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

Ernst Bertone Oehninger,

C.-Y. Cynthia Lin Lawell, James N. Sanchirico, and Michael R. Springborn

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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 et al. (2016a,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 et al. (2016a) 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 et al. (2016b) that such changes in behavior can affect the diversity of crops planted.

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[1] Bertone Oehninger: University of California at Davis, ebertone@ucdavis.edu. Lin Lawell: University of California at Davis, cclin@primal.ucdavis.edu. Sanchirico: University of California at Davis, jsanchirico@ucdavis.edu. Springborn: University of California at Davis, mspringborn@ucdavis.edu.

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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 Worldwide, about 70 percent of groundwater withdrawn is used in agriculture, and in some countries, the percent of groundwater extracted for irrigation can be as high as 90 percent (National Groundwater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 et al. (2016a,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 et al. (2016a,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 et al. (2016a) 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 et al. (2016b) 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 et al. (2016a,b). Section 4 concludes.

2. Literature Review

2.1. Effects of climate change on agriculture

The literature analyzing the effects of climate change on agriculture includes a strand which examines the effects of climate change on farmland values and/or agricultural profits. Schlenker, Hanemann and Fisher (2006) link farmland values to climatic, soil, and socioeconomic variables for U.S. counties east of the 100th meridian, the historical boundary for agriculture not primarily dependent on irrigation. Their estimated coefficients are consistent with the experimental results. They use their model to estimate the potential impacts on farmland values for a range of recent warming scenarios. The predictions are very robust: more than 75% of the counties in their sample show a statistically significant effect, ranging from moderate gains to large losses, with losses in the aggregate that can become quite large under scenarios involving sustained heavy use of fossil fuels (Schlenker, Hanemann and Fisher, 2006).

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. Their preferred estimates indicate that climate change will increase annual profits by $1.3 billion in 2002 dollars, or 4 percent. This estimate is robust to numerous specification checks and is relatively precise, suggesting that large negative or positive effects are unlikely. The authors also find that the hedonic approach—which is the standard in the previous literature—is unreliable because it produces estimates that are extremely sensitive to seemingly minor choices about control variables, sample, and weighting (Deschênes and Greenstone, 2007).

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), and show how some of the other critiques may have little basis.

Projecting the impacts of climate change on agriculture requires knowing or assuming how farmers will adapt. However, empirical estimates of the effectiveness of this private adaptation are scarce and the sensitivity of impact assessments to adaptation assumptions is not well understood. 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. The difference between the impacts of climate change projected using the short-run (limited adaptation) and long-run (substantial adaptation) response curves can be interpreted as the private adaptation potential. 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. Decomposing the variance in 2040 projected yields and farm profits using an ensemble of 13 climate model runs, they find that the rate at which farmers will adapt to rising temperatures is an important source of uncertainty (Moore and Lobell, 2014).

Ricardian (hedonic) analyses of the impact of climate change on farmland values typically assume additively separable effects of temperature and precipitation with model estimation being implemented on data aggregated across counties or large regions. Fezzi and Bateman (2015) use a large panel of farm-level data to investigate the potential bias induced by such approaches. Consistent with the literature on plant physiology, the authors observe significant nonlinear interaction effects, with more abundant precipitation acting as a mitigating factor for increased heat stress. This interaction disappears when the same data are aggregated in the conventional manner, leading to predictions of climate change impacts that are significantly distorted (Fezzi and Bateman, 2015).

Donaldson and Smith (2016) quantify the macro-level consequences of climate change. Using an extremely rich micro-level data set that contains information about the productivity—both before and after climate change—of each of 10 crops for each of 1.7 million fields covering the surface of the earth, the authors find that the impact of climate change on these agricultural markets would amount to a 0.26 percent reduction in global GDP when trade and production patterns are allowed to adjust. Since the value of output in their 10 crops is equal to 1.8 percent of world GDP, this corresponds to about one-sixth of total crop value (Costinot, Donaldson and Smith, 2016).

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. 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. They 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. The slope of the decline above the optimum is significantly steeper than the incline below it. The same nonlinear and asymmetric relationship is found when the authors isolate either time-series or cross-sectional variations in temperatures and yields. Holding current growing regions fixed, area-weighted average yields are predicted to decrease by 30-46% before the end of the century under the slowest (B1) warming scenario and decrease by 63-82% under the most rapid warming scenario (A1FI) under the Hadley III model (Schlenker and Roberts, 2009).

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. Models that omit soil moisture overestimate the detrimental effects of temperature. Thus, climate change impacts on agriculture are likely to be driven by both heat and drought stresses, and that their relative role can vary depending on the climate change scenario and farmer ability to adapt (Ortiz-Bobea, 2015b).

According to Roberts, Schlenker and Eyer (2013), research from two alternative schools of thought find different projected impacts from climate change. On the one hand, crop models that are based on plant physiology and developed and refined from field experiments over many decades usually predict modestly negative to positive 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).

Recent reduced-form econometric models of climate change impacts on agriculture assume that climate is additive, and therefore that weather variables included as regressors can be aggregated over several months that include the growing season Ortiz-Bobea (2015a). Ortiz-Bobea (2015a) develops a simple model to show how this assumption imposes implausible characteristics on the production technology that are in serious conflict with the agricultural sciences. He tests this assumption using a crop yield model of U.S. corn that accounts for variation in weather at various times of the growing season. Results strongly reject temporal additivity and suggests that weather shocks such as extreme temperatures are particularly detrimental toward the middle of the season around flowering time, in agreement with the scientific literature on crop development and phenology. The additivity assumption tends to underestimate the range of adaptation possibilities available to farmers, thus overstating projected climate change impacts on the sector (Ortiz-Bobea, 2015a).

Lee and Sumner (2015) establish quantitative relationships between the evolution of climate and cropland using daily climate data for a century and data on allocation of land across crops for six decades in a specific agro-climatic region of California. The authors use these relationships to project how climate scenarios reported by the Intergovernmental Panel on Climate Change would drive cropland patterns into 2050. Results show that projections of warmer winters, particularly from 2035 to 2050, cause lower wheat area and more alfalfa and tomato area. Only marginal changes in area are projected for tree and vine crops, in part because although they are lower, chill hours remain above critical values (Lee and Sumner, 2015).

Miao, Khanna and Huang (2016) investigate the effect of crop price and climate variables on rainfed corn and soybean yields and acreage in the United States using a large panel dataset for the 1977–2007 period. Instrumental variables are used to control for endogeneity of prices in yield and acreage regressions, while allowing for spatially auto-correlated errors. The authors find that an increase in corn price has a statistically significant positive impact on corn yield, but the effect of soybean price on soybean yields is not statistically significant. The estimated price elasticities of corn yield and acreage are 0.23 and 0.45, respectively. Of the increase in corn supply caused by an increase in corn price, they find that 33.8% is due to price-induced yield enhancement and 66.2% is due to price-induced acreage expansion. They also find that the impact of climate change on corn production ranges from -7% to -41% and on soybean ranges from -8% to -45%, depending on the climate change scenarios, time horizon, and global climate models used to predict climate change. The authors show that the aggregate net impact of omitting price variables is an overestimation of the effect of climate change on corn yield by up to 9% and on soybean yield by up to 15% (Miao, Khanna and Huang, 2016).

Climate change shifts the distributions of a set of climatic variables, including temperature, precipitation, humidity, wind speed, sunshine duration, and evaporation. Zhang, Zhang and Chen (forthcoming) explore the importance of those additional climatic variables other than temperature and precipitation. Using county-level agricultural data from 1980 to 2010 in China, the authors find that those additional climatic variables, especially humidity and wind speed, are critical for crop growth. Therefore, omitting those variables is likely to bias the predicted impacts of climate change on crop yields. In particular, omitting humidity tends to overpredict the cost of climate change on crop yields, while ignoring wind speed is likely to underpredict the effect. Their preferred specification indicates that climate change is likely to decrease the yields of rice, wheat, and corn in China by 36.25%, 18.26%, and 45.10%, respectively, by the end of this century (Zhang, Zhang and Chen, forthcoming).

Scientists estimate that U.S. Corn Belt crop yields will increase or decrease, on average, and become more variable with climate change. Corn and soybean farming dominates this region, but studies typically do not assess the joint impact of new distributions of corn and soybean yields on markets. Thompson et al. (forthcoming) use a structural economic model with projections of climate-driven yield changes to simulate these effects. 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 (Thompson et al., forthcoming).

Understanding the potential impacts of climate change on economic outcomes requires knowing how agents might adapt to a changing climate. 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. Longer run adaptations appear to have mitigated less than half--and more likely none--of the large negative short-run impacts of extreme heat on productivity. Limited recent adaptation implies substantial losses under future climate change in the absence of countervailing investments (Burke and Emerick, 2016).

Climate models predict more weather extremes in the coming decades. Weather shocks can directly reduce crop production, but their effect on food markets is partly buffered by storage and supply responses that can be complex and nuanced. 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. Their estimates of this effect in the case of wheat and soybeans suggest that it may be considerable: 25–50% of crop production lost to a shock in the Southern Hemisphere is offset six months later by increased production in the North. These results have implications for the potential effects of climate change on global food markets, for how we model these interactions and, possibly, for the design of trade and production-related policies that aim to leverage this inter-hemispheric buffer more effectively (Lybbert, Smith and Sumner, 2014).

Olen, Wu, and Langpap (2016) use the 2007 Farm and Ranch Irrigation Survey database developed by the U.S. Department of Agriculture to assess the impact of water scarcity and climate on irrigation decisions for producers of specialty crops, wheat, and forage crops. They estimate an irrigation management model for major crops in the West Coast (California, Oregon and Washington), which includes a farm-level equation of irrigated share and crop-specific equations of technology adoption and water application rate (orchard/vineyard, vegetable, wheat, alfalfa, hay, and pasture). They find that economic and physical water scarcity, climate, and extreme weather, 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. Water application rates are least responsive to surface water cost or groundwater well depth for producers of orchard/vineyard. Water supply institutions influence producers' irrigation decisions. Producers who receive water from federal agencies use higher water application rates and are less likely to adopt water-saving irrigation technologies for some crops. Institutional arrangements, including access to distinct water sources (surface or ground) and whether surface water cost is fee based, also affect the responsiveness of water application rates to changes in surface water cost (Olen, Wu and Langpap, 2016).

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).

2.2. Agricultural groundwater

We also review the relevant economics literature on agricultural groundwater. 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 historic reported water-use, weather data, 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 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).

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, 2016b; Lin and Pfeiffer, 2015; Pfeiffer and Lin, 2009; Pfeiffer and Lin, 2010; Pfeiffer and Lin, 2014a; Pfeiffer and Lin, 2014b; Sears et al., 2016).

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, 2016b; Sears et al., 2016).

Lin Lawell (2016a) 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, 2016a; Lin Lawell, 2016b).

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.

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., 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).

3. A Review of Our Research

Our research in Bertone Oehninger et al. (2016a,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 et al. (2016a,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 weather 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. In Bertone Oehninger et al. (2016a,b), we evaluate the effects of temperature, precipitation, and humidity on the behavior of farmers in that same region, over a longer period of time (17 years, from 1996 to 2012).

To construct a detailed panel data set of annual data for over 20,000 groundwater-irrigated fields in western Kansas from 1996 to 2012, we use data related to water rights, water use, and crop choice 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.

Weather 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 et al. (2016a,b), we consider several specifications of the climate-related variables. These climate specifications are summarized in Table 1.

In specification Y1, the climate variables are: annual average temperature, annual average temperature squared, total precipitation, total precipitation squared, and annual average humidity.

In specification Y2, the climate variables are: average temperature over the last 3 years squared, average temperature over the last 3 years squared, total precipitation over the last 3 years, total precipitation over the last 3 years squared, and annual average humidity.

In specification Y3, the climate variables are: annual fraction of days with maximum temperature greater than 86 degrees Fahrenheit (°F),[2] annual fraction of days with maximum temperature greater than 86°F squared, summer fraction of days with maximum temperature greater than 86°F, summer fraction of days with maximum temperature greater than 86°F squared, annual precipitation, annual precipitation squared, and annual average humidity.

In specification Y4, the climate variables are: average temperature over the last 3 years, average temperature over the last 3 years squared, total precipitation over the last 3 years, total precipitation over the last 3 years squared, annual average humidity, average temperature over the first 4 months of the year (before the crop decision), average temperature over the first 4 months of the year (before the crop decision) squared, average precipitation over the first 4 months of the year (before the crop decision), average precipitation over the first 4 months of

[2] 86 degrees Fahrenheit is equivalent to 30 degrees Celsius.

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

In specification Y5, the climate variables are: average temperature over the last 3 years, average temperature over the last 3 years squared, total precipitation over the last 3 years, total precipitation over the last 3 years squared, annual average humidity, fraction of days with maximum temperature greater than 86°F over the first 4 months of the year (before the crop decision), fraction of days with maximum temperature greater than 86°F over the first 4 months of the year (before the crop decision) squared, average precipitation over the first 4 months of the year (before the crop decision), average precipitation over the first 4 months of the year (before the crop decision) squared, and average humidity over the first 4 months of the year (before the crop decision).

In specification M1, the climate variables are: average monthly average temperature over last 3 years for each month of the year, average monthly average temperature over last 3 years for each month of the year squared, average monthly precipitation over last 3 years for each month of the year, average monthly precipitation over last 3 years for each month of the year squared, and average monthly humidity over last 3 years for each month of the year.

In specification M2, the climate variables are: average fraction of days (out of the days in that month with data) that have maximum temperature greater than 86°F over the last 3 years for each month of the year, average fraction of days (out of the days in that month with data) that have maximum temperature greater than 86°F over the last 3 years for each month of the year squared, average monthly precipitation over last 3 years for each month of the year, average monthly precipitation over last 3 years for each month of the year squared, and average monthly humidity over last 3 years for each month of the year .

Our econometric model of a farmer's irrigation water pumping decision in Bertone Oehninger et al. (2016a) 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.

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 et al. (2016a). According to our results in Bertone Oehninger et al. (2016a), 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 et al. (2016a,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 et al. (2016a,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 et al. (2016a) 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 et al. (2016b) that such changes in behavior can affect the diversity of crops planted.

Our research in in Bertone Oehninger et al. (2016a,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

		Y1	Y2	Y3	Y4	Y5	M1	M2
Annual	Average Temperature (°F)	✓						
	Total Precipitation (in)	✓		✓				
	Average Humidity (%)	✓	✓	✓	✓	✓		
	Maximum Temperature (°F)							
	Fraction of Days with Max Temp > 86°F			✓				
	Fraction of Days in Summer with Max Temp >86°F			✓				
	Average Temperature in Jan-Apr (°F)				✓			
	Total Precipitation in Jan-Apr (in)				✓	✓		
	Average Humidity in Jan-Apr (%)				✓	✓		
	Fraction of Days in Jan-Apr with Max Temp > 86°F					✓		
3-Year Average	Average Temperature (°F)		✓		✓	✓		
	Total Precipitation (in)		✓		✓	✓		
	Monthly Temperature (°F)						✓	
	Monthly Precipitation (in)						✓	✓
	Monthly Humidity (%)						✓	✓
	Monthly Fraction of Days with Max Temp > 86°F							✓

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.