The Effects of Climate Change on Crop Choice and Agricultural Variety[1]

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Abstract

Climate change has the potential to impact crop choice and agricultural variety, with possible implications for agricultural productivity. In this paper, we analyze the effects of changes in temperature, precipitation, and humidity on farmers' decisions regarding crop acreage, whether to plant multiple crops, and irrigation technology in western Kansas. Our results show that changes in climate variables influence crop acreage allocation decisions, the choice to plant multiple crops, and the choice of irrigation technology. We find that it is important to account for the margins of whether to plant multiple crops and of the choice of irrigation technology in addition to the crop acreage margin. We also find that it is important to also evaluate the effects of climate-related variables by month rather than only at an annual level. The outcome of this research provides a better understanding of how changes in temperature, precipitation, and humidity affect agricultural variety, and therefore of the possible implications of climate change for agricultural productivity.

Keywords: agriculture, climate change, land-use change, crop choice, agricultural variety
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1. Introduction

Climate change has the potential to impact crop choice and agricultural variety, with possible implications for agricultural productivity. In this paper, we analyze the effects of changes in temperature, precipitation, and humidity on farmers' decisions regarding crop acreage, whether to plant multiple crops, and irrigation technology in western Kansas.

Our research focuses on agriculture in the High Plains (Ogallala) Aquifer system of the Midwestern United States. The economy of the region is based almost entirely on irrigated agriculture. The alfalfa, corn, sorghum, soybeans, and wheat grown there is used for local livestock production or exported from the region. The small local communities support the agricultural industry with farm implement dealers, schools, restaurants, and other services. The state governments are also greatly concerned with supporting their agricultural industry (Lin and Pfeiffer, 2015).

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

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

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

For the empirical analysis, we use a unique detailed field-level data set. We model three margins that affect agricultural variety: crop acreage, the choice to plant multiple crops, and irrigation technology. For the crop acreage margin, we estimate the farmer's choice of how many acres to allocate to each crop using a censored regression model. For the multiple crop margin, we estimate the farmer's choice of whether to plant multiple crops using a discrete response model. For the irrigation technology margin, we estimate the farmer's choice of irrigation technology using discrete response models. In addition to temperature, precipitation, and humidity, we also control for other factors that may affect these decisions, including depth to groundwater, precipitation, irrigation technology, saturated thickness, recharge, soil moisture, crop prices, and energy prices.

Our results show that changes in climate variables influence crop acreage allocation decisions, the choice to plant multiple crops, and the choice of irrigation technology. We find that it is important to account for the margins of whether to plant multiple crops and of the choice of irrigation technology in addition to the crop acreage margin. We also find that it is important to also evaluate the effects of climate-related variables by month rather than only at an annual level.

The balance of our paper proceeds as follows. We review the previous literature in Section 2. We describe our data in Section 3, our methods in Section 4, and our results in Section 5. Section 6 concludes.

2. Literature Review

2.1. Climate change and farmland values

We build upon the previous literature analyzing the effects of climate change on agriculture.[2] This literature includes a strand which examines the effects of climate change on farmland values and/or agricultural profits. Schlenker, Hanemann and Fisher (2006) estimate the potential impacts of global warming on farmland values for a range of scenarios, and find a statistically significant effect, ranging from moderate gains to large losses, in more than 75% of the counties in their sample, with losses in the aggregate that can become quite large under scenarios involving sustained heavy use of fossil fuels. Deschênes and Greenstone (2007) measure the economic impact of climate change on U.S. agricultural land by estimating the effect of random year-to-year variation in temperature and precipitation on agricultural profits, and find that climate change will increase annual profits by $1.3 billion in 2002 dollars, or 4 percent. Wang et al. (2017) employ a stochastic frontier approach to examine how climate change and extreme weather affect U.S. agricultural productivity using 1940-1970 historical weather data as the norm, and find that more heat waves and drier conditions will tend to lower agricultural productivity, with impacts that vary by region.

Analyses of the effects of climate change on farmland values and/or agricultural profits can be sensitive to the model specification and the data used. In contrast to Deschênes and Greenstone (2007), Fisher et al. (2012) find that the potential impact of climate change on U.S. agriculture is likely negative. Fisher et al. (2012) attribute the different results in Deschênes and Greenstone (2007) to (1) missing and incorrect weather and climate data; (2) the use of older climate change projections rather than the more recent and less optimistic projections from the Fourth Assessment Report; and (3) difficulties in the profit measure due to the

[2] For a more extensive review of the literature on the effects of climate change on agriculture, see Bertone Oehninger, Lin Lawell and Springborn (2017).

confounding effects of storage. Deschênes and Greenstone (2012) acknowledge the coding and data errors in their 2007 paper that were uncovered by Fisher et al. (2012), but show how some of the other critiques may have little basis. Fezzi and Bateman (2015) use a large panel of farm-level data to investigate the potential bias induced by assuming additively separable effects of temperature and precipitation and by using data aggregated across counties or large regions.

2.2. Climate change and crop yields

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

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

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

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

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

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

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

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

2.3. Climate change and economic outcomes

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

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

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

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

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

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.

2.4. Climate change and adaptation

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

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

Bento et al. (2017) propose a novel approach to estimate adaptation to climate change based on a decomposition of meteorological variables into long-run trends and deviations from those trends (weather shocks). Their estimating equation simultaneously exploits weather variation to identify the impact of weather shocks, and climatic variation to identify the effect of longer-run observed changes. They then compare the simultaneously estimated short- and long-run effects to provide a measure of adaptation (Bento et al, 2017).

2.5. Agricultural biodiversity

In addition to the literature on climate change and agriculture, we also build upon the literature on agricultural diversity. According to the United Nations Food and Agriculture Organization (FAO), agricultural variety is one of the main components of agricultural biodiversity, or agrobiodiversity. Agrobiodiversity itself is a vital subset of biodiversity, which is developed and actively managed by farmers, herders and fishers (FAO, 2004). Therefore, changes in crop variety can affect regional biodiversity levels.

Fiszbein (2017) examines the role of agricultural diversity in the process of development. Using data from U.S. counties and exploiting climate-induced variation in agricultural production patterns, the author shows that mid-19th century agricultural diversity had positive long-run effects on population density and income per capita. Examining the effects on development outcomes over time, Fiszbein (2017) finds that early agricultural diversity fostered structural change during the Second Industrial Revolution. Besides stimulating industrialization, agricultural diversity boosted manufacturing diversification, patent activity, and new labor skills, as well as knowledge- and skill-intensive industries. These results are consistent with the hypothesis that diversity spurs the acquisition of new ideas and new skills because of the presence of cross-sector spillovers and complementarities (Fiszbein, 2017).

Crop biodiversity has the potential to enhance resistance to strains due to biotic and abiotic factors, and to improve crop production and farm revenues. To investigate the effect of crop biodiversity on crop productivity, Bellora et al. (2017) build a probabilistic model based on ecological mechanisms to describe crop survival and productivity according to diversity. From this analytic model, they derivd reduced forms that are empirically estimated using detailed field data of South African agriculture combined with satellite derived data. Their results confirm that diversity has a positive and significant impact on crop survival odds. They show the consistency of these results with the underlying ecologic and agricultural mechanisms (Bellora et al, 2017).

3. Data

The main crops grown in western Kansas are alfalfa, corn, sorghum, soybean, and wheat (High Plains Regional Climate Center, 2014). To examine the crop season divisions for each of the main crops grown in Kansas, we apply a method developed by Ortiz-Bobea (2013) to examine season divisions for Illinois corn. In particular, we use data from the Crop Progress and Condition weekly survey by the U.S. Department of Agriculture (USDA) National Agricultural Statistics Service (NASS), which provides state-level data on farmer activities and crop phenological stages from early April to late November, to construct season divisions for each of the main Kansas crops. Figure 1 plots the crop season divisions for 2016 for Kansas alfalfa, corn, sorghum, soybean, and wheat, respectively.

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

We build on the data used in previous empirical analyses of agriculture in western Kansas (Pfeiffer and Lin, 2009; Pfeiffer and Lin, 2010; Pfeiffer and Lin, 2012; Pfeiffer and

Lin, 2014a; Pfeiffer and Lin, 2014b; Pfeiffer and Lin, 2014c; Lin and Pfeiffer, 2015; Lin Lawell, 2016; Lin Lawell, 2017), which spanned 10 years between 1996 and 2005, and have extended the data set to cover the years 1996 to 2012.

Data related to water rights, water use, and crop choice are from the Water Information Management and Analysis System (WIMAS), which was created by the Kansas Department of Agriculture (Division of Water Resources and Kansas Geological Survey). Specific data related to wells' characteristics (for example depth) was obtained from the Water Well Completion Records (WWC5) Database, also created by the Kansas Geological Survey. Figure 1 presents the location of all the points of diversion we use in our data set.

Climate data, including temperature, precipitation and humidity, was obtained from the High Plains Regional Climate Center (HPRCC), which contains information from the Automated Weather Data Network and also the National Weather Service & Cooperative Observer Network. The furthest the closest weather station is to any field is 93.65 miles. Thus, for each field, we average each climate variable over all the stations within 93.65 miles of that field.[3]

Following the work of Ortiz-Bobea (2015a,b), we control for soil moisture. Soil moisture data was obtained from NASA's NLDAS-2 (North American Land Data Assimilation System), the same source used by Ortiz-Bobea (2015a,b). Figures 2a and 2b present the soil moisture content in the 0-10 cm layer for the state of Kansas in 1996 and 2012, respectively.

We obtained crop prices for sorghum and alfalfa from the USDA – ERS Feed Grains Database. Futures prices for corn, soybeans, wheat, feeder cattle, live cattle, live hogs and oats

[3] An alternative 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 is to use inverse distance weighting. We find that the weather variables calculated by these two methods are highly correlated: the correlation between the climate variables obtained from our technique of averaging over the close stations and the climate variables calculated using inverse distance weighting is over 0.971 for all weather 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, using inverse distance weighting for the climate variables is unlikely to change our results by much.

are from quandl.com. Energy prices are from the Energy Information Administration (EIA) for Kansas.

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

4. Methods

5.1. Climate variable specifications

We consider several specifications of the climate variables T_{it} faced by each farmer *i* in each time period *t*. These climate specifications are summarized in Table 2. Each specification also includes squared values of the relevant temperature and precipitation variables.

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

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

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

(°F),[4] summer fraction of days with maximum temperature greater than 86°F, annual precipitation, and annual average humidity.

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

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

[4] 86 degrees Fahrenheit is equivalent to 30 degrees Celsius.

specification M1, the climate variables T_{it} are average monthly average temperature over past 3 years for each month of the year, average monthly precipitation over past 3 years for each month of the year, and average monthly humidity over past 3 years for each month of the year.

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

5.2. *Econometric model*

We model three margins that affect agricultural variety: crop acreage, the choice to plant multiple crops, and irrigation technology.

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

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

where n_{ict} is the number of acres planted to each crop *c*; T_{it} are climate-related variables, including temperature, precipitation, and humidity; $p_{\tilde{c}t}$ are crop price futures (for delivery at harvest) for crop $\tilde{c}$ and $\{p_{\tilde{c}t}\}_{\tilde{c}}$ is the set of crop price futures for all crops; x_{it} is a vector of plot-level variables including irrigation technology, average evapotranspiration, recharge, slope, soil quality, quantity of water authorized for extraction, field size,[5] depth to groundwater, saturated thickness,; e_t are energy prices; and z_{it-1} is a vector of lagged dummy variables indicating if various crops were planted in the previous season to account for crop rotation patterns. The coefficients of interest are the coefficients on the climate variables T_{it} in the cropland allocation models in equation (1).

In particular, for each crop (alfafa, corn, sorghum, soybeans, and wheat), we run a tobit regression of the acres allocated to that crop on the climate variables, controlling for alfafa price, corn price, sorghum price, soybeans price, wheat price, a dummy for using a center pivot irrigation system, a dummy for using a center pivot irrigation system with dropped nozzles, evapotranspiration, recharge, slope, a dummy for irrigated capability class=1, field size, depth to groundwater, natural gas price, diesel price, electricity price, saturated thickness, soil moisture, a dummy for whether alfafa was planted last year, a dummy for whether corn was planted last year, a dummy for whether sorghum was planted last year, a dummy for whether soybeans were planted last year, and a dummy for whether wheat was planted last year. For robustness, we also run tobit regressions of crop acreage that include farmer random effects and year effects.

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

[5] 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 conditional water demand is conditional on crop acreage, and since doing so best enables us to calculate and interpret the intensive and extensive margins and total marginal effect.

("polyculture"), we only use observations where more than one crop type was planted on that field in that year.

A second margin that affects agricultural variety is the choice of whether to plant multiple crops or one crop only. For the multiple crop extensive margin, we estimate the farmer's choice of whether to plant multiple crops using a discrete response model. In particular, we run the following probit regression of the dummy variable I_{it}^{multi} for planting more than one crop on the climate-related variables T_{it} and control variables:

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

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

In particular, we run a probit regression of the dummy variable I_{it}^{multi} for planting more than one crop on the climate variables, controlling for alfafa price, corn price, sorghum price, soybeans price, wheat price, a dummy for using a center pivot irrigation system, a dummy for using a center pivot irrigation system with dropped nozzles, evapotranspiration, recharge, slope, a dummy for irrigated capability class=1, field size, depth to groundwater, natural gas price, diesel price, electricity price, saturated thickness, and soil moisture.

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

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

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

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

In particular, we run a probit of center pivot sprinkler use on the climate variables, controlling for acres planted to alfalfa, acres planted to corn, acres planted to sorghum, acres planted to soybeans, acres planted to wheat, alfalfa price, corn price, sorghum price, soybeans price, wheat price, evapotranspiration, recharge, slope, a dummy for irrigated capability class=1, field size, depth to groundwater, natural gas price, diesel price, electricity price, saturated thickness, and soil moisture.

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

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

$$\begin{aligned}\frac{dn_{ict}}{dT_j}=&\frac{d\Pr(I_{it}^{multi}=1)}{dT_j}E[n_{ict}\mid I_{it}^{multi}=1]+\Pr(I_{it}^{multi}=1)\frac{dE[n_{ict}\mid I_{it}^{multi}=1]}{dT_j}\\&-\frac{d\Pr(I_{it}^{multi}=1)}{dT_j}E[n_{ict}\mid I_{it}^{multi}=0]+\left(1-\Pr(I_{it}^{multi}=1)\right)\frac{dE[n_{ict}\mid I_{it}^{multi}=0]}{dT_j}\end{aligned}, \tag{5}$$

where $\frac{d\Pr(I_{it}^{multi}=1)}{dT_j}$ is the marginal effect from the probit multiple crop regression in equation (2); $E[n_{ict} \mid I_{it}^{multi}=1]$ is the mean crop acreage for crop *c* in the data set over all observations in which farmers planted multiple crops; $\Pr(I_{it}^{multi}=1)$ is the fraction of observations in which farmers planted multiple crops; $\frac{dE[n_{ict} \mid I_{it}^{multi}=1]}{dT_j}$ is the marginal effect from the crop acreage regression in equation (1) conditional on planting multiple crops; $E[n_{ict} \mid I_{it}^{multi}=0]$ is the mean crop acreage for crop *c* in the data set over all observations in which farmers planted only one crop; and $\frac{dE[n_{ict} \mid I_{it}^{multi}=0]}{dT_j}$ is the marginal effect from the crop acreage regression in equation (1) conditional on planting only one crop.

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

$$\begin{aligned}\frac{dn_{ict}}{dT_j} &= \frac{d\Pr(I_{it}^{sprink}=1)}{dT_j}E[n_{ict} \mid I_{it}^{sprink}=1]+\Pr(I_{it}^{sprink}=1)\frac{dE[n_{ict} \mid I_{it}^{sprink}=1]}{dT_j}\\ &+\frac{d\Pr(I_{it}^{nozzle}=1)}{dT_j}E[n_{ict} \mid I_{it}^{nozzle}=1]+\Pr(I_{it}^{nozzle}=1)\frac{dE[n_{ict} \mid I_{it}^{nozzle}=1]}{dT_j}\\ &-\left(\frac{d\Pr(I_{it}^{sprink}=1)}{dT_j}+\frac{d\Pr(I_{it}^{nozzle}=1)}{dT_j}\right)E[n_{ict} \mid I_{it}^{sprink}=0, I_{it}^{nozzle}=0]\\ &+\left(1-\Pr(I_{it}^{sprink}=1)-\Pr(I_{it}^{nozzle}=1)\right)\frac{dE[n_{ict} \mid I_{it}^{sprink}=0, I_{it}^{nozzle}=0]}{dT_j}\end{aligned}, \quad (6)$$

where $\frac{d\Pr(I_{it}^{sprink}=1)}{dT_j}$ is the marginal effect from the probit center pivot sprinkler use regression in equation (3); $E[n_{ict} \mid I_{it}^{sprink}=1]$ is the mean crop acreage for crop *c* 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; $\frac{dE[n_{ict} \mid I_{it}^{sprink}=1]}{dT_j}$ is the marginal effect from the crop acreage regression in equation (1) conditional on using a center pivot sprinkler irrigation system; $\frac{d\Pr(I_{it}^{nozzle}=1)}{dT_j}$ is the marginal effect from the probit center pivot sprinkler with drop nozzles use regression in equation (4); $E[n_{ict} \mid I_{it}^{nozzle}=1]$ is the mean crop acreage for crop *c* 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; $\frac{dE[n_{ict} \mid I_{it}^{nozzle}=1]}{dT_j}$ is the marginal effect from the crop acreage regression in equation (1) conditional on using a center pivot sprinkler with drop nozzles irrigation system; $E[n_{ict} \mid I_{it}^{sprink}=0, I_{it}^{nozzle}=0]$ is the mean crop acreage for crop c 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 $\frac{dE[n_{ict} \mid I_{it}^{sprink}=0, I_{it}^{nozzle}=0]}{dT_j}$ is the marginal effect from the crop acreage regression in equation (1) conditional on not using either a center pivot sprinkler irrigation system or a center pivot sprinkler with drop nozzles irrigation system.

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

5. Results

Table 3 presents the coefficients on each of the j climate variables T_{jit} in T_{it} in the probit multiple crop regressions in which the dependent variable is a dummy for planting more than one type of crop on that field in that year. Table 3a presents the results for the specifications that use annual climate variables (Y1, Y2, Y3, Y4, and Y5). Table 3b presents the results for climate specification M1. Table 3c presents the results for climate specification M2.

Table 4 presents the total marginal effect given by equation (5) of each of the j climate variables T_{jit} in T_{it} accounting for the crop acreage margin and the multiple crop margin. Table 4a presents the results for the specifications that use annual climate variables (Y1, Y2, Y3, Y4, and Y5). None of the annual temperature variables have a significant total marginal effect on the crop acreage of any crop. The fraction of days in January-April with maximum temperature greater than 86°F has a significant negative total marginal effect on acres planted to sorghum. Precipitation has a significant positive total marginal effect on acres planted to corn and possibly also on acres planted on soybeans. In climate specification Y5, precipitation in January-April has a significant negative total marginal effect on acres planted to sorghum. The total marginal effect of humidity is mixed.

Table 4b presents the results for the total marginal effect given by equation (5) given by equation (5) of each of the j climate variables T_{jit} in T_{it} accounting for the crop acreage margin and the multiple crop margin for climate specification M1. Monthly temperature has no significant total marginal effect on crop acreage for any crop. The total marginal effects of monthly precipitation on crop acreage can be significant and positive in February and November. The total marginal effect of humidity on crop acreage is mixed.

Table 4c presents the results for the total marginal effect given by equation (5) given by equation (5) of each of the j climate variables T_{jit} in T_{it} accounting for the crop acreage margin and the multiple crop margin for climate specification M2. The fraction of days with maximum temperature exceeding 86°F over the past 3 years has a significant negative total marginal effect on acres planted to alfafa in April; on acres planted to corn in January and September; on acres planted to sorghum in April and September; on acres planted to soybeans in May and September; and on acres planted to wheat in April and September. The fraction of days with maximum temperature exceeding 86°F over the past 3 years has a significant positive total marginal effect on acres planted to sorghum in November; on acres planted to soybeans in March; and on acres planted to wheat in October and November. Monthly precipitation in January, February, and November over the past 3 years can have a significant positive total marginal effect on crop acreage. The total marginal effect of monthly humidity is mixed.

Table 5 presents the total marginal effect given by equation (5) of each of the *j* climate variables T_{jit} in T_{it} accounting for the crop acreage margin and the multiple crop margin, using the results of the regressions that include farmer random effects and year effects. Table 5a presents the results for the specifications that use annual climate variables (Y1, Y2, Y3, Y4, and Y5). None of the annual temperature variables have a significant total marginal effect on the crop acreage of any crop.

Table 5b presents the results for the total marginal effect given by equation (5) given by equation (5) of each of the *j* climate variables T_{jit} in T_{it} accounting for the crop acreage margin and the multiple crop margin for climate specification M1, using the results of the regressions that include farmer random effects and year effects. Monthly temperature has no significant total marginal effect on crop acreage for any crop. Monthly precipitation has no significant total marginal effect on crop acreage for any crop. The total marginal effect of humidity on crop acreage is mixed.

Table 5c presents the results for the total marginal effect given by equation (5) given by equation (5) of each of the *j* climate variables T_{jit} in T_{it} accounting for the crop acreage margin and the multiple crop margin for climate specification M2, using the results of the regressions that include farmer random effects and year effects. The fraction of days with maximum temperature exceeding 86°F over the past 3 years has no significant total marginal effect on acreage planted for any crop. Monthly precipitation can have a significant total marginal effect on crop acreage. The total marginal effect of monthly humidity is mixed.

Table 6 presents the total marginal effect given by equation (6) of each of the *j* climate variables T_{jit} in T_{it} accounting for the crop acreage margin and the irrigation technology margin. Table 6a presents the results for the specifications that use annual climate variables (Y1, Y2, Y3, Y4, and Y5). None of the annual temperature variables have a significant total marginal effect on crop acreage for any crop. The fraction of days in January-April with maximum temperature greater than 86°F has a significant negative total marginal effect on acres planted to corn and to sorghum, and a significant positive total marginal effect on acres planted to soybeans. Precipitation has a significant positive total marginal effect on acres planted to soybeans and can have a significant total marginal effect on acres planted to other crops as well.

Table 6b presents the results for the total marginal effect given by equation (6) accounting for the crop acreage margin and the irrigation technology margin for climate specification M1. Monthly temperature has no significant total marginal effect on crop acreage for any crop. Monthly precipitation can have significant total marginal effects on crop acreage.

Table 6c presents the results for the total marginal effect given by equation (6) accounting for the crop acreage margin and the irrigation technology margin for climate specification M2. The fraction of days with maximum temperature exceeding 86°F over the past 3 years has a significant negative total marginal effect on acres planted to alfafa in January, March, April, and November; on acres planted to corn in May and September; on acres planted to sorghum in January and April; on acres planted to soybeans in September; and on acres planted to wheat in March and April. The fraction of days with maximum temperature exceeding 86°F over the past 3 years has a significant positive total marginal effect on acres planted to alfafa in May; on acres planted to corn in March and October; on acres planted to soybeans in March and November; and on acres planted to wheat in October and November. Monthly precipitation can have significant total marginal effects on crop acreage.

Table 7 presents the total marginal effect given by equation (6) of each of the *j* climate variables T_{jit} in T_{it} accounting for the crop acreage margin and the irrigation technology margin, using the results of the regressions that include farmer random effects and year effects. Table 7a presents the results for the specifications that use annual climate variables (Y1, Y2, Y3, Y4, and Y5). The annual fraction of days with maximum temperature greater than 86°F has a significant positive total marginal effect on acres planted to wheat. The summer fraction of days with maximum temperature greater than 86°F has a significant positive total marginal effect on acres planted to corn and a significant negative total marginal effect on acres planted to wheat. The fraction of days in January-April with maximum temperature greater than 86°F has a significant negative total marginal effect on acres planted to alfafa and to soybeans, and a significant positive total marginal effect on acres planted to wheat. Precipitation has a significant total marginal effect on crop acreage.

Table 7b presents the results for the total marginal effect given by equation (6) accounting for the crop acreage margin and the irrigation technology margin for climate specification M1, using the results of the regressions that include farmer random effects and year effects. Monthly temperature has no significant total marginal effect on crop acreage for any crop. Monthly precipitation can have significant total marginal effects on crop acreage.
Table 7c presents the results for the total marginal effect given by equation (6) accounting for the crop acreage margin and the irrigation technology margin for climate specification M2, using the results of the regressions that include farmer random effects and year effects. The fraction of days with maximum temperature exceeding 86°F over the past 3 years has a

significant negative total marginal effect on acres planted to alfafa in January, March, April, and November; on acres planted to corn in May and September; on acres planted to sorghum in January and April; on acres planted to soybeans in September; and on acres planted to wheat in March. The fraction of days with maximum temperature exceeding 86°F over the past 3 years has a significant positive total marginal effect on acres planted to alfafa in May and October; on acres planted to corn in March; on acres planted to sorghum in October; on acres planted to soybeans in January, March, and November; and on acres planted to wheat in October and November. The results are similar to those in Table 7c that did not include farmer random effects. Monthly precipitation can have significant total marginal effects on crop acreage.

6. Conclusion

Climate change has the potential to impact crop choice and agricultural variety, with possible implications for agricultural productivity. In this paper, we analyze the effects of changes in temperature, precipitation, and humidity on farmers' decisions regarding crop acreage, whether to plant multiple crops, and irrigation technology in western Kansas.

Our results show that annual average temperature and monthly average temperature do not have a significant total marginal effect on crop acreage, but the fraction of days with maximum temperature exceeding 86°F can have a significant total marginal effect on crop acreage for some crops in some months. The sign of the total marginal effects of temperature, precipitation, and humidity on crop acreage vary depending on the crop, the specification, and/or month. We therefore find that climate change can potentially affect agricultural variety.

We find that it is important to account for the margins of whether to plant multiple crops and of the choice of irrigation technology in addition to the crop acreage margin. We also find that it is important to also evaluate the effects of climate-related variables by month rather than only at an annual level.

According to the United Nations Food and Agriculture Organization (FAO), agricultural variety is one of the main components of agricultural biodiversity, or agrobiodiversity. Agrobiodiversity itself is a vital subset of biodiversity, which is developed and actively managed by farmers, herders and fishers (FAO, 2004). Therefore, changes in crop variety can affect regional biodiversity levels.

Many of our results show that higher temperatures and less rain could increase the probability of planting more than one crop. Therefore climate change could eventually increase biodiversity levels in some regions where mono-cropping is predominant.

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

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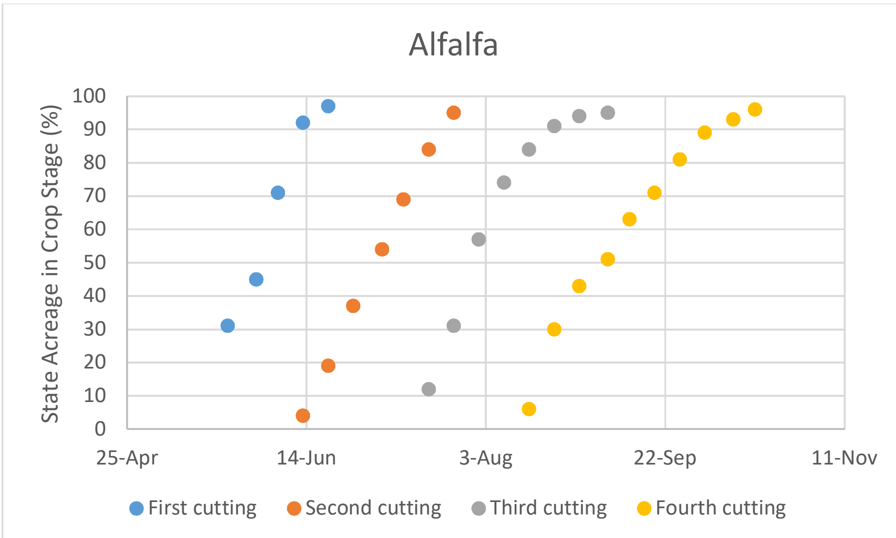
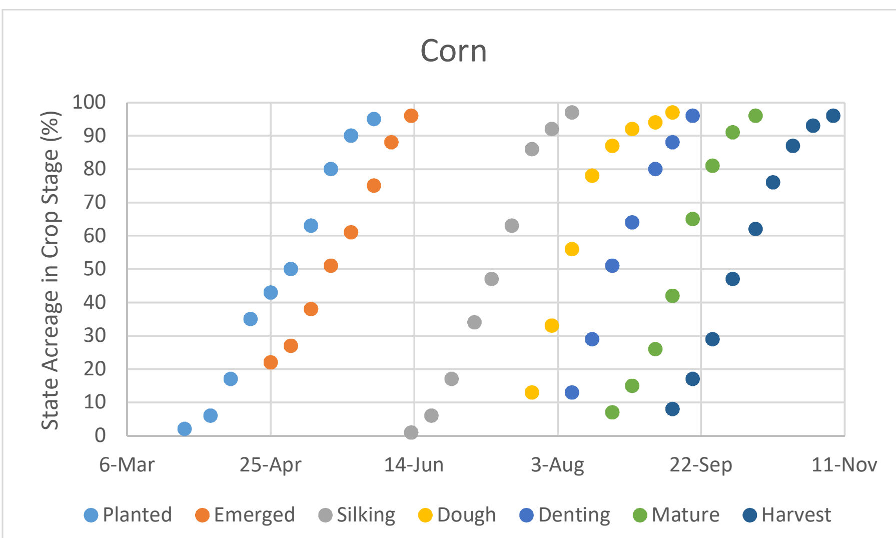
Figure 1: Season divisions for crops in Kansas

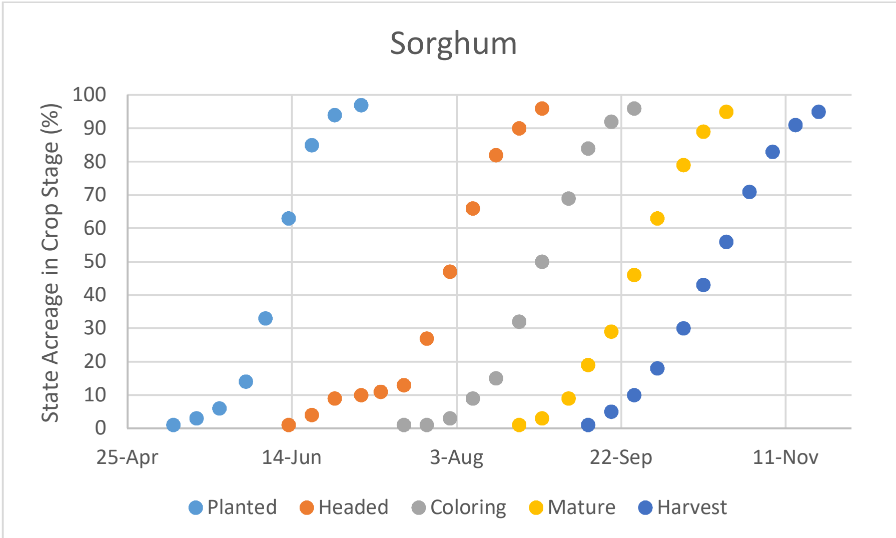
(a) Season divisions for Kansas alfalfa



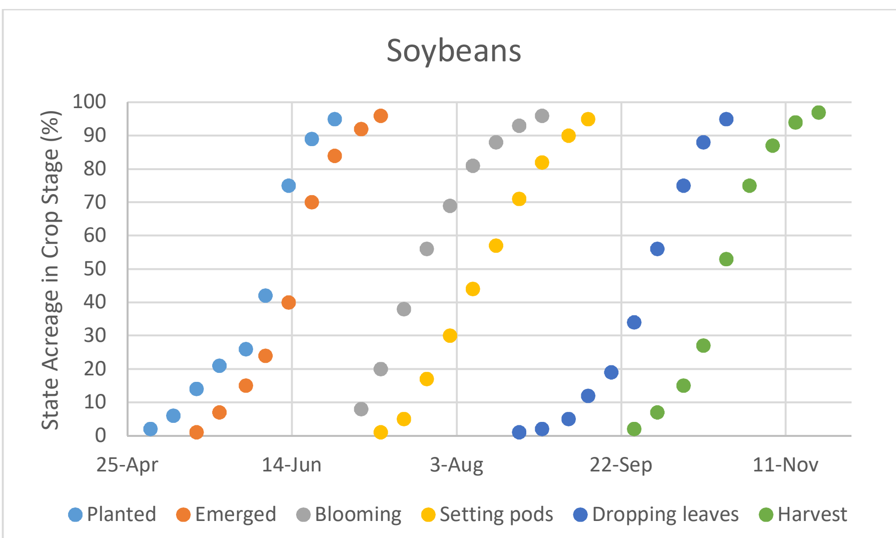
(b) Season divisions for Kansas corn



(c) Season divisions for Kansas sorghum



(d) Season divisions for Kansas soybeans



(e) Season divisions for Kansas wheat

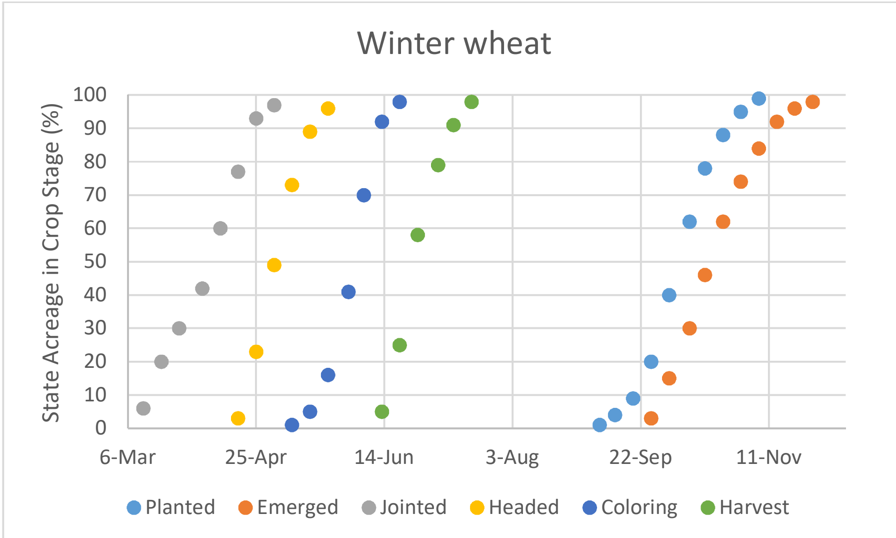
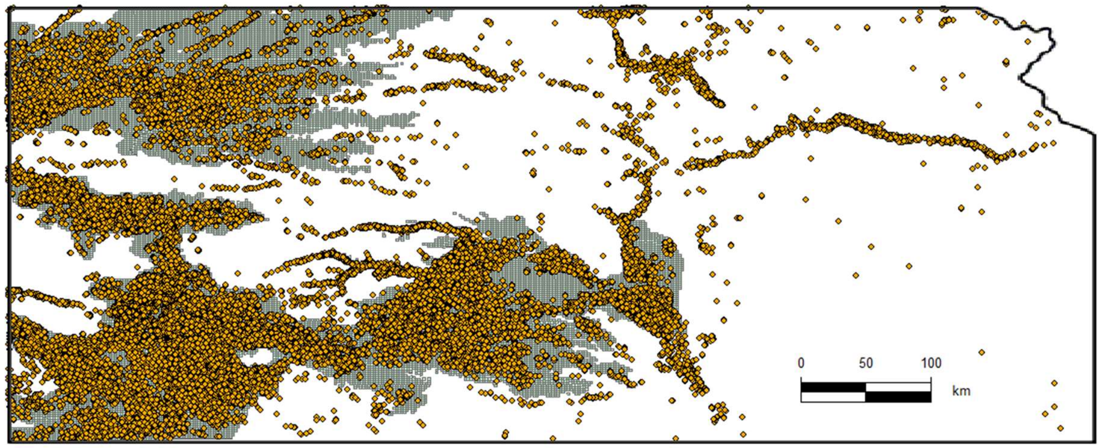


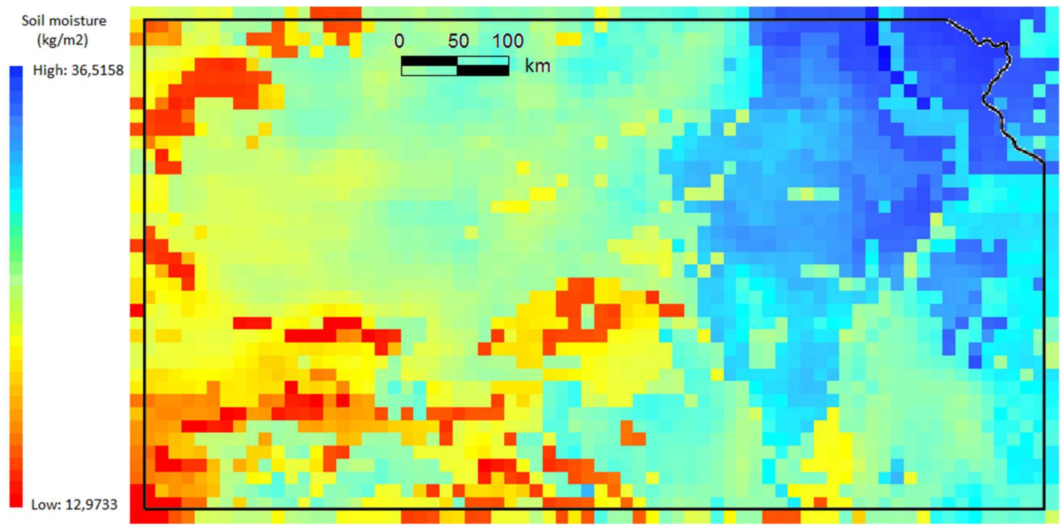
Figure 2: Location of all the points of diversion we use in our data set



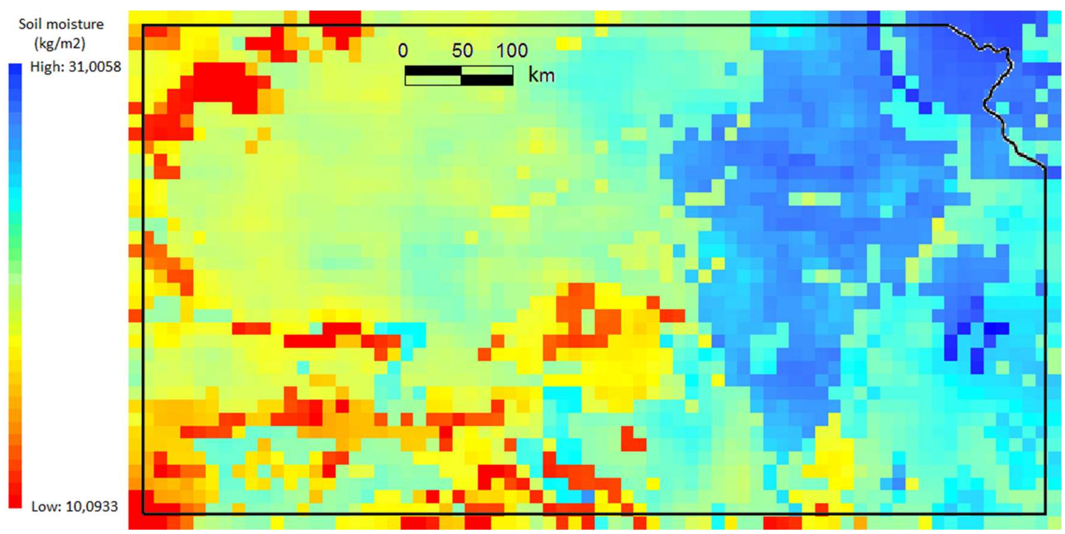
Notes: The black border indicates the Kansas state boundaries. The gray area shows the portion of the High Plains Aquifer that underlies western Kansas.

Figure 3: Soil moisture content

(a) 1996



(b) 2012



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

Table 1a. Summary statistics for choice variables

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

Table 1b. Summary statistics for control variables

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

Table 1c. Summary statistics for annual climate variables

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

Table 1d. Summary statistics for monthly climate variables

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

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

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

Table 2. Climate Specifications

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 3a: Coefficients on climate variables in multiple crop probit regressions, Annual climate variables

Dependent variable is the probability of planting more than one crop	Coefficient on Linear Variable	Coefficient on Squared Variable
Climate Specification Y1		
Annual average temperature (°F)	0.185***	-0.00173***
	(0.0332)	(0.000306)
Annual precipitation (in)	-0.0110***	0.000177***
	(0.000759)	(1.52e-05)
Annual average humidity (%)	-0.00504***	
	(0.000358)	
Climate Specification Y2		
Average temperature over the past 3 years (°F)	0.272***	-0.00254***
	(0.0495)	(0.000457)
Average total precipitation over the past 3 years (in)	-0.0113***	8.09e-05***
	(0.000653)	(5.27e-06)
Annual average humidity (%)	-0.00320***	
	(0.000372)	
Climate Specification Y3		
Annual fraction of days with max temp > 86°F	4.997***	-9.056***
	(0.502)	(0.974)
Summer fraction of days with max_temp > 86°F	-1.562***	0.895***

	(0.147)	(0.0970)
Annual precipitation (in)	-0.0111***	0.000177***
	(0.000760)	(1.52e-05)
Annual average humidity (%)	-0.00451***	
	(0.000370)	
Climate Specification Y4		
Average temperature over the last 3 years (°F)	0.319***	-0.00302***
	(0.0565)	(0.000523)
Average total precipitation over the last 3 years (in)	-0.0106***	7.62e-05***
	(0.000685)	(5.49e-06)
Annual average humidity (%)	-0.00184***	
	(0.000514)	
Annual temperature in Jan-Apr (°F)	0.0406**	-0.000389*
	(0.0133)	(0.000164)
Annual precipitation in Jan-Apr (in)	-0.134***	0.0408***
	(0.0109)	(0.00413)
Annual humidity in Jan-Apr (%)	0.00119***	
	(0.000237)	
Climate Specification Y5		
Average temperature over the last 3 years (°F)	0.345***	-0.00321***
	(0.0564)	(0.000524)
Total precipitation over the last 3 years (in)	-0.0104***	7.44e-05***
	(0.000680)	(5.47e-06)

Annual average humidity (%)	-0.00264***	
	(0.000513)	
Fraction of days in Jan-Apr with max temp > 86°F	0.431	4.576
	(0.263)	(6.156)
Annual precipitation in Jan-Apr (in)	-0.0694***	0.0251***
	(0.00970)	(0.00392)
Annual humidity in Jan-Apr (%)	0.000502*	
	(0.000234)	

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

Table 3b: Coefficients on climate variables in multiple crop probit regressions, Climate specification M1

Dependent variable is the probability of planting more than one crop	Coefficient on Linear Variable	Coefficient on Squared Variable
Avg. temperature (°F) over the past 3 years during month of:		
January	-0.0366*	0.000545*
	(0.0160)	(0.000260)
February	-0.00292	1.65e-05
	(0.0187)	(0.000269)
March	0.254***	-0.00252***
	(0.0300)	(0.000337)
April	0.193***	-0.00162***
	(0.0507)	(0.000475)
May	-0.131	0.000809
	(0.0699)	(0.000559)
June	-0.150	0.000745
	(0.101)	(0.000685)
July	-0.00785	0.000457
	(0.118)	(0.000721)
August	0.352***	-0.00256***
	(0.106)	(0.000674)
September	0.545***	-0.00371***
	(0.0558)	(0.000412)
October	-0.125**	0.000883*
	(0.0415)	(0.000375)
November	0.144***	-0.00168***

	(0.0247)	(0.000298)
December	0.0918***	-0.00161***
	(0.0233)	(0.000374)
Avg. precipitation (in) over the past 3 years during month of:		
January	-0.0667*	0.0771***
	(0.0299)	(0.0179)
February	-0.108***	0.0555***
	(0.0270)	(0.0121)
March	-0.0868***	0.0197***
	(0.0120)	(0.00258)
April	0.0239	-0.0122*
	(0.0173)	(0.00479)
May	0.0187**	-0.00369***
	(0.00689)	(0.000982)
June	-0.0440***	0.00981***
	(0.00923)	(0.00128)
July	-0.0146*	-0.00372***
	(0.00680)	(0.000860)
August	0.0195***	-2.88e-05
	(0.00513)	(0.000446)
September	-0.0855***	0.0178***
	(0.0107)	(0.00208)
October	-0.0735***	0.0195***
	(0.0121)	(0.00304)
November	-0.0987***	0.00952*
	(0.0147)	(0.00462)
December	-0.0102	0.00734*

	(0.0112)	(0.00366)
Avg. humidity (%) over the past 3 years during month of:		
January	0.00944***	
	(0.00127)	
February	-0.0145***	
	(0.00163)	
March	-0.000742	
	(0.00134)	
April	-5.63e-05	
	(0.00167)	
May	0.00278	
	(0.00175)	
June	-0.0164***	
	(0.00177)	
July	0.0191***	
	(0.00186)	
August	-0.00659***	
	(0.00192)	
September	0.00607***	
	(0.00164)	
October	-0.00888***	
	(0.00152)	
November	0.00402**	
	(0.00133)	
December	0.00662***	
	(0.00143)	

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

Table 3c: Coefficients on climate variables in multiple crop probit regressions, Climate specification M2

Dependent variable is the probability of planting more than one crop	Coefficient on Linear Variable	Coefficient on Squared Variable
Avg. fraction of days with max temp > 86°F over the past 3 years during month of:		
January	20.13***	-3,096***
	(2.788)	(381.5)
February		
March	-2.596**	-13.05
	(0.821)	(53.51)
April	-0.236	5.512***
	(0.206)	(1.029)
May	1.110***	-1.284***
	(0.156)	(0.266)
June	0.191	-0.356
	(0.215)	(0.189)
July	0.550	-0.467
	(0.619)	(0.380)
August	0.130	-0.0341
	(0.224)	(0.165)
September	1.894***	-2.037***
	(0.146)	(0.176)
October	-0.209	4.244***
	(0.238)	(1.112)
November	-0.745	-39.89***

	(0.522)	(9.714)
December	-	-
Avg. precipitation (in) over the past 3 years during month of:		
January	-0.142***	0.0957***
	(0.0252)	(0.0168)
February	-0.165***	0.0525***
	(0.0228)	(0.0109)
March	-0.0757***	0.0122***
	(0.0110)	(0.00216)
April	-0.0113	0.000772
	(0.0163)	(0.00458)
May	0.0527***	-0.00669***
	(0.00708)	(0.00100)
June	-0.0242*	0.00695***
	(0.00960)	(0.00129)
July	0.00174	-0.00412***
	(0.00631)	(0.000866)
August	-0.00356	0.000761
	(0.00431)	(0.000421)
September	-0.0792***	0.0214***
	(0.00940)	(0.00188)
October	-0.0441***	0.0130***
	(0.0111)	(0.00288)
November	-0.0455***	0.000302
	(0.0112)	(0.00448)
December	-0.0295**	0.00298

	(0.00935)	(0.00324)
Avg. humidity (%) over the past 3 years during month of:		
January	-0.00118	
	(0.00107)	
February	-0.00204*	
	(0.000919)	
March	0.00267*	
	(0.00118)	
April	0.00489***	
	(0.00128)	
May	-0.00192	
	(0.00168)	
June	-0.0129***	
	(0.00174)	
July	0.00792***	
	(0.00143)	
August	-0.00581***	
	(0.00148)	
September	0.00947***	
	(0.00128)	
October	-0.00686***	
	(0.00145)	
November	0.00276**	
	(0.000983)	
December	0.00709***	
	(0.00120)	

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

Table 4a: Total marginal effect including multiple crop margin, Annual climate variables

	Alfalfa	**Corn**	**Sorghum**	**Soybeans**	**Wheat**
Climate Specification Y1					
Annual average temperature (°F)	0.68	1.289	4.509	4.545	0.897
	(21.929)	(9.137)	(33.749)	(12.564)	(25.502)
Annual precipitation (in)	-0.009	0.794**	0.712	1.075*	-0.428
	(0.75)	(0.293)	(1.183)	(0.458)	(0.916)
Annual average humidity (%)	0.841***	0.487***	1.284***	-0.041	0.132
	(0.147)	(0.067)	(0.239)	(0.094)	(0.167)
Climate Specification Y2					
Average temperature over the past 3 years (°F)	0.752	2.51	9.126	7.03	1.482
	(32.071)	(13.24)	(48.116)	(16.758)	(36.369)
Average total precipitation over the past 3 years (in)	0.141	0.359*	0.412	0.48	0.181
	(0.354)	(0.163)	(0.607)	(0.247)	(0.461)
Annual average humidity (%)	0.758***	0.159*	0.868***	-0.372***	0.003
	(0.155)	(0.069)	(0.247)	(0.093)	(0.171)
Climate Specification Y3					
Annual fraction of days with max temp > 86°F	-37.357	-83.124	76.799	40.423	-47.047
	(317.203)	(134.591)	(485.767)	(175.302)	(381.197)
Summer fraction of days with max temp > 86°F	24.622	53.303	-13.18	24.84	24.704
	(85.667)	(38.543)	(132.753)	(52.402)	(100.319)
Annual precipitation (in)	0.041	0.907**	1.056	1.651***	-0.499

	(0.751)	(0.289)	(1.155)	(0.437)	(0.91)
Annual average humidity (%)	0.625***	0.364***	1.286***	-0.162	0.055
	(0.156)	(0.071)	(0.249)	(0.097)	(0.183)
Climate Specification Y4					
Average temperature over the last 3 years (°F)	2.186	3.349	9.302	8.545	0.633
	(36.587)	(15.144)	(54.492)	(19.186)	(39.764)
Average total precipitation over the last 3 years (in)	0.119	0.363*	0.381	0.492	0.201
	(0.374)	(0.170)	(0.630)	(0.256)	(0.478)
Annual average humidity (%)	0.931***	-0.229*	1.417***	-1.026***	-0.441
	(0.224)	(0.100)	(0.349)	(0.141)	(0.256)
Annual temperature in Jan-Apr (°F)	-0.716	-1.655	-0.267	-1.541	0.694
	(8.550)	(3.530)	(12.525)	(5.088)	(8.719)
Annual precipitation in Jan-Apr (in)	-0.904	9.303***	0.715	6.132	-0.409
	(6.046)	(2.589)	(8.777)	(3.296)	(7.463)
Annual humidity in Jan-Apr (%)	-0.201	-0.127*	-0.303	0.026	0.411**
	(0.113)	(0.051)	(0.181)	(0.071)	(0.139)
Climate Specification Y5					
Average temperature over the last 3 years (°F)	-0.496	0.999	29.156	16.786	6.915
	(46.48)	(18.797)	(98.344)	(43.4)	(73.55)
Total precipitation over the last 3 years (in)	0.157	0.461*	-1.58	0.522	-0.984
	(0.498)	(0.226)	(1.243)	(0.622)	(0.926)
Annual average humidity (%)	2.748***	0.014	5.332***	-2.658***	0.804
	(0.302)	(0.134)	(0.678)	(0.333)	(0.512)

Fraction of days in Jan-Apr with max temp > 86°F	8.232	-57.635	-1020.781*	258.016	-37.455
	(171.821)	(76.103)	(414.902)	(197.323)	(292.616)
Annual precipitation in Jan-Apr (in)	-5.980	5.911*	-32.38*	0.248	-15.403
	(7.077)	(2.917)	(15.008)	(6.663)	(12.223)
Annual humidity in Jan-Apr (%)	-0.470**	-0.176**	-2.322***	0.999***	-0.291
	(0.145)	(0.063)	(0.346)	(0.172)	(0.242)

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

Table 4b: Total marginal effect including multiple crop margin, Climate specification M1

	Alfalfa	Corn	Sorghum	Soybeans	Wheat
Avg. temperature (°F) over the past 3 years during month of:					
January	2.975	0.939	2.77	1.312	-0.488
	(19.06)	(7.347)	(25.655)	(10.32)	(17.002)
February	-2.188	-1.759	3.640	-5.731	0.900
	(13.926)	(5.997)	(19.396)	(8.431)	(14.489)
March	-3.894	-1.298	7.404	4.588	1.107
	(32.855)	(13.471)	(44.417)	(19.707)	(30.725)
April	-3.107	-1.108	9.719	-5.871	-0.930
	(40.204)	(17.035)	(55.605)	(24.158)	(40.413)
May	2.736	-2.909	-5.931	-8.375	-3.892
	(60.71)	(24.886)	(84.247)	(36.251)	(60.967)
June	5.280	7.056	2.282	7.558	16.608
	(76.825)	(32.132)	(109.544)	(46.986)	(76.532)
July	-1.001	-4.723	-17.769	6.238	-14.841
	(88.147)	(36.635)	(115.4)	(50.146)	(87.029)
August	-4.266	1.883	13.952	-2.279	1.914
	(83.018)	(34.587)	(110.594)	(46.79)	(77.526)
September	-2.071	-4.665	-13.344	-5.007	-11.146
	(46.044)	(20.067)	(67.167)	(31.123)	(52.043)
October	1.436	5.78	0.989	8.323	6.433
	(39.041)	(16.098)	(53.451)	(23.654)	(38.568)
November	0.918	1.748	6.187	5.492	4.425
	(17.884)	(8.143)	(26.301)	(11.466)	(19.273)
December	-2.614	-1.808	-4.957	-5.146	1.472

	(20.242)	(8.265)	(28.234)	(10.892)	(21.139)
Avg. precipitation (in) over the past 3 years during month of:					
January	2.297	10.319	-1.824	-4.814	-13.511
	(16.463)	(6.939)	(23.156)	(9.404)	(17.943)
February	41.465*	20.055**	-6.641	35.793***	4.941
	(16.922)	(6.878)	(22.025)	(8.647)	(17.716)
March	3.768	1.193	23.744*	7.363	0.278
	(8.331)	(3.428)	(11.542)	(4.653)	(8.818)
April	-0.652	4.644	-2.587	-3.755	-9.773
	(13.157)	(5.246)	(19.03)	(7.225)	(14.407)
May	-2.834	3.073	2.906	1.814	3.036
	(5.407)	(2.179)	(7.148)	(2.967)	(5.349)
June	-2.433	-2.137	-1.727	0.006	1.914
	(7.288)	(2.888)	(10.831)	(4.042)	(8.928)
July	-1.209	1.467	-5.195	-3.526	-2.085
	(6.288)	(2.582)	(9.101)	(3.984)	(6.494)
August	5.163	0.579	3.242	4.367	-0.226
	(3.538)	(1.445)	(5.241)	(2.496)	(4.227)
September	-2.461	1.083	-4.124	1.72	-9.916
	(7.927)	(3.235)	(11.814)	(4.626)	(8.847)
October	-2.262	2.019	-11.438	2.342	4.602
	(9.189)	(3.843)	(12.672)	(5.255)	(9.118)
November	0.181	15.333***	38.971**	25.492***	25.723**
	(8.907)	(3.552)	(12.21)	(4.907)	(9.492)
December	1.082	-0.094	-1.549	-2.376	-10.113
	(7.404)	(3.094)	(10.269)	(4.273)	(7.16)
Avg. humidity (%) over the past 3 years during month of:					

January	-0.133	0.283	1.058	0.495	0.913
	(0.642)	(0.274)	(0.932)	(0.390)	(0.65)
February	-0.537	-0.284	3.012*	-1.592**	-0.005
	(0.823)	(0.359)	(1.197)	(0.53)	(0.866)
March	0.916	0.149	-2.224*	1.446**	-0.767
	(0.725)	(0.299)	(1.044)	(0.443)	(0.752)
April	0.07	0.609	0.078	-1.938***	2.39*
	(0.961)	(0.389)	(1.424)	(0.569)	(1.019)
May	1.35	-0.687	1.65	-0.432	1.511
	(0.965)	(0.4)	(1.414)	(0.569)	(0.983)
June	0.910	1.067**	-3.76**	1.938***	-1.639
	(0.993)	(0.395)	(1.403)	(0.531)	(1.051)
July	-0.284	-0.992*	-2.52*	2.997***	-2.232*
	(0.900)	(0.389)	(1.267)	(0.552)	(0.922)
August	-1.332	-0.467	3.573**	-2.751***	0.469
	(0.886)	(0.398)	(1.296)	(0.555)	(0.91)
September	0.211	-0.347	-1.209	-1.481**	-2.057*
	(0.808)	(0.348)	(1.263)	(0.491)	(0.856)
October	0.159	1.337***	1.076	5.081***	-0.966
	(0.756)	(0.329)	(1.138)	(0.494)	(0.802)
November	-1.401	-0.194	0.336	-1.526***	2.05**
	(0.729)	(0.305)	(1.061)	(0.445)	(0.74)
December	2.037**	-0.411	0.550	-3.136***	2.038*
	(0.731)	(0.308)	(1.106)	(0.451)	(0.799)

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

Table 4c: Total marginal effect including multiple crop margin, Climate specification M2

	Alfalfa	Corn	Sorghum	Soybeans	Wheat
Avg. fraction of days with max temp > 86°F over the past 3 years during month of:					
January	-1656.546	-1963.169***	-988.953	938.877	-2193.40
	(1137.138)	(541.596)	(1680.655)	(813.401)	(1243.384)
February					
March	2.516	311.000	542.568	720.904**	-470.323
	(423.412)	(179.559)	(599.129)	(245.553)	(467.203)
April	-303.684*	-109.301	-502.797*	-106.112	-313.699*
	(139.239)	(58.982)	(201.187)	(80.287)	(138.603)
May	112.808	-46.216	81.989	-166.993*	6.473
	(148.974)	(58.696)	(189.424)	(83.897)	(136.484)
June	102.31	55.186	66.184	27.023	181.637
	(169.224)	(69.12)	(243.665)	(100.301)	(169.862)
July	-23.022	23.798	190.615	163.049	-48.74
	(498.96)	(208.427)	(647.621)	(291.709)	(489.2)
August	7.535	19.560	22.095	-64.779	100.836
	(156.25)	(67.294)	(218.532)	(93.095)	(169.283)
September	-101.557	-155.824***	-353.069*	-140.54*	-328.826**
	(114.611)	(47.155)	(155.479)	(63.554)	(121.182)
October	289.466	90.601	366.575	80.494	546.305**
	(182.475)	(77.74)	(257.477)	(112.768)	(181.796)
November	83.417	69.922	1046.156*	133.696	770.59*
	(327.088)	(137.125)	(513.181)	(209.948)	(369.957)
December					

Avg. precipitation (in) over the past 3 years during month of:					
January	-1.949	28.322***	43.691*	18.332*	15.96
	(14.758)	(6.284)	(20.472)	(8.219)	(15.661)
February	19.884	27.332***	19.132	51.204***	9.575
	(13.811)	(5.741)	(18.469)	(7.398)	(14.661)
March	-0.976	-1.044	13.474	6.523	-2.827
	(7.076)	(2.98)	(9.511)	(4.006)	(7.55)
April	-6.988	3.284	-2.229	4.022	-11.991
	(11.895)	(4.827)	(17.607)	(6.682)	(13.594)
May	-0.531	2.126	-0.573	-0.526	2.353
	(5.157)	(2.068)	(7.086)	(2.865)	(5.281)
June	-3.151	-5.448	-6.344	-4.07	-9.091
	(7.441)	(2.973)	(10.59)	(4.118)	(8.524)
July	-1.609	0.919	-2.94	-1.562	0.143
	(5.672)	(2.331)	(8.055)	(3.632)	(5.909)
August	1.988	0.944	0.537	3.694	2.142
	(3.183)	(1.299)	(4.648)	(2.355)	(3.659)
September	1.438	1.246	3.311	1.182	-3.996
	(7.087)	(2.853)	(10.293)	(4.078)	(7.873)
October	1.842	1.233	-9.154	-0.748	7.703
	(8.285)	(3.445)	(11.455)	(4.762)	(8.331)
November	2.885	14.921***	30.557**	26.349***	32.919***
	(7.425)	(2.956)	(9.859)	(4.08)	(8.068)
December	-8.066	1.425	2.944	5.284	-14.918*
	(6.876)	(2.846)	(9.412)	(3.900)	(6.612)
Avg. humidity (%) over the past 3 years during month of:					
January	-0.642	0.933***	0.865	1.034**	1.399*
	(0.552)	(0.234)	(0.8)	(0.342)	(0.55)

February	0.011	-0.256	0.713	-0.263	1.106*
	(0.47)	(0.199)	(0.668)	(0.288)	(0.479)
March	0.251	-1.083***	-1.643	0.162	-2.537***
	(0.635)	(0.263)	(0.875)	(0.365)	(0.667)
April	-0.033	0.459	0.579	-1.79***	3.468***
	(0.686)	(0.293)	(1.043)	(0.445)	(0.723)
May	1.155	-0.37	1.252	-0.507	-1.633
	(0.849)	(0.363)	(1.247)	(0.516)	(0.904)
June	0.453	0.894*	-0.85	1.755***	0.071
	(0.92)	(0.376)	(1.249)	(0.5)	(0.955)
July	0.558	0.524	2.174*	2.829***	1.299
	(0.766)	(0.325)	(1.088)	(0.472)	(0.756)
August	-1.747*	-0.148	-0.604	-1.383**	-1.146
	(0.75)	(0.313)	(1.114)	(0.45)	(0.766)
September	0.474	-1.841***	-2.978**	-3.102***	-2.011**
	(0.66)	(0.284)	(0.934)	(0.393)	(0.673)
October	0.688	0.597*	4.536***	2.857***	1.088
	(0.672)	(0.303)	(0.983)	(0.453)	(0.716)
November	-1.653**	0.151	-1.051	-0.733*	0.802
	(0.520)	(0.222)	(0.725)	(0.325)	(0.513)
December	2.126***	0.053	-0.503	-1.456***	0.187
	(0.616)	(0.258)	(0.918)	(0.41)	(0.63)

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

Table 5a: Total marginal effect including multiple crop margin, Annual climate variables, Random Effects

	Alfalfa	Corn	Sorghum	Soybeans	Wheat
Climate Specification Y1					
Annual average temperature (°F)	0.245	10.472	12.429	5.107	-1.892
	(19.611)	(61.578)	(34.036)	(48.781)	(25.491)
Annual precipitation (in)	0.447	-0.713	1.816	-2.453	-0.352
	(0.863)	(2.663)	(1.449)	(2.187)	(0.940)
Annual average humidity (%)	0.643***	0.957	-1.279***	-1.044*	-0.056
	(0.194)	(0.598)	(0.362)	(0.456)	(0.176)
Climate Specification Y2					
Average temperature over the past 3 years (°F)	0.608	15.631	16.907	4.387	-1.317
	(28.852)	(87.031)	(46.787)	(67.188)	(13.103)
Average total precipitation over the past 3 years (in)	0.486	-1.410	0.219	-1.044	0.174
	(0.475)	(1.575)	(0.901)	(1.203)	(0.19)
Annual average humidity (%)	-0.029	1.277	-1.753***	-0.321	-0.152
	(0.237)	(0.718)	(0.432)	(0.527)	(0.097)
Climate Specification Y3					
Annual fraction of days with max temp > 86°F	-132.439	42.970	-11.771	89.500	46.826
	(382.724)	(1326.68)	(706.565)	(986.16)	(160.288)
Summer fraction of days with max temp > 86°F	18.062	-16.912	49.448	22.349	-24.965
	(157.237)	(568.486)	(287.37)	(397.434)	(61.642)
Annual precipitation (in)	0.201	-0.663	2.258	-2.643	-0.311

	(0.901)	(2.898)	(1.514)	(2.29)	(0.363)
Annual average humidity (%)	0.425*	0.536	-1.692***	-1.026*	0.093
	(0.202)	(0.642)	(0.377)	(0.487)	(0.086)
Climate Specification Y4					
Average temperature over the last 3 years (°F)	-0.786	10.223	22.205	4.623	-0.832
	(33.444)	(95.878)	(53.772)	(76.093)	(14.872)
Average total precipitation over the last 3 years (in)	0.529	-1.450	0.073	-1.431	0.223
	(0.487)	(1.572)	(0.927)	(1.247)	(0.195)
Annual average humidity (%)	-0.311	5.681***	-1.223*	1.637*	-0.355**
	(0.291)	(0.949)	(0.542)	(0.719)	(0.123)
Annual temperature in Jan-Apr (°F)	0.269	2.771	-2.251	3.034	0.476
	(7.984)	(23.40)	(13.847)	(18.322)	(3.246)
Annual precipitation in Jan-Apr (in)	4.497	-13.686	-6.221	-17.683	-5.256*
	(5.515)	(17.509)	(9.326)	(14.497)	(2.41)
Annual humidity in Jan-Apr (%)	0.070	-2.173**	-0.481	-0.527	0.233**
	(0.185)	(0.697)	(0.372)	(0.532)	(0.083)
Climate Specification Y5					
Average temperature over the last 3 years (°F)	-1.321	0.734	26.696	14.003	3.411
	(29.658)	(18.071)	(100.196)	(45.207)	(74.508)
Total precipitation over the last 3 years (in)	-0.034	0.912**	-2.225	0.518	-1.681
	(0.431)	(0.288)	(1.652)	(0.876)	(1.239)
Annual average humidity (%)	0.747**	-1.205***	6.839***	-3.078***	2.739***
	(0.256)	(0.159)	(0.944)	(0.477)	(0.669)

Fraction of days in Jan-Apr with max temp > 86°F	-14.48	29.704	-17.226	-127.593	119.691
	(163.483)	(98.538)	(598.976)	(283.644)	(432.062)
Annual precipitation in Jan-Apr (in)	-0.599	7.212*	-23.151	-3.128	-16.676
	(5.065)	(3.064)	(18.665)	(8.282)	(14.512)
Annual humidity in Jan-Apr (%)	-0.074	0.037	-3.298***	0.380	-1.052*
	(0.154)	(0.093)	(0.636)	(0.301)	(0.453)

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

Table 5b: Total marginal effect including multiple crop margin, Climate specification M1, Random Effects

	Alfalfa	Corn	Sorghum	Soybeans	Wheat
Avg. temperature (°F) over the past 3 years during month of:					
January	1.390	2.039	-3.570	4.555	0.855
	(17.959)	(43.027)	(28.756)	(33.261)	(7.41)
February	-5.971	6.394	3.374	1.329	0.608
	(13.955)	(37.272)	(26.018)	(30.728)	(5.947)
March	-2.027	5.448	5.240	7.156	0.233
	(28.931)	(74.863)	(51.881)	(60.283)	(12.587)
April	-4.607	1.618	10.17	-7.801	-1.649
	(39.825)	(99.308)	(67.603)	(81.978)	(17.299)
May	-0.691	1.890	-0.611	3.819	1.895
	(54.554)	(145.583)	(98.845)	(118.504)	(23.831)
June	3.090	9.691	3.208	10.390	2.747
	(70.171)	(183.485)	(122.746)	(143.818)	(29.269)
July	6.250	-1.916	1.820	-11.439	-3.729
	(79.678)	(194.09)	(133.486)	(164.106)	(34.521)
August	-0.344	-0.583	-7.459	3.906	1.225
	(71.516)	(178.138)	(121.877)	(144.551)	(30.775)
September	-1.772	-12.527	-9.621	3.356	0.905
	(41.863)	(114.94)	(80.213)	(93.978)	(18.081)
October	4.780	1.542	3.532	-9.660	-2.537
	(35.061)	(86.695)	(59.806)	(71.592)	(14.852)
November	-0.018	-1.880	5.585	-1.799	-0.538
	(17.793)	(46.141)	(32.316)	(38.254)	(7.83)
December	-3.342	1.942	-0.395	6.134	0.514

	(17.493)	(43.35)	(28.764)	(37.703)	(8.154)
Avg. precipitation (in) over the past 3 years during month of:					
January	4.659	6.644	0.523	0.757	2.724
	(14.391)	(36.365)	(24.296)	(31.206)	(6.226)
February	12.644	2.693	2.931	11.063	-4.438
	(15.153)	(34.725)	(22.889)	(30.8)	(6.733)
March	2.525	-1.041	2.108	-4.119	-2.950
	(7.441)	(18.585)	(12.26)	(16.652)	(3.255)
April	3.405	-15.863	-6.900	-3.912	-1.200
	(11.066)	(30.675)	(19.275)	(25.962)	(4.704)
May	4.138	1.646	2.306	-11.077	1.722
	(4.759)	(11.28)	(7.556)	(9.699)	(1.948)
June	-3.065	-9.559	6.162	-10.665	-0.962
	(6.427)	(18.143)	(11.425)	(15.333)	(2.756)
July	4.886	-8.816	-13.697	-6.026	0.806
	(5.541)	(15.232)	(10.2)	(12.037)	(2.343)
August	0.722	3.352	1.096	8.245	0.353
	(3.149)	(8.542)	(6.217)	(7.297)	(1.341)
September	-0.832	-3.957	8.339	-15.126	-1.846
	(7.448)	(19.404)	(12.575)	(16.65)	(3.242)
October	-2.587	-5.599	-2.784	-0.813	-0.249
	(8.444)	(21.336)	(14.239)	(17.62)	(3.649)
November	3.653	2.558	9.844	-3.777	1.548
	(8.442)	(20.852)	(13.759)	(17.492)	(3.56)
December	-1.965	-2.116	1.792	0.785	-0.259
	(8.009)	(18.966)	(12.892)	(15.343)	(3.313)
Avg. humidity (%) over the past 3 years during month of:					

January	0.09	2.14	1.612	2.624*	0.485
	(0.623)	(1.57)	(1.065)	(1.252)	(0.268)
February	-1.006	1.42	0.043	-2.358	-0.418
	(0.791)	(2.092)	(1.459)	(1.659)	(0.335)
March	0.542	-3.063	-1.585	1.133	0.172
	(0.651)	(1.724)	(1.19)	(1.374)	(0.275)
April	1.110	-0.197	-0.956	-2.193	1.223***
	(0.862)	(2.308)	(1.533)	(1.837)	(0.359)
May	-1.786*	0.443	3.533*	-1.420	-0.445
	(0.902)	(2.428)	(1.61)	(1.906)	(0.386)
June	0.981	1.226	-1.674	3.993	0.218
	(0.964)	(2.531)	(1.621)	(2.09)	(0.423)
July	1.351	-0.621	4.990***	-2.210	-1.820***
	(0.855)	(2.119)	(1.489)	(1.731)	(0.364)
August	-0.934	-1.304	-3.76*	-2.284	0.715*
	(0.812)	(2.129)	(1.487)	(1.715)	(0.347)
September	1.038	-0.316	-4.062**	2.173	-0.042
	(0.755)	(2.007)	(1.339)	(1.575)	(0.32)
October	2.996***	-0.665	1.69	-5.419***	-1.436***
	(0.736)	(1.958)	(1.383)	(1.564)	(0.321)
November	-1.27	1.93	-0.376	3.977**	1.467***
	(0.699)	(1.806)	(1.235)	(1.41)	(0.292)
December	-1.946**	1.751	0.852	1.474	0.337
	(0.687)	(1.848)	(1.22)	(1.499)	(0.299)

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

Table 5c: Total marginal effect including multiple crop margin, Climate specification M2, Random Effects

	Alfalfa	Corn	Sorghum	Soybeans	Wheat
Avg. fraction of days with max temp > 86°F over the past 3 years during month of:					
January	-1060.236	-1187.573	-22.049	303.271	29.73
	(1307.898)	(683.928)	(3490.889)	(2040.173)	(2528.562)
February					
March	-128.823	426.314	-13.016	1.700	-157.425
	(492.698)	(231.269)	(1253.029)	(624.185)	(931.769)
April	-67.56	26.955	-62.14	0.692	17.158
	(163.563)	(76.161)	(423.934)	(205.329)	(298.244)
May	57.167	-127.8	58.164	-51.974	90.816
	(163.757)	(74.131)	(402.248)	(212.203)	(290.253)
June	-16.584	27.023	52.965	-170.659	143.544
	(194.806)	(90.295)	(505.803)	(254.29)	(363.444)
July	-11.497	5.118	140.291	76.245	-79.163
	(568.258)	(266.412)	(1394.25)	(744.646)	(1060.347)
August	-5.181	-1.704	35.736	-48.106	-43.915
	(191.912)	(89.843)	(489.055)	(255.612)	(361.791)
September	-25.694	-83.643	-11.576	-163.927	165.483
	(129.046)	(60.029)	(328.298)	(160.747)	(243.803)
October	25.932	-13.879	35.733	-59.537	127.686
	(214.749)	(102.067)	(564.699)	(295.608)	(400.971)
November	-51.236	70.018	30.564	224.341	-47.78
	(374.487)	(175.035)	(1049.096)	(533.573)	(726.376)
December					

Avg. precipitation (in) over the past 3 years during month of:					
January	-11.099	26.426***	0.071	29.907	-6.343
	(17.28)	(7.984)	(42.647)	(21.097)	(32.997)
February	-3.322	34.821***	5.401	75.205***	-16.094
	(15.446)	(7.032)	(36.817)	(17.8)	(28.8)
March	-3.459	4.679	9.310	-2.542	-18.459
	(8.49)	(3.85)	(20.192)	(10.086)	(16.332)
April	-9.534	7.675	-25.073	8.243	-11.855
	(13.291)	(6.002)	(34.827)	(16.779)	(26.871)
May	-2.659	5.386*	2.867	-2.476	-12.283
	(5.727)	(2.584)	(13.716)	(6.922)	(10.641)
June	2.201	-9.274*	-15.208	-7.693	1.954
	(8.29)	(3.758)	(21.341)	(10.337)	(16.628)
July	-4.846	2.293	-20.677	-12.512	-14.279
	(6.604)	(3.095)	(17.645)	(9.556)	(12.575)
August	-4.321	4.033*	3.833	15.075*	8.825
	(3.667)	(1.716)	(9.557)	(6.197)	(7.333)
September	-6.927	-0.729	-5.483	35.653***	-29.852
	(8.797)	(3.942)	(21.861)	(10.532)	(16.961)
October	3.67	0.145	-26.532	1.379	-16.196
	(9.959)	(4.565)	(25.316)	(12.497)	(18.287)
November	-17.708*	3.992	13.847	45.429***	-20.298
	(8.803)	(4.012)	(20.676)	(10.481)	(16.432)
December	4.055	-0.854	31.012	20.587	-10.241
	(9.159)	(4.101)	(22.165)	(10.971)	(16.104)
Avg. humidity (%) over the past 3 years during month of:					
January	-0.108	0.454	4.904**	1.046	3.416**
	(0.618)	(0.289)	(1.607)	(0.828)	(1.112)

February	-1.119*	-0.41	-4.174**	-1.051	-4.626***
	(0.544)	(0.259)	(1.388)	(0.746)	(1.03)
March	1.550*	-0.67*	-2.957	0.871	0.572
	(0.704)	(0.324)	(1.771)	(0.894)	(1.338)
April	-0.056	1.152**	4.513*	-5.364***	3.839*
	(0.782)	(0.377)	(2.159)	(1.134)	(1.524)
May	0.495	-2.539***	-2.029	6.802***	-1.739
	(0.951)	(0.461)	(2.561)	(1.313)	(1.847)
June	-1.032	0.646	0.871	-1.996	0.682
	(1.107)	(0.509)	(2.738)	(1.396)	(2.092)
July	0.731	0.487	5.017*	7.931***	-2.44
	(0.849)	(0.408)	(2.151)	(1.157)	(1.54)
August	1.511	0.42	-0.005	-7.224***	-3.084
	(0.895)	(0.414)	(2.32)	(1.162)	(1.645)
September	0.567	-0.629	-1.096	-4.844***	4.329**
	(0.738)	(0.361)	(1.918)	(1.007)	(1.387)
October	-0.904	0.483	2.016	4.727***	-4.327**
	(0.754)	(0.379)	(2.027)	(1.116)	(1.459)
November	-0.796	0.427	0.194	-4.269***	5.086***
	(0.587)	(0.284)	(1.548)	(0.867)	(1.087)
December	2.160**	-1.265***	-0.964	-1.721	3.206*
	(0.743)	(0.345)	(1.947)	(1.032)	(1.389)

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

Table 6a: Total marginal effect including irrigation technology margin, Annual climate variables

	Alfalfa	Corn	Sorghum	Soybeans	Wheat
Climate Specification Y1					
Annual average temperature (°F)	0.155	0.943	8.486	9.533	-0.166
	(17.419)	(9.814)	(24.868)	(15.095)	(13.607)
Annual precipitation (in)	-0.894	0.522	-0.816	2.456***	-1.401**
	(0.592)	(0.341)	(0.825)	(0.559)	(0.465)
Annual average humidity (%)	2.172***	0.659***	1.862***	-1.214***	-0.347***
	(0.114)	(0.08)	(0.173)	(0.115)	(0.093)
Climate Specification Y2					
Average temperature over the past 3 years (°F)	-3.136	2.401	18.461	17.074	-0.61
	(25.123)	(14.144)	(36.086)	(20.229)	(19.826)
Average total precipitation over the past 3 years (in)	0.083	0.377	-0.549	0.640*	-0.197
	(0.288)	(0.198)	(0.43)	(0.306)	(0.228)
Annual average humidity (%)	2.492***	0.222**	1.921***	-1.654***	0.117
	(0.12)	(0.08)	(0.181)	(0.115)	(0.097)
Climate Specification Y3					
Annual fraction of days with max temp > 86°F	102.255	-219.883	270.658	243.113	97.472
	(249.331)	(160.78)	(355.996)	(215.812)	(199.007)
Summer fraction of days with max_temp > 86°F	-40.643	99.021	-111.079	8.402	-48.095
	(67.194)	(54.715)	(99.313)	(65.319)	(55.288)
Annual precipitation (in)	-0.765	0.322	-0.107	4.188***	-1.297**

	(0.592)	(0.33)	(0.808)	(0.534)	(0.46)
Annual average humidity (%)	2.057***	0.528***	2.281***	-1.383***	-0.271**
	(0.121)	(0.085)	(0.182)	(0.119)	(0.1)
Climate Specification Y4					
Average temperature over the last 3 years (°F)	-4.15	3.837	17.553	22.762	-1.451
	(28.212)	(16.797)	(40.731)	(23.046)	(22.265)
Average total precipitation over the last 3 years (in)	0.058	0.417*	-0.598	0.664*	-0.251
	(0.303)	(0.206)	(0.444)	(0.317)	(0.237)
Annual average humidity (%)	3.323***	-0.178	4.166***	-3.288***	-0.058
	(0.171)	(0.131)	(0.254)	(0.172)	(0.143)
Annual temperature in Jan-Apr (°F)	1.941	-3.213	3.243	-5.435	3.865
	(6.676)	(3.784)	(9.341)	(5.939)	(4.953)
Annual precipitation in Jan-Apr (in)	-9.195	17.465***	-23.196***	14.181***	-21.814***
	(4.765)	(3.429)	(6.615)	(4.048)	(3.973)
Annual humidity ub Jan-Apr (%)	-0.147	-0.497***	-0.656***	-0.073	0.857***
	(0.087)	(0.099)	(0.133)	(0.09)	(0.078)
Climate Specification Y5					
Average temperature over the last 3 years (°F)	-2.148	2.22	26.084	14.807	2.468
	(27.874)	(15.661)	(40.503)	(22.961)	(22.175)
Total precipitation over the last 3 years (in)	0.066	0.355	-0.785	0.818**	-0.207
	(0.3)	(0.196)	(0.44)	(0.311)	(0.235)
Annual average humidity (%)	3.225***	0.057	4.034***	-3.043***	0.043
	(0.18)	(0.11)	(0.264)	(0.175)	(0.149)

Fraction of days in Jan-Apr with max temp > 86°F	3.822	-176.466**	-597.528***	301.138**	61.755
	(103.363)	(66.882)	(158.256)	(102.201)	(84.065)
Annual precipitation in Jan-Apr (in)	-4.070	4.919	-25.781***	4.401	-11.832***
	(4.258)	(2.991)	(5.942)	(3.556)	(3.507)
Annual humidity in Jan-Apr (%)	-0.451***	-0.15*	-1.746***	1.071***	-0.015
	(0.088)	(0.062)	(0.133)	(0.088)	(0.071)

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

Table 6b: Total marginal effect including irrigation technology, Climate specification M1

	Alfalfa	Corn	Sorghum	Soybeans	Wheat
Avg. temperature (°F) over the past 3 years during month of:					
January	-0.711	1.325	1.976	8.003	3.143
	(14.942)	(6.867)	(20.395)	(13.079)	(10.848)
February	3.027	-7.031	13.934	-7.304	4.602
	(10.995)	(5.603)	(15.353)	(10.504)	(8.669)
March	-2.202	-3.892	2.877	6.113	2.091
	(26.184)	(12.499)	(36.617)	(24.239)	(20.023)
April	6.192	-9.94	10.533	-4.441	-7.026
	(31.529)	(15.76)	(44.501)	(29.939)	(24.426)
May	0.714	-0.658	-0.743	-11.946	4.357
	(47.913)	(22.984)	(66.451)	(44.021)	(36.531)
June	-4.866	16.751	-2.273	4.387	11.459
	(60.368)	(29.987)	(85.821)	(58.181)	(45.655)
July	-16.493	3.624	-19.881	14.753	-24.297
	(68.691)	(33.471)	(92.583)	(61.008)	(51.987)
August	-4.720	-2.022	22.083	-4.750	12.116
	(64.856)	(31.591)	(89.012)	(57.796)	(49.134)
September	-0.494	-9.685	-16.918	-5.454	7.366
	(37.829)	(18.675)	(53.143)	(38.347)	(29.232)
October	-4.946	15.667	5.793	0.549	-6.802
	(30.531)	(14.913)	(42.575)	(28.706)	(23.719)
November	5.122	2.908	0.858	6.712	-4.975
	(14.104)	(7.518)	(20.273)	(14.199)	(11.58)
December	3.922	-6.733	-5.382	-10.619	7.750

	(16.2)	(7.531)	(21.575)	(13.364)	(12.653)
Avg. precipitation (in) over the past 3 years during month of:					
January	38.790**	2.273	25.391	-4.275	10.555
	(13.016)	(6.35)	(17.733)	(11.542)	(10.039)
February	48.584***	15.898*	-37.721*	92.12***	-25.364*
	(13.159)	(6.265)	(17.319)	(10.767)	(10.18)
March	6.378	-2.222	7.202	22.596***	-10.587*
	(6.756)	(3.166)	(8.738)	(5.725)	(5.177)
April	-17.694	7.706	-15.244	-6.355	-0.174
	(10.834)	(4.997)	(14.242)	(9.19)	(8.05)
May	-5.423	8.158***	8.509	1.888	-3.387
	(4.287)	(2.008)	(5.607)	(3.677)	(3.175)
June	8.849	-5.612*	-7.347	-3.938	-6.857
	(5.937)	(2.766)	(8.196)	(5.073)	(4.506)
July	-7.073	6.184*	-18.796**	-15.096**	5.555
	(5.184)	(2.451)	(6.873)	(4.999)	(3.836)
August	0.231	-0.436	0.259	17.352***	-1.655
	(2.861)	(1.37)	(3.959)	(2.693)	(2.202)
September	6.263	-9.816**	0.536	37.209***	-17.678***
	(6.559)	(3.05)	(8.743)	(5.791)	(4.884)
October	8.783	-3.808	-32.292**	3.524	-7.886
	(7.324)	(3.573)	(9.974)	(6.556)	(5.684)
November	-16.68*	10.647**	41.544***	71.823***	6.386
	(7.039)	(3.315)	(9.439)	(6.042)	(5.228)
December	-20.453***	-0.396	4.373	7.784	7.404
	(5.721)	(2.834)	(8.222)	(5.301)	(4.39)

Avg. humidity (%) over the past 3 years during month of:					
January	-3.963***	0.726**	3.437***	4.204***	1.168**
	(0.509)	(0.252)	(0.721)	(0.479)	(0.39)
February	0.301	-0.877**	3.415***	-1.794**	-0.887
	(0.653)	(0.335)	(0.934)	(0.653)	(0.507)
March	1.726**	0.034	-6.556***	0.83	0.983*
	(0.576)	(0.28)	(0.798)	(0.539)	(0.438)
April	0.384	1.764***	5.117***	-4.45***	0.877
	(0.775)	(0.369)	(1.062)	(0.703)	(0.586)
May	8.178***	-3.539***	1.565	0.168	-2.55***
	(0.777)	(0.376)	(1.077)	(0.709)	(0.585)
June	-6.334***	4.112***	-6.033***	4.639***	3.54***
	(0.808)	(0.373)	(1.065)	(0.666)	(0.613)
July	-3.021***	-0.546	-0.977	6.923***	-6.738***
	(0.707)	(0.362)	(0.987)	(0.676)	(0.543)
August	5.605***	-3.292***	5.73***	-6.155***	0.328
	(0.708)	(0.369)	(1.004)	(0.688)	(0.557)
September	-3.438***	1.014**	-3.903***	-6.464***	3.355***
	(0.646)	(0.324)	(0.934)	(0.608)	(0.493)
October	-5.504***	5.164***	1.635	9.189***	-5.713***
	(0.594)	(0.304)	(0.859)	(0.601)	(0.467)
November	-0.689	0.339	2.498**	-4.259***	5.808***
	(0.570)	(0.284)	(0.807)	(0.544)	(0.439)
December	9.445***	-3.74***	0.143	-6.325***	0.683
	(0.584)	(0.289)	(0.815)	(0.556)	(0.45)

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

Table 6c: Total intensive margins including irrigation technology margin, Climate specification M2

	Alfalfa	Corn	Sorghum	Soybeans	Wheat
Avg. fraction of days with max temp > 86°F over the past 3 years during month of:					
January	-9970.972***	-1609.155	-3815.914**	1152.78	-346.493
	(959.263)	(1513.105)	(1336.587)	(1023.366)	(840.988)
February					
March	-856.634*	1322.863***	-271.39	946.033**	-1841.821***
	(337.338)	(207.364)	(476.691)	(303.699)	(264.108)
April	-552.254***	-62.323	-724.334***	-18.058	-199.975*
	(111.388)	(66.313)	(156.167)	(101.059)	(86.23)
May	405.717***	-217.085***	55.826	-195.316	51.718
	(118.965)	(60.996)	(155.872)	(105.999)	(87.183)
June	68.435	111.246	85.777	-133.903	181.271
	(136.297)	(78.319)	(184.489)	(123.148)	(100.47)
July	0.896	58.238	484.248	113.53	-228.804
	(400.925)	(225.994)	(546.962)	(364.184)	(309.645)
August	-14.979	-25.744	5.322	1.204	58.469
	(124.294)	(78.465)	(174.015)	(115.378)	(99.949)
September	107.241	-204.183***	-124.404	-355.582***	117.538
	(92.742)	(50.784)	(122.842)	(79.971)	(71.046)
October	-58.11	386.92***	353.445	-126.1	343.879**
	(144.127)	(90.078)	(202.898)	(140.712)	(113.147)
November	-1207.348***	-53.807	262.998	1694.679***	683.975**
	(263.271)	(188.509)	(374.621)	(254.541)	(209.673)
December					
Avg. precipitation (in) over the past 3 years during month of:					

January	-36.301**	41.352***	7.981	75.835***	-4.826
	(11.645)	(8.07)	(15.897)	(10.326)	(9.324)
February	-29.082**	47.072***	4.995	99.745***	-12.776
	(10.688)	(6.575)	(14.524)	(9.229)	(8.639)
March	-7.067	2.718	16.151*	10.015*	-1.48
	(5.626)	(4.055)	(7.534)	(5.013)	(4.533)
April	-27.367**	6.844	-5.761	8.351	-7.919
	(9.861)	(5.264)	(13.06)	(8.433)	(7.485)
May	1.885	6.402**	3.38	-2.468	-4.749
	(4.088)	(2.184)	(5.411)	(3.547)	(3.048)
June	18.236**	-15.581***	-8.408	-11.214*	-4.94
	(5.984)	(3.311)	(8.102)	(5.168)	(4.579)
July	-7.243	1.712	-15.122*	-8.261	1.21
	(4.644)	(2.972)	(6.123)	(4.541)	(3.489)
August	-3.284	2.789	2.379	7.485**	2.328
	(2.587)	(2.583)	(3.484)	(2.525)	(2.055)
September	9.707	-3.59	-1.282	28.425***	-13.038**
	(5.756)	(3.304)	(7.728)	(5.101)	(4.332)
October	14.311*	-2.873	-28.238**	-0.607	-4.897
	(6.518)	(3.675)	(8.981)	(5.911)	(5.072)
November	-14.104*	22.059***	32.882***	56.197***	-16.436***
	(5.83)	(3.436)	(7.839)	(5.022)	(4.471)
December	-22.454***	-4.627	17.308*	34.041***	0.019
	(5.257)	(2.944)	(7.569)	(4.847)	(4.113)
Avg. humidity (%) over the past 3 years during month of:					
January	-2.879***	0.663*	4.188***	5.315***	1.506***
	(0.435)	(0.27)	(0.622)	(0.419)	(0.336)
February	-1.095**	0.377	-3.206***	-1.372***	-1.657***
	(0.372)	(0.245)	(0.521)	(0.359)	(0.29)
March	2.703***	-1.026**	-0.928	-0.761	-0.179
	(0.498)	(0.342)	(0.68)	(0.451)	(0.393)

April	3.771***	0.644	2.905***	-5.58***	1.548***
	(0.548)	(0.366)	(0.793)	(0.545)	(0.431)
May	4.014***	-4.587***	-0.81	2.19***	-1.094*
	(0.674)	(0.46)	(0.96)	(0.639)	(0.533)
June	-4.192***	2.511***	0.076	2.855***	2.759***
	(0.736)	(0.479)	(0.992)	(0.626)	(0.576)
July	-1.886**	1.833***	4.276***	5.689***	-3.549***
	(0.603)	(0.400)	(0.846)	(0.582)	(0.464)
August	2.341***	-1.012**	0.979	-4.079***	-1.121*
	(0.593)	(0.378)	(0.842)	(0.553)	(0.459)
September	1.809***	-1.399***	-2.913***	-8.134***	2.667***
	(0.519)	(0.339)	(0.734)	(0.488)	(0.406)
October	-3.636***	2.020***	7.201***	7.946***	-0.93*
	(0.535)	(0.414)	(0.773)	(0.553)	(0.435)
November	-1.442***	1.015***	-1.011	-2.591***	2.694***
	(0.408)	(0.3)	(0.583)	(0.404)	(0.317)
December	4.603***	-1.092***	-3.279***	-4.871***	-0.985**
	(0.482)	(0.295)	(0.684)	(0.49)	(0.373)

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

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

	Alfalfa	Corn	Sorghum	Soybeans	Wheat
Climate Specification Y1					
Annual average temperature (°F)	-2.485	0.843	19.194	13.772	-2.421
	(9.48)	(9.468)	(25.946)	(15.637)	(14.25)
Annual precipitation (in)	-1.109**	0.139	-0.525	3.074***	-1.574**
	(0.402)	(0.368)	(1.053)	(0.673)	(0.596)
Annual average humidity (%)	2.551***	0.655***	1.256***	-2.958***	-0.243
	(0.088)	(0.093)	(0.243)	(0.171)	(0.133)
Climate Specification Y2					
Average temperature over the past 3 years (°F)	-0.689	1.486	22.473	16.884	-1.675
	(14.625)	(13.972)	(37.645)	(21.316)	(20.75)
Average total precipitation over the past 3 years (in)	-1.147***	0.939***	-0.651	0.784	-0.242
	(0.221)	(0.232)	(0.586)	(0.426)	(0.324)
Annual average humidity (%)	4.877***	-1.309***	1.423***	-3.258***	0.738***
	(0.113)	(0.105)	(0.293)	(0.206)	(0.158)
Climate Specification Y3					
Annual fraction of days with max temp > 86°F	53.375	-429.368*	957.89	-244.207	931.923***
	(191.62)	(181.432)	(524.112)	(326.823)	(272.306)
Summer fraction of days with max_temp > 86°F	-85.445	195.58**	-151.813	182.186	-339.075**
	(84.219)	(71.238)	(216.946)	(131.647)	(107.187)
Annual precipitation (in)	-0.617	0.135	0.806	3.052***	-0.937

	(0.46)	(0.376)	(1.117)	(0.703)	(0.617)
Annual average humidity (%)	1.831***	0.326***	1.906***	-3.527***	0.703***
	(0.098)	(0.098)	(0.258)	(0.178)	(0.142)
Climate Specification Y4					
Average temperature over the last 3 years (°F)	3.848	1.323	20.225	12.707	-1.75
	(16.765)	(16.663)	(42.61)	(24.603)	(23.49)
Average total precipitation over the last 3 years (in)	-1.111***	0.925***	-0.411	0.897*	-0.089
	(0.228)	(0.24)	(0.6)	(0.439)	(0.332)
Annual average humidity (%)	4.156***	-1.343***	2.137***	-2.454***	0.146
	(0.14)	(0.149)	(0.377)	(0.253)	(0.205)
Annual temperature in Jan-Apr (°F)	-2.289	-1.395	6.279	2.578	3.096
	(4.13)	(3.696)	(10.168)	(6.311)	(5.335)
Annual precipitation in Jan-Apr (in)	-6.055*	7.166*	-30.372***	10.965*	-15.637***
	(2.705)	(3.335)	(7.046)	(4.29)	(4.068)
Annual humidity in Jan-Apr (%)	-0.018	-0.156	-0.453	-1.012***	0.657***
	(0.089)	(0.114)	(0.26)	(0.171)	(0.143)
Climate Specification Y5					
Average temperature over the last 3 years (°F)	2.073	0.765	28.653	15.895	0.066
	(16.018)	(15.231)	(41.665)	(23.899)	(22.842)
Total precipitation over the last 3 years (in)	-1.146***	0.965***	-0.546	0.644	-0.109
	(0.227)	(0.232)	(0.601)	(0.44)	(0.332)
Annual average humidity (%)	4.779***	-1.298***	2.713***	-2.702***	0.404*
	(0.137)	(0.126)	(0.364)	(0.244)	(0.195)

Fraction of days in Jan-Apr with max temp > 86°F	-215.817*	66.03	-244.735	-826.431***	609.372***
	(84.961)	(79.184)	(231.586)	(147.901)	(124.249)
Annual precipitation in Jan-Apr (in)	-8.867**	6.611*	-34.677***	8.844*	-12.688**
	(2.741)	(3.049)	(7.141)	(4.274)	(4.052)
Annual humidity in Jan-Apr (%)	0.051	-0.133	-1.161***	-0.772***	0.452***
	(0.081)	(0.077)	(0.231)	(0.152)	(0.124)

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

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

	Alfalfa	Corn	Sorghum	Soybeans	Wheat
Avg. temperature (°F) over the past 3 years during month of:					
January	-5.004	6.353	1.068	11.617	0.183
	(8.061)	(6.773)	(20.626)	(13.614)	(11.499)
February	3.811	-8.535	14.486	-2.672	2.651
	(6.316)	(5.940)	(17.093)	(12.532)	(9.958)
March	-0.503	-2.705	-1.568	-1.878	6.055
	(13.243)	(11.787)	(35.149)	(25.044)	(20.187)
April	8.293	-6.592	4.788	0.473	-8.102
	(18.002)	(16.515)	(45.623)	(32.773)	(27.373)
May	-1.651	-0.780	-3.911	-12.439	5.600
	(25.579)	(22.709)	(66.808)	(47.565)	(38.741)
June	-9.434	10.348	0.982	6.363	8.562
	(31.518)	(29.431)	(82.132)	(60.385)	(47.166)
July	-7.129	0.283	-10.473	-4.045	-12.764
	(37.081)	(33.18)	(91.307)	(64.229)	(55.212)
August	-1.412	4.606	16.834	15.535	0.778
	(32.623)	(29.759)	(83.261)	(58.232)	(48.846)
September	3.6	-11.395	-10.043	-10.482	12.526
	(19.186)	(17.666)	(50.332)	(39.528)	(29.489)
October	-4.24	5.332	5.908	-2.801	-7.634
	(15.637)	(14.029)	(40.008)	(29.117)	(23.829)
November	2.223	4.655	-1.851	2.789	-6.607
	(7.916)	(7.567)	(21.19)	(15.529)	(12.703)
December	5.679	-7.490	-1.521	-11.023	9.447

	(8.231)	(7.119)	(20.501)	(13.506)	(12.925)
Avg. precipitation (in) over the past 3 years during month of:					
January	5.952	16.032**	10.070	-11.644	-0.957
	(6.64)	(5.925)	(16.765)	(11.594)	(10.083)
February	6.698	30.255***	-30.666	105.715***	-22.218*
	(6.69)	(6.049)	(16.471)	(10.996)	(10.337)
March	-0.849	9.226**	8.977	15.143*	-12.323*
	(3.537)	(3.025)	(8.544)	(5.951)	(5.308)
April	-14.932**	6.104	-17.066	-0.47	-1.687
	(5.599)	(4.602)	(13.38)	(8.96)	(8.056)
May	0.296	5.09**	10.028	3.498	-0.355
	(2.203)	(1.882)	(5.222)	(3.694)	(3.154)
June	10.062**	-12.382***	-2.136	-10.666*	-2.836
	(3.082)	(2.7)	(7.819)	(5.414)	(4.65)
July	-4.100	4.217	-12.472	-18.335***	5.724
	(2.634)	(2.254)	(6.584)	(4.958)	(3.867)
August	-3.051*	7.79***	-3.89	21.707***	-3.112
	(1.471)	(1.316)	(3.709)	(2.785)	(2.226)
September	1.81	-0.934	-2.139	44.439***	-22.527***
	(3.499)	(3.028)	(8.761)	(6.031)	(5.307)
October	3.24	0.494	-27.978**	2.053	-6.334
	(3.861)	(3.469)	(9.633)	(6.766)	(5.876)
November	-10.821**	17.323***	34.707***	92.665***	-7.293
	(3.908)	(3.41)	(9.343)	(6.58)	(5.72)
December	-6.813	-10.179**	8.364	13.515*	-2.443
	(3.527)	(3.128)	(9.137)	(6.241)	(5.169)

Avg. humidity (%) over the past 3 years during month of:					
January	-1.554***	-0.029	2.205**	4.181***	2.686***
	(0.284)	(0.256)	(0.712)	(0.517)	(0.422)
February	-0.653	0.99**	2.245*	0.865	-3.737***
	(0.365)	(0.334)	(0.958)	(0.705)	(0.549)
March	0.822**	-0.939***	-5.383***	-1.406*	1.174**
	(0.301)	(0.274)	(0.77)	(0.57)	(0.45)
April	1.770***	0.868*	5.016***	-4.181***	1.399*
	(0.401)	(0.354)	(1.03)	(0.734)	(0.59)
May	3.449***	-2.938***	-2.005	0.568	-0.64
	(0.426)	(0.382)	(1.077)	(0.769)	(0.63)
June	-3.986***	2.986***	-2.431*	4.53***	2.66***
	(0.465)	(0.394)	(1.117)	(0.758)	(0.689)
July	-2.349***	1.657***	-0.414	4.943***	-7.013***
	(0.382)	(0.367)	(0.961)	(0.727)	(0.579)
August	3.63***	-1.325***	5.175***	-3.577***	-0.508
	(0.371)	(0.354)	(0.974)	(0.720)	(0.568)
September	-1.970***	-0.923**	-2.544**	-7.640***	3.779***
	(0.344)	(0.324)	(0.897)	(0.649)	(0.515)
October	-2.365***	2.976***	-0.735	6.16***	-4.52***
	(0.335)	(0.317)	(0.864)	(0.669)	(0.519)
November	0.283	-0.500	4.182***	-1.729**	4.779***
	(0.315)	(0.286)	(0.813)	(0.597)	(0.47)
December	6.572***	-3.782***	0.625	-6.148***	1.788***
	(0.316)	(0.295)	(0.781)	(0.583)	(0.484)

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

Table 7c: Total intensive margins including irrigation technology margin, Climate specification M2, Random Effects

	Alfalfa	Corn	Sorghum	Soybeans	Wheat
Avg. fraction of days with max temp > 86°F over the past 3 years during month of:					
January	-2407.037***	-1441.027	-2797.988*	3144.561**	-724.435
	(503.436)	(1505.23)	(1394.787)	(1065.335)	(849.64)
February					
March	-974.303***	900.800***	-101.357	932.552**	-1401.216***
	(172.711)	(206.478)	(509.853)	(325.344)	(279.968)
April	-315.404***	30.751	-885.835***	-56.459	-92.326
	(57.008)	(65.169)	(172.183)	(107.404)	(92.224)
May	345.703***	-225.385***	103.654	-198.886	42.466
	(56.982)	(58.431)	(161.386)	(110.105)	(88.05)
June	7.852	40.949	168.267	-178.095	180.318
	(69.422)	(77.518)	(195.943)	(129.238)	(106.37)
July	31.39	7.243	412.872	117.312	-260.279
	(197.845)	(220.067)	(573.555)	(384.157)	(321.565)
August	-5.645	50.505	-34.57	118.778	-38.756
	(67.122)	(79.473)	(198.414)	(131.991)	(109.08)
September	-9.085	-104.233*	-155.506	-433.22***	195.276**
	(45.295)	(49.608)	(131.218)	(83.779)	(73.839)
October	266.383***	-43.701	562.348*	-153.554	421.696***
	(74.309)	(88.825)	(220.417)	(151.673)	(119.528)
November	-356.489**	147.636	701.257	1551.573***	338.413
	(130.228)	(185.179)	(404.327)	(271.517)	(216.333)
December					

Avg. precipitation (in) over the past 3 years during month of:					
January	-30.469***	31.223***	11.735	77.712***	-2.441
	(5.971)	(7.975)	(17.17)	(11.031)	(9.856)
February	-30.509***	43.872***	-18.612	106.556***	-30.735***
	(5.17)	(6.369)	(15.008)	(9.403)	(8.746)
March	-12.08***	5.222	8.331	8.054	-3.03
	(2.93)	(4.029)	(8.248)	(5.365)	(4.833)
April	-11.19*	4.797	-5.53	8.466	-8.759
	(4.785)	(5.002)	(13.284)	(8.43)	(7.456)
May	-0.998	7.954***	2.768	-0.383	-2.518
	(2.017)	(2.116)	(5.518)	(3.609)	(3.095)
June	12.193***	-10.56***	-4.393	-17.211**	-1.164
	(2.905)	(3.194)	(8.405)	(5.294)	(4.649)
July	1.722	1.053	-14.082*	-12.119*	-2.545
	(2.325)	(2.927)	(6.672)	(4.861)	(3.657)
August	-5.66***	5.521*	-0.833	12.643***	1.461
	(1.322)	(2.568)	(3.666)	(2.671)	(2.117)
September	7.48*	-1.159	-5.023	30.151***	-11.001*
	(2.996)	(3.381)	(8.759)	(5.514)	(4.955)
October	3.105	1.987	-26.465**	-1.414	-2.07
	(3.489)	(3.707)	(10.223)	(6.488)	(5.549)
November	-9.035**	12.623***	39.342***	67.327***	-18.287***
	(3.078)	(3.522)	(8.478)	(5.473)	(4.858)
December	-0.809	-4.001	30.193**	26.689***	-12.497*
	(3.083)	(3.164)	(9.306)	(5.794)	(4.884)
Avg. humidity (%) over the past 3 years during month of:					
January	-1.19***	0.113	3.771***	4.756***	1.53***

	(0.215)	(0.261)	(0.65)	(0.429)	(0.344)
February	0.538**	-0.48*	-3.02***	-1.547***	-1.748***
	(0.19)	(0.243)	(0.556)	(0.384)	(0.306)
March	1.041***	-0.342	-1.325	-1.362**	0.271
	(0.246)	(0.332)	(0.707)	(0.462)	(0.396)
April	-0.288	1.627***	2.059*	-5.793***	1.762***
	(0.272)	(0.36)	(0.839)	(0.573)	(0.449)
May	6.122***	-3.966***	0.29	2.725***	-1.481**
	(0.333)	(0.452)	(1.009)	(0.675)	(0.55)
June	-3.192***	0.848	1.745	2.438***	2.881***
	(0.39)	(0.489)	(1.09)	(0.714)	(0.628)
July	-0.320	0.671	5.236***	7.313***	-4.308***
	(0.297)	(0.392)	(0.869)	(0.605)	(0.468)
August	-0.185	0.994**	0.502	-4.745***	-1.08*
	(0.313)	(0.381)	(0.928)	(0.602)	(0.499)
September	0.568*	-0.938**	-3.808***	-9.207***	2.695***
	(0.255)	(0.336)	(0.77)	(0.527)	(0.415)
October	1.685***	0.369	6.052***	7.01***	-1.782***
	(0.264)	(0.406)	(0.802)	(0.569)	(0.442)
November	-3.353***	1.041***	0.521	-1.609***	3.358***
	(0.205)	(0.297)	(0.625)	(0.447)	(0.331)
December	2.728***	-1.872***	-2.566***	-4.731***	0.686
	(0.259)	(0.297)	(0.761)	(0.523)	(0.411)

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