[Online Appendix for “Measuring water misallocation in California,” by Will Rafey]

Online Appendix – Data and Estimation Details

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A Details of primary data sources

A.1 Jurisdictional boundaries

State, county boundaries from CA government. There are 58 counties in California.

Irrigation district boundaries come from the DWR's file of all public water agencies (DWR, 2025c). This data includes 4,022 polygons, but there are fewer than one hundred (92) special irrigation districts in California (LAO, 2002), as well as 38 public water conservation districts, some of which also deliver large volumes of water for irrigation.

I first filter the primary data by restricting to districts with "irrigation" in the name, which gives 102 district names after merging multiple polygons that belong to the same district.

I then manually add 28 names listed among major irrigation districts, compiled from some Google searches for the major irrigation districts of California and a ChatGPT v4 search. I match these 28 names to their counterparts in the DWR file of public water agencies.

The result is 130 irrigation water districts.

A.2 Hydrological boundaries

Subwatersheds. HUC12 designations from USGS (2023). Taking the subwatersheds that are labeled by USGS as "CA" indicate that California covers three HUC2 regions—15, 16, and 18—with 110, 136, and 4207 local subwatersheds (HUC12 units). A few of these subwatersheds overlap with other states.

Regions. Definition of San Joaquin and Tulare River Valleys are HUC4 codes 1803 and 1804. Definition of Sacramento River Valley is HUC4 code 1802.

A.3 Agricultural field data

I use DWR maps for water years 2014, 2016, 2018, 2019, 2020, 2021, 2022, 2023 (DWR, 2017, 2019, 2021, 2022a, 2023, 2024a, 2025a,b).

California water years are defined from 1 October of the preceding year to September 30 of the current year, so that

- WY 2014 ≡ 10/1/2013–9/30/2014
- WY 2016 ≡ 10/1/2015–9/30/2016
- WY 2018 ≡ 10/1/2017–9/30/2018
- WY 2019 ≡ 10/1/2018–9/30/2019
- WY 2020 ≡ 10/1/2019–9/30/2020
- WY 2021 ≡ 10/1/2020–9/30/2021
- WY 2022 ≡ 10/1/2021–9/30/2022
- WY 2023 ≡ 10/1/2022–9/30/2023

To construct crop types, I use the `CROPTYP2` field.

To construct tree ages, I use the `YR_PLANTED` field. This field exists from 2020 onwards.

A.4 Tree growing times

I use special reports of the California Field Office of the USDA's National Agricultural Statistics Service on almonds, citrus, plums, grapes, olives, peaches, pistachios, and walnuts (USDA, various).

For each perennial crop, I obtain from these reports the length of years from year planted to first harvest, i.e., the model's "time-to-build."

A.5 Crop yields and price data

I use annual data, 1980–2022, collected by the California County Agricultural Commissioners, jointly with NASS/USDA Census (CCAC, 2024).

This data is at the year × county × commodity level, and includes acreage, physical output, yield (output per acre), and average price per physical unit of output.

A.6 Drought conditions

DWR San Joaquin and Sacramento River Indices + Eight-River Index (DWR, 2024d)

A.7 Surface water network data

USGS NHD, specifically major rivers and streams designated by DWR (USGS, 2022)

DWR's maps of local canals (DWR, 2022b)

DWR's map of the State Water Project (DWR, 2022c)

A.8 Surface water rights data

eWRIMS (SWRCB, 2024a)

Delta flow accounts (Gartrell *et al.*, 2022)

A.9 Surface water diversion data

Annual Reports (SWRCB, 2024b)

A.10 Surface water trades data

Bulletin 132 (DWR, 2024c)

A.11 Surface water prices data

Libecap (2009) + WestWater Research, LLC (2025)

A.12 Groundwater aquifer data

Bulletin 118 (DWR, 2024b)

A.13 Groundwater well data

I use Well Completion Reports (DWR, 2025d) from the California DWR's Online System for Well Completion Reports.

A.14 Pumping costs data

CEC public record request by the author in July 2024 (CEC, 2023).

A.15 Input costs data

USDA 2002, 2007, 2012, 2017, 2022 Ag Census (USDA, 2023a,b,c,d, 2024).

A.16 Gridded reference evapotranspiration

I use data from CIMIS (CIMIS, 2024), scraped daily grid from 10/1/2003–12/31/2023.

Each day of ETo (mm) is a 2km×2km `.asc` file.

A.17 Crop coefficients

I take crop coefficients from DWR manuals (DWR, 1989, 1994) posted on the current CIMIS website.

A.18 Effective precipitation

I use PRISM data (PRISM, 2025), scraped daily grid from 10/1/2003–12/31/2023.

Each day of precipitation (mm) is a 4km×4km `.tiff` file.

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B Details of data construction

B.1 Crop definitions and crosswalks

I match crop types

- across years in the DWR data
- to USDA crop types
- to crop coefficients

DWR year-to-year concordance

While DWR crop categories are mostly stable from 2014–2023, there are a few exceptions.

For temporal consistency, when DWR introduces or removes sub-categories between years, I use the original aggregate category that exists for all years 2014–2023:

- Field crops — corn, sorghum, and sudan (F16) bundles subsequently disaggregated codes, corn – field and sweet (F6), grain sorghum (F7), sudan (F8), and hybrid sorghum/sudan (F13).
- Mixed pasture — mixed pasture (P3), also includes clover (P2), native pasture (P4), induced high water table native pasture (P5), and other unspecified pasture (P). Note that alfalfa (P1) remains distinct, and for evapotranspiration purposes, I use different crop coefficients for alfalfa (P1), clover (P2), and mixed pasture (P3,P4,P5,P).
- Truck crops — miscellaneous truck crops (T18) also includes subsequently disaggregated categories, artichokes (T1), asparagus (T2), beans – green (T3), celery (T7), peas (T11), mixed truck – four or more crops (T17), Asian leafy vegetables (T29), plus generic T.
- Stone fruits — I use the pre-2021 plums, prunes and apricots category (D16) to collect apricots (D2), plums (D7), and prunes (D8); pre-2021 DWR maps do not distinguish among D2, D7, and D8 (while maps from 2021 onwards do not include D16).
- Unspecified citrus — citrus and subtropical (C) merges primary citrus DWR codes, C and grapefruit (C1), lemons (C2), and oranges (C3) into C, since the DWR maps do not distinguish among C1–C3. Other subtropicals such as dates (C4), avocados (C5), olives (C6), kiwis (C8), and miscellaneous subtropicals (C7) remain separate.
- Miscellaneous deciduous — miscellaneous deciduous (D10) includes generic D, D9 (figs), mixed deciduous (D11), and pecans (D17). Pecans do not appear as a category until 2021.
- Potatoes — potatoes and sweet potatoes (T31) aggregates the older DWR codes T12 (potatoes) and T13 (sweet potatoes) into one tuber/root-crop category, since not all years distinguish between T12 and T13.

The final specification is in Table A12.

DWR to CCAC concordance

CCAC data is unusually detailed among agricultural data, and disaggregates crop commodity varieties at a resolution that is, in many cases, finer than the field-level DWR crop classifications. For example, the DWR crop classification V (vineyards) corresponds to three distinct commodities: wine grapes (216299), table grapes (216199), and raisins (216399). As another example, the DWR crop classification C (citrus) corresponds to oranges navel (201119), oranges unspecified (201999), oranges valencia (201519), grapefruits (202999), kumquats (207999), lemons (204999), limes (205999), tangelos (206999), and tangerines (203999).

In other cases, the level of resolution of the two datasets coincide. For example, the DWR crop classifications of D12 (almonds), D13 (walnuts), D14 (pistachios), R1 (rice), R2 (wild rice), G2 (wheat), F1 (cotton), T20 (strawberries), each have a single matching commodity code.

Table A13 shows the assignment that I construct between CCAC commodity codes and DWR codes, following the 2021 DWR LandIQ guidance on specific crops.

DWR to crop coefficients concordance

Crop coefficient crop categories are often coarser than DWR crop codes. Table A14 characterizes the match that I construct by hand from DWR crop codes to crop coefficient crop categories.

Additional assumptions.

Pasture. Alfalfa (P1) can be grown year-round and is usually planted and harvested (cut) multiple times (6–8) per year in California; each growing cycle takes about one month. I calculate crop evapotranspiration for each feasible harvest of alfalfa following the DWR crop calendars:

- Sacramento Valley – seven cuttings (from mid-February to September)
- San Joaquin Valley – six cuttings (from mid-February to August)
- Imperial Valley – eight cuttings (from mid-March to August + November + January)

To construct annual water use for alfalfa fields, in the benchmark I assume a full alfalfa rotation involving the typical harvest.

For grass-clover pasture (P2), I use the statewide crop coefficients for "grass-clover" (1.05) and for mixed pasture, native pasture, and induced high-water-table native pasture (P3, P4, and P5) I use statewide crop coefficients for "grazed pasture" (0.9).

Others. I do not account for crops whose crop coefficients do not appear in DWR manuals for the Central Valley: avocados, berries, Christmas trees.

B.2 Final crop definitions

Table A12 reports how the above procedure leads to the following crop types that I use in analysis.

B.3 Crop evapotranspiration algorithm

<u>Gridded reference evapotranspiration</u>

I construct daily reference evapotranspiration (2km) and precipitation (4km) from 10/1/2003–12/31/2023 for each HUC12 watershed by taking the daily average across all grid cells intersecting that watershed. This lowers the dimensionality of the data from $500 \times 552 = 2.76 \cdot 10^5$ grid cells to ≈ 4000 watersheds.

I interpolate grid cells over HUC12 watersheds, then assign to fields via HUC12.

<u>Crop coefficients</u>

I manually transcribe crop coefficients and corresponding growing calendar dates from DWR manuals (DWR, 1989, Table 1) and (DWR, 1994, Table 1) to region×crop.

Crop coefficients $\vartheta_{\iota c}(\tau)$, vary by crop type c, phase of the growing cycle in which τ lies, and region i.

The crop coefficient approach implies a finite number (e.g., $k = 3$) of values or "crop coefficients" $\vartheta^k_{\iota c}$, together with growing season indicators τ_k, so that the piecewise linear functions that characterize daily crop water demand as a proportion of actual reference evapotranspiration are constructed as

$$\vartheta_{\iota c}(\tau) = \vartheta^k_{\iota c}\mathbf{1}\{\tau \in (\tau_{k-1}, \tau_k]\}$$

for each $\tau \in \{0, 1, \ldots, 365\}$, with $\tau_0 \equiv 0$.

<u>Effective precipitation</u>

Effective precipitation is the cumulative rainfall incident to a field during the crop's growing season.

I parallelize this process across the 4453 HUC12s, calculating [crop evapotranspiration] and [crop evapotranspiration net effective precipitation] for each crop and year.

Specifically, my code runs nine 500-HUC12-size batches in parallel, once for crop evapotranspiration and once for crop evapotranspiration net effective precipitation. Each script takes between 9–11 hours to compute in R version 4.2.2 (2022-10-31) – "Innocent and Trusting", or about 160–180 hours overall.

Annual crop evapotranspiration, $\zeta_{\iota ct}$, for field ι, calculated via

$$\zeta_{\iota ct} = \sum_{\tau=1}^{365} \zeta_{\iota ct}(\tau)$$

where $\zeta_{\iota ct}(\tau) = \sum_{h,r} \texttt{DWR\_crop\_coeff}_{c,r} \cdot \texttt{CIMIS\_ref\_et}_{\tau,h} \mathbf{1}_{\iota \in h,r}$ for HUC12 subwatersheds h and regions $r \in \{\text{SV}, \text{SJ}, \text{other}\}$.

B.4 Discussion of alternative evapotranspiration measures

The approach that I take to calculate crop evapotranspiration accounts for (i) how irrigators apply water to fields, (ii) counterfactual evapotranspiration for crops not grown, in the spirit of work such as Nunn and Qian (2011) and Costinot *et al.* (2016) work using model estimates of counterfactual soil productivity, (iii) direct ways to interpret and assess measurement error.

A popular alternative is to export the output of ensemble models of "realized evapotranspiration," such as those used by Leonard *et al.* (2025), Boser *et al.* (2022), or Wong *et al.* (2025). These methods use "ready-built" measures of water use downloaded from existing satellite data aggregators like OpenET. A comparison of these methods in recovering the water actually applied to fields is subject to ongoing work (Ayres *et al.*, 2026); here, I briefly remark on some of the drawbacks of some of the "ready-built" sources," in addition to the lack of the advantages (i)–(iii) of my approach above: it is derived from opaque machine-learning ensembles; even as an accurate measure of water that leaves the surface, it may not correspond directly to the volume of water applied; it introduces new sources of measurement error not present in the use of direct crop evapotranspiration calculations; it can be subject to API download limits that make it difficult to imagine using for the scale of the exercise of this paper (every location in all of California every day for nearly two decades). I thank Bryan Leonard and Corisa Wong for extensive and thoughtful discussions on this question.

B.5 Average crop prices

In several cases, county-level yield and price data is available for a richer collection of USDA/CCAC crop commodity codes than the DWR field-level crop codes (Table A13).

A natural approach to value crop c on field ι in year t is to aggregate across different USDA crop commodity codes $c_k \in c$ to construct average yield and price measures.

To construct average prices, for each county j and year t, for each crop c, I calculate the numerator as the sum of revenue,

$$\texttt{usda\_rev}_{jc_kt} \equiv \texttt{usda\_price}_{jc_kt}\texttt{usda\_yield}_{jc_kt}\texttt{usda\_acres}_{jc_kt},$$

average county price ($\texttt{usda\_price}_{jc_kt}$) times average county yield ($\texttt{usda\_yield}_{jc_kt}$) times total reported county acreage ($\texttt{usda\_acres}_{jc_kt}$) over all commodity codes $c_k \in c$, and the denominator as the sum of all acres over $c_k \in c$, $\sum_{c_k \in c} \texttt{usda\_acres}_{jc_kt}$, so that the average revenue per acre for crop type c for all fields $i \in j$ is then

$$P_{ict} = \frac{\sum_{c_k \in c} \texttt{usda\_rev}_{jc_kt}}{\sum_{c_k \in c} \texttt{usda\_acres}_{jc_kt}}.$$

B.6 Average planting costs

To measure average costs as a share of revenue, I divide total operating expenses by total commodity revenue for each county.

To measure revenue, I use

- group_desc = "income"
- domain_desc = "total"
- unit_desc = "$"
- short_desc = "commodity totals - sales, measured in $"

To measure average "planting costs"—which include seed, chemical, fertilizer, fuel, and electricity use, as well as labor (contract and hired), agricultural customwork, machinery rental, and supplies and repairs—I include expenses for

- ag services, machinery rental
- ag services, customwork
- ag services, other
- ag services, utilities
- chemical totals
- fertilizer totals, incl lime & soil conditioners
- fuels, incl lubricants
- labor, contract
- labor, hired
- seeds & plants totals
- supplies & repairs, (excl lubricants)

I omit the following expense categories, which correspond either to (a) livestock and animal production not well-suited for crop evapotranspiration methods or (b) financial accounting categories like depreciation, interest, rent, and taxes:

- animal totals
- depreciation
- feed
- interest, non-real estate
- interest, real estate
- rent, cash, land & buildings
- taxes, property, real estate & non-real estate, (excl paid by landlord)

To measure the denominator in the share of planting, harvesting, labor, and irrigation costs as a share of overall reported operating expenses, I use

- group_desc = "expenses"
- domain_desc = "total"
- unit_desc = "$"
- short_desc = "expense totals, operating - expense, measured in $"

Addressing measurement error in the input cost share

It is important that the average planting or input cost share does not exceed 1 because a violation would imply unprofitable agricultural operations. For three counties overlapping the Central Valley, input costs shares narrowly exceed 1: El Dorado (1.02 and 1.04 in 2007, 2017), Nevada (2002, 2007, 2012, 2017), and Trinity (2007, 2017, 2022). Nevada and Trinity (1.019 and 1.063) have revenue less than 10M each (10.2M and 3.26M average revenue per year, or 0.0002474208 and 0.0000790843 of the 41bn average statewide revenue). Every one of these shares fall below 1, to 0.59–0.87, after dropping hired labor costs; these are counties with a lot of pasture and farm animals.

To address measurement error, I calculate the 99th and 1st percentiles of the field-level input cost share distribution (0.8608212 and 0.4401906) implied after matching county-level input cost shares to the field-level data. I then use these percentiles to winsorize input cost shares above and below the 99th and 1st percentiles, respectively.

B.7 Water infrastructure

Surface water network

For each field, I calculate its distance to the nearest river and canal and the identity of that river and canal.

B.8 Water rights

Main source is SWRCB (2024a), `water_rights_list_2024-01-20.csv`.

69,114 rows.

Auxiliary data sources on priority date (SWRCB, 2023) and diversions (SWRCB, 2024b) come from the annual reports, filed under Title 23, Sections 847 and 925, of the California Code of Regulations.

Priority date

To determine priority year, I use the `priority_date` field, unless it is missing, in which case I try the

- `permit_original_issue_date`
- `effective_date`

fields in succession.

I also get additional year data from `water-rights-annual-report.csv`, the field `year_diversion_commenced`, which I match to the original ledger by water right application number.

Active irrigation water rights

I keep all water rights with the "Irrigation" `use_code`

I drop all water rights with `water_use_status` of

- `"Cancelled","Closed","Inactive","Pending","Rejected","Revoked"`

I keep all water rights with nonzero `use_net_acreage`

Face value

I take the recorded `face_value_amount`, but this is not reported for Statements of Diversion and Use, so for water right types equal to "Statement of Div and Use," I use the `ini_reported_div_amount`.

Diversions

For diversion data in Table 1 and Figure A8, I use Annual Reports.

B.9 Groundwater drilling

Geography

Wells are geocoded at the 1x1 mile section level ("the majority of well completion reports have been spatially registered to the center of the 1x1 mile Public Land Survey System section that the well is located in," DWR, 2025d).

This coarseness makes matching specific wells to specific fields impossible without considerable measurement error. Instead, I calculate aggregate statistics, such as the total capacity and number of active irrigation wells in each field's HUC12 sub-watershed. I interpret these statistics as measures of local groundwater well density in the area of the field.

Active irrigation wells

I restrict the sample to well reports where the planned use / former use variable (`planneduseformeruse`) is `Water Supply Irrigation - Agriculture` (99,246 reports of 1,101,450).

I further restrict to reports of record type `New` (92,848 reports), dropping the other record types: Destruction (2689 reports), Drill and Destroy (16), Modification or Repair (3693).

Volume

I convert well records to volumetric capacity with the `wellyield` (gallons per minute, gpm) scaled by 1.613 to convert to acre-feet per year assuming pumping 24hr/day, since 1 acre-foot equals 325,851 gallons, so $\frac{60 \cdot 24 \cdot 365}{325851} = 1.613$.

B.10 Main field-level dataframe

To each field from 2014–2023, I attach the following data:

- Crop evapotranspiration from Section B.3
  - both for actual crop planted and all counterfactual crops not planted
  - primary measure is net of effective precipitation; effective precipitation also recorded
- Crop prices and yields from Section A.5
- Average planting/input costs from Section B.6
- Indicator for the year being a drought ("C" or "critical" designation) from Section A.6
- Proximity to surface water network: identity of nearest river and canal; distance to nearest river and canal from Section A.7
- Identity of water right owner: closest point of diversion from Section B.8
- Local density of groundwater drilling
  - Watershed-level groundwater well capacity per irrigated acre

Auxiliary calculations

- Drought transition probabilities using the data from Section A.6

B.11 Subsamples used in estimation

The MLE/GMM loops involve three estimating subsamples, one for within-orchard planting costs, one for across-field costs within the reliable component of a water right, and one for across-field costs within the unreliable component of the water right. Tables A2, A3, and A4 contain summary statistics for each.

Orchard optimal regeneration subsample

For orchards that survive to 2020, I can observe whether the farmer cuts down or retains the orchard in 2021, 2022, and 2023. I also observe the type and the age of the orchard.

I drop C4 (dates) and C5 (avocados) which are rarely grown and do not have sufficient variation in culling rates.

For vineyards, I do not see ages—current remote sensing technology used is unable to detect the age structure of vineyards (author's correspondence with DWR engineers)—even though I observe the cutting-down decision. Consequently, I assume that vineyards exhibit the same regional yield decline and fixed costs as those that I am able to estimate for miscellaneous deciduous orchards.

See Table A2 for some summary statistics.

New perennial planting decisions subsample

For orchards that survive to 2020, I can observe the field-level perennial crop choice in the year planted. For vineyards, which do not include ages, I randomly assign a year planted by drawing with replacement from the empirical distribution of non-vineyard perennial years planted.

See Table A3 for some summary statistics.

Annual planting decisions subsample

For all fields, fallow or otherwise, I can observe field-level annual crop choices.

See Table A4 for some summary statistics.

Watershed-level sample

For regressions in Table A15, I run regressions at the watershed (HUC10) level.

For each HUC10, to construct the pre-1914 water rights share, I sum face value amounts for the irrigation water rights discussed in Section B.8 before and after 1914.

C Details of estimation algorithm

Data structure

The data takes the form $\{t, \kappa_{\iota t}, c_{\iota t}, x_{\iota t}, P_{ict}, A_{\iota ct}, \zeta_{\iota ct}, z_{\iota t}\}$, where

- $t \in \{2004, 2005, \ldots, 2023\}$ is year
- $c_{\iota t} \in \mathcal{C}_i$ is the crop choice for field ι year t
- $x_{\iota t} \in \{0, 1, 2, \ldots\}$ is the age of the orchard for field ι in year t
- $\kappa_{\iota t} \in \{0, 1\}$ is the renewal choice to cut down the orchard ($\kappa_{\iota t} = 1$) or not between t to $t + 1$
- $(P_{it}, A_{\iota t}) = \{P_{ict}, A_{\iota ct}\}_c$ are the vector of county-level average realized crop prices and yields scaled to irrigator i and field ι
- $\{\zeta_{\iota ct}\}_c$ are the vector of crop irrigation requirements (realized evapotranspiration net effective precipitation)
- $z_{\iota t}$ are other covariates:
  - time-invariant: region $\in \{\mathrm{SJ}, \mathrm{SV}\}$, watershed (HUC10) and subwatershed (HUC12), county, county average input cost shares, irrigation district, soil quality, proximity to surface water transport network, surface water rights, proximity to groundwater well capacity
  - time-varying: drought indicator, s_t

The estimator outlined below intends to find the parameters for each i that best rationalize the joint distribution

$$\{t, \kappa_{\iota t}, c_{\iota t}, x_{\iota t}, P_{ict}, A_{\iota ct}, \zeta_{\iota ct}, z_{\iota t}\}$$

as solutions to (11), (12), and (13), using variation in $z_{\iota t}$ where possible.

State transitions

I focus on only one source of evolving randomness that requires numerical integration:

- drought state $s_{t+1} \in \{0, 1\}$ at $t + 1$

Optimal regeneration

We operationalize (12) as follows.

(a) Policy functions.

For a given set of parameters $\theta = (\sigma^i_{\epsilon^r}, \sigma^i_{\epsilon^p}, \vartheta, \xi)$, we can define the probabilities of culling and not culling crop c at age x for irrigator i at t as

$$\mathbb{P}_i(\kappa_t | s_t, c_t, x_t, \theta) = \begin{cases} \varphi\left(-\frac{1}{\sigma^i_{\epsilon^r}}\left[\alpha_{\iota ct}(x, \theta_c) P_{ict} - \xi_{ic_x t} + \xi_{i0t} + \beta \overline{V}_i(\iota, c, x+1, s) - \beta \overline{V}_i(\iota, 0, 0, s)\right]\right) & \text{if } \kappa_t = 1 \\ 1 - \varphi\left(-\frac{1}{\sigma^i_{\epsilon^r}}\left[\alpha_{\iota ct}(x, \theta_c) P_{ict} - \xi_{ic_x t} + \xi_{i0t} + \beta \overline{V}_i(\iota, c, x+1, s) - \beta \overline{V}_i(\iota, 0, 0, s)\right]\right) & \text{if } \kappa_t = 0, \end{cases} \tag{A1}$$

where $\varphi(x) \equiv e^x / (1 + e^x)$ and

$$\alpha_{\iota ct}(x, \theta_c) = \frac{1}{\zeta_{\iota ct}} \exp\{-\theta_c (x - \overline{\theta}_c)\} \cdot \mathbf{1}(x > \overline{\theta}_c) \cdot A_{\iota ct}$$

parametrizes time-to-build, $\overline{\theta}_c$, and the rate of yield decline with age, θ_c, for each crop c, given the observed $A_{\iota ct}$, the average yield per acre in i's county for crop c in year t.

(b) Value functions.

Note that the ex-ante value functions can be obtained via a fixed point using the policy functions in (A1) as

$$\begin{aligned} \overline{V}_i(\iota, c, x, s) = {} & \mathbb{P}_i(0 | s_t, c_t, x_t, \theta)\left[\alpha_{\iota ct}(x, \theta_c) P_{ict} - \xi_{ic_x t} + \beta \overline{V}_i(\iota, c, x+1, s)\right] \\ & + \mathbb{P}_i(1 | s_t, c_t, x_t, \theta)\left[\beta \overline{V}_i(\iota, 0, 0, s) - \xi_{i0t}\right] + \sigma^i_{\epsilon^r} \gamma \end{aligned} \tag{A2}$$

where γ is Euler's constant to account for the logit selection term $\mathbb{E}[\varepsilon_j|\varepsilon_j \geq \max_k \varepsilon_k] = \gamma$, or the closed-form

$$\overline{V}_i(\iota, c, x, s) = \sigma^i_{\epsilon^r} \ln\left(\exp\left\{\frac{\alpha_{\iota ct}(x, \theta_c)P_{ict} - \xi_{ic_xt} + \beta\overline{V}_i(\iota, c, x+1, s)}{\sigma^i_{\epsilon^r}}\right\} + \exp\left\{\frac{\beta\overline{V}_i(\iota, 0, 0, s) - \xi_{i0t}}{\sigma^i_{\epsilon^r}}\right\}\right) \tag{A3}$$

since ε is T1EV.

As x grows, $\alpha_{\iota ct}(x, \cdot)$ falls and $\mathbb{P}_i(0|x, \cdot) \to 1$. To keep the space of trees ages tractable, we assume that trees do not live longer than one century. That is, the renewal-choice-specific logit draws cease after $x = 100$ and the tree is automatically cut down, so that

$$V_i(\iota, c, 100, s) = -\xi_{i0t} + \beta\overline{V}_i(\iota, 0, 0, s).$$

(c) MLE. Then the likelihood of observing a sequence of replanting decisions, crop choices, and ages for field ι is given by

$$\begin{aligned}\ell_{\iota,\kappa}((\kappa_0, c_0, x_0), (\kappa_1, c_1, x_1), \ldots, (\kappa_T, c_T, x_T); \theta) &= \prod_{t=0}^{T} \mathbb{P}_{i,\kappa}(\kappa_t|s_t, c_t, x_t, \theta) \\ &= \prod_{t=0}^{T}(1 - \mathbb{P}_{i,\kappa}(0|s_t, c_t, x_t, \theta))^{1-\kappa_{\iota t}}\mathbb{P}_{i,\kappa}(1|s_t, c_t, x_t, \theta)^{\kappa_{\iota t}}\end{aligned}$$

and the log-likelihood for the full data within i is $\mathcal{L}_\kappa(\theta_i) = \sum_{\iota \in i} \ln \ell_{\iota,\kappa}\left((t, \kappa_{\iota t}, c_{\iota t}, x_{\iota t})_{t=0}^T; \theta_i\right)$.

(d) Estimation sample. We observe tree ages only from 2020 onwards. This allows us to construct

$$(\kappa_{\iota t}, c_{\iota t}, x_{\iota t})_{\iota, t}$$

along with all of the other observables for $t \in \{2020, 2021, 2022\}$, for all ι in the data such that $x_{\iota t} > 0$. In other words, we use observed cutting decisions $\kappa_{\iota t}$ between 2020–21, 2021–22, and 2022–23.

Perennial crop choice

We operationalize (13) as follows.

(a) Policy functions.

For a given set of parameters $(\sigma^i_{\epsilon^p}, \xi)$ and the value functions above, $\overline{V}_i$, conditional on replanting a perennial crop, the probability of choosing crop c can be obtained from (13) as

$$\mathbb{P}_i(c|s_t, x_t = 0, \overline{V}_i, \theta) = \exp\left(\frac{1}{\sigma^i_{\epsilon^p}}\left[\overline{V}_i(\iota, c, 1, s) - \xi_{c_0t}\right]\right) \Bigg/ \sum_{c' \in \mathcal{C}^p_i} \exp\left(\frac{1}{\sigma^i_{\epsilon^p}}\left[\overline{V}_i(\iota, c', 1, s) - \xi_{c'_0t}\right]\right) \tag{A4}$$

for each $c \in \mathcal{C}^p_i$.

(b) Value functions.

Again, because ε is T1EV, the ex-ante value function at the point of renewal takes the closed-form

$$\overline{V}_i(\iota, 0, 0, s) = \sigma^i_{\epsilon^p} \ln\left(\sum_{c \in \mathcal{C}^p_i} \exp\left\{\frac{\beta\overline{V}_i(\iota, c, 1, s) - \xi_{c_0t}}{\sigma^i_{\epsilon^p}}\right\}\right).$$

(c) MLE. Then the likelihood of observing field ι replant $c_{\iota t}$ among $\mathcal{C}^p_i$ at t is

$$\ell_{\iota,p}(c_{\iota t}|s_t, x_{\iota t} = 0) = \mathbb{P}_i(c_{\iota t}|s_t, x_{\iota t} = 0, \overline{V}_i, \theta),$$

and the log-likelihood for the full data is $\mathcal{L}_p(\theta_i) = \sum_{\iota,t} \ln \ell_{\iota,p}(c_{\iota t}|s_t, x_{\iota t} = 0)$.

(d) Estimation sample. We observe tree ages from 2020–2023, so we can reconstruct the last planting decision $c_{\iota t}$ for each field ι in the data for which $x_{\iota t'} > 0$ for some $t' \geq 2020$ (i.e., each field for which the orchard survives long enough in our data for us to observe its age), by noting that $x_{\iota t} = 0$ at $t \equiv t' - x_{\iota t'}$.

Under the assumption that trees are not cut down in the first fifteen years of their lifespan, we can apply this procedure to construct a set of planting decisions in each year

$$t \in \{2004, 2006, \ldots, 2020\}$$

by tracing its age back to the time of planting, using more recent data from 2023 to recover crop choices for the years 2010–2020, allowing us to assemble a dataset of planting choices at renewal,

$$\{\mathbf{1}\{c_{\iota t} = c | x_{\iota t} = 0\}\}_{c \in \mathcal{C}_i^p, i, t},$$

along with all other observables, for all (i, t) such that $x_{\iota t} = 0$ and $t \in \{2004, 2006, \ldots, 2020\}$.

Annual crops

We operationalize (11) as follows.

(a) Policy functions. For a given set of parameters $(\sigma^i_{\epsilon^a}, \xi)$,

$$\mathbb{P}_{\iota,a}(c|s_t, \theta_a) = \exp\left(\frac{1}{\sigma^i_{\epsilon^a}}\left[\alpha_{\iota ct} P_{ict} - \xi_{c_0 t}\right]\right) \Bigg/ \sum_{c' \in \mathcal{C}_i^a} \exp\left(\frac{1}{\sigma^i_{\epsilon^a}}\left[\alpha_{\iota c' t} P_{ic' t} - \xi_{c'_0 t}\right]\right) \tag{A5}$$

where $\alpha_{\iota ct} \equiv A_{\iota ct}/\zeta_{\iota ct}$ is constructed directly from observables.

(b) MLE. Then the likelihood of observing field ι plant annual crop $c_{\iota t}$ among $\mathcal{C}_i^a$ at t is

$$\ell_{\iota,a}(c_{\iota t}|s_t, \theta_a) = \mathbb{P}_{\iota,a}(c_{\iota t}|s_t, \theta_a),$$

and the log-likelihood for the full data is $\mathcal{L}_a(\theta) = \sum_{\iota,t} \ln \ell_{\iota,a}(c_{\iota t}|s_t, c \in \mathcal{C}_i^a; \theta_a)$.

(c) Estimation sample. We observe field-level choices from $t \in \{2014, 2016, 2018, 2019, 2020, 2021, 2022, 2023\}$ and yields and prices through 2022. Note that if one is willing to use only aggregate—i.e., county-level—shares for the annual crop planting decisions, one can use CCAC data going back to 1980.

These directly allow us to construct field-level decisions for annual crops,

$$\{\mathbf{1}\{c_{\iota t} = c\}\}_{c \in \mathcal{C}_i^a, i, t},$$

along with all other observables.

D Details of counterfactuals

1/ Valuation of water rights.

Each water right consists of

- a set of fields

assigned to each of

- two reliability classes,

observed

- annually from 2014–2022.

The estimates above of unobservable heterogeneity in planting costs within each water right then delivers a unique value for each water right $\times$ reliability class.

2/ Counterfactual water allocations.

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 transient)—I can partition water rights into subsets indexed by k, so that $\mathcal{J} = \cup_k \mathcal{J}_k$.

I then consider the following partitions of water rights, along various hydrological and institutional boundaries:

- Regions — $\mathcal{J}_{\text{SV}}$, $\mathcal{J}_{\text{SJ}}$, $\mathcal{J}_{\text{other}}$
- 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
- Subwatersheds (HUC12) — e.g., $\mathcal{J}_{180400010803}$, $\mathcal{J}_{180300031406}$, $\mathcal{J}_{180201580404}$, etc

For each k, I calculate measures of dispersion (interquartile, interdecile ranges) across the water rights

$$i \in \mathcal{J}_k$$

as well as various values of reallocating different quantities of water within the set $\mathcal{J}_k$ of water rights.

Online Appendix – Supplementary Tables

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Table A1. Descriptive Statistics — Field-Level Water Use

Statistic	N	Mean	St. Dev.	Min	Max
year	2,909,976	2,019.245	2.799	2,014	2,023
acres	2,909,976	23.041	40.963	0.000	7,668.464
year_planted	630,685	2,005.401	12.429	1,984	2,023
culled	451,450	0.041	0.199	0	1
age	630,685	16.125	12.406	0	39
etc_cum_af	2,379,246	2.747	0.913	0.002	6.523
eff_precip	2,379,246	0.121	0.089	0.000	0.706
soil_index	2,702,587	2.642	1.300	1.000	8.000
drought	2,909,976	0.365	0.481	0	1
rev_acre	2,444,127	7,300.440	10,422.570	0.000	154,941.800
price_index	2,184,918	3.767	5.151	0.001	38.247
yield_index	2,193,575	1.349	4.583	0.000	2,025.000
avg_input_cost	2,909,976	0.607	0.101	0.440	0.861
wr_dist	2,909,976	6,149.687	8,497.385	2.870	100,040.400
wr_priority_year	2,909,976	1,949.469	50.330	1,700	2,023
vol	2,853,016	76,237.310	522,205.600	0.000	8,692,800.000
vol_acre	2,006,794	58.605	1,638.680	0.000	103,333.300
gw_mc	2,738,045	57.862	32.016	24.924	378.013
river_dist	2,909,976	7,825.478	7,204.301	0.341	54,178.650
canal_dist	2,909,976	25,890.800	34,794.900	0.022	241,612.600
swp_dist	2,909,976	58,019.640	51,615.990	0.015	366,113.800
well_af	2,834,954	89,728.460	131,667.800	0.000	858,485.400
static_water_level	2,738,045	115.655	110.472	2.000	1,220.342
well_af_acre	2,834,954	7.439	108.833	0.000	120,892.800

variable	N	n_unique	most_common	most_common_2
huc12	2,909,976	2,180	180201590400 (42486)	180400020205 (29774)
district	2,909,976	118	unassigned (1768344)	Turlock Irri (71911)
county	2,909,976	57	Fresno (258448)	Tulare (256393)
river	2,909,976	214	Sacramento R (240386)	San Joaquin (233151)
canal	2,909,976	150	Tehama-Colus (252901)	Mokelumne Aq (181684)
wr	2,909,976	7,547	T033399 (31356)	A000360 (29850)
id	2,234,410	480,403	0100001 (6)	0100003 (6)
crop	2,909,976	44	V (542158)	D12 (328486)
commodity_code_et	2,909,976	35	216299 (542158)	261999 (329585)
region	2,909,976	3	SJ (1286770)	other (1116079)
wy_type	1,793,897	5	C (656500)	W (465765)
class	2,862,399	3	perennial (1678314)	annual (1184085)

Summary statistics for the main dataset built to characterize all observed water rights at the field-year level, 2014–2023. See Appendix B.10 for more details.

Table A2. Descriptive Statistics — Field-Level Orchard Replacement

Statistic	N	Mean	St. Dev.	Min	Max
year	451,450	2,021.014	0.818	2,020	2,022
acres	451,450	21.172	30.158	0.00000	606.066
year_planted	451,450	2,004.497	12.219	1,984	2,022
culled	451,450	0.041	0.199	0	1
age	451,450	16.517	12.207	0	38
etc_cum_af	401,684	3.253	0.601	1.304	5.917
eff_precip	401,684	0.086	0.035	0.002	0.435
soil_index	419,560	2.626	1.364	1.000	8.000
drought	451,450	0.672	0.469	0	1
rev_acre	446,985	7,006.769	4,930.214	0.000	39,518.500
price_index	437,832	1.965	1.419	0.312	36.682
yield_index	437,832	1.679	0.610	0.035	5.833
avg_input_cost	451,450	0.586	0.102	0.440	0.861
wr_dist	451,450	6,001.025	5,892.139	11.007	98,708.300
wr_priority_year	451,450	1,945.818	49.975	1,700	2,023
vol	447,019	84,240.340	441,868.800	0.000	8,692,800.000
vol_acre	310,056	53.200	1,600.544	0.000	67,200.000
gw_mc	439,543	61.386	34.309	25.283	378.013
river_dist	451,450	8,280.399	7,073.189	6.070	51,549.570
canal_dist	451,450	12,448.680	17,095.380	0.393	234,675.700
swp_dist	451,450	48,111.540	26,401.490	8.686	337,166.600
well_af	448,497	103,564.100	137,099.600	0.000	858,485.400
static_water_level	439,543	127.814	118.383	3.238	1,220.342
well_af_acre	448,497	7.350	23.357	0.000	6,173.843

variable	N	n_unique	most_common	most_common_2
huc12	451, 450	1, 268	180201590400 (13018)	180701030103 (7322)
district	451, 450	105	unassigned (230906)	Alta Irrigat (18276)
county	451, 450	54	Tulare (72330)	Fresno (54002)
river	451, 450	152	Kings River (51309)	Sacramento R (44153)
canal	451, 450	137	San Diego Aq (33496)	Los Angeles (27988)
wr	451, 450	3, 258	A000360 (8290)	S000381 (7159)
id	451, 450	165, 487	0100005 (3)	0100010 (3)
crop	451, 450	16	D12 (134820)	C (91315)
commodity_code_et	451, 450	12	261999 (135549)	201999 (91315)
region	451, 450	3	SJ (270561)	other (102097)
wy_type	349, 353	3	C (234326)	D (115027)

Summary statistics for the estimation sample used to estimate the Rust optimal regeneration model for perennial crops as described in Appendix B.10.

Table A3. Descriptive Statistics — Field-Level Perennial Choice

Statistic	N	Mean	St. Dev.	Min	Max
year	16,203,024	1,403.519	919.169	0	2,023
acres	16,203,024	18.193	27.668	0.00000	606.066
chosen	16,203,024	0.056	0.229	0	1
year_planted	11,339,964	2,005.408	12.429	1,984	2,023
etc_cum_af	6,526,374	3.297	0.634	0.393	6.200
eff_precip	6,526,374	0.114	0.054	0.002	0.427
soil_index	14,655,528	2.717	1.416	1.000	8.000
drought	11,339,964	0.282	0.450	0	1
rev_acre	10,479,174	6,572.970	7,684.791	0.000	111,186.600
price_index	10,387,697	2.379	3.595	0.001	58.701
yield_index	10,387,768	1.361	2.054	0.000	196.211
avg_input_cost	16,203,024	0.603	0.100	0.440	0.861
wr_priority_year	16,203,024	1,948.724	48.910	1,700	2,023
vol	16,048,494	69,737.630	409,768.200	0.000	8,692,800.000
vol_acre	11,589,084	75.801	1,972.421	0.000	103,333.300
gw_mc	15,833,124	60.165	34.129	25.214	378.013
well_af	16,108,578	84,527.790	121,648.300	0.000	858,485.400
static_water_level	15,833,124	123.601	117.763	3.000	1,220.342
well_af_acre	16,108,578	7.187	53.286	0.000	22,659.080

variable	N	n_unique	most_common	most_common_2
crop	16, 203, 024	18	C (900168)	C4 (900168)
id_yy	16, 203, 024	900, 168	2007949 2020 (18)	2007932 2020 (18)
huc12	16, 203, 024	1, 442	180201590400 (326646)	180701030103 (185904)
district	16, 203, 024	106	unassigned (9493362)	Consolidated (586854)
county	16, 203, 024	55	Tulare (1953522)	Fresno (1775448)
wr	16, 203, 024	4, 609	A000360 (245304)	S000381 (206712)
commodity_code_et	16, 203, 024	13	211999 (2700504)	226999 (2700504)
region	16, 203, 024	3	SJ (8277300)	other (5625018)

Summary statistics for the estimation sample used to estimate the perennial crop choice decision, conditional on planting. The unit is the field-year-crop level, for all possible crop choices. See Appendix B.10 for more details.

Table A4. Descriptive Statistics — Field-Level Annual Choice

Statistic	N	Mean	St. Dev.	Min	Max
year	26,758,810	2,018.611	2.552	2,014	2,022
acres	26,758,810	30.170	53.631	0.000	7,668.464
chosen	26,758,810	0.038	0.192	0	1
etc_cum_af	13,125,765	2.277	1.057	0.000	7.021
eff_precip	13,125,765	0.089	0.091	0.000	0.660
soil_index	25,764,778	2.557	1.134	1.000	8.000
drought	26,758,810	0.409	0.492	0	1
rev_acre	25,308,757	8,862.912	16,103.630	0.000	154,941.800
price_index	23,055,052	2.183	1.523	0.001	38.247
yield_index	23,315,703	1.577	18.337	0.000	2,025.000
avg_input_cost	26,758,810	0.615	0.104	0.440	0.861
wr_priority_year	26,758,810	1,950.325	52.637	1,700	2,023
vol	25,836,018	84,543.390	651,302.900	0.000	8,692,800.000
vol_acre	17,416,516	24.649	701.024	0.000	103,333.300
gw_mc	23,775,076	54.237	27.640	24.924	378.013
well_af	25,288,562	97,947.900	146,252.900	0.000	858,485.400
static_water_level	23,775,076	103.145	95.373	2.000	1,220.342
well_af_acre	25,288,562	7.601	23.765	0.000	7,845.108

variable	N	n_unique	most_common	most_common_2
crop	26,758,810	26	F1 (1029185)	F10 (1029185)
id_yy	26,758,810	1,029,185	1_yy2014 201 (26)	2_yy2014 201 (26)
huc12	26,758,810	1,979	180600051509 (374348)	180400020205 (363948)
district	26,758,810	115	unassigned (17246320)	Imperial Irr (1110460)
county	26,758,810	57	Monterey (2077530)	Merced (1583920)
wr	26,758,810	6,571	T033399 (701350)	T033398 (395200)
commodity_code_et	25,729,625	19	323999 (3087555)	101999 (2058370)
region	26,758,810	3	other (11743316)	SJ (9047818)

Summary statistics for the estimation sample used to estimate the annual crop choice decision, conditional on planting. The unit is the field-year-crop level, for all possible crop choices. See Appendix B.10 for more details.

Table A5. All Crop Land Shares, 2020

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

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

Table A6. Example of Agricultural Data

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

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

Table A7. Example of Crop Water Efficiencies

A. Top 95%-ile

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

B. Bottom 5%-ile

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

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

Table A8. Illustrative Hazard Rate Regressions, 2020–2022

Dependent Variable:	culled
Model:	(1)
Variables	
log(age)	0.0298***
	(0.0005)
C6 olives	−0.0019
	(0.0016)
D1 apples	0.0157***
	(0.0035)
D12 almonds	0.0302***
	(0.0010)
D13 walnuts	0.0185***
	(0.0012)
D14 pistachios	−0.0088***
	(0.0009)
D15 pomegranates	0.0201***
	(0.0041)
D16 apricots etc	0.0521***
	(0.0024)
D3 cherries	0.0262***
	(0.0025)
D5 peaches	0.0647***
	(0.0022)
Fixed-effects	
region	✓
Fit statistics	
Observations	399,512
R^2	0.01689
Within R^2	0.01635

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

Illustrative linear regression at the field×year level for perennial orchards at least three years old in 2020, 2021, or 2022. Outcome is 1 if the orchard is cut down in the following water year. Omitted crop type is citrus (C).

Table A9. Groundwater Marginal Cost Gradients Across the Delta

	San Joaquin	Sacramento	diff	ratio	diff, USD/af
0	2	2	0	1	24.3
0.1	27.8	15.2	12.6	1.8	28.0
0.2	40	25	15	1.6	28.7
0.3	58.8	31.3	27.5	1.9	32.3
0.4	75.2	43.9	31.3	1.7	33.4
0.5	98.6	59.1	39.5	1.7	35.8
0.6	129.0	72	57.0	1.8	40.9
0.7	179.6	87.5	92.0	2.1	51.0
0.8	266.6	107.6	159.0	2.5	70.4
0.9	391.4	155	236.4	2.5	92.9
1	1,220.3	525	695.3	2.3	225.9

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

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

Table A10. MLE Estimates of Planting Costs – Replanting

region / tree type	N	θ_c	$\xi_{c0}(0)$	$\xi_{c0}(1)$	$\overline{V}(c,0\|1)$	$\overline{V}(c,0\|0)$
SV / walnuts	29,649	0.012	2.53	2.27	15.58	15.59
SJ / walnuts	27,443	0.010	1.67	1.40	16.13	16.16
SV / citrus	906	0.000	0.80	0.13	17.74	17.97
SJ / citrus	59,376	0.007	2.00	2.00	16.16	16.16
SV / olives	6,059	0.002	1.07	1.53	17.11	17.04
SJ / olives	4,768	0.006	1.67	1.27	16.48	16.53
SV / almonds	23,728	0.047	4.07	3.73	13.10	13.11
SJ / almonds	108,040	0.044	3.33	3.33	13.56	13.56
SV / cherries	364	0.024	2.60	1.67	14.86	14.93
SJ / cherries	8,147	0.005	0.80	0.73	17.10	17.12
SV / misc. deciduous	2,839	0.006	0.00	0.67	18.26	17.98
SJ / misc. deciduous	5,581	0.004	0.67	0.33	17.41	17.52
SV / pistachios	984	0.009	2.13	3.20	15.97	15.93
SJ / pistachios	25,445	0.006	4.00	3.27	15.96	15.98
SV / pomegranates	96	0.018	0.00	0.60	18.01	17.74
SJ / pomegranates	2,331	0.006	1.13	0.80	16.76	16.83
SV / peaches/nectarines	3,335	0.050	1.87	2.07	14.40	14.39
SJ / peaches/nectarines	16,048	0.041	1.40	1.60	15.08	15.05
SV / kiwis	836	0.007	1.73	2.00	16.30	16.28
SJ / kiwis	635	0.014	5.00	4.33	14.90	14.91
SV / misc. subtropical fruits	1,026	0.009	3.80	5.00	15.61	15.60
SJ / misc. subtropical fruits	272	0.000	0.93	0.87	17.57	17.58
SV / apples	820	0.005	0.07	1.07	18.09	17.74
SJ / apples	812	0.009	0.60	0.00	17.33	17.59
SV / avocados	3	0.000	5.00	5.00	17.04	17.04
SJ / avocados	142	0.011	1.73	0.00	16.37	16.82
SV / dates	6	0.030	5.00	1.73	14.06	14.16
SJ / dates	41	0.050	0.73	0.80	15.92	15.90
SV / pears	1,561	0.003	1.67	1.20	16.82	16.89
SJ / pears	252	0.002	1.47	0.53	17.16	17.35
SV / plums, prunes, apricots	5,660	0.014	0.80	1.47	16.55	16.43
SJ / plums, prunes, apricots	7,892	0.018	1.20	1.00	16.07	16.11
SV / grapes	2,839	0.006	0.00	0.67	18.26	17.98
SJ / grapes	5,581	0.004	0.67	0.33	17.41	17.52

Rust (1987) maximum likelihood estimates of planting costs by region×tree type. Column (1) reports number of field-level observations from 2020–2023. Column (2) reports estimated rate of yield decay, θ_c. Columns (3) and (4) reports replanting costs without and with drought, $\xi_{c0}(0)$ and $\xi_{c0}(1)$. Columns (5)–(6) report implied value functions $\overline{V}(c,0|s)$ in dimensionless units (i.e., before being scaled by marginal products) using the discount factor $\beta = 0.95$ (so that full production every year with zero planting costs delivers $\overline{V} = 20$). See Appendix C for estimation details.

Table A11. Measuring Misallocation – Field-Level

A. Dispersion

	N	gft_q50up	gft_q75up	gft_q90	gft_q99	shadow_IQR	shadow_IDR
all [A]	1	0.688	1.423	1.242	3.108	589.009	1,439.722
year [B]	7	0.684	1.405	1.269	3.219	544.397	1,453.526
region [C]	2	0.603	1.245	1.125	2.579	456.056	1,061.785
region-year [D]	14	0.583	1.229	1.116	2.704	442.489	1,052.141
ry-class [E]	28	0.476	1.071	0.987	2.833	308.514	783.514
ryclass-county [F]	482	0.413	0.758	0.758	1.742	204.643	455.043
ryclass-district [G]	1,331	0.382	0.772	0.658	2.003	337.582	617.506
ryclass-river [H]	1,161	0.423	0.783	0.708	1.814	266.767	531.969
ryclass-canal [I]	2,116	0.364	0.665	0.611	1.634	305.379	627.690
ry-huc12 [J]	5,729	0.381	0.672	0.672	1.711	360.822	649.530
ryclass-huc12 [K]	9,476	0.288	0.493	0.545	1.303	252.766	472.372
ry-wr [L]	27,254	0.393	0.701	0.668	1.562	205.819	383.662
ryclass-wr [M]	38,376	0.296	0.533	0.533	1.174	155.213	280.198
year-pre1914 [N]	14	0.677	1.397	1.250	3.110	572.448	1,468.583
ry-pre1914 [O]	28	0.582	1.227	1.108	2.708	452.800	1,073.084
ryclass-pre1914 [P]	56	0.476	1.064	0.980	2.660	317.088	805.266

B. Distortions

	gft_q50up	gft_q75up	gft_q90	gft_q99	shadow_IQR	shadow_IDR
across_regions [A-C]	0.086	0.178	0.118	0.529	132.953	377.937
across_years [A-B]	0.004	0.018	−0.026	−0.111	44.612	−13.804
bundle_within_ry [D-E]	0.107	0.158	0.129	−0.128	133.974	268.627
bundle_within_hy [J-K]	0.093	0.179	0.127	0.409	108.056	177.159
bundle_within_wry [L-M]	0.096	0.168	0.135	0.387	50.605	103.464
across_county [E-F]	0.064	0.313	0.229	1.091	103.871	328.471
across_district [E-G]	0.094	0.300	0.330	0.830	−29.068	166.008
across_river [E-H]	0.053	0.288	0.279	1.019	41.748	251.546
across_canal [E-I]	0.112	0.406	0.376	1.199	3.135	155.824
within_county [F-M]	0.116	0.225	0.225	0.567	49.430	174.845
within_district [G-M]	0.086	0.238	0.125	0.828	182.369	337.308
within_river [H-M]	0.127	0.250	0.175	0.640	111.553	251.771
within_canal [I-M]	0.068	0.132	0.078	0.459	150.166	347.492
between_pre1914_ryc [E-P]	0.0001	0.007	0.007	0.172	−8.574	−21.752
between_pre1914_ry [D-O]	0.001	0.002	0.008	−0.004	−10.312	−20.943

Version of Table 7 without estimated planting costs within a water right.

Table A12. DWR Crops

aggregate_crop_code	aggregate_crop_description	member_crop_codes
C	Citrus and Subtropical	C;C1;C2;C3
C4	Dates	C4
C5	Avocados	C5
C6	Olives	C6
C7	Miscellaneous Subtropical Fruits	C10;C11;C7;C9
C8	Kiwis	C8
D1	Apples	D1
D10	Miscellaneous Deciduous	D;D10;D11;D17;D9
D12	Almonds	D12
D13	Walnuts	D13
D14	Pistachios	D14
D15	Pomegranates	D15
D16	Plums, Prunes and Apricots	D16;D2;D7;D8
D3	Cherries	D3
D5	Peaches and Nectarines	D5
D6	Pears	D6
F1	Cotton	F1
F10	Beans (Dry)	F10
F11	Miscellaneous Field Crops	F;F11;F5
F12	Sunflowers	F12
F14	Millet	F14
F15	Sugar cane	F15
F16	Corn, Sorghum and Sudan	F13;F16;F6;F7;F8
F2	Safflower	F2
F3	Flax	F3
F4	Hops	F4
G2	Wheat	G2
G6	Miscellaneous Grain and Hay	G;G6;G7
P1	Alfalfa and Alfalfa Mixtures	P1
P3	Mixed Pasture	P;P2;P3;P4;P5
P6	Miscellaneous Grasses	P10;P6;P7;P8;P9
R1	Rice	R;R1
R2	Wild Rice	R2
T10	Onions and Garlic	T10
T16	Flowers and Christmas Trees	T16
T18	Miscellaneous Truck Crops	T;T1;T11;T17;
T18	Miscellaneous Truck Crops	T18;T2;T29;T3;T7
T19	Bush Berries	T19
T20	Strawberries	T20
T21	Peppers	T21
T22	Broccoli	T22
T23	Cabbage	T23
T24	Cauliflower	T24
T25	Brussels sprouts	T25

Stable grouping of DWR crop codes across years as described in Appendix B.1.

Table A12 (cont'd). DWR Crops (2/2)

aggregate_crop_code	aggregate_crop_description	member_crop_codes
T27	Greenhouse	T27
T30	Lettuce/Leafy Greens	T14;T30;T8
T31	Potatoes or Sweet Potatoes	T12;T13;T31
T32	Tomatoes	T15;T26;T32
T4	Cole Crops	T4
T6	Carrots	T6
T9	Melons, Squash and Cucumbers	T9
YP	Young Perennials	YP

Stable grouping of DWR crop codes across years as described in Appendix B.1.

Table A13. DWR-USDA Crop Crosswalk

commodity_code	crop_cat	crop_name
202999	C	grapefruit all
204999	C	lemons all
201999	C	oranges unspecified
207999	C	kumquats
205999	C	limes all
201119	C	oranges navel
206999	C	tangelos
201519	C	oranges valencia
203999	C	tangerines and mandari
224999	C4	dates
221999	C5	avocados all
226999	C6	olives
218819	C7	cactus fruits
218839	C7	cherimoyas
228019	C7	guavas
229999	C8	kiwifruit
211999	D1	apples all
225999	D10	figs dried
264999	D10	pecans
266999	D10	chestnuts
218299	D10	persimmons
261999	D12	almonds all
263999	D13	walnuts english
268079	D14	pistachios
218399	D15	pomegranates
217999	D16	apricots all
215199	D16	plums
215999	D16	plums dried
215399	D16	plumcots
213199	D3	cherries sweet
212999	D5	peaches unspecified
212199	D5	peaches freestone
212399	D5	peaches clingstone
218199	D5	nectarines
214999	D6	pears unspecified
214199	D6	pears bartlett
214899	D6	pears asian
121299	F1	cotton lint unspecif
169999	F10	beans dry edible uns
161741	F10	beans blackeye (peas
161742	F10	beans garbanzo
161132	F10	beans lima baby dry
161131	F10	beans lima large dry
161199	F10	beans lima unspecifi

Match of DWR crop codes (field-level data) to USDA/CCAC commodity codes (yield and price data) as described in Appendix B.1.

Table A13 (cont'd). DWR-USDA Crop Crosswalk (2/3)

commodity_code	crop_cat	crop_name
132999	F11	sugar beets
323999	F16	corn sweet all
393999	F11	horseradish
398699	F11	mint
158316	F12	sunflower seed plant
114991	F16	sorghum grain
323999	F16	corn sweet all
114992	F16	sorghum silage
188899	F16	hay sudan
158269	F2	safflower
101999	G2	wheat all
113999	G6	barley unspecified
112999	G6	oats grain
188499	G6	hay grain
111991	G6	corn grain
104999	G6	rye grain
194799	G6	pasture forage misc.
115991	G6	triticale
181999	P1	hay alfalfa
194599	P3	pasture irrigated
892999	P6	nursery turf
173079	P6	seed bermuda grass
174412	P6	ryegrass perennial a
106199	R1	rice milling
198199	R2	rice wild
358999	T10	onions
335999	T10	garlic all
372999	T10	onions green and shall
851999	T16	christmas trees and cu
301999	T18	artichokes
302999	T18	asparagus unspecifie
304399	T18	beans fresh unspecif
316999	T18	celery unspecified
361999	T18	peas green unspecifi
305999	T18	beets garden
316199	T18	celery fresh market
376999	T18	swiss chard
398559	T18	cilantro
330999	T18	eggplant all
333999	T18	anise (fennel)
387999	T18	leeks
357999	T18	okra
359999	T18	parsley
360999	T18	parsnips

Match of DWR crop codes to USDA/CCAC commodity codes as described in Appendix B.1.

Table A13 (cont'd). DWR-USDA Crop Crosswalk (3/3)

commodity_code	crop_cat	crop_name
367999	T18	radishes
380999	T18	turnips all
381999	T18	greens turnip and must
239999	T19	berries bushberries
238199	T19	berries blueberries
230639	T19	berries blackberries
236199	T19	berries raspberries
237999	T20	berries strawberries
237299	T20	berries strawberries
237199	T20	berries strawberries
363999	T21	peppers bell
364999	T21	peppers chili hot
340999	T30	lettuce head
374999	T30	spinach unspecified
342999	T30	lettuce leaf
341999	T30	lettuce romaine
339999	T30	lettuce unspecified
391999	T31	potatoes all
392999	T31	potatoes sweet
378299	T32	tomatoes processing
398399	T32	tomatoes cherry
378199	T32	tomatoes fresh marke
378999	T32	tomatoes unspecified
307919	T4	brolloli unspecified
310999	T4	cabbage head
314999	T4	cauliflower unspecif
308999	T4	brussels sprouts
322999	T4	collard greens
307199	T4	brolloli fresh marke
309999	T4	cabbage chinese and sp
314199	T4	cauliflower fresh ma
337999	T4	kale
313999	T6	carrots unspecified
354299	T9	melons unspecified
375999	T9	squash
325999	T9	cucumbers
343999	T9	melons cantaloupe
348999	T9	melons honeydew
344999	T9	melons casaba
354999	T9	melons watermelon
366999	T9	pumpkins
216199	V	grapes table
216299	V	grapes wine
216399	V	grapes raisin
216999	V	grapes unspecified

Match of DWR crop codes to USDA/CCAC commodity codes as described in Appendix B.1.

Table A14. DWR–Crop Coefficient Concordance

dwr_crop	dwr_name	commodity_code_et	dwr_crop	dwr_name	commodity_code_et
G	S G - Gra	101999	T27	Greenhou	
G2	Wheat	101999	T30	Lettuce	340999
G6	Miscellan	101999	T31	Potato o	391999
G7	Mixed gra	188499	T32	toes (all	378299
R	SR-Rice:	106199	D	S D - Dec	211999
R1	ce	106199	D1	Apples	211999
R2	ldRice. (	106199	D2	Apricots	217999
F	S F - Fie	323999	D3	Cherries	213199
F1	Cotton	121299	D5	Peaches a	212999
F2	Safflower	158269	D6	Pears	214999
F5	Sugar bee	132999	D7	Plums	215199
F6	Corn (fie	323999	D8	Prunes	215199
F10	Beans (d	169999	D10	Miscella	211999
F11	Miscella	323999	D11	Mixed de	211999
F12	Sunflowe	158316	D12	Almonds	261999
F16	Corn,Sor	323999	D13	Walnuts	263999
P	S P - Pas	181999	D14	Pistachi	268079
P1	Alfalfa and	181999	D15	Pomegran	211999
P2	Clover	181999	D16	Plums, P	215199
P3	Mixed pas	194599	D17	Pecans	261999
P4	Native pa	194599	C	S C - Cit	201999
P5	Induced h	194599	C2	Lemons	204999
P6	Miscellan	194599	C3	Oranges	201999
P7	Turf farm	892999	C4	Dates	226999
T	S T - Tru	340999	C5	Avocados	226999
T1	Artichok	301999	C6	Olives	226999
T4	Cole crop	313999	C7	Miscellan	229999
T6	Carrots	313999	C8	Kiwis	229999
T8	Lettuce (	340999	C10	Eucalypt	229999
T9	Melons sq	354299	V	S V - Vin	216299
T10	Onions and	358999	V2	Wine grap	216299
T12	Potatoes	391999	YP	S YP Youn	
T13	Sweet po	391999			
T15	Tomatoes	378299			
T16	Flowers	851999			
T17	Mixed (f	340999			
T18	Miscella	340999			
T19	Bush ber	237999			
T20	Strawber	237999			
T21	Peppers	363999			

Match of DWR crop codes (field-level data) to crop coefficient codes used to calculate evapotranspiration as described in Appendix B.1. Descriptive character strings are truncated to eight characters for concision.

Table A15. Dispersion of Marginal Products of Water

	Moment of the water productivity distribution:							
	ln(mean)				ln(median)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
perennial water rights share	1.309			0.854	1.301			0.844
	(0.107)			(0.105)	(0.120)			(0.129)
1(south of the Delta)		1.024		0.767		1.024		0.771
		(0.069)		(0.070)		(0.080)		(0.088)
pre-1914 water rights share			0.167	0.0001			0.159	−0.009
			(0.123)	(0.077)			(0.131)	(0.095)
1(drought_year)	−0.003	0.023	0.027	0.005	−0.004	0.022	0.026	0.003
	(0.018)	(0.018)	(0.019)	(0.018)	(0.022)	(0.023)	(0.024)	(0.022)
Mean of dependent variable	6.038	6.038	6.038	6.038	5.945	5.945	5.945	5.945
Observations	1,669	1,669	1,669	1,669	1,669	1,669	1,669	1,669
Adjusted R^2	0.340	0.410	0.006	0.529	0.265	0.324	0.004	0.415

Some descriptive linear regressions. The unit of observation is the watershed-year distribution of marginal products of water, 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: (a) ln(median), (b) ln(mean), (c) 10th percentile, and (d) interquartile range of the volume-weighted distribution of water productivities in each watershed-year.

Explanatory variables:
"perennial (reliable) water rights share" ≡ share of water used to irrigate perennials.
"South of the Delta" ≡ San Joaquin and Tulare River Basins. Omitted category is North of the Delta ≡ Sacramento River Basin.
"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.
"Drought year" ≡ critical (C) water-year, from the SJI-SVI Eight River Index.

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

Table is continued on the next page ↪

Table A15 (cont'd). Dispersion of Marginal Products of Water

	Moment of the water productivity distribution:							
	ln(q10)				IQR			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
perennial water rights share	0.960			0.698	0.186			0.058
	(0.116)			(0.142)	(0.092)			(0.117)
1(south of the Delta)		0.658		0.433		0.224		0.227
		(0.087)		(0.105)		(0.075)		(0.091)
pre-1914 water rights share			0.236	0.135			−0.134	−0.178
			(0.118)	(0.103)			(0.092)	(0.085)
1(drought_year)	0.033	0.053	0.055	0.038	−0.008	−0.004	−0.004	−0.006
	(0.027)	(0.028)	(0.028)	(0.027)	(0.023)	(0.023)	(0.023)	(0.023)
Mean of dependent variable	5.339	5.339	5.339	5.339	0.592	0.592	0.592	0.592
Observations	1,669	1,669	1,669	1,669	1,669	1,669	1,669	1,669
Adjusted R^2	0.152	0.141	0.011	0.209	0.007	0.023	0.004	0.032

Table A15, continued.

Explanatory variables:
"perennial (reliable) water rights share" ≡ share of water used to irrigate perennials.
"South of the Delta" ≡ San Joaquin and Tulare River Basins. Omitted category is North of the Delta ≡ Sacramento River Basin.
"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.
"Drought year" ≡ critical (C) water-year, from the SJI-SVI Eight River Index.

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

Table A16. Role of Drought in Replanting Costs

	N	avg_vol	gft_q50up	gft_q75up
A	1	115, 382, 621	0.315	0.543
A1	1	115, 382, 621	0.319	0.550
B	7	16, 483, 231	0.312	0.532
B1	7	16, 483, 231	0.316	0.539
C	2	57, 691, 310	0.233	0.456
C1	2	57, 691, 310	0.236	0.463
D	14	8, 241, 615	0.226	0.447
D1	14	8, 241, 615	0.230	0.453
E	28	4, 120, 807	0.214	0.422
E1	28	4, 120, 807	0.217	0.429
F	471	244, 973	0.115	0.242
F1	471	244, 973	0.119	0.247
G	1, 073	107, 532	0.059	0.186
G1	1, 073	107, 532	0.063	0.192
H	1, 063	108, 544	0.098	0.228
H1	1, 063	108, 544	0.102	0.233
I	1, 525	75, 660	0.023	0.113
I1	1, 525	75, 660	0.027	0.119
J	4, 235	27, 245	0.003	0.085
J1	4, 235	27, 245	0.008	0.091
K	6, 501	17, 748	−0.048	−0.008
K1	6, 501	17, 748	−0.044	−0.003
L	26, 991	4, 274	−0.032	−0.015
L1	26, 991	4, 274	−0.027	−0.009
M	38, 029	3, 034	−0.161	−0.161
M1	38, 029	3, 034	−0.156	−0.156
N	14	8, 241, 615	0.306	0.520
N1	14	8, 241, 615	0.310	0.527
O	28	4, 120, 807	0.222	0.437
O1	28	4, 120, 807	0.225	0.443
P	56	2, 060, 403	0.214	0.412
P1	56	2, 060, 403	0.218	0.419

Version of Panel B of Table 8 that contrasts forced replanting (reliable water reallocated within the year) not in a drought year with replanting in a drought year. Rows with "1" suffix (A1, B1, C1, ...) use drought-year replanting costs for the forced replanting.

Online Appendix – Supplementary Figures

A1 Water Sources and Flow Network A-5
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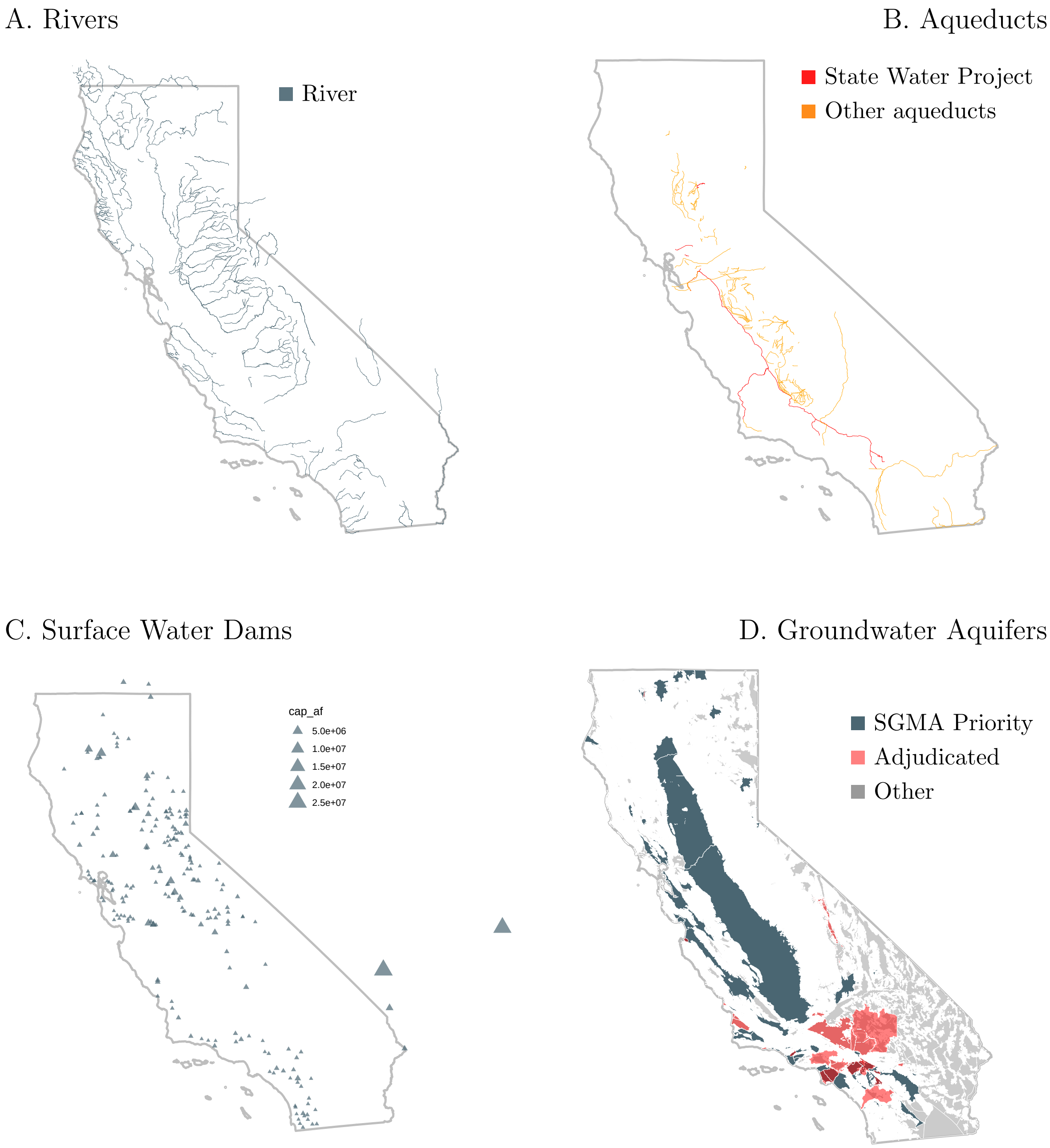


Figure A1. Water Sources and Flow Network

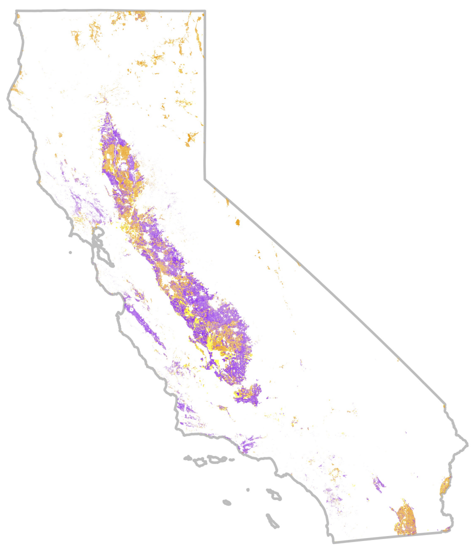
A. Major California rivers. *Source*: USGS National Hydrography Dataset.

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

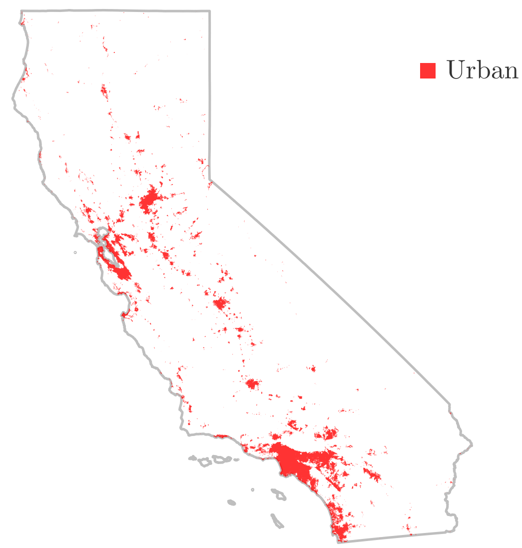
C. Dams. Locations from CDEC. Capacities (acre-feet) from CDEC.

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

A. Irrigated Agriculture



B. Urban Development



C. Environmental Sites

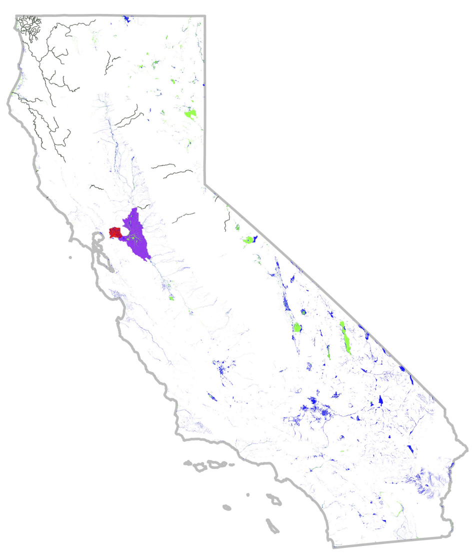


Figure A2. Economic Values of Water Use

A. Irrigated agriculture

■ Perennial crops ■ Annual crops

B. Urban areas

■ Urban

C. Environmental sites

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

(a) All California

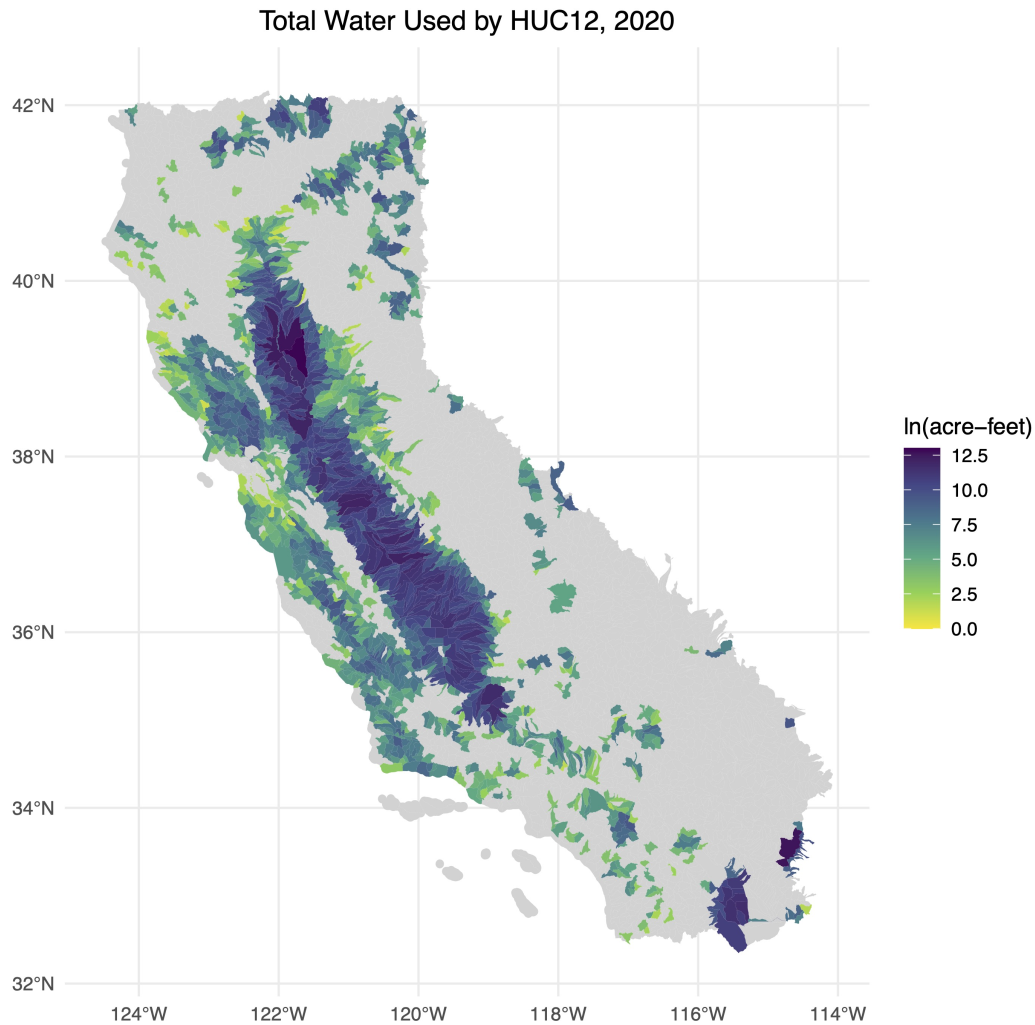


Figure A3. Implied Agricultural Water Rights, All California

Version of Figure 5 containing watershed-level estimates for the entire state of California in 2020.

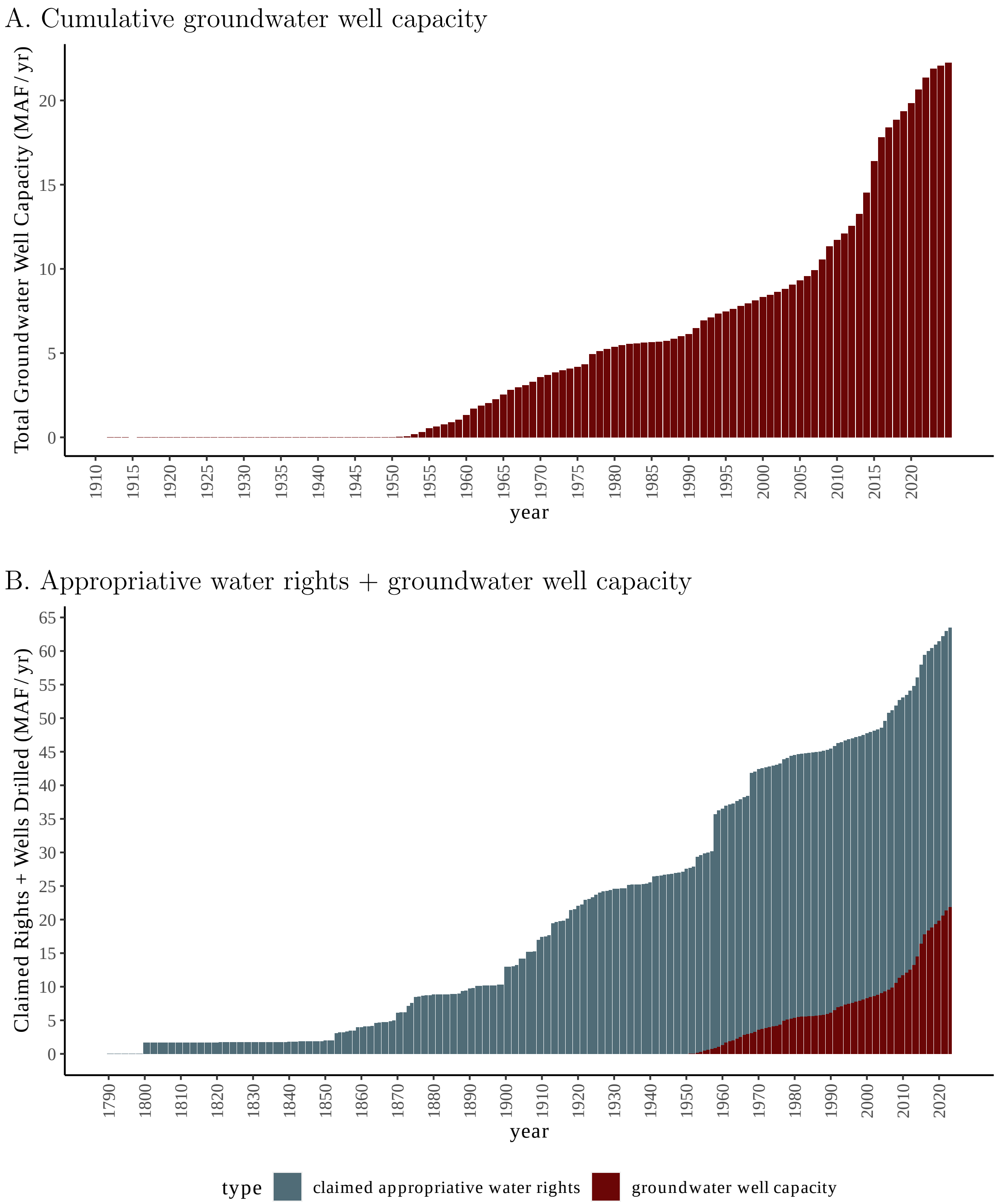


Figure A4. Groundwater Wells Drilled, Central Valley Irrigators

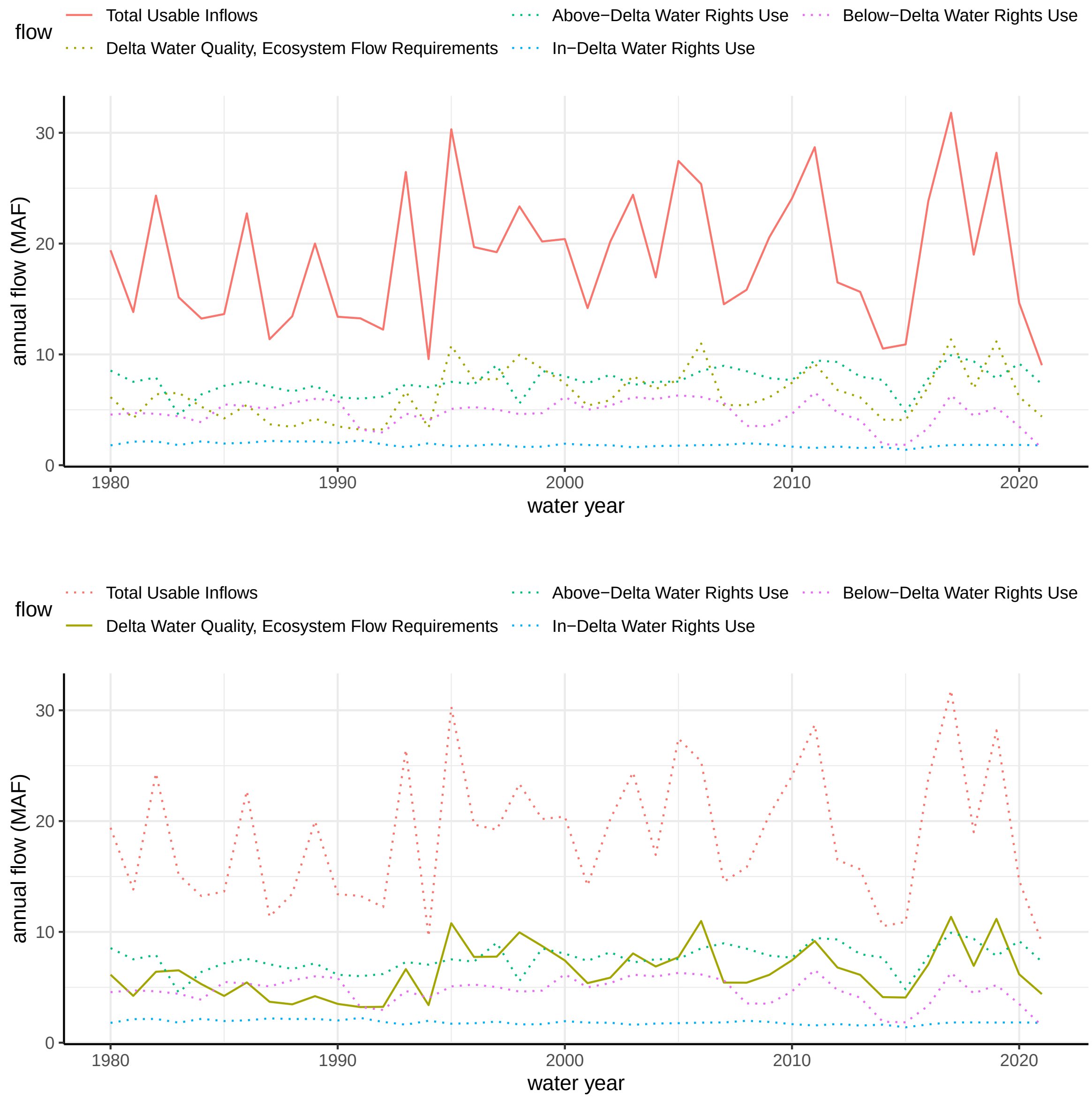


Figure A5. Total Usable Inflows + Environmental Requirements, 1980–2021

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

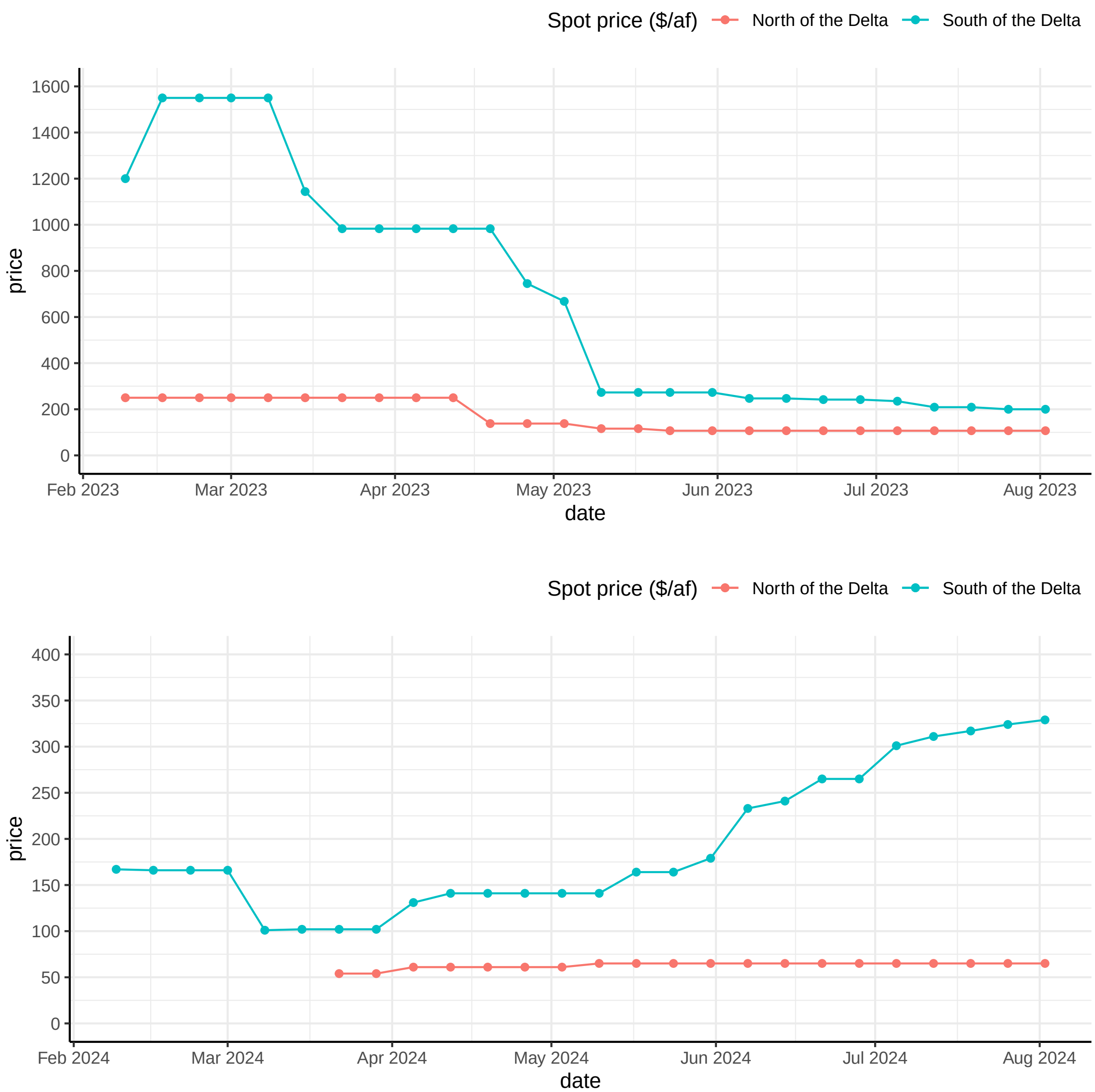
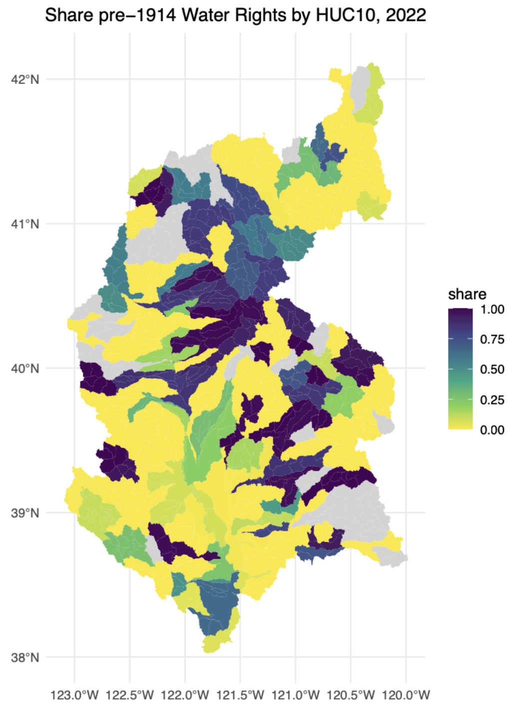
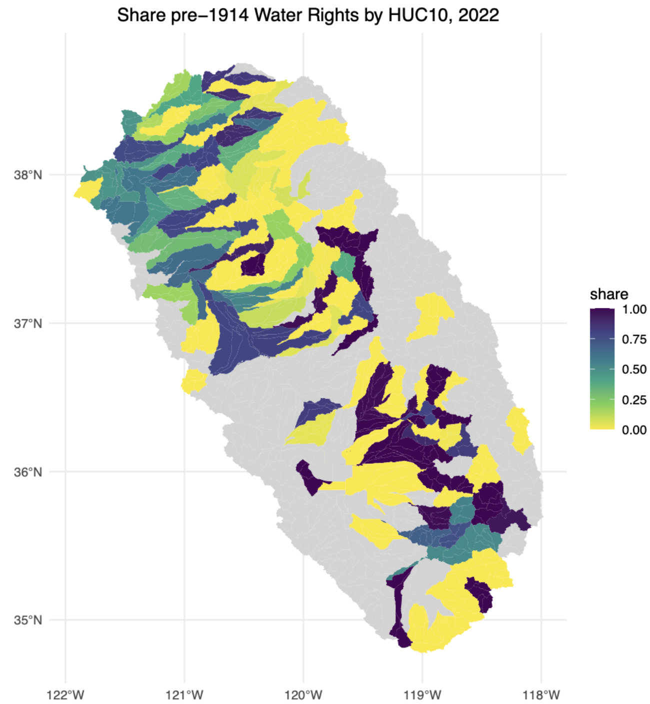


Figure A6. Cross-Delta Water Price Gradients, 2023–2024

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



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



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

Figure A7. Historical Water Rights By Watershed

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

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

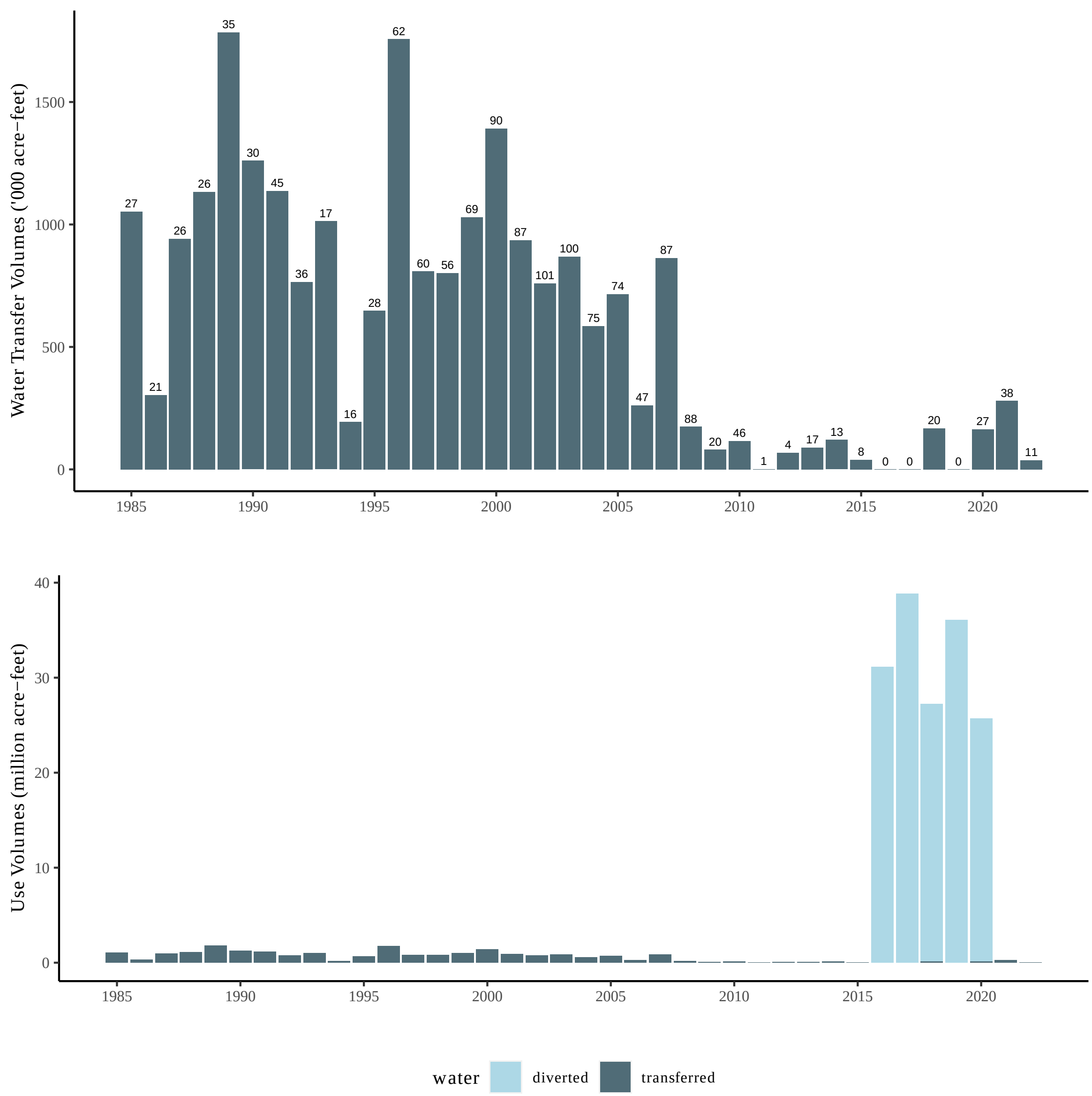


Figure A8. Historical Water Transfers, 1985–2022

Source. In Panel A, public records request to DWR (Bulletin 132) + manual cleaning. Vertical axis plots the total volume in each year, with the number of distinct trades listed at the top of each column. Post-2010 DWR data likely undercounts multi-year transfers, so transfer quantities after 2010 should be assumed to omit transactions. (Also note that none of this data is used for estimation.) In Panel B, the volumes in Panel A are reported alongside post-2016 diversion reports under 2015 S.B. 88.

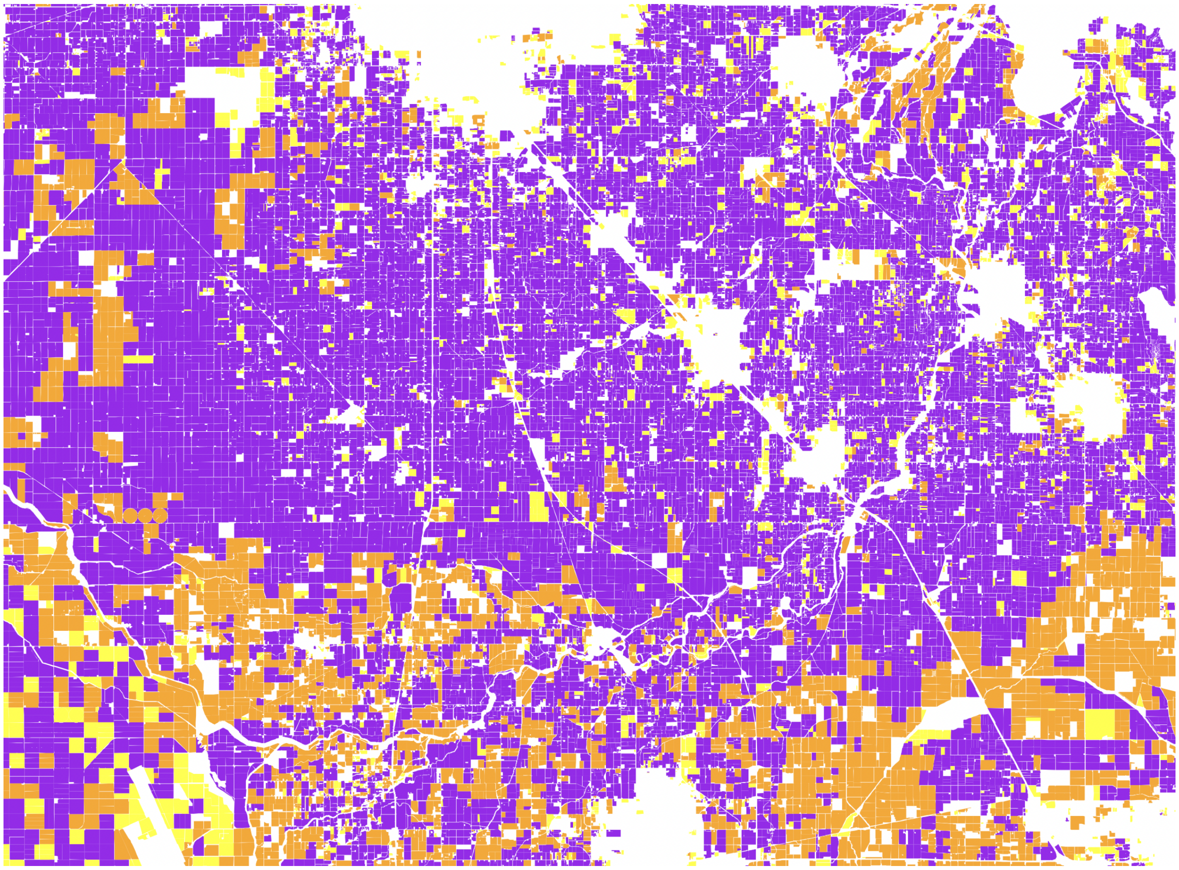
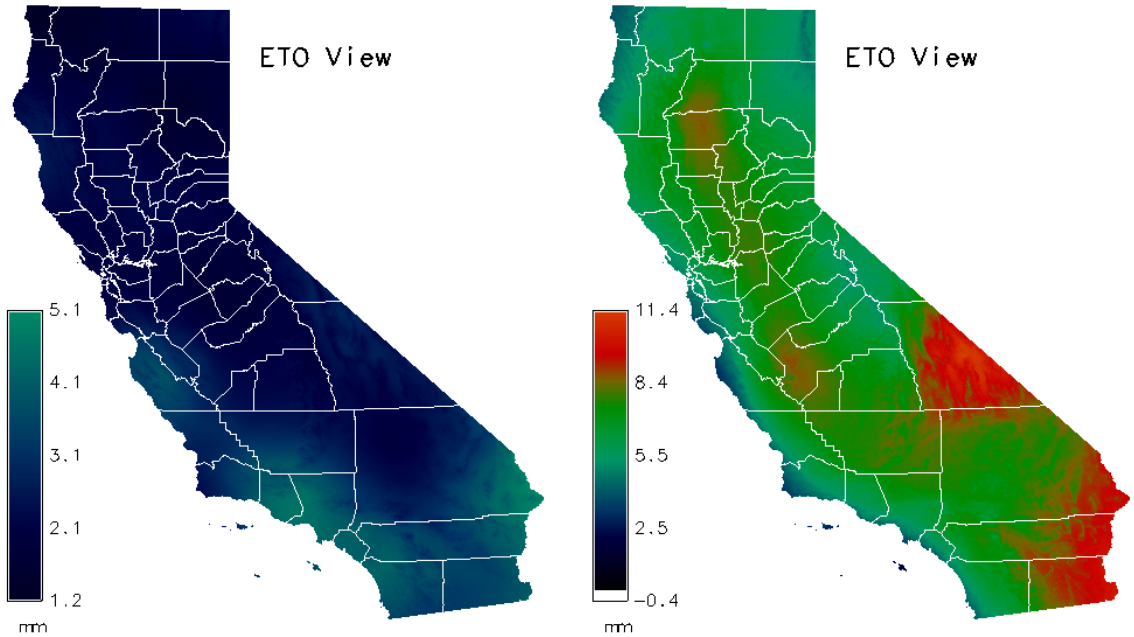


Figure A9. Example of Land Allocation Data

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



31 October 2023 1 July 2024

Figure A10. Example of Evapotranspiration Data

Example of daily reference evapotranspiration from CIMIS.

A. B.

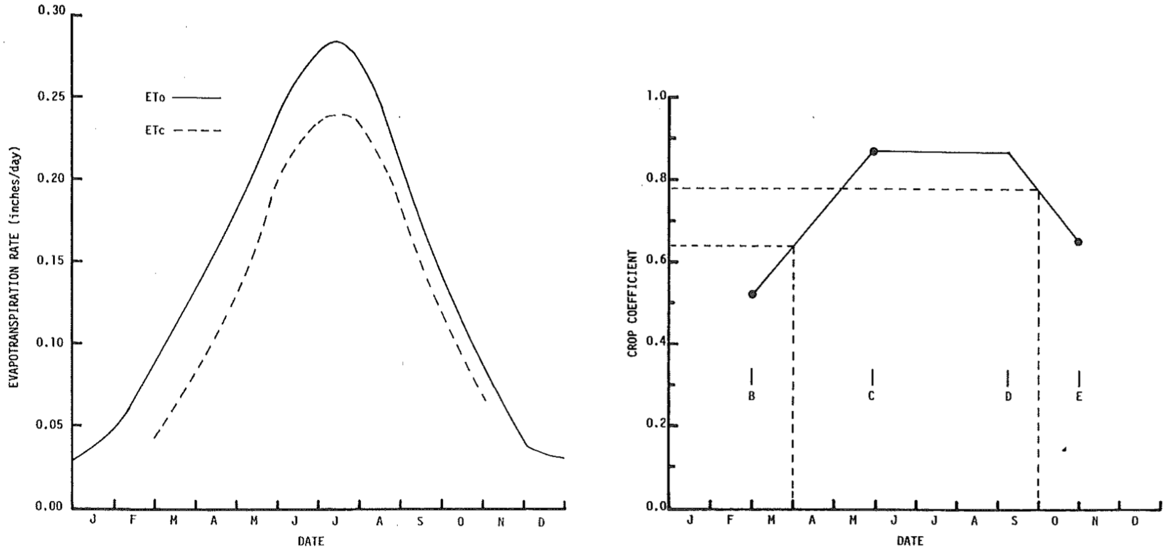
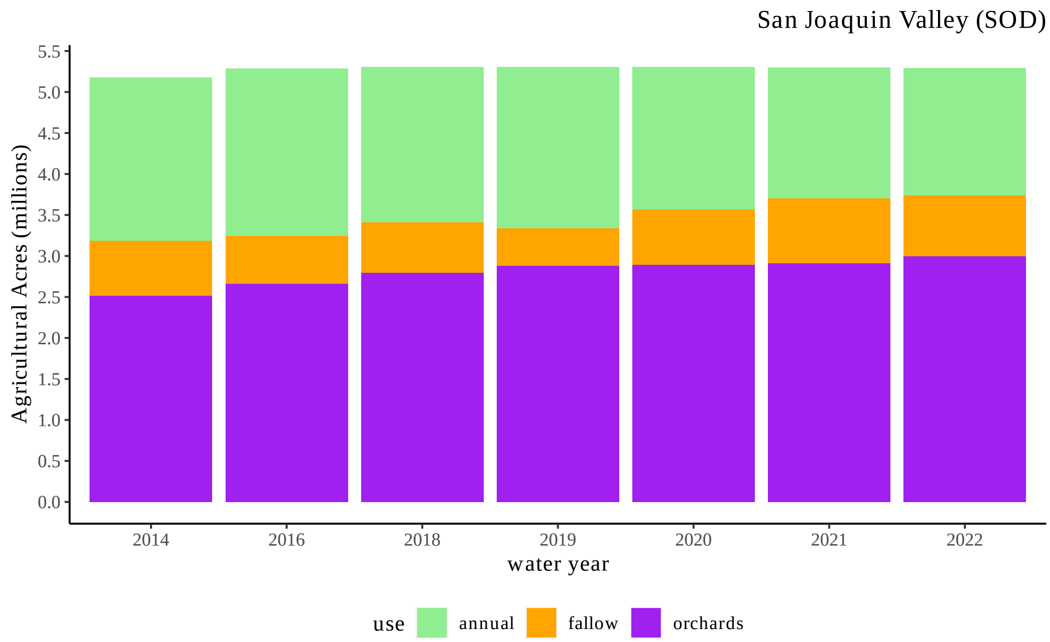


Figure A11. Example of Crop Coefficients

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

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

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



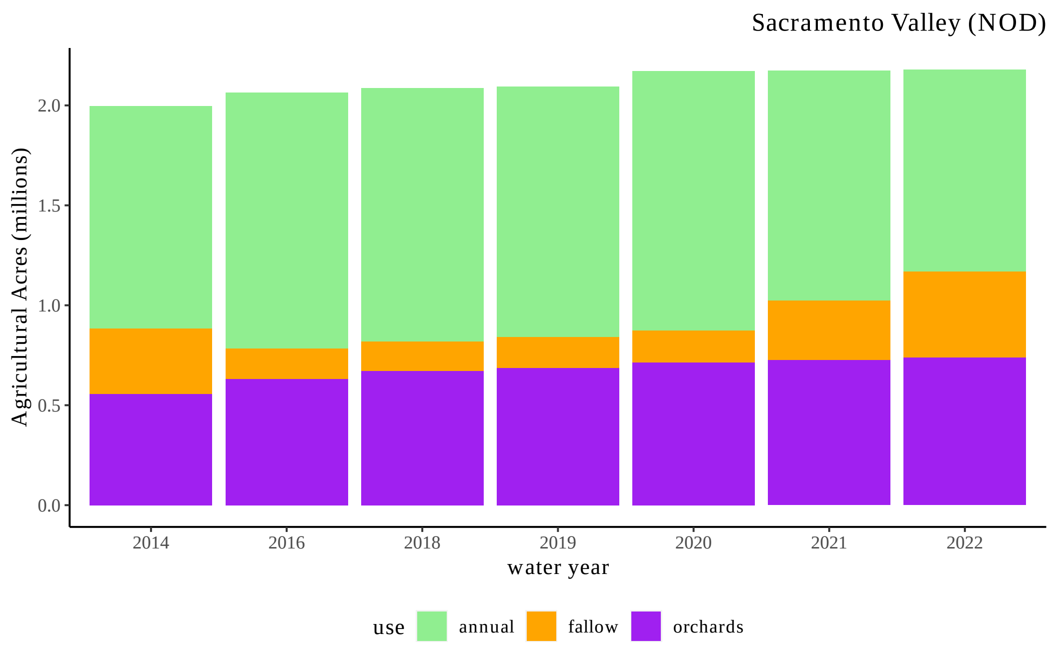


Figure A12. Planting Decisions, 2014–2022

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

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

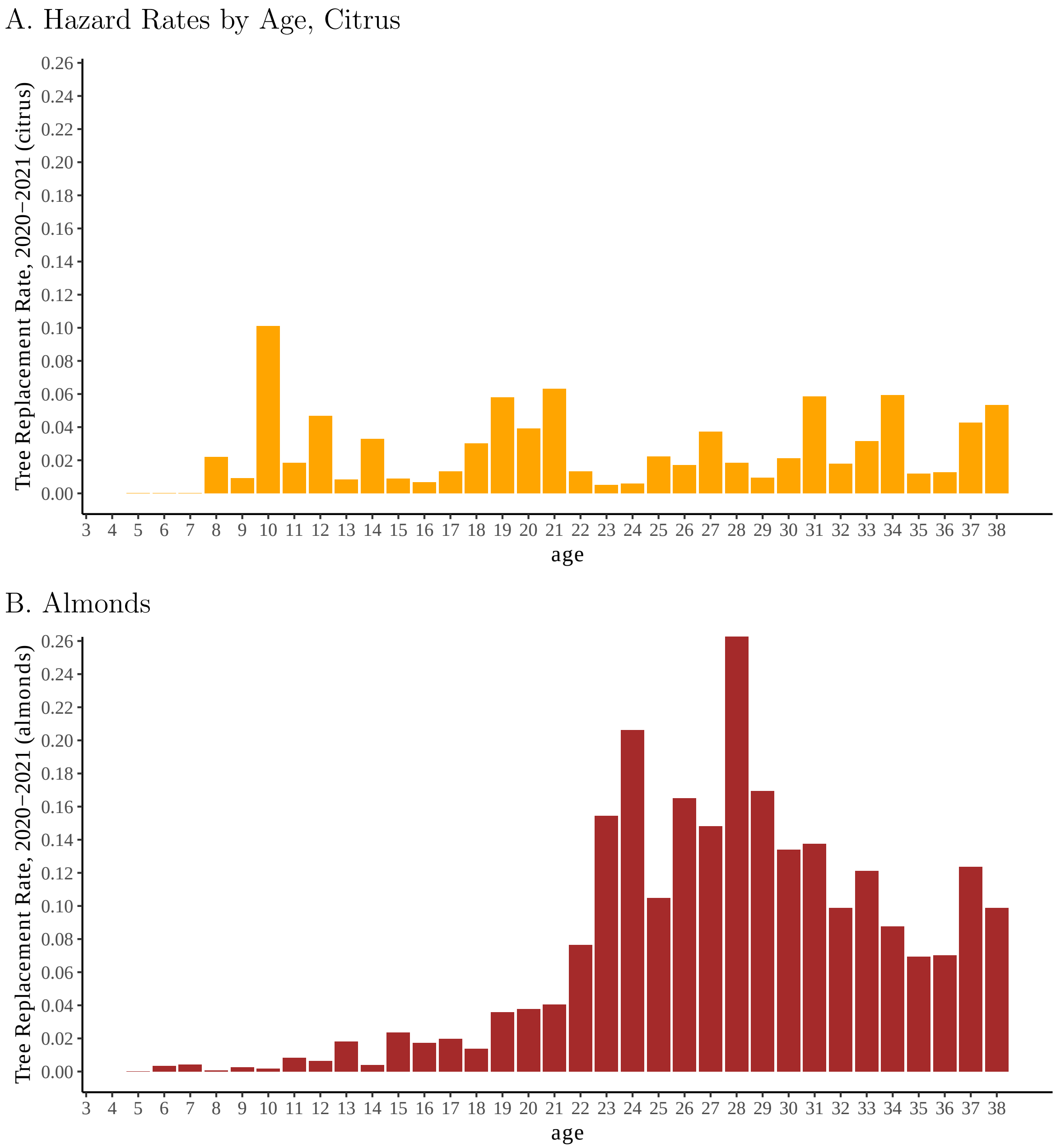
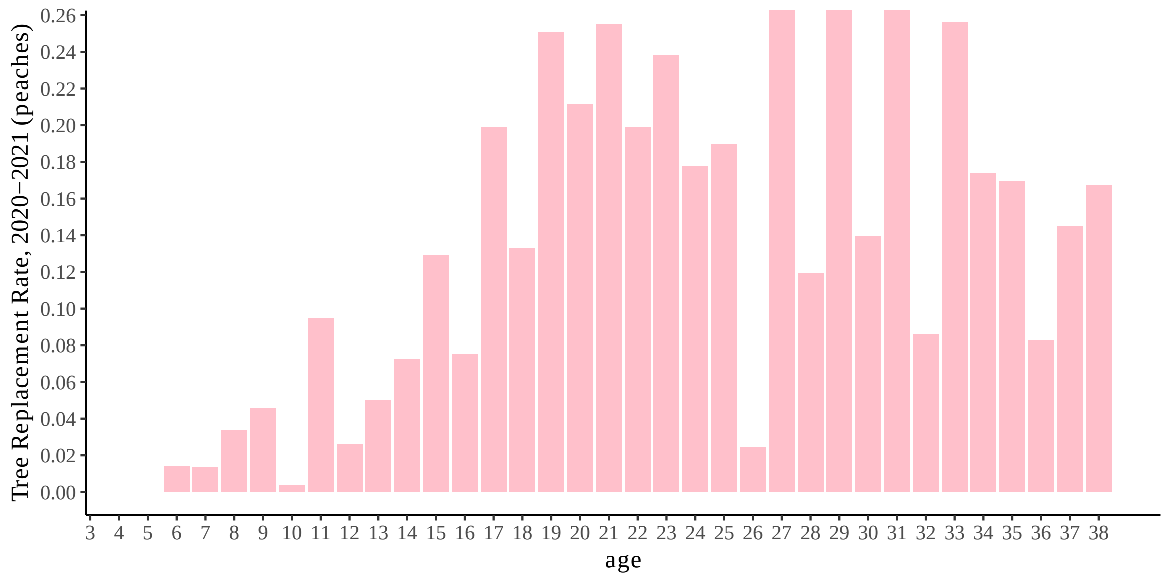


Figure A13. Orchard Demographics by Crop

Additional results for Figure 3.

C. Peaches



D. Pistachios

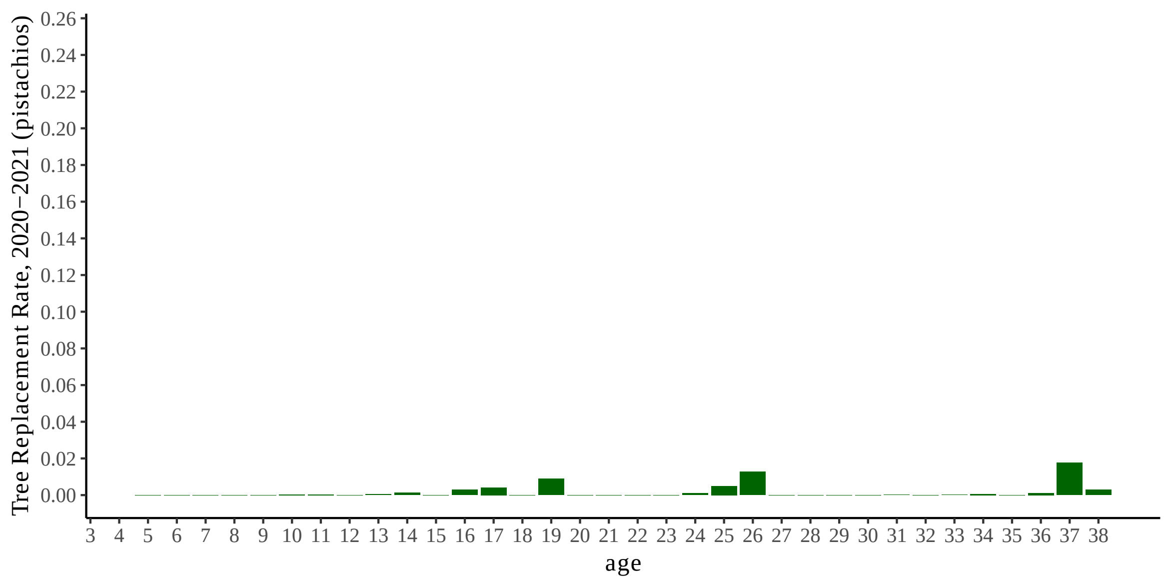


Figure A13 (cont'd). ORCHARD DEMOGRAPHICS BY CROP

Additional results for Figure 3.

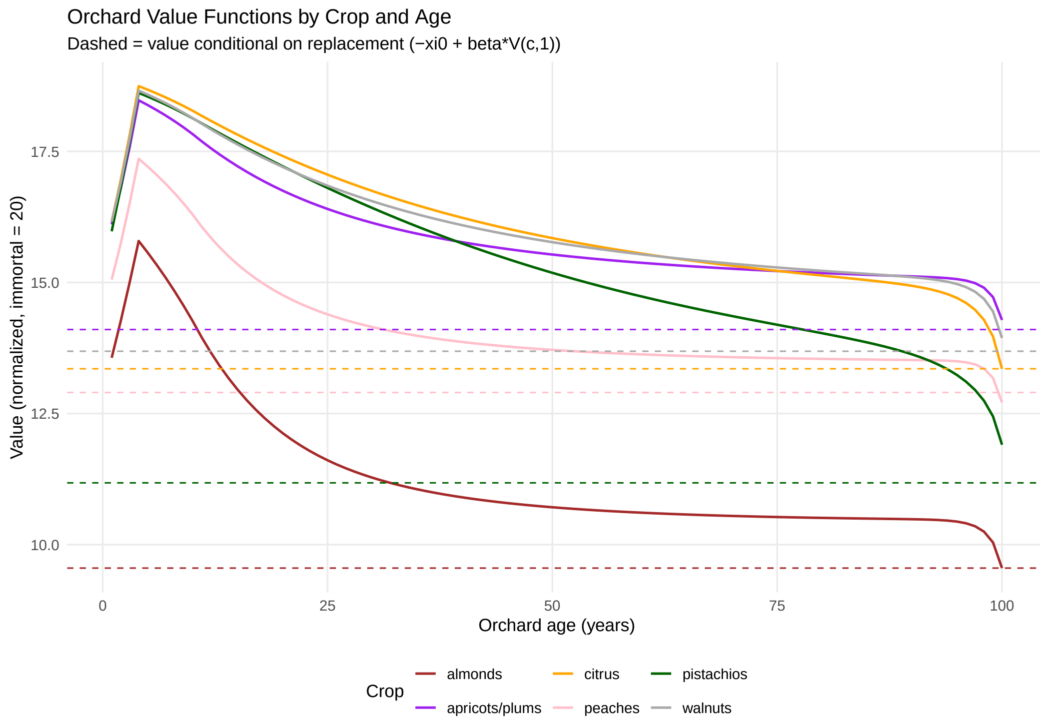


Figure A14. Rust (1987) Value Functions

Rust (1987) value functions for selected crops in the San Joaquin.