Optimal and Sustainable Groundwater Use: Evidence from Nebraska*

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Abstract

The agricultural sector is the primary water consumer in the US. Groundwater is one of its main sources, with 65% of irrigated farmland relying on groundwater for their water supply. Groundwater use presents a common pool problem: if a farmer pumps groundwater, she decreases the aquifer's water table and thus increases the cost of pumping for farmers in the same aquifer. Studying such a problem is challenging due to a lack of markets and data on groundwater use. In this paper, I leverage detailed farmer-level data on (ground)water use, crop choices, and crop yields to study the equilibrium implications of the current groundwater costs. I focus on the Ogallala Aquifer in Nebraska. In order to estimate the effect of water costs on water use and crop choices, I combine a crop-growth model with an economic model. I use the crop-growth model to recover the precise relation between water use and crop yields. I use the economic model to estimate the marginal cost of water for farmers. I then quantify how farmers respond to water costs by switching which crop they plant or changing the water use per planted crop. I find that farmers are inelastic to water costs: a 10% increase in the water cost would decrease water use by 3%. Moreover, I find that farmers adapt to higher water costs by both reducing the water use per planted crop and fallowing the land. Lastly, I utilize my estimates to compute the optimal and sustainable tax on groundwater use.

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1 Introduction

The agricultural sector is the largest water consumer in the US. It accounts for 80% of the nation's consumptive water use, a figure that escalates to 90% in Western US (Christian-Smith et al., 2012; Aillery, 2004). Groundwater is one of its main sources, with 65% of irrigated farmland relying on groundwater for their water supply.[1] Groundwater use is largely unrestricted in the country (Costello et al., 2015; Bruno & Jessoe, 2021), which has led to a systematic depletion of most of its aquifers. Policymakers are thus concerned about the sustainability of the current groundwater utilization, actively seeking the necessary policies to address this issue.[2]

Farmers' groundwater use crucially depends on the energy cost. The energy required to pump groundwater, in turn, depends on the aquifer's water table: the lower the water table, the higher the cost of pumping a unit of water. Aquifers are spread across multiple farmers' land; hence, groundwater use presents a common pool problem: if a farmer pumps groundwater, she decreases the aquifer's water table and thus increases the cost of pumping for farmers in the same aquifer. This problem is both static and dynamic. If farmers use more groundwater than the yearly aquifer's recharge rate, next year's water table will be lower and, thus, there will be an increase in the cost of pumping.[3] Studying this problem is challenging; usually, there are neither markets nor data on groundwater use.

In this paper, I leverage detailed farmer-level data on water use, crop choices, and crop yields to study farmers' groundwater use decisions and their implications for optimal groundwater management policies. I focus on the Ogallala Aquifer in Nebraska. I develop a structural model where farmers endogenously decide which crop to plant and how much water to use in their planted crops, given the cost of groundwater. I combine this model with a crop-growth model to recover the precise (agronomic) relation between water use and crop yields. I then estimate how farmers would respond to changes in the cost of water and how much of such a response would be done through crop choices and water use per planted crop.

[1] Source: Irrigation and Water Management Survey, 2018

[2] See, for example, "America Is Using Up Its Groundwater Like There's No Tomorrow" (NYT, 2023)

[3] There are other negative externalities associated with groundwater use such as the deterioration of soil and even air quality (Provencher & Burt, 1993).

I find that farmers are inelastic to water costs. A 10% increase in the average marginal cost of water, for example, implies a 3% decrease in total water use. Moreover, farmers respond to water cost increases by decreasing their water use per planted crop and fallowing the land. Lastly, I utilize my estimates to compute the optimal and sustainable tax on groundwater use.

I focus on Nebraska for various reasons. First, the Ogallala Aquifer, which covers almost all of Nebraska, is one of the most important sources of water for US farmers, covering 30% of the US-irrigated farmland. Second, Nebraska's main irrigated crops are at the top of the irrigated crops in the West: corn, soybean, alfalfa, and wheat. Third, irrigation is widely spread in the state. In 2017, for example, 43% of the harvested cropland was irrigated. Lastly, Nebraskan farmers overwhelmingly rely on groundwater as their source of water. In 2018, for example, groundwater accounted for 86% of their total water use.

My main data source is the "Irrigation and Water Management Survey - Farm and Ranch Irrigation Survey" (IWMS-FRIS), which is conducted by the United States Department of Agriculture (USDA). This survey is run every five years, a year after the agricultural census, as a repeated cross-section. It is representative of all American farmers who irrigate their land. I access individual records of such a survey for 2018, 2013, and 2008. More specifically, I observe, at a farmer level: groundwater, surface, and off-farm water use; crop choices and crop yields; water use per crop; energy expenses on pumping water; technology used to irrigate the land; and the farmer's county. Two facts from the data motivate the structure of my model. First, a farmer's water use largely depends on the crop she planted. In 2018, for example, the average acre-feet-of-water per acre used to irrigate alfalfa was 62% higher than the one for soybeans. Second, even within a given crop, the irrigation rate varies widely. In 2018, for example, the average acre-feet-of-water per acre used to irrigate soybeans was 0.5, and its standard deviation was 0.32.

To understand the effect of the current water costs on groundwater use, I develop a two-stage model on crop choices and water use. In the first stage of the model, farmers decide which crop to plant. More precisely, they compute the expected profitability of each crop, taking expectations over the weather, and plant the crop that maximizes their expected utility. In the second stage of the model, the weather is realized, and farmers decide how much water and fertilizers to use to maximize profits.

I allow farmers to differ in their individual-level productivity, their marginal cost of water, and their preferences for planting different crops. This creates some empirical challenges for estimation. First, I need a strategy to disentangle individual-level productivity from other parameters, i.e., the marginal cost of water. Second, I need to consider farmers' responses on unobserved inputs, i.e., fertilizer application. I overcome these challenges by combining my economic model with a crop-growth model. The crop-growth model gives me a precise relation between inputs, especially water use, and yields. I thus use it to approximate a production function per crop-county, the smallest unit in which I observe the farmer. Then, I assume that the farmer's production function is the product of her individual-level productivity and the crop-growth-model production function. Since I observe water use, I can jointly recover the individual-level productivity and the fertilizer application by the optimality conditions of my model. More precisely, I recover these two unknowns from two model-implied equations. With individual-level productivity, fertilizer application, and water use, I can flexibly recover the marginal cost of water per farmer from the first-order condition for water use in my model.

With the individual estimates for productivity and the marginal cost of water, I compute the expected profitability per crop and farmer. More specifically, I compute the optimal water-fertilizer input decision and thus profitability, given the weather. I then take the expected profits of each crop as the average profits over the potential weather. Lastly, I use the estimated profits to recover the preference parameters over crops using a discrete-choice model.

My model thus allows me to analyze how farmers would respond to changes in the groundwater cost. Furthermore, it allows me to estimate the relation between the aquifer's water table and the cost of pumping water. My main findings are the following. First, I find that the marginal cost of water is rather heterogeneous within the region: the average marginal cost per acre-feet of water is 137 USD, whereas the standard deviation is 148 USD. The variation can be partially explained by observables in the data, such as the aquifer's water table underneath the farmer's land. I then quantify the relation between the marginal cost of water and the aquifer's water table. I find that the water table has a significant and relevant effect on the marginal cost of obtaining groundwater: in my preferred specification, a decrease of 1 foot on the water table increases the water cost per acre-feet by 5.4 USD. Lastly, I estimate the preference parameters to analyze how farmers respond to changes in water costs. More specifically, I quantify when farmers opt to switch crops and when they decide to change the water intensity per planted crop. I find that farmers are inelastic to water costs and that the two main margins of adaptation to an increase in water costs are decreasing water use per planting crop and fallowing the land: for local increases in the water cost, farmers decrease their water use per planted crop; for larger increases in the water cost, they fallow their land.[4]

Finally, I utilize my estimates to evaluate policies that induce more sustainable groundwater use. More precisely, I propose a common policy to solve the externality: a tax on groundwater use. The trade-offs of such a tax are the following. On the one hand, taxing groundwater may decrease the farmer's profits, as it would increase the cost of one of her inputs. On the other hand, taxing groundwater would decrease the total water use and thus may decrease the aggregate cost of pumping groundwater. As explained before, the problem is dynamic: taxing groundwater this year implies a higher aquifer's water table and, hence, a lower cost of pumping next year. The problem is also stochastic: different weather paths imply different marginal values of pumping water and, hence, different optimal groundwater use. I include both considerations in the taxation problem.

I propose two potential tax rates. First, I find the optimal tax considering farmers only, the tax that would maximize the expected present value of farmers' profits. For 2018, I find

[4] A caveat of my model is that it does not include irrigation technology investment, another source for farmers' adaptation to higher water costs. The effect of such an omission could go in either direction. On the one hand, if farmers respond to higher water costs by increasing their pump capacity, the depletion process may accelerate. On the other hand, if farmers respond to higher water costs by improving irrigation efficiency, the depletion process may slow down. I am currently working on strategies to precisely determine the effect of this omission.

that such a tax is 13 USD, a 10% increase from the average marginal cost. As expected, the optimal tax implies a slower depletion of the aquifer relative to the no-tax scenario, internalizing the (dynamic) externality of using groundwater in the farmer's problem.

Farmers, however, are not the only beneficiaries of the aquifer. Groundwater can be used residentially and the availability of water is valuable to society for precautionary reasons. Hence, I compute the tax that would push groundwater use to sustainable levels, the tax that would induce an (expected) groundwater use equal to the aquifer's recharge rate. For 2018, I find that this tax is 170 USD, a 124% increase from the average marginal cost. As the Ogallala Aquifer is large and deep in the region, this tax is probably an upper bound on how much policymakers should tax groundwater use.

Related Literature. This paper contributes to three trends in the literature. First, it contributes to the literature on farmers' elasticity of groundwater costs. The results of such a literature are somehow dispersed. For example, Burlig et al. (2021) and Smith et al. (2017) find an elasticity of -1.12 and -0.77, whereas Bruno and Jessoe (2021) and Hendricks and Peterson (2012) find an elasticity of -0.18 and -0.10. My estimated elasticity is -0.34, closer to Pfeiffer and Lin (2014). Moreover, I contribute to the understanding of the mechanisms that explain such an elasticity by combining a crop-growth model with an economic model, a particularly well-suited strategy for counterfactual analysis. I use the crop-growth model to precise the relation between irrigation and yields and combine it with an economic model and farmer-level data to comprehend water decisions.[5] Consequently, I can quantify how water costs translate into farmers' water demand, how much of such a demand can be explained by crop choices and water use per planted crop, and how policy changes can affect water demand.

A second line of research focuses on groundwater optimal management and governance. For instance, Merrill and Guilfoos (2018) and Timmins (2002) discuss groundwater optimal dynamic extraction. Sampson et al. (2023) and Ayres et al. (2021) quantify the equilib-

[5]For more details on the benefits of using a crop-growth model to precise the relation between water use and crop yield please check Foster and Brozović (2018).

rium effects of defining groundwater property rights. Edwards (2016) studies the heterogeneous benefits of groundwater management given the aquifer's characteristics. Edwards and Guilfoos (2021) explores the conditions that generate different groundwater governance worldwide. My contribution to this line of research is empirical. I estimate the equilibrium implications of the current groundwater costs by combining farmer-level data with a crop-growth model and an economic model. I utilize the estimates of my model to quantify the effects of optimal and suboptimal groundwater taxation.

Lastly, this paper contributes to the literature on water markets. In this line of research, Hagerty (2019) and Rafey (2023) discuss surface water markets for California and Australia, respectively. Closer to my work, Bruno and Sexton (2020) discuss the potential benefits of establishing groundwater markets for California, and Smith et al. (2017) studies the benefits of taxing groundwater use in Colorado. My paper is closer to the latter. I quantify the effects of taxing groundwater use, which could be considered a price on its use. I contribute to this line of research by estimating such effects flexibly and parsimoniously, combining a crop-growth model with an economic model.

2 Insitutional Context and Data

2.1 Institutional Context

The primary water source for Nebraskan farmers is groundwater. Farmers access groundwater by pumping it from wells, and thus, the main cost associated with groundwater use is the energy cost. The cost of pumping, in turn, depends on the aquifer's water table: the lower the water table, the higher the cost of pumping a unit of water. Aquifers are spread across multiple farmers' land; hence, groundwater use presents a common pool problem: if a farmer pumps groundwater, she decreases the aquifer's water table and, thus, increases the cost of pumping for other farmers in the same aquifer. The institutional context is therefore relevant to understand the extent of the common pool problem.

In Nebraska, groundwater is ruled by "correlative rights": farmers can use groundwater as far as it is beneficial for them to do so. Formally, the law states that farmers should use a "reasonable" amount of groundwater. The term, however, is not defined precisely. In practice, groundwater use is regulated locally by 23 autonomous Natural Resource Districts. The main requirement regarding groundwater withdrawal is the registration of new irrigation wells. In order to avoid excess water use in small geographic regions, every new well has to be constructed at a pre-determined distance from the pre-existing wells.

Some Nebraskan farmers also use surface water. Surface water is governed by the "appropriative rule," which dictates that water is allocated on a "first-in-time, first-in-right" basis. Whenever there is a water shortage, water rights are assigned first to whoever got the right first in time, then to whoever got the right second in time, and so on. Surface water is regulated by the Nebraska Department of Natural Resources.

2.2 Data: Irrigation and Water Management Survey (IWMS)

My primary data source is the "Irrigation and Water Management Survey - Farm and Ranch Irrigation Survey" (IWMS-FRIS) for 2018, 2013, and 2008. IWMS-FRIS is a follow-up survey from the Agricultural Census directed by the USDA. It consists of a representative sample of all American farmers who irrigate their land. I have access to individual records of such surveys. Specifically, I have detailed information, at a farmer-level, of: groundwater use, surface water use, and off-farm water use, both in acres and acre-feet;[6] crop choices and yields; the amount of water used in each crop; irrigation systems' technology; and gross sales for irrigated and non-irrigated land.

I focus on the Ogallala Aquifer in Nebraska. Figure 1 shows the Ogallala Aquifer and Nebraska's location on it. Nebraska is an interesting state to study for various reasons. First, the Ogallala Aquifer, which covers almost all of Nebraska, is one of the most important sources of water for American farmers: it covers approximately 30% of the irrigated land. The aquifer has been increasingly depleted in the last decades. Figure 2 presents the average depth to water of the Ogallala Aquifer in Nebraska in the years of my study.[7] The water table also

[6] An acre-foot is the amount of water needed to cover an acre of land one-foot depth.
[7] "Depth to water" is the distance between the surface and the water table.

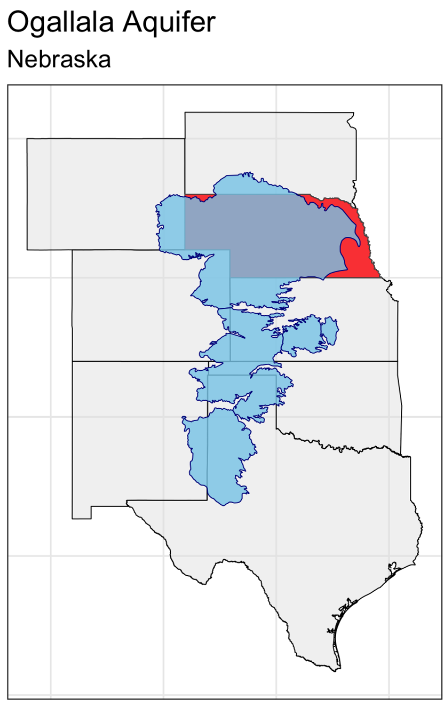

Figure 1: Ogallala Aquifer

Notes: The figure shows the location of the Ogallala Aquifer, also known as the High Plain Aquifer and the eight states in which it is spread. Nebraska is filled in red.

Variable	Mean	SD	N Farmers
Prop. of Cropland Irrigated	0.58	0.35	14,732
Groundwater, Prop. Water Used	0.86	0.31	12,937
Number of Wells	4.30	6.48	15,561
Energy Expenses Pump, USD	18,783	32,372	12,465
Energy Expenses Pump, Prop. Sales	0.04	0.07	12,465

Table 1: IWMS Nebraska, Descriptive Statistics - 2018

Notes: "Prop." refers to proportion, as in "Proportion of Cropland Irrigated." I use the sample weights to do this table, as indicated by the NASS.

varies within the state. Figure 3 shows the distribution by county.

Second, irrigation is widely spread in the state. In 2017, for example, 43% of the harvested cropland was irrigated. The main source of irrigation water is groundwater. In 2018, for example, 86% of the water Nebraskan farmers used was groundwater. Moreover, farmers are heterogenous in the state. The average number of wells for a Nebraskan farmer in 2018 was 4.3, whereas its standard deviation was 6.48. Table 1 describes the data for 2018 in further detail. Tables 18 and 19, in the appendix, describe the data for 2013 and 2008.

Lastly, its fourth main irrigated crops, corn, soybean, alfalfa, and wheat, are at the top of

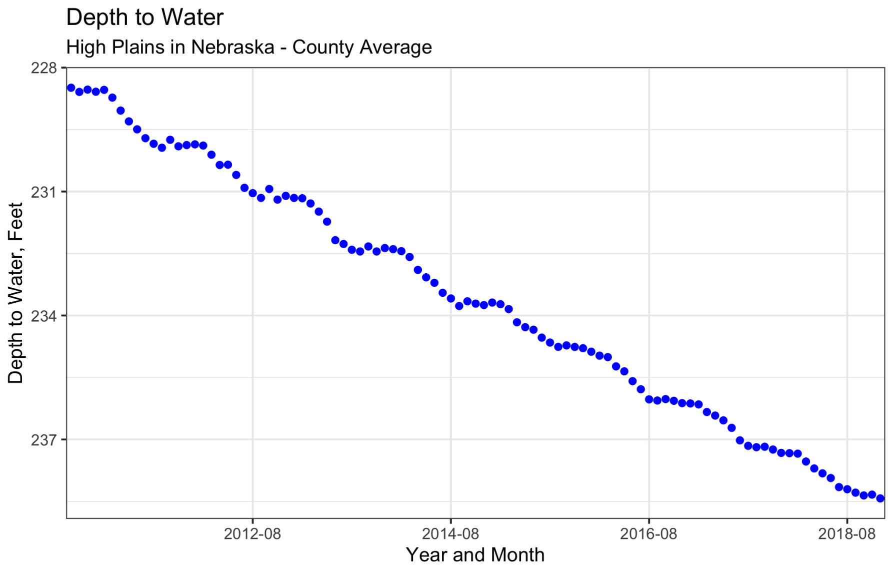

Figure 2: Depth to Water - Nebraska

Notes: "Depth to Water" refers to the distance from the surface to the water table. Thus, the the higher the depth to water, the lower the water table. The y-axis is reversed to reflect such a relation. For this figure, I keep only the USGS wells that have data in the whole period 2008-2018

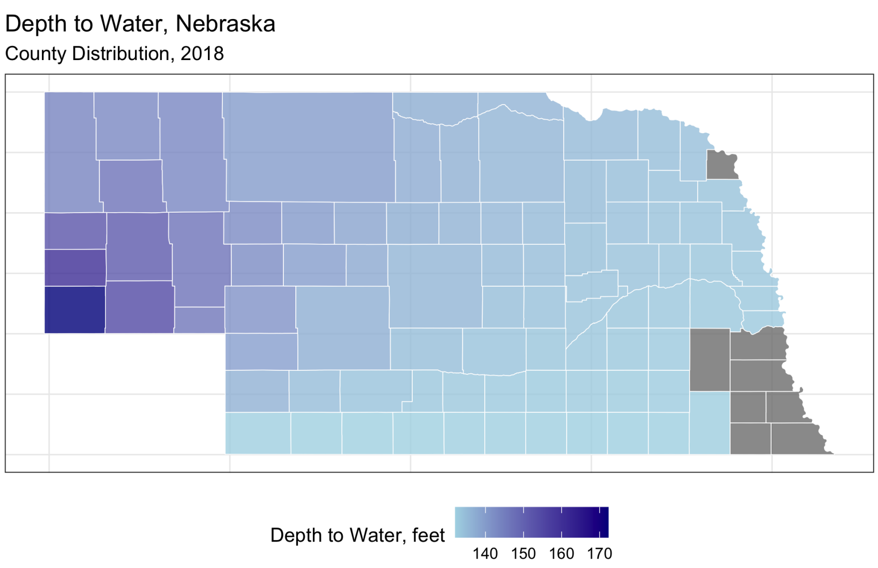

Figure 3: Depth to Water - Nebraska, 2018

Notes: "Depth to Water" refers to the distance from the surface to the water table. Thus, the the higher the depth to water, the lower the water table. For this figure, I use all the USGS wells in the Northern High Plain that have data in 2018.

Crop	Land, Mi Acres	Water, Mill AcF	Water, AcF/Acre	N Farm
Corn, grain	4.52	2.89	0.64	10,581
Soybean	2.20	1.10	0.50	7,821
Alfalfa	0.33	0.26	0.81	2,584
Wheat	0.06	0.04	0.65	370

Table 2: IWMS Nebraska, Main Crops - 2018

Notes: The acreage of each crop is reported in millions of acres. Water use is reported in millions of acre-feet. I use the sample weights to do this table, as indicated by the NASS.

irrigated crops in the West. The water intensity varies by crop. In 2018, for example, alfalfa utilized 0.81 acre-feet-per-acre on average, whereas soybean utilized 0.5. Table 2 shows the main crops for Nebraska in 2018. Table 8, in the appendix, shows the main crops for all of the West. I add tables 20 and 21, which include the main Nebraskan crops in 2013 and 2008, in the appendix.

2.3 Data: Other Sources

I complement my primary dataset with numerous others. Since I use a crop-growth model to understand the effect of water on yields, I need data on soil quality; I use SoilGrids (Poggio et al., 2021). SoilGrids collects standard soil quality characteristics, such as the percentage of clay in the soil and its nitrogen level. Since SoilGrids provides data at a 250mx250m level and I observe only farmers' county, I aggregate such data using the Cartographic Boundary Files from the United States Census Bureau (USCB).

The crop-growth model I use, DSSAT, simulates the photosynthesis process. Thus, I also need data on solar irradiance. I get such data from NASA POWER. As before, I aggregate the data at the county level using USCB maps.

In order to understand the extent of the common pool problem, I need data on the water table of the Ogallala Aquifer. USGS provides such data: it has numerous wells across the US which monitor water tables. Figure 4 illustrates their location. I approximate the water table at a county level using the inverse of the distance between the county's centroid and the wells at less than 100km of distance.

Lastly, I collect PRISM data on weather variables, precisely maximum temperature, min-

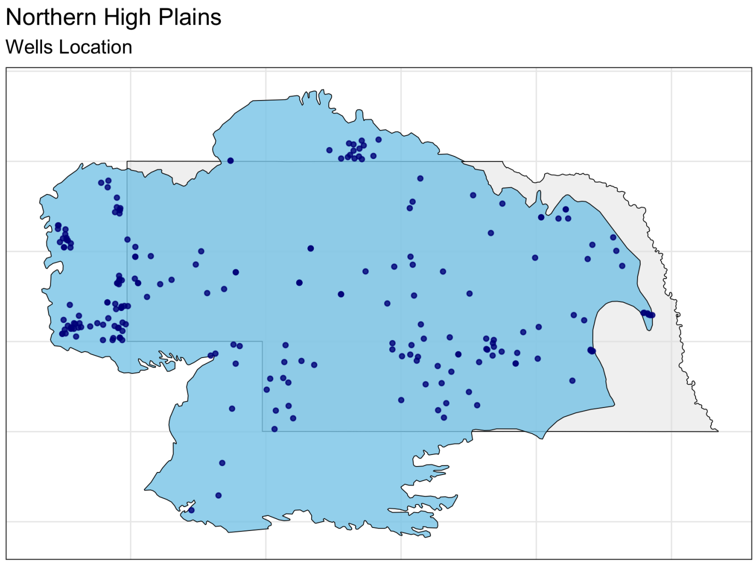

Figure 4: Wells Location - USGS

Notes: The figure illustrates in dark blue the wells' location that USGS monitors in the Northern High Plains, the Northern Aquifer within the Ogallala Aquifer.

imum temperature, and precipitation; Cropland Data Layer (CDL) data on crop rotation; GebreEgziabher et al. (2022) for data on Ogallala's location; and USDA data on crop prices.

3 Model

In this section, I propose a model of (ground)water demand for farmers. I allow farmers to differ in their water demand due to their individual-level productivity, marginal cost of water, and preferences over planting crops. I complement the model with the recharge process of the aquifer that farmers use to obtain groundwater.

3.1 Water Demand

I divide the farmer's problem into two stages. First, she has to decide which crop to plant. Then, she needs to decide whether to irrigate the land - and how much.

I solve the model by backward induction. In the second stage of the model, the farmer observes the weather at the beginning of the stage and decides on irrigation thereafter; thus, there is no uncertainty on the final yield given the farmer's inputs (i.e., the farmer knows the production function). Then, a farmer i, who decided to plant crop j, maximizes:

$$\max_{w_i, \mathbf{x}_i} \; p_j f_j^i(w_{ij}, \mathbf{x}_{ij}; S_i) - c_i(w_{ij}) - \mathbf{p}_\mathbf{x} \mathbf{x}_{ij} \tag{1}$$

where p_j is the market price of crop j; w_{ij} is the water use by farmer i in crop j; $\mathbf{x}_{ij}$ is the vector of other inputs used by farmer i in crop j (e.g., fertilizers); S_i are the soil and weather conditions that farmer i faces; $f_j^i(w_{ij}, \mathbf{x}_{ij}; S_i)$ is the production function for crop j and farmer i; $c_i(w_{ij})$ is the cost function of obtaining w_{ij} units of water for farmer i (e.g., the cost of pumping); and $\mathbf{p}_\mathbf{x}$ is the vector of other-inputs' prices. I assume $f_j^i(w, \mathbf{x}; S)$ is continuous and concave for all $w, x \in \mathbf{x}$, and $c_i(w_{ij})$ is continuous and convex.

Thus, the FOCs for the farmer are:

$$\frac{\partial f_j^i(w_{ij}, \mathbf{x}_{ij'}; S_i)}{\partial w} = \frac{c_i(w_{ij})}{p_j} \tag{2}$$

$$\frac{\partial f_j^i(w_{ij}, \mathbf{x}_{ij}; S_i)}{\partial x} = \frac{p_x}{p_j}, \forall x \in \mathbf{x} \tag{3}$$

I denote the solution of Equations (2) and (3) as $(w_{ij}^*, \mathbf{x}_{ij}^*)$.

I then define the optimal profitability for farmer i who chose crop j as:

$$v_{ij} \equiv p_j f_j^i(w^*, \mathbf{x}^*; S_i) - c_w(w^*) - p_\mathbf{x} \mathbf{x}^* \tag{4}$$

In the first stage of the model, the farmer plants the crop that maximizes her utility. More specifically:

$$\max_j \; \alpha_j + \beta \mathbb{E}[v_{ij}] + \epsilon_{ij} \tag{5}$$

where the expectation is taking over different weather realizations; α_j is the constant term for crop j; β is the marginal value of the expected profits for farmers; v_{ij} is the profit for farmer i of choosing crop j given the weather; and ϵ_{ij} is an unobserved taste shock on planting crop j. I assume that ϵ_{ij} is distributed Extreme Value Type 1 (EVT1).

Thus, the expected total acreage planted of crop j is:

$$A_j = \sum_i a_i \frac{e^{\alpha_j + \beta \mathbb{E}(v_{ij})}}{\sum_j e^{\alpha_j + \beta \mathbb{E}(v_{ij})}} \tag{6}$$

where a_i is the total acreage operated by farmer i.

3.2 Water Supply

The other side of the market is the "water supply," the aquifer's recharge process. Following Ayres et al. (2021) and Merrill and Guilfoos (2018), I model the aquifer height as:

$$\dot{h}(t) = R - (1 - \alpha) \sum_i w_i(h(t)) \tag{7}$$

where $h(t)$ is the aquifer height at time t; R is the recharge rate of the aquifer; α is the water use for irrigation which returns to the aquifer; and $w_i(h(t))$ is the water use by farmer i given an aquifer height of $h(t)$. The discrete approximation of such an equation would be:

$$\Delta h(t + 1) = R - (1 - \alpha) \sum_i w_i(h(t)) + \epsilon_t \tag{8}$$

4 Estimation

In my data, I observe the farmers' water use, crop choices, and crop yields. I want to estimate the farmers' production function per crop, marginal cost of water, and preference parameters over planted crops. I proceed in two steps. First, I combine my model with a crop-growth model to estimate the production-function parameters and the marginal cost of water. Second, I use these estimates plus the distribution of the crop choices to recover the preference parameters over crops.

4.1 Parametrization

In my model, I allow farmers to be heterogeneous in their production function and their marginal cost of water. I have thus two empirical challenges to overcome. First, I do not observe individual-level production functions; I only observe farmers' water use and yield per crop. Second, I do not observe other inputs used by farmers, especially fertilizer application, which is an essential input in the farmer's problem. I use a crop-growth model to overcome both of these challenges. More specifically, I use the "Decision Support System for Agrotechnology Transfer" (DSSAT) software (Hoogenboom et al., 2019; Jones et al., 2003). DSSAT works precisely as a (simulated) production function: given the weather, soil quality, and inputs applied to the crop, it returns an (expected) yield. Figure 5 shows an example of DSSAT for corn 2018 for Sheridan, Nebraska. I describe DSSAT in further detail in the appendix A.5.

I then assume the individual-level production function is the product of the crop-specific individual-level productivity and the DSSAT production function, namely:

$$q_j^i = f_j^i(w_{ij}, \mathbf{x}_{ij}; S_i) = \gamma_{ij} f_j(w_{ij}, \mathbf{x}_{ij}; S_i) \tag{9}$$

where q_j^i is the yield for farmer i in crop j; γ_{ij} is the productivity of farmer i in crop j; and $f_j(w, \mathbf{x}; S)$ is the DSSAT-expected-yield for crop j. In the US, nitrogen is the main fertilizer. For the sake of simplicity and data limitations, I assume nitrogen is the only other input in the farmer's decision.[8]

I make two further parametrization assumptions to my model. First, I want to recover the relation between the marginal cost of groundwater and the aquifer's water table. Thus, I parameterize the farmers' marginal cost of groundwater as a linear function of the aquifer's water table, namely:

$$c_i'(w) = \alpha_g + \beta_g WT_{l(i)} + \epsilon_i \tag{10}$$

[8] Unfortunately, I do not have data on phosphorous (or potassium) levels in the soil; thus, I cannot add them to my estimation. The DSSAT-simulated yield, however, is very close to the yield observed in the data, which suggests I am not missing much for such an omission.

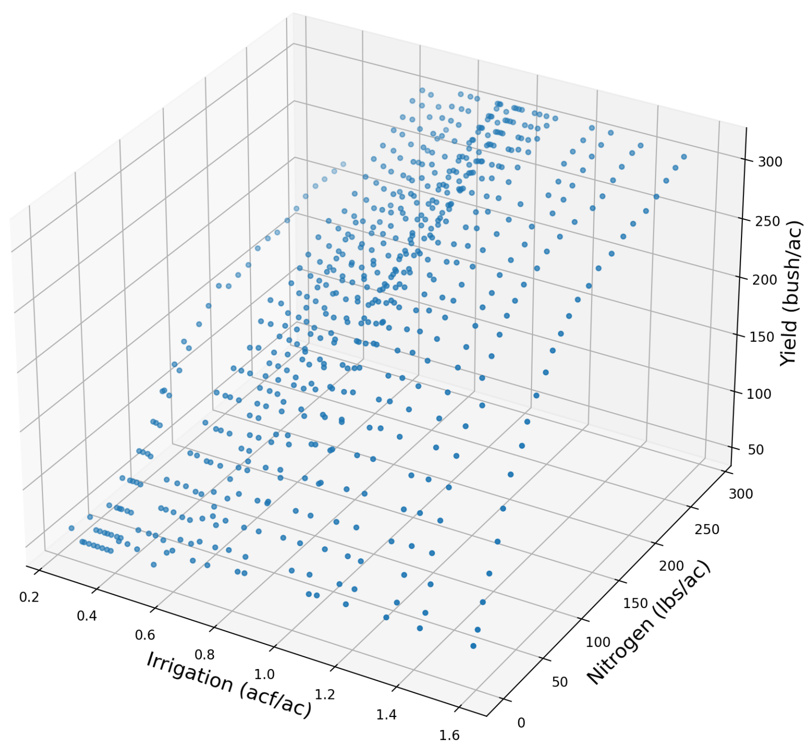

Figure 5: Example Corn, DSSAT - Sheridan, Nebraska. 2018

Notes: The figure shows a smooth approximation of the DSSAT outcome for simulated yields in Sheridan, Nebraska, in 2018. "Irrigation (acf/ac)" refers to the irrigation rate computed in acre-feet per acre. "Nitrogen (lbs/ac)" refers to pounds of nitrogen applied to the crop per acre. "Yield (bush/ac)" refers to bushels of corn harvested per acre.

where α_g is the (average) marginal cost of pumping groundwater; β_g is the cost increment for having a lower water table, $WT_{l(i)}$, for farmers in the county $l(i)$; and ϵ_i is the error term.

Lastly, in the second stage of the model, I estimate crop substitution. More specifically, I need to compute the expected profitability of each crop. I, however, do not observe farmers choosing every crop. Thus, I need to make an assumption on the productivity parameter for the non-planted crops. I follow the Hicks-neutrality assumption, common in the literature closely (Hicks, 1932; Rafey, 2023), with a small adjustment. Specifically, I assume that the productivity of farmer i on the non-planted crop j' is:

$$\gamma_{ij'} = \gamma_{j't(i)} + \gamma_i \tag{11}$$

where $\gamma_{j't(i)}$ reflects shocks on the productivity of planting crop j' at time $t(i)$, the year I observe farmer i, which were missed to be considered by DSSAT; and γ_i is the individual-level productivity of farmer i. This gives me an upper bound on the productivity for other crops: since the farmer is presumably more productive in the crop she chose, assigning the productivity from the chosen crop to the non-chosen crops, after controlling for crop-year fixed effects, would likely be an upper bound on her actual productivity on the non-chosen crops.

4.2 Estimation

For the estimation, I first approximate the crop-growth model production function. After that, I need to estimate the following parameters: $\gamma_{i\mathbf{j}}$, the productivity of farmer i for each crop; (α_g, β_g), the parameters for the marginal cost of water; $(\alpha_{\mathbf{j}}, \beta)$, the parameters of the crop choice model; and R and α, the recharge rate and the returned proportion of water to the aquifer.

4.2.1 Crop-Growth Model

I use the crop-growth model to approximate a production function per crop-county-year, the smallest unit in which I observe the farmer. This approximation is demanding: as a crop-growth model simulates the growing stages of the crop, I need to define both the irrigation rate *and* the timing of irrigation. DSSAT, however, allows for a better alternative: I can choose the targeted soil moisture levels rather than irrigation dates. I can then recover the irrigation rate given the soil moisture targeted. I present additional necessary assumptions in the appendix A.5.

I then simulate 625 combinations of irrigation rates and nitrogen use per county-crop-year, a thousand times each. I interpolate and smooth the simulated production function using a quadratic approximation:

$$y_{ijct} = \alpha_{ijct} + \beta_{w1_{ct}} w_{ijct} + \beta_{w2_{ct}} w_{ijc}^2 + \beta_{f1_{ct}} f_{ijct} + \beta_{f2_{ct}} f_{ijct}^2 + \beta_{w1f1_{ct}} w_{ijct} f_{ijct} + \epsilon_{ijct} \tag{12}$$

where y_{ijct} is the average simulated yield for crop j at county c at time t; w_{ijct} is the irrigation rate for crop j at county c at time t; f_{ijct} is the fertilizer rate for crop j at county c at time t; and ϵ_{ijct} is the error term.[9] I then interpolate the crop-county-year production function using the estimates $(\tilde{\alpha}_{ijct}, \tilde{\beta}_{w1_{ct}}, \tilde{\beta}_{w2_{ct}}, \tilde{\beta}_{f1_{ct} f_{ijct}}, \tilde{\beta}_{f2_{ct}}, \tilde{\beta}_{w1f1_{ct}})$, which I recover for a linear regression. I denote such an approximation $f_j(w, x; S_{ct})$. For the sake of notation, I call the production function for farmer i who is located at county c at time t simply as $f_j(w, x; S_i)$.

4.2.2 Productivity Parameters

I recover the productivity parameter and the fertilizer application per farmer i on her chosen crop j non-parametrically. Essentially, I recover two unknowns from two model-implied equations. Specifically, I recover both productivity level and fertilizer use from the production-function equation and the first-order condition equation:

$$\gamma_{ij} = \frac{q_j^i}{f_j(w_{ij}, x_{ij}; S_i)} \tag{13}$$

$$\frac{\partial f_j(w_{ij}, x_{ij}; S_i)}{\partial x_{ij}} = \frac{p_x}{p_j \gamma_{ij}} \tag{14}$$

[9] The process for soybean and alfalfa is slightly simpler. As both crops fix nitrogen in the soil and do not use much nitrogen fertilizer, I do not run the regression for all fertilizer-irrigation combinations. Instead, I run a quadratic regression on water use only for different fertilizer rates, and then I take the average on them.

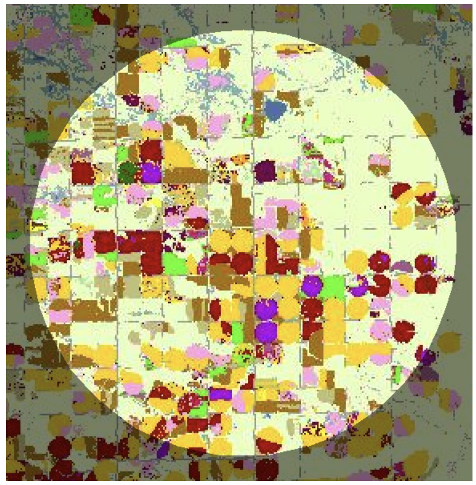

Figure 6: Sheridan, Nebraska. 2018

Notes: The imagine was obtained by the USDA CroplandCROS website. Each color represents a crop. Crops planted in a circular fashion are irrigated using a central pivot system.

where (13) comes directly from (9), and (14) comes from (9) and the FOCs of (3). Since I already approximate $f_j(w_{ij}, x_{ij}; S_i)$, I observe everything but (γ_{ij}, x_{ij}); hence I simply recover the two unknowns from these two equations.

A note here. In principle, I could treat each farmer as a unit. This, however, would not follow closely how farmers decide on irrigation (and fertilizer applications). Most Nebraskan farmers have a central pivot system to irrigate their land. They use such a system location-by-location. Figure 6 illustrates this point. Each color in the image represents a crop. Crops planted in a circular fashion are irrigated using a central pivot system. Since the smallest unit I observe the farmer is the crop, I assume each farmer decides irrigation separately per crop and may have a different productivity and marginal cost of water per crop. For simplicity, I call "farmer" the crop-farmer unit.

With γ_{ij} per farmer, then, I can estimate the productivity terms, $(\gamma_{\mathbf{j}t}, \gamma_{\mathbf{i}})$, from a fixed-effect regression:

$$\gamma_{ij} = \gamma_{jt(i)} + \gamma_i \tag{15}$$

where $\gamma_{jt(i)}$ is the crop times year fixed effects; and γ_i is the residual of the regression.

4.2.3 Cost Parameters

With γ_{ij}, I can recover the marginal cost of water from equations (9) and the FOC (3):

$$p_j \gamma_{ij} \frac{\partial f_j(w_{ij}, x_{ij}; S_i)}{\partial w} = c_i'(w_{ij}) \equiv c_{ij} \tag{16}$$

Notice this gives me, non-parametrically, a unique marginal cost of water per farmer. I thus recover all the parameters of the farmer's second stage of the model. I use such parameters to estimate the profitability of each crop in the first stage of the model.

Unfortunately, I can only approximate the aquifer's water table at a county level.[10] To recover the effect to the aquifer's water table on the marginal cost of water, thus, I aggregate marginal cost at a county-year level and run:

$$c_{lt} = \alpha_{gt} + \beta_g WT_{lt} + \epsilon_{lt} \tag{17}$$

where c_{lt} is the weighted-by-acreage marginal cost of water for county l at year t; α_{gt} is the year fixed effect; β_g is the increase in water cost due to a lower water table; and WT_{lt} is the water table at county l in year t. I recover α_{gt} and β_g from a linear regression.

4.2.4 Crop Choice and Aquifer Parameters

With the productivity and cost parameters, I can construct the expected profits of each crop given the weather. More precisely, I can solve:

$$(w^*, x^*) : \max_{w,x} p_j \gamma_{ij} f_j(w, x; S_{it}) - c_i(w) - p_{xt} x \tag{18}$$

where I change my notation slightly: S_{it} now includes the realized weather at t. Let's call the solution of such a problem v_{ijt}^*:

$$v_{ijt}^* \equiv p_j \gamma_{ij} f_j(w^*, x^*; S_{it}) - c_i(w^*) - p_{xt} x^* \tag{19}$$

[10] I have a noisy measure of the aquifer's water table at the beginning of the growing season. For the sake of completeness, I also run the regression using such a variable.

From there, I recover the annual return of each crop given the weather.

Rather than choosing crops annually, however, farmers choose crop rotations. Thus, I modify my model slightly and assume farmers choose a crop rotation every other year. Figure 7 illustrates the main crop rotations in Nebraska. Following such figure, I group crops as follows: (i) {Corn, Soybean}; (ii) {Corn, Corn}; (iii) {Alfalfa, Alfalfa}; (iv) {Wheat, Fallow}; (v) {Fallow, Fallow}.[11]

Since I observe annual crops rather than crop rotations, I need a few more assumptions to identify in which crop rotation the farmer is. The only problematic crop is corn, as corn appears in the soybean-corn rotation and corn-corn rotation. For simplicity, I assume the farmer is in the corn-soybean rotation unless soybean covers, on average, less than 5% of the land in the county where the farmer is located in the years of my study.[12]

I make two more assumptions. First, I reduce the choice set of farmers depending on their county. Specifically, I assume that a crop rotation is available in a county only if at least 5% of its land was covered by such a rotation in the years of my study. Second, I need an assumption for the rotation {fallow, fallow}. In Sections 4.2.2 and 4.2.3, I recover the productivity and the marginal cost of water per farmer-crop using the wedge between the expected yield and the observed yield. For fallow land, however, I do not have an estimate on either of them - by its very definition, fallow land does not produce any yield. I thus do a lower bound exercise: for every farmer that fallow part of their land, I assume that the marginal cost of water in the portion of the land equals the highest marginal cost of water that I estimate for such a farmer. Similarly, I assume that the productivity for each crop equals the minimum productivity for such a crop-farmer. These are likely a lower bound on the marginal cost of water and an upper bound on the productivity of the farmer in their fallow land, and reasons why farmers decided to fallow their land in the first place.

With an abuse of notation, I call j the crop rotation. I then estimate the expected profits

[11]For the sake of completeness, I am currently expanding the model to add the {Wheat, Corn} rotation. Since wheat does not appear frequently in my data, I do not expect such an expansion would change the results significantly.

[12]I am expanding the model so that if the farmer is planting corn, I assume she is on the corn-corn rotation with a certain probability and in the corn-soybean rotation with a certain probability, following county-specific rotation patterns.

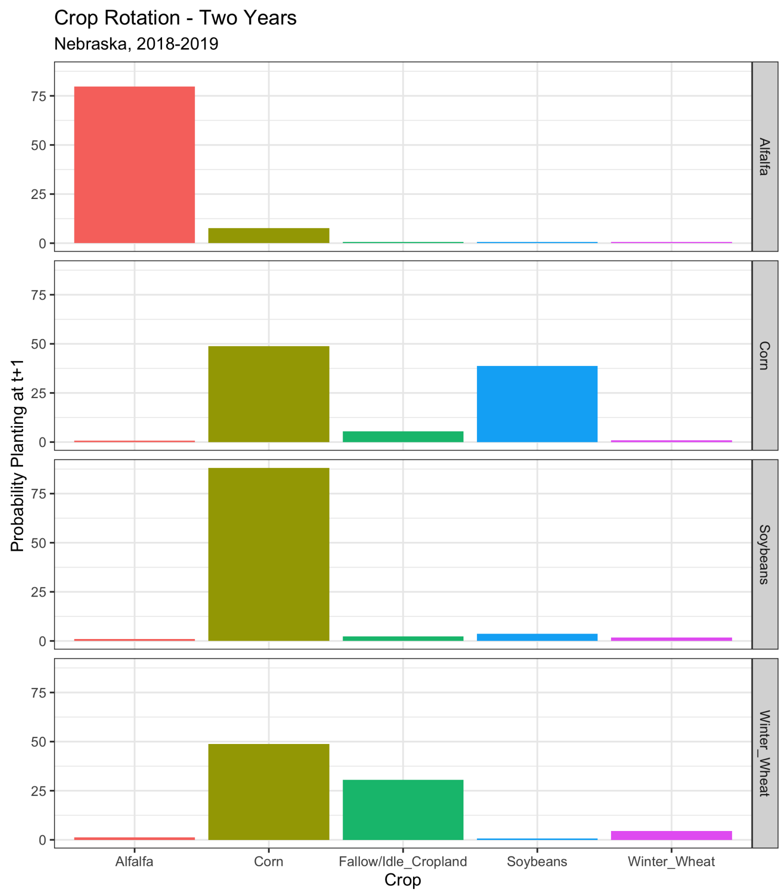

Figure 7: Transition Probability - Weighted Average. Nebraska, 2018-2019

Notes: The figure shows the transition probabilities from one crop to another from 2018 to 2019. On the right-hand side of the figure, the crop planted in 2018 is displayed. On the x-axis, the crop planted in 2019 is shown. On the y-axis, the probability or proportion of each one of the crops is illustrated. This figure was created using the CDL dataset for 2018 and 2019. The probabilities are calculated as the proportion of pixels that were originally in 2018 the crop display at the right-hand side of the figure, and in 2019 the ones on the x-axis.

of choosing a crop rotation j for farmer i as the numerical average of the optimal yield given the weather. I observe the weather from 1984 to 2018. For 2018, then, I have:

$$\tilde{\mathbb{E}}(v_{ij}) = \frac{1}{34} \sum_{t=1984}^{2017} v^{*}_{ijt} \tag{20}$$

With that, I estimate the crop choice by a multinomial logit:

$$(\alpha_j, \beta) : \max_{\alpha_j, \beta} \sum_i a_i \left[\sum_j p_{ij} \log \left(\frac{e^{\alpha_j + \beta \mathbb{E}(v_{ij})}}{1 + \sum_j e^{\alpha_j + \beta \mathbb{E}(v_{ij})}} \right) + \left(1 - \sum_j p_{ij} \right) \log \left(\frac{1}{1 + \sum_j e^{\alpha_j + \beta \mathbb{E}(v_{ij})}} \right) \right] \tag{21}$$

where a_i is the total amount of acreages farmer i planted of crop j; p_{ij} is equal to one if farmer i chose crop j; and the outside option is fallowing the land.

Lastly, I calibrate the recharge rate for the Ogallala aquifer in Nebraska, R, following McMahon, Böhlke, and Carney (2007), and the percentage of groundwater use for irrigation which returns to the aquifer, α, following Merrill and Guilfoos (2018).

As shown in Figure 11, the Ogallala Aquifer is large. If I used a single-cell model and consider the whole aquifer as a unit, I would likely underestimate the extent of the groundwater externality (Brozović, Sunding, & Zilberman, 2010). Thus, I consider each county, the smallest geographical unit I observe, an independent cell.[13]

5 Results

As described in the estimation section, I estimate the productivity parameters and the marginal cost of water non-parametrically. I assume farmers take crop and fertilizer prices as given, which I display in Table 25 in the appendix.

Table 3 summarises the non-parameteric results. First, the individual-level productivity has a close-to-one mean and a low variance. Figure 8 illustrates its distribution. Conceptually, this means that the county explains most of the variation in crop yields - and the crop-growth model projects yields accurately. I add the heterogeneity on productivity per crop

[13] I am extending the model to consider the full hydrology connectivity across counties.

	Mean	SD	Obs
γ_{ij}	0.93	0.23	58,003
c_{ij}	217.80	203.31	58,003
c^*_{ij}	137.20	148.07	37,711

Table 3: Productivity and Marginal Cost

Notes: This table presents the non-parametric estimators on productivity, γ_{ij}*, and marginal cost of water,* c_{ij}*.* c^*_{ij} *refers to the estimated marginal cost excluding 2013. I use sample weights in this table, as suggested by the NASS.*

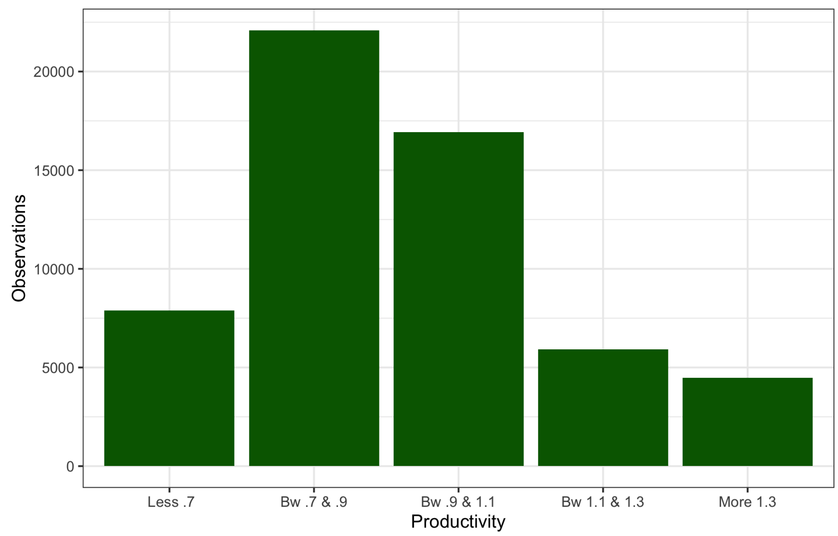

Figure 8: Productivity Per Crop

Notes: The figure shows the distribution of the non-parametric estimation of the productivity per crop. The x-axis can be read as follows: "Less .7" means that the productivity estimated was less than 0.7; "Bw .7 & .9" means that the productivity estimated was more than 0.7 and less or equal to 0.9; "More 1.3" means the productivity estimated was more than 1.3. The y-axis counts the frequency of these events.

in Appendix A.6. Table 4 shows the fixed-effects regression for productivity per crop. The variation across years is not large, although the crop-growth model predicts the data best in the last year of my sample, 2018.

Second, there is substantial variation in the marginal cost of obtaining water: its mean is almost as high as its standard deviation. This could be explained by many factors. First, farmers differ in observables. For example, farmers have different numbers of wells and various technologies to irrigate their land. I am currently expanding the paper to correlate these factors with the marginal cost of water. Farmers may also differ in unobservables, such as the characteristics of the aquifer below their land. My model is flexible in these terms precisely because of that. Including the heterogeneity in the marginal cost of obtaining water

Dependent Variable:	Productivity, γ_{ij}
Model:	(1)
Variables	
Alfalfa	1.0150***
	(0.0555)
Corn	0.7415***
	(0.0086)
Soybean	0.9095***
	(0.0123)
Wheat	0.6884***
	(0.1989)
Alfalfa × 2013	0.1989**
	(0.0755)
Corn × 2013	0.2717***
	(0.2717)
Soybean × 2013	0.2028***
	(0.0185)
Wheat × 2013	0.3253**
	(0.1074)
Alfalfa × 2018	0.2328***
	(0.0679)
Corn × 2018	0.1145***
	(0.0126)
Soybean × 2018	-0.0248
	(0.0180)
Wheat × 2018	0.2385*
	(0.0964)
Fit statistics	
Observations	2,599
R^2	0.2601

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 4: Depth to Water and Marginal Cost of Water - Regression

Notes: The dependent variable is the productivity term, γ_{ij}. The explanatory variables are the crop times year fixed effects. I use the acreage as weights for this regressions.

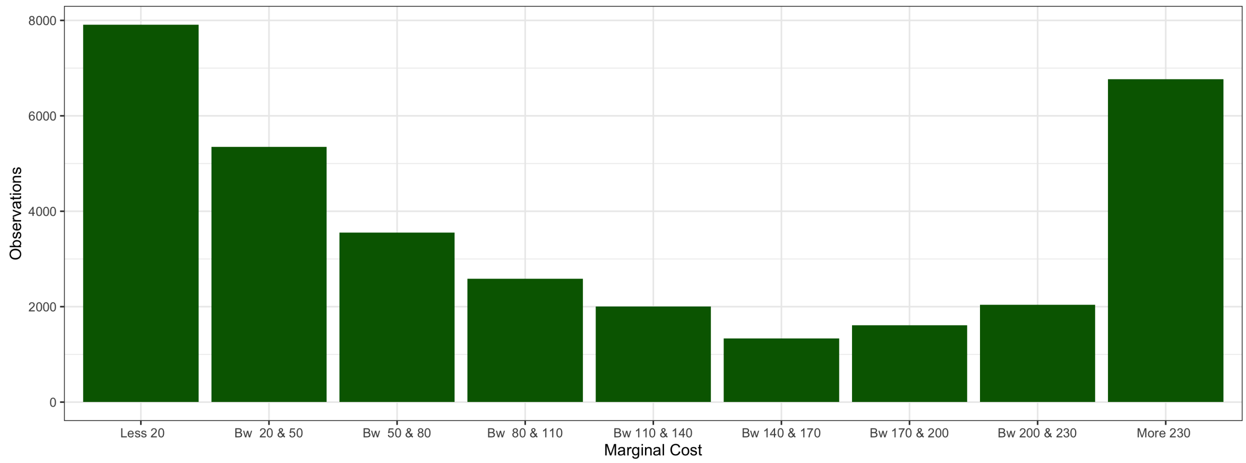

Figure 9: Productivity Per Crop

Notes: The figure shows the distribution of the non-parametric estimation of the marginal cost of water. The x-axis can be read as follows: "Less 20" means that the estimated marginal cost is less than 20 USD per acre-foot in 2018 prices; "Bw 20 & 50" that the estimated marginal cost is more than 20 USD and less than 50 USD per acre-foot in 2018 prices; "More 230" means that the estimated marginal cost is more than 230 USD per acre-foot in 2018 prices. The y-axis counts the frequency of these events. I exclude 2013.

is thus relevant to the counterfactual analysis. I discuss that further in the next section.

A note here: the estimates for 2013 are exceptionally high. In 2013, precipitations were atypically low as it was the use of groundwater, which probably implied that farmers were (physically) restricted that year.[14] The marginal cost would thus not extrapolate correctly to average years. I then exclude 2013 from the rest of the paper.[15] Figure 9 illustrates the distribution of the marginal cost of water excluding such a year.

Third, the depth of water has a significant effect on the marginal cost of water. Table 5 shows the exact (linear) relation. In my preferred specification, an increase of 1 foot in the depth to water increases the groundwater cost by 5.4 dollars.[16] This result may be increasingly problematic for farmers in the region, as the aquifer has been systematically depleted in the last decades.

Lastly, I estimate the crop-choice parameters using a multinomial logit. Table 6 shows the logit estimates. The expected profitability of each crop is, naturally, an important factor when determining crop choices. In equilibrium, the expected profits per acre is 576 USD.

[14] I add Table 14 to the weather patterns in the years of my study.
[15] I am currently working on strategies to identify the physically restricted farmers.
[16] The farmer-level specification has both noise and missing values; thus, I prefer the county-level specification.

Dependent Variable:	Marginal Cost, 2018-USD	
Model:	(1)	(2)
Variables		
Depth to water, feet (County)	5.427**	
	(0.0570)	
Depth to water, feet (Farmer)		0.245*
		(0.0186)
Fixed-effects		
year	Yes	Yes
Fit statistics		
Observations	142	1,007
R^2	0.34	0.27

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 5: Depth to Water and Marginal Cost of Water - Regression

Notes: "Depth to water, feet" refers to the distance between the surface and the water table in feet. "Marginal Cost, 2018-USD" is the marginal cost of water for farmers in my sample in USD in 2018 prices. "County" means that both the dependent and independent variable are aggregated at a county level. "Farmer" means that both the dependent and independent variable are aggregated at a farmer level. I use for farmers by acreage planted and sample weights.

Thus, an increase of 10% on the profitability of a crop would increase the probability that a crop is chosen over fallow land by 5.07%.

6 Counterfactual Policies

I utilize my previous estimates to simulate policies that induce more sustainable groundwater use. Specifically, I propose a common policy to fix the externality: taxing groundwater use. The trade-off at hand is that increasing the water tax would decrease the per-period farmers' profits, but it would also decrease water use, and thus, it may decrease aggregate water costs and push toward sustainability.

A caveat of my analysis is that I do not allow farmers to adapt to higher water costs over time. The effect of this omission may increase or decrease the extent of the problem. On the one hand, if farmers decide to respond to higher water costs by creating more wells or increasing their pump capacity, the depletion process may accelerate, and so may the average

	Dependent variable:
	Crop Rotation Chosen
Alfalfa-Alfalfa	-1.201***
	(0.235)
Corn-Soybean	0.531**
	(0.234)
Corn-Corn	0.172
	(0.208)
Wheat-Fallow	-1.670***
	(0.236)
Expected Profits	0.088***
	(0.023)
Observations	1,681
Log Likelihood	-1037.512
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 6: Logit Estimation - Crop Choice

Notes: The table presents the estimations for the multinomial logit estimation. "Alfalfa-Alfalfa", "Corn-Soybean", "Corn-Corn", and "Wheat-Fallow" are the constant for these crop-rotations. The omitted rotation is "Fallow-Fallow". "Expected Profits" refers to expected profits in 100s of USD dollars at 2018 prices. All variables are decided at an acre level. I weighted observations using farmers' acreage and sample weights.

cost of water. On the other hand, if farmers respond to higher water costs by improving irrigation efficiency and thus reducing their water demand, the depletion process may slow down. I am currently working on strategies to identify the effects of such an omission.

6.1 Taxing Problem

The water authority has to decide the water tax given the aquifer's recharge rate and the agents' response to such a tax. I add more notation to make the problem more tractable. First, I have N farmers, indexed by $i \in \{1, ..., N\}$. Second, I have J potential crops to be chosen by a farmer, indexed by $j \in \{1, ..., J\}$. R is the natural recharge rate of the aquifer, and α is the proportion of water use for irrigation, which returns to the aquifer. I denote the aquifer's height at time t as $h(t)$. The water authority thus decides $p(h(t))$, the tax on water given the aquifer's height. The only state variable, s_t, is the weather at time t, with $s_t \in \{1, 2, ..., S\}$ and $\phi(s)$ the probability realized weather is s. Lastly, farmer i responds to the water tax on two margins: (i) the probability of choosing crop j, $\psi_{ij}(p,h)$; (ii) the water use when choosing crop j, $w_{ij}(p,h;s)$. I define $v_{ij}(p,h;s)$, the (optimal) per-period profit of farmer i when choosing crop j.

I do all the counterfactuals using the farmers' estimates and crop prices for 2018. I calibrate the aquifer's recharge rate following McMahon et al. (2007) and the irrigation water that returns to the aquifer following Merrill and Guilfoos (2018). I add my calibration assumptions in Table 25 in the appendix.

6.2 Optimal Solution

I compute the optimal tax considering the dynamic nature of the problem. The water authority thus maximizes the expected total profits dynamically, given the current aquifer's height.

Following my model, the timing of the problem is as follows. First, the water authority decides the price given the aquifer's height. Initially, I assume that the water authority chooses a unique price per county, regardless of the water table. Second, each farmer decides which crop to plant given the aquifer's height, the water tax, and the taste shocks per crop. Third, the weather is realized, and each farmer decides the water use. Fourth, the aquifer's height is updated, given its recharge rate and the total water use. Lastly, the process starts over with the new aquifer's height.

The water authority decides the price in the first step, taking expectations over the other steps. More specifically,

$$
\begin{aligned}
V(h) &= \max_{p} \sum_{s} \left[\sum_{i} \sum_{j} \psi_{ij}(p,h)[v_{ij}(p,h;s) + p w_{ij}(p,h;s)] + \beta \mathbb{E}_{\epsilon}[V(h';p,s,\epsilon)] \right] \phi(s) \\
\text{s.t. } & h'(p,h;s,\epsilon) = h + R - (1-\alpha) \sum_{i} \sum_{j} \mathbf{1}[\epsilon : i \text{ chooses } j] \times w_{ij}(p,h;s)
\end{aligned}
\tag{22}
$$

where $\psi_{ij}(p,h)$ is the probability that farmer i chooses crop j given the water tax p and the aquifer's height h; $v_{ij}(p,h;s)$ is the per-period profit of farmer i on crop j given water tax p, the aquifer's height h, and the weather s; β is the discount factor; h' is the aquifer's height the next period; ϵ is the taste shocks; $\phi(s)$ is the probability that the realized weather is s; R is the recharge rate of the aquifer; α is the proportion of water used for irrigation which returns to the aquifer; and $w_{ij}(p, h; s)$ is the expected water use of farmer i on crop j given the water price p, the aquifer's height h, and the weather s.

Assuming each county is independent of the other, and thus that the aquifer's recharge process is county-specific, I find that the weighted-by-acreage optimal tax is 12.89 USD, a 10% increase from the baseline.

6.3 Sustainable Use

An alternative policy would be taxing groundwater use so that the (expected) water use equals the recharge rate, given the current aquifer's height. Specifically,

$$p : \sum_{s} \left[\sum_{i} \sum_{j} w_{ij}(p, h; s) \psi_{ij}(p, h) \right] \phi(s) = \frac{R}{(1-\alpha)} \tag{23}$$

where $w_{ij}(p, h; s)$ is the water use of farmer i when choosing crop j given the water tax p, the aquifer's height h, and the weather s; $\psi_{ij}(p, h)$ is the probability that farmer i chooses crop j given the water tax p and the aquifer's height h; $\phi(s)$ is the probability that the realized weather is s; R is the recharge rate of the aquifer; and α is the proportion of water use for irrigation which returns to the aquifer.

Assuming each county is independent of the other, and thus that the aquifer's recharge process is county-specific, I find that the weighted-by-acreage sustainable tax is 170.27 USD, a 124% increase from the baseline.

6.4 Comparison Across Policies

Figure 10 illustrates the differences in the aquifer's depletion rate for both counterfactuals and the no-tax scenario. Formally, I simulate the process for a hundred years, with a hundred different weather paths each; that is, a hundred different realizations of a hundred years of weather. For the weather, I use a random sample, with replacement, from the period 1984-

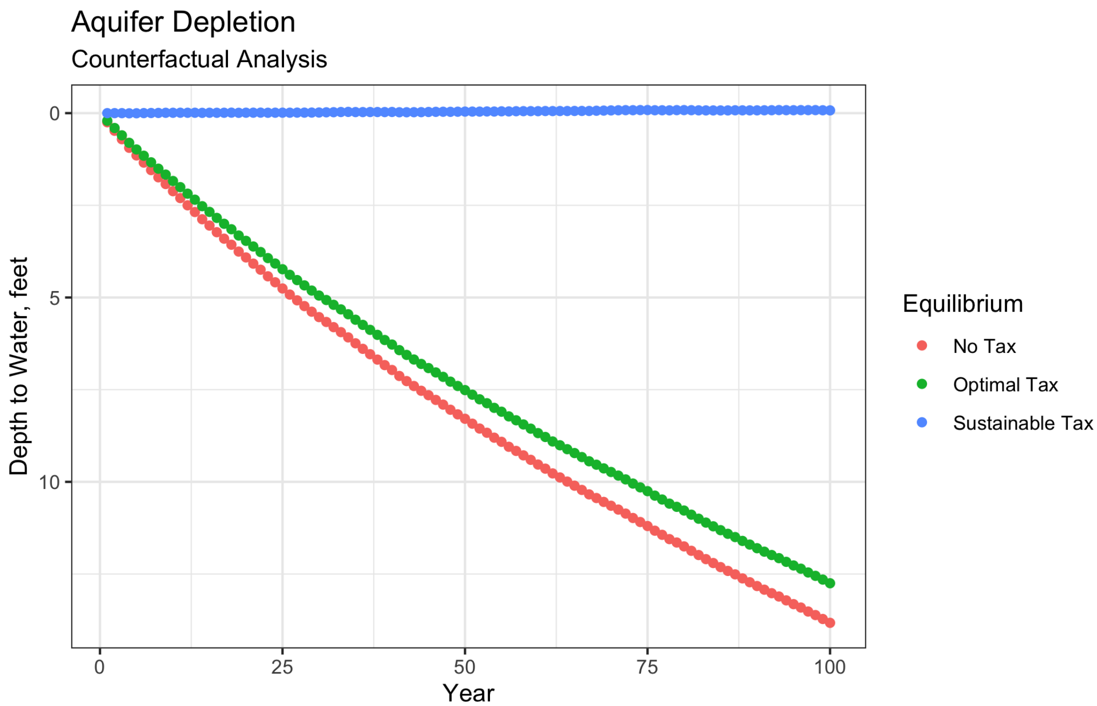

Figure 10: Depth to Water, Evolution

Notes: "Depth to Water" refers to the distance from the surface to the water table. Thus, the higher the depth to water, the lower the water table. The y-axis is inverted to reflect this relation. Furthermore, the y-axis unit is the (simulated) increase in depth to water from the year 2018. The x-axis is the year of the simulation. The yearly depth to water is the average across simulations and acreage-weighted counties.

2018 of realized weather. Table 25, in the appendix, shows other calibration assumptions.

The results can be summarised as follows. First, the sustainable tax implies that, by its very definition, there is no depletion of the aquifer. From an economic point of view, this might be too extreme of a policy: the aquifer is large and deep in the region, so it would be hard to argue that no depletion is the optimal policy. Naturally, the loss on total profits of such a policy is large; on average, farmers would lose 20% of their present-value profits.

The optimal tax, which would maximize the present value of profits for farmers, is thus closer to the no-tax scenario. Nevertheless, the tax indicates that the current levels of groundwater use are not optimal - the tax implies that the depletion rate slows down. The acreage-weighted-average gains of such a tax imply a 0.13% increase in present-value profits. These gains vary considerably across counties: some counties should not tax groundwater use, while others would gain approximately 1% from optimal taxation.

7 Conclusion

I leverage detailed farmer-level data on water use, crop choices, and crop yields to study the equilibrium implications of the current groundwater costs in the Ogallala Aquifer in Nebraska. In my analysis, I combine a crop-growth model with an economic model. I use the crop-growth model to recover the precise (agronomic) relation between water use and yields. I use the economic model to quantify the main margins of adaptations for farmers for various water costs. My model allows me to separately identify the individual-level productivity, marginal cost of water, and crop preferences of farmers.

My main findings are the following. First, farmers are rather heterogeneous in their marginal cost of groundwater in the region. For example, the average marginal cost of obtaining groundwater is 137 USD dollars in 2018 prices, while the standard deviation is 148 USD. Second, the water table has a relevant effect on the cost of obtaining groundwater. Third, farmers are inelastic to water costs, and they adapt to higher water costs by reducing the water use per planted crop and fallowing the land. Lastly, I utilize the estimates of my model to compute the optimal and sustainable tax on water use.

There are some venues to expand my work. First, my model is static. Farmers, however, can adapt to higher water costs by investing in wells or irrigation technology. I am currently working on strategies to precisely identify the effects of such an omission. Second, I focus my work on groundwater use, as that is the primary water source for Nebraskan farmers. In other places in the US, farmers also use plenty of surface water or buy water in the market. It would be interesting to study the effect of the optimal groundwater policy on other water sources. Lastly, climate change will likely affect farmers' water demand. The combination of a crop-growth model with economics is an exciting tool to employ to study this issue. The crop-growth model gives a precise relation between weather and yields, and economics can help us translate such a relation to water demand. I plan to keep working on this trend of the literature to include the effect that climate change may have on the optimal water policy.

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A Appendix

A.1 Groundwater Use - Tragedy of the Commons

Conceptually, the problem is similar to the tragedy of the commons. I follow Ayres et al. (2021). There is a unique aquifer. Farmers are identical and atomic. Then, the representative farmer maximizes:

$$\max_{w} \pi(w, h) \tag{24}$$

where w is the amount of groundwater used, and h is the height of the aquifer (that is, the distance between the bottom of the aquifer and the water level). I assume the function is concave, continuous, and single-peaked at w for all h. I further assume the higher the aquifer, the cheapest it is to pump, that is, $\pi_{wh} > 0$. Then, the farmer has a unique solution for its problem for each h, $w_o(h)$.

Formally, the recharge process is continuous. Specifically, I assume:

$$\dot{h}(t) = R - N \times w(h(t)) \tag{25}$$

where R is the recharge rate and N is the number of farmers. In equilibrium, then,

$$\dot{h}^o(t) = R - N \times w_o(h(t)) \tag{26}$$

The optimal level of water usage, however, is the solution of:

$$\begin{aligned} \max_{w(t),h(t)} \int_0^\infty & e^{-\rho t} \pi(w(t), h(t)) dt \\ \text{s.t. } & \dot{h}(t) = R - N w(t) \end{aligned} \tag{27}$$

which clearly does not have the same solution.

A.2 IWMS-FRIS - Summary Statistics

In this section, I add the summary statistics for the Western US.[17] Table 7 describes the data for for 2018. Groundwater is a major water source, both in the percentage of water used and in the percentage of gross sales. This hasn't changed much in the last ten years; Tables 9 and 10 describe the data for 2013 and 2008.

Variable	Mean	SD	N Farmers
Prop. of Cropland Irrigated	0.71	0.39	168,523
Groundwater, Prop. Water Used	0.39	0.47	169,057
Number of Wells	1.39	5.21	209,922
Energy Expenses Pump, USD*	18,647	82,186	105,475
Energy Expenses Pump, Prop. Sales*	0.12	0.91	105,475

Table 7: IWMS West, Descriptive Statistics - 2018

*Notes: Western USA includes all the states that have some territory at the west of the 100-meridian; that is: North Dakota, South Dakota, Nebraska, Kansas, Oklahoma, Texas, Montana, Wyoming, Colorado, New Mexico, Idaho, Utah, Arizona, Washington, Oregon, Nevada, and California. "Prop." refers to proportion, as in "Proportion of Cropland Irrigated," which naturally varies between 0 and 1. *For "Energy Expenses Pump(ing)", I include only farmers who expend more than 0 dollars pumping water.*

Table 8 describes the main irrigated crops in the western US in 2018. In acreage, corn for grain is the main crop. In acre-feet of water use, however, alfalfa is the main one. The numbers look similar for 2013 and 2008; I add them in Tables 11 and 12.

[17] "Western US" includes all the states that have some territory at the west of the 100-meridian; that is North Dakota, South Dakota, Nebraska, Kansas, Oklahoma, Texas, Montana, Wyoming, Colorado, New Mexico, Idaho, Utah, Arizona, Washington, Oregon, Nevada, and California.

Crop	Land, Mill Acres	Water, Mill AcF	Water, AcF/Acre	N Farmers
Corn, grain	8.09	8.33	1.03	20,539
Alfalfa	6.10	11.46	1.88	47,654
Fruits and Nuts	4.42	8.39	1.90	45,347
Hay, other	3.18	5.06	1.59	24,433
Soybean	2.86	1.63	0.57	10,612
Wheat	2.18	3.07	1.41	7,996
Vegetables	2.10	2.87	1.49	9,223

Table 8: IWMS West, Main Crops - 2018

Notes: Western USA includes all the states that have some territory at the west of the 100-meridian. That means North Dakota, South Dakota, Nebraska, Kansas, Oklahoma, Texas, Montana, Wyoming, Colorado, New Mexico, Idaho, Utah, Arizona, Washington, Oregon, Nevada, and California. The acreage of each crop is reported in millions of acres. Water use is reported in millions of acre-feet. As indicated by the USDA, I use the survey weights for this table.

Variable	Mean	SD	N Farmers
Prop. of Cropland Irrigated	0.72	0.38	170,002
Groundwater, Prop. Water Used	0.42	0.48	167,210
Number of Wells	1.56	5.09	196,873
Energy Expenses Pump, USD*	20,505	81,978	104,740
Energy Expenses Pump, Prop. Sales*	0.14	1.05	104,740

Table 9: IWMS West, Descriptive Statistics - 2013

*Notes: Western USA includes all the states that have some territory at the west of the 100-meridian; that is: North Dakota, South Dakota, Nebraska, Kansas, Oklahoma, Texas, Montana, Wyoming, Colorado, New Mexico, Idaho, Utah, Arizona, Washington, Oregon, Nevada, and California. "Prop." refers to proportion, as in "Proportion of Cropland Irrigated," which naturally varies between 0 and 1. *For "Energy Expenses Pump(ing)", I include only those who expend more than 0 dollars pumping water.*

Tables 9 and 10 describe the data for 2013 and 2008, respectively. Tables 11 and 12 display the main crops for 2013 and 2008, respectively.

A.2.1 Yield and Water Use

Water use depends heavily on crop choices (see, for example, Table 8 and 2). Interestingly, water explains an important portion of yield variability within a county. Table 13 shows the relation between water and yields for the Western USA.

Variable	Mean	SD	N Farmers
Prop. of Cropland Irrigated	0.79	0.34	158,124
Number of Wells	1.14	4.28	254,491
Energy Expenses Pump, USD*	18,292	73,948	121,535
Energy Expenses Pump, Prop. Sales*	0.12	0.86	121,535

Table 10: IWMS West, Descriptive Statistics - 2008

*Notes: Western USA includes all the states that have some territory at the west of the 100-meridian; that is: North Dakota, South Dakota, Nebraska, Kansas, Oklahoma, Texas, Montana, Wyoming, Colorado, New Mexico, Idaho, Utah, Arizona, Washington, Oregon, Nevada, and California. "Prop." refers to proportion, as in "Proportion of Cropland Irrigated," which naturally varies between 0 and 1. *For "Energy Expenses Pump(ing)", I include only farmers who expend more than 0 dollars pumping water.*

Crop	Land, Mill Acres	Water, Mill AcF	Water, AcF/Acre	N Farmers
Corn, grain	8.09	1.32	1.63	20,539
Alfalfa	6.10	11.39	1.87	47,654
Fruits and Nuts	4.42	6.76	1.53	45,347
Hay, other	3.18	6.42	2.02	24,433
Soybean	2.86	2.74	0.96	10,612
Wheat	2.18	4.53	2.08	7,996
Vegetables	2.10	3.13	1.49	9,223

Table 11: IWMS West, Main Crops - 2013

Notes: Western USA includes all the states that have some territory at the west of the 100-meridian. That means North Dakota, South Dakota, Nebraska, Kansas, Oklahoma, Texas, Montana, Wyoming, Colorado, New Mexico, Idaho, Utah, Arizona, Washington, Oregon, Nevada, and California. The acreage of each crop is reported in millions of acres. Water use is reported in millions of acre-feet. As indicated by the USDA, I use the survey weights for this table.

Crop	Land, Mill Acres	Water, Mill AcF	Water, AcF/Acre	N Farmers
Corn, grain	8.09	1.07	1.32	20,539
Alfalfa	6.10	1.21	1.98	47,654
Fruits and Nuts	4.42	9.63	2.18	45,347
Hay, other	3.18	6.11	1.92	24,433
Soybean	2.86	2.33	8.17	10,612
Wheat	2.18	5.61	2.58	7,996
Vegetables	2.10	3.80	1.81	9,223

Table 12: IWMS West, Main Crops - 2008

Notes: Western USA includes all the states that have some territory at the west of the 100-meridian. That means: North Dakota, South Dakota, Nebraska, Kansas, Oklahoma, Texas, Montana, Wyoming, Colorado, New Mexico, Idaho, Utah, Arizona, Washington, Oregon, Nevada, and California. The acreage of each crop is reported in millions of acres. Water use is reported in millions of acre-feet. As indicated by the USDA, I use the survey weights for this table.

Model:	Corn, Grain - Bu (1)	Alfalfa - Ton (2)	Soybean - Bu (3)	Wheat - Bu (4)
Variables				
Water	12.65***	0.4099***	4.046***	6.446***
	(2.541)	(0.0477)	(1.499)	(2.009)
Water^2	-1.772***	-0.0198***	-0.5693*	-1.830**
	(0.5681)	(0.0073)	(0.3012)	(0.9198)
Fixed-effects				
county	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	5,754	8,992	4,772	2,272
R^2	0.42111	0.39475	0.68679	0.53092

Clustered (county) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 13: Yields and Water, Western US. IWMS-FRIS 2018, 2013, 2008

Notes: The dependent variables are the yield per acre of the mentioned crops. Corn for grain, soybeans, and wheat are measured in bushels of product. Alfalfa is measured in tons of dry matter. The independent variables are acre-feet and acre-feet squared per acre of water applied to the corresponding crop. The errors are clustered at the county level.

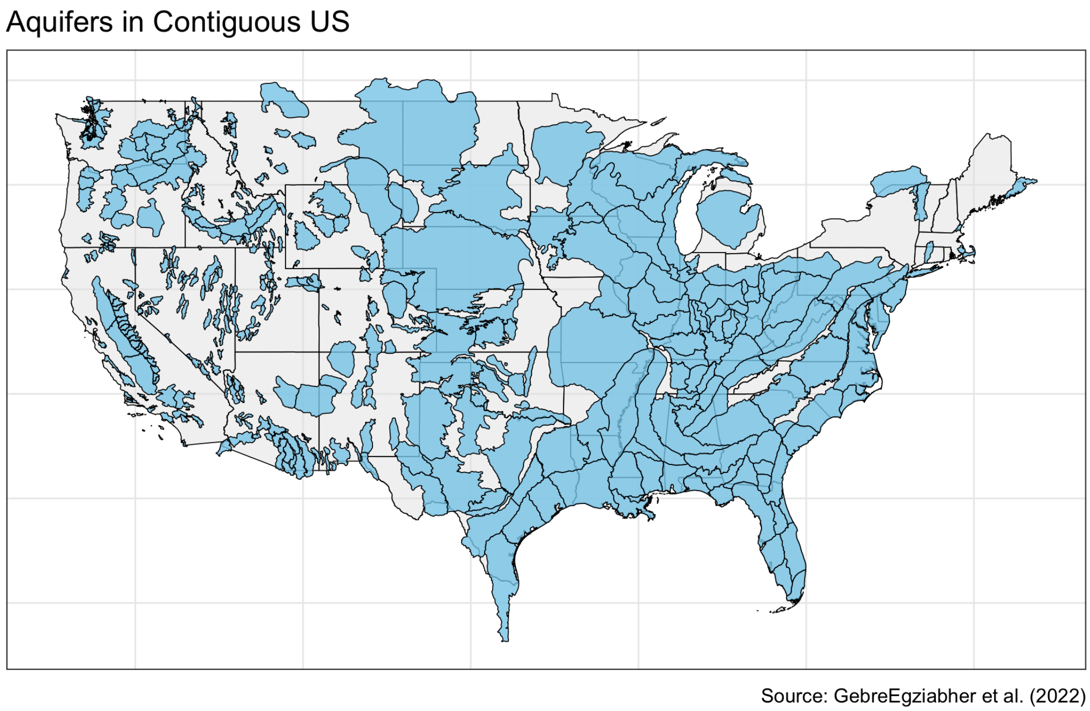

Figure 11: Aquifers' Location
Notes: The source of this map is GebreEgziabher et al. (2022). You can download the shape files directly from this link.

A.3 Aquifers' location

In this section, I plot the aquifers' location in the USA. Figure 11 shows their location.

A.4 Nebraska - Summary Statistics

In this section, I add summary statistics for Nebraska. First, I add two plots on Nebraska's climate. Figure 12 illustrates the average precipitation and Figure 13 reflects the average temperature.

Second, I add Table 14, which shows the year-to-year variation of weather for the years of my study.

Third, I show the heterogeneity in soil quality within Nebraska. Figure 14 and 15 illustrate the case of clay and silt per county in Nebraska.

Fourth, I add the historical depletion of the Ogallala Aquifer in the region. Figure 16 illustrates it.

Lastly, I move to the descriptions regarding IWMS-FRIS.

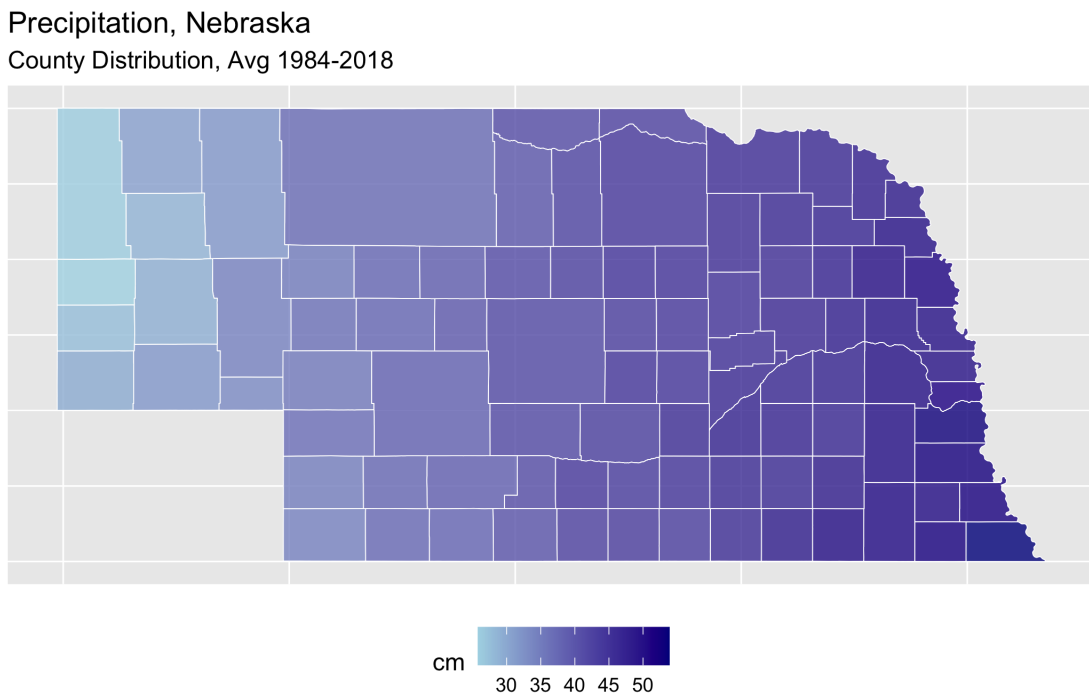

Figure 12: Precipitation - Nebraska, 1984-2018

Notes: "Precipitation" refers to the average yearly cm of precipitation in the growing season in Nebraska, April to August. I include data from 1984 to 2018.

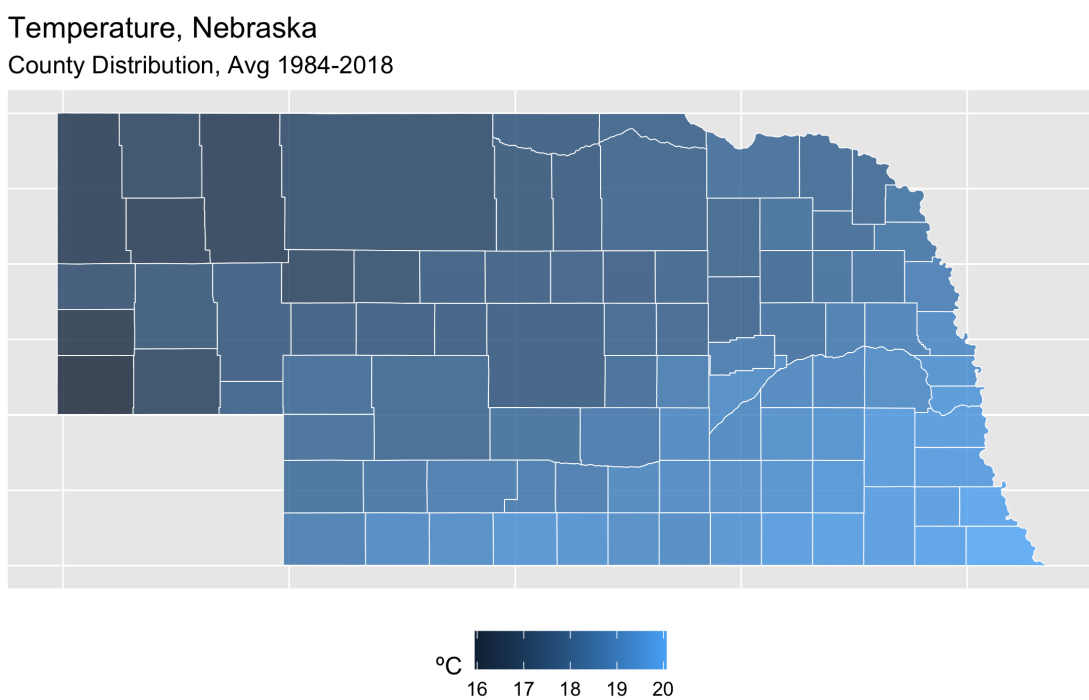

Figure 13: Average Temperature - Nebraska, 1984-2018

Notes: "Temperature" refers to the average temperature in ºC in the growing season in Nebraska, April to August. I include data from 1984 to 2018. The average temperature is calculated as the simple average between the maximum and the minimum temperature.

Year	Precipitation	Max Temperature	Min Temperature
2008	492.81	24.24	9.94
2013	393.33	24.32	10.40
2018	509.55	24.70	10.97

Table 14: Weather, Nebraska - 2018, 2013, 2008

Notes: "Precipitation" refers to the total precipitation in mm. "Max Temperature" and "Min Temperature" refer to the maximum and minimum temperature in ºC. I include only the months for the growing season in Nebraska, April to August. These are averages over counties, where I weighted counties by total area.

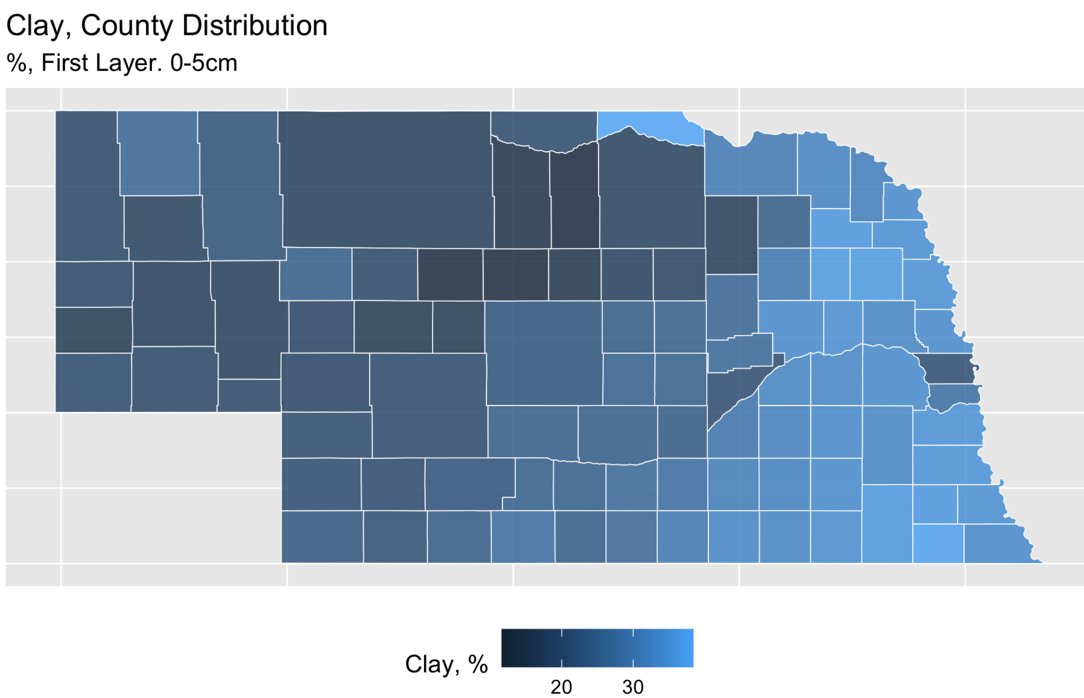

Figure 14: Clay, % - First Layer, Nebraska

Notes: The figure illustrates the average percentage of clay in the first layer of the soil per county in Nebraska. The first layer of the soil is defined from 0cm to 5cm in depth.

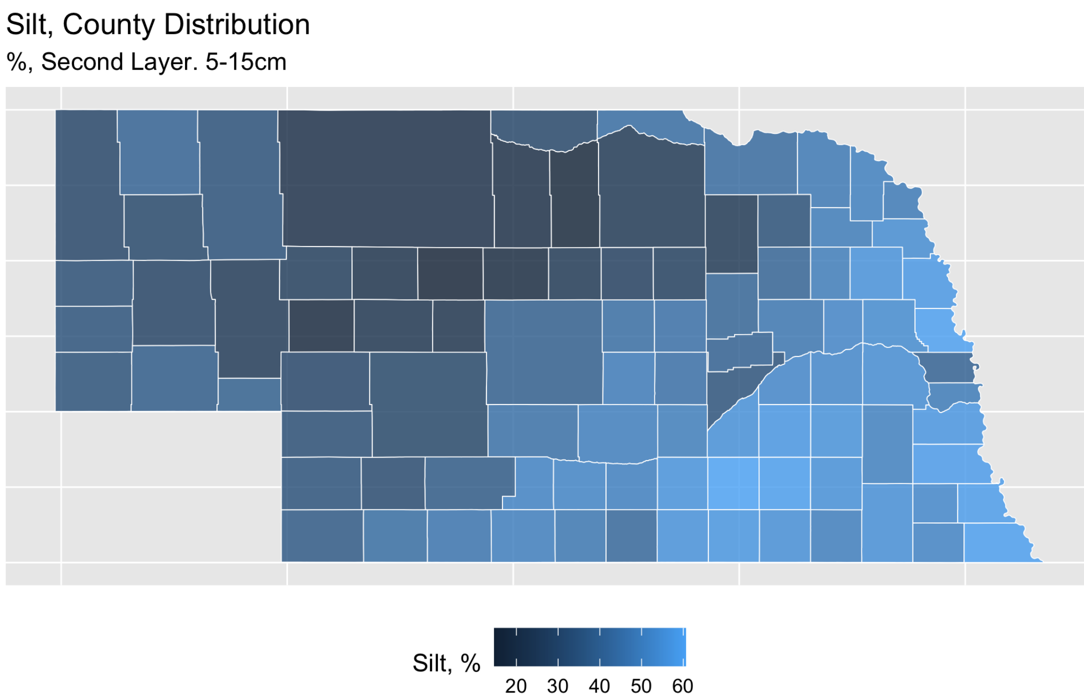

Figure 15: Silt, % - Second Layer, Nebraska

Notes: The figure illustrates the average percentage of silt in the second layer of the soil per county in Nebraska. The second layer of the soil is defined from 5cm to 15cm in depth.

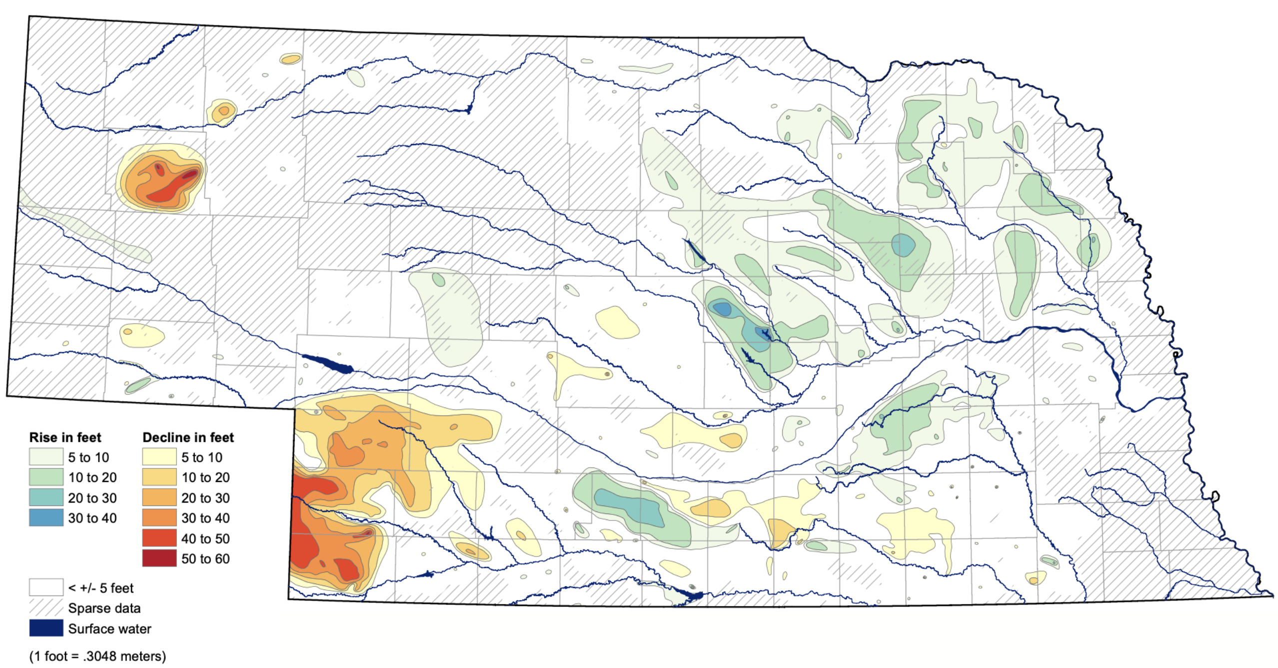

Figure 16: Historical Change in the Water Table - Ogallala Aquifer, Nebraska

Notes: The source of this figure is Young et al. (2019). It shows the historical change in the Ogallala Aquifer's water Table in Nebraska. This figure is Figure 16 in Young et al. (2019).

Crop	Yield		Water Use		Num of
	Mean	SD	Mean	SD	Farmers
Corn, Grain	216.07	29.68	0.64	0.40	10,581
Soybeans	65.53	8.82	0.50	0.32	7,821
Alfalfa	5.19	1.46	0.81	0.64	2,584
Wheat	73.25	21.20	0.65	0.34	370

Table 15: Water Use, IWMS Nebraska - 2018

Notes: The table shows the yields and irrigation rates for the main crop in Nebraska. Yield is shown in bushels for corn, soybeans, and wheat, and in tons for alfalfa. Irrigation is displayed in acre-feet per acre.

Crop	Yield		Water Use		Num of
	Mean	SD	Mean	SD	Farmers
Corn, Grain	199.48	27.09	1.04	0.51	13,915
Soybeans	59.80	10.91	0.88	0.38	8,990
Alfalfa	5.34	1.69	1.09	0.48	3,234
Wheat	69.79	9.79	0.57	0.20	947

Table 16: Water Use, IWMS Nebraska - 2013

Notes: The table shows the yields and irrigation rates for the main crop in Nebraska. Yield is shown in bushels for corn, soybeans, and wheat, and in tons for alfalfa. Irrigation is displayed in acre-feet per acre.

A.4.1 IWMS-FRIS - Additional summary statistics

I add the additional summary statistics for the IWMS-FRIS. Tables 15, 16, and 17 describe the dispersion on yields and irrigation rates for the main crops in Nebraska for 2018, 2013, and 2008. Tables 18 and 19 describe the data for 2013 and 2008, respectively. Tables 20 and 21 display the main crops for 2013 and 2008, respectively.

A.5 Crop-Growth Model: DSSAT

In this section, I describe DSSAT in further detail. As described in its webpage, the "Decision Support System for Agrotechnology Transfer (DSSAT) is a software application program that

Crop	Yield		Water Use		Num of
	Mean	SD	Mean	SD	Farmers
Corn, Grain	183.06	28.80	0.74	0.37	12,530
Soybeans	54.52	10.21	0.57	0.29	10,541
Alfalfa	4.60	1.83	0.84	0.49	2,956
Wheat	56.92	25.06	0.66	0.42	1,000

Table 17: Water Use, IWMS Nebraska - 2008

Notes: The table shows the yields and irrigation rates for the main crop in Nebraska. Yield is shown in bushels for corn, soybeans, and wheat, and in tons for alfalfa. Irrigation is displayed in acre-feet per acre.

Variable	Mean	SD	N Farmers
Prop. of Cropland Irrigated	0.64	0.35	16,475
Groundwater, Prop. Water Used	0.90	0.26	15,662
Number of Wells	4.68	6.95	16,491
Energy Expenses Pump, USD	24,560	44,785	16,491
Energy Expenses Pump, % Sales	0.06	0.10	16,491

Table 18: IWMS Nebraska, Descriptive Statistics - 2013

Notes: "Prop." refers to proportion, as in "Proportion of Cropland Irrigated." As indicated by the USDA, I use the survey weights for this table.

Variable	Mean	SD	N Farmers
Prop. of Cropland Irrigated	0.66	0.32	15,983
Number of Wells	3.40	5.74	22,718
Energy Expenses Pump, USD	15,522	33,448	22,718
Energy Expenses Pump, % Sales	0.05	0.06	16,224

Table 19: IWMS Nebraska, Descriptive Statistics - 2008

Notes: "Prop." refers to proportion, as in "Proportion of Cropland Irrigated." As indicated by the USDA, I use the survey weights for this table.

Crop	Land, Mi Acres	Water, Mill AcF	Water, AcF/Acre	N Farm
Corn, grain	5.35	5.57	1.04	13,915
Soybean	1.94	1.70	0.88	8,990
Alfalfa	0.24	0.26	1.09	3,234
Wheat	0.12	0.07	0.57	947

Table 20: IWMS Nebraska, Main Crops - 2013

Notes: The acreage of each crop is reported in millions of acres. Water use is reported in millions of acre-feet. As indicated by the USDA, I use the survey weights for this table.

Crop	Land, Mi Acres	Water, Mill AcF	Water, AcF/Acre	N Farm
Corn, grain	5.06	3.74	0.74	12,530
Soybean	2.27	1.30	0.57	10,541
Alfalfa	0.24	0.20	0.84	2,956
Wheat	0.17	0.02	0.66	1,000

Table 21: IWMS Nebraska, Main Crops - 2008

Notes: The acreage of each crop is reported in millions of acres. Water use is reported in millions of acre-feet. As indicated by the USDA, I use the survey weights for this table.

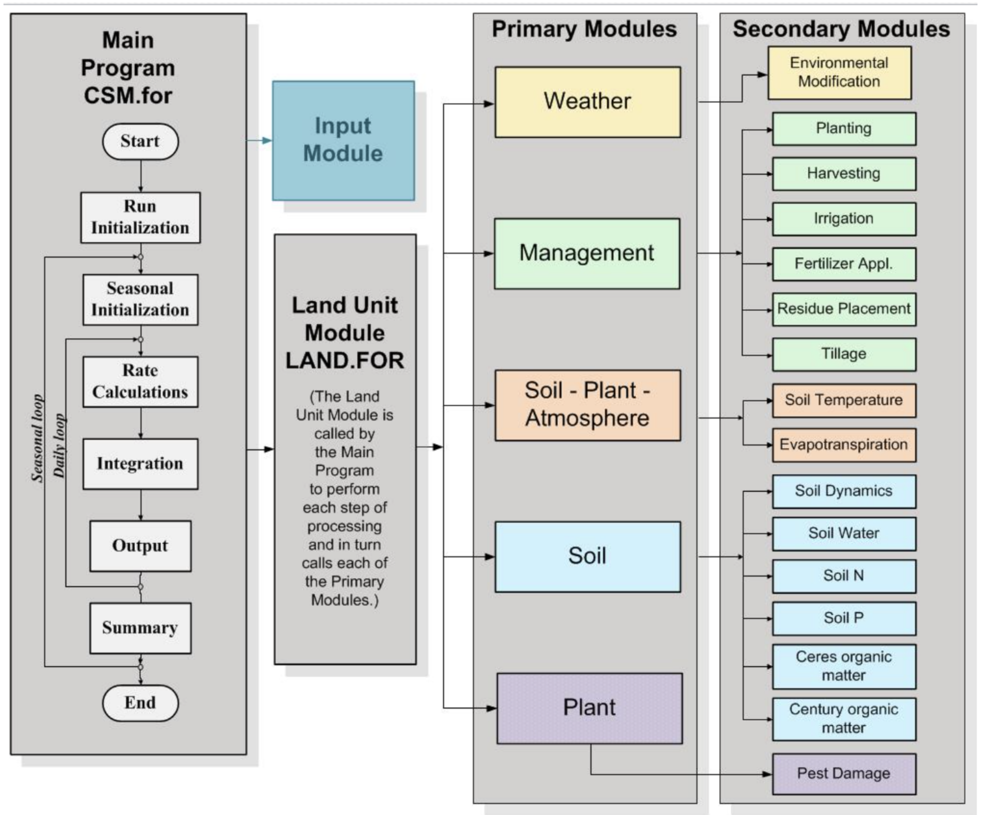

Figure 17: DSSAT - Modules

Notes: You can find further information on DSSAT here. This figure was obtained from the following here.

comprises dynamic crop growth simulation models for over 42 crops." From an economics perspective, it works as a (simulated) production function: for a given weather, soil quality, and other inputs, the model returns an (expected) yield.

In practice, DSSAT works as a sequence of differential equations. It is divided into five modules. Each module simulates the evolution of its main variables on a daily basis and then interacts with the other modules to simulate the growing stages of the crop. The five modules are the weather module, the management module, the soil-plant-atmosphere module, the soil module, and the plant module. Figure 17 illustrates DSSAT modules in further detail.

In order to simulate the crop yields for the main crops in my analysis, I modify the inputs of three of the modules: the weather module, the soil module, and the management module. For weather, I use data from PRISM, which I then aggregate at a county level using maps from the US Census Bureau. For soil quality, I use data from SoilGrids, which I also aggregate at a county level using maps for the US Census Bureau.

	Corn	Soybeans	Alfalfa	Wheat
Planting Date	04-15	05-01	05-01	09-01
Plant Poulation (plants/m^2)	8	35	700	270
Row Spacing (cm)	64	64	4	16
Planting Depth (cm)	7	6	2	4
Nitrogen Application (avg, kg/ha)	170	17	13	66
Nitrogen Application (date)	03-01	03-01	05-01	07-01

Table 22: DSSAT - Simulation Assumptions

Notes: The table displays additional assumptions needed to run DSSAT. Units of variables are shown as in DSSAT. The dates are in mm-dd format. The plant population is in seed per square meter. The row spacing and planting depth are in centimeters. Nitrogen application is in kilograms per hectare.

Within the management module, I choose the planting dates using the NebGuide for the University of Nebraska-Lincoln Extension, Institute of Agricultural and Natural Resources. For planting population, I follow the Minnesota Agricultural Experimental Station. For cultivars, I chose the 2650-2700 GDD for corn, the maturity group 3 for soybean, the default option for wheat, and the CUF 101 for alfalfa.

As described in the main text, I allow the irrigation rate and the fertilizer rate to vary optimally per farmer. More specifically, I allow the targeted soil moisture to vary between 0% and 100%. I simulate the nitrogen application rate using the last Tailored Report from the USDA as the central point. You can find such reports here.

Table 22 summarises some additional assumptions on farmers' behavior.

A.5.1 Conversion Rates

DSSAT inputs and outputs are in units per hectare. For yields and nitrogen application, DSSAT asks for kilograms per hectare; for irrigation, DSSAT asks for millimeters per hectare.

Table 23 displays the conversion rates I use to transform units when needed.

A.6 Results - Hetetrogeneity per Crop

In this section, I show heterogeneity in productivity per crop: Table 24 displays some summary statistics, while Figure 18 shows its distribution.

	Conversion Rate
Bushels to kilograms	
Corn	25.4000
Soybeans	27.2255
Wheat	27.2255
Tons to kilograms	1,000
Kilograms to pounds	2.2046
Short-tons to pounds	2,000
Acre-feet to liters	1,233,000
Millimeters per hectare to liters	10,000
Hectares to acres	2.4710

Table 23: Conversion Table

	Mean	SD	Obs
γ_{corn}	0.88	0.16	29,698
$\gamma_{soybean}$	0.94	0.23	23,447
$\gamma_{alfalfa}$	1.21	0.70	4,150
γ_{wheat}	0.86	0.29	708

Table 24: Productivity and Marginal Cost

Notes: This table presents the non-parametric estimators on productivity per crop, γ, I use sample weights in this table, as suggested by the NASS.

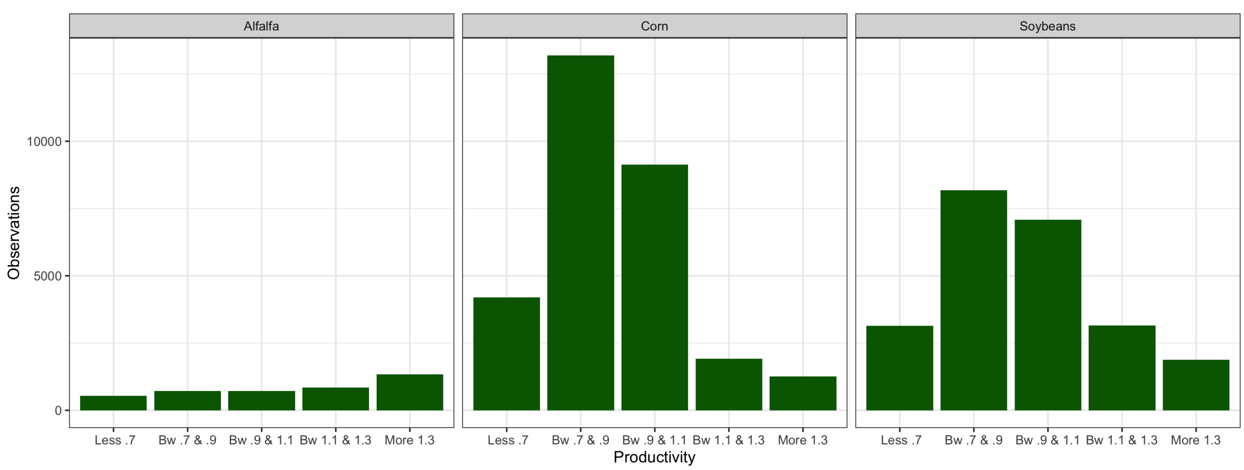

Figure 18: Productivity Per Crop

Notes: The figure shows the distribution of the non-parametric estimation of the productivity per crop. The x-axis can be read as follows: "Less .7" means that the productivity estimated was less than 0.7; "Bw .7 & .9" means that the productivity estimated was more than 0.7 and less or equal to 0.9; "More 1.3" means the productivity estimated was more than 1.3. The y-axis counts the frequency of these events.

A.7 Calibration

In this section, I calibrate the crop prices and the recharge rate for the aquifer. Table 25 shows the calibration.

	2008	2013	2018	Source
Prices (USD, 2018)				
Corn (bu)	4.27	4.59	3.37	Agricultural Market Service, USDA
Soybeans (bu)	9.82	13.67	7.85	Agricultural Market Service, USDA
Alfalfa (ton)	57.09	87.57	62.60	Agricultural Market Service, USDA
Wheat (bu)	9.15	7.52	4.78	Agricultural Market Service, USDA
Nitrogen (lb)	0.29	0.29	0.20	Economic Research Survey, USDA
Aquifer				
Recharge Rate (acf)		1,470,509		McMahon et al. (2007)
Water Returned to Aquifer (α)		0.2		Merrill and Guilfoos (2018)
Counterfactual assumptions				
Discount rate (β)		0.98		
Simulated years		100		

Table 25: Model: Additional Calibration

Notes: This figure shows the calibration of prices and aquifer's characteristics. All prices are in 2018-USD. Corn, soybeans, and wheat are in bushels of product. A bushel of corn is 25.40 kg. A bushel of soybeans or wheat is 27.21 kg. Alfalfa is in tons. The recharge rate is in acre-feet per year.