The Effects of Climate Change on Agricultural Groundwater Extraction[1]

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Abstract

This paper analyzes the effects of temperature and precipitation on groundwater extraction for agriculture. For our empirical analysis, we use a unique data set that combines well-level groundwater extraction data with climatic, hydrological, and economic data for Kansas, a state that overlies the High Plains (Ogallala) Aquifer. Our results show that farmers' expectations and decisions may depend in part on recent climate history, and that the effects of contemporaneous temperature and precipitation may be different from the effects of average annual temperature and precipitation over the past 3 years. Annual average temperature and average temperature over the first 4 months of the year (before the crop decision) both have a significant positive total marginal effect on groundwater extraction. In contrast, average annual temperature over the past 3 years has a significant negative total marginal effect. For climate variables based on precipitation, we find that aggregating to an annual level may obscure important within-year effects. Our research provides a better understanding of how temperature and precipitation affect agricultural groundwater extraction, and therefore of the possible implications of climate change for agriculture and groundwater.

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1. Introduction

Many of the world's most productive agricultural basins depend on groundwater and have experienced declines in water table levels (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 Worldwide, about 70 percent of groundwater withdrawn is used in agriculture, and in some countries, the percent of groundwater extracted for irrigation can be as high as 90 percent (National Groundwater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, 2020). 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; Sears and Lin Lawell, 2019).

Climate change has the potential to impact groundwater in several ways. One channel is behavioral: changes in weather and climate may indirectly impact groundwater extraction by causing changes in agricultural land use and changes in agricultural practices that then result in changes in water availability. For example, changes in weather and climate may cause farmers to change the crops they plant; the irrigation technology they use; or, conditional on their crop acreage and irrigation technology decisions, the amount of water they apply -- all of which are changes in farmer behavior and decisions that have implications for groundwater extraction and availability.

A second channel is geophysical: 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 focus on the first, behavioral channel and analyze the effects of temperature and precipitation on groundwater extraction for agriculture. 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 groundwater extracted is used for crop production. The economy of the region is based almost entirely on irrigated agriculture (Lin and Pfeiffer, 2015).

For our empirical analysis, we use a unique data set that combines well-level groundwater extraction data with climatic, hydrological, and economic data for Kansas, a state that overlies a portion of the High Plains Aquifer. Our econometric model of a farmer's irrigation water pumping decision has two components: the intensive margin and the extensive margins. For the intensive margin, we estimate the farmer's water demand conditional on his decisions regarding crop acreage allocation and irrigation technology. We model two extensive margins: crop acreage 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 irrigation technology extensive margin, we estimate the farmer's choice of irrigation technology using discrete response models. In addition to temperature and precipitation, we also control for other factors that may affect groundwater extraction, including hydrological and field characteristics (evapotranspiration, recharge, slope, soil quality, soil moisture, field size, depth to groundwater,[2] saturated thickness[3]), humidity, the quantity authorized for extraction, irrigation technology, crop prices, energy prices, expected future crop prices, expected future energy prices, groundwater extraction by neighbors, grower effects, and a time trend.

We make several contributions to the literature. First, while there have been many studies of the effects of climate change on crop yields and farmland values, we are one of only a few papers that analyze the effects of climate change on agricultural groundwater extraction. We use detailed grower-level panel data on groundwater use, crop choice, crop acreage, and irrigation technology to do so.

Second, our empirical analysis incorporates many of the improvements on statistical and econometric analyses of the effects of climate change that have been suggested in the previous literature, including using high frequency data on climate (Schlenker and Roberts, 2009; Lee and Sumner, 2015); considering multiple crops (Thompson et al., 2017); controlling for soil moisture (Ortiz-Bobea et al., 2019), crop prices (Miao, Khanna and Huang, 2016), and humidity (Zhang, Zhang and Chen, 2017); trying specifications based extreme temperatures instead of mean temperatures (Massetti and Mendelsohn, 2019); not assuming that weather variables can be aggregated over several months (Ortiz-Bobea, 2015; Gammans, Mérel and Ortiz-Bobea, 2017); and considering farmers' expectations (Lemoine, 2017). We also analyze several different specifications for the climate variables.

Our results show that farmers' expectations and decisions may depend in part on recent climate history, and that the effects of annual average temperature may be different from the effects

[2] The depth to groundwater 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).

[3] 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).

of average annual temperature over the past 3 years. For example, we find that annual average temperature and average temperature over the first 4 months of the year (before the crop decision) both have a significant positive total marginal effect on groundwater extraction. In contrast, average annual temperature over the past 3 years has a significant negative total marginal effect.

Our result that the effects of contemporaneous temperature and precipitation may be different from the effects of average annual temperature and precipitation over the past 3 years suggests that farmers may make medium- or long-term decisions based on recent climate history over the past 3 years, and that conditional on the recent climate history over the past 3 years, may then make additional short-run adjustments based on temperature and precipitation before the crop decision and over the current year.

We find that the climate variables influence the demand for water by farmers, crop acreage allocation decisions, and the choice of irrigation technology. Moreover, the extensive and intensive margins can often go in opposite directions.

Our results for temperature tend to be fairly robust across different climate variable specifications and different model specifications. In contrast, our results for precipitation are robust at the monthly level, but generally less robust at the annual level. For climate variables based on precipitation, we find that aggregating to an annual level may obscure important within-year effects of climate and may yield misleading estimates of the effects of climate change.

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 methods in Section 4, our data in Section 5, and our results in Section 6. Section 7 discusses our results and concludes.

2. Previous Literature

2.1. Effects of climate change on agriculture

We build upon the previous literature analyzing the effects of climate change on agriculture.[4] This literature includes a strand which examines the effects of climate change on farmland values and/or agricultural profits (Schlenker, Hanemann and Fisher, 2006; Deschênes and Greenstone, 2007; Wang et al., 2019; Fisher et al., 2012; Deschênes and Greenstone, 2012),

[4] For a more extensive review of the literature on the effects of climate change on agriculture, see Bertone Oehninger, Lin Lawell and Springborn (2020a).

which, taken together, shows that analyses of the effects of climate change on farmland values and/or agricultural profits can be sensitive to the model specification and the data used. Fezzi and Bateman (2015) use a large panel of farm-level data to investigate the potential bias induced by assuming additively separable effects of temperature and precipitation and by using data aggregated across counties or large regions.

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

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

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

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

Another way to improve on statistical and econometric analyses of the effects of climate change on crop yields is to include soil moisture. Using a state-of-the art dataset with very high spatial (14 km) and temporal (1h) resolution and a 31-year panel of corn yields covering 70% of U.S. production, Ortiz-Bobea et al. (2019) finds that corn yield is highly sensitive to soil moisture toward the middle of the season around flowering time, and that models that omit soil moisture overestimate the detrimental effects of temperature.

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

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

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

When analyzing the effects of climate change of agriculture, it is also important to consider farmers' expectations about the future distribution of weather (Lemoine, 2017), and also how farmers will adapt (Kelly, Kolstad and Mitchell, 2005; Moore and Lobell, 2014; Burke and Emerick, 2016; Lemoine, 2019; Bento et al., 2020).

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. Kolstad and Moore (2020) review methods that use historical data on weather, climate, economic activity, and other variables to statistically measure the effect of climate on economic outcomes.

We build upon the previous literature analyzing the effects of climate change on agriculture in several ways. First, while there have been many studies of the effects of climate change on crop yields and farmland values, we are one of only a few papers that analyze the effects of climate change on agricultural groundwater extraction. Second, our empirical analysis incorporates many of the improvements on statistical and econometric analyses of the effects of climate change that have been suggested in this previous literature, including using high frequency data on climate (Schlenker and Roberts, 2009; Lee and Sumner, 2015); considering multiple crops (Thompson et al., 2017); controlling for soil moisture (Ortiz-Bobea et al., 2019), crop prices (Miao, Khanna and Huang, 2016), and humidity (Zhang, Zhang and Chen, 2017); trying specifications based extreme temperatures instead of mean temperatures (Massetti and Mendelsohn, 2019); not assuming that weather variables can be aggregated over several months (Ortiz-Bobea, 2015; Gammans, Mérel and Ortiz-Bobea, 2017); and considering farmers' expectations (Lemoine, 2017). We also analyze several different specifications for the climate variables.

2.2. Agricultural groundwater

We also build upon the previous economics literature on agricultural groundwater.[5] This literature includes papers estimating the demand for irrigation water. Using panel data from a period of water rate reform, Schoengold, Sunding and Moreno (2006) estimate the price elasticity of irrigation water demand. Hendricks and Peterson (2012) estimate irrigation water demand and the elasticity of demand using field-level panel data from Kansas over 16 years and controlling for field-farmer and year fixed effects. Mieno and Brozovic (2017) find evidence of substantial measurement errors in irrigation costs resulting in attenuation and amplification bias in the price

[5] For a discussion of the economics of groundwater, see Sears and Lin Lawell (2019).

elasticity of irrigation water consumption on the intensive margin. Dermyer (2011) develops a water budget model to predict irrigation withdrawals from the High Plains Aquifer based on crop-specific evapotranspiration, and validates the model based on historical data on water use, weather, and land use.

We build in particular on the literature analyzing agricultural groundwater in the High Plains Aquifer. Pfeiffer and Lin (2014a) analyze incentive-based groundwater conservation policies in Kansas and find that measures taken by the state of Kansas to subsidize a shift toward more efficient irrigation systems have not been effective in reducing groundwater extraction. The subsidized shift toward more efficient irrigation systems has in fact increased extraction through a shift in cropping patterns. Better irrigation systems allow more water-intensive crops to be produced at a higher marginal profit. The farmer has an incentive to both increase irrigated acreage and produce more water-intensive crops (Lin, 2013a; Lin, 2013b; Lin, 2013d; Lin Lawell, 2016; Lin and Pfeiffer, 2015; Pfeiffer and Lin, 2009; Pfeiffer and Lin, 2010; Pfeiffer and Lin, 2014a; Pfeiffer and Lin, 2014b; Sears, Lim and Lin Lawell, 2018; Sears et al., 2020).

Li and Zhao (2018) similarly find that water extraction in the High Plains Aquifer region of Kansas moderately increases after adoption of Low Energy Precise Application (LEPA) irrigation technology, and show that this rebound effect is in general higher for farmers with larger water rights. Tsvetanov and Earnhardt (2020) find that the retirement of water rights in High Priority Areas in Kansas substantially reduces groundwater extraction. Carnes (2020) investigates the roles of values, beliefs, and norms in water conservation decisions made by producers on the High Plains Aquifer.

Using data from the High Plains Aquifer, Pfeiffer and Lin (2012) empirically examine whether the amount of water one farmer extracts depends on how much water his neighbor extracts and find that on average, the spatial externality causes over-extraction that accounts for about 2.5 percent of total pumping (Pfeiffer and Lin, 2012; Pfeiffer and Lin, 2015; Lin Lawell, 2016; Sears et al., 2020). Pfeiffer and Lin (2014c) examine if energy prices impact groundwater extraction from the High Plains Aquifer, and find that increasing energy prices would affect crop selection decisions, crop acreage allocation decisions, and the demand for water by farmers (Pfeiffer and Lin, 2014c; Sears et al., 2020).

Bertone Oehninger and Lin Lawell (forthcoming) develop an empirical model to examine whether agricultural groundwater users faced with prior appropriation property rights to groundwater in western Kansas exhibit dynamic, forward-looking behavior consistent with dynamic management. They find that although farmers are allotted a time-invariant maximum amount of groundwater that they can extract each year, they still behave in a manner consistent with dynamic management.

We also build on the literature analyzing the effects of climate change on water use for agriculture (Mieno and Brozovic, 2013; Mukherjee and Schwabe, 2015; Olen, Wu, and Langpap, 2016; Ponce et al., 2016). For a detailed review of the empirical literature on climate change adaptation and water resource management, see Olmstead (2014).

3. The High Plains Aquifer in Kansas

The High Plains Aquifer (also known as the Ogallala Aquifer) is the principal source of groundwater in the Great Plains region of the United States. Exploitation of the High Plains Aquifer began in the late 1800s but was greatly intensified after the "Dust Bowl" decade of the 1930s (Miller and Appel, 1997). Accounting 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).

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).

In Kansas, planting decisions for corn tend to be made by around April; planting decisions for alfafa, sorghum, and soybeans tend to be made by around May; and planting decisions for winter wheat tend to be made by around October (Bertone Oehninger, Lin Lawell and Springborn, 2020b). Thus, the weather in the first four months of the year are likely to be part of the information set of the farmer when he makes his decisions about crop acreage, whether to plant multiple crops, and agricultural water use for that year.

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. In 2013, three times more water was pumped from the High Plains Aquifer in Kansas than the estimated natural recharge rate (Buchanan et al., 2015). Due to the importance of irrigated agriculture to the multi-state region, the imbalance in water use threatens long-term economic stability (Dermyer, 2011). The Kansas Water Office and Kansas Department of Agriculture warn that if the current high rates of groundwater extraction continue, 70% of High Plains Aquifer in Kansas will be depleted within 50 years (Kansas Water Office and Kansas Department of Agriculture, 2015). 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. Methods

4.1. Climate variable specifications

In this paper, we analyze the effects of temperature and precipitation on groundwater extraction for agriculture. In particular, we create "climate variables" that are calculated from data on temperature and precipitation. We consider several specifications of the climate variables C_{it} faced by each farmer i in each time period t. These climate specifications are summarized in Table 1. Each specification includes different climate variables that are calculated from which are calculated from weather variables (temperature, precipitation, and humidity), and also includes squared values of the relevant temperature and precipitation variables.

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

Since farmers' expectations and decisions may depend in part on recent climate history, we also try a specification that also include as climate variables averages of weather variables over the past 3 years. Thus, in specification Y2, the climate variables C_{it} are annual average temperature, average annual temperature over the past 3 years, annual precipitation, total precipitation over the past 3 years, and annual average humidity.

It is possible that what matters most in terms of temperature is not annual average temperature, but the fraction of days in the year and over the summer with maximum temperature above a threshold value. We choose 86 degrees Fahrenheit (°F), which is equivalent to 30 degrees Celsius, as our threshold, following the previous literature showing temperatures above 30 degrees Celsius to be very harmful to crop yields (Schlenker and Roberts, 2009). In specification Y3, the climate variables C_{it} therefore are annual fraction of days with maximum temperature greater than 86 degrees Fahrenheit (°F), summer fraction of days with maximum temperature greater than 86°F, annual precipitation, and annual average humidity.

In Kansas, planting decisions for corn tend to be made by around April; planting decisions for alfafa, sorghum, and soybeans tend to be made by around May, and planting decisions for winter wheat tend to be made by around October (Bertone Oehninger, Lin Lawell and Springborn, 2020b). Thus, the weather in the first four months of the year are likely to be part of the information set of the farmer when he makes his decisions about crop acreage, whether to plant multiple crops, and agricultural water use for that year.

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

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

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

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

4.2. Groundwater extraction

Building on previous empirical models of water demand (Schoengold, Sunding and Moreno, 2006; Hendricks and Peterson, 2012), our fixed effects regression model for groundwater extraction is given by:

$$w_{it} = h(C_{it}, n_{it}, x_{it}, \alpha_i, t), \tag{1}$$

where w_{it} is the amount of water extracted by farmer *i* in year *t*; C_{it} are the climate variables, which are calculated from weather variables (temperature, precipitation, and humidity); $n_{it} = \{n_{ict}, n_{ict}^2 \mid c \in \{alfalfa,\ corn,\ sorghum,\ soybeans,\ wheat\}\}$ are the crop acreage variables, including the number of acres n_{ict} planted to each crop *c* and the number of acres planted to each crop squared; x_{it} are the controls, including hydrological and field characteristics (evapotranspiration, recharge, slope, soil quality, soil moisture, field size, depth to groundwater, saturated thickness), the quantity authorized for extraction, irrigation technology, crop prices (alfalfa price, corn price, sorghum price, soybean price, and wheat price) from the previous year,[6] energy prices (diesel price, electricity price, and natural gas price), expected future crop prices (10-year projections for corn price, sorghum price, soybean price, and wheat price), expected future energy prices (10-year projections for diesel price, electricity price, and natural gas price), and groundwater extraction by neighbors (lagged extraction by neighbors, and lagged quantity authorized for extraction by neighbors); α_i are grower fixed effects; and t is a time trend.

The grower fixed effects α_i control for unobservable grower characteristics such the number years of experience in farming. The time trend t controls for unobservable trends that affect all fields over time. We are unable to include year fixed effects because some ofour controls, including crop prices, expected future crop prices, and expected future energy prices, are common to all fields in a given year. We use robust standard errors.

We use water extraction intensity (in acre-feet of water per acre) as our dependent variable w_{it}. In an alternative specification, we use water extraction (in acre-feet) instead of water extraction intensity (in acre-feet of water per acre) as our dependent variable.

We try an instrumental variable (IV) fixed effects specification in we use the lagged quantity authorized for extraction by neighbors as an instrument for neighbors' lagged extraction instead of as a dynamic variable, to address the potential endogeneity of neighbors' lagged extraction. We also try using the current year's crop prices instead of the previous year's crop prices as controls, and then instrumenting for the current year's crop prices using the previous year's crop prices to address the endogeneity of current-year crop prices. We also try an instrumental variable (IV) fixed effects specification in which we instrument for the current year's

[6] We use previous-year crop prices instead of current-year crop prices for three reasons. First, crop prices at the end of the current season are endogenous to groundwater extraction decisions made during the season. Second, since this year's crop prices are not known for certainty until the end of the season, we assume farmers' best guess for this year's crop prices is last year's crop prices. Third, Bertone Oehninger and Lin Lawell (forthcoming) find that using current-year crop prices instead of previous-year crop prices yields the wrong sign on crop prices: the significant coefficients on crop prices are negative instead of positive. Our results for the climate variables are robust to whether we use current-year crop prices or previous-year crop prices. We also try using the current year's crop prices instead of the previous year's crop prices as controls, and then instrumenting for the current year's crop prices using the previous year's crop prices as instrumental varaibles to address the endogeneity of current-year crop prices. Our results for the climate variables are robust to whether we use current-year crop prices (instrumented for by previous-year crop prices) or previous-year crop prices as our controls for crop prices.

crop acreage using the previous year's crop acreage to address the endogeneity of current-year crop acreage.

The climate variable C_{it}, which are calculated from weather variables (temperature, precipitation, and humidity), are exogenous to a farmer's water demand decision. Conditional on the many covariates we control for, including the plot-level variables x_{it}, expected future crop prices, expected future energy prices, and lagged groundwater extraction by neighbors are exogenous to the farmer's water demand decisions. Expected future crop prices and expected future energy prices are exogenous to an individual farmer's current water pumping decision because one single farmer's water pumping decision is unlikely to affect expected future crop prices or expected future energy prices, particularly those 10 years later. We mitigate concerns about endogeneity of groundwater extraction by neighbors by using their lagged values. The quantity authorized for extraction by neighbors within a 1-mile radius at time $t-1$ is exogenous to a farmer's water demand decisions because it is pre-determined. As mentioned above, we also try an instrumental variable (IV) fixed effects specification in we use the lagged quantity authorized for extraction by neighbors as an instrument for neighbors' lagged extraction to address the potential endogeneity of neighbors' lagged extraction.

4.3. Total marginal effect: Crop acreage

We also estimate an econometric model of a farmer's irrigation water pumping decision that accounts for the extensive margin in addition to the intensive margin. The intensive margin of the groundwater extraction decision is the farmer's groundwater extraction holding crop acreage constant, as given by our empirical model for groundwater extraction in equation (1) above.

The 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 left-censored at zero, we estimate the acreage n_{ict} allocated to each crop *c* by each farmer *i* in each time period *t* using the following set of random effects tobit regressions:

$$n_{ict} = g(C_{it}, x_{it}, z_{it-1}, \alpha_i, t),\ c = \textit{alfalfa, corn, sorghum, soybeans, wheat}, \qquad (2)$$

where n_{ict} is the number of acres planted to crop *c*; C_{it} are the climate variables, which are calculated from weather variables (temperature, precipitation, and humidity); x_{it} are the controls, including hydrological and field characteristics (evapotranspiration, recharge, slope, soil quality, soil moisture, field size,[7] depth to groundwater, saturated thickness), the quantity authorized for extraction, irrigation technology, crop prices (alfalfa price, corn price, sorghum price, soybean price, and wheat price) from the previous year,[8] energy prices (diesel price, electricity price, and natural gas price), expected future crop prices (10-year projections for corn price, sorghum price, soybean price, and wheat price), expected future energy prices (10-year projections for diesel price, electricity price, and natural gas price), and groundwater extraction by neighbors (lagged extraction by neighbors, and lagged quantity authorized for extraction by neighbors); z_{it-1} is a vector of lagged dummy variables for each crop (alfalfa, corn, sorghum, soybeans, and wheat), indicating if that crop was planted in the previous season to account for crop rotation patterns (Hendricks, Smith and Sumner, 2014); α_i are grower random effects; and *t* is a time trend.

The climate variables C_{it}, which are calculated from weather variables (temperature, precipitation, and humidity), are exogenous to a farmer's crop acreage decisions. Conditional on the many covariates we control for, including the plot-level variables x_{it}, expected future crop prices, expected future energy prices, and groundwater extraction by neighbors are exogenous to the farmer's crop acreage decisions. Expected future crop prices and expected future energy prices are exogenous to an individual farmer's current crop acreage decisions because one single farmer's crop acreage decisions are unlikely to affect expected future crop prices or expected future energy prices, particularly those 10 years later. We mitigate concerns about endogeneity of groundwater extraction by neighbors by using their lagged values. The quantity authorized for extraction by neighbors within a 1-mile radius at time $t-1$ is exogenous to a farmer's crop acreage decisions because it is pre-determined.

Following the empirical models of total marginal effects in Moore, Gollehon and Carey, (1994), Pfeiffer and Lin (2014c) and Bertone and Lin Lawell (forthcoming), we calculate the total marginal effect of each of the *j* climate variables C_{jit} in accounting for the crop acreage extensive margin and the intensive margin as the sum of the effect along the intensive margin from the

[7] All else equal, we expect the acres allocated to the chosen crop to be greater when the field size is greater. We use crop acreage rather than fraction of field planted to the crop as our dependent variable since our groundwater extraction regressions model groundwater extraction conditional on crop acreage, and since doing so best enables us to calculate and interpret the intensive and extensive margins and total marginal effect.

[8] We use previous-year crop prices instead of current-year crop prices for two reasons. First, crop prices at the end of the current season are endogenous to crop acreage decisions made at the beginning of the season. Second, since crop prices are not known for certainty until the end of the season, we assume farmers' best guess for this year's crop prices is last year's crop prices.

groundwater extraction model in equation (1) and the effects along the extensive margin from the crop acreage allocation models in equation (2):[9]

$$\frac{dw}{dC_j} = \frac{\partial w}{\partial C_j} + \sum_c \frac{\partial w}{\partial n_c}\frac{\partial n_c}{\partial C_j}. \tag{3}$$

We calculate the standard errors for the total intensive margin, the total extensive margins, and the total marginal effects using the Delta Method (DeGroot, 1986).

4.4. Total marginal effect: Crop acreage and irrigation technology

In addition to the crop acreage extensive margin, a second extensive 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 random effects probit regression for center pivot sprinkler use:

$$\Pr(I_{it}^{sprink} = 1) = \Phi(C_{it}, n_{it}, x_{it}, \alpha_i, t), \tag{4}$$

where I_{it}^{sprink} is a dummy variable for center pivot sprinkler use by farmer *i* in year *t*; C_{it} are the climate variables, which are calculated from weather variables (temperature, precipitation, and humidity); $n_{it} = \{n_{ict}, n_{ict}^2 \mid c \in \{alfalfa, corn, sorghum, soybeans, wheat\}\}$ are the crop acreage variables, including the number of acres n_{ict} planted to each crop *c* and the number of acres planted to each crop squared; x_{it} are the controls, including hydrological and field characteristics (evapotranspiration, recharge, slope, soil quality, soil moisture, field size, depth to groundwater, saturated thickness), the quantity authorized for extraction, crop prices (alfalfa price, corn price, sorghum price, soybean price, and wheat price), energy prices (diesel price, electricity price, and natural gas price), expected future crop prices (10-year projections for corn price, sorghum price, soybean price, and wheat price), expected future energy prices (10-year projections for diesel price, electricity price, and natural gas price), and groundwater extraction by neighbors (lagged extraction by neighbors, and lagged quantity authorized for extraction by neighbors); α_i are grower random effects; and *t* is a time trend.

[9] 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.

We run a similar random effects probit regression of center pivot sprinkler with drop nozzles use:

$$\Pr(I_{it}^{nozzle} = 1) = \Phi(C_{it}, n_{it}, x_{it}, \alpha_i, t), \tag{5}$$

where I_{it}^{nozzle} is a dummy variable for center pivot sprinkler with drop nozzle use by farmer *i* in year *t*; C_{it} are the climate variables, which are calculated from weather variables (temperature, precipitation, and humidity); $n_{it} = \{n_{ict}, n_{ict}^{\;2} \mid c \in \{alfalfa,\ corn,\ sorghum,\ soybeans,\ wheat\}\}$ are the crop acreage variables, including the number of acres n_{ict} planted to each crop *c* and the number of acres planted to each crop squared; x_{it} are the controls, including hydrological and field characteristics (evapotranspiration, recharge, slope, soil quality, soil moisture, field size, depth to groundwater, saturated thickness), the quantity authorized for extraction, crop prices (alfalfa price, corn price, sorghum price, soybean price, and wheat price), energy prices (diesel price, electricity price, and natural gas price), expected future crop prices (10-year projections for corn price, sorghum price, soybean price, and wheat price), expected future energy prices (10-year projections for diesel price, electricity price, and natural gas price), and groundwater extraction by neighbors (lagged extraction by neighbors, and lagged quantity authorized for extraction by neighbors); α_i are grower random effects; and *t* is a time trend.

The climate variables C_{it}, which are calculated from weather variables (temperature, precipitation, and humidity), are exogenous to a farmer's choice of irrigation technology. Conditional on the many covariates we control for, including the plot-level variables x_{it}, expected future crop prices, expected future energy prices, and groundwater extraction by neighbors are exogenous to the farmer's choice of irrigation technology. Expected future crop prices and expected future energy prices are exogenous to an individual farmer's current choice of irrigation technology because one single farmer's choice of irrigation technology is unlikely to affect expected future crop prices or expected future energy prices, particularly those 10 years later. We mitigate concerns about endogeneity of groundwater extraction by neighbors by using their lagged values. The quantity authorized for extraction by neighbors within a 1-mile radius at time $t-1$ is exogenous to a farmer's choice of irrigation technology because it is pre-determined.

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

$$\begin{aligned}\frac{dw}{dC_j} &= \frac{d\,\Pr(I_{it}^{sprink}=1)}{dC_j}E[w\,|\,I_{it}^{sprink}=1]+\Pr(I_{it}^{sprink}=1)\frac{dE[w\,|\,I_{it}^{sprink}=1]}{dC_j}\\ &+\frac{d\,\Pr(I_{it}^{nozzle}=1)}{dC_j}E[w\,|\,I_{it}^{nozzle}=1]+\Pr(I_{it}^{nozzle}=1)\frac{dE[w\,|\,I_{it}^{nozzle}=1]}{dC_j}\\ &-\left(\frac{d\,\Pr(I_{it}^{sprink}=1)}{dC_j}+\frac{d\,\Pr(I_{it}^{nozzle}=1)}{dC_j}\right)E[w\,|\,I_{it}^{sprink}=0,I_{it}^{nozzle}=0]\\ &+\left(1-\Pr(I_{it}^{sprink}=1)-\Pr(I_{it}^{nozzle}=1)\right)\frac{dE[w\,|\,I_{it}^{sprink}=0,I_{it}^{nozzle}=0]}{dC_j}\end{aligned}, \tag{6}$$

where $\frac{d\,\Pr(I_{it}^{sprink}=1)}{dC_j}$ is the marginal effect from the probit center pivot sprinkler use regression in equation (4); $E[w\,|\,I_{it}^{sprink}=1]$ 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; $\frac{dE[w\,|\,I_{it}^{sprink}=1]}{dC_j}$ is the total marginal effect calculated in equation (5) conditional on using a center pivot sprinkler irrigation system; $\frac{d\,\Pr(I_{it}^{nozzle}=1)}{dC_j}$ is the marginal effect from the probit center pivot sprinkler with drop nozzles use regression in equation (5); $E[w\,|\,I_{it}^{nozzle}=1]$ 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; $\frac{dE[w\,|\,I_{it}^{nozzle}=1]}{dC_j}$ is the total marginal effect calculated in equation (3) conditional on using a center pivot sprinkler with drop nozzles irrigation system; $E[w\,|\,I_{it}^{sprink}=0,I_{it}^{nozzle}=0]$ 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 $\frac{dE[w \mid I_{it}^{sprink}=0, I_{it}^{nozzle}=0]}{dC_j}$ is the total marginal effect calculated in equation (3) conditional on not using either a center pivot sprinkler irrigation system or a center pivot sprinkler with drop nozzles irrigation system.

We calculate the standard errors for the total intensive margin, the total extensive margins, and the total marginal effects using the Delta Method (DeGroot, 1986).

5. Data

For our empirical analysis, we have constructed a detailed panel data set of annual data for over 29,000 groundwater-irrigated fields in western Kansas from 1996 to 2012. 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), which spanned 10 years between 1996 and 2005, and have extended the data set to cover the years 1996 to 2012.

Groundwater extraction data at the "point of diversion" level (usually a single well that irrigates a single field) was collected from the Water Information Management and Analysis System (WIMAS), which is maintained by the Kansas Department of Agriculture, Division of Water Resources. The data set includes spatially referenced pumping data at the source (well or pump) level on water rights, water extraction, crop choice, field characteristics, and irrigation technology for all irrigation wells in Kansas. Although there may be more than one point of diversion on what a producer considers a "field", we assume for the analysis, following Pfeiffer and Lin (2014a) and Pfeiffer and Lin (2014c), that one point of diversion irrigates one field. We use only those grower-year observations for which the grower was authorized to extract a positive amount of water that year. 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 A1 in the Appendix presents the location of all the points of diversion we use in our data set.

Weather data for calculating our climate variables, 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 the National Weather Service and Cooperative Observer Network. Our weather data set includes weather data from 13 stations in western Kansas. The furthest the closest weather station is to any field is 93.65 miles. For each field, for each climate variable, we calculate a weighted average using all the stations within 93.65 miles (the furthest the closest weather station is to any field) of that field so that the data from each station within 93.65 miles of that field is weighted inversely proportional to its distance to the field. In particular, each of the j climate variables C_{jit} for grower $\underline{i}$ at time t is calculated as the following inverse-distance weighted average of the values of climate variable C_{jkt} at weather station k:

$$C_{jit} = \frac{\sum_{k=1}^{K} C_{jkt} \frac{I\{d_{ik} \le \bar{d}\}}{d_{ik}}}{\sum_{k=1}^{K} \frac{I\{d_{ik} \le \bar{d}\}}{d_{ik}}}, \tag{7}$$

where $K = 13$ is the number of weather stations in western Kansas in our data set; d_{ik} is the distance (in miles) between field i and weather station k; $\bar{d} = 93.65$ is furthest the closest weather station is to any field (in miles); and $I\{d_{ik} \le \bar{d}\}$ is an indicator variable for weather station k being within $\bar{d} = 93.65$ miles (the furthest the closest weather station is to any field) of field i.[10]

For soil quality, we use the irrigated capability class, which is a dummy variable equal to 1 if the soil is classified as the best soil for irrigated agriculture with few characteristics that would limit its use, and zero otherwise.

Following the work of Ortiz-Bobea et al. (2019), we control for soil moisture. Soil moisture data on the soil moisture content in the 0-10 cm layer was obtained from NASA's NLDAS-2 (North American Land Data Assimilation System), the same source used by Ortiz-Bobea et al. (2019). Figure A2 in the Appendix plots the soil moisture content (measured in kg/m2) 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.

[10] An alternative to inverse distance weighting is to averaging each climate variable over all the stations within 93.65 miles (the furthest the closest weather station is to any field) of that field. We find that the climate variables calculated by these two methods are highly correlated: the correlation between the climate variables obtained from inverse distance weighting and from averaging over the close stations is over 0.971 for all climate variables except for the average monthly fraction of days with maximum temperature exceeding 86°F during the months of January, February, and March, for which the correlations are all over 0.927. Thus, averaging instead of using inverse distance weighting for the climate variables is unlikely to change our results by much.

Crop prices for alfalfa and sorghum are from the USDA – ERS Feed Grains Database. For alfalfa price, we use the yearly average price for "alfalfa hay" received by farmers, averaged from May one year to April the following year. For sorghum price, we use the cash prices for "No. 2 yellow, Kansas City, MO" at principal markets, averaged over January to March.

Crop prices for corn, soybeans, and wheat are from quandl.com. For corn price, we use the average of daily corn future prices, averaged over January to March, for a contract that expires in September. For soybean price, we use the average of daily soybean future prices, averaged over January to March, for a contract that expires in September. For wheat price, we use the average of daily wheat future prices, averaged over January to March, for a contract that expires in September.

Energy prices are from the Energy Information Administration (EIA) for Kansas. For diesel price, we use the annual price of diesel for the Midwest. For electricity price, we use the annual price of commercial electricity for Kansas. For natural gas price, we use the annual price of commercial natural gas for Kansas.

We obtain 10-year projections for future crop prices for corn, sorghum, soybeans, and wheat from the USDA Economics, Statistics and Market Information System (ESMIS). We obtain 10-year projections for future energy prices for natural gas, electricity, and diesel from the Energy Information Administration (EIA) Annual Energy Outlook. Bertone Oehninger and Lin Lawell (forthcoming) find that results are robustness to whether we use 10-year projections, 9-year projections, 8-year projections, or 7-year projections.

We construct two variables related to a farmer's neighbors. One variable is the quantity of water extracted by neighbors within a 1-mile radius at time $t-1$, summed over all neighbors within a 1-mile radius at time $t-1$. The second variable is the quantity authorized for extraction by neighbors within a 1-mile radius at time $t-1$, summed over all neighbors within a 1-mile radius at time $t-1$.[11]

Summary statistics for the decision variables, annual climate variables, monthly climate variables, and control variables are presented in Tables A1a, A1b, A1c, and A1d, respectively, in

[11] We include extraction by neighbors and the quantity authorized for extraction by neighbors instead of the groundwater stock of neighbors (for example, as proxied by the depth to groundwater of neighbors) in our empirical model since previous extraction by neighbors and the quantity authorized for extraction by neighbors are more likely to be observable to a farmer than is the neighbors' groundwater stock. In previous empirical work on spatial externalities, Pfeiffer and Lin (2012) similarly examine the effects of extraction by neighbors rather than the effects of neighbors' groundwater stock.

the Appendix. As seen in Table A1a in the Appendix, corn accounts for most of the crop acreage on average. Center pivot sprinklers are used in 36% of the grower-year observations, and center pivot with drop nozzles are used in 31% of the grower-year observations.

6. Results

6.1. Groundwater extraction

Table A2 in the Appendix presents the results of our base-case fixed effects (FE) regressions for groundwater extraction for each of our annual climate variable specifications. At the bottom of the table, we present the total intensive margin for each the climate variables in each annual climate variable specification, which we calculate as the total average effect of the climate variable on groundwater extraction evaluated at the mean values of the respective climate variable in the data.

For robustness, Table 2 compares the total intensive margin (total average effects) of the climate variables from our base-case specification in Table A2 in the Appendix to the total intensive margin (total average effects) of the climate variables from two alternative specifications of the groundwater fixed effects regressions for each annual climate variable specification. In Specification (Alt-A), we use water extraction (in acre-feet) instead of water extraction intensity (in acre-feet of water per acre) as our measure of groundwater extraction for the dependent variable. In Specification (Alt-B), we use current-year crop prices instead of previous-year crop prices as controls.

For additional robustness, Table 3 presents the total intensive margin (total average effects) of several instrumental variable (IV) fixed effects (IV-FE) regressions of groundwater extraction. In instrumental variable (IV) fixed effects (IV-FE) Specification (Alt-C), we use the lagged quantity authorized for extraction by neighbors as an instrument for neighbors' lagged extraction instead of as a control, to address the potential endogeneity of neighbors' lagged extraction. In instrumental variable (IV) fixed effects (IV-FE) Specification (Alt-D), we use the lagged quantity authorized for extraction by neighbors as an instrument for neighbors' lagged extraction instead of as a control, to address the potential endogeneity of neighbors' lagged extraction; and we use the current year's crop prices instead of the previous year's crop prices as controls. In instrumental variable fixed effects (IV-FE) Specification (Alt-E), we use the current year's crop prices instead of the previous year's crop prices as controls, and then instrument for the current year's crop prices using the previous year's crop prices to address the endogeneity of current-year crop prices. In instrumental variable (IV) fixed effects (IV-FE) Specification (Alt-F), we use the lagged quantity authorized for extraction by neighbors as an instrument for neighbors' lagged extraction instead of as a control, to address the potential endogeneity of neighbors' lagged extraction; and we use the current year's crop prices instead of the previous year's crop prices as controls, and then instrument for the current year's crop prices using the previous year's crop prices to address the endogeneity of current-year crop prices. In instrumental variable (IV) fixed effects (IV-FE) Specification (Alt-G), we use the lagged crop acreage and lagged crop acreage squared as instruments for crop acreage and crop acreage squared, to address the potential endogeneity of crop acreage.

The results for annual climate variables based on temperature are robust across the different base-case and alternative specifications in Tables 2 and 3, while the results for annual climate variables based on precipitation are generally less robust.

In particular, across the different specifications in Tables 2 and 3, we find the following robust results for the total intensive margin. In terms of climate variables based on temperature, we find that annual temperature has positive total intensive margin that is significant when the specification also additionally controls for average annual temperature over the past 3 years (Specifications Y1 and Y2). Similarly, average temperature over the first 4 months of the year (before the crop decision) has a significant positive total intensive margin (Specification Y4). In contrast, average annual temperature over the past 3 years has a significant negative total intensive margin (Specifications Y2, Y4, and Y5).

The annual fraction of days with maximum temperature exceeding 86 degrees Fahrenheit has a significant negative total intensive margin (Specification Y3). Similarly, the annual fraction of days in the first 4 months of the year (before the crop decision) with maximum temperature exceeding 86 degrees Fahrenheit has a significant negative total intensive margin (Specification Y5). In contrast, the fraction of days in the summer with maximum temperature exceeding 86 degrees Fahrenheit has a significant positive total intensive margin (Specification Y3).

In terms of climate variables based on precipitation, the only somewhat robust result is that total precipitation over the past 3 years has a negative total intensive margin that is sometimes significant (Specifications Y2, Y4, and Y5). For the other climate variables based on precipitation (annual precipitation, precipitation in the first 4 months of the year (before the crop decision)), neither the sign nor the significance of the total intensive margin is robust across the different specifications in Tables 2 and 3.

As seen in Table A2 in the Appendix, the results of our base-case fixed effects (FE) show that the coefficients on humidity, crop acreage, and irrigation technology variables are robust across the different annual climate specifications. As expected, the use of a center pivot sprinkler rather than a center pivot sprinkler with drop nozzles is associated with a higher groundwater extraction intensity conditional on crop acreage; dropped nozzle packages (also called low-pressure nozzles or low energy precision application (LEPA)) are attached to center pivots and suspend the sprinkler heads between about 2 feet above the ground to just above the canopy of the crop, increase the efficiency of water applied to the field by decreasing the amount lost to evaporation and drift, especially in hot and windy climates, and require less pump pressure to operate (New and Fipps, 1990; Pfeiffer and Lin, 2014a).

6.2. Total marginal effect: Crop acreage

Tables A3a-A3e in the Appendix present the results of our base-case random effects tobit regressions of crop acreage allocated to alfalfa, corn, sorghum, soybeans, and wheat, respectively, for each of our annual climate variable specifications in Bertone Oehninger, Lin Lawell and Springborn (2020b). Results show that each of the climate variables has a statistically significant effect on crop acreage decisions for at least one crop.

Table 4 presents the total intensive margin $\left(\frac{\partial w}{\partial C_j}\right)$, total extensive margin $\left(\sum_c \frac{\partial w}{\partial n_c}\frac{\partial n_c}{\partial C_j}\right)$, and the total marginal effect $\left(\frac{dw}{dC_j}=\frac{\partial w}{\partial C_j}+\sum_c \frac{\partial w}{\partial n_c}\frac{\partial n_c}{\partial C_j}\right)$ of each climate variable in each annual climate variable specification, as calculated using the groundwater extraction regression results from Table A2 in the Appendix, and the crop acreage regressions results in Tables A3a-A3e in the Appendix. Groundwater extraction w is extraction intensity in acre-feet per acre. For each crop c, the number of acres n_c planted to crop c is in acres and is evaluated at its mean value in the data.

In terms of climate variables based on temperature, we find that the total intensive margin and the total crop acreage extensive margin can go in opposite directions, and, when they do, the total intensive margin dominates and the sign of the total marginal effect is the sign of the total intensive margin. For the annual average temperature over the past 3 years, the total intensive margin is significant and negative, but the total crop acreage extensive margin is significant and positive; the total marginal effect is significant and negative (Specifications Y2, Y4, and Y5). Similarly, the annual fraction of days in the first 4 months of the year (before the crop decision) with maximum temperature exceeding 86 degrees Fahrenheit has a significant negative total intensive margin but a significant positive total crop acreage extensive margin; the total marginal effect is significant and negative (Specification Y5). Likewise, the fraction of days in the summer with maximum temperature exceeding 86 degrees Fahrenheit has a significant positive total intensive margin and a significant negative total crop acreage extensive margin; the total marginal effect is significant and positive (Specification Y3).

For the one climate variable based on precipitation whose total intensive margin is robust across the different specifications in Tables 2 and 3 -- total precipitation over the past 3 years -- we also find that the total intensive margin and the total crop acreage extensive margin go in opposite directions. Total precipitation over the past 3 years has a negative total intensive margin that can be significant across the different specifications in Tables 2 and 3, but a positive total crop acreage extensive margin that can be significant across the different annual climate variable specifications in Table 4; the total marginal effect is not significant at a 5% level (Specifications Y2, Y4, and Y5).

In terms of total marginal effect of the climate variables based on temperature, we find that annual average temperature has a significant positive total marginal effect (Specifications Y1 and Y2). Similarly, average temperature over the first 4 months of the year (before the crop decision) has a significant positive total marginal effect (Specification Y4). In contrast, average annual temperature over the past 3 years has a significant negative total marginal effect (Specifications Y2, Y4, and Y5).

The annual fraction of days with maximum temperature exceeding 86 degrees Fahrenheit has a significant negative total marginal effect (Specification Y3). Similarly, the annual fraction of days in the first 4 months of the year (before the crop decision) with maximum temperature exceeding 86 degrees Fahrenheit has a significant negative total marginal effect (Specification Y5). In contrast, the fraction of days in the summer with maximum temperature exceeding 86 degrees Fahrenheit has a significant positive total marginal effect (Specification Y3).

6.3. Monthly climate variables

Table A4 in the Appendix presents the results of our base-case fixed effects (FE) regressions for groundwater extraction for both of our monthly climate variable specifications.

For robustness, Figures A3-A4 in the Appendix present the total intensive margin (total average effects) of the monthly climate variables from our base-case groundwater fixed effects regressions, as well as from two alternative specifications of the groundwater fixed effects regressions, for each monthly climate variable specification. In one alternative specification, we use water extraction (in acre-feet) instead of water extraction intensity (in acre-feet of water per acre) as our measure of groundwater extraction for the dependent variable. In another alternative specification, we use current-year crop prices instead of previous-year crop prices as controls.

As seen in Figures A3a-A3b in the Appendix, the total intensive margin of the monthly climate variables in the monthly climate variable specification M1 are robust to whether the dependent variable is water extraction (in acre-feet) instead of water extraction intensity (in acre-feet of water per acre), and whether the crop prices are the current-year crop prices or the previous-year crop prices.

Similarly, as seen in Figures A4a-A4b in the Appendix, the total intensive margin of the monthly climate variables in the monthly climate variable specification M2 are robust to whether the dependent variable is water extraction (in acre-feet) instead of water extraction intensity (in acre-feet of water per acre), and whether the crop prices are the current-year crop prices or the previous-year crop prices.

The total intensive margin, total crop acreage extensive margin, and total marginal effect of average monthly temperature over the past 3 years in monthly climate variable specification M1 is presented in Figure 1a. Average monthly temperature over the past 3 years has a significant positive total intensive margin for the months of April, August, and November; and a significant negative total intensive margin for the month of June. In terms of the total crop acreage extensive margin, average monthly temperature over the past 3 years for the month of May has a significant positive total crop acreage extensive margin. The total marginal effect of average monthly temperature over the past 3 years is significant and positive for the months of August and November; and significant and negative for the month of June.

The total intensive margin, total crop acreage extensive margin, and total marginal effect of average monthly precipitation over the past 3 years in monthly climate variable specification

M1 is presented in Figure 1b. Average monthly precipitation over the past 3 years has a significant positive total intensive margin for the months of June, September, and November; and a significant negative total intensive margin for the months of March, April, and July. In terms of the total crop acreage extensive margin, average monthly precipitation over the past 3 years has a significant negative total crop acreage extensive margin for the months of September and October. The total marginal effect of average monthly precipitation over the past 3 years is significant and positive for the months of June, September, and November; and significant and negative for the months of March, April, and July.

The total intensive margin, total crop acreage extensive margin, and total marginal effect of average monthly fraction of days with maximum temperature over 86 degrees Fahrenheit over the past 3 years in monthly climate variable specification M2 is presented in Figure 2a. Average monthly fraction of days with maximum temperature over 86 degrees Fahrenheit over the past 3 years has a significant positive total intensive margin for the month of March; and a significant negative total intensive margin for the month of July. In terms of the total crop acreage extensive margin, average monthly fraction of days with maximum temperature over 86 degrees Fahrenheit over the past 3 years for the month of November has a significant positive total crop acreage extensive margin. The total marginal effect of average monthly fraction of days with maximum temperature over 86 degrees Fahrenheit over the past 3 years is significant and positive for the month of March; and significant and negative for the month of July.

The total intensive margin, total crop acreage extensive margin, and total marginal effect of average monthly precipitation over the past 3 years in monthly climate variable specification M2 is presented in Figure 2b. Average monthly precipitation over the past 3 years has a significant positive total intensive margin for the months of February, June, and August; and a significant negative total intensive margin for the months of March and October. In terms of the total crop acreage extensive margin, average monthly precipitation over the past 3 years does not have a total crop acreage extensive margin that is significant at a 5% level for any month. The total marginal effect of average monthly precipitation over the past 3 years is significant and positive for the months of February, June, and August; and significant and negative for the months of March and October.

The robust results for average monthly precipitation over the past 3 years across the 2 monthly climate specifications in Figures 1b and 2b are the following. Average monthly precipitation over the past 3 years has a robust significant negative total intensive margin and total marginal effect for the month of March; and a robust significant positive total intensive margin and total marginal effect for the month of June. Thus, higher average precipitation over the past 3 years in March, prior to the crop acreage decision and prior to the beginning of the crop season, leads the grower to use less groundwater conditional on crop acreage and less groundwater overall. In contrast, higher average precipitation over the past 3 years in June, during the crop season, leads the grower to use more groundwater conditional on crop acreage and more groundwater overall.

6.4. Total marginal effect: Crop acreage and irrigation technology

Tables A5a and A5b in the Appendix present the results of our base-case random effects probit regressions of center pivot sprinkler use and center pivot sprinkler with dropped nozzles use, respectively, for each of our annual climate variable specifications.

Table A6 in the Appendix presents the total marginal effect $\left(\frac{dw}{dC_j} = \frac{\partial w}{\partial C_j} + \sum_c \frac{\partial w}{\partial n_c}\frac{\partial n_c}{\partial C_j}\right)$ and the total marginal effect including the irrigation technology extensive margin of each climate variable in each annual climate variable specification, as calculated using the groundwater extraction regression results from Table A2, the crop acreage regressions results in Tables A3a-A3e in the Appendix, and the random effects probit regressions of irrigation technology in Tables A5a-A5b in the Appendix. Groundwater extraction w is extraction intensity in acre-feet per acre. For each crop c, the number of acres n_c planted to crop c is in acres and is evaluated at its mean value in the data. Similarly, for each irrigation system, water use conditional on irrigation system is evaluated at its mean value in the data. While the signs of the total marginal effects are robust to whether the irrigation technology extensive margin is also included, and while the magnitudes of the total marginal effects are relatively robust as well, none of the total marginal effects are statistically significant at a 5% level when the irrigation technology extensive margin is included.

The insignificant total marginal effects when the irrigation technology extensive margin is also included may be a possible indication that the adoption of irrigation technology may be one way in which farmers adapt to climate change. These results are potentially consistent with the results of Pfeiffer and Lin (2014a), who find that the adoption of efficient irrigation technology may lead farmers to increase rather than decrease groundwater extraction, in part due to a rebound effect whereby farmers who adopt efficient irrigation technology also respond by planting more water intensive crops and increasing their irrigated acreage (Pfeiffer and Lin, 2014a; Sears et al., 2018). We hope to further explore the irrigation technology extensive margin in future work.

7. Discussion and Conclusion

In this paper, we analyze the effects of temperature and precipitation on groundwater extraction for agriculture in the High Plains (Ogallala) Aquifer in Kansas. Our empirical analysis incorporates many of the improvements on statistical and econometric analyses of the effects of climate change that have been suggested in the previous literature, including using high frequency data on climate (Schlenker and Roberts, 2009; Lee and Sumner, 2015); considering multiple crops (Thompson et al., 2017); controlling for soil moisture (Ortiz-Bobea et al., 2019), crop prices (Miao, Khanna and Huang, 2016), and humidity (Zhang, Zhang and Chen, 2017); not assuming that weather variables can be aggregated over several months (Ortiz-Bobea, 2015; Gammans, Mérel and Ortiz-Bobea, 2017); and considering farmers' expectations (Lemoine, 2017). We also analyze several different specifications for the climate variables.

There are several main features of our results worth highlighting. First, our results show that farmers' expectations and decisions may depend in part on recent climate history, and that the effects of contemporaneous temperature and precipitation may be different from the effects of average annual temperature and precipitation over the past 3 years. Consistent with the previous literature (Kelly, Kolstad and Mitchell, 2005; Kolstad and Moore, 2020), we find that the short- and long-run effects of climate change may differ.

In particular, we find that climate variables based on annual average temperature over the past 3 years and total precipitation over the past 3 years have a negative effect on the intensive margin (water use conditional on crop acreage and irrigation technology decisions) and a positive effect on the crop acreage extensive margin. Thus, when a grower experiences higher values of annual average temperature over the past 3 years, she uses less groundwater conditional on crop acreage, and increases the acreage of more water-intensive crops. Similarly, when a grower experiences higher values of total precipitation over the past 3 years, she may tend to use less groundwater conditional on crop acreage, and may tend to increase the acreage of more water-intensive crops; the total marginal effect is not significant at a 5% level.

In contrast to annual average temperature over the past 3 years, we find that annual temperature has positive total intensive margin that is significant when the specification also additionally controls for average annual temperature over the past 3 years. Thus, conditional on the recent temperature history over the past 3 years, the grower uses more groundwater conditional on crop acreage when the current year is warmer. Similarly, average temperature over the first 4 months of the year (before the crop decision) and the fraction of days in the summer with maximum temperature exceeding 86 degrees Fahrenheit both have a significant positive total intensive margin: the grower uses more groundwater conditional on crop acreage when the current year is warmer. In contrast to total precipitation over the past 3 years, annual precipitation has mixed effects on groundwater extraction at the intensive margin that are not robust.

Our result that the effects of contemporaneous temperature and precipitation may be different from the effects of average annual temperature and precipitation over the past 3 years suggests that farmers may make medium- or long-term decisions based on recent climate history over the past 3 years, and that conditional on the recent climate history over the past 3 years, may then make additional short-run adjustments based on average temperature before the crop decision and over the current year.

Our second main result is that, consistent with the previous literature (Hendricks and Peterson, 2012), we find that it is important to account for both the intensive and extensive margins. Our results show that the climate variables influence the demand for water by farmers, crop acreage allocation decisions, and the choice of irrigation technology. Estimates of the total marginal effect of climate-related variables that do not account for the intensive and extensive margins may yield misleading results.

In particular, in terms of climate variables based on temperature, we find that the total intensive margin and the total crop acreage extensive margin can go in opposite directions, and, when they do, the total intensive margin dominates and the sign of the total marginal effect is the sign of the total intensive margin. For the annual average temperature over the past 3 years, the total intensive margin is significant and negative, but the total crop acreage extensive margin is significant and positive; the total marginal effect is significant and negative. Similarly, the annual fraction of days in the first 4 months of the year (before the crop decision) with maximum temperature exceeding 86 degrees Fahrenheit has a significant negative total intensive margin but a significant positive total crop acreage extensive margin; the total marginal effect is significant and negative. Likewise, the fraction of days in the summer with maximum temperature exceeding

86 degrees Fahrenheit has a significant positive total intensive margin and a significant negative total crop acreage extensive margin; the total marginal effect is significant and positive.

For the one climate variable based on precipitation whose total intensive margin is robust across the different specifications -- total precipitation over the past 3 years -- we also find that the total intensive margin and the total crop acreage extensive margin go in opposite directions. Total precipitation over the past 3 years has a negative total intensive margin that can be significant across the different specifications, but a positive total crop acreage extensive margin that can be significant across the different annual climate variable specifications; the total marginal effect is not significant at a 5% level.

Our third main result is that, consistent with the previous literature (Ortiz-Bobea, 2015; Gammans, Mérel and Ortiz-Bobea, 2017), we find that aggregating climate-related variables to an annual level may obscure important within-year effects of climate and may yield misleading estimates of the effects of climate change. At the annual level, total precipitation over the past 3 years does not have a total marginal effect that is significant at a 5% level, and the other annual climate variables based on precipitation yield mixed results. At the monthly level, we find important within-year effects of climate variables based on monthly precipitation that may contribute in part to the mixed results at the annual level. In particular, using monthly climate variables we find the robust result that higher average precipitation over the past 3 years in March, prior to the crop acreage decision and prior to the beginning of the crop season, leads the grower to use less groundwater conditional on crop acreage and less groundwater overall; while higher average precipitation over the past 3 years in June, during the crop season, leads the grower to use more groundwater conditional on crop acreage and more groundwater overall. Thus, for climate variables based on precipitation, aggregating to an annual level may obscure important within-year effects.

Our fourth main result is that our results for temperature tend to be fairly robust across different climate variable specifications and different model specifications. Our results for precipitation are robust at the monthly level, but generally less robust at the annual level. Thus, for climate-related variables based on precipitation, aggregating the variables to an annual level may obscure important within-year effects of climate and may yield misleading estimates of the effects of climate change.

There are several potential avenues for future research. First, in our paper we estimate an econometric model of groundwater extraction conditional on crop acreage and irrigation technology decisions, and we also estimate an econometric model of a farmer's irrigation water pumping decision that accounts for both the intensive margin and the extensive margins, where the extensive margins are the crop acreage and irrigation technology decisions and the intensive margin is the groundwater extraction decision holding crop acreage and irrigation technology constant. Groundwater extraction, crop acreage, and irrigation technology may be at least partially jointly determined and jointly chosen, however, crop acreage and irrigation technology may therefore be endogenous to groundwater extraction. These endogeneity concerns are mitigated in part because crop acreage and irrigation technology decisions are made by the beginning of the season while groundwater extraction decisions are made throughout the season; thus, crop acreage and irrigation technology decisions tend to be pre-determined before much of the groundwater extraction decisions are made. We further address concerns about the endogeneity of crop acreage and irrigation technology by controlling for crop prices, grower fixed effects, and other determinants of crop acreage, irrigation technology, and groundwater extraction in our empirical model of groundwater extraction. In future work, we hope to develop a structural econometric model of grower's groundwater extraction, crop acreage, and irrigation technology decisions that more explicitly models their joint and simultaneous nature.

A second avenue for potential future research to analyze well ownership. In our paper, we have modeled neighbors as all neighbors within one mile of a given farmer. In previous empirical work, Pfeiffer and Lin (2012) contrast the behavioral response to extraction by nearby neighbors with extraction from nearby wells that the grower himself controls, and finds that the average effect of extraction at neighboring wells owned by the same grower is smaller than the effects of neighboring wells owned by others. In future work, we hope to identify ownership and distinguish among wells owned by the same groundwater user and wells owned by other groundwater users.

A third avenue for potential future research regards more fully modeling both the dynamic and strategic dimensions of groundwater extraction. Sears, Lim and Lin Lawell (2019) present a dynamic game framework for analyzing spatial groundwater management, characterizing the Markov perfect equilibrium resulting from non-cooperative behavior, and comparing it with the socially optimal coordinated solution. In future work, we hope to more explicitly model both the dynamic and strategic dimensions of groundwater extraction by developing and estimating a structural econometric model of the dynamic game among groundwater users in the High Plains Aquifer, building on structural econometric models of dynamic games that have been developed to model petroleum production and extraction (Lin, 2013c; Kheiravar, Lin Lawell and Jaffe, 2020) and open access groundwater extraction in California (Sears, Lin Lawell and Walter, 2020).

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

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Table 1. Climate Variable Specifications

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

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

Table 2: Total Intensive Margin from Groundwater Extraction Fixed Effects Regressions

	Dependent variable is:		
	Extraction intensity (acre-feet per acre)	*Extraction (acre-feet)*	*Extraction intensity (acre-feet per acre)*
	FE	FE	FE
Previous-Year Crop Prices	Y	Y	N
Current-Year Crop Prices	N	N	Y
	(Base)	(Alt-A)	(Alt-B)
Climate Specification Y1			
Annual average temperature (°F)	0.217	62.874**	1.319***
Annual precipitation (in)	-0.102***	0.174	0.108***
Climate Specification Y2			
Annual average temperature (°F)	2.632***	487.43***	3.942***
Average annual temperature over the past 3 years (°F)	-5.564***	-907.43***	-6.492***
Annual precipitation (in)	-0.124***	1.108	0.110***
Total precipitation over the past 3 years (in)	-0.016***	-5.202***	-0.053***
Climate Specification Y3			
Annual fraction of days with max temp > 86°F	-2,600.25***	-315,296***	-3,751.69***
Summer fraction of days with max temp > 86°F	749.79***	110,181***	1,081.35***
Annual precipitation (in)	-0.048***	5.966***	0.084***
Climate Specification Y4			
Average annual temperature over the last 3 years (°F)	-4.522***	-60.8.36***	-3.907***
Average temperature in Jan-Apr (°F)	1.073***	88.852**	1.138***
Total precipitation over the last 3 years (in)	-0.026***	-4.291***	-0.045***

Precipitation in Jan-Apr (in)	0.132	-51.52	-0.174
Climate Specification Y5			
Average annual temperature over the last 3 years (°F)	-3.499***	-501.3***	-3.245***
Fraction of days in Jan-Apr with max temp > 86°F	-6.866.18***	-1.15E6***	-6,303***
Total precipitation over the last 3 years (in)	-0.010*	-2.114**	-0.034***
Precipitation in Jan-Apr (in)	10.04***	1,282.4***	8.21***

Notes: For each annual climate variable specification, the base specification (Base) is the same base-case fixed effects (FE) Base Specification that is in Table A2 in the Appendix. Total intensive margin is the total average effect evaluated at the means values of the variables in the data. Robust standard errors are calculated using the Delta Method. The controls include humidity, crop acreage variables, irrigation technology, hydrological and field characteristics (evapotranspiration, recharge, slope, soil quality, soil moisture, field size, depth to groundwater, saturated thickness), the quantity authorized for extraction, crop prices (alfalfa price, corn price, sorghum price, soybean price, and wheat price), energy prices (diesel price, electricity price, and natural gas price), expected future crop prices (10-year projections for corn price, sorghum price, soybean price, and wheat price), expected future energy prices (10-year projections for diesel price, electricity price, and natural gas price), groundwater extraction by neighbors (lagged extraction by neighbors, and lagged quantity authorized for extraction by neighbors), grower fixed effects, and a time trend. Significance codes: *** p<0.001, ** p<0.01, * p<0.05.

Table 3: Total Intensive Margin from Groundwater Extraction IV-FE Regressions

	Dependent variable is: Extraction intensity (acre-feet per acre)					
	FE	IV-FE	IV-FE	IV-FE	IV-FE	IV-FE
Previous-Year Crop Prices	Y	Y	N	N	N	N
Current-Year Crop Prices	N	N	Y	Y	Y	Y
IV for Neighbor Extraction	N	Y	Y	N	Y	N
IV for Crop Prices	N	N	N	Y	Y	N
IV for Crop Acreage	N	N	N	N	N	Y
	(Base)	(Alt-C)	(Alt-D)	(Alt-E)	(Alt-F)	(Alt-G)
Climate Specification Y1						
Annual average temperature (°F)	0.217	0.287	1.472***	0.152	0.220	0.202
Annual precipitation (in)	-0.102***	-0.116***	0.092***	-0.134***	-0.139***	-0.113***
Climate Specification Y2						
Annual average temperature (°F)	2.632***	2.671***	4.041***	2.289***	2.318***	2.285***
Average annual temperature over the past 3 years (°F)	-5.564***	-5.557***	-6.449***	-5.269***	-5.223***	-5.224***
Annual precipitation (in)	-0.124***	-0.134***	0.098***	-0.169***	-0.172***	-0.154***
Total precipitation over the past 3 years (in)	-0.016***	-0.017***	-0.053***	-0.007	-0.008	-0.010*
Climate Specification Y3						
Annual fraction of days with max temp > 86°F	-2,600.25***	-2,696.67***	-3,944.34***	-4,052.82***	-4,133.86***	-3,762.29***
Summer fraction of days with max temp > 86°F	749.79***	776.21***	1,131.75***	1,069.65***	1,090.09***	1,107.75***
Annual precipitation (in)	-0.048***	-0.058***	0.070***	-0.057	-0.058	-0.032**
Climate Specification Y4						
Average annual temperature over the last 3 years (°F)	-4.522***	-4.419***	-3.734***	-4.06***	-3.950***	-4.157***

Average temperature in Jan-Apr (°F)	1.073***	1.122***	1.196***	1.018***	1.067***	1.064***
Total precipitation over the last 3 years (in)	-0.026***	-4.419***	-0.043***	-0.021**	-0.023***	-0.024***
Precipitation in Jan-Apr (in)	0.132	-0.113	-0.375	-2.217**	-2.377***	-1.793*
Climate Specification Y5						
Average annual temperature over the last 3 years (°F)	-3.499***	-3.315***	-3.011***	-3.496***	-3.323***	-3.446***
Fraction of days in Jan-Apr with max temp > 86°F	-6.866.18***	-7,200.93***	-6,697.58***	-6,672.02***	-6,991.72***	-7,336.04***
Total precipitation over the last 3 years (in)	-0.010*	-0.011**	-3.011***	-0.010	-0.012	-0.013**
Precipitation in Jan-Apr (in)	10.04***	9.847***	8.347***	7.637***	7.650***	8.441***

Notes: For each annual climate variable specification, the base specification (Base) is the same base-case fixed effects (FE) Base Specification that is in Table A2 in the Appendix. In instrumental variable (IV) fixed effects (IV-FE) Specification (Alt-C), we use the lagged quantity authorized for extraction by neighbors as an instrument for neighbors' lagged extraction instead of as a control, to address the potential endogeneity of neighbors' lagged extraction. In instrumental variable (IV) fixed effects (IV-FE) Specification (Alt-D), we use the lagged quantity authorized for extraction by neighbors as an instrument for neighbors' lagged extraction instead of as a control, to address the potential endogeneity of neighbors' lagged extraction; and we use the current year's crop prices instead of the previous year's crop prices as controls. In instrumental variable fixed effects (IV-FE) Specification (Alt-E), we use the current year's crop prices instead of the previous year's crop prices as controls, and then instrument for the current year's crop prices using the previous year's crop prices to address the endogeneity of current-year crop prices. In instrumental variable (IV) fixed effects (IV-FE) Specification (Alt-F), we use the lagged quantity authorized for extraction by neighbors as an instrument for neighbors' lagged extraction instead of as a control, to address the potential endogeneity of neighbors' lagged extraction; and we use the current year's crop prices instead of the previous year's crop prices as controls, and then instrument for the current year's crop prices using the previous year's crop prices to address the endogeneity of current-year crop prices. In instrumental variable (IV) fixed effects (IV-FE) Specification (Alt-G), we use the lagged crop acreage and lagged crop acreage squared as instruments for crop acreage and crop acreage squared, to address the potential endogeneity of crop acreage. Total intensive margin is the total average effect evaluated at the mean values of the variables in the data. Robust standard errors are calculated using the Delta Method. The controls include humidity, crop acreage variables (number of acres planted to each crop (alfalfa, corn, sorghum, soybeans, and wheat) and the number of acres planted to each crop squared), irrigation technology, hydrological and field characteristics (evapotranspiration, recharge, slope, soil quality, soil moisture, field size, depth to groundwater, saturated thickness), the quantity authorized for extraction, crop prices (alfalfa price, corn price, sorghum price, soybean price, and wheat price), energy prices (diesel price, electricity price, and natural gas price), expected future crop prices (10-year projections for corn price, sorghum price, soybean price, and wheat price), expected future energy prices (10-year projections for diesel price, electricity price, and natural gas price), groundwater extraction by neighbors (lagged extraction by neighbors, and lagged quantity authorized for extraction by neighbors), grower fixed effects, and a time trend. Significance codes: *** p<0.001, ** p<0.01, * p<0.05.

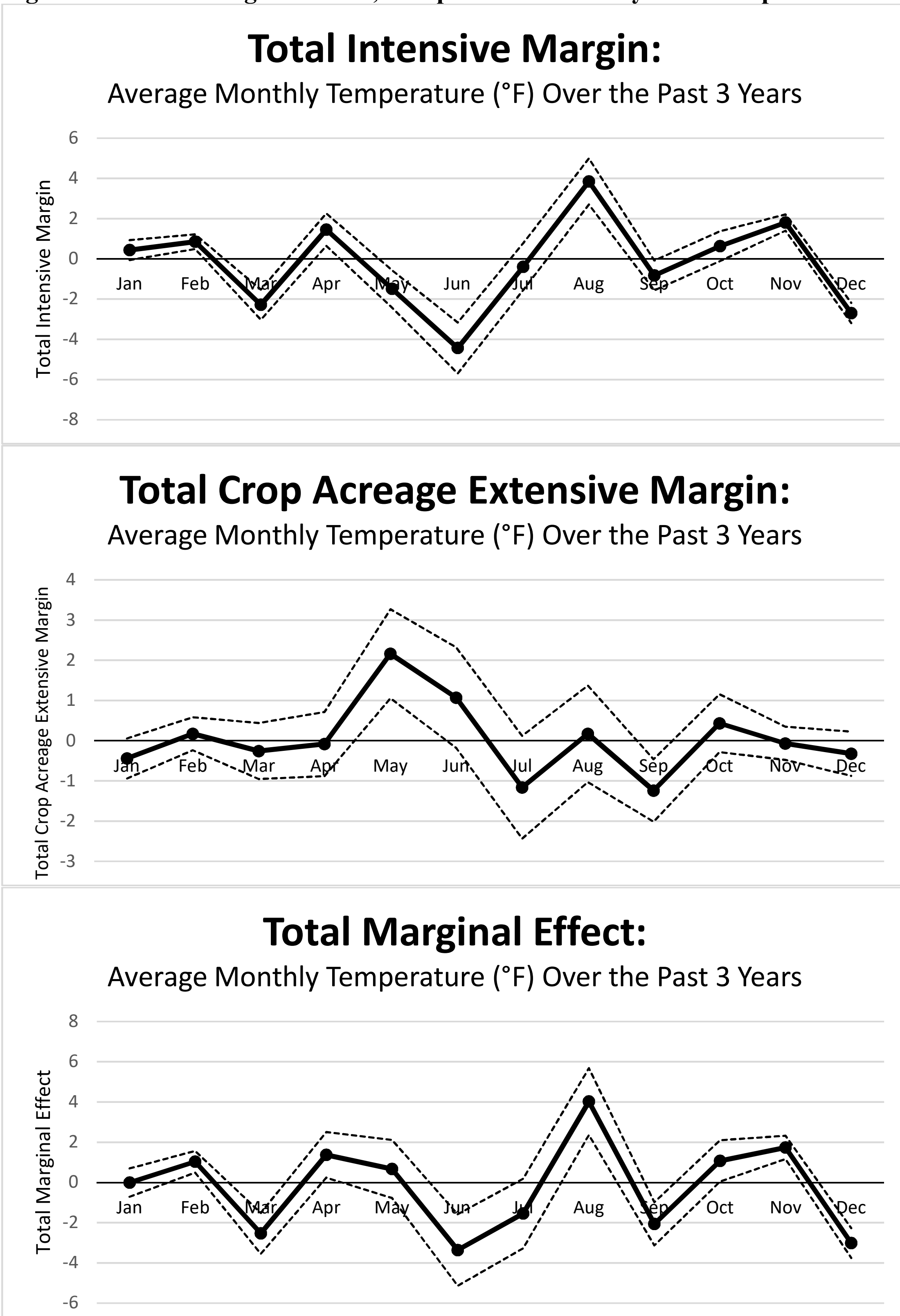
Table 4. Total Marginal Effect, Annual Climate Variables

	Total intensive margin $\left(\frac{\partial w}{\partial C_j}\right)$	Total crop acreage extensive margin $\left(\sum_c \frac{\partial w}{\partial n_c}\frac{\partial n_c}{\partial C_j}\right)$	**TOTAL MARGINAL EFFECT** $\left(\frac{dw}{dC_j}=\frac{\partial w}{\partial C_j}+\sum_c \frac{\partial w}{\partial n_c}\frac{\partial n_c}{\partial C_j}\right)$ (Base)
Climate Specification Y1			
Annual average temperature (°F)	0.217	0.670**	0.887**
	(0.156)	(0.230)	(0.278)
Annual precipitation (in)	-0.102***	0.065***	-0.037
	(0.012)	(0.015)	(0.019)
Climate Specification Y2			
Annual average temperature (°F)	2.632***	-0.096	2.536***
	(0.191)	(0.272)	(0.332)
Average annual temperature over the past 3 years (°F)	-5.564***	1.584***	-3.981***
	(0.290)	(0.475)	(0.557)
Annual precipitation (in)	-0.124***	0.063***	-0.061**
	(0.013)	(0.016)	(0.020)
Total precipitation over the past 3 years (in)	-0.016***	0.008	-0.009
	(0.005)	(0.005)	(0.007)
Climate Specification Y3			
Annual fraction of days with max temp > 86°F	-2,600.25***	155.21	-2.445.04***
	(126.72)	(194.59)	(223.90)
Summer fraction of days with max temp > 86°F	749.49***	-100.45**	649.04***
	(26.39)	(37.23)	(45.63)
Annual precipitation (in)	-0.048***	0.019	-0.029
	(0.011)	(0.015)	(0.019)

Climate Specification Y4			
Average annual temperature over the last 3 years (°F)	-4.522***	1.349**	-3.173***
	(0.261)	(0.429)	(0.503)
Average temperature in Jan-Apr (°F)	1.073***	-0.132	0.941***
	(0.066)	(0.095)	(0.116)
Total precipitation over the last 3 years (in)	-0.026***	0.013*	-0.013
	(0.005)	(0.005)	(0.007)
Precipitation in Jan-Apr (in)	0.132	-1.544	-1.412
	(0.626)	(1.116)	(1.280)
Climate Specification Y5			
Average annual temperature over the last 3 years (°F)	-3.499***	0.951*	-2.547***
	(0.253)	(0.408)	(0.481)
Fraction of days in Jan-Apr with max temp > 86°F	-6.866.18***	2,517.34***	-4,348.85***
	(347.00)	(528.98)	(632.64)
Total precipitation over the last 3 years (in)	-0.010*	0.013*	0.003
	(0.005)	(0.005)	(0.007)
Precipitation in Jan-Apr (in)	10.04***	-1.130	8.909***
	(0.65)	(1.032)	(1.219)

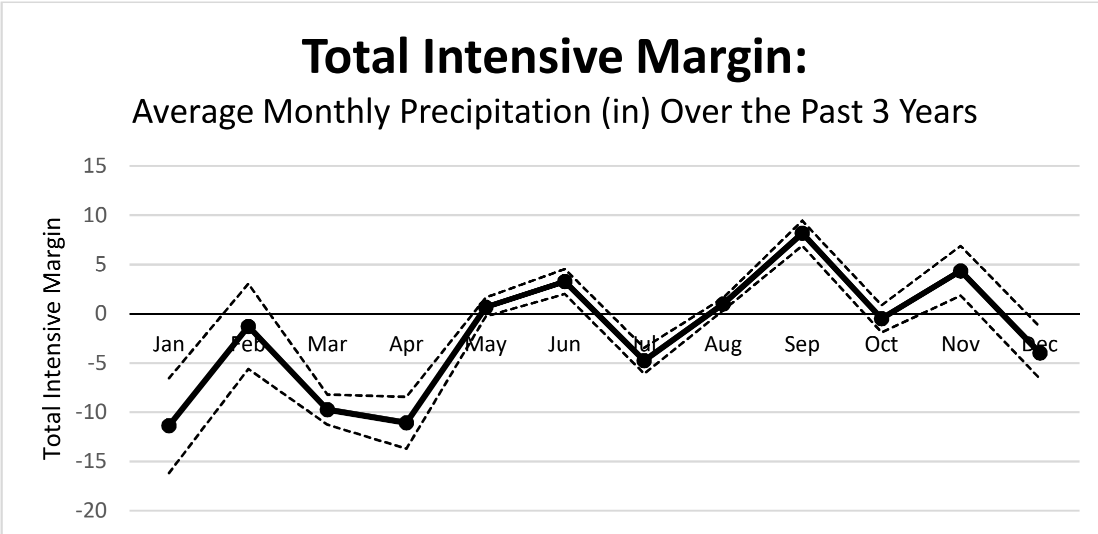
Notes: Standard errors are in parentheses. Groundwater extraction w is extraction intensity in acre-feet per acre. For each crop c, the number of acres n_c planted to crop c is in acres and is evaluated at its mean value in the data. Results are calculated using the groundwater extraction regression results from the base-case annual climate variable specifications in Table A2 in the Appendix, and the crop acreage regressions results in Tables A3a-A3e in the Appendix. Significance codes: *** p<0.001, ** p<0.01, * p<0.05.

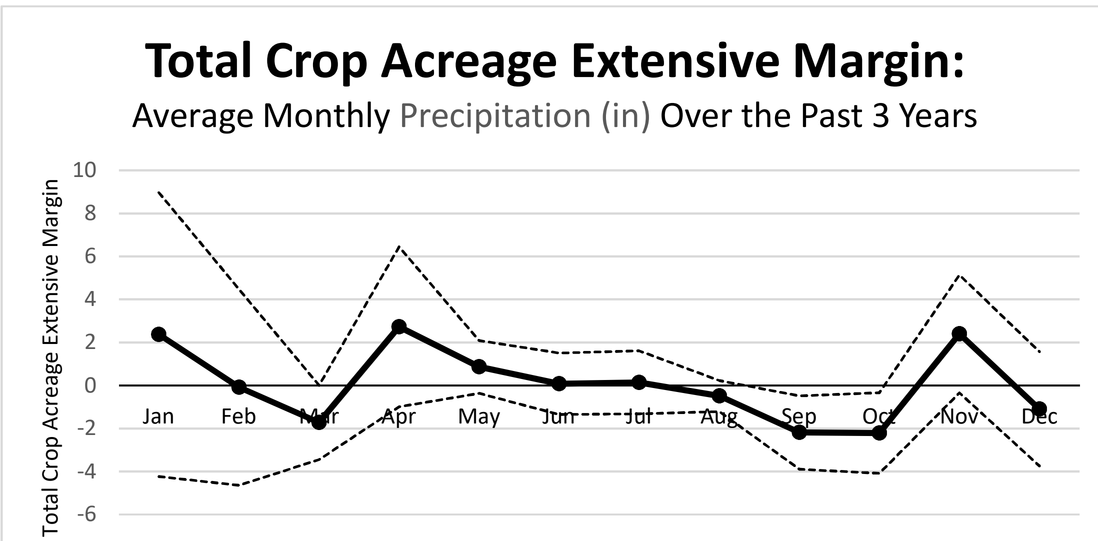
Figure 1a. Total Marginal Effect, Temperature: Monthly Climate Specification M1



Note: Dotted lines indicate the 95% confidence interval.

Figure 1b. Total Marginal Effect, Precipitation: Monthly Climate Specification M1





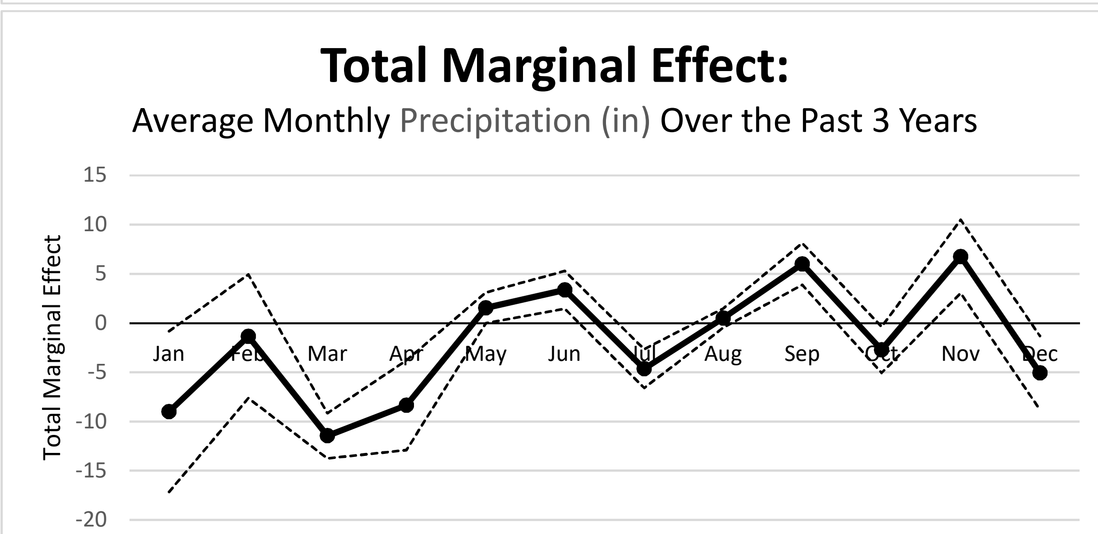
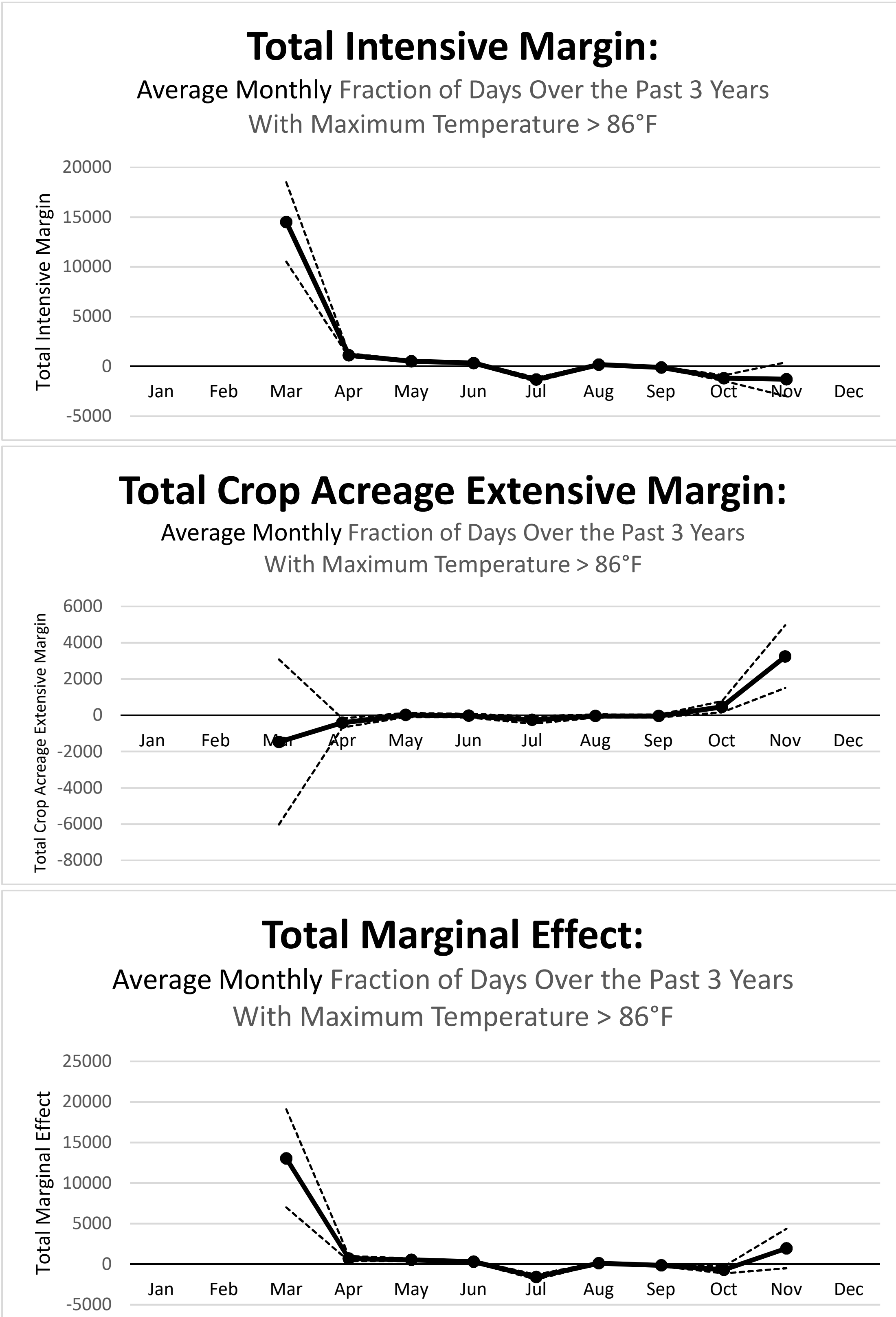
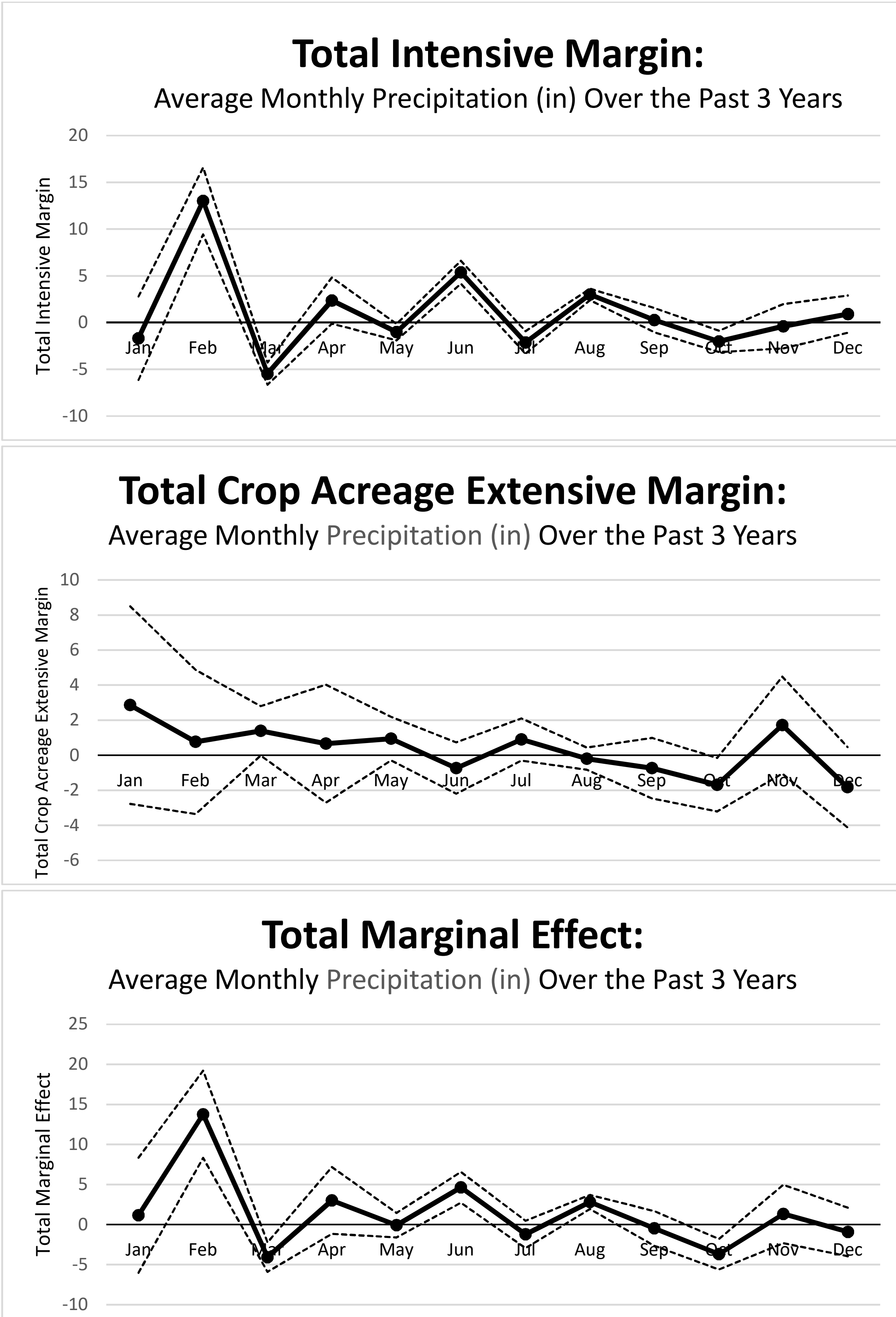


Figure 2a. Total Marginal Effect, Temperature: Monthly Climate Specification M2



Note: Dotted lines indicate the 95% confidence interval.

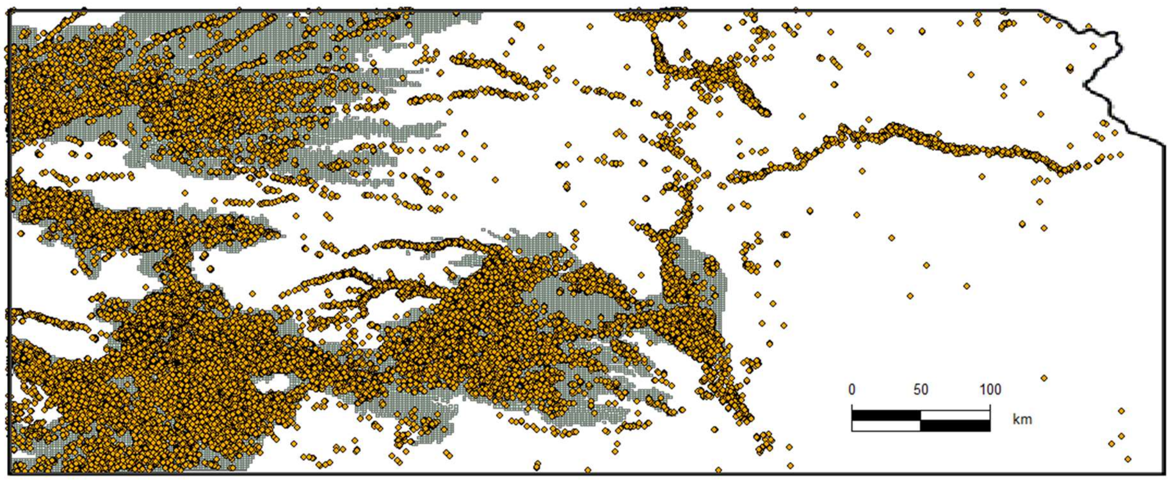
Figure 2b. Total Marginal Effect, Precipitation: Monthly Climate Specification M2



Note: Dotted lines indicate the 95% confidence interval.

Appendix

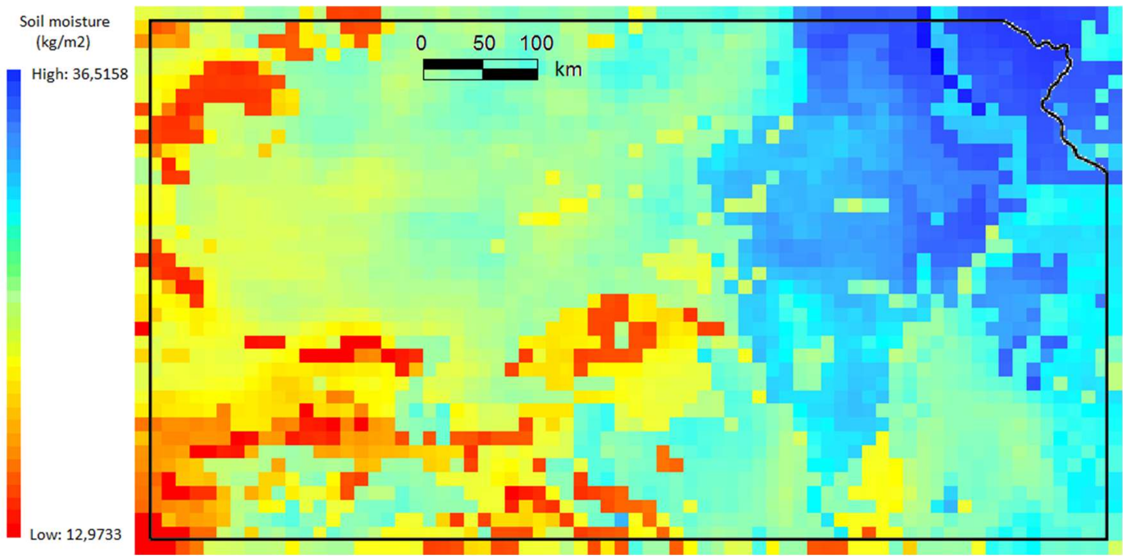
Figure A1: Location of all the points of diversion we use in our data set



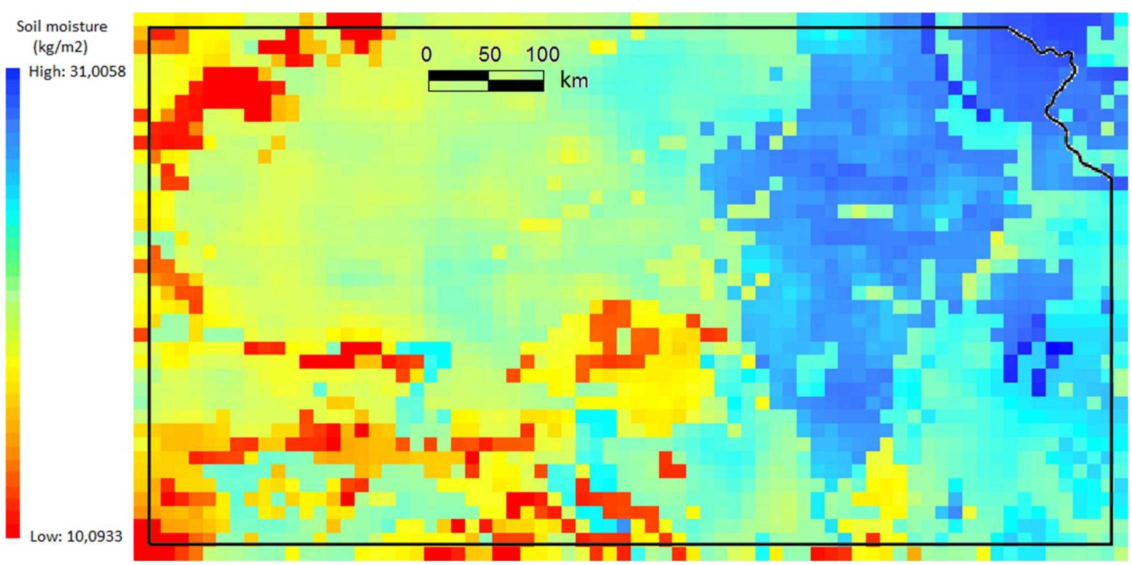
Notes: The black border indicates the Kansas state boundaries. The gray area shows the portion of the High Plains Aquifer that underlies western Kansas.

Figure A2: 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 1. The black border indicates the Kansas state boundaries.

Table A1a. Summary Statistics for Decision Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Groundwater extraction					
Extraction (acre-feet)	293,342	172.38	122.60	0	1988.64
Extraction intensity (acre-feet/acre)	291,694	1.167	0.557	0	17.415
Crop acreage					
Acres planted with alfalfa (acres)	293,342	11.43	38.34	0	640
Acres planted with corn (acres)	293,337	64.08	74.51	0	640
Acres planted with sorghum (acres)	293,342	5.07	23.87	0	620
Acres planted with soybeans (acres)	293,342	12.27	35.23	0	550
Acres planted with wheat (acres)	293,337	16.92	43.47	0	625
Irrigation technology					
Center pivot sprinkler use (dummy)	293,342	0.36	0.48	0	1
Center pivot sprinkler with drop nozzles use (dummy)	293,342	0.32	0.46	0	1

Table A1b. Summary Statistics for Annual Climate Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Temperature					
Annual average temperature (°F)	293,342	54.21	1.53	50.42	58.25
Average annual temperature over the past 3 years (°F)	293,342	54.15	1.29	50.93	57.72
Annual fraction of days with max temp > 86°F	293,342	0.23	0.04	0.13	0.30
Summer fraction of days with max temp > 86°F	293,342	0.69	0.11	0.38	0.93
Average temperature in Jan-Apr (°F)	293,342	40.16	2.21	34.05	46.99
Annual fraction of days in Jan-Apr with max temp > 86°F	293,342	0.014	0.0133	0	0.0541
Precipitation					
Annual precipitation (in)	293,342	18.60	6.30	6.31	51.81
Total precipitation over the past 3 years (in)	293,342	56.95	13.42	30.29	97.70
Precipitation in Jan-Apr (in)	293,342	0.95	0.41	0.19	2.73
Humidity					
Annual average humidity (%)	293,342	64.11	4.65	51.80	77.29
Average humidity in Jan-Apr (%)	293,342	64.27	8.32	45.04	84.13

Table A1c. 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	293,342	30.74	2.09	16.87	42.22
February	293,342	34.44	2.76	23.91	45.14
March	293,342	42.75	2.40	35.02	56.18
April	293,342	52.37	2.35	44.23	61.04
May	293,342	63.34	1.94	57.64	70.59
June	293,342	73.14	1.80	68.27	79.11
July	293,342	78.67	1.84	72.86	86.19
August	293,342	76.39	2.08	69.95	85.55
September	293,342	67.56	1.89	61.07	77.30
October	293,342	54.79	1.83	44.37	61.21
November	293,342	42.00	2.21	30.63	52.03
December	293,342	31.81	2.11	18.72	38.40
Avg. fraction of days with max temp > 86°F over the past 3 years during month of:					
January	293,342	0.00	0.00	0	0.03
February	293,342	0.00	0.00	0	0.07
March	293,342	0.00	0.00	0	0.03
April	293,342	0.05	0.03	0	0.23
May	293,342	0.22	0.06	0	0.55
June	293,342	0.56	0.09	0.23	0.93
July	293,342	0.79	0.08	0.53	1
August	293,342	0.67	0.14	0.26	0.97
September	293,342	0.36	0.10	0.07	0.82
October	293,342	0.07	0.03	0	0.32
November	293,342	0.00	0.01	0	0.1
December	293,342	0.00	0.00	0	0

Avg. precipitation (in) over the past 3 years for month of:					
January	293,342	0.36	0.30	0	2.22
February	293,342	0.48	0.30	0	2.66
March	293,342	1.30	0.68	0	6.96
April	293,342	1.63	0.50	0.26	4.98
May	293,342	2.76	1.46	0.13	9.87
June	293,342	2.97	1.11	0.34	7.89
July	293,342	3.02	1.62	0.07	10.98
August	293,342	3.09	2.13	0.003	15.59
September	293,342	1.52	0.91	0.04	5.65
October	293,342	1.49	0.68	0	6.23
November	293,342	0.55	0.53	0	4.11
December	293,342	0.58	0.56	0	4.02
Avg. humidity (%) over the past 3 years during month of:					
January	293,342	66.57	4.96	51.39	91.46
February	293,342	65.89	8.20	37.66	90.99
March	293,342	62.01	6.96	41.19	80.44
April	293,342	60.50	7.11	19.38	78.83
May	293,342	65.10	4.40	45.21	78.75
June	293,342	63.94	4.33	43.64	76.80
July	293,342	62.56	5.09	39.85	83.24
August	293,342	66.08	7.00	43.93	81.86
September	293,342	63.13	5.68	39.25	79.06
October	293,342	64.45	5.00	42.62	84.15
November	293,342	65.45	5.27	41.56	84.86
December	293,342	68.92	4.50	54.55	86.45

Table A1d. Summary Statistics for Control Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Hydrological and field characteristics					
Evapotranspiration, average (in)	293,342	55.12	1.07	43.54	62.39
Recharge (in)	293,267	1.34	1.22	0.3	6
Slope (% of distance)	290,456	1.08	0.87	0.01	8.68
Irrigated Capability Class=1 (dummy)	293,342	0.17	0.37	0	1
Soil moisture content in the layer 0-10 cm (kg/m^2)	274,305	22.42	4.08	11.67	35.46
Field size (acres)	293,342	181.94	102.13	60	640
Depth to groundwater (ft)	293,342	123.42	78.17	4.72	396.48
Saturated thickness (ft)	293,342	120.17	113.73	-257.35	643.91
Authorized quantity					
Quantity authorized for extraction (acre-feet)	273,422	290.12	199.79	0.37	2400
Crop prices					
Alfalfa price ($/ton)	293,342	119.41	36.52	80.42	211.92
Corn price (cents/bushel)	293,342	340.77	129.90	224.28	629.03
Sorghum price ($/cwt)	293,342	5.58	2.52	3.27	11.26
Soybean price (cents/bushel)	293,342	774.93	285.90	451.95	1353.64
Wheat price (cents/bushel)	293,342	465.97	199.62	287.94	968.91
Energy prices					
Diesel price ($/gal)	293,342	2.17	0.99	1.023	3.899
Electricity price (cents/kwh)	293,342	7.03	0.93	6.2	9.24
Natural gas price ($/mcf)	293,342	8.60	2.58	4.61	12.44
Future crop prices					
Corn price, 10-year projection ($/bushel)	293,342	3.13	0.65	2.35	4.65
Sorghum price, 10-year projection ($/bushel)	293,342	2.89	0.61	2.1	4.35
Soybean price, 10-year projection ($/bushel)	293,342	7.39	1.69	5.6	11.35
Wheat price, 10-year projection ($/bushel)	293,342	4.35	0.80	3	5.9

Future energy prices					
Diesel price, 10-year projection ($/million Btu)	293,342	13.75	7.19	7.87	28.63
Electricity price, 10-year projection ($/million Btu)	293,342	21.42	3.61	17.2	28.17
Natural gas price, 10-year projection ($/million Btu)	293,342	5.76	1.73	3.44	9.05
Groundwater extraction by neighbors					
Extraction by neighbors in *t*-1 (acre-feet)	293,342	728.32	625.14	0	5404.05
Quantity authorized for extraction by neighbors in *t*-1 (acre-feet)	293,342	1084.79	919.79	0	15162

Table A2. Groundwater Extraction Fixed Effects Regression Results

	Dependent variable is: Extraction intensity (acre-feet per acre)				
	FE	FE	FE	FE	FE
Annual Climate Variable Specification	Y1	Y2	Y3	Y4	Y5
	(Y1, Base)	(Y2, Base)	(Y3, Base)	(Y4, Base)	(Y5, Base)
Temperature					
Annual average temperature (°F)	-0.121***	-0.959***			
	(0.036)	(0.044)			
Annual average temperature (°F), squared	0.00074*	0.0078***			
	(0.00033)	(0.0004)			
Average annual temperature over the past 3 years (°F)		1.914***		1.543***	1.107***
		(0.068)		(0.061)	(0.0591)
Average annual temperature over the past 3 years (°F), squared		-0.0164***		-0.0133***	-0.0101***
		(0.0006)		(0.0006)	(0.000540)
Annual fraction of days with max temp > 86°F			10.95***		
			(0.666)		
Annual fraction of days with max temp > 86°F, squared			-27.20***		
			(1.320)		
Summer fraction of days with max temp > 86°F			-5.274***		
			(0.247)		
Summer fraction of days with max temp > 86°F, squared			4.777***		
			(0.167)		
Average temperature in Jan-Apr (°F)				-0.321***	
				(0.0126)	
Average temperature in Jan-Apr (°F), squared				0.00335***	
				(0.000156)	
Annual fraction of days in Jan-Apr with max temp > 86°F					8.819***
					(0.367)
Annual fraction of days in Jan-Apr with max temp > 86°F, squared					-137.5***
					(6.940)

Precipitation					
Annual precipitation (in)	-0.0030	-0.0039*	-0.0068***		
	(0.0016)	(0.0017)	(0.0015)		
Annual precipitation (in), squared	-0.00034***	-0.00042***	-0.00014***		
	(0.00004)	(0.00005)	(0.00004)		
Total precipitation over the past 3 years (in)		0.0110***		0.0125***	0.00748***
		(0.0013)		(0.0013)	(0.00130)
Total precipitation over the past 3 years (in), squared		-5.89e-05***		-8.30e-05***	-3.73e-05***
		(0.94e-05)		(0.95e-05)	(9.37e-06)
Precipitation in Jan-Apr (in)				-0.0253*	-0.122***
				(0.0111)	(0.0110)
Precipitation in Jan-Apr (in), squared				0.0009	0.0584***
				(0.0036)	(0.00373)
Humidity					
Annual average humidity (%)	0.0022***	0.0023***	0.0024***	0.0127***	0.00916***
	(0.0006)	(0.0007)	(0.0006)	(0.000747)	(0.000736)
Average humidity in Jan-Apr (%)				-0.0115***	-0.00486***
				(0.000433)	(0.000396)
Crop acreage variables					
Acres planted with alfalfa (acres)	0.00201***	0.00203***	0.00204***	0.00202***	0.00201***
	(0.000126)	(0.000125)	(0.000123)	(0.000125)	(0.000124)
Acres planted with alfalfa (acres), squared	-7.09e-06***	-7.10e-06***	-7.09e-06***	-7.08e-06***	-7.06e-06***
	(0.69e-06)	(0.69e-06)	(0.67e-06)	(0.69e-06)	(0.68e-06)
Acres planted with corn (acres)	0.00197***	0.00197***	0.00198***	0.00197***	0.00197***
	(0.00005)	(0.00005)	(0.00005)	(0.00005)	(0.00005)
Acres planted with corn (acres), squared	-6.61e-06***	-6.60e-06***	-6.64e-06***	-6.58e-06***	-6.59e-06***

	(0.21e-06)	(0.21e-06)	(0.21e-06)	(0.21e-06)	(0.21e-05)
Acres planted with sorghum (acres)	-0.000527***	-0.000513***	-0.000524***	-0.000512***	-0.000538***
	(0.00009)	(0.00009)	(0.00009)	(0.00009)	(0.00009)
Acres planted with sorghum (acres), squared	-1.11e-06*	-1.19e-06**	-1.07e-06*	-1.22e-06**	-1.08e-06*
	(0.47e-06)	(0.46e-06)	(0.47e-06)	(0.47e-06)	(0.47e-06)
Acres planted with soybeans (acres)	0.00159***	0.00156***	0.00163***	0.00158***	0.00159***
	(0.00009)	(0.00009)	(0.00009)	(0.00009)	(0.00009)
Acres planted with soybeans (acres), squared	-6.90e-06***	-6.78e-06***	-7.03e-06***	-6.84e-06***	-6.88e-06***
	(0.62e-06)	(0.61e-06)	(0.63e-06)	(0.61e-06)	(0.61e-06)
Acres planted with wheat (acres)	-0.00170***	-0.00178***	-0.00171***	-0.00174***	-0.00173***
	(0.00007)	(0.00007)	(0.00007)	(0.00007)	(0.00007)
Acres planted with wheat (acres), squared	6.47e-07*	8.28e-07**	6.92e-07*	7.67e-07*	7.23e-07*
	(3.26e-07)	(3.21e-07)	(3.24e-07)	(3.25e-07)	(3.21e-07)
Irrigation technology					
Center pivot sprinkler use (dummy)	0.00855*	0.0108*	0.00793	0.0120**	0.0110*
	(0.00431)	(0.00426)	(0.00429)	(0.00427)	(0.00428)
Center pivot sprinkler with drop nozzles use (dummy)	-0.00541	-0.00209	-0.0131	-0.00991	-0.00703
	(0.00730)	(0.00730)	(0.00731)	(0.00728)	(0.00730)
Controls	Y	Y	Y	Y	Y
Time Trend	Y	Y	Y	Y	Y
Grower Fixed Effects	Y	Y	Y	Y	Y

Total Intensive Margin					
Total average effects of:					
Temperature					
Annual average temperature (°F)	0.217	2.632***			

	(0.156)	(0.191)			
Average annual temperature over the past 3 years (°F)		-5.564***		-4.522***	-3.499***
		(0.290)		(0.261)	(0.253)
Annual fraction of days with max temp > 86°F			-2,600.25***		
			(126.72)		
Summer fraction of days with max temp > 86°F			749.49***		
			(26.39)		
Average temperature in Jan-Apr (°F)				1.073***	
				(0.066)	
Annual fraction of days in Jan-Apr with max temp > 86°F					-6.866.18***
					(347.00)
Precipitation					
Annual precipitation (in)	-0.102***	-0.124***	-0.048***		
	(0.012)	(0.013)	(0.011)		
Total precipitation over the past 3 years (in)		-0.016***		-0.026***	-0.010*
		(0.005)		(0.005)	(0.005)
Precipitation in Jan-Apr (in)				0.132	10.04***
				(0.626)	(0.65)
# Observations	241,091	241,091	241,091	241,091	241,091
# Growers	29,323	29,323	29,323	29,323	29,323

Notes: Robust standard errors are in parentheses. The controls include hydrological and field characteristics (evapotranspiration, recharge, slope, soil quality, soil moisture, field size, depth to groundwater, saturated thickness), the quantity authorized for extraction, crop prices (alfalfa price, corn price, sorghum price, soybean price, and wheat price) from the previous year, energy prices (diesel price, electricity price, and natural gas price), expected future crop prices (10-year projections for corn price, sorghum price, soybean price, and wheat price), expected future energy prices (10-year projections for diesel price, electricity price, and natural gas price), and groundwater extraction by neighbors (lagged extraction by neighbors, and lagged quantity authorized for extraction by neighbors). Significance codes: *** p<0.001, ** p<0.01, * p<0.05.

Table A3a. Crop Acreage Random Effects Tobit Regression Results for Alfafa

	Dependent variable is number of acres allocated to Alfafa				
	(Y1)	(Y2)	(Y3)	(Y4)	(Y5)
Temperature					
Annual average temperature (°F)	124.5***	14.71			
	(22.49)	(29.68)			
Annual average temperature (°F), squared	-1.129***	-0.146			
	(0.206)	(0.273)			
Average annual temperature over the past 3 years (°F)		261.8***		245.1***	258.1***
		(41.28)		(35.09)	(33.81)
Average annual temperature over the past 3 years (°F), squared		-2.389***		-2.241***	-2.352***
		(0.380)		(0.323)	(0.312)
Annual fraction of days with max temp > 86°F			-653.5		
			(361.3)		
Annual fraction of days with max temp > 86°F, squared			1,702*		
			(734.4)		
Summer fraction of days with max temp > 86°F			74.82		
			(136.3)		
Summer fraction of days with max temp > 86°F, squared			-102.4		
			(93.70)		
Average temperature in Jan-Apr (°F)				7.804	
				(9.250)	
Average temperature in Jan-Apr (°F), squared				-0.0924	
				(0.114)	
Annual fraction of days in Jan-Apr with max temp > 86°F					-336.8
					(209.1)
Annual fraction of days in Jan-Apr with max temp > 86°F, squared					4,778
					(3,834)
Precipitation					
Annual precipitation (in)	-2.707**	-1.119	-3.889***		
	(0.949)	(1.028)	(0.984)		

	(1)	(2)	(3)	(4)	(5)
Annual precipitation (in), squared	0.0649**	0.0389	0.0975***		
	(0.0249)	(0.0267)	(0.0254)		
Total precipitation over the past 3 years (in)		-2.116***		-2.160***	-2.154***
		(0.603)		(0.586)	(0.585)
Total precipitation over the past 3 years (in), squared		0.0131**		0.0140**	0.0138**
		(0.00433)		(0.00430)	(0.00429)
Precipitation in Jan-Apr (in)				5.931	7.232
				(6.767)	(6.647)
Precipitation in Jan-Apr (in), squared				-4.609	-5.900*
				(2.480)	(2.532)
Humidity					
Annual average humidity (%)	2.803***	3.711***	3.169***	4.020***	4.025***
	(0.279)	(0.318)	(0.284)	(0.381)	(0.380)
Average humidity in Jan-Apr (%)				-0.333	-0.414*
				(0.215)	(0.202)
Dummies for Previous Year's Crop Choice	Y	Y	Y	Y	Y
Crop Price Variables	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Time Trend	Y	Y	Y	Y	Y
Grower Random Effects	Y	Y	Y	Y	Y
# Observations	242,542	242,542	242,542	242,542	242,542
# Growers	29,376	29,376	29,376	29,376	29,376

Notes: These results are from the base-case specification in Table 3a in Bertone Oehninger, Lin Lawell and Springborn (2020b). Standard errors are in parentheses. The dummies for previous year's crop choice are lagged dummy variables for each crop (alfalfa, corn, sorghum, soybeans, and wheat), indicating if that crop was planted in the previous year. The crop price variables include crop prices (alfalfa price, corn price, sorghum price, soybean price, and wheat price) from the previous year. The controls include hydrological and field characteristics (evapotranspiration, recharge, slope, soil quality, soil moisture, field size, depth to groundwater, saturated thickness), irrigation technology, energy prices (diesel price, electricity price, and natural gas price), expected future crop prices (10-year projections for corn price, sorghum price, soybean price, and wheat price), expected future energy prices (10-year projections for diesel price, electricity price, and natural gas price), groundwater extraction by neighbors (lagged extraction by neighbors, and lagged quantity authorized for extraction by neighbors). Significance codes: *** p<0.001, ** p<0.01, * p<0.05.

Table A3b. Crop Acreage Random Effects Tobit Regression Results for Corn

	Dependent variable is number of acres allocated to Corn				
	(Y1)	(Y2)	(Y3)	(Y4)	(Y5)
Temperature					
Annual average temperature (°F)	11.91	18.35			
	(8.461)	(11.30)			
Annual average temperature (°F), squared	-0.114	-0.137			
	(0.0776)	(0.104)			
Average annual temperature over the past 3 years (°F)		-55.29***		-59.06***	-44.81***
		(15.73)		(13.14)	(12.91)
Average annual temperature over the past 3 years (°F), squared		0.480***		0.552***	0.421***
		(0.144)		(0.121)	(0.119)
Annual fraction of days with max temp > 86°F			-414.0**		
			(145.8)		
Annual fraction of days with max temp > 86°F, squared			342.8		
			(296.6)		
Summer fraction of days with max temp > 86°F			285.4***		
			(53.76)		
Summer fraction of days with max temp > 86°F, squared			-120.5**		
			(37.21)		
Average temperature in Jan-Apr (°F)				14.29***	
				(3.263)	
Average temperature in Jan-Apr (°F), squared				-0.187***	
				(0.0403)	
Annual fraction of days in Jan-Apr with max temp > 86°F					49.12
					(91.91)
Annual fraction of days in Jan-Apr with max temp > 86°F, squared					-2,583
					(1,702)
Precipitation					
Annual precipitation (in)	6.047***	-1.084**	3.148***		
	(0.263)	(0.407)	(0.393)		

Annual precipitation (in), squared	-0.0414***	0.0240*	-0.0715***		
	(0.00189)	(0.0103)	(0.00977)		
Total precipitation over the past 3 years (in)		5.933***		5.741***	5.762***
		(0.246)		(0.260)	(0.260)
Total precipitation over the past 3 years (in), squared		-0.0412***		-0.0399***	-0.0398***
		(0.00176)		(0.00189)	(0.00189)
Precipitation in Jan-Apr (in)				10.81***	9.122***
				(2.704)	(2.626)
Precipitation in Jan-Apr (in), squared				-3.949***	-4.139***
				(0.943)	(0.945)
Humidity					
Annual average humidity (%)	-1.655***	-1.771***	-0.339**	-1.696***	-1.555***
	(0.135)	(0.131)	(0.121)	(0.163)	(0.160)
Average humidity in Jan-Apr (%)				-0.104	-0.226*
				(0.0966)	(0.0889)
Dummies for Previous Year's Crop Choice	Y	Y	Y	Y	Y
Crop Price Variables	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Time Trend	Y	Y	Y	Y	Y
Grower Random Effects	Y	Y	Y	Y	Y
# Observations	242,537	242,537	242,537	242,537	242,537
# Growers	29,376	29,376	29,376	29,376	29,376

Notes: These results are from the base-case specification in Table 3b in Bertone Oehninger, Lin Lawell and Springborn (2020b). Standard errors are in parentheses. The dummies for previous year's crop choice are lagged dummy variables for each crop (alfalfa, corn, sorghum, soybeans, and wheat), indicating if that crop was planted in the previous year. The crop price variables include crop prices (alfalfa price, corn price, sorghum price, soybean price, and wheat price) from the previous year. The controls include hydrological and field characteristics (evapotranspiration, recharge, slope, soil quality, soil moisture, field size, depth to groundwater, saturated thickness), irrigation technology, energy prices (diesel price, electricity price, and natural gas price), expected future crop prices (10-year projections for corn price, sorghum price, soybean price, and wheat price), expected future energy prices (10-year projections for diesel price, electricity price, and natural gas price), groundwater extraction by neighbors (lagged extraction by neighbors, and lagged quantity authorized for extraction by neighbors). Significance codes: *** p<0.001, ** p<0.01, * p<0.05.

Table A3c. Crop Acreage Random Effects Tobit Regression Results for Sorghum

	Dependent variable is number of acres allocated to Sorghum				
	(Y1)	(Y2)	(Y3)	(Y4)	(Y5)
Temperature					
Annual average temperature (°F)	146.6***	4.451			
	(32.07)	(43.38)			
Annual average temperature (°F), squared	-1.252***	-0.129			
	(0.294)	(0.397)			
Average annual temperature over the past 3 years (°F)		326.4***		362.1***	332.0***
		(60.92)		(50.29)	(49.45)
Average annual temperature over the past 3 years (°F), squared		-2.750***		-3.150***	-2.828***
		(0.559)		(0.464)	(0.457)
Annual fraction of days with max temp > 86°F			-1,047		
			(536.9)		
Annual fraction of days with max temp > 86°F, squared			3,164**		
			(1,109)		
Summer fraction of days with max temp > 86°F			78.66		
			(203.7)		
Summer fraction of days with max temp > 86°F, squared			-72.55		
			(142.9)		
Average temperature in Jan-Apr (°F)				6.464	
				(12.75)	
Average temperature in Jan-Apr (°F), squared				-0.0560	
				(0.157)	
Annual fraction of days in Jan-Apr with max temp > 86°F					828.7*
					(324.3)
Annual fraction of days in Jan-Apr with max temp > 86°F, squared					-24,791***
					(5,977)
Precipitation					
Annual precipitation (in)	-0.165	2.047	-1.628		
	(1.310)	(1.403)	(1.352)		

	(1)	(2)	(3)	(4)	(5)
Annual precipitation (in), squared	-0.0178	-0.0580	0.0435		
	(0.0327)	(0.0348)	(0.0333)		
Total precipitation over the past 3 years (in)		-2.286**		-0.716	-0.708
		(0.818)		(0.793)	(0.795)
Total precipitation over the past 3 years (in), squared		0.00934		-0.00191	-0.00210
		(0.00594)		(0.00586)	(0.00586)
Precipitation in Jan-Apr (in)				-60.80***	-52.86***
				(9.916)	(9.612)
Precipitation in Jan-Apr (in), squared				16.79***	12.56***
				(3.471)	(3.510)
Humidity					
Annual average humidity (%)	2.523***	2.859***	3.113***	4.123***	4.360***
	(0.401)	(0.462)	(0.418)	(0.561)	(0.553)
Average humidity in Jan-Apr (%)				-0.690*	-1.150***
				(0.336)	(0.315)
Dummies for Previous Year's Crop Choice	Y	Y	Y	Y	Y
Crop Price Variables	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Time Trend	Y	Y	Y	Y	Y
Grower Random Effects	Y	Y	Y	Y	Y
# Observations	242,542	242,542	242,542	242,542	242,542
# Growers	29,376	29,376	29,376	29,376	29,376

Notes: These results are from the base-case specification in Table 3c in Bertone Oehninger, Lin Lawell and Springborn (2020b). Standard errors are in parentheses. The dummies for previous year's crop choice are lagged dummy variables for each crop (alfalfa, corn, sorghum, soybeans, and wheat), indicating if that crop was planted in the previous year. The crop price variables include crop prices (alfalfa price, corn price, sorghum price, soybean price, and wheat price) from the previous year. The controls include hydrological and field characteristics (evapotranspiration, recharge, slope, soil quality, soil moisture, field size, depth to groundwater, saturated thickness), irrigation technology, energy prices (diesel price, electricity price, and natural gas price), expected future crop prices (10-year projections for corn price, sorghum price, soybean price, and wheat price), expected future energy prices (10-year projections for diesel price, electricity price, and natural gas price), groundwater extraction by neighbors (lagged extraction by neighbors, and lagged quantity authorized for extraction by neighbors). Significance codes: *** p<0.001, ** p<0.01, * p<0.05.

Table A3d. Crop Acreage Random Effects Tobit Regression Results for Soybeans

	Dependent variable is number of acres allocated to Soybeans				
	(Y1)	(Y2)	(Y3)	(Y4)	(Y5)
Temperature					
Annual average temperature (°F)	17.80	-118.5***			
	(18.77)	(26.14)			
Annual average temperature (°F), squared	-0.0787	1.055***			
	(0.171)	(0.237)			
Average annual temperature over the past 3 years (°F)		229.1***		149.5***	153.7***
		(34.56)		(27.94)	(27.35)
Average annual temperature over the past 3 years (°F), squared		-1.928***		-1.190***	-1.246***
		(0.316)		(0.258)	(0.253)
Annual fraction of days with max temp > 86°F			-2,216***		
			(333.6)		
Annual fraction of days with max temp > 86°F, squared			4,681***		
			(679.5)		
Summer fraction of days with max temp > 86°F			1,031***		
			(124.0)		
Summer fraction of days with max temp > 86°F, squared			-687.1***		
			(86.29)		
Average temperature in Jan-Apr (°F)				-20.20**	
				(7.668)	
Average temperature in Jan-Apr (°F), squared				0.239*	
				(0.0932)	
Annual fraction of days in Jan-Apr with max temp > 86°F					-813.8***
					(211.8)
Annual fraction of days in Jan-Apr with max temp > 86°F, squared					16,412***
					(3,831)
Precipitation					
Annual precipitation (in)	5.493***	2.753**	7.369***		

	(0.892)	(0.962)	(0.902)		
Annual precipitation (in), squared	-0.0893***	-0.0251	-0.130***		
	(0.0212)	(0.0231)	(0.0213)		
Total precipitation over the past 3 years (in)		5.383***		6.247***	6.013***
		(0.600)		(0.574)	(0.580)
Total precipitation over the past 3 years (in), squared		-0.0404***		-0.0452***	-0.0438***
		(0.00438)		(0.00420)	(0.00423)
Precipitation in Jan-Apr (in)				-13.77*	-15.10**
				(6.076)	(5.818)
Precipitation in Jan-Apr (in), squared				4.419*	5.015*
				(1.981)	(1.976)
Humidity					
Annual average humidity (%)	-2.207***	-3.423***	-2.447***	-1.771***	-1.995***
	(0.277)	(0.314)	(0.286)	(0.375)	(0.365)
Average humidity in Jan-Apr (%)				-1.482***	-1.153***
				(0.233)	(0.218)
Dummies for Previous Year's Crop Choice	Y	Y	Y	Y	Y
Crop Price Variables	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Time Trend	Y	Y	Y	Y	Y
Grower Random Effects	Y	Y	Y	Y	Y
# Observations	242,542	242,542	242,542	242,542	242,542
# Growers	29,376	29,376	29,376	29,376	29,376

Notes: These results are from the base-case specification in Table 3d in Bertone Oehninger, Lin Lawell and Springborn (2020b). Standard errors are in parentheses. The dummies for previous year's crop choice are lagged dummy variables for each crop (alfalfa, corn, sorghum, soybeans, and wheat), indicating if that crop was planted in the previous year. The crop price variables include crop prices (alfalfa price, corn price, sorghum price, soybean price, and wheat price) from the previous year. The controls include hydrological and field characteristics (evapotranspiration, recharge, slope, soil quality, soil moisture, field size, depth to groundwater, saturated thickness), irrigation technology, energy prices (diesel price, electricity price, and natural gas price), expected future crop prices (10-year projections for corn price, sorghum price, soybean price, and wheat price), expected future energy prices (10-year projections for diesel price, electricity price, and natural gas price), groundwater extraction by neighbors (lagged extraction by neighbors, and lagged quantity authorized for extraction by neighbors). Significance codes: *** p<0.001, ** p<0.01, * p<0.05.

Table A3e. Crop Acreage Random Effects Tobit Regression Results for Wheat

	Dependent variable is number of acres allocated to Wheat				
	(Y1)	(Y2)	(Y3)	(Y4)	(Y5)
Temperature					
Annual average temperature (°F)	67.71***	-41.16			
	(17.23)	(23.23)			
Annual average temperature (°F), squared	-0.625***	0.306			
	(0.159)	(0.213)			
Average annual temperature over the past 3 years (°F)		238.8***		159.5***	98.59***
		(32.76)		(26.78)	(26.45)
Average annual temperature over the past 3 years (°F), squared		-2.108***		-1.446***	-0.889***
		(0.302)		(0.248)	(0.245)
Annual fraction of days with max temp > 86°F			2,222***		
			(278.3)		
Annual fraction of days with max temp > 86°F, squared			-3,298***		
			(569.7)		
Summer fraction of days with max temp > 86°F			-1,040***		
			(98.70)		
Summer fraction of days with max temp > 86°F, squared			598.3***		
			(68.42)		
Average temperature in Jan-Apr (°F)				-33.12***	
				(6.450)	
Average temperature in Jan-Apr (°F), squared				0.421***	
				(0.0797)	
Annual fraction of days in Jan-Apr with max temp > 86°F					922.0***
					(175.4)
Annual fraction of days in Jan-Apr with max temp > 86°F, squared					-14,017***
					(3,232)
Precipitation					
Annual precipitation (in)	1.993**	3.784***	-1.710*		
	(0.723)	(0.764)	(0.733)		

Annual precipitation (in), squared	-0.0845***	-0.129***	0.0238		
	(0.0187)	(0.0198)	(0.0187)		
Total precipitation over the past 3 years (in)		-3.161***		-2.697***	-2.644***
		(0.455)		(0.448)	(0.449)
Total precipitation over the past 3 years (in), squared		0.0231***		0.0199***	0.0195***
		(0.00326)		(0.00326)	(0.00326)
Precipitation in Jan-Apr (in)				-7.096	-4.939
				(5.472)	(5.269)
Precipitation in Jan-Apr (in), squared				-3.418	-1.989
				(2.043)	(2.038)
Humidity					
Annual average humidity (%)	0.407	1.291***	0.926***	0.734*	0.575
	(0.212)	(0.241)	(0.221)	(0.302)	(0.297)
Average humidity in Jan-Apr (%)				0.768***	1.018***
				(0.182)	(0.169)
Dummies for Previous Year's Crop Choice	Y	Y	Y	Y	Y
Crop Price Variables	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Time Trend	Y	Y	Y	Y	Y
Grower Random Effects	Y	Y	Y	Y	Y
# Observations	242,537	242,537	242,537	242,537	242,537
# Growers	29,376	29,376	29,376	29,376	29,376

Notes: These results are from the base-case specification in Table 3e in Bertone Oehninger, Lin Lawell and Springborn (2020b). Standard errors are in parentheses. The dummies for previous year's crop choice are lagged dummy variables for each crop (alfalfa, corn, sorghum, soybeans, and wheat), indicating if that crop was planted in the previous year. The crop price variables include crop prices (alfalfa price, corn price, sorghum price, soybean price, and wheat price) from the previous year. The controls include hydrological and field characteristics (evapotranspiration, recharge, slope, soil quality, soil moisture, field size, depth to groundwater, saturated thickness), irrigation technology, energy prices (diesel price, electricity price, and natural gas price), expected future crop prices (10-year projections for corn price, sorghum price, soybean price, and wheat price), expected future energy prices (10-year projections for diesel price, electricity price, and natural gas price), groundwater extraction by neighbors (lagged extraction by neighbors, and lagged quantity authorized for extraction by neighbors). Significance codes: *** p<0.001, ** p<0.01, * p<0.05.

Table A4. Groundwater Extraction Regression Results: Monthly Climate Variables

	Dependent variable is: Extraction intensity (acre-feet per acre)	
	(M1)	(M2)
Avg. temperature (°F) over the past 3 years during month of:		
January	-0.102**	
	(0.0377)	
January, squared	0.00139*	
	(0.000649)	
February	-0.204***	
	(0.0318)	
February, squared	0.00264***	
	(0.000452)	
March	0.622***	
	(0.0771)	
March, squared	-0.00681***	
	(0.000874)	
April	-0.488***	
	(0.0941)	
April, squared	0.00433***	
	(0.000890)	
May	0.591***	
	(0.115)	
May, squared	-0.00417***	
	(0.000916)	
June	1.695***	
	(0.167)	
June, squared	-0.0111***	
	(0.00113)	
July	0.168	
	(0.165)	
July, squared	-0.000986	
	(0.00101)	
August	-1.521***	
	(0.157)	
August, squared	0.00962***	
	(0.00101)	
September	0.237*	

	(0.0931)	
September, squared	-0.00198**	
	(0.000684)	
October	-0.272**	
	(0.0856)	
October, squared	0.00196*	
	(0.000794)	
November	-0.408***	
	(0.0398)	
November, squared	0.00524***	
	(0.000471)	
December	0.494***	
	(0.0398)	
December, squared	-0.00809***	
	(0.000636)	
Avg. fraction of days with max temp > 86°F over the past 3 years during month of:		
January		-24.19***
		(3.977)
January, squared		966.9*
		(385.4)
February		
February, squared		
March		-4.797***
		(1.100)
March, squared		484.2***
		(67.82)
April		-1.426***
		(0.289)
April, squared		20.06***
		(1.672)
May		-3.938***
		(0.269)
May, squared		5.797***
		(0.561)
June		-0.898**
		(0.313)
June, squared		2.333***
		(0.300)
July		12.75***
		(0.960)
July, squared		-8.158***
		(0.602)
August		-1.567***

		(0.334)
August, squared		1.105***
		(0.250)
September		1.149***
		(0.260)
September, squared		-0.893**
		(0.304)
October		3.581***
		(0.396)
October, squared		-16.80***
		(2.100)
November		5.128***
		(0.994)
November, squared		-36.07
		(24.19)
December		
December, squared		
Avg. precipitation (in) over the past 3 years for month of:		
January	-0.143***	0.0423
	(0.0365)	(0.0347)
January, squared	-0.102***	-0.0157
	(0.0223)	(0.0207)
February	0.0597	-0.259***
	(0.0414)	(0.0338)
February, squared	-0.0107	0.107***
	(0.0178)	(0.0147)
March	0.218***	0.194***
	(0.0185)	(0.0165)
March, squared	-0.0541***	-0.0307***
	(0.00422)	(0.00329)
April	0.212***	-0.0432
	(0.0245)	(0.0224)
April, squared	-0.0564***	0.0120
	(0.00671)	(0.00630)
May	-0.0800***	-0.00282
	(0.0103)	(0.00990)
May, squared	0.00248	-0.00325*
	(0.00158)	(0.00145)
June	-0.0395**	-0.135***
	(0.0144)	(0.0141)
June, squared	0.0102***	0.0169***
	(0.00198)	(0.00193)

July	0.0616***	0.0282*
	(0.0116)	(0.0116)
July, squared	-0.0132***	-0.00587***
	(0.00184)	(0.00168)
August	0.0148	-0.0613***
	(0.00966)	(0.00761)
August, squared	0.00264**	0.00830***
	(0.000879)	(0.000837)
September	-0.243***	-0.0230
	(0.0168)	(0.0160)
September, squared	0.0430***	0.00151
	(0.00331)	(0.00338)
October	0.0440*	0.0389**
	(0.0175)	(0.0138)
October, squared	-0.00288	-0.0107***
	(0.00370)	(0.00304)
November	-0.180***	-0.0672**
	(0.0261)	(0.0227)
November, squared	0.0329***	-0.00227
	(0.00930)	(0.00875)
December	0.0444*	-0.0155
	(0.0190)	(0.0170)
December, squared	-0.0279**	0.00642
	(0.00929)	(0.00705)
Avg. humidity (%) over the past 3 years during month of:		
January	0.0208***	0.0176***
	(0.00197)	(0.00150)
February	-0.00918***	-0.00353*
	(0.00231)	(0.00145)
March	-0.00819***	-0.0110***
	(0.00216)	(0.00177)
April	-0.00731***	-0.000608
	(0.00217)	(0.00184)
May	0.0342***	-0.0345***
	(0.00296)	(0.00248)
June	-0.0140***	0.0325***
	(0.00311)	(0.00302)
July	-0.00120	-0.0159***
	(0.00306)	(0.00242)
August	-0.0198***	0.00412*
	(0.00225)	(0.00200)
September	0.0110***	0.0202***
	(0.00219)	(0.00213)
October	-0.0211***	-0.0196***
	(0.00234)	(0.00184)

November	0.0190***	0.0311***
	(0.00200)	(0.00147)
December	0.00372	-0.00423**
	(0.00221)	(0.00163)
Crop acreage variables		
Acres planted with alfalfa (acres)	0.00206***	0.00206***
	(0.000123)	(0.000123)
Acres planted with alfalfa (acres), squared	-7.15e-06***	-7.15e-06***
	(6.72e-07)	(6.70e-07)
Acres planted with corn (acres)	0.00195***	0.00196***
	(4.87e-05)	(4.88e-05)
Acres planted with corn (acres), squared	-6.56e-06***	-6.57e-06***
	(2.13e-07)	(2.13e-07)
Acres planted with sorghum (acres)	-0.000519***	-0.000529***
	(8.98e-05)	(8.93e-05)
Acres planted with sorghum (acres), squared	-1.15e-06*	-1.11e-06*
	(4.66e-07)	(4.60e-07)
Acres planted with soybeans (acres)	0.00160***	0.00160***
	(8.90e-05)	(8.85e-05)
Acres planted with soybeans (acres), squared	-6.96e-06***	-6.94e-06***
	(6.12e-07)	(6.09e-07)
Acres planted with wheat (acres)	-0.00179***	-0.00180***
	(6.51e-05)	(6.51e-05)
Acres planted with wheat (acres), squared	8.63e-07**	8.94e-07**
	(3.18e-07)	(3.18e-07)
Irrigation technology		
Center pivot sprinkler use (dummy)	0.00965*	0.00986*
	(0.00429)	(0.00428)
Center pivot with drop nozzles use (dummy)	-0.00562	-0.00790
	(0.00735)	(0.00731)
Controls	Y	Y
Time Trend	Y	Y
Grower Fixed Effects	Y	Y

Total Intensive Margin

Total average effects of:

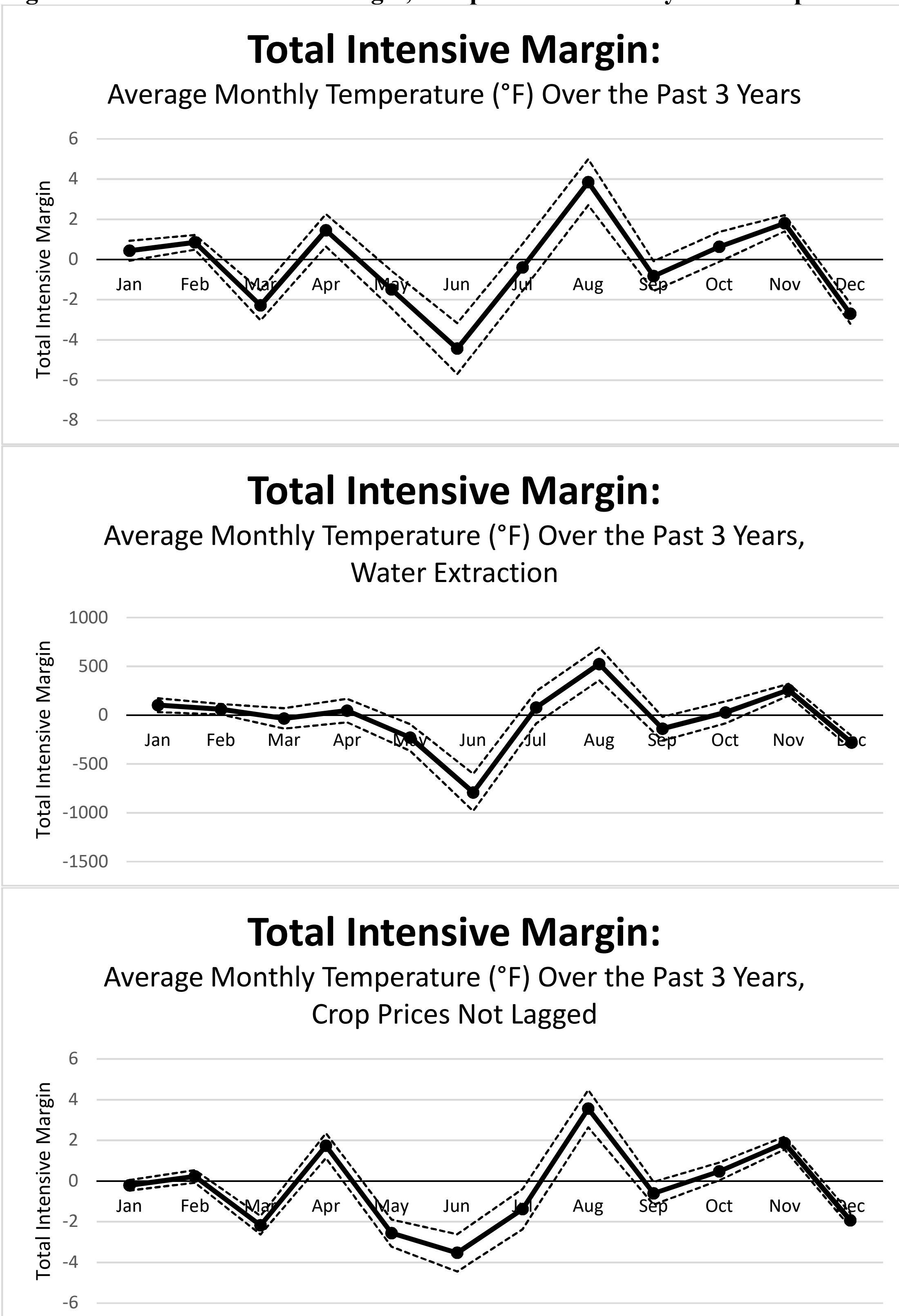
Avg. temperature (°F) over the past 3 years during month of:

January	0.432	
	(0.252)	
February	0.852***	
	(0.184)	
March	-2.279***	
	(0.380)	
April	1.452***	
	(0.410)	
May	-1.494**	
	(0.472)	
June	-4.432***	
	(0.646)	
July	-0.390	
	(0.595)	
August	3.847***	
	(0.585)	
September	-0.824*	
	(0.378)	
October	0.634	
	(0.378)	
November	1.803***	
	(0.203)	
December	-2.693***	
	(0.254)	
Avg. fraction of days with max temp > 86°F over the past 3 years during month of:		
January		19,313.8*
		(7,708.0)
February		
March		14,521.2***
		(2,034.6)
April		1,121.9***
		(93.6)
May		529.4***
		(51.6)
June		325.7***
		(42.0)
July		-1,325.2***
		(98.7)
August		170.8***
		(39.0)
September		-102.4**
		(35.3)
October		-1,172.4***
		(147.0)

November		-1,293.4***
		(870.8)
December		
Avg. precipitation (in) over the past 3 years for month of:		
January	-11.363***	-1.685
	(2.453)	(1.277)
February	-1.267	13.009***
	(2.208)	(1.823)
March	-9.736***	-5.455***
	(0.777)	(0.606)
April	-11.068***	2.357
	(1.342)	(1.260)
May	0.694	-1.017*
	(0.493)	(0.453)
June	3.286***	5.374***
	(0.646)	(0.629)
July	-4.770***	-2.120***
	(0.674)	(0.615)
August	0.992**	3.010***
	(0.325)	(0.310)
September	8.185***	0.273
	(0.649)	(0.663)
October	-0.509	-2.016***
	(0.711)	(0.584)
November	4.360***	-0.380
	(1.284)	(1.208)
December	-3.973**	0.909
	(1.338)	(1.015)
# Observations	241,091	241,091
# Growers	29,323	29,323

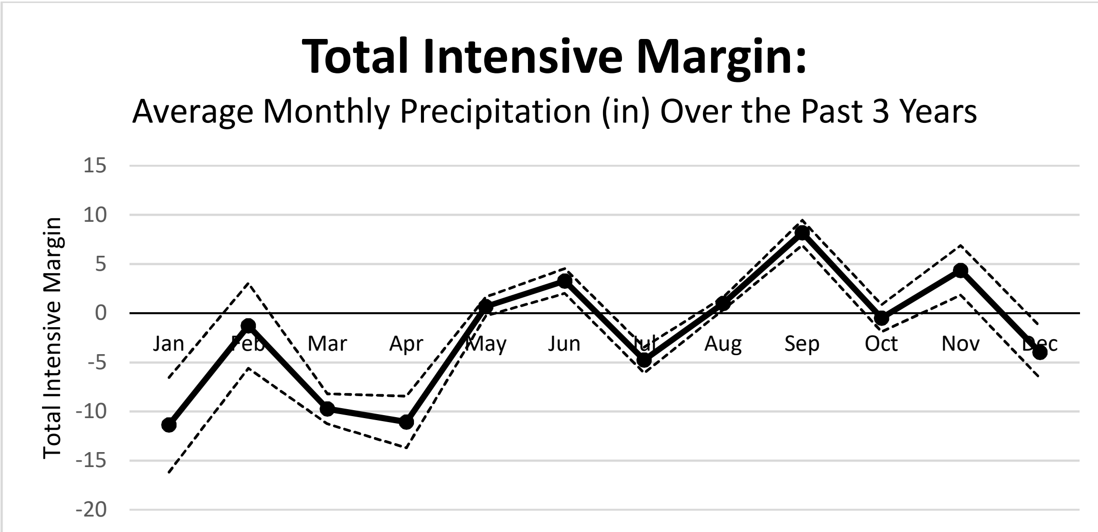
Notes: Robust standard errors are in parentheses. The controls include hydrological and field characteristics (evapotranspiration, recharge, slope, soil quality, soil moisture, field size, depth to groundwater, saturated thickness), the quantity authorized for extraction, crop prices (alfalfa price, corn price, sorghum price, soybean price, and wheat price) from the previous year, energy prices (diesel price, electricity price, and natural gas price), expected future crop prices (10-year projections for corn price, sorghum price, soybean price, and wheat price), expected future energy prices (10-year projections for diesel price, electricity price, and natural gas price), and groundwater extraction by neighbors (lagged extraction by neighbors, and lagged quantity authorized for extraction by neighbors). Significance codes: *** p<0.001, ** p<0.01, * p<0.05.

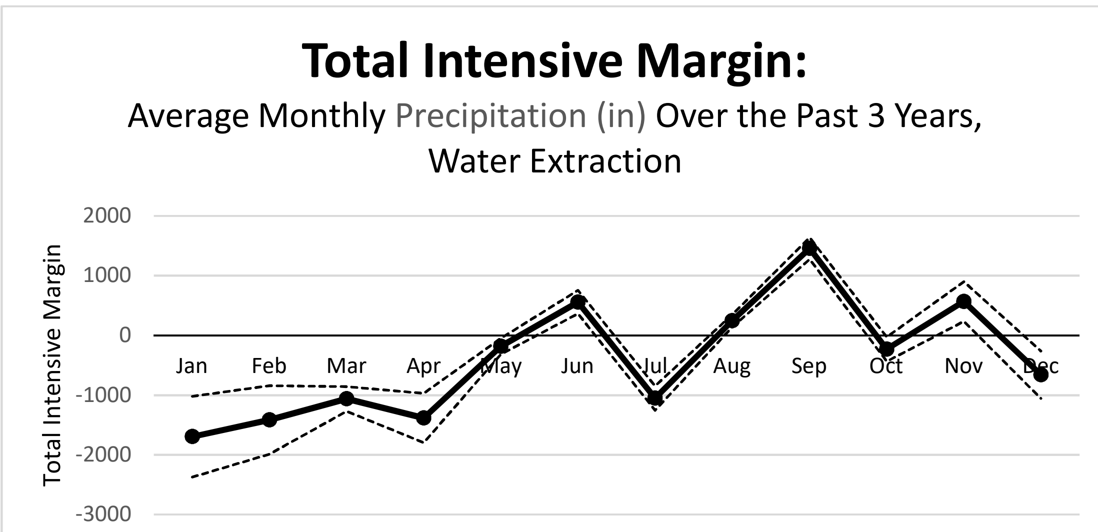
Figure A3a. Total Intensive Margin, Temperature: Monthly Climate Specification M1

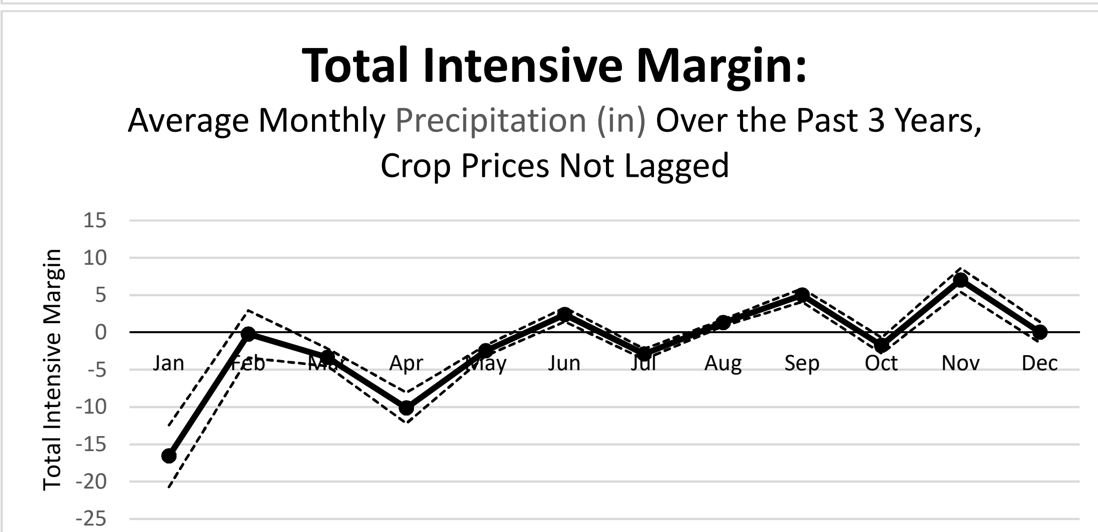


Note: Dotted lines indicate the 95% confidence interval.

Figure A3b. Total Intensive Margin, Precipitation: Monthly Climate Specification M1

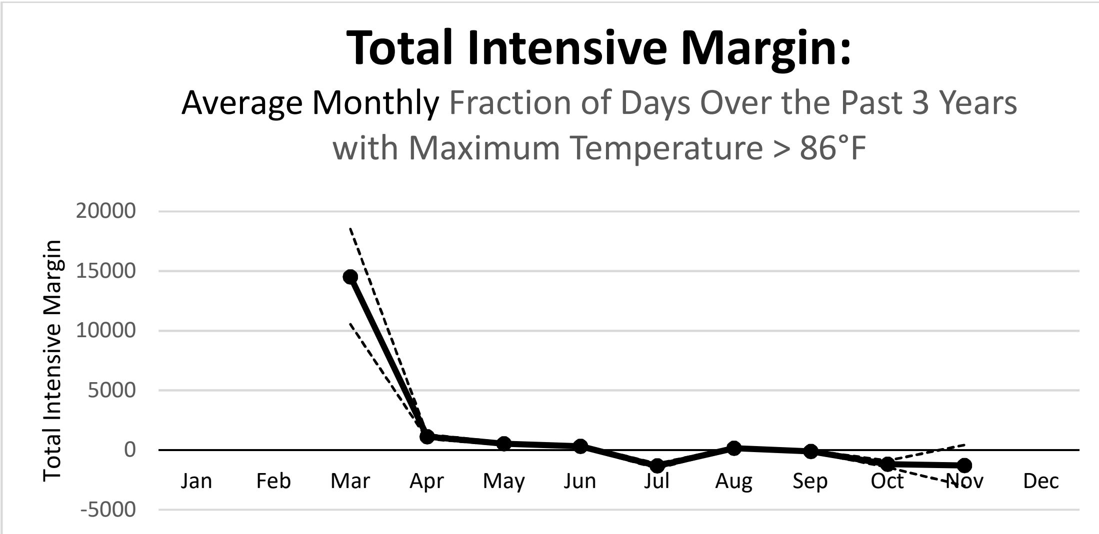


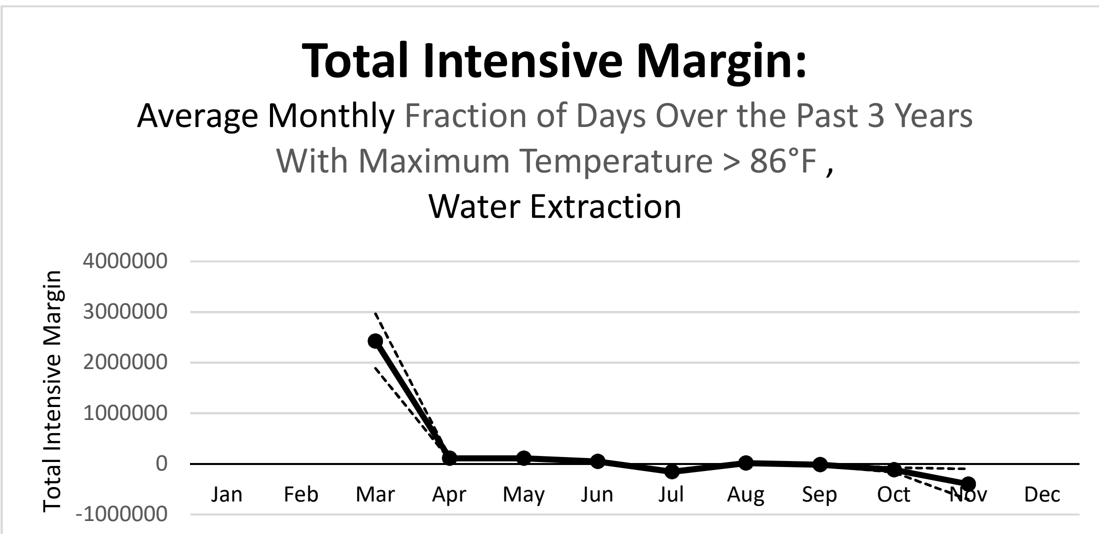


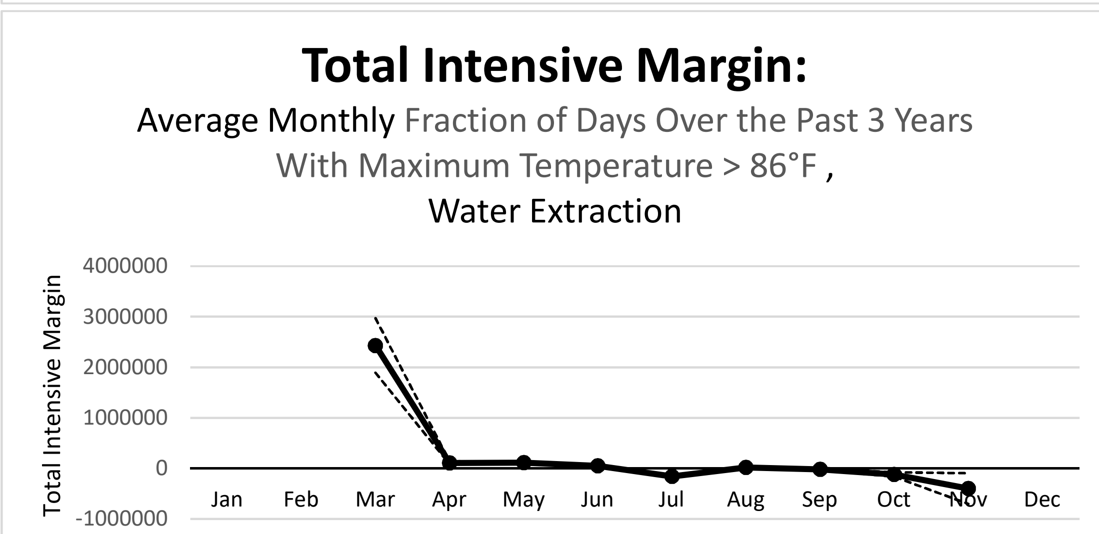


Note: Dotted lines indicate the 95% confidence interval.

Figure A4a. Total Intensive Margin, Temperature: Monthly Climate Specification M2

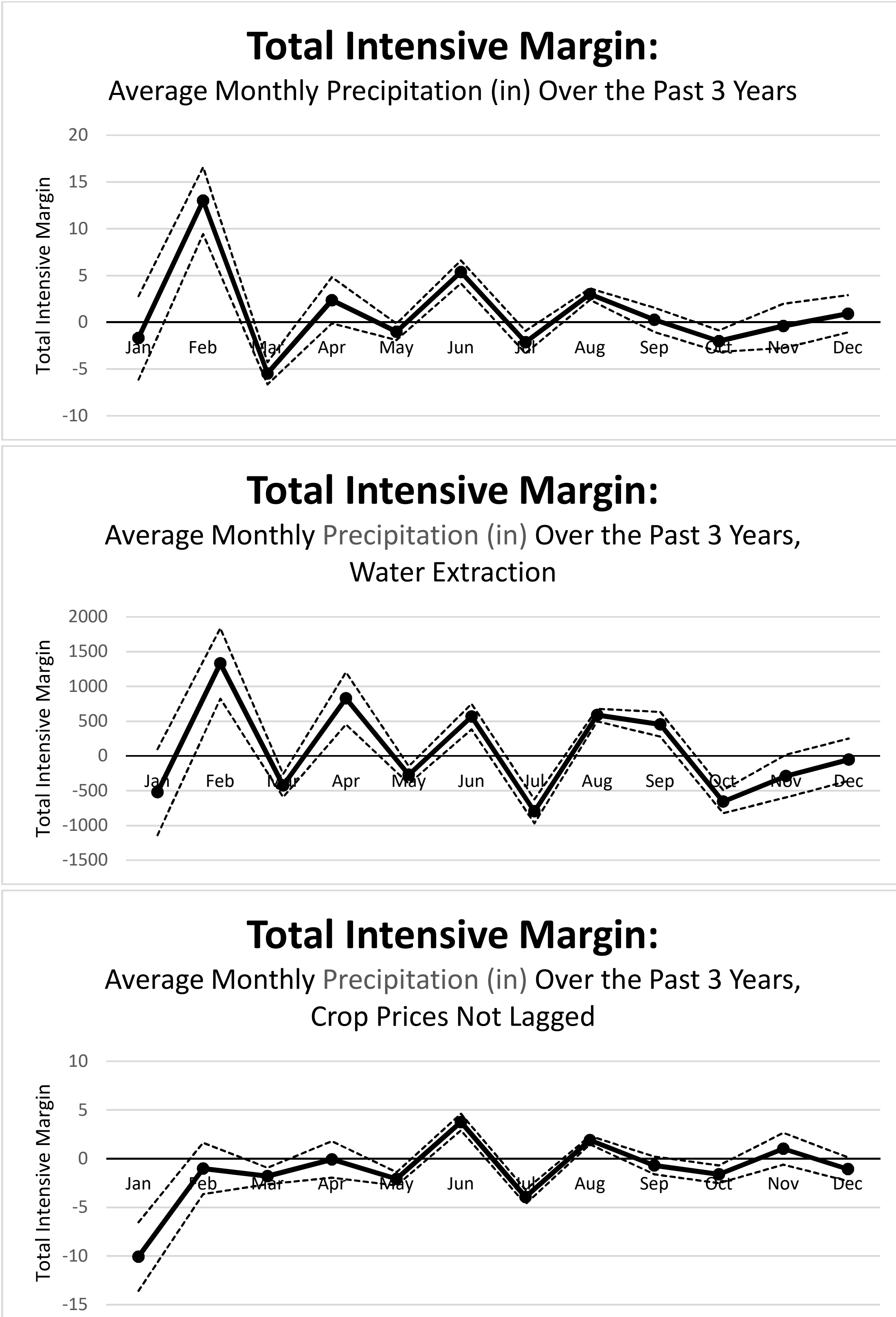






Note: Dotted lines indicate the 95% confidence interval.

Figure A4b. Total Intensive Margin, Precipitation: Monthly Climate Specification M2



Note: Dotted lines indicate the 95% confidence interval.

Table A5a. Irrigation Technology Random Effects Probit Regression Results: Center Pivot Sprinkler

	Dependent variable is: Probability of center pivot sprinkler use				
	(Y1)	(Y2)	(Y3)	(Y4)	(Y5)
	RE	RE	RE	RE	RE
	Base	Base	Base	Base	Base
Temperature					
Annual average temperature (°F)	0.151	0.0197			
	(0.205)	(0.189)			
Annual average temperature (°F), squared	-0.00177	-0.000573			
	(0.00185)	(0.00175)			
Average annual temperature over the past 3 years (°F)		0.382		0.423	0.799*
		(0.385)		(0.432)	(0.401)
Average annual temperature over the past 3 years (°F), squared		-0.00364		-0.00428	-0.00761*
		(0.00349)		(0.00395)	(0.00364)
Annual fraction of days with max temp > 86°F			-18.91***		
			(3.575)		
Annual fraction of days with max temp > 86°F, squared			26.03***		
			(6.724)		
Summer fraction of days with max temp > 86°F			-1.999		
			(1.307)		
Summer fraction of days with max temp > 86°F, squared			3.044**		
			(0.929)		
Average temperature in Jan-Apr (°F)				-0.118	
				(0.0782)	
Average temperature in Jan-Apr (°F), squared				0.00210*	
				(0.00101)	
Annual fraction of days in Jan-Apr with max temp > 86°F					-23.55***
					(1.789)
Annual fraction of days in Jan-Apr with max temp > 86°F, squared					517.2***
					(38.23)

Precipitation					
Annual precipitation (in)	0.00505	0.0136**	-0.000718		
	(0.00471)	(0.00440)	(0.00510)		
Annual precipitation (in), squared	-0.000227*	-0.000219**	-0.000113		
	(8.93e-05)	(8.32e-05)	(9.23e-05)		
Total precipitation over the past 3 years (in)		-0.0144*		0.00248	-0.000352
		(0.00667)		(0.00685)	(0.00696)
Total precipitation over the past 3 years (in), squared		4.39e-05		-7.65e-05	-6.44e-05
		(4.60e-05)		(4.91e-05)	(4.98e-05)
Precipitation in Jan-Apr (in)				-0.499***	-0.496***
				(0.0701)	(0.0731)
Precipitation in Jan-Apr (in), squared				0.0905***	0.0795***
				(0.0172)	(0.0196)
Humidity					
Annual average humidity (%)	-0.00495	0.00188	-0.00117	-0.00341	-0.00776*
	(0.00321)	(0.00366)	(0.00309)	(0.00312)	(0.00317)
Average humidity in Jan-Apr (%)				0.00758***	0.00997***
				(0.00179)	(0.00165)
Crop acreage variables					
Acres planted with alfalfa (acres)	0.00161***	0.00162***	0.00160***	0.00162***	0.00160***
	(0.000407)	(0.000408)	(0.000408)	(0.000409)	(0.000410)
Acres planted with alfalfa (acres), squared	-1.81e-06	-1.87e-06	-1.80e-06	-1.86e-06	-1.80e-06
	(1.73e-06)	(1.74e-06)	(1.74e-06)	(1.75e-06)	(1.76e-06)
Acres planted with corn (acres)	0.00153***	0.00156***	0.00151***	0.00156***	0.00155***
	(0.000184)	(0.000184)	(0.000184)	(0.000184)	(0.000184)
Acres planted with corn (acres), squared	-1.14e-06	-1.21e-06	-1.11e-06	-1.19e-06	-1.16e-06
	(6.37e-07)	(6.37e-07)	(6.35e-07)	(6.38e-07)	(6.37e-07)
Acres planted with sorghum (acres)	-0.00160**	-0.00163**	-0.00160**	-0.00165**	-0.00160**
	(0.000522)	(0.000522)	(0.000524)	(0.000521)	(0.000522)
Acres planted with sorghum (acres), squared	7.75e-06**	7.93e-06**	7.79e-06**	8.01e-06**	7.88e-06**

	(2.77e-06)	(2.77e-06)	(2.78e-06)	(2.77e-06)	(2.78e-06)
Acres planted with soybeans (acres)	0.00145***	0.00147***	0.00143***	0.00147***	0.00142***
	(0.000346)	(0.000347)	(0.000347)	(0.000345)	(0.000346)
Acres planted with soybeans (acres), squared	-2.54e-07	-3.45e-07	-3.11e-07	-3.42e-07	-2.03e-07
	(2.05e-06)	(2.05e-06)	(2.05e-06)	(2.03e-06)	(2.04e-06)
Acres planted with wheat (acres)	0.000623	0.000669*	0.000642*	0.000663*	0.000694*
	(0.000326)	(0.000328)	(0.000327)	(0.000328)	(0.000330)
Acres planted with wheat (acres), squared	-1.99e-06	-2.09e-06	-2.04e-06	-2.10e-06	-2.22e-06
	(1.68e-06)	(1.69e-06)	(1.69e-06)	(1.69e-06)	(1.70e-06)
Controls	Y	Y	Y	Y	Y
Time Trend	Y	Y	Y	Y	Y
Grower Random Effects	Y	Y	Y	Y	Y
# Observations	260,894	260,894	260,894	260,894	260,894

Notes: Robust standard errors are in parentheses. The controls include hydrological and field characteristics (evapotranspiration, recharge, slope, soil quality, soil moisture, field size, depth to groundwater, saturated thickness), the quantity authorized for extraction, crop prices (alfalfa price, corn price, sorghum price, soybean price, and wheat price), energy prices (diesel price, electricity price, and natural gas price), expected future crop prices (10-year projections for corn price, sorghum price, soybean price, and wheat price), expected future energy prices (10-year projections for diesel price, electricity price, and natural gas price), and groundwater extraction by neighbors (lagged extraction by neighbors, and lagged quantity authorized for extraction by neighbors). Significance codes: *** $p<0.001$, ** $p<0.01$, * $p<0.05$.

Table A5b. Irrigation Technology Random Effects Probit Regression Results: Center Pivot Sprinkler with Dropped Nozzles

	Dependent variable is: Probability of center pivot sprinkler with dropped nozzles use				
	(Y1)	(Y2)	(Y3)	(Y4)	(Y5)
	RE	RE	RE	RE	RE
	Base	Base	Base	Base	Base
Temperature					
Annual average temperature (°F)	-1.869***	-0.163			
	(0.394)	(0.538)			
Annual average temperature (°F), squared	0.0155***	0.000179			
	(0.00366)	(0.00516)			
Average annual temperature over the past 3 years (°F)		-4.477***		-5.744***	-5.396***
		(1.227)		(0.990)	(0.917)
Average annual temperature over the past 3 years (°F), squared		0.0392***		0.0496***	0.0464***
		(0.0116)		(0.00920)	(0.00847)
Annual fraction of days with max temp > 86°F			14.24		
			(7.319)		
Annual fraction of days with max temp > 86°F, squared			-30.88		
			(15.92)		
Summer fraction of days with max temp > 86°F			-5.753		
			(3.322)		
Summer fraction of days with max temp > 86°F, squared			2.787		
			(2.203)		
Average temperature in Jan-Apr (°F)				0.347**	
				(0.126)	
Average temperature in Jan-Apr (°F), squared				-0.00496**	
				(0.00152)	
Annual fraction of days in Jan-Apr with max temp > 86°F					-5.329
					(4.684)
Annual fraction of days in Jan-Apr with max temp > 86°F, squared					-63.58
					(76.97)

Precipitation					
Annual precipitation (in)	0.0192	-0.0171	0.0480*		
	(0.0189)	(0.0236)	(0.0191)		
Annual precipitation (in), squared	-1.57e-05	0.000706	-0.000866		
	(0.000476)	(0.000645)	(0.000503)		
Total precipitation over the past 3 years (in)		0.0541***		0.0513**	0.0514**
		(0.0154)		(0.0164)	(0.0164)
Total precipitation over the past 3 years (in), squared		-0.000334**		-0.000250*	-0.000215
		(0.000112)		(0.000117)	(0.000117)
Precipitation in Jan-Apr (in)				0.261	0.209
				(0.246)	(0.245)
Precipitation in Jan-Apr (in), squared				-0.0404	-0.117
				(0.115)	(0.117)
Humidity					
Annual average humidity (%)	-0.0308***	-0.0398***	-0.0327***	-0.0377***	-0.0450***
	(0.00665)	(0.00726)	(0.00729)	(0.00902)	(0.00789)
Average humidity in Jan-Apr (%)				0.00510	0.00691
				(0.00880)	(0.00575)
Crop acreage variables					
Acres planted with alfalfa (acres)	0.000749	0.000852	0.000708	0.000861	0.000928
	(0.000781)	(0.000775)	(0.000787)	(0.000774)	(0.000776)
Acres planted with alfalfa (acres), squared	-1.71e-06	-1.94e-06	-1.62e-06	-1.93e-06	-2.05e-06
	(3.22e-06)	(3.18e-06)	(3.24e-06)	(3.17e-06)	(3.17e-06)
Acres planted with corn (acres)	0.00239***	0.00228***	0.00226***	0.00224***	0.00223***
	(0.000386)	(0.000385)	(0.000392)	(0.000386)	(0.000387)
Acres planted with corn (acres), squared	-2.75e-06	-2.47e-06	-2.53e-06	-2.38e-06	-2.39e-06
	(1.41e-06)	(1.42e-06)	(1.44e-06)	(1.42e-06)	(1.42e-06)
Acres planted with sorghum (acres)	-0.00105	-0.00101	-0.00113	-0.000979	-0.00102
	(0.00102)	(0.00102)	(0.00104)	(0.00102)	(0.00103)
Acres planted with sorghum (acres), squared	3.65e-06	3.61e-06	3.83e-06	3.53e-06	3.61e-06

	(5.42e-06)	(5.37e-06)	(5.55e-06)	(5.40e-06)	(5.43e-06)
Acres planted with soybeans (acres)	0.00125	0.00110	0.00126	0.00102	0.00102
	(0.000835)	(0.000831)	(0.000850)	(0.000835)	(0.000839)
Acres planted with soybeans (acres), squared	-4.93e-07	1.70e-07	-8.62e-07	4.96e-07	5.22e-07
	(5.47e-06)	(5.44e-06)	(5.58e-06)	(5.48e-06)	(5.51e-06)
Acres planted with wheat (acres)	-0.000725	-0.000621	-0.000812	-0.000616	-0.000654
	(0.000631)	(0.000626)	(0.000644)	(0.000630)	(0.000634)
Acres planted with wheat (acres), squared	3.54e-06	3.21e-06	3.85e-06	3.19e-06	3.29e-06
	(3.15e-06)	(3.12e-06)	(3.23e-06)	(3.15e-06)	(3.18e-06)
Controls	Y	Y	Y	Y	Y
Time Trend	Y	Y	Y	Y	Y
Grower Random Effects	Y	Y	Y	Y	Y
# Observations	260,894	260,894	260,894	260,894	260,894

Notes: Robust standard errors are in parentheses. The controls include hydrological and field characteristics (evapotranspiration, recharge, slope, soil quality, soil moisture, field size, depth to groundwater, saturated thickness), the quantity authorized for extraction, crop prices (alfalfa price, corn price, sorghum price, soybean price, and wheat price), energy prices (diesel price, electricity price, and natural gas price), expected future crop prices (10-year projections for corn price, sorghum price, soybean price, and wheat price), expected future energy prices (10-year projections for diesel price, electricity price, and natural gas price), and groundwater extraction by neighbors (lagged extraction by neighbors, and lagged quantity authorized for extraction by neighbors). Significance codes: *** p<0.001, ** p<0.01, * p<0.05.

Table A6. Total Marginal Effect including Irrigation Technology Extensive Margin

	TOTAL MARGINAL EFFECT $\left(\frac{dw}{dC_j} = \frac{\partial w}{\partial C_j} + \sum_c \frac{\partial w}{\partial n_c} \frac{\partial n_c}{\partial C_j}\right)$	TOTAL MARGINAL EFFECT Including Irrigation Technology Extensive Margin
Climate Specification Y1		
Annual average temperature (°F)	0.887**	1.395
	(0.278)	(3.176)
Annual precipitation (in)	-0.037	-0.039
	(0.019)	(0.233)
Climate Specification Y2		
Annual average temperature (°F)	2.536***	2.513
	(0.332)	(4.220)
Average annual temperature over the past 3 years (°F)	-3.981***	-2.657
	(0.557)	(9.351)
Annual precipitation (in)	-0.061**	-0.044
	(0.020)	(0.312)
Total precipitation over the past 3 years (in)	-0.009	-0.019
	(0.007)	(0.097)
Climate Specification Y3		
Annual fraction of days with max temp > 86°F	-2.445.04***	-2,608.9
	(223.90)	(2,732.9)
Summer fraction of days with max temp > 86°F	649.04***	722.18

	(45.63)	(622.16)
Annual precipitation (in)	-0.029	-0.052
	(0.019)	(0.245)
Climate Specification Y4		
Average annual temperature over the last 3 years (°F)	-3.173***	-1.501
	(0.503)	(7.724)
Average temperature in Jan-Apr (°F)	0.941***	0.805
	(0.116)	(1.271)
Total precipitation over the last 3 years (in)	-0.013	-0.022
	(0.007)	(0.102)
Precipitation in Jan-Apr (in)	-1.412	-1.233
	(1.280)	(33.390)
Climate Specification Y5		
Average annual temperature over the last 3 years (°F)	-2.547***	-1.058
	(0.481)	(7.115)
Fraction of days in Jan-Apr with max temp > 86°F	-4,348.85***	-3,181.7
	(632.64)	(7,073.2)
Total precipitation over the last 3 years (in)	0.003	-0.004
	(0.007)	(0.102)
Precipitation in Jan-Apr (in)	8.909***	7.581
	(1.219)	(34.060)

Notes: Standard errors are in parentheses. Groundwater extraction *w* is extraction intensity in acre-feet per acre. For each crop *c*, the number of acres n_c planted to crop *c* is in acres and is evaluated at its mean value in the data. Similarly, for each irrigation system, water use conditional on irrigation system is evaluated at its mean value in the data. Results are calculated using the groundwater extraction regression results from Table A2 in the Appendix, the crop acreage regressions results in Tables A3a-A3e in the Appendix, and the random effects probit regressions of irrigation technology in Tables A5a-A5b in the Appendix. Significance codes: *** p<0.001, ** p<0.01, * p<0.05.