Do Climate Signals Matter? Evidence from Agriculture

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Abstract

The foreseeable impacts of climate change on humans depend critically on the ability of societies to adapt to new climatic signals. Recent literature based on the US experience suggest little to no adaptation to climate trends in crop agriculture. We revisit this question with a novel panel econometrics framework that allows yearly outcomes to jointly respond to contemporaneous weather and climate signals, delivering estimates of both short-run and long-run climate change impacts within a single regression framework. In our most conservative model, which strictly relies on the existence of trends in climate to identify adaptation potential, we find evidence of adaptation to beneficial temperatures (as captured by growing degree days) and precipitation, for both corn and soybean yields. Evidence of adaptation to extreme heat is more nuanced, with suggestive evidence of adaptation for corn and no evidence for soybeans. The presence of adaptation matters for the calculation of warming impacts: the net counterfactual impacts of warming are negative in the short run but become positive in the long run.

JEL codes: Q54, C23, Q16
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1 Introduction

The impacts of climate change on humans depend critically on the ability of societies to adapt to new climatic signals. Agriculture is one of the economic sectors most reliant on weather, and as such, perhaps the one most vulnerable to climate change (Fisher et al., 2012). While some world regions may benefit from global warming, global food production is expected to be hurt by climate change (Lobell et al., 2011; Porter et al., 2014). The US is a major player in world markets for agricultural products and most recent estimates of climate change impacts for US agriculture are negative, sometimes alarmingly so (Schlenker and Roberts, 2009; Miao et al., 2015; Schauberger et al., 2017; Roberts et al., 2017). Of particular concern is the fact that in the US, large negative warming impacts have been found in both cross-sectional and panel studies, a pattern that has been interpreted as indicative of lack of farmer adaptation (Roberts and Schlenker, 2011). This is concerning, as farmer adaptation has been shown to effectively increase yields in other settings (Di Falco et al., 2011). A recent study by Burke and Emerick (2016) adds to this argument by showing that US county corn yields respond to heat exposure comparably in a panel estimation with county fixed effects (argued to capture short-run effects) and in a long-differences (LD) estimation that exploits variation in county climate trends (argued to capture long-run effects).

A central issue when comparing marginal responses obtained from panel and LD models is that whenever the panel approach delivers a pure short-run response, it is unlikely that the LD approach delivers a pure long-run response, and *vice versa*. For either climate is stationary during the period of observation, in which case climate variation as calculated in the LD model only reflects weather randomness around the endpoints of the study period, or climate trends do exist, but in that case we would expect the panel model to partially reflect long-run effects since the variation used in estimation is partly driven by long-run climatic trends, not just weather fluctuations (Carter et al., 2018).[1] Because either the panel or the LD model (or both) deliver estimates that reflect a combination of short-run and long-run outcomes, failure to find a statistically significant difference between the two estimates need not imply that the short- and long-run effects are indistinguishable. That is, the LD-panel comparison may fail to detect adaptation even if it is present. Yet whether—and if so, how much—the agricultural sector can adapt to changes in climate should be of primary interest to policy makers. Ignoring the adaptation potential of agriculture might steer policy makers into making suboptimal policy choices (Auffhammer, 2018) or misdirecting public funding aimed at addressing the impacts of climate change.

In this paper, we propose a novel econometric framework that allows the identification of both short-run and long-run responses and provides a simple and transparent test of climatic adaptation. Our framework usefully extends the quadratic models introduced by Schlenker (2017) and Mérel and Gammans (2019) to the case where climate is non-stationary during the period of observation. In these original frameworks, as well as in an alternative approach discussed in Dell et al. (2014), identification of adaptation is obtained in a panel regression by exploiting variation in the interaction of weather and time-invariant climate. Such interaction allows climate to modulate

[1]Burke and Emerick (2016) actually exploit *residual* county-level trends around state trends, but the argument carries over to that case as well.

the marginal effect of weather, the idea being that locations with, say, hot climates, should respond differently to hot weather than locations with cool climates.[2] Given that many regions have experienced trends in climate over the past decades, it is unclear that defining climate as a fixed average is appropriate. Like Cui (2019) who looks at the effect of climatic trends on acreage allocation, we define climate as a rolling average of past weather. This innovation allows us to exploit both cross-sectional and temporal variation in climates to estimate the effect of climate on yields.

Using temporal variation in climate also affords us the opportunity to address an often-neglected source of potential omitted variable bias of a kind reminiscent of, though distinct from, that inherent in cross-sectional approaches: interactions between location-specific time-invariant factors and weather. Examples of such variables are soil variables (e.g., soil water retention) or photoperiodicity (i.e., daytime length) that may interact with weather. Land quality, and soils in particular, are likely to affect the weather-yield response (Du et al., 2017). For brevity, we will refer to all time-invariant location-specific variables that interact with weather as "soil-weather interactions," with the understanding that factors beyond soils may interact with weather. Mérel and Gammans (2019) provide a thorough econometric treatment of the root causes of this type of omitted variable bias in the context of quadratic models and recommend testing the sensitivity of estimates to the inclusion of available soil-weather interactions in the regression. This paper takes a different and perhaps more radical approach to the problem by allowing the coefficient on weather variables to systematically vary by location, thereby non-parametrically controlling for these omitted soil-weather interactions. In addition, the regression includes smooth (polynomial) location-specific time trends, meaning that identification of adaptation arises solely from the interaction of *climatic trends* with *weather*, as climatic trends themselves would be subsumed in the locational trends.

Our analysis using US county crop yield data reveals that relying on such interactions, as opposed to simpler climate-weather interactions under the assumption of climate stationarity, affects both the extent of measured climatic adaptation and the calculated long-run climatic impacts. For instance, our preferred identification strategy delivers estimates of adaptation that are markedly larger for growing-degree days (a standard measure of exposure to beneficial temperatures) and precipitation. Estimates of adaptation to extreme heat are more similar between the two approaches, and not always statistically significant. We further show that estimates that rely on climate-trend

[2]For a discussion regarding the difference between the approaches of Schlenker (2017) and Dell et al. (2014), see Mérel and Gammans (2019).

and weather interactions imply counterfactual impacts of warming that are negative in the short run but become positive once long-run adaptation is accounted for. For corn, long-run estimates of a 1°C warming lie between +4% and +7%; short-run impact estimates lie between -5% and -6%. These impact estimates are statistically significant, even when using an estimate of the covariance matrix that allows for within-state and across-time correlations. In contrast, long-run impact estimates that rely on cross-sectional climatic variation, either totally or partially, are consistently negative, and in line with estimates obtained by previous studies.

Which of those long-run impact estimates should we trust? On the one hand, estimates based on weather-climate interactions exploit an admittedly richer source of climatic variation. To the extent that cross-sectional differences in climate are larger than secular changes in climate at given locations, these estimates better capture adaptation that may happen in response to large climatic changes. As an illustration, although our counterfactual exercise only involves a 1°C warming, the biggest locational trends in temperature we observe in our data are about plus or minus 0.2°C per decade over about four decades, with many locations experiencing weaker trends. In contrast, average climates in the cross-section range from about 13°C to 27°C.

On the other hand, exploiting large cross-sectional climatic differences in settings where these differences may correlate with other determinants of yield is questionable from an identification perspective. In fact, this very concern has led many in the literature to criticize hedonic approaches and favor panel approaches with fixed effects (Deschênes and Greenstone, 2007; Blanc and Schlenker, 2017).

Despite the discrepancies in counterfactual warming impacts across models identified from different sources of climatic variation, one general conclusion can be supported by our analysis: US yield patterns reveal significant and economically meaningful adaptation to temperature. For instance, even in the approach that exploits cross-sectional climatic differences, the negative impact estimates of warming on corn yield are less negative in the long run than in the short run, by about a third.

2 Empirical strategy

We index locations by $i = 1, \ldots, I$ and time periods (years) by $t = 1, \ldots T$. Specializing to the case of uni-dimensional weather (which we relax in our empirical applications), the most flexible model considered in this paper has the following structure:

$$y_{it} = \alpha_i + \beta_{i1} x_{it} + \beta_2 x_{it}^2 + \beta_3 \left(x_{it} - \mu_{it} \right)^2 + f_i(t) + \epsilon_{it} \tag{1}$$

where y_{it} is the outcome variable (the logarithm of crop yield) in location i in year t, x_{it} denotes contemporaneous weather in location i and year t (e.g., average temperature or growing degree days or cumulative precipitation), μ_{it} denotes the climate in location i and year t, defined as a moving average computed over the preceding Y years (i.e., $\mu_{it} \equiv \frac{1}{Y}\sum_{s=t-Y}^{t-1} x_{is}$), and $f_i(t)$ is a smooth polynomial function of time capturing secular changes in location i (including any secular changes in climatic conditions). We expect the coefficient β_3 to be nonpositive. That is, conditional on weather, locations for which climate is close to that weather should fare better, other things equal, than locations for which climate is far from it. The presence of the smooth time trend implies that identification of the coefficient β_3 does not arise from trends in climate themselves, as in Burke and Emerick (2016), but rather from the interaction of weather with climate trends, i.e., $x_{it} \times (\mu_{it} - \bar{\mu}_i)$, where $\bar{\mu}_i$ denotes the average climate of location i during the period of observation (the interaction $x_{it} \times \bar{\mu}_i$ itself being irrelevant for identification due to the presence of the term $\beta_{i1} x_{it}$). In our view, this is an advantage as county-level trends in relevant factors other than climatic trends could potentially be driving secular changes in county outcomes, for instance geographically differentiated technological progress unrelated to climatic trends. By controlling for county-level trends and relying instead on the interaction of climatic trends with weather, our approach is less susceptible to confounding factors than a strategy purely reliant on climatic trends. Because we allow for location-specific slopes β_{i1}, it is also immune to the presence of soil-weather interactions, which is a potential issue in studies that assume a stationary climate during the period of observation (Mérel and Gammans, 2019).

More formally, assume that $\mu_{it} = \bar{\mu}_i + \nu_i \left(t - \bar{t}\right)$, where ν_i is interpreted as the climatic trend rate in location i, i.e., the rate of change of climate with respect to time and $\bar{t} \equiv \frac{1}{T}\sum_{s=1}^{T} s$ so that $\bar{\mu}_i$ indeed represents the mean climate in location i across the observation period. Assume further that $f_i(t) = \gamma_{i1} t + \gamma_{i2} t^2$ is used to control for smooth locational trends. Then, denoting $\mu_i \equiv \bar{\mu}_i - \nu_i \bar{t}$, Equation (1) can be rewritten as

$$\begin{aligned} y_{it} \quad = \quad & \underbrace{\alpha_i + \beta_3 \mu_i^2}_{\alpha_i'} + \underbrace{\left(\beta_{i1} - 2\beta_3 \mu_i\right)}_{\beta_{i1}'} x_{it} + \underbrace{\left(\beta_2 + \beta_3\right)}_{\beta_2'} x_{it}^2 + \underbrace{\left(-2\beta_3\right)}_{\beta_3'} \nu_i t x_{it} \\ & + \underbrace{\left(\gamma_{i1} + 2\beta_3 \mu_i \nu_i\right)}_{\gamma_{i1}'} t + \underbrace{\left(\gamma_{i2} + \beta_3 \nu_i^2\right)}_{\gamma_{i2}'} t^2 + \epsilon_{it} \end{aligned}$$

making it explicit that β_3', and thus β_3, are identified from residual variation in the product between climatic trends and weather.

A less flexible model, which relies on interactions between weather and *both* climatic *means* and climatic *trends*, is obtained by constraining β_{i1} to be identical across locations:

$$\begin{aligned} y_{it} &= \underbrace{\alpha_i + \beta_3\mu_i^2}_{\alpha_i'} + \beta_1 x_{it} + \underbrace{\left(\beta_2 + \beta_3\right)}_{\beta_2'} x_{it}^2 + \underbrace{\left(-2\beta_3\right)}_{\beta_3'} \left(\mu_i + \nu_i t\right) x_{it} \\ &\quad + \underbrace{\left(\gamma_{i1} + 2\beta_3\mu_i\nu_i\right)}_{\gamma_{i1}'} t + \underbrace{\left(\gamma_{i2} + \beta_3\nu_i^2\right)}_{\gamma_{i2}'} t^2 + \epsilon_{it}. \end{aligned}$$

This latter model benefits from a broader source of variation than the full model for identification of the coefficient β_3. Indeed, variation in $\mu_i x_{it}$, in addition to variation in $\nu_i t x_{it}$, identifies β_3. However, this model is subject to potential bias from omitted variables of the form $\zeta_i x_{it}$, whereas model (1) is not. The case for the more flexible model should thus be clear, just as a panel approach with fixed effects may be preferable to a pooled panel approach due to the potential presence of time-invariant omitted variables correlated with climate. Of course, the tradeoff here is that while it is not uncommon to observe outcomes across locations with widely varying climates, at least for geographically broad regions, it is less clear that climates may have changed sufficiently over the observation period to generate useful residual variation in $\nu_i t x_{it}$, raising concerns about whether climatic adaptation, even if present in the underlying DGP, can be detected by exploiting climatic trends around mean climate—or more precisely their interaction with weather.

In our empirical application, we estimate model (1) and its simpler variant on US corn and soybean yields. In both instances, we find evidence of adaptation to various climatic variables of relevance for crop production. However, the patterns of adaptation differ across specifications, indicating that soil-weather interactions are plausibly of concern and that the more flexible approach with location-specific weather slopes may be warranted to identify adaptation, and thus long-run responses to climate.

Before moving on to estimation, it is useful to understand the structure of adaptation implied by model (1) and its restriction to the case where $\beta_{i1} = \beta_1 \; \forall i$. As pointed out by Mérel and Gammans (2019), the structure with quadratic weather response and quadratic climate penalty term in Equation (1) reflects the longstanding concept in production economics that, to the extent that some actions can be varied in the long run but not the short run and the outcome of interest is an optimized value, the long-run response to climate should be the outer envelope of the collection of short-run responses—just like the firm's long-run average cost curve, obtained by varying capital in response to output, is the lower envelope of the firm's short-run average cost functions for given values of the capital input. The same idea of defining the long run as an outer envelope of short-run possibilities is used by Mendelsohn et al. (1994) to motivate the Ricardian approach to climate change impact assessment.

In model (1), the long-run response function would be

$$y_i^{\mathrm{LR}}(x) = \alpha_i + \beta_{i1}x + \beta_2 x^2$$

while the short-run response function at location i would be

$$y_i^{\mathrm{SR}}(x) = \alpha_i + \beta_{i1}x + \beta_2 x^2 + \beta_3 \left(x - \bar{\mu}_i\right)^2$$

clearly a function that is tangent to the long-run response at $x = \bar{\mu}_i$. Of course, Equation (1) is not the *only* parametric structure that yields a long-run response that is the outer envelope of short-run responses. Nonetheless, it does so in a relatively parsimonious fashion while allowing for non-monotonicity and non-linearity of both short- and long-run response functions. More importantly, among the various quadratic specifications used in the climate panel literature, it is the only variant that actually results in tangency of short-run responses with a common long-run response function. The other paper we are aware of that uses this framework, besides our own previous work, is Schlenker (2017), of which Equation (1) is a special case. All other specifications that have been used previously, e.g., those implied by Deschenes and Kolstad (2011), Dell et al. (2014), or Moore and Lobell (2015) result in short-run response functions that intersect the long-run response. Finally, commonly used models that specify a quadratic in weather without climatic information included in the regression deliver a single response curve, the interpretation of which is far from being trivial (Mérel and Gammans, 2019).

[Figure 1 about here.]

One caveat is in order. The long-run response function is, strictly speaking, common to all locations (or "global") only up to certain normalizations. First, the presence of the fixed effect α_i in Equation (1) implies that each location's long-run response function is allowed differ from others' through vertical translation, i.e., a change in the vertical intercept. This type of flexibility is typical of panel approaches with fixed effects. Second, in the model with location-specific slope parameters β_{i1}, it is also the case that each location's long-run response function is allowed differ from others' through *horizontal* translation. Indeed, in that most flexible variant, only the long-run coefficient on the squared coefficient, capturing the curvature of the long-run response, β_2, is common to all locations. (The coefficient on the penalty term, β_3, and therefore the curvature of the short-run response, are also common to all locations.) Figure 1 depicts the adaptation process for a unidimensional weather variable x. For simplicity, only four locations with disjoint weather supports at a given point in time (t) are represented. The weather means (μ_{it}) are represented on the horizontal axis. The short-run (thin line) and long-run (thick line) response functions are depicted for each location's climate support. Panel (a) focusses on the restricted model with common slope coefficient. In that case, a quadratic long-run response function is recovered by vertical translation of the location-specific long-run response functions. Panel (b) depicts the adaptation process in a model with location-specific slope coefficients. A quadratic long-run response function can be recovered by translating location-specific long-run response functions both vertically *and* horizontally.

In addition to generating a long-run response function that is the outer envelope of location-specific short-run responses, the specification in Equation (1) also has a behavioral foundation, as shown in Schlenker (2017) and Mérel and Gammans (2019). We refer the reader to these papers for a formal derivation. The idea is as follows: if one assumes that conditional on contemporaneous weather, climate affects current outcomes only through long-run behavioral choices (e.g., long-run investments made by agents in response to climate signals), then Equation (1) can be obtained as the result of a simple long-run expected-outcome optimization problem.

Of course, different specifications of adaptation could be conceived. Even within the quadratic framework, alternative specifications of the climate penalty are possible. In this paper, we explore two such additional variants. The first variant replaces the calculated climate μ_{it} by its fitted value against a smooth (quadratic) trend. Specifically, we first estimate the following location-level regression

$$\mu_{it} = a_i + b_i t + c_i t^2 + e_{it}$$

and plug its predicted value $\hat{\mu}_{it} = \hat{a}_i + \hat{b}_i t + \hat{c}_i t^2$ into the penalty term instead of μ_{it}. The idea behind this variant is to remove any temporal variation in locational climate that is arising from exceptional weather events, the reason being that long-run investments are more likely to be made in response to "actual," smooth climatic changes than to variations in climate that arise purely from the presence of extreme weather events in the historical period used to calculate climate.

The second variant investigated in this paper replaces the penalty $\beta_3 \left(x_{it} - \mu_{it}\right)^2$

by $\beta_3 \int (x_{it} - x)^2 \, dF_{it}(x)$, where $F_{it}(x)$ denotes the c.d.f. of weather (i.e., climate) in location i at time t. Here, the idea is that climate as captured by a simple average taken over previous years may be a poor indicator of actual past exposure to given environmental conditions. This is because a calculated average that happens to be close to a given weather realization may in fact mask repeated exposure to extremes. In that sense, this alternative specification is more "demanding" in terms of what conditions are required for adaptation to take place: it has to be the case that *all* past weather occurrences—not simply their average—are close to contemporaneous weather for the penalty term to vanish.

Because these two variants lead to results very similar to those obtained from the main model, they are not reported in the main text. The results with smoothed climate are reported in Appendix C, and those with alternative penalty term in Appendix D.

3 Data and trends in climate

We obtain US county-level data on corn and soybean yields over the period of 1950-2017 from USDA QuickStats. Consistent with Schlenker et al. (2006) and Schlenker and Roberts (2009), our analysis focuses on counties east of the 100th meridian. We obtain historical weather information over 1950-2017 from the PRISM gridded dataset, which is at a 4 km resolution (PRISM Climate Group, 2018). Following the approach of Schlenker and Roberts (2009), we aggregate weather data to the county level using farmland areas as weights. We focus on weather and climate during the growing season defined as April to October. Like Schlenker (2017), we consider three weather variables: growing degree days, heat degree days, and cumulative precipitation. For corn, we define growing degree days from 10-29°C and define heat degree days above 29°C. For soybeans, we define growing degree days from 10-30°C and define heat degree days above 30°C. Degree days are computed after interpolating the intra-day distribution of temperatures using maximum and minimum temperature data.[3]

[Table 1 about here.]

[Table 2 about here.]

Tables 1 and 2 present summary statistics of yields, weather, and climate for corn and soybeans, respectively. For each crop, we limit the sample of counties to those

[3]We used data and code made available by Wolfram Schlenker to generate these data. See http://www.columbia.edu/~ws2162/links.html.

having planted the crop for more than 90% of the years included in the sample period. Although corn- and soybean-producing regions overlap, the number of corn counties is larger than that of soybean counties because some counties have only started planting soybeans in more recent years. The means and standard deviations of GDD and precipitation variables are generally comparable across corn and soybean samples. HDD variables for corn have higher mean values and larger standard deviations than for soybeans, as the HDD cutoff for corn is 1°C lower than that for soybeans. The geographical distribution of climate variables is shown in Appendix A.[4]

To investigate whether climatic trends are present in corn- and soybean-producing regions during the period of observation, we first calculate 30-year moving averages of growing-season weather, and fit a linear trend for each county over the period from 1980 to 2017.[5] Although we use growing degree days and heat degree days in our empirical application, for illustrative purposes we focus on trends in average growing season temperature. Specifically, we calculate a 30-year moving average of growing-season mean temperature, denoted as μ_{it}^T, and then estimate the following regression: $\mu_{it}^T = a_i^T + b_i^T \times t + e_{it}^T$. The coefficient b_i^T can be interpreted as the climatic trend in temperature for county i. We estimate an analogous regression on the logarithm of a 30-year moving average of growing-season precipitation. As a result, the county-specific linear climate trends are characterized by b_i^T and b_i^P and are measured in degrees (Celsius) and percentages, respectively.

[Figure 2 about here.]

Panel (a) of Figure 2 portrays the geographical distribution of county-level climate trends in growing-season average temperature since 1980. Most counties on the East Coast have experienced substantial warming, with average temperature going up by more than 0.2°C per decade in some counties. Parts of the Upper Midwest and areas along the Arkansas-Mississippi border have also experienced warming. However, a large region including parts of Nebraska, South Dakota, Kansas, Missouri, and nearly all of Iowa have experienced either relatively constant temperature or have cooled. The cooling trends are particularly strong in some counties, beyond -0.15°C per decade.

Panel (b) of Figure 2 shows climate trends in growing-season cumulative precipitation. Several spatial clusters in the northern regions feature clear increasing trends.

[4]The maps in Appendix A are based on the average of the climates (defined as 30-year averages from past years) across the years 1980–2017. They correspond to the climate figures reported in the lower panel of Table 1.

[5]We include only counties that have planted either corn or soybeans for more than 90% of years between 1980-2017.

The increasing rates of some counties in South Dakota, Michigan, and New York are around or above 5% per decade. In the southern half of the sample, trends have generally been more modest with slightly increasing trends in Tennessee and northern Mississippi and slight drying trends in Arkansas, the Carolinas, and Texas.

[Figure 3 about here.]

Figure 3 shows the statistical distribution of climate trends across counties. Dark blue coloring indicates that the trend coefficients are statistically significant, while pale blue coloring indicates that they are not. Most trends are statistically significant, except for those close to zero. In Panel (a), we can see that, although the majority of counties have experienced warming trends, roughly a third of counties have experienced cooling. Panel (b) shows that, on the whole, US production regions have become wetter across our sample, with the distribution centered around an increase in precipitation of 2% per decade. The presence of statistically significant trends in temperatures and precipitation bodes well for our empirical strategy, as our preferred specifications exploit interactions between such trends and weather to identify climatic adaptation. However, we note that temperature trends across counties in our sample generally have magnitudes (about ±0.1°C per decade) much smaller than the changes predicted to occur over the century, raising questions about whether recent climatic variation can reliably be utilized to extrapolate into future climate.

4 Estimation results

In what follows we report results from estimating Equation (1) on US corn and soybean yields. We report results for the flexible specification with slope coefficients varying by location ($\beta_{i1} \neq \beta_{j1}$) as well as the restricted model with common slope (β_1). We also report results from a simpler model that assumes stationary climates during the observation period and replaces the moving average μ_{it} by the overall sample mean $\frac{1}{T}\sum_s x_{is}$. All models include quadratic locational trends. For models with non-stationary climates, we compute the moving average capturing historical climate using various period lengths: 20, 25, and 30 years. Because we only have access to historical climate data for a fixed period of time, namely 1950–2017, these choices imply different sample sizes, with the smallest sample corresponding to the 30-year definition of climate and covering the period 1980–2017. For the model with stationary climate, we compute climate over the entire 1950–2017 period and use all years in the sample. As a result, this specification is estimated using the largest sample of years.

To facilitate comparisons across model specifications, we also estimate all models on a common sample of years going from 1980 to 2017. Results for these models are shown in Appendix B.

We report two sets of standard errors. The first set accounts for spatial correlation using a variant of the method of Conley (1999) and assumes away time correlation.[6] The second set allows for regional (state) clusters and allows for arbitrary correlation between locations and across years within a cluster, as in Fisher et al. (2012).

4.1 Corn

Based on previous work by Schlenker and Roberts (2009), Burke and Emerick (2016), and Schlenker (2017), we select the following as the relevant weather variables: growing degree-days (GDD), heat degree-days (HDD), and precipitation (prec), computed over the growing season from April to October.

[Table 3 about here.]

Results are shown in Table 3 for various specifications. Column (1) suggests that there has been clear adaptation to beneficial GDD and precipitation. These conclusions are not invalidated when using different definitions of climates (columns (2)–(3)). Columns (1)–(3) also indicate adaptation to heat as measured by HDD, although the estimate on the penalty term is not as precise, and its statistical significance depends upon the choice of standard error and climate definition.

[Figure 4 about here.]

Figure 4 depicts the geographical distribution of the estimates of the county-specific slope coefficients β_{1i}, for each of the three dimensions of weather and using the model with the 30-year definition of climate. We would expect these coefficients to vary smoothly over space, because soils, and perhaps other factors relevant to yield, tend to vary smoothly over space. The figure largely confirms this intuition, particularly for GDD, where there is a clear north-south gradient. The spatial pattern of the slope estimates is therefore consistent with the premise that soil-weather interactions may be present (where "soil" should be understood as any time-invariant locational factor). Whether such interactions would bias estimates of adaptation that rely, entirely

[6] We use neighboring relationships across locations rather than geographical distance to construct our weights. We apply Newey-West weights to these neighboring relationships. We allow for correlations between neighbors up to the sixth degree. The average distance between a county centroid and the centroid of its sixth-degree neighbors is 240 km in the sample.

or partially, on interactions between fixed climate means and weather, depends on whether this spatial pattern correlates with that of climate means. At least for the case of GDD, we would expect that it does, so we expect differences in adaptation estimates between the flexible specification and its restriction to common slope coefficients.

Note that the coefficient on the long-run quadratic term (β_2) is positive and significant for GDD in columns (1)–(3), while it is negative (but not always statistically significant, and definitely not if we hold the sample to the years 1980–2017, see Appendix B) for the less flexible specifications shown in columns (4)–(7). Based on prior research by Schlenker et al. (2006), one might expect a peak in the GDD-yield relationship, reflecting optimal growing conditions. The fact that our estimate in columns (1)–(3) is positive does not mean that extreme climates are necessarily more favorable to yields however, because in the flexible model slope coefficients vary by locations. As a result, to understand the actual distribution of marginal effects across climates, one must look at β_2 in conjunction with the set of location-specific slopes β_{1i}.

[Figure 5 about here.]

Specifically, the estimated marginal effect of a weather characteristic, evaluated at a location's mean climate, is $\widehat{\frac{\partial \ln y_i}{\partial x_i}}(\bar{\mu}_i) = \hat{\beta}_{1i} + 2\hat{\beta}_2\bar{\mu}_i$. Figure 5 depicts the geographical distribution of these long-run marginal effects for each weather variable, based on the 30-year definition of climate. The figure clearly shows that although the estimate of β_2 for GDD is positive, the implied long-run marginal effects are more positive in northern counties (which are cooler than southern counties). For a few southernmost counties, the point estimates of the marginal effect are even negative. In contrast, for HDD the distribution of long-run marginal effects shows that southern counties have small and negative marginal effects, while northern counties have larger negative effects. This pattern is consistent with the analysis of Schlenker et al. (2006) and Schlenker (2017), who both model the effect of HDD using a square root function and find a negative coefficient, indicating that heat exposure reduces yields at a declining rate.

Comparison of columns (1)–(3) with columns (4)–(7) of Table 3 reveals how using different sources of identification changes the estimates of adaptation (as captured by β_3). In column (7), only cross-sectional differences in climates (computed as simple averages throughout the sample period) are used for identification (more specifically, the interaction of such climates with weather identify β_3). In columns (4)–(6), both cross-sectional and time-series variation in climates (computed as moving averages) are used, while in columns (1)–(3) only time-series variation is used. Although estimates become less precise as variation is eliminated, for both GDD and precipitation we observe a stark increase in the magnitude of the adaptation coefficient β_3. This appears to confirm that soil-weather interactions (i.e., variables of the form $\zeta_i x_{it}$) bias the estimates reported in columns (4)–(7). Because columns (1)–(3) control for these interactions through the terms $\beta_{1i} x_{it}$, the estimates of β_3 in these models are purged of such bias. The analysis of Mérel and Gammans (2019) further suggests that the biases arising from these omitted variables should be of the same magnitude, but of opposite signs, on the estimates of β_2 and β_3. The pattern of changes between columns (4)–(6) and (1)–(3) is consistent with this theory.

The same differences do not apply to the effect of HDD: coefficient estimates are comparable across all columns, but become less precise as cross-sectional variation is eliminated from identification. One plausible explanation is that the spatial pattern of HDD slope coefficients does not correlate with that of climatic HDD: there does not seem to be a clear north-south gradient, as is the case for GDD slope coefficients. This hypothesis is confirmed by comparing maps of average climate over the period 1980–2017, shown in Appendix A, with Figure 4 showing the map of estimated slope coefficients. Whereas there seems to be a clear cross-sectional correlation between average climate and the slope coefficients for both GDD and precipitation, this is much less the case for HDD. Simple correlation coefficients indicate a correlation of -0.99 for GDD, -0.60 for precipitation, and 0.21 for HDD. The very large correlation coefficient for GDD could plausibly be caused by photoperiodicity, which correlates perfectly with latitude. Indeed, it is natural to expect the beneficial effect of GDD to be modulated by length of day. Here we find that northern counties have less negative values for β_{1i}^{GDD}, implying that holding everything else constant, counties with longer daylength during summer would benefit more from GDD.

In Appendices B, C, and D, we show results of specifications that differ from Table 3 in three separate dimensions: the sample of years selected; the use of a "smoothed" measure of climate; and the use of an alternative penalty specification. The results are generally robust to these changes.

4.2 Soybeans

We conduct a parallel analysis for soybeans. The only difference is that we change the threshold used to calculate GDD and HDD from 29 to 30°C.

[Table 4 about here.]

Detailed results are provided in Table 4. Based on the more conservative specification (columns (1)–(3)), it appears that there has been clear adaptation to the amount of GDD and to precipitation, but no adaptation to heat as captured by HDD.

[Figure 6 about here.]

Figure 6 depicts the geographical distribution of the estimated slope coefficients, based on the 30-year definition of climate. As for corn, there seems to be a clear geographic pattern to the heterogeneity in slopes, consistent with the presence of omitted variables that vary smoothly over space. For GDD and precipitation, these variables appear to be correlated with climate, as suggested by the large changes in estimated coefficients once we allow for slope heterogeneity. Again, changes are of similar magnitudes, but opposite signs, for the estimates of β_2 and β_3, consistent with the bias formulas provided in Mérel and Gammans (2019).

Figure 7 depicts the distribution of marginal weather effects. As was the case for corn, the figure shows patterns consistent with expectations. Notably, the marginal benefit from additional GDD is larger in northern areas, and the marginal damage from HDD is lower in southern areas.

5 Does adaptation matter? Future climate scenarios

We exploit our estimates of the short- and long-run relationships between weather variables and crop yield to investigate three stylized climatic scenarios: a uniform warming by 1 °C and increases/decreases in precipitation by 20%. Although our warming scenario is modest in magnitude relative to scenarios generally considered in the literature, we are limited by the amount of climatic variation present in our model with location-varying slopes, which is identified only from climatic trends.

[Table 5 about here.]

[Figure 7 about here.]

Table 5 shows predicted changes in production under the 1°C warming scenario. Changes are calculated at the county level and then aggregated using average yield and acreage over the reference period, chosen as 1987–2016.[7] To calculate the relative change in yield at the county level, we add 1°C to the daily temperature data for each year in the reference period. We then recalculate growing and heat degree days in each year. The change in climate is computed by taking the difference in 30-year weather

[7]We choose 1987–2016 as our reference period to compute current climate because this is the last 30-year period used to compute climate in the sample used for estimation.

averages between the projection and reference periods. The relative change in yield is calculated using our regression coefficients, multiplied by the change in the values of the regressor between the two periods.[8] Maps of county-level yield impacts in the long run and the short run for our preferred specification (based on column (1) of Tables 3 and 4) are shown in Figure 8.

These results indicate that the effect of adaptation to temperature, as captured by the penalty terms on growing and heat degree days, matter a lot for warming impacts. For both corn and soybeans, calculated effects of the 1°C warming are negative in the short run yet positive in the long run. For corn, short-run effects based on the estimates in columns (1)–(3) of Table 3 are between -5% and -6%. This value is close to that reported in Schlenker and Roberts (2009) for a comparable warming scenario. Once adaptation is accounted for, the calculated effect ranges from +3.9% to +6.7%. Impact estimates based on columns (4)–(6) of Table 3, which also exploit cross-sectional climatic variation, also show significant effects of temperature adaptation. Short-run impacts are about -8.5%, whereas long-run impacts are about -5.5%. That is, although adaptation is not predicted to overturn negative short-run effects in this specification, the negative short-run impacts are nonetheless reduced in magnitude, by around a third.

Comparable patterns are found for soybeans, although the impact estimates tend to be less negative (more positive) across all models. Long-run impacts calculated from the flexible models, presented in columns (1)–(3) of Table 4, range from +6.5% to +11.3%. Short-run impact estimates for these same models lie near zero, suggesting that soy producers would be unable to take advantage of a warming climate without engaging in adaptive behavior. Impact estimates based on columns (4)–(6) of Table 4 are more negative and imply smaller benefits of adaptation, with long-run impacts ranging from -2.1% to -3.1% and short-run impacts ranging from -3.3% to -4.0%. These results show that using a different source of identification for adaptation effects on yield dramatically changes predicted warming impacts.

[Table 6 about here.]

Table 6 shows predicted changes in production under -20% and +20% changes in precipitation. These impacts are calculated using the same methodology as the warming estimates shown in Table 5. In general, we find small net effects of precipitation

[8]For a handful of counties in the flexible model, the 1°C warming brings the HDD count beyond the minimum implied by the estimated quadratic response function. We tried to cap the effect of HDD at the value achieved at this minimum since it is agronomically unlikely that further heat exposure could ever become beneficial, conditional on GDD. Results were very similar to those reported here.

changes, as in Schlenker and Roberts (2009). This is due in part to the considerable heterogeneity in the effect of precipitation on yields across counties. Figures 9 and 10 show county-level impacts of each precipitation scenario for our preferred specification. Unsurprisingly, locations with lower baseline precipitation typically benefit from an increase in precipitation, with the opposite being the case for wetter reference climates. Although we find statistically significant adaptation to precipitation in most models and scenarios, in most cases the differences are too small to be meaningful in an economic sense. These results are supportive of the view that the largest impacts of climate change on agriculture will be channeled through changes in temperature exposure.

[Figure 8 about here.]

[Figure 9 about here.]

6 Discussion

This paper uses a novel identification strategy to decipher long-run adaptation to climatic changes in US crop agriculture. We exploit county-level climatic trends over the historical period within an econometric framework that allows for adaptation in a parametric fashion. The framework relies upon the idea that locations that are used to a given weather realization will perform better under such realization than locations that are not. With the inclusion of flexible locational trends, our regression framework identifies climatic adaptation strictly from variations in the interaction of weather with climatic trends. This strategy differs from that of Burke and Emerick (2016), which directly attributes trends in yield at the county level to trends in county climate, once common state-level trends have been netted out.

We begin by showing that US rainfed counties have experienced climatic trends over the period 1980–2017, with some experiencing warming, others cooling, and many increases in growing-season precipitation. Here, climate is computed using past weather averages over a large number of years. By exploiting these trends, our analysis then shows the existence of statistically significant and economically meaningful adaptation to temperature over the historical period. This finding implies that crop yields are predicted to respond differently to changes in climate in the short run and in the long run. Indeed, a uniform 1°C warming would imply a 5–6% reduction in corn production in the short run yet a 4–7% increase in the long run. Smaller discrepancies still arise between short-run and long-run effects when cross-sectional differences in climate, which are large across US counties, are used for identification through climate-weather interactions.

One may be skeptical about the results obtained in our most flexible specification that strictly relies on climate-trend and weather interactions insofar as it suggests that long-run adaptation may completely overturn the negative short-run impacts of warming. While such a large adaptation effect cannot be ruled out in theory, a clear limitation of this approach is that it exploits temporal climatic signals conditional on location that are admittedly weaker than the changes of interest for climate impact analysis. A similar criticism would apply to the long-difference approach, however, especially when it exploits county trends that are *residual* to state trends. The approach that assumes stationary climate and the hybrid approach with single slope coefficients exploit larger cross-sectional differences through the interaction of climate and weather. However, one may be worried that this large variation correlates with unobservables that interact with weather, like soils or photoperiodicity. Controlling for such unobservables is important as they may not change when locational climate changes.

Although the different identification strategies explored in this paper lead to different counterfactual warming impacts, which some may find troubling, our analysis consistently shows significant and economically meaningful adaptation to temperature signals in US county yield data.

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Appendices

A Average climates

[Figure 10 about here.]

B Results from the sample 1980-2017

[Table 7 about here.]

[Table 8 about here.]

C Results with smoothed climatic trends

C.1 Corn

[Table 9 about here.]

[Table 10 about here.]

C.2 Soybeans

[Table 11 about here.]

[Table 12 about here.]

D Results with alternate specification of the climate penalty

D.1 Corn

[Table 13 about here.]

[Table 14 about here.]

D.2 Soybeans

[Table 15 about here.]

[Table 16 about here.]

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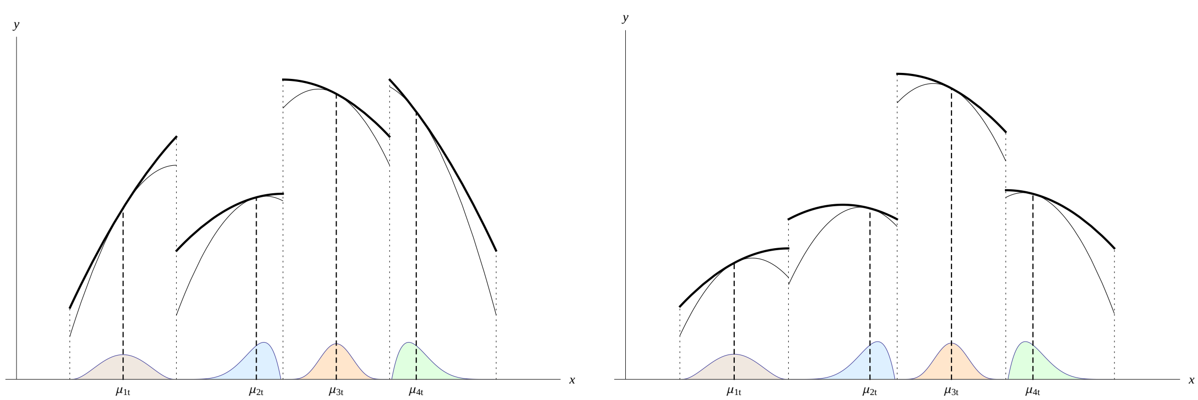
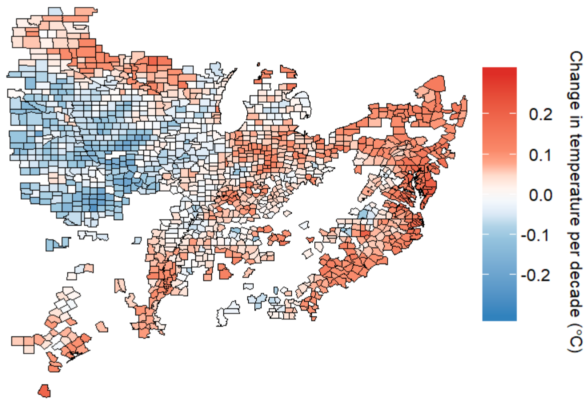
Figure 1 Graphical representation of the adaptation process

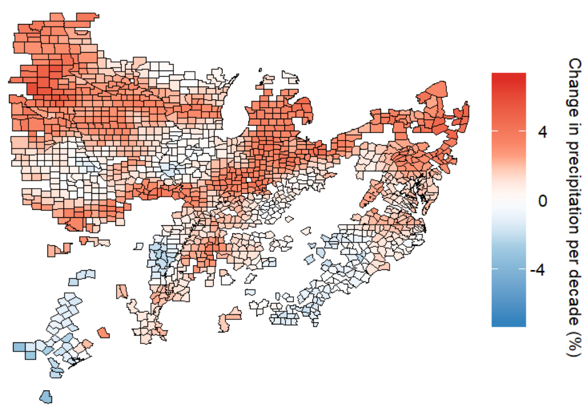


(a) Adaptation with common slope coefficients (b) Adaptation with location-specific slope coefficients

Figure 2 Maps of climate trends

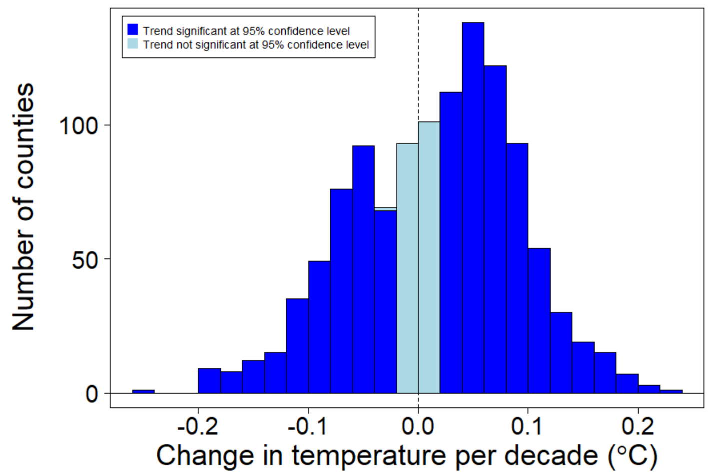


(a) Temperature

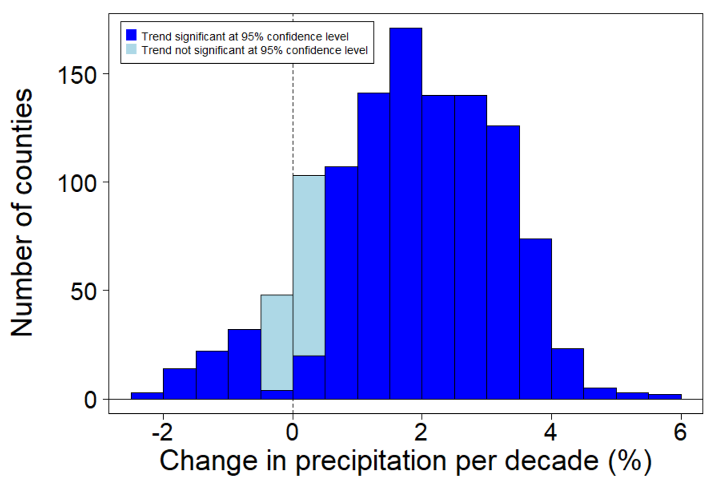


(b) Precipitation

Figure 3 Distributions of climate trends

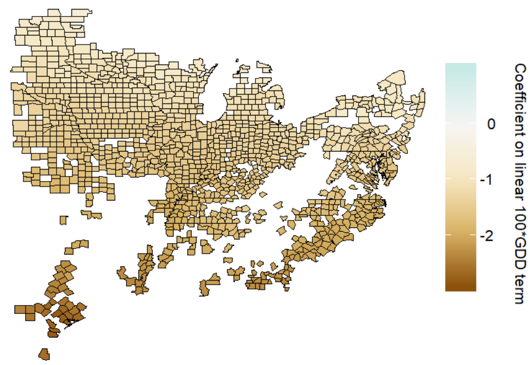


(a) Temperature

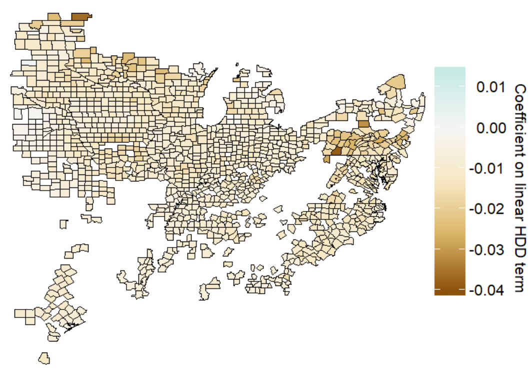


(b) Precipitation

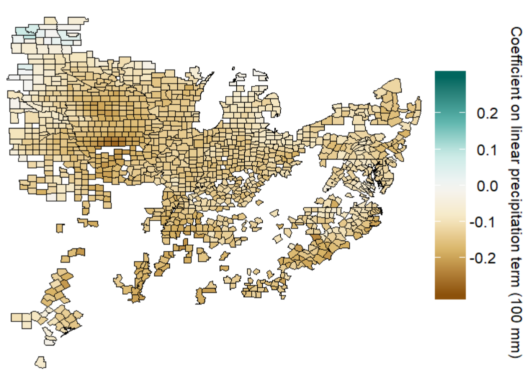
Figure 4 Geographical distribution of weather slope coefficients (US corn)



(a) GDD

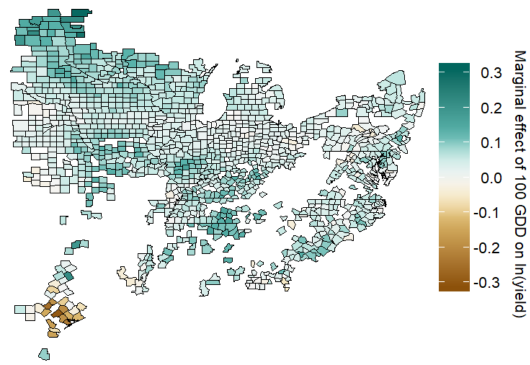


(b) HDD

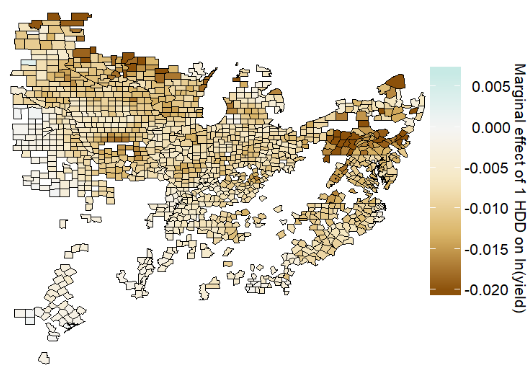


(c) Precipitation

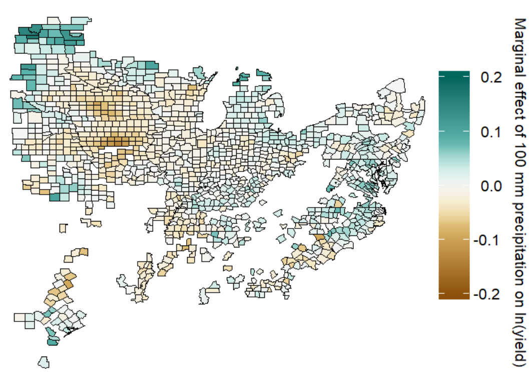
Figure 5 Geographical distribution of marginal climatic effects (US corn)



(a) GDD

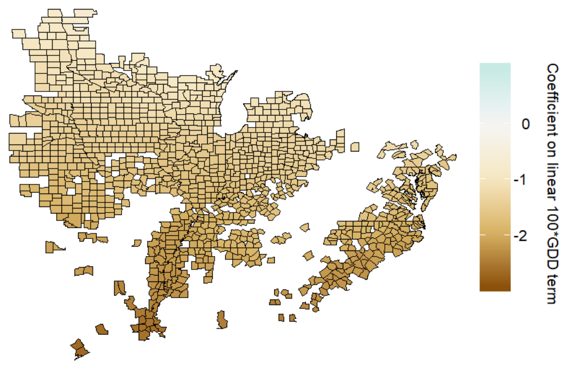


(b) HDD

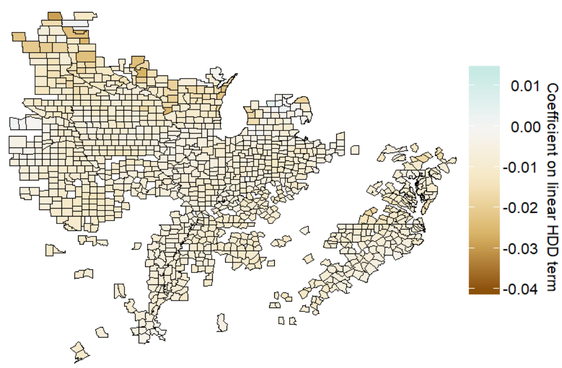


(c) Precipitation

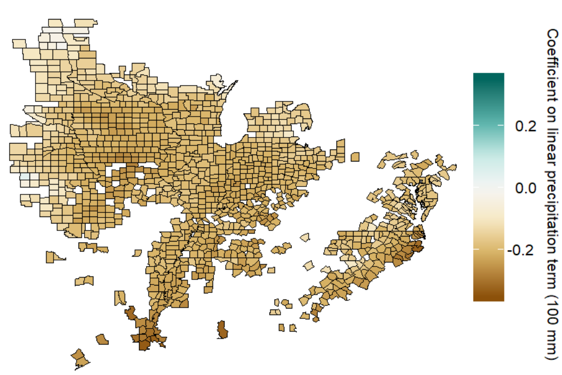
Figure 6 Geographical distribution of weather slope coefficients (US soybeans)



(a) GDD

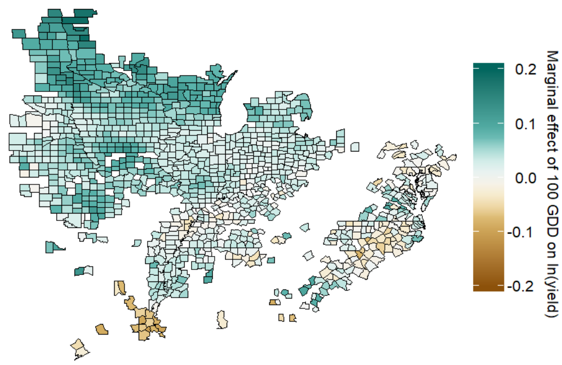


(b) HDD

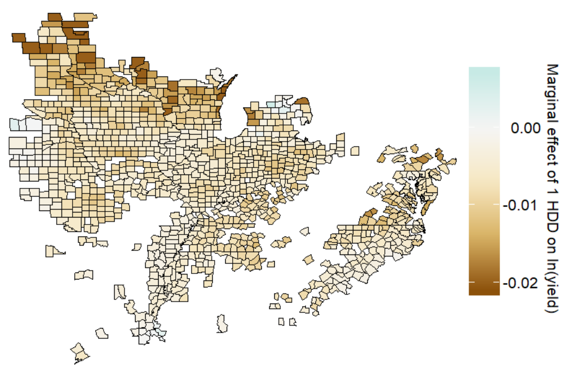


(c) Precipitation

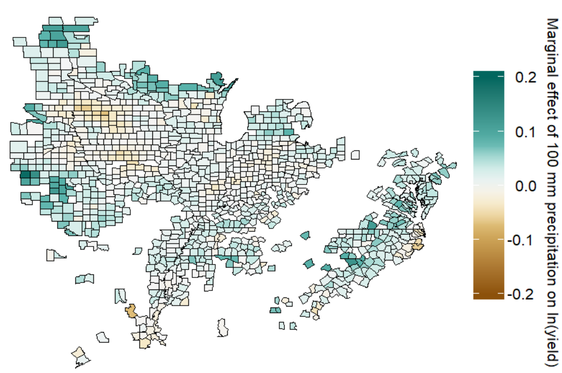
Figure 7 Geographical distribution of marginal climatic effects (US soybeans)



(a) GDD

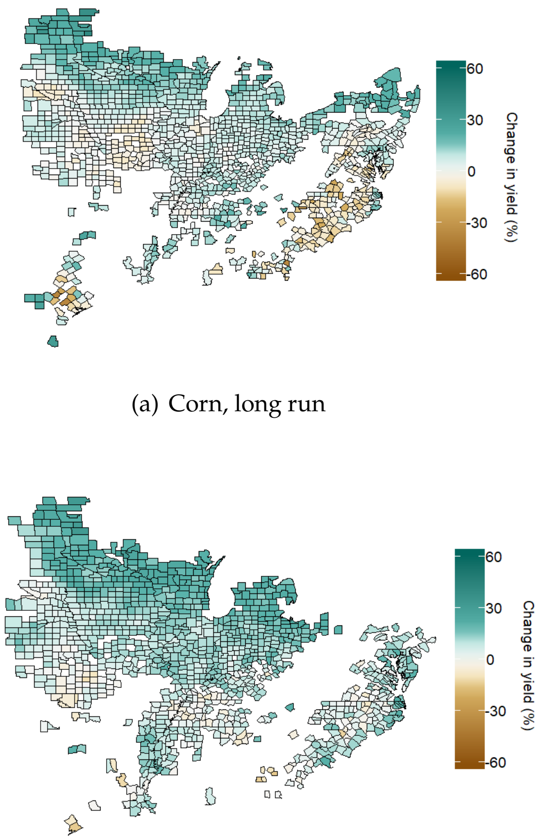


(b) HDD



(c) Precipitation

Figure 8 Maps of 1°C warming impacts



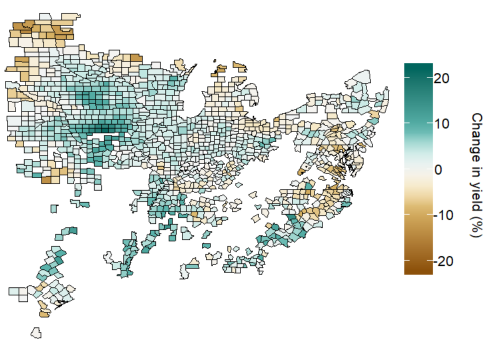
(a) Corn, long run

(b) Corn, short run

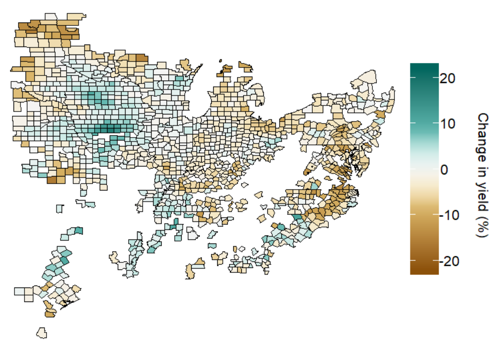
(c) Soybeans, long run

(d) Soybeans, short run

Figure 9 Maps of -20% precipitation impacts



(a) Corn, long run



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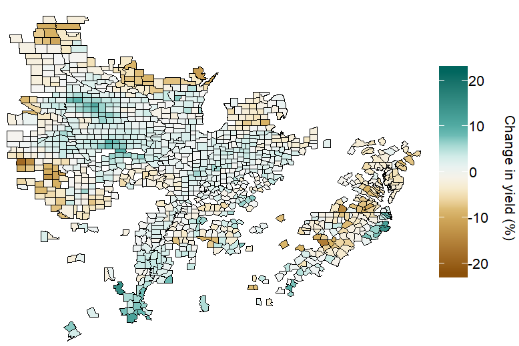
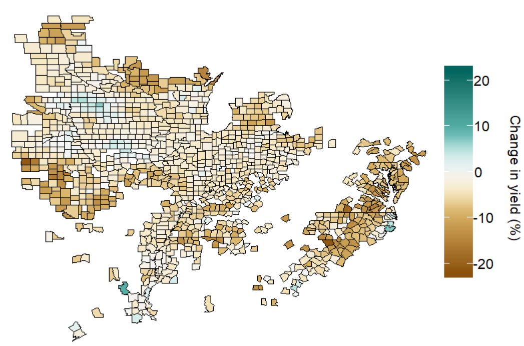
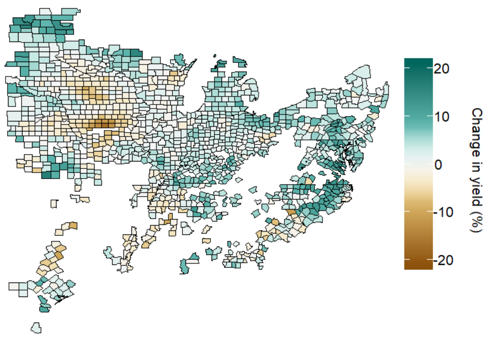


(c) Soybeans, long run

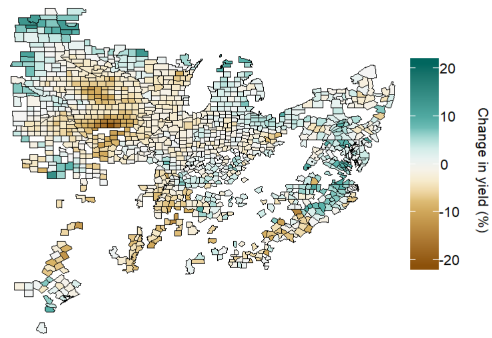


(d) Soybeans, short run

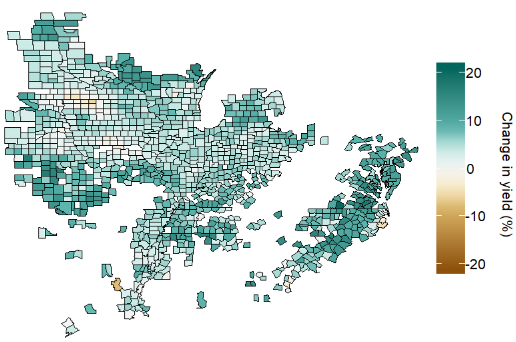
Figure 10 Maps of +20% precipitation impacts



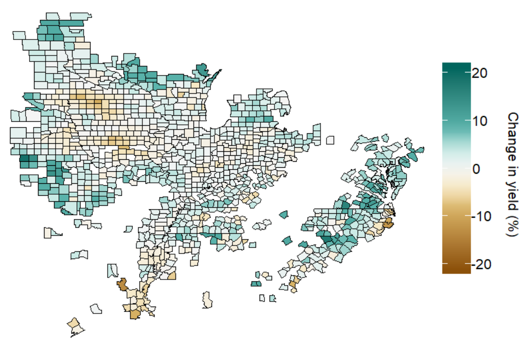
(a) Corn, long run



(b) Corn, short run

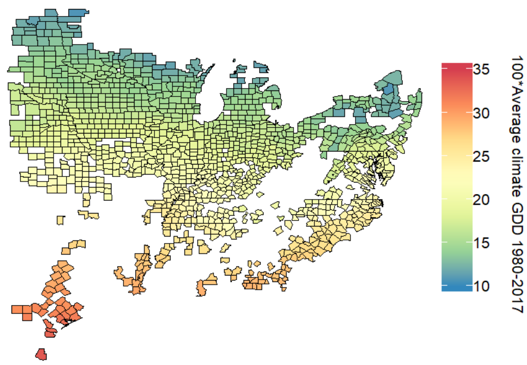


(c) Soybeans, long run

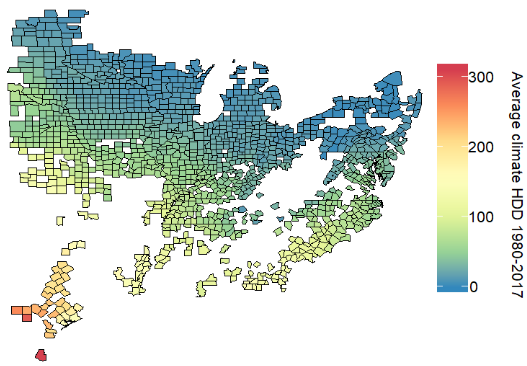


(d) Soybeans, short run

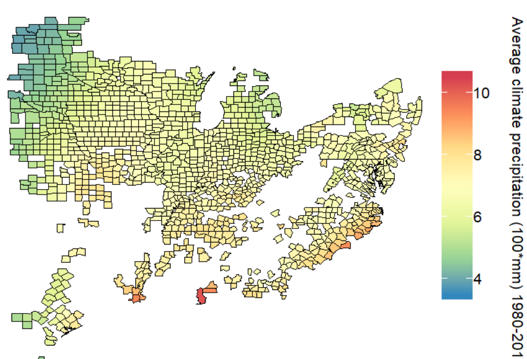
Figure 11 Maps of average climates (corn)



(a) GDD



(b) HDD



(c) Precipitation

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Table 1 Summary statistics, US corn

	mean	std. dev.	min.	max.
	1950–2017			
ln yield	4.42	0.53	-1.20	5.51
GDD 10–29°C (100°C; weather)	19.09	4.09	8.67	30.99
HDD 29°C (weather)	43.30	38.10	0.00	333.93
Precip. (100mm; weather)	6.68	1.60	1.50	16.30
Observations	72,532			
# counties	1,086			
	1980–2017			
ln yield	4.70	0.37	1.95	5.51
GDD 10–29°C (100°C; weather)	19.46	4.63	8.59	35.45
GDD 10–29°C (100°C; climate)	19.28	4.44	10.53	34.31
HDD 29°C (weather)	49.00	51.49	0.00	492.30
HDD 29°C (climate)	48.54	42.69	1.03	348.77
Precip. (100mm; weather)	6.86	1.61	1.65	16.30
Precip. (100mm; climate)	6.66	0.88	3.69	10.69
Observations	47,509			
# counties	1,274			

Notes: The 1950-2017 sample includes counties that have planted corn for more than 90% of years between 1950-2017, and the 1980–2017 sample includes counties that have planted corn for more than 90% of years between 1980–2017. Rolling climate variables for the 1980–2017 sample are constructed by averaging weather over the previous 30 years.

Table 2 Summary statistics, US soybeans

	mean	std. dev.	min.	max.
	1950–2017			
ln yield	3.36	0.40	-0.36	5.44
GDD 10–30°C (100°C; weather)	19.27	4.06	9.02	32.09
HDD 30°C (weather)	29.80	32.41	0.00	276.27
Precip. (100mm; weather)	6.71	1.56	1.58	16.30
Observations	56,892			
# counties	849			
	1980–2017			
ln yield	3.53	0.33	-0.36	4.29
GDD 10–30°C (100°C; weather)	20.07	4.41	8.24	34.08
GDD 10–30°C (100°C; climate)	19.90	4.17	10.55	32.62
HDD 30°C (weather)	33.19	33.86	0.00	305.86
HDD 30°C (climate)	32.93	25.69	1.41	136.91
Precip. (100mm; weather)	6.94	1.62	1.79	17.82
Precip. (100mm; climate)	6.73	0.87	3.76	10.69
Observations	43,161			
# counties	1,154			

Notes: The 1950-2017 sample includes counties that have planted soybeans for more than 90% of years between 1950-2017, and the 1980–2017 sample includes counties that have planted soybeans for more than 90% of years between 1980–2017. Rolling climate variables for the 1980–2017 sample are constructed by averaging weather over the previous 30 years.

Table 3 Corn regression results

	Flexible model			Single slope			Stationary climate
	30 yrs	25 yrs	20 yrs	30 yrs	25 yrs	20 yrs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				6.76e-02***	7.84e-02***	8.03e-02***	1.13e-01***
β_1^{GDD}	—	—	—	(1.79e-02)	(1.73e-02)	(1.66e-02)	(1.68e-02)
				[2.51e-02]	[2.19e-02]	[2.11e-02]	[1.98e-02]
	3.99e-02***	2.71e-02***	3.09e-02***	-5.49e-04	-9.58e-04*	-1.04e-03**	-1.93e-03***
β_2^{GDD}	(7.36e-03)	(6.51e-03)	(5.51e-03)	(4.46e-04)	(4.28e-04)	(4.17e-04)	(4.35e-04)
	[9.39e-03]	[7.49e-03]	[6.63e-03]	[5.94e-04]	[5.21e-04]	[5.18e-04]	[4.91e-04]
	-4.34e-02***	-3.00e-02***	-3.43e-02***	-8.39e-03***	-7.51e-03***	-8.43e-03***	-4.37e-03
β_3^{GDD}	(7.62e-03)	(6.55e-03)	(5.73e-03)	(2.50e-03)	(2.23e-03)	(2.28e-03)	(2.03e-03)
	[8.81e-03]	[7.72e-03]	[6.43e-03]	[2.02e-03]	[2.53e-03]	[2.47e-03]	[2.73e-03]
				-9.77e-03***	-9.54e-03***	-9.53e-03***	-8.95e-03***
β_1^{HDD}	—	—	—	(3.23e-04)	(3.19e-04)	(3.18e-04)	(3.82e-04)
				[6.71e-04]	[7.23e-04]	[7.30e-04]	[7.39e-04]
	1.69e-05	3.55e-05**	9.03e-06	1.98e-05***	1.98e-05***	1.99e-05***	1.87e-05***
β_2^{HDD}	(1.08e-05)	(1.07e-05)	(9.05e-06)	(1.38e-06)	(1.37e-06)	(1.34e-06)	(2.11e-06)
	[1.57e-05]	[1.59e-05]	[1.36e-05]	[4.25e-06]	[3.75e-06]	[3.72e-06]	[4.42e-06]
	-2.75e-05*	-4.40e-05***	-1.69e-05	-3.15e-05***	-2.84e-05***	-2.64e-05***	-3.28e-05***
β_3^{HDD}	(1.08e-05)	(1.01e-05)	(8.70e-06)	(3.34e-06)	(3.22e-06)	(3.29e-06)	(5.71e-06)
	[1.52e-05]	[1.40e-05]	[1.29e-05]	[7.73e-06]	[3.89e-06]	[4.00e-06]	[8.19e-06]
				3.11e-03	3.32e-02	3.98e-02	5.34e-02
β_1^{prec}	—	—	—	(1.86e-02)	(1.91e-02)	(1.93e-02)	(1.92e-02)
				[3.42e-02]	[3.53e-02]	[3.47e-02]	[3.37e-02]
	9.64e-03	2.85e-03	7.61e-03	-4.38e-04	-2.24e-03	-2.76e-03	-4.28e-03*
β_2^{prec}	(5.50e-03)	(4.63e-03)	(4.15e-03)	(1.33e-03)	(1.35e-03)	(1.36e-03)	(1.36e-03)
	[6.32e-03]	[5.87e-03]	[7.86e-03]	[2.50e-03]	[2.56e-03]	[2.47e-03]	[2.46e-03]
	-1.51e-02***	-1.02e-02**	-1.48e-02**	-5.24e-03	-5.24e-03	-5.25e-03**	-2.06e-03
β_3^{prec}	(5.33e-03)	(4.30e-03)	(3.86e-03)	(1.93e-03)	(1.79e-03)	(1.70e-03)	(2.06e-03)
	[4.96e-03]	[4.37e-03]	[5.86e-03]	[3.29e-03]	[3.22e-03]	[2.51e-03]	[3.52e-03]
County FE	✓	✓	✓	✓	✓	✓	✓
County trends	✓	✓	✓	✓	✓	✓	✓
# counties	1,274	1,342	1,321	1,274	1,342	1,321	1,086
Years	1980–2017	1975–2017	1970–2017	1980–2017	1975–2017	1970–2017	1950–2017
Observations	47,509	56,506	62,210	47,509	56,506	62,210	72,532

Notes: The dependent variable is the logarithm of corn yield. Columns (1)–(3) estimate model (1) allowing for county-specific slope coefficients, using varying lengths of time to calculate rolling climate. Columns (4)–(6) estimate model (1) restricting slope coefficients to be identical across counties, using varying lengths of time to calculate rolling climate. Column (7) estimates (1) restricting slope coefficients to be identical across counties and assuming climate is constant across time in a given county. Conley standard errors are in parentheses, state-clustered standard errors are in square brackets. Stars reflect the state-cluster standard errors: (*), (**), (***) indicate the estimate is significant at the 90%, 95% and 99% confidence level respectively. Each sample covers US counties east of the 100th meridian for which yield data is available for at least 90% of the sample years.

Table 4 Soybeans regression results

	Flexible model			Single slope			Stationary climate
	30 yrs	25 yrs	20 yrs	30 yrs	25 yrs	20 yrs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				1.25e-01***	1.04e-01***	9.95e-02***	9.83e-02***
β_1^{GDD}	—	—	—	(1.55e-02)	(1.48e-02)	(1.43e-02)	(1.46e-02)
				[1.78e-02]	[1.69e-02]	[1.71e-02]	[2.10e-02]
	4.10e-02***	3.43e-02***	2.58e-02***	-2.29e-03***	-1.62e-03***	-1.46e-03***	-1.49e-03***
β_2^{GDD}	(7.26e-03)	(5.28e-03)	(4.74e-03)	(3.96e-04)	(3.69e-04)	(3.55e-04)	(3.80e-04)
	[7.60e-03]	[7.99e-03]	[4.59e-03]	[4.55e-04]	[4.65e-04]	[4.59e-04]	[5.10e-04]
	-4.01e-02***	-3.48e-02***	-2.70e-02***	-1.44e-03	-3.15e-03*	-3.66e-03**	-2.84e-03**
β_3^{GDD}	(7.50e-03)	(5.28e-03)	(4.87e-03)	(2.01e-03)	(1.74e-03)	(1.75e-03)	(1.68e-03)
	[7.40e-03]	[7.89e-03]	[4.98e-03]	[1.91e-03]	[1.61e-03]	[1.77e-03]	[1.16e-03]
				-7.93e-03***	-8.00e-03***	-7.83e-03***	-6.78e-03***
β_1^{HDD}	—	—	—	(3.80e-04)	(3.91e-04)	(3.75e-04)	(3.88e-04)
				[5.88e-04]	[5.98e-04]	[5.49e-04]	[6.25e-04]
	2.26e-05	4.09e-05***	-7.62e-06	1.96e-05***	1.95e-05***	1.78e-05***	8.32e-06
β_2^{HDD}	(1.51e-05)	(1.46e-05)	(1.30e-05)	(2.55e-06)	(2.50e-06)	(2.44e-06)	(2.89e-06)
	[1.60e-05]	[1.30e-05]	[9.42e-06]	[5.58e-06]	[4.95e-06]	[4.77e-06]	[7.30e-06]
	-1.54e-05	-2.88e-05**	1.81e-05	-1.49e-05	-1.23e-05	-8.48e-06	-3.99e-06
β_3^{HDD}	(1.54e-05)	(1.33e-05)	(1.21e-05)	(4.86e-06)	(4.38e-06)	(4.19e-06)	(5.04e-06)
	[2.05e-05]	[1.41e-05]	[1.27e-05]	[9.16e-06]	[8.46e-06]	[8.20e-06]	[1.02e-05]
				3.14e-02	6.64e-02**	6.83e-02**	8.99e-02***
β_1^{prec}	—	—	—	(1.73e-02)	(1.81e-02)	(1.70e-02)	(2.24e-02)
				[3.19e-02]	[2.85e-02]	[2.70e-02]	[2.19e-02]
	1.55e-02***	1.74e-03	1.49e-03	-1.32e-03	-3.46e-03*	-3.69e-03*	-5.49e-03***
β_2^{prec}	(4.51e-03)	(3.68e-03)	(2.89e-03)	(1.23e-03)	(1.26e-03)	(1.18e-03)	(1.60e-03)
	[5.30e-03]	[4.33e-03]	[4.37e-03]	[2.33e-03]	[2.04e-03]	[1.90e-03]	[1.54e-03]
	-2.30e-02***	-1.05e-02***	-9.82e-03***	-6.58e-03**	-5.42e-03**	-5.05e-03**	-1.97e-03
β_3^{prec}	(4.58e-03)	(3.58e-03)	(2.83e-03)	(1.64e-03)	(1.54e-03)	(1.45e-03)	(1.91e-03)
	[5.69e-03]	[4.00e-03]	[3.78e-03]	[3.12e-03]	[2.73e-03]	[2.46e-03]	[2.06e-03]
County FE	✓	✓	✓	✓	✓	✓	✓
County trends	✓	✓	✓	✓	✓	✓	✓
# counties	1,154	1,180	1,136	1,154	1,180	1,136	849
Years	1980–2017	1975–2017	1970–2017	1980–2017	1975–2017	1970–2017	1950–2017
Observations	43,161	49,849	53,461	43,161	49,849	53,461	56,892

Notes: The dependent variable is the logarithm of soybean yield. Columns (1)–(3) estimate model (1) allowing for county-specific slope coefficients, using varying lengths of time to calculate rolling climate. Columns (4)–(6) estimate model (1) restricting slope coefficients to be identical across counties, using varying lengths of time to calculate rolling climate. Column (7) estimates (1) restricting slope coefficients to be identical across counties and assuming climate is constant across time in a given county. Conley standard errors are in parentheses, state-clustered standard errors are in square brackets. Stars reflect the state-cluster standard errors: (*), (**), (***) indicate the estimate is significant at the 90%, 95% and 99% confidence level respectively. Each sample covers US counties east of the 100th meridian for which yield data is available for at least 90% of the sample years.

Table 5 Climate impacts of a 1°C uniform warming (relative to 1987-2016)

	Flexible model			Single slope			Stationary climate
	30 yrs	25 yrs	20 yrs	30 yrs	25 yrs	20 yrs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Corn long-run (%)	6.68	3.60	3.94	-5.17	-5.48	-5.67	-5.04
	[2.52]	[1.91]	[1.70]	[0.74]	[0.68]	[0.66]	[0.75]
Corn short-run (%)	-5.33	-5.67	-5.38	-8.40	-8.39	-8.75	-7.67
	[0.86]	[0.69]	[0.67]	[0.85]	[0.89]	[0.85]	[0.83]
Soybeans long-run (%)	11.32	10.35	6.49	-3.14	-2.28	-2.07	-2.39
	[2.10]	[2.38]	[1.36]	[0.56]	[0.54]	[0.54]	[0.77]
Soybeans short-run (%)	-0.13	-0.07	-0.34	-3.99	-3.52	-3.34	-3.30
	[0.84]	[0.67]	[0.53]	[0.69]	[0.74]	[0.71]	[0.60]

Notes: Impacts are relative to the average climate, acreage, and yield of the reference period 1987-2016 . Standard errors are based on the state-cluster approach.

Table 6 Climate impacts of -20% and +20% changes in precipitation (relative to 1987-2016)

	Flexible model				Single slope				Stationary climate
	30 yrs (1)	25 yrs (2)	20 yrs (3)		30 yrs (4)	25 yrs (5)	20 yrs (6)		(7)
-20% Precipitation									
Corn long-run (%)	2.72	1.06	1.41		0.29	-0.83	-0.87		-0.37
	[0.96]	[0.86]	[1.07]		[0.69]	[0.73]	[0.80]		[0.75]
Corn short-run (%)	0.06	-0.73	-1.19		-0.64	-1.76	-1.79		-0.71
	[0.60]	[0.48]	[0.28]		[0.59]	[0.59]	[0.65]		[0.76]
Soybeans long-run (%)	1.02	-1.29	-1.23		-2.05	-3.22	-3.09		-3.04
	[0.64]	[0.65]	[0.67]	[0.68]	[0.73]	[0.75]		[0.65]	
Soybeans short-run (%)	-3.19	-3.21	-3.04		-3.25	-4.21	-4.02		-3.40
	[0.70]	[0.55]	[0.46]		[0.69]	[0.76]	[0.78]		[0.68]
+20% Precipitation									
Corn long-run (%)	0.68	-0.06	1.27		-0.44	0.05	-0.11		-1.05
	[1.33]	[1.24]	[1.71]		[0.59]	[0.57]	[0.55]		[0.57]
Corn short-run (%)	-1.98	-1.85	-1.33		-1.36	-0.88	-1.03		-1.39
	[0.50]	[0.52]	[0.69]		[0.63]	[0.60]	[0.56]		[0.56]
Soybeans long-run (%)	4.63	1.93	1.78		1.57	1.95	1.73		1.03
	[1.3]	[1.02]	[1.00]		[0.69]	[0.68]	[0.66]		[0.58]
Soybeans short-run (%)	0.42	0.01	-0.03		0.37	0.95	0.80		0.68
	[0.37]	[0.32]	[0.34]		[0.49]	[0.53]	[0.52]		[0.56]

Notes: Impacts are relative to the average climate, acreage, and yield of the reference period 1987–2016. Standard errors are based on the state-cluster approach.

Table 7 Corn regression results (1980-2017 sample)

	Flexible model			Single slope			Stationary climate
	30 yrs	25 yrs	20 yrs	30 yrs	25 yrs	20 yrs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
β_1^{GDD}	—	—	—	6.76e-02***	6.60e-02***	6.59e-02***	7.75e-02***
				(1.79e-02)	(1.76e-02)	(1.73e-02)	(1.86e-02)
				[2.51e-02]	[2.46e-02]	[2.39e-02]	[2.57e-02]
β_2^{GDD}	3.99e-02***	3.88e-02***	2.82e-02***	-5.49e-04	-5.15e-04	-5.29e-04	-8.81e-04
	(7.36e-03)	(6.88e-03)	(6.05e-03)	(4.46e-04)	(4.40e-04)	(4.33e-04)	(4.61e-04)
	[9.39e-03]	[7.15e-03]	[6.56e-03]	[5.94e-04]	[5.83e-04]	[5.69e-04]	[6.06e-04]
β_3^{GDD}	-4.34e-02***	-4.30e-02***	-3.16e-02***	-8.39e-03***	-9.03e-03***	-9.08e-03***	-5.55e-03***
	(7.62e-03)	(7.31e-03)	(6.53e-03)	(2.50e-03)	(2.56e-03)	(2.58e-03)	(2.41e-03)
	[8.81e-03]	[6.89e-03]	[6.42e-03]	[2.02e-03]	[2.03e-03]	[2.19e-03]	[2.16e-03]
β_1^{HDD}	—	—	—	-9.77e-03***	-9.63e-03***	-9.52e-03***	-9.55e-03***
				(3.23e-04)	(3.16e-04)	(3.13e-04)	(3.23e-04)
				[6.71e-04]	[6.58e-04]	[6.50e-04]	[6.65e-04]
β_2^{HDD}	1.69e-05	4.41e-05***	2.58e-05**	1.98e-05***	1.96e-05***	1.88e-05***	1.78e-05***
	(1.08e-05)	(1.08e-05)	(8.84e-06)	(1.38e-06)	(1.36e-06)	(1.32e-06)	(1.28e-06)
	[1.57e-05]	[1.46e-05]	[1.29e-05]	[4.25e-06]	[4.18e-06]	[3.95e-06]	[3.97e-06]
β_3^{HDD}	-2.75e-05*	-5.31e-05***	-3.39e-05***	-3.15e-05***	-3.00e-05***	-2.80e-05***	-2.78e-05***
	(1.08e-05)	(1.03e-05)	(8.41e-06)	(3.34e-06)	(3.16e-06)	(3.13e-06)	(3.26e-06)
	[1.52e-05]	[1.27e-05]	[1.04e-05]	[7.73e-06]	[6.57e-06]	[5.69e-06]	[6.94e-06]
β_1^{prec}	—	—	—	3.11e-03	1.84e-03	-3.78e-03	-3.89e-03
				(1.86e-02)	(1.85e-02)	(1.88e-02)	(1.95e-02)
				[3.42e-02]	[3.36e-02]	[3.23e-02]	[3.65e-02]
β_2^{prec}	9.64e-03	9.08e-03	8.90e-03	-4.38e-04	-3.20e-04	5.64e-05	1.36e-04
	(5.50e-03)	(5.01e-03)	(4.69e-03)	(1.33e-03)	(1.31e-03)	(1.33e-03)	(1.39e-03)
	[6.32e-03]	[5.90e-03]	[6.24e-03]	[2.50e-03]	[2.46e-03]	[2.35e-03]	[2.68e-03]
β_3^{prec}	-1.51e-02***	-1.44e-02***	-1.41e-02***	-5.24e-03	-5.54e-03*	-5.99e-03**	-6.48e-03*
	(5.33e-03)	(4.79e-03)	(4.45e-03)	(1.93e-03)	(1.86e-03)	(1.84e-03)	(2.11e-03)
	[4.96e-03]	[4.41e-03]	[4.53e-03]	[3.29e-03]	[3.22e-03]	[2.95e-03]	[3.81e-03]
County FE	✓	✓	✓	✓	✓	✓	✓
County trends	✓	✓	✓	✓	✓	✓	✓
# counties	1,274	1,274	1,274	1,274	1,274	1,274	1,274
Years	1980–2017	1980–2017	1980–2017	1980–2017	1980–2017	1980–2017	1980–2017
Observations	47,509	47,509	47,509	47,509	47,509	47,509	47,509

Conley standard errors are shown in ()
State-clustered standard errors are shown in []
Significance levels based on standard errors in []: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8 Soybeans regression results (1980-2017 sample)

	Flexible model			Single slope			Stationary climate
	30 yrs	25 yrs	20 yrs	30 yrs	25 yrs	20 yrs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
β_1^{GDD}	—	—	—	1.25e-01***	1.27e-01***	1.26e-01***	1.35e-01***
				(1.55e-02)	(1.55e-02)	(1.53e-02)	(1.58e-02)
				[1.78e-02]	[1.75e-02]	[1.73e-02]	[1.78e-02]
β_2^{GDD}	4.10e-02***	2.83e-02***	2.49e-02***	-2.29e-03***	-2.34e-03***	-2.33e-03***	-2.56e-03***
	(7.26e-03)	(6.12e-03)	(5.15e-03)	(3.96e-04)	(3.96e-04)	(3.89e-04)	(3.95e-04)
	[7.60e-03]	[7.68e-03]	[5.90e-03]	[4.55e-04]	[4.49e-04]	[4.46e-04]	[4.59e-04]
β_3^{GDD}	-4.01e-02***	-2.72e-02***	-2.35e-02***	-1.44e-03	-1.12e-03	-1.24e-03	1.60e-03
	(7.50e-03)	(6.28e-03)	(5.30e-03)	(2.01e-03)	(2.02e-03)	(2.00e-03)	(2.48e-06)
	[7.40e-03]	[7.61e-03]	[5.96e-03]	[1.91e-03]	[2.01e-03]	[2.08e-03]	[4.98e-06]
β_1^{HDD}	—	—	—	-7.93e-03***	-7.91e-03***	-7.85e-03***	-7.87e-03***
				(3.80e-04)	(3.78e-04)	(3.75e-04)	(3.84e-04)
				[5.88e-04]	[5.79e-04]	[5.76e-04]	[5.83e-04]
β_2^{HDD}	2.26e-05	2.96e-05**	4.12e-06	1.96e-05***	1.97e-05***	1.88e-05***	1.85e-05***
	(1.51e-05)	(1.61e-05)	(1.40e-05)	(2.55e-06)	(2.56e-06)	(2.52e-06)	(2.48e-06)
	[1.60e-05]	[1.49e-05]	[1.06e-05]	[5.58e-06]	[5.44e-06]	[5.26e-06]	[4.98e-06]
β_3^{HDD}	-1.54e-05	-2.07e-05	4.44e-06	-1.49e-05	-1.40e-05*	-1.21e-05	-1.30e-05
	(1.54e-05)	(1.50e-05)	(1.32e-05)	(4.86e-06)	(4.48e-06)	(4.38e-06)	(4.65e-06)
	[2.05e-05]	[1.74e-05]	[1.39e-05]	[9.16e-06]	[8.15e-06]	[7.78e-06]	[7.95e-06]
β_1^{prec}	—	—	—	3.14e-02	3.35e-02	3.72e-02	3.93e-02
				(1.73e-02)	(1.70e-02)	(1.70e-02)	(1.81e-02)
				[3.19e-02]	[3.04e-02]	[2.91e-02]	[3.24e-02]
β_2^{prec}	1.55e-02***	1.22e-02***	4.48e-03	-1.32e-03	-1.48e-03	-1.79e-03	-1.89e-03
	(4.51e-03)	(4.00e-03)	(3.42e-03)	(1.23e-03)	(1.20e-03)	(1.18e-03)	(1.28e-03)
	[5.30e-03]	[4.55e-03]	[5.39e-03]	[2.33e-03]	[2.20e-03]	[2.10e-03]	[2.35e-03]
β_3^{prec}	-2.30e-02***	-1.98e-02***	-1.21e-02**	-6.58e-03**	-6.43e-03**	-5.91e-03**	-6.07e-03*
	(4.58e-03)	(3.99e-03)	(3.36e-03)	(1.64e-03)	(1.57e-03)	(1.54e-03)	(1.72e-03)
	[5.69e-03]	[4.58e-03]	[5.19e-03]	[3.12e-03]	[2.91e-03]	[2.76e-03]	[3.24e-03]
County FE	✓	✓	✓	✓	✓	✓	✓
County trends	✓	✓	✓	✓	✓	✓	✓
# counties	1,154	1,154	1,154	1,154	1,154	1,154	1,154
Years	1980–2017	1980–2017	1980–2017	1980–2017	1980–2017	1980–2017	1980–2017
Observations	43,161	43,161	43,161	43,161	43,161	43,161	43,161

Conley standard errors are shown in ()
State-clustered standard errors are shown in []
Significance levels based on standard errors in []: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9 Corn regression results, smoothed climate

	Flexible model			Single slope		
	30 yrs	25 yrs	20 yrs	30 yrs	25 yrs	20 yrs
	(1)	(2)	(3)	(4)	(5)	(6)
β_1^{GDD}	—	—	—	6.91e-02***	7.95e-02***	8.63e-02***
				(1.79e-02)	(1.74e-02)	(1.70e-02)
				[2.50e-02]	[2.20e-02]	[2.11e-02]
β_2^{GDD}	4.21e-02***	2.96e-02***	2.87e-02***	-5.92e-04	-9.79e-04*	-1.20e-03**
	(7.44e-03)	(6.54e-03)	(5.97e-03)	(4.46e-04)	(4.28e-04)	(4.27e-04)
	[9.88e-03]	[8.16e-03]	[7.89e-03]	[5.90e-04]	[5.22e-04]	[5.12e-04]
β_3^{GDD}	-4.72e-02***	-3.39e-02***	-3.36e-02***	-8.32e-03***	-7.66e-03***	-7.71e-03***
	(8.06e-03)	(6.93e-03)	(6.50e-03)	(2.59e-03)	(2.31e-03)	(2.41e-03)
	[9.75e-03]	[9.02e-03]	[8.34e-03]	[2.19e-03]	[2.67e-03]	[2.63e-03]
β_1^{HDD}	—	—	—	-9.75e-03***	-9.57e-03***	-9.58e-03***
				(3.20e-04)	(3.18e-04)	(3.16e-04)
				[6.68e-04]	[7.23e-04]	[7.28e-04]
β_2^{HDD}	2.75e-05	4.22e-05***	2.80e-05**	2.01e-05***	2.01e-05***	2.02e-05***
	(1.24e-05)	(1.15e-05)	(1.07e-05)	(1.39e-06)	(1.38e-06)	(1.33e-06)
	[2.16e-05]	[1.50e-05]	[1.24e-05]	[4.34e-06]	[3.85e-06]	[3.76e-06]
β_3^{HDD}	-4.02e-05*	-5.43e-05***	-3.89e-05***	-3.36e-05***	-3.13e-05***	-3.02e-05***
	(1.30e-05)	(1.19e-05)	(1.11e-05)	(3.45e-06)	(3.52e-06)	(3.57e-06)
	[2.39e-05]	[1.32e-05]	[1.16e-05]	[8.32e-06]	[4.76e-06]	[4.41e-06]
β_1^{prec}	—	—	—	5.37e-04	3.24e-02	4.68e-02
				(1.88e-02)	(1.94e-02)	(1.95e-02)
				[3.42e-02]	[3.58e-02]	[3.65e-02]
β_2^{prec}	1.60e-02**	3.97e-03	6.24e-03	-2.14e-04	-2.19e-03	-3.29e-03
	(6.31e-03)	(5.11e-03)	(4.63e-03)	(1.34e-03)	(1.36e-03)	(1.37e-03)
	[8.08e-03]	[7.61e-03]	[8.76e-03]	[2.51e-03]	[2.59e-03]	[2.61e-03]
β_3^{prec}	-2.24e-02***	-1.17e-02*	-1.42e-02*	-5.93e-03*	-5.49e-03	-4.64e-03
	(6.39e-03)	(5.01e-03)	(4.56e-03)	(2.04e-03)	(1.94e-03)	(1.87e-03)
	[7.17e-03]	[6.29e-03]	[7.32e-03]	[3.50e-03]	[3.40e-03]	[3.05e-03]
County FE	✓	✓	✓	✓	✓	✓
County trends	✓	✓	✓	✓	✓	✓
# counties	1,274	1,342	1,321	1,274	1,342	1,321
Years	1980–2017	1975–2017	1970–2017	1980–2017	1975–2017	1970–2017
Observations	47,509	56,506	62,210	47,509	56,506	62,210

Conley standard errors are shown in ()
State-clustered standard errors are shown in []
Significance levels based on standard errors in []: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10 Corn regression results, smoothed climate (1980-2017 sample)

	Flexible model			Single slope		
	30 yrs	25 yrs	20 yrs	30 yrs	25 yrs	20 yrs
	(1)	(2)	(3)	(4)	(5)	(6)
				6.91e-02***	6.80e-02***	6.71e-02***
β_1^{GDD}	—	—	—	(1.79e-02)	(1.77e-02)	(1.77e-02)
				[2.50e-02]	[2.46e-02]	[2.45e-02]
	4.21e-02***	4.41e-02***	3.72e-02***	-5.92e-04	-5.67e-04	-5.46e-04
β_2^{GDD}	(7.44e-03)	(7.09e-03)	(6.33e-03)	(4.46e-04)	(4.42e-04)	(4.41e-04)
	[9.88e-03]	[7.85e-03]	[7.11e-03]	[5.90e-04]	[5.80e-04]	[5.80e-04]
	-4.72e-02***	-4.99e-02***	-4.34e-02***	-8.32e-03***	-8.90e-03***	-9.23e-03***
β_3^{GDD}	(8.06e-03)	(7.91e-03)	(7.24e-03)	(2.59e-03)	(2.66e-03)	(2.72e-03)
	[9.75e-03]	[8.29e-03]	[7.69e-03]	[2.19e-03]	[2.28e-03]	[2.33e-03]
				-9.75e-03***	-9.66e-03***	-9.57e-03***
β_1^{HDD}	—	—	—	(3.20e-04)	(3.17e-04)	(3.14e-04)
				[6.68e-04]	[6.66e-04]	[6.64e-04]
	2.75e-05	3.93e-05**	3.48e-05**	2.01e-05***	1.97e-05***	1.93e-05***
β_2^{HDD}	(1.24e-05)	(1.13e-05)	(9.90e-06)	(1.39e-06)	(1.38e-06)	(1.36e-06)
	[2.16e-05]	[1.77e-05]	[1.45e-05]	[4.34e-06]	[4.27e-06]	[4.18e-06]
	-4.02e-05*	-5.20e-05***	-4.78e-05***	-3.36e-05***	-3.25e-05***	-3.20e-05***
β_3^{HDD}	(1.30e-05)	(1.17e-05)	(1.03e-05)	(3.45e-06)	(3.48e-06)	(3.53e-06)
	[2.39e-05]	[1.89e-05]	[1.56e-05]	[8.32e-06]	[7.63e-06]	[7.28e-06]
				5.37e-04	-7.68e-04	-4.23e-03
β_1^{prec}	—	—	—	(1.88e-02)	(1.89e-02)	(1.90e-02)
				[3.42e-02]	[3.44e-02]	[3.44e-02]
	1.60e-02**	1.64e-02**	1.80e-02**	-2.14e-04	-1.36e-04	9.83e-05
β_2^{prec}	(6.31e-03)	(6.06e-03)	(5.86e-03)	(1.34e-03)	(1.34e-03)	(1.34e-03)
	[8.08e-03]	[7.97e-03]	[8.19e-03]	[2.51e-03]	[2.51e-03]	[2.50e-03]
	-2.24e-02***	-2.27e-02***	-2.44e-02***	-5.93e-03*	-6.05e-03*	-6.46e-03*
β_3^{prec}	(6.39e-03)	(6.14e-03)	(5.95e-03)	(2.04e-03)	(2.03e-03)	(2.03e-03)
	[7.17e-03]	[6.96e-03]	[7.16e-03]	[3.50e-03]	[3.48e-03]	[3.46e-03]
County FE	✓	✓	✓	✓	✓	✓
County trends	✓	✓	✓	✓	✓	✓
# counties	1,274	1,274	1,274	1,274	1,274	1,274
Years	1980–2017	1980–2017	1980–2017	1980–2017	1980–2017	1980–2017
Observations	47,509	47,509	47,509	47,509	47,509	47,509

Conley standard errors are shown in ()
State-clustered standard errors are shown in []
Significance levels based on standard errors in []: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11 Soybeans regression results, smoothed climate

	Flexible model			Single slope		
	30 yrs (1)	25 yrs (2)	20 yrs (3)	30 yrs (4)	25 yrs (5)	20 yrs (6)
β_1^{GDD}	—	—	—	1.26e-01*** (1.55e-02) [1.76e-02]	1.04e-01*** (1.47e-02) [1.69e-02]	1.02e-01*** (1.45e-02) [1.75e-02]
β_2^{GDD}	4.93e-02*** (7.64e-03) [8.37e-03]	4.36e-02*** (5.61e-03) [8.19e-03]	3.04e-02*** (4.91e-03) [6.11e-03]	-2.32e-03*** (3.96e-04) [4.52e-04]	-1.61e-03*** (3.68e-04) [4.64e-04]	-1.54e-03*** (3.58e-04) [4.70e-04]
β_3^{GDD}	-5.04e-02*** (8.19e-03) [8.63e-03]	-4.58e-02*** (5.85e-03) [8.60e-03]	-3.38e-02*** (5.31e-03) [6.56e-03]	-1.40e-03 (2.08e-03) [2.00e-03]	-3.22e-03* (1.81e-03) [1.73e-03]	-3.60e-03** (1.85e-03) [1.77e-03]
β_1^{HDD}	—	—	—	-7.94e-03*** (3.79e-04) [5.88e-04]	-7.98e-03*** (3.92e-04) [5.99e-04]	-7.92e-03*** (3.78e-04) [5.62e-04]
β_2^{HDD}	4.64e-05** (1.68e-05) [2.23e-05]	3.04e-05** (1.59e-05) [1.49e-05]	3.78e-05** (1.52e-05) [1.53e-05]	2.00e-05*** (2.57e-06) [5.62e-06]	1.93e-05*** (2.53e-06) [5.01e-06]	1.91e-05*** (2.47e-06) [4.95e-06]
β_3^{HDD}	-4.24e-05 (1.78e-05) [2.79e-05]	-2.06e-05 (1.58e-05) [1.83e-05]	-2.75e-05 (1.50e-05) [1.89e-05]	-1.67e-05* (5.07e-06) [9.56e-06]	-1.30e-05 (4.82e-06) [9.37e-06]	-1.25e-05 (4.70e-06) [9.45e-06]
β_1^{prec}	—	—	—	3.14e-02 (1.74e-02) [3.26e-02]	6.39e-02** (1.85e-02) [3.05e-02]	6.18e-02** (1.75e-02) [2.93e-02]
β_2^{prec}	1.94e-02*** (4.95e-03) [6.01e-03]	6.22e-03 (4.19e-03) [6.22e-03]	8.69e-03 (3.51e-03) [5.62e-03]	-1.31e-03 (1.24e-03) [2.38e-03]	-3.28e-03 (1.29e-03) [2.19e-03]	-3.22e-03 (1.22e-03) [2.07e-03]
β_3^{prec}	-2.79e-02*** (5.19e-03) [6.65e-03]	-1.55e-02** (4.26e-03) [6.13e-03]	-1.77e-02*** (3.65e-03) [5.34e-03]	-6.87e-03** (1.72e-03) [3.32e-03]	-5.96e-03* (1.66e-03) [3.09e-03]	-5.96e-03** (1.60e-03) [2.87e-03]
County FE	✓	✓	✓	✓	✓	✓
County trends	✓	✓	✓	✓	✓	✓
# counties	1,154	1,180	1,136	1,154	1,180	1,136
Years	1980–2017	1975–2017	1970–2017	1980–2017	1975–2017	1970–2017
Observations	43,161	49,849	53,461	43,161	49,849	53,461

Conley standard errors are shown in ()
State-clustered standard errors are shown in []
Significance levels based on standard errors in []: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12 Soybeans regression results, smoothed climate (1980-2017 sample)

	Flexible model			Single slope		
	30 yrs	25 yrs	20 yrs	30 yrs	25 yrs	20 yrs
	(1)	(2)	(3)	(4)	(5)	(6)
β_1^{GDD}	—	—	—	1.26e-01***	1.27e-01***	1.28e-01***
				(1.55e-02)	(1.54e-02)	(1.54e-02)
				[1.76e-02]	[1.75e-02]	[1.74e-02]
β_2^{GDD}	4.93e-02***	3.82e-02***	2.94e-02***	-2.32e-03***	-2.35e-03***	-2.38e-03***
	(7.64e-03)	(6.83e-03)	(5.74e-03)	(3.96e-04)	(3.94e-04)	(3.93e-04)
	[8.37e-03]	[8.57e-03]	[7.32e-03]	[4.52e-04]	[4.48e-04]	[4.47e-04]
β_3^{GDD}	-5.04e-02***	-3.89e-02***	-3.01e-02***	-1.40e-03	-1.09e-03	-9.17e-04
	(8.19e-03)	(7.40e-03)	(6.35e-03)	(2.08e-03)	(2.10e-03)	(2.14e-03)
	[8.63e-03]	[9.31e-03]	[8.04e-03]	[2.00e-03]	[2.14e-03]	[2.27e-03]
β_1^{HDD}	—	—	—	-7.94e-03***	-7.92e-03***	-7.92e-03***
				(3.79e-04)	(3.79e-04)	(3.78e-04)
				[5.88e-04]	[5.85e-04]	[5.84e-04]
β_2^{HDD}	4.64e-05**	3.75e-05	4.30e-05**	2.00e-05***	1.99e-05***	2.01e-05***
	(1.68e-05)	(1.72e-05)	(1.58e-05)	(2.57e-06)	(2.58e-06)	(2.58e-06)
	[2.23e-05]	[2.34e-05]	[1.95e-05]	[5.62e-06]	[5.57e-06]	[5.52e-06]
β_3^{HDD}	-4.24e-05	-3.07e-05	-3.61e-05	-1.67e-05*	-1.57e-05*	-1.63e-05*
	(1.78e-05)	(1.76e-05)	(1.61e-05)	(5.07e-06)	(4.94e-06)	(4.94e-06)
	[2.79e-05]	[2.85e-05]	[2.44e-05]	[9.56e-06]	[9.18e-06]	[9.15e-06]
β_1^{prec}	—	—	—	3.14e-02	3.15e-02	2.89e-02
				(1.74e-02)	(1.74e-02)	(1.74e-02)
				[3.26e-02]	[3.23e-02]	[3.19e-02]
β_2^{prec}	1.94e-02***	1.86e-02***	1.82e-02***	-1.31e-03	-1.34e-03	-1.17e-03
	(4.95e-03)	(4.72e-03)	(4.38e-03)	(1.24e-03)	(1.23e-03)	(1.22e-03)
	[6.01e-03]	[5.92e-03]	[5.86e-03]	[2.38e-03]	[2.35e-03]	[2.31e-03]
β_3^{prec}	-2.79e-02***	-2.72e-02***	-2.69e-02***	-6.87e-03**	-6.90e-03**	-7.16e-03**
	(5.19e-03)	(4.96e-03)	(4.63e-03)	(1.72e-03)	(1.71e-03)	(1.69e-03)
	[6.65e-03]	[6.41e-03]	[6.32e-03]	[3.32e-03]	[3.29e-03]	[3.24e-03]
County FE	✓	✓	✓	✓	✓	✓
County trends	✓	✓	✓	✓	✓	✓
# counties	1,154	1,154	1,154	1,154	1,154	1,154
Years	1980–2017	1980–2017	1980–2017	1980–2017	1980–2017	1980–2017
Observations	43,161	43,161	43,161	43,161	43,161	43,161

Conley standard errors are shown in ()
State-clustered standard errors are shown in []
Significance levels based on standard errors in []: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13 Corn regression results, alternative penalty structure

	Flexible model			Single slope		
	30 yrs	25 yrs	20 yrs	30 yrs	25 yrs	20 yrs
	(1)	(2)	(3)	(4)	(5)	(6)
β_1^{GDD}	—	—	—	6.61e-02 (1.77e-02) [2.47e-02]	7.87e-02 (1.73e-02) [2.18e-02]	8.09e-02 (1.64e-02) [2.07e-02]
β_2^{GDD}	5.09e-02*** (7.35e-03) [8.18e-03]	2.54e-02*** (6.26e-03) [7.21e-03]	2.51e-02*** (5.09e-03) [6.36e-03]	-5.21e-04 (4.42e-04) [5.85e-04]	-9.69e-04* (4.27e-04) [5.17e-04]	-1.06e-03** (4.13e-04) [5.08e-04]
β_3^{GDD}	-5.58e-02*** (7.88e-03) [8.52e-03]	-2.84e-02*** (6.41e-03) [8.21e-03]	-2.92e-02*** (5.31e-03) [6.70e-03]	-9.07e-03*** (2.58e-03) [2.14e-03]	-7.38e-03*** (2.25e-03) [2.69e-03]	-8.64e-03*** (2.27e-03) [2.61e-03]
β_1^{HDD}	—	—	—	-9.74e-03*** (3.20e-04) [6.69e-04]	-9.55e-03*** (3.17e-04) [7.27e-04]	-9.54e-03*** (3.16e-04) [7.32e-04]
β_2^{HDD}	1.29e-05 (9.71e-06) [1.45e-05]	3.92e-05*** (9.32e-06) [1.37e-05]	1.45e-05 (7.03e-06) [1.26e-05]	1.98e-05*** (1.37e-06) [4.24e-06]	2.00e-05*** (1.37e-06) [3.88e-06]	2.01e-05*** (1.34e-06) [3.85e-06]
β_3^{HDD}	-2.36e-05 (9.85e-06) [1.46e-05]	-4.95e-05*** (9.07e-06) [1.13e-05]	-2.31e-05* (6.75e-06) [1.28e-05]	-3.17e-05*** (3.36e-06) [7.76e-06]	-2.99e-05*** (3.30e-06) [4.55e-06]	-2.80e-05*** (3.28e-06) [4.80e-06]
β_1^{prec}	—	—	—	-9.14e-04 (1.86e-02) [3.42e-02]	2.60e-02 (1.91e-02) [3.60e-02]	3.87e-02 (1.92e-02) [3.50e-02]
β_2^{prec}	1.25e-02** (5.21e-03) [5.96e-03]	7.35e-03 (4.59e-03) [5.01e-03]	6.76e-03 (3.89e-03) [7.17e-03]	-1.11e-04 (1.32e-03) [2.50e-03]	-1.70e-03 (1.34e-03) [2.60e-03]	-2.67e-03 (1.35e-03) [2.49e-03]
β_3^{prec}	-1.83e-02*** (5.17e-03) [5.31e-03]	-1.50e-02*** (4.39e-03) [4.09e-03]	-1.44e-02*** (3.68e-03) [5.36e-03]	-5.87e-03* (1.96e-03) [3.42e-03]	-6.20e-03* (1.83e-03) [3.37e-03]	-5.58e-03** (1.72e-03) [2.57e-03]
County FE	✓	✓	✓	✓	✓	✓
County trends	✓	✓	✓	✓	✓	✓
# counties	1,274	1,342	1,321	1,274	1,342	1,321
Years	1980–2017	1975–2017	1970–2017	1980–2017	1975–2017	1970–2017
Observations	47,509	56,506	62,210	47,509	56,506	62,210

Conley standard errors are shown in ()
State-clustered standard errors are shown in []
Significance levels based on standard errors in []: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14 Corn regression results, alternative penalty structure (1980-2017 sample)

	Flexible model			Single slope		
	30 yrs	25 yrs	20 yrs	30 yrs	25 yrs	20 yrs
	(1)	(2)	(3)	(4)	(5)	(6)
β_1^{GDD}	—	—	—	6.61e-02*** (1.77e-02) [2.47e-02]	6.58e-02*** (1.76e-02) [2.46e-02]	6.70e-02*** (1.72e-02) [2.35e-02]
β_2^{GDD}	5.09e-02*** (7.35e-03) [8.18e-03]	3.32e-02*** (6.57e-03) [7.28e-03]	2.09e-02*** (5.53e-03) [6.76e-03]	-5.21e-04 (4.42e-04) [5.85e-04]	-5.14e-04 (4.40e-04) [5.83e-04]	-5.71e-04 (4.31e-04) [5.58e-04]
β_3^{GDD}	-5.58e-02*** (7.88e-03) [8.52e-03]	-3.80e-02*** (7.03e-03) [7.41e-03]	-2.47e-02*** (6.05e-03) [6.99e-03]	-9.07e-03*** (2.58e-03) [2.14e-03]	-9.06e-03*** (2.57e-03) [2.07e-03]	-8.97e-03*** (2.60e-03) [2.31e-03]
β_1^{HDD}	—	—	—	-9.74e-03*** (3.20e-04) [6.69e-04]	-9.62e-03*** (3.15e-04) [6.67e-04]	-9.50e-03*** (3.13e-04) [6.56e-04]
β_2^{HDD}	1.29e-05 (9.71e-06) [1.45e-05]	3.81e-05*** (1.02e-05) [1.48e-05]	2.62e-05*** (7.73e-06) [8.70e-06]	1.98e-05*** (1.37e-06) [4.24e-06]	1.96e-05*** (1.35e-06) [4.25e-06]	1.89e-05*** (1.33e-06) [4.05e-06]
β_3^{HDD}	-2.36e-05 (9.85e-06) [1.46e-05]	-4.84e-05*** (9.91e-06) [1.48e-05]	-3.54e-05*** (7.55e-06) [8.84e-06]	-3.17e-05*** (3.36e-06) [7.76e-06]	-3.06e-05*** (3.21e-06) [7.09e-06]	-2.90e-05*** (3.20e-06) [6.40e-06]
β_1^{prec}	—	—	—	-9.14e-04 (1.86e-02) [3.42e-02]	-2.60e-03 (1.85e-02) [3.39e-02]	-7.19e-03 (1.88e-02) [3.23e-02]
β_2^{prec}	1.25e-02** (5.21e-03) [5.96e-03]	1.16e-02** (4.96e-03) [5.44e-03]	9.63e-03* (4.40e-03) [5.79e-03]	-1.11e-04 (1.32e-03) [2.50e-03]	2.03e-05 (1.31e-03) [2.47e-03]	3.29e-04 (1.33e-03) [2.34e-03]
β_3^{prec}	-1.83e-02*** (5.17e-03) [5.31e-03]	-1.76e-02*** (4.87e-03) [4.53e-03]	-1.54e-02*** (4.26e-03) [4.36e-03]	-5.87e-03* (1.96e-03) [3.42e-03]	-6.30e-03* (1.91e-03) [3.34e-03]	-6.67e-03** (1.88e-03) [3.02e-03]
County FE	✓	✓	✓	✓	✓	✓
County trends	✓	✓	✓	✓	✓	✓
# counties	1,274	1,274	1,274	1,274	1,274	1,274
Years	1980–2017	1980–2017	1980–2017	1980–2017	1980–2017	1980–2017
Observations	47,509	47,509	47,509	47,509	47,509	47,509

Conley standard errors are shown in ()
State-clustered standard errors are shown in []
Significance levels based on standard errors in []: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15 Soybeans, alternative penalty structure

	Flexible model			Single slope		
	30 yrs (1)	25 yrs (2)	20 yrs (3)	30 yrs (4)	25 yrs (5)	20 yrs (6)
β_1^{GDD}	—	—	—	1.27e-01	1.06e-01	1.01e-01
				(1.55e-02)	(1.48e-02)	(1.42e-02)
				[1.75e-02]	[1.64e-02]	[1.67e-02]
β_2^{GDD}	3.27e-02***	2.81e-02***	1.79e-02***	-2.35e-03***	-1.65e-03***	-1.51e-03***
	(7.05e-03)	(5.26e-03)	(4.31e-03)	(3.95e-04)	(3.69e-04)	(3.52e-04)
	[8.05e-03]	[6.98e-03]	[4.23e-03]	[4.51e-04]	[4.51e-04]	[4.49e-04]
β_3^{GDD}	-3.22e-02***	-2.89e-02***	-1.98e-02***	-1.32e-03	-2.99e-03*	-3.65e-03*
	(7.43e-03)	(5.35e-03)	(4.45e-03)	(2.06e-03)	(1.77e-03)	(1.76e-03)
	[8.34e-03]	[7.48e-03]	[4.84e-03]	[1.99e-03]	[1.72e-03]	[1.89e-03]
β_1^{HDD}	—	—	—	-8.00e-03***	-8.03e-03***	-7.90e-03***
				(3.81e-04)	(3.92e-04)	(3.73e-04)
				[5.92e-04]	[6.08e-04]	[5.44e-04]
β_2^{HDD}	5.91e-05***	5.08e-05***	2.40e-05**	2.05e-05***	1.98e-05***	1.90e-05***
	(1.42e-05)	(1.33e-05)	(9.92e-06)	(2.51e-06)	(2.47e-06)	(2.38e-06)
	[1.35e-05]	[1.34e-05]	[1.06e-05]	[5.42e-06]	[4.75e-06]	[4.72e-06]
β_3^{HDD}	-5.32e-05***	-3.98e-05***	-1.17e-05	-1.74e-05**	-1.36e-05*	-1.14e-05
	(1.41e-05)	(1.22e-05)	(9.33e-06)	(4.72e-06)	(4.41e-06)	(4.25e-06)
	[1.56e-05]	[9.91e-06]	[1.46e-05]	[8.72e-06]	[7.98e-06]	[8.52e-06]
β_1^{prec}	—	—	—	3.50e-02	6.98e-02**	6.74e-02**
				(1.73e-02)	(1.80e-02)	(1.70e-02)
				[3.11e-02]	[2.81e-02]	[2.73e-02]
β_2^{prec}	4.78e-03	-4.71e-03	2.84e-05	-1.59e-03	-3.73e-03*	-3.63e-03*
	(4.44e-03)	(3.45e-03)	(2.82e-03)	(1.23e-03)	(1.25e-03)	(1.18e-03)
	[5.58e-03]	[4.83e-03]	[4.51e-03]	[2.26e-03]	[2.02e-03]	[1.92e-03]
β_3^{prec}	-1.26e-02**	-4.28e-03	-8.73e-03**	-6.19e-03**	-5.09e-03*	-5.23e-03**
	(4.62e-03)	(3.48e-03)	(2.85e-03)	(1.68e-03)	(1.58e-03)	(1.50e-03)
	[6.07e-03]	[4.73e-03]	[4.04e-03]	[3.09e-03]	[2.77e-03]	[2.52e-03]
County FE	✓	✓	✓	✓	✓	✓
County trends	✓	✓	✓	✓	✓	✓
# counties	1,154	1,180	1,136	1,154	1,180	1,136
Years	1980–2017	1975–2017	1970–2017	1980–2017	1975–2017	1970–2017
Observations	43,161	49,849	53,461	43,161	49,849	53,461

Conley standard errors are shown in ()
State-clustered standard errors are shown in []
Significance levels based on standard errors in []: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16 Soybeans, alternative penalty structure (1980-2017 sample)

	Flexible model			Single slope		
	30 yrs	25 yrs	20 yrs	30 yrs	25 yrs	20 yrs
	(1)	(2)	(3)	(4)	(5)	(6)
β_1^{GDD}	—	—	—	1.27e-01***	1.28e-01***	1.28e-01***
				(1.55e-02)	(1.55e-02)	(1.53e-02)
				[1.75e-02]	[1.71e-02]	[1.72e-02]
β_2^{GDD}	3.27e-02***	1.87e-02***	1.15e-02**	-2.35e-03***	-2.39e-03***	-2.40e-03***
	(7.05e-03)	(6.27e-03)	(4.76e-03)	(3.95e-04)	(3.96e-04)	(3.90e-04)
	[8.05e-03]	[6.92e-03]	[5.14e-03]	[4.51e-04]	[4.39e-04]	[4.45e-04]
β_3^{GDD}	-3.22e-02***	-1.79e-02**	-9.98e-03*	-1.32e-03	-8.43e-04	-5.62e-04
	(7.43e-03)	(6.52e-03)	(4.92e-03)	(2.06e-03)	(2.05e-03)	(2.02e-03)
	[8.34e-03]	[7.50e-03]	[5.57e-03]	[1.99e-03]	[2.12e-03]	[2.16e-03]
β_1^{HDD}	—	—	—	-8.00e-03***	-7.93e-03***	-7.84e-03***
				(3.81e-04)	(3.80e-04)	(3.75e-04)
				[5.92e-04]	[5.88e-04]	[5.77e-04]
β_2^{HDD}	5.91e-05***	5.01e-05***	1.83e-05**	2.05e-05***	1.99e-05***	1.88e-05***
	(1.42e-05)	(1.60e-05)	(1.25e-05)	(2.51e-06)	(2.54e-06)	(2.51e-06)
	[1.35e-05]	[1.32e-05]	[8.92e-06]	[5.42e-06]	[5.32e-06]	[5.25e-06]
β_3^{HDD}	-5.32e-05***	-4.10e-05***	-9.06e-06	-1.74e-05**	-1.50e-05*	-1.26e-05
	(1.41e-05)	(1.49e-05)	(1.19e-05)	(4.72e-06)	(4.52e-06)	(4.52e-06)
	[1.56e-05]	[1.25e-05]	[1.17e-05]	[8.72e-06]	[7.88e-06]	[7.91e-06]
β_1^{prec}	—	—	—	3.50e-02	3.97e-02	4.03e-02
				(1.73e-02)	(1.70e-02)	(1.70e-02)
				[3.11e-02]	[2.95e-02]	[2.90e-02]
β_2^{prec}	4.78e-03	3.85e-04	1.02e-03	-1.59e-03	-1.95e-03	-2.01e-03
	(4.44e-03)	(3.89e-03)	(3.32e-03)	(1.23e-03)	(1.20e-03)	(1.19e-03)
	[5.58e-03]	[5.68e-03]	[5.33e-03]	[2.26e-03]	[2.14e-03]	[2.08e-03]
β_3^{prec}	-1.26e-02**	-8.60e-03	-9.20e-03*	-6.19e-03**	-5.86e-03**	-5.83e-03**
	(4.62e-03)	(3.97e-03)	(3.37e-03)	(1.68e-03)	(1.61e-03)	(1.60e-03)
	[6.07e-03]	[5.82e-03]	[5.30e-03]	[3.09e-03]	[2.89e-03]	[2.80e-03]
County FE	✓	✓	✓	✓	✓	✓
County trends	✓	✓	✓	✓	✓	✓
# counties	1,154	1,154	1,154	1,154	1,154	1,154
Years	1980–2017	1980–2017	1980–2017	1980–2017	1980–2017	1980–2017
Observations	43,161	43,161	43,161	43,161	43,161	43,161

Conley standard errors are shown in ()
State-clustered standard errors are shown in []
Significance levels based on standard errors in []: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$