Hydro-economically Optimized Water Allocation with Climate Change, Managed Groundwater Recharge, and Prioritized Wetland Deliveries to Moderate Human-nature Water Use Conflicts

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Abstract

Climate change challenges water management in Mediterranean climate regions, including extreme precipitation events, long-term groundwater overdrafts, and insufficient water supply to sustain agriculture and the environment simultaneously. Most of the Mediterranean climate regions are well-developed landscapes. Historical water system channelization for agricultural use disturbed the natural water system balance and modified wetland and aquatic ecosystems, incurring human-nature water use conflicts. It is crucial to produce decision-support information for regional water allocation to agriculture, the environment, and urban areas, as well as to prepare for changes in the water systems brought by climate change. Optimized water allocation with climate change can reconcile environmental water use with agricultural and urban water use to minimize trade-offs and replenish water storage, particularly underground. Simulation-economic optimization models (SOMs) simultaneously optimize water allocation over long-term local hydroclimate features. However, realistic consideration of management constraints such as managed groundwater recharge and prioritized wetland deliveries are rarely combined with simulated water allocation optimization under climate change scenarios. We utilized a landscape-level, implicit stochastic deterministic linear hydro-economic optimization model with limited foresight to understand the combined impacts of climate change and water management policies on local water allocation decisions in California for the historical period 1921-2003 and climate change future 2042-2123. The timeframe is defined by the available hydrological time series. We found that in water-abundant regions in California, the biggest reduction in agricultural water use will be seen in the normal and dry years of its Mediterranean climate, while water-scarce regions will see the biggest reduction in wet years. The human-nature water use conflicts, intensified by climate change, are the reasons behind this contrast. We compared users' willingness to pay for water by region and create water pricings to generate cost-efficient water allocations. The results showed that arid regions (the northern part of San Joaquin Valley and the South Bay area in our case study) will see the largest increase in water economic values. Users in these regions are expected to be willing to pay more for water than other regions for both agricultural and environmental water uses. Water allocation based on water pricing can cost-efficiently moderate human and nature water use conflicts. We concluded with the co-benefit between managed groundwater recharge and ecosystem conservation coming along with such cost-efficient water allocation strategies with the measurements of groundwater level across scenarios.

Keywords: Water allocation optimization, Sustainable groundwater management, Environmental water use, Agricultural water use, Climate change

1. Introduction

Under climate change, hydroclimatic variability and extreme precipitation events impact water resources, agricultural production, and biodiversity worldwide. Some regions will have more frequent extreme flood and drought events and dramatic swings between wet and dry conditions than historically, a phenomenon known as hydroclimatic alteration (Stevenson et al., 2022). Hydroclimatic alteration fundamentally changes water availability for environmental and human water uses (Vaux, 2012), worsening human-nature water use conflicts (Derepasko et al., 2021). When some regions saw unmet water demand, groundwater pumping typically increased to compensate for reduced surface water availability (Wada & Bierkens, 2014). However, long-term overdrafts and sustainable groundwater management (CWRCB, 2021) will limit future pumping and intensify the water shortage for all competing water uses, which will drive water prices up (Kearney et al., 2014). The rising cost of water and budgetary constraints on environmental water use will impede refuge delivery targets in some regions (CVPIA 2024). Such water allocation and management issues challenge regions such as Spain, Australia, and California, which are facing water scarcity due to climate change and socioeconomic factors (Berbel & Esteban, 2019).

Simulation–optimization methods (SOMs) were introduced and evaluated as an effective approach for optimizing water allocations with the changing availability of water resources (Azadi et al., 2021; Moghadam et al., 2022). Mehrabian & Lucas (2006) compared the performance of various SOM algorithms in solving multi-objective functions, including invasive weed optimization (IWO) algorithm, genetic algorithms (GAs), memetic algorithms, particle swarm optimization (PSO), shuffled frog leaping (SFL). However, institutional responses to changing water supply and demands were shaped by regional hydroclimate and historical patterns of water use (Herman et al., 2018), the suitability of SOMs in optimizing water allocation usually requires a deep understanding of local hydrological regimes and water management constraints (Derepasko et al., 2021). To improve the suitability of SOMs and inform institutional water policy, surface water dynamics, including streamflow and precipitation predictions, were added to SOMs. (Taormina & Chau, 2015; Wu & Chau, 2013). Wu et al. made further improvements by including surface water and groundwater (SW-GW) modeling of SW-GW dynamics(Wu et al., 2015). How climate change and management scenarios will impact such conflicts is left for future studies. Hadis et al. (2022) studied how long-term climatic factors impact water allocation decisions. Yang et al. (2009) proposed an approach for integrating the multi-objective genetic algorithm (MOGA) with the groundwater simulation model to include groundwater management levels. None of them, however, simultaneously addressed human-nature water competition under climate change and how climate change adapted water management policies impact water allocation decisions. In addition, when humans and nature compete for limited water resources, a high-efficiency water allocation system is necessary (Zilberman & Schoengold, 2005). Studies such as Null & Prudencio (2016) provided combined climate and management scenarios but did not consider the change in water economic values. This omission may not generate the most cost-efficient water allocation. Cost-efficient climate-responsive water allocation may consider water availability and scarcity, water market, and pricing (Tanaka et al., 2006). Derepasko et al. (2021) proposed using water pricing as an efficient way to optimize water allocation and reduce scarcity.

We used CALVIN, a landscape-level, implicit stochastic deterministic linear optimization model with limited foresight to meet environmental water use and groundwater sustainable requirements at the lowest cost to humans (Draper, 2001; Draper et al., 2003). Existing alternative hydrologic approaches or optimization algorithms, such as explicit stochastic optimization, cannot catch the persistence of drought phenomena and the heterogeneous features of large geographical information, and are therefore considered impractical for meeting unique local water allocation optimization requirements (Herman et al., 2018). We used the limited-foresight optimization to minimize water scarcity costs to human use in California with combined climate change and water management scenarios over a period of 82 years (historical: 1922-2003, dummy future years: 2042-2123) based on the available historical hydrological time series (Dogan et al., 2015). Water allocation optimization over a wide span of 82-year historical hydrology (perfect foresight) can respond to interannual and seasonal features; however, it may not produce realistic management strategies, therefore limited foresight (Draper, 2001) was used to optimize allocation in a sequence of every single year.

California's water allocation strategies are transferable to other regions facing water scarcity with climate change such as Spain and Australia. In California, water allocation decisions are based on water year types, that is, comparing runoff in the current year to average runoff to classify water years as wet, normal, or dry (Null & Viers, 2013). The swings between wet and dry years in California provide a broad scale demonstration for water management with climate change uncertainties.

Federal policies in the US, like the Endangered Species Act or hydropower relicensing, require that the water used by the environment is treated as constraints on in-stream flows, reservoir operations, or refuge deliveries in California (McManamay et al., 2023). Refuge deliveries, specifically, have two levels - Level 4, which is required for optimal wetland and wildlife habitat development and management, and Level 2, which is the average historical habitat deliveries before 1989 (CVPIA 1937). Historically, about 90% of the Level 2 deliveries and only half the incremental Level 4 were typically met (Singh & Lund, 2015). Meeting environmental water use targets is important since more than 80%of native freshwater fish are in decline and at risk of extinction this century in California (Escriva-Bou et al., 2018). Optimized water allocations with the ever-changing hydroclimatic normal, sustainable groundwater use, and managed environmental water use modeling are necessary to meet the water requirements of human activity and nature.

Table 1. Combined climate change and water management scenarios and descriptions

Scenario names	Scenario description	Environmental water use	Climate condition	Groundwater overdraft
Historical	Historical business-as-usual	Historical	Historical	Overdraft
DREAM	California Dreamin'	Increased for non-dry years	Warm-wet (MIROC5)	No-overdraft
BBAU	Bad Business-As-Usual	Historical	Warm-wet (MIROC5)	Overdraft
EEM	Everyone Equally Miserable	Increased for non-dry years	Hot-dry (HadGEM2)	No-overdraft
DUST	Central Valley Dustbowl	Historical	Hot-dry (HadGEM2)	Overdraft

In this study, we conducted a scenario analysis to reconcile human-nature water use conflict, that is, to optimize human use of water allocation with minimized cost while conserving groundwater and meeting wetland delivery requirements. We analyzed five alternative scenarios

(Table 1) varying in (1) climate vulnerability: historical, warm-wet, and warm-dry climates; (2) environmental water use: historical or meeting full Level 4 deliveries; (3) sustainable groundwater management with and without controlling for long-term overdraft (Table 1). To facilitate inter-project comparison, we used the scenario names developed by the California Landscape Conservation Cooperative (2018) and published in Wilson et al. (2022). We generated water allocation ratios of competing human-nature water use by water year types. We also produced water pricing references for a cost efficient water allocation system under climate change and institutional management changes. Finally, we evaluated the outcome of managed groundwater recharge to show the co-benefits of nature and human productivity in the optimized water allocations.

2. Method

2.1. Network hydrological alteration with climate change

2.1.1. Surface water hydrology change

Hydroclimate change in the CALVIN hydrological network for this study includes shifted surface water and groundwater availability with climate change, Groundwater and stream flow interaction changes, changes in environmental water use constraints, as well as groundwater pumping controls. Figure 1 presents the linear optimization function used by the network optimization approach of CALVIN and the steps of modifying historical flows and constraints to create future combined climate change and management scenarios. First, we used a monthly summary of the VIC Model Output of Daily Runoff for 1/8th Degree (Hamman et al., 2018), a CMIP5 BCSD product, to calculate the surface water inflow change factors in climate change scenarios compared to the historical inflow (Reclamation, 2014). We downloaded the data product from January 1950 to January 2099 (Maurer et al., 2001). We chose a drainage area and outlet location closest to a major reservoir node location in eight of the sub-regions in the CALVIN network. We summarized the future average runoffs for each of the 12 months of a water year (Oct-Sep) across the 50-year timeframe under climate change from October 2040 to September 2090.

We summarized the historical average runoffs between Oct 1950 and Sep 2000. The surface water inflow change factor was the ratio of the climate change future average monthly runoffs to the historical average. The change factor was applied to CALVIN's 82-year monthly surface water hydrology (1922-2003) simulated by C2VSIM (Brush & Dogrul, 2013), to generate the dummy future 82-year hydrology with climate change (2042-2123), corresponding to each of the historical years by the change factor. The CALVIN water network is described in detail in Supplementary Information.

The HadGEM2 and MIROC5 climate models were chosen to represent hot-dry and warm-wet under the representative concentration pathway 8.5 to consider the two extremes of climate change impacts. These two climate models belong to the top four climate models selected by the California Department of Water Resources (CADWR) Climate Change Technical Advisory Group based on the criteria of the global/regional climate pattern and California's hydrological regimes (Pierce et al., 2018). Under climate change, two other CADWR candidate models, including CanESM2 and CNRM_CM5, would produce excess surface water flows in winter and spring months (Supplementary Information Figure 3). If excess flows are disproportionately larger than the demand, the system cannot use all the water supply available, potentially causing infeasibility for the optimization functions.

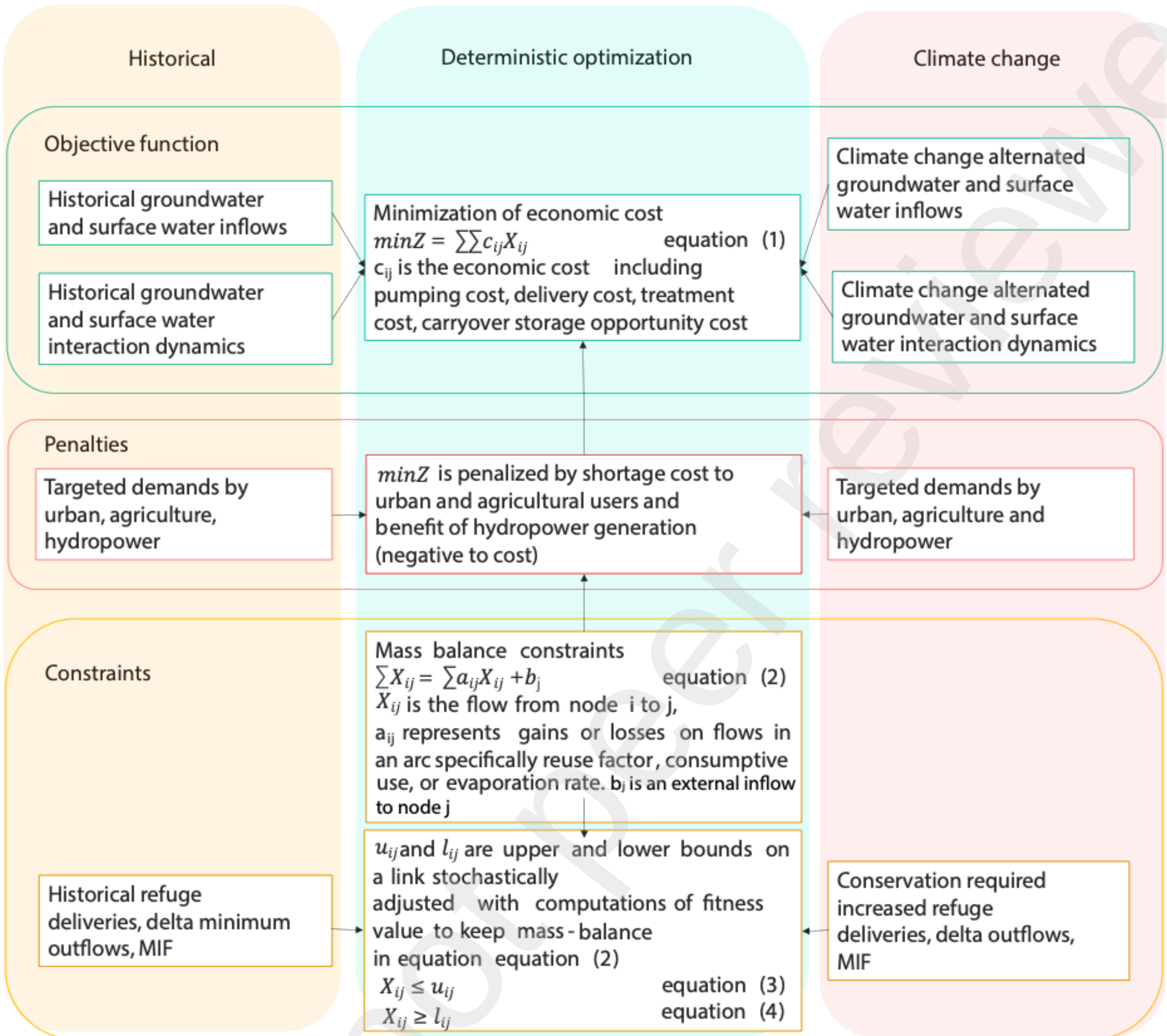

Figure 1 Conceptual simulation-optimization model framework

2.1.2. Groundwater hydrology change

Climatic factors that affect groundwater levels include precipitation-induced deep percolation and stream-groundwater interactions. We applied an empirical cubic relationship between precipitation (P) and groundwater deep percolation (D_p) (Equation 5) with an R-squared bigger than 0.9 derived by Dogan et al. (2015) to calculate the change in deep percolation under climate change. The historical groundwater deep percolation values were regressed against the historical precipitation to establish the empirical cubic relationship for each groundwater basin, and climate change deep percolation was calculated with the established relationship and projected precipitations. Historical precipitation data and deep percolation were acquired from the C2VSim model's groundwater budget. Future precipitation data were collected from the Multivariate Adaptive Constructed Analogs (MACA) downscaled precipitation (P) under climate change scenarios from https://www.climatologylab.org/maca.html (Abatzoglou & Brown, 2012) for each groundwater basin and the two selected climate models, HadGEM2 and MIROC5 . We added the first-order derivative of a cubic relationship with respect to precipitation to historical groundwater inflows to get the change in deep percolation (ΔD_P) (Equation 6).

$$D_P = a \cdot P + b \cdot P^2 + c \cdot P^3 \qquad \text{Equation 5}$$

$$I_{future} = I_{historical} + \Delta D_P \qquad \text{Equation 6}$$

Where I is groundwater inflow, a, b, and c denote regression parameters, and ΔD_P change in deep percolation.

2.1.3. Groundwater and surface water interactions

Dynamic interaction between ground and surface water, called local runoffs (Q_s), increases with precipitation and decreases with deep percolation. Therefore, we found the future local runoff as the historical local runoff, plus an incremental change in precipitation (ΔP) minus an incremental change in deep percolation(ΔD_P) (Dogan et al., 2015).

2.2. Limited foresight optimization

We used implicit deterministic optimization because the simulated 82-year hydrological time series vary across space (hydrological conceptual model shown in Supplementary information Figure 2). Therefore, spatial and temporal water network structure was implicitly embedded in the optimization. Interannual variations in historical water availability across regions of California with water year type changes were also integrated. By permuting historical inflows by change factors incurred by climate change, we could generate future hydrological time series that preserve California's water year change pattern (Herman et al., 2018). We assumed the targeted water demands are consistent across scenarios since the demand values used were already projected to future demand levels with economic development and population increase (Howitt et al., 2003; Pulido-velazquez & Jenkins, 2002; Ritzema, 2002). The stochasticity of the model is in its constraints, since while searching a statewide minimum cost solution, the model is adjusting constraints to keep water mass in balance.

The optimization problem is a linear optimization model that has the objective function (Figure 1, equation (1)) of minimizing the system-wide operational costs and water delivery cost (details of cost components in Supplementary Information Table 5) and is penalized by shortage costs to agricultural and urban users under physical and environmental constraints (Figure 1, equations 3-4) (Draper et al., 2003). Physical constraints refer to the capacity of the physical facilities of the water distribution network in California, such as reservoirs, pumping and power plants, aqueducts, and treatment plants. Environmental constraints are minimum in-stream flow (MIF) requirements (details of MIF requirements can be found in Ferreira & Tanaka (2002)).

Limited foresight uses sequential runs of the stochastic optimization model, specifically 82 linked consecutive runs for each year to form the optimal operating policy over the entire 82-year period of analysis. Each run has an optimized carryover storage value function defined by a non-linear search algorithm (Draper, 2001). The time horizon for each run is reduced to a fraction (1/n, n=82 in this case) of the whole period of analysis. CALVIN has been evolving from decades of previous research efforts (Dogan et al., 2019; Draper et al., 2003; Herman et al., 2018; Maskey et al., 2022). Although it was proved in previous studies of smaller regions that limited foresight produced more realistic results for reservoir operation management implications than perfect foresight (Arnold, 2016a; Khadem et al., 2018; Sencan & Mount, 2022), this is the first time that limited foresight was applied to assist statewide water allocation under climate change, demonstrating CALVIN's flexibility in resolving water manage system challenges evolving with time. The water allocation scenario analysis included wet and dry year shifts (Ficklin et al., 2022). The water year index (WYI) would change with climate change (Null & Viers, 2013). The method of determining future scenario water year types was included in supplementary information.

2.3. Managed groundwater recharge

In the managed groundwater recharge scenarios, ending groundwater level equals beginning level for all groundwater basins in the Central Valley to control long-term overdraft. We simulated managed groundwater recharge by running CALVIN in perfect foresight, that is, optimization over the whole 82-year period (Dogan et al., 2015). Another perfect foresight without groundwater overdraft control was run for the historical hydrological scenario without managed groundwater recharge. Yearly carry-over storage was required from these two perfect foresight runs were used by the limited foresight optimization. Initial and ending groundwater storage for each year of the 82-year time series was preassigned as an input to the limited foresight optimization to control the minimum constraints on carry-over groundwater levels when carryover storage functions were defined by a non-linear search algorithm (Perry & Praskieviez, 2017). Evolutionary algorithms (EAs) were previously used to quantify carryover storages with overdraft control explicitly (Arnold, 2016b). However, the shortage cost in controlling groundwater overdrafts on a yearly basis in EAs is around 50% higher than controlling overdrafts in the long term as perfect foresight does. This perfect foresight method takes progressive steps of controlling long-term overdrafts and minimizes overall shortage costs. Seasonal groundwater storages were modeled dynamically with limited foresight.

2.4. Prioritized wetland deliveries

Environmental water requirements, including wetland deliveries, are simplified in this study to Shasta carryover storage, minimum Bay Delta outflows, and minimum instream flow requirements from the Sacramento River to the Mono River's 18 basins and eight refuge nodes. The refuges in the model are the aggregation of many smaller refuges, which may allow the model to render refuge deliveries more efficiently than is possible. We increased all the minimum instream flows in the scenarios by 20%. Minimum Delta outflows also increased by 20% except in dry years as this flow is relatively small in dry years (Mount & Gartrell, 2020). Shasta's carryover was set at the same level as the historical level in the study. These ratios were determined arbitrarily. Still, they can be at the discretion of water managers and other stakeholders with specific values for all channels for policy analysis purposes. The refuge deliveries were increased by different percentages based on the region in which they are located to meet Level 4 full delivery requirements (Supplementary Information Table 1). A full Level 4 delivery here means a full 75% Level 2 refuge and 100% incremental Level 4 refuge deliveries (Central Valley Joint Venture, 2006). We increased refuge water deliveries only in normal (above normal and below normal) and wet years. Both surveyed expert opinion data (Singh & Lund, 2015) and CVPIA's refuge water supply documents (CVPIA, 1937) were referenced to identify the insufficiencies in historic environmental use. The ratio of full Level, 4 environmental deliveries vs historical environmental deliveries, was calculated based on acquired insufficiencies to modify environmental water use in the hydrological networks of the CALVIN. All network hydrology modifications were implemented in R programming language (included in data and code availability).

3. Results

3.1. Water allocations with climate change

Although water allocation varies dramatically across water year types, on a statewide average, roughly 40% of water was for environmental use (minimum in-stream flows and refuge deliveries), 40% for agriculture, and 20% for urban water use (Table 2). Urban water use ratios are bigger than those listed by Mount & Hanak (2019). In our results, dry years will see a 4% decrease in agricultural water use, and environmental water use will increase by around 3%, no matter the scenario.

Table 2. Water allocation rations on state average of different scenarios

	dry			normal			wet		
	Environment	Agriculture	Urban	Environment	Agriculture	Urban	Environment	Agriculture	Urban
Historical	0.36	0.43	0.21	0.38	0.43	0.19	0.38	0.43	0.19
Dust	0.40	0.38	0.22	0.40	0.40	0.19	0.40	0.41	0.19
EEM	0.39	0.39	0.22	0.46	0.36	0.18	0.46	0.36	0.18
BBAU	0.39	0.39	0.22	0.37	0.42	0.21	0.37	0.43	0.20
DREAM	0.40	0.38	0.22	0.47	0.35	0.18	0.46	0.35	0.18

The overall water availability decreased by about 9%, around 5,000 million m^3 across all scenarios as a whole in California. In the normal years, the changes in water allocation became distinct across different scenarios; that is, hot-dry scenarios caused 1% more agricultural water use reduction than warm-wet scenarios. Conservation requirements in the warm-wet scenarios decreased the agricultural water use by 3% more than in the hot-dry scenarios, with 7% and 4% differences from the respective scenarios without conservation requirements. The environmental water use allocation ratio increased from 2%-9% percent because of a decrease in agricultural water use, except in bad-business-as-usual scenarios when agricultural water use was as substantial as the historical level. The warm-wet DREAM scenario had the biggest proportional environmental water use. In the wet years, the environmental water allocation ratios were not very different from normal years in the hot-dry scenarios. However, in both the warm-wet and hot-dry scenarios, agricultural water ratios were 1% higher than the normal years (1,000 million m^3 more) when there weren't conservation requirements.

Climate change and conservation requirements have a much greater impact on agricultural water delivery in the San Joaquin Valley. Figure 2 interestingly shows that the greatest impact was in the wet years for San Joaquin Valley, but Sacramento Valley was impacted mostly in dry and normal years with conservation constraints under climate change. The reason behind this is that environmental water use is highest in wet years in the San Joaquin Valley (including the South Bay region): around 11,000 million m^3 annually, which is more than four times the environmental water used in dry years and twice the amount used in normal years. In the Sacramento Valley and Delta, environmental water use was highest in normal years, about 26,000 million m^3 annually for conservation management requirements under climate change. Conservation requirements increased the environmental water use by almost 5000 million m^3 in Sacramento Valley.

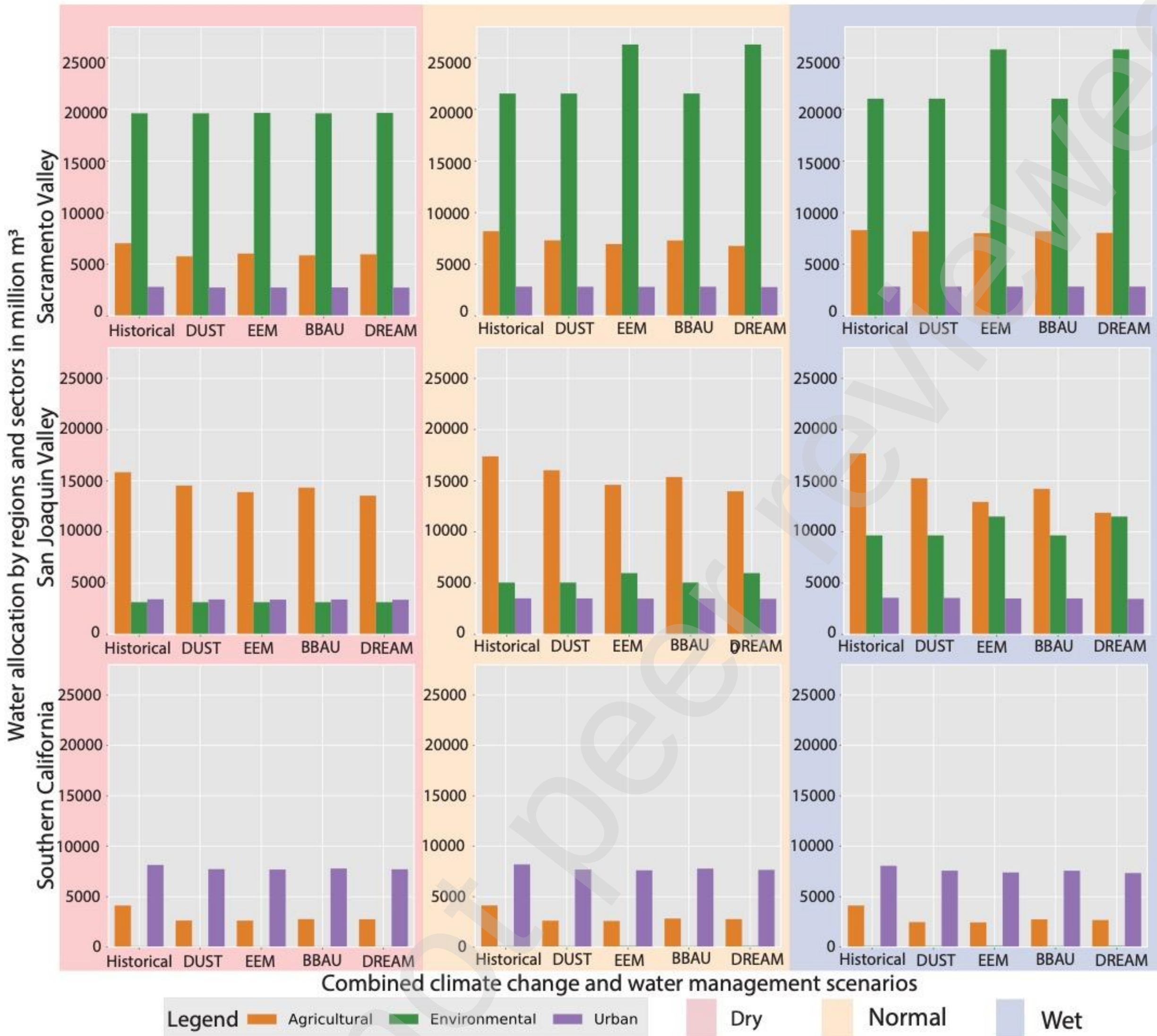

Figure 2 Optimized average annual water allocation to users by water year types across regions in California under all combined scenarios (Historical: historical business-as-usual, DUST: Central Valley Dustbowl, EEM: Everyone equally miserable, BBAU: Bad business-as-usual, DREAM: California Dreamin')

Environmental water use didn't change in Southern California because the historical environmental water use in that region is comparatively minimal. There was no obvious decrease in urban deliveries, except in Southern California (800 million m^3 decrease in annual delivery), and less seasonal variance than agricultural and environmental water use (Figure 2).

Senior agricultural water rights are 68% greater during the spring runoff (Null & Prudencio, 2016), which is historically from April to June. Climate change and conservation requirements can reduce monthly agricultural delivery by up to 1,200 million m^3 a month in July alone (Figure 3). That equals 5% of California's total normal-year agricultural surface water supply (Lund et al., 2018). Due to a possible delayed spring runoff under climate change, agricultural delivery decreased from March in the San Joaquin Valley compared to historical levels by up to 500 million m^3 in the wet years and 250 million m^3 in the normal years. In the Sacramento Valley, agricultural water delivery reduction under climate change started in May in dry and normal years in all scenarios by around 200 million m^3 (Figure 3).

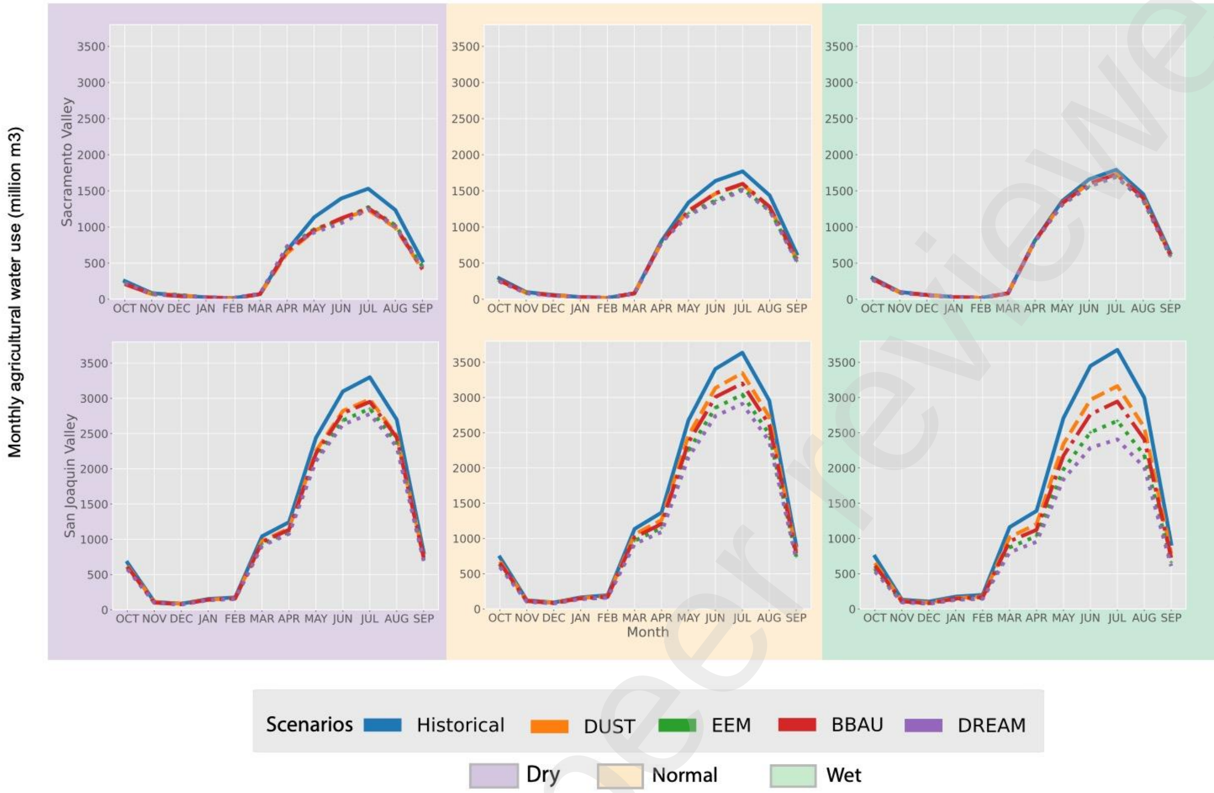

Figure 3 Monthly agricultural water deliveries of five combined climate and management scenarios

There were almost no agricultural or urban delivery changes in the wet years in the Sacramento Valley Delta, even with conservation management requirements. In the Sacramento Valley, conservation requirements only influenced agricultural delivery in normal and dry years.

3.2. Water supply portfolio with climate change

CALVIN allocated water with minimized operation/shortage cost by choosing groundwater pumping (GWP) versus surface water diversion (SWD), constrained infrastructure capacity for storage and conveyance, based on spatial-temporal water availability indicated by the time services hydrological data and the targeted deliveries determined by demands. Agricultural water use was supplied by either GWP or SWD. In an urban water supply portfolio, there are alternatives to GWP and SWD, which include desalinated water (DESAL) and non-potable and potable reuse water (NPR/PR).

Under future combined scenarios, agricultural surface water supply decreased across the state with climate change while the needs for agricultural groundwater supply increased. However, agricultural groundwater supply levels stay the same for the Sacramento Valley. The San Joaquin Valley increased the supply of groundwater across all future scenarios by up to 100 million m^3 annually, but management requirements limited allocation availability by around 50 million m^3 annually (Figure 4). However, sustainable groundwater, and biodiversity conservation restrictions/guidelines/requirements only affect the agricultural groundwater supply in the San Joaquin Valley. Sustainable groundwater and biodiversity conservation restrictions/guidelines/requirements also decreased the urban groundwater supply in Sacramento Valley by about 12 million m^3 per year. In sum, climate change will increase the agricultural needs for groundwater conveyance infrastructure in San Joaquin Valley by up to 100 million m^3 and in the Sacramento Valley by 12 million m^3.

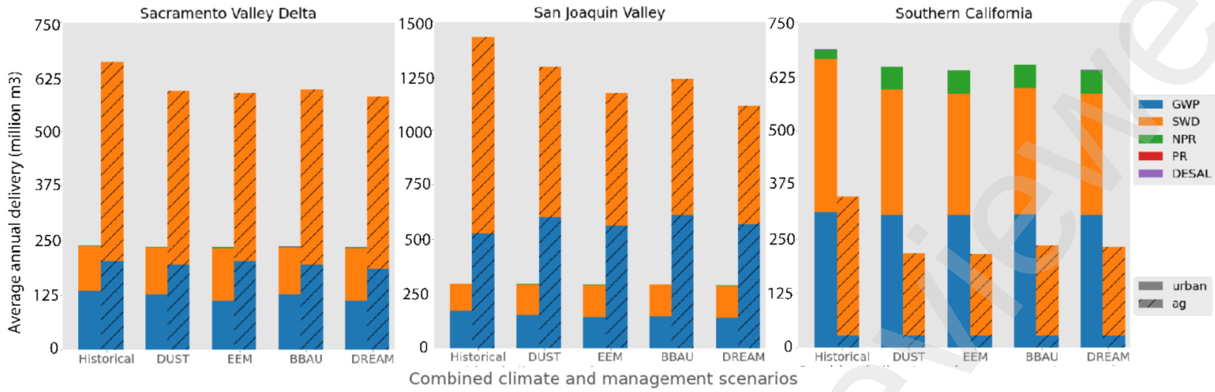

Figure 4 Water supply portfolio across California. GWP (groundwater pumping); SWD (surface water diversion); NPR (non-potable reuse); PR (potable reuse); DESAL (desalinated water).

Southern California's surface water supply decreased for both urban and agricultural purposes. Limits on surface water supply drove users to seek new water supply alternatives with constraint use of groundwater, such as NPR and DESAL. The re-use of non-portable water as a supply source increased with combined climate change and management scenarios in all regions. These trends were also evident in the Central Valley, but Figure 4 does not show the increase in water reuse because the historic infrastructure for it was minimal in both the Sacramento and San Joaquin Valleys. Overall, climate change will increase the need for water reuse infrastructure expansion across California.

3.3. The nature-human water use conflicts

Although the constrained environmental water use varies by water years and months, we found significant tradeoffs between agricultural water use and environmental water use in the San Joaquin Valley across all water year types with climate change, as shown in Figure 2 and Figure 3. Our results show that this trade-off will cause about a 30% reduction (5,000 million m^3) in agricultural water use in wet years and a 20% reduction in dry and normal years (3,500 million m^3) (Figure 5).

The State Water Board's new flow objectives for the Lower San Joaquin River and its tributaries allocate a percentage of unimpaired flow (bypassed from reservoirs and released into rivers) from February through June for environmental use. Therefore, the environmental water uses in the San Joaquin Valley peaks in March (Figure 5). These high environmental water use months coincide with the active agricultural months from March to July in the San Joaquin Valley. Senior agricultural water rights are 68% greater during the spring runoff, which is historically from April to June.

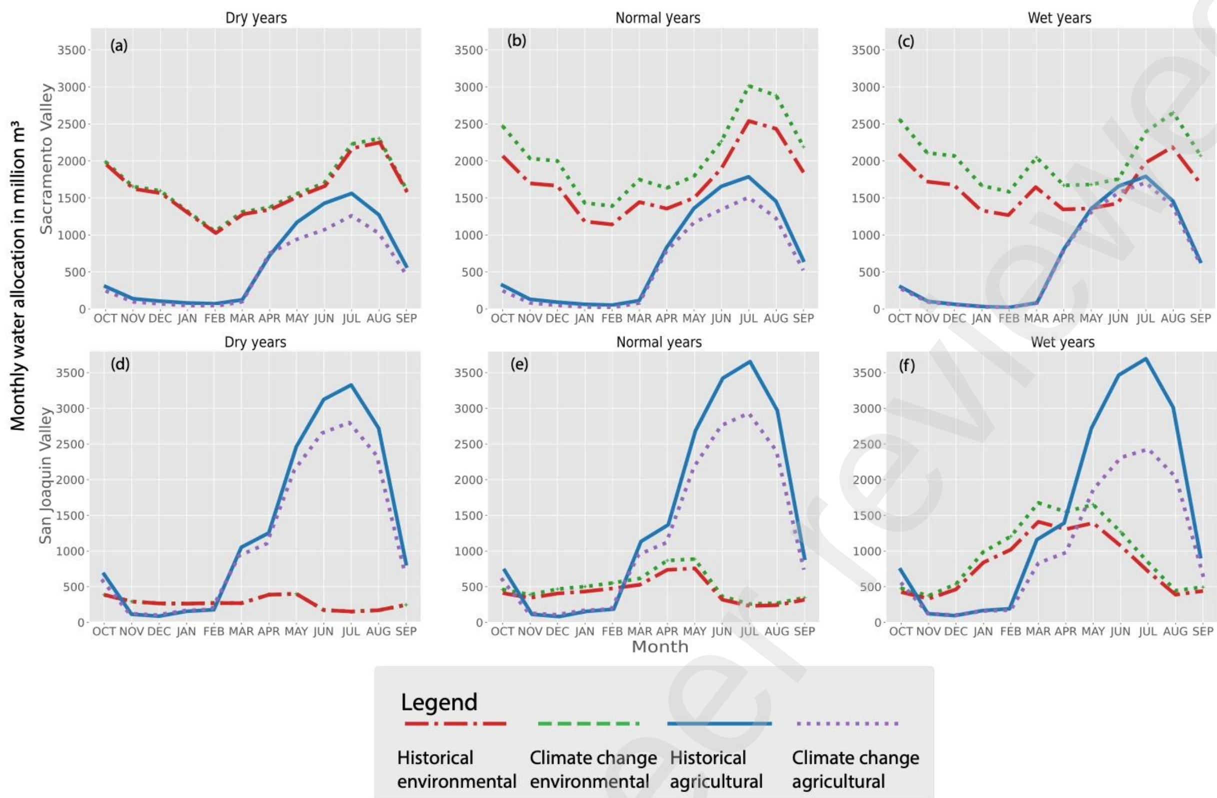

Figure 5 Average monthly agricultural water use and environmental water use in million m^3 by water year types in all combined scenarios in the Sacramento Valley Delta (a-c) and the San Joaquin Valley. Historical environmental includes historical climate and historical water use. Climate change environmental (EEM scenario) includes hot-dry condition, sustainable groundwater use, and increased environmental water use.

3.4. The use of water pricing for efficient water allocation

Water reallocation through the water market could potentially alleviate water scarcity for agricultural and urban users. Section 1707 of the California Water Code (SWRCB, 2022) permits water purchases for environmental use Click or tap here to enter text.. This potential of the water market to alleviate scarcity can be approximated using differences in willingness to pay for an additional thousand m^3 of water supply among competing water uses across different regions (Figure 6). We used the average benefit of an additional unit of water as water price, indicated by LaGrange multipliers of the optimization constraints (Jie & Yan, 2021). Water prices were differentiated by competing water users since water has different economic values to different users even in the same region under the same scenario. For the environmental water use price, the monetary value allowed us to evaluate the biodiversity conservation benefit on the same scale as urban and agricultural water use benefits. However, it may not necessarily represent a realistic market trading price.

We found that environmental water use has the highest expected prices overall based on mean prices across all water year types in Figure 5. A reduction in environmental water use will cause the highest monetary opportunity cost. The mean price also showed that different climate change and water management scenarios have the most significant influences on environmental water prices compared to urban and agricultural water prices. The hot-dry condition with targets of saving water and increasing environmental water use (EEM scenario) drove the environmental water price up to $1,700 per thousand m^3 in the Upper Sacramento Valley region. In the San Joaquin Valley South Bay region, the EEM scenario made the environmental water price about 100 times more expensive than the historical level. Agricultural water prices were also impacted by climate change and conservation targets, particularly across all Central Valley regions. Controlling groundwater overdrafts and prioritizing environmental delivery made the agricultural water price in the San Joaquin Valley South Bay almost 10 times the historical level. Climate change impacts the agricultural water use of the Tulare Basin and Southern California more than the other regions. Urban users in Southern California would be likely to pay the highest price among all urban users, followed by Upper Sacramento Valley urban users, who are willing to pay more under climate change.

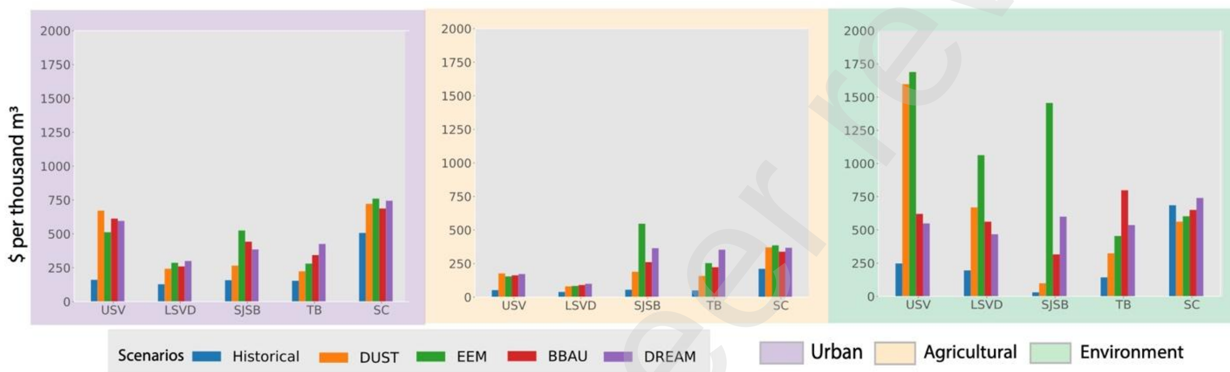

Figure 6 Regional mean water prices for an additional unit of water supply to urban, agricultural, and environmental users across regions in California by water year types. From right to left of the x axis: SC (Southern California), TB: Tulare Basin, SJSB: San Joaquin Valley South Bay, LSVD: Lower Sacramento Valley Delta, USV: Upper Sacramento Valley, Historical: historical business-as-usual, DUST: Central Valley Dustbowl, EEM: Everyone equally miserable, BBAU: Bad business-as-usual, DREAM: California Dreamin')

Water prices vary annually, and the interannual variation amplitude is the biggest in dry years among all water year types for all competing water uses (Figure 7). We determined the deviation from the average willingness-to-pay of the whole period by looking at the boxplot figures on willingness-to-pay across dry, wet, and normal years, respectively (Figure 6). Overall, environmental water values saw higher interannual variation than urban and agriculture, and the upper Sacramento Valley region had the largest variation. In the wet years, the water management requirements of the California Sustainable Groundwater Management Act (SGMA) consistently increased the water prices in all sectors across all the regions compared to scenarios without water management requirements. That is not only hydroclimate condition but also water management and policies drove the changes in water market value. With climate change water trading market should be more flexible in pricing in response to the more volatile water values change. The water allocation with minimized water allocation costs across the state presented here implicates the cost-efficient way of moving water around across the space and water use sectors with climate change.

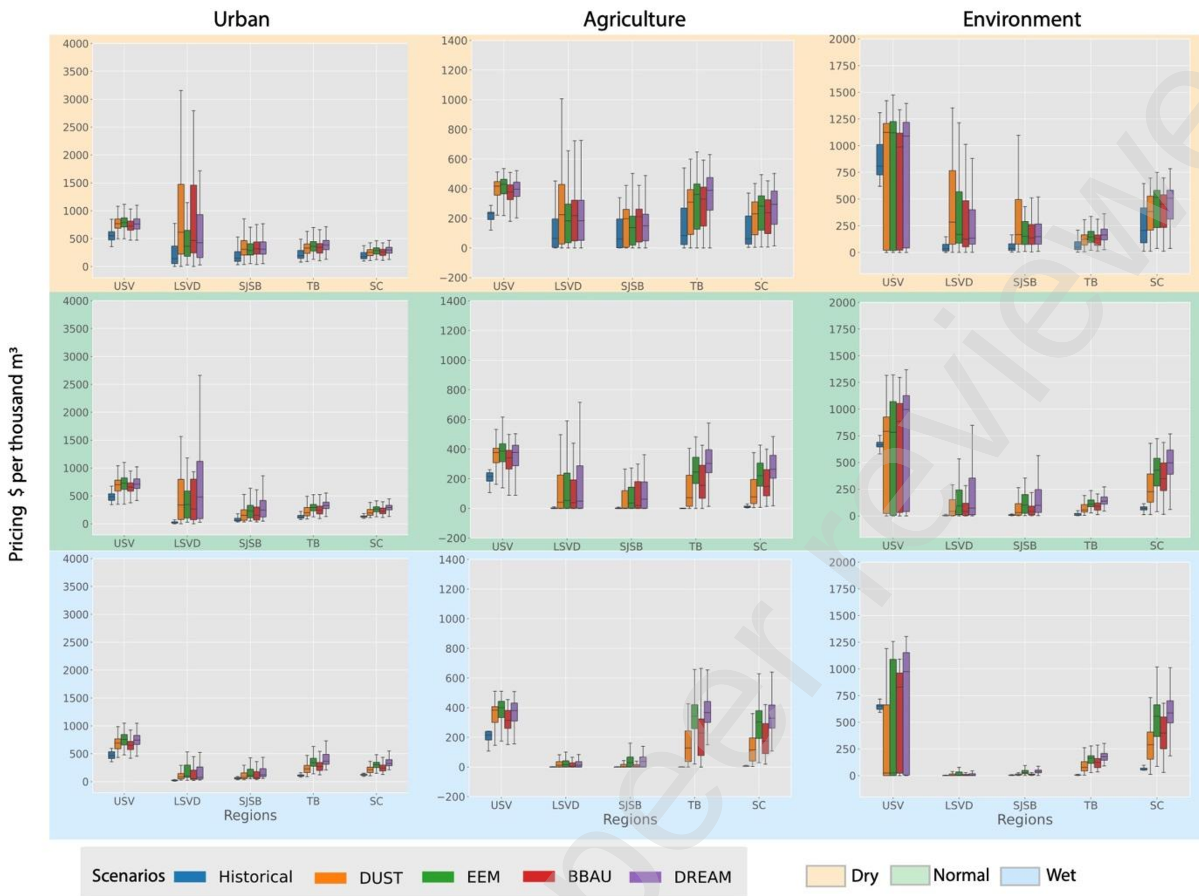

Figure 7 Distribution of willingness-to-pay for an additional unit of water supply to urban, agricultural, and environmental uses across regions in California by water year types. Box-plot center lines show mean prices; box limits are water price upper and lower quartiles; whiskers are the minimum and maximum water prices in the focal water year type and scenario. (from right to left of the x-axis: SC: Southern California, TB: Tulare Basin, SJSB: San Joaquin Valley South Bay, LSVD: Lower Sacramento Valley Delta, USV: Upper Sacramento Valley, Scenarios: Historical: historical business-as-usual, DUST: Central Valley Dustbowl, EEM: Everyone equally miserable, BBAU: Bad business-as-usual, DREAM: California Dreamin')

3.5. Co-benefits of ecosystem conservation and groundwater recharge

Increasing environmental water use to fulfill the full Level 4 refuge delivery would co-benefit groundwater recharge particularly in the San Joaquin Valley even without long-term overdraft control (Figure 8). In the wet years, full Level 4 deliveries would increase the groundwater level by around 200 million m^3 on average during the period from February to July in the hot-dry DUST scenario. If the climate condition was warm-wet, the co-benefit between increasing environmental water use and groundwater recharge was most prominent in the normal year when all months saw a bigger increase with full Level 4 deliveries than without full Level 4 deliveries.

Overall, the Sacramento Valley had groundwater levels consistent with historical levels in both dry and normal years in the climate change scenario. However, groundwater levels decreased in wet years across all seasons due to increased levels of water scarcity caused by climate change and persistent environmental and agricultural water use demands across the state. Environmental water use demands alone decreased groundwater levels by around 200 million m^3. In the San Joaquin Valley, we saw a decrease in winter groundwater and increase in spring and summer groundwater levels with climate change because of the seasonal environmental water use fluctuations as seen in Figure 5 in both dry and normal years. In wet years, the San Joaquin Valley groundwater levels increased across all seasons, which is likely due to reduced agricultural demand leaving more water in the environment.

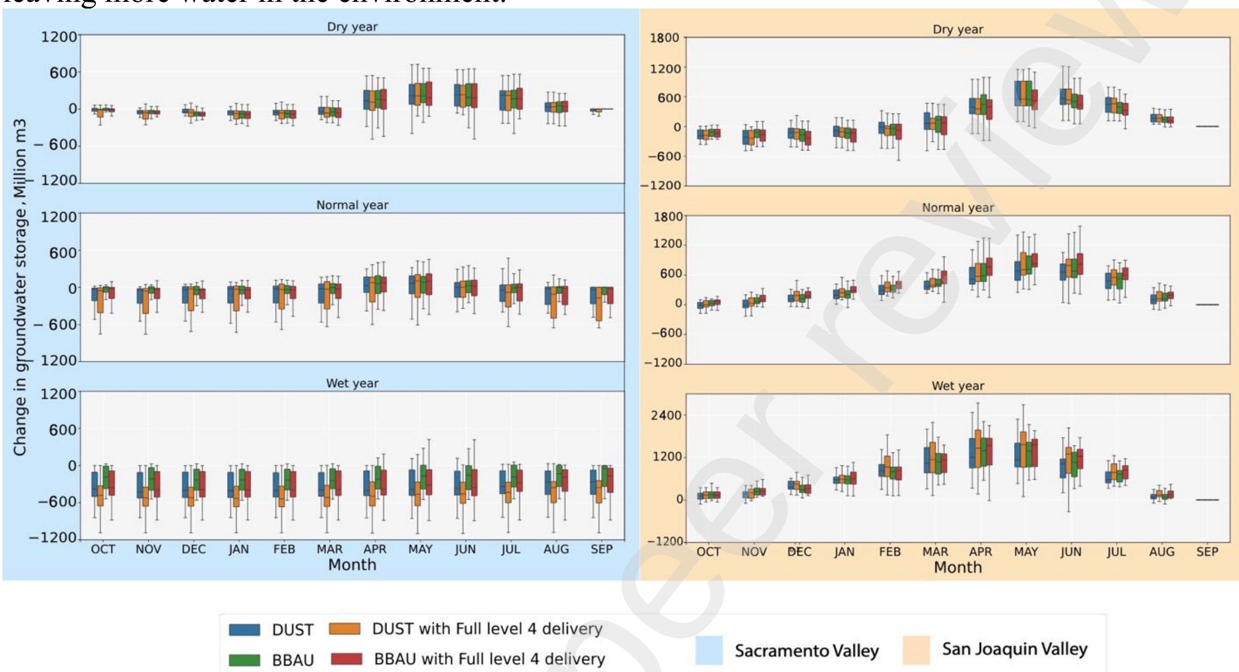

Figure 8 Groundwater level changes compared to historical levels by month in different water year types with and without increasing environmental water use for full Level 4 deliveries. Box limits show groundwater level upper and lower quartiles in the focal month water year type per scenario; whiskers show the minimum and maximum groundwater levels in the focal month and water year type per scenario; the solid line within the box shows the median groundwater level.

4. Conclusion

Given the change from normal to more severe extremes and shifting water year types of thresholds, water allocation decisions based on stationary historical data may not apply to the future with a changing hydroclimate (Null & Viers, 2013b). Redistributing water across space and time/ across regions and seasons according to different water year types will help maintain the historical proportions of water allocation to competing users as hydrographs shift under climate change while minimizing economic cost. In this study, we detail specific allocation recommendations for climate change-adapted water management according to region, water use, and different climate and management scenarios. Our study uniquely identifies the seasonal conflicts between agricultural and environmental water use under climate change. When it comes to environmental use, particularly in the San Joaquin Valley, environmental water uses peak time conflicts with the agricultural growing season. Our results can reconcile human and environmental water use with minimized water allocation cost at a landscape level while sustainably managing groundwater and conserving biodiversity.

Under climate change, the economic value of water increases due to intensifying competition between humans and nature and increased water shortage severity. The use of water pricing and a cost-efficient water allocation can increase the efficacy of water management that is adapted to climate change and extreme hydrological events. We present the variations in these economic values across the State of California that demonstrate market fluidity for water trading. Controlling groundwater overdrafts and prioritizing environmental delivery would drive the agricultural water delivery price in the San Joaquin Valley South Bay region significantly higher than in other regions. We found that the price of agricultural water use is almost 10 times the historical price. The willingness to pay for environmental water is as high as $1,700 per thousand m^3 under hot-dry conditions with water management scenarios, indicating a very high economic benefit for environmental water use. The environmental water price may not represent the real market price (price can be impacted by other socio-economic factors, such as environmental justice); however, the estimation allows us to compare the benefits of environmental water use with agricultural and urban water use on the same monetary scale. The wide variation in water economic values across regions and sectors shows potential for a water market and water trading. We suggest that our modeled water prices be used to design pricing schemes for different water use sectors to promote cost-efficient water allocation.

Although water management increases agricultural shortage and water costs, such costs can be compensated by the ecological benefits of conserving biodiversity and groundwater recharge. Increasing environmental water use to fulfill the full Level 4 refuge delivery will co-benefit groundwater recharge particularly in the San Joaquin Valley and increase the groundwater level by around 200 million m^3 on average during the period from February to July in the hot-dry scenario. If the climate condition is warm-wet, there are still prominent co-benefits between increasing environmental water use and groundwater recharge as we saw a bigger increase in groundwater levels by around 150 million m^3 with full Level 4 deliveries than without full Level 4 deliveries. In our study, we developed hydro-economic optimized water allocation recommendations and market mechanisms for cost-efficient water management that benefits both human and nature water uses while minimizing the shortage costs to all in future scenarios with climate change.

Data Availability

Hydroclimatic projection data can be accessed from https://gdo-dcp.ucllnl.org/downscaled_cmip_projections/dcpInterface.html#About. Data for intermediate, and final results of this study are available from GitHub repository https://github.com/lily6966/CALVIN-INFEWS/tree/main

Code Availability

The CALVIN model's source code is available in a GitHub repository https://github.com/ucd-cws/calvin. Code used to generate the figures and analysis in this study are available from GitHub repository https://github.com/lily6966/CALVIN-INFEWS/tree/main

Supplementary Information

Supplementary Information is provided with the publication.

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L. Li, J. Viers, J. Medellin-Azuara, K. Vache, S. Khan, and M. Conklin conceived and designed this study. J. Rodriguez-Flores, S. Cole, and J. Medellin-Azuara designed agriculture land use optimization for targeted agricultural applied water and shortage cost. L. Li, S. Null, and J. Viers designed hydroclimate and policy representations for combined scenarios. L. Li designed the surface water hydrology change projection. L. Li and S. Null designed environmental water use change condition representation. M. Dogan designed the groundwater hydrology change projection. K. Vache designed a mapping method for projected groundwater basin precipitation data acquisition. L. Li designed the computational methodology and processed data. L. Li, M. Maskey, and J. Medellin-Azuara designed the analysis of the model products. L. Li wrote the first draft of the manuscript, and all authors contributed substantially to revisions.

Conflict of Interest Statement

All authors declare that they have no competing interests.

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