The impact of extreme weather on farm finances: farm-level evidence from Kansas

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Our understanding of how extreme weather affects US agriculture is largely based on the analysis of yields or productivity using aggregate data. We use a unique farm-level panel dataset from Kansas to shed light on the specific channels farmers rely on to cope with weather shocks. Our panel tracks close to 7,000 farms over 4 decades across Kansas, which comprises both irrigated and rainfed systems. We find that a 1°C warming reduces gross income by 7% and net income by 66%. These impacts would have been even greater without crop insurance payments and inventory adjustments, which reduce temperature-induced income losses by 51% and 16%, respectively. As expected, irrigation reduces net income loss due to extreme temperature by almost half. We find limited heterogeneity in these effects across farm types, although larger farms appear slightly less sensitive to heat. Finally, we find that farmland values, which make up the majority of farm wealth, have appreciated more slowly in areas experiencing more rapid warming. (JEL Codes: Q54, Q14)

Keywords: extreme temperature, farm income

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1 Introduction

A vast literature analyzes the effects of extreme weather on a variety of agricultural outcomes, with the goal of measuring climate change impacts. Most work explores the effects of weather on crop yields (Lobell and Field, 2007; Schlenker and Roberts, 2009; Miller et al., 2021). These studies provide a nuanced understanding of how weather inputs affect the production of specific commodities, but provide limited understanding of how these shocks affect farmers' financial bottom line, which also reflects prices, expenses, transfers, and various management practices. Even studies analyzing the effects of weather on Total Factor Productivity (TFP), which provides a summary understanding of how weather affects all agricultural outputs conditional on farmer inputs (Ortiz-Bobea et al., 2018, 2021), do not directly measure financial impacts.

Income and profit measures capture the welfare of agricultural producers, as well as their incentives for climate adaptation. A few US based studies have explored the effect of weather on profits (Deschênes and Greenstone, 2007; Lambert, 2014), however these studies focus on narrow measures of income or are based on data with sparse temporal resolution, which precludes assessing inter-annual economic phenomena (Fisher et al., 2012). These year-to-year farm-level adjustments, along with government programs and payments, are critical drivers of farm financial outcomes and stability (Diffenbaugh et al., 2021). Understanding their role in mitigating the impacts of extreme weather requires disaggregated data with a high temporal resolution.

In this study, we harness a detailed farm-level panel dataset to explore both the direct effects of weather on gross and net farm income and the predominant tools or channels for mitigating income shocks. Specifically, we examine the role of crop insurance indemnities, government payments, adjustments in crop inventories, and irrigation in modulating the impact of high temperatures on farm income. We also explore whether recent trends in local climate may have been capitalized in farmland assets.

Answering these questions requires detailed annual financial information, which is rare. We obtain such data from a unique farm-level panel dataset from the Kansas

Farm Management Association (KFMA) which spans four decades (1981-2020) and covers thousands of farms. The KFMA offers accounting and financial analysis services for farmers, including tax preparation. KFMA's affiliation with Kansas State University has led to a partnership for provision of farm-level data for research and outreach purposes, including tracking farm financial health across the state. These data provide key advantages relative to county-level data from the Census of Agriculture. First, the temporal granularity allows exploring the role of various mechanisms that operate from year to year, such as changes in inventory. Second, the farm-level resolution can shed light on how different types of farm operations cope with extreme weather. Third, disaggreted data avoids potential bias related to use of aggregated data in climate impact studies (Bigelow and Jodlowski, 2023; Fezzi and Bateman, 2015).

Our main empirical strategy exploits spatial and temporal variation in weather, conditioned on farm and year fixed effects, to estimate its effect on income. This panel estimation, thus, relies on comparing, within a given year, farm-specific weather deviations from the local mean. Because farmers cannot anticipate weather several months in advance, many of their decisions made early in the season (e.g., crop acreage) remain fixed. However, farmers may respond to weather conditions as they unfold, possibly leading to changes in inputs within the season.

Our analysis focuses on two main farm income measures, namely gross and net income. Gross farm income captures all sources of farm income in a year. The weather effects on gross income thus reflects their influence on current sales, changes in inventories, as well as government payments and indemnities from crop insurance. On the other hand, our measure of net farm income reflects gross income net of all expenses. This means that weather effects on net income also reflect changes in farm costs, such as expenses made for inputs, irrigation, and farm operations.

One key focus of our study is sources of heterogeneity in how weather affects farm income. Improving understanding of this heterogeneity could help enhance adaptation as the climate changes. Weather shocks can be buffered through various channels, including farming practices or via government programs. For instance, farmers may smooth their income by increasing grain storage in years with a bumper crop, and draw down their inventory in years with a poor harvest. The location of the farm could also be critical, such as proximity to an aquifer which can allow irrigation and dampen the detrimental effect of drought and heat (Tack et al., 2017; Troy et al., 2015). In addition, several government programs are designed to support farm income when prices or yields declines. For instance, crop insurance is a well-known policy tool that protects U.S. crop farmers against weather risk (Diffenbaugh et al., 2021).

We also explore longer term phenomena. While weather shocks affect contemporaneous farm finances, it is still unclear whether recent climatic trends are being capitalized in farm assets, such as farmland values. To identify these long-term effects, we exploit spatial variation in county-level warming trends across the state to estimate their impact on the growth rate of farmland values. 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. These impacts would have been even greater without several risk management tools. We find that crop insurance payments and crop inventory sales mitigate nearly 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 suffer 37% (using KFMA data) and 55% (using High Plains Aquifer data) less net-income loss. We also find evidence that farms in the top 50th percentile of the land area distribution experience 13% lower net-income loss in response to extreme heat compared to farms in the bottom 50th percentile.

Finally, we find that temperature changes over recent decades are associated with slower growth in farm wealth. Over the 30 years period, real 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 increase in temperature over our study period. This translates to almost 9% and 5% reduction in the growth rate of farmland value and farm equity, respectively. This finding suggests that long-run impacts of a changing climate on US agriculture are emerging.

This paper makes key contributions to the literature. First, we provide a 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). Specifically, we extend previous work by examining climate adaptation in agriculture from a financial lens. Furthermore, by comparing gross and net income effects, we present implicit evidence regarding how extreme temperature can impact production costs within the season which may inform the estimation of the cost of adaptation to climate change (Sulser et al., 2021; McCarl, 2007; Parry, 2009).

The paper is structured as follows. We describe the data sources and the construction of key variables in section 2. In section 3 we discuss the empirical methodology and we report the results and robustness checks in section 4. We conclude in section 5.

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 rarely exist, and when they do, 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 provides financial analysis and accounting services for Kansas agricultural producers. This detailed data on farm production and finances is available to researchers through KFMA's affiliation and partnership with Kansas State University.

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 planted acreage. Their sample average are 111, 32, and 68 bushels/acre, 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

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

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 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,

[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.

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]

To examine heterogeneity based on farm size, we use the KFMA data to compute a binary measure indicating large farms. Median farm size in our sample is 1370 acres. We classify farms above 1370 acres as large farms and rest as small farms.

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
Farm Size					
Total Acres	72,322	0	34663	1786	1610
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 focus on the time frame of at least 30 years. We start by creating a sub-sample of KFMA

[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.

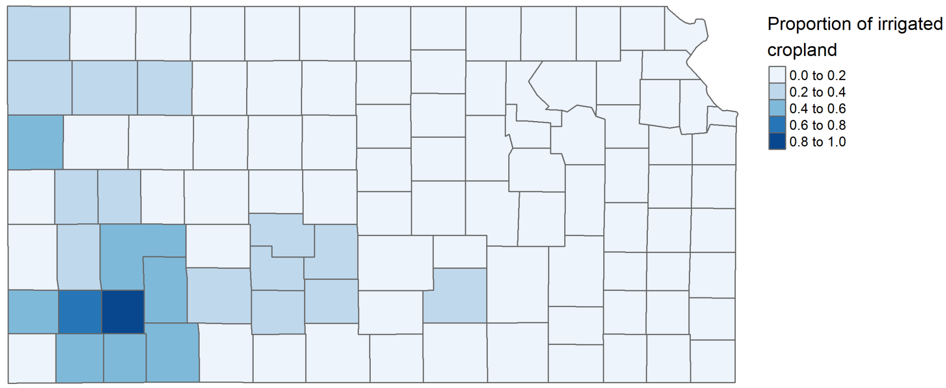


Figure 1: Irrigated Cropland

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]

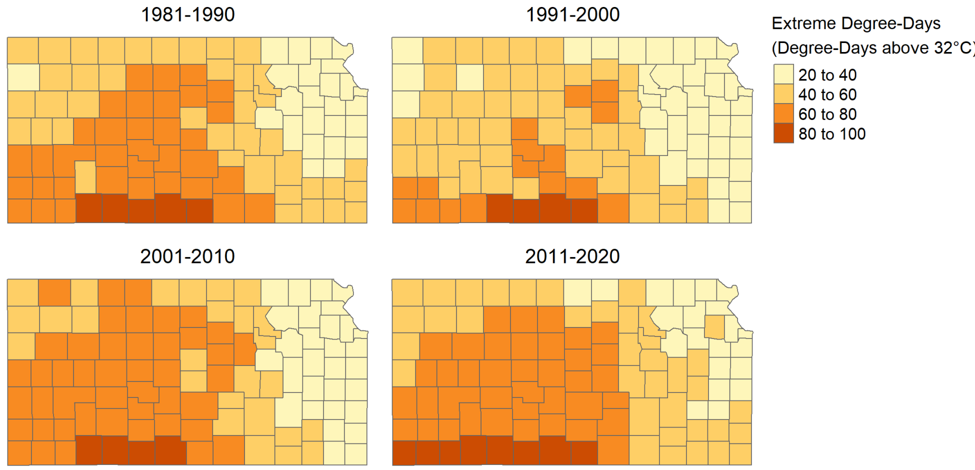
[5]We use National Land Cover Database (NLCD)'s 2016 gridded data to extract cropland pixels. We define cropland as any pixel identified as grassland, pasture, or cultivated crops.

[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

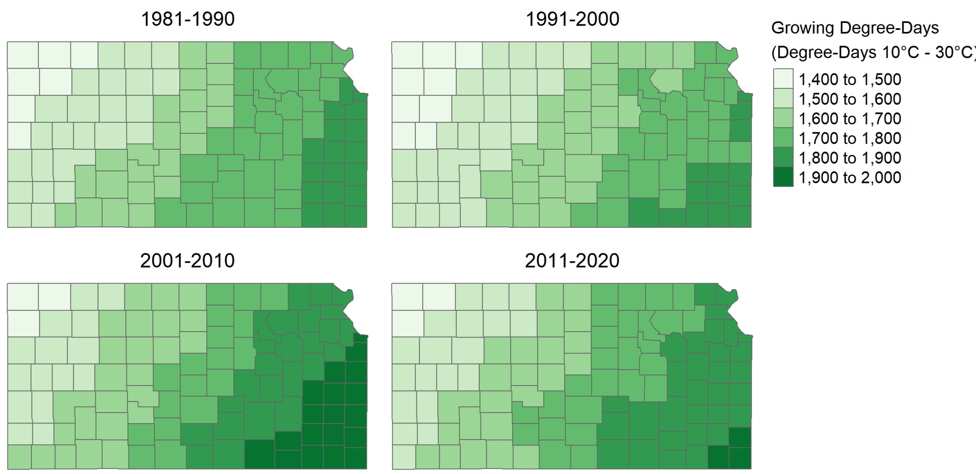
In a manner similar to EDD, we use monthly exposure bins from the crop growing season to compute a yearly measure of growing degree-days (GDD), defined as degree-days between 10°C and 30°C. An average farm in our sample experiences 50 EDD and 1730 GDD in the crop growing season of each year (Table 1). 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).

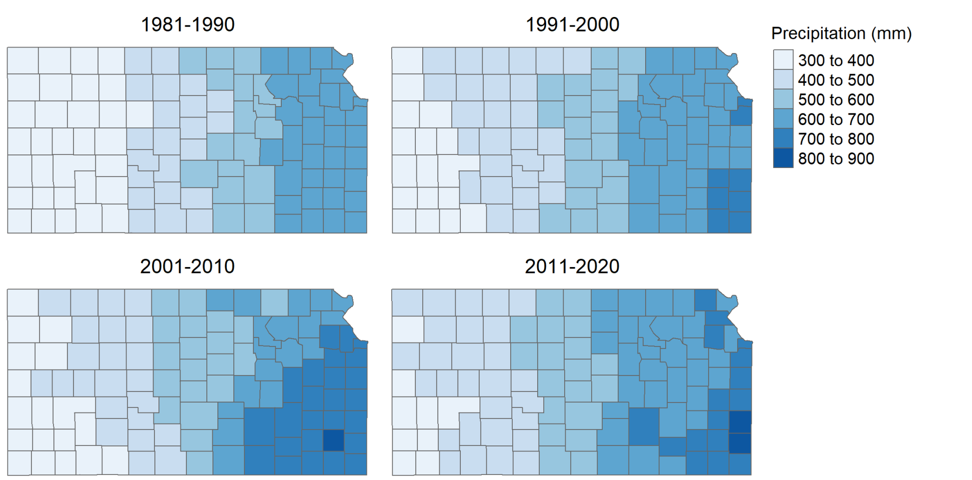
sharp decline in crop yields.



(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.

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

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 $Preip_{ct}^2$ 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 (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 ($EDD_{1^\circ C}$ and $GDD_{1^\circ C}$). The impact (in percentage) of 1°C uniform warming is: $(e^{\beta_{EDD}(EDD-EDD_{1^\circ C})+\beta_{GDD}(GDD-GDD_{1^\circ C})}-1)\times 100$ 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.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Last, we find that the impact of extreme temperature on income measures differs by farm size. Table 6 shows that farms in the top 50th percentile of the farmland area distribution experience 33% and 13% lower gross and net income effects compared to the rest of the farms, respectively.

Table 6: Heterogeneous Effect by Farm Size

	(1) Gross Farm Income	(2) Net Farm Income
EDD	-0.003***	-0.054***
	(0.001)	(0.012)
Large Farm	0.410***	0.441**
	(0.019)	(0.211)
EDD × Large Farm	0.001*	0.006*
	(0.000)	(0.003)
Num.Obs.	72,322	72,322
R^2 Adj.	0.704	0.275

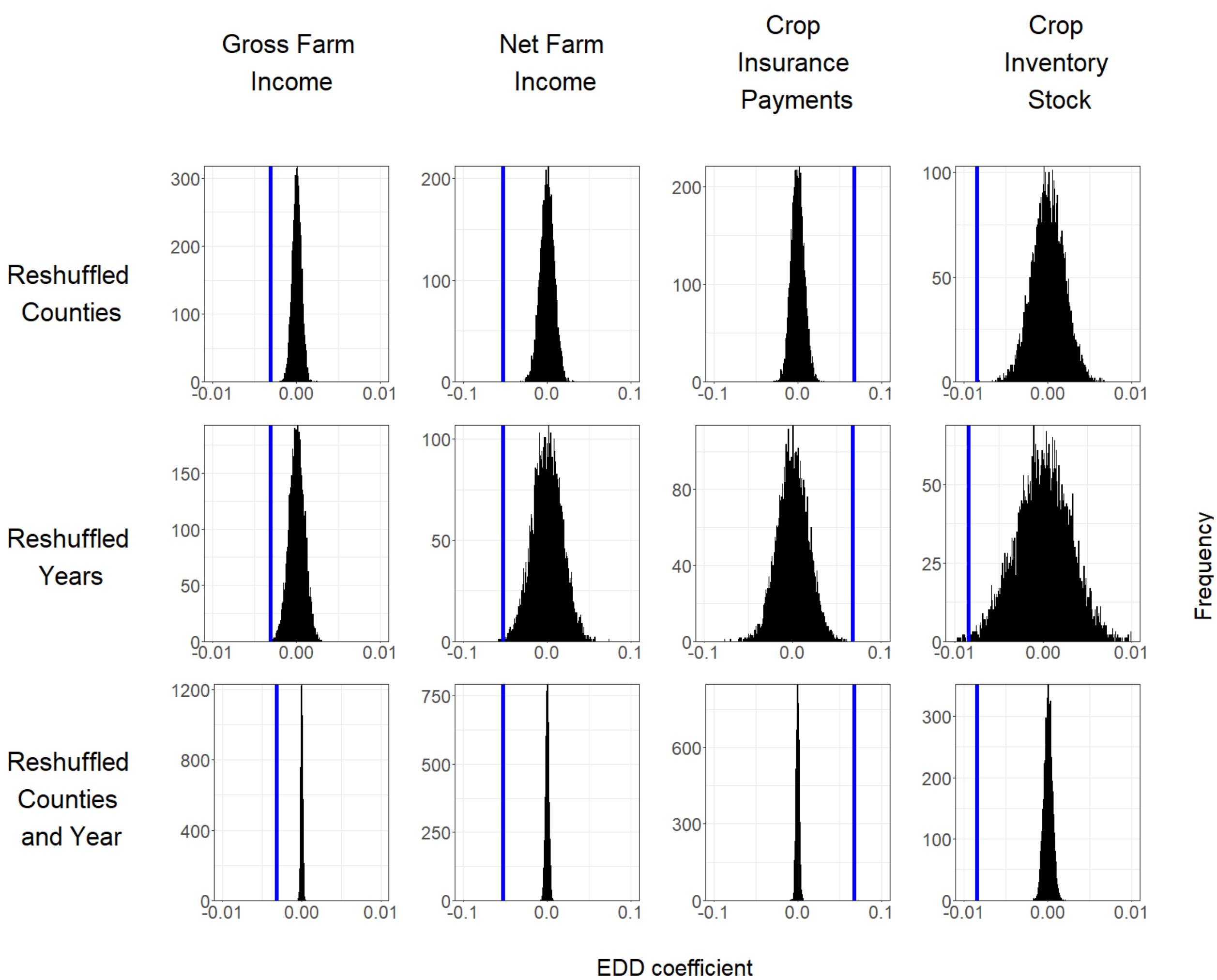
Dependent variables are inverse hyperbolic sine transformed. All columns control for growing degree-days, second order polynomial of precipitation, and farm and year fixed effects. Spatial HAC standard errors are reported in parentheses.
* p < 0.1, ** p < 0.05, *** p < 0.01

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 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

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

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 7. 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 7: Impact of EDD growth on Farmland Value growth and Farm Equity growth

	(1) Δ Land Value	(2) Δ Land Value	(3) Δ Equity	(4) 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.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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

[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%.

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 net income loss, respectively. Third, using two alternative measures of irrigation, we find that farms with above-average irrigation access experience at least 37% lower 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 financial well-being of Kansas farm operations is highly sensitive to weather shocks, both in the short and term run. Farm-level measures and government programs partially mitigate the impact of extreme weather. These practices and policies play an important role in smoothing farm income shocks, as intended. Their influence on facilitating climate adaptation is an important topic for future research and policy design. The financial impact of weather shocks on farm operations is transmitted to lenders, insurance companies, agribusiness, and rural communities.

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Appendix

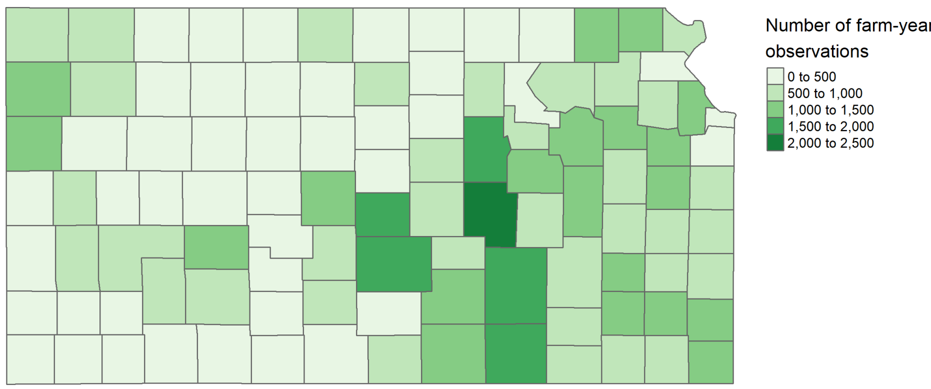
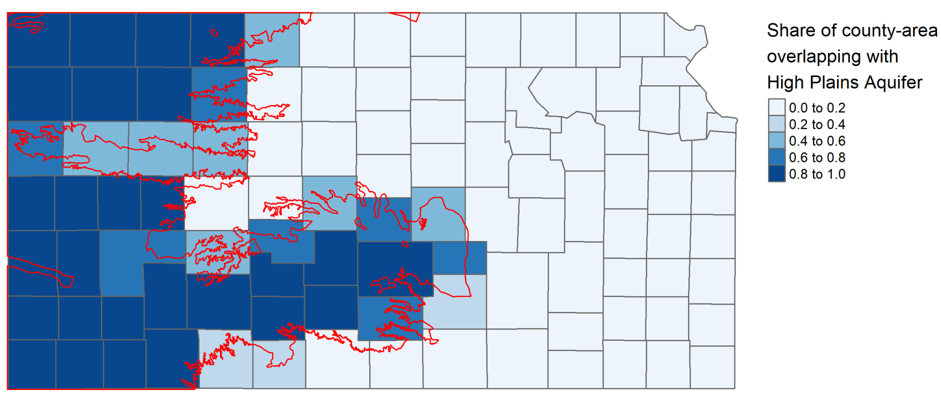
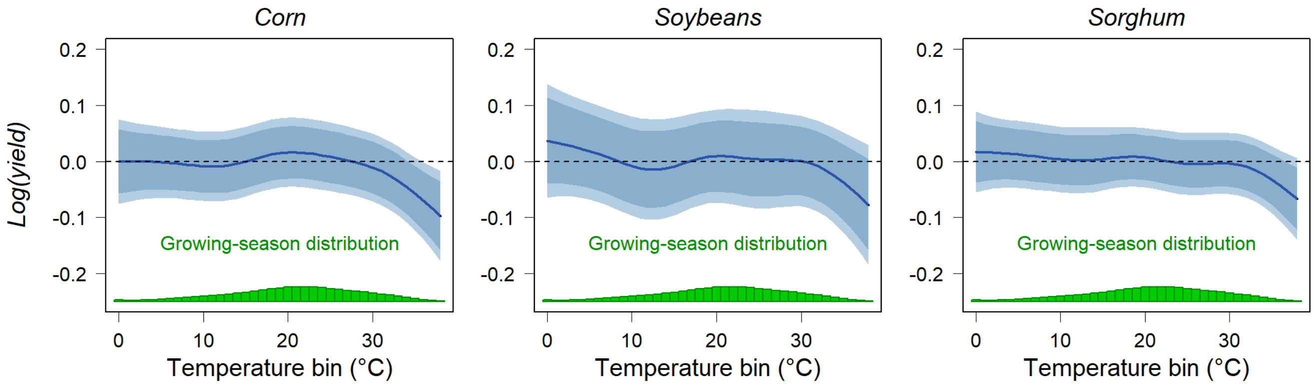


Figure A1: Spatial distribution of the KFMA dataset observations



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)

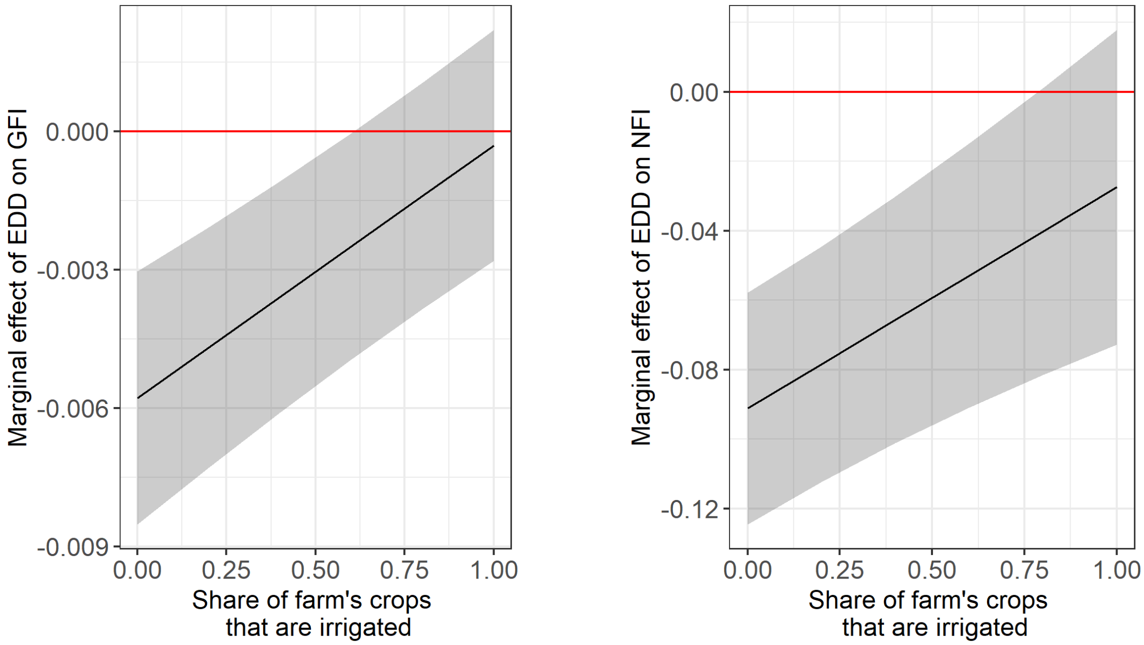
	(1) Gross Farm Income	(2) Net Farm Income
EDD	-0.003***	-0.053***
	(0.001)	(0.012)
Irrigated crops (share)	0.155***	-2.625***
	(0.054)	(0.887)
EDD × Irrigated crops (share)	0.004***	0.041***
	(0.001)	(0.012)
Num.Obs.	70,628	70,628
R^2 Adj.	0.702	0.274

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)

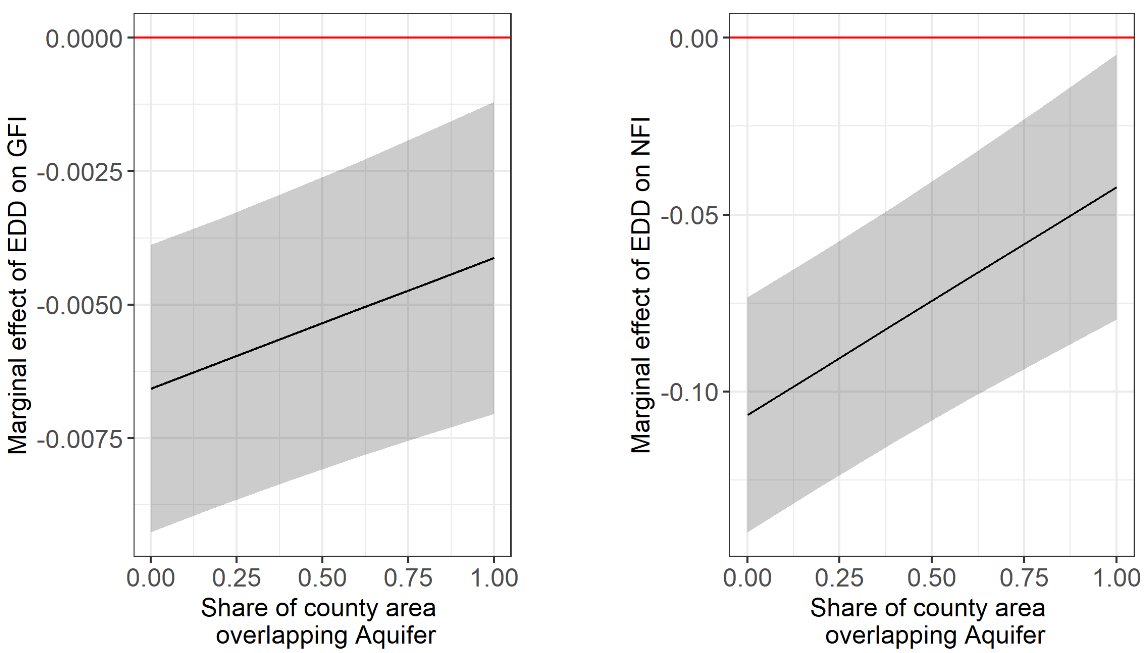
	(1) Gross Farm Income	(2) Net Farm Income
EDD	-0.004***	-0.065***
	(0.001)	(0.012)
EDD × Aquifer overlap (share)	0.002***	0.047***
	(0.000)	(0.008)
Num.Obs.	72,322	72,322
R^2 Adj.	0.691	0.276

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



(a) Gross Farm Income (b) Net Farm Income

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



(a) Gross Farm Income (b) Net Farm Income

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