The changing value of agricultural adaptation to surface water scarcity

Antonia Marcheva*

August 13, 2025

Abstract

In California agriculture, farmers can adapt to water scarcity either through water conserving practices or water intensifying practices. The private value of these choices changes throughout the growing season as farmers make temporarily irreversible planting decisions. Using variation in announcements about the quantity of surface water available to different irrigation districts, I find that farmers switch crops in response to the earliest information, then extract more groundwater and fallow crops, and finally drill wells only in response to shocks occurring when the growing season begins. Overall, farmers' adaptation to the earliest information has the largest private impact on profits, while well drilling has a large and persistent effect of social costs, primarily from a permanent 0.2% increase in groundwater used after a moderate sized shock to surface water availability. Overall, this paper demonstrates that adaptation choices can differ as the surface water allocation approaches, with different private benefits and social costs.

1 Introduction

Private adaptation to weather and climate is a necessary avenue for limiting the effects of climate change (Carleton et al., 2024). Agriculture is particularly vulnerable, and recent research estimates that each degree Celsius of warming could reduce per capita daily food production by more than 100 calories. However, adaptation can alleviate 34% of production losses (Hultgren et al., 2022). Both the promise and the peril of agricultural adaptation comes from relying on private actors. Farmers adapt according to a choice set, in which some options might be privately costly, some irreversible, and some might have externalities. Sometimes farmers switch crops, which tailors adaptation to the temperature and water availability in the region (Kurukulasuriya and Mendelsohn, 2008). Sometimes, farmers invest in irrigation capital, which has significant externalities and might make them more sensitive to water scarcity in the long run (Hornbeck and Keskin, 2014). The benefits of adaptation depend critically on which choices farmers make.

In this paper, I study when farmers in California choose between water saving and water intensifying choices in response to short-term shocks to the surface water supply. Every year, farmers face a series of temporarily irreversible decisions which change the options in their adaptation choice set and the private benefits of those options. The state and federal government allocates water for the dry season, though the final allocation quantity remains uncertain until the total snowpack is realized. I study the adaptation decisions that farmers make as the dry season water supply state is revealed through increasingly accurate forecasts,

*Many thanks for the helpful comments from Serkan Aglasan, Eric Edwards, Todd Gerarden, Adrian Haws, Jeffrey Hadachek, Nick Hagerty, Michael Hanemann, PJ Hill, Katrina Jessoe, Ashley Langer, Derek Lemoine, Matthew MacLachlan, Kyle Meng, Ben Norton, Ivan Rudik, Tiemen Woutersen, and Nicholas Vreugdenhil. I have received compensation for presenting research findings as a graduate fellow at the Property and Environment Research Center.

at the same time as certain decisions become fixed. Farmers can switch between types of annual crops with differing water intensities, increase groundwater extraction, drill new wells or fallow land. Groundwater extraction has particularly large externalities, costing the state billions of dollars annually (Moran et al., 2014).

I answer three questions about farmers' adaptation to surface water scarcity. First, which actions do farmers take in response to forecasted surface water scarcity, and does the form of adaptation chosen change based on water supply forecasts issued at different lead times? Second, how does surface water scarcity affect farmers' overall profit outcomes, and how does adaptation diminish the direct effect of surface water scarcity? Finally, what are the social costs of the adaptation actions chosen?

To study the different decisions prompted by surface water information, I use surface water allocation announcements forecasting the government's projections about how much surface water it can deliver to different irrigation districts. These surface water forecasts are announced over important decision periods of the growing season, and differ according to the canals that districts are connected to. I estimate the effect of relative surface water availability shocks within districts and climate-region-years on the number of wells drilled in districts, crop choices, and the change in depth to the groundwater table. I include the entire path of forecasts in the estimating equation so that I identify the effect of information at different times using the incorrect components of each forecast, which are not ex-ante known (as in Shrader (2023)). With proper controls, I can identify whether these decisions respond to the short-term water information, and which information within a year is useful to which decision.

I find that short-term water information affects all decisions that I study. Receiving forecasts of low surface water early in the planting season shifts farmers toward water conservation by idling crops, planting earlier crops, single-cropping versus double cropping fields, and planting lower water intensive annuals. For low water news that comes in the late planting season, I find a shift toward higher groundwater extraction and crop idling. Well drilling is only affected by shocks to the finalized surface water allocation, which arrives at the beginning of the dry season.

I then explore how these adaptation decisions affect farmers' overall outcomes. I follow the literature on measuring the value ex-ante adaptation by regressing agricultural profits on surface water forecasts and final surface water allocation (Shrader, 2023). The coefficient on the water forecasts quantifies the profit-maximizing adaptive behavior given a certain forecast, which is different from how much better off farmers are for having a forecast and being able to adapt. I estimate the latter by comparing profit outcomes for districts in years where they received their first surface water allocation forecast before and after February 1st, which depended on department policy.

I find that farmers take the costliest adaptation measures prior to the first surface water allocation forecast. Accounting for these adaptation costs nearly doubles the estimated private cost of a marginally lower surface water allocation. Of course, farmers take adaptive measures because they would have been worse off for not taking them. Overall, I find that having a surface water forecast prior to February 1st diminishes the total cost of a 1% decrease in the surface water allocation by 23%, about $1.2 million for the average county.

I end the paper by studying the social costs of the adaptation choices, which I build up in three parts. I first study the asymmetries of responses to surface water information which allows me to see whether there are net effects of responses throughout time. I find that the effect of increased groundwater extraction roughly cancels itself out over time, though well drilling increases due to the worst water news without decreasing in

response to good news. Therefore, increases in groundwater use over time comes from well drilling. Then, I study whether, and for how long wells drilled are excess, using local projections (Jordà, 2005). Well drilling increases water use above the baseline for at least four years after the allocation shock occurs, and there is evidence of a small, permanent increase in wells. Finally, I study how farm decisions change after the irreversible well investment. I use exogenous changes in well drilling costs as an instrument for new wells within a local projections framework to estimate the path of new crop acreage resulting from 'surprising' new wells. New wells increase perennial acreage, primarily from the lowest water category, low-water field crops, which represents an increase in groundwater used annually, especially during droughts. New wells also increase the depth to the water table.

Overall, I estimate the permanent increase of groundwater use due to a one-time moderate surface water allocation decrease to be about 0.04% from baseline. I monetize the social cost using groundwater tax rates proposed by the Sustainable Groundwater Management Act, designed to limit groundwater extraction to safe yield, as a proxy for the common-pool externalities. Overall, this one-time surface water shock has a social cost of about $2 million 2024 dollars.

My results show that timing of information matters for the value of adaptation because in agriculture (and many other cases), the lead time up to an event affects the choice set. The changing value of adaptation over time should inform policy decisions about the provision of information, including in the California water setting. I find that having early surface water forecasts lowers the private losses from surface water scarcity, and that early adaptation responses are the least socially costly. Yet, the US Bureau of Reclamation inconsistently provides surface water allocation forecasts prior to February 1st, because of concerns about reliability (USBR, 1992). As long as a surface water forecast is even a marginal improvement on the outside information, which is nearly always possible because the surface water allocation is endogenous from the forecasting agency's perspective, then issuing earlier surface water forecasts is welfare improving.

This paper contributes to the growing literature on forecast-enabled ex-ante adaptation, which demonstrates that anticipatory responses substantially reduce weather-related damages (Molina and Rudik (2022), Shrader et al. (2023), Downey et al. (2023), Shrader (2023)). I explicitly link the value of adaptation to the specific actions people undertake. While previous research has identified the behavioral mechanisms underlying adaptation benefits, such as Shrader (2023) who shows that fishers reduce production costs after adverse El Nino forecasts, I extend my analysis to adaptation actions with diverse characteristics, including externalities and permanence. These features introduce social costs and long-term consequences that complicate the traditional narrative of the benefits of ex-ante adaptation to short-term weather.

I also build on the prior work of Anand (2023), who finds that earlier information significantly reduces traffic mortality during extreme winter. I provide complementary evidence that longer forecast leads increases the value of adaptation, while revealing that individuals fundamentally alter their adaptation strategies at different time horizons. This finding, like Anand (2023), challenges the theoretical model of Millner and Heyen (2021) which suggests that long-run predictability becomes irrelevant when people can continuously adjust their actions. In contrast, since the available set of adaptation options evolves as a forecasted event approaches, long-term predictability becomes crucial when some adaptive measures have social costs or are irreversible. Finally, while Burlig et al. (2024) show that farmers in India tailor investments to monsoon forecasts given their stated prior beliefs, my research highlights the critical limitations that emerge when forecasts arrive too late for optimal adaptation.

I also add to the literature on institutions governing water management. A growing literature explores

California's complicated water regime (Hagerty and Bruno (2024), Ayres et al. (2021), Hagerty (2023)), which is economically relevant because the state produces more agricultural output (in dollars) than any other (Ruth, Timothy, 2017). My paper studies the surface water allocation forecasts specifically, which concerns a substantial amount of annual agricultural water. I also add to the literature in water economics on the substitution between groundwater and surface water (Burt (1964), Ferguson (2024)) which is important because of the wedge between the private and social benefit of these resources. Bruno et al. (2024) documents the same mechanism for substitution that I do, where surface water delivery quantities affect the number of wells drilled in California. Since information provision can affect adaptation choices even before regulation is in place, my paper is policy relevant because many aquifers globally lack regulation (Jasechko et al., 2024), as California's did until recently (Hagerty and Bruno, 2024).

Finally, I contribute to the agricultural economics literature on sequential and intra-annual decision making, which has long recognized that farmers' choices are best understood as multi-step processes that evolve as new information becomes available throughout the growing season (Antle, 1983). However, I contribute a rare empirical study in this literature, confirming with a real-world case the intuition that adaptation choices change over the growing season because of previously fixed decisions (Ortiz-Bobea, 2021). Understanding sequential decisions and adaptation will become more important as weather and water conditions become more volatile.

The paper proceeds as follows. Section 2 covers the essential background for this paper, while section 3 combines the background into a timeline of decisions that guides the intuition of the results. Section 4 describes the data sources I use. In section 5 I estimate the timing of different adaptation decisions, and in section 6 I estimate the aggregate benefits of adaptation. Section 7 describes the social costs of the adaptation decisions made at different times, and section 8 concludes.

2 Background

2.1 California's agriculture and climate

Ample sunlight, mild winters and fertile soil makes California a major supplier of permanent crops like tree nuts and citrus (2/3rds of the US total) and other high-valued crops like vegetables and berries (1/3 of the US total), primarily in an inland region called the Central Valley (Ruth, Timothy (2017), California Department of Food and Agriculture (2023)). However, agricultural water demand and the natural water availability are mismatched. The majority of the state's precipitation (75%) falls north of the Central Valley, and the majority of the Central Valley's precipitation falls between October and April (90%), which is outside of the hot summer months and the main fruiting season, when crop water demands are the highest (CA State Climatologist, 2025). Therefore, agriculture in California depends on irrigation, facilitated by large infrastructure projects for the storage and conveyance of surface water, and also private groundwater access. California uses more irrigation water in agriculture than any other state (16% of the nation's total), and the majority of irrigated land is in the Central Valley (75%) (US Geological Survey (2025), Dieter et al. (2018)).

Despite the high presence of permanent crops, more than 2/3rds of California's irrigated acreage is devoted to growing annual crops, allowing farmers the opportunity to make different planting decisions yearly (Bauer, 2022). Because of the long growing season, annual crops are planted at various times throughout the year. Typically, cool season crops are planted either between December and February, or July and September, while

warm season crops are planted between March and June. Grains are usually planted in the fall, from October to December. High summer temperatures make the average crop water requirement for warm weather crops much higher than cool weather crops, though there is a lot of variation between annuals planted at the same time[1]. Farmers in Central California have commonly used crop switching for drought management (Visser et al., 2024).

2.2 Surface water projects and surface water allocation forecasts

The state of California and the US Bureau of Reclamation each built systems of reservoirs and canals between the 1930s and 1960s for flood control and water delivery across California. These state and federal water infrastructure projects are referred to respectively as the State Water Project (SWP) and Central Valley Project (CVP). These projects deliver a substantial portion of their water to agriculture (one-third of SWP, and one-half of CVP), and combined deliver about 19% of the water used in agriculture yearly (Bureau of Reclamation (2024), Department of Water Resources (2024)). Irrigation districts gained access to a set delivery quantity from these projects by signing long-term contracts in the 1960s, in return for covering capital and operating costs. Through these arrangements, districts with project contracts have received heavily subsidized surface water (Sharp and Carini, 2004). The majority of water districts charged agricultural users less than \$50/ acre foot for surface water in 2021, and many paid much less, while groundwater rates tend to be higher, and the market rate for surface water higher still[2] (Aquaoso (2021)).

However, the amount of surface water that projects are able to deliver varies from year to year because of the variability in snowpack in the Sierra Nevada mountains, which supplies the majority of the water in California's developed surface water infrastructure (Soderquist and Luce (2020), de Guzman et al. (2022)). Specifically to aid agricultural decision makers, the Department of Water Resources and Bureau of Reclamation publish a forecast at the start of the planting season for the percent of a district's surface water contract their projects are expected to fulfill[3] (USBR, 1992). Updates to the initial surface water delivery projection are announced irregularly until the final delivery percent is finalized in May or June at the start of the dry season. I call the series of project forecasts "surface water allocation forecasts", and the final realization the "final surface water allocation". Despite the surface water allocation forecasts coming from different agencies, they have similar characteristics, and follow similar methodologies due to the joint administration of the water projects (US Bureau of Reclamation and the California Department of Water Resources, 1986). Appendix figure A.1 shows examples of what the surface water allocation forecasts have looked like through time. The forecasts have been disseminated through newspapers, bulletins, and websites. Low surface water allocation forecasts are especially salient, making front page news in many agricultural communities. Figure A.2 further shows the importance of the surface water allocation forecasts to water users. Out of all water-related news topics in California published by the Department of Water Resources and the Bureau of Reclamation, the highest median page views are for surface water allocation announcements.

[1] For example, though they are both warm season crops, cotton requires almost three times as much water to grow as dry beans.

[2] Burlig et al. (2020) estimates the average marginal cost of groundwater to be \$50 an acre foot, though a short survey of agricultural districts groundwater rates suggest that groundwater is usually a bit more expensive, around \$200, which is 2-3 times districts' surface water rates. The surface water market price can fluctuate dramatically, from \$150 in wet years to \$1300, as proxied by the Nasdaq Veles water prices index.

[3] The intention is clearly stated in the CVP operations criteria: "all of the agricultural contractors need to know about their water allocation as soon as possible so that they can make timely decisions and appropriate plans for using their allocated water supply." (USBR, 1992)

The other major source of agricultural surface water in central California comes from streamflow originating in the Sierra Nevada. Irrigation districts and other public entities hold the vast majority of these legal diversion rights (81% of water), obtained from the State Water Resources Control Board[4] (Grantham and Viers, 2014). Although on paper, these rights operate on a system of priority, because of a lack of monitoring and enforcement, rights holders in the same watersheds will face similar streamflow shocks in the same year (Weiser, 2014).

2.3 Well drilling and groundwater

Groundwater supplies 40% of agricultural water in regular water years, and substantially more in dry years (Greenspan et al., 2024). The Central Valley aquifer is the second-most utilized in the United States, where on average 2.4 million acre-feet more water was extracted annually than was recharged(US Geological Survey, 2025). The severity of the overdraft has resulted in concerns about groundwater depletion and other externalities including saltwater intrusion (Goebel et al., 2019), arsenic contamination (Smith et al., 2018), infrastructure and property damage through subsidence (Borchers et al., 2014), an increase in the future costs of extraction, and a permanent decrease in aquifer storage capacity (Smith and Majumdar, 2020), in addition to the standard common pool externality. Nevertheless, until 2014 only 7% of the state's groundwater basins had defined property rights, none of which were in the Central Valley (Ayres et al., 2018). The California legislature passed the Sustainable Groundwater Management Act in 2014 to address unsustainable groundwater extraction, though no anticipatory responses have been detected through 2022, and many of the Central Valley's regulated basins failed to meet the act's guidelines for management planning through 2024 (Bruno and Hagerty (2024), State Water Resources Control Board (2024).

To access groundwater, farmers can drill private wells. The State Water Resources Control Board has required well drilling permits since 1990, which imposed a time delay on drilling[5] (GEI Consultants, 2017). While physically drilling a well takes only a week, permitting and demand queues delays drilling by one to six months[6]. Well drilling is a moderate investment for most farms. Agricultural wells in the last decade have typically cost between $50,000 and $500,000, which is between 25% and 250% of the average farm's yearly income (Smith (2014), United States Department of Agriculture (2022)).

3 Conceptual Framework

In this section, I combine the pieces of the farming context in California to explain why surface water supply shocks at different times of the year could result in different margins of adaptation with different private and social costs. Whether and when farmers actually respond to short-term water supply information with these actions is the empirical question I answer in later sections.

Farmers in California seek to maximize their lifetime profits by producing crops. Every year, farmers face a long agricultural season with several decision periods. There is an early planting season, spanning from October to January, a mid planting season, spanning from February to March, a late planting season, running from April to May, and a dry season spanning June to September. In each of these periods, farmers receive new information about surface water available to them in the dry season, which becomes more accurate as

[4]Individuals hold less than 1% of water.
[5]Permits are virtually always granted.
[6]From the testimonies of two well drilling contractors.

the dry season approaches. Surface water and groundwater are perfect substitutes that are essential inputs to crops. Surface water is always the least expensive option for irrigating their crops, and groundwater is only available if the farmer has invested in a groundwater well. There is also a backstop source of water on the surface water market which is significantly more expensive than groundwater.

In each planting period, farmers make a variety of decisions, some of which are short-run and only have consequences within the current year, and some of which are long-run, having consequences across years. The first option is crop choice. Farmers choose to plant any portion of her unplanted fields with annual crops or permanent crops suited to planting in that period. Once a field is planted, that field cannot be planted with another crop until the following year (for annuals), or until the year after abandonment (permanent crops). Crops differ in characteristics by their profitability and water intensity. Although every planting period has crops of a variety of water intensities, on average later planting periods have crops of higher water intensities. Second, farmers can also choose to drill a well to access groundwater. The cost is a one-time fixed cost of well installation, which varies with depth to the water table and the capacity of the well, and is usually substantial relative to a farmer's income. The benefit of a well is the sum of discounted additional profits from having access to groundwater forever, which is determined by the long-run expectations of dry-season surface water. Importantly, the irreversibility of the fixed costs of investment, plus the uncertainty of future surface water availability means there is an option value of drilling. A well can be drilled anytime, but there is a delay between making the drilling decision and having access to groundwater ranging between 1 and 6 months, where the probability of longer delays increases during drier years. Third, farmers can choose to extract more groundwater using wells that they already have, up to the capacity of their well, paying a per-unit cost of extraction, typically only from the electricity cost to run a well pump. Finally, in every period, regardless of past decisions, farmers can choose to abandon crops by ceasing to water what was already planted.

At different times within a year, the choice set changes due to timing constraints and previously fixed decisions, which has implications for the private and social value of those choices. Conditional on the year's dry-season surface water availability, receiving accurate dry-season surface water information earlier is always more privately beneficial, because there are more adaptation options to choose from, and the decisions would be better tailored to actual water conditions. By the time the dry season arrives, the only options left for adjusting to surface water supply shocks are crop abandonment, groundwater extraction, and well drilling, though the well would likely not even be available for use in the current year. The well value changes throughout the season for two reasons. First, the probability of being able to use the well in the current year decreases. Second, the short, medium run and long-term surface water availability becomes more certain, affecting the direct expectations of the value added of the well, as well as the option value. Which effect dominates is an empirical question.

In periods of the year when well drilling and groundwater extraction are chosen relatively more, the social cost of water supply shocks is higher because of the resulting increases in groundwater withdrawn which has large unpriced externalities. The social costs of the two differ because a new groundwater well likely has a permanent effect. Not only will groundwater be applied on the current crop mix, but having a well influences future cropping decisions by decreasing the marginal cost of water in dry years, which could result in an even greater amount of groundwater used. The size of the externality depends on when the well would have been drilled otherwise (i.e. how long the well remains excess). On the other hand, crop choice has low social costs. Because surface water is allocated to rights holders and contract holders, tailoring crops to the level

of surface water available allows farmers to maximize private benefits without imposing costs on other users of the water.

In table 1, I summarize the time periods, climate, government actions, information available, decisions available, and costs and benefits of the remaining decisions, as outlined in the conceptual framework and background, for farmers in water districts with contracts to surface water projects. The table highlights how the responses to water information and consequences of those responses evolve within a year because of changing constraints.

Table 1: Timeline of agricultural decisions, costs of decisions, climate, and government actions

Season	**Early planting**	**Mid planting**	**Late planting**	**Dry season**
Months	Oct - Jan	Feb - Mar	Apr - May	Jun - Sep
Climate	Rainy, cool	Rainy, cool	Some rain, warm	No rain, hot
Government action	None	- Provide surface water allocation forecast	- Provide surface water allocation forecast	- Deliver surface water to districts
Info available	- Last year's water availability - Weather forecasts	- Early surface water allocation forecast - Weather forecasts - Snowpack forecast	- Mid surface water allocation forecast - Weather forecasts - Snowpack forecast	- Final surface water allocation - Weather forecasts - Final snowpack
Decisions available	- Plant early crops - Choose mid crops - Choose late crops - Drill well (likely usable this year) - Change ground-water extraction - Abandon permanent crops	- Plant mid crops - Choose late crops - Drill well (likely usable this year) - Change ground-water extraction - Abandon permanent crops - Abandon annual crops	- Plant late crops - Drill well (unlikely usable this year) - Change ground-water extraction - Abandon permanent crops - Abandon annual crops	- Drill well (unlikely usable this year) - Change ground-water extraction - Abandon permanent crops - Abandon annual crops
This year's private cost of remaining decisions	Low	Medium	Medium	High
Social cost of remaining decisions	Low	Medium	Medium	High

4 Data

4.1 Surface Water Forecasts

I digitize all surface water allocation forecast announcements for the Central Valley Project and State Water Project, which have been published since 1967, with multiple forecast updates over multiple regions yearly (California Department of Water Resources (2024b), California Department of Water Resources (2024a), US

Bureau of Reclamation (2024)). Though California farmers get information about surface water availability from a variety of sources, only these surface water allocation forecasts apply to a specific and measured source of surface water.

The CVP and SWP announce their first surface water allocation forecast in the early or mid planting season, and follow up with an average of 2.8 updates, roughly on a monthly basis, until the beginning of the dry season. I construct a panel of the newest information available to farmers at the start of the mid-planting season, late-planting season and dry season, using the surface water allocation forecasts closest to, but not beyond, February 1st, April 1st and June 1st. Table A.2 in the Appendix shows that farmers receive surface water allocation updates in these periods in most years. In some years, agencies did not publish updates in periods where the surface water allocation forecast stayed the same. The SWP typically publishes surface water allocation forecasts earlier, and finalizes its surface water allocation earlier, while in 47% of years, the CVP did not issue a first surface water allocation forecast before February 1st[7].

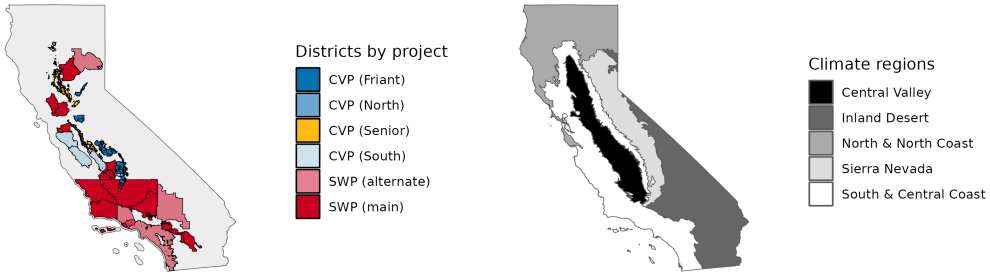
Overall, even though the forecasts come from different agencies, they are comparable. In appendix figure A.3, I plot binscatters comparing surface water forecasts from the State Water Project and Central Valley Project, showing that a given surface water forecast or final allocation has the same signal for both projects on average. The average surface water allocation forecast near February 1st was 36% for the SWP and 41% for the CVP. Both agencies also use the same conservative forecast rule, evidenced by the higher average final surface water allocation, at 61% on average for the SWP and 60% on average for the CVP.

In years when there is no surface water allocation forecast update between February 1 and April 1, or between April 1 and June 1, I carry over the most recent surface water allocation forecast, to match the intention of the agency in retaining the previous projection. In contrast, the February 1st forecast is missing in years when the USBR's policy is to publish later forecasts. Farmers still need to make early decisions based on expected surface water availability[8]. Therefore, I fill the missing data by predicting the first forecast empirically, using observables available by February 1st, which approximates the process of forming project surface water availability expectations. I select variables using LASSO, a machine learning method for prediction which shrinks irrelevant predictors to zero by adding a penalty term to the ordinary least squares objective function (Tibshirani, 1996). I train the model individually over every district in years when early surface water forecasts were observed, using the 'one-standard-error' rule for the penalty parameter, which selects the most parsimonious model whose prediction error is within one standard error of the minimum, because of the limited number of observations (Friedman et al., 2010). More information about the variables included in the LASSO process, the variables selected, and the prediction accuracy can be found in Appendix B.1. In case my imputation procedure drives the results, I include several robustness checks with different imputation methods, including (1) multi-level multiple imputation (Rubin, 1987), (2) using the first forecast published (usually in the middle of February for missing observations), and (3) using the previous year's surface water allocation adjusted downward based on the empirical distribution of conservative bias. I also try dropping district-years that did not receive an early surface water forecast. I include more detail about these imputations in Appendix B.1.

[7]The CVP's reasoning is forecast reliability: "no reliable forecasts of seasonal runoff are available before February" (USBR, 1992). However, there are many spans of time where the CVP still published a forecast before February 1st.

[8]"Stanislaus County farmer Daniel Bays, who grows tree and row crops in Westley, said he was already making planting decisions and preparing ground in the fall. 'To wait until March 1 to decide whether or not you're going to farm is a little late," he said. 'It could get wet for the rest of March, and you're unable to get out and prep the fields to plant.'" `https://mavensnotebook.com/2025/03/12/ag-alert-initial-cvp-water-allotment-may-not-increase-plantings/`

Figure 1: Districts with surface water project contracts and crop regions



Note: The left panel shows the project districts in the sample. The districts shaded in blue are the 98 junior Central Valley Project contractors in the data. The different shades show areas with contracts to different canals that receive different surface water allocation forecasts. There is more detail in the data than the map, as the CVP Friant and CVP other category have multiple contract types. The yellow districts represent senior rights to the Central Valley Project, who usually have higher surface water allocation forecasts, and are curtailed in fewer years. I include these districts only in robustness checks. The districts in red have contracts to the State Water Project, which usually receive the same surface water allocation forecast across the state, with the exception of the districts shaded lighter, who have different contract terms. The right panel shows 5 major climate regions in California, aggregated up from level 3 ecoregions, which are areas that share similar climate, geology, and soils. These areas roughly delineate planting areas, groundwater basins and surface water basins in California as well, and are generally regarded as distinct agricultural areas. The districts span three of these climate regions, with the majority in the Central Valley.

4.2 Water districts

I use a map of 3556 water districts from California's state geoportal, augmented with alternate maps from some missing districts (California State Geoportal (2022), Public Policy Institute of California (2025), Department of Water Resources (2025b), Department of Water Resources (2025a)). I determine which districts have contracts with the surface water projects by matching names of water districts and lists of contractors using a crosswalk file from Hagerty (2022) (California Department of Water Resources (2024b), US Bureau of Reclamation (2025)). Through this process, I am able to match all 29 SWP contractors, 98 of 99 junior CVP contractors, and 81 of 89 senior CVP contractors. Figure 1 shows the geographical distribution of districts, where the colors differentiate the project contracts that each district has, and therefore the surface water forecast they receive. There is slightly more variation in the data than is present on the map because the CVP Friant, SWP alternate, CVP senior, and CVP other categories each have multiple types of contracts. For districts that have contracts with multiple projects, I scale the forecasts by the average quantity delivered from each project (U.S. Bureau of Reclamation, 2025). Overall, the project districts represent a large share of California agriculture, covering 47% of cropland California Department of Conservation, Farmland Mapping and Monitoring Program (2020).

The right panel of figure 1 shows climate regions across the state, aggregated up from level 3 ecoregions to crop planting regions, which in California roughly delineates planting seasons, groundwater basins, surface water basins, and precipitation regions (U.S. Environmental Protection Agency (2025), Pittenger (2015)). In my strongest fixed effects specification, I interact time fixed effects with these crop regions in case trends for districts in these regions differ. I overall observe 184 districts in the Central Valley, 27 in in the South and Central Coast, 5 in the Inland Desert region, and 1 in the Sierra Nevada region.

4.3 Agriculture and crop choice

For my crop-choice analysis, I use 30m x 30m crop data from USDA's cropland data layer, which runs annually back through 2007, covering years with a variety of water conditions (Boryan et al., 2011). I aggregate crop classes by planting time and watering intensity to identify whether farmers change their decision-making across either margin[9]. To make these broad crop categories, I first assign crop planting times using the USDA's usual planting and harvesting dates for US field crops (state level) and for vegetables (county level), and I supplement missing crop categories with the University of California's recommended planting times for vegetables across the four climate regions in the right panel of figure 1 (USDA, NASS (1997), USDA, NASS (2007), Pittenger (2015)). I assign watering intensity for annual crops using crop water needs equations, which is a set of water intensity coefficients and growing length from the Food and Agriculture Organization, and requires the input of planting times and local evapotranspiration, the latter of which I get from the University of California's Cooperative Extension (Brouwer and Heibloem (1986), UC Cooperative Extension and California DWR (2000)). I categorize high and low water intensity crops at the mean water use, weighted by crop area, within planting times and climate regions so that the relative water intensity represents reasonable crop choices in each region. Therefore, I have four annuals classifications depending on planting time and watering intensity: early, high-water annuals (1%), early, low-water annuals (8%), late, high-water annuals (12%), late, low-water annuals (8%). I show examples of representative crops for each climate region, planting time and category in Appendix table A.2. The overall pattern shows that annuals planted later in the year are typically more water intensive, and crop timing and water intensity depends on region. In the main specification, I omit crops that are planted both before and after the dry season because I cannot isolate which information these crops are responding to. I aggregate the remaining agricultural land classes into four other groups: perennials (29%), idled and fallowed land (27%), double-cropped and alfalfa (10%), and annuals with different planting times (5%).

4.4 Well Drilling and groundwater

I measure well drilling decisions using well completion reports publicly available from California's Department of Water Resources (California Department of Water Resources, 2024c). Well drilling contractors have been required to report well completion, modification and removal within 60 days of the action since 1967, giving me the universe of completed wells (Department of Water Resources, 1981). The data include the date completed, location (to a 1 mile section), purpose (agriculture, monitoring, etc) and action taken (completion, removal, etc) for each well. My main variable of interest is the sum of agricultural wells completed in a district between February and August, which should capture most well drilling decisions responding to surface water supply forecasts and realizations after accounting for the drilling delay[10]. In total, I observe 36,663 agricultural wells drilled in the districts that I study from 1967-2022. By the end of the sample there is about 1 agricultural well for every 185 acres of agricultural land in these districts.

For depth to the groundwater table, I take an unbalanced panel of over 5 million monitoring well measurements from California's Department of Water Resources, and I interpolate a seasonal groundwater depth raster at a 1 kilometer resolution, using the inverse-distance-weighted depth to the groundwater table for well measurements within 5 kilometers (California Department of Water Resources, 2025). The interpolation

[9] Aggregating the data reduces misclassification (Lark et al., 2021).

[10] 82% of wells include a purpose.

allows me to get more frequent and higher spatial resolution on groundwater depth observations, since few monitoring wells exist throughout my long panel. The procedure should also be reasonable given California's relatively homogeneous aquifers.

4.5 Other variables: farm profits, weather, streamflow forecasts

For the maximized values needed in this analysis, farm revenues, costs, and profits, I use the BEA's county-level farm income and expenses dataset, which ran from 1969 to 2024. I measure crop revenues with cash receipts from crops, and crop inputs using the sum of all production expenses, excluding livestock purchased and feed purchased. I calculate profits by subtracting the costs from the revenues. For streamflow forecasts, I use the Department of Water Resources's forecasts for dry-season runoff as a percent of the average, which it began publishing in its snow survey in 1955 (Department of Water Resources, 2024). I digitize these runoff forecasts from 1965-2022, assigning them to districts based on which subbasin the centroid of the district intersects with, since streamflow relates to stream diversion rights. Finally, temperature and precipitation data comes from NOAA's nClimGrid (Durre et al., 2022).

5 Actions taken in response to surface water supply shocks

5.1 Methods

I explore the intensity of cropping and well drilling due to surface water information known at different points in the planting season, using the following model:

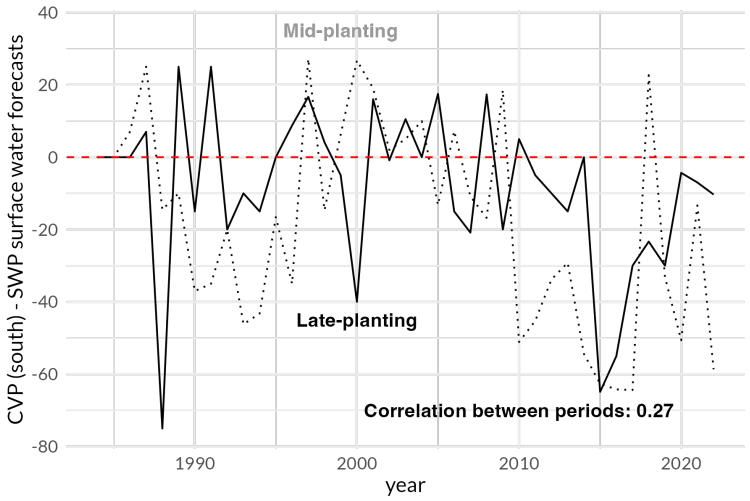
$$A_{dt} = \exp(\beta_1 s_{dt-1} + \beta_2 \hat{s}^{\text{mid}}_{dt} + \beta_3 \hat{s}^{\text{late}}_{dt} + \beta_4 s_{dt} + X_{dt} + \gamma_d + \gamma_{rt} + \varepsilon_{dt}) \tag{1}$$

A_{dt} is the amount of action A taken by district d in year t. s_{dt-1} is the previous year's surface water allocation shortfall, or 100 - the previous surface water allocation, and it provides the earliest information about the next surface water allocation, s_{dt}. $\hat{s}^{\text{mid}}_{dt}$ is the surface water allocation forecast shortfalls available at the mid-planting season and f^{late}_{dt} is the surface water allocation forecast shortfall available at the late-planting season. The first three variables effectively serve as lagged information about s_{dt}. X_{dt} is a set of district-year specific controls, and γ_d and γ_{rt} are district and climate-region by year fixed effects.

Each β identifies how a specific period contributes to changes in the level of the action A. Like Shrader (2023), including both the surface water allocation and the forecasts identifies the direct effect and the adaptation effect. Unlike Shrader, although $\hat{s}^{\text{late}}$ is the best information about the allocation, I include earlier information to estimate earlier adaptation. Each $\hat{s}$ and s variables econometrically capture innovations that deviate from prior $\hat{s}$ and s, and the fixed effects compare those deviations relative to the average for the district and other districts in the year[11]. Figure 2 shows an example of the variation in the surface water forecasts. The plot shows mid-planting and late-planting season surface water forecasts for districts with standard contracts to the State Water Project and the southern portion Central Valley Project. The plot makes apparent that the district with worse surface water allocation forecasts changes from year to year, and also sometimes within years. The difference in forecasts is correlated, but weakly (correlation coefficient

[11]This identification strategy has the flavor of macroeconomic papers on the identification of news shocks in VAR frameworks (Barsky and Sims, 2011).

Figure 2: Difference in surface water allocation forecasts between projects, for the mid-planting season and late-planting season



Note: This figure shows the difference in the forecasts across years for CVP districts in the southern portion of the Central Valley, and districts with the standard SWP contract. two different forecast regions in my study, across years. Positive values reflect better surface water allocation forecasts for the CVP. I plot the mid-planting season difference (the forecast available around February 1) and the late-planting-season difference (the forecast available around April 1). The plot makes apparent that the project with worse surface water allocation forecasts changes from year to year. Further, the project with the worse surface water availability also sometimes changes within years. The difference in forecasts is correlated, but weakly (correlation coefficient = 0.27), meaning that surface water allocation forecasts evolve quite differently from one another within a year despite having similar patterns on average.

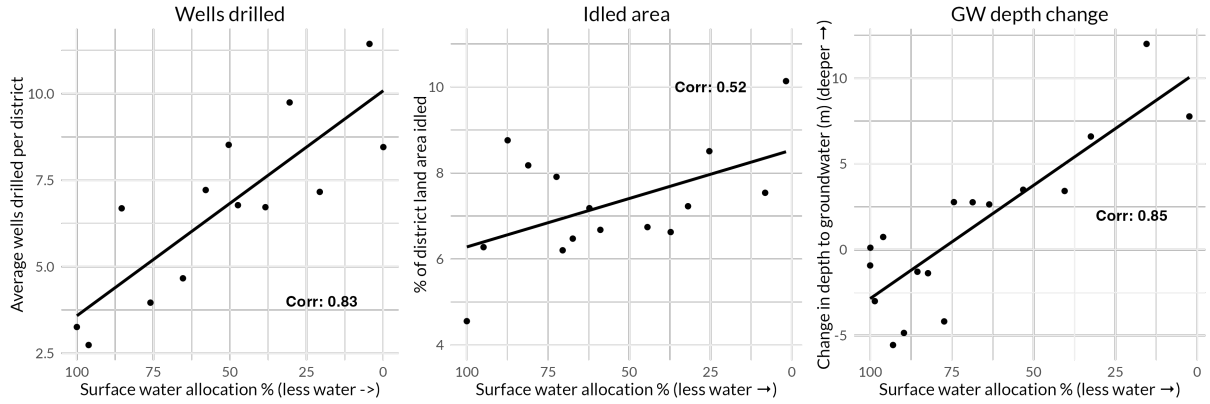
= 0.27), meaning that surface water allocation forecasts evolve quite differently from one another within a year despite having similar patterns on average.

A_{dt} can be either the total number of wells drilled in district d between February and August, or the total number of acres in d planted in crop type C, usually observed at the peak harvest season, or the depth to the groundwater table in feet, which proxies for extraction. Since A_{dt} is always bounded below by zero, where zeros usually reflect a meaningful choice, I estimate the model using PPML (Silva and Tenreyro, 2006). Further, Poisson regressions naturally represent the aggregation of individual choices (Cameron and Trivedi, 2013). Since Poisson regressions are not typical in the crop-choice literature, I check the robustness of my Poisson results using a simple multinomial logit crop choice model, following Kurukulasuriya and Mendelsohn (2008)[12]. However, Poisson has the benefits of easy interpretation and the ability to account for district-specific fixed effects.

There are three main sources of endogeneity. The first is that districts respond to surface water availability in a way that might affect other districts' decisions, especially for well drilling which has a fixed number of contractors in the short-term. Therefore, I include neighboring districts' well drilling decisions, and neighboring districts' groundwater extraction as a control in X for the respective regressions. The second source of endogeneity comes from local weather and alternative water sources, which are both correlated with surface water allocation forecasts and likely with adaptation decisions. So, for all three choices I include controls for temperature, precipitation, and streamflow forecasts and realizations, and for lagged

[12]The major benefit of multinomial logit is that choice probabilities are jointly estimated, so that a factor that makes one choice more likely makes another less likely.

Figure 3: Raw data binscatter: Adaptation actions on surface water allocation forecasts



Note: On all plots, the x axes are flipped so that a stronger shock to surface water supply (a lower surface water allocation) corresponds to a higher adaptive action. The left plot shows the average number of wells drilled, the middle plot shows the average percent idled area, and the right plot shows the change in a district's average depth to the groundwater table from the prior year, all binned by the surface water allocation forecast. Every plot shows a strong relationship between low surface water allocations and taking adaptive action.

depth to the groundwater table when it is not the dependent variable. The last source of endogeneity is that there is some autocorrelation in the forecasts which might correlate with past capital-intensive decisions like perennial planting and well drilling, which affect current decisions through the diminishing returns to wells, and switching costs (Scott, 2014). I account for this source of endogeneity by including the lagged perennial acreage in districts, and the lagged cumulative wells in districts in the crop and well choice regressions respectively.

In my main specifications, I cluster standard errors at the district level because surface water forecasts apply to specific districts. For most forecasts, the treatment (weather) is not applied to a specific location, so spatial correlation robust are usually more applicable (Shrader, 2023). In robustness checks, I employ a combination of Conley (1999) and Newey and West (1987) standard errors with various distance cutoffs and time lags to show that my results are robust to multiple standard error specifications.

5.2 Results

Figure 3 plots the raw data relationships of the final surface water allocation percents against three of the adaptation actions to low surface water taken by farmers. Worse surface water allocations correspond strongly with higher uptake of each of the farm adaptation options. Although the raw data plots cannot confirm whether farmers respond specifically to the allocation forecasts, they give strong evidence for farmers adapting to surface water supply changes in general, across water conservation and water intensification options, the latter across both the intensive and extensive margins. Leaving adaptation to water scarcity up to private decision-makers therefore can result in choices with low or high social costs.

The causal empirical specification uses variation in responses to surface water allocation forecasts specifically to determine whether there are patterns to when farmers take one choice over another. Figure 4 displays the results of the PPML regressions of each of the adaptation choices on surface water information. Table B.3 in the appendix shows the coefficient estimates for the same regressions, as well as alternative

specifications. Each row in the figure shows the results for a different adaptation margin. I use surface water forecast shortfall so that a worse surface water outcome. All of the coefficients and standard errors have been transformed to show a percent change in the action with a one percentage point decrease in the surface water allocation forecast. Broadly, the patterns are the same as the raw data plots: a decrease in the surface water allocation projected causes farmers to take adaptive actions. The details, though, are illuminating.

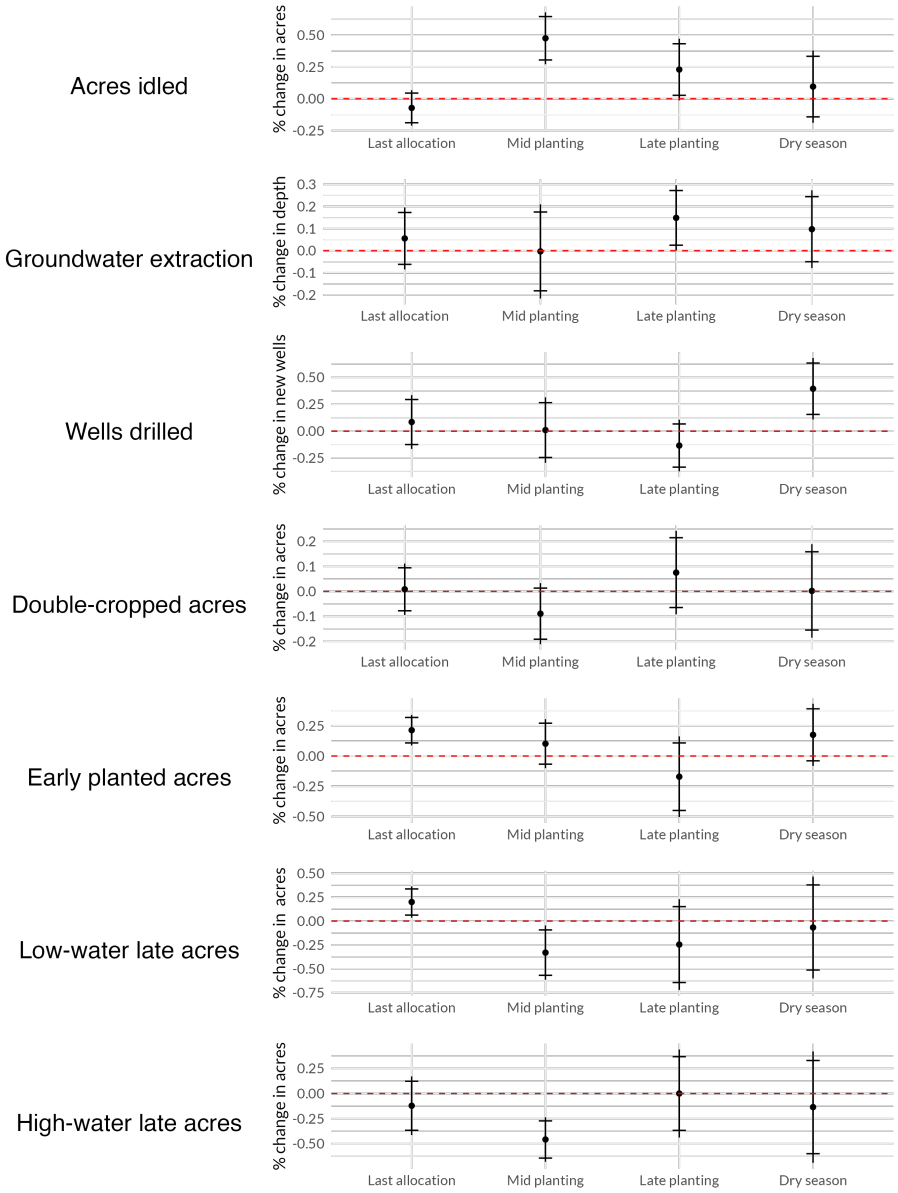
For crop choice, the general pattern is that farmers conserve water when surface water news is worse. They switch to earlier, and lower-water-intensity types of annuals, or they fallow more acres. Farmers take these water conserving choices using early information. Farmers use information available prior to the February 1st forecast to make early crop planting decisions, and farmers use the February 1st surface water allocation forecast to make late-season planting decisions, which is consistent with farmers needing to plan before planting. These patterns show that surface water allocation forecasts may in general come too late for water conservation. The latest decision made is crop idling, which increases by .48% and .23% for every 1% decrease in the surface water allocation forecast by February 1st and April 1st respectively. Overall, this is an increase of about 7,000 idled acres over all districts for a marginal change in surface water availability.

The second row shows the response of groundwater depth, in feet, to surface water information, where a positive effect means the groundwater table became deeper, which I use as a proxy for groundwater extraction. Overall, marginal changes in information early in the planting season do not have a significant impact on the depth to the groundwater table, which is consistent with the early-planting season tendency toward tailoring crops to the surface water allocation shown in the crop choice regressions. Surface water for project districts tends to be cheaper than groundwater, so that avoiding more groundwater use is privately optimal for many farmers. By April 1st, in the late-planting season, most crops are already determined, and then marginally worse information results in a strong decrease in the depth to the groundwater table, reflecting increased groundwater pumping by these districts. The average depth to the water table is about 330 feet, which means that a marginal change in surface water information results in a decrease in the groundwater table of about half a foot. Table B.3 shows the results are robust to other specifications and different standard errors.

The third row shows how the aggregation of private well drilling decisions over a district responds to surface water allocation information. Even though well drilling is a long-term investment, the regressions show that farmers respond to short-term surface water availability information by drilling. At the mean level of agricultural wells drilled yearly during February - August (484), the response to a marginal decrease in the surface water allocation is approximately 2 wells. Even more surprisingly, farmers do not respond to the surface water forecasts at the time that a well might be available for use in that year, but they respond to last-minute changes in the surface water allocation. These changes in the allocation at the dry season are likely the most privately costly. Actual allocations may change beliefs about long-run surface water availability and forward-looking farmers might want to avoid receiving such a bad shock to profits again, and investing in a well substantially reduces that risk. Also, in high water years, the final adjustment to surface water allocations is positive because of the conservative bias of early forecasts. A year with a low surface water allocation shock gives information about the medium-term drought conditions in California, making the likelihood of needing a well over the medium term more certain, and increasing farmers' value of exercising their well drilling option. I show whether these surface water allocation shocks change medium and long-term beliefs with local projections in the following subsections.

The adaptation response results are robust to different specifications. Appendix table B.3 shows that I get

Figure 4: Coefficient estimates on surface water forecasts and allocation shortfall (100% - forecast) for different adaptation choices



Note: This figure shows the coefficient responses to the full specification of equation (1), including controls for alternate water sources, neighbors' choices, and past capital-intensive choices, and district and climate region-year fixed effects. The coefficient estimates are displayed sow that a higher number is a higher surface water allocation shortfall shock (100% - forecast). Each row is one PPML regression, with the dependent variable listed on the left. The points show the coefficient estimates of a 1 point change in the surface water allocation or forecast available at each of the time periods. The 90 and 95 percent confidence intervals are also plotted, clustered at the district level. The figure shows that different choices occur at different times in the growing season, where crop choices respond to earlier surface water allocations and forecasts, and water intensifying choices usually respond to the late-planting season forecast and dry season allocation.

the same response pattern if I model crop choice using multinomial logit rather than Poisson. Table B.3 shows that the well drilling and groundwater depth results are robust to changing the imputation of the missing February forecasts. The first column shows virutally the same result for multiple imputation, the second column shows similar magnitudes (but lower significance for well drilling) if I use the lagged surface water allocation deflated by the empirical bias, and the third column shows consistent results for well drilling if I simply drop the missing observations. Table B.3 shows the results are also robust to changing the dependent variable in the well drilling regression, including by changing the time frame of wells drilled (shortening the time frame and using the entire year), and winsorizing the wells variable more, though a modest level of winsorization is needed. The final two columns show that the results are also robust to using project-type by year fixed effects, comparing all junior CVP, senior CVP and SWP districts to eachother, which makes sure that the results are not driven by bad comparisons across projects. The final robustness check, figure B.5 shows that the results are robust to using a combination of Conley and Newey-West standard errors across a variety of cutoffs.

I also explore the heterogeneity of well drilling responses to different characteristics. Unlike annual planting and groundwater withdrawal decisions, well drilling is not a recurring annual choice. Once a well is drilled, a farmer no longer needs to make a well drilling decision. So, at the district level, we should view a diminishing return to wells. I interact the surface water allocation forecasts in the main specification with the log of the lagged number of wells in a district, and plot the marginal response to the final surface water allocation in appendix figure B.4. The plot matches the economic intuition that districts' responses to information is significantly higher than the average response when a district's number of wells is low. As a district's number of wells increases, the district stops responding to low surface water allocations with well drilling. Two other plots show districts' responses to forecasts interacted with the percent of surface water originating from project water and the percent of district land in perennials. Districts respond more strongly as either of these variables increase.

The main specification clearly shows that on average, farmers in project districts respond to surface water allocation forecasts by changing annual cropping patterns, changing the amount of groundwater extracted, and changing drilling patterns. However, the main specification on its own cannot show whether these private adaptation responses to the particular information are socially costly on net, which is the topic of study of the following section.

6 Private value of adaptive actions

6.1 Methods

In this section, I study the private value of adaptation to surface water scarcity. Forecasts only have private value through how they change inputs and actions, so accordingly I examine how revenue, inputs and profits change in response to surface water allocation forecasts. I closely follow Shrader (2023) who shows that by including both forecasts and realized values in a regression on a maximized outcome, one can identify both the value of adaptation and the direct effect of the final weather outcome. The estimating equation is

$$Y_{ct} = \exp(\beta_1 s_{ct-1} + \beta_2 \hat{s}_{ct}^{\text{mid}} + \beta_3 s_{ct} + X_{ct} + \gamma_c + \gamma_t + \varepsilon_{ct}) \tag{2}$$

which is similar to equation (1), except that where s_{ct} denotes a surface water allocation for county c in

year t. I aggregate surface water allocation forecasts to the county level by assigning the correct forecasts to counties based on the districts within the counties, and then weighting the forecasts by the proportion of water from each project in the county, approximated by the state's water model (Department of Water Resources, 2022). X_{ct} again controls for non-project water availability from streamflow, precipitation, and depth to the water table, as well as demand from temperature. Omitted variables are crop storage and government payments, which are correlated with profits and surface water availability; I control for these using crop inventory changes and aggregate government payouts from the BEA data (Fisher et al., 2012).

Although I use the best data possible, Y_{ct} measures the profits and revenues over all agricultural land in a county, not only districts with project contracts. Since the controls should capture farms' responses due to other water available, the main problem is measurement error in my dependent variable. In the appendix I model counties' heterogeneous responses to surface water allocation forecasts by interacting $\hat{s}$ and s with the amount of project water a district receives in an average year. However, I likely will end up with less precise estimates than if I had district-level profits.

A drawback of equation (2) for estimating the value of information is that it does not tell us anything about the counterfactual case of not having a surface water forecast at all. Unlike most forecasting contexts, California surface water forecasts do provide variation in years where there were no mid-planting season surface water forecasts, which in the previous section were found to be important for agricultural decisions. I can therefore estimate the value of being provided a surface water forecast versus relying on alternate information. I modify the previous estimating equation by including only information available in all county years, s_{t-1}, and interacting s_t by the county's Central Valley Project contract quantity, in percentage of total surface water quantity, P, and the percent of Central Valley Project districts that received a surface water allocation forecast prior to February 1st, T.

$$\begin{aligned} Y_{ct} = \exp(&\beta_1 s_{ct-1} + \beta_2 s_{ct} + \\ &\beta_3 s_{ct} \times \mathrm{P}_c + \beta_4 s_{ct} \times \mathrm{T}_t + \beta_5 s_{ct} \times \mathrm{P}_c \times \mathrm{T}_t + \\ &X_{ct} + \gamma_c + \gamma_t + \varepsilon_{ct}) \end{aligned} \tag{3}$$

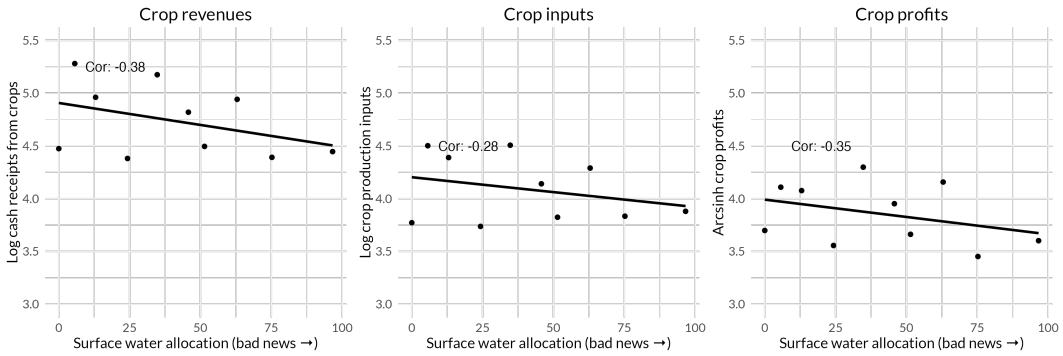
6.2 Results

In figure 5 I show a binscatter of logged crop revenues and crop inputs on the surface water allocation, with both variables residualized by county and year fixed effects. Revenues and inputs respond strongly and negatively to lower surface water allocations. Despite the lowering intensity of production, farmers experience much lower profit in years where their county faces the lowest residualized surface water allocations, meaning that surface water is important for farmers' outcomes.

How much of the cost of low surface water allocations is borne during the planting stages, and how much is directly because of the low water allocation? Figure 6 shows the direct effect and total effect (including adaptation) of a marginal decrease in the surface water allocation. The grey point on the left shows the unbiased direct effect, β_3 in equation (2), of surface water allocations on inputs, revenue and profits, conditioning on all of the other variables. The red point to the right shows the direct effect plus the adaptation effect, $\beta_1 + \beta_2 + \beta_3$.

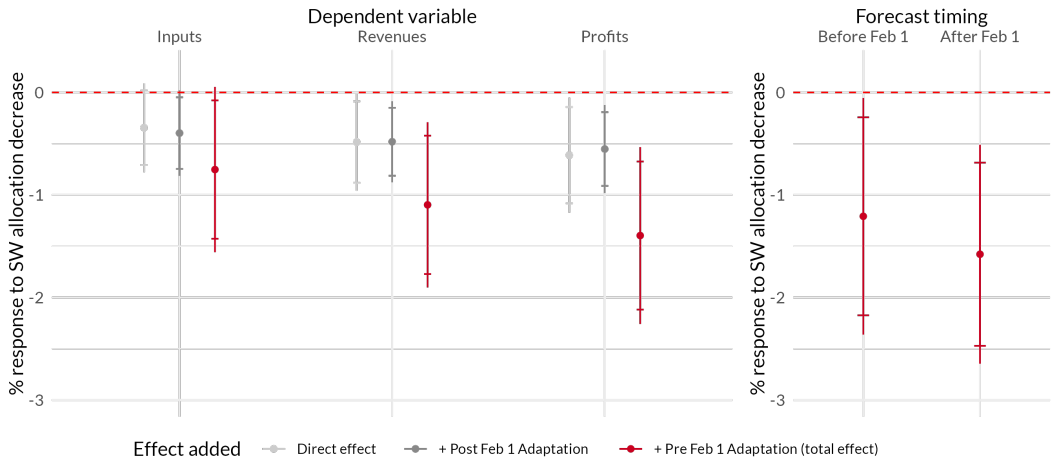
Like the raw data, it is clear that a marginal decrease in the surface water allocation decreases profits directly, by about 0.6% for every 1% decrease in the surface water allocation. Therefore, the surface water

Figure 5: Binscatter of county-level crop revenues and inputs, on the surface water allocation, controlling for county and year fixed effects



Note: All variables are transformed before being binned, and in units of millions of dollars. For profits, I use the hyperbolic arcsin transform because 7% of observations are negative, which should be comparable to the others since the mean of profits is $318 > 10$ (Bellemare and Wichman, 2020). I measure crop revenues with cash receipts from crops, and crop inputs using the sum of all production expenses, excluding livestock purchased and feed purchased. For profits, I subtract the costs from the revenues.

Figure 6: Direct and adaptation effects of surface water forecasts and allocations shortfall on revenues, inputs and profits



Note: These plots show the results of the estimations of equations (2) and (3). In the left panel, each group of coefficients shows the results for a different dependent variable. The lightest grey point to the left only includes the current year's surface water allocation. The middle point includes the mid planting season allocation forecast, while the right-most black point includes last year's allocation. The rightmost point is the unbiased coefficient on the direct effect. For the right plot, the left blue point shows the effect of a surface water allocation decrease on profit for CVP districts without a mid-planting season surface water allocation forecast ($\beta_2 + \beta_3 P_c$ at the mean percent of CVP water, P_c), and the right point shows the effect for CVP districts with a mid-planting season allocation forecast ($\beta_2 + \beta_3 P_c + \beta_4 P_c$).

from the projects is valuable to California agriculture. Adding the adaptation effect nearly doubles the decrease in profits from a surface water allocation decrease. This shows that adaptation is privately costly for farmers. The other pattern shown in the figure is that the main costs of adaptation are borne prior to the mid-planting season forecast, when farmers are adapting by switching between crops.

The plot to the right shows the results of the estimation of equation (3), where the left point shows the effect of a surface water allocation decrease on profit for CVP districts without a mid-planting season surface water allocation forecast ($\beta_1+\beta_2+\beta_3 P_c$ at the mean percent of CVP water, P_c), and the right point shows the full effect for CVP districts with a mid-planting season allocation forecast ($\beta_1+\beta_2+\beta_3 P_c+\beta_4 P_c$). Overall, the negative effect of the forecast is lower for districts without access to the earlier forecast, suggesting that having a forecast allows for more adaptation, a counterfactual not usually estimable. Overall, I find that having a surface water forecast prior to February 1st diminishes the total cost of a 1% decrease in the surface water allocation by 23%, about $1.2 million for the average county.

7 Social costs of private adaptation to surface water supply shocks

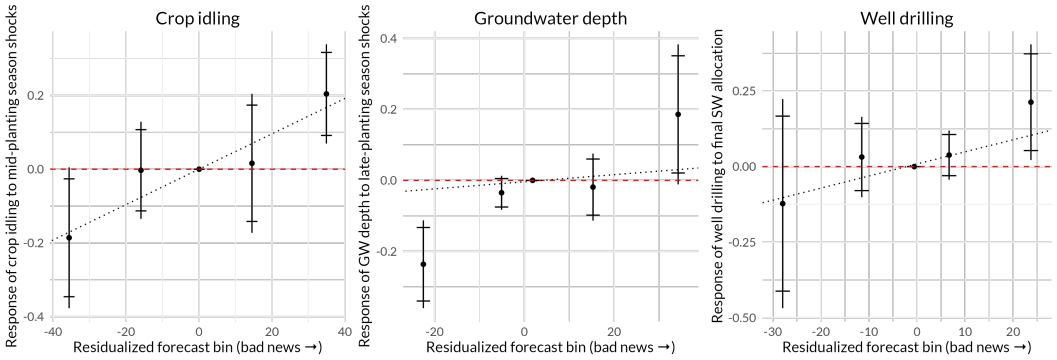
Private adaptation in response to specific surface water supply information is socially costly if it increases groundwater use on net. I study changes in overall groundwater extraction in three ways. First, I examine the asymmetry of adaptation responses to different surface water supply shocks. For example, if farmers decrease groundwater extraction in response to positive shocks at the same rate as they increase groundwater extraction in response to negative shocks, the main social cost of private adaptation is through the time value of water. Second, I study how long groundwater wells remain excess. Likely, many wells are drilled by farmers who already have a high well value and who likely would have drilled within a few years. Then, shifting forward in time these wells drilled still has the social cost of extracting non-renewable water earlier. However, a surface water allocation shock might be large enough to shift farmers' beliefs about surface water availability, and therefore result in some wells drilled that would not have been drilled otherwise. Finally, I also examine how well drilling, a capital-intensive adaptation, affects later farm decisions. I look first at the effect of exogenous new wells on the depth to the water table to check that well drilling truly does affect groundwater depth. Then, I study how well drilling affects later crop choice. I use these results to estimate the change in groundwater use from private adaptation, and approximate the social cost using a plausible value of the groundwater externality.

7.1 Asymmetry of responses: social costs of adaptation are from well drilling

I examine whether the average response to well drilling, groundwater depth change and crop idling is non-linear by using five bins of the residualized surface water allocation forecasts in lieu of the continuous forecast in regression equation (1). I residualize using all fixed effects and controls so that the bin reflects same level as the variation used in the main analysis, and I only bin the one surface water forecast time that each action responds to for statistical power.

Figure 7 shows different asymmetric responses for each of the adaptation choices. Of all of the adaptation options, crop idling is closest to linear, showing that farmers are sensitive to relative water abundance and scarcity when choosing the number of acres to plant and harvest. The strongest effect is for the worst surface water forecast shocks, where crop idling significantly increases. In contrast, the change in groundwater depth

Figure 7: Adaptation responses by surface water forecast bin

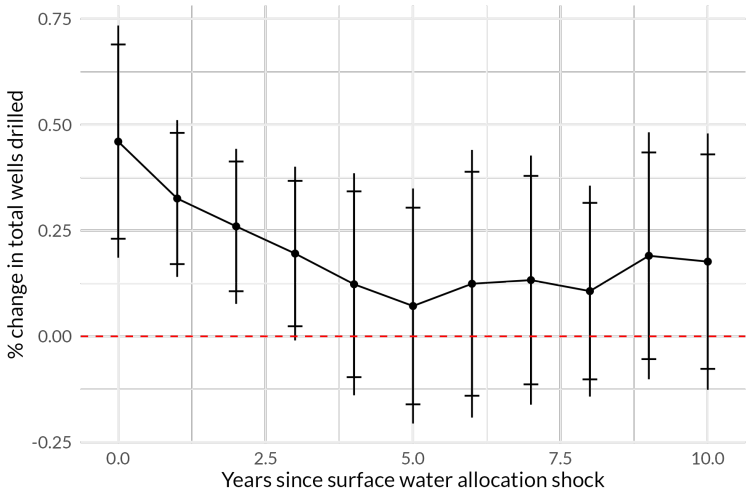


Note: These three plots show the coefficients on three adaptation responses for the main surface water forecast each responded to, when the surface water forecast is binned after being residualized. Bins are equally spaced, except that the outliers smaller than the .005 quantile and larger than the 0.995 quantile, which are put in the first and final bins respectively. On the plot, the coefficient estimate is shown, with the 90th and 95th percent confidence intervals, spaced according to the average value in each bin. The dotted line shows the linear estimate displayed in the main column in table B.3.

is highly non-linear, where the positive coefficient is driven by the best surface water forecast shocks, showing that farmers extract significantly less groundwater only in years of surprising surface water abundance. Otherwise, farmers extract groundwater consistently, revealed by the other three bins not being statistically different from the middle reference. The first two plots together show that in low surface water years, farmers idle more crops rather than extract more groundwater. The right plot shows that the positive coefficient on well drilling in response to forecasts comes from the response to bad news. Farmers do not put off drilling in response to positive surface water allocation shocks.

The asymmetry plots show that the social cost of private adaptation in response to surface water forecasts comes from the extensive margin response of groundwater well drilling. Farmers do not change their groundwater extraction patterns very much in response to different surface water allocation forecasts. The middle plot shows that farmers treat good surface water news as a windfall, but otherwise adjust their cropping patterns to maintain a consistent level of groundwater withdrawals. The pattern in the plot suggests that the constant withdrawals arise mainly from farmers extracting at the physical capacity of their wells, rather than a response to the marginal cost of groundwater. In response to a surface water supply shock, the marginal benefit of groundwater use increases. As long as the marginal cost pattern of groundwater stays the same, there should be some evidence of an increase in groundwater use as surface water news gets worse. Instead, groundwater use remains constant, so farmers already maximize groundwater used. There are two implications to explore. First, when farmers gained access to groundwater, we can expect that they changed their behaviors to use as much groundwater as was available to them. Second, farmers therefore can only adapt along the extensive margin in response to bad news, by drilling more wells. The extensive margin response to bad news is clear in the third plot. Gaining access to more groundwater through well drilling is socially costly if farmers use more groundwater because of drilling. Not only does that result seem inevitable, but it also seems plausible that farmers would change long-term farm decisions toward more water-intensive crops to again maximize groundwater extracted. The social cost of the adaptation to surface water forecasts also depends on how long the wells remain excess, which is what I study next.

Figure 8: Dynamic well drilling response to a surface water allocation shock



Note: This plot shows the cumulative dynamic well drilling response to a surface water allocation shock in year zero, using local projections. A coefficent of zero shows that the number of wells drilled is the same as the expected trend.

7.2 Dynamics of well drilling: most wells are temporarily excess, some may be permanent

I study when wells would have been drilled had it not been for the surface water allocation shock using local projections (Jordà, 2005). Local projections will show the impulse response of a surface water allocation shock in year t on the path of cumulative new wells in a water district from immediately before the shock occurred $(t-1)$ until the year $t+h$. The estimating equation is nearly identical to equation (1), except that the dependent variable is the sum of wells drilled in a district from year $t-1$ to year $t+h$, and I also add the standard local projections controls, the path of surface water forecast shocks and the path of recent wells drilled, through the addition of lags of these variables. I include three lags of each, but results are robust to different numbers of lags. I then run $h = 10$ separate regressions, and plot the path of coefficients in figure 8.

Similar to the main estimate, the number of wells in a district in the year that a surface water allocation shock occurs is about 0.46% higher than the expected trend[13] The deviation from trend decreases monotonically for the four years after the shock occurs, until the increase becomes insignificant. For the most part, the wells drilled in response to surface water shocks are shifted forward in time, which likely suggests changes to medium-term surface water beliefs. Farmers would have drilled wells soon, but a low surface water allocation shock suggests the following several years might have low surface water availability making wells worth the investment immediately. Despite the insignificance of a long-term trend, there is still a real social cost to the shifting forward of wells in time. Groundwater is likely used earlier, leaving less time to regulate the aquifer and shifting externalities forward in time.

Despite the insignificance of the long-term trend, the percent change in total wells drilled levels off above zero, suggesting there might be some non-excess wells drilled in response to surface water allocation shocks.

[13]The coefficient estimat differs from the main specification because of the local projections controls.

Permanent effects can come from a shift in individual farmers' future beliefs about the value of wells, or due to the proportional shift upward in everybody's well value which moves the entire path of well drilling forward in time. The average point estimate four years after the surface water allocation shock and beyond is .132, which is 29% of the magnitude of the coefficient in the first year. More than 1/4 of the well response might be permanent.

7.3 Post-well drilling farm decisions: farms increase water intensity after drilling

Intuitively, groundwater extraction should increase if farms drill groundwater wells because the value of a well comes from groundwater use. I quantify the magnitude of the increased extraction through the dynamic changes in the depth to the water table. Likely, farmers also make different cropping choices after drilling a well because of having permanent access to a surface water substitute with a stable marginal price. I also explore the dynamic paths of crop choices after drilling. Like previously, I study the dynamic paths of groundwater depth and crop acreage using local projections.

In particular, the crop choice analysis I propose suffers from the simultaneity bias of the well drilling and crop choice decisions. Districts with higher valued crops are more likely to drill wells, which was illustrated in appendix table B.4, and perhaps more likely to plant more high valued crops. Also, the value of crops factors directly into the value of wells. If high water crops become more valuable, then the value of wells increases too because groundwater adds more net profit per unit. I instrument for exogenous new wells using well drilling cost shifters, which affects the well supply curve without affecting crop choice except through the wells choice. I interact the groundwater depth at the start of the year with well input costs. For my main analysis, I use yearly steel piping prices from FRED, since large diameter steel piping is common for well casing in large agricultural wells. I check for robustness to other well inputs including oil drilling machinery prices (a proxy for water well drilling machinery) and plastic piping prices (PVC casing is common for smaller agricultural wells).

Local projections can be combined with instrumental variables analysis straightforwardly, by performing two-stage least squares in each of the h local projections regressions (LP-IV) (Jordà et al., 2015). In addition to the standard instrumental variables assumptions, IV with local projections requires a third assumption of lead-lag exogeneity, where the instrument is uncorrelated with future and past well drilling (Stock and Watson, 2018). Fortunately, the standard local projections controls (past well drilling) makes the instrument valid. A drawback of LP-IV is that I cannot use PPML, and so instead I use the logarithm of the crop acreage dependent variables plus one, which has problems for interpretation (Chen and Roth, 2024).

Because the local projections analysis of crop choice requires leads and lags of crop acreage, the short panel in the Cropland Data Layer is not ideal. I also am not directly studying surface water forecasts in this section, so I am not bound to district-level data. therefore, I perform the main analysis using a county-level dataset of harvested cropland available from 1980 to 2022 from California's Agricultural Commissioner (CA Agricultural Commissioner, National Agricultural Statistics Service, 2025). I aggregate all variables to the county level. I use the same weather and streamflow controls as previously to be consistent with the previous specifications and to increase precision. I use spatial-HAC standard errors as in the previous robustness checks because the treatment is interacted with changes in groundwater depth, which is correlated over space.

Table 2 shows the first stage table for my main instrument, where each column adds more controls and fixed effects. It is unclear what direction the coefficient on the instrument should go. Given a steel pipe

Table 2: First stage: wells drilled in response to well prices

	(1)	(2)	(3)	(4)	main
Last GW depth × steel pipe price	0.401*	0.369*	0.345**	0.416***	0.431***
	(0.214)	(0.214)	(0.160)	(0.147)	(0.139)
Last year's GW depth (100 ft)	−2.454***	24.444**	8.703	11.100*	8.608
	(0.390)	(11.225)	(7.292)	(6.402)	(5.828)
Steel pipe price	0.068				
	(0.060)				
Local projections controls	no	no	yes	yes	yes
Other controls	no	no	no	yes	yes
County FEs	no	yes	yes	yes	yes
Year FEs	no	yes	yes	yes	no
Region x Year FEs	no	no	no	no	yes
F-stat	3.466	8.215	8.711	12.331	13.497
Num. obs.	2166	2166	2109	2072	2072
R^2 (full model)	0.026	0.802	0.842	0.838	0.843

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

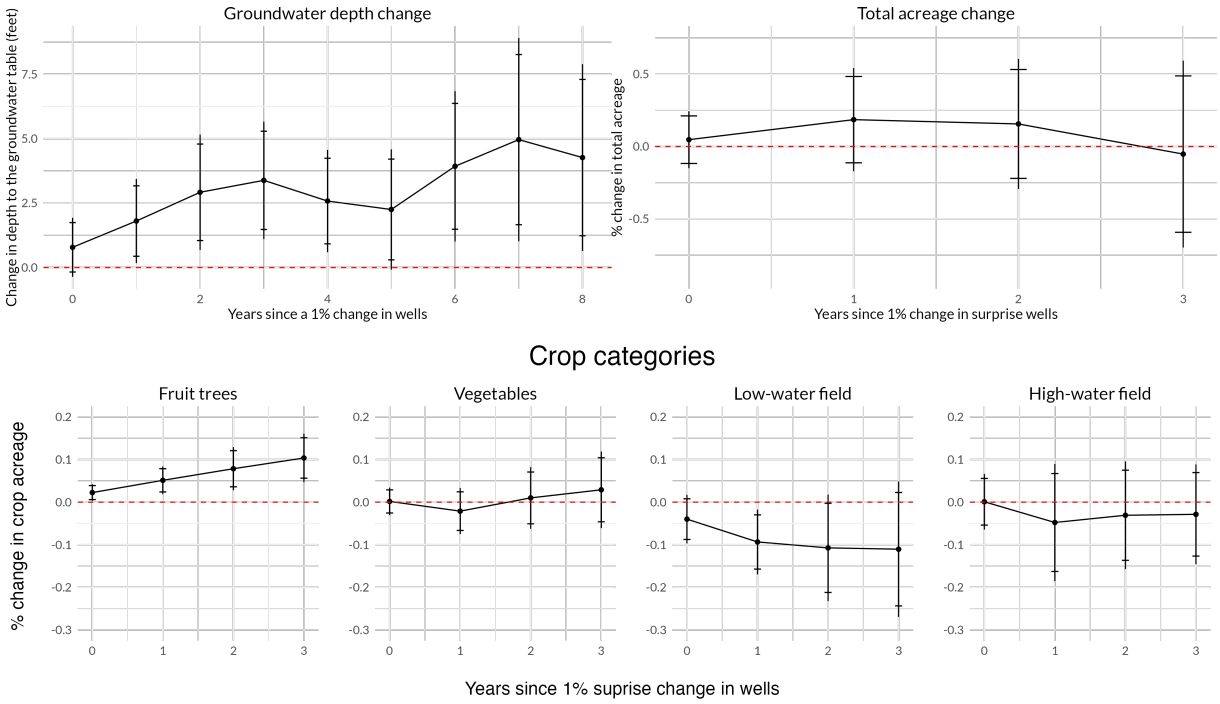
Note: These plots show regressions of the logged number of agricultural wells drilled in a county on the interaction of the previous year's groundwater depth and the current steel pipe price. Each column adds stronger fixed effects or controls. (1) is the raw data, (2) adds county and year fixed effects, (3) adds local projections controls (3 years of lagged well drilling), (4) adds other surface water availability controls, and (5) adds region-year fixed effects. The interacted term is the main instrument in my analysis, which has an F-statistic of 13.5 in the main specification.

price in year t, the interaction tells us whether the price affects regions with deeper or shallower groundwater more. The positive coefficient in the table suggests that areas with deeper groundwater are affected less. Although these areas require more steel pipe inputs, the cost of steel piping increases linearly with depth, while other costs (like pumps, the expected value of electricity costs) increase quadratically with depth. Because of already very high prices for deep groundwater regions, the well price could increase relatively less. Overall, the instrument is strongly predictive and has a moderate F-statistic of 13.5. The positive, marginally significant, coefficient on last year's groundwater depth is more likely showing the endogeneous relationship between groundwater demand and well drilling, which is why the un-interacted groundwater depth variable cannot be an instrument for well drilling.

For the dynamic path of groundwater extraction, I estimate the local projections with standard local projections rather than LP-IV. The value-added of groundwater jointly determines well drilling choices and groundwater extraction choices. However, local projections directly controls for well demand through lags of previous well drilling choices.

Figure 9 shows the dynamic consequences of well drilling on acreage and groundwater depth change. The depth to the groundwater table increases continually after wells are drilled, at the rate of about half a foot a year for a one percent increase in wells. Total acreage stays the same, though it masks the trend of substitution across crop categories. Immediately, counties with new wells see more fruit trees and fewer low-water, low-valued field crops, and these trends increase over time. There is no change for high-valued annuals like vegetables. Overall, these trends suggest not only an increase in water useage in drought years, but also in an average year, as fruit trees can use several times as much water as low-water field crops like wheat.

Figure 9: Local projections of changes in groundwater depth and crop acreage with a 1% increase in wells



Note: Each plot shows the dynamic effect of a 1% increase in wells in year t on either the depth to the groundwater table or the change in crop acreage, using local projections. The acreage plots are estimated with LP-IV, and have fewer years because of the decreasing strength of the instrument as the panel gets smaller. The error bars show 90 and 95% confidence bounds for Conley standard errors accounting for spatial correlation within 120 km and temporal correlation within 2 years (since it is a short panel).

7.4 Aggregating the social cost estimates

I now take the previous estimates of changes in behavior to see how a one-unit change in the surface water allocation affects changes in groundwater use, both temporarily as well drilling catches back up to trend, and permanently, assuming that the persistent effect in the local projections plot in figure **??** is truly above zero. I first estimate the increase in groundwater use from the change in the groundwater table, and then I compare these estimates with the implied change from crop choices.

A one percent decrease in the residualized final surface water allocation results in a 0.46% increase in wells, about 0.03 wells per district on average, which remains excess for 1 year 78% of the time, two years 56% of the time, three years 34% of the time, and forever 28% of the time. A 1% change in wells results in a decline of the water table by about half a foot a year, so the wells change from a surface water allocation shock, multiplied by the average agricultural area in a district, and the average storage of the aquifer implies an average of 290 acre feet extracted over the time that the wells are excess for one district, and 15 acre feet permanently [14]. Using $25 as a lower bound for the value of groundwater, the baseline tax set by SGMA to begin to address the stock externalities (Willis, 2024), the average social cost of one district's response to a marginal allocation shock is $3440 over the first three years in net-present discounted dollars, and $6200 forever.

The crop responses to new wells shows that districts plant more perennials, transitioning from both high water field crops (about 20% of the time) and low-water field crops (about 80% of the time). Even though some high-water field crops require the same amount of water as perennials, high-water field crops can be fallowed and so usually use less water overall, meaning that both of these transitions likely lead to water intensification. On average, about 27% of land is idled. Given the probability of idling, and the assumption that high-water annuals use the same amount of water as perennials, and low-water annuals use half, planting a perennial requires about 2.25 acre feet more water per year. Perennials are also a dynamic choice, so having a new well gives districts a head start in growing them and transitioning to the high water intensity crop. The average district has about 8500 acres in perennials, so that the new wells resulting from a marginal change in the surface water allocation would result in about 5 new perennial acres. Over the time that wells are excess, before well drilling catches up to trend, about 25 acre feet of groundwater is used in the district, for a discounted value of $543. About 1 acre of perennial land remains permanently excess, resulting in a 2.5 acre feet increase in water, costing the state $1027 for the rest of time. Thus, the switch to perennials makes up about 16% of the increased water use.

Districts are hit with a 1% residualized surface water shock about 43% of the time, and 5% of the time get a shock 10 times the marginal shock. If we assume that in 10 years, every district gets hit only with a 5% shock twice, it results in a 130,000 acre foot decline in the aquifer before the well drilling trend catches up, and 15,300 acre feet extra withdrawn every year permanently, which is about a 0.2% increase in agricultural groundwater withdrawals. The social cost of the groundwater induced by adaptation to short-term forecast errors is 10 million total over ten years.

[14] The average storage in the aquifer is porosity, the amount of empty space in the soil. Most studies assume the porosity to be 20% (Argus et al., 2022).

8 Conclusion

In this paper, I find that the way farmers adapt to new information about water scarcity changes throughout the planting and growing season. Early in the planting season, farmers respond to low expected surface water through adaptation mechanisms with low social costs, like crop switching and crop idling. Later in the season, farmers adapt by intensifying groundwater use, both by extracting more groundwater and drilling more wells. Some of the groundwater intensification response is permanent, driven by a small proportion of excess wells. My results show that timing of information matters for the value of adaptation because in agriculture (and many other cases), the lead time up to an event affects the choice set.

References

Anand, V. (2023). Does getting forecasts earlier matter? evidence from winter advisories and vehicle crashes.

Antle, J. M. (1983). Testing the stochastic structure of production: a flexible moment-based approach. *Journal of Business & Economic Statistics 1*(3), 192–201.

Aquaoso (2021). California agricultural water prices by water district. `https://aquaoso.com/water-trends/california-agricultural-water-prices/`. [Online; accessed 24-June-2025].

Argus, D. F., H. R. Martens, A. A. Borsa, E. Knappe, D. N. Wiese, S. Alam, M. Anderson, A. Khatiwada, N. Lau, A. Peidou, et al. (2022). Subsurface water flux in california's central valley and its source watershed from space geodesy. *Geophysical Research Letters 49*(22), e2022GL099583.

Ayres, A. B., E. C. Edwards, and G. D. Libecap (2018). How transaction costs obstruct collective action: The case of california's groundwater. *Journal of Environmental Economics and Management 91*, 46–65.

Ayres, A. B., K. C. Meng, and A. J. Plantinga (2021). Do environmental markets improve on open access? evidence from california groundwater rights. *Journal of Political Economy 129*(10), 2817–2860.

Barsky, R. B. and E. R. Sims (2011). News shocks and business cycles. *Journal of monetary Economics 58*(3), 273–289.

Bauer, R. (2022, July). California farmland: The largest food producer in the us. `https://farmtogether.com/learn/blog/california-farmland-the-largest-food-producer-in-the-us`. Senior PR & Communications Manager.

Bellemare, M. F. and C. J. Wichman (2020). Elasticities and the inverse hyperbolic sine transformation. *Oxford Bulletin of Economics and Statistics 82*(1), 50–61.

Borchers, J. W., M. Carpenter, V. K. G. Grabert, B. Dalgish, and D. Cannon (2014). *Land subsidence from groundwater use in California*. California water foundation Sacramento, CA, USA.

Boryan, C., Z. Yang, R. Mueller, and M. Craig (2011). Monitoring us agriculture: The us department of agriculture, national agricultural statistics service, cropland data layer program. *Geocarto International 26*(5), 341–358.

Brouwer, C. and M. Heibloem (1986). *Irrigation Water Management: Irrigation Water Needs*. Number 3 in Training Manual. Rome, Italy: Food and Agriculture Organization of the United Nations. Prepared jointly by the International Institute for Land Reclamation and Improvement and the FAO Land and Water Development Division. Drawings by J. van Dijk.

Bruno, E. M., J. Hadachek, N. Hagerty, and K. Jessoe (2024). External costs of climate change adaptation: Groundwater access.

Bruno, E. M. and N. Hagerty (2024). Anticipatory effects of regulating the commons. Technical report, Working paper.

Bureau of Reclamation (2024). Central valley project. [Online; accessed 10-January-2025].

Burlig, F., A. Jina, E. M. Kelley, G. V. Lane, and H. Sahai (2024). Long-range forecasts as climate adaptation: Experimental evidence from developing-country agriculture. Technical report, National Bureau of Economic Research.

Burlig, F., L. Preonas, and M. Woerman (2020). Groundwater, energy, and crop choice. *Work. Pap., Univ. Chicago. https://epic. uchicago. edu/wp-content/uploads/2020/12/Groundwater-Energy-And-Crop-Choice. pdf*.

Burt, O. R. (1964). The economics of conjunctive use of ground and surface water.

CA Agricultural Commissioner, National Agricultural Statistics Service (2025). County ag commissioners' data listing. `https://www.nass.usda.gov/Statistics_by_State/California/Publications/AgComm/index.php`. Accessed: 29 October 2024.

CA State Climatologist (2025). California precipitation. `https://cw3e.ucsd.edu/wp-content/uploads/2015/02/CA_Precip_final.pdf#:~:text=As%20can%20be%20seen%20in%20Figure%201%2C,Ocean%20delivering%20rain%20and%20snow%20to%20California.`, Last accessed on 2025-04-02.

California Department of Conservation, Farmland Mapping and Monitoring Program (2020). 2006 fmmp shapefiles. `https://gis.conservation.ca.gov/portal/home/item.html?id=edd5b2f8b83345758695f407478d546e`. Shapefile dataset, originally created 2006, posted July 28, 2020, updated November 22, 2022.

California Department of Food and Agriculture (2023). California Agricultural Statistics Review 2021-2022.

California Department of Water Resources (2024a). Archived bulletin 120. Accessed 10 October 2024.

California Department of Water Resources (2024b). Swp water contractors. Accessed 10 October 2024.

California Department of Water Resources (2024c). Well completion reports. `https://water.ca.gov/Programs/Groundwater-Management/Wells/Well-Completion-Reports`. Accessed: 29 October 2024.

California Department of Water Resources (2025). Periodic groundwater level measurements. `https://data.cnra.ca.gov/dataset/periodic-groundwater-level-measurements`. Seasonal and long-term groundwater level data collected statewide by DWR and cooperating agencies. Accessed: 29 July 2025.

California State Geoportal (2022). i03 waterdistricts. https://gis.data.ca.gov/datasets/45d26a15b96346f1816d8fe187f8570d_0/about.

Cameron, A. C. and P. K. Trivedi (2013). *Regression analysis of count data*. Number 53. Cambridge university press.

Carleton, T., E. Duflo, B. K. Jack, and G. Zappalà (2024). Adaptation to climate change. In *Handbook of the Economics of Climate Change*, Volume 1, pp. 143–248. Elsevier.

Chen, J. and J. Roth (2024). Logs with zeros? some problems and solutions. *The Quarterly Journal of Economics 139*(2), 891–936.

Conley, T. G. (1999). Gmm estimation with cross sectional dependence. *Journal of econometrics 92*(1), 1–45.

de Guzman, S., M. L. Anderson, E. Lynn, and P. Coombe (2022). Indicators of climate change in california. *Office of Environmental Health Hazard Assessment*.

Department of Water Resources (1981). Water well standards: The state of california. Technical report. https://www.countyofglenn.net/sites/default/files/Environmental_Health/WP_DWR_Bulletin_74-81.pdf.

Department of Water Resources (2022). Water portfolios and balances. https://water.ca.gov/Programs/California-Water-Plan/Data-and-Tools,.

Department of Water Resources (2024). Bulletin 120 and water supply index. *California Cooperative Snow Surveys*. https://cdec.water.ca.gov/snow/bulletin120/.

Department of Water Resources (2024). State water project. [Online; accessed 10-January-2025].

Department of Water Resources (2025a). Oro loma water district groundwater sustainability agency (gsa) – basin 5-022.07 delta-mendota. https://sgma.water.ca.gov/portal/gsa/print/302.

Department of Water Resources (2025b). Pre-sgma statewide groundwater management plans. https://gis.data.ca.gov/datasets/i07-presgma-groundwatermanagementplans. Based on legislative actions: AB 3030 (1992), SB 1938 (2002), and AB 359 (2011). For Groundwater Management Plan documents, contact SGMPS@water.ca.gov. No access or distribution constraints.

Dieter, C. A., M. A. Maupin, R. R. Caldwell, M. A. Harris, T. I. Ivahnenko, J. K. Lovelace, N. L. Barber, and K. S. Linsey (2018). Estimated use of water in the united states in 2015. Circular 1441, U.S. Geological Survey.

Downey, M., N. Lind, and J. G. Shrader (2023). Adjusting to rain before it falls. *Management science 69*(12), 7399–7422.

Durre, I., M. F. Squires, R. S. Vose, A. Arguez, W. S. Gross, J. R. Rennie, and C. J. Schreck (2022, May). NOAA's nClimGrid-Daily Version 1 – Daily gridded temperature and precipitation for the Contiguous United States since 1951. Technical report, NOAA National Centers for Environmental Information. Available since 6 May 2022.

Ferguson, B. (2024). Trade frictions in surface water markets. Technical report, Working paper.

Fisher, A. C., W. M. Hanemann, M. J. Roberts, and W. Schlenker (2012). The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather: comment. *American Economic Review 102*(7), 3749–3760.

Friedman, J., T. Hastie, and R. Tibshirani (2010). Regularization paths for generalized linear models via coordinate descent. *Journal of Statistical Software 33*(1), 1–22.

GEI Consultants (2017). Summary of land use and well permitting. Technical report, West Placer County. `https://westplacergroundwater.com/wp-content/uploads/2019/10/Land-Use-Authorities_Final-1.pdf`.

Goebel, M., R. Knight, and M. Halkjær (2019). Mapping saltwater intrusion with an airborne electromagnetic method in the offshore coastal environment, monterey bay, california. *Journal of Hydrology: Regional Studies 23*, 100602.

Grantham, T. E. and J. H. Viers (2014). 100 years of california's water rights system: patterns, trends and uncertainty. *Environmental Research Letters 9*(8), 084012.

Greenspan, K., S. Cole, and C. Peterson (2024, June). Groundwater in california. Fact Sheet.

Hagerty, N. (2022). Adaptation to surface water scarcity in irrigated agriculture. *Unpublished, Working Paper*.

Hagerty, N. (2023). What holds back water markets? transaction costs and the gains from trade. *Unpublished, Working Paper*.

Hagerty, N. and E. Bruno (2024). Anticipatory effects of regulating the commons. *Unpublished, Working Paper*.

Hornbeck, R. and P. Keskin (2014). The historically evolving impact of the ogallala aquifer: Agricultural adaptation to groundwater and drought. *American Economic Journal: Applied Economics 6*(1), 190–219.

Hultgren, A., T. Carleton, M. Delgado, D. R. Gergel, M. Greenstone, T. Houser, S. Hsiang, A. Jina, R. E. Kopp, S. B. Malevich, et al. (2022). Estimating global impacts to agriculture from climate change accounting for adaptation. *Available at SSRN 4222020*.

ICF (2024). Draft environmental impact report. long-term operations of the state water project. *Prepared for California Department of Water Resources*.

Jasechko, S., H. Seybold, D. Perrone, Y. Fan, M. Shamsudduha, R. G. Taylor, O. Fallatah, and J. W. Kirchner (2024). Rapid groundwater decline and some cases of recovery in aquifers globally. *Nature 625*(7996), 715–721.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American economic review 95*(1), 161–182.

Jordà, Ò., M. Schularick, and A. M. Taylor (2015). Betting the house. *Journal of international economics 96*, S2–S18.

Kurukulasuriya, P. and R. Mendelsohn (2008). Crop switching as a strategy for adapting to climate change. *African Journal of Agricultural and Resource Economics 2*(1), 105–126.

Lark, T. J., I. H. Schelly, and H. K. Gibbs (2021). Accuracy, bias, and improvements in mapping crops and cropland across the united states using the usda cropland data layer. *Remote Sensing 13*(5), 968.

Millner, A. and D. Heyen (2021). Prediction: the long and the short of it. *American Economic Journal: Microeconomics 13*(1), 374–398.

Molina, R. and I. Rudik (2022). The social value of predicting hurricanes.

Moran, T., J. Choy, and C. Sanchez (2014). The hidden costs of groundwater overdraft. *Water in the West*.

Newey, W. K. and K. D. West (1987). Hypothesis testing with efficient method of moments estimation. *International Economic Review*, 777–787.

Ortiz-Bobea, A. (2021). The empirical analysis of climate change impacts and adaptation in agriculture. In *Handbook of agricultural economics*, Volume 5, pp. 3981–4073. Elsevier.

Pittenger, D. (2015). *California Master Gardener Handbook–2nd Ed.* Oakland, CA: University of California Agriculture and Natural Resources. Publication Number: 3382, 756 pages.

Public Policy Institute of California (2025). Ppic sacramento valley and delta surface water availability. `https://www.ppic.org/data/ppic-sacramento-valley-and-delta-surface-water-availability/`.

Rubin, D. B. (1987). *Multiple Imputation for Nonresponse in Surveys*. Wiley Series in Probability and Statistics. John Wiley & Sons.

Ruth, Timothy (2017). Overall u.s. crop production is concentrated in california and the midwest. `https://www.ers.usda.gov/data-products/ag-and-food-statistics-charting-the-essentials/agricultural-production-and-prices`. [Online; accessed 24-June-2025].

Scott, P. (2014). Dynamic discrete choice estimation of agricultural land use.

Sharp, R. and S. Carini (2004). California water subsidies: Large agribusiness operations – not small family farmers – are reaping a windfall from taxpayer-subsidized cheap water.

Shrader, J. (2023). Improving climate damage estimates by accounting for adaptation. *Available at SSRN 3212073*.

Shrader, J. G., L. Bakkensen, and D. Lemoine (2023). Fatal errors: The mortality value of accurate weather forecasts. Technical report, National Bureau of Economic Research.

Silva, J. S. and S. Tenreyro (2006). The log of gravity. *The Review of Economics and statistics*, 641–658.

Smith, R., R. Knight, and S. Fendorf (2018). Overpumping leads to california groundwater arsenic threat. *Nature communications 9*(1), 2089.

Smith, R. G. and S. Majumdar (2020). Groundwater storage loss associated with land subsidence in western united states mapped using machine learning. *Water Resources Research 56*(7), e2019WR026621.

Smith, S. (2014). Desperate californian farmers are drilling for water like never before. *Associated Press*.

Soderquist, B. S. and C. H. Luce (2020). Climate change vulnerability and adaptation for infrastructure and recreation in the sierra nevada. In *Climate Change Effects on Hydrologic Processes and Water Resources in the Sierra Nevada*, Chapter 3. Albany, CA: U.S. Department of Agriculture, Forest Service, Pacific Southwest Research Station.

State Water Resources Control Board (1995). Water quality control plan for the san francisco bay/sacramento-san joaquin delta estuary. *Prepared for California Department of Water Resources*. 95-1WR.

State Water Resources Control Board (2024). Groundwater basins. *Sustainable Groundwater Management Act*. `https://www.waterboards.ca.gov/sgma/groundwater_basins/`.

Stock, J. H. and M. W. Watson (2018). Identification and estimation of dynamic causal effects in macroeconomics using external instruments. *The Economic Journal 128*(610), 917–948.

Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society Series B: Statistical Methodology 58*(1), 267–288.

UC Cooperative Extension and California DWR (2000, August). *A Guide to Estimating Irrigation Water Needs of Landscape Plantings in California: The Landscape Coefficient Method and WUCOLS III*. Sacramento, CA: University of California Cooperative Extension and California Department of Water Resources. Photography by L.R. Costello and K.S. Jones; publication design by A.S. Dyer.

United States Department of Agriculture, N. A. S. S. (2022). 2022 census of agriculture. Accessed April 8, 2025.

US Bureau of Reclamation (2024). Summary of water supply allocations. Accessed 10 October 2024.

U.S. Bureau of Reclamation (2025). 2025 water delivery monthly tables. `https://www.usbr.gov/mp/cvo/`. Accessed: 29 July 2025. Data provided by the Central Valley Operations Office (Region 10).

US Bureau of Reclamation (2025). Cvp water users/contractors and other sources. `https://www.usbr.gov/mp/cvp-water/water-contractors.html`,.

US Bureau of Reclamation and the California Department of Water Resources (1986). *Agreement Between the United States of America and the State of California for the Coordinated Operation of the Central Valley Project and the State Water Project*. Washington, DC, USA: US Bureau of Reclamation and the California Department of Water Resources.

U.S. Environmental Protection Agency (2025). Ecoregions of north america. `https://www.epa.gov/eco-research/ecoregions-north-america`. Accessed: 20 July 2025.

US Geological Survey (2025). California's central valley. `https://ca.water.usgs.gov/projects/central-valley/about-central-valley.html`, Last accessed on 2025-04-02.

USBR (1992). Central valley project operations criteria and plan. [Online; accessed 10-January-2025].

USDA, NASS (1997, December). *Usual Planting and Harvesting Dates for U.S. Field Crops*. Number 628 in Agriculture Handbook. Washington, DC: USDA. Agricultural Handbook Number 628.

USDA, NASS (2007, May). *Vegetables: Usual Planting and Harvesting Dates*. Number 507 in Agriculture Handbook. Washington, DC: USDA. Agriculture Handbook Number 507.

Visser, M. A., G. Kumetat, and G. Scott (2024). Drought, water management, and agricultural livelihoods: Understanding human-ecological system management and livelihood strategies of farmer's in rural california. *Journal of Rural Studies 109*, 103339.

Weiser, M. (2014). California toughens enforcement of water violations.

Willis, N. (2024, August). Sgma's groundwater costs could slash fruit and nut production, study finds. *Valley Ag Voice*. Includes photo "newly planted almond trees" (Richard Thornton / Shutterstock.com).

A Data and Context

Table A.2: Surface Water Allocation Forecast Timing Summary Statistics

	SWP		CVP (south)	
Time Period	% with updates	Mean allocation %	% with updates	Mean allocation %
Near Feb 1 (Forecast)	97.96	38.39	53.06	40.50
Near Apr 1 (Forecast)	73.47	54.10	89.80	45.36
Near June 1 (Final)	46.94	60.00	63.27	60.77

Note: This is a summary of the surface water allocation forecasts that I observe, for the State Water Project and the southern portion of the Central Valley Project (which is representative of the timing of the other CVP regions).

Table A.2: Typical crops at each planting time by region, and watering requirement

Region		**Early planting**	**Late planting**
Central Valley	Low Water	Wheat (170mm) Carrots (150mm)	Corn (700mm) Tomatoes (650mm)
	High Water	Sugarbeets (220mm) Onions (500mm)	Rice (1100mm) Cotton (1000mm)
Inland Desert	Low Water	Broccoli (140mm) Wheat (270mm)	Corn (780mm) Squash (470mm)
	High Water	Watermelons (470mm) Tomatoes (900mm)	Cotton (1200mm) Tomatoes (930mm)
South Coast	Low Water	Wheat (240mm) Carrots (275mm)	Dry beans (370mm) Peas (150mm)
	High Water	Strawberries (800 mm) Garlic (475mm)	Tomatoes (600mm) Corn (600mm)

Figure A.1: Four examples of how a farmer would encounter a surface water allocation forecast



Advance-Register

City eyes new police station

Army paid $124 for 9-inch piece of string

TIP chief may work part time

Season chore

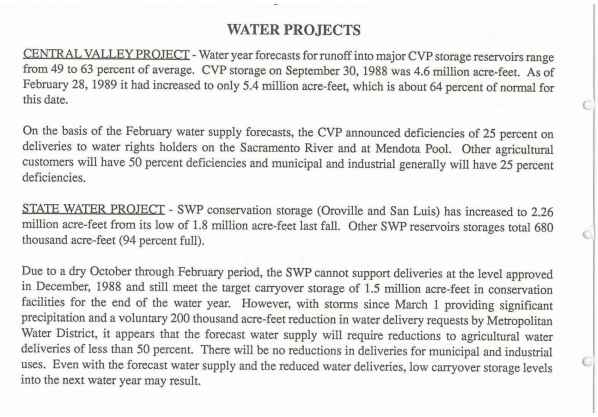
County reps discuss their fiscal plight

Snack tax ends, welfare cuts start

State Water Project delivery projected at only 10 percent

Excessive force case against police officers goes to trial

(a) Front page of December 1, 1992 Tulare Advance Register, with the State Water Project initial allocation making the bottom of the page



WATER PROJECTS

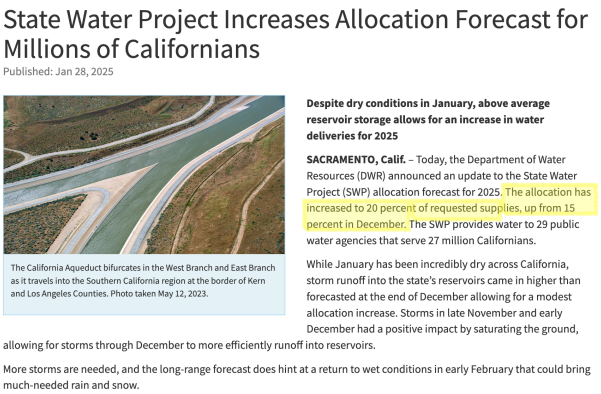
CENTRAL VALLEY PROJECT - Water year forecasts for runoff into major CVP storage reservoirs range from 49 to 63 percent of average. CVP storage on September 30, 1988 was 4.6 million acre-feet. As of February 28, 1989 it had increased to only 5.4 million acre-feet, which is about 64 percent of normal for this date.

On the basis of the February water supply forecasts, the CVP announced deficiencies of 25 percent on deliveries to water rights holders on the Sacramento River and at Mendota Pool. Other agricultural customers will have 50 percent deficiencies and municipal and industrial generally will have 25 percent deficiencies.

STATE WATER PROJECT - SWP conservation storage (Oroville and San Luis) has increased to 2.26 million acre-feet from its low of 1.8 million acre-feet last fall. Other SWP reservoirs storages total 680 thousand acre-feet (94 percent full).

Due to a dry October through February period, the SWP cannot support deliveries at the level approved in December, 1988 and still meet the target carryover storage of 1.5 million acre-feet in conservation facilities for the end of the water year. However, with storms since March 1 providing significant precipitation and a voluntary 200 thousand acre-feet reduction in water delivery requests by Metropolitan Water District, it appears that the forecast water supply will require reductions to agricultural water deliveries of less than 50 percent. There will be no reductions in deliveries for municipal and industrial uses. Even with the forecast water supply and the reduced water deliveries, low carryover storage levels into the next water year may result.

(b) A screenshot from the Department of Water Resources' snow survey published in March 1989 (these are published, February, March, April, May and October), and each of the early-year snow surveys include information like this, highlighting allocation decisions made by both projects



State Water Project Increases Allocation Forecast for Millions of Californians

Published: Jan 28, 2025

The California Aqueduct bifurcates in the West Branch and East Branch as it travels into the Southern California region at the border of Kern and Los Angeles Counties. Photo taken May 12, 2023.

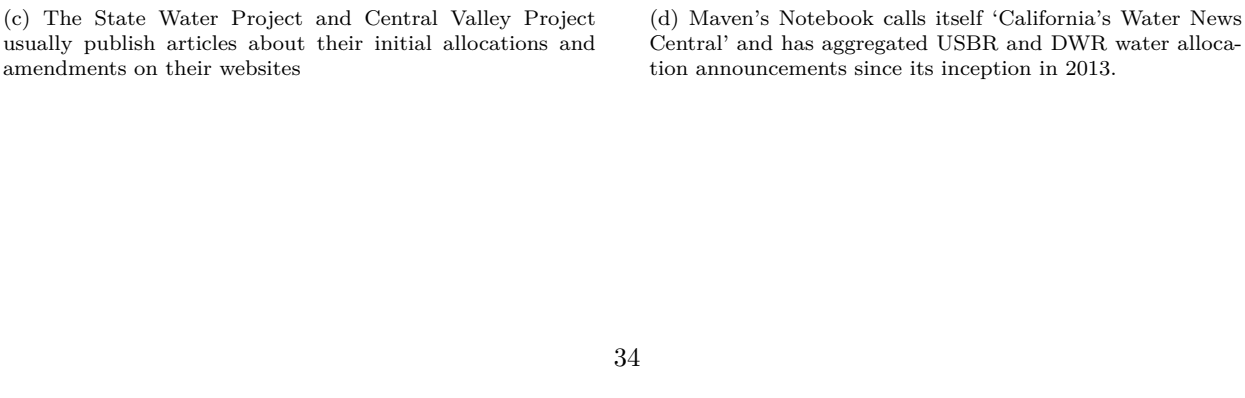
Despite dry conditions in January, above average reservoir storage allows for an increase in water deliveries for 2025

SACRAMENTO, Calif. – Today, the Department of Water Resources (DWR) announced an update to the State Water Project (SWP) allocation forecast for 2025. The allocation has increased to 20 percent of requested supplies, up from 15 percent in December. The SWP provides water to 29 public water agencies that serve 27 million Californians.

While January has been incredibly dry across California, storm runoff into the state's reservoirs came in higher than forecasted at the end of December allowing for a modest allocation increase. Storms in late November and early December had a positive impact by saturating the ground, allowing for storms through December to more efficiently runoff into reservoirs.

More storms are needed, and the long-range forecast does hint at a return to wet conditions in early February that could bring much-needed rain and snow.

(c) The State Water Project and Central Valley Project usually publish articles about their initial allocations and amendments on their websites



Irrigation contractors north of Delta allocated 75%; Irrigation contractors south of Delta allocated 15%

From the Bureau of Reclamation:

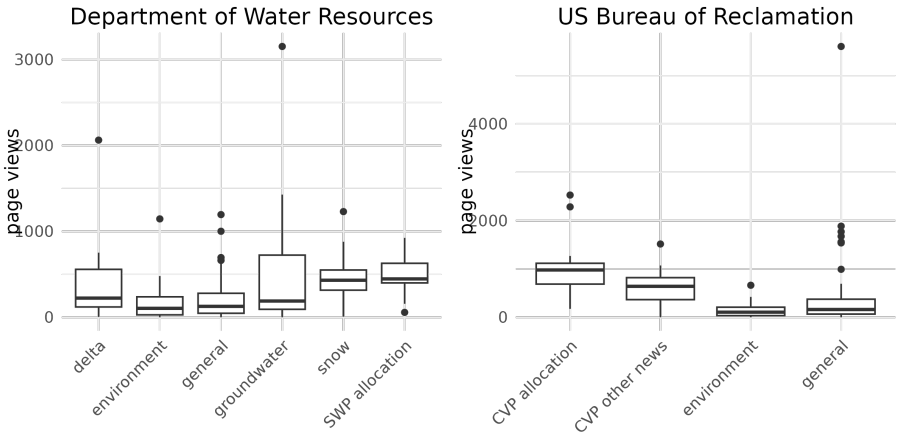
BUREAU OF RECLAMATION

Today, the Bureau of Reclamation announced initial 2024 water supply allocations for Central Valley Project water users. Water supply allocations are based on an estimate of water available for delivery to Central Valley Project water users and reflect current reservoir storage, precipitation, and snowpack in the Sierra Nevada.

"The wet hydrologic conditions we experienced during the 2023 water year left most of our reservoirs in good shape as we progressed to the 2024 water year," **said California-Great Basin Regional Director Karl Stock**. "Precipitation totals this water year started off slowly, evidenced by the fact we were well below average at the time of the Feb. 1 water supply forecast. Since that time, several storms have boosted the Sierra Nevada snowpack, bringing us to near normal conditions for Northern California. It is likely we will see the water supply benefits from these storms in the March 1 forecast update. At the same time, we have to be prepared for and respond accordingly to the possible re-emergence of drier conditions."

(d) Maven's Notebook calls itself 'California's Water News Central' and has aggregated USBR and DWR water allocation announcements since its inception in 2013.

Figure A.2: Page views by subject on California water news aggregator



Note: Distribution of page views by topic on Maven's Notebook, a California water news aggregator. News collected on May 1, 2025, spanning 5 years.

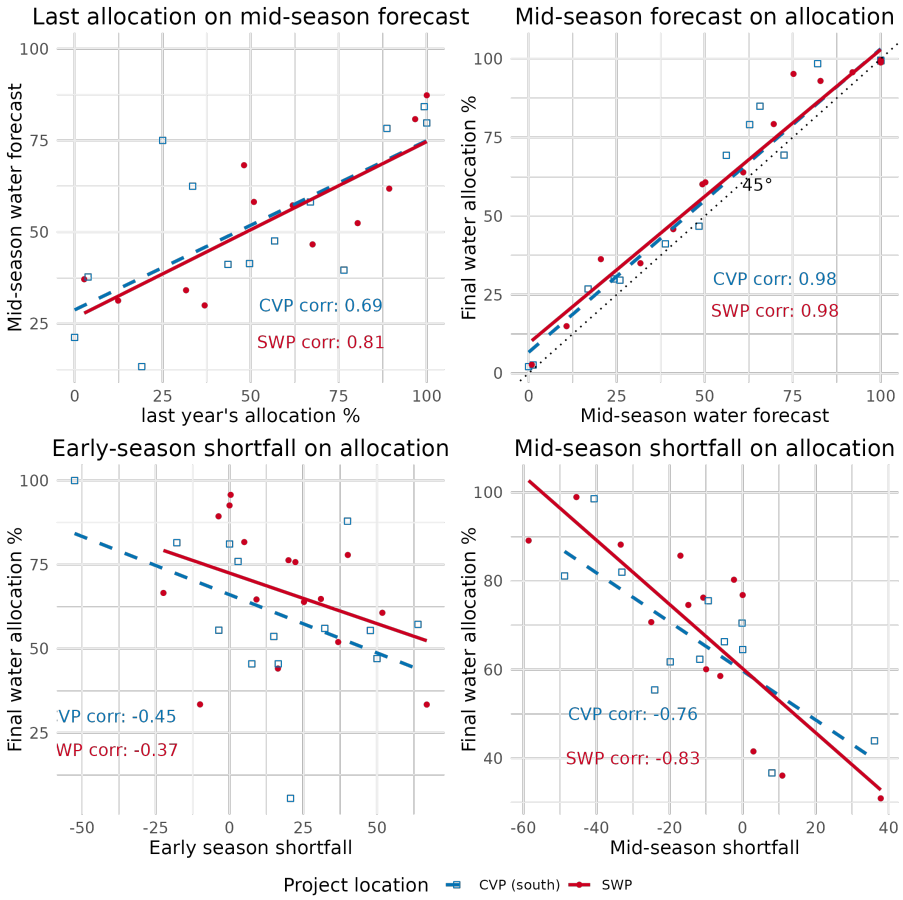
Over time, project allocations and announcements have changed in two major ways. The first is that allocations have generally decreased, in part because of drought, and in part because of environmental flows required under the Endangered Species Act[15]. Second, the 1993 Biological Opinion related to California's endangered fish recommended that the projects issue conservative water allocation forecasts (State Water Resources Control Board, 1995). Therefore, since 1995 the State Water Resources Control Board has asked the projects report the tenth-percentile statistic for the February allocation forecast. I show in the results section of the paper that the projects change in the

B Supplementary Results

B.1 LASSO results

[15]Some species that have been protected include the Chinook salmon, delta smelt and steelhead trout (ICF, 2024)

Figure A.3: Relation of project forecasts to each other: across districts and across months in a year



Note: The top left panel shows how the binned average of last year's surface water allocation percent corresponds to the average late-planting season surface water forecast (before April 1st) for the State Water Project (in red dots and solid line) and the Central Valley Project's southern districts, (blue squares and dashed line). I use the late planting season forecast because there is actual rather than imputed data in all years. There is a positive association between these data, showing that there is autocorrelation in forecasts over time. The lines also virtually overlap, showing that the autocorrelation of forecasts across projects is the same in expectation. The plot to the right shows an analagous pattern, exploring the relation between one year's late planting season surface water forecast and the same year's final surface water allocation. The points are highly correlated, showing that the delivery percent is predictable by mid-season. I also plot a dotted 45 degree line illustrating that forecasts are revised upward, although in the same pattern across projects.

Table B.3: Districts' adaptation responses to surface water allocation forecasts

1. Crop choice	Idle	Double	Early-low	Early-high	Late-low	Late-high
100% - last year's SW allocation	−0.07	0.00	0.24***	0.25	0.23***	−0.11
	(0.07)	(0.05)	(0.08)	(0.18)	(0.09)	(0.15)
100% - mid-planting SW forecast	0.48***	−0.08	0.07	0.06	−0.44*	−0.47***
	(0.10)	(0.06)	(0.12)	(0.25)	(0.25)	(0.11)
100% - late-planting SW forecast	0.23*	0.07	−0.20	−0.34	−0.26	−0.01
	(0.12)	(0.08)	(0.18)	(0.22)	(0.23)	(0.22)
100% - final SW allocation	0.10	−0.00	0.23	0.04	0.01	−0.12
	(0.15)	(0.10)	(0.15)	(0.14)	(0.29)	(0.28)
Omitted vars. controls	yes	yes	yes	yes	yes	yes
District FEs	yes	yes	yes	yes	yes	yes
Region-year FEs	yes	yes	yes	yes	yes	yes
SE cluster	district	district	district	district	district	district
Num. obs.	1614	1598	1614	1548	1539	1493
Pseudo R^2	0.96	0.94	0.93	0.86	0.94	0.96

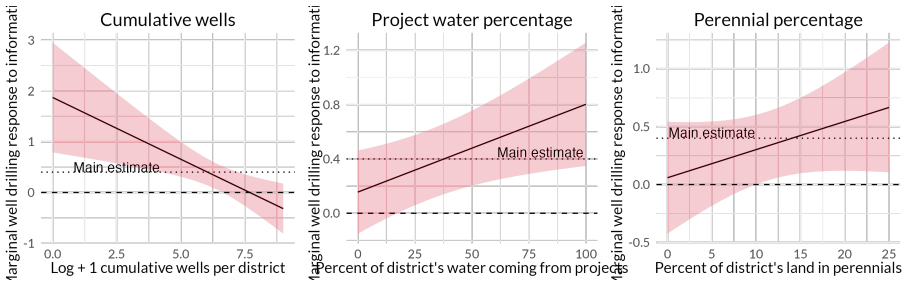
2. Groundwater depth change	(1)	(2)	(3)	main	(5)	w/senior
100% - last year's SW allocation	−0.01	0.06	−0.02	0.06	0.06	0.15**
	(0.07)	(0.07)	(0.06)	(0.07)	(0.12)	(0.08)
100% - mid-planting SW forecast	−0.04	−0.04	0.06	−0.00	−0.00	0.15
	(0.11)	(0.11)	(0.10)	(0.11)	(0.18)	(0.11)
100% - late-planting SW forecast	0.19**	0.14*	0.21***	0.15**	0.15***	0.24***
	(0.07)	(0.07)	(0.07)	(0.08)	(0.06)	(0.07)
100% - final SW allocation	−0.01	0.11	−0.03	0.10	0.10	0.07
	(0.09)	(0.09)	(0.08)	(0.09)	(0.11)	(0.08)
Specs. same as well choice						
Num. obs.	4899	4899	4893	4893	4893	9855
Pseudo R^2	0.78	0.80	0.78	0.80	0.80	0.80

3. Well drilling choice	(1)	(2)	(3)	main	(5)	w/senior
100% - last year's SW allocation	0.07	0.09	0.10	0.08	0.08	0.01
	(0.11)	(0.13)	(0.12)	(0.13)	(0.14)	(0.12)
100% - mid-planting SW forecast	0.01	0.02	0.01	0.01	0.01	0.07
	(0.13)	(0.16)	(0.12)	(0.16)	(0.20)	(0.15)
100% - late-planting SW forecast	−0.16	−0.10	−0.15	−0.13	−0.13	−0.07
	(0.12)	(0.13)	(0.12)	(0.12)	(0.13)	(0.11)
100% - final SW allocation	0.27**	0.36**	0.30**	0.40***	0.40***	0.25*
	(0.14)	(0.14)	(0.14)	(0.15)	(0.14)	(0.15)
Omitted vars. controls	no	no	yes	yes	yes	yes
District FEs	yes	yes	yes	yes	yes	yes
Year FEs	yes	no	yes	no	no	no
Region x year FEs	no	yes	no	yes	yes	yes
SE cluster	district	district	district	district	Spatial-HAC	district
Num. obs.	4459	4439	4453	4433	4433	8273
Pseudo R^2	0.58	0.59	0.59	0.60	0.60	0.66

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

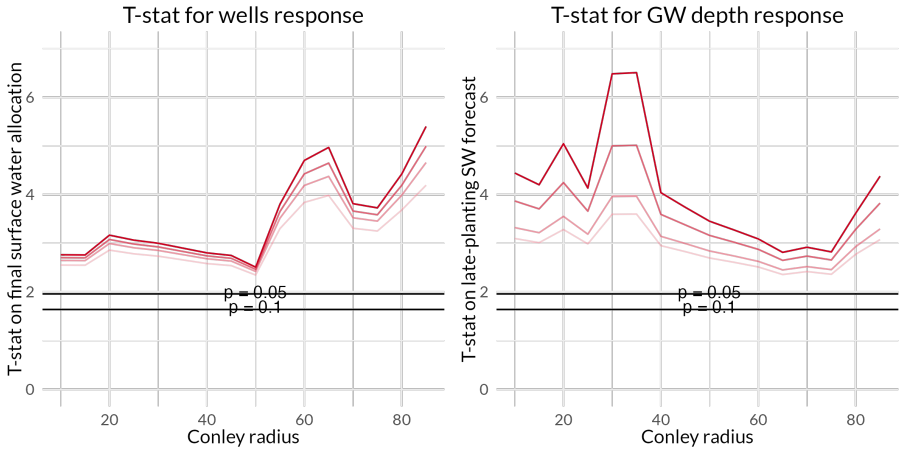
Note: This table shows PPML regressions of crop choice, groundwater depth and well drilling responses to surface water information learned during the planting season. The coefficients have been transformed to percent changes, and the standard errors are delta-method adjusted. The crop choice regressions vary only by dependent variable crop category, with observation counts differing as not all districts grow every crop type. Controls include alternate water sources (streamflow forecasts, precipitation, temperature, lagged groundwater depth and wells), and lagged perennial acreage to account for switching costs. Groundwater depth measures average annual depth to water table (feet), while well drilling counts total wells drilled February-August. Columns represent different specifications: (1) year and district fixed effects only, (2) district and year-by-climate-region fixed effects, (3) all controls (alternate water sources and neighbors' groundwater extraction and well drilling choices for the depth and well regressions respectively) with basic fixed effects, (4) all controls with strong fixed effects, (5) spatial/autocorrelation robust standard errors, and (6) includes senior project districts.

Figure B.4: Heterogeneity of well drilling responses to information based on district characteristics



Note: To generate these plots, I run the main specification for the well drilling response regression, interacting each of the surface water forecast variables by the heterogeneity variables displayed in these tables, first the lagged log of the cumulative number of wells drilled in the district, second, the percent of district surface water from project sources, and third, the percent of district land planted in perennials on average. I show the estimated heterogeneous effect along with its 95% confidence interval. I display the main estimated coefficient without these interactions as the dotted line at y = 0.4. Overall, the response of well drilling is stronger when districts have fewer wells, depend more on project water, and have more perennials.

Figure B.5: T-statistic of main coefficient using spatial and autocorrelation robust standard errors



Note: These plots show the T-statistic of the main significant coefficients for the well drilling response regression and groundwater depth regression displayed in table B.3, which are on the final surface water allocation and late-planting season surface water forecast respectively. The x-axis shows a variety of Conely radii, and the darker lines represent the T-static for higher time lags, using 1, 5, 10, and 20. Overall, the main coefficients remain significant for any spatial radius and time lag displayed.

Table B.3: Multinomial logit: response of crop choice to forecast shortfall

	Double	Early-high	Early-low	Idle	Late-high	Late-low
(Intercept)	20.416***	3.669***	14.529***	2.357	7.479***	1.011
	(2.369)	(0.174)	(2.24)	(2.442)	(2.195)	(2.084)
100% - last year's SW allocation	0	0.002	0.001	0	-0.006*	-0.002
	(0.004)	(0.012)	(0.005)	(0.003)	(0.004)	(0.004)
100% - mid-planting SW forecast	0.006	0.01	-0.003	-0.005	0.002	-0.008**
	(0.004)	(0.011)	(0.004)	(0.003)	(0.003)	(0.004)
100% - late-planting SW forecast	-0.001	0.002	0	0.009*	-0.003	-0.003
	(0.008)	(0.023)	(0.008)	(0.006)	(0.007)	(0.007)
100% - final SW allocation	0.006	0	0.001	-0.004	-0.009	-0.004
	(0.008)	(0.023)	(0.009)	(0.006)	(0.007)	(0.008)
Stream runoff realization	-0.012	0.099	-0.225	0.017	-0.105	-0.119
	(0.306)	(1.087)	(0.308)	(0.241)	(0.223)	(0.227)
Stream runoff forecast	0.684	1.205	0.334	0.392	-0.272	-0.283
	(0.631)	(1.831)	(0.665)	(0.497)	(0.499)	(0.516)
Log lag cumulative wells	-0.225**	-0.482	-0.5***	-0.674***	-0.566***	-0.769***
	(0.101)	(0.336)	(0.104)	(0.081)	(0.082)	(0.085)
Rainfall	-0.002	-0.006	0	0.001	0	0.001
	(0.002)	(0.007)	(0.002)	(0.001)	(0.001)	(0.001)
Temperature	-0.131	0.076	-0.081	0.104	-0.104	0.066
	(0.096)	(0.305)	(0.101)	(0.08)	(0.079)	(0.081)
Central Valley = 1	4.774***	0.355	4.283***	1.304	5.019***	2.214*
	(1.286)	(0.843)	(1.584)	(1.003)	(1.141)	(1.257)
Inland Desert = 1	4.604*	-0.654***	2.983***	0.804	0.446***	-0.193
	(2.473)	(0.15)	(0.902)	(1.706)	(0.036)	(0.406)
Sierra Nevada = 1	7.76***	4.197***	3.394***	-0.527***	-1.086***	-1.083***
	(0.059)	(0.028)	(0.017)	(0.006)	(0.001)	(0.001)
South Coast = 1	3.278***	-0.229	3.869***	0.777	3.101***	0.074
	(1.383)	(0.858)	(1.612)	(1.03)	(1.174)	(1.359)
GW depth in 2000	-0.374***	0.113	-0.13	-0.233***	-0.482***	0.004
	(0.093)	(0.273)	(0.08)	(0.068)	(0.076)	(0.055)
Log area (km^2)	0.208***	0.387	0.323***	0.514***	0.639***	0.51***
	(0.078)	(0.272)	(0.078)	(0.062)	(0.062)	(0.061)
Log groundwater use	-0.078***	-0.022	-0.062**	-0.049**	-0.115***	-0.084***
	(0.029)	(0.078)	(0.03)	(0.022)	(0.022)	(0.024)
Log field crop price	-3.837***	-1.674***	-2.856***	-0.653	-1.473***	-0.415
	(0.56)	(0.529)	(0.667)	(0.553)	(0.567)	(0.566)
Log non-project ag water	-0.01	0.099	0.004	0.015	-0.009	0.027
	(0.025)	(0.071)	(0.026)	(0.02)	(0.02)	(0.02)

Note: This table shows a model of crop choice response to surface water allocation forecasts using multinomial logit. I include the same controls and surface water forecast variables, but since I omit fixed effects, all variables after temperature are to account for differences across districts and years.

Table B.3: Robustness checks: method of imputation

	Dep var = Wells drilled			Dep. var = GW depth		
	M.I.	Last year	No impute	M.I.	Last year	No impute
100% - last year's SW allocation	0.08	0.06	0.03	0.07*	0.02	−0.01
	(0.10)	(0.12)	(0.15)	(0.04)	(0.04)	(0.05)
100% - mid-planting SW forecast	0.01	0.00	0.24	0.02	0.03	0.09
	(0.11)	(0.07)	(0.19)	(0.03)	(0.03)	(0.07)
100% - late-planting SW forecast	−0.10	−0.02	−0.21	0.10**	0.10*	0.04
	(0.14)	(0.11)	(0.27)	(0.05)	(0.06)	(0.11)
100% - final SW allocation	0.34**	0.19	0.39	−0.02	−0.00	0.00
	(0.17)	(0.16)	(0.30)	(0.05)	(0.06)	(0.14)
Omitted vars. controls	yes	yes	yes	yes	yes	yes
District FEs	yes	yes	yes	yes	yes	yes
Year FEs	yes	yes	yes	yes	yes	yes
Region x year FEs	yes	yes	yes	yes	yes	yes
SE cluster	district	district	district	district	district	district
Num. obs.	4567	4567	3178	4902	5031	3627
Pseudo R^2	0.60	0.60	0.63	0.80	0.80	0.81

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: This table shows the main regression specifications for wells drilled and groundwater depth as in table B.3, where I change the method of imputation for the mid-planting (February 1st) surface water allocation forecast. The first column for both dependent variables uses multiple imputation where imputations are grouped by contract type. The second column uses the previous year's final surface water allocation, deflated empirically to capture the bias in the early surface water allocation forecasts. The final column drops observations where there is no mid-planting surface water allocation forecast.

Table B.3: Robustness checks: dependent variable specification and fixed effects

	Dep var = Wells drilled						GW depth
	main	(2)	(3)	(4)	(5)	(6)	(7)
100% - last year's SW allocation	0.08	−0.12	0.06	0.12	0.05	0.12	0.02
	(0.13)	(0.19)	(0.11)	(0.13)	(0.11)	(0.15)	(0.04)
100% - mid-planting SW forecast	0.01	−0.10	0.05	0.01	0.02	−0.07	0.09
	(0.16)	(0.16)	(0.13)	(0.16)	(0.15)	(0.19)	(0.08)
100% - late-planting SW forecast	−0.13	−0.34**	−0.02	−0.11	−0.10	−0.02	0.11**
	(0.12)	(0.17)	(0.11)	(0.13)	(0.11)	(0.12)	(0.04)
100% - final SW allocation	0.40***	0.47**	0.31**	0.37**	0.28**	0.36**	−0.07
	(0.15)	(0.20)	(0.13)	(0.15)	(0.13)	(0.16)	(0.06)
Omitted vars. controls	yes	yes	yes	yes	yes	yes	yes
District FEs	yes	yes	yes	yes	yes	yes	yes
Region x year FEs	yes	yes	yes	yes	yes	no	no
Right type x year FEs	no	no	no	no	no	yes	yes
SE cluster	district	district	district	district	district	district	district
Winsorize level	99.5%	100%	99%	99.5%	99.5%	99.5%	N/A
Dep. var timeframe	Feb-Aug	Feb-Aug	Feb-Aug	Feb-June	Jan-Dec	Feb-Aug	N/A
Num. obs.	4433	4432	4432	4330	4443	8292	9855
Pseudo R^2	0.60	0.78	0.48	0.57	0.66	0.66	0.82

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: The first column shows the main well drilling specification shown in table B.3 for reference. The next four columns each change the well drilling variable. Column (2) shows the results without winsorization, and column (3) shows the results with stronger winsorization (99% instead of 99.5%). Column (4) decreases the time period of well completion I study to February-June, and column (5) expands it to the entire year. The final two columns use right-type by year fixed effects for the well drilling and groundwater depth regressions.