# Improving Agronomic Structure in Econometric Models of Climate Change Impacts

**Ariel Ortiz-Bobea**

Department of Agricultural & Resource Economics, University of Maryland
Symons Hall, Rm. 2200, College Park, MD 20742
Email: aortizbobea@arec.umd.edu

***Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2011 AAEA & NAREA Joint Annual Meeting Pittsburgh, Pennsylvania, July 24-26, 2011***

# Improving Agronomic Structure in Econometric Models of Climate Change Impacts

Ariel Ortiz-Bobea*

May 3, 2011

**Abstract**

Economists are relying on agronomic concepts to construct weather or climate independent variables and improve the reliability and efficiency of econometric models of climate change impact on U.S. agriculture. The use of cumulative heat measures in agronomy (growing degree-days), has recently served as a basis for the introduction of plurimonthly calendar heat variables in these models. However, season-long weather conditions seem at odds with conventional agronomic wisdom that emphasizes crucial differences in crop stage sensitivity to environmental stress. In this paper I show that weather variables matched to key corn development stages provide an enhanced and more stable fit than their calendar counterparts. More importantly, the proposed season-disaggregated framework yields very different implications for adaptation than its calendar counterparts as it indicates that most of the projected yield damages are accounted during the flowering period, a relatively short period in the crop cycle. This should open the door to more advanced yield models that account for additional possibilities of adaptation and thus provide a more nuanced outlook on the potential impacts of climate change on crop yields.

**Key words:** *agriculture, climate change, corn, degree-days, phenology, proxy, yield.*

**JEL codes:** Q54, C23

*Department of Agricultural and Resource Economics, University of Maryland, Symons Hall, Rm. 2200, College Park, MD 20742, USA. Email: aortizbobea@arec.umd.edu

# 1 Introduction

Econometric studies assessing the potential welfare impacts of climate change on the U.S. agriculture seem inconclusive (e.g.Mendelsohn, Nordhaus and Shaw, 1994;Schlenker, Hanemann and Fisher, 2005;Deschenes and Greenstone, 2007). The current methodology typically consists in exploring a reduced-form relationship between monthly or plurimonthly measures of weather or climate[1] and auxiliary variables such as land prices or yearly net revenue. Although the methodological debate has focused on the vulnerability to omitted variable-bias and the econometric techniques to handle it, a greater concern may be the limited room left for adaptation policy analysis. Indeed, the aggregated structure of these studies impedes unpacking some of the possible channels through which potential impacts come about. To clarify these mechanisms, for instance, economists are focusing on statistical crop yield models based on large-scale observational data. Because these models are based on revealed farmer behavior they are in principle better suited to account for farmer adaptation than their mechanistic process-based counterparts in which farmer decisions are arbitrary inputs.

Statistical yield models are increasingly relying on weather variables with more pronounced agronomic underpinnings as means to improve estimates and to clarify some of the bio-physical mechanisms at play. A recent trend is the use of plurimonthly (henceforth, calendar) weather variables, seemingly grounded on the long-established agronomic use of thermal time (measured in growing degree-days or GDD), a cumulative heat measure traditionally used for predicting crop development and growth. Weather variables in these models are aggregated over fixed and usually long time windows, e.g. April to September, as to partially or fully contain the actual growing season. However, season-long weather conditions as key explanatory factors of yield seem at odds with conventional agronomic wisdom and the structure of crop process models that account for crucial differences in crop intra-seasonal sensitivities to environmental stress. This paper seeks to improve this approach.

Calendar weather variables can be considered *proxies* for the "true" or relevant and mostly sub-season weather variables in explaining yield. If we reconcile the plant development processes of yield

[1] I define weather as short-run meteorological conditions within a given year and location whereas climate corresponds to the long-run characteristics of such conditions over many years. Statistically speaking, weather may be defined as a multivariate random variable $W$ with a joint climatic distribution $f(w|\theta)$ with vector parameter $\theta$ caracterizing its moments and cross-moments.

determination (the subject of process models) with that of a yield data generating process underlying a stochastic framework (the subject of statistical models) it can be argued that the predictive power of arbitrary calendar weather variables in statistical models stems from correlations with relevant (but omitted) weather variables corresponding to conditions during key crop stages. For instance, a large and consensual agronomic literature documents the short-lived flowering period of cereal and leguminous field crops as the most critical period for yield (Smith and Hamel, 1999; Fageria et al., 2006). A stress at this point of the crop cycle induces reproductive malfunction that irreversibly cuts yield potential by reducing the number of grains per plant that can be filled and *a fortiori* harvested. In this context, strong intraseasonal weather correlation, which seems to be the rule, would tend to confer strong predictive power to calendar proxy weather variables. This phenomena coupled with inconclusive results in attempts to capture the distinct effect of weather shocks during flowering over large areas (e.g. see appendix in Schlenker and Roberts, 2009) have reinforced the adoption of such calendar variables.

Calendar proxy variables can be misleading in a climate change impact context. Their validity fundamentally lies on the maintained stability of their correlation with the relevant sub-seasonal weather variables in the long-run. This is a strong assumption as farmers would arguably change planting dates or cultivar choice, shifting the time-frame of those relevant weather variables and thus inevitably altering the correlation with the fixed calendar time-frames. For instance, the season-long calendar framework implies that the effect of a given weather shock on yield is identical all throughout the crop cycle. Given that growing seasons are several months long, this implies very little room for adaptation.

Alternatively, calendar variables may be interpreted as *mismeasured* versions of the "true" weather variables. Although the distinction is subtle and seems rather semantic for weather variables, this interpretation is associated with well-known estimation challenges such as biases in unknown directions when the measurement error in the independent variable is correlated with the dependent variable; a problem that may be amplified by going "within" with fixed effects models as described by Griliches and Hausman (1986). Here lies the interest in comparing estimation and impact results from OLS and fixed effects models using both, calendar and alternative, more precisely measured weather variables. Are the measurement errors in calendar variables classical and lead to attenuation bias? Or do these happen to be correlated with yield (perhaps through the correlation with an omitted relevant weather variable) and thus lead to bias in unknown direction?

In this paper I propose the adoption of disaggregated weather variables that match key stages of the growing season (henceforth, phenological variables) in statistical yield models. I distinguish three key time windows of the crop cycle, following a typical classification: the vegetative, flowering and grain-filling stages. The objective is to improve the current approach in the literature by recognizing crucial differences in yield sensitivity to weather shocks across these different time windows. It is a step towards reconciling statistical and process models as means to derive a more transparent picture of the environmental constraints faced by farmers. For instance, this framework suggests that the effect of weather shocks on yield is stage-specific, much like in the crop process models. Given that the most sensitive stage, i.e. flowering, is short-lived, this suggests a more nuanced scenario in which simple management decisions can play a decisive role in avoiding the coincidence of flowering with expected hot or dry spells during the season.

There are successful precedents using phenologically-based weather variables in statistical yield models (see Dixon et al., 1994 or Kaufmann and Snell, 1997). However, previous studies concerned smaller geographical areas, explored a limited number of statistical models (e.g. only OLS) or did not systematically explore the implications in terms of estimation difficulties and in terms of projected climate impacts and adaptation. Also, these could not consider recently introduced heat variables to the field (e.g. GDD).

The paper uses corn as a case study and encompasses 15 U.S. States, representing over 90% of national production for the 1985-2005 sample period. The approach is to compare estimation and impact results stemming from the same models (OLS and fixed effects) using both, the standard calendar and the new phenological variables. In order to neutrally assess the role of the windows of weather aggregation in these models, I rely on spatially uniform climate change scenarios of daily temperature increases rather than on actual climate change projections with regional heterogeneity (I assume no changes in precipitation for the moment). The key objective is to assess whether aggregating weather within a fixed time-frame that does not clearly coincide with the actual growing season or crop stages carries any substantial shortcomings. Figure 1 illustrates how the corn growing season varies across states and within a state from year to year. A common season-long aggregation window used in the literature, i.e. April to September, is indicated with dashed lines and visibly accounts in different ways for additional weather outside the growing season across different States.

Also, note that including separate weather variables for the month of July to capture weather during the corn flowering period may be inappropriate.

This paper aims to contribute to the construction of more sound weather variables for use in econometric climate change impact assessments on agriculture. In this sense, I examine the implications of the time-frame for weather aggregation and explore some of the limitations and opportunities of increasingly popular season-long heat variables. Preliminary results suggest that use of season-long calendar variables is *not* an innocuous simplification and carries crucial consequences in terms of impacts and adaptation possibilities. The paper is organized as follows. Section 2 provides an overview of degree-days and discusses their use as predictors of yield. Section 3 presents the methodology and section 4 describes the data and how the weather variables were constructed. Section 5 discusses estimation and impact results from different models that lead to the conclusion in section 6.

## 2 Degree-days: an unusual input

Formally, GDD is a unit of measurement of a physical quantity called "thermal time"[2] which is a measure of cumulative temperature over time. Graphically, thermal time corresponds to the area jointly lying 1- below the graph of the air temperature-time curve $h(t)$, 2- between two temperature thresholds, $\underline{h}$ and $\overline{h}$, and 3- between two points in time, $t_0$ and $t_1$. Mathematically, thermal time $T$ can be expressed as

$$T(\overline{h}, \underline{h}, t_0, t_1) = \int_{t_0}^{t_1} H(t)dt \qquad \text{where } H(t) = \begin{cases} \overline{h} - \underline{h} & \text{if } h(t) > \overline{h} \\ h(t) - \underline{h} & \text{if } h(t) \in ]\underline{h}; \overline{h}] \\ 0 & \text{if } h(t) \leqslant \underline{h} \end{cases} \tag{1}$$

The idea behind this measure emerged heuristically almost three centuries ago (Wang, 1960) to predict plant *phenology* or *development*, that is, the pace of the succession of plant stages from planting to maturity. Indeed, plant *development* is generally considered to be linear in GDD and temperature thresholds $\underline{h}$ and $\overline{h}$ are, in fact, empirically established to match this linearity condition. Corn thresholds have been are usually set at 8 and 32ºC. As an illustration, if there are more GDD available between $t_0$ and $t_1$, i.e. the integral in (1) is larger between these 2 time points,

[2] In the same way seconds are unit of time and squared inches units of surface.

then the same cultivar (under non-limiting conditions) will have reached a more advanced stage of development at $t_0$. Similarly, maturity for the same cultivar is reached sooner if exposed to more GDD.

Note the key distinction between crop *development rate,* which is a rate of maturation progress (e.g. stages/day), and crop *yield*, which is a measure of mass per harvested surface (e.g. bushels/acre). GDD are mainly used today by farmers and agricultural extension agents to predict the timing of plant and pest maturity which facilitates scheduling field operations (e.g. sowing, pesticide application) or choosing a cultivar. Indeed, cultivar maturity rating is generally provided by seed companies in terms of the cultivar's GDD requirement to reach maturity. For instance, relatively low GDD requirements characterize short-season cultivars that are typically used in northern or colder regions with shorter growing seasons.

To my knowledge GDD have not been used as direct predictors of crop *yield*. There might, however, exist a correlation between available GDD in a given region and yield through the *choice of the cultivar*. Regions with more available GDD indicate a longer non-freezing period allowing farmers to chose longer-season cultivars if water availability is not the binding constraint in determining the length of the growing season. When possible, farmers opt for longer season-cultivars as they tend to produce higher yields by the mere fact the crops spend more time in the field accumulating biomass.

Conceptually, increases in GDD by themselves may not appear to be detrimental for yield, unless it is inadvertently correlated with detrimental omitted variables. This is possible, as increases of GDD are driven by increases in temperatures that may lead to increases in very high and detrimental temperatures that are not really accounted in GDD measurements. A region or a year with more available GDD indicate a longer non-freezing and growing-season period which is a relaxation of the Spring and Fall frost date constraints that drive planting dates and cultivar choice in much of the U.S. Consequently, GDD might not theoretically exhibit negative marginal returns[3].

A new type of degree-day concept, coined Harmful or Damaging Degree Days (DDD), was introduced in Schlenker et al. (2006) to separately account for the cumulative effect of heat above a

[3] At worst, a year with unexpectedly higher GDD, i.e. a year for which the farmer did not anticipate by choosing a longer-season cultivar, would lead to *ceteris paribus* a faster development and earlier maturity. This could be slightly detrimental to yield (personal communication from Prof. Roger Elmore: relmore@iastate.edu) but the agronomic literature on this is virtually non-existant.

high temperature threshold, e.g. 34ºC. Although this is not a conventional variable in phenological disciplines (see Smith and Hamel, 1999; Fageria et al., 2006; Hudson and Keatley, 2009) it should conceptually capture the cumulative exposure to very high temperatures which are expected to be damaging for yield.

# 3 The proposed approach

## 3.1 A framework for weather aggregation windows

The key aspect of the proposed approach is the comparative use of different time windows of weather aggregation and the systematic analysis of the estimation and projected impact results. The choice of the time window of aggregation has been a traditional challenge. Crop production is affected throughout the growing season by daily weather occurrences. These short-run weather patterns are extremely serially correlated causing collinearity of regressors in the estimation when time weather frames are very short. The traditional remedy is to average temperatures and to add precipitation over a few monthly periods. Recently, the introduction of degree-days into the literature has shifted the emphasis to cumulative heat variables over time and away from temperature averages. Wether heat is captured with average temperature or degree-days, the problem of the time-windows of aggregation remains because crop production is inherently *non-time-separable.*

Crop development can be separated into many stages[4] and statistically accounting for weather conditions for each one is probably not feasible (data limitations) or even desirable (collinearity). A useful framework to develop reasonable and testable candidate time windows is the "yield component analysis" approach used in agronomy. This approach is extensively used by crop breeders as well as yield forecasters (e.g. USDA). In this framework, yield per acre $Y$ is physically decomposed as a product of "yield components"

[4]For corn, for instance, development is formally grouped into vegetative and reproductive sub-stages. The vegetative stage is separated into many substages going from emergence (VE), passing through each $n$th-leaf appearance (V($n$)), up to the development of the last tassel branch (male flower) or tasseling (VT). The reproductive stage is separated into silking (R1), blister (R2), milking (R3), doughing ( R4), denting (R5) and finishes with physiological maturity (R6) when corn is harvested for grain.

$$Y = \prod_{i=1}^{n} C_i \tag{2}$$

where $C_i$ is the $i$th yield component. In the case of corn, these components may be $C_1$ ="number of ears per acre", $C_2$ ="number of kernel rows per ear", $C_3$ ="number of kernels per row", and $C_4$ ="weight per kernel". The realization of each component value is realized sequentially throughout the crop cycle and depends on genetic characteristics of the cultivar and environmental conditions such as weather or managerial decisions (e.g. input levels, sowing density).

In order to affect yield, weather inputs should affect yield components in equation (2). The key part is that each yield component approximately corresponds to a particular development stage. Weather during the vegetative stages affect how many plants are left standing and how well these will develop their leaves. Weather during the flowering period (tasseling/silking) irreversibly influences how many grains per plant will be viable. According to Fageria et al.(2006, p.89) *"it is well understood that water deficiency and extreme temperatures during flowering reduces grain yield more than any other stage of growth"*. Finally, weather after the flowering period and up to maturation determine how well each grain fills and thus influences the weight per grain. Of course, these stages are not independent partly because of the multiplicative nature of yield components. However, it provides a first approximation with three commonly accepted stages: 1- a vegetative period, during which plants are mainly allocating inputs to developing the stem and leafs, 2- the flowering period, during which corn is silking and flowers are being pollinated, and 3- the grain-filling period, during which the plant is mainly invested in redirecting resources to grains. This classification is also found in Smith and Hamel(1999, p.172) or Fageria et al.(2006, p.93).

### 3.2 Comparative approach

Following other studies in the literature I first estimate the effect of the weather variables on yield and subsequently multiply the estimated parameters by the projected changes in climate for the corresponding time window to obtain potential yield impacts. This approach accounts for intraseasonal farmer adaptation but may not account for longer-term adaptations such as change in cultivar, crop, planting dates or the adoption of mitigating investments such as irrigation. The nature of the weather variables in this study follow the literature (e.g. Schlenker, Hanemann and Fisher, 2005;Deschenes and Greenstone, 2007) and include precipitation, GDD and DDD.

The objective is to examine how alternative time-frames of aggregation perform in terms of model fit, plausibility of functional form of weather variables and of the resulting projected impacts. In this regard it is desirable to factor out regional differences in projected climate change when comparing impact results. Consequently, I adopt spatially uniform scenarios of 1, 2 and 3$^{o}$C daily temperature increases rather than actual climate change scenarios from General Circulation Models (GCM). The proposed scenarios fall within the range of current GCM models.

I proceed to compare weather variables in 2 ways. The first is to compare how season-long calendar weather variables (SLC), aggregated from April to September, compare to phenological season-long weather variables (SLP), aggregated from sowing to maturity. Figure 1 shows the discrepancies between the two types of variables. How does the weather occurring when corn is *not* in the field influencing estimation coefficients and ultimately impacts?

The second step is to compare models with disaggregated weather variables. The phenological disaggregated models have separate weather variables for the vegetative, flowering and grain-filling stages. On the other hand, Schlenker and Roberts, 2009 has argued that the month of July should roughly account for the flowering period in corn as seen in figure 1. Therefore, I proceed to create disaggregated calendar variables with separate weather variables for the April-June period, somewhat representing the vegetative stage, the month of July, representing the flowering stage, and the August-September period, representing the grain-filling stage. I also contrast these findings with those of season-long models.

For the disaggregated models I carry out a sensitivity analysis to test the relevance of the chosen flowering window. For this purpose I constructed a series of weather and climate datasets for which the aggregation window for the flowering period is shifted by 1 to 4 weeks, before and after, the actual flowering period window. If the flowering window is relevant and presents distinctive sensibility to weather shocks than other stages, then moving the window of aggregation off the actual flowering period should decrease model fit. It should also decrease the projected impacts because the window is capturing the effects of weather shocks outside the true flowering period. I conduct a similar exercise for the month of July, when the window for the month is shifted. I contrast results from both calendar and phenological sensitivity analysis.

## 4 Variables and data sources

### 4.1 Production

County-level corn yield and planted acreage as well as corn progress data were obtained online from USDA/NASS. Corn progress data is observed with a weekly resolution at the State level and indicates the percentage of a State's corn acreage in a particular stage (i.e. planted, emerged, silking, doughing, dented, mature, harvested). For the purpose of constructing weather variables I use stage "median acreage dates" which correspond to the date for which a given State has reached 50% of its acreage for that stage. For a few States and years the median acreage date was not available by interpolation. This is the case when the reporting started late (the State had already surpassed the 50% acreage line) or stopped too early (the State had not yet reached the 50% acreage line). In those marginal cases I proceeded to extrapolation to obtain the median acreage date

The limiting factor in determining the sample period and area was the crop progress data. These progress reports are available since 1981 for most States. I initially put together a balanced panel for 15 states from different agroclimatic regions[5], regrouping 1,302 counties from 1985 to 2005. As in Schlenker and Roberts (2009) I limited the sample to counties lying East of the 100th meridian West as to exclude counties that are heavily irrigated. Yields in those counties would arguably respond differently to weather that non-irrigated ones. The sample therefore excludes Colorado and the Western Great Plains. The dataset remains fairly large with 1,192 counties corresponding to about 90% of national corn production.

### 4.2 Weather

Detailed raw weather data was obtained from Schlenker and Roberts (2009) which provides interpolated *daily* observations with precipitation, minimum, maximum and average temperatures, for virtually every $2.5 \times 2.5$ mile grid of the lower 48 states from 1950 to 2005. The dataset was constructed by combining the *spatial* resolution of the monthly but spatially refined Parameter-elevation Regressions on Independent Slopes Model (PRISM) dataset from the Climate group at

[5] Corn Belt (Illinois, Indiana, Iowa, Missouri, Ohio), Lake States (Michigan, Minnesota, Wisconsin), NorthEast (Pennsylvania), Appalachian (Kentucky, North Carolina), Northern Plains (Kansas, Nebraska, South Dakota), Mountain States (Colorado).

Oregon State University (which is USDA's official climatological data) and the *temporal* resolution of daily weather data from sparsely located weather stations across the country. The dataset is reportedly fairly accurate at the daily level for temperature but less so for precipitation. Since agricultural data is at the county level, daily county level weather observations were generated from the detailed dataset over the agricultural land in each county following indications in the dataset. I also computed daily GDD and DDD fitting a sine curve passing through the consecutive temperature extremes.

Calendar weather variables were obtained by aggregating daily precipitation, GDD and DDD over the calendar period of interest, i.e., April-September (season-long calendar variables) and April-June, July and August-Septeber (disaggregated calendar variables). Similarly, phenological weather variables were obtained by aggregating precipitation, GDD and DDD over the stage of interest. The vegetative stage is defined from the median date of sowing to 2 weeks before that of silking/flowering. The flowering stage is defined as 2 weeks before and after the median date of silking. The grain-filling stage is defined from 2 weeks after the median date of silking to the median date of maturity. Note that, unfortunately, crop progress data and median dates are obtained at the State level and are applied unselectively to all counties in the same State for each year[6].

Summary statistics for precipitation, GDD and DDD for aggregated and disaggregated calendar and phenological variables are found in table 1. As an illustration, figure 2 shows the distributions for calendar and phenological season-long precipitation and GDD variables. As expected, the calendar season-long variables have *larger* means than their season-long phenological counterparts given that the time window of aggregation is wider as seen in figure 1. Note that the variation in calendar GDD is more pronounced than for their phenological counterparts. This is likely due to the inclusion in the calendar variables of additional Spring and Fall weather that tends to be much more variable. Distributions for precipitation and GDD tend to be "bell-shaped" while DDD is heavily skewed to the left because high temperatures exceeding 34ºC rarely occur in the sample.

[6]There is, of course, variation in these dates within a State and year. However, these are generally very small as could be noticed by comparing district-level with State-level progress data for the Illinois. If the data is well collected, this seems to suggest that there is as much variation within a district in crop progress as there is within a State.

### 4.3 Climate change scenarios

As pointed out above I chose not use actual GCM projection data in order to neutrally assess how the coefficients obtained from the estimation performed in terms of simulated temperature increases. I constructed three scenarios of spatially uniform daily temperature increases of 1, 2 and 3ºC. These fall within common ranges of GCM models.

To construct these scenarios I added 1, 2 or 3ºC to both, the minimum and maximum temperature of every day, year and county in the sample during the 1950 to 2005 period. I then computed the corresponding GDD and DDD calendar and phenological weather variables for each year and scenario. I then calculate the corresponding climate variables for each calendar or phenological time window by averaging the weather variables over the 56 years. This assumes that there is no significant warming during the period. The projections are simply derived by taking the difference between the "temperature-augmented" scenarios and the observed baseline climate scenario. I subsequently multiply these climate projections by the regression coefficients to obtain projected yield impacts.

## 5 Estimation model

In exploring the role of calendar weather variables I present side-by-side OLS with Fixed Effects (FE) models. The objective is to assess how the introduction of FE change coefficients and translates in projected impacts. Robust standard errors are used for all models. As an illustration the FE model for both calendar and phenological weather variables:

$$y_{it} = \sum_p \left(\beta_{1,p}\ \mathrm{Prec}_p + \beta_{2,p}\ \mathrm{Prec}_p^2 + \beta_{3,p}\ \mathrm{GDD}_p + \beta_{4,p}\ \mathrm{GDD}_p^2 + \beta_{5,p}\ \mathrm{DDD}_p + \beta_{6,p}\ \mathrm{GDD}_p^2\right) + \Psi_s(t) + \alpha_i + \epsilon_{it}$$

where $y_{it}$ is yield (bu/acre) in county $i$ in year $t$, $p$ is the period of weather aggregation (April to September, sowing to maturity, April to June, sowing to silking, etc.), $\Psi_s(t)$ is a State-specific quadratic time-trend and $\alpha_i$ a county-specific fixed effect. Note that the weather variables are scaled by the number of days in the aggregation period. This does not make a real difference for the calendar models because the weather variables have the same time length for all counties. However, this is not the case for the phenological variables because the growing periods may be different across the U.S. as shown in table 1. This would allow comparison in magnitudes between coefficients of different models and would also remove the effect of season length from the phenological coefficients.

Summary statistics in table 1 show that calendar weather variables have values that exceed their phenological counterparts. This weather "augmentation" during periods when crops are *not* in the field may be interpreted as measurement error in the regressors. This error is possibly correlated with the regressors because the amount of the "augmentation" should be related to the agroclimatic conditions which are captured in the regressors. The question is whether this measurement error is correlated or not with the dependent variable. If the measurement error is classical, i.e. white noise, then we expect an attenuation bias and lower coefficients with calendar variables than with phenological ones.

On the other hand, if the measurement error of calendar weather variables is correlated with yield then we expect a bias on weather coefficients that depend on the magnitude and direction of this correlation. Furthermore, this bias may increase with the introduction of fixed effect in our panel model as the variance of the noise relative to the variance of signal increases[7].

Following common practice I included all weather variables with linear and quadratic terms. For precipitation and GDD, the interpretation has been that these weather inputs initially provide positive but diminishing marginal returns and might exhibit an optimum value in the sample value range. This suggests that we expect $\beta_1$, $\beta_3 > 0$ and $\beta_2$, $\beta_4 < 0$. For these two variables I compute the implicit extremum which is in principle a maximum. For GDD, for example, the extreme value corresponds to $GDD^* = -\beta_3/2\beta_4$. The effect of DDD is negative in principle, so the inclusion of a quadratic is for added flexibility. $\beta_5$ is expected to be negative and there is no *a priori* expectation for the sign of $\beta_6$. If GDD is an appropriate explanatory variable for yield than we should perceive consistency in the signs and magnitudes of coefficients between calendar and phenological models. A good benchmark is to observe how consistent are the signs and magnitudes of the coefficients for

[7]See Griliches and Hausman (1986).

precipitation.

### 5.1 Season-long weather models

Table 2 combines results from the regression output, implicit extrema for precipitation and GDD and projected climate change impacts. Models "C" and "P" correspond to models with calendar and phenological weather variables. Model type "1" and "2" refer to OLS and FE.

Models C1 and C2 correspond to the weather window aggregation commonly used in the literature. These models yields the typical "hill-shaped" form for precipitation and GDD, indicating that they first yield positive but diminishing marginal returns. Projected impacts are negative and significantly higher for the FE model (C2). A closer look, however, unveils that GDD is a key variable driving negative impacts, accounting over 50% of the total impacts in the third scenario under C2. Indeed, the sample mean is around the implicit optimum for GDD, suggesting that further increases in GDD would be negative overall. This goes against the common interpretation of the role of GDD which is argued to be a measure of "beneficial" heat in this literature. As discussed in Section 2, GDD should not be conceptually causing damages, unless, of course, it happens to be correlated with detrimental variables to yield.

Models P1 and P2 are "test" models aiming at assessing how results change when weather is accounted exactly during the growing season and not over a fixed calendar period. Unlike the C models, impacts turn out to be negative with OLS (P1) or positive with FE (P2). Precipitation and DDD seem to possess the same qualitative behavior than in calendar models but GDD presents an significant change. The signs of the GDD coefficients are inverted now suggesting a "U" shape. For the OLS model (P1), the sample mean falls to the right of the implicit minimum indicating that increases in temperature would yield additional GDD per day during the growing season which positively contributes yield. In the FE model (P2), the sample mean is falls below the implicit minimum, thus additional GDD are detrimental, but the effect is almost 0. The results for GDD in these models seem more likely than for the C1-C2 models where GDD played a leading role in driving negative impacts.

This inconsistency of GDD between C and P models suggests that it is not -as is- an appropriate explanatory variable for yield because it does not exhibit a plausible functional. It appears that the the weather corresponding to the discrepancy between April-September and Sowing-Maturity, that is, the weather when the crops are *not* in the field, may be correlated with omitted variables that negatively affect yield, particularly in the "within county" dimension. This would explain how the introduction of fixed effect in C2 and P2 result in an absolute downward effect on impacts of about 8 to 10 percentage points in the third scenario when compared to the OLS models C1 and P1. As pointed out before, GDDs were not developed as predictors of yield but to assist in pacing the succession of crop stages.

### 5.2 Disaggregated weather models

One of the implicit assumptions of models based on season-long weather variables is that the effect of weather is somewhat similar throughout crops stages. As pointed out above, the flowering stage is considered to be a vulnerable stage of crop production. Table 3A presents the regressions results from disaggregated models, table 3B presents the extremum values for Precipitation and GDD derived from the quadratic regression coefficients, and table 3C presents the results from the simulated climate change scenarios for each model.

The fit of all models substantially increases with disaggregated weather variables, whether these are calendar or phenological, but more so for phenological. Table 3A shows that GDD seems to be the variable driving most of the damage, not DDD, and that this damage is overwhelmingly concentrated in the flowering period. This is valid for *all* models. The OLS versions C1d and P1d deliver qualitatively different impact results. On the other hand the the disaggregated phenological model (P2d) yields similar results than its calendar counterpart (C2d) but also to the season-long calendar FE model (P2), with impacts in the range of -15% for the third scenario. However, the P2d model clearly shows that the impact is concentrated in the flowering period. This has important implications for adaptation, as negative impacts of heat could be mitigated with rather simple management decisions (cultivar choice, sowing date).

In order to verify the pertinence of the flowering stage as a key stage I carried out a sensitivity analysis. I constructed a series of datasets for which the window of the flowering period was shifted 1 to 4 weeks before and after the actual flowering stage. If the flowering stage is a relevant time window for capturing a particularly sensitive stage to weather shocks, then the fit of the model should be enhanced when the flowering window matches the flowering period. Figure 3 shows the results. It is clear that the fit, in terms of reduction of Root Mean Squared Error (RMSE) from a baseline model without weather variables, is the highest when the window matches the flowering stage (model "0"). When the window is shifted away from the flowering stage, the fit decreases. It is likely that the fit remains high due to intra-seasonal correlations between those shifted windows and the weather at the flowering stage. Indeed, those windows are 4-weeks wide and have significant overlap. As an example, note that the OLS "model 0" almost performs as well as the fixed effects season-long calendar (SLC) or phenological (SLP).

I conducted a similar exercise for the disaggregated calendar models and shifted the aggregation window for the month of July. Unlike the flowering stage, there is no clear pattern of enhanced fit centered in July. Moreover, I separated the sample into counties falling on either side of the 40th parallel north (corresponding to the Kansas/Nebraska frontier) which roughly splits the sample in half (North: 661, South: 531). The pattern of a "peak" persists for the subsamples for the flowering window sensitivity check. However, there is no discernible pattern for the month of July when looking at the subsamples.

On the other hand, the projected damages of temperature increases should be the highest at the point when the flowering window matches the flowering stage because it is precisely at this point that sensitivity to heat should be the greatest. Figure 4 confirms this point.

Regression results and sensitivity checks suggest that the flowering stage is indeed much more sensitive to weather shocks than alternative windows around that same stage. They also suggest that the predictive power of the model is substantially improved by including separate weather variables for this stage.

## 6 Conclusion

The possibility to obtain crop progress data coupled with detailed weather data allows the construction of weather variables that match crop stages. This makes possible accounting for the weather when it should in principle matter the most for crops. The use of season-long calendar weather variables is widespread in climate change impact studies. It appears that these variables derive their predictive power from correlations with relevant but omitted sub-seasonal weather variables.

The reliance on them yields a rather bleak outlook for US corn yields because they limit the possibility of considering simple adaptations. Indeed, if the extreme heat is primarily responsible for yield reduction due to its occurrence at the moment of flowering, then the adaptation possibilities become much more clear.

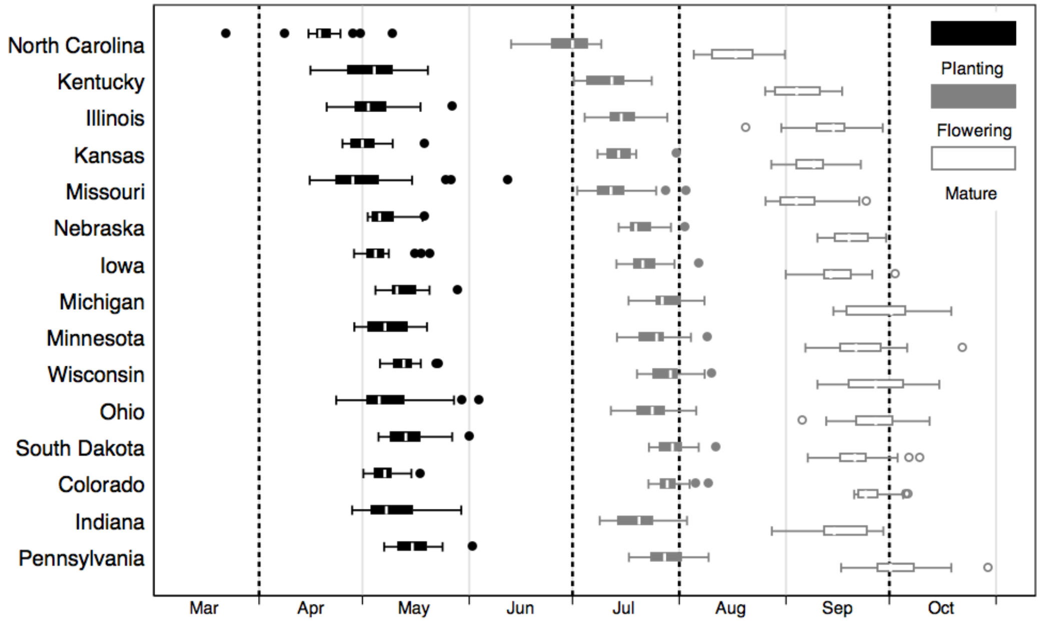
These preliminary findings show that the flowering stage captures the largest bulk of the damage on US corn yields. This could be shown even with highly aggregated data and rather wider flowering window of 4 weeks. This confirms, at such a large scale, agronomic findings in the field.

The findings in this paper show that the negative effect on corn yield stemming from the vulnerability of the flowering period is tied to GDDs, which are not, in principle, predictors of yield. It is possible that this variable is closely correlated with other omitted measures of heat that do play a role during this stage.

An important finding is that, growing-degrees days, which are considered measures of "beneficial" heat are found to be one of the main drivers of negative impacts in weather variable specifications similar to Schlenker et al. (2005); Deschenes and Greenstone (2007). This situation probably stems from correlations between GDD and omitted weather variables that are not captured in the damaging degree-days (DDD) variable. A possible path is to explore weather variables matched to crop stages and the approach in Schlenker and Roberts (2009). The use of GDD may have to be confined to a use closer to what it has been intended to, that is, in predicting phenology and perhaps explain yield *indirectly* through the choice of the cultivar.

This paper serves as a cautionary note for climate change studies based on fixed, season-long calendar weather variables. The robustness provided by the consistency of coefficients of certain weather variables is likely due to correlations with relevant but omitted and sub-seasonal weather variables. The current climate change impact projections may possibly be avoided with management decisions such as changing the planting date or the cultivar used. There is of course a large role to play for plant breeding in developing cultivar with more robust reproductive organs.

Figure 1: Timing of planting, flowering and maturity of corn across 15 U.S. States.




*Note*: Box plots indicate the year-to-year distribution (1985-2005) of a State's median planting, flowering/silking and maturity dates, i.e. when 50% of that State's acreage reaches a particular stage in a given year. Dashed lines illustrate the typical April-to-September calendar period used in econometric studies. The month of July is also indicated and has been proposed as an appropriate time-frame to capture the corn flowering period.

Figure 2: Distributions of key calendar and phenological variables.

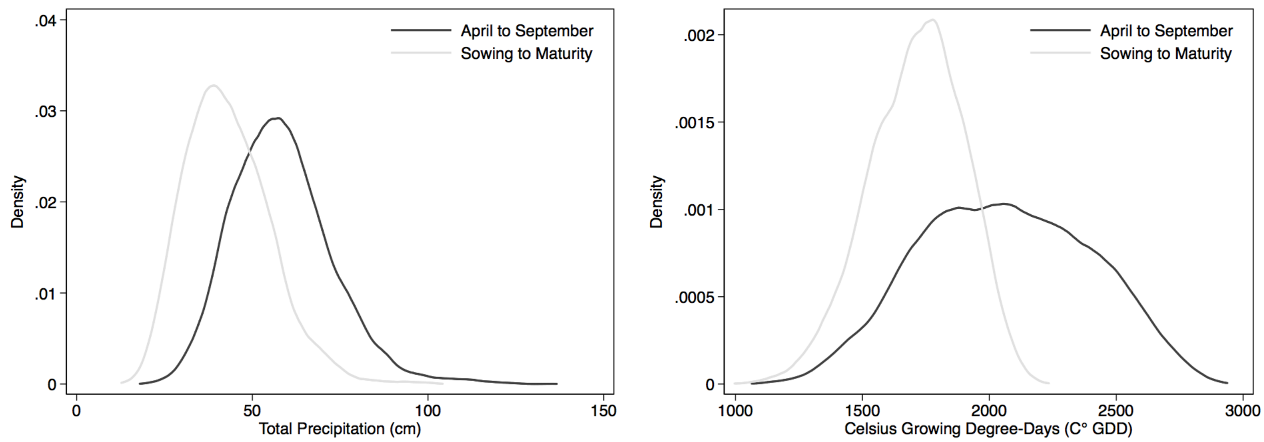
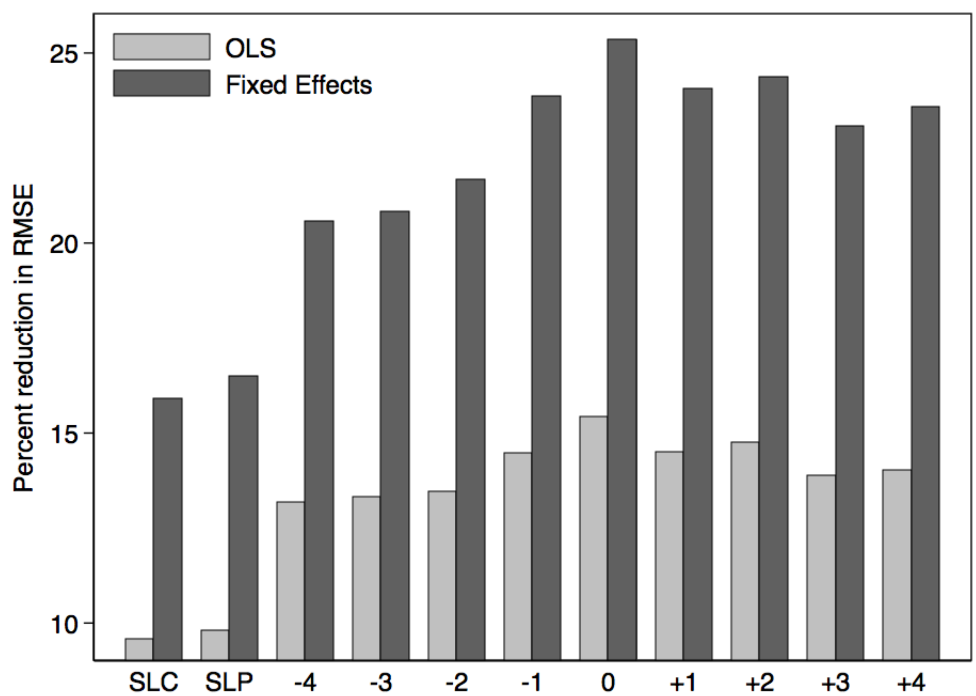
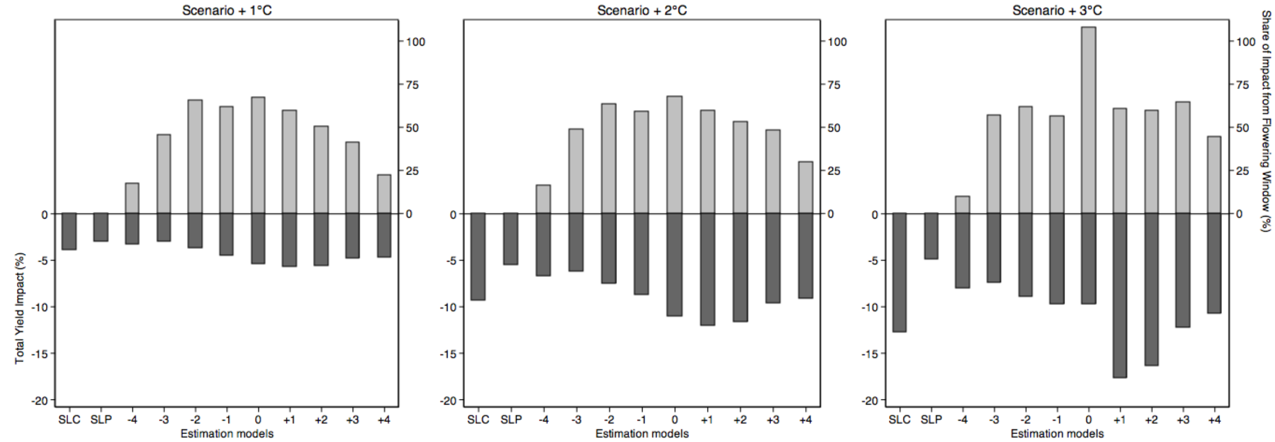



Figure 3: Improved fit when weather at the flowering period is separately accounted for




*Note:* The graph represents the percentage reduction in Root Mean Square Error (RMSE) from a model without weather variables. "SLC" is the Season-Long Calendar model with weather aggregation from April to September. "SLP" is the Season-Long Phenological model with aggregation from sowing to maturity. The remaining models have dissaggregated weather variables for the Vegetative, Flowering and Grain-filling stages. Model's "0" window of aggregation for flowering matches the actual flowering period. The other models had the flowering aggregation window shifted from the actual flowering period. For instance, model "+2" had its flowering window shifted 2 weeks after the actual flowering period.

Figure 4: Yield impacts and the contribution of the flowering window




*Note:* "SLC" is the Season-Long Calendar model with weather aggregation from April to September. "SLP" is the Season-Long Phenological model with aggregation from sowing to maturity. The remaining models have dissaggregated weather variables for the Vegetative, Flowering and Grain-filling stages. Model's "0" window of aggregation for flowering matches the actual flowering period. The other models had the flowering aggregation window shifted from the actual flowering period. For instance, model "+2" had its flowering window shifted 2 weeks after the actual flowering period.

Table 1. Summary statistics for calendar and phenological weather variables.

| | Calendar | | | | Phenological | | | |
|---|---|---|---|---|---|---|---|---|
| Variable | Mean | $\sigma$ | Min. | Max. | Mean | $\sigma$ | Min. | Max. |
| Season-long variables | | | | | | | | |
| | *April − September* | | | | *Sowing − Maturity* | | | |
| Number of days | 183 | - | - | - | 132.3 | 10.7 | 104.0 | 163.0 |
| Precipitation (cm) | 58.4 | 14.4 | 18.0 | 136.6 | 43.1 | 12.3 | 12.7 | 104.2 |
| Degree days (8-32ºC) or GDD | 2060.8 | 336.2 | 1063.5 | 2937.6 | 1713.4 | 188.6 | 996.4 | 2234.4 |
| Degree days (>34ºC) or DDD | 2.2 | 4.8 | 0 | 53.5 | 2.1 | 4.5 | 0 | 45.3 |
| Disaggregated variables | | | | | | | | |
| | *April − June* | | | | *Vegetative* | | | |
| Number of days | 91 | - | - | - | 59.9 | 6.8 | 38.0 | 80.0 |
| Precipitation (cm) | 29.7 | 9.7 | 7.6 | 71.6 | 20.7 | 8.4 | 1.9 | 62.8 |
| Degree days (8-32ºC) or GDD | 810.9 | 171.0 | 354.5 | 1293.9 | 697.4 | 75.0 | 405.9 | 1021.3 |
| Degree days (>34ºC) or DDD | 0.3 | 1.1 | 0 | 16.8 | 0.4 | 1.3 | 0 | 17.3 |
| | *July* | | | | *Flowering/Silking* | | | |
| Number of days | 31 | - | - | - | 28.1 | 0.3 | 28.0 | 29.0 |
| Precipitation (cm) | 10.5 | 5.3 | 0.4 | 61.8 | 9.2 | 4.6 | 0.2 | 46.0 |
| Degree days (8-32ºC) or GDD | 482.9 | 61.5 | 235.2 | 635.6 | 433.6 | 57.3 | 222.0 | 575.2 |
| Degree days (>34ºC) or DDD | 1.1 | 2.3 | 0 | 32.0 | 0.8 | 2.0 | 0 | 24.3 |
| | *August − September* | | | | *Grain-filling* | | | |
| Number of days | 61 | - | - | - | 44.4 | 6.8 | 20.0 | 72.0 |
| Precipitation (cm) | 18.2 | 7.4 | 1.4 | 84.3 | 13.3 | 6.1 | 0.5 | 48.8 |
| Degree days (8-32ºC) or GDD | 767.0 | 123.5 | 403.4 | 1114.9 | 584.6 | 108.8 | 192.3 | 873.1 |
| Degree days (>34ºC) or DDD | 0.9 | 2.4 | 0 | 44.8 | 0.9 | 2.3 | 0 | 31.6 |

TABLE 2. Regression and projected impact results with season-long weather variables.

| | (C1) | | (C2) | | (P1) | | (P2) | |
|---|---|---|---|---|---|---|---|---|
| Regression results: | | | | | | | | |
| County Fixed Effects | no | | yes | | no | | yes | |
| Quadratic time trend by State | yes | | yes | | yes | | yes | |
| Coefficients (timescaled) | | | | | | | | |
| | *April − September* | | | | *Sowing − Maturity* | | | |
| Precipitation | 333.4 | | 329 | | 309.5 | | 322.9 | |
| Precipitation squared | -2.607 | | -2.555 | | -2.971 | | -3.08 | |
| GDD | 22.81 | | 27.32 | | -7.409 | | -6.606 | |
| GDD squared | -0.00545 | | -0.007 | | 0.00237 | | 0.00167 | |
| DDD | -754.5 | | -756.2 | | -505.6 | | -469.2 | |
| DDD squared | 21.09 | | 18.26 | | 15.75 | | 11.91 | |
| Degrees of freedom | 21,301 | | 20,286 | | 21,301 | | 20,286 | |
| Adjusted $R$ squared | 0.475 | | 0.688 | | 0.478 | | 0.692 | |
| RMSE | 21.87 | | 16.87 | | 21.82 | | 16.75 | |
| F-statistic | 602.7 | | 541.1 | | 683.6 | | 587.6 | |
| Extremum values for: | | | | | | | | |
| Precipitation (cm) | 63.94 | △ | 64.38 | △ | 52.09 | △ | 52.42 | △ |
| GDD | 2091.5 | △ | 1951.8 | △ | 1560.9 | ▽ | 1979.8 | ▽ |
| Climate change impact: | | | | | | | | |
| Scenario $+1^{\circ}C$ | | | | | | | | |
| GDD contribution (%) | 0.3 | | -1.0 | | 0.7 | | -0.6 | |
| DDD contribution (%) | -2.4 | | -3.0 | | -1.9 | | -2.4 | |
| Total impact (%) | -2.1 | | -3.9 | | -1.2 | | -3.0 | |
| Total impact (bu/acre) | -2.7 | | -5.0 | | -1.6 | | -3.8 | |
| Scenario $+2^{\circ}C$ | | | | | | | | |
| GDD contribution (%) | -0.6 | | -3.4 | | 1.7 | | -0.8 | |
| DDD contribution (%) | -4.1 | | -5.9 | | -2.8 | | -4.7 | |
| Total impact (%) | -4.7 | | -9.3 | | -1.0 | | -5.5 | |
| Total impact (bu/acre) | -5.9 | | -11.8 | | -1.3 | | -7.0 | |
| Scenario $+3^{\circ}C$ | | | | | | | | |
| GDD contribution (%) | -2.6 | | -7.4 | | 3.2 | | -0.8 | |
| DDD contribution (%) | -0.7 | | -5.4 | | 1.5 | | -4.2 | |
| Total impact (%) | -3.4 | | -12.7 | | 4.7 | | -4.9 | |
| Total impact (bu/acre) | -4.3 | | -16.2 | | 6.0 | | -6.3 | |

*Note:* All regression coefficients are significant at the 0.1% level. Extremums are derived from the quadratic relationship used in the estimation for the corresponding variable. Maximum and minimum values are marked with △ and ▽ , respectively.

TABLE 3A. Regression results from disaggreagated weather variables.

| | (C1d) | (C2d) | (P1d) | (P2d) |
|---|---|---|---|---|
| Regression results: | | | | |
| County Fixed Effects | no | yes | no | yes |
| Quadratic time trend by State | yes | yes | yes | yes |
| Coefficients (time-scaled) | | | | |
| | *April − June* | | *Vegetative* | |
| Precipitation | 207.0 | 158.9 | 149.8 | 141.2 |
| Precipitation squared | -3.4 | -2.6 | -3.4 | -3.2 |
| GDD | 12.9 | 23.3 | -6.6 | -4.6 |
| GDD squared | -0.006 | -0.012 | 0.006 | 0.002 |
| DDD | 13.8 x | -225.6 | -115.2 | -135.1 |
| DDD squared | 15.5 | 25.2 | 19.4 | 17.8 |
| | *July* | | *Flowering/Silking* | |
| Precipitation | 99.0 | 91.8 | 90.9 | 87.6 |
| Precipitation squared | -2.6 | -2.5 | -2.5 | -2.4 |
| GDD | 13.3 | 15.1 | 14.3 | 12.5 |
| GDD squared | -0.016 | -0.019 | -0.021 | -0.020 |
| DDD | -85.0 | -77.4 | -65.4 | -72.6 |
| DDD squared | 6.0 | 4.0 | 6.9 | 5.1 |
| | *August − September* | | *Grain-filling* | |
| Precipitation | 5.5 x | 17.0 | 42.8 | 52.0 |
| Precipitation squared | -0.3 | -0.4 | -1.2 | -1.3 |
| GDD | 5.6 | 1.7 x | 0.5 * | 1.8 |
| GDD squared | -0.005 | -0.003 | 0.001 | 0.000 x |
| DDD | -216.2 | -165.8 | -194.1 | -166.7 |
| DDD squared | 6.9 | 5.5 | 7.1 | 5.8 |
| Degrees of freedom | 21,289 | 20,274 | 21,289 | 20,274 |
| Adjusted $R$ squared | 0.534 | 0.741 | 0.541 | 0.754 |
| RMSE | 20.6 | 15.4 | 20.5 | 15.0 |
| F-statistic | 579.8 | 572.5 | 635.7 | 644.7 |

*Notes:* All coefficients have p-values below 0.001 unless noted. 0.01 <p-values< 0.05 are marked with *. p-value > 0.05 are marked with x Models C and P correspond to calendar and phenological weather variables. Indicator 1 and 2 refer to weighted least squares and fixed effects. The indicator d refer to disaggregated. Prime models indicate that GDD was dropped as a variable.

TABLE 3B. Derived extremum weather values by crop stage.

| | (C1d) | | (C2d) | | (P1d) | | (P2d) | |
|---|---|---|---|---|---|---|---|---|
| Extremum values for: | | | | | | | | |
| | *April − June* | | | | *Vegetative* | | | |
| Precipitation (cm) | 30.7 | △ | 30.3 | △ | 22.3 | △ | 22.4 | △ |
| GDD | 1107.5 | △ | 961.4 | △ | 595.3 | ▽ | 1427.9 | ▽ |
| | *July* | | | | *Flowering/Silking* | | | |
| Precipitation (cm) | 19.1 | △ | 18.6 | △ | 18.4 | △ | 18.2 | △ |
| GDD | 416.2 | △ | 398.0 | △ | 344.0 | △ | 321.3 | △ |
| | *August − September* | | | | *Grain-filling* | | | |
| Precipitation (cm) | 10.4 | △ | 19.6 | △ | 17.9 | △ | 19.4 | △ |
| GDD | 597.9 | △ | 262.0 | △ | -178.2 | - | 5645.9 | - |

*Notes:* Extremums are derived from the quadratic relationship used in the estimation for the variable. Maximum and minimum values are marked with with △ and ▽, respectively.

TABLE 3C. Impact results from disaggreagated weather variables.

| | (C1d) | (C2d) | (P1d) | (P2d) |
|---|---|---|---|---|
| Scenario $+1^{o}C$ | | | | |
| Vegetative GDD contribution (%) | 2.2 | 2.3 | 1.1 | -1.7 |
| Vegetative DDD contribution (%) | 0.3 | -0.2 | 0.0 | -0.1 |
| Flowering GDD contribution (%) | -1.5 | -2.3 | -2.8 | -3.2 |
| Flowering DDD contribution (%) | -0.3 | -0.7 | 0.2 | -0.4 |
| Grain-filling GDD contribution (%) | -1.1 | -2.4 | 1.5 | 1.2 |
| Grain-filling DDD contribution (%) | -1.3 | -1.0 | -1.3 | -1.2 |
| Total impact (%) | -1.8 | -4.2 | -1.3 | -5.4 |
| Total impact (bu/acre) | -2.2 | -5.4 | -1.7 | -6.9 |
| Scenario $+2^{o}C$ | | | | |
| Vegetative GDD contribution (%) | 3.9 | 3.6 | 2.6 | -3.2 |
| Vegetative DDD contribution (%) | 1.1 | -0.4 | 0.6 | 0.0 |
| Flowering GDD contribution (%) | -3.6 | -5.3 | -6.1 | -7.0 |
| Flowering DDD contribution (%) | -0.1 | -1.3 | 1.4 | -0.4 |
| Grain-filling GDD contribution (%) | -2.6 | -5.0 | 3.0 | 2.3 |
| Grain-filling DDD contribution (%) | -3.1 | -2.3 | -3.1 | -2.7 |
| Total impact (%) | -4.4 | -10.7 | -1.7 | -11.0 |
| Total impact (bu/acre) | -5.6 | -13.6 | -2.2 | -14.0 |
| Scenario $+3^{o}C$ | | | | |
| Vegetative GDD contribution (%) | 5.1 | 3.6 | 4.5 | -4.6 |
| Vegetative DDD contribution (%) | 2.9 | 0.0 | 2.8 | 1.5 |
| Flowering GDD contribution (%) | -6.2 | -8.8 | -10.0 | -11.3 |
| Flowering DDD contribution (%) | 2.1 | -1.0 | 5.0 | 0.8 |
| Grain-filling GDD contribution (%) | -4.4 | -7.8 | 4.5 | 3.5 |
| Grain-filling DDD contribution (%) | -5.1 | -3.7 | -4.8 | -4.4 |
| Total impact (%) | -5.7 | -17.7 | 1.9 | -14.5 |
| Total impact (bu/acre) | -7.2 | -22.6 | 2.4 | -18.5 |

*Notes:* All reported regression coefficients are significant at the 0.1% level. Extremums are derived from the quadratic relationship used in the estimation for the variable. Maximum and minimum values are marked with with $\triangle$ and $\bigtriangledown$, respectively.

## References

**Deschenes, Olivier and Michael Greenstone**, "The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather," http://www.atyponlink.com/AEAP/doi/abs/10.1257/aer.97.1.354 March 2007.

**Dixon, Bruce L., Steven E. Hollinger, Philip Garcia, and Viswanath Tirupattur**, "Estimating Corn Yield Response Models to Predict Impacts of Climate Change," *Journal of Agricultural and Resource Economics*, July 1994, *19* (1), 58–68.

**Fageria, N. K., V. C. Baligar, Ralph B. Clark, and R. B. Clark**, *Physiology of crop production*, Routledge, May 2006.

**Griliches, Zvi and Jerry A. Hausman**, "Errors in variables in panel data," *Journal of Econometrics*, 1986, *31* (1), 93–118.

**Hudson, I. L and M. R Keatley**, *Phenological research: methods for environmental and climate change analysis*, Springer Verlag, 2009.

**Kaufmann, Robert K. and Seth E. Snell**, "A Biophysical Model of Corn Yield: Integrating Climatic and Social Determinants," *American Journal of Agricultural Economics*, February 1997, *79* (1), 178–190. ArticleType: primary_article / Full publication date: Feb., 1997 / Copyright © 1997 Agricultural & Applied Economics Association.

**Mendelsohn, Robert, William D. Nordhaus, and Daigee Shaw**, "The Impact of Global Warming on Agriculture: A Ricardian Analysis," *The American Economic Review*, September 1994, *84* (4), 753–771. ArticleType: primary_article / Full publication date: Sep., 1994 / Copyright © 1994 American Economic Association.

**Schlenker, Wolfram and Michael J. Roberts**, "Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change," *Proceedings of the National Academy of Sciences of the United States of America*, September 2009, *106* (37), 15594–15598.

**_ , W. Michael Hanemann, and Anthony C. Fisher**, "Will U.S. Agriculture Really Benefit from Global Warming? Accounting for Irrigation in the Hedonic Approach," *The American Economic Review*, March 2005, *95* (1), 395–406. ArticleType: primary_article / Full publication date: Mar., 2005 / Copyright © 2005 American Economic Association.

**_ , _ , 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.

**Smith, D. L and C. Hamel**, *Crop yield: physiology and processes*, Springer, 1999.

**Wang, Jen Yu**, "A Critique of the Heat Unit Approach to Plant Response Studies," *Ecology*, October 1960, *41* (4), 785–790. ArticleType: primary_article / Full publication date: Oct., 1960 / Copyright © 1960 Ecological Society of America.