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Extreme Dry Spells and Larger Storms in the U.S. Midwest Raise Crop Prices

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Abstract

The U.S. Midwest produces about a third of global corn and soybeans, two of the most important crops for humanity. Earlier literature has found that corn and soybean output is sensitive to weather in a nonlinear manner: yields benefit from moderate rain and temperatures, and generally suffer under drought, excessive rain and extreme heat. In this study we explore how changing weather patterns and extreme events in the U.S. Midwest have impacted the valuation of corn and soybeans. Using data for 1971-2019 we find that the distribution of regional summer rain has experienced a significant shift towards the right since 1993, with a marked increase in extreme rain episodes. Prior to 1993, dry spells during the summer led to strongly higher crop prices and were exacerbated by extreme heat. Since 1993, extreme dry spells and larger storms have been both associated with price increases in the 10% range. We also find that the nonlinear price response to weather is compatible with the impact of weather on terminal yields. Our results suggest that changing weather patterns and extreme events in the U.S. Midwest have a strong influence in the valuation of corn and soybeans.

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1. Introduction

Corn and soybeans are two of the most important sources of calories for humanity and for animal feed. The U.S. Midwest has produced in recent decades about 33% of global corn and 34% of global soybeans [Wang et al., 2020]. Has a changing climate influenced the valuation of corn and soybeans grown in the U.S. Midwest? Are more extreme weather events affecting crop prices? How large is this price impact? Earlier work has found that high temperatures, drought and excessive rain are all detrimental to corn and soybean yields [Tannura et al., 2008, Schlenker and Roberts, 2009, Miao et al., 2016, Lesk et al., 2016, Vogel et al., 2019]. Soil moisture, which depends on precipitation, evapotranspiration driven by temperature and local soil characteristics has been recently shown to explain spatial and interannual variability in yields [Ortiz-Bobea et al., 2019, Rigden et al., 2020, Proctor et al., 2022]. Hence, a changing climate has the potential to deeply affect growing crop conditions around the world. Early projections of crop damages from increased precipitation induced by climate change in the U.S. include Rosenzweig et al. [2002]. More recent work has found a strongly negative average impact of global warming on crop yields and agricultural productivity [Lobell et al., 2011, Hsiang et al., 2017, Zhao et al., 2017, Jägermeyr et al., 2021, Ortiz-Bobea et al., 2021] that is, however, heterogeneous across space.

Negative climate effects on yields are already apparent in Europe [Moore and Lobell, 2015]. The U.S. Midwest is expected to suffer a decrease in agricultural productivity if summer temperatures over 30 degrees Celsius increase in frequency [Schlenker and Roberts, 2009, Lobell et al., 2013]. However, this negative effect has apparently not materialized yet. On the contrary, Mueller et al. [2016], Tollenaar et al. [2017], Butler et al. [2018] and Rizzo et al. [2022] found that the U.S. Midwest has experienced increasing yields caused in part by a higher frequency of moderate temperatures that allow earlier planting, a decrease in the incidence of extreme temperatures and higher precipitation during the summer. Although weather for growing corn and soybeans has improved on average, crops have become more sensitive to droughts [Lobell et al., 2014] and weather extremes have increased spatial yield correlations [Tack and Holt, 2016].

Unlike work on yields, direct estimates for the impact of weather shocks on crop prices are scarce. Work has explored the effect of El Niño / La Niña oscillation on corn and soybean price volatility [Peri, 2017] and the effect of global temperature anomalies since 1999 on corn and soybeans among other commodities [Makkonen et al., 2021]. In this paper we focus on the market impact of changing weather patterns and extreme events during the corn and soybean growing seasons since 1971 in the U.S. Midwest.

Market prices differ from yields in two fundamental aspects. First, there is no meaningful spatial heterogeneity in prices. The widely followed prices of corn and soybeans at the Chicago Mercantile Exchange (CME) reflect global demand and aggregate expected supply including that from all of the U.S. Midwest, therefore concealing fixed spatial variability in soil quality. Second, unlike yields, which are measured once a year, crop prices are available at any time during the growing season and dynamically incorporate the most recent information on expected output at future harvest. These considerations lead us to focus on the immediate response of market prices to higher frequency regional rain and temperature measures that are first in the causal chain from weather to slower moving variables such as soil moisture, and to subsequent yields. In addition, timely rain and temperature information has been widely followed by farmers and other market participants and has been historically available for many decades.

Informed by the nonlinear relationship between weather and physical output, we study the effect that U.S. Midwest weather shocks during June, July and August from 1971 to 2019 had on contemporaneous corn and soybean percentage CME price changes, also called returns. The region we consider comprises all of twelve states: Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota and Wisconsin. Our data sources for daily rain and temperature measures are 854 weather stations (Methods). Our main findings are summarized as follows. First, we provide empirical evidence of a strong increase in summer precipitation and larger storms in the U.S. Midwest since the early nineties. Then, we show that the emergence of stronger precipitation has been followed by an economically significant and previously undocumented nonlinear market response. Since the early nineties, crop price increases in the 10% range have been caused not only by dry spells and extreme heat, but also by extreme rain. Last, we find evidence suggesting that the market response to precipitation shocks is compatible with their impact on subsequently realized yields.

2. Results

2.1. Extreme summer rain has become more prevalent in the U.S. Midwest

We investigate the potential existence and timing of a statistically and agronomically significant change in the distribution of daily rain and temperature variables in the U.S. Midwest over the last half century. While climate change induced by global warming is a global phenomenon, its expression is highly heterogeneous across countries and regions. Our approach to assess weather patterns in the U.S. Midwest is agnostic and data driven. Because crop prices at the CME respond to aggregate supply including that from the entire U.S. Midwest, we work with time series of rain and temperature constructed as spatial averages over the entire region.[1] Table A.1 (Extended Data) presents summary statistics for weather variables with daily and monthly frequencies.

We split the 1971-2019 period in two contiguous time intervals and perform a Kolmogorov-Smirnov test to identify the rolling date t_c that maximizes the distance between the empirical cumulative distributions of weather variables recorded before and after t_c (figure B.3, Extended Data). Figure 1(a) displays the empirical distributions of daily rain during summers (June, July and August) between June 1, 1971 to June 30, 1992, and for July 1, 1992 to August 30, 2019. Average daily rain was 12.7% larger since July 1, 1992 than prior to that date. This increase is also very significant in agronomic terms. Figure 1(b) shows the percentage difference in summer precipitation in U.S. Midwest counties, comparing the 1971-1992 period against 1993-2019.

[1] Alternative averaging schemes, including weighting weather variables in each state by state share of crop production, led to very similar results to those presented in this paper.

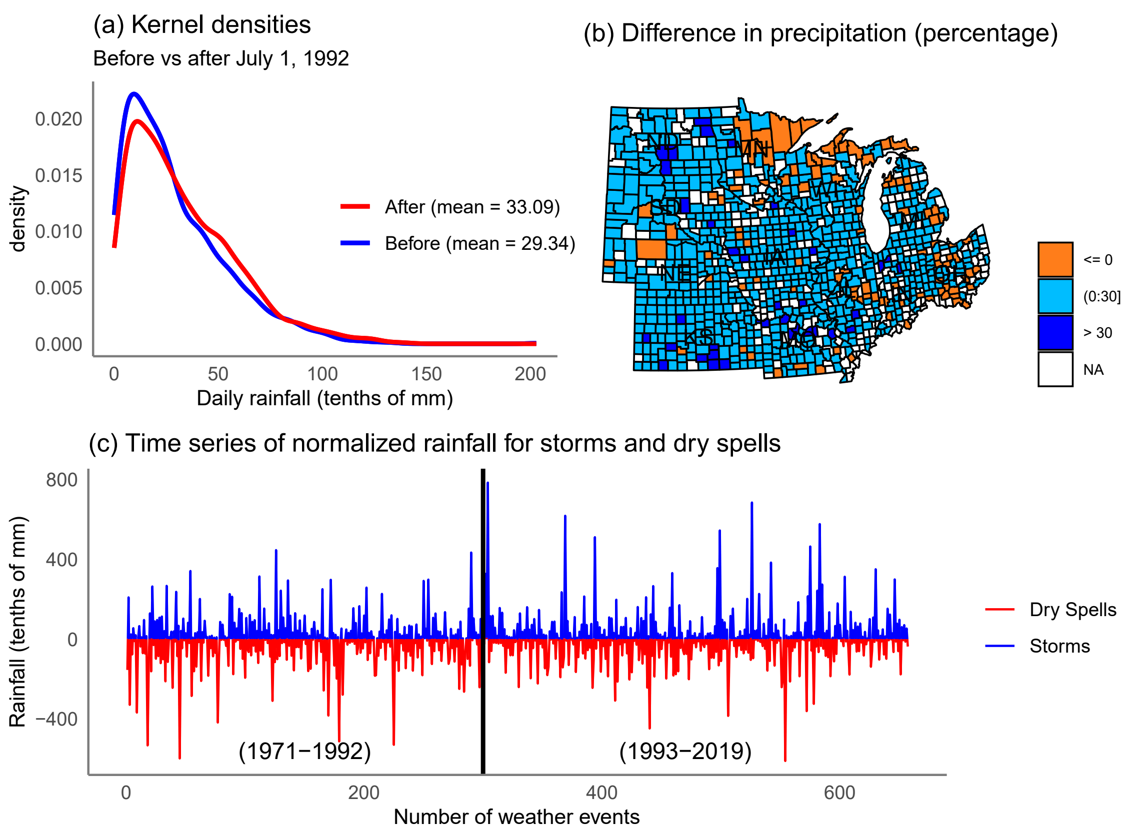

Figure 1: Rain patterns in the U.S. Midwest for June, July and August, 1971-2019. Figure 1(a) displays distributions of daily, spatially averaged rain, before and after July 1, 1992. This is the date that maximizes the Kolmogorov-Smirnov distance between the empirical distributions for two adjacent and non-overlapping periods spanning 1971-2019. Figure 1(b) displays differences in county mean daily rain between 1971-1992 and 1993-2019. Figure 1(c) displays the time series of normalized rain magnitudes for storms and dry spells. Storms are defined as two or more consecutive days with daily rain above 30 tenths of a mm. Dry spells include any day not in a storm.

Although some counties had a decline in mean precipitation, the rise was largely homogeneous in space and important in magnitude.

Weather patterns in the U.S. Midwest during the summer are often the consequence of structured fronts that tend to flow eastwards and last for several days. Thus, we introduce weather events defined in terms of precipitation spatially averaged over the U.S. Midwest. We define a storm as two or more consecutive days with daily rain measure above 30 tenths of a mm, close to mean daily precipitation for 1971-1992. Any day not in a storm belongs in a dry spell. Hence, we decompose each summer in a time sequence of weather events where storms and dry spells alternate with each other. Average event length between 1971 and 2019 was 6.3 days. We associate to each weather event the magnitude of rain over its length normalized by subtracting 30 tenths of a mm per day (Methods). Summary statistics for weather events are in table A.2 (Extended Data). Normalized storm magnitudes increased in size from a mean of 90 tenths of a mm prior to 1993 to 98 tenths of a mm since then. Standard deviations increased from 76 to 112 tenths of a mm. The time series of normalized weather event magnitudes in figure 1(c) suggests an increase in episodes of extreme rain in the post 1993 period. Dry spell episodes became less severe, with a reduction in their mean from -101 to -79 tenths of a mm. We complement our analysis on daily and event frequencies with a change-point in mean analysis for U.S. Midwest monthly rainfall (table A.3, Extended Data). We find that monthly rain had a statistically significant change in its mean, from 909 tenths of mm prior to 1993 to 1,010 tenths of mm since then, with significant precipitation increases for all quartiles.

Our overall finding is an increase in precipitation and extreme rain on daily, weather event and monthly frequencies during the growing season in the U.S. Midwest. Increases in average and extreme rain in the Midwest and other U.S. regions have been reported in earlier work [Kunkel et al., 2003, Arguez et al., 2012, Feng et al., 2016, Mueller et al., 2016, Davenport and Diffenbaugh, 2021, Davenport et al., 2021]. Attribution of rain increase to anthropogenic warming has gained strength in recent years but natural decadal climate variability should not be disregarded [Armal et al., 2018, Lesk and Anderson, 2021]. We interpret the magnitude of our estimates as evidence of strongly changing weather patterns but refrain from claiming a direct causal link to global warming.

Tests for changes in spatially averaged summer temperature measures in the U.S. Midwest were much less conclusive than for rain. The Kolmogorov-Smirnov statistic for the mean temperature series (figure B.3(b) in Extended Data) was maximized on August 16, 1998. Figures B.4(a,b) (Extended Data) show a slight shift in the distribution of spatially averaged daily temperature with a mean increase by two tenths of a degree Celsius from the first to second periods. This is a temperature variation that is small in agronomic terms and spatially heterogeneous. While the eastern and southern edges of the U.S. Midwest seem to have warmed up slightly on average, this is not the case for its central part that exhibits many instances of cooling as in Mueller et al. [2016]. Daily time series of Extreme Degree Days (EDD) and Growing Degree Days (GDD) with threshold in 30 degrees Celsius, which are temperature measures widely validated by the literature for their relevance in explaining crop yields, did not exhibit a visible break in figure B.4(c) (Extended Data). Additional statistical tests, for a change-point in mean analysis on U.S. Midwest monthly EDD and GDD, are in table A.3 (Extended Data) and are not conclusive about a change in temperature measures. The literature [Mueller et al., 2016, Butler et al., 2018] has found a decrease in extreme heat events in certain parts of the U.S. Midwest by studying centennial trends, differences across nonconsecutive decades and agricultural intensification at the county and weather station level. Perhaps as a consequence of our spatial averaging, and unlike the case of rain, we find no consistent pattern of summer temperature changes across the U.S. Midwest as a whole since 1971.

2.2. Dry spells and larger storms lead to higher crop prices

We explore the response of corn and soybean prices to weather events that occurred in the U.S. Midwest during June, July and August, which are months after planting and before harvest for these crops. We work with futures contracts that are traded daily at the CME during the growing season and expire in November (for soybean) or December (for corn) of each year in our sample. A futures contract essentially endows its buyer with the right and obligation to acquire a certain crop on expiration date in exchange for the price set by the market at the original trading date. Futures prices fluctuate during the growing season in response to variations in expected supply driven by weather shocks. In our estimations, weather shocks will be associated to storms and dry spells or monthly weather measures. Unreported results on daily frequency were less significant than those presented in this paper. We attribute this to a signal to noise ratio in daily data that is lower than that implicit in storms, dry

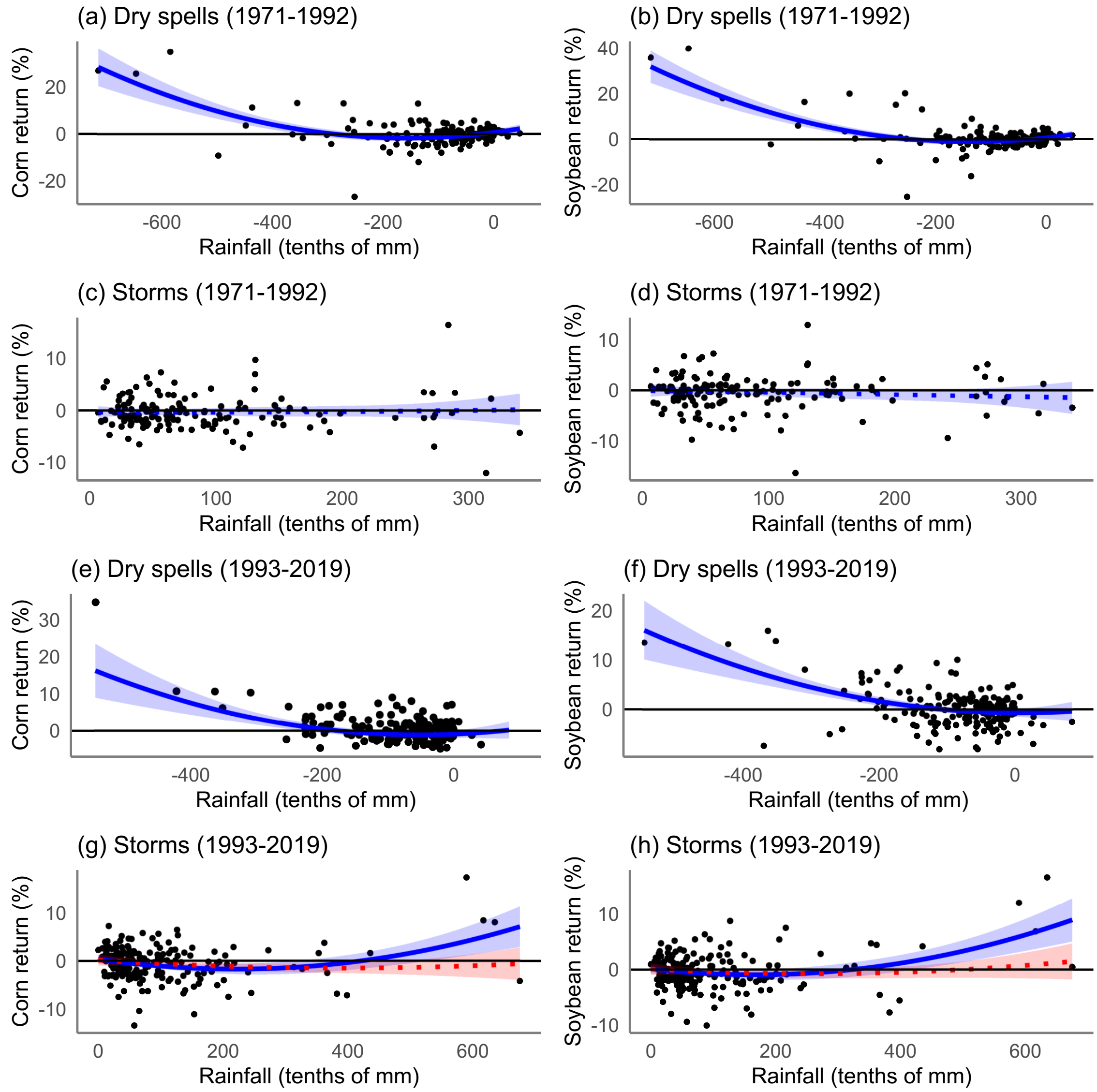

Figure 2: Impact of event rain on crop market returns. Dots are all historical records for normalized event rain and contemporaneous crop price returns. Solid blue lines show fitted quadratic models for normalized event rain and crop returns, holding all other variables in ((6), Methods) constant at their median values. Solid red lines are model ((6), Methods) estimated on the restricted subset of post 1993 rain-return pairs that approximates the distribution of storms over 1971-1992. Bands represent the 95% confidence interval for the fitted model. Dotted lines are models with no statistically significant coefficients. Full regression results for both figures are in tables table A.4 and A.6 (Extended Data).

spells and monthly weather measures which allow for an agronomically significant accumulation of rain and heat. A model grounded on the nonlinear relation between rain, temperature and yields in the literature leads to a relation between weather shocks and market returns ((4), Methods) to be tested by time series regressions ((6), Methods) of crop returns on linear and quadratic terms in precipitation, as well as on EDD, GDD and economic controls (Methods). Motivated by the increase in precipitation since 1993, we split our sample into 1971-1992 and 1993-2019 periods. Summers in each of these two periods are split into a sequence of non-overlapping time intervals (storms and dry spells, or calendar months) that define the time grid for the time series regression. Figure 2 displays events' normalized rain, contemporaneous returns and fitted quadratic effects of rain for each period and type of event, holding all other variables constant at their median values. Figures 2(a,b,e,f) show that models fitted to dry spells explain corn and soybean returns in excess of 20% prior to 1993 and in the 10% range since then. Storms prior to 1993 in figures 2(c,d) were smaller than 340 tenths of a mm and did not lead to statistically significant price increases. Figures 2(g,h) show that storms since 1993 were as large as 675 tenths of a mm and had a statistically significant effect on returns, reaching the vicinity of 10% in extreme cases. Therefore, since 1993, market prices seem to incorporate the notion that extreme dry spells and extreme rain are both harmful to plant growth.

To understand the source of the nonlinear response to precipitation in figure 2(g,h) we construct a counterfactual sample for storms since 1993 that approximates the distribution of storms that occurred prior to 1993. We match storms in the second period to others in the first period by closely aligning their rain magnitudes. The net effect of this construction is essentially eliminating large storms from the second period (Methods and figure B.5 in Extended Data). Figures 2(g,h) show in red the fitted relationships between crop returns and normalized storm magnitudes for the matched samples. In the absence of the most extreme precipitation events, above almost 400 tenths of a mm, we no longer find a statistically significant market response to storms. This suggests that the impact associated to storm events since 1993 is mainly due to large storms that were not present prior to 1993. Full regression results behind figure 2 are in tables A.4 for unmatched data and A.6 for storm data matched to 1971-1992, respectively (Extended Data).

To quantify the impact of extreme heat on crop returns we combine estimates for regression coefficients in table A.4 with those for ((5), Methods) and for EDD statistics under dry spells reported in table A.2 (Extended Data). A standard deviation of EDD under a dry spell led to 1.6% and 1.2% additional corn returns before and after 1993, respectively, and 1.9% additional soybean return prior to 1993. These are effects beyond what was explained by the magnitude of the dry spell. Normalized EDD under dry spells is a strongly skewed variable. Maximum values of EDD in the historical record are about 10 standard deviations therefore extreme heat would make a very large contribution to market returns.

One potential concern about our weather event construction could be the availability of short-term weather forecasting technology in recent decades that would decouple daily market returns from contemporaneous daily weather. However, our event regressions are on a significantly lower frequency than daily because average storm and dry spell lengths since 1993 were 5.0 and 7.1 days, respectively. While strongly significant results in table A.4 suggest that information is revealed to market participants during the course of weather events, we consider two additional regression specification for robustness purposes. First, we run regressions ((6), Methods) on events constructed using precipitation lagged from -1 to $+1$ day relative to the daily market return. This specification captures short-term weather forecasting and information processing delays. Regression estimates are in table A.7 (Extended Data) and the effect of rain through statistically significant fitted models is displayed in figure B.2. The strong positive impact of extreme dry spells across periods and crops remains in place. The tendency towards positive returns for large storms since 1993 is apparent too. The impact for EDD under dry spells in table A.7 is quantitatively close to that in table A.4. A second robustness regression specification defines the weighting factor in ((6,) Methods) as the contribution of the U.S. Midwest to global rather than U.S. output. This is to reflect that CME prices aggregate to some extent supply and demand beyond the U.S. Estimated coefficients in table A.8 are different from those in table A.4 but lead to quantitatively similar weather price impact after adjustment for the change in weighting. This simply reflects that market shares are very slowly moving variables across decades and unrelated to short-term weather fluctuations.

2.3. Crop prices' nonlinear response to precipitation is compatible with subsequent yields

Is the nonlinear market response to precipitation consistent with the effect of the latter on yields? Unlike market returns, which can be measured on arbitrary frequency and can be regressed against short-term weather events, yields are measured annually.

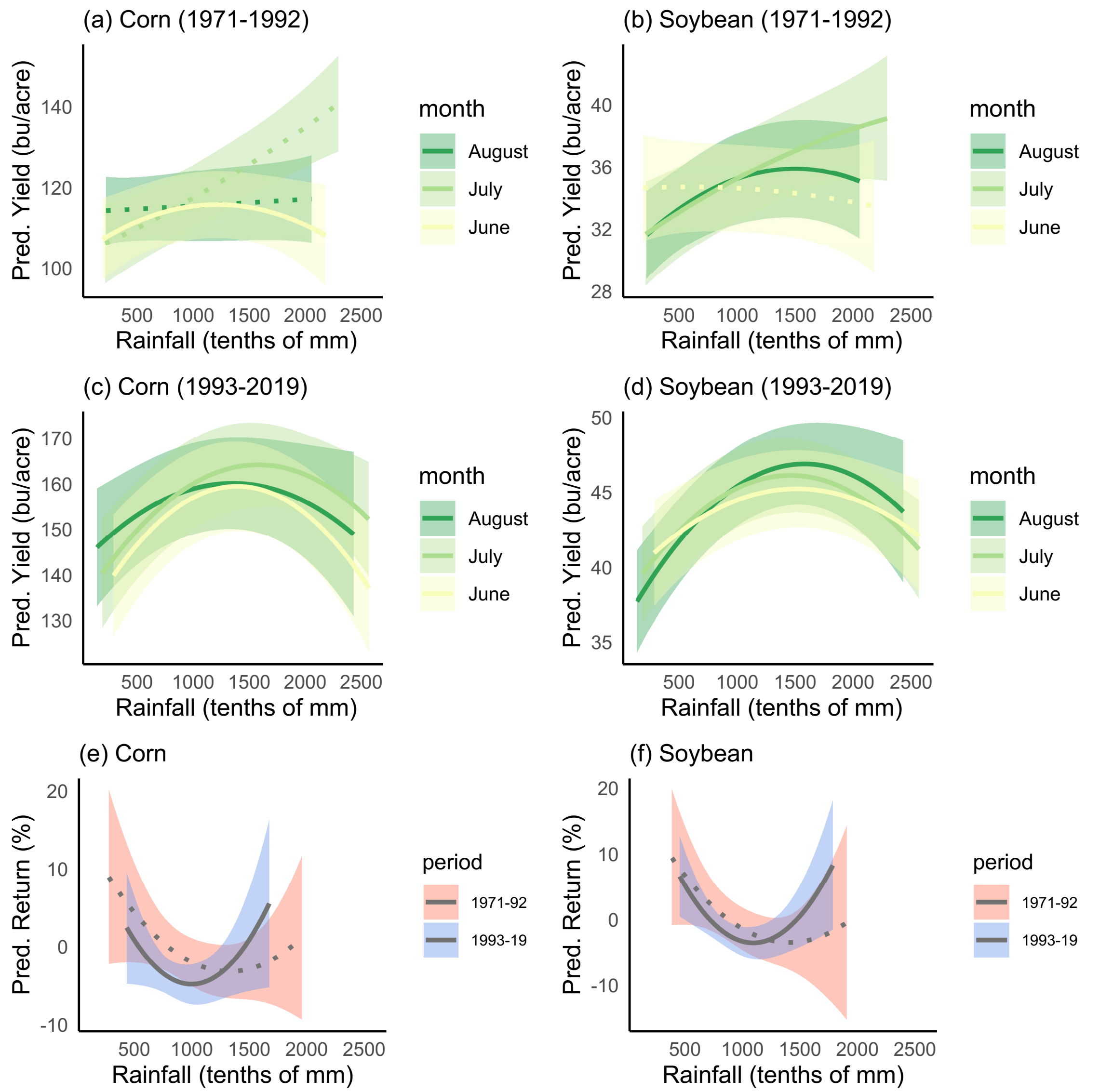

Figure 3: Impact of monthly rain on yields and crop market returns. Figures 3(a,b,c,d) show fitted quadratic relationships for crop yields and monthly rain before and after 1993, holding all other variables in ((7), Methods) constant at their median values. Figures 3(e,f) show fitted quadratic relationships for monthly crop returns and contemporaneous monthly rain, holding all other variables in ((6), Methods) constant at their median values. Bands represent the 95% confidence intervals. dotted lines are models with no statistically significant rain coefficients. Full regression results are in table A.9 (Extended Data).

We turn then to work with monthly data, using time series data for market returns and state-level panel data for the relationship between weather and yields. Monthly frequency allows for the accumulation of rain and heat over longer time intervals, hence alleviating potential concerns over the effect of short-term forecasting in our event regressions. Monthly weather data is reported and used in absolute physical units. The quadratic model that relates precipitation to yields and returns assumes that the yield response is quadratic in the accumulation of rain over subintervals during the summer ((2), Methods) and leads to ((4), Methods) for the impact of rain on returns. In this model, the amount of rain that maximizes plant growth, and therefore terminal yield, also exerts the strongest downward pressure on crop prices therefore minimizing returns. Motivated by the model, we regress market returns ((6), Methods) and yields ((7), Methods) on monthly weather measures. Results are in table A.9 (Extended Data).

Figures 3(a,b,c,d) show that fitted quadratic relationships between crop yields and monthly rain, holding all other variables constant at their median values, became more strongly nonlinear since 1993. The shape of the yield response to rain is consistent with harmful impacts of scarce or excessive rain. The amounts of monthly rain that maximized yields since 1993 are between 1,350 (corn yields on August rain) and 1,580 (soybean yields on August rain) tenths of a mm. This is close to earlier estimates [Tannura et al., 2008, Miao et al., 2016]. Mean monthly rain increased from 909 tenths of a mm in earlier decades to 1,010 tenths of a mm since 1993. Therefore, the mean of the shifted distribution of rain has still been below optimal for yields according to our estimates.

Figures 3(e,f) show fitted quadratic relationships for monthly crop returns and contemporaneous monthly rain holding all other variables constant at their median values. The strongly convex effect for monthly rain on crops returns becomes significant after 1993. In the case of corn in the 1993-2019 period, the minimum return is at 1,084 tenths of a mm. For soybeans, the minimum occurs at 1,300 tenths of a mm. These levels of rain are about 20% lower than those that maximize yields. Potential explanations for this difference include a more nuanced relationship between yields and rain than in ((2), Methods), quadratic accumulation of rain in timescales other than monthly, and forms of risk aversion among market participants that would distort ((4), Methods). Given the simplicity of our model for yields and returns, and the noise around our estimates, we interpret our results as generally supportive for the notion that agricultural commodity markets are pricing the nonlinear impact of precipitation in manner that is compatible with production fundamentals. Statistically significant coefficients for GDD and EDD on yields in table A.9 are generally positive and negative respectively, as expected on biological grounds. In line with this, we also find a strong positive effect of EDD on crop returns, except for soybeans in the most recent period.

3. Discussion

We explored in this paper the effects of changing weather patterns and extreme events in the U.S. Midwest, a major crop producing region, on the prices of corn and soybeans. We found that a large increase in summer rain since 1993, relative to earlier decades, has led to extreme precipitation events and associated price increments that were not visible prior to 1993. Dry spells, particularly those with high temperatures, have remained a source of positive returns. Single extreme weather events have lead in recent decades to price increments in the 10% range, which is highly significant in economic terms. The nonlinear market response to weather is generally consistent in its shape with the estimated impact of rain and temperature on yields. We have attempted to provide results that are robust to advances in weather forecasting [Bauer et al., 2015] and information processing by market participants that have happened since 1971. Advances in agronomic practices, including adaptation in response to climate change [Mase et al., 2017, Hatfield et al., 2018, Liu and Basso, 2020], are likely to mitigate the impact of weather on yields and might have modulated the impact of weather on markets. Disentangling the precise time-varying contribution of climate adaptation from the high-frequency link between weather and crop prices is challenged by the lack of spatial variability in prices. Increase in irrigation, that as of 2023 is still used in a very minor proportion of corn and soybean farms in the U.S. Midwest, could weaken the link between scarce rain and returns but could potentially strengthen, through evapotranspiration, the market impact of excessive precipitation [Mueller et al., 2016].

Our findings complement earlier work on the effect of shifting weather patterns on agriculture in the U.S. Midwest [Schlenker and Roberts, 2009, Mueller et al., 2016, Tollenaar et al., 2017, Butler et al., 2018, Rizzo et al., 2022]. An explicit distinction has been made [Lesk et al., 2020] between the positive impact of higher precipitation on U.S. corn and soybean yields, and the negative impact of the most extreme hourly rain episodes. The nonlinear behavior in figures 2(g,h) suggests that market participants are aware of this differential impact. The market impact of dry heat in corn is consistent with the damage provoked by extreme dry heat on yields [Ting et al., 2023]. Our paper is an early contribution to a research agenda on valuation and risk management in crop markets under climate risk. Potential avenues for future work include quantifying the impact of compound extremes in market prices [Haqiqi et al., 2021, Ting et al., 2023], exploring the interplay between weather shocks, planting decisions during spring and market returns; and exploring the empirical performance of more complex models that condition the impact of an extreme weather event on moisture or accumulated precipitation since the start of the summer.

Our findings suggest that the negative effects of extreme weather on agricultural output and economic activity would also operate through sharp price increases with potential redistributive effects. Local farmers affected by a negative output shock could be partially compensated by higher prices [Sajid et al., 2023]. Given the integrated nature of corn and soybean markets, producers in Brazil, Argentina and elsewhere could benefit from higher prices [Headey and Hirvonen, 2023]. And consumers around the world would face higher costs, increased volatility and potential food insecurity [Ahmed et al., 2009, Nelson et al., 2014, Bellemare, 2015, Headey and Martin, 2016, Haile et al., 2017, Davis et al., 2021, Hasegawa et al., 2021, De Winne and Peersman, 2021]. Corn price spikes would also interact with the energy sector through the ethanol mandate [Diffenbaugh et al., 2012]. Coupling our estimated crop price responses with long-term forecasts from large scale climatological models may contribute to better long-term economic forecasts and food price volatility estimates.

4. Methods

4.1. Weather data

We obtained daily precipitation and temperature data from NOAA (National Oceanic and Atmospheric Association)'s GHCN (Global Historical Climate Network) dataset. We focus on data for June, July and August in the U.S. Midwest from 1971 to 2019. Some weather stations have missing data on certain dates so we kept for our regressions those that cover (i.e. have non-missing data) at least 95% of the period[2]. This left us with 854 weather stations roughly evenly distributed across the twelve states of the Midwest (figure B.1, Extended Data). Only in the construction of maps in figures 1 and B.4 we relaxed our acceptance threshold and worked with 960 rather than 854 stations to have finer spatial granularity.

Table A.1 (Extended Data) displays summary statistics for our raw weather data. Rain and temperature are reported in daily and monthly frequencies, and averaged over the U.S. Midwest. In line with the literature, we report summary statistics for Growing Degree Days (GDD) and Extreme Degree Days (EDD), which measure the exposure that crops have experienced to healthy growing conditions and to excessively hot weather, respectively.

[2]The choice of the 95% threshold is somewhat arbitrary. It has been previously used in the literature (see Kunkel et al. [2003] and Rajah et al. [2014]). NOAA also flags certain observations that do not meet their quality criteria, likely as measurement or data entry errors. These were categorized as missing data in our analysis. Alternative thresholds around 95% were tried and neither the number of stations nor the underlying indexes showed significant variation.

4.2. Weather events

We decompose each summer in a temporal sequence of weather events in which storms and dry spells alternate with each other during summers from 1971 to 2019. We proceed as follows. Let R_t be the spatial average of rain fallen over the U.S. Midwest on day t, where all seven days of the week are treated equally. Let F_t represent rain information learnt by market participants on day t. In our baseline formulation, used in figure 2 and regressions in table A.4, we adopt $F_t = R_t$. As a robustness check in table A.7 we also consider the possibility that weather is anticipated by very short-term weather forecasting or priced with certain delay. In this case we use $F_t = (R_{t-1} + R_t + R_{t+1})/3$ as a precipitation measure that aggregates information about rain that has fallen recently or that is very likely to fall in the near future.

Because markets can only react on trading days, we account for weekends by adding $F_{saturday}$ and F_{sunday} to F_{monday}. A storm event is defined as two or more consecutive trading days where F_t in each day is above a certain threshold. For Tuesdays to Fridays, we set the threshold at 30 tenths of a mm, which is close to the mean daily rain for the 1971-1992 period. For Mondays, the threshold is 90 tenths of a mm to account for the fact traders incorporate on this day information revealed during the weekend.

We define the magnitude of rain event as the sum of F_t during the life of the event minus their means (30 or 90 tenths of a mm per day, depending on the day of the week). Defined in this manner, storms can be interpreted as multi-day events with higher than usual rain. Any time interval confined between storms or by the start or end of the summer is a dry weather event. Dry spells are usually associated with a negative rain magnitude but there may be an exception if a single, isolated day experienced very large rain. Figure 1(c) displays the time series of weather events and their magnitudes. Casual observation reveals that large storms have seemed more prevalent after 1992. The number of weather events per summer increased very slightly, from 13.0 in the first period to 13.4 in the second one.

The construction just outlined for rain is also applied to Growing Degree Days (GDD) and Extreme Degree Days (EDD) using the historical daily temperature record.

4.3. Additional data sources

Data on corn and soybean futures contracts prices were gathered from Reuters Datastream. From Federal Reserve Economic Data St. Louis we gathered monthly data on spot crude oil price (WTI). We use the "Nominal Broad Dollar Index – Goods Only" from the Federal Reserve Bank for a measure of the exchange rate/strength of the U.S. dollar. Our choice of controls is standard in the literature. The oil price is included as a control as it relates to global commodity demand and crop production costs. To account for demand fluctuations, we also considered the Index of Global Real Economic Activity in industrial commodity markets, as in Kilian [2019], on a monthly basis and the Baltic dry index on a daily basis since 1985. Corn and soybean yields per state on yearly frequency were gathered from the USDA.

4.4. A model for weather and crop returns

An extensive literature relates weather to crop yields. Schlenker and Roberts [2009] relied on U.S. data between 1950 and 2005 to find that corn and soybean yields had an inverse U-shaped response to rain during the growing season from May to

August. Rain is beneficial to crops up to a certain threshold. Beyond that, crops suffer. Crop yields were slightly increasing as a function of temperature up to the vicinity of 30 degrees Celsius, and sharply decreasing after exposure to temperatures beyond that threshold. Using data for the United States from 1977 to 2007, Miao et al. [2016] found that corn and soybean yields had an inverse U-shaped response to monthly rain during June, July and August. They also found corn and soybean yields positively related to Growing Degree Days and negatively related to Extreme Degree Days[3]. In earlier work, Tannura et al. [2008] used data between 1960 and 2006 for Indiana, Illinois and Iowa, to find an inverted-U relationship between corn and soybean yields in the U.S. Midwest and rain in each of the months of June, July and August. These works find that corn and soybean yields are generally increasing for up to the vicinity of 6 inches (1,524 tenths of mm) of monthly summer rain and tend to decrease for heavier precipitation. Schlenker and Roberts [2009] report that the nonlinear relationship between yield and temperature between 1950 and 1977 was the same as the one between 1978 and 2005.

We explore the effect of weather shocks on the dynamics of crop prices. Farmers in twelve states in the U.S. Midwest grow corn and soybeans and sell their output in a competitive market. We focus on corn and soybean price changes during a single growing season, after seeds have been planted at $t = 0$. This allows us to assume that output variations at harvesting time T at the end of the summer are due to yield variability caused by weather shocks and unrelated demand shocks, and not due to planting decisions. The terminal yield obtained at harvesting time is highly

[3]Defined as Overheat Degree Days in Miao et al. [2016]

sensitive to weather during the months of June, July and August. Regional output is harvested at T and added to typically small existing stocks, for final regional supply Q_T measured in metric tons. Total expected supply at T, conditional on information available to participants at the Chicago Mercantile Exchange during the growing summer at time $t \leq T$ is

$$E_t[Q_T]. \tag{1}$$

Uncertainty about supply at harvesting time is a function of the yield per unit of land, which depends on technology chosen prior to the growing season and on weather. In the absence of significant irrigation, as it is the case for the bulk of corn and soybeans in the U.S. Midwest, water intake is provided exclusively by rain. We split the summer in non-overlapping periods $j = 1, ..., T$ to model the link between weather and terminal yields on time periods that allow for the accumulation of a significant amount of rain or heat. Let R_j, GDD_j and EDD_j be the spatial averages of rain, Growing Degree Days and Extreme Degree Days that occurred during period j over the U.S. Midwest. Let Y_T and A_T be terminal yield and harvested area, respectively. Based on the nonlinear relationship between weather and yields identified in the literature and time-separability [Schlenker and Roberts, 2009], we postulate that

$$Y_T = \sum_{j=1}^{T} \alpha_0 + \alpha_1 (R_j - R^*)^2 + \alpha_2 GDD_j + \alpha_3 EDD_j. \tag{2}$$

where $\alpha_1 < 0, \alpha_2 > 0, \alpha_3 < 0$. In this expression, R^* is the agronomically optimal amount of rain. Insufficient or excessive precipitation hurts crops. In the case of a monthly partition for the summer, $R^* \approx 1,500$ tenths of a mm.

Market expectations of terminal output are updated during the summer. We assume that short-term weather shows no predictability in time beyond very short-term forecasts available at the start of period j. Therefore, the change in expected terminal output that occurs during period j depends on weather measures revealed contemporaneously. Let E_j be the conditional expectation based on information available at the start of period j. Taking conditional expectations in (2) we write

$$E_{j+1}[Y_T] - E_j[Y_T] = \alpha_1(\hat{R}_j - R^*)^2 + \alpha_2\hat{G}DD_j + \alpha_3\hat{E}DD_j - EW, \tag{3}$$

where hatted variables are measures for rain, EDD and GDD and EW is the unconditional expectation of weather shocks (precipitation and temperature) for period j. Weather-related contributions in (2) associated to periods other than j are either known if they already occurred, or have the same conditional expected value as seen from periods j and $j+1$. Hence, they all cancel away and do not contribute to (3). The change in expected output in period j is driven exclusively by weather shocks at j. Let P_j^T be the price observable at $j \leq T$ associated with a Chicago Mercantile Exchange future contract expiring at T. Under a standard model for supply and demand for T, with constant elasticities and multiplier $\beta > 0$, the price change due to an exogenous supply shock is

$$\frac{P_{j+1}^T - P_j^T}{P_j^T} \approx -\beta W_{year}^{Midwest}(\alpha_1(\hat{R}_j - R^*)^2 + \alpha_2\hat{G}DD_j + \alpha_3\hat{E}DD_j - EW), \tag{4}$$

where

$$W_{year}^{Midwest} = \frac{A_{year}^{Midwest}}{GlobalOutput_T + Inventories_T} \tag{5}$$

is a measure of the importance of U.S. Midwest production in the U.S or global market for corn or soybeans (before being multiplied by local yield variations). Crop prices are also influenced by global demand fluctuations that we assume uncorrelated to local weather. These and other financial variables are taken into consideration in the empirical estimation of the model through appropriate controls.

4.5. Regression specifications

Our regressions for crop returns on weather data are grounded on (4) and their structure is

$$\begin{aligned}\frac{P_{j+1}^T - P_j^T}{P_j^T} &= \beta_0 + \beta_1 W_j R_j + \beta_2 W_j R_j^2 + \beta_3 W_j EDD_j + \beta_4 W_j GDD_j \\ &+ Controls_j + \epsilon_j, \quad j = 1, ..., N_{intervals\, in\, period},\end{aligned} \tag{6}$$

where $\frac{P_{j+1}^T - P_j^T}{P_j^T}$ is the percentage price change, or return, of a crop future contract during a weather event or month, and R, EDD and GDD are weather measures that accumulate precipitation, Extreme Degree Days and Growing Degree Days that are contemporaneous to the crop return. The weight W captures the share of the U.S. Midwest in the market for that crop. In our empirical work we construct a measure for W_j using physical production forecasts and inventories measures available on May of each year and leave W_j constant during each summer. Bruno et al. [2017] consider low frequency inventory measures constructed from USDA published statistics (therefore already in physical units) and a higher frequency inventory proxy give by the slope of the term structure that correlates strongly with inventories but has no physical units. Because the determination of P_j^T depends on the combined effect of expected global output at T and available inventories in the denominator of (5), we choose to work with statistics published in May of each year on existing inventories and expected output. Standard controls to explain price changes, when available in the frequency of our weather variables, are the contemporaneous returns on the WTI spot crude oil price, the Nominal Major Currencies Dollar Index (Goods Only) from the U.S. Federal Reserve, the Baltic Dry Index that captures global commodity demand, and the Index of Global Real Economic Activity in industrial commodity markets [Kilian, 2019]. By working with returns and local shocks, all variables included in (6) are stationary and all regressors are plausibly exogenous.

Our regressions for yields on weather data are grounded on (2) and their structure is

$$\begin{aligned} Y_{s,y} = \beta_0 + \sum_{m=June}^{August} \beta_{1,m} R_{s,y,m} + \sum_{m=June}^{August} \beta_{2,m} R_{s,y,m}^2 + \\ + \sum_{m=June}^{August} \beta_{3,m} GDD_{s,y,m} + \sum_{m=June}^{August} \beta_{4,m} EDD_{s,y,m} + \mu_s + \lambda_y + \epsilon_{s,y}, \end{aligned} \tag{7}$$

The subscripts refer to individual states (s), year (y) and month ($m =$ June, July and August). Y is the annual yield (measured in bushels per acre), and R, GDD and EDD are, respectively, weather measures that accumulate precipitation, Extreme Degree Days and Growing Degree Days over a month during the summer. State-fixed effect μ_s controls for average yield, and year-fixed effect λ_y for time-varying regional shocks common to all states. These parameters seek to control for technological change, among other non weather-related factors.

4.6. Matching storms: 1971-1992 vs 1993-2019

We use a 1:1 matching scheme to create a counterfactual sample of storms for the second period (1993-2019) with the sample size and distribution of storms from the first period (1971-1992). A 1:1 matching selects pairs of observations composed by an observation from each period. Pairs are selected by minimizing the average pairwise Mahalanobis distance of all pairs in their precipitation magnitudes. Observations from the second period that are not paired to one in the first period are removed from the sample. It implies that very large storms, that were not present in the first sample, are largely removed from the matched sample. Figure B.5 compares the two distributions (1971-1992 vs 1993-2019) before and after matching. Table A.5 presents some descriptive statistics to assess balance between the two periods. Table A.6 shows in its third columnd the estimated regressions of crop returns for the storms from 1993-2019 matched to 1971-1992.

5. Competing interests and acknowledgments

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Colorado Denver.

6. Author contributions

NM and MC conceptualized and designed the study and wrote the original draft. MC, NM and EM collected and analyzed data. All authors edited and reviewed the paper.

7. Data Availability

Code to download and organize the data as well as perform analyses and produce the tables and figures in this paper will be publicly available from: https://github.com/magcornejo/weatherevents_cropprices

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8. Extended Data

Table A.1: Summary statistics for daily and monthly weather variables.

Variable	Min	Mean	Median	Max	SD	N
Daily Rain (tenths mm)	0.0	31.5	25.3	202.8	24.8	4508
Daily Mean Temperature (tenths deg Celsius)	113.6	220.1	221.5	289.3	27.22	4508
Monthly Rain (tenths mm)	384.0	964.6	960.8	1836.1	262.3	147
Monthly Mean Temperature (tenths deg Celsius)	178.1	219.9	220.2	262.0	15.59	147
Monthly GDD (tenths deg Celsius)	2945	4289	4298	5588	513	147
Monthly EDD (tenths deg Celsius)	0.0	5.8	2.2	85.0	10.4	147

Notes: Daily rain is spatially averaged across the U.S. Midwest. Daily mean temperature is defined at each location as the simple average between the minimum and maximum local temperature during the day and then averaged spatially. Monthly rain is the sum of daily rain within a month. Monthly mean temperature is the average of daily mean temperature within a month. Monthly GDD and Monthly EDD are, respectively, the sum of daily GDD and daily EDD. GDD at the weather station level is constructed as a step function: it is zero if the local daily mean temperature is below 80 tenths of degree Celsius, it takes the value of mean temperature minus 80 if the mean temperature for the day is between 80 and 300 tenths of degree Celsius and it takes the value of 220 if mean temperature is above 300 tenths of degree Celsius. Daily and monthly GDD cannot be negative and are bounded by 220 and 6,820, respectively. Daily EDD is a step function that takes the value of zero if mean temperature is below 300 tenths of degree Celsius and takes the value of mean temperature minus 300 if mean temperature for that day is above 300 tenths of degree Celsius. Daily and monthly EDD cannot be negative and are not bounded from above.

Table A.2: Summary statistics for summer weather event variables, 1971-1992 and 1993-2019 periods.

Variable	Period	Min	Mean	Median	Max	SD	N
Storm Event Rain (tenths mm)	1971-1992	6.77	89.59	62.75	340.44	75.50	148
	1993-2019	0.03	98.01	58.86	675.15	111.77	195
Dry Spell Event Rain (tenths mm)	1971-1992	-715.15	-101.13	-68.40	46.91	120.39	163
	1993-2019	-554.94	-79.09	-53.14	83.82	85.67	209
Storm Event GDD (tenths deg Celsius)	1971-1992	-235.58	-1.48	-10.75	247.56	84.47	148
	1993-2019	-443.65	6.78	12.40	418.34	108.23	195
Storm Event EDD (tenths deg Celsius)	1971-1992	-2.94	-0.36	-0.59	9.35	1.51	148
	1993-2019	-4.74	-0.29	-0.56	10.20	1.64	195
Dry Spell Event GDD (tenths deg Celsius)	1971-1992	-598.66	2.62	-10.74	1815.00	247.76	163
	1993-2019	-635.28	3.76	-0.26	1164.67	190.10	209
Dry Spell Event EDD (tenths deg Celsius)	1971-1992	-6.70	0.29	-0.61	65.67	6.43	163
	1993-2019	-4.71	-0.13	-0.75	43.48	4.27	209

Note: a storm event is defined as two or more consecutive days with daily rain above 30 tenths of mm. Dry spells are formed by days that do not belong in a storm event. In all cases event variables are normalized by subtracting the daily historical average during 1971-1992 multiplied by the duration of the event. GDD and EDD associated to an event are the sums of daily GDD and EDD during the life of the event.

Table A.3: Upper panel: Identification of a change in the distribution of weather variables over the 1971-2019 period by change-point in mean tests for spatially averaged U.S. Midwest monthly rainfall and temperature measures. Methods are a change-point in mean (CPM) test [Hinkley, 1970], step indicator saturation [SIS, as in Pretis et al., 2018], a Bayesian change point (BCP) analysis [Wang and Emerson, 2015], and a classification tree. Lower panel: summary statistics for monthly weather variables before and since 1993.

	Rain	Temp.	GDD	EDD
Change in mean by CPM	June 1992	June 2010	June 2010	-
Change in mean by SIS	June 1993	June 1992	-	August 1980
Change in mean by BCP	June 1992	-	-	June 1980
Change in mean by TREE	June 1992	-	-	August 1980

	Rain	Temp.	GDD	EDD
Min 1971-1992	384.0	178.1	2944.6	0.00
Min 1993-2019	513.9	190.4	3312.8	0.00
1st. Quart. 1971-1992	762.9	208.1	3888.8	0.53
1st. Quart. 1993-2019	828.9	208.7	3892.9	0.53
Mean 1971-1992	908.8	219.5	4277.0	6.39
Mean 1993-2019	1010.1	220.1	4299.6	5.34
Median 1971-1992	935.5	220.0	4311.7	3.01
Median 1993-2019	982.2	220.2	4291.9	1.81
3rd. Quart. 1971-1992	1065.0	232.0	4697.1	7.02
3rd. Quart. 1993-2019	1139.4	230.7	4668.6	5.52
Max 1971-1992	1650.2	252.0	5305.3	85.01
Max 1993-2019	1836.1	262.0	5588.1	54.22
Std. Dev 1971-1992	249.1	16.3	534.0	11.84
Std. Dev 1993-2019	265.5	15.0	497.8	9.11

Table A.4: Estimated coefficients for regressions of crop returns on contemporaneous weather shocks specified by (6).

	Corn return (%)			
	(1971-1992)		(1993-2019)	
	Storms	Dry spells	Storms	Dry spells
W × Rain	−0.005	**0.224**∗∗∗	**−0.191**∗∗	0.074
	(0.097)	(0.078)	(0.077)	(0.085)
W × Rain^2	0.00004	**0.00072**∗∗∗	**0.00043**∗∗	**0.00072**∗∗
	(0.00040)	(0.00020)	(0.00018)	(0.00032)
W × GDD	−0.050∗	−0.018	−0.030	0.007
	(0.028)	(0.028)	(0.029)	(0.024)
W × EDD	−0.832	**1.946**∗∗∗	2.121	**2.876**∗∗
	(1.152)	(0.645)	(1.760)	(1.269)
FX	−0.79	18.74	7.87	−51.64
	(40.07)	(47.70)	(35.84)	(55.23)
BDI			−2.80	2.85
			(4.86)	(8.00)
WTI			7.37	14.79∗
			(9.75)	(8.41)
Const.	−0.436	0.804∗	0.498	−0.740∗
	(0.591)	(0.448)	(0.460)	(0.419)
Observations	148	163	190	204
Adjusted R^2	0.003	0.358	0.088	0.306

	Soybean return (%)			
	(1971-1992)		(1993-2019)	
	Storms	Dry spells	Storms	Dry spells
W × Rain	−0.010	**0.065**∗∗	−0.037∗	−0.002
	(0.030)	(0.027)	(0.022)	(0.019)
W × Rain^2	−0.000002	**0.00024**∗∗∗	**0.00011**∗∗	**0.00016**∗∗
	(0.00010)	(0.00006)	(0.00005)	(0.00008)
W × GDD	−0.010	0.001	−0.006	0.005
	(0.009)	(0.006)	(0.008)	(0.005)
W × EDD	**−1.198**∗∗∗	**0.709**∗∗∗	0.042	−0.169
	(0.400)	(0.163)	(0.513)	(0.276)
FX	5.71	−39.86	−37.86	−60.87
	(52.54)	(34.33)	(37.24)	(39.49)
BDI			−3.67	2.31
			(5.75)	(5.08)
WTI			−0.41	**16.61**∗∗
			(9.44)	(6.91)
Const.	−0.355	0.794∗	0.138	**−0.731**∗∗
	(0.578)	(0.448)	(0.399)	(0.290)
Observations	148	162	190	204
Adjusted R^2	0.034	0.541	0.135	0.266

Note: a storm is defined as two or more consecutive days with rain above 30 tenths of a mm. A dry spell is any sequence of days not in a storm. Daily rain, growing degree days (GDD) and extreme degree days (EDD) are spatially averaged over the U.S. Midwest and summed up over the duration of each weather event after normalization by their 1971-1992 daily means. The factor W is the share of the U.S. Midwest in U.S. crop production. Controls include WTI oil price, Baltic Dry Index and the Nominal Major Currencies Dollar Index. Statistical significance based on heteroskedasticity and autocorrelation consistent standard errors in parentheses, ∗p<0.1; ∗∗p<0.05; ∗∗∗p<0.01.

Table A.5: Descriptive statistics for storm normalized magnitude. Full sample periods, and matched to 1971-1992.

	Min	Q1	Median	Mean	Q3	Max	S.D.
Storms 1971-1992 (full sample)	6.78	36.72	62.31	89.23	117.97	340.44	75.61
Storms 1993-2019 (full sample)	0.03	34.86	58.86	98.01	120.08	675.15	111.77
Storms 1993-2019 (matched to 1971-1992)	0.03	36.42	62.57	87.17	115.52	366.57	74.34

Note: We use a 1:1 matching scheme to create a counterfactual sample of storms for the second period (1993-2019) with the sample size and distribution of storms from the first period (1971-1992). Observations from the second period that are not paired to one in the first period are removed from the sample. Very large storms, that were not present in the first sample, are largely removed from the matched sample. A storm is defined as two or more consecutive days with rain above 30 tenths of a mm.

Table A.6: Estimated coefficients for regressions of crop returns on contemporaneous storm shocks. Comparison with the estimation for 1993-2019 storms matched to the 1971-1992 distribution.

	Corn return (%)		
	1971-1992 (full sample)	1993-2019 (full sample)	1993-2019 (matched to 1971-2019)
	Storms	Storms	Storms
W × Rain	−0.005	**−0.191****	−0.161
	(0.097)	(0.077)	(0.100)
W × Rain^2	0.00004	**0.00043****	0.00038
	(0.00040)	(0.00018)	(0.00032)
W × GDD	−0.050*	−0.030	−0.048*
	(0.028)	(0.029)	(0.029)
W × EDD	−0.832	2.121	1.660
	(1.152)	(1.760)	(1.852)
FX	−0.79	7.87	−0.84
	(40.07)	(35.84)	(32.64)
BDI		−2.80	**−10.55****
		(4.86)	(4.38)
WTI		7.37	5.50
		(9.75)	(10.15)
Const.	−0.436	0.498	0.356
	(0.591)	(0.460)	(0.527)
Observations	148	190	150
Adjusted R^2	0.003	0.088	0.059

	Soybean return (%)		
	1971-1992 (full sample)	1993-2019 (full sample)	1993-2019 (matched to 1971-2019)
	Storms	Storms	Storms
W × Rain	−0.010	−0.037*	−0.035
	(0.030)	(0.022)	(0.029)
W × Rain^2	−0.000002	**0.00011****	0.00013
	(0.00010)	(0.00005)	(0.00010)
W × GDD	−0.010	−0.006	−0.013*
	(0.009)	(0.008)	(0.008)
W × EDD	**−1.198*****	0.042	0.148
	(0.400)	(0.513)	(0.483)
FX	5.71	−37.87	−45.21
	(52.54)	(37.24)	(37.57)
BDI		−3.67	**−10.37****
		(5.75)	(4.66)
WTI		−0.41	2.08
		(9.44)	(9.52)
Const.	−0.355	0.138	0.197
	(0.578)	(0.399)	(0.476)
Observations	148	190	150
Adjusted R^2	0.034	0.135	0.081

Note: We use a 1:1 matching scheme to create a counterfactual sample of storms for the second period (1993-2019) with the sample size and distribution of storms from the first period (1971-1992). Observations from the second period that are not paired to one in the first period are removed from the sample. Very large storms, that were not present in the first sample, are largely removed from the matched sample. A storm is defined as two or more consecutive days with rain above 30 tenths of a mm. Daily rain, growing degree days (GDD) and extreme degree days (EDD) are spatially averaged over the U.S. Midwest and summed up over the duration of each storm after normalization by their 1971-1992 daily means. The factor W is the share of the U.S. Midwest in U.S. crop production. Controls include WTI oil price, Baltic Dry Index and the Nominal Major Currencies Dollar Index. Statistical significance based on heteroskedasticity and autocorrelation consistent standard errors in parentheses, *p<0.1; **p<0.05; ***p<0.01.

Table A.7: Regressions of crop returns on weather events that aggregate rain and temperature measures lagged from −1 to +1 days to the daily market return.

	Corn return (%)			
	(1971-1992)		(1993-2019)	
	Storms	Dry spells	Storms	Dry spells
W × Rain	0.509	**0.202****	−0.143*	0.052
	(0.100)	(0.094)	(0.077)	(0.087)
W × Rain^2	−0.00023	**0.00069*****	**0.00023*****	**0.00073****
	(0.00029)	(0.00025)	(0.00006)	(0.00031)
W × GDD	−0.027	−0.019	−0.062*	0.009
	(0.037)	(0.028)	(0.036)	(0.029)
W × EDD	0.957	**1.772*****	2.941*	2.500*
	(2.586)	(0.630)	(1.711)	(1.442)
FX	51.15	38.95	−15.56	−32.90
	(59.48)	(45.49)	(47.10)	(53.46)
BDI			0.58	0.38
			(6.42)	(7.78)
WTI			10.17	18.75*
			(10.15)	(9.99)
Const.	−0.441	0.754	−0.133	−0.619
	(0.522)	(0.568)	(0.436)	(0.378)
Obs.	137	148	169	185
Adjusted R^2	−0.009	0.293	0.071	0.294

	Soybean return (%)			
	(1971-1992)		(1993-2019)	
	Storms	Dry spells	Storms	Dry spells
W × Rain	0.002	0.061*	**-0.042****	−0.006
	(0.031)	(0.033)	(0.016)	(0.020)
W × Rain^2	−0.00006	**0.00025*****	**0.00008*****	**0.00017****
	(0.00009)	(0.00008)	(0.00001)	(0.00007)
W × GDD	−0.009	0.004	−0.008	0.001
	(0.011)	(0.007)	(0.009)	(0.005)
W × EDD	−0.156	**0.718*****	0.222	−0.221
	(0.814)	(0.216)	(0.393)	(0.265)
FX	67.30	−22.83	**−67.68****	−33.89
	(62.64)	(35.13)	(34.25)	(41.22)
BDI			−0.87	2.00
			(4.65)	(5.17)
WTI			9.86	**24.48*****
			(8.55)	(8.01)
Const.	−0.506	0.844	−0.031	**−0.637****
	(0.574)	(0.583)	(0.346)	(0.271)
Obs.	136	147	169	185
Adjusted R^2	0.014	0.466	0.232	0.297

Note: daily rain, growing degree days (GDD) and extreme degree days (EDD) are spatially averaged over the U.S. Midwest and summed up over the duration of the event. The factor W is the share of the U.S. Midwest in U.S. crop production. Controls include the WTI oil price, the Baltic Dry Index and the Nominal Major Currencies Dollar Index. Statistical significance based on heteroskedasticity and autocorrelation consistent standard errors in parentheses, *p<0.1; **p<0.05; ***p<0.01.

Table A.8: Regressions of crop returns on contemporaneous weather events weighted by World output and inventories

	Corn return (%)			
	(1971-1992)		(1993-2019)	
	Storms	Dry spells	Storms	Dry spells
W × Rain	0.017	**0.535*****	**−0.549****	0.249
	(0.241)	(0.200)	(0.237)	(0.247)
W × Rain^2	0.00006	**0.00168*****	**0.00126****	**0.00230*****
	(0.00100)	(0.00049)	(0.00053)	(0.00087)
W × GDD	−0.121*	−0.037	−0.088	0.022
	(0.066)	(0.071)	(0.089)	(0.073)
W × EDD	−1.917	**4.508*****	7.036	**7.399****
	(2.653)	(1.537)	(5.192)	(3.517)
FX	0.80	23.16	8.66	−52.18
	(39.84)	(48.63)	(34.65)	(54.47)
BDI			−3.07	2.66
			(4.76)	(8.04)
WTI			7.41	14.48*
			(9.73)	(8.39)
Const.	−0.534	0.820*	0.431	−0.751*
	(0.588)	(0.492)	(0.470)	(0.413)
Observations	148	163	190	204
Adjusted R^2	0.005	0.344	0.089	0.315

	Soybean return (%)			
	(1971-1992)		(1993-2019)	
	Storms	Dry spells	Storms	Dry spells
W × Rain	0.017	**0.132****	−0.119*	0.006
	(0.067)	(0.061)	(0.063)	(0.057)
W × Rain^2	−0.00012	**0.00049*****	**0.00035*****	**0.00061*****
	(0.00022)	(0.00012)	(0.00013)	(0.00023)
W × GDD	−0.020	0.006	−0.023	0.014
	(0.018)	(0.016)	(0.025)	(0.015)
W × EDD	**−2.606*****	**1.597*****	0.257	−0.213
	(0.821)	(0.401)	(1.629)	(0.887)
FX	11.42	−36.81	−35.31	−58.65
	(54.22)	(32.85)	(37.52)	(39.46)
BDI			−4.498	2.63
			(5.94)	(4.95)
WTI			0.65	**16.17****
			(9.30)	(6.63)
Const.	−0.730	0.741	0.147	**−0.736*****
	(0.570)	(0.484)	(0.401)	(0.280)
Observations	148	162	190	204
Adjusted R^2	0.036	0.548	0.158	0.289

Notes: Daily rain, growing degree days (GDD) and extreme degree days (EDD) are spatially averaged over the U.S. Midwest and summed up over the duration of the event. The factor W is the share of the U.S. Midwest in World crop production. Controls include the WTI oil price, the Baltic Dry Index and the Nominal Major Currencies Dollar Index. Statistical significance based on heteroskedasticity and autocorrelation consistent standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table A.9: Regressions of crop yields and crop returns on monthly rain, temperature and controls.

	Corn yield (bu/acre)		Soybean yield (bu/acre)	
	(1971-1992)	(1993-2019)	(1971-1992)	(1993-2019)
Rain june	**0.0198****	**0.0449*****	0.0008	**0.0086*****
Rain june^2	**−0.0000082****	**−0.0000161*****	−0.0000005	**−0.0000029*****
Rain july	0.0122*	**0.0388*****	**0.0054****	**0.0118*****
Rain july^2	0.0000018	−0.0000123*	−0.0000007	**−0.0000040*****
Rain aug	0.0014	**0.026*****	**0.0078****	**0.0139*****
Rain aug^2	0.0000001	**−0.0000096*****	**−0.0000026****	**−0.0000044*****
GDD30 june	−0.0010	0.0034	0.0008	**0.0032****
GDD30 july	−0.00035	**0.0112*****	−0.0001	**0.0049*****
GDD30 aug	−0.0062	0.0024	0.0003	0.0005
EDD30 jun	**0.433*****	−0.071	0.018	**−0.063*****
EDD30 july	−0.046	**−0.147****	−0.009	−0.027
EDD30 aug	−0.070	−0.033	**−0.062****	**−0.063****
State Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	264	324	264	324
Adjusted R^2	0.217	0.152	0.134	0.271

	Corn return (%)		Soybean return (%)	
	(1971-1992)	(1993-2019)	(1971-1992)	(1993-2019)
W × Rain	-0.025	**-0.282****	-0.075	**-0.078****
W × Rain^2	-0.00001	**0.00013****	0.00003	**0.00003****
W × GDD	0.096	0.028	0.003	0.002
W × EDD	**1.707****	**3.182****	**0.495****	0.496
Const.	−3.145	−1.434	11.264	9.981
Controls	Yes (1)	Yes (3)	Yes (1)	Yes (3)
Observations	66	81	66	81
Adjusted R^2	0.128	0.167	0.118	0.060

Upper panel: estimated coefficients for panel regressions of crop yields (state, year) on weather shocks (state, year, month). Daily rain, growing degree days (GDD) and extreme degree days (EDD) are summed up over each month for each state in the U.S. Midwest. Statistical significance based on Wild cluster bootstrapped standard errors, *p<0.1; **p<0.05; ***p<0.01. Lower panel: Estimated coefficients for regressions of crop returns on contemporaneous monthly weather specified by (6). Daily rain, growing degree days (GDD) and extreme degree days (EDD) are spatially averaged over the U.S. Midwest and summed up over each month. The factor W is the share of the U.S. Midwest in U.S. crop production. Controls include the WTI oil price, the Index of Global Real Economic Activity and the Nominal Major Currencies Dollar Index. Statistical significance based on heteroskedasticity and autocorrelation consistent standard errors, *p<0.1; **p<0.05; ***p<0.01.

Table A.10: Correlation of weather event shocks.

Correlation 1971-1992 N obs: 322	Event rain	Event GDD	Event EDD
Event rain	1.00		
Event GDD	-0.30	1.00	
Event EDD	-0.27	0.52	1.00

Correlation 1993-2019 N obs: 404	Event rain	Event GDD	Event EDD
Event rain	1.00		
Event GDD	-0.17	1.00	
Event EDD	-0.19	0.61	1.00

Notes: Rain, growing degree days and extreme degree days are normalized for 1971-2019 by subtracting the mean values of the corresponding unnormalized variables for 1971-1992.

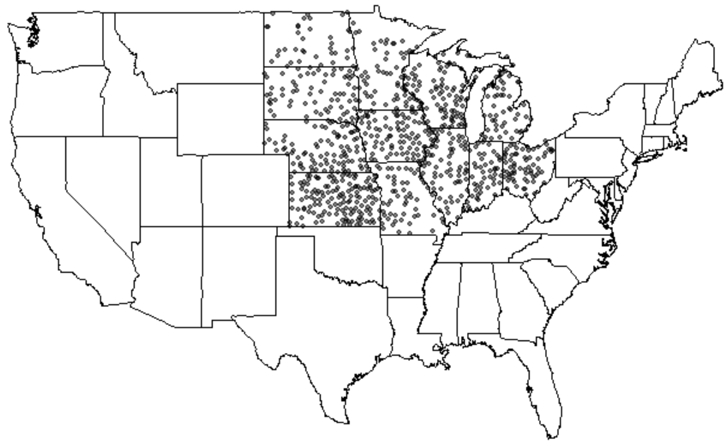

Figure B.1: Spatial distribution of 854 weather stations in the Midwest.

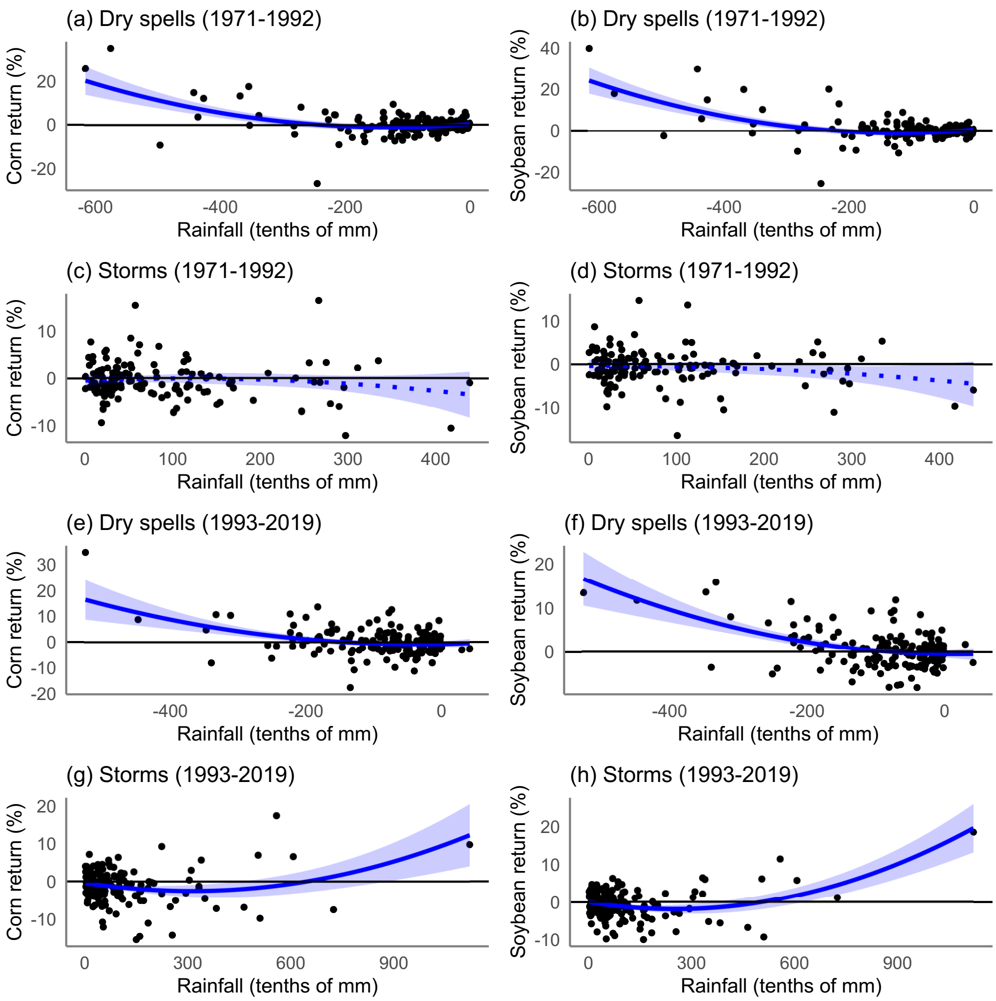

Figure B.2: Impact of event rain on crop returns. These figures show the fitted quadratic relationships between crop returns and normalized rainfall for each period and type of event as estimated in table A.7, holding all other variables constant at their median values. Bands represent the 95% confidence interval for the fitted models. The range for event rain is the historical record of normalized event rain for each period.

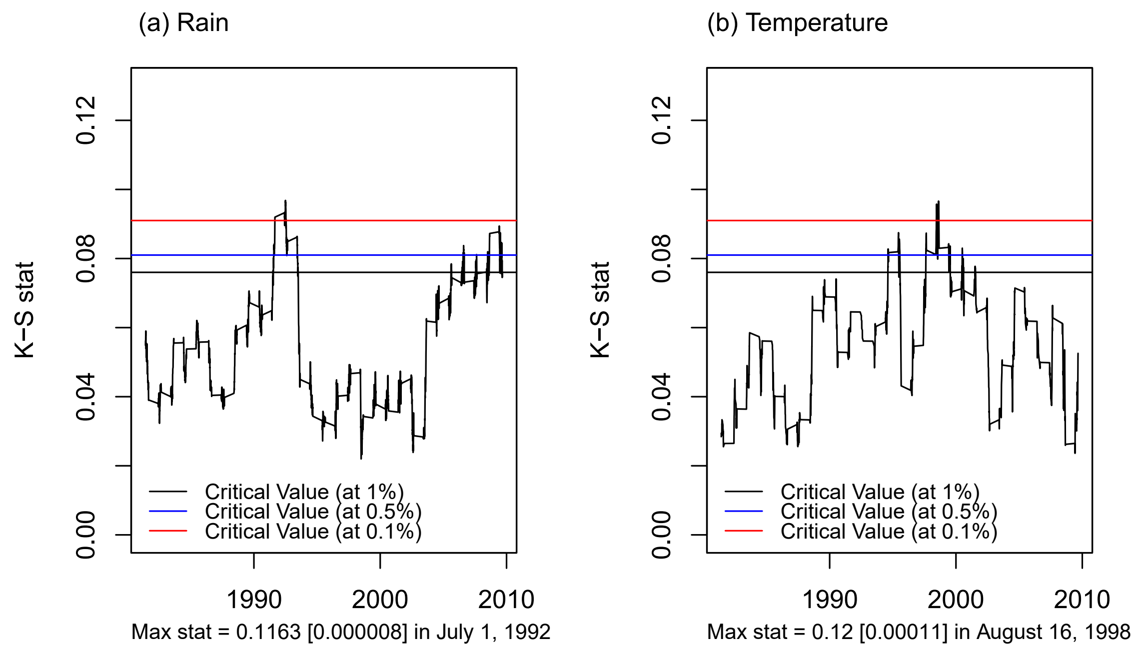

Figure B.3: Rolling Kolmogorov-Smirnov statistic for daily summer (June, July and August) rain and temperature. Using an initial window of 920 summer days (approx. 10 years) we calculate the Kolmogorov-Smirnov statistic to quantify the distance between the empirical cumulative distributions of daily, spatially averaged rain and temperature before and after the reference date t_c. This runs from August 31, 1980 to June 1, 2010 to ensure that the distributions are estimated with at least 920 summer days from 10 years of data.

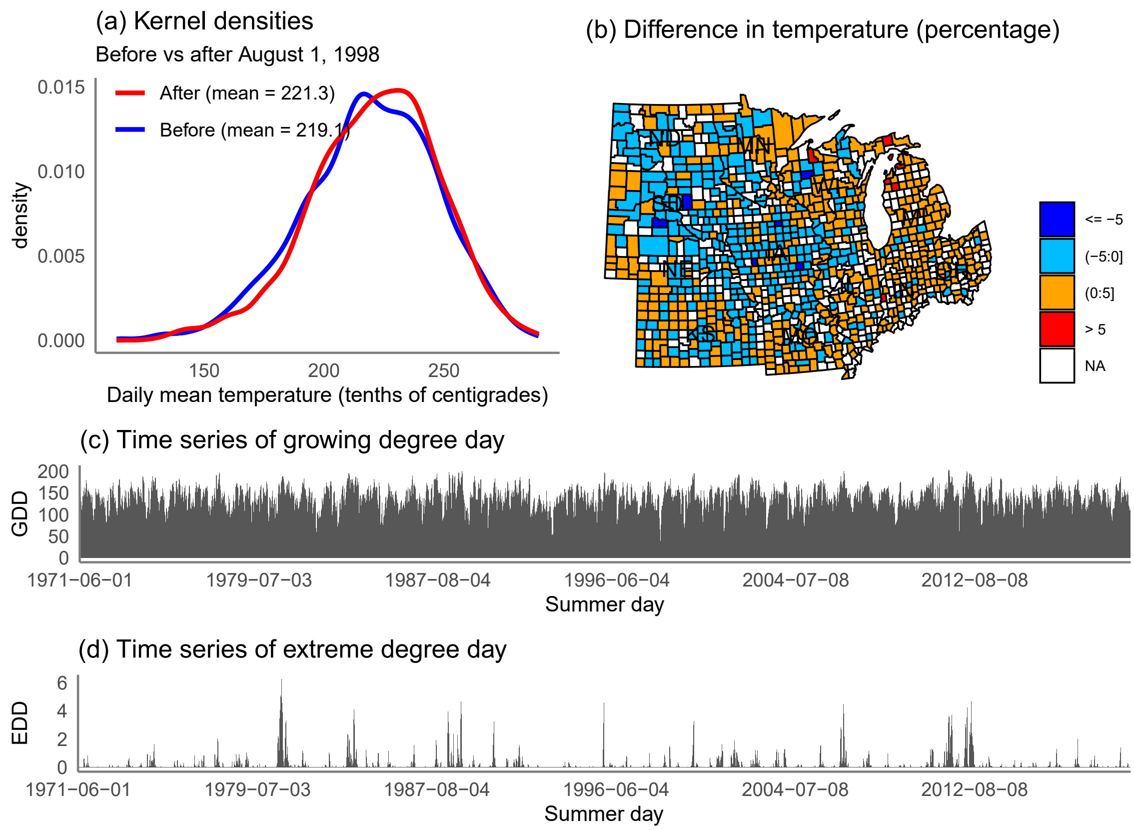

Figure B.4: Temperature patterns in the U.S. Midwest for June, July and August, 1971-2019. Figure B.4(a) displays distributions of daily, spatially averaged temperatures, before and after August 16, 1998. This is the date that maximizes the Kolmogorov-Smirnov distance between the empirical distributions for two adjacent, non-overlapping periods spanning 1971-2019. Figure B.4(b) displays differences in county mean daily temperature between 1971-1998 and 1999-2019. Figure B.4(c) displays the time series of daily, spatially averaged, Growing Degree Days and Extreme Degree Days.

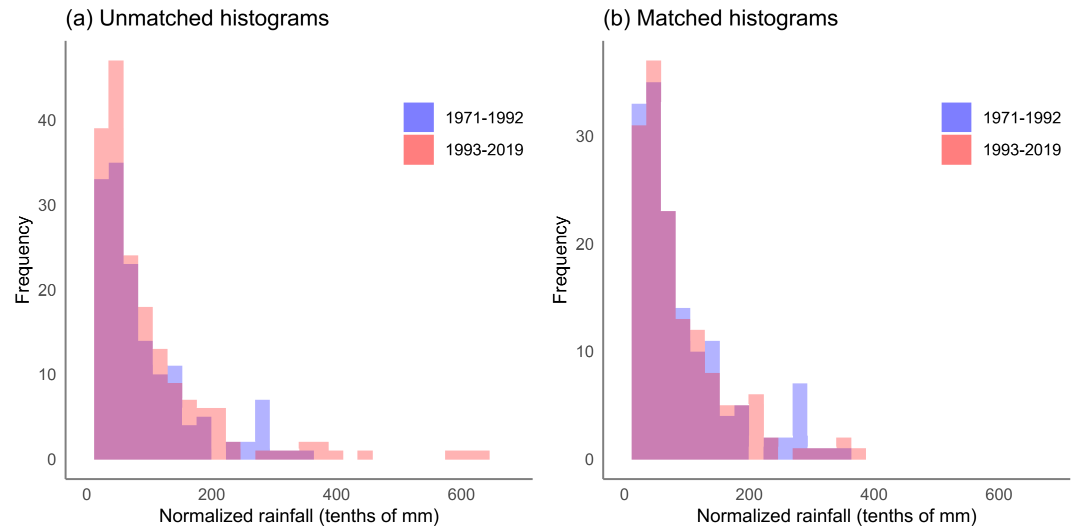

Figure B.5: Histograms for original data (a), and storms in 1993-2019 matched to those from 1971-1992 (b). Darkest section represents superposition of both histograms in each figure. We use a 1:1 matching scheme to create a counterfactual sample of storms for the second period (1993-2019) with the sample size and distribution of storms from the first period (1971-1992). Observations from the second period that are not paired to one in the first period are removed from the sample. Very large storms, that were not present in the first sample, are largely removed from the matched sample. A storm is defined as two or more consecutive days with rain above 30 tenths of a mm.