Climate Change, Groundwater, Crop Choice, and Irrigation Technology: A Review of Recent Studies[1]

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Abstract

Climate change has the potential to impact groundwater availability in several ways. For example, it may cause farmers to change the crops they plant or the amount of water they apply, both of which have implications for water availability. Climate change can also affect water availability directly via changes in precipitation and evapotranspiration patterns. In this paper, we review the literature on climate change, agriculture, and groundwater, including our research in Bertone Oehninger, Lin Lawell and Springborn (2017a,b) analyzing the effects of climate change on groundwater extraction for agriculture using an econometric model of a farmer's irrigation water pumping decision that accounts for both the intensive margin (water use) and the extensive margins (crop acreage, whether to plant multiple crops, and irrigation technology). Our results in Bertone Oehninger, Lin Lawell and Springborn (2017a) show that changes in climate variables influence crop acreage allocation decisions, the choice to plant multiple crops, the choice of irrigation technology, and the demand for water by farmers. We find in Bertone Oehninger, Lin Lawell and Springborn (2017b) that such changes in behavior can affect the diversity of crops planted.

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1. Introduction

The management of groundwater resources is an issue that reaches far and wide; regions around the world are struggling with ways to reign in extraction from aquifers that have been deemed over-exploited, and many of the world's most productive agricultural basins depend almost exclusively on groundwater. The food that consumers eat, the farmers who produce that food, and the local economies supporting that production are all affected by the availability of groundwater (Lin Lawell, 2016b). Worldwide, about 70 percent of groundwater withdrawn is used in agriculture, and in some countries, the percent of groundwater extracted for irrigation can be as high as 90 percent (National Groundwater Association, 2016). Thus, any investigation into the economics of groundwater must consider the agricultural industry. This paper focuses on the groundwater used for agriculture.

Many of the world's most productive agricultural basins depend on groundwater and have experienced declines in water table levels. Increasing competition for water from cities and environmental needs, as well as concerns about future climate variability and more frequent droughts, have caused policy makers to declare "water crises" and look for ways to decrease the consumptive use of water (Lin Lawell, 2016b).

Climate change has the potential to impact groundwater availability in several ways. First, changes in climate may indirectly impact groundwater availability by causing changes in agricultural land use and changes in agricultural practices that then result in changes in water availability. For example, climate change may cause farmers to change the crops they plant or the amount of water they apply, both of which have implications for water availability.

Second, climate change may affect water availability directly. For example, changing climates may result in melting snowcaps and/or changes in precipitation which would affect the availability of water for agriculture.

In this paper, we review the literature on climate change, agriculture, and groundwater, including our research in Bertone Oehninger, Lin Lawell and Springborn (2017a,b), which focuses on the groundwater used for agriculture in the High Plains (Ogallala) Aquifer system of the Midwestern United States. The High Plains Aquifer provides a useful case study to generate general insights regarding agricultural groundwater and is also important in its own right, as 99 percent of the water extracted there is used for crop production, and the economy of the region is based almost entirely on irrigated agriculture (Lin and Pfeiffer, 2015). The High Plains Aquifer is critical to the economic life of Kansas and the surrounding states, but water is being withdrawn from the aquifer much faster than it is being recharged. Due to the importance of irrigated agriculture to the multi-state region, the imbalance in water use threatens long-term economic stability (Dermyer, 2011). A better understanding of the effects of climate change on agriculture and groundwater in the High Plains Aquifer is therefore important for the sustainable management of agricultural groundwater both in that system and also more generally worldwide.

In Bertone Oehninger, Lin Lawell and Springborn (2017a,b), we analyze the effects of climate change on groundwater extraction for agriculture using an econometric model of a farmer's irrigation water pumping decision that accounts for both the intensive margin (water use) and the extensive margins (crop acreage, whether to plant multiple crops, and irrigation technology). Our results in Bertone Oehninger, Lin Lawell and Springborn (2017a) show that changes in climate variables influence crop acreage allocation decisions, the choice to plant multiple crops, the choice of irrigation technology, and the demand for water by farmers. We find in Bertone Oehninger, Lin Lawell and Springborn (2017b) that such changes in behavior can affect the diversity of crops planted.

The balance of our paper proceeds as follows. Section 2 reviews the literature on climate change, agriculture, and groundwater. Section 3 reviews our research in Bertone Oehninger, Lin Lawell and Springborn (2017a,b). Section 4 concludes.

2. Literature Review

2.1. Climate change and farmland values

We build upon the previous literature analyzing the effects of climate change on agriculture. This literature includes a strand which examines the effects of climate change on farmland values and/or agricultural profits. Schlenker, Hanemann and Fisher (2006) estimate the potential impacts of global warming on farmland values for a range of scenarios, and find a statistically significant effect, ranging from moderate gains to large losses, in more than 75% of the counties in their sample, with losses in the aggregate that can become quite large under scenarios involving sustained heavy use of fossil fuels. Deschênes and Greenstone (2007) measure the economic impact of climate change on U.S. agricultural land by estimating the effect of random year-to-year variation in temperature and precipitation on agricultural profits, and find that climate change will increase annual profits by $1.3 billion in 2002 dollars, or 4 percent.

Wang et al. (2017) employ a stochastic frontier approach to examine how climate change and extreme weather affect U.S. agricultural productivity using 1940-1970 historical weather data as the norm. They find that more heat waves drier conditions will tend to lower a state's productivity. They find that the same degree changes in temperature or precipitation will have uneven impacts on regional productivities, with Delta, Northeast, and Southeast regions incurring much greater effects than other regions (Wang et al., 2017).

Analyses of the effects of climate change on farmland values and/or agricultural profits can be sensitive to the model specification and the data used. In contrast to Deschênes and Greenstone (2007), Fisher et al. (2012) find that the potential impact of climate change on U.S. agriculture is likely negative. Fisher et al. (2012) attribute the different results in Deschênes and Greenstone (2007) to (1) missing and incorrect weather and climate data; (2) the use of older climate change projections rather than the more recent and less optimistic projections from the Fourth Assessment Report; and (3) difficulties in the profit measure due to the confounding effects of storage. Deschênes and Greenstone (2012) acknowledge the coding and data errors in their 2007 paper that were uncovered by Fisher et al. (2012), but show how some of the other critiques may have little basis. Fezzi and Bateman (2015) use a large panel of farm-level data to investigate the potential bias induced by assuming additively separable effects of temperature and precipitation and by using data aggregated across counties or large regions.

2.2. Climate change and crop yields

In addition to the above strand of literature examining the effects of climate change on farmland values and/or agricultural profits, the literature analyzing the effects of climate change on agriculture also includes a strand that examines the effects of climate change on crop yields and/or acreage. Research from two alternative schools of thought find different projected impacts from climate change on crop yields (Roberts, Schlenker and Eyer, 2013). On the one hand, crop models that are based on plant physiology and developed and refined from field experiments over many decades usually predict positive or only modestly negative impacts from projected warming and rising carbon dioxide concentrations, both globally and in the U.S. On the other hand, results from statistical analyses provide evidence that most of the world's key staple grains and legumes are critically sensitive to high temperatures in rain-fed environments (Roberts, Schlenker and Eyer, 2013).

One way to improve on statistical and econometric analyses of the effects of climate change on crop yields is to use high frequency data on climate. Schlenker and Roberts (2009) pair a panel of county-level yields for corn, soybeans, and cotton with a new fine-scale weather dataset that incorporates the whole distribution of temperatures within each day and across all days in the growing season, and find that yields increase with temperature up to 29°C for corn, 30°C for soybeans, and 32°C for cotton, but that temperatures above these thresholds are very harmful. Lee and Sumner (2015) establish quantitative relationships between the evolution of climate and cropland in a specific agro-climatic region of California using daily climate data for a century and data on allocation of land across crops for six decades, and find that projections of warmer winters, particularly from 2035 to 2050, cause lower wheat area and more alfalfa and tomato area.

The recent statistical yield literature emphasizes the importance of flexibly accounting for the distribution of growing-season temperature to better represent the effects of warming on crop yields. Gammans, Mérel and Ortiz-Bobea (2017) estimate a flexible statistical yield model using a long panel from France to investigate the impacts of temperature and precipitation changes on wheat and barley yields, and find that crop yields are predicted to be negatively affected by climate change under a wide range of climate models and emissions scenarios..

Ortiz-Bobea (2015a) develops a simple model to show how models that assume weather variables can be aggregated over several months that include the growing season impose implausible characteristics on the production technology that are in serious conflict with the agricultural sciences; tend to underestimate the range of adaptation possibilities available to farmers; and thus overstate projected climate change impacts on the sector (Ortiz-Bobea, 2015a).

Another way to improve on statistical and econometric analyses of the effects of climate change on crop yields is to include soil moisture. Using a state-of-the art dataset with very high spatial (14 km) and temporal (1h) resolution and a 31-year panel of corn yields covering 70% of U.S. production, Ortiz-Bobea (2015b) finds that corn yield is highly sensitive to soil moisture toward the middle of the season around flowering time, and that models that omit soil moisture overestimate the detrimental effects of temperature.

It is also important include crop prices in statistical and econometric analyses of the effects of climate change on crop yields. Miao, Khanna and Huang (2016) show that when price variables are omitted, the effect of climate change is overestimated by up to 9% for corn yields and up to 15% on for soybean yields.

Another variable that is important to include in statistical and econometric analyses of the effects of climate change on crop yields is humidity. Zhang, Zhang and Chen (2017) explore the importance of additional climatic variables other than temperature and precipitation, and find that omitting humidity tends to overpredict the cost of climate change on crop yields, , while ignoring wind speed is likely to underpredict the effect (Zhang, Zhang and Chen, 2017).

In statistical and econometric analyses of the effects of climate change on crop yields, it is also important to consider multiple crops rather than narrowly focusing on only a single crop. Thompson et al. (2017) use a structural economic model with projections of climate-driven yield changes to simulate the joint impact of new distributions of corn and soybean yields on markets, and their findings suggest that a narrow focus on a single crop in this key growing region risks underestimating the impact on price distributions and average crop receipts, and can lead to incorrect signs on estimated impacts.

2.3. Climate change and other economic outcomes

The literature analyzing the effects of climate change on agriculture also includes a strand that examines the effects of climate change on trade and other macro-level outcomes. Lybbert, Smith and Sumner (2014) explore how inter-hemispheric trade and supply responses can moderate the effects of weather shocks on global food supply by enabling potential intra-annual arbitrage. They find that in the case of wheat and soybeans, 25–50% of crop production lost to a shock in the Southern Hemisphere is offset six months later by increased production in the North (Lybbert, Smith and Sumner, 2014).

Costinot, Donaldson and Smith (2016) quantify the macro-level consequences of climate change, and find that the impact of climate change on agricultural markets from 10 crops would amount to a 0.26 percent reduction in global GDP when trade and production patterns are allowed to adjust corresponding to about one-sixth of total crop value (Costinot, Donaldson and Smith, 2016).

Lemoine (2017) formally analyzes the consequences of a change in climate for economic outcomes. He shows that those consequences are driven by changes in the distribution of realized weather and by expectations channels that capture how anticipated changes in the distribution of weather affect current and past investments. Although a rapidly growing empirical literature seeks to estimate the costs of future climate change from time series variation in weather, these studies omit the expectations channels. Quantifying the expectations channels requires estimating how forecasts affect outcome variables and simulating how climate change would alter forecasts (Lemoine, 2017).

Identifying the effect of climate on societies is central to understanding historical economic development, designing modern policies that react to climatic events, and managing future global climate change. Hsiang (2016) reviews, synthesizes, and interprets recent advances in methods used to measure effects of climate on social and economic outcomes. Because weather variation plays a large role in recent progress, the author formalizes the relationship between climate and weather from an econometric perspective and discusses their use as identifying variation, highlighting tradeoffs between key assumptions in different research designs and deriving conditions when weather variation exactly identifies the effects of climate. He then describes advances in recent years, such as parameterization of climate variables from a social perspective, nonlinear models with spatial and temporal displacement, characterizing uncertainty, measurement of adaptation, cross-study comparison, and use of empirical estimates to project the impact of future climate change. The paper concludes by discussing remaining methodological challenges (Hsiang, 2016).

2.4. Climate change and adaptation

Projecting the impacts of climate change on agriculture requires knowing or assuming how farmers will adapt. Moore and Lobell (2014) assess the potential effectiveness of private farmer adaptation in Europe by jointly estimating both short-run and long-run response functions using time-series and cross-sectional variation in subnational yield and profit data. They calculate the private adaptation potential as the difference between the impacts of climate change projected using the short-run (limited adaptation) and long-run (substantial adaptation) response curves. The authors find high adaptation potential for maize to future warming but large negative effects and only limited adaptation potential for wheat and barley. Overall, agricultural profits could increase slightly under climate change if farmers adapt but could decrease in many areas if there is no adaptation (Moore and Lobell, 2014).

Burke and Emerick (2016) exploit large variation in recent temperature and precipitation trends to identify adaptation to climate change in U.S. agriculture, and use this information to generate new estimates of the potential impact of future climate change on agricultural outcomes. They find that longer run adaptations have mitigated less than half--and more likely none--of the large negative short-run impacts of extreme heat on productivity (Burke and Emerick, 2016).

Increasing aridity, more frequent and intense drought, and greater degrees of water scarcity create unique challenges for agriculture. In response to these challenges, which often manifest themselves as lower and more variable surface water supplies, as well as depleted and degraded ground water supplies, growers tend to seek opportunities to adapt. One option for growers to reduce their exposure to water scarcity and heightened uncertainty is to diversify their water supply. Indeed, access to a portfolio of supplies is one way in which water and irrigation districts, as well as individual growers, are responding to the changing landscape of water resource availability. Mukherjee and Schwabe (2015) evaluate the benefits to irrigated agriculture from having access to multiple sources of water. With farm-level information on 1,900 agricultural parcels across California, they use the hedonic property value method to investigate the extent that growers benefit from having access to multiple sources of water (i.e., a water portfolio). Their results suggest that while lower quality waters, less reliable water, and less water all negatively impact agricultural land values, holding a water portfolio has a positive impact on land values through its role in mitigating the negative aspects of these factors and reducing the sensitivity of agriculture to climate-related factors. From a policy perspective, such results identify a valuable adaptation tool that irrigation districts may consider to help offset the negative impacts of climate change, drought, and population increases on water supply availability and reliability (Mukherjee and Schwabe, 2015).

Bento et al. (2017) propose a novel approach to estimate adaptation to climate change based on a decomposition of meteorological variables into long-run trends and deviations from those trends (weather shocks). Their estimating equation simultaneously exploits weather variation to identify the impact of weather shocks, and climatic variation to identify the effect of longer-run observed changes. They then compare the simultaneously estimated short- and long-run effects to provide a measure of adaptation. They also applied their methodology to study the impact of climate change on air quality, and estimate the so-called climate penalty on ozone. This penalty means that climate change might offset some of the improvements in air quality expected from reductions in ozone precursors. Their results show evidence of adaptive behavior. If adaptive responses were not taken into account, the climate penalty on ozone would be overestimated by approximately 17 percent. They also find that adaptation in counties with levels of ozone above the EPA's standards appears to be over 66 percent larger than adaptation in counties in "attainment". This difference is what they call regulation-induced adaptation, and the remainder is their measure of residual adaptation (Bento et al, 2017).

2.5. Agricultural groundwater demand

We also review the relevant economics literature on agricultural groundwater.[2] This literature includes papers estimating the demand for irrigation water. Using panel data from a period of water rate reform, Schoengold, Sunding and Moreno (2006) estimate the price elasticity of irrigation water demand. Price elasticity is decomposed into the direct effect of water management and the indirect effect of water price on choice of output and irrigation technology. Their model is estimated using an instrumental variables strategy to account for the endogeneity of technology and output choices in the water demand equation. Their estimation results indicate that the price elasticity of agricultural water demand is 0.79, which is greater than that found in previous studies (Schoengold, Sunding and Moreno, 2006).

Dermyer (2011) chooses seven target counties overlying the High Plains Aquifer to develop a method of predicting water-use based on land-use and weather records. A water budget model was created to predict irrigation withdrawals from the High Plains Aquifer based on crop-specific evapotranspiration, and the model was validated based on historical data on water use, weather, and land use. In the seven target counties, predicted water use matched historic reported water use with a slope of 1.015. This model could be used to predict future irrigation demand under different land-use and climate conditions. Additionally, the link between withdrawals and groundwater levels is examined for the seven target counties. In some

[2] For a discussion of the economics of groundwater, see Sears and Lin Lawell (forthcoming).

counties, the change in water surface elevation was correlated with water-use, but in others, the amount of water withdrawn from the aquifer had no impact on the water table (Dermyer, 2011).

2.6. Agricultural groundwater in the High Plains Aquifer

We also build on the literature analyzing agricultural groundwater in the High Plains Aquifer. Pfeiffer and Lin (2014a) analyze incentive-based groundwater conservation policies in Kansas and find that measures taken by the state of Kansas to subsidize a shift toward more efficient irrigation systems have not been effective in reducing groundwater extraction. The subsidized shift toward more efficient irrigation systems has in fact increased extraction through a shift in cropping patterns. Better irrigation systems allow more water-intensive crops to be produced at a higher marginal profit. The farmer has an incentive to both increase irrigated acreage and produce more water-intensive crops (Lin, 2013a; Lin, 2013b; Lin, 2013d; Lin Lawell, 2016; Lin and Pfeiffer, 2015; Pfeiffer and Lin, 2009; Pfeiffer and Lin, 2010; Pfeiffer and Lin, 2014a; Pfeiffer and Lin, 2014b; Sears et al., 2017).

Pfeiffer and Lin (2012) empirically examine whether the amount of water one farmer extracts depends on how much water his neighbor extracts. Their econometric model is spatially explicit, taking advantage of detailed spatial data on groundwater pumping from the portion of western Kansas that overlies the High Plains Aquifer system. Using an instrumental variable and spatial weight matrices to overcome estimation difficulties resulting from simultaneity and spatial correlation, they find that on average, the spatial externality causes over-extraction that accounts for about 2.5 percent of total pumping. Kansas farmers would apply 2.5 percent less water in the absence of spatial externalities (Pfeiffer and Lin, 2012; Pfeiffer and Lin, 2015; Lin Lawell, 2016; Sears et al., 2017) .

Lin Lawell (2017) develops an empirical model to test whether groundwater users faced with the prior appropriation doctrine are behaving in a manner consistent with a dynamic model of nonrenewable resource extraction. She finds that despite the incentives given to groundwater users to pump their maximum allowable amount in each year by the prior appropriation doctrine, farmers extract water consistent with a dynamic model of resource extraction. While producers are allotted a time-invariant maximum amount that they can extract each year, they still consider their remaining stock of water, pumping by nearby neighbors, and projections of future commodities prices when making crop choice and pumping decisions. Her results therefore provide evidence that farmers recognize the nonrenewable nature of the resource that they manage, even though their property rights do not (Lin Lawell, 2017; Lin Lawell, 2016).

Li and Zhao (2016) study the role of imperfectly enforced water rights in restricting water use and limiting the rebound effects of LowEnergy Precise Application (LEPA) irrigation technology, as well as farmer incentives to preserve their water rights. Using data from the Ogallala-High Plains Aquifer region of Kansas, they find that restricting water rights can reduce water extraction even when ex post the water rights are not binding, and these effects are more pronounced after the adoption of LEPA, thereby reducing the technology's rebound effects of raising water extraction. The rebound effects arise from LEPA adopters switching to more water intensive crops as well as irrigating more intensively. Larger water right holders extract more water because they irrigate larger fields and also because they irrigate more intensively. Farmers have incentive to preserve their water rights in response to the use-it-or-lose-it clause of the water right system, but the associated water waste is insignificant.

2.7. Agricultural groundwater and energy

In some areas, agriculture that depends on irrigation from groundwater dominates both peak period energy use and the consumption of water. Energy is a key input for pumping water from aquifers. This linkage means that public policies and contract terms designed for either factor may affect the use of the other factor (Mieno and Brozovic, 2013). Mieno and Brozovic

(2013) look in particular at the effects on groundwater use of energy supply interruptions. They analyze the intra-seasonal irrigation decisions of individual agricultural producers facing stochastic energy supply interruption and rainfall using stochastic dynamic programming. The authors find that agricultural producers should increase the amount of water applied per irrigation opportunity to hedge against the risk of future energy outages. Further, numerical analysis calibrated to intensive irrigation in Nebraska, USA, where groundwater use is regulated, shows that random energy supply interruption could increase the total amount of water consumption despite reduced opportunities for irrigation. This finding indicates that energy supply interruptions could have adverse effects on groundwater use, potentially complicating the management of water resources. They also find that changes in the distribution of rainfall, as may accompany climate change, exacerbate the effects of energy supply interruptions on total groundwater consumption (Mieno and Brozovic, 2013).

Pfeiffer and Lin (2014c) examine if energy prices impact groundwater extraction, and find that energy prices have an effect on both the intensive and extensive margins. Increasing energy prices would affect crop selection decisions, crop acreage allocation decisions, and the demand for water by farmers. Their estimated total marginal effect, which sums the effects on the intensive and extensive margins, is that an increase in the energy price of $1 per million btu would decrease water extraction by an individual farmer by 5.89 acre-feet per year (Pfeiffer and Lin, 2014c; Sears et al., 2017) .

2.8. Water and climate change

We also build on the literature analyzing the effects of climate change on water use for agriculture. Olen, Wu, and Langpap (2016) analyze the impact of water scarcity and climate on irrigation decisions for producers of specialty crops, wheat, and forage crops. They find that economic and physical water scarcity, climate, and extreme weather conditions such as frost, extreme heat and drought significantly impact producers' irrigation decisions. Producers use sprinkler technologies or additional water applications to mitigate risk of crop damage from extreme weather (Olen, Wu and Langpap, 2016).

Ponce et al. (2016) analyze the economic impacts of changes in water availability due to climate change by including water as a production factor within a global CGE model and applying the model to a new database they construct to explicitly consider water endowments, precipitation changes, and unitary irrigation costs. Results suggest different economic consequences of climate change depending on the specific region. Impacts are related to changes in crop production, endowment demands, and international trade.

3. A Review of Our Research

Our research in Bertone Oehninger, Lin Lawell and Springborn (2017a,b) focuses on the groundwater used for agriculture in the High Plains (Ogallala) Aquifer system of the Midwestern United States. There, 99 percent of the water extracted is used for crop production; the remaining one percent is used for livestock, domestic, and industrial purposes. The economy of the region is based almost entirely on irrigated agriculture. The alfalfa, corn, sorghum, soybeans, and wheat grown there is used for local livestock production or exported from the region. The small local communities support the agricultural industry with farm implement dealers, schools, restaurants, and other services. The state governments are also greatly concerned with supporting their agricultural industry (Lin and Pfeiffer, 2015).

Exploitation of the High Plains Aquifer system began in the late 1800s but was greatly intensified after the "Dust Bowl" decade of the 1930s (Miller and Appel, 1997). Aided by the development of high capacity pumps and center pivot systems, irrigated acreage went from 1 million acres in 1960 to 3.1 million acres in 2005, and accounts for 99 percent of all groundwater withdrawals (Kenny and Hansen, 2004). Irrigation converted the region from the "Great American Desert" into the "Breadbasket of the World" (Lin and Pfeiffer, 2015).

Increased access to the High Plains Aquifer increased agricultural land values and initially reduced the impact of droughts. Over time, however, land use adjusted toward high-value water-intensive crops and drought sensitivity increased (Hornbeck and Keskin, 2014). Similarly, measures taken by the state of Kansas to subsidize a shift toward more efficient irrigation systems led to perverse effect of increasing extraction through a shift in cropping patterns (Pfeiffer and Lin, 2014a; Lin and Pfeiffer, 2015).

The High Plains Aquifer underlies approximately 174,000 square miles. It is the principle source of groundwater in the Great Plains region of the United States. Also known as the Ogallala Aquifer, the High Plains Aquifer system is now known to include several other aquifer formations. The portion of the aquifer that underlies western Kansas, however, pertains mainly to the Ogallala Aquifer (Miller and Appel, 1997; Lin and Pfeiffer, 2015).

The High Plains aquifer is underlain by rock of very low permeability that creates the base of the aquifer. The distance from this bedrock to the water table is a measure of the total water available and is known as the saturated thickness. The saturated thickness of the High Plains aquifer in Kansas ranges from nearly zero to over 300 feet (Buddemeier, 2000; Lin and Pfeiffer, 2015).

The depth to water is the difference between the altitude of the land surface and the altitude of the water table. In areas where surface and groundwater are hydrologically connected, the water table can be very near to the surface. In other areas, the water table is much deeper; the depth to water is over 400 feet below the surface in a portion of southwestern Kansas (Miller and Appel, 1997; Lin and Pfeiffer, 2015).

Recharge to the Kansas portion of the High Plains aquifer is relatively small. It is primarily by percolation of precipitation and return flow from water applied as irrigation. The rates of recharge vary between 0.05 and 6 inches per year, with the greatest rates of recharge occurring where the land surface is covered by sand or other permeable material (Buddemeier, 2000; Lin and Pfeiffer, 2015).

The main crops grown in western Kansas are alfalfa, corn, sorghum, soybean, and wheat (High Plains Regional Climate Center, 2014). Corn production accounts for more than 50 percent of all irrigated land (Buddemeier, 2000). Soil types and access to high volumes of irrigation water determine the suitability of a particular piece of land to various crops (Lin and Pfeiffer, 2015).

For our empirical analysis in Bertone Oehninger, Lin Lawell and Springborn (2017a,b), we have constructed a detailed panel data set of annual data for over 20,000 groundwater-irrigated fields in western Kansas from 1996 to 2012 containing climate conditions, water use, irrigation type, crops planted, and soil moisture.

We build on the data used in previous empirical analyses of groundwater in western Kansas (Pfeiffer and Lin, 2009; Pfeiffer and Lin, 2010; Pfeiffer and Lin, 2012; Pfeiffer and Lin, 2014a; Pfeiffer and Lin, 2014b; Pfeiffer and Lin, 2014c; Lin and Pfeiffer, 2015; Lin Lawell, 2016a; Lin Lawell, 2016b), which spanned 10 years between 1996 and 2005, and have extended the data set to cover the years 1996 to 2012.

Data related to water rights, water use, and crop choice are from the Water Information Management and Analysis System (WIMAS), which was created by the Kansas Department of Agriculture (Division of Water Resources and Kansas Geological Survey). Specific data related to wells' characteristics (for example depth) was obtained from the Water Well Completion Records (WWC5) Database, also created by the Kansas Geological Survey.

Climate data, including temperature, precipitation and humidity, was obtained from the High Plains Regional Climate Center (HPRCC), which contains information from the Automated Weather Data Network and also the National Weather Service & Cooperative

Observer Network. The furthest the closest weather station is to any field is 93.65 miles. Thus, for each field, we average each weather variable over all the stations within 93.65 miles of that field.

Following the work of Ortiz-Bobea (2015a,b), we control for soil moisture. Soil moisture data was obtained from NASA's NLDAS-2 (North American Land Data Assimilation System), the same source used by Ortiz-Bobea (2015a,b).

We obtained crop prices for sorghum and alfalfa from the USDA – ERS Feed Grains Database. Futures prices for corn, soybeans, wheat, feeder cattle, live cattle, live hogs and oats are from quandl.com. Energy prices are from the Energy Information Administration (EIA) for Kansas.

In Bertone Oehninger, Lin Lawell and Springborn (2017a,b), we consider several specifications of the climate-related variables. These climate specifications are summarized in Table 1. Each specification also includes squared values of the relevant temperature and precipitation variables.

We try several specifications of the annual climate variables. In specification Y1, the climate variables T_{it} are annual average temperature, annual precipitation, and annual average humidity. This specification assumes that each year farmers have rational expectations, so that they make decisions based on the current year's actual climate.

However, since farmers must make their crop choice and water use decisions for a given year before the end of the year, and therefore before they know what the actual annual climate for that year will be, we also try a specification using climate variables that are averages of climate variables over the past 3 years. This specification assumes that farmers form expectations about the current year's climate based on the climate from the past 3 years. Thus, in specification Y2, the climate variables T_{it} are average annual temperature over the past 3 years, total precipitation over the past 3 years, and annual average humidity.

It is possible that what matters most in terms of temperature is not annual average temperature, but the fraction of days in the year and over the summer with maximum temperature above a threshold value. In specification Y3, the climate variables T_{it} therefore are annual fraction of days with maximum temperature greater than 86 degrees Fahrenheit (°F),[3] summer fraction of days with maximum temperature greater than 86°F, annual precipitation, and annual average humidity.

Since farmers make their crop choice and water use decisions at the beginning of the season, after they have already seen the climate in the first 4 months of that year, we also try a specification using climate variables that are based on the climate in the first 4 months of year, as well as based on averages of climate variables over the past 3 years. This specification assumes that farmers form expectations about the current year's climate based on the climate from the past 3 years as well as on what they have seen about the current year so far (i.e., the first 4 months of that year). In specification Y4, the climate variables T_{it} therefore are average annual temperature over the past 3 years, average temperature over the first 4 months of the year (before the crop decision), total precipitation over the past 3 years, precipitation over the first 4 months of the year (before the crop decision), annual average humidity, and average humidity over the first 4 months of the year (before the crop decision).

It is possible that the measure of temperature in the first 4 months that matters is not the average temperature over those first 4 months, but the fraction of days in the first 4 months with maximum temperature above a threshold value. In specification Y5, the climate variables T_{it} therefore are average annual temperature over the past 3 years, the fraction of days with maximum temperature greater than 86°F over the first 4 months of the year (before the crop decision), total precipitation over the past 3 years, precipitation over the first 4 months of the

[3] 86 degrees Fahrenheit is equivalent to 30 degrees Celsius.

year (before the crop decision), annual average humidity, and average humidity over the first 4 months of the year (before the crop decision).

For the specifications using climate variables for each month individually, we average the monthly climate variables over the last 3 years to better measure expectations. In specification M1, the climate variables T_{it} are average monthly average temperature over past 3 years for each month of the year, average monthly precipitation over past 3 years for each month of the year, and average monthly humidity over past 3 years for each month of the year.

It is possible that the measure of monthly temperature that matters is not the monthly temperature, but the fraction of days in the month with maximum temperature above a threshold value. In specification M2, the climate variables T_{it} therefere are average fraction of days (out of the days in that month with data) that have maximum temperature greater than 86°F over the past 3 years for each month of the year, average monthly precipitation over past 3 years for each month of the year, and average monthly humidity over past 3 years for each month of the year.

Our econometric model of a farmer's irrigation water pumping decision in Bertone Oehninger, Lin Lawell and Springborn (2017a) has two components: the extensive margins and the intensive margin. We model three extensive margins: crop acreage, the choice to plant multiple crops, and irrigation technology. For the crop acreage extensive margin, we estimate the farmer's choice of how many acres to allocate to each crop using a censored regression model. For the multiple crop extensive margin, we estimate the farmer's choice of whether to plant multiple crops using a discrete response model. For the irrigation technology extensive margin, we estimate the farmer's choice of irrigation technology using discrete response models. For the intensive margin, we estimate the farmer's water demand conditional on his decisions regarding crop acreage allocation, whether to plant multiple crops, and irrigation technology.

In addition to temperature, precipitation and humidity, we also control for other factors that may affect groundwater extraction, including depth to groundwater, precipitation, irrigation technology, saturated thickness, recharge, crop prices, and energy prices. Following the work of Ortiz-Bobea (2015a,b), we also control for soil moisture.

For the crop acreage extensive margin, we estimate the farmer's choice of how many acres to allocate to each crop using a censored regression model. In particular, for each crop (alfafa, corn, sorghum, soybeans, and wheat), we run a tobit regression of the acres allocated to that crop on the climate variables, controlling for alfafa price, corn price, sorghum price, soybeans price, wheat price, a dummy for using a center pivot irrigation system, a dummy for using a center pivot irrigation system with dropped nozzles, evapotranspiration, recharge, slope, a dummy for irrigated capability class=1, field size, depth to groundwater, natural gas price, diesel price, electricity price, saturated thickness, soil moisture, a dummy for whether alfafa was planted last year, a dummy for whether corn was planted last year, a dummy for whether sorghum was planted last year, a dummy for whether soybeans were planted last year, and a dummy for whether wheat was planted last year. Table 2 presents the results of the tobit regressions for crop acreage for alfafa, corn, sorghum, soybeans, and wheat for climate specification Y5, our preferred climate specification. For robustness, we also run tobit regressions of crop acreage that include farmer random effects and year effects.

To account for the possibility that farmers may choose to plant multiple crops in a given year, for each of the 7 climate variable specifications, we run three sets of crop acreage regressions. In the first set ("all"), we use all observations, regardless of how many different types of crops were planted. Here, we assume that the total acreage was equally divided among all crops planted on that field in that year. In the second set ("monoculture"), we only use observations where only one crop type was planted on that field in that year. In the third set ("polyculture"), we only use observations where more than one crop type was planted on that field in that year.

For the multiple crop extensive margin, we estimate the farmer's choice of whether to plant multiple crops using a discrete response model. In particular, we run a probit regression in which the dependent variable is a dummy for planting more than one type of crop on that field in that year. We regress this dummy the climate variables, controlling for alfafa price, corn price, sorghum price, soybeans price, wheat price, a dummy for using a center pivot irrigation system, a dummy for using a center pivot irrigation system with dropped nozzles, evapotranspiration, recharge, slope, a dummy for irrigated capability class=1, field size, depth to groundwater, natural gas price, diesel price, electricity price, saturated thickness, and soil moisture. Table 3 presents the results of the multiple crop probit regression for climate specification Y5, our preferred climate specification.

For the irrigation technology extensive margin, we estimate the farmer's choice of irrigation technology using discrete response models. In particular, we run a probit of center pivot sprinkler use on the climate variables, controlling for acres planted to alfalfa, acres planted to corn, acres planted to sorghum, acres planted to soybeans, acres planted to wheat, alfalfa price, corn price, sorghum price, soybeans price, wheat price, evapotranspiration, recharge, slope, a dummy for irrigated capability class=1, field size, depth to groundwater, natural gas price, diesel price, electricity price, saturated thickness, and soil moisture. Table 4a presents the results of the center pivot sprinkler use probit regression for climate specification Y5, our preferred climate specification.

Similarly, we run a probit of center pivot sprinkler with drop nozzles use on the climate variables, controlling for acres planted to alfalfa, acres planted to corn, acres planted to sorghum, acres planted to soybeans, acres planted to wheat, alfalfa price, corn price, sorghum price, soybeans price, wheat price, evapotranspiration, recharge, slope, a dummy for irrigated capability class=1, field size, depth to groundwater, natural gas price, diesel price, electricity price, saturated thickness, and soil moisture. Table 4b presents the results of the center pivot sprinkler with drop nozzle use probit regression for climate specification Y5, our preferred climate specification.

For the intensive margin, we estimate the farmer's water demand conditional on his decisions regarding crop acreage allocation, whether to plant multiple crops, and irrigation technology. In particular, we run an OLS regression of water use on the climate variables, controlling for acres planted to alfafa, acres planted to alfafa squared, acres planted to corn, acres planted to corn squared, acres planted to sorghum, acres planted to sorghum squared, acres planted to soybeans, acres planted to soybean squared, acres planted to wheat, acres planted to wheat squared, a dummy for using a center pivot irrigation system, a dummy for using a center pivot irrigation system with dropped nozzles, evapotranspiration, recharge, slope, a dummy for irrigated capability class=1, field size, depth to groundwater, natural gas price, diesel price, electricity price, saturated thickness, and soil moisture. Table 5 presents the results of the water use regression for climate specification Y5, our preferred climate specification. We also run another set of regressions using water intensity (in acre-feet of water per acre) instead of water use (in acre-feet) as the dependent variable. For robustness, we also run water use and water intensity regressions that include farmer random effects and year effects.

We calculate the total marginal effects accounting for the extensive margins and intensive margin for each of the climate specifications in Bertone Oehninger, Lin Lawell and Springborn (2017a). According to our results in Bertone Oehninger, Lin Lawell and Springborn (2017a), annual average temperature and the average monthly average temperature over the past 3 years do not have a significant total marginal effect on water use, but the fraction of days with maximum temperature exceeding 86°F has a significant positive total marginal effect on water use in the fall and possibly also in January-April and in the spring. The average annual temperature over the last 3 years has a significant positive total marginal effect on water intensity. Monthly temperature over the last 3 years, and the monthly fraction of days with maximum temperature exceeding 86°F over the last 3 years can have a significant positive total marginal effect on water intensity in January-April and in some months. The sign of the total marginal effects of precipitation and humidity vary depending on the specification and/or month, and whether the effect is on water use or water intensity.

Our results in Bertone Oehninger, Lin Lawell and Springborn (2017a,b) therefore show that changes in climate variables influence crop acreage allocation decisions, the choice to plant multiple crops, the choice of irrigation technology, and the demand for water by farmers. We find that it is important to account for the extensive margins of whether to plant multiple crops and of the choice of irrigation technology in addition to the crop acreage extensive margin and the intensive margin. We also find that it is important to evaluate the effects of climate-related variables by month rather than only at an annual level.

4. Conclusion

Climate change has the potential to impact groundwater availability in several ways. For example, it may cause farmers to change the crops they plant or the amount of water they apply, both of which have implications for water availability. Climate change can also affect water availability directly via changes in precipitation and evapotranspiration patterns.

In this paper, we review the literature on climate change, agriculture, and groundwater, including our research in Bertone Oehninger, Lin Lawell and Springborn (2017a,b) analyzing the effects of climate change on groundwater extraction for agriculture using an econometric model of a farmer's irrigation water pumping decision that accounts for both the intensive margin (water use) and the extensive margins (crop acreage, whether to plant multiple crops, and irrigation technology). Our results in Bertone Oehninger, Lin Lawell and Springborn

(2017a) show that changes in climate variables influence crop acreage allocation decisions, the choice to plant multiple crops, the choice of irrigation technology, and the demand for water by farmers. We find in Bertone Oehninger, Lin Lawell and Springborn (2017b) that such changes in behavior can affect the diversity of crops planted.

Our research in in Bertone Oehninger, Lin Lawell and Springborn (2017a,b) provides a better understanding of how climate change affects groundwater extraction, crop choice, and irrigation technology decisions.

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Table 1. Climate Specifications

Climate Variable	Y1	Y2	Y3	Y4	Y5	M1	M2
Temperature							
Annual average temperature (°F)	✓						
Average annual temperature over the past 3 years (°F)		✓		✓	✓		
Annual fraction of days with max temp > 86°F			✓				
Summer fraction of days with max temp > 86°F			✓				
Average temperature in Jan-Apr (°F)				✓			
Fraction of days in Jan-Apr with max temp > 86°F					✓		
Avg. monthly temperature over the past 3 years (°F)						✓	
Avg. monthly fraction of days with max temp > 86°F over the past 3 years							✓
Precipitation							
Annual precipitation (in)	✓		✓				
Total precipitation over the past 3 years (in)		✓		✓	✓		
Precipitation in Jan-Apr (in)				✓	✓		
Avg. monthly precipitation over the past 3 years (in)						✓	✓
Humidity							
Annual average humidity (%)	✓	✓	✓	✓	✓		
Average humidity in Jan-Apr (%)				✓	✓		
Avg. monthly humidity over the past 3 years (%)						✓	✓

Note: Specifications also include squared values of the relevant temperature and precipitation variables.

Table 2: Crop Acreage Tobit Regressions, Climate Specification Y5

	Dependent variable is acres planted to:				
	Alfalfa	Corn	Sorghum	Soybeans	Wheat
	(1)	(2)	(3)	(4)	(5)
Climate Variables					
Average temperature over the last 3 years (°F)	268.2***	-91.21***	293.9***	71.43*	96.27***
	(33.98)	(14.49)	(49.53)	(27.97)	(26.82)
Average temperature over the last 3 years (°F) squared	-2.502***	0.864***	-2.478***	-0.524*	-0.868***
	(0.315)	(0.134)	(0.458)	(0.259)	(0.249)
Total precipitation over the last 3 years (in)	0.401	1.968***	-0.884	2.353***	-0.331
	(0.382)	(0.186)	(0.566)	(0.402)	(0.297)
Total precipitation over the last 3 years (in) squared	-0.00258	-0.0133***	0.000651	-0.0134***	0.00101
	(0.00310)	(0.00148)	(0.00451)	(0.00314)	(0.00239)
Fraction of days in Jan-Apr with max temp >86°F	24.21	-3.398	-503.5*	310.9*	298.3*
	(147.4)	(69.87)	(227.2)	(146.8)	(118.4)
Fraction of days in Jan-Apr with max temp >86°F squared	-595.1	-5,201**	-3,592	-158.5	-8,520**
	(3,540)	(1,682)	(5,385)	(3,439)	(2,867)
Total precipitation in Jan-Apr (in)	0.482	17.57***	-36.66***	-4.702	-3.815
	(5.703)	(2.544)	(8.158)	(4.939)	(4.591)
Total precipitation in Jan-Apr (in) squared	-2.615	-7.146***	5.818	4.674*	-4.168*
	(2.417)	(1.036)	(3.270)	(1.880)	(1.985)
Average humidity (%)	3.243***	0.170	4.001***	-3.020***	0.0237
	(0.311)	(0.149)	(0.457)	(0.302)	(0.256)
Average humidity in Jan-Apr (%)	-0.492**	-0.273***	-1.716***	1.046***	-0.00127
	(0.151)	(0.0718)	(0.230)	(0.152)	(0.120)
Controls					
Alfalfa price ($/ton)	0.710***	0.146**	0.00964	-0.755***	-0.115
	(0.0935)	(0.0460)	(0.141)	(0.0940)	(0.0767)

Corn price (cents/bsh)	-0.181***	0.138***	-0.580***	-0.225***	-0.0429
	(0.0471)	(0.0222)	(0.0672)	(0.0440)	(0.0384)
Sorghum price ($/cwt)	2.749	-7.497***	28.36***	5.450*	3.882*
	(2.083)	(1.040)	(3.134)	(2.123)	(1.751)
Soybeans price (cents/bsh)	-0.0717***	0.0427***	-0.0423*	0.0856***	0.0445***
	(0.0131)	(0.00631)	(0.0191)	(0.0127)	(0.0105)
Wheat price (cents/bsh)	0.0471**	-0.0626***	0.0974***	0.103***	-0.0527***
	(0.0166)	(0.00784)	(0.0239)	(0.0155)	(0.0133)
Alfalfa was planted in previous year (dummy)	268.1***	-56.80***	-7.367**	-41.01***	-8.196***
	(1.433)	(0.975)	(2.661)	(2.345)	(1.424)
Corn was planted in previous year (dummy)	-36.37***	125.4***	-7.283***	101.8***	15.79***
	(1.096)	(0.528)	(1.495)	(1.173)	(0.793)
Sorghum was planted in previous year (dummy)	-20.05***	-3.355**	220.9***	63.68***	29.10***
	(2.256)	(1.020)	(2.287)	(1.877)	(1.349)
Soybeans was planted in previous year (dummy)	-22.94***	65.50***	45.97***	113.3***	27.93***
	(1.855)	(0.705)	(2.028)	(1.274)	(1.157)
Wheat was planted in previous year (dummy)	3.227*	-9.266***	66.99***	4.892***	183.6***
	(1.333)	(0.612)	(1.685)	(1.326)	(0.959)
Center pivot sprinkler (dummy)	7.886***	21.62***	-26.26***	17.55***	6.980***
	(1.200)	(0.597)	(1.788)	(1.240)	(0.975)
Center pivot with drop nozzles (dummy)	7.430***	28.31***	-25.70***	9.807***	9.034***
	(1.766)	(0.815)	(2.445)	(1.668)	(1.321)
Average evapotranspiration (in)	2.102**	2.274***	2.921*	5.966***	-3.106***
	(0.806)	(0.369)	(1.167)	(0.704)	(0.637)
Recharge (in)	-2.169**	-5.540***	-2.044*	13.67***	-9.135***
	(0.814)	(0.320)	(0.945)	(0.522)	(0.631)
Slope (% of distance)	7.734***	-1.736***	6.868***	-7.561***	-0.102
	(0.512)	(0.282)	(0.846)	(0.618)	(0.463)
Dummy for irrigated capability class=1	-18.43***	-12.84***	12.39***	-4.965***	2.179*
	(1.616)	(0.652)	(1.884)	(1.431)	(0.999)

Field size (ac)	0.0662***	0.142***	0.125***	0.00965	0.215***
	(0.00525)	(0.00259)	(0.00732)	(0.00627)	(0.00373)
Depth to groundwater (ft)	-0.0649***	0.0732***	0.0786***	-0.334***	0.0376***
	(0.00968)	(0.00493)	(0.0150)	(0.0120)	(0.00759)
Natural gas price ($/mcf)	-2.916***	-3.727***	4.059***	8.432***	0.472
	(0.798)	(0.385)	(1.221)	(0.757)	(0.658)
Diesel price ($/gal)	-9.649*	7.989***	-30.01***	-37.84***	2.826
	(4.473)	(2.153)	(6.888)	(4.282)	(3.692)
Electricity price (cents/kwh)	7.450***	-14.70***	35.47***	35.41***	-8.334***
	(2.191)	(1.054)	(3.365)	(2.211)	(1.769)
Saturated thickness (ft)	0.0242***	0.111***	-0.0754***	-0.0152**	-0.00586
	(0.00486)	(0.00261)	(0.00789)	(0.00543)	(0.00426)
Soil moisture (kg/m^2)	-3.350***	0.0943	2.242***	0.943***	-0.0778
	(0.128)	(0.0703)	(0.229)	(0.148)	(0.118)
Constant	-7,627***	2,197***	-9,435***	-3,101***	-2,646***
	(929.7)	(397.2)	(1,356)	(768.1)	(733.0)
Sigma	108.0***	102.6***	157.5***	143.7***	119.3***
	(0.552)	(0.213)	(1.183)	(0.663)	(0.472)
Observations	261,595	261,590	261,595	261,595	261,590

Notes: Standard errors are in parentheses. Significance codes: * p<0.05, ** p<0.01, *** p<0.001.

Table 3: Multiple crop probit regression, Climate specification Y5

Dependent variable is probability of planting multiple crops	
Climate variables	
Average temperature over the last 3 years (°F)	0.345***
	(0.0564)
Average temperature over the last 3 years (°F) squared	-0.00321***
	(0.000524)
Total precipitation over the last 3 years (in)	-0.0104***
	(0.000680)
Total precipitation over the last 3 years (in) squared	7.44e-05***
	(5.47e-06)
Fraction of days in Jan-Apr with max temp >86°F	0.431
	(0.263)
Fraction of days in Jan-Apr with max temp >86°F squared	4.576
	(6.156)
Total precipitation in Jan-Apr (in)	-0.0694***
	(0.00970)
Total precipitation in Jan-Apr (in) squared	0.0251***
	(0.00392)
Average humidity (%)	-0.00264***
	(0.000513)
Average humidity in Jan-Apr (%)	0.000502*
	(0.000234)
Controls	
Alfalfa price ($/ton)	-0.000908***
	(0.000164)
Corn price (cents/bsh)	-5.07e-05
	(7.56e-05)
Sorghum price ($/cwt)	0.0127***
	(0.00274)
Soybeans price (cents/bsh)	1.89e-05
	(2.03e-05)
Wheat price (cents/bsh)	-7.43e-05*
	(2.97e-05)
Center pivot sprinkler (dummy)	-0.126***
	(0.00219)
Center pivot with drop nozzles (dummy)	-0.141***
	(0.00301)
Average evapotranspiration (in)	-0.0110***
	(0.00136)
Recharge (in)	-0.00293*
	(0.00116)
Slope (% of distance)	-0.0344***
	(0.00105)
Dummy for irrigated capability class=1	0.0803***
	(0.00239)
Field size (ac)	0.00154***
	(9.34e-06)

Depth to groundwater (ft)	-7.86e-05***
	(1.85e-05)
Natural gas price ($/mcf)	0.00780***
	(0.00143)
Diesel price ($/gal)	0.0228**
	(0.00785)
Electricity price (cents/kwh)	0.00810*
	(0.00399)
Saturated thickness (ft)	-0.000350***
	(9.53e-06)
Soil moisture (kg/m^2)	0.0103***
	(0.000260)
Observations	281,148

Notes: Standard errors are in parentheses. Significance codes: * p<0.05, ** p<0.01, *** p<0.001.

Table 4a: Center pivot sprinkler use probit regression, Climate specification Y5

Dependent variable is probability of center pivot sprinkler use	
Climate variables	
Average temperature over the last 3 years (°F)	0.260***
	(0.0531)
Average temperature over the last 3 years (°F) squared	-0.00227***
	(0.000491)
Total precipitation over the last 3 years (in)	-0.0225***
	(0.000625)
Total precipitation over the last 3 years (in) squared	0.000106***
	(5.11e-06)
Fraction of days in Jan-Apr with max temp >86°F	-1.090***
	(0.229)
Fraction of days in Jan-Apr with max temp >86°F squared	8.550
	(5.400)
Total precipitation in Jan-Apr (in)	0.0916***
	(0.00903)
Total precipitation in Jan-Apr (in) squared	0.00679
	(0.00346)
Average humidity (%)	-0.00443***
	(0.000464)
Average humidity in Jan-Apr (%)	0.00993***
	(0.000211)
Controls	
Acres planted to alfafa	0.000324***
	(2.11e-05)
Acres planted to corn	0.000427***
	(1.13e-05)
Acres planted to sorghum	-0.000224***
	(3.37e-05)
Acres planted to soy	0.000524***
	(2.33e-05)
Acres planted to wheat	0.000165***
	(1.87e-05)
Alfalfa price ($/ton)	0.00429***
	(0.000145)
Corn price (cents/bsh)	-0.00419***
	(6.64e-05)
Sorghum price ($/cwt)	0.0170***
	(0.00244)
Soybeans price (cents/bsh)	0.000810***
	(1.79e-05)
Wheat price (cents/bsh)	0.000529***
	(2.69e-05)
Average evapotranspiration (in)	-0.00416**
	(0.00128)
Recharge (in)	-0.00431***

	(0.00110)
Slope (% of distance)	0.0110***
	(0.000940)
Dummy for irrigated capability class=1	-0.0518***
	(0.00225)
Field size (ac)	-0.000193***
	(9.37e-06)
Depth to groundwater (ft)	-0.000316***
	(1.70e-05)
Natural gas price ($/mcf)	-0.0159***
	(0.00130)
Diesel price ($/gal)	-0.111***
	(0.00718)
Electricity price (cents/kwh)	-0.0575***
	(0.00369)
Saturated thickness (ft)	-6.33e-05***
	(8.52e-06)
Soil moisture (kg/m^2)	-0.00535***
	(0.000233)
Observations	281,143

Notes: Standard errors are in parentheses. Significance codes: * p<0.05, ** p<0.01, *** p<0.001.

Table 4b: Center pivot sprinkler with drop nozzles use probit regression, Climate specification Y5

Dependent variable is probability of center pivot sprinkler with drop nozzle use	
Climate variables	
Average temperature over the last 3 years (°F)	-0.205***
	(0.0452)
Average temperature over the last 3 years (°F) squared	0.00180***
	(0.000420)
Total precipitation over the last 3 years (in)	0.0106***
	(0.000724)
Total precipitation over the last 3 years (in) squared	-8.24e-05***
	(5.51e-06)
Fraction of days in Jan-Apr with max temp >86°F	-1.725***
	(0.313)
Fraction of days in Jan-Apr with max temp >86°F squared	14.92**
	(5.026)
Total precipitation in Jan-Apr (in)	-0.0159
	(0.0150)
Total precipitation in Jan-Apr (in) squared	-0.00424
	(0.00702)
Average humidity (%)	-0.00497***
	(0.000474)
Average humidity in Jan-Apr (%)	0.000292
	(0.000403)
Controls	
Acres planted to alfafa	0.000114***
	(1.59e-05)
Acres planted to corn	0.000270***
	(7.86e-06)
Acres planted to sorghum	-0.000159***
	(2.39e-05)
Acres planted to soy	0.000252***
	(1.63e-05)
Acres planted to wheat	2.05e-05
	(1.30e-05)
Alfalfa price ($/ton)	0.0807***
	(0.00669)
Corn price (cents/bsh)	0.0282***
	(0.00337)
Sorghum price ($/cwt)	-2.089***
	(0.00580)
Soybeans price (cents/bsh)	-0.00110
	(0.00283)
Wheat price (cents/bsh)	0.000686
	(0.00136)
Average evapotranspiration (in)	-0.00548***
	(0.000829)
Recharge (in)	-0.00326***

	(0.000761)
Slope (% of distance)	0.00123
	(0.000655)
Dummy for irrigated capability class=1	-0.0214***
	(0.00151)
Field size (ac)	-9.73e-05***
	(5.97e-06)
Depth to groundwater (ft)	0.000119***
	(1.18e-05)
Natural gas price ($/mcf)	0.140
	(0.131)
Diesel price ($/gal)	-0.668*
	(0.286)
Electricity price (cents/kwh)	0.116
	(0.471)
Saturated thickness (ft)	-2.30e-06
	(7.48e-06)
Soil moisture (kg/m^2)	-0.00558***
	(0.000173)
Observations	281,143

Notes: Standard errors are in parentheses. Significance codes: * p<0.05, ** p<0.01, *** p<0.001.

Table 5: Water use regression, Climate specification Y5

	Dependent variable is water use (acre-feet)
Climate variables	
Average temperature over the last 3 years (°F)	183.4***
	(10.72)
Average temperature over the last 3 years (°F) squared	-1.574***
	(0.0993)
Total precipitation over the last 3 years (in)	-0.955***
	(0.124)
Total precipitation over the last 3 years (in) squared	0.00898***
	(0.00100)
Fraction of days in Jan-Apr with max temp >86°F	1,238***
	(45.24)
Fraction of days in Jan-Apr with max temp >86°F squared	-20,647***
	(993.2)
Total precipitation in Jan-Apr (in)	-58.30***
	(1.784)
Total precipitation in Jan-Apr (in) squared	20.34***
	(0.735)
Average humidity (%)	0.796***
	(0.0714)
Average humidity in Jan-Apr (%)	0.335***
	(0.0327)
Controls	
Acres planted to alfafa	0.528***
	(0.00867)
Acres planted to alfafa squared	-0.000342***
	(3.98e-05)
Acres planted to corn	0.398***
	(0.00464)
Acres planted to corn squared	0.000166***
	(1.73e-05)
Acres planted to sorghum	-0.0830***
	(0.0144)
Acres planted to sorghum squared	0.000276***
	(7.91e-05)
Acres planted to soy	0.328***
	(0.0115)
Acres planted to soy squared	-5.70e-05
	(7.43e-05)
Acres planted to wheat	-0.0852***
	(0.00807)
Acres planted to wheat squared	0.000342***
	(4.11e-05)
Center pivot sprinkler (dummy)	-0.801
	(0.438)
Center pivot with drop nozzles (dummy)	1.918***

	(0.579)
Average evapotranspiration (in)	-0.216
	(0.268)
Recharge (in)	-3.157***
	(0.230)
Slope (% of distance)	-1.038***
	(0.205)
Dummy for irrigated capability class=1	-10.75***
	(0.480)
Field size (ac)	0.423***
	(0.00207)
Depth to groundwater (ft)	0.345***
	(0.00354)
Natural gas price ($/mcf)	-5.279***
	(0.172)
Diesel price ($/gal)	9.278***
	(0.723)
Electricity price (cents/kwh)	2.515***
	(0.609)
Saturated thickness (ft)	0.148***
	(0.00189)
Soil moisture (kg/m^2)	-3.279***
	(0.0510)
Constant	-5,234***
	(293.1)
Observations	281,143
R-squared	0.492

Notes: Standard errors are in parentheses. Significance codes: * p<0.05, ** p<0.01, *** p<0.001.