Producer Responses to Surface Water Availability and Implications for Climate Change Adaptation

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Abstract

Climate change is predicted to bring changes in weather and water availability. The effect on agriculture depends on the ability of producers to modify their practices in response to changing distributions. We develop a two-stage theoretical model of producer planting and irrigation decisions and use a unique dataset to empirically estimate how irrigated agricultural producers respond to changes in expected water availability and deviations from expectations. As water supplies decrease, producers respond by planting fewer acres and concentrating the application of water. Highlighting the importance of adaptation, failure to account for this behavioral response overstates climate change impacts by 29%.

1. Introduction

Widespread consensus now exists that climate change is occurring (Stocker et al., 2013). Changes in precipitation and temperature patterns are expected to have widespread impacts on agricultural systems (Mendelsohn et al. 1994, Schlenker et al. 2005, Deschenes and Greenstone 2007, Schlenker and Roberts 2009, Massetti and Mendelsohn 2011) but the size and nature of these impacts will not only depend on how the climate changes, but also on the ability of producers to adapt. Irrigated agriculture accounts for almost half of all agricultural revenue in the U.S., yet due to data limitations and other estimation challenges, there exists a gap in the understanding of how producers in this sector might respond to climate change. While all producers can respond to changing expectations and random weather realizations, the available margins of adjustment in irrigated agriculture differ from those available to dryland producers. In this paper, we investigate how irrigated agricultural producers respond to changes in expectations about the availability of water as well as year-to-year fluctuations in weather and the availability of irrigation water. We then explore what this implies for the ability of producers to adapt to climate change.

Recent empirical studies of agricultural climate change impacts fall into two broad categories. The first focuses primarily on dryland production and uses random fluctuations in annual weather to identify the impacts of temperature on crop yields (Schlenker and Roberts 2009) and agricultural profit (Deschenes and Greenstone 2007). Results suggest that an increase in average temperature could increase agricultural profit but that extreme temperatures may have large negative consequences for US agriculture. While this method is well-identified, it does not allow for producer responses to changes in weather distributions that could offset some of the observed impacts of variation in weather realizations. The second category of studies uses a cross-sectional Hedonic approach to investigate how agricultural land value depends on climate variables such as temperature and rainfall averages (Schlenker et al., 2005) and on expected water availability (Schlenker et al., 2007). At the opposite extreme, this approach allows for costless behavioral and institutional adjustments as climate and water availability change.

Our approach uses random fluctuations in weather and water availability for identification but allows for changing behavior in response to expectations of surface water availability. Specifically, we use the Colorado spring snowpack to model expected water supplies. We then examine producer responses to deviations from expectations. This novel approach provides new insight into the potential for agricultural adaptation to climate change by allowing for producer responses to observable changes in the distribution of water availability.

The existing literature has focused on climate change impacts on dryland agriculture because the decision to irrigate is largely endogenous and not fully observed. Producers can choose the quantity of water to apply in a given season. Olen et al. (2015) find that climate and weather significantly influence irrigation behavior on the West Coast of the US. In addition, Schlenker et al. (2005) find that controlling for surface water (e.g., Mendelsohn and Dinar 2003) does not adequately capture the difference in impacts between irrigated and dryland counties in the US. Schlenker et al. (2007) address this by using data on irrigation district water availability to estimate the impact of water on agricultural land values in California.

We overcome these challenges by using a unique measure of surface water availability in Northeastern Colorado. The South Platte River Basin (SPRB) presents an ideal setting for measuring the role of surface water because of spatial and temporal variability in its supply. Producers in the SPRB receive surface water in the summer from snowmelt and reservoirs that fill in the winter. The variation in surface water supplies across years and counties generates sufficient variation to estimate the impact of 1) surface water *expectations* on planting decisions and 2) agricultural season water *realizations* on producer outcomes, including harvested acres and crop yields. These two impacts can be separately identified because of the temporal difference between surface water storage (in the winter) and use (during the summer).

While we use data from one region of Colorado, quantifying these impacts provides new insights into the impacts of variability in surface water supplies on irrigated agriculture across many arid regions of the world. It also highlights potential differences from dryland impacts. The results have important policy implications because efficient surface water management can mitigate negative impacts of climate change (Fischer et al. 2007). On the other hand, if surface supplies decrease as temperatures increase, climate change impacts can become magnified.

Structural models have also been used in the economics literature to mitigate concerns regarding the endogeneity of irrigation decisions but they impose more assumptions about producer behavior. For example, hydroeconomic models have been used to investigate the impacts of droughts and other water supply issues (Harou et al. 2009). Positive mathematical programming also provides a useful tool in evaluating regional impacts of water policies (Howitt 1995, Graveline and Mérel 2014).

Here, a two-stage theoretical model demonstrates how a producer adjusts planting decisions in response to expectations about the weather and surface water availability. The model then describes the nature of a producer's irrigation decision conditional on acres planted. To test the hypotheses from the theoretical model, we use the US Department of Agriculture Natural Resource Conservation Service's Surface Water Supply Index (SWSI) as a measure of surface water expectations and confirm that Colorado producers plant more acres of irrigated corn in years when a high water supply is expected during the irrigation season. This innovation allows climate change scenarios to include changes in producer behavior that account for updated *expectations* of water availability. This is a useful departure from using only annual weather realizations to predict the agricultural impacts of climate change.

Next, we use a feature of the Prior Appropriation Doctrine (PAD), which governs water rights in the western US, to construct a county-level measure of surface water supply. Under PAD, older, or 'more senior' water rights have priority over newer rights. A "call" is placed on junior water rights when water supplies are insufficient to fulfill senior water rights[i]. If a senior rights holder cannot access needed water, s/he can 'call' all rights within a basin with a more junior status. Junior water rights holders cannot use their right during the period of a call, resulting in less water available over the season. We find that producers respond to shocks by concentrating available water onto fewer acres to maintain high yields on harvested acres. Using "calls", which are exogenously driven by weather events, as the basis for our identification strategy, we avoid endogeneity concerns typical of this type of study.

In the context of irrigated agriculture in the SPRB, it is important to control for county fixed effects and a time trend. First, counties vary in their access to surface water on average and this affects planting decisions. Next, moving across space involves significant changes in altitude, slope, expected weather, and soil type and these factors influence agricultural productivity (Ortiz-Bobea 2013). The inclusion of county fixed effects and a time trend help minimize omitted variable bias: the former controlling for unobserved, time-invariant differences across counties, the latter controlling for factors such as population growth that takes water from agriculture (Goodman 2000).

Some evidence exists on the ability for producers to adapt to climate change. Burke and Emerick (2013) find little evidence of producer adaptation that minimizes climate change impacts on yields and farm revenue. This may occur as dryland producers do not have significantly different expectations about the weather from year to year. It is possible that access to irrigation water could offset some of the negative impacts of climate change (Adams 1989). Of course, this relies on continued access to water supplies.

In the region studied here, we find that the ability to adjust planting decisions to changes in expected surface water increases county profits by approximately $541,000 per year. We also find that investment in public water storage infrastructure that substitutes for declining natural storage can increase profits by $301,000 per county-year. Therefore, the ability to adapt to climate change at the individual producer level and at the basin level can decrease the negative impacts of climate change.

In the following section, we present a simple, two-stage mathematical model that highlights the margins of adjustment available to producers who rely on surface water irrigation. Next, an empirical setting and model are described to test the hypotheses generated by the theoretical model. Parameter estimates are used to calculate the impacts of climate change on profit and yields in the SPRB. Finally, we discuss results and conclude.

2. Theoretical Model

Our analysis focuses on producers who rely on surface water for irrigation. The model presented characterizes how variation in expected and realized surface water supplies affects producer decisions regarding planting, harvesting, and irrigation. A producer makes decisions in two stages, reflecting planting decisions based on expectations of available water and irrigation and harvest decisions in response to observed realizations. While this two-stage approach has been used in the context of groundwater (Foster et al. 2014), surface water differs because both weather and the quantity of irrigation water available are random variables while groundwater well capacities are known upfront.

2.1 Decision Environment

Consider a profit maximizing producer who, at the beginning of each irrigation season (stage 1), decides the number of irrigated acres, L, to plant. We assume that the producer is water constrained, implying that no land constraint binds. The producer faces a per-acre planting cost of c.

In stage 2, conditional on planting decisions, the producer makes a decision regarding how much to irrigate per acre, a, assumed to be constant across acres, and how much land to harvest, $H \leq L$. As of stage 2, the realization of weather and surface water availability has occurred. This represents a simplification because irrigation decisions are made on a daily basis before full information about the weather is revealed. Nevertheless, separating irrigation decisions into *ex ante* planting decisions and *ex post* irrigation decisions captures the role of risk in planting while accounting for the ability to adjust irrigation as conditions are revealed.

The producer faces a per-acre harvest cost of d and receives p dollars per unit of output harvested. Reflecting gravity-fed surface water systems, water can be applied at no cost. Conditional on harvesting an acre, per-acre output produced is $y = f(w;\theta)$ and is a function of the amount of water available to the plant, w, and a set of random non-water weather conditions, θ, distributed with mean μ_θ and variance, σ_θ^2. Assume that $f_w \geq 0$ and $f_\theta > 0$ so that more water and higher θ translate (weakly) into yield increases.

The total amount of water available to an acre is a random variable, $w = s + a$. s represents the total amount of water available absent any irrigation and is comprised of the sum of available pre-season soil moisture and agricultural season precipitation. Every acre receives a realization of $\tilde{s}$ plus the amount of irrigation water applied, a. The irrigator is constrained in the total amount of water applied such that $Ha \leq A$, where A is a random variable that represents the total amount of surface water available to the producer. Both $\tilde{s}$ and $\tilde{A}$ represent realizations of the random variables assumed to be symmetric around means μ_s and μ_A with variances $\sigma_s$and σ_A respectively.

The key information realization between stages 1 and 2 comes from a draw of $\tilde{\theta}$, $\tilde{s}$, and $\tilde{A}$. At the time of the stage-1 decision, both are unknown, meaning the producer makes planting decisions to maximize *expected* profits, facing uncertainty in both water availability and the weather. The producer does, however, account for the ability to make irrigation decisions optimally in stage 2 after $\tilde{s}$, $\tilde{\theta}$, and $\tilde{A}$ are realized. Mathematically, the producer's stage-1 problem can be expressed as:

$$\max_{\boldsymbol{L}\geq \boldsymbol{0}} \ \boldsymbol{E}[\boldsymbol{pH}^*(\boldsymbol{p},\boldsymbol{d},\boldsymbol{s},\boldsymbol{A},\boldsymbol{L},\boldsymbol{\theta})\boldsymbol{f}(\boldsymbol{a}^*(\boldsymbol{p},\boldsymbol{d},\boldsymbol{s},\boldsymbol{A},\boldsymbol{L},\boldsymbol{\theta})+\boldsymbol{s};\boldsymbol{\theta})-\boldsymbol{cL}-\boldsymbol{dH}^*(\boldsymbol{p},\boldsymbol{d},\boldsymbol{s},\boldsymbol{A},\boldsymbol{L},\boldsymbol{\theta})] \qquad (1)$$

where $H^*(p,d,s,A,L,\theta)$ and $a^*(p,d,s,A,L,\theta)$ are optimal stage-2 decisions. The first-order condition (FOC) of this problem states that:

$$\boldsymbol{E}\left[\boldsymbol{p}\left(\frac{\partial \boldsymbol{H}^*}{\partial \boldsymbol{L}}\boldsymbol{f}\big(\boldsymbol{a}^*(\boldsymbol{p},\boldsymbol{d},\boldsymbol{s},\boldsymbol{A},\boldsymbol{L},\boldsymbol{\theta})\big)+\boldsymbol{H}^*\frac{\partial \boldsymbol{f}}{\partial \boldsymbol{a}}\frac{\partial \boldsymbol{a}}{\partial \boldsymbol{L}}\right)-\boldsymbol{c}-\boldsymbol{d}\frac{\partial \boldsymbol{H}^*}{\partial \boldsymbol{L}}\right]=\boldsymbol{0} \qquad (2)$$

The solution to this FOC, $L^*(p,d,c,s,A,L,\theta)$ characterizes the optimal planting decision. To obtain $H^*(p,d,s,A,L,\theta)$ and $a^*(p,d,s,A,L,\theta)$, we solve the stage-2 decision, conditional on planting decisions and realizations of water availability:

$$\max_{\boldsymbol{H},\boldsymbol{a}\geq \boldsymbol{0}} \quad \boldsymbol{pHf}\big(\tilde{\boldsymbol{s}}+\boldsymbol{a};\tilde{\boldsymbol{\theta}}\big)-\boldsymbol{dH} \qquad \boldsymbol{s.t.}$$

$$\boldsymbol{0}\leq \boldsymbol{H}\leq \boldsymbol{L} \qquad (3)$$

$$\boldsymbol{Ha}\leq \tilde{\boldsymbol{A}}$$

where the first constraint restricts producers to only harvesting acres that were planted and the second to applying no more than the total amount of surface water available to them. As of stage 2, random variables are realized, indicated by the tildes. Note that the number of acres harvested enters the objective function linearly. Therefore, either no acres are harvested or the optimal H occurs when one of the constraints binds. In addition to this,

$$\boldsymbol{pHf_w \geq 0} \tag{4}$$

The subscript indicates a first derivative with respect to the variable.

Equation 4 exactly equals zero if the water availability constraint does not bind or only weekly binds, given the number of acres harvested[ii]. The solution to this stage, $H^*(p, d, \tilde{s}, \tilde{A}, L, \tilde{\theta})$ and $a^*(p, d, \tilde{s}, \tilde{A}, L, \tilde{\theta})$, identifies optimal harvest and irrigation decisions, but does not consider planting costs which are sunk as of the second stage. The solution is used in Equation 1, which can then be solved for the optimal choice of L, accounting for stage-2 decisions.

2.2. Model Predictions for Surface Water Use

The predictions from both the first- and second-stage problems depend on assumptions made regarding the functional form for $f(\tilde{s} + a; \theta)$. Consistent with empirically estimated agronomic yield functions (Berck and Helfand 1990, Letey 1991, Carey and Zilberman 2002, Schneekloth and Andales 2009), we narrow our focus to the set of production functions for which the following is true:

$$\boldsymbol{f_w(w;\theta) = \begin{cases} 0 & if\ w < LB \\ g > 0 & if\ LB \geq\ w < UB \\ 0 & if\quad w > UB \end{cases}} \tag{5}$$

where LB denotes an agronomic minimum quantity of water needed for the crop to grow and UB represents the point beyond which additional water has zero marginal impact on yields.

A minimum water requirement, together with the presence of fixed planting costs implies that economic (as opposed to agronomic) lower bounds also exist in both model stages. Let LB^P and LB^H denote the minimum quantity of water needed to produce yields sufficient to recover per-acre total and harvest costs respectively. In this case,

$$\boldsymbol{pf(LB^P;\theta)\ = c + d} \text{ and } \boldsymbol{pf(LB^H;\theta) = d} \tag{6}$$

Note that $LB^P > LB^H$. As defined, a producer chooses not to plant if known water availability is less than LB^P. Conditional on planting an acre, harvest occurs as long as available water exceeds LB^H. Without loss of generality, we further restrict our attention to the cases where UB

is greater than both economic lower bounds and $\tilde{s}$ is less than LB^P. Together these imply that we consider only irrigated crops that have the potential to recover planting and harvest costs but the decision is risky.

We now explore how planting and irrigation decisions in this model are influenced by expected and realized water availability.

Observation 1: Given insufficient water supplies, it is optimal to fully irrigate a subset of planted acres.

To illustrate this, suppose a producer with a given $\tilde{s}$ has enough water, $\tilde{A}$ to supply $H_0 < L^*$ acres with $w_0 \in (LB^H, UB)$. Since the marginal productivity of water is constant and equal to g in this range, there exists $\epsilon > 0$ such that the same quantity of water could be applied on $H_0 - \epsilon$ acres without decreasing total production. In fact, as long as $w_0 H_0 < UB * H_0$, harvesting fewer acres can increase total production because the inframarginal water between 0 and LB on ϵ acres has zero marginal product but when transferred, the marginal product equals g. Therefore, revenue does not decrease while costs decrease by ϵd because fewer acres are harvested. This remains true until $w_0 = UB$ for all harvested acres. Therefore, the existence of fixed per-acre harvest costs drive the producer to fully irrigates every harvested acre[iii].

Observation 2: Negative shocks to water availability result in extensive margin adjustments.

Observation 2 follows directly from Observation 1. If $\tilde{A} \leq (UB - s)L^*$, the producer is unable to fully irrigate all planted acres. Given that the producer prefers to fully irrigate any acre harvested over partially irrigating, in periods of shortage the producer will reduce irrigated acreage rather than reducing per acre application rates. With a negative shock to water availability, this implies fewer acres are harvested.

Together, observations 1 and 2 suggest that we would expect harvested acreage to fall, but not yields in response to a negative shock to water supplies.

Observation 3: An increase (decrease) in expected water increases (decreases) the number of acres planted.

Observation 3 can be shown through further analysis of Equation 2. First, note that the optimal number of acres harvested, given that all harvested acres are fully irrigated, is $H^* = \min\left\{\frac{\tilde{A}}{UB-s}, L^*\right\}$. Therefore, in stage 1, the marginal impact of increasing L is:

$$\boldsymbol{\frac{\partial \pi}{\partial L} = \begin{cases} -c & if\ \tilde{A} \leq (UB-S)L \\ pf(UB;\theta) - (c+d) & o.w. \end{cases}} \tag{7}$$

where the first case occurs when an additional acre is planted but not harvested. The second case occurs when more acres could be harvested if planted.

The optimal choice of L^* in stage 1 sets $E\left[\frac{\partial \pi}{\partial L}\right] = 0$. Consider $L^*_{\bar{\mu}_A}$ which represents the optimal level of acres planted given expectation of $\bar{\mu}_A$ so that $E\left[\frac{\partial \pi}{\partial L}\right]_{\mu_A = \bar{\mu}_A} = 0$. This implies that:

$$\boldsymbol{\begin{aligned} E\left[\frac{\partial \pi}{\partial L}\right] &= pr\left(\frac{A}{L^*_{\bar{\mu}}} \leq UB - s\right) * (-c) \\ &\quad + pr\left(\frac{A}{L^*_{\bar{\mu}}} > UB - s\right)\big(pf(UB;\theta) - (c+d)\big) = 0. \end{aligned}} \tag{8}$$

Let $g\left(\frac{A}{L}; \mu_A, \sigma_A^2\right)$ be the probability distribution function of $\frac{A}{L}$. This implies that the probability that $\frac{A}{L} > UB - s$ is decreasing in L, as planting more acres results in a lower probability of fully irrigating all acres planted. Equivalently, the probability that $\frac{A}{L} < UB - s$ increases in L. Substituting $g\left(\frac{A}{L}; \mu_A, \sigma_A^2\right)$ in to Equation 8,

$$\boldsymbol{c \int_{-\infty}^{UB-s} g\left(\frac{A}{L^*_{\bar{\mu}}}; \bar{\mu}_A, \sigma_A^2\right) dA = \big(pf(UB;\theta) - (c+d)\big) \int_{UB-s}^{\infty} g\left(\frac{A}{L^*_{\bar{\mu}}}; \bar{\mu}_A, \sigma_A^2\right) dA} \tag{9}$$

Holding L^* constant, if μ_A increases from $\bar{\mu}_A$ to $\hat{\mu}_A$, then the left-hand side of Equation 9 decreases while the right-hand side increases. In order to maintain equality, L^* must increase, resulting in $L^*_{\hat{\mu}_A} > L^*_{\bar{\mu}_A}$.

2.3 Soil Moisture and Weather

Given that we have modeled precipitation and soil moisture as perfect substitutes for irrigation water, we might expect changes in expectations to have similar impacts as expected surface water. This is likely true with intermediate levels of soil moisture but in practice, when soil moisture reaches extreme levels, planting becomes difficult and can result in lower productivity as producers alter the timing of planting in response. Therefore, while the model predicts that higher soil moisture should lead to more acres planted, this impact may be nonlinear, as producers cannot control oversaturation of fields due to extreme weather events.

Finally, the impact of θ in this model depends on how temperature impacts the location of LB and UB as well as maximum yields. Evidence suggests that temperature increases from low levels can have a positive impact on crop growth while increases in high temperatures have a negative impact (Schlenker and Roberts 2009). Therefore, conditional on having sufficient water to fully irrigate, we expect nonlinear impacts on yields for all acres harvested.

3. Data and Context

To test the theoretical predictions presented above we focus our analysis on the South Platte River Basin (SPRB) of Colorado. We concentrate on this region because data on agricultural water deliveries are available and, unlike in other regions in CO, groundwater supplies are administered under the same legal framework as surface water. According to the State Water Plan (Colorado's Water Plan 2015), the SPRB "has the greatest concentration of irrigated agricultural land in Colorado" (2nd draft, p. 43). We focus on counties that are not over the Ogallala Aquifer and thus depend mostly on surface water from the Rocky Mountains. In 2010, surface water accounted for more than 90% of irrigation water used in this region (United States Geological Survey). Surface water supplies rely on reservoirs as well as melting snowpack that accumulates during the winter before the agricultural season. Therefore, producers form an expectation for the amount of surface water to be delivered later in the season based on the snowpack in a basin's headwaters region. Note, however, that actual water delivered does not correspond perfectly to beginning-season expectations because random events (e.g., sublimation that causes snow to convert to water vapor[iv] or dust that lands on snow) can rapidly change the amount of surface water available for agricultural (or other) use. This can cause unexpected shocks in the amount of surface water available to some producers. Figure 1 presents the land irrigated by surface water in the SPRB, as well as a map of all water basins in Colorado. In the analysis, we include all counties that have some land area within the SPRB.

[Figure 1]

In the SPRB, we explore planting, irrigation, and harvesting decisions for irrigated corn. According to Schneekloth and Andales (2009), corn requires 20-30 inches of water to reach full irrigation (UB) in the region. It also needs at least 10 inches of water for any growth to occur. In the SPRB, mean initial season soil moisture is 9.6 inches of water-height equivalent with a 10^{th} and 90^{th} percentile of 6.3 and 11.78 inches respectively. Therefore, it is unlikely that soil moisture alone could provide enough water to reach UB. This means that surface water supplies are needed to fully irrigate corn in the region[v]. Observed fluctuations in initial soil moisture, on the other hand, are unlikely to provide enough water to fully irrigate corn without surface water.

3.1 Agricultural Data

The agricultural data used to test responses to surface water availability come from the USDA National Agricultural Statistics Survey (NASS). We obtain county-year acreage (harvested and planted) data as well as yields per acre harvested for irrigated corn[vi].

Table 1Table 1 presents overall basin-wide averages for the variables used in the analysis. In addition, averages from 2000 and 2002 are presented to demonstrate variation between and wet and dry year respectively. The NASS data create an unbalanced panel for the time period 1982-2010.

[Table 1]

3.2 Weather Data

In order to measure historical agricultural season weather, we use daily minimum and maximum temperature as well as precipitation from Oregon State University's high resolution spatial climate data model, PRISM (PRISM Climate Group 2015). We choose PRISM over other weather data alternatives because of its consistent spatial and temporal coverage (Auffhammer et al. 2013). Colorado's extreme topography, including large changes in altitude, means that the weather varies significantly across space, even within a county. To account for this, we use the 2001 National Land Cover Database (NLCD) to identify agricultural land and only use PRISM output from model grid cells that contain agricultural land.

While the weather data are available on a daily basis, agricultural statistics are only available annually. To create annual weather variables while capturing the role of extremes, we follow the standard in the agronomy literature and use growing degree days (GDD) (Wilson and Barnett 1983, Bassetti and Westgate 1993, Herrero and Johnson 1980) and harmful degree days (HDD). This allows for beneficial heat in some range while extreme heat can harm productivity. Following Snyder (1985) we assume that temperature within a day follows a sinusoidal pattern connecting daily minimum and maximum temperatures (Schlenker and Roberts 2006) and define the cut-off between GDDs and HDDs at 30 degrees C. We also assume that temperatures below 8 degrees do not contribute to crop growth. Therefore, a GDD corresponds to temperatures between 8 and 30 degrees C. To construct agricultural season weather, we sum the GDDs and HDDs that occur between April and September. This is also done for precipitation to create annual agricultural season precipitation and precipitation squared.

3.3 Expected Surface Water Supply

In the SPRB, surface water supplies flow from melting snow that falls over the winter. Reservoirs allow water managers to control the timing of surface water releases within and across seasons. The USDA Natural Resources Conservation Service maintains a basin-specific surface water supply index (SWSI) for all of Colorado. SWSI measures monthly mountain-based surface water supply. It ranges from -4 (severe drought) to 4 (abundant supply) and includes snowpack as well as reservoir levels for the entire basin. In this analysis we use the average of March and April SWSI to capture surface water *expectations* at the time of planting. Some counties[vii] in the SPRB have land in the Arkansas Basin in addition to the SPRB. To allow for this, each county's SWSI is the average SWSI weighted by the amount of agricultural land in each basin. Figure 2 demonstrates that the March/April SWSI varies considerably across time in the SPRB. This provides exogenous variation in the expectations that producers have for available surface water in a given year.

[Figure 2]

3.4 Soil Moisture Data

Monthly soil moisture data at the county level come from a model developed by the National Oceanographic and Atmospheric Administration (Huug van den Dool et al. 2003). Climate Prediction Center soil moisture data were provided by the NOAA/OAR/ESRL PSD, located in Boulder, Colorado, USA, (http://www.esrl.noaa.gov/psd/). Each of the agricultural fields in the NLCD was assigned the soil moisture of the cell that contains it. County-month observations are created by averaging across all agricultural fields in a county in each month.

3.5 Surface Water Calls

Yield and surface water allocation decisions ultimately depend on the amount of surface water delivered to a producer. We create a variable that captures the intensity of a negative surface water shock by utilizing a feature of the Doctrine of Prior Appropriation which governs water allocation in Colorado. According to Colorado law, all surface water users must own a right to use water. Older rights have a higher 'priority' than newer rights. If a senior water right holder cannot fulfill the right, s/he can 'call' junior rights holders. During a call, any user in a basin with a more junior right cannot exercise the right. Therefore, from the perspective of a junior rights holder, a call represents a negative shock to surface water supply. Importantly, because water rights are defined based on their historical diversions from the stream, senior water rights holders must utilize their rights when available or risk having the right taken away or redefined (often referred to as "use-it-or-lose-it").

Data on the surface water source for agricultural land as well as the relevant water right for the land's water source are obtained from the Colorado Decision Support System (CDSS). A call history tells the timing and length of calls from specific water rights. This information is used to map called water rights to agricultural land in the SPRB.

First, water rights are mapped to each diversion structure through which water flows in the basin. Water rights data describe the seniority of the water right by indicating the date of establishment[viii]. Next, the history of calls in the SPRB is assigned to each structure-year. During a call, the called structure must refrain from diverting water under that right. Therefore, the shock to surface water supply is created by multiplying the duration of each call by a right's allowable flow rate if the right is junior to the calling right. Consistent with the State of Colorado[ix], it is assumed that producers would water an average of 12 hours per day if the call did not occur. The amount of called water is summed across the agricultural season and across rights belonging to a structure to produce a quantity of called water for each structure. We consider called water during the period from June to September.

The final step includes mapping called water to the agricultural land it corresponds to in order to construct county level called water. Therefore, we use 2005 agricultural land data from CDSS for the SPRB. Each plot of land is mapped to the diversion structure through which water is obtained. The water rights associated with a plot's structure are divided among land parcels in proportion to the size of the parcel. The annual quantity of called water per land area is summed across all parcels within a county to produce a county-year measurement of agricultural surface water, in acre-feet. This variable is used to model expected called water as a function of beginning-year water observations. Deviations from expectations become an exogenous shock to surface water supplies. We use the combined dataset to investigate producer responses to expected water supplies and shocks to supply.

4. Empirical Model

Using the data described in the previous section, we investigate the impact of water supply expectations and shocks on agricultural planting and harvest decisions and crop yields.

4.1 Stage-1 Planting Decision

Consistent with the theoretical model, stage 1 of the empirical model investigates the number of acres planted in corn in county c in year t. L_{ct} is a function of expected surface water at the time of planting, initial soil moisture levels, and producer expectations about future prices. In the SPRB, corn is planted during the months of April and May. Therefore, the March and April SWSI values reflect the information that producers have about surface water supplies at the time of planting and are used as a proxy for μ_A from the theoretical model. ISM_{ct} is a measure of initial soil moisture in March and April in county c in year t and informs a belief about μ_s. To allow for potentially nonlinear effects of $SWSI_{ct}$ and ISM_{ct} they enter the regression model through a function, $W(SWSI_{ct}, ISM_{ct}; \beta)$. We include the average Chicago Mercantile Exchange December future price for corn in March and April as a proxy for producer's output price expectations at the time of harvest. We assume this price is exogenous to county production in Colorado but provides producers with a reasonable expectation regarding the price of corn at the time of harvest. The stage-1 model is therefore:

$$\boldsymbol{L_{ct} = \alpha_c + W(SWSI_{ct}, ISM_{ct}; \beta) + \delta p_t + \gamma t + u_{ct}} \qquad (10)$$

Where α_c is a county fixed effect that controls for differences in soil type, elevation, and other time invariant factors. p_t is the corn future price. A trend is included to allow for factors that evolve over time such as the conversion of agricultural lands due to urbanization. Finally, u_{ct} is a random error term and is clustered at the county level. Identification of the marginal impact of $SWSI_{ct}$ requires that, conditional on county fixed effects, a time trend, soil moisture levels, and prices, the annual realization of $SWSI_{ct}$ is orthogonal to the error term. This would occur as long as the snowpack in a given basin and year is random from the perspective of agricultural producers.

We estimate Equation 10 including $SWSI_{ct}$ and ISM_{ct} linearly as well as allowing for their interaction and the square of ISM_{ct}.

4.2 Modeling Expectations

Next, we model the expected called water in county c in year t as a function of the March/April SWSI. We do this to generate a measure of unexpected deviations in called water, used to explain responses to water availability in stage 2. $Calls_{ct}$ is the county-year variable created by summing called water across the agricultural year and across fields in a county. We assume that the expected number of calls depends on initial season expectations and a trend to reflect the impact of increasing demands by municipal and industrial water users driven by population growth over time. Therefore,

$$\boldsymbol{Calls_{ct} = \alpha_c + \beta_0 SWSI_t + \beta_1 year_t + \epsilon_{ct}} \tag{11}$$

The realization of called water often differs from expectation. Therefore, we use the predicted residual from Equation 11, $\hat{\epsilon}_{ct}$, as an exogenous shock to surface water that a producer has available during the agricultural season. This exercise is repeated for expected agricultural season soil moisture as a function of initial soil moisture levels.

4.3 Stage-2 Harvest Decision

Finally, we model the impact of an exogenous shock to water supplies on agricultural decisions and output. The stage-2 outcome, y_{ct} is modeled as:

$$\boldsymbol{y_{ct}} = \boldsymbol{\alpha_c} + \boldsymbol{\beta_0}\hat{\epsilon}_{ct} + \boldsymbol{\beta_1 HDD_{ct}} + \boldsymbol{\beta_2 GDD_{ct}} + \boldsymbol{\beta_3 P_{ct}} + \boldsymbol{\beta_4 P_{ct}^2} + \boldsymbol{\delta p_t} + \boldsymbol{\gamma t} + \boldsymbol{v_{ct}} \qquad (12)$$

where y_{ct} is irrigated corn acres harvested or yield in county c in year t. $\hat{\boldsymbol{\epsilon}}_{\boldsymbol{ct}}$ is a vector of unexpected water availability and potentially includes surface water and soil moisture shocks as well as interactions between them. We include measures of precipitation (P_{ct} and P_{ct}^2) and temperature (HDD_{ct} and GDD_{ct}) to investigate the role of agricultural season weather. Finally, we control for the December future price as of July[x] to allow for variations away from planting season price expectations. To test robustness, we also estimate Equation 12 with planting season controls (planting month price, SWSI, and soil moisture). A time trend is included to control for factors such as technological change in agricultural productivity. Finally, county fixed effects control for time-invariant differences across counties and v_{ct} is a random error term. To correctly estimate the standard errors in this second-stage model, we bootstrap because $\hat{\boldsymbol{\epsilon}}_{\boldsymbol{ct}}$ is an estimated variable, resulting in larger standard errors than normal (Murphy and Topel 1985).

The effect of surface water shocks on yields and harvesting decisions is identified if, conditional on expected availability, prices, and weather, the occurrence of a call is unexpected. One concern includes the ability for producers to use groundwater in response to surface water shocks. In this case, our results show a net impact of surface water shocks after producers respond by increasing groundwater use. If producers can substitute groundwater for surface water, our estimates represent lower bound impacts of water shortages. In practice, groundwater-surface water linkages mean that when surface water is called in the SPRB, groundwater also faces restrictions.

Another identification concern involves inter-basin transfers through projects such as the Colorado-Big Thompson project that transfers water from the west slope of the Rockies (and the Colorado River Basin) to the east slope (SPRB). These transfers are often correlated with shocks to one basin because they are used to mitigate the negative impacts of supply shocks. While this also biases our results towards zero, the majority of surface water in the South Platte basin is native water (total C-BT water supplies are approximately 15% of agricultural water on average[xi]).

5. Econometric Results

5.1 Stage-1 Planting Decision

Estimation results for the stage-1 planting decision are presented in Table 2. Three alternative specifications are estimated: linear and non-linear models of soil moisture, as well as soil moisture interacted with I_{ct} . Coefficient estimates across all three specifications are consistent, suggesting that expected surface water availability influences corn planting decisions while initial soil moisture levels play a limited role. The first column of Table 2 shows that the impact of the planting season SWSI is positive and significant at the 10% level. A move from extreme drought (SWSI=-2) to normal water supplies (SWSI=0) leads to ~900 additional acres planted on average (or 2% of average county irrigated corn acreage). The magnitude of this impact indicates that producers respond to changes in expectations of surface water availability in an economically significant way (an increase of 900 acres is equivalent to the impact of a 16% increase in corn price).

The impact of initial soil moisture is not statistically significant from zero. This remains true when soil moisture enters the regression as a quadratic (column 2) and when interacted with $SWSI_{ct}$ (column 3). Two possible explanations exist for this. First, the response to variations in initial soil moisture conditions may be limited given that even under the best conditions, expected precipitation during the growing season is insufficient to fully satisfy crop water demands for corn. If some producers anticipate getting "called" during the irrigation season, they may not plant regardless of early season soil moisture conditions. Alternatively, it is also possible that effect of soil moisture during stage 1 is nonlinear in a way not fully captured by our model. While never statistically significant, the coefficients on soil moisture imply that more soil moisture is beneficial at relatively low levels. On the other hand, too much soil moisture leads to a decrease in corn planted. This is consistent with anecdotal evidence that wet springs prevent producers from planting some acres of corn.

[Table 2]

Initial soil moisture conditions do, however, impact planting decisions, in an indirect way. Figure 3 presents the implied marginal effects (with 90% confidence intervals) of planting season SWSI across different initial soil moisture levels associated with the estimates presented in column 3 of Table 2. It becomes clear that the impact of surface water expectations on corn planting decisions is largest when initial soil moisture is low.

Finally, the sign of the coefficient on the Chicago corn futures price is positive across all three specifications. This suggests that, not surprisingly, higher prices incentivize an increase in irrigated acres planted.

[Figure 3]

5.2. Stage-2 Harvesting Decision

Table 3 presents estimation results for models of expected calls and seasonal soil moisture (Equation 11). As expected, higher SWSI corresponds to a decrease in the amount of water called during the summer. There is a trend in called water equal to approximately 3,000 acre-feet per year (equal to less than 1% of annual diversions in the basin (South Platte Roundtable)). This can be explained by population growth in the region of almost 1.5 million people over the time span considered here (https://www.colorado.gov/pacific/dola/node/104466). If population growth resulted in 500,000 additional households with an average of 2.5 people per household, this corresponds to 0.14 acre-feet transferred to municipal use, or approximately 51.5 gallons per capita per day of additional municipal water per household-year. Given that a portion of the new M&I demand over this period would be met through the purchase of water rights (not effecting calls), as opposed to growing into existing supplies (would affect calls), this number is consistent with expectations.

[Table 3]

The impacts of agricultural season weather and water supply shocks on harvested acres and yields per acre harvested are presented in Table 4. As before, three alternatives specifications were estimated to test the robustness of the results. Coefficient estimates are consistent across all three specifications and suggest that unexpected shocks in surface water supplies lead to a reduction in irrigated acreage and have a negative, but statistically insignificant, impact on average yields.

An acre-foot of unexpected called water corresponds to a decrease in acres harvested of 0.09 acres (Column 1). On the other hand, unexpected water shocks do not lead to lower yields per acre harvested (Column 4). These results are consistent with Observation 1 and 2 and the hypothesis that, faced with shortages, irrigators concentrate available surface water supplies on a subset of planted acreage, thereby minimizing yield losses on harvested acres.

[Table 4]

Agricultural season temperature significantly affects corn yields but does not influence the number of acres harvested. Consistent with agronomic predictions, growing degree days increase yields while harmful degree days result in decreased crop yields despite access to irrigation water. In contrast to Mendelsohn and Dinar (2003), this suggests that higher average temperatures could negatively affect irrigated crop yields if it also means an increase in the number of days with high temperatures.

Interestingly, while producers concentrate water on fewer acres when called, weather does not affect acres harvested. Instead, producers continue irrigating all acres planted even when high heat means reduced yields. We hypothesize that this could occur if high heat reduces yields even when sufficient water is available to fully irrigate the crop. Therefore, without an unexpected shortage of surface water, all acres can remain fully irrigated but with lower yields. Also, yields do not fall sufficiently low to make harvesting unviable.

While precipitation has the potential to increase yields, this variable likely also captures the effect of factors that correlate with rain and could affect crop growth (e.g., wind, cloud cover, etc.), especially when controlling for soil moisture.

Coefficients on soil moisture shocks have an unexpected sign. Point estimates suggest that soil moisture greater than what was expected can damage crop yields. This is consistent with nonlinear impacts of soil moisture. While moderate levels of soil moisture are beneficial, higher levels can harm yields (e.g., through flooding and water-logging). To test the robustness of results to the inclusion of the soil moisture variable, columns 3 and 6 in Table 4 present estimates of Equation 12 without this variable. The coefficients on weather and water realizations do not change with the exclusion of the soil moisture shock variable.

Higher expected water supplies increase the number of acres harvested but decrease the yield per acre harvested. This could occur because more acres are planted but with decreasing marginal quality. The agricultural season corn price (December future price in July) does not affect the number of acres harvested but appear to increase yields. Interestingly, higher planting season price decreases yields. This is consistent with producers using marginal lands when price expectations are high. Finally, there has been an upward trend in irrigated corn yields across the time period of our study but no statistically significant change in the number of acres harvested.

6. Economic Impact of Weather and Surface Water

Global climate change will affect temperature and water availability in Colorado (Lukas et al. 2014). For example, under the emissions scenario, Representative Concentration Pathway 4.5, statewide annual temperatures will rise by 1.4-2.8 degrees Celsius (C) by 2050[xii]. Precipitation patterns are expected to change but no consensus exists about changes in overall annual precipitation. Nevertheless, changes in temperature will likely decrease spring snow pack. The period of peak runoff in the state is projected to move forward 1-3 weeks.

We use our econometric results to simulate the effects of these changes in climate on irrigated agriculture and assess the value of adaptation by updating expectations about water availability. We also explore the benefit of adaptation by maintaining surface water supplies at current levels through improved storage infrastructure and management.

To obtain estimates of profits from irrigated agriculture in the basin, we assume a corn output price of \$4.98 per bushel, pre-harvest costs of \$419.50 per acre of corn planted, and \$52.92 per acre of corn harvested (Colorado State University Extension Service 2010 Crop Enterprise Budget[xiii]). We exclude fixed costs such as general farm overhead, assuming that these do not change as producers marginally adjust the intensive and extensive margins of production. Average irrigated yields in 2010 were 184 bushels per acre. Given this, profit for an average county with 40,589 acres planted and 32,486 acres harvested equals \$11,021,327.

To estimate the impact of climate change and how updating beliefs about water availability mitigates damages, we compare the simulated profit losses that result with and without updating expectations at the time of planting. In the base climate change simulation considered here, daily average temperatures rise by 2 degrees C and spring surface water supplies fall by 2 SWSI units. This corresponds to a warmer world with a new average expected water supply equivalent to a moderate drought today.

Adding 2 degrees C to daily minimum and maximum temperatures in the PRISM dataset leads to an increase in HDDs of 36 and an increase in GDDs of 253. Using our coefficient estimates, this corresponds to a change in irrigated corn yield of -9.5 bushels per acre. This represents a 6% decline in irrigated yields. For comparison, Schlenker and Roberts (2009) predict a decrease in dryland corn yields of 30-46%. This suggests that irrigation water has the ability to mitigate some of the crop yield losses predicted for dryland agriculture (though base yields are lower for dryland). Allowing for updated beliefs, this yield loss and a decrease in water supply cause county gross[xiv] irrigated corn profits to fall by $1.8 million per county-year for a total of $22 million across the 12 counties. This change comes from the combined effect of reduced yields and fewer acres planted[xv].

We now compare the base profit loss with the loss that occurs when producers continue planting as if water availability were maintained at current levels. We assume that without updating expectations, the number of acres planted continues at the historic average. The number of acres harvested, however, falls to the level associated with the 2-unit reduction in SWSI. Given this, average county profit falls by $2.4 million when compared to current levels. This is an additional decrease of $541,000 per county-year relative to the case where producers adjust to less water by planting fewer acres. Across the 12 counties of the study, this results in a gain of $6.5 million per year because of the ability to adapt to changes in expected water availability. Therefore, if the ability to reduce acres planted because of changing expectations is ignored, the negative impact of climate change is over-stated by 29%.

Next, we investigate the gains from investment in water infrastructure that maintains surface water availability at current levels despite warmer temperatures and decreased natural storage as snowpack. This could occur through increased intra-seasonal storage capacity that continues to allow surface water availability to align with its demand in agriculture. If surface water supplies are maintained, extensive margins are likely to remain at historical levels while only reduced yields from higher temperatures are experienced by producers. If this occurs, county average profits fall by $1.5 million dollars as a result of climate change.

The increased-storage scenario suggests that county irrigated corn profits would be ~$301,000 greater per year with more reliable water supplies. This corresponds to ~3% of annual profits or 16% of base profit losses from climate change. Across the 12 counties of the study, this translates into an annual agricultural willingness-to-pay (WTP) for maintaining water supplies of $3.6 million. Using a discount rate of 3%, this implies a present value WTP for infrastructure improvements of $120.5 million.

The WTP for water infrastructure is not larger because of the yield losses that occur despite better access to irrigation water. While higher temperatures are good for irrigated corn in the range of GDDs (8-30 degrees C), the increase in HDDs more than cancels out this beneficial effect. This highlights the importance of allowing for nonlinear impacts of temperature on crop growth.

Overall, climate change is projected to bring negative impacts to irrigated agriculture in the SPRB of Colorado. Nevertheless, profit losses can be partially offset through producer-level adaptation as well as state or basin-level investment in better storage. The magnitude of the benefits of adaptation is substantial but is not likely to fully offset the predicted profit loss from lower yields in the basin.

7. Discussion and Conclusion

Here, we have explored the implications of climate change for irrigated agriculture in the western United States, allowing for producer responses to changing distributions and realizations of water supply. In irrigated agriculture, producers have the ability to choose the allocation of scarce water across planted land. We show theoretically that the optimal allocation of scarce water involves concentration of the water on fewer acres in order to maintain high yields while incurring lower harvest costs. In addition, producers receive a signal about surface water supplies at the time of planting. This allows adjustment of planting decisions based on expectations.

This represents a novel attempt to conceptualize and measure the margins along which producers can respond to variation in expectations about water availability. This has important implications for the ability of irrigated agricultural producers to respond to climate change. It also represents a contribution to the empirical climate change literature, which has focused disproportionately on dryland agriculture. Impacts on irrigated crops differ from dryland impacts because surface water can mitigate some of the negative impacts of agricultural season weather. Investigation of alternative climate change scenarios demonstrate that climate change will significantly affect irrigated corn yields by ~6% and that the number of irrigated acres would fall without further investment in supplies. Overall, the ability for producers to modify planting decisions as expectations change leads to an increase in basin profits of $6.5 million dollars a year compared to the case when producers do not update expectations.

This study has several shortcomings that must be recognized. First, while we capture changes in expected surface water availability, we do not model changes in expected weather. As the climate changes, producers will adjust based on warmer temperatures distributions as well. Given the lack of clear variation in historical temperature means during our study period, we cannot empirically capture the role of changes in these expectations. As is common with empirical climate change impacts studies, we have not accounted for the ability of producers to adapt to long-run changes in temperature and precipitation. We also cannot capture all the margins along which producers can adapt. For example, if the timing of snowmelt changes, producers may adjust the timing of planting and watering. Better data are needed to capture the behavior along these margins. Also, it is possible that hotter temperatures on average could incentivize the adoption of more heat and drought-tolerant corn varieties. These factors have not been considered here but deserve attention in the climate change impacts literature.

United States crop insurance policies may also affect irrigation decisions. For example, some crop insurance programs require full irrigation to insure land as ‘irrigated’ (USDA). This could partly explain the extensive margin adjustment observed in this study as producers are reluctant, for insurance reasons, to deficit irrigate insured cropland.

Finally, our climate change scenario assumes that the variance in unexpected water shocks in the United States does not change. In reality, changing precipitation patterns may make drought more frequent even if average rainfall remains constant. If unexpected surface water supply shocks become more frequent, our profit simulations do not account for the resulting change in the proportion of planted acres that is harvested. Also, with increased drought, the impacts on profit could be especially large in some years.

Despite these simplifications, the results presented here have several policy implications. First, the net impact of climate change will depend on the use of the acres that are not planted in irrigated corn and policy could influence the use of newly dried land. It is also clear that better information about changing weather distributions can mitigate negative climate change impacts. Therefore, research and outreach efforts that inform producers about expected weather and water availability as of the planting season can greatly reduce the negative impacts associated with a hot, dry year.

Another policy implication that follows from this research is that more reliable storage infrastructure can better align producer expectations with realized surface water availability, mitigating economic losses from shocks to production and maintaining acres in production. Part of the adaptation process likely involves collective action and coordination. For example, while individual producers respond to updated expectations, constructing increased storage capacity requires public institutions, potentially complicating this adaptation pathway.

Finally, policymakers may value the maintenance of land in agriculture because of potential economy-wide effects. Keeping land in production can continue to support economically vibrant rural communities (Hornbeck and Keskin 2015, Jablonski and Schmit 2015).

Overall, agriculture in much of the Western United States depends on the availability of surface water. The impacts of climate change include changes in agricultural season temperatures as well as surface water supplies that form over the winter. A full understanding of the impacts of climate change on US agricultural must account for these changes as well as producer responses to the changes. The work presented here represents a first attempt at empirically modeling climate change impacts while explicitly accounting for producer adaptation in response to information about surface water availability.

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Table 1: Data Summary: Variable Means

	Overall	2000	2002
Acres of Irrigated Corn Planted	40589	46956	32350
	(50906)	(53616)	(39944)
Acres of Irrigated Corn Harvested	32486	37722	23950
	(38260)	(39599)	(26912)
Corn Yield Per Irrigated Acre Harvested (Bushels)	148	151	145
	(20)	(17)	(20)
Corn Price (Mar-Apr Average of December Future Cents/Bushel	266	256	250
	(46)	n.a.	n.a.
Planting SWSI (March and April Average)	0.8	1.8	-2.0
	(1.6)	(0)	(0.1)
Called Water, June-Sept (acre-ft)	39132	42193	112263
	(77043)	(51856)	(154677)
Harmful Degree Days (Degrees C)	16	25	34
	(12)	(14)	(14)
Growing Degree Days (Degrees C)	1517	1662	1652
	(173)	(163)	(150)
Precipitation (mm)	146	100	132
	(37)	(26)	(20)
Observations	257	9	10

Table presents the mean of variables across all years (column 2) and for 3 sample years used in the econometric analysis (columns 3-5). Variables are for the South Platte Water Division of Colorado.

Table 2: Water Supply Expectations and Planting of Irrigated Acres

VARIABLES	(1) Acres of Irrigated Corn Planted	(2) Acres of Irrigated Corn Planted, Nonlinear Soil Moisture	(3) Acres of Irrigated Corn Planted, Soil Moisture SWSI Interaction
Mar-Apr SWSI	453.0*	352.5**	3,820
	(235.9)	(147.0)	(2,735)
Mar-Apr Soil Moisture	-2.738	161.2	14.11
	(6.313)	(175.0)	(15.89)
Mar-Apr Soil Moisture Squared		-0.354	
		(0.376)	
SWSI*Soil Moisture			-16.62
			(12.96)
December Future Price in Mar-Apr	20.36**	20.66**	18.44**
	(7.591)	(7.942)	(6.986)
Year	-695.5	-709.6	-673.3
	(498.7)	(510.9)	(483.2)
Constant	1.422e+06	1.433e+06	1.375e+06
	(993,088)	(1.000e+06)	(960,728)
Fixed Effects	County	County	County
Observations	257	257	257
R-squared	0.136	0.141	0.144
Number of Counties	12	12	12

Note: Standard errors clustered at the county.

*** p<0.01, ** p<0.05, * p<0.1

Table 3: Predicting Agricultural Season Water Loss

VARIABLES	(1) Summer Called Water	(2) July Soil Moisture
Mar-Apr SWSI	-4,271*	
	(2,216)	
Mar-Apr Soil Moisture		0.574***
		(0.0284)
Year	2,979*	-1.391***
	(1,470)	(0.204)
Constant	-5.897e+06*	2,897***
	(2.929e+06)	(409.3)
Fixed Effects	County	County
Observations	257	257
R-squared	0.164	0.268
Number of Counties	12	12

Note: Standard errors clustered at the county.

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Impact of Weather and Water Shocks on Irrigated Corn Acres Harvested and Yields

VARIABLES	(1) Acres of Irrigated Corn Harvested	(2) Acres of Irrigated Corn Harvested	(3) Acres of Irrigated Corn Harvested	(4) Irrigated Corn Yield	(5) Irrigated Corn Yield	(6) Irrigated Corn Yield
Water Supply Shocks						
Unexpected Called Water	-0.0877*	-0.0872*	-0.0839*	5.63e-06	2.99e-06	5.15e-06
	(0.04988)	(0.04961)	(0.00003)	(0.00003)	(0.00003)	(0.00003)
Unexpected Soil Moisture	-67.30	-66.26		-0.0399*	-0.0391*	
	(49.13885)	(48.91267)		(0.02261)	(0.02256)	
Agricultural Season Weather						
Harmful Degree Days	-82.00	-43.87	-83.71	-0.792***	-0.946***	-0.963***
	(104.3951)	(138.58525)	(0.1976)	(0.15065)	(0.18309)	(0.1976)
Growing Degree Days	-6.187	-8.072	5.932	0.0799***	0.0924***	0.100***
	(6.95059)	(9.2247)	(0.02172)	(0.01871)	(0.02302)	(0.02172)
Precipitation (mm)	134.2	137.9	102.3	0.164	0.258*	0.234*
	(90.9109)	(120.27243)	(0.1308)	(0.14061)	(0.13569)	(0.1308)
Precipitation Squared (mm)	-0.365	-0.385	-0.298	-0.000358	-0.000570	-0.000505
	(0.23377)	(0.28298)	(0.00046)	(0.00049)	(0.00047)	(0.00046)
Planting Season Controls						
Mar-Apr Soil Moisture		-7.047	-12.73		0.0389	0.036
		(14.28592)	(0.02279)		(0.02379)	(0.02279)
December Future Price in Mar-Apr		-1.539	-6.310		-0.133***	-0.139***
		(46.18316)	(0.03788)		(0.03968)	(0.03788)
Mar-Apr SWSI		494.7	577.5*		-1.361*	-1.297*
		(367.36068)	(0.73645)		(0.71013)	(0.73645)
Other Controls						
December Future Price in July	44.21	44.85	36.77	-0.0175	0.0879**	0.0857**
	(31.60493)	(62.04975)	(0.03938)	(0.02319)	(0.0386)	(0.03938)
Year	-572.7	-552.2	-578.7	1.269***	1.224***	1.208***
	(480.93056)	(471.61303)	(0.2118)	(0.21228)	(0.22144)	(0.2118)
Constant	1.162e+06	1.125e+06	1.165e+06	-2,504***	-2,438***	-2,413***
	(956782.46)	(935177.33)	(397.71)	(400.48)	(415.98)	(397.71)
Fixed Effects	County	County	County	County	County	County
Observations	257	257	257	230	230	230
R-squared	0.263	0.265	0.237	0.503	0.523	0.518
Number of Counties	12	12	12	11	11	11

Note: Boostrapped standard errors. Columns 1 and 4 include only agricultural season (post planting) variables. Columns 2, 3, 5, and, 6 control for planting season variables. Columns 3 and 6 omit soil moisture shock to test robustness of result.

*** p<0.01, ** p<0.05, * p<0.1

Figure 1: Map of Colorado Water Basins, Counties, and SPRB Agricultural Land

Source: Colorado's Decision Support Systems Map Viewer,
http://cdss.state.co.us/onlineTools/Pages/MapViewer.aspx

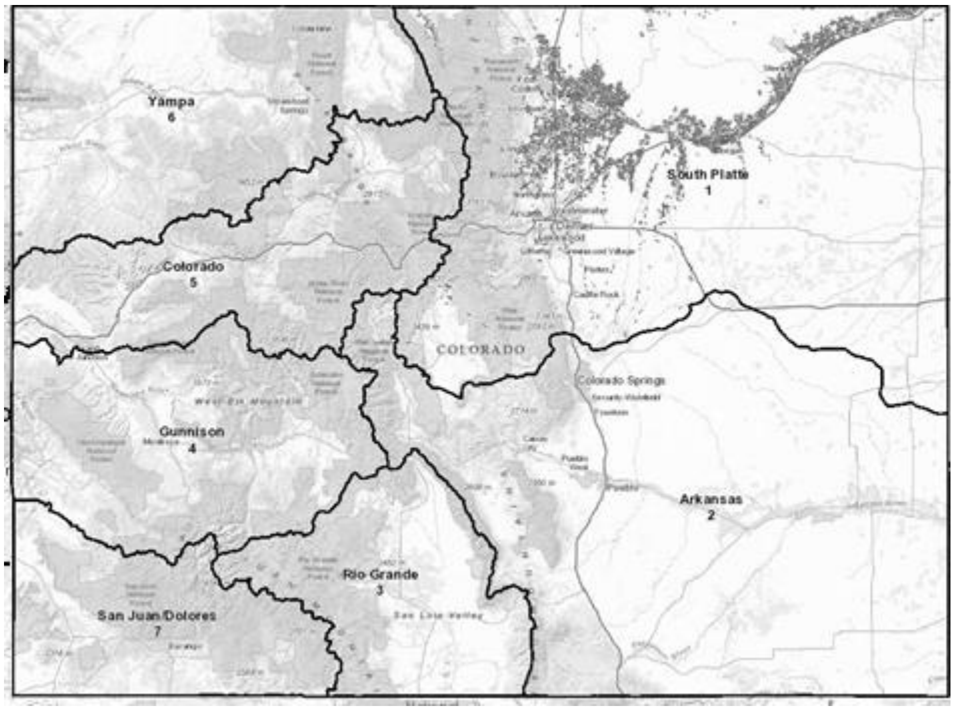


Figure 2: March and April Average Surface Water Supply Index for SPRB, 1982-2010

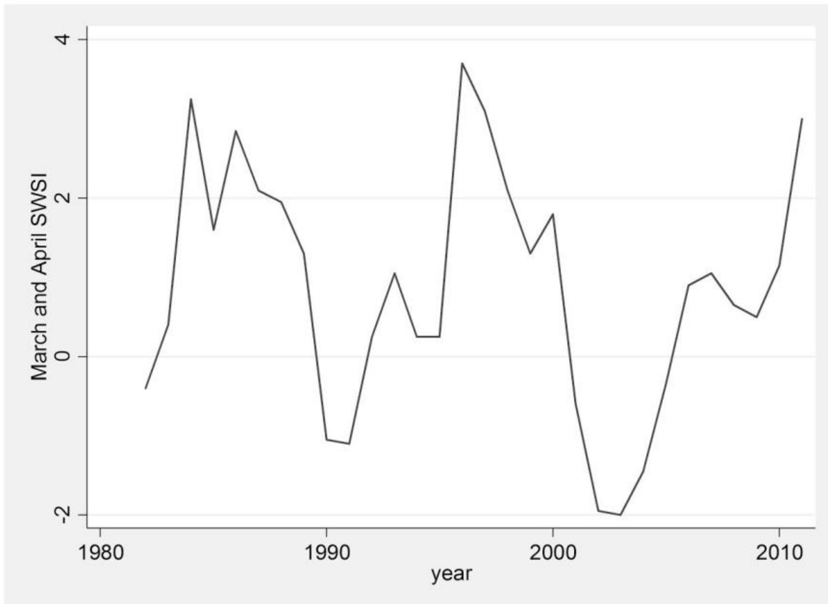
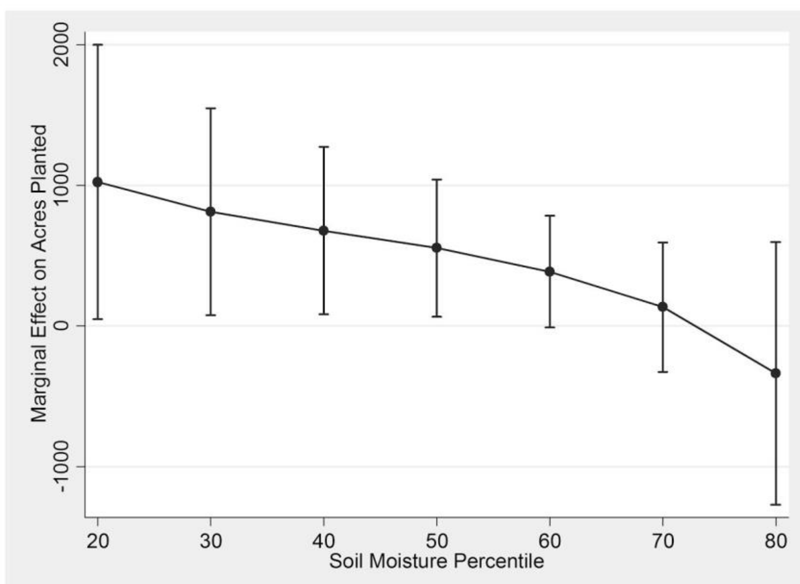


Figure 3: Marginal Effect of SWSI at Different Soil Moisture Levels



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[i] Under the PAD, water rights holders who fail to divert water when it is available risk losing their right, suggesting that even for the water right holder actually placing the call, a disconnect exists between the decision to make the call and the immediate need for water

[ii] Solving using a Lagrangian multiplier λ for the water constraint, $pHf_1 = \lambda$ where $\lambda \geq 0$ if $Ha - \tilde{A} = 0$ and $\lambda = 0$ otherwise.
[iii] Note, this results holds for large values of LB and high fixed costs even when $f(w;\theta)$ is concave between LB and UB.
[iv] Certain weather conditions are known to speed this process, including low humidity and dry winds. Winds known as the Chinook (or snow eater) winds can vaporize snowpack, resulting in a shock to surface supplies (USGS).
[v] According to the PRISM dataset (described below), average growing season precipitation is roughly 5.7 inches (146 mm).
[vi] When counting irrigated acreage, NASS requests that producers 'Include as irrigated any land to which partial, supplemental, or preplant irrigation water was applied' (USDA NASS 2013 Farm and Ranch Irrigation Survey).
[vii] Douglas, Elbert, Logan, Park, and Teller counties.
[viii] The date of the water right is reported in days since December 31[st] 1849.
[ix] Information provided by Sara Dunn (Ray Liesman), Division 1 Water Court, "South Platte River Basin."
[x] Results are robust to the month chosen for this price.
[xi] Calculation based on an average delivery of 232,500 acre-feet from the C-BT (310,000*0.75) and on USGS data on total surface water use by agriculture in the Basin in 2010 (~1.5 million acre-feet)
[xii] Under RCP 8.5, this range is from 1.9 to 3.6 degrees C.
[xiii] Available at http://www.coopext.colostate.edu/ABM/cropbudgets.htm
[xiv] This is the gross impact as some irrigated corn acres may be replaced by other crops.
[xv] For this calculation, we assume a constant proportion of acres planted is harvested. This exercise also assumes homogeneous land. If lower margin land is taken out of production first, this impact represents an upper bound estimate. Finally, we do not account for a trend in population growth. If this results in less land in irrigated agriculture, our estimates could be overstated.
[xvi]