The benefits and costs of agricultural adaptation to surface water scarcity

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Abstract

I ask how farmers respond to surface water scarcity in California, a setting where they might adapt through socially costly actions like unregulated groundwater extraction, or water conserving actions like land fallowing. Using variation in region-specific sub-annual surface water forecasts, I empirically estimate that farmers increase groundwater use more than they conserve water, especially at the end of the planting season. Meanwhile, farmers make well investments at least partially in response to average declines in surface water availability, fundamentally changing their adaptation choice set. After drilling, I find that farmers plant more water-intensive crops and conserve less water. My paper contributes one of the first studies of agricultural adaptation on a broad set of choices, demonstrating adaptation potential in drying agricultural regions globally. These choices reveal important information about the benefits and costs of adaptation. Short-run ex-ante adaptation has higher social gains than implied by the standard estimating techniques through the external benefits from avoiding groundwater extraction. On the other hand, ex-post and long-run adaptation impose substantial external costs and result in a long-term decline in society's ability to adapt.

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Most major agricultural areas globally have experienced warming and drying on average over the last half-century (Lobell and Di Tommaso, 2025), as well as more frequent droughts (Hoover and Smith, 2025), meaning that short and long-term water stress will become pervasive in many regions. The future of global food production depends on how much farmers can adapt to these conditions. So far, the economics literature has found that adaptation recovers a moderate-at-best proportion of lost yields, estimated using methods that abstract away from adaptation actions[1]. Unless we know what actions farmers take to adapt to weather and climate shocks, we cannot make informed policy suggestions to improve on the dismal projections.

Further, the moderate yield recovery may actually overstate the true benefits of adaptation if farmers adapt primarily with unsustainable groundwater extraction. Groundwater is insufficiently managed globally, and extensively used in irrigation. Farmers apply groundwater on 38% of irrigated land (Nagaraj et al., 2021), and groundwater substantially declined in 36% of aquifers over the last 40 years[2] (Jasechko et al., 2024). If farmers adapt by applying groundwater unsustainably, their ability to adapt declines over time, resulting in diminished future adaptation benefits (Lemoine, 2018). Fishman (2018) and Hornbeck and

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[1] Burke and Emerick (2016) find that long-run adaptation had no effect on yield losses from past climate change, while Hultgren et al. (2022) estimate that agricultural adaptation will reduce up to 30% of yield losses.

[2] Of course, this is only a proxy for a lack of management. It is theoretically possible for the optimal policy to be to deplete groundwater. However, there are no estimates for the actual percent of aquifers unmanaged globally. We do know that virtually no through 2022, virtually no transboundary basins, which cover multiple countries, were managed (Eckstein, 2021).

Keskin (2014) have documented how groundwater depletion leads to future drought sensitivity. Adapting through unregulated groundwater use also leads to common pool externalities and other physical externalities like saltwater intrusion (Goebel et al., 2019), arsenic leaching (Smith et al., 2018), infrastructure damage through subsidence (Borchers et al., 2014), declines in neighboring wells (Sears et al., 2017), and a permanent decrease in aquifer storage capacity (Smith and Majumdar, 2020). The externalities are costly and might severely diminish the social benefits of adaptation deriving from yield increases.

In this paper, I ask "how do farmers adapt to surface water scarcity?" The answer informs us not only about how adaptation occurs currently, but also whether current strategies are sustainable over time or socially costly. I study farmers in California, a context where farmers already face yearly surface water uncertainty, long-run declines in surface water availability, and a historically unmanaged aquifer, common ingredients in agriculture under climate change. These farmers might take two broad types of actions in response to expected and realized surface water scarcity. The first is water conservation, where farmers lower their total water use. Since I cannot observe water application directly, I study land fallowing and crop switching as conservation outcomes. The second type of action is groundwater intensification, where a farmer shifts her surface water use to a substitute water source. I study change in depth to the groundwater table as a proxy for extraction, and well drilling as groundwater intensifying outcomes.

I aim to measure how much farmers take each type of action in preparation for future surface water scarcity. I can estimate the adaptation response empirically because California has variation in forecasted surface water scarcity that differs over the state and across years. Over 200 water districts have contracts from the state or federal government for surface water deliveries in the dry summer growing season. Because of exogenous differences in snowpack which differentially fill reservoirs, water districts will receive different amounts of surface water. The government aids farmers' decision-making through providing surface water allocation forecasts. The first comes out in the early planting season, and then is updated in the mid and late planting season.

I construct one of the broadest datasets of adaptation choices yet compiled, including district-level crop choices, land fallowing choices, change in depth to the groundwater table, well drilling, and various proxies for water application, combined with surface water forecasts and updates spanning from 1967 until 2022. I regress the cumulative levels of adaptation actions for a water district between the beginning of the year and summer on the initial forecast and two surface water updates. The coefficient on each of the three components of surface water information identifies the amount of an adaptation action resulting from a marginal surface water allocation change announced in the early, mid and late planting season, which accounts for farmers' choice sets changing over the planting season.

I find that farmers adapt with both water conservation and groundwater intensification. Specifically, a 1 percentage-point decrease in the surface water forecast leads to a 0.25% decrease in high water acreage, a 0.2% increase in low-water acreage, a 0.26% increase in idled acreage, a 0.22% increase in well drilling and a 0.08% increase in the depth to the groundwater table on average. My estimating strategy also recovers trends in adaptation across a planting season. Both the crop idling and groundwater extraction responses are highest at the end of the planting season. Using evapotranspiration, a proxy for total water application, as a dependent variable, I can both support and explain my results: in the early and mid planting season, adaptation generally tends to lower total water use. Farmers switch crops and likely plan for lower water application. However, by the end of the season, news about higher water scarcity tends to increase water application in general, consistent with groundwater extraction being one of the most flexible adaptation options left. Therefore, with late-season surface water shocks, farmers not only replace the entirety of their surface water shortfall with groundwater, but even exceed it. Adaptation through groundwater use is pervasive in the setting.

My results also showed that farmers drilled wells in response to a surface water allocation shock, suggesting that the groundwater intensity of adaptation might even increase. In order to tie the wells drilled to adaptation, I need to identify when those wells would have been drilled absent the surface water shock, important for actually estimating social costs of adaptation. I use local projections (Jordà, 2005) to trace out the cumulative change in wells from a surface water allocation shock in a given year. I find that the farmers who drilled in response to a shock did so about three to five years earlier than they otherwise would have[3]. The shift forward in time represents a real social cost because having a well likely changes farmers' future water use choices. After drilling, farmers gain access to the choice to extract (more) groundwater, which permanently lowers the marginal cost of surface water during drought, and therefore the risk of high prices.

To be able to estimate the change in the groundwater intensity of adaptation following a well being drilled, I conduct two additional empirical analyses. The first captures how the sensitivity of the adaptation actions to surface water scarcity from the main specification changes as the district's well stock increases. I take the main estimating equation and interact the three periods of surface water information by the lag of the cumulative wells in a district. I find that water conserving actions decrease as the well stock increases. Further, farmers become much less sensitive to surface water information early in the planting season relative to later in the planting season, which can be explained by the value of preparation decreasing because wells offer certainty in groundwater availability.

Second, I study how new wells affect the types of acreage planted. If the stability in water prices induces farmers to plant more perennials, the value of adaptation through groundwater also increases through the higher opportunity cost of fallowing. The challenge of estimating new acreage caused by wells drilled is that both choices are made simultaneously, as the future expected value of perennials factors into the crop decision and well decision. Therefore, I use exogenous changes in well drilling costs as an instrument for new wells. My main instrument is the interaction of the lag of the number of well drilling contractors in a district (competition) and annual steel pipe prices (a necessary input). Even the first stage reveals important information for adaptation: I recover how aggregate well drilling responds to a change in well value, through the cost. Overall, I find that a 100% increase in the price of steel pipe, about a 5% increase in the total cost of a large well, results in about 0.65 fewer wells per district in an average year, nearly a 10% decline on average.

In the second stage I estimate the local average treatment effect for the subset of farmers with well values somewhat close to the threshold of drilling, in a year where surface water scarcity is not necessarily high. Since crop choice might change over a few years after a well is drilled, I use the exogenous new wells as a shock in a local projections framework (Jordà et al., 2015). After a 'surprising' new well is drilled in a county, I find that nearly all annual acreage declines, but is slightly more than replaced by perennial acreage over a period of four years. The shift suggests that the way that groundwater lowers downside risk is incredibly valuable to farmers. The results are in line with estimates in the appendix showing that farmers extract about 1800 acre feet per year on the average new well, enough to irrigate 450 acres with about 3.5 feet of

[3]Although short run shocks do not result in permanent new wells, long-run surface water declines do. In an appendix analysis, I use show that an exogenous permanent decline in surface water deliveries permanently increases the well stock. My estimates imply that 8.5% of wells drilled annually are directly because of long-term scarcity.

water per year, sufficient for many perennials. Overall, my results all point to farmers adapting primarily and increasingly through groundwater use.

What is the social consequence of farmers adapting extensively through groundwater extraction? It depends on the full external cost of groundwater use, and there are no estimates for this value. However, I can compare the private net benefit of adaptation with the changes in groundwater use to back out the size of the externality that would cancel out the social benefit of adaptation. I estimate the private net benefit of adaptation using the conceptual framework laid out in (Shrader, 2023). In the baseline framework, I would regress farm profits (available at the county level) on the surface water allocation forecast and realization, and the coefficient on the forecast would recover the value of adaptation. In my context, farmers make choices based on multiple forecasts across the planting season, so I update the framework for multiple decision periods. Also, since farmers tailor their adaptation investments specifically to the level of surface water expected, I modify the baseline framework so that the benefit of adaptation is measured by a forecast becoming marginally more accurate rather than by a forecast marginally increasing. In practice, I simply interact the forecast by an indicator for whether it over-estimated or under-estimated the final surface water allocation.

I find that a marginally more accurate surface water allocation forecast does not affect ex-post county incomes early in the planting season, but does improve county level income by about \$550,000 in the mid-planting season. The result implies that inputs can be flexibly adjusted in the early-planting season, though adaptation becomes constrained later. The result also means that farmers would have been better off if they could have made decisions earlier, even though adaptation in the late-planting season is much more groundwater intensive. Therefore, groundwater intensity is not crucial for high private values of adaptation.

The full value of mid-season adaptation, however, includes not only the private value to farmers, but also the social value of avoiding excess groundwater extraction in the late-planting period. I show that even given a moderate average externality value, the value of shifting news about a surprise shortfall from the late-planting season to the mid-planting season comes primarily from reductions in groundwater use. However, the water intensity of ex-post adaptation and the increasing rate of adaptation with groundwater over time meant that in general, external costs were significant in adaptation.

Ultimately, I show that understanding the mechanisms of agricultural adaptation is key to correctly estimating adaptation's benefit in the presence of unregulated resources. Farmers in California will face a decreasing ability to adapt in the long run, at the same time that surface water quantities continue to decline and become more irregular. Further, as farmers are already facing consequences of climate change, they are pressured to adapt more than previously, exacerbating future declines in adaptation.

My paper contributes to the climate adaptation literature in three ways. Carleton et al. (2024) explains that the literature exists in two independent strands, the first describing mechanisms of adaptation and the second identifying the value of adaptation broadly in order to correctly estimate climate damages. I contribute to both strands and act as a rare bridge across the two, showing that the mechanisms fundamentally affect the value of adaptation.

First, I contribute to the literature on forecasts for ex-ante adaptation, which finds that anticipatory responses substantially reduce weather-related damages (Molina and Rudik (2022), Shrader et al. (2023), Downey et al. (2023), Shrader (2023)). My paper adds to the literature in three ways. I modify the baseline framework of Shrader (2023) by estimating the benefit of adaptation across multiple intra-annual periods, potentially useful in agricultural adaptation where actions vary across the year. Second, I join Anand

(2023) in adding more evidence for the importance of lead times in forecasts in some contexts, challenging the theoretical model of Millner and Heyen (2021), which concludes that long-run predictability becomes irrelevant when people can continuously adjust their actions. Third, I am one of the few studies to examine the value of adaptation through forecasts in an agricultural setting, despite agriculture being the industry most affected by climate change. Burlig et al. (2024) also studies agriculture, but examines the value of the forecast itself, rather than using the forecast to identify the value of adaptation. Fourth, I study how long-run adaptation (well drilling) affects agents' responses to forecasts for the first time.

On the mechanisms side, I undertake the broadest study of farmers' adaptation actions, contributing to our knowledge of how farmers adapt. Other papers have estimated a few of the potential mechanisms, either showing what actions are effective for promoting climate resilience, or what farmers actually do in response to weather shocks. Michler et al. (2019) and Auffhammer and Carleton (2018) showed that conservation agriculture practices reduced farmers' sensitivity to climate shocks. Fishman (2018) and Hornbeck and Keskin (2014) showed that investment in wells and groundwater extraction led or will lead to more sensitivity to drought. Blakeslee et al. (2020) find little evidence of farmers adapting to long-run water scarcity within agriculture, instead shifting industries. Burlig et al. (2024) and Hagerty (2022) both examine multiple adaptation choices, though neither examines a socially costly adaptation directly. I have the only paper studying both conservation and groundwater intensification choices, and both long and short-run decisions, comparing the uptake, consequences and value of both.

Crucially, my paper shows how bridging the two literatures is key to understanding the value of adaptation. Deschenes (2022) is the only other paper I am aware of has studied both strands at the same time, showing that adaptation to increasing temperatures decreased mortality but increased electricity use and hence emissions. However, Deschenes (2022) neither directly measures uptake of the long-term adaptation strategy (air conditioner adoption) nor calculates the actual benefit of adaptation. Otherwise, the literature assumes that the value of adaptation comes from private actors optimizing over an abstract choice vector, using the envelope theorem to argue that adaptation choices do not affect first-order benefits (e.g. Carleton et al. (2022), Shrader (2023)). Papers valuing adaptation this way also typically use yield as a dependent variable, which is not directly tied to farmers' welfare (Schlenker and Roberts (2009), Burke and Emerick (2016), Hultgren et al. (2022)). My paper reveals the previous methods of estimating aggregate adaptation fail to capture the actual benefits. Farmers change their adaptation strategies across a season, reflecting changing private costs over time, and unregulated groundwater extraction has non-trivial external costs.

In addition to the climate adaptation literature, my paper contributes to the water economics literature. A growing area of the literature studies California's complex water institutions(Hagerty and Bruno (2024), Bruno et al. (2024), Bruno and Jessoe (2021), Ayres et al. (2021), Hagerty (2023), Regnacq et al. (2016)). I am one of the first papers to study the surface water allocation forecasts specifically, public information predicting public water availability, which concerns about 19% of annual agricultural water. I also add to the literature on the substitution between groundwater and surface water. These resources are close to perfect substitutes for inputs, but there is a wedge between the private and social value of these resources. Much of the empirical work in the area examines the hydrological connection between surface water and groundwater (Kuwayama and Brozović (2013), Wheeler et al. (2021)), but less is known about the elasticity of substitution between the resources. Ferguson (2024) estimates the elasticity of substitution in California using the state's estimates of water use, while I study substitution over time through local well investment choices.

The paper proceeds as follows. Section 1 covers the essential background, while section 2 covers the data. Section 3 estimates the how farmers adapt in the short-run, and section 4 explores the consequences of well drilling. Section 5 describes the conceptual model behind estimating the net private benefit, and applies the conceptual model to empirics. Section 6 ties together the results in a discussion of the net private benefits and external costs of adaptation, and section 7 concludes.

1 Background

1.1 California's agriculture and climate

Ample sunlight, mild winters and fertile soil has made 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 (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

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

subsidized surface water (Sharp and Carini, 2004). The majority of water districts charged agricultural users less than \$50/ acre foot for surface water in 2021, and many paid much less, while groundwater rates tend to be higher, and the market rate for surface water higher still[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). The forecasts have been disseminated through newspapers, bulletins, and websites. Appendix figure A.2 shows examples of what the surface water allocation forecasts have looked like through time. Low surface water allocation forecasts are especially salient, making front page news in many agricultural communities. Figure A.3 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.

In addition to yearly surface water uncertainty, long-term surface water availability has decreased over time, and will continue to decrease. Between 2000 and 2020, the April 1st Sierra snowpack was only 80% of the 1950-1980 average, and snowpack is expected to decrease by 48-65% of the historical April 1st average by 2100 (California Department of Water Resources (2025a), California Office of Environmental Health Hazard Assessment (OEHHA) (2024)). Project water allocations have also been declining about one point per year since 1975 to reflect the reality of lower surface water availability. One surprising, and permanent surface water shock occurred during my study period, allowing a rare way to identify adaptation to long-run changes in surface water availability. In 1992, the Central Valley Project Improvement Act redistributed 14% of CVP water from contractors to environmental uses in order to comply with the Endangered Species Act (Water Education Foundation, 2025). The State Water Project was also affected due to the coordinated operations of the projects (McClurg and Sudman, 2000). I plot a summary of the variation of surface water allocations within years and across years in appendix figure A.1.

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

[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.

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. On average 2.4 million acre-feet more water was extracted annually than was recharged (US Geological Survey, 2025). The severity of the overdraft has resulted in concerns about groundwater depletion and other externalities including saltwater intrusion (Goebel et al., 2019), arsenic contamination (Smith et al., 2018), infrastructure and property damage through subsidence (Borchers et al., 2014), an increase in the future costs of extraction, and a permanent decrease in aquifer storage capacity (Smith and Majumdar, 2020), in addition to the standard common pool externality. Nevertheless, until 2014 only 7% of the state's groundwater basins had defined property rights, none of which were in the Central Valley (Ayres et al., 2018). The California legislature passed the Sustainable Groundwater Management Act in 2014 to address unsustainable groundwater extraction. However, 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: adaptation in a year and over time

Now, I combine the pieces of the context to motivate how to study how farmers adapt to surface water scarcity. I previously showed that surface water scarcity occurs both in the short-run, through uncertain yearly surface water availability, and in the long-run, through persistent declines in surface water availability. Thus, profit-maximizing farmers would respond though annual and long-run adjustments. I first characterize the profit-maximizing problem in words to show how to conduct the empirical analysis of both timeframes of adaptation.

A farmer aims to maximize her lifetime profits from crop production given exogenous, uncertain yearly surface water which also has a long-run shift in availability. The farmer's choices of short and long-run inputs respond to the changes in surface water. In a simple dynamic optimization setting where short and long-run adaptation options are separate inputs into a production function, we can separate the short-run adaptation problem from the long-run one. Even while dynamically optimizing, a farmer still sets the marginal benefit of short-run adaptation to the marginal cost of short-run adaptation. Therefore, I study the short-run adaptation problem separately from the long-run adaptation problem.

[8] Permits are virtually always granted.

[9] From the testimonies of two well drilling contractors.

By exploring a farmer's short-run adaptation to surface water scarcity, I learn about how farmers adjust when exposed to surface water shocks, something that is currently unknown in the literature. Intuitively, how a farmer can adjust depends on when in the planting season she learns information. At different times within a year, the choice set changes due to timing constraints and previously fixed decisions. 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. Thus, even a farmer's yearly adaptation is a decision problem with several periods.

Grounding this in reality, there is an early planting season, spanning from October to December, a mid planting season, spanning from January to March, and a late planting season, running from April until the start of the dry season in June. Then, the dry season / harvest season continues until September. In each of the three periods before the dry season, farmers receive new information about surface water available to them in the dry season, which becomes more accurate as the dry season approaches. In each planting period, farmers can make a variety of short-run decisions. 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 choose to extract more groundwater using wells that they already have, up to the capacity of their well, paying a per-unit cost of extraction, typically only from the electricity cost to run a well pump. Finally, in every period, regardless of past decisions, farmers can choose to abandon crops by ceasing to water what was already planted. By the time the dry season arrives, the only options left for adjusting to surface water supply shocks are crop abandonment and groundwater extraction. Through my empirical analysis, I will learn whether farmers actually use these different options, and to what degree.

In figure 1, I summarize the farmer's short run problem in a timeline, which illustrates how the timing of precipitation and information aligns with the decisions available to the farmer, highlighting why the private value of different adaptation decisions change over a year.

Then, there is long-run adaptation through well drilling. The benefit of a well is the sum of discounted additional profits from having access to groundwater forever, which is partly determined by the long-run expectations of dry-season surface water. In general, surface water availability has been declining, though it is not straightforward to find variation in long-run beliefs about surface water availability to measure how surface water availability affects wells. A large portion of the value of wells also comes from the price of crops. Since high-water intensity perennial crops increased greatly in value over time, the overall value of wells has also exogenously increased. 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 irreversibility of the fixed costs of investment, plus the uncertainty of future surface water availability means there is an option value of drilling.

Although well drilling is a long-run decision, a well is drilled within a particular year. Short-run surface water information can have an effect on well drilling by changing the current year's payoffs from a well, which matters if well value is increasing across farmers generally. 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. 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. Wells also affect short-run adaptation by giving farmers the choice to substitute with more groundwater, rather than conserve surface water.

Empirically, we do not know how much farmers respond to long-run water scarcity by drilling wells. Farmers without wells have a lower well value than farmers who do have wells. If the marginal product of water is low enough for farmers without wells, we will see them exit farming rather than drilling. Otherwise, declines in surface water availability should lead to drilling.

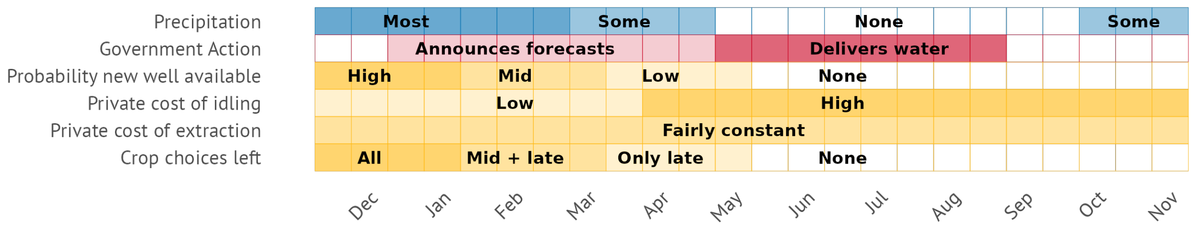
Understanding adaptation choices is important for informing policy and for exploring the viability of agriculture under higher surface water scarcity. However, knowing farmers' choices is also important for estimating the social costs of adaptation. Well drilling and groundwater extraction result in large unpriced externalities. New wells are particularly socially costly because having a well decreases the marginal cost of water in dry years and decreases the risk of high surface water prices (if farmers purchase surface water from the market), which might result in a more water intensive crop mix and thus more water use every year, and fewer water conserving choices made in dry years. 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 surface water. To understand the full picture of adaptation and its external costs, I explore the consequences of well drilling, the timing of drilling decisions, and the relative level of water conserving and groundwater intensifying actions.

2 Data

2.1 Unit of observation: water districts

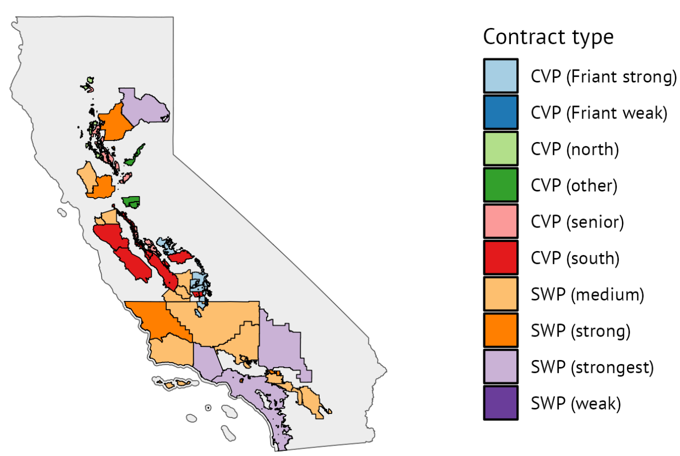
I use a map of 3556 water districts from California's state geoportal, augmented with alternate maps from some missing districts (California State Geoportal (2022), Public Policy Institute of California (2025), Department of Water Resources (2025b), Department of Water Resources (2025a)). I determine which districts have contracts with the surface water projects by matching names of water districts and lists of contractors using a crosswalk file from Hagerty (2022) (California Department of Water Resources (2024b), US Bureau of Reclamation (2025)). Through this process, I am able to match all 29 SWP contractors, 98 of 99 junior CVP contractors, and 81 of 89 senior CVP contractors. Figure 2 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).

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



Note: The figure summarizes the background, and illustrates the different timing of information and environmental conditions that contributes to the complications in the farmer's annual adaptation problem. The top line shows the timing of precipitation in the year, showing no precipitation in the dry season. The second line shows the government's main interventions. They announce forecasts for surface water allocations prior to the dry season, and then deliver water during the dry season. The next four rows show facts about the four adaptation actions. The first is the probability that a well drilling decision will result in a new well usable during the current year's dry season. The probability decreases as the dry season approaches because of demand queues and permitting. The next adaptation is idling. Early idling decisions are privately cheaper because the farmer never planted any crops. Late idling decisions are expensive because they are equivalent to crop abandonment, meaning the farmer lost her investment. The private cost of extraction stays fairly constant throughout the season. The bottom row is annual crop choices. Early in the planting season, the farmer can still choose whether to plant in early, mid, or late-season crops. As time continues, the choices diminish.

Figure 2: Districts with surface water project contracts



Note: The map shows the project districts in the sample, colored by the broad contract types which govern their allocation forecast. The contract type explains whether the district gets Central Valley Project (CVP) water or State Water Project (SWP) water, along with the canal or seniority associated with each contract. There is more variation than what is present on the map. CVP (other) makes up 3 types of contracts, and each SWP district can technically have its own forecasting seniority.

2.2 Treatment variable: surface water forecasts

I digitize all surface water allocation forecast announcements for the Central Valley Project and State Water Project, which have been published since 1967, with multiple forecast updates over multiple regions yearly (California Department of Water Resources (2024b), California Department of Water Resources (2024a), US Bureau of Reclamation (2024)). Though California farmers get information about surface water availability from a variety of sources, only these surface water allocation forecasts apply to a specific and measured source of surface water.

The CVP and SWP announce their first surface water allocation forecast in the early or mid planting season, and follow up with an average of 2.8 updates, roughly on a monthly basis, until the beginning of the dry season. I construct a panel of the newest information available to farmers at the start of the mid-planting season, late-planting season and dry season, using the surface water allocation forecasts closest to, but not beyond, February 1st, April 1st and June 1st. Table A.1 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.2, I plot binscatters comparing surface water forecasts from the State Water Project and Central Valley Project, showing that a given surface water forecast or final allocation has the same signal for both projects on average. The average surface water allocation forecast near February 1st was 36% for the SWP and 41% for the CVP. Both agencies also use the same conservative forecast rule, evidenced by the higher average final surface water allocation, at 61% on average for the SWP and 60% on average for the CVP.

In years when there is no surface water allocation forecast update between February 1 and April 1, or between April 1 and June 1, I carry over the most recent surface water allocation forecast, to match the intention of the agency in retaining the previous projection. In contrast, the February 1st forecast is missing in years when the USBR's policy is to publish later forecasts. Farmers still need to make early decisions based on expected surface water availability[11].

2.3 Water conservation choices: crop choice and land fallowing

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 2 (USDA, NASS (1997),

[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.

[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).

USDA, NASS (2007), Pittenger (2015)). I assign watering intensity for annual crops using crop water needs equations, which is a set of water intensity coefficients and growing length from the Food and Agriculture Organization, and requires the input of planting times and local evapotranspiration, the latter of which I get from the University of California's Cooperative Extension (Brouwer and Heibloem (1986), UC Cooperative Extension and California DWR (2000)). I categorize high and low water intensity crops at the mean water use, weighted by crop area, within planting times and climate regions so that the relative water intensity represents reasonable crop choices in each region. Therefore, I have four annuals classifications depending on planting time and watering intensity: early, high-water annuals (1%), early, low-water annuals (8%), late, high-water annuals (12%), late, low-water annuals (8%). I show examples of representative crops for each climate region, planting time and category in Appendix table A.2. The overall pattern shows that annuals planted later in the year are typically more water intensive, and crop timing and water intensity depends on region. In the main specification, I omit crops that are planted both before and after the dry season because I cannot isolate which information these crops are responding to. I aggregate the remaining agricultural land classes into four other groups: perennials (29%), idled and fallowed land (27%), double-cropped and alfalfa (10%), and annuals with different planting times (5%).

2.4 Groundwater intensification choices: well drilling, groundwater extraction and total water application

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.

I proxy for groundwater extraction using changes in depth to the groundwater table, data that has been collected for decades. 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, 2025c). 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.

I also collect a variable for total water application to compare overall conservation and groundwater intensification. A major way farmers adjust water is through the amount of application on their fields (Burlig et al., 2020). Like most regions, California has no data for actual water application. The best proxy for water application across my entire period comes from an 800-meter grid of evapotranspiration from

[13] 82% of wells include a purpose.

Reitz et al. (2023). Evapotranspiration measures plant transpiration and the evaporation of water from all surfaces measured in meters per year, proxying for applied water in dry locations. The authors use machine learning to train a model of evapotranspiration including remotely sensed evapotranspiration data beginning in the 2010s, ground-level observational data beginning in the 1990s, and regional water balances through the 1880s. The output is the best existing estimates of water application over time.

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 How do farmers adapt to short-term surface water scarcity?

3.1 Methods: an empirical model of sequential adaptation

The goal for the main analysis in my paper is to estimate the portion of a district's (summer) dry-season adaptation level deriving from a surface water supply shock occurring at a specific time in the (spring) planting season. During the dry season, the only surface water available is an uncertain quantity delivered by the state or federal government through canals, and natural streamflow. Farmers can prepare for annual surface water scarcity because they receive forecasts about water deliveries.

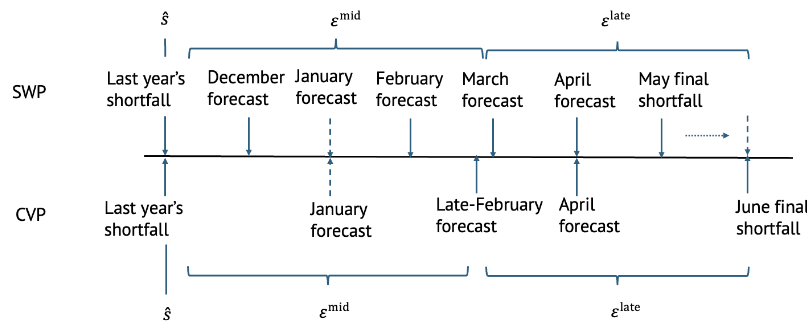
For the remainder of the paper, instead of surface water allocations I will use 'shortfalls' as a more intuitive measure of scarcity. A shortfall is defined as 100% - the surface water allocation forecast percentage.

I can identify actions taken due to surface water shortfall forecasts from a particular time in the growing season because the government announces different shortfall forecasts to different districts at several points in the planting season. However, since some districts have contracts with the federal government, and some have contracts with the state government, the forecast announcement times are not consistent for all districts. I summarize the average forecasting behavior of each government and the choices that I make when constructing shortfall variables in figure 3.

The arrows in the figure show when each government agency announces a forecast. The forecasts on the top of the timeline are announced by the SWP, and the bottom ones are announced by the CVP. Dotted lines reflect times when forecasts are only sometimes announced. I choose my surface water shortfall variables according to two criteria. First, baseline information should be available to all districts when they start making planting decisions. Noticeably, the first forecasts for the CVP occur relatively late in the planting season. I choose the previous year's shortfall as the baseline information $\hat{s}$ in the main specification since it is the most comparable early information relevant to both types of contracts[14]. Second, information should

[14] Recall that forecasts prior to February are extremely unreliable anyway

Figure 3: Timing of forecasts from different projects



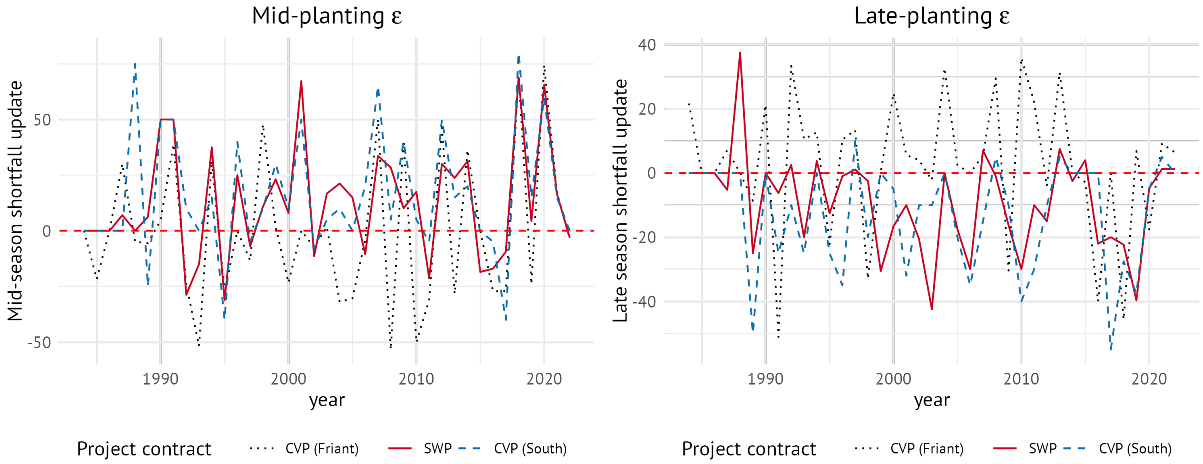
Note: This figure shows when each project tends to announce its forecast information. The arrows in the figure show when each agency announces a forecast. The forecasts on the top of the timeline are announced by the SWP, and the bottom ones are announced by the CVP. Dotted lines reflect times when forecasts are only sometimes announced.

be consistently announced to all districts, and far enough apart to retain sufficient variation. Therefore, I use the forecasts announced around late-February or the beginning of March, and also immediately prior to the dry season around May and June. I define shortfall 'updates' as the differences between the newest and previous forecast. The mid-planting-season update is given by ε^{mid}, which is the difference between the March shortfall forecast and the baseline shortfall forecast, and the late-planting-season update is given by $\varepsilon^{\text{late}}$, the difference between the final shortfall and the March shortfall forecast. Positive updates mean that surface water scarcity became worse. I choose different baselines and shortfall updates in the appendix.

I will use the variation in the baseline shortfall forecast and shortfall updates across the ~ 200 water districts in my data to estimate how districts respond to shocks to surface water availability learned at different points in the planting season. Figure 4 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 Valley Project contract, and the Central Valley Project contract to water on the Friant Canal. The line falling above zero the shortfall is positive, which is bad surface water news. The news across 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.

My main econometric model is shown in equation 1. A_{dt} is the level of an adaptation action, for example land fallowing, observed in the dry season in district d in year t, given the baseline shortfall forecast and two shortfall updates. Intuitively, each coefficient of interest, β_1, β_2 and β_3, reflects approximately the percent change in the district's number of acres fallowed. The difference in the coefficients reflects if a different amount of fallowing can be attributed to a marginal shortfall shock from a different time in the planting season. By using district and year fixed effects, I compare a water district's adaptation choices to itself over time, which is the best comparison available. I will identify the effect of information on adaptation levels if there are no unobserved factors varying at the district-year level affecting both deviations in information and deviations in adaptation. I next describe each piece of the estimating equation in detail.

Figure 4: 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 mid-seniority State Water Project contract, the south-of-delta Central Valley Project contract, and the stronger 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.

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

I study five water conserving and groundwater intensifying 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). The second is the level the depth to the groundwater table, a proxy for groundwater extraction, since the βs can be interpreted as a change in depth with a change in information. The third is land fallowing, so that A_{dt} is the number of idled acres in a district observed during the peak harvest time. In the another set of regressions, A_{dt} is the number of acres at peak harvest in other crop groups: low-water annuals, high-water annuals and perennials[15]. Finally, I also use district-level average evapotranspiration across the planting and dry season to proxy for changes in total water application. Since A_{dt} is bounded below by zero, and zeros reflect a meaningful choice, I estimate the model using PPML[16] (Silva and Tenreyro, 2006). Poisson regressions naturally represent the aggregation of individual binary choices (Cameron and Trivedi, 2013).

X_{dt} is a set of district-year specific controls that control for endogeneity between the forecasts and the adaptation choice. There are three 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

[15]Since Poisson regressions are not typical in the crop-choice literature, I check the robustness of my Poisson results using a simple multinomial logit crop choice model, following Kurukulasuriya and Mendelsohn (2008).

[16]The shape of the ET variable also makes OLS a reasonable choice. I use OLS in the appendix for reference.

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.

For some analyses, alternative adaptation decisions might pose a source of endogeneity. Because adaptation decisions might be substitutes or complements, each A_{dt} modelled by equation (1) is one of several simultaneous equations. Consider the choices of crop fallowing and groundwater extraction. If crop fallowing is the dependent variable, and I control for groundwater extraction, each β isolates the direct effect of surface water shortfalls on crop fallowing. If I fail to control for groundwater extraction, then β also captures how shortfall increased groundwater extraction, and then how groundwater extraction changed fallowing. In my analysis, I actually do not want to control for these mechanisms because they reflect part of the adaptation response. However, I compare the main results with those controlling for alternate adaptation decisions using the control function approach (Imbens and Newey, 2009). I describe the methods and results in Appendix B.1.

Finally, ν_{dt} is the error term. In my main specifications, I cluster standard errors at the contract level, designating each district with a different pattern of surface water forecasts as having a different contract. Therefore, I have 35 contracts in my dataset. In other forecasting papers, the treatment (weather) is not applied to a specific location, so spatial-correlation-robust standard errors 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.

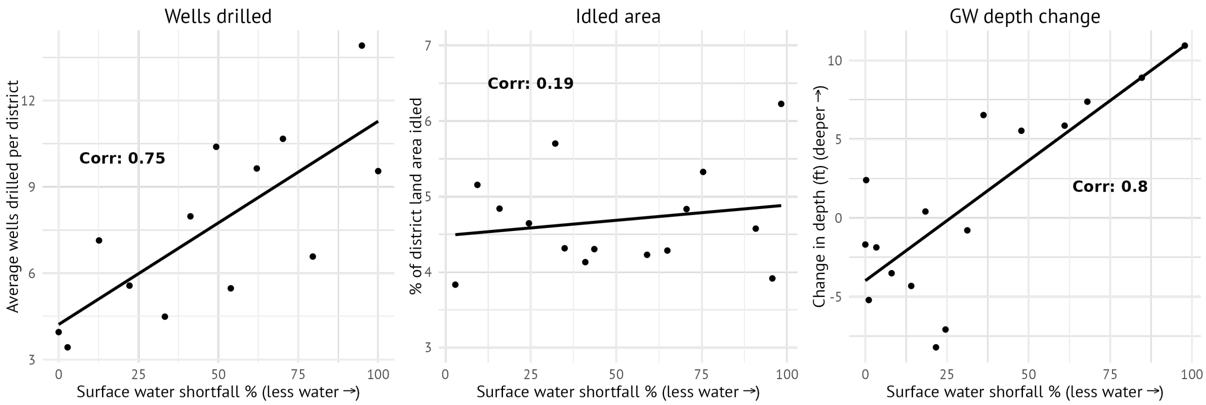
3.2 Results

I motivate my main results by showing that in the raw data, farmers act decisively in years with high surface water shortfalls. Figure 5 shows a simple raw-data binscatter of wells drilled, idled land and the change in depth to the groundwater table on the final surface water shortfall percent. The raw data relationships are displayed in figure 5. Higher shortfalls correlate strongly with higher uptake of each of the farm adaptation options. The main empirical specification will confirm that these patterns are causal, and also reveal when in the season farmers make different decisions.

In figure 6, I show the causal effect of an increase in shortfall announced in the early, mid, and late planting season on seven different adaptation actions. I plot three coefficients for each action, corresponding to the β coefficients in equation 1. The coefficient represents the percent change in an action observed during the dry season resulting from a one-point increase in announced shortfall in a particular period. The coefficients are organized by shortfall announcement timing, either the baseline forecast, the mid-planting season shortfall update, or the late planting season shortfall update. The numerical results are in Appendix B.2. 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.

The left panel displays the results for the water-conserving choices, specifically, crop selection decisions. Low-water annuals are denoted by black x's, high water annuals by red dots, idled acreage by blue boxes

Figure 5: Raw data binscatter: adaptation actions on final surface water shortfalls



Note: On all plots, the x axes reflect shortfall, a lower surface water allocation. 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.

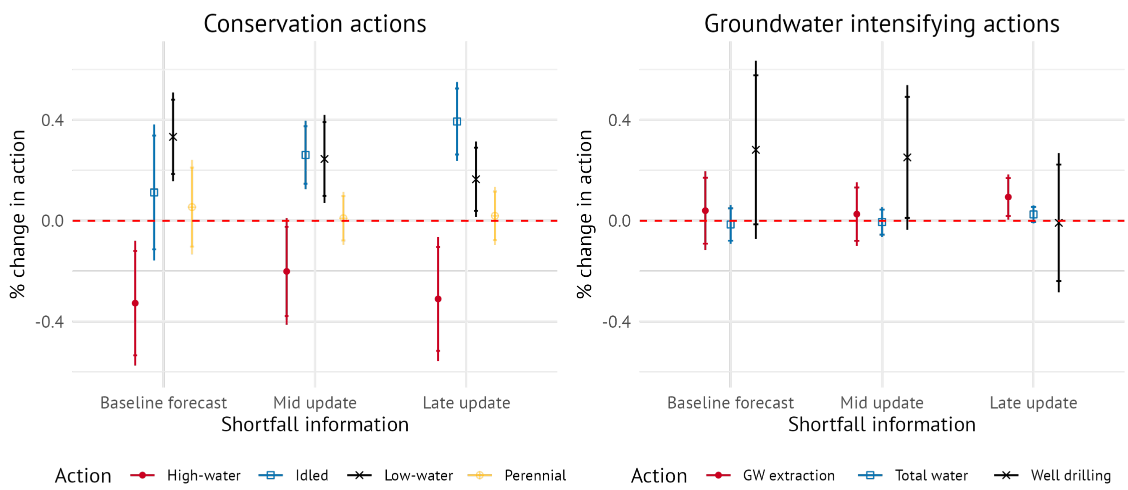
and perennial acreage by yellow diamonds. A positive coefficient means that a one-point increase in shortfall led to an increase in planted acreage in a particular category. I find that a one-point increase in shortfall in any period of the year leads to an average of a .27% increase in idled acreage, a 0.23% increase in low-water acreage, a 0.26% increase in high-water acreage, and a 0.03% increase in perennial acreage, a shift in about 25 acres for the average district.

The right panel shows the response of groundwater intensifying actions to surface water allocation shortfall, which are the percent changed in wells drilled (black x's), groundwater extraction (red dots), proxied by the increase in depth to the groundwater table, and the change in total water applied (blue boxes), proxied with evapotranspiration. A one point increase in shortfall results in a 0.18% increase in well drilling on average, a 0.01% increase in total water applied, and a 0.04% increase in groundwater extraction, about 2 new wells across all districts, a decline in the water table by about half-an-inch, and an increase in water application by 1/80 of an inch.

The general trends results are consistent with the raw data plots from figure 5. In response to surface water shortfall, farmers take both water conserving and groundwater intensifying actions. All of the crop choices indicate farmers adjust their crop acreage in response to expected surface water availability. Farmers plant fewer high-water crops, and increase low-water crops and fallowing. However, farmers' average adjustment to their perennial acreage is only about 15% the size of the other responses, and is the only statistically insignificant response. The response makes intuitive sense: the opportunity cost of abandoning perennial acreage is high. In contrast, farmers do respond through the other long-term investment choice, well drilling. The major question raised by this result is about the additionality of these wells. Are farmers adapting by drilling wells a few years early, or drilling wells they never would have otherwise? I answer this question in section 4.

My results also reflect important patterns in adaptation across the planting season, especially for groundwater intensifying actions. Farmers only drill wells in response to early changes in information, and they only extract additional groundwater in response to last-minute surprises in surface water shortages. For conservation actions, most coefficients remain statistically significant throughout the growing season, showing

Figure 6: 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 (1), 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 dependent variable listed in the legend is one PPML regression. 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 contract level.

that farmers continue to adapt with crop choice as they receive new information, although the crop idling response may be larger in response to information at the end of the planting season.

These results paint a broad picture of the way that farmers in California are adapting in aggregate to short-run surface water scarcity. Early in the planting season, farmers across the state especially take water conserving actions with lower private costs, like switching from high-water acreage to low water acreage. These choices keep water use nearly the same, meaning that on average, farmers almost fully substitute their surface water shortfall with additional groundwater, supported by the positive (though insignificant) coefficient on groundwater extraction. Therefore, either within or across districts, farmers take a mixed conservation-groundwater substitution strategy early in the season. At the same time, farmers drill wells. For well drilling, there is a yearly tension between the option value of delaying drilling until the final surface water shortfall is certain, and the short-term gain of being able to use groundwater in the current year. The results show that the latter mechanism dominates in year-to-year adaptation.

Late in the planting season, farmers respond differently to shortfall shocks. When water becomes scarce right before the dry season, groundwater extraction increases at more than twice the rate observed earlier in the season. In fact, on average farmers over-adapt to surface water shortfall, evidenced by the overall increase in total water application. Something about late-season surface water shocks increases the value of every unit of water, shifting out the marginal benefit curve. One possible explanation is that earlier investments were tailored to specific conditions. For example, a farmer might plant tomatoes in wet years and wheat in dry years. Getting a late surface water shock conditional on having planted wheat raises groundwater use to offset lost surface water. However, conditional on having planted tomatoes, the farmer will need to use much more water because tomatoes are sensitive to water stress, and the farmer no longer has options to adjust any other inputs. Despite the increases in total water application, farmers continue to conserve water especially through land idling, suggesting that water requirements greatly increase under announcements of late-season water stress.

Understanding farmers' adaptation strategies is crucial because they compensate for lost surface water, which has defined property rights, by pumping groundwater, which imposes external costs on others. Equation (2) demonstrates how my estimates can determine what proportion of lost surface water farmers replace through conservation versus groundwater substitution. The framework is straightforward: the total change in applied water equals the change in surface water supply (due to the shock) plus the change in groundwater use. Using observed data, I can estimate how much the surface water allocation changes in each period following a shock. The second row of the equation explains that the gap between increased groundwater pumping and decreased surface water represents either conservation or additional water applied beyond baseline levels. I observe part of the conservation response through crop switching and land fallowing. I connect actions with changes in water use by making assumptions about water saved[17]. The residual is composed of unobserved conservation (a negative component) and excess water application (a positive component). For my back-of-the-envelope estimation, I assume one component is zero.

$$\begin{aligned} \Delta\text{Total water applied} &= \Delta\text{Groundwater extraction} + \Delta\text{Change in surface water allocation} \\ &= \Delta\text{Observed conservation} + \Delta\text{Unobserved Conservation} + \Delta\text{Excess water applied} \end{aligned} \tag{2}$$

In figure 7 I summarize how farmers make up for the lost surface water allocations on average across the state. The blue portions of the bar chart reflect water saved through observed and unobserved conservation actions, while the red bars show groundwater use. In periods where water application does not increase, farmers replace 100% of the shortfall using one of the two actions. A bar higher than 100% shows that farmers take adaptation actions to more than offset the surface water shortfall.

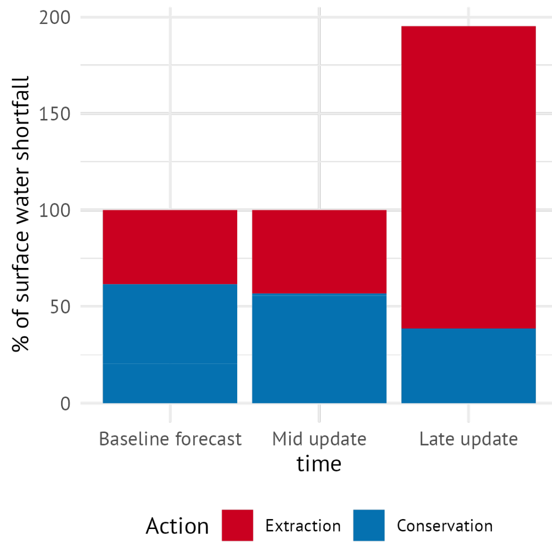
Early on, conservation dominates water use changes. More than half of lost surface water is offset through water-saving measures, both observed (idling fields and switching to low-water crops) and unobserved (shifting planting times, purchasing surface water on the market, storing precipitation, selecting different crop varieties and implementing soil management practices)[18]. As the season advances, however, farmers increasingly turn to groundwater. By the end of the planting season, groundwater substitution becomes three times more prevalent than at the start, making it the dominant adaptation strategy when late-season shortages occur.

Therefore, especially late-season conservation results in large increases in groundwater use. Through my calculation, I estimate that the average surface water shortfall shock is about 160 acre feet of surface water, consistent with 1% of a typical delivery from the data. After a late-season shortfall shock, a typical district would use 235 acre-feet more groundwater, enough to supply 500 households for a year. Scaling up to the

[17] In particular, 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.

[18] Not shown in the plot, my estimates suggest unobserved conservation accounts for roughly 36% of total conservation early in the season, though this share declines as the year progresses.

Figure 7: Percent of surface water shortfall shock replaced by each type of action



Note: This figure shows the back-of-the envelope calculations for the percent of a surface water shortfall made up with either conservation (observed through fallowing and crop switching, plus unobserved through the residual), or groundwater extraction. To calculate these percentages, I use the estimates from 6, combined with the relationship in equation (2). The y-axis shows the percent of a surface water shortfall replaced with a particular adaptation practice. I omit any change in groundwater from new wells.

entire Central Valley Project, which delivers 5 million acre-feet to farms annually, farmers would substitute to 78,000 acre feet more groundwater, or 0.8% of annual groundwater use in California.

This subsection gave a broad picture of agricultural adaptation: farmers adapt with many types of actions, and their choices change depending on when they get new shortfall information in a year. Although conservation is an important part of adaptation, farmers drastically increase groundwater use following late-season shortfall shocks. However, my main specification misses two parts of the story in characterizing adaptation. First, I take water districts as a homogeneous group. Likely, different types of farmers take the different adaptation actions I study. Second, I miss how patterns of adaptation change over time, especially as farmers make more investments in wells. The remainder of my analysis on how farmers adapt tackle these questions. First, though, I turn to a brief discussion in the robustness of the main result.

3.3 Robustness checks

My adaptation results are robust to a variety of alternate specifications. Appendix Section B.2 presents five robustness tests for each of the seven adaptation choices. First, I omit all controls. This specification reduces the statistical significance of groundwater intensifying actions, especially groundwater extraction, though coefficient magnitudes and directions remain unchanged. I find that controlling for neighbors' extraction is important for statistical significance. Second, I add a control function for alternative adaptation choices to the main specification, effectively shutting down substitution and complementarity channels. The magnitudes of groundwater-intensifying actions increase slightly, though not significantly, consistent with the intuition that holding crop choice fixed would increase groundwater intensification. Third, I use Conley standard errors to account for spatial correlation within 100 kilometers (slightly larger than the average California county). Conley errors generally strengthen my results: most coefficients become more significant or retain similar significance levels. The one exception is the late-season low-water crop response, which loses statistical significance. However, since low-water crops tend to be planted early, Conley errors actually move my results closer to my ex-ante expectations. Fourth, I use January shortfall forecasts as the baseline for surface water information rather than the previous year's shortfall. I fill missing early forecasts with the nearest forecast (in space). The exception is high-water crop responses which become statistically significant only in the earliest period, and well drilling responses which become statistically significant only in the mid-update period. Neither result changes my story, though better early-planting season data might have revealed more interesting patterns. Fifth, I estimate the model using OLS rather than PPML. OLS is inappropriate for most adaptation choices, especially well drilling. Histograms in Appendix figure B.1 shows that fitting count data (wells) and skewed data (groundwater depth) with OLS results simultaneously in too many points being very well fit and very badly fit. Consequently, most OLS results are statistically insignificant. For dependent variables better suited to OLS (evapotranspiration and crop idling), the OLS coefficients match the PPML signs.

Finally, I estimate crop choice using multinomial logit (Appendix Section B.3), with perennial acreage as the omitted category since permanent crops are insensitive to short-run scarcity shocks. The log-odds from multinomial logit align in direction with my main specification, confirming that my crop results are not driven by the unconventional choice of Poisson estimation.

3.4 Heterogeneity by the well stock, district location, and shock direction

I conclude this section with three heterogeneity analyses to fill in the picture about how farmers adapt. In the first two tests, I see how farmers' adaptation decisions differ if they are in water districts with more wells, or in different locations. These tests answer whether different farmers might choose different adaptation methods, which helps to clarify the interpretation of the main result. The last heterogeneity test examines whether farmers respond differently to positive and negative shortfall shocks. Currently, I estimate the effect of a linear shock on adaptation, which implies that good surface water shocks would lower groundwater use as much as bad shocks raise groundwater use. If the effect is not linear, however, external costs do not net out over time.

I first examine adaptation in districts with different amounts of wells. Districts with more wells not only have the option to extract more groundwater, but wells also lower the value of 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, her costs saved through conservation decreases. To test the heterogeneous response, I interact the three components of surface water shortfall from equation (1) with an indicator for a district being in the second or third tercile for wells-per-area. I allow a district's category to change over time so that I can compare districts to themselves because there is selection across space. In table 1 I show the results for three adaptation responses: groundwater extraction, total water application, and crop idling.

The first three rows show the adaptation responses for districts with the lowest number of wells in a given area. The baseline category tends to include older years (with a median year of 1995 versus 1998) and tends to include more districts in temperate agricultural areas. Overall, conservation responses are stronger than in the main specification. Total water applied significantly decreases with shortfalls, and the idling response

Table 1: Adaptation by number of wells

	Extraction	Total Water	Idling
Baseline shortfall	-0.07	-0.11^{**}	0.20
	(0.11)	(0.05)	(0.28)
Mid-season shortfall update	-0.06	-0.19^{***}	0.38^{***}
	(0.08)	(0.06)	(0.15)
Late-season shortfall update	0.03	0.03	0.44^{***}
	(0.09)	(0.02)	(0.12)
Baseline × Mid wells	0.19	0.13^{***}	0.17
	(0.11)	(0.03)	(0.25)
Baseline × High wells	0.07	0.14^{***}	-0.32
	(0.12)	(0.03)	(0.25)
Mid update × Mid wells	0.12^{*}	0.23^{***}	0.05
	(0.07)	(0.04)	(0.17)
Mid update × High wells	0.07	0.22^{***}	-0.43^{*}
	(0.07)	(0.06)	(0.22)
Late update × Mid wells	0.10	-0.02	0.01
	(0.08)	(0.02)	(0.15)
Late update × High wells	0.03	0.04	-0.37^{**}
	(0.08)	(0.03)	(0.15)
Controls	yes	yes	yes
District FEs	yes	yes	yes
Year FEs	yes	yes	yes
SE cluster	contract	contract	contract
Num. obs.	4923	4500	1634
Pseudo R^2	0.77	0.10	0.98

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

Note: This table shows the main regression in equation (1), interacting each of the shortfall components by the wells-per-area tercile of a district, which can change over time. The baseline category in the first three rows are the districts with the fewest wells. Each coefficient estimate is the percent change (0.07 = 0.07%) in an adaptation action with a 1-point increase in shortfall. Each column is a different adapation action. The first column is groundwater extraction, proxied by change in the depth to the groundwater table. The second column is total water application, proxied by evapotranspiration. The final column is acres idled. Each regression uses the main specification, which includes district and year fixed effects, controls for alternative water sources, neighbors' water demand, and the log of the total number of wells in a district. Standard errors are clustered at the contract level, which is the level that shortfall forecasts differ.

is strong.

The next six rows compare the baseline results with district-years in the second and third terciles of wells. The wells-tercile category compares many districts to themselves – almost 2/3rds of districts change wells terciles. Farmers in districts with more wells conserve less water. These districts increase their water application relative to low-wells districts, so that total water application remains roughly constant with and without surface water shortfall shocks. The idling response also disappears for districts with the highest number of wells.

Overall, I find that districts with the most wells and districts with the fewest wells adapt in nearly opposite ways. This means the overall adaptation patterns shown in my previous results don't represent what a typical district does. Instead, they reflect an average across districts that are actually behaving quite differently from each other. This is the first evidence in my paper that long-term decisions shape short-term adaptation patterns. Because wells are permanent, each well-drilling decision likely pushes farmers toward relying more heavily on groundwater over time. I explore this long-term shift in greater detail in the next section.

In the next heterogeneity test, I study how adaptation differs across regions in the state. In California, groundwater availability and planting dates vary considerably across the state. In appendix figure A.5 I show a map aggregating ecological regions into 3 large regions with similar planting times and groundwater access. Planting times matter because a March 1st surface water forecast might be relatively early for some districts, and late for others. The South and Central Coast includes districts along the Pacific Coast and in the rainier area between the Sierra Nevada and Central Valley. The weather in these regions tend to be cooler, meaning that planting times are later. These regions also have some important groundwater basins, though they tend to be smaller and have better governance. The Central Valley has a deep aquifer and a long agricultural season spanning most of the year. The Inland Desert regions tend to plant early and have minimal groundwater access, therefore relying heavily on surface water. To study heterogeneity across regions, I let the temperate South and Central Coast be the baseline, and compare adaptation actions in the Central Valley and Inland Desert by interacting the three components of surface water shortfall from equation (1) with an indicator for a district being in either region.

I show the results in Appendix Table B.9. Overall, districts in the temperate region in the state adapt less than the average district. In contrast, the majority of the groundwater extraction effect comes from the Central Valley, the region with the least regulated and most abundant groundwater, and also the most perennial acreage. I do not find convincing evidence that different regions respond to information in different times. Desert regions might start responding to shortfall shocks by idling earlier, though the other patterns show mixed results.

In the final heterogeneity test, I examine whether farmers have different adaptation responses to good and bad news about surface water shortfall. I interact the two shortfall updates with an indicator for whether the update was positive (bad news). Since positive updates are rare, I also define a 0-shortfall decrease as bad news, given a bad initial forecast (greater than 40%) since the shortfall forecast nearly always declines across the planting season. I show the results in Appendix table B.10.

Farmers exhibit a pronounced asymmetry in their responses to water availability shocks: they adapt far more aggressively to positive shortfall news (bad news) than they scale back adaptation when conditions improve. This pattern is particularly evident in water application decisions, which respond only to late-season announcements of increased shortfall. The asymmetry extends to groundwater extraction, where bad news triggers a response nearly four times larger than good news (though statistical significance on the interacted term is marginal, $p = 0.12$). Land idling decisions show a similar pattern, more than doubling in response to negative shocks. Therefore, adaptation to shocks lead to increased groundwater use and idling from the no-shocks baseline over time.

The whole of section 3 has pointed to groundwater intensive adaptation, and the potential for increasingly groundwater intensive adaptation as the well stock increases. Since the majority of groundwater basins remained virtually unmanaged throughout the entire study period spanning from 1967-2022, farmers did not internalize the social costs of their yearly adaptation. The social benefit of adaptation came at the cost of enormous amounts of lost resource wealth.

4 The well investment: agricultural adaptation in the presence of an unregulated aquifer

Section 3 showed that agricultural adaptation to short-run shocks was socially costly because of heavy substitution toward unmanaged groundwater. At the same time, districts drilled wells, especially due to shortfall shocks early in the planting season. While well drilling does not directly impose social costs, the previous section already showed evidence that a higher well stock correlates with substantially lower water conservation. In this section, I explore the external costs arising specifically from the well drilling decision.

Since wells are a permanent investment, any social costs deriving from a well drilled because of a shortfall shock in one year might last for several years. The duration of the external costs arising from the shock depends on when a well would have been drilled absent the shock. Therefore, I begin the section by studying the additionality of wells.

Then, I examine where the external wells come from, by studying how new wells causally change farmers' behavior. Drilling a well 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. In particular, I study whether well drilling affects crop choice behavior over the span of several years.

Broadly, in this section I shift from examining how farmers adapt to exploring the consequences of their adaptation choices, a key reason for knowing how farmers adapt. Yet, in answering these questions, I will additionally learn about adaptation to long-run water scarcity, and why farmers take the well drilling decision over other decisions, completing my analysis about 'how' farmers adapt.

4.1 Are wells drilled in response to short-term shocks additional?

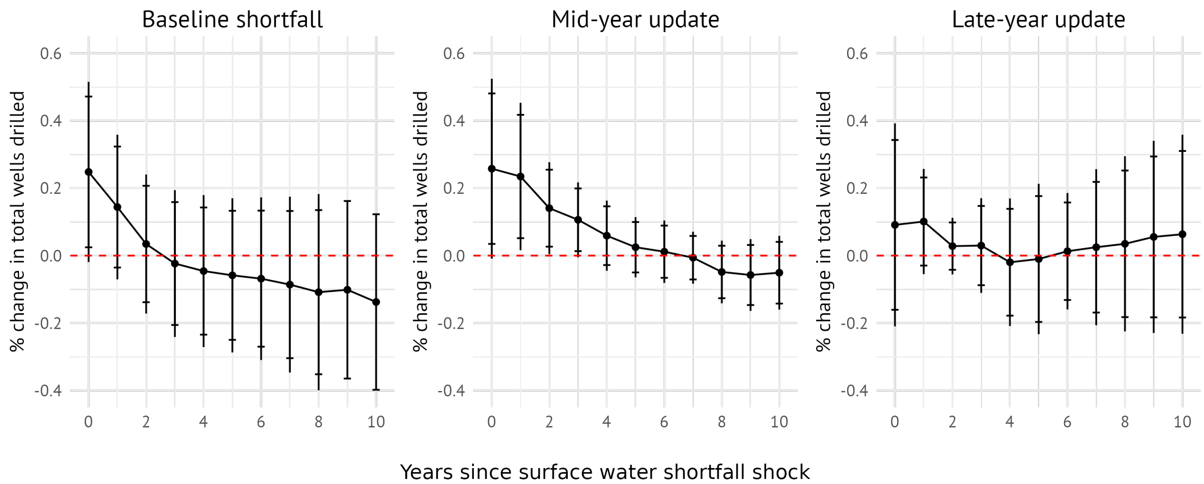
In this subsection, I study whether wells drilled in response to short-term shocks are additional, and for how long. In answering the question, I will learn how long behavior changes from a short-run shock lasts, important for measuring the persistence of external costs.

To study additionality, I trace the dynamic impact of a one-time surface water shortfall shock on the stock of wells in a district using local projections (Jordà, 2005). I 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 (1), 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 8. 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 6[19]. For the information that farmers responded to with well drilling, the initial surface water allocation and mid-year update, the

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

Figure 8: Dynamic well drilling response to surface water allocation shocks



Note: This plot shows the local projections estimates of the cumulative number of new wells in a district in the years following a surface water shortfall shock in year zero. A coefficent of zero shows that the number of wells drilled is the same as the expected trend.

cumulative number of wells in a district decreases monotonically after the shock occurs, and levels off at no effect after 3 years for the baseline forecast and 5 years for the mid-year update. Since farmers would not have drilled wells immediately after the shock, there are persistent social costs to drilling if wells affect farmers' behavior.

Wells shifting forward in time matters especially because continually, new farmers shifted their wells forward in time across my period of study. The reason shortfall shocks contributed to continuous new wells is because the value of wells increased steadily over time. I explain the intuition using a simple well value function in equation (3):

$$\begin{aligned} V(well = 0, \hat{s}, \bar{s}) = \max_{well \in \{0,1\}} \{ & \mathbb{E}(\pi(\hat{s}, well = 0) + \beta \mathbb{E}(V(well = 0, \bar{s}, \bar{s}), \\ & \mathbb{E}(\pi(\hat{s}, well = 1) + \underbrace{\beta \mathbb{E}(V(well = 1, \bar{s}, \bar{s}) - C}_{\text{stopping value}} \} \end{aligned} \tag{3}$$

A farmer chooses to drill a well when the value of drilling now is greater than the value of waiting. Three inputs determine the farmer's decision, the current year's forecasted shortfall $\hat{s}$, the expectation of the future average shortfall $\bar{s}$, and the well cost C. The outcome of decision has two terms. The first is the current year's profit, which depends only on the realized shortfall this year, and whether or not the farmer has a well. The value of a well increases when shortfall is higher. The second term is the expected value function in the next period. The stopping value is the expected sum of profits throughout time, given having drilled.

Even if a shortfall shock conveys no information about long-run surface water availability, a sufficiently severe short-term shock could induce a farmer with a relatively high stopping value to drill based solely on current-year profit considerations. If the value of having a well increases over time (though an increase in $\bar{s}$), new farmers will choose to drill in response to short-term shocks.

A long-run increase in well values is unlikely to be driven by the shortfall shocks themselves, as evidenced by the absence of permanent effects in the local projections results. If shortfall shocks were updating farmers' beliefs about long-run water availability, they would permanently shift the net present value of drilling upward for all farmers, accelerating drilling decisions and producing a persistent effect. Therefore, some other time-varying factor, such as declining surface water availability and the increasing price of perennials has driven the increase in long-run well values[20]. In appendix section B.6 I prove that the well stock permanently increased for water districts with contracts subject to a regulation that permanently shifted 14% of their surface water to environmental uses in 1992.

The wells drilled in response to shortfall shocks are a key piece of the story of short and long-run agricultural adaptation in California, driving persistently higher well stocks even if a specific farmer only drills a few years early. In any case, there is still a real social cost to drilling wells early. Farmers can extract groundwater earlier, and are incentivized to make other production adjustments earlier. Therefore, society bears the costs of externalities from extraction starting this year rather than several years from now, and eliminating more future scarcity rents under regulation.

4.2 How does well drilling affect future cropping choices?

Well drilling has social costs if wells incentivize farmers to switch to more socially costly behavior. Two primary ways farmers might change behavior is through new groundwater extraction, and switching crops. There is actually no data for extraction from specific wells in California, a challenge other papers have overcome in creative ways (Burlig et al., 2020). Therefore, it is actually not obvious how much a farmer would extract from a new well. I answer the question in detail in appendix section B.7, where I show that farmer extract on average up to the capacity of a small commercial agricultural well across all water years, a significant shift in water use. However, since wells increasing extraction is obvious, I focus on farmers' crop switching behavior after drilling.

Well drilling imposes social costs if it incentivizes farmers to adopt more socially costly behaviors. Farmers might change their behavior in two primary ways: by extracting additional groundwater and by switching to different crops. California lacks well-specific extraction data, a challenge other studies have addressed through creative approaches (Burlig et al., 2020), making it unclear ex-ante how much farmers extract from new wells. In appendix section B.7, I show that farmers extract on average up to the capacity of a small commercial agricultural well across all water years, which is a substantial shift in water use. Since farmers drill wells in order to extract groundwater, I focus on the question with the less obvious answer: do farmers change what they grow after drilling?

Crop choice matters independently of groundwater extraction levels. Perennial crops have higher opportunity costs of fallowing because they take several years to reach peak fruit production and remain productive for several decades, meaning that fallowing sacrifices both the sunk establishment costs and many years of future returns. Perennials are also highly profitable. Consequently, a farmer with a new well might switch to perennial crops to increase profitability, simultaneously locking herself into watering her fields even in very dry years.

Studying how wells cause crop shifting requires both dynamics and instrumental variables. I study the crop decision dynamically because farmers often cannot switch crops immediately. I use instrumental

[20] Also in appendix section B.6 I show the strong trends in increasing shortfalls and increasing perennial prices, as well as the nearly linear increase in cumulative wells drilled over time.

variables because the value of crops directly determines the cropping choice, and the value of a well.

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.

To isolate the effect of new wells on crop choice, I use well-specific supply shifters as an instrument. I construct the instrument from the interaction of two variables that capture different well supply shocks. The first measures market power in well drilling. Higher market power should increase well prices, holding all else equal. In my main specification, I measure market power by counting the number of well drilling contractors operating in each area. Specifically, I define a contractor as an entity that drilled at least two wells over the sample period. I determine each contractor's operational area as the 25-kilometer buffer around the convex hull of all wells they drilled, and operational lifetime as the time between drilling their first and last well. I then count how many contractors' operational areas overlap each location in each year, capturing the number of drillers capable of serving an area at a given time. This approach separates the supply measure from well demand in two ways. First, not all contractors drill wells every year, so the count reflects potential supply capacity rather than realized demand. Second, contractors cannot enter the market immediately due to certification requirements and machinery investments, creating a lag between demand shocks and supply responses. 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 which might correlate with well demand. Thus, I interact the market power variable with 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 for agricultural wells. I check for robustness to other well inputs including oil drilling machinery prices (a proxy for water well drilling machinery) and plastic piping prices (PVC casing is common for smaller agricultural wells).

Studying the dynamic effects of well drilling on cropping decisions using local projections would require at least 50 years of data to avoid bias (Herbst and Johannsen, 2024), longer than the crop data span in the main analysis. Therefore, I use county-level data from California's Agricultural Commissioner, the longest panel of harvested cropland available for California, spanning from 1980 to 2022 (CA Agricultural Commissioner, National Agricultural Statistics Service, 2025). I aggregate the same control variables used previously to the county level.

Equation (4) shows the first stage of my instrumental variables specification. Y_{ct} is the number of wells drilled between January and August. N_{ct} denotes the number of contractors, and P_t denotes the input prices. The excluded instrument is $\log(N_{ct}) \times P_t$. I leave prices in level terms because it is the indexed price since 2010. I include all of the controls as in the district-level estimation, X_{ct}, but use county and year fixed effects. I leave the well decision in linear terms because there is no clear way to transform the dependent variable given many zero values (Chen and Roth, 2024). I show the results of the first stage estimation in

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

	First stage			Reduced Form (Perennial)	
	(1)	(2)	(3)	(2)	(3)
Log contractors × Steel pipe index	0.05^{*}	0.07^{*}	0.07^{*}	48.86^{**}	48.62^{**}
	(0.03)	(0.04)	(0.04)	(20.14)	(20.09)
Log contractors	0.84	8.15	8.23	7204.03^{**}	7395.39^{**}
	(2.46)	(6.58)	(6.52)	(3384.79)	(3423.74)
Steel pipe price index	-0.19				
	(0.12)				
F-stat	39	30	39	NA	NA
Controls	no	no	yes	no	yes
County FEs	no	yes	yes	yes	yes
Year FEs	no	yes	yes	yes	yes
Standard Errors	Conley-NW	Conley-NW	Conley-NW	Conley-NW	Conley-NW
Num. obs.	2223	2223	2223	2223	2223
R^2 (full model)	0.05	0.66	0.67	0.48	0.48

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

Note: The first three columns show the first stage for how the number of wells are affected by the instrument. The last three columns show the reduced form for how the number of perennials three years after new wells are drilled 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. I use a combination of Conley standard errors (100km) and Newey-West standard errors (2 time lags) because the treatment is correlated across space and time.

table **??**.

$$Y_{ct} = \alpha_1 \log(N_{ct}) \times P_t + \alpha_2 \log(N_{ct}) + X_{ct} + \gamma_c + \gamma_t + \nu_{ct} \tag{4}$$

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, to show that in the raw data wells respond negatively to steel piping prices, and positively to contracts. 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. I find a positive coefficient on the instrument in the first stage, showing that districts with more contractors are less affected by increases in steel pipe prices. The instrument is statistically significant across all specifications, and has a high F-stat of nearly 40 in the main specification. The next three columns show the results of the reduced form estimation, where the dependent variable is the third lead of perennial acreage. Factors that increase wells in year t strongly increase perennials in year $t + 3$.

The instrument induces a small shift in well drilling costs, affecting farmers whose well values are close to the drilling threshold. Given that well values are increasing over time, these marginal farmers would likely have drilled within a few years regardless. Therefore, the local average treatment effect captures crop switching behavior for the most policy-relevant population: those on the margin of drilling in the near term.

The first-stage estimation reveals important information about aggregate drilling behavior by characterizing the shape of the demand curve. The well demand curve orders farmers by their drilling threshold price on the y-axis, indicating how many additional farmers would drill given a small change in well values. Crucially, from the farmer's perspective, a given change in well value has the same effect whether it stems from lower costs or higher benefits.

The first-stage results suggest that drilling decisions are quite responsive to price changes in aggregate. To quantify this responsiveness, I calculate a lower bound on the price elasticity of demand. The key challenge is determining how much drilling competition shields farmers from steel price increases. Assuming a conservative upper bound that competition totally eliminates pass-through, a 1-point increase in the steel price index (approximately 1%) raises total well installation costs by at most 0.5%.[21] Combining this upper-bound price increase with the first-stage estimate of the quantity response, I calculate a lower-bound price elasticity of demand of 0.7[22]. After learning more about the external costs of well drilling, this value will give an idea about how many excess wells were drilled absent regulation.

Figure 9 presents the second-stage results of the dynamic IV specification, showing how crop composition and total acreage change after a farmer drills a new well. Perennial acreage increases steadily by approximately 200 acres per year beginning in the second year after drilling, while three other crop categories decline. Total harvested acreage initially falls before returning to baseline or slightly above.

These results reveal a substantial restructuring of farm operations following well installation. The dynamics unfold in two distinct phases. In the first year after drilling, total acreage declines as farmers prepare land for conversion to perennials. They immediately reduce high-water field crops and vegetables, but because newly planted perennials require several years to mature, the perennial effect is precisely zero in year one. In subsequent years, farmers continue substituting away from all annual crop types toward perennials, and total acreage recovers to pre-drilling levels. Notably, pasture and hay acreage remains unchanged, consistent with this category representing a distinct type of agricultural operation less integrated with intensive cropping systems.

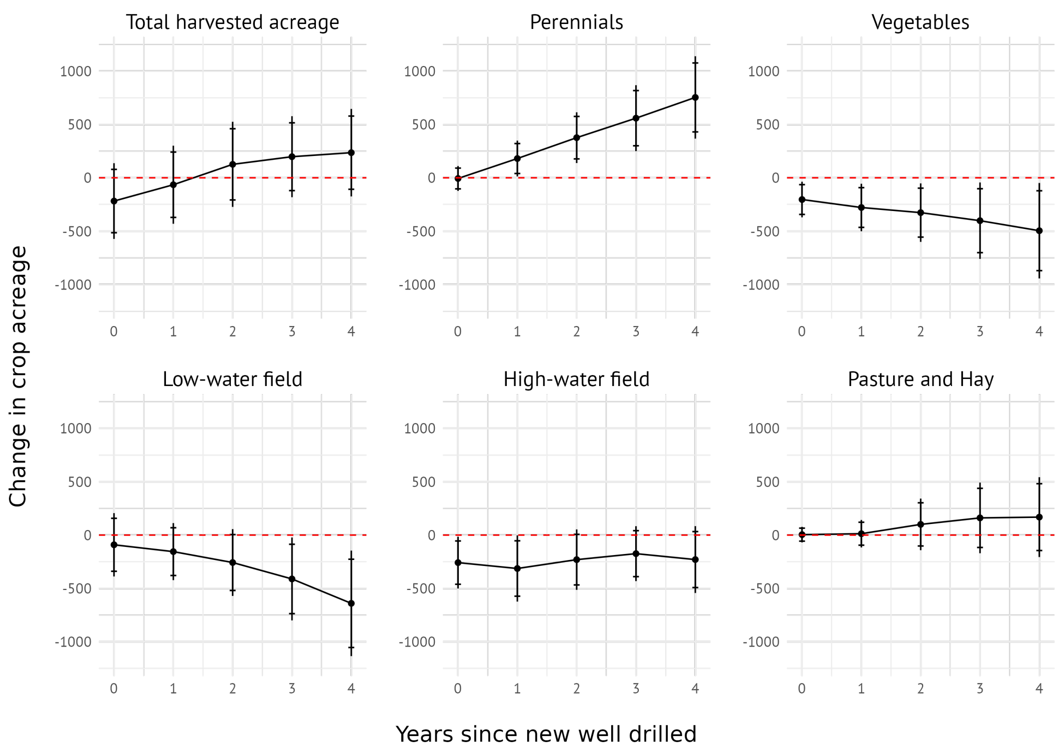
The change in cropping patterns increases groundwater use in three ways. First, farmers shift toward higher-water crops on average. While some vegetables and high-water field crops like cotton require water comparable to perennials, low-water field crops require only a fraction of that amount. The transition from low-water field crops to perennials therefore increases water use in any given year. Second, the high opportunity cost of fallowing perennials strengthens farmers' incentives to irrigate even during extreme droughts when surface water allocations are minimal. Third, total harvested acreage may increase slightly, expanding the area requiring irrigation.

Combining the dynamic paths of well drilling and cropping decisions, this section demonstrates that adaptation to short-run surface water shocks drives the persistent expansion of socially costly groundwater extraction. The mechanism operates through a self-reinforcing cycle: farmers drill wells in response to marginal changes in well value, then extract an estimated 1,800 acre-feet per year (appendix section B.7), a level consistent with their shift toward water-intensive perennial crops. The increase in well values continually amplifies this pattern, making adaptation progressively more water-intensive over time. This is confirmed by the finding in section 3 that farmers in districts with higher well stocks conserve significantly less water,

[21] The per-foot marginal cost of well installation is about \$50, and the per-foot total cost is about \$105. If the entire marginal cost were steel piping (an overestimate), then a 1% increase in steel prices yields a total cost increase of 50/105   0.5% (California Valley Floor Groundwater Sustainability Agency, 2020).

[22] Specifically, $\frac{\text{(0.07 (estimate of well increase) /20 (mean of wells))*100}}{\text{0.5\% (upper bound on price increase) *1 (pass through to districts with fewer contractors}}$.

Figure 9: Local projections of changes in crop acreage with 1 new well



Note: Each plot shows the dynamic effect of drilling 1 new well in year t on the change in crop acreage in different categories. The coefficients are estimated with LP-IV. The error bars show 90 and 95% confidence bounds for Conley standard errors accounting for spatial correlation within 100 km and temporal correlation within 2 years (since it is a short panel).

revealing how individual adaptation choices collectively undermine water conservation efforts.

Combining the dynamic paths of well drilling and cropping decisions, this section demonstrates that adaptation to short-run surface water shocks is a key driver in the persistent expansion of socially costly groundwater extraction. Building on section 3's finding that higher well stocks correlate with reduced conservation, I show that new wells drilled for adaptation also reshape agricultural choices beyond the adaptation response. When farmers adapt to a surface water shortfall in a given year by drilling a well, they not only increase groundwater extraction that year but commit to substantially higher extraction for years to follow. The failure to manage groundwater therefore creates a dual distortion: it makes both immediate groundwater extraction and well drilling artificially cheap. Specifically, farmers drill wells in response to marginal changes in well value and subsequently extract an estimated 1,800 acre-feet per year (appendix section B.7), consistent with their shift toward water-intensive perennial crops.

Section 3 established that farmers adapt primarily through groundwater extraction and well drilling, while this section demonstrates that well drilling triggers persistent changes in both extraction levels and cropping patterns, extending the effects of short-term adaptation far into the future. These changes impose social costs through aquifer depletion.

However, farmers adapt in the way that increases their profit the most. My paper currently can say nothing about how much society gains and loses from the way that farmers in California adapt. In the next section, I empirically estimate the total benefit from all adaptation actions to benchmark the external costs against.

5 Private value of adaptation to surface water scarcity

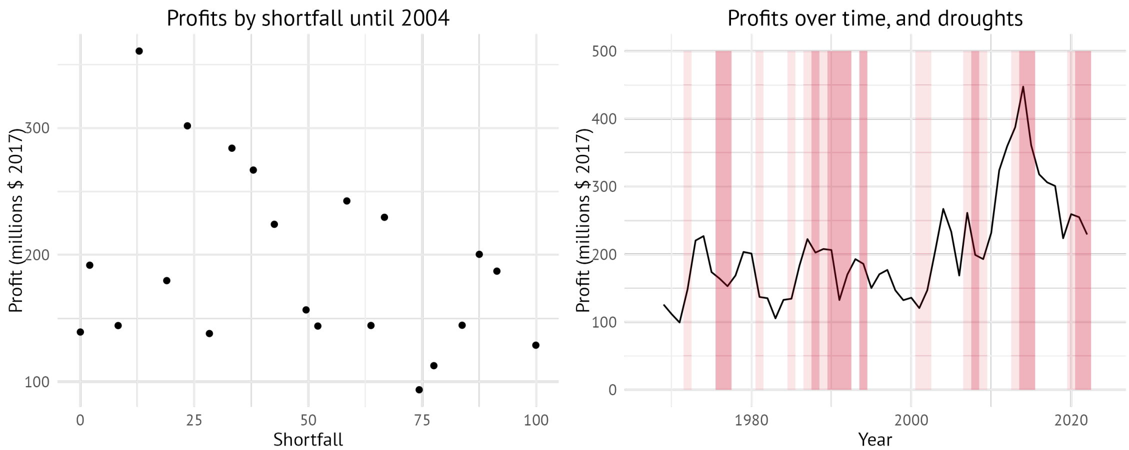
Throughout this paper, I have shown that farmers respond to information about surface water shortfalls by taking a variety of conservation and groundwater intensifying actions. I have not shown any evidence yet for how effective these actions are in recovering lost profits from surface water shocks.

Surface water scarcity is costly for farms. Figure 10 shows how surface water scarcity correlates with low county-level agricultural profits in the raw data. The left plot shows the binscatter of profits and shortfall from 1968 until 2004, the period when deflated profits remained relatively constant. The county-years with the highest profits also had relatively low shortfall. The right plot shows the entire time series of profits averaged across all counties. Plotted behind the time series are bars indicating 'dry' (light red) and 'critically dry' (dark red) years, as declared by the Department of Water Resources. Even when profits increased dramatically between 2005 and 2015, dry years accompanied profit declines.

In this section, I estimate the value of the entire set of adaptation actions that farmers take, including those unobserved in my analysis. These estimates contextualize the rest of the paper. First, they provide a reference point for the external costs documented earlier. Understanding both the benefits and costs reveals the net welfare implications of current adaptation patterns and, by extension, the potential gains from improved groundwater governance. Second, I will learn how much farmers gain from undertaking costly behavioral changes, information useful for designing effective and equitable water policies.

I begin this section by showing how to estimate the private net benefit of adaptation, through extending the estimating framework in the literature to the multiple forecast components present in my study. The main intuition is that the profit gained for making the forecast marginally closer to the realization is equivalent to the benefit of short-run adaptation. Afterward, I apply the framework to data.

Figure 10: Raw data plots of profits and surface water scarcity



Note: The left plot shows a binscatter of profit and shortfalls from the period spanning from 1968 until 2004. This was the period where crop profits (in 2017 \$) stayed relatively constant. Overall, the periods with the lowest shortfalls have the highest profits. The right plot shows the time series of average profits over time, with drought bars behind the series. The darkest drought bars show years declared 'critically dry' by the Department of Water Resources (the worst rating) and the lighter bars were declared 'dry'. Overall, even though profits increase later in the sample, dry periods often experienced declines in profits.

5.1 Conceptual framework for the benefit of adaptation

The goal of the conceptual framework is to explain how a marginal increase in accuracy of surface water information in a particular period of the year identifies the net private benefit of adaptation. The simple model builds on Shrader (2023) by incorporating multiple periods of information and clarifying the role of the accuracy of the forecast in the benefit of adaptation. After building the intuition, I apply the model to data.

Farmers take adaptation choices throughout the year based on surface water information available at a certain time in order to maximize a static profit function[23]. As I showed in section 3, farmers take different adaptation choices at different points 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, $\{early, mid, late\}$, where actions are more valuable when surface water scarcity s is higher. By the time that profits are realized, ex-ante adaptation a^*_{early} and mid-season adaptation a^*_{mid} are already determined. Ex-post adaptation a_{late} occurs right after the final shortfall is revealed.

The final profits depend on the realized surface water shortfall, s. 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 by:

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

[23]The static profit function is not as restrictive as it seems in this context. Standard dynamic models decompose the farmer's problem into two parts: choosing capital variables (e.g. well investments), and choosing variable inputs (e.g., annual extraction, annual crop mix) that adjust annually. My profit function captures the latter, the annual optimization over variable inputs conditional on the current state, which is identical whether farmers are fully forward-looking or myopic. The framework can accommodate a profit function that changes over time through time fixed effects

A simple thought experiment clarifies how the value of adaptation can be measured through forecasts. Imagine there are two identical farmers indexed by i, j, who end up with the same realized shortfall s. Both farmers received a shortfall forecast that underestimated the final shortfall, but the first farmer's underestimate was slightly higher, $\hat{s}_i < \hat{s}_j$. Farmer i prepared for slightly better conditions, and planted slightly more water intensive crops. Then, when both farmers receive s shortfall at the end of the season, farmer i had slightly lower profits. The difference between their profits, given that they both received the same amount of water in the end, reflects the value of having slightly better information earlier in the season.

I can show formally how the value of the initial forecast affects profits, conditional on the final shortfall, by differentiating the profit function in equation (5.1) by $\hat{s}$:

$$\frac{d\Pi}{d\hat{s}} : \underbrace{\frac{d\Pi(s)}{da^*_{early}}\frac{da^*_{early}}{d\hat{s}} + \frac{d\Pi(s)}{da^*_{mid}}\frac{da^*_{mid}}{da^*_{early}}\frac{da^*_{early}}{d\hat{s}}}_{\text{value of ex-ante adaptation}} + \underbrace{\frac{d\Pi(s)}{da^*_{mid}}\frac{da^*_{mid}}{d\hat{s}^{mid}}}_{\text{value of mid-season adaptation}} \underbrace{\frac{d\hat{s}^{mid}}{d\hat{s}}}_{1} + \underbrace{\frac{d\Pi(s)}{ds}}_{\text{direct effect}} \underbrace{\frac{ds}{d\hat{s}}}_{1} \tag{5}$$

The farmer's profit changes through three channels. The first two combine to make up the value of ex-ante adaptation. If a farmer faced a marginally higher $\hat{s}$, she would marginally change her early adaptation choice, and because of the substitution across adaptation periods, her mid-season adaptation choice as well. The value of adaptation is the change in net benefits from the change in actions coming from a change in information. 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. Since the shortfall s is defined as the forecast $\hat{s}$ plus the updates, marginally changing the forecast also changes the final shortfall, resulting in the direct effect term appearing in the equation.

If I take the derivative of profit with respect to the other components of shortfall information, I would recover the following information:

$$\begin{aligned} \frac{d\Pi}{d\hat{s}} &: \ \text{Value of ex-ante adaptation} + \text{Value of mid-season adaptation} + \text{Direct effect of scarcity} \\ \frac{d\Pi}{d\varepsilon^{mid}} &: \ \text{Value of mid-season adaptation} + \text{Direct effect of scarcity} \\ \frac{d\Pi}{d\varepsilon^{late}} &: \ \text{Direct effect of scarcity} \end{aligned} \tag{6}$$

By using the actual forecasts and realizations rather than the forecast components ($\hat{s}$, $\hat{s} + \varepsilon^{mid} = \hat{s}^{mid}$, $\hat{s} + \varepsilon^{mid} + \varepsilon^{late} = s$), I can identify each value of adaptation and the direct effect of scarcity directly. Equation (7) translates the theory into an empirical model. The value of ex-ante adaptation is given by β_1, the value of mid-season adaptation is given by β_2 and the direct effect of water scarcity is given by β_3.

$$\Pi_i = \beta_1 \hat{s}_i + \beta_2 \hat{s}_i^{mid} + \beta_3 s_i + \nu_i \tag{7}$$

Equation (7) gives a true value of adaptation when we define adaptation as the change in profit deriving from ex-ante actions. However, as defined, the equation can and often will estimate a negative value of adaptation. Consider again farmers i and j. Now, both farmers received an overestimate of shortfall, except that farmer i's shortfall forecast was higher: $\hat{s}_i > \hat{s}_j$. Farmer i fallows a few extra fields. Then, when both farmers receive s shortfall at the end of the season, farmer i had slightly lower profits because j harvested closer to the optimal level of fields for the water conditions. The marginal benefit of i's additional adaptation was negative.

More generally, consider the first term in equation (5) $\frac{d\Pi(s)}{da^*_{early}}\frac{da^*_{early}}{d\hat{s}}$. By assumption, $\frac{da^*_{early}}{d\hat{s}}$ is positive (a farmer idles 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 accuracy of the shortfall forecast. If $\hat{s} > s$, then shortfall is already forecasted higher than the realization and 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.

Estimating the equation (7) by pooling situations where the forecast was higher and lower than the realization will recover the average realized value of adaptation, which itself is interesting. For example, a negative realized value of adaptation will reveal that over-adapting is more costly than underadapting on average.

However, in my paper I am interested in 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. I use the best agricultural profits data available, which is at the county level spanning from 1967 to 2022. I aggregate district-level shortfall forecasts to the county level, 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[24] (Department of Water Resources, 2022).

Equation (8) shows the estimating equation, analogous to equation (7), incorporating the intuition that forecast accuracy matters for my preferred estimate of the value of adaptation. Y_{ct} measures the agricultural profits in a county, which I construct by subtracting the total agricultural expenses from yearly cash receipts. Since 9% of profit observations are negative, I opt to use OLS rather than PPML.

$$\begin{aligned} Y_{ct} =& \beta_1^{low} L_{ct}^{\text{base}} \hat{s}_{ct} + \beta_1^{high} H_{ct}^{\text{base}} \hat{s}_{ct} + \beta_2^{low} L_{ct}^{\text{mid}} \hat{s}_{ct}^{\text{mid}} + \beta_2^{high} H_{ct}^{\text{mid}} \hat{s}_{ct}^{\text{mid}} \\ & + \beta s_{ct} + X_{ct} + \gamma_c + \gamma_t + \varepsilon_{ct} \end{aligned} \tag{8}$$

To measure the value of a marginally more accurate forecast, I interact the two shortfall forecasts with an indicator for whether the forecast underestimated or overestimated the realization of shortfall. L_{ct}^{base} for example is the indicator for whether the baseline shortfall was lower than the realization, and H_{ct}^{mid} is the

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

indicator for whether the mid-season forecasted shortfall was higher than the realization. In my main results, since my estimand of interest is the value of the accuracy of the forecast, I combine the estimates so that $\beta_1 = \frac{1}{2}(\beta_1^{low} + \beta_1^{high})$ = Value of ex-ante adaptation.

The variation in equation 8 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.

X_{ct} includes the same controls as the previous estimation, including temperature, precipitation, depth to the water table, and long-term adaptation through cumulative wells drilled. I control more carefully for non-project water rights since my county profits data covers districts with other types of surface water rights. Particularly, I control for streamflow forecasts. I also control for crop storage and government payments, which are correlated with revenues and surface water availability (Fisher et al., 2012) using crop inventory changes and aggregate government payouts from the BEA data. Given the controls, the βs can be interpreted as measuring the change in outcomes due to specifically to changes in surface water shortfall forecasts.

The level profit variable contains numerous outliers and exhibits an upward trend in the second half of the period (previously shown in figure 10), both of which may bias coefficient estimates. To assess how addressing these issues affects my results, I present five specifications. The first uses the baseline specification. The second and third winsorize profits at the 2.5% and 5% levels to mitigate outlier effects. The fourth and fifth winsorize to the 2.5% level and then address the profit trend: the fourth interacts county fixed effects with an indicator for the post-2005 period, while the fifth restricts the sample to data prior to 2005, when profits began their upward trajectory.

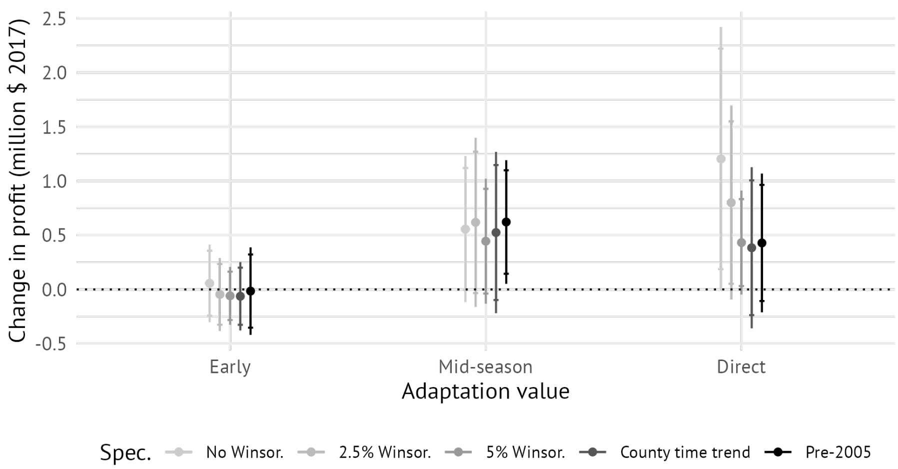
5.3 Results

I plot the net private benefit of early and mid-season adaptation and the direct effect of water scarcity across five specifications in figure 11. The coefficients on early and mid-season adaptation reflect the benefit, in millions of dollars, of having made the forecast marginally more accurate during the period. The coefficient on the direct effect of shortfall measures how an increase in shortfall affects profits.

The private value of early and mid-season adaptation remains consistent across all five specifications. Early adaptation has no detectable effect on profits, while mid-season adaptation yields approximately $500,000 per one-point improvement in forecast accuracy, which is roughly 0.3% of a county's total profits. In contrast, the estimated direct effect of shortfall varies considerably across specifications. Controlling for outliers and trends drives the shortfall coefficient toward zero. While the estimate is never negative as might be expected if surface water scarcity imposed costs, the lack of stability across specifications precludes meaningful interpretation.

The zero-value of early adaptation indicates that marginally more accurate early shortfall forecasts do not increase farm profits. One possible explanation is that early forecasts are too inaccurate for farmers to rely on as meaningful signals. However, section 3 shows that farmers do respond to early information with observable actions. A more plausible explanation is therefore that early forecasts arrive sufficiently in advance of the dry season that farmers have flexibility to adjust their decisions as updated information becomes available. In contrast, mid-season forecast accuracy has positive value, meaning that farmers are better off if the mid-season forecast is closer to the realization. Although I cannot estimate how much farmers adjust inputs at the end of the season to avoid losses because I can never see the no-adjustment counterfactual, the mid-season adaptation value can be interpreted as the value of being able to adjust

Figure 11: Private benefit of adaptation



Note: This plot shows the estimated private value of early adaptation, estimated from the average of β_1^{low} and β_1^{high}, mid-season adaptation, from the average of β_2^{low} and β_2^{high}, and the direct effect of adaptation, from β_3 from equation (8). For the values of adaptation, the y-axis shows the change in profit from the shortfall forecast being one point closer to the actual shortfall. The direct effect shows how increasing the shortfall affects profit. Each coefficient shows a different specification. The first is the standard specification without addressing the outliers and trends in the profit variable. The second specification winsorizes the profit variable on both ends at the 2.5% level. The third specification winsorizes at the 5% level. The fourth interacts the county fixed effect with an indicator for being late in the period. The fifth uses the subset of data only until 2005, after which profits begin to steeply increase. Overall, the direct effect is sensitive to the specification, which is not surprising given the spread of the profit variable. The estimates for adaptation are consistent across specifications, however.

inputs in the mid-season rather than the end of the season. In contrast, mid-season forecast accuracy has positive value, indicating that farmers benefit when mid-season forecasts more closely match actual water availability. While I cannot directly estimate end-of-season input adjustments, since the counterfactual of no adjustment is never observed, the positive mid-season adaptation value reveals the benefit of shifting farm decision making from the late to the mid-planting season.

To solidify the intuition, we can imagine a farmer who gets a low baseline forecast and plants a low-water winter crop to conserve water for her main summer plantings, some of which she might have to forego anyway. However, throughout the winter she gets news that there will be more surface water allocated than expected. The farmer has time to make use of the extra water by either planting all of her fields with a second crop in June, or even by planting a more water-intensive crop than previously planned, making up the vast majority of the profits from the bad forecast. In contrast, in response to a bad shortfall forecast in March, she plans to plant a portion of her fields in beans instead of tomatoes. However, when she gets better water news in April, she cannot switch to the more profitable crop, and those fields also cannot be double-cropped due to planting timing. She faces lower profits than if she had better information. Therefore, the value of ex-ante adaptation rises after the early planting season, and falls after the mid-planting season, driven by increasing constraints, and possibly improving information, as the dry season approaches.

Despite private profits being fully adjustable after decisions are made early in the year, some early choices lock farmers in to socially costly behavior. In particular, farmers drill more wells in response to early shortfall shocks. My results suggest that farmers do not get substantially extra benefit from making a drilling decision in January versus March, likely because their well would likely be completed by the dry season either way.

However, if the farmer waited until March to drill, the social cost might be lower: good news about water in March might result in delaying drilling for a year, which would delay the farmer's transition to perennials.

However, combining these results with those from the previous sections, the dominating pattern is that earlier adaptation, especially in the mid-season, is both privately valuable and relatively less socially costly. Late-season adjustments are less privately valuable and more socially costly. In the final section, I discuss what the alignment of private and social benefit means for policy and the impacts of climate change.

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

6.1 The external costs and benefits of short-run ex-ante adaptation

Farmers and society benefit when farmers can adapt early to surface water scarcity in California. When farmers receive shortfall information during the mid-planting season rather than late in the season, they extract less groundwater and earn higher profits, though they become slightly more likely to drill new wells. Each section of my paper quantifies one component of these benefits. Section 3 estimates how groundwater extraction changes when farmers receive information at different times. I calculate the statewide value by multiplying this change in groundwater depth by total groundwater use and the average externality cost. Section 4 examines well drilling decisions, showing that new wells remain additional for several years and increase water extraction. I value this effect by multiplying the additional groundwater use by the average externality cost. Section 5 directly estimates farmers' private profit from receiving information early. Figure 12 synthesizes these findings by showing the total benefit, to both farmers and society, of providing shortfall information during the mid-planting season rather than the late-planting period, for a 1-point increase in water shortfall, using $40/acre-foot as the average externality of groundwater use in the state[25].

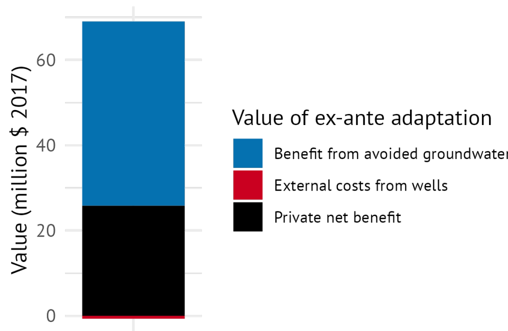
Even using assuming a small externality, the benefits from avoided groundwater dominate the value of ex-ante adaptation. About 63%, and 43 million dollars in benefit comes from farmers taking more conserving actions in the mid-planting season. The rest comes from the benefit farmers get from being able to better tailor their actions. A study focusing only on farmer benefits of adaptation would have missed more than half of the adaptation value. Shifting the shortfall shock to the mid-planting period comes at the small cost of about 3.5 additional wells across the state, creating about $0.7 million dollars worth of damage.

In the case of short-term adaptation, farm and social benefits align. Better mid-season water forecasts increase farmers' profits while reducing external costs. This is good news in many politically constrained governments: investing in improved forecasts is often feasible even when managing aquifers is not, and there are sizable benefits.

However, climate change directly undermines short-term water forecasting capabilities. In California, surface water shortfall forecasts improved steadily until the mid-2000s, when accuracy began declining. By 2022, the 5-year rolling standard deviation between February and May shortfall forecasts for the State

[25] $40 is the per-unit extraction fee charged under the Sustainable Groundwater Management Act for districts who did not establish their own fees Vad (2024). However, transition fees, the fee that agencies apply on water excess of safe yield in order to curb excess extraction (socially suboptimal useage), is a more intuitive proxy for an externality. These transition water fees range from $90 to $210 (Greenspan et al., 2024). I would use an estimated value if it existed. A few papers discuss the externality in their empirical analysis. (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.

Figure 12: Value of farmers adapting in the mid-season period vs. ex-post



Note: This plot shows the estimated value of giving farmers information about a marginal surface water shortfall shock in the mid-planting period rather than the late-planting season period. The benefit from avoided groundwater comes from section 3, where I found that in the late-planting period, groundwater depth increased by 0.07%, approximately 9% of the standard change in groundwater depth, versus close to zero in the late-planting period. I multiply this change by the average groundwater use in agriculture (12 million acre feet) and an estimate of the value of the externality. The private net benefit comes from section 5, where I found that the average county earned \$0.55 million more when the shortfall forecast was more accurate. The external cost from wells comes from the average increase in wells across the state from a shock in the mid-planting period ($\sim$ 3.5) multiplied by the increase in groundwater use from a well, the length of time the well is additional, and the value of the groundwater externality.

Water Project had deteriorated to 1994 levels (see appendix figure A.4). This erosion of forecasting accuracy represents an often-overlooked cost of climate change: it diminishes our capacity to adapt effectively. The Department of Water Resources' plan to improve forecasts is therefore a policy with potentially significant social benefits (California Department of Water Resources, 2020).

6.2 Externally costly adaptation

While short-run ex ante adaptation to surface water shortfalls in California generates social benefits, ex post and long-term adaptation often impose substantial social costs through excessive groundwater extraction. Farmers face only the private cost of pumping groundwater, while the full social cost includes two additional components: physical externalities such as land subsidence and water quality degradation, and the intertemporal scarcity rent representing the opportunity cost of current versus future extraction.

The absence of effective groundwater regulation, combined with climate change, creates a compounding problem. Climate change accelerates groundwater depletion through two mechanisms: it incentivizes both greater extraction from the existing stock and increased investment in extraction capacity. This excess current adaptation erodes farmers' future adaptive capacity, leaving them more vulnerable to subsequent climate shocks. Simultaneously, as climate change increases the future marginal value of groundwater for adaptation, current extraction destroys even more resource wealth.

The climate adaptation literature studying agricultural responses to climate change typically abstracts away from how farmers adapt, thereby overlooking both the external costs of adaptation and whether adaptive capacity persists over time. My research reveals that these external costs are substantial. During ex post adaptation, over 75% of farmers' adaptive response generates external costs. In aggregate across California, farmers' ex post response to a marginal surface water shock increases statewide water use by nearly 3%, approximately 1 million additional acre-feet annually.[26]

Moreover, adaptation has become increasingly water-intensive over time. Farmers respond to a 1% increase in well value with at least a 0.7% increase in drilling activity, while surface water shortfalls accelerate drilling timelines by 3 to 5 years. Each new well imposes large external costs through immediate increased extraction, reduced conservation incentives, and expansion of perennial crops—externalities that likely sum to $1.4 million in present value for a moderately-sized commercial well.[27] Yet farmers currently pay only $50,000 to $500,000 to drill a well. The marginal well owner has the lowest-valued current use, and therefore appropriates groundwater from much higher-valued future uses, exemplifying the misallocation inherent in unregulated common-pool resources.

7 Conclusion

This paper examines how California farmers have adapted to growing surface water scarcity and what their adaptive strategies mean for long-term sustainability. My analysis focuses on farmers' responses to government forecasts of yearly surface water shortfalls. I categorize their adaptation into two types: water-conserving actions like crop switching, and groundwater-intensifying actions like well drilling and increased pumping. While farmers pursue both strategies, they rely much more heavily on groundwater extraction when responding to late-season shortfall announcements.

One key finding is that farmers adapt in the short run by drilling wells earlier than planned. Surface water shortfalls accelerate drilling decisions by 3-5 years, and new farmers continue entering the well market because well values have been rising throughout the study period. Once farmers drill, they shift toward more water-intensive crops and immediately increase extraction. Areas with higher well density also show less water conservation. The overall pattern is clear: adaptation to surface water scarcity in California has become increasingly groundwater-dependent over time.

Farmers' short-run ex ante adaptation, planning ahead for anticipated shortfalls, delivers considerable private benefits while imposing relatively modest social costs. Therefore, restricting groundwater access need not eliminate farmers' capacity to adapt. Yet, the prevailing pattern in adaptation over time is that farmers have undermined their own future adaptive capacity through both current overdraft and accelerating investment in extraction infrastructure.

Ultimately, this research demonstrates how climate change and common-pool resource problems amplify each other. Unregulated groundwater access undermines the long-term value of climate adaptation, while climate change accelerates the race to deplete the resource. My paper demonstrates the increasing value of regulating both common-pool resources and mitigating climate-change.

References

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

[26] The calculation: 0.07% represents about 9% of average total extraction. With yearly average groundwater use of 12 million acre-feet, ex post adaptation adds roughly 1 million acre-feet, or 3% of the 30 million acre-feet used annually.

[27] Based on estimated annual extraction of 1,800 acre-feet per well, discounted at an average externality of $40 per acre-foot, yielding a net present external cost of $1.44 million.

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

Auffhammer, M. and T. A. Carleton (2018). Regional crop diversity and weather shocks in india. *Asian Development Review 35*(2), 113–130.

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

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

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

Blakeslee, D., R. Fishman, and V. Srinivasan (2020). Way down in the hole: Adaptation to long-term water loss in rural india. *American Economic Review 110*(1), 200–224.

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

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

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

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

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

Bruno, E. M. and K. Jessoe (2021). Missing markets: Evidence on agricultural groundwater demand from volumetric pricing. *Journal of Public Economics 196*, 104374.

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

Burke, M. and K. Emerick (2016). Adaptation to climate change: Evidence from us agriculture. *American Economic Journal: Economic Policy 8*(3), 106–140.

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

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

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

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

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

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

California Department of Water Resources (2020). How DWR research is improving forecasting for california's variable climate. https://water.ca.gov/News/Blog/2020/How-DWR-Research-is-Improving-Forecasting-for-California-s-Variable-Climate. Accessed: 2025-11-11.

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

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

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

California Department of Water Resources (2025a). Climate change and water. https://water.ca.gov/Programs/All-Programs/Climate-Change-Program/Climate-Change-and-Water. Accessed: 2025-10-20.

California Department of Water Resources (2025b). Drought. https://water.ca.gov/water-basics/drought. Accessed: 2025-09-30.

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

California Office of Environmental Health Hazard Assessment (OEHHA) (2024, July). Snow-water content. https://oehha.ca.gov/climate-change/epic-2022/impacts-physical-systems/snow-water-content#:~:text=The%20amount%20of%20water%20stored%20in%20the,record%20low%20of%205%20percent%20in%202015. Accessed: 2025-10-20.

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

California Valley Floor Groundwater Sustainability Agency (2020, November). Well drilling costs (eis attachment). `https://cvfpb.ca.gov/wp-content/uploads/2020/11/8b.-EIS-Attachment-Well-Drilling-Costs.pdf`. Accessed: 2025-11-09.

Callaway, B. and P. H. Sant'Anna (2021). Difference-in-differences with multiple time periods. *Journal of econometrics 225*(2), 200–230.

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

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

Carleton, T., A. Jina, M. Delgado, M. Greenstone, T. Houser, S. Hsiang, A. Hultgren, R. E. Kopp, K. E. McCusker, I. Nath, et al. (2022). Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits. *The Quarterly Journal of Economics 137*(4), 2037–2105.

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

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

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

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

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

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

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

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

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

Deschenes, O. (2022). The impact of climate change on mortality in the united states: Benefits and costs of adaptation. *Canadian Journal of Economics/Revue canadienne d'économique 55*(3), 1227–1249.

Deschênes, O. and M. Greenstone (2007). The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. *American economic review 97*(1), 354–385.

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

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

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

Eckstein, G. (2021). International law for transboundary aquifers: a challenge for our times.

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

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

Fishman, R. (2018). Groundwater depletion limits the scope for adaptation to increased rainfall variability in india. *Climatic change 147*(1), 195–209.

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

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

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

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

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

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

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

Herbst, E. P. and B. K. Johannsen (2024). Bias in local projections. *Journal of Econometrics 240*(1), 105655.

Hoover, D. L. and W. K. Smith (2025). The growing threat of multiyear droughts. *Science 387*(6731), 246–247.

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

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

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

Imbens, G. W. and W. K. Newey (2009). Identification and estimation of triangular simultaneous equations models without additivity. *Econometrica 77*(5), 1481–1512.

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

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

Jordà, Ò. (2023). Local projections for applied economics. *Annual Review of Economics 15*(1), 607–631.

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

Kunkel, F. (1960). *Time, Distance and Drawdown Relationships in a Pumped Ground-water Basin*, Volume 433. US Department of the Interior, Geological Survey.

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

Kuwayama, Y. and N. Brozović (2013). The regulation of a spatially heterogeneous externality: Tradable groundwater permits to protect streams. *Journal of Environmental Economics and Management 66*(2), 364–382.

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

Lemoine, D. (2018). Estimating the consequences of climate change from variation in weather. Technical report, National Bureau of Economic Research.

Lobell, D. B. and S. Di Tommaso (2025). A half-century of climate change in major agricultural regions: Trends, impacts, and surprises. *Proceedings of the National Academy of Sciences 122*(20), e2502789122.

McClurg, S. and R. S. Sudman (2000). Central valley project improvement act update. *Western Water*. Excerpt.

Michler, J. D., K. Baylis, M. Arends-Kuenning, and K. Mazvimavi (2019). Conservation agriculture and climate resilience. *Journal of environmental economics and management 93*, 148–169.

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

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

Montiel Olea, J. L. and M. Plagborg-Møller (2021). Local projection inference is simpler and more robust than you think. *Econometrica 89*(4), 1789–1823.

Nagaraj, D., E. Proust, A. Todeschini, M. C. Rulli, and P. D'Odorico (2021). A new dataset of global irrigation areas from 2001 to 2015. *Advances in Water Resources 152*, 103910.

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

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

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

Regnacq, C., A. Dinar, and E. Hanak (2016). The gravity of water: Water trade frictions in california. *American Journal of Agricultural Economics 98*(5), 1273–1294.

Reitz, M., W. E. Sanford, and S. Saxe (2023). Ensemble estimation of historical evapotranspiration for the conterminous us. *Water Resources Research 59*(6), e2022WR034012.

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

Schlenker, W. and M. J. Roberts (2009). Nonlinear temperature effects indicate severe damages to us crop yields under climate change. *Proceedings of the National Academy of sciences 106*(37), 15594–15598.

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

Sears, L., C.-Y. L. Lawell, D. Lim, G. Torres, and M. T. Walter (2017). Interjurisdictional spatial externalities in groundwater management. Technical report, Working Paper, University of Davis.

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

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

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

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

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

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

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

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

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

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

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

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

UC Master Gardener Program (2025). Time of planting. https://mg.ucanr.edu/. University of California Agriculture and Natural Resources (UC ANR).

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

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

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

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

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

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

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

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

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

Vad, J. (2024). State board to vote on reducing extraction fees for probationary basins. *San Joaquin Valley Water*.

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

Water Education Foundation (2025). California water timeline. `https://www.watereducation.org/aquapedia/california-water-timeline`. Accessed October 20, 2025.

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

Wheeler, S. A., A. Zuo, and J. Kandulu (2021). What water are we really pumping? the nature and extent of surface and groundwater substitutability in australia and implications for water management policies. *Applied Economic Perspectives and Policy 43*(4), 1550–1570.

A Data and Context

Table A.1: Surface Water Allocation Forecast Timing Summary Statistics

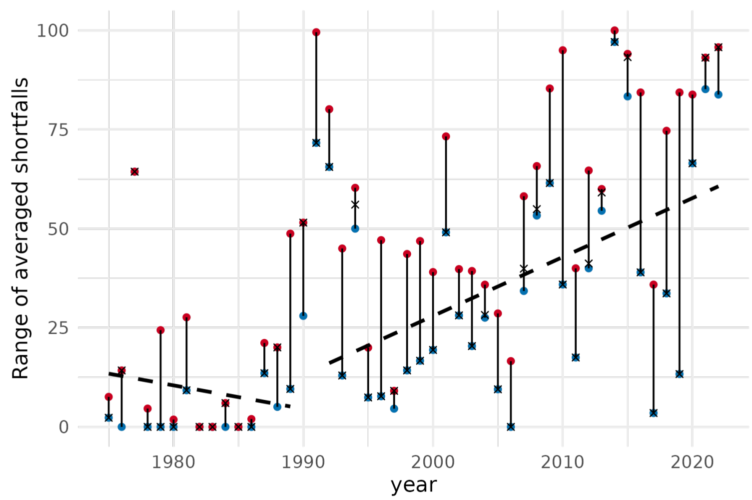
	SWP		CVP (south)	
Time Period	% with updates	Mean allocation %	% with updates	Mean allocation %
Near Feb 1 (Forecast)	97.96	38.39	53.06	40.50
Near Apr 1 (Forecast)	73.47	54.10	89.80	45.36
Near June 1 (Final)	46.94	60.00	63.27	60.77

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[28]. 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

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

Figure A.1: Range of shortfall within a year and across years



Note: This figure summarizes the surface water allocation shortfall variation within a year and across years. For the within-year variation, I plot the averages surface water shortfalls across contracts for each the February, March and June forecasts. The lowest and highest average shortfall of the year are plotted here, as well as a line to denote the range. An 'x' denotes the final shortfall allocation. I also plot the long-run trends of the final shortfall allocation, with a break at 1992 to illustrate the change in forecasting policy at that point from the Central Valley Project Improvement Act

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

Figure A.2: Four examples of how a farmer would encounter a surface water allocation forecast

Advance-Register

City eyes new police station

Army paid $124 for 9-inch piece of string

TIP chief may work part time

Season chore

County reps discuss their fiscal plight

Snack tax ends, welfare cuts start

State Water Project delivery projected at only 10 percent

Excessive force case against police officers goes to trial

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

WATER PROJECTS

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

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

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

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

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

State Water Project Increases Allocation Forecast for Millions of Californians

Published: Jan 28, 2025

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

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

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

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

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

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

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

From the Bureau of Reclamation:

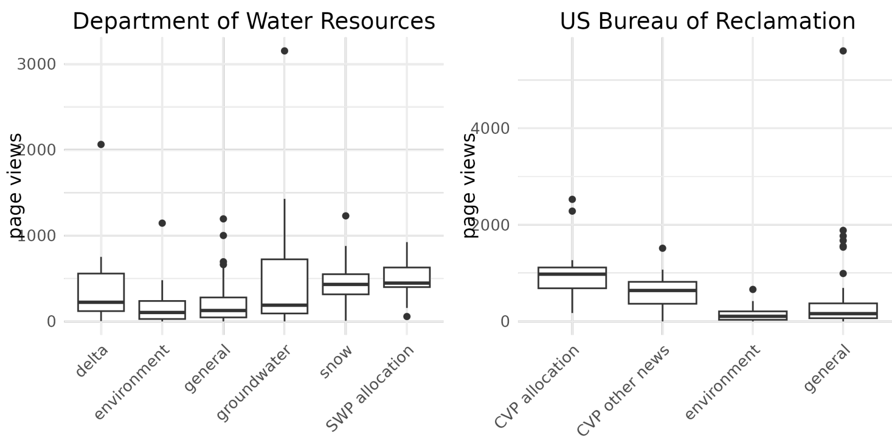
BUREAU OF RECLAMATION

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

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

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

Figure A.3: Page views by subject on California water news aggregator

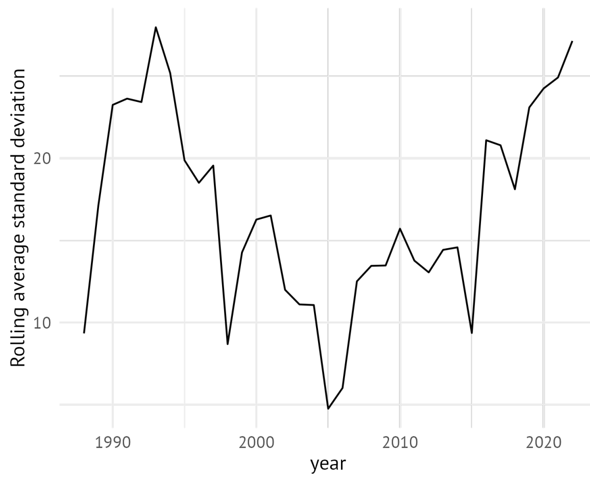


Note: Distribution of page views by topic on Maven's Notebook, a California water news aggregator. News collected on May 1, 2025, spanning 5 years.

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

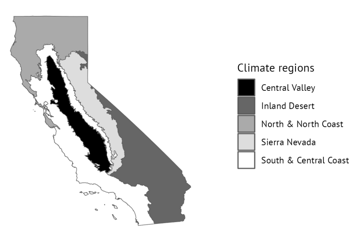
Region		**Early planting**	**Late planting**
Central Valley	Low Water	Wheat (170mm) Carrots (150mm)	Corn (700mm) Tomatoes (650mm)
	High Water	Sugarbeets (220mm) Onions (500mm)	Rice (1100mm) Cotton (1000mm)
Inland Desert	Low Water	Broccoli (140mm) Wheat (270mm)	Corn (780mm) Squash (470mm)
	High Water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

Figure A.4: Rolling average standard deviation of difference between February shortfall forecast and May shortfall



Note:

Figure A.5: California ecological regions



Note: This map shows the five major ecological regions in California relevant for agriculture, shows climate regions across the state, aggregated up from level 3 ecoregions to crop planting regions (UC Master Gardener Program, 2025). The regions differ by growing season, and also generally in water availability. The Central Valley has a long growing season, and access to a deep aquifer. The South and Central Coast has cooler weather, with some important aquifers. The Inland desert region has an early planting season (winter) and has minimal groundwater and relies heavily on surface water supplies. There is minimal cropland in the North Coast and Sierra Nevada, and I observe no water districts in these two regions

B Supplementary Results

B.1 Control function approach to control for simultaneous adaptation actions

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. The results using the control function approach are shown in column 3 of each of the regression tables in section B.2.

B.2 Alternative specifications for the main regression, and the coefficient estimates

Table B.1: Well drilling responses

	Main	No controls	All controls	Conley errors	New timing	OLS
Baseline shortfall	0.28	0.25	0.30	0.28^{***}	0.15	0.33
	(0.18)	(0.18)	(0.18)	(0.10)	(0.11)	(0.37)
Mid-season shortfall update	0.25^{*}	0.23	0.25^{*}	0.25^{***}	0.28^{*}	0.13
	(0.15)	(0.14)	(0.14)	(0.06)	(0.16)	(0.23)
Late-season shortfall update	-0.01	-0.02	-0.01	-0.01	0.01	-0.83^{*}
	(0.14)	(0.14)	(0.14)	(0.12)	(0.15)	(0.42)
Omitted vars. controls	yes	no	yes	yes	yes	yes
Control function	no	no	yes	no	no	no
Baseline forecast	Last year	Last year	Last year	Last year	January	Last year
District FEs	yes	yes	yes	yes	yes	yes
Year FEs	yes	yes	yes	yes	yes	yes
SE cluster	contract	contract	contract	Conley 100 km	contract	contract
Num. obs.	4674	4686	4640	4674	4697	4910
Pseudo R^2	0.61	0.61	0.61	0.61	0.61	0.75

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

Note: These columns show six alternate specifications for the well drilling response to surface water shortfalls from section 3. The dependent variable is the total number of wells drilled in a district between January and August. The first column is the main specification, plotted in figure 6. The main specification includes early-season precipitation, early-season temperature, the lagged depth to the groundwater table and the lagged cumulative number of wells in a district as controls, as well as district and year fixed effects. The standard errors are clustered at the contract level. For the first five columns estimated with PPML, the coefficients roughly show the percent change in an action with a one-point increase in the surface water shortfall from each of the three periods in the planting season. The second column omits all controls except for fixed effects. The third column includes all baseline controls, adding the control function for groundwater extraction and crop choice. The fourth column uses standard errors robust to spatial correlation, using a radius slightly larger than the average county in California. The fifth column uses the January forecast as the baseline information, rather than the previous year's final shortfall. Since not all district-years have forecast information in January, I make the assumption that nearby districts with forecasts have the most relevant information, and fill missing information using the closest local information. The final column is the same specification as the first, but estimated with OLS.

Table B.2: Depth to groundwater responses

	Main	No controls	All controls	Conley errors	New timing	OLS
Baseline shortfall	0.04	-0.01	0.03	0.04	0.06	-2.02
	(0.07)	(0.08)	(0.08)	(0.05)	(0.08)	(9.63)
Mid-season shortfall update	0.02	-0.00	0.01	0.02	0.02	-2.09
	(0.06)	(0.06)	(0.06)	(0.05)	(0.06)	(6.34)
Late-season shortfall update	0.08^{*}	0.04	0.09^{**}	0.08^{***}	0.07^{*}	2.31
	(0.04)	(0.05)	(0.04)	(0.03)	(0.04)	(4.54)
Omitted vars. controls	yes	no	yes	yes	yes	yes
Control function	no	no	yes	no	no	no
Baseline forecast	Last year	Last year	Last year	Last year	January	Last year
District FEs	yes	yes	yes	yes	yes	yes
Year FEs	yes	yes	yes	yes	yes	yes
SE cluster	contract	contract	contract	Conley 100 km	contract	contract
Num. obs.	4923	4923	4488	4923	4950	4923
Pseudo R^2	0.75	0.75	0.76	0.75	0.75	0.81

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

Note: These columns show six alternate specifications for the change in depth to the groundwater table response to surface water shortfalls from section 3. The dependent variable is the level depth to the groundwater table in the dry season (absolute value) in feet. The change in depth to the groundwater table is a proxy for groundwater extraction. The first column is the main specification, plotted in figure 6. The main specification includes early-season precipitation, early-season temperature, the lagged depth to the groundwater table and the lagged cumulative number of wells in a district, and the regional groundwater depth as controls, as well as district and year fixed effects. The standard errors are clustered at the contract level. For the first five columns estimated with PPML, the coefficients roughly show the percent change in an action with a one-point increase in the surface water shortfall from each of the three periods in the planting season. The second column omits all controls except for fixed effects. The third column includes all baseline controls, adding the control function for groundwater extraction and crop choice. The fourth column uses standard errors robust to spatial correlation, using a radius slightly larger than the average county in California. The fifth column uses the January forecast as the baseline information, rather than the previous year's final shortfall. Since not all district-years have forecast information in January, I make the assumption that nearby districts with forecasts have the most relevant information, and fill missing information using the closest local information. The final column is the same specification as the first, but estimated with OLS.

Table B.3: Evapotranspiration responses

	Main	No controls	All controls	Conley errors	New timing	OLS
Baseline shortfall	−0.01	−0.00	−0.04	−0.01	−0.03	−0.09
	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.09)
Mid-season shortfall update	−0.01	−0.00	−0.02	−0.01	−0.00	−0.05
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.06)
Late-season shortfall update	0.03	0.03	0.02	0.03	0.03^{*}	0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Omitted vars. controls	yes	no	yes	yes	yes	yes
Control function	no	no	yes	no	no	no
Baseline forecast	Last year	Last year	Last year	Last year	January	Last year
District FEs	yes	yes	yes	yes	yes	yes
Year FEs	yes	yes	yes	yes	yes	yes
SE cluster	contract	contract	contract	Conley 100 km	contract	contract
Num. obs.	4500	4513	4465	4500	4524	4500
Pseudo R^2	0.18	0.18	0.18	0.18	0.18	0.85

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

Note: These columns show six alternate specifications for the evapotranspiration response to surface water shortfalls from section 3. The dependent variable is average evapotranspiration, measured in meters per year. Evapotranspiration is a proxy for the total amount of water applied. The first column is the main specification, plotted in figure 6. The main specification includes early-season precipitation, early-season temperature, the lagged depth to the groundwater table and the lagged cumulative number of wells in a district as controls, as well as district and year fixed effects. The standard errors are clustered at the contract level. For the first five columns estimated with PPML, the coefficients roughly show the percent change in an action with a one-point increase in the surface water shortfall from each of the three periods in the planting season. The second column omits all controls except for fixed effects. The third column includes all baseline controls, adding the control function for groundwater extraction and crop choice. The fourth column uses standard errors robust to spatial correlation, using a radius slightly larger than the average county in California. The fifth column uses the January forecast as the baseline information, rather than the previous year's final shortfall. Since not all district-years have forecast information in January, I make the assumption that nearby districts with forecasts have the most relevant information, and fill missing information using the closest local information. The final column is the same specification as the first, but estimated with OLS.

Table B.4: Idling responses

	Main	No controls	All controls	Conley errors	New timing	OLS
Baseline shortfall	0.18	0.24^{*}	0.15	0.18	0.13	-307.90
	(0.12)	(0.12)	(0.13)	(0.11)	(0.14)	(412.74)
Mid-season shortfall update	0.24^{***}	0.25^{***}	0.19^{**}	0.24^{***}	0.26^{***}	227.67
	(0.08)	(0.08)	(0.09)	(0.06)	(0.07)	(282.99)
Late-season shortfall update	0.40^{***}	0.44^{***}	0.38^{***}	0.40^{***}	0.44^{***}	504.41^{*}
	(0.07)	(0.07)	(0.08)	(0.10)	(0.07)	(281.03)
Omitted vars. controls	yes	no	yes	yes	yes	yes
Control function	no	no	yes	no	no	no
Baseline forecast	Last year	Last year	Last year	Last year	January	Last year
District FEs	yes	yes	yes	yes	yes	yes
Year FEs	yes	yes	yes	yes	yes	yes
SE cluster	contract	contract	contract	Conley 100 km	contract	contract
Num. obs.	1938	1946	1934	1938	1940	1938
Pseudo R^2	0.98	0.98	0.98	0.98	0.98	0.94

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

Note: These columns show six alternate specifications for the idling response to surface water shortfalls from section 3. The dependent variable is the number of idled acres in a district. There are fewer observations than the earlier actions because crop data only spans from 2007-2022. The first column is the main specification, plotted in figure 6. The main specification includes early-season precipitation, early-season temperature, the lagged depth to the groundwater table and the lagged cumulative number of wells in a district, and the lagged total perennial area as controls, as well as district and year fixed effects. The standard errors are clustered at the contract level. For the first five columns estimated with PPML, the coefficients roughly show the percent change in an action with a one-point increase in the surface water shortfall from each of the three periods in the planting season. The second column omits all controls except for fixed effects. The third column includes all baseline controls, adding the control function for groundwater extraction and crop choice. The fourth column uses standard errors robust to spatial correlation, using a radius slightly larger than the average county in California. The fifth column uses the January forecast as the baseline information, rather than the previous year's final shortfall. Since not all district-years have forecast information in January, I make the assumption that nearby districts with forecasts have the most relevant information, and fill missing information using the closest local information. The final column is the same specification as the first, but estimated with OLS.

Table B.5: Perennial planting responses

	Main	No controls	All controls	Conley errors	New timing	OLS
Baseline shortfall	0.05	0.12	0.05	0.05	0.09	-343.18
	(0.10)	(0.12)	(0.10)	(0.09)	(0.09)	(473.86)
Mid-season shortfall update	0.02	0.03	0.02	0.02	-0.00	-341.25
	(0.05)	(0.06)	(0.05)	(0.04)	(0.06)	(227.19)
Late-season shortfall update	0.03	0.06	0.03	0.03	-0.01	-1041.44^{**}
	(0.06)	(0.07)	(0.06)	(0.05)	(0.06)	(397.17)
Omitted vars. controls	yes	no	yes	yes	yes	yes
Control function	no	no	yes	no	no	no
Baseline forecast	Last year	Last year	Last year	Last year	January	Last year
District FEs	yes	yes	yes	yes	yes	yes
Year FEs	yes	yes	yes	yes	yes	yes
SE cluster	contract	contract	contract	Conley 100 km	contract	contract
Num. obs.	1938	1946	1934	1938	1940	1938
Pseudo R^2	0.98	0.98	0.98	0.98	0.98	0.97

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

Note: These columns show six alternate specifications for the perennial response to surface water shortfalls from section 3. The dependent variable is the number of perennial acres in a district. There are fewer observations than the earlier actions because crop data only spans from 2007-2022. Perennial acreage is primarily a placebo, since farmers should not drastically adjust permanent acreage in response to surface water shocks. The first column is the main specification, plotted in figure 6. The main specification includes early-season precipitation, early-season temperature, the lagged depth to the groundwater table and the lagged cumulative number of wells in a district, and the lagged total perennial area as controls, as well as district and year fixed effects. The standard errors are clustered at the contract level. For the first five columns estimated with PPML, the coefficients roughly show the percent change in an action with a one-point increase in the surface water shortfall from each of the three periods in the planting season. The second column omits all controls except for fixed effects. The third column includes all baseline controls, adding the control function for groundwater extraction and crop choice. The fourth column uses standard errors robust to spatial correlation, using a radius slightly larger than the average county in California. The fifth column uses the January forecast as the baseline information, rather than the previous year's final shortfall. Since not all district-years have forecast information in January, I make the assumption that nearby districts with forecasts have the most relevant information, and fill missing information using the closest local information. The final column is the same specification as the first, but estimated with OLS.

Table B.6: High-water cropping responses

	Main	No controls	All controls	Conley errors	New timing	OLS
Baseline shortfall	-0.24^{**}	-0.22^{**}	-0.26^{**}	-0.24^{*}	-0.35^{***}	669.52
	(0.11)	(0.09)	(0.10)	(0.12)	(0.08)	(525.62)
Mid-season shortfall update	-0.19^{**}	-0.20^{**}	-0.20^{**}	-0.17	-0.14	202.51
	(0.09)	(0.09)	(0.09)	(0.11)	(0.10)	(209.02)
Late-season shortfall update	-0.25^{**}	-0.24^{**}	-0.26^{**}	-0.25^{*}	-0.17	386.37
	(0.11)	(0.11)	(0.11)	(0.13)	(0.14)	(371.64)
Omitted vars. controls	yes	no	yes	yes	yes	yes
Control function	no	no	yes	no	no	no
Baseline forecast	Last year	Last year	Last year	Last year	January	Last year
District FEs	yes	yes	yes	yes	yes	yes
Year FEs	yes	yes	yes	yes	yes	yes
SE cluster	contract	contract	contract	Conley 100 km	contract	contract
Num. obs.	1906	1914	1902	1906	1908	5774
Pseudo R^2	0.99	0.99	0.99	0.99	0.99	0.38

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

Note: These columns show six alternate specifications for the high-water acreage response to surface water shortfalls from section 3. The dependent variable is the number of high-water annual acres in a district, which are typically planted late in the planting season. There are fewer observations than the earlier actions because crop data only spans from 2007-2022. The first column is the main specification, plotted in figure 6. The main specification includes early-season precipitation, early-season temperature, the lagged depth to the groundwater table and the lagged cumulative number of wells in a district, and the lagged total perennial area as controls, as well as district and year fixed effects. The standard errors are clustered at the contract level. For the first five columns estimated with PPML, the coefficients roughly show the percent change in an action with a one-point increase in the surface water shortfall from each of the three periods in the planting season. The second column omits all controls except for fixed effects. The third column includes all baseline controls, adding the control function for groundwater extraction and crop choice. The fourth column uses standard errors robust to spatial correlation, using a radius slightly larger than the average county in California. The fifth column uses the January forecast as the baseline information, rather than the previous year's final shortfall. Since not all district-years have forecast information in January, I make the assumption that nearby districts with forecasts have the most relevant information, and fill missing information using the closest local information. The final column is the same specification as the first, but estimated with OLS.

Table B.7: Low-water cropping responses

	Main	No controls	All controls	Conley errors	New timing	OLS
Baseline shortfall	0.35^{***}	0.38^{***}	0.35^{***}	0.35^{**}	0.45^{***}	750.47^{**}
	(0.10)	(0.09)	(0.10)	(0.16)	(0.11)	(363.10)
Mid-season shortfall update	0.26^{***}	0.29^{***}	0.25^{***}	0.26^{*}	0.24^{***}	355.39^{**}
	(0.10)	(0.10)	(0.09)	(0.15)	(0.09)	(163.32)
Late-season shortfall update	0.17^{**}	0.17^{**}	0.22^{***}	0.17	0.11	424.00
	(0.08)	(0.08)	(0.08)	(0.18)	(0.08)	(257.65)
Omitted vars. controls	yes	no	yes	yes	yes	yes
Control function	no	no	yes	no	no	no
Baseline forecast	Last year	Last year	Last year	Last year	January	Last year
District FEs	yes	yes	yes	yes	yes	yes
Year FEs	yes	yes	yes	yes	yes	yes
SE cluster	contract	contract	contract	Conley 100 km	contract	contract
Num. obs.	1906	1914	1902	1906	1908	5774
Pseudo R^2	0.97	0.96	0.97	0.97	0.97	0.37

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

Note: These columns show six alternate specifications for the low-water acreage response to surface water shortfalls from section 3. The dependent variable is the number of low-water annual acres in a district, which are typically planted earlier in the planting season. There are fewer observations than the earlier actions because crop data only spans from 2007-2022. The first column is the main specification, plotted in figure 6. The main specification includes early-season precipitation, early-season temperature, the lagged depth to the groundwater table and the lagged cumulative number of wells in a district, and the lagged total perennial area as controls, as well as district and year fixed effects. The standard errors are clustered at the contract level. For the first five columns estimated with PPML, the coefficients roughly show the percent change in an action with a one-point increase in the surface water shortfall from each of the three periods in the planting season. The second column omits all controls except for fixed effects. The third column includes all baseline controls, adding the control function for groundwater extraction and crop choice. The fourth column uses standard errors robust to spatial correlation, using a radius slightly larger than the average county in California. The fifth column uses the January forecast as the baseline information, rather than the previous year's final shortfall. Since not all district-years have forecast information in January, I make the assumption that nearby districts with forecasts have the most relevant information, and fill missing information using the closest local information. The final column is the same specification as the first, but estimated with OLS.

B.3 Multinomial logit crop responses

I aggregate the Cropland Data Layer classifications into 7 categories which reflect crops with different planting times, watering intensities, and planting intensities to reflect the qualitatively different substitutions available. Low-water crops are typically planted in the winter, and are usually grains. High-water crops are typically planted late in the year, like rice and cotton. I also include a category for mixed-water crops, which can be low-water if they are planted early, and high-water if they are planted late, like many vegetables. Double crops have two or more planting times, like alfalfa and double-cropped grains. Perennial (permanent) crops include fruit trees and nut trees. The last two categories are idled fields, and non-agricultural fields.

$$\begin{aligned}\mathbb{C} =&\{\text{low-water}, \text{high-water}, \text{mixed-water},\\ &\text{double-cropped}, \text{non-ag}, \text{idle}, \text{perennial}\}\end{aligned}$$

Consider a farmer i who decides every year whether to plant her field in one of each seven crop categories. Of course, some of these decisions are dynamic, and several papers have modelled the dynamics of the decision ((Scott, 2014), Burlig et al. (2020)). My simpler model is intended to capture short-term annual cropping decisions relative to the dynamic category (perennials) which I find in my main empirical specification does not respond very much to short-term information.

The simple multinomial logit model is shown in equation B.3. The fraction of all of the fields planted in crop $c, j \in \mathbb{C}$ depends on the shortfall information, as well as other controls including the district-level past wells drilled, field crop prices, weather, depth to the water table, ecological region, groundwater availability, and total average water availability.

$$P(c_{it}|Z_{it}, \mathbb{C}, \beta) = \frac{e^{Z_{it}^{c}\beta}}{\sum_{j\in\mathbb{C}} e^{Z_{ft}^{j}\beta}}$$

The results are shown in table B.8.

Table B.8: Multinomial logit: response of crop choice to forecast shortfall

varname	double	early	idle	late	mixed	non_ag
(Intercept)	20.181***	10.027***	9.471***	12.864***	13.805***	5.75***
	(0.087)	(0.136)	(0.32)	(0.287)	(0.31)	(0.314)
Baseline forecast	1.063***	0.771***	0.367***	-0.052	0.084**	0.01
	(0.062)	(0.068)	(0.051)	(0.05)	(0.038)	(0.04)
Mid shortfall update	0.43***	0.259***	0.094*	-0.044	0.165***	0.098***
	(0.063)	(0.07)	(0.052)	(0.05)	(0.039)	(0.041)
Late shortfall update	0.544***	-0.086	-0.064	-0.33***	0.156***	0.252***
	(0.073)	(0.078)	(0.059)	(0.057)	(0.045)	(0.051)
Log lag cumulative wells	-0.278***	-0.485***	-0.647***	-0.568***	-0.232***	-0.249***
	(0.015)	(0.016)	(0.013)	(0.013)	(0.011)	(0.012)
Rainfall	-0.001***	-0.001***	0.001**	-0.001**	0.002***	0.002***
	(0)	(0)	(0)	(0)	(0)	(0)
Temperature	-0.132***	-0.125***	0.08***	-0.128***	0.036***	0.035***
	(0.013)	(0.015)	(0.01)	(0.011)	(0.008)	(0.008)
Central Valley = 1	4.488***	3.255***	1.341***	4.423***	0.899***	-2.442***
	(0.178)	(0.236)	(0.118)	(0.214)	(0.116)	(0.115)
Inland Desert = 1	4.612***	1.902***	4.472***	2.078***	3.357***	1.939***
	(0.342)	(0.332)	(0.162)	(0.139)	(0.162)	(0.155)
Sierra Nevada = 1	7.544***	1.825***	2.41***	3.067***	6.635***	6.277***
	(0.305)	(0.003)	(0.014)	(0.008)	(0.204)	(0.183)
South Coast = 1	3.537***	3.045***	1.248***	3.296***	2.914***	-0.024
	(0.193)	(0.242)	(0.123)	(0.22)	(0.12)	(0.118)
GW depth in 2000	-0.583***	-0.513***	-0.497***	-0.638***	0.029**	0.244***
	(0.015)	(0.017)	(0.014)	(0.013)	(0.014)	(0.016)
log(-1 * lag_depth)	0.116***	0.122***	0.18***	0.234***	-0.246***	-0.164***
	(0.021)	(0.023)	(0.018)	(0.018)	(0.016)	(0.019)
Log area (km^2)	0.22***	0.48***	0.523***	0.534***	0.159***	0.432***
	(0.016)	(0.018)	(0.013)	(0.013)	(0.012)	(0.013)
Log groundwater use	-0.008*	0.001	-0.02***	0.003	-0.01***	-0.13***
	(0.004)	(0.005)	(0.003)	(0.004)	(0.003)	(0.003)
log(price_field)	-3.694***	-2.037***	-1.778***	-2.464***	-2.313***	-0.754***
	(0.044)	(0.064)	(0.07)	(0.084)	(0.065)	(0.065)
Log non-project ag water	0.004	0.017***	0.025***	0.01***	0.035***	-0.062***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)

Note: These are the log-odds coefficients of a multinomial logit model of crop choice in response to information throughout the growing season. The omitted category is perennial acreage, which I show in my main results respond very little to short term information because of the high cost of switching crops from year to year. 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.

B.4 Heterogeneity results

Table B.9: Heterogeneity by location

	Extraction	Total water	Idling
Baseline shortfall	-0.06	-0.19^{***}	-0.13
	(0.08)	(0.05)	(0.26)
Mid-season shortfall update	-0.02	-0.33^{***}	0.11
	(0.08)	(0.07)	(0.15)
Late-season shortfall update	-0.07	0.02	0.07
	(0.10)	(0.04)	(0.15)
Baseline × Central Valley	0.15	0.21^{***}	0.26
	(0.10)	(0.03)	(0.24)
Baseline × Desert	-0.36^{***}	0.05	0.13
	(0.12)	(0.06)	(0.25)
Mid update × Central Valley	0.07	0.37^{***}	0.18
	(0.09)	(0.06)	(0.16)
Mid update × Desert	-0.22^{*}	-0.48^{***}	0.31^{*}
	(0.13)	(0.15)	(0.17)
Late update × Central Valley	0.19^{*}	0.02	0.33^{**}
	(0.10)	(0.04)	(0.14)
Late update × Desert	-0.03	0.27^{**}	0.50^{***}
	(0.19)	(0.12)	(0.17)
Controls	yes	yes	yes
District FEs	yes	yes	yes
Year FEs	yes	yes	yes
SE cluster	contract	contract	contract
Num. obs.	4923	4500	1634
Pseudo R^2	0.77	0.10	0.98

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

Note: This table shows the main regression in equation (1), interacting each of the shortfall components by an indicator for whether the district is in the South and Central Coast (baseline category), the Central Valley or the Inland Desert, shown in the map in Appendix figure A.5. The baseline category in the first three rows are the districts in the temperate coastal region. Each coefficient estimate is the percent change (0.07 = 0.07%) in an adaptation action with a 1-point increase in shortfall. Each column is a different adapation action. The first column is groundwater extraction, proxied by change in the depth to the groundwater table. The second column is total water application, proxied by evapotranspiration. The final column is acres idled. Each regression uses the main specification, which includes district and year fixed effects, controls for alternative water sources, neighbors' water demand, and the log of the total number of wells in a district. Standard errors are clustered at the contract level, which is the level that shortfall forecasts differ.

Table B.10: Heterogeneity by news

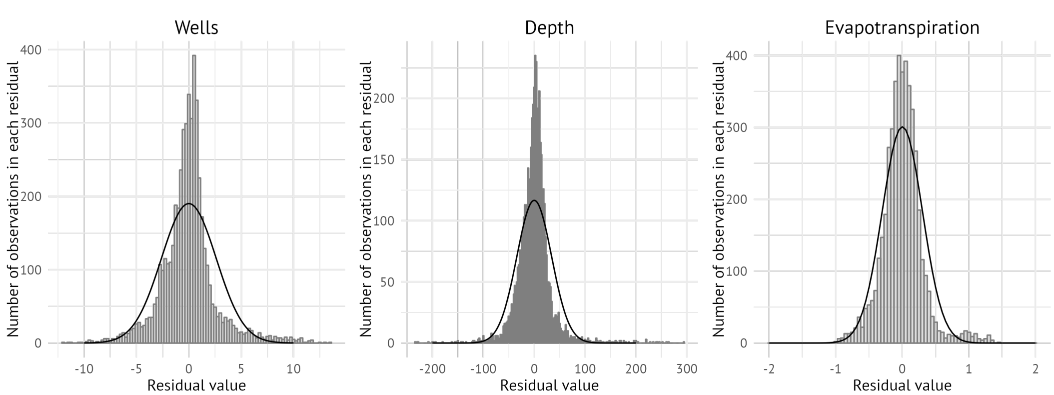
	Extraction	Total Water	Idling
Baseline shortfall	−0.00	−0.03	0.08
	(0.08)	(0.04)	(0.16)
Mid-season shortfall update	−0.04	−0.00	0.12
	(0.06)	(0.03)	(0.14)
Late-season shortfall update	0.02	−0.02	0.39*
	(0.03)	(0.03)	(0.23)
Mid update × Bad news	0.05	−0.02	0.11
	(0.06)	(0.04)	(0.17)
Late update × Bad news	0.07	0.09***	0.56**
	(0.05)	(0.02)	(0.26)
Controls	yes	yes	yes
District FEs	yes	yes	yes
Year FEs	yes	yes	yes
SE cluster	contract	contract	contract
Num. obs.	4923	4500	1634
Pseudo R^2	0.77	0.10	0.98

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

Note: This table shows the main regression in equation (1), interacting each of the shortfall updates by an indicator for whether the district received bad shortfall news, defined by the shortfall increasing, or by the shortfall equalling zero given a low initial surface water shortfall forecast. The baseline category is good surface water news. Each coefficient estimate is the percent change (0.07 = 0.07%) in an adaptation action with a 1-point increase in shortfall. Each column is a different adapation action. The first column is groundwater extraction, proxied by change in the depth to the groundwater table. The second column is total water application, proxied by evapotranspiration. The final column is acres idled. Each regression uses the main specification, which includes district and year fixed effects, controls for alternative water sources, neighbors' water demand, and the log of the total number of wells in a district. Standard errors are clustered at the contract level, which is the level that shortfall forecasts differ.

B.5 Distributions

Figure B.1: Distributions of residuals using OLS



B.6 Do farmers drill wells as a long-term adaptation strategy?

Separating the study of short and long-term surface water supply on well drilling is tightly connected to new advancements in the climate econometrics literature. Deschênes and Greenstone (2007) showed using the envelope theorem that the effect of deviations in local weather from the average on economic outcomes identify the effect of climate. However, Lemoine (2018) clarifies the theory primarily by showing that capital and resource-intensive adaptation makes the effect of short-term weather fluctuations differ from the effect of long-term climate. My paper will explore whether the theoretical advancement has practical implications in California agriculture.

Lemoine (2018) lays out reasons for why agents might adapt differently in the long-term than the short term. First, agents might only pay for long-term investments if the climate permanently changed. Second, a change in short-run forecasts is different from a permanent change in expected weather. Third, reactions to short-run weather and long-term climate are different.

The well choice value function V is made up of three inputs, whether the well has been drilled yet ($well \in \{0,1\}$), the current year's forecasted shortfall $\hat{s}$ and the expectation of the future average shortfall $\bar{s}$. In future periods, the forecasted shortfall is just the average expected shortfall. The farmer makes the choice to drill a well when the value of drilling now is greater than the value of waiting.

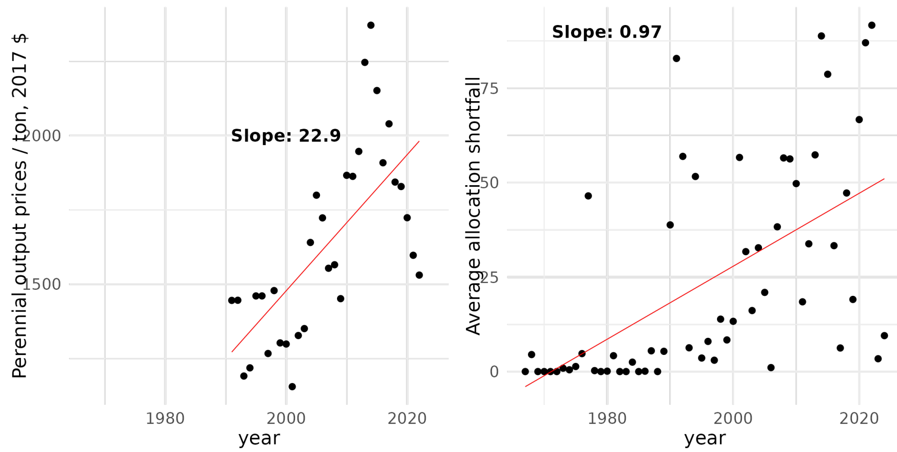
By studying the effect of short term shortfall on wells in section 3, I was targetting the first part of the value function, the current year profit: $\pi(\hat{s}, well)$. I found that changing $\hat{s}$ did not result in a permanent increase in wells, suggesting that $\hat{s}$ does not contribute very much to beliefs about $\bar{s}$. In this section, I target how a change in $\bar{s}$ affects the decision.

The main reason the climate econometrics literature exists is because it is difficult to find identifying variation from differences in climate, and it is analogously more difficult to identify adaptation to long-run surface water availability. Hagerty (2022) has one of the only papers studying long-run adaptation using quasi-random variation in long-run conditions. His paper also studies water scarcity in California, using a regression discontinuity across water districts with different quantities of water rights. Instead, I use a change in surface water allocation policy which applied only to water districts with project rights.

In October 1992, the US Congress passed the Central Valley Project Improvement Act, which redistributed 800,000 acre feet, about 14% of CVP water, of water from contractors to environmental uses. The act was highly controversial, and marked a fundamental and permanent change in the operation and goals of the Central Valley Project. The State Water Project was also affected due to the coordinated operations of the projects (McClurg and Sudman, 2000). the state had very little ability to curtail forms of water rights at the time, and thus no other rights were affected. Pressure for a law to protect the environment in the Sacramento-San Joaquin delta had been mounting since 1978, when the State Water Board issues Water Rights Decision 1485 requiring SWP and CVP to meet Delta water quality standards. However, no significant legislation had been passed, and no proposal had met either the State Water Board nor the EPA's requirements (Water Education Foundation, 2025).

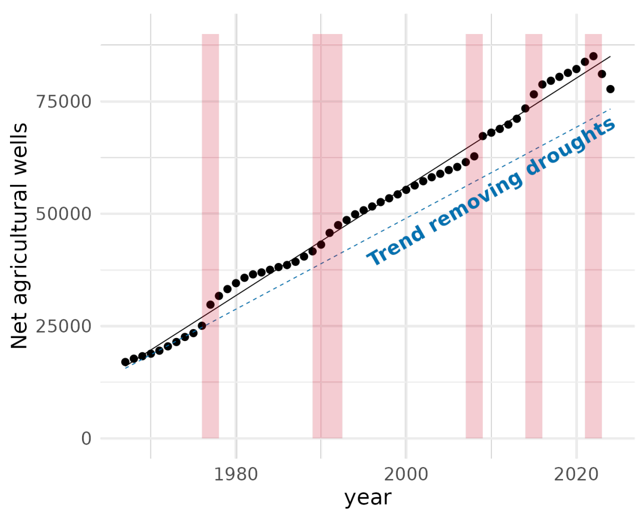
I use the passage of the Central Valley Project Improvement Act to identify the effect of a permanent decrease in surface water for districts with project contracts. Since no surface water market existed at the time, only the project districts were affected. Districts with other forms of water rights make up the control group. I use a differences-in-differences type of event study design to estimate how districts facing the permanent decrease in surface water drilled wells compared to the rest. Equation (9) shows the estimating strategy:

Figure B.2: Long-run determinants of well drilling: perennial prices and surface water shortfalls



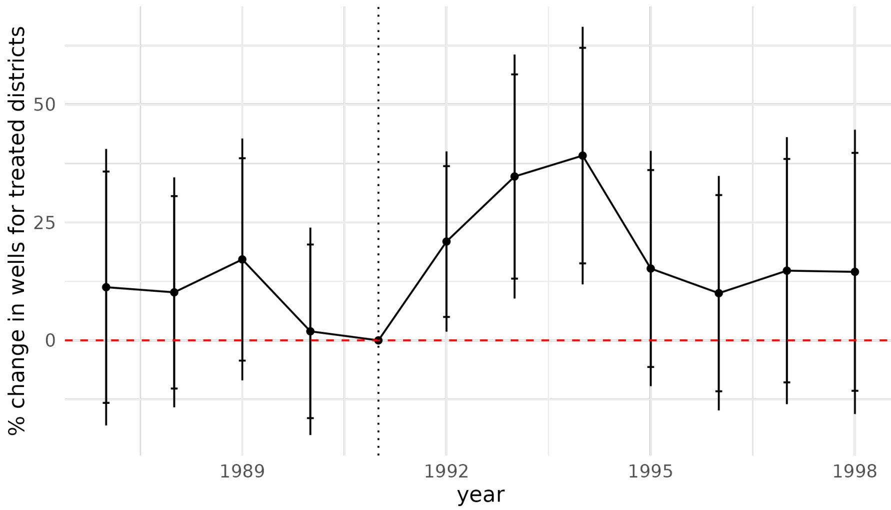
Note:

Figure B.3: 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, 2025b). 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.

Figure B.4: Wells drilled in project relative to non-project districts after CVP Improvement Act



$$A_{dt} = \exp(\sum_{y\in\{1987,\ldots,1998\}} \beta_y P_d \times \mathbb{1}(t = y) + X_{dt} + \gamma_d + \gamma_t + \nu_{dt}) \tag{9}$$

P_d is an indicator variable for districts with project contracts. $\mathbb{1}(t = y)$ is an indicator variable for the year being equal to y, since the event occurs at the same time for all districts. β_y is the difference in the level of well drilling for project and non-project districts in year t. For my main specification, I continue to use a PPML regression since it best captures the well drilling decision. In robustness checks, I instead use (Callaway and Sant'Anna, 2021) to address any potential problems doing differences-in-differences with multiple periods, using a logged dependent variable.

Figure B.4 shows the result. The baseline year is 1991, the year before the Central Valley Project Improvement Act was passed. In 1992, project districts drilled 25% more wells than they would have absent the act. In 1993 and 1994, project districts drilled nearly 40% more wells than otherwise. By 1995 and beyond, the treatment effect drops, and is not statistically different from zero.

Unlike the short-term drilling result, the number of wells drilled in response to the permanent shift in surface water availability is not temporary. Six years after the shock, there is no evidence in the well drilling trend reversing to capture wells that would have been drilled several years in the future. Also, compared to the short-term results, the amount of well drilling increase is huge. Officially, 14% of CVP water was reallocated to environmental uses. Empirically, I find that post 1992, districts' allocation was on average 13 percentage points less, after accounting for a time trend. Therefore, the treatment in the event study was 14 times larger every year than the marginal shortfall change I explored in section 3, but the well drilling effect was 350 times larger, and permanent.

B.7 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.

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 (10) 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 B.11.

$$Y_{dt} = \alpha_1 N_{dt} \times P_t + \alpha_2 N_{dt} + X_{dt} + \gamma_d + \gamma_t + \nu_{dt} \tag{10}$$

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

Table B.11: 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

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

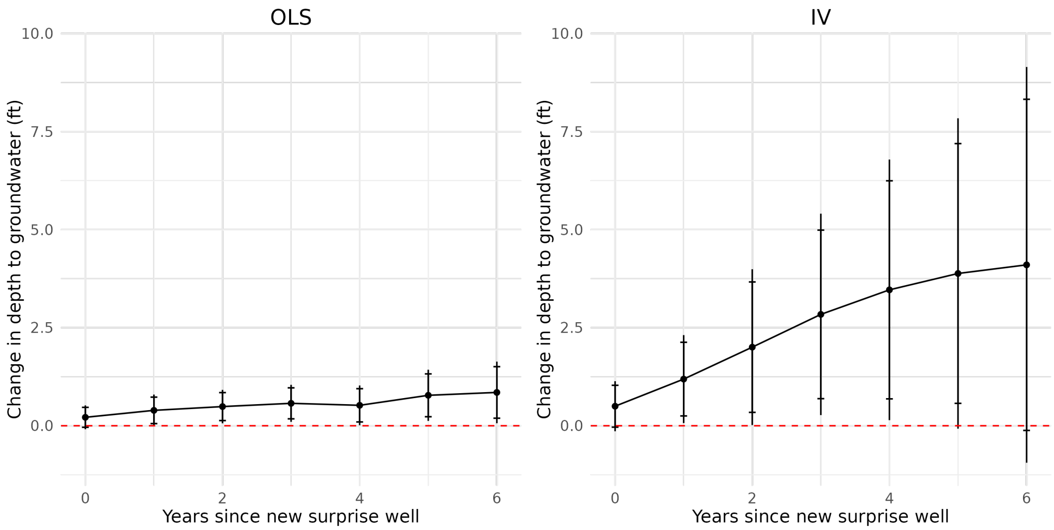
Note: The first three columns show the first stage for how the number of wells are affected by the instrument, and the last three columns show the reduced form for how the depth to the groundwater table is affected by the instrument. The instrument is the first row, the interaction of the number of contractors 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.

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 B.5. 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 variables. 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

Figure B.5: Change in depth to the groundwater table with 1 new well in a district



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)[29]. 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[30]. 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.

[29]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.

[30]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.