Measuring water misallocation in California

Preliminary and Incomplete

Will Rafey*

October 18, 2025

Abstract

This paper proposes and applies new methods to value water rights and assess misallocation across competing uses in California, the world's fifth largest economy. The empirical strategy combines detailed microdata on farms, evapotranspiration, historical water rights, and the hydrological flow network in order to isolate sources of inefficiency within the hydrological network, assess distributional implications of water access under current property rights, and evaluate alternative mechanisms for water reallocation.

JEL Classifications: L1, L2, Q1, Q25, D23, D61
Keywords: water rights, misallocation, California

---

*UCLA Department of Economics and NBER. John Asker, Fiona Burlig, Allan Collard-Wexler, Jackson Dorsey, Eric Edwards, Jeremy Fox, Nick Hagerty, Ellen Hanak, Matt Kahn, Bryan Leonard, Victoria Marone, Guillermo Marshall, and Daniel Xu, and seminar participants at AEA/ASSA TPUG, Columbia, Columbia GSB, Duke, PERC, Texas A&M, University of British Columbia, UCLA, UT Austin, and the Yale School of the Environment provided many helpful thoughts and comments. Defne Ertem, Sage Haroche, Ariana Ramos, David Tofer, and Maria Trubetskaya provided exceptional research assistance. This work was conducted with support from the UCLA Hellman Society of Fellows, the Council on Research of the Academic Senate of the Los Angeles Division of the University of California, and the Property and Environment Research Center Lone Mountain Fellowship. All errors are my own.

1 Introduction

Methods to value existing water property rights are critical to design and assess a range of increasingly important environmental and economic policies. This paper proposes and applies a unified approach to value water property rights in settings where they are rarely or never traded. The approach combines insights from recent work on agricultural production, equilibrium land use, and factor misallocation in a setting where water use can be inferred over time from detailed remote sensing data on crop choices, orchard ages, yields, prices, and local evapotranspiration data on weather and soil conditions used to manage irrigation in real time.

The analysis is framed in the context of California, which is intrinsically economically important, notorious for its legacy water rights, and a place with modern, high-resolution data newly collected over the last decade in response to growing concerns with water scarcity. Most of the state's water is owned and used by sophisticated irrigators who plant a diverse collection of crops, but rarely trade water rights. On one hand, many express concern with water misallocation in California given that the earliest, or most "senior," appropriative water rights—many of which date to the 19$^{\text{th}}$ century—have priority over later claims when water is scarce. On the other hand, California water infrastructure supports the largest agricultural sector and population of any state in the United States.[1] This paper is an attempt to think about water misallocation in this setting, which is especially important given new hydrological and climatic challenges that alter water scarcity and abundance across space by intensifying the hydrological cycle and creating new environmental concerns that may require reallocating existing sources of water to solve.

I focus on water users above and below the most important component of the water conveyance system in California, the Sacramento–San Joaquin River Delta, through which water must flow in order to reach the southern parts of the state. In particular, I use very detailed high-dimensional data, combined with a model of agricultural production and irrigation scheduling for nearly forty distinct crops—including annual crops like wheat, rice, and hay that must be replanted each year, and perennial crops such as almonds, oranges, and pistachios grown on trees that live for decades—to make some statements about the productivity

[1] The service area of just one of the two largest surface water infrastructure projects in California contains what would be the eighth-largest economy in the world (DWR, 2023).

of water use at a very fine level of resolution, and then think about what that might or might not imply about misallocation.

To take advantage of this new high-resolution data, the paper develops a microeconomic model useful to value water rights and misallocation building on two key ingredients not present in prior work. First, I follow the insight of Burness and Quirk (1979) to imagine water rights as random variables that give owners access to certain volumes of water in certain states of the world. As I show in the data, water rights on paper differ significantly in terms of actual water available for diversion, both for water rights with the same face value and within the same water right over time.[2,3] In the model, water rationing will arise differentially across the network and water right priority tiers, through the interaction of (a) equilibrium diversion decisions by owners of water rights and (b) exogenous idiosyncratic and aggregate shocks to water abundance and physical crop water requirements. Up to water conveyance and delivery costs, the optimal water allocation can be obtained when all users face a shadow value of water that corresponds to the marginal use value, which can be (and often is!) zero or even negative. Testing for misallocation in this incomplete model is challenging even in a fully-connected network without flow constraints: with sufficient heterogeneity across water users or water rights, unobserved planting or other adjustment costs can rationalize any water allocation.

Second, I embed a tractable set of Rust (1987) regenerative optimal stopping problems within the model of water rights, in order to model investments in capital varieties that require uninterrupted water inputs to survive. Water rights are typically perpetual, granting owners access to a sequence of annual water endowments over an infinite horizon, and the reliability of these rights are critical for high-value investment in cities, orchards, and vineyards that rely on continued water access across diverse conditions. I can take this to the data because, like Rust (1987) but unlike any prior work in California of which I am aware, I observe the full age structure of all orchards in California, as well as the panel of replanting

[2]The cutoffs that determine priority across competing water rights—the "priority date" or first year of the claim—differ considerably across users, with more senior water rights receiving approximately similar allocations in drought and non-drought years, but junior rights being severely curtailed. With constraints on water trade, this implies differential surface water rationing across the network and within tranches. Senior water rights are disproportionately owned by irrigators rather than cities, but many irrigators also rely on junior rights claims.

[3]Where feasible, farms also complement surface water with groundwater by incurring Burlig *et al.* (2024) pumping costs as functions of aquifer depth and extraction volume.

decisions. This aspect of the analysis—complementary investment based on the infinite sequence of annual water endowments—allows me to account for some of the adjustment costs that otherwise hinder the analysis of misallocation. That is, it allows me to microfound and estimate what are, in the simplest version of the model, unspecified planting costs that can rationalize any allocation of water. These complementary investments are also crucial to accomodate the fact that my estimates of water used for irrigation in the Central Valley exhibit high degrees of persistence, despite immense cyclical and stochastic components of surface water supply. Even during extreme drought, water volumes used for perennial crops, as well as many annual crops replanted each year, exhibit little variation.

In the model, farmers decide each year how to allocate their water endowment across annual and perennial crops. Conditional on allocating water to some perennial crops, such as trees in orchards or vines in vineyards, farmers then decide whether to maintain or cut down the trees or vines. As in Rust (1987), the productivity of the unit of capital investment depreciates over time—tree yield declines with age—and the farm faces an optimal stopping problem of when to replant, thereby renewing the asset, switching to a different variety of long-lived perennial crop, switching the status of the water to grow annual crops, or trading the water allocation to another user.

Understanding misallocation across water rights in this model, then, starts from each water right's history of planting decisions, which, together with local growing conditions, determine its sequence of annual productivities. In this setting, there exists a wide range of cross-sectional dispersion in marginal products that need not correspond to any real inefficiency, for the same reason as in models of capital misallocation under uncertainty and adjustment costs (Asker *et al.*, 2014). Planting decisions are characterized by location of use, tree type, and tree age—e.g., some water will be embodied in newly-planted orchards that have yet to bear fruit, some in productive orchards, some in vineyards, and some used flexibly to grow annual crops—and determine the water's annual productivity, as well as the adjustment costs related to its reallocation. For example, orchards typically remain productive for ten to thirty years, with some crops (e.g., pistachios) having no yield declines for more than one hundred years.

A key step in combining the two ingredients introduced above—state-contingent Burness and Quirk (1979) water rights and state-dependent Rust (1987) optimal investment—into a tractable empirical model is to distinguish between the permanent and transient components of a water right. In general, variable water rights make the optimal crop allocation nonseparable across fields, I cannot directly apply the canonical Scott (2013) approach to simplify the general equilibrium dynamics of land use by studying a continuum of independent field-level choices. However, when water, not land, is the binding constraint, I can analyze a more tractable problem in "water space," where units of water rather than land are assigned to different crops, making the problem separable even when water constraints bind. As these water-level decisions can be made independently from another, I can leverage the computationally tractable Berry (1994) discrete choice apparatus and its extensions (e.g., Gowrisankaran and Rysman, 2012) to value water at an extremely fine level of spatial and temporal resolution, allowing for unobserved heterogeneity in planting costs that can help explain the diverse allocations of water to crops. Unlike existing revealed-preference models of land use, which will rationalize inefficient uses of water through differences in farmer tastes for crops, this paper's model will not directly foreclose questions of water misallocation because the assumption used to identify planting costs is that, given the various water rights that they own, a farm will grow the most valuable crops.

Four main empirical findings flow from interpreting the data through the lens of the model and its estimates. First, using data on field-level planting decisions, crop evapotranspiration, agricultural yields and prices, the model allows me to estimate irrigation volumes and annual marginal products of water, or "water productivities," for every field in California from 2014–2022. I find that estimated marginal products of water exhibit significant dispersion within and across regions, as well as remarkable persistence over time as mentioned earlier, despite large hydrological variability, with greater dispersion and lower average water values during drought. As emphasized above, this dispersion in annual water values cannot be interpreted directly as evidence of misallocation due to unobserved differences in planting costs.

Second, combining the water productivity estimates with data on the hydrological flow network, I document a clear gradient in estimated water values above and below the most critical chokepoint in the network, the Sacramento-San Joaquin Delta, with persistently higher values below the constraint, where trade constraints are likely to bind. I show that this gradient mirrors gaps in willingness-to-pay to extract groundwater obtained from well depths, as well as the typical price gradient among the few annual water allocation trades from

1980–2024, which further support the hypothesis that Delta flow constraints lead to water misallocation. This finding corroborates some of the longstanding policy concerns that have led to extensive debate in California over the construction of new conveyance infrastructure in the Delta. Those conversations typically focus on the opportunity to reallocate water from agricultural users in the Sacramento Valley to large urban suppliers in southern California; these results indicate possible gains from trade even within agricultural uses, which is important given that most of California's water is used for agriculture and many marginal values of urban water use are not clearly greater than perennial irrigation.[4]

Third, combining the water productivity estimates with administrative data on all water rights on paper, I find that water values correlate with the seniority of water rights; watersheds endowed with more senior water rights exhibit less dispersion in marginal values and higher values overall. These findings provide support for theories of complementarity in capital investments and more reliable senior water rights (Burness and Quirk, 1979) as well as more general models of directed technical change (Acemoglu, 2002) where more abundant factor supply leads to innovation that raises that factor's productivity.[5] However, the finding that more senior water owners are more productive on average contravenes the common perception (and prediction of some models of moral hazard) of more wasteful water use by senior water owners ("use-it-or-lose-it").

Fourth, combining water productivity estimates with the full age distribution of tree varieties, I find an endogenous partition of water rights, where most (>90%) of the water used by orchards is "locked in" in a given year, in the sense that it would typically not make economic sense to reallocate to other uses. This follows directly from the observed orchard demographics and an assumption—strongly supported by the data and the implied economic costs of the counterfactual—that farmers almost never cut down orchards in the first decade of their productive life. The resulting endogenous distribution of water-augmenting capital varieties—reminiscent of the Atkeson and Kehoe (1999) mi-

[4]About 80% of California's water is used for agriculture. While this paper focuses on irrigation, similar arguments here apply to water that sustains human populations, which also entails large fixed investments in housing stock that require reliable water supply to operate. A major open empirical question is the extent to which water scarcity, versus other zoning and land use restrictions that create barriers to new development, inhibits urban development and expansion (see, e.g., Edelstein, 2025 for progress in this direction).

[5]Two countervailing forces are at work: abundance raises the value of such investments, but also lowers equilibrium factor prices (Acemoglu, 2002). If water is not priced at its opportunity cost, however, there will be no countervailing equilibrium price channel.

crofoundation for low short-run and large long-run energy price elasticities in macroeconomics—provides an explanation for why aggregate water demand appears conspicuously inelastic to fluctuations in aggregate water surface supplies by factors of two or more. It also has implications for long-run water contracts in the design of water markets—because very little of California's water can be productively reallocated within a year, partial reforms to liberalize annual trade without also allowing longer-run trades seem unlikely to deliver substantial gains.[6]

Beyond the work cited above, this paper makes two primary contributions to the existing literature. One, the paper's general empirical model enables the valuation of water rights by combining the rich detail of agricultural production models with some of the information implied from revealed preference about crop choices and replanting decisions within fields over time. Modern agricultural production models can make use of rich data and do not rely on revealed preference, which allow them to deliver large differences across water values (D'Odorico *et al.*, 2020; Medellin-Azuara *et al.*, 2022). However, these models typically rule out unobservable heterogeneity that correlates with water use, rather than using observed decisions to learn about unobservable heterogeneity. In contrast, modern equilibrium models of land use (Scott, 2013; Burlig *et al.*, 2024), when identified with valid instruments, can recover certain forms of unobservable heterogeneity from aggregate data in a consistent way, for the same reason as in other product markets (Berry *et al.*, 1995). However, the source of that advantage—to rely on revealed preference and quasi-experimental price shifters to recover valuations—can limit the ability of these models to test for arbitrary misallocation. The key idea here to combine the two approaches without foreclosing the analysis of misallocation is that, holding fixed a given water right of a certain type in a given location, the crop choices made for that water right can reveal information about the relative planting costs across different potential crops, as well as the costs of renewal and replanting for perennial crops like almonds, pistachios, or wine grapes—even when that water could have a much greater value elsewhere.

Two, the paper's substantive empirical work contributes the new findings on the value of water in California discussed above: how value varies with flow constraints in the surface water network, characteristics of historical water property rights, and over time through equilibrium investment decisions. Each of these as-

[6]Under California law, trading water rights for more than one year or water rights with pre-1914 seniority status involve several additional legal frictions than annual trades.

pects of water interact to determine the value of water reallocation,[7] a recurring question in this literature—whether places that so rarely trade water on markets, like California (Hanak *et al.*, 2021; Hagerty, 2023), stand to gain by introducing more advanced water markets. Valuing water rights across competing uses is central to answering this question, but has been inhibited by data issues with extant water contracts and prices,[8] except in rare cases like Australia (Rafey, 2023). This paper confronts the challenge of valuing water without trades, by far the most common situation worldwide. It follows in the line of supply-side industrial organization papers like Borenstein *et al.* (2002), Syverson (2004), and Asker *et al.* (2019) to start with details of the production process—for example, the physics of electricity, oil, and water flow at the point of generation, extraction, or diversion—and try to learn from the resulting distribution of economic activity, tailoring the analysis as close as possible to the observed set of producers. This allows the study of rich distributions of marginal water productivities over time and across the hydrological network and varied hydrological conditions. Working with water use data also lets me account for conjunctive use of surface and groundwater, an important limitation to previous research in California.

In addition to the primary contributions, this builds on a large body of work using extensive satellite imagery to characterize economic activity on the surface of the Earth and address measurement issues with conventional economic data.[9] Much of this study's empirical progress is enabled by observables beyond land cover; here, differentiated capital varieties implied by tree planting dates and local water requirements implied by daily evapotranspiration. Finally, a broader literature documents significant dispersion in marginal products across various factors, like capital, labor, land, and oil; how we interpret that dispersion is

[7]Some recent work on California water includes Gartrell *et al.* (2017), Hanak *et al.* (2021), Ayres *et al.* (2021), Zeff *et al.* (2021), Medellin-Azuara *et al.* (2022), Hagerty (2023, 2022), Burlig *et al.* (2024), and Leonard *et al.* (2025), as well as recent PhD dissertations analyzing groundwater regulations and labor on small farms (Sum, 2024), urban-agricultural water price gaps (Ferguson, 2024), and water impact fees and housing development (Edelstein, 2025).

[8]See Rafey (2023, pp. 433–434) for a discussion. Water is rarely traded, the terms of these contracts are often unobserved, and water rates are typically not market prices, but rather fees set formulaically by utilities or irrigation districts to recover fixed costs.

[9]On evapotranspiration, see D'Odorico *et al.* (2020), Wong *et al.* (2021), Boser *et al.* (2022), and Leonard *et al.* (2025). On groundwater subsidence, see Carleton *et al.* (2025). Beyond water, the satellite data renaissance has enabled progress on several other problems in the economics of land use and the environment, such as deforestation (Burgess *et al.*, 2012; Souza-Rodrigues, 2019; Hsiao, 2021; Balboni *et al.*, forthcoming), agriculture (Scott, 2013; Costinot *et al.*, 2016), and wetland conservation (Aronoff and Rafey, 2023).

obviously a challenge and this is one paper in that line of thinking.[10]

The rest of the paper starts with some background on California water institutions from an economic perspective in Section 2. I then introduce the model in Section 3, describe what I do with data in Section 4, and finally provide some results and some discussion of the limitations of interpreting the estimates as allocative inefficiency in Section 5.

2 Institutional details

This section discusses where California's water comes from, where we move it and how, and who uses it. This context will then allow us to think about overlapping water rights and some of the constraints on water reallocation.

2.1 Water sources and supply network

The water in California comes from two places. About 200 million acre feet in an average year falls from the sky, or about four to five times as much water as the entire state uses annually. Most of this water is not directly usable, but some stays in the mountains, turns into snow, and then slowly melts down into valleys through massive rivers. The triangles in Figure A1A depict the dams built in California to capture this surface water, modulate its variability, and deliver it to where it is most economically useful. This surface water then travels throughout California, flowing through the rivers plotted in Figure A1C, and the network of canals, primarily operated by the State Water and the Central Valley Projects, depicted in Figure A1D, which move water from Northern California and, critically, as shown in detail in the inset with more precision, through the Sacramento–San Joaquin Delta.

Surface water exhibits large cyclical and stochastic components, as illustrated by the useable river inflows in Figure 1. Annual volumes from 1980–2021 for the Sacramento and San Joaquin River Basins, given existing conveyance infrastructure, range from less than 10 million acre-feet to more than 30 million acre-feet across years.

The natural surface water flow network also serves as the origin of California's groundwater. Much of the water that lands on California seeps into the earth

[10] On misallocation and its discontents, see, e.g., Hsieh and Klenow (2009), Midrigan and Xu (2014), Adamopoulos and Restuccia (2014), Asker *et al.* (2014, 2019), Baqaee and Farhi (2020).

over many thousands of years, forming the gigantic aquifers depicted in Figure A1B. The dark blue aquifer in the Central Valley is the state's largest source of groundwater, though aquifers also serve as important water sources in the Central Coast, where there are a lot of vineyards, and in southern California, especially for municipal users in desert areas.

2.2 Water users

The water that travels through the hydrological network has three main competing users in California: irrigators who use water to grow crops; people who drink water to not die; and ecosystems, which rely on natural flows to survive and thrive.[11] The water rights defined for these different uses are primarily owned by irrigators, and in particular, as I show below, many of the irrigation water rights were established prior to the complete settlement of California. Figure A3 reports a map of agricultural production in California in 2020. It shows just two colors; purple corresponds to perennial crops such as almonds, pistachios, oranges, and grapes, and orange corresponds to annual crops like wheat, rice, and pasture.

Agricultural users comprise about 70–80% of California water use, or 30–35 million acre-feet of water, in a given year. Most of the agriculture occurs in the Central Valley.[12] In contrast, Figure A3, Panel B, shows where the people are. Although California is the largest state by population in the US, it is sparsely populated outside of Los Angeles and the Bay Area; in the aggregate, municipal uses account for only about 15% of water in California. Finally, water flows serve critical ecological functions. Water throughout the network delivers value to the species that live in the rivers and water bodies; I discuss some of these values in Section 2.4 below.

2.3 Water rights, contracts, and rationing

The immense cyclical and stochastic components of water supply and flow create several difficulties with specifying well-defined water property rights. Most water rights in the western United States emerged based on historical claims by original

[11] California also generates a lot of hydroelectricity, but hydroelectricity is typically a "non-consumptive" use that does not compete with agricultural or municipal uses.

[12] While the main focus of this study is the Central Valley, agriculture also occurs in the Central Coast as well as the Imperial Irrigation District in the southeast corner of the state that uses senior Colorado River rights, as seen in Figure A3, Panel A.

water users. The fundamental problem is that these "appropriative" rights are typically defined at the place of use ("point of diversion"), and not the point of origin. This creates significant problems if (and only if) multiple competing uses conflict with one another, because they then have to be reconciled. In an ideal world, if we know exactly where all the water is coming from, for example, from a single dam, then we just define property rights over the water in the dam. One still needs to charge users along the conveyance network for transmission costs and solve the optimal routing problem, but there's no incompleteness because we have fully specified the rights over the water.

But historically, surface water rights are often defined in ways that depart from this ideal case, because water comes from so many diverse places and water abundance varies across so many states of the world. Water property rights evolved in California, and the western United States more broadly—and, similarly in places like Australia—by granting property rights to people who claimed them. In California, many of these claims originated when people started moving to California during the Gold Rush in 1848. California also has some very large infrastructure projects, which create a close to complete property rights case, because they involve constructing large dams with known volumetric capacities, and we can subdivide and tranche the rights over units of water held in the dam.

Appropriative surface water rights are defined by two attributes. First, a "face value" amount, denominated in acre-feet per year, which equals the maximum amount of water that the user can take in a given year. Second, a "priority" year or tranche, which determines how water rationing occurs in states of the world in which the water right conflicts with other rights. Rationing can arise due to (i) shocks that lead to lower river inflows and aggregate water availability and (ii) excess demand by other water rightsholders with greater or equal seniority. In other words, if there is no water in the river, you cannot take the water; furthermore, even when there is water in the river, that water may not be legally yours when other, overlapping water rights have legal priority over your appropriation. All of this implies that rationing can occur in some, but not all, states of the world, as reported in Table 1. This fact is also partly why climate change raises new risks for water rights, because only in states of the world where supply constraints bind is it important to sort out these competing claims.[13]

[13] A separate but related concern with appropriative rights defined by historical use, distinct from inefficient rationing across users, is that these rights can create perverse "use it or lose it" incentives. In practice, the threshold to show beneficial use is very low. And, in part to

Figure 2 reports the claims for water for irrigation. Panel A shows cumulative claims from 1790 to 2020. Before the 1914 Water Commission Act, there were already nearly 20 million acre-feet of water claims, close to the total amount of water that the Central Valley uses today. While these administrative records do contain measurement issues, they show clear evidence of large legacy rights that date prior to California becoming part of the US,[14] as well as an uptick in cumulative water rights when people start moving California to mine gold, using water-reliant methods like sluice boxes and hydraulic mining. Water claims also provided for the new population; for example, Pacific Gas and Electric (PG&E), which remains the largest utility in California today, owns many large water rights that date to the 1860's and 70's. Cumulative rights grow over time; in particular, Figure 2 shows large jumps in 1940 and 1960, the completion decades of the state's two largest infrastructure conveyance projects, which significantly expanded available surface water supply. By the 1980s, all sources of surface water for the Central Valley have been fully appropriated.

In contrast to appropriative surface rights, property rights to groundwater are tied to the land. While there have been some regulations that have started to change the way people drill for groundwater in California, broadly, the landowner's right in California extends to subsurface drilling rights.[15] Figure A4, Panel A, shows meaningful groundwater extraction capacity relative to appropriative rights, with about 20–25 million acre-feet of capacity of groundwater wells by 2022.[16] Figure A4, Panel B, which stacks cumulative well capacity together with appropriative water rights, shows that farmers start to drill for groundwater as surface water becomes fully appropriated.

An important aspect of groundwater, unlike most surface water, is its nontrivial marginal extraction cost. The cost of extracting water from a well can be

encourage people to transfer water rights, and to avoid the kind of overuse incentives under a use-it-or-lose-it regime, since the 1970's, it's been very clear in California law that, in most cases, even if you don't use the water, you still own the water rights.

[14] One can see similar patterns in land parcel data. There are still ranches exactly the size of Spanish land grants, because many of these land rights were given as concessions to landowners when the United States annexed California from Mexico in 1848 (Gates, 1991, pp. 3–13).

[15] This subsurface water is, essentially, open-access; if your land sits above an aquifer you can drill as much water as you want, limited by rising extraction costs as aquifer levels fall. The California Sustainable Groundwater Management Act, passed in 2014, aimed to limit groundwater extraction in critically overdrafted regions; how its regional objectives will be enforced in practice remain unclear more than a decade after the law's passage.

[16] In California, you need to get a permit to drill a well, and so there about a million of these well reports, about 100,000 of which are in the Central Valley.

calculated in proportion to drilling depth ("lift-height") (Timmins, 2002). Table A5 calculates these costs using data on all the wells that have been drilled, showing meaningful differences across watersheds within the Central Valley, as well as difference of about a factor of two in average lift heights and implied pumping costs above and below the Delta.

2.4 Trade constraints and frictions

Constraints on water trade among owners of water rights arise for several reasons. One reason is flow requirements for ecosystems. Figure A3, Panel C illustrates some of the environmental assets in California. The purple polygon is the legal boundary of the Sacramento–San Joaquin Delta, and this has a lot of environmental value. Many endangered species that inhabit the Delta are federally regulated under the Endangered Species Act of 1973. The Delta is also ecologically critical to prevent saltwater intrusion because drains into the Pacific Ocean through the San Francisco Bay. California hydrology has been so altered from its natural state that the saline ocean water could overrun the Delta without minimum outflows from the Delta to protect California from turning into a wasteland. These environmental priorities restrict how water can be moved through this state, stipulating certain seasonal outflow requirements to maintain species and deliver environmental value in the Delta. Figure A5 plots variation in the water used for environmental requirements over 1980–2022.

Infrastructural constraints on water transport also limit water transfers. The Central Valley, where most of California's agriculture occurs, is largely divided between the Sacramento Basin and the San Joaquin Basin. Water flow through the Delta to southern California must be lifted at the bottom of the Delta before it can flow into the San Joaquin River Valley.[17] This is the primary flow constraint that precludes greater reallocation of water across these two basins. While significant volumes of water flow through the Delta each year (about 4–8m acre-feet)—the source of much of the water used in the southern component of the network—there are still considerable water volumes consumed in the North that may not be able to cross the Delta.[18]

[17] Only two pumping plants transport water out of the Delta, the (federal) Bill Jones and (state) Harvey Banks Pumping Plants. The proposed Bethany Reservoir Pumping Plant, which would convey about 400,000 acre feet more water to flow through the Delta to southern users, is planned for completion by 2040 at an estimated cost of about $20 billion.

[18] Another, more general, friction to trade is the prospect of legal challenges to water owners

In part due to these constraints, annual trade in water allocation rights in California (Hanak *et al.*, 2021) appears to usually be less than one percent of water use and never much more, even during severe drought.[19] Despite this sparsity, there are a few transactions. I did my best to pull as much water trading data as I could for these two regions and then construct price distributions across the regions, so that we could compare them. The results corroborate estimates of Regnacq *et al.* (2016) and Hagerty (2023) of large transaction costs across the Delta. The ratio of these prices, reported in the rightmost column in Table 2, ranges between one-and-a-half and two or two-and-half through the deciles. Corroborating these long-run differences, Figure 3 shows, in 2023, two lines. The blue shows prices south of the Delta (SOD), the water that has to go through the Delta in the San Joaquin River Valley. The red line is the prices of the water that are transacted above the flow constraint in the north of the Delta. One can see a large wedge, a factor of three or four, even out to August, when people start wanting water to plant. Prices are very flat along the red line, north of the Delta, where there is plenty of water. But the SOD price exhibits much larger fluctuations. The lower panel of Figure 3 shows a similar pattern in the year 2024. Taken together, these prices would suggest a wide Delta price gradient if one takes the data seriously—approximately a factor of two, even towards the end of the growing season. This motivates my analysis below of how water productivity and water use differ across these two regions.

who propose to transfer some or all of their water property rights to another user. For example, imagine that someone who takes water from one location on a network instead declines to take that water so that someone else in the network can take more. In principle, that reallocation would affect other flows throughout the network. So, anybody between the two counterparties can litigate. Under the California Environmental Quality Act of 1970, there also needs to be environmental review to make sure that all the species whose existences and locations and habitats have been predicated on the existing distribution of water are not adversely affected. This has, in practice, turned out to be an easy way to obtain standing to file lawsuits and obtain injunctions against proposed water transfers.

[19] Figure A7 reports California water trades from 1985 to 2022. The units are in acre-feet, and range in the top panel from zero to one-and-a-half million acre feet. The numbers on the top of the bars are the number of trades. For example, in 1993, you have 17 trades, in 1994, 16 trades. This is a very sparse market. The lower panel of Figure A7 report the same trade volumes alongside the reported water volumes used (after mid-2010s legislation introduced mandatory reporting requirements), to emphasize that trade volumes are less than one percent of water.

3 Model

This section introduces an empirical model of water rights and irrigated agricultural production to clarify some of the economic mechanisms at work in the institutions described above, and to motivate the use of data to explore the possibilities of water misallocation in the subsequent section.

I specify the model in two ways. First, I outline a general model of irrigation and water rights for which I can estimate annual marginal products of water under a relatively small set of assumptions that leave water rights, the water market, and planting costs unspecified. Water misallocation is not identified from the distribution of water productivities without further structure, such as assumptions that unobserved planting costs are the same across certain places in the network. Second, I specialize the general model to a fully-specified model of equilibrium water use, which provides a microfoundation for heterogeneous planting costs under the assumption that permanent and transient water rights can be distinguished. The planting costs and implied values of water rights can be identified in the fully-specified model with panel data on farms with sufficiently similar planting costs and instruments for crop prices.

3.1 Irrigation technology

Irrigators, the main users of water, indexed by i, produce various crops indexed by c. Agricultural calendars operate on an annual basis, so we think about annual production in each year t.[20] Total annual crop production, Q_{ict}, is a function of the land that the farmer uses and the irrigation that they apply to the field. On farm i in year t, each crop c has a potential yield per acre, A_{ict}. Annual production technology for irrigator i, crop c, in year t, is then given by

$$Q_{ict} = A_{ict} \min \left\{ K_{ict}, \left(\frac{w_{ict}(\tau)}{\omega_{ict}(\tau)} \right)_{\tau=0}^{365} \right\} \tag{1}$$

where output Q_{ict} is measured in tons, the irrigation application rate $w_{ict}(\tau)$ is measured in acre-feet/day, land K_{ict} in acres, and yield A_{ict} in tons per acre, with $A_{ict} = 0$ for $c =$ fallow. The key feature of (1) is to allow the value of daily irrigation $w_{ict}(\tau)$ in production to depend on each crop's inherent water efficiency,

[20] Some crops are grown more than once a year. While the empirical work below abstracts from multi-cropping, to incorporate it, just let c index each potential multi-crop combination.

$\omega_{ict}(\tau)$, which corresponds to how much water the crop needs, in theory, on day τ of that year. For example, $\omega_{ict}(\tau)$ will be zero in times when the crop needs no water, and $\omega_{ict}(\tau)$ will be larger as you need to provide more irrigation.

Water efficiency differs (i) across crops at the same location and year, (ii) across locations for the same crop and year, and (iii) across years within locations growing the same crop. The reason that the function $\omega_{ict} : [0, 365] \to \mathbb{R}_+$ varies with i, c, and t is that location influences the climate conditions that determine the plant's water demand through local soil characteristics, daily weather conditions, and the relevant growing season. For example, a crop will typically need more water on hotter, windier, or sunnier days, and more water when fully grown than when still a seedling.

In addition to equation (1), the key assumption that I will make in order to learn about the water used in California from the crop choices that I see is that irrigation scheduling for each crop over its growing season is optimal. These assumptions are stated on endogenous objects, but straightforward to state in terms of primitives:

A1. No overwatering over the growing season (nonnegative marginal irrigation costs or declining yield).
A2. No deficit irrigation over the growing season, i.e., $K_{ict} \leq \min_\tau \frac{w_{ict}(\tau)}{\omega_{ict}(\tau)}$ in equilibrium.

Assumption A1 rules out farms that irrigate more than the crop would need, which can be microfounded with any nonzero marginal cost of irrigation, or a yield function where yield declines if you overwater the crop. Similarly, A2 rules out under-irrigation. While there is immense interest in deficit irrigation—conceptually, it would be great if you could get more for less—agronomy experiments have largely found that deficit irrigation is not a viable strategy in most settings because under-watering severely compromises crop yield.[21] No-deficit irrigation will be violated by pasture planting with multiple cuts in a single year (e.g., alfalfa), where deficit irrigation corresponds to fewer plantings within the year. Regardless of their microfoundations, A1 and A2 give us the ability to use (1) to combine observed land allocations K_{ict} with crop-location-day irrigation efficiencies for the crops to recover the amount of water used for irrigation on

[21] One can think about the global production function in water as quadratic, a parabola where yield declines very fast on either side of the optimal amount of water that the plant needs.

each field, via the integral

$$W_{ict} = K_{ict} \cdot \int_{0}^{365} \omega_{ict}(\tau) d\tau \tag{2}$$

because water demand coincides with optimal irrigation requirements.

Crucially, A1 and A2 restrict how farms irrigate the crop they have planted in a given field, not how they choose which crop to plant. The assumptions do not restrict equilibrium crop choices nor require that the assignment of land or water rights to crops is optimal.

3.2 Sketch of the farm's problem

Given the production technology in (1), the farm will solve a problem that I first specify at a general level that I do not directly take the data. Suppose that an irrigator has some amount of land, $\overline{K}_i$, and water rights, $\widetilde{W}_{it}$, which they can assign to different crops c at t, given some general planting cost function $\Gamma_{it}(K)$ that depends on the full vector of crop choices. The land allocation solves

$$\max_{\{K_c\}} \sum_c P_{ict} Q_{ict} - \Gamma_{it}(K) \tag{3}$$

such that $\sum_c K_c = \overline{K}_i$ and $\sum_c K_{ict} \int_0^{365} \omega_{ict}(\tau) d\tau \leq \widetilde{W}_{it}$. That is, the farm's crop choices maximize profits given their productivities embedded in Q_{ict}, the prices that they obtain for each crop, the planting and other costs Γ_{it}, and constraints that the farm uses as much land as they have—one of the crop categories is fallowing, so this constraint always binds—and such that they do not go beyond the water rights that they have, $\widetilde{W}_{it}$. If, for example, the cost function Γ_{it} is linear, the two constraints in (3) form a convex polytope that one explores to find the optimal crop choice.

Several aspects of (3) are worth noting. One, farmers take output prices, P_{ct}, as given, which seems not implausible given that these are agricultural commodities. Aggregate yield shocks and acreage in California may affect these prices, but the output market is assumed to be perfectly competitive. Two, planting costs are a function Γ_{it} of the full vector of crop choices. In the fully-specified dynamic setting of Section 3.3, this Γ_{it} reflects underlying technological primitives, the farm's (endogenous) past decisions, and the implications of current decisions for (endogenous) future decisions and payoffs. Here, all of these details are represented implicitly by an unknown function that varies with i and t.

Three, the value function $V_{it}(\overline{K}_i, \widetilde{W})$, defined as the maximand of (3) at $\widetilde{W}_{it} = \widetilde{W}$, reveals the value of water rights through farm i's water constraint at t. Various comparative statics with respect to attributes of that water right can then be used to trace the value of the water right through the changes in irrigator i's value at t. In doing so, we obtain the marginal (shadow) value of changing the water right,

$$\frac{\partial V_{it}}{\partial \widetilde{W}} = \underbrace{\sum_c \frac{A_{ict} P_{ct}}{\omega_{ict}} \frac{\partial W_{ict}}{\partial \widetilde{W}}}_{\Delta \text{ marginal products}} - \underbrace{\sum_c \frac{\partial \Gamma_{it}}{\partial K_c} \frac{\partial K_{ict}}{\partial \widetilde{W}}}_{\Delta \text{ planting costs}} . \tag{4}$$

The general expression for the shadow value in (4) consists of two terms. One is the change in the annual marginal product of water, which depends on how water is reallocated across crops and each crop's value per unit water. The other is the change in planting costs, including dynamic considerations embedded in Γ_{it}. A farm might, for example, reallocate land to crops with much higher annual marginal products under a different $\widetilde{W}$, but that reallocation could involve new planting costs such that the total value of (4) is not large. Alternatively, switching costs may be so great that the change in water rights does not change the crops grown, i.e., $\frac{\partial}{\partial \widetilde{W}} W_{ict} = 0$ for all c.

One goal of writing down the derivative in (4) is to point out that, to the extent that planting costs are similar across different irrigators, we can study the difference in annual marginal products of water as a way to compare the true value of the water right (embodied in the crops that are being grown) in some place i with the value of the water right (embodied in crops) in some other place j. This motivates the analysis of the joint distribution of the annual marginal products of water and the allocation of land, $\{K_{ict}, \frac{A_{ict} P_{ct}}{\int \omega_{ict}(\tau) d\tau}\}_{i,c,t}$, studied in Section 5.

A related goal is to emphasize that, where planting costs differ meaningfully across i and j, differences in marginal products across i and j need not be evidence of inefficiency. For example, where irrigators embody water in different kinds of trees, planting costs depend on the history of a farm's crop choices. In this case, systematic differences in marginal products of water could be entirely efficient; reflecting differences in optimal investment, not misallocation. This is reminiscent of Asker *et al.* (2014), who show how substantial cross-sectional dispersion in marginal products of capital can arise in models of investment by firms with different productivity shocks over time, even when very little of the dispersion is welfare-relevant in the sense that there exists a feasible reallocation to improve allocative efficiency.

3.3 Farm's problem, fully specified

To address this ambiguity, I now specialize the above model to specify planting costs across fields that reflect the evolving opportunity cost of replanting long-lived orchards of different ages and varied types, in order to (a) more directly capture the varied value of water rights across reliability tiers and sunk investments and (b) obtain primitives to study alternative water allocation mechanisms. While this requires some additional structure on the cost function Γ_{it} and equilibrium behavior that determines crop choices, the exercise will remain disciplined by the additional panel data that I have on the age of trees and within-orchard planting and replanting decisions.

Water rights. Water rights are random variables that are realized at the start of each year, $\widetilde{W}_{it} \sim G_i$. For tractability, I distinguish between the reliable and transient component of each water right,

$$\widetilde{W}_{it} = W_i^p + W_{it}^a, \tag{5}$$

with the reliable component of the water right defined as delivering water almost surely, i.e., $G_i(W_i^p) = \mathbb{P}_i(\widetilde{W}_{it} \geq W_i^p) = 1$. In practice, such rights can be a senior surface water right that always delivers water, or a surface water right that delivers in fewer than all years combined with a groundwater well that can make up the difference in low surface water years.[22] The decomposition in (5) allows me to define values for different units of water in the water right; without loss of generality, I index the units (acre-feet) of a water right $\iota \in [0, \widetilde{W}_{it}]$ such that the first $\iota \in [0, W_i^p]$ units are reliable.

Flow payoffs. I assume that water, not land, is the scarce factor of production. Each year, a unit ι (acre-foot) of water allocated by farm i to a crop $c \in \mathcal{C}$

[22] As the earlier discussion of priority and rationing indicated, this random variable could depend on all the equilibrium different decisions of everyone else in the network. But from the farm's standpoint as a producer, they just care about the probability that they have a certain amount of water $\widetilde{W}_{it}$. Also note that $\widetilde{W}_{it}$ captures all available water—both surface and groundwater—even while costs may differ depending on the source. Variable irrigation costs, such as groundwater pumping, are accounted for as "planting costs" in the model.

of age $x \in \{0, 1, 2, \dots\}$ delivers a payoff, denominated in \$/af, of

$$\pi_{it}(c, x) - \xi_{ic_x t} + \sigma_\epsilon \varepsilon_{c_x t}(\iota), \tag{6}$$

where $\pi_{it}(c, x) = \alpha_{ict}(x) P_{ct} = \frac{A_{ict}(x)}{\int \omega_{ict}(\tau) d\tau} P_{ct}$ is the revenue (\$/af) from the crop derived from equation (1) and assumptions A1 and A2, given the (random) per-acre-foot yield coefficient $\alpha_{ict}(x)$, observed crop prices P_{ct}, average planting costs $\xi_{ic_x t}$, and idiosyncratic planting costs $\sigma_\epsilon \varepsilon_{c_x t}(\iota)$, independently and identically distributed Type 1 Extreme Value (T1EV) at the acre-foot-crop-age-level, scaled by the parameter $\sigma_\epsilon \in [0, \infty)$.

Interannual choice sets. In equation (6), payoffs to i depend on the year t as well as the state of the water right, (c, x). Dynamics arise because the state of the water unit, (c, x), can determine the choice set of the farmer. For annual planting, the problem is truly static; age $x = 0$ and the choice set is $c \in \mathcal{C}^a$. For new perennial plantings, $c \in \mathcal{C}^p$ and the age in the next period becomes $x = 1$. For perennial plantings with age $x > 0$, the choice set becomes either to maintain the orchard, leading to $(c, x + 1)$, or to cut down the tree to return to $(0, 0)$. Consequently, when growing a given perennial crop, the farm's subproblem resembles a Rust (1987) optimal regenerative stopping problem with a Gowrisankaran and Rysman (2012) renewal value that depends on the payoffs for all perennial crops in the choice set; when selecting a new perennial planting, the farm's problem can be reduced to a static Berry *et al.* (1995) discrete choice over payoffs that correspond to the value functions derived below.

Equilibrium values of water. Farms discount periods with a common factor $\beta < 1$. The value of a water right committed for x years to a perennial crop c can be constructed recursively via

$$\begin{aligned} V_i(c, x) = \max \big\{ &\alpha_{ict}(x) P_{ct} - \xi_{ic_x t} + \sigma_\epsilon \varepsilon_{c_x t}(\iota) + \beta \overline{V}_i(c, x + 1), \\ &-\xi_{i0t} + \sigma_\epsilon \varepsilon_{0t}(\iota) + \beta \overline{V}_i(0, 0) \big\}, \end{aligned} \tag{7}$$

for $x > 0$, with the overline $\overline{V}_i$ denoting the ex-ante value function prior to drawing the ε shocks that period, and

$$V_i(0, 0) = \max_{c \in \mathcal{C}^p} \left\{ \overline{V}_i(c, 1) - \xi_{ic_1 t} + \sigma_\epsilon \varepsilon_{c_1 t}(\iota) \right\} \tag{8}$$

at the event of replanting.

Two special cases of (7)–(8) illustrate the generality of this empirical model as a way to value water rights. First, as $\sigma_\epsilon \to 0$, field-crop-level heterogeneity in planting costs vanish. If, in this case, crop prices and planting costs are also time-invariant, there will be a perennial crop c_i^* that always maximizes (8). Further, when $\frac{\partial}{\partial x}\alpha_{ict}(x) < 0$, there exists a finite stopping time x_i^* at which replacement becomes optimal, so that the value of the water right (8) admits the simple closed form:

$$V_i(0,0) = \frac{1}{1-\beta^{x_i^*}} \sum_{s \leq x_i^*} \beta^s \left[\alpha_{ic^*t}(s)P - \xi_{ic^*}\right] - \frac{\beta^{x_i^*}}{1-\beta^{x_i^*}}\xi_{i0}. \tag{9}$$

In this case, the water right's value equals the net-present-discounted profits from growing and harvesting the best crop for its optimal lifespan, then replanting the same crop for a cost ξ_{i0}, ad nauseam, ad infinitum. Second, as $\sigma_\epsilon \to \infty$, any pattern of choices in a finite sample can be explained by the model. In this sense, the model nests the case in which microdata on water use and marginal products cannot reveal anything about misallocation.

Importantly, the additional heterogeneity in planting costs across crop types and the evolution in crop prices, switching costs, and yields do not qualitatively change the nature of the farm's problem from the simpler case of (9) above. The basic economic principle is always the same: a water right tied to a specific location and irrigator is used by that irrigator to grow the most valuable crop or sequence of crops. The additional heterogeneity simply enriches the decision space to better account for data where an otherwise identical (on observables) water right is observed to be used to grow a different sequence of crops over time. Misallocation, in this model, arises from the way in which nontradable water rights are tethered to specific locations and irrigators, not from mistakes made by irrigators in the use of the water they own.

3.4 Identification

The previous section describes the choices for a single irrigator owning a given water right. Practically, we would like to use data from many irrigators, and within the same irrigator over time, to estimate the structural parameters. Here, I describe the additional assumptions across and within irrigator choices over time that one can use to identify planting costs; these are the standard assumptions used in the dynamic discrete choice literature (Rust, 1987; Berry, 1994; Berry *et al.*, 1995; Gowrisankaran and Rysman, 2012; Scott, 2013), described here for the model of water rights where water, not land, is the scarce factor of production:

A3. Planting costs from revealed preference. Water uses ι across i can be aggregated to known sets M of positive measure, such that each M satisfies:

(i) Price instruments (Berry, 1994). Shifters Z_{ict} of P_{ct} such that $\mathbb{E}[Z_{ict}\xi_{ict}] = 0$.

(ii) Common choice sets (Berry *et al.*, 1995; Scott, 2013). Some interval $\iota \in M$ with the same average planting costs ξ_{ict} and curvature σ_ϵ.

(iii) Common, stable beliefs over future states (Rust, 1987; Gowrisankaran and Rysman, 2012). P_{ct} follows the same law across $\iota \in M$; the evolution of $\{\xi_{ict}\}$ is stable over t and common across i.

Under Assumption A3(ii), aggregate choices over $\iota \in M$ can be used to recover the planting costs that rationalize annual planting decisions at the start of the year—which, by assumption, do not depend on future periods. For annual crops, the share of water in M allocated to $c \in \mathcal{C}^a$ rather than the outside option (s^a_{0t}) can be written as

$$\ln \mathbb{P}_i(c(\iota) = c) = \ln s^a_{0t} + \frac{1}{\sigma_{\epsilon^a}} \int_M \alpha_{ict}(0) P_{ct} - \xi_{c_0 t} d\iota, \tag{10}$$

for each annual crop $c \in \mathcal{C}^a$ in each year t and each interval M. Under A3(iii), choices for $i \in M$ reveal the planting costs and yield curvature that rationalize within-orchard decisions over time, because the assumption of common beliefs over future states within M mean that the only variation in choices arises through the structural parameters ξ and σ_ϵ. Let $i_{it}(c, x) = 1$ if i chooses the renewal action at (c, x); then the odds ratio that characterizes the choice probability can be obtained by integrating over $\iota \in M$,

$$\ln \frac{\mathbb{P}_i(i_{it}(c, x) = 1)}{1 - \mathbb{P}_i(i_{it}(c, x) = 1)} = \frac{1}{\sigma_\epsilon} \int_M \alpha_{ict}(x) P_{ct} - \xi_{ic_x t} + \xi_{i0t} + \beta \overline{V}_i(c, x+1) - \beta \overline{V}_i(0, 0) d\iota. \tag{11}$$

Finally, for irrigation water rights $\iota \in M$ that share both common planting costs and beliefs, i.e., A3(ii) and A3(iii), aggregate choices over $\iota \in M$ can be used to recover the planting costs that rationalize new perennial planting decisions at the start of the year. The share is only calculated for newly planted perennials ($i_{i,t-1} = 1$) in that year:

$$\ln \mathbb{P}_i(c_{it}(\iota) = c | i_{i,t-1} = 1) = \ln s^p_{0t} + \frac{1}{\sigma_{\epsilon^p}} \int_M \overline{V}_i(c, 1) - \xi_{c_0 t} d\iota, \tag{12}$$

which is identical to the previous equation (10) except choice-specific payoffs depend on the value functions derived from the full lifecycle of perennial planting.

The core identification concern in this model is explicit from the equilibrium planting and replanting decisions characterized by (10), (11), and (12). Equilibrium water use across water rights and over time and reflects differences in water right reliability G_i, water productivity, $\alpha(x)$, and unobserved planting costs ξ, all of which could be correlated with crop prices P. The broad strategy to address these concerns uses the model of irrigation scheduling (A1–A2) and observed land allocations to recover water productivity across space, time, and crops, and infer water water rights' reliability, and uses the model of revealed preference with panel data over new and replanting decisions (A3) to identify the curvature of yield over time within an orchard, $\alpha'(x)$, and the extent of heterogeneity, σ_ϵ, across fields. Identifying the latter requires instruments that shift payoffs to planting, such as instruments for crop prices (Scott, 2013); the intuition is that the distribution of planting cost heterogeneity can be identified with these instruments via the responsiveness of planting decisions—if large (quasi-)random shifts in a given crop's expected price at the time of planting induce limited changes in water allocated to that crop, relative planting costs must be quite heterogeneous to explain the few marginal users; in contrast, larger changes in planting decisions imply less heterogeneous planting costs across fields.

3.5 Measuring misallocation

As emphasized, the model delivers a microfoundation to value water rights. To value i's water rights, which recall are distributed via G_i, let $(c_i(\iota), x_i(\iota))_{\iota\in i}$ denote the state of i's planting decisions. Then the value of the water right G_i is

$$\mathcal{V}_i(G_i) = \int_0^\infty \overline{V}_i(c_i(\iota), x_i(\iota))dG_i(\iota),$$

which can be decomposed into the reliable and unreliable components as

$$\mathcal{V}_i(G_i) = \int_0^{W_i^p} \overline{V}_i(c_i(\iota), x_i(\iota))dG_i(\iota) + \int_{W_i^p}^\infty \overline{V}_i(c_i(\iota), x_i(\iota))dG_i(\iota), \qquad (13)$$

where the first integral integrates only over the distribution of planting decisions, since $G_i(w) = 1$ for all $w \in [0, W_i^p]$, while the second integral integrates over the probability distribution of the remaining (unreliable) rights.

Asymmetric incentives for trade. Interestingly, equation (13) shows how the presence of reliable water rights lead short-run incentives for water trade to generally differ from long-run incentives, due to the rigidities associated with water rights invested in perennial crops with nonzero ages. In particular, i's reservation utility, or minimum price at which they will sell a marginal unit of reliable water, equals the lowest opportunity cost of keeping the water within their existing orchard fleet, $\{c_i(\iota), x_i(\iota)\}_\iota$,

$$\partial_- \mathcal{V}_i = \min_\iota \overline{V}_i(c_i(\iota), x_i(\iota))$$

whereas their willingness to pay for a unit of new reliable water, if their land constraint does not bind, equals its value in new production, $\partial_+ \mathcal{V}_i = \overline{V}_i(0,0)$. Given that $V_i(c_i(\iota), x_i(\iota))$ is bounded below by $\beta \overline{V}_i(0,0)$, since the latter includes the option to cut down the orchard and newly plant to obtain $\overline{V}_i(0,0)$, generally this implies that reliable water rights will be less valuable to transfer until the tree capital in which they are embodied is sufficiently depreciated.

Aggregate effects of reallocation. Let the vector $\mathbf{V} = (\mathcal{V}_i)_i$ collect the values of existing water rights across owners i and the matrix $\left[\frac{\partial \mathbf{V}}{\partial \ln \widetilde{W}}\right] = \left(\frac{\partial \mathbf{V}_i}{\partial \ln \widetilde{W}_j}\right)_{i,j}$ collect the semi-elasticities of the value functions with respect to one's own and others' water rights. Consider a vector of water right changes, $\Delta \ln \widetilde{W} = (\Delta \ln \widetilde{W}_i)_i$. As Baqaee and Sangani (2025, Proposition 5) show, the aggregate value of this water reallocation, $\sum_i \mathcal{V}_i$, can be approximated via the quadratic form

$$\Delta \ln \sum_i \mathcal{V}_i = \mathbf{V}'(\Delta \ln \widetilde{W}) + \frac{1}{2}(\Delta \ln \widetilde{W})' \left[\frac{\partial \mathbf{V}}{\partial \ln \widetilde{W}}\right] (\Delta \ln \widetilde{W}), \tag{14}$$

so that the approximate aggregate value of the reallocation reflects the correlation of the reallocation vector with the productivity of existing values and their curvature.

4 Data and empirical approach

I now describe the empirical analysis. A centerpiece of this project is very high-resolution satellite data that tracks irrigated crop choices at the field level in California for nearly forty different crops.[23] Yield and price data come the Cal-

[23]This data is costly to produce: one needs to train the model to recognize all of the land-use patterns, with extensive ground-truthing to verify the model's classification. This data was

ifornia County Agricultural Commissioners, 1980–2022, collated by the USDA Census. I take evapotranspiration data from California's Irrigation Management System, and crop coefficients from the DWR, to measure water efficiencies at the crop level at different locations. I then compare different places using the US Geological Service hydrological network, which allows me to partition California into the components of the river network that are relevant for the analysis.

4.1 Fields

California farms grow a wide range of crops under the current system of water property rights. I observe about forty distinct crops, $\{K_{ict}\}$, by field-year in annual data from 2014–2022. To illustrate the granularity of this data, Figure A8 shows an map of a subset of the field-level data near Fresno. I just have two colors because I want to emphasize the abundance of perennial orchards as well as annual crops. In practice, this data has about 40 different colors, and one could construct a rainbow picture.

To understand this diversity, Table A1 reports long-run average shares of farmland statewide and for the two Central Valley regions, the Sacramento and San Joaquin Valleys, over this period, for all crops with at least a 0.5% land share. Given that 78% of the state's agricultural land lies in the two Central Valley regions, statewide shares broadly approximate Central Valley totals, with a few small exceptions—for example, avocados, while iconically Californian, are mainly grown farther south; leafy vegetables like lettuce and broccoli are more commonly grown along the coast; and alfalfa is more frequently observed outside the Central Valley.

Table A1 also shows some meaningful differences between the Sacramento and the San Joaquin. Both places involve harvests from large quantities of almond and walnut trees, though San Joaquin irrigators grow more almonds (21.6% of land relative to 11.6%), while Sacramento farmers grow more walnuts (10.7% relative to 3.5%). San Joaquin growers also plant grapes (9.8% of irrigated land), pistachios (8.2%), sweet corn (9.7%) and orange trees (4.5%), at much higher rates than Sacramento farmers. Notably, Sacramento growers plant a great deal of rice (19.7% of irrigated land), a water-intensive but relatively low-value crop almost never grown in the San Joaquin.

funded through the Department of Water Resources and has been improved, corroborated, and verified, and is used for policymaking in California to track water use.

4.2 Trees

As mentioned in the introduction, a key element of the data is field-level information on the year of planting for orchards observed in 2020, 2021, and 2022. Plant dates range from 1984–2022, as depicted in Figure 4. Table 3 documents the significance of replanting decisions across farms. Orchard investments exhibit extremely high persistence. Among the 2.97 million acres of fields growing perennial crops observed in my data in 2020, the unconditional annual probability that a tree is cut down between WY 2020 and 2022 is 2.8% statewide. Without correcting for differences in water consumption across tree types that correlate with optimal replanting times, this implies that, in the observed equilibrium, more than 97% of water used in a given year by perennial crops is "committed" to forms of capital with potentially costly adjustment.

Table 3 also shows important heterogeneity in replanting decisions across crop types and ages. Age is a key determinant of replanting; farmers cut down trees planted in the 1990s—between two and three decades old—at an annual rate of 8.3%, in contrast to 2.5% for trees in the second decade of their life, and 0.9% for the first decade. The broad pattern—at least, given existing surface and groundwater rights—is that irrigators appear to have strong economic incentives not to cut down trees for at least two decades, though these rates vary quite meaningfully across crops. Peach and other stone fruit trees live the shortest productive lives, with annual hazard rates of 2.6% in the first decade of life, then climbing rapidly to between 14–17%. Almond trees last longer, with low probabilities of annual replacement ($< 3\%$) in the first two decades, rising to 16% in the third decade. Walnut, orange, and olive tree replacement rates remain below 2–3% for the first three decades of their lives, but replacement rates rise in their fourth decade to 8.3%, 4.4%, and 2.9%, respectively. Pistachio trees appear to live forever, with annual replacement rates in the data never above 1%.[24]

These differences across ages and crop types are important to explain the difference in unconditional replanting rates across the hydrological network; 2.6% in the San Joaquin and 3.2% in the Sacramento River Valley. Most of this aggregate difference appears to reflect the San Joaquin's large share of orange and pistachio trees—which live much longer than the other tree types, and comprise about 13% of irrigated land in the San Joaquin in 2020 relative to <1% in the Sacramento—as well as the much larger share of peach and stone fruit trees in

[24] Pistachio trees have been documented to maintain yields for up to three hundred years.

the Sacramento River Valley, which live the shortest fruitful lifespans.

4.3 Irrigation

The calculation of irrigation water demand, the functions $\omega_{ict}(\tau)$, is conceptually very straightforward, but computationally somewhat involved. The surface of climate data allows us to calculate, in theory, how much water a plant would need in a given location i on day τ, what is known as "reference evapotranspiration," $\eta_{it}(\tau)$. Since the 1980s, the state of California has published reference evapotranspiration for irrigators, who use the information in the same way that you might check the weather. Irrigators input this data into their irrigation scheduling algorithms to calculate how much water they should apply to their crops. These calculations use what are known as crop coefficients, $\vartheta_{ic}(\tau)$, which parametrize the demand of water for the crop over time given its location and growing season.

Figure A9 gives some examples of the daily gridded reference evapotranspiration data. I show maps at the end of October and in mid-July to emphasize how different the growing conditions can be at different points in the year. From the beginning of the California water year in October, it becomes less water-intensive to grow plants through December and January, and then as spring and summer arrive, it becomes necessary to use more water to grow the same crops.

Irrigators then combine reference evapotranspiration, $\eta_{it}(\tau)$, with crop coefficients, $\vartheta_{ic}(\tau)$, that vary by crop type c, phase of the growing cycle in which τ lies, and by i through regional differences in optimal growing seasons and soil quality, to determine per-acre crop water demand, defined as $\omega_{ict}(\tau) = \eta_{it}(\tau)\vartheta_{ic}(\tau)$. For example, Figure A10 shows monthly crop coefficients, $\vartheta_{ic}(\tau)$, for almonds in the San Joaquin Valley. The curve plots the crop coefficients from the government's recommendations for optimal irrigation. Over time, as the almond tree grows lots of leaves and starts to bear almonds, it needs more water, so $\vartheta_{ic}(\tau)$ rises. The annual water that the almond tree requires is then obtained by integrating under the curve that interacts the crop coefficient with reference evapotranspiration. The black line plots reference evapotranspiration over time, the same variable depicted in the maps of Figure A9, and then the dotted line is the realized demand of the crop based on the crop coefficients. This is the engineering behind how we grow crops, and it is the same for annual crops, with more seasonal variability because annual crops start from zero before growing up to be harvested.

4.4 Estimated water use

The model of irrigation scheduling then implies realized water demand, though the optimal irrigation weights $\int \omega_{ict}(\tau)d\tau$ for each crop and the land allocated to grow these crops, via the identity (2) that follows from (1) and Assumptions A1 and A2. Figure A2, Panel A, shows the implied water use in California in 2020 across watersheds. As expected, most of the state's water is used in the Central Valley, where large areas of land are used for agriculture and irrigators grow very water-intensive crops. Figure 6 zooms in to compare upstream and downstream regions. On the left is the water used North of the Delta, in the Sacramento River Basin, and the right total water used in the San Joaquin River Basin.

4.5 Crop prices and yields

In addition to observed crop choices and estimated water demand, annual marginal products require crop prices and yields. I use California-wide realized prices P_{ct} and county-wide yields A_{ict} for all fields i in a given county growing crop c and year t, substituting California-wide yields for counties where Census redacts yields (those without enough production). Table A2 considers a local HUC12 watershed in the Sacramento River Valley, showing the three largest crops that were produced by acreage. Yields and prices each vary quite a lot between years. The implied revenue-per-acre for different crops, also reported, underly the estimates of the marginal products of water.

4.6 Marginal products of water

I now report the revenue per acre foot of water corresponding to the marginal product of water for that specific field for that crop,

$$\alpha_{ict}P_{ct} \equiv \frac{A_{ict}P_{ct}}{\int \omega_{ict}(\tau)d\tau}. \tag{15}$$

Table A3 shows approximately the 95th percentile of revenue per unit water, on the order of about $4,000 per acre-foot. This significantly exceeds the water prices reported earlier, which range no more than a thousand dollars per acre-foot in the most constrained case in 2024 in the southern Delta. As we look instead at the bottom distribution of these shadow values of water in the lower half of Table A3, one sees very different mixes of crops. Wheat and hay, annual crops that have much lower value per acre, use reasonable amounts of water. These crops use a lot less water per acre than pistachios, avocados, pears, et cetera, but even though they use less water, they still have much lower values per acre-foot, because their yields and prices are so low.

4.7 Planting costs

To measure average planting costs, I use cost data from the bidecadal USDA Agricultural Census, which reports county-level input costs in 2002, 2007, 2012, 2017, 2022. I construct average input cost shares for each county, including expenditure on seeds, plants, chemicals, fertilizer, fuels, utilities, supplies and repair, contract labor, hired labor, and machinery rental. I omit operating costs labeled taxes, interest, depreciation, livestock, feed, and custom and other agricultural services. I assume that these average planting costs are allocated across crops in proportion to that crop's revenue, which can be microfounded with a model of flexible factor choice and constant output elasticities with respect to input expenditures (see Rafey, 2023, p. 451).

To recover unobserved planting costs, with estimates of water use and annual marginal products, I require the additional structure of the model in Section 3.3. I estimate unobserved planting costs separately across the reliable and transient components of water rights, since the two types involve very different decision problems. To infer water right reliability, I assume local volumes of reliable water rights $\{W_i^0\}_i$ correspond to the minimum volume of water used for perennial crops across 2014–2022, so that the distribution of unreliable water rights, $\{W_{it}^1\}_{i,t}$, is the residual volume of water used across all crops each year.

Unbiased estimates of the extent of heterogeneity across unreliable water rights—i.e., the scale parameter σ_ϵ in (10)—cannot be obtained with OLS because crop prices will correlate with ξ_{ict}. I estimate the scale parameters by instrumenting for crop prices using lagged yield shocks, controlling for crop and year fixed effects. Such lagged yield shocks are often used to identify agricultural supply elasticities; they shift current agricultural commodity prices through expectations and commodity storage (Roberts and Schlenker, 2013). The water productivity coefficients, $\{\alpha_{ict}\}_{c \in \mathcal{C}^a}$, necessitate numerical integration for the same reasons as the random coefficients in Berry *et al.* (1995).

Similar instruments also identify the sensitivity of perennial crop choice at the time of planting to the expected net present discounted value of returns, since the observed planting shares used to estimate these structural parameters are endogenous to crop yield, prices, and water productivities. For perennial water rights, the Rust (1987) method searches for parameters such that the optimal regenerative stopping problem implies similar replacement rates and planting choices. I jointly estimate σ_ϵ and the dynamic parameters, θ and the ξ_{ct}'s, via a Berry (1994) nested fixed point algorithm embedded in the Rust (1987) value functions, an approach similar in spirit to Gowrisankaran and Rysman (2012). I numerically integrate over the water productivity coefficients for perennial crops, $\{\alpha_{ict}\}_{c\in\mathcal{C}^p}$, in the same way as for annual crops.

Table A7 reports some preliminary estimates of planting costs for newly-planted perennial crops, based on a region-year panel from 1984–2020, for the northern and southern regions, with choices restricted to perennial crops with at least 1% share of water use in each region. In estimation, I set $\beta = 0.95$, constrain average expected planting costs to be nonzero and not to exceed the crop's total net present discounted revenue, and use current and lagged yield shocks as instruments to form GMM moments from $\mathbb{E}[\xi'_{ict}(1, Z_{ic,t-1}, Z_{ict})] = 0$. The current estimates do not reject a common σ_ϵ across both regions. The reference utility is constructed using almond planting costs inferred from almond total net present discounted revenue and almond orchard land prices (about \$25,000/acre in the Sacramento Valley, \$30,000/acre in Tulare, and \$35,000/acre in the San Joaquin).

Columns 1–3 of Table A7 show some of the variation in the data underlying the estimates. The first and second columns show the average share of water used, and the average annualized net-present-discount-value of revenue flows, $\mathbb{E}_{it}[\frac{1}{1-\beta}\sum_{t\geq 0}\beta^t(1 - i_{it}(c,t))\alpha_{ict}(t)P_{ct}]$, for the different crop types; broadly, the Berry *et al.* (1995) style estimator aims to find planting costs that rationalize these water shares given the expected revenue flows. The differences in optimal replacement rates, $i_{it}(c,x)$, across crops create an additional subtlety; the third column reports a measure of aggreggate replanting rate, $\mathbb{E}_{it}[\sum_{t\geq 0}\beta^t\prod_{s=0}^{t-1}(1 - i_{is}(c,s))i_{it}(c,t)]$; for pistachios, this is close to zero (0.05) because pistachio trees are hardly ever cut down; it is much higher (≈ 0.5) for stone fruits like peaches and cherries that are replaced earlier, and takes on more medium values for moderately long-lived almonds and walnuts. This variation alters the expected revenue flows on which planting costs are based; crops with higher replanting rates have lower annualized NPDV revenue flows but also return to the renewal action, receiving $\overline{V}(0,0)$, sooner than the other crops.

The estimate of the scale parameter, σ_ϵ, is 4015.87, implying own-price planting elasticities ranging 0.34–1.16 across the first and third quartiles and cross-price elasticities ranging between 0.01–0.07. Columns 4–5 of Table A7 report parameter estimates for planting costs, ξ_{ict}, common across all $i \in r$ for the two regions considered; the within-crop standard deviation across years shows that planting costs vary meaningfully across years but that most of the variation in planting costs is across crops. Column 6 reports the predicted shares. When $\{\xi\}$ is unconstrained, these predicted shares should match observed shares by construction, in the Berry (1994) fixed point algorithm; when $\{\xi\}$ is constrained, they need not match observed shares perfectly—indeed, model fit is particularly poor for the most and least popular crops, almonds and olives, underpredicting the share allocated to the former and overpredicting the latter.

A final source of differential planting costs are costs of irrigation. Reliable water rights with greater groundwater shares will be more costly; further, meaningful differences exist in groundwater extraction costs across space. The first two columns of Table A5 show the average well depth across the San Joaquin and the Sacramento. And in fact, the typical well in the San Joaquin is about twice as deep as the typical well in Sacramento—about 40% deeper. This will translate into differences in variable pumping costs that are meaningful in terms of groundwater extraction, although they don't come close to the magnitude of the differences in marginal products from the shadow values. However, as the rightmost column of Table A5 shows, extraction costs differ across regions by about a factor of two through the empirical distribution of watershed-level costs. One interpretation of this difference is that the farmers in the San Joaquin are willing to to pull groundwater for a cost of almost twice that of the Sacramento River Basin, providing some evidence of misallocation, which would be more severe if we consider intertemporal or environmental externalities of groundwater overextraction. Another is that these marginal groundwater costs should be accounted for in the valuation of a region's water rights, implying a smaller gap in water values across regions through the higher pumping costs incurred to maintain the reliability of water rights in the San Joaquin and Tulare River Basins.

5 Results

I now use the estimates of water use, annual marginal products, and planting costs to study water allocation in California. Throughout, I emphasize comparisons between the value of water used above and below the Sacramento-San Joaquin Delta, and what might that imply about the efficiency of the allocation of water in California.

5.1 Regional hydrological network and water values

Figure 8 plots the value per acre foot of water at the HUC12 level.[25] The lighter green colors are lower values, ranging from zero about \$2,500/af, and one can see much lighter shades of green north of the Delta, particularly in the northern part of the Sacramento River Valley, relative to the much darker patterns below in the San Joaquin River Basin. These patterns illustrate a systematic difference across these two regions, as well as substantial dispersion within each region.

Table 5 reports deciles of the realized marginal water values for 2020; Panel A conditions the distribution on region. To construct this distribution, also reported in Figure 7, we take all the water used in a region, e.g., the San Joaquin Valley, and for each unit of water, we calculate its value. So, for example, three acre-feet of water used to grow an acre of almonds implies three units of almond water values. One then continues across crops to construct the empirical distribution of water values reported in Table 5. The leftmost column of Panel A is the empirical distribution of water values in the San Joaquin, south of the Delta. The ratio of the two regional distributions is striking—at least, it implies, depending on your story of relative planting costs, that we should move a lot of water to the south that we have not. This is the sharp difference between these two places that we saw in Figure 8. Most of the difference across watersheds comes from the first through sixth or seventh decile, places where, in the San Joaquin, irrigators are still growing a lot of these high-value fruits and nuts, whereas Sacramento grows more of the annual crops.

Alternatively, we could think of the question posed by the rightmost columns of Table 5 as whether the distribution of marginal values of water for the San Joaquin, the southern component of the network, first-order stochastically dom-

[25] A HUC12 subwatershed covers about 40 square miles; this is the finest partition of the USGS (2013) hydrological network.

inates the distribution in the north. It's clear that it doesn't, in particular, in the tails, but for most of the distribution, the marginal values of water are significantly higher in the lower part the network.

In considering flow constraints as an explanation for the difference in these productivity distributions, it is interesting to compare the ratios in these water values with the earlier differences discussed in water prices for trades above or below the Delta chokepoint. Recalling Table 2, the Delta price ratio typically ranged from one-and-a-half to two or two-and-half. And this price ratio is somewhat comparable to that derived from the microfoundations of the crop model, suggesting that, as we think about interpreting these results, flow constraints could be important. That is, revisiting the water price gradient in light of the similar gradient in estimated marginal products suggests, potentially, that there could be some value to relaxing flow constraints in the Delta through infrastructure or changes in environmental law.

5.2 Investment, planting costs, and water values

As emphasized throughout this paper, places below the Delta and with more senior water rights also have more investment in orchards. The last column of Table 7 shows that both region and historical priority predict significantly higher shares of perennial water uses, and Figure A11 shows these differences are highly persistent over 2014–2022. If the planting costs are proportional to the value of the crop, then they should be differenced out in the comparison between these two distributions, but not otherwise. Figure 7, Panel B shows the large effect of removing average planting costs from the distribution of water values: in general, because input costs for higher-value crops rise more than proportionally with the value of the crop, comparing marginal water products alone can overstate dispersion. In addition to these average planting costs, unobservable, idiosyncratic planting costs will also affect any interpretation of the differences that integrates under the empirical distributions of marginal products to obtain hypothetical gains from trade, which I do not do here.

Table 5, Panel B explores the differences between perennial and annual crops in terms of annual marginal products of water. As expected, the distribution of marginal products of water applied to perennial crops comes close to stochastically dominating the distribution for annual crops, with deciles ratios between the 10% and 90%-iles ranging between 1.06–2.15. However, as shown in Panels A and B of Figure 9, conditioning on perenniality does not fully explain the Delta gradient in water productivity. Panel B shows ratios of perennial marginal products in the interdecile range of the regional distributions of between 0.99–1.43, so that the San Joaquin River Valley plants more valuable perennial crops per unit of water than the Sacramento. The differences are more striking among annual crops: the San Joaquin grows much more water-efficient annual crops, in \$/af, than in the Sacramento Valley—marginal products remain similar across the two regions until the median unreliable water right, at which point the ratio of the distributions rises, to more than a factor of two in the upper deciles.

A final question is how planting costs change the comparisons within perennial crops. As discussed in Section 4.7, the estimated extent of heterogeneity in planting costs across fields do not differ across regions, but the average planting cost estimates and choice sets across perennial crops do differ meaningfully. Subject to the current simplifications used in the preliminary estimation procedure, the final three columns of Table A7 report the implied value of planting each perennial crop, $\overline{V}(c, 1)$, the average planting cost conditional on choosing c, $\mathbb{E}[\xi_{ct} + \varepsilon_{ict}(\iota) | c_{it}(\iota) = c] = \xi_{ct} + \sigma_\epsilon \gamma$, where $\gamma \approx 0.57$ is Euler's constant, and finally the ex-ante value of an average *de novo* or uncommitted reliable water right in the two regions, $\overline{V}_r(0, 0)$. As some types of orchards last longer than others, the option value of replanting a new perennial crop differentially influences the value of the water use; for example, as peach trees depreciate relatively swiftly, the value of the renewal action becomes a more important part of the value of planting such a crop than, for example, pistachio trees, where most of the water value reflects the flow of revenue over time from continued production. Overall, the estimates of the value of a new, uncommitted reliable water right, $\overline{V}_r(0, 0)$, narrow the gap between the two regions and preserve the sign of the Delta gradient, with the long-run value of water rights in the southern component of the network, net of planting costs, about 10% higher than in the northern component.

5.3 Water values and historical property rights

Finally, I consider how water productivity dispersion within watersheds correlates with features of the hydrological network and the legacy of historical property rights. Specifically, I ask how standard Syverson (2004) measures of the empirical distribution of water productivities—over water rights in each watershed-year from 2014–2022—correlate with fixed attributes of historical property rights (the share of paper water rights at baseline with priority dates prior to 1914, depicted in Figure A6), the share of "reliable" water rights used to grow perennials, and the hydrological network (location above or below the Delta, and an indicator for drought that varies by year but not watershed). These regressions are descriptive and should not be interpreted as causal, but reveal some interesting patterns.

Tables 6–7 reports the results, of which three are noteworthy. First, the correlations corroborate earlier discussion about intra- and inter-regional dispersion in marginal products. Within a HUC10 watershed, the interquartile range of the log marginal products (the first of Syverson (2004)'s four measures of productivity dispersion) averages about 0.5, in line with the dispersion discussed above. Further, mean and median marginal products south of the Delta are significantly greater than than the North, consistent with the regional comparisons in the previous section, as well as the results of Table , which show the stability of the Delta gradient in annual marginal products from 2014–2022.

Second, Table 6 interestingly shows that interquartile and interdecile ranges increase during drought years, contrasting findings in settings with functioning water markets, where water trade can lower misallocation in times of scarcity (Rafey, 2023). Further, the mean, median, and bottom 10%-ile values fall, indicating the drought's negative effects on water productivity throughout the distribution. However, the result in column (7) of Table 7 provides some evidence (consistent with findings in Hagerty, 2022) that the least productive crops are being fallowed during these droughts.

Third, a legacy of senior water rights predicts less dispersion in the marginal value of water. Tables 6–7 show that watersheds with greater pre-1914 water rights have significantly lower interquartile and interdecile ranges, higher median and means, and much higher bottom decile values. These are weaker effects than for the share of perennial crops—a more direct proxy for reliable water rights—which predict considerably more productive uses of water.

The principle mechanism behind both the geographic and historical seniority correlations appears to be investment in perennial crops. As the last column of Table 7 shows, places with more senior water rights or below the Delta also invest more by planting perennial crops, providing some evidence of the greater reliability—and higher value—of these water rights, and contravening a story of moral hazard where senior rightsholders waste water rather than risk expropriation of inherited water rights.

6 Conclusion

This paper outlined some economics of water property rights and a framework for evaluating water misallocation. The general approach captures three important sources of water value not present in some prior empirical models. First, equilibrium investment in complementary forms of capital, such as trees in orchards, will raise the productivity of water use; these investment costs need to be subtracted from the marginal product of water to determine the water owner's reservation value, and they also imply rigidities that limit short-run water reallocation and create value from commitment to longer-run water trades. Second, water rights often have random components, and the probability of rationing affects the value of the water right and comparisons across water owners. When annual spot markets are incomplete and investment gives rise to adjustment costs, the probability of rationing will affect the value of the right nonlinearly, with more reliable rights creating more value than a mean-preserving spread of those rights across multiple less-reliable tiers. Third, inherent differences in water productivity across locations, correlated with the observed use of water rights, make learning about the counterfactual values of water not straightforward.

The empirical work currently delivers two findings. First, empirically, there seems to be significantly greater marginal products of water used in places below the network bottleneck—where water can be scarce due to flow constraints—and places endowed with senior water rights that are more reliable during drought. These complementary investments are what we might expect in most models of factor-augmenting technical change. Second, this gradient in marginal values has some implications for welfare that depend on the extent to which the gradient reflects planting costs consistent with more senior appropriative rights, or more welfare-relevant constraints on trade. More work is needed to sift through these competing explanations for the dispersion in marginal products, including—but not limited to—finalizing the estimation of planting costs, which is under way.

References

Acemoglu, D. (2002). Technical change, inequality, and the labor market. *Journal of Economic Literature*, **40** (1), 7–72.

Adamopoulos, T. and Restuccia, D. (2014). The size distribution of farms and international productivity differences. *American Economic Review*, **104** (6), 1667–1697.

Aronoff, D. and Rafey, W. (2023). Conservation priorities and environmental offsets: Markets for Florida wetlands. *NBER Working Paper*, **31495**.

Asker, J., Collard-Wexler, A. and De Loecker, J. (2019). (Mis)allocation, market power, and global oil extraction. *American Economic Review*, **109** (4), 1568–1615.

—, — and Loecker, J. D. (2014). Dynamic inputs and resource (mis)allocation. *Journal of Political Economy*, **122** (5), 1013–1063.

Atkeson, A. and Kehoe, P. (1999). Models of energy use: Putty-putty versus putty-clay. *American Economic Review*, **89** (4), 1028–1043.

Ayres, A., Meng, K. and Plantinga, A. (2021). Do environmental markets improve on open access? Evidence from California groundwater rights. *Journal of Political Economy*, **129** (10).

Balboni, C., Burgess, R. and Olken, B. (forthcoming). The origins and control of forest fires in the tropics. *Review of Economic Studies*.

Baqaee, D. and Farhi, E. (2020). Productivity and misallocation in general equilibrium. *Quarterly Journal of Economics*, **135** (1), 105–163.

— and Sangani, K. (2025). Quotas in general equilibrium. *Working Paper*.

Berry, S. (1994). Estimating discrete-choice models of product differentiation. *RAND Journal of Economics*, **25** (2), 242–262.

—, Levinsohn, J. and Pakes, A. (1995). Automobile prices in market equilibrium. *Econometrica*, **63** (4), 841–890.

Borenstein, S. *et al.* (2002). Measuring market inefficiencies in California's restructured wholesale electricity market. *American Economic Review*, **92** (5), 1376–1405.

Boser, A., Caylor, K., Larsen, A., Pascolini-Campbell, M., Reager, J. and Carleton, T. (2022). Field scale crop water consumption estimates reveal potential water savings in California agriculture. *Nature Communications*, **15** (2366).

Burgess, R., Hansen, M., Olken, B., Potapov, P. and Sieber, S. (2012). The political economy of deforestation in the tropics. *Quarterly Journal of Economics*, **127** (4), 1707–1754.

Burlig, F., Preonas, L. and Woerman, M. (2024). Groundwater and crop choice in the short and long run. *Energy Institute at Haas Working Paper*.

Burness, H. S. and Quirk, J. (1979). Appropriative water rights and the efficient allocation of resources. *American Economic Review*, **69** (1), 25–37.

Carleton, T., Crews, L. and Nath, I. (2025). Agriculture, trade, and the spatial efficiency of global water use. *Working Paper*.

Costinot, A., Donaldson, D. and Smith, C. (2016). Evolving comparative advantage and the impact of climate change in agricultural markets: Evidence from 1.7 million fields around the world. *Journal of Political Economy*, **124** (1), 205–248.

D'Odorico, P., Chiarelli, D., Rosa, L., Bini, A., Zilberman, D. and Rulli, M. C. (2020). The global value of water in agriculture. *Proceedings of the National Academy of Sciences*, **117** (36), 21985–21993.

DWR (2023). *State Water Project drives California's economy.* Tech. rep., California Department of Water Resources.

Edelstein, B. (2025). Water scarcity management and housing markets: Evidence from water impact fees in Colorado. *Job Market Paper, UPenn.*

Ferguson, B. (2024). Trade frictions in surface water markets. *Job Market Paper, Stanford GSB.*

Gartrell, G., Mount, J., Hanak, E. and Gray, B. (2017). *A new approach to accounting for environmental water: Insights from the Sacramento-San Joaquin Delta.* Tech. rep., Public Policy Institute of California.

Gates, P. (1991). *Land and law in California: Essays on land policies.* Ames, Iowa: Iowa State University Press.

Gowrisankaran, G. and Rysman, M. (2012). Dynamics of consumer demand for new durable goods. *Journal of Political Economy*, **120** (6), 1173–1219.

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

— (2023). What holds back water markets? Transaction costs and the gains from trade. *Working Paper, Montana State University.*

Hanak, E., Sencan, G. and Ayres, A. (2021). *California's water market.* Tech. rep., Public Policy Institute of California.

Hsiao, A. (2021). Coordination and commitment in international climate action. *JMP, MIT.*

Hsieh, C.-T. and Klenow, P. (2009). Misallocation and manufacturing TFP in China and India. *The Quarterly Journal of Economics*, **74** (4), 1403–1448.

Leonard, B., Costello, C. and Kroetz, K. (2025). The economics of contracting for conservation. *Working Paper.*

Medellin-Azuara, J. *et al.* (2022). *Economic impacts of the 2020–22 drought on California agriculture.* Tech. rep., U.C. Merced Water Systems Management Lab Report for the California Department of Food and Agriculture.

Midrigan, V. and Xu, D. Y. (2014). Finance and misallocation: Evidence from plant-level data. *American Economic Review*, **104** (2), 422–458.

Rafey, W. (2023). Droughts, deluges, and (river) diversions: Valuing market-based water reallocation. *American Economic Review*, **113** (2).

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

Roberts, M. and Schlenker, W. (2013). Identifying supply and demand elasticities of agricultural commodities: Implications for the US ethanol mandate. *American Economic Review*, **101** (6), 2265–2295.

Rust, J. (1987). Optimal replacement of GMC bus engines: An empirical model of Harold Zurcher. *Econometrica*, **55** (5), 999–1033.

Scott, P. (2013). Dynamic discrete choice estimation of agricultural land use. *Working Paper.*

Souza-Rodrigues, E. (2019). Deforestation in the Amazon: A unified framework for estimation and policy analysis. *Review of Economic Studies*, **86** (6), 2713–2744.

Sum, S. (2024). Trading water and work: Labor and production shifts under California's groundwater markets. *Job Market Paper, UCSD*.

Syverson, C. (2004). Market structure and productivity: A concrete example. *Journal of Political Economy*, **112** (6), 1181–1222.

Tiew, A. (2025). E.U. trade restrictions, heterogeneity among Malaysian oil palm farmers, and limiting deforestation. *Working Paper, NYU*.

Timmins, C. (2002). Measuring the dynamic efficiency costs of regulators' preferences: Municipal water utilities in the arid West. *Econometrica*, **70** (2), 603–629.

USGS (2013). *Federal standards and procedures for the National Watershed Boundary Dataset (WBD), Fourth edition*. Tech. rep., USGS and USDA, Natural Resource Conservation Service.

Wong, A. J., Jin, Y., Medellín-Azuara, J., Paw, K. T., Kent, E. R., Clay, J. M., Gao, F., Fisher, J. B., Rivera, G., Lee, C. M., Hemes, K. S., Eichelmann, E., Baldocchi, D. D. and Hook, S. J. (2021). Multiscale assessment of agricultural consumptive water use in California's Central Valley. *Water Resources Research*, **57** (9).

Zeff, H., Hamilton, A. L., Malek, K., Herman, J. D., Cohen, J. S., Medellin-Azuara, J., Reed, P. M. and Characklis, G. W. (2021). California's food-energy-water system: An open source simulation model of adaptive surface and groundwater management in the Central Valley. *Environmental Modelling and Software*, **141** (105052).

Table 1. Natural Variability and Water Rationing

	Wet	Dry	Dry, pre-1914	Dry, post-1914
0	0	0	0	0
0.1	0	0	0	0
0.2	0.0002	0	0.001	0
0.3	0.031	0.002	0.032	0
0.4	0.105	0.040	0.093	0.016
0.5	0.234	0.120	0.191	0.086
0.6	0.426	0.251	0.356	0.203
0.7	0.676	0.475	0.593	0.400
0.8	0.935	0.774	0.890	0.714
0.9	1	1	1	1
1	1	1	1	1

Central Valley irrigators' reported annual water diversions divided by reported face value — deciles of the **water right $\times$ year** distribution, 2010–2023.

Columns (3) and (4) split the sample by water right priority date, into rightsholders whose claims date before ("pre-1914") and after ("post-1914") the 1914 Water Commission Act. Wet and (critically) dry water-year designations $\equiv$ the California Eight River Index (Sacramento River + San Joaquin River Runoff).

Source. Author's calculation using SWRCB WRIMS data. 27,010 wet year diversion statements; 26,750 critically dry year diversion statements.

Table 2. Surface Water Price Gradients Across the Delta

	San Joaquin (SOD)	Sacramento (NOD)	diff	ratio
0	5.2	1.1	4.1	4.7
0.1	30.8	43.6	−12.9	0.7
0.2	48.8	51.3	−2.5	1.0
0.3	71.2	60.6	10.6	1.2
0.4	102.5	65	37.5	1.6
0.5	146.7	65	81.7	2.3
0.6	166	83.1	82.9	2.0
0.7	241.6	107	134.6	2.3
0.8	278.4	133.5	145.0	2.1
0.9	983	250	733	3.9
1	1,550	342.3	1,207.7	4.5

Distribution of annual surface water allocation prices (2024 $/af), trade-level, over assembled trades 1987–2009 (Libecap 2011) and 2022–2023 (WestWater, LLC).

Table 3. Hazard Rate by Decade Planted, 2020–2022

tree_type	acres_2020	haz_CA	haz_SV	haz_SJ
all /	2,970,885	0.028	0.032	0.026
1980s /	340,255	0.056	0.076	0.049
1990s /	353,306	0.083	0.073	0.092
2000s /	879,352	0.025	0.022	0.025
2010s /	1,397,972	0.009	0.012	0.008
/ oranges unspecified	299,025	0.021	0.030	0.020
/ olives	48,269	0.006	0.008	0.010
/ almonds all	1,390,516	0.030	0.024	0.031
/ walnuts english	426,503	0.021	0.018	0.023
/ pistachios	460,887	0.001	0.003	0.001
/ peaches unspecified	65,854	0.082	0.107	0.077
1980s / oranges unspecified	79,438	0.044	0.067	0.043
1990s / oranges unspecified	58,230	0.019	0.038	0.018
2000s / oranges unspecified	72,489	0.025	0.011	0.023
2010s / oranges unspecified	88,868	0.002	0.000	0.006
1980s / olives	14,055	0.029	0.031	0.035
1990s / olives	5,770	0.008	0.012	0.012
2000s / olives	16,121	0.013	0.013	0.020
2010s / olives	12,323	0.003	0.013	0.000
1980s / almonds all	52,929	0.093	0.084	0.095
1990s / almonds all	137,412	0.164	0.117	0.178
2000s / almonds all	464,376	0.029	0.027	0.030
2010s / almonds all	735,800	0.003	0.000	0.004
1980s / walnuts english	72,678	0.083	0.092	0.070
1990s / walnuts english	66,512	0.030	0.021	0.036
2000s / walnuts english	104,072	0.008	0.006	0.012
2010s / walnuts english	183,241	0.012	0.011	0.011
1980s / pistachios	50,966	0.008	0.016	0.007
1990s / pistachios	40,435	0.004	0.000	0.004
2000s / pistachios	127,947	0.001	0.001	0.001
2010s / pistachios	241,538	0.000	0.002	0.000
1980s / peaches unspecified	3,834	0.173	0.372	0.134
1990s / peaches unspecified	4,088	0.174	0.174	0.174
2000s / peaches unspecified	22,154	0.148	0.170	0.143
2010s / peaches unspecified	35,778	0.026	0.041	0.024

Average share of perennial trees cut down (annual "hazard rate") between WYs 2020–21 and WYs 2021–22, by decade of original planting date and crop type. Reported for the top six perennial crops, by acreage among Central Valley irrigators in 2020. Calculated for all of California, for the Sacramento Valley (SV) and San Joaquin and Tulare River Basins (SJ).

Table 4. New Perennial Planting Decisions, 2000–2020

Dependent Variable:			$\mathbf{1}$(choose c)		
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
log(yield$_{ict}$×price$_{ict}$)	−0.0675***	0.0549***	0.0640***	0.1541***	0.1675***
	(0.0225)	(0.0126)	(0.0167)	(0.0217)	(0.0295)
Instruments				✓	✓
Fixed-effects					
region-year	✓	✓		✓	
region-crop		✓		✓	
region-crop-year			✓		✓
Fit statistics					
Observations	417,586	417,586	417,586	407,575	407,575
R^2	0.01424	0.19760	0.21985	0.19328	0.21773
Within R^2	0.00818	0.00305	0.00240	−0.00402	−0.00153

Clustered (crop-year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Illustrative linear regression at the field-crop-year-planted level for newly-planted perennial orchards from 2000–2020. Outcome is 1 if the crop planted equals c and 0 otherwise.

Columns (1)–(3) regress choice on log annual marginal products and covariates. Columns (4)–(5) instrument for log annual marginal products, $\ln(\text{yield}_{ict}\times\text{price}_{ict})$, with $\ln(\text{yield}_{ic,t-1}\times\text{price}_{ic,t-1})$.

Table 5. Average Estimated Water Values, 2020

A. Distribution of water values per acre-foot by region

	San Joaquin (SOD)	Sacramento (NOD)	diff	ratio
0	27.80	28.58	−0.78	0.97
0.1	87.59	128.82	−41.23	0.68
0.2	163.86	164.92	−1.06	0.99
0.3	229.88	240.07	−10.19	0.96
0.4	259.55	248.55	11.00	1.04
0.5	318.25	298.24	20.01	1.07
0.6	377.77	302.96	74.80	1.25
0.7	669.29	315.29	354.00	2.12
0.8	895.32	347.14	548.18	2.58
0.9	1,991.35	432.39	1,558.96	4.61
1	7,871.46	880.26	6,991.20	8.94

B. Distribution of water values per acre-foot by reliability

	Perennial crops	Annual crops	diff	ratio
0	42.09	27.80	14.29	1.51
0.1	182.70	87.59	95.11	2.09
0.2	291.37	163.86	127.51	1.78
0.3	494.68	229.88	264.80	2.15
0.4	537.35	259.55	277.80	2.07
0.5	583.52	318.25	265.27	1.83
0.6	661.68	377.77	283.91	1.75
0.7	725.91	669.29	56.62	1.08
0.8	1,567.66	895.32	672.34	1.75
0.9	2,109.74	1,991.35	118.39	1.06
1	3,630.11	7,871.46	−4,241.34	0.46

Annual marginal values of water ($/af), Central Valley irrigators, WY 2020.

Table 6. Dispersion, Water Rights, and Network Structure

	Moment of the water value distribution:					
	IQR	IDR	ln(median)	ln(mean)	ln(q10)	share_per
	(1)	(2)	(3)	(4)	(5)	(6)
pre-1914 water rights share	-0.146^{*}	-0.155	0.189	0.213^{*}	0.299^{**}	0.094^{*}
	(0.086)	(0.112)	(0.135)	(0.120)	(0.145)	(0.053)
1(south of the Delta)	0.171^{**}	0.370^{***}	0.266^{**}	0.228^{**}	-0.047	0.216^{***}
	(0.072)	(0.091)	(0.106)	(0.094)	(0.114)	(0.041)
1(drought_year)	0.050^{***}	0.061^{***}	-0.076^{***}	-0.042^{**}	-0.082^{***}	0.013^{**}
	(0.019)	(0.022)	(0.022)	(0.018)	(0.024)	(0.006)
Mean of dependent variable	0.482	0.841	6.442	6.506	5.997	0.653
Observations	1,640	1,640	1,640	1,640	1,640	1,903
Adjusted R^2	0.021	0.051	0.032	0.036	0.015	0.108

Some descriptive linear regressions. The unit of observation is the watershed-year distribution of marginal water values, over all Central Valley (Sacramento, San Joaquin, and Tulare) HUC10 watersheds and water years with land use data (2014, 2016, 2018–2022) and water property rights claimed up to the baseline (2013).

Outcomes defined using Syverson (2004) measures of productivity dispersion:
(1)–(3) interquartile range, (4)–(6) ln(median),
(7)–(9) 10th percentile ln(water productivities).

See Table 7 for results on the interdecile range, ln(volume-weighted mean), and more.

Explanatory variables:
"pre-1914 water rights share" ≡ reported pre-1914 face value (in af-year) by irrigators, divided by reported face value for all water rights with priority date before 2014.
"perennial (reliable) water rights share" ≡ share of water used to irrigate perennials.
"South of the Delta" ≡ San Joaquin and Tulare River Basins. Omitted category is North of the Delta ≡ Sacramento River Basin.
"Drought year" ≡ critical (C) water-year, from the SJI-SVI Eight River Index.

Robust (HC0) standard errors clustered at the HUC10 level.

Table 7. More Dispersion, Water Rights

	Moment of the water value distribution:						
	ln(mean)			IDR			share_per
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
perennial water rights share	0.859			0.038			
	(0.096)			(0.122)			
pre-1914 water rights share		0.253			−0.090		0.094
		(0.120)			(0.121)		(0.053)
1(south of the Delta)			0.252			0.353	0.216
			(0.093)			(0.091)	(0.041)
1(drought_year)	−0.058	−0.042	−0.042	0.060	0.061	0.060	0.013
	(0.018)	(0.018)	(0.018)	(0.022)	(0.022)	(0.022)	(0.006)
Mean of dependent variable	6.506	6.506	6.506	0.841	0.841	0.841	0.653
Observations	1,640	1,640	1,640	1,640	1,640	1,640	1,903
Adjusted R^2	0.158	0.016	0.025	0.0004	0.002	0.047	0.108

Additional results for Table 6.

Outcomes defined using Syverson (2004) measures of productivity dispersion:
(1)–(3) ln(volume-weighted mean),
(4)–(6) interdecile range.

Outcomes in columns (7) and (8) correspond to covariates.

See Table 6 for variable definitions.

Robust (HC0) standard errors clustered at the HUC10 level.

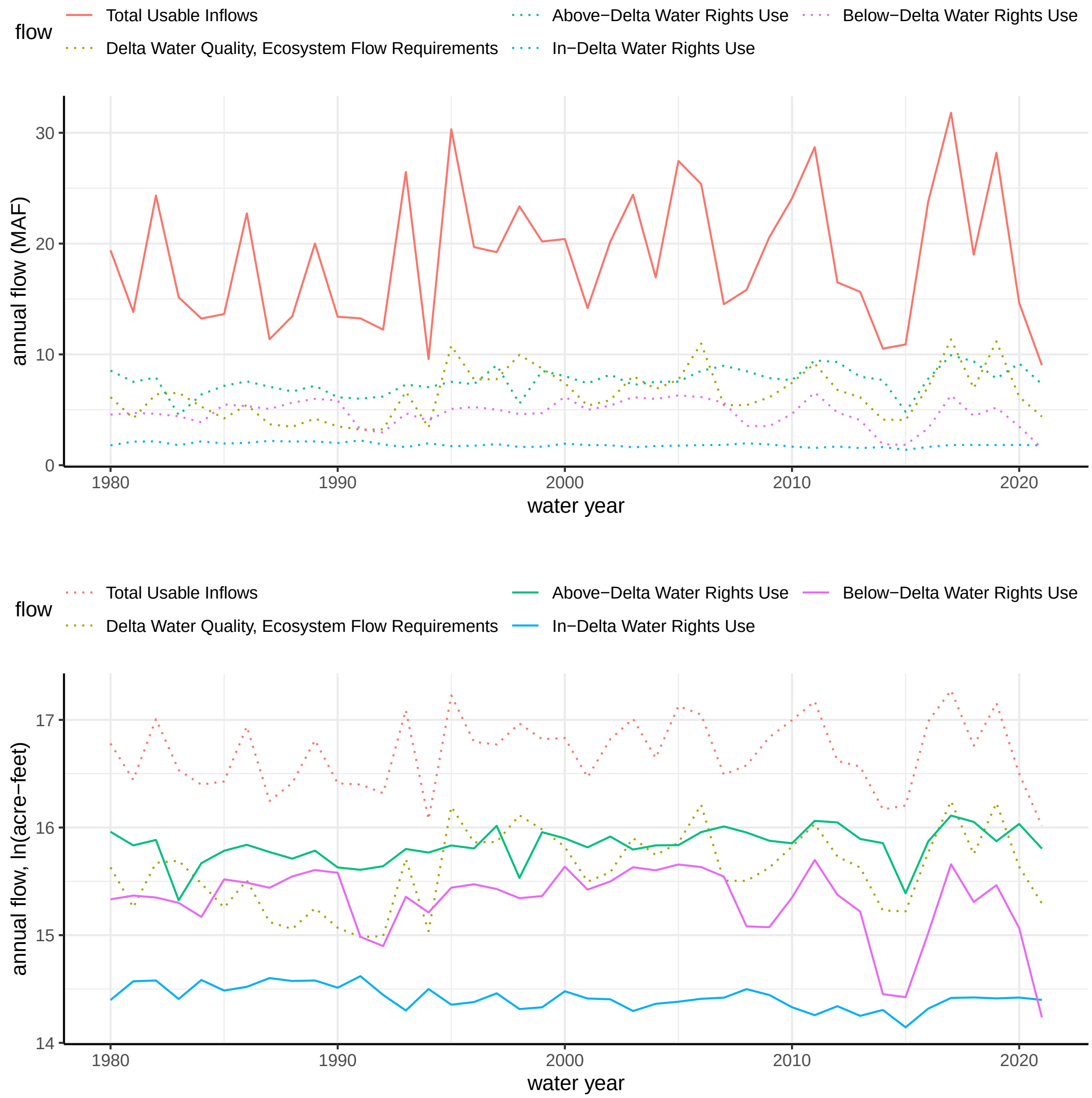
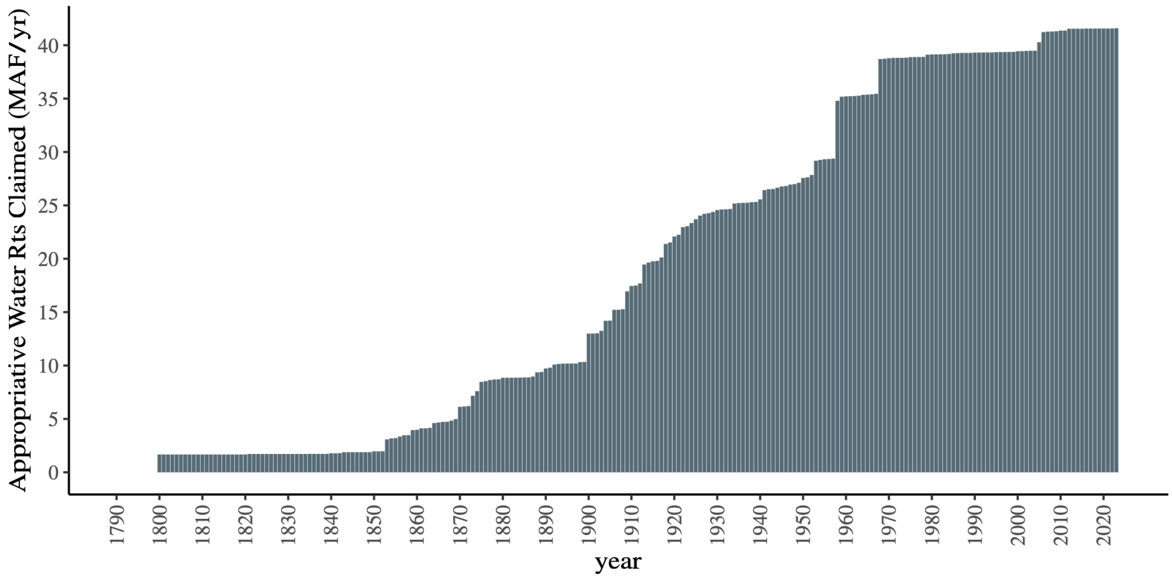


Figure 1. Total Usable Inflows + Appropriative Rights, 1980–2021

Source. Author's calculations from data in Gartrell, et al. (2022).

NB. Vertical axes differ in the two panels.

(a) Irrigation Water Rights, by Priority Date



(b) Irrigation Water Rights, by Seniority and Point of Diversion

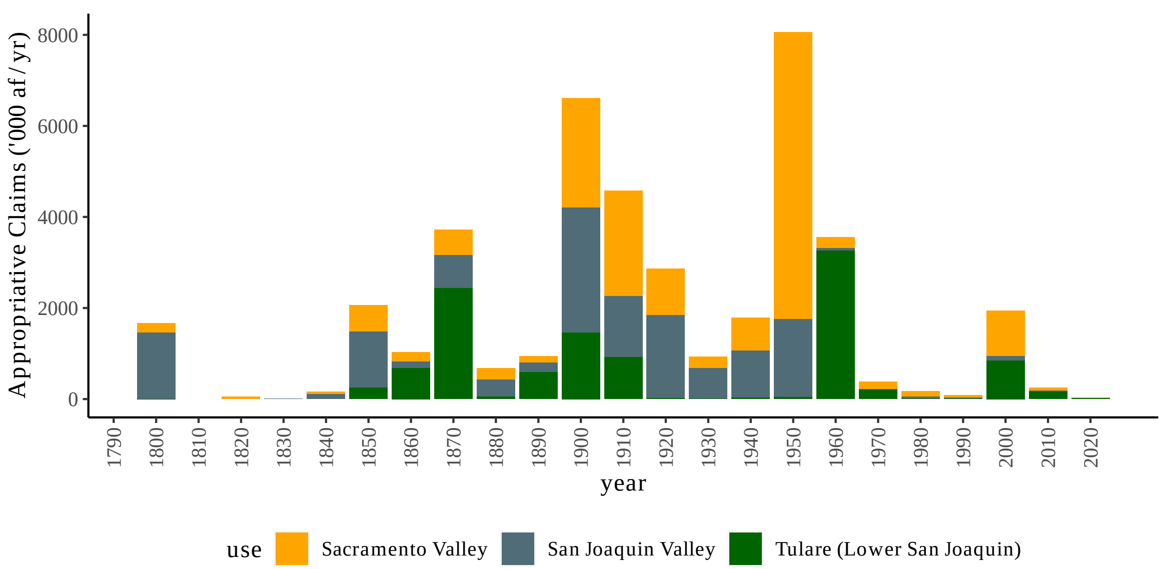


Figure 2. The Legacy of Appropriative Water Rights

Source. Author's calculations using the California State Water Resources Control Board Water Rights Information Management System. Central Valley irrigation water rights only. 2,571 water rights claimed prior to 1914; 3,069 water rights claimed after 1914. See Figure A6 for richer spatial distribution of water rights.

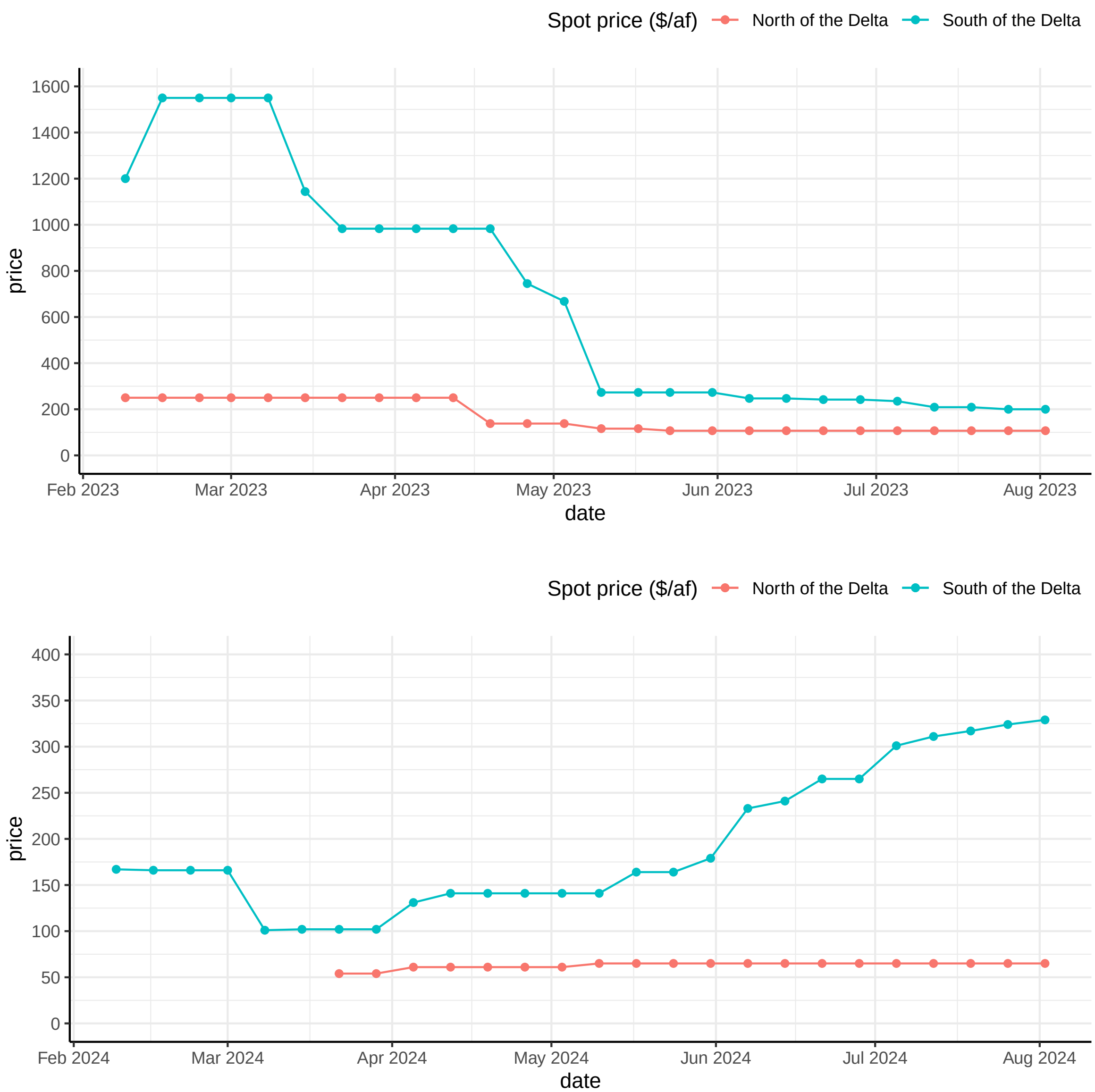
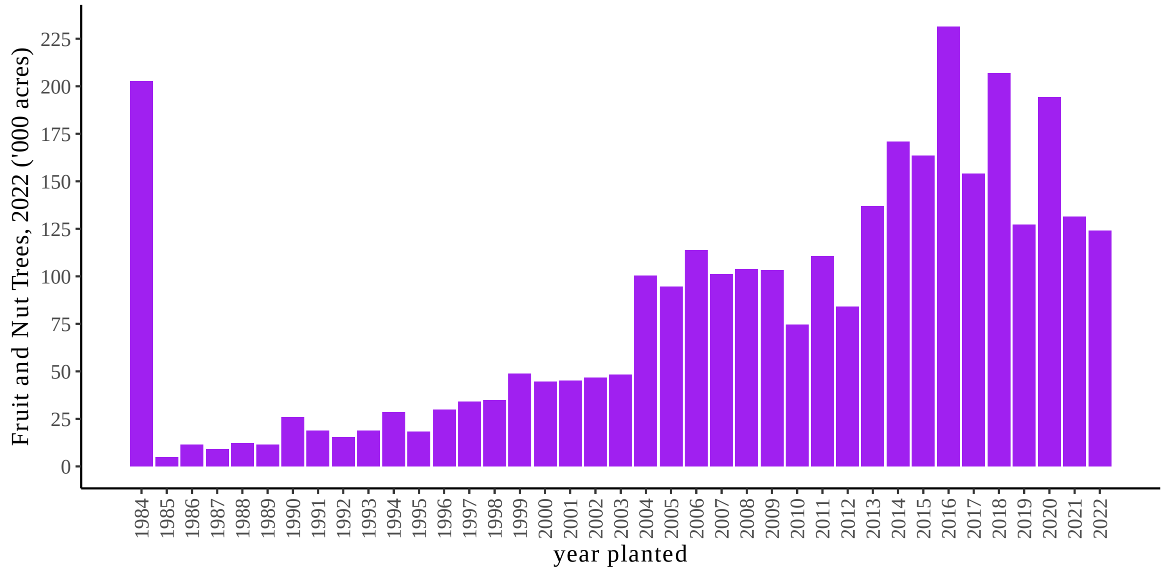


Figure 3. Cross-Delta Water Price Gradients, 2023–2024

Source. Author's calculations from data reported by WestWater Research, LLC.

A. Age Distribution, 2022



B. Hazard Rates by Age, 2021–2022

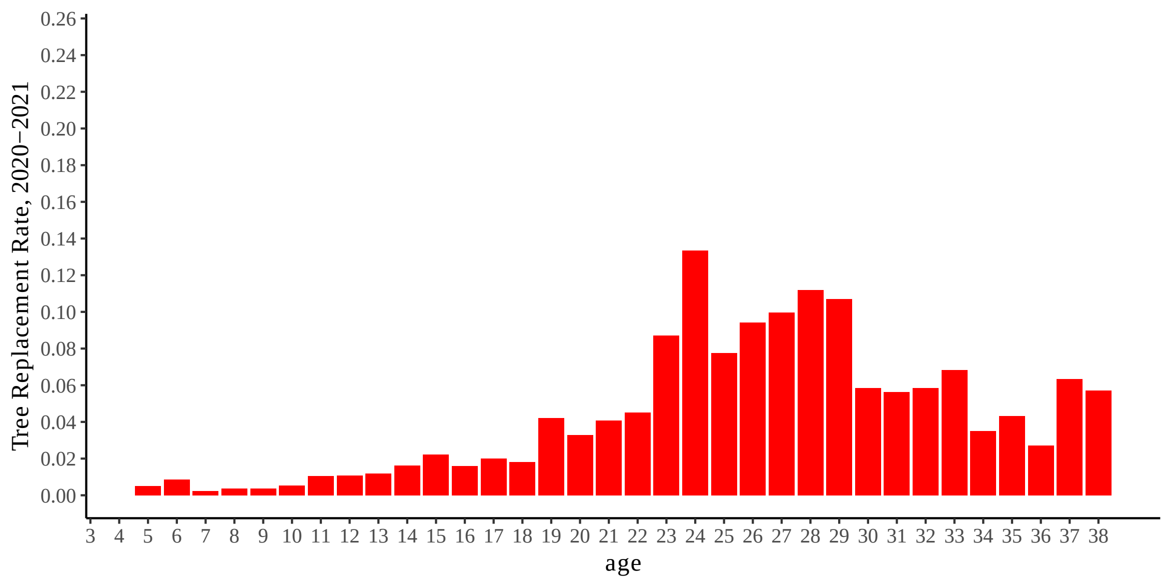
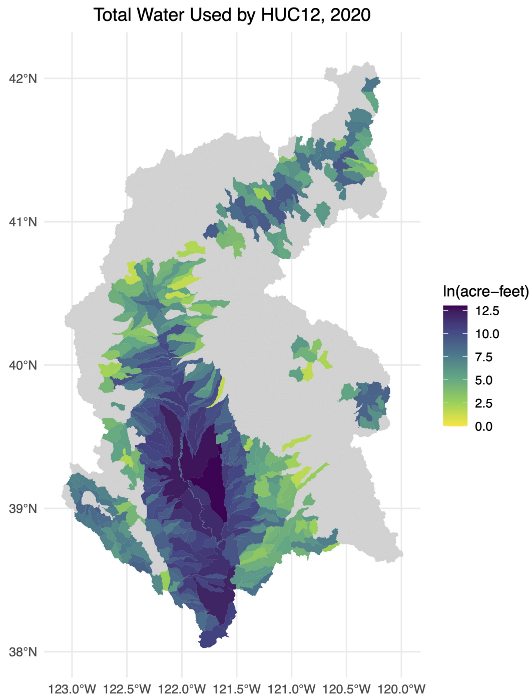


Figure 4. Orchard Demographics

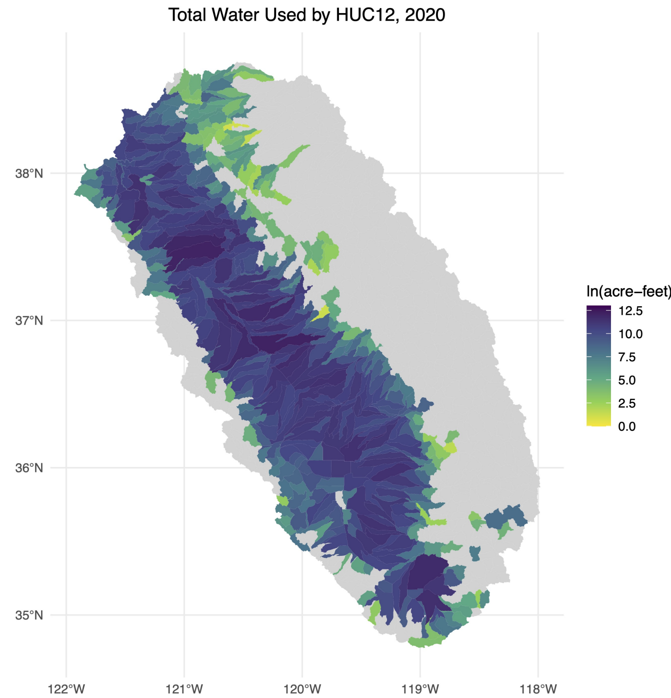
Age distribution of all Central Valley orchards, 2022. Average orchard in 2020 was planted 12.3 years ago.

The data does not distinguish between trees planted in 1984 or in earlier years; read "1984" as "≤1984" (but also consider reading *1984*...).

Source. Author's calculations from DWR data described in the text.



(a) Sacramento River Basin (North of the Delta)

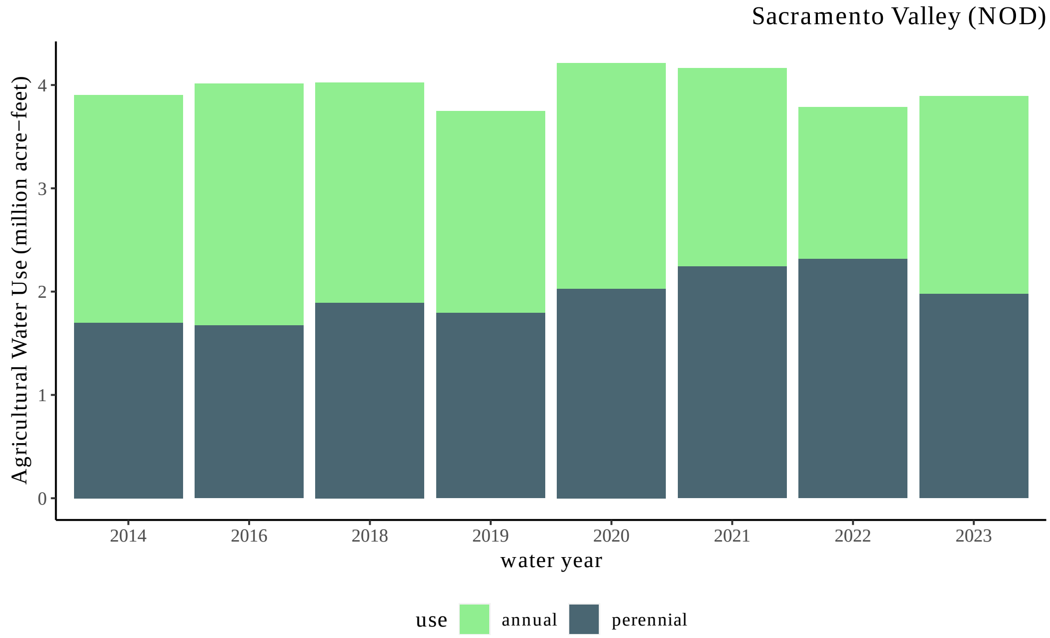


(b) San Joaquin River Basin (South of the Delta)

Figure 5. Implied Agricultural Water Rights, by Location

Implied agricultural water rights by subwatershed (HUC12), ln(acre-feet), 2020. See Figure A2 for map of all California.

A. North of the Delta



B. South of the Delta

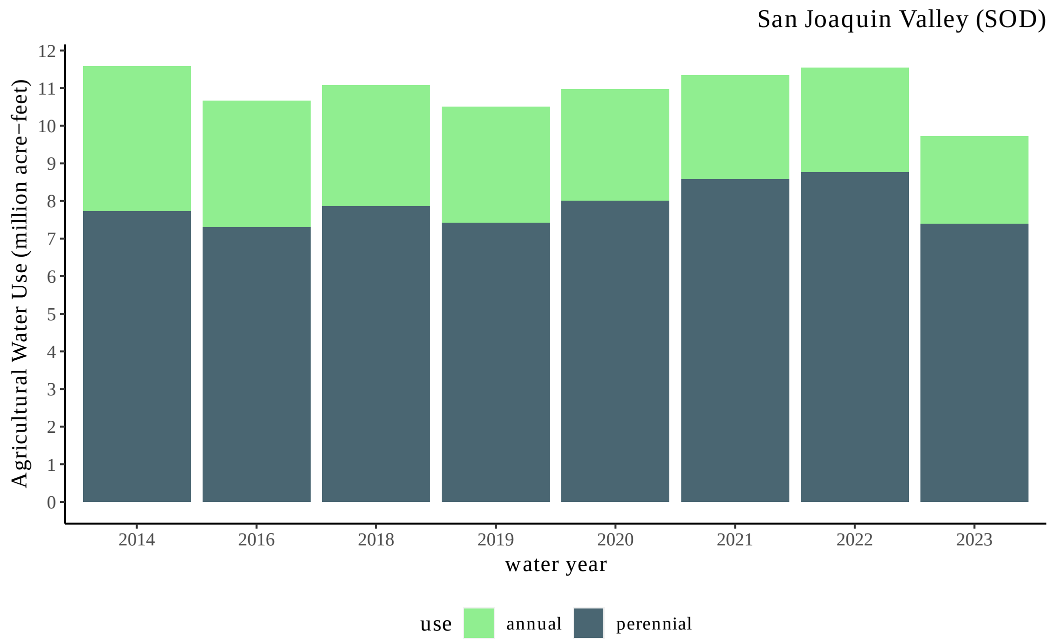
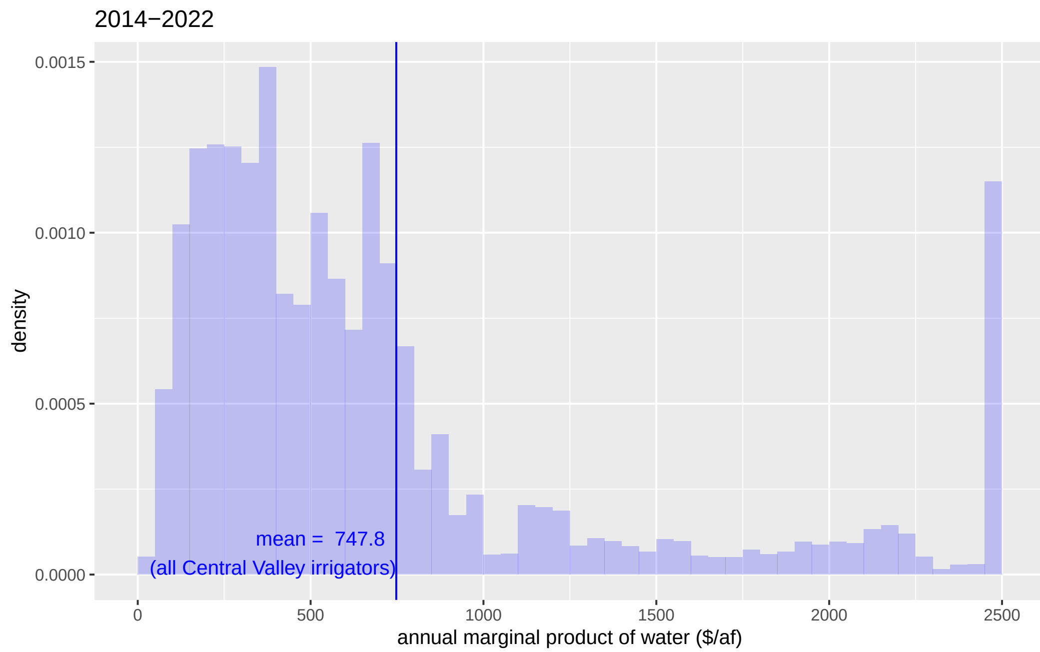


Figure 6. Implied Agricultural Water Rights, by Reliability Class

Implied water rights reliability, 2014–2023, inferred from agricultural uses.

A. Water Values



B. Planting Costs

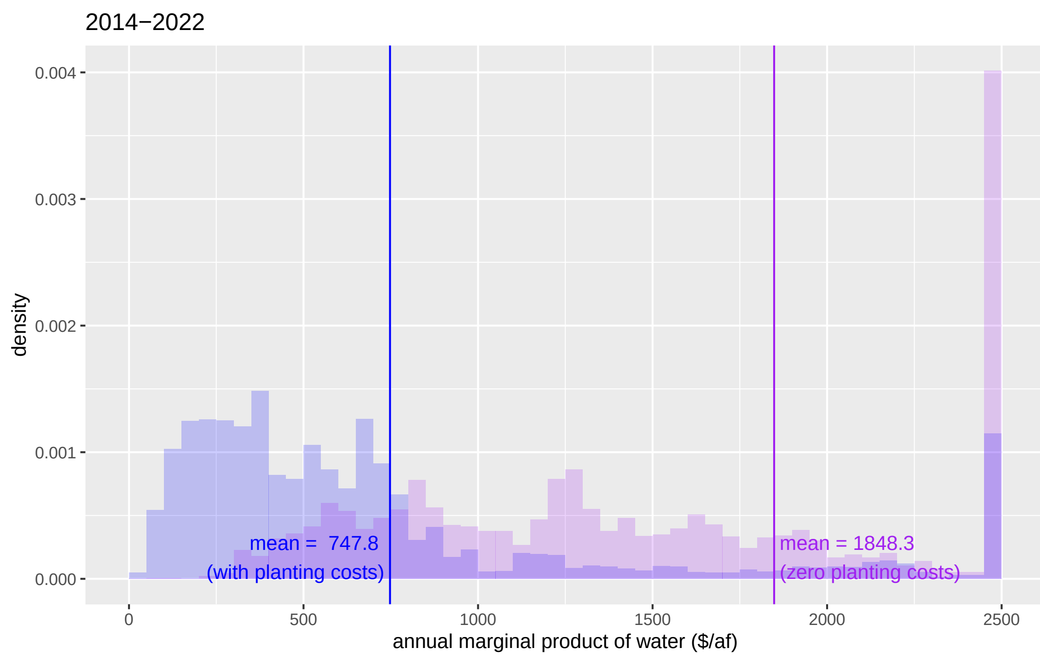
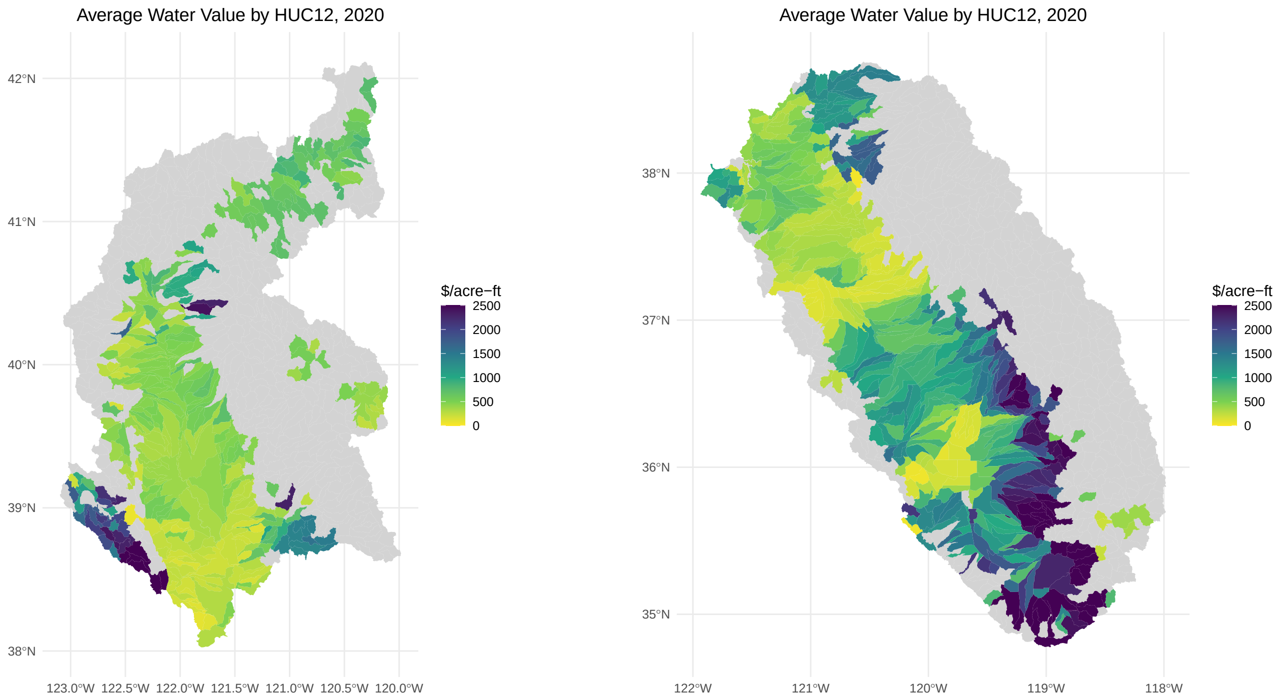


Figure 7. Annual Marginal Values of Water, $/af, 2014–2022

A. Estimated annual water values (marginal products of water net of average planting costs), 2014–2022. Rightmost bin includes all values ≥$2500/af.

B. Estimated annual water values and marginal products, 2014–2022.



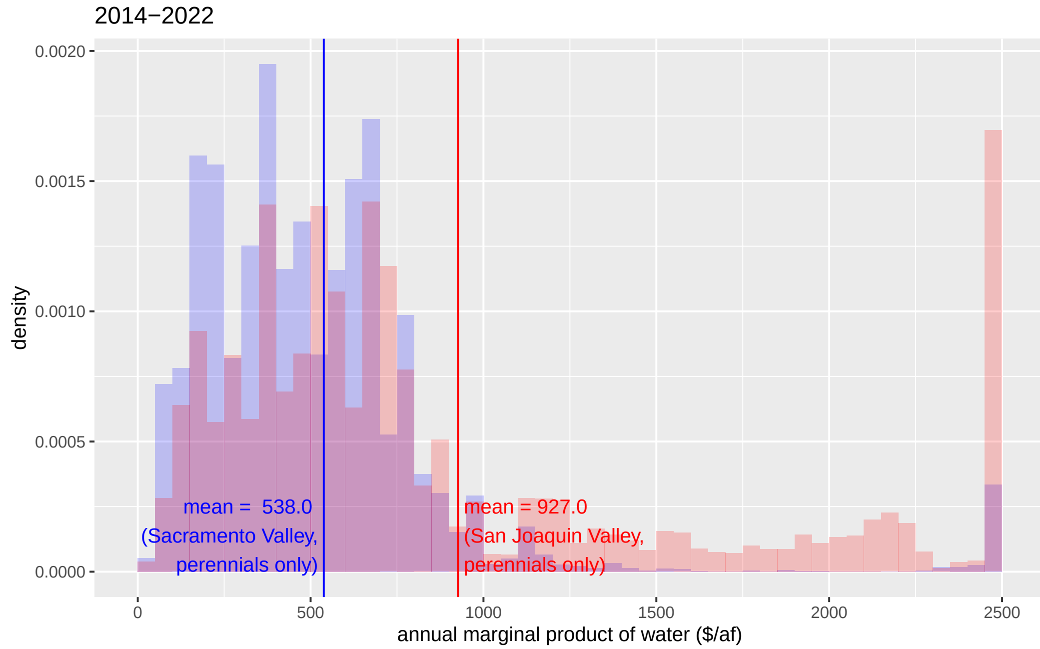
(a) Sacramento River Basin (North of the Delta)

(b) San Joaquin River Basin (South of the Delta)

Figure 8. Annual Marginal Values of Water, $/af, 2020

Estimated annual marginal values (marginal products net planting costs) of water, 2020.

A. Reliable Water Rights



B. Variable Water Rights

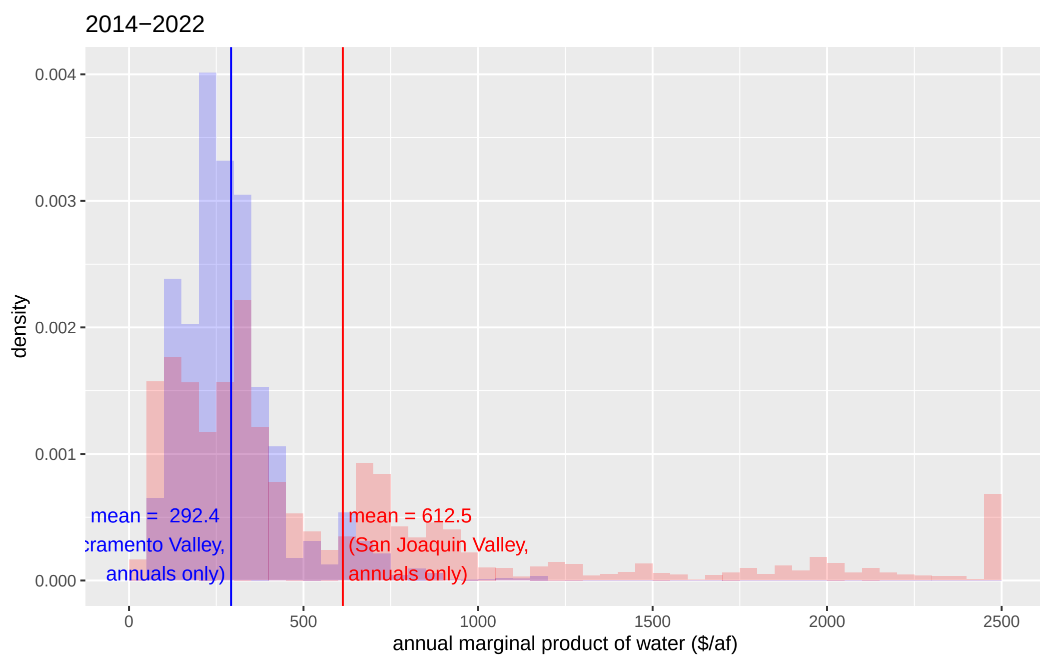


Figure 9. Marginal Values by Region and Reliability Class

Estimated marginal values of water, 2014–2022.

Reliable water rights ≡ water used for perennial crops. Variable ≡ annual crops.

Online Appendix – Supplementary Tables

Table A1. All Crop Land Shares, 2020

crop	share_CA	share_SJ	share_SV
C oranges unspecified	0.032	0.045	0.000
C5 avocados all	0.006	0.000	0.000
C6 olives	0.005	0.004	0.013
D12 almonds all	0.146	0.216	0.116
D13 walnuts english	0.044	0.035	0.107
D14 pistachios	0.048	0.082	0.006
D16 plums	0.005	0.004	0.013
D3 cherries sweet	0.004	0.007	0.001
D5 peaches unspecified	0.007	0.011	0.005
D8 plums dried	0.002	0.000	0.008
F1 cotton lint unspecified	0.021	0.036	0.001
F10 beans dry edible unspecified	0.004	0.004	0.006
F12 sunflower seed planting	0.005	0.000	0.022
F16 corn sweet all	0.065	0.097	0.024
F2 safflower	0.005	0.006	0.008
G2 wheat all	0.023	0.026	0.022
G6 hay grain	0.039	0.024	0.042
I1 fallow (1-3 yrs)	0.015	0.015	0.014
I4 fallow (4+ yrs)	0.012	0.015	0.004
P1 hay alfalfa	0.074	0.054	0.052
P3 pasture irrigated, mixed	0.049	0.021	0.079
P4 pasture irrigated, native	0.014	0.000	0.033
P6 misc pasture	0.019	0.004	0.013
R rice	0.003	0.000	0.013
R1 rice milling	0.045	0.002	0.197
R2 rice wild	0.001	0.000	0.006
T10 onions	0.007	0.008	0.001
T15 tomatoes processing	0.019	0.025	0.024
T18 misc truck	0.014	0.004	0.002
T30 lettuce head	0.011	0.002	0.000
T32 tomatoes processing	0.007	0.008	0.010
T4 broccoli, cabbage, etc	0.008	0.001	0.000
T9 melons unspecified	0.007	0.008	0.008
V grapes wine	0.088	0.098	0.023
X fallow	0.094	0.093	0.094
YP young perennial	0.015	0.019	0.017

Land shares by all crops with at least 0.5% acreage in at least one of the two regions. Central Valley irrigators, calculated for WY 2020.

Table A2. Example of Agricultural Data

year	crop	crop_name	acres	yield	price	rev/acre
2014	D6	pears unspecified	2857.8	12.5	973.6	3434.7
2016	D6	pears unspecified	2755.5	15.2	1069.4	4688.0
2018	D6	pears unspecified	2678.5	11.2	941.0	3061.6
2019	D6	pears unspecified	2787.5	16.0	450.7	2131.9
2020	D6	pears unspecified	2739.3	11.9	1021.6	3435.6
2021	D6	pears unspecified	2788.0	19.0	649.3	3271.9
2022	D6	pears unspecified	2751.0	19.1	751.6	3844.7
2014	F16	corn sweet all	7237.8	8.1	507.9	1787.2
2016	F16	corn sweet all	7073.8	10.1	464.1	2027.4
2018	F16	corn sweet all	5191.0	9.2	485.0	1937.4
2019	F16	corn sweet all	4979.6	10.1	405.5	1840.4
2020	F16	corn sweet all	4301.3	14.4	564.3	3494.3
2021	F16	corn sweet all	4094.1	8.4	532.4	1804.1
2022	F16	corn sweet all	4877.2	9.0	477.0	1780.1
2014	V	grapes	2707.2	6.9	889.3	2529.3
2016	V	grapes	3650.1	6.7	923.4	2581.1
2018	V	grapes	4557.7	7.3	1024.9	3175.4
2019	V	grapes	4578.1	6.9	970.6	2922.8
2020	V	grapes	4855.7	6.2	789.6	2033.6
2021	V	grapes	4799.8	7.8	781.5	2330.4
2022	V	grapes	4756.9	7.4	826.0	2401.6

Example of agricultural acreage, yields, prices for the three most commonly-planted crops by acreage in HUC12 #180201630702 (Beaver Lake-Sacramento River).

Table A3. Example of Crop Water Efficiencies

A. Top 95%-ile

	year	crop	crop_name	acres	ω_{ict} (af/acre)	revenue/af
231747	2020	C5	avocados all	169.62	2.55	4397.16
627492	2020	T10	onions	217.53	1.49	4395.87
687594	2020	F16	corn sweet all	7.81	1.86	4382.60
619519	2020	D6	pears unspecified	12.05	2.80	4358.52
683065	2020	D14	pistachios	9.90	1.39	4356.88
677584	2020	D6	pears unspecified	10.63	2.81	4346.57
307508	2020	C5	avocados all	167.29	2.59	4326.93
637180	2020	D16	plums	245.26	2.96	4318.76
245572	2020	C5	avocados all	23.37	2.61	4307.35
308614	2020	C5	avocados all	56.97	2.61	4301.22
310826	2020	C5	avocados all	107.18	2.61	4296.90
682512	2020	D14	pistachios	68.53	1.41	4295.48
94050	2020	C5	avocados all	942.86	2.61	4294.76
891546	2020	D14	pistachios	90.84	1.41	4290.29
309167	2020	C5	avocados all	569.41	2.62	4289.47
688147	2020	F16	corn sweet all	0.85	1.90	4284.35
311379	2020	C5	avocados all	239.89	2.63	4274.65
636627	2020	D16	plums	4.84	2.99	4271.80
636074	2020	D16	plums	4.02	3.00	4271.01
231194	2020	C5	avocados all	94.25	2.63	4267.27
677031	2020	D6	pears unspecified	156.29	2.86	4265.33

B. Bottom 5%-ile

	year	crop	crop_name	acres	ω_{ict} (af/acre)	revenue/af
69935	2020	G6	hay grain	188.38	1.69	302.97
418871	2020	G2	wheat all	24.32	1.76	303.02
90949	2020	G6	hay grain	10.15	1.69	303.08
685977	2020	G6	hay grain	35.72	1.69	303.27
429378	2020	G2	wheat all	74.45	1.76	303.39
245789	2020	G6	hay grain	281.02	1.69	303.40
78230	2020	G6	hay grain	16.80	1.69	303.44
901094	2020	G6	hay grain	1337.38	1.69	303.45
292241	2020	G6	hay grain	109.98	1.69	303.45
192148	2020	G6	hay grain	96.55	1.68	303.51
161173	2020	G2	wheat all	36.82	1.76	303.58
870126	2020	G6	hay grain	1627.70	1.68	303.60
800448	2020	G6	hay grain	945.64	1.68	303.60
291688	2020	G6	hay grain	10575.79	1.68	303.97
424954	2020	G2	wheat all	101.59	1.76	304.00
582013	2020	G6	hay grain	107.15	1.68	304.11
309384	2020	G6	hay grain	69.95	1.68	304.12
866255	2020	G6	hay grain	43.23	1.68	304.22
431037	2020	G2	wheat all	106.34	1.76	304.23
906624	2020	G6	hay grain	153.94	1.68	304.24
245236	2020	G6	hay grain	356.06	1.68	304.47

Example of optimal irrigation application rates and revenue per-acre-foot of water applied, for various watershed-crops.

Table A4. Illustrative Hazard Rate Regressions, 2020–2022

Dependent Variable:	$\mathbf{1}$(cut down i between 2020-22)
Model:	(1)
Variables	
age	0.0046***
	(8.56×10^{-5})
C6 olives	−0.0068
	(0.0045)
D1 apples	0.0320***
	(0.0094)
D12 almonds	0.0852***
	(0.0027)
D13 walnuts	0.0480***
	(0.0032)
D14 pistachios	−0.0285***
	(0.0025)
D15 pomegranates	0.0639***
	(0.0114)
D16 apricots etc	0.1448***
	(0.0066)
D3 cherries	0.0724***
	(0.0070)
D5 peaches	0.1754***
	(0.0058)
Fixed-effects	
region	✓
Fit statistics	
Observations	128,240
R^2	0.04231
Within R^2	0.04201

Clustered (id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Illustrative linear regression at the field level for perennial orchards at least three years old in 2020. Outcome is 1 if the orchard is cut down in WYs 2020–21, 2021–22, or 2022–23. Omitted crop type is citrus (C).

Table A5. Groundwater Marginal Cost Gradients Across the Delta

	San Joaquin	Sacramento	diff	ratio	diff, USD/af
0	2	2	0	1	24.3
0.1	26.3	14.6	11.7	1.8	27.7
0.2	37.7	22.4	15.3	1.7	28.8
0.3	54.7	30.2	24.5	1.8	31.4
0.4	73.4	38.4	35.0	1.9	34.5
0.5	96.5	57.0	39.5	1.7	35.8
0.6	120	70	50	1.7	38.8
0.7	173.3	86.3	87.0	2.0	49.6
0.8	252.5	110.2	142.3	2.3	65.6
0.9	386.1	155.8	230.3	2.5	91.1
1	1,220.3	578	642.3	2.1	210.5

Distribution of static water levels (depth in feet) and implied marginal pumping cost per acre-foot, watershed-level.

Costs calculated for each irrigation well using observed lift height (static water level + 86' average drawdown) from well reports, a pumping efficiency of 0.53 from CEC (2023), and a marginal agricultural electricity rate of 0.15$/kWh from Burlig *et al.* (2024). Table reports capacity-weighted averages of all wells in each HUC12 subwatershed.

Table A6. Marginal Water Products Across the Delta, 2014–2022

San Joaquin (SOD)	Sacramento (NOD)	diff	ratio
1,845.24	1,621.89	223.34	1.14
1,614.35	1,323.44	290.91	1.22
1,731.79	1,226.50	505.29	1.41
1,623.34	1,231.81	391.54	1.32
1,673.84	1,180.39	493.45	1.42
1,631.02	1,234.76	396.27	1.32
1,445.07	1,131.77	313.30	1.28

Average annual marginal product of water ($/af), Central Valley irrigators.

San Joaquin ≡ San Joaquin River Basin (HUC4 1803) and Tulare Lake (HUC4 1804).
Sacramento ≡ Sacramento River Basin (HUC4 1802).

Table A7. Estimated Planting Costs

	share_af	mean_rev	replant	xi_ct_mean	xi_ct_sd	s_pred	$\overline{V}(c,1)$	xi_ct_condo	$\overline{V}(0,0)$
SJ D16 apricots etc	0.02	1,319.87	0.40	−8,305.25	1,057.46	0.08	5,191.01	−5,987.23	9,682.39
SJ C oranges	0.12	872.34	0.34	−5,382.12	1,500.02	0.12	4,132.18	−3,064.09	9,682.39
SJ C6 olives	0.01	651.10	0.27	−5,884.48	94.54	0.09	3,263.31	−3,566.46	9,682.39
SJ D12 almonds	0.49	579.76	0.36	−4,738.84	861.34	0.09	4,078.03	−2,420.82	9,682.39
SJ D13 walnuts	0.12	372.83	0.26	−4,052.52	1,181.24	0.13	2,921.92	−1,734.49	9,682.39
SJ D14 pistachios	0.12	2,381.71	0.05	−4,003.39	1,450.62	0.13	2,856.41	−1,685.37	9,682.39
SJ D15 pomegranates	0.01	1,582.86	0.12	−5,315.30	232.30	0.09	2,737.67	−2,997.28	9,682.39
SJ D3 cherries	0.02	1,177.70	0.47	−8,252.21	142.43	0.09	5,713.42	−5,934.18	9,682.39
SJ D5 peaches	0.02	1,008.90	0.50	−8,401.86	358.99	0.09	5,817.46	−6,083.84	9,682.39
SJ V vineyards	0.07	908.90	0.39	−6,675.69	1,142.97	0.10	4,679.42	−4,357.67	9,682.39
SV D16 apricots etc	0.07	697.17	0.40	−6,466.91	765.03	0.12	4,198.99	−4,148.89	8,758.65
SV C6 olives	0.03	711.26	0.27	−5,687.88	171.27	0.11	3,074.26	−3,369.86	8,758.65
SV D12 almonds	0.38	483.10	0.36	−4,913.94	596.32	0.11	3,647.62	−2,595.91	8,758.65
SV D13 walnuts	0.45	348.36	0.26	−1,341.00	527.55	0.22	2,654.26	977.03	8,758.65
SV D14 pistachios	0.01	2,501.32	0.05	−5,611.38	383.44	0.11	2,930.73	−3,293.36	8,758.65
SV D5 peaches	0.01	1,122.23	0.50	−8,175.60	428.51	0.11	5,472.04	−5,857.57	8,758.65
SV D6 pears	0.01	1,529.81	0.30	−6,853.27	486.99	0.11	4,145.14	−4,535.25	8,758.65
SV V vineyards	0.04	1,071.82	0.39	−7,042.67	426.40	0.11	4,482.62	−4,724.65	8,758.65

Average planting cost estimates for perennial crops by region (San Joaquin and Sacramento Valley). The estimated scale parameter is $\hat{\sigma}_\epsilon = 4015.87$; see Table **??** for implied elasticities.

Online Appendix – Supplementary Figures

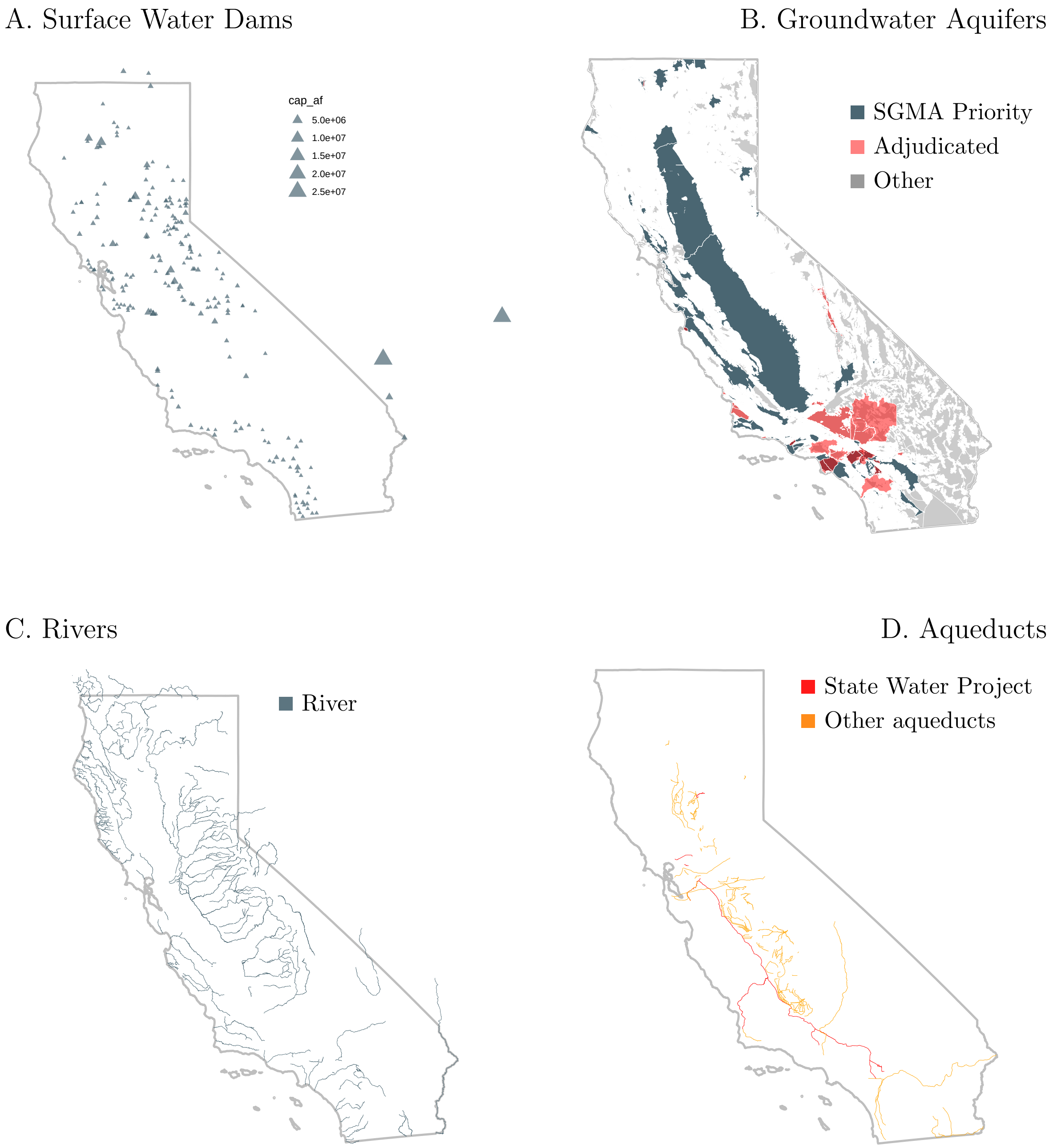


Figure A1. Water Sources and Flow Network

A. Dams. Locations from CDEC. Capacities (acre-feet) from CDEC.

B. Bulletin 118 groundwater basins. *Source*: CA Department of Water Resources.

C. Major California rivers. *Source*: USGS National Hydrography Dataset.

D. Major aqueducts. *Source*: CA DWR.

(a) All California

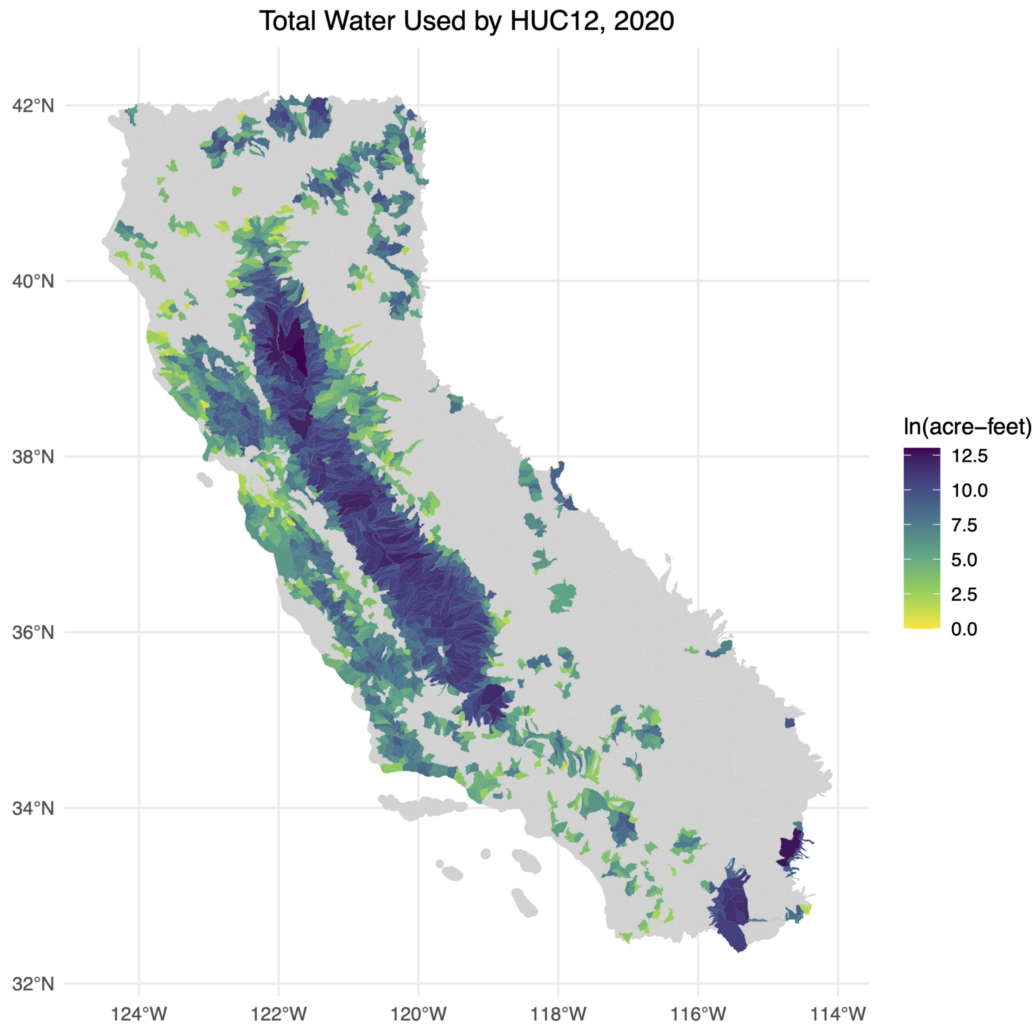


Figure A2. Implied Agricultural Water Rights, All California

Version of Figure 6 containing watershed-level estimates for the entire state of California in 2020.

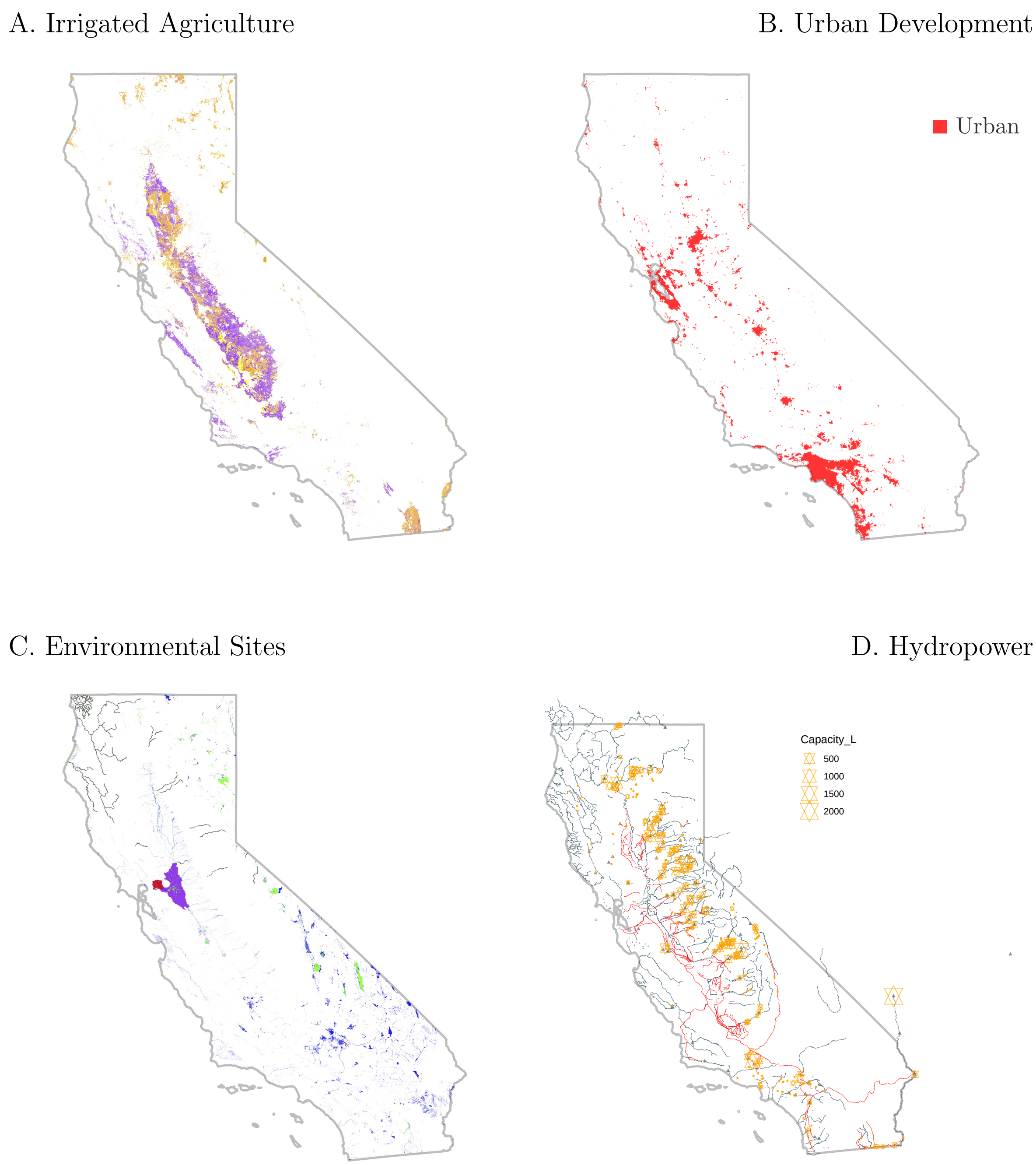


FIGURE A3. ECONOMIC VALUES OF WATER USE AND WATER FLOW

A. Irrigated agriculture

■ Perennial crops ■ Annual crops

B. Urban areas

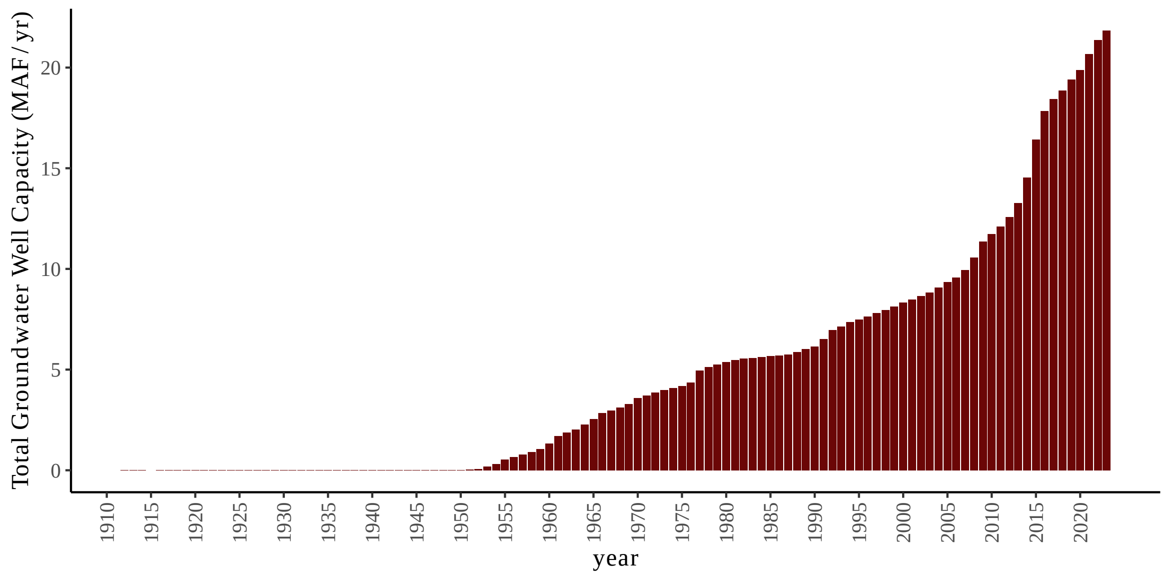
■ Urban

C. Environmental sites

■ Legal Delta ■ Suisun Marsh ■ NCCAG Wetlands ■ NCCAG Vegetation ■ Wild Rivers

D. Hydropower.

A. Cumulative groundwater well capacity



B. Appropriative water rights + groundwater well capacity

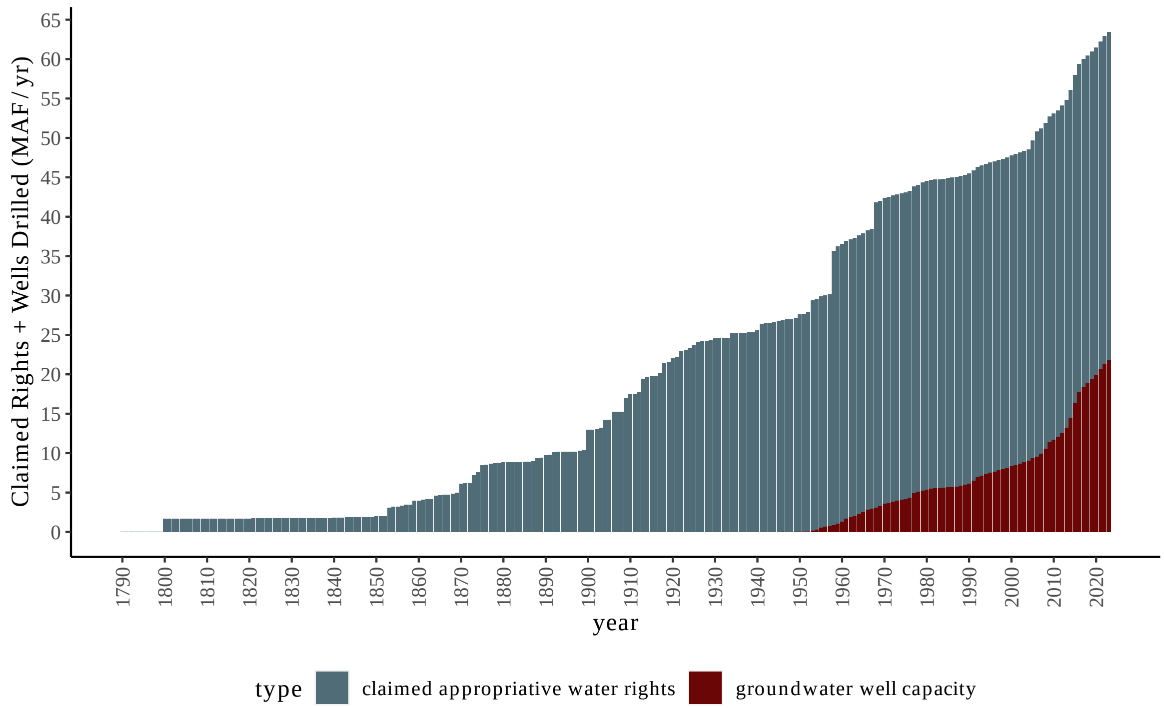


Figure A4. Groundwater Wells Drilled, Central Valley Irrigators

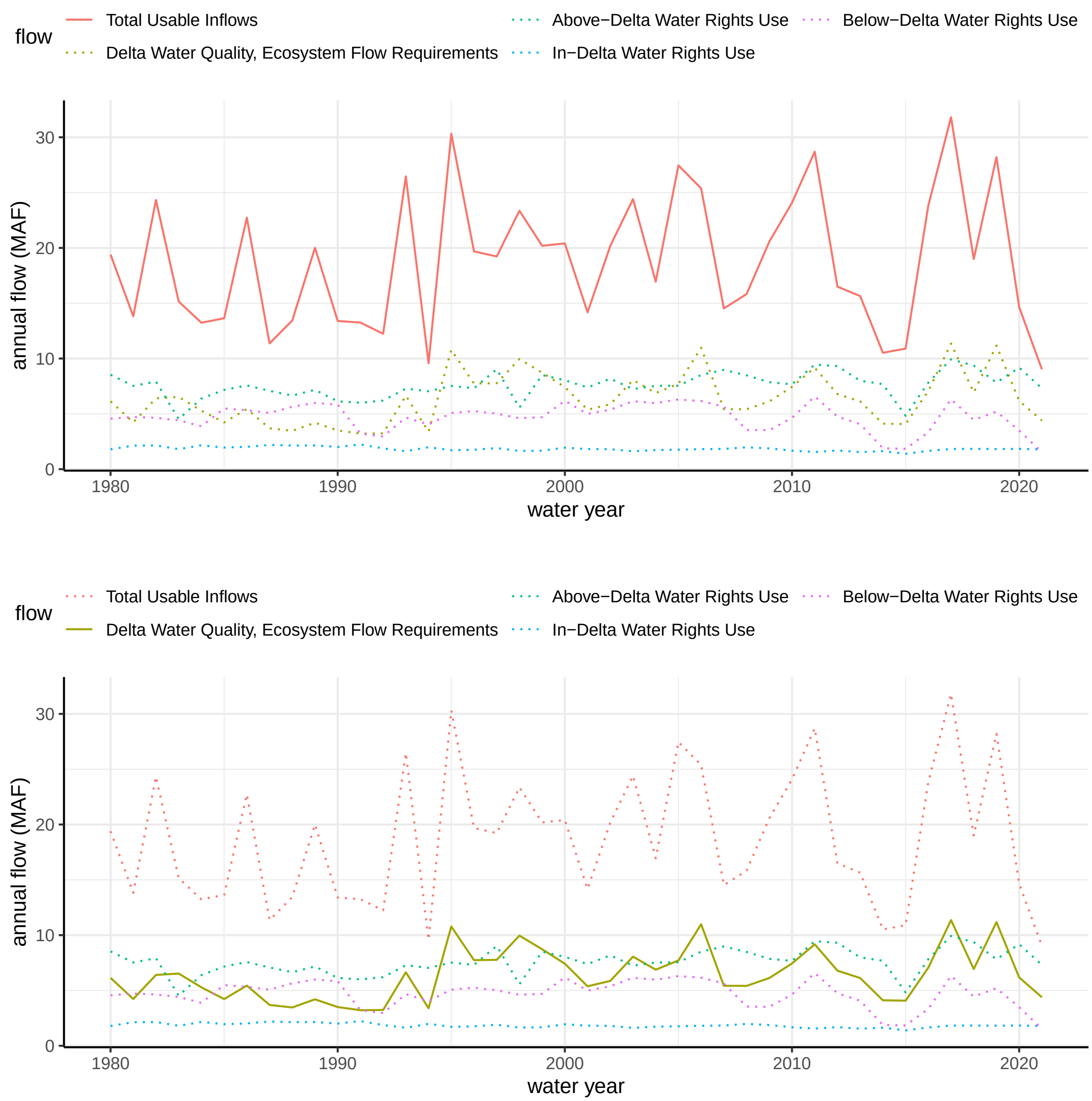
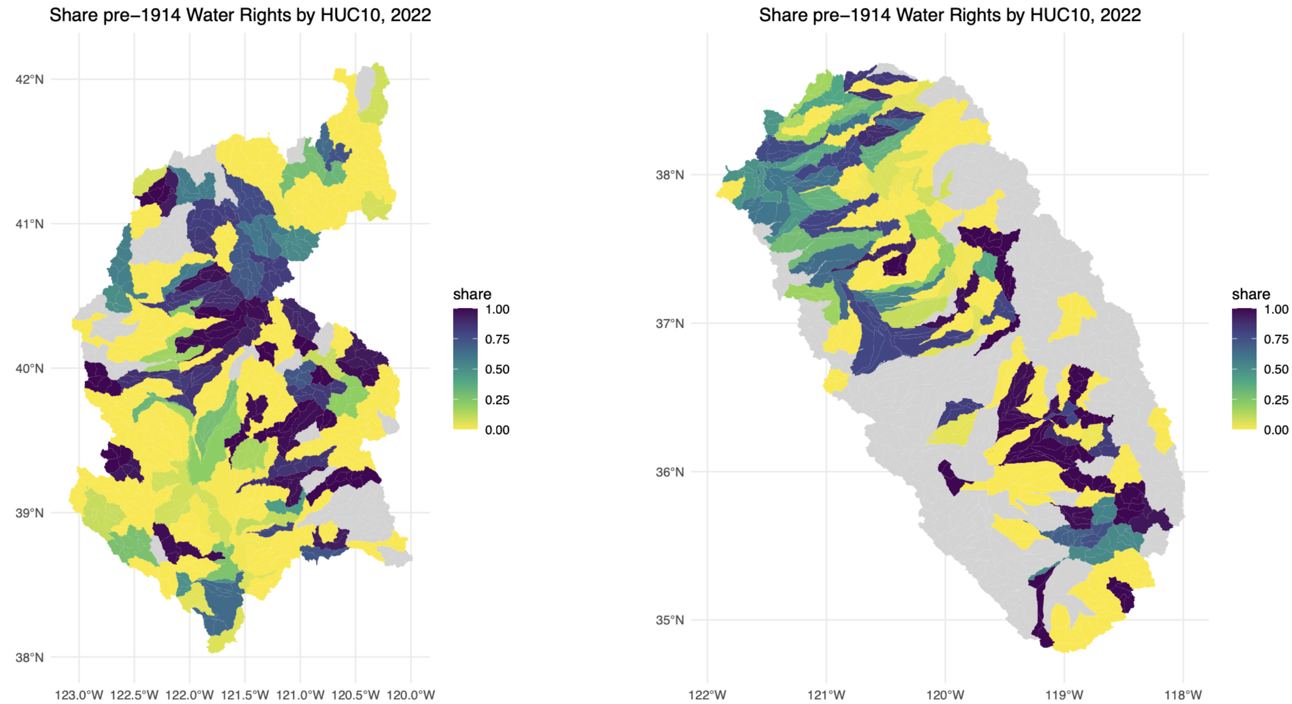


Figure A5. Total Usable Inflows + Environmental Requirements, 1980–2021

Source. Author's calculations from data in Gartrell, et al. (2022).



(a) Sacramento River Basin (North of the Delta)

(b) San Joaquin River Basin (South of the Delta)

Figure A6. Historical Water Rights By Watershed

Share of pre-1914 surface water rights by HUC10 regional watershed and river basin. Irrigation water rights only. Surface water rights assigned to HUC10 watersheds by principal point of diversion.

Source. Author's calculations using the California State Water Resources Control Board Water Rights Information Management System.

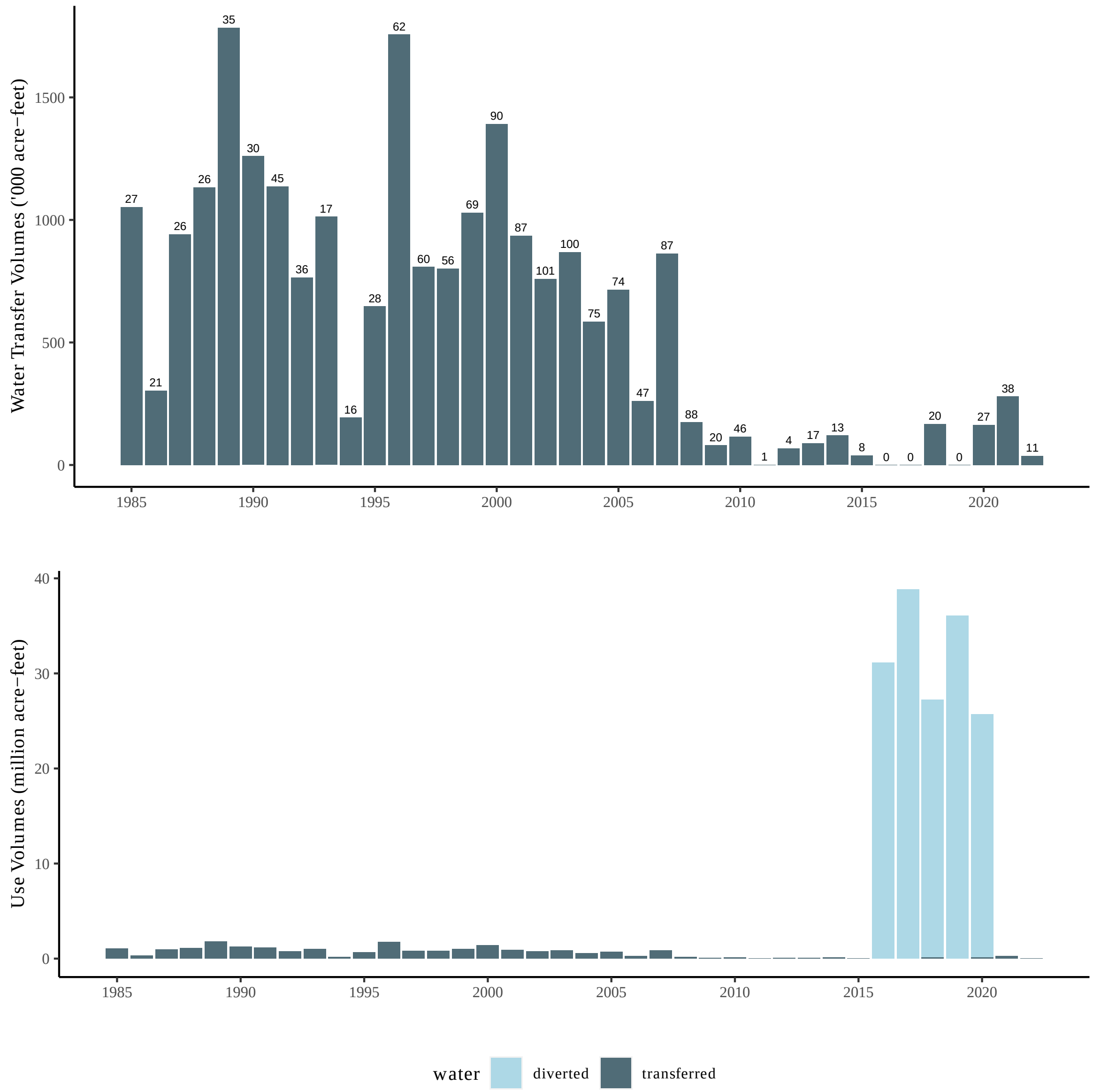


FIGURE A7. HISTORICAL WATER TRANSFERS, 1985–2022

Source. In Panel A, public records request to DWR + manual cleaning. Vertical axis plots the total volume in each year, with the number of distinct trades listed at the top of each column. Eric Edwards brought to my attention that the post-2010 DWR data likely undercounts multi-year transfers, I am working on fixing this. (Also note that none of this data is used for estimation.) In Panel B, the volumes in Panel A are reported alongside post-2016 diversion reports under 2015 S.B. 88.

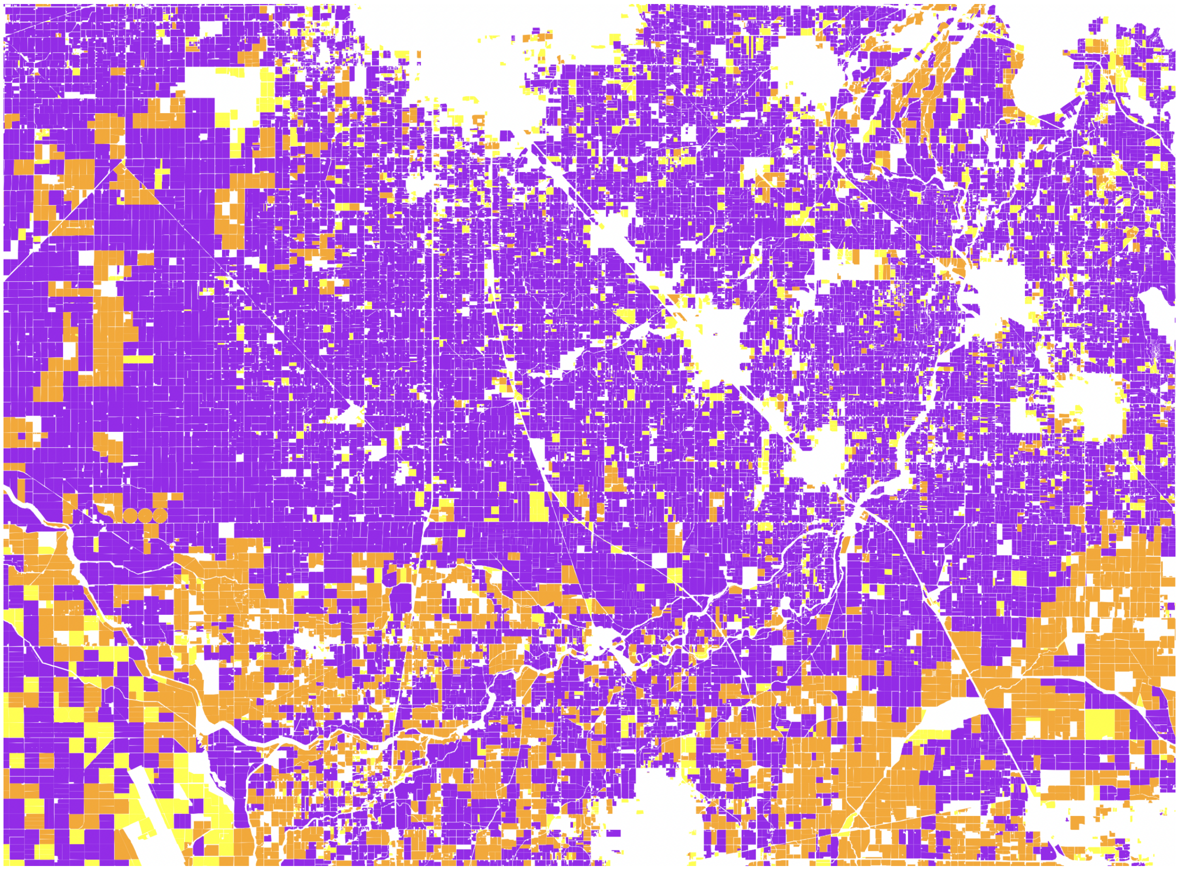
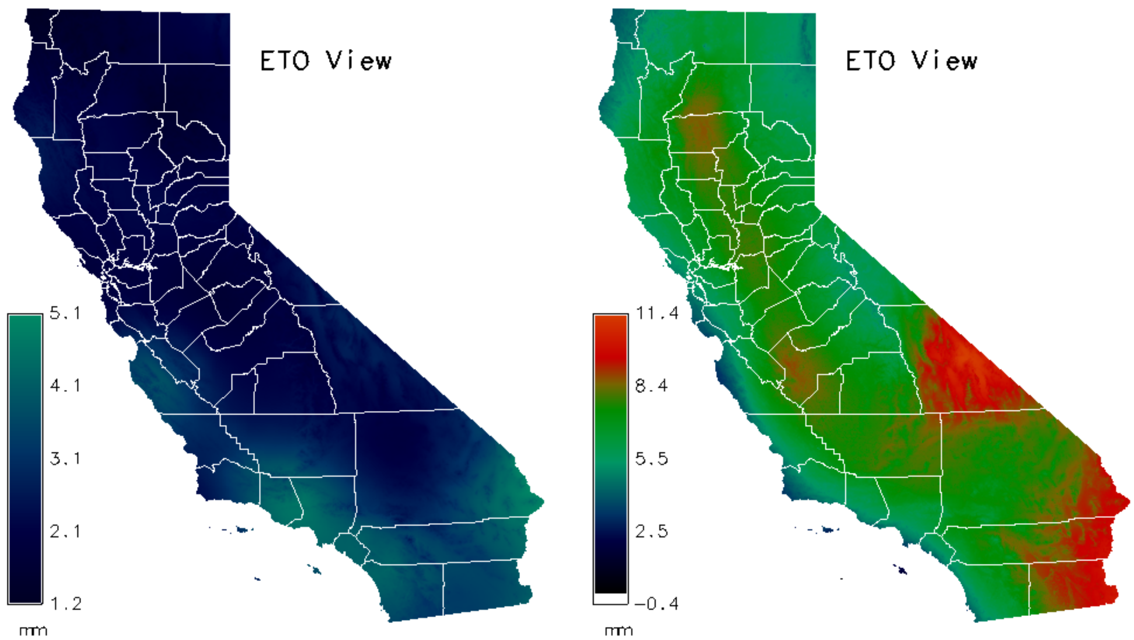


Figure A8. Example of Land Allocation Data

Land use and crop choices in 2020, near Fresno. ■ perennial ■ annual.



31 October 2023 1 July 2024

Figure A9. Example of Evapotranspiration Data

Example of daily reference evapotranspiration from CIMIS.

A. B.

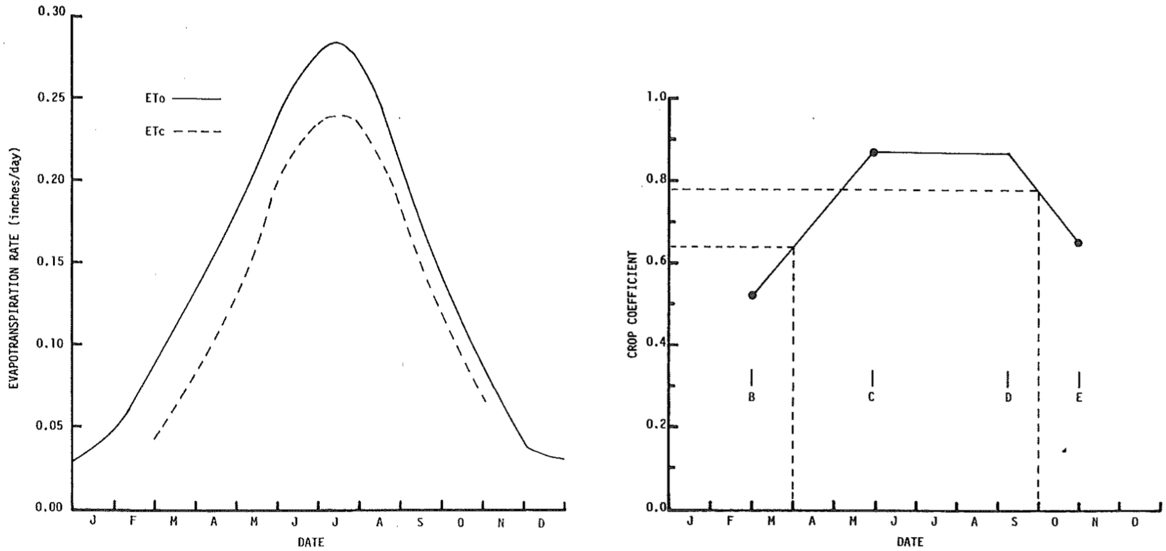


Figure A10. Example of Crop Coefficients

Panel A. Reference (ETo) and crop (ETc) evapotranspiration for almonds near Bakersfield, CA.

Panel B. Crop coefficients for almonds in the San Joaquin Valley. Segment B is leafout, C is 60% ground shading, E is leafdrop.

Source. California Department of Water Resources (DWR) Leaflet 21428, Figures 1–2.

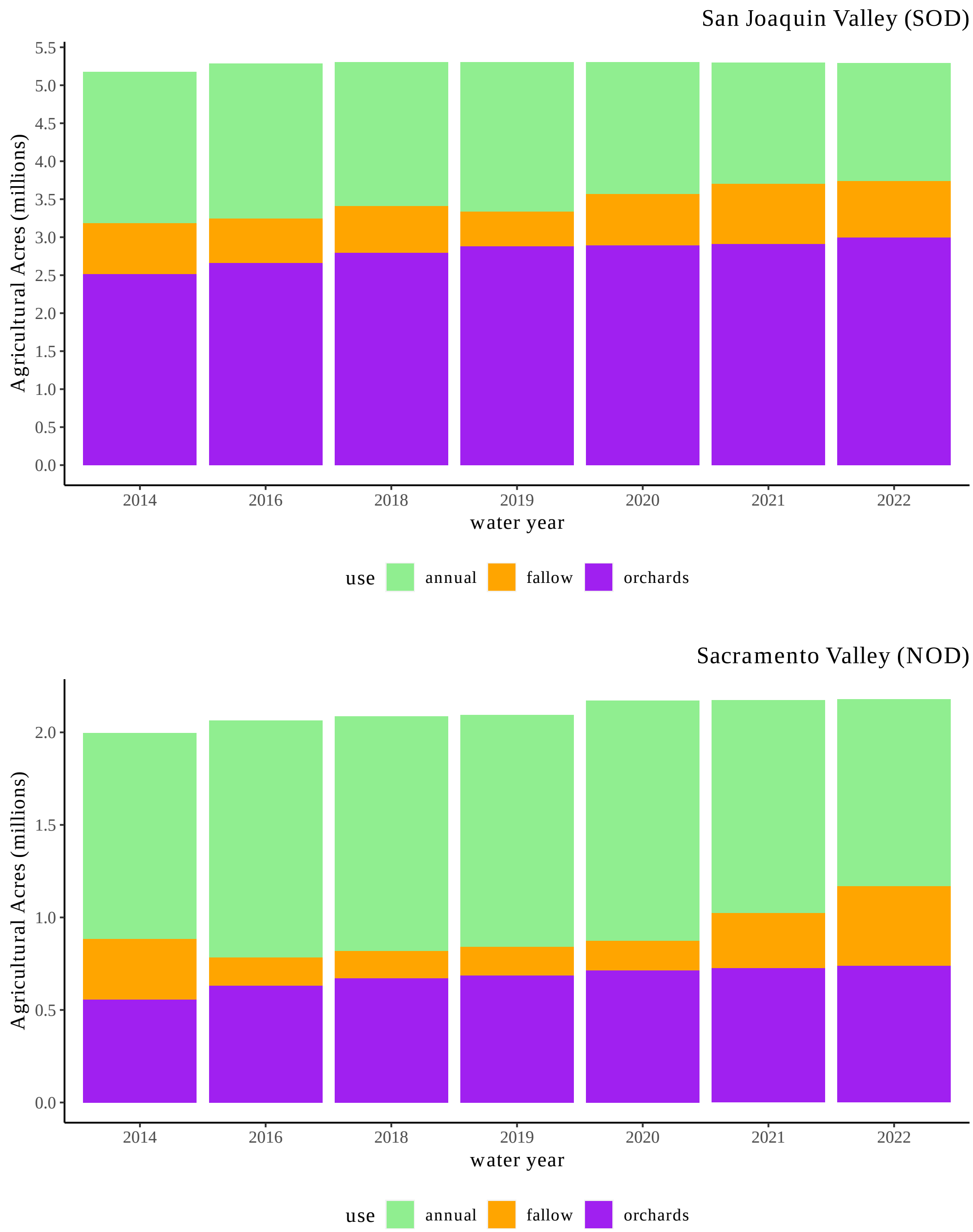


Figure A11. Planting Decisions, 2014–2022

Irrigated land allocated to perennial, annual, and fallow crop choices.

San Joaquin ≡ San Joaquin River Basin (HUC4 1803) and Tulare Lake (HUC4 1804).
Sacramento ≡ Sacramento River Basin (HUC4 1802).

A.

B.

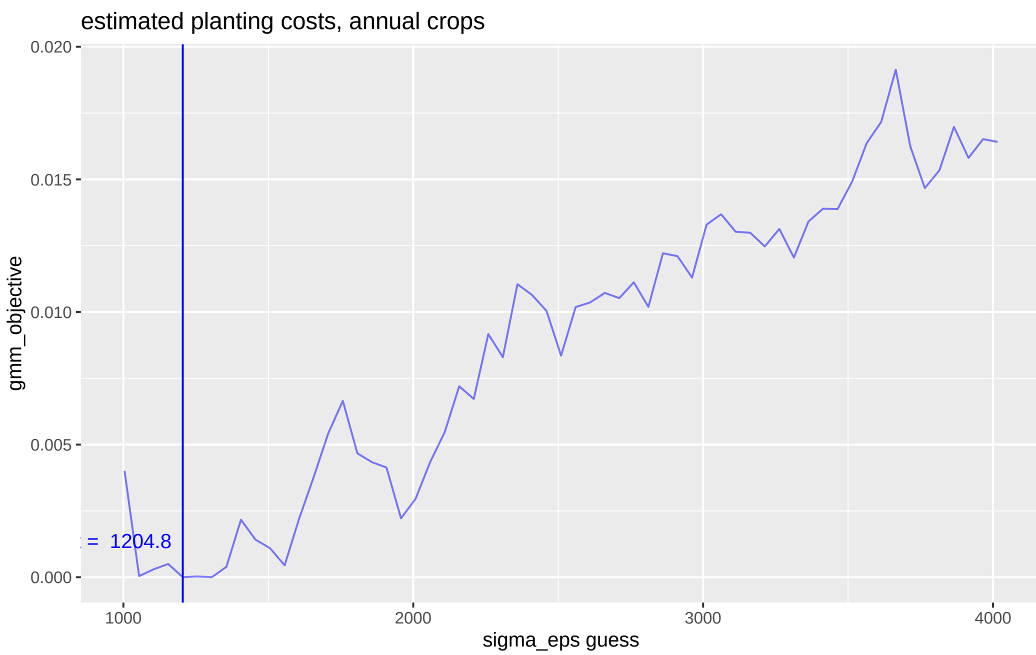


Figure A12. GMM Objective Function

GMM objective evaluated on a grid of σ_ϵ for perennial (panel A) and annual (panel B) planting decisions.