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The Impact of Climate Change on Yield Growth and the Mitigating Role of Irrigation in the Corn Belt

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Abstract

This paper examines how climate change and adaptation through irrigation have affected corn yield growth within the US Corn Belt since the 1960s. We combine corn yield and irrigation data from the USDA National Agricultural Statistics Service with ERA5-Land gridded temperature data. We adopt an augmented long-difference framework to i) assess the impact of extreme temperature trends from 1960 to 2023 on corn yield growth in Corn Belt counties since the 1960s and ii) estimate the potential of irrigation to mitigate this impact. Our findings reveal significant upward trends in extreme degree days (EDD) above 29°C across more than half of Corn Belt counties. We highlight that the varying magnitudes of these trends, alongside differential adoption rates of irrigation between counties, have played a crucial role in explaining the disparities in long-term corn yield trends within the region. Specifically, we show that irrigation offsets about 80% of the adverse impact of EDD on corn yields. Based on a counterfactual analysis, we find that current corn yields are about 6.5% lower, on average, than they would be in a non-climate change scenario.

Keywords: Climate Change, Yields, Irrigation, Corn Belt

JEL Classification: Q15 , Q54

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1 Introduction

According to a survey conducted by the Center for Commercial Agriculture of Purdue University in 2019, 78% of farmers in the United States (US) were not too worried about climate change. Moreover, 77% declared they had made no changes in their farm in response to climate change. Meanwhile, a growing number of studies highlight and predict substantial impacts of climate change on US agriculture. Agricultural productivity is projected to decrease in the US over the course of the 21st century (Liang et al. 2017). In particular, many studies using statistical or process-based crop models project important yield reductions for corn in the future (Schlenker and Roberts 2009; DeLucia et al. 2019; Liu and Basso 2020). Climate change is also expected to raise crop prices substantially, by lowering crop supplies in the context of inelastic demands (Baker et al. 2018; Crane-Droesch et al. 2019). For instance, Baker et al. (2018) estimate an increase of about 25% for the price of corn by 2050. Burchfield (2022) even projects that most of the Corn Belt region of the US Midwest will become unsuitable for corn cultivation by the end of the century.

Considering the above results, the absence of serious concern among US farmers might seem paradoxical. However, several reasons might explain this gap. Firstly, since the mid-twentieth century, the central-eastern US has experienced unexpectedly weak warming trends, especially during summer (Wilson et al. 2023). This well-known "warming hole" has been linked to natural climate variability as well as human factors, such as agricultural practices (e.g. irrigation) and aerosol emissions (Banerjee, Polvani, and Fyfe 2017; Mueller et al. 2016; Nocco, Smail, and Kucharik 2019). Most of the country's agricultural activities are in the central-eastern US and summer is the most important season for agriculture there. Therefore, the warming hole might have made climate change less discernible in this region. Since this phenomenon has been accompanied by upward trends in rainfall, some researchers even find evidence that it has been beneficial to corn yields so far (Butler, Mueller, and Huybers 2018; Partridge et al. 2019). Secondly, widespread climate shocks on crops trigger price increases, which sometimes benefit farmers (Bolster et al. 2023). Finally, long-established programs managed by the Federal Government aim at insuring farmers against income losses (Crane-Droesch et al. 2019).

Even if climate change has not been a source of concern for most US farmers up to now, it has still affected people's welfare through its impacts on agriculture. Commodity price increases hurt consumers' well-being or food safety (Bolster et al. 2023). Moreover, the average $12 billion in crop losses insured annually by the Federal Government are supported by US taxpayers. Diffenbaugh, Davenport, and Burke (2021) estimate that temperature trends in the US have caused 19% of the crop losses insured between 1991 and 2017. Furthermore, by compensating for the costs of climate change, federal "safety net" programs might dissuade farmers from adopting strategies to cope with it. To prevent these impacts, it is therefore essential that the US government promote suitable adaptive strategies to farmers.

Against this background, this paper enhances the understanding of US agricultural policy challenges in two ways. First, unlike previous studies, we find that climate change has already been detrimental to yields in the Corn Belt. More precisely, our results suggest that, in the absence of climate change since 1960, average corn yields would have been about 6.5% higher in recent years. The discrepancy with regards to previous studies lies partly in our finer measure of extreme temperatures, based on hourly ERA5-land data, which better captures the occurrences of temperatures harmful to corn. Indeed, our measures of extreme temperatures present significant upward trends in more than half of Corn Belt counties since 1960, contrary to what is shown in studies using rougher measures (Butler, Mueller, and Huybers 2018; Partridge et al. 2019). Our findings thus highlight the necessity for US farmers to urgently adopt adaptive strategies in response to climate change.

Second, we seek to provide information for comparing the benefits and costs of different adaptation strategies so that the most efficient can be promoted to US farmers. Accordingly, we assess the efficiency of irrigation in mitigating the harmful impact of extreme temperatures on corn yields. Schlenker and Roberts (2009) and Butler and Huybers (2013) provide evidence that irrigation can reduce the sensitivity of corn to extreme temperatures. However, their pieces of evidence are limited since irrigation is not the focus of their analyses. Therefore, we aim at providing a more accurate assessment of this beneficial influence of irrigation.

To that end, we adopt an augmented version of the long-difference approach developed by Burke and Emerick (2016). These authors calculate multi-decadal-long differences in several climate variables and corn yields at the county level. Then, they conduct a cross-sectional analysis to investigate whether counties experiencing greater long-term increases in extreme temperatures have correspondingly lower increases in corn yields. As expected, their findings indicate a negative relationship between extreme temperature increases and corn yields. Since the magnitude of the relationship does not differ significantly from what they find based on annual time-series variability, the authors emphasize a lack of adaptation to global warming in US corn agriculture.

We augment the above approach by introducing an interaction term that incorporates the evolution of corn irrigation at the county level into our specification of the relationship between long-run changes in extreme temperatures and yields. We justify the addition of this interaction term by a simple theoretical framework. This improvement is made possible by constructing an original dataset of the evolution of corn irrigation since the 1960s at the county level. We also improve the approach by calculating our long-differences from regressions on time trends, rather than relying on the difference between five-year averages around endpoints. This yields more consistent long-term changes by exploiting all the time-series information available. Additionally, it allows us to examine the significance of the trends. Based on this improved long-difference approach, we find that irrigation has mitigated the adverse impact of extreme temperatures changes on corn yields. Hence, the conclusion drawn by Burke and Emerick (2016) regarding the lack of significant adaptation to climate change in the US Corn Belt must be qualified in light of our findings.

We focus our attention on one crop, namely corn, because it enables us to produce more relevant estimates. Moreover, corn is the crop for which the most spatially and temporally extended historical data on yields and irrigation are available in the US. This provides us with important statistical power for analyzing the long-term effects of climate change on yields. Besides, corn accounted for 35.5% of US crop production in 2021, and the US plays a crucial part in global corn production. According to the USDA World Agricultural Supply and Demand Estimates (WASDE) of January 2024, over 30% of global corn production and exports originated from the US in 2021. Hence, the interplay between climate change and agricultural productivity in key regions like the Corn Belt carries significant implications not only for regional dynamics but also for global food security.

The remainder of the paper is organised as follows. Section 2 provides a detailed explanation of our empirical strategy. Section 3 describes the data used in our analysis. Section 4 presents our results. Finally, in Section 5, we summarize our findings and provide concluding remarks.

2 Empirical Strategy

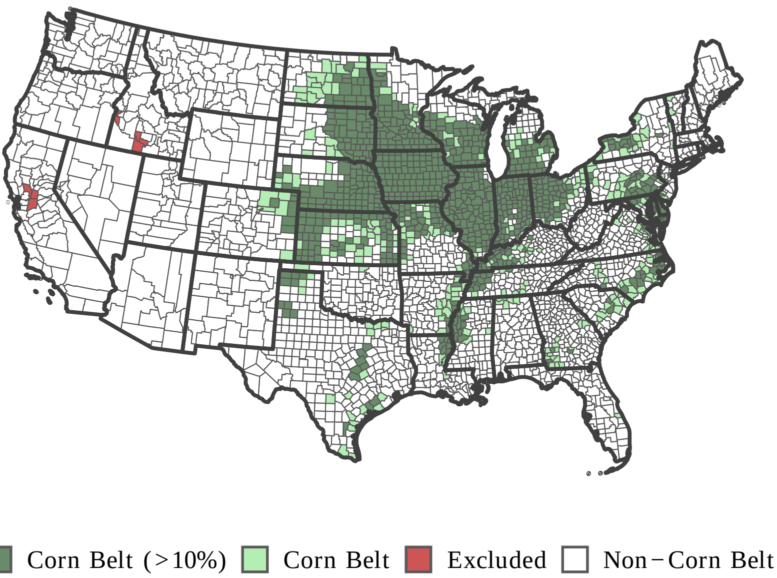
We carry out an empirical analysis composed of three steps. Firstly, we investigate whether long-run trends in extreme temperatures have occurred among Corn Belt counties since 1960. Secondly, we examine whether the heterogeneity in the magnitude of these trends along with the differential irrigation adoption rates between counties can explain the disparities in long-run trends in corn yields within the Corn Belt. Finally, we look further into the implications of our estimates based on two counterfactual analyses.

2.1 Corn Belt delimitation

Since we focus on the Corn Belt, we must delimitate this region before carrying out the analysis mentioned above. The objective of this delimitation is to obtain a sample which includes only counties with significant areas of corn cultivation. To that end, we follow the approach of Green et al. (2018), which delimitate the Corn Belt from the calculation of county-level areal fractions of corn cultivation. Their calculations are based on USDA National Agricultural Statistics Service (NASS) Crop Data Layers (CDL) which provide satellite-based crop detection at a 30-meter resolution over the contiguous US. In their study, they propose three delineations depending on the threshold used for the calculated areal fraction of corn. Their narrower delimitation only includes counties where corn covers over 20% of the area, resulting in a mostly contiguous Corn Belt spanning approximately $650,000km^2$. Their most extended delimitation corresponds to a 5% threshold and covers an area of about $1,600,000km^2$. We retain the latter threshold in our baseline analysis. We thus include in our sample any county with an areal fraction of corn higher than 5% in any year of CDL data since 2008 or Agricultural Census data since 1997 (see Section 3.1 for details). We select the lowest threshold of 5% because the cross-sectional nature of our approach required that we did not restrict the number of counties in our sample too much. Unlike Green et al. (2018), we also consider Agricultural Census data on harvested corn (for grain) area. This allows us to extend our analysis back to 1997 and include counties historically part of the Corn Belt but no longer classified as such.

Based on the 5% threshold, our delimitation of the Corn Belt includes 1,171 counties.[1] We illustrate this delineation in Figure 1 below.[2] Six counties were not included in some analyses described below for reasons related to data availability. This is discussed in Section 3.

Figure 1: Corn Belt delineation



Notes: This map illustrates our Corn Belt delineation based on the proportion of corn area over the total land area of every county. Our baseline delineation combines both the "Corn Belt" and "Corn Belt (>10%)" categories and includes any county with at least 5% of corn areal fraction for any year of CDL or Agricultural Census data. The "excluded" category corresponds to counties meeting this criterion but considered too remote to belong to the Corn Belt.

[1] Note that our delimitation includes 1,171 counties after having removed a few counties located in Idaho and California. We considered the inclusion of these geographical outliers into the Corn Belt delineation to be irrelevant.

[2] Figure 1 also depicts a narrower delineation of the Corn Belt adopted in a robustness check and based on an alternative 10% threshold (see Section C.2 of the Appendix)

2.2 First step: evaluation of long-run changes in extreme temperatures

The first step consists in investigating whether significant long-run trends in extreme temperatures have occurred since 1960 among Corn Belt counties. The extreme-temperature measure we focus on is extreme degree days above 29°C (EDD). This variable captures both the intensity and frequency of the occurrences of temperatures above 29°C. It quantifies the duration, in days, for which temperatures have exceeded 29°C, with each hour weighted according to the magnitude of the excess. For example, one hour at 35°C represents $6/24 = 0.25$ EDD ($6°C \times 1/24day$), which is identical to six hours at 30°C ($1°C \times 6/24day$). One hour with a temperature lower than 29°C corresponds to 0 EDD.

We sum the EDD values of all hours of each corn growing season (April to September) from 1960 to 2023 for every county in our Corn Belt to obtain annual county-level EDD values. Details about the data and method used for calculating these annual EDD at the county-level are provided in Section 3.2. This measure was chosen because temperatures above 29°C have been shown to be very harmful for corn productivity and to explain a substantial share of corn yield variations (D'Agostino and Schlenker 2016). Lobell et al. (2013) use a process-based crop model to show that EDD harm corn yields mainly through raising vapour pressure deficit, which in turn lowers the transpiration efficiency of plants, thereby exposing them to water stress. Furthermore, as our analysis only exploits the cross-sectional heterogeneity in temperature trends in order to explain the differences in yield trends, we need a temperature measure with a consistent and homogeneous effect on corn yields across counties. Indeed, we show that the effect of EDD on corn yields, estimated in the time-series dimension for each county separately, is significant in virtually all counties and always has a negative sign when significant. The results of this secondary time-series analysis are presented in Section B of the Appendix.

Our approach to investigate the presence of a significant long-term trend in EDD for a given county consists in regressing the EDD time-series for this county on deterministic specifications of time from 1960 to 2023 and examining if the regressions are significant. We consider two specifications: one which is simply linear in time and one which is quadratic. Both regressions are estimated, by Ordinary Least Squares (OLS), for each county. If one of the regressions proves to be significant according to a robust Fisher test (at the 10% level) while the other does not, we retain the significant one. If both regressions are significant or insignificant, we retain the quadratic time trend if and only if the coefficient associated with the quadratic term is significant (also at the 10% level). Then, in order to quantify the total magnitude of the time trend for every county, we calculate the fitted values for years 1960 and 2023 (the first and last years of data, respectively) based on the selected specification. These values are denoted EDD_{1960} and EDD_{2023} respectively. We then subtract the former from the latter. For every county, we thus obtain the total long-run change in EDD from 1960 to 2023, and we can examine the significance of the underlying time trend. The results of this approach are presented in Section 4.1. We check the robustness of our results to the method for selecting the specification of the time trend in Section C.1 of the Appendix.

2.3 Second step: long-term relationship between yields, climate and irrigation

After having estimated the long-run change in EDD for each county as described above, we apply the same methodology to estimate long-run changes in corn yields since 1960.[3] Therefore, for every county in our delimited Corn Belt, we have the long-run evolution of EDD since 1960 along with the corresponding long-run evolution of corn yields. This allows us to cross-sectionally analyse the impact of long-run trends in EDD on trends in corn yields.

Relying on previous results regarding the relationship between EDD and corn yields, we expect that counties having experienced faster long-run increases in EDD will exhibit slower increases in yields. However, in the long run, adaptation could take place and mitigate the impact of EDD on yields. In such a case, the coefficient of a simple regression of long-run changes yields on long-run changes in EDD would incorporate such mitigation effect. Nevertheless, such a coefficient might be biased if the adaptation strategy is correlated to climate change but can boost yields independently of it. Irrigation is one adaptation strategy that might correspond to such a case. Schlenker and Roberts (2009) and Butler and Huybers (2013) provide evidence that irrigation mitigates the harmful impact of extreme temperatures on corn yields. Hence, if a county experiences a stronger increase in EDD than another, but invests considerably in irrigation infrastructure, this investment should narrow the gap in yield growth between the two counties (by mitigating the impact of climate change). But, at the same time, it is possible that the former county initially has a warm climate with high EDD normals. Then, investments in irrigation infrastructure would raise yields even in the absence of any long-term change in EDD, by adapting crops to the initially adverse climate. Therefore, the county experiencing the stronger long-run increase in EDD might also experience a faster increase in yields because irrigation has not only mitigated the impact of climate change but has also increased the initial level of yields. Put another way, since long-run changes in EDD are correlated with initial EDD levels, which in turn influence investments in irrigation and their beneficial effect on yield growth, a simple regression of long-run changes in yields on changes in EDD suffers from an omitted variable bias.

We now illustrate this point with a short and simple theoretical framework. This framework also provides justification for the econometric specification of this second step of our empirical approach.

Let's denote R_t, the average yield in a given county in period t. We begin with expressing R_t as the area-weighted average of irrigated yields, R_{It}, and non-irrigated yields, R_{Nt}:

$$R_t = \theta_t R_{It} + (1 - \theta_t) R_{Nt} \tag{1}$$

where θ_t represents the fraction of corn area irrigated in that county in period t.

[3] Results for this approach applied to corn yields are presented in Section D of the Appendix. We use annual corn yields at the county level from 1960 to 2023, obtained from USDA NASS survey data. Details about these data are provided in Section 3.1.

We can easily rearrange the previous equation in the following way:

$$R_t = \theta_t(R_{It} - R_{Nt}) + R_{Nt} \tag{2}$$

Now, for sake of simplicity, we suppose that R_{It} and R_{Nt} linearly depend on EDD in period t:[4]

$$R_{Nt} = \beta_N EDD_t \tag{3}$$

$$R_{It} = \beta_I EDD_t \tag{4}$$

We expect β_N to be negative (i.e. an increase in EDD deteriorates non-irrigated yields). The sign of β_I (the sensitivity of irrigated yields to EDD) is more uncertain, but we expect it to be higher (i.e. less negative) than β_N.

Then, substituting Equations 3 and 4 in Equation 2 yields:

$$R_t = \tilde{\beta}\theta_t EDD_t + \beta_N EDD_t \tag{5}$$

with $\tilde{\beta}$ defined as the difference between β_I and β_N (expected to be positive). From Equation 5 above, denoting R_{LD} the difference between R_{2023} and R_{1960}, we can write:

$$R_{LD} = \tilde{\beta}(\theta_{2023}EDD_{2023} - \theta_{1960}EDD_{1960}) + \beta_N EDD_{LD} \tag{6}$$

It is clear from Equation 6 that R_{LD} negatively depends on the change in EDD_{LD}, namely the change in EDD from 1960 to 2023, through the coefficient β_N. However, it also responds positively to the long-difference of a variable corresponding to the interaction between EDD and the irrigation fraction, through the coefficient $\tilde{\beta}$. The latter coefficient incorporates two important features. First, let's suppose that the fraction of corn irrigated, θ_t, is fixed and denote it simply θ. Then, we have, from Equation 6:

$$R_{LD} = (\tilde{\beta}\theta + \beta_N)EDD_{LD} \tag{7}$$

In this case, R_{LD} is determined by the evolution of EDD resulting from climate change. The interaction between $\tilde{\beta}$ and θ, corresponds to the magnitude of the mitigation of climate change impact due to irrigation.

Now, let's assume that there is no climate change, so that $EDD_{1960} = EDD_{2023} = EDD$, and that irrigation can vary between both periods again. Then Equation 6 becomes:

[4] Note that we implicitly suppose that EDD_t is the same for irrigated and non-irrigated areas within a county. This assumption appears to be reasonably non-restrictive, given the strong spatial correlation of climate and the relatively small area of most counties in our sample..

$$R_{LD} = \tilde{\beta} EDD \theta_{LD} \tag{8}$$

In Equation 8, it is the evolution of the fraction of corn irrigated, θ_{LD}, that causes R_{LD}, depending on $\tilde{\beta}$ and the level of EDD. Thus, $\tilde{\beta}$, in conjunction with EDD, represents the magnitude of adaptation to climate (not to climate change). When both θ_t and EDD_t are allowed to vary, both the mitigation-of-climate-change and the adaptation-to-climate effects are at work. Indeed, we can rearrange Equation 6 to make both effects visible:

$$R_{LD} = \tilde{\beta} EDD_{1960} \theta_{LD} + (\tilde{\beta}\theta_{2023} + \beta_N) EDD_{LD} \tag{9}$$

The first term of Equation 9 corresponds to the adaptation-to-climate effect, which operates even in the absence of climate change (i.e. $EDD_{LD} = 0$) through the evolution of the fraction of corn acreage irrigated (θ_{LD}). The second term represents the mitigation-of-climate-change effect. It can be at work without any change in the irrigation infrastructure ($\theta_{LD} = 0$). From this equation, we can see that if EDD_{LD} is correlated with the product of EDD_{1960} and θ_{LD}, a simple regression of R_{LD} on EDD_{LD} will be biased because the adaptation-to-climate (not climate change) effect will be incorporated in the coefficient associated to EDD_{LD}. The correlation between EDD_{LD} and $EDD_{1960}\theta_{LD}$ equals about 0.23 in our sample, which suggests a potential importance of accounting for the latter variable in our specification.

Hence, the second step of our empirical approach consists in estimating both coefficients of Equation 6 based on our cross-section of Corn Belt counties. In this way, we seek to evaluate the importance of long-run changes in EDD, along with adaptation through irrigation infrastructure, in explaining the differential long-run trends in corn yields observed among Corn Belt counties.[5] Note that we estimate a modified version of Equation 6 where all variables (i.e. R_{LD}, EDD_{LD} and $(\theta EDD)_{LD}$) are standardized to account for the fact that our time-series of corn yields are shorter in some counties. For instance, corn yield data in Texas and New York are only available since 1968 and 1972, respectively. Hence, for any county i, we define $\overline{R}_{LD,i}$ as the ratio of $R_{LD,i}$ to $(T_i - 1)$, with T_i being the number of observations in the yield time-series of county i. We equivalently define $\overline{EDD}_{LD,i}$ and $\overline{(\theta EDD)}_{LD,i}$. Moreover, an intercept is included in the specification. Thus, we estimate the following equation:

$$\overline{R}_{LD,i} = \tilde{\beta} \overline{(\theta EDD)}_{LD,i} + \beta_N \overline{EDD}_{LD,i} + \alpha + \epsilon_i \tag{10}$$

The variables in this specification must then be interpreted as annual average changes instead of total changes during our study period. However, the coefficients (except the intercept) are theoretically the same as in Equation 6 above.

A challenge arises when attempting to account for the evolution of irrigation infrastructure, as no comprehensive historical data at the county-level about the specific irrigation of corn are available. Indeed, county-level data about the irrigated acreage

[5] see Section D of the Appendix for details about the latter trends.

of corn are only available in the 1960s for Colorado, Kansas, Louisiana, Nebraska, Oklahoma, South Dakota, and Texas.[6]

For the remaining States in our sample, no such data are available. However, there is evidence that corn irrigation was negligible in most counties of these States around 1960. Indeed, in the majority of these States, virtually all counties either do not irrigate their corn acreage or have minimal irrigation infrastructure even today (see Figure A2 in Section A of the Appendix for our recent measure of irrigation infrastructure). The exceptions are Arkansas, Georgia, Mississippi, and Missouri where some corn growing areas are currently highly irrigated. According to the 1964 Agricultural Census, there was no irrigation of corn in Missouri in 1964. In Georgia and Mississippi, the irrigated fractions of corn for grain were slightly above 0.2% in 1964, against about 55% as of the 2017 Census. In Arkansas, 2.4% of corn (for grain) acreage was irrigated in 1964, against 85.7% as of the 2017 Census. Hence, for all States lacking county-level irrigation data for corn at the beginning of our sample period, we assume that θ_{1960} is equal to zero in every county.

As for current irrigation, the approach is the same for all counties in our sample. For each county, we select the highest of the corn irrigation fractions reported in 2012 and 2017 Agricultural Censuses. We select the highest of both values because we try to measure irrigation capacity. Hence, such capacity may not be fully utilized in a particular year, resulting in the 2017 value being lower than the 2012 value in some cases.

The results of the estimation of Equation 10 by OLS are presented in Table 1 of Section 4.2. We also estimate the simple regression of $\overline{R}_{LD}$ on $\overline{EDD}_{LD}$ (i.e. without the first term on the right-hand side of Equation 10) and display the results in Table 1. In this manner, we examine how much the omission of $\overline{(\theta EDD)}_{LD}$ alters the estimate of the coefficient associated with $\overline{EDD}_{LD}$.

2.4 Third step: counterfactual analyses

After having estimated the long-term effects of EDD and irrigation on corn yields, we carry out two counterfactual experiments. Such experiments aim at providing insight into the magnitude of these effects in the context of the observed trends in EDD and corn-irrigation development since the 1960s.

2.4.1 Non-climate change scenario

Our first counterfactual analysis seeks to assess the magnitude of the changes in current corn yields induced by the long-term trends in extreme temperatures that we measure since 1960. It consists in assuming a null EDD long-difference in every county of our sample and evaluating the changes in current yield normals - compared to the normals that we observe - resulting from this assumption.

[6]The sources of the data about corn irrigation in the 1960s differ depending on the state. Two out of the three sources present missing information which lowers the accuracy of our measures in some cases. Please see Section 3.3 for details.

Formally, we first calculate a counterfactual yield standardized long-difference for each county, denoted $\overline{R}^0_{LD,i}$ based on the following equation:

$$\overline{R}^0_{LD,i} = \hat{\tilde{\beta}}(\theta_{2023,i}EDD_{1960,i} - \theta_{1960,i}EDD_{1960,i}) \times \frac{1}{T_i} + \hat{\alpha} + e_i \tag{11}$$

with $\hat{\tilde{\beta}}$ the estimate of $\tilde{\beta}$ resulting from the estimation of Equation 10 by OLS (see Table 1) and e_i the residual for county i. Note that the second term on the right-hand side of Equation 10 does not appear in Equation 11 above. This is precisely because we assume that $EDD_{LD,i} = 0$ for every county i in this counterfactual analysis. Moreover, in the first term, we substitute $EDD_{1960,i}$ for $EDD_{2023,i}$ for consistency with the no-EDD long-difference assumption. Once that we have calculated $\overline{R}^0_{LD,i}$ for each county in the sample, we multiply it by the corresponding T_i to obtain the total corn yield long-difference for county i. Then, we add this total long-difference to $R_{1960,i}$ to obtain the counterfactual current value of corn yield normals in county i, denoted $R^0_{2023,i}$.

The underlying objective of this approach is to evaluate to what extent human-induced climate change might have already affected yield growth in the Corn Belt. Hence, we call this first analysis the "non-climate change" scenario in what follows. However, this objective might not be fully achievable with such a simple experiment. Indeed, several studies dealing with the warming-hole problem for the central-eastern US highlight the strong internal climate variability in this region in recent decades (Kumar et al. 2013; Eischeid et al. 2023). Such a variability might have dampened the emergence of global warming in this region so far. For instance, Eischeid et al. (2023) explain the recent lack of summertime warming in central-eastern US from the persistent and unusual intensification of the water cycle observed over the region, mostly attributed to internal variability. Their results suggest that, in the absence of this phenomenon, regional warming would have been stronger in recent years. Since our analysis does not distinguish long-term internal variability from external climate change, we might understate the losses in yields caused by the latter.

Moreover, it is worth noting that climate change can have both anthropogenic and natural sources. Indeed, it is well known that solar and volcanic activities can influence the climate system, independently from human societies. Hence, we cannot entirely attribute our observed trends in EDD to human activities since these natural factors could have been at work for our period and region of interest. However, the IPCC (2023) provides evidence that climate change from natural sources has been negligible for many decades over North America. These results do not precisely concern the central-eastern US but still provide some confidence that human activities have been the predominant factor behind climate change in the Corn Belt since 1960. We provide the results of this non-climate change scenario in Section 4.3.1.

2.4.2 Non-irrigation development scenario

Our second counterfactual analysis focuses on the contribution of the long-term developments of corn irrigation in the Corn Belt to current corn yields in the region.

Precisely, it consists in assuming that the current corn irrigated fraction has remained equal to its value of the 1960s in each county of our sample. In this manner, we can estimate and compare what today's corn yields would have been in the absence of adaptation through irrigation (and assuming no substitution with another form of adaptation) during the period under study. We denote the current yield normals derived from this second scenario by R^N_{2023}.

This second analysis aims at providing insights into the importance of current irrigation in preserving reasonable yields within the relevant areas of the Corn Belt. Such insights appear valuable since climate change is expected to threaten water availability in at least some parts of the region, potentially making it difficult to sustain current irrigation levels in the future (McPherson et al. 2023). This second analysis may inform policymakers in guiding farmers towards more (or less) parsimonious water usage, or alternative adaptation strategies such as crop switching (Rising and Devineni 2020). Section 4.3.2 describes the results of this second counterfactual analysis.

3 Data

3.1 Corn acreage and yield data

In order to delineate our Corn Belt, we needed data about corn acreage at the county-level. We used two data sources about corn acreage. First, we used county-level data on harvested acreage of corn (for grain) from the Agricultural Censuses since 1997. For every county with at least some corn area, we calculated the areal fraction of corn by dividing the harvested acreage of corn by the county's total land area (as of 2010 from the US Census Bureau). Due to disclosure avoidance rules, Agricultural Census data are hidden for some counties. Therefore, we completed these data with USDA NASS Crop Data Layers (CDL). The CDL are crop-specific land cover data at a 30-meter resolution produced from satellite imagery. They are available annually for the entire Contiguous US (CONUS) since 2008. For every year between 2008 and 2023, we attribute a value of 1 to any gridpoint containing corn and 0 for any other gridpoint. Then, we average all gridpoint values within every county to obtain county-level areal proportions of corn.

Corn yield data at the county level are from USDA NASS annual surveys. Due to missing years for some counties in the Corn Belt, we retain only the counties with at least 45 annual observations of corn yields since 1960. We therefore exclude six counties from the 1,171 counties included in our delineated Corn Belt. Note also that in Colorado, Texas, and New York states, corn yield data are only available since 1963, 1968 and 1972 respectively.

3.2 Climate data

The temperature data we use to calculate extreme degree days are hourly 2-meter temperatures from ERA5-Land. ERA5-Land is a reanalysis dataset providing gridded data at a $0.1° \times 0.1°$ resolution over the global land surface (Muñoz Sabater 2019).

We begin with calculating hourly EDD above 29°C for every gridpoint in the dataset. Hence, for any gridpoint g at any hour h, we calculate $EDD_{g,h}$ as:

$$EDD_{g,h} = \begin{cases} (T_{g,h} - 29) \times \frac{1}{24} & \text{if } \; T_{g,h} > 29 \\ 0 & \text{otherwise} \end{cases}$$

with $T_{g,h}$ the temperature (in Celsius degrees) in gridpoint g at hour h. We then sum $EDD_{g,h}$ over all hours of each annual corn growing season (from April 1$^{\text{st}}$ to September 30$^{\text{th}}$) from 1960 to 2023.

At this stage, we have annual EDD values at the gridpoint level for every gridpoint in the dataset. As we seek to include only the areas where corn is frequently grown when averaging EDD values to the county level, we use USDA NASS Crop Frequency Layer (CFL) for corn. The corn CFL indicates the number of years for which corn has been grown on a specific 30-meter gridpoint over the 2008-2023 period. Taking into account the fact that corn is often grown in rotation with soybean and that land may lie fallow in some years (Green et al. 2018), at least five years of corn were considered necessary for a CFL gridpoint to be retained as a frequent-corn gridpoint. Then, we remove from our dataset all EDD gridpoints containing no frequent-corn gridpoint. Finally, we average the values from the remaining EDD gridpoints in a county, by weighting each EDD gridpoint according to the number of frequent-corn gridpoints within it. In this manner, we obtain county-level yearly EDD values corresponding to the areas where frequent corn cultivation is the most important.

3.3 Irrigation data

The data sources about corn irrigation in the beginning of our study period differ depending on the state. For Colorado, Nebraska and South Dakota, data are from surveys conducted by USDA NASS in the beginning of the 1960s. For Nebraska and South Dakota, the survey year is 1960 while for Colorado, it is 1963, according to the first year of data on corn yields we have. For Kansas, Louisiana, and Oklahoma we use data from the 1959 Agricultural Census. For Texas, we use the 1969 Agricultural Census, since corn yield data began in 1968 in Texas. It is worth mentioning that the way corn irrigated acreage is measured varies slightly depending on the source of the data. In some cases, the information about the exact fraction of irrigated corn (for grain) is missing. To deal with these cases, we develop an approach which enables us to derive intervals to which the missing values necessarily belong. Then, based on these intervals, we derive estimates of these values while assessing the uncertainty surrounding these estimates. This approach is extensively discussed in Section A.1 of the Appendix.

The most recent measure of irrigation infrastructure is obtained from selecting the highest value for the fraction of corn (for grain) irrigated between the 2012 and 2017 Agricultural Censuses for every county. In some counties, the exact value for one year, or both, is hidden due to disclosure avoidance practices. However, USDA NASS Agricultural Census Web Maps still provide an interval to which the true value belongs.

In some cases, we therefore have to estimate the exact value of the irrigated fraction of corn as the midpoint of the interval to which it belongs. Note that this issue introduces uncertainty regarding the accurate value of the irrigated fraction of corn for 31% of counties. This is detailed in Section A.2 of the Appendix.

4 Results

4.1 First-step results

In Figure 2 below, we first illustrate the chosen type of time trend for each county based on the methodology described in Section 2.2. Among the 1,171 counties for which we have calculated EDD, 652 present a significant time trend (at the 10% significance level) representing 55.7% of our sample.[7] It is clear from Figure 2 that a majority of counties display an upward linear trend. However, 100 counties, most of them located in the southwest of the region and the southern Mississippi Portal, present accelerating quadratic trends. This suggests that the pace of increase in EDD may be greater for these counties in the future than what it has been thus far. This is even more concerning since this pace has already been substantial in the southwestern part of the region, as we describe below. Additionally, we observe slowing quadratic trends in some counties around Illinois through Ohio. A cluster of counties in the northwest presents downward time trends, although none of them is significant. Note that this pattern is fairly preserved when using the AIC to select the trend types, except that the slowing quadratic type is retained for only one county in that case (see Figure C1.1 in the Appendix).

We now shift our focus to the values derived for the difference between EDD_{1960} and EDD_{2023} (i.e for EDD_{LD}). This variable is illustrated in Figure 3 and Table D1 provides summary statistics for EDD_{LD}. We observe a positive value (i.e an increase in EDD) for 1,127 counties out of the 1,171 under consideration. Moreover, all the significant time trends correspond to positive values of EDD_{LD}. The mean of the variable equals 13.66 (the median is 8.86). These results contrast with those from Butler, Mueller, and Huybers (2018), who find downward EDD trends in most parts of the Midwest since 1981. This difference is likely due to the fact that these authors calculate EDD simply based on daily T_{max} data. Yet, the warming-hole literature has shown that this phenomenon applies to daily maximum temperatures more than to other aspects of temperatures (Wilson et al. 2023; Eischeid et al. 2023). Therefore, Butler, Mueller, and Huybers (2018) might measure trends in T_{max} rather than actual trends in EDD. Using hourly-based EDD measures, we demonstrate that the occurrence of temperatures above 29°C has steadily increased since 1960 in most Corn Belt counties.

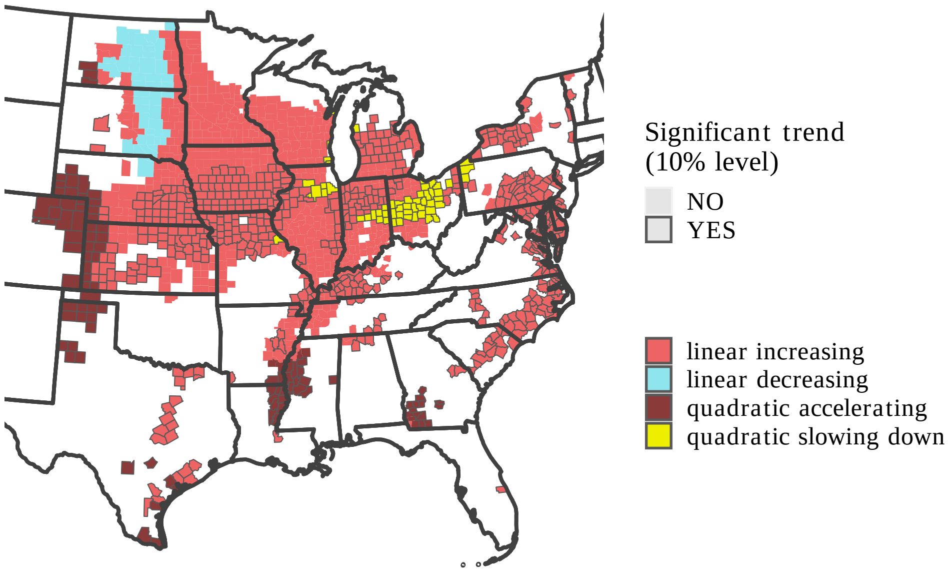
However, there is substantial heterogeneity across counties. Indeed, the standard deviation equals 15.01, with -3.71 as the minimum value (although associated with an insignificant time trend) and the maximum value reaching 98.59. Figure 3 shows that counties located in the southwestern part of the Corn Belt have undergone stronger long-term increases in EDD compared to those in the northern and eastern parts. In

[7] Here we perform inference based on the standard errors robust to heteroskedasticity and autocorrelation proposed by Newey and West (1994).

particular, Texas emerges as the state most affected by long-run increases in EDD, with an average increase of 69.28 across its counties. On the contrary, North Dakota is the less affected state, with an average value equal to -0.35. This pattern strongly reflects that of EDD normals in 1960 (see Figure D2 for a map of EDD_{1960}). Indeed, the coefficient of determination of the simple OLS regression of EDD_{LD} on EDD_{1960} equals 66%. This is not surprising, as warmer counties either meet or exceed the threshold of 29°C more frequently. Hence, a similar increase in temperature will trigger a more substantial increase in EDD within counties that have an initially warmer climate.

We then exploit the considerable cross-county heterogeneity in long-run EDD changes to investigate whether it can explain the differential corn yield trends observed among Corn Belt counties since 1960.

Figure 2: Selected type of time trend for EDD

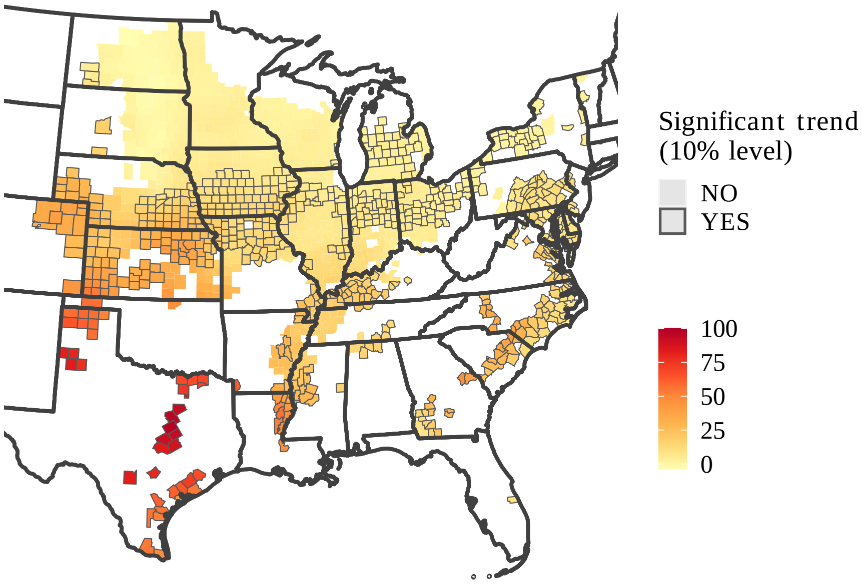


Notes: This map illustrates the type of time trend which has been selected for every county regarding the evolution of EDD from 1960 to 2023. See Section 2.2 for a description of the selection method. Significance is determined according to standard errors robust to heteroskedasticity and autocorrelation.

4.2 Second-step results

As shown earlier, over half of the counties in the Corn Belt have undergone significant trends in EDD since 1960, and there is considerable cross-county heterogeneity in these trends. Now, we investigate whether this heterogeneity can account for the disparities

Figure 3: EDD long-differences (1960-2023)



Notes: This map illustrates our estimated long-difference for EDD over the 1960-2023 period in every county, denoted as EDD_{LD}. This variable corresponds to the difference between the values of EDD in 1960 and 2023 fitted according to the time trend which have been selected for a given county. See Figure 2 above for the selected type of trend in every county. Significance is determined according to standard errors robust to heteroskedasticity and autocorrelation.

observed in the long-run trends of corn yields across counties. Of particular interest is our investigation into whether irrigation has played a role in mitigating the impact of EDD changes on corn yields.

To carry out these analyses, we first estimate Equation 10 without including the first term which is supposed to capture the adaptation-to-climate and the mitigation-of-climate-change effects presented in Section 2.3. Omitting this variable produces a biased estimate of the coefficient associated with $\overline{EDD}_{LD}$ because the latter variable is correlated with the beneficial effect of the evolution of irrigation. To evaluate the magnitude of this bias, we then estimate the complete form of Equation 10 and compare the results of both regressions.

Table 1 presents the results. In the simple regression of $\overline{R}_{LD}$ on $\overline{EDD}_{LD}$, our estimated coefficient equals -0.48 and is highly significant. Interestingly, the 95% confidence interval for this estimate does not include the average coefficient estimate across counties obtained when running the time-series regressions of corn yields on EDD, which is -0.64 (see Section B of the Appendix). This finding is rather inconsistent with that of Burke and Emerick (2016). Indeed, they find that the estimated effect of EDD on corn yields from a cross-sectional long-difference regression (such as ours) is close to that obtained from a panel fixed-effects regression. They interpret this similarity as indicative of the absence of significant adaptation to warming trends in the Corn Belt.

The results presented in the second column of Table 1 provide further evidence that this statement should be qualified. In fact, both coefficients estimated from the complete form of Equation 10 are significant with the expected sign. The estimate of the coefficient associated with $\overline{EDD}_{LD}$ is equal to -1.11. It corresponds to β_N in Equation 10, which represents the effect of EDD on corn yields in non-irrigated areas. It is more than twice as large as the coefficient from the first column, and the difference between both estimates is strongly significant. Therefore, omitting the variable capturing adaptation through irrigation leads to underestimating substantially the harmful impact of EDD on yields for non-irrigated corn.

Interestingly, the impact that we estimate for rainfed corn is (significantly) much larger than what Butler and Huybers (2013) find for the most sensitive rainfed areas of the Corn Belt (their most negative estimate is about -0.55) using time-series regressions. Our cross-section estimate is more consistent with the findings of our own time-series analysis, but a gap still remains. Indeed, an estimate equal to -1.11 corresponds to the 10% quantile of our time-series estimates, which means that only a few counties exceed such a negative estimate for the impact of EDD (see Section B in the Appendix for a description of our time-series results). The more negative estimates that we obtain in both the cross-section and the time-series with respect to Butler and Huybers (2013) could be due to the fact that they control for the (supposedly beneficial) influence of growing degree days (GDD) in their specification. In addition, they run their regressions by imposing a positive and negative coefficients for GDD and EDD, respectively. Most importantly, they calculate degree days based on daily average temperatures instead of hourly measures. This former approach has been shown by Schlenker and Roberts (2009) to be far less efficient in predicting yields because the most extreme temperatures are averaged out.

Besides, the estimate of the coefficient for $\overline{(\theta EDD)}_{LD}$ equals 0.90. According to Equation 10, it corresponds to the difference between β_I and β_N, the former being the effect of EDD on yields in irrigated areas. We thus demonstrate that the harmful impact of EDD on corn yields is weakened by irrigation. More precisely, each 10 percentage points increase in the proportion of irrigated corn in a county generates a reduction of about 0.09 in the negative impact of EDD on corn yields. This is similar to the result of Butler and Huybers (2013) which find that counties that irrigated at least 10% of their acreage have a sensitivity to EDD which is 0.08 smaller on average. Additionally, our point estimates suggest that the irrigation of corn mitigates 81% of the impact of EDD. This is also consistent with the result of Lobell et al. (2013) which suggests that the predominant channel through which EDD affect corn yields is through raising plant water stress.

Furthermore, summing both estimated coefficients yields an estimate of β_I equal to -0.21. According to a robust Wald test, this parameter is significantly different from zero. This means that irrigation does not fully mitigate the impact of EDD on corn yields. Nonetheless, irrigation does alleviate this impact in large part. Moreover, a number of counties within our delineated Corn Belt have notably raised their acreage of irrigated corn since the 1960s. As can be seen from Figure 4, most of these counties are located in the Mississippi Portal, the north of Nebraska, Kansas and Georgia. The rest are disseminated across the region. The substantial increases in corn irrigation in the Mississippi Portal and northern Nebraska likely explain most of the remarkable pace at which corn yields have increased in these areas since the 1960s (see Figure D1). This is confirmed by our second counterfactual analysis, whose results are presented in the next section.

Given the extent to which irrigation can reduce the impact of EDD on yields and the surge in corn irrigation since 1960 in several parts of the Corn Belt, we state that adaptation to global warming have already occurred in some parts of the region. Note that the inclusion of the first term of Equation 10 in the specification raise the coefficient of determination from 5.8% to 42.6%. Hence, by considering only the long-term changes in EDD and irrigation, we are able to explain more than 40% of the heterogeneity in corn yield trends across Corn Belt counties since 1960.

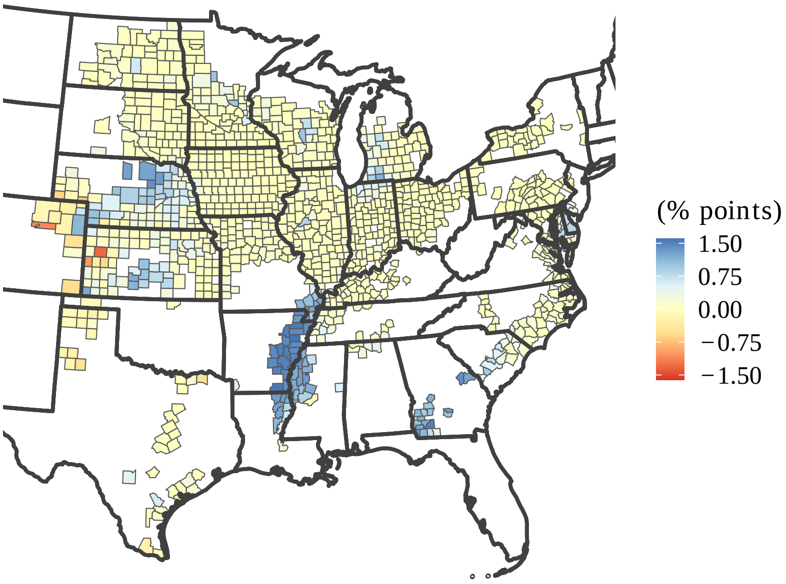
Table 1: OLS regression results for Equation 10

	Eq. 10 (first term omitted)	Eq. 10
Intercept	1.881***	1.875***
	[1.852, 1.911]	[1.846, 1.904]
$\overline{EDD}_{LD}$	−0.477***	−1.113***
	[−0.603, −0.350]	[−1.257, −0.969]
$\overline{\theta EDD}_{LD}$		0.902***
		[0.836, 0.969]
Num.Obs.	1165	1165
R2	0.058	0.426
R2 Adj.	0.057	0.425
β_I	-	-0.211
Wald-stat of $\beta_I = 0$	-	11.739***

* p < 0.1, ** p < 0.05, *** p < 0.01

Notes: This table presents the results of the OLS estimations based on Equation 10. The 95% confidence intervals based on heteroskedasticity-robust standard errors are indicated in brackets.

Figure 4: Irrigated proportion of corn: standardized long-differences



Notes: This map illustrates the standardized long-difference in the proportion of irrigated corn, denoted $\overline{\theta}_{LD}$, for every county in the Corn Belt. This variable is defined, for a given county, as the difference between present-day proportion of irrigated corn and that of the 1960s, multiplied by 100 and divided by the length of the time-series for that county. Proportions of corn irrigated in the 1960s at the county-level are taken from different sources (see Section A for details).

4.3 Third step results

4.3.1 Non-climate change scenario

Our first counterfactual scenario investigates the magnitude of the losses in corn yields induced by the long-term increases in extreme temperatures previously shown. Recall that we assume a null EDD long-difference in every county of our sample to assess the relative changes in current yield normals - compared to the normals that we observe - resulting from this assumption.

Figure 5 maps the percentage difference between observed current yield normals and the normals that we derive based on our assumption of zero changes in EDD. Overall, observed corn yield normals are lower than "non-climate change" normals in virtually all counties of the Corn Belt. This is consistent with the positive long-differences in EDD that we have identified for these counties. The only exception is the group of counties, located in the northwest of the region, characterized by slight downward trends in EDD as shown previously (see Figure 3). On average, we find a 6.6% loss in corn yield normals - relative to the non-climate change baseline - due to long-term changes in EDD across Corn Belt counties. According to our estimates, the current average corn yield would have been 181.83 bushels per acre in the absence of warming, compared to the observed average of 170.48 bushels per acre.

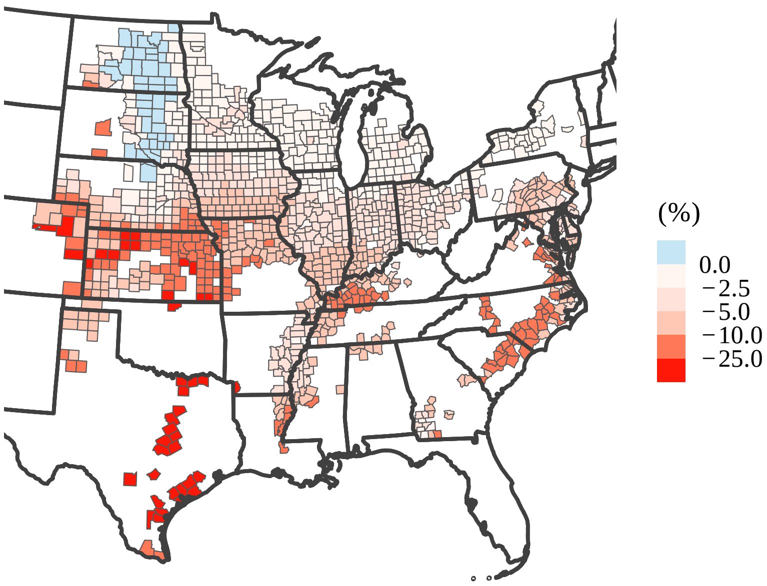
Figure 5 shows that the average loss masks considerable heterogeneity across counties. Specifically, we estimate strong losses from climate change in the southern part of the region, particularly in the south-west, and moderate-to-low losses towards the north. The greatest losses from climate change are found in eastern and southern Texas, where most counties have experienced yield losses greater than 25% relative to the non-climate change scenario. Some counties located in Kansas and Colorado have also witnessed losses of similar magnitudes. The highest loss equals 58.4% and is located in Guadalupe County, Texas. The extreme losses in these counties are due to the combined effects of strongly increasing EDD and relatively low irrigation (see Figure 3 and Figure A2). Most counties in Kansas, Kentucky and the Carolinas have also experienced important losses, ranging between 10% and 25%. These losses are also driven by relatively strong increases in EDD with no development of corn irrigation. In the southern parts of Iowa and Illinois, the two most important corn-producing states, many counties have suffered losses between 5% and 10% due to climate change, which is still substantial. The northern areas of both states, as well as Indiana and Ohio, have experienced more moderate losses, between 2.5% and 5%. For the northernmost states of the Corn Belt, we estimate losses lower than 2.5% compared to the non-climate change scenario, because trends in EDD have been weak and largely insignificant.

Our results suggest that long-term changes in EDD have somewhat widened cross-county disparities in corn yield normals. Indeed, the variance of current yield normals equals 29.38 in the non-climate change scenario, while it equals 32.73 in observed yield data. This slight increase in variance coincides with an accentuated leftward skewness of the distribution as a result of climate change: the coefficient of skewness equals -0.84 in the observed data against -0.68 in the non-climate change case. Figure D3 in the Appendix illustrates these changes by providing a comparison of both distributions.

Such changes have occurred because EDD increases have more strongly affected southern areas, which were already the less productive.

It is worth mentioning that some areas have avoided large losses thanks to very high irrigation levels. Counties located in Northern Texas represent striking examples. These counties have witnessed losses comparable to those of Southern Iowa despite experiencing much stronger increases in EDD. A similar observation can be made for most counties in the Mississippi Portal. The importance of the development of corn irrigation since the 1960s in improving corn yields by adapting to increasingly warm climate conditions is assessed in detail in our second counterfactual analysis.

Figure 5: Changes in current yield normals due to climate change



Notes: This map illustrates the percentage differences between observed corn yield normals, $R_{2023,i}$ and the normals derived from our counterfactual non-climate change scenario, $R^0_{2023,i}$. The latter constitute the denominator.

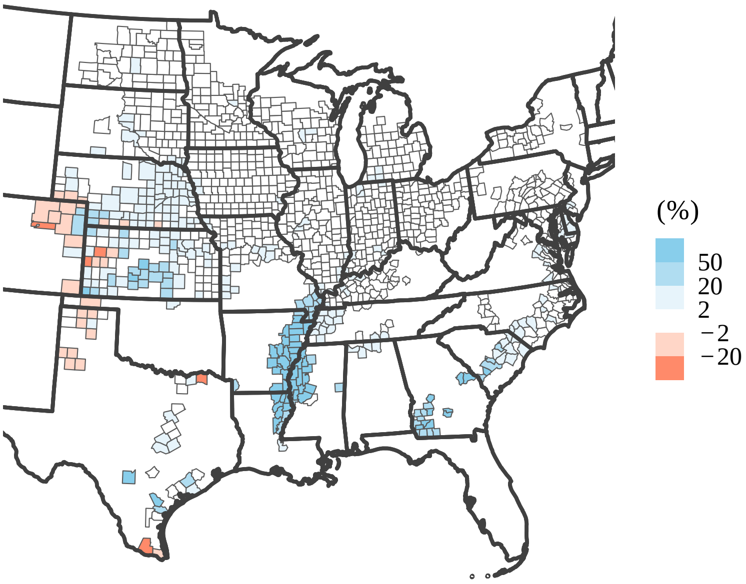
4.3.2 Non-irrigation development scenario

This second counterfactual analysis consists in simulating what corn yield normals would currently be if corn irrigation had remained equal to its levels of the 1960s, and comparing these simulated normals to the observations. Figure 6 displays the percentage change in current yield normals arising from the evolution of irrigation for every county. Unsurprisingly, the difference is negligible in most counties, as a result of the absence of significant changes in the proportion of irrigated corn in these counties. However, some areas have experienced large changes in corn yields due to sizable trends in corn irrigation. On one hand, several counties in Colorado, Kansas and Texas have undergone significant yield losses because corn irrigation has decreased since 1960s. In five counties, these losses exceed 20%. Two of them nearly reach 50% and the highest loss goes just beyond 60%. The two most important losses are located in Kansas and stem from tremendous reductions in corn irrigation (see Figure 4) in combination with a warm climate (see Figure D2), where the impacts of irrigation changes are even more critical. Indeed, recall that the effect of changes in irrigation is more pronounced in warmer (and warming) climates, as shown in Equation 9 of our theoretical model. This property appears even more clearly when looking at the two counties in Texas having losses above 20%. These counties present only slight downward trends in corn irrigation. However, they are among the hottest counties in our sample, so that the slight reductions in irrigation trigger very large losses in yields.

On the other hand, a large number counties in the central Great Plains, in Texas, and along the Mississippi Portal the Southern Seaboard have experienced considerable gains through the development of corn irrigation. In Nebraska, virtually all counties have benefited from gains in corn yields between 2% and 20%. Several counties in central Kansas present gains higher than 20%, some of them passing the threshold of 50%. Note that counties in Nebraska tend to have similar, or larger, irrigation increases than counties in Kansas. In spite of that, irrigation changes have more benefited to the latter counties on average, because of their warmer climate. The Mississippi Portal has witnessed the most important gains from the development of corn irrigation, with an average gain of 74.37% and a median gain of 68.31%. These impressive gains arise as a result of maximum irrigation developments (from 0% to 100% in many counties) in conjunction with a warm climate. Note that the largest relative gain corresponds to Bee County, Texas, with a gain equal to 258.58%. The observed yield normal in this county equalled 78.68 bushels per acre in 2023. Our analysis suggests that, absent irrigation development, this county's yield normal would only have been equal to 21.94 bushels per acre.

Overall, this second counterfactual experiment reveals how much irrigation currently contributes to corn yields in several areas of the Corn Belt. Going back to the irrigation levels of the 1960s would be extremely detrimental to yields in these areas.

Figure 6: Changes in current yield normals due to irrigation development



Notes: This map illustrates the percentage difference between observed corn yield normals, $R_{2023,i}$ and the normals derived from our counterfactual non-irrigation development scenario, $R^N_{2023,i}$. The latter constitute the denominator.

5 Conclusion

In this study, we have first used climate data from the ERA5-Land reanalysis dataset in order to examine long-run trends in extreme degree days above 29°C in the Corn Belt since 1960. ERA5-Land data have a high spatial resolution ($0.1° \times 0.1°$) and a high temporal frequency (hourly). Accurately measuring temperatures in both the time and spatial dimensions has been shown to be very important for identifying extreme temperature occurrences and their impact on crop yields (Schlenker and Roberts 2009; D'Agostino and Schlenker 2016). Moreover, the fine spatial resolution of the climate data allows us to measure extreme temperatures only in corn cultivation areas, by combining them with satellite-based corn land cover data.

Hence, we show that climate change has already translated to significant upward trends in extreme degree days in 55.7% of Corn Belt counties. The southwest of the region is the most affected area, for which accelerating trends are identified, suggesting that even faster increases are to be expected in the future.

Next, we have considered the role of irrigation as a form of adaption to mitigate the impact of these upward trends on corn yields. We have constructed measures of corn irrigation in the 1960s at the county-level based on different sources, including Agricultural Census archives. We have compared these measures with present-day irrigation of corn to examine whether, and where, irrigation has developed since the 1960s. We show that corn irrigation has substantially grown in the Mississippi Portal and in Nebraska, as well as in Georgia and Kansas.

We have proposed a simple theoretical framework providing us with a formal specification of how irrigation interacts with extreme temperatures in determining corn yield growth. We then have empirically estimated this specification and found that irrigation offsets 80% of the impact of extreme temperatures on corn yield growth. We also have shown that omitting the role of irrigation produces a biased estimate of the long-run impact of extreme degree days on corn yields. However, further research might be needed to understand why our cross-sectional estimate of the negative effect of extreme temperatures on rainfed corn yields is larger than the same effect estimated in time-series. An avenue for research on this matter might be the potential importance of certain agricultural practices in improving corn yields while cooling the climate through increased transpiration or aerosol pollution Wilson et al. (2023). Indeed, omitting such practices would generate a bias in our estimate of the long-term effect on extreme temperatures on yields, towards a more negative estimate.

Finally, we have proposed two counterfactual analyses to better gauge the magnitude of our estimates in the context of the observed trends in EDD and corn-irrigation development since the 1960s. According to our estimates, climate change has already reduced corn yields among Corn Belt counties by 6.6% on average. However, we show that the important development of corn irrigation since the 1960s has raised corn yields substantially in several parts of the region. These results highlight the need for adaptation policies in US agriculture. This is even more urgent since the persistence of the warming hole in recent decades has been shown to be driven in large part by internal climate variability (Eischeid et al. 2023). Hence, this phenomenon might recede and reveal the true impacts of human-induced climate change on US agriculture in a near future.

Our results also suggest that irrigation is very effective in adapting to a warming climate. Nonetheless, Marshall et al. (2015) provide evidence that some regions will experience increasingly limited water supplies due to the influence of climate change on the water cycle. Therefore, developing irrigation might be irrelevant compared to other forms of adaptation. Deeper investigations about the benefits and shortcomings of irrigation and other adaptation options would be welcome.

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Appendix

A Irrigation data details

A.1 Irrigation in the 1960's

As already mentioned in Section 3.3, the sources of the data about corn irrigated acreage at the beginning of our study period differ depending on the state. For some states (Kansas, Louisiana and Oklahoma) we use the 1959 Agricultural Census data. For Texas, we use the 1969 Agricultural Census data. For Colorado, Nebraska and South Dakota, the data are from USDA NASS surveys. Below, we describe the differences in how corn irrigated acreage is measured according to each source.

1959 Agricultural Census

In the 1959 Agricultural Census, a distinction is made between the farms that fully irrigate their corn acreage and those that partially irrigate it. For farms in the former category, the acreages of corn for all purposes and corn for grain are reported separately. However, regarding farms in the latter category, only the irrigated acreage of corn for all purposes is provided, with no information about the specific irrigated acreage of corn for grain. This lack of complete information rules out the exact calculation of the irrigated fraction of corn for grain in most counties, where partly irrigated farms represent a non-negligible share of corn irrigated acreage. However, this share generally remains limited. This enables us to to calculate reliable estimates of the irrigated fractions of corn for grain and assess the uncertainty associated with these estimates.

We formally describe our approach as follows. Let A_c and A_g represent the total acreages of corn for all purposes and corn for grain, respectively, in any county. We also denote $I_{c,f}$ and $I_{g,f}$ the irrigated acreages of corn for all purposes and corn for grain belonging to fully irrigated farms. We similarly denote $I_{c,p}$ and $I_{g,p}$ the irrigated acreages belonging to partly irrigated farms. Finally, we define the share of corn-for-grain acreage that is irrigated, F_g, as follows:

$$F_g = \frac{I_{g,f} + I_{g,p}}{A_g} \tag{12}$$

Our objective is to estimate F_g with the value of $I_{g,p}$ being unknown.

Our approach first consists in identifying the lower and upper feasible bounds for $I_{g,p}$, which we denote $I_{g,p,min}$ and $I_{g,p,max}$, respectively. We identify $I_{g,p,max}$ based on the two following conditions: i) F_g must be lower than 1 since it represents the share of corn-for-grain acreage that is irrigated, and ii) $I_{g,p}$ must be lower than $I_{c,p}$ because corn for grain is a component of corn for all purposes. It follows from the first condition that $I_{g,p}$ must be lower than $A_g - I_{g,f}$. Hence, $I_{g,p,max}$ corresponds to the lowest of $I_{c,p}$ and $Ag - I_{g,f}$. It turns out that $I_{c,p}$ is always the upper bound for the counties in our sample.

To determine the lower bound, $I_{g,p,min}$, we further define F_o as follows:

$$F_o = \frac{(I_{c,f} - I_{g,f}) + (I_{c,p} - I_{g,p})}{A_c - A_g} \tag{13}$$

It represents the share of the acreage of corn for another purpose than grain which is irrigated.

We then point out two other conditions: i) $I_{g,p}$ must be positive, and ii) F_o must be lower than 1, by definition. The second condition implies that:

$$I_{g,p} \geq I_{c,f} - I_{g,f} + I_{c,p} - (A_c - A_g) \tag{14}$$

Therefore, $I_{g,p,min}$ is equal to the maximum of the quantity on the right-hand side of Equation 14 and 0.

Once we have calculated the correct values for $I_{g,p,min}$ and $I_{g,p,max}$, we deduce the interval to which F_g necessarily belongs. Since we need a single value for F_g for each county, we finally check whether the fraction of the acreage of corn for all purposes that is irrigated, denoted F_c, falls within this interval. If so, we assume that the irrigated fraction of corn for grain is the same as that of corn for all purposes, i.e. $F_g = F_c$. Otherwise, this assumption is not plausible, and we simply estimate F_g as the midpoint of the interval. Note that we have also investigated the simple case where F_g is systematically estimated as the interval midpoint. Both options lead to virtually identical results.

Note that the ranges of the intervals can be regarded as measures of the uncertainty surrounding our estimates of F_g. We thus provide here a description of the main features of this uncertainty for the counties in the three states for which data from the 1959 Census were used. In Oklahoma, there is only one county with irrigation data available, where there were no farms with partly irrigated corn acreage, resulting in no uncertainty for that county. Among the ten counties of Louisiana in our sample, the maximum interval range equals 2.20 (on a percentage basis) and the mean range is 0.34. Hence, the uncertainty is negligible for these counties. However, the 56 counties located in Kansas with available data present some considerable uncertainties. The median interval range in Kansas, equal to 3.98, indicates that the uncertainty remains very low for most counties. The higher average range, equal to 8.30, reflects the fact that a few counties have very high uncertainty levels, with the maximum interval range equal to 57.84. However, 90% of counties in Kansas (i.e. all but 6 counties) remain below a range of 17.92.

1969 Agricultural Census

In the 1969 Agricultural Census data, the issue described above is solved. Nevertheless, a new issue arises : the data only reports the irrigated acreage for farms that have sold more than 2,500$ of agricultural products during the year, thereby excluding very small farms. Thus, corn (for grain) irrigated fractions calculated from these data might be misleading if small farms constitute a significant share of the acreage and irrigate at a different rate compared to larger farms.

However, as in the previous case, we can assess the uncertainty due to this drawback in any given county by constructing an interval to which the correct value for the irrigated fraction of corn necessarily belongs. Indeed, even if the data regarding the irrigated acreage for very small farms are lacking, the total corn acreage for these farms is still provided. Hence, the total corn acreage in the county (i.e. for all categories of farm combined) is available in the data.

Based on this information, we can then consider two borderline cases. The lower case consists in assuming that very small farms do not irrigate any of their corn acreage. In this case, the total irrigated acreage of corn in the county would correspond to the value reported for larger farms. Thus, dividing this value by the total corn acreage in the county, we obtain a lower bound for the irrigated fraction of corn in that county. The opposite case involves assuming that the entire corn acreage of very small farms is irrigated, thus providing an upper bound to the irrigated fraction of corn.

Given the way these intervals are constructed, they systematically include the value of the corn irrigated fraction of larger farms. In our baseline analysis, we therefore select this value as the point estimate for each county, assuming some homogeneity between very small farms and larger farms within a county. We checked the robustness of our results by using the midpoint of each interval instead, and found that they are virtually unchanged.

As in the case of the 1959 Census, interval ranges represent the uncertainty surrounding the point estimate for every county. Recall that Texas is the only state concerned by the 1969 Census in our data. For the 39 counties in Texas, the median and mean interval ranges both equal approximately 10.5 (on a percentage basis) which, although considerable, remains reasonable. The maximum interval range equals 39.4, which is substantial. However, 90% of these counties (i.e. all except 4 counties) do not exceed an interval range of 19.01.

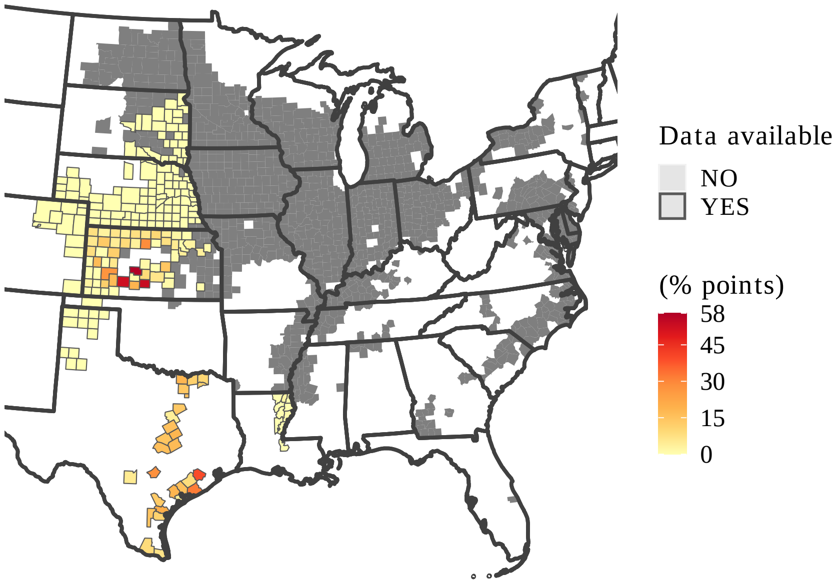
USDA NASS surveys

The USDA NASS surveys conducted in the 1960s provide data on the irrigated acreage of corn for grain. To our knowledge, these data do not involve any particular issue.

Uncertainty mapping

Figure A1 shows the spatial distribution of uncertainty ranges for all counties with irrigation data available in the 1960s. The ranges are null for all counties in Colorado, Nebraska and South Dakota since, as mentioned above, there is no required information missing from USDA NASS survey data. Note that the concept of uncertainty we are dealing with here only includes the uncertainty due to information gaps in the data. It is very likely that USDA NASS survey data present some inaccuracies, especially due to sampling error, which we can't assess.

Figure A1: Uncertainty ranges for the irrigated fraction of corn for grain in the 1960s



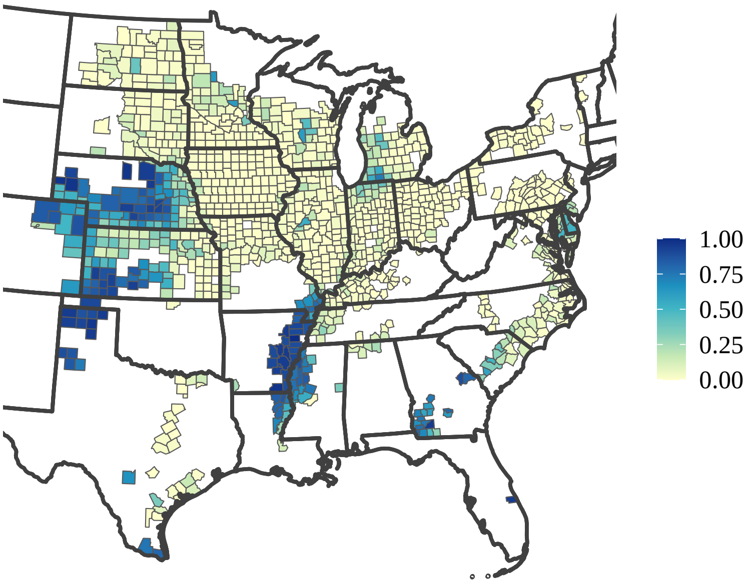
Notes: This map illustrates the uncertainty ranges associated with our estimates of the percentage of irrigated corn in the 1960s for each county. The data sources and the methods used for calculating these estimates and uncertainty ranges differ depending on the state. This is discussed in detail in Section A.1.

A.2 Present-day irrigation

Present-day irrigation levels are determined by selecting the highest of the irrigated fractions of corn (for grain) reported in the Agricultural Censuses of 2012 and 2017. However, exact fractions are sometimes hidden for non-disclosure reasons. In such cases, we use USDA NASS Agricultural Census Web Maps (ACWM) data, which provide an interval within which the hidden value falls. The intervals are as follows : less than 5%, between 5% and 20%, between 20% and 40%, between 40% and 70%, between 70% and 90%, and above 90%. Hidden values do not always introduce uncertainty about our measure of irrigation infrastructure. Indeed, in many cases, the exact value is hidden for one year but it is available for the other year. In such circumstances, three cases can occur. First, the available exact value might fall below the lower bound of the interval provided in the ACWM for the hidden value. It follows that the hidden value is higher than the available one and should be selected as the maximum. In this case, we estimate it using the midpoint of the corresponding interval, introducing uncertainty into our irrigation measure. The second case is the inverse : the available value exceeds the upper bound of the interval for the hidden one. Hence, the former is clearly higher than the latter. We select it as the maximum and it does not introduce uncertainty. The last case occurs when the available value falls within the same interval as the hidden one. In such a case, we can't determine which value is the maximum. For our baseline analysis, we decided to choose the available exact value but this choice is quite arbitrary and, again, involves uncertainty. We have checked the robustness of our results by choosing the midpoint of the interval instead. Results are virtually identical to the baseline.

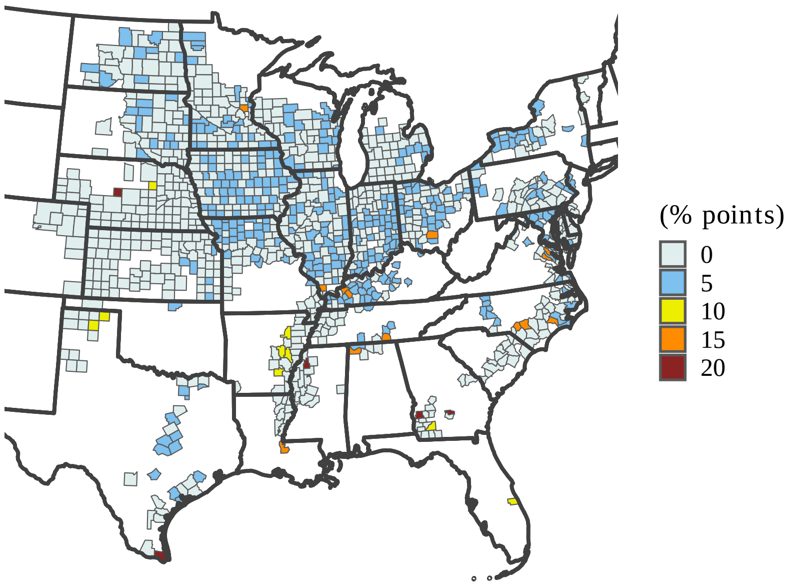
Figure A2 shows the resulting present-day irrigated fractions of corn for all counties within our delineated Corn Belt. Additionally, Figure A3 illustrates the ranges of uncertainty resulting from hidden values. Overall, uncertainty about the maximum value of the irrigated fraction of corn affects 31% of counties. This map clearly shows that the great majority of these counties actually present very reasonable uncertainty ranges, equal to 5 on a percentage basis. None of the counties in our sample has an uncertainty range exceeding 20 regarding present-day corn irrigated fractions.

Figure A2: Present-day proportion of irrigated corn



Notes: This map illustrates our county-level measure of the present-day proportion of irrigated corn, denoted θ_{2023}. This measure corresponds to the maximum proportion of irrigated corn between the 2012 and 2017 Agricultural Censuses. When required, missing values are replaced by an estimate equal to the midpoint of the interval to which the exact value belongs according to the Agricultural Census Web Maps. For details about this measure, see Section A.2.

Figure A3: Present-day uncertainty ranges for the irrigated fraction of corn for grain



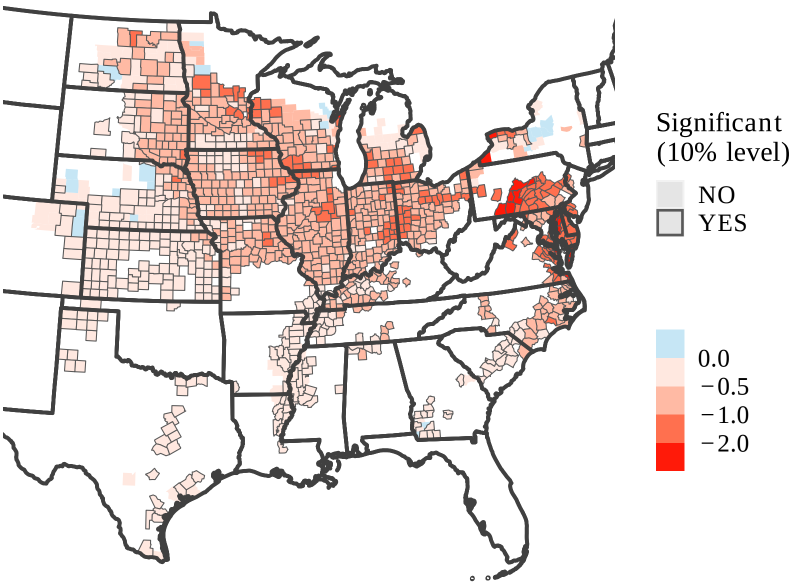
Notes: This map illustrates the uncertainty ranges associated with our measures of the current percentage of irrigated corn for each county. These uncertainties are due to hidden values in the Agricultural Censuses of 2012 and 2017 for some counties. When required, hidden values are replaced by an estimate equal to the midpoint of the interval to which the exact value belongs, thus generating uncertainty. See Section A.2 for details.

B Time-series effects of EDD on corn yields

For every county in our sample, we run a time-series linear regression of annual corn yields on EDD. Before running the regressions, we make the series stationary by removing the time trends estimated based on the approach described in Section 2.2. We undertake this time-series analysis to examine whether the effect of EDD on corn yields is similar across all counties within our delineated Corn Belt. This is important since our baseline estimations are cross-sectional, implying a certain level of homogeneity among counties regarding the investigated relationship. Figure B1 presents each county's estimate of the coefficient corresponding to EDD in the simple linear regression of corn yields on EDD. In 88% of counties, the coefficient is significantly different from zero (at the 10% level). The coefficient is always negative where significant. The mean coefficient estimate equals -0.64 (see the last row of Table D1 for descriptive statistics about these coefficient estimates).

However, there is some heterogeneity. Indeed, the 5% quantile is -1.32 while the 95% quantile is -0.10 (resulting in an amplitude of 1.22), and the standard deviation equals 0.62. Since we control for the influence of irrigation in our baseline analysis, we regress our cross-section of EDD coefficient estimates on county-level measures of (present-day) corn irrigation. This allows us to explore the extent to which this heterogeneity persists when irrigation is accounted for. We show that cross-county differences in current irrigation capacity explain 9.4% of the heterogeneity in EDD coefficients. Consequently, the residual standard deviation decreases to 0.59 and the aforementioned amplitude reduces to 1.05. We consider this remaining heterogeneity reasonably weak.

Figure B1: Time-series EDD coefficient estimates



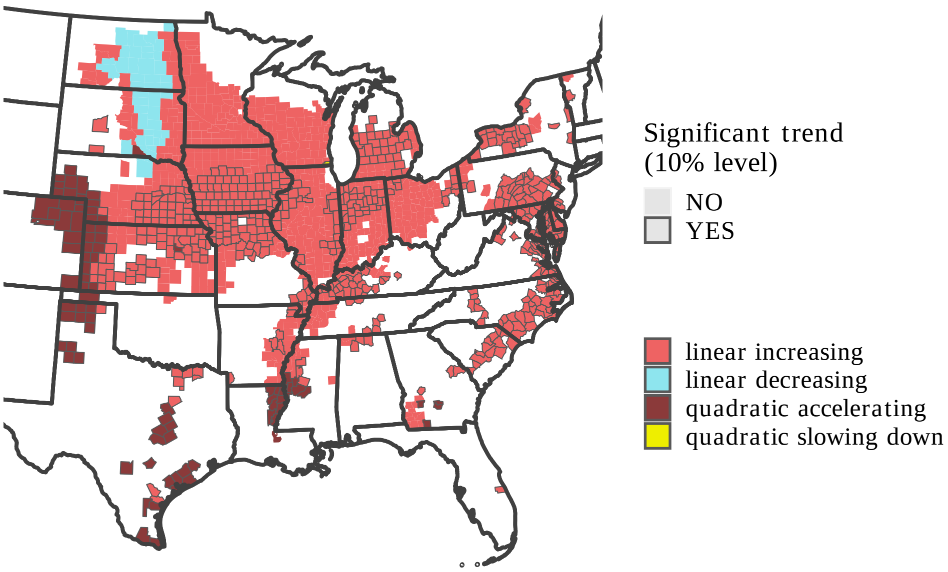
Notes: This map illustrates the estimates of the coefficient associated with EDD in the time-series regression of corn yields on EDD, estimated separately for each county. Before running the regressions, corn yields and EDD are detrended according to the type of time trend selected by the approach described in Section 2.2. Significance is determined based on heteroskedasticity-robust standard errors.

C Robustness checks

C.1 Robustness to the method for selecting the time trend

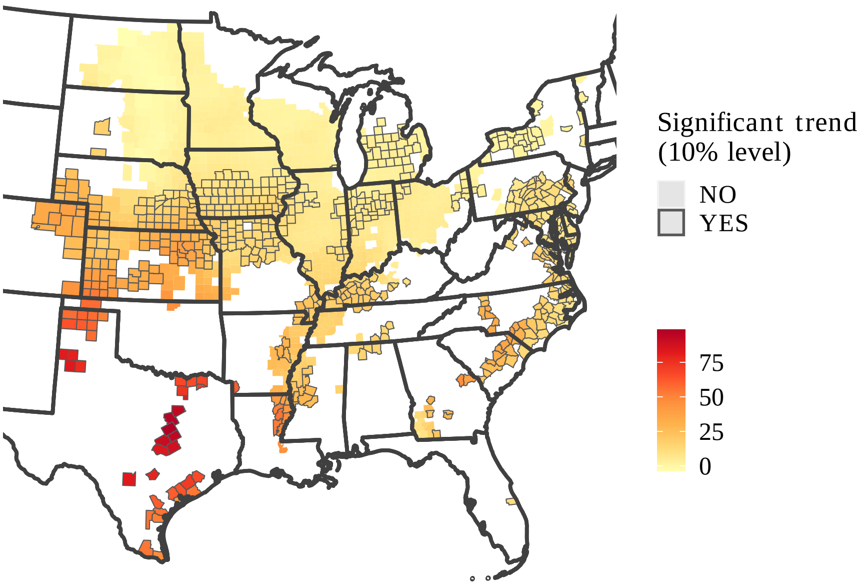
We replicate the approach presented in Section 2.2 with one difference: we select between linear and quadratic time trends according to the Akaike Information Criterion (AIC). The results of this robustness check are displayed in Figure C1.1 and Figure C1.2. These are very similar to the baseline. However, the proportion of counties with a significant trend is slightly lower (49.8% instead of 55.7%). In addition, the number of counties for which the slowing quadratic trend is retained decreases to just one (from the 55 of the baseline case).

Figure C1.1: Selected type of time trend for EDD according to the AIC



Notes: This map illustrates the type of time trend which has been selected for every county regarding the evolution of EDD since 1960. Here, unlike the baseline case, the selection has been made according to the AIC. Significance is determined according to standard errors robust to heteroskedasticity and autocorrelation.

Figure C1.2: EDD long-differences (1960-2023) according to AIC time trend selection



Notes: This map illustrates our estimated long-difference for EDD over the 1960-2023 period in every county, denoted as EDD_{LD}. This variable corresponds to the difference between the values of EDD in 1960 and 2023 fitted according to the time trend selected for a given county. Here, unlike the baseline case, the types of time trend have been selected according to the AIC. Significance is determined according to standard errors robust to heteroskedasticity and autocorrelation.

C.2 Robustness to the delineation of the Corn Belt

We present the results of the replication of our baseline analyses on a narrower delineation of the Corn Belt in Table C2.1 below. This narrower delineation includes any county with an areal fraction of corn higher than 10% (instead of 5%) in at least one year of CDL or Agricultural Census data. The results in Table C2.1 are virtually identical to the baseline shown in Table 1.

Table C2.1: OLS regression results for Equation 10 (narrower Corn Belt)

	Eq. 10 (first term omitted)	Eq. 10
Intercept	1.937***	1.950***
	[1.907, 1.967]	[1.918, 1.982]
$\overline{EDD}_{LD}$	-0.527***	-1.196***
	[-0.687, -0.367]	[-1.404, -0.989]
$\overline{\theta EDD}_{LD}$		0.899***
		[0.798, 0.999]
Num.Obs.	859	859
R2	0.073	0.401
R2 Adj.	0.072	0.400
β_I	-	-0.298
Wald-stat of $\beta_I = 0$	-	14.392***

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

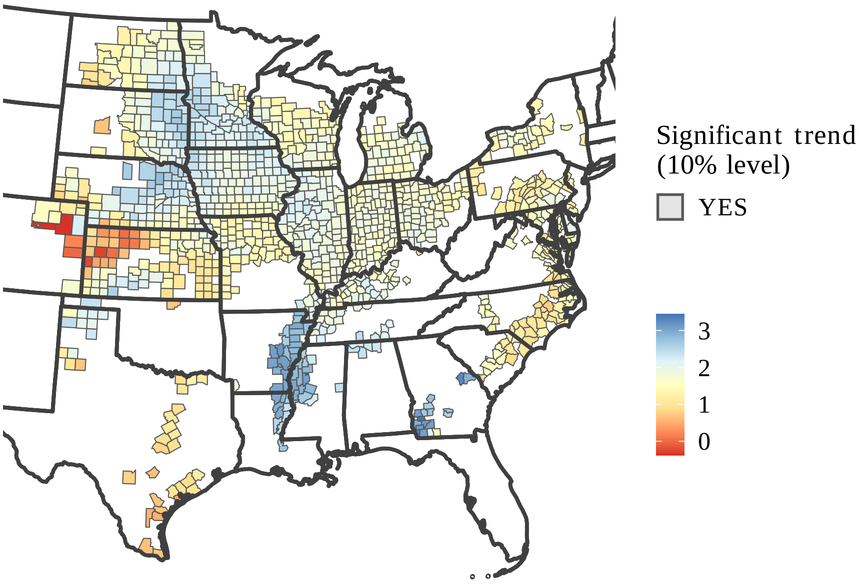
Notes: This table presents the results of the OLS estimations of Equation 10 based on a narrower delineation of the Corn Belt. This narrower delineation includes any county with an areal fraction of corn higher than 10% in at least one year of CDL or Agricultural Census data. The 95% confidence intervals based on heteroskedasticity-robust standard errors are indicated in brackets.

D Supplementary information

D.1 Long-run differences in corn yields

Figure D1 below presents the results of the approach described in Section 2.2 applied to corn yields instead of EDD. Note that, since the yield time-series are shorter in some states (e.g. Colorado, Texas and New York), the long-run differences are standardized according the number of yield observations in each county (see Equation 10 of Section 2.3 for details about this standardization). Thus, they must be interpreted as average year-to-year changes instead of total changes during the period under study.

Figure D1: Corn yield standardized long-differences (1960-2023)

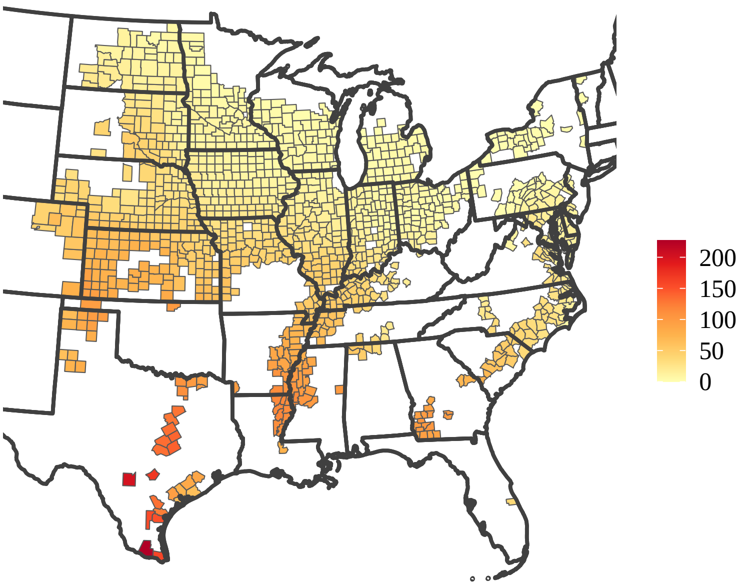


Notes: This map illustrates our standardized long-difference in corn yields over the 1960-2023 period for every county, denoted as $\overline{R}_{LD}$. This variable corresponds to the difference between the first and last years available in the values of corn yields fitted according to the time trend selected for each county. Significance is determined according to standard errors robust to heteroskedasticity.

D.2 Normals of EDD in 1960

Figure D2 below depicts the values for EDD in 1960 fitted from the regression on a time trend selected for each county with the approach described in Section 2.2.

Figure D2: EDD normals in 1960

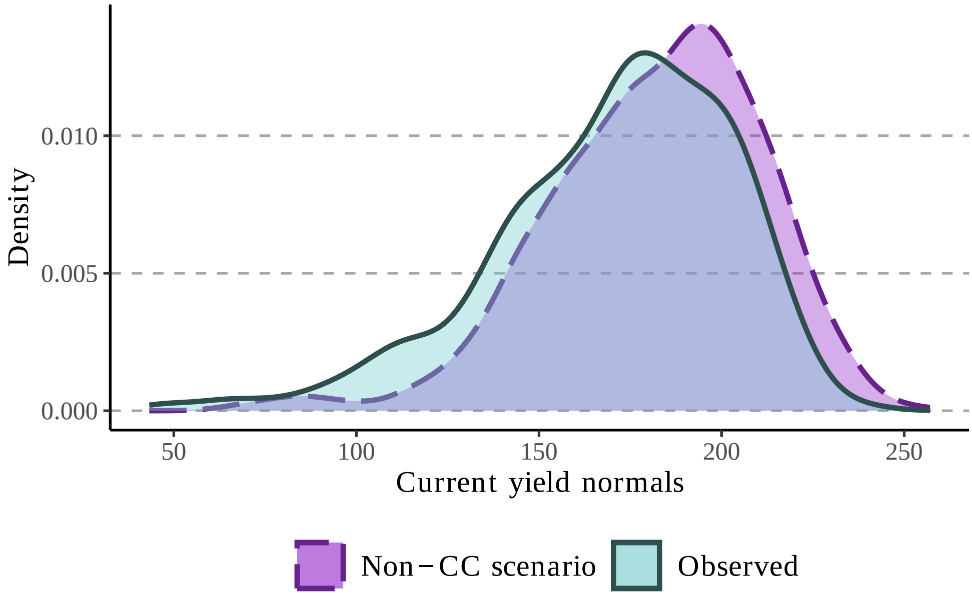


Notes: This map illustrates the values of EDD in 1960 fitted according to the time trend selected for each county. See Figure 2 for the selected type of trend in every county.

D.3 Distributions of current yield normals

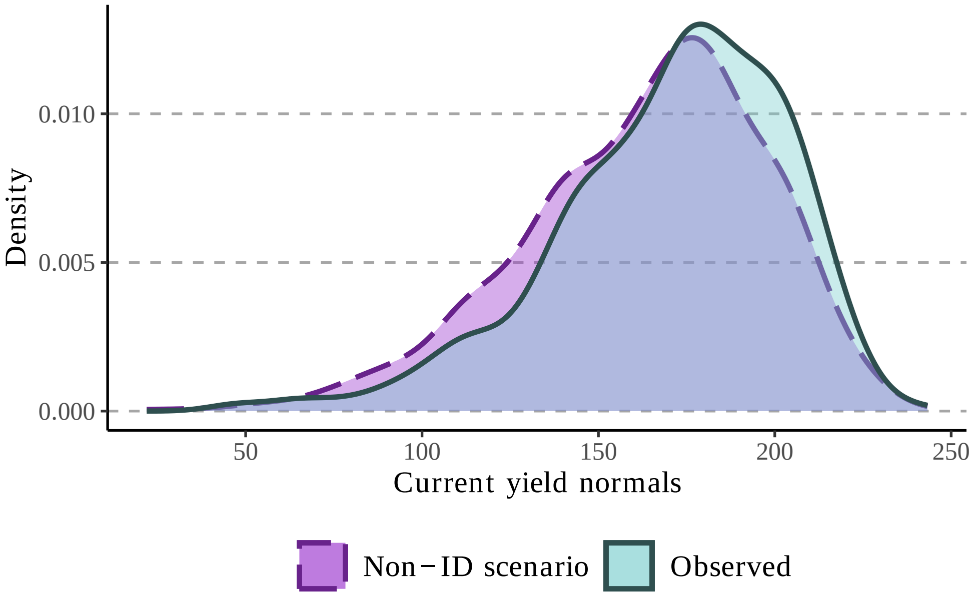
Figure D3 provides a comparison of the cross-county distribution of current corn yield normals in the observations, i.e. the variable R_{2023}, with the distribution derived from the non-climate change scenario, corresponding to the variable R^0_{2023}. Figure D4 is analogous to Figure D3 with the distribution of R^N_{2023} replacing that of R^0_{2023}.

Figure D3: Distributions of current yields normals: observed vs non-climate change scenario



Notes: The graph shows the cross-county distribution of observed current corn yield normals, i.e. R_{2023} (in cyan), alongside that of the counterfactual yield normals derived under the non-climate change scenario, i.e. R^0_{2023} (in purple). The sample includes the 1,165 counties of our delineated Corn Belt. For details about the non-climate change scenario and the calculation of R^0_{2023}, see Section 2.4.

Figure D4: Distributions of current yields normals: observed vs non-irrigation development scenario



Notes: The graph shows the cross-county distribution of observed current corn yield normals, i.e. R_{2023} (in cyan), alongside that of the counterfactual yield normals derived under the non-irrigation development scenario, i.e. R^N_{2023} (in purple). The sample includes the 1,165 counties of our delineated Corn Belt. For details about the non-irrigation development scenario and the calculation of R^N_{2023}, see Section 2.4.

D.4 Descriptive statistics

Table D1 provides the main descriptive statistics for our variables of interest.

Table D1: Descriptive statistics for the main variables of interest

Variables	Obs.	Mean	Std.Dev.	Min.	Q1	Median	Q3	Max.
$EDD_{LD,i}$	1171	13.66	15.01	-3.71	3.97	8.86	17.83	98.59
$\overline{EDD}_{LD,i}$	1165	0.22	0.25	-0.06	0.06	0.14	0.28	1.96
$\theta_{2023,i}$	1165	0.16	0.27	0.00	0.00	0.03	0.17	1.00
$\overline{\theta}_{LD,i}$ (% points)	1165	0.17	0.35	-1.31	0.00	0.04	0.18	1.60
$\overline{R}_{LD,i}$	1165	1.78	0.50	-0.37	1.52	1.80	2.03	3.44
$\hat{\beta}_{EDD,i}$	1165	-0.64	0.62	-15.83	-0.82	-0.59	-0.37	1.31
$R_{2023,i}$	1165	170.48	32.73	43.29	150.60	175.11	195.18	243.28
$R^0_{2023,i}$	1165	181.83	29.38	63.78	163.34	185.54	202.90	257.07
$R^N_{2023,i}$	1165	163.25	34.32	21.94	141.42	168.65	186.95	242.32

Notes: This table provides the main descriptive statistics for the most important variables in our analyses. Statistics regarding $\overline{\theta EDD}_{LD,i}$ are not included because they have no meaningful interpretation. Note that we provide separate descriptive statistics for $EDD_{LD,i}$ and $\overline{EDD}_{LD,i}$. This is because the statistics provided for the former relate to the full sample of the 1,171 counties for which we have EDD data. $EDD_{LD,i}$ is calculated from exactly 1960 to 2023 for all counties so that it does not need any standardization to be comparable across space. It is the variable we focus on in Section 4.1 for sake of clarity. On the contrary, $\overline{EDD}_{LD,i}$ is the explanatory variable we use in our regressions. It is not calculated over the exact same time length for all counties, hence the standardization. $\hat{\beta}_{EDD,i}$ corresponds to the variable mapped in Figure B1.