The benefits and costs of agricultural adaptation to surface water scarcity

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Abstract

In the absence of climate change mitigation, society's avoided climate damages come primarily from private actors taking adaptive actions. However, when adaptation choices interact with other market failures, like common pool resources, the net benefit of adaptation is less clear. In this paper, I study the actions that farmers in California take to adapt to surface water scarcity, and I quantify the value of that adaptation. I exploit variation in surface water delivery forecasts and forecast updates across irrigation districts within years to identify farmers' adaptation strategies. The results reveal that farmers adapt with both water-conserving crop choice practices and water-intensifying well drilling and extraction practices, though groundwater intensification far outpaces conservation. In the long run, I find that farmers rely less on short-term adaptation, and more on groundwater extraction facilitated through well drilling, which results in a transition to even higher water intensity crops. To estimate adaptation's overall private net benefit, I extend the standard conceptual and empirical framework from the literature to accommodate multiple intra-annual adaptation decision periods. I find that the value of adaptation to water scarcity is highly specific to the amount of surface water available because both under-forecasts and over-forecasts of scarcity appear to decrease profits. Thus, adaptation to water scarcity is important for farmers' outcomes, but also damaging to society. I estimate that for the adaptation to the average marginal surface water scarcity shock, the social costs make up about 20% of the net benefits of adaptation. My paper highlights that abstracting away from the actual decisions could result in severely overvaluing adaptation.

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After decades of academic debate, the literature has converged on the conclusion that climate change will severely damage agricultural production (Schlenker and Roberts (2009), Costinot et al. (2016), Hultgren et al. (2022)). The answer to the related, and equally important, question about how much farmers can adapt to a changing climate is unclear at best, and contradictory at worst. Papers studying adaptation in aggregate have found moderate (Hultgren et al. (2022)) to no (Schlenker and Roberts (2009), Burke and Emerick (2016)) ability to avoid losses, while papers studying specific adaptation actions find that farmers do respond to weather or drought shocks (Hagerty (2022), Burlig et al. (2024)). Farmers' responses sometimes make them more resilient to weather damage (Auffhammer and Carleton (2018), Michler et al. (2019)) and sometimes make them more sensitive to weather and water scarcity in the long run (Hornbeck and Keskin (2014), Fishman (2018)). In this paper, I seek to unify the themes in the literature by connecting adaptation actions to the value of adaptation. In settings with perfect information and no pre-existing distortions the specific adaptation actions do not matter for economic value because farmers' maximized profits are the

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social benefit, regardless of the adaptation action (Carleton et al., 2024). In agriculture however, among other distortions, farmers often adapt to surface water scarcity using a partially non-renewable common pool groundwater resource (Fishman, 2018)[1]. I study the context of farmers in California who irrigate intensively with groundwater in years with low surface water, leading to a rapidly depleting aquifer (Jasechko et al. (2024), Department of Water Resources (2025a)).

In the presence of groundwater extraction externalities, the actions that farmers take in response to surface water scarcity informs us about the social value of adaptation. When surface water availability is low, farmers might choose to conserve water, or substitute toward groundwater by extracting from existing wells and drilling new wells. Although farmers take the action with the highest private benefit, the social costs vary among the options leaving the net social benefit of adaptation unclear. Furthermore, the private value of the choices depends on the timing of information and previous adaptation decisions. Farmers make choices sequentially within a year (Antle, 1983) so that early choices (like cropping) determine the choice set and values of alternatives (fallowing vs groundwater extraction) later in the year. Long-term adaptation strategies like well drilling permanently alters the value of alternative adaptation choices, since well drilling lowers the marginal cost of groundwater use. Understanding the patterns of adaptation to surface water scarcity is important since groundwater basins remain unmanaged and precipitation is decreasing and becoming more variable in many irrigation-reliant regions like California (Chandanpurkar et al., 2025).

In this paper, I ask the broad question "how do farmers adapt to surface water scarcity, and what are the consequences of that adaptation?" I answer the question in four steps. First, I study whether farmers in California make water conserving (crop choice and land fallowing) decisions and/or water intensifying (well drilling and groundwater extraction) decisions in response to surface water scarcity information learned within a year. Then, I study how the long-term adaptation option, well drilling, affects later adaptation decisions. Next, I estimate the overall private benefit of short and long-term adaptation. Finally, I compare the private benefits with my estimates about the increases in water use from adaptation to suggest how the private and social value might compare and be changing over time.

To explore how farmers adapt to water scarcity in the short run (within a year), I design my empirical framework to account for sequential decisions. Short run adaptation in agriculture is characterized by decisions with fixed lead times, made as weather and water availability in the growing season becomes more certain. I use a conceptual model to show that a simple econometric model that includes the baseline surface water availability forecast and adjustments allows me to estimate the actions taken due to information available at different times. Therefore, I need variation in surface water availability across units revealed over the agricultural season.

In my context, I leverage the differences in surface water allocation forecasts to empirically identify different adaptation actions over time. In California, over 200 water districts have contracts for surface water deliveries in the dry summer growing season. The governments that run the infrastructure projects announce initial surface water forecasts around the early planting season, and update their projections over time. Because of exogenous differences in snowpack which differentially fill reservoirs, different districts receive different forecasts and updates over the year. I construct a panel of the most recent forecast known at three points in the year: the early planting season, mid planting season and late planting season, which spans from 1967 until 2022. I then regress adaptation actions (crop choice, crop fallowing, well drilling and

[1]Other reasons for studying adaptation actions include choice sets being constrained (like in development contexts), so that offering new means of adaptation can be beneficial (Macours et al., 2012). Another is imperfect information or imperfect beliefs (Kala, 2017)

groundwater extraction) on the surface water availability announced in each of the three periods.

I find that short-term water information affects all decisions that I study. A one-point decrease in the surface water availability in each point in the planting season shifts farmers toward water conservation by idling crops and planting less water intensive annuals. At the same time, this bad surface water news shifts farmers toward higher groundwater extraction and more well drilling. Put in terms of changes in water use, I estimate that groundwater intensification increases through groundwater extraction five times more than it decreases through water conservation. The coefficients on the different periods in the year show that farmers adapt to surface water news at a similar rate throughout the season, with the exception of well drilling which diminishes as the dry season approaches. Separating the effects by positive and negative surface water availability updates ('good' and 'bad' surface water news), I find that the coefficient estimates are much larger in magnitude for news about decreasing surface water, showing that over time there is a net increase in groundwater use from these short-term adaptation actions.

For the second step of the analysis, I study how adaptation changes over time as farmers take the capital-intensive well drilling option. There are many potential avenues to explore, and I focus on four. In the first, I learn about how much earlier wells are drilled due to short-run surface water shocks using local projections (Jordà, 2005), in order to explain the well drilling choice. Well drilling in response to short-run surface water shocks makes the most sense if wells are increasing in value generally, and surface water scarcity causes some already relatively high well values to cross the threshold of profitability a few years early[2]. Then, I see how previous well drilling affects the sensitivity of adaptation actions to surface water scarcity by interacting the lag of the cumulative wells drilled in a district with the three periods of surface water information from the main estimating equation. Afterward I study how groundwater extraction increases due to new wells using exogenous changes in well drilling costs unrelated to groundwater depth as an instrument for new wells. Thus, I estimate the increases in extraction for the subset of farmers with a well value somewhat close to the threshold of drilling, in a year where surface water scarcity is not necessarily high. The local average treatment effect captures how the farmers likely to drill a well in the coming decades might act in an average water year. Finally, I explore the path dependence of future adaptation decisions through how farm cropping decisions change solely from the fact of having a well. To avoid the simultaneity of cropping and well decisions, and since crop choice might not respond in the current year, I use the same instrument within a local projections framework (Jordà et al., 2015).

Overall, I find that past well drilling decisions change the way that farmers adapt. First of all, in response to surface water shocks, wells are drilled about four years earlier that they otherwise would have been, which fits the narrative of a modest change in well value for farmers with values close to the threshold for drilling. Although the increase in wells relative to the counterfactual is temporary, the shift forward in time represents a real social cost if wells imply an increase in groundwater use[3]. From the heterogeneity analysis, I find that wells change annual adaptation behavior in two ways. Wells especially decrease the amount of ex-ante adaptation, suggesting that the value of preparation decreases. Second, water conserving practices tend to decrease overall, while groundwater extraction increases at the time of the surface water allocation

[2]In California, it is likely the case that well values increased cover time. Crop output prices increased, well technology improved, and average surface water availability decreased over my period of study.

[3]While the aquifer remains unmanaged, users extract until the marginal benefit of water use is driven down to current extraction cost, rather than rising at the rate of interest as Hotelling's rule (or a modified rule with partial recharge) prescribes. As a result, the shadow value of the groundwater stock is far below the efficient level, and this gap widens as the aquifer is depleted. Therefore, faster depletion implies that by the time the aquifer is managed, the value of the stock will be even lower than if a well was not drilled four years early.

realization. The instrumental variables specification confirms that groundwater extraction increases the year when a well is drilled, even though the local average treatment effect does not estimate the groundwater use increase in years only when surface water scarcity was high, most likely implying that since surface water is both constrained and has an artificially low price, water use will increase when wells are drilled even though groundwater is more expensive. Last, I find that farmers increase agricultural land area, and high-water crop acreage, particularly in perennials, after drilling 'surprising' new wells. In all, my results point to the investment in well capital leading to increases in groundwater extraction along several margins.

In the final portion of my analysis, I study the net benefit of the adaptation decisions. The conceptual framework in the literature shows that we can estimate the value of adaptation by regressing outcomes like profits on both forecasts and realizations (Shrader, 2023). I extend the conceptual framework to include the sequential decision making and ex-post adaptation characteristic of the agricultural context. I show that in a regression of profits on my the three periods of surface water forecasts, each coefficient on information represents the value of the decisions taken in that period, which includes both the unanticipated actions taken and the planned future actions decided upon in the current period. Since I previously found that wells diminish the value of preparatory action, I conduct a heterogeneity analysis where I interact the surface water information with the lag of the cumulative wells.

I find that the most beneficial adaptation occurs early in the planting season, prior to the first surface water allocation forecast. Through adaptation, farmers can virtually insulate themselves from the direct effect of surface water scarcity. I also find that these specific surface water allocation forecasts have value, meaning that historically these forecasts have had information in them, and that adjusting forecasting policy might affect farmers outcomes.

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 marginal surface water shock has a social cost of about $4 million 2017 dollars summed across all water districts in the study. The social costs make up about 1/4 of the private benefits of adaptation. My results show that the social costs of adaptation might make up a substantial portion of the private benefits of adaptation. In contexts with unmanaged resources, relying on private actors to address the consequences of climate change may create future problems of resource depletion.

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 adaptation to climate change in agriculture. There are two main bodies of work. The first studies adaptation in aggregate, using the methods in the climate econometrics literature, including cross-sectional analyses and long differences, to identify how climate damages are lessened through adaptation (examples include Mendelsohn and Dinar (2003), Burke and Emerick (2016), Hultgren et al. (2022)). The second strand of literature studies specific adaptation choices, either exploring the choices that farmers make (Hagerty (2022), Burlig et al. (2024), Blakeslee et al. (2020)), or how farmers' choices can lower their sensitivity to weather shocks (Michler et al. (2019), Auffhammer and Carleton (2018)) or increase their sensitivity to weather shocks through groundwater investment (Fishman (2018), Hornbeck and Keskin (2014)). My paper bridges the literatures by combining what choices are being made with the value of those choices.

In the first vein, Hagerty (2022) finds that farmers fallow land in response to short-run water scarcity and transition land out of agriculture in response to water scarcity, Burlig et al. (2024) finds that farmers use a variety of strategies in response to monsoon forecasts including changing cultivated area, crop type, and farm inputs, and Blakeslee et al. (2020) finds that farmers in India facing long-term water scarcity shift a portion of their income to non-agricultural work. In the other vein, Michler et al. (2019) finds that conservation practices can diminish farmers' sensitivity to deviations in rainfall, (Auffhammer and Carleton, 2018) finds

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 extends the conceptual framework in the literature to the agricultural context. Section 4 describes the data sources I use. In section 5 I estimate the timing of different adaptation decisions, as well as the static social costs of adaptation. In section 6 I estimate the aggregate benefits of adaptation. Section 7 describes the dynamic social costs of the adaptation decisions stemming from well drilling, and section 8 concludes.

1 Background

1.1 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[4]. Farmers in Central California have commonly used crop switching for drought management (Visser et al., 2024).

1.2 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

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

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[5] (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[6] (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 B.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 B.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.

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[7] (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).

1.3 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.,

[5] 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.

[6] 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)

[7] Individuals hold less than 1% of water.

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[8] (GEI Consultants, 2017). While physically drilling a well takes only a week, permitting and demand queues delays drilling by one to six months[9]. 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)).

1.4 Combining the background

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 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

[8] Permits are virtually always granted.
[9] From the testimonies of two well drilling contractors.

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 3, 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.

2 Data

2.1 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

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 groundwater extraction - Abandon permanent crops	- Plant mid crops - Choose late crops - Drill well (likely usable this year) - Change groundwater extraction - Abandon permanent crops - Abandon annual crops	- Plant late crops - Drill well (unlikely usable this year) - Change groundwater extraction - Abandon permanent crops - Abandon annual crops	- Drill well (unlikely usable this year) - Change groundwater 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

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 B.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[10].

Overall, even though the forecasts come from different agencies, they are comparable. In appendix figure B.4, 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

[10]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.

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[11].

2.2 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 (2025c), Department of Water Resources (2025b)). 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.

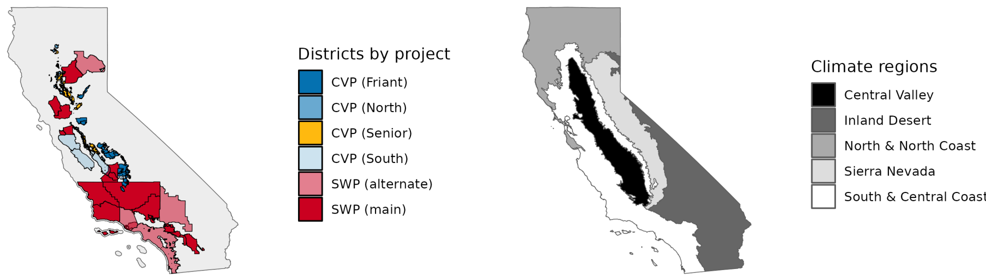
2.3 Agriculture and crop choice

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[12]. 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),

[11]"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/

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

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.

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 B.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%).

2.4 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[13]. 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, 2025b). The interpolation 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.

2.5 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).

3 Actions taken in response to surface water supply shocks

3.1 Methods

In this section, I study which adaptation actions farmers take in response to surface water scarcity, and whether they take different actions in response to information revealed at different points in the year, which will allow us to understand how sequential decision-making changes adaptation behavior. The government announces the final amount of project surface water available to water districts around June. However, the final surface water allocation is revealed throughout the growing season, first with a baseline surface water allocation forecast in January or earlier, and then with updates irregularly throughout the season. Therefore, the contractual share of project surface water delivered is composed of several parts, which I simplify into three parts for the empirical analysis:

$$\underbrace{s}_{\text{June SW allocation shortfall}} = \underbrace{\hat{s}}_{\text{Jan. SW forecast shortfall}} + \underbrace{\varepsilon^{\text{mid}}}_{\text{March 1st forecast update}} + \underbrace{\varepsilon^{\text{late}}}_{\text{June 1st forecast update}} \tag{1}$$

[13] 82% of wells include a purpose.

Where the shortfall is defined as the amount of a contract not fullfilled, or 100% - the surface water allocation forecast percentage, and the updates are defined as the previous surface water forecast shortfall minus the current surface water forecast shortfall. Both ε components represent how the surface water forecast has changed from the previous announcement between the time of the previous announcement and either March 1st or June 1st. I could regress the levels of adaptation decisions on s to learn the sensitivity of different kinds of adaptation to surface water scarcity. Instead, I regress the levels of adaptation decisions on the three components to learn about why different decisions are taken. As long as I have variation in how information updates across districts within years, then I can identify how each component results in the level of an adaptation action.

I estimate the following econometric model:

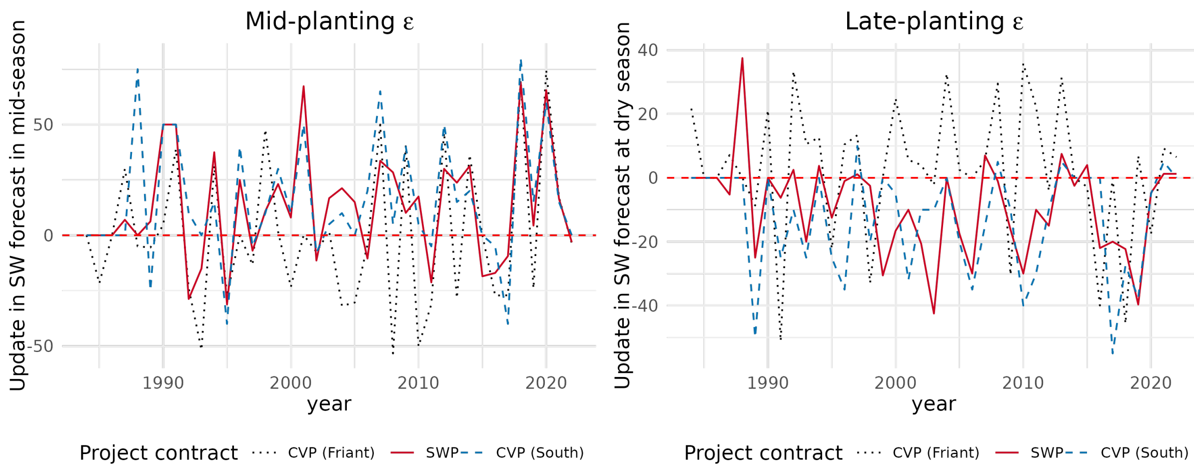
$$A_{dt} = \exp(\beta_1 \hat{s}_{dt} + \beta_2 \varepsilon_{dt}^{\text{mid}} + \beta_3 \varepsilon_{dt}^{\text{late}} + X_{dt} + \gamma_d + \gamma_{rt} + \nu_{dt}) \tag{2}$$

A_{dt} is the cumulative level of action A observed in the dry season, after all surface water information has been revealed, in district d in year t. I study four actions. The first is well drilling, so that A_{dt} is the cumulative number of wells drilled in district d until the end of the dry season (January - August). Second, I study groundwater extracted, which is proxied by the change in the depth to the groundwater table. A_{it} is the level depth to the groundwater table in feet at the end of the dry season (August), so that the βs can be interpreted as changes in depth. Third, I consider land fallowing, so that A_{dt} is the number of idled acres in a district, as observed during the peak harvest time. In the final set of regressions, A_{dt} is the number of acres at peak harvest in other annual crop groups, grouped by water intensity. 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). Poisson regressions naturally represent the aggregation of individual binary 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 fractional logit crop choice model, following Kurukulasuriya and Mendelsohn (2008)

There are three coefficients of interest, β_1, β_2 and β_3, each a component of information from (1). β_2 for example equals $\frac{d\log(A_{dt})}{d\varepsilon_{dt}}$, and so is approximately the percent change in an adaptation action with a 1 point increase in the shortfall update. Because of the definition of this variable, a 1 point increase in the shortfall update is a decrease in the announced surface water allocation by 1 percentage point, for example going from 80% of the contract to 79% of the contract delivered. The intuition from the conceptual framework can guide our interpretation of the coefficients. β_1 is the sum of the changes in the cumulative adaptation observed due to ex-ante choices and expected ex-post choices, where ex-post refers to the periods of time after the baseline surface water forecast where new information is revealed. β_2 captures the adjustments made due to the changes in information between the baseline forecast and the middle of the planting season, which includes adaptation expected to be taken later in the season. Finally, β_3 includes ex-post adjustments due to the change in surface water availability since the middle of the season. The direct effect of surface water availability comes from $\beta_1 + \beta_2 + \beta_3$.

I identify the response of adaptation actions to surface water scarcity information revealed in different times of the year using the variation in forecast updates across regions. Figure 2 shows an example of the variation using forecasts for three different contracts present in the data. I plot ε^{mid} (the left plot) and $\varepsilon^{\text{late}}$ (the right plot) for districts with the standard State Water Project contract, the south-of-delta Central

Figure 2: Variation in the data: ε^{mid} and $\varepsilon^{\text{late}}$ for three major project contracts



Note: The plot shows the levels of ε^{mid} (the left plot) and $\varepsilon^{\text{late}}$ (the right plot) for districts with the standard State Water Project contract, the south-of-delta Central Valley Project contract, and the Friant Canal Central Valley Project. The line falling above zero means that the current surface water allocation forecast is lower than the previous information, or that the shortfall increased. The plot shows that there is often a lot of correlation between the forecasts, yet there are differences in the magnitude of ε, even within the same project.

Valley Project contract, and the Central Valley Project contract to water on the Friant Canal. The line falling above zero means that the current surface water allocation forecast is lower than the last, or that the shortfall is positive. The news across project contracts is correlated, showing that districts get hit with high and low surface water years at the same time. For mid-year forecast updates, the correlation between the lines range from 0.57 and 0.71, and for late forecast updates the correlation ranges from 0.18 to 0.52. Despite the high correlation, there remains a considerable amount of variation in how districts' surface water allocations evolve throughout the year.

X_{dt} is a set of district-year specific controls that control for endogeneity between information and the adaptation choice. There are four main sources of endogeneity. The first is peer effects: one district's response to surface water availability sometimes affects other districts' responses. Peer effects is especially a problem for well drilling which has a fixed number of contractors in the short-term, so that a higher demand for wells may increase the price, and certainly increases the wait time. 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 depth to the groundwater table when it is not the dependent variable. The third 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.

The final, and most complicated, source of endogeneity is the alternative adaptation decisions. Because the adaptation decisions are substitutes, each A_{dt} modelled by equation (2) one of several simultaneous equations. Since I have a non-linear model of adaptation decisions, I control for the endogeneity from these alternative decisions using control functions (Imbens and Newey, 2009). Intuitively, the residual of estimated adaptation decisions conditional on exogenous variables still includes the effect of the other adaptation choices on the decision. Including those residuals in my regression control for the endogeneity. Although I will not control for all alternate decisions, including control functions for the main adaptation substitutes will allow us to see how important the bias from this source of endogeneity is. The requirements for excluded instruments in control functions follows the intuition of standard instrumental variables. I use instruments that capture surprising changes in adaptation-specific input prices, which only affect a substitute choice only through the level of the other choice. For the well drilling control function, I use the interaction of steel pipe prices and the depth to the groundwater table, as well as the interaction of the number of well drilling contractors and drilling machinery prices. For the crop idling control functions I use the interaction of prime farmland and fertilizer prices. For groundwater extraction, I use the interaction of electricity prices and regulation on extraction.

Finally, ν_{dt} is the error term. 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.

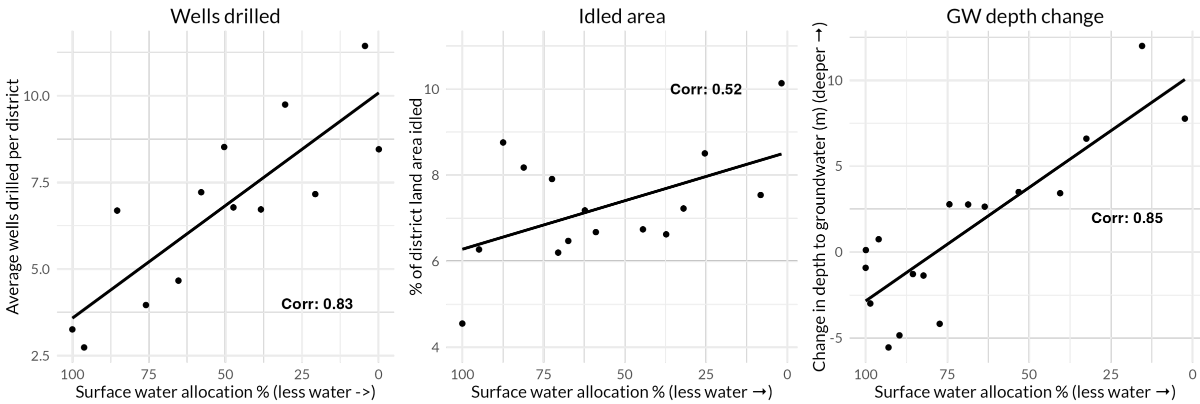
3.2 Results

The first result is that farmers respond to water scarcity using both water intensifying and water conserving adaptation practices. I motivate this fact using a simple raw-data binscatter of wells drilled, idled land and the change in depth to the groundwater table on the final surface water allocation percent. The raw data relationships are displayed in figure 3. Worse surface water allocations correlate 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. Because groundwater extraction is unregulated and has a higher social cost than water conservation, it would be socially beneficial for some portion of adaptation through groundwater use to be substituted with adaptation through water conservation. The main empirical specification explores why farmers take one decision over another in the context of information timing.

In figure 4, I plot the main β coefficients of the PPML regressions, which show how each adaptation action responds to the components of the surface water shortfall revealed at different times throughout the season. 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: an increase in surface water shortfall causes farmers to take both water conserving and water intensifying adaptive actions.

The left plot shows changes in crop choice, which is usually a water conserving adaptation choice, because farmers can tailor their acreage to the amount of surface water that they expect. The blue squares and black x's are water saving crop choices, through idling and low-water acreage respectively. Low-water acres are typically planted early in the year, when lower temperatures drastically reduce crop water requirements.

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.

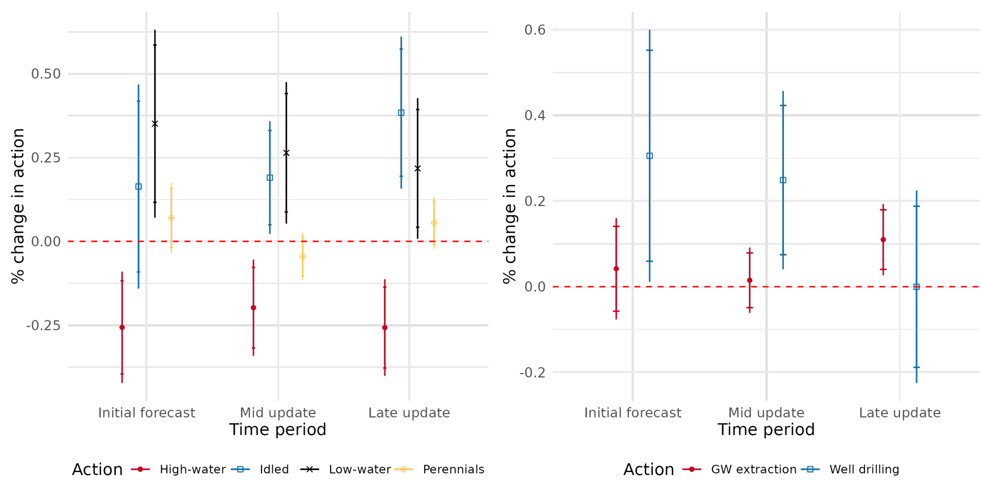
Coefficients on these choices are positive and significant, showing that farmers fallow crops and plant lower-water-intensity annuals in low surface water years. On the other hand, high-water acreage is represented by the red dots on the plot. High water acreage decreases in response to surface water allocation shortfall. The multinomial logit crop choice results in appendix table C.5 shows the same patterns.

The different coefficients show how the crop responses change over the growing season. Overall, most coefficients remain statistically significant throughout the growing season, showing that farmers continue to adapt with crop choice as they receive new information. The patterns in the magnitude of the coefficients suggest that I am capturing a true effect. By the late surface water allocation update, farmers respond less by increasing low water acres, since there are few low-water options left. The idling response remains strong, and the decrease in high water crops becomes even larger than previous. Since high-water crops are often planted in April and May (e.g. cotton and rice), there is still flexibility to decrease acreage in these crops in response to late surface water shortfall news. These coefficients translate to roughly 8.4, 11, and 12.2 new idled acres in each period for the average district, 1.5, 0.75, and 0.65 new low-water annuals for the average district and 1.6, 1.32 and 2.6 fewer high-water annuals for the average district for a marginal change in the surface water shortfall.

The right plot shows the response of groundwater intensifying actions to surface water allocation shortfall, which are the percent changed in wells drilled (blue boxes) and the percent increase in the depth to the groundwater table, in feet (red dots) which I use as a proxy for groundwater extraction. Like the raw data plots suggested, farmers increase groundwater intensifying adaptation in response to surface water allocation shortfall. The change in depth to the groundwater table is especially high and statistically significant in response to the latest surface water information announced. In contrast, well drilling decisions clearly decrease as the dry season approaches. Even though well drilling is a long-term investment, the regressions show that farmers respond to short-term surface water availability information by drilling.

Both of these patterns make sense in light of the constraints of adaptation in the setting. Groundwater extraction on existing wells can occur at any time, and therefore is the most flexible of the adaptation

Figure 4: Coefficient estimates on percent changes in actions with a 1 percentage-point change in surface water information

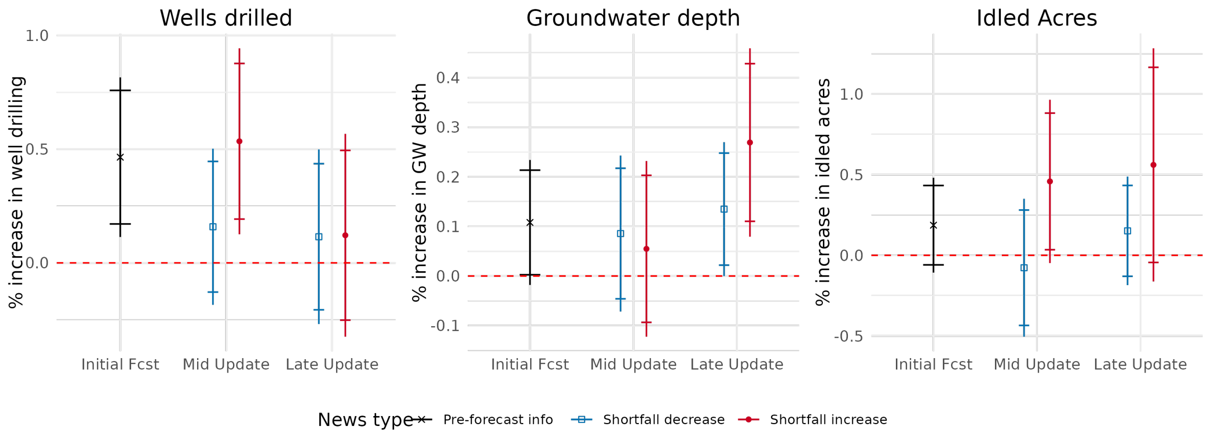


Note: This figure shows the coefficient responses to the full specification of equation (2), including controls for alternate water sources, neighbors' choices, and past capital-intensive choices, control functions for other adaptation choices, and district and climate region-year fixed effects. Each point is one PPML regression, with the dependent variable listed in the legend. 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.

options I consider. It is constrained only by the capacity of the well. For well drilling, there is a yearly tension between the option value of delaying drilling until the final surface water shortfall is realized, which will give the farmer more information about long-term surface water availability, and the short-term gain of being able to use groundwater a year early if the surface water shortfall is especially high. Farmers would be incentivized to make drilling decisions early in the latter case because of the delay between the drilling decision and completion of the well, caused by permitting and demand queues. The pattern of drilling that I find shows that farmers tend to make drilling decisions early to ensure that they can use their well in the current dry season. The estimated coefficients suggest that depth to the groundwater table increases by 0.1, 0.03 and 0.14 feet for the average district for every marginal increase in the surface water allocation shortfall over the three periods of the year, and that approximately 1 out of every 62, 100 and 150 districts drill a new agricultural well.

The adaptation response results are robust to omission of controls, and different fixed effects. The main coefficient estimates and these alternate specifications can be found in appendix table C.5. The results are robust to a variety of other specifications as well. Appendix table C.5 shows that I get the same response pattern if I model crop choice using multinomial logit rather than Poisson. Table C.5 shows the results are robust to different versions of the dependent variable, including by changing the specific time of observation of the adaptation action (e.g. by using wells drilled all year), and different winsorization levels. A modest level of winsorization of wells drilled is required for statistical significance. The results are also robust to project-type by year fixed effects, which compare within the categories of junior CVP, senior CVP, and SWP contracts, which makes sure that the results are not driven by bad comparisons across projects. The final robustness check, figure C.7 shows that the results are robust to using a combination of Conley and Newey-West standard errors across a variety of cutoffs.

Figure 5: Heterogeneous adaptation responses by increasing and decreasing surface water shortfall



Note: These three plots show the coefficients on three adaptation responses for each time period, where the updates are separated into 'good' and 'bad' news if the surface water shortfall decreased ($\varepsilon < 0$, shown by blue boxes) or increased ($\varepsilon \geq 0$, shown in red dots) respectively. I estimate these effects by interacting the surface water allocation updates (ε) in equation (2) by an indicator. 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. Overall, the general trend in the results show that the adaptation response is generally larger in the case of bad news. I also find insignificant results in the same periods where I found no significant response in figure 4.

3.3 Heterogeneity by news direction and district characteristics

I have established that farmers take both water conserving and groundwater intensifying adaptation actions in response to increases in forecasted and actual surface water allocation shortfall. However, if the effects are really linear, then changes in adaptation should balance out over time and space as sometimes districts take more adaptive actions than usual, and sometimes they take less. In the case of linear adaptation responses, there are still social costs of groundwater extraction if groundwater tends to be depleted heterogeneously across space; there is also a time-value of groundwater. Yet, the social costs will be substantially higher if farmers respond to bad news by extracting groundwater more than they respond to good news by decreasing groundwater use.

I examine whether farmers have different adaptation responses to good and bad news about surface water shortfall by interacting the surface water allocation updates (ε) in equation (2) by an indicator variable which equals one when surface water shortfall increased (bad news, $\varepsilon \geq 0$) and zero when it decreased (good news, $\varepsilon < 0$). In figure 5 I plot the differential adaptation responses in cases of increasing and decreasing shortfall. The blue boxes show the marginal adaptation response for a 1 percentage point increase in the shortfall when the shortfall update was negative, and thus shows the effect of marginally worse good news. The red dots show the marginal adaptation response when the shortfall update was positive, and thus is marginally worse bad news. The overall trend in the plot shows that in periods that had significant effects in figure 4, the adaptation response tends to be larger and more statistically significant when the shortfall update is positive than when it is negative. Both the water conserving and groundwater intensifying actions display the same trend. Farmers have strong adaptation responses to bad surface water news, and potentially very little response to good surface water news.

The most important insight from the heterogeneous response analysis is that positive surface water shortfall updates increase adaptation actions without commensurate decreases in adaptation in years where the shortfall decreases. If adaptation responses increase groundwater use in response to a bad surface water shortfall shock, then over time groundwater use is higher than it would have been absent surface water shortfall shocks, potentially leading to a social cost of adaptation.

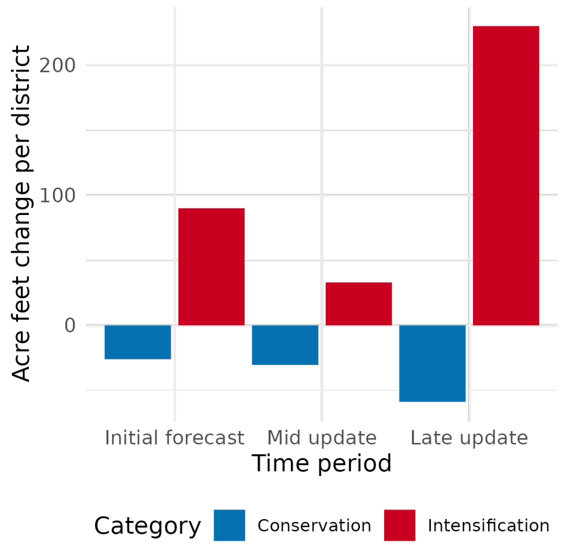
In order to understand the characteristics of farm adaptation, I conduct a few other heterogeneity analyses, which I include in the appendix. Well drilling likely changes over time since it is not a recurring annual choice like annual cropping and groundwater extraction. Once a well is drilled, a farmer 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 C.6. 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. In an alternate heterogeneity analysis, I make sure that I am convincingly capturing the effect of the surface water allocation forecast by interacting the estimated percent of surface water in the district that comes from surface water projects with the surface water allocation forecasts and updates. As expected, a higher percent of project water results in a stronger well drilling response to the surface water allocation forecast changes. Finally, I also interact the percent of a district's land in perennials with the surface water allocation forecasts, and I find that districts respond with well drilling when they have more land in perennials. The final result shows some of the complementarities in choices in agriculture.

3.4 Change in water use through adaptation

Not only do farmers use water-intensifying and water conserving strategies to adapt, but they tend to adapt when surface water shortfall updates are positive, and not when they are negative, suggesting there could be a long-run net positive increase in groundwater withdrawals from adaptation. To conclude this section, I approximate the magnitude of changes in water use from both types of actions. I assume that low-water acreage uses 2 acre feet per year, high-water acreage uses 4 acre feet per year, and fallowed acreage uses 0. I do not calculate substitution patterns in this paper, so I make the following assumptions: low-water acreage is substituted from high-water acreage, and the rest of the high-water acreage change becomes fallowed land. Since I observe more land fallowing than other changes in acres (I do not include pasture land, or perennial land in this crop choice analysis), I assume that other fallowed land saves 3 acre feet per year on average. For change in groundwater extraction, I assume an equal groundwater level change over all planted acres in the district. I multiply the acres by the groundwater level change by the estimated porosity of the aquifer, which is the measure of groundwater storage per volume of earth (Ojha et al., 2018). The change in groundwater use from new wells is complicated. I omit the estimate in the current analysis, returning to it after section 7 where I study dynamic consequences of well drilling.

Figure 6 shows the results of the back-of-the-envelope calculation for every period. In response to a 1 percentage point increase in the surface water allocation shortfall in every period, the average district increases groundwater use by about 635 acre feet, and decreases water use by about 130 acre feet. The main takeaway is that even without including the effects of new groundwater wells, farmers increase groundwater use up to 7 times more than they decrease surface water use in certain periods of the year, and groundwater use is always at least twice as strong as the water conservation effect. Because groundwater extraction is

Figure 6: Change in water used after a 1 percentage point change in surface water shortfall



Note: This figure shows the back-of-the envelope calculations for decreases in water use from water conservation from changing crop choice, and groundwater intensification from groundwater extraction, using the estimates in figure 4. I omit any change in groundwater from new wells. The y-axis shows the acre feet change for every district from a marginal increase in surface water shortfall resulting from these changing adaptation practices.

socially costly, this result raises the question about how socially beneficial adaptation to water scarcity is. To study the net benefit of adaptation, I estimate the aggregate private value of adaptation in the next section. Afterward, I explore the less straightforward, but potentially important dynamic social costs from the well drilling decision.

4 How farmers adapt in the long-run: effects of well drilling

In section 3 I studied how farmers in California respond to surface water scarcity in the short run. However, the average surface water availability decreased throughout my period of study, irrespective of drought, as shown in appendix figure B.4. Therefore, aside from annual decisions, farmers will make long run decisions to adapt to more permanent surface water scarcity. Two of the major long run decisions are well drilling and permanent land fallowing.

Well drilling can lead to increases in external costs across multiple dimensions. Drilling a well fundamentally changes the characteristics of the choices in the adaptation choice set, both by allowing the groundwater extraction choice, and by permanently decreasing the downside risk of high water prices. Surface water has much higher price volatility than groundwater; across years, the median percent change in the surface water price was 68%, (Nasdaq, 2025), whereas groundwater prices fluctuate approximately 12% per year[14]. Thus,

[14] The price of groundwater goes up proportionally in electricity price and depth to the groundwater table. I show this by rearranging the physical equation of lift from Burlig et al. (2020) to calculate price per acre foot: Price / AF = (depth to groundwater × electricity price × 1.0241) / pump efficiency (%). This means that at the average yearly increase in electricity prices for pumping, 1.9% (Burlig et al., 2020) and the median absolute change in the depth to the groundwater table (10.4%) the groundwater price change is about 12%.

drilling a well can change the relative value of short-run adaptation options, and could lead to longer-run changes in average water use, from cropping decisions.

I build the picture of the long-run effects of well drilling in four parts. First, I estimate when the wells drilled in response to short-run shortfall shocks would have been drilled otherwise, using local projections. I study these wells because they complete the picture on the social costs of adaptation resulting from short-term shortfall shocks. Then, I study how making well investments affects short-term adaptation choices, by estimating how a district's well stock affects the sensitivity of adaptation actions to shortfall shocks. Afterward, I explore how drilling wells affect longer-run water use decisions on farms. I first see how new wells increase district groundwater use in normal water years. Then, I finish the section by studying how exogenous new wells affect farmers' crop choices over time.

4.1 How do short run shocks affect the longer-run stock of wells?

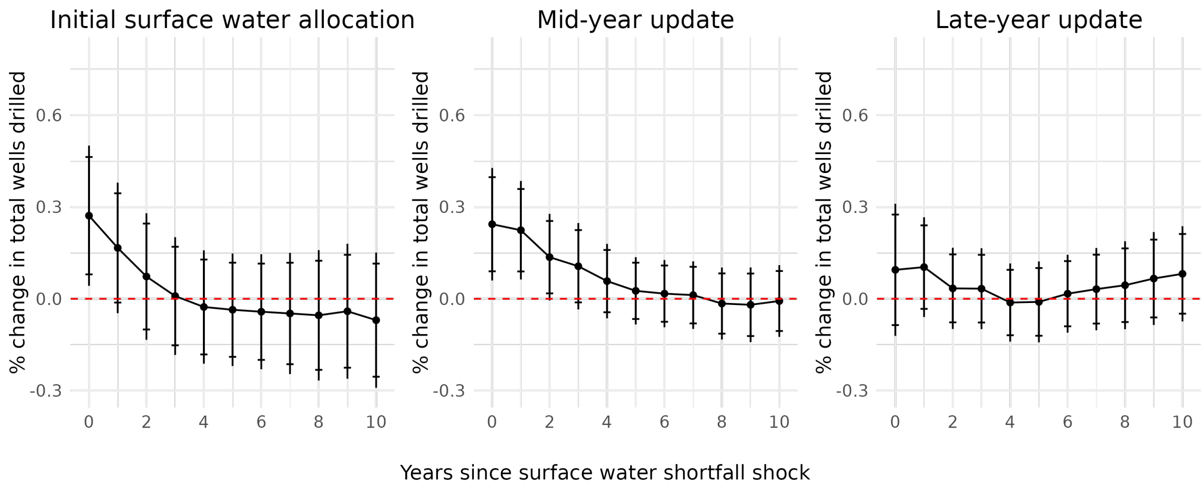
Section 3 showed that some wells are drilled because of short-run shocks. A short-run shock is a small shift in the surface water supply that nudges some farmers with a well value near the threshold of drilling to drill. As well values in California are rising over time, these short run shocks contribute to earlier long-run adaptation over my period. This subsection traces the dynamic impact of a one-time surface water shortfall shock on the stock of wells in a district. Through this analysis I learn how much earlier wells are drilled than they would have been otherwise, which allows me to quantify the longer-term social costs of adaptation to short-run surface water supply shocks.

I estimate the dynamic effect of the short-run shortfall shock using local projections (Jordà, 2005). Local projections will estimate the impulse response of a surface water shortfall shock in year t on the cumulative stock of wells in a water district over horizons $h = 0, 1, ..., H$ (i.e., from year t through year $t + H$), relative to the pre-shock baseline. The key identification assumption is that surface water shortfall shocks are exogenous conditional on past information, meaning the shock in t is not affected by contemporaneous well-drilling decisions (Jordà, 2023). The estimating equation is similar to equation (2), where the major difference is that the dependent variable is the sum of wells drilled in a district from year t to year $t+h$. I also include two lags of the number of wells drilled and the previous shocks, which is standard in local projections for ensuring the exogeneity of the shock and correcting for bias in the standard errors (Montiel Olea and Plagborg-Møller, 2021). I then run $H = 10$ separate regressions.

I plot the effect of the shortfall shock over time in figure 7. Each plot shows the path of coefficients for one of the three shortfall components, and the points are the coefficient estimates for each of the time horizons, $h = 0, 1, ..., H$. The first point, for $h = 0$, corresponds to the year the surface water shortfall shock occurred, and is hence virtually the same as the short-term adaptation effect from figure 4[15]. For the information that well drilling responded significantly to, the initial surface water allocation and mid-year update, the same trend appears. The effect of a surface water shortfall shock on the cumulative number of wells in a district decreases monotonically after the shock occurs, and levels off at no effect. Therefore, the wells drilled in response to the surface water shortfall shocks would have been drilled only a few years in the future. About half of the wells drilled in response to initial surface water would have been drilled the next year. For wells drilled in response to a shock in at the mid-year update time, about half would have been drilled within three years.

[15]The coefficient estimates differ from the main specification because of the local projections controls.

Figure 7: Dynamic well drilling response to surface water allocation shocks



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.

Despite the short-run effect lasting for a short time, there is still a real social cost to drilling wells early. Groundwater will be extracted earlier, and farms will adjust other inputs earlier. Therefore, society bears the costs of externalities from extraction starting this year rather than several years from now. Also, stored groundwater is more socially valuable than the marginal extracted groundwater unit because of the scarcity rents that can be collected under future regulation. Extracting too early lowers long-term welfare.

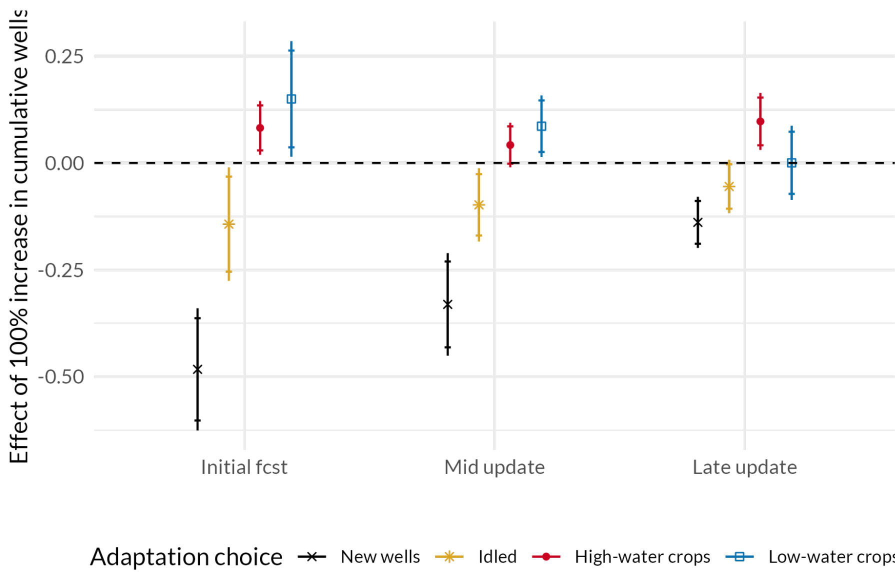
The dynamic analysis showed that small shortfall shocks shift some wells forward in time. When I calculate the costs of adaptation to short-run shocks in the final section of the paper, I need to account for the additional water used in each of the periods that districts had more wells than their counterfactual trend. Combined with the general well drilling trend from figure 14, we learn that these small shocks play a continual role in the long-term adaptation story, shifting the farmers with the highest well values to drill earlier.

4.2 How does well drilling affect short-term adaptation?

Next, I explore how the continuous trend in well drilling affects how farmers adapt to the short-term surface water shortfall shocks that I studied in section 3. Drilling a well lowers the value of water conservation. Groundwater acts as a backstop resource during dry years, when surface water prices increase much faster than groundwater costs. When a farmer gets access to groundwater, the costs saved through conservation decreases.

I estimate how the stock of wells in a district affects the district's sensitivity to adaptation through the actions studied in section 3. I take the original estimating equation (2) and interact the components of information by the log of the lagged cumulative wells in a water district, a pre-determined variable. The interaction term will show whether having more wells affects the districts' adaptation to short run shortfall shocks. The interaction effect of lagged log cumulative wells and surface water scarcity components is shown in figure 8.

Figure 8: Interaction of the logged stock of wells and shortfall components



Note: This plot shows the results of the main specification in equation (2), where the main regression coefficients are interacted by the logged lag cumulative wells in a water district. I plot the coefficients of the interaction.

In comparison with the baseline results, the coefficients on the interaction term reverse the effects of surface water scarcity on nearly every conservation decision. Idled acreage decreases as the stock of wells increases, and the switch to high-water crops increases. Low-water crops also increase, the sole exception to the pattern; however, the increase in low water crops might be substitution from idling rather than high-water crops. Also, the coefficients on the earlier information tend to be larger in magnitude than the latest information. I also plot the coefficient on the interaction term for the regression of new wells. Although the number of agricultural wells in the state consistently rose over the last 60 years, figure 8 shows that districts drill fewer wells as the well stock increases, suggesting diminishing returns to drilling within districts.

This analysis illuminates the first long-run cost of well drilling: well drilling diminishes the propensity of farmers to adapt in the short run. Section 3 showed that in the short-run, districts adapt most with water-intensive adaptation. A trend away from short-run adaptation is socially costly if long-run adaptation is even more water intensive. We might guess that it is. The next two subsections explore how much more water farmers use after drilling.

4.3 How much does groundwater use increase after well drilling?

We expect well drilling to increase groundwater use. However, there are several details that are not obvious. First, we do not know ex ante whether farmers use groundwater in years with a normal allocation of surface water. Since groundwater tends to be more expensive in normal surface water years, farmers would use groundwater if districts set the price of surface water lower than the marginal product of water (given that the water district usually imposes limits on the quantity of surface water that can be purchased). Second, there is the fundamental unknown in water management in California: how much water do farmers extract from a given well? In this section, I regress depth to the groundwater table over time on new wells drilled in a particular year. I explore the dynamic path using local projections with instrumental variables.

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). The independent variable of interest is the projected number of new wells in a county, and the dependent variable of interest is the level change in acreage in a particular crop j between year t to $t+h$. In the local projections framework, the standard IV exogeneity requirement requires that the instrument should only be correlated with the contemporaneous shock and not with leads or lags of the shock (Stock and Watson, 2018). Including lagged well drilling as controls helps address potential violations of this assumption by accounting for the predictable component of drilling activity.

Groundwater extraction and well drilling are simultaneously determined by surface water scarcity, weather, prior wells drilled, and a host of other variables. I use well supply shifters as an instrument to capture well drilling decisions unaffected by current water conditions. I construct an instrument using the interaction of two variables that capture different well supply shocks. The first is a measure of market power in the well drilling market. Higher market power should increase the price of wells holding all else equal. In my main specification, I measure market power by counting the number of well drilling companies operating in the area. I specifically I take the 25 kilometer buffer around the convex hull of all wells drilled by a contractor over all time, where contractors are defined by an entity that drilled at least two wells, and the lifetime of the contractor is taken as the time period between its first and last well drilled. Not all contractors drill wells every year, so the variable captures the number of drillers capable of drilling in an area at a given time, while separating the variable directly from well demand. Further, the instrument is not directly connected to well demand since contractors cannot enter the market immediately due to certifications and machinery investments required. In robustness check, I alter the buffer, alter the definition of the time in business, and redefine market power using the Herfindahl-Hirschman Index (HHI) over the number of wells drilled in a particular year.

The number of contractors varies across space and time, though the spatial pattern of the number of contractors remains similar. Thus, I interact the market power variable with another variable affecting well supply: well input prices. 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, and this variable exists across most of my analysis. 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). Steel piping prices are definitely exogenous to the extraction decision except through wells drilled, making the instrument valid.

Equation (3) shows the first stage of my instrumental variables specification. Y_{dt} is the number of wells drilled between January and August. N_{dt} denotes the number of contractors, and P_t denotes the input prices. The excluded instrument is $N_{dt} \times P_t$. I include these as level variables because they are distributed close to normally in my data. I include all of the controls as in my previous estimation, X_{dt}, and the same fixed effects. The first stage estimates the well decision linearly, as required by the assumptions of two-stage least squares. There is no clear way to transform the dependent variable in my case. Many districts choose 0 wells in some t creating problems for interpreting a log transformation (Chen and Roth, 2024). I show the results of the first stage estimation in table 2.

$$Y_{dt} = \alpha_1 N_{dt} \times P_t + \alpha_2 N_{dt} + X_{dt} + \gamma_d + \gamma_t + \nu_{dt} \tag{3}$$

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

	First stage			Reduced Form		
	(1)	(2)	(3)	(1)	(2)	(3)
Contractors × Steel pipe price ($100)	0.006^{***}	0.004^{***}	0.004^{***}	0.063^{**}	0.042^{***}	0.043^{***}
	(0.001)	(0.001)	(0.001)	(0.025)	(0.011)	(0.011)
Contractors	0.016^{***}	0.016^{***}	0.017^{***}	0.056	0.128	0.127
	(0.004)	(0.004)	(0.004)	(0.098)	(0.082)	(0.087)
Steel pipe price ($100)	-0.637^{***}			3.497		
	(0.143)			(4.540)		
Controls	no	no	yes	no	no	yes
District FEs	no	yes	yes	no	yes	yes
Year FEs	no	yes	yes	no	yes	yes
F-stat	132	132	127	NA	NA	NA
Num. obs.	4882	4882	4923	4882	4882	4882
Adj. R^2 (full model)	0.181	0.760	0.761	0.069	0.805	0.805

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

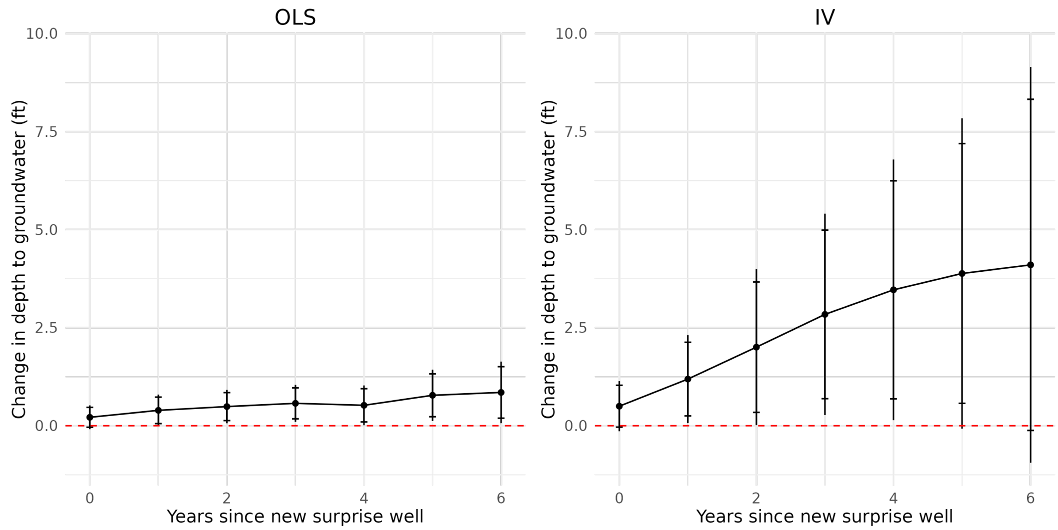
Note: The first three columns show the first stage for how the number of wells are affected by the instrument, and the last three columns show the reduced form for how the depth to the groundwater table is affected by the instrument. The instrument is the first row, the interaction of the number of contractors and the current steel pipe price. The other two variables are included in the regression. Each column adds stronger fixed effects or controls. (1) has no controls or fixed effects, meant for building intuition. (2) adds year and district fixed effects and (3) adds all of the controls.

The first stage results show that the well supply variables empirically affect the number of wells in an intuitive way. The first column regresses the number of wells only on the well supply variables. Even without including fixed effects, the coefficients on the first two variables remain similar across all specifications, giving suggestive evidence that these variables are not determined by the drilling decision. In the raw data, a higher steel pipe price significantly negatively correlates with drilling. The second and third columns include the appropriate fixed effects. Overall, as the number of contractors increases in a district relative to the district's average and that year's average, the number of wells drilled increases. Therefore, adding more contractors appears to actually shift the well supply curve out. The direction on the coefficient of the actual instrument is not ex-ante obvious. It shows that as steel pipe prices rise, how an additional contractor contributes to the number of wells in a district. The positive coefficient means that during periods of high steel pipe prices, the number of contractors influences well drilling even more. Intuitively, increases in input prices matter less in districts with more contractors, perhaps because the firms continue to compete in prices. The instrument is highly statistically significant across all specifications.

The instrument I propose induces a minor shift in the value of wells through the well cost. Therefore, the farmers affected are those with well values close to the threshold of drilling into drilling, and who might have drilled a few years in the future. These farmers are different from the rest of the population, who will not drill for several decades, who who had drilled several decades prior. Nevertheless, the local average treatment effect is interesting and relevant. The two-stage least squares results will capture changes in extraction for the farmers likeliest to drill next.

I then show how a new well affects the depth to the groundwater table within a local projections framework, and plot the results in figure 9. The left panel shows the cumulative change in depth to the groundwater table using OLS within each of the local projections regressions. The right panel uses instrumental vari-

Figure 9: Change in depth to the groundwater table with 1 new well in a district



ables. New agricultural wells lead to increases in depths to the water table, by 0.8 after 6 years in the OLS specification, and a little more than 4 feet after 6 years in the IV specification. It makes sense for the OLS estimate to be biased downward because across time, as districts have a higher well stock they drill less (as recently shown) but also would extract the most groundwater.

The IV estimate is quite high, averaged over a district. The USGS's theoretical estimates of groundwater drawdown from large agricultural wells predict that at a distance of 1 mile of the well, a moderately large agricultural well (1000 gallons per minute) would draw down the aquifer about 2 feet after 1 year, and the largest agricultural wells (4000 gallons per minute) would draw down the aquifer about 8 feet (Kunkel, 1960)[16]. The IV estimates are reasonable given the USGS theoretical estimates, if farmers are drilling large wells and extracting large quantities immediately. My estimates imply that about 1800 acre feet of water are extracted in the first year in the average district, which is approximately the capacity of a 1000 GPM well. Theoretical groundwater drawdown predicts a logarithmic change in depth to the groundwater table if groundwater is being extracted at a constant rate. The IV estimates show the expected levelling off over time, though the rate of change in the first four years is fairly linear, suggesting increasing extraction in the first few years.

This subsection reveals that farmers use new wells immediately and extensively. The local average treatment effect captures the effect of drilling a well in an average year, since the well supply shocks I use are not related to surface water supply. Yet, the instrumental variables estimates are consistent with farmers having drilled large agricultural wells, and extracting large quantities in the average year[17]. Thus, the marginal new well drillers do not merely supplement their surface water with groundwater, but rather greatly increases the water intensity of the farm.

[16]The USGS model also predicts that drawdown is higher close to the well; about 4 feet and 11 feet for the moderate and large wells at a distance of 1000 feet. Drawdown is also the fastest in the beginning. After 10 years, the drawdown of these wells at 1 mile is about 3 feet and 11 feet respectively.

[17]The raw data shows that the proportion of the highest capacity wells (greater than 2000 GPM) increased from 5% to 15% of new wells drilled between 1990 and 2015.

4.4 How do farmers change cropping patterns after drilling?

The previous analysis showed that farmers extract large amounts of groundwater from new wells, resulting in a persistent change in farm water use. There was also a suggestive pattern that farmers might be increasing their extraction over time. I finish my study of the effects of well drilling by exploring how drilling affects the water intensity of agriculture through cropping decisions. Drilling a well gives farmers permanent access to a surface water substitute with a stable marginal price, which increases the value of higher-water acreage and decreases risk of crop losses, especially for perennials.

Like in the previous analysis, I use local projections with instrumental variables. I need to study the crop decision dynamically because new wells change the value of planting different crops, but farmers often cannot switch immediately. Instrumental variables are required particularly because the value of crops directly determines the cropping choice, and the value of a well. The same instrument as the previous analysis is valid here since well supply shifters only affect cropping choices through making wells cheaper.

My original dataset will not allow me to study the dynamic effects of well drilling on cropping, however. The Cropland Data Layer is short, which leads to bias in local projections (Herbst and Johannsen, 2024). Therefore, I perform the main analysis on the longest panel of harvested cropland available for California, which spans from 1980 to 2022 from California's Agricultural Commissioner (CA Agricultural Commissioner, National Agricultural Statistics Service, 2025). I aggregate the same control variables used previously to the county level. Otherwise, the analysis proceeds in the same way.

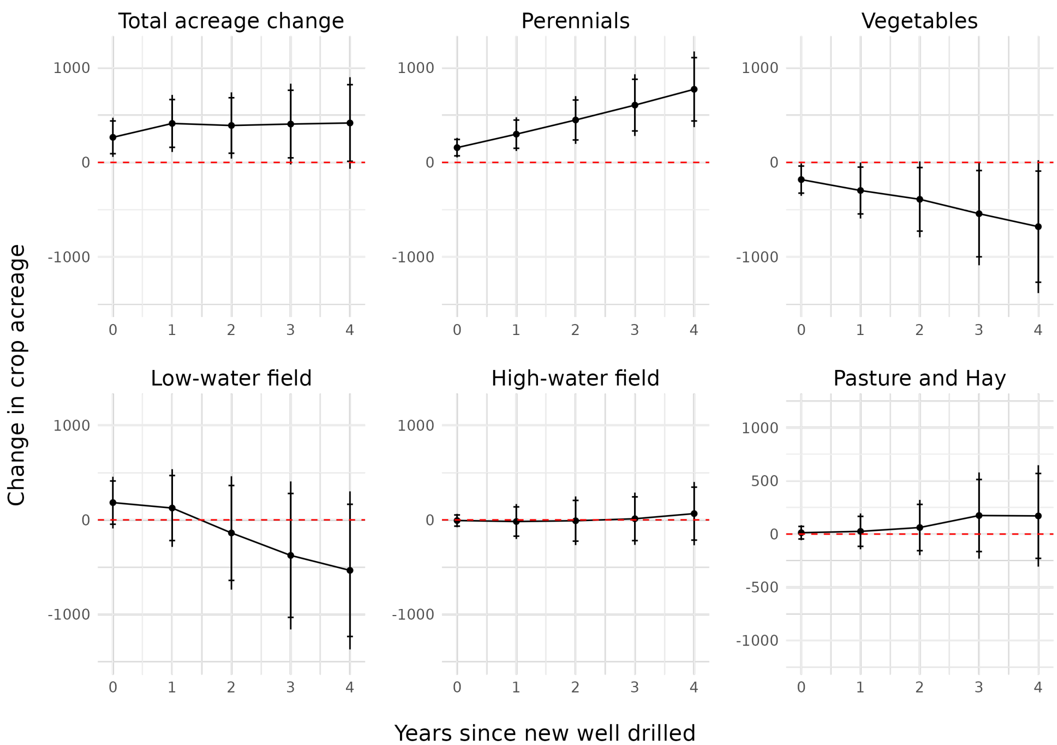
Figure 10 shows the dynamic consequences of well drilling on acreage. Total acreage increases immediately after drilling, originating from an increase in perennials and (relatively) low-water field crops like grains and corn. The total acreage change stabilizes at around 450 acres, driven over time by increasing perennial acreage. Perennial acreage increases seemingly at the expense of vegetable acreage.

These cropping changes explain the groundwater extraction results from the previous subsection. I found that groundwater extraction increases immediately. Similarly, new wells result in an immediate increase in harvested acreage, where farms begin by planting low-valued, but low-labor (and therefore easier-to-plant) field crops. They then shift over time to the highest-water crop category, perennials. A large portion of the new perennial acreage comes from high-valued vegetable acreage. This shift is intuitive. Both crop types are high-valued, and require good soil quality, sunshine, and high amounts of labor for harvesting, making them potential substitutes for farms in certain locations in California. However, the shift across these crop types generally means an increased water requirement over time. During growing periods, these crops require similar quantities of water, though perennials need to be watered year-round. Perennials also have a higher opportunity cost of fallowing, meaning that many more farmers will opt to water perennials during dry spells. Thus, well drilling drove major changes in agricultural production within California.

4.5 Adaptation to surface water scarcity led to groundwater intensification in the long run

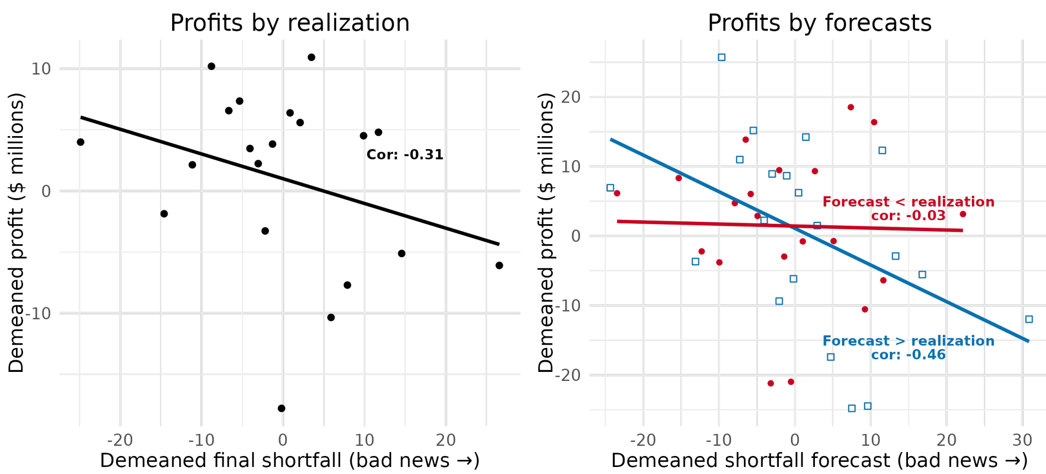
Section 4 showed how well drilling led to changes in short-run adaptation, and major increases in water used over time through an expansion of irrigated land and a shift toward higher-water intensity crops. The first two subsections showed how a portion of well drilling can be directly attributed to shocks to surface water availability.

Figure 10: Local projections of changes in 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. 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).

Figure 11: Binscatters of county-level profits on the surface water shortfall, controlling for county and year fixed effects



Note: Both plots demean the level of profits by county and year fixed effects, after winsorizing profits at the 5% and 95% level. The left plot bins the demeaned final shortfall, and the right plot bins by the demeaned shortfall forecast, after grouping observations by whether the demeaned difference between the realization and the forecast was higher or lower than zero. This process embeds the assumption that farmers rationally update the forecasts to mean zero bias.

5 Private value of adaptation to surface water scarcity

Surface water scarcity is bad for farms. The left panel in figure 11 shows that after controlling for county and year fixed effects, higher shortfalls correlate with lower profit[18]. The previous sections went into detail identifying how farmers take adaptation measures to avoid net profit losses. This section quantifies the value of all of the actions that farmers take in different periods throughout the year.

The net private benefit of adaptation comes from the profits that farmers are able to save through choosing appropriate actions for the level of surface water shortfall realized during the dry season. In agriculture, many of these actions, like crop choice, must be made well before the realization of the surface water shortfall. The benefit of adaptation therefore crucially depends on the accuracy of the surface water shortfall forecasts. The right panel in figure 11 illustrates this fact in the raw data. When the surface water shortfall forecast was higher than the realized shortfall, higher shortfall forecasts correlate with lower profits. Intuitively, a higher shortfall forecast is further away from the truth, and thus adaptation becomes less appropriate for the realized level of shortfall. On the other hand, when the forecasted shortfall was lower than the realization, the negative effects of higher shortfall forecasts disappear. In this case, a higher shortfall forecast results in adaptation better suited for the actual level of surface water.

I begin this section with a simplified conceptual framework that will give us an idea of how to estimate the value of adaptation to surface water scarcity. The main intuition is that value of the accuracy of the forecast is equivalent to the benefit of short-run adaptation. By capturing how much more profit farmers earn if the forecast was one point closer to the realization, we capture the value determined by the specific

[18]The negative relationship between surface water shortfall depends on the unit and time controls, since log revenues and years have a correlation of 0.97, average shortfall and years have a correlation of 0.62, and average shortfall and average revenue have a correlation of 0.25. In appendix figure B.5, I show that the negative relationship between revenues and shortfall appears as soon as I at least control for a year trend and the average shortfall in a county.

actions tailored to the level of the forecast that cannot be perfectly adjusted later. Afterward, I apply the framework to data and show the results. Valuing farmers' actions will allow us to understand the relative magnitude of the problem of the social costs of adaptation.

5.1 Conceptual framework

In this conceptual framework, I design a stylized model of current-year net benefit (profits) for a farmer, incorporating the sequential adaptation empirically observed in section 3. I then show how changing information at different periods in the growing season identifies the value of adaptation. I conclude by showing how to use the model to derive the benefit of adaptation empirically. This conceptual framework builds on Shrader (2023) by examining a context with multiple periods of adaptation within a year.

Farmers take adaptation choices throughout the year based on information available at a certain time in order to maximize a static profit function[19]. As I showed in section 3, farmers take different adaptation choices within a year, revealing that ex-post profits depend on the actions taken in several periods within a year, and that the actions in different periods are not perfectly substitutable. Therefore, I differentiate an abstract action a by the time in the year it is taken, $\{early, mid, late\}$. By the time that profits are realized, ex-ante adaptation a^*_{early} and mid-season adaptation a^*_{mid} are already determined; they are implicit functions of the information available at the time and previous adaptation. Ex-post adaptation a_{late} occurs right after the final shortfall is revealed. Let adaptation actions be increasing in surface water scarcity, so that $\frac{da_{early}}{d\hat{s}} > 0$.

The final profits also depend on the realized surface water shortfall directly, s, as is intuitive and reflected in figure 11. As defined throughout the paper, the final shortfall is made up of the shortfall forecast, and the two updates across the year: $\equiv \hat{s} + \varepsilon^{\text{mid}} + \varepsilon^{\text{late}}$. To simplify the framework, I assume that each component is independent. Thus, the realized profits for one year is given symbolically by:

$$\max_{a_{late}} \quad \Pi(s, a^*_{early}, a^*_{mid}, a_{late})$$

The value of adaptation comes from the following experiment: imagine there are two identical farmers, with the same s. Then, for the first farmer, we change $\hat{s}$. Now, the first farmer both received a different forecast, and ends up with a marginally higher s. The farmers now likely have different profits by the end of the season. The first farmer's profit changed because $\hat{s}$ changed, which led to different actions (say, idling an extra field) early in the season, and also because the final shortfall is slightly higher. The first channel is the value of adaptation. The second channel is the direct effect of water scarcity. I show how marginally altering each piece of information allows us to identify three pieces of information: the value of ex-ante adaptation, the value of mid-season adaptation, and the direct effect of water scarcity.

First, I show how the net benefit for a farmer changes if we alter the initial shortfall forecast:

$$\frac{d\Pi}{d\hat{s}} : \underbrace{\frac{d\Pi(s)}{da^*_{early}}\frac{da^*_{early}}{d\hat{s}} + \frac{d\Pi(s)}{da^*_{mid}}\frac{da^*_{mid}}{da^*_{early}}\frac{da^*_{early}}{d\hat{s}}}_{\text{value of ex-ante adaptation}} + \underbrace{\frac{d\Pi(s)}{da^*_{mid}}\frac{da^*_{mid}}{d\hat{s}^{mid}}}_{\text{value of mid-season adaptation}} \underbrace{\frac{d\hat{s}^{mid}}{d\hat{s}}}_{1} + \underbrace{\frac{d\Pi(s)}{ds}}_{\text{direct effect}} \underbrace{\frac{ds}{d\hat{s}}}_{1} \tag{4}$$

[19] I abstract away from the dynamic adaptation choice in this simple framework. See the appendix in the future for the dynamic adaptation choices.

The farmer's profit changes through four channels. The first two combine to make up the value of ex-ante adaptation. If we marginally changed $\hat{s}$, we would marginally change the early adaptation choice, and changing the early adaptation choice inherently changes the mid-season adaptation choice as well. The value of adaptation appears in the same way as it does in (Shrader, 2023). It is how the net benefits change as actions change. I recover an estimate of these benefits precisely because I observe profits after all choices have been made; given the later shortfall information, a^*_{early} and a^*_{mid} are not optimal, so the derivative of realized profit with respect to these terms is not zero. Changing $\hat{s}$ keeping all other shortfall components ε^{mid} and ε^{late} constant changes the later information, $\hat{s}^{mid}$ and s marginally, by definition. Thus, changing the early shortfall forecast changes mid-season adaptation through the change in mid-season information, and also directly impacts profits through changing shortfall. I could analogously alter either ε^{mid} or ε^{late}. I summarize the result:

$$\begin{aligned}
\frac{d\Pi}{d\hat{s}} &: \quad \text{Value of ex-ante adaptation} + \text{Value of mid-season adaptation} + \text{Direct effect of scarcity} \\
\frac{d\Pi}{d\varepsilon^{mid}} &: \quad \text{Value of mid-season adaptation} + \text{Direct effect of scarcity} \\
\frac{d\Pi}{d\varepsilon^{late}} &: \quad \text{Direct effect of scarcity}
\end{aligned} \tag{5}$$

Equation (5) translates simply into an empirical model. Each derivative can be estimated through a regression of profits on the shortfall component. If I include all three in the same regression, as shown in equation (13), I can separately identify each. The value of ex-ante adaptation is given by $\beta_1 - \beta_2$, the value of mid-season adaptation is given by $\beta_2 - \beta_3$ and the direct effect of water scarcity is given by β_3.

$$\Pi_i = \beta_1 \hat{s}_i + \beta_2 \varepsilon_i^{mid} + \beta_3 \varepsilon_i^{late} + \nu_i \tag{6}$$

Before estimating the empirical model, we need to think carefully about the sign of the value of adaptation. Of course, adaptation is valuable in expectation. However, it is not necessarily valuable after the realization. Consider a farmer who receives a surface water shortfall forecast of 100%. She expects to get no water, and therefore abandons all of her crops. However, suppose her realized shortfall is 0%. The realized value of her ripping up her fields was net negative. More generally, consider the first term in equation (12) $\frac{d\Pi(s)}{da^*_{early}} \frac{da^*_{early}}{d\hat{s}}$. Assume that the shortfall forecast increases marginally. $\frac{da^*_{early}}{d\hat{s}}$ is positive by assumption (a farmer abandons slightly more fields with a higher shortfall). Whether this is good for realized profits depends on the sign of $\frac{d\Pi(s)}{da^*_{early}}$, which ultimately depends on the relative values of $\hat{s}$ and s. If $\hat{s} > s$, or shortfall is already forecasted higher than the realization, then marginally increasing the shortfall makes the information less accurate. $\frac{d\Pi(s)}{da^*_{early}} < 0$; the farmer adapted more than the optimum already. With a higher $\hat{s}$, the farmer would adapt slightly less appropriately than before. However, if $\hat{s} < s$, then marginally increasing the shortfall would make information slightly better, and the adaptive actions would be more appropriate. $\frac{d\Pi(s)}{da^*_{early}} > 0$ because the farmer would have preferred to take more adaptive actions had she known the realized value of the shortfall.

Thus, since I am using realized profit to measure the value of adaptation, the realized value of adaptation can, and often is, negative. Estimating the equation by pooling farmers i together will recover the average realized value of adaptation, which itself might be an interesting value. For example, a negative realized value of adaptation will tell us that over-adapting is more costly than underadapting on average. However, typically we are more interested in how the net profit gained from tailoring investments marginally better. A farmer could tailor her investments better if an erroneously low forecast was marginally higher, and an erroneously high forecast was marginally lower. Separately identifying the β coefficients for these two cases gives a more intuitive estimate of the benefit of adaptation.

5.2 Empirical Methods

I now apply my conceptual framework to data, expanding equation (13) to the panel structure of my dataset.

Equation (7) approximates the thought experiment in the conceptual framework. The most comparable units over time is a county to itself. The panel fixed effects allow me to study how a county's outcomes change marginally adjusting the different shortfall components in different years, relative to the adjustments of all other counties to themselves. I incorporate the intuition from the end of the conceptual framework, by measuring two different coefficients on the shortfall forecast and mid-season shortfall update, for whether the forecasted shortfall is lower than the realization denoted by the indicator $L_{ct} = 1$ or whether the forecasted shortfall is higher than the realization denoted by the indicator $H_{ct} = 1$. Now, $\beta_1^l ow$ is the amount that profit changes due to shortfall increasing by a marginal amount to become more accurate.

$$\begin{aligned} Y_{ct} =& \beta_1^{low} L_{ct}\hat{s}_{ct} + \beta_1^{high} H_{ct}\hat{s}_{ct} + \beta_2^{low} L_{ct}\varepsilon_{ct}^{\text{mid}} + \beta_2^{high} H_{ct}\varepsilon_{ct}^{\text{mid}} \\ &+ \beta_3^{low} L_{ct}\varepsilon_{ct}^{\text{late}} + \beta_3^{high} H_{ct}\varepsilon_{ct}^{\text{late}} + X_{ct} + \gamma_c + \gamma_t + \varepsilon_{ct} \end{aligned} \tag{7}$$

I use the best agricultural revenues and profits data available, which is at the county level. Therefore, I aggregate my previous district-level dataset to the county level, which is the best way to handle this multi-level data structure (Foster-Johnson and Kromrey, 2018). I construct the ε_{ct} by determining which contracts exist within the county, and weighting the forecasts that correspond to those contracts by the proportion of water from each project in the county, approximated by the state's water model[20] (Department of Water Resources, 2022).

The variation in equation 7 comes from how the average surface water forecast in a county differs across the state within a year. The map in figure **??** shows that districts with similar forecasts are often clustered together, meaning that a lot of the variation across the state will be retained in the county-level dataset.

Y_{ct} measures the agricultural profits in a county, which I construct by subtracting the total agricultural expenses from yearly cash receipts. I have a measure of crop-specific cash receipts, though since I do not have an analogous measure of crop-specific expenses I cannot construct profits and therefore leave these estimates to the appendix. Since 9% of profit observations are negative, I opt to use OLS rather than PPML. Although there are a fair number of outliers, the distribution of the profit data follows a somewhat normal distribution anyway, especially after applying fixed effects. To account for some especially large observations, I winsorize the profits at both ends, at the 5% level. The appendix shows the results are robust to winsorizing instead to the 2.5% or 7.5% levels, and most results stay the same without winsorizing at all.

X_{ct} again controls for non-project water availability from streamflow, precipitation, and depth to the water table, and long-term adaptation through cumulative wells drilled, so that the βs can be interpreted as

[20] When a county has multiple contract types with the same project in one county, I take the average within the project

actually measuring the change in outcomes due to only changes in surface water forecasts. Other omitted variables include crop storage and government payments, which are correlated with revenues and surface water availability (Fisher et al., 2012); I control for these using crop inventory changes and aggregate government payouts from the BEA data.

5.3 Results

I plot the net private benefit of ex-ante and mid-season adaptation and the direct effect of water scarcity in figure 12. The estimates are separated by whether the early surface water shortfall forecast was less than or greater than the realization. The coefficients show how profits change directly, or through adaptation if we increased the shortfall forecast in each period by one percentage point.

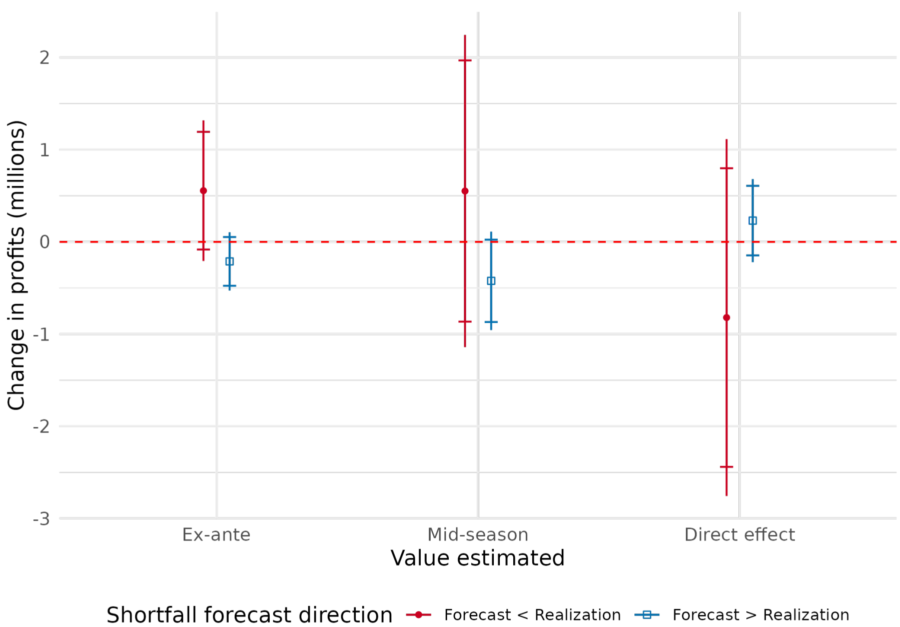
Overall, the results point to adaptation being beneficial in the directions that we would expect. If we increased the shortfall forecast in the years when the shortfall forecast was too low, the average counties would have seen a \$550,000 increase in profits, about 0.4% of average annual profits. These results are not statistically significant, but remain similar magnitudes across winsorization levels. The value of increasing the shortfall forecast by one percentage point when it is too high is statistically significant, and negative. Farmers become worse off when the forecast is less accurate. Recast in terms of accuracy, If the forecast had been one percentage point closer to the actual realization of shortfall, counties would have earned \$212,000 more in the ex-ante period and \$423,000 more in the mid-season period.

The direct effect of surface water shortfall follows a similar pattern. Counties that receive a marginally lower allocation after already having a lower-than-forecasted allocation face a decrease in profits of about \$821,000, about 0.56% of normal. On the other hand, there is suggestive evidence of a slight increase in profits if the surface water shortfall increases to be closer to the forecast.

The standard errors on the erroneously low forecasts are much larger than the standard errors for erroneously high forecasts. Likely, this has more to do with data limitations than a fact about the setting. Only about 10% of observations had erroneously high forecasts, showing that the state successfully meets its forecasting goals. Setting a different threshhold for over-forecasts is unclear. In some years, no increase in shortfall might be good and unsurprising (as when the shortfall forecast is already only 5%). In other years, no increase might bad and surprising, as if the year started out with a 50% shortfall forecast and conditions seemed normal. If I could correctly specify beliefs, we would likely see more precision in the case of too-low shortfall forecasts, and likely stronger negative estimates for too-high shortfall forecasts, since they are currently pooled with some estimates that might be positive. Therefore, we should take the plot as suggestive.

The results also show that ex-ante and mid-season adaptation are comparably valuable in my setting. My results cannot conclude anything about the relative value of these forms of adaptation for agriculture generally; rather, the amount that farmers in California benefit from a marginally more accurate shortfall forecast depends on how they have adapted to these forecasts overall. Information available at the early planting season is usually uncertain (correlation between early forecast and final realization: 0.59), while mid-season information is much more accurate (correlation between mid-season shortfall and final realization: 0.91). Therefore, in a case where earlier information was less uncertain, we might see farmers taking more consequential decisions earlier. Or, if earlier information was more certain, farmers might be able to make more beneficial mid-season decisions generally. Thus, the value of adaptation in counterfactual environments is unclear.

Figure 12: Private benefit of adaptation to surface water allocation shortfall



Note: These plots show the results of the estimations of equations (7), after transforming the coefficients to recover the value of ex-ante, mid-season and late-season adaptation. Specifically, the first group of coefficients show $\beta_1 - \beta_2$, and the second group shows $\beta_2 - \beta_3$, and the final group shows β_3. The coefficients for the first two groups can be interpreted as the change in profits for a 1 percentage point change in the surface water allocation forecast through adaptation, and the direct effect of the change in shortfall in the last group. The dependent variable, annual agricultural profits, has been winsorized at the 5 and 95% level. The two coefficients for each estimate shows the effect of raising the surface water forecast when it was lower than the realization (in red) and higher than the realization (in blue).

Overall, the results show that adaptation to surface water scarcity nearly fully determines farm outcomes in California. Instead of the direct effect surface water shortfall always being bad for farms, the negative effect seems isolated to the case when the realization is already higher than the forecast. Farmers' profits depend on the accuracy of the final shortfall rather than its level. Although the estimating framework cannot recover the value of ex-post adaptation, the direct effect shows at least that farms cannot fully reverse the effects of wrong information in the last period through late-season adaptation. Also, the fact that over-adapting to expected bad conditions is so costly in the short-run might have driven the transition to longer-term adaptation.

6 Discussion: the benefits and costs of agricultural adaptation to surface water scarcity

6.1 The external costs and benefits of adaptation in the short run

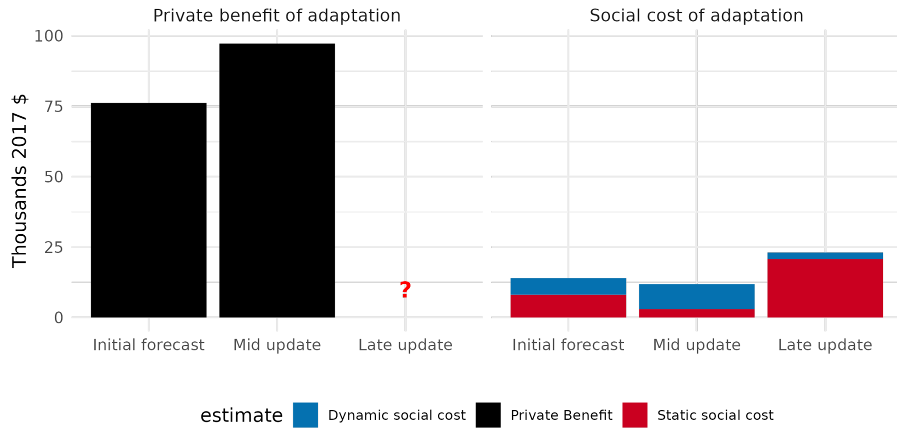
I take my previous estimates to show the average net benefit and external costs of short-run adaptation to a one-unit change in surface water shortfall. Section 3 already estimated the static change in water use from adaptation in a given year. Section 4 showed how much farmers drill wells in response to short-run shocks, which has a small persistence over time. In this subsection, I estimate the change in water use from well drilling specifically tied to short-run shortfall shocks. Then, the final piece required to quantify the costs of adaptation is the social cost of a marginal acre foot of water used.

The longer-run social costs from a one-time shortfall shock occur because of the wells drilled earlier than they otherwise would have been. Section 4 shows how farmers immediately extract large amounts of groundwater, and also transition to even higher intensity crop acreage. I estimate the persistent water use by multiplying the fraction of new wells that persist each year after a shock by the change in groundwater depth over agricultural land, and the aquifer storage constant. I discount the value of water used in later years by a factor of 0.95. The details of the derivation are in the appendix, but the result is shown as the dynamic social cost in figure 13.

It is not obvious how to quantify the value of the excess groundwater extracted. There are no comprehensive empirical estimates for the size of the groundwater extraction externality in California. A few papers describe the externality empirically. (Sears et al., 2017) shows the implied relative groundwater externalities through differences in groundwater pumping. Like my paper, (Bruno et al., 2024) identifies channels through which adaptation leads to externalities in California. Therefore, the best baseline estimate for the externality of groundwater extraction comes from per-unit taxes newly imposed by the Sustainable Groundwater Management Act (SGMA). The act imposes per-acre groundwater pumping fees. The first, lower, tier of fees applies to groundwater units extracted within a basin's 'safe yield,' the amount of extracted groundwater that will be recharged. A second, higher, tier of groundwater fees applies to 'transition water,' groundwater used above safe yield as basins transition to sustainability. The intention of the price is explicitly to curb groundwater use excess of what the state has deemed the socially optimal quantity, and thus can approximate the value of the externality. According to Greenspan et al. (2025), these transition water fees range from \$90 to \$210. I apply the lower bound homogeneously across all regions in my estimates of the social cost of groundwater extraction.

Figure 13 shows the summary of the benefits and costs of a district adapting in the short run to a

Figure 13: Marginal net private value and social costs of short-run adaptation for one district



marginal increase in surface water scarcity. The benefits were estimated for counties in section 5. I divide the estimates by the average number of districts in a county, which is likely an overestimate of the benefit since not all agricultural land is in a water district. These are shown by the black bars in the figure. The static social costs come from multiplying the estimated water use change from figure 6 by the externality, shown by the lower red section of the social cost bars. The dynamic social cost is stacked on top, in blue.

Clearly the benefits outweigh the costs of adaptation for the average district's adaptation choices. However, the social costs are not negligible. In the ex-ante period, the social cost of the average adaptation actions taken make up 18% of the private net benefits, and in the mid-season period, the social cost makes up 12% of the benefits. Although we cannot know for sure the value of ex-post adaptation, if it happened to be as valuable as mid-season adaptation, the social cost would make up almost 25% of the net benefit. The estimates of the value of adaptation depend crucially on the value of the externality. Some groundwater districts have assigned the per-unit groundwater tax more than twice the level that I set, which would result in social costs more than twice as high.

The results reflect the snapshot of benefits and costs for the average district at the average surface water shortfall shock. Intuitively, however, districts continue to adapt with groundwater until the marginal net private benefit of adaptation is zero, or the benefits of adaptation equal the costs. The presence of social costs shifts up the marginal social cost of adaptation. Since the marginal social costs are substantial at the average level of adaptation, as long as groundwater externalities are increasing in extraction, we should expect the social cost to be substantially higher as adaptation increases.

6.2 The benefits and costs of long-run adaptation through well drilling

Social costs make up a substantial portion of adaptation to short-run surface water scarcity. However, my paper shows that over time, farmers in California have transitioned to long-term adaptation through well drilling, which is even more water intensive. In this subsection, I explain what my paper shows about the value of long-run adaptation, and how the definition of adaptation in the literature makes it difficult to define adaptation in my case.

New wells drilled have a net private benefit of around zero. If the net private benefit was much larger than zero, then the farmer would have drilled earlier. However, in section 4 I showed that once a farmer drills a well, she uses around 1800 acre feet of water in the first year, and that quantity likely increases slightly over time. If we add up 1800 acre feet over time, apply a discount rate of 0.95, and an average externality of $35/acre foot, the social cost of drilling a well is $1.26 million dollars. The average well costs between $50,000 and $500,000, meaning that the gross benefit of an average well is much lower than the external costs from drilling. Such high external costs relative to the benefit of wells does not mean that no wells should ever be drilled. Rather, the marginal driller should have a well value of $1.26 million dollars higher than the marginal driller currently does.

Table 3: Value of a new well

Marginal gross private benefit	**Marginal net private benefit**	**External costs**
$0.5 million	$0	$1.26 million

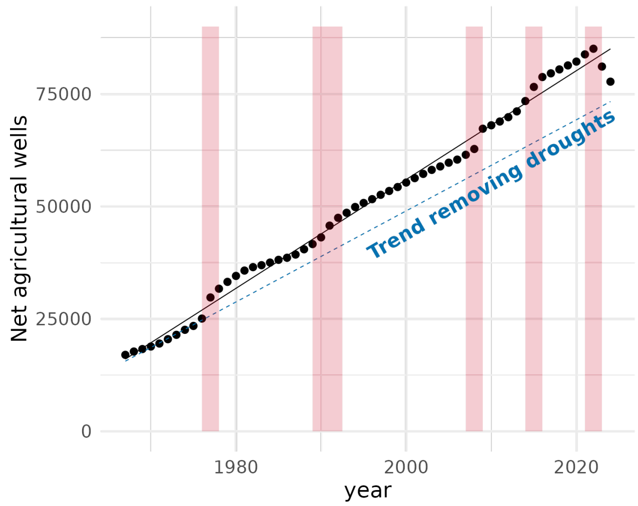
Although the benefits and external costs of the marginal well are intuitive at least in theory, labelling these values the 'benefits' and 'external costs' of adaptation could be misleading. Farmers in California continually drilled wells over my period of study, reflecting that the value of wells across the state increased consistently. In figure 14 I plot the cumulative net number of agricultural wells (new wells minus removed wells) in California over time, with major droughts indicated with red bars (California Department of Water Resources, 2025a)[21]. The black line behind the number of annual wells shows the linear trend. Over the course of more than 50 years, the cumulative number of wells rose virtually linearly, with oscillations occurring around the major droughts. The plot suggests that the value of wells increased for reasons other than due to decreases in surface water availability. A major reason is likely the dramatic increase in the price of perennials over the period, as shown in appendix figure B.4.

Various papers in the literature define adaptation to be the change in inputs as the climate changes (Carleton et al. (2024), Shrader (2023)). So, to find the value of wells as long-term adaptation, we would need to remove the effect of drilling due to increasing perennial prices, holding the surface water availability fixed. Whether to consider the cross-derivative between perennial prices and surface water scarcity as adaptation is so far unclear. To avoid this confusion, in my paper, I only focused on well drilling due to well-defined shocks to surface water availability.

Although separating the well value from perennial prices and surface water scarcity is outside of the scope of this (already very long) paper, I use figure 14 to give a suggestion about the magnitude of these different components. The blue dashed line shows the cumulative wells trend after setting new wells in drought years equal to the new wells in the most recent non-drought year. The slope of the cumulative wells apart from the droughts is almost parallel to the blue dashed line, while the droughts acted like level shifts in the cumulative well trend. If droughts truly shifting up everyone's well values at the same time, we can approximately conclude that 15% of new wells, the difference between the lines, came purely from droughts.

[21] Permanently inactive wells are required by law to be removed (Health and Safety Code - HSC, 1996).

Figure 14: Net cumulative agricultural wells in California



Note: The dots in this figure shows the net number of agricultural wells in California: the sum of those drilled subtracted from those removed. It is mandatory to remove permanently inactive wells. The red line behind the dots shows the linear trend of wells, and the red bars behind the figure show the major droughts as defined by the California Department of Water Resources (California Department of Water Resources, 2025a). The blue dashed line shows the cumulative wells trend after setting new wells in drought years equal to the new wells in the most recent non-drought year.

6.3 The joint market failures: climate change and unmanaged natural resources

Farmers overinvest in capital to extract from the groundwater stock because the price of groundwater does not reflect either the scarcity of groundwater, or the physical externalities associated with excess extraction. My paper adds that climate change decreases the quantity of the substitute source of water, which further drove up the private value of groundwater extraction, increasing the social costs of adaptation. Therefore, if unmanaged groundwater is used for adaptation, and if externalities increase in extraction, then climate change increases the social costs of unregulated natural resources. An accurate accounting of the costs of climate change would have to take into consideration the intensification of the market failure from common pool resources. And there are many such cases: agricultural yield reductions could lead to more cleared land in important forests with weak property rights, higher ocean temperatures strains fish populations complicated unmanaged fisheries, and wildfire risk increases the social costs of failing to invest in the public good of forest management. Pricing carbon addresses several market failures at once. However, since carbon is not adequately priced in California, regulators need to impose a second-best groundwater price, which additionally captures how climate change increases the private value of groundwater.

6.4 Information as a potential policy solution in absence of management

In many cases, neither managing the common pool resource, nor pricing carbon is an option politically available to the regulator. California was in this category until 2024, when it began to price groundwater. Prior to 2024, an important policy lever for shifting farmers' behavior was through the presentation of surface water information. Unlike for weather forecasts, the Department of Water Resources and US Bureau of Reclamation issued forecasts for quantities of surface water that the agencies themselves controlled. Thus, the agencies had the best information about their future choices, and issued the most relevant information regarding the surface water available.

As explained in section 1, the agencies used their control over forecasts attempting to meet their objectives of helping farmers' decisions, subject to their own preferences about withholding unreliable forecasts. Further, in 1995 the State Water Resources Control Board asked these agencies to publish conservative surface water allocation forecasts in order to protect environmental flows for endangered species (State Water Resources Control Board, 1995), ostensibly to induce farmers to plan more conservatively even though the average allocation remained the same. The decision was salient and unpopular among water districts, evidenced by the litigation against the US Bureau of Reclamation specifically regarding the conservative statistic (Wes, 1994).

Thus, the forecast characteristics varied over time in a way that most forecasts do not. Therefore, I uniquely have some variation over time in how different information environments led to different adaptation benefits and costs for farmers. Particularly, there were three years where the US Bureau of Reclamation decided to wait longer than the preceding period to publish a forecast. In 1988, the USBR issued a vague initial surface water allocation forecast (no percentages announced) on February 15th, and announced percent allocations on February 23rd. Until that time, the first forecast had always been published by February 1st, and after 1988, it was published by February 1st again. In 2005, the US Bureau of Reclamation issued forecasts on February 23rd again, though this marked a permanent shift toward later forecasts. In 2016, the Bureau of Reclamation issued their first forecast on April 1st, deviating from their pattern of issuing a first forecast in the third week of February[22].

These temporary and permanent changes in forecasting policy result in natural experiment where the forecast for a portion of surface water in some counties is delayed unexpectedly. I use a standard 2-period differences in differences design to study how profits and well drilling for counties changed between the year before the forecasting time shock and after, based on a treatment level proportional to the quantity of a county's agricultural water coming from the Central Valley Project. Using three separate differences in differences is most straightforward here because each shock is preceded by a period of at least ten years with the same forecasting timing. Equation (8) formalizes my estimation strategy.

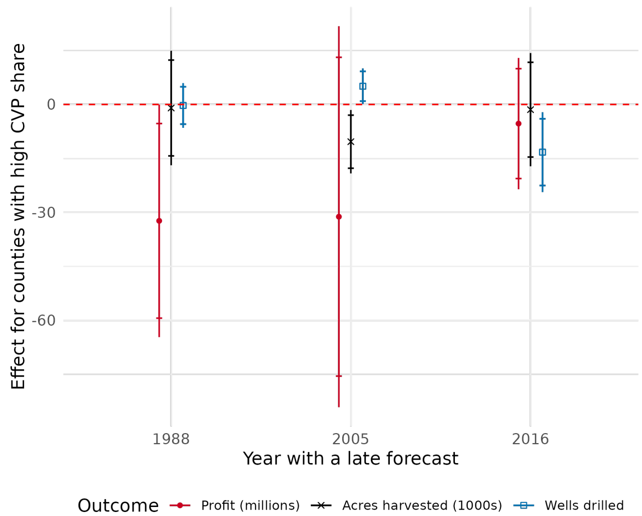
$$Y_{ct} = \alpha Q_c \times D_t + X_{ct} + \gamma_c + \gamma_t + \varepsilon_{ct} \tag{8}$$

Q_c is an indicator variable for having a high proportion of Central Valley Project water. I use 10% of water coming from CVP as the threshold in the main specification, which is the average amount of CVP water that counties get; about 1/4 of counties get at least 10% CVP water. The results are robust to multiple thresholds, which I include the appendix. D_t is an indicator for the year in which the Central Valley Project surface water allocation forecast was delayed. α_1 is the coefficient of interest, and it captures how much the profit or well drilling Y_{ct} is affected by a marginal increase in the amount of the county's water subject to a delay. In the three differences in differences regressions, I use the years $t \in \{1985, 1986\}, t \in \{2004, 2005\}, t \in \{2015, 2016\}$.

I plot the main differences-in-differences effect, the α coefficient from equation (8), for each of three differences-in-differences regressions which cover a year when the US Bureau of Reclamation surprisingly delayed their first surface water allocation forecast. The coefficients show the percent change in profit if the

[22]In a conversation I had with the Farm Bureau, the director I spoke with called the delay in 2016 an "absolute disaster".

Figure 15: How delays in surface water allocation forecasts affect profits



Note: These plots show the main differences-in-differences coefficient, α from equation (8), for each of three differences-in-differences regressions. Each regression covers a year when the US Bureau of Reclamation surprisingly delayed their first surface water allocation forecast. The coefficients show the percent change in profit if the county's agricultural water portfolio had one percentage point more water from the Central Valley Project on average. The average county gets 10% of its agricultural water from CVP on average, though some counties have 0% and some have up to 75%.

county's agricultural water portfolio had one percentage point more water from the Central Valley Project on average.

Overall, the delay of a Central Valley Project surface water allocation forecast decreased profit for counties with a high amount of CVP water in the year that the forecast was delayed. The coefficient estimate of the effect of the delay in forecast stayed negative for in all three years, but the magnitude declined and became less significant. The magnitudes are economically relevant, however. In 1988, for example, the delay cost the average county more than \$30 million, about 10% of the average agricultural profits.

The results for effects on adaptation are less clear. There seemed to be very little effect on acres harvested or well drilling in most years. Well drilling might have increased in response to the delay in 2005, and decreased in response to the delay in 2016 (by 33% of the average county!). These years had very different surface water availabilities, which could explain why the delays might have given different signals. 2005 was a good water year, and 2016 was the last year of a major drought.

The estimates show that even though farmers have some information about surface water allocations, shifting the first official surface water allocation forward in time is privately costly for farmers, regardless of the type of water year, and regardless of the adaptation actions they take under uncertainty. The lack of a clear pattern in adaptation shows that adjusting information provision likely will not automatically result in social gains or costs.

7 Conclusion

In this paper, I find that farmers adapt to surface water scarcity using both water conserving and groundwater intensifying adaptation actions. Overall, farmers increase their groundwater extracted many times more than they decrease surface water use. Further, through well drilling, the increase in groundwater extraction is long-lasting. Although the private benefit of adaptation outweighs the social costs, the social costs are large in magnitude. This suggests that the overall benefits of adaptation in agriculture may be lower than initially thought, and that we might need to think carefully about how to incentivize socially beneficial private adaptation.

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A Extended Conceptual framework

Here I describe my conceptual framework for fixing ideas. This framework builds upon Shrader (2023) which shows how to identify the benefits of adaptation to forecasts from observable, ex post data. I expand upon this by accounting for sequential decisionmaking that occurs before and after observing the forecast and realization of weather.

A.1 Baseline framework: only ex-ante adaptation

I first begin with re-casting the original Shrader framework for my setting. Expected profit-maximizing farmers take ex-ante adaptation actions a_{early} given expectations about surface water shortfall $\hat{s}$. Thus, farmers choose a^*_{early} by:

$$\max_{a_{early}} \quad pf(a_{early})\mathbb{E}_{t-1}[g(\hat{s})] - c_{early}a_{early}$$

Where $\mathbb{E}_{t-1}[g(\hat{s})]$ is the function representing how shortfall is expected to affect revenues. Let ex-post revenues be given by:

$$y = pf(a^*_{early})\Bigg(\mathbb{E}_{t-1}[g(\hat{s})] + h(\hat{s}, \varepsilon)\Bigg) \tag{9}$$

Let $\Bigg(\mathbb{E}_{t-1}[g(\hat{s})] + h(\hat{s}, \varepsilon)\Bigg)$ be the realization of how shortfall actually affected revenues, which is given by $g(s)$ in Shrader (2023). $h(\cdot)$ is a function representing the way realized damages differ from the expectation, given by $\int_{\hat{s}}^{\hat{s}+\varepsilon} g(s)ds$. I explicitly define the realized shortfall effect as a modification from the expected shortfall effect because it more easily allows me to build in sequential decision making.

In Shrader (2023) the object of interest is direct damages from shortfall, which is defined as the derivative of revenues with respect to realized shortfall, conditional on optimal adaptation. Taking the derivative of (9) with respect to $\Bigg(\mathbb{E}_{t-1}[g(\hat{s})] + h(\hat{s}, \varepsilon)\Bigg)$ equals $pf(a^*_{early})$. The problem with estimating direct damages empirically by simply regressing realized revenues on realized shortfall is that realized shortfall is correlated with expected shortfall, which is correlated with expected revenues through ex-ante adaptation. The way we can address the bias is by including the expected shortfall in the regression.

I keep the assumption from the original framework that the way that the shortfall updates is unpredictable, so that $\frac{d\mathbb{E}[h(\hat{s},\varepsilon)]}{d\mathbb{E}_{t-1}[g(\hat{s})]} = 0$. The derivative of realized revenues with respect to expected shortfall is

$$\frac{\partial y}{\partial \mathbb{E}_{t-1}[g(\hat{s})]} = p\frac{df(a^*_{early})}{da^*_{early}}\frac{da^*_{early}}{d\mathbb{E}_{t-1}[g(\hat{s})]}\bigg(\mathbb{E}_{t-1}[g(\hat{s})] + h(\hat{s},\varepsilon)\bigg) + pf(a^*_{early})$$

The first term gives the value of adaptation. It shows how realized revenues would have been different if the shortfall forecast was marginally higher, given the actual realization of shortfall. The second term is the same direct effect of the shortfall as given by the derivative of realized revenues on realized shortfall. Thus, including the forecast of the shortfall in the regression of realized revenues on the realized shortfall identifies both the direct effect of the shortfall and the benefit of adaptation.

A.2 Extended framework: multiple periods of adaptation

In agriculture, farmers make decisions throughout the planting and growing season. Early in the planting season, farmers have the least constraints, but also the least information. For example, in a year with a low shortfall forecasted (a high amount of surface water), the farmer might choose to plant water intensive annuals. If mid-way through the planting season she learns that shortfall is higher than she initially thought, she might stop watering some fields, or she might plan to extract more groundwater.

To incorporate intra-annual adaptation into the previous framework, I consider three decision periods in a year. In the early decision period, $\hat{s}$ is known, and a_{early} may be chosen for cost c_{early}. In decision period 2, the surface water shortfall is updated to $\hat{s}_{mid}$, and the new information in the update is $\varepsilon_{mid} \sim N(0, \sigma_{mid})$, where $\hat{s}_{mid} = \hat{s} + \varepsilon_{mid}$, and farmers purchase inputs a_{mid} for cost c_{mid}. In the late period, the realized surface water shortfall s is realized, where $s = \hat{s}_{mid} + \varepsilon_{late} = \hat{s} + \varepsilon_{mid} + \varepsilon_{late}$, and farmers can make any final input choices they would like, a_{late} for cost c_{late}. Later adaptation is less expensive than earlier adaptation because it is less constrained, $c_{early} \leq c_{mid} \leq c_{late}$.

Consider how a_{early} changes from the previous framework.

$$\max_{a_{early}} \quad pf(a_{early}, \mathbb{E}[a_{mid}], \mathbb{E}[a_{late}]))\mathbb{E}_{t-1}[g(\hat{s})] - c_{early}a_{early} - c_{mid}\mathbb{E}[a_{mid}] - c_{late}\mathbb{E}[a_{late}]$$

I put later adaptation decisions in expectation operators to signify that farmers choose inputs with some expectation about their future choices, but no certainty.

The early adaptation decision is implicitly defined by:

$$\begin{aligned} &p\bigg[\frac{df}{da_{early}} + \frac{df}{d\mathbb{E}[a_{mid}]}\frac{d\mathbb{E}[a_{mid}]}{da_{early}} + \frac{df}{d\mathbb{E}[a_{late}]}\frac{d\mathbb{E}[a_{late}]}{d\mathbb{E}[a_{mid}]}\frac{d\mathbb{E}[a_{mid}]}{da_{early}} + \frac{df}{d\mathbb{E}[a_{late}]}\frac{d\mathbb{E}[a_{mid}]}{da_{early}}\bigg]\mathbb{E}_{t-1}[g(\hat{s})] \\ &= c_{early} + c_{mid}\frac{d\mathbb{E}[a_{mid}]}{da_{early}} + c_{late}\bigg[\frac{d\mathbb{E}[a_{late}]}{da_{early}} + \frac{d\mathbb{E}[a_{late}]}{d\mathbb{E}[a_{mid}]}\frac{d\mathbb{E}[a_{mid}]}{da_{early}}\bigg] \end{aligned} \tag{10}$$

The early adaptation decision is a function of the expected later choices, and the prices of those later choices. How much the later choices affect the early adaptation choice depends to the extent that the adaptation periods are substitutes and complements. If the adaptation options are substitutes (for example, planting low water annuals in the early period means that a farmer cannot plant high water annuals in the mid period) decreases the marginal revenue from adapting in the early period.

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Now, consider realized profit in the case of sequential adaptation:

$$\begin{aligned}\pi = \max_{a_{late}} \quad & pf(a^*_{early}, a^*_{mid}, a_{late})\Big(\mathbb{E}_{t-1}[g(\hat{s})] + h_{mid}(\hat{s}, \varepsilon_{mid}) + h_{late}(\hat{s} + \varepsilon_{mid}, \varepsilon_{late})\Big) \\ & - c_{early}a^*_{early} - c_{mid}a^*_{mid} - c_{late}a_{late}\end{aligned} \tag{11}$$

In the period where profits and revenues are realized, the previous stages of adaptation decisions are set. The farmer will maximize her profits by choosing ex-post adaptation a^*_{late}, which might differ from her expected choice of a_{late} because of the difference between the expected and realized shortfall.

Like in the baseline model, we can take the derivative of realized revenues or profits to understand what a regression of outcomes on the components of information can tell us. Let y again denote realized profits, and let the shorthand symbols $\hat{g}$ correspond to $\mathbb{E}_{t-1}[g(\hat{s})]$, h_{mid} correspond to $h_{mid}(\hat{s}, \varepsilon_{mid})$ and h_{late} correspond to $h_{late}(\hat{s} + \varepsilon_{mid}, \varepsilon_{late})$. In the framework in Shrader (2023), we can found the value of ex-ante adaptation conditional on the realization of surface water scarcity. When adaptation can be driven by multiple components of information, the derivative becomes complicated. It is simpler to take the derivative of the revenues with respect to each component of information, and then to rearrange. Equation (12) shows the result of taking these derivatives.

$$
\begin{aligned}
\frac{dy}{d\hat{g}} : p\Bigg[& \underbrace{\frac{df}{da^*_{early}}\frac{da^*_{early}}{d\hat{g}}}_{\text{Ex-ante adaptation}} + \underbrace{\frac{df}{da^*_{mid}}\frac{da^*_{mid}}{da^*_{early}}\frac{da^*_{early}}{d\hat{g}} + \frac{df}{da_{late}}\frac{da_{late}}{da^*_{mid}}\frac{da^*_{mid}}{da^*_{early}}\frac{da^*_{early}}{d\hat{g}} + \frac{df}{da_{late}}\frac{da_{late}}{da^*_{early}}\frac{da^*_{early}}{d\hat{g}}}_{\text{Effect of ex-ante adaptation on later decisions}} + \\
& \underbrace{\frac{df}{da^*_{mid}}\frac{da^*_{mid}}{d\hat{g}}}_{\text{Mid-season adjustments}} + \underbrace{\frac{df}{da_{late}}\frac{da_{late}}{da^*_{mid}}\frac{da^*_{mid}}{d\hat{g}}}_{\text{Mid-season adjustments on later decisions}} + \\
& \underbrace{\frac{df}{da_{late}}\frac{da_{late}}{d\hat{g}}}_{\text{Ex-post adaptation}} \Bigg](\hat{g} + h_{mid} + h_{late}) + \underbrace{pf(a^*_{early}, a^*_{mid}, a_{late})}_{\text{Direct effect of shortfall}} \\
\frac{dy}{dh_{mid}} : \Bigg[& \underbrace{\frac{df}{da^*_{mid}}\frac{da^*_{mid}}{dh_{mid}}}_{\text{Mid-season adjustments}} + \underbrace{\frac{df}{da_{late}}\frac{da_{late}}{da^*_{mid}}\frac{da^*_{mid}}{dh_{mid}}}_{\text{Mid-season adjustments on later decisions}} + \\
& \underbrace{\frac{df}{da_{late}}\frac{da_{late}}{dh_{mid}}}_{\text{Ex-post adaptation}} \Bigg](\hat{g} + h_{mid} + h_{late}) + \underbrace{pf(a^*_{early}, a^*_{mid}, a_{late})}_{\text{Direct effect of shortfall}} \\
\frac{dy}{dh_{late}} : \Bigg[& \underbrace{\frac{df}{da_{late}}\frac{da_{late}}{dh_{late}}}_{\text{Ex-post adaptation}} \Bigg](\hat{g} + h_{mid} + h_{late}) + \underbrace{pf(a^*_{early}, a^*_{mid}, a_{late})}_{\text{Direct effect of shortfall}}
\end{aligned}
\tag{12}
$$

The first term shows how realized revenues would have been different if the initial forecast was different, $\frac{dy}{d\hat{g}}$, given the later components of information h_{mid} and h_{late}. There are several channels present. $\hat{g}$ represents the effect of the early shortfall forecast on realized revenues. The early shortfall forecast affects the ex-ante adaptation in the early period, the first term. Since the early shortfall forecast affects ex-ante adaptation, it also affects later adaptation through the choice of ex-ante adaptation, which are summarized in the following three terms. The early shortfall forecast also determines the level of the shortfall in the mid-season period, and thus directly affects mid-season adaptation. The mid-season adaptation choice affects late-season adaptation. Finally, the early shortfall forecast determines the level of shortfall in the late-season period, thus directly affecting ex-post adaptation.

To make things concrete, consider that the adaptation choice in the early period is the share of low-water annual acreage, the adaptation choice in the mid period is fallowing land and the adaptation choice in the final period is groundwater extraction. A marginally higher shortfall early in the year likely increases a farmer's proportion of low-water annuals, and through that initial choice, will decrease the farmer's eventual fallowing decision and groundwater extraction decision. However, a lower shortfall also directly increases fallowing in the mid-season period, which in turn lowers the groundwater extraction needed in the late-season period (second line). And a higher shortfall directly increases the groundwater that a farmer will extract in the final period, all else equal.

Across the three derivatives, the same terms appear. The direct and indirect mid-season adaptation effects for example appear in both $\frac{\partial y}{\partial \hat{g}}$ and $\frac{\partial y}{\partial h_{mid}}$. Thus, we can identify the value of adaptation by rearranging coefficients in a regression of revenues on the components of information:

$$y = \beta_1 \hat{g} + \beta_2 h_{mid} + \beta_3 h_{late} + \nu \tag{13}$$

β_1 represents $\frac{\partial y}{\partial \hat{g}}$. Let the benefit of early adaptation be denoted by B_{early}, the benefit of mid-season adaptation be given by B_{mid} the benefit of late-season adaptation be given by B_{late}, and direct effect of shortfall be given by D. Then, $\beta_1 = B_{early} + B_{mid} + B_{late} + D$, $\beta_2 = B_{mid} + B_{late} + D$ and $\beta_3 = B_{late} + D$. The benefit of ex-ante adaptation is therefore identified by $\beta_1 - \beta_2$ and the benefit of mid-season adjustments is identified by $\beta_2 - \beta_3$.

It becomes apparent that in a case with ex-post adaptation, the regression of revenues on forecasts or forecast components cannot separately identify the value of ex-post adaptation and the direct effect of shortfall. In contrast, we can identify the direct effect of shortfall when profits are the dependent variable because the derivative of realized profits with respect to ex-post adaptation, $\frac{\partial \pi}{\partial a_{late}}$, equals zero by standard profit maximization. Otherwise, the other benefits of adaptation theoretically equal the same value whether I use revenues or profits.

A.3 Adaptation choices in the model

In the conceptual framework, farmers make adaptation choices to maximize profits, and $\frac{da_{late}}{dh_{late}}$, $\frac{da_{mid}}{dh_{mid}}$, etc, are critical components in driving how profits and revenues change with respect to surface water forecasts and updates. I only observe adaptation choices after $\hat{g}$, h_{mid} and h_{late} are all revealed. Let a^j refer to a specific adaptation choice, like crop fallowing. In this section, I explain what we can learn from a regression of the sum of adaptation choices after all of the surface water shortfall information has been revealed on the components of the surface water shortfall information

The first order condition on early adaptation from equation 10 showed that early adaptation depends on costs of adaptation, the substitution of adaptation decisions across periods, and the initial surface water shortfall forecast. Expectations of the later shortfall forecasts enter the implicit function through expectations on the future adaptation actions.

Consider a specific adaptation action, like crop fallowing $\tilde{a}$. The crop fallowing I observe at the end of the season is the sum of all of the crop fallowing decisions in the early, mid and late period:

$$\tilde{a} = \tilde{a}^*_{early} + \tilde{a}^*_{mid} + \tilde{a}^*_{late}$$

Taking the derivative of $\tilde{a}$ with respect to $\hat{g}$, h_{mid} or h_{late} can be interpreted as studying how a farmer's crop fallowing decisions over the season would differ if we marginally changed one component of information, holding all else equal. Like in the previous section, changing $\hat{g}$ for example would affect $\tilde{a}_{early}$, $\tilde{a}_{mid}$, and $\tilde{a}_{late}$ directly, and would also affect each adaptation choice through the substitution across periods. From the farmer's perspective in the early season, it is not the same to fallow crops early or late; fallowing early means not planting at all, while fallowing late could mean already having sunk numerous inputs into a field.

When calculating the value of adaptation in a period, the substitution across adaptation types is only important as far as it changes the marginal benefit of adaptation in a period. When parsing apart adaptation actions taken at a certain time from the ex-post totals, we cannot ignore the substitution across periods. In the regression of

$$\tilde{a} = \beta_1 \hat{g} + \beta_2 h_{mid} + \beta_3 h_{late} + \nu \quad (14)$$

And we do the same rearranging method as before, $\beta_2 - \beta_3 = (1 + \frac{d\tilde{a}^*_{late}}{d\tilde{a}^*_{mid}})\frac{d\tilde{a}^*_{mid}}{dh_{mid}}$. We do not recover the mid-season adjustments taken unless late-season adaptation is not affected by mid-season adaptation at all. In the case of fallowing, likely the opposite is true: fallowing fields in the mid-season is nearly a perfect substitute ($\frac{d\tilde{a}^*_{late}}{d\tilde{a}^*_{mid}} \sim -1$) for fallowing fields in the late-season because a field cannot be fallowed more than once. A zero coefficient could mean perfect substitution and it could mean no adaptation in the mid-season.

Instead, simply studying the effects of adaptation actions on the components of the shortfall can tell us about the sensitivity of the sum of each adaptation action to surface water shortfall revealed in different periods. The same effect throughout the year would reflect that constraints and preferences over adaptation options remain similar, while differing effects show changes in constraints and preferences. Understanding these differences will allow us to get a sense of how farm adaptation changes over a planting season even though we cannot perfectly identify the quantity of actions taken in each period. I begin by characterizing these actions over time.

B Data and Context

Table B.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).

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[23]. 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

C Supplementary Results

C.1 LASSO results

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

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

(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:

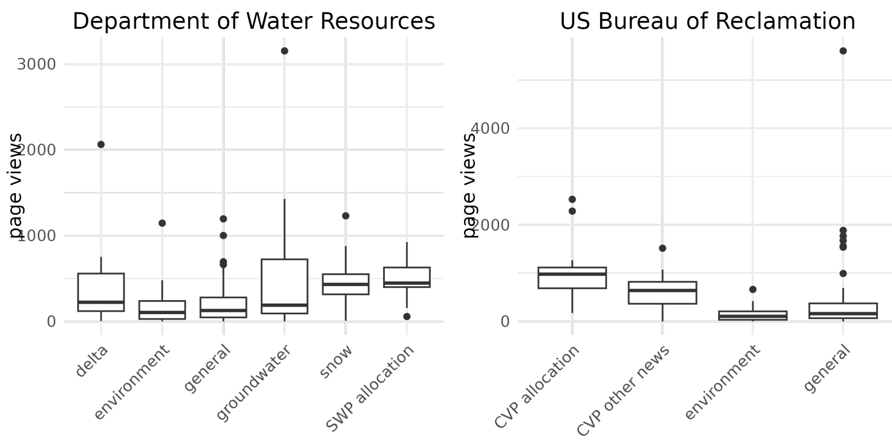
— BUREAU OF — RECLAMATION

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

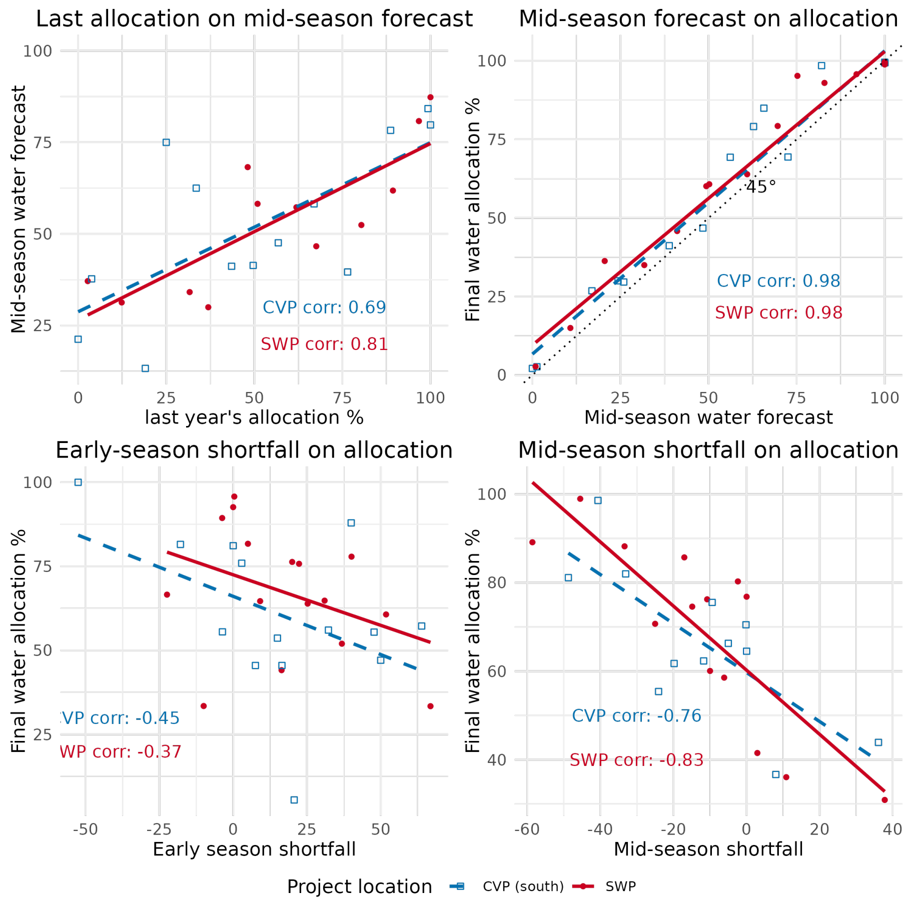


Note: Distribution of page views by topic on Maven's Notebook, a California water news aggregator. News collected on May 1, 2025, spanning 5 years.

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

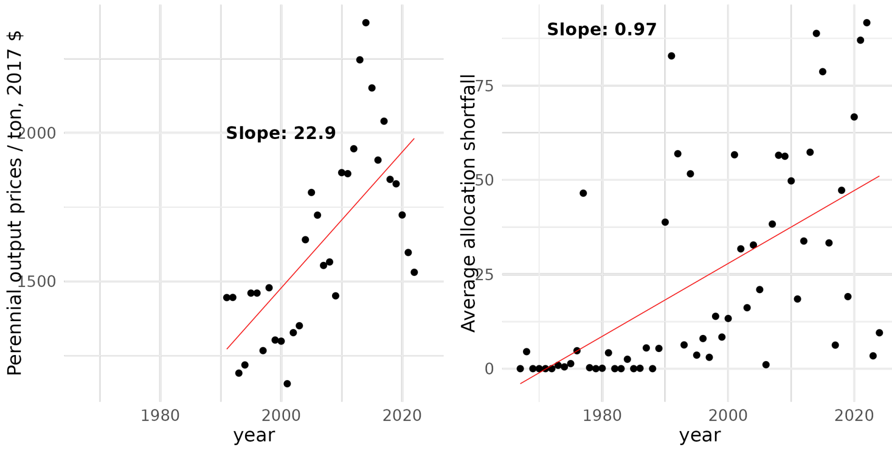
Region		**Early planting**	**Late planting**
Central Valley	Low Water	Wheat (170mm) Carrots (150mm)	Corn (700mm) Tomatoes (650mm)
	High Water	Sugarbeets (220mm) Onions (500mm)	Rice (1100mm) Cotton (1000mm)
Inland Desert	Low Water	Broccoli (140mm) Wheat (270mm)	Corn (780mm) Squash (470mm)
	High Water	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 B.3: Relation of project forecasts to each other: across districts and across months in a year



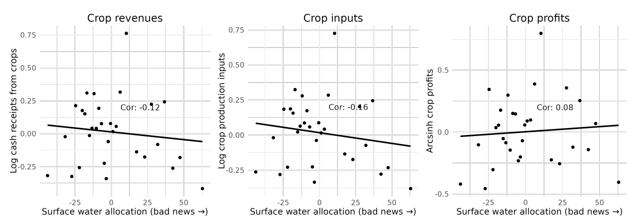
Note: The top left panel shows how the binned average of last year's surface water allocation percent corresponds to the average late-planting season surface water forecast (before April 1st) for the State Water Project (in red dots and solid line) and the Central Valley Project's southern districts, (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.

Figure B.4: Caption



Note:

Figure B.5: Farm outcomes on final shortfall, only controlling for time trends and mean shortfall



	Revenues	Costs
Initial SW forecast shortfall	-0.04	-0.03
	(0.17)	(0.15)
Mid-planting SW update	-0.08	-0.01
	(0.10)	(0.08)
Late-planting SW update	-0.09^{**}	-0.07^{**}
	(0.04)	(0.03)
Omitted vars. controls	yes	yes
County FEs	yes	yes
Year FEs	yes	yes
SE cluster	Conley-Spatial	Conley-Spatial
Num. obs.	2208	2208
Pseudo R^2	0.97	0.96

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

Table C.5: 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.

Table C.5: Multinomial logit: response of crop choice to forecast shortfall

	double	early	idle	late	non_ag
(Intercept)	21.066***	10.214***	9.343***	14.841***	6.009***
	(0.72)	(0.742)	(0.537)	(0.613)	(0.503)
100% - last year's SW allocation	1.224***	0.84***	0.446***	-0.008	0.035
	(0.071)	(0.076)	(0.055)	(0.056)	(0.047)
Mid-planting SW update	0.536***	0.294***	0.167***	0.008	0.064
	(0.071)	(0.077)	(0.057)	(0.056)	(0.048)
Late-planting SW update	0.612***	-0.089	-0.04	-0.292***	0.165***
	(0.081)	(0.086)	(0.064)	(0.063)	(0.059)
Log lag cumulative wells	-0.259***	-0.477***	-0.619***	-0.62***	-0.242***
	(0.017)	(0.018)	(0.014)	(0.014)	(0.013)
Rainfall	-0.001***	-0.002***	0	0	0.001***
	(0)	(0)	(0)	(0)	(0)
Temperature	-0.137***	-0.144***	0.067***	-0.126***	0.014
	(0.015)	(0.016)	(0.011)	(0.012)	(0.009)
Central Valley = 1	4.314***	3.175***	1.105***	5.056***	-2.537***
	(0.243)	(0.289)	(0.183)	(0.266)	(0.169)
Inland Desert = 1	4.57***	1.813***	4.207***	2.669***	1.694***
	(0.41)	(0.554)	(0.224)	(0.583)	(0.209)
Sierra Nevada = 1	8.742***	2.247***	3.014***	3.245***	7.044***
	(0.284)	(0.004)	(0.028)	(0.003)	(0.312)
South Coast = 1	3.44***	2.979***	1.016***	3.871***	-0.192
	(0.258)	(0.298)	(0.19)	(0.272)	(0.174)
GW depth in 2000	-0.533***	-0.446***	-0.479***	-0.513***	0.275***
	(0.02)	(0.021)	(0.016)	(0.016)	(0.019)
log(-1 * lag_depth)	0.087***	0.078***	0.183***	0.226***	-0.189***
	(0.024)	(0.026)	(0.02)	(0.02)	(0.022)
Log area (km^2)	0.166***	0.455***	0.507***	0.517***	0.462***
	(0.018)	(0.019)	(0.014)	(0.014)	(0.014)
Log groundwater use	-0.016***	-0.007	-0.022***	-0.005	-0.136***
	(0.005)	(0.005)	(0.003)	(0.004)	(0.003)
log(price_field)	-3.797***	-2.025***	-1.724***	-2.904***	-0.767***
	(0.15)	(0.157)	(0.115)	(0.128)	(0.103)
Log non-project ag water	0.006	0.024***	0.026***	0.026***	-0.058***
	(0.004)	(0.005)	(0.003)	(0.003)	(0.003)

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.

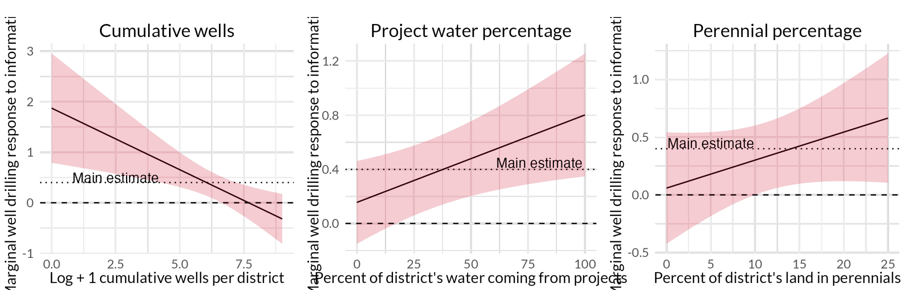
Table C.5: Robustness checks: method of imputation

	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 C.5, 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.

Figure C.6: 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.

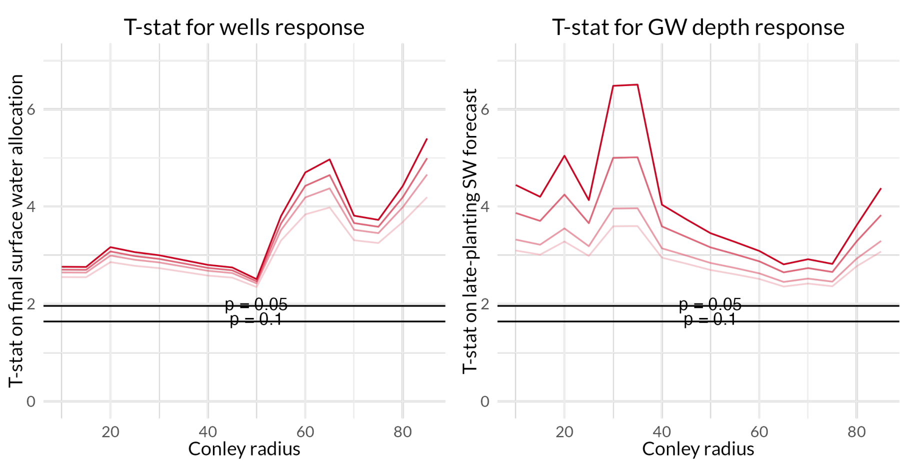
Table C.5: Robustness checks: dependent variable specification and fixed effects

	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 C.5 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.

Figure C.7: 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 C.5, 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.