The Effects of Climate Change on Agricultural Groundwater Extraction[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 analyze the effects of changes in temperature, precipitation, and humidity 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 research focuses on the groundwater used for agriculture in the High Plains (Ogallala) Aquifer system of the Midwestern United States. Our results 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 also evaluate the effects of climate-related variables by month rather than only at an annual level.

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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, 2016). Worldwide, about 70 percent of groundwater withdrawn is used in agriculture, and in some countries, the percent of groundwater extracted for irrigation can be as high as 90 percent (National Groundwater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 exclusively 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, 2016).

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 analyze the effects of changes in temperature, precipitation, and humidity on groundwater extraction for agriculture using an econometric model of a farmer's irrigation water pumping decision that accounts for both the intensive and extensive margins.

Our research 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).

For our empirical analysis, we use a unique data set that combines well-level groundwater extraction data with physical, hydrological, and economic data. Our econometric model of a farmer's irrigation water pumping decision 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, soil moisture, crop prices, and energy prices.

Our results 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 also evaluate the effects of climate-related variables by month rather than only at an annual level.

The balance of our paper proceeds as follows. We review the previous literature in Section 2. We provide background information on the High Plains Aquifer in Kansas in Section 3. We describe our data in Section 4, our methods in Section 5, and our results in Section 6. Section 7 concludes.

2. Literature Review

2.1. Effects of climate change on agriculture

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) 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. They use their model to 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 (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. 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).

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).

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.

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. Results reveal a nonlinear and asymmetric relationship: the slope of the decline above the optimum is significantly steeper than the incline below it (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 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. 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 are projected for tree area and vine crop area (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 over the period 1977–2007. They use instrumental variables to address the endogeneity of prices in yield and acreage regressions, while allowing for spatially auto-correlated errors. They 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 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 (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 these additional climatic variables other than temperature and precipitation. Using county-level agricultural data from 1980 to 2010 in China, the authors find that these additional climatic variables, especially humidity and wind speed, are critical for crop growth. 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).

Thompson et al. (forthcoming) 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. 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).

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).

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).

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).

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 build upon the previous 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).

Hendricks and Peterson (2012) estimate irrigation water demand using field-level panel data from Kansas over 16 years. The cost of pumping varies over time due to changes in energy prices, and across space due to differences in the depth to water. The authors exploit this variation to estimate the demand elasticity while controlling for field-farmer and year fixed effects.

Mieno and Brozovic (forthcoming) find evidence of substantial measurement errors in irrigation costs resulting in attenuation and amplification bias in the price elasticity of irrigation water consumption on the intensive margin. Their results indicate that measurement errors in irrigation costs can lead to misleading policy implications related to water and energy pricing as a tool to conserve water.

Dermyer (2011) develops a water budget model to predict irrigation withdrawals from the High Plains Aquifer based on crop-specific evapotranspiration, and the model is validated based on historic reported water-use, weather data, and land-use. In some counties, the change in water surface elevation is 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, 2016; 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, 2016; Sears et al., 2016).

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 Low Energy 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.

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. 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. They also find that changes in the distribution of rainfall that 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).

Mukherjee and Schwabe (2015) evaluate the benefits to irrigated agriculture from having access to multiple sources of water (i.e., a water portfolio). They find 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. Having access to multiple sources of water may therefore be 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. The High Plains Aquifer in Kansas

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).

To examine the crop season divisions for each of the main crops grown in Kansas (alfalfa, corn, sorghum, soybean, and wheat), we apply a method developed by Ortiz-Bobea (2013) to examine season divisions for Illinois corn. In particular, we use data from the Crop Progress and Condition weekly survey by the U.S. Department of Agriculture (USDA) National Agricultural Statistics Service (NASS), which provides state-level data on farmer activities and crop phenological stages from early April to late November, to construct season divisions for each of the main Kansas crops. Figure 1 plots the crop season divisions for 2016 for Kansas alfalfa, corn, sorghum, soybean, and wheat, respectively.

The High Plains Aquifer is extremely important 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 agricultural groundwater use in the High Plains Aquifer is therefore important for sustainable agricultural groundwater management.

4. Data

For our empirical analysis, 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, 2016; Lin Lawell, 2017), which spanned 10 years between 1996 and 2005, and have extended the data set to cover the years 1996 to 2012. 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. Figure 2 presents the location of all the points of diversion we use in our data set.

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). Figures 3a and 3b present the soil moisture content in the 0-10 cm layer for the state of Kansas in 1996 and 2012, respectively.

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.

Summary statistics for the choice variables, control variables, annual climate variables, and monthly climate variables are presented in Tables 1a, 1b, 1c, and 1d, respectively.

5. Methods

5.1. Climate variable specifications

We consider several specifications of the climate-related variables T_{it} faced by each farmer *i* in each time period *t*. These climate specifications are summarized in Table 2.

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

In specification Y2, the climate variables T_{it} 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 T_{it} 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 T_{it} 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

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

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 Y5, the climate variables T_{it} 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).

For the specifications using monthly climate variables, 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 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 T_{it} 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 .

5.2. Econometric model

Our econometric model of a farmer's irrigation water pumping decision has two components: the extensive margins and the intensive margin.

One extensive margin of the groundwater extraction decision is the crop acreage allocation decision. Since the dependent variables (the number of acres planted to each crop) are censored by sample selection, we estimate the acreage n_{ict} allocated to each crop *c* by each farmer *i* in each time period *t* using the following tobit regression:

$$n_{ict} = g(T_{it}, \{p_{\tilde{c}t}\}_{\tilde{c}}, x_{it}, e_t, z_{it-1}),\ c = \textit{alfalfa, corn, sorghum, soybeans, wheat}, \qquad (1)$$

where n_{ict} is the number of acres planted to each crop *c*; T_{it} are climate-related variables, including temperature, precipitation, and humidity; $p_{\tilde{c}t}$ are crop price futures (for delivery at harvest) for crop $\tilde{c}$ and $\{p_{\tilde{c}t}\}_{\tilde{c}}$ is the set of crop price futures for all crops; x_{it} is a vector of plot-level variables including irrigation technology, average evapotranspiration, recharge, slope, soil quality, quantity of water authorized for extraction, field size,[3] depth to groundwater, saturated thickness,; e_t are energy prices; and z_{it-1} is a vector of lagged dummy variables indicating if various crops were planted in the previous season to account for crop rotation patterns. The coefficients of interest are the coefficients on the climate variables T_{it} in the cropland allocation models in equation (1).

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

[3] All else equal, we expect the acres allocated to the chosen crop to be greater when the field size is greater.

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. 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.

A second intensive margin is the choice of whether to plant multiple crops or one crop only. 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 the following probit regression of the dummy variable I_{it}^{multi} for planting more than one crop on the climate-related variables T_{it} and control variables:

$$\Pr(I_{it}^{multi}=1)=\Phi(T_{it},\{p_{ct}\}_c,x_{it},e_t)\,, \tag{2}$$

where $\Pr(\cdot)$ denotes probability and $\Phi(\cdot)$ denotes the standard normal cumulative distribution function.

In particular, we run a probit regression of the dummy variable I_{it}^{multi} for planting more than one 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, and soil moisture.

A third intensive margin is the choice of irrigation technology. For the irrigation technology extensive margin, we estimate the farmer's choice of irrigation technology using discrete response models. In particular, we run the following probit regression of the dummy variable I_{it}^{sprink} for center pivot sprinkler use on the climate-related variables T_{it}, controlling for acres $\{n_{ict}\}_c$ planted to each crop, crop price futures $\{p_{ct}\}_c$ for each crop, plot-level variables x_{it}, and energy prices e_t:

$$\Pr(I_{it}^{sprink}=1)=\Phi(T_{it},\{n_{ict}\}_c,\{p_{ct}\}_c,x_{it},e_t)\,. \qquad (3)$$

We run a similar probit regression of the dummy variable I_{it}^{nozzle} for center pivot sprinkler with drop nozzles, this time also including the dummy variable I_{it}^{sprink} for center pivot sprinkler use as an additional regressor:

$$\Pr(I_{it}^{nozzle}=1)=\Phi(T_{it},\{n_{ict}\}_c,\{p_{ct}\}_c,x_{it},e_t,I_{it}^{sprink})\,. \qquad (4)$$

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.

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.

The intensive margin of the groundwater extraction decision is the farmer's water demand conditional on his decisions regarding crop acreage allocation, whether to plant multiple crops, and irrigation technology, which is estimated using ordinary least squares (OLS):

$$w_{it} = h(T_{it}, n_{ict}*, x_{it}, e_t)\,, \tag{5}$$

where w_{it} is the amount of water extracted by farmer *i* in year *t*. In the water demand equation (5), we include number of acres planted to each crop and the number of acres planted to each crop squared.[4]

In particular, we run an OLS regression of water use on 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, soil moisture, and the climate variables. 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.

[4] Schoengold, Sunding and Moreno (2006) develop and apply a reduced-form econometric model of a conditional water demand function, explaining water use at a particular location as a function of land allocation, relative prices, and other factors such as environmental characteristics.

The total marginal effect of each of the *j* climate variables T_{jit} in T_{it} accounting for the crop acreage extensive margin and the intensive margin is the sum of the effect along the intensive margin from the water demand equation (5) and the effects along the crop acreage extensive margin from the cropland allocation models in equation (1) (Moore, Gollehon and Carey, 1994):[5]

$$\frac{dw}{dT_j} = \frac{\partial w}{\partial T_j} + \sum_c \frac{\partial w}{\partial n_c *} \frac{\partial n_c *}{\partial T_j}. \tag{6}$$

The total marginal effect of each of the *j* climate variables T_{jit} in T_{it} accounting for the crop acreage extensive margin, the multiple crop extensive margin, and the intensive margin is given by:

$$\begin{aligned} \frac{dw}{dT_j} = & \frac{d\,\Pr(I_{it}^{multi}=1)}{dT_j} E[w \mid I_{it}^{multi}=1] + \Pr(I_{it}^{multi}=1) \frac{dE[w \mid I_{it}^{multi}=1]}{dT_j} \\ & - \frac{d\,\Pr(I_{it}^{multi}=1)}{dT_j} E[w \mid I_{it}^{multi}=0] + \left(1-\Pr(I_{it}^{multi}=1)\right) \frac{dE[w \mid I_{it}^{multi}=0]}{dT_j} \end{aligned}, \tag{7}$$

where $\frac{d\,\Pr(I_{it}^{multi}=1)}{dT_j}$ is the marginal effect from the probit multiple crop regression in equation (2); $E[w \mid I_{it}^{multi}=1]$ is the mean water use in the data set over all observations in which farmers planted multiple crops; $\Pr(I_{it}^{multi}=1)$ is the fraction of observations in which farmers planted multiple crops; $\frac{dE[w \mid I_{it}^{multi}=1]}{dT_j}$ is the total marginal effect calculated in equation (6) conditional on planting multiple crops; $E[w \mid I_{it}^{multi}=0]$ is the mean water use in the data set over

[5] Another possible decision is the decision not to irrigate some acres. Unfortunately, the data does not permit us to analyze this decision. We only observe if the entire field was not irrigated, but we do not observe whether part of the field was not irrigated, nor do we observe the number of acres that were not irrigated.

all observations in which farmers planted only one crop; and $\frac{dE[w \mid I_{it}^{multi}=0]}{dT_j}$ is the total marginal effect calculated in equation (6) conditional on planting only one crop.

The total marginal effect of each of the *j* climate variables T_{jit} in T_{it} accounting for the crop acreage extensive margin, the irrigation technology extensive margin, and the intensive margin is given by:

$$\begin{aligned}\frac{dw}{dT_j} = & \frac{d\,\Pr(I_{it}^{sprink}=1)}{dT_j} E[w \mid I_{it}^{sprink}=1] + \Pr(I_{it}^{sprink}=1)\frac{dE[w \mid I_{it}^{sprink}=1]}{dT_j} \\ & + \frac{d\,\Pr(I_{it}^{nozzle}=1)}{dT_j} E[w \mid I_{it}^{nozzle}=1] + \Pr(I_{it}^{nozzle}=1)\frac{dE[w \mid I_{it}^{nozzle}=1]}{dT_j} \\ & - \left(\frac{d\,\Pr(I_{it}^{sprink}=1)}{dT_j} + \frac{d\,\Pr(I_{it}^{nozzle}=1)}{dT_j}\right) E[w \mid I_{it}^{sprink}=0, I_{it}^{nozzle}=0] \\ & + \left(1-\Pr(I_{it}^{sprink}=1)-\Pr(I_{it}^{nozzle}=1)\right)\frac{dE[w \mid I_{it}^{sprink}=0, I_{it}^{nozzle}=0]}{dT_j}\end{aligned}, \quad (8)$$

where $\frac{d\,\Pr(I_{it}^{sprink}=1)}{dT_j}$ is the marginal effect from the probit center pivot sprinkler use regression in equation (3); $E[w \mid I_{it}^{sprink}=1]$ is the mean water use in the data set over all observations in which farmers used a center pivot sprinkler irrigation system; $\Pr(I_{it}^{sprink}=1)$ is the fraction of observations in which farmers used a center pivot sprinkler irrigation system; $\frac{dE[w \mid I_{it}^{sprink}=1]}{dT_j}$ is the total marginal effect calculated in equation (6) conditional on using a center pivot sprinkler irrigation system; $\frac{d\,\Pr(I_{it}^{nozzle}=1)}{dT_j}$ is the marginal effect from the probit center pivot sprinkler with drop nozzles use regression in equation (4); $E[w \mid I_{it}^{nozzle}=1]$ is the mean water use in the data set over all observations in which farmers used a center pivot sprinkler with drop nozzles irrigation system; $\Pr(I_{it}^{nozzle}=1)$ is the fraction of observations in which farmers used a center pivot sprinkler with drop nozzles irrigation system; $\frac{dE[w \mid I_{it}^{nozzle} = 1]}{dT_j}$ is the total marginal effect calculated in equation (6) conditional on using a center pivot sprinkler with drop nozzles irrigation system; $E[w \mid I_{it}^{sprink} = 0, I_{it}^{nozzle} = 0]$ is the mean water use in the data set over all observations in which farmers did not use either a center pivot sprinkler irrigation system or a center pivot sprinkler with drop nozzles irrigation system; and $\frac{dE[w \mid I_{it}^{sprink} = 0, I_{it}^{nozzle} = 0]}{dT_j}$ is the total marginal effect calculated in equation (6) conditional on not using either a center pivot sprinkler irrigation system or a center pivot sprinkler with drop nozzles irrigation system.

Standard errors for the total marginal effects are calculated using the Delta Method (DeGroot, 1986).

6. Results

Table 3 presents the total crop acreage extensive margin of each of the j climate variables T_{jit} in T_{it}. Table 3a presents the results for the specifications that use annual climate variables (Y1, Y2, Y3, Y4, and Y5). None of the annual temperature or annual precipitation variables in climate specifications Y1, Y2, Y3, and Y4 have a significant total crop acreage extensive margin. In climate specification Y5, the fraction of days in January-April with maximum temperature greater than 86°F can have a significant negative total crop acreage extensive margin on water use. Also in climate specification Y5, precipitation can have a significant negative total crop acreage extensive margin on water use but a significant positive total crop acreage extensive margin on water intensity.

Table 3b presents the results for the total crop acreage extensive margin for climate specification M1. Monthly average temperature does not have a significant total crop acreage extensive margin for any month. Monthly average precipitation in February can have a significant positive total crop acreage extensive margin. Monthly average precipitation in September, November, and December can have a significant total crop acreage extensive margin.

Table 3b presents the results for the total crop acreage extensive margin for climate specification M2. The average fraction of days with maximum temperature exceeding 86°F can have a significant negative total crop acreage extensive margin in January and March; a significant positive total crop acreage extensive margin in October and November; and a significant total crop acreage extensive margin in September. Average monthly precipitation can have a significant positive total crop acreage extensive margin in January, February, and September; a significant negative total crop acreage extensive margin in December; and a significant total crop acreage extensive margin in November.

Table 4 presents the total intensive margin of each of the *j* climate variables T_{jit} in T_{it}. Table 4a presents the results for the specifications that use annual climate variables (Y1, Y2, Y3, Y4, and Y5). In climate specifications Y1, Y2, and Y3, precipitation has a significant negative total intensive margin on water use and water intensity. When separately considering precipitation in January-April and average total precipitation over the last 3 years (climate specifications Y4 and Y5), precipitation in January-April has a significant negative total intensive margin on water use and water intensity, while average total precipitation over the last 3 years may have a significant positive total intensive margin on water intensity. Temperature has a significant positive total intensive margin on water intensity in climate specification Y4, but no significant total intensive margin on water use in any of the annual climate specifications. The fraction of days in January-April with maximum temperature greater than 86°F has a significant positive total intensive margin on both water use and water intensity. The total intensive margin of humidity is mixed.

Table 4b presents the results for the total intensive margin for climate specification M1. Monthly temperature has no significant total intensive margin on water use. The total intensive margins of monthly precipitation on water use are significant and negative in most months, but can be significant and positive in May, June, October, and December. The total intensive margin of humidity on water use is significant and negative in February, May, July, October, and December; and significant and positive in March, April, August, September, and November. Monthly temperature, precipitation, and humidity all have significant positive total intensive margins on water intensity for most months.

Table 4c presents the results for the total intensive margin for climate specification M2. The fraction of days with maximum temperature exceeding 86°F over the past 3 years has a significant negative total intensive margin on water use in February and May; and a significant positive total intensive margin on water use in June, October, and November. The total intensive margins of monthly precipitation can be significant and positive in January, May, September, and October; and can be significant and negative in February, July, August, November, and December. The total intensive margins of monthly humidity are can be significant and positive in March, April, June, July, September, November, and December; and significant and negative in the other months. The fraction of days with maximum temperature exceeding 86°F, precipitation, and humidity all have significant positive total intensive margins on water intensity for most months.

Table 5 presents the total marginal effect given by equation (6) of each of the *j* climate variables T_{jit} in T_{it} accounting for the crop acreage extensive margin and the intensive margin. Table 5a presents the results for the specifications that use annual climate variables (Y1, Y2, Y3, Y4, and Y5). None of the annual temperature or precipitation variables have a significant total marginal effect on water use. The total marginal effect of humidity on water use is mixed. The average temperature over the last 3 years has a significant positive total marginal effect on water intensity. The fraction of days in January-April with maximum temperature greater than 86°F has a significant positive total marginal effect on both water use and water intensity. The total marginal effects of precipitation and humidity on water intensity are mixed.

Table 5b presents the results for the total marginal effect given by equation (6) accounting for the crop acreage extensive margin and the intensive margin for climate specification M1. Monthly temperature has no significant total marginal effect on water use. The total marginal effects of monthly precipitation on water use can be significant and negative in January, September, and November; and can be significant and positive in February. The total marginal effect of humidity on water use is mixed. The total marginal effect of temperature on water intensity is significant and positive in February, August, September, and December. The total marginal effect of precipitation on water intensity can be significant and positive in each month. The total marginal effect of humidity on water intensity is mixed.

Table 5c presents the results for the total marginal effect given by equation (6) accounting for the crop acreage extensive margin and the intensive margin for climate specification M2. The fraction of days with maximum temperature exceeding 86°F over the past 3 years can have a significant negative total marginal effect on water use in April and September; a significant positive total marginal effect on water use in October; and a significant negative total marginal effect in November for farmers planting multiple crops but a significant positive total marginal effect in November for farmers planting one crop only. The total marginal effects of monthly precipitation can be significant and positive in January, February, September, October, and November; and can be significant and negative in December. The total marginal effects of monthly humidity can be significant and positive in March, April, July, November, and December; and can be significant and negative in January, February, May, August, September, and October. The fraction of days with maximum temperature exceeding 86°F can have a significant positive total marginal effect on water intensity in March, April, May, June, July, and September. Precipitation can have a significant positive total marginal effect on water intensity in all months except March and April. Humidity can have a significant positive total marginal effect on water intensity in February, March, May, July, September, October, November, and December; and a significant negative total marginal effect in January and April.

Table 6 presents the total marginal effect given by equation (7) of each of the *j* climate variables T_{jit} in T_{it} accounting for the crop acreage extensive margin, the multiple crop extensive margin, and the intensive margin. Table 6a presents the results for the specifications that use annual climate variables (Y1, Y2, Y3, Y4, and Y5). None of the annual temperature or precipitation variables have a significant total marginal effect on water use. The total marginal effect of humidity on water use can be significant and positive. The average temperature over the last 3 years has a significant positive total marginal effect on water intensity. The fraction of days in January-April with maximum temperature greater than 86°F has a significant positive total marginal effect on water intensity. The total marginal effect of precipitation on water intensity is mixed. Humidity has no significant total marginal effect on water intensity.

Table 6b presents the results for the total marginal effect given by equation (7) accounting for the crop acreage extensive margin, the multiple crop extensive margin, and the intensive margin for climate specification M1. Monthly temperature has no significant total marginal effect on water use. The total marginal effects of monthly precipitation on water use is significant and negative in January and September; and significant and positive in February. The total marginal effect of humidity on water use is significant and negative in February and October; and significant and positive in March, May, November, and December. The total marginal effect of temperature on water intensity is significant and positive in February, August, September, and December. The total marginal effect of precipitation on water intensity is significant and positive in January, April, July, August, September, November, and December. The total marginal effect of humidity on water intensity is significant and positive in March, June, July, September, October, and November.

Table 6c presents the results for the total marginal effect given by equation (7) accounting for the crop acreage extensive margin, the multiple crop extensive margin, and the intensive margin for climate specification M2. The fraction of days with maximum temperature exceeding 86°F over the past 3 years has a significant negative total marginal effect on water use in September; and a significant positive total marginal effect on water use in October and November. The total marginal effects of monthly precipitation are significant and positive in January, February, and November; and significant and negative in December. The total marginal effects of monthly humidity are significant and positive in July and December; and significant and negative in January and August. The fraction of days with maximum temperature exceeding 86°F has a significant positive total marginal effect on water intensity in April, May, June, July, and September. Precipitation has a significant positive total marginal effect on water intensity in June, August, October, and December. Humidity has a significant positive total marginal effect on water intensity in March, May, June, September, October, November, and December; and a significant negative total marginal effect in April.

Table 7 presents the total marginal effect given by equation (8) of each of the *j* climate variables T_{jit} in T_{it} accounting for the crop acreage extensive margin, the irrigation technology extensive margin, and the intensive margin. Table 7a presents the results for the specifications that use annual climate variables (Y1, Y2, Y3, Y4, Y5). None of the annual temperature or precipitation variables have a significant total marginal effect on water use. The total marginal effect of humidity on water use can be significant and positive. The average temperature over the last 3 years has a significant positive total marginal effect on water intensity. The fraction of days in January-April with maximum temperature greater than 86°F has a significant positive total marginal effect on both water use and water intensity. The total marginal effect of precipitation on water intensity can be significant and positive. The total marginal effect of humidity on water intensity can be significant and positive.

Table 7b presents the results for the total marginal effect given by equation (8) accounting for the crop acreage extensive margin, the multiple crop extensive margin, and the intensive margin for climate specification M1. Monthly temperature has no significant total marginal effect on water use. The total marginal effects of monthly precipitation on water use is significant and negative in November; and significant and positive in February, June, and October. The total marginal effect of humidity on water use is significant and negative in February, September, and October; and significant and positive in March, November, and December. The total marginal effect of temperature on water intensity is significant and positive in February, August, September, and December. The total marginal effect of precipitation on water intensity is significant and positive in all months except December. The total marginal effect of humidity on water intensity is significant and positive in March, May, July, October, November, and December; and significant and negative in January and September.

Table 7c presents the results for the total marginal effect given by equation (8) accounting for the crop acreage extensive margin, the irrigation technology extensive margin, and the intensive margin for climate specification M2. The fraction of days with maximum temperature exceeding 86°F over the past 3 years has a significant positive total marginal effect on water use in October. The total marginal effects of monthly precipitation are significant and positive in January, February, September, and November; and significant and negative in December. The total marginal effects of monthly humidity are significant and positive in

March, July, November and December; and significant and negative in January, February, May, August, and October. The fraction of days with maximum temperature exceeding 86°F has a significant positive total marginal effect on water intensity in March, May, June, July, and September. Precipitation has a significant positive total marginal effect on water intensity in February, May, June, September, October, and November. Humidity has a significant positive total marginal effect on water intensity in February, March, May, July, September, October, November, and December; and a significant negative total marginal effect in January.

7. Conclusion

Our results show that 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 past 3 years, and the monthly fraction of days with maximum temperature exceeding 86°F over the past 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 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 also evaluate the effects of climate-related variables by month rather than only at an annual level.

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.

The outcome of this research provides a better understanding of how changes in temperature, precipitation, and humidity affect agricultural groundwater extraction, and therefore of the possible implications of climate change for agriculture and groundwater.

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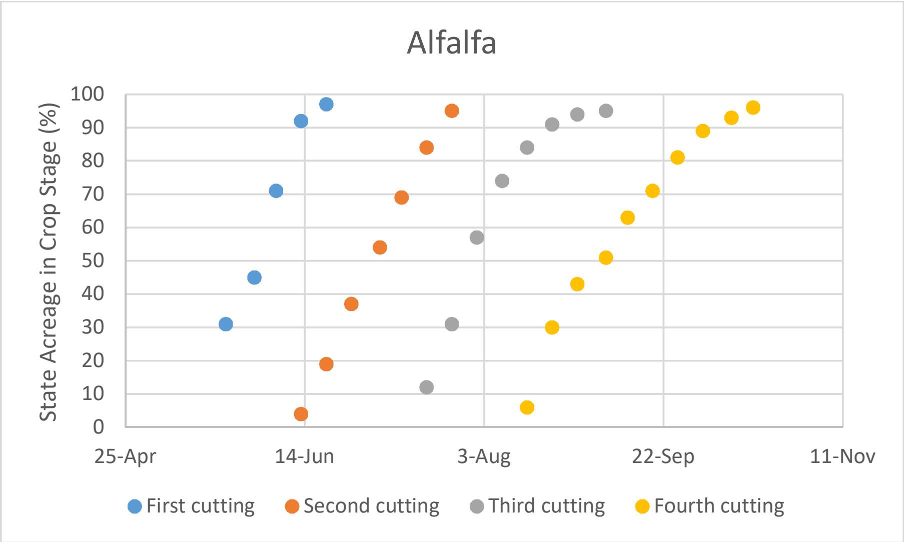
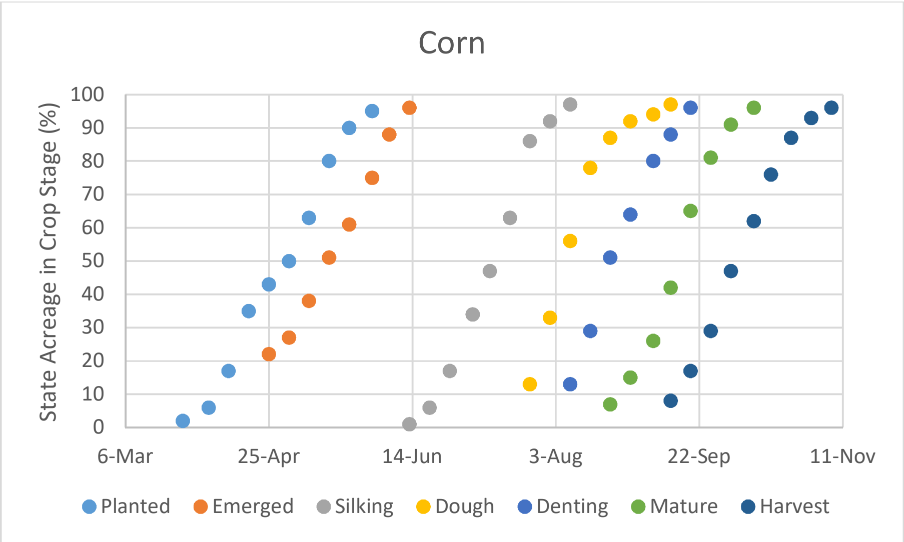
Figure 1: Season divisions for crops in Kansas

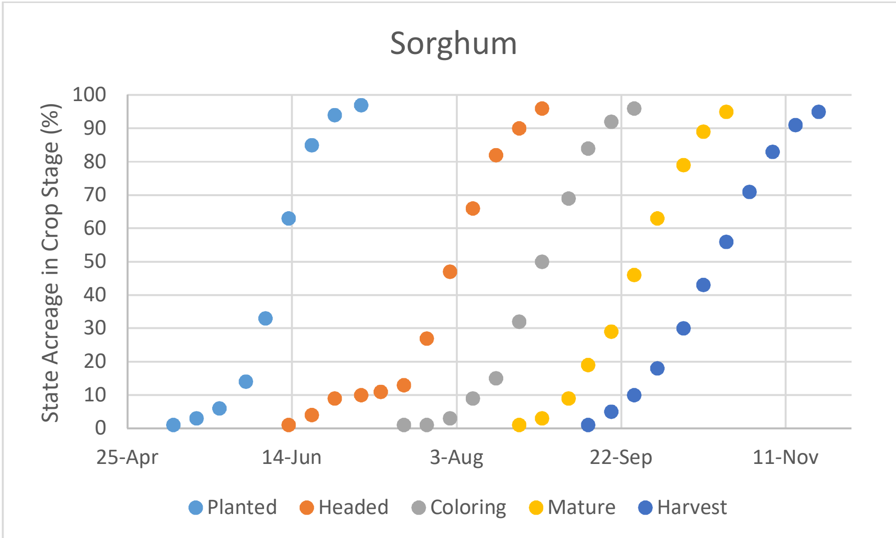
(a) Season divisions for Kansas alfalfa



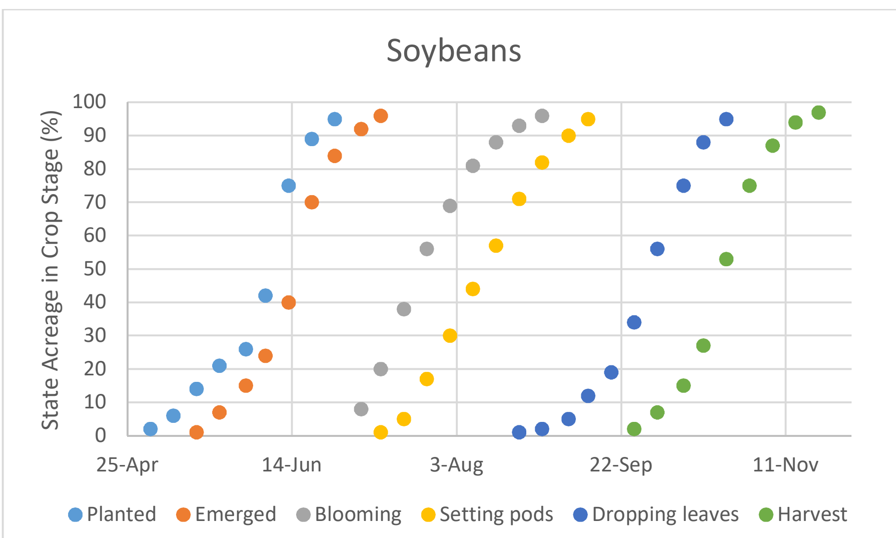
(b) Season divisions for Kansas corn



(c) Season divisions for Kansas sorghum



(d) Season divisions for Kansas soybeans



(e) Season divisions for Kansas wheat

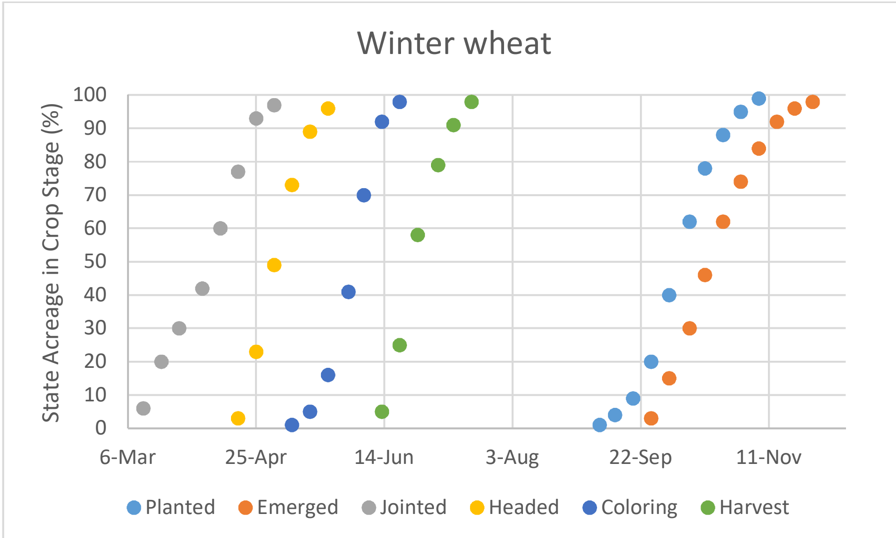
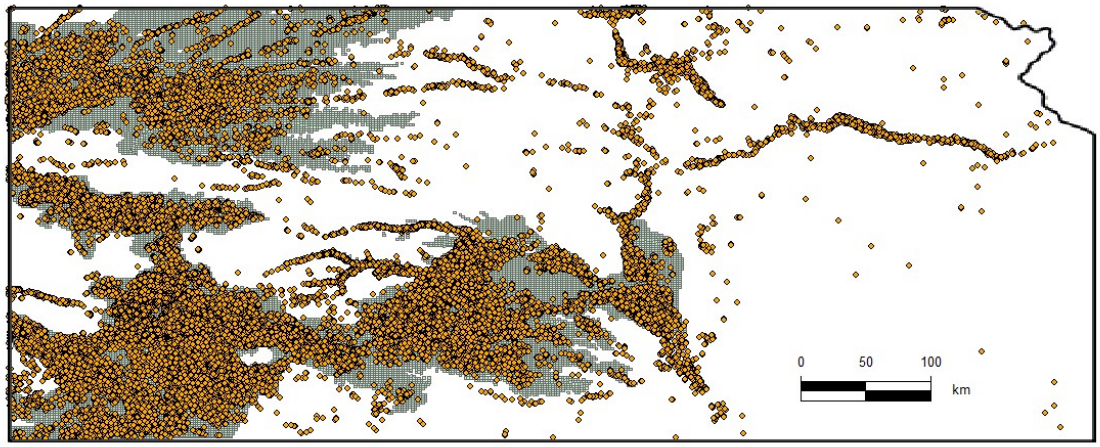


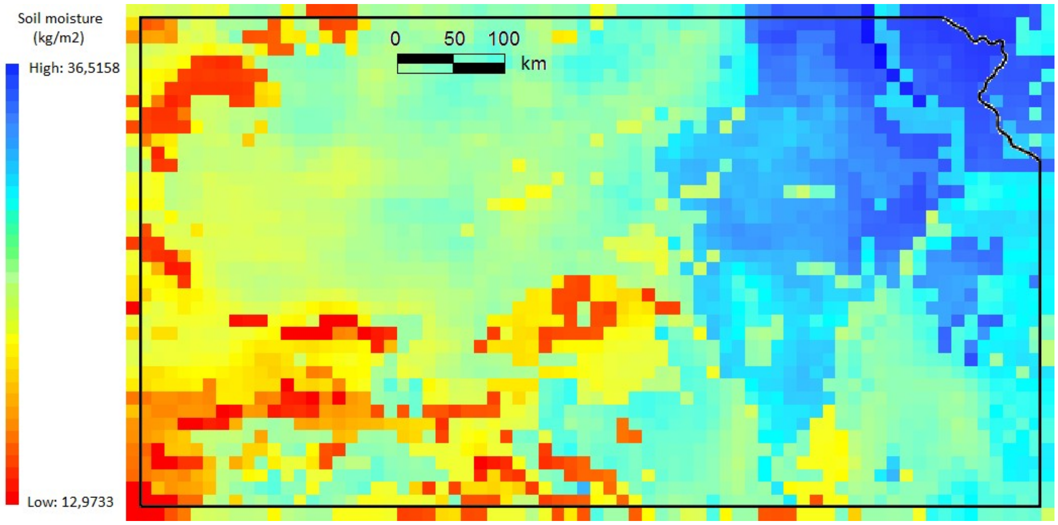
Figure 2: Location of all the points of diversion we use in our data set



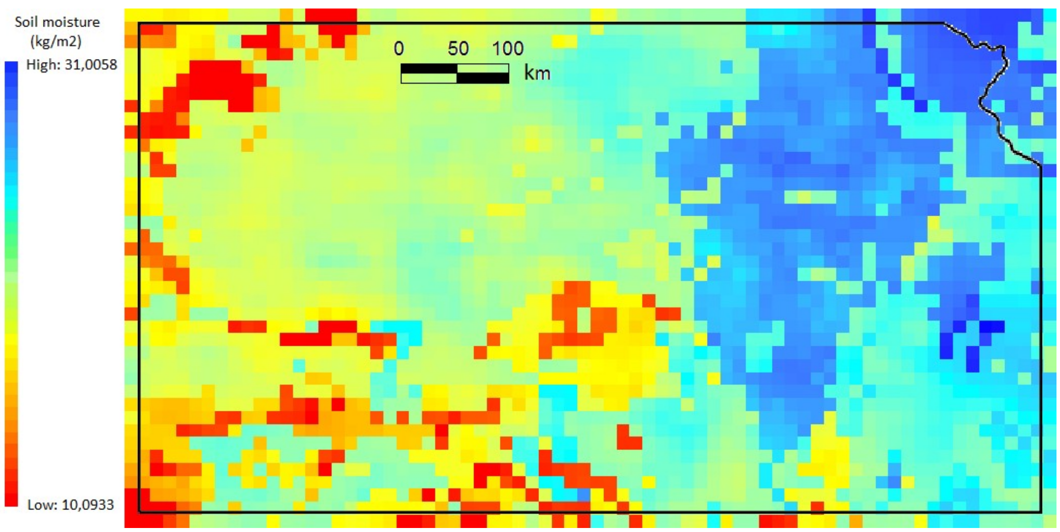
Notes: The black border indicates the Kansas state boundaries. The gray area shows the portion of the High Plains Aquifer that underlies western Kansas.

Figure 3: Soil moisture content

(a) 1996



(b) 2012



Notes: The figures plot the soil moisture content (measured in kg/m^2) in the 0-10 cm layer for the state of Kansas in 1996 and 2012. Blue pixels indicate higher moisture whereas red pixels indicate lower moisture. The area represented in the figures is the same as the area represented in Figure 2. The black border indicates the Kansas state boundaries.

Table 1a. Summary statistics for choice variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Water use (acre-feet)	302742	172.64	123.29	0	1988.64
Water intensity (acre-feet/acre)	301043	1.17	0.56	0	17.42
Acres planted with alfalfa (acres)	302742	11.46	38.55	0	640
Acres planted with corn (acres)	302737	63.83	74.6	0	640
Acres planted with sorghum (acres)	302742	5.06	23.82	0	620
Acres planted with soybeans (acres)	302742	12.08	34.98	0	550
Acres planted with wheat (acres)	302737	17.03	43.57	0	625
Multiple crops (dummy)	302742	0.4	0.49	0	1
Center pivot sprinkler use (dummy)	302742	0.36	0.48	0	1
Center pivot with drop nozzles use (dummy)	302742	0.31	0.46	0	1

Table 1b. Summary statistics for control variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Alfalfa price ($/ton)	302742	119.24	36.45	80.42	211.92
Corn price (cents/bsh)	302742	340.13	129.64	224.28	629.03
Sorghum price ($/cwt)	302742	5.57	2.52	3.27	11.26
Soybeans price (cents/bsh)	302742	773.57	285.41	451.95	1353.64
Wheat price (cents/bsh)	302742	464.99	199.22	287.94	968.91
Evapotranspiration	302742	55.13	1.05	43.54	62.39
Recharge	302667	1.32	1.21	0.3	6
Slope	299697	1.08	0.87	0.01	8.68
Irrigated capability class=1 (dummy)	302742	0.17	0.38	0	1
Field size (acres)	302742	183.19	103.25	60	640
Depth to groundwater (ft)	302742	124.45	78.29	4.72	396.48
Natural Gas price ($/mcf)	302742	8.59	2.58	4.61	12.44
Diesel price ($/gal)	302742	2.16	0.98	1.02	3.9
Electricity price (cents/kwh)	302742	7.02	0.93	6.2	9.24
Saturated thickness (ft)	302742	120.41	114.01	-266.11	643.91
Soil moisture (kg/m^2)	282986	22.43	4.07	11.67	35.46

Table 1c. Summary statistics for annual climate variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Annual average temperature (°F)	302742	54.09	1.52	50.42	58.08
Annual precipitation (in)	302742	18.47	5.87	7.58	51.81
Annual average humidity (%)	302742	63.94	4.46	51.8	76.42
Average temperature over the past 3 years (°F)	302742	54.04	1.29	50.93	57.57
Average total precipitation over the past 3 years (in)	302742	56.45	12.77	33.45	97.7
Annual fraction of days with max temp > 86°F	302742	0.23	0.04	0.13	0.30
Summer fraction of days with max temp > 86°F	302742	0.69	0.11	0.38	0.93
Annual temperature in Jan-Apr (°F)	302742	40.16	2.21	34.05	46.99
Annual precipitation in Jan-Apr (in)	302742	0.95	0.41	0.19	2.73
Annual humidity in Jan-Apr (%)	302742	64.27	8.32	45.04	84.13
Annual fraction of days in Jan-Apr with max temp > 86°F	302742	0.014	0.0133	0	0.0541

Table 1d. Summary statistics for monthly climate variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Avg. temperature (°F) over the past 3 years during month of:					
January	302742	30.71	2.07	16.87	41.89
February	302742	34.37	2.74	23.91	45.09
March	302742	42.65	2.38	35.02	56.19
April	302742	52.21	2.37	44.27	60.68
May	302742	63.17	1.93	57.69	70.24
June	302742	73	1.81	68.28	78.73
July	302742	78.56	1.82	72.83	86.16
August	302742	76.26	2.08	69.9	84.68
September	302742	67.42	1.88	61.07	77
October	302742	54.64	1.85	44.71	61.19
November	302742	41.87	2.24	31.88	51.74
December	302742	31.79	2.07	18.69	37.86
Avg. precipitation (in) over the past 3 years for month of:					
January	302742	0.35	0.29	0	1.99
February	302742	0.48	0.29	0	2.5
March	302742	1.29	0.66	0	6.95
April	302742	1.61	0.5	0.28	4.9
May	302742	2.68	1.36	0.16	8.86
June	302742	2.95	1.03	0.34	7.95
July	302742	3.01	1.54	0.12	10.98
August	302742	3.01	1.83	0.01	15.59
September	302742	1.5	0.89	0.04	5.24
October	302742	1.5	0.66	0	5.3

November	302742	0.54	0.52	0	3.97
December	302742	0.58	0.56	0	3.8
Avg. humidity (%) over the past 3 years during month of:					
January	302742	66.4	4.86	51.39	90.57
February	302742	65.68	8.13	37.94	90.99
March	302742	61.79	6.85	43.52	80.44
April	302742	60.36	7.02	31.99	78.83
May	302742	64.9	4.28	45.21	78.2
June	302742	63.62	4.19	44.24	76.73
July	302742	62.18	5.04	40.15	83.04
August	302742	65.8	6.85	46.12	81.86
September	302742	62.94	5.58	42.08	79.06
October	302742	64.35	4.74	44.29	82.79
November	302742	65.4	5.17	43.56	83.76
December	302742	68.81	4.49	56.42	86.41
Avg. fraction of days with max temp > 86°F over the past 3 years during month of:					
January	302742	0	0	0	0.03
February	302742	0	0	0	0.07
March	302742	0	0	0	0.03
April	302742	0.05	0.03	0	0.22
May	302742	0.21	0.06	0	0.55
June	302742	0.56	0.09	0.23	0.92
July	302742	0.79	0.07	0.52	1
August	302742	0.67	0.14	0.26	0.97
September	302742	0.36	0.1	0.07	0.8
October	302742	0.07	0.03	0	0.32

November	302742	0	0.01	0	0.1
December	302742	0	0	0	0

Table 2. 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 3a: Total crop acreage extensive margin, Annual climate variables

	Water use			Water intensity		
	All	Monoculture	Polyculture	All	Monoculture	Polyculture
Climate Specification Y1						
Annual average temperature (°F)	3.078	11.963	-0.317	0.00459	-0.00314	-0.00865
Annual precipitation (in)	0.897	1.928	0.680	0.00778	-0.00039	0.00296
Annual average humidity (%)	0.893***	3.197***	-0.259	0.00461***	0.0002	-0.00339***
Climate Specification Y2						
Average temperature over the past 3 years (°F)	3.347	21.12	-2.985	-0.0082	-0.0039	-0.0287
Average total precipitation over the past 3 years (in)	0.554	1.36	0.354	0.0039	-0.0023	0.0014
Annual average humidity (%)	0.62***	2.343***	-0.53***	0.0024*	0.0021	-0.0041***
Climate Specification Y3						
Annual fraction of days with max temp > 86°F	47.626	-6.654	-15.318	-0.1894	-0.3999	0.0072
Summer fraction of days with max temp > 86°F	19.996	88.677	28.597	0.2833	0.1286	0.0771
Annual precipitation (in)	1.392*	3.014	0.764	0.0091	-0.0004	0.003
Annual average humidity (%)	0.72***	2.625***	-0.511**	0.003**	0.0005	-0.0046***
Climate Specification Y4						
Average temperature over the last 3 years (°F)	5.338	22.089	-3.015	0.0036	0.0152	-0.0315
Average total precipitation over the last 3 years (in)	0.553	1.372	0.377	0.0041	-0.0025	0.0015
Annual average humidity (%)	0.299	1.282*	-0.934***	-0.0007	0.0029	-0.0066***
Annual temperature in Jan-Apr (°F)	-2.511	-2.683	-1.39	-0.0227	-0.0028	-0.0061
Annual precipitation in Jan-Apr (in)	9.811	17.312	9.359	0.115**	-0.0652	0.0549
Annual humidity in Jan-Apr (%)	-0.36***	0.206	-0.095	-0.003***	-0.0012	0.000

Climate Specification Y5						
Average temperature over the last 3 years (°F)	2.321	36.606	-5.9234	-0.028	0.001	-0.0505
Total precipitation over the last 3 years (in)	0.608	-0.705*	0.4172	0.004	0.01	0.0018
Annual average humidity (%)	0.449*	5.045***	-0.8963***	0.000	-0.005	-0.0065***
Fraction of days in Jan-Apr with max temp > 86°F	85.120	-325.101**	154.4898	1.037	2.582	1.2277
Annual precipitation in Jan-Apr (in)	3.602	-27.378***	9.1435	0.071	0.061	0.0683*
Annual humidity in Jan-Apr (%)	0.109	-1.176***	0.3295**	0.002	0.006	0.0027***

Significance codes: * p<0.05, ** p<0.01, *** p<0.001.

Table 3b: Total crop acreage extensive margin, Climate specification M1

	Water use			Water intensity		
	All	Monoculture	Polyculture	All	Monoculture	Polyculture
Avg. temperature (°F) over the past 3 years during month of:						
January	2.54	-6.48	3.334	0.0029	0.0183	0.0013
February	-5.512	1.263	-6.64	-0.052	-0.0178	-0.033
March	-0.99	24.404	-3.941	-0.0138	-0.0143	-0.014
April	-2.238	7.800	-5.333	-0.0015	-0.0387	-0.0289
May	-4.63	-24.287	-1.411	-0.0327	0.0394	-0.0088
June	4.735	39.967	1.192	-0.0056	-0.054	-0.0065
July	1.887	-40.577	10.467	0.0777	0.0813	0.0806
August	-7.638	0.861	-6.848	-0.0952	-0.0263	-0.056
September	-4.833	-34.009	0.858	-0.0202	0.1021	0.0193
October	4.041	18.804	4.67	0.0237	-0.0489	0.0177
November	6.343	30.112	-0.537	0.0455	-0.0277	-0.0024
December	-4.767	-3.684	-4.05	-0.0325	-0.0134	-0.0094
Avg. precipitation (in) over the past 3 years during month of:						
January	16.626	-34.716	2.515	0.0556	0.1793	-0.0292
February	69.593***	78.565*	52.424***	0.4885***	-0.0392	0.2637**
March	10.733	24.024	-1.687	0.0758	-0.0473	-0.0302
April	-6.217	-18.94	6.914	-0.0256	0.0389	0.0336
May	0.729	-1.501	1.178	-0.0033	-0.03	-0.0023
June	1.725	21.363	-5.993	0.0393	-0.024	-0.0086
July	-5.286	-20.846	4.758	-0.0238	0.0031	0.0257
August	5.940	11.373	5.747	0.0341	0.0093	0.0229
September	12.811	-21.489	2.954	0.1108*	0.0282	0.0245

October	7.351	17.82	1.666	0.0991	-0.0259	0.033
November	15.853*	60.518**	2.675	0.0057	-0.187*	-0.0571
December	-7.911	-42.418*	5.823	-0.0745	0.0603	0.0187
Avg. humidity (%) over the past 3 years during month of:						
January	-0.568	-4.183*	0.787	-0.012**	-0.0048	-0.0022
February	-1.207	1.259	-2.033**	-0.008	-0.01	-0.0116**
March	1.699**	3.785*	1.195	0.0152**	0.0103	0.0113**
April	-1.157	-3.682	0.074	-0.014*	-0.0143	-0.0049
May	2.743**	12.647***	-1.895*	0.0237***	-0.0138	-0.0062
June	0.243	-10.396***	2.403**	-0.0045	0.0335***	0.0087
July	1.291	-2.679	1.886*	0.0214***	0.009	0.0153**
August	-0.900	0.122	-3.43***	-0.0078	-0.0119	-0.0204***
September	-3.299***	-5.833**	1.323	-0.0222***	0.0128	0.0072
October	2.809***	-0.126	3.379***	0.0213***	-0.0073	0.0159***
November	-2.467***	-0.793	-2.172**	-0.0294***	-0.0003	-0.0137***
December	0.930	12.235***	-2.265**	0.0094	-0.0065	-0.009*

Significance codes: * p<0.05, ** p<0.01, *** p<0.001.

Table 3c: Total crop acreage extensive margin, Climate specification M2

	Water use			Water intensity		
	All	Monoculture	Polyculture	All	Monoculture	Polyculture
Avg. fraction of days with max temp > 86°F over the past 3 years during month of:						
January	-4842.32***	-5689.167	920.427	-25.848**	6.9213	9.9121
February						
March	540.816	1121.064	575.835	6.3982*	-1.3199	3.1976
April	-221.495	-1518.231***	82.979	-0.1892	1.1499	1.090
May	37.509	281.165	-26.043	0.3186	-0.139	-0.0988
June	7.971	501.246	-43.782	-0.4499	-0.2294	-0.4703
July	51.557	375.249	-93.397	0.2245	0.2725	-0.6434
August	-24.022	-16.251	25.722	-0.2682	-0.9242	0.0638
September	-154.315	-1052.131***	-101.906	-0.8099	3.087**	-0.1626
October	18.522	1307.375**	40.317	-1.2179	-2.8042	-0.502
November	-183.716	3865.222***	-483.852	-3.6605	-6.2853	-2.1922
December						
Avg. precipitation (in) over the past 3 years for month of:						
January	25.235*	105.258**	9.142	0.1003	-0.2095	0.0096
February	41.24***	95.377**	42.271**	0.2089*	-0.1369	0.1852*
March	0.042	-10.262	-6.497	-0.0199	0.006	-0.0548
April	-6.27	-21.31	5.074	-0.0261	0.0401	0.0307
May	2.872	-7.177	1.329	0.0216	-0.0008	-0.0043
June	-0.115	-7.049	-5.571	0.0353	0.0599	-0.005
July	-4.749	-9.869	4.219	-0.015	-0.0264	0.0267
August	1.557	10.264	2.459	-0.0029	-0.0037	0.0103
September	14.153*	15.922	0.141	0.1108*	0.0094	0.0106
October	8.472	20.348	3.909	0.0971	-0.0517	0.0374
November	19.676**	93.168***	1.896	0.0866	-0.2311**	-0.0346
December	-1.868	-42.639**	1.773	-0.0428	0.0644	-0.0009
Avg. humidity (%) over the past 3 years during month of:						
January	0.2	-1.577	0.093	-0.0092*	-0.0072	-0.0046

February	-0.534	3.676**	-0.049	0.0038	-0.0165***	0.0022
March	0.841	-2.895	-0.397	0.0079	0.0242***	0.0011
April	-0.296	2.057	-1.259	-0.0062	-0.0156*	-0.0106**
May	0.997	4.172	0.667	0.012*	-0.0018	0.0073
June	-0.232	1.151	-0.385	-0.0107	0.0169*	-0.004
July	1.769**	7.203***	1.192	0.0107*	-0.017*	0.0038
August	-0.483	-8.59***	-1.556*	0.0008	0.0051	-0.0083*
September	-2.461***	-8.033***	-0.292	-0.0139**	0.0206***	0.0011
October	1.303*	5.121**	0.359	-0.0022	-0.0157*	-0.003
November	-1.48**	-4.488***	-0.654	-0.0139***	-0.0008	-0.0044
December	0.471	8.112***	0.258	0.0116**	0.0046	0.0036

Significance codes: * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Table 4a: Total intensive margin, Annual climate variables

	Water use			Water intensity		
	All	Monoculture	Polyculture	All	Monoculture	Polyculture
Climate Specification Y1						
Annual average temperature (°F)	4.199	3.241	4.102	0.012	0.018	0.010
Annual precipitation (in)	-1.637***	-2.485***	-0.876**	-0.016***	-0.02***	-0.009***
Annual average humidity (%)	0.151**	0.329***	0.163	-0.000	0.001***	-0.002***
Climate Specification Y2						
Average temperature over the past 3 years (°F)	12.483	9.181	14.232	0.050	0.055	0.050
Average total precipitation over the past 3 years (in)	-0.152	-0.546***	0.094	-0.004***	-0.005***	-0.002
Annual average humidity (%)	-0.225***	-0.203***	0.006	-0.003***	-0.003***	-0.003***
Climate Specification Y3						
Annual fraction of days with max temp > 86°F	20.438	19.724	2.148	0.036	0.073	0.009
Summer fraction of days with max temp > 86°F	121.48***	104.635***	135.291*	0.681***	0.741***	0.635*
Annual precipitation (in)	-0.659***	-1.473***	-0.020	-0.009***	-0.013***	-0.004**
Annual average humidity (%)	0.048	0.222***	0.150	0,000	0.001*	-0.001*
Climate Specification Y4						
Average temperature over the last 3 years (°F)	18.428	12.992	22.420	1.661***	1.676***	1.232***
Average total precipitation over the last 3 years (in)	-0.151	-0.509**	0.024	0.004***	0.005***	0.002
Annual average humidity (%)	-0.040	-0.063	0.460**	0.000	0.001*	0.001
Annual temperature in Jan-Apr (°F)	-2.512	-1.182	-3.675	0.051**	0.054*	0.010
Annual precipitation in Jan-Apr (in)	-16.729***	-17.944***	-15.227**	0.509***	0.507***	0.454***
Annual humidity in Jan-Apr (%)	-0.067*	0.236***	-0.456***	0.002***	0.003***	0.000

Climate Specification Y5						
Average temperature over the last 3 years (°F)	13.287	8.553	16.893	0.038	0.031	0.047
Total precipitation over the last 3 years (in)	0.059	-0.216	0.198	-0.002	-0.003*	0.000
Annual average humidity (%)	0.796***	0.341***	1.623***	0.003***	0.001**	0.004***
Fraction of days in Jan-Apr with max temp > 86°F	653.686***	624.882***	642.496***	5.268***	5.412***	4.883***
Annual precipitation in Jan-Apr (in)	-19.523***	-14.472***	-23.991***	-0.101***	-0.089***	-0.104***
Annual humidity in Jan-Apr (%)	0.335***	0.59***	0.013	0.005***	0.006***	0.003***

Significance codes: * p<0.05, ** p<0.01, *** p<0.001.

Table 4b: Total intensive margin, Climate specification M1

	Water use			Water intensity		
	All	Monoculture	Polyculture	All	Monoculture	Polyculture
Avg. temperature (°F) over the past 3 years during month of:						
January	-7.671	-3.813	-12.378	0.147***	0.172***	0.107**
February	1.649	3.824	1.188	0.382***	0.386***	0.375***
March	1.416	-2.498	0.999	0.203***	0.215***	0.158*
April	-2.324	0.627	-4.521	0.246***	0.363***	0.108
May	4.041	5.127	7.288	0.314**	0.169	0.272
June	16.017	9.401	18.474	0.697***	0.821***	0.230
July	10.045	-0.285	20.547	0.063	0.499*	1.588***
August	-8.235	-0.749	-9.259	0.546***	0.372*	1.628***
September	5.333	7.430	5.078	1.119***	1.321***	0.615***
October	-1.604	-3.744	-3.273	0.206***	0.156*	0.203*
November	4.450	1.782	4.200	0.160***	0.281***	0.168**
December	-3.813	-3.693	-3.326	0.549***	0.584***	0.449***
Avg. precipitation (in) over the past 3 years during month of:						
January	-32.723***	-23.858***	-64.217***	0.205***	0.194***	0.183***
February	-3.562	-10.296*	-4.754	0.084**	0.062	0.053
March	-12.27***	-13.537***	-11.777*	0.059***	0.063***	0.035
April	-1.146	-1.877	3.490	0.334***	0.334***	0.285***
May	1.873	-4.011**	8.11*	0.049***	0.055***	0.085***
June	10.264***	3.988	16.106***	0.031*	0.024	0.101***
July	-0.925	-0.824	1.412	0.091***	0.096***	0.102***
August	-9.513***	-8.047***	-12.654***	0.087***	0.107***	0.084***
September	-17.694***	-12.75***	-27.571***	0.149***	0.117***	0.163***

October	7.368**	5.098	5.045	0.055***	0.057**	0.084**
November	-47.842***	-39.500***	-60.769***	0.281***	0.314***	0.227***
December	5.818**	9.418***	12.336**	0.073***	0.084***	0.096***
Avg. humidity (%) over the past 3 years during month of:						
January	-0.101	0.022	0.770	0.001	0.001	0.007***
February	-3.546***	-1.735***	-4.198***	0.011***	0.012***	0.010***
March	2.701***	1.456***	3.329***	0.009***	0.012***	0.009***
April	1.542***	1.491***	2.061**	0.009***	0.007**	0.006*
May	-1.818***	-1.881***	-3.356***	0.006***	0.003	0.006*
June	-0.020	0.314	0.219	0.001	0.004	0.004
July	-0.941**	-2.419***	0.166	0.019***	0.023***	0.010**
August	0.285	1.395***	0.084	0.008***	0.009***	0.000
September	0.834**	1.243***	1.681**	0.006***	0.008***	0.004
October	-4.805***	-5.981***	-3.069***	0.042***	0.047***	0.024***
November	6.797***	6.446***	6.888***	0.047***	0.048***	0.038***
December	1.156***	1.264***	-0.436	0.011***	0.015***	0.000

Significance codes: * p<0.05, ** p<0.01, *** p<0.001.

Table 4c: Total intensive margin, Climate specification M2

	Water use			Water intensity		
	All	Monoculture	Polyculture	All	Monoculture	Polyculture
Avg. fraction of days with max temp > 86°F over the past 3 years during month of:						
January						
February	-4835.88***	-4380.97***	-6059.57***	25.805***	28.475***	20.938***
March	-389.373	-185.51	-630.347	4.26***	3.071**	3.131*
April	-77.624	35.774	-11.637	1.635***	1.992***	0.932*
May	-70.923*	-88.643**	-85.713	3.155***	3.388***	3.465***
June	301.873***	244.454***	328.849**	3.094***	3.957***	1.695***
July	122.226	47.299	142.672	7.043***	6.920***	5.791***
August	-53.257	-20.07	-36.663	1.671***	1.825***	0.892
September	11.519	125.473***	-15.661	4.328***	4.737***	3.266***
October	507.649***	409.813***	562.388***	1.562***	2.115***	0.670
November	241.278*	92.136	-263.98	0.245	2.066**	1.508
December						
Avg. precipitation (in) over the past 3 years for month of:						
January	16.313***	0.984	14.108	0.119***	0.052	0.211***
February	-7.774	-21.052***	0.992	0.173***	0.139***	0.12**
March	0.218	-0.228	1.513	0.023	0.016	0.049*
April	-3.119	-5.044	3.174	0.095***	0.068*	0.091*
May	4.700**	-0.117	10.618**	0.071***	0.035**	0.104***
June	-2.360	-3.395	-0.865	0.097***	0.128***	0.024
July	-4.191**	-2.544	-4.722	0.067***	0.076***	0.065***
August	-5.640***	-6.818***	-5.377**	0.088***	0.110***	0.073***
September	7.133***	2.163	5.027	0.018	0.036*	0.026
October	9.296***	11.212***	4.415	0.137***	0.17***	0.075**
November	-0.360	-11.672***	-0.599	0.088***	0.111***	0.047*
December	-16.199***	-13.700***	-15.714***	0.087***	0.095***	0.046**
Avg. humidity (%) over the past 3 years during month of:						
January	-1.384***	-0.65***	-1.309***	0.001	0.000	0.004*

February	-1.204***	-1.271***	-1.43***	0.015***	0.014***	0.016***
March	2.219***	2.104***	2.273***	0.014***	0.015***	0.011***
April	1.889***	0.473*	3.027***	0.007***	0.002	0.006**
May	-5.082***	-5.221***	-5.818***	0.034***	0.034***	0.030***
June	0.544	1.601***	-1.023	0.004*	0.008***	0.003
July	2.516***	1.188***	3.641***	0.005**	0.004*	0.009***
August	-1.239***	-0.666*	-1.161*	0.005***	0.004	0.007**
September	2.188***	3.235***	3.074***	0.026***	0.026***	0.024***
October	-3.385***	-3.879***	-2.924***	0.026***	0.028***	0.018***
November	3.295***	3.437***	3.362***	0.028***	0.029***	0.026***
December	2.589***	1.662***	2.563***	0.008***	0.008***	0.003

Significance codes: * p<0.05, ** p<0.01, *** p<0.001.

Table 5a: Total marginal effect, Annual climate variables

	Water use			Water intensity		
	All	Monoculture	Polyculture	All	Monoculture	Polyculture
Climate Specification Y1						
Annual average temperature (°F)	7.278	15.204	3.785	0.017	0.015	0.002
	(20.859)	(61.277)	(26.44)	(0.149)	(0.229)	(0.138)
Annual precipitation (in)	-0.740	-0.558	-0.196	-0.008	-0.021*	-0.006
	(0.677)	(2.183)	(0.703)	(0.005)	(0.008)	(0.004)
Annual average humidity (%)	1.044***	3.526***	-0.096	0.004***	0.001	-0.005***
	(0.145)	(0.426)	(0.181)	(0.001)	(0.002)	(0.001)
Climate Specification Y2						
Average temperature over the past 3 years (°F)	15.829	30.301	11.247	0.041	0.051	0.021
	(29.87)	(84.458)	(40.174)	(0.218)	(0.339)	(0.213)
Average total precipitation over the past 3 years (in)	0.402	0.814	0.448	0.000	-0.007	0.000
	(0.369)	(1.108)	(0.428)	(0.003)	(0.004)	(0.002)
Annual average humidity (%)	0.395**	2.14***	-0.524**	-0.001	-0.001	-0.007***
	(0.149)	(0.424)	(0.185)	(0.001)	(0.002)	(0.001)
Climate Specification Y3						
Annual fraction of days with max temp > 86°F	68.064	13.07	-13.171	-0.153	-0.327	0.016
	(288.808)	(872.398)	(341.649)	(2.108)	(3.349)	(1.834)
Summer fraction of days with max temp > 86°F	141.476	193.312	163.887	0.964	0.87	0.712
	(81.329)	(239.257)	(94.151)	(0.585)	(0.897)	(0.501)
Annual precipitation (in)	0.733	1.541	0.744	0.000	-0.013	-0.001
	(0.677)	(2.139)	(0.715)	(0.005)	(0.008)	(0.004)

Annual average humidity (%)	0.768***	2.847***	-0.361	0.003**	0.001	-0.006***
	(0.152)	(0.444)	(0.187)	(0.001)	(0.002)	(0.001)
Climate Specification Y4						
Average temperature over the last 3 years (°F)	23.766	35.081	19.405	1.665***	1.691***	1.201***
	(33.849)	(94.414)	(46.669)	(0.248)	(0.374)	(0.248)
Average total precipitation over the last 3 years (in)	0.402	0.863	0.401	0.009**	0.002	0.004
	(0.387)	(1.15)	(0.455)	(0.003)	(0.005)	(0.002)
Annual average humidity (%)	0.259	1.219*	-0.474	-0.001	0.004	-0.006***
	(0.226)	(0.613)	(0.289)	(0.002)	(0.002)	(0.002)
Annual temperature in Jan-Apr (°F)	-5.023	-3.865	-5.066	0.028	0.051	0.004
	(7.954)	(22.004)	(10.034)	(0.058)	(0.084)	(0.054)
Annual precipitation in Jan-Apr (in)	-6.918	-0.632	-5.867	0.624***	0.442***	0.509***
	(5.712)	(15.83)	(7.337)	(0.042)	(0.068)	(0.039)
Annual humidity in Jan-Apr (%)	-0.427***	0.442	-0.551***	-0.001	0.001	0.000
	(0.105)	(0.313)	(0.126)	(0.001)	(0.001)	(0.001)
Climate Specification Y5						
Average temperature over the last 3 years (°F)	15.608	45.159	10.969	0.009	0.031	-0.004
	(33.711)	(111.372)	(46.614)	(0.246)	(0.565)	(0.246)
Total precipitation over the last 3 years (in)	0.667	-0.921	0.615	0.003	0.008	0.002
	(0.384)	(1.439)	(0.453)	(0.003)	(0.007)	(0.002)
Annual average humidity (%)	1.245***	5.386***	0.727**	0.003	-0.003	-0.002
	(0.228)	(0.79)	(0.282)	(0.002)	(0.004)	(0.001)
Fraction of days in Jan-Apr with max temp > 86°F	738.806***	299.781	796.986***	6.304***	7.993***	6.11***
	(129.147)	(468.043)	(160.654)	(0.938)	(2.289)	(0.86)

Annual precipitation in Jan-Apr (in)	-15.92**	-41.85*	-14.848*	-0.03	-0.028	-0.036
	(5.148)	(17.143)	(6.782)	(0.037)	(0.091)	(0.035)
Annual humidity in Jan-Apr (%)	0.444***	-0.586	0.342**	0.007***	0.011***	0.006***
	(0.109)	(0.398)	(0.128)	(0.001)	(0.002)	(0.001)

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

Table 5b: Total marginal effect, Climate specification M1

	Water use			Water intensity		
	All	Monoculture	Polyculture	All	Monoculture	Polyculture
Avg. temperature (°F) over the past 3 years during month of:						
January	-5.131	-10.293	-9.044	0.150	0.190	0.109
	(16.827)	(45.049)	(19.073)	(0.123)	(0.158)	(0.106)
February	-3.863	5.087	-5.452	0.33***	0.368**	0.342***
	(13.136)	(35.098)	(15.537)	(0.095)	(0.132)	(0.084)
March	0.427	21.906	-2.942	0.189	0.201	0.144
	(30.227)	(80.115)	(34.131)	(0.222)	(0.282)	(0.189)
April	-4.562	8.427	-9.854	0.244	0.324	0.079
	(37.715)	(100.535)	(45.155)	(0.273)	(0.373)	(0.243)
May	-0.59	-19.16	5.877	0.281	0.208	0.264
	(56.276)	(153.556)	(66.54)	(0.409)	(0.563)	(0.361)
June	20.752	49.368	19.666	0.691	0.767	0.224
	(73.053)	(198.964)	(87.301)	(0.525)	(0.725)	(0.467)
July	11.932	-40.862	31.014	0.140	0.580	1.668**
	(81.596)	(211.059)	(101.757)	(0.587)	(0.798)	(0.542)
August	-8.235	-0.749	-9.259	0.546***	0.372*	1.628***
	(27.978)	(25.847)	(57.119)	(0.152)	(0.187)	(0.261)
September	0.500	-26.579	5.937	1.099***	1.423**	0.634*
	(45.379)	(124.109)	(51.704)	(0.328)	(0.472)	(0.279)
October	2.437	15.061	1.397	0.23	0.107	0.221
	(35.965)	(96.667)	(42.041)	(0.262)	(0.354)	(0.229)
November	10.793	31.895	3.663	0.206	0.254	0.165
	(17.456)	(46.776)	(21.455)	(0.126)	(0.177)	(0.114)
December	-8.58	-7.377	-7.376	0.516***	0.570**	0.44***

	(18.558)	(50.101)	(22.599)	(0.136)	(0.192)	(0.123)
Avg. precipitation (in) over the past 3 years during month of:						
January	-16.097	-58.574	-61.701**	0.260*	0.190	0.154
	(15.398)	(42.358)	(18.939)	(0.111)	(0.158)	(0.1)
February	66.031***	68.268	47.67*	0.573***	0.368**	0.317**
	(15.282)	(39.733)	(19.443)	(0.111)	(0.132)	(0.103)
March	-1.537	10.488	-13.464	0.135*	0.201	0.005
	(7.793)	(21.236)	(9.229)	(0.057)	(0.282)	(0.049)
April	-7.364	-20.816	10.404	0.309***	0.324	0.319***
	(12.583)	(36.094)	(14.346)	(0.091)	(0.373)	(0.076)
May	2.602	-5.511	9.288	0.046	0.208	0.083**
	(4.949)	(13.099)	(5.857)	(0.036)	(0.563)	(0.031)
June	11.99	25.35	10.113	0.07	0.767	0.093*
	(6.843)	(20.522)	(7.715)	(0.05)	(0.725)	(0.042)
July	-6.211	-21.669	6.17	0.067	0.580	0.127***
	(6.039)	(16.914)	(6.405)	(0.043)	(0.798)	(0.035)
August	-3.573	3.326	-6.906	0.121***	0.372*	0.107***
	(3.368)	(10.232)	(3.798)	(0.024)	(0.187)	(0.021)
September	-4.883	-34.238	-24.617**	0.26***	1.423**	0.188***
	(7.568)	(21.765)	(8.429)	(0.055)	(0.472)	(0.046)
October	14.719	22.918	6.71	0.154*	0.107	0.117*
	(8.594)	(22.917)	(10.121)	(0.062)	(0.354)	(0.054)
November	-31.989***	21.018	-58.094***	0.287***	0.254	0.17**
	(8.286)	(22.7)	(10.126)	(0.060)	(0.177)	(0.053)
December	-2.093	-32.999	18.158*	-0.001	0.57**	0.115**
	(6.73)	(17.985)	(8.098)	(0.049)	(0.192)	(0.044)
Avg. humidity (%) over the past 3 years during month of:						

January	-0.669	-4.160*	1.557*	-0.011*	-0.004	0.005
	(0.612)	(1.667)	(0.751)	(0.004)	(0.006)	(0.004)
February	-4.753***	-0.476	-6.231***	0.003	0.002	-0.002
	(0.806)	(2.19)	(0.976)	(0.006)	(0.008)	(0.005)
March	4.4***	5.241**	4.524***	0.025***	0.022**	0.020***
	(0.698)	(1.922)	(0.844)	(0.005)	(0.007)	(0.004)
April	0.385	-2.191	2.135*	-0.005	-0.007	0.001
	(0.92)	(2.612)	(1.082)	(0.007)	(0.01)	(0.006)
May	0.925	10.766***	-5.251***	0.03***	-0.011	0.000
	(0.921)	(2.564)	(1.094)	(0.007)	(0.009)	(0.006)
June	0.222	-10.082***	2.622*	-0.003	0.037***	0.013*
	(0.936)	(2.631)	(1.098)	(0.007)	(0.01)	(0.006)
July	0.350	-5.098*	2.052	0.04***	0.032***	0.026***
	(0.875)	(2.324)	(1.107)	(0.006)	(0.009)	(0.006)
August	-0.615	1.517	-3.346**	0.001	-0.003	-0.020***
	(0.889)	(2.339)	(1.113)	(0.006)	(0.009)	(0.006)
September	-2.465**	-4.590*	3.004**	-0.016**	0.021*	0.011*
	(0.792)	(2.254)	(0.962)	(0.006)	(0.008)	(0.005)
October	-1.996**	-6.107**	0.31	0.064***	0.04***	0.040***
	(0.75)	(2.056)	(0.978)	(0.005)	(0.008)	(0.005)
November	4.33***	5.653**	4.716***	0.017***	0.048***	0.024***
	(0.694)	(1.919)	(0.856)	(0.005)	(0.007)	(0.005)
December	2.086**	13.499***	-2.701**	0.021***	0.008	-0.009
	(0.714)	(2.035)	(0.887)	(0.005)	(0.008)	(0.005)

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

Table 5c: Total marginal effect, Climate specification M2

	Water use			Water intensity		
	All	Monoculture	Polyculture	All	Monoculture	Polyculture
Avg. fraction of days with max temp > 86°F over the past 3 years during month of:						
January						
February						
March	151.442	935.554	-54.512	10.658***	1.751	6.329*
	(372.726)	(1098.417)	(399.449)	(2.955)	(4.316)	(2.722)
April	-299.119	-1482.46***	71.342	1.446	3.141*	2.022*
	(1106.919)	(356.16)	(2158.098)	(0.962)	(1.305)	(0.851)
May	-33.414	192.522	-111.756	3.473***	3.249*	3.367***
	(160.441)	(354.351)	(231.322)	(0.987)	(1.264)	(0.83)
June	309.844	745.7	285.067	2.644*	3.728*	1.225
	(160.097)	(446.858)	(188.543)	(1.158)	(1.623)	(1.009)
July	173.783	422.548	49.275	7.268*	7.192	5.148
	(468.979)	(1190.43)	(548.666)	(3.431)	(4.462)	(2.982)
August	-77.28	-36.32	-10.941	1.402	0.9	0.955
	(149.753)	(396.89)	(185.532)	(1.093)	(1.553)	(0.99)
September	-142.796	-926.658**	-117.567	3.518***	7.824***	3.104***
	(106.563)	(285.227)	(125.94)	(0.782)	(1.105)	(0.676)
October	526.171**	1717.188***	602.705**	0.344	-0.689	0.168
	(171.614)	(468.266)	(199.306)	(1.253)	(1.704)	(1.073)
November	57.563	3957.357***	-747.832*	-3.415	-4.219	-0.684
	(310.958)	(919.878)	(367.481)	(2.286)	(3.453)	(1.991)
December						
Avg. precipitation (in) over the past 3 years for month of:						
January	41.548**	106.242**	23.25	0.219*	-0.157	0.221*

	(13.725)	(37.042)	(17.103)	(0.101)	(0.144)	(0.091)
February	33.466**	74.325*	43.263**	0.382***	0.002	0.305***
	(12.61)	(33.221)	(16.277)	(0.093)	(0.133)	(0.086)
March	0.260	-10.490	-4.985	0.004	0.022	-0.006
	(6.604)	(17.53)	(8.14)	(0.048)	(0.069)	(0.043)
April	-9.389	-26.355	8.247	0.068	0.109	0.122
	(11.461)	(33.128)	(13.25)	(0.084)	(0.127)	(0.071)
May	7.572	-7.294	11.947*	0.093**	0.034	0.1***
	(4.751)	(13.086)	(5.682)	(0.035)	(0.049)	(0.03)
June	-2.475	-10.444	-6.436	0.133**	0.188*	0.019
	(6.884)	(19.865)	(7.931)	(0.051)	(0.078)	(0.043)
July	-8.940	-12.413	-0.503	0.052	0.05	0.092**
	(5.407)	(15.145)	(5.782)	(0.039)	(0.055)	(0.031)
August	-4.083	3.445	-2.918	0.085***	0.106**	0.083***
	(3.023)	(9.165)	(3.389)	(0.022)	(0.034)	(0.018)
September	21.286**	18.086	5.169	0.129**	0.046	0.037
	(6.651)	(18.952)	(7.628)	(0.049)	(0.073)	(0.041)
October	17.768*	31.56	8.324	0.234***	0.118	0.112*
	(7.647)	(20.527)	(9.178)	(0.056)	(0.077)	(0.049)
November	19.316**	81.496***	1.297	0.175***	-0.12	0.012
	(6.792)	(18.314)	(8.414)	(0.05)	(0.073)	(0.045)
December	-18.067**	-56.339***	-13.942	0.044	0.16**	0.046
	(6.163)	(16.471)	(7.465)	(0.046)	(0.061)	(0.041)
Avg. humidity (%) over the past 3 years during month of:						
January	-1.184*	-2.227	-1.216	-0.009*	-0.007	-0.001
	(0.527)	(1.421)	(0.648)	(0.004)	(0.005)	(0.003)
February	-1.738***	2.405*	-1.479**	0.019***	-0.002	0.019***
	(0.451)	(1.217)	(0.543)	(0.003)	(0.005)	(0.003)
March	3.06***	-0.791	1.876**	0.022***	0.039***	0.012**
	(0.588)	(1.615)	(0.717)	(0.004)	(0.006)	(0.004)
April	1.593*	2.53	1.768*	0.001	-0.014*	-0.005
	(0.673)	(1.89)	(0.815)	(0.005)	(0.007)	(0.004)
May	-4.085***	-1.049	-5.151***	0.046***	0.033***	0.037***

	(0.817)	(2.257)	(1.01)	(0.006)	(0.009)	(0.005)
June	0.312	2.752	-1.408	-0.007	0.025**	-0.001
	(0.856)	(2.295)	(1.041)	(0.006)	(0.009)	(0.006)
July	4.285***	8.391***	4.833***	0.015**	-0.013	0.013**
	(0.735)	(1.974)	(0.914)	(0.005)	(0.007)	(0.005)
August	-1.722*	-9.256***	-2.717**	0.006	0.009	-0.001
	(0.716)	(1.99)	(0.886)	(0.005)	(0.007)	(0.005)
September	-0.273	-4.798**	2.782***	0.012**	0.046***	0.025***
	(0.633)	(1.679)	(0.792)	(0.005)	(0.006)	(0.004)
October	-2.082**	1.242	-2.565**	0.024***	0.012	0.015***
	(0.684)	(1.795)	(0.864)	(0.005)	(0.007)	(0.005)
November	1.815***	-1.051	2.708***	0.014***	0.028***	0.021***
	(0.498)	(1.319)	(0.607)	(0.004)	(0.005)	(0.003)
December	3.06***	9.774***	2.821***	0.020***	0.012*	0.007
	(0.592)	(1.684)	(0.716)	(0.004)	(0.006)	(0.004)

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

Table 6a: Total marginal effect including the multiple crop extensive margin, Annual climate variables

Variable	Water use	Water intensity
Climate Specification Y1		
Annual average temperature (°F)	10.540	0.010
	(39.854)	(0.166)
Annual precipitation (in)	-0.542	-0.014**
	(1.354)	(0.005)
Annual average humidity (%)	1.920***	0.000
	(0.279)	(0.001)
Climate Specification Y2		
Average temperature over the past 3 years (°F)	22.550	0.040
	(55.749)	(0.248)
Average total precipitation over the past 3 years (in)	0.603	-0.004
	(0.718)	(0.003)
Annual average humidity (%)	0.973***	-0.003
	(0.280)	(0.001)
Climate Specification Y3		
Annual fraction of days with max temp > 86°F	25.727	-0.322
	(564.381)	(2.400)
Summer fraction of days with max temp > 86°F	171.951	0.861
	(155.874)	(0.658)
Annual precipitation (in)	1.087	-0.007
	(1.330)	(0.005)
Annual average humidity (%)	1.423***	-0.001
	(0.291)	(0.001)
Climate Specification Y4		
Average temperature over the last 3 years (°F)	28.55	1.495***
	(62.668)	(0.277)
Average total precipitation over the last 3 years (in)	0.619	0.003
	(0.747)	(0.003)
Annual average humidity (%)	0.483	0
	(0.405)	(0.002)
Annual temperature in Jan-Apr (°F)	-4.076	0.031
	(14.515)	(0.063)
Annual precipitation in Jan-Apr (in)	-4.378	0.478***
	(10.454)	(0.049)
Annual humidity in Jan-Apr (%)	0.077	0.001

	(0.202)	(0.001)
Climate Specification Y5		
Average temperature over the last 3 years (°F)	31.327	0.017
	(71.906)	(0.375)
Total precipitation over the last 3 years (in)	-0.360	0.006
	(0.908)	(0.005)
Annual average humidity (%)	3.431***	-0.003
	(0.502)	(0.003)
Fraction of days in Jan-Apr with max temp > 86°F	516.441	7.141***
	(297.408)	(1.501)
Annual precipitation in Jan-Apr (in)	-31.596**	-0.028
	(11.024)	(0.06)
Annual humidity in Jan-Apr (%)	-0.197	0.009***
	(0.250)	(0.001)

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

Table 6b: Total marginal effect including the multiple crop extensive margin, Climate specification M1

Variable	Water use	Water intensity
Avg. temperature (°F) over the past 3 years during month of:		
January	-9.881	0.158
	(28.534)	(0.11)
February	0.789	0.358***
	(22.83)	(0.096)
March	13.030	0.171
	(50.835)	(0.197)
April	1.755	0.221
	(65.161)	(0.269)
May	-9.91	0.235
	(98.674)	(0.401)
June	36.200	0.555
	(128.848)	(0.526)
July	-10.039	1.008
	(138.635)	(0.588)
August	-5.298	0.884**
	(46.041)	(0.286)
September	-12.175	1.098***
	(79.431)	(0.329)
October	8.725	0.158
	(61.879)	(0.249)
November	20.615	0.217
	(30.515)	(0.129)
December	-7.684	0.520***
	(32.348)	(0.136)
Avg. precipitation (in) over the past 3 years during month of:		
January	-60.187*	0.287*
	(27.626)	(0.118)
February	58.364*	0.151
	(26.031)	(0.114)
March	-0.212	0.017
	(13.648)	(0.057)
April	-8.687	0.354***
	(23.048)	(0.094)
May	0.421	0.049
	(8.45)	(0.035)
June	19.612	0.035
	(12.985)	(0.055)
July	-11.529	0.117**

	(10.638)	(0.041)
August	-0.234	0.109***
	(6.461)	(0.027)
September	-31.3*	0.167**
	(13.781)	(0.056)
October	15.951	0.068
	(14.768)	(0.06)
November	-13.436	0.159*
	(14.671)	(0.062)
December	-12.434	0.133**
	(11.613)	(0.047)
Avg. humidity (%) over the past 3 years during month of:		
January	-1.582	-0.002
	(1.087)	(0.004)
February	-3.217*	0.003
	(1.424)	(0.006)
March	4.93***	0.021***
	(1.243)	(0.005)
April	-0.449	-0.004
	(1.672)	(0.007)
May	4.393**	-0.007
	(1.652)	(0.007)
June	-5.44**	0.03***
	(1.69)	(0.007)
July	-1.661	0.026***
	(1.529)	(0.007)
August	-0.634	-0.009
	(1.543)	(0.007)
September	-1.354	0.016**
	(1.459)	(0.006)
October	-3.78**	0.041***
	(1.344)	(0.006)
November	5.392***	0.038***
	(1.242)	(0.005)
December	7.164***	0.000
	(1.316)	(0.006)

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

Table 6c: Total marginal effect including the multiple crop extensive margin, Climate specification M2

Variable	Water use	Water intensity
Avg. fraction of days with max temp > 86°F over the past 3 years during month of:		
January		
February		
March	459.485	4.038
	(707.687)	(3.125)
April	-846.426	2.633**
	(897.085)	(0.932)
May	86.185	3.203***
	(236.147)	(0.884)
June	554.07	2.754*
	(287.377)	(1.16)
July	266.557	6.400*
	(774.85)	(3.245)
August	-23.642	0.909
	(260.559)	(1.133)
September	-588.03**	5.85***
	(184.08)	(0.78)
October	1280.161***	-0.413
	(299.63)	(1.202)
November	2033.864***	-2.637
	(583.619)	(2.372)
December		

Avg. precipitation (in) over the past 3 years during month of:		
January	70.639**	0.007
	(24.182)	(0.104)
February	58.462**	0.143
	(21.803)	(0.096)
March	-9.56	0.018
	(11.39)	(0.049)
April	-12.668	0.115
	(21.207)	(0.089)
May	0.949	0.058
	(8.437)	(0.035)
June	-8.341	0.117*
	(12.656)	(0.054)
July	-8.286	0.071
	(9.558)	(0.038)
August	0.911	0.097***
	(5.776)	(0.023)
September	12.439	0.045
	(12.039)	(0.05)
October	22.048	0.117*
	(13.272)	(0.055)
November	47.865***	-0.059
	(11.843)	(0.051)
December	-40.013***	0.118**
	(10.586)	(0.043)
Avg. humidity (%) over the past 3 years during month of:		

January	-1.854*	-0.004
	(0.927)	(0.004)
February	0.78	0.006
	(0.793)	(0.004)
March	0.362	0.028***
	(1.049)	(0.004)
April	2.365	-0.011*
	(1.218)	(0.005)
May	-2.758	0.035***
	(1.469)	(0.006)
June	0.700	0.016*
	(1.497)	(0.007)
July	7.188***	-0.004
	(1.285)	(0.005)
August	-6.79***	0.006
	(1.294)	(0.005)
September	-1.468	0.036***
	(1.099)	(0.004)
October	-0.492	0.015**
	(1.183)	(0.005)
November	0.544	0.025***
	(0.86)	(0.004)
December	7.179***	0.009*
	(1.088)	(0.004)

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

Table 7a: Total marginal effect including irrigation technology extensive margin, Annual climate variables

Variable	Water use	Water intensity
Climate Specification Y1		
Annual average temperature (°F)	7.479	0.018
	(21.564)	(0.148)
Annual precipitation (in)	-0.915	-0.009
	(0.709)	(0.005)
Annual average humidity (%)	1.033***	0.004**
	(0.183)	(0.001)
Climate Specification Y2		
Average temperature over the past 3 years (°F)	16.203	0.044
	(31.898)	(0.221)
Average total precipitation over the past 3 years (in)	0.304	0.000
	(0.446)	(0.003)
Annual average humidity (%)	0.446*	0.000
	(0.182)	(0.001)
Climate Specification Y3		
Annual fraction of days with max temp > 86°F	28.895	-0.420
	(368.571)	(2.535)
Summer fraction of days with max temp > 86°F	157.041	1.064
	(132.661)	(0.906)
Annual precipitation (in)	0.533	-0.001
	(0.683)	(0.005)
Annual average humidity (%)	0.767***	0.003*
	(0.194)	(0.001)
Climate Specification Y4		
Average temperature over the last 3 years (°F)	24.218	1.668***
	(38.781)	(0.268)
Average total precipitation over the last 3 years (in)	0.332	0.008*
	(0.467)	(0.003)
Annual average humidity (%)	0.2	-0.001
	(0.315)	(0.002)
Annual temperature in Jan-Apr (°F)	-5.375	0.025
	(8.399)	(0.058)
Annual precipitation in Jan-Apr (in)	-6.088	0.629***
	(8.293)	(0.057)
Annual humidity in Jan-Apr (%)	-0.419	-0.001

	(0.258)	(0.002)
Climate Specification Y5		
Average temperature over the last 3 years (°F)	15.606	0.009
	(34.771)	(0.241)
Total precipitation over the last 3 years (in)	0.583	0.002
	(0.435)	(0.003)
Annual average humidity (%)	1.134***	0.002
	(0.235)	(0.002)
Fraction of days in Jan-Apr with max temp > 86°F	712.819***	6.119***
	(148.599)	(1.024)
Annual precipitation in Jan-Apr (in)	-15.242*	-0.027
	(7.224)	(0.05)
Annual humidity in Jan-Apr (%)	0.544***	0.007***
	(0.144)	(0.001)

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

Table 7b: Total marginal effect including irrigation technology extensive margin, Climate specification M1

Variable	Water use	Water intensity
Avg. temperature (°F) over the past 3 years during month of:		
January	-4.992	0.151
	(11.047)	(0.079)
February	-3.692	0.331***
	(9.377)	(0.066)
March	0.344	0.188
	(19.576)	(0.141)
April	-5.434	0.238
	(26.362)	(0.187)
May	-0.097	0.284
	(38.828)	(0.276)
June	21.648	0.698
	(51.599)	(0.363)
July	11.293	0.135
	(58.543)	(0.412)
August	-7.922	0.549*
	(34.808)	(0.225)
September	-0.522	1.092***
	(30.5)	(0.217)
October	2.844	0.233
	(24.126)	(0.172)
November	11.049	0.208*
	(12.218)	(0.086)
December	-8.574	0.516***
	(12.776)	(0.091)
Avg. precipitation (in) over the past 3 years during month of:		
January	-15.758	0.264***
	(11.047)	(0.078)
February	63.255***	0.553***
	(10.817)	(0.077)
March	-2.259	0.129***
	(5.308)	(0.038)
April	-8.294	0.302***
	(8.782)	(0.062)
May	2.946	0.049*
	(3.434)	(0.024)
June	12.122*	0.071*
	(4.801)	(0.034)
July	-5.826	0.071*

	(3.938)	(0.028)
August	-3.407	0.123***
	(2.322)	(0.016)
September	-4.377	0.263***
	(5.134)	(0.037)
October	14.749*	0.155***
	(5.917)	(0.042)
November	-30.037***	0.303***
	(5.898)	(0.042)
December	-3.047	-0.006
	(4.664)	(0.033)
Avg. humidity (%) over the past 3 years during month of:		
January	-0.822	-0.012***
	(0.443)	(0.003)
February	-4.411***	0.006
	(0.576)	(0.004)
March	4.261***	0.024***
	(0.495)	(0.003)
April	0.527	-0.004
	(0.646)	(0.005)
May	1.012	0.03***
	(0.65)	(0.005)
June	0.25	-0.003
	(0.664)	(0.005)
July	0.233	0.04***
	(0.644)	(0.004)
August	-0.841	-0.001
	(0.65)	(0.004)
September	-2.803***	-0.019***
	(0.577)	(0.004)
October	-1.983***	0.064***
	(0.534)	(0.004)
November	4.528***	0.018***
	(0.49)	(0.003)
December	2.239***	0.022***
	(0.51)	(0.004)

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

Table 7c: Total marginal effect including irrigation technology extensive margin, Climate specification M2

Variable	Water use	Water intensity
Avg. fraction of days with max temp > 86°F over the past 3 years during month of:		
January		
February		
March	284.009	11.513***
	(452.736)	(3.19)
April	-315.572	1.343
	(650.322)	(0.958)
May	-37.298	3.442***
	(126.727)	(0.817)
June	316.408	2.689*
	(167.708)	(1.159)
July	163.446	7.194*
	(458.425)	(3.192)
August	-77.271	1.401
	(173.42)	(1.197)
September	-144.832	3.506***
	(104.131)	(0.726)
October	549.947**	0.517
	(188.301)	(1.304)
November	172.738	-2.54
	(441.93)	(3.039)
December		

Avg. precipitation (in) over the past 3 years during month of:		
January	41.71*	0.221
	(18.66)	(0.128)
February	32.18*	0.373***
	(14.41)	(0.100)
March	-0.241	0.000
	(9.553)	(0.066)
April	-10.403	0.061
	(10.932)	(0.076)
May	7.889	0.095**
	(4.487)	(0.031)
June	-2.721	0.13**
	(6.912)	(0.048)
July	-8.589	0.055
	(6.594)	(0.045)
August	-3.793	0.087
	(6.664)	(0.045)
September	21.575**	0.13**
	(7.069)	(0.049)
October	18.071*	0.237***
	(7.461)	(0.052)
November	20.824**	0.186***
	(7.568)	(0.052)
December	-18.982***	0.039
	(5.716)	(0.04)

Avg. humidity (%) over the past 3 years during month of:		
January	-1.232*	-0.009*
	(0.595)	(0.004)
February	-1.599**	0.02***
	(0.555)	(0.004)
March	2.933***	0.021***
	(0.797)	(0.005)
April	1.867*	0.003
	(0.831)	(0.006)
May	-4.134***	0.045***
	(1.059)	(0.007)
June	0.125	-0.008
	(1.111)	(0.008)
July	4.306***	0.016*
	(0.91)	(0.006)
August	-1.945*	0.004
	(0.859)	(0.006)
September	-0.271	0.012*
	(0.759)	(0.005)
October	-2.19*	0.023***
	(0.99)	(0.007)
November	2.031**	0.016**
	(0.71)	(0.005)
December	3.16***	0.02***
	(0.64)	(0.004)

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