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U.S. Crop Yields Redux: Weather Effects versus Human Inputs

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a. Introduction:

Agriculture is a resource-intensive activity. It currently uses a substantial portion of the Earth's natural resources: crop production, pasture and livestock grazing systems occupy around 40% of total land area, nitrogen fertilizer applied to agricultural land comprises more than half of the global reactive nitrogen attributable to human activity and agricultural production consumes more fresh water than any other human activity since it accounts for 80% of all freshwater consumption (Cassman 2003). Water is one of the key determinants of agricultural land productivity. Adequate water supply to crops is essential to achieve maximum yield and greater stability, enabling also greater scope for diversification. The success of irrigation in improving food security and fostering rural welfare during the last decades is undeniable but inappropriate water management t can contribute to a series of environmental problems.

The dramatic increase in world crop production observed over the 40-year period from 1960 to 2000 was greater than the increase in the demand for these products producing a decrease in the real prices of the agricultural commodities. This increase in production was attributed to land expansion, but is also the result of increasing yields due to new technologies and management techniques, mechanization and an increase in the use of chemicals, fertilizers, pesticides and water from irrigation systems (Tilman et al., 2001). However, during the last decade several authors observed a reduction in global yield growth rates for corn, wheat, rice and soybeans (Alston et al., 2010 and World Bank Report, 2008) that was followed by an increase in prices after 2008 marking the end to the period of low agricultural commodity prices. Looking at total factor productivity (TFP)[1] growth, several authors found a slowdown in North America (United States and Canada), Oceania and Sub-Saharan Africa (Fuglie (2012), Ball et al. (2013) and USDA-ERS (2015)) when comparing the period 1990-2010 with previous years.

Looking into the future, it is estimated that world population will increase by 30% to reach more than 9 billion people by 2050; and given expected higher income, per capita consumption of protein will induce

[1] TFP growth rate is a multifactor productivity measure given by the growth rate of an output index minus the growth rate of an index of inputs. The growth rate of yields is a partial productivity measure referring to the growth of output per unit of land.

an increase in cereal production of at least 70% over current levels; quantity attainable without incorporating new land if the yield growth rates increase at least 1.33% per year (Fulginiti and Perrin, 2010). If the observed decline in agricultural productivity growth continues, the average global yield growth rate for the main crops could fall below 1.3% increase per year, lower than the amount needed to reach the production goal for 2050. Thus, the food production increases needed to satisfy future demand will put greater stress on existing cropland and natural resources; additionally, if the prices rise there will be also greater pressure to convert natural ecosystems to cropland. Climate change, a final source of concern, is likely to aggravate the situation.

During the last decades it has been a widespread accepted idea that climate is being severely affected by anthropogenic increases in CO_2 levels in the atmosphere. There are three channels through which this is likely to affect agricultural production: a) higher amount of CO_2 in the atmosphere may have a positive effect on some crop plants (but also on weeds) given that it can act as a carbon fertilizer; b) higher temperatures might produce an increase in the level of the oceans that could result in floods in coastal areas and salinization of the underground aquifers; and c) changes in temperature, precipitation and solar radiation will affect yields with different intensity across regions (Ruttan 2002). Focusing on this last issue, considering different scenarios of future trends in climate, several authors have found that the impact that climate change will have over agriculture production will most likely be negative (Lobell, 2007 and Schlenker and Roberts, 2009).

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 from different regions. Lobell (2007) uses national crop yield data for 1961-2002 and climate and crop location datasets to estimate the impact of changes in the diurnal temperature range (DTR = Tmax - Tmin) on the cereal grain yields of the major producing countries, finding 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 effect depending on the region. This study does not account for the effect of changes in precipitation, solar radiation and CO2 fertilization changes.

Another global study that includes average monthly temperature but also precipitation and changes in the growing season has been done by Lobell et al. (2011). They analyze at country scale the changes in recent climate trends (1980-2008) during the growing season of major crop yields (maize, wheat, rice and soybeans). Their results reveal significant positive trends in temperature changes for nearly all major growing areas (excluding the United States) and significantly smaller precipitation trends with mixed results across regions. Additionally, no consistent global shift in growing season of average precipitation was found. When analyzing the effect of these trends on the major crops yields, they found statistically significant impacts of average temperature and precipitation. A 1ºC increase in average temperature decreases 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 up to the point at which further increases become harmful; observed average precipitation was higher than this threshold value thus the median estimate was negative. Additionally, the effect of precipitation was found to be less important than the effect of temperatures.

All the studies mentioned above use average temperature to measure the effect of different temperatures on yield. Another measure that is increasingly used is the agronomic measure "growing degree days" (Zalom, 1983 and Snyder, 1985)[2]. Schlenker and Roberts (2009) use this measure 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 with different specifications finding that there is an increasing positive relation between temperatures and crop yield up to 29-32ºC (depending on the crop). Temperatures above these thresholds are found to reduce yields significantly at an increasingly negative rate. The effect of precipitation was found to be significant and

[2] A degree day is defined as 24 hours with the temperature one degree above certain threshold.

with an inverted U shape with different levels of yield maximizing values depending on the crop (25 inches for corn and 27.2 inches for soybeans).

Finally, Roberts et al. (2012) also use the growing degree days measure to try to estimate the impact of temperatures on Illinois corn yields for 1950-2010. They also consider a measure of extreme temperatures (extreme heat degree days), precipitation and vapor pressure deficit (VPD). Extreme temperatures were found to have a robust negative effect on yields, particularly in rain fed areas. Precipitation again was found to have an inverted U shape with yield maximizing level lower than the observed mean in the specification without VPD and higher in the specification with VPD. This study does not consider the effect of purchased farm inputs either.

Mentioned estimations have two important omissions. First, they only consider counties with rain-fed agriculture, those east of the 100º meridian, while production increases have also been related to irrigation developments mostly west of the 100º meridian. Second, their studies control for natural characteristics like precipitation but do not allow for purchased farm inputs that capture embodied innovations and reflect profit maximizing behavior of producers. These inputs have had a pivotal role in increased yields and are under the control of the farmer; it is important then to understand the contribution of these versus other inputs not under farmers' control.

All of the studies mentioned above omit applying agent-based decision models; prices, farmers' behavior and other human inputs are not taken into account when testing their hypotheses and in their estimations.

The economic perspective

The econometric estimation of production functions took impulse after the work of Cobb and Douglas in 1928. Initially it was mainly used for macroeconomic analysis but after a methodological paper by Tintner (1944) it was increasingly used in empirical agricultural microeconomic analysis (Tintner and Brownlee (1944), Heady and Dillon (1961) and Mundlak (1961)). The analysis was extended with the parallel development of the "dual" literature on cost functions, factor demand systems, and flexible functional forms that became more prevalent after the 1970s. The basic idea of duality is that every point in the production function is related uniquely with a vector of price ratios and vice versa. Hence, variations in prices will produce variations in quantities. Under duality, the technology is summarized by profit, cost or revenue functions (Mundlak, 2001). There is still a pending debate about the benefits and weakness of each type of approach with no conclusive results about which one is better.

To the more restrictive Cobb Douglas functional form, more flexible forms were added; the most important were the constant elasticity of substitution (CES) function (Arrow et al., 1961), quadratic functions (Heady and Dillon, 1961) and quadratic functions in logarithms (translog) (Christensen et al., 1973). These quadratic functional forms are considered to be flexible because they provide a second order approximation to the unknown true functional form. The problem with these forms is that they contain many variables that usually move together and, given the paucity of data, the estimated parameters usually have low precision. Under rational economic behavior, first order conditions of profit maximization allow estimation of a system of equations that includes the production function and the derived demand for inputs (or factor shares) allowing a more robust estimation given the additional information. (Mundlak 2001).

Griliches and Mairesse (1995) state that the empirical implementation of econometric production functions is affected by a number of issues such as the imposition of the correct functional form, the relevancy and the possibility of measurement errors in the data and the incorrect assumption of independence of the input variables. The problem of the independence of the variables is broadly explained by Marschak and Andrews (1944); in summary, the economist cannot assume that the amount of fertilizer or other inputs employed by the firm is independent of the firm's output because these inputs are chosen by the producer himself on a maximizing behavior, making the inputs endogenous and therefore the OLS estimates of the production function will be biased and will lack the desired econometric properties. One way to solve the simultaneity issue is to assume profit maximization and use the observed factor shares as estimates of the relevant production function parameters (Griliches and Mairesse, 1995).

Either by using a primal or a dual approach authors have estimated the incidence of different inputs on agricultural production in the United States. Griliches (1963) and Hayami and Ruttan (1970) estimate the production elasticity of fertilizer to be between .10 and .20; for chemicals, Ball (1985) estimates an increasing cost share, from 0.028 in 1948 to 0.08 in 1979. These two results differ from Antle and Capalbo (1988) who found lower values for the combined cost shares of fertilizer and chemicals, increasing from 0.04 in 1960 to 0.06 in 1980. For the rates of technical change there is even more variability; while Ray (1982) and Capalbo and Denny (1986) report increases between 1.3 and 1.8 percent per year for the period between 1962 and 1978, other authors found rates of technical change near zero or even technological regression (Hazilla and Kopp (1986) and Brown and Christensen (1981)). For further details and a review of the evolution of empirical work on production functions see Antle and Capalbo (1988) and Mundlak (2001).

While all the economic production function estimation studies account for human inputs and generally account for farmers' behavior and the prices of inputs, they neglect environmental variables. An important step towards understanding the evolution of agricultural production under different climate scenarios is to carefully estimate the effect that different temperatures and precipitation have on agricultural productivity without disregarding the inputs under farmers' control. Another issue of importance, given the developments of the last 60 years, is the study of rain-fed as well as irrigated agriculture. These are the objectives of our analysis; we do not know of any other study with these objectives that considers this set of variables and assumptions.

Another important characteristic of our analysis is its study area. We look at 101 counties spread along the 41st parallel north, from the Rocky Mountains to the Mississippi River; this is a major cereal production area in the United States and in the world. It includes a vast gradient of weather but also soil and underground water characteristics that are representative of agriculture in Nebraska and Iowa but also other regions in the world. This agro-ecosystem 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. Given the broad characteristics of this area, results obtained from this study are relevant to several other temperate crop regions in the world.

The remaining sections of this article are organized as follows. In the next two sections the theoretical and empirical models are described. The data used is presented after the empirical model followed by the results and the conclusions.

b. 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 a vector of output and input prices and the characteristics of the environment (weather, soil organic matter and year). Factors are assumed to be mobile and their rental prices are determined by their marginal product. We denote the variable input vector by X, output per acre or yield by Y, the corresponding price vectors as w and p respectively and the environment variables vector as e. The production possibility set T is defined as the set of all feasible input and output combinations given the environmental characteristics and is assumed to be closed, bounded, strictly convex and to exhibit constant returns to scale. Under these conditions, and since profit maximization is assumed, the competitive equilibrium can also be characterized at any point in time as the solution to the problem of maximizing profits subject to the technology, the environment and a vector of positive output and input prices:

$$\max_{X} \pi = \; p \cdot Y - w \cdot X \;\; ; (e; X, Y) \in T; \; p \gg 0, w \gg 0 \qquad (1)$$

The first order conditions are given by differentiation of the profit by each of the j inputs,

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

where X_j is the input j.

We can now define the primal yield meta-production function (common underlying production function of each county) that will take the general form:

$$Y = f(X, e) \tag{2}$$

Where, under constant returns to scale, the output and all the inputs have been scaled down by the land factor. An estimation of an average yield function is preferable if the data being analyzed are subject to heteroskedasticity (Jacobs et al., 2006).

Given profit maximization and perfect competition, from equations (1.a) and (2):

$$\frac{\partial \ln f(X, e)}{\partial \ln X_j} = \frac{\partial f(X, e)}{\partial X_j} \cdot \frac{X_j}{f(X, e)} = \frac{w_j}{p} \cdot \frac{X_j}{Y} = s_j \tag{3}$$

where s_j is the share of the input j in the total cost of production. The derivative of the log of the production function with respect to the log of the input j (i.e. the production elasticity of j) is equal to the cost share of that input in the total cost.

Single equation estimates are likely to be affected by biases and identification issues; a system of equations that estimates jointly the production function and first-order conditions of profit maximizing including equality and cross-equation parameter constraints, robustly captures the production and technical parameters since it is based on the assumption that the sample reflects both optimizing behavior as well as the technology. (León-Ledesma et al., 2010). The factor shares variations observed in the sample can be attributed to differences in the input ratios given the different possible locations along the production function (Mundlak, 2000). From the econometric point of view, the system of equations when, containing cross-equation parameter constraints, augments the degrees of freedom and might enhance the efficiency of the estimation and parameter identification (León-Ledesma et al., 2010).

Additionally, quadratic production functions with many parameters relative to the number of observations might suffer from low precision and might result in imprecise parameters. The joint estimation of the factor shares and the production function, with or without the binding constraint between the estimates of the production function and the share equations, 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).

Joint estimation of a system that includes the production functions and the factor shares allows estimation of technological change and its factor biases. As Antle and Capalbo (1988) explain, this change refers to variations in the production process as a result of improved ways of using existing resources (disembodied technical change), through variations in input quality (embodied technical change); or through the implementation of new processes and new inputs. If there is disembodied technological change, then it can be modeled as a shift in the production surface.

After specifying a functional form for the yield production function, the complete system that includes the production function and derived demand equations for inputs can be estimated jointly. The estimated parameters are then used to obtain elasticities, marginal effects, and other characteristics of the technology.

c. Empirical Model:

For the empirical application the production function in (2) is assumed to follow a semi transcendental logarithmic functional form (Christensen et al., 1973). Assuming a translog specification allows for more flexibility since it does not impose a priori restrictions on the structure of the technology (it allows for a non-linear relationship between the dependent variable and the factors of production) and provides a local second order approximation to any production frontier. The following semi translog production function is estimated:

$$y_{it} = \alpha_0 + \sum_{j=1}^{3} \beta_j x_{ijt} + \frac{1}{2}\sum_{j=1}^{3}\sum_{k=1}^{3} \beta_{jk} x_{ijt} x_{ikt} + \sum_{w=1}^{3} \omega_w d_{iwt} + \sum_{w=1}^{3} \omega_{w3} d_{iwt} x_{i3t} + \theta_1\, r_{it} + \frac{1}{2}\theta_{11}\, r_{it}^2 + \theta_{13} r_{it} x_{i3t} + \theta_2\, som_{it} + \theta_{23} som_{it} x_{i3t} + \tau_1\, t_i + \frac{1}{2}\tau_2\, t_i^2 + \sum_{j=1}^{3} \varphi_j t_i x_{ijt}, \qquad (4)$$

where i = 1,…,101 are the counties; t = 1,…,49 are the time periods; $j = k$ = 1,…,3 are factors of production, w = 1,…,3 are the temperature degree day intervals, *som* is level of soil organic matter and r is precipitation. The coefficients α_0, α_1, β_j, β_{jk}, τ_1, τ_2, φ_j, ω_w, ω_{w3}, θ_1, θ_{11}, θ_2 and θ_{23} are the parameters to be estimated. For each county i, y_t is log of biomass yield Y_t produced at year t; x_{jt} is a vector of log of fertilizer, log of chemicals and percentage of irrigated land at year t; t_t a proxy for technical change and it is the number of years since the beginning of the analysis where 1960 = 1 and d_{iwt} is a vector of degree days intervals.

As we mentioned in the previous section, the shortcoming of the high flexibility of this functional form is that since the number of interaction terms explodes easily, usually there are high levels of collinearity that are likely to decrease the precision of the estimated parameters. We included the full set of interactions of variables that are under farmer's control and can motivate changes in his behavior (fertilizer, chemicals and irrigation) and those relative to the time trend (to account for technical change and its biases). We do not include the full set interactions of the environmental variables (soil organic matter, intervals of degree days and precipitation) that are not controlled by the farmer. Given the importance that irrigation has in this region, we do include the interactions of irrigation with soil organic matter, to account for the benefits of irrigation on different degrees of land quality; the degree-days intervals, to study how irrigation is used to mitigate heat stress; and with precipitation, to study how irrigation is used to mitigate water stress and to account for the substitutability of water from precipitation and water from irrigation. For simplicity, the descriptions presented in this section do not include these interactions between irrigation and the environmental variables but they are included in the estimation and their effects are described in the results section.

Given that the translog production function satisfies symmetry (Young's Theorem) equation (4) includes half of the possible second order parameters, i.e. we include 10 ($\sum_{j=1}^{4} j$) second order interaction terms instead of 20.

The translog production function is *additively separable* if $\beta_{jk} = 0 \; \forall \; j \neq k$ and *strongly separable* if $\beta_{jk} = 0 \; \forall \; j, k$, and equivalent to a Cobb-Douglas production function with input biases of technological change. Since the Cobb-Douglas production function is nested into the Translog production function, we can test if the former is a better specification than the latter by restricting the second order coefficients to be equal to zero and doing a Wald test.

Monotonicity requires the marginal product of all inputs to be positive or that the estimated shares be nonnegative. Monotonicity will be tested at each data point.

Given the translog specification defined in equation (4) and the assumptions of profit maximization and perfect competition, the factor shares are,

Share of fertilizer $\quad SH_{ti}^{1} = \beta_1 + \beta_{11} x_{i1t} + \beta_{12} x_{i2t} + \beta_{13} x_{i3t} + \beta_{51} t_{it} \quad$ (6)

Share of chemicals $\quad SH_{ti}^{2} = \beta_2 + \beta_{21} x_{i1t} + \beta_{22} x_{i2t} + \beta_{23} x_{i3t} + \beta_{52} t_{it} \quad$ (7)

We have included only share equations for the purchased farm inputs since they have observable prices and are part of the variable cost of the farmer.[3]

Equations (4), (6) and (7) are jointly estimated using a three stage least square approach (Zellner & Theil, 1962). This system includes cross-equation parameter due to equality and symmetry constraints that relate the share equations coefficients with coefficients in the production function.

The flexible nature of the translog production function does not impose a priori restrictions on the value of the output elasticities, returns to scale, elasticities of substitution or technical change.

[3] We lack county level information on labor and capital.

The first derivative of the translog production function with respect to the log of each of the inputs j corresponds to the production elasticities that, given our assumptions of profit maximization and perfect competition, are equal to the factor shares. These elasticities are both time and county specific and vary with input use. Let them be equal to γ_{ijt} and be defined as:

$$\gamma_{ijt} = \left(\frac{\partial y_{it}}{\partial x_{ijt}}\right) = \left(\frac{\partial Y_{it}}{\partial X_{ijt}}\right) \cdot \left(\frac{x_{ijt}}{y_{it}}\right) = \beta_j + \sum_{k \neq j}^{4} \beta_{jk} x_{ikt} + \varphi_j t_i \tag{8}$$

Production function estimates of scale economies can be obtained as the sum of the production elasticities of each output. We define the elasticity of scale as

$$RTS(X_{ijt}, t) = \sum_{j=1}^{3} \gamma_{ijt} = \sum_{j=1}^{3} \frac{\partial y_{it}}{\partial x_{ijt}} \tag{9}$$

A production function is said to exhibit constant returns to scale (CRS) if $\sum_{k=i}^{K} \beta_j x_{ijt} = 1$. Given that our estimation of the production function per unit of land input assumes the existence of CRS on the inputs included, the difference of the elasticity of scale from one is accounting for land.

When the estimation includes a time trend t as a proxy for technical change, the first derivative of the production function with respect to the time trend t can be interpreted as the primal rate of technical change. Given our specification, it is defined as:

$$\frac{dy_{it}}{dt} = \tau_1 + \tau_2 t_i + \sum_{j=1}^{3} \varphi_j x_{ijt} \tag{10}$$

This measure is both time and county specific and varies with input use. According to its effects on relative input utilization, the rate of technical change can be further decomposed into effects due to pure technical change and biased technical change, where the latter show the effect of technology on the use of various inputs, indicating changes in their productivity. Following Chambers (1988), the biases of technical change can be defined as

$$B_j = \frac{\partial s_j}{\partial t} = \varphi_j, \forall j \qquad (11)$$

The translog production function is Hicks neutral if *t* is separable from all of the *j* inputs. This will be given if $\varphi_j = 0, \forall j$. Technical change is also said to be unbiased (or share neutral) if it does not affect the relative cost shares (i.e. the derivative of the logarithm of the share with respect to time must be the same for all shares). In our specification this will imply that $\varphi_j = \varphi_k, \forall j, k$. Hence, Hicks neutrality implies share neutrality. If $\varphi_j > \varphi_k$ the technical change is said to be biased toward input *j*; if $\varphi_j < \varphi_k$ the technical change is said to be biased toward input *k*. Additionally, if $\varphi_j > 0$ it is said that technical change was input *j* using and if the opposite inequality holds the technical change it is said to be input *j* saving.

From the marginal product (MP) it can be easily estimated the marginal rate of technical substitution (MRTS) between two production factors as,

$$-MRTS_{jkt} = \frac{MP_{kit}}{MP_{jit}} = \frac{X_{ijt}}{X_{ikt}} \frac{\beta_k + \sum_{j=1}^{3} \beta_{jk} x_{ikt} + \varphi_k t_i}{\beta_j + \sum_{k=1}^{3} \beta_{jk} x_{ijt} + \varphi_j t_i} \qquad (12)$$

This marginal rate of technical substitution will show us the additional amount of input *j* that is needed to replace one unit of input *k* when output is constant. Input substitution is a critical issue in determining the capacity of firms to adapt to changing economic conditions. Allen's partial elasticity of substitution measures the change in the MRTS as we move along the isoquant between two inputs or, in other words, the degree of substitutability of inputs while holding output constant and allowing them to adjust optimally to factor prices changes. It can be computed by first estimating the second derivatives of the Translog function. This is,

$$f_{jk} = \frac{\partial^2 Y_{it}}{\partial X_j \partial X_k} = \frac{\beta_{jk} Y_{it}}{X_j X_k} + \frac{MP_{jit}\, MP_{kit}}{Y_{it}} - \delta_{jk} \frac{MP_{jit}}{X_j} \qquad (13)$$

where δ_{jk} is the Kronecker's delta between *j* and *k* with δ_{jk}=1 if *j*=*k* and δ_{jk}= 0 if $j \neq k$. Then, let us define f_j = MP_j and the bordered Hessian matrix F as

$$F = \begin{bmatrix} 0 & f_1 & f_2 & f_3 & f_4 \\ f_1 & f_{11} & f_{12} & f_{13} & f_{14} \\ f_2 & f_{21} & f_{22} & f_{23} & f_{24} \\ f_3 & f_{31} & f_{32} & f_{33} & f_{34} \\ f_4 & f_{41} & f_{42} & f_{43} & f_{44} \end{bmatrix} \quad (14)$$

We can now define Allen's partial elasticities of substitution as

$$\sigma_{jk}^{a} = \frac{\sum_{j=1}^{4} X_j f_j}{X_j X_k} \frac{F_{jk}}{|F|} \quad (15)$$

where $|F|$ is the determinant of the bordered Hessian F and F_{jk} is the cofactor of F for the inputs j and k. If σ_{jk}^{a}<0 the inputs are substitutes and if σ_{jk}^{a}>0 the inputs are complements. If the production function is separable in inputs X_j and X_k, then a change in the quantity of another input does not change the optimal factor proportions between these two inputs. The Allen partial elasticities of substitution are the most used measures of substitution but they are not free of critics (Chambers (1988), Blackorby and Russell (1989)). After estimating the Allen partial substitution elasticities, following Chambers (1988) the Morishima elasticity of substitution can be easily derived as,

$$\sigma_{jk}^{m} = \frac{X_k f_k}{X_j f_j} (\sigma_{jk}^{a} - \sigma_{kk}^{a}) \quad (16)$$

This elasticity is not symmetric since $\sigma_{jk}^{m} \neq \sigma_{kj}^{m}$. Inputs *j* and *k* are Morishima substitutes if σ_{jk}^{m}<0 and they are Morishima complements if σ_{jk}^{m}> 0. When inputs are Allen substitutes, they are also Morishima substitutes, but the converse does not always hold. The Morishima elasticity is a more economically relevant concept since it is an exact measure of how the *j*, *k* input ratio responds to a change in w_k (Chambers, 1988), for this reasons, our estimation of the Allen elasticities of substitution is just a means to obtain the Morishima elasticities of substitution.

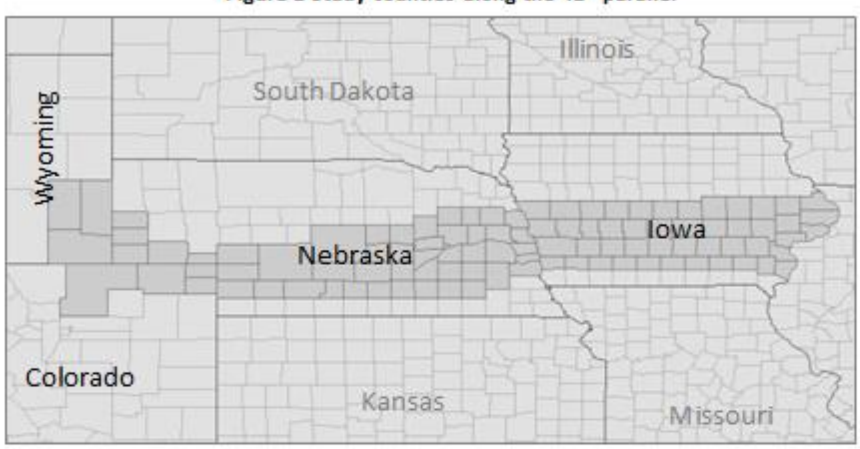
Since the farmers take decisions about the desired yield and the amount of fertilizer and chemicals needed to produce it simultaneously, an instrumental variables approach is used to avoid endogeneity issues. For this purpose, indexes of prices of these inputs were used as instrumental variables. Given 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.

The STATA package version 12.0 was used for the econometric estimations.

Data description:

The area of analysis consists of 101 counties spread along the 41º N latitude parallel in the U.S. Midwest; this is a 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). This 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 underground water characteristics makes this region representative of agriculture of other temperate regions in the world.

Figure 1 Study counties along the 41st parallel



The dependent variable is the log of the total amount of agricultural biomass produced per hectare planted from all crops. As it can be seen in figure 2, the most important commodities produced in the area during the period were, in order of quantity, corn, soybean, wheat and hay; with greater concentration on these commodities in the last decades.

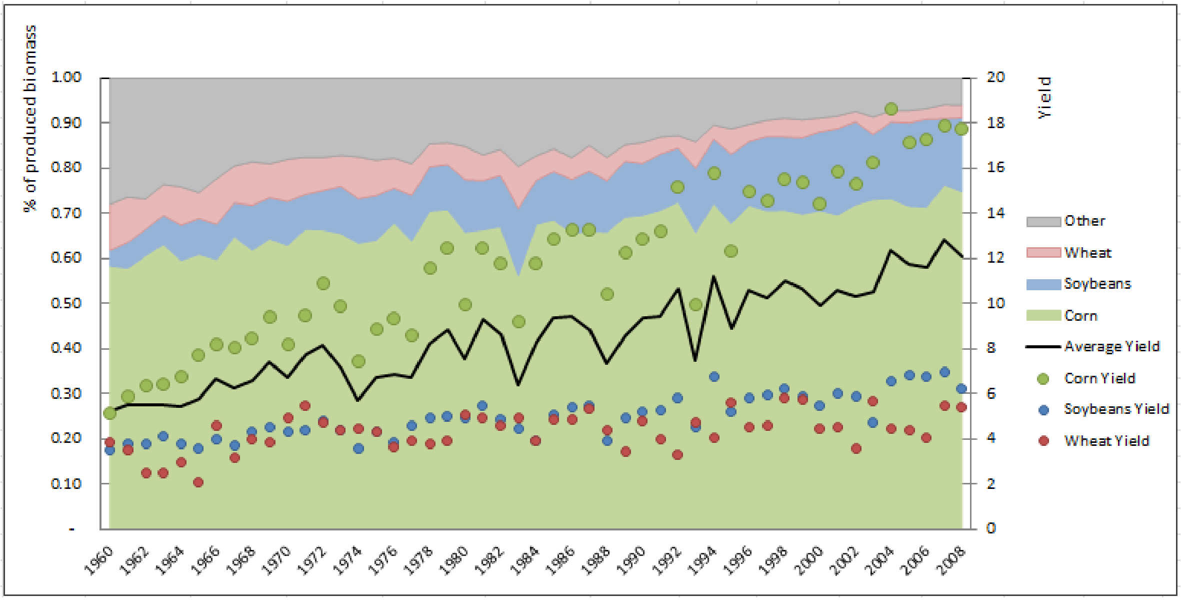
The unit of measurement is megagrams (Mg) of above-ground dry matter produced. Coefficients to convert to metric tons (i.e. tonnes) from bushels were 0.0254 for corn, sorghum and rye and 0.0272 for wheat and soybeans.

The unharvested biomass for each crop was calculated 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 literature (Hay, 1995; Unkovich et at., 2010). The following harvest indexes were used: corn and sorghum for grain 50%; corn and sorghum for silage and hay 100%; soybeans, rye and barley 40% and other minor crops 35-85%.

The harvested and unharvested estimated 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 & Connors (1992): corn and sorghum for grain, barley and rye 14.5%; corn and sorghum for silage 55%; wheat 13.5%; soybeans and beans 13% and other minor crops 10-78%.

The county-level yields were obtained by dividing the estimated DM total 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). Figure 2 depicts the evolution of the share of produced biomass per crop and the average yield per hectare planted for the main crops.

Figure 2 – Share of total biomass produced and yield (tons per hectare planted) through time per crop

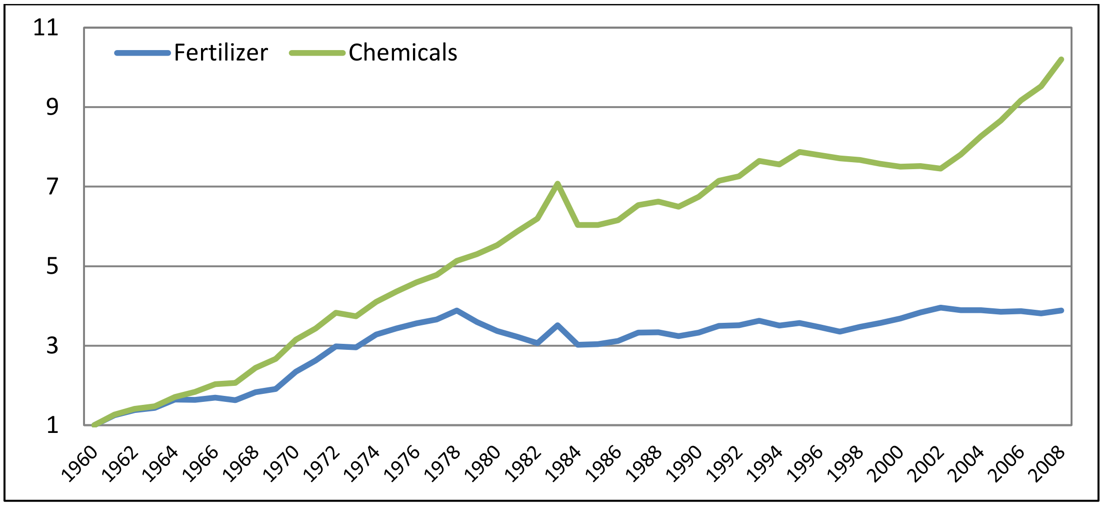


During the last decades there was greater concentration in the production of corn and soybeans. There was an important increase in the average yield that was mainly motivated by a substantial increase in corn productivity; soybeans and wheat also had increases in yield but they were modest.

The independent variables consist of the traditional inputs that are under farmers' control and of environmental variables. The inputs considered are fertilizer, chemicals and irrigation, and the environmental variables are soil organic matter, precipitation and degree days. Indexes are constructed for all variables at the county level.

Fertilizer and Chemical inputs are measured in implicit quantity indexes per hectare planted. These indexes were estimated from the county expenditures on these inputs published by the Census of Agriculture as reported by USDA, National Agricultural Statistics Service. The quantity indexes were constructed for each census year by dividing the reported 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. Figure 3 shows the evolution of these indexes for the aggregate of the study area. It is noticeable the rapid increase in chemicals use and the stagnation in the use of fertilizers.

Figure 3 - Average indexes of fertilizer and chemical use per hectare planted (1960-2008)



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[4]. Figure 4 illustrates the time path of the irrigation ratio by state; Figure 5 depicts the geographical distribution of irrigation ratio in 2008.

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

Figure 4 – Average irrigation ratios per state (1960-2008)

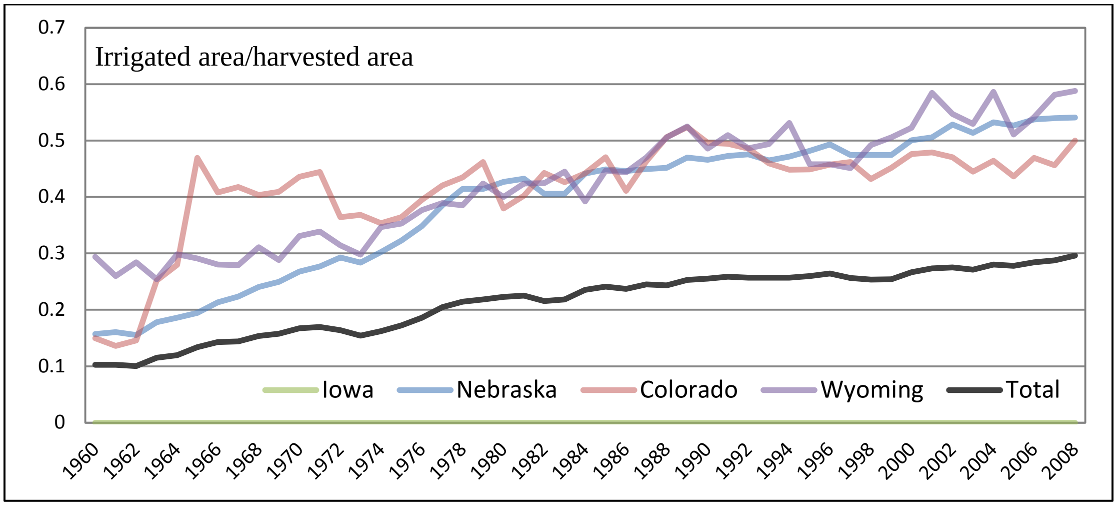
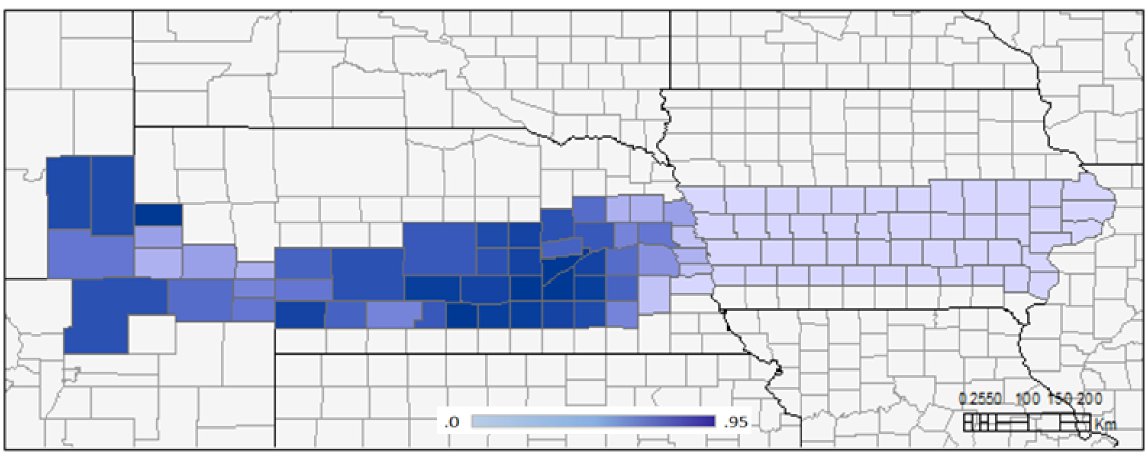
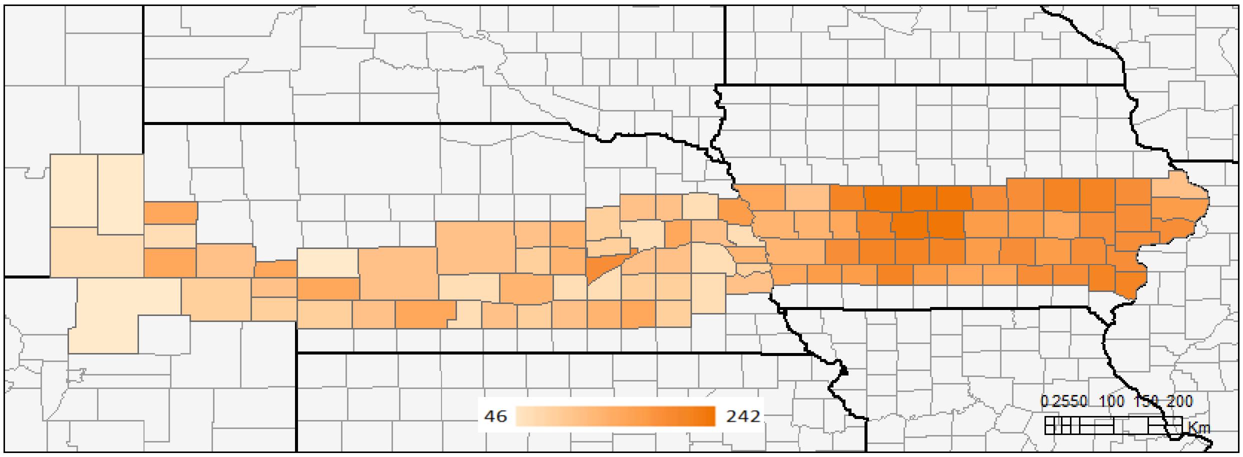


Figure 5 - Irrigated land as a fraction of planted land (2008)



To account for the differences in soil quality we include the megagrams 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 SOC levels for the period 1960-2008 retroactively from 2010 initial values using modified versions of the DK model (Liska et al 2011). An approximate SOC to soil organic matter (SOM) conversion factor of 2.0 was then applied to obtain the series for SOM (Liska et al (2011)). As figure 6 illustrates, this variable shows higher values for central and eastern Iowa and decreasing values as we move to the west.

Figure 6 - Soil organic matter (SOM) in Mg/ha, 2008



Turning to the weather variables, data on degree days and precipitation were estimated from weather stations' data collected from the High Plains Regional Climate Center[5]. From this data, a daily precipitation value (in centimeters) and daily maximum and minimum temperatures were estimated for each county in the sample and for each day during the growing season (March to August). The method used for this estimation was a linear interpolation from the 5 closest stations to the center of each county. Using a Shepard inverse distance function:

$$u(x_k) = \sum_{i=0}^{5} \frac{w_{ik}\, x_i}{\sum_{j=0}^{5} w_{jk}}, \qquad \text{where } w_{ik} = \frac{1}{{d_{ik}}^2},$$

where x_k denotes the interpolated value for county k, x_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 was then used to estimate the yearly precipitation and degree day intervals that we use in the estimation.

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)

[5] http://www.hprcc.unl.edu/data/historical/index.php

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 et al. 1991). Given the particular importance that is given to climate impacts in this study, we estimated several intervals of degree days. Each interval accounts for the proportion of each day during the growing season (March to August) when the temperature was inside its boundaries. Our set of three intervals covers all the temperatures higher than 0ºC. The lower temperature interval, *DD0029,* 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.

There are several methods to estimate degree days; our approach is an adaptation Snyder's method (R. L. Snyder – 1984). Snyder uses a sine curve method to approximate diurnal temperatures from maximum and minimum data; daily degree accumulations are estimated by integrating the area under the sine curve. Using our estimated daily values of minimum and maximum temperature we adapt Snyder's method to estimate degree days for temperature intervals (with upper and lower bounds). The estimation algorithm differs depending on the position of the interval with respect to the lower and upper bound. There are three different cases:

Case 1: When the daily minimum temperature is above the upper bound of the interval being considered, the degree days for that day and interval are equal to 0.

Case 2: When the interval being considered lies between the daily minimum and maximum temperatures the following equation is used:

$$absDDLOWUP = \frac{\left[(M_{LOW} - THR_{LOW})\left(\frac{\pi}{2} - \theta\right) + W\cos(\theta)\right]}{\pi} - \frac{\left[(M_{UP} - THR_{UP})\left(\frac{\pi}{2} - \theta\right) + W\cos(\theta)\right]}{\pi}$$

where $\theta = \arcsin[\frac{i-M}{w}]$, M= $\frac{Max+Min}{2}$, $W = \frac{Max-Min}{2}$, LOW and UP are the lower and upper bounds respectively and i is the lower or upper bound temperature.

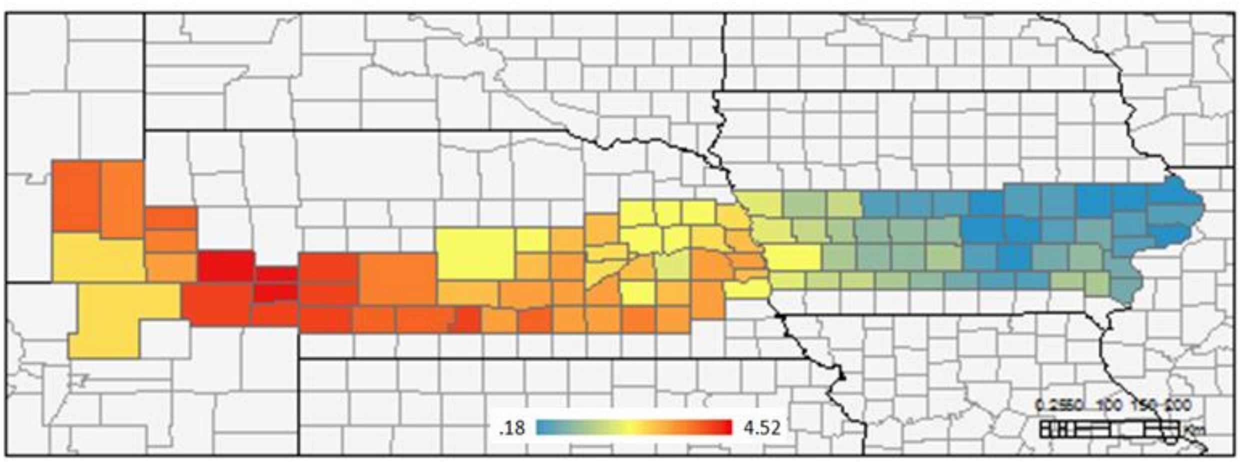
Case 3: When the daily maximum temperature is below the lower bound of the interval being considered, the degree days for that interval are equal to 0.

The value obtained for each interval was divided by the total number of degree days observed for that day. This way we convert the intervals into fractions of a day with temperature ranging in that interval.

We initially estimated 40 degree day intervals, one for each unitary change in temperature from 0ºC to 40ºC[6]. We then aggregated this intervals to obtain the desired degree day intervals: we summed the values of all the intervals from 0ºC to 29ºC to obtain the DD0029 interval, we summed the values from the intervals from 30ºC to 34ºC to obtain the DD3035 interval and finally we summed the values of all the intervals from 35ºC to 40ºC to obtain the DD35plus interval.

Figure 7 depicts the numbers of degree days for the 2008 growing season for the two higher degree day intervals (DD3035 and DD35plus). It can be seen that there is an increasing amount of days with temperatures higher than 30ºC towards the west, from eastern Iowa to western Nebraska.

Figure 7 – Number of degree days with more than 30ºC (2008 growing season)



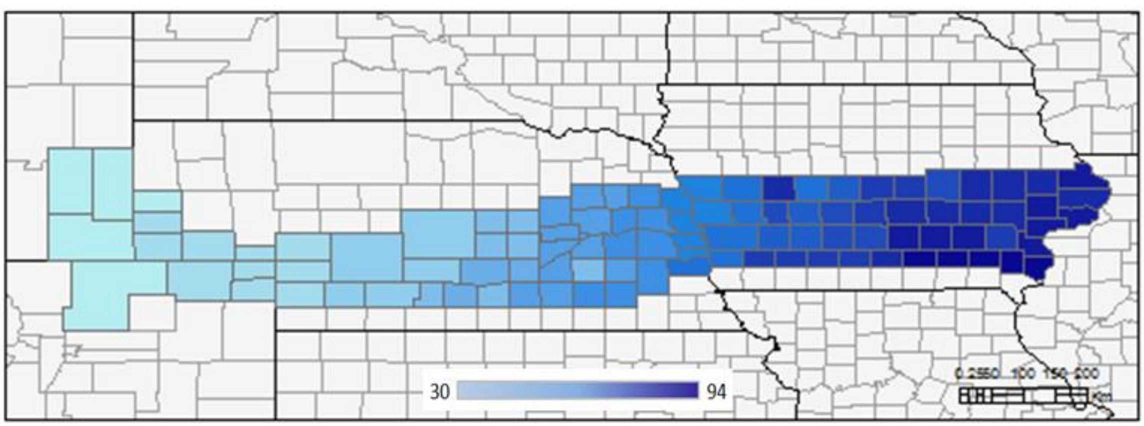
The precipitation variable measures, in centimeters, the total amount of precipitation registered during the growing season. To estimate these values, for each county, the estimated daily values for each county

[6] Since the 40ºC degree interval does not have an upper bound it also accounts for temperatures higher than 40ºC.

(that were obtained by interpolation) were added for each year to have an estimate of total precipitation. Figure 8[7] includes 3 figures that characterize precipitation in our dataset. As it can be seen in figure 8.a, there is a substantial decrease in average precipitation towards the West; while in counties in East Iowa the average yearly precipitation was over 90 cm, in counties in West Nebraska, Colorado and Wyoming the average yearly precipitation was 30cm. Figure 8.b evidences a normal distribution for precipitation with around 90% of the observations receiving between 10cm and 30cm of precipitation. Finally, figure 8.c shows that although there is no trend in precipitation during the period, there is high variability between years, with 1993 showing the highest amount of precipitation and 1994 showing one of the lowest level observed during the period of analysis. Additionally, figure 8.c shows that generally, there is higher amount of precipitation in Iowa than in Nebraska, Colorado and Wyoming[8] (NCW).

Figure 8 – Precipitation (cm)

Figure 8.a – Yearly average precipitation (cm)



[7] While Figure 8.a represents yearly precipitation, figures 8.b and 8.c represent precipitation during the growing season (March to August). A final version of this chapter will show precipitation for the growing season in the three figures.

[8] In this study, counties will frequently be divided between counties in Iowa and counties in Nebraska, Colorado and Wyoming (NCW). Given the lack of irrigation in Iowa and higher precipitation, this differentiation is done to check for differences in the estimates for counties with and without irrigation.

Figure 8.b – Precipitation frequency

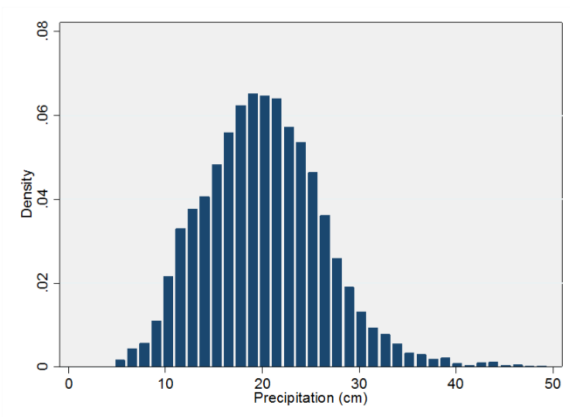
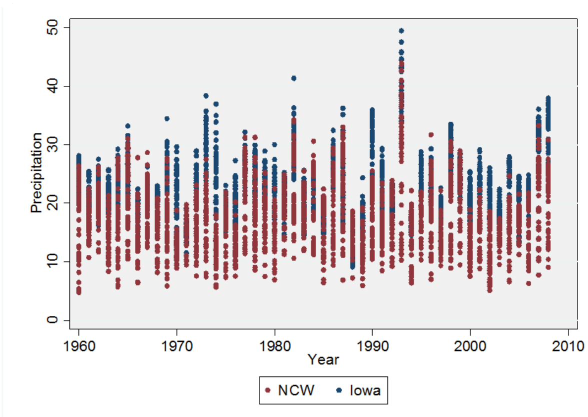


Figure 8.c – Precipitation per year



As seen in figure 7 and figure 8, the area of study shows a rich variability in weather variables. Precipitation increases towards the East and temperature degree days increases toward the West.

Summary statistics are presented in table 1 in the Appendix.

d. Results:

The parameters obtained by the joint estimation of equations 4, 6 and 7 can be seen in Table A.1 in the Appendix. 22 out of 26 estimated parameters are significantly different from zero at the 99% confidence level and 1 parameter at 95% confidence level. The production function estimation's pseudo R squared is .6853. Although the 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 was conducted to compare the translog specification versus the Cobb-Douglas specification; results reject 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 ($\forall\, j \neq k$).

A multicollinearity test by variance inflator factor (vif) on the independent variables was done to quantify the severity of possible multicollinearity. This test provides a measure of how much the variance of the estimated regression is increased by multicollinearity. Our highest estimate was a value of 6.57 for chemicals, lower than the 10 critical value used for absence of multicollinearity.

Given that the presence of outliers (among other reasons) can lead to heteroskedastic errors we proceed to employ a "pairs bootstrap" methodology (Freedman, 1981) for the estimation. Following McKinnon (2002) and Flachaire (2004) pairs bootstrapping gives robust estimates under heteroskedasticity. Additionally, a standard 3SLS estimation was done to check for consistency of the results finding 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. Given the lack of irrigation in Iowa we exclude this state for the estimation of monotonicity and quasiconcavity violations since it is not possible to estimate the bordered Hessian matrix for a translog form when some inputs are equal to 0. The percentages of monotonicity violations are 1.07% for fertilizer, 1.29% for chemicals and 12.24% for irrigation. Looking at the bordered Hessian determinants we can estimate quasiconcavity violations at each data point, 50.4% of the observations do not fulfill the quasiconcavity condition.

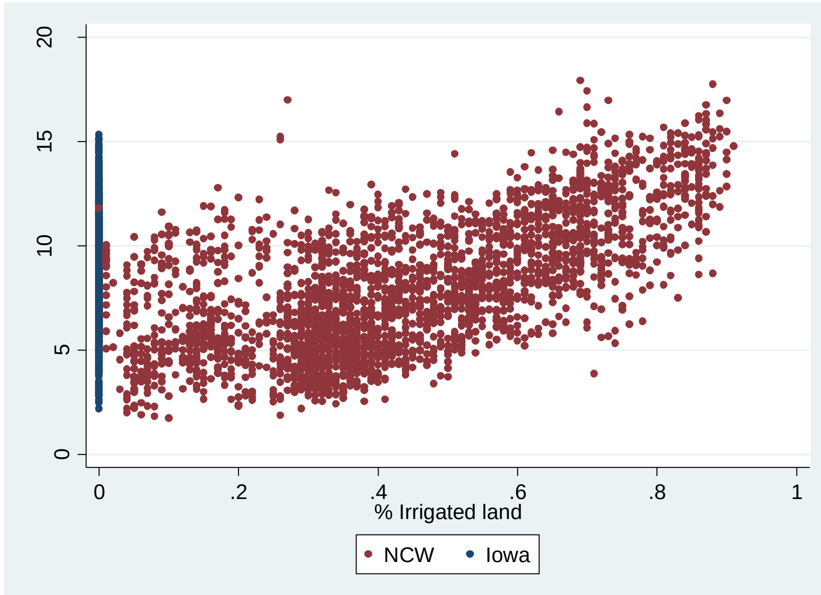
The elasticities of production estimated as described in equation 8 are shown in Table 1. Since the translog specification allows the estimation of the elasticities for each data point, we only show average elasticities for each variable. The p-values included in the table are at their means and were estimated using the delta method.

Table 1 - Elasticities of production estimated at their means

Variable	Elasticity	P-Value
Fertilizer	0.074	0.002
Chemicals	0.050	0.002
Irrigation ratio	0.234	0.019
Soil organic matter	0.072	0.051
Time Trend	0.011	0.000

All the production elasticities with the exception of irrigation are significantly different from zero at the 99% confidence level, while irrigation is significant at the 95% confidence level. Our estimate of the production elasticity of fertilizer (0.07) is similar to Saha et al. (1997) but is lower than the .10-.17 estimated by Headley (1968), Hayami and Ruttan (1970) and Griliches (1983). Our estimate of the production elasticity of chemicals (0.05) is similar to Ball's (1985) parametric share of 0.057. Our estimate of the production elasticity of irrigation tells us that approximately one fourth (0.23) of the agricultural production in our study area can be associated to the use of irrigation; if we convert a hectare of land from rain-fed to irrigated, we should expect, on average, a 23% increase inyields. This estimate is higher than Coelli and Rao (2005) estimate of the shadow share (0.141) of irrigation in the United States for the period 1980-2000. Considering the evolution of the elasticity during the period of analysis we observe a positive trend, from .12 during the 1960s to 0.30 during the 2000s. If we only account for the counties that have any irrigation (counties in Nebraska, Colorado and Wyoming (NCW)) the average elasticity of irrigation rises to 0.43; the exclusion of Iowa significantly shifts our estimated elasticity. Figure 9 depicts a scatterplot of biomass yield and levels of irrigation.

Figure 9 – Yield (Mg per ha) and Percentage of irrigated land.

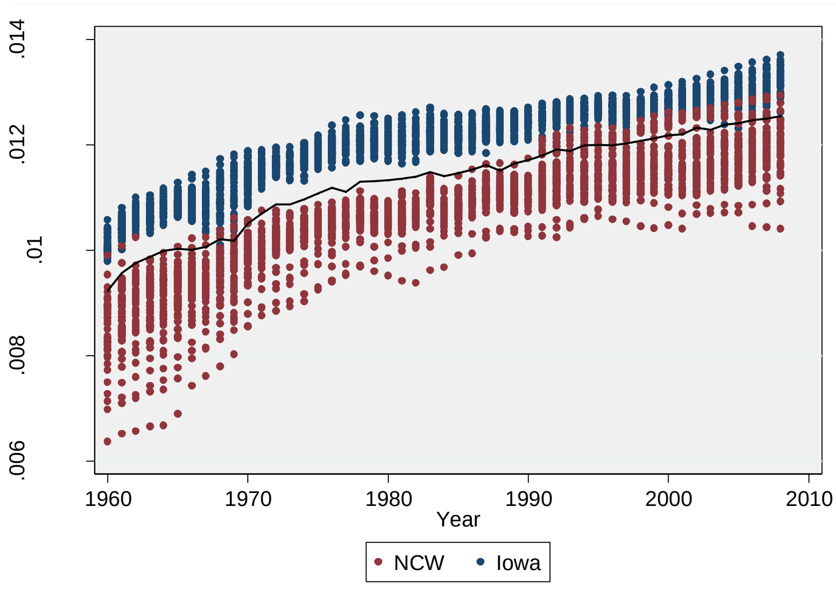


As shown in the figure, observations with higher levels of irrigation tend to be associated with higher yields. Additionally, given the high levels of precipitation and no irrigation in Iowa we can observe that the remaining states in the sample compensate lower levels of precipitation with higher levels of irrigation; by increasing the amount of irrigated land they are able to obtain yields attainable by counties in Iowa that are not irrigated.

Table 1 additionally includes the average production elasticity of soil organic matter. This elasticity was found to be positive and significant at the 95% confidence level, indicating that soil quality accounts for 7% of the variability in yields. Disaggregating these estimates between Iowa and the remaining states shows that this variable is highly significant for Iowa's productivity, its average elasticity is .16, while the estimate for the remaining states is around zero and non-significant.

Our estimate of the primal rate technical change is included in Table 2 and it was estimated as determined by equation (10). To estimate the weighted average values, the estimated technical change of each observation was weighted by the share of that county in the total output produced during the same year. Our estimated average rate of technical change during 1960-2009 is 1.13%. This average change is lower than the total factor productivity (TFP) growth rate of 1.78% estimated Alston et al. (2010) for 1949-2002 and the USDA-ERS (2015) TFP change of 1.56% for 1960-2008. Figure 10 depicts a scatterplot with the evolution of technical change for each county and the weighted average technical change.

Figure 10 – Estimated technical change per year for each county



Looking into figure 10, we observe a positive but decreasing growth rate of technical change for counties from both groups, from an average of 0.98% in the 1960s to 1.20% in the 2000s[9]. This slowdown in the growth rate of technical change is similar to the USDA-ERS (2015) estimate for the TFP change in U.S. agriculture. A Wald test on the φ_j coefficients rejects the hypothesis of Hicks neutral technical change. Table 3 shows the biases of technical change and their p-values. The technological change was fertilizer- and chemical-using (biased towards fertilizer) 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.

[9] The outlier that can be observed in the graph is Howard county in Nebraska, with a technical change of .6%

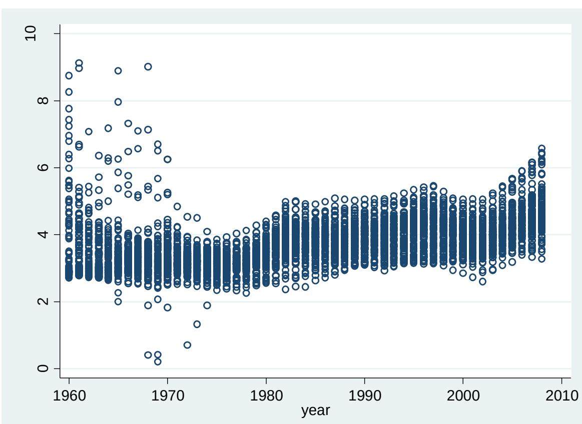
Table 3 - Biases of technical change

Input	Bias	P-Value
Fertilizer	0.0006	0.0000
Chemical	0.0005	0.0000
Irrigation	-0.0020	0.0200

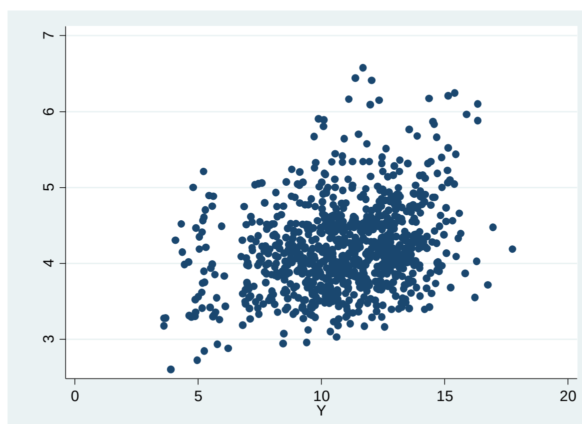
The estimated marginal rate of technical substitution between fertilizer and chemicals on average was found to be equal to 3.5. This means that if we reduce the amount of fertilizer used in one unit, we can keep the yield constant by increasing the amount of chemicals used in 3.5 units[10]. As figure 11 shows, this relation has changed during the period of analysis.

Figure 11 – Marginal rate of technical substitution between fertilizer and chemicals.

a) MRTS per year.



b) MRTS per yield of biomass (2000-09).



After a period of higher variability during 1960-1975 the average MRTS between fertilizer and chemicals started increasing, from 3.12 in 1975 to 4.76 in 2009 (figure 11a), this growth was not related to a decrease in the marginal product of chemicals but with a faster increase in the marginal product of fertilizers. The evolution in the MRTS can be explained by the change in the crop output mix (see figure

[10] Where the base unit is the total amount of fertilizer or chemical used in Adams County, Nebraska, in 1960.

2) but mainly with the increase in agricultural productivity; higher yield levels are associated with higher levels of fertilizer and chemicals consumption per hectare of land, thus higher quantities of chemicals are required to compensate a decrease in the use of fertilizer as the yield increases (figure 11b). Additionally, the Morishima elasticities of substitution were estimated for each data point following equation 16. The average Morishima elasticities of substitution between fertilizer and chemicals were found to be negative, implying that these inputs are substitutes in production.

Climate Impact

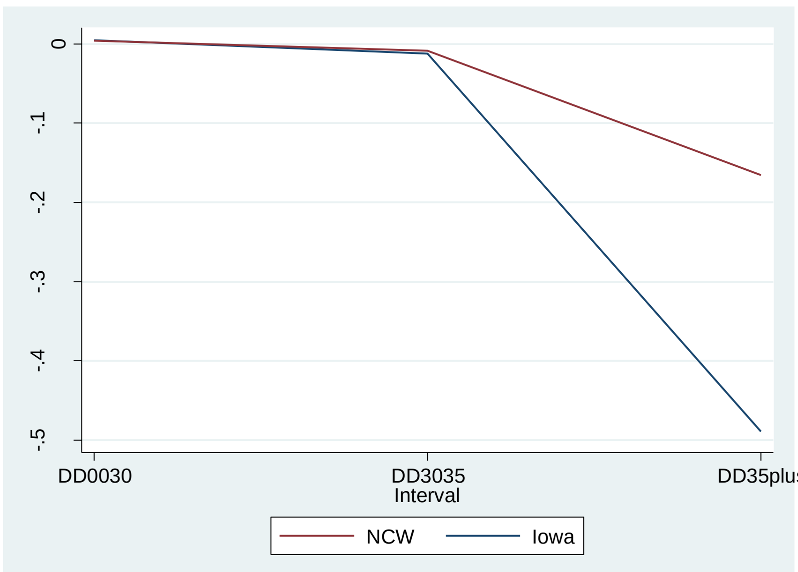
As shown by other authors, results show a non-linear increasingly negative effect of higher temperatures on expected crop yields. While temperatures lower than 30ºC where found to have a positive effect on yields, temperatures higher than 30ºC have an increasing negative impact. Table 4 shows the marginal impact of each degree day interval on expected yield.

Table 4 - Climate Impact on Yields

Variable	Marginal effect	P-Value
DD0030	0.0043	0.0009
DD3035	(0.0101)	0.0252
DD3540	(0.2712)	0.0477
Precipitation	(0.0568)	0.0673

On average, each extra day of temperatures between 30ºC and 35ºC is expected to reduce yields by 1.0 % and each extra day with temperatures greater than 35ºC is expected to decrease yields by 27.1%. For the lower temperature intervals, an extra day with temperatures positive but smaller than 30ºC is expected to have a positive effect of 0.4%. Comparing our results with Schlenker and Roberts (2009) findings, we find similar impacts of temperatures to 35ºC, but after this threshold our estimate indicates a more severe effect. Their estimate of around 6% decrease in yield is significantly lower than our estimate of 27.1%. Roberts et al. (2012) find similar estimates for temperatures between 10ºC and 29ºC, and for days with temperatures higher than 29ºC. They estimate a negative effect of 6.2% for each extra day but this estimate is not directly comparable to ours given the difference in temperature ranges. It is important to remember that these authors only looked at counties east of the 100 meridian so they do not include irrigated agriculture, while this is an important component in our sample. Figure 12 depicts the marginal effects of temperatures under each interval for counties in Iowa versus counties in the remaining states (NCW). We can observe that given the lack of irrigation, the negative impact of the higher degree day interval is more severe in Iowa than in the states that irrigate.

Figure 12 – Marginal effect of Degree Day temperature intervals on Yield



Irrigation greatly alleviates the harmful effect of higher temperatures. It can be effectively used to offset the negative impact of temperatures above 35ºC. The effect of irrigation on a hectare of land converted from non-irrigated to irrigated is expected to outweigh the negative impact of temperatures above 35ºC.[11]

Our estimates of the effect of precipitation on yields were not significant. These results are different from those of Lobell (2007), Schlenker and Roberts (2009) and Roberts et al. (2012) who found that the effect of this variable is significant and follows an inverted U shape; that is, there is a positive effect of

[11] The interaction coefficients between the degree day intervals and irrigation are the following (p-values in parenthesis): DD0030: -0.0012 (0.569) – DD3035: 0.0082 (0.321) – DD35plus: 0.7379 (0.000).

precipitation until a certain threshold after which the effect becomes negative. The difference in the significance of the results might be explained by the area of study, While they include regions with no or low irrigation, our analysis additionally includes counties with a high percentage of irrigated land. For these counties, since farmers compensate for the lack of precipitation with higher levels of irrigation, variability in precipitation does not seem to be strongly associated to with variability in yields.

To compare with results in Schlenker and Roberts (2009) we run an OLS regression of yields on weather variables and county dummies, similar to what they estimated. Results are presented in table 5.

Table 5 - OLS estimated with county fix effects

Dependent variable: Ln(Yield)		
Variable	Coefficient	P-Value
dd0030	0.009	0.000
dd3035	-0.026	0.000
dd3540	-0.243	0.000
Precipitation	0.387	0.029
Precipitation sq	-0.078	0.009

These results are similar to our main specification. There is a significant increasing negative effect of higher temperatures on crop yield, while days with positive temperatures lower than 30ºC have a small positive effect, each accumulated day with temperatures between 30ºC and 35ºC will decrease yields by 3% and each accumulated day with temperatures higher than 35ºC will decrease yields by 22%[12]. Our estimated negative impact of the higher temperature interval is more harmful than Schlenker and Roberts' (2009) estimate but, similar to them, precipitation is significant and is characterized by an inverted U shape. Figure 13 depicts a scatterplot of yields and precipitation (cm).

[12] We find the same nonlinear temperature effect if we additionally control for irrigation.

Figure 13 – Yield (Mg per ha) and Precipitation (cm).

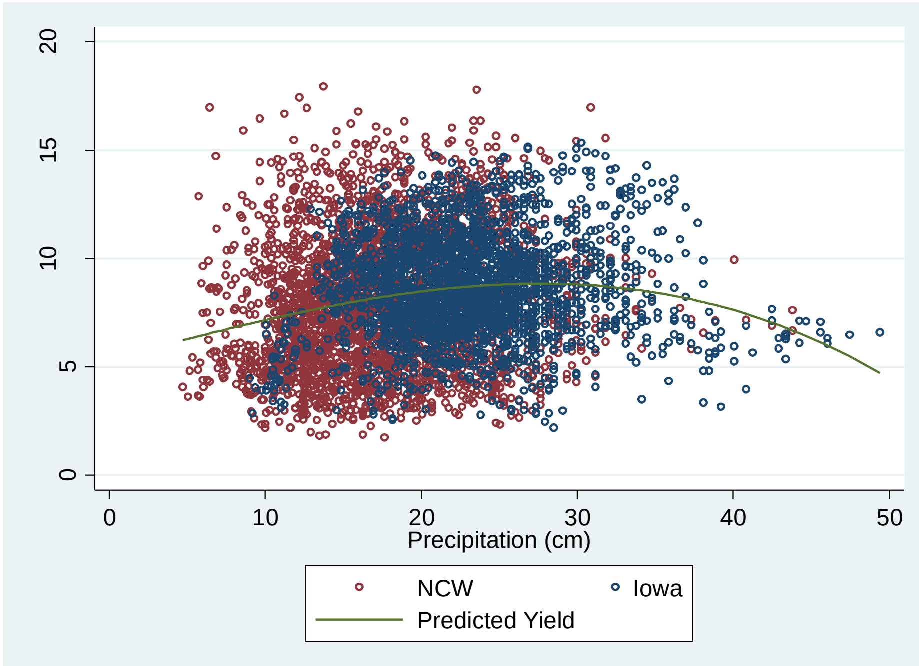


Figure 13 shows that on average counties in Iowa have higher levels precipitation, as was observed in Figure 8. The predicted yield line shows an inverted U shape with a maximum predicted yield attainable at 30cm of precipitation.

e. Conclusions:

This article has provided evidence of the interaction between climate and producer behavior in the production of crop output in the Great Plains. Given the climatic and hydrologic variability observed in our area of analysis, these conclusions might be representative of other temperate regions of the world.

Results quantify the critical effects that high temperatures have on agricultural productivity. After controlling for irrigation, other managed inputs, soil characteristics, precipitation, and technological change, we found a negative and substantially increasing (nonlinear) effect of temperatures over 30 ºC on crop yields. While a full day of temperatures between 0ºC and 30ºC has a small positive effect on yield, a full day with temperatures between 30ºC and 35ºC decreases expected yield by 1% and a full day of temperatures over 35ºC decreases yields by 27.1%. Precipitation was not found to have a significant effect on yield changes.

Our results are *qualitatively* similar to the findings in Schlenker and Roberts (2009) but provide additional information. First, we estimate that in areas where irrigation is available, the harmful effect of temperatures above 35ºC can be offset by the use of irrigation. Semi-arid areas like western Nebraska and eastern Colorado and Wyoming, for example, compensate the higher temperatures and the lack of precipitation with high levels of irrigation. Hence, the transformation of rainfed to irrigated land is an effective mechanism to cope with possible increases in average temperatures but policy recommendations promoting this transformation should also consider underground water sustainability issues that increased irrigation could generate. Further research on this issue is needed.

Second, the contribution of fertilizer and chemicals to yield changes is significant; production elasticities highlight the increasing importance of fertilizer and chemicals on yields. Studies that try to determine climate change impact on agricultural productivity that do not account for these human inputs might wrongly attribute changes in yields to changes in climatic variables, with the possibility of underestimating the impacts of predicted changes in temperature or precipitation.

Finally, the technical change estimated during the period of analysis was found positive but decreasing with an average growth rate during the period of analysis of 1.1%. This change has been fertilizer and chemicals using and irrigation saving.

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Appendix

Table A.1 - Summary Statistics

Complete region (101 counties)				
Variable	Mean	Std. Dev.	Min	Max
Fertilizer	19.28	7.88	0.04	48.19
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	14.14	0.00	48.00
Precipitation (cm)	20.16	6.17	4.70	49.50
dd0029	164.44	5.54	147.68	178.83
dd3035	4.05	2.26	0.14	12.78
dd3640	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	0.00	0.00	0.00	0.00	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
Precipitation (cm)	23.15	5.50	9.06	49.50	18.42	5.26	5.05	43.98
Time period	24.00	14.15	0.00	48.00	24.00	14.15	0.00	48.00
dd0029	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
dd3640	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
Precipitation (cm)	12.99	2.77	5.96	20.44	10.00	2.65	4.70	16.53
Time period	24.00	14.18	0.00	48.00	24.00	14.19	0.00	48.00
dd0029	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
dd3640	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

```
Three-stage least-squares regression, iterated
```

Equation	Obs	Parms	RMSE	"R-sq"	chi2	P
lny	4949	25	.2078713	0.6853	103779.63	0.0000
shfertpHP	4949	4	.0166306	0.4598	2803.97	0.0000
shchempHP	4949	4	.0083336	0.6505	8669.87	0.0000

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

	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Normal-based [95% Conf.	Interval]
lny						
x1	2.021755	.4516406	4.48	0.000	1.136556	2.906955
lnfertpha60	.0361004	.0008613	41.91	0.000	.0344122	.0377885
lnchempha60	.0085364	.0006192	13.79	0.000	.0073228	.00975
x6	1.663486	.1648163	10.09	0.000	1.340452	1.98652
lnx5	.1637831	.0179693	9.11	0.000	.1285639	.1990022
x1sq	1.289814	.0632666	20.39	0.000	1.165814	1.413814
lnfertpha60sq	.0158817	.0018429	8.62	0.000	.0122697	.0194936
lnchempha60sq	.0103626	.0012366	8.38	0.000	.0079388	.0127863
x6sq	-.2834184	.0267855	-10.58	0.000	-.3359169	-.2309198
x1_fertha	.0130618	.0014324	9.12	0.000	.0102542	.0158693
x1_chemha	-.0043459	.0009047	-4.80	0.000	-.0061192	-.0025727
x1_x6	-.1965469	.0516825	-3.80	0.000	-.2978428	-.0952511
x15	-.3944665	.0464869	-8.49	0.000	-.4855791	-.3033538
fertha_chemha	-.0062367	.0015397	-4.05	0.000	-.0092544	-.003219
dd0029	.0045933	.0006879	6.68	0.000	.003245	.0059416
dd3035	-.0121009	.0028529	-4.24	0.000	-.0176925	-.0065092
dd3640	-.4892373	.0357502	-13.68	0.000	-.5593063	-.4191682
dd0029x1	-.0011986	.0020643	-0.58	0.562	-.0052446	.0028475
dd3035x1	.0081963	.0073539	1.11	0.265	-.006217	.0226096
dd3640x1	.7397308	.0855388	8.65	0.000	.5720779	.9073837
t	.0095509	.0010422	9.16	0.000	.0075082	.0115936
tsq	.0000161	.0000186	0.87	0.386	-.0000203	.0000525
x1t	-.0019801	.0008313	-2.38	0.017	-.0036093	-.0003508
fertha_t	.000649	.0000378	17.18	0.000	.000575	.0007231
chemha_t	.0004568	.0000228	20.07	0.000	.0004122	.0005014
_cons	-2.246315	.2884751	-7.79	0.000	-2.811716	-1.680914
shfertpHP						
x1	.0130618	.0014324	9.12	0.000	.0102542	.0158693
lnfertpha60	.0158817	.0018429	8.62	0.000	.0122697	.0194936
lnchempha60	-.0062367	.0015397	-4.05	0.000	-.0092544	-.003219
t	.000649	.0000378	17.18	0.000	.000575	.0007231
_cons	.0361004	.0008613	41.91	0.000	.0344122	.0377885
shchempHP						
x1	-.0043459	.0009047	-4.80	0.000	-.0061192	-.0025727
lnfertpha60	-.0062367	.0015397	-4.05	0.000	-.0092544	-.003219
lnchempha60	.0103626	.0012366	8.38	0.000	.0079388	.0127863
t	.0004568	.0000228	20.07	0.000	.0004122	.0005014
_cons	.0085364	.0006192	13.79	0.000	.0073228	.00975

```
Endogenous variables:  lny shfertpHP shchempHP lnfertpha60 lnchempha60
     lnfertpha60sq lnchempha60sq x1_fertha x1_chemha fertha_chemha fertha_t
     chemha_t
Exogenous variables:   x1 x6 lnx5 x1sq x6sq x1_x6 x15 dd0029 dd3035 dd3640
     dd0029x1 dd3035x1 dd3640x1 t tsq x1t fertpr1960 chempr1960 fertpr1960sq
     chempr1960sq fertpr60_x1 chempr60_x1 chempr60_t fertpr60_t
     fert_chem_pr1960
```

Ref: X1: Irrigation ratio - lnfertpha60: ln(fertilizer) - lnchempha60: ln(chemical) - x6: ln(precipitation) - lnx5: ln(som) – shfertpHP: share of fertilizer – shchempHP: share of chemicals.