Adaptation to Water Scarcity in Irrigated Agriculture

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Abstract

How much can societies adapt to environmental change? I provide evidence on this question by studying surface water, a resource that is projected to become scarcer in much of the world yet is critical to sectors such as irrigated agriculture. To identify adaptation, I compare the long-run and short-run effects of water scarcity on agriculture, which I estimate using institutional variation in water allocation in California. First, I estimate long-run effects using spatial discontinuities in average water supplies at the borders between neighboring water utilities, where farmland is otherwise similar. Then, I estimate short-run effects using weather-driven fluctuations in water supplies from year to year. Using high-resolution satellite data on land use, I find that short-run water scarcity reduces crop area and crop revenue (as predicted by crop choices). Long-run water scarcity shifts land-use patterns in different ways but reduces predicted crop revenue by 85 percent as much as in the short run, implying adaptation is limited. Absent new investments or policy changes, future declines in surface water supplies are likely to notably reduce the land area and output of agriculture.

Keywords: agricultural supply, climate impacts, drought, environmental change, geographic regression discontinuity, institutional persistence, remote sensing.

JEL Codes: Q15, Q24, Q25, Q54.

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1 Introduction

Climate change is projected to affect the global economy in many ways, but its future costs will depend on how much we can adapt. In response to temporary shocks to environmental conditions, people have limited ability to respond. But when an environmental change instead arrives as a permanent shift, people may be able to respond in a wider range of ways. Effects of short-run weather fluctuations are straightforward to estimate, thanks to abundant data and rich temporal variation (see Hsiang 2016 and Auffhammer 2018b for reviews of this literature). However, effects of persistent, long-run environmental conditions are difficult to estimate well. Past experience in long-run conditions varies only in the cross section, where omitted variables are a major concern (Deschênes and Greenstone 2007). For many aspects of climate change, it remains an open question how large these long-run effects are, and how much adaptation is possible.

This paper provides evidence on adaptation to surface water scarcity in irrigated agriculture. Water resources worldwide are projected to be affected dramatically by climate change. As precipitation patterns shift, drought and flood risks heighten, glaciers melt and snowpacks shrink, water availability in rivers and streams will become more variable in much of the world and generally decline in areas that are already dry (IPCC 2007; World Bank Group 2016). Water management is already challenging, with water shortages in India and Zimbabwe, floods in the Midwestern United States, and drought in Australia dominating international headlines in 2019 alone. Surface water is critical to many sectors of the economy, but the sector affected most may be agriculture: 42 percent of global crop output is irrigated, and agriculture accounts for 70 percent of global water withdrawals (FAO 2012). Despite its importance, water scarcity has seen far less empirical evidence on its economic effects than other aspects of climate change.

To measure adaptation, I estimate and compare the effects of long-run and short-run water scarcity on agricultural outcomes, using two distinct sources of variation in water allocation in California. Here, institutional history has created a system of surface water allocation in which availability varies not only erratically from year to year, but also sharply and persistently across geography. First, I estimate the effects of long-run permanent differences in water scarcity using spatial discontinuities in average water supplies – a new research design that overcomes prior limitations in the literature. Then, I estimate the effects of short-run temporary shocks to water scarcity using inter-annual fluctuations in water supplies. Because both effects are estimated in the same sample, I can compare them directly. The difference between these short-run and long-run effects reveals the extent to which agriculture has adapted.

To measure the effects of long-run surface water supplies, I use spatial discontinuities in average water supplies at the boundaries between neighboring water utilities called irrigation districts. These irrigation districts hold long-term entitlements to divert or receive surface water supplies, which they distribute evenly to farms within their service area. The volume of these entitlements vary widely across districts due to quirks of history. As a result, boundaries between adjacent districts feature large differences in average water supplies on otherwise similar cropland. By limiting the comparison to fields within a short distance of the boundary, I can effectively hold location constant while varying only average water supply. This sharp cross-sectional comparison allows me to interpret any differences in agricultural decisions and output across the boundaries as long-run effects of water availability.

To measure the effects of short-run surface water supplies, I use year-to-year fluctuations in water supplies that are driven by weather. Yearly water supplies are determined by allocation percentages set by government agencies using algorithms that consider only environmental conditions. Conditional on a farm's average water availability over time, these allocation percentages are plausibly unrelated to other factors that would affect agricultural decisions and output. Fixed effects allow me to control for average water availability, farm-specific unobservable factors, and common shocks to statewide water availability or the agricultural economy.

I estimate these effects for all farmland in California between 2007 and 2018 using remote sensing data that provides three billion observations of land use and crop choice. Only remote sensing data can provide the high spatial resolution needed for a regression discontinuity design, which requires precise matches between each field's outcomes and its location relative to irrigation district boundaries. My basic outcome variables are binary indicators for categories of crops and land uses. I combine this land-use data with comprehensive data on surface water deliveries, diversions, and allocations in California, which I compiled for all wholesale users over several decades. Assembling new data on water supplies allows me to overcome the data limitations that have been a significant constraint to research on the economic impacts of water scarcity.

To summarize the economic value of agricultural land use, I also construct a measure of crop revenue as predicted by crop choice (hereafter, predicted crop revenue). I construct this measure by combining field-level crop observations with more aggregated crop production data. Specifically, I assign to each field the average revenue per acre earned by the observed crop in the same county and year. This measure primarily captures revenue effects that operate through the channel of crop choice. It may miss any *within-county* changes in crop yields or quality due to under-watering, but these are likely to be minor. Under-watering is rare in California since farmers can always pump groundwater (English et al. 2002; Christian-Smith et al. 2012), and crop choice is a feasible margin of adjustment since water allocations are announced prior to the start of the growing season. Field-level data on yields is not available to directly assess this assumption, but I show that crop choice is the primary margin of response in county-level data: surface water supplies have large effects on revenue but little effect on crop yields.

My analysis yields three key findings. First, the short-run effects of surface water scarcity are economically large. In years when farms receive less water than usual, crop area declines. Farmers preserve orchards and other perennials, but they fallow land that would otherwise be planted with high-value annual crops. Predicted crop revenue falls: I estimate that a 10-percent drop in surface water supply reduces revenue by 3.6 percent in the same year.

Second, I find some evidence of adaptation to water scarcity. When farms experience water scarcity as a long-term average instead of a short-term shock, they permanently retire land instead of holding it fallow. This former cropland is converted to grassland, which can be used to graze livestock. Farmers further adapt by shifting to a higher-value mix of crops. They also may shift away from high-water crops toward low-water crops, but this evidence is weaker.

Third, the economic value of this adaptation is small. Despite these observed shifts in land use, predicted crop revenue declines by nearly as much in the long run as in the short run. I find that a 10-percent decrease in average surface water supply reduces average predicted crop revenue by 3.1 percent in the long run, an effect 85 percent as large as the short-run effect. Even when farmers have time to reallocate factors of production and make adaptive investments, the short-run effects of water scarcity on revenue appear to be mitigated only slightly.

Translating these results to full climate impacts is beyond the scope of this paper. Accurate projections would require scientific models of climate, snowpack, hydrology, reservoir and conveyance operations, and water allocations. What is known is that surface water supplies are projected to decrease in California and many other parts of the world over the next few decades. My results imply that these declining supplies are likely to result in substantial shifts in land use and losses to agricultural revenue.

Like all projections based on past experience, this evidence can predict future events only so far as other factors remain constant. Policy reforms, infrastructure investments, and technological innovation would all likely affect the path of climate impacts. For example, I show that long-run effects are larger in more water-scarce areas, suggesting that expanded water markets or other allocative reforms could shrink total revenue losses. Another consideration is that estimates in this paper are conditional on groundwater resources. I show indirect evidence that substitution to groundwater is an important margin of response,[1] so if continued extraction depletes aquifers, future groundwater substitution may become less feasible and revenue losses could increase.

Two other limitations of this analysis are important to keep in mind. First, crop revenue is not a direct measure of social welfare. It reflects the gross output of a major sector of the economy, but changes in revenue will be different from changes in profits or producer surplus, since expenditures covary with revenues as farmers switch crops in response to water

[1] I cannot directly estimate the groundwater response due to lack of data, since California does not systematically monitor groundwater pumping.

supplies. Data availability constrains my ability to make welfare statements. Second, my long-run estimates may be overstated (and adaptation understated) due to general equilibrium effects. California produces a large share of total output for many crops, so price effects may lead farmers to sort into crops by comparative advantage in water availability, exaggerating cross-sectional differences. All research designs using cross-sectional comparisons share this limitation.

One contribution of this paper is to introduce spatial discontinuities as a way to measure the long-run effects of an environmental variable affected by climate change. This approach uses arguably weaker assumptions than previous approaches in the literature. One approach, launched by Mendelsohn et al. (1994), estimates cross-sectional relationships between climate and economic outcomes. This approach relies on a selection-on-observables assumption, which is prone to bias from omitted variables. A newer approach uses long differences to measure how locations have responded to differential trends in climate over multiple decades (Dell et al. 2012; Burke and Emerick 2016). This approach accounts for many kinds of unobserved factors, but differential climate trends themselves might still be confounded by other spatially-varying factors.[2] The spatial discontinuity design compares observations in the cross section, so it measures a true long-run response, but it also uses sharp geographic variation that allows me to cleanly isolate the influence of water supplies from other spatially-correlated factors. I find that a selection-on-observables design can replicate the spatial discontinuity results, but only when it both adjusts for a rich set of physical covariates and compares within matched pairs of neighboring irrigation districts.

This paper also provides new evidence on the economic importance of surface water. While a growing literature shows that groundwater availability has large economic effects in agricultural economies (Hornbeck and Keskin 2014; Sekhri 2014; Blakeslee et al. 2019; Ryan and Sudarshan 2019), empirical evidence on surface water has been constrained by a lack of available data. Previous studies have been limited to either the extensive margin of irrigation (Hansen et al. 2011; Ji and Cobourn 2018; Jones et al. 2019), cross-sectional comparisons (Mendelsohn and Dinar 2003; Schlenker et al. 2007; Olen et al. 2015; Edwards and Smith 2018), or short-run variation in panel data (Xu et al. 2014; Manning et al. 2017; Khan et al. 2017).[3] In contrast, I provide reliable evidence of the long-run effects of intensive-margin differences in surface water supplies, through assembly of new data and identifying variation. I find that surface water, like groundwater, has significant economic impacts on agriculture in both the short run and the long run.

My approach to measuring adaptation is conceptually similar to several previous studies that estimate and compare short- and long-run effects of environmental conditions. Some of

[2] Another approach, spatial first differences, was recently proposed by Druckenmiller and Hsiang (2018). This approach can handle many types of place-specific unobservable factors, though it relies on a particular assumption about their spatial gradient that may not apply in all settings.

[3] A different body of work employs agronomic, mathematical programming, or hydrological-economic optimization models (e.g. Hurd et al. 2004; Medellín-Azuara et al. 2007; Connor et al. 2009) instead of econometric or statistical models.

these works estimate long-run effects using long differences (Hornbeck 2012) or lags in long panels (Taraz 2017), while others use cross-sectional comparisons (Moore and Lobell 2014). The contribution of my approach is to estimate the long-run effects in a regression discontinuity design, which can alleviate identification concerns. Another approach to adaptation estimates the response of economic outcomes to weather variables while allowing these responses to vary by climate (e.g., Barreca et al. 2016; Heutel et al. 2018; Carleton et al. 2018; Auffhammer 2018a). Projections using this approach still ultimately rely on a cross-sectional assumption, e.g., that if Minnesota were given the climate of Texas, it would respond to weather in the same way as Texas does now.

Finally, in studying the impacts of irrigation districts, this paper also joins a broader literature on path dependence in long-run development (Acemoglu et al. 2001; Dell 2010; Bleakley and Lin 2012). A number of studies have shown that institutional arrangements in early frontier settlement have led to persistent differences in economic development (Bleakley and Ferrie 2015; Alston and Smith 2019; Smith 2019), including specifically in surface water resources (Libecap 2011; Leonard and Libecap 2019). This paper is one of few to quantitatively study the long-run effects of local self-governing organizations that manage natural resources. I find persistent differences in land use between neighboring irrigation districts that were initially endowed with different water entitlements decades ago, revealing enduring misallocation and failure of Coasian bargaining.

2 Background

Agriculture in California relies on surface water irrigation. Virtually all agriculture in California is irrigated, not rainfed. California's agricultural regions have fertile soil – producing 13 percent of the country's total agricultural output by value – but very little rainfall, especially during the summer growing season. Instead, growers irrigate their land using water that mostly originates in nearby mountain ranges as rain and snow. Runoff from these mountains flows through rivers and streams, is temporarily stored in reservoirs, and then is delivered to farms via canals. Half of all surface water in California is diverted for human use, and agriculture consumes 80 percent of that quantity. Of all water used for irrigation, surface water makes up 61 percent, while groundwater contributes the remaining 39 percent (California Department of Water Resources, 2015).

Surface water is distributed to farms via irrigation districts. Most farmland in California is organized into irrigation districts.[4] Irrigation districts are cooperative organizations that were established by local groups of farmers starting in the 1860s through the 1950s. Most

[4]Throughout this paper, I use the term "irrigation district" to refer to any organization that holds a water right or project contract and provides or sells water to irrigators within a defined service area. This concept encompasses a variety of legal designations—besides irrigation districts, there are water districts, county water agencies, water conservation and flood control districts, reclamation districts, and mutual water companies.

are incorporated as local government agencies called special districts; others are non-profit organizations or for-profit companies (Henley 1957). Irrigation districts supply water to farmers within their jurisdiction, by diverting water from upstream rivers or major canals and distributing it to farmers through their own smaller, local canal systems. In a long-prevailing norm, districts divide available water evenly across the farmland within their jurisdiction, on a per-acre basis regardless of shortage or surplus (Schlenker et al. 2007). Supplying water is the paramount (if not only) purpose of irrigation districts; in some cases they produce hydroelectric power as a byproduct of diverting water, but otherwise their purview is limited to water, often by law (Teilmann 1963).

The service areas, or jurisdictions, of irrigation districts have well-defined and persistent boundaries. Irrigation districts were initially created in order to finance and construct local canal systems, a club good that lends itself to collective action. Historical narratives suggest boundaries were determined by arbitrary initial social groupings of farmers (Adams 1929); they very rarely coincide with other administrative or natural boundaries, such as counties or watersheds. Boundaries today remain bound by the fixed infrastructure of the local canal systems.

Spatial patterns of water allocation persist over time. Surface water is assigned to irrigation districts according to long-term entitlements. Two basic types of entitlements exist. One is *water rights*, which allow a district to divert a certain amount of water per year from a nearby river or stream. The other is *project contracts*, which allow a district to receive delivery of a certain amount of water per year from major canals operated by the federal and state governments. These canals are part of large water projects that store and transport water across hundreds of miles throughout the state. In California one project is run by the state government, the State Water Project (SWP), and two projects are run by the federal governent, the Central Valley Project (CVP) and the Lower Colorado Project.

Water rights are based on the principle of "prior appropriation" – they belong to the first user that claimed the water, and they last indefinitely, so long as the water continues to be used. Irrigation districts claimed water rights at their time of establishment. Project contracts were first awarded between 1930 and 1973, at the time that each branch of infrastructure was built. Contracts last indefinitely in the Lower Colorado Project and for 30- or 40-year terms in the CVP and SWP. Upon expiration of initial contracts, virtually all have been renewed under the same terms. Some entitlements are held by individual farms that lie outside of any irrigation district, but irrigation districts hold the majority of entitlements by volume. Within an irrigation district, entitlements are held by the district itself on behalf of its member farms.

The result of this history is a spatial distribution of water to farmland that has changed little in over 40 years. Water entitlements are tied to a specific place of use; they are usually sold together with land. Transferring water rights and project contracts from one location to another is possible but difficult, due to regulatory hurdles and transaction costs (Regnacq et al. 2016; Hagerty 2019).

Water supplies fluctuate from year to year. Water entitlements vary from district to district, but actual water supplies can also vary widely from year to year for the same district. A project contract specifies only a fixed maximum entitlement of water per year. Government agencies assign water *allocations* each year using algorithms that consider only weather, reservoir levels, and other environmental conditions. A district's allocation in a given year is the product of its time-invariant maximum entitlement and a year-specific allocation percentage. These allocation percentages are set separately for each of 13 different contract categories, so they can differ across districts in the same year according to historical priority order and regional differences in hydrological conditions.

Farmers have good information about water supplies before making crop planting decisions. Allocation percentages are first announced in early spring, prior to the start of the growing season; although the percentages are often revised into late spring and even summer, revisions are generally small. In addition, allocation percentages are broadly predictable from winter precipitation and reservoir levels, which are public knowledge and highly salient to farmers, so even the initial announcements are not a surprise.

Water allocations largely determine water supplies, but not fully. Supplies can differ from allocations for a few reasons. First, the projects have several programs under which districts can purchase or otherwise receive supplemental amounts of water. Second, districts can store water in the projects' reservoirs, banking it one year and receiving it in a later year. Third, districts can buy or sell volumes of water with each other in a within-year spot market.

3 Data

Agricultural data. For land use, I use a remote sensing product from the U.S. Department of Agriculture (USDA), the Cropland Data Layer. This identifies crops at every pixel in a 30-meter grid for the entire United States, in each year from 2007 through 2018. California alone has 300 million pixels per year with 119 distinct land-use classifications. I aggregate pixels to farm fields (defined as quarter quarter sections in the Public Land Survey System), keeping the modal land use within each field.[5] This leaves about 450,000 observations per year. Aggregating to fields reduces noise and computational time without losing much information signal, since cropping patterns closely follow field definitions.

For summary measures, I weight observed land-use choices by average per-acre revenue or water needs. Revenue weights come from the County Agricultural Commissioners' Re-

[5]Quarter quarter sections are typically 40 acres, or a square with sides 0.25 mile (400 meters) in length. For parts of the state that were never surveyed, I create a new 200-meter grid.

ports, which give total acreage, quantity harvested, and revenue for 70 crop categories in each county and year. I construct per-acre revenue in several ways; my preferred definition uses constant prices (multiplying yield quantity per acre by a constant average price per quantity for each crop) to eliminate price effects. Neither crop-specific expenditures nor profit data is available at a spatial resolution able to support a regression discontinuity design.

Crop water needs weights come from Cal-SIMETAW, the agricultural water balance model developed by the California Department of Water Resources, for the California Water Plan Update 2018. Model output gives applied water per acre for each of 20 crop categories, 278 geographical regions (detailed analysis unit by county), and 36 years (1980-2015). Estimates are based on weather and plant physiology along with expert knowledge of soils, geology, and irrigation practices.

Water supplies. I assemble the universe of surface water supplies and allocations in California, by user, sector, and year, from 1993 through 2016. (No direct measurements of groundwater extraction exist for most of California.) Surface water supplies come from four sources: the Central Valley Project (CVP), the State Water Project (SWP), the Lower Colorado Project, and surface water rights. Supplies from these projects are called deliveries, and supplies from surface water rights are called diversions. Throughout the paper, I use "supply" to refer to the sum of deliveries and diversions.

Allocations are calculated by multiplying a baseline maximum quantity by a year-varying allocation percentage. These allocation percentages, set according to weather and hydrologic conditions, are determined yearly for each of 13 separate contract types in the CVP and SWP. For the CVP, allocation percentages vary across both years and contract types; for the SWP, allocation percentages are constant across users, varying only across years. For water rights and the Lower Colorado Project, allocation percentages are always 100 percent.

Project deliveries, maximum contract amounts, and yearly percentage allocations are assembled from archives of the California Department of Water Resources (DWR) and U.S. Bureau of Reclamation (USBR). Diversions on the basis of surface water rights are taken from reports collected by the State Water Resources Control Board (SWRCB). This compilation uses recently available data made possible by a law that required all surface water rights holders to report their water use starting in 2010.

For irrigation district boundaries, I combine georeferenced digital maps from the DWR, the California Atlas, and the California Environmental Health Tracking Program. I keep one boundary definition for each water user whose boundary includes any cropland. My final variables are water supply and allocations per acre, which I calculate by assuming irrigation water is distributed evenly and then dividing each district's total agricultural supplies and allocations by its total area of cropland. To create a list of neighboring district pairs, I identify all pairs of districts whose boundaries come within 5 km of each other.

To match districts across many water supply and boundary datasets, I build a large crosswalk file that accounts for variations and errors in names as well as mergers and name changes across time. Further details of sources, cleaning, and processing of these variables are described in the appendix to Hagerty (2019).

Figure 1 plots average annual water allocations (per acre of cropland) by irrigation district across California. Large differences are apparent across districts even within the same region. These differences in water allocations between neighboring districts represent my identifying variation in long-run water supplies.

Appendix Figure A1 plots allocation percentages over time for 12 categories of water entitlements (i.e., water rights and 11 project contract types). Districts holding different types of entitlements experience different patterns of water scarcity over time. This differential movement in allocation percentages represents my identifying variation in short-run water supplies.

Covariates. For weather covariates, I use gridded data from Schlenker and Roberts (2009), derived from PRISM monthly data and daily weather station observations. This gives daily minimum and maximum temperatures and precipitation on a 4-km grid for the contiguous United States. I follow their methods to construct the following secondary variables at the quarter-year level: total precipitation, time spent at different temperatures, degree days, and vapor pressure deficit (Roberts et al. 2013).

Soil characteristics are mapped at relatively high spatial resolution by the National Cooperative Soil Survey. I use variables from tables matched to soil polygons contained in the Gridded Soil Survey Geographic Database (gSSURGO), provided publicly by the National Resources Conservation Service of the USDA. Groundwater depth and quality are interpolated (by kriging within year) from observation well readings collected from a variety of sources and made public by the California Natural Resources Agency and the Groundwater Ambient Monitoring and Assessment Program of the California State Water Resources Control Board.

Outcome variables. Throughout my analysis, I focus on 12 main outcome variables of three types:

- **Land use categories.** Binary variables indicating the category of observed land use: *Crops planted* (any crops planted), *Fallow* (idle cropland, not yet converted to a non-crop use), *Grassland* (unirrigated rangeland; often grazed by livestock), *Natural vegetation* (all other uses, including forest, shrubland, barren land, and wetlands). These four categories are mutually exclusive and exhaustive, summing to one.[6] Occasionally I combine grassland and natural vegetation into a single *non-cropland* variable.

[6] Observations with development are excluded from the sample since they are likely driven by different processes but are highly spatially correlated, potentially introducing spurious results.

- **Crop choice categories.** Pairs of binary variables that divide crops along three dimensions: *Perennial* vs. *Annual* crops (whether the crop requires a multi-year investment; see Table 1, Panel B); *High-water* vs. *Low-water* crops (whether required irrigation amounts are above or below mean); and *High-value* vs. *Low-value* crops (whether average revenue per acre is above or below median). If no crop is planted, these all equal zero.

- **Summary measures.** Continuous variables summarizing land use and crop choice along two dimensions: *Predicted crop revenue* (per-acre revenue using time-constant prices) and *Water needs* (required crop irrigation amounts). These variables assign a value to each field using data specific to each county, year, and crop.

I analyze the discrete variables as untransformed linear probability and the continuous variables in an inverse hyperbolic sine (arcsinh) transformation. Small changes in variables in arcsinh can be interpreted approximately as proportional changes in the underlying variable, in the same way as the natural logarithm (Bellemare and Wichman 2019). The advantage of arcsinh is that it admits values of zero, which I have in both continuous variables. To reduce the influence of extreme outliers that may be erroneous, I winsorize water and revenue variables at the 0.5 and 99.5 percentiles.

Summary statistics. Summary statistics for the final merged dataset appear in Table 1. There are 3.8 million field-year observations, of which 61 percent have crops planted. Average water supply is 2.7 acre-feet per acre per year (or simply feet per year), and average allocations are 79 percent of maximum volume. Variation in levels of water supply is much larger between districts than within districts over time, but variation in percentage terms is similar in the two dimensions. The average acre generates $2,032 in revenue in 2009 dollars and has 2.2 acre-feet per year of crop water needs. The most common categories of crops are almonds and pistachios, alfalfa, grains, grapes, rice, corn, and cotton.

4 Empirical Strategy

4.1 Conceptual framework

Weather can affect a broad range of outcomes, with potentially very different effects in the short term and the long term. In the short term, in response to a single realization of weather variables, people, firms and other agents have limited scope to adjust their behavior. But in the long term, with knowledge of the full distribution of weather variables, agents can adapt, making decisions and investments that reduce negative impacts or take advantage of positive impacts.

Similar reasoning can be applied to water availability in irrigated agriculture. If water is only going to be scarce this year, farmers can choose to fallow some land, but it might be costly to learn to irrigate differently or plant a new type of crop. But if water is always scarce, then farmers are likely to have invested more in the knowledge and equipment that is necessary to grow crops less water-intensively. In this way, long-run levels of water availability may have different effects on agricultural outcomes than short-run fluctuations. If these long-run effects of typical water availability are smaller than the short-run effects of water supply shocks, the difference can be attributed to adaptation: the actions taken by farmers to optimize their production to the local climate.

To formalize this intuition, I make the simplifying assumption that all information about past and future water availability for a given location i can be summarized by mean water supply $\bar{w}_i$ across years. Outcome Y_{it} in year t is a function of fixed location characteristics X_i, this year's realized water supply w_{it}, and adaptive capital A_i. I define adaptive capital as decisions and investments that are influenced only by location and long-run water supplies, not current-year supply:

$$Y_{it} = f\big(w_{it}, A_i(\bar{w}_i, X_i); X_i\big).$$

Current-year water supply can be written in terms of deviations from its mean: $w_{it} = \bar{w}_i + \tilde{w}_{it}$. The derivatives of the outcome with respect to each of these components are:

$$\underbrace{\frac{dY_{it}}{d\tilde{w}_{it}}}_{\text{short run effect}} = \underbrace{\frac{\partial f}{\partial w_{it}}}_{\text{direct effect}} \quad \text{and} \quad \underbrace{\frac{dY_{it}}{d\bar{w}_i}}_{\text{long run effect}} = \underbrace{\frac{\partial f}{\partial w_{it}}}_{\text{direct effect}} + \underbrace{\frac{\partial f}{\partial A_i}\frac{dA_i}{d\bar{w}_i}}_{\text{adaptation effect}} .$$

The first equation shows the short-run effect: the derivative of the outcome with respect to year-to-year deviations from mean water supply. This short-run effect is equal to the direct effect of water supply, including any short-term responses such as crop choice and factor reallocation, but without any long-run adaptive investments. The second equation shows the long-run effect: the derivative of the outcome with respect to the mean water supply. This long-run effect is equal to the direct effect of water supply plus the indirect effect of mean water supply through the channel of adaptive investments. Substituting and rearranging, these derivatives imply that the difference between the short-run and long-run effects gives the adaptation effect:

$$\underbrace{\frac{\partial f}{\partial A_i}\frac{dA_i}{d\bar{w}_i}}_{\text{adaptation effect}} = \underbrace{\frac{dY_{it}}{d\bar{w}_i}}_{\text{long run effect}} - \underbrace{\frac{dY_{it}}{d\tilde{w}_{it}}}_{\text{short run effect}} .$$

This expression is useful because I cannot directly observe the adaptation effect, but I can estimate the short-run and long-run effects. Measuring the short-run effect requires estimating the effect of year-to-year water supply fluctuations on an outcome, holding constant mean water supply, adaptive investments, and all other location-specific characteristics. Measuring the long-run effect requires estimating the effect of long-term average water supply, allowing agents to make adaptive investments over long periods of time and reach a steady state – while holding constant all other location-specific characteristics.

4.2 Short-run effects

My main specification regresses outcomes (for field i within district d in year t) on the natural log of per-acre water supply in that district in the same year:

$$Y_{idt} = \gamma \ln(WaterSupply)_{dt} + \alpha_{id} + \lambda_t + \varepsilon_{idt}. \tag{1}$$

Field fixed effects α_{id} absorb mean water supplies, leaving γ to measure the effects of percentage deviations from mean water supplies. These fixed effects also control for all other field-specific, time-invariant factors that affect the outcome. Time fixed effects λ_t control for year-specific shocks to water availability or the agricultural economy. In some specifications, I also include local time-varying covariates $\mathbf{X}_{idt}$, such as weather variables.

Because irrigation districts can adjust their yearly water supplies in response to drought or crop needs, I instrument for $\ln(WaterSupply)_{dt}$ with $\ln(WaterAllocation)_{dt}$, which districts cannot influence. This approach ensures that the short-run effect is identified using only the portion of the variation in water supply that is driven by weather conditions. For ease of interpretation, I construct $WaterAllocation_{dt}$ so that it has the same units as $WaterSupply_{dt}$: I multiply each district's yearly allocation percentage by its maximum water entitlement and divide by acres of cropland. However, results are driven purely by the yearly allocation percentage, since after a natural log transformation, maximum entitlement and cropland area are subsumed by the fixed effects.

I cluster standard errors in two dimensions: by field, and by district-year. Clustering by field allows for arbitrary serial correlation within the unit of observation (Bertrand et al. 2004), while clustering by district-year allows for arbitrary spatial correlation within district, a relatively large geographic area. Because fields have no special economic significance (farmers likely make decisions simultaneously over several fields), I weight observations by land area so that results are more representative of aggregate effects. I refrain from including more restrictive time effects (such as county-by-year), since these would consume most of the useful variation in water supply fluctuations and reduce statistical power.

Identification assumptions. Three key assumptions are required to interpret results of this regression as the causal impact of short-run water supply fluctuations on outcomes. One is that a field's water allocation percentage is as good as randomly assigned, conditional on mean allocations (subsumed in the field fixed effect) and statewide water availability (subsumed in the year fixed effect). This is plausible given that these allocation percentages are determined by government agencies using algorithms that depend only on environmental conditions. They cannot be manipulated by farmers or irrigation districts, and they are likely unrelated to determinants of local water demand, since the weather conditions that matter for allocations are separated from farms in both space (the mountains vs. the valley) and time (the winter rainy season vs. the summer growing season).

The clearest threats to this identifying assumption are regional time-varying factors that correlate with both water allocations and agricultural outcomes. Local precipitation and other weather could still present a concern, so in a robustness check I control for a host of weather variables in both the current and previous year.[7] Another threat may be trends in crop suitability that diverge across regions, due to factors such as local processing capacity or changes in the local climate. In another robustness check I include county-specific linear time trends, which control for any unobserved factors in each county that vary at a constant rate over time.

The other two identifying assumptions are associated with the instrument. One is exclusion: that water allocations affect agricultural outcomes only through water supplies. While this assumption cannot be directly tested, it seems appropriate. Each year's allocation percentages are determinations related specifically to water supplies in that year; they are not used for any other regulatory decisions. The other assumption is relevance: that short-term fluctuations in water allocations have a meaningful effect on short-term fluctuations in water supplies. This may not be true if, for example, districts had access to a perfectly efficient water market—but in fact allocations are fairly persistent. The binned scatter plot in Figure A3(a) shows that allocations are highly predictive of water supplies, following a close linear relationship. The first-stage regression estimate reported in Table 2, Panel A shows that allocations are a strong instrument. The first-stage F-statistic is well over 100, which easily surpasses conventional rule-of-thumb thresholds.

4.3 Long-run effects

To build intuition for my long-run regression specification, first consider two neighboring irrigation districts d, ordered by mean water supply, with the more water-rich district indicated by a binary variable $MoreWater_d$. I can measure the effect of being in this district, relative to its more water-scarce neighbor, by regressing average outcome $\bar{Y}_{id}$ for field i on this treatment indicator:

$$\bar{Y}_{id} = \pi MoreWater_d + \alpha + f(DistanceBorder_{id}) + \varepsilon_{id} \tag{2}$$

while controlling flexibly for distance to the district border and limiting the sample to observations close to the border. If I assume that mean water supply is the only attribute of the districts that affects $\bar{Y}_{id}$, I can find the per-unit effect of mean water supply by dividing the coefficient π by the difference in mean water supplies between the two districts. An equivalent estimator would regress $\bar{Y}_{id}$ on mean log water supply $\overline{\ln(WaterSupply)}_d$,

[7] Quarterly sums or means of precipitation, temperature, degree days, and vapor pressure difference for the nearest grid point to the field.

instrumenting $\overline{\ln(WaterSupply)}_d$ with $MoreWater_d$.

My main specification uses not one but all 532 pairs of neighboring irrigation districts that can be found in California. I stack Equation 2 for all such pairs into a single regression, pooling the coefficient of interest β but allowing all other parameters to vary by border pair b and border segment s:

$$\bar{Y}_{idbs} = \beta\overline{\ln(WaterSupply)}_d + \alpha_{bs} + f_{bs}(DistanceBorder_{idb}) + \varepsilon_{idbs} \tag{3}$$

I instrument the continuous treatment variable $\overline{\ln(WaterSupply)}_d$ with the binary indicator $MoreWater_{db}$. This instrument scales the reduced-form effect (of being in the relatively water-rich district of each pair) by the first-stage effect (the average difference in log water supply between water-rich and water-scarce neighbors) so that it can be interpreted in units of water quantity.

This is still a sharp RD design, not fuzzy, since $\overline{\ln(WaterSupply)}_d$ is perfectly collinear with $MoreWater_{db}$ for each pair of districts; the instrument does not adjust for omitted variables bias. Another sensible specification would forgo the instrument and simply estimate Equation 3 using ordinary least squares. However, the IV specification has the additional advantage of correcting for possible measurement error in $\overline{\ln(WaterSupply)}_d$. This property is especially attractive since it improves symmetry with the short-run estimates, which are also instrumented, making them more comparable.

The running variable $DistanceBorder_{idb}$ is the perpendicular distance to the nearest point along the border between the pair of districts. This variable controls for one geographic dimension, but not parallel distance along the border (Keele and Titiunik 2015). To ensure the regression is comparing observations that are actually near each other in both dimensions, border segments s split each border pair into 5-kilometer pieces.[8] To handle any remaining spatial imbalances within border segments, I also include latitude and longitude as two additional running variables that enter separately for each border pair$\times$border segment.

I limit the sample to a window of observations close to the border, using local linear regression for the RD function $f_{bs}(DistanceBorder_{idb})$ (following Gelman and Imbens 2014) with triangular kernel weights (following Cattaneo et al. 2018). Slopes of the running variable are estimated separately on each side of each border: $f_{bs}(DistanceBorder_{idb}) = \psi_{bs}DistanceBorder_{idb} + \varphi_{bs}DistanceBorder_{idb}MoreWater_{db}$. Although several algorithms exist for optimally choosing the bandwidth of this window (Imbens and Kalyanaraman 2011; Cattaneo et al. 2018), none is designed for a complex specification with many stacked discontinuities (Dell and Olken 2018). Therefore, I show results using a range of bandwidths, while using 10 km as the preferred specification. This choice strikes a balance between the goals of comparing similar land areas (which would argue for a narrow window) and preserving statistical power (arguing for a wider window).

[8] A segment is defined as the 5-kilometer grid cell containing the nearest point on the district border.

To avoid capturing the effects of other spatial discontinuities, I define border pairs b as unique combinations of district pair, county, and top-level soil type (defined precisely as dominant-condition soil order). These pairs ensure land is compared only within the same county and the same broad soil type. Any district pairs whose border is coterminous with a county or soil order boundary are effectively eliminated; without data on both sides of the border pair, they do not contribute to the estimate. Starting with the 532 district pairs, there are 938 district pair×county combinations, 2,079 border pairs (district pair×county×soil order), and 6,783 border pair×border segment combinations. The main specification thus pools nearly 7,000 simultaneous RDs.

I cluster standard errors by irrigation district, for three reasons: (1) to allow for arbitrary spatial correlation within district, a reasonably large area; (2) because district is the main unit of treatment, from the standpoint of experimental design (Abadie et al. 2017); and (3) to avoid counting the same observation multiple times when it appears in more than one permutation of neighboring districts.

Pre-treatment balance. A key assumption required to interpret the result of this regression as a causal effect is continuity: that all other pre-treatment factors change only smoothly, not discontinuously, at the district boundaries. Pre-treatment factors are those that were determined prior to the development of widespread irrigation, like climate and soil quality. Virtually all potentially relevant pre-treatment factors are measurable physical characteristics of the land or its surroundings. High-resolution data on these factors is readily available, thanks to decades of public investment in soil surveys. These datasets are the same ones used by farmers, scientists, and real estate agents, so it is hard to imagine a pre-treatment factor that has large effects on farmers' crop choice decisions but remains unobserved. Other factors that might be relevant to agricultural land use today – such as processing plant locations or other place-specific investments – are causally downstream of the creation of irrigation districts. These factors are outcomes, not threats to identification, and should be taken into account in measuring long-run effects of irrigation districts.

To assess the continuity assumption, I examine 22 variables drawn from weather, soil survey, and groundwater data. Because these variables likely cover the most important determinants of crop productivity and comparative advantage, they represent direct tests of the assumption. They also provide indirect evidence for whether this assumption is plausible when extended to variables that are unmeasured or unexamined.

Figure 2 plots 12 of these variables as a function of distance to the boundary between pairs of irrigation districts; nine other variables are shown in Appendix Figure A2. Each pair is arranged so that the district with greater mean water allocations appears on the right (positive distance) and the district with lesser mean water allocations is on the left (negative distance). Fixed effects for border pair×border segment are partialed out from the variables before plotting, so the graphs show the average patterns within each individual RD comparison. Visual inspection confirms that all variables appear roughly continuous at the border. Appendix Table B1 confirms quantitatively that these variables are well-balanced at the border: No variable has an RD coefficient that is greater than 5 percent of its within-pair standard deviation, and most are smaller than 1 percent.

This evidence supports the assumption that pre-treatment factors vary continuously at irrigation district borders. At the same time, there appear to be systematic patterns, and moderate average differences, in pre-treatment variables within irrigation districts away from the borders. This fact suggests that a simple cross-sectional comparison of neighbor pairs may not be sufficient to account for pre-treatment differences, and results from the RD design are more likely to merit a causal interpretation.

Other identification assumptions. Continuity is the main assumption required to interpret each boundary effect as the causal effect of the district itself, but two more assumptions are needed to interpret these district effects as the causal effect of mean water supply. One of these is relevance: that there is a significant difference in mean water supply between neighboring districts. If water supplies were assigned evenly across districts, there would be no first-stage relationship between the *MoreWater* indicator and mean water supply. But large differences between neighbors do exist; relatively water-rich districts enjoy 3.0 feet of surface water per year on average, while their relatively water-scarce neighbors get an average of only 1.5 feet of water per year. This difference of more than double is shown as the first-stage graph in Figure 3(a).

The other assumption is the exclusion restriction: that mean water supplies are the only way in which districts affect agricultural production. This assumption would be violated if districts offer other kinds of services or privileges, and if these activities are more commonly provided by relatively water-rich districts. This is unlikely since irrigation districts in California generally exist only to deliver surface water to farmers (and sometimes other water users). Systematic data on irrigation districts in California is scarce, but I am creating a new dataset from information hand-collected from their websites. Future versions of this paper will examine robustness of the results to these additional covariates, describing irrigation districts' governance and internal policies. Another way this assumption could be violated is if mean water supplies in the observed data are not sufficient to fully describe historical water supply patterns. In robustness checks, I examine whether results are sensitive to alternative definitions of the mean water supply variable.

In a typical RD design, another assumption requires that people have not been able to sort or manipulate their location relative to the cutoff or boundary. The analogous assumptions in my setting would be that (a) district boundaries were not drawn (and have not changed) to selectively include or exclude land owned by people who are more or less productive at farming, and (b) more productive farmers from water-scarce districts have not systematically chosen to buy land on the periphery of a neighboring water-rich district.

While data is not available to directly assess these assumptions,[9] there is little reason to believe sorting of skills to land would concentrate immediately around district borders. More importantly, all of my outcome variables are functions of observed land use, so they are purged of any field- or farmer-specific characteristics that are reflected only in yields and not land use choices.

A related concern is that people might move water across the boundary, leading to mismeasurement of average water supplies. This is unlikely to occur on a large scale, since each irrigation district has its own internal canal system that is usually not connected to other districts. Irrigation districts also generally prohibit individual farmers from transacting with external agents. However, very close to the boundary, some water could be transferred between neighboring fields that fall in separate districts, or within a single farm operation that straddles the boundary. To address this concern, I test the sensitivity of the results to manipulation of water supplies near district boundaries by running "donut hole" regressions, which exclude observations that fall within windows of various widths around the boundary.

5 Short-run Results

Table 2 reports estimates of the effects of water supply on agricultural outcomes in the short run, as estimated by instrumental variables regressions of the form in Equation 1. Binned scatter plots of the corresponding reduced-form relationships are shown in Appendix Figure A3.

5.1 Land use: Drought leads to fallowing, not exit from agriculture

The simplest question to answer with land use data is whether crops are grown at all. In Table 2, the coefficient in Panel B, column 1 is positive, indicating that water allocations increase the probability of planting crops. The coefficient implies that a 10 percent increase in water supply results in an increase in the share of land being cropped of 0.48 percentage points.

When water availability increases cropped area, what land uses decline? The answer is fallowed land. Water availability decreases the share of fallow land (Panel B, column 2) but does not affect the share of non-cropland, since the effects on both grassland (Panel B, column 3) and natural vegetation (Panel B, column 4) are both precise zeros. Evidently, short-run droughts and surpluses lead farmers to switch cropland between cropped and fallow, with no entry or exit from agriculture.

These shifts are statistically significant, and their size is moderate. Another way of interpreting the estimates is that a one-year drought that reduces water supply by one standard

[9] The typical McCrary (2008) density test is inapplicable to this setting, since the distribution of land across space is uniform and cannot be manipulated.

deviation (56 log points, or 33 percent) leads farmers to reduce cropped area by 2.7 percentage points. This change would represent a 26 percent increase in land fallowed (on a base of 10.3 percent) but only a 4 percent decrease in land cropped (on a base of 60.6 percent). If crop production were Leontief in surface water and no other substitution were possible, cropped area would necessarily respond one-for-one with water supply. The fact that the estimated coefficient is much smaller than 1 suggests that farmers have alternative margins of response that they prefer to fallowing.

5.2 Crop choice: Farmers fallow high-value, low-water annuals

Next, how do water allocations affect which types of crops are grown? Annual crops drive virtually all of the crop response: the effect of short-term water availability on annuals is very similar to the effect on crops planted (Panel B, column 5), while perennial crops are unaffected (Panel B, column 6). This makes sense, because short-run fluctuations in surface water are by definition temporary, while investments in orchards and other perennial crops are long-term decisions. Under rational expectations, it is not worth suddenly planting more perennials in response to a one-year water surplus, nor is it worth ripping out valuable plants in response to a one-year water shortage.

Low-water crops also drive most of the crop response: short-term water supplies do not affect the share of high-water crops (Panel C, column 1) but they raise the share of low-water crops (Panel C, column 2). One might have expected changes in water supply to lead farmers to switch between low-water and high-water crops; instead, farmers appear to preserve their high-water crops and instead switch land between low-water crops and fallowing. This pattern can be rationalized if high-water crops are either more profitable or have greater fixed costs of production.

High-value crops also account for most of the crop response: changes in water availability increase the share of high-value crops (Panel C, column 3) much more than they affect the share of low-value crops (Panel C, column 4). One might have expected droughts would lead farmers to fallow the lowest-value crops first, but high-value crops may in fact be less profitable or have fewer fixed costs of production.

5.3 Summary measures: Drought reduces predicted crop revenue

Moving beyond coarse groupings of crops, what is the effect of short-run water availability on crop water needs and the overall value of crops grown? Both have a clear positive relationship (Panel C, columns 5-6). Receiving additional water allocations leads farmers to make land use decisions that require more water and earn more revenue; conversely, short-term water shortages reduce predicted crop revenue and water needs.

Regression coefficients for these variables can be viewed as approximate elasticities. For crop water needs, the regression estimate implies that a 10 percent increase in water supply results in only a 0.76 percent increase in crop water needs. This seems surprisingly small, since the relationship is much less than one-for-one. The most likely explanation is that farmers substitute to groundwater when they face cutbacks in surface water supply.

For predicted crop revenue, the estimated elasticity (0.36) implies that a 10 percent increase in water supply increases predicted revenue by 3.6 percent. This is an economically large magnitude, though it is still somewhat smaller than the one-for-one benchmark that would be expected if farmers have no substitution ability. Recall that these summary measures are not directly observed; the predicted revenue variable simply reports the average revenue per acre earned by the observed crop in each county and year. Therefore, this measure of crop revenue mostly reflects only the effects of water allocations that operate through the channel of crop choice. Water allocations could also raise the field-specific yields or quality of crops, but these channels would not be captured by this variable.

5.4 Decompositions: Extensive margin drives revenue effects

How much of the overall change in predicted crop revenue can be attributed to changes in the various land use and crop choice categories? A typical back-of-the-envelope decomposition is sensitive to choices of means and challenging to implement in this setting because outcomes are linked (an increase in the share of one category necessarily requires a decrease in the share of another category). Instead, I construct new measures of crop revenue using only variation between two or three broad categories of land use. For example, for annuals vs. perennials vs. uncropped land, each observation of an annual crop is assigned the mean revenue across all annual crops, instead of using the crop-specific revenue.[10] If the effect of water allocations on this new measure is equal to the effect on the original predicted crop revenue variable, it suggests that the land-use changes among the chosen categories fully explain the main effect. If the effect on the new measure is zero, it suggests that the main effect is driven entirely by land-use changes *within* the chosen categories.

Appendix Figure A4 (left side) shows the effects on these limited-variation measures of crop revenue, scaled by the effect on the original crop revenue variable, with full regression results reported in Appendix Table B9, Panel A. Variation between cropland and non-cropland explains none of the revenue effect—consistent with the null effects previously estimated for non-cropland. In contrast, variation between cropped and uncropped land explains nearly the full revenue effect. Further subdivisions of crops by life cycle, water needs, or value contribute very little to the explanatory power of the categories. This result suggests that movement between crops is of relatively minor importance. The extensive margin—whether or not any crops are planted—appears to account for essentially all the effects of short-term water allocations on predicted crop revenue.

[10] To preserve spatial variation, I take means within field over time, so that whenever a field has an annual crop, it is assigned the revenue for the typical annual crop grown on that field, not all annual crops statewide.

5.5 Irrigation intensity is not a primary margin of response

Prior knowledge indicates that crop choice is likely to be the primary margin of response in California, but in principle water availability could also affect irrigation intensity for the same crop. Irrigation intensity could affect actual crop revenue, due to reduced yields or diminished quality, but may not be fully reflected in my measure of predicted crop revenue, which relies on remote sensing observations of land use. If these channels are also present, the revenue effects of water availability will be underestimated.

Data is not available to directly assess the effects of *within-county* changes in water availability on crop revenue. However, I can use county-level variation to investigate the relative contributions of crop choice and crop yields to crop revenue. Appendix Table B3 presents three lines of evidence supporting the notion that revenue effects are driven by crop choice rather than yield differences. First, revenue effects are essentially unchanged when yields are held constant. Column 2 reports the effect of water supplies on a definition of predicted crop revenue constructed using constant yields; the point estimate is very similar to the baseline specification repeated in Column 1, in which yields are allowed to vary by county and year.

Second, yields themselves are affected by only a small amount. Column 3 reports the effect of water supplies on the usual definition of predicted crop revenue, but interacting all fixed effects with crop indicators. The resulting regression uses only within-crop variation, allowing the estimate to be interpreted as an average percentage change in crop yield. The estimated effect is less than 5 percent of the effect on overall crop revenue.

Third, the same results obtain when using only county-level variation, indicating the small yield effects are not merely an artifact of insufficient statistical power. Columns 4-6 repeat the regressions from columns 1-3, but averaging water supplies and allocations by county-year. Despite this artificial increase in measurement error, revenue effects remain sizeable with and without varying yields, and yield effects remain small. Column 7 confirms that the first-stage relationship remains strong after aggregating by county.

Since crop choice effects are similar when using only county-level variation as when using the full district-level variation, it would be reasonable to expect yield effects to also show up in county-level data. The fact that yield effects are instead small at the county level suggests that district- or field-level changes in yields are unlikely to be important margins of agricultural response to water scarcity in the short run. In the long run, these other channels are even less likely to be present, since farmers have more time to switch to crops that are better suited to their long-term water availability.

5.6 Robustness checks

Weather conditions. To confirm that the estimated short-run effects are driven by surface water allocations and not local weather conditions, Appendix Table B2 shows the results of regressions that include a host of variables describing weather in both the current and previous year.[11] Results are very similar, supporting a causal interpretation of the short-run regressions.

Regional trends. Appendix Table C1 reports results from regressions that include county-specific time trends. These trends adjust for regionally-divergent trends in crop suitability or other unobservable factors. Results are again very similar to the main specification.

Price effects. Appendix Table B4 further explores sensitivity of the results to the definition of predicted crop revenue. My preferred variable definition (column 3, repeated from the main results in Table 2) multiplies the average yield per acre for the observed crop (in the same county and year) by a constant price earned by the crop on average (across all counties and years). Allowing prices to vary across counties and years (column 1) or only across years (column 2) might introduce omitted variables bias, but it also might capture important gains from local comparative advantage. These effect magnitudes are slightly smaller than the preferred definition but very similar, suggesting price effects are small.

Functional form. Another concern might be the extent to which results are sensitive to the particular functional form of the inverse hyperbolic sine transformation. Column 6 of Appendix Table B4 shows the estimate for which the dependent variable is instead linear, in dollars per acre. The coefficient on predicted crop revenue is again moderately large. It implies that a 10 percent increase in water supply results in a $23 increase in predicted revenue. How this linear effect compares to the elasticity depends on the choice of mean: an effect of $23 translates to 1.1 percent using the arithmetic sample mean of predicted revenue ($2,032), and 21 percent using the geometric sample mean ($111), bracketing the arcsinh effect of 3.6 percent.

To explore sensitivity of the results to the functional form of the dependent variable, Appendix Table C2 shows regressions in which water supplies and allocations are expressed linearly, in acre-feet per acre, instead of their natural log transformation. Results are qualitatively very similar to the main specification despite the change in units; whether marginal effects are smaller or larger depends on the choice of base.[12]

OLS. Finally, Appendix Table C3 shows the results of regressions estimated by ordinary least squares (OLS) instead of instrumental variables. Coefficients are smaller, illustrating the need to use an instrument for water supply. Irrigation districts are likely able to acquire additional water when their water needs and potential revenue are high, undoing the negative effects of water shortages and biasing the OLS toward zero.

A limitation of this analysis is that it does not incorporate year-to-year variation in water

[11]Weather variables are: total precipitation and its square, flexible parameterizations of average temperature and degree days, and average vapor pressure difference (a measure of humidity), each per quarter.

[12]Marginal effects are smaller in terms of standard deviations: the effect of a one-standard deviation increase in linear water supply (0.33 ft) is 12 percent of predicted crop revenue, while the effect of a one-standard deviation increase in the natural log of water supply (0.56) is 20 percent of predicted crop revenue. However, marginal effects are larger in terms of means: an elasticity of 0.36 translates to a 14 percent effect per foot of water (using the mean of 2.65 feet), which is smaller than the linear estimate of 38 percent per foot.

supply (diversions) on the basis of surface water rights. This data is unavailable, so I assume supply from water rights is constant over time. All identifying variation comes from year-to-year changes in deliveries from the federal and state water projects. In reality, rights-holders may sometimes experience unobserved shortages, which would likely be correlated with deliveries from project contracts. To the extent that this is true, the first-stage regression of water supply on water allocations may be underestimated, leading short-run estimates to be overstated.[13] However, this limitation is unlikely to make a major difference to the results, since true diversions from water rights are known to have low year-to-year variation relative to project contracts. This is because most rights held by irrigation districts are more senior than the projects themselves, so water rights experience fewer cutbacks.

6 Long-run Results

Graphs in Figure 3 plot mean outcome variables by distance to the boundary between pairs of irrigation districts. Like the graphs for pre-treatment variables in Figure 2, pairs are arranged so that the district with greater mean water allocations appears on the right (positive distance) and the district with lower mean water allocations is on the left (negative distance). Because farmland near the border is otherwise very similar, any discontinuous change in outcomes at a distance of zero can be interpreted as the effect of being in a relatively water-rich irrigation district. Graph (a) gives an idea of how large the difference in water supply is between districts on the left and the right. At the border, the mean water supply jumps approximately 0.6 log units, implying that, for the average pair of neighboring districts, one district has twice the annual water supply of the other.

Table 3 reports corresponding estimates of the effects of water supply on agricultural outcomes in the long run, as estimated by IV-RD regressions of the form in Equation 3. Effects are estimated separately for three RD bandwidths: 25 km, 10 km, and 5 km. Smaller bandwidths can reduce omitted variables concerns, while larger bandwidths can reduce noise and the influence of any spillovers among observations extremely close to the border. I cite results for a bandwidth of 10 km, but coefficient magnitudes are broadly similar across bandwidths.

6.1 Land use: Water scarcity turns cropland to grassland

Crop planting increases in response to greater mean water supply (graph (a)), with a 10 percent increase in water supply leading to a 0.5 percentage point increase in the share of land being cropped (Panel B, column 1). Unlike a short-run shock, long-run water availability does not appear to affect the share of fallow land (graph (c) and Panel B, column

[13] Allocations may also be mismeasured for surface water rights, and they would also be expected to be correlated with allocations from project contracts. In principle, this leaves the direction of bias unsigned. In practice, simulations (available upon request) suggest that bias away from zero is more likely and any bias toward zero would be very small.

2). Instead, cropped area increases at the expense of non-cropland (graph (d)), specifically grassland (Panel B, column 3) rather than natural vegetation (Panel B, column 4). In other words, long-run water scarcity leads farmers to take cropland permanently out of production and let it turn to grassland. Grassland (i.e., rangeland) is a more valuable land use than fallow land, since it can be used to graze livestock, and it likely creates positive ecological externalities.

These shifts are statistically significant and of similar magnitude to the short-run shifts in land use. Similar amounts of land are shifted out of crops in response to both short-run and long-run water scarcity, but in the short run this land is fallowed, while in the long run it becomes grassland. Still, the effects are moderate and much smaller than one-for-one.

6.2 Crop choice: Response comes from low-value annual crops

Next, I examine what types of crops respond to differences in mean water supply. Just as in the short run, annual crops drive most of the crop response: greater mean water supply increases the share of annual crops (graph (e) and Panel B, column 5), while perennial crops appear unaffected (graph (f) and Panel B, column 6). It may be surprising that perennials do not respond even when farmers have time to adjust long-term investments, but it may be that orchards, vineyards, and similar crops are so profitable that they are planted in well-suited areas regardless of surface water availability.

The increase in cropped area appears to be shared between high-water and low-water crops. Although discontinuities in these outcomes are less visibly obvious (graphs (g)-(h)) and more sensitive to bandwidth (Panel C, columns 1-2), the balance of the evidence suggests that they respond to long-run water availability in similar proportions. This result stands in contrast with the short-run results, which found effects for low-water crops and not high-water crops.

Low-value crops account for the full crop response in the long run: mean water supply does not affect the share of high-value crops (graph (j) and Panel C, column 3) but it does raise the share of low-value crops (graph (k) and Panel C, column 4). This result again contrasts with the short-run results, in which high-value crops accounted for most of the crop response. This difference may be evidence of adaptive investments: high-value crops appear to be easier to switch in response to short-run shocks, but the low-value crops are those that change when farmers have time to make decisions that are optimal for the long run.

6.3 Summary measures: Long-run water scarcity reduces predicted revenue

Using continuous measures to summarize effects on the full set of crops, long-run water availability increases total crop water needs (graph (i)) as well as the overall value of crops grown (graph (l)). The water-needs elasticity of 0.12 (Panel C, column 5) is larger in magnitude than the short-run elasticity, suggesting that crop choice may be more sensitive to surface water availability in the long run than in the short run.

The elasticity of predicted crop revenue with respect to mean water supplies is 0.26 to 0.38 depending on bandwidth (Panel C, column 7), implying that a 10 percent increase in mean water supply leads to a 3-4 percent increase in predicted revenue. Compared with the short-run elasticity of 0.36, this response is similar or slightly smaller.

6.4 Decompositions: Extensive margin drives predicted revenue effects

I perform the same decomposition exercise for long-run effects as for short-run effects, estimating the effects of long-run water availability on measures of predicted crop revenue constructed using only variation across certain land-use categories.[14] Appendix Figure A4 (right side) shows these effects scaled by the effect on the original predicted crop revenue variable, and full regression results are reported in Appendix Table B9, Panel B. Variation between cropland and non-cropland explains about half of the revenue effect, while variation between cropped and uncropped land explains more than 100 percent of the revenue effect. The fact that these categories over-explain the revenue effect suggests that farmers also switch to lower-value land uses within each category in response to long-run water supplies, which is consistent with the finding that changes in cropped area are driven by low-value crops.

Further subdivisions of crops contribute little to the explanatory power of these categories. As in the short run, this result suggests that movement between crops is of relatively minor importance, and the extensive margin appears to account for the full effects of long-term water availability.

6.5 Sensitivity checks

Spatial regression discontinuities can be set up in multiple ways. To test whether results are sensitive to particular elements of the main specification, Appendix C reports estimates from regressions with various modifications. Specifically, these checks use a rectangular kernel instead of a triangular one (Table C4), omit running variables in latitude and longitude (Table C5), omit border segments in favor of simpler border pair fixed effects (Table C6), use smaller border segments of 2 km instead of 5 km (Table C7), and restrict the sample using a stricter definition of neighboring districts (Table C10). Across these specifications, all results are very similar to the main specification. Some estimates are less precise when using smaller border segments, but this is to be expected since stringent fixed effects are more demanding of the data.

In this research design, IV estimation is not necessary for omitted variables bias. Appendix Table C11 shows the results from running OLS instead of IV. Most estimates are very

[14] To preserve spatial and temporal variation, I take means within district pair×year.

similar to the main specification. The one difference is that there now appears to be a fallowing response and a smaller grassland response. The IV estimate may be more reliable, since it guards against measurement error in the water supply variable.

Finally, I can again examine whether the predicted revenue results are sensitive to the particular way the outcome variable is constructed. Results, in Appendix Table B6, are virtually unchanged across five different definitions of predicted revenue (columns 1-5). Estimates for predicted crop revenue expressed linearly (column 6) are less precise, which is unsurprising given the high skewness of the untransformed revenue variable.

6.6 Ruling out alternative explanations

Endogenously chosen district boundaries. One possible threat to a causal interpretation of this RD design is if district borders were determined in ways that included or excluded land based on productivity or comparative advantage. As discussed earlier, most of the relevant factors are physical characteristics that are observable today and do not exhibit large differences at the boundaries between neighboring districts. Still, it is possible that even small differences in land characteristics could lead to differences in land use. To gain confidence that land characteristics are not driving the apparent effects of long-run water scarcity, Appendix Table B5 includes as control variables the full set of soil, climate, and groundwater variables listed in Appendix Table B1. Results are virtually unchanged.

Water sharing across boundaries. Another possible threat to identification is if individual farmers move water across irrigation district boundaries. This would tend to smooth out the differences in water supplies between neighboring districts and lead my estimates to understate the true long-run effects. This kind of trading is unlikely to be widespread. First, irrigation districts typically operate their own systems of local canals that are not directly connected to each other, so it would be physically difficult to transport water in this way. Second, irrigation districts typically forbid individual farmers from buying or selling surface water outside of the district.

Less unlikely is that a single farm operation might straddle the border between two districts, such that it shares water from either or both districts across multiple fields managed together as a single operation. To explore sensitivity of the results to fields immediately surrounding district borders, I can exclude observations that fall within close distances of the border. Appendix Table C12 sets this "donut hole" at 0.57 km (the half diagonal of one quarter section) and Appendix Table C13 sets it at 1.14 km (the half diagonal of one section). Results are very similar to the main specification.

Incomplete definition of long run. How long is the long-run? Are my cross-sectional comparisons really capturing long run adaptation? The ideal dependent variable would be expected water supply, which is unobserved. The likely best proxy of expectations is recent allocations and supply, during the same timespan as outcome data. This has the advantage of being orthogonal to the short-run variation by construction, so they can be estimated using the same data and be as comparable as possible. However, if patterns of water availability have changed over time, it is possible that measures of water supplies from earlier years carry additional information about expectations.

To check whether results are sensitive to the timespan of water supplies measured, Appendix Table C8 shows estimates in which the water allocation instrument is defined using pre-sample data (1993-2006 instead of 2007-2018), and Appendix Table C9 shows estimates in which both the instrument and the water supply treatment variable use pre-sample data. Estimates are smaller, but I cannot reject that the predicted crop revenue effect is the same. One interpretation is that more adaptation has taken place over time, and that this was not a long enough time span to observe the full range of possible adaptation. Alternatively, expectations may have changed over time, so this is no longer the right measure. If so, mismeasured expectations would be expected to lead to attenuation bias.

6.7 Is the regression discontinuity necessary?

An important question in the climate impacts literature is whether cross-sectional regressions can recover unbiased estimates of the causal effects of long-run environmental variables. This paper's setting offers a unique opportunity to answer this question, since the RD estimates presumably represent unbiased causal effects. Appendix Table B7 reports estimated coefficients from regressions of each of the land use and summary outcome variables on mean surface water supply using several alternative research designs. All regressions instrument for supply with district indicators as usual, but they use different approaches to address omitted variables bias. The right-most column repeats RD estimates from Table 3 for reference.

The results are mixed. On one hand, no single approach alone—a cubic control in two-dimensional space (column 1), a rich set of physical covariates (column 2), county fixed effects (column 3), or district neighbor pair fixed effects (column 4)—comes very close to reproducing the pattern of results found by RD. On the other hand, a specification that combines all four of these approaches (column 5) does produce results remarkably similar to the RD; many of the point estimates are nearly identical.

This exercise suggests that it is possible, at least in some settings, for cross-sectional regressions to recover unbiased causal effects of long-run environmental variables. However, the data requirements to do so may be high—here, both rich covariates and sub-county variation in water availability are needed to replicate the RD results. In addition, typical climate impacts studies may suffer from greater omitted variables bias than this setting, which features unusually large variation in the relevant environmental variable over relatively short distances.

7 Adaptation

7.1 Adaptation to long-run water scarcity

Comparing the effects of water availability in the short run and the long run reveals the extent to which agriculture has adapted to water scarcity in California. Figure 4 plots the short-run and long-run effects as estimated in the preferred specifications, along with the adaptation effect. (These effects are listed with more numerical precision in Appendix Table B8.) To show the effects of water scarcity—the converse of water availability—I flip the sign of the original estimates. The adaptation effect, then, is defined as the difference between the short-run and long-run effects. It answers the question: How does land use change as a short-term drought becomes the new long-term average?

First, overall land use changes. Farmers reduce cropped area by a nearly equal amount in response to both short-run drought and long-run scarcity. The difference is what happens to this land. In the short run, cropland is merely fallowed, but in the long run, it becomes grassland. Comparing these two responses, the net adaptation effect is to move fallow cropland into permanent retirement. This shift is direct evidence of adaptive investments: transitioning cropland to grassland is costly in the short run (since it removes the yearly option of planting crops) but more profitable than leaving land fallow (since grassland can be used to graze livestock and may require less maintenance).

Second, the mix of crops planted changes. The most prominent shift is away from low-value crops and toward high-value crops. There is also some evidence of a shift away from high-water crops toward low-water crops, though this shift is not statistically significant. The shares of annuals and perennials remain the same. Shifts toward higher-value and lower-water crops are also evidence of adaptive investments: they result in a greater value of production per unit of water inputs but evidently are too costly to undertake in the short run.

Third, the overall revenue value of these changes is small. Despite evidence of adaptive investments, little of the short-run effect of drought on predicted crop revenue is mitigated in the long run. The elasticity of predicted crop revenue with respect to water scarcity is -0.36 in the short run and -0.31 in the long run, implying that 85 percent of short-run revenue effects persist into the long run. Although shifting away from cropland and toward higher-value crops allows farmers to alleviate some of the immediate effects of water scarcity, these revenue value of these shifts is low. Differential land-use responses reduce the predicted revenue elasticity by only 0.06 in the long run.

7.2 Adaptation in sensitivity to short-run shocks

How do differences in long-run environmental conditions affect the sensitivity to short-run shocks? This is a distinct question from the effects of long-run differences on outcome levels. So far the literature on climate impacts has simply examined how short-run weather effects vary with climate. Although each treatment effect is causal, the differences among them may not be.

Because my research design has plausibly exogenous variation in both short-run and long-run water scarcity, I can interact them to estimate the causal effect of long-run scarcity on short-run sensitivity. Stated another way, when farmers are used to drier average conditions, are they better able to handle droughts?

To answer this question, I estimate variations of Equation 1 in which I allow heterogeneity in the elasticity γ. Specifically, I estimate the effects of short-run shocks separately in bins x of distance to border, while controlling for the average effect of short-run shocks for each district pair and border segment:[15]

$$Y_{idtbs} = \big(\alpha_{bs} + \sum_{x} \beta_x\big) \ln(WaterAllocation)_{dt} + \alpha_{id} + \lambda_t + \varepsilon_{idtbs}. \tag{4}$$

Figure 5 plots estimates of the coefficients β_x, plus the overall mean effect of water allocations, by distance to border.[16] Immediately around the border, the estimated short-run elasticities are very similar on each side of the border. There is no evidence of a discontinuity, suggesting there is no causal effect of long-run water supplies on sensitivity to short-run water supply shocks. If anything, the short-run elasticity is larger in water-scarce districts (left side of the graph), not smaller. This evidence is more consistent with a common concave production function than a story in which adaptation changes the shape of the production function. These results stand in contrast to some of the climate impacts literature, which find that extreme temperatures are less damaging in places that are more used to them (e.g., Carleton et al. 2018; Heutel et al. 2018).

8 Damages and Policy

8.1 Revenue losses from future climate change

The analysis above measures the effects of water scarcity in California in recent experience. In principle, these estimates can be coupled with projections from climate models to predict the likely economic impacts of future changes to agricultural water supplies. In practice, the steps required to translate projected precipitation to water supplies are complex and uncertain. Water supplies depend not only on total precipitation but also seasonal runoff patterns, reservoir storage capacity, flood control decisions, estuary conditions, and envi-

[15] To simplify estimation and avoid weak instrument problems, I estimate the reduced-form effects of water allocations rather than the instrumented effects of water supplies.

[16] I estimate this in several steps using the Frisch-Waugh-Lovell theorem. (1) Partial out fixed effects α_{id} and λ_t from both Y_{idtbs} and $\ln(WaterAllocation)_{dt}$; call the residuals $\tilde{Y}_{idtbs}$ and $\tilde{W}_{dt}$. (2) Estimate the overall reduced-form effect by regressing $\tilde{Y}_{idtbs}$ on $\tilde{W}_{dt}$. (3) Partial out pair-specific coefficients by regressing $\tilde{Y}_{idtbs}$ on the vector $\alpha_{bs}\tilde{W}_{dt}$; call the residuals $\tilde{\tilde{Y}}_{idtbs}$ and $\tilde{\tilde{W}}_{dt}$. (4) Estimate the coefficients of interest β_x by regressing $\tilde{\tilde{Y}}_{idtbs}$ on $\sum_x \beta_x \tilde{\tilde{W}}_{dt}$. (5) Add the overall effect to each β_x.

ronmental regulations.

Globally, arid and semi-arid regions are projected to experience increasing water scarcity (IPCC 2007). In California, precipitation is expected to become more volatile and drought more frequent, but there is no clear consensus on the direction of mean precipitation and runoff (Bedsworth et al. 2018). However, declines are expected in the volume of water that can be effectively stored both within and across years, since reduced snowpack will shift runoff into the wet season when reservoirs have little spare capacity. This is likely to result in reduced surface water availability for agriculture, especially in dry years (Knowles et al. 2018).

A detailed account of how changes in seasonal runoff and reservoir storage will affect water allocations throughout California is neither available in the literature nor within the scope of this paper. However, I can conduct a back-of-the-envelope calculation to get a sense of orders of magnitude. Suppose a future scenario in which all water supplies are reduced by 13 percent. This is the decline that one report projects by 2060 for one category of surface water allocations, average annual exports from the Sacramento–San Joaquin Delta (Wang et al. 2018). Applying my long-run elasticity estimate to California's total agricultural revenue ($50.1 billion in 2017) suggests that a 13 percent uniform decline in water supplies would lead to average annual revenue losses of $2.0 billion, with a 95-percent confidence interval of $(\$0.2, \$3.7)$ billion. In addition to these mean impacts, revenue losses are likely to be especially large during individual drought years.

An important caveat here is that crop revenue is not directly interpretable as social welfare. It reflects the gross output of a major sector of the economy, but it does not directly reflect the economic costs or benefits of irrigation water. For example, expenditures on other factors of production likely change in response to water supplies, regardless of whether farmers switch crops (e.g., different inputs and equipment required) or not (e.g., groundwater pumping and other compensatory inputs). A full welfare account would need to consider producer surplus, consumer surplus, and any positive or negative externalities of agricultural decisions.

Another limitation is that past experience will predict future impacts only so far as all other factors remain constant. These factors include current water allocation policy, the distribution of property rights, existing patterns of urban development, infrastructure for water storage and conveyance, groundwater resources, technological innovation and adoption, and crop prices. In the future, policy changes and institutional reforms may be able to further alleviate the effects of water scarcity. I turn to a brief exploration of the possible impacts of two such factors.

8.2 Surface water allocation policy

My estimates of long-run effects are conditional on the present distribution of surface water supplies. How much scope is there for water reallocation to reduce the total revenue losses of water scarcity? To help answer this question, I can look at how long-run effects of water scarcity varies with the level of average water supplies.

Figure 6 plots long-run effects of water supplies on predicted crop revenue, by bins of mean water supplies. The effects of additional water supplies are very large in water-scarce areas (places that receive less than 2 acre-feet per acre of surface water per year), with elasticities of 0.6 to 0.8. Meanwhile, effects are quite small in places that receive moderate to high amounts of surface water on average.[17] This heterogeneity suggests that water reallocation could reduce the total revenue losses from water scarcity. If a unit of surface water were transferred from a typical water-rich place to a typical water-scarce place, the revenue gains from additional water in the water-scarce place would outweigh the revenue losses from less water in the water-rich place.

Such reallocation could occur in multiple ways. One way is by fiat: relevant government actors could reform how water rights are defined and/or renegotiate project delivery contracts (or their future renewals). Another is through market mechanisms, which governments could facilitate by lowering transaction costs in water transfers, by clarifying property rights, reducing regulatory barriers, or setting up a centralized marketplace (Gray et al. 2015; Hagerty 2019). However, it is important to note that reducing total revenue losses does not necessarily improve welfare. The social benefits would depend on the correlation beween the impacts of water scarcity on revenue and profits, and how this correlation varies across places with more and less water. In addition, reallocating water may introduce social costs from negative ecological externalities.

8.3 Groundwater and its management

My estimates of the impacts of surface water scarcity are inclusive of endogenous groundwater pumping responses. Farmers may deal with receiving less surface water by pumping more groundwater—but over the long run this can deplete groundwater stocks, raising the cost of groundwater extraction and reducing options for handling surface water scarcity. To predict the future impacts of surface water, it is important to consider this feedback mechanism, as well as the role of groundwater management policy.

A full account of groundwater feedbacks is beyond the scope of this paper. The relevant model would require knowledge of (1) how surface water affects groundwater extraction, (2) how groundwater extraction affects groundwater levels, and (3) how groundwater levels affect groundwater extraction. The first is challenging due to data limitations, the second due to geological complexity, and the third due to endogeneity problems. Despite these

[17] These bin-specific effects are not statistically significantly different from each other, but in an alternative specification with a linear interaction, the coefficient is negative and significantly different from zero. Heterogeneity is not driven by functional form; effects here are shown as elasticities, but heterogeneity is even greater in the effects of linear changes in mean water supplies. A ten-percent change on a base of 1 unit represents a much smaller change in the level of water supplies than a ten-percent change on a base of 5 units, and yet this smaller change in water supplies still yields a larger effect on predicted revenue.

challenges, I can use the available data to partially illuminate the role of groundwater in adaptation to surface water scarcity and then discuss the directions of its likely future impacts.

Circumstantial evidence suggests that groundwater has a major role in how farmers respond to surface water scarcity. The elasticity of crop water needs with respect to surface water is 0.08 in the short run and 0.12 in the long run. The fact that both are much smaller than 1 suggests that farmers are meeting the water needs of their crops through other methods. One possible method is reduced water application rates, via deficit irrigation in the short run and installation of water-efficient irrigation technologies (e.g., drip or sprinkler) in the long run. But since production functions are concave and 60 percent of all irrigated acreage in California uses some form of efficient irrigation (U.S. Department of Agriculture 2019), water application rates alone seem unlikely to explain this large discrepancy. That leaves groundwater irrigation as the remaining explanation.

In addition, long-run surface water scarcity appears to lead to greater groundwater depletion. Appendix Figure A5 plots groundwater depths by binned distance to the border between pairs of neighboring irrigation districts. For this outcome it is more useful to compare average levels on each side of the graph, despite a potentially weakened causal interpretation, than to measure a discontinuity at the border. (Spatial discontinuities in groundwater depths are unlikely, since aquifers are connected and water does not stop at administrative boundaries.) Excluding the relatively small number of observations in the tails, groundwater depths appear to be greater (i.e., more depleted) in districts with relatively lower surface water supplies. This pattern does not appear to be driven only by pre-existing differences in hydrology: comparing depths in 2007-18 to depths in 1993-06 (Figure 2, graph (k)) reveals that groundwater levels are not only lower but also falling faster in places with less surface water.

Groundwater feedback, then, is likely to exacerbate the future economic impacts of surface water scarcity. Depleted groundwater stocks will raise the cost of future extraction, lowering the probability that farmers will substitute to groundwater. Farmers will be more likely to switch crops or land uses at a revenue loss. The questions left for future research are the magnitudes: by how much, and by when.

Policy choices in groundwater management policy can influence this path of future impacts. Groundwater levels can be raised or maintained through quantity restrictions, such as those being considered in California under the Sustainable Groundwater Management Act. Such quantity restrictions are likely to reduce crop revenue in the short term, but raise it in the long term relative to a no-regulation scenario. How groundwater regulation will alter the effects of surface water scarcity is less clear. Short-run effects of surface water may not change much if regulations allow year-to-year banking and borrowing of extraction permits, but they will likely be exacerbated if regulations are inflexible. Long-run effects of surface water are likely to be directly exacerbated by quantity restrictions but ameliorated by raised aquifer levels. The net effect is ambiguous.

How will groundwater pumping restrictions affect crop revenue? I can perform a back-of-the-envelope estimate under a strong assumption. If one unit of groundwater is perfectly substitutable for one unit of surface water in the long run, then their elasticities are equal up to a scale factor (the ratio of total groundwater to total surface water). On average, groundwater makes up 39 percent of agricultural water use (California Department of Water Resources, 2015), and the preferred long-run elasticity of revenue with respect to surface water was 0.31. The groundwater elasticity would then be $0.31 \times 0.39/(1 - 0.39) = 0.20$, suggesting that a 10-percent reduction in groundwater extraction would reduce crop revenue by 2 percent.

9 Conclusion

This paper provides evidence on the extent of adaptation to climate change by estimating the short- and long-run effects of water scarcity. I study the case of irrigated agriculture in California, a setting that is not only economically important but also convenient for causal inference. First, I find that farmers reduce cropped area in response to both short-run drought and long-run water scarcity. Effects have similar magnitudes and are concentrated among annual crops. Second, I find some evidence of adaptation. Land shifted out of crop production is held fallow in the short run but converted to grassland in the long run. Over time, farmers are able to shift out of low-value crops and toward a higher-value (and possibly less water-intensive) mix of crops. Third, I find that the elasticities of predicted crop revenue with respect to water scarcity are economically large, but much less than one-for-one: 0.36 in the short run and 0.31 in the long run. Fourth, I find that the extent of adaptation is small – the long-run elasticity is nearly as large as the short-run elasticity, indicating that only about one-sixth of the short-run impacts are mitigated in the long run.

These results highlight the critical role of surface water in the economic impacts of climate change. Back-of-the-envelope calculations suggest that future water scarcity may reduce agricultural revenue by billions of dollars per year in California alone – without even considering the effects of rising temperatures, which are also projected to be large (Bedsworth et al. 2018). While a large share of the world's agricultural production is irrigated, many prior empirical studies of the effects of climate change on agriculture either exclude regions of irrigated agriculture or account for only the extensive margin of irrigation. My results show that these omissions lead to underestimates of the total effects of climate change on the economy.

My analysis leaves open several areas for future research. For one, my long-run effects could be combined with climate, hydrological, and reservoir operations models to predict the likely costs of climate-induced shifts in water supply over the next several decades. For another, short-run estimates seem to be a decent guide to long-run impacts in the context of surface water scarcity in agriculture, but whether this holds true for other channels of climate change remains unknown. Last, groundwater resources and policy choices will have key roles in determining the extent to which past experience becomes relevant to the future. Further research may be able to better identify which sorts of policy reforms might best reduce the impacts of water scarcity.

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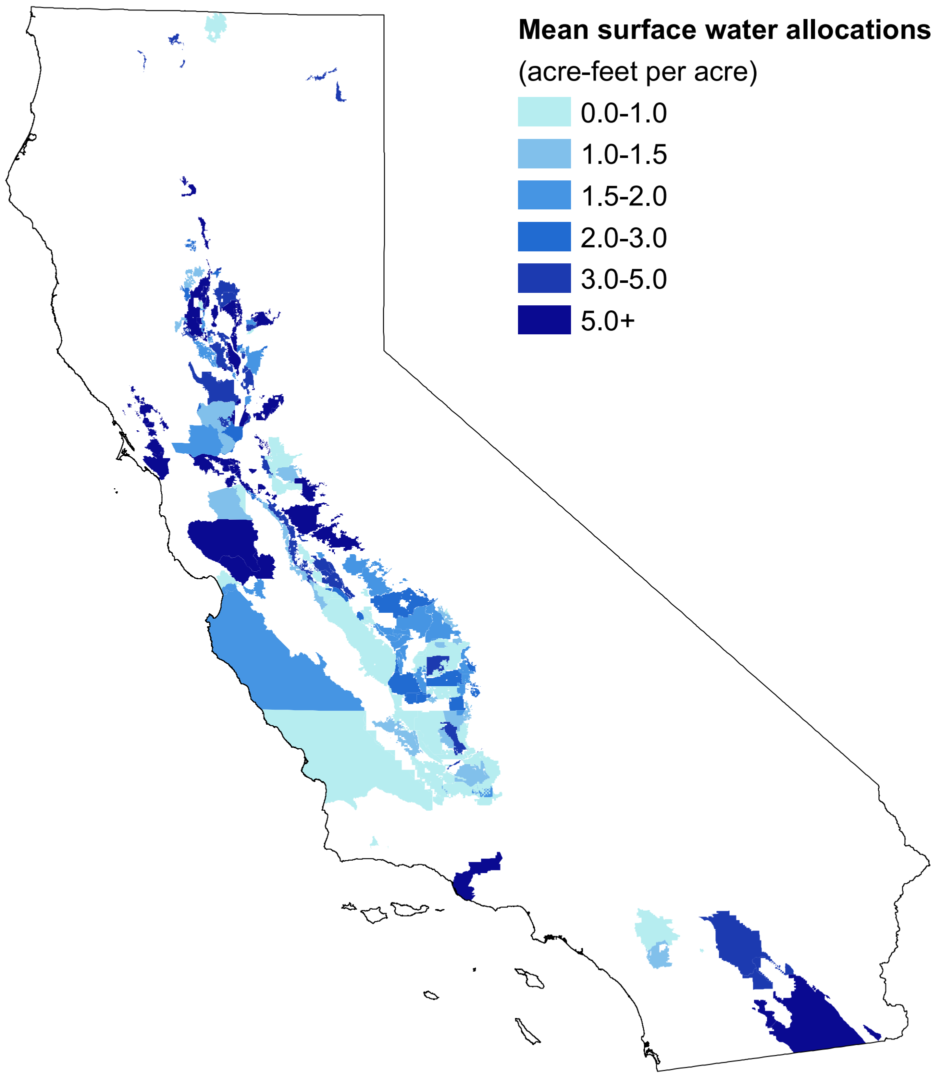
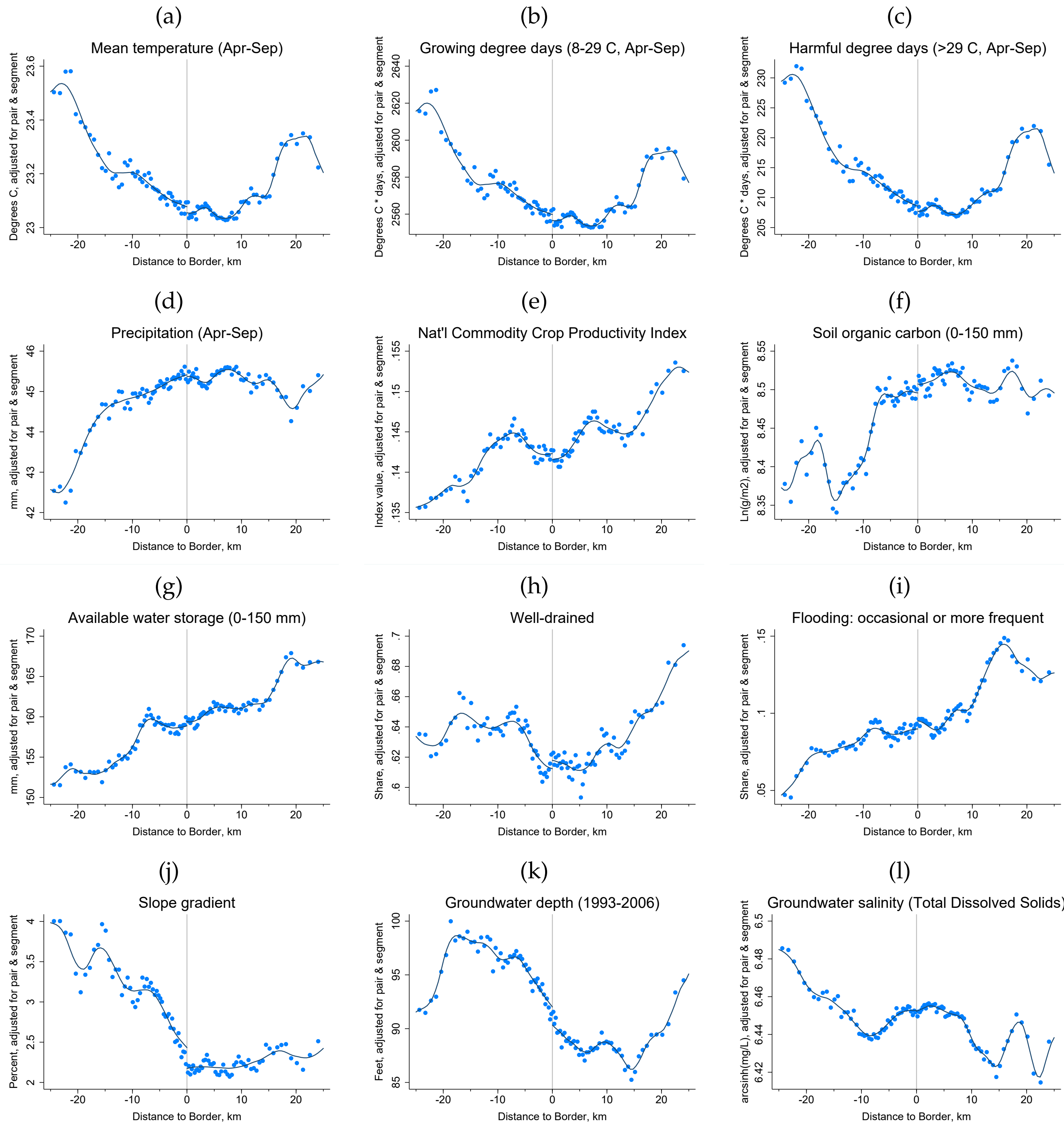
Figure 1: Surface water allocation by irrigation district in California



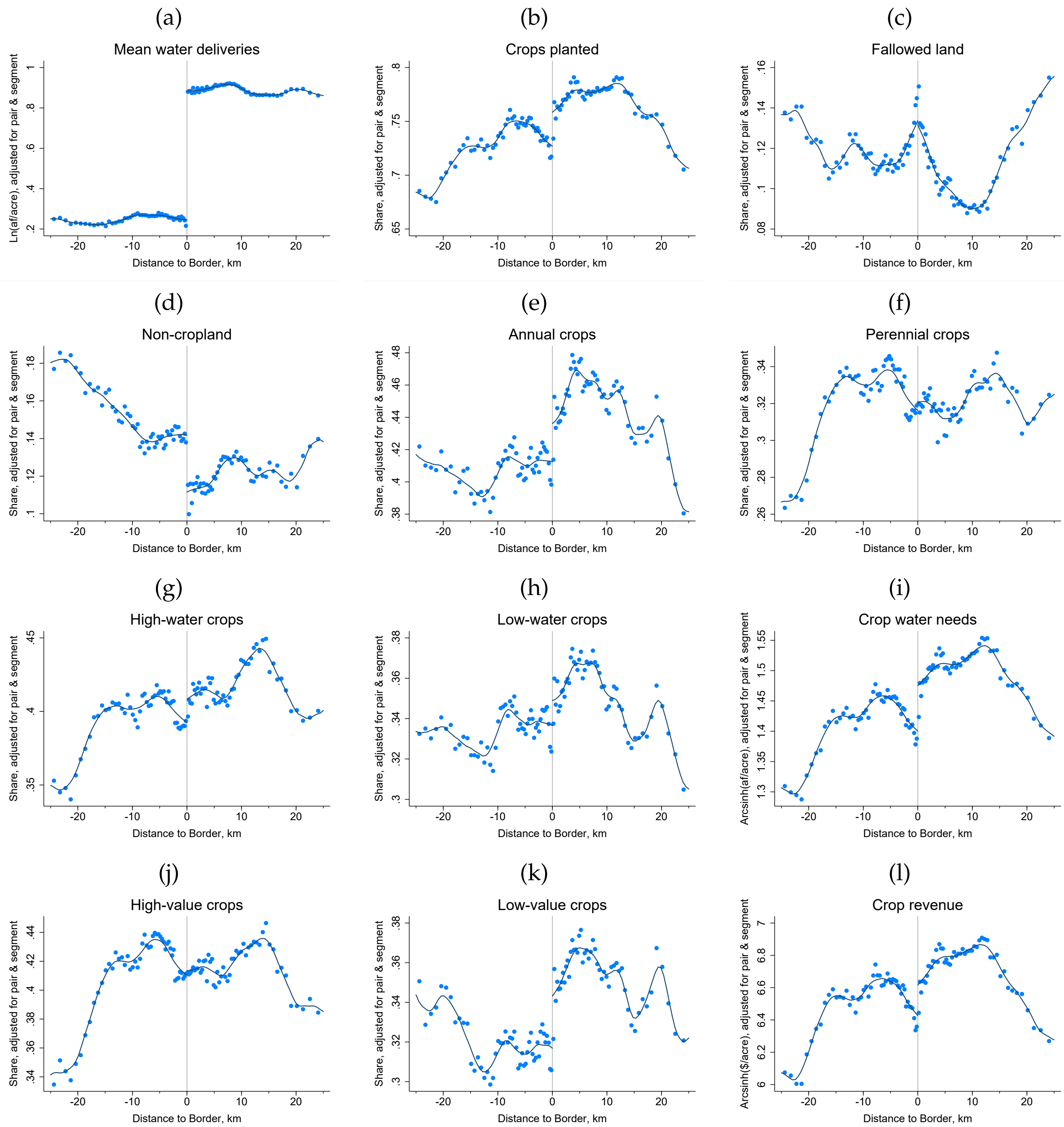
Map plots mean surface water allocations per acre of cropland by irrigation district, 2007-2018. Water allocations equal the sum of all surface water rights and allocations from the federal and state water projects that are held by a district and used in agriculture. Data and irrigation district boundaries come from a combination of sources as described in the text. I use the term "irrigation district" broadly to refer to water districts, water agencies, mutual water companies, and other organizations that deliver water to agricultural consumers within a defined service area.

Figure 2: Pre-treatment factors are continuous across irrigation district borders



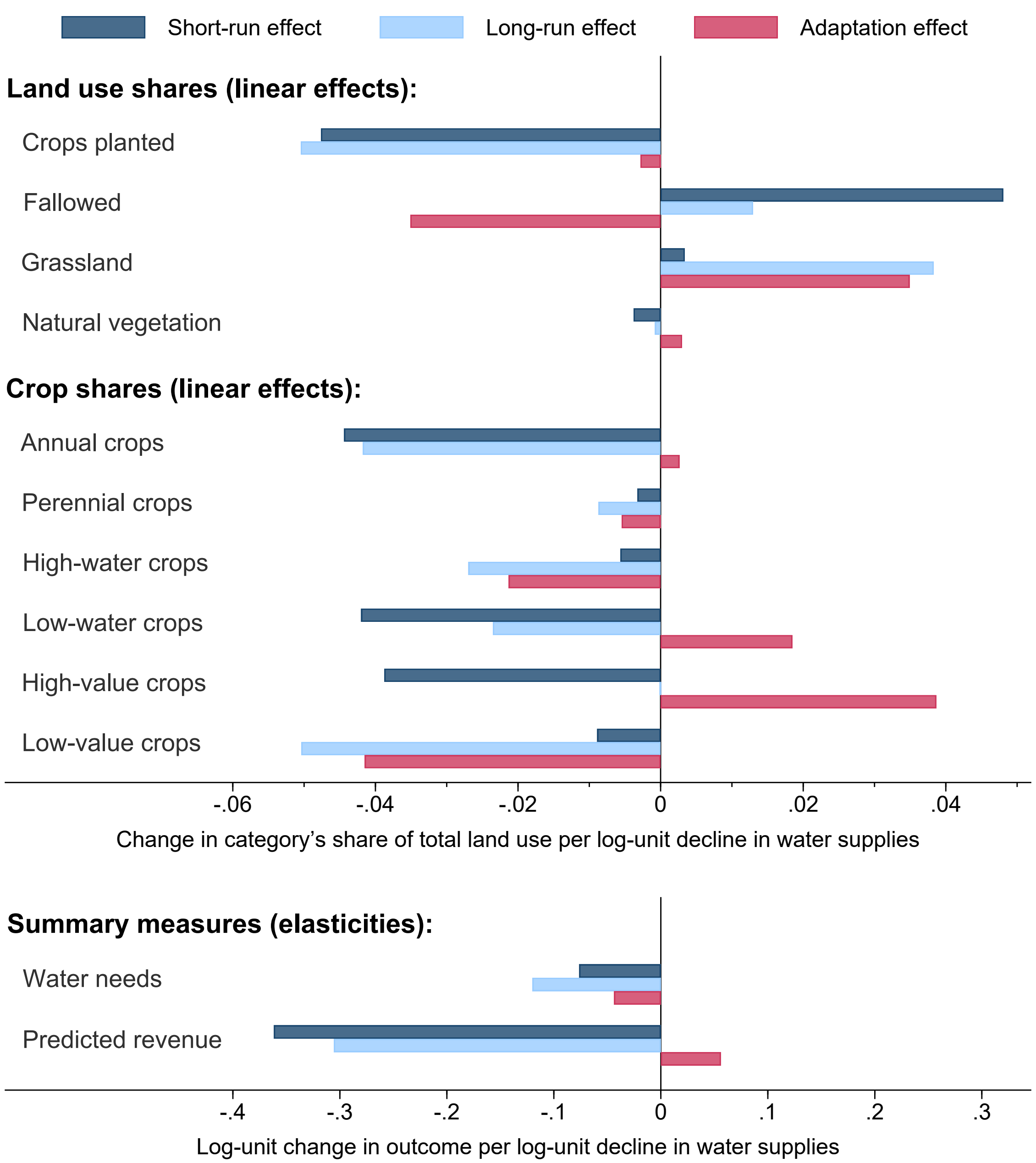
Graphs plot the mean outcome within each quantile bin of distance to the border between a pair of neighboring irrigation districts. Each pair of districts is ordered so that the district with greater mean water allocations is on the right (positive distance). Outcome variables are described in Table B1. Observations are farm fields (typically 40 acres) weighted by area and linked to outcome raster data by nearest grid point. District pairs are centered before plotting in the following sense: I calculate the mean value of the outcome within each district, subtract the midpoint of each pair's district means, and add the grand mean of the sample. Nonparametric trend lines are plotted separately on each side of the border using local linear regression.

Figure 3: Long-run effects of water availability (comparing between neighboring pairs of irrigation districts)



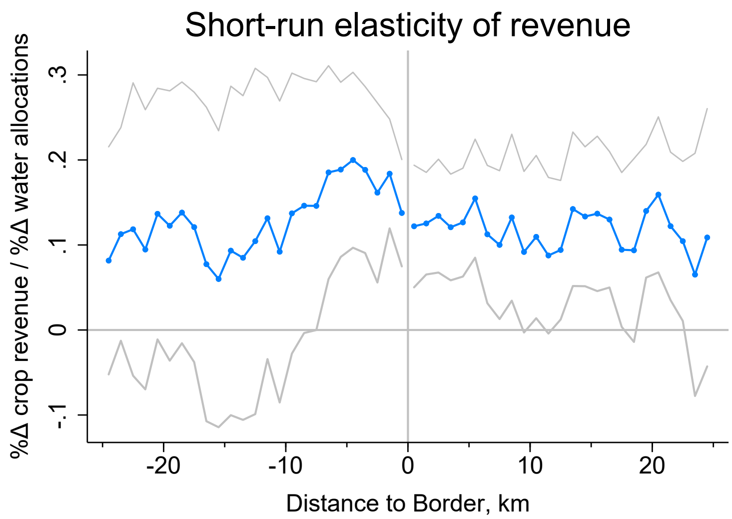
Graphs plot the mean outcome within each quantile bin of distance to the border between a pair of neighboring irrigation districts. Each pair of districts is ordered so that the district with greater mean water allocations is on the right (positive distance). Observations are farm fields (typically 40 acres) weighted by area; each point represents approximately 11,000 observations. Outcomes represent means over 2007-2018 of functions of crop choice in remote sensing data; those transformed by the natural log (ln) or the inverse hyperbolic sine (arcsinh) can be interpreted approximately as proportional changes (0.1 $\approx$ 10%). District pairs are centered before plotting in the following sense: I calculate the mean value of the outcome within each district, subtract the midpoint of each pair's district means, and add the grand mean of the sample. Data density varies across district pairs, so plots are unbalanced over the support of the running variable; their global shapes incorporate compositional effects. Nonparametric trend lines are plotted separately on each side of the border using local linear regression. Statistical inference is left for Table 3, in which regressions also incorporate pair-specific running variables.

Figure 4: Adaptation to water scarcity



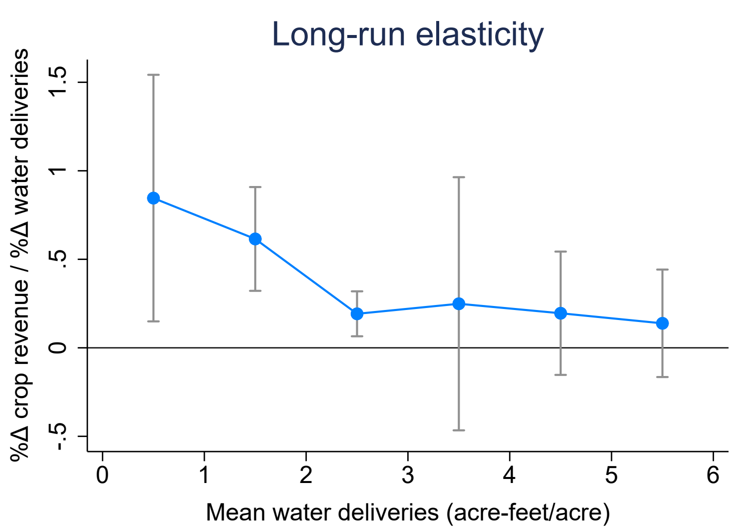
Graphs plot the short-run, long-run, and adaptation effects of water scarcity. Short-run and long-run effects of water scarcity are the negative of the estimated effects of water availability from the preferred regression specifications (Table 2 and Table 3 with a 10-km bandwidth). Adaptation effects are estimated by subtracting the short-run effect from the long-run effect; they can be interpreted as the ways in which land use and crop choices would change over time as an initial one-year water shortage turns into the "new normal" long-term average water supply.

Figure 5: Effect of long-run water availability on sensitivity to short-run water allocation shocks



Graph plots estimated reduced-form elasticities of predicted crop revenue with respect to short-run water allocations. Each pair of districts is ordered so that the district with greater mean water allocations is on the right (positive distance). Estimates are binned coefficients from a regression of predicted crop revenue on the natural log of water allocations, in which the effect of water allocations is allowed to vary by distance to border within district pairs, parameterized as 1-km bins (Equation 4). Regressions also control for field and year fixed effects as well as the overall effect of water allocations within each district pair×border segment; the overall mean effect of water allocations is added back to the distance bin coefficients before plotting. Gray lines plot 95-percent confidence intervals.

Figure 6: Long-run effect heterogeneity by mean water availability



Graph plots estimated elasticities of predicted crop revenue with respect to long-run water supplies, by bins of mean water supplies per year (specifically, the midpoint of mean water supplies between the two districts of each pair). Bins have width of 1 acre-feet per acre, except for the last bin which also contains the small number of district pairs with a mean greater than 6 acre-feet per acre. Gray bars plot 95-percent confidence intervals.

Table 1: Summary statistics

Panel A. Summary statistics

	Observations	Mean	Std. Dev.	Minimum	Maximum	Within-district S.D.	Between-district S.D.
Year	3,815,232	2012.5	3.5	2007	2018		
Field area (acres)	3,815,232	34.4	11.9	0.1	79.9		
Surface water							
Supply (acre-feet/acre/year)	3,815,232	2.65	2.14	0.01	10.33	0.33	2.10
Allocations (acre-feet/acre/year)	3,815,232	2.79	2.41	0.01	11.15	0.38	2.79
Ln (Supply)	3,815,232	0.615	0.938	-4.490	2.335	0.562	0.669
Ln (Allocations)	3,815,232	0.522	1.238	-4.627	2.411	0.298	0.660
Allocation percentage	3,815,232	0.790	0.294	0	1		
Land use							
Cropped	3,815,232	0.606	0.489	0	1		
Fallow	3,815,232	0.103	0.304	0	1		
Grassland	3,815,232	0.159	0.365	0	1		
Natural vegetation	3,815,232	0.132	0.339	0	1		
Crop outcomes							
Water needs (acre-feet/acre/year)	3,815,229	2.18	2.04	0.00	8.00		
Revenue (2009$/acre/year)	3,460,126	2,032	3,143	0	74,586		
arcsinh (Water needs)	3,815,229	1.16	1.00	0.00	2.78		
arcsinh (Revenue)	3,460,126	5.40	3.80	0.00	11.91		

Panel B. Crop characteristics by category

Crop category	Share	Mean water needs per acre (acre-feet)	Mean revenue per acre (2009$)
Perennial, long-term crops			
Almonds, pistachios	13.5%	4.82	5,081
Grapes	6.0%	3.88	7,735
Citrus, other subtropical fruit	2.4%	3.83	6,683
Other tree fruits, nuts	3.8%	4.03	4,811
Annual & short-term crops			
Alfalfa	7.7%	4.97	1,303
Grains	7.0%	1.31	622
Rice	5.9%	2.89	1,594
Corn	4.3%	2.61	868
Cotton	3.7%	3.62	1,736
Tomatoes	2.5%	2.59	4,171
Safflower	0.6%	1.99	453
Onions, garlic	0.5%	3.03	5,943
Melons, squash, cucumbers	0.3%	2.41	5,844
Sugar beets	0.2%	3.62	2,187
Dry beans	0.2%	2.12	1,215
Potatoes	0.2%	1.72	7,825
Pasture, grass	0.1%	7.58	125
Other vegetables, berries	1.0%	1.94	18,128
Other field crops	0.7%	2.67	1,036
Not crops			
Grassland (unirrigated rangeland)	15.9%	0.00	11
Fallow	10.3%	0.00	0
Natural vegetation	13.2%	0.00	0

Panel A reports statistics of water supplies and crop outcomes in California, using data from 2007 through 2018. Observations are farm fields (typically 40 acres) per year. Statistics (except for the number of observations) are weighted by area; water supply, allocations, and revenue variables are winsorized at the 0.5 and 99.5 percentiles. Standard deviations (S.D.) within district are the standard deviation of residuals from a regression of each variable on farm field and year fixed effects (water supply variables do not vary across fields within a district). Standard deviations between districts are the standard deviation of field-level means over time. Panel B reports characteristics by crop category, with shares of overall land use. Crop categories correspond to those in water use data; revenue data breaks these further into 70 categories of crops. The groupings of perennial versus annual crops are meant to capture whether a crop requires a long-term (multi-year) investment; some crops listed under annual (e.g., alfalfa, strawberries, artichokes) are technically biennials or perennials but can be harvested within a year.

Table 2: Short-run effects of water availability

Panel A. First-stage effect of water allocations on water supply

	Ln (Supply)
	(1)
Ln (Allocations)	0.357 ***
	(0.032)
F-statistic	124.6
Field fixed effects	✓
Year effects	✓
Observations	3,815,232
Clusters	2,172

Panel B. Short-run effects of water availability (instrumental variables)

	Land use (categories sum to one)				*Crop choice*	
	Crops planted	Fallow	Grassland	Natural uses	Annual crops	Perennial crops
	(linear probability)				*(linear probability)*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Supply)	0.048 **	-0.048 ***	-0.003	0.004	0.044 **	0.003
	(0.019)	(0.018)	(0.005)	(0.004)	(0.018)	(0.005)
Field fixed effects	✓	✓	✓	✓	✓	✓
Year effects	✓	✓	✓	✓	✓	✓
Observations	3,815,232	3,815,232	3,815,232	3,815,232	3,815,232	3,815,232
Clusters	2,172	2,172	2,172	2,172	2,172	2,172

Panel C. Short-run effects of water availability (instrumental variables)

	Crop choice				*Summary measures*	
	High-water	Low-water	High-value	Low-value	Water needs	Crop revenue
	(linear probability)				*(inverse hyperbolic sine)*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Supply)	0.006	0.042 **	0.039 ***	0.009	0.076 ***	0.362 **
	(0.014)	(0.018)	(0.012)	(0.010)	(0.029)	(0.160)
Field fixed effects	✓	✓	✓	✓	✓	✓
Year effects	✓	✓	✓	✓	✓	✓
Observations	3,815,232	3,815,232	3,815,232	3,815,232	3,815,229	3,459,809
Clusters	2,172	2,172	2,172	2,172	2,172	2,165

Table shows coefficients from regressions of the variable in each column header on the variables listed in rows, using panel data from 2007-2018. In Panels B and C, the treatment variable (natural log of water supply) is instrumented with the natural log of water allocations. Observations are farm fields (typically 40 acres) per year and are weighted by area. All outcome variables are functions of remote sensing data; those transformed by the inverse hyperbolic sine (arcsinh) can be interpreted approximately as proportional changes ($0.1 \approx 10\%$). Standard errors are shown in parentheses and clustered both by district-year and by field. * p<.1, ** p<.05, *** p<.01.

Table 3: Long-run effects of water availability

Panel A. First-stage relationship (mean difference in mean water supply across border pairs)

	Ln (Mean Water Supply)		
	(1)	*(2)*	*(3)*
More water-rich district of each pair	0.591 ***	0.590 ***	0.600 ***
	(0.047)	(0.051)	(0.051)
Bandwidth	25 km	10 km	5 km
F-statistic	155.2	135.9	136.0
Border pair × border segment	✓	✓	✓
Distance × pair × segment	✓	✓	✓
Distance × pair × segment × More	✓	✓	✓
Latitude × pair × segment	✓	✓	✓
Longitude × pair × segment	✓	✓	✓
Observations	1,079,977	543,541	264,828
Clusters	180	180	178

Panel B. Long-run effects of water availability (instrumental variables)

	Land use (categories sum to one)				*Crop choice*	
	Crops planted	Fallow	Grassland	Natural uses	Annual crops	Perennial crops
	(linear probability)				*(linear probability)*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Mean Supply)						
Bandwidth: 25 km	0.064 ***	-0.010	-0.053 ***	-0.001	0.036 *	0.028
	(0.021)	(0.015)	(0.017)	(0.005)	(0.019)	(0.020)
Bandwidth: 10 km	0.050 ***	-0.013	-0.038 ***	0.001	0.042 **	0.009
	(0.017)	(0.016)	(0.011)	(0.005)	(0.019)	(0.014)
Bandwidth: 5 km	0.042 ***	-0.012	-0.031 ***	0.000	0.032 *	0.010
	(0.015)	(0.015)	(0.010)	(0.005)	(0.019)	(0.013)
Border pair × border segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment × More	✓	✓	✓	✓	✓	✓
Latitude × pair × segment	✓	✓	✓	✓	✓	✓
Longitude × pair × segment	✓	✓	✓	✓	✓	✓
Observations (10 km bandwidth)	543,541	543,541	543,541	543,541	543,541	543,541
Clusters	180	180	180	180	180	180

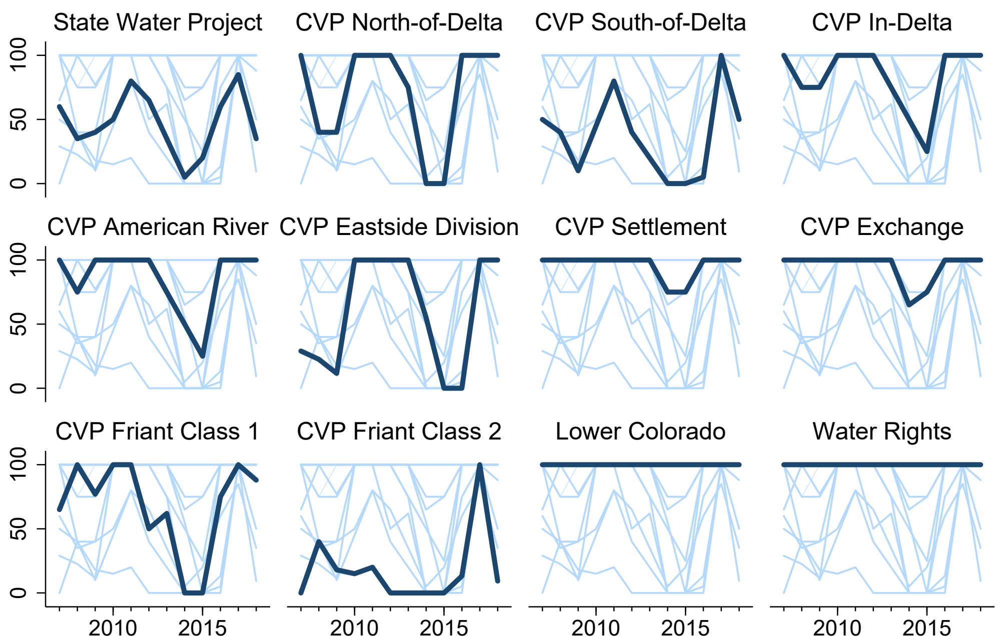
Panel C. Long-run effects of water availability (instrumental variables)

	Crop choice				*Summary measures*	
	High-water	Low-water	High-value	Low-value	Water needs	Crop revenue
	(linear probability)				*(inverse hyperbolic sine)*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Mean Supply)						
Bandwidth: 25 km	0.047 **	0.017	0.017	0.047 ***	0.157 ***	0.381 **
	(0.022)	(0.014)	(0.022)	(0.016)	(0.046)	(0.148)
Bandwidth: 10 km	0.027	0.024 *	0.000	0.050 ***	0.120 ***	0.306 **
	(0.018)	(0.013)	(0.018)	(0.015)	(0.039)	(0.137)
Bandwidth: 5 km	0.023	0.020	0.000	0.042 ***	0.102 ***	0.256 **
	(0.016)	(0.013)	(0.017)	(0.015)	(0.034)	(0.123)
Border pair × border segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment × More	✓	✓	✓	✓	✓	✓
Latitude × pair × segment	✓	✓	✓	✓	✓	✓
Longitude × pair × segment	✓	✓	✓	✓	✓	✓
Observations (10 km bandwidth)	543,541	543,541	543,541	543,541	543,541	543,011
Clusters	180	180	180	180	180	180

Regressions combine spatial regression discontinuities (RDs) for 532 pairs of neighboring irrigation districts, using data from 2007-2018 collapsed to cross-sectional means. Data is limited to observations within the specified bandwidth of the border; estimates using different bandwidths are from separate regressions. RDs include fixed effects for border pair×border segment; border pair represents district pair×county×dominant soil order, and border segment breaks each border up into 5-km grid cells. Running variables (distance to border, latitude, and longitude, with distance estimated separately on each side of each border) are each interacted with these fixed effects, yielding 6,783 simultaneous RDs with a single pooled treatment coefficient. In Panels B and C, the treatment variable (natural log of mean water supply) is instrumented with the "More" indicator for the relatively water-rich district of each pair of neighbors (measured by mean water allocations over the same period). Observations are farm fields, weighted by area with a triangular kernel. Standard errors are shown in parentheses and clustered by district. * p<.1, ** p<.05, *** p<.01.

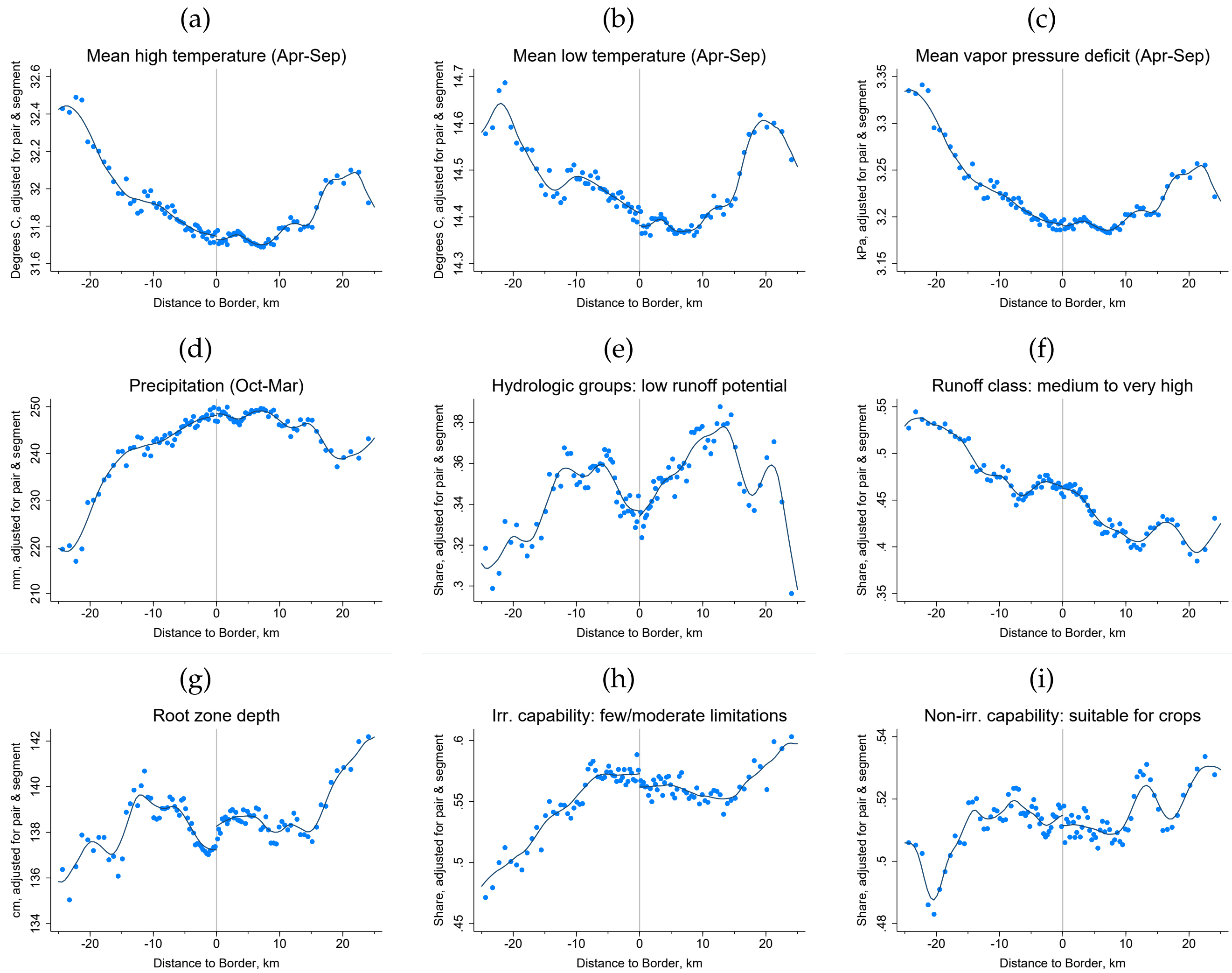
A Appendix Figures

Figure A1: Surface water allocation percentages over time by type of entitlement



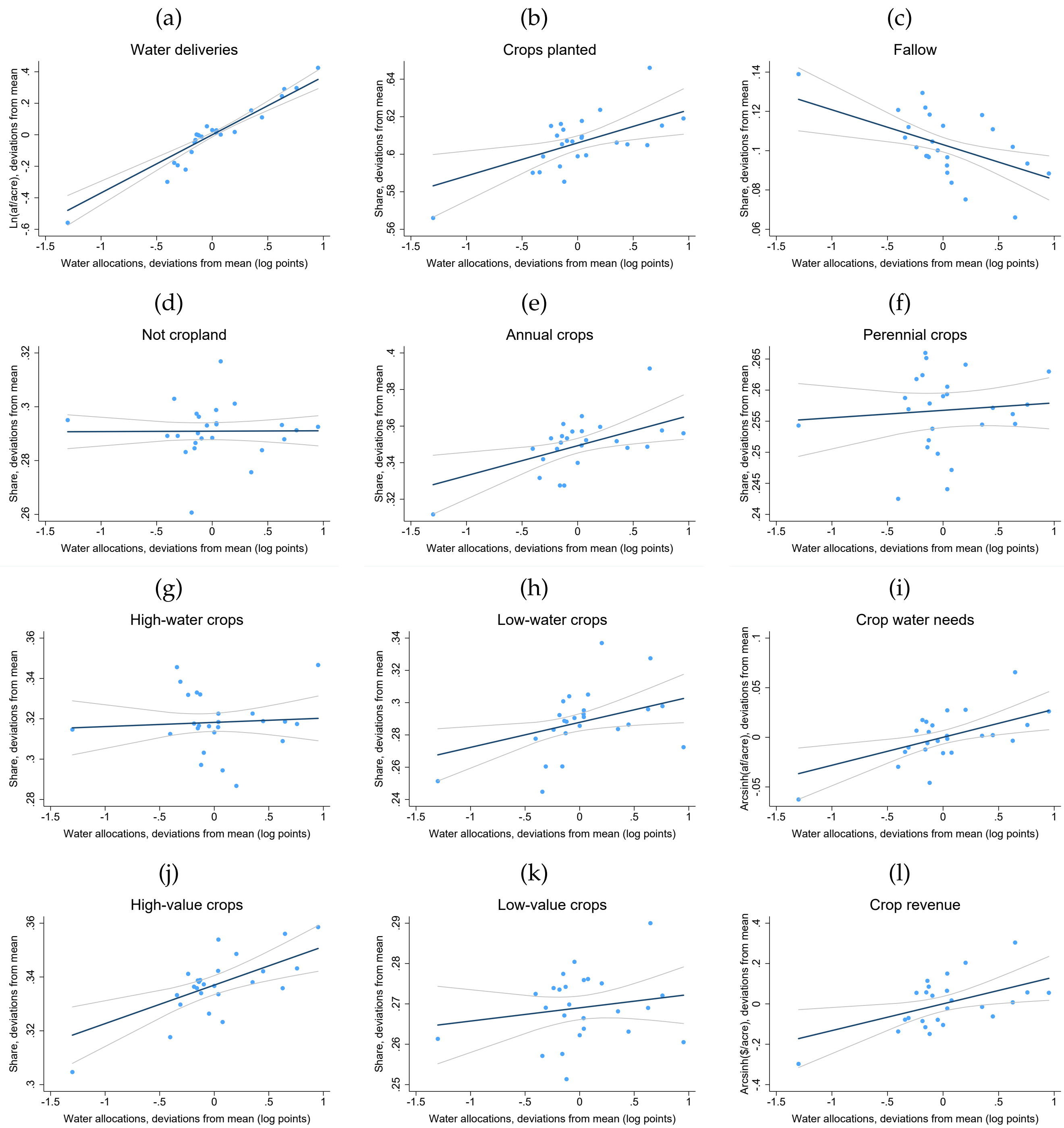
Graph plots allocation percentages over time, 2007-2018, for each of 12 surface water entitlement type. Thick dark lines plot allocations for the subtitled entitlement type; thin light lines plot the other 11 entitlement types for comparison. A value of 100 means a district is allocated 100 percent of its maximum entitlement volume, and a value of 0 means it is allocated no surface water in that year. Entitlement types refer to classes of contracts with the federal and state water projects, or to directly-held water rights. Allocation percentages are set according to weather and environmental conditions by the government agencies that operate the water projects.

Figure A2: Continuity of additional pre-treatment factors across irrigation district borders



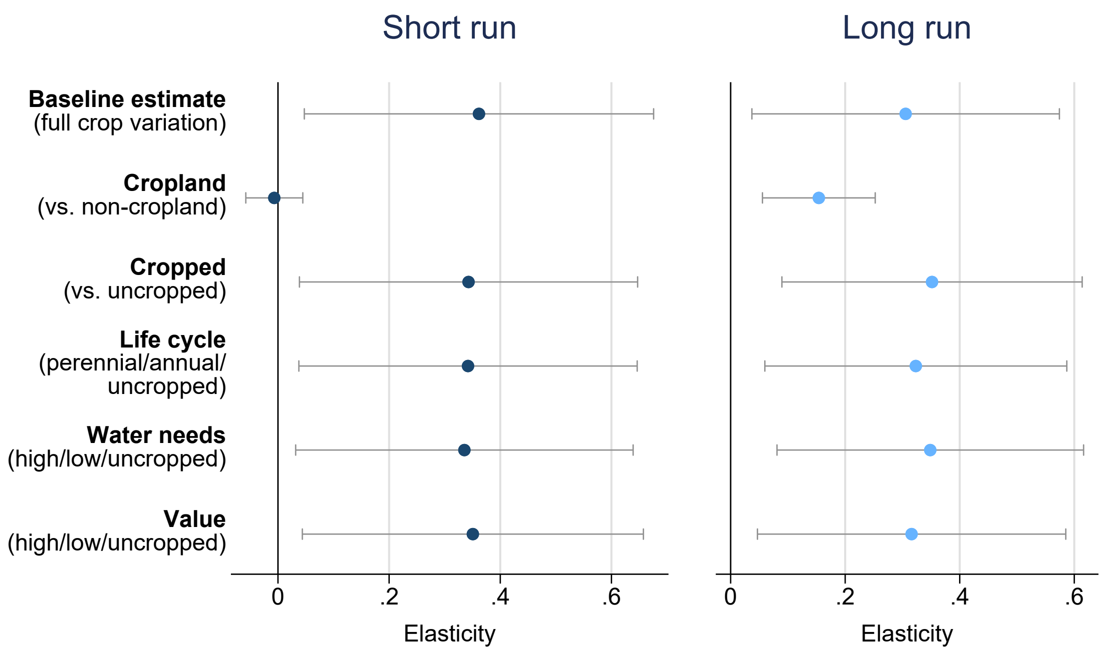
Graphs plot the mean outcome within each quantile bin of distance to the border between a pair of neighboring irrigation districts. Each pair of districts is ordered so that the district with greater mean water allocations is on the right (positive distance). Outcome variables are described in Table B1. Observations are farm fields (typically 40 acres) weighted by area and linked to outcome raster data by nearest grid point. District pairs are centered before plotting in the following sense: I calculate the mean value within each district, subtract the midpoint of each pair's district means, and add the grand mean of the sample. Nonparametric trend lines are plotted separately on each side of the border using local linear regression.

Figure A3: Short-run effects of water availability (within irrigation districts over time)



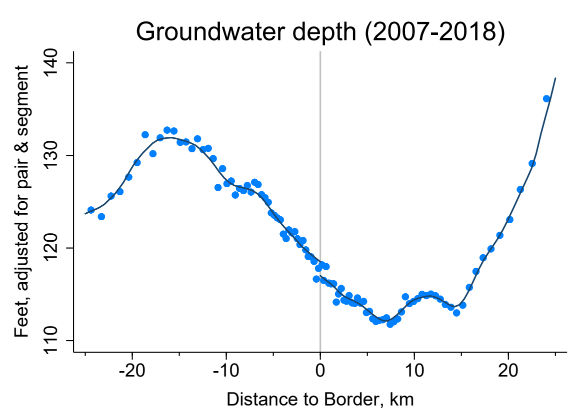
Graphs plot the mean outcome within each quantile of water allocation mean deviations. Observations are farm fields (typically 40 acres) per year, weighted by area; each point represents approximately 150,000 observations. Outcome variables are functions of crop choice in remote sensing data during 2007-2018; those transformed by the natural log (ln) or the inverse hyperbolic sine (arcsinh) can be interpreted approximately as proportional changes (0.1 $\approx$ 10%). Farm field and year means are partialed out from all variables (outcome variables as well as water allocations) before plotting, and the overall sample mean is added back to variables expressed as shares. Resulting graphs show the relationship between year-to-year fluctuations in water allocations, relative to average water allocations for that farm, and same-year anomalies in cropping decisions, relative to that farm's typical cropping decisions, while also controlling for year-specific changes in statewide average water allocations and cropping decisions. Trend lines show linear regressions (and their 95 percent confidence intervals) fitted to the underlying residuals for each graph. These regressions are identical to the first stage (plot (a)) and reduced-form (plots (b)-(f)) relationships from an instrumental variables fixed effects regression of cropping outcomes on yearly water supply, instrumenting supply with yearly water allocations.

Figure A4: Decomposition of predicted revenue effects by categories of variation



Graph plots estimated effects of water availability on measures of predicted crop revenue as constructed using only variation across specified categories of crops, as compared with the baseline estimates (in which revenue is constructed using the full variation across crops). For example, variation in the extensive margin (of cropped vs. uncropped) explains close to the full effect in both the short and long run, suggesting that the intensive margin (movement between crops) is of relatively minor importance. The specified categories slightly under-explain short-run effects (suggesting that farmers switch to higher-revenue crops within each category in response to short-run shocks) and slightly over-explain long-run effects (suggesting that farmers switch to lower-revenue crops within each category in response to long-run differences). Full regression results are shown in Table B9.

Figure A5: Effect of long-run water scarcity on groundwater levels



Graphs plot the mean outcome within each quantile bin of distance to the border between a pair of neighboring irrigation districts. Each pair of districts is ordered so that the district with greater mean water allocations is on the right (positive distance). Observations are farm fields (typically 40 acres) weighted by area and linked to outcome raster data by nearest grid point. District pairs are centered before plotting in the following sense: I calculate the mean value of the outcome within each district, subtract the midpoint of each pair's district means, and add the grand mean of the sample. Nonparametric trend lines are plotted separately on each side of the border using local linear regression.

B Appendix Tables

Table B1: Pre-treatment factors are well-balanced across irrigation district boundaries

			Pairwise comparisons (more vs. less water-rich neighbors)					
			Matched regression			Regression discontinuity		
	Mean	SD within pairs	Diff.	p-value	Normalized diff.	Diff.	p-value	Normalized diff.
Climate variables (1980-2017 means)								
Precipitation, Apr-Sep (mm)	45.3	6.0	-0.44	0.18	-0.022	0.01	0.66	0.001
Precipitation, Oct-Mar (mm)	250.3	31.9	-1.81	0.29	-0.014	0.03	0.76	0.000
Mean temperature, Apr-Sep (degrees C)	22.85	0.32	0.021	0.43	0.013	-0.005	0.00	-0.003
Mean high temperature, Apr-Sep (degrees C)	31.45	0.43	0.034	0.16	0.018	-0.003	0.01	-0.002
Mean low temperature, Apr-Sep (degrees C)	14.26	0.48	0.007	0.84	0.005	-0.007	0.00	-0.004
Mean vapor pressure deficit, Apr-Sep (kPa)	3.14	0.11	0.0077	0.20	0.022	-0.0001	0.77	0.000
Harmful degree days (>29 C), Apr-Sep	203	13	1.14	0.33	0.015	-0.16	0.00	-0.002
Growing degree days (8-29 C), Apr-Sep	2526	47	2.51	0.50	0.011	-0.73	0.00	-0.003
Soil variables								
National Commodity Crop Productivity Index, maximum	0.133	0.065	0.003	0.24	0.030	-0.002	0.02	-0.019
Soil organic carbon, within 150 mm (ln(g/m2))	8.46	0.63	0.10	0.00	0.107	-0.01	0.34	-0.016
Available water storage, within 150 mm (mm)	157.8	37.2	4.17	0.03	0.090	-0.80	0.21	-0.017
Slope gradient (percent)	3.73	6.37	-1.67	0.00	-0.167	-0.13	0.01	-0.013
Root zone depth (cm)	138	25	0.81	0.34	0.027	-0.22	0.70	-0.007
Drainage is good, neither poor nor excessive (=1)	0.67	0.38	-0.068	0.01	-0.145	0.001	0.95	0.001
Flooding occurs occasionally or more frequently (=1)	0.07	0.19	0.026	0.03	0.104	0.001	0.66	0.005
Hydrologic group has low runoff potential (=1)	0.34	0.40	0.007	0.71	0.016	0.000	0.95	-0.001
Runoff class is medium to very high (=1)	0.48	0.39	-0.063	0.00	-0.127	0.005	0.43	0.011
Irrigated land capability: few to moderate crop limitations (=1)	0.55	0.44	-0.014	0.57	-0.028	-0.024	0.00	-0.049
Non-irrigated land capability: at all suitable for crops (=1)	0.43	0.26	0.042	0.00	0.086	0.002	0.64	0.004
Drought-vulnerable landscape (=1)	0.25	0.37	-0.016	0.28	-0.037	-0.005	0.54	-0.012
Groundwater variables								
Groundwater depth, mean during 1993-2006 (feet)	90.6	45.9	-4.72	0.27	-0.058	0.10	0.79	0.001
Groundwater salinity, total dissolved solids (arcsinh(mg/L))	6.53	0.15	-0.009	0.51	-0.026	0.002	0.09	0.006

Table shows average differences across borders between neighboring pairs of irrigation districts, comparing districts with relatively greater and lesser mean water allocations within each pair. Differences are calculated via pairwise matched regression (i.e., a regression of each outcome on border pair fixed effects and an indicator for the relatively water-rich district of each pair) and via regression discontinuity (of the form in Equation 3, with a 10-km bandwidth). Differences are expressed as simple differences (i.e., the coefficient from these regressions, along with the p-value from a test of the null that the coefficient is zero) and as normalized differences (i.e., the coefficient divided by the root mean square of the standard deviations of the variable on each side of the border). Means and standard deviations are tabulated for the full regression-discontinuity sample, in which observations may appear more than once as part of multiple border pairs. Observations are farm fields (typically 40 acres) weighted by area. Standard deviations (SD) within pairs are calculated as the standard deviation of the residuals of the pairwise matched regression. Climate variables come from PRISM via Schlenker and Roberts (2009); soil variables come from the SSURGO database; and groundwater variables come from state of California data as described in the text.

Table B2: Short-run effects of water availability (including weather covariates)

Panel A. Including weather covariates

	Land use (categories sum to one)				*Crop choice*	
	Crops planted	Fallow	Grassland	Natural uses	Annual crops	Perennial crops
	(linear probability)				*(linear probability)*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Supply)	0.047 **	-0.046 ***	-0.005	0.004	0.042 **	0.005
	(0.020)	(0.018)	(0.005)	(0.003)	(0.018)	(0.006)
Weather variables	✓	✓	✓	✓	✓	✓
Lagged weather variables	✓	✓	✓	✓	✓	✓
Field fixed effects	✓	✓	✓	✓	✓	✓
Year effects	✓	✓	✓	✓	✓	✓
Observations	3,175,060	3,175,060	3,175,060	3,175,060	3,175,060	3,175,060
Clusters	1,810	1,810	1,810	1,810	1,810	1,810

Panel B. Including weather covariates

	Crop choice				*Summary measures*	
	High-water	Low-water	High-value	Low-value	Water needs	Crop revenue
	(linear probability)				*(inverse hyperbolic sine)*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Supply)	-0.015	0.062 ***	0.030 **	0.017 *	0.071 **	0.398 **
	(0.013)	(0.020)	(0.013)	(0.010)	(0.030)	(0.168)
Weather variables	✓	✓	✓	✓	✓	✓
Lagged weather variables	✓	✓	✓	✓	✓	✓
Field fixed effects	✓	✓	✓	✓	✓	✓
Year effects	✓	✓	✓	✓	✓	✓
Observations	3,175,060	3,175,060	3,175,060	3,175,060	3,175,059	3,052,523
Clusters	1,810	1,810	1,810	1,810	1,810	1,810

See notes for Table 2. Weather variables include quarterly sums or means of precipitation, the square of precipitation, temperature and degree days in several bins, and vapor pressure difference for the nearest grid point to the field. Lagged weather variables are the same variables from the previous year.

Table B3: Short-run revenue effects are driven by crop choice, not yield differences

	Crop revenue *(inverse hyperbolic sine)*						*First stage*
	Varying yields	*Constant yields*	*Yields only*	*Varying yields*	*Constant yields*	*Yields only*	Ln (Supply, county mean)
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
Ln (Supply)	0.362 **	0.375 ***	0.017 ***				
	(0.160)	(0.144)	(0.006)				
Ln (Supply, county mean)				0.404 **	0.434 *	0.032 *	
				(0.195)	(0.250)	(0.017)	
Ln (Allocations, county mean)							0.656 ***
							(0.036)
Yields	Per county and year	Constant	Per county and year	Per county and year	Constant	Per county and year	
Field fixed effects	✓	✓					
County fixed effects				✓	✓		✓
Year effects	✓	✓		✓	✓		✓
Crop-by-field fixed effects			✓				
Crop-by-county fixed effects						✓	
Crop-by-year fixed effects			✓			✓	
Observations	3,459,809	3,815,219	3,178,145	3,460,126	3,815,219	3,460,093	3,815,232
Clusters	2,165	2,172	2,164	28	28	28	28

See notes for Table 2. Predicted crop revenue is constructed as a function of remote sensing data, multiplying field-level crop indicators by county-level vectors of yields and prices. Revenue effects reflect both crop choice and yield margins in columns 1 and 4, only the crop choice margin in columns 2 and 4 (by holding yields constant when constructing the variable), and only the yield margin in columns 3 and 6 (by interacting the fixed effects with crop indicators). Regressions use district-level variation in water supply in columns 1-3 and county-level variation (taking means by cropland area) in columns 4-7. (Prices are constant over time in all columns, to estimate the value of yields and exclude general equilibrium effects.) Columns 4-7 cluster standard errors by county.

Table B4: Short-run effects of water availability (alternative revenue definitions)

	Crop revenue					
	(inverse hyperbolic sine)					*(2009$/acre)*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Supply)	0.325 **	0.321 **	0.362 **	0.285 *	0.375 ***	229.7 **
	(0.161)	(0.157)	(0.160)	(0.146)	(0.144)	(95.21)
Yields	Per county and year	Per county and year	Per county and year	Per county	Constant	Per county and year
Prices	Per county and year	Per year	Constant	Per year	Constant	Constant
Field fixed effects	✓	✓	✓	✓	✓	✓
Year effects	✓	✓	✓	✓	✓	✓
Observations	3,459,809	3,459,809	3,459,809	3,643,181	3,815,219	3,459,809
Clusters	2,165	2,165	2,165	2,168	2,172	2,165

See notes for Table 2. Predicted crop revenue is constructed as a function of remote sensing data, multiplying crop indicators by vectors of yields and prices. Columns in this table show results from different methods of constructing these revenue measures, allowing or suppressing variation in yields and prices across counties and years. Revenue is originally expressed in 2009$ per acre per year; when transformed by the inverse hyperbolic sine (arcsinh) it can be interpreted approximately as proportional changes (0.1 ≈ 10%).

Table B5: Long-run effects of water availability (including physical covariates)

Panel A. Including covariates

	Land use (categories sum to one)				*Crop choice*	
	Crops planted	Fallow	Grassland	Natural uses	Annual crops	Perennial crops
	(linear probability)				*(linear probability)*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Mean Supply)						
Bandwidth: 25 km	0.066 ***	-0.015	-0.051 ***	0.000	0.029	0.037 *
	(0.021)	(0.016)	(0.017)	(0.005)	(0.020)	(0.021)
Bandwidth: 10 km	0.051 ***	-0.016	-0.038 ***	0.002	0.039 *	0.013
	(0.018)	(0.016)	(0.011)	(0.005)	(0.020)	(0.015)
Bandwidth: 5 km	0.043 ***	-0.012	-0.031 ***	0.001	0.030	0.012
	(0.015)	(0.016)	(0.009)	(0.005)	(0.019)	(0.013)
Border pair × border segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment × More	✓	✓	✓	✓	✓	✓
Latitude × pair × segment	✓	✓	✓	✓	✓	✓
Longitude × pair × segment	✓	✓	✓	✓	✓	✓
Climate covariates	✓	✓	✓	✓	✓	✓
Soil covariates	✓	✓	✓	✓	✓	✓
Groundwater covariates	✓	✓	✓	✓	✓	✓
Observations (10 km bandwidth)	504,435	504,435	504,435	504,435	504,435	504,435
Clusters	176	176	176	176	176	176

Panel B. Including covariates

	Crop choice				*Summary measures*	
	High-water	Low-water	High-value	Low-value	Water needs	Crop revenue
	(linear probability)				*(inverse hyperbolic sine)*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Mean Supply)						
Bandwidth: 25 km	0.051 **	0.015	0.025	0.041 **	0.167 ***	0.421 ***
	(0.022)	(0.015)	(0.023)	(0.017)	(0.047)	(0.154)
Bandwidth: 10 km	0.027	0.025 *	0.003	0.048 ***	0.125 ***	0.324 **
	(0.019)	(0.013)	(0.019)	(0.016)	(0.040)	(0.141)
Bandwidth: 5 km	0.021	0.021	0.001	0.041 ***	0.104 ***	0.266 **
	(0.016)	(0.013)	(0.018)	(0.016)	(0.035)	(0.124)
Border pair × border segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment × More	✓	✓	✓	✓	✓	✓
Latitude × pair × segment	✓	✓	✓	✓	✓	✓
Longitude × pair × segment	✓	✓	✓	✓	✓	✓
Climate covariates	✓	✓	✓	✓	✓	✓
Soil covariates	✓	✓	✓	✓	✓	✓
Groundwater covariates	✓	✓	✓	✓	✓	✓
Observations (10 km bandwidth)	504,435	504,435	504,435	504,435	504,435	503,905
Clusters	176	176	176	176	176	176

See notes for Table 3. Covariates included in these estimates are the set of variables listed in Table B1.

Table B6: Long-run effects of water availability (alternative revenue definitions)

	Crop revenue					
	(inverse hyperbolic sine)					*(2009$/acre)*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Mean Supply)						
Bandwidth: 25 km	0.365 **	0.378 **	0.381 **	0.395 ***	0.385 ***	217.8 *
	(0.148)	(0.148)	(0.148)	(0.145)	(0.147)	(115.2)
Bandwidth: 10 km	0.288 **	0.303 **	0.306 **	0.311 **	0.304 **	97.3
	(0.137)	(0.137)	(0.137)	(0.131)	(0.133)	(82.6)
Bandwidth: 5 km	0.238 *	0.254 **	0.256 **	0.265 **	0.261 **	55.7
	(0.123)	(0.123)	(0.123)	(0.118)	(0.119)	(72.5)
Yields	Per county and year	Per county and year	Per county and year	Per county	Constant	Per county and year
Prices	Per county and year	Per year	Constant	Per year	Constant	Constant
Border pair × border segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment × More	✓	✓	✓	✓	✓	✓
Latitude × pair × segment	✓	✓	✓	✓	✓	✓
Longitude × pair × segment	✓	✓	✓	✓	✓	✓
Observations (10 km bandwidth)	543,011	543,011	543,011	543,541	543,541	543,011
Clusters	180	180	180	180	180	180

See notes for Table 3. Predicted crop revenue is constructed as a function of remote sensing data, multiplying crop indicators by vectors of yields and prices. Columns in this table show results from different methods of constructing these revenue measures, allowing or suppressing variation in yields and prices across counties and years. Revenue is originally expressed in 2009$ per acre per year; when transformed by the inverse hyperbolic sine (arcsinh) it can be interpreted approximately as proportional changes ($0.1 \approx 10\%$).

Table B7: Long-run effects of water availability (alternative research designs)

Dependent variable in rows (each cell is a separate regression)	Cubic control in lat & lon	Physical covariates	County fixed effects	Matched regression	All previous controls	Regression discontinuity (10 km bw)
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Crops planted (=1)	0.062	0.024	0.149 ***	0.097 ***	0.048 **	0.050 ***
	(0.039)	(0.035)	(0.048)	(0.024)	(0.020)	(0.017)
Fallow (=1)	-0.019	-0.011	-0.038	-0.011	-0.030 **	-0.013
	(0.020)	(0.017)	(0.029)	(0.014)	(0.014)	(0.016)
Grassland (=1)	-0.018	-0.011	-0.048	-0.069 ***	-0.030 *	-0.038 ***
	(0.032)	(0.032)	(0.042)	(0.020)	(0.016)	(0.011)
Natural uses (=1)	-0.024	-0.002	-0.064 **	-0.017	0.012 **	0.001
	(0.030)	(0.010)	(0.031)	(0.010)	(0.005)	(0.005)
Annual crops (=1)	0.093 *	0.085 **	0.108	0.099 ***	0.047 **	0.042 **
	(0.055)	(0.040)	(0.077)	(0.030)	(0.022)	(0.019)
Perennial crops (=1)	-0.031	-0.061	0.042	-0.002	0.001	0.009
	(0.048)	(0.046)	(0.071)	(0.028)	(0.021)	(0.014)
High-water (=1)	0.070 *	0.038	0.116 **	0.055 **	0.045 **	0.027
	(0.036)	(0.038)	(0.058)	(0.023)	(0.022)	(0.018)
Low-water (=1)	-0.009	-0.014	0.033	0.042 **	0.003	0.024 *
	(0.041)	(0.034)	(0.054)	(0.018)	(0.016)	(0.013)
High-value (=1)	-0.030	-0.062	0.017	0.007	-0.003	0.000
	(0.044)	(0.048)	(0.052)	(0.028)	(0.025)	(0.018)
Low-value (=1)	0.092 **	0.086 **	0.132 **	0.090 ***	0.051 **	0.050 ***
	(0.044)	(0.038)	(0.056)	(0.026)	(0.020)	(0.015)
Water needs (arcsinh)	0.156 **	0.072	0.334 ***	0.204 ***	0.120 **	0.120 ***
	(0.077)	(0.075)	(0.103)	(0.052)	(0.046)	(0.039)
Crop revenue (arcsinh)	0.377	0.058	1.073 ***	0.556 ***	0.310 **	0.306 **
	(0.284)	(0.258)	(0.349)	(0.167)	(0.151)	(0.137)
Crop revenue (2009$/acre)	4.0	-224.8	492.7	236.4	152.5	97.3
	(285.0)	(292.4)	(353.7)	(150.7)	(119.5)	(82.6)
Latitude & longitude (2D cubic)	✓				✓	
Climate/soil/groundwater covariates		✓			✓	
County fixed effects			✓		✓	
Border pair				✓	✓	
Border pair × border segment						✓
Distance × pair × segment						✓
Distance × pair × segment × More						✓
Latitude × pair × segment						✓
Longitude × pair × segment						✓
Observations	318,136	243,516	318,136	1,338,514	1,158,233	543,541
Clusters	182	176	182	182	176	180

See notes for Table 3. Each cell reports the estimated effect of long-term mean water supply on the dependent variable listed in each row, using the research design listed in each column. In column 2, covariates are the set of variables listed in Table B1. Matched regressions in Column 4 use the same border-pair indicators that form the basis of the regression discontinuity design. Results from Table 2 are repeated in column 6 for convenience. The number of observations differs between columns primarily because in matched-pair designs (columns 4-6), fields that belong to districts with multiple neighbors enter the sample multiple times.

Table B8: Adaptation to water scarcity

	Short-run effect			Long-run effect			Adaptation effect (from SR to LR)		
	(estimate)	(s.e.)		(estimate)	(s.e.)		(difference)	(s.e.)	
Land use (categories sum to 1)									
Crops planted	-0.048	(0.019)	**	-0.050	(0.017)	***	-0.003	(0.025)	
Fallow	0.048	(0.018)	***	0.013	(0.016)		-0.035	(0.024)	
Grassland	0.003	(0.005)		0.038	(0.011)	***	0.035	(0.012)	***
Natural vegetation	-0.004	(0.004)		-0.001	(0.005)		0.003	(0.006)	
Crop choice									
Annual crops	-0.044	(0.018)	**	-0.042	(0.019)	**	0.003	(0.026)	
Perennial crops	-0.003	(0.005)		-0.009	(0.014)		-0.005	(0.015)	
High-water crops	-0.006	(0.014)		-0.027	(0.018)		-0.021	(0.023)	
Low-water crops	-0.042	(0.018)	**	-0.024	(0.013)	*	0.018	(0.023)	
High-value crops	-0.039	(0.012)	***	0.000	(0.018)		0.039	(0.022)	*
Low-value crops	-0.009	(0.010)		-0.050	(0.015)	***	-0.042	(0.018)	**
Summary measures									
Water needs	-0.076	(0.029)	***	-0.120	(0.039)	***	-0.044	(0.049)	
Crop revenue	-0.362	(0.160)	**	-0.306	(0.137)	**	0.056	(0.211)	

Table lists the short-run, long-run, and adaptation effects of water scarcity. Short-run and long-run effects of water scarcity are the negative of the estimated effects of water availability from the preferred regression specifications (Table 2 and Table 3 with a bandwidth of 10 km). Adaptation effects are estimated by subtracting the short-run effect from the long-run effect; they can be interpreted as the ways in which land use and crop choices would change over time as an initial one-year water shortage turns into the "new normal" long-term average water supply. Standard errors are shown in parentheses. * p<.1, ** p<.05, *** p<.01.

Table B9: Decomposition of revenue effects to categories of variation

Panel A. Short-run effects

	Crop revenue *(inverse hyperbolic sine)*					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Supply)	0.362 **	-0.007	0.343 **	0.342 **	0.335 **	0.351 **
	(0.160)	(0.026)	(0.155)	(0.155)	(0.155)	(0.157)
Categories of variation	All crops (original estimate)	Cropland vs. non-cropland	Cropped vs. uncropped	Annuals, perennials, uncropped	High-water, low-water, uncropped	High-value, low-value, uncropped
Field fixed effects	✓	✓	✓	✓	✓	✓
Year effects	✓	✓	✓	✓	✓	✓
Observations	3,459,809	3,459,809	3,459,809	3,459,809	3,459,809	3,459,809
Clusters	2,165	2,165	2,165	2,165	2,165	2,165

Panel B. Long-run effects

	Crop revenue *(inverse hyperbolic sine)*					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Mean Supply)						
Bandwidth: 25 km	0.381 **	0.198 ***	0.432 ***	0.422 ***	0.444 ***	0.409 **
	(0.148)	(0.065)	(0.155)	(0.160)	(0.159)	(0.160)
Bandwidth: 10 km	0.306 **	0.154 ***	0.352 ***	0.323 **	0.349 **	0.316 **
	(0.137)	(0.050)	(0.134)	(0.135)	(0.137)	(0.137)
Bandwidth: 5 km	0.256 **	0.130 ***	0.293 **	0.277 **	0.291 **	0.266 **
	(0.123)	(0.046)	(0.119)	(0.118)	(0.121)	(0.123)
Categories of variation	All crops (original estimate)	Cropland vs. non-cropland	Cropped vs. uncropped	Annuals, perennials, uncropped	High-water, low-water, uncropped	High-value, low-value, uncropped
Border pair × border segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment × More	✓	✓	✓	✓	✓	✓
Latitude × pair × segment	✓	✓	✓	✓	✓	✓
Longitude × pair × segment	✓	✓	✓	✓	✓	✓
Observations (10 km bandwidth)	543,011	543,011	543,011	543,011	543,011	543,011
Clusters	180	180	180	180	180	180

Tables show regression estimates that use only variation across specified categories of crops. In the main results, predicted crop revenue is constructed by assigning crop-specific per-acre revenue values to field-specific observations of crop choice. Results here instead collapse these crop observations to broad categories. For example, in column 4, each observation of an annual crop is assigned the mean revenue across all annual crops, instead of using the crop-specific revenue. To preserve spatial and temporal variation, means are taken within field in Panel A, and within district pair×year in Panel B. For additional details, see notes for Table 2 (for Panel A) and Table 3 (for Panel B).

C Supplemental Appendix Tables

Table C1: Short-run effects of water availability (including county-specific time trends)

Panel A. Including county-specific time trends

	Land use (categories sum to one)				*Crop choice*	
	Crops planted	Fallow	Grassland	Natural uses	Annual crops	Perennial crops
	(linear probability)				*(linear probability)*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Supply)	0.047 ***	-0.045 ***	-0.005	0.002	0.037 **	0.010 **
	(0.018)	(0.017)	(0.005)	(0.003)	(0.016)	(0.005)
Field fixed effects	✓	✓	✓	✓	✓	✓
Year effects	✓	✓	✓	✓	✓	✓
Time trend × county	✓	✓	✓	✓	✓	✓
Observations	3,815,232	3,815,232	3,815,232	3,815,232	3,815,232	3,815,232
Clusters	2,172	2,172	2,172	2,172	2,172	2,172

Panel B. Including county-specific time trends

	Crop choice				*Summary measures*	
	High-water	Low-water	High-value	Low-value	Water needs	Crop revenue
	(linear probability)				*(inverse hyperbolic sine)*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Supply)	0.009	0.038 **	0.041 ***	0.006	0.078 ***	0.334 **
	(0.014)	(0.017)	(0.012)	(0.009)	(0.028)	(0.153)
Field fixed effects	✓	✓	✓	✓	✓	✓
Year effects	✓	✓	✓	✓	✓	✓
Time trend × county	✓	✓	✓	✓	✓	✓
Observations	3,815,232	3,815,232	3,815,232	3,815,232	3,815,229	3,459,809
Clusters	2,172	2,172	2,172	2,172	2,172	2,165

See notes for Table 2. In this table, regressions include a linear slope in year interacted with county indicators.

Table C2: Short-run effects of water availability (with linear treatment variable and instrument)

Panel A. Linear treatment variable and instrument

	Land use (categories sum to one)				*Crop choice*	
	Crops planted	Fallow	Grassland	Natural uses	Annual crops	Perennial crops
	(linear probability)				*(linear probability)*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Supply (acre-feet per acre)	0.047 ***	-0.039 ***	-0.006	-0.002	0.036 ***	0.012 **
	(0.010)	(0.010)	(0.005)	(0.004)	(0.011)	(0.006)
Field fixed effects	✓	✓	✓	✓	✓	✓
Year effects	✓	✓	✓	✓	✓	✓
Observations	3,815,232	3,815,232	3,815,232	3,815,232	3,815,232	3,815,232
Clusters	2,172	2,172	2,172	2,172	2,172	2,172

Panel B. Linear treatment variable and instrument

	Crop choice				*Summary measures*	
	High-water	Low-water	High-value	Low-value	Water needs	Crop revenue
	(linear probability)				*(inverse hyperbolic sine)*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Supply (acre-feet per acre)	-0.010	0.058 ***	0.026 ***	0.022 ***	0.083 ***	0.375 ***
	(0.010)	(0.014)	(0.009)	(0.007)	(0.017)	(0.091)
Field fixed effects	✓	✓	✓	✓	✓	✓
Year effects	✓	✓	✓	✓	✓	✓
Observations	3,815,232	3,815,232	3,815,232	3,815,232	3,815,229	3,459,809
Clusters	2,172	2,172	2,172	2,172	2,172	2,165

See notes for Table 2. In this table, the instrument (water allocations) and the treatment variable (water supply) are expressed in acre-feet per acre, instead of their natural log transformation.

Table C3: Short-run effects of water availability (OLS regressions)

Panel A. OLS regressions

	Land use (categories sum to one)				*Crop choice*	
	Crops planted	Fallow	Grassland	Natural uses	Annual crops	Perennial crops
	(linear probability)				*(linear probability)*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Supply)	0.019 *	-0.022 **	0.000	0.003	0.021 **	-0.002
	(0.010)	(0.009)	(0.004)	(0.002)	(0.010)	(0.004)
Field fixed effects	✓	✓	✓	✓	✓	✓
Year effects	✓	✓	✓	✓	✓	✓
Observations	3,815,232	3,815,232	3,815,232	3,815,232	3,815,232	3,815,232
Clusters	2,172	2,172	2,172	2,172	2,172	2,172

Panel B. OLS regressions

	Crop choice				*Summary measures*	
	High-water	Low-water	High-value	Low-value	Water needs	Crop revenue
	(linear probability)				*(inverse hyperbolic sine)*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Supply)	0.000	0.018 *	0.016 **	0.003	0.026 *	0.133
	(0.008)	(0.010)	(0.008)	(0.004)	(0.016)	(0.085)
Field fixed effects	✓	✓	✓	✓	✓	✓
Year effects	✓	✓	✓	✓	✓	✓
Observations	3,815,232	3,815,232	3,815,232	3,815,232	3,815,229	3,459,809
Clusters	2,172	2,172	2,172	2,172	2,172	2,165

See notes for Table 2. In this table, estimates come from ordinary least squares regressions instead of instrumental variables.

Table C4: Long-run effects of water availability (with a rectangular kernel)

Panel A. Rectangular kernel

	Land use (categories sum to one)				*Crop choice*	
	Crops planted	Fallow	Grassland	Natural uses	Annual crops	Perennial crops
	(linear probability)				*(linear probability)*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Mean Supply)						
Bandwidth: 25 km	0.076 ***	-0.009	-0.065 ***	-0.002	0.039 **	0.037
	(0.026)	(0.015)	(0.023)	(0.005)	(0.019)	(0.026)
Bandwidth: 10 km	0.055 ***	-0.015	-0.040 ***	0.000	0.046 **	0.009
	(0.018)	(0.016)	(0.013)	(0.005)	(0.020)	(0.016)
Bandwidth: 5 km	0.045 ***	-0.010	-0.036 ***	0.001	0.030	0.015
	(0.017)	(0.016)	(0.010)	(0.005)	(0.019)	(0.014)
Border pair × border segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment × More	✓	✓	✓	✓	✓	✓
Latitude × pair × segment	✓	✓	✓	✓	✓	✓
Longitude × pair × segment	✓	✓	✓	✓	✓	✓
Observations (10 km bandwidth)	543,541	543,541	543,541	543,541	543,541	543,541
Clusters	180	180	180	180	180	180

Panel B. Rectangular kernel

	Crop choice				*Summary measures*	
	High-water	Low-water	High-value	Low-value	Water needs	Crop revenue
	(linear probability)				*(inverse hyperbolic sine)*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Mean Supply)						
Bandwidth: 25 km	0.060 **	0.016	0.033	0.043 **	0.186 ***	0.457 ***
	(0.027)	(0.015)	(0.028)	(0.017)	(0.057)	(0.171)
Bandwidth: 10 km	0.032	0.024	0.002	0.054 ***	0.131 ***	0.338 **
	(0.019)	(0.015)	(0.019)	(0.016)	(0.041)	(0.141)
Bandwidth: 5 km	0.028	0.016	0.002	0.042 ***	0.110 ***	0.270 **
	(0.017)	(0.014)	(0.019)	(0.016)	(0.037)	(0.135)
Border pair × border segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment × More	✓	✓	✓	✓	✓	✓
Latitude × pair × segment	✓	✓	✓	✓	✓	✓
Longitude × pair × segment	✓	✓	✓	✓	✓	✓
Observations (10 km bandwidth)	543,541	543,541	543,541	543,541	543,541	543,011
Clusters	180	180	180	180	180	180

See notes for Table 3. In this table, a rectangular kernel is used instead of a triangular kernel.

Table C5: Long-run effects of water availability (without controls for longitude and latitude)

Panel A. Not controlling for latitude and longitude

	Land use (categories sum to one)				*Crop choice*	
	Crops planted	Fallow	Grassland	Natural uses	Annual crops	Perennial crops
	(linear probability)				*(linear probability)*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Mean Supply)						
Bandwidth: 25 km	0.063 ***	-0.011	-0.053 ***	0.001	0.037 *	0.026
	(0.020)	(0.014)	(0.017)	(0.004)	(0.019)	(0.020)
Bandwidth: 10 km	0.049 ***	-0.012	-0.038 ***	0.001	0.039 **	0.010
	(0.017)	(0.015)	(0.011)	(0.005)	(0.018)	(0.015)
Bandwidth: 5 km	0.039 ***	-0.010	-0.030 ***	0.001	0.031 *	0.008
	(0.015)	(0.014)	(0.010)	(0.005)	(0.018)	(0.013)
Border pair × border segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment × More	✓	✓	✓	✓	✓	✓
Latitude × pair × segment						
Longitude × pair × segment						
Observations (10 km bandwidth)	543,541	543,541	543,541	543,541	543,541	543,541
Clusters	180	180	180	180	180	180

Panel B. Not controlling for latitude and longitude

	Crop choice				*Summary measures*	
	High-water	Low-water	High-value	Low-value	Water needs	Crop revenue
	(linear probability)				*(inverse hyperbolic sine)*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Mean Supply)						
Bandwidth: 25 km	0.047 **	0.015	0.015	0.048 ***	0.155 ***	0.379 ***
	(0.021)	(0.014)	(0.022)	(0.016)	(0.044)	(0.142)
Bandwidth: 10 km	0.029	0.020	-0.002	0.051 ***	0.119 ***	0.302 **
	(0.018)	(0.013)	(0.018)	(0.015)	(0.037)	(0.131)
Bandwidth: 5 km	0.024	0.015	-0.003	0.042 ***	0.097 ***	0.233 *
	(0.016)	(0.013)	(0.017)	(0.014)	(0.033)	(0.120)
Border pair × border segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment × More	✓	✓	✓	✓	✓	✓
Latitude × pair × segment						
Longitude × pair × segment						
Observations (10 km bandwidth)	543,541	543,541	543,541	543,541	543,541	543,011
Clusters	180	180	180	180	180	180

See notes for Table 3. In this table, running variables in latitude and longitude are omitted.

Table C6: Long-run effects of water availability (without controlling for border segment)

Panel A. No border segments (only pair fixed effects)

	Land use (categories sum to one)				*Crop choice*	
	Crops planted	Fallow	Grassland	Natural uses	Annual crops	Perennial crops
	(linear probability)				*(linear probability)*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Mean Supply)						
Bandwidth: 25 km	0.058 **	0.000	-0.053 ***	-0.005	0.044 **	0.014
	(0.023)	(0.015)	(0.020)	(0.004)	(0.020)	(0.022)
Bandwidth: 10 km	0.042 ***	-0.001	-0.040 ***	-0.001	0.036 **	0.006
	(0.015)	(0.014)	(0.012)	(0.005)	(0.017)	(0.015)
Bandwidth: 5 km	0.029 **	0.001	-0.029 ***	-0.001	0.030 *	-0.001
	(0.014)	(0.014)	(0.009)	(0.005)	(0.017)	(0.012)
Border pair	✓	✓	✓	✓	✓	✓
Distance × pair	✓	✓	✓	✓	✓	✓
Distance × pair × More	✓	✓	✓	✓	✓	✓
Latitude × pair	✓	✓	✓	✓	✓	✓
Longitude × pair	✓	✓	✓	✓	✓	✓
Observations (10 km bandwidth)	543,932	543,932	543,932	543,932	543,932	543,932
Clusters	180	180	180	180	180	180

Panel B. No border segments (only pair fixed effects)

	Crop choice				*Summary measures*	
	High-water	Low-water	High-value	Low-value	Water needs	Crop revenue
	(linear probability)				*(inverse hyperbolic sine)*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Mean Supply)						
Bandwidth: 25 km	0.042 *	0.017	0.005	0.053 ***	0.143 ***	0.342 **
	(0.023)	(0.014)	(0.024)	(0.018)	(0.050)	(0.159)
Bandwidth: 10 km	0.027	0.015	-0.003	0.045 ***	0.108 ***	0.249 **
	(0.017)	(0.013)	(0.016)	(0.014)	(0.035)	(0.118)
Bandwidth: 5 km	0.012	0.017	-0.008	0.037 ***	0.074 **	0.154
	(0.014)	(0.012)	(0.015)	(0.014)	(0.030)	(0.106)
Border pair	✓	✓	✓	✓	✓	✓
Distance × pair	✓	✓	✓	✓	✓	✓
Distance × pair × More	✓	✓	✓	✓	✓	✓
Latitude × pair	✓	✓	✓	✓	✓	✓
Longitude × pair	✓	✓	✓	✓	✓	✓
Observations (10 km bandwidth)	543,932	543,932	543,932	543,932	543,932	543,402
Clusters	180	180	180	180	180	180

See notes for Table 3. In this table, regression discontinuities are performed at the level of border pairs (district pair× county×dominant soil order) instead of border pair×border segment.

Table C7: Long-run effects of water availability (using smaller border segments)

Panel A. Smaller border segments (2 km)

	Land use (categories sum to one)				*Crop choice*	
	Crops planted	Fallow	Grassland	Natural uses	Annual crops	Perennial crops
	(linear probability)				*(linear probability)*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Mean Supply)						
Bandwidth: 25 km	0.053 **	0.000	-0.058 ***	0.005	0.030	0.023
	(0.023)	(0.020)	(0.020)	(0.007)	(0.020)	(0.018)
Bandwidth: 10 km	0.044 **	-0.001	-0.046 ***	0.004	0.029	0.015
	(0.021)	(0.021)	(0.014)	(0.007)	(0.020)	(0.016)
Bandwidth: 5 km	0.038 **	-0.001	-0.038 ***	0.001	0.022	0.016
	(0.019)	(0.020)	(0.011)	(0.007)	(0.021)	(0.014)
Border pair × border segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment × More	✓	✓	✓	✓	✓	✓
Latitude × pair × segment	✓	✓	✓	✓	✓	✓
Longitude × pair × segment	✓	✓	✓	✓	✓	✓
Observations (10 km bandwidth)	542,979	542,979	542,979	542,979	542,979	542,979
Clusters	180	180	180	180	180	180

Panel B. Smaller border segments (2 km)

	Crop choice				*Summary measures*	
	High-water	Low-water	High-value	Low-value	Water needs	Crop revenue
	(linear probability)				*(inverse hyperbolic sine)*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Mean Supply)						
Bandwidth: 25 km	0.041 *	0.012	0.009	0.045 ***	0.131 **	0.282
	(0.023)	(0.013)	(0.024)	(0.017)	(0.053)	(0.173)
Bandwidth: 10 km	0.032	0.012	0.000	0.044 ***	0.112 **	0.239
	(0.022)	(0.013)	(0.022)	(0.016)	(0.050)	(0.174)
Bandwidth: 5 km	0.031	0.007	-0.002	0.040 **	0.101 **	0.208
	(0.020)	(0.014)	(0.021)	(0.016)	(0.043)	(0.155)
Border pair × border segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment × More	✓	✓	✓	✓	✓	✓
Latitude × pair × segment	✓	✓	✓	✓	✓	✓
Longitude × pair × segment	✓	✓	✓	✓	✓	✓
Observations (10 km bandwidth)	542,979	542,979	542,979	542,979	542,979	542,449
Clusters	180	180	180	180	180	180

See notes for Table 3. In this table, border segments are defined as two-kilometer grid cells, instead of five-kilometer grid cells.

Table C8: Long-run effects of water availability (using pre-sample water allocations)

Panel A. Pre-sample instrument

	Land use (categories sum to one)				*Crop choice*	
	Crops planted	Fallow	Grassland	Natural uses	Annual crops	Perennial crops
	(linear probability)				*(linear probability)*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Mean Supply)						
Bandwidth: 25 km	0.044 **	0.003	-0.047 ***	0.000	0.022	0.022
	(0.020)	(0.015)	(0.018)	(0.005)	(0.019)	(0.020)
Bandwidth: 10 km	0.029 *	0.001	-0.031 ***	0.001	0.029	0.000
	(0.017)	(0.015)	(0.011)	(0.005)	(0.020)	(0.013)
Bandwidth: 5 km	0.033 **	-0.005	-0.029 ***	0.000	0.028	0.005
	(0.016)	(0.015)	(0.009)	(0.005)	(0.020)	(0.012)
Border pair × border segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment × More	✓	✓	✓	✓	✓	✓
Latitude × pair × segment	✓	✓	✓	✓	✓	✓
Longitude × pair × segment	✓	✓	✓	✓	✓	✓
Observations (10 km bandwidth)	543,541	543,541	543,541	543,541	543,541	543,541
Clusters	180	180	180	180	180	180

Panel B. Pre-sample instrument

	Crop choice				*Summary measures*	
	High-water	Low-water	High-value	Low-value	Water needs	Crop revenue
	(linear probability)				*(inverse hyperbolic sine)*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Mean Supply)						
Bandwidth: 25 km	0.026	0.017	0.007	0.036 **	0.110 **	0.232
	(0.021)	(0.015)	(0.023)	(0.016)	(0.044)	(0.143)
Bandwidth: 10 km	0.003	0.026 *	-0.015	0.044 ***	0.068 *	0.143
	(0.017)	(0.014)	(0.018)	(0.015)	(0.036)	(0.132)
Bandwidth: 5 km	0.005	0.029 **	-0.008	0.042 ***	0.073 **	0.188
	(0.016)	(0.013)	(0.017)	(0.016)	(0.034)	(0.123)
Border pair × border segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment × More	✓	✓	✓	✓	✓	✓
Latitude × pair × segment	✓	✓	✓	✓	✓	✓
Longitude × pair × segment	✓	✓	✓	✓	✓	✓
Observations (10 km bandwidth)	543,541	543,541	543,541	543,541	543,541	543,011
Clusters	180	180	180	180	180	180

See notes for Table 3. In this table, the instrument (the "More" indicator for the district of each pair that has relatively greater water allocations) is defined using mean water allocations over 1993-2006, instead of 2007-2018.

Table C9: Long-run effects of water availability (using pre-sample water allocations and supplies)

Panel A. Pre-sample treatment variable and instrument

	Land use (categories sum to one)				*Crop choice*	
	Crops planted	Fallow	Grassland	Natural uses	Annual crops	Perennial crops
	(linear probability)				*(linear probability)*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Mean Supply, 1993-2006)						
Bandwidth: 25 km	0.046 **	0.004	-0.050 ***	0.000	0.023	0.023
	(0.021)	(0.016)	(0.019)	(0.005)	(0.020)	(0.021)
Bandwidth: 10 km	0.031 *	0.001	-0.033 ***	0.001	0.030	0.000
	(0.018)	(0.016)	(0.012)	(0.005)	(0.021)	(0.014)
Bandwidth: 5 km	0.035 **	-0.005	-0.031 ***	0.000	0.030	0.006
	(0.017)	(0.016)	(0.010)	(0.006)	(0.021)	(0.013)
Border pair × border segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment × More	✓	✓	✓	✓	✓	✓
Latitude × pair × segment	✓	✓	✓	✓	✓	✓
Longitude × pair × segment	✓	✓	✓	✓	✓	✓
Observations (10 km bandwidth)	543,541	543,541	543,541	543,541	543,541	543,541
Clusters	180	180	180	180	180	180

Panel B. Pre-sample treatment variable and instrument

	Crop choice				*Summary measures*	
	High-water	Low-water	High-value	Low-value	Water needs	Crop revenue
	(linear probability)				*(inverse hyperbolic sine)*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Mean Supply, 1993-2006)						
Bandwidth: 25 km	0.028	0.018	0.008	0.038 **	0.115 **	0.244
	(0.022)	(0.015)	(0.024)	(0.017)	(0.046)	(0.151)
Bandwidth: 10 km	0.003	0.028 *	-0.016	0.047 ***	0.072 *	0.152
	(0.018)	(0.015)	(0.019)	(0.016)	(0.038)	(0.141)
Bandwidth: 5 km	0.005	0.031 **	-0.009	0.044 ***	0.077 **	0.199
	(0.017)	(0.014)	(0.018)	(0.016)	(0.036)	(0.131)
Border pair × border segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment × More	✓	✓	✓	✓	✓	✓
Latitude × pair × segment	✓	✓	✓	✓	✓	✓
Longitude × pair × segment	✓	✓	✓	✓	✓	✓
Observations (10 km bandwidth)	543,541	543,541	543,541	543,541	543,541	543,011
Clusters	180	180	180	180	180	180

See notes for Table 3. In this table, both the treatment variable (the natural log of mean water supply) and the instrument (the "More" indicator for the district of each pair that has relatively greater water allocations) are defined using means over 1993-2006, instead of 2007-2018.

Table C10: Long-run effects of water availability (using only close neighbor pairs)

Panel A. Only close neighbor pairs (each side has data within one quarter section [0.57 km])

	Land use (categories sum to one)				*Crop choice*	
	Crops planted	Fallow	Grassland	Natural uses	Annual crops	Perennial crops
	(linear probability)				*(linear probability)*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Mean Supply)						
Bandwidth: 25 km	0.066 ***	-0.005	-0.058 ***	-0.002	0.032	0.034
	(0.022)	(0.016)	(0.019)	(0.005)	(0.020)	(0.022)
Bandwidth: 10 km	0.051 ***	-0.012	-0.038 ***	0.000	0.035 *	0.016
	(0.018)	(0.016)	(0.011)	(0.005)	(0.020)	(0.015)
Bandwidth: 5 km	0.044 ***	-0.013	-0.031 ***	-0.001	0.032 *	0.012
	(0.016)	(0.015)	(0.010)	(0.005)	(0.019)	(0.013)
Border pair × border segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment × More	✓	✓	✓	✓	✓	✓
Latitude × pair × segment	✓	✓	✓	✓	✓	✓
Longitude × pair × segment	✓	✓	✓	✓	✓	✓
Observations (10 km bandwidth)	325,377	325,377	325,377	325,377	325,377	325,377
Clusters	165	165	165	165	165	165

Panel B. Only close neighbor pairs (each side has data within one quarter section [0.57 km])

	Crop choice				*Summary measures*	
	High-water	Low-water	High-value	Low-value	Water needs	Crop revenue
	(linear probability)				*(inverse hyperbolic sine)*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Mean Supply)						
Bandwidth: 25 km	0.052 **	0.014	0.014	0.052 ***	0.163 ***	0.376 **
	(0.023)	(0.015)	(0.024)	(0.017)	(0.050)	(0.161)
Bandwidth: 10 km	0.032 *	0.019	0.005	0.046 ***	0.124 ***	0.319 **
	(0.018)	(0.014)	(0.018)	(0.016)	(0.040)	(0.142)
Bandwidth: 5 km	0.024	0.021	0.001	0.043 ***	0.106 ***	0.275 **
	(0.016)	(0.013)	(0.017)	(0.015)	(0.035)	(0.124)
Border pair × border segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment × More	✓	✓	✓	✓	✓	✓
Latitude × pair × segment	✓	✓	✓	✓	✓	✓
Longitude × pair × segment	✓	✓	✓	✓	✓	✓
Observations (10 km bandwidth)	325,377	325,377	325,377	325,377	325,377	324,971
Clusters	165	165	165	165	165	165

See notes for Table 3. In this table, estimates include only border pairs that have data within one half diagonal of one quarter section (0.57 km) on each side of the border.

Table C11: Long-run effects of water availability (OLS regressions)

Panel A. OLS regressions

	Land use (categories sum to one)				*Crop choice*	
	Crops planted	Fallow	Grassland	Natural uses	Annual crops	Perennial crops
	(linear probability)				*(linear probability)*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Mean Supply)						
Bandwidth: 25 km	0.055 ***	-0.024 ***	-0.029 ***	-0.002	0.047 ***	0.007
	(0.013)	(0.007)	(0.011)	(0.004)	(0.012)	(0.012)
Bandwidth: 10 km	0.047 ***	-0.027 ***	-0.019 ***	-0.001	0.048 ***	-0.001
	(0.009)	(0.006)	(0.006)	(0.004)	(0.011)	(0.008)
Bandwidth: 5 km	0.050 ***	-0.030 ***	-0.020 ***	0.000	0.051 ***	-0.001
	(0.009)	(0.006)	(0.006)	(0.004)	(0.010)	(0.008)
Border pair × border segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment × More	✓	✓	✓	✓	✓	✓
Latitude × pair × segment	✓	✓	✓	✓	✓	✓
Longitude × pair × segment	✓	✓	✓	✓	✓	✓
Observations (10 km bandwidth)	543,541	543,541	543,541	543,541	543,541	543,541
Clusters	180	180	180	180	180	180

Panel B. OLS regressions

	Crop choice				*Summary measures*	
	High-water	Low-water	High-value	Low-value	Water needs	Crop revenue
	(linear probability)				*(inverse hyperbolic sine)*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Mean Supply)						
Bandwidth: 25 km	0.030 **	0.024 *	0.016	0.039 ***	0.129 ***	0.379 ***
	(0.013)	(0.013)	(0.015)	(0.014)	(0.026)	(0.092)
Bandwidth: 10 km	0.021 **	0.026 **	0.005	0.042 ***	0.112 ***	0.337 ***
	(0.009)	(0.011)	(0.010)	(0.011)	(0.019)	(0.073)
Bandwidth: 5 km	0.026 ***	0.024 **	0.007	0.043 ***	0.116 ***	0.345 ***
	(0.009)	(0.010)	(0.010)	(0.011)	(0.017)	(0.069)
Border pair × border segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment × More	✓	✓	✓	✓	✓	✓
Latitude × pair × segment	✓	✓	✓	✓	✓	✓
Longitude × pair × segment	✓	✓	✓	✓	✓	✓
Observations (10 km bandwidth)	543,541	543,541	543,541	543,541	543,541	543,011
Clusters	180	180	180	180	180	180

See notes for Table 3. In this table, regressions are estimated by ordinary least squares instead of instrumental variables.

Table C12: Long-run effects of water availability (excluding a narrow "donut hole" around the border)

Panel A. Excluding observations within one quarter-section of the border (0.57 km)

	Land use (categories sum to one)				*Crop choice*	
	Crops planted	Fallow	Grassland	Natural uses	Annual crops	Perennial crops
	(linear probability)				*(linear probability)*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Mean Supply)						
Bandwidth: 25 km	0.077 ***	-0.011	-0.062 **	-0.004	0.035 *	0.042
	(0.027)	(0.014)	(0.026)	(0.005)	(0.019)	(0.028)
Bandwidth: 10 km	0.058 ***	-0.018	-0.040 ***	0.000	0.048 **	0.010
	(0.020)	(0.016)	(0.015)	(0.005)	(0.021)	(0.021)
Bandwidth: 5 km	0.055 ***	-0.027 *	-0.027 **	-0.001	0.035 *	0.020
	(0.019)	(0.016)	(0.013)	(0.007)	(0.021)	(0.021)
Border pair × border segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment × More	✓	✓	✓	✓	✓	✓
Latitude × pair × segment	✓	✓	✓	✓	✓	✓
Longitude × pair × segment	✓	✓	✓	✓	✓	✓
Observations (10 km bandwidth)	520,002	520,002	520,002	520,002	520,002	520,002
Clusters	180	180	180	180	180	180

Panel B. Excluding observations within one quarter-section of the border (0.57 km)

	Crop choice				*Summary measures*	
	High-water	Low-water	High-value	Low-value	Water needs	Crop revenue
	(linear probability)				*(inverse hyperbolic sine)*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Mean Supply)						
Bandwidth: 25 km	0.068 **	0.009	0.033	0.044 **	0.194 ***	0.483 ***
	(0.028)	(0.016)	(0.030)	(0.019)	(0.059)	(0.171)
Bandwidth: 10 km	0.038 *	0.020	0.002	0.056 ***	0.143 ***	0.382 **
	(0.023)	(0.016)	(0.023)	(0.020)	(0.045)	(0.152)
Bandwidth: 5 km	0.044 **	0.011	0.010	0.045 **	0.140 ***	0.418 ***
	(0.022)	(0.017)	(0.024)	(0.020)	(0.043)	(0.154)
Border pair × border segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment × More	✓	✓	✓	✓	✓	✓
Latitude × pair × segment	✓	✓	✓	✓	✓	✓
Longitude × pair × segment	✓	✓	✓	✓	✓	✓
Observations (10 km bandwidth)	520,002	520,002	520,002	520,002	520,002	519,515
Clusters	180	180	180	180	180	180

See notes for Table 3. In this table, estimates exclude observations within the half diagonal of one quarter section (0.57 km).

Table C13: Long-run effects of water availability (excluding a wider "donut hole" around the border)

Panel A. Excluding observations within one section of the border (1.14 km)

	Land use (categories sum to one)				Crop choice	
	Crops planted	Fallow	Grassland	Natural uses	Annual crops	Perennial crops
	(linear probability)				(linear probability)	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Mean Supply)						
Bandwidth: 25 km	0.082 **	0.004	-0.083 **	-0.004	0.020	0.063 *
	(0.034)	(0.015)	(0.037)	(0.006)	(0.019)	(0.035)
Bandwidth: 10 km	0.052 **	-0.004	-0.054 **	0.005	0.041 *	0.011
	(0.023)	(0.016)	(0.021)	(0.006)	(0.024)	(0.027)
Bandwidth: 5 km	0.047 *	-0.012	-0.045 **	0.010	-0.002	0.050
	(0.026)	(0.020)	(0.019)	(0.007)	(0.029)	(0.031)
Border pair × border segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment × More	✓	✓	✓	✓	✓	✓
Latitude × pair × segment	✓	✓	✓	✓	✓	✓
Longitude × pair × segment	✓	✓	✓	✓	✓	✓
Observations (10 km bandwidth)	490,921	490,921	490,921	490,921	490,921	490,921
Clusters	179	179	179	179	179	179

Panel B. Excluding observations within one section of the border (1.14 km)

	Crop choice				Summary measures	
	High-water	Low-water	High-value	Low-value	Water needs	Crop revenue
	(linear probability)				(inverse hyperbolic sine)	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Ln (Mean Supply)						
Bandwidth: 25 km	0.085 **	-0.003	0.059	0.023	0.216 ***	0.492 **
	(0.035)	(0.018)	(0.037)	(0.021)	(0.076)	(0.201)
Bandwidth: 10 km	0.041	0.011	0.005	0.047 **	0.137 **	0.293 *
	(0.028)	(0.019)	(0.028)	(0.022)	(0.053)	(0.166)
Bandwidth: 5 km	0.071 **	-0.023	0.032	0.015	0.147 **	0.330
	(0.031)	(0.025)	(0.032)	(0.026)	(0.061)	(0.214)
Border pair × border segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment	✓	✓	✓	✓	✓	✓
Distance × pair × segment × More	✓	✓	✓	✓	✓	✓
Latitude × pair × segment	✓	✓	✓	✓	✓	✓
Longitude × pair × segment	✓	✓	✓	✓	✓	✓
Observations (10 km bandwidth)	490,921	490,921	490,921	490,921	490,921	490,500
Clusters	179	179	179	179	179	179

See notes for Table 3. In this table, estimates exclude observations within the half diagonal of one section (1.14 km).