The impact of extreme weather on farm finance - evidence from Kansas

Osama Sajid[1+] Jennifer Ifft[2*] Ariel Ortiz-Bobea[1*]

April 15, 2023

Keywords: extreme temperature, weather, finance, agriculture

Building on a large literature on the weather-agriculture nexus which focuses primarily on the impacts of weather shocks on agricultural yield and productivity, we examine the contemporaneous impact of extreme temperature on farm income. We use a detailed farm-level panel dataset from the Kansas Farm Management Association, containing 6958 farms spanning 1981-2020. We find that extreme temperature reduces net income by 60% more than gross income, which shows that extreme temperature not only reduces farm output but also increases farm expenses. The estimated effects are substantial, with a 1°C warming associated with a 66% reduction of net farm income. The impact would have been even greater if farmers were not relying on crop insurance payments and inventory adjustment, both of which are found to reduce the temperature-induced income loss by approximately 51% and 16%, respectively. We also found that highly irrigated farms experience 37% less net-income loss due to extreme temperature. Furthermore, we quantify the impact of extreme temperature on farm wealth in the long run — over the past 30 years, rising temperatures have caused a decline in the growth of farmland value and farm equity. (JEL Q54, Q14)

[1]Dyson School of Applied Economics and Management, Cornell University
[2]Department of Agricultural Economics, Kansas State University
[*]These authors contributed equally to this work
[+]Corresponding author: os223@cornell.edu

1 Introduction

A major part of the existing research on US climate-agriculture nexus examines the impact of weather shocks on crop yields or agricultural productivity (Schlenker and Roberts, 2009; Ortiz-Bobea et al., 2018, 2021; Miller et al., 2021). However, these output based measures fail to truly capture farmers' welfare. Climate shocks affect multiple other determinants of farmers' welfare such as disaster payments (Diffenbaugh et al., 2021), farm input choice (Aragón et al., 2021), and income from inventory adjustment, none of which are reflected in farm output. For instance, high temperatures might lead farmers to adjust their inputs by using more irrigation in order to protect farm output. This adjustment, however, will also increase farm expenses due to costs associated with irrigation. Output based measures will reflect the positive role of irrigation in protecting output but will ignore the increased costs borne by the farmers, thus underestimating the effects of extreme weather. Financial measures such as net farm income do a much better job of representing the holistic impact of climate change on farmers' wellbeing because it includes input and output costs and quantities, disaster payments, as well as inventory adjustments.

The impact of weather shocks on farm income can be buffered through a number of government policies and adaptation practices. Crop insurance and payments through government programs are well-known policy tools protecting farmers against climate risk (Diffenbaugh et al., 2021). Adaptation measures on the part of farmers such as storing excess harvest in years of bumper crop for later use can also help mitigate losses induced by extreme weather - grain storage capacity on US farms has expanded substantially over the past 20 years (Janzen and Swearingen, 2020). Similarly, farm location characteristics such as proximity to aquifer can allow better access to water for irrigation, offering timely protection from high temperatures (Tack et al., 2017; Troy et al., 2015).

Although we find evidence in support of the use of such risk management tools, we do not know the extent to which they mitigate the financial impact of extreme weather. It is important to quantify that because the availability, cost, and reliability of such tools might drastically change in future given the increased risk of higher temperatures (Crane-

Droesch et al., 2019; Wu et al., 2020), in which case the current estimates of the climate damages (which account for *present-day* adaptation practices) would become less trustworthy. Additionally, by examining the buffering role of these tools on net income, rather than on output based measures, we are able to capture the benefit of these tools net of the costs associated with their adoption. Previous related work, relying on county-level (Deschênes and Greenstone, 2007) as well as farm-level (Lambert, 2014) data examines the impact of weather on net income without being able to separate its impact on risk management tools such as crop insurance payments and inventory adjustments (Fisher et al., 2012), as all these are part of the income measure.

This study explores the effect of weather fluctuation on farms' gross and net income. More importantly, it examines the role of various income smoothing and risk management mechanisms such as crop insurance payments, crop inventories, government payments, and irrigation in modulating the impact of exposure to high temperature on farm income. While a lot of the emphasis in the literature has been on contemporaneous effects of weather shocks, it is unclear how these translate to long term impacts. To explore this, we also analyze the long-term impact of recent climate trends on trends in farm wealth.

Answering these questions requires detailed annual financial information, which we obtain through a unique farm-level panel dataset from the Kansas Farm Management Association (KFMA) spanning four decades from 1981 to 2020. This paper is one of the very few studies which has used farm-level data to estimate the financial impacts of temperature on the agricultural sector. Using the more commonly available county-level census data would have concealed variation in farm income and adaptation measures within each county. Furthermore, the annual observations of KFMA data allow capturing the impact of weather outside the select census years.

Our empirical strategy exploits spatial and temporal variation in weather, conditioned on farm and year fixed effects, to uncover contemporaneous impacts on income as well as on disaster payments and inventory changes. This panel estimation, thus, relies on comparing, within a given year, farm specific deviations of weather from the sample mean of weather for each farm. Because farmers cannot anticipate weather several months in advance and many of their decisions are made early in the season (e.g., crop acreage), we consider these weather shocks exogenous, in line with the literature (Dell et al., 2014).

While occasional weather shocks affect contemporaneous farm finances, it is unclear whether climatic trends over several decades are leading to long-term impacts on measures of farm wealth such as farmland values. Rising temperatures can lower farmland values by negatively affecting crop yields as well as by limiting the local financing available to support land prices (Bergman et al., 2020). To identify these long-term effects, we use cross-county spatial variation in the growth rate of extreme temperature over 30 years to estimate its impact on the growth rate of farmland values and farm equity over the same time period. There is potential unobserved heterogeneity across farms that our approach is not able to control for, so this approach has some threats to validity. However, it allows us to uncover effects of a changing climate (temperature changes over multiple decades), rather than weather (year-to-year changes in temperature). Our approach is similar to the long-difference approach of Burke and Emerick (2016), with the key difference being that we use the average growth rate of weather, relying on all data points over a long time period while Burke and Emerick (2016) uses the difference in weather between the two points in time — the beginning and end years of a long time period.

While we find that extreme temperature causes a contemporaneous decline in gross income, we find even greater effects on net income. A 1°C uniform warming would decrease gross income and net income by approximately 7% and 66%, respectively. Converting these percentages to dollar values show that for an average farm, the decline in net income is almost 1.6 times larger than the decline in gross income. Our back-of-the-envelope calculation indicates that temperature rise equivalent to that of the well-known 2012 Midwestern drought would wipe out the yearly net farm income. While the income impacts are large, they would have been even greater if farmers were not relying on risk management tools. We find that crop insurance payments and crop inventory sales help recover almost 51% and 16% of the net income loss observed before accounting for these income buffers, respectively. Furthermore, access to irrigation acts as a buffer against extreme temperature — using two alternative irrigation measures, we found that farms with above-average access to irrigation feature 37% (using KFMA data) and 55% (using High Plains Aquifer data) less net-income loss.

Last, we find that temperature changes over the recent decades have slowed down the growth in farm wealth. Over the 30 years period, farmland values and farm equity grew by 53% and 107%, respectively. We find that they would have grown by an additional 2.5 to 5.5 percentage points (depending on model specification) had there been no long-run increase in temperature over 30 years. This translates to almost 9% and 5% reduction in the growth rate of farmland value and farm equity, respectively. This highlights the long-run impact of a changing climate on the US agricultural sector.

This paper makes key contributions to the literature. To our knowledge, we provide the first comprehensive examination of the income smoothing role of multiple risk management and adaptation measures adopted by farmers in the face of climate change. Our analysis of the mediating role of insurance and irrigation on the *weather-income* relationship extends previous work examining the role of these instruments on the *weather-yield* relationship (Annan and Schlenker, 2015; Wang et al., 2021; Regmi et al., 2022; Tack et al., 2017; Zaveri and B Lobell, 2019). In this way, this study makes an important contribution by examining climate adaptation in agriculture from a financial lens. Furthermore, by comparing gross and net income effects, we are able to present evidence regarding the impact of extreme temperature on farm expenses, and thus indirectly on the cost of adaptation to climate change (Sulser et al., 2021; McCarl, 2007; Parry, 2009).

This paper is structured as follows. We describe the data sources and the construction of key variables in the next section. Section 3 explains the empirical methodology and section 4 reports the results and placebo checks. Section 5, the last section, concludes the paper.

2 Data description

2.1 Farm Data

Analyzing the impact of weather on farm financial performance and adaptation responses requires detailed farm-level data, which are often confidential and thus difficult to obtain. Furthermore, long-term farm-level data such as the US Census of Agriculture do not provide annual observations which are necessary to understand the dynamic adjustments of inventory. In this study, we rely on a unique dataset from the KFMA which helps farmers fill out their taxes and in exchange, they provide detailed data on farm production and finances that may be used for research purposes. The dataset provides a unique view of crop yields and farm finances from 1981 to 2020 across 6958 unique farms in a state with very contrasting agricultural systems, including irrigated and dryland agriculture with dwindling groundwater resources. Figure A1 in the appendix shows the distribution of the KFMA sample across counties in Kansas.

Participation in the KFMA is voluntary which means some farms can drop out over time, making the panel dataset unbalanced. There is a large variation in the number of years each farm occurs in the dataset, with some farms surveyed for just 1 year while others being surveyed for all 39 years. On average, we observe farms for 10.4 years. The dataset has 72,323 distinct farm-year observations. As a robustness check, we also provide our main results using the balanced subset of the panel.

We measure farm financial well-being through gross and net income. Table 1 shows the summary statistics of all the KFMA variables used in our analysis. Net income ranges from a minimum of \$-2,188,300 to a maximum of \$3,995,200, with the mean value being \$65,600. Gross income ranges from a minimum of \$-133,600 to a maximum of \$17,595,400, with the mean value being \$396,100.[1] For each farm-year observation, we also compute yields of three major crops (corn, soybeans, and sorghum) by dividing the amount of crop produced by the acreage. Their sample average are 111, 32, and 68 bushels/acre,

[1] We convert all financial metrics in real terms (2015 USD).

respectively.

Our analysis seeks to understand how alternative sources of income can compensate contemporaneous financial losses stemming from extreme weather. We focus on 3 sources of additional income: government payments, crop insurance indemnities, and income received by selling crop inventory stock. Although data on government payments are available throughout the sample period, data on crop insurance are only available from 1993 onward. This is presumably due to large increase in uptake of crop insurance in US since 1990s due to the Crop Insurance Reform Act of 1994 (Glauber, 2013). We also limit the time period of analysis of crop inventory to 1993 and beyond because this variable measured different outcomes in the pre-1993 and post-1993 period in the KFMA data.

Farms in our sample receive approximately \$32,500 and \$20,200 on average through government payments and crop insurance payments, each year. We construct the variable of crop insurance payments only for farms which have purchased an insurance policy, which we indirectly measure by checking if a farm has made any crop insurance related expense in that year.[2] Approximately 78% of the farm-year observations falls within this category. Such farms have higher total income, are larger (in terms of acres operated), and generate a larger portion of their total farm income from crops as compared to livestock.[3] Crop inventory stock is the sum of inventories of cash crops, grains, and hay and forage. A typical farm in our sample holds \$159,500 of crop inventory which is more than twice the yearly net income.

To understand the role of irrigation in mediating the financial impacts of extreme weather, we use the KFMA data to compute the share of irrigated cropland for each farm-year observation. Figure 1 shows a county level plot of this measure. While there is considerable irrigation in Western Kansas, most of the cropland in the state is actually not irrigated. In fact, our sample shows that on average, only 9% of cropland is irrigated. Using this information, we classify farms as 'highly irrigated' if the irrigated area of their

[2]We follow the approach of Regmi et al. (2022) as the KFMA data does not directly report information on enrollment in any crop insurance program.

[3]For farms which made an insurance related expense, the mean value of gross farm income, acres operated, and crop income to total income ratio are \$475,957, 2040, and 0.82, respectively. For the other farms, these numbers are \$335,530, 1619, and 0.48, respectively.

cropland is at least 9% in that year. We use this binary measure as the key indicator of irrigation use in our analysis.

As irrigation use is a key part of our analysis, we consider an alternative measure of irrigation which acts as a robustness check for our main measure. This second measure relies on the fact that a significant portion of the state overlaps with the High Plains Aquifer, a primary source of irrigation water in Kansas. Using map from the U.S. Geological Survey, we compute the proportion of each county's area overlapping with the Aquifer. We use a binary measure of irrigation access, indicating if the share of county-area's overlap is above the sample average.[4]

Table 1: Summary Statistics of Variables at the Farm-Year Level

	N	Min	Max	Mean	SD
Weather					
EDD	72,323	2	219	49	28
GDD	72,323	1,214	2,134	1,732	152
Precipitation (mm)	72,323	125	1,371	574	186
Farm Finances ($\$_{2015}$)					
Net Farm Income	72,322	-2,188,260	3,995,200	65,627	142,952
Gross Farm Income	72,322	-133,618	17,595,446	396,134	510,037
Government Payments	72,322	-3,294	2,503,424	32,540	44,187
Crop Insurance	36,230	-54,743	2,603,398	20,246	61,323
Total crop inventory	46,535	-9,634	7,898,887	159,532	274,199
Crop yield (bushels/acre)					
Corn	35,467	0.00	2,500.00	110.66	49.18
Soybeans	43,150	0.00	2,392.93	31.54	19.92
Sorghum	44,749	0.00	1,552.00	67.69	29.60
Irrigation					
High irrigated crop share (binary)	70,628	0	1	0.21	0.41
High aquifer access (binary)	72,323	0	1	0.33	0.47
Share of farm's crops that are irrigated	70,628	0.00	1.00	0.09	0.21
Share of county area on aquifer	72,323	0.00	1.00	0.27	0.39
Year	72,323	1981	2020	1998	10.83

EDD = Extreme Degree-Days, GDD = Growing Degree-Days

The last part of the analysis explores how long-term trends of climatic variables may have an impact on measures of farm wealth. To conduct our long-term analysis we fo-

[4]Figure A2 shows the Aquifer boundary and the share of county area overlapping with the Aquifer. Both our irrigation measures shows that the Western side of Kansas is most irrigated.

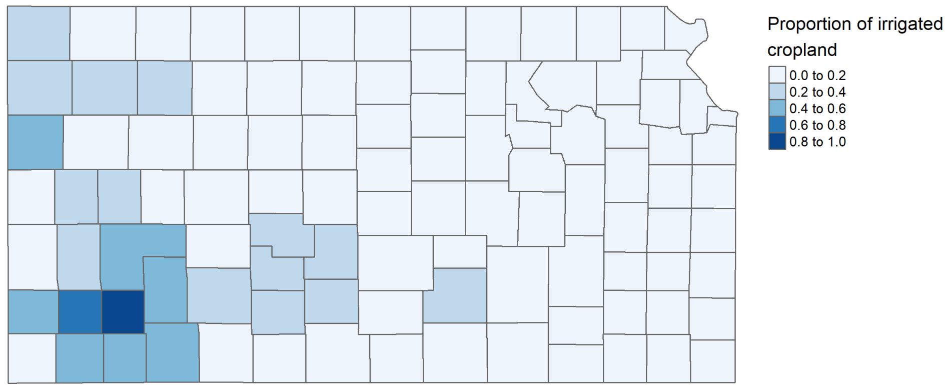


Figure 1: Irrigated Cropland

cus on the time frame of at least 30 years. We start by creating a sub-sample of KFMA farms which have panel length of at least 30 years. For each farm in this sub-sample, we compute the average annual growth rate of land values and average annual growth rate of farm equity over the whole time period during which the farm is surveyed. Land value (price per acre) is calculated by dividing the monetary value of owned land by the acreage of owned land. Farm equity is computed by subtracting total debt (sum of current loans, intermediate loans, long-term loans, and accounts payable) from total capital managed (total farm assets plus value of rented land). Table 2 shows summary statistics of all long-run variables. Land values grew by 1.8% per annum while farm equity grew by 3.6% per annum, respectively.

Due to confidentially concerns, the KFMA does not provide the exact address of each farm. However, we do obtain the county in which the farm is located, which we rely on to merge all KFMA observations to county-level weather data.

Table 2: Summary Statistics of Long-run Variables at the Farm Level

Long-run yearly average growth (%)	N	Mean	SD
Climate			
EDD	529	0.33	0.59
GDD	529	0.17	0.05
Precipitation (mm)	529	0.43	0.26
Farm Finances ($\$_{2015}$)			
Land Value	516	1.75	4.99
Farm Equity	529	3.56	2.94

2.2 Weather Data

We construct county-level weather variables from the PRISM data, which provides daily maximum and minimum temperature since 1981 at a 4-km resolution across the lower 48 states (Daly et al., 1997). Previous work has shown that the effects of temperature are nonlinear even within the day (Schlenker and Roberts, 2009). We construct measures of exposure to various temperature bins by fitting a sine curve on the daily temperature extremes in order to retrieve the length of exposure to different temperature intervals between the two extremes (Ortiz-Bobea, 2021). We then compute the average level of exposure for all temperature bins (from -10°C to +50°C in 1°C increments) for all the Kansas counties, weighted by the cropland pixels in each county.[5] This gives us the crop-weighted exposure (in hours) in each of the 61 bins for each month in years 1981-2020 for all 105 Kansas counties.

Having too little exposure to extreme bins can lead to noisy estimates, so we aggregate extreme bins to obtain enough exposure at the tails for proper estimation of temperature effects. Specifically, we top and bottom code the 61 bins, reducing them to 39 bins from 0°C to 38°C. For ease of understanding, we also convert the binned exposure from hours to days by dividing all binned exposures by 24. We then use binned exposures from the crop growing season (months of April to September) to compute a yearly measure of extreme degree-days (defined as degree-days above 32°C and henceforth referred as EDD) - our main measure of exposure to extreme temperature. EDD is a two-dimensional measure of thermal time, computed as the product of temperature (in 1°C increments) above 32°C and the exposure (in days) at each of those temperature points. It is considered a more appropriate measure than just the number of days above 32°C because it gives more weight to higher temperatures — farther a temperature point is from 32°C, more detrimental is its effect. The threshold of approximately 32°C is well established in the literature as crop yields start declining once temperature crosses this limit.[6]

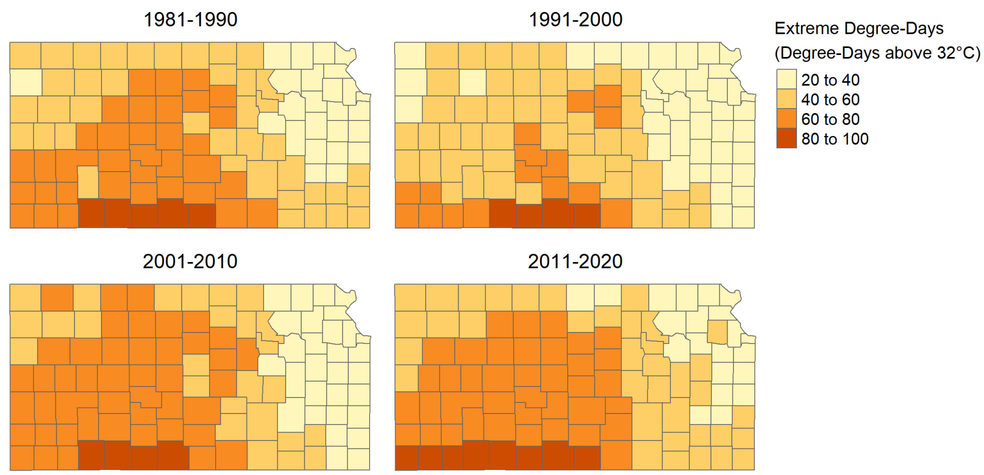
[5] We use National Land Cover Database (NLCD)'s 2016 gridded data to extract cropland pixels. We define cropland as any pixel identified as grassland, pasture, or cultivated crops.

[6] In Figure A3, we confirm this threshold by fitting a cubic spline of exposure to all temperature bins on crop yields following Ortiz-Bobea (2021). Results show that exposure to temperature above 32°C leads to a

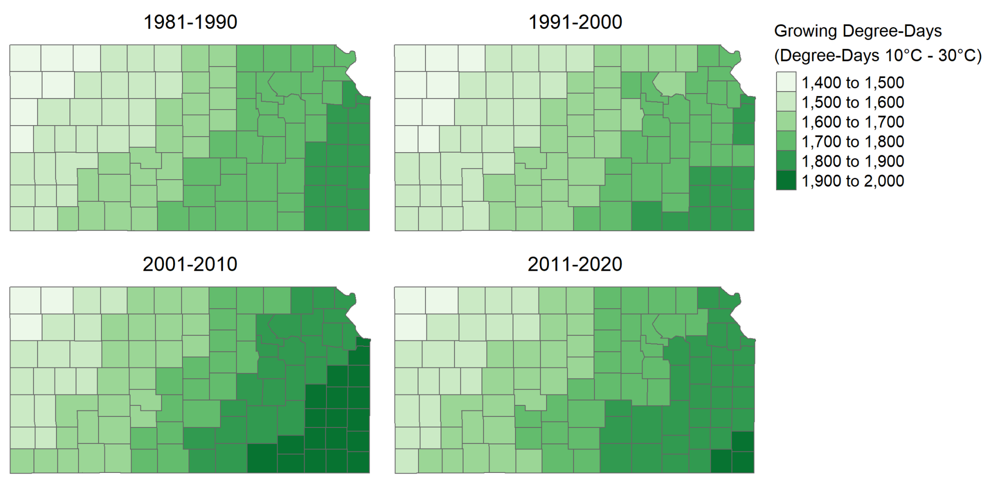
In a manner similar to EDD, we use monthly exposure bins from the crop growing season to compute a yearly measure of growing degree-days (GDD), defined as degree-days between 10°C and 30°C. An average farm in our sample experiences 50 EDD and 1730 GDD in the crop growing season of each year (Table 1). Figures 2a-2b shows EDD and GDD for Kansas counties, separately for 4 decades between 1981 to 2020 (time period of our analysis). Finally, we use yearly EDD and GDD data to construct their average annual growth rate over long run (30 years or more) for use in the long-run model. The growth rates of EDD and GDD are 0.3% and 0.2% per annum, respectively (Table 2). Unsurprisingly, it should be noted that EDD grew by almost double the rate of GDD over the past several decades.

To control for precipitation which might correlate with the temperature and the outcome variables, we construct a measure of cumulative yearly precipitation (in mm) in the crop growing season by summing monthly PRISM precipitation data. A typical farm in our sample experiences 570 mm of precipitation each year in the growing season (Table 1). Figure 2c shows the spatial distribution of precipitation over the time period of our analysis. We also construct annual average growth rate of precipitation to use as a control variable in our long-run model. Precipitation grew by 0.4% each year (Table 2).

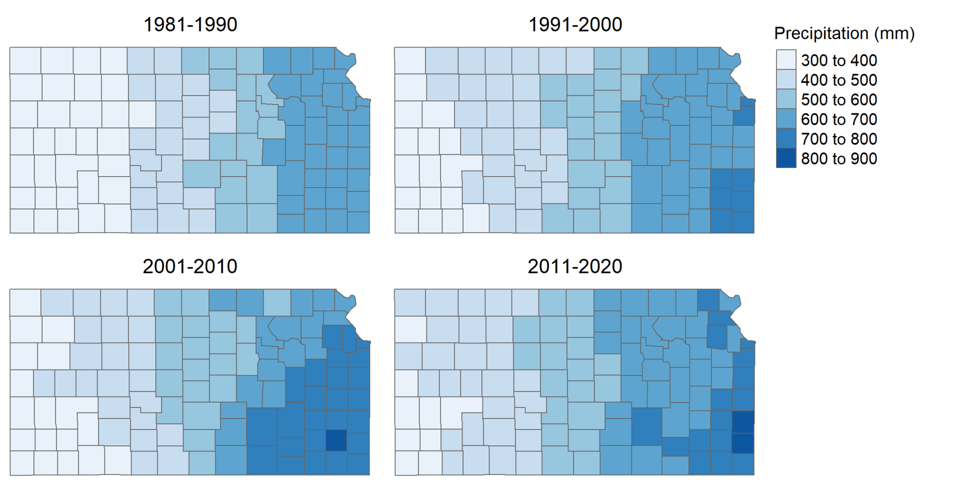
sharp decline in crop yields.



(a) Extreme Degree-Days



(b) Growing Degree-Days



(c) Precipitation

Figure 2: Growing Season Weather Data by Decade

3 Empirical Strategy

3.1 Main model

We begin by estimating the short-run causal impact of EDD on multiple farm outcomes using Equation 1.

$$Y_{fct} = \beta_o + \beta_1 EDD_{ct} + \beta_2 GDD_{ct} + \beta_3 Preip_{ct} + \beta_4 Precip^2_{ct} + \mu_f + \lambda_t + \varepsilon_{fct} \tag{1}$$

where Y_{fct} is the farm-level outcome variable of interest for farm f in county c in year t. EDD_{ct} and GDD_{ct} are extreme degree-days and growing degree-days, respectively, in the growing season of year t in county c. $Preip_{ct}$ and $Preip^2_{ct}$ are cumulative precipitation and its squared term. μ_f are farm fixed effects - they control for all time-invariant farm level characteristics such as farm size, location, and owner characteristics. λ_t are year fixed effects - they control for shocks common to all farms in a given year. We are using year fixed effects instead of time trend which is common with the crop yield models because yields have a clear upward trend overtime, while financial variables fluctuate with other indicators in the economy such as crop prices which do not follow a linear upward trend. We do, however, recognize that using year fixed effects in a state-level study would purge considerable variation in the weather variables, which could render our estimates less precise under certain forms of measurement error (Fisher et al., 2012). We employ spatial heteroskedasticity and autocorrelation consistent (HAC) standard errors (Conley, 1999) in all our estimates, using Bartlett Kernel with a distance cutoff of 200 miles.[7]

The first set of farm outcome variables, Y_{fct}, is (log) crop yield of three major crops - corn, soybeans, and sorghum. We estimate this relationship to confirm the validity of our EDD measure. The second group of outcome variables represented by Y_{fct} is farm income. It includes two key variables - (Inverse hyperbolic sine) gross farm income and net farm income. We use these two income measures because the first one just represents the value of farm output while the second also takes into account the value of farm inputs, and

[7] We also tried using a cutoff of 500 miles and the results were unchanged.

it's important to see how the impact of extreme temperature differs across both. We use inverse hyperbolic sine instead of log for income and all other financial measures because of zero and negative values in the financial data.[8] The interpretation of coefficients would be similar to the case if we were to use log of the dependent variables (Bellemare and Wichman, 2020).

The third set of variables included in Y_{fct} include inverse hyperbolic sine of government payments, crop insurance payments, and year-end crop inventory stock. These represent three sources of complementary income made available to farms during years of extreme temperature. We estimate this model to gauge the capacity of these three sources in minimizing total income loss and thus their potential as an adaptation mechanism in face of heat shocks. Our hypothesis is that farms will receive payments from government and insurance contracts and will sell their inventory stock in order to recover (at least some part of) lost income. We also examine lagged impact (up to 2 years) of EDD to verify whether there is any delay in the receipt of government payments and crop insurance payments.

The final empirical model of the short-run analysis tests the role of irrigation in buffering any negative impact of extreme temperature on farm income. We model this heterogeneous impact of access to irrigation on EDD-income relationship using Equation 2.

$$\begin{aligned} Y_{fct} =& \beta_o + \beta_1 EDD_{ct} + \beta_2 Irrigation_{fct} + \beta_3 EDD_{ct} \times Irrigation_{fct} \\ &+ \beta_3 GDD_{ct} + \beta_4 Preip_{ct} + \beta_5 Precip^2_{ct} + \mu_f + \lambda_t + \varepsilon_{fct} \end{aligned} \tag{2}$$

where Y_{fct} is gross and net farm income and $Irrigation_{fct}$ represents our irrigation measure - a dummy variable indicating whether farm f's share of irrigated land is greater than the sample average. As mentioned earlier, we also rely on a second measure of irrigation as a robustness check for our first measure. This second measure is a dummy variable indicating whether county c's share of area overlapping with the High Plains Aquifer is

[8] The share of zero and negative values for the financial variables is as follows: 1) Net Farm Income: 0.24, 2) Gross Farm Income: 0.0007, 3) Government payments: 0.06, 4) Crop Insurance: 0.37, 5) Crop Inventory: 0.05

greater than the sample average. β_3 is our main coefficient of interest which represents the difference in the impact of EDD on the outcome variable in highly irrigated farms as compared to less irrigated farms. As an additional robustness check, we also present results using continuous measures (instead of the binary measures) of the same irrigation variables mentioned above. In particular, we use the share of irrigated land at the farm level and the share of county-area overlapping with the Aquifer, where both these measures are measured on a continuous scale of 0 to 1.

3.2 Long-run model

To examine if any of the short-run impacts of extreme temperature builds up to make long-run changes in farm wealth, we estimate a "long trends" model using Equation 3. In this model, we harness the spatial variation in growth rate of extreme temperature over long run across farms in different counties.

$$\Delta Y_{fc} = \beta_o + \beta_1 \Delta EDD_c + \beta_2 \Delta GDD_c + \beta_3 \Delta Precip_c + \varepsilon_{fc} \tag{3}$$

where $\Delta\ Y_{fc}$ is the average yearly growth rate of real land price and farm equity for farm f in county c over at least 30 years. $\Delta\ EDD_c$ is the average yearly growth rate of EDD for county c over the same time period. The model also includes the average yearly growth rate of GDD and precipitation for county c. In a manner similar to the panel model, we employ spatial standard errors in this analysis, again using a cutoff of 200 miles.

As our variable of interest, EDD_c, is defined at the county level, we cannot control for county fixed effects in our analysis. However, we can include a dummy for a geographical unit larger than the county but smaller than the whole state. The KFMA data provides one such variable as the KFMA divides the state of Kansas into 6 associations for administrative purposes. Each association is a group of 16 neighboring counties, on average. We thus also estimate Equation 3 after controlling for association fixed effects, where the estimation relies on comparing trends within each association. This is done to purge any confounding due to unobserved factors, such as regional real estate trends, that are common to counties within each association and have correlation with long-run weather trends.

4 Results

4.1 Main Results

Our first set of results replicate well-known findings that extreme temperatures are detrimental to crop yields — Table A1 shows that an increase in EDD causes a decline in yields. Our key coefficient measures the impact of 1 additional EDD, which is difficult to interpret because of the nature of the variable. For ease of interpretation, we also report the impact associated with a 1°C uniform warming in all the regression tables.[9] A uniform warming of 1°C causes 18%, 16%, and 20% decline in the yield of corn, soybeans, and sorghum, respectively.

Table 3 reports the impact of extreme temperature on gross and net farm income. The coefficients of EDD and the effect size associated with 1°C warming should not be compared across columns because they are interpreted as percentage changes, and not changes in dollar values. Gross income and net income decreases by 7% and 66%, respectively with a 1°C warming.[10] To better understand that, we can place these numbers in reference to the 2012 drought which caused approximately a 1.6°C warming in the growing season in Kansas compared to the long-run average. It was the largest drought in recent US history, caused by an extreme heat wave. A temperature increase similar to that experienced in the 2012 drought would reduce gross and net farm income by 11% and 105%, respectively. As gross and net income include all sources of income such as

[9] The impact of uniform warming is calculated as follows: We reconstruct our data of exposure to temperature bins by assuming that temperature has increased by 1°C at all times. We use this data to recompute the two temperature measures ($EDD_{1°C}$ and $GDD_{1°C}$). The impact (in percentage) of 1°C uniform warming is: $(e^{\beta_{EDD}(EDD-EDD_{1°C})+\beta_{GDD}(GDD-GDD_{1°C})} - 1) \times 100$ where β_{EDD} and β_{GDD} are coefficients of EDD and GDD respectively.

[10] Results using the balanced panel of our dataset are presented in Table A2 and are found to be similar to those obtained using the full sample.

crop insurance payments and income support from government, these effects show that high temperatures have extremely damaging contemporaneous impacts on farm income, even after accounting for additional income made available to farms during years of extreme temperature.

Comparing the monetary value of temperature driven losses of the two income measures reveal that for an average farm, net income loss is roughly 1.6 times the size of gross income loss — a 1°C warming leads to $27,729 and $43,313 decline in gross income and net income, respectively.[11] This means that extreme temperature not only negatively impacts the value of farm output, but also increase farm expenses. These increased costs could have resulted from temperature induced adjustments made by farms such as increased use of certain inputs (e.g., irrigation) or paying more for insurance premium, for instance.

Table 3: Impact of Extreme Degree-Days on Farm Income

	(1) Gross Farm Income	(2) Net Farm Income
EDD	-0.003***	-0.050***
	(0.001)	(0.012)
Num.Obs.	72,322	72,322
Impact of 1°C warming (%)	-6.9	-66.1
R^2 Adj.	0.69	0.274

Dependent variables are inverse hyperbolic sine transformed.
All columns control for growing degree-days, second order polynomial of precipitation, and farm and year fixed effects.
Spatial HAC standard errors are reported in parentheses.
* p < 0.1, ** p < 0.05, *** p < 0.01

Although we find large negative impacts of extreme temperature on farm income even after accounting for compensatory payments made available to farms, it is important to examine the role of such payments in buffering the overall income decline. Table 4 reports the impact of extreme temperature on such additional sources of income. We do not

[11] For an average farm in our sample, 1°C warming leads to $27,729 decline in GFI (7% (effect size associated with 1°C warming) of $3,96,134 (sample average of GFI) = $27,729), and $43,313 decline in NFI (66% (effect size associated with 1°C warming) of $65,627 (sample average of NFI) = $43,313). NFI loss / GFI loss = 43,313 / 27,729 = 1.6

find a link between extreme temperature and government payments in a particular year. However, we do notice a jump in the receipt of government payments two years after an episode of extreme temperature (columns 1 and 2). Crop insurance payments increase contemporaneously as well as with a lag of 1 year (columns 3 and 4). Furthermore, the value of crop inventory stocks decline after an increase in extreme temperature (columns 5 and 6) which indicates that farmers sell their inventory to recoup the lost income.[12] A 1°C warming increases crop insurance payments by 324% and decreases the value of year-end crop inventory stocks by 15%. Of the net income loss experienced without accounting for these additional payments, 51% is shielded by crop insurance payments and 16% by the sale of crop inventory.[13] Overall, these findings point to the significant role of risk management strategies, especially that of crop insurance in buffering the contemporaneous income loss caused by extreme heat.

[12]Theoretically, a decline in the value of inventory does not necessarily represent a fall in quantity as the total value not only depends on the quantity but also on unit price. However, it is very unlikely that crop prices fall during a drought year. In fact, prices rise during periods of extreme temperature because of negative shock to crop supply. This makes us quite confident that our results indeed represent a fall in the quantity of inventory holdings and not a fall in its unit price.

[13]1°C warming leads to an increase in crop insurance payments by $65,593 (324% (effect size associated with 1°C warming) of $20,245 (sample average of CI) = $65,593). 1°C warming leads to $20,008 decline in total crops inventory (15% (effect size associated with 1°C warming) of $1,33,387 (sample average of inventory) = $20,008).
NFI loss as a result of 1°C warming = $43,313. NFI loss as a result of 1°C warming in the absence of crop insurance payments and in the absence of sale of crop inventories = $43,313 + $65,593 + $20,008 = $1,28,914. Crop insurance payments as a percentage of total NFI loss = ($65,593 / $1,28,914) × 100 = 51%. Income from inventory sale as a percentage of total NFI loss = ($20,008 / $1,28,914) × 100 = 16%.

Table 4: Impact of Extreme Degree-Days on Disaster Payments and Inventory

	(1) Government Payments	(2) Government Payments	(3) Crop Insurance Payments	(4) Crop Insurance Payments	(5) Crop Inventory Stock	(6) Crop Inventory Stock
EDD	0.001	0.001	0.065***	0.059***	-0.008***	-0.007***
	(0.002)	(0.002)	(0.009)	(0.009)	(0.002)	(0.002)
EDD_L1		0.003		0.025**		-0.007***
		(0.003)		(0.011)		(0.002)
EDD_L2		0.009***		0.004		0.001
		(0.003)		(0.010)		(0.002)
Num.Obs.	72,322	53,102	36,230	29,669	46,535	37,627
Impact of 1°C warming (%)	3.7		324.3		-15.3	
Time period	1981-2020	1981-2020	1993-2020	1993-2020	1993-2020	1993-2020
R^2 Adj.	0.558	0.569	0.311	0.315	0.577	0.581

Dependent variables are inverse hyperbolic sine transformed. All columns control for growing degree-days, second order polynomial of precipitation, and farm and year fixed effects. Columns with lagged EDD also control for lagged GDD and lagged precipitation. Spatial HAC standard errors are reported in parentheses.
* p < 0.1, ** p < 0.05, *** p < 0.01

We find evidence that access to irrigation limits some of the temperature driven income loss. Table 5 shows that farms having a high share of irrigated crops experience approximately 37% less net income loss as compared to the rest of the farms.[14] We carry out a number of robustness checks to confirm this protective role of irrigation. First, we use county-level Aquifer overlap as an alternative measure of irrigation. The results using that measure (presented in Table A3) shows that farms in counties with larger than average overlap with the Aquifer experience approximately 55% less net income loss.[15] Second, we present results with continuous irrigation measures (instead of binary measures) in Table A4 and Table A5. As interaction terms involving continuous measures are better interpreted through marginal effects, we present the marginal effect of EDD on income, for varying levels of both our continuous irrigation measures in Fig. A5 and Fig.

[14]Net income loss avoided due to large irrigated cropland = 0.020/0.054 = 37%. Gross income loss avoided due to large irrigated cropland = 0.002/0.003 = 67%.

[15]Net income loss avoided due to HPA = 0.035/0.064 = 54.7%. Gross income loss avoided due to HPA = 0.002/0.004 = 50%.

A4. The marginal effect appears less negative as access to irrigation increases.

Table 5: Role of Irrigation in Protecting Farm Income

	(1) Gross Farm Income	(2) Net Farm Income
EDD	-0.003***	-0.054***
	(0.001)	(0.012)
High share of irrigated crops	0.147***	-0.767**
	(0.020)	(0.348)
EDD × High share of irrigated crops	0.002***	0.020***
	(0.000)	(0.006)
Num.Obs.	70,628	70,628
R^2 Adj.	0.703	0.274

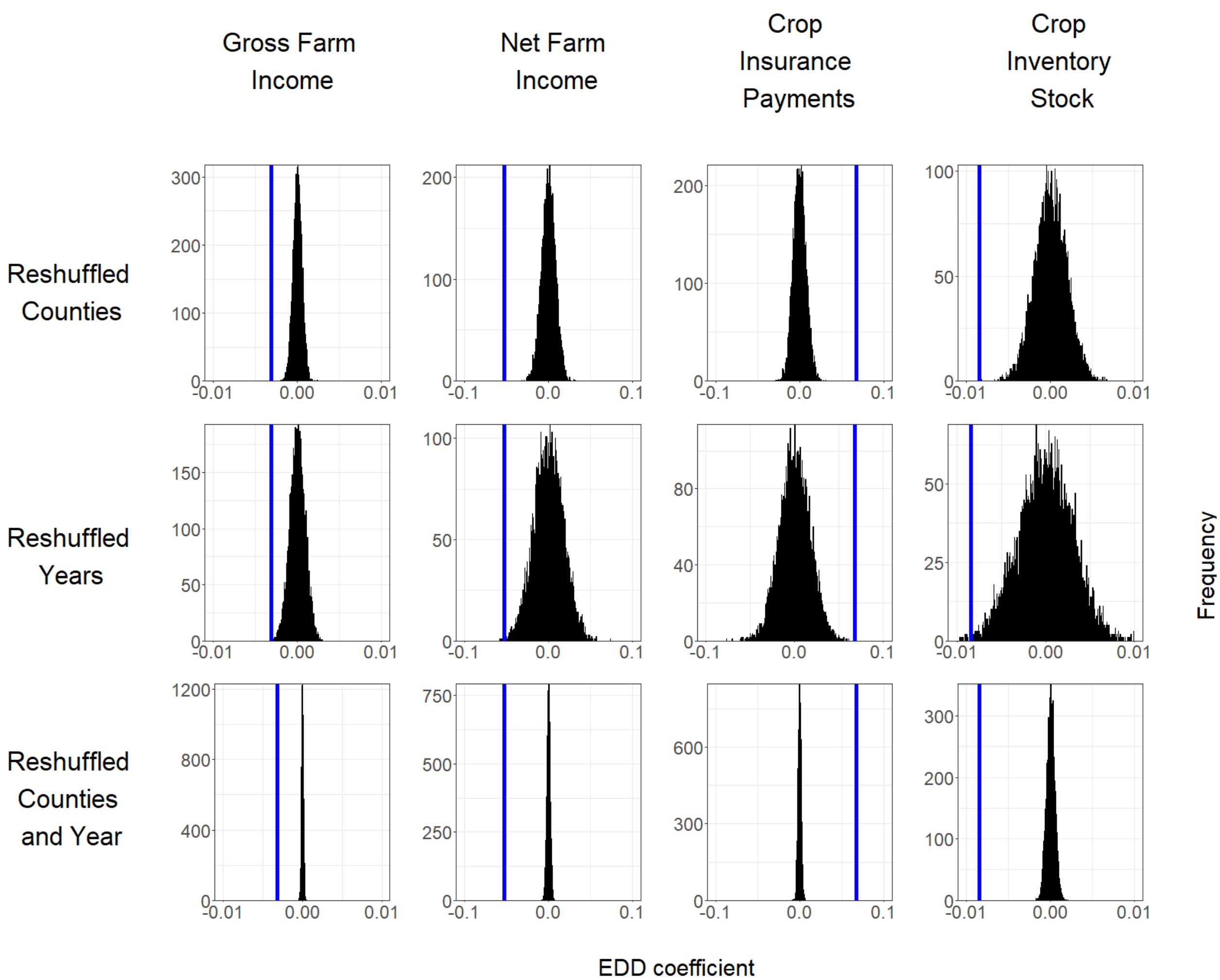
Dependent variables are inverse hyperbolic sine transformed.
All columns control for growing degree-days, second order polynomial of precipitation, and farm and year fixed effects.
Spatial HAC standard errors are reported in parentheses.
* p < 0.1, ** p < 0.05, *** p < 0.01

4.2 Placebo checks

To confirm that our estimates are not found by chance, we carry out a battery of placebo checks on four key outcome variables discussed earlier - gross farm income, net farm income, crop insurance payments, and crop inventory stock. In three separate sets of placebo checks, we create 10,000 reshuffled datasets where we mismatch 1) counties, 2) years, and 3) counties and years for all observations in our data, and then re-estimate our regression model using each of these datasets. To put in differently, a farm located in county c and observed in year t is assigned the weather variable of any county other than county c, of any year other than year t, or both at the same time. We should, on average, obtain no effect by mismatching the weather data with the outcome data. By redoing this multiple times we can recover the distribution of "spurious" effects.[16] Figure 3 shows the distribution of EDD coefficients derived from using the 10,000 reshuffled datasets in each category. As expected, we find that these estimates are centered around 0, and they

[16] In other words, this is the distribution of the "no effect" null hypothesis.

have minimum variance when we mismatch both counties and years. We also mark the sample estimate derived originally without any reshuffling, and it can be seen that it does not overlap with the distribution of spurious estimates.



This figure shows the distribution of EDD coefficient associated with four key outcome variables. These coefficients are derived from 10,000 reshuffled datasets in each reshuffling category. Vertical blue line shows the coefficient obtained from data without any reshuffling.

Figure 3: Placebo Checks with Mismatched Weather Variables

4.3 Long-run results

Finally, we report the results of the long-trends model (Equation 3) in Table 6. Columns 1 and 3 show estimates without controlling for association fixed effects, while columns 2 and 4 show estimates after controlling for association fixed effects. EDD coefficients are negative and statistically significant at conventional levels in all specifications, implying that long-run growth rates in weather negatively affect the growth rates of farmland value and farm equity. Over the 30-year period, land value and farm equity grew by 53% and 107%, respectively. Our estimates suggest that in the absence of EDD growth, land value would have grown by an additional 5 percentage points, and farm equity would have grown by an additional 5.6 percentage points. Thus, over a 30-year period, changing weather has led to approximately a 9% and 5% decline in the growth rate of land values and farm equity, respectively.[17] Association fixed effects reduces the absolute magnitude of the EDD coefficients by almost 50%.

Table 6: Impact of EDD growth on Farmland Value growth and Farm Equity growth

	(1)	(2)	(3)	(4)
	Δ Land Value	Δ Land Value	Δ Equity	Δ Equity
Δ EDD (%)	-0.523***	-0.225***	-0.585***	-0.281*
	(0.127)	(0.067)	(0.152)	(0.152)
Num.Obs.	516	516	529	529
Association FE	No	Yes	No	Yes
R^2 Adj.	0.007	0.044	0.017	0.124

Dependent variables: Long-run growth rate of real land values and farm equity.
Independent variable: Long-run growth rate of extreme degree-days. All columns control for long-run growth rate of growing degree-days and precipitation.
Spatial HAC standard errors are reported in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

[17] Δ EDD over 30 years = 0.33% × 30 = 9.6%. Δ Land Value over 30 years = 1.75% × 30 = 52.5%. Δ Farm Equity over 30 years = 3.56% × 30 = 107%.
Change in Δ Land Value over 30 years due to EDD = 9.6 × -0.523= -5.02 percentage points. Δ Land Value over 30 years (had there been no EDD growth) = 52.5 (growth rate over 30 years shown by data) - (- 5.02) = 57.52%. Percentage decline in Δ Land Value due to EDD = (5.02/57.52) × 100 = 8.7% .
Change in Δ Farm Equity over 30 years due to EDD = 9.6 × -0.585= -5.62 percentage points. Δ Farm Equity over 30 years (had there been no EDD growth) = 107 (growth rate over 30 years shown by data) - (- 5.62) = 112.62%. Percentage decline in Δ Farm Equity due to EDD = (5.62/112.62) × 100 = 5%.

5 Conclusion

Our study sheds light on the impacts of extreme weather and changing climatic conditions on farm financial performance. We are able to conduct this work by accessing a detailed panel dataset spanning decades of farm finances in the state of Kansas. We examine the impact of extreme temperature on farm income in the short-run, and on farmland value and farm wealth in the long-run. Furthermore, we also shed light on the role of financial and non-financial instruments in reducing the heat-driven negative impact on income.

We find four key results. First, exposure to extreme temperature leads to a decline in both gross and net farm income, with the impact on net income almost 1.6 times the impact on gross income. The magnitude of income loss is large as 1°C warming is estimated to cause 66% decline in net income. Second, crop insurance payments and the selling of crop inventory stocks helps recover 51% and 16% of the income loss, respectively. Third, using two alternative measures of irrigation, we find that farms with above-average irrigation access experience at least 37% less net income loss. Last, we find evidence that the growth rates of farmland values and farm equity have slowed down by 9% and 5%, respectively, over a 30 year period due to rise in extreme temperatures.

The results of this study are important for farmers, agriculture policy makers, insurance firms, and farm lenders. The new insight from our paper can improve the functioning of farm credit markets; lenders should now be better able to assess changing weather-related risks arising from climate change and their role in supporting the transition to more resilient farming systems. Furthermore, our key finding of large reliance on crop insurance in buffering harmful effects of temperature raises questions on its future as a risk management tool in a world with increasing temperatures, providing food for thought for stakeholders in crop insurance industry.

References

Annan, F. and W. Schlenker (2015). Federal crop insurance and the disincentive to adapt to extreme heat. *American Economic Review 105*(5), 262–66.

Aragón, F. M., F. Oteiza, and J. P. Rud (2021). Climate change and agriculture: Subsistence farmers' response to extreme heat. *American Economic Journal: Economic Policy 13*(1), 1–35.

Bellemare, M. F. and C. J. Wichman (2020). Elasticities and the inverse hyperbolic sine transformation. *Oxford Bulletin of Economics and Statistics 82*(1), 50–61.

Bergman, N. K., R. Iyer, and R. T. Thakor (2020). The effect of cash injections: Evidence from the 1980s farm debt crisis. *The Review of Financial Studies 33*(11), 5092–5130.

Burke, M. and K. Emerick (2016). Adaptation to climate change: Evidence from us agriculture. *American Economic Journal: Economic Policy 8*(3), 106–40.

Conley, T. G. (1999). Gmm estimation with cross sectional dependence. *Journal of econometrics 92*(1), 1–45.

Crane-Droesch, B., E. Marshall, S. Rosch, A. Riddle, J. Cooper, S. Wallander, et al. (2019). Climate change and agricultural risk management into the 21st century. *Economic Research Report-Economic Research Service, USDA* (266).

Daly, C., G. Taylor, and W. Gibson (1997). The prism approach to mapping precipitation and temperature. In *Proc., 10th AMS Conf. on Applied Climatology*, pp. 20–23.

Dell, M., B. F. Jones, and B. A. Olken (2014). What do we learn from the weather? the new climate-economy literature. *Journal of Economic literature 52*(3), 740–798.

Deschênes, O. and M. Greenstone (2007). The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. *American economic review 97*(1), 354–385.

Diffenbaugh, N. S., F. V. Davenport, and M. Burke (2021). Historical warming has increased us crop insurance losses. *Environmental Research Letters 16*(8), 084025.

Fisher, A. C., W. M. Hanemann, M. J. Roberts, and W. Schlenker (2012). The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather: comment. *American Economic Review 102*(7), 3749–60.

Glauber, J. W. (2013). The growth of the federal crop insurance program, 1990—2011. *American Journal of Agricultural Economics 95*(2), 482–488.

Janzen, J. and B. Swearingen (2020). Changes in us grain storage capacity. *farmdoc daily 10*(204).

Lambert, D. K. (2014). Historical impacts of precipitation and temperature on farm production in kansas. *Journal of Agricultural and Applied Economics 46*(4), 439–456.

McCarl, B. A. (2007). Adaptation options for agriculture, forestry and fisheries. a report to the unfccc secretariat financial and technical support division. In *United Nations Framework Convention on Climate Change*.

Miller, N., J. Tack, and J. Bergtold (2021). The impacts of warming temperatures on us sorghum yields and the potential for adaptation. *American Journal of Agricultural Economics 103*(5), 1742–1758.

Ortiz-Bobea, A. (2021). The empirical analysis of climate change impacts and adaptation in agriculture. In *Handbook of Agricultural Economics*, Volume 5, pp. 3981–4073. Elsevier.

Ortiz-Bobea, A., T. R. Ault, C. M. Carrillo, R. G. Chambers, and D. B. Lobell (2021). Anthropogenic climate change has slowed global agricultural productivity growth. *Nature Climate Change 11*(4), 306–312.

Ortiz-Bobea, A., E. Knippenberg, and R. G. Chambers (2018). Growing climatic sensitivity of us agriculture linked to technological change and regional specialization. *Science advances 4*(12), eaat4343.

Parry, M. L. (2009). Assessing the costs of adaptation to climate change: a review of the unfccc and other recent estimates.

Regmi, M., J. B. Tack, and A. M. Featherstone (2022). Does crop insurance influence crop yield impacts of warming temperatures? a farm-level analysis.

Schlenker, W. and M. J. Roberts (2009). Nonlinear temperature effects indicate severe damages to us crop yields under climate change. *Proceedings of the National Academy of sciences 106*(37), 15594–15598.

Sulser, T., K. D. Wiebe, S. Dunston, N. Cenacchi, A. Nin-Pratt, D. Mason-D'Croz, R. D. Robertson, D. Willenbockel, and M. W. Rosegrant (2021). *Climate change and hunger: Estimating costs of adaptation in the agrifood system*. Intl Food Policy Res Inst.

Tack, J., A. Barkley, and N. Hendricks (2017). Irrigation offsets wheat yield reductions from warming temperatures. *Environmental Research Letters 12*(11), 114027.

Troy, T. J., C. Kipgen, and I. Pal (2015). The impact of climate extremes and irrigation on us crop yields. *Environmental Research Letters 10*(5), 054013.

Wang, R., R. M. Rejesus, and S. Aglasan (2021). Warming temperatures, yield risk and crop insurance participation. *European Review of Agricultural Economics 48*(5), 1109–1131.

Wu, W.-Y., M.-H. Lo, Y. Wada, J. S. Famiglietti, J. T. Reager, P. J.-F. Yeh, A. Ducharne, and Z.-L. Yang (2020). Divergent effects of climate change on future groundwater availability in key mid-latitude aquifers. *Nature communications 11*(1), 3710.

Zaveri, E. and D. B Lobell (2019). The role of irrigation in changing wheat yields and heat sensitivity in india. *Nature communications 10*(1), 1–7.

Appendix

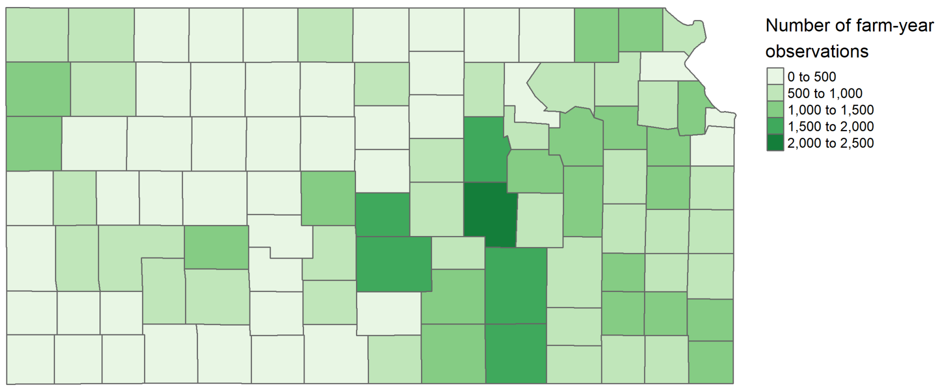
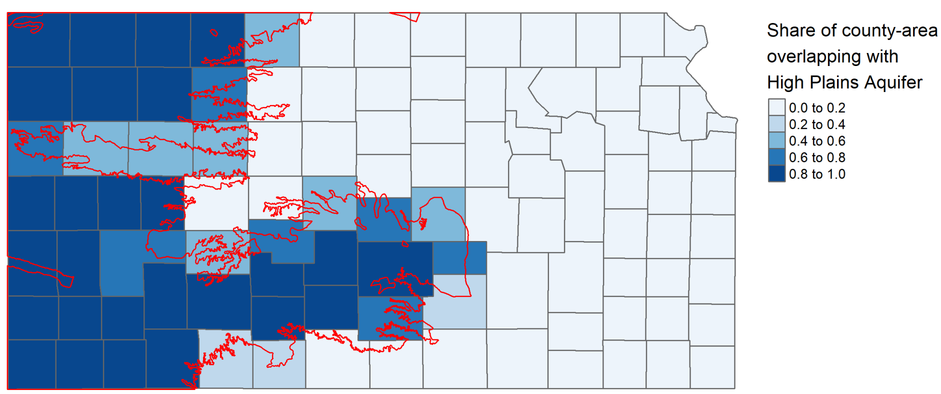
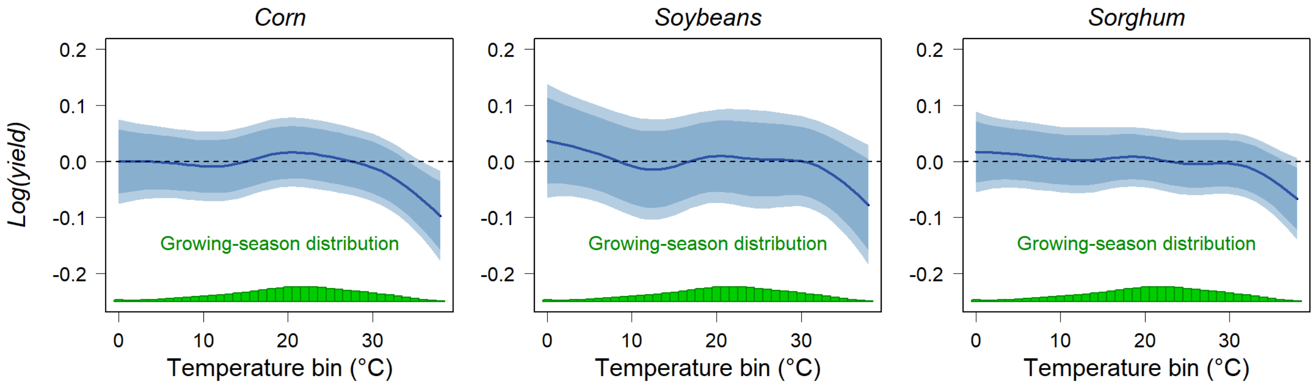


Figure A1: Spatial distribution of the KFMA dataset observations



High Plains Aquifer's boundary shown in red.

Figure A2: Map indicating the spatial extent of the High Plains Aquifer in Kansas



Note: The data covers farm-level crop yields from 1981 to 2020. We control for second order polynomial of precipitation, and farm and year fixed effects. Bands show 95% and 99% confidence intervals, derived from spatial HAC standard errors. The growing season goes from Apr. to Sept. The sample size is 35,204, 42,852, and 44,376 farm-year observations for corn, soybeans, and sorghum, respectively.

Figure A3: Impact of Exposure to Varying Temperature Bins on Crop Yields

Table A1: Impact of Extreme Degree-Days on Crop Yields

	(1) Corn Yield	(2) Soybeans Yield	(3) Sorghum Yield
EDD	-0.011***	-0.008***	-0.010***
	(0.001)	(0.001)	(0.001)
Num.Obs.	35,204	42,852	44,376
Impact of 1°C warming (%)	-18.4	-15.8	-20.1
R^2 Adj.	0.545	0.572	0.465

Dependent variables are logged. All columns control for growing degree-days, second order polynomial of precipitation, and farm and year fixed effects. Spatial HAC standard errors are reported in parentheses.
* p < 0.1, ** p < 0.05, *** p < 0.01

Table A2: Impact of Extreme Degree-Days on Income - Balanced Panel

	(1) Gross Farm Income	(2) Net Farm Income
EDD	-0.003**	-0.062*
	(0.001)	(0.032)
Num.Obs.	1,920	1,920
Impact of 1°C warming (%)	-4.8	-72.4
R^2 Adj.	0.835	0.209

Dependent variables are inverse hyperbolic sine transformed.
All columns control for growing degree-days, second order polynomial of precipitation, and farm and year fixed effects.
Spatial HAC standard errors are reported in parentheses.
* p < 0.1, ** p < 0.05, *** p < 0.01

Table A3: Role of Irrigation in Protecting Farm Income - High Plains Aquifer (binary measure)

	(1) Gross Farm Income	(2) Net Farm Income
EDD	-0.004***	-0.064***
	(0.001)	(0.012)
EDD × Large overlap of aquifer	0.002***	0.035***
	(0.000)	(0.006)
Num.Obs.	72,322	72,322
R^2 Adj.	0.691	0.276

Dependent variables are inverse hyperbolic sine transformed.
All columns control for growing degree-days, second order polynomial of precipitation, and farm and year fixed effects.
Spatial HAC standard errors are reported in parentheses.
* p < 0.1, ** p < 0.05, *** p < 0.01

Table A4: Role of Irrigation in Protecting Farm Income - Irrigated crop share (continuous measure)

	(1) Gross Farm Income	(2) Net Farm Income
EDD	-0.003***	-0.053***
	(0.001)	(0.012)
Irrigated crops (share)	0.155***	-2.625***
	(0.054)	(0.887)
EDD × Irrigated crops (share)	0.004***	0.041***
	(0.001)	(0.012)
Num.Obs.	70,628	70,628
R^2 Adj.	0.702	0.274

Dependent variables are inverse hyperbolic sine transformed.
All columns control for growing degree-days, second order polynomial of precipitation, and farm and year fixed effects.
Spatial HAC standard errors are reported in parentheses.
* p < 0.1, ** p < 0.05, *** p < 0.01

Table A5: Role of Irrigation in Protecting Farm Income - High Plains Aquifer (continuous measure)

	(1) Gross Farm Income	(2) Net Farm Income
EDD	-0.004***	-0.065***
	(0.001)	(0.012)
EDD × Aquifer overlap (share)	0.002***	0.047***
	(0.000)	(0.008)
Num.Obs.	72,322	72,322
R^2 Adj.	0.691	0.276

Dependent variables are inverse hyperbolic sine transformed.
All columns control for growing degree-days, second order polynomial of precipitation, and farm and year fixed effects.
Spatial HAC standard errors are reported in parentheses.
* p < 0.1, ** p < 0.05, *** p < 0.01

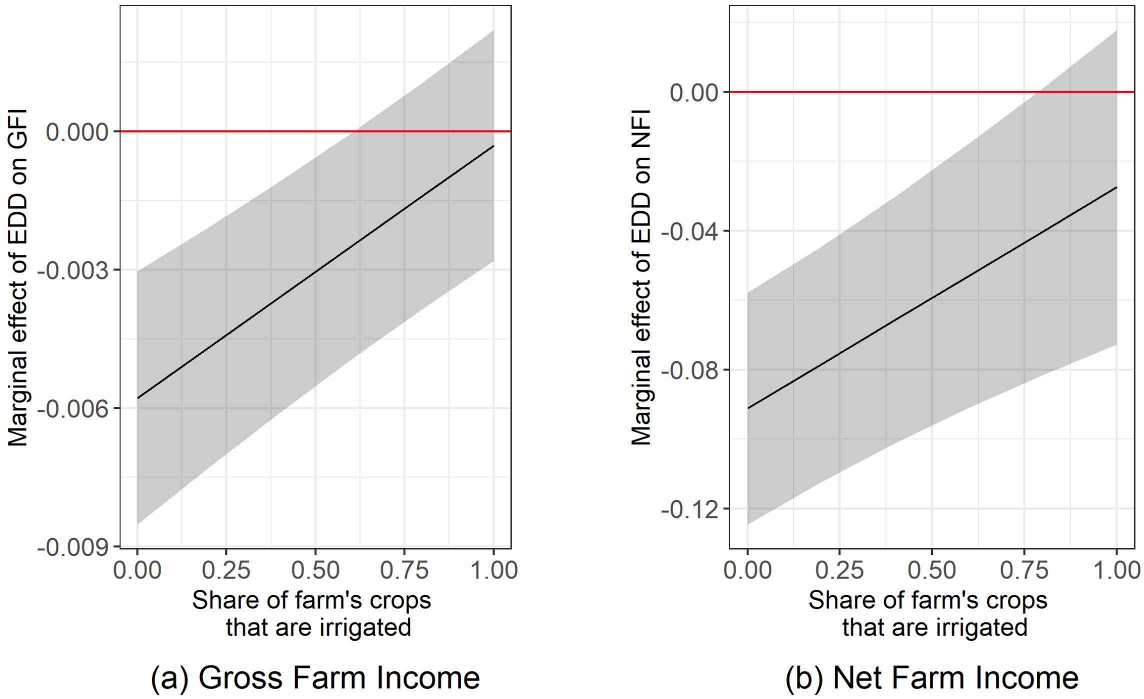


Figure A4: Heterogeneous Impact of EDD on Income by Share of Irrigated Crops

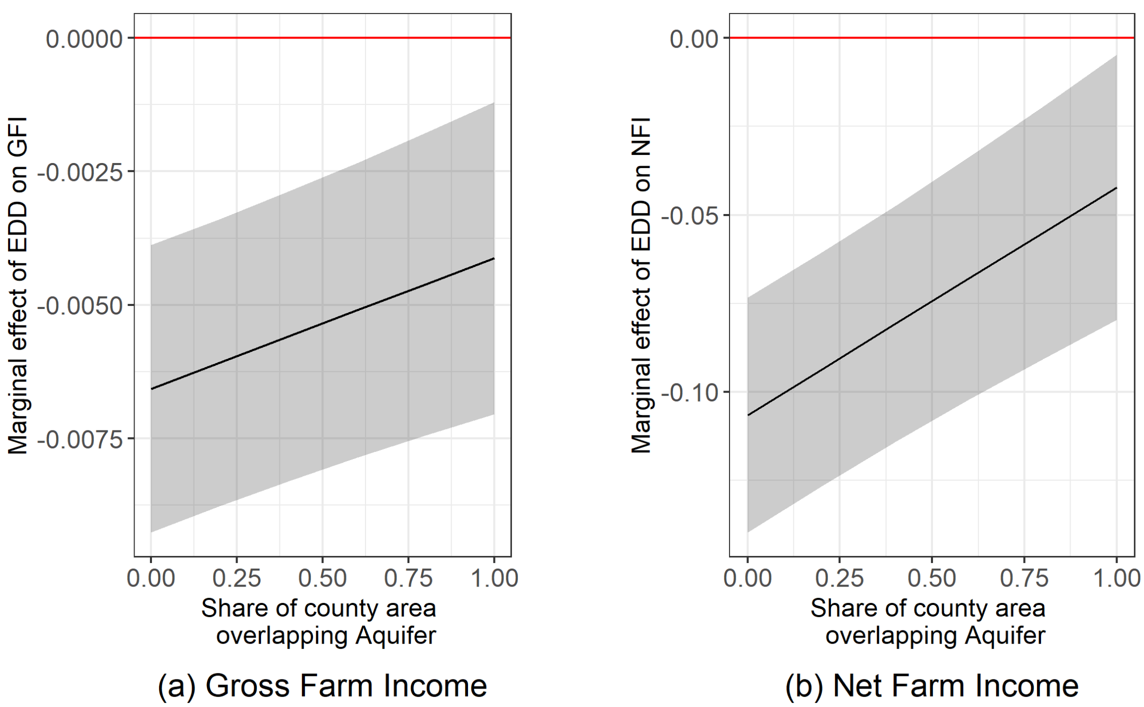


Figure A5: Heterogeneous Impact of EDD on Income by Aquifer Overlap