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 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 groundwater.[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 respond to changes in the cost of water and how much of such a response is done through crop choices and water use per planted crop. I find that

[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).

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 irrigated farmland in the USA. Second, Nebraska's main irrigated crops are at the top of the irrigated crops in the country: 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 "one of the most complete profiles of irrigation in the United States" (Olen, Wu, & Langpap, 2016). It is conducted every five years by the United States Department of Agriculture (USDA), 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 same average 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, while its standard deviation was 0.3.

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 - most importantly, I want to disentangle individual-level productivity from the marginal cost of water. Second, I need to consider the farmers' responses on unobserved inputs, such as 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 irrigation rates, and yields. Thus, I use it to approximate a production function per crop-county, the smallest unit in which I observe the farmer. I then 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 specifically, I recover these two unknowns from two model-implied equations. Using the individual-level productivity, the optimal fertilizer application, and the observed water use, I flexibly recover the marginal cost of water per farmer from the first-order condition on water from my model.

With the individual estimates for productivity and the marginal cost of water, I compute the expected profitability per crop and farmer. More precisely, I compute, for each farmer, the optimal water-fertilizer usage and hence profitability of every crop given the weather, and then, I vary the weather to calculate the expected profitability of each crop. 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 groundwater costs. 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 in the region: the average marginal cost per acre-feet of water is 133 USD, while the standard deviation is 148 USD. The variation can be partially explained by observables, 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 5.5 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]

Lastly, I utilize my estimates to evaluate policies that would induce a more sustainable use of groundwater. More precisely, I propose a common policy to solve the externality: a tax on groundwater use. The trade-off of such a tax is the following. On the one hand, taxing groundwater may decrease the farmers' profits, as it would increase the cost of one of their inputs. On the other hand, taxing groundwater would decrease the total water use and thus may decrease the aggregate cost of pumping groundwater. In addition, the effect of taxing groundwater use has a dynamic and a stochastic dimension. Firstly, lowering groundwater use one year generates a higher aquifer's water table the next year and, hence, a lower cost of pumping water in such a year. Secondly, different weather paths imply different (marginal) values of groundwater and, hence, different optimal groundwater usages. I include both dimensions in the taxation problem.

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

[4] A caveat of my model is that it does not include irrigation technology investment, another potential source for farmers' adaptation to water scarcity. 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.

would imply a 12% increase in the (average) marginal cost of water. As expected, the optimal tax decreases the depletion rate of the aquifer relative to the no-tax scenario, internalizing the groundwater-use externality 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. Furthermore, there are other externalities associated to groundwater use that are hard to include in an economic model, such as the deterioration of soil and even air quality. To account for this, I compute the "sustainable tax," the tax that would avoid the aquifer's depletion entirely. For 2018, I find that this tax would be much higher, implying a 125% increase in the average marginal cost of water. As the Ogallala Aquifer is (still) large and deep in the region, this tax is likely 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, somewhere in the middle of the previous estimates and 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 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 study 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.

The second line of research that I contribute to focuses on groundwater optimal management and governance. For instance, Merrill and Guilfoos (2018) and Timmins (2002)

[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).

discuss groundwater optimal dynamic extraction. Sampson et al. (2023) and Ayres et al. (2021) quantify the equilibrium 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 sustainable groundwater taxation.

Lastly, this paper contributes to the growing 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 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, hence, increases the cost of pumping for other farmers in the same aquifer. The institutional context is therefore relevant to understanding 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 (Christian-Smith et al., 2012). Formally, the law states that farmers are entitled to use a "reasonable and beneficial" amount of groundwater.[6] These terms, however, are not defined precisely. Groundwater use is regulated locally by twenty-three autonomous Natural Resource Districts. Each district must "maintain a ground water management plan" with information regarding the groundwater characteristics within the district and goals on groundwater management and "submit amendments to such a plan to the Director of Natural Resources." Districts can "adopt and promulge rules and regulations necessary" to manage groundwater usage. Until 2018, the last year of my study, the main requirement regarding groundwater withdrawal was the registration of new irrigation wells. In order to avoid excess water use in small geographic regions, new wells have to be constructed at a pre-determined distance from the pre-existing wells.[7]

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), which is "one of the most complete profiles of irrigation in the United States" (Olen et al., 2016).

IWMS-FRIS is a follow-up survey from the Agricultural Census directed by the USDA. It is a repeated cross-section and is representative of all US farmers who irrigate their land. I have access to individual records of such a survey for 2018, 2013, and 2008. More precisely,

[6]Source: Nebraska Ground Water Management and Protection Act, 2021

[7]The regulation for some districts has evolved since. The Upper Niobrara White Natural Resources District, for example, has currently a detailed plan for the regulation of groundwater use moving forward that monitors the water table evolution with respect to a 1990 baseline. The effect of such regulation would be interesting to study in future work.

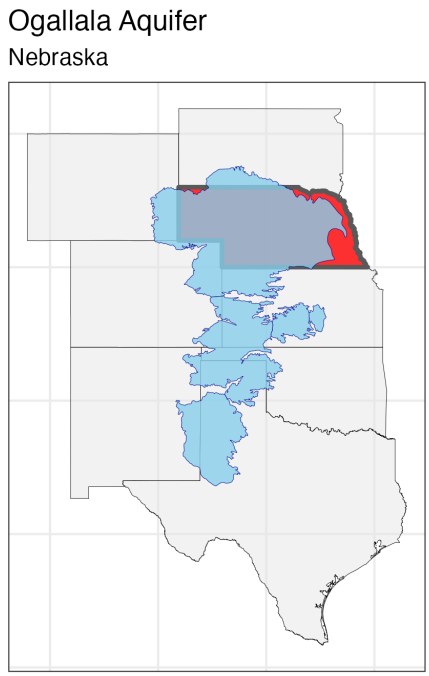

Figure 1: Ogallala Aquifer

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.

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;[8] crop choices and yields; the amount of water used in each crop; irrigation 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,[9] 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.[10] The water table also 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

[8]An acre-foot is the amount of water needed to cover an acre of land one-foot depth.

[9]Formally, a few other aquifers cover small portions of Nebraska as well. I add their exact location in Figure A.2 in Appendix A.2.

[10]"Depth to water" is the distance between the surface and the water table.

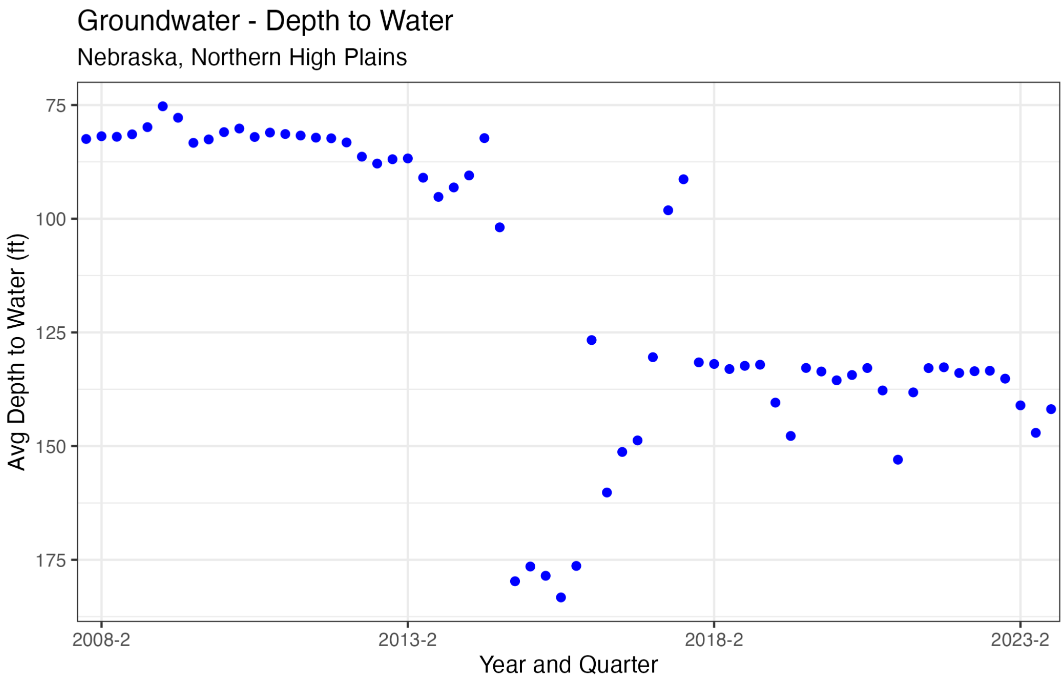

Figure 2: Depth to Water - Nebraska

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 use all the USGS wells in the Northern High Plains Aquifer that have data in the period 2008-2023.

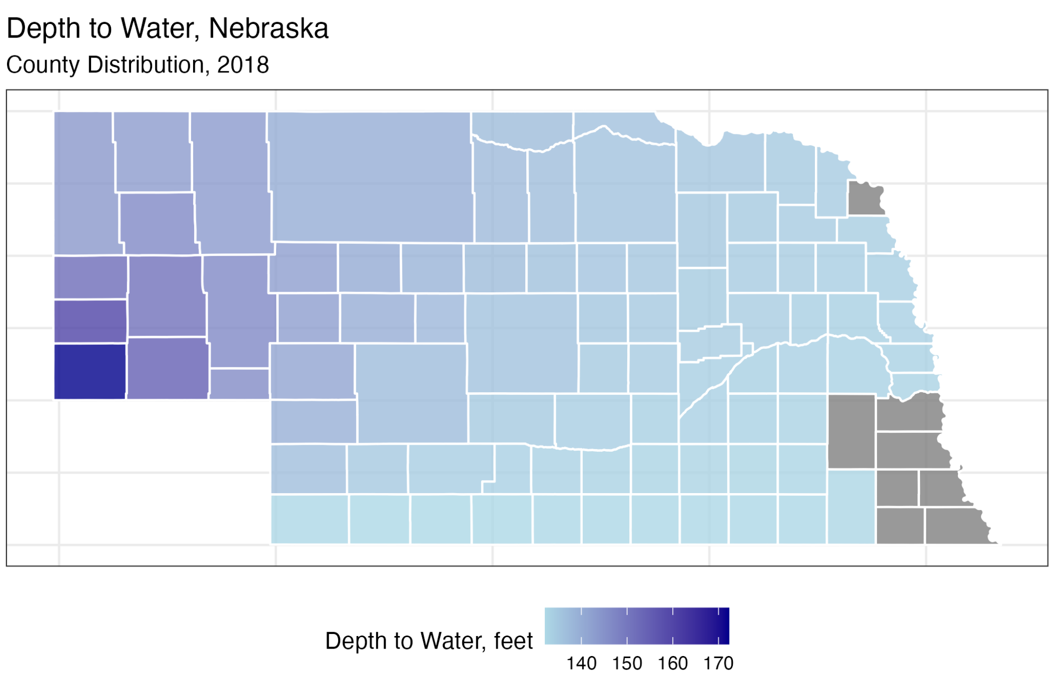

Figure 3: Depth to Water - Nebraska, 2018

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, the north part of the Ogallala Aquifer, that have data in 2018. In gray are the counties that do not have any land above the Ogallala Aquifer.

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.

Crop	Land, Mill 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.

example, 86% of farmers' water use was groundwater. Moreover, farmers are heterogeneous in the state. The average number of wells for a Nebraskan farmer in 2018 was 4.3, while its standard deviation was 6.48. Table 1 describes the data for 2018 in further detail. Tables A.12 and A.13, in the appendix, describe the data for 2013 and 2008.

Lastly, its main irrigated crops, corn, soybean, alfalfa, and wheat, are at the top of 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 A.2, in the appendix, shows the main crops for all of the West. I also include Tables A.14 and A.15, which describe 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 irrigation on yields, I need data on soil quality; I use SoilGrids (Poggio et al., 2021). SoilGrids is "a system for global digital soil mapping that makes use of global soil profile information and covariate data to model the spatial distribution of soil properties across the globe."[11] SoilGrids provides standard soil quality characteristics (e.g., percentage of clay in the soil) for standard layers of the soil (e.g., the first layer from 0cm to 5cm of depth). Since SoilGrids provides data at a 250mx250m level and I observe the farmers' county only, I aggregate such data using the Cartographic Boundary Files from the United States Census Bureau (USCB). Figures A.5 and A.6, in the appendix, illustrate examples of soil quality per county in Nebraska.

The crop-growth model I use, DSSAT, simulates the photosynthesis process; thus, I need data on solar irradiance. I get such information from an open-source data: NASA POWER. NASA POWER provides daily data on solar irradiance for all continental USA at a 1x1 degrees. I download such data and aggregate it at the county level using USCB maps.

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 in Nebraska. I approximate the water table at a county level using the inverse of the distance between the county's centroid and the wells that are at less than 100 km of distance.

In Nebraska, farmers tend to choose crop rotations rather than annual crops. To study the crop rotation patters in the region, I use data from the Cropland Data Layer (CDL). CDL provides panel satellite data that indicates, at 30mx30m resolution, which crops are planted in all of contiguous USA.

Lastly, I collect PRISM data on weather variables, precisely maximum temperature, minimum temperature, and precipitation; 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, their marginal cost of water, and their preferences over crops. I complement the model with the aquifer's water

[11] Source: SoilGrids' webpage.

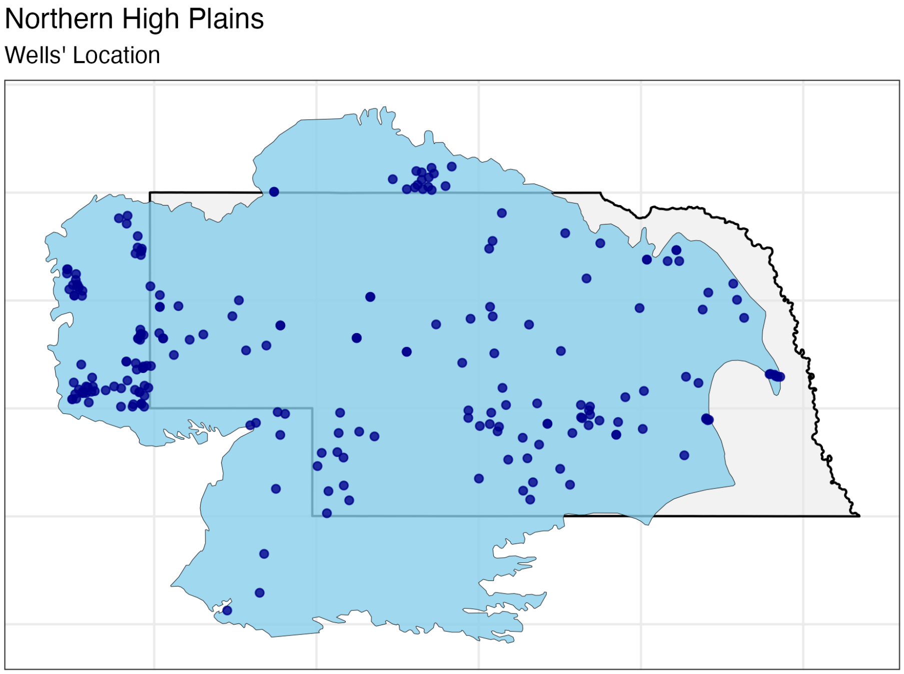

Figure 4: Wells' Location - USGS

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.

availability and recharge process.

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:

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

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 for farmer i; $f_j^i(w_{ij}, \mathbf{x}_{ij}; S_i)$ 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 (i.e., the cost of pumping); and $\mathbf{p_x}$ 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 (expected) utility. More specifically, the farmer decides:

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

where the expectation is taking over 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.[12]

[12]The word "farmer" is used loosely here. In the estimation section, I define "farmer" as a plot of land that belongs to a farmer. I explain it in further detail in section 4.2.2.

3.2 Water Supply

The other side of the market is the "water supply," namely 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 $h(t)$.

4 Estimation

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 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. Then, 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. Thus, I have two empirical challenges to overcome. First, I do not observe individual-level production functions; I only observe farmers' water use and crop yields. 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).

From an economic point of view, DSSAT works precisely as a (simulated) production

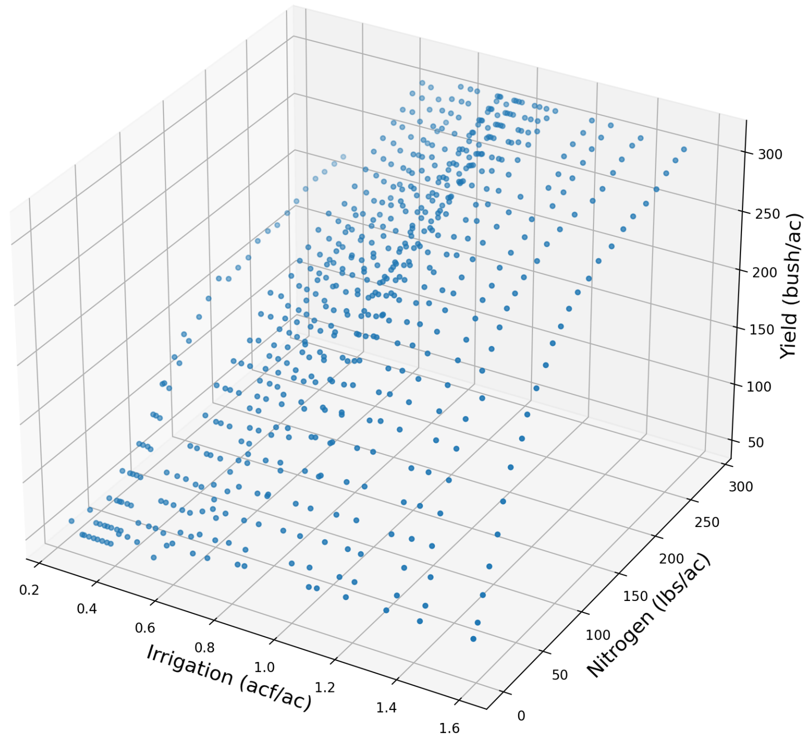

Figure 5: Example Corn, DSSAT - Sheridan, Nebraska. 2018

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.

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 2018, which simulates corn yield for various input usages in Sheridan, Nebraska. I describe DSSAT in further detail in the appendix A.4.

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

$$q_j^i = f_j^i(w_{ij}, \mathbf{x}_{ij}; S_i) = \gamma_{ij} f_j(w_{ij}, \mathbf{x}_{ij}; S_i) \tag{8}$$

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.[13]

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:

$$c_i'(w) = \alpha_g + \beta_g WT_i + \epsilon_i \tag{9}$$

where α_g is the (average) marginal cost of pumping groundwater; β_g is the cost increment for having a lower water table, WT_i; and ϵ_i is the error term.

In the second stage of the model, I study crop-choice preferences. In order to do so, I need to compute the expected profitability of each crop. Unfortunately, I do not observe farmers choosing every crop. Hence, I need to make an assumption on the productivity parameter for the non-planted crops. I follow the Hicks-neutrality assumption, which is common in the literature (Hicks, 1932; Rafey, 2023), with a small adjustment. Specifically, I assume that the productivity of farmer i on the non-planted crop j' is:

$$\gamma_{ij'} = \gamma_{j't(i)} + \gamma_i \tag{10}$$

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 presumably gives me an upper bound on the productivity of the farmer for non-planted crops: since the farmer is likely more productive in the crop that she chose, assigning the productivity from the chosen crop to the non-chosen crops, after controlling for crop-year fixed-effects, would be an upper bound on her actual productivity.

[13]Unfortunately, I do not have data on phosphorous (or potassium) levels in the soil; thus, I cannot add them to my estimation. Regardless of this omission, DSSAT closely predicts observed yields, which suggests I am not omitting much.

4.2 Estimation

My estimation goes as follows. First, I approximate the crop-growth model production function per crop-county-year. After that, I estimate the main parameters of my model: $\gamma_{i\mathbf{j}}$, 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. Lastly, I calibrate the aquifer's parameters: R, the recharge rate; and α, 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 at crop-county-year level, the smallest unit in which I observe the farmer. This approximation is challenging: 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. Fortunately, DSSAT allows for a better alternative: it allows me to 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 assumptions about the DSSAT simulation in the appendix A.4.

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:

$$y_{ijct} = \alpha_{jct} + \beta_{w1ct} w_{ijct} + \beta_{w2ct} w_{ijct}^2 + \beta_{f1ct} f_{ijct} + \beta_{f2ct} f_{ijct}^2 + \beta_{wfct} w_{ijct} f_{ijct} + \epsilon_{ijct} \tag{11}$$

where y_{ijct} is the i's simulated yield for crop j at county c at time t; w_{jct} is the i's irrigation rate for crop j at county c at time t; f_{ijct} is the i's fertilizer rate for crop j at county c at time t; and ϵ_{ijct} is the error term.[14]

I then interpolate the crop-county-year production function using the estimates ($\tilde{\alpha}_{jct}$, $\tilde{\beta}_{w1ct}, \tilde{\beta}_{w2ct}, \tilde{\beta}_{f1ct}, \tilde{\beta}_{f2ct}, \tilde{\beta}_{wfct}$), which I recover for a linear regression. I denote such an approx-

[14]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.

imation $f_j(w, x; S_{ct})$. To simplify 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.

I recover both the productivity parameter and the fertilizer use from the production-function equation and the first-order condition equations:

$$\gamma_{ij} = \frac{q_j^i}{f_j(w_{ij}, x_{ij}; S_i)} \tag{12}$$

$$\frac{\partial f_j(w_{ij}, x_{ij}; S_i)}{\partial x_{ij}} = \frac{p_x}{p_j \gamma_{ij}} \tag{13}$$

where (12) comes directly from (8), and (13) comes from the combination of (8) and (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 model-implied equations.

As explained in the model section, I use the word "farmer" loosely. Formally, the relevant decision unit of my problem depends on the level at which the farmer or operator decides. Such a level could be larger or smaller than an observed operator. Most Nebraskan farmers have a central pivot system to irrigate their land, which they use on a location basis. Figure 6 illustrates this point. Each color in the image represents a crop. Crops planted in a circular fashion are irrigated crops using a central pivot system. Ideally, then, I would like to define each location as a unit of decision. Since the smallest unit I observe is the farmer-crop, I assume that each farmer decides irrigation by crop and I allow her productivity and marginal cost of water to differ by crop. For simplicity, I call "farmer" the crop-farmer unit.

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

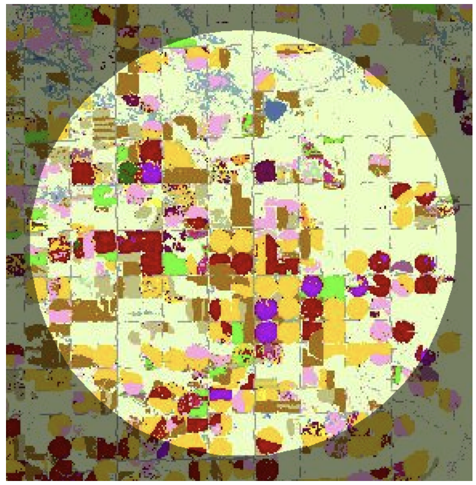

Figure 6: Sheridan, Nebraska. 2018

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.

$$\gamma_{ijt} = \gamma_j + \gamma_{jt} + \gamma_i \tag{14}$$

where γ_j is the crop fixed effect; γ_{jt} is the crop times year fixed effects; and γ_i is the residual of such a regression.

4.2.3 Cost Parameters

With γ_{ij}, I can recover the marginal cost of water from equations (8) and (3):

$$p_j \gamma_{ij} \frac{\partial f_j(w_{ij}, x_{ij}; S_i)}{\partial w} = c_i'(w_{ij}) \equiv c_{ij} \tag{15}$$

Notice this gives me, non-parametrically, a unique marginal cost of water per farmer. I thus recover all the parameters of the farmer's production and cost functions. I use these parameters to estimate the profitability of each crop for the first stage of my model.

Unfortunately, I can only approximate the aquifer's water table at a county level.[15] To recover the effect to the aquifer's water table on the marginal cost of water, thus, I aggregate

[15] 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.

marginal cost at a county-year level and run:

$$c_{lt} = \alpha_{gt} + \beta_g WT_{lt} + \epsilon_{lt} \tag{16}$$

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 Parameters

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

$$(w^*, x^*) : \max_{w,x} p_j \gamma_{ij} f_j(w, x; S_{it}) - c_i(w) - p_{xt} x \tag{17}$$

where I change my notation slightly: S_{it} now includes the realized weather at t. I call the solution of such a problem v^*_{ijt}:

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

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 a figure, I group crops as follows: (i) {Corn, Soybean}; (ii) {Corn, Corn}; (iii) {Alfalfa, Alfalfa}; (iv) {Wheat, Fallow}; (v) {Fallow, Fallow}.

Since I observe annual crops rather than crop rotations, I need a few more assumptions to identify which crop rotation the farmer is planting. 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 of the county where the farmer is located.

I make two more assumptions. First, I reduce the choice set of farmers depending on their county. More precisely, 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 add 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. By its very definition, I cannot construct such a wedge for fallow land. I thus do a lower bound exercise: for every farmer that fallows part of their land, I assume that the marginal cost of water in that part of the land equals the highest marginal cost of water that I estimate for such a farmer. Similarly, I assume that his productivity in that part of the land equals the minimum productivity for such a 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, as these are probably reasons why the farmer fallow her land in the first place.

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

$$\tilde{\mathbb{E}}(v_{ij}) = \frac{1}{34} \sum_{t=1984}^{2017} v^*_{ijt} \tag{19}$$

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

$$(\alpha_j, \beta) : \max_{\alpha_j, \beta} \sum_i a_i \left[\sum_j p_{ij} \log \left(\frac{e^{\alpha_j + \beta \mathbb{E}(v_{ij})}}{1 + \sum_j e^{\alpha_j + \beta \mathbb{E}(v_{ij})}} \right) + \left(1 - \sum_j p_{ij} \right) \log \left(\frac{1}{1 + \sum_j e^{\alpha_j + \beta \mathbb{E}(v_{ij})}} \right) \right] \tag{20}$$

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.

4.2.5 Aquifer Parameters

Lastly, I discretize the aquifer's recharge process. More precisely, I re-write Equation (7) as:

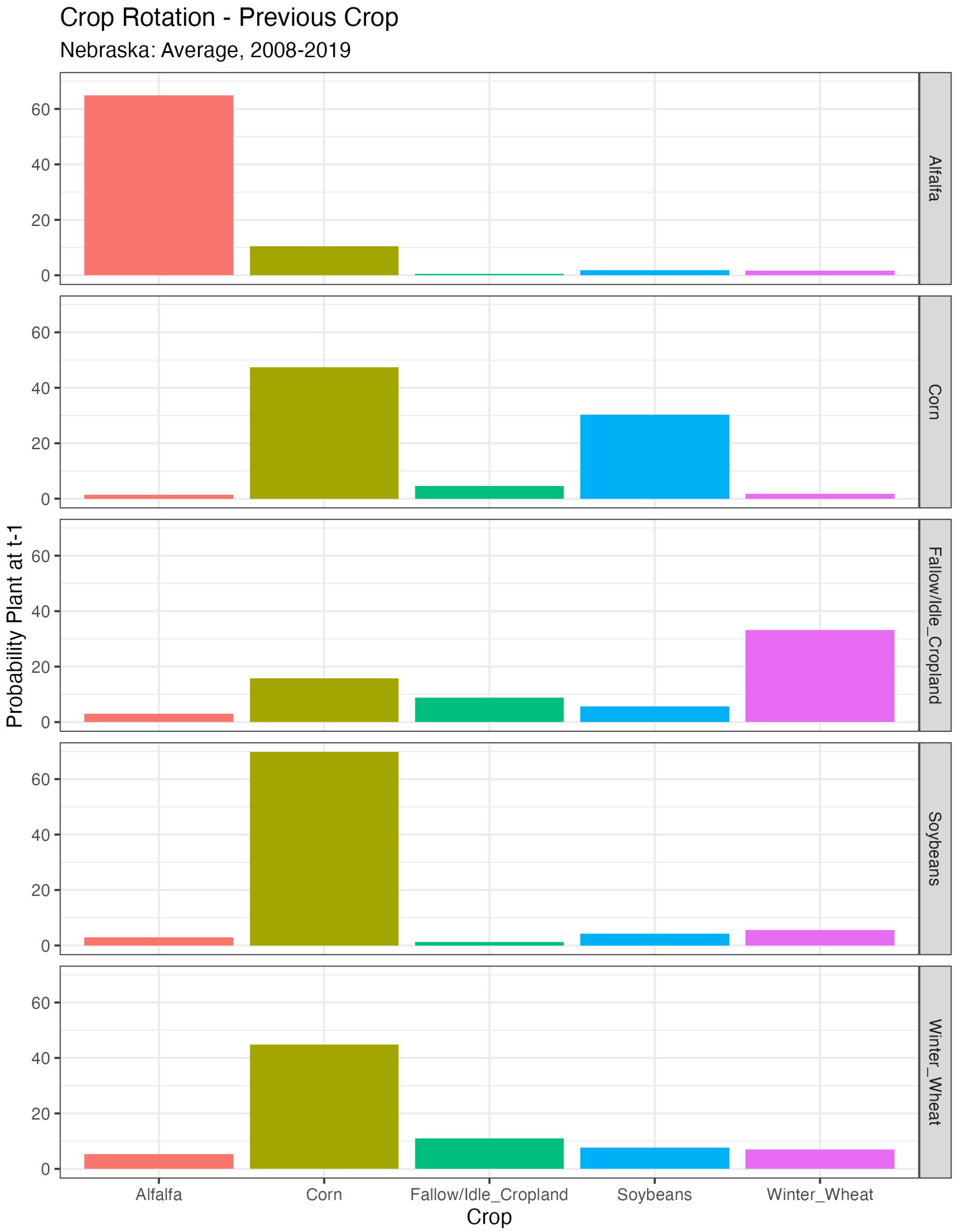

Figure 7: Transition Probability - Weighted Average. Nebraska, 2018-2019

Notes: The figure shows the transition probabilities from one crop to another, on average, from 2008 to 2019. The crop planted in the period t is displayed on the right-hand side of the figure. On the x-axis, the crop planted in $t-1$ 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 2008-2019. The probabilities are calculated as the proportion of pixels at $t-1$ that are the crop display at the right-hand of the figure at t.

$$\Delta h(t) = R - (1-\alpha)\sum_i w_i(h(t)) + \epsilon_t \tag{21}$$

Since I only observe water use for the whole growing season, I discretize the problem so that a period is a year. 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 A.1, the Ogallala Aquifer is large. If I use 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.[16]

5 Results

As described in the estimation section, I recover the individual-level productivity and the distribution of the marginal cost of water non-parametrically. I also assume that farmers take crop and fertilizer prices as given. I display such prices in Table A.20 in the appendix.

Table 3 summarizes the non-parametric 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 crop-growth model projects yields accurately: since the productivity term is constructed as the ratio between the agronomically projected yield and the observed yield, this ratio should be close to one. I show the heterogeneity on productivity per crop in Table A.18 in the appendix.

	Mean	Standard Deviation	Weighted Obs
γ_{ij}	0.93	0.23	57,807
c_{ij}	212.83	203.34	57,807
c^*_{ij}	132.83	147.79	37,543

Table 3: Productivity and Marginal Cost

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

[16] A potential extension of the model would consider the full hydrology connectivity across counties.

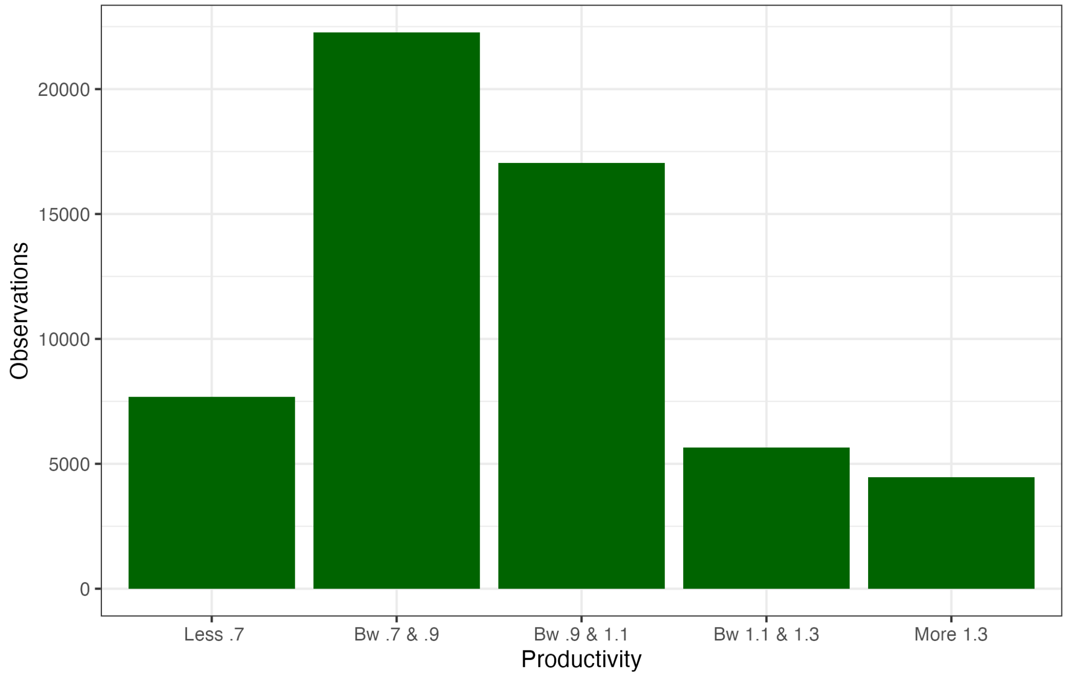

Figure 8: Productivity Per Crop

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.

Second, the marginal cost of water varies substantially across farmers. For example, its standard deviation is almost as high as its mean. Figure 9 illustrates its distribution in further detail. This high variance can be explained by many factors. First, farmers differ in observables. For example, farmers have different numbers of wells per acre. Table A.19, in the appendix, shows that the number of wells per acre correlates negatively with the marginal cost of water. Farmers also differ in unobservables, such as the characteristics of the aquifer beneath their land. My estimation procedure is flexible precisely to recover this unobserved heterogeneity correctly. This will be important when running the counterfactual analysis.

A note here: the estimates of the marginal cost of water are exceptionally high in 2013, as shown in Table 3. In 2013, precipitation and groundwater use were atypically low, which likely means that farmers were (physically) restricted that year (see, for example, Rad et al. (2020)).[17] Hence, the marginal cost of water from that year can not be extrapolated to other years. I thus exclude 2013 for the rest of my analysis.

[17] I add Table A.8 to the weather patterns in the years of my study.

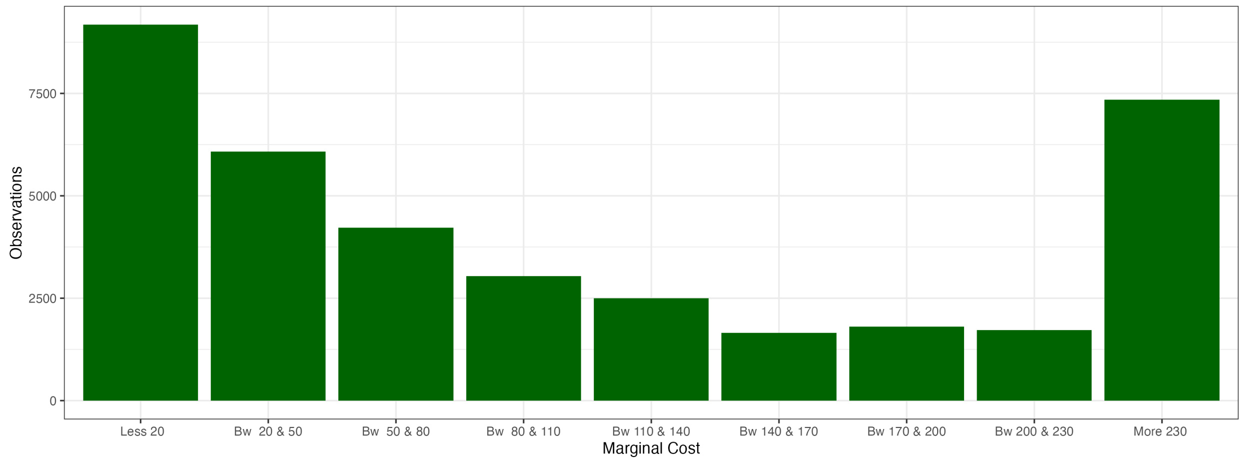

Figure 9: Productivity Per Crop

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 for this figure.

Third, Table 4 shows the fixed-effect regression for productivity per crop. The estimate on productivity is rather stable across years; yet, the crop-growth model predicts 2018 data best. This could be partially explained by the soil-quality data. SoilGrids uses data for 2020 only. Although soil quality does not change much in the short-run, this could explain why the model predicts 2018 data better.

Fourth, the depth of water has a significant effect on the marginal cost of groundwater. Table 5 shows the exact linear relation. I run two specification: one at a county level and another at the farmer level. Regardless of the specification, the correlation between the water table and the marginal cost of groundwater is positive. Unfortunately, the farmer-level specification has many missing values and plenty of noise. Thus, my preferred specification is the county level one. In such a specification, an increase of 1 foot in the depth to water increases the groundwater cost by 5.5 USD. Note that this relation was recovered from an economic model. Hence, it includes not only the monetary cost of groundwater extraction but also its opportunity and dynamic costs.

Fifth, I estimate the crop-choice parameters using a multinomial logit. Table 6 shows my estimates. Importantly, the expected profitability of a crop has a significant effect on its

Dependent Variable:	Productivity, γ_{ij}
Model:	(1)
Variables	
Alfalfa	1.008***
	(0.0554)
Corn	0.7410***
	(0.0086)
Soybean	0.9067***
	(0.0123)
Wheat	0.6839***
	(0.0599)
Alfalfa × 2013	0.1921*
	(0.0754)
Corn × 2013	0.2659***
	(0.0121)
Soybean × 2013	0.2011***
	(0.0185)
Wheat × 2013	0.3184**
	(0.1072)
Alfalfa × 2018	0.2389***
	(0.0678)
Corn × 2018	0.1146***
	(0.0126)
Soybean × 2018	-0.0210
	(0.0180)
Wheat × 2018	0.2420*
	(0.0962)
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.

Dependent Variable:	Marginal Cost, 2018-USD	
Model:	(1)	(2)
Variables		
Depth to water, feet (County)	5.493**	
	(0.0822)	
Depth to water, feet (Farmer)		0.096
		(0.0892)
Fixed-effects		
year	Yes	Yes
Fit statistics		
Observations	147	1,205
R^2	0.32	0.21

*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 acreage planted and sample weights in this regressions, as suggested by the NASS.

probability of being chosen. In equilibrium, the average expected profitability per acre is 576 USD. Thus, an increase of 10% in the profitability of the average crop would increase the probability of it being chosen by 5.9%.

Lastly, I recover the model-implied elasticity of water. Using my previous estimates, I find that farmers are rather inelastic to water costs. In 2018, for example, the model-implied elasticity is -0.34. That is somewhere in the middle of what has been previously found in the literature (Burlig et al., 2021; Smith et al., 2017; Bruno & Jessoe, 2021; Hendricks & Peterson, 2012; Pfeiffer & Lin, 2014). Importantly, my estimation procedure allows me to recover the elasticity for each and every point in the water demand curve and, thus, it is well-suitable for the counterfactual analysis.

	Dependent variable:
	Crop Rotation Chosen
Alfalfa-Alfalfa	-0.884***
	(0.177)
Corn-Corn	0.110
	(0.221)
Corn-Soybean	0.385
	(0.254)
Wheat-Fallow	-1.701***
	(0.238)
Expected Profits	0.099***
	(0.024)
Observations	1,677
Log Likelihood	-1,036
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 hundred USD dollars at 2018 prices. All variables are decided at an acre level. I weighted observations using farmers' acreage and sample weights.

6 Counterfactual Policies

I utilize my previous estimates to simulate policies that would induce a more sustainable use of groundwater. More precisely, I propose a common policy to fix the externality: taxing groundwater use. The trade-off at hand is the following: increasing the water tax decreases the per-period farmers' profits, but it also decreases water use and, thus, it may decrease aggregate water costs and push toward sustainability.[18]

To simplify my analysis, I make two assumptions. First, I do not allow farmers to adapt to higher water costs by investing in new technologies. The effect of this omission may accelerate or diminish the depletion problem. On the one hand, if farmers decide to respond to higher water costs by constructing more wells or increasing their pump capacity, the depletion process may accelerate, and so may the (average) cost of water. On the other hand, if farmers respond to higher water costs by improving irrigation efficiency and thus reducing water demand, the depletion process may slow down. Second, I fix prices at the

[18] I describe the analytical problem a bit more detail in Section A.7 in the appendix.

2018 level. I do so simply to focus on the cost of pumping groundwater exclusively - the model can be extended to include the stochastic nature of prices.

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 that 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, with $s_t \in \{1, 2, ..., S\}$ and $\phi(s)$ the probability that the realized weather is s. Moreover, 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 $v_{ij}(p, h; s)$ as the (optimal) per-period profit of farmer i when choosing crop j.

I solve the counterfactual using the farmers' estimates from the previous section and the crop and fertilizer 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 the rest of my calibration assumptions in the appendix (Table A.20).

6.1.1 Optimal Use Policy

The optimal tax should consider the dynamic nature of the problem at hand. I assume that the water authority maximizes the (expected) aggregate profits, given the current aquifer's height and the dynamic effects of including a tax on groundwater use.

Following my model, the timing of the problem is as follows. First, the water authority decides the tax given the aquifer's height. For simplicity, I assume that the water authority chooses a unique tax 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 on crops.

Third, the weather is realized, and each farmer decides how much water (and fertilizers) to use. Fourth, the aquifer's height is updated, given its recharge rate and the total water use. Lastly, the process starts anew with the updated aquifer's height.

The water authority decides the tax in the first step, taking expectations over the rest of the steps. More specifically, at the county level, the water authority decides:

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

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.

6.1.2 Sustainable Use Policy

An alternative (and more simple) policy would be taxing groundwater use so that the (expected) water use equals the aquifer's recharge rate, given the current aquifer's height. I call such a tax the sustainable tax.

More specifically, the water authority would tax water use so that:

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

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.

6.2 Solution

6.2.1 Further Assumptions

I make a few more assumptions to solve for each policy. First, I assume counties are independent of one another and, thus, the aquifer's recharge process is county-specific. The model can be extended to include counties' connectivity. Second, I simulate the process for a hundred different weather paths of a hundred years each. For the weather simulation, I use a random sample, with replacement, of the realized weather in the period 1984-2018. In the appendix, I show other calibration assumptions (Table A.20). Lastly, I display my results weighting the tax by the acreage operate by each taxed farmer.

6.2.2 Comparison Across Policies

The policies generate dissimilar results. On the one hand, the optimal tax would imply a 12% increase in the (average) marginal cost of water. On the other hand, the sustainable tax would imply a 124% increase in the (average) marginal cost of water. Figure 10 illustrates the aquifer's depletion for the counterfactual and the no-tax scenarios for various weather paths. Figure 11 shows the average crop mix for each policy.

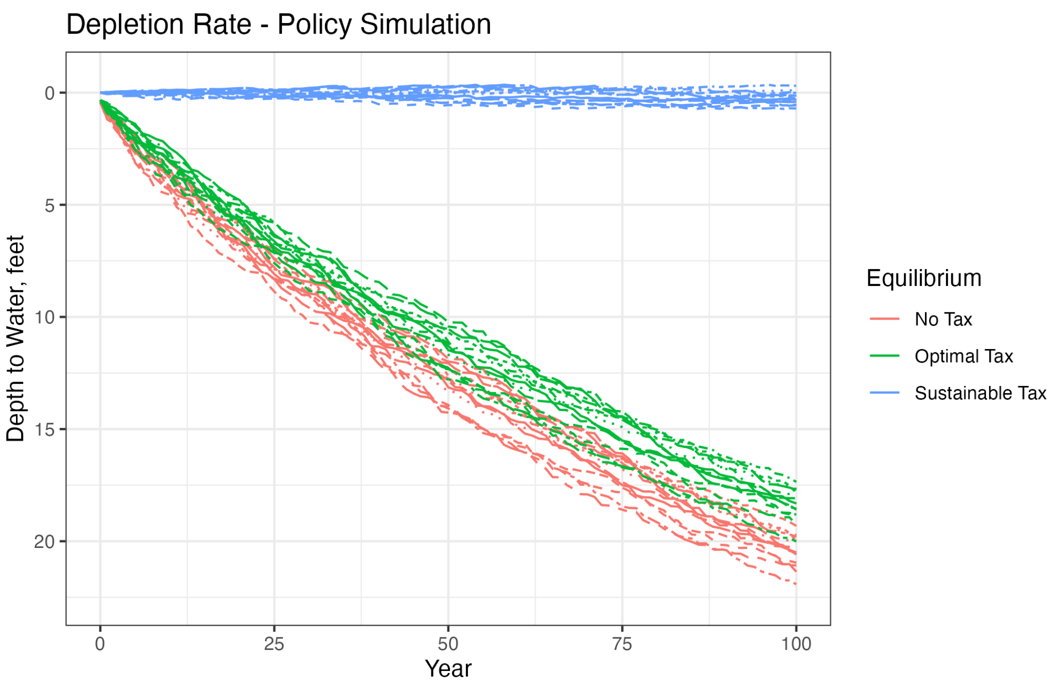

Figure 10: Depth to Water, Evolution

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 increase in depth to water from 2018 onward. The x-axis is the year of the simulation. Each line reflects a weather path simulation. The yearly depth to water is the average across counties and is weighted by the operated farmland.

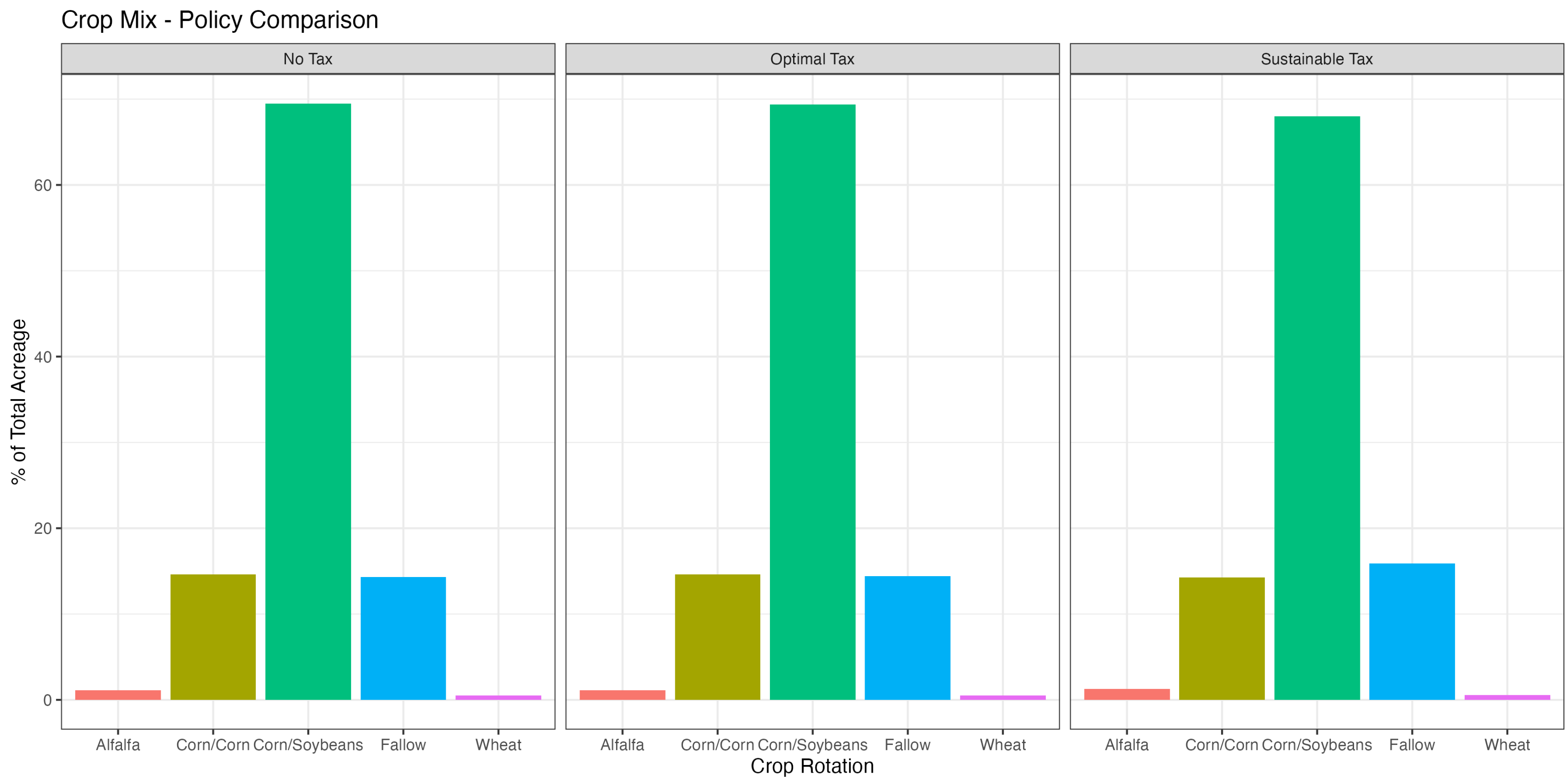

Figure 11: Counterfactual Policies - Crop Mix

Notes: "Crop" refers to the crop rotation. "Alfalfa" means the alfalfa-alfalfa crop rotation. "Corn/corn" reflects the corn-corn crop rotation. "Corn/Soybeans" reflects the corn-soybeans crop rotation. "Fallow" illustrates the fallow-fallow crop rotation. "Wheat" refers to the wheat-fallow crop rotation. On the y-axis, I present the percentage of such a rotation in each equilibrium. "No Tax," "Optimal Tax," and "Sustainable Tax" refer to the simulation of the associated policy. The percentage of crop mix is taking over all rounds and weather paths simulations.

By its very definition, the sustainable tax implies that there is no depletion of the aquifer. From an economic point of view, however, this might be too demanding for farmers. The farmers' total loss of such a policy is large: on average, farmers lose 7.1% of their (present-valued) profits. Farmers would respond to such a high tax by changing their crop mix. More specifically, farmers would fallow more land, as shown in Figure 11.

The optimal tax, which maximizes the present value of the total profits of farmers, is closer to the no-tax scenario. Nevertheless, the tax indicates that the current levels of groundwater use are too high - the depletion rate should slow down. On average, the optimal tax implies that water use would decrease by 3.77% with respect to the no tax-scenario. Furthermore, farmers would increase their (present-value) profits by 0.87%.

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. 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, the marginal cost of groundwater is heterogeneous in the region. For example, the average marginal cost of obtaining groundwater is 133 USD dollars in 2018 prices, while the standard deviation is 148 USD. Second, the water table has a significant 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 more land. Lastly, I utilize the estimates of my model to compute the optimal and sustainable tax on water use.

I see some venues to expand my work. First, I focus my work on groundwater, as that is the primary water source for Nebraskan farmers. In other places in the US, farmers also use plenty of surface water. It would be interesting to study the effect of the optimal groundwater policy when other water sources are relevant. Second, climate change will likely affect farmers' water demand and, thus, optimal taxation on groundwater use. 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.

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A Appendix

A.1 IWMS-FRIS - Summary Statistics

In this section, I add the summary statistics for the Western US.[19] Table A.1 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 A.3 and A.4 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 A.1: 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 A.2 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 A.5 and A.6.

A.1.1 Yield and Water Use

Water use depends heavily on crop choices (see, for example, Table 2 and Table A.2). Interestingly, water explains an important portion of yield variability within a county. Table A.7 shows the relation between water and yields for the Western USA.

[19] "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 A.2: 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 A.3: 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.*

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 A.4: 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 A.5: 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 A.6: 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 A.7: 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.

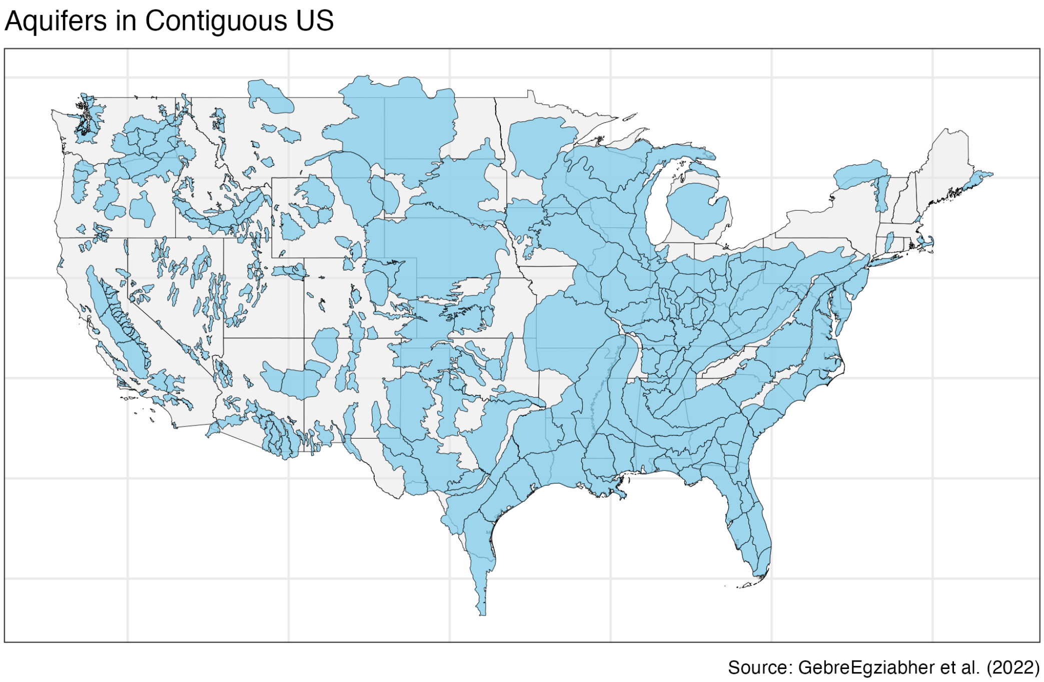

Figure A.1: Aquifers' Location

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

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 A.8: 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.

A.2 Aquifers' location

In this section, I plot the aquifers' location in the USA. Figure A.1 shows the location of all aquifers; Figure A.2 zooms on Nebraska.

A.3 Nebraska - Summary Statistics

In this section, I add summary statistics for Nebraska. First, I characterize Nebraska's climate. Figure A.3 illustrates the average precipitation and Figure A.4 reflects the average temperature. Table A.8 shows the year-to-year variation of weather for the years of my study.

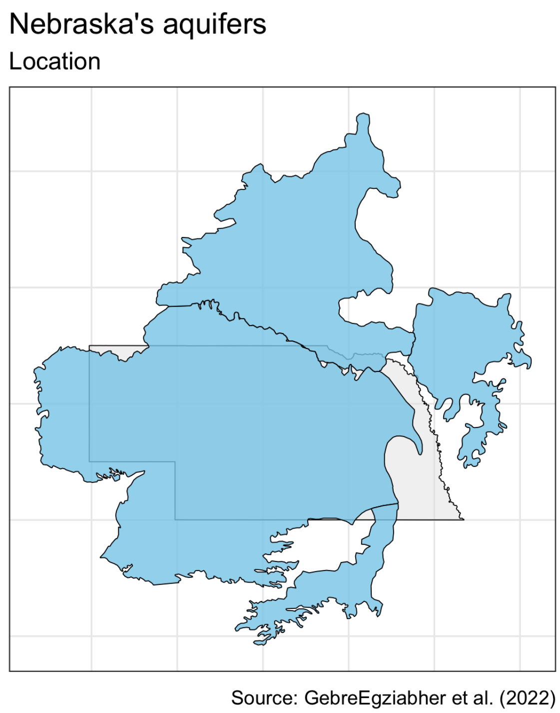

Figure A.2: Aquifers beneath Nebraska

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

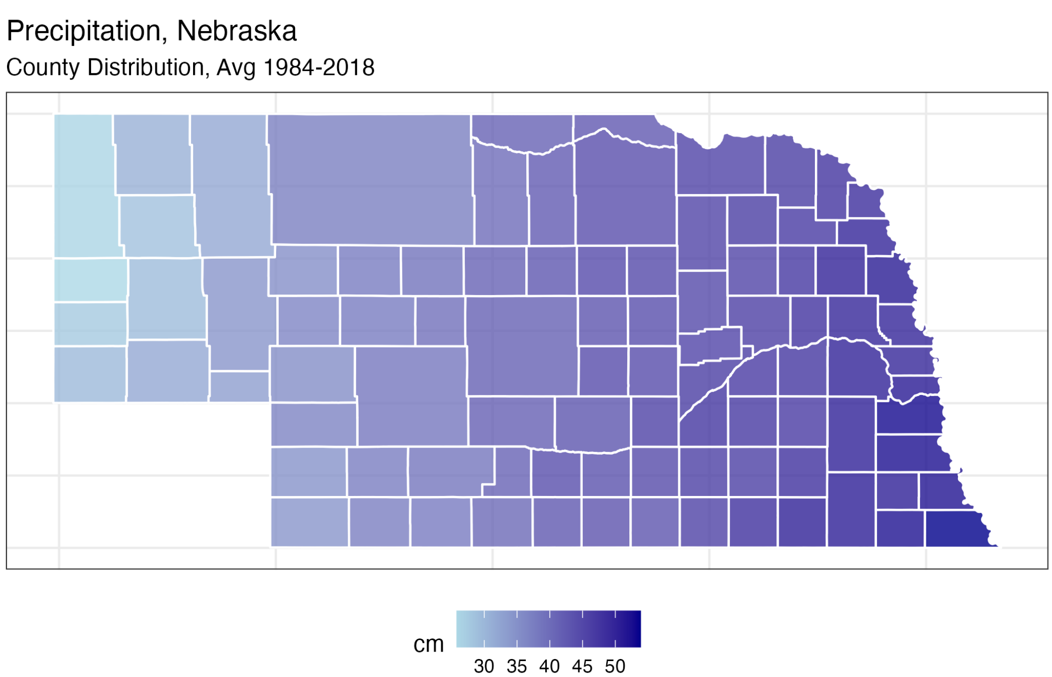

Figure A.3: Precipitation - Nebraska, 1984-2018

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.

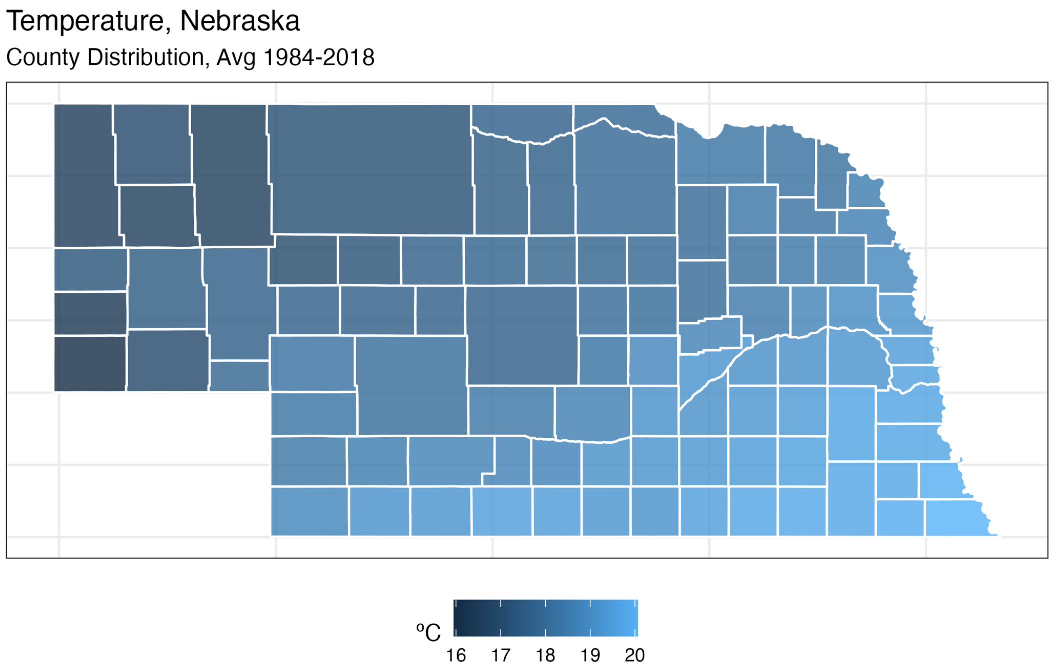

Figure A.4: Average Temperature - Nebraska, 1984-2018

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.

Second, I show the heterogeneity in soil quality within Nebraska. Figure A.5 and A.6 illustrate the case of clay and silt per county in Nebraska.

Lastly, I add the historical depletion of the Ogallala Aquifer in the region. Figure A.7 illustrates it.

A.3.1 IWMS-FRIS - Additional summary statistics

In this section, I add additional summary statistics for the IWMS-FRIS for Nebraska. Tables A.9, A.10, and A.11 describe the dispersion on yields and irrigation rates for the main crops for 2018, 2013, and 2008. Tables A.12 and A.13 describe the data for 2013 and 2008, respectively. Tables A.14 and A.15 display the main crops for 2013 and 2008, respectively.

A.4 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

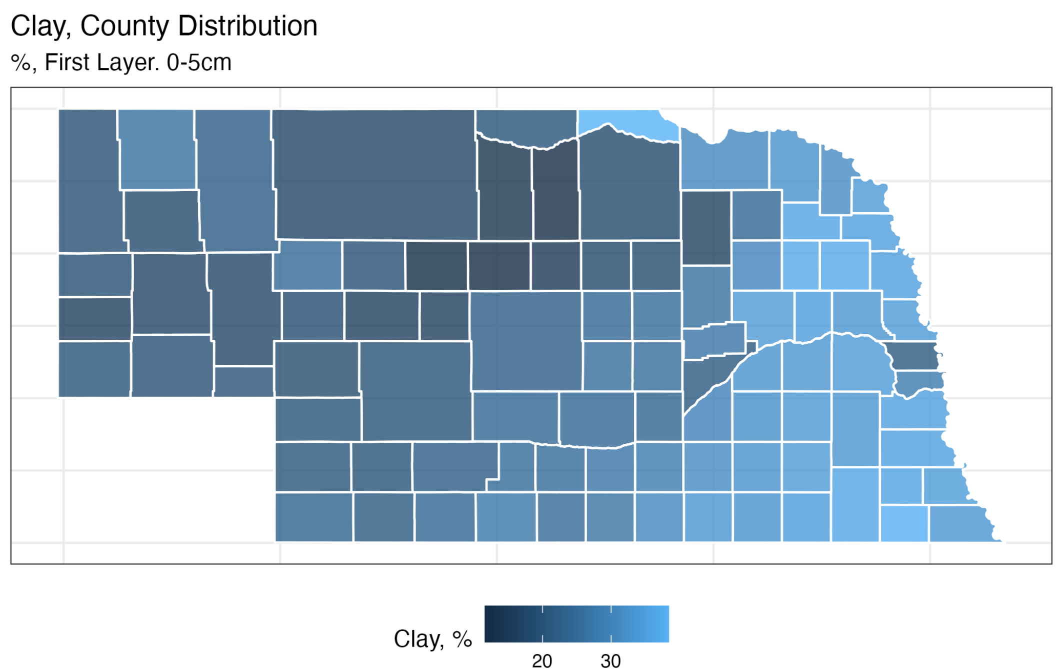

Figure A.5: Clay, % - First Layer, Nebraska

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.

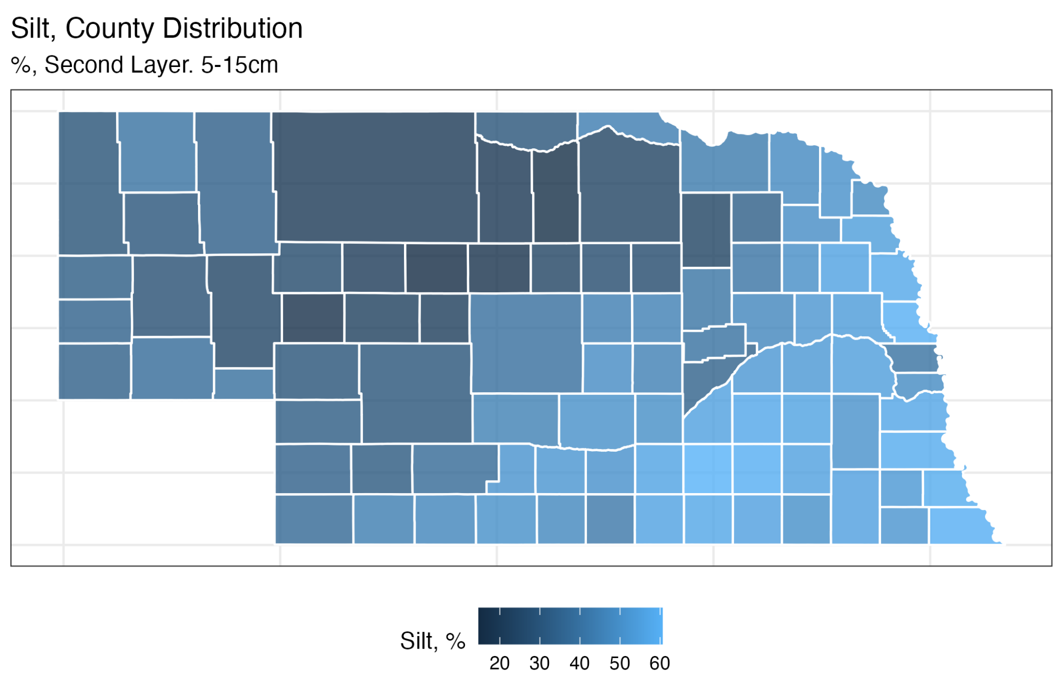

Figure A.6: Silt, % - Second Layer, Nebraska

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.

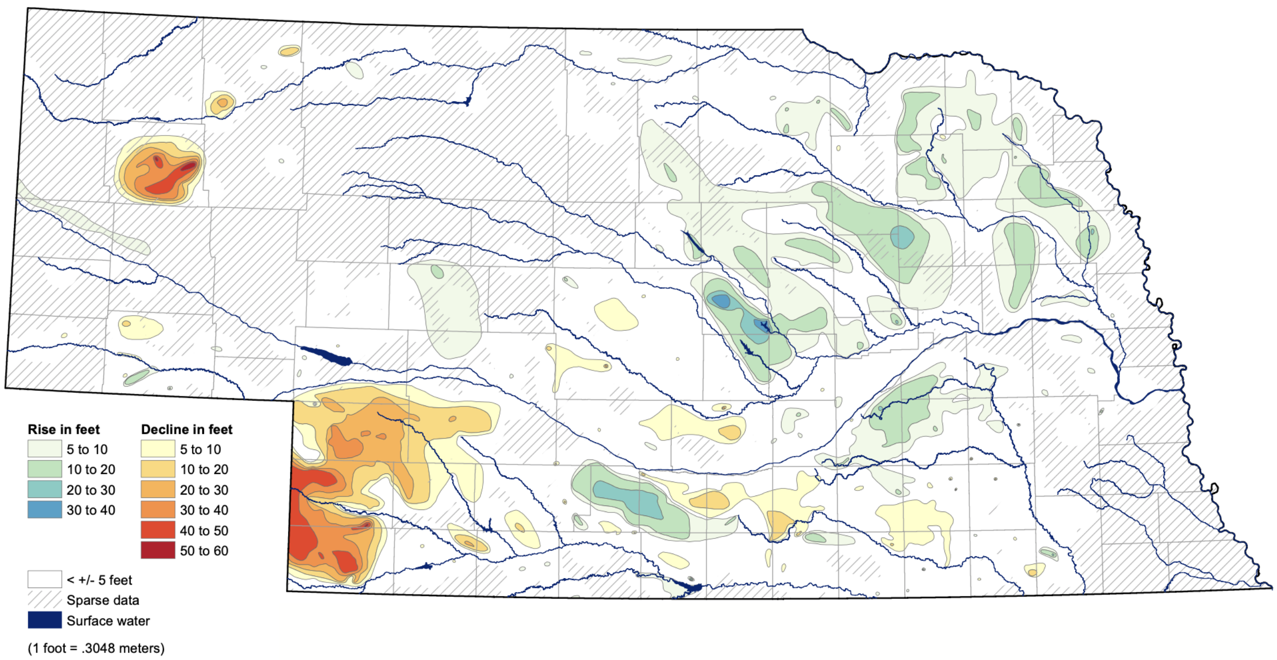

Figure A.7: Historical Change in the Water Table - Ogallala Aquifer, Nebraska
Notes: The source of this figure is Young et al. (2019). It shows the historical change in the Ogallala Aquifer's water table in Nebraska. This figure is Figure 16 in Young et al. (2019).

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 A.9: 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 A.10: 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.

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 A.11: 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 A.12: 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 A.13: 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 A.14: 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 A.15: 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.

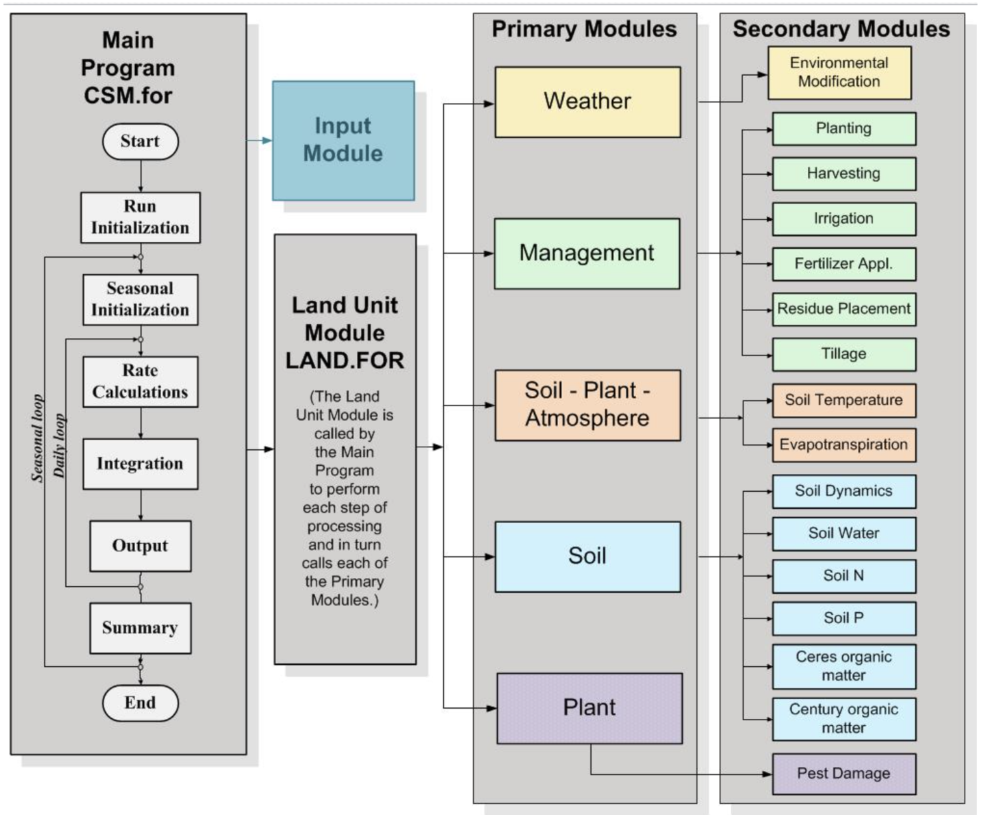

Figure A.8: DSSAT - Modules

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 A.8 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 A.16: 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 A.16 summarises some additional assumptions on farmers' behavior.

A.4.1 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 A.17 displays the conversion rates I use to transform units when needed.

A.5 Additional Results

In this section, I show some additional results.

First, I show the heterogeneity in productivity per crop. Table A.18 displays some summary statistics, while Figure A.9 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 A.17: Conversion Rate 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 A.18: 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.*

Second, I show the relation between the marginal cost of groundwater extraction and the number of wells per acre.

A.6 Calibration

In this section, I show the calibration assumptions on the crop and fertilizer prices, the recharge rate for the aquifer, the proportion of water used for irrigation that returns to the aquifer, and the discount rate for the counterfactual analysis.

Table A.20 shows such calibration assumptions.

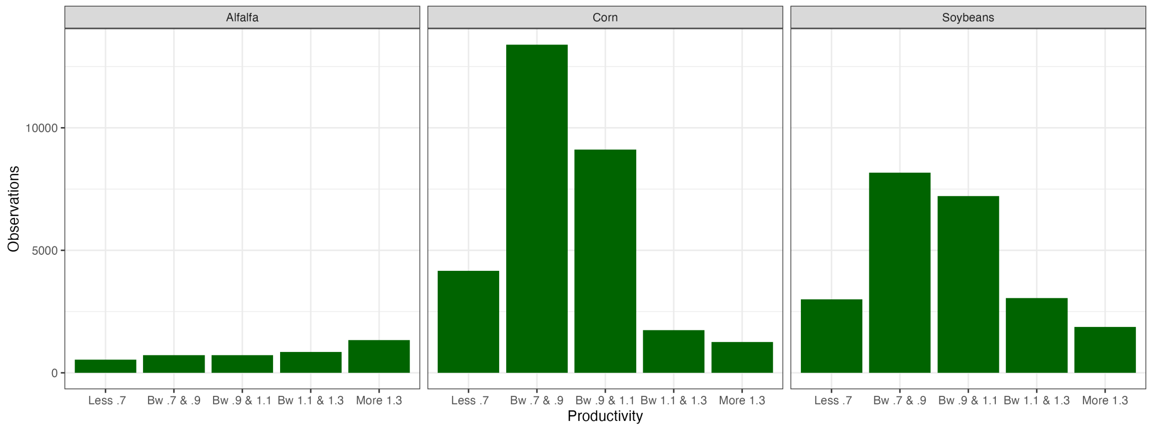

Figure A.9: Productivity Per Crop

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.

Dependent Variable:	Marginal Cost, 2018-USD
Model:	(1)
Variables	
Wells per Acre	-3,404.8*
	(462.6)
Fixed-effects	
year	Yes
Fit statistics	
Observations	1,205
R^2	0.23

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

Table A.19: Marginal Cost of Water and Wells per Acre - Regression

Notes: "Wells per acre" refers to the number of wells per acre of the land operate by the farmer. "Marginal Cost, 2018-USD" is the marginal cost of water for farmers in my sample in USD in 2018 prices. I use acreage planted and sample weights in this regressions, as suggested by the NASS.

	2008	2013	2018	Source
Prices (USD, 2018)				
Corn (bu)	4.34	4.53	3.37	Agricultural Market Service, USDA
Soybeans (bu)	10.23	13.62	7.88	Agricultural Market Service, USDA
Alfalfa (ton)	58.89	86.14	62.89	Agricultural Market Service, USDA
Wheat (bu)	9.57	7.54	4.61	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 A.20: 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.

A.7 Groundwater Use - Tragedy of the Commons

Conceptually, the problem is a case of 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:

$$\max_w \pi(w, h)$$

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:

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

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

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

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

$$\max_{w(t),h(t)} \int_0^\infty e^{-\rho t}\pi(w(t),h(t))dt$$
$$\text{s.t. } \dot{h}(t) = R - Nw(t)$$

which clearly does not have the same solution.