Irrigation and Climate Effects on Land Productivity in the U.S. Central Plains

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Abstract:

Considering different scenarios of future trends in climate, several authors have found that the impact that climate change will have on agriculture will most likely be negative. Most of these studies consider regions with low level of irrigation and do not control for purchased farm inputs. An important step towards understanding the evolution of agricultural production is to carefully estimate the effect that different temperatures and precipitation have on agricultural productivity considering also inputs under farmers' control and the farmers' profit-maximizing behavior. This research develops a county level biomass production function for an 800-mile climatic gradient from the Rocky Mountains to the Mississippi River (41N). Our results quantify the critical effects that high temperatures have on agricultural productivity in the region, after controlling for irrigation, other managed inputs, soil characteristics, precipitation, and technological change. We find a negative and increasing (nonlinear) effect of temperatures over 30ºC on crop yields; a full day of temperatures between 30ºC and 35ºC decreases expected yield by 1.7% and a day of temperatures over 35ºC decreases yields by 23.1%. In addition, converting rainfed crops to irrigated crop will produce a sharp decrease in the negative impact of the higher temperature interval.

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An analysis of high temperatures and irrigation impact on crop yields

Abstract

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Introduction

The dramatic increase in world crop production observed over the 40-year period from 1960 to 2000 was attributable partly to land expansion, but it was also the result of increasing yields due to new technologies and management techniques, including mechanization and an increase in the use of chemicals, fertilizers, pesticides and water from irrigation systems (Tilman et al., 2001). During the last decade, several authors observed a reduction in global yield growth rates for corn, wheat, rice and soybeans (Alston, Babcock and Pardey, 2010 and World Bank Report 2008).

Studies indicate that climate has been and will be severely affected by increases in CO_2 levels in the atmosphere. Changes in temperature, precipitation and solar radiation will affect yields with different intensity across regions (Ruttan 2002). Most agronomic studies of the effects of weather on crop yields are based on field experiments and are aimed to account for the biological effect of different temperatures on specific crops (Ritchie and Nesmith, 1991). Other studies use historical data to look into the effect of climate on crop yield in different regions. In the latter category, looking to the United States and other important agricultural producers, several authors have found that the impact of climate change on agriculture production will most likely be negative (Schlenker and Roberts, 2009, Lobell, Schlenker and Costa-Roberts, 2011, Fisher et al., 2012, Urban et al., 2012, and Nelson et al, 2014).

Yields reflect not only the impact of precipitation and temperature, but the decisions taken by individuals, given their market expectations. To understand yield performance, it is important to include not only the natural environment, but the market environment.[4] This includes prices expected to be paid for inputs and received for the products. Choices are made not just to increase yields but to obtain profits as a means of enterprise survival. Our study uses an agent-based decision making model to understand yield performance and the impact of weather variables on crop yields across a transect of the Great Plains of the U.S. We then compare our results with those in the literature that have only included weather variables.

Background

Lobell (2007) uses national crop yield data and climate and crop location datasets for 1961-2002 to estimate the impact of changes in the diurnal temperature range (DTR = Tmax - Tmin) on the cereal grain yields of major producing countries. He found a non-linear negative response of yields to increases in average temperature and a generally non-significant effect of increases in DTR, with positive or negative effects depending on the region.

Another global study by Lobell, Schlenker and Costa-Roberts (2011) include average monthly temperature but also precipitation and changes in the growing season. It studies the impact of changes in climate trends (1980-2008) on major crop yields (maize, wheat, rice and soybeans) at a country level scale. It reveals positive trends in temperature for nearly all major growing areas (excluding the United States) and smaller precipitation trends with mixed results across regions. A 1ºC increase in average temperature was found to decrease yields by up to 10% for low latitude countries and has mixed results for high latitude countries depending on the crop. Increases in precipitation have a positive effect on yields for most crops and countries but beyond a threshold level further increases become harmful. Observed average precipitation increase was higher than this threshold level thus the median estimated impact was negative. Additionally, the effect of precipitation was found to be less important than the effect of temperatures.

The studies mentioned above use average temperature to measure effects on yield. Another measure of temperature impact on yields that is increasingly used is the agronomic measure “growing degree days” (Zalom and Goodell, 1983 and Snyder, 1985)[5]. These measure the amount of time during the growing season during which the temperature was within specific ranges. Schlenker and Roberts (2009) use this concept to estimate the effect of weather on aggregate farm yields in the United States. They regress corn, wheat and cotton yields in counties east of the 100º meridian on weather variables during the years 1950-2005 using alternative specifications. They find that there is an increasing positive relation between temperatures and crop yield up to 29-32ºC (with variations depending on the crop). Temperatures above these thresholds are found to reduce yields significantly and at an increasingly negative rate. Precipitation was found to significantly affect yields. This effect follows an inverted U pattern with different levels of yield-maximizing values depending on the crop (25 inches for corn and 27.2 inches for soybeans).

Roberts, Schlenker and Eyer (2012) also use the growing degree days measure to estimate the impact of temperatures on corn yields in Illinois for the years 1950-2010. They consider the impact of extreme temperatures measured by extreme heat degree days, precipitation and vapor pressure deficit (VPD). Extreme temperatures were found to have a robust negative effect on yields. Precipitation effects were found to have an inverted U shape, consistent with previous studies, with yield maximizing levels lower than the observed mean in the specification that did not include VPD.

The studies mentioned have two important omissions. First, in the U.S. they mostly studied rain-fed agriculture[6], counties east of the 100º meridian. Irrigation developments from 1950's on have been an important source of production increases in general and specifically in the region west of the 100º meridian in the U.S Plains. Second, their studies control for the natural environment, precipitation and temperature, which are not under the control of farmers, but do not allow a role for human decision making in the production process. Yields used in these studies are a result of human management decisions as well as the natural environment. How much and what to produce as well as how much and which inputs to use are producers' choices within the environment they face. This environment includes prices received and paid and the available technology, as well as natural phenomena. To understand aggregate yields it is important to allow for agent-based decisions as well as natural phenomena not under human control, which is the objective of this research.

Theoretical framework

We assume that production decisions are made by profit-maximizing farmers who operate under perfect competition in all commodities and factor markets. Farmers choose their optimum production and input requirements, subject to the production function $Y = f(X,e)$, output and input prices and the characteristics of the environment (weather, soil, etc), as the solution to the following problem

$$\max_X \ \pi = p \cdot Y - \boldsymbol{z} \cdot \boldsymbol{X} \ \ ; Y = f(X,e); \ p \gg 0, \boldsymbol{z} \gg 0 \ \ , \qquad (1)$$

where output per hectare is Y with price p, the variable input vector is $\boldsymbol{X}$ with corresponding price vector $\boldsymbol{z}$, and the environment variables are vector $\boldsymbol{e}$. Following Chambers (1988) the production function $f(\boldsymbol{X},\boldsymbol{e})$ is assumed to be finite, nonnegative, real valued, and single valued for all nonnegative and finite $\boldsymbol{X}$, everywhere twice-continuously differentiable, non-decreasing in $\boldsymbol{X}$, and quasi-concave, fulfilling the weak essentiality condition.

The first order interior conditions for profit maximization are,

$$\frac{\partial \pi}{\partial X_j} = p \cdot \frac{\partial Y}{\partial X_j} - z_j = 0, \ \mathrm{j} = 1, \dots, \mathrm{J} \quad . \tag{1.a}$$

From equations (1) and (1.a) and using logarithms:

$$\frac{\partial \ln f(\boldsymbol{X},\boldsymbol{e})}{\partial \ln X_j} = \frac{\partial f(\boldsymbol{X},\boldsymbol{e})}{\partial X_j} \cdot \frac{X_j}{f(X,e)} = \gamma_j = \frac{z_j}{p} \cdot \frac{X_j(\boldsymbol{z},\boldsymbol{e})}{Y} = s_j \ (\boldsymbol{z}, \boldsymbol{e}) \quad j = 1, \dots J \tag{2}$$

where γ_j is the production elasticity of input j and, under optimizing behavior, its share in total cost s_j. Thus under the conditions of this model, the production elasticity of input j is equal to the cost share of that input, capturing the essence of the firm's choice of input levels given expectations about natural circumstances as reflected by $\boldsymbol{e}$.

We are able to estimate the effect of the environmental variables $\boldsymbol{e}$ (degree days, precipitation and soil carbon) on yields as

$$\frac{\partial \ln f(\boldsymbol{X},\boldsymbol{e})}{\partial e_u} = \mu_u \qquad u = 1, \dots, U \quad , \tag{3}$$

where e_u is an environmental variable. This expression indicates the impact, expressed as a fraction of output, of a one-unit change in temperatures (measured in degree days) and of one percentage point change in precipitation and in soil carbon (both variables are in logarithms). Different from the estimates in previous studies, our estimates of the impact of weather variables are thus obtained from an agent-based model that controls for the simultaneous decisions made by the farmer given market as well as natural and technological conditions.

The following expression represents the rate of technical change (sometimes referred to as Total Factor Productivity change), expressed as a fraction of current production per unit change in *t*:

$$\frac{\partial \ln f(\boldsymbol{X},\boldsymbol{e},t)}{\partial t} = \frac{\partial TFP}{\partial t} \quad . \tag{4}$$

According to its effects on relative input productivity, the rate of technical change can be further characterized in terms of input biases. Bias in technical change reflects the effect of innovations on the use of various inputs. We choose to use Chambers' (1988) overall biases that measure changes in shares, rather than Hicksian pair-wise biases[7], as they are more intuitive, defined as:

$$B_j = \frac{\partial s_j(\boldsymbol{X},\boldsymbol{e},t)}{\partial t} \quad \forall\ j \quad . \tag{5}$$

Technological change is Hicks neutral if these biases are all zero, i.e., if t is separable for each of the j inputs. Technical change is said to be unbiased (or share neutral) if it does not affect the relative cost 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.

Empirical Model

Single equation estimates of the production function will be affected by biases and identification issues due to the firms' simultaneity in choice of output and inputs. A system of equations that estimates jointly the production function and the inverse input demand equations in (2) allows for endogeneity of input choice and makes it obvious that the output produced and the inputs used are manifestations of a single decision making process tempered by expectations about natural phenomena. The estimates of the weather impact in (3) control for the farmers' market behavior given expectations about weather and should be different than pure technical responses measured on experimental plots. Models that do not explicitly account for this behavior will err in indicating the impact of weather on yields because they do not account for adaptive decision-making.

For this application the semi-transcendental logarithmic functional form (Christensen, Jorgenson and Lay, 1973) is chosen to approximate the production function in (1) and the corresponding shares in (2).[8] This specification is flexible as it provides a local second order approximation to any production technology, minimizing a priori restrictions on its structure. The following system of equations[9] is estimated:

$$y_{it} = \alpha_0 + \sum_{j=1}^{3} \beta_j x_{ijt} + \frac{1}{2}\sum_{j=1}^{3}\sum_{k=1}^{3} \beta_{jk} x_{ijt} x_{ikt} + \sum_{w=1}^{3} \omega_w d_{iwt} + \sum_{w=1}^{3} \omega_{w3} d_{iwt} x_{i3t} +$$

$$\theta_1 r_{it} + \frac{1}{2}\theta_{11} r_{it}^2 + \theta_{13} r_{it} x_{i3t} + \theta_2\, som_{it} + \theta_{23} som_{it} x_{i3t} + \tau_1 t + \frac{1}{2}\tau_2 t^2 + \sum_{j=1}^{3} \varphi_j t\, x_{ijt},$$

$$s_{1it} = \beta_1 + \beta_{11} x_{i1t} + \beta_{12} x_{i2t} + \beta_{13} x_{i3t} + \varphi_1 t \qquad (6)$$

$$s_{2it} = \beta_2 + \beta_{21} x_{i1t} + \beta_{22} x_{i2t} + \beta_{23} x_{i3t} + \varphi_2 t$$

where i = 1,…,101 are counties; t = 1,…,49 are years introduced as a proxy for technology; j, k = 1, 2, 3 are controllable factors of production, fertilizer, chemicals and irrigation respectively and w = 1, 2, 3 are the temperature intervals. Under the assumption of constant returns to scale, the output and all the inputs have been divided by land.[10] For each county i and each year t, y_{it} is logarithm of biomass yield Y; s_{1it} is the share of fertilizer, s_{2it} is the share of chemicals, x_{it} is a vector of the logarithms of fertilizer and chemicals per hectare, and the fraction of agricultural land irrigated; t is a proxy for technical change measured as years since the beginning of the analysis starting with 1960 = 1; *som* is the logarithm of the level of soil organic matter; r_{it} is the logarithm of precipitation; and $\boldsymbol{d}_{iwt}$ is a vector of degree days intervals. The coefficients α_0, β_j, β_{jk}, ω_w, ω_{w3}, θ_1, θ_{11}, θ_{13}, θ_2, θ_{23}, τ_1, τ_2, and φ_j are the parameters to be estimated.

We included the interactions between variables that represent farmer's choices of inputs (fertilizer, chemicals and irrigation), and technology (time trend). In addition we account for the environmental variables (soil organic matter, 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 land.

The properties of equality of coefficients across equations as well as symmetry, are imposed before estimation while monotonicity and quasiconcavity are checked at each data point after estimation. Monotonicity requires that the marginal product of all inputs be nonnegative or that the estimated share be nonnegative. Quasiconcavity requires that the determinant of the bordered Hessian be negative semidefinite.

Since the Cobb-Douglas production function (Cobb and Douglas, 1928) is nested in the translog production function when all second order coefficients are zero, we use a Wald test to check if the former is as good as the latter in capturing this technology.

Equations (6) are jointly estimated using a three stage least squares approach (Zellner and Theil, 1962). Since the farmers take decisions about the desired yield and the amount of fertilizer and chemicals needed to produce it simultaneously, an instrumental variables approach is used to avoid further 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.[11]

As established in equation (2) 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}. These elasticities vary with time (t) and county inputs (i, j) in the following way:

$$\gamma_{ijt} = \left(\frac{\partial y_{it}}{\partial x_{ijt}}\right) = \left(\frac{\partial Y_{it}}{\partial X_{ijt}}\right) \cdot \left(\frac{X_{ijt}}{Y_{it}}\right) = \beta_j + \sum_{k \neq j}^{3} \beta_{jk}\, x_{ikt} + \varphi_j\, t \qquad (7)$$

The most important results of our study are found in estimates of the impact on yields of the natural environment $\boldsymbol{e}$, in particular the weather variables that condition management decisions. Per equation (3) the following semi-elasticity captures the impact of degree days:

$$\mu_{ddit} = \frac{\partial y_{it}}{\partial d_w} = \omega_w + \omega_{w3} x_{i3t} \qquad w = dd0030, dd3035, dd35 \qquad (8)$$

while the precipitation and soil carbon elasticities are:

$$\mu_{somit} = \frac{\partial y_{it}}{\partial som_{it}} = \theta_2 + \theta_{23} x_{i3t} \quad (9)$$

$$\mu_{rit} = \frac{\partial y_{it}}{\partial r_{it}} = \theta_1 + \theta_{11} r_{it} + \theta_{13} x_{i3t} \quad (10)$$

As stated in equation (4), the first derivative of the production function with respect to the time trend *t*, used as a proxy for technical change, can be interpreted as the primal rate of technical change in county *i*, year *t*:

$$\frac{\partial y_{it}}{\partial t} = \tau_1 + \tau_2 t + \sum_{j=1}^{3} \varphi_j x_{ijt} \quad (11)$$

The biases in technical change (5) also vary with time and input use and are:

$$B_j = \frac{\partial s_j}{\partial t} = \varphi_j , \quad \forall j \quad (12)$$

If $B_j > 0$ the technical change is biased toward input *j*; if $B_j < 0$ the technical change biased against input *j*. In this way we are able to estimate if agricultural technical change in the Great Plains has been biased for or against the use of irrigation, important in the context of this study.

Data description

The unit of analysis is the county, the area of analysis consists of 101 counties spread along the 41º N latitude parallel in the U.S. Midwest, examined over the period 1960-2008. This area is chosen because it encompasses an 800-mile climatic gradient from the Rocky Mountains to the Mississippi River that includes 47 counties in Nebraska, 47 counties in Iowa, 4 counties in Colorado and 3 counties in Wyoming (figure 1). The area ranges from rain-fed crops with high precipitation and high soil carbon in the east to highly irrigated crops with low precipitation and moderate soil carbon in the west. This vast gradient of weather, soil and ground water characteristics makes this region ideal for re-evaluating the impact of weather on production.

[Figure 1]

The dependent variable is the logarithm of the total amount of agricultural biomass produced (a more general measure than individual crop production) in the county, in dry megagrams (Mg) per hectare planted (harvested crop plus estimated crop residual, aggregated across all crops). Coefficients used to convert to megagrams from bushels were 0.0254 for corn, sorghum and rye and 0.0272 for wheat and soybeans.

The unharvested biomass for each crop was estimated by multiplying the reported harvested production by one minus the respective harvest index, where this index is the fraction of the above-ground biomass that is usually harvested according to the agronomic literature (Hay, 1995; Unkovich et at., 2010). The following harvest indexes were used: 0.50 for corn and sorghum for grain; 1.00 for corn and sorghum for silage and hay; 0.40 for soybeans, and 0.35-0.85 for rye and barley and other minor crops.

The estimated total production for each crop was converted to dry matter (DM) by multiplying the metric tons produced by one minus the respective moisture index of that crop. The indexes used follow Loomis and Connor (1992): 0.145 for corn and sorghum for grain, 0.145 for barley and rye; 0.55 for corn and sorghum for silage; 0.135 for wheat; 0.13 for soybeans and beans and 0.10-0.78 for other minor crops.

The county-level yields were obtained by dividing the biomass produced by the total planted area for all crops for each county. Annual harvested production and planted land data were obtained from the U.S. Department of Agriculture's National Agricultural Statistical Service (USDA-NASS).

The independent variables under farmers' control include quantities of fertilizer and chemicals, and the fraction of planted area that was irrigated. The variables not under farmers' control are the environmental variables. These are soil organic matter, precipitation and degree days.

Fertilizer and chemical inputs are measured as implicit indexes of quantity per hectare planted. These indexes were estimated from the county expenditures on these inputs published by the Census of Agriculture as reported by USDA-NASS. The quantity indexes were constructed for each census year by dividing the reported total expenditure by price indexes obtained from USDA-ERS for fertilizers and USDA-NASS for chemicals (base 1990-1992=100). These implicit quantities were then divided by total planted area to obtain indexes of quantities applied per hectare by county and census year. Since the census is done generally every five years, the missing years were estimated by linear interpolation of these county quantity indexes between census years (implying an inelastic demand for these inputs between census years). Finally, these indexes were divided by the index in Adams County, Nebraska, for year 1960, converting them to a multilateral index.

The irrigation variable is the ratio of planted land that has been irrigated to total planted land. There is an important variability in percentage of irrigated land across time and space with higher values in the center of Nebraska and zero values in Iowa[12].

To account for the differences in soil quality we include average megagrams (Mg) of soil organic matter (SOM) per hectare for each county. This variable was obtained from Lakoh (2012). Using 2010 data on Soil Organic Carbon (SOC) from the Soil Survey Geographic Database (SSURGO), Lakoh estimated average SOC levels per county for 2010, then estimated levels for the period 1960-2008 retroactively from 2010 initial values using modified versions of the DK model as described by Liska et al. (2014). An approximate SOC to soil organic matter (SOM) conversion factor of 2.0 was then applied to convert the series to SOM (Liska et al., 2014).

Turning to the weather variables, data on degree days and precipitation were estimated from weather station data collected from the United States Historical Climatology Network. From these data, a county average daily precipitation value (in centimeters) and county average daily maximum and minimum temperatures were constructed from temperature and precipitation results for each day during the growing season (March to August). To obtain county-level values for these daily observations, we used a weighted average of data from the 5 closest stations to the center of each county. For weighting, we used a Shephard inverse distance function:

$$u(q_k) = \sum_{i=0}^{5} \frac{b_{ik}\, q_i}{\sum_{j=0}^{5} b_{jk}}, \qquad \text{where } b_{ik} = \frac{1}{{d_{ik}}^2}, \tag{13}$$

where q_k denotes the interpolated value for county k, q_i is the measurement at weather station i, and d is the distance from the weather station i to the center of county k. These daily data at the county level were then used to construct the yearly precipitation and degree days data for each county.

To measure the impact of temperatures on yield we use an adaptation of the agronomic measure “growing degree days.” Following this literature, a growing degree day is defined as the amount of time (in days) where the temperature is above a certain threshold; one degree-day is accumulated when the temperature is one degree above the threshold for a 24-hour period (Ritchie and Nesmith, 1991). To estimate degree days we adapt Snyder’s (1985) method, which uses a bell-shaped curve to estimate from maximum and minimum daily temperatures the number of hours during the day that the temperature was within a specific interval. We convert these values into fractions of a day, then sum the fractions over the growing season to provide the variables for this analysis[13].

We constructed growing season degree day variables for three intervals that cover all the temperatures higher than 0ºC. The lower temperature interval, *dd0030*, covers the degree days from 0ºC to less than 30ºC, the next interval, *dd3035*, covers the range 30ºC to less than 35ºC and the higher temperatures interval, *dd35plus*, covers temperatures equal or higher than 35ºC.

Figure 2 depicts the average numbers of degree days for the growing season for the hottest degree day interval, *dd35plus*. It can be seen that there is an increasing amount of time with temperatures higher than 35ºC moving from eastern Iowa to western Nebraska.

[Figure 2]

[Figure 3]

The precipitation variable used is the logarithm of the total amount of precipitation, in centimeters, accumulated during the growing season. To construct these values, the estimated daily values for each county (weighted averages constructed using equation 13) were added for March through August. As shown in figure 3, there is a substantial decrease in average precipitation towards the West. In counties in eastern Iowa the average yearly precipitation was near 60 cm, in counties in western Nebraska, Colorado and Wyoming the average yearly precipitation was below 30 cm.

As seen in figure 2 and figure 3, the area of study shows a rich variability in weather variables. Precipitation increases towards the East and temperature degree days increase toward the West.

Summary statistics are presented in table A.1 in the Appendix.

Results

The parameters obtained by the joint estimation of equations (6), using iterated Three-Stage Least Squares, are shown in table A.2 in the Appendix. Before focusing on weather effects, we discuss the characteristics of the technology estimated and results of post estimation tests. Of the 25 parameters estimated, 22 are significantly different from zero at the 99% confidence level. The pseudo R squared is 0.702. Although this standard goodness of fit cannot be interpreted as the proportion of the variance explained when estimating a three-stage least squares system of equations, it still provides a useful indication of the overall predictive power of the estimators (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 rejects the hypothesis that all the inputs are additively separable ($\forall\ j, k$) and strongly separable ($\forall\ j \neq k$), meaning that the translog specification is preferred to a Cobb-Douglas specification.

We employ a "pairs bootstrap" methodology (Freedman, 1981) for the estimation of the standard errors. Following MacKinnon (2002) and Flachaire (2004) pairs bootstrapping gives robust estimates under heteroskedasticity. Additionally, we estimated the system using standard 3SLS to check for robustness of results and found no qualitative changes in the significance of the estimated parameters.

Evaluated at the average of the observations, the technology is monotone for all the inputs, but this is not true at each data point. The percentages of monotonicity violations are 1.71% for fertilizer, 2.57% for chemicals and 0% for irrigation. The determinants of the bordered Hessian indicate quasiconcavity violations at 11.34% of the observations. Given the lack of irrigation in Iowa we do not account for this state in the previously reported monotonicity and quasiconcavity violations since it is not possible to estimate the bordered Hessian matrix for a translog specification when some inputs are equal to 0.

The elasticities of production estimated as described in equation (7) are shown in table 1. Since the translog specification allows the estimation of the elasticities for each data point, we only show average elasticities for each variable. The standard errors included in the table are evaluated at the means of the variables and they were estimated using the delta method.

[Table 1]

The production semi-elasticity of irrigation is significantly different from zero at the 95% confidence level, while the other elasticities are significant at the 99% confidence level. Our estimate of the production elasticity of fertilizer (0.193) is greater than Saha, Shumway and Havenner (1997) and Headley (1968), Hayami and Ruttan (1970) and Griliches (1963) who find values from 0.10 to 0.17. Our estimate of the production elasticity of chemicals (0.167) is greater than Ball's (1985) estimate of 0.057. The semi-elasticity of irrigation implies an increase in yields of 36.6% when irrigating[14]. This estimate is much higher than the Coelli and Rao (2005) estimate of 14.1% for the whole United States during 1980-2000. The interaction coefficients of irrigation and fertilizer and irrigation and chemicals reflect a positive effect of irrigation on fertilizer productivity and a negative effect on chemicals productivity. Additionally, if we only account for the counties that have any irrigation (counties in Nebraska, Colorado and Wyoming (NCW hereafter)) the average semi-elasticity of irrigation rises to 0.53; the exclusion of Iowa significantly shifts the estimate of this average elasticity. Except for Iowa where no irrigation is present due to adequate precipitation, the counties in the remaining states (NCW) compensate for lower levels of precipitation with higher levels of irrigation. By increasing irrigated land these counties are able to obtain yields similar to Iowa rainfed counties. Figure 4 shows the relationship between biomass yields and share of irrigated land in our study.

[Figure 4]

Table 1 also includes the average production elasticity for soil organic matter (SOM). This elasticity was found to be positive and significant at the 95% confidence level, indicating that a 10% increase in SOM induces a 0.13% increase in yields. This variable is more important in Iowa as the average elasticity for these counties is 0.07 while the estimate for the counties in NCW is close to zero.

The estimated rate of technical change, also known as the rate of total factor productivity (TFP) change, was calculated using equation (11). As shown in table 1, the estimated average rate of technical change during 1960-2009 is 0.3% per year. This is lower than the 1.78% estimated by Alston, Babcock and Pardey (2010) for all of U.S. agriculture in 1949-2002 and lower than the 1.56% calculated by the USDA-ERS (2015) in 1960-2008. We note that many counties in the NCW irrigated areas have improved their relative rate of technical change from 1960 to 1980 and that the dispersion of the rate across counties has decreased considerably.

Using a Wald test, the hypothesis of Hicks neutrality was rejected. Table 2 shows the biases of technical change calculated using equation (12) and their standard errors. Technical change was fertilizer- and chemical-using and irrigation-saving. These results can be taken as evidence of a shift in the production technology that induced the use of commercial inputs and an increase in the efficiency of water use for irrigation, both consistent with expectations.

[Table 2]

Weather Impact

We focus now on the impacts of weather variables on yields and on decision making in agriculture of this Midwest region, the issue of interest in this study. Similar to other authors, we find a non-linear increasingly negative effect of higher temperatures on crop yields. While temperatures lower than 30ºC were found to have a positive effect on yields, higher temperatures have an increasing negative impact. Table 3 shows the marginal impact of each degree day interval on expected yield.

[Table 3]

The higher temperatures are of interest here. Our estimates indicate that for each extra day of temperatures between 30ºC and 35ºC, yields are expected to be reduced by 1.6 %. For even higher temperatures, above 35ºC, each extra day of exposure is predicted to decrease yields by 23.0%. Comparing our results with those of Schlenker and Roberts (2009), we find similar impacts of temperatures up to 35ºC, but above this threshold, they estimate yield reductions of about 6% for each day of exposure, compared to our estimate of 23.13%. Roberts, Schlenker and Eyer (2012) find similar estimates to ours for temperatures between 10ºC and 29ºC. For days with temperatures higher than 29ºC they estimate a negative effect of 6.2%, which is not inconsistent with our estimates of 1.6% for 30-35 degree days and 23.13% for days above 35ºC[15]. These two studies focused on corn and soybean yields in rain fed counties in the U.S. east of the 100th meridian and their models give no role to management. We instead use an economic decision-making model focused on total biomass yields in a subset of counties in Iowa, Nebraska, Colorado and Wyoming that include rain-fed and irrigated agriculture.

Our estimates indicate that converting land from rainfed to irrigated production decreases the negative effect of an extra day with high temperatures by 58%. Figure 6 depicts the marginal effects of temperatures for counties in Iowa versus counties in the remaining states (NCW). We observe that, given the lack of irrigation in Iowa, the negative impact of degree days (-31% per 24 hours above 35 ºC) is more severe than in the counties in the states that use irrigation to counter higher temperatures (-15% per 24-hours above 35 ºC). These temperature-irrigation interactions on Midwest agriculture yields, are new and not found in any of the previous studies.

[Figure 6]

Irrigation thus alleviates much of the harmful effect of higher temperatures. By converting a hectare of land from rainfed to irrigated production, about three-fourths of the negative impact of high temperatures on biomass yields is ameliorated[16].

With respect to precipitation, our estimates of the effects in individual counties were highly significant, but when we average these effects and their standard errors as in table 3, we found that the average effect was only marginally significant statistically[17]. Similar to Lobell (2007), Schlenker and Roberts (2009) and Roberts, Schlenker and Eyer (2012), we found that the effect of this variable follows an inverted U shape. Because of the negative interaction coefficient between irrigation and rainfall, the amount of rainfall during the growing season that maximizes yield is affected by irrigation: it is 47.51 cm with no irrigation[18], compared to 35.13 cm under irrigation. This difference is 12.38 cm. Irrigation substitutes for about 12.38 cm, or about 25%, of natural rainfall during the growing season. The negative interaction coefficient for irrigation and precipitation means both that the marginal product of precipitation is lower under irrigation and that the marginal product of irrigation is lower as precipitation increases, both of which are inherently logical and expected.

Conclusions

This study provides evidence of the impact of weather on irrigated and rainfed agricultural production in the Great Plains. We show that irrigation increases biomass yields in this region by about 36.6%, that extreme temperatures decrease biomass yields by 1.6% for each 24-hours subjected to 30ºC and 35ºC temperatures and 23% for each 24- hours above 35ºC. Our results further show that irrigated agriculture reduces these adverse impacts by about 58%. The estimated effect of growing season precipitation follows the expected inverted U shape, with maximum yields occurring at about 47.51 cm without irrigation, and 35.13 cm with irrigation.

In contrast to agronomic studies of yield, this economic study includes the results of both weather and decisions made by farmers given their market and natural environments. This improves our estimates of weather effects by adjusting them to account for adaptive behavior by farmers in their choice of irrigation and quantities of fertilizer and chemicals.

Our results are *qualitatively* similar to Schlenker and Roberts' (2009) findings but provide additional information. First, we are able to disentangle the yield impacts of unabated weather itself from the effects of management on weather impacts. In the absence of this interaction information, as is the case for most weather-yield studies, the effects of weather itself are likely to be underestimated. Second, we estimate that the harmful effect of temperatures above 35ºC can be substantially offset by the use of irrigation. In semi-arid areas like western Nebraska and eastern Colorado and Wyoming, for example, farmers compensate for both higher temperatures and lower precipitation by choosing high levels of irrigation. Hence, the transformation of rainfed to irrigated land is an effective mechanism to cope with possible increases in average temperatures. Third, we are able to estimate the contribution of fertilizer and chemicals to yield changes; with production elasticities of 0.19 and 0.17, respectively. Fourth, we find that technical change in this region and during the period of analysis was, on average, 0.3%, and was fertilizer and chemicals using.

Our results quantify the critical effects that high temperatures have on agricultural productivity in the context of an agent-based model. Given the climatic and hydrologic variability observed in our area of analysis, these conclusions might be representative of other temperate regions of the world.

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Tables and Figures

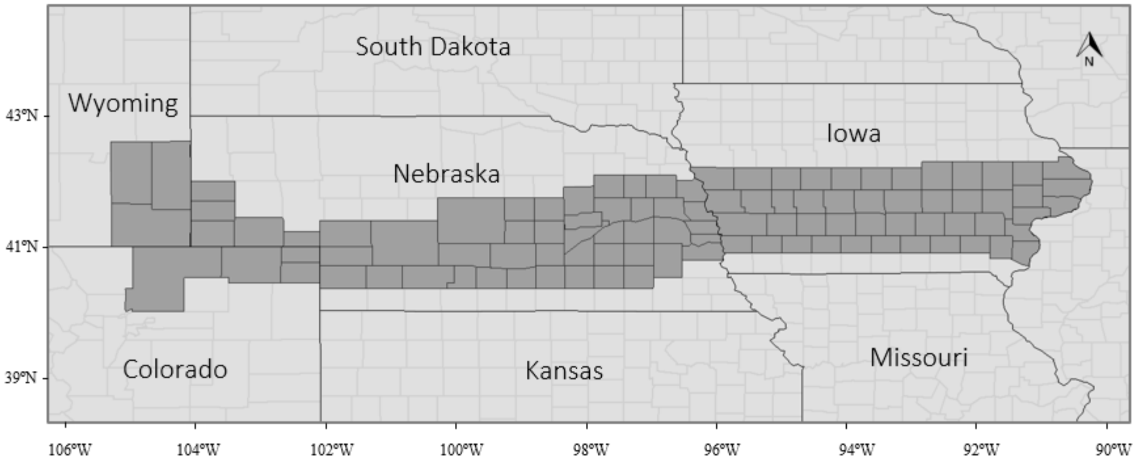

Figure 1. Study counties along the 41st parallel north

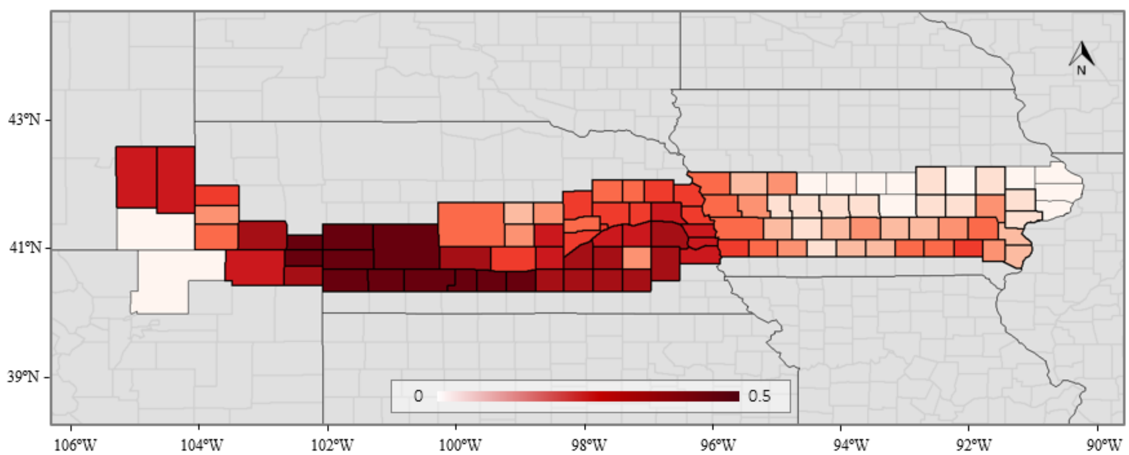

Figure 2. Average number of degree days above 35°C during the growing season in study counties, 1960-2008

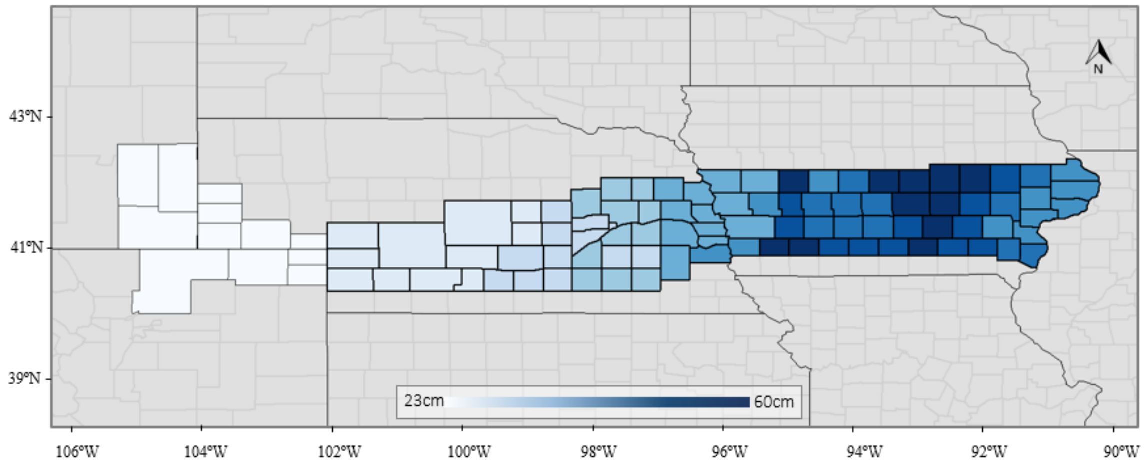

Figure 3. Average growing season precipitation (cm) in study counties, 1960-2008

Table 1. Elasticities and Semi-elasticities of Production Estimated at their Means in Study Counties along the 41st Parallel North in Iowa, Nebraska, Colorado and Wyoming, 1960-2008

Variable	Elasticity	Std. Err.
Fertilizer	0.193	0.005
Chemicals	0.167	0.007
Irrigation ratio	0.366[a]	0.047
Soil organic matter	0.013	0.016
Time Trend	0.003[a]	<0.001

[a]semi-elasticity

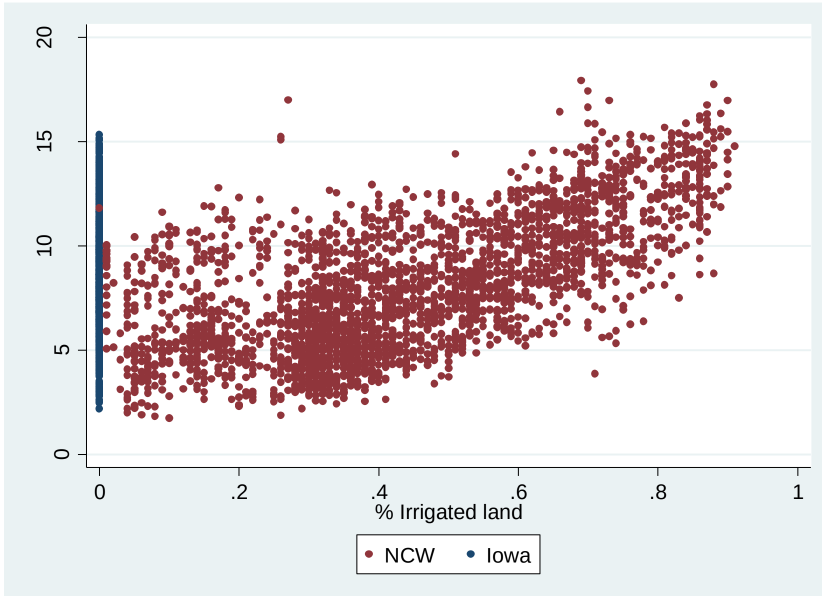

Figure 4. Yield (Mg per ha) (online) and percentage of irrigated land in counties in Iowa, Nebraska, Colorado and Wyoming (NCW), 1960-2008

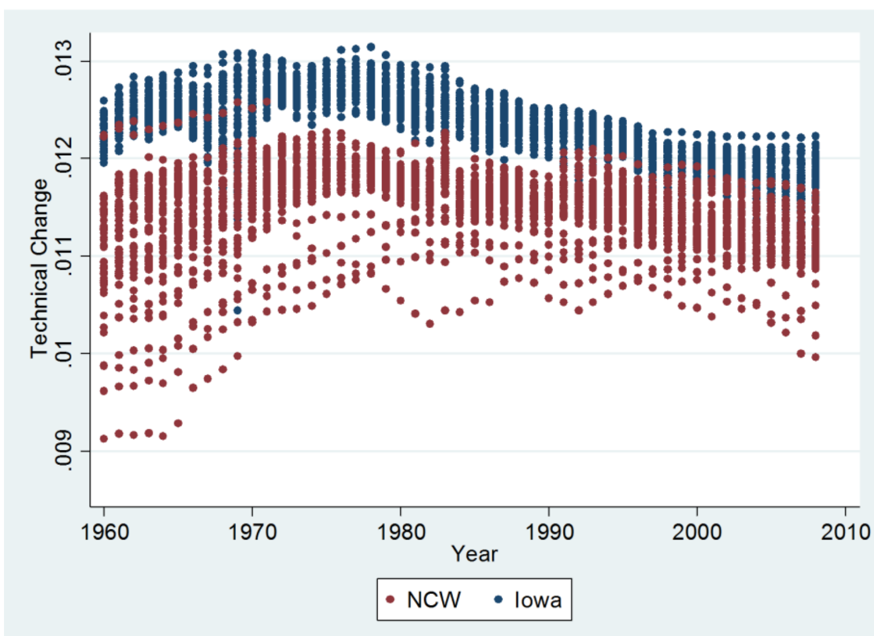

Figure 5. Estimated rate of technical change per year for each county in selected counties of Iowa, Nebraska, Colorado and Wyoming, 1960-2008

Table 2. Biases of Technical Change Estimated at their Means in Study Counties along the 41st Parallel North in Iowa, Nebraska, Colorado and Wyoming, 1960-2008

Input	Bias	Std. Err.
Fertilizer	0.0005	<0.001
Chemical	0.0004	<0.001
Irrigation	-0.00023	0.0008

Table 3 – Average Impact of Weather Variables on Biomass Yields, Estimated in Study Counties along the 41st Parallel North in Iowa, Nebraska, Colorado and Wyoming, 1960-2008

Variable	Marginal effect	Std. Err.
dd0030 (days)	0.0036	0.0070
dd3035 (days)	-0.0169	0.0026
dd35plus (days)	-0.2631	0.0303
Precipitation (ln(cm))	-0.0637	0.0197

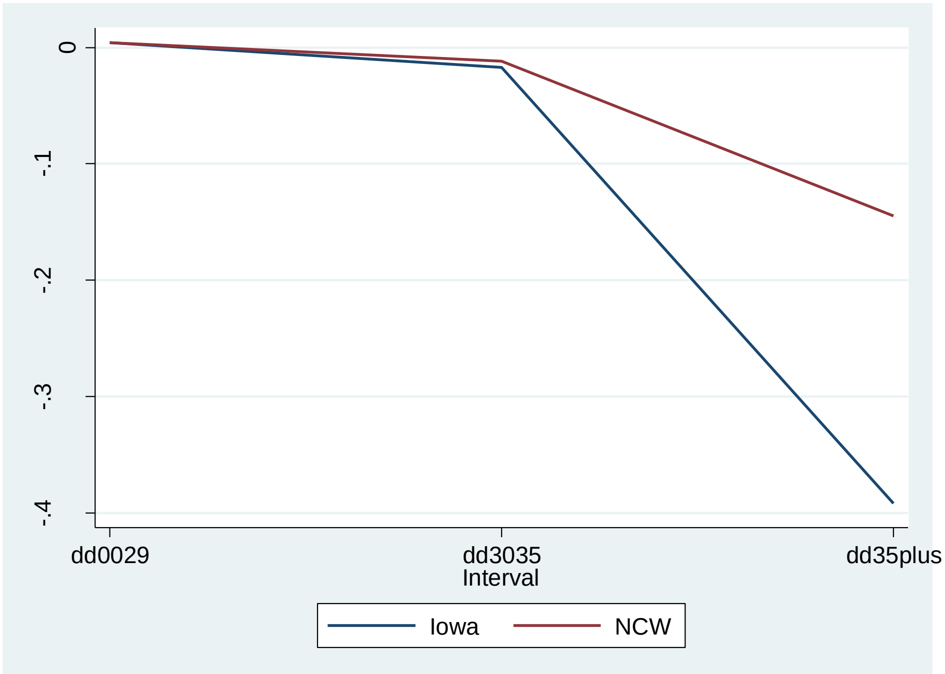

Figure 6. Marginal effect of degree day temperature intervals on biomass yield for subset of counties in Iowa, Nebraska, Colorado, and Wyoming, 1960-2008

Table A.1 - Summary Statistics in Study Counties along the 41st Parallel North in Iowa, Nebraska, Colorado and Wyoming, 1960-2008

Complete region (101 counties)				
Variable	Mean	Std. Dev.	Min	Max
Chemicals	13.18	7.12	0.24	44.52
Irrigation ratio	0.23	0.27	0.00	0.91
SOM (Mg/ha)	136.53	49.17	46.55	316.70
Time period	24.00	14.15	0.00	48.00
Precipitation (cm)	51.20	15.68	11.94	125.73
dd0030	164.44	5.54	147.68	178.83
dd3035	4.05	2.26	0.14	12.78
dd35plus	0.13	0.22	0.00	1.90
Share Fertilizer	0.06	0.02	0.00	0.25
Share Chemicals	0.03	0.01	0.00	0.10

	Iowa (47 counties)				Nebraska (47 counties)			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Fertilizer	21.56	6.34	0.27	44.40	17.92	8.65	0.04	48.19
Chemicals	16.38	6.45	2.62	44.52	10.79	6.54	0.24	32.28
Irrigation ratio	-	-	-	-	0.45	0.22	0.00	0.91
SOM (Mg/ha)	175.89	39.01	101.08	316.70	106.33	24.12	62.67	175.80
Time period	24.00	14.15	0.00	48.00	24.00	14.15	0.00	48.00
Precipitation (cm)	58.80	13.96	23.01	125.73	46.80	13.35	12.83	111.71
dd0030	165.89	5.45	147.68	178.83	163.50	5.29	148.83	177.27
dd3035	3.21	2.09	0.14	12.78	4.92	2.13	0.26	12.05
dd35plus	0.06	0.17	0.00	1.56	0.20	0.25	0.00	1.90
Share Fertilizer	0.06	0.02	0.00	0.16	0.06	0.03	0.00	0.25
Share Chemicals	0.03	0.01	0.01	0.10	0.03	0.01	0.00	0.08

	Colorado (4 counties)				Wyoming (3 counties)			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Fertilizer	15.48	6.21	1.21	32.10	10.07	4.59	0.78	21.93
Chemicals	9.46	6.23	1.08	27.50	5.50	3.13	0.41	11.24
Irrigation ratio	0.35	0.14	0.01	0.68	0.43	0.14	0.17	0.83
SOM (Mg/ha)	88.31	16.26	60.44	108.30	57.00	10.71	46.55	73.20
Time period	24.00	14.18	0.00	48.00	24.00	14.19	0.00	48.00
Precipitation (cm)	32.99	7.03	15.14	51.92	25.39	6.73	11.94	41.99
dd0030	161.47	4.94	148.96	174.28	160.58	4.98	147.69	172.34
dd3035	4.41	2.12	0.27	9.18	3.04	1.72	0.26	8.09
dd35plus	0.20	0.20	0.00	0.91	0.12	0.16	0.00	0.82
Share Fertilizer	0.06	0.02	0.00	0.11	0.05	0.03	0.00	0.15
Share Chemicals	0.03	0.01	0.00	0.07	0.02	0.01	0.00	0.05

Table A.2 - Parameters Estimated Using Iterated Three-stage Least-Squares

Three-stage least-squares regression, iterated

Equation	Obs	Parms	RMSE	"R-sq"	chi2	P
lny	4949	25	.1916884	0.7022	100523.88	0.0000
sharefert	4949	4	.0295918	0.3451	1467.25	0.0000
sharechem	4949	4	.0162825	0.5987	6747.21	0.0000

(1) [sharefert]lnchempha60 - [sharechem]lnfertpha60 = 0
(2) - .5*[lny]lnfertpha60sq + [sharefert]lnfertpha60 = 0
(3) - [lny]fertha_chemha + [sharefert]lnchempha60 = 0
(4) - [lny]x1_fertha + [sharefert]x1 = 0
(5) - [lny]fertha_t + [sharefert]t = 0
(6) - .5*[lny]lnchempha60sq + [sharechem]lnchempha60 = 0
(7) - [lny]x1_chemha + [sharechem]x1 = 0
(8) - [lny]chemha_t + [sharechem]t = 0
(9) - [lny]lnfertpha60 + [sharefert]_cons = 0
(10) - [lny]lnchempha60 + [sharechem]_cons = 0

	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Normal-based [95% Conf.	Interval]
lny						
x1	1.897078	.3832981	4.95	0.000	1.145828	2.648329
lnfertpha60	.0833962	.0011319	73.68	0.000	.0811778	.0856147
lnchempha60	.0197663	.0005874	33.65	0.000	.018615	.0209177
lnx6	2.403443	.1691807	14.21	0.000	2.071855	2.735031
lnx5	.0658375	.0162649	4.05	0.000	.0339589	.0977161
x1sq	.0946995	.0671738	1.41	0.159	-.0369587	.2263576
lnfertpha60sq	.0591603	.0035104	16.85	0.000	.0522801	.0660406
lnchempha60sq	.041926	.0024152	17.36	0.000	.0371923	.0466597
lnx6sq	-.3119567	.0210561	-14.82	0.000	-.353226	-.2706874
x1_fertha	.0121514	.0020195	6.02	0.000	.0081932	.0161096
x1_chemha	-.0140799	.0011928	-11.80	0.000	-.0164178	-.0117419
x1_x6	-.2198005	.0431516	-5.09	0.000	-.304376	-.1352249
x15	-.2706849	.0404083	-6.70	0.000	-.3498838	-.191486
fertha_chemha	-.012756	.0014155	-9.01	0.000	-.0155303	-.0099816
dd0030	.0030203	.0006389	4.73	0.000	.001768	.0042726
dd3035	-.0224774	.0027797	-8.09	0.000	-.0279254	-.0170293
dd35plus	-.374998	.0344756	-10.88	0.000	-.4425689	-.307427
dd0030x1	.0030523	.0018099	1.69	0.092	-.000495	.0065995
dd3035x1	.0286606	.0061365	4.67	0.000	.0166333	.040688
dd35plusx1	.5771791	.0866024	6.66	0.000	.4074415	.7469167
t	-.0012032	.0010686	-1.13	0.260	-.0032977	.0008912
tsq	.0000602	.0000194	3.10	0.002	.0000222	.0000983
x1t	-.0032466	.0009228	-3.52	0.000	-.0050552	-.0014381
fertha_t	.0007974	.0000451	17.67	0.000	.0007089	.0008858
chemha_t	.0006428	.0000391	16.45	0.000	.0005662	.0007194
_cons	-3.706356	.3501841	-10.58	0.000	-4.392704	-3.020007
sharefert						
x1	.0121514	.0020195	6.02	0.000	.0081932	.0161096
lnfertpha60	.0295802	.0017552	16.85	0.000	.02614	.0330203
lnchempha60	-.012756	.0014155	-9.01	0.000	-.0155303	-.0099816
t	.0007974	.0000451	17.67	0.000	.0007089	.0008858
_cons	.0833962	.0011319	73.68	0.000	.0811778	.0856147
sharechem						
x1	-.0140799	.0011928	-11.80	0.000	-.0164178	-.0117419
lnfertpha60	-.012756	.0014155	-9.01	0.000	-.0155303	-.0099816
lnchempha60	.020963	.0012076	17.36	0.000	.0185961	.0233299
t	.0006428	.0000391	16.45	0.000	.0005662	.0007194
_cons	.0197663	.0005874	33.65	0.000	.018615	.0209177

Endogenous variables: lny sharefert sharechem lnfertpha60 lnchempha60 lnfertpha60sq lnchempha60sq x1_fertha x1_chemha fertha_chemha fertha_t chemha_t

Exogenous variables: x1 lnx6 lnx5 x1sq lnx6sq x1_x6 x15 dd0030 dd3035 dd35plus dd0030x1 dd3035x1 dd35plusx1 t tsq x1t fertpr1960 chempr1960 fertpr1960sq chempr1960sq fertpr60_x1 chempr60_x1 chempr60_t fertpr60_t fert_chem_pr1960

Footnotes

1. Support acknowledgements.

2. Corresponding author information.

3. Coauthors credentials

4. Nelson et al. (2014) use five crop models, two climate models, nine global economic models, and seven climate change scenarios to show that the impact of climate change in global agriculture require integration across these models.

5. A degree day is defined as 24 hours with temperatures one degree above certain threshold.

6. Except for Schlenker and Roberts 2009 when considering cotton yields.

7. Hicksian pair-wise biases are defined as the change in the marginal rate of substitution between two inputs as a result of technical change and their sum for each input result in the overall measure of bias in (5).

8. Quadratic production functions with many parameters relative to the number of observations might suffer from low precision and might result in imprecise parameter estimates. The joint estimation of the factor shares and the production function leads to higher efficiency since the higher information present in the joint estimation can compensate for the information inadequacy in the production function alone (Ray, 1982).

9. We have included only share equations for fertilizers and chemicals because we lack county level information on labor, capital, and cost of irrigation.

10. An estimation of an average yield function is preferable if the data being analyzed are subject to heteroskedasticity (Jacobs, Smith and Street, 2006).

11. Reg3 command in STATA version 12.0 was used for the econometric estimations.

12. Given the minimal levels of irrigation present in Iowa, USDA does not report the amount of planted land that was irrigated.

13. This is necessary because of the area under the approximation curve.

14. Given that irrigation is not a logarithm, the percentage change in yield will be given by exp(.263)=.2313.

15. We also ran an OLS regression of yields on weather variables and county dummies that is closer to the specification used by Schlenker and Roberts (2009). We again found a significant increasingly negative effect of higher temperatures on biomass yield.

16. The interaction coefficients between the degree day intervals and irrigation are the following (p-values in parenthesis): dd0030: 0.003 (0.0023); dd3035: 0.0286 (0.0069); dd35plus: 0.577 (0.070).

17. Coefficient estimates related to precipitation are all highly significant.

18. Grassini et al. (2011) report a 90 cm water supply required to achieve mean yield full potential, around 45% of it (~40.5cm) from seasonal water supply.