Measuring water misallocation in California

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Abstract

This paper proposes and applies new methods to value water rights and assess misallocation across competing uses in California, the world's fourth 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.

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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 and create 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 of water use at a very fine level of resolution, and then think about what that

[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).

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 decisions. This aspect of the analysis—complementary investment based on the

[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.

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 accommodate 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 perma-

nent 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 one 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 1987–2024, 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-

[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.

augmenting capital varieties—reminiscent of the Atkeson and Kehoe (1999) microfoundation 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

[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.

rights, and over time through equilibrium investment decisions. Each of these aspects 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

[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), Wong *et al.* (2025), 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, 2026; Balboni *et al.*, forthcoming), agriculture (Scott, 2013; Costinot *et al.*, 2016), and wetland conservation (Aronoff and Rafey, 2023).

factors, like capital, labor, land, and oil; how we interpret that dispersion is 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.

[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).

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 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.

[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.

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 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 initial claimants. Many claims in California originated when people started moving to the state in the Gold Rush of 1848. Figure 2, which depicts cumulative, reported face values of current water rights for irrigation in the Central Valley by decade claimed from 1800–2020, shows nearly 20 million acre-feet of water claims prior to the 1914 Water Commission Act. These records contain measurement issues, but show evidence of large legacy rights that date prior to California becoming part of the US,[13] as well as water claims that grow as people start moving to California to mine gold with water-reliant methods like sluice boxes and hydraulic mining. Figure 2 also shows large jumps in cumulative rights 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.

These appropriative surface water rights are defined by two attributes. First, a "face value" amount, denominated in acre-feet per year, which equals the maxi-

[13] 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).

mum 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, an owner of an appropriative water right cannot take water if there is no divertable water in the river; even when there is water in the river, they may not take water when other, overlapping water rights have legal priority. 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.[14]

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 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 differences of about a factor of two in average lift heights and implied pumping

[14] 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 encourage people to transfer water rights, and to avoid the kind of overuse incentives under a use-it-or-lose-it regime, since the 1970s, it's been very clear in California law that, in most cases, the owner retains full ownership rights even if they do not use the water.

[15] This subsurface water is, essentially, open-access, 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, drilling a well requires a permit ("well report"), so there about a million of these well reports, about 100,000 of which are in the Central Valley.

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 it 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, stipulating certain seasonal outflow requirements to maintain species and deliver environmental value in the Delta. Figure A6 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 4–8 million 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 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

In part due to these constraints, annual trade in water allocation rights in California—as is well-known in this literature (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 to construct price distributions for each region. The comparisons corroborate estimates of Regnacq *et al.* (2016) and Hagerty (2023) of large transaction costs across the Delta. The ratio of regional prices, reported in the rightmost column in Table 2, ranges mainly between 1.2 and 2.3 in the interquartile range. Corroborating these 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 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.

3 Model

This section introduces an empirical model of water rights and irrigated agriculture 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

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 A8 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, there were 17 trades in 1993 and 16 trades in 1994. This is a very sparse market. The lower panel of Figure A8 reports 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.

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 assumptions that permanent and transient water rights can be distinguished and that a water right owner allocates water efficiently within each reliability tier of their water right. The planting costs and implied values of water rights can then be identified in the fully-specified model with micro panel data on fields within a water right and instruments for crop prices.

3.1 Irrigation technology

Irrigators, the main users of water, indexed by i, produce various crops indexed by c with fields (units of water) indexed by $\iota \in i$. Agricultural calendars operate on an annual basis, with 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 field ι in year t, each crop c has a potential yield per acre, $A_{\iota ct}$. Annual production for irrigator i, crop c, in year t, is then given by

$$Q_{ict} = \sum_{\iota \in i} A_{\iota ct} \min \left\{ K_{\iota ct}, W_{\iota ct} \right\} \tag{1}$$

where output Q_{ict} is measured in tons, yield $A_{\iota ct}$ in tons per acre (with $A_{\iota ct} = 0$ for $c =$ fallow), land $K_{\iota ct}$ in acres, and effective annual field-level irrigation in acre-feet per year is calculated as

$$W_{\iota ct} = \min_{\tau} \left\{ \frac{w_{\iota ct}(\tau)}{\zeta_{\iota ct}(\tau)} \right\}_{\tau=0}^{365}, \tag{2}$$

using the field-level irrigation application rate $w_{\iota ct}(\tau)$ in acre-feet/day. The key feature of (1) is to allow the value of daily irrigation $w_{\iota ct}(\tau)$ in production to depend on each field's inherent and crop-specific water efficiency, $\zeta_{\iota ct}(\tau)$, which corresponds to how much water the crop needs in acre-feet per acre, in theory,

[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.

on day τ of that year and field ι. A crop's water demand varies over the growing season and with climate conditions. For example, $\zeta_{\iota ct}(\tau)$ will be zero in times when the crop needs no water, and $\zeta_{\iota ct}(\tau)$ will be larger as the crop becomes thirstier.

The irrigation scheduling algorithm allows water efficiency to differ (i) across crops at the same location ι and year t, (ii) across locations $\iota \in i$ for the same crop and year, and (iii) across years t within a location ι growing the same crop c. The reason $\zeta_{\iota ct} : [0, 365] \to \mathbb{R}_+$ will vary with ι, 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.

Equations (1)–(2) make no restrictions on how a farm chooses which crop to plant. To make progress, however, once a crop is planted on a given field, I will always restrict how farms irrigate that crop within the year. Specifically, the key assumption that I 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 on field ι 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), i.e., $w_{\iota ct}(\tau)/K_{\iota ct} \leq \zeta_{\iota ct}(\tau)$ for all τ.
A2. No deficit irrigation over the growing season, i.e., $K_{\iota ct} \leq \min_\tau \frac{w_{\iota ct}(\tau)}{\zeta_{\iota ct}(\tau)}$.

Assumption A1 rules out farms that irrigate more than the crop needs, which can be microfounded with any nonzero marginal cost of irrigation, or a yield function where overwatering lowers yield. Similarly, A2 rules out under-irrigation. While there is immense interest in deficit irrigation—conceptually, it would be great to 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.[22] Regardless of their microfoundations, A1 and A2 imply that, at the field level, water demand coincides with

[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.
[22] However, one can proceed (as I do) with data or a model of the number of alfalfa cuts.

optimal irrigation requirements. This lets me use (1)–(2) to take field-level crop choices $K_{\iota ct}$ and crop-location-day irrigation efficiencies to characterize optimal irrigation on day τ as $w^*_{\iota ct}(\tau) = K_{\iota ct}\zeta_{\iota ct}(\tau)$. I then identify total water use—the annual volume of the water right i used in equilibrium—from data on land use and crop evapotranspiration each day of year t, via

$$W_{it} = \sum_{\iota,c} K_{\iota ct} \cdot \int_0^{365} \zeta_{\iota ct}(\tau) d\tau. \tag{3}$$

Note that while A1 and A2 clearly restrict input demand within a year on a given field, they impose no restrictions on crop choice—which occurs prior to within-year irrigation—or the assignment of water across water rights.

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 to 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

$$\max_{\{K_{\iota c}\}} \sum_c P_{ict} Q_{ict} - \Gamma_{it}(K) \tag{4}$$

such that $\sum_{\iota,c} K_{\iota c} = \overline{K}_i$ and $W_{it} \leq \widetilde{W}_{it}$. 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 (4) form a convex polytope that one explores to find the optimal crop choice.

Equation (4) is intended to emphasize how the value of water rights will, in general, depend on two critical economic forces in addition to the marginal product of water analyzed in Section 3.1. First, the vicissitudes of water scarcity or abundance, given that a water right $\widetilde{W}_{it}$ is a random variable. Second, what I refer to as "planting costs," written in (4) as some arbitrary 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.

The value function $V_{it}(\overline{K}_i, \widetilde{W})$, defined as the maximand of (4) at $\widetilde{W}_{it} = \widetilde{W}$, then 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,

$$\frac{\partial V_{it}}{\partial \widetilde{W}} = \underbrace{\sum_{\iota,c} \frac{A_{\iota ct} P_{ict}}{\int \zeta_{\iota ct}(\tau) d\tau} \frac{\partial \int w^*_{\iota ct}(\tau) d\tau}{\partial \widetilde{W}}}_{\Delta \text{ marginal products}} - \underbrace{\sum_{c} \frac{\partial \Gamma_{it}}{\partial K_c} \frac{\partial K_{ict}}{\partial \widetilde{W}}}_{\Delta \text{ planting costs}}, \tag{5}$$

the sum of two components; first, 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; second, the change in marginal 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 (5) is not large. Alternatively, switching costs may be so great that the change in water rights does not change the crops grown, so that (5) vanishes.

The reason I write down the derivative in (5) is to emphasize when we can, and when we cannot, learn about the value of water rights from data on the joint distribution of the marginal productivity of a resource and its allocation. To the extent that planting costs are similar across different irrigators, the difference in annual marginal products of water is a valid 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 i'. When planting costs are identical, the joint distribution of the annual marginal products of water and the allocation of land, $\{K_{\iota ct}, \frac{A_{\iota ct} P_{ict}}{\int \zeta_{\iota ct}(\tau) d\tau}\}_{\iota,c,i,t}$, is sufficient to characterize misallocation among hydrologically connected, freely transferable water rights. In contrast, where planting costs differ meaningfully across i and i', differences in marginal products across i and i' 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.[23] The richer model below is designed to account for both possibilities.

3.3 Farm's problem, fully specified

I now specialize and extend 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. This model allows me to (a) more directly capture the varied value of water rights by decomposing planting costs across reliability tiers and sunk investments and (b) obtain some necessary ingredients 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 microdata that I have on the age of trees and within-orchard planting and replanting decisions across many fields within the same water right.

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 permanent ("reliable") and transient ("unreliable") component of each water right,

$$\widetilde{W}_{it} = W_i^p + W_{it}^a, \tag{6}$$

with the reliable component of the water right defined as delivering water almost surely, i.e., $G_i(w) = 0$ for all $w < W_i^p$, so that $\mathbb{P}(\widetilde{W}_{it} \geq W_i^p) = 1$. The decomposition in (6) allows me to define values for different units of water in the water right; without loss of generality, I index the units of a water right $\iota \in [0, \widetilde{W}_{it}]$ such that the first $\iota \in [0, W_i^p]$ units are reliable.

In practice, reliable 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. While $\widetilde{W}_{it}$ captures all available water—both surface and groundwater—the costs of using that water may differ depending on the source. Variable irri-

[23] 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.

gation costs are accounted for with idiosyncratic "planting costs" defined below that differ by water right × reliability tier × year. The source of water in a given year—surface, ground, or a combination—affects idiosyncratic irrigation costs because (i) diverting surface water and pumping groundwater entail quite different costs, (ii) the share of pumping can vary over time and across space with the surface water right's seniority and abundance of surface water (determining the share of groundwater use), and (iii) the cost of pumping varies with electricity prices, groundwater regulation, and the local well depth (determining the marginal cost of a unit of groundwater).[24,25]

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

$$\pi_{\iota t}(c, x) - \xi_{ic_x t} + \sigma^i_{\epsilon^k} \varepsilon_{ct}(\iota), \tag{7}$$

where $\pi_{\iota t}(c, x) = \alpha_{\iota ct}(x) P_{ict} = \frac{A_{\iota ct}(x)}{\int \zeta_{\iota ct}(\tau) d\tau} P_{ict}$ is the revenue (\$/af) from the crop derived from equation (1) and assumptions A1 and A2, given the (random) field-level ι yield-per-unit-water coefficient $\alpha_{\iota ct}(x)$, observed crop prices P_{ict}, irrigator i's relative planting costs $\xi_{ic_x t}$, and the field ι's idiosyncratic planting costs $\sigma^i_{\epsilon^k} \varepsilon_{ct}(\iota)$, independently and identically distributed Type 1 Extreme Value (T1EV) at the field-crop-level, scaled by $\sigma^i_{\epsilon^k} \in [0, \infty)$, which determines the extent of heterogeneity across fields ι within the water right i; this scalar is indexed $k \in \{a, p, r\}$ to differ across the annual, perennial, and renewal choice sets defined below. In addition, I assume that irrigators take output prices, P_{ict}, as given. Aggregate yield shocks and acreage in California may affect these prices, but agricultural commodity markets are assumed to be perfectly competitive.

Interannual choice sets. In equation (7), payoffs on ι depend on the year t as well as the state of the water right, (c, x). Dynamics arise because the state

[24] As the earlier discussion of priority and rationing indicated, this random variable could depend on all the equilibrium different decisions of other users in the network. But from the farm's standpoint as a producer, they care only about G_i, the probability that they have a certain amount of water, $\widetilde{W}_{it}$.

[25] A related but distinct issue are the implications of the origin of the water right for the counterfactuals discussed below. The source of the water used in a directed hydrological network affects the interpretation of reallocation; surface water often travels hundreds of miles, while groundwater remains local. While groundwater-to-groundwater reallocation cannot occur across aquifer boundaries, surface water reallocation can affect groundwater use through users of both surface and groundwater (conjunctive users).

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 $c \in \mathcal{C}_i^a$. For new perennial plantings, $c \in \mathcal{C}_i^p$ 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. 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 and random coefficients that correspond to the $\alpha_{\iota ct}(x)$ that I take from field-level crop evapotranspiration data discussed below.

Aggregate uncertainty. An attractive aspect of the Rust (1987) approach to optimal renewal is that stochastic state transitions due to observable events are straightforward to incorporate into the model. Only data and computational limits restrict this. I focus on arguably the most important such random, yet persistent, state of the world for irrigation in California, an indicator for drought. It is plausible—and will turn out to be the case in the resulting estimates—that the replanting/renewal costs that create frictions to adjust reliable water rights committed to orchards differ under drought conditions.

Irrigators hold rational expectations about drought transitions: they observe the current drought state when they decide whether to renew their orchard and when they decide which new perennial crop to grow; they incorporate the stochastic and persistent features of the drought process when they calculate the expected value of these choices; and, consequently, the value of the water right also depends on the drought state.

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

$$\begin{aligned} V_i(\iota, c, x) = \max \big\{ & \alpha_{\iota ct}(x) P_{ict} - \xi_{ic_x t} + \sigma^i_{\epsilon^r} \varepsilon_{ct}(\iota) + \beta \overline{V}_i(\iota, c, x + 1), \\ & -\xi_{i0t} + \sigma^i_{\epsilon^r} \varepsilon_{0t}(\iota) + \beta \overline{V}_i(\iota, 0, 0) \big\}, \end{aligned} \tag{8}$$

for $x > 0$, with the overline $\overline{V}_i$ denoting the ex-ante value function prior to

drawing the ε shocks for the field ι that period, and

$$V_i(\iota, 0, 0) = \max_{c \in \mathcal{C}_i^p} \left\{ \overline{V}_i(\iota, c, 1) - \xi_{ic_1 t} + \sigma^i_{\epsilon^p} \varepsilon_{ct}(\iota) \right\} \tag{9}$$

at the event of replanting.

Two special cases of (8)–(9) illustrate the generality of this empirical model as a way to value water rights. First, as $\sigma^i_\epsilon = \{\sigma^i_{\epsilon^k}\}_k \to 0$, within-water-right 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 (9). Further, when $\frac{\partial}{\partial x}\alpha_{\iota ct}(x) < 0$ for all $x \geq a$ for some bounded $a > 0$, there exists a finite stopping time x_ι^* at which replacement becomes optimal, so that the value of the water right (9) admits the simple closed form:

$$V_i(\iota, 0, 0) = \frac{1}{1 - \beta^{x_\iota^*}} \sum_{s < x_\iota^*} \beta^s \left[\alpha_{\iota c^* t}(s) P - \xi_{ic^*} \right] - \frac{\beta^{x_\iota^*}}{1 - \beta^{x_\iota^*}} \xi_{i0}. \tag{10}$$

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 $\sigma^i_\epsilon \to \infty$, any pattern of choices in a finite sample within the water right 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 (10) 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 of the value of water rights

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 additional assumptions within irrigator choices over time that one can use to identify planting costs; these are related to standard assumptions used in the dynamic discrete choice literature (Rust, 1987; Berry, 1994; Gowrisankaran and Rysman, 2012; Berry and Haile, 2024), 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 $\iota \in i$ within water right i possess:

(i) Price instruments (Berry and Haile, 2024). Shifters $Z_{\iota ct}$ of P_{ict} such that $\mathbb{E}[Z_{\iota ct}\xi_{ict}] = 0$ and $\mathbb{P}(\frac{\partial c_{it}(\iota)}{\partial Z_{\iota ct}} \neq 0) > 0$.

(ii) Common average unobserved characteristics (Berry *et al.*, 1995). Fields within the same water right, $\iota \in i$, have the same average planting costs ξ_{ict}, and the same curvature $\sigma^i_{\epsilon^k}$ across $c \in \mathcal{C}^k_i$.

(iii) Common beliefs over future states (Rust, 1987) and Gowrisankaran and Rysman (2012) inclusive value sufficiency for the renewal action.

With Assumption A3, the fully-specified model is identified. Under A3(i)–A3(ii), choices within a water right across fields $\iota \in i$ can be used to recover the relative planting costs that rationalize planting decisions at the start of each year—which, by assumption, do not depend on future periods. For annual crops, the probability of water ι allocated to $c \in \mathcal{C}^a_i$ is

$$\mathbb{P}(c_{it}(\iota) = c) = \exp\left\{\frac{1}{\sigma^i_{\epsilon^a}}\left(\alpha_{\iota ct}(0)P_{ict} - \xi_{ict}\right)\right\} / \sum_{c' \in \mathcal{C}^a_i} \exp\left\{\frac{1}{\sigma^i_{\epsilon^a}}\left(\alpha_{\iota c't}(0)P_{ic't} - \xi_{ic't}\right)\right\} \tag{11}$$

for each annual crop $c \in \mathcal{C}^a_i$ in each year t and each water right i.

Under A3(iii), choices for $\iota \in i$ reveal the planting costs and yield curvature that rationalize within-orchard decisions over time, because the assumption of common beliefs over future states within i means that the only variation in choices arises through the structural parameters θ, ξ, and σ. Let $\kappa_{it}(\iota, c, x) = 1$ if i chooses to renew ι at (c, x) and normalize $\sigma^i_{\epsilon^r} \equiv 1$; then the odds ratio that

characterizes the renewal probability for ι can be obtained as

$$\ln \frac{\mathbb{P}(\kappa_{it}(\iota, c, x) = 1)}{1 - \mathbb{P}(\kappa_{it}(\iota, c, x) = 1)} = \alpha_{\iota ct}(x) P_{ict} - \xi_{ic_x t} + \xi_{i0t} + \beta \overline{V}_i(\iota, c, x+1) - \beta \overline{V}_i(\iota, 0, 0). \tag{12}$$

For fields $\iota \in i$ that share both common planting costs and beliefs, i.e., A3(ii) and A3(iii), micro choices for each $\iota \in i$ can be used to recover the planting costs that rationalize new perennial planting decisions at the start of the year; that is, for newly planted perennials (ι such that $\kappa_{i,t-1}(\iota, \cdot, \cdot) = 1$) in that year:

$$\mathbb{P}(c_{it}(\iota) = c | \kappa_{\iota,t-1} = 1) = \exp\left\{ \frac{1}{\sigma^i_{\epsilon^p}} \left(\overline{V}_i(\iota, c, 1) - \xi_{ict} \right) \right\} / \sum_{c' \in \mathcal{C}^p_i} \exp\left\{ \frac{1}{\sigma^i_{\epsilon^p}} \left(\overline{V}_i(\iota, c', 1) - \xi_{ic't} \right) \right\} \tag{13}$$

which is analogous to the previous equation (11) except choice-specific payoffs depend on the value functions derived from the full lifecycle of the dynamic choice, as in Gowrisankaran and Rysman (2012).

The necessity of—and intuition for—price variation in Assumption A3(i) is the same as in canonical discrete choice models with micro data (Berry and Haile, 2024). The concern is that equilibrium planting and replanting decisions, characterized by (11), (12), and (13), reveal the core identification concern in this model, as well as standard approaches to address the endogeneity. Equilibrium water use across water rights and over time reflects differences in water right reliability G_i, water productivity, $\alpha(x)$, the drought state s, and unobserved planting costs ξ, all of which could be correlated with crop prices P.

Here, price instruments allow moments of the distribution of planting cost heterogeneity to be identified via the responsiveness of crop choices—if large (quasi-)random shifts in a given crop's price at the time of planting induce limited changes in water allocated to that crop by the owner of the water right, then relative planting costs must be quite heterogeneous to explain the small measure of marginal fields; in contrast, larger changes in planting decisions imply less heterogeneous planting costs across fields. Section 4.9 describes the estimation algorithm in detail after describing the exact data in my empirical work.

3.5 Measuring misallocation

As emphasized, the model delivers a microfoundation to value water rights. To value water right i, which recall is 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

$$\mathcal{V}_i(G_i) = \int_0^{W_i^p} \overline{V}_i(\iota, c_i(\iota), x_i(\iota)) dG_i(\iota) + \int_{W_i^p}^\infty \overline{V}_i(\iota, c_i(\iota), x_i(\iota)) dG_i(\iota), \tag{14}$$

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

Asymmetric incentives for trade. Interestingly, equation (14) shows how the presence of reliable water rights leads 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 value, or minimum price at which they may sell a marginal unit of reliable water, equals the lowest opportunity cost of keeping the water within their existing orchard fleet, $\{c_i(\iota), x_i(\iota)\}_\iota$,

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

whereas their marginal value for a unit of new reliable water, if their land constraint does not bind, equals its value in new production, $\partial_+ \mathcal{V}_i = \overline{V}_i(0, 0, s)$. Given that $\overline{V}_i(c_i(\iota), x_i(\iota), s)$ includes the option to cut down the orchard and renew to obtain $\overline{V}_i(0, 0, s)$, 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, so that total surplus equals $\sum_i \mathcal{V}_i$. A natural question—and a first step towards exploring the space of counterfactual water allocations—is to ask how a vector of water right changes, $\Delta \ln \widetilde{W} = (\Delta \ln \widetilde{W}_i)_i$, will affect total surplus in the economy. In partial equilibrium, water reallocation always creates social value when water moves from lower to higher marginal value uses. More generally, this need not hold—if water used by some irrigators also creates or diminishes value for others (spillovers), then moving wa-

ter from a water owner with a lower value to a water owner with a higher value can lower aggregate surplus. We can make progress with a matrix that summarizes complementarities in water use across firms, $\left[\frac{\partial}{\partial \ln \widetilde{W}}\mathbf{V}\right] \equiv \left(\frac{\partial}{\partial \ln \widetilde{W}_j}\mathbf{V}_i\right)_{i,j}$, by collecting the semi-elasticities of the value functions with respect to one's own and others' water rights.

With $\left[\frac{\partial}{\partial \ln \widetilde{W}}\mathbf{V}\right]$, one can then fully characterize to second-order the value of reallocation. As Baqaee and Sangani (2025, Proposition 5) show, the aggregate value of this water reallocation can be approximated via the quadratic form

$$\Delta \ln \sum_i \mathcal{V}_i = \mathbf{V}'(\Delta \ln \widetilde{W}) + \frac{1}{2}(\Delta \ln \widetilde{W})' \left[\frac{\partial \mathbf{V}}{\partial \ln \widetilde{W}}\right] (\Delta \ln \widetilde{W}), \tag{15}$$

which reflects the correlation of the reallocation vector with the marginal productivity of current water rights, adjusted for the possibility of spillovers off the diagonal of $\left[\frac{\partial}{\partial \ln \widetilde{W}}\mathbf{V}\right]$.

Summary of identifying assumptions. The two most important unobserved sources of planting cost heterogeneity, that rationalize dispersion in marginal products that I do not want to interpret as inefficiency, can be seen in the data I introduce below on (i) the dispersion in apparent marginal products of water across units of water within a given water right of a given reliability class and (ii) for the reliable component of a given water right, the dispersion in water productivity over time, through the lifecycle of an orchard.

The model assumes that the water within a given water right (of a given reliability) is allocated efficiently at the time of planting (discrete crop choice), and that the reliable water is committed and re-committed to perennial crops efficiently (optimal regenerative stopping). This implies that every unit of water within a given water right has the same average value within a year, and that units within a given reliable water right have the same counterfactual values of short- and long-run reallocation (that differ based on the age structure, through the optimal regenerative stopping).

In contrast, the model does not require that misallocation across water rights take any specific form. The reason is that, with microdata within water rights, I do not have to use variation in crop choices across water rights to identify any structural parameters of the model.

This flexibility reflects the inherent incompleteness of the water markets. However, to identify counterfactual misallocation, I do (necessarily) take a stance

on which water rights can, in some idealized counterfactual, be exchanged with one another. To do this, I focus on four natural frictions or constraints on trade, (i) distortions within connected components of the network such as irrigation districts, rivers, and canals, due to the difficulty of transferring water rights; (ii) distortions across regions reflecting infrastructural or conveyance capacity constraints on trade; (iii) distortions over time reflecting infrastructural or water storage constraints on trade across years; and (iv) distortions in property rights to trade across reliability classes.

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.[26] Yield and price data come from the California County Agricultural Commissioners, 1980–2022, collated by the USDA Census. I take evapotranspiration data from California's Irrigation Management Information System, and crop coefficients from the DWR, to measure water efficiencies at the crop level at different locations, for observed as well as counterfactual crop choices. I then compare different places in the hydrological network, which allows me to partition California into various 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, $\{K_{\iota ct}\}$, by field-year (ι, t), in annual data from 2014–2023. To illustrate the granularity of this data, Figure A9 maps a subset of the field-level data near Fresno. The binary coloring emphasizes the abundance of perennial orchards (reliable rights) and annual crops (unreliable rights); in practice, the data distinguishes among about forty different crops.

To further explore this diversity, Table A1 reports long-run average shares of farmland statewide and for the two Central Valley regions, the Sacramento and

[26] 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 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.

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 meaningful differences between the Sacramento and the San Joaquin River Valleys. Both regions harvest large quantities of almonds and walnuts, though San Joaquin irrigators grow more almond trees (21.6% of land relative to 11.6%), while Sacramento farmers grow more walnut trees (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.

4.2 Trees

As mentioned in the introduction, a key element of the data is novel field-level information on the year of planting for orchards observed in 2020, 2021, 2022, and 2023. 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 2023 is 3.1% 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 96% 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 9.0%, in contrast to 3.8% for trees in the second decade of their life, and 0.8% 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 14–17%. Almond trees last longer, with low probabilities of annual replacement ($\approx 5\%$) in the first two decades, rising to 18% in the third decade. Walnut, orange, and olive tree replacement rates remain below 2–4% for the first three decades of their lives, but replacement rates rise in their fourth decade to 8.4%, 4.4%, and 3.1%, respectively. Pistachio trees appear to live forever, with annual replacement rates in the data rarely above 1%.[27]

These differences across ages and crop types are important to explain the difference in unconditional replanting rates across the hydrological network; for example, 5.1% in the San Joaquin and 7.3% in the Sacramento River after three decades of production. 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 less than 1% in the Sacramento—as well as the much larger share of peach and stone fruit trees in the Sacramento River Valley, which live the shortest fruitful lifespans.

4.3 Irrigation

The calculation of irrigation water demand, the functions $\zeta_{\iota ct}(\tau)$, 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," $\eta_{\iota t}(\tau)$. Since the 1980s, the state of California has published reference evapotranspiration for irrigators, who use the information in the same way that we 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, $\vartheta_{\iota c}(\tau)$, which parametrize the demand of water for the crop over time given its location and growing season.

Figure A10 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

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

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, $\eta_{\iota t}(\tau)$, with crop coefficients, $\vartheta_{\iota c}(\tau)$, 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 $\zeta_{\iota ct}(\tau) = \eta_{\iota t}(\tau)\vartheta_{\iota c}(\tau)$. For example, Figure A11 shows monthly crop coefficients, $\vartheta_{\iota c}(\tau)$, 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 $\vartheta_{\iota c}(\tau)$ 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 A10, 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 $\int \zeta_{\iota ct}(\tau)d\tau$ for each crop and the land allocated to grow these crops, via the identity (3) 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 county-level realized prices P_{ict} and yields A_{ict} for all fields ι in a given county growing crop c and year t, sub-

stituting 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, underlie the estimates of the marginal products of water.

4.6 Planting and other irrigation costs

To measure average planting costs, I use cost data from the 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).

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. To measure groundwater costs, I use well reports to construct average watershed aquifer depths and then follow standard engineering calculations to convert depth into water pumping costs using average electricity rates and pump efficiencies from data on Central Valley irrigators (CEC, 2023). This translates into differences in variable pumping costs, reported as a ratio in the rightmost column, that are meaningful in terms of groundwater extraction—about a factor of two—although in levels they do not come close to the magnitude of the differences in marginal products from the shadow values. Accounting for these marginal groundwater costs in the valuation of a region's water rights will lead to a smaller gap in water values across regions, as irrigators in the San Joaquin and Tulare River Basins incur higher pumping costs to maintain the reliability of their water rights.[28]

[28] Another interpretation of this difference—in a model in which water is not a binding constraint, but instead farms continuously extract groundwater up to their marginal value for the water—would be that the farmers in the San Joaquin are willing to pull groundwater for a cost

4.7 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 ι for that crop,

$$\alpha_{\iota ct}(x_{\iota t})P_{ict} \equiv \frac{A_{\iota ct}P_{ict}}{\int \zeta_{\iota ct}(\tau)d\tau}, \tag{16}$$

as well as the marginal product net of average county planting costs. 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. Across crops, looking at the bottom distribution of these shadow values of water in the lower half of Table A3, one sees much different mixes of crops than in the upper reaches of the distribution. Wheat and pasture—annual crops that have much lower value per acre—use reasonable amounts of water. These crops use much 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.

Average output is the marginal output of each field in the Leontief model specified above, but revenue per acre-foot is not a sufficient statistic for the marginal product when irrigators also adjust planting costs proportionally with greater irrigation volumes. I account for the average planting costs using the data from Section 4.6 by multiplying revenue per acre-foot by $1 - \chi_i$, where χ_i is the long-run average revenue share of input costs in i's county. Accounting for these costs has large consequences for the levels of the field-level water marginal products, as Figure 7, Panel B shows. The effect on dispersion is much more muted than the effect on levels, but in general, adjusting marginal products for average input costs works to tighten the empirical distribution, because average input cost shares in counties with higher-value crops rise greater than proportionally with the value of the crop.

of almost twice that of the Sacramento River Basin. In such a model, a farmer's value for water can be inferred directly from groundwater pumping costs, and the data here would indicate some evidence of misallocation, which could be even more severe if we consider intertemporal or environmental externalities of groundwater overextraction.

4.8 Hydrology

I compile several federal and state data sources on the hydrological network—including rivers, canals, hydrological regions, rivers, canals, and groundwater wells (USGS, 2019; DWR, 2022, 2025)—which I then match to water rights in order to discipline the counterfactual analysis to interpretable and feasible reallocations.

I also use more than a century of historical California river inflows to calculate the state transition probabilities of random and persistent state variable, drought, that affects the switching costs. For tractability, I use a binary indicator defined as whether the San Joaquin River Index is deemed Critical (C).[29] The data indicate that California transitions in and out of drought with a conditional probability that depends on the prior year's drought state: while the probability of transitioning from non-drought to drought is about 0.12, but the probability of remaining in drought from one year to the next is close to 0.5.

Empirically, drought appears to affect several economic outcomes. In regressions of various observables on the drought indicator with crop-by-subwatershed fixed effects, drought lowers yields by about 5% and raises irrigation water requirements (evapotranspiration) by about 0.13 feet relative to a normal year (in wet years, water requirements are -0.24 feet less). At the same time, crop prices rise by about 16% in drought; in total, drought lowers the marginal product of water by an average of 4.7%.

Drought also affects irrigators' replanting choices. In a linear probability model that regresses an indicator for cutting down a given orchard on the annual drought indicator and crop-by-subwatershed fixed effects, the probability of cutting down an orchard rises by 0.008 in drought years, or an increase of $.008/.041 = 19.7\%$ from the average culling probability of 0.041. This empirical finding is consistent with an economic model of optimal renewal—the above evidence shows that drought is a stochastic but highly persistent state variable that significantly affects crop yields, prices, and optimal irrigation levels—and

[29] In practice, observed hydrological conditions include continuous and higher-dimensional processes; e.g., annual inflows, dam reservoir levels, et cetera. The challenge is that expanding the state space to include more general processes will introduce enormous computational complexity into the value function contraction mapping within the nested fixed point algorithm used to estimate the model and simulate counterfactuals. In addition, while I use more than a century of hydrological records to calculate drought state transitions, I only observe renewal decisions from 2020–2023, which limits my ability to estimate a richer model of how water owners respond to varying hydrological conditions.

motivates the inclusion of state transitions between drought and non-drought years.

4.9 Estimating unobserved planting costs

To tractably estimate the model from panel data on field-level crop choices, replanting decisions, optimal irrigation, and annual marginal products, I employ the additional structure of the model in Section 3.3. I estimate unobserved planting costs separately across the reliable and unreliable components of water rights, since the two types involve distinct decision problems.

The estimation procedure for reliable water rights aims to to recover two sources of planting costs first, within-field costs that differ over the lifecycle of a given orchard (time-to-build, the rate that yield declines with age, and the fixed cost of replanting); second, across-field costs that differ over fields within a water right (relative costs of planting different crops). I obtain these components in two steps.

First, I run a standard full-solution Rust (1987) nested fixed point algorithm derived from (12) for each perennial crop×region pair to recover crop-region-specific yield decay rates θ_c, crop-region-drought-state-specific fixed renewal costs $\xi_0(s)$, and the value functions for committing water to a specific perennial crop in a given region at each drought state. For time-to-build, newly-planted young perennials require between three to six years to mature and learn to bear fruit and this "time-to-build" follows known agronomic calendars, so I use reports from USDA to specify, for each crop, the years until first harvest, $\overline{\theta}_c$, with $\alpha_{\iota ct}(x) = 0$ for $x < \overline{\theta}_c$. After maturing, orchard stock depreciates, with yield decaying over time with the age of the trees. I estimate a constant decay rate θ_c for each crop after the first decade of the orchard's life, so that $\frac{\partial \alpha_{\iota ct}(x)}{\partial x} = 0$ for $x \in (\overline{\theta}_c, 10)$ and $\frac{\partial \alpha_{\iota ct}(x)}{\partial x} = -\theta_c e^{-(x-10)\theta_c}$ for $x > 10$. When the orchard is cut down, the owner incurs a fixed cost of replanting, ξ_c. This step is separable from the subsequent discrete crop choice problem at the time of planting (conditional on renewal) due to the assumptions discussed above.

Second, using value functions from the first step, I run GMM with a Berry (1994) contraction and lagged yield shocks as instruments for current crop prices to estimate relative planting costs across crops $c \in \mathcal{C}_i^k$ from the panel micro data on field-years (ι, t) within each water right i and reliability tier $k \in \{a, r\}$, scaling the flow payoffs for reliable water rights (perennials) with the Rust (1987)

values obtained in the first step. Specifically, for each water right i, I construct discrete crop choice moments from fields $\iota \in i$ based on the score functions of the likelihoods implied by (11) and (13). For each candidate $\sigma_\epsilon^i = \sigma$, I run an inner-loop Berry (1994) contraction to obtain the average $\hat{\xi}_{ict}(\sigma)$'s from the discrete choice problem of optimal assignment of fields ι to crops c within a water right i that best match the water-right-level choice probabilities. Given these $\hat{\xi}_{ict}(\sigma)$'s, I then estimate the curvature $\hat{\sigma}^i_{\epsilon^k}$ for $k \in \{a, p\}$ by minimizing an objective function constructed by differentiating the likelihood functions given by (11) and (13) with respect to the σ to construct moments that should vanish for the true parameter value,

$$\mathbb{E}[Z'_{\iota ct} h(c_{\iota t}, P_{ict}; \sigma, \xi)] = 0,$$

using instruments $Z_{\iota ct}$ for the endogenous P_{ict}, so that I grid search for σ to minimize the moment conditions

$$\sum_{\iota} g_\iota(\sigma, \xi)$$

where $h(\cdot; \sigma, \xi) = \frac{\partial \ell}{\partial \sigma} = \alpha_{\iota ct}(x_{\iota t}) P_{ict} \left(\mathbf{1}_{c_{\iota t} = c} - \mathbb{P}(c_{it}(\iota) = c | \sigma, \xi) \right)$ is the (MLE) score function, which vanishes at the true (σ, ξ). The estimator can be understood as a GMM version of the textbook maximum likelihood estimator for static multinomial logit discrete choice (over the value functions $\overline{V}_i(\iota, 0, 0)$, with choice sets $\mathcal{C}_i$ constructed among all crops observed to be grown in a given water right at any time during the panel), with two modifications. First, the inner-loop Berry (1994) contraction reduces the dimension of the parameter space for each water right so, for each i, I search for $\sigma_\epsilon^i \in \mathbb{R}_+$ instead of $(\sigma_\epsilon^i, \{\xi_{ict}\}_c) \in \mathbb{R}_+ \times \mathbb{R}^{|\mathcal{C}_i|}$. Second, I include price instruments $Z_{\iota ct} \equiv (1, P_{ic,t-1})$, which are necessary for identification even with the microdata (Berry and Haile, 2024). The estimate $\hat{\sigma}_\epsilon^i$ determines the magnitude of the unobserved logit shocks across units of water ι within the water right i. Together with ξ, I can construct the *de novo* value of the water right i as

$$\overline{V}_i(0, 0, s) = \int_i \sigma^i_{\epsilon^p} \log \left(\sum_{c \in \mathcal{C}_i^p} \exp \left\{ \frac{1}{\sigma^i_{\epsilon^p}} V_i(\iota, c, 0) - \xi_{ict} \right\} \right) d\iota,$$

and its decomposition into the units in a given year, reliable committed rights $\{V_i(\iota, c, x)\}_{\iota \in i}$, and annual rights $\{\overline{V}_i(\iota)\}_{\iota \in i}$.

The Rust (1987) estimates of yield curves and replacement (replanting) fixed costs appear in Table 5 Panel A. Overall, the structural estimates imply that the net-present-discounted-value of operating an orchard ranges from 83–91% of the value of an orchard producing the average yield in every year that lives forever; equivalently, replanting costs, time-to-build, and age-related yield declines comprise 9–17% of the long-run expected value of an eternally fruitful, immortal orchard. This value reflects two components that vary across crops: how crop c's yield evolves with age x (time-to-build and the rate of age-related yield declines) and its fixed cost of replanting.

The main heterogeneity in replacement cost estimates occurs across crops, as seen in Table A7. This corresponds to the descriptive evidence on replanting patterns from the discussion in Section 4.2 of Table 3. Almonds have total replanting and regeneration costs equal to about 26% of the long-run value of the orchard, whereas pistachio costs are closer to 16% of the long-run value, with negligible yield decays ($\hat{\theta}_c \approx 0.002$ and 0.004 in Sacramento and San Joaquin, respectively) relative to almonds ($\hat{\theta}_c \approx 0.024$ and 0.024). Like almonds, stone fruits such as apricots also have large yield declines ($\hat{\theta}_c \approx 0.020$ and 0.012), but lower replacement costs ($\hat{\xi}_c \approx 0.95$, 1.45 relative to 2.0), so total costs over the lifecycle equal only about 19–20% of the orchard's long-run value.[30]

Drought significantly lowers the fixed cost of replanting. The mean estimated replacement cost in drought ($\hat{\xi}_{c0}$ drought $= 1.11$) is about 21% lower than in non-drought years ($\hat{\xi}_{c0} = 1.41$), with an even starker gap for the bottom quartile (0.44 vs. 0.99). This is consistent with the evidence discussed above that orchard culling rises by about 20% in drought years: when yields fall and water requirements rise, the option value of maintaining an aging orchard declines, lowering the threshold for optimal replacement. Despite this, the long-run value of a committed orchard along the optimal path, $\overline{V}_i(c, x, s)$, is nearly identical across drought states—the median differs by less than 1%—reflecting the transient nature of drought's impact on the continuation value when the transition probability back to non-drought is approximately 0.5.

The relative planting costs across crops appear in Table 5 Panels B–C, which shows estimates from the discrete choice model in Section 3.3. Variation in mean relative planting costs ξ_{ict} within each water right i is apparent; the standard

[30] Within the same crop, the estimates do not differ much across regions; for example, almond planting costs over the lifecycle are 25.9% in the San Joaquin and 25.9% in Sacramento, apricot planting costs over the lifecycle are 19.5% and 21.7% in the two regions, respectively.

deviation of ξ_{ict} over c for fixed i and t ranges between 0–1.57 for perennial rights and 0.30–1.66 for annual rights. The scale of heterogeneity, given by the estimated $\hat{\sigma}^i_\epsilon$, also varies across rights; across reliable rights (i.e., perennial crops), $\hat{\sigma}^i_{\epsilon^p}$ averages 2.49, ranging 0.2 and 3.0 between the first and third quartile. Unreliable rights, i.e., annual crops, exhibit greater heterogeneity, with $\hat{\sigma}^i_{\epsilon^a}$ averaging 2.85 with an interquartile range of 0.8 to 3.4.

The estimated $\hat{\sigma}^i_{\varepsilon^p}$ and $\hat{\sigma}^i_{\varepsilon^a}$ parameters, combined with the logit structure of (11) and (13), imply own-price elasticities of crop choice at the field level equal to $\frac{1}{\sigma^i_\varepsilon}[1 - \mathbb{P}(c_{it}(\iota) = c|\sigma, \xi)] \cdot \alpha_{\iota ct}(x_{\iota t})P_{ict}$. For perennial planting decisions, with median $\hat{\varepsilon^p}_i = 1.40$, the elasticity scales as $0.71 \cdot (1 - s_{\iota c}) \cdot \alpha_{\iota ct}P_{ict}$. Given the wide range of marginal products—from close to zero to roughly \$4,000/af at the 95th percentile—own-price elasticities vary substantially across crops and water rights. Annual crop choices, with median $\hat{\sigma}^i_{\varepsilon^a} = 2.00$ and typically larger choice sets, have proportionally lower elasticities for a given level of revenue per acre-foot.

The cross-price elasticity of choosing crop c with respect to P_{ict} is proportional to the choice probability of the rival crop c' and its marginal product per acre-foot, $\frac{1}{\sigma^i_\varepsilon}\mathbb{P}(c_{it}(\iota) = c'|\sigma, \xi) \cdot \alpha_{\iota c't}(x_{\iota t})P_{ic't}$. For perennial crops, where choice sets are small (median $|\mathcal{C}^p_i| = 2$), a price increase for one crop displaces planting of the alternatives roughly in proportion to their baseline shares. For annual crops, where choice sets are larger (median $|\mathcal{C}^a_i| = 4$), cross-price effects are more dispersed.

5 Results

I now use the estimates of water use, annual marginal products, and planting costs to study water allocation in California. Section 5.1 constructs values for each water right and discusses the primary drivers of average value; Section 5.2 studies dispersion within the the empirical distribution of water values. Section 5.3 explains the approach taken to counterfactuals and some of its limitations; Sections 5.4–5.6 report the results and Section 5.7 discusses sensitivity of the main results to various assumptions.

5.1 Sources of water value

Figure 8 plots the value per acre-foot of water at the HUC12 level.[31] The lighter green colors are lower values, ranging from zero to about $2,500/af. Table 6 reports deciles of the realized marginal water values for 2020; Panel A conditions the distribution on region.

Three observable—and interrelated—features of water rights strongly predict greater value. First, reliability. Table 6, Panel B explores the differences between reliable and unreliable water rights, i.e., water used to grow perennial and annual crops, respectively. 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.

Second, location below the flow constraint in the Sacramento–San Joaquin Delta. In Figure 8, 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. Tables 7 and A18 show that mean and median marginal products south of the Delta are significantly greater than the North, Table A6 shows the Delta gradient is stable over 2014–2022, and Table 6 shows this pattern extends to the deciles of the water value distribution. Most of the difference across watersheds comes from the first through sixth or seventh decile, places where, in the San Joaquin, irrigators grow high-value fruits and nuts rather than the annual crops in Sacramento.[32]

A key mechanism behind the regional correlations appears to be investment in perennial crops. Column (6) of Table 7 shows significantly higher shares of perennial water uses south of the Delta, and Figure A12 shows these differences are stable over 2014– 2022. However, conditioning on reliability 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

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

[32] 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, reported in Table 2. That price gradient appears comparable to that implied by the microfoundations of the crop model, suggesting the possible importance of flow constraints (examined in Section 5.4).

0.99–1.43, so that the San Joaquin River Valley plants more valuable perennial crops per unit of water than the Sacramento. Figure 9B shows that the differences are more striking among annual crops: the San Joaquin grows much more water-efficient annual crops 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.

Third, historical priority. To study how productivity dispersion correlates with the legacy of historical property rights, Table 7 regresses standard Syverson (2004) measures of the empirical distribution of productivities—here, water productivity by water right in each watershed-year from 2014–2022—on fixed attributes of historical property rights (the share of paper water rights at baseline with priority dates prior to 1914, depicted in Figure A7), the share of "reliable" water rights used to grow perennials, and features of the hydrological network (location above or below the Delta, and an indicator for drought). These regressions are descriptive and should not be interpreted as causal, but reveal some interesting patterns.

A legacy of senior water rights predicts less dispersion in the marginal value of water. Table 7 shows that watersheds with greater pre-1914 water rights have less dispersion, 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. In particular, places with more senior water rights invest more by planting perennial crops (Table 7, column (6)), providing 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.

5.2 Sources of dispersion

Given the empirical distribution of water rights in California from 2014–2022, Table 8 shows how productivity dispersion varies across and within various observable sets of hydrological and institutional boundaries, as a preliminary step in the subsequent analysis of allocative efficiency.

With various observable characteristics of water rights—location of the right within the hydrological network (hydrological region or subwatershed, river, and

canal) and reliability of the right (reliable versus unreliable)—I can partition water rights into subsets indexed by k, so that $\mathcal{J} = \cup_k \mathcal{J}_k$. Specifically, I consider the following partitions: regions (i.e., $\mathcal{J}_{\text{SV}}$, $\mathcal{J}_{\text{SJ}}$, $\mathcal{J}_{\text{other}}$) counties (e.g., $\mathcal{J}_{\text{Kern County}}$, $\mathcal{J}_{\text{Tulare County}}$, $\mathcal{J}_{\text{Fresno County}}$, etc), water districts (e.g., $\mathcal{J}_{\text{unassigned}}$, $\mathcal{J}_{\text{Westlands}}$, $\mathcal{J}_{\text{Semitropic}}$, etc), rivers (e.g., $\mathcal{J}_{\text{Kern River}}$, $\mathcal{J}_{\text{San Joaquin River}}$, $\mathcal{J}_{\text{Kings River}}$, $\mathcal{J}_{\text{Sacramento River}}$, etc), canals (e.g., $\mathcal{J}_{\text{California Aqueduct}}$, $\mathcal{J}_{\text{Tehama-Colusa Canal}}$, $\mathcal{J}_{\text{Mokelumne Aqueduct}}$, etc), and HUC12 subwatersheds (e.g., $\mathcal{J}_{180400010803}$, $\mathcal{J}_{180300031406}$, $\mathcal{J}_{180201580404}$, etc, (Buttonwillow Slough / Lone Willow Slough, Muddy Creek / Frontal Buena Vista Lake Bed, Drumheller Slough / Butte Creek), etc).

Table 8 shows the average volume of water rights in each of these partitions and reports measures of dispersion (interquartile, interdecile ranges). As expected, the dispersion in water values among water rights falls as we look at narrower collections of water rights. The interquartile range across all water rights in the Central Valley is about \$300/af, and nearly identical across rights within each year; the average range falls to \$140/af within regions, and \$100/af within regions and reliability classes. Restricting to within irrigation districts further halves the interquartile range, to \$60/af on average among districts, with similar effects within-county (\$50/af) or within-river (\$60/af). Within a local subwatershed, the average interquartile range among water rights of the same reliability class is only \$30/af.

5.3 Counterfactuals

Finally, with the empirical distribution of water rights and their values, I explore four questions related to water market design: one, I consider traditional allocative efficiency by revisiting the standard question of (static or long-run) trade across water rights in the hydrological network; two, I explore the importance of stochastic attributes of water rights by assessing trade across states of the world, reliable; three, I explore the value of water storage by assessing trade across years; four, I explore the importance of the investment channel by contrasting the (extremely limited) short-run water reallocation opportunities with the (much larger) long-run water reallocation opportunities.

The main challenge for counterfactuals is that identifying misallocation requires more assumptions than recovering the values of water across users: the dispersion in true water values at the observed allocation can reflect a combination of (a) feasibility constraints, (b) trade frictions, and (c) allocative ineffi-

ciency. The work above to construct the empirical distribution of the true value of water rights required ruling out measurement error as an explanation, but otherwise did not restrict trade constraints or frictions. For counterfactuals to identify misallocation—that is, to disentangle dispersion that reflects feasibility constraints or trade costs from dispersion that evinces true misallocation—one must take a stance on what (counterfactual) reallocations can occur and at what cost.

To make progress, I draw on additional observables—related to the hydrological network and institutional and jurisdictional boundaries—to follow the comparative approach of Asker *et al.* (2019), which can decompose allocative efficiency into various institutional and hydrological constraints and frictions. Their method is well-suited to study misallocation in settings with many overlapping sources of inefficiency—e.g., unobserved distortions due to market structure, political economy, et cetera—and for which the researcher observes certain characteristics relevant to plausible sources of misallocation (e.g., in Asker *et al.*, 2019, the identity of the cartel member countries and the country of each oil well) alongside the microdata on each unit of production. The approach involves two steps. First, calculate counterfactual values of constrained-efficient allocations under different constraints: i.e., for each k, obtain various values of reallocating different quantities of water among water rights $i \in \mathcal{J}_k$. Second, compare output under the constrained-efficient allocations to decompose distortions into within- and across-components, by subtracting the value of a given constrained-efficient allocation (e.g., within-year, within-region) from the value of a slightly less-constrained allocation (e.g., within-year, across-region), to attribute misallocation to a given distortion (e.g., across-region).

5.4 Reallocation across space

Revisiting traditional reallocation across space—trade in water rights within the hydrological network—is not difficult because I observe the location of each water right within the hydrological network, as well as other institutional attributes that largely correspond to geography (e.g., irrigation district).

A natural initial place to look for opportunities to reallocate water across space without violating hydrological constraints is among water rights that are likely to be fully hydrologically connected, such as water rights in a given year and reliability class within the same irrigation district or along the same river or canal.

Panel A of Table 8, columns 2–5, take four approaches to obtain constrained-efficient allocations: `gft_q50up` (`gft_q75up`) reallocates water assuming that the land constraint of each existing water right is twice (thrice) that of observed; `gft_q90` (`gft_q99`) assumes all water rights in a given subset produce at the 90%-ile (99%-ile) productivity.

Panel B of Table 8 shows predicted gains from within-district water reallocation—the value of reallocating water rights within districts (in the same year and reliability class) relative to the value of reallocating water within water rights in the same year and reliability class—that range from 14–22% of output in case I and 22–35% of output in case II. This allocative inefficiency indicates frictions to—or prospective gains from—water trade, since the water used within these jurisdictions should not typically be subject to hydrological constraints. Alternatively, this implies that the combination of hydrological constraints, water reliability tiers, and within-water-right planting costs cannot fully explain water misallocation.

Another place to look for opportunities to reallocate is across regions with known flow constraints, such as the upper and lower components of the Central Valley. The interpretation of these calculations is less about misallocation and trading frictions per se that help to explain the distortions above, but instead to speak to the prospective value of relaxing the existing water transport constraints through greater infrastructure investments. Water reallocation between the upper and lower Central Valley—across the Sacramento-San Joaquin Delta (i.e., A-C)—could increase value by 17–24% of output across cases I–II. Reallocating water across regions, rivers, or canals can increase surplus by 10–18% in case I and 33–46% in case II.

5.5 Reallocation across states of the world

The natural way to reallocate water across states of the world is to bundle several unreliable water rights into reliable water rights. Here, I assume that I can observe reliable water rights through perennial crops. I also can observe less reliable rights through annual crops. A natural counterfactual is how valuable it would be to convert less-reliable to reliable rights (by bundling unreliable rights into smaller, reliable rights).

The comparative analysis indicates that bundling unreliable water rights into more reliable water rights within the same local watershed can, in the long run,

increase total surplus by 4–16%. This result, reported in Table 8, is obtained by comparing the value of the efficient allocation within a local watershed within a huc12-year and within a water-right-year, with (J, L) and without (K, M) the additional constraint on reliability class (J-K and L-M).

5.6 Reallocation over time

Water reallocation over time can be accomplished through large-scale water storage; California has dam capacity roughly equal to one year of the entire state's water consumption, and has experimented extensively with groundwater recharge (water storage in existing aquifers). Interestingly, the intertemporal allocation of water seems efficient: reallocating water across years does not seem to create much value. The reason is the enormous persistence in water use from year to year documented in Figure 6. The final finding—limited inter-annual gains from trade, despite perfect foresight about future water abundance and scarcity—contrasts sharply with the interregional, within-river, and within-canal prospective gains from trade across water rights. It indicates limited value for the construction of new water storage projects. It is consistent with reliance on groundwater and persistent use of water across years.

5.7 Robustness, sensitivity, and extensions

A final result is the importance of unobserved planting costs (within water rights) to the bottom-line estimates. For example, row M1 in Table 9 shows that the average interquartile and interdecile ranges of values within a water right are \$155/af and \$280/af, respectively, or about half of the overall dispersion in water values across water rights (row A in Table 8) or one-fourth to one-fifth of overall dispersion in water values across fields (row A1 in Table A10). The predicted value of case I and II reallocations within a water right—assumed not to exist at all under A3–equal 29% and 50% of the overall value (Table A10, row M).

Misattributing this underlying heterogeneity to productivity instead of planting costs substantially inflates measures of productivity dispersion and predicted gains from trade. Without within-water-right planting costs, interquartile and interdecile dispersion rises to \$600/af and \$1450/af (Table A10, row A), respectively, from \$300/af and \$550/af in the preferred specification that includes within-water-right planting costs. Likewise, the implied distance between the

current and "efficient" allocation (Table 9, Panel A, columns 2–5) under a specification that does not adjust for within-water-right planting costs is about 1.5-4x the gains implied across water rights in the benchmark.

Interestingly, Table A10 also shows that the predicted Asker *et al.* (2019)-style gains (constructed by comparing constrained-efficient allocations across constraints—used to assess the value of relaxing some, but not all, constraints—to value more plausible reallocations) are not much affected by the inclusion of within-water-right planting costs.[33] This would be the case if the unobserved within-water-right planting costs are not so correlated with the various constraints analyzed. This shows the robustness of comparative analysis in the style of Asker *et al.* (2019), relative to comparisons only between the least-cost or efficient allocation with the observed allocation.

Finally, on robustness to irrigation scheduling algorithm assumptions—the results on water misallocation that I find below are made based on comparisons across and between water rights; as these assumptions are sustained across all users and all fields, if they are violated, the bottom-line results on water misallocation will be affected only to the extent that the assumption fails systematically for certain subsets of water rights in ways that correlate with the water rights' characteristics used to delineate trading opportunities.

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

[33] E.g., without planting costs the relative misallocation within districts, rivers, and canals ranges from 7-13% (compared with 14–22%) in case I and 13–25% (compared with 22-35%) in case II (see Panel B of Table A10).

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. Accounting for competing explanations for the dispersion in marginal products, including—but not limited to—estimation of planting costs within water rights and accounting for reliability and hydrological constraints—are crucial to the bottom-line calculations.

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Table 1. Natural Variability and Water Rationing

	Wet Year	Dry Year	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** × **year** distribution, 2010–2023.

Columns (1) and (2) split the sample by water-year designation. Columns (3) and (4) split the sample in column (2) 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 ≡ 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 2022–2024 (WestWater, LLC).

Table 3. Hazard Rate by Decade Planted, 2020–2023

tree_type	acres_2020	haz_CA	haz_SV	haz_SJ
all / all	2,946,282	0.031	0.029	0.031
1980s /	340,265	0.056	0.073	0.051
1990s /	353,317	0.090	0.092	0.098
2000s /	879,380	0.038	0.028	0.041
2010s /	1,373,320	0.008	0.007	0.009
/ citrus	299,035	0.022	0.035	0.020
/ olives	48,271	0.013	0.009	0.026
/ almonds	1,390,560	0.042	0.037	0.044
/ walnuts	426,517	0.026	0.020	0.032
/ pistachios	460,901	0.001	0.002	0.001
/ plums, prunes and apricots	70,817	0.065	0.058	0.078
1980s / citrus	79,441	0.044	0.051	0.042
1990s / citrus	58,232	0.021	0.042	0.019
2000s / citrus	72,491	0.024	0.012	0.020
2010s / citrus	88,871	0.004	0.045	0.007
1980s / olives	14,056	0.031	0.023	0.047
1990s / olives	5,770	0.022	0.008	0.046
2000s / olives	16,121	0.018	0.016	0.036
2010s / olives	12,324	0.003	0.011	0.002
1980s / almonds	52,930	0.110	0.103	0.102
1990s / almonds	137,416	0.189	0.182	0.197
2000s / almonds	464,391	0.052	0.037	0.055
2010s / almonds	735,823	0.010	0.004	0.011
1980s / walnuts	72,681	0.084	0.085	0.083
1990s / walnuts	66,514	0.041	0.031	0.051
2000s / walnuts	104,075	0.017	0.010	0.026
2010s / walnuts	183,247	0.011	0.008	0.014
1980s / pistachios	50,968	0.006	0.013	0.006
1990s / pistachios	40,436	0.004	0.007	0.003
2000s / pistachios	127,951	0.001	0.001	0.001
2010s / pistachios	241,546	0.001	0.002	0.001
1980s / plums, prunes and apricots	12,701	0.076	0.070	0.108
1990s / plums, prunes and apricots	16,779	0.143	0.142	0.143
2000s / plums, prunes and apricots	15,987	0.074	0.049	0.103
2010s / plums, prunes and apricots	25,349	0.014	0.009	0.026

Average share of perennial trees cut down (annual "hazard rate") between WYs 2020–21, WYs 2021–22, and WYs 2022–23 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, 2004–2022

Dependent Variable:	chosen				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
$\ln(\alpha_{\iota ct} P_{ict})$	−0.0696	0.0309	0.0287	0.0733	0.0595
	(0.0164)	(0.0076)	(0.0078)	(0.0140)	(0.0155)
Instruments				✓	✓
Fixed-effects					
region-year	✓	✓		✓	
region-crop		✓		✓	
region-crop-year			✓		✓
Fit statistics					
Observations	2,337,203	2,337,203	2,337,203	2,337,176	2,337,176
R^2	0.01587	0.18235	0.19766	0.18036	0.19704
Within R^2	0.01425	0.00129	0.00067	−0.00115	−0.00011

Clustered (crop-year) standard-errors in parentheses

Illustrative linear regression at the field-crop-year-planted level for newly-planted perennial orchards from 2004–2022. Outcome is 1 if the crop planted equals c and 0 otherwise.

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

Table 5. MLE Estimates of Planting Costs

A. Optimal Regeneration (Rust)

Statistic	q25	Median	Mean	q75
N	361.2	1,590.5	9,306.833	5,759.8
theta	0.003	0.006	0.010	0.012
xi0	0.988	1.650	1.409	2.000
xi0_drought	0.438	1.100	1.106	1.950
V_1_c	16.007	16.744	16.640	17.484
V_1_c_drought	16.027	16.887	16.683	17.520

B. New Planting (Perennial)

Statistic	q25	Median	Mean	q75
vol	1,687.568	6,998.288	45,509.900	35,539.050
N	2	7	50.428	40
N_c	1	2	2.594	4
sig	0.200	1.400	2.494	3.000
msqe	0.000	0.0001	0.004	0.002
xi_mean	−0.667	−0.196	−0.518	0.000
xi_sd	0.000	0.302	0.899	1.572
E_mean	306.643	465.702	498.745	640.722
E_pred	346.659	554.949	691.407	719.148

C. New Planting (Annual)

Statistic	q25	Median	Mean	q75
vol	205.481	1,438.583	10,772.900	5,086.994
N	11	32	142.915	102
N_c	2	4	4.967	7
sig	0.800	2.000	2.850	3.400
msqe	0.00000	0.0001	0.002	0.001
xi_mean	−0.822	−0.383	−0.609	−0.116
xi_sd	0.302	0.937	1.175	1.660
E_mean	346.987	530.325	678.469	803.262
E_pred	437.329	640.175	1,023.516	900.935

Panel A. Summary of Rust (1987) maximum likelihood estimates of planting cost parameters over region×tree types. N corresponds to the number of field-level observations from 2020–2023 within each region×tree type subsample; year-planted data starts in 2020.

Panel B. Summary of GMM estimates of relative crop planting cost parameters over all reliable water rights. N corresponds to the number of field-level observations from 2004–2022 within each water right reconstructed from planting dates from field-level data in 2020–2023; evapotranspiration data starts in 2004.

Panel C. Summary of GMM estimates of planting cost parameters over all unreliable water rights. N corresponds to the number of field-level observations from 2014–2022 within each water right; field-level data starts in 2014 and yield data stops in 2022.

See Appendix C for estimation details. See Tables A7, A8, and A9 for additional results.

TABLE 6. AVERAGE ESTIMATED WATER VALUES, 2020

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

	San Joaquin (SOD)	Sacramento (NOD)	diff	ratio
0	25.60	23.48	2.12	1.09
0.1	140.09	87.25	52.84	1.61
0.2	189.56	119.54	70.02	1.59
0.3	198.09	149.04	49.06	1.33
0.4	243.08	156.08	87.00	1.56
0.5	276.14	179.17	96.97	1.54
0.6	299.55	184.29	115.26	1.63
0.7	344.43	213.12	131.31	1.62
0.8	505.02	220.52	284.50	2.29
0.9	1,188.41	254.54	933.88	4.67
1	9,207.11	897.94	8,309.18	10.25

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

	Perennial crops	Annual crops	diff	ratio
0	19.19	25.60	−6.41	0.75
0.1	492.25	140.09	352.17	3.51
0.2	528.54	189.56	338.98	2.79
0.3	560.93	198.09	362.83	2.83
0.4	598.99	243.08	355.91	2.46
0.5	641.45	276.14	365.31	2.32
0.6	776.81	299.55	477.27	2.59
0.7	1,045.28	344.43	700.86	3.03
0.8	1,540.72	505.02	1,035.70	3.05
0.9	2,257.93	1,188.41	1,069.51	1.90
1	3,103.81	9,207.11	−6,103.31	0.34

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

Table 7. 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	−0.179	−0.175	−0.029	−0.020	0.118	−0.027
	(0.086)	(0.113)	(0.103)	(0.087)	(0.108)	(0.050)
1(south of the Delta)	0.245	0.470	1.027	1.026	0.645	0.310
	(0.073)	(0.091)	(0.079)	(0.068)	(0.087)	(0.039)
1(drought_year)	−0.004	−0.045	0.022	0.023	0.053	0.017
	(0.023)	(0.029)	(0.023)	(0.018)	(0.028)	(0.005)
Mean of dependent variable	0.592	1.114	5.945	6.038	5.339	0.428
Observations	1,669	1,669	1,669	1,669	1,669	2,043
Adjusted R^2	0.032	0.068	0.323	0.410	0.143	0.180

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) interquartile range, (2) interdecile range, (3) ln(median), (4) ln(mean), (5) 10th percentile, of the volume-weighted distribution of water productivity. Column (6) share of water used for perennial crops.

See Table A18 for additional results.

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.
"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 8. Measuring Misallocation in California

A. Dispersion

	N	gft_q50up	gft_q75up	gft_q90	gft_q99	shadow_IQR	shadow_IDR
all [A]	1	0.594	1.056	0.978	2.832	304.341	550.464
year [B]	7	0.591	1.037	0.900	2.669	291.410	525.914
region [C]	2	0.424	0.813	0.715	2.130	141.420	325.028
region-year [D]	14	0.412	0.804	0.709	2.081	143.241	322.691
ry-class [E]	28	0.327	0.686	0.641	1.847	106.571	235.851
ryclass-county [F]	471	0.186	0.349	0.334	0.929	51.706	111.305
ryclass-district [G]	1,073	0.165	0.331	0.306	1.015	41.626	87.926
ryclass-river [H]	1,063	0.221	0.358	0.370	0.866	60.561	119.161
ryclass-canal [I]	1,525	0.147	0.224	0.236	0.632	51.361	107.861
ry-huc12 [J]	4,235	0.105	0.222	0.243	0.501	54.343	102.510
ryclass-huc12 [K]	6,501	0.062	0.106	0.119	0.235	29.374	54.121
ry-wr [L]	26,991	0.037	0.158	0.211	0.284	28.825	53.292
ryclass-wr [M]	38,029	0	0	0	0	0	0
year-pre1914 [N]	14	0.584	1.031	0.938	2.649	270.420	532.549
ry-pre1914 [O]	28	0.416	0.802	0.698	1.931	146.139	334.645
ryclass-pre1914 [P]	56	0.318	0.679	0.665	1.790	116.377	256.054

B. Distortions

	gft_q50up	gft_q75up	gft_q90	gft_q99	shadow_IQR	shadow_IDR
across_regions [A-C]	0.170	0.243	0.263	0.702	162.921	225.436
across_years [A-B]	0.003	0.019	0.079	0.162	12.931	24.550
bundle_within_ry [D-E]	0.085	0.117	0.069	0.234	36.669	86.840
bundle_within_hy [J-K]	0.043	0.116	0.123	0.266	24.970	48.389
bundle_within_wry [L-M]	0.037	0.158	0.211	0.284	28.825	53.292
across_county [E-F]	0.140	0.337	0.307	0.918	54.866	124.546
across_district [E-G]	0.162	0.355	0.335	0.832	64.945	147.925
across_river [E-H]	0.106	0.328	0.270	0.981	46.011	116.689
across_canal [E-I]	0.180	0.462	0.404	1.215	55.210	127.990
within_county [F-M]	0.186	0.349	0.334	0.929	51.706	111.305
within_district [G-M]	0.165	0.331	0.306	1.015	41.626	87.926
within_river [H-M]	0.221	0.358	0.370	0.866	60.561	119.161
within_canal [I-M]	0.147	0.224	0.236	0.632	51.361	107.861
between_pre1914_ryc [E-P]	0.009	0.008	−0.025	0.057	−9.806	−20.203
between_pre1914_ry [D-O]	−0.004	0.001	0.011	0.150	−2.899	−11.954

Panel A. Dispersion in estimated water values under successively tighter constraints on feasible reallocation, Central Valley irrigators, WY 2014–2022 average. Each row reports counterfactual gains from trade and measures of productivity dispersion within the indicated partition of water rights. *N* reports the number of groups in the partition. `gft_q50up` and `gft_q75up` report the percentage gain in total water value from reallocating water within each group, assuming the land constraint of each existing water right is twice and three times that observed, respectively. `gft_q90` and `gft_q99` report the gain from equalizing all water rights within each group to the 90th and 99th percentile productivity. `shadow IQR` and `shadow IDR` report the average interquartile and interdecile range ($/af) of estimated marginal water values within each partition.

Partitions are indexed by combinations of year (y), region (r: Sacramento, San Joaquin, or other), reliability class (class: perennial or annual), and increasingly narrow hydrological or institutional boundaries: county, irrigation district, river, canal, HUC12 subwatershed (huc12), and individual water right (wr). Row [M] (ryclass-wr) assigns each water right to its own group, so within-group dispersion is zero by construction (Assumption A3). Rows [N]–[P] replace the regional partition with a pre-1914/post-1914 priority date partition.

Panel B. Distortions attributable to specific constraints, obtained by differencing Panel A rows. For example, `across regions` [A–C] measures the value of cross-regional reallocation by subtracting line C from line A; `within district` [G–M] measures within-district misallocation net of within-water-right planting costs; `bundle within hy` [J–K] measures the value of converting unreliable water rights into reliable rights within local subwatersheds.

See Table 9 for the role of within-water-right planting costs and Table A10 for field-level marginal products.

Table 9. Measuring Misallocation – Role of Planting Costs

	N	gft_q50up	gft_q75up	gft_q90	gft_q99	shadow_IQR	shadow_IDR
A	1	0.594	1.056	0.978	2.832	304.341	550.464
A1	1	0.688	1.423	1.242	3.108	589.009	1,439.722
B	7	0.591	1.037	0.900	2.669	291.410	525.914
B1	7	0.684	1.405	1.269	3.219	544.397	1,453.526
C	2	0.424	0.813	0.715	2.130	141.420	325.028
C1	2	0.603	1.245	1.125	2.579	456.056	1,061.785
D	14	0.412	0.804	0.709	2.081	143.241	322.691
D1	14	0.583	1.229	1.116	2.704	442.489	1,052.141
E	28	0.327	0.686	0.641	1.847	106.571	235.851
E1	28	0.476	1.071	0.987	2.833	308.514	783.514
F	471	0.186	0.349	0.334	0.929	51.706	111.305
F1	482	0.413	0.758	0.758	1.742	204.643	455.043
G	1,073	0.165	0.331	0.306	1.015	41.626	87.926
G1	1,331	0.382	0.772	0.658	2.003	337.582	617.506
H	1,063	0.221	0.358	0.370	0.866	60.561	119.161
H1	1,161	0.423	0.783	0.708	1.814	266.767	531.969
I	1,525	0.147	0.224	0.236	0.632	51.361	107.861
I1	2,116	0.364	0.665	0.611	1.634	305.379	627.690
J	4,235	0.105	0.222	0.243	0.501	54.343	102.510
J1	5,729	0.381	0.672	0.672	1.711	360.822	649.530
K	6,501	0.062	0.106	0.119	0.235	29.374	54.121
K1	9,476	0.288	0.493	0.545	1.303	252.766	472.372
L	26,991	0.037	0.158	0.211	0.284	28.825	53.292
L1	27,254	0.393	0.701	0.668	1.562	205.819	383.662
M	38,029	0	0	0	0	0	0
M1	38,376	0.296	0.533	0.533	1.174	155.213	280.198
N	14	0.584	1.031	0.938	2.649	270.420	532.549
N1	14	0.677	1.397	1.250	3.110	572.448	1,468.583
O	28	0.416	0.802	0.698	1.931	146.139	334.645
O1	28	0.582	1.227	1.108	2.708	452.800	1,073.084
P	56	0.318	0.679	0.665	1.790	116.377	256.054
P1	56	0.476	1.064	0.980	2.660	317.088	805.266

Version of Table 8, Panel A, comparing baseline result (attributing dispersion within a water right to heterogeneous planting costs) to no heterogeneity in planting costs within a water right (Table A10). Rows with "1" suffix (A1, B1, C1, ...) are the no-planting-cost specification.

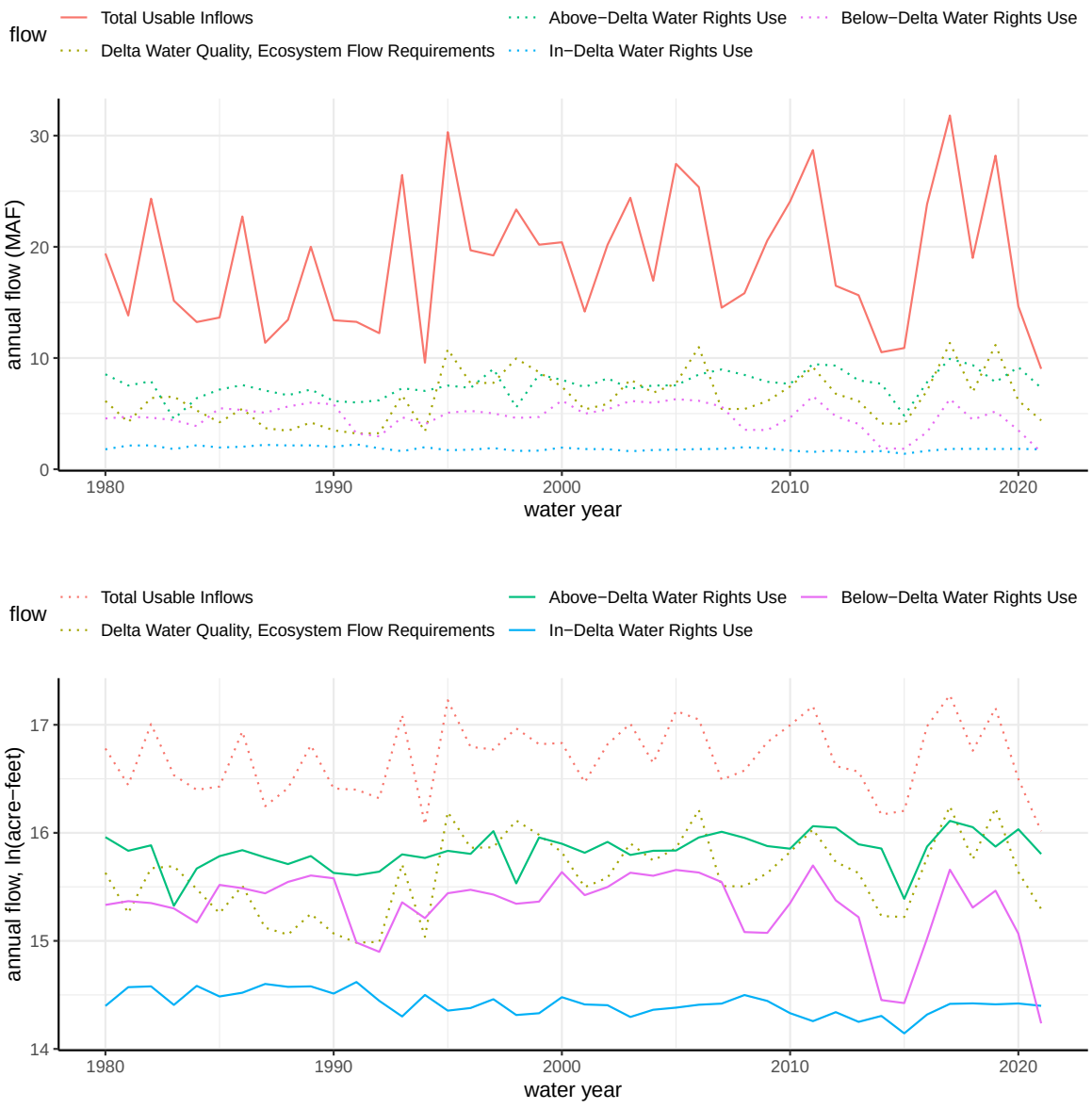
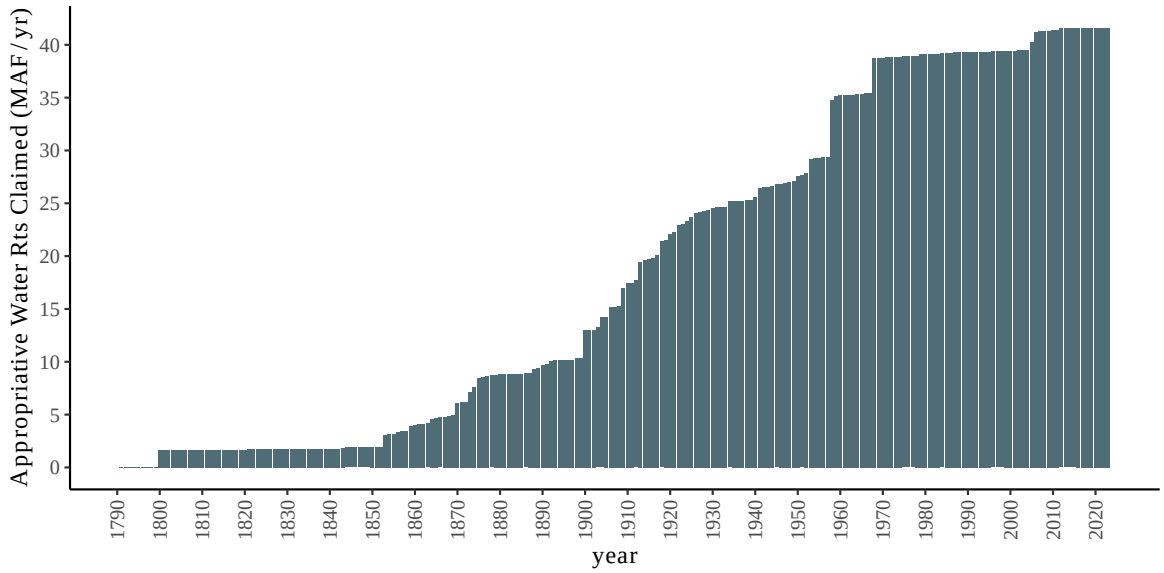


FIGURE 1. TOTAL USABLE INFLOWS + APPROPRIATIVE RIGHTS, 1980–2021

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 Priority and Point of Diversion

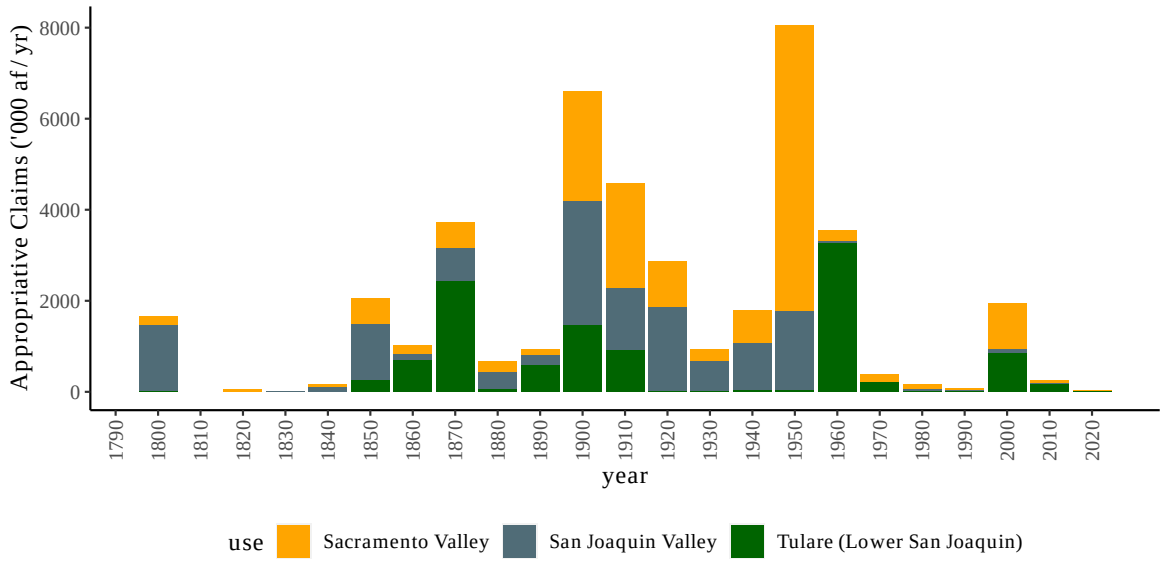


FIGURE 2. THE LEGACY OF APPROPRIATIVE WATER RIGHTS

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 A7 for richer spatial distribution of water rights.

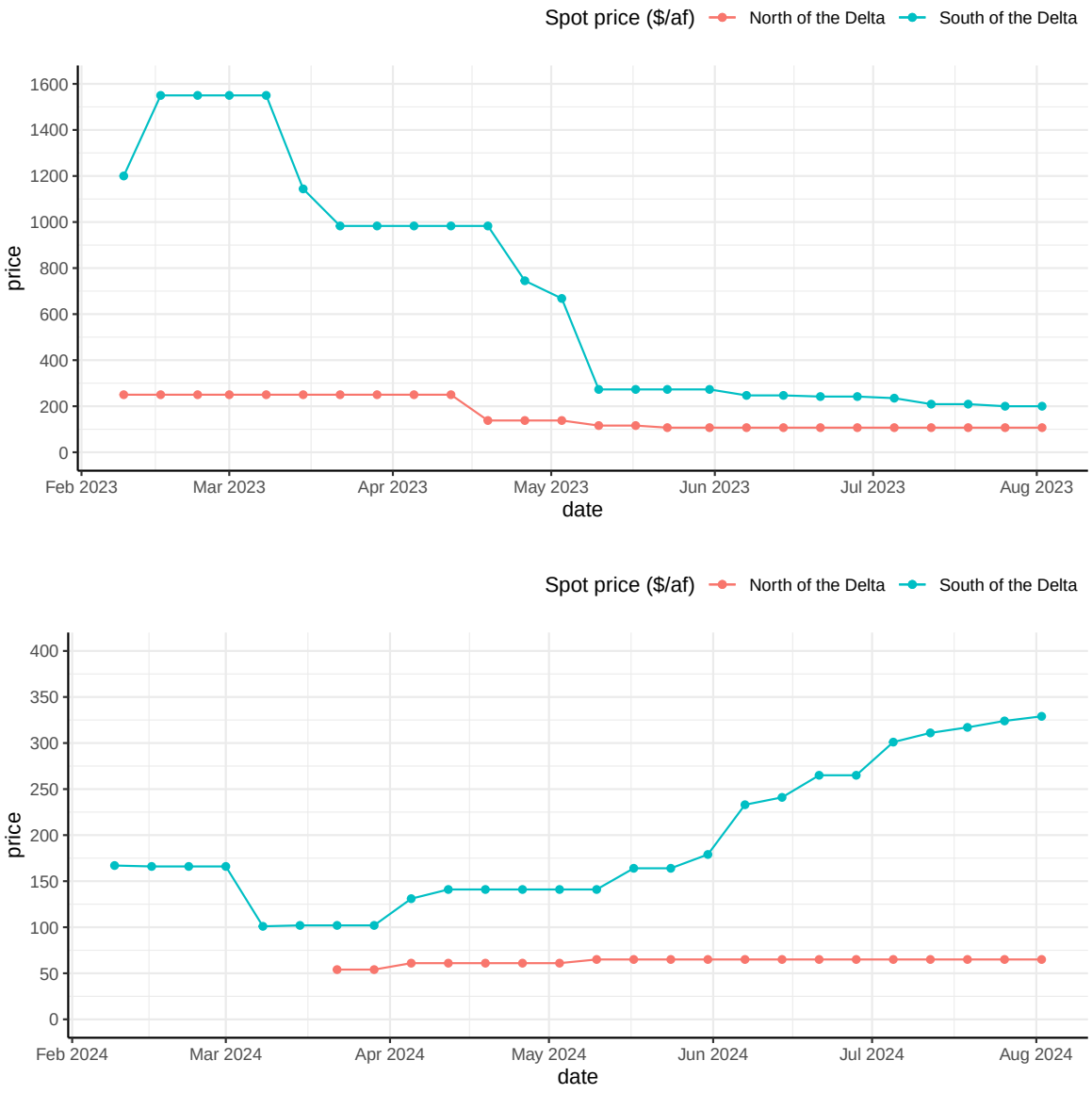
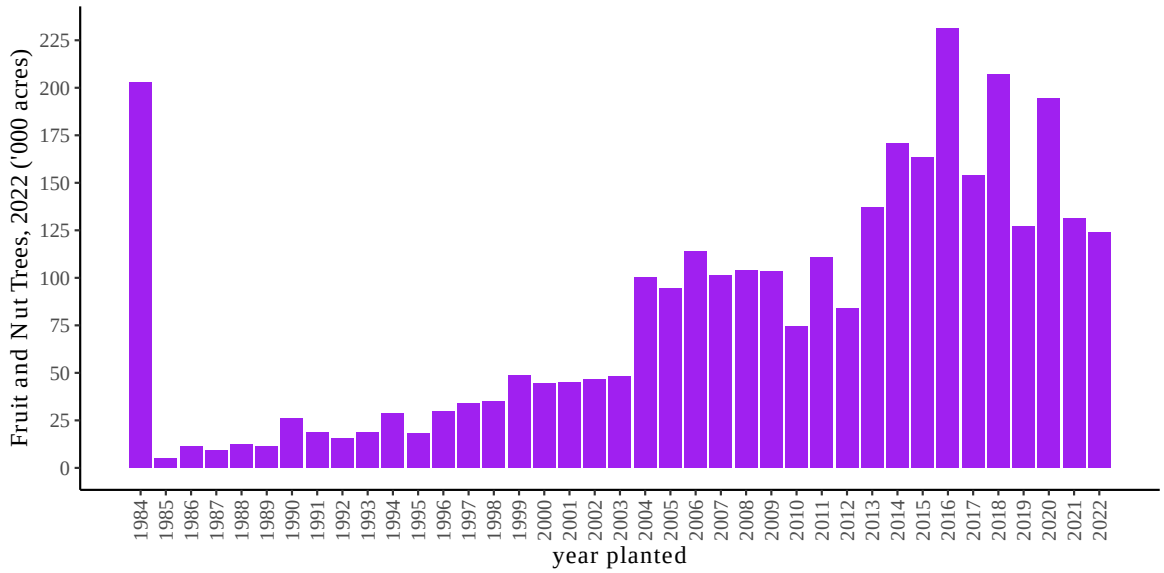


FIGURE 3. CROSS-DELTA WATER PRICE GRADIENTS, 2023–2024

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

A. Age Distribution, 2022



B. Hazard Rates by Age, 2021–2022

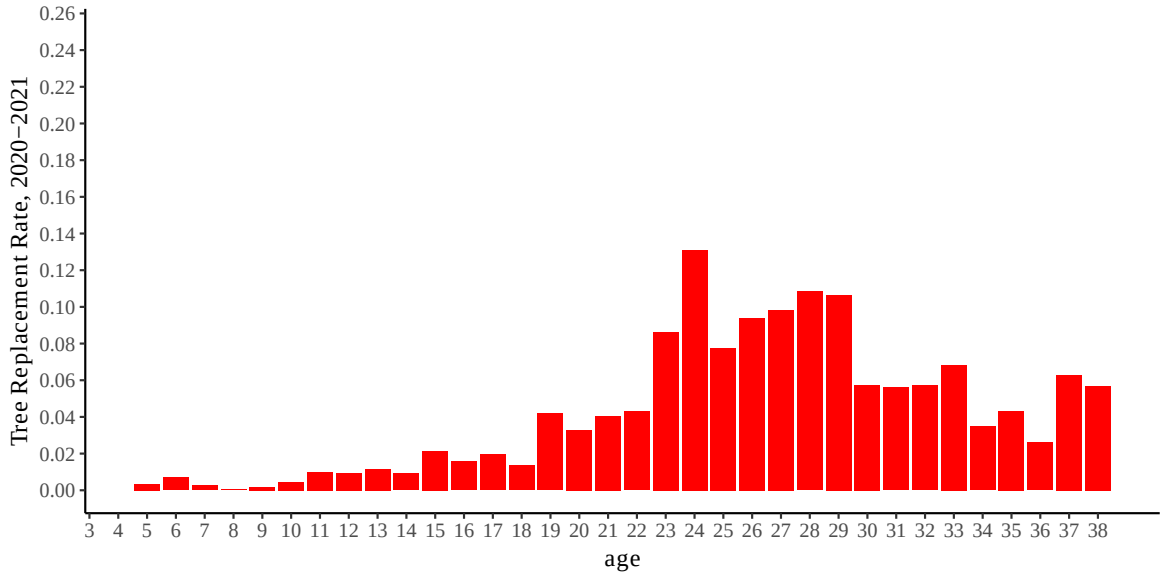
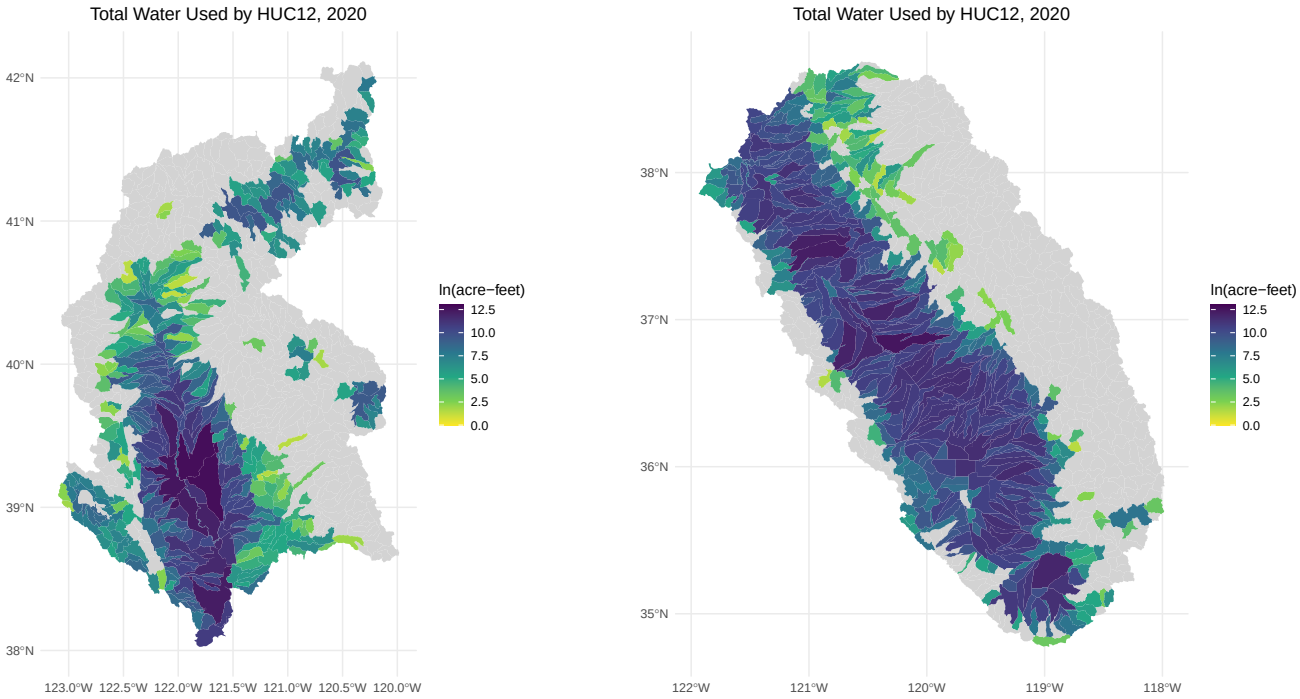


FIGURE 4. ORCHARD DEMOGRAPHICS

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.



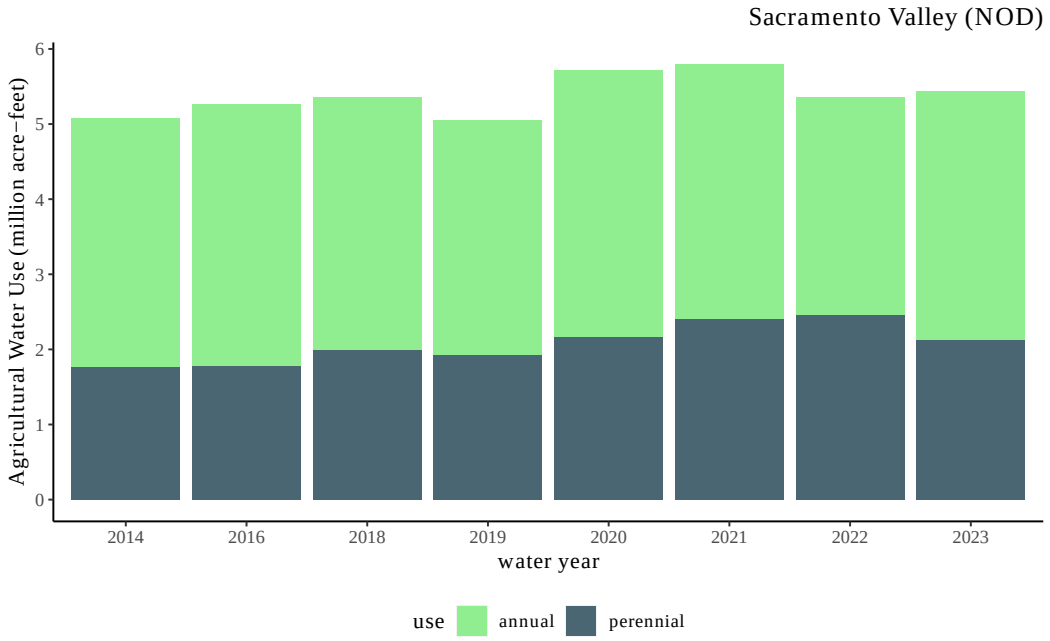
(a) Sacramento River Basin (North of the Delta)

(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

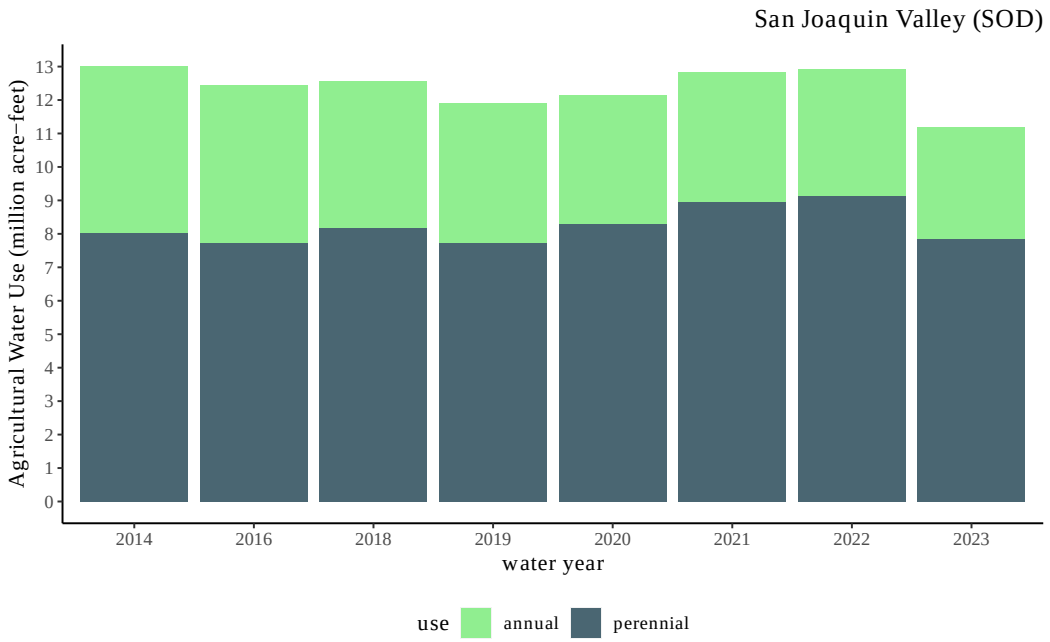
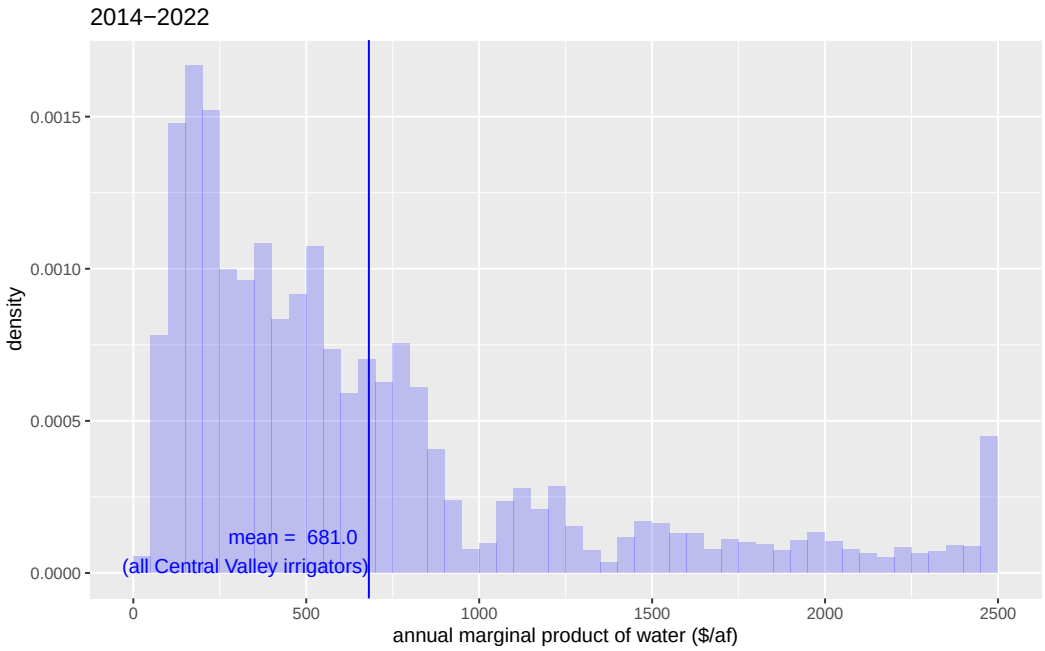


FIGURE 6. IMPLIED AGRICULTURAL WATER RIGHTS, BY RELIABILITY CLASS

Implied water rights reliability, 2014–2023, inferred from agricultural uses. Reliable water rights ≡ water used for perennial crops. Variable ≡ annual crops.

A. Water Values



B. Planting Costs

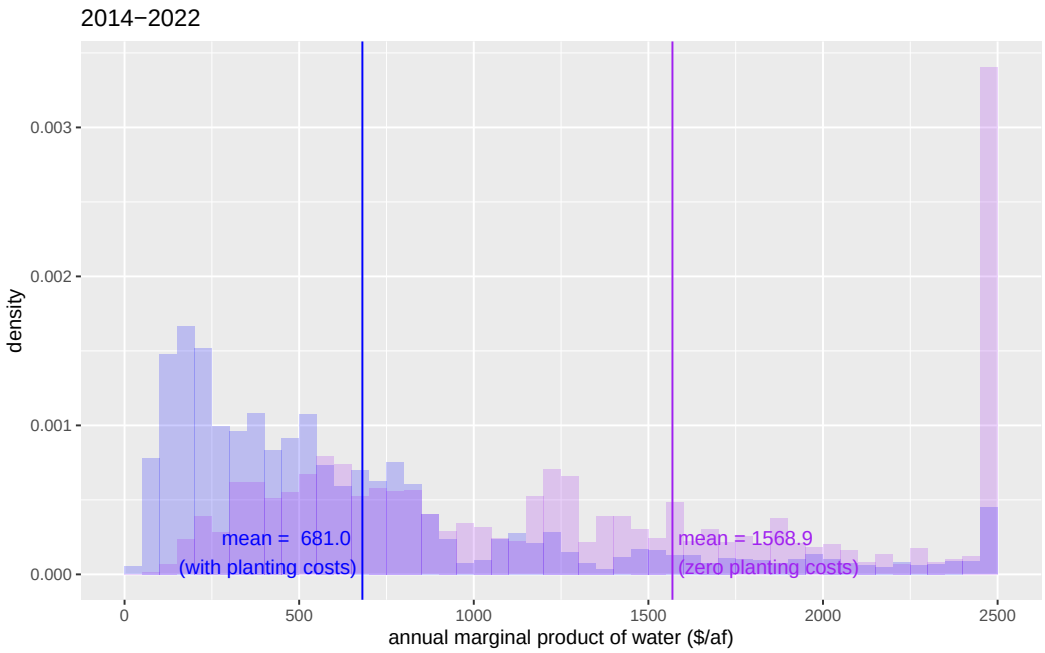
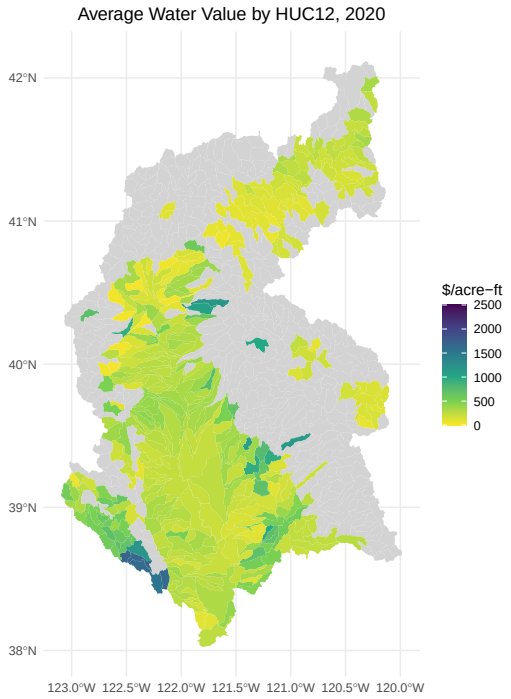


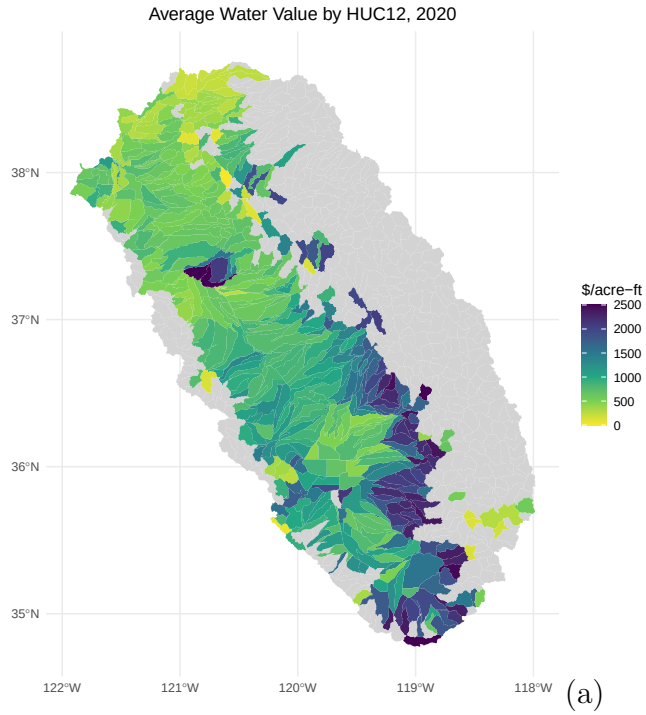
FIGURE 7. ANNUAL MARGINAL VALUES OF WATER, $/AF, 2014–2022

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

B. Estimates with (blue) and without (purple) average planting costs, 2014–2022.



Sacramento River Basin
(North of the Delta)



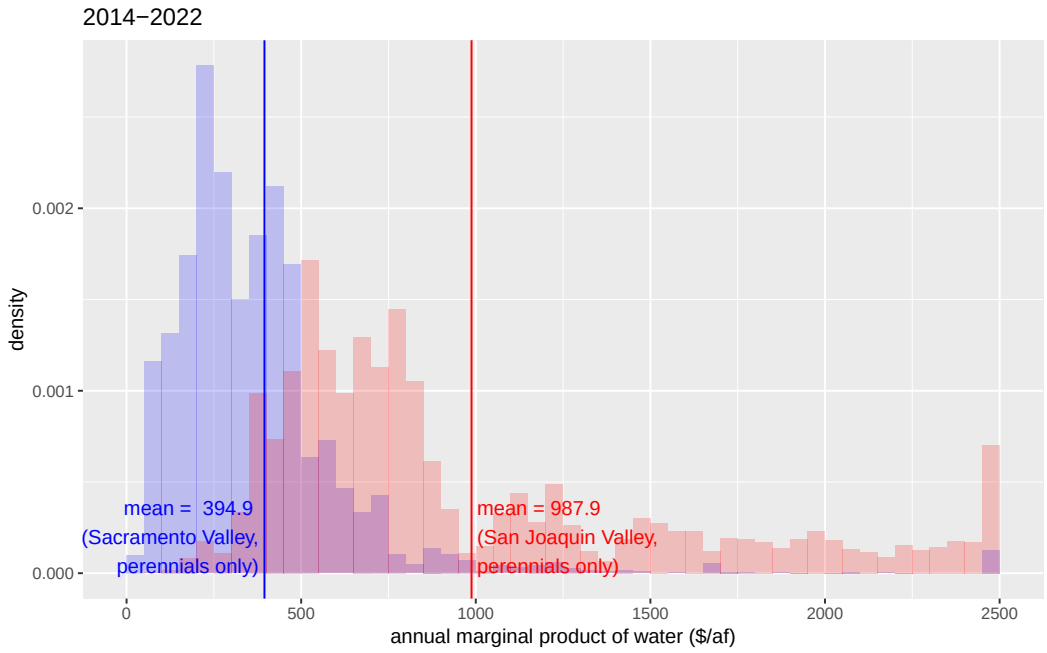
(a)

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

FIGURE 8. ANNUAL MARGINAL VALUES OF WATER, $/AF, 2020

Average estimated annual marginal values (marginal products net of average planting costs) of water by subwatershed (HUC12), 2020.

A. Reliable Water Rights



B. Variable Water Rights

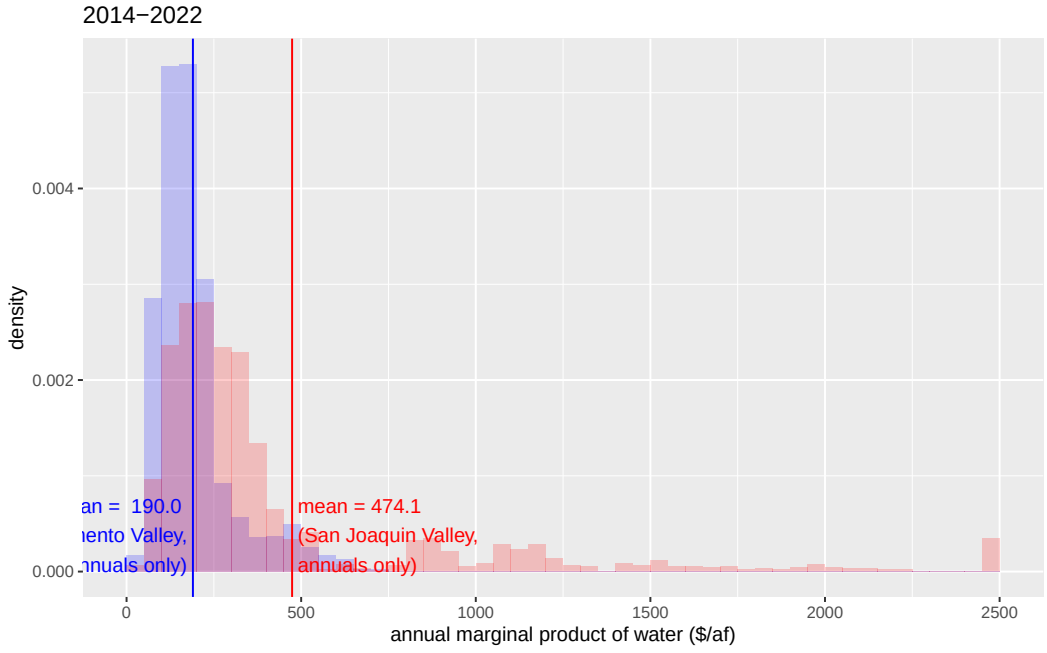


FIGURE 9. MARGINAL VALUES BY REGION AND RELIABILITY CLASS

Estimated marginal values of water, 2014–2022.

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