Crop Yield Response Function and Ex Post Economic Threshold:
The Impacts of Crop Growth Stage-specific Weather Conditions on Crop Yield[1]

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Abstract

There have been two parallel approaches to modeling crop yields as a function of weather (and management): crop growth simulation modeling and, more recently, parsimonious statistical models of crop yields that require many fewer variables to estimate. Our motivating objective is to take into account the phenological detail present in process-based crop simulation models to estimate much less data intensive empirical models capable of informing crop management and adaptation to climate change. In the field of *climate econometrics* (Hsiang, 2016), the crop yield response function has become one of the most widely studied topics in applied econometric analysis of climate impacts and adaptation. Since Schlenker and Roberts (2009), there have been continuous efforts to improve econometric specification of crop yield response functions: the importance of temperature relative to precipitation (Lobell and Burke, 2008), specification bias (Cooper et al., 2017), and spatial aggregation bias (Yun et al., 2015). Despite these advances, however, two fundamental economic and agronomic components are largely ignored: the economic meaning of *ex post* data (Hsiang, 2016), and differential impacts of weather in specific plant growth stages. To fill this gap, this study tries to answer two research questions: 1) how do we interpret estimated weather impacts as an ex-post economic thresholds in crop yield response functions? and 2) do temperature and precipitation have different impacts on crop yields at different plant growth stages? To this end, this paper starts from the discussion in Hsiang (2016) on the economic meaning of *ex post* data, and then, implements econometric crop yield response function analysis with county-level corn yields in the 12 state US Corn Belt region from 1981-2015.

Key words: Crop Yield Response Function, Growth Stages, Panel Estimation Approach, Economic Threshold, Weather Condition

I. Introduction

Understanding the impacts on crop yields of acute and chronic weather events during the growing season is fundamental to agronomic and agricultural meteorology research (often, "agro-climatic" research) since the inception of these fields. More recently, a broader set of scientific disciplines have been applying econometric and statistical methods to estimate yield response to weather during the growing season. Most of this research has used county-level crop yield data from USDA-NASS together with a gridded weather data product such as PRISM (Daly et al., 2008) to construct a county-level weather data set that typically consists of maximum and minimum temperature, the corresponding growing degree days and precipitation. The majority of this research has estimated correlations and nonlinear relationships between yield and weather variables based on the *entire* growing season. Attention to sub-seasonal temperature and precipitation has been limited in the statistical modeling of yield response literature (Cooper et al., 2017 is a notable exception). When detailed crop cultivar and management data on fertility, planting date and tillage are available, for instance, these variables may be included to estimate an empirical production function rather than a reduced-form relationship between a small set of crucial explanatory variables and crop yield. Detailed spatially referenced yield and management data are rarely available beyond the scale of experimental research plots, and these data are closely guarded even after researchers publish their results. Similar data from real farms with variation in management, weather and soils are privately held and strictly protected by farmers themselves and custom farm management and machinery companies working for them.

A separate but related area within the agro-climatic literature on agricultural production utilizes process-based crop growth simulation models (e.g. Rosenzweig, et al. 2014) to investigate management changes (e.g. no-till, fertilizer application rates and timing, irrigation) and crop responses to projected climate change. These models contain a very large number of parameters, in some cases hundreds, and simulate crop phenology at the field scale based on daily weather data and information about soils. There are crop cultivar specific parameters that influence vegetative and reproductive growth processes, plant water stress, and ceiling temperature impacts. Such models vary widely, but often simulate daily plant water availability, soil moisture, and sometimes include other detailed processes such carbon and nitrogen cycling or trace gas fluxes from soils. Process-based crop models, like statistical models, are based on empirical estimates of the relationship between weather, management and physical conditions during specific crop growth and development stages. When used correctly, these models are parameterized based on crop- and site-specific conditions to conduct simulations over a larger set of "fields" at many geographical grid points throughout a county, region or larger study area with temporal and spatial variation.

In the most basic sense, these two methodological approaches are based on the same underlying data generating process for crop yield, whereby weather, as the daily manifestation of climate, together with physical site characteristics and management combine to determine harvested yield. One fundamental difference is that econometric models of yield response in the agro-climatic literature typically have counties as the smallest observational unit for crop yield. This leaves weather data and basic soil properties as the main variables available to explain yield variation because specific management information is unobservable and highly heterogeneous across farms. The largely plot-based experimental literature that is the basis for yield response relationships in process-based models is closely aligned with the basic crop sciences where observational units are as small as a single plant or several square meters of a crop. Despite both approaches centering around the crop yield data generating process (DGP), process-based simulation models seek to replicate the DGP in a given physical and climatic environment such that changing management or climate can be studied, whereas econometric yield response estimation seeks to understand the GDP and attribute variation in the outcome variable to different explanatory factors.

One of the single-largest differences, in practice, between statistical and process-based crop growth modeling approaches is the level of temporal detail within an individual growing season. At two extremes are daily temporal resolution in a process-based model and a statistical yield model based only on full-length growing season weather variables (e.g. cumulative growing degree-days, total precipitation). Our objective is to incorporate intra-seasonal weather at critical phenological stages into econometric models of yield response. We will do this by introducing phenologically relevant weather variables (e.g. extreme heat) at critical times during the growing season (e.g. pollination, grain filling) based on established impacts from the agronomic and crop sciences literature. Additional weather-related variables (e.g. planting date when later than desired) may also be informative with respect to yield.

The intent of this approach is to incorporate as much agronomic knowledge as possible to identify the empirical effect of weather at specific points in the growing season. The practical motivation for this approach is to suggest management actions or adaptations that econometric models of yield response to seasonal weather cannot. Identifying threshold temperatures and non-linear yield impacts from extreme temperatures (e.g. Schlenker and Roberts, 2009) is helpful to motivate the need for breeding and plant genetic developments to adapt to predicted climate change, but does not immediately suggest anything that farmers themselves can do to mediate the effects of climate variability and change going forward.

II. Economic and Agronomic Framework of Econometric Approach

2.1. Crop Yield Response as *Ex Post* Economic Threshold

Even though econometric models of crop yield response to weather have become popular, a limited amount of attention has been paid to how to economically interpret weather impacts, i.e., marginal effects or average change in crop yield. In this study, we emphasize the fact that the data used to estimate econometric crop yield response models are *ex post* observations. In contrast to experimental data from a laboratory or field experiment, crop producers can only control so many variables that directly and indirectly determine yield. Weather uncertainty, soil quality (except over the long term) and site characteristics such as drainage cannot be manipulated by farmers. Farmer's knowledge and experience with unexpected weather and environmental constraints are the basis for optimizing management. As Gramig and Yun (2016) point out, these environmental factors directly constrain producers' behavior through days suitable for field work (DSFW). In this study, we follow Hsiang (2016) and interpret weather impact on the crop yield response function as an *ex post* economic threshold.

Adopting the formulaic derivation in Hsiang (2016), we assume that farmers are optimizing their yields (Y) corresponding to weather realization ($\boldsymbol{c}$) of the climate ($\boldsymbol{C}$) as:

$$(1)\quad Y(\boldsymbol{C}) = Y[\boldsymbol{b}^*(\boldsymbol{C}), \boldsymbol{c}(\boldsymbol{C})] = \max_{\boldsymbol{b}\in\boldsymbol{R}^N} z[\boldsymbol{b}(\boldsymbol{C}), \boldsymbol{c}(\boldsymbol{C})],$$

where $\boldsymbol{b}$ is a vector of N possible *ex ante* farmer practices or actions that are chosen by farmers based on the climate (plus field and economic considerations) and $\boldsymbol{b}^*$ is the optimum action. Farmers optimize their yield following their objective function (z), which could be profit or harvest maximization (or cost minimization). For the k-th element of climate component C_k, we can derive the marginal effects of realized weather $\boldsymbol{c}_k$ (e.g. total precipitation in a given period) from the total derivative (see Hsiang, 2016 pp.54-56) of crop yields in Equation (1), without loss of generality, as:

$$(2)\ \frac{\partial Y}{\partial \boldsymbol{c}_k} = \frac{dY}{d\boldsymbol{C}_k}.$$

We note that other terms of the total derivative in Equation (2) vanish due to their zero and unit values. Equation (2) means that the marginal effect of realized weather on crop yields is equal to the total impact of climate *locally*. We adopt a regression equation for the crop yield response function as $E[Y|\boldsymbol{c}] = f(\boldsymbol{c})$. Based on equations (1) and (2), we assert an important economic meaning. A crop yield response function measures the effect of realized weather in each individual year and farmers' management practices, that are *ex post* optimized, based on the long-term climate in a given location. Therefore, any weather variable threshold impacts revealed in estimated crop yield response functions are as much economic thresholds as they are agro-climatic thresholds.

2.2. Phenological Stage Specific Weather Impacts on Crop Yields

In the agronomic literature (see review in Hatfield et al., 2011) certain weather impacts on crop yields are known to vary depending on the growth stage when weather conditions are experienced. To illustrate we briefly review the findings for corn growth stages depicted in Figure 1.

-- Figure 1 about here --

A widely found result is that pollen viability decreases when exposed to temperatures greater than 35°C (Herrero and Johnson, 1980; Schoper et al., 1987; Dupuis and Dumas, 1990). Further, Fonseca and Westgate (2005) found that duration of pollen viability before silk reception is affected by pollen moisture content that is strongly dependent on vapor pressure deficit. Crafts-

Brander and Salvucci (2002) report a higher ceiling temperature with reduced leaf photosynthesis rate above 38°C. Maize yields are correlated with daily maximum temperature during the grain filling period and, more generally, are strongly correlated with meteorological droughts (Mishra and Cherkauer, 2010). Using field-level data Lobell et al. (2014) found that despite trend maize yield improvements in the Midwest, sensitivity to drought has actually increased. The optimal temperature range during reproductive stages is 18–25°C (Muchow et al., 1990) and exposure to higher than optimal temperature accelerates plant development in annual crops, which shortens the life cycle and results in smaller plants with lower yield potential due to less cumulative light interception (Hatfield et al., 2011). Hatfield and Prueger (2004) determined that if rainfall is less dispersed over the growing season, falling in fewer, larger precipitation events there will be less soil infiltration leading to the potential for moisture deficit stress in plants. In summary, temperature, meteorological drought, and soil moisture are important components in corn growth phenology.

In econometric studies of crop yields, temperature and precipitation variables are included to control for yield responses to extreme heat and moisture (e.g. Schlenker and Roberts, 2009). Roberts et al. (2012) consider vapor pressure deficit and exposure to solar radiation to study functional form specification. These studies are the most generally accepted benchmark model for econometric crop yield response function in economics. Two neglected factors that are important in the agronomy literature stand out: meteorological drought and growth stage specific weather impacts. Meteorological drought could be managed econometrically as omitted variable bias and handled using a spatially correlated error structure (Anselin et al., 2004; Schlenker and Roberts, 2009). A more straightforward econometric alternative is to add a meteorological drought index like the standardized precipitation index (SPI) (McKee et al., 1993) to a regression model.

The second factor points a finger at using only cumulative weather conditions over the entire growing season to explain yield impacts. For example, Schlenker and Roberts (2009) use growing degree days (GDD) and total precipitation for the period from March to August in their regression model. Even though they perform the robustness check of results with different numbers and groupings of months, all their analysis describes cumulative heat and precipitation measures on annual crop yield. Different specific vegetative and reproductive phenological periods, that together constitute the dates each year that crops are growing, are covered by March-August; Figure 2 is a plot of typical planting, growth and harvest periods for 1981 to 2015 (USDA-NASS) during the calendar year for the twelve Corn Belt States.[2]

-- Figure 2 about here --

From figure 2 it is clear that March-August covers most of planting and growth dates, but excludes the harvest period. Therefore a cumulative weather variable approach excludes weather conditions during harvest, when yield is already determined. County crop yields are *ex post* observations reflecting the entire crop season and the aggregation of many decentralized farmer management decisions. Weather conditions during the harvest period, after physiological maturity commonly referred to as “black layer,” typically only affect grain quality and may have important economic impacts through, for instance, the cost of grain drying. Weather conditions this late in the cropping season may influence the ability to harvest (e.g. DSFW in Gramig and Yun, 2016), but only in the most extreme case of prevented autumn harvest would this ultimately affect yield. This kind of delay is exceedingly uncommon unless planting was also very late.

[2] The data details are in the following section.

The current study explores these two gaps in econometric crop yield response function research to determine whether greater insights for weather risk management or climate change adaptation are obtainable. Starting from the econometric model specification in Schlenker and Roberts (2009), we implement the same analysis with and without monthly SPI variables to account for meteorological drought during May-August. In addition, we estimate all of the specified models of weather impacts on crop yield using both cumulative (full cropping season length) and planting/growth/harvest period specific weather variables.

III. Econometric Models and Data

Agricultural and resource economists have used econometrics to estimate crop responses, not only to climate (Dixon et al. 1994; Schlenker and Roberts 2009) but management practices themselves (e.g. yield response to nitrogen fertilizer in Boyer et al. 2013) due to the clear intuition along the lines of a biological production function. In general, a functional specification assumes a direct relationship between crop growth and agro-environmental factors like temperature, water availability, and soil fertility conditions. From an economic viewpoint, yield response is an output from a (not necessarily explicit) combination of management and inputs together with agro-environmental conditions. The two most generally adopted weather variables in yield response models are temperature and precipitation. As Schlenker and Roberts (2009) empirically demonstrated, temperature has nonlinear effects on crop yield, but Roberts et al. (2012) state that they have not found a functional form for precipitation that significantly improves statistical fit relative to a simple quadratic form. Based on these empirics and the specification in much of the previous literature, we can represent the above crop yield response function as an econometric equation following Schlenker and Roberts (2009) as:

(3) $y_{it} = h(T_{it}) + g(P_{it}) + \beta_1 t + \beta_2 t^2 + \mu_i + \varepsilon_{it}$

where $h(\cdot)$ is a nonlinear function of temperature (T), $g(\cdot)$ is a quadratic form of precipitation (P), $\beta_1$and β_2 are coefficients of a quadratic annual time trend (t) to account for technical changes over time, and μ_i is a region fixed-effect term.

In a regression functional form, we could write Equation (3) as:

(4) $y_{it} = \int_{\underline{h}}^{\overline{h}} g(h)\varphi_{it}dh + \gamma_1 P_{it} + \gamma_1 P_{it}^2 + \beta_1 t + \beta_2 t^2 + \mu_i + \varepsilon_{it}$

where $\int_{\underline{h}}^{\overline{h}} g(h)\varphi_{it}dh = \sum_{k=1}^{m} \delta_k \sum_{h=-1}^{39} T_k\,(h + 0.5)[\Phi_{it}(h+1) - \Phi_{it}(h)] = \sum_{k=1}^{m} \delta_k x_{it,k}$, $T_k(\cdot)$ is an m-th order Chebyshev polynomial and Φ_{it} is the cumulative distribution function of heat in county i and year t. Equation (4) can be extended by adding four additional SPI variables for May, June, July and August to more directly capture sub-seasonal meteorological drought.

In addition to the benchmark regression of Equation (3), this study addresses the importance of various weather impacts at the subseason level. As shown previously in Gramig and Yun (2016), weekly weather conditions are the key determinant of days suitable for fieldwork (DSFW) that, cumulatively, can influence crop yields if planting is delayed several weeks. DSFW are a constraint on timely farmer management actions, $\boldsymbol{b}$ in Equation (1), such as side-dressing fertilizer several weeks after corn planting. Identifying weather-based economic thresholds that occur at specific crop growth stages may convey more actionable information about the weather impacts on crop yields. To this end, this paper extends Equation (3) by assuming additive separability of weather variables as in Hsiang (2016) as:

(5) $y_{it} = \sum_{j=1}^{3} h_j(T_{it}) + \sum_{j=1}^{3} g_j(P_{it}) + \beta_1 t + \beta_2 t^2 + \mu_i + \varepsilon_{it}$,

where j is crop growth stage: 1=planting period, 2=growing period(s), and 3=harvesting period. For $h_j(\cdot)$ and $g_j(\cdot)$, we adopt the nonlinear and quadratic specification in Equation (4) and include the SPI variables in Equation (5) in our analysis.

For empirical analysis, we construct an unbalanced panel data set of county-level corn yields from 1981-2015 in the US Corn Belt. Annual corn yield data comes from the United States Department of Agriculture's National Agricultural Statistics Service (USDA-NASS). County boundaries do not change and we use the county boundary map from NASS released with the 2012 Census of Agriculture to construct spatially consistent variables for our dataset.[3] In particular, we construct county-level growing degree days (GDD), temperature, and precipitation variables using synthetic daily weather data from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) for each of the planting, growing and harvesting periods that span the annual crop growing season. To exclude non-agricultural areas within a county, we calculate the agricultural area from the National Land Cover Database (NLCD)[4] and calculate area weighted average cumulative and sub-season GDD and precipitation variables. Sub-season specific weather variables are constructed for planting, growing and harvest periods based on beginning and ending dates of historical weekly crop progress report data from NASS. The three month lagged SPI index for each county (1981–2015) is calculated for May-August using monthly PRISM precipitation data. Table 1 summarizes geographical ranges and availability of these data.

-- Table 1 about here --

[3] The shapefile of 2012 county boundary map is available from:
https://www.agcensus.usda.gov/Publications/2012/Online_Resources/Ag_Atlas_Maps/ (Retrieved 2. 4. 2017.)
[4] The NLCD database is available for 1992, 2001, 2006, and 2011. We use 1992 areas for 1981 – 1995, 2001 areas for 1996 – 2003, 2006 areas for 2004 – 2008, and 2011 areas for 2009 – 2015.

IV. Results

Following Equations (3) and (5), we construct and implement fourteen separate regressions to compare planting, growth and harvest period specific versus cumulative weather variables both with and without monthly SPI for May-August. The estimation results including the sub-season weather variables are reported in Table 2.

-- Table 2 about here –

It is interesting to note that all weather variables are statistically significant for all three p/g/h periods. Because stage-specific models assume complete separability of weather conditions for each period, the statistical significance of variables in the harvest period (models (3), (7), and (8) in Table 2) indicates that the observed crop yields are significantly correlated with weather conditions in the harvest period, in addition to weather variables during the planting and growth periods, but the estimated temperature parameters are generally largest for the growth period, even in the full model (8).

Perhaps more noteworthy is the statistical significance ($p<0.01$) and robust magnitude of SPI coefficients in models (4), (6), and (8) of Table 2, especially when compared to total precipitation variables. This is empirical evidence, no matter how unsurprising this finding may be, that meteorological drought is an important factor in determining crop yields. More interestingly, the signs of all SPI variable estimates are robust. Wetter conditions in May and July contribute to crop yield while more moisture in June and August has the opposite influence. This suggests that crop yield response to droughty conditions varies across vegetative and reproductive stages within the overall growth period, roughly from May-August. This initial analysis does not isolate vegetative and reproductive components of corn growth and development, but this will be analyzed in greater detail as this research continues.

From an econometric standpoint of global fit, the growth period only model (2) is the best in terms of AIC while all periods and SPI of model (8) has the best Adjusted R-squared. Given that the model (8) AIC is much higher than for model (2), the higher adjusted R-squared may very well be a result of the larger (indeed, the largest) number of explanatory variables in model (8). From model (2) and general robustness of statistical significance across estimates of variables during the growth periods (g), weather conditions during the growth period between planting and harvests are the most important factors determining crop yields. It is worth noting how similar the Adjusted R-squared and AIC are for models (2) and (4), the only difference being the inclusion of SPI. To discuss the economic thresholds of GDD and precipitation variables, the next step in this research is to conduct an impact analysis of marginal changes in weather variables.

The estimations results of cumulative weather conditions on crop yield response are in Table 3.

-- Table 3 about here --

Model (9) is the same model in Schlenker and Roberts (2009). What immediately stands out is that model (9) is not the best-fit model in terms of either AIC or adjusted R-squared, that distinction belongs to model (12). Two findings follow directly upon closer inspection of cumulative planting and growth period weather model (12). First, all SPI estimates are statistically significant, which means the omission of meteorological drought in cumulative weather condition models is resulting in serious omitted variable bias when you consider the difference in the magnitude of polynomial term estimates when monthly SPI is added to the Schlenker and Roberts (2009) model (9). As argued previously in Yun et al. (2015), this omission may be remedied by adopting a proper econometric method such as a random effects model. Second, weather conditions during harvest period clearly do not contribute anything to models of cumulative weather impact on corn yield. The weather during planting and growth periods are revealed to have larger impacts on corn yield than when including in the harvest period in cumulative weather variables. To discuss the economic thresholds of GDD and precipitation, we need to have the impact analysis of marginal changes of weather variables, which are the next step in this ongoing research.

V. Discussions and Further Steps

The preliminary results from an exploratory econometric analysis of corn yield response to weather in twelve Corn Belt states are presented with discussion of the following topics. First, we present the estimated growth stage-specific marginal effects of both temperature and precipitation in our data. As previously demonstrated by the agronomic literature, weather impacts on yield are different across crop phenological growth periods, suggesting that farmers' management efforts to prevent yield loss could potentially vary by growth stage. Second, the implied economic thresholds for temperature and precipitation from crop yield response function estimation are narrower than the range of these variables identified in the agro-climate literature. It is well known that agronomically supported weather ranges (and thus ceiling temperatures) are a necessary but not a sufficient condition to achieve yield potentials. Therefore, more narrow ranges delineate economic thresholds and imply more nuanced changes in crop selection/management or land-use may be required under long-term climate change. Finally, weather extremes such as acute extreme heat or heavy rain events more severely affect yield during grain filling and planting periods, respectively. In contrast to prior econometric analysis of crop yield response to agro-climatic variables, we discuss the management implications of our empirical findings in an effort to inform adaptation in cropping systems management.

Three further analyses will be implemented next and follow directly from the current estimation results. First, an impact analysis of marginal changes in weather variables will be performed to provide a similar plot to the nonlinear impact of the heat variable in Schlenker and Roberts (2009). Because our interpretation is of an *ex post* economic threshold, we will discuss the meaning of these thresholds in terms of economic and management considerations. Second, the same analysis will be performed for soybean and winter wheat. Based on the agronomic literature, we expect soybean to yield similar findings in cumulative weather variable models. It is, however, not clear whether phenological stage-specific results will also show similar weather impacts, especially with respect the meteorological drought variables we introduced to this literature. Depending upon crops and cultivar, stage-specific management is different and thus, there could be a different impact pattern. In the case of wheat, it is expected to see the similar but more weakly robustness results than for corn as shown in Schlenker and Roberts (2009). Last, we will discuss the differences in weather impacts between experiment-based model and economic threshold model. Because economic thresholds are the revealed output from the optimization under uncertainty and given production knowledge/skills, they are a different concept than agro-environmental thresholds derived from the controlled experiments. For example, the temperature maximum (about 30 ºF) to avoid corn yield damage identified in Schlenker and Roberts (2009, p. 2.) is an economic threshold, but not an agronomic limit (35 ºF) beyond which corn will cease to grow as identified in literature (Hatfield et al. 2011).

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Table 1. Descriptive Statistics

# of observations = 35,883[a]	Mean	Std.Dev.	Minimum	Maximum
Corn Yield (bushel/ac)	121	35.3857	0.0000	236.0000
GDD (degree days): 5°C - 35°C				
Planting Period	56.1346	10.2359	25.34406	104.8428
Growing Period	89.3691	11.1062	34.7016	119.0000
Harvest Period	63.4591	13.5844	16.9101	98.1635
Precipitation (mm)				
Planting Period	196.6350	104.2638	5.1133	800.9366
Growing Period	275.7629	105.194	9.1021	983.6005
Harvest Period	183.4953	98.5414	5.7710	788.5217
Standardized Precipitation Index (SPI)				
May	0.0027	0.9899	-3.9725	3.6163
June	0.0008	1.0013	-4.6097	3.2230
July	0.0003	1.0037	-4.0240	3.1560
August	0.0039	0.9824	-4.5106	3.6744

a Unbalanced county-level panel for twelve Corn Belt states, 1981–2015

Table 2. Estimation results of phenological stage-specific crop yield function (corn, 1981-2015)

	(1) p-only	(2) g-only	(3) h-only	(4) g+spi	(5) pg	(6) pg+spi	(7) pgh	(8) pgh+spi
	Estimate p-val	Estimate p-val	Estimate p-val	Estimate p-val	Estimate p-val	Estimate p-val	Estimate p-val	Estimate p-val
pxitemp1	-0.6795*				-1.6051***	-1.4326***	-1.3585***	-1.2455***
	(0.3944)				(0.3211)	(0.3214)	(0.3203)	(0.3204)
pxitemp2	-0.0519				-0.7334***	-0.6132***	-0.6531***	-0.5736**
	(0.2791)				(0.2278)	(0.2279)	(0.2274)	(0.2275)
pxitemp3	0.2027				-0.8116***	-0.6768***	-0.6816***	-0.5725**
	(0.3213)				(0.2623)	(0.2623)	(0.2615)	(0.2615)
pxitemp4	0.6984***				0.3202*	0.3812**	0.2375	0.2851
	(0.2295)				(0.1879)	(0.1880)	(0.1881)	(0.1881)
pxitemp5	0.4838**				0.1328	0.2067	0.1341	0.2011
	(0.2271)				(0.1860)	(0.1860)	(0.1860)	(0.1860)
pxitemp6	0.3729**				1.0917***	1.0748***	0.9743***	0.9668***
	(0.1789)				(0.1469)	(0.1473)	(0.1468)	(0.1472)
pxitemp7	-0.2503**				0.1776**	0.1770**	0.1693*	0.1843**
	(0.1095)				(0.0900)	(0.0902)	(0.0898)	(0.0900)
pxitemp8	-0.1754*				0.6165***	0.5864***	0.5275***	0.5110***
	(0.0935)				(0.0769)	(0.0771)	(0.0768)	(0.0769)
gxitemp1		-2.9207***		-2.8038***	-2.8278***	-2.6107***	-2.9999***	-2.6906***
		(0.6853)		(0.6849)	(0.6828)	(0.6825)	(0.6823)	(0.6824)
gxitemp2		1.7358***		1.5404**	1.5186**	1.3395**	1.4743**	1.1761*
		(0.6682)		(0.6678)	(0.6657)	(0.6656)	(0.6646)	(0.6648)
gxitemp3		-3.9646***		-3.7881***	-3.7612***	-3.5181***	-3.4792***	-3.1620***
		(0.6223)		(0.6221)	(0.6193)	(0.6193)	(0.6195)	(0.6200)
gxitemp4		3.7450***		3.5453***	3.5951***	3.3889***	3.3567***	3.0646***
		(0.5688)		(0.5686)	(0.5656)	(0.5658)	(0.5654)	(0.5659)
gxitemp5		-2.7873***		-2.5883***	-2.6679**	-2.4556***	-2.3624***	-2.0876***
		(0.4572)		(0.4572)	(0.4544)	(0.4547)	(0.4549)	(0.4556)
gxitemp6		1.7216***		1.6470***	1.8256***	1.7173***	1.6900***	1.5071***
		(0.3620)		(0.3619)	(0.3598)	(0.3599)	(0.3590)	(0.3594)
gxitemp7		-0.6978***		-0.7014***	-0.8340***	-0.7839***	-0.7835***	-0.6876***
		(0.2027)		(0.2027)	(0.2018)	(0.2018)	(0.2015)	(0.2017)
gxitemp8		-0.1134		-0.0328***	0.1002***	0.1204	0.1616	0.1397
		(0.1205)		(0.1209)	(0.1204)	(0.1207)	(0.1205)	(0.1207)
hxitemp1			0.4991***				-0.0328	-0.0117
			(0.0709)				(0.0595)	(0.0601)
hxitemp2			0.9009***				-0.4024***	-0.3670***
			(0.0506)				(0.0450)	(0.0464)
hxitemp3			1.4177***				-0.0736	-0.0284
			(0.0853)				(0.0721)	(0.0736)
hxitemp4			1.5908***				-0.2814***	-0.1917**
			(0.0900)				(0.0773)	(0.0788)

Note: * p-value < 10%, ** p-value < 5%, and *** p-value < 1%. Standard errors are in parenthesis. Variable prefixes p, g and h indicate the planting, growth, and harvest periods, respectively, with variable names of the form xitemp# indicating the terms of 8-th order Chebyshev polynomials of temperature, and prec denotes total precipitation.

Table 2. Estimation results of phenological stage-specific crop yield function (corn, 1981-2015, continued)

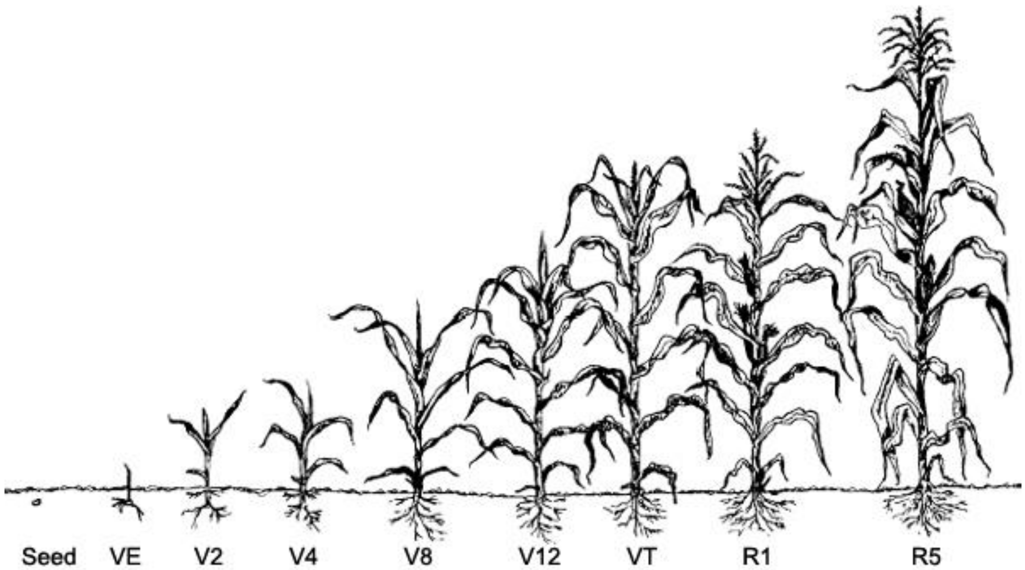
	(1) p-only	(2) g-only	(3) h-only	(4) g+spi	(5) pg	(6) pg+spi	(7) pgh	(8) pgh+spi
	Estimate p-val	Estimate p-val	Estimate p-val	Estimate p-val	Estimate p-val	Estimate p-val	Estimate p-val	Estimate p-val
hxitemp5			1.2605***				-0.0338	0.0374
			(0.1032)				(0.0868)	(0.0880)
hxitemp6			0.9398***				-0.0441	0.0723
			(0.1035)				(0.0877)	(0.0889)
hxitemp7			0.7543***				0.0811	0.1656**
			(0.0774)				(0.0644)	(0.0653)
hxitemp8			0.4430***				0.2034***	0.2622***
			(0.0705)				(0.0589)	(0.0596)
pprec	0.0006***				5.98E-06***	-0.0001	0.0000	0.0000
	(0.0000)				(3.80E-05)	(0.0001)	(0.0000)	(0.0001)
pprec_sq	0.0000***				-2.85E-07***	0.0000**	0.0000***	0.0000***
	(0.0000)				(7.03E-08)	(0.0000)	(0.0000)	(0.0000)
gprec		0.0017***		0.0018***	0.0017***	0.0017***	0.0016***	0.0017***
		(0.0000)		(0.0001)	(4.65E-05)	(0.0001)	(0.0000)	(0.0001)
gprec_sq		-2.37E-06***		-2.44E-06***	-2.32E-06***	0.0000***	0.0000***	0.0000***
		(6.56E-08)		(6.19E-08)	(6.62E-08)	(0.0000)	(0.0000)	(0.0000)
hprec			-2.48E-05				0.0000	-0.0001
			(4.95E-05)				(0.0000)	(0.0000)
hprec_sq			3.89E-07***				0.0000**	0.0000***
			(9.39E-08)				(0.0000)	(0.0000)
spiMay				0.0049***		0.0075***		0.0101***
				(0.0018)		(0.0020)		(0.0021)
spiJun				-0.0219***		-0.0135***		-0.0197***
				(0.0024)		(0.0025)		(0.0026)
spiJul				0.0146***		0.0196***		0.0113***
				(0.0023)		(0.0023)		(0.0024)
spiAug				-0.0160***		-0.0127***		-0.0083***
				(0.0027)		(0.0029)		(0.0029)
t	0.0132***	0.0030***	0.0158***	0.0024***	0.0026***	0.0026***	0.0018***	0.0016***
	(0.0006)	(0.0005)	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
t_sq	0.0000	0.0002***	0.0000**	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
R2	0.2562	0.5031	0.2659	0.5058	0.5105	0.5121	0.5186	0.5199
Adj R2	0.2315	0.4866	0.2416	0.4893	0.4941	0.4956	0.5023	0.5036
AIC	542.2119	169.1745	578.4503	171.4117	173.2942	178.0182	175.9123	181.0321

Note: * p-value < 10%, ** p-value < 5%, and *** p-value < 1%. Standard errors are in parenthesis. Variable prefixes p, g and h indicate the planting, growth, and harvest periods, respectively, with variable names of the form xitemp# indicating the terms of 8-th order Chebyshev polynomials of temperature, and prec denotes total precipitation.

Table 3. Estimation results of cumulative weather conditions on crop yield response function (corn, 1981 – 2015)

	(9) MA	(10) MA+spi	(11) pg	(12) pg + spi	(13) pgh	(14) pgh+spi
	Estimate	Estimate	Estimate	Estimate	Estimate	Estimate
xitemp1	-28.0780***	-28.0850***	-2.5995***	-2.5963***	-1.7815***	-1.8344***
	(1.3337)	(1.3233)	(0.1225)	(0.1218)	(0.1228)	(0.1226)
xitemp2	-10.4410***	-8.7704***	-1.2134***	-1.2301***	-0.7883***	-0.9316***
	(0.9102)	(0.9052)	(0.1176)	(0.1169)	(0.0761)	(0.0774)
xitemp3	-8.4882***	-8.6441***	-1.2252***	-1.2747***	0.7082***	0.6444***
	(1.2909)	(1.2797)	(0.1242)	(0.1233)	(0.1219)	(0.1215)
xitemp4	19.8930***	20.7350***	0.4887***	0.4171***	1.9243***	1.8214***
	(1.0088)	(1.0017)	(0.1296)	(0.1289)	(0.0894)	(0.0895)
xitemp5	8.8933***	8.5811***	0.3482***	0.2856**	2.1411***	2.0667***
	(1.1847)	(1.1795)	(0.1182)	(0.1177)	(0.1112)	(0.1108)
xitemp6	17.9880***	20.5450***	0.4499***	0.4338***	1.6437***	1.6494***
	(1.0777)	(1.0749)	(0.1297)	(0.1291)	(0.1056)	(0.1051)
xitemp7	-3.7990***	-3.7829***	-0.3465***	-0.3355***	0.3315***	0.3806***
	(0.8759)	(0.8698)	(0.0824)	(0.0820)	(0.0818)	(0.0816)
xitemp8	0.4585	2.3641**	-0.1116	-0.1193	0.4612***	0.4831***
	(0.9465)	(0.9447)	(0.0919)	(0.0915)	(0.0882)	(0.0877)
prec	0.0014***	0.0006***	0.0013***	0.0015***	0.0005***	0.0007***
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
prec_sq	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
spiMay		0.0442***		0.0074***		0.0099***
		(0.0038)		(0.0020)		(0.0020)
spiJun		-0.0391***		-0.0427***		-0.0404***
		(0.0024)		(0.0024)		(0.0024)
spiJul		0.0216***		0.0169***		0.0089***
		(0.0023)		(0.0024)		(0.0024)
spiAug		0.0548***		0.0097***		0.0122***
		(0.0043)		(0.0025)		(0.0021)
t	0.0114***	0.0104***	0.0093***	0.0085***	0.0075***	0.0069***
	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
t_sq	0.0000***	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
R2	0.4840	0.4934	0.4861	0.4944	0.4630	0.4707
Adj R2	0.4669	0.4765	0.4690	0.4775	0.4451	0.4531
AIC	208.6512	197.3548	204.4499	195.3884	250.5708	243.3941

Note: * p-value < 10%, ** p-value < 5%, and *** p-value < 1%. Standard errors are in parenthesis. p, g and h indicate the planting, growth, and harvest periods, respectively. Variable names of the form xitemp# indicating the terms of 8-th order Chebyshev polynomials of temperature, and prec denotes total precipitation.



Vegetative Stages	
Stage	**Description**
VE	Emergence
V1	One leaf with collar visible
V2	Two leaves with collars visible
V(n)	(n) leaves with collars visible
VT	Last branch of tassel is completely visible

Reproductive Stages	
Stage	**Description**
R1	Silking - silks visible outside the husks
R2	Blister - kernels are white and resemble a blister in shape
R3	Milk - kernels are yellow on the outside with a milky inner fluid
R4	Dough - milky inner fluid thickens to a pasty consistency
R5	Dent - nearly all kernels are denting
R6	Physiological maturity - the black abscission layer has formed

Source: Purdue University Extension, https://extension.entm.purdue.edu/fieldcropsipm/corn-stages.php

In analysis, we adopt planting, growth and harvest periods without the separation of vegetation and reproductive stages in growth period.

Figure 1. Corn Growth Stages

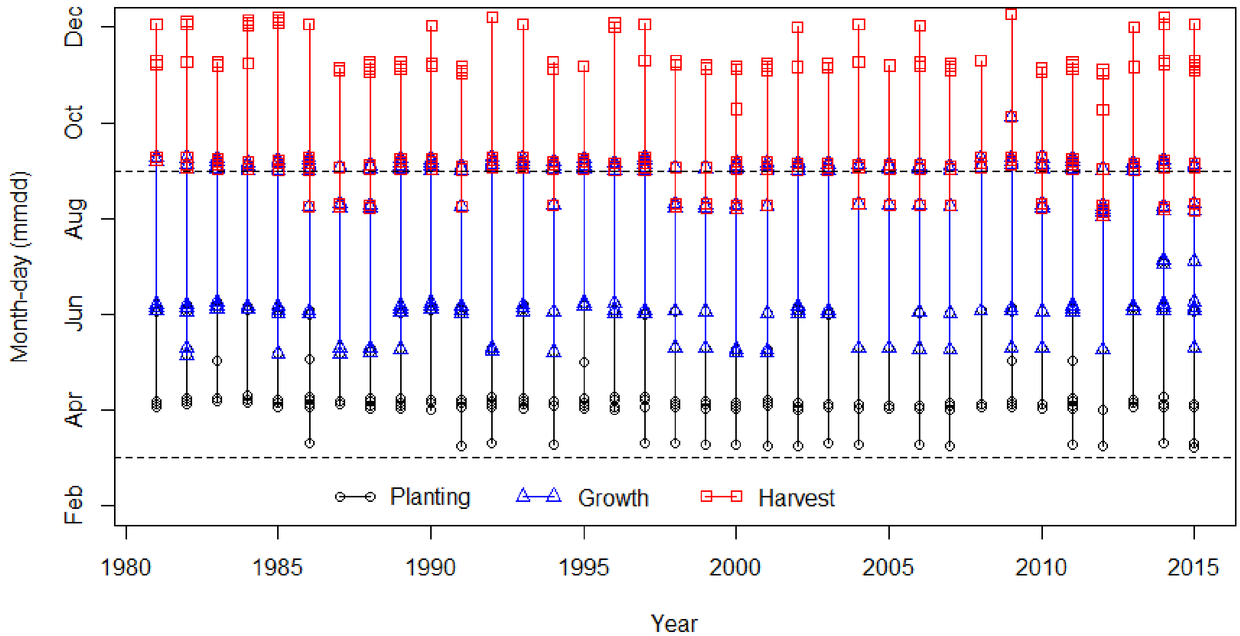


Figure 2. Planting, growth, and harvest periods from 12 Corn Belt States, 1981- 2015