Farmer Response to Policy Induced Water Reductions: Evidence from the Colorado River

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Abstract

Surface water supplies are becoming increasingly strained pushing policy makers to find solutions to facilitate reductions in water use, though there is limited evidence on how farmers respond to policy driven reductions in surface water supplies. This paper uses a difference-in-differences framework to compare the response of farmers to a bundle of policies reducing deliveries from the Colorado River by 35%. I find that on average, farmers reduce the amount of land planted but plant more water intensive crops leading to a net zero effect on total estimated water use compared to the counterfactual. The average effect hides important heterogeneity by estimated groundwater costs, with those in areas with more expensive groundwater experiencing larger changes in production and water use. Overall the results suggest that farmers are using groundwater to offset a significant amount of the surface water loss. These findings have important consequences for understanding the relative tradeoffs policy makers face when implementing policies that protect surface water sources.

Keywords: agricultural production, drought, surface water, groundwater, water policy.

JEL Codes: Q15, Q25, Q28, Q38, Q54.

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1 Introduction

Surface water supplies are becoming increasingly strained as growing population increases demand while climate change reduces supply. Policy makers are facing increased urgency in dealing with surface water scarcity, because surface water supplies water to residents in some of the largest cities and over 20 million acres of agriculture in the US alone (NASS, 2018). Concern over growing scarcity has led to an increase in policy interventions aimed at reducing surface water use, though there is little empirical evidence about the direct consequences of the possible policy choices.

This paper examines the agricultural consequences of a bundle of policies implemented to reduce the use of surface water from the Colorado River. The Colorado River is a relevant context, as it is both highly over-allocated and an important water source for much of the American Southwest. About 85% of its water irrigates 5.5 million acres of farmland while the remaining water supplies over 10 million people in major cities such as Los Angeles, San Diego, Las Vegas and Tijuana (Maupin, Ivahnenko, and Bruce, 2018).

The analysis in this paper relies on a natural experiment, where a subset of Arizona farmers experienced a bundle of policy shocks which reduced the volume of water deliveries from the Colorado River to these farmers by 35% from 2015-2021. In response to the policy induced changes in water supplies, farmers may adapt by changing how they use water by adjusting the amount of land planted, the types of crops planted, and the amount of water used per crop. They may also adapt by drilling new groundwater wells to substitute the forgone surface water. An interesting aspect of the setting of this natural experiment is that the bundle of policies was actually two distinct policies: 1. a reduction in surface water prices in exchange for a reduction in water deliveries from 2015-2019 (here on denoted as the Forbearance program), which was then completely replaced by 2. a quantity restriction on surface water supplies in 2020-2021 (here on denoted the Federal Restriction program). Under both policies, preexisting minimum delivery requirements were removed.

Due to historic policies surrounding water rights, only the one subset of farmers was subject to both policy shocks, and comparable farmers elsewhere in Arizona and California were unaffected. This natural experiment lends itself to a difference-in-differences methodology. Using this framework, I examine how farmers respond to the reduction in surface water deliveries directly through changes in the amount and types of crops planted and the number of groundwater wells drilled. I additionally use heterogeneity by estimated groundwater costs to indirectly provide evidence on groundwater substitution.

I find that in contrast with the large reduction in surface water deliveries, on average there was a limited impact on water use. On average, the estimated water used per acre was unaffected by the reduction in surface water since water savings from reductions in the amount of land planted (9 percentage points) were offset by increases in the amount of alfalfa (a relatively water intensive crop) planted. These average changes in production hide important effect heterogeneity driven by access to groundwater. Farmers with access to relatively cheap groundwater appear to have been minimally impacted on average compared to those with relatively high groundwater costs, who instead reduced both the amount and water-intensity of the crops that were planted. Those with high cost groundwater experienced a statistically insignificant reduction in water use of 4.1 inches per acre relative to those with low groundwater costs.

This paper contributes to existing work by presenting new evidence on how farmers respond to policies regulating surface water access. Much of the previous work on adaptation to surface water scarcity has relied on identification from short term, inter-annual variation in precipitation (Manning, Goemans, and Maas, 2017; Ji and Cobourn, 2018; Xie et al., 2019; Cobourn et al., 2021; Hagerty, 2021), instead of anticipated policy implementation. Because the policy shock exposes farmers to less uncertainty, they may be able to more fully offset the expected surface water loss and resulting output loss. However, I find a similar response under the policy-induced variation for fallowing (19% increase) but much larger effect for cropped land (22% decrease) as Hagerty (2021) finds for precipitation induced variation for farmers in California (a 26% increase in fallowing and 4% decrease in cropped land for a 33% reduction in surface water supply). Other research on surface water scarcity has focused on adaptation to long-run, gradual changes in water access (Burke and Emerick, 2016; Hornbeck and Keskin, 2014; Fishman, Jain, and Kishore, 2019; Smith, 2021; Feng, Oppenheimer, and Schlenker, 2012; Gray and Wise, 2016; Nawrotzki et al., 2017; Blakeslee, Fishman, and Srinivasan, 2020) as opposed to sudden shocks, while I am able to identify farmer adaptation to a sudden, anticipated change in water access.

Additionally, this paper is able to compare the relative merits of two different policy approaches aimed at reducing surface water demand in a fixed context. To my knowledge there is no empirical evidence directly comparing how farmers respond to different policies regulating surface water access. Existing research has instead focused on understanding farmer response to singular policies regulating water access, either through pricing (Fishman et al., 2016; Smith et al., 2017; Hrozencik et al., 2021; Burlig, Preonas, and Woerman, 2021) or quota restrictions (Drysdale and Hendricks, 2018), making direct comparison difficult since the contexts of each are different. While consideration needs to be given to the sequential nature of the policies examined in this analysis, it is still relevant and informative to compare the different outcomes since the set of exposed farmers, concurrent policies, and resulting water reductions are identical across the two.

Lastly, this paper contributes to the existing literature by quantifying the effects of the Forbearance Program and Federal Restriction. The main result finds a null effect on estimated total water use under the programs, and there is suggestive evidence that this is due to substitution to groundwater. Previous work has already shown that groundwater plays a valuable role in smoothing surface water shocks (Tsur and Tomasi, 1991; Mukherjee and Schwabe, 2015). Additionally, while groundwater substitution has already been acknowledged by stakeholders, the quantification of the effects by this paper are important for the discussion on how to regulate water moving forward.

Details of the policies and historical context used for identification are presented in section 2. Data and the empirical methodology are outlined in section 3. The main results are presented in section 4 and discussed in section 5. Section 6 concludes.

2 Background

2.1 Central Arizona Project

The construction of the Central Arizona Project (CAP), a 336 mile long canal from the Colorado River to central Arizona was approved in 1968. The goal for the canal was to bring about 1.6 million acre-feet[1] (AF) of water to central Arizona to supply growing urban areas and reduce groundwater extraction by agricultural users (CAP, 2016a). In 1973, the Central Arizona Water Conservation District (CAWCD) was established to manage CAP water supplies and repay the federal government for CAP construction costs. CAP construction was completed in 1993.

To enforce reductions in groundwater use, two stipulations were attached to CAP water access with regards to groundwater. The first was that CAP recipients were not allowed to pump groundwater from within the service area for use outside of the service area (CAP, 2016a). The second was that users must use their entire allotment of "reasonably available" CAP water before being able to use groundwater (CAP, 2002). In combination, these two policies limited the availability of groundwater access for farmers in the CAP service area.

CAWCD defines its service area as three counties: Pima, Pinal, and Maricopa. Within these three counties, CAP delivers water to Native Nations, municipal systems, industrial users, and 15 primary irrigation districts (Ikeya, 2021). Irrigation districts are regional organizations who coordinate water deliveries from CAP to end use farmers and manage infrastructure (e.g. canals, pumps, and wells), benefiting from economies of scale. CAWCD allocates water to irrigation districts based on the number of CAP eligible acres in the irrigation district, with CAP eligibility defined by being irrigated between 1958 and 1968 (CAP, 2016a). While there are 15 irrigation districts CAWCD identifies as consistently serving, the number of districts served is subject to water availability and demand, with more or fewer irrigation districts receiving water in any given year.

Originally, irrigation districts were entitled to a fixed share of CAP water, but the price of this water was unaffordable for irrigation districts (CAP, 2016a). The Arizona Water Settlement Act of 2004 renegotiated water diversions to provide cheaper, but not guaranteed, water to irrigation districts. Since 2004 irrigation districts are entitled to "Ag Pool" water, which is the leftover part of Arizona's allotment of Colorado River water after all other entitlements (Native Nations, municipal, and industrial) have been filled. Irrigation districts

[1] An acre-foot of water is the volume of water required to cover an acre of land in water to a depth of one foot.

are charged delivery rates per AF by CAWCD to offset the energy costs for delivery (CAP, 2016a). The Ag Pool water supply from 2004 to 2014 was consistently around 400,000 AF (CAP, 2023).

The delivery process of water within irrigation districts to farmers is heterogeneous. In the largest district, the Maricopa-Stanfield Irrigation and Drainage District, farmers order water deliveries from the district, constrained by an annual allotment which is determined by previous use and acreage, and pay per AF an almost equivalent rate that the district is charged (MSIDD, 2021a; MSIDD, 2021b). In San Carlos Irrigation and Drainage District, farmers receive water from both CAP and the San Carlos Reservoir, with CAP water being available only to farms with at least 5 acres of land. Additionally, farmers are required to purchase their full allotment of Colorado River water and are charged at a mark up per acre of land (SCIDD, 2022). Under drought conditions, the Maricopa-Stanfield Irrigation and Drainage District reports drilling new groundwater wells and rehabilitating old wells, while the San Carlos Irrigation and Drainage District reports relying on water in the San Carlos Reservoir (MSIDD, 2021b; SCIDD, 2022).

2.2 Forbearance Program

In 2014, CAWCD announced the start of the Ag Pool Forbearance Program, beginning in 2015. The goal of the program was to reduce use of Ag Pool water and leave the forgone supplies in Lake Mead to help buffer declining lake levels due to drought (CAP, 2017). Under the Forbearance Program, districts who had used their entire CAP allotment in four of the five preceding years could agree to reduce their water deliveries. In exchange, these districts would receive reduced costs on the water that they did receive, and had the stipulation that they must use all of their allotted CAP water before any groundwater waived (Ikeya, 2021).

The Forbearance Program consisted of five separate phases, each of which offered a variation of reductions in CAP deliveries in exchange for discounts on remaining deliveries (Appendix Table A3 outlines the differences in the phases). The first phase, Ag Forbearance 1, was implemented between 2015 and 2016. Under this stage, irrigation districts agreed to forbear at least 23% of their CAP allotment and at most the lesser of 75% or 20,000 AF of their allotment. In exchange for reducing deliveries, the districts would receive reduced pumping charges on their remaining deliveries of \$36/AF and \$38/AF in 2015 and 2016 respectively (CAP, 2014). 12 irrigation districts participated. The Ag Forbearance 2 Program was also implemented in 2016, allowing participants in Ag Forbearance 1 to further reduce deliveries by 12% in 2016 in exchange for a discount of \$8/AF on deliveries in 2017 and 2018 (CAP, 2015).

Additionally, Ag Forbearance 3 was initially implemented in 2016, but was then extended indefinitely. In contrast to programs 1 and 2, Ag Forbearance 3 offered no compensation to participating districts but allowed districts to reduce their CAP water deliveries to zero (CAP, 2016b). In essence, this program waived the requirement that CAP recipients use their full allotment of "reasonably available" Ag Pool water before being able to use groundwater. 9 irrigation districts participated in Ag Forbearance 3 to some degree.

In 2018, both Ag Forbearance 4 and Ag Forbearance 5 were made available for districts who had participated in the previous forbearance programs and who still had water to forbear (4 districts). Ag Forbearance 4 offered a discount in 2019 delivery rates by \$7/AF in exchange for a reduction in deliveries equal to the lesser of 2.5% or 2,000 AF in both 2018 and 2019 (CAP, 2017). Forbearance 5 similarly offered a discount of \$4/AF for the following two years in exchange for a total reduction on 10,000 AF in 2018. Ag Forbearance 5 was also implemented in 2019, though no districts participated. The Ag Forbearance 5 agreement stipulated that in the event of a Federal Shortage announcement on the Colorado River in 2020 irrigation districts would be refunded the amount equal to the total pumping energy charge they would have received in 2020 (CAP, 2018).

While each phase of the larger Forbearance Program was heterogeneous in implementation, the policy approach was consistent between 2015 and 2019. Irrigation districts were allowed to voluntarily reduce water deliveries via CAP. In exchange they received discounted delivery rates on the water they did receive. Additionally starting in 2016, irrigation districts were not required to use their full CAP allotment before using alternative, potentially cheaper water sources. The reduction in deliveries to CAP Ag Pool users over time starting in 2015 is highlighted in Figure 1, which shows volumes of annual Ag Pool water delivered via CAP (CAP, 2023).

Figure 1: CAP Water Deliveries

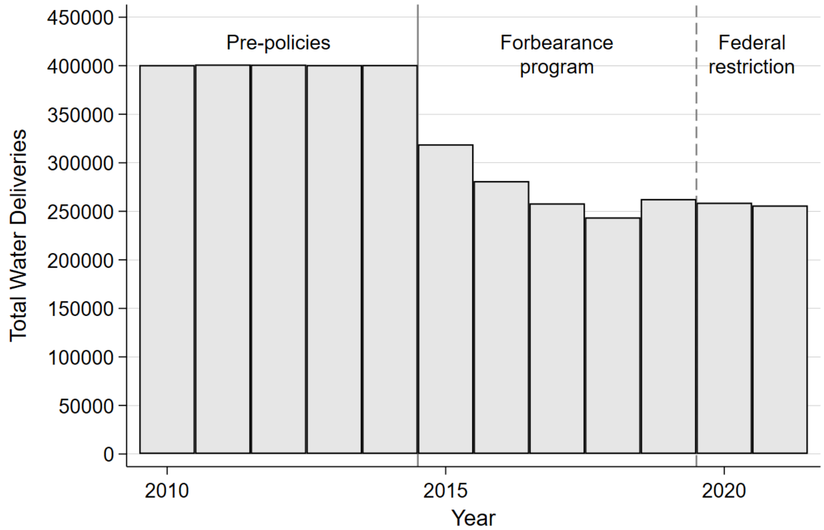


Figure plots the total amount of Ag Pool deliveries from the Colorado River to irrigation districts via the Central Arizona Project (CAP). Deliveries are measured in acre feet of water. The vertical lines denote the beginning of the Forbearance Program in 2015 and Federal Restriction in 2020. Data on water deliveries over time is publicly available on the CAP website.

2.3 Federal Restriction

The Lower Basin Drought Contingency Plan was agreed upon by stakeholders in Arizona, Nevada, and California in May of 2019. The Drought Contingency Plan (DCP) supplemented regulations from the 2007 Interim Guideline to define threshold levels, based on the water levels in Lake Mead, at which water deliveries from the Colorado River would be curtailed (*DCP* 2019). The thresholds and their respective curtailments are shown in Figure A1. The Tier 0 Federal Restriction was set to be enacted for a given year if predicted levels for Lake Mead on January 1st of that year were below 1,090 ft but above 1,075 ft. Under a Tier 0 restriction, Arizona agreed to reduce Colorado River water deliveries by 192,000 AF. This reduction in delivery is not directly compensated and enforced by the Department of the Interior who manages the deliveries from the Colorado River to Arizona, Nevada, and California (*DCP* 2019).

In August of 2019, the U.S. Bureau of Reclamation released their predicted levels for Lake Mead, showing predicted levels to be below 1,090 ft (USBR, 2019). Because of the

DCP agreement, this resulted in the implementation of a Tier 0 restriction starting in 2020, reducing Arizona's deliveries[2] . Because the Ag Pool water from CAP is the "excess" part of Arizona's Colorado River supply, the reduction in deliveries came entirely from the CAP Ag Pool meaning that only farmers using CAP Ag Pool water were affected by the restriction (CAP, 2021). Other Colorado River water users in Arizona and California were unaffected. Due to continued declines in Lake Mead levels, the Tier 0 restriction continued into 2021 and was upgraded to a Tier 1 restriction in 2022.

Additionally, while the forbearance program incentivized voluntary reductions in water deliveries, the Tier 0 restriction made reductions no longer voluntary. This implicitly means that the Tier 0 restriction completely replaced the Forbearance Program starting in 2020, though the restrictions on alternative water sources remained lifted (Ag Program 3). Direct comparison of the Forbearance Program and Federal Restriction is shown in Table 1.

Table 1: Comparison of Forbearance Program and Federal Restriction

	Pre-policy	Forbearance Program	Federal Restriction
Year announced		2014	2019
Years implemented		2015-2019	2020-2021
Maximum total deliveries	400,000af	400,000af	257,000af
Minumum delivery	Must use full allocation	No	No
Surface water price range	[$39, $49]	Discounted: [$36, $55] Undiscounted: [$53, $63]	[$56, $56]

Table compares water deliveries, prices, and groundwater regulations for CAP users under the two policies. Prices are from historic water delivery reports (2010-2014)[3], requested information from CAP (2014 - 2019), and rate schedules available online[4].

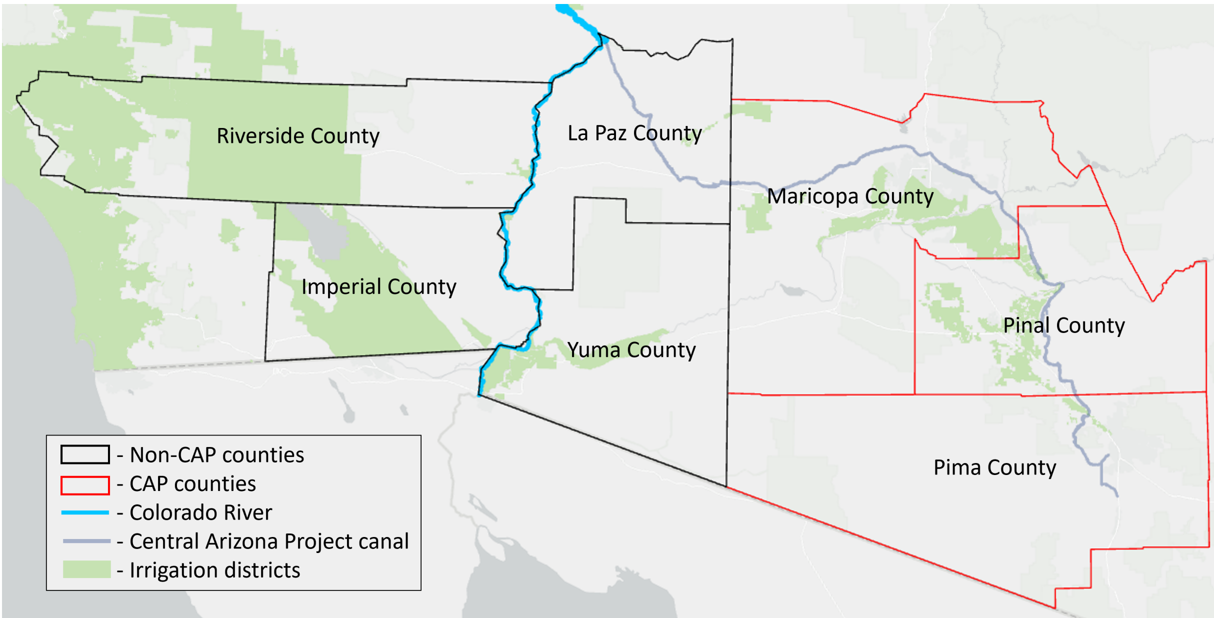
[2]The Arizona DCP Implementation Plan consists of agreements on how Arizona will implement different parts of the DCP should they occur, including a section outlining state managed water transfers to CAP. The Arizona DCP Implementation Plan only accounts for Tier 1 restrictions and above and does not require mitigating water supplies be sent to CAP under a Tier 0 restriction.

3 Data and Methods

In response to a negative water supply shock, farmers have several possible avenues for adjustment. First, they may respond by changing how much water they use for production by 1. reducing the amount of crops planted, 2. planting less water intensive crops, or 3. irrigating with less water per acre. Alternatively instead of changing the amount of water used they could change where they are getting their water from by replacing lost surface water with existing groundwater sources, new groundwater sources, or other surface water sources. At the parcel-level, the amount of crops planted, the types of crops planted, and the development of new groundwater wells is available to the econometrician by compiling several data sources. Since these choices are undoubtedly determined in large part by local environmental characteristics, this analysis compares CAP system parcels to non-CAP system parcels that are similar on observable characteristics and located in the Colorado River basin in Southern California and Arizona.[5] In California, parcels are selected from Riverside and Imperial county while in Arizona parcels are located in Pinal, Maricopa, Pima, La Paz, or Yuma county. See Figure 2 for a map of the Colorado River, CAP canal, and sample counties. Further details on the process of selecting the final sample and data compilation are in Appendix Section A.1.

[5] I do not include any parcels located within Native American reservations, due to differing water rights.

Figure 2: Map of Study Region



Map of CAP and non-CAP counties outlined in red and black respectively. Farms in all seven counties rely on surface water from the Colorado River, shown in bright blue. Only the CAP counties use water from the Central Arizona Project canal, shown in light blue. Most farms are located in an area served by an irrigation district, denoted in green, though some farms are outside of irrigation districts.

3.1 Data

Crop data

Estimating cropping behavior is common among the existing literature, in part because a wide array of detailed data is readily available. This analysis relies on land coverage data from the National Agricultural Statistics Service's Cropland Data Layer (CDL). The data is derived from satellite imaging and provides annual, spatial data on acreage and crop type planted. By overlaying parcel boundary lines that are publicly available from county assessors, the CDL data are used to construct annualized data on the share of land that is left fallow or cropped as well as the share of planted land that is occupied by different types of crops at the parcel level. I use parcels as the level of observation, as opposed to common land units or other land survey grids as other papers have done, since it is more reflective of the true population of interest: farms. For understanding crop specific changes, I narrow my analysis to the five most common crops in the region: alfalfa, other hays, cotton, barley, and durum wheat. These five crops make up the majority of the crops in each county, with alfalfa being the most common, as shown in Table A1.

To construct an estimate of total parcel-level water use, I combine the CDL data on area planted and crop type with estimates of crop specific water needs in Arizona's Salt River Valley reported by Erie et al., 1981[6]. For each parcel in a given year, I estimate an index value that is the average of the crop specific water needs, weighted by the share of land in the parcel that is occupied by the crop. Formally, denoting water intensity of parcel p as i_p,

$$i_p = \frac{\sum_c \text{consumptive water use}_c \cdot \text{acres}_c}{\text{total acres}_p} \tag{1}$$

This measure is bounded between 0 and 74.3, as 74.3 inches is the consumptive water use of alfalfa which is the most water intense of the five main crops c, and is interpreted as an estimate of the parcel level mean acre feet of water (converted to inches) used per acre. Alfalfa, cotton, and other hays are more water intensive than barley and durum wheat, and will be denoted in the remainder of this paper as "high water use crops" for brevity.

For each of the five main crops observed in the CDL, I collect annual state-level average yield per acre and price received per unit of yield from the National Agricultural Statistics Service's Annual Statistical Bulletins for California and Arizona.[7] I use this data to construct annual measures of price received per acre for each of the five main crops which I use for supplemental analyses.

[6]The water needs of crops are highly dependent on external environmental factors as well as crop characteristics. For example, Hanson et al., 2008 found that alfalfa grown in Imperial Valley in southern California required 76 inches of water, while in Scott Valley in northern California alfalfa only required 33 inches of water. While Erie et al., 1981 is older and potentially outdated, it has the benefit of uniformly measuring water needs in central Arizona for all of the sample crops. The Salt River Valley overlaps Maricopa, Pinal, and Gila counties.

[7]Arizona: `https://www.nass.usda.gov/Statistics_by_State/Arizona/Publications/Annual_Statistical_Bulletin/index.php`
California: `https://www.nass.usda.gov/Statistics_by_State/California/Publications/Annual_Statistical_Reviews/index.php`

Groundwater data

In addition to changing how water is used, farmers may change where they are getting their water from. Unfortunately direct measurements of water used from alternative sources is unavailable, so I instead examine investment in new agricultural groundwater wells and variation in the cropping decisions by estimated groundwater costs. For digging new wells, in both California and Arizona entities must submit a well drilling application, though the governing authority differs by location. In Arizona, well application data for the whole state is compiled and made publicly available through the Arizona Department of Water Resources.[8] In California data on new non-agricultural wells is available through the California Department of Water Resources, but for agricultural wells this data is maintained at the county level and only Riverside county is available[9]. These data sets for Arizona and Riverside county contain the wells' coordinates, permit application dates, and a categorization for the type of well. I remove wells that are classified as being for environmental monitoring, aquifer recharge, other special uses, or specifically non-irrigation use (i.e. exempt). I then use the date of permit application and coordinates to identify new wells at the parcel level to measure changes in groundwater investment and proxy for alternative water supplies.

While wells are observable, the cost of groundwater extraction is not. As discussed in Burlig, Preonas, and Woerman (2021), groundwater costs are a function of the localized groundwater depth, electricity rates, and pump characteristics. To approximate groundwater pumping costs I use publicly available data from the California Natural Resources Agency[10] and the Arizona Department of Water Resources[11] containing depth to groundwater measurements for observation wells across the sample area over time, and marginal electricity rates for irrigation pumping manually collected from the relevant utility providers for the year 2023. For each year, I interpolate a raster file of groundwater depths using inverse distance weighting of the observed points in the given year. I then link parcels to the relevant interpolated groundwater measure multiplied by the marginal electricity price of the

[8] Registry of Wells in Arizona: `https://azwatermaps.azwater.gov/wellreg`

[9] Department of Environmental Health Water Well Finder: `https://countyofriverside.maps.arcgis.com/apps/webappviewer/index.html?id=52a006e2361d4819bc0dc711b53f5533`

[10] `https://data.cnra.ca.gov/dataset/periodic-groundwater-level-measurements`

[11] `https://new.azwater.gov/gis`

relevant utility provider and a constant. The constant is the ratio of the average kWh per AF conversion factor to average operating pump efficiency estimated in Burlig, Preonas, and Woerman (2021), since these relevant pump characteristics are unavailable in my sample.

NDVI data

To better understand the intensive margin of how much water is applied to a given area of crops, I would ideally directly observe how much water is used to irrigate per acre. Unfortunately this is unobserved, so I instead proxy for this outcome using the Normalized Difference Vegetation Index (NDVI) measured by MODIS aboard the Terra satellite, accessed via NASA's EarthData portal. A higher NDVI value reflects more photosynthesis and higher evapotranspiration, which in turn means that the plants are consuming more water. If farmers are applying less water to a given amount of a specific crop, we would expect the NDVI value to be lower. I compile the MODIS data to get an annual, parcel-level average NDVI measure. Note that this aggregate measure captures the amount of water applied, the types of crops planted, and the amount of crops planted.

See Section A.1 for more details on the full data compilation process, and Section A.2 for sources of supplementary data sets.

3.2 Empirical estimation specifications

The goal of this analysis is to understand how farmers respond to reductions in surface water access through either changing how they use the remaining water or substitute towards alternative water sources. The main regression specification I employ uses a difference-in-differences framework comparing non-CAP parcels to CAP parcels before and after 2015, when the initial reduction in water deliveries occurred. I define a parcel as being in CAP if it is in one of the 15 irrigation districts that are identified by CAP as being consistent recipients of CAP water (Ikeya, 2021). As discussed in Section 2.1, CAP itself defines its service area as encompassing three counties since the exact irrigation districts served in a given year depends on needs and supplies. I repeat the main analyses with alternative definitions of treatment with respect to irrigation districts in Appendix Table A4. While the point estimates are of varying magnitudes across the specifications, the effect direction and statistical significance is largely unchanged.

For each outcome of interest y for parcel p in period t, I estimate

$$\begin{aligned} y_{p,t} =& \alpha + \lambda_1 \mathbb{1}(\text{After 2015}) + \lambda_2 \mathbb{1}(\text{In CAP}) + \beta_1 \mathbb{1}(\text{After 2015}) \mathbb{1}(\text{In CAP}) + \\ & \delta_p + \delta_t + \gamma X_{p,t} + \varepsilon_{p,t} \end{aligned} \tag{2}$$

where δ_p captures either an irrigation district or parcel-level fixed effect and δ_t is a year fixed effect. When using irrigation district level fixed effects, the vector $X_{p,t}$ measures the parcel-level environmental features: elevation, soil hydrologic group[12], mean temperature between June and October of year t, accumulated precipitation and its square from June to October in year t, depth to groundwater in year t, and parcel size. Only temperature, precipitation, and groundwater depth vary with time, the rest are defined by their values in the year 2020. Additionally, I include pre-2015 average planting decisions for the share of the parcel left fallow, share of the parcel with any crops, and the share of the five main crops planted that are high water use crops. For the parcel-level fixed effect specification, $X_{p,t}$ contains only the temperature, precipitation, and groundwater depth controls since all other covariates are time invariant. For all specifications standard errors are clustered at the irrigation district level, since irrigation districts coordinate the water deliveries, and parcels outside of an irrigation district are dropped.[13]

For the main analyses, I consider the combination of the Forbearance Program and Federal Restriction as a larger policy bundle since they were equally effective at reducing surface water deliveries. It is interesting though to use the differences in the policy implementations (price incentive versus quantity restriction) to begin a discussion on effect heterogeneity in outcomes under different implementations. To do this, I expand the main

[12] The soil hydrologic group is an index of the rate that water infiltrates a soil.

[13] Irrigation districts coordinating water deliveries means that access to river water is assigned at the irrigation district level (clustered treatment assignment). Additionally, as shown in Section 4.3 there is treatment effect heterogeneity. Following Abadie et al., 2017 I cluster standard errors.

analyses to an event-study framework following the specification

$$y_{p,t} = \alpha + \delta_t + \delta_p + \sum_{j=1}^{11} \beta_j \mathbb{1}(t = j)\mathbb{1}(\text{In CAP}) + \gamma X_{p,t} + \varepsilon_{p,t} \tag{3}$$

where the vector of climate controls is unchanged, δ_t measures the year fixed effect and δ_p reflects a parcel-level fixed effect. While a perfect comparison of the two policy implementation strategies is difficult in this context due to the sequential nature of the policies, the setting used for this analysis provides a unique opportunity to gain a better understanding of trade-offs between price and quantity strategies. To my knowledge, no other paper has been able to directly compare outcomes of water regulation policies where the same group of farmers were exposed to two policies that resulted in the same decline in surface water with the only difference being the way the policies were implemented.

3.3 Identification

The underlying assumption for the claim of exogeneity to hold is that the assignment of junior rights to CAP water in 1968 influences modern changes in crop production or investment only through the mandatory reduction of water use in times of shortage and the threat of this reduction. Note that before 2020, there had never been a mandatory resduction in deliveries. While it is likely that the junior rights standing is related to level differences in modern production, it is less likely to be related to differential changes in modern production. Due to the aggregated, spatial nature of CAP water rights assignment though, there are several possible ways in which this assumption might fail.

The first potential avenue for failure is confounding through localized shocks, such as a climate shock or crop demand shock, which disproportionately affects parcels in the CAP or non-CAP counties. Examining county specific trends reveals a sudden increase in cropping in the non-CAP counties through 2019-2021. While technically this shock does not violate any of the necessary assumptions for the difference-in-differences, it is concerning that it could indicate that not all parcels in the control counties are ideal controls. To tighten up the observed similarities of the control parcels to CAP parcels, I use propensity score matching to select a subset of parcels from the non-CAP counties to act as controls. For each parcel in the full sample of parcels in an irrigation district, I estimate a propensity score as the linear function

$$\mathbb{P}(\text{In CAP}) = \alpha + \lambda \text{Planting average}_p + \gamma \text{Water trends}_p + \varepsilon_p \tag{4}$$

The vector *Planting average*$_p$ includes the average of planting decisions from 2010 through 2014, with the share of the parcel left fallow, the share of the parcel with any crop, the estimated water use index, and of the five main crops planted the share that are high water use. Lastly, I explicitly control for parcel-level trends in water use with *Water trends*$_p$ which contains the estimated coefficients from parcel-specific regressions of the water used per acre constructed from equation 1 on year and the depth to groundwater (winsorized at 0.5 and 99.5 percentiles) on year for 2010-2014.

I then use nearest neighbor matching with replacement on the estimated propensity scores, selecting for each treated parcel up to three control parcels that have a propensity score within 0.01 of the treated parcel's propensity score. The observable characteristics of the unselected non-CAP parcels, selected non-CAP parcels, and CAP parcels are shown in Table 2. Since the matched non-CAP parcels are more similar on observables than the unmatched parcels, my preferred specification uses the matched sample for all of my main analyses. Table A5 in the Appendix presents the main results estimated on the unmatched sample, a sample matched using coarsened exact matching on quintiles of the same set of variables, and propensity score matching using only Arizona parcels. The takeaways are largely unchanged under the alternative matching procedures. The unmatched sample is quite different in the estimated net water use effect, due to differences in the estimated effect on high water use crops. This suggests that the matching is important for homogenizing the types of crops planted across treated and control groups (see Table A1).

Table 2: Average Parcel Characteristics

	Not matched control	Matched control	Matched treated
Panel A: Environmental characteristics			
Acres	63.45	54.36	28.25
	(80.84)	(88.23)	(70.63)
Temperature (C)	26.26	26.87	29.75
	(3.957)	(3.953)	(0.638)
Elevation (m)	38.27	53.97	399.9
	(131.2)	(133.5)	(60.03)
Precipitation (mm)	26.58	30.37	84.54
	(19.02)	(22.92)	(39.93)
Soil quality	2.705	2.511	2.383
	(1.025)	(1.118)	(0.748)
Cost per KWh ($)	0.0920	0.0914	0.0828
	(0.00627)	(0.00868)	(0.0164)
Depth to groundwater	104.6	98.39	198.2
	(52.54)	(49.18)	(99.88)
Panel B: Decision characteristics			
Share of parcel that is agriculture	0.761	0.647	0.596
	(0.285)	(0.339)	(0.361)
Share of parcel that is developed	0.0899	0.118	0.253
	(0.155)	(0.201)	(0.329)
Water use index	18.60	23.91	23.12
	(22.00)	(25.48)	(23.36)
Share of parcel that is left fallow	0.0654	0.101	0.181
	(0.154)	(0.203)	(0.265)
Share of planted land with high water use crops	0.679	0.853	0.916
	(0.416)	(0.306)	(0.245)
Labor index	1.690	2.372	2.477
	(2.273)	(2.725)	(2.562)
Price index	412.6	458.7	423.2
	(462.5)	(509.6)	(389.9)
Number of wells applied for since 2010	0.00257	0.00374	0.00125
	(0.0537)	(0.0687)	(0.0373)
Number of parcels	6225	8022	14376
Parcel-year observations	74700	96264	172512

Table presents average parcel characteristics for agriculture parcels in CAP and non-CAP counties. Panel A presents exogenous parcel features, averaged over 2010-2021. Soil quality is a categorical variable measuring water infiltration rate, where a value of 1 reflects high infiltration while 4 and higher reflects low infiltration. Cost per KWh measures the average electric price of energy used for irrigation. Panel B presents potentially policy varying outcomes, averaged from 2010-2014. Agriculture land is defined as planted with any crop or fallow land, while urban land is developed. Planted land contains one of the five selected crops. The labor and price index measures are constructed identical to equation 1, except using the hours of labor [14] and average price received for each crop rather than water needs.

A second source of potential confounding stems from differences in irrigation technology due to variation in water rights (Smith, 2021), as differential irrigation could lead to differential changes in soil salinity since more water efficient irrigation systems can lead to a build up of harmful salinity that would otherwise be "washed out" of the soil by less efficient irrigation (Morford, 2014). Using aggregate data from the 2018 Irrigation and Water Management Survey performed by the USDA National Agricultural Statistics Service, farms in California are much more likely to use drip, trickle, or low-flow micro sprinklers (around 65%) than farms in Arizona (15%).[15]. Since more efficient water use would imply a faster accumulation of salts in the soil, the higher uptake of drip irrigation in the control counties could increase the average soil salinity for non-CAP users, biasing the estimated coefficients of interest towards zero. More detailed data on parcel level irrigation technology is unavailable.

Lastly, a potential concern with the identification strategy is that the reduction in surface water, while only directly affecting CAP parcels, could have had spillover effects to the non-CAP parcels. The most likely way this could happen is if non-CAP farmers were aware that the production of CAP farmers would be reduced due to water shortages and increased their own production in response, introducing potential bias. The most common crops grown in the sample area are cotton and alfalfa, both of which are produced across the US and exported abroad. For alfalfa, in 2010 the US produced about 145 million tons with less than 2% of that total coming from Arizona. Similarly for cotton, Arizona in total produced about 3.5% of the total US production (NASS, 2017). Since production by CAP farmers is relatively small in the total market, it seems unlikely that any changes in CAP production would result in changes in other producers' behavior.

[15]Gravity or sprinkler systems are the alternative to drip irrigation systems. They are considered to be inefficient compared to drip systems, when measuring efficiency as the share of applied water used by the crop (Frisvold et al., 2018)

4 Empirical Results

4.1 Estimated water per acre

I start by examining how the reduction in surface water deliveries starting in 2015 impacted the overall water use on a parcel. To do so, I use the constructed estimate of water use per acre, from equation 1, that combines both how much farmers planted with the types of crops being planted. The results of this analysis are shown in Table 3. From left to right, the models include more controls starting with the most basic specification without controls in column 1 to the most rigorous specification in column 4 with year and parcel fixed effects as well as controls for time-varying parcel characteristics. Across the alternative specifications used with the matched sample, the reduction in surface water deliveries is associated with a reduction in average water use per acre between 0.3 and 0.7 inches, that is not statistically different from zero.

Table 3: Effect of Policies on Estimated Water Per Acre

	(1)	(2)	(3)	(4)
Indicator for 2015 or later	-2.840*			
	(1.163)			
In CAP county	-2.286			
	(2.132)			
CAP × Post 2015	0.056	0.056	-0.371	-0.651
	(1.321)	(1.321)	(1.355)	(1.196)
Pre-2015 treated average	23.115	23.115	23.115	23.115
Fixed effect	None	ID, Year	ID, Year	Parcel, Year
Climate controls	No	No	Yes	Yes
Obs	268,776	268,776	266,328	266,328
R-Squared	0.005	0.068	0.519	0.658

Table presents the main specification for the outcome of the constructed water use index (equation 1). *CAP* is an indicator for a parcel in an irrigation district that uses CAP water. *Post 2015* is an indicator for the observation being in 2015-2021. Column 1 contains no controls, while column 2 introduces an irrigation district fixed effect and a year fixed effect. Climate controls are included in columns 3. A parcel fixed effect replaces the irrigation district fixed effect in column 4, and only the time varying climate controls are included. Matched controls are weighted by the number of treated parcels they are matched to in columns 1 to 4. Observations not linked to an irrigation district are dropped. Standard errors are clustered at the irrigation district level and are shown in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$

4.2 Change in water use

Farmers could change their planting decisions along three margins: the amount of crops planted, the types of crops planted, and the amount of water used per crop. The first two outcomes are directly observable in the CDL data, and Table 4 presents the coefficient estimates for these outcomes under the difference-in-differences analysis framework. Looking first at the amount of crops planted, columns 1 through 3 suggest that farmers permanently retire land with the reductions in surface water, as the share of the parcel that is cropped falls an average of 9 percentage points while the share of the parcel that is left fallow increases by 3 percentage points, though the point estimate is statistically insignificant. This would suggest that farmers view the reductions in surface water as a long term change, since they are not maintaining the unplanted land for future use. Hagerty (2021) also finds that long run changes in water supplies leads to retirement of land as opposed to fallowing. Column 3 presents suggestive evidence that farmers are reallocating their land away from agriculture and toward urban development, however due to data limitations of the CDL this analysis is highly subject to measurement error and requires further investigation.

Columns 4 through 8 present the changes in the crop-specific share of total planted land. Column 4 shows that alfalfa was the most commonly planted crop before 2015 for CAP parcels, with about 65% of the planted land being occupied by alfalfa, and post-2015 there was a statistically significant increase in area occupied by 9 percentage points. Cotton and other hays, the other most water intensive crops, experienced negligible changes in the relative amounts planted. In contrast the low water use crops barley and durum wheat, which were also some of the least popular (of the main five) before 2015, were planted even less after 2015, with the share of planted land occupied reducing by 4 percentage points for barley. In total, columns 4 through 8 show that farmers after the surface water shock consolidated their plantings towards alfalfa, cotton, and other hays; high water use and relatively high value crops. It does not appear that farmers partake in crop switching as an adaptive measure, potentially due to differences in the price received for crops or due to switching costs from investment or learning.

Table 4: Effect of Policies on Cropping Decisions

	(1) Fallowed Land	(2) Cropped Land	(3) Developed Land	(4) Alfalfa	(5) Cotton	(6) Barley	(7) Durum Wheat	(8) Other Hay
CAP × Post 2015	0.035	-0.093***	0.087***	0.087***	-0.005	-0.038***	-0.009	0.020
	(0.018)	(0.019)	(0.022)	(0.022)	(0.017)	(0.007)	(0.009)	(0.020)
Pre-2015 treated average	.181	.415	.253	.646	.157	.056	.017	.022
Sample	Matched sample	Matched sample	Matched sample	Matched sample	Matched sample	Matched sample	Matched sample	Matched sample
Fixed effect	Parcel, Year	Parcel, Year	Parcel, Year	Parcel, Year	Parcel, Year	Parcel, Year	Parcel, Year	Parcel, Year
Climate controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	266,328	266,328	266,328	217,487	217,487	217,487	217,487	217,487
R-Squared	0.551	0.763	0.839	0.543	0.513	0.252	0.187	0.400

Table presents the main specification for the outcomes of the share of a parcel left fallow (1), cropped(2), or developed (3) and the share of total planted land occupied by specific crops (4-8). *CAP × Post 2015* is the estimate of β_1 from equation 2. All columns contain a parcel and year fixed effect and time varying climate controls. Matched controls are weighted by the number of treated parcels they are matched to. Observations not linked to an irrigation district are dropped. Standard errors are clustered at the irrigation district level and are shown in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$.

Alternatively, it is possible that while farmers were planting more water intensive crops they were actually applying less water to the crops, as found by Drysdale and Hendricks (2018) for Kansas. Unfortunately without parcel level measures of the water applied per acre it is impossible to directly test this option. As a second best, I use parcel level average NDVI to proxy for evapotranspiration, which in turn is indicative of the water available to plants. I repeat my main regression specification (equation 2) on the natural log of parcel average NDVI in Table 5. I find that after 2015 the average NDVI value for a CAP parcel increased by 3 percent. It is important to remember that similar to the constructed water use index measure, the parcel level average NDVI is also affected by the amount and types of crops planted in addition to the amount of water applied to the crops. Since Table 3 shows no change in estimated water needs based on the amount and types of crops planted, the increase in NDVI could suggest a small increase in the amount of water applied to crops, as opposed to reductions in water application to conserve water.

Overall, the analysis examining changes in NDVI suggests that farmers did not meaningfully reduce the amount of water used per crop. This analysis is noisy though, as NDVI is subject to many unobserved factors (eg. solar irradiance, precipitation, etc). As a supplemental analysis, I compile county specific yields per acre for the five main crops over time from the NASS Annual Statistical Bulletins for California and Arizona. Table A6 in the Appendix shows that there is little difference in the change in yield per acre between the treated and control counties due to the policies. This further supports the results from Table 5 that farmers are not significantly reducing the amount of water used per crop.

The bundle of policies reduced surface water deliveries by approximately 35% each year from 2015 through 2021. If there was a one-to-one reduction in water use per acre, a 35% reduction over the baseline 23.1 inches per acre would result in an average decline of 8.1 inches. Instead, the data shows that there was little change in total water use. While between 2015 and 2021 farmers on average reduced the relative amount of land planted, they also planted more alfalfa leading to no meaningful change in water needs. The contrast between this result and the reduction in CAP deliveries implies farmers were using water from alternative sources.

Table 5: Effect of Policies on Log of NDVI

	(1)	(2)	(3)	(4)
CAP × Post 2015	0.031*	0.031*	0.039*	0.028*
	(0.014)	(0.014)	(0.015)	(0.013)
Fixed effect	None	ID, Year	ID, Year	Parcel, Year
Climate controls	No	No	Yes	Yes
Obs	268,775	268,775	266,328	266,328
R-Squared	0.172	0.311	0.534	0.973

Table presents the main specification for the outcome of the natural log of parcel NDVI. *CAP × Post 2015* is the estimate of β_1 from equation 2. Column 1 contains no controls, while column 2 introduces an irrigation district fixed effect and a year fixed effect. Climate controls are included in columns 3. A parcel fixed effect replaces the irrigation district fixed effect in column 4, and only the time varying climate controls are included. Matched controls are weighted by the number of treated parcels they are matched to. Observations not linked to an irrigation district are dropped. Standard errors are clustered at the irrigation district level and are shown in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$

4.3 Alternative water sources

The substitution of Colorado River water with alternative sources is a common theme among the irrigation district notices to consumers and the agreements that comprise the Forbearance Program, in part because for some CAP users groundwater is cheaper than CAP water (MSIDD, 2021b; SCIDD, 2022; CAP, 2016b). To explore the extent that farmers shift to alternative sources, I would ideally be able to observe exactly how much water farmers use from each source. Unfortunately this granularity of data is unavailable, so as a second best I approximate access to alternative water sources, specifically groundwater, with the observed drilling of groundwater wells and a constructed estimate of groundwater extraction costs.

I first examine the outcome of drilling new groundwater wells. Regulation around drilling wells is very location specific, so that in some irrigation districts farmers are able to drill and use private wells while others the district drills and maintains the wells. To accommodate this variation, I estimate equation 2 for the outcomes of an indicator for any new well applications submitted for both the sample of parcels and a collapsed sample aggregated to the irrigation district level. For the irrigation district level analysis I also estimate the effect on the number of applications, conditional on applying. Column 1 of Table 6 shows there is no effect on well drilling at the parcel level. In contrast, at the irrigation district level column 2 shows a 19 percentage point increase in the probability of drilling a new well, a doubling over the base rate of 19 percent. Additionally, conditional on applying for a well, the aggregate of farms in CAP districts apply for 0.3 more wells than the aggregate of farms in control irrigation districts, though the effect is statistically insignificant and estimated on a very small sample.

The increase in groundwater well drilling in CAP districts aligns with anecdotal evidence that districts are supplying farmers with more groundwater and less surface water. However, two drawbacks with this analysis are that drilling wells is a rare event and it captures groundwater investment at an extensive margin only. Instead of drilling new wells farmers may rehabilitate existing wells, additionally new wells that are being drilled may be deeper and larger than their counterfactual counter parts (Migoya, 2023), characteristics that are not consistently observed in the data.

Table 6: Effect of Policies on Well Drilling

	Parcel	Irrigation district	
	New well	New well	Number of wells
CAP × Post 2015	0.0007	0.1946*	0.3256
	(0.000)	(0.083)	(0.573)
Pre-2015 treated average	0	.187	1.286
Fixed effect	Parcel, Year	ID, Year	ID, Year
Climate controls	Yes	No	No
Obs	266,328	552	98

Table presents the main specification for the outcome of the probability of applying to drill a new well and the number of applications, conditional on applying. *CAP × Post 2015* is the estimate of β_1 from equation 2. Column 1 is at the parcel level of analysis and includes parcel and year fixed effects and parcel level climate controls. Columns 2 and 3 are at the irrigation district level and contain irrigation district and year fixed effects only. Matched controls for column 1 are weighted by the number of treated parcels they are matched to. Observations not linked to an irrigation district are dropped. Standard errors are clustered at the irrigation district level and are shown in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$.

As an alternative, I examine heterogeneity in cropping decisions by estimated groundwater costs. The goal of this analysis is to use differential impacts by groundwater access, proxied by estimated costs, to understand the role of groundwater in supplementing forgone surface water supplies. I estimate groundwater costs following Burlig, Preonas, and Woerman (2021), constructing a measure of dollars per acre foot that is a function of depth to groundwater and local electricity costs for irrigation pumping. I then categorize parcels into low, medium, and high groundwater cost tertiles based on the distribution of CAP parcels' average groundwater costs pre-2015 and re-estimate the main crop analyses interacting the difference-in-differences coefficients with the groundwater cost categories. The sample is smaller than the main analysis sample used previously due to some parcels being outside the boundary of known utility providers, and therefore having a missing value for electricity costs.

The results of this analysis are shown in Table 7, where the coefficients are interpreted as the difference in effect for the medium and high cost groundwater parcels compared to those with low cost groundwater. While statistically imprecise, the magnitudes of the coefficient point estimates tell an interesting story. Column 1 shows that average reductions in the constructed water used per acre measure are increasing with groundwater costs, with parcels associated with high groundwater costs reducing water per acre about 4 inches more than those with lower cost groundwater. Similarly, these high groundwater cost parcels also see a relative reduction in NDVI (column 2), an increase in fallowing (column 3), and a reduction in the total amount of crops planted (column 4). Aggregating the high water use crops (alfalfa, cotton, and other hay) to create a measure of the share of the five main crops that are high water use, column 5 shows high groundwater cost parcels also plant less high water use crops. In total, Table 7 highlights significant heterogeneity in the point estimates by estimated groundwater costs, with parcels with high groundwater costs being more adversely affected. Again, while statistically imprecise, the analysis provides strong suggestive evidence that groundwater substitution is used to offset surface water shocks.

4.4 Effect dynamics

As discussed in section 2, an interesting aspect of the setting of this analysis is that the consistent reduction in surface water deliveries over time is actually the result of two sequential policies. The first policy, announced first in 2014, offered discounts on CAP water conditional on reducing deliveries. The discount structure of the Forbearance Program was then completely replaced by the Federal Restriction, announced in 2019, which instituted a limit on the total amount of water that could be delivered via CAP. Both policies waived the need to use the full allotment of CAP water before other sources.

Expanding the main analyses to the event study specification outlined in equation 3

Table 7: Heterogeneity in Cropping by Groundwater Costs

	(1) Water per Acre	(2) Log of NDVI	(3) Fallowed	(4) Cropped	(5) High Water Crops
CAP × Post 2015	-1.010	0.029	0.031	-0.098***	0.039***
	(2.153)	(0.018)	(0.019)	(0.015)	(0.010)
CAP × Post 2015 × Medium	-3.180	-0.048	0.030	-0.067**	0.013
	(2.358)	(0.025)	(0.021)	(0.024)	(0.012)
CAP × Post 2015 × High	-4.143	-0.094	0.079	-0.077	-0.122**
	(3.217)	(0.074)	(0.062)	(0.049)	(0.043)
Fixed effect	Parcel, Year	Parcel, Year	Parcel, Year	Parcel, Year	Parcel, Year
Climate controls	Yes	Yes	Yes	Yes	Yes
Obs	241,740	241,740	241,740	241,740	179,091
R-Squared	0.649	0.971	0.533	0.731	0.287

Table presents the main specification for the outcomes of the estimated water used per acre, log of NDVI, share of a parcel left fallow, cropped, and the share of planted land occupied by high water use crops. *CAP × Post 2015 × Medium* and *CAP × Post 2015 × High* are the estimates of β_1 from equation 2 interacted with indicators for medium and high estimated groundwater costs. The omitted category is low groundwater costs. All columns contain a parcel and year fixed effect and time varying climate controls. Matched controls are weighted by the number of treated parcels they are matched to. Observations not linked to an irrigation district are dropped. Standard errors are clustered at the irrigation district level and are shown in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$.

reveals interesting effect dynamics, as shown in Figure 3. With the implementation of the Forbearance Program in 2015, farmers immediately increased the water intensity of their plantings by planting more water intensive crops, leading to an increase in NDVI as well. They did not immediately change the amount of crops planted or amount of land left fallow.

As discussed in Section 2.2, the Forbearance Program incentives evolved over time, with the dollar value of the available discount decreasing with time between 2015 and 2019. The volume of deliveries over this time declined and then stabilized while, similarly, the observed crop production was also stable over time for the most part. This behavior implies that the main driver of delivery reductions under the Forbearance Program was the Ag Forbearance 3 program, which waived the delivery minimum indefinitely since delivery volume and planting choices did not respond to incentive reduction. This supports the results from Table 7, that those in areas with access to cheaper groundwater sources were able to reduce their CAP deliveries with little harm.

In 2019 there was a sudden decrease in the relative water intensity compared to the

Figure 3: Policy Effect Dynamics

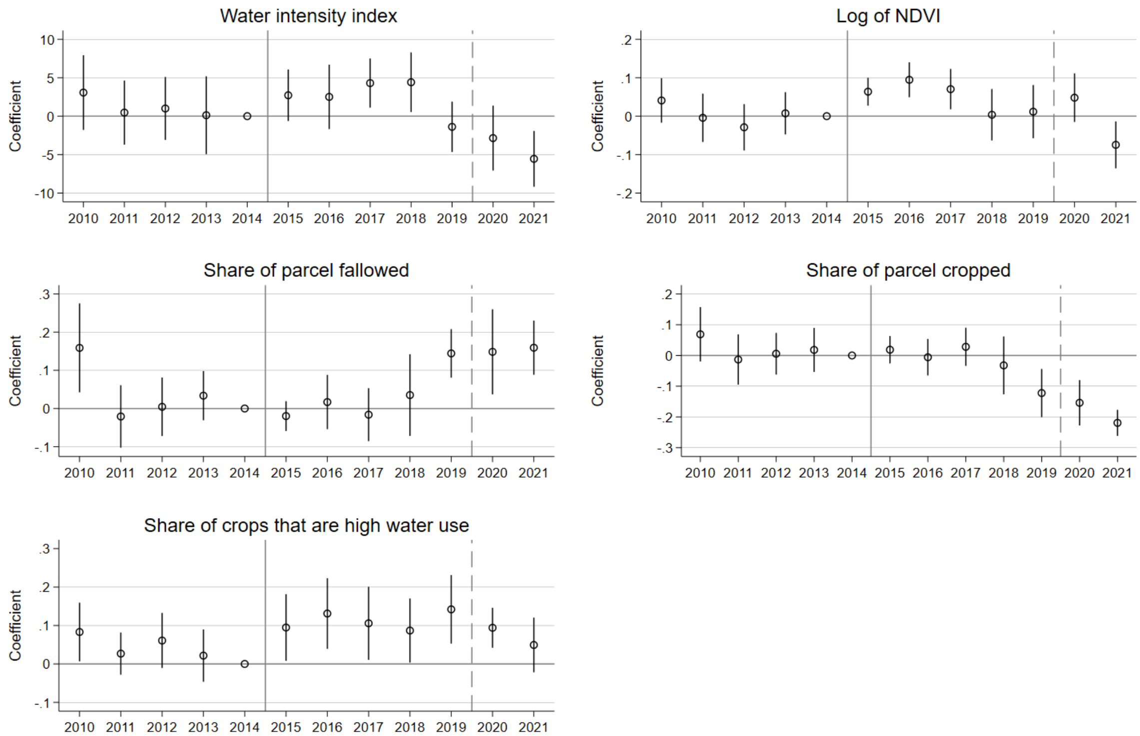


Figure plots the coefficients from the interaction of an indicator for CAP service and the year of the observation. Vertical lines denote the start of the policies, note that both policies were announced the year before implementation. The omitted interaction is for the year 2014. The specification includes climate controls and year and parcel fixed effects. Observations not linked to an irrigation district are dropped. Standard errors are clustered at the irrigation district level. 95% confidence intervals are shown by the vertical bars.

counterfactual due to a sudden increase in the amount of land left fallow and a reduction in the amount of land planted. Plotting the share of land left fallow and cropped separately over time (Appendix Figure A2) for the weighted matched sample shows that the sudden divergence in 2019 is due to a shock experienced by all of the counties in the control group that greatly reduced control group fallowing and increased control group planting. The treated group is unaffected by this shock, and experienced no change in fallowing over time. This sudden change in control group planting does not technically violate the difference-in-differences assumptions, and instead reflects a change that the treated group *should* have experienced. It does, however, make separating the effect of the distinct policies difficult, and is potentially concerning for the external validity of the main analyses. Table A7 in the Appendix re-estimates the main results on a subsample cutting off 2019-2021. The main analyses includes 2019 to 2021 though, since the lack of adjustment in 2019 is potentially an important impact of the reductions in deliveries: treated farmers may have been constrained by the available water supplies and unable to increase production as they would have in absence of the policy. While noisy due to the thin samples, Appendix Figure A3 helps justify this hypothesis, since those in low groundwater cost areas experienced a smaller jump in relative water use than those with higher costs, due to more stable relative fallowing and cropping rates.

Even with the sudden change in control group planting between 2018 and 2019, it is still informative to examine the difference in outcomes between 2019 (the last year of the Forbearance Program) and 2020-2021. Figure 3 shows that during this narrower time window there was little change in fallowing, but a gradual decline in the cropped area, leading to a net reduction in estimated water use. One explanation for the decline in cropped area is that the removal of the remaining financial incentives from the Forbearance Program tightened some users budget constraints, reducing the amount of water they could afford. Additionally, the reduction in cropping but not fallowing could indicate that farmer's view the Federal Restriction as more permanent, leading to land retirement.

Overall, there is very little difference on outcomes between the two policies. This makes sense - if the Forbearance Program worked primarily through waiving the delivery minimum, then removing the financial incentives should have had little impact. Additionally, since the voluntary reductions in deliveries under the Forbearance Program equated to the required reductions under the Federal Restriction, and the minimum delivery continued to be waived, there should be little change in the net amount of water available to end users.

5 Discussion

In total, the results show that on average farmers' water use is minimally impacted by the reductions in deliveries, likely due to substitution to alternative sources, and only those who do not have affordable substitutes fallow crops and grow less water-intensive crops.

5.1 Change in water use

The results from Tables 3 and 4 find that while on average farmers reduced the amount of cropped land, they planted more alfalfa leading to a net zero effect on water use. The continued planting of high water use crops is a finding that is consistent with previous research on California farmers (Burlig, Preonas, and Woerman, 2021; Hagerty, 2021). Other research has found a greater reliance on crop switching in different climate contexts (Cobourn et al., 2021), which is likely to be related to differences in precipitation supplementing irrigation and the types of crops available.

To understand the cost of the policies for farmers, I construct a parcel level measure of dollar return per inch of water used, based on the amount of each of the five main crops planted and the water needs per crop. Estimating equation 2 for this outcome (Table A8) shows that there is a \$2.70 reduction in the return per inch of water used (scales to \$32.40 reduction per acre foot). This value reflects a direct loss to the farmer compared to pre-2015 returns. This number is likely an underestimate of the true cost of the reductions in land planted, since it ignores the associated externalities such as health consequences from increased exposure to dust and agricultural chemicals for nearby populations (Sharratt, Wendling, and Feng, 2010; Johnston et al., 2019), and changes in local labor demand.

5.2 Alternative water sources

The results from the analysis of this paper suggest that farmers rely heavily on groundwater substitution to almost entirely replace lost surface water delivieries. This is important from a policy stand point as it emphasizes the interconnection of groundwater and surface water and the need to manage them jointly. Since groundwater is a scarce resource itself, diverting excess surface water demand to groundwater is not a sustainable solution in the long run. To further highlight this, Figure 4 presents the average depth to water[16], measured with monitoring wells in the CAP served counties over time. A striking feature of the figure is that the slope of the line is fairly stable near zero pre-2014. After the first surface water restrictions

[16]Depth to water is the standard way of measuring aquifer water supplies. It is measured as the distance between the ground surface and the level of the water within. Increasing depth equates to a reduction in the amount of water in the aquifer.

are implemented in 2015 though the slope becomes positive and remains so throughout the remaining time frame, reflecting a relative increase in withdrawals to inflows[17]. This dynamic provides further evidence that farmer's rely on groundwater substitution, but also threatens that excess groundwater extraction is likely to further increase groundwater pumping costs as depth increases. This has important implications for equity since, as Table 7 shows, the burden of surface water restrictions appears to be borne predominantly by those who cannot afford groundwater.

Figure 4: Changes in Aquifer Depth

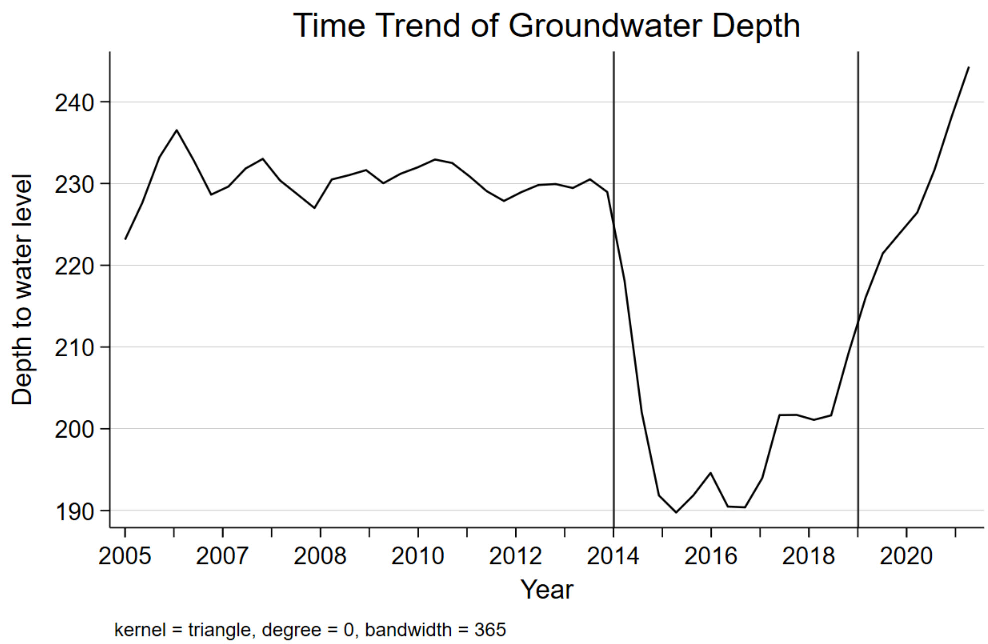


Figure plots the kernel smoothed average depth to water level in feet taken from monitoring wells across the three treatment counties. Depth to water level is from the Arizona Department of Water Resources' Groundwater Site Inventory dataset, `https://new.azwater.gov/gis`.

6 Conclusion

This paper examines how Arizona farmers on the Colorado River respond to a bundle of policies reducing surface water deliveries by 35%. The bundle consisted of policies removing

[17]The sudden decrease in depth to water in 2014-2015 is most likely due to a particularly wet monsoon season in 2014 and unrelated to trends in groundwater extraction.

minimum delivery restrictions, offereing financial incentives for reduced demand, and capping delivery quantities. The analysis uses parcel-level data on the amount and types of crops planted, groundwater well drilling, and constructed groundwater costs to examine how farmers adapt the way they use water and the water sources they use. Identification comes from the allocation of historic water rights, which exposed a subset of farmers to the policies reducing surface water access, while similar farmers in the region were unaffected.

In contrast with the large decline in surface water deliveries, the analysis in this paper finds a limited impact on farmers' water use. In aggregate, the estimated water used per acre for a parcel was unchanged by the surface water reduction, in part because while the amount of cropped land declined, farmers also planted more alfalfa, a water intensive crop. While not directly observable, the analysis also suggests farmers supplemented their lost surface water supplies with groundwater. This conclusion is drawn from the large heterogeneity observed in cropping outcomes, where farmers facing high groundwater costs reduced the amount of crops planted and the amount of high water use crops planted. These adaptations lead to an average reduction in water used per acre of 4.1 inches for these farmers facing higher groundwater costs, compared to those with lower estimated costs. There was little variation in response across the two policies, suggesting that the financial incentives were less important than waiving the minimum delivery requirement.

Understanding how farmers respond to policy induced surface water scarcity is important for future water management. Water scarcity is a growing threat and protecting water resources is non-debatable, but reducing water use can come with costs. Reductions in planting reduces immediate farmer welfare through lost revenue which may trickle into the surrounding economy (Bickel, Duval, and Frisvold, 2020). Additionally, increases in fallowed land may increase exposure to airborne particulate matter and agricultural chemicals which can have negative health consequences for individuals in the surrounding area (Sharratt, Wendling, and Feng, 2010; Johnston et al., 2019). While substitution of surface water with groundwater mitigates these concerns, it increases use of an already over-exploited resource. Overdraft of groundwater aquifers can lead to deterioration of water quality, and subsidence (sinking land), and even further reduce surface water flows (Bartolino and Cunningham, 2003). Because of this, groundwater substitution is not a sustainable adaptive strategy. Policy makers then need to move forward bearing in mind that restricting surface water through policies similar to those examined here are not long term solutions.

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Online Appendices

A Data Supplement

A.1 Data construction details

The main sample used for the analysis compiles data from several sources to create a balanced panel of parcel-level observations. I started by collected parcel boundary shape files from the individual county assessors offices for each of the seven counties. The level of detail available for each parcel varied greatly across counties, with some providing owner information and detailed land use descriptions (e.g. identifying a parcel as a vineyard versus a citrus orchard) and others providing only a unique identifier and boundary. I select only parcels in the Colorado River watershed and not on a Native American Reservation.

I first link the parcels with the USDA Cropland Data Layer (CDL) for the years 2010-2021. This raster data set spatially measures annual crop coverage and land use across the US at a spatial scale of 30x30 meter pixels, with each pixel denoting the modal crop type, natural land, or developed land within it. For each parcel, I used ArcGIS's "Summarize Categorical Raster" command to count the number of pixels belonging to each land use and crop type, as well as the total number of pixels contained within the parcel boundaries. It is worth noting that satellite imaging and pixel aggregation are subject to non-classical measurement error. Specifically, since each pixel is assigned a binary value for having a certain type of crop as the modal type or not, any error is negatively correlated with the observed outcome. The probability of measurement error is a function of image quality and detail, so it is influenced by geographic features such as slope, elevation, and cloud cover (Aliz-Garcia and Millimet, 2021). Since the sample used in the analysis covers a relatively small, homogeneous area of land, it seems reasonable that the probability of measurement error is the same across parcels.

Using the pixel counts, I constructed the share of a parcel that is fallow (cropped) as the number of pixels in a parcel categorized as fallow (with any crop) divided by the total number of pixels in the parcel. The share of crops that are high (low) water use is constructed as the number of pixels in a parcel that are classified as alfalfa, other hay, or cotton (barley or durum wheat) divided by the total number of pixels in the parcel that are categorized as alfalfa, other hay, cotton, barley, or durum wheat.

To measure crop water needs, I could use the state level average amount of water applied for each crop type, which is available in 2013 and 2018 from the USDA irrigation census. I avoid this measure though, since it also implicitly accounts for changes in water applied due to changing water supplies or irrigation technologies. Another data source of water needs is Cal-SIMETAW, which measures crop evapotranspiration across California to measure crop water needs. While very recent and comprehensive data, the main limitation with this measure is that water needs vary greatly due to environmental factors so that water needs in northern California are very different from those in central Arizona for the same crop. I instead use consumptive water use from Erie et al., 1981 even though it is potentially outdated, since it provides estimates of the minimum water needed for each crop, it is invariant to endogenous changes in irrigation technology, and it is specific to southern Arizona. I identify water needs for the five most common crops, which as shown in Table A1 make up over 80% of the crops in CAP counties and are a significant share of crops in non-CAP counties as well.

Since the parcel boundaries include all parcels in the county, I use observed planting trends to select a subsample of parcels that are likely to be farms. I keep parcels that are more than an acre in size, have a non-zero pixel count, and have one of the five crops of interest at least twice between 2010 and 2014. Then, for each parcel-year observation in the subsample before 2014 that includes information on the type of land use, I estimate the share of the parcel that is used for any type of crop or left fallow. I use the fifth percentile of this distribution to define a threshold value of 7.5%, dropping any parcels where the share of land left fallow or dedicated to crops never exceeds the threshold value between 2010-2014. The goal of this restriction is to limit the inclusion of parcels which are either subject to small measurement error or are not growing crops for market sale (e.g. personal gardens). Table A2 shows that these sample restrictions do a fairly good job of identifying the correct share of land that is considered agriculture land (rows 1 and 3), however in the sample Maricopa county is significantly over-represented while Riverside county is significantly under-represented with respect to parcels/farms (rows 2 and 4). This discrepancy is likely due to the Farm Census measuring farms, which are not necessarily a one-to-one link with parcels, and some of the California counties being outside of the Colorado River

Table A1: County Level Crop Choice

	CAP			Non-CAP			
	Maricopa	Pima	Pinal	La Paz	Yuma	Imperial	Riverside
Percent of land in agriculture	49.57	71.20	65.73	34.55	74.91	69.59	49.75
Cotton	16.36	49.86	42.80	42.48	5.189	0.234	2.116
Barley	6.476	6.604	7.872	3.844	0.180	0.0137	4.260
Durum wheat	2.634	21.22	3.339	4.293	7.609	16.29	1.217
Alfalfa	56.73	12.99	32.61	31.25	28.61	39.54	23.67
Other hay	1.116	1.470	0.692	0.474	1.208	19.72	2.926
Fallow	37.45	16.42	31.55	42.77	5.185	13.60	17.22
Share of agriculture land with selected crops or fallow	83.32	92.15	87.32	82.34	42.80	75.80	34.19

Table presents average planting choices of agriculture parcels in the relevant county. Agriculture parcels are defined as those that are at least an acre in size, have at least 7.5% of their land in agriculture and have one of the five selected crops for two years between 2010 and 2014. Land in agriculture is defined as land that grows any type of crop or that is fallow. Each row for a given crop type or fallow reflects the average percent of the land in agriculture dedicated to that crop type. These five crops constitute a significant share of the crops planted in the sample counties.

watershed. Lastly, I drop parcels where the owner is identified as Fondomonte Arizona LLC or Arizona Valley Farm LLC. These two entities are known to be extremely large commercial farms which rely almost exclusively on groundwater, and as such are identifiable as not being treated though in the treated counties.

I then link the selected parcels to environmental attributes such as elevation, soil characteristics, temperature, precipitation, and the relevant service area for electric utilities

Table A2: Sample to Census Comparison

	CAP			Non-CAP			
	Maricopa	Pima	Pinal	La Paz	Yuma	Imperial	Riverside
Percent of sample land area	20	4	24	5	13	27	7
Percent of sample parcels	42	2	17	1	11	17	9
Percent of census farm land	14	2	19	8	13	31	14
Percent of census farms	21	5	11	2	10	8	44

Table compares the sample in 2012 with the distribution of farms and agriculture land as measured by the 2012 NASS Agricultural Census. For the sample, land measures the percent of the total acres captured by the sample that are in each respective county. Parcels measures the percent of the sample observations in each county. For the census, land measures the percent of the total cropland acres of farmland in each county. Farms denotes the percent of cropland farms in each county.

and irrigation districts. I then link parcels to well locations and interpolated groundwater depth measures. Lastly, I link parcels to NDVI measured by MODIS aboard the Terra satellite, accessed via NASA's EarthData portal.[18] NDVI measures vegetation density using infrared and visible radiation, and is closely related to evapotranspiration by plants. The data is available for 16 day intervals at a 250 meter gridded resolution. I aggregate the data up to a yearly average NDVI value at a 250 meter gridded resolution, then take the average for each parcel of the aggregated grid cells for each year to get an annual, parcel-level average NDVI measure.

A.2 Supplemental data sources

Colorado River basin boundary: Shapefile of the boundary of the Colorado River watershed and service areas is from The Babbitt Center for Land and Water Policy at the Lincoln Institute of Land Policy.[19]

[18] MOD13Q1 version 6.1 at `https://search.earthdata.nasa.gov/search`

[19] `https://coloradoriverbasin-lincolninstitute.hub.arcgis.com/datasets/lincolninstitute::colorado-river-basin-hydrological-boundaries-with-areas-served-by-colorado-river/explore?location=35.798875\%2C-111.196487\%2C6.76`

Native American reservation boundaries: Boundaries for Native American reservations are from the National Geospatial Data Asset Portfolio dataset Federal American Indian Reservations, accessed through ArcGIS's Living Atlas repository.

Irrigation districts: Shapefiles containing the boundaries of irrigation districts are publicly accessible through the Arizona[20] and California[21] Department of Water Resources GIS databases.

Utility providers: Shapefiles of utility provider service areas are publicly available through the California Energy Commission[22] and the Utilities Division of the Arizona Corporation Commission[23] upon request. Per-kWh costs of energy for agricultural irrigation were manually compiled from providers' websites and rates documentation.

Geographic and climate data Data on precipitation and temperature are from the National Oceanic and Atmoshperic Administration's Climate Prediction Center.[24] Soil quality is from the USDA Soil Survey Geographic Database's Soil Hydrologic Group raster contained in ArcGIS's Living Atlas data repository. Elevation is measured from the USGS Ground Surface Elevation raster, also available through ArcGIS's Living Atlas.

[20] https://gisdata2016-11-18t150447874z-azwater.opendata.arcgis.com/datasets/irrigation-district-1

[21] https://gis.data.ca.gov/datasets/45d26a15b96346f1816d8fe187f8570d_0/about

[22] https://cecgis-caenergy.opendata.arcgis.com/datasets/electric-load-serving-entities-iou-pou/explore?location=33.600778\%2C-115.168189\%2C7.84

[23] https://www.azcc.gov/docs/default-source/utilities-files/electric/map-of-arizona\%27s-electric-companies.pdf?sfvrsn=3983c502_6

[24] https://www.cpc.ncep.noaa.gov/

B Supplementary Figures and Tables

B.1 Figures

Figure A1: Drought Contingency Plan Restriction Thresholds

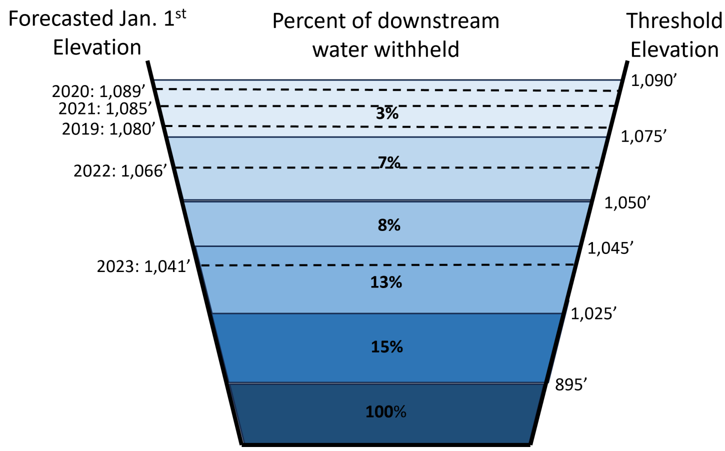

Figure graphically depicts water delivery restrictions under the Drought Contingency Plan for Lower Basin states. The threshold values based on the depth of Lake Mead are shown on the right and the corresponding reductions (as a percent of total allocations) in Colorado River water deliveries to the Lower Basin states are shown in the center. The forecasted Lake Mead elevation for January 1st of each year is shown on the left. Forecasted depths from the U.S. Bureau of Reclamation 24-Month studies (USBR, 2019).

Figure A2: Fallowing and Cropped Land Over Time

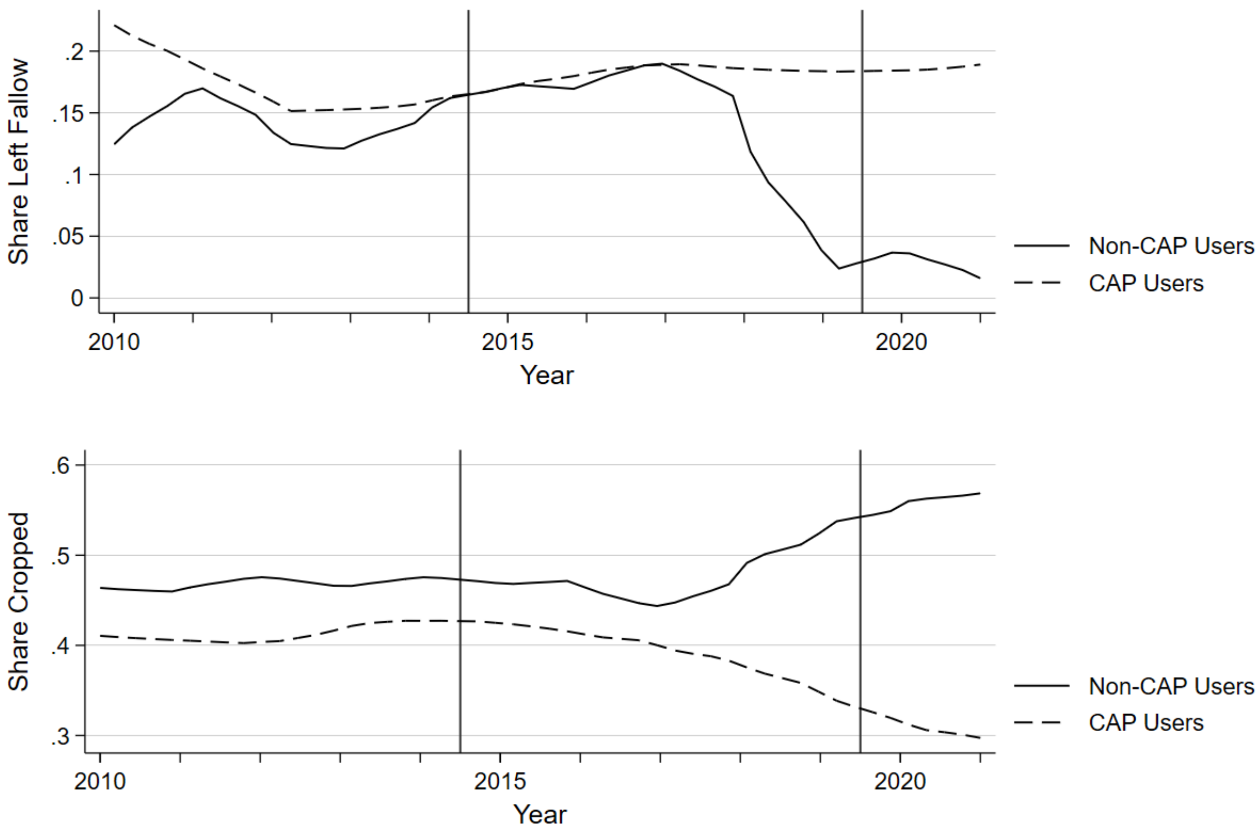

Figure depicts the kernel weighted local polynomial smoothed share of a parcel left fallow or cropped over time for CAP and non-CAP parcels. Matched controls are weighted by the number of treated parcels they are matched to. Observations not linked to an irrigation district are dropped.

Figure A3: Heterogeneity in Planting Event Study

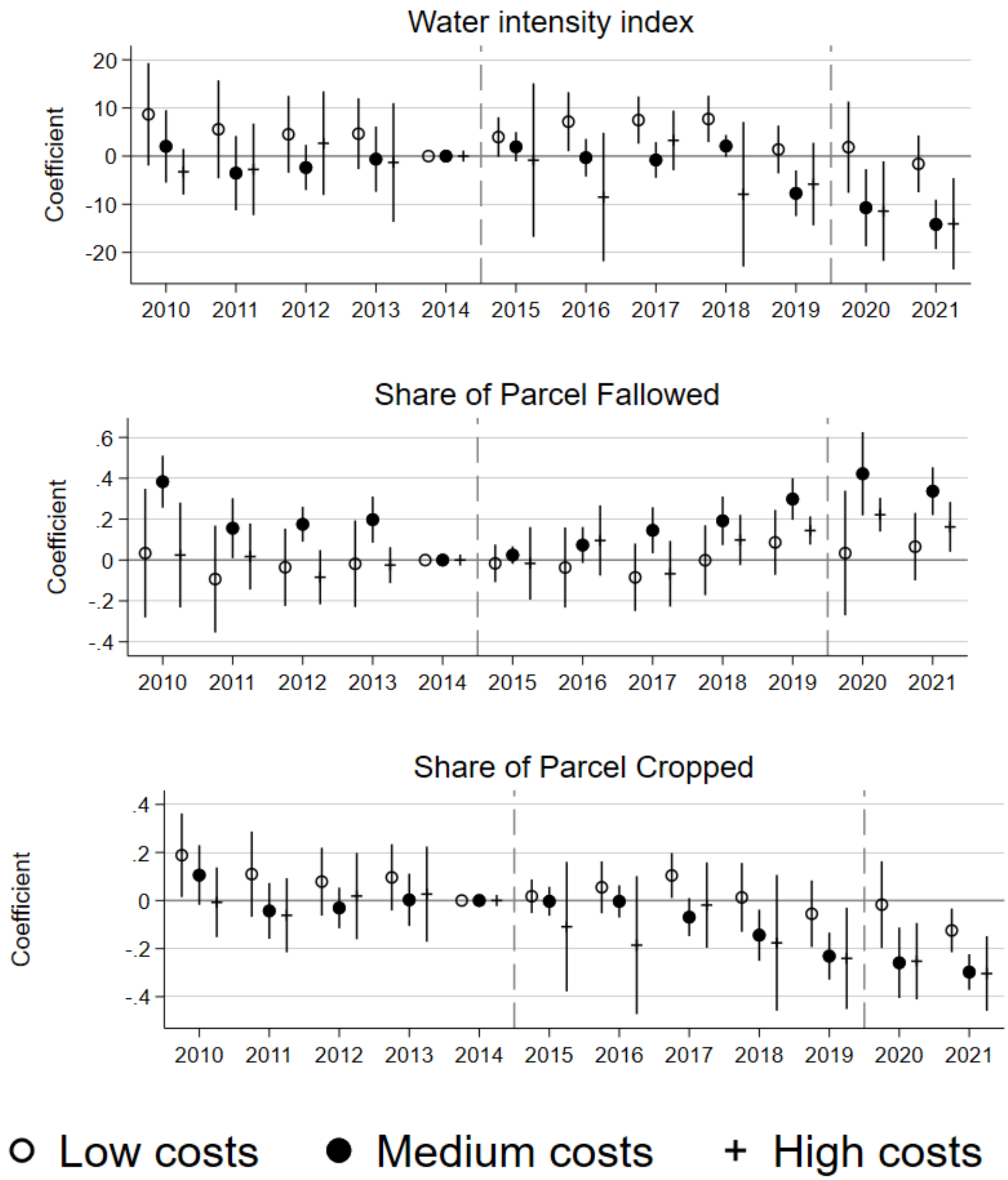

Figure plots the coefficients from the interactions of an indicator for CAP service, the year of the observation, and the tertile of estimated groundwater costs. Vertical lines denote the start of the policies. The omitted interaction is for the year 2014. The specification includes climate controls and year and parcel fixed effects. Observations not linked to an irrigation district are dropped. Standard errors are clustered at the irrigation district level. 95% confidence intervals are shown by the vertical bars.

B.2 Tables

Table A3: Forbearance Program Phases

Forbearance Program	1	2	3	4	5
Years implemented	2015, 2016	2016,	2016-present	2018, 2019	2018, 2019
Forbearance amount	23%-75%	12%	0-100%	2.5%	5%
Rate discount	$17, $19	$8	$0	$7	$4
Number of participants	12	11	9	3	4

Table outlines differences in programs that in aggregate define the Forbearance Program. The amount of water participating districts were required to forbear is show in line 2, and the discount per acre foot on subsequent deliveries received for participation is shown in line 3.

Table A4: Alternative Treatment Definitions

	(1)	(2)	(3)	(4)	(5)
	Water per Acre	Log of NDVI	Fallowed	Cropped	High Water Crops
Panel A: In CAP Irrigation District					
CAP × Post 2015	-0.651	0.028*	0.035	-0.093***	0.062***
	(1.196)	(0.013)	(0.018)	(0.019)	(0.015)
Obs	266,328	266,328	266,328	266,328	200,438
R-Squared	0.658	0.973	0.551	0.763	0.264
Panel B: In Irrigation District in CAP County					
CAP × Post 2015	1.644	0.051**	0.010	-0.069**	0.063***
	(1.454)	(0.015)	(0.016)	(0.021)	(0.017)
Obs	334,020	334,019	334,020	334,020	256,407
R-Squared	0.666	0.974	0.543	0.770	0.261
Panel C: In CAP County					
CAP × Post 2015	-1.091	0.049**	0.044	-0.088***	0.053***
	(2.023)	(0.018)	(0.031)	(0.024)	(0.014)
Obs	476,124	476,052	476,124	476,124	353,626
R-Squared	0.663	0.970	0.544	0.750	0.282

Table estimates the main coefficients of interest from equation 2 on samples using different treatment definitions. Panel A repeats the main analysis, defining treatment as parcels that are in one of the 15 primary irrigation districts. Panel B defines treatment as parcels that are in any irrigation in one of the three CAP counties. Panel C defines treatment as parcels that are in one of the three CAP counties. Each treated sample is rematched to control observations. All columns contain a parcel and year fixed effect and time varying climate controls. Matched controls are weighted by the number of treated parcels they are matched to. Standard errors are clustered at the irrigation district, with no irrigation district its own group, and are shown in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$.

Table A5: Alternative Sample Selections

	(1) Water per Acre	(2) Log of NDVI	(3) Fallowed	(4) Cropped	(5) High Water Crops
Panel A: Propensity Score					
CAP × Post 2015	-0.651	0.028*	0.035	-0.093***	0.062***
	(1.196)	(0.013)	(0.018)	(0.019)	(0.015)
Obs	266,328	266,328	266,328	266,328	200,438
R-Squared	0.658	0.973	0.551	0.763	0.264
Panel B: Unmatched					
CAP × Post 2015	-4.354***	-0.007	0.010	-0.086***	-0.037
	(0.942)	(0.015)	(0.015)	(0.016)	(0.034)
Obs	339,516	339,515	339,516	339,516	259,134
R-Squared	0.615	0.976	0.546	0.772	0.367
Panel C: Coarsened Exact					
CAP × Post 2015	-1.324	0.023	0.034*	-0.076***	0.046*
	(0.701)	(0.028)	(0.014)	(0.015)	(0.019)
Obs	188,076	188,075	188,076	188,076	140,621
R-Squared	0.652	0.973	0.591	0.775	0.294
Panel D: Arizona Only					
CAP × Post 2015	-1.329	0.067**	0.037*	-0.066**	0.058***
	(0.915)	(0.024)	(0.015)	(0.020)	(0.012)
Obs	206,424	206,424	206,424	206,424	153,232
R-Squared	0.709	0.973	0.570	0.762	0.318

Table estimates the main coefficients of interest from equation 2 on samples selected with alternative methods. Panel A repeats the main analysis, selecting via propensity score matching. Panel B uses an unmatched sample. Panel C uses coarsened exact matching on quintiles of the variables from equation 4. Panel D uses the propensity score matching procedure only for parcels in Arizona. All columns contain a parcel and year fixed effect and time varying climate controls. Matched controls are weighted by the number of treated parcels they are matched to. Observations not linked to an irrigation district are dropped. Standard errors are clustered at the irrigation district and are shown in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$.

Table A6: County Level Crop Yields

	CAP			Non-CAP		
	Before	After	Difference	Before	After	Difference
Cotton	1469.11	1366.94	-102.17	1883.31	1774.25	-109.06
	(36.97)	(47.70)	(71.27)	(76.63)	(91.29)	(128.35)
Alfalfa	8.77	8.52	-0.25	8.33	7.84	-0.49
	(0.14)	(0.24)	(0.27)	(0.15)	(0.16)	(0.22)
Barley	119.60	121.71	2.11	131.39	129.46	-1.93
	(2.08)	(2.12)	(3.07)	(12.02)	(5.77)	(12.55)
Durum wheat	102.20	98.87	-3.33	96.25	97.59	1.33
	(3.61)	(1.87)	(3.69)	(9.90)	(4.85)	(9.84)
Other hay	4.50	4.64	0.14	6.25	6.52	0.27
	(0.09)	(0.06)	(0.10)	(0.43)	(0.41)	(0.61)

Table presents average crop yields per acre for CAP and non-CAP counties from 2010 to 2015, 2015 to 2021, and the difference between the two. Standard deviations are shown in parentheses.

Table A7: Pre-2019 Difference-in-Differences Analysis

	(1)	(2)	(3)	(4)	(5)
	Water per Acre	Log of NDVI	Fallowed	Cropped	High Water Crops
CAP $\times$ Post 2015	3.085*	0.059***	-0.041*	-0.006	0.071**
	(1.206)	(0.007)	(0.015)	(0.010)	(0.021)
Obs	199,746	199,746	199,746	199,746	152,253
R-Squared	0.691	0.976	0.619	0.789	0.308

Table repeats the main analyses on the subsample of parcels observed from 2010-2018. *CAP $\times$ Post 2015* is the estimate of β_1 from equation 2. All columns contain a parcel and year fixed effect and time varying climate controls. Matched controls are weighted by the number of treated parcels they are matched to. Observations not linked to an irrigation district are dropped. Standard errors are clustered at the irrigation district and are shown in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$

Table A8: Dollar Return per Water Applied

	(1)	(2)	(3)	(4)
Indicator for 2015 or later	0.546			
	(1.298)			
In CAP county	-2.030			
	(1.094)			
CAP $\times$ Post 2015	3.730*	-2.596*	-2.399*	-2.701*
	(1.630)	(1.009)	(0.995)	(1.014)
Pre-2015 treated average	17.488	17.488	17.488	17.488
Fixed effect	None	ID, Year	ID, Year	Parcel, Year
Climate controls	No	No	Yes	Yes
Obs	124,681	124,681	122,987	120,714
R-Squared	0.082	0.502	0.504	0.594

Table presents the main specification for the outcome of the estimated dollar return per inch of water used, measured as the ratio of price index over water index, both constructed from equation 1. *CAP × Post 2015* is the estimate of β_1 from equation 2. All columns contain a parcel and year fixed effect and time varying climate controls. Matched controls are weighted by the number of treated parcels they are matched to. Observations not linked to an irrigation district are dropped. Standard errors are clustered at the irrigation district and are shown in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$