Investigating the financial impact of extreme weather on Midwestern farmers

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Abstract : We examine the impact of weather on farm finances in the state of Kansas using using temperature data and a long farm-level panel dataset. Extreme temperature is found to reduce yields for major crops — an additional day above 32°C can cause up to 6 percent reduction in yields. We then found that weather-driven crop yield anomalies are contemporaneously associated with gross and net farm income, where 1 percent reduction in yield anomaly leads to a reduction (in the same year) of median gross and net farm income by 0.3 and 1.1 percent respectively. Last, we found that long-run changes (over at least 20 year period) in crop yields are positively related with long-run changes in real land values. Overall, our results suggest that weather impact crop yields which in turn impact both short-run measures of farm finances as well as long-run farm wealth.

1 Introduction

The agriculture sector is on the front lines of climate change. Crop and livestock production depends on access to healthy soil, adequate water supplies and predictable weather conditions, all of which are more difficult to access and manage as the climate changes. Farmers already experience higher temperatures, increasingly variable rainfall and more frequent droughts, and floods that threaten crop and livestock production. For instance, Ortiz-Bobea et al. (2021) finds that anthropogenic climate change has already slowed down global agricultural productivity growth. And in the US, Ortiz-Bobea et al. (2018) find that agriculture is growing increasingly sensitive to higher temperatures.

Although relationship between extreme weather and crop yields is well established, there is limited understanding about how weather directly affects farmers' financial well-being. This study aims to fill this gap by estimating the impact of weather on farm finances. The focus on financial health is key because it is a more proximate measure of farmers' welfare than crop yields. Furthermore, understanding farm's financial vulnerability to weather shocks can improve the functioning of farm credit markets. Without such insights, it is difficult for agricultural lenders to properly assess changing weather-related risks arising from climate change and their role in supporting the transition to more resilient farming practices and systems.

Literature on the impact of climate change on farm finances has primarily focused on farm profits, but the findings of such studies are subject to considerable debate due to differences in model specification and the ability to account for adaptation (Deschênes and Greenstone, 2007; Fisher et al., 2012; Deschênes and Greenstone, 2012). One recent study which has looked at a larger variety of farm financial variables is Bergman et al. (2020) - they find that during the financial crisis of 1980s, weather-driven cash flow shocks had a significant impact on land prices, loan delinquencies and bank failure rates. Climate change has also been identified as a key driver of increases in crop insurance payments in US - Diffenbaugh et al. (2021) finds that climate accounts for 20% of the total insurance payments to farmers from 1991 to 2017.

We use a panel dataset of farms enrolled in the Kansas Farm Management Association (KFMA) program. Our data spans years from 1973 till 2020, with farms varying in their panel length. It provides information on a range of farm aspects ranging from detailed production variables to financial ratios.

We start the analysis by confirming weather-yield relationship and find that exposure to temperature above 32°C results in sharp decline in yield across multiple crop types. We then move on to estimate the contemporaneous association between weather-driven crop yields and farm financial well-being. We find that a positive crop yield anomaly increases gross and net farm income. As expected, we also find that government payments and crop insurance go up when yields are lower. Last, we examine the relationship between long-run changes in (climate-driven) crop yields and land prices. Land prices are a slow moving indicator of long-run changes in land productivity and thus of long-term farmers' well-being. We find that crop yields and land values are closely related over long-run.

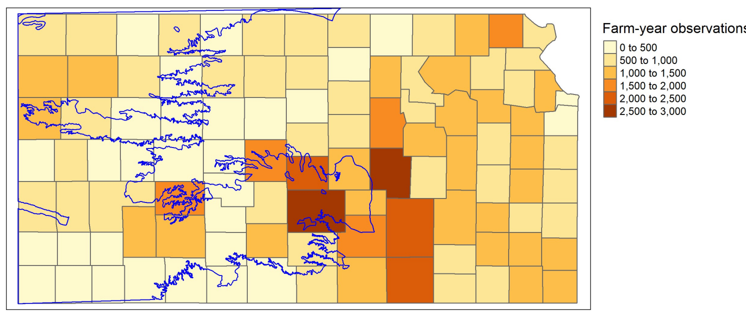
This study is one of the very few studies linking weather to farm financial performance and the first one to use farm-level data to establish that relationship. Farm-level data allows us to use a much larger number of observations, and will allow us in future analysis to uncover heterogeneities which won't be possible with county level data.

We provide a description of the data and key variables in Section 2. Empirical methodology is laid out in Section 3 while Section 4 reports the results. Section 5 concludes our paper.

2 Data description

2.1 Farm Data

We use a long-term farm-level panel dataset developed by the Kansas Farm Management Association (KFMA). The dataset has detailed production and financial information for farmers across Kansas, providing a unique view of crop yields and farm finances from 1973 to 2020 across a large number of farms in a state with very contrasting agricultural systems (including irrigated and dryland agriculture with dwindling groundwater resources). Fig 1 shows a snapshot of the distribution of the KFMA sample across counties in Kansas. We also utilize data on the physical extent of the High Plains Aquifer which will be used in future to test for heterogeneity in the impact of extreme temperatures with respect to access to irrigated water (see blue line in Fig 1).



Note : Map shows the number of farm-year observations for each Kansas county. Blue line represents the boundary of High Plains Aquifer.

Figure 1: Spatial distribution of KFMA farms

2.1.1 Short-run metrics

To study the contemporaneous effect of weather-driven yield anomalies on farm financial performance, we compute an aggregate measure of short-run yield anomaly encompassing all crop types [1]. To create this measure, we compute the weighted average of detrended crop yields. Crop-specific yield Y_{ft} (in log) for corn, soybeans, wheat, sorghum, sugarbeats, alfalahay, and silage grown on farm f in year t is regressed on year trend variable t (Equation 1)[2]. Short-run yield anomaly $YieldAnomaly_{ft}$ is computed by taking the weighted average of the residual ε_{ft} from Equation 1, where weights w_{ft} are the proportion of land area dedicated to each crop type c in farm f and year t (Equation 2).

$$Y_{ft} = \beta_o + \beta_1 t + \mu_f + \varepsilon_{ft} \tag{1}$$

[1] We use yield *anomalies* (deviations from the average log farm yield) rather than yield *levels* (bushels per acre) because the latter are not comparable across crop types.

[2] We estimate this equation separately for each crop type.

$$YieldAnomaly_{ft} = \sum_{c \in f} (\varepsilon_{ft} \times w_{ft}) \tag{2}$$

We use three key metrics as measures of short-term financial performance namely gross farm income, net farm income, and current ratio. Gross farm income equals value of farm production plus accrual feed purchased. Net farm income equals value of farm production minus cash operating expenses minus depreciation minus an accrued income-expense. Current ratio (available only for post 2002 period) is a ratio of current assets to current liabilities - it is used to measure the ability of a farm to pay off its short-term debt. We also use two measures indicating financial support offered to farms in times of distress - government payments and crop insurance (latter only available for post 1993 period). We convert all these financial metrics (except current ratio) to real terms (expressed in year 2000 USD).

Table 1 shows the summary statistics of short-run measures. Average value of yield anomaly is 0 by construction. Median farm in our sample earns gross farm income of $ 213,000 and net farm income of $ 33,000. Government payments and crop insurance are $ 13,000 and $700 respectively for a median farm while current ratio is 1.73. There is huge difference between mean and median values of crop insurance and current ratio, indicating presence of considerable outliers.

Table 1: Summary statistics of short-run variables at farm-year level

	N	Mean	Median	SD
Yield anomaly (log)	80284	0.00	0.02	0.24
Gross Farm Income ($)	80284	299 403.25	213 384.82	316 428.73
Net Farm Income ($)	80284	52 891.22	33 479.99	109 887.98
Current Ratio	24229	5037.89	1.73	605 005.75
Government Payments ($)	80284	22 374.27	13 121.05	30 591.19
Crop Insurance ($)	41515	12 563.89	737.77	40 416.27

2.1.2 Long-run metrics

We construct long-run measures of growth in crop yield in order to estimate their association with agricultural land values (a long-run measure of farm wealth). As no fixed definition of *long-run* exists, we use 3 different time spans to reflect that in our analysis, namely 20, 30, and 40 years. We start by creating 3 sub-samples of our data, limiting the sample to farms which have panel length of atleast 20, 30, and 40 years respectively. For each farm in these 3 sub-samples, we compute an average annual yield growth rate, $CropSpecificYieldGrowth_f$, of each crop (corn, soybeans, wheat, sorghum, sugarbeats, alfalahay, and silage) over the whole time period during which the farm is observed. We then compute an aggregate measure of long-run crop-yield growth rate, $YieldGrowth_f$, by calculating the weighted average of all the crop specific growth rates, weighting them by the proportion of land area dedicated to each type of crop c in farm f (Equation 3). In a similar manner, we construct a measure of average annual long-run growth in land values (in real prices - using 2000 as the base year) for all the farms in the 3 sub-samples.

$$YieldGrowth_f = \sum_{c \in f}(CropSpecificYieldGrowth_f \times w_f) \tag{3}$$

Table 2 shows the summary statistics of the two long-run growth variables in each of the three sub-samples. Yearly average growth in crop yield is between 0.6 to 0.8 percent while the growth in real land values is around 3 percent.

Table 2: Summary statistics of long-run variables at farm level

	$\geq 20 years$			$\geq 30 years$			$\geq 40 years$		
	N	Mean	SD	N	Mean	SD	N	Mean	SD
Yearly growth in crop yield (%)	1554	0.62	2.36	700	0.64	1.56	193	0.81	0.71
Yearly growth in land values (%)	1554	3.52	5.11	700	3.06	3.48	193	3.29	3.19

2.2 Weather Data

We construct county-level variables from the PRISM data at Oregon State University. This database provides daily observations since 1981 at a 4-km resolution across the lower 48 states. We aggregate the gridded PRISM data to compute the total number of days spent under each temperature bin (from -10°C to +50°C in 1°C increments) during crop-growing season (Apr. to Sept.) for each year. We also compute total precipitation during the same season. County-year weather variables are then merged with KFMA panel data.

3 Empirical Methodology

As any impact of climate on farm financial health is likely to be driven by its impact on crop production, we start our analysis by examining the impact of temperature on crop yields. We model crop yield as a function of exposure to multiple temperature bins, following the natural cubic spline specification of Ortiz-Bobea (2021). Temperature exposure is divided into 39 bins where the first bin is the cumulative exposure from -10°C to 0°C, the last bin is the cumulative exposure from 38°C to 50°C, and the middle 37 bins each define exposure ranging from 1°C to 37°C. We use a basis matrix to project 39 bins into a smaller space of 7 bins, thus reducing the number of regressors defining temperature exposure to 7.

$$LogYield_{fct} = \beta_o + \sum_{n=1}^{7} \beta_n z_{ct}^k + \beta_8 p_{ct} + \psi(t) + \mu_f + \varepsilon_{fct} \tag{4}$$

Equation 4 illustrates the regression equation. $LogYield_{fct}$ is the crop yield (in log) for farm f located in county c in year t. z_{ct}^k represents the 7 temperature bins, each representing the exposure (in days) during growing season (Apr. to Sept.) in county c in year t. These 7 regressors are derived after reducing the dimensionality of 39 bins using basis matrix. p_{ct} is a matrix representing linear and quadratic variables for precipitation (in mm/day). $\psi(t)$ is a matrix of linear and quadratic year time trend. μ_f represents farm fixed effect to control for any time invariant farm-level characteristics which correlate both with crop yield and weather. Standard errors are clustered at year level. We estimate this equation separately for three main crops - corn, soybeans, and sorghum. As a last step, we recover marginal effects evaluated at each of the 39 temperature bins by premultiplying the vector containing the 7 estimated coefficients by the basis matrix. The main reason for using the cubic spline approach is to allow the marginal effects to vary smoothly across neighboring bins rather than assuming that neighboring marginal effects are uncorrelated.

After establishing a strong link between temperature and crop yields (see Results section), we then move on to estimate the relationship between crop yields, farm finances, and agricultural land values. In this analysis, we use crop yields as a proxy of weather. Equation 5 tests the association between contemporaneous crop yield anomalies and short-run metrics of farm finances.

$$FarmFinance_{ft} = \beta_o + \beta_1 YieldAnomaly_{ft} + \beta_2 t + \mu_f + \lambda_t + \varepsilon_{ft} \tag{5}$$

$FarmFinance_{ft}$ include short-run financial metrics - gross farm income, net farm income, current ratio, government payments, and crop insurance for farm f in year t. $YieldAnomaly_{ft}$ is the average of current and last year's crop-weighted yield anomaly (in log). We control for farm fixed effect (μ_f) to purge any influence of time invariant farm characteristics affecting both the yield and farm finances. t and λ_t are linear time trend and year fixed effect respectively. We cluster standard errors at year and association level[3].

Last, we estimate the association between long-run changes in weather driven yields and long-run changes in land values through a cross-sectional regression represented by Equation 6.

$$LandValue_f = \beta_o + \beta_1 YieldGrowth_f + \varepsilon_f \tag{6}$$

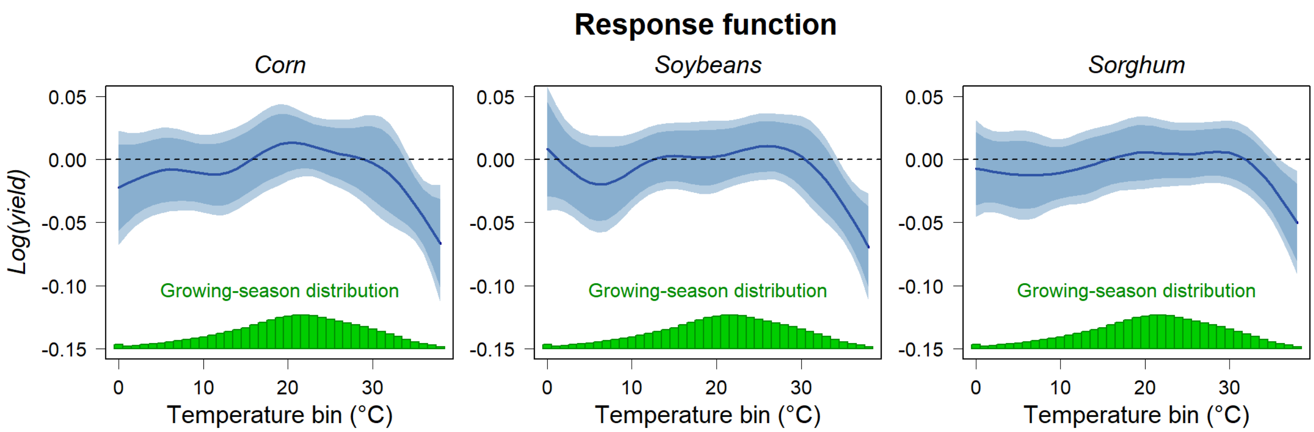
$LandValue_f$ and $YieldLongRun_f$ are the average yearly growth rate of real land price

[3]There are 6 associations within the state of Kansas according to KFMA administrative framework.

and crop yield for farm f over the 20, 30, and 40 year period.

4 Results

Fig 2 shows the yield response function to temperature change for three major crops — corn, soybeans, and sorghum. Temperatures above 32°C lead to a sharp and statistically significant decline in crop yields. One additional day above 32 °C can cause up to 6 percent decline in yields. These preliminary results are in line with the existing literature on climate change impacts, giving us confidence to carry out analysis on farm finances.



Note : The data covers farm-level crop yields from 1981 to 2020. We control for farm fixed effects, precipitation, and year time trend. Standard errors clustered at year level. Bands show 95% and 99% confidence intervals. Growing-season goes from Apr. to Sept. each year. Sample size is 34996, 42596, and 44050 farms for corn, soybeans, and sorghum respectively.

Figure 2: Effects of temperature on crop yields

Table 3 shows the result of Equation 5. All financial metrics are strongly related with contemporaneous crop yield anomaly - a reduction in yield anomaly leads to a reduction in financial performance. 1 percent reduction in current (and last) year's crop yield anomaly is associated with $614 and $366 reduction in gross farm income and net farm income respectively. These estimates translate to a loss of 0.3 percent and 1.1 percent of the median gross farm income and net farm income in our sample. Coefficients on cash support variables show the expected negative sign where 1 percent reduction in yield anomaly is associated with $30 and $322 increase in government payments and crop insurance respectively. Although our results show a positive relationship between yield and current ratio, the coefficient is statistically insignificant.

Table 3: Contemporaneous association between yield anomaly and financial metrics

	GFI	NFI	CR	GP	CI
Yield anomaly (log)	61 395.540***	36 565.084***	8833.250	−3089.652+	−32 233.581**
	(5648.806)	(4993.415)	(11 518.613)	(1243.959)	(5715.485)
Num.Obs.	80 284	80 284	24 229	80 284	41 515
R2	0.821	0.459	0.064	0.637	0.401
R2 Adj.	0.804	0.406	−0.067	0.601	0.338
R2 Within	0.145	0.120	0.001	0.302	0.178

GFI = Gross Farm Income, NFI = Net Farm Income, CR = Current Ratio, GP = Government Payments, CI = Crop Insurance. All dependant variables are in dollar terms except current ratio.
Independent variable is the average of current and last years yield anomaly (in log).
We control for Farm FE, Year FE, and yearly time trend.
Std. errors clustered at year and association level.
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4 shows the result of Equation 6, where each column shows the regression coefficient associated with different time spans over which the long-run growth rates are calculated. We see a stronger relationship between growth rates of crop yield and land price when time span is longer. 1 percentage point increase in the yearly average growth rate of crop yields over 40 years (or more) is associated with 0.7 percentage point increase in yearly average growth rate of real land values. This association is reduced to 0.2 and 0.1 percentage points when the minimum threshold of time span is reduced to 30 and 20 years respectively.

Table 4: Association between long-run growth of yields and farm land prices

	Growth in land value	Growth in land value	Growth in land value
Growth in yield (%)	0.098+	0.179*	0.712*
	(0.055)	(0.084)	(0.319)
Num.Obs.	1554	700	193
Time span (years)	≥ 20	≥ 30	≥ 40
R2	0.002	0.006	0.025
R2 Adj.	0.001	0.005	0.020

This table shows the result of farm-level cross-sectional regression of long-run growth in land value on long-run growth in yields, under varying long-run time spans.
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5 Conclusion

This paper attempts to study the impact of weather on farm financial performance by using a farm-level panel dataset for Kansas spanning almost 5 decades. We document three findings in this paper. First, we estimate the causal relationship between crop yield and temperature at farm level, finding that temperature extremes are determinetal to yields. In particular, our results suggest that one additional day above 32°C causes a reduction of approximately 5 percent in yield for corn, soybeans, and sorghum. We then estimate the association between weather-driven crop yield anomalies (deviation in yield from the average) and short-run measures of farm finances. A reduction in yield anomaly leads to a decline in gross and net farm income and a rise in government payments and crop insurance. Last, we find that long-run growth in crop yields in associated with long-run growth in real land prices. These findings confirm that weather impacts crop yields which in turn impact both short-run as well as long-run measures of farm finances and farm wealth.

In future, we aim to analyze the relationship between financial performance and weather fluctuations over different economic conditions and policy regimes; as well as considering the impact of multiple versus single weather shocks and whether the relationship between climate and financial performance has evolved over time. For example, financial performance may be more sensitive to climate during economic downturns

(Bergman et al., 2020). Furthermore, the role of aquifers in buffering the impact of extreme weather will be examined, as they not only provide a stable source of water for irrigation but also help maintain soil moisture and enable vegetation to maintain higher evaporation during periods of high temperature (Mu et al., 2021).

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