A half century of yield growth along the forty-first parallel of the Great Plains

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Abstract

We examine a half-century of crop yield growth along an 800-mile transect in the U.S. Great Plains. The main contributors to growth were non-specific technical change +53%, irrigation +26%, fertilizer +13% and chemicals +10%. Environmental changes were small and had a minor impact. The wide range of agroclimatic conditions produced significant sub-regional deviations. Irrigation was important in the more arid and warmer areas of the west, while fertilizer and chemicals were more important in the humid east. Sensitivity to weather has increased in the rainfed regions of the east while it has decreased in irrigated regions of the west.

1. Introduction

The potential for crop production to support the burgeoning world population, in the face of climate change, has motivated dozens of studies reported during the new millennium. Many of these, including this one, have been statistical studies examining the sources of the dramatic increase in aggregate crop yields since the 1950s (See Alston, Babcock and Pardey, 2010, for a collection of studies about the main agricultural producing countries). They have examined the impacts on yields of such factors as weather, management intensification, irrigation, and non-specific technical change.

What can be said of these efforts? Most of them have measured the response to factors mentioned, but few have gone the step further to estimate the contribution of these factors to observed yield increases. Temperate zone studies have generally found substantial negative crop yield responses to high temperature, with response to precipitation varying by region. Because climate changes are predicted to increase temperatures in most areas of the globe, the general conclusions have been that climate change will decrease crop yield growth (Schlenker and Roberts, 2009; Lobell, Schlenker and Costa-Roberts, 2011; Fisher et al., 2012; Urban et al., 2012; Roberts, Schlenker and Eyer, 2012; Nelson et al, 2014; and Zhao et al., 2017). Some global studies of the agricultural sector growth suggest that technical change will continue to increase production (Fuglie, 2012), while experimental plot studies indicate that higher CO_2 concentrations in the crop canopy will also increase crop yields (Long et al., 2004). The likely trend of crop yields in the presence of climate change still remains poorly understood.

A number of recent papers have examined the sources of growth in aggregate crop and livestock production between 1960 and 2004, using mostly the same well-used state-level data set from USDA (ERS, 2017). Chambers and Pieralli (2020) provide a review of most of them. Of these, only Chambers and Pieralli (2020) and Njuki, Bravo-Ureta, and O'Donnell (2018) attempt to include the contributions of weather in the growth decomposition. These two studies differ markedly from ours in that they examine state-level aggregate crop and livestock technology for the entire U.S., whereas we examine county-level crop technology along a transect of 101 counties. Our approach required a more painstaking assembly of county-level data for estimating production function parameters, but it allows us to distinguish technology responses more narrowly by evaluating predicted yield responses using individual county annual observations and by grouping them into five subregions along the gradient.

Studies of changes in *aggregate* crop yields face a scale paradox: it is local weather, soil, and management conditions that actually determine yield changes, but it is yields aggregated to the regional and global scale that will provide "a broader perspective on what's going on with agriculture and weather" (Chambers and Pieralli, 2020, p. 26). Pixel-level data are available to examine yield growth at only a tiny sample of any country's crop production surface, but pixel-level crop growth models and experimental plots can reveal a fundamental understanding of how plants grow and respond to stimuli. Geographically aggregated yield response, on the other hand, represents an amalgam of pixel-level responses that may not closely resemble that for individual pixels, or may as in the current study mask micro-level response and contribution phenomena. Here we examine county-level crop technology in a search for insights not evident from recent studies that have examined state-level data on aggregated crop production.

In this study, we examine a half-century of crop yield growth along an 800-mile transect of the forty-first parallel North in the U.S. Great Plains (41st || hereafter), between the Rocky Mountains and the Mississippi River. Why this particular set of counties? One consideration is that it is intermediate in size between national-level and pixel-level levels of aggregation we mention above, providing a relatively compact area of the plains that is nonetheless heterogeneous with respect to soils, climate, and water resources. This we expected to allow us to identify the yield impact of these variables, along with producers' responses in the use of fertilizers, chemicals and irrigation, yet still allow us to characterize the production relationships as a single technology. The agricultural history and natural environment of the transect provide a rich set of observations for examining how agricultural technology and weather have interacted to double agricultural yields between 1960 and 2008. While the plains of this transect were all prairies prior to settlement by Europeans, the gradient in temperatures, precipitation, soils, and groundwater availability provide an opportunity for inferring much about agricultural technology from county-level data. Our analysis enables us to identify the separate contributions of input intensification, irrigation, soil organic matter, weather, and of a residual time trend interpreted as non-specific technical change by estimating a general biomass yield response function for the 41st|| transect, from which we draw inferences for five subregions along the transect by evaluating the resulting model using annual observation of weather and soil conditions in each county. This county-level analysis of crop yields reveals substantial heterogeneity in contributions to output growth.

2. Theoretical framework

We assume that production decisions are made by profit-maximizing farmers who operate under perfect competition in all commodity and factor markets. Farmers choose their optimum production and input requirements, subject to the production function *Y= f (**X**, z, **e**, t),* output and input prices, the characteristics of the environment (weather, soil, etc.) and a time trend that we interpret as non-specific technical change. We model these choices as the solution to the following problem

$$\max_{X} \pi = p \cdot Y - \boldsymbol{w} \cdot \boldsymbol{X} \;\; ; Y = f(\boldsymbol{X}, \boldsymbol{Z}, \boldsymbol{e}, t);\; p \gg 0, \boldsymbol{w} \gg 0 \,, \qquad (1)$$

where output is *Y* with price *p*, the variable input vector is ***X*** with corresponding price vector ***w***, ***Z*** is s vector of quasifixed inputs, and the environmental variables are represented by vector ***e*** and non-specific technical change is *t.*

The first order interior conditions for profit maximization are

$$\frac{\partial \pi}{\partial X_j} = p \cdot \frac{\partial f(\boldsymbol{X}, \boldsymbol{Z}, \boldsymbol{e}, t)}{\partial X_j} - w_j = 0, \qquad j = 1, \dots, J \qquad (1.a)$$

From equations (1) and (1.a) the marginal impact of variable inputs, expressed in logarithms, is:

$$\frac{\partial \ln f(\boldsymbol{X}, \boldsymbol{Z}, \boldsymbol{e}, t)}{\partial \ln X_j} = \frac{\partial f(\boldsymbol{X}, \boldsymbol{Z}, \boldsymbol{e}, t)}{\partial X_j} \cdot \frac{X_j}{f(\boldsymbol{X}, \boldsymbol{Z}, \boldsymbol{e}, t)} = \gamma_j = \frac{w_j}{p} \cdot \frac{X_j}{Y}\bigg|_{\boldsymbol{X}^*} = s_j \qquad (2.a)$$

with $j = 1, \dots, J$ and where γ_j is the production elasticity of input *j*, which when evaluated at optimum input levels ***(X*)*** is its share in total revenue, s_j. Thus, under the conditions of this model, the production elasticity of input *j* is equal to the revenue share of that input, capturing the essence of the firm's choice of input levels. The marginal effect on yields of changes in quasifixed inputs Z_h that are measured in levels are semielasticities:

$$\frac{\partial \ln f(\boldsymbol{X}, \boldsymbol{Z}, \boldsymbol{e}, t)}{\partial Z_h} = \eta_h \qquad h = 1 \dots H \qquad (2b)$$

The marginal effect on yields of an environmental variable e_v that is measured in logarithms is the elasticity:

$$\frac{\partial \ln f(\boldsymbol{X}, \boldsymbol{Z}, \boldsymbol{e}, t)}{\partial e_v} = \mu_v \qquad v = 1, \ldots, V \qquad (3.a)$$

where e_v is an environmental variable measured in logarithms. If the environmental variable is measured in levels rather than logs, the marginal effect can be expressed as the following semi-elasticity:

$$\frac{\partial \ln f(\boldsymbol{X}, \boldsymbol{Z}, \boldsymbol{e}, t)}{\partial e_u} = \mu_u \qquad (3.b)$$

which is the change in logarithm of output (approximately the proportional change) per one-*unit* change in e_u, whereas the elasticities in (3a) are standard elasticities (approximately the percentage change in yield per *one percent* change in e_v).

Different from the estimates in previous crop yield and state-level studies[i], our estimates of the impact of environmental variables are thus obtained from a model that controls for the simultaneous decisions made by the farmer given market prices as well as natural and technological conditions.

The rate of technical change (TC) is:

$$\frac{\partial \ln f(\boldsymbol{X}, \boldsymbol{Z}, \boldsymbol{e}, t)}{\partial t} = TC \qquad (4)$$

According to its effects on relative input productivity, the nature of technical change can be further characterized in terms of input biases. The bias measure we use identifies change in optimal input share due to technical change, under constant prices, defined as:

$$B_j = \frac{\partial s_j}{\partial t} \quad \forall \ j \qquad (5)$$

Technical change is said to be unbiased if all biases are zero, i.e., if it does not affect revenue shares. Hence, Hicks neutrality implies share neutrality. If $B_j > 0$ the technical change is said to be *biased toward input j*, or *j-using*; if $B_j < 0$ the technical change is said to be *biased against input j*, or *j-saving*.

Equations (2), (3) and (4) indicate *marginal* effects on yields of inputs, environmental variables, and non-specific technical change, respectively. To study the contributions of each of these factors to yield growth over a given period, we couple these marginal effects with observed changes in the amounts of these factors during the period in a growth decomposition à la Solow [ii] (1957) based on the total differential of the production function:

$$d\ln Y = \sum_{j=1}^{J}\gamma_j \cdot d\ln X_j + \sum_{h=1}^{H}\eta_h \cdot d\ln Z_h + \sum_{v=1}^{V}\mu_v \cdot d\, e_v + \sum_{u=1}^{U}\mu_u \cdot d\, e_u + TC \qquad (6)$$

where the first and second right hand side terms are output growth attributed to changes in variable and quasifixed inputs, the third and fourth are changes attributed to environmental factors that can be measured in logarithms (e_v) or in levels (e_u), and the last is output growth attributed to non-specific technical change. In our application below, we evaluate equation (6) for annual changes measured at the county level.

3. Empirical Specification

While Njuki, Bravo-Ureta, and O'Donnell (2018) estimate a state-level parametric stochastic frontier Cobb-Douglas production function for crops and livestock combined, and Chambers and Pieralli (2020) calculate a non-parametric deterministic production frontier for crops and livestock combined, we opt to econometrically estimate a system of equations that estimates jointly the county-level crop production function and the inverse input demand equations (Christensen, Jorgenson and Lau, 1973) implied by equation (2a). This joint estimation allows for endogeneity of input choice and makes it obvious that output produced and inputs used are manifestations of a single decision-making process tempered by expectations about natural phenomena. The estimates of the environmental impact in (3a and 3b) control for the farmers' behavior given expectations about these environmental factors (weather for example) and will, in general, be different from pure technical environmental responses measured on experimental plots.

We chose the transcendental logarithmic (translog) functional form to represent the production function in (1) and the corresponding derived demand for fertilizer and chemicals as shares in (2a). This specification is flexible as it provides a local second order approximation to any production technology, minimizing *a priori* restrictions on its structure. After adding random errors (that we assume are contemporaneously correlated across equations suggesting the three stage least squares approach that we use later) the following system of equations is estimated:

$$y_{it} = \alpha_0 + \sum_{j=1}^{2} \beta_j x_{ijt} + \frac{1}{2}\sum_{j=1}^{2}\sum_{s=1}^{2} \beta_{js} x_{ijt} x_{ist} + \delta_1 Z_{it} + \frac{1}{2}\delta_{11} Z_{it}^2 + \frac{1}{2}\sum_{j=1}^{2} \delta_{jz} Z_{it} x_{ijt} + \theta_1 r_{it}$$

$$+ \frac{1}{2}\theta_{11} r_{it}^2 + \theta_{1z} r_{it} Z_{it} + \sum_{w=1}^{3} \omega_w DD_{iwt} + \sum_{w=1}^{3} \omega_{wz} DD_{iwt} Z_{it}$$

$$+ \sum_{w=1}^{3} \omega_{rw} DD_{iwt} r_{it} + \theta_2 som_{it} + \theta_{2z} som_{it} Z_{it} + \tau_1 t + \frac{1}{2}\tau_2 t^2 + \sum_{j=1}^{2} \varphi_j t x_{ijt}$$

$$+ \varphi_z t Z_{it} + \rho_k + \lambda_j + \varepsilon_{it}$$

(7)

$$s_{1it} = \beta_1 + \beta_{11}x_{i1t} + \beta_{12}x_{i2t} + \delta_{1z}Z_{it} + \varphi_1 t + \varepsilon_{1it}$$

$$s_{2it} = \beta_2 + \beta_{21}x_{i1t} + \beta_{22}x_{i2t} + \delta_{2z}Z_{it} + \varphi_2 t + \varepsilon_{2it}$$

where y_{it} is logarithm of observed biomass yield *Y* (tons per hectare) in county *i* year *t*; $\boldsymbol{x}_{ijt}$ is a vector of the logarithms of quantity of fertilizer (for *j=1*) and chemicals (for *j=2*) applied per hectare; Z_{it} is the fraction of agricultural land irrigated; r_{it} is the logarithm of growing season precipitation in centimeters; $\boldsymbol{DD}_{iwt}$ is a vector of the number of degree days during the growing season in three temperature intervals, *w*=1,2,3; *som* is the logarithm of the level of soil organic matter in megagrams per hectare; ρ_k is a fixed effect for region *k* as compared to region 1, *k* is the region in which the county is situated, with *k* = 2,3,4,5; λ_i is a fixed effect for county *i* as compared to Adams County, NE. We exclude one county dummy per region to avoid singularity when combining county and regional fixed effects; s_{1it} is the share of fertilizer; s_{2it} is the share of chemicals[iii]; the variable *t* is year starting with 1960 = 1, a proxy for non-specific technical change[iv]; and ε_{it} are the error terms which are assumed contemporaneously correlated across equations. We do not include a derived demand (share) equation for irrigation because this variable represents a capital stock (share of cropland irrigated) rather than a variable input and is thus exogenous to the within-year decisions that we are examining here.

The coefficients α_0, *β's, δ's, ω's*, *θ's*, *τ's*, *φ's, ρ's and λ's* are the parameters to be estimated. We included all the interactions between variables that represent farmer's choices of inputs (fertilizer, chemicals), the quasifixed input (irrigation ratio) and the technical change time trend. In addition, we account for the environmental variables (soil organic matter, three intervals of degree days, and precipitation) that condition farmers' choice, adding interactions of irrigation with precipitation, which allows us to examine how irrigation mitigates water stress and to account for the substitutability between them. We also add interactions of irrigation with degree-days, to study how irrigation mitigates heat stress; and of irrigation with soil organic matter, to examine the benefits of irrigation on different types of soils. We include regional and county fixed effects in equation (7) to capture the potential of omitted variables correlated with the regressors.

Equality of coefficients across equations as well as symmetry were imposed during estimation while monotonicity was checked at each data point after estimation. Equations (7) were jointly estimated using an iterated three-stage least squares approach. Since the farmers make decisions about the desired yield and the amount of fertilizer and chemicals needed to produce it simultaneously, an instrumental variables approach was used to avoid endogeneity issues. For this purpose, indexes of prices of these inputs were used as instruments. Given that the interactions of the instrumented inputs, fertilizer, and chemicals, with themselves and with the other variables are also endogenous, instruments for these interactions were also created.[v]

As Auffhammer et al. (2013) describes, for observations with 'smaller spatial scales' such as county level weather data, an acceptable level of randomness across time but a low level of variation across space is assumed. To overcome the potential of biased standard errors due to spatial correlation, we followed his recommendation and use a group bootstrap estimation procedure where years are resampled and replaced.

Since the Cobb-Douglas production function is nested in the translog production function, we use a Wald test to check if the former is as good as the latter in capturing this technology.

As established in equation (2a), the first derivative of the translog production function with respect to the logarithm of each input corresponds to the production elasticities γ_{ijt} that, given our assumptions of profit maximization and perfect competition, are equal to the factor shares s_{ijt} for input *j* in county *i* in year *t*. These elasticities vary with time (*t*) and county inputs (*i, j*) in the following way:

$$\gamma_{ijt} = \left(\frac{\partial y_{it}}{\partial x_{ijt}}\right) = \left(\frac{\partial Y_{it}}{\partial X_{ijt}}\right) \cdot \left(\frac{X_{ijt}}{Y_{it}}\right) = \beta_j + \sum_{s=1}^{2} \beta_{js} x_{ist} + \varphi_j t \quad . \tag{8}$$

The quasifixed factor z_{it} is the fraction of cropland equipped for irrigation, which represents investment decisions taken before the seasonal production decisions. In this case the impact of irrigation, equation (2b), is represented by the following semi-elasticity:

$$\eta_{it} = \left(\frac{\partial y_{it}}{\partial Z_{i,t}}\right) = \left(\frac{\partial Y_{it}}{\partial Z_{i,t}}\right) \cdot \left(\frac{1}{Y_{it}}\right)$$

$$= \delta_1 + \delta_{11} Z_{it} + \sum_{j=1}^{2} \delta_{jz} x_{ijt} + \theta_{1z} r_{it} + \sum_{w=1}^{3} \omega_{wz} DD_{iwt} + \theta_{2z} som_{it} + \varphi_z t\,. \tag{9}$$

For the impact of the natural environment, ***e***, on yields, as per equations (3a) and (3b), elasticities or semi-elasticities are estimated, depending on how the variable is defined. The following semi-elasticities identify the marginal impact of degree days in county *i* in year *t*:

$$\mu_{wit} = \frac{\partial y_{it}}{\partial DD_w} = \omega_w + \omega_{wz} Z_{it} + \omega_{rw} r_{it} \qquad w = DD0030, DD3035, DD35 \tag{10}$$

while the soil carbon (*SOM*) and precipitation (*r*) elasticities are:

$$\mu_{som,it} = \frac{\partial y_{it}}{\partial som_{it}} = \theta_2 + \theta_{2z} Z_{it} \tag{11}$$

and

$$\mu_{rit} = \frac{\partial y_{it}}{\partial r_{it}} = \theta_1 + \theta_{11} r_{it} + \theta_{1z} Z_{it} + \sum_{w=1}^{3} \omega_{rw} DD_{iwt} \tag{12}$$

As indicated in equation (4), the first derivative of the production function with respect to the time trend *t* we interpret as the rate of technical change in county *i* in year *t*:

$$\frac{\partial y_{it}}{\partial t} = TC = \tau_1 + \tau_2 \, t + \sum_{j=1}^{2} \varphi_j x_{ijt} + \varphi_z Z_{it} \, . \tag{13}$$

The biases in technical change (5) are:

$$B_j = \frac{\partial s_j}{\partial t} = \varphi_j \, , \quad \forall \, j \, . \tag{14}$$

If $B_j > 0$ the technical change is input *j* using; if $B_j < 0$ the technical change input *j* saving.

The contributions of intensification, irrigation, environment and non-specific technical change to year-to-year yield changes for each county (*i.e.*, yield growth decomposition) are obtained using equation (6) and equations (8)-(13):

$$dy = \sum_{j=1}^{2} \gamma_j d(x_j) + \eta_{irrigation} d(Z) + \mu_{0030} d(DD0030) + \mu_{3035} d(DD3035) + \mu_{35} d(DD35) + \mu_{som} d(som) + \mu_r d(r) + TC \tag{15}$$

where for simplicity, we have omitted subscripts for time and county. This decomposition allows identification of the variables that have mattered the most in understanding the impressive crop yield increases in the U.S. central plains during the half century under study.

4. **Data description**

Most of the variables used are unique to this analysis, in Appendix A we describe in some detail how we generated them. The units of analysis consist of 101 counties clustered along the 41st parallel North in the U.S. Midwest (Figure 1), examined over the period 1960-2008[vi]. This transect was chosen because it encompasses a diverse 800-mile agroclimatic gradient from the Rocky Mountains to the Mississippi River, including highly irrigated farms with low precipitation and moderate soil carbon in the west to rain-fed crops with high precipitation and high soil carbon in the east. The range of conditions allows us the opportunity to identify the contribution of various environmental conditions and irrigation technology as well as farmer-chosen inputs to yield growth. After estimation of equations (7) we evaluate the estimated yield function at annual observations in each county and group them in five relatively homogeneous subregions from west to east. Basic statistics for the variables used are shown in Appendix Table A2, along with figures illustrating how yields, input use, irrigation technology, and environmental variables vary across the subregions.

(Figure 1)

The variables used in the estimation of the system of equations (7) are biomass yields, fertilizers, chemicals, share of land irrigated, soil organic matter, a time trend, temperatures, and precipitation. Fixed effects are included for subregions and counties. Labor and machinery are not included due to a lack of data at county level for crops. Although crop yield response studies do not usually include these variables, studies of aggregate crop and livestock agricultural productivity do. USDA (ERS, 2017) reports that for the period 1960-2004 the annual growth rate of labor in these states has been approximately -1.6% and the growth rate of capital (excluding land) has been approximately -0.23%.

To calculate average county biomass yield we sum the biomass produced by all crops in a county, measured in bone-dry megagrams (Mg), then divide that by total hectares planted[vii]. The biomass produced includes both the harvested crop and the residual above-ground biomass left in the field that is potentially available for harvest by grazing or as biomass stock. Hence, we are examining a more complete measure of production than just the harvested portion of any individual crop. We use biomass yield for several reasons. Because it is closely related to the concept of net primary production (NPP) used by many physical scientists in studies of weather and climate impacts and to the global carbon balance (Prince et al., 2001), our results are relevant to those areas of study. Also, these “residuals” have value for livestock grazing and potentially as feedstock for cellulosic bioenergy and plastics[viii]. Appendix Figures A1 and A2 in show this biomass yield by county (average 1960-2008) and by year (per region) respectively.

Across the region, average yields increased about 124% from 1960 to 2008, for an average compound rate of 1.66%. This aggregate yield increase masks substantial variation by subregion: in subregions 2 and 3 with their increases in irrigation, yields increased by 190%, compared to 96% in the more humid eastern subregion.

Factor intensification is measured by the amount of fertilizers and chemicals used. Those variables are under farmers’ control. Irrigation technology is not under farmers’ control within the annual observation period. Environmental variables, not under farmers’ control, are soil organic matter, precipitation, and temperatures. Non-specific technical change, which we represent with the passage of time, is certainly under human control.

Fertilizer and chemical inputs are expressed as indexes of quantity applied per hectare. These are obtained using expenditures from the Census of Agriculture and state-level price indexes from USDA (ERS, 2017) productivity accounts. They are expressed as indexes relative to the quantity used in Adams County, Nebraska, in 1960. Average levels by county are shown in Appendix A. Shares of fertilizer and chemicals are obtained by dividing expenditures by value of production.

Irrigation we express as the share of irrigated land in each county. This was calculated as the ratio of the area of irrigated land planted to crops to the area of all land planted to crops, from USDA NASS. While it would have been desirable to use quantity of water actually applied, this information is not available. The simple measure that we use has a useful interpretation: its parameter estimate is an approximation of the increase in biomass yield for irrigated relative to non-irrigated production. As illustrated in Appendix Figure A6, the percentage of irrigated land varies considerably across the transect, with higher values in the center of Nebraska and zero values in Iowa[ix].

To account for the differences in soil quality across space and time, we include average megagrams (Mg) of soil organic matter (SOM) per hectare for each county from Lakoh (2013) and Liska et al. (2014). As illustrated in Appendix Figure A7, we observe increasing quantities of SOM as we move from west to east and decreasing levels through time. The average value of SOM for region 1 (west) was 94 Mg ha^{-1}, while for region 5 (east) it was 183 Mg ha^{-1}.

County-level weather variables (temperatures in degree-days and precipitation in centimeters) were estimated from individual weather station data collected from the United States Historical Climatology Network. From these data, county average daily precipitation and county average daily maximum and minimum temperatures were obtained for each day during the growing season (March to August). County-level values for precipitation and temperatures were constructed as the weighted average of observations from the five closest weather stations to the center of each county. These observations were weighted using a Shephard inverse distance approach as follows:

$$q_k = \sum_{i=1}^{5} \frac{b_{ik}\, q_i}{\sum_{j=1}^{5} b_{jk}} \ , \ \text{where} \ b_{ik} = \frac{1}{{d_{ik}}^2} \qquad (16)$$

where q_k denotes the weighted value for county k, q_i is the measurement at weather station i, and d_{ik} is the distance from weather station i to the center of county k. Daily averages at county level were then used to construct the growing season precipitation and degree days variables for each county, explained further in the next paragraph.

To measure the impact of temperatures on yield we use an adaptation of the agronomic measure "growing degree days". We measure the amount of time, expressed in 24-hour days, the crop is exposed to temperatures in one of three ranges: 0ºC to less than 30ºC; 30ºC to less than 35ºC; and 35ºC or higher. In Appendix A we describe in more detail how these variables were constructed from weather reporting stations in each county. The average amount of time crops were exposed to temperatures above 35ºC by county is illustrated in Appendix Figure A8. This measure of high temperatures mostly increases from east to west.

We measure precipitation as the total amount of precipitation during the growing season measured in centimeters. As shown in Appendix Figure A9, there is a substantial decrease in average precipitation as we move from east to west. Region 1, in the west, received an average of 30.8 cm, while in region 5, in eastern Iowa, the average precipitation was almost twice that much, 59.1 cm. Finally, we represent non-specific disembodied technical change with a year variable, *t*, based on 1960=1[x].

5. **Results and discussion**

We estimated the parameters in the system of equations (7) using Iterated 3-Stage Least Squares (I3SLS). Eighteen of the twenty-nine parameters (not including the fixed effects) estimated in the system of equations (7) are significantly different from zero at the 99% confidence level, three are different from zero at the 95% confidence level and one at the 90% confidence level. The pseudo-R squared is 0.846. This standard goodness of fit measure provides a useful indication of the overall predictive power of the estimators although it cannot be explicitly interpreted as the proportion of the variance explained when estimating a three-stage least squares system of equations as we do (Toft and Bjørndal, 1997). A Wald test rejects the nested Cobb-Douglas form as a better specification. The Wald test on the β_{jk} coefficients equal to zero ($\forall\, j, k$) rejects the hypothesis that all the inputs are additively separable, and strongly separable ($\forall\, j \neq k$), indicating that the translog specification is preferred to a Cobb-Douglas specification. A Wald test on the φ_j coefficients equal to zero rejects the hypothesis of Hicks neutrality.

To account for spatial correlation, we follow Auffhammer et al. (2013) and use a grouped bootstrap methodology for the estimation of the standard errors. Additionally, we estimated the system using standard 3SLS to check for robustness of results and found minimal qualitative changes in the significance of the estimated parameters except for the significance of the county dummies. The Wu-Hausman endogeneity test on fertilizer and chemicals rejected the null hypothesis that these variables are exogenous, thus we instrumented these variables and their interactions using price indexes. Parameter estimates are presented in Appendix Table A3.

We used the parameter estimates and observations to estimate elasticities and semi elasticities of fertilizers, chemicals, irrigation, soil organic matter, weather, and a time trend to represent technical change using equations (8)-(13). These were evaluated at each data point, then averaged across observations within each of the five regions of interest. They are reported in Table 1.

(Table 1)

The estimated average production elasticity of fertilizer (0.112) for the entire region is consistent with previous estimates by Griliches (1964), Hayami and Ruttan (1970), Antle (1983) and Saha, Shumway and Havenner (1997). The estimated production elasticity of chemicals (0.058) is virtually identical to the 0.057 estimated by Ball (1985). On average, our elasticities indicate that a 1% increase in fertilizer increased biomass yield by 0.11% and a 1% increase in chemicals resulted in a yield increase of approximately 0.06%.

The transect-wide estimate of the irrigation semi-elasticity (1.577) implies that predicted yield with and without irrigation increases by 158%. García-Suárez, Fulginiti and Perrin (2018) estimate irrigation semi-elasticity for the entire High Plains aquifer region at 0.511 (that study includes counties over the aquifer from South Dakota to Texas). Part of the benefit of irrigation is achieved by reducing the impact of high temperatures, as indicated by the impact of irrigation on the DD35plus semi-elasticity[xi].

Soil organic matter (SOM) has been declining since cultivation began on these prairie soils. We estimate its average marginal elasticity at 0.054, but it is not significantly different from zero. Calculated regional SOM elasticities ranged from 0.11-0.13 in the central regions to 0.003 in the east.

On average, an extra 24 hours (one day) of temperatures above 35°C decreased yields by 25.6%, while the marginal effect of an extra day between 30°C and 35°C would decrease yields by only 2.7%, an important result that supports similar estimates in the literature. For example, we can compare our results with other studies of similar scope focused on just weather effects. Schlenker and Roberts (2009) and Roberts, Schlenker and Eyer (2012) find similar impacts of temperatures up to 30ºC, but above this threshold, they estimate yield reductions of only 6% and 6.2%, respectively, for each day of exposure. These two studies focused on corn and soybean yields in rainfed counties in the U.S. east of the 100th meridian. A more recent study by Burke and Emerick (2016) finds that exposures of corn to temperatures above 29ºC produce decreases of 0.44%-0.56%, depending on the model, for each one degree increase above this threshold.[xii]

In the east, the comparable negative impacts of the two ranges of high temperatures rise to 39.9% and 3.3%, while in the irrigated regions of the west (regions 1 and 2) they fall to 6.8% and 2.9% respectively. If we disaggregate 1960-2008 trends in heat sensitivity estimates by region, results are not homogeneous. Regions in the west (regions 1 and 2) saw a considerable decrease in sensitivity with marginal damage decreasing from 14.1% to 1.9% when comparing the 1960s to the 2000s, mainly due to increased irrigation. Region 4, which has low irrigation, saw a much smaller decrease from 35.9% to 32.5% during the same period. Region 5, which has no irrigation, saw an *increase* in the marginal damage from 39.5% to 40.9% during the same period. Ortiz-Bobea, Knippenberg and Chambers (2018) and Chambers and Pieralli (2020) also find increased weather sensitivity in rainfed agricultural areas in the U.S., in particular in the Midwest region. Our estimates additionally indicate that irrigation is a successful means to reduce heat stress, consistent with findings in Kukal and Irmak (2018).

A marginal increase of 1 cm (0.39 inch) of precipitation along this transect would on average *decrease* yields[xiii] by 9.8%. This average response again masks geographical and temporal variations. For example, in the west (region 1), an additional centimeter of precipitation would *increase* yields on average by 10.2%. During the wettest decade (the 90s) the region-wide response to an additional centimeter was -14.2%, while during the driest decade (the 70s) the response was -6.7%.

The estimated time trend, our proxy for unidentified, non-specific technical change, increased yield by an average of 0.9% per year[xiv]. This variable can be interpreted as capturing the trend in marginal effects of unidentified changes in yield from innovations such as variety improvement, higher quality and quantity of machinery and labor, improvements in management, and similar technology variables for which we have no data available at the level of county agriculture. The negligible and insignificant coefficient estimate for the variable time squared (0.00005) indicates that, ceteris paribus, the 0.9% annual rate of improvement remained stable over the time period. In terms of the biases in technical change, we find it to have been irrigation saving (with a cross-coefficient of -0.001), and fertilizer and chemicals using (cross-coefficients of +0.0008 and +0.0004, respectively), which means that other things equal, the ratio of irrigation to fertilizer and chemicals would fall as technology advances. We note, however, that despite the technical change bias against irrigation, the share of land that is irrigated increased by about 30% over the 1960-2008 period, due to complementarities with other inputs, and it would have increased even faster had technological change not been biased against it.

Contributions of human controlled factors to yield change during 1960-2008

We use our estimates of regional and transect-level elasticities and semi-elasticities to decompose the observed yield change, 1960-2008, into contributions from intensification, irrigation, soil organic matter, weather, and nonspecific technical change (using equation 15, page 12) [xv].

Estimated human-controlled contributions to yield change for 1960-2008 are shown by region in Figure 2, indicating that human-controlled factors explain most of the overall change in observed yields during this half-century. Estimated contributions across the transect by decade are shown in Figure 3.

(Figures 2 and 3)

Increases in irrigation over this period contributed to yield increases of 33%, 74%, 68% and 18% in regions 1, 2, 3, and 4 but had no contribution to yield growth in 5 because irrigated areas were virtually non-existent. Across the 41st || transect, irrigation contributed an average yield increase of about 26%. Most of these increases in irrigation occurred during the first two decades, as indicated in Figure 3. Intensification in the form of higher fertilizer and chemical use per hectare contributed to yield increases of about 13% and 11%, respectively, across the 41st || transect (Figure 2), with most of this occurring during the 1960s and 1970s (Figure 3). The fertilizer contributions occurred almost exclusively during the 60s, while chemical contributions continued throughout the 1960-2008 period. Regions 1, 2 and 3 show higher contributions of fertilizer than do regions 4 and 5, consistent with the increases in irrigation, as they are complementary inputs. It is notable from Figure 3 that the contributions of fertilizer and chemicals to yield growth occurred almost completely between 1960 and 1990. This is an encouraging finding, given the recent National Academy of Science (2021) study expressing concern about the potential pollution impacts of the fertilizer increases that might be necessary to feed the growing world population.

As we noted earlier, the nature of the studies by Chambers and Pieralli (2020), CP hereafter, and by Njuki, Bravo-Ureta, and O'Donnell (2018), NBO hereafter, differ markedly from ours in that they consider causes of growth in the entire U.S. agricultural sector during 1969-2004 (all crops and livestock products combined) and they use state-level data. It is useful to compare their decompositions of causes of growth with our results for just aggregated crop yields along a more homogeneous transect of the Great Plains. Considering the simple average of the results of their studies for the four states in our study, their estimates of 1960-2004 changes in output due to technical change were 69% in NBO and 54% in CP compared to our 53%. These are more similar than we would have anticipated given the empirical differences in geographic and commodity scope. Finally, the estimated contributions of changes in inputs for the four states averaged NBO +31%[xvi] and CP +1.4% versus our +50% (irrigation, chemicals and fertilizer). These differences may at first be surprising, but conceptually they are different because we do not include all inputs in our study. Had we been able to include quantities of labor and capital per area of crop production at the county level, we would likely have found them to have decreased, which would have reduced our estimate of the contribution of input changes to yield change.

Our results show that technological change contributed somewhat more to the yield gains in the two eastern subregions (Figure 2), where there was no prospect for increases from irrigation, and little incentive to increase rates of application of fertilizer and chemicals. What does *this unspecified technological change* consist of? In a widely cited summary of growth in maize yields, Duvick (2005) notes that yield per plant has been nearly constant, but technological progress has allowed more plants to be grown per hectare, due to genetic changes along with complementary advances in management, chemicals and machinery. Duvick expresses confidence that similar gains will continue for at least a few decades, The future path of this non-specific technical change remains a crucial issue that we do not explore further in this study.

Contributions of environmental factors to yield change during 1960-2008.

At the aggregate level across the 41st || transect, environmental factors have contributed to a yield change of only about -0.7% in 1960-2008. This includes a negative impact of -0.5% due to a depletion of soil organic matter (SOM) and a small negative impact of -0.2% due to weather as we have measured it (Figure 4). CP also find a negligible weather[xvii] contribution of -1.76%, on average for the states in our analysis. Similarly, NBO report negligible average annual weather contributions[xviii] of 0.016% (0.72% cumulative contribution) for the same states. Both NBO and CP comment on the heterogeneity of weather responses across states and therefore suggest the desirability of a more local analysis, as we have provided in this study.

Geographically, a positive contribution of precipitation change in region 1 (4.4%) was partially offset by negative contributions of precipitation change in regions 2, 3, 4, and 5 where it was a little too wet by the end of the period of analysis. The aggregate outcome also masks some significant variations in temperature contributions through time. For example, an increase in very hot weather (temperatures over 35°C) contributed to a positive 7-9% yield increase in regions 1 and 2, while it reduced yields 6-9% in regions 3 to 5 (Figure 5). An increase in 35°C+ days across the transect during the 1980s, the warmest decade, contributed a 7% decrease in transect average yield, only to have half of that offset by yield increases due to a reduction in such days in the 1990s and 2000s. Note from Figure 4 that the net weather contributions were more dramatic in region 1 (the west) than elsewhere, due to net weather improvements in that region over the period. An important insight here for examining the impacts of weather is that aggregate data (i.e. for the 41st ||) do not reveal the very real impacts of changes in weather at the subregion level, because these impacts tend to be canceled out across areas. But analysis of aggregate relationships using local data, as we have done here, can reveal the marginal responses to local weather and the muted aggregate responses as well.

(Figure 4 & 5)

The final environmental variable we considered was soil organic matter (SOM). The data revealed a steady reduction of SOM through time and a steady reduction across space from east to west. For the full 41st || transect across the entire period, changes in yield due to changes in SOM were small – an average SOM reduction of about 15.7% resulted in a biomass yield reduction of about 0.5%. While these effects of soil organic matter loss through time were small, differences in SOM levels of 182 Mg/ha in the east versus 100 Mg/ha in the west account for a yield difference of as much as 8%.

6. Conclusions

This research examined crop biomass yield growth during 1960-2008 on an 800-mile transect of the Great Plains along the 41st parallel North, between the Rocky Mountains and the Mississippi River, to determine the relative contributions of natural factors and human factors to this growth. The range of agroecological conditions along this transect is large, with potential implications for crop yield growth in other temperate zone producing regions. Rather than focus on specific crops, we measured county yield as the entire above-ground amount of biomass produced by all crops combined divided by total area in those crops, in accord with the ecological notion of net primary agricultural yield.

In order of importance, on average across counties, our estimates of contributors to the transect-wide half-century yield increases are these: non-specific technical change +53%, irrigation +26%, fertilizer +13%, chemicals +11%. Weather changes contributed to a decrease in yields of just -0.2%, while reductions in soil organic matter contributed to a decrease in yields of -0.5%.

While technical change was the main source of yield growth in every sub-region, the contributions of the remaining factors of production vary substantially across sub-regions. Increased area under irrigation was more important than technical change for the central high plains (regions 2 and 3), where it produced increases in average yields of 74% and 68%, respectively. In the east, where irrigation is virtually nonexistent, greater use of fertilizer and chemicals were the second most important reasons for yield growth, each of which contributed yield increases of about 10%. Notably, most of these latter increases occurred during the first half of the period, providing some optimism for the possibility that the yield increases needed to feed future world population growth may be achieved with smaller increases in fertilizer and chemical pollution than some have feared.

Losses of soil organic matter through time made a very small average contribution to yield reductions of about -0.5% across the entire transect, but about -1.3% in region 3. Furthermore, regional differences in average SOM levels of 182 Mg/ha in the east versus 100 Mg/ha in the west account for a yield difference of about 8%.

We find that the dramatic biomass yield increases along this transect during this time period were almost entirely attributable to human-controlled interventions rather than environmental changes. The fraction of crop area irrigated in the western half of this transect increased dramatically between the 1960s and 2000s, from about a quarter of all cropland to about half. This increased yields by about 58% in those subregions, but increased the average yield for the entire transect by only about 26% because of the absence of irrigation in the east. Intensification, in terms of additional quantities of fertilizers and chemicals, contributed to yield increases of about 23%, but in the last decade the contribution declined to less than 2%, except in region 2 where application rates continued to increase. Our results offer some empirical basis for evaluating simulation studies of world food production such as that by Johnson, et al (2016), who assumed that intensification of existing crop area would increase yields by 50-90% and that extensification to natural areas would cause those areas to lose 25% of their soil carbon.

The small environmental contributions to yield growth along this 41st|| transect do not imply that temperature and precipitation had no marginal impacts: yield response to changes in precipitation and temperatures above 35°C were quite large. The small weather contributions to yield growth over the half-century are due to the fact that there was very little net change in weather between the beginning and end of the period, even though the marginal effects of precipitation and temperature are quite significant. It is notable, however, that the sensitivity of biomass yield to the amount of time exposed to temperatures over 35°C increases from the west where the response is -4.3, to the east where it is -40. This is consistent with the estimated impacts of irrigation in reducing heat stress.

What do our results portend for yield growth during the coming decades? Projections of climate change (U.S. Global Change Research Program, 2017, 2018) in this region, due to increased atmospheric CO_2, suggest that periods of hot weather might increase by 10% in this area, which would decrease average biomass yields by -2.6%. This decrease might be partially offset by the increase in yields predicted from the CO_2 fertilization effect suggested by experimental data and by some aspects of farmer adaptation (like changes in planting and harvesting dates). Projections of precipitation change along this 41st || transect are roughly neutral, but a decrease would decrease yields in the west, while it could increase yields in the east. The potential for further expanding the irrigated area to increase average yield is minimal, given concerns about the sustainability of groundwater supplies. For both environmental and economic reasons, there is little prospect that fertilizer and chemical applications will increase. Our results also indicate that along this transect the yield growth rate from non-specific technical change has stabilized at around 1% per year. Our research does not predict the future path of yields along this transect, but we must hope for continued or accelerating technological advances if the region is to contribute its share of needed increases in agricultural output.

7. Acknowledgments

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Tables

Table 1. Estimated average transect-wide marginal effects of variables on biomass yield, by region*

Variable	Type of response	Region					
		41st ‖	1	2	3	4	5
Fertilizer, quantity index	elasticity	0.112	0.102	0.123	0.119	0.108	0.111
Chemicals, quantity index	elasticity	0.058	0.048	0.046	0.052	0.062	0.066
Irrigation ratio, 0-1	semi-elasticity	1.577	1.203	1.229	1.124	1.818	1.941
Time trend, years	semi-elasticity	0.009	0.008	0.008	0.008	0.009	0.009
Soil organic matter, Mg/ha	elasticity	0.054	0.083	0.115	0.124	0.023	0.003
DD0030, days	semi-elasticity	0.001	0.001	0.002	0.002	0.001	0.000
DD3035, days	semi-elasticity	-0.027	-0.040	-0.019	-0.011	-0.031	-0.033
DD35plus, days	semi-elasticity	-0.256	-0.043	-0.093	-0.127	-0.343	-0.399
Precipitation, cm	elasticity	-0.098	0.102	0.006	-0.023	-0.130	-0.212

Figures captions:

Figure 1. Study counties along the 41st parallel North, U.S. Great Plains

Figure 2. Human-controlled contributions to crop yield change along the 41st parallel North, by region, 1960-2008

Figure 3. Human-controlled contributions to crop yield change along the 41st parallel North, by decade, 1960-2008

Figure 4. Weather contributions to crop yield change along the 41st parallel North, by region, 1960-2008

Figure 5. Contributions of temperatures above 35°C to crop yield changes along the 41st parallel North, by decade and region, 1960-2008

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[i] Njuki, Bravo-Ureta, and O'Donnell (2018) estimate a state-level stochastic Cobb-Douglas production function for crops and livestock combined. Chambers and Pieralli (2020) use a programming technique to fit a nonparametric and deterministic technology to state-level data for crops and livestock combined. Both use a state-level data set developed by USDA (ERS, 2017), then obtain state and regional estimates of the technology by evaluating the general model using state-level variables.

[ii] Our productivity decomposition is exactly like that in Solow (1957). He also includes a time trend that he defines as "The variable t for time appears in F to allow for technical change" (page 312, after equation (1)). It captures exogenous neutral disembodied technical change at a constant exponential rate as also stated by Solow on page 313 "… then $A(t) = e^{at}$ or in discrete approximation $A\ (t)\ (I + a)^{t}$…".

[iii] We have included only share equations for fertilizers and chemicals because we lack county-level information on labor, and capital used exclusively on crops. Other studies have used state-level indexes developed by USDA (ERS, 2017) for crops and livestock combined.

[iv] In Solow's calculations of his Table 1 there is no estimation as he approximates marginal products by prices so the calculations are nonparametric and nonstochastic and the only way to obtain the shift of the production function through time is by obtaining a residual. When econometrically estimating the shift, we have an opportunity to include a time trend to capture it as in his equation (1), then add an error term to capture the stochastic nature of the econometric approach.

[v] Reg3 command in STATA version 16.0 was used for the econometric estimations.

[vi] Counties by sub-region are listed in Appendix Table A1.

[vii] A reviewer has pointed out that we do not have any measure of whatever biomass may have been produced on land that was planted but not harvested. Excluding this amount would result in an underestimate of biomass yield per planted acre. We note, however that the ratio of harvested to planted area across our sample was 95%, so we surmise that any such underestimate has not affected our conclusions. Schlenker and Roberts (2009) found that "results are very similar" whether they used yield per planted acre or yield per harvested acre in an analysis of county-level yields of corn, soybean and cotton.

viii One priority of the U.S.Department of Energy is to support the development of cost-effective strategies, technologies, and systems to sustainably harvest and deliver volumes of biomass feedstock : https://www.energy.gov/eere/bioenergy/feedstock-supply .

ix Given the minimal levels of irrigation present in Iowa, USDA (ERS, 2017) does not report the amount of planted land that was irrigated.

x Some of the technical change not captured by this exogenous time trend or by changes in embodied technical change in the inputs could be captured by the residual added in the econometric estimation. If there are climatic trends not captured by the variables we use (degree days and precipitation) the time trend could be capturing some of this information, particularly if these trends are monotonic. But if there are common trends in the variables the inclusion of a time trend is essential as it detrends the series and allows for more efficient estimation.

xi The parameter of the interaction term between irrigation and DD35plus is statistically significant and equal to 0.452.

xii Fisher et al (2012) in a comment correcting Deschenes and Greenstone (2007) who use county level data for the whole U.S. also find substantial negative impact of hot weather on corn yields, soybean yields and profits although "…the impacts are smaller in magnitude than earlier estimates…" (page 3755, first paragraph). A response by Deschênes and Greenstone (2012) acknowledges that once data and coding errors were corrected they also find a significant negative effect of weather on yields and profits with the effects on profits small because they are "…more amenable to adaptation even in the short run..."

xiii This somewhat surprising result is completely consistent with Tannura, et al (2008), whose estimates for corn in Iowa, Illinois and Indiana indicated optimum monthly precipitation levels were close to the average levels.

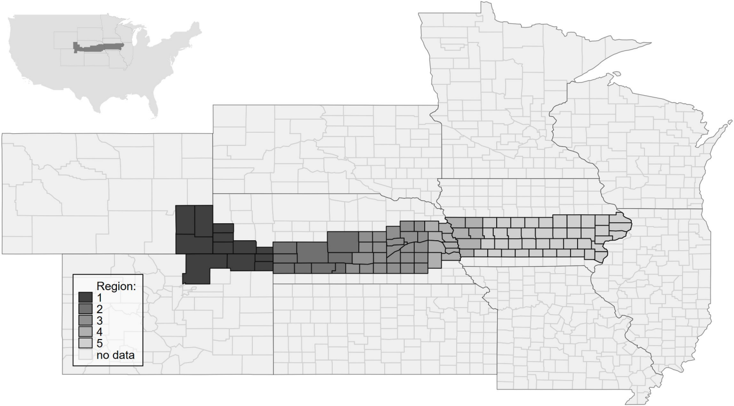
xiv Njuki, Bravo-Ureta & O'Donnell (2018) using state-level data estimate a 1.2% growth rate for the aggregate (crops plus livestock) U.S. agricultural sector during 1960-2004.

xv To calculate year-to-year contributions of each factor (fertilizer, chemicals, soil organic matter, precipitation) measured in logarithms, we multiply the change in the log of the input times the average production elasticity of that input between two consecutive years. For factors (irrigation, time, degree days) measured in levels, we multiply the change in the level of the input times the average production semi-elasticity of that input between two consecutive years.
Changes between period t_1 and t_N are estimated as: $[(1 + \text{mean change in factor of interest})^N] - 1$. Log changes are converted to percentage changes using the equation: percent change in y = exp(dlny)-1.

xvi Our calculation. For each of the four states in our study between 1960 and 2004, using their equation (5), their estimated parameters and the USDA (ERS, 2017) 1960 and 2004 input values. We report the simple average for the four states.

xvii They capture weather using two variables, state-level observations on degree days between 8°C and 30°C between March and August, and inches of precipitation during the same period.

xviii Their environmental index includes four variables, state-level averages of growing season temperature and cumulative precipitation and intra-annual standard deviations from daily temperature and precipitation; adjusted for seasonality.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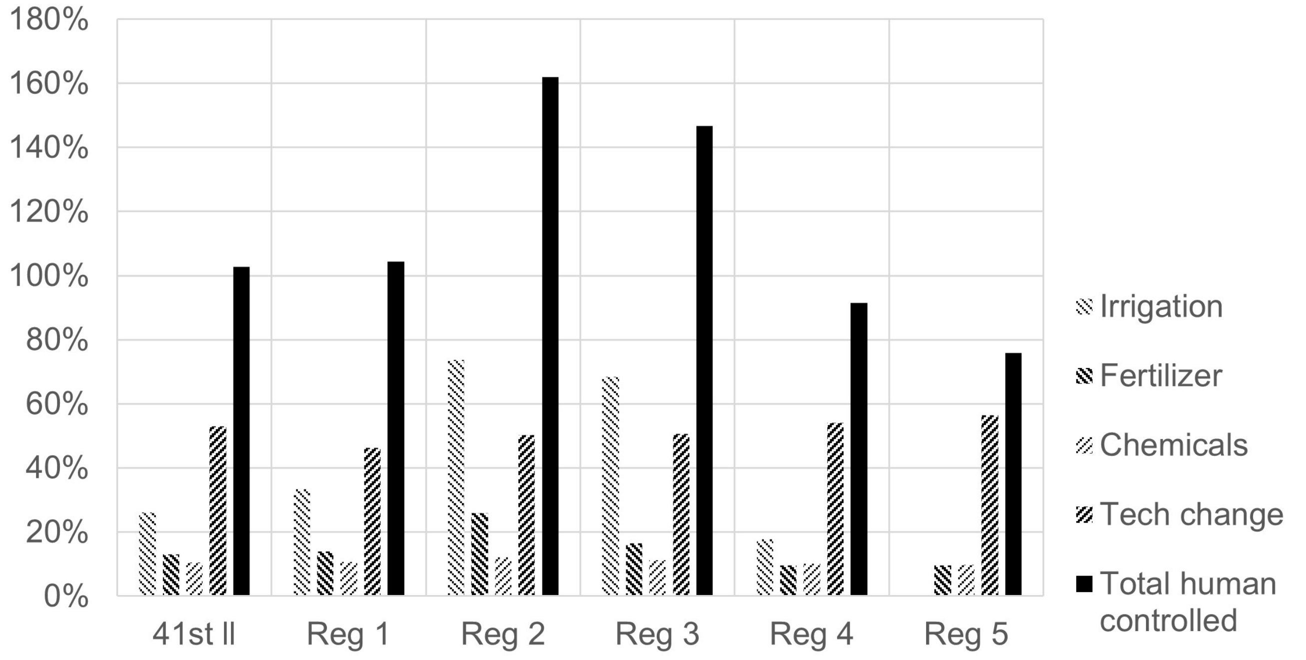
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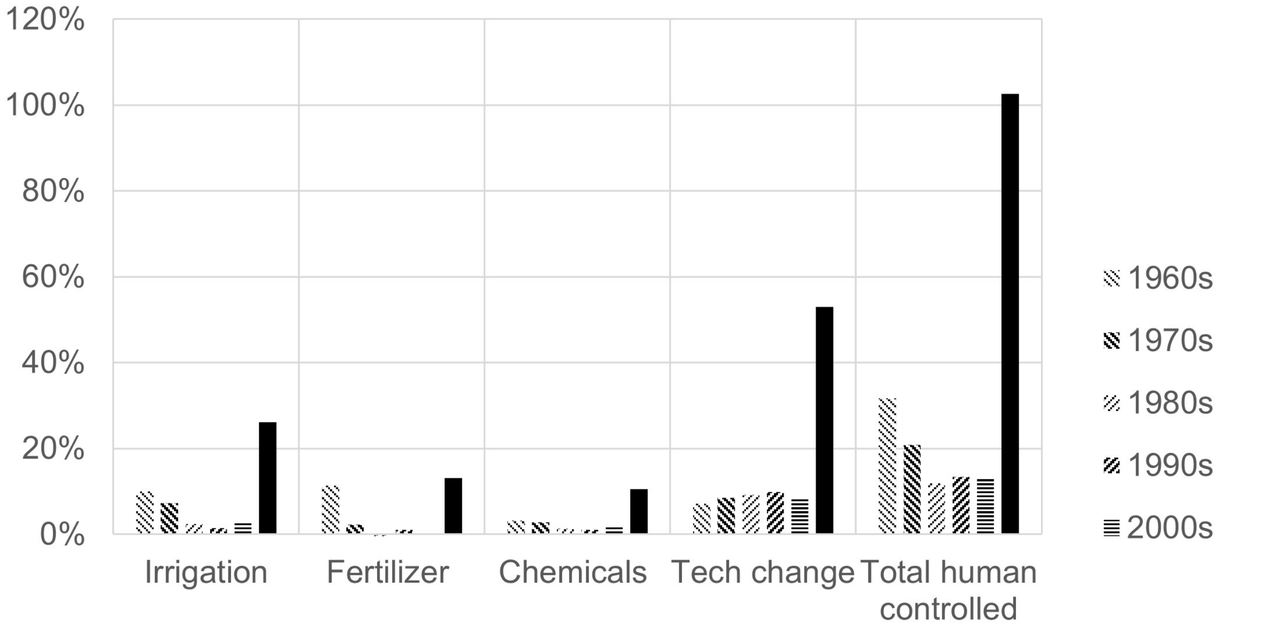

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60%
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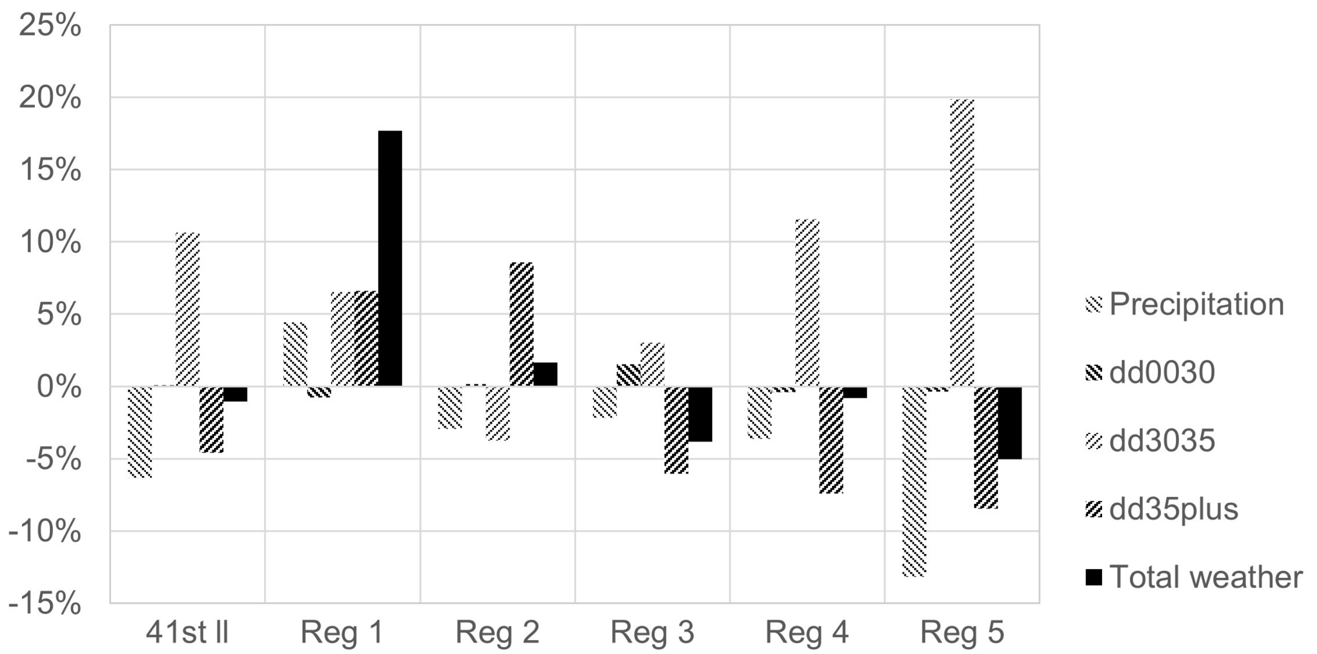
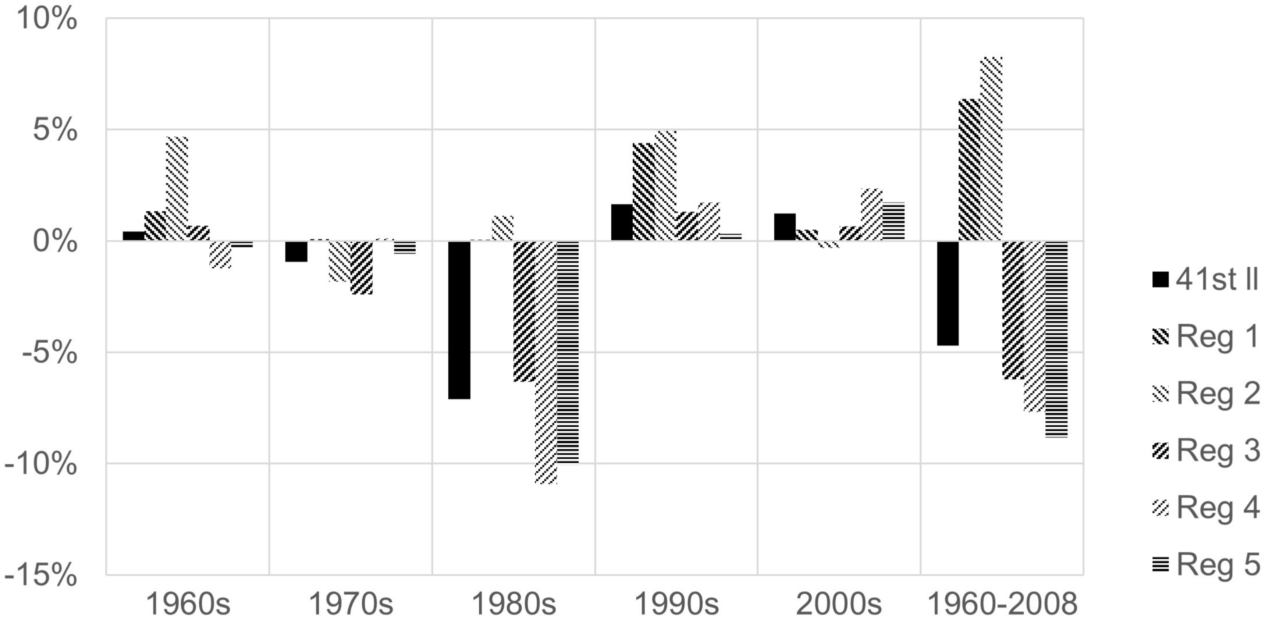
0%
Irrigation
Fertilizer
Chemicals
Tech change
Total human controlled
1960s
1970s
1980s
1990s
2000s


25%
20%
15%
10%
5%
0%
-5%
-10%
-15%
41st ll
Reg 1
Reg 2
Reg 3
Reg 4
Reg 5
Precipitation
dd0030
dd3035
dd35plus
Total weather


10%
5%
0%
-5%
-10%
-15%
1960s
1970s
1980s
1990s
2000s
1960-2008
41st ll
Reg 1
Reg 2
Reg 3
Reg 4
Reg 5