How do heat waves, cold waves, droughts, hail and tornadoes affect US agriculture?

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Abstract

We estimate the impact of extreme events on corn and soybeans yields, and on agricultural land values in the Eastern United States. We find the most harmful event is a severe drought but that cold waves, heat waves, and storms all reduce both corn and soybean yields. Over 80% of the damage from extreme events is caused by droughts and cold waves with heat waves causing only 6% of the damage. Including extreme events in a panel model of weather alters how temperature affects yields, making cold temperature more harmful and hot temperatures less harmful. Extreme events have no effect on farmland values probably because American farmers are buffered from extreme events by subsidized public crop insurance.

Keywords: Climate change, agriculture, extreme events, heat waves, droughts.

JEL codes: Q1, Q54

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1 Introduction

There is a large literature that studies how climate and weather affect agricultural productivity using a wide range of methods: large agro-economic models that combine atmospheric science, plant science and agricultural economics (Adams et al. 1990), econometric "Ricardian" models that estimate the relationship between climate and land values (Mendelsohn, Nordhaus, and Shaw 1994), and weather impact models that empirically estimate how temperature affects the yield functions using weather shocks (Schlenker and Roberts 2009).

Surprisingly, few studies systematically investigate the impact of extreme weather events on agriculture (Mendelsohn 2007, IPCC 2012). The Mendelsohn study found crop failure rates varied with climate in a systematic fashion across the country. However, this study is the first to estimate the impact of extreme weather events on both crop yields and farmland value. Our goal is to provide a better explanation of how weather and climate affect agricultural productivity and to improve estimates of future climate change. Extreme weather events are often cited as being the major source of damage from climate change, but little is known about how they really affect agricultural productivity.

The definition of climatic extremes is quite challenging. One common thread across all definitions is that extreme events are infrequent. The IPCC Special report on extreme events (SREX) (IPCC 2012) classifies both heat waves and droughts as right tail events in the local distribution of temperature and water availability. Weather extremes are site and season specific. It is not yet clear how climate change will alter the frequency or intensity of the extreme events considered in this paper.

The definition of extreme events varies across the literature. For example Rosenzweig et al. (2001) use fixed thresholds to define extreme temperature events. Alternatively, one could define extreme temperature events as everything beyond two standard deviations from the mean. If only the mean of the temperature distribution rises, a fixed threshold would suggest more frequent extreme temperatures events while the two standard deviation definition would suggest no change. Climatologists would tend to argue for yet a third definition where extreme events are the outcome of unusual meteorological conditions. For example, a heat wave is caused by a rare phenomenon of blocking high pressure zones that trap air masses in a single place for several days in a row. They tend to happen in the United States in a region of the southern Great Plains (better known as the Dust Bowl). Droughts are caused by extended high pressure zones that lead to unusually low rain and often higher temperature. Storms such as tornadoes are caused by strong differences between surface and upper atmospheric temperatures creating a temporary heat engine.

Heat waves, cold waves, droughts, and wet spells are the weather extremes that create the largest damages to agriculture (IPCC 2012). There are many definitions of heat/cold waves and of dry/wet spells, but one common thread is that duration matters. Heat waves are prolonged periods of extreme temperatures. Droughts are prolonged periods with dry conditions. The underlying hypothesis is that damages are cumulative and not perfectly time separable.

Temperature bin models, such as those used by Schlenker and Roberts (2009) and Deschenes and Greenstone (2007) are not well-suited to study heat waves. The temperature bins models assume that the effect of temperature is time-separable. But it matters whether high temperatures persist for one hour every other week or for several days in a row. The extreme temperature bins imprecisely capture some effects of the heat waves. In this paper, we show that the negative impact associated with extreme temperature bins are greatly reduced if heat waves are introduced. In this paper we estimate the impact of five categories of extreme weather events: heat waves, cold waves, droughts, hail, and tornados. We first study how they affect crop yields using the intertemporal variation in a panel of weather over counties. We then test how the cross-section variation of the long-term frequency of weather extremes affects land values.

The rest of the paper is structured as follows. Section 2 describe methods and Section 3 illustrates the data and the working definitions of extreme events used in the paper. Section 4 presents and discusses results. Section 5 describes robustness tests and Conclusions follow.

2 Methods

We estimate the impact of year-to-year variation in extreme events on yields of corn and soybeans using a panel fixed-effect model that resembles the temperature bins models introduced by Schlenker and Roberts (2009). We estimate the impact of climatologies of extreme events on land values using an enhanced version of the Mendelsohn, Nordhaus, and Shaw (1994) Ricardian model enhanced by Massetti and Mendelsohn (2011) and Massetti, Mendelsohn, and Chonabayashi (2015). Our regional scope is the United States, limited to the counties east of the 100^{th} meridian (Schlenker, Hanemann, and Fisher 2005).

2.1 Crop yield model

We estimate the following model:

$$y_{i,t} = \alpha + \sum_{j=-1,0,3,6,\ldots}^{J} \beta_j x_{i,j,t} + \gamma_1 P_{i,t} + \gamma_2 P_{i,t}^2 + \boldsymbol{\eta} X_{i,t} + \boldsymbol{\varphi} E_{i,t} + \eta_i + \epsilon_{i,t} \tag{1}$$

where $y_{i,t}$ is the log of yield per hectare in county *i* in year t, $x_{i,t,j}$ is the number of 3-hour time intervals, days or consecutive days with mean temperature within a 3°C interval in year t, $P_{i,t}$ is the amount of rainfall during April-September in year t, $X_{i,t}$ contains a state by year quadratic time trend, $E_{i,t}$ is a vector of extreme events observed in county *i* in time t, and η_i is a county fixed effect.

Our temperature bins measure how many days are observed with temperature within each 3 °C interval from April to September. Schlenker and Roberts (2009) use hourly temperatures instead. They count the number of hours during which temperature is observed at each 3 °C wide interval. They then divide by 24 the total number of hours to express the total time in days. In previous work we have shown that the yield response function estimated using mean daily temperature better reflects the agronomic hill-shaped relationship between temperature and crop productivity (Massetti and Mendelsohn 2015). The hourly temperature data does not reveal that cold temperatures are harmful for crop development.

We group together high temperature bins that account for less than 1% data. These very rare temperature bins may act as dummy variables for extreme events. We also group the coldest temperature bins because they are usually not significant. Although we limit our observations to the period that goes from April to September, farmers can easily adjust planting dates waiting until when the warm season has started. We consider the relevant threshold to be 6 °C for both corn and soybeans. We test the robustness of results to our choice by estimating models with all temperature bins.

Throughout the paper we present standard errors corrected for spatial correlation following Conley (1999).[1]

[1] We use the Conley (1999) panel data equivalent algorithm developed by Solomon Hsiang and available at http://www.solomonhsiang.com/computing/stata-code. The covariance matrix estimator is obtained using the inverse distance weighted average of spatial autocovariances that fall within a Bartlett kernel that stretches along the north/south east/west dimensions. We use a constant cutoff point equal to 500 km. We consider serial correlation over time for five lags.

2.2 Land values

We use a traditional Ricardian model of the relationship between land value and climate (Mendelsohn, Nordhaus, and Shaw 1994):

$$V_{i,t} = \beta\, h(C_i) + \gamma X_{i,t} + \theta Z_i + \epsilon_{i,t} \qquad (2)$$

where $V_{i,t}$ is the log of land value per hectare at time *t* for observation *i*, $h(\cdot)$ is a generic function of the vector of climate variables C, $X_{i,t}$ is a set of socio-economic variables that vary over time, Z_i is a set of geographic and soil characteristics that are fixed over time, and ε is assumed to be a random component. We use a quadratic model of temperature and precipitation in the four seasons as in Ricardian analysis it provides more accurate estimates than a one season climate model (Massetti, Mendelsohn, and Chonabayashi 2015). We test the results using alternative specifications for climate variables, with and without state fixed effects. We use weights equal to the amount of farmland in each county *i* at time *t* (Deschenes and Greenstone 2007).

3 Data

3.1 Crop and Agricultural Land Data

We use data on corn and soybeans crop yields and harvested acres for counties east of the 100th meridian for the years 1979-2007 from the USDA National Agricultural Statistical Service.

The Ricardian model is estimated using a balanced panel built by Massetti and Mendelsohn (2011, 2012) and expanded by Massetti, Mendelsohn, and Chonabayashi (2015) using US Agricultural Census data for 1982, 1987, 1992, 1997, 2002 and 2007. We use the following time varying socio-economic variables: income per capita, population density, population density squared, residential house price index. We also control for a set of geographic, time invariant characteristics at counties centroids: latitude, elevation, and distance from major metropolitan areas. We use USGS data to estimate the average annual surface and ground water use per hectare of farmland during 1982-2007. Finally, we control for some important soil characteristics: salinity, percentage of soil subject to flooding, percentage of land with low drainage, soil erodibility, average slope length factor, percentage of sand and of clay, minimum available water capacity, and permeability. We include 2,406 out of the 2,471 counties east of the 100th meridian.

3.2 Temperature Data

This paper relies on 2 meter air temperature data from the North American Regional Reanalysis (NARR) data set (Mesinger et al. 2006). Data is available from 1979 to present. Robustness tests use temperature and precipitation data from Schlenker and Roberts (2009) and from the ERA-INTERIM dataset (Dee et al. 2011).[2]

Table 1 presents summary statistics of temperature and precipitation data during April-September. Note that the very high temperature bins are extremely rare. The extreme temperatures are observed during heat waves.

	Corn	Soybeans
Temperature bins (% of days between April and September)		
< 0	0.4%	0.4%
0-2	0.7%	0.6%
3-5	1.6%	1.5%
6-8	3.3%	3.2%
9-11	5.6%	5.5%
12-14	7.8%	7.7%
15-17	11%	11%
18-20	15%	15%
21-23	19%	19%
24-26	20%	21%
27-29	13%	13%
30-32	2.4%	2.2%
33-35	0.28%	0.26%
≥ 36	0.0053%	0.0053%
Precipitations (cm/month)	9.7	9.7

Table 1. Summary statistics of temperature bins

3.3 Heat and cold waves.

The Special Report on Extreme Events by the IPCC (IPCC 2012) defines an heat wave as a period of abnormally hot weather. The National Oceanographic and Atmospheric Administration defines a heat wave as a period of abnormally and uncomfortably hot and unusually humid weather. Typically a heat wave lasts two or more days.[3] These definitions are vague but provide useful guidance on how to build a practical rule to determine whether a heat wave has occurred or not. The definition of a cold wave usually mirrors that of a heat wave.

[2] Robustness tests using different climate datasets not implemented yet.
[3] http://w1.weather.gov/glossary

First, both the IPCC and the NOAA suggest that heat waves are right tail events in the local distribution of temperature. There is not an absolute temperature threshold beyond which a high temperature event can be characterized as a heat wave. The temperature threshold changes over space and over the seasons. According to both definitions heat waves are harmful because they are unexpected.

Second, both the IPCC and the NOAA suggest that the duration of the warm spell is important. Heat waves are prolonged periods with abnormally high temperatures. Implicitly, this assumes that the effect of extreme heat is cumulative over time. Unfortunately there is no clear indication on how long the warm spell should last to be considered a heat wave.

We assume that a heat wave occurs when the county-level daily mean temperature is in the extreme right tail of the distribution for several days without interruption. We use the county long-term monthly distribution of daily mean temperature to determine whether extreme temperatures are observed or not. We experiment with 1.5 and 2 standard deviations from the mean as cut-off points.[4] We then count how many times we observe the daily temperature higher than the cut-off point for one to two, three to five, six to nine, nine to twelve, and above twelve days without interruption during each month. We then aggregate all counts over the months from April to September.

Our working definitions for heat and waves follow the guidelines set by both the IPCC and the NOAA. The heat wave is a location and time specific extreme temperature event that lasts a prolonged amount of time. We define cold waves analogously.

3.4 Drought

The IPCC SREX report defines drought as "A period of abnormally dry weather long enough to cause a serious hydrological imbalance. Drought is a relative term, therefore any discussion in terms of precipitation deficit must refer to the particular precipitation-related activity that is under discussion." (IPCC 2012). This definitions presents challenges analogous to the definition of heat waves.

There are two main perspectives from which drought can be defined. Soil moisture drought (or agricultural drought) refer to insufficient moisture in the soil. Soil moisture drought indicators measure the imbalance between supply and demand of water. These indicators reflects management decisions (e.g. crop choice), soil, other geographic characteristics and temperature. Usually, drought indicators can also be used to measure excessive presence of water, which may be equally harmful for crop

[4] The distribution of daily mean temperature is left-skewed and almost truncated to the right. Extreme temperature above 2 standard deviations from the mean are almost never observed in the Eastern United States.

development. Meteorological drought refers instead to a lack of precipitation. A third type that we do not use in this paper is the hydrological drought, which refers to negative anomalies in the flow of rivers, in the level of lakes or in groundwater levels.

Drought is a recurring feature of all climates in any region because it is defined with respect to average climate in each region. Drought should not be confused with aridity, which indicates a persistent scarcity of water (IPCC 2012).

We use the Palmer Drought Severity Index (PDSI) from the NOAA climate divisions dataset to measure the severity of soil moisture drought. The PSDI index measures the severity of a dry or wet spell. The index generally ranges from -6 to +6, with negative values denoting dry spells and positive values indicating wet spells (Table 3). We consider values of the PDSI between -0.5 and -3 to be indicators of moderate drought. Values below -3 are considered to be indicators of severe drought. Analogously, we build indicators of moderate and sever wet spells. We count how many times a dry or a wet spell are observed from April to September in each climate division. We find county-level PSDI indexes by averaging census division values with weights proportional to area coverage.

We use the Standardized Precipitation Index (SPI) from the NOAA climate divisions dataset. For each calendar month the total amount of rainfall during a period that ranges from one month to twenty four months in the past is compared to the climatology of rainfall. The indicator measures the number of standard deviations that separate average monthly precipitation over the chosen time span from the mean precipitation. For example, the three month SPI for August 2015 is built by averaging rainfall over June, July and August 2015 and by counting the number of standard deviations that separate this short-term average from the long-term climatology, for the same location.

3.5 Hail

Hail has severe negative consequences for crops. The actual extent of the damage depends on the stage of growth of the plant. Hail can impact the development of the plant and can shutter the mature crop. Hail during the middle stages of development causes the largest damage Busch (1975). Hailstorms last only minutes and are heavily localized, but can be destructive. Hail risk is idiosyncratic and losses are generally limited for insurers. Hail insurance is one of the earliest forms of weather insurance, with crop-hail insurance programs available in France, Germany and Italy since the early 1800’s.

We use the NOAA Storm Events database for extreme weather events to estimate the number of hail events reported in each county from April to September, per 100 square miles. In robustness tests we also control for hail size.

3.6 Tornados

Tornadoes, like hail, have a destructive impact on crops but the spatial extent of damages is limited. We use the NOAA Storm Events database to count how many tornadoes are observed during the months from April to September in each county, per 100 square miles. We separate tornados in two groups: mild storms and Cat 3 or above storms.[5]

	Corn				Soybeans			
	Mean	St. Dev.	Min	Max	Mean	St. Dev.	Min	Max
Cold wave (count, Apr-Sep)	0.99	1.29	0	10.0	1.00	1.30	0	10.0
Heat wave (count, Apr-Sep)	0.12	0.37	0	4.00	0.12	0.39	0	4.00
Drought - PDSI Moderate (count, Apr-Sep)	0.66	0.68	0	2.0	0.65	0.68	0	2.0
Drought - PDSI Extreme (count, Apr-Sep)	0.04	0.10	0	0.50	0.03	0.10	0	0.50
Hail (count Apr-Sep / 100 sq. miles)	0.31	0.55	0	10.9	0.34	0.58	0	11.4
Tornado (Cat < 3) count, Apr-Sep / 100 sq. miles)	0.05	0.14	0	3.1	0.06	0.14	0	3.1
Tornado (Cat ≥ 3) (count, Apr-Sep / 100 sq. miles)	0.004	0.031	0	1.1	0.004	0.033	0	1.1

Notes: all coefficients have been multiplied by 100.

Table 2. Summary statistics of extreme weather events

4 Results and discussion

We start by estimating the impact of heat and cold waves, drought, hail and tornadoes on crop yields separately. We then consider the joint impact of all extreme events.

We assume that a heat wave occurs when the mean daily temperature is above the two standard deviations from the long-term distribution of the monthly mean temperature for at least three consecutive days during each month from April to September. We count all the heat wave events during the months from April to September in each year. We proceed analogously to determine the number of

[5] Enhanced Fujita Scale describes the strength of the tornado based on the amount and type of damage caused by the tornado. We use the category EF2 to separate moderate from severe tornados. Category EF2 tornadoes generate significant damage. Wind speed is between 113 – 157 mph.

cold waves. We then estimate model (1) using heat waves and cold waves together with temperature bins and a quadratic functional form of average rainfall.

As shown in Table 3, the independent regressions of each event reveal that a single cold wave event reduces corn crop yields in a county by 2.2% and soybeans yields by 0.8%. A heat wave event is more harmful and reduces corn yields by 3.5% and soybeans yields by 2.1%. The results for corn yields are significant at the 1% and 5% level, for soybeans they are significant at the 10% level. Drought events are unambiguously harmful for both corn and soybeans. Moderate droughts reduce corn yields by 3.2% and soybeans yields by 1.9%. A severe drought event reduces corn yields by 36.4% and soybeans yields by 21.2%. The estimates are all significant at the 1% level. These results are consistent with the 30% corn yield reduction in the US Midwest during the drought and heat wave of 1988 reported in Rosenzweig et al. (2001). Hail events also impact both corn and soybeans yields. One additional event over 100 square kilometers of the county area reduces corn yields by 0.9% and soybeans yields by 0.8%. These point estimates are robust across yields and model specifications, but are significant only at the 10% level. A mild tornado reduces corn yields by about 1.3% and soybeans yields by 1.7% and a strong tornado reduces corn yields by 1.7% and soybean yields by 4.7%, though the effects are not statistically significant.

	Corn	Soybeans	Corn	Soybeans
	Separately		All extreme events	
Cold Wave (count, Apr-Sep)	-2.16***	-0.82*	-1.73***	-0.53
	[0.45]	[0.43]	[0.45]	[0.43]
Heat Wave (count, Apr-Sep)	-3.48**	-2.11*	-2.83**	-1.73
	[1.44]	[1.18]	[1.44]	[1.13]
Drought - PDSI Moderate (count, Apr-Sep)	-3.23***	-1.86***	-3.29***	-1.93***
	[0.72]	[0.64]	[0.71]	[0.64]
Drought - PDSI Extreme (count, Apr-Sep)	-36.4***	-21.2***	-29.84***	-18.34***
	[6.17]	[5.46]	[6.07]	[5.23]
Hail (count/100 sq. miles, Apr-Sep)	-0.91*	-0.85*	-0.88*	-0.75
	[0.54]	[0.52]	[0.71]	[0.64]
Tornado (Cat < 3) (count/100 sq. miles, Apr-Sep)	-1.3	-1.74	-1.41	-3.41***
	[1.22]	[1.42]	[1.13]	[1.02]
Tornado (Cat ≥ 3) (count/100 sq. miles, Apr-Sep)	-1.59	-4.7	-0.83	-4.1
	[4.31]	[4.03]	[4.22]	[3.96]

Notes: Notes: all coefficients have been multiplied by 100. A total of 55,030 county-year observations is used to estimate the corn yield model. 46,658 county-year observations are used to estimate the soybeans yield model. Unbalanced panels used for both corn and soybeans models. The corresponding temperature coefficients are displayed in Figure A - 2. All standard errors corrected for spatial correlation.

Table 3. Impact of extreme weather events on corn and soybeans yields.

When we jointly include all extreme events in model (1) we find that the sign of the coefficients and their magnitude do not change significantly. The impact of heat and cold waves on soybeans becomes insignificant. Droughts continue to be severely and significantly harmful. The hail coefficient is also largely unchanged. Tornados are still harmful but insignificant, except for moderate tornadoes and soybeans.

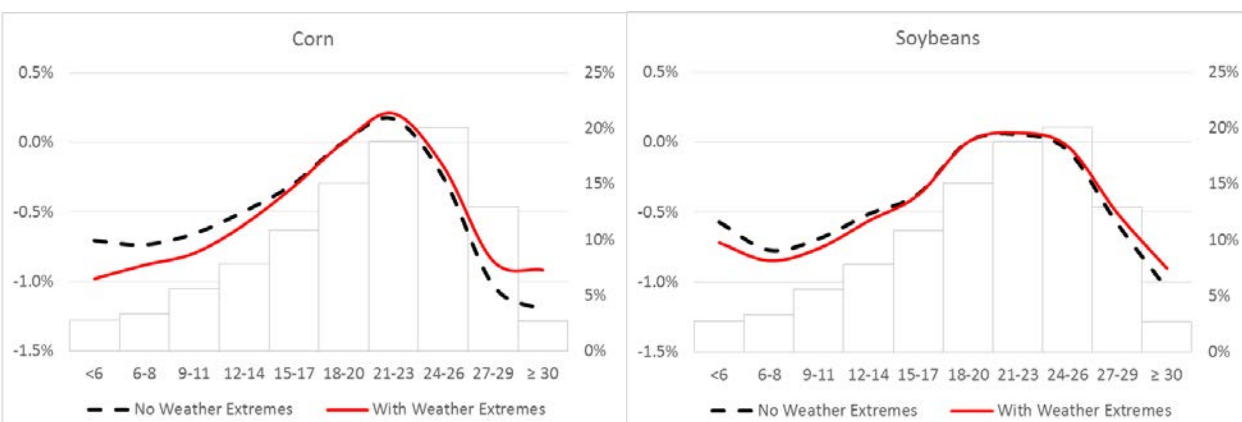
This first set of results clearly indicates that extreme weather events affect crop yields. Droughts are particularly harmful and their omission may underestimate the impact of future climate change on crop yields if the frequency with which droughts occur increases.

Multiplying the damage per event times the probability of each event yields the expected damage per year in each county from extreme events. Table 4 presents the expected damage for each extreme event. The impacts of mild and strong storms are added together. Although each cold event is only moderately harmful, cold waves happen every year. The expected damage from cold events is 2.1% for corn yields and 0.8% for soybeans yields. Although individual heat waves are more harmful, they happen less often and so the expected damage from heat waves is much smaller than from cold waves accounting for losses of only 0.4% per year for corn yields and 0.2% per year for soybean yields. Although moderate droughts are less harmful per event, they account for more harm than severe droughts. Moderate droughts cause expected damage of 2.1% a year for corn and 1.2% for soybean whereas severe drought cause expected damage of 1.2% a year for corn yields and 0.7% a year for soybean yields. The expected damage from hail is only 0.3% each year. The expected damage from tornadoes is only 0.07% per year on corn and 0.12% per year on soybeans. Over half the damage from extreme events are consequently caused by droughts. The next largest risk to corn and soybeans is from cold waves. Hail, heat waves, and tornadoes altogether are responsible for only 12% of the expected damage from extreme events for corn and 19% of the damage to soybeans.

Extreme Event	Corn	Soybeans
Cold Wave	-2.1%/year	-0.8%/year
Heat Wave	-0.4%/year	-0.2%/year
Drought	-3.3%/year	-1.9%/year
Hail	-0.3%/year	-0.3%/year
Tornado	-0.07%/year	-0.12%/year
TOTAL	**-6.2%/year**	**-3.3%/year**

Table 4. Expected Damage by Extreme Events on Corn and Soybeans

One interesting question is whether the omission of extreme weather events from model (1) affects the estimates of the temperature coefficients. We compare the two yield functions for corn and soybeans in Figure 1. The inclusion of weather extremes do not change the overall hill-shape of the yield function with respect to temperature nor does it change the estimates in the central part of the temperature distribution. However, the inclusion of extreme events does change the shape of the distribution in both tails. The damage function shifts downward on the cold side of the distribution and upwards on the warm side of the distribution. Adding extreme events effectively makes cold temperatures more harmful and high temperature less harmful. The effect is stronger for corn than for soybeans.



Notes: all coefficients have been multiplied by 100.

Figure 1. Temperature effects on yields, with and without extreme events.

When these changes are introduced into an estimation of climate change impacts, they substantially change the results. For example, with a 3°C uniform warming, the impact of warming on corn yields is equal to -31.9% [-26.1%, 37.6%] without extreme events but -20.6% [-26.9%, -14.2%] with extreme events. This is equivalent to a 35% reduction of the point estimates. The 95% confidence interval is in brackets. For soybeans, a 3°C uniform warming scenario implies a yield change of -30.7% [-36.2%, -25.2%] without extreme events, and -24.8% [-31.0%, -18.7%] with extreme events included.

These results suggest that the omission of extreme weather variables moderately bias the estimates of temperature coefficients. Omitting extreme events appears to bias the temperature coefficients especially near the tails of the distribution. Models that rely on intertemporal weather shocks to estimate climate effects still need to pay attention to include all the relevant variables in order to avoid omitted variable bias.

Finally, we test whether extreme weather events affect land values in the Eastern United states using the Ricardian model. Note that we use climatologies of extreme events rather than annual observations. The impact of the extreme event on land values is identified using the cross-section variation in the frequency with which the weather extremes are observed in different counties. Average temperature and precipitations are controlled using a standard quadratic functional form of seasonal temperature and precipitation means.

In general, we do not find that extreme weather events significantly affect land values in the Eastern United States. The result does not change if we use temperature and precipitation only during the growing season or temperature bins.

We suspect that extreme events have no effect on the land value of farms in the United States because they are protected from extreme events by subsidized public crop insurance. The crop insurance reimburses for all extensive losses from extreme events. Yet, the premiums for this insurance are the same no matter what the climate risk of the farm.

5 Robustness tests

We start by testing the impact of cold and heat waves. We have defined heat (cold) waves as three or more consecutive days with temperature above (below) 2 standard deviations from the long-term monthly mean. We test if the results are stable when we use 1.5 standard deviations from the mean as a cut-off point and when we classify as heat/cold waves only abnormal spells five or more days long. We also test whether the functional form used to describe average temperature conditions alters the magnitude and sign of the heat/cold wave coefficients. Table 5 reports the results.

	> 3 days 2 stdev	> 3 days 1.5 stdev	> 5 days 2 stdev	> 5 days 1.5 stdev	All temperature bins	Average Temperature
CORN						
cold wave	-2.16***	-1.27***	-2.76***	-1.36***	-0.55**	-3.88***
	[0.45]	[0.32]	[0.52]	[0.37]	[0.23]	[0.56]
heat wave	-3.48**	-2.1***	-7.72	-5.48***	-5.83**	-5.58***
	[1.44]	[0.64]	[5.05]	[1.5]	[2.84]	[1.69]
SOYBEANS						
cold wave	-0.82*	-0.63**	-0.98**	-0.55	-0.7	-2.56***
	[0.43]	[0.31]	[0.49]	[0.35]	[1.15]	[0.47]
heat wave	-2.11*	0.36	-3.28	-3.04**	-2.6**	-4.25***
	[1.18]	[0.57]	[3.11]	[1.35]	[1.16]	[1.24]

Notes: all coefficients have been multiplied by 100.

Table 5. Robustness test of heat/cold wave coefficients.

Changing the cut-off point and the duration required for heat and cold waves does not change the sign of the coefficients but it changes the magnitude of the coefficients. The changes are predictable and are a sign that our working definition of heat and cold waves works well. When we shift from 2 to 1.5 standard deviations the impacts become smaller and in some cases non-significant. When we increase the duration requirement, the heat and cold waves become more harmful. The results when we use all temperature bins or when we use a quadratic specification of growing season temperature are also consistent with what we find in our preferred specification. The use of average temperature significantly increases the negative impacts of the temperature extremes, probably because the average temperature model is not as good as the temperature bin model at controlling for the impact of extreme temperatures.

Using five days or longer heat or cold spells to define heat or cold waves also does not alter the results when we use all extreme events together (Table 6).

	CORN	SOYBEANS	CORN	SOYBEANS
	Extreme cold/heat > 3 days		Extreme cold/heat > 5 days	
cold wave	-1.73***	-0.53	-2.2***	-0.31
	[0.45]	[0.43]	[0.51]	[0.6]
heat wave	-2.83**	-1.73	-6.72	-2.34
	[1.44]	[1.13]	[5.35]	[4.3]
Drought - PDSI Moderate (months, during Apr-Sep)	-3.29***	-1.93***	-3.17***	-3.12***
	[0.71]	[0.64]	[0.72]	[0.8]
Drought - PDSI Extreme (months, during Apr-Sep)	-29.84***	-18.34***	-31.12***	-27.65***
	[6.07]	[5.23]	[6.11]	[6.5]
Hail (events during Apr-Sep / 100 square miles)	-0.88*	-0.75	-0.81	-0.96**
	[0.71]	[0.64]	[0.72]	[0.8]
Tornado (Cat < 3) (events during Apr-Sep / 100 square miles)	-1.41	-3.41***	-1.34	-1.78
	[1.13]	[1.02]	[1.13]	[1.49]
Tornado (Cat ≥ 3) (events during Apr-Sep / 100 square miles)	-0.83	-4.1	-1.02	-3.37

Notes: all coefficients have been multiplied by 100.

Table 6. Robustness test of alternative heat/cold wave specifications with all extreme events.

We test a heat and cold wave bins model. We count the number of times we observe heat and dry spells of different duration and we include the distribution of the extreme temperature events during the growing season, from April to September. We continue using 2 standard deviations from the long-term monthly mean as the cut-off point. Table 7 present interesting results. For corn, we find that cold spells are usually more harmful than hot spells. Longer duration cold spells are more harmful than short duration spells. The results for heat waves are surprising. Only extremely long heat waves cause significant damage to corn yields. The effect of twelve or more days with temperature above 2 standard deviations above the long-term monthly mean reduce crop yields by 36%. This result suggest that farmers may have adapted to extreme heat events, but the very exceptional ones. The results for soybeans are less intuitive. Only the moderately long cold waves have a significantly negative effect on yields. Heat waves do not have a significant impact on yields. The extreme heat waves have a positive and significant impact, which raises questions on the validity of the result.

	CORN	SOYBEANS
cold wave < 3 days	-5.87**	-3.9*
	[2.57]	[2.23]
cold wave 3 ≤ days < 6	-6.03**	-5.42**
	[2.7]	[2.33]
cold wave 6 ≤ days < 9	-7.58**	-1.53
	[2.76]	[2.47]
cold wave 9 ≤ days < 12	-10.86***	-3.52
	[2.81]	[2.31]
cold wave ≥ 12 days	-6.91***	-2.8
	[2.76]	[2.47]
heat wave < 3 days	5.27**	2.54
	[2.44]	[2.04]
heat wave 3 ≤ days < 6	3.2	0.78
	[2.67]	[2.22]
heat wave 6 ≤ days < 9	2.21	-4.43
	[5.06]	[3.55]
heat wave 9 ≤ days < 12	-8.86	4.27
	[7.65]	[4.78]
heat wave ≥ 12 days	-35.6***	21.04***
	[6.63]	[7.19]

Notes: all coefficients have been multiplied by 100.

Table 7. Impact of heat and cold wave of different duration.

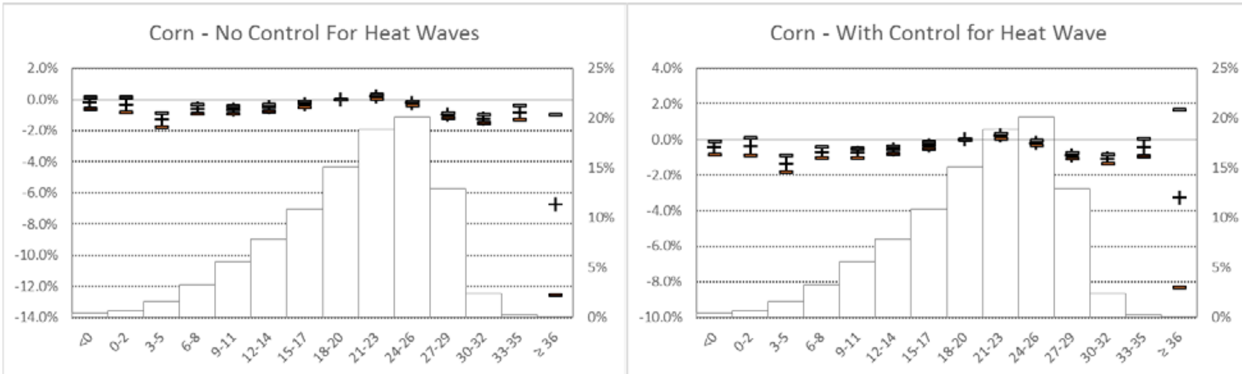
We proceed by separating extreme temperature events in spring and summer. This similar to interact the extreme temperature events with temperature levels. Heat waves in spring achieve temperature levels that are much lower than heat waves in summer. Cold waves in summer are milder than cold waves in spring. We present results in Table 8. Cold waves in spring are significantly very harmful for corn, harmful but not always significant for soybeans. Soybeans suffer from cold waves in summer, while corn does not. Moderate length heat waves in spring are significantly positive for corn, but not significant for soybeans. Heat waves are harmful for corn in summer, especially the nine to twelve days heat waves, which reduce yields by almost 60%. Heat waves in summer are instead beneficial for soybeans.

Figure 6 displays yield functions estimated using all temperature bins, without and with controls for heat waves. The last temperature bin in the model without controls for heat waves indicates very harmful impacts from just one day with temperature at or above 36 °C. After we introduce a control variable for heat waves the last two temperature bins become non-significant. This suggests that duration matters. Only a proper characterization of heat waves can describe the impact of the extreme temperature on yields.

	CORN	SOYBEANS
cold wave < 3 days - spring	-20.19***	-9.61*
	[6.06]	[5.73]
cold wave 3 ≤ days < 6 - spring	-22.19***	-6.91
	[6.51]	[5.83]
cold wave 6 ≤ days < 9 - spring	-12.69**	-7.62
	[6.34]	[5.81]
cold wave 9 ≤ days < 12 - spring	-18.88***	-8.76
	[6.13]	[5.86]
cold wave ≥ 12 days - spring	-15.34**	-7.25
	[6.34]	[5.81]
cold wave < 3 days - summer	8.76*	-11.74***
	[4.84]	[4.1]
cold wave 3 ≤ days < 6 - summer	8.15	-13.29***
	[4.99]	[4.06]
cold wave 6 ≤ days < 9 - summer	5.51	-7.59*
	[4.94]	[4.04]
cold wave 9 ≤ days < 12 - summer	2.03	-9.94**
	[4.99]	[4.08]
cold wave ≥ 12 days - summer	6.02	-9.12**
	[4.56]	[3.79]
heat wave < 3 days - spring	16.72**	7.6
	[5.96]	[5.54]
heat wave 3 ≤ days < 6 - spring	10.71*	2.56
	[5.95]	[5.51]
heat wave 6 ≤ days < 9 - spring	16.49**	-2.26
	[8.3]	[6.87]
heat wave 9 ≤ days < 12 - spring	28.38***	-2.78
	[7.44]	[6.79]
heat wave ≥ 12 days - spring	-9.27**	9.11**
	[4.68]	[3.81]
heat wave < 3 days - summer	-9.47*	10.52**
	[4.89]	[3.87]
heat wave 3 ≤ days < 6 - summer	-6.3	6.31
	[6.79]	[4.57]
heat wave 6 ≤ days < 9 - summer	-21.02**	11.7*
	[9.64]	[6.14]
heat wave 9 ≤ days < 12 - summer	-51.23***	24.64***
	[7.53]	[8.34]
heat wave ≥ 12 days - summer	138.23	-142.94*
	[141.52]	[85.66]

Notes: all coefficients have been multiplied by 100.

Table 8. Impact of heat and cold wave of different duration, in spring and summer.



Notes: On the primary vertical axis impact on yields in percentage. The vertical axis measures the impact of substituting one day with mean temperature in a given bin with a day with mean temperature between 18 and 20 °C, the reference temperature level in our analysis. The dotted lines indicate the 95% confidence interval corrected for spatial correlation. The underlying histograms depict the mean daily temperature distributions over the counties and years included in the panel regression. The frequency of daily temperature observations is measured on the secondary axis. On the horizontal axis temperature measured in °C.

Figure 2. The effect of controlling for heat waves in temperature bins models.

	CORN	SOYBEANS
Drought - SPI 12 months SPI < -2.5 (months, during Apr-Sep)	-43.24**	-36.3**
	[21.35]	[14.92]
Drought - SPI 12 months -2.5 ≤ SPI < 1.0 (months, during Apr-Sep)	-12.91*	-2.04
	[7.67]	[7.86]
Drought - SPI 12 months -1.0 ≤ SPI < 0 (months, during Apr-Sep)	-2.45	-3.05
	[2.5]	[2.43]
Wet spells - SPI 12 months SPI > 2.5 (months, during Apr-Sep)	-15.77	-5.64
	[11.21]	[10.35]
Wet spells - SPI 12 months 1.0 < SPI ≤ 2.5 (months, during Apr-Sep)	1.15	5.87
	[2.5]	[2.43]
Wet spells - SPI 12 months 0 < SPI ≤ 1.0 (months, during Apr-Sep)	-7.59***	-4**
	[1.9]	[1.61]

Notes: The SPI index measures the number of months during the growing season during which the average precipitation during the previous 12 months is 0 to 1, 1 to 2.5 or more than 2.5 standard deviations from the long-term mean during the same period.

Table 9. Alternative specification for droughts and wet spells.

We test the model using the SPI, an indicator of meteorological drought and wet spells, to test if the results are robust to alternative specifications of dry and wet spells. Table 10 reports the results. We find confirms the finding that extreme droughts are significantly and severely harmful, for both crops. Wet spells are also generally harmful. However, only the less intense ones are significantly harmful.

	CORN	SOYBEANS
cold wave < 3 days	-5.85**	-6.56**
	[2.56]	[3.09]
cold wave 3 ≤ days < 6	-5.7**	-12.18***
	[2.69]	[3.3]
cold wave 6 ≤ days < 9	-7.78***	-3.64
	[2.72]	[3.09]
cold wave 9 ≤ days < 12	-10.89***	-8.73**
	[2.78]	[3.12]
cold wave ≥ 12 days	-7.04***	-4.98*
	[2.72]	[3.09]
heat wave < 3 days	5.41**	5.69**
	[2.44]	[2.79]
heat wave 3 ≤ days < 6	3.91	4.65
	[2.61]	[2.91]
heat wave 6 ≤ days < 9	3.83	-2.49
	[5]	[4.86]
heat wave 9 ≤ days < 12	-7.18	7.51
	[8.07]	[10.84]
heat wave ≥ 12 days	-36.2***	31.33***
	[6.78]	[7.69]
Drought - SPI 12 months SPI < -2.5 (months, during Apr-Sep)	-47.05**	-20.68
	[21.61]	[25.53]
Drought - SPI 12 months -2.5 ≤ SPI < 1.0 (months, during Apr-Sep)	-8.06	-14
	[7.29]	[11.99]
Drought - SPI 12 months -1.0 ≤ SPI < 0 (months, during Apr-Sep)	-0.71	-6.45**
	[2.46]	[3.23]
Wet spells - SPI 12 months SPI > 2.5 (months, during Apr-Sep)	-18.8*	-4.81
	[11.36]	[10.49]
Wet spells - SPI 12 months 1.0 < SPI ≤ 2.5 (months, during Apr-Sep)	2.74	8.86*
	[4.67]	[4.81]
Wet spells - SPI 12 months 0 < SPI ≤ 1.0 (months, during Apr-Sep)	-7.36***	-2.54
	[1.9]	[1.96]
Hail (events during Apr-Sep / 100 square miles)	-1.08**	-1.08**
	[0.52]	[0.44]
Tornado (Cat < 3) (events during Apr-Sep / 100 square miles)	-0.86	-1.86
	[1.09]	[1.41]
Tornado (Cat ≥ 3) (events during Apr-Sep / 100 square miles)	-0.73	-4.1
	[4.25]	[4.49]

Notes: all coefficients multiplied by 100 to express percentage change of yields.

Table 10. Alternative specification including all extreme events.

We include the alternative indicators for heat and cold waves and for dry and wet spells into a model with also hail and tornados and we do not find significant changes to the results. The full model amplifies the negative impact of extreme heat waves and extreme droughts for corn yields. The impact of hail events is remarkably stable, and tornadoes remain not significantly harmful.

	Corn	Soybeans
Hail - diam < 0.5''	15.09**	12.85**
	[5.59]	[6.18]
Hail 0.5'' ≤ diam < 1.0''	-0.4	-0.46
	[0.7]	[0.72]
Hail 1.0'' ≤ diam < 1.5''	-1.32*	-1.61**
	[0.77]	[0.79]
Hail 1.5'' ≤ diam < 2.0''	-1.1	-0.63
	[0.93]	[0.9]
Hail diam ≥ 2''	-3.04*	-1.6
	[0.77]	[0.79]

Notes: all coefficients multiplied by 100 to express percentage change of yields.

Figure 3. Impact of hail events, differentiated by hail size.

Finally, we test whether controlling for the size of hail changes the impact of hail events. We find that small hail is actually beneficial. This is a counterintuitive results that require further investigation. Hail of larger size is instead always harmful. Very large hail is particularly harmful for crop yields, but less so for soybeans.

Future drafts of the paper will include robustness tests using different temperature and precipitation datasets.

6 Conclusions

We provide a careful assessment of the impact of heat waves, cold waves, drought, hail and tornadoes on US agriculture. We estimate the impacts of these extreme events on corn and soybeans yields and on farmland values. We find that extreme events reduce corn yields by 6% and soybean yields by 3% per year. Droughts are especially harmful explaining over half of these expected losses. Cold spells cause an additional 34% of the damage to corn and an additional 24% of the damage to soybeans. Heat waves cause about 6% of the damage of extreme events.

Despite these large damages from extreme events, we find that extreme events do not affect farmland values at all. It appears that the subsidized public crop insurance effectively protects farmers from extreme events. They are compensated for most losses and yet pay a uniform low premium to have insurance. Consequently, farmers in locations such as the southern Great Plains with very high damages from extreme events (25% per year) consequently have the same farmland values as farms in places such as the Corn Belt with low expected damages of only 3% per year.

We also demonstrate that the omission of extreme events bias the coefficients of temperature bin models. Specifically, including extreme events reduces the harmful effects of high temperatures and increases the harmful effects of low temperatures. This suggests that most existing weather panel models are biased because they omit measures of extreme events. In order to accurately estimate future climate change impacts it is necessary to correctly attribute impacts to all different weather events.

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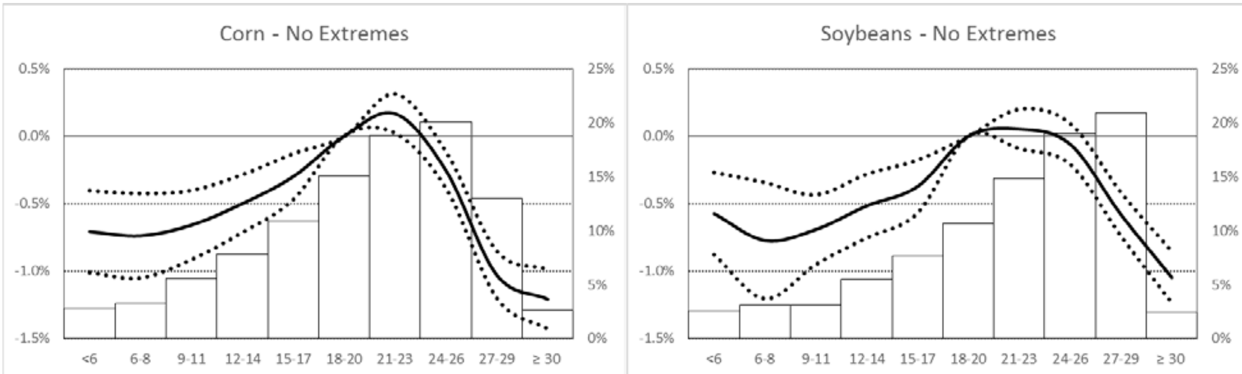
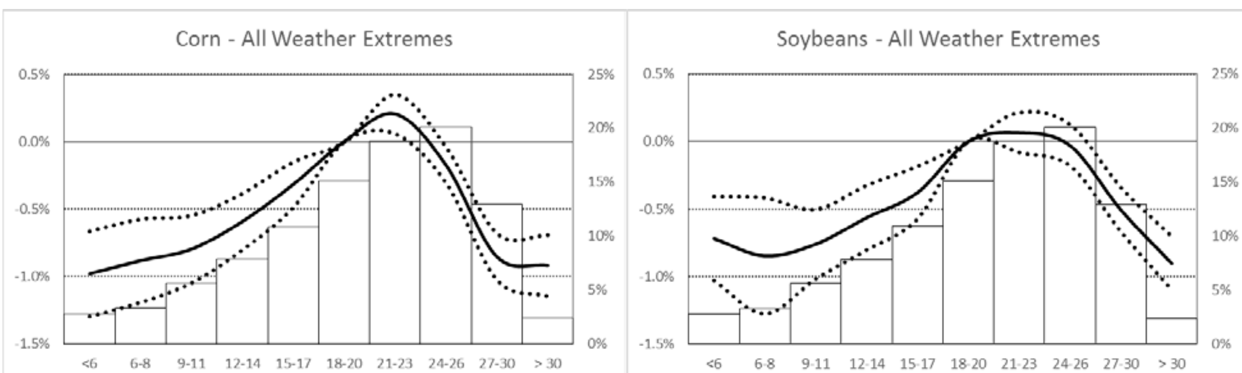
Appendix



Notes: On the primary vertical axis impact on yields in percentage. The vertical axis measures the impact of substituting one day with mean temperature in a given bin with a day with mean temperature between 18 and 20 °C, the reference temperature level in our analysis. The dotted lines indicate the 95% confidence interval corrected for spatial correlation. The underlying histograms depict the mean daily temperature distributions over the counties and years included in the panel regression. The frequency of daily temperature observations is measured on the secondary axis. On the horizontal axis temperature measured in °C.

Figure A - 1. Temperature effects, with 95% confidence interval corrected for spatial correlation.



Notes: On the primary vertical axis impact on yields in percentage. The vertical axis measures the impact of substituting one day with mean temperature in a given bin with a day with mean temperature between 18 and 20 °C, the reference temperature level in our analysis. The dotted lines indicate the 95% confidence interval corrected for spatial correlation. The underlying histograms depict the mean daily temperature distributions over the counties and years included in the panel regression. The frequency of daily temperature observations is measured on the secondary axis. On the horizontal axis temperature measured in °C.

Figure A - 2. Temperature effects in models that include extreme events.