-03
	(8.53)	(4.18)	(2.40)	(5.93)	(5.03)
Precipitation Squared	-2.15E-04	-1.17E-04	-4.34E-05	-8.73E-05	-7.43E-05
	(8.65)	(4.16)	(3.01)	(5.93)	(5.46)
R^2	0.80	0.74	0.74	0.65	0.60
Number of Observations	41977	26792	35538	52987	51320
Number of Counties	826	551	898	2264	2218
County Fixed Effect	Yes	Yes	Yes	Yes	Yes
State Yield Trend	Yes	Yes	Yes	Yes	Yes

Notes: Table gives coefficient estimates and t-values in parentheses. The latter are adjusted for spatial correlation of contemporaneous error terms following Conley (1999). Temperature variables are modeled as Chebyshev polynomials.

Table 5: Model Comparison Test for Out-Of-Sample Prediction Accuracy

		Granger Weight		MGN Statistic	
	RMSE	Dummy Variables	Chebyshev Polynomials	Dummy Variables	Chebyshev Polynomials
Dummy Variables	0.226				
Chebyshev Polynomials	0.229	1.001		11.23	
Monthly Averages	0.237	0.731	0.676	13.99	10.07
Degree Days 8-29°C, >29°C (Thom)	0.240	0.983	0.988	21.89	18.69
Degree Days 8-32°C, >34°C (Thom)	0.247	0.980	0.974	27.27	24.41
Degree Days 8-32°C (Daily Mean)	0.252	0.993	0.977	30.57	27.56
Degree Days 8-29°C (Daily Mean)	0.253	0.990	0.970	31.42	28.32

Notes: The first column present the root mean squared out-of sample prediction error (RMS). A lower out-of sample prediction error implies that the model is better at explaining the variable of interest. Models are ordered from best out-of-sample prediction to worst.

The remaining columns present pairwise model comparisons between the dummy-variable and Chebychev models and all inferior models (remaining comparisons are given in an appendix). The second and third column give the Granger weight on the model listed in the column. An optimal combined forecast is derived as a weighted average of the two forecasts (where the weights sum to 1). The last two columns display the standard-normal distributed Morgan-Newbold-Granger (MGN) statistic of equal forecasting accuracy.

Each model is estimated using the same 85% of the data and yields are forecasted out-of-sample for the omitted 15%. Dummy variables and Chebyshev Polynomials are the models developed in this paper; monthly averages uses a quadratic specification in both average temperature and total precipitation for the months January, April, July, and October (Mendelsohn et al. 1994); Thom's formula uses monthly average temperature data to extrapolate degree days (which are based on daily data) (Schlenker et al. 2006); truncated daily averages first derive the average temperature for each day from daily temperature readings and then construct degree days from this average (Deschenes and Greenstone 2006).

Table 6: Predicted Impacts of Global Warming on Corn

	Medium-term 2020-2049				Long-term 2070-2099			
Variable	**Mean**	**Min**	**Max**	**Std**	**Mean**	**Min**	**Max**	**Std**
				Climate Scenario Hadley HCM3 - B1				
Chebyshev Polynomial								
Temperature	-29.36	-66.80	11.14	18.95	-47.96	-86.78	12.88	19.48
Precipitation	-0.23	-4.13	4.13	0.84	-0.37	-8.01	3.87	1.08
Total	-29.47	-68.05	7.62	19.13	-48.07	-87.29	8.94	19.70
1°C Dummy Intervals								
Temperature	-28.55	-61.67	11.93	17.21	-45.89	-82.25	18.97	17.62
Precipitation	-0.19	-4.98	4.36	1.00	-0.31	-8.59	4.09	1.21
Total	-28.60	-63.20	12.10	17.53	-45.95	-83.08	14.59	17.96
				Climate Scenario Hadley HCM3 - A1				
Chebyshev Polynomial								
Temperature	-33.73	-72.82	10.64	18.46	-81.35	-98.17	-10.53	13.77
Precipitation	-0.24	-4.75	3.77	0.86	-0.98	-11.14	6.29	1.89
Total	-33.82	-73.69	8.24	18.68	-81.44	-98.33	-8.93	13.89
1°C Dummy Intervals								
Temperature	-32.50	-67.43	12.83	16.57	-80.21	-98.60	-9.62	14.34
Precipitation	-0.20	-5.14	3.98	1.03	-1.00	-12.01	6.12	2.18
Total	-32.54	-68.60	10.01	16.93	-80.28	-98.74	-7.57	14.52
	Medium-term 2020-2049				**Long-term 2070-2099**			
Model	**Impact**	**t-value**	**Gain**	**Loss**	**Impact**	**t-value**	**Gain**	**Loss**
				Climate Scenario Hadley HCM3 - B1				
Polynomial	-22.34	(21.29)	69	2092	-44.17	(26.69)	6	2229
Dummy Intervals	-22.72	(20.46)	87	2085	-43.56	(17.69)	12	2211
				Climate Scenario Hadley HCM3 - A1				
Polynomial	-28.74	(22.99)	31	2145	-79.92	(51.44)	0	2275
Dummy Intervals	-29.05	(20.53)	55	2119	-79.07	(12.40)	0	2275

Notes: The first twelve rows list predicted percentage changes in crop yields for eastern counties using both specifications for the two extreme climate scenarios. Each set of three rows reports impacts attributable to changing temperatures and precipitation, as well as total impacts. The last four rows report the area-weighted impacts (including t-values) as well as how many of the 2275 counties either had statistically significant gains or losses at the 95% level.

Table 7: Comparison of Predicted Climate Impacts For Various Models

	HCM3-A1		HCM3-A2		HCM3-B1		HCM3-B2	
	20-49	**70-99**	**20-49**	**70-99**	**20-49**	**70-99**	**20-49**	**70-99**
Farmland Area Weighted Climate Impacts								
Dummy Variable	-29.05	-79.07	-27.66	-69.96	-22.72	-43.56	-23.13	-50.87
5th-order Chebyshev Polynomial	-28.74	-79.92	-27.19	-71.05	-22.34	-44.17	-22.58	-50.98
Monthly Averages	-20.82	-71.43	-17.47	-60.23	-13.75	-36.84	-14.14	-34.27
Degree Days 8-29°C, >29°C (Thom)	-25.33	-82.30	-23.53	-71.53	-19.42	-42.31	-19.81	-48.00
Degree Days 8-32°C, >34°C (Thom)	-20.99	-78.89	-20.01	-64.75	-16.83	-35.70	-17.57	-41.09
Degree Days 8-32°C (Daily Mean)	-14.95	-55.88	-15.53	-45.01	-12.58	-26.04	-13.69	-29.33
Degree Days 8-29°C (Daily Mean)	-12.88	-45.63	-13.65	-36.90	-11.02	-22.18	-12.21	-24.80
Mean Absolute Prediction Error Compared to Preferred Model								
5th-order Chebyshev Polynomial	2.78	2.13	2.76	2.27	2.51	3.10	2.65	3.09
Monthly Averages	7.59	9.87	11.23	11.01	10.61	7.60	9.20	13.71
Degree Days 8-29°C, >29°C (Thom)	6.20	3.73	6.01	5.02	5.39	6.62	5.66	7.25
Degree Days 8-32°C, >34°C (Thom)	7.06	5.60	7.91	7.75	6.23	7.25	6.98	8.97
Degree Days 8-32°C (Daily Mean)	11.16	18.11	11.19	19.54	9.58	12.64	10.20	16.98
Degree Days 8-29°C (Daily Mean)	15.25	29.93	15.18	30.03	13.12	18.87	13.85	24.49

Notes: The table compares predicted impacts on corn yields under various scenarios. Climate scenarios are evaluated for four emissions scenarios: A1, A2, B1, B2 in the medium-term 20-49 (2020-2049) and long-term 70-99 (2070-2099). The first seven rows give the farmland-area weighted impacts in percentage points. The last six rows give the mean absolute prediction error in percentage points compared to our preferred model using dummy variables for each 1°C degree interval (Models are described in Table 5).

Table 8: Predicted Impacts of Global Warming on Soybeans

	Medium-term 2020-2049				Long-term 2070-2099			
Variable	**Mean**	**Min**	**Max**	**Std**	**Mean**	**Min**	**Max**	**Std**
	Climate Scenario Hadley HCM3 - B1							
Chebyshev Polynomial								
Temperature	-20.40	-59.44	17.16	16.71	-35.94	-80.17	25.57	19.14
Precipitation	0.05	-5.17	3.00	0.98	0.02	-6.55	3.69	1.11
Total	-20.26	-61.15	14.40	17.17	-35.79	-81.15	22.29	19.65
1°C Dummy Intervals								
Temperature	-19.99	-59.01	18.13	16.17	-34.83	-80.82	26.63	18.51
Precipitation	0.08	-5.33	2.93	1.02	0.06	-6.48	3.84	1.14
Total	-19.82	-61.07	15.42	16.68	-34.66	-81.80	23.39	19.06
	Climate Scenario Hadley HCM3 - A1							
Chebyshev Polynomial								
Temperature	-23.95	-65.08	17.42	16.65	-72.58	-96.75	7.91	16.93
Precipitation	0.08	-4.34	3.44	1.03	-0.48	-10.78	3.76	2.04
Total	-23.78	-66.41	14.45	17.18	-72.54	-97.09	9.70	17.27
1°C Dummy Intervals								
Temperature	-23.33	-65.27	18.42	16.05	-71.95	-96.84	12.46	16.91
Precipitation	0.10	-4.48	3.58	1.08	-0.45	-11.13	3.98	2.11
Total	-23.13	-66.74	15.50	16.64	-71.90	-97.18	11.32	17.28
	Medium-term 2020-2049				**Long-term 2070-2099**			
Model	**Impact**	**t-value**	**Gain**	**Loss**	**Impact**	**t-value**	**Gain**	**Loss**
	Climate Scenario Hadley HCM3 - B1							
Polynomial	-16.02	(18.63)	205	1724	-33.81	(24.31)	72	1931
Dummy Intervals	-15.86	(18.05)	200	1690	-33.13	(20.18)	72	1924
	Climate Scenario Hadley HCM3 - A1							
Polynomial	-20.89	(20.38)	149	1818	-72.03	(48.70)	3	2069
Dummy Intervals	-20.60	(19.26)	147	1811	-71.35	(17.36)	3	2067

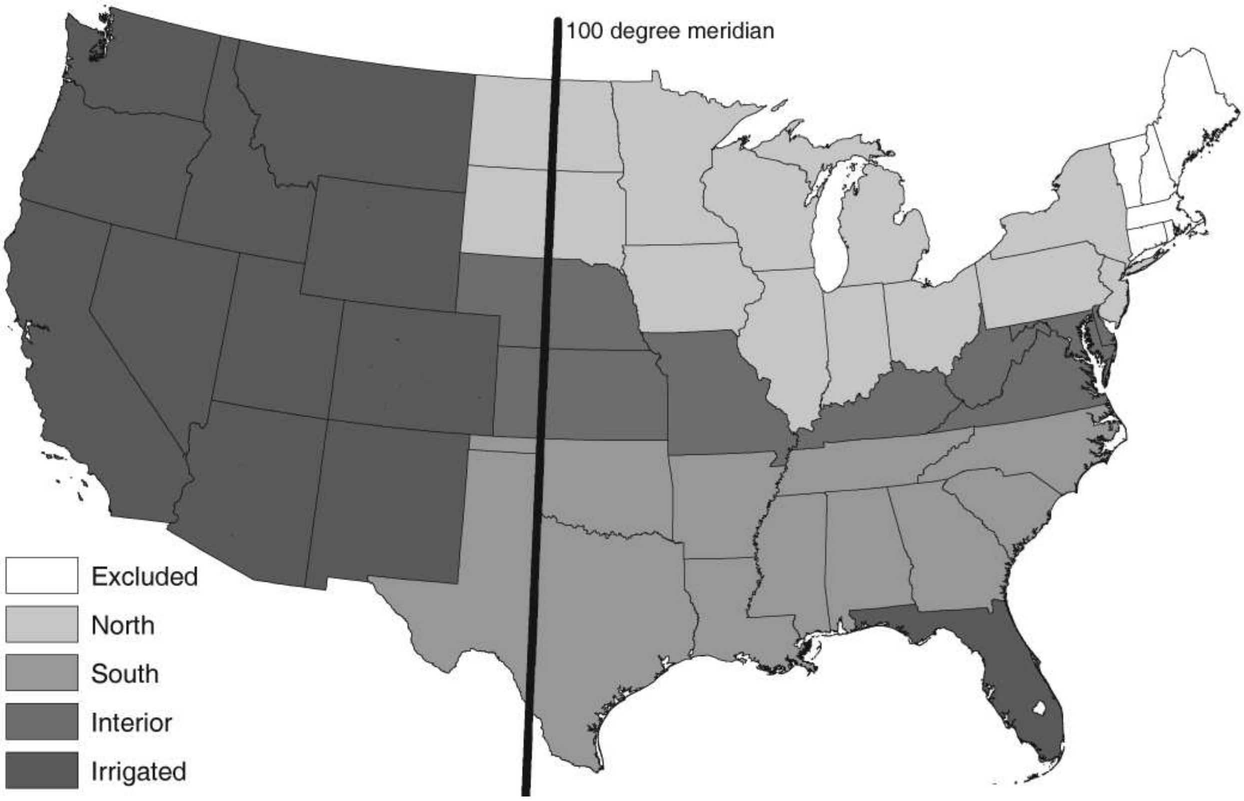
Notes: The first twelve rows list the predicted percentage change in crop yields for eastern counties using both specifications for the two extreme climate scenarios. Each set of three rows reports impacts attributable to changing temperatures and precipitation, as well as total impacts. The last four rows give the area-weighted impact (including t-value) as well as how many of the 2075 counties either had statistically significant gains or losses at the 95% level.

Table 9: Predicted Impacts of Global Warming on Cotton - Upland

	Medium-term 2020-2049				Long-term 2070-2099			
Variable	**Mean**	**Min**	**Max**	**Std**	**Mean**	**Min**	**Max**	**Std**
			Climate Scenario Hadley HCM3 - B1					
Chebyshev Polynomial								
Temperature	-13.87	-60.61	24.57	18.54	-24.32	-84.20	38.64	24.91
Precipitation	-0.93	-4.92	3.78	1.70	-1.11	-8.18	5.17	2.12
Total	-14.93	-60.19	19.74	17.23	-25.52	-84.21	33.24	23.60
1°C Dummy Intervals								
Temperature	-13.82	-48.15	27.31	15.38	-19.16	-64.18	37.23	18.66
Precipitation	-0.76	-4.01	3.06	1.39	-0.91	-6.69	4.19	1.73
Total	-14.64	-47.59	23.29	14.35	-20.08	-63.88	35.17	17.70
			Climate Scenario Hadley HCM3 - A1					
Chebyshev Polynomial								
Temperature	-14.29	-71.37	26.79	18.73	-72.43	-98.68	25.44	20.28
Precipitation	-0.51	-5.35	2.23	1.48	-1.37	-11.04	8.26	2.98
Total	-14.89	-71.32	23.60	17.83	-73.21	-98.66	22.31	19.22
1°C Dummy Intervals								
Temperature	-13.05	-47.54	26.68	14.55	-53.74	-90.08	62.42	19.72
Precipitation	-0.41	-4.36	1.81	1.21	-1.12	-9.03	6.69	2.44
Total	-13.52	-47.65	24.09	13.83	-54.58	-89.85	58.43	18.60
	Medium-term 2020-2049				**Long-term 2070-2099**			
Model	**Impact**	**t-value**	**Gain**	**Loss**	**Impact**	**t-value**	**Gain**	**Loss**
			Climate Scenario Hadley HCM3 - B1					
Polynomial	-18.37	(5.19)	85	587	-31.26	(6.07)	43	696
Dummy Intervals	-18.20	(5.52)	64	667	-25.45	(4.40)	37	680
			Climate Scenario Hadley HCM3 - A1					
Polynomial	-19.06	(4.76)	95	559	-77.92	(17.27)	1	956
Dummy Intervals	-17.45	(4.48)	59	645	-59.64	(6.64)	8	903

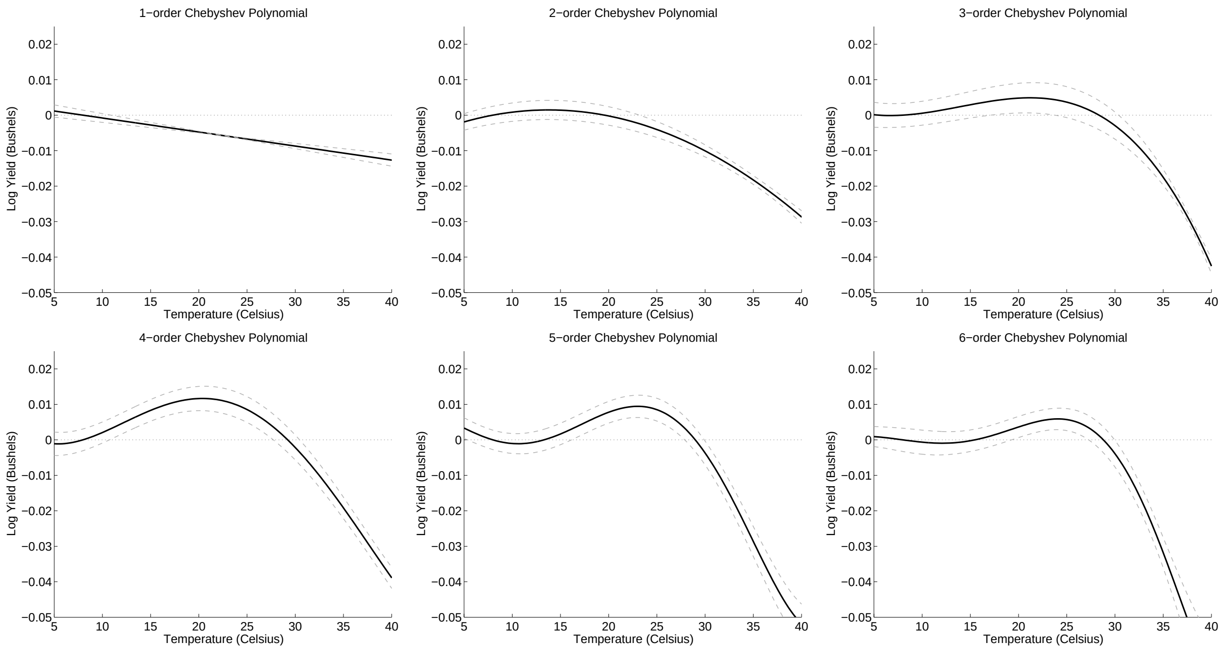
Notes: The first twelve rows list the predicted percentage change in crop yields for southern and western counties using both specifications for the two extreme climate scenarios. Each set of three rows reports impacts attributable to changing temperatures and precipitation, as well as total impacts. The last four rows give the area-weighted impact (including t-value) as well as how many of the 980 counties either had statistically significant gains or losses at the 95% level.

Figure 1: Classification of States/Counties in Analysis



Notes: Graph displays the classification of counties used in various regressions. We label the union of northern, interior, and southern states as eastern states.

Figure 2: Nonlinear Relation Between Temperature and Corn Yields



Notes: Panels display changes in annual log yield if the crop is exposed for one day to a particular temperature. Impacts are normalized relative to a temperature of 8°C. The 95% confidence band is added as dashed lines.

Figure 3: County Fixed Effects

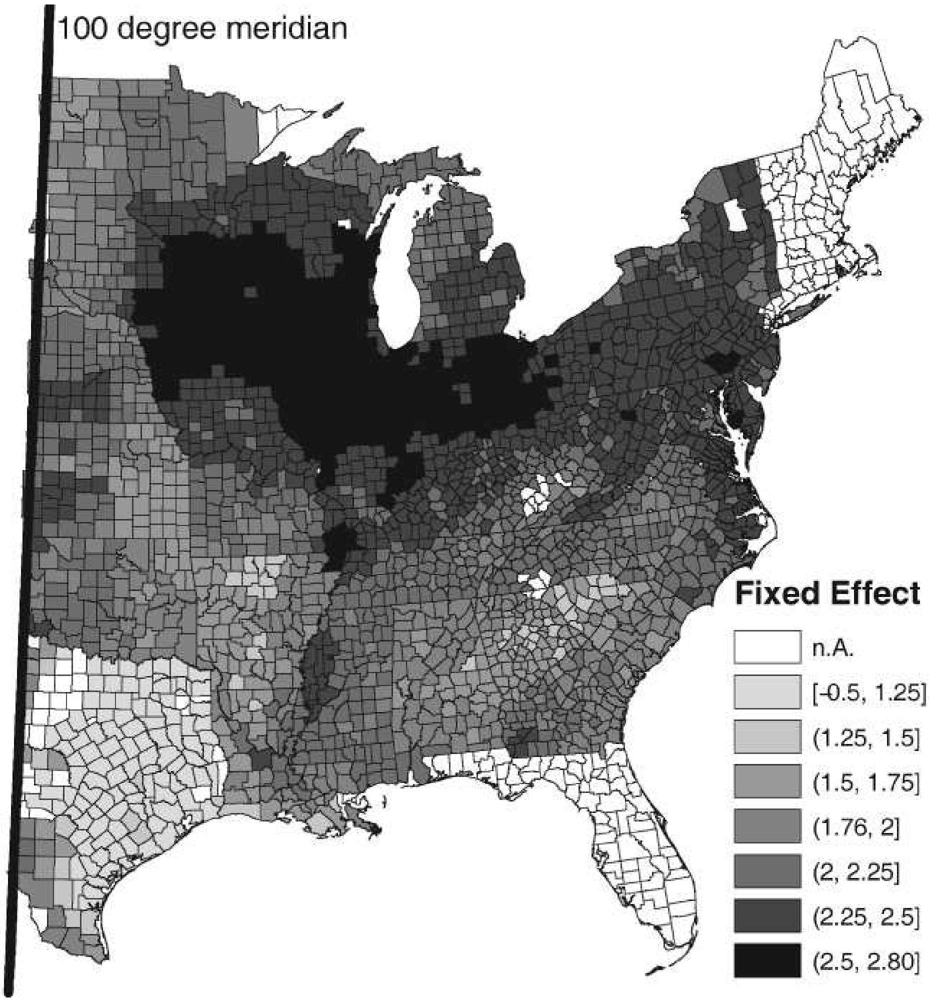
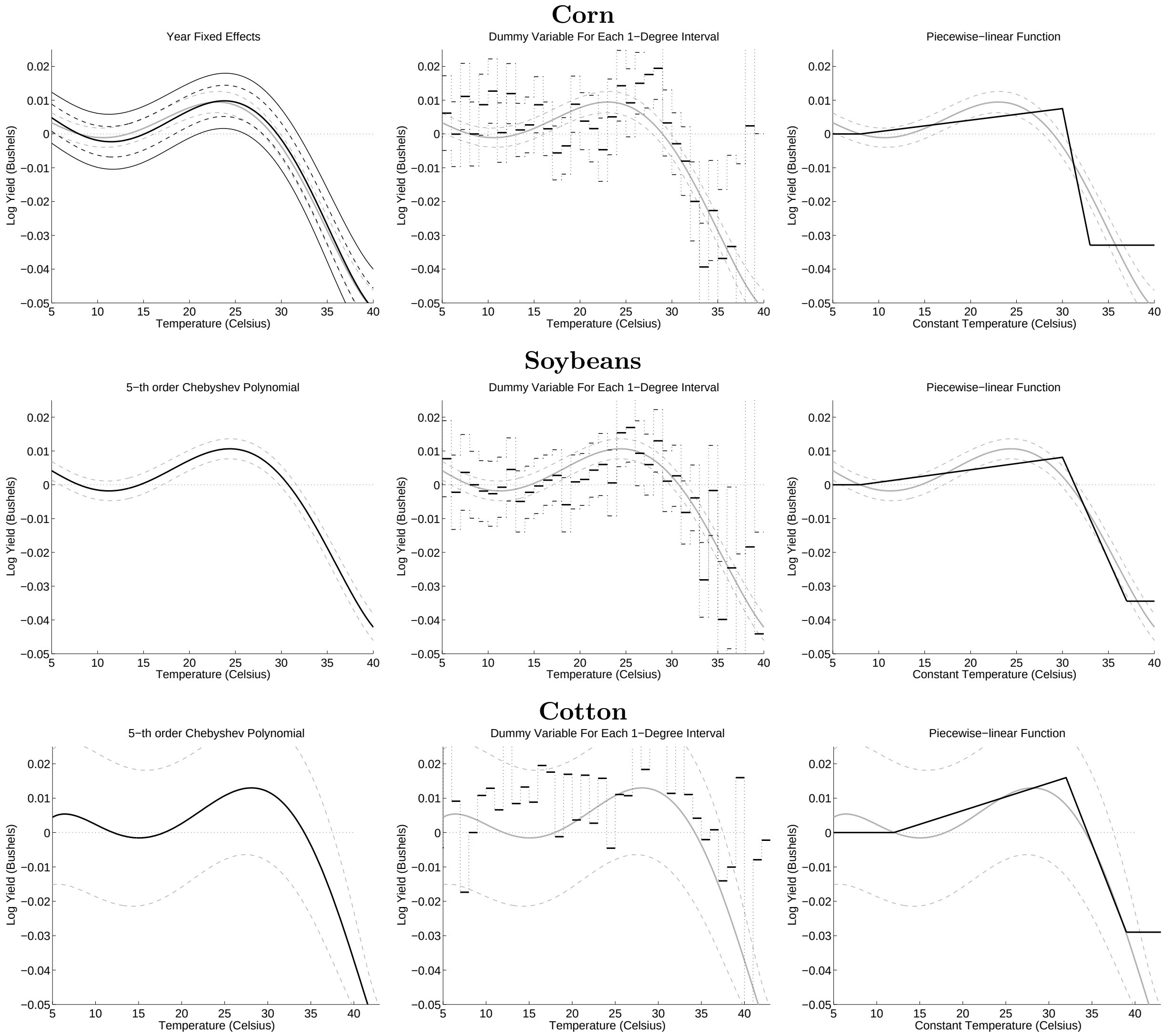
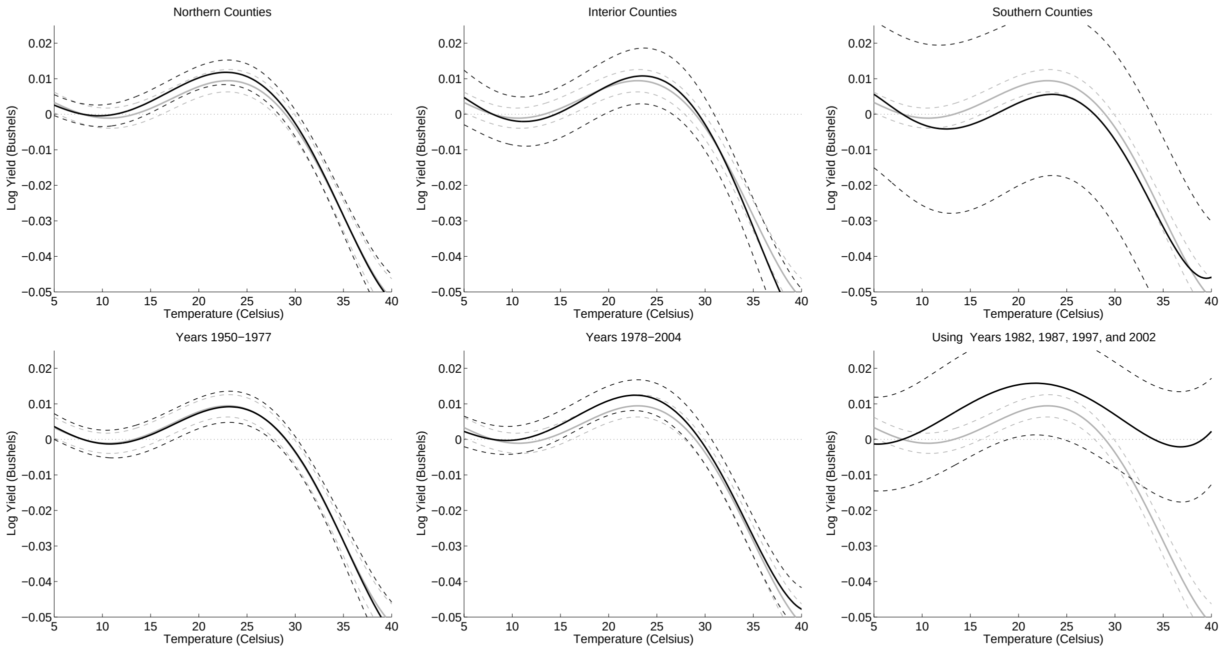


Figure 4: Nonlinear Relation Between Temperature and Corn, Soybean, and Cotton Yields for Different Functional Forms



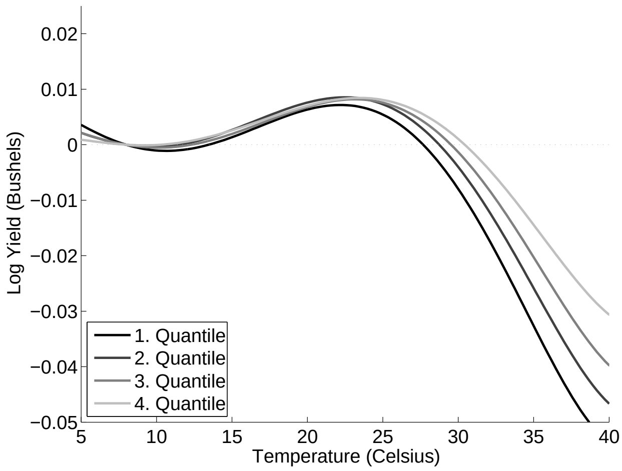
Notes: Panels display the impact of a given temperature for one day of the growing season on yearly log yields. The first row use corn yields, the second row soybean yields, and the last row cotton yields. The left column use a 5th-order Chebyshev polynomial (which are added in grey in the remaining columns), the middle column uses dummies for each 1-degree interval, and the right column uses a piecewise-linear function. The top left panel also displays the results if we use year fixed effects (black lines) instead of quadratic time trends by state (grey lines). It also shows two confidence bands: the black dashed band uses Conley's nonparametric approach, while the solid black band use 10000 bootstrap simulations where we resample years. Curves are relative to a temperature of 8°C in the first two rows, and relative to 12°C in the last row.

Figure 5: Nonlinear Relation Between Temperature and Corn Yields for Subsets of Counties or Years



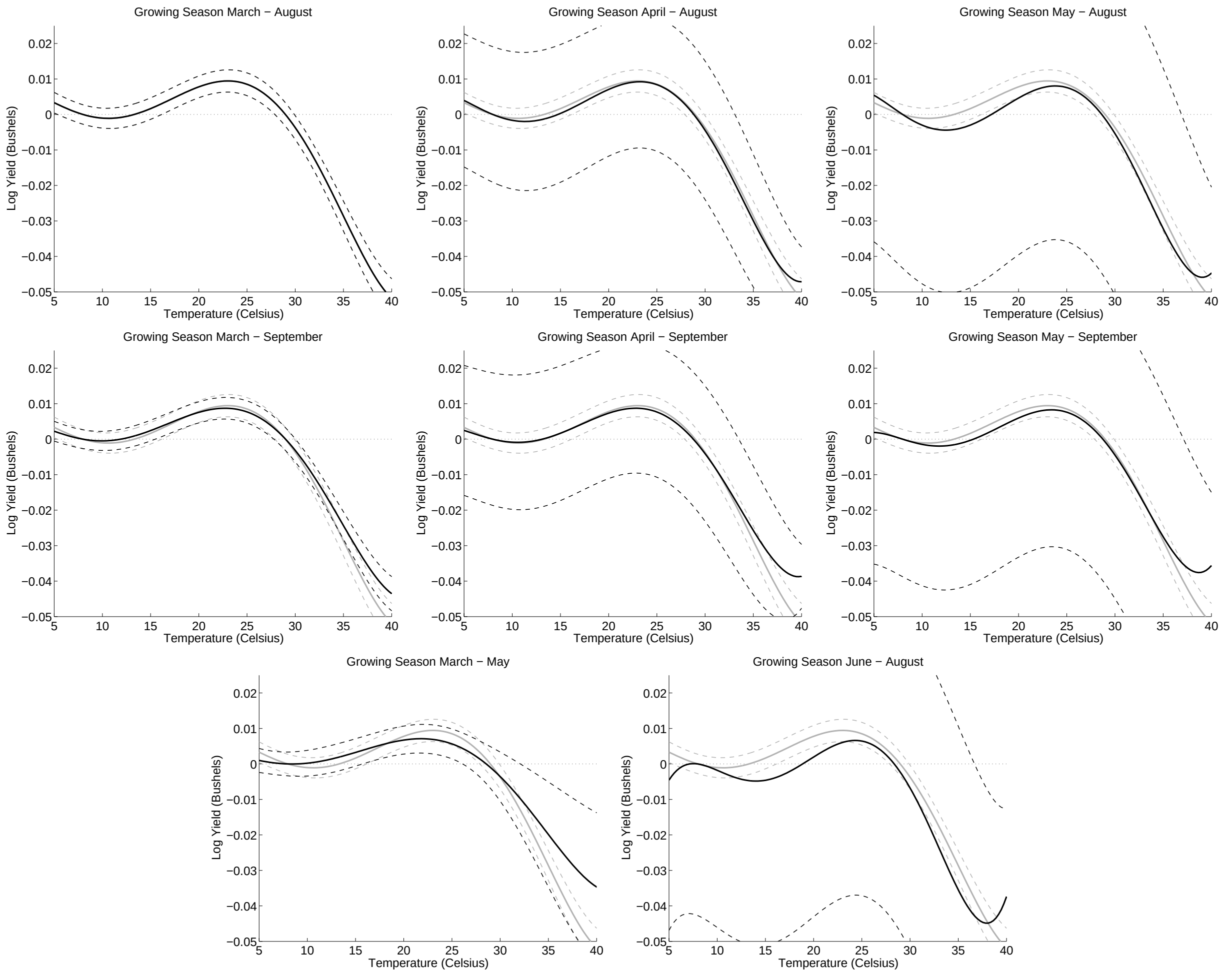
Notes: Panels display changes in annual log yield if the crop is exposed for one day to a particular temperature. Impacts are normalized relative to a temperature of 8°C. Results from the pooled model are added in grey for comparison. The 95% confidence band, after adjusting for spatial correlation, is added as dashed lines.

Figure 6: Nonlinear Relation Between Temperature and Corn Yields By Precipitation Quartile



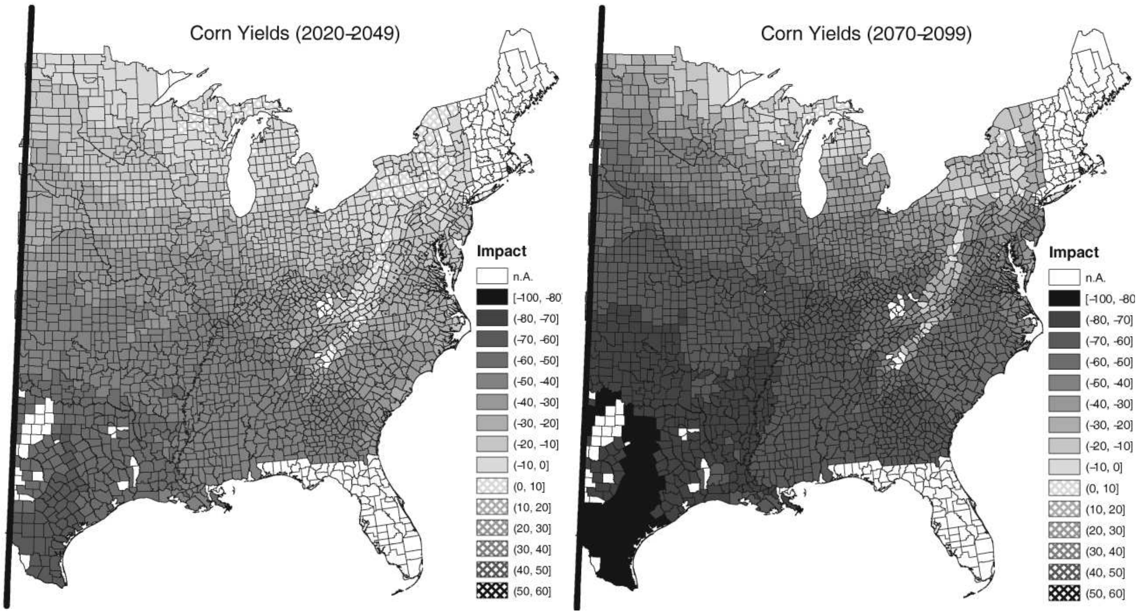
Notes: Panel displays Chebyshev-polynomials between the effect of each 1-day time period at a given temperature in the growing season and yearly log yields by precipitation quartiles for the months June and July.

Figure 7: Nonlinear Relation Between Temperature and Corn Yields for Various Definitions of the Growing Seasons



Notes: Panels display changes in annual log yield if the crop is exposed for one day to a particular temperature. Impacts are normalized relative to a temperature of 8°C. Columns of the first two rows differ by the first month of the growing season: March, April, or May. The first two rows differ by the end of the growing season: August or September. The third row splits the six-months default growing season into two three-months intervals to test time separability. The default relationship (March-August) is added as grey background in the remaining graphs. The 95% confidence band, after adjusting for spatial correlation, is added as dashed lines.

Figure 8: Geographic Distribution of Climate Impacts



Notes: Panels display predicted impacts under the B2 scenario for our preferred dummy variables approach using the 55-year history of corn yields.