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Irrigation and Historical Reductions in the Interannual Variability of Midwestern Maize Yield

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E-mail: phuybers@fas.harvard.edu**Keywords:** irrigation, maize, yield**Abstract**

Model-based studies indicate that climate change will increase agricultural yield variability, with major implications for price volatility and food security. We examine the historical variability of US Midwestern maize yields and find that the sign and magnitude of the variability trend depend on the metric used for measurement. Using a detrended coefficient of variation (CV'), we observe a decline in variability over 1950–2009 in Nebraska, with consistent results over 1970–2009 in counties across Nebraska, Kansas, and Colorado. Using detailed annual yield and irrigation data, we fit a fixed-effects model and find that irrigation is the primary driver of the historical decline in county-level CV'. Findings are consistent when controlling for variability in growing and killing degree days, mean precipitation, and the variability of precipitation, as well as when allowing for nonlinearities. We also find that increases in irrigation are associated with reduced variability in rainfed yields within the same county, suggesting that irrigated fields also confer benefits to rainfed fields. Our results underscore the importance of irrigation for stabilizing agricultural productivity, but also highlight that yield volatility would increase if irrigation is reduced, for example, because of depletion of aquifers.

1 Introduction

Much of the literature on the impact of climate change on agriculture focuses on potential declines in mean yields on account of rising surface temperatures [1, 2]. There is also concern regarding the degree to which climate change will make crop yields more variable [3, 4, 5]. A recent study projected a 7–19% increase in the variance of log yields per degree Celsius of warming for major grains across the globe [6]. Increased variability increases the odds of simultaneous global production shocks due to the global dominance of a small number of maize exporters [4]. In addition to consequences for global trade, yield variability has major implications for smallholder farmers that may be disconnected from global markets [7].

One mechanism through which climate change is expected to increase yield variability is exposure to higher temperatures. Warming that makes hot conditions more frequent implies greater yield variability [4] on account of a nonlinear response to temperature whereby yields decrease rapidly in hotter conditions [8]. Increased yield volatility has also been found to accrue from higher vapor pressure deficits driving greater covariance between high temperatures and low soil moisture [6]. Consistent with these mechanisms, model-based studies project rising future variability: the coefficient of variation of US maize yield has been projected to increase by 47% by 2030–2050 relative to a 1980–2000 baseline [9], and the interannual variance of summer crop yields has been projected to rise globally due to changes in temperature and water supply [6].

Another important consideration is how modification in farming practices can stabilize yields. Whereas warming is expected to lead to greater yield variability, increases in irrigation have been shown to stabilize interannual crop yields [10, 11, 12, 13]. Irrigation is often considered to be protective against high temperatures, as indicated by lower yield sensitivities to high temperatures [10]. An alternative hypothesis is that high temperatures are a proxy for moisture stress and that irrigation directly alleviates water limitations [14]. In either case, increased irrigation is expected to result in decreased yield volatility.

Whether warming, tighter covariance between temperature and soil moisture, and changes in irrigation and other practices have raised or lowered yield variability is not obvious a priori, so the historical record is worth establishing. Reported trends disagree in sign, and the disagreement follows from the choice of metric and from the region examined. Expressing yield anomalies as percent departures from a five-year running mean, variability fell significantly on 19–33% of global harvested area over 1981–2010 and rose on 9–22%, with the area of decrease two to three times the area of increase for maize and soybean and the two comparable for wheat [3]. The standard deviation of percent deviations from trend yield likewise fell for world and regional corn, rice, soybean, and wheat between 1981–2001 and 2002–2022 [15]. Measured in yield units, the picture shifts. Over 2000–2019 the standard deviation of spline-detrended anomalies rose on 20% of global harvested area and fell on 16%, yet the coefficient of variation rose on only 58% of the area where the standard deviation rose, which Iizumi and colleagues attribute to rising average yields [16]. Regional results diverge from the global ones. For US maize, variability relative to trend yield rose in lower-production counties of the Southeast, Texas, and South Dakota between 1980 and 2010 while falling across the Corn Belt and Nebraska [17].

Prior work names irrigation as a likely cause of falling variability without testing it directly. Iizumi and Ramankutty identify the expansion of irrigated area as a well-known reason for decreased regional yield variability but state that no global historical dataset allows them to evaluate crop-specific technological trends [3]. A later global analysis includes irrigation intensity among its predictors of yield anomaly and ranks it among the less influential variables, which the authors partly attribute to irrigation equipment not guaranteeing water during drought [16]. USDA records resolve irrigated fraction annually for 72 Nebraska counties over six decades, and for 108 counties across Nebraska, Kansas, and Colorado from 1970, giving the within-county variation needed to test the relationship between irrigation and yield variability. Our objective is to determine the role of irrigation in reducing the interannual variability of Midwestern maize yield. We hypothesize that historical increases in irrigated fraction account for the majority of the decline in variability, and we test this with a two-way fixed-effects panel regression that controls for temperature and precipitation variability. Because the inferred trend depends on how variability is measured, we define our variability metric in the methods before turning to the regression.

2 Data and Methods

2.1 Data

We use county-level maize yield data from the USDA’s National Agricultural Statistics Service (NASS). NASS reports yield in bushels per acre and harvested area in acres, separately for irrigated and non-irrigated production within each county. These designations are survey-based and indicate whether a field is equipped for irrigation. They do not indicate whether irrigation water was applied in a given year. We refer to non-irrigated yields as *rained*. We compute the fraction of harvest that is irrigated as irrigated harvested acres divided by total harvested acres, and this fraction is our main explanatory variable.

Daily temperature and precipitation are from NCEI’s nClimGrid-Daily; these begin in 1951, so the decadal average for the 1950s misses one year. We summarize temperature through growing degree days (GDD) and killing degree days (KDD), computed over the April–October growing season for maize in the Midwest and measured in degree-days. GDD is the sum over the growing season of the amount by which daily average temperature exceeds 10°C, counting temperatures above 30°C as 30°C; KDD is the sum of the amount by which daily average temperature exceeds 30°C. The regression uses the decadal standard deviations of GDD and KDD, σ_{GDD} and σ_{KDD} , together with the decadal mean and decadal standard deviation of precipitation, μ_{precip} and σ_{precip} . Precipitation is measured as the sum of daily average precipitation over the growing season in mm. GDD and KDD are positively and moderately correlated (0.68), and the correlation between their standard deviations, which are the quantities that enter the regression, is weaker but still positive (0.32).

The use of GDD and KDD as indicators of temperature’s effect on yields has been well-documented in prior work. Schlenker and Roberts [8] show that the yield–temperature relationship is well represented by a piecewise-linear form that rises to a threshold and then declines sharply, which is what cumulative growing and killing degree days encode. Butler and Huybers [18] use the same two indices to show that the sensitivity of US maize to extreme heat varies by region and growth phase. More recent work suggests that killing degree days proxy in part for soil-moisture limitation [14, 19], although this remains an open question.

Separate irrigated and non-irrigated records are sparse before 1950 and are unevenly available across counties and years. We include a county in a given decade when it has at least seven years of

both irrigated and non-irrigated yield in that decade, which is enough to fit a decadal trend and estimate variability. Applying this rule from 1950 gives 72 counties, all in Nebraska, with mostly continuous records through 2009. Requiring only records from 1970 onward gives a broader network of 108 counties across Nebraska, Kansas, and Colorado, where we still observe a statistically significant effect of irrigation on CV' , with a similar magnitude. Changing the threshold of available years from seven years to six or eight also does not substantially change the magnitude or statistical significance of the regression coefficients (supplementary tables S1-S4). For the comparison of variability metrics in the following section, we also use total-yield records for these 72 counties back to 1920.

2.2 Measuring interannual yield variability

The inferred trend depends on how variability is measured (Figure 1). We consider three preprocessings (raw, detrended, and log yields) and two metrics (the standard deviation and the CV). For maize in Custer County, the standard deviation of raw yields rises at 0.77 bushels/acre per decade and that of detrended yields at 0.41 bushels/acre per decade. The standard deviation of log yields instead falls at -0.05 per decade because log yields track fractional variation — their standard deviation approaches the CV when variability is small. The CV declines under all three preprocessings, at -0.043 , -0.038 , and -0.025 per decade. Averaged over the 72 counties the same split holds: the standard deviation rises for raw and detrended yields, at 1.4 and 1.2 bushels/acre per decade, and falls for log yields at -0.09 log(bushels/acre) per decade, while the CV declines in every case, at -0.061 , -0.054 , and -0.040 for raw, detrended, and log yields per decade.

We compute the coefficient of variation, CV, as the standard deviation of yield over an 11-year rolling window divided by the mean over the same window (Figure 1g). Because we are interested in interannual variability, we take one more step and work with the coefficient of variation of detrended yields, abbreviated CV' (Figure 1h). We fit a quadratic to each running 11-year interval, subtract it to obtain residual yields, and compute CV' as the standard deviation of the residuals divided by the fitted value at the middle year, to which the CV' is assigned.

We use CV' for two reasons. Mean yield has risen substantially over the period, so the standard deviation rises with it and conflates the level of yield with its variability; dividing by the mean removes that dependence and makes counties with different yields more comparable. It also separates irrigation's effect on yield variability from its effect on mean yield, the distinction we need to attribute the historical decline. How CV' compares with other metrics is taken up in the Discussion.

2.3 Estimating the role of irrigation

To estimate the effect of irrigation on yield variability, we use a two-way fixed-effects panel regression on the 72 Nebraska counties described above. For the panel we detrend yields with a quadratic fit in non-overlapping 10-year blocks and compute one CV' per county-decade, so that the observations are independent. Each county contributes one observation per decade, giving $N = 432$ county-decade observations between 1950 and 2009. We fit the fraction of irrigated harvest with linear, quadratic, and cubic terms and add controls for temperature and precipitation variability, as well as mean precipitation. The cubic term does not dramatically improve goodness-of-fit beyond the quadratic, and we do not report terms above cubic order.

In its most complete form, the two-way fixed effects model is specified as,

$$CV'_{it} = \beta_1 I_{it} + \beta_2 I_{it}^2 + \beta_3 I_{it}^3 + \beta_4 \sigma_{GDD,it} + \beta_5 \sigma_{KDD,it} + \beta_6 \sigma_{prcp,it} + \beta_7 \mu_{prcp,it} + \beta_8 I \times \sigma_{prcp,it} + \beta_9 I \times \sigma_{KDD,it} + \alpha_i + \gamma_t + \varepsilon_{it}. \quad (1)$$

Here CV'_{it} is the detrended coefficient of variation for county i and decade t , and I is the fraction of harvested area that is irrigated, entered with a linear term and, in some versions, quadratic and cubic terms. The α_i and γ_t terms are county and decade fixed effects. We cluster standard errors at the county level.

County fixed effects absorb time-invariant differences between counties that influence both irrigated fraction and CV' , such as soil characteristics or long-standing agricultural practices. Decade fixed effects absorb changes common to all counties within a decade, such as climate and technology trends specific to that decade. Together they let us isolate the association between irrigation and yield variability.

Some specifications add interaction terms between the fraction irrigated and the climate-variability controls, $I \times \sigma_{prcp}$ and $I \times \sigma_{KDD}$, which test whether the effect of climate variability on yield variability depends on the level of irrigation. σ_{KDD} and σ_{prcp} are positively and

moderately correlated (0.52); however, in addition to specifications with both interaction terms, specifications that include only one of the two interaction terms also are statistically significant for total yield, motivating the inclusion of both terms. Results from these additional specifications are shown in Tables S5 and S6. We center the interacted standard deviations at their sample means, so that the coefficient on the fraction irrigated, β_1 , is interpretable at average climate conditions.

3 Results

3.1 Irrigation drives the decline in yield variability

We first show that irrigated and rainfed yields have different and roughly stable CV', so that the decline in total CV' primarily reflects a shift in composition towards irrigated harvest. Figure 2 plots CV' for irrigated, rainfed, and total yields across the 72 counties from 1950 to 2009 and demonstrates that the overall decline in CV' tracks the growth in irrigated fraction. Irrigated area rose from 15% of harvest in the 1950s to 63% in the 2000s, moving total CV' from near the rainfed curve toward the irrigated one. By the 2000s, most Nebraskan farmland becomes irrigated except for a strip in the easternmost portion of the state (Figure 4).

We quantify the effects of irrigation using eight different specifications of a two-way fixed-effects regression of CV' on the fraction of irrigated harvest (Table 1). The effect of fraction irrigated on CV' is negative and significant in every specification. In Model 1, with county fixed effects only, $\beta_1 = -0.306$ [−0.339 to −0.273, 95% c.i.], implying that moving from fully rainfed to fully irrigated lowers CV' by 0.306 units. Adding decade fixed effects in Model 2 raises adjusted R^2 to 0.72 and reduces β_1 to −0.160 [−0.211 to −0.109, 95% c.i.], indicating that some of the decline is common to all counties within a decade and could be related to other factors such as fertilizer, pesticide, or management trends.

Model 3 adds the climate controls, σ_{GDD} , σ_{KDD} , μ_{prcp} , and σ_{prcp} . They raise adjusted R^2 without substantially changing the irrigation coefficient. Killing-degree-day variability enters positive and significant, so greater variability in damaging heat raises yield variability, consistent with the documented sensitivity of maize to GDDs and KDDs [20]. The effect of precipitation variability is positive and significant, and mean precipitation negative, so more variable water supply raises CV' while wetter counties have lower CV'. The fraction-irrigated coefficient stays negative and significant throughout.

Models 4 and 5 add a quadratic term and Models 6 and 7 a cubic term. The linear coefficient is negative and the quadratic positive, so the marginal reduction in CV' diminishes at higher irrigation fractions (Figure 3). Model 7 implies that raising irrigation from 0 to 25% of harvested area lowers CV' by about 0.16, whereas raising it from 50% to 75% lowers CV' by only about 0.02 units. The cubic term removes an upturn in CV' at very high irrigation that the quadratic imposes. The nonlinear terms improve fit. Relative to the linear model with fixed effects and controls (Model 3), the quadratic (Model 5) and cubic (Model 7) models have higher adjusted R^2 and lower Akaike and Bayesian information criteria (AIC and BIC). AIC falls by 93 for the quadratic and by 105 for the cubic, and the cubic improves BIC over the quadratic by only about 8. We take the quadratic as sufficient to describe the shape and report the cubic to show that the upturn is an artifact of the quadratic form. Changing the sample to the 108 counties with data available after 1970 leaves the effect of irrigation on CV' statistically significant and of similar magnitude in all models. The control variables also remain significant across most models, with the exception of σ_{prcp} .

Model 8 adds interactions between the fraction irrigated and the climate-variability terms. The interaction of irrigation with killing-degree-day variability is −0.018 per degree-day and with precipitation variability is −0.00113 per mm, both significant: where more of the harvest is irrigated, a given increase in heat or precipitation variability raises CV' by less. Because the interacted terms are centered, β_1 remains near −0.16 and is interpretable as the effect of irrigation at mean climate. This is consistent with irrigated yields being buffered against climate variability. When the sample is changed to the 108 counties with data available after 1970, interaction terms are not statistically significant at the $\alpha = 0.05$ level. The coefficient on fraction irrigated remains statistically significant and a similar magnitude in these specifications.

3.2 Evidence for an irrigation-driven spillover effect onto rainfed yields

We also find that a higher irrigated fraction is associated with lower rainfed CV' (Table 2). In the linear model with county and decade fixed effects, the coefficient on the fraction irrigated is about 60% of the size of the corresponding coefficient for total yield, so irrigation in a county is associated with reduced variability even on fields that are not themselves irrigated. This is consistent with the curvature in the total-yield model, where the marginal effect of irrigation weakens as more of the county is already irrigated (Figure 3).

Several physical pathways could carry such a spillover but our data do not distinguish among them. Irrigation lowers daytime temperatures through increased evapotranspiration [21, 22], and this cooling can be transported downwind; irrigation has been found to cool downwind US Midwest August temperatures by up to 3°C, approaching the effect of direct irrigation [23]. Evapotranspiration also raises humidity in the surrounding air [24, 25], can increase rainfall on nearby rainfed fields [26], and can increase cloud cover, which cools daytime temperatures and raises diffuse radiation and photosynthetic efficiency [27]. Cooling and added humidity in particular co-occur and act on plants together, so the observed stabilization cannot be attributed to temperature alone.

The rainfed and total-yield results differ in how irrigation interacts with climate variability. For total yield, the interactions of irrigation with killing-degree-day and precipitation variability are negative and significant (Table 1): irrigation dampens the transmission of climate variability into yield variability. For rainfed yield, neither interaction is significant, and adding quadratic and cubic terms does not consistently improve fit (Table 2). The spillover onto rainfed yields therefore appears as a shift in the level of CV' rather than as a change in sensitivity to climate variability, and its marginal effect does not diminish toward higher irrigation fractions as the direct effect on total yield does.

For total yield, rising irrigated fraction lowers CV' primarily by shifting harvested area toward the irrigated component, whose CV' is roughly a third that of rainfed yield. Whereas irrigated CV' shows no detectable dependence on irrigated fraction, rainfed CV' falls as irrigated fraction rises. Rainfed area is smallest where irrigation is most extensive, however, so this shift contributes little to the total. The reduction in rainfed CV' is evidence for the environmental pathways described above.

Our analysis operates at the county-decade scale, so it captures the aggregate association between irrigated fraction and rainfed CV' but cannot resolve where within a county the effect arises or through which pathway. The pathways described above act over scales ranging from adjacent fields to downwind regions, and each is consistent with a county-level signal. Furthermore, irrigated fields are not evenly distributed within a county, so the causes and mechanics of this rainfed shift may differ depending on the geography of a given county. We also cannot rule out measurement error as an alternative explanation for the rainfed level effect. NASS classifies fields as irrigated or rainfed from survey responses. If rising irrigation in a county raises the chance that irrigated fields are recorded as rainfed, the rainfed series becomes partly irrigated and its CV' falls for compositional reasons. Whether NASS classification accuracy has changed over time is worth investigating but is beyond our scope.

4 Discussion and Conclusions

An increase in irrigation explains the majority of the historical decline in maize yield variability in the US Midwest. Across the total-yield specifications the coefficient on the fraction of irrigated harvest is negative and statistically significant, and adjusted R^2 exceeds 0.5. Variability declined on average over both the 1950–2009 and 1970–2009 periods, and the decline tracks the growth in irrigated fraction rather than a change in the variability of irrigated or rainfed yields taken on their own. Short-term movements in CV' within individual decades relate to killing-degree-day variability, for which we also find a substantial effect.

The spatial record within Nebraska corroborates this. Counties with higher irrigation show lower CV' across decades, and as irrigation spread across the state CV' fell in the same counties (Figure 4). Specifically, eastern Nebraska counties had lower irrigation and higher CV' in the 1960s and 1970s; as irrigation expanded there, CV' declined.

We demonstrate that the choice of variability metric influences the inferred trend, which is also corroborated by prior analyses. Kukal and Irmak [12] quantify irrigation's effect as the percent reduction in interannual variability between rainfed and irrigated production, with variability measured as a coefficient of variation. Kucharik and Ramankutty [28] compare irrigated and rainfed maize yields over the twentieth century, measuring variability as the percent deviation from fitted yield, and find rainfed yields the more variable. Leng [17] reports declining county-level maize variability across the Midwest and finds that irrigation reduced variability in Nebraska. Leng measures variability as the standard deviation of linearly detrended yield anomalies in 15-year windows normalized by mean yield, whereas we quadratically detrend in 11-year windows.

Our primary contribution is the attribution. The aforementioned studies estimate irrigation's effect from the contrast between irrigated and rainfed production. We estimate it from a two-way fixed-effects panel regression that directly includes irrigation as an explanatory variable and controls for temperature and precipitation variability, which separates irrigation's contribution

from common decade trends and from time-invariant county differences and identifies it as the primary driver of the historical decline. We also find lower variability in rainfed yields where irrigated fraction is higher. Prior work shows that irrigation cools surface temperatures [24, 29, 30]; this result extends that effect to the interannual variability of yield.

Döring and Reckling adjust CV to remove the mean-dependence that follows from Taylor's power law [31], which allows them to compare the variability of cropping systems as if they share a common mean yield. We ask how the variability of yield changed as irrigation expanded and do not apply this adjustment. Irrigation raises mean yield while compressing variability, so the mean–variance relationship is part of what we study, and its slope carries agronomic content, including the input intensity and risk posture that accompany higher-yielding production. County and decade fixed effects absorb the cross-county and cross-decade differences in mean yield that motivate the adjustment, so our estimates do not reflect a spurious mean-driven gradient in CV'.

Attributing the pathway by which irrigation reduces yield variability is complicated because soil and plant hydrology are intertwined with temperature. Agricultural intensification cools the hottest local temperatures through increased evapotranspiration, within the Midwest [32] and globally [30], so irrigation may itself reduce the variability of growing- and killing-degree days. Comparing the decade-fixed-effects models with and without climate controls, the irrigation coefficient changes by only a few percent, which suggests that once decade-level trends are removed, the residual covariation between irrigation and climate variability is modest, though the change is somewhat larger in the nonlinear models. Causality remains difficult to establish, since irrigation-driven cooling may account for part of the reduced degree-day variability, and other co-evolving practices, such as investment in improved cultivars or soil management, may contribute to both the rise in irrigation and the fall in CV'.

Model-based studies project that climate change will raise yield variability [4, 6, 9]. Historically the opposite has occurred within the region that we study, driven by irrigation, which buffers variability and raises mean yields [33]. Where irrigation is already extensive, the curved shape of the irrigation–CV' relationship implies diminishing returns. Expansion elsewhere is constrained by water. Half of the global expansion in irrigation over the past 25 years has occurred in regions that were already water-stressed [34]. In parts of the US Southern High Plains, offsetting multi-decade water deficits would require reductions in withdrawals large enough to preclude current production [35]. Many aquifers are in decline from overpumping [36], including the High Plains aquifer that supplies much of the irrigation in Nebraska, Kansas, and Colorado [37] and that underlies the counties in which we measure the decline in CV'. If irrigation contracts while climate change simultaneously raises the variability of rainfed production, volatility could rise from both directions at once. Irrigation has stabilized Midwestern maize yields over six decades, but whether it continues to do so depends on the water supply.

Data availability

Yield and irrigation data are from the USDA National Agricultural Statistics Service (NASS), available at <https://quickstats.nass.usda.gov/>. Temperature data used to compute GDD and KDD, as well as average daily precipitation data, are from the nClimGrid-Daily product, available at <https://www.ncei.noaa.gov/products/land-based-station/nclimgrid-daily>.

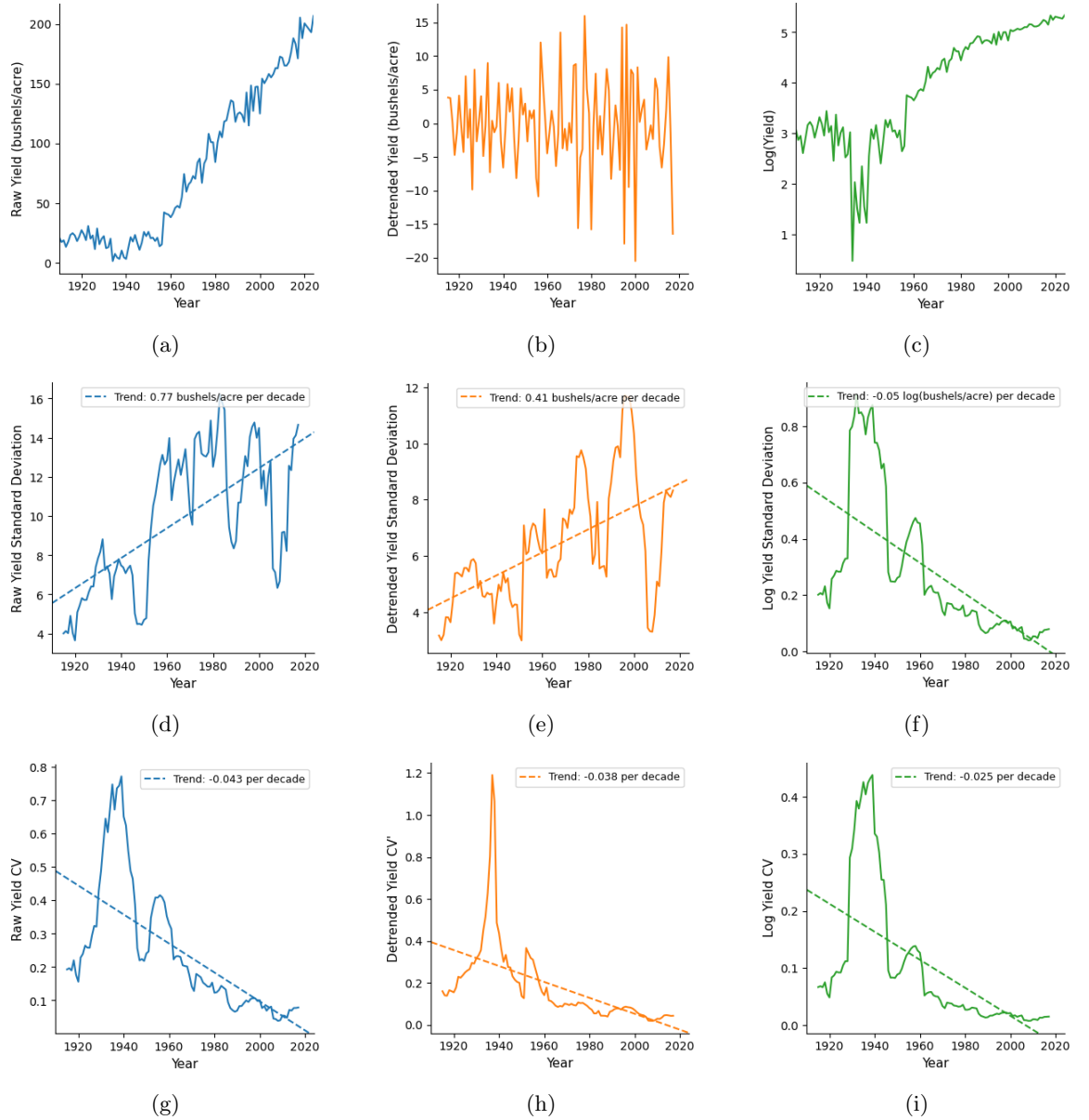


Figure 1: Various methods of quantifying yield and its variability, shown for Custer County, Nebraska. Panels a–c depict measures of yield: raw yield, detrended yield, which removes the underlying upward yield trend in order to isolate variability, and $\log(\text{yield})$. Panels d–i show that different measures of variability give different conclusions about trends over time. Panel h depicts CV' , coefficient of variation of detrended yield, discussed in Section 2.2. The standard deviation increases for raw and detrended yield but declines for $\log(\text{yield})$, whereas the coefficient of variation declines for all three.

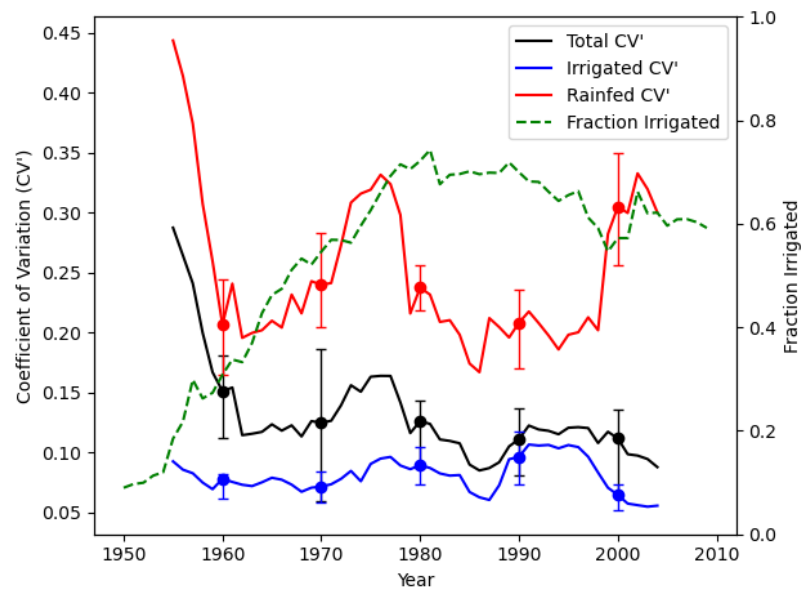


Figure 2: Average coefficient of variation (CV') of yield and average fraction irrigated for 72 counties with complete data for total, irrigated, and rainfed corn yields between 1950 and 2009. CV' is the rolling coefficient of variation over 11-year windows centered on the middle year. Error bars show the 25th to 75th percentile for the year beginning each decade. Average fraction irrigated for a given year is measured as the average of the irrigated harvest divided by the total harvest for each county. Over time, as the fraction of harvest that is irrigated increases, the CV' of total yield shifts closer to the CV' of irrigated yield, resulting in a downward trend in the CV' of total yield.

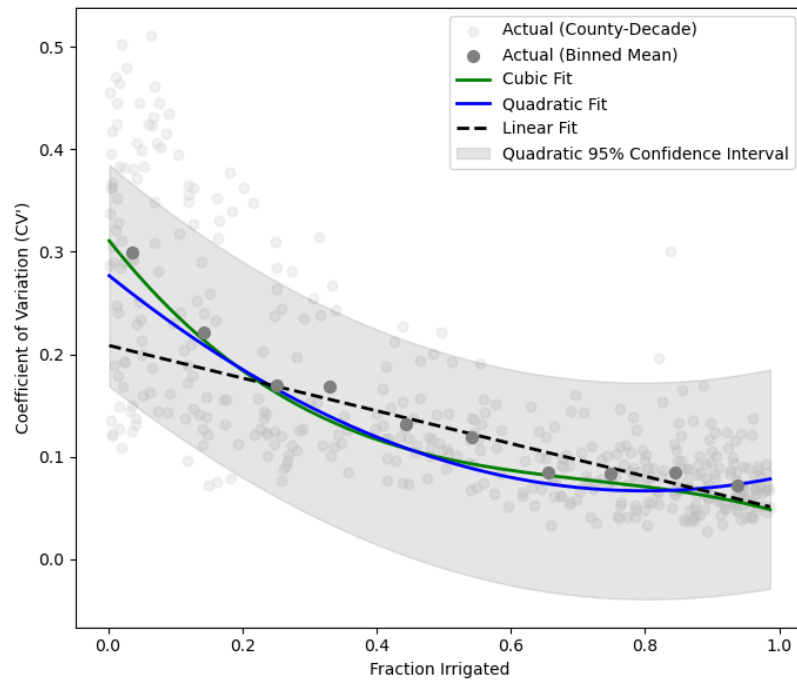


Figure 3: Relationship between irrigation and CV' . The predicted effect is shown using coefficients from linear, quadratic, and cubic models with county and decade fixed effects (Models 2, 4, and 6) and no additional climate controls. Each datapoint represents a specific county-decade. The shaded region shows a 95% confidence interval for observations for the quadratic model, calculated on the reference county and decade. The vertical position of each curve is set by the average fixed effect across counties and decades, added to the model intercept.

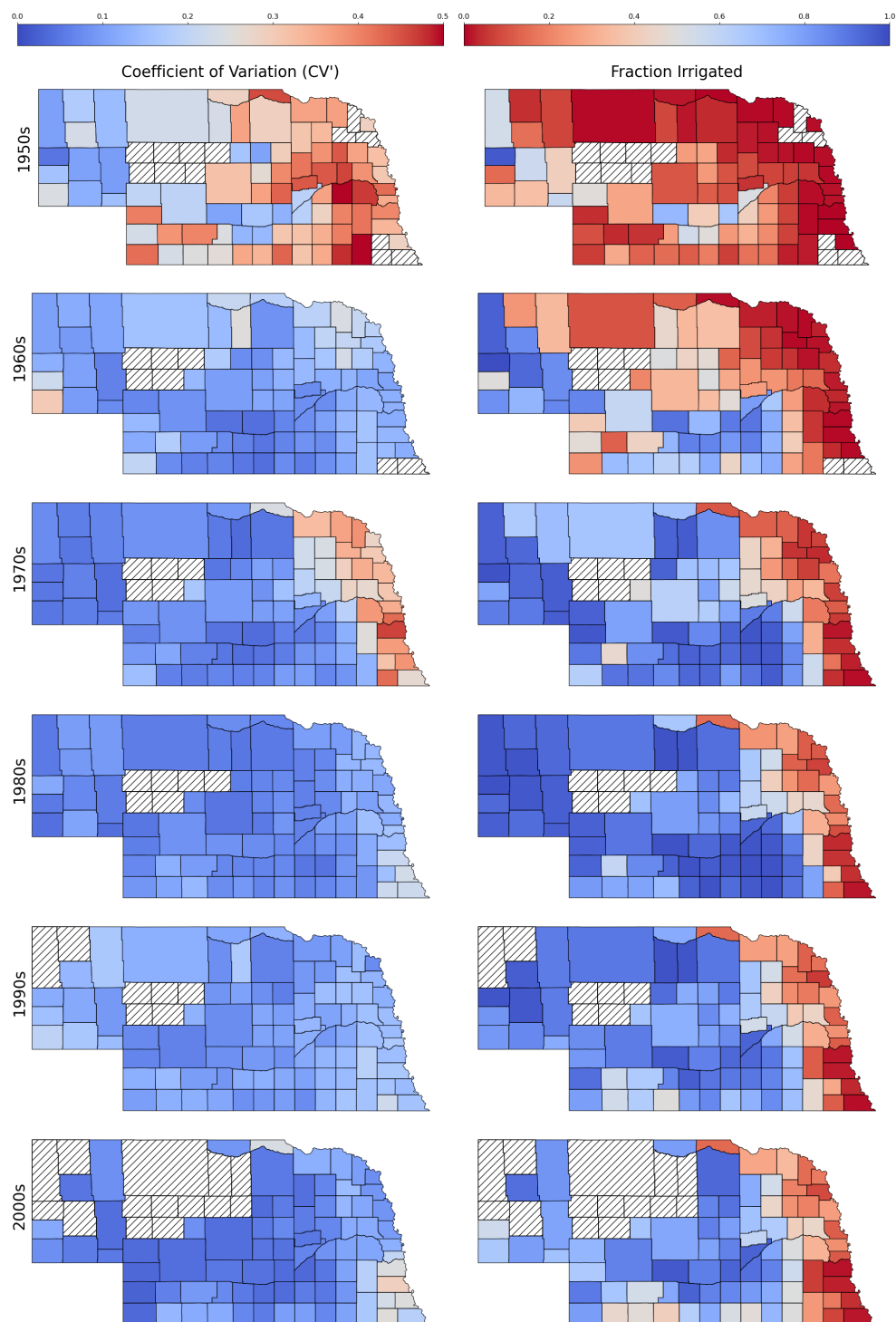


Figure 4: County-level CV' (left) and fraction of harvest that is irrigated (right) across decades. CV' is calculated using standard deviation of detrended yield divided by the mean for a given county and decade. Counties with declining CV' across decades generally correspond to those with increasing irrigation. Counties with diagonal hatching have less than seven years of available data in a given decade. Note that blue shading indicates low CV' but high irrigation.

	(1) Linear	(2) Linear (FE)	(3) Linear (FE + Controls)	(4) Quadratic (FE)	(5) Quadratic (FE + Controls)	(6) Cubic (FE)	(7) Cubic (FE + Controls)	(8) Linear (FE + Controls + Interactions)
Fraction Irrigated	-0.306*** (0.017)	-0.160*** (0.026)	-0.146*** (0.027)	-0.528*** (0.054)	-0.569*** (0.055)	-0.828*** (0.128)	-0.912*** (0.128)	-0.157*** (0.023)
Fraction Irrigated ²	—	—	—	0.330*** (0.041)	0.377*** (0.042)	1.04*** (0.243)	1.18*** (0.244)	—
Fraction Irrigated ³	—	—	—	—	—	-0.480*** (0.153)	-0.538*** (0.159)	—
Fraction Irrigated $\times \sigma_{KDD}$	—	—	—	—	—	—	—	-1.80 $\times 10^{-2}$ *** (5.74 $\times 10^{-3}$)
Fraction Irrigated $\times \sigma_{prec}$	—	—	—	—	—	—	—	-1.13 $\times 10^{-3}$ *** (3.80 $\times 10^{-4}$)
σ_{GDD}	—	—	1.19 $\times 10^{-4}$ (3.03 $\times 10^{-4}$)	—	6.64 $\times 10^{-4}$ ** (3.12 $\times 10^{-4}$)	—	8.32 $\times 10^{-4}$ *** (3.10 $\times 10^{-4}$)	-1.35 $\times 10^{-4}$ (3.12 $\times 10^{-4}$)
σ_{KDD}	—	—	1.09 $\times 10^{-2}$ *** (3.46 $\times 10^{-3}$)	—	1.19 $\times 10^{-2}$ *** (3.58 $\times 10^{-3}$)	—	1.26 $\times 10^{-2}$ *** (3.49 $\times 10^{-3}$)	1.76 $\times 10^{-2}$ *** (4.30 $\times 10^{-3}$)
μ_{prec}	—	—	-5.20 $\times 10^{-4}$ *** (2.10 $\times 10^{-4}$)	—	-5.00 $\times 10^{-4}$ *** (1.60 $\times 10^{-4}$)	—	-4.60 $\times 10^{-4}$ *** (1.60 $\times 10^{-4}$)	-5.20 $\times 10^{-4}$ *** (1.80 $\times 10^{-4}$)
σ_{prec}	—	—	2.90 $\times 10^{-4}$ *** (1.10 $\times 10^{-4}$)	—	3.90 $\times 10^{-4}$ *** (1.10 $\times 10^{-4}$)	—	3.10 $\times 10^{-4}$ *** (1.10 $\times 10^{-4}$)	9.30 $\times 10^{-4}$ *** (3.10 $\times 10^{-4}$)
Intercept	0.351*** (0.014)	0.345*** (0.016)	0.517*** (0.105)	0.386*** (0.016)	0.442*** (0.079)	0.417*** (0.022)	0.433*** (0.075)	0.599*** (0.093)
R ²	0.604	0.769	0.783	0.804	0.826	0.809	0.832	0.801
Adj. R ²	0.524	0.719	0.733	0.760	0.785	0.766	0.792	0.753
AIC	-954	-1177	-1197	-1246	-1290	-1254	-1302	-1229
BIC	-657	-859	-863	-924	-952	-929	-960	-887
N Obs	432	432	432	432	432	432	432	432

Table 1: Results of a regression of CV' on the irrigated fraction of harvest across decades and counties. All models include county fixed effects, and additional decadal fixed effects are denoted with "FE". Models that include controls for the standard deviation of GDD and KDD (degree-days) and the mean and standard deviation of precipitation (mm) are indicated with "Controls". In models with interaction terms, variables that are standard deviations are centered at their sample means. Standard errors clustered at the county level are shown in parentheses, and *, **, and *** denote significance at the $\alpha = 0.1$, $\alpha = 0.05$, and $\alpha = 0.01$ levels.

	(1) Linear	(2) Linear (FE)	(3) Linear (FE + Controls)	(4) Quadratic (FE)	(5) Quadratic (FE + Controls)	(6) Cubic (FE)	(7) Cubic (FE + Controls)	(8) Linear (FE + Controls + Interactions)
Fraction Irrigated	-0.306*** (0.029)	-0.097** (0.039)	-0.078** (0.034)	-0.100 (0.079)	-0.124* (0.073)	-0.219 (0.218)	-0.250 (0.194)	-0.080** (0.033)
Fraction Irrigated ²	—	—	—	0.003 (0.059)	0.040 (0.058)	0.285 (0.426)	0.335 (0.385)	—
Fraction Irrigated ³	—	—	—	—	—	-0.190 (0.272)	-0.198 (0.249)	—
Fraction Irrigated $\times \sigma_{KDD}$	—	—	—	—	—	—	—	-1.02 $\times 10^{-2}$ (7.03 $\times 10^{-3}$)
Fraction Irrigated $\times \sigma_{prep}$	—	—	—	—	—	—	—	-1.50 $\times 10^{-4}$ (4.00 $\times 10^{-4}$)
σ_{GDD}	—	—	-6.65 $\times 10^{-5}$ (5.10 $\times 10^{-4}$)	—	-8.20 $\times 10^{-6}$ (5.48 $\times 10^{-4}$)	—	5.37 $\times 10^{-5}$ (5.48 $\times 10^{-4}$)	-1.20 $\times 10^{-4}$ (5.03 $\times 10^{-4}$)
σ_{KDD}	—	—	2.30 $\times 10^{-2}$ *** (4.94 $\times 10^{-3}$)	—	2.81 $\times 10^{-2}$ *** (4.99 $\times 10^{-3}$)	—	2.33 $\times 10^{-2}$ *** (5.04 $\times 10^{-3}$)	2.69 $\times 10^{-2}$ *** (6.13 $\times 10^{-3}$)
μ_{prep}	—	—	-7.20 $\times 10^{-4}$ *** (2.40 $\times 10^{-4}$)	—	-7.20 $\times 10^{-4}$ *** (2.40 $\times 10^{-4}$)	—	-7.10 $\times 10^{-4}$ *** (2.30 $\times 10^{-4}$)	-7.30 $\times 10^{-4}$ *** (2.30 $\times 10^{-4}$)
σ_{prep}	—	—	4.80 $\times 10^{-4}$ *** (1.60 $\times 10^{-4}$)	—	4.90 $\times 10^{-4}$ *** (1.60 $\times 10^{-4}$)	—	4.60 $\times 10^{-4}$ *** (1.60 $\times 10^{-4}$)	5.50 $\times 10^{-4}$ *** (3.00 $\times 10^{-4}$)
Intercept	0.514*** (0.023)	0.497*** (0.022)	0.745*** (0.123)	0.498*** (0.023)	0.737*** (0.122)	0.510*** (0.034)	0.736*** (0.120)	0.841*** (0.127)
R ²	0.383	0.725	0.758	0.725	0.759	0.726	0.759	0.760
Adj. R ²	0.259	0.665	0.702	0.664	0.702	0.664	0.702	0.703
AIC	-659	-998	-1046	-996	-1045	-995	-1044	-1045
BIC	-362	-681	-712	-675	-707	-669	-702	-703
N Obs	432	432	432	432	432	432	432	432

Table 2: Results of a regression of rainfed CV' on the fraction of harvest in each decade that was irrigated in a given county. All models include fixed effects for the county. Models that include additional fixed effects for the decade are denoted with "FE." Models that include controls for the standard deviation of GDD and KDD (degree-days) and the mean and standard deviation of precipitation (mm) are indicated with "Controls". In models with interaction terms, variables that are standard deviations are centered at their sample means. Standard errors clustered at the county level are shown in parentheses, and *, **, and *** denote significance at the $\alpha = 0.1$, $\alpha = 0.05$, and $\alpha = 0.01$ levels.

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