ADVANCING HYDRO-ECONOMIC OPTIMIZATION TO IDENTIFY VULNERABILITIES AND ADAPTATION OPPORTUNITIES IN CALIFORNIA'S WATER SYSTEM

A Report for:

California's Fourth Climate Change Assessment

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Edmund G. Brown, Jr., *Governor*

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PREFACE

California's Climate Change Assessments provide a scientific foundation for understanding climate-related vulnerability at the local scale and informing resilience actions. These Assessments contribute to the advancement of science-based policies, plans, and programs to promote effective climate leadership in California. In 2006, California released its First Climate Change Assessment, which shed light on the impacts of climate change on specific sectors in California and was instrumental in supporting the passage of the landmark legislation Assembly Bill 32 (Núñez, Chapter 488, Statutes of 2006), California's Global Warming Solutions Act. The Second Assessment concluded that adaptation is a crucial complement to reducing greenhouse gas emissions (2009), given that some changes to the climate are ongoing and inevitable, motivating and informing California's first Climate Adaptation Strategy released the same year. In 2012, California's Third Climate Change Assessment made substantial progress in projecting local impacts of climate change, investigating consequences to human and natural systems, and exploring barriers to adaptation.

Under the leadership of Governor Edmund G. Brown, Jr., a trio of state agencies jointly managed and supported California's Fourth Climate Change Assessment: California's Natural Resources Agency (CNRA), the Governor's Office of Planning and Research (OPR), and the California Energy Commission (Energy Commission). The Climate Action Team Research Working Group, through which more than 20 state agencies coordinate climate-related research, served as the steering committee, providing input for a multisector call for proposals, participating in selection of research teams, and offering technical guidance throughout the process.

California's Fourth Climate Change Assessment (Fourth Assessment) advances actionable science that serves the growing needs of state and local-level decision-makers from a variety of sectors. It includes research to develop rigorous, comprehensive climate change scenarios at a scale suitable for illuminating regional vulnerabilities and localized adaptation strategies in California; datasets and tools that improve integration of observed and projected knowledge about climate change into decision-making; and recommendations and information to directly inform vulnerability assessments and adaptation strategies for California's energy sector, water resources and management, oceans and coasts, forests, wildfires, agriculture, biodiversity and habitat, and public health.

The Fourth Assessment includes 44 technical reports to advance the scientific foundation for understanding climate-related risks and resilience options, nine regional reports plus an oceans and coast report to outline climate risks and adaptation options, reports on tribal and indigenous issues as well as climate justice, and a comprehensive statewide summary report. All research contributing to the Fourth Assessment was peer-reviewed to ensure scientific rigor and relevance to practitioners and stakeholders.

For the full suite of Fourth Assessment research products, please visit www.climateassessment.ca.gov. This report advances the understanding of the cost of water supply shortage under a range of future climates and examines possible adaptations to operations and infrastructure to help mitigate these impacts.

ABSTRACT

Long-term shifts in the timing and magnitude of reservoir inflows will affect water supply reliability in California. Hydro-economic models can help explore climate change concerns by identifying system vulnerabilities and adaptation strategies for statewide water operations. This work contributes a new open-source limited foresight implementation of the CALVIN model, a hydro-economic model including roughly 90% of California's urban and agricultural water demands. The model includes the ability to determine water allocations on an annual basis without knowledge of future availability, and to efficiently evaluate ensembles of streamflow projections representing a range of possible future climates. We then assess the vulnerability of the statewide system to changes in total annual runoff and the fraction of runoff occurring during winter, which primarily depends on temperature. Results are analyzed with a focus on adaptation strategies, aided by the economic representation of water demand in the model. These strategies include changes to reservoir operating policies, and conveyance and storage expansion. As water availability decreases, model results show quadratic increases in shortage cost, and corresponding increases in the marginal costs of adaptation strategies and environmental flow constraints. Reservoirs adapt to warmer climates by increasing average storage levels in winter and routing excess runoff to downstream reservoirs with available capacity. Both small and large changes to reservoir operations were observed compared to historical hydrology, showing that no single operating strategy achieves optimality for all reservoirs. Increasing the fraction of winter flow causes small increases in total shortage cost, indicating the ability to manage a changing hydrologic regime with adaptive reservoir operations. The results of this project improve estimates of the cost of climate change to California's water system under a range of future conditions and highlight adaptation strategies that minimize costs of increased hydrologic variability.

Keywords: water supply, drought, economic impacts, adaptation

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HIGHLIGHTS

- A new open-source implementation of the CALVIN hydro-economic model has been developed, which includes limited foresight and more efficient runtime for evaluating scenario ensembles.
- A range of plausible future scenarios are developed by sampling changes in water availability, representing changes in annual precipitation, and the fraction of winter runoff, which represents increasing temperature. These scenarios are compared to the Fourth Assessment streamflow projections to understand possible changes to runoff timing and magnitude.
- Water supply vulnerability is examined by considering shortage costs at the statewide and regional level. Water shortage costs are more sensitive to annual water availability than runoff timing, particularly reductions of 20-30%. Results also show an increased sensitivity to changes in runoff timing in very dry scenarios.
- Economical adaptation strategies include substantial changes to optimal reservoir operations in dry scenarios, particularly for the large reservoirs in Northern California. This low-cost adaptation requires little new infrastructure.
- The marginal value of additional reservoir capacity is generally low compared to the value of operational changes. Several conveyance facilities for urban delivery are identified where it may be worthwhile to increase capacity to improve robustness to scenarios with reduced water availability.

WEB LINKS

- HOBBES Web Interface: https://hobbes.ucdavis.edu/
- Open-source CALVIN model: https://github.com/ucd-cws/calvin

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1: Introduction

1.1 Climate Change and California Water Supply

The projected impacts of climate change, including increases in extreme floods and droughts, pose substantial challenges to long-term water security in California [*Hayhoe et al.*, 2004; *Maurer*, 2007; *Yoon et al.*, 2015]. Successful adaptation of water resources policy and infrastructure will be informed by realistic models of human-hydrological interaction with climate change and variability. Hydro-economic optimization models provide a promising means to study adaptation capacity, as they allow the future behavior of the water system to be driven by economics, subject to regulatory and infrastructure constraints, without the need to determine changes to existing operating rules [*Hanak and Lund*, 2012a]. Prior studies have employed optimization models to evaluate the cost of water supply adaptation under climate warming [*Lund et al.*, 2003; *Tanaka et al.*, 2006; *Medellín-Azuara et al.*, 2008; *Connell-Buck et al.*, 2011a]; however, cost estimates thus far have represented an optimistic lower bound due to modeling assumptions of perfect foresight and statewide markets. An opportunity exists to improve hydro-economic optimization of California's water system by relaxing these assumptions to better align with realistic allocation practices. The resulting model can then be used to identify vulnerable infrastructure components and inform adaptation strategies to improve California's water security.

Various water resources models have been used to emulate California's complex water management and explore infrastructure and policy alternatives [*Draper et al.*, 2003]. CALSIM (California Simulation model), WEAP (Water Evaluation and Planning model), and CALVIN (CALifornia Value Integrated Network) are some of the more comprehensive water planning models for California, but many local and regional models exist for individual irrigation districts and water utilities [e.g., *Yates et al.*, 2009; *Lempert and Groves*, 2010; *Connell-Buck et al.*, 2011b; *California Department of Water Resources*, 2014]. Planning models can also be used to explore potential institutional adaptations to climate change, including legal changes to water rights, changes to water pricing, implementation or expansion of water banking, water transfers, and changes in operation of water infrastructure including dams, reservoirs, conveyance infrastructure, and levees [*Loomis et al.*, 2006; *Olmstead*, 2014]. The California Water Plan Update 2013 addresses climate adaptation by predicting water demands in 2050 and evaluating the success of adaptation strategies such as recycled municipal water, conjunctive management of groundwater, and improved water-use efficiency of urban and agricultural users [*California Department of Water Resources*, 2014].

Hydrologic records and climate model projections provide abundant evidence that freshwater resources are vulnerable to climate change [*IPCC*, 2013]. While climate change models generally agree on rising temperatures, projections of precipitation remain uncertain. For example, various downscaled global circulation models (GCMs) for California predict a range of both drier and wetter futures [*Vicuna and Dracup*, 2007]. Most recently, Allen and Luptowitz [2017] project California to receive more precipitation on average in the future due to increase in the El Niño phenomenon. Both short-term and long-term changes in water availability due to changes in precipitation, temperature, snowpack accumulation, humidity, and other important factors have the potential to negatively affect local economies. Higher order effects like prolonged drought can depress agricultural production, while intensified storms may impose costly flood

damages to infrastructure. Uncertainty is inherent in developing climate change projections, but important decisions regarding water infrastructure and operations must be made regardless of agreement in model projections [*Dettinger*, 2005].

A primary element of studying the effects of climate change is identifying system vulnerabilities and measuring system performance under possible projected climates. The IPCC defines vulnerability as "a function of the character, magnitude, and rate of climate variation (the climate hazard) to which a system is exposed, and of non-climatic characteristics of the system, including its sensitivity, and its coping and adaptive capacity" [*Intergovernmental Panel on Climate Change*, 2007]. More specifically for water resources, vulnerability is defined as the severity of the likely consequences of system failure [*Hashimoto et al.*, 1982]. Vulnerabilities limit a water system's ability to perform in a variety of operating conditions; identifying such vulnerabilities is key to developing successful climate adaptation plans. By subjecting a water resources planning model to a range of possible operating conditions, vulnerabilities can be identified and plans can be established to better adapt to extreme hydrologic events.

The prospect of climate vulnerability requires infrastructure and operations to be robust or adaptable to a range of possible futures beyond those for which the system was designed. Recent efforts in this area are discussed in several review papers [*Herman et al.*, 2015; *Maier et al.*, 2016]. Such frameworks are useful in climate modeling because of the variety of GCMs and emissions scenarios available, and the uncertainty of what future climate will be realized. Accounting for the uncertainty in these projections creates more system flexibility to adapt to a range of possible parameters. U.S. government agencies at various levels, such as the Metropolitan Water District of Southern California, U.S. Bureau of Reclamation, Denver Water, and the California Department of Water Resources have used robustness-based approaches in their planning processes [*Weaver et al.*, 2013]. The goal of these studies is to identify future vulnerable conditions leading to inability to meet water delivery objectives, develop computational tools to define a portfolio of management options reflecting different management strategies, and to evaluate these portfolios across a range of simulated future scenarios to quantify the relative benefits realized in each scenario [*Groves et al.*, 2013].

This work employs a bottom-up vulnerability assessment using an ensemble of climate scenarios to identify climate vulnerabilities and adaptation strategies for California water supply management. Here we assess the vulnerability of the statewide system to changes in total annual runoff (representing changes in precipitation) and the fraction of runoff occurring during the winter months (primarily a function of temperature). An ensemble of scenarios is sampled and compared to long-term streamflow projections. This sensitivity analysis technique samples a wide range of input parameters and analyzes the optimization results in each scenario. These scenarios are evaluated using a new open-source version of the CALVIN model, a network flow optimization model encompassing roughly 90% of the urban and agricultural water demands in California, which can run scenario ensembles on a parallel computing cluster. The economic representation of water demand in the model yields several advantages for this type of analysis: optimized reservoir operating policies to minimize shortage cost, and the marginal value of adaptation opportunities, defined by shadow prices on infrastructure and regulatory constraints. This study contributes an ensemble evaluation of a large-scale network model to investigate uncertain climate projections, and an approach to interpret the results of economic optimization for long-term adaptation strategies.

1.2 Hydroeconomic Modeling

Hydro-economic optimization models integrating water resources infrastructure, management policies, and economic values have aided decision making for decades [*Harou et al.*, 2009]. When a water supply system is represented as a network of storage and demand nodes, connected by links representing conveyance infrastructure, the least-cost water allocation for the network can be determined via optimization. The CALVIN model [*Draper et al.*, 2003] uses the network flow optimization approach to minimize the statewide operating and scarcity costs of water supply, subject to infrastructure and regulatory constraints. For the purpose of climate change assessments, hydro-economic optimization offers several advantages relative to simulation modeling: water demands are treated as economic functions rather than fixed requirements, and marginal values of promising infrastructure and policy options are identified automatically during the model run. This study seeks to improve the realism of the CALVIN hydro-economic model for climate impact assessment.

Building on work from prior California Climate Assessments, hydro-economic optimization is used in this study to identify promising adaptation strategies for California's water system. Because the optimization model is formulated as a network flow problem, the shadow prices for each constraint are computed automatically. Shadow prices can be interpreted as the benefit of relaxing each constraint ($ per acre-foot of water), which in physical terms represents either an expansion of storage/conveyance capacity, or a modification of environmental flow requirements. This process locates the facilities in the system for which adaptations would prove most valuable, depending on the hydrologic inputs chosen. The optimal allocations include agricultural and urban supplies, drawn from surface reservoirs and groundwater. In previous studies, the agricultural water allocations from CALVIN have been post-processed using the SWAP model [*Howitt et al.*, 2012] to estimate cropping patterns under climate change.

Prior work has addressed the economically-driven adaptation of California's water system to climate change. Tanaka et al. (2006) combine climate change scenarios with population growth through the end of the century, with several important findings: (1) agricultural users in the Central Valley are most vulnerable to climate warming; (2) on average, the value of expanding conveyance capacity is substantially higher than the value of expanding storage; (3) changes to the conjunctive use of surface and groundwater will be needed to buffer against climate variability; and (4) environmental flow requirements can be met, but those which require water to leave the managed system will create high shortage costs for urban and agricultural users during drought. Medellín-Azuara et al. (2008) reach similar conclusions for a particularly dry climate scenario, with additional recommendations for optimal operating rules under climate warming in terms of the amplitude of the reservoir drawdown-refill cycle and the balance of storage between reservoirs. Connell-Buck et al. (2011a) disaggregate the impacts of rising temperature from decreasing runoff, noting that the latter leads to more pronounced economic impacts than warming alone. In these prior studies, it was recognized that the assumption of perfect foresight may lead to an optimistic assessment of costs and adaptation strategies. This contrasts with simulation studies which neglect integrated, economically-driven adaptation to climate and population changes and thus may suggest overly negative outcomes [*Medellín-Azuara et al.*, 2008]. This study aims to improve estimates between these two extremes.

1.3 Contributions

This work furthers four interrelated objectives:

- *Improve the realism of modeled climate adaptation costs*. This study optimizes water allocation on an annual timestep, reflecting limited foresight of water availability. It also employs a regional representation of water trading, relaxing the assumption of perfect statewide markets to align with realistic allocation practices. Restricting allocation to the regional scale provides an opportunity to study the geographic distribution of shortage costs during future droughts.
- *Improved representation of institutional constraints*. This study improves the realism of hydro-economic optimization by incorporating institutional constraints represented by the enforcement of water rights.
- *Adaptation strategies*: This work identifies the most economically promising strategies for climate adaptation via sensitivity analysis. A significant advantage of optimization models is that sensitivity values are computed automatically during the model run and represent the marginal value of relaxing each constraint. Constraints may represent infrastructure or policy limitations, as well as water availability; in either case, the dual variables resulting from the optimization will identify the most valuable adaptations in the system.
- *Robustness analysis*: Projections of future water availability in California remain highly uncertain, largely due to uncertainty in precipitation. In addition to running the model for the assigned hydrologic scenarios, this work considers a range of scenarios with more severe dry periods to determine the range of potential adaptation costs, with a focus on how optimal adaptation strategies change under increasingly severe scenarios.

In achieving these scientific objectives, a new open-source version of the CALVIN model is created to provide the flexibility to perform these analyses (https://github.com/ucd-cws/calvin). It is available online for researchers around the world, and in California agencies, to study California's water supply system.

2: Methods

2.1 CALVIN Model

Network flow programming is an apt tool for studying infrastructure systems like transportation, energy, and water resources. CALVIN is a hydro-economic optimization model of California's water network with an 82-year hydrologic input dataset. Under baseline conditions, this period represents the hydrology from 1922-2003, but it can be modified to represent any period of this length. Economics are represented by demand functions developed for urban and agricultural areas throughout California, which assign a cost of water shortage to a range of delivery volumes. Figure 1 shows the regions of California included in the CALVIN model. Areas excluded from the model have comparatively low water consumption.

The network flow structure in CALVIN is represented by a set of nodes and links subject to constraints. A node is defined by a location element and temporal element. A link connects two nodes and has the following properties: flow (decision variable), unit cost, amplitude (loss factor), lower bound, and upper bound. This structure allows the model to deliver water both across the network within a specified time step and to represent storage at reservoirs as links between two time steps at a specified location.

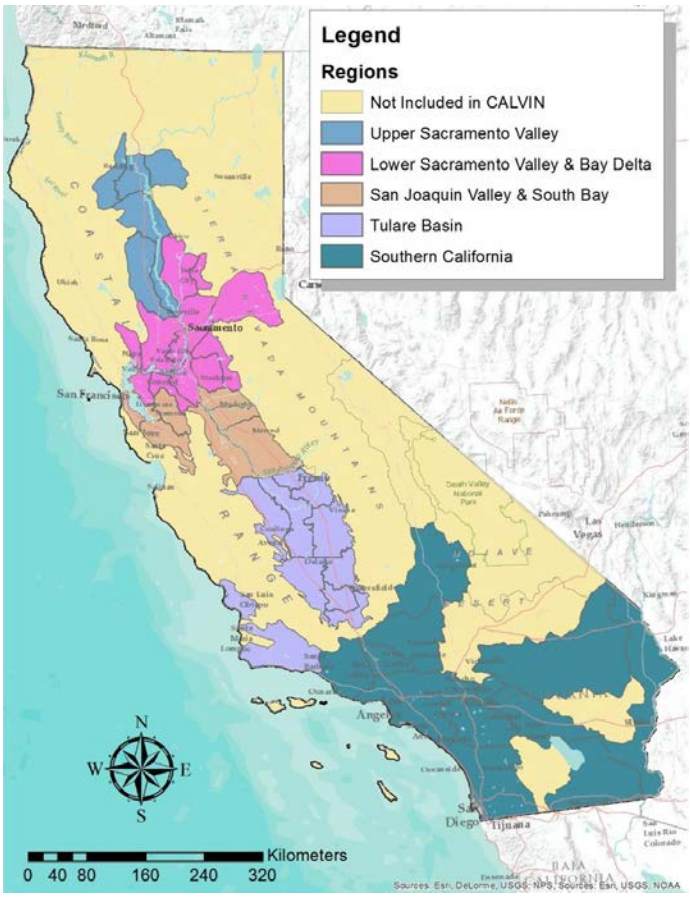

Figure 1: California regions represented in CALVIN. From Dogan (2015).

The CALVIN model solves the network flow problem using linear programming to optimize flow over all links in the network to minimize the combined cost of water shortage and operations. Hydrology-related inputs include surface and groundwater hydrology, environmental flow constraints, and wildlife water deliveries. Model results include valuable management information about combined operations of surface and groundwater reservoirs, environmental flows, and hydropower. Outputs also include economic data, including shortage costs in drought years, and marginal values of storage and conveyance capacity.

CALVIN contains most of California's water system in a single model. It represents economics in a linear programming framework to operate the system in an economically efficient way. Hydro-economic models like CALVIN provide an opportunity for water resources modelers to analyze potential changes to operations without assuming that current reservoir operating rules and conveyance agreements will remain static, suggesting how optimal operations of the system might be modified in the future (Olmstead 2014).

2.1.1 Agricultural and Urban Demands

Projected urban and agricultural water demands are based on the year 2050 considering changes in land use, per capita water use, and population growth. This comprises roughly 90% of the water demands in California, divided into an average of 25 MAF/year for agricultural demand, and 12 MAF/year for urban demand [*Dogan*, 2015]. The demand functions, along with all hydrologic data, are exported from the HOBBES database [*Medellin-Azuara et al.*, 2013],

which is freely available online. The demand functions are piecewise-linear representations of quadratic functions, reflecting diminishing returns to water delivery. In the optimization model, each piece of the curve is represented by a separate link.

2.1.2 Limited Foresight

Prior modeling studies have considered perfect foresight of water availability over a planning horizon of several decades, providing an optimistic lower bound of adaptation costs by allowing the model to reduce allocations long in advance of severe droughts. In reality, costs will be higher due to limited forecasting ability. The theory behind limited foresight modeling for California systems was first developed by Draper [2001]. This task will aim to optimize statewide water allocations on a more realistic annual timestep.

In the context of hydro-economic modeling, limited foresight can be introduced in several ways. First, end-of-period reservoir storage can be constrained to a static value. Second, a cost could be assigned to the carryover storage volume in each reservoir, allowing the optimization method to reduce allocations in the current period to avoid potentially larger shortage costs in the following period. This results in the optimal carryover storage cost function, along with the implied optimal hedging rule for the storage-release curve of a single reservoir [*Draper and Lund*, 2004]. For multiple reservoirs, as in the case of California's water system, a separate cost function would need to be defined for each reservoir. This greatly increases the dimension of the parameter search space, resulting in a challenging computational task. Instead, we use constant carryover storage constraints for each reservoir, after testing a range of possible constraints to identify the one with the minimum statewide cost. Comparison to costs in the perfect foresight case will also highlight the value of improved forecasting.

2.1.3 Water Rights

Beyond the assumptions of perfect foresight and statewide markets, the realism of hydro-economic optimization can be improved by incorporating institutional constraints, which may prevent the modeled optimal allocation of water but nevertheless must be respected in the real system. This task incorporates tools from concurrent work in the key area of water rights.

The enforcement and curtailment of water rights plays an important role during times of shortage, as seen during the 2012-16 drought. While the formulation of the CALVIN model follows the economic principles that nominally guide curtailment decisions—for example, restricting agricultural deliveries in favor of higher-value urban uses—it does not enforce riparian and appropriative rights prior to determining the optimal allocation. To overcome this limitation, we draw from ongoing work on the Drought Water Rights Allocation Tool (DWRAT), developed in collaboration with the State Water Resources Control Board [*Lord et al.*, 2018]. DWRAT provides two advantages to improve the realism of hydro-economic modeling: first, a database of all water rights in California, and second, an optimization model to enforce them, subject to water availability in a particular basin. Specifically, the DWRAT framework develops intra-basin estimates of full natural flow using a statistical model, then solves two linear programs in sequence to determine curtailments for riparian and appropriative rights holders, respectively (Lund et al., 2014). Water allocations and curtailments provided by DWRAT will allow basin-scale water rights to be respected prior to solving for the minimum-cost allocation with CALVIN. Urban water use may also be curtailed to provide benefits elsewhere in the system [*Ragatz*, 2012]. The DWRAT model is employed for the Sacramento River Basin, providing an opportunity for a pilot study in one of the largest CALVIN regions.

2.2 Climate Scenarios

The downscaled climate projections include 10 different climate models at 2 emissions levels (RCP 4.5 and 8.5), totaling 20 climate scenarios, to analyze how climate change will impact California water resources [*Pierce et al.*, 2014]. These precipitation and temperature scenarios are downscaled and routed through the Variable Infiltration Capacity (VIC) hydrologic model [*Liang et al.*, 1994] to produce streamflow at 58 locations throughout California. Many of these correspond directly to CALVIN reservoir inflow sites or can be mapped to them by correlation. Because only a comparatively smaller set of the streamflow locations are bias-corrected, we propose a strategy to impose hydrologic perturbations on the historical data based on the relative ratios of future to historical monthly inflows.

2.2.1 Rim Inflow Multipliers

Combining the information provided by the GCM projections with the CALVIN model allows modelers to understand how California may adapt to changes in timing and magnitude of reservoir inflows. Instead of using the direct streamflow values outputted by the GCM model, a perturbation method is used to modify CALVIN's historical hydrology to reflect the GCM's behavior, following an approach originally developed by California state agencies [*Miller et al.*, 2001]. The application of perturbation ratios to model climate change in the CALVIN model has been implemented in previous studies [*Tanaka et al.*, 2006; *Medellín-Azuara et al.*, 2008; *Harou et al.*, 2010; *Connell-Buck et al.*, 2011b]. These ratios are applied to rim inflows, which are the water volumes input to the model originating outside the model domain.

The perturbation method requires two time periods to be identified: a historical period and a future period. For the Fourth Assessment scenarios, the historical period is defined as 1950-2000 and the future period is defined as 2070-2100. This future climate period extends past the demand projections (2050) to explore the impacts of potentially more severe climate change on the system. A multiplier is calculated by dividing the average streamflow of the study period by historical period for every month, yielding 12 multipliers for each location provided. The locations provided for the downscaled hydrology projections are matched with CALVIN inflows. For example, Figure 2 shows the 12 perturbation ratio multipliers for the inflow to Shasta Lake. Some CALVIN inflow locations are not included in the downscaled scenarios, so a correlation analysis was performed to determine the most highly correlated rim inflow from CALVIN's historical hydrology data and apply the same multiplier to the missing rim inflows. These multipliers are then applied to CALVIN historic hydrology and the model is optimized. Multipliers for the inflow at Shasta Lake are shown in Figure 2 with the baseline value (1.0) representing historical hydrology. Multipliers greater than 1.0 indicate a wetter monthly average compared to the scenario's historic period; multipliers less than 1.0 represent a smaller

monthly average compared to the historic period.

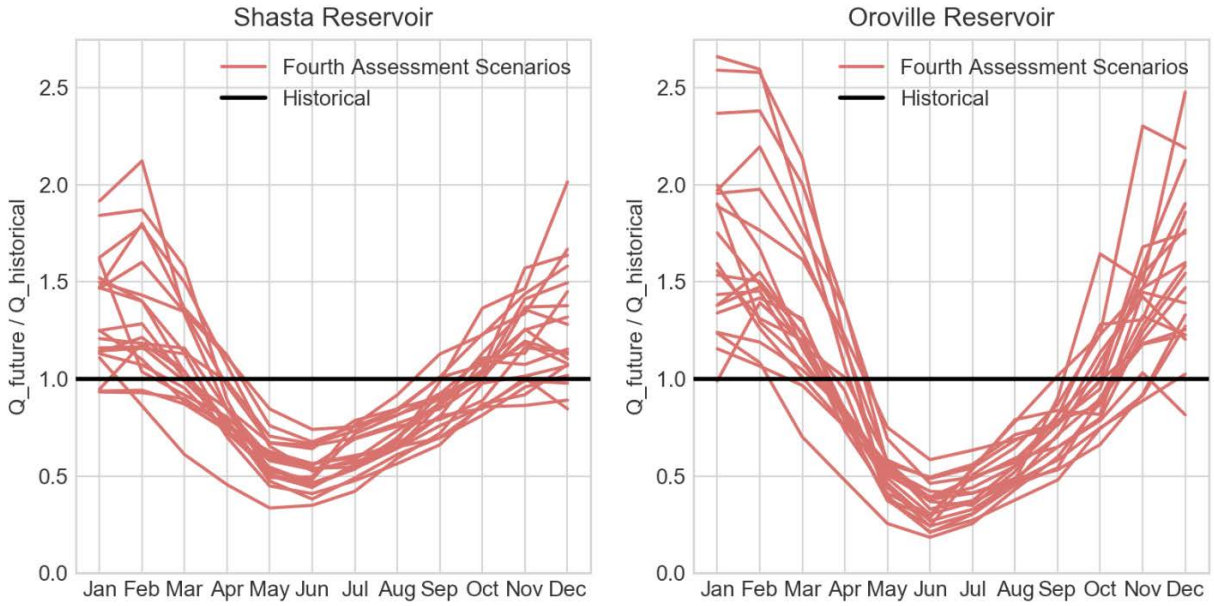

Figure 2: Example monthly runoff multipliers for downscaled hydrology projections, inflow to Shasta and Oroville Reservoirs. Values greater than 1.0 represent months that are wetter than historical on average, regardless of the absolute volume of runoff in that month.

As shown in Figure 2, these monthly perturbations shift the hydrology of each year according to the same pattern. It captures seasonal shifts but does not expand the range of wet and dry annual extremes. In future work it may be possible to develop a method to incorporate seasonal shifts while also increasing the inter-annual variance of flows. The rim inflow multipliers used for this study, along with explanations of correlations between sites, are available in the project Github repository (https://github.com/ucd-cws/calvin/tree/master/calvin/data/fourth-assessment-data).

2.2.2 Sensitivity Analysis Scenarios

In addition to the downscaled hydrology projections, this work explores how California water operations would be optimally altered with shifts in the magnitude and timing of streamflow. In particular, this study focuses on drier scenarios with an increased fraction of runoff arriving in the winter months due to rising temperatures. These changes are imposed via a systematic sampling approach, creating an ensemble of plausible synthetic scenarios which are not linked to any specific time period of future projection.

To measure the timing and magnitude of inflows, the winter index and water availability metrics are used, respectively. The winter index is defined as the fraction of average annual inflow volume from November through April for each climate scenario, divided by the historical average inflow from November through April. Winter index (WI) values greater than 1 indicate a larger proportion of inflows arriving in the winter compared to historical, which would occur with rising temperatures and reduced snowpack.

$$Winter\ Index\ (WI) = \frac{\frac{\sum Average\ Inflows\ from\ Nov\ thru\ Apr\ \ (Scenario)}{Average\ Yearly\ Inflow\ (Scenario)}}{\frac{\sum Average\ Inflows\ from\ Nov\ thru\ Apr\ \ (Historical)}{Average\ Yearly\ Inflow\ (Historical)}}$$

This metric represents increasing temperatures statewide, which yield more precipitation falling as rain rather than snow compared to current conditions; the snowpack that does accumulate also melts faster and earlier than in recent history.

Water availability (WA) is defined as the sum of all rim inflows, representing all water entering the model each year. A drier scenario will see a decrease in average water availability, and a change of 0% represents the average water availability of CALVIN's original hydrology (35.3 MAF/year statewide). Figure 3 shows the 25 scenarios sampled for this experiment, organized into four quadrants: Warm-Dry, Warm-Wet, Cool-Dry, and Cool-Wet. Each axis represents a range of the timing and magnitude scenarios and each square point in the plot represents a sampled scenario with the indicated average water availability and winter index. Importantly, this naming convention and sampling strategy assumes that temperature is the primary variable affecting the seasonality of runoff. It would be possible to have higher winter runoff, for example, due to changing storm patterns in the future rather than increasing temperatures. For this study, we assume that changes in monthly runoff will be primarily driven by temperature and precipitation from shifting snow to rain.

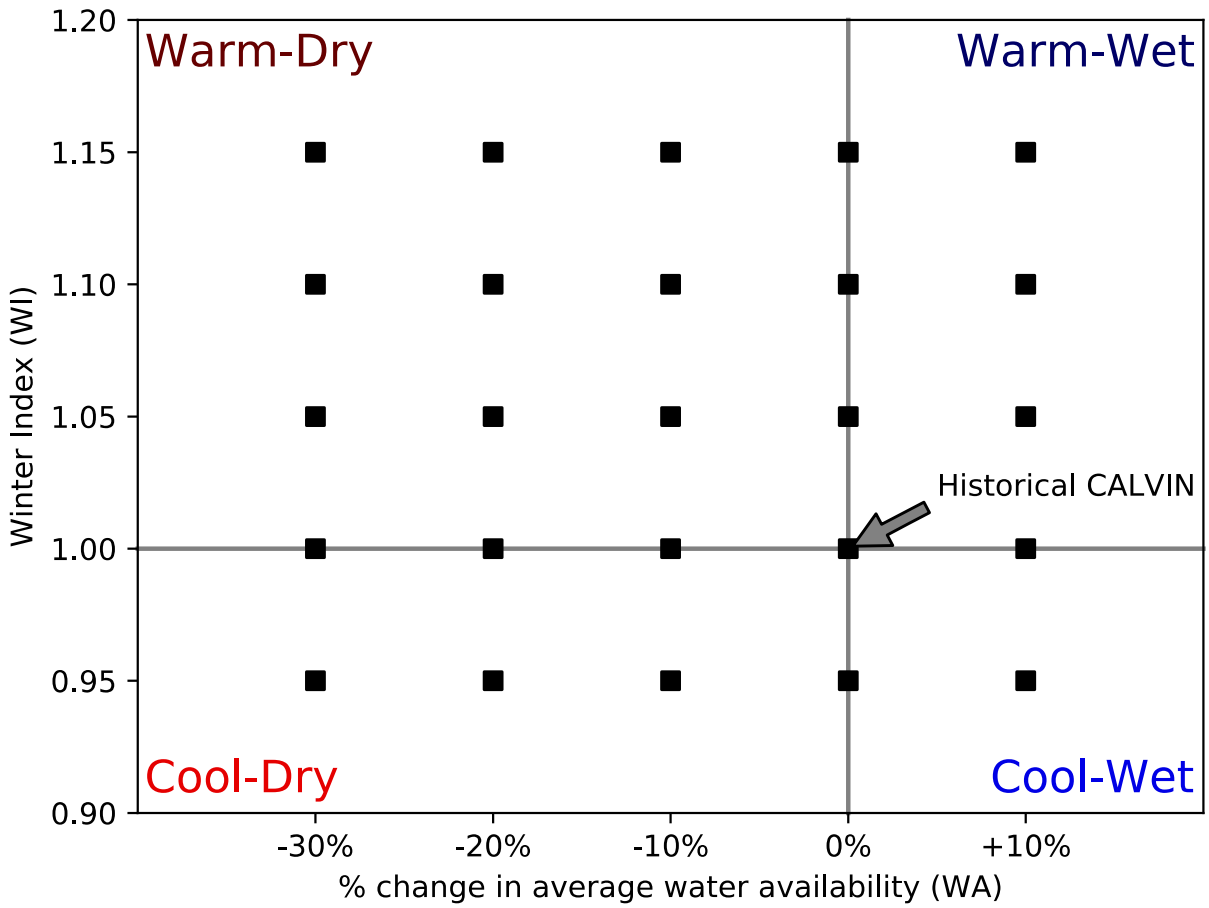

Figure 3: Scenarios varying water availability and winter index developed for sensitivity analysis

To alter the statewide winter index, each rim inflow must be altered individually. Figure 4 below shows the two largest rim inflows by volume (Shasta and Oroville reservoirs) and how their average monthly inflows were altered for the winter index permutations. The winter index values shown in Figure 3 are relabeled as follows: 'cold' scenarios refer to a WI of 0.95, 'Warm1' refers to a WI of 1.05, 'Warm2' refers to a WI of 1.10, and 'Warm3' refers to a WI of 1.15. The scenarios plotted in Figure 4 have the historical water availability with varying winter indexes. The Fourth Assessment scenarios all indicate some amount of warming in the future, but the sensitivity analysis sampling conducted here includes a few colder scenarios to build a more complete picture of the impact of runoff seasonality on the water supply system. These scenarios are not a core focus of the study and are not intended to represent a reduced likelihood of warmer scenarios in the future, which all climate models currently indicate. A similar logic is followed for sampling scenarios drier than the historical record. While many of the current climate projections suggest a wetter future with more extreme storms, this remains highly uncertain. We therefore analyze dry scenarios as well.

To apply the changes in timing and magnitude, multipliers for each month were developed to modify the historical hydrology to reflect the changes in timing and water availability for the given scenario. This method is similar to the perturbation ratio, but the multiplier is calculated based on the degree of change in winter index and water availability. Monthly ratios for each rim inflow were developed manually, ensuring that the fraction of winter runoff and the total

volume of annual runoff match the intended scenario values. In general, there are many possible ways to assign monthly multiplier values to obtain these outcomes, since there are multiple winter months.

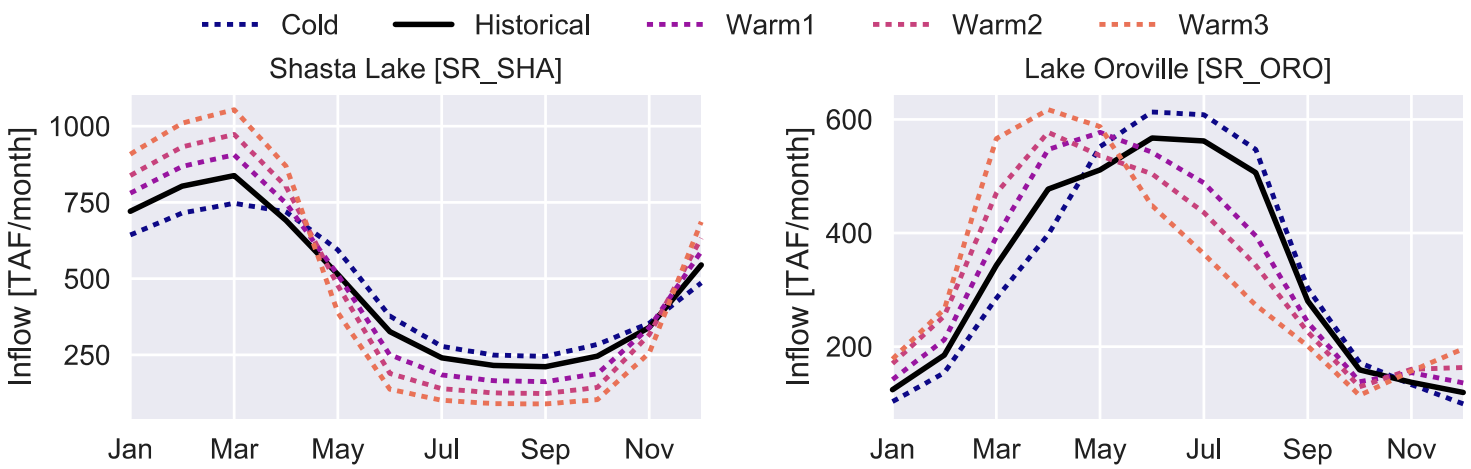

Figure 4: Modified Inflows for Shasta and Oroville reservoirs, by perturbing the Winter Index. These modifications are implemented so that the total annual volume remains the same.

2.3 Computational Experiments

In this study, the model improvements (Section 2.1) and climate scenario evaluation (Section 2.2) were pursued as parallel efforts, and their results are analyzed independently in this report. The model improvements are now available for future research efforts, including but not limited to application to climate change scenarios.

The CALVIN model contains over 5 million decision variables with the full 82-year hydrology and piecewise-linear objective functions. To incorporate climate scenarios, the matrix of links needs to be edited from the historical hydrology. Altering the upper and lower bounds of links in a heavily constrained network often leads to over-constrained systems and subsequent model infeasibilities. The model therefore includes an option for "debug mode" which allows the user to reconcile model infeasibilities. Debug mode adds two additional nodes, a source and sink node, which are linked to all other nodes in the network. These links have an extreme cost ($2 million/acre foot) and are included only to add or remove water when the network is otherwise infeasible. The magnitude of the debug flows is used to adjust the bounds of links within the network to allow model feasibility. The algorithm includes rules that prevent changes to bounds on certain links, including reservoir capacity constraints, reservoir carryover storage requirements, and conveyance constraints. In addition, a record of reduced links is maintained as the algorithm progresses to track which links are reduced for quality control of model results. This process increases the runtime considerably due to solving the model several times before outputting a result, but eliminates the need for the user to change the bounds manually. Figure 5 outlines the algorithm for this automatic debugging process.

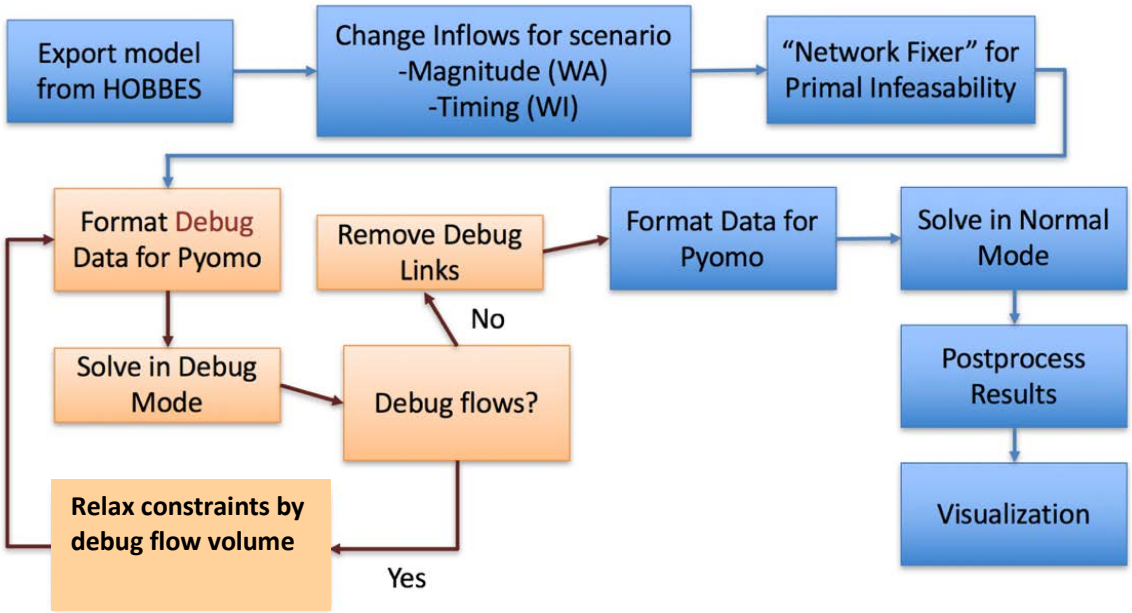

Figure 5: Algorithm to remove infeasibilities in the CALVIN model using a "debug mode". WA and WI refer to the water availability and winter index, respectively, as defined in Section 2.2.2.

The original implementation of CALVIN used the HEC-PRM solver package, requiring roughly 7 days to solve without an initial solution specified. Advances in computing technology, including parallel computing and open-source linear programming solvers, allow the new implementation of the model to be solved within 2 hours for the historical hydrology scenario without an initial solution. Here we use the Pyomo library, written in the Python programming language [*Hart et al.*, 2012], which provides a high-level interface for problem formulation that can be linked to different solvers. For this study, 45 CALVIN runs (20 downscaled scenarios, plus 25 for the sensitivity analysis) were performed on the UC Davis HPC1 high performance computing cluster. The downscaled scenarios represent the current best-known approximation of future precipitation and temperature, while the sensitivity analysis scenarios aim to provide a more comprehensive sampling of the space of possible futures. Each scenario required an average of 9-12 hours to solve. Some model runs that required fewer debug iterations completed within 4 hours, while other scenarios took 3 days to reach a feasible solution. Model results are then post-processed into comma-separated value (CSV) format including timeseries of reservoir storage, dual values, and water supply portfolios. Overall, runtimes are significantly improved with the updated model, which for the first time enables an ensemble of climate scenarios to be evaluated.

The results of the CALVIN scenarios are then analyzed for potential adaptation strategies by investigating water supply portfolios, reservoir operations, and the marginal values of infrastructure capacity expansion. Reservoirs play key roles in managing the state's water resources, so operations of the state's largest reservoirs are examined to understand operating strategies change with water availability and winter index. Changes in operations due to the winter index relative to historical hydrology indicate general adaptation strategies for accommodating warmer climates. Economic outputs such as shortage cost and marginal value

identify infrastructure vulnerabilities and inform on the economic impact of varying water availability and winter index. Finally, conveyance expansion, reservoir expansion, and value of environmental flows are also analyzed to understand how their economic value changes with the magnitude and timing parameters.

3: Results: Model Improvements

This section describes results related to model improvements (runtime, limited foresight, and water rights), conducted separately in parallel to the application of climate change scenarios (Section 4). All results include the perfect foresight assumption except for Section 3.2, which develops and tests the limited foresight version of the model.

3.1 Solver Runtime Comparison

Several state-of-the-art linear programming solvers are available, and it is useful to see how they scale with the number of decision variables for a water allocation problem of this size. Moving the model to a new software platform enables the ensemble evaluation of climate scenarios, among other applications, and runtime benchmarks are an important part of this. For this problem, the number of decision variables can be controlled by the number of years used in the optimization. Here we experiment with model runs of 1, 5, 10, 40, and 82 years of hydrologic data, and record the solver runtime required in each case in debug mode, excluding time for file reading and writing. Four solvers are tested: CBC [*Forrest and Lougee-Heimer*, 2005], Gurobi [*Gurobi*, 2014], and CPLEX [*IBM*, 2009], and GLPK [*Makhorin*, 2008]. Ten trials are performed for each combination of solver and model size, for a total of 200 model runs. Tests are performed on the UC Davis HPC1 cluster, which contains 60 nodes each with 64 GB of RAM and two 8-core dual-threaded CPUs running at 2.4 GHz. The CPLEX, Gurobi, and CBC solvers use shared-memory parallelization on 32 threads, while GLPK is run in serial.

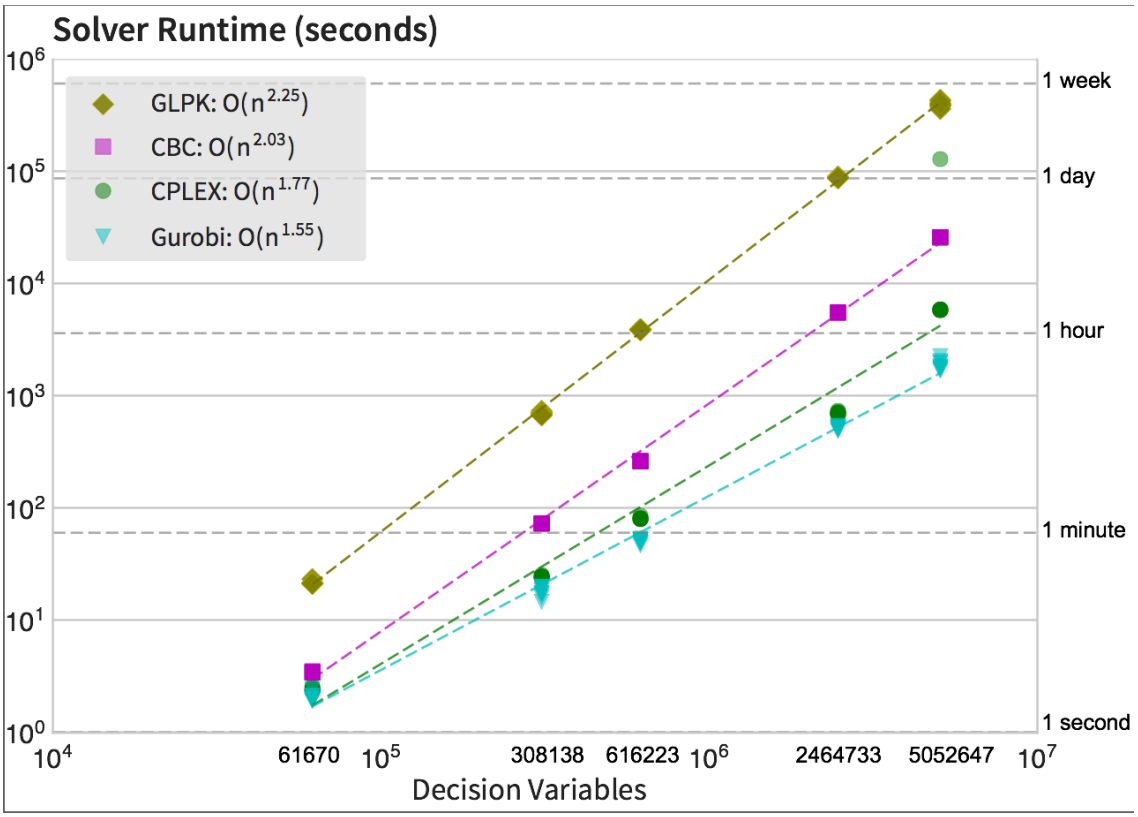

Figure 6: Solver runtimes with linear trend lines on logarithmic scale. Runtimes do not include time for file reading and writing.

Figure 6 shows solver runtimes with increasing numbers of decision variables. Gurobi requires the least amount of time to find a feasible solution for all model sizes. Gurobi requires just over 1 hour to solve the largest model, with about five million decision variables in debug mode, while GLPK (serial) requires roughly 4.5 days. The speedup is partially a function of parallelization, but also the use of different techniques used by each solver. As indicated by the regression lines, solver solution times show a polynomial relationship with the number of decision variables. Runtimes are consistent between trials, with only one outlier for CPLEX with the largest model size (a runtime of 1 day in Figure 6). The Gurobi solver is therefore used for the remainder of the experiments in this study. These results provide an application-focused benchmark for large-scale network optimization problems.

3.2 Limited Foresight

In the full 82-year model, the operation of surface and groundwater storage can be optimized with perfect foresight of future droughts and wet periods. The limitations of this assumption have been long recognized [e.g., *Newlin et al.*, 2002; *Tanaka et al.*, 2006]. Moving to a new software platform offers the flexibility to investigate the alternative assumption of limited foresight, where sequential annual optimizations apply the end-of-period storage from each year as the beginning-of-period inputs for the following year. The key challenge is defining optimization constraints or values for the end-of-period (EOP) minimum carryover storage. To analyze the effect of these carryover constraints, we vary them as a percentage of available surface reservoir capacity above dead pool, from 0% to 50% in steps of 5%. Groundwater

storage volumes are constrained to the optimal end-of-year values from the full 82-year run with perfect foresight. It is a simplifying assumption that the large surface reservoirs would be operated for the same carryover targets as a percentage of their respective capacities; this may increase costs relative to individually specified carryover targets. More advanced methods to assign economic value to carryover storage at individual reservoirs are presented in [*Draper*, 2001; *Draper and Lund*, 2004].

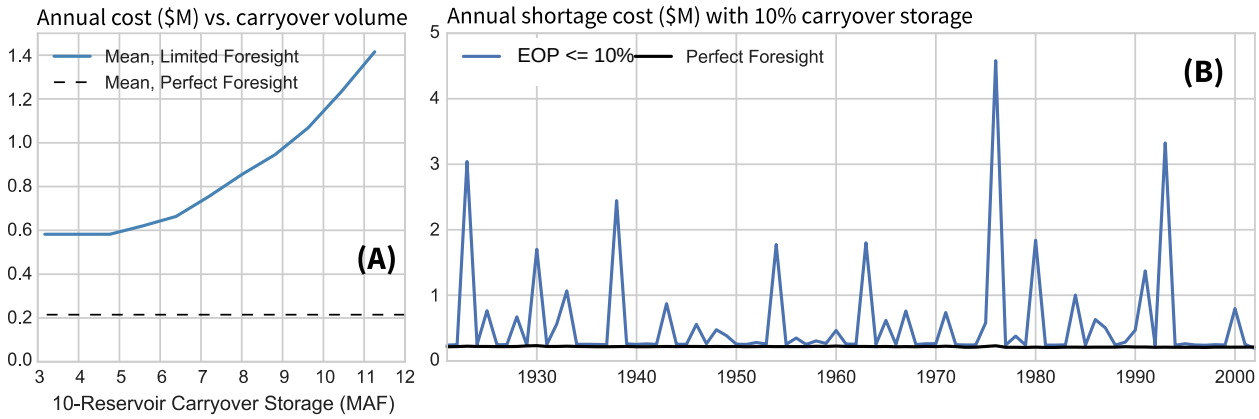

Figure 7: (A) Average statewide annual cost as a function of the end-of-period (EOP) storage volume in the 10 largest reservoirs, given in million acre-feet (MAF). (B) Timeseries of annual shortage cost with an end-of-period constraint of 10% above dead pool.

Figure 7a shows that a carryover storage constraint of about 5 million acre-feet (MAF), or roughly 10% above dead pool, results in the minimum statewide average annual cost. Notably, the average annual shortage cost is approximately three times that in the perfect foresight case. Beyond that point, costs will increase because storing too much for future years causes shortage in the current year. The timeseries in Figure 7b shows that the limited foresight optimization is prone to spikes in annual shortage cost during drought years, whereas the perfect foresight model more evenly distributes cost over the period. This reflects a more realistic management policy, since accurate forecasts of drought events are not available years in advance.

The limited foresight version of the model was created as a parallel effort in this study, so the application of the model to projected climate change scenarios instead uses the perfect foresight version. However, the limited foresight version is now available for future studies.

3.3 Water Rights

Water rights locations and diversion volumes were drawn from the Drought Water Rights Allocation Tool (DWRAT) [*Lord et al.*, 2018], which is based on a statewide database of water rights from the State Water Resources Control Board (SWRCB). In this experiment, only water rights in the Sacramento River basin were considered. Figure 8 shows their locations:

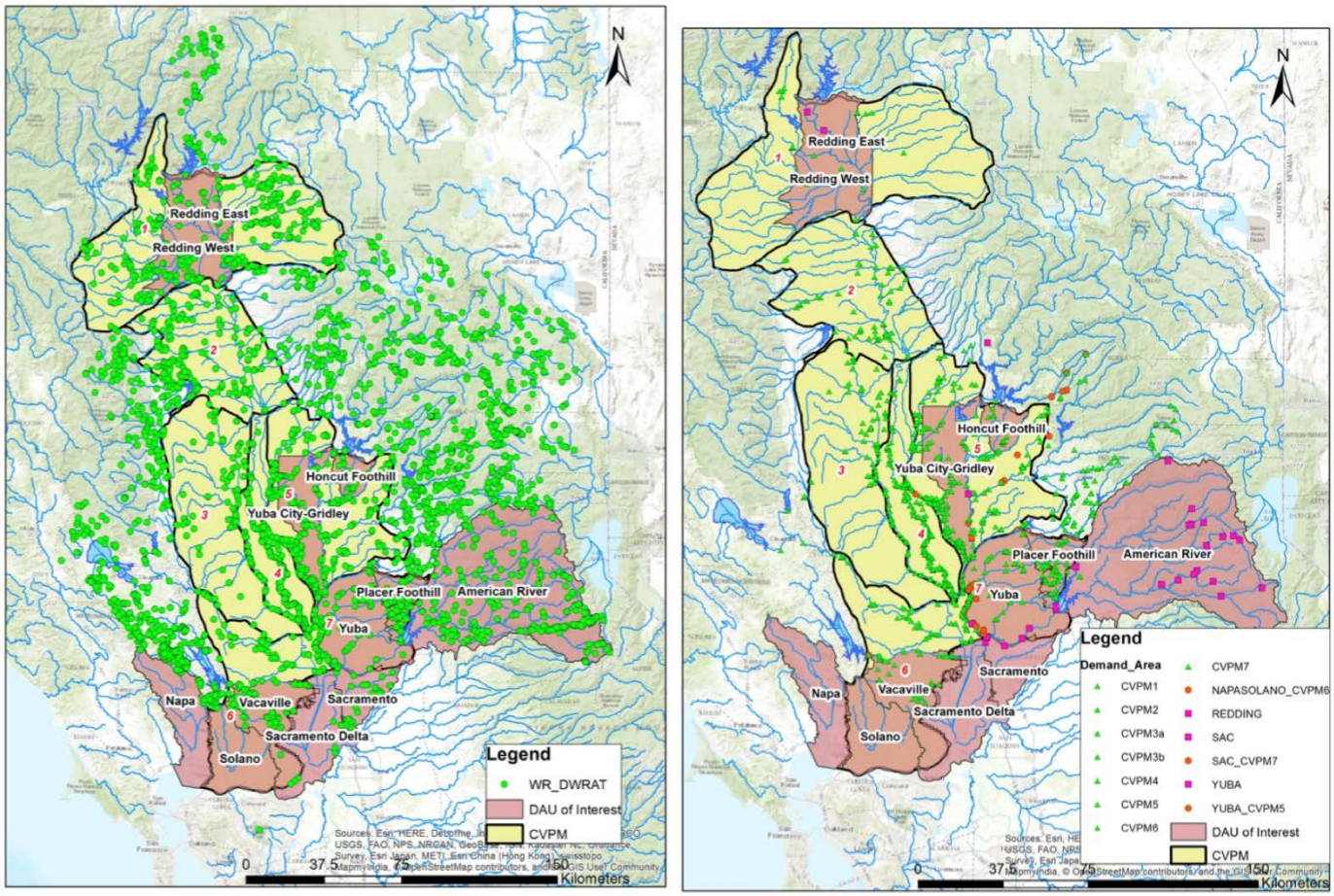

Figure 8: (Left) Location of water rights in the Sacramento River basin from the SWRCB database; (Right) the subset of water rights that align with water demands in the CALVIN model, divided by urban and agricultural regions. The agricultural regions are defined based on the Central Valley Production Model (CVPM).

Many of the rights shown in Figure 8 have a small diversion volume and do not have a large effect on the basin-wide water balance. Therefore, only the larger rights that align with water demands in the CALVIN model were considered in this study. Specifically, the experiment focuses only on urban water rights to determine their effect on modeled allocations. Each of these water rights was assigned to a specific CALVIN demand region (i.e., a node in the network). Figure 9 shows the subset of urban water rights that were considered in this study, stacked by monthly demand volume. The total water use is dominated by only a few large water rights, though the basin-wide total, which peaks at roughly 40 TAF/month in the summer, is fairly low relative to agricultural water demands in the Sacramento Valley, and small compared to urban demands elsewhere in the state.

The water rights volumes taken from the DWRAT model reflect the possibility of curtailment during dry years. These volumes are then used to fix the lower bounds in the CALVIN network optimization during dry years. In other words, we assume that rights holders will divert their full allocation in these years, removing the potential for the model to allocate this water to a higher-value use as it normally would. The goal is to determine the extent to which this

increases the regional water shortage cost, removing the assumption of efficient markets for water trading.

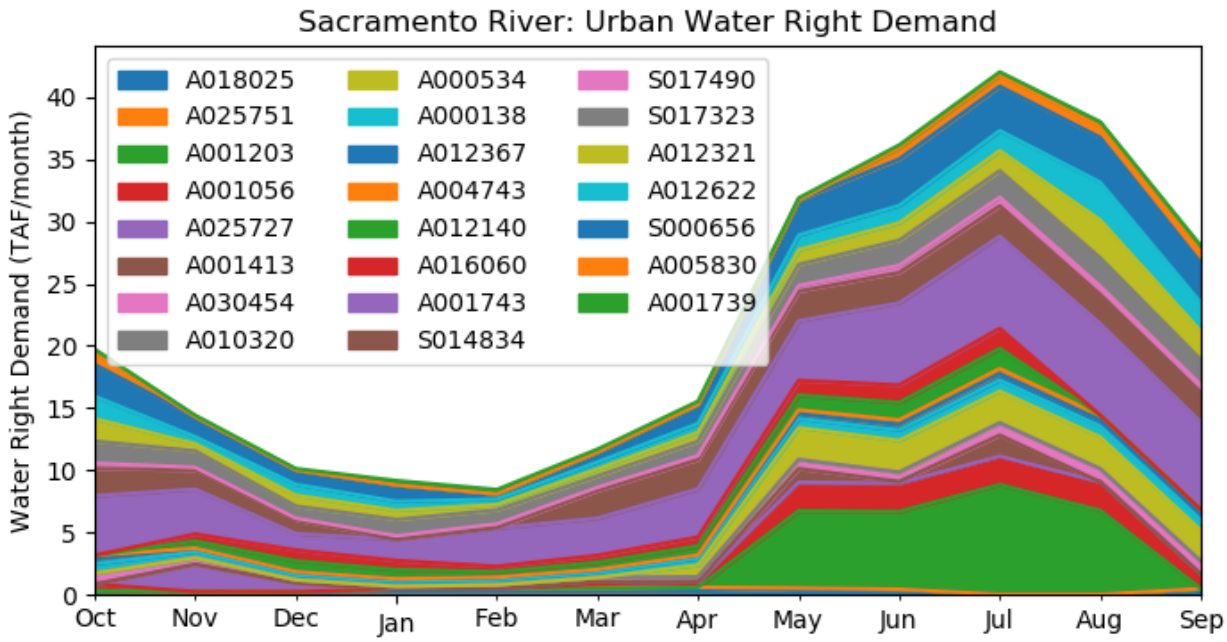

Figure 9: Volume of water demand from rights considered in this study (Sacramento basin urban water rights). Each water right is identified by its application ID, defined by the SWRCB. Appropriative rights begin with "A", and riparian rights begin with "S".

Results from this experiment are shown in Figure 10. The change in shortage volumes when urban water rights are assumed fixed rather than tradeable is negligible, given the limited scope of water rights included in the experiment. Regional average shortage volumes are within 0.01 TAF/month of the baseline scenario, suggesting that the volume of water rights considered in this experiment is small relative to statewide demands, and that the optimization model is able to adjust operations to overcome these small changes in the flow constraints to maintain optimal regional shortage costs.

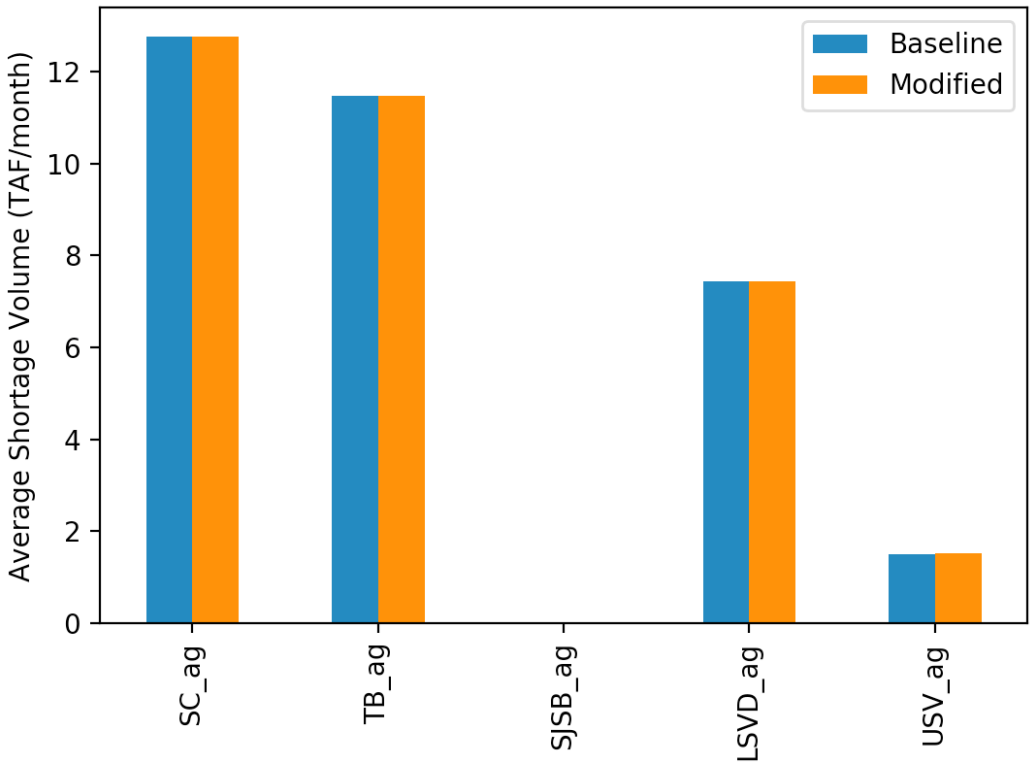

Figure 10: Regional agricultural water shortage costs in the modified network with water rights constraints, for each of the five CALVIN regions: Southern California (SC), Tulare Basin (TB), San Joaquin and South Bay (SJSB), Lower Sacramento Valley and Delta (LSVD), and Upper Sacramento Valley (USV). The modified scenario includes water rights, while the baseline scenario does not.

Larger experiments, beyond the scope of this study, would include a more extensive subset of water rights that can be mapped to CALVIN demand nodes. With fewer options available for trading, shortage costs would be hypothesized to increase. As a proof-of-concept, the ability to integrate water rights data into the hydro-economic optimization is a first step toward removing the statewide assumption of perfect water markets.

4: Results: Model Application

4.1 Fourth Assessment Scenarios

The downscaled climate projections for the Fourth Assessment include 10 different climate models (GCMs) at 2 emissions levels (RCP 4.5 and 8.5), totaling 20 climate scenarios. These are used to perturb CALVIN hydrology to analyze how climate change will impact water resources in California. These projections generally indicate a wetter future, possibly with rainfall arriving in more extreme events, increasing the potential for flooding and exacerbating the tradeoff between flood risk and water supply. Despite predictions of increased average precipitation at certain locations in the state, this does not change the fact that multi-year droughts are a permanent feature of California water supply.

These downscaled hydrology projections were mapped to CALVIN rim inflows using the perturbation ratio method described in Section 2.2.1. Once the multipliers were applied, the average water availability and winter index were calculated for each scenario, shown in Table 1. Most of the scenarios show a higher average annual water availability than the historical scenario, and all of them have a winter index greater than 1.0, indicating an increased fraction of annual runoff occurring during November-March. Figure 11 shows a scatter plot of the scenarios according to these two variables.

Table 1: Average annual water availability and winter index for the downscaled hydrology scenarios. Winter index refers to the fraction of annual runoff occurring in November-March. Scenarios marked in blue have equal or higher average annual water availability compared to the historical scenario, while those marked in orange have lower availability.

SCENARIO	AVERAGE ANNUAL WATER AVAILABILITY (MAF/YR)	WINTER INDEX
HISTORICAL CALVIN	35.3	1
ACCESS1-0_RCP45	38.0	1.09
ACCESS1-0_RCP85	33.7	1.14
CANESM2_RCP45	40.9	1.14
CANESM2_RCP85	50.5	1.22
CCSM4_RCP45	39.1	1.13
CCSM4_RCP85	40.8	1.18
CESM1-BGC_RCP45	37.2	1.09
CESM1-BGC_RCP85	39.3	1.18
CMCC-CMS_RCP45	35.3	1.02
CMCC-CMS_RCP85	37.0	1.00
CNRM-CM5_RCP45	47.5	1.17
CNRM-CM5_RCP85	51.6	1.26
GFDL-CM3_RCP45	36.7	1.07
GFDL-CM3_RCP85	35.3	1.11
HADGEM2-CC_RCP45	38.3	1.06
HADGEM2-CC_RCP85	38.8	1.06
HADGEM2-ES_RCP45	33.1	1.03
HADGEM2-ES_RCP85	37.6	1.07
MIROC5_RCP45	33.3	1.04
MIROC5_RCP85	32.8	1.03

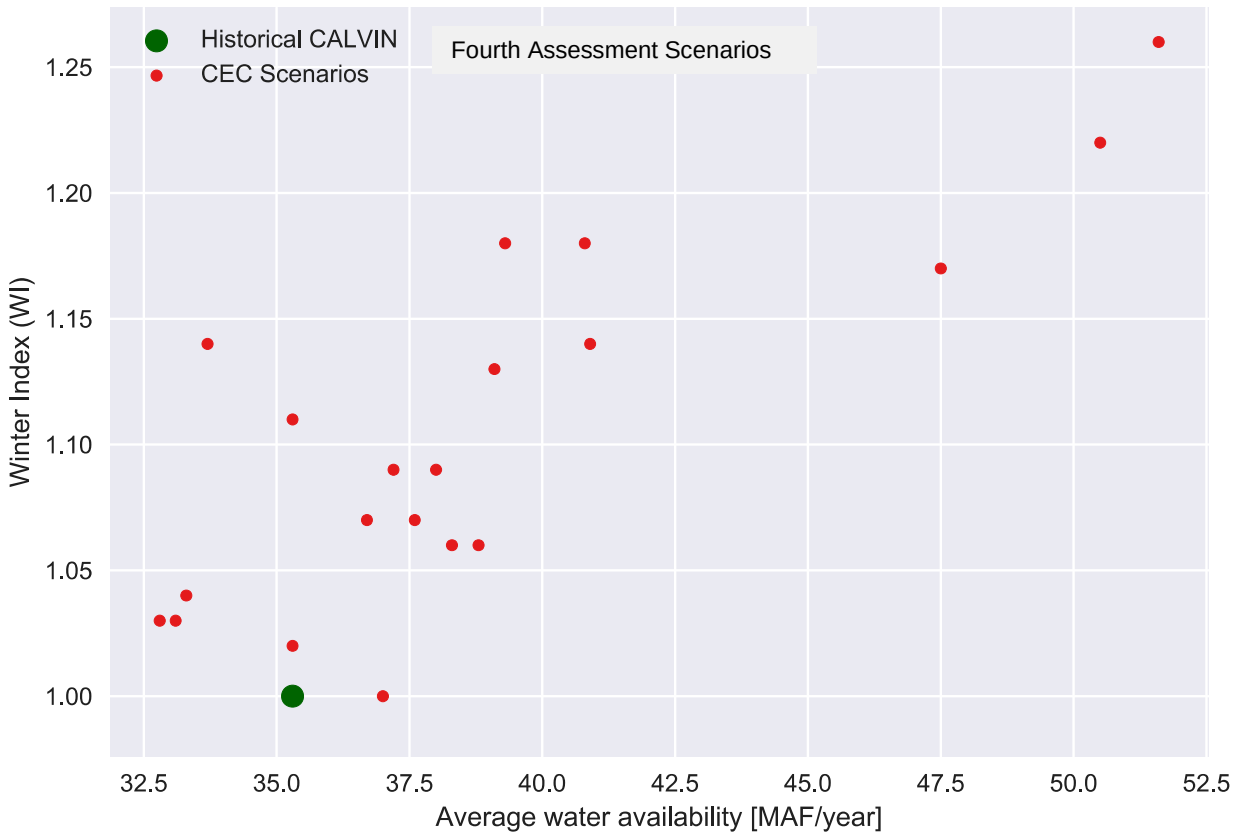

Figure 11: Downscaled hydrology scenarios plotted according to average annual water availability and winter index.

These scenarios were evaluated in the CALVIN model to assess changes in the optimal water supply portfolio throughout the state under different hydrologic conditions, as well as overall changes in cost. Table 2 shows the water supply portfolio for the average year of each scenario compared to the historical scenario. The average deliveries may not exactly match the average annual water availability due to storage and conveyance capacity limitations throughout the system. Further, although the reuse and desalination values appear fixed, they are being optimized under the same infrastructure constraints.

Table 2: Average optimal water supply portfolios (statewide, MAF/year) for the downscaled hydrology projections. Perfect foresight is assumed for these model runs. Portfolios are composed of five sources: groundwater pumping (GWP), surface water deliveries (SWD), non-potable reuse (NPR), potable reuse (PR), and desalination (DESAL). Agricultural and urban conservation are implicitly represented in the difference between delivery and total demand, which CALVIN estimates as roughly 36.6 MAF/year (i.e., the total delivery in the wettest scenarios shown below).

Scenario	GWP	SWD	NPR	PR	DESAL	Average Water Availability [MAF/year]	Average Deliveries [MAF/year]	Winter Index
Historical CALVIN	13.3	22.9	0.12	0	0.01	35.3	36.4	1
ACCESS1-0_rcp45	13.6	22.3	0.12	0	0.01	40.3	36.0	1.09
ACCESS1-0_rcp85	13.8	21.2	0.15	0	0.01	34.1	35.2	1.14
CanESM2_rcp45	13.3	23.0	0.12	0	0.01	41.2	36.5	1.14
CanESM2_rcp85	13.3	23.2	0.12	0	0.01	60.2	36.6	1.22
CCSM4_rcp45	13.5	22.8	0.12	0	0.01	40.6	36.3	1.13
CCSM4_rcp85	13.5	22.6	0.12	0	0.01	46.1	36.3	1.18
CESM1-BGC_rcp45	13.3	23.1	0.12	0	0.01	41.1	36.5	1.09
CESM1-BGC_rcp85	13.4	23.0	0.12	0	0.01	49.3	36.5	1.18
CMCC-CMS_rcp45	13.5	22.7	0.12	0	0.01	39.8	36.2	1.02
CMCC-CMS_rcp85	13.6	22.3	0.12	0	0.01	41.5	36.0	1.00
CNRM-CM5_rcp45	13.3	23.2	0.12	0	0.01	46.3	36.6	1.17
CNRM-CM5_rcp85	13.3	23.2	0.12	0	0.01	59.8	36.6	1.26
GFDL-CM3_rcp45	13.5	22.7	0.12	0	0.01	36.5	36.3	1.07
GFDL-CM3_rcp85	13.5	22.5	0.12	0	0.01	35.1	36.2	1.11
HadGEM2-CC_rcp45	13.5	22.6	0.12	0	0.01	39.9	36.2	1.06
HadGEM2-CC_rcp85	13.5	22.5	0.12	0	0.01	36.7	36.2	1.06
HadGEM2-ES_rcp45	13.4	22.7	0.12	0	0.01	32.5	36.3	1.03
HadGEM2-ES_rcp85	13.5	22.7	0.12	0	0.01	41.2	36.3	1.07
MIROC5_rcp45	13.5	22.3	0.12	0	0.01	27.9	36.0	1.04
MIROC5_rcp85	13.6	22.1	0.13	0	0.01	35.0	35.8	1.03

The delivery volumes from each source do not change significantly regardless of the water availability in each scenario, some of which are more than 50% greater than historical reservoir inflows. This result is due to CALVIN's optimization structure where there is no economic benefit to delivering additional water. The utility of this model lies in learning how to efficiently allocate shortage in times of water scarcity and does not include the necessary tools, such as optimizing flood pool rules, to study how California might adapt to manage a wetter climate.

4.2 Identifying Vulnerabilities

For the sensitivity analysis component of the study, 25 scenarios were sampled according to total water availability (from -30% to +10% of historical) and the fraction of annual runoff in the winter, or "winter index" (from -5% to +15% of historical), as described in Section 2.2.2. The statewide water shortage costs incurred in these scenarios under the perfect foresight assumption are shown in Figure 12.

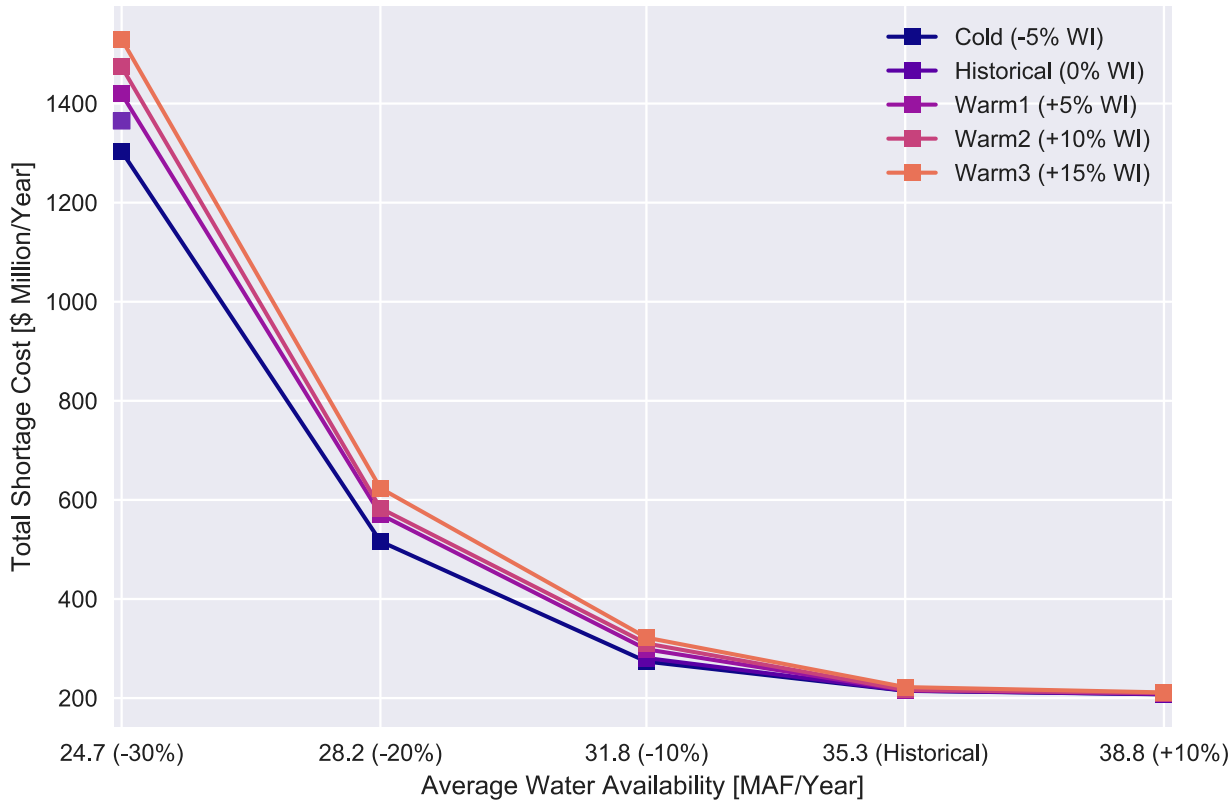

Figure 12: Total statewide water shortage costs (annual average) in the sensitivity analysis scenarios. The point for Historical in the -20% scenario is missing due to a failed model run, as explained in Figure 13.

Shortage costs increase across all scenarios as average water availability decreases, and as the winter index (i.e., the fraction of reservoir inflow arriving during the winter) increases. Shortage cost for the set of scenarios at 0% and +10% average water availability is roughly $200 million per year. The increase in shortage cost appears quadratic with respect to water availability, as scarcity cost increases more severely with incremental decreases in average water availability. A slight and moderate increase in shortage cost occurs from 0% to -10% and -10% to -20% average water availability. Shortage cost approximately doubles as average water availability is lowered to -30% of the historical average inflows. This spike in shortage cost is the first indicator of a statewide vulnerability to drought occurring between -20% and -30% annual water availability. Costs would likely increase more rapidly under the limited foresight assumption.

For a given water availability, increasing the winter index yields small increases in shortage cost. Drier scenarios increase shortage costs between each winter index increment. As water

becomes scarcer, the model has less flexibility to modify operations because all water has been allocated to a demand (which would incur an additional shortage if deliveries were curtailed) or an instream flow requirement, for which curtailments are not permitted in the model.

Shortage costs can also be explored individually for CALVIN's five geographic regions: the Upper Sacramento Valley (USV), Lower Sacramento Valley & Delta (LSVD), San Joaquin & South Bay (SJSB), Tulare Basin (TB), and Southern California (SC). The statewide total of shortage costs increases quadratically with decreasing water availability, but this is not necessarily the case in each region, as shown in Figure 13. Southern California experiences the highest shortage cost out of all regions, even in wetter scenarios. Tulare Basin assumes the second-largest shortage cost among the regions but sees a dramatic increase in shortage costs from -20% to -30% average water availability. USV, LSVD, and SJSB incur incrementally greater shortage with water reductions but on a much smaller scale compared to TB and SC.

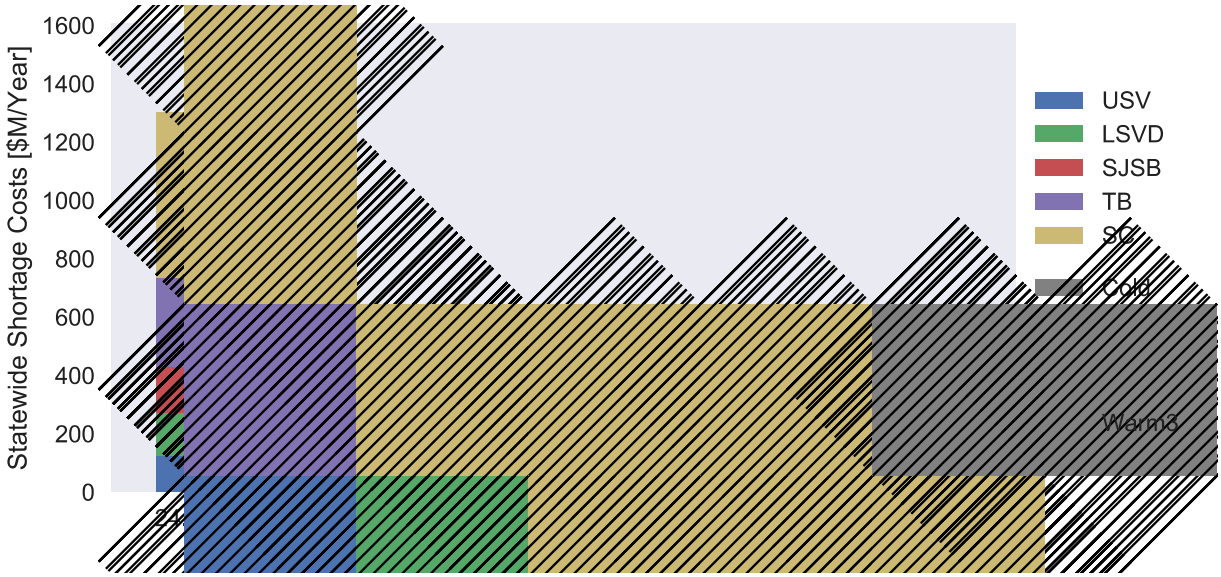

Figure 13: Average annual shortage costs by region. The missing value corresponds to a failed model run (i.e., where debug mode was not able to identify feasible solutions in a given number of iterations).

Both urban and agricultural demands in CALVIN can incur shortage costs. Figure 14 shows the difference in shortage costs between urban and agricultural demands in each region when water availability is decreased by 30% on average. Urban shortage costs are overwhelmingly incurred in Southern California, with minimal urban shortage costs in the other regions. This is due to high willingness-to-pay among urban users in Southern California, as well as limited opportunities to replace surface water shortages with other sources. Southern California has small agricultural total shortage cost, but Tulare Basin agriculture bears the largest share of agricultural shortage costs at -30% water. USV, LSVD, and SJSB also incur significant agricultural shortage cost. Total agricultural shortage costs exceed urban shortage costs due to urban areas having a greater willingness to pay for water than agricultural regions, so lower-value agricultural demands are more likely to be shorted. Additionally, agricultural water use is several times greater than urban use by volume.

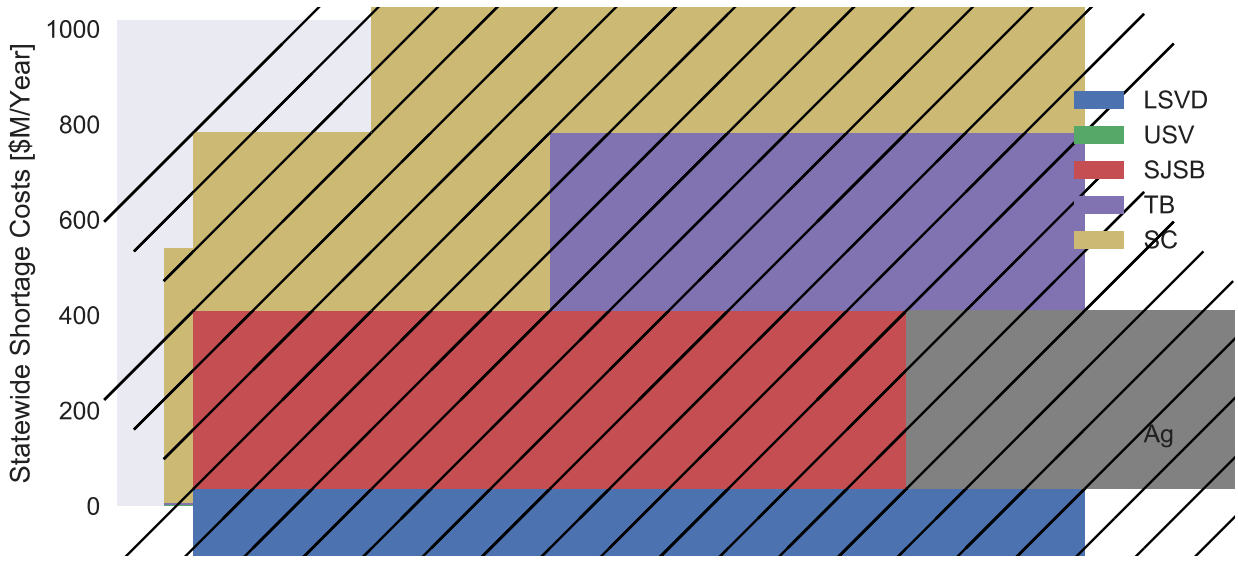

Figure 14: Agricultural and urban shortage costs by region at -30% water availability relative to the historical scenario

Figures 15 shows contour plots of changing shortage costs, statewide and in each region, with changes in winter index and water availability. This is a graphical approach to determine the sensitivity of the system to changes in climate, and to identify future scenarios that may result in vulnerable water supplies for the state. The nearly vertical contour lines on each plot indicate that shortage costs are primarily determined by changes in water availability (x-axis) with only slight influence from changing the winter index (y-axis). In all regions excluding Southern California, little to no shortage costs are incurred as water availability decreases to -10%. Even with water availability greater than historical, Southern California still incurs shortage costs in urban water uses, as seen in Figure 14. As water availability decreases, the gradient of shortage costs with winter index increases, reflecting the fact that the system is more sensitive to temperature changes in drier scenarios.

Given the inherent uncertainty in GCM-derived climate scenarios, this type of "bottom-up" vulnerability assessment can be valuable to determine key thresholds in the system before analyzing the likelihood of specific climate changes [*Dessai and Hulme*, 2004; *Brown et al.*, 2012]. The results in Figure 15 are independent of any ensemble of climate models and emissions scenarios, meaning they can serve as a template for evaluating the impact of different climate scenarios in the future, provided that they can be mapped onto the same axes of average water availability and winter index. Overall, results indicate that the system is robust to small average decreases in water availability, but exhibits much larger shortage costs under larger reductions of roughly 30%. The x-axis in Figure 15 reflects changes to the average water availability, a metric which does not specifically focus on the severity of multi-year drought periods.

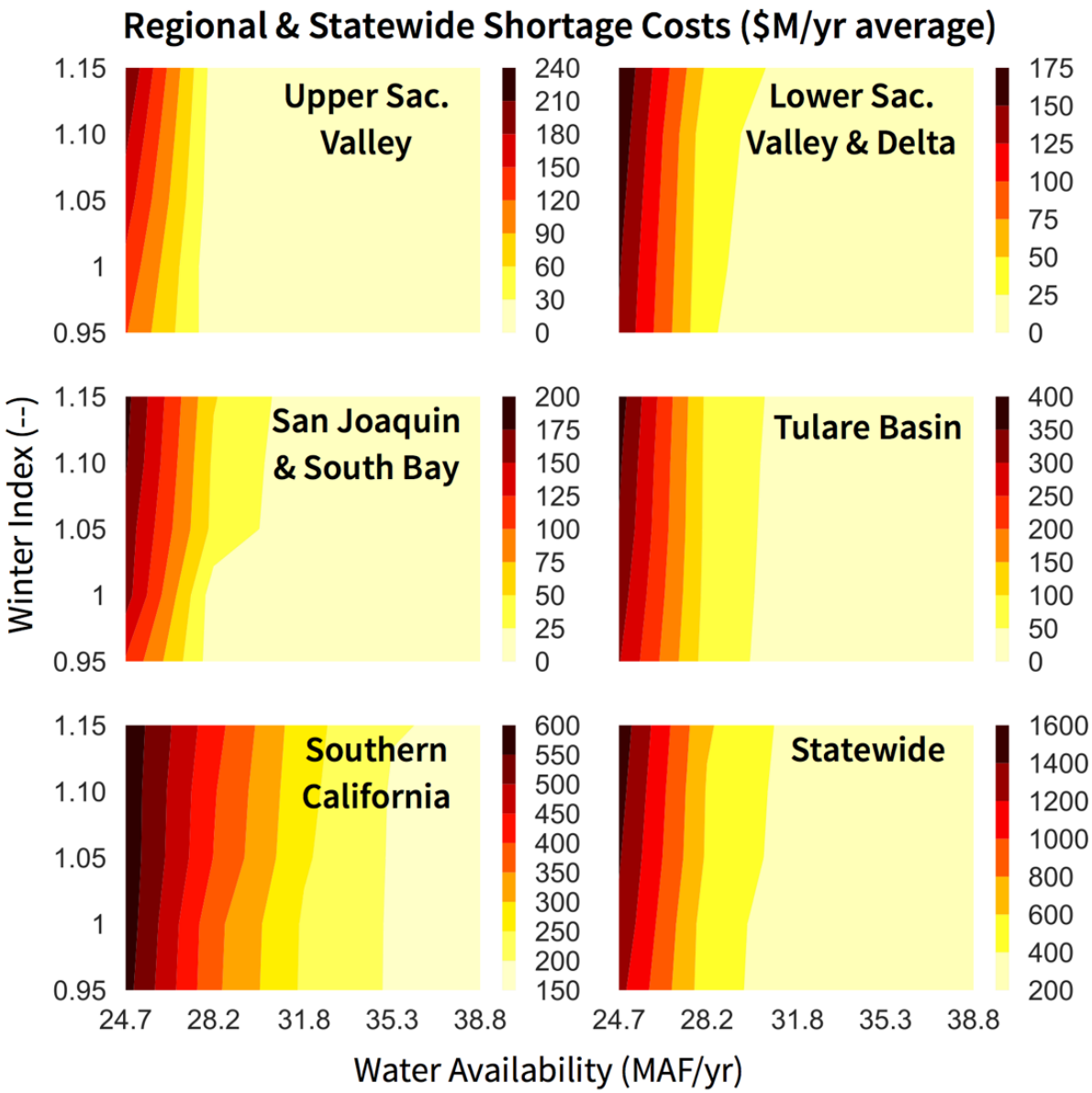

Figure 15: Contour plots of water shortage cost, regional and statewide, as a function of water availability and winter index

4.3 Identifying Adaptation Strategies

Because CALVIN is an optimization model, the model runs included in the sensitivity analysis scenarios in Figure 15 have automatically adjusted water supply operations to account for a potentially warmer and drier future. Here we explore what optimal changes were made under different scenarios to understand what opportunities might exist for changing operations. These fall into five categories: water supply portfolios, reservoir operations, environmental flows,

reservoir capacity expansion, and conveyance expansion. The latter three are represented in the model output by marginal values, indicating the value of changing the required flow or infrastructure capacity by one unit. However, these have not been changed in the model runs because they are not decision variables in the optimization, only constraints.

4.3.1 Water Supply Portfolios

Across the state, five water supply types are represented: groundwater pumping, surface water delivery, non-potable reuse, direct potable reuse, and desalination. Each region in CALVIN has access to surface and groundwater, but only urban areas have access to reuse and desalination. This is a simplification, as agricultural areas also have opportunities for water reuse, including groundwater banking.

Table 3 outlines how the portfolio of the five water supplies changes under different scenarios of winter index (WI) and water availability (WA). Surface water deliveries are maintained with little scarcity when water availability is reduced by 10%, but significant shortage appears in the -20% and -30% scenarios. Groundwater pumping is fairly constant throughout all scenarios due to the simplistic representation of groundwater allocation in the CALVIN model. Specifically, the unit cost of groundwater pumping does not account for increased energy cost due to declining water tables, or more importantly, the costs of drilling deeper wells. Non-potable Reuse increases from roughly 120 to 580 TAF/year as scenarios become drier. Surface water deliveries remain similar as water availability decreases to -10% in yearly inflows, but deliveries are significantly reduced by the 30% decrease scenarios. Delivery volume is negligibly affected by the winter index, indicating again that temperatures have less effect than changes in average precipitation and runoff.

Table 3: Optimal water supply portfolio (statewide) in scenarios defined by changes in water availability and winter index

		AVERAGE WATER SUPPLY PORTFOLIO [MAF/YR]					
Water Availability	Winter Index	Groundwater Pumping	Surface Water Delivery	Non-Potable Reuse	Direct Potable Reuse	Desal-ination	Total
+10%	COLD	13.2	23.1	0.12	0	0.0091	36.5
+10%	HISTORICAL	13.2	23.1	0.12	0	0.0091	36.5
+10%	WARM1	13.3	23.1	0.12	0	0.0091	36.5
+10%	WARM2	13.3	23.0	0.12	0	0.0091	36.5
+10%	WARM3	13.3	23.0	0.12	0	0.0091	36.4
0%	COLD	13.3	23.0	0.12	0	0.0091	36.4
0%	HISTORICAL	13.3	22.9	0.12	0	0.0091	36.4
0%	WARM1	13.3	22.9	0.12	0	0.0091	36.4
0%	WARM2	13.3	22.9	0.12	0	0.0091	36.4
0%	WARM3	13.4	22.9	0.12	0	0.0091	36.3
-10%	COLD	13.4	22.6	0.12	0	0.0091	36.1
-10%	HISTORICAL	13.4	22.6	0.12	0	0.0091	36.1
-10%	WARM1	13.4	22.5	0.12	0	0.0091	36.0
-10%	WARM2	13.4	22.4	0.13	0	0.0091	35.9
-10%	WARM3	13.4	22.2	0.13	0	0.0091	35.8
-20%	COLD	13.7	21.0	0.24	0	0.0091	35.0
-20%	WARM1	13.7	20.7	0.41	0	0.0091	34.8
-20%	WARM2	13.7	20.5	0.52	0	0.0091	34.8
-20%	WARM3	13.7	20.3	0.53	0	0.0091	34.6
-30%	COLD	13.5	18.4	0.58	0	0.0091	32.6
-30%	HISTORICAL	13.5	18.3	0.58	0	0.0091	32.4
-30%	WARM1	13.5	18.2	0.58	0	0.0091	32.3
-30%	WARM2	13.5	18.1	0.58	0	0.0091	32.1
-30%	WARM3	13.5	17.9	0.58	0	0.0091	32.0

In all scenarios shown in Table 3, most water supply continues to come from surface and groundwater supplies, though the balance shifts depending on surface water shortage. These model runs did not test scenarios in which the capacity of reuse and desalination operations were expanded, which could be a subject for future work.

4.3.2 Reservoir Operations

The model outputs can be analyzed to find optimal changes in reservoir operations, defined by monthly storage decisions, in these different climate scenarios. Figure 16 shows the total statewide surface reservoir storage across all scenarios. The dashes of the lines represent different levels of water availability, and the colors of the lines represent the winter index. The 0% and -10% water availability scenarios have a similar shape, minimum, and maximum.

Within each water availability scenario, the variation in winter index shows a slightly larger peak in total storage in May and a moderate decrease in minimum value in October. Overall, the effect of the scenarios with higher winter index is more pronounced at the 0 and -10% scenarios, whereas the reduction in water availability plays a larger role in the -20% and -30% scenarios.

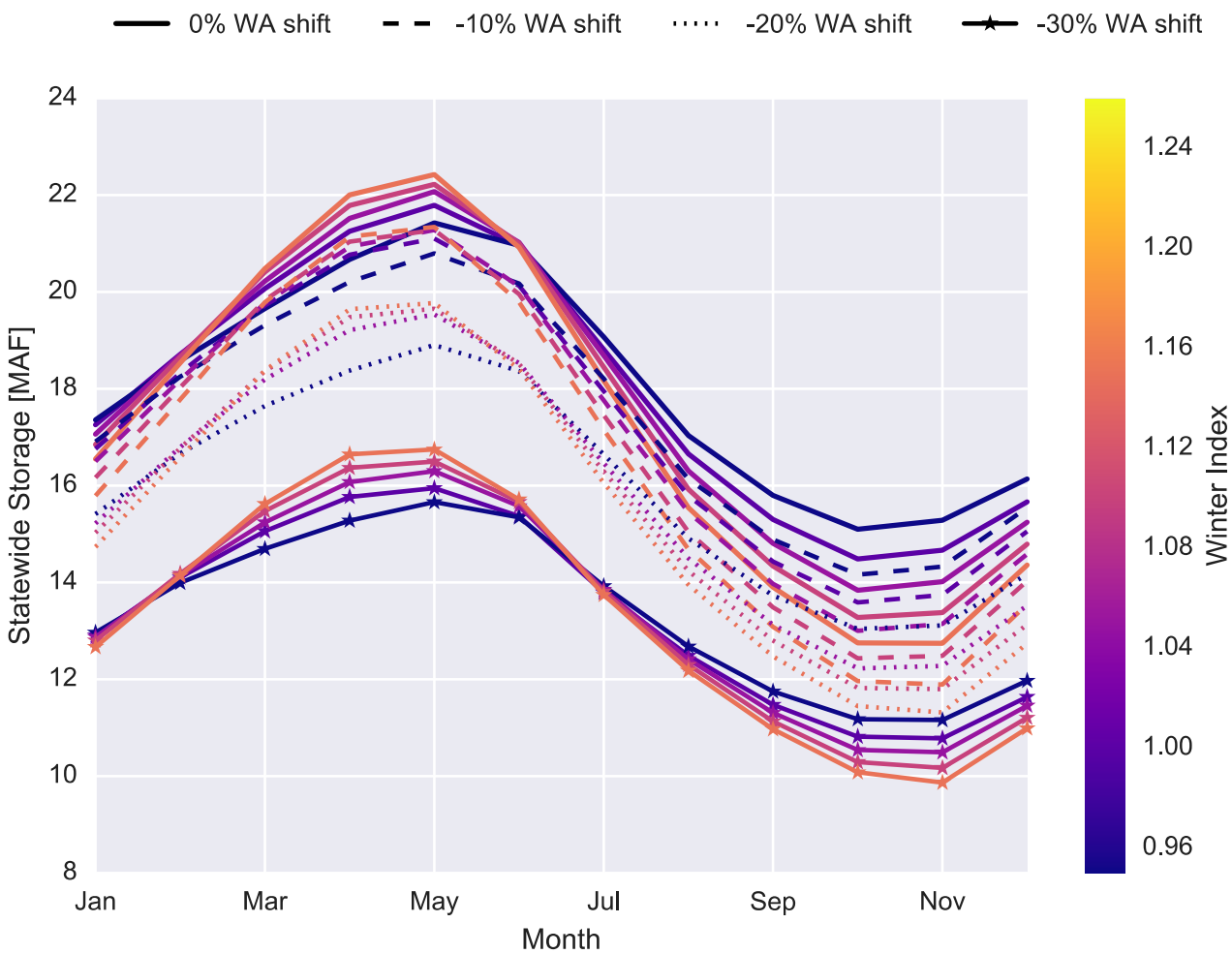

Figure 16: Statewide monthly average surface reservoir storage in each scenario. Higher values of the winter index (colorbar) indicate higher ratios of November-March runoff.

Breaking down the statewide aggregate reveals four categories of behavior shown among the reservoirs. The four categories are as follows.

Reservoirs with major operations shift at -30% water availability

Like the statewide total storage, several reservoirs including Shasta Lake see similar average storages in the 0%, -10%, and -20% water availability scenarios where the winter index plays a more significant role in determining end of water year storage, due to the changes in reservoir inflow timing based on temperature. The winter index shows a much larger influence on reservoir operations than it does for overall water shortage costs, suggesting that the reservoir operations are being adjusted to compensate for hydrologic changes in a way that maintains deliveries as best as possible. In the -30% water availability scenario for these reservoirs, average storage levels drop considerably and show up to a 500 TAF difference in monthly storage across the various winter index values. Figure 17 shows an example of these changes for Shasta Reservoir.

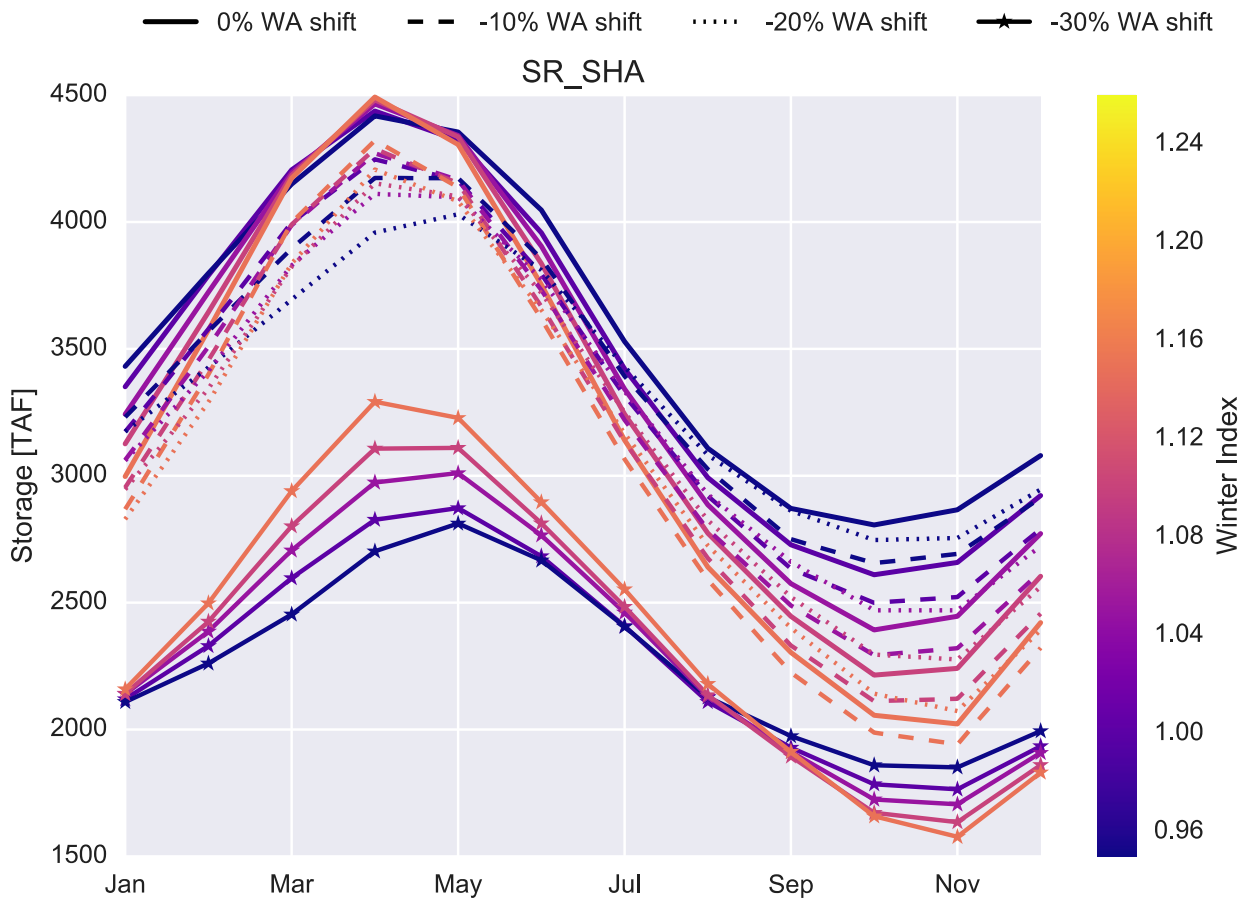

Figure 17: Shasta Reservoir average monthly storage in sampled climate scenarios

Gradual decrease in storage with decreasing water availability

In contrast to Shasta Lake, reservoirs including Lake Oroville, Folsom Lake, and New Bullards Bar show no clear definition between scenarios at different water availabilities. Average monthly storage values decrease with decreasing water availability, but only gradually in comparison to the large shift in operations at Shasta. For Lake Oroville (Figure 18), average storage values are closely banded within 200 thousand acre feet (TAF) from March through June, and afterwards the band expands through November. As above, higher winter index values, associated with warmer scenarios, have decreased the carryover storage values compared to lower winter index values, associated with colder scenarios. Due to Oroville's large capacity, the band of storage values in November across scenarios is much wider compared to those of smaller reservoirs.

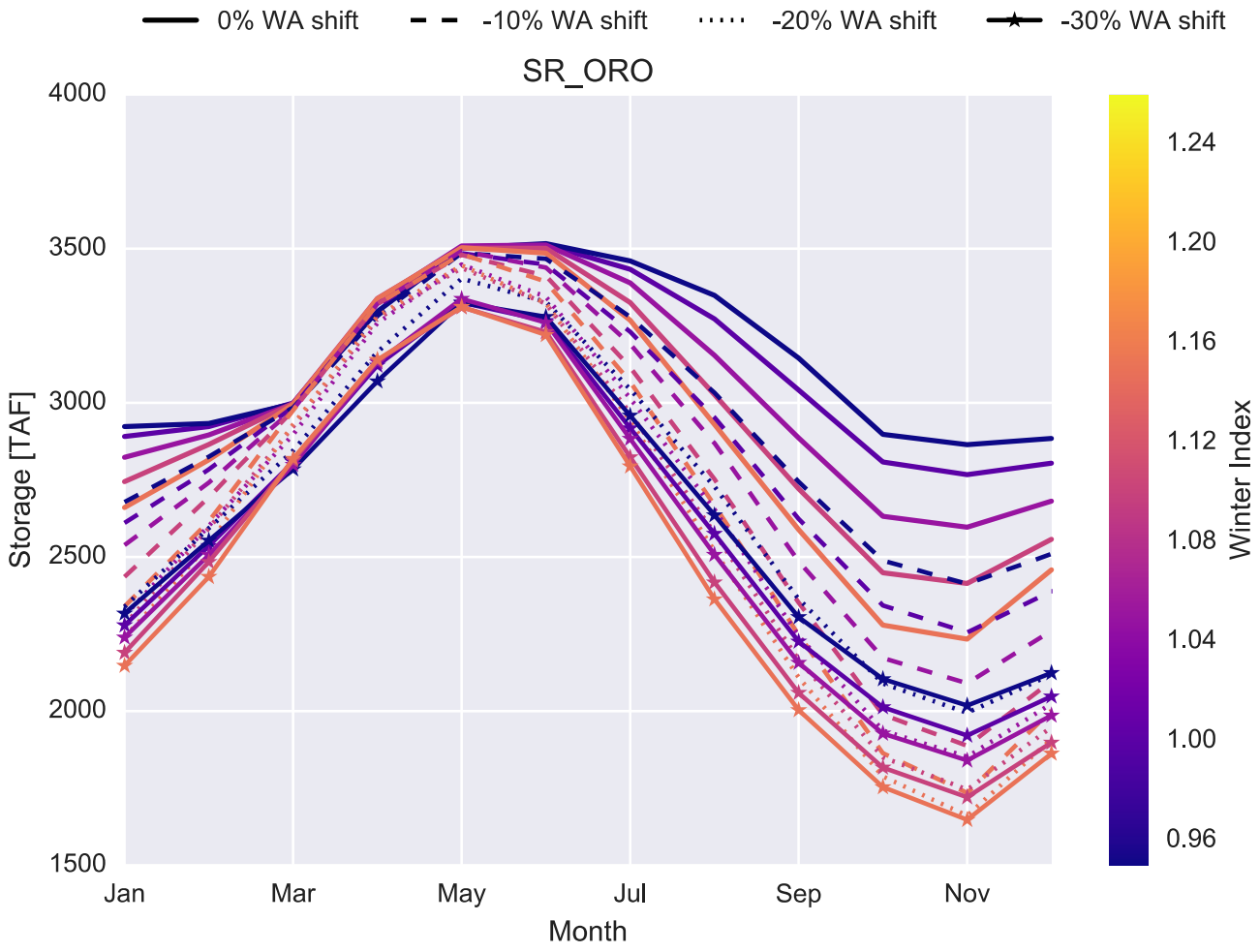

Figure 18: Lake Oroville average monthly storage in sampled climate scenarios

Moderate decrease in storage with decreasing water availability

A third category of reservoirs, grouped by their similar operations, is represented by a moderate decrease in average monthly storage as monthly water availability decreases. Trinity

Lake (shown in Figure 19) shows similar behavior to Shasta Lake but with larger decreases in between the 0% and -20% WA scenarios, suggesting that its operations are changed in scenarios that do not deviate as severely from the historical hydrology. A trend is still visible between reservoir storage and the winter index of each scenario, indicating that temperature-based effects on inflow timing are causing optimal operations to change. The similar operations observed for Trinity and Shasta reservoirs makes sense, as they are within close proximity to each other and both have a large storage volume. The decreases in optimal storage observed with decreases in water availability are in part a function of simply having less water to store, but also reflect deliberate choices by the optimization model about how much water is worth releasing versus storing for the future in these drier scenarios.

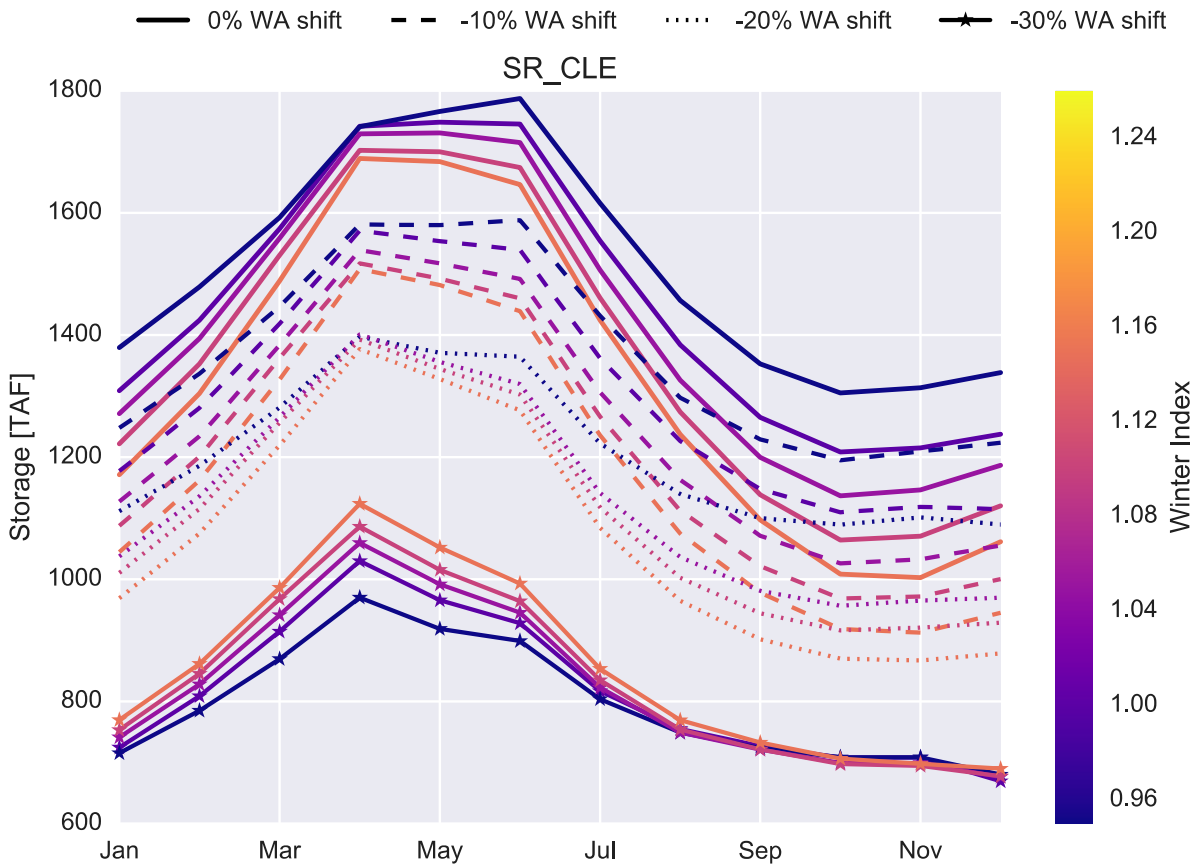

Figure 19: Trinity Lake average monthly storage in sampled climate scenarios

Buffering capacity of San Luis Reservoir

Representing the fourth and final category of reservoir behavior are off-stream reservoirs, such as San Luis Reservoir. Off-stream storage facilities can have more flexible operations that are less impacted by hydrologic changes, and thus play an important role in statewide operations. Among the largest reservoirs in the state, San Luis serves as an off-stream storage facility for operating the State Water Project (SWP) and Central Valley Project. Although the reservoir

capacity is 2 million acre feet (MAF), reservoir levels are typically far below capacity depending on the time of year. This extra reservoir space is utilized in the climate scenarios to capture excess streamflow unable to be stored at upstream facilities like Shasta and Oroville, which can be pumped out of the Sacramento-San Joaquin Delta. The optimal storage operations for San Luis Reservoir are shown in Figure 20. Unlike other large reservoirs, San Luis storage values increase considerably during the wet season between the 0% and -10% water availability scenarios, showing that in some of these moderately dry scenarios there will be increased opportunities for storage south of the Delta. In the -30% water availability scenarios, the operations of San Luis have converged and do not change regardless of the temperature scenario, with a storage peak in the winter and early spring, followed by a drawdown throughout the irrigation season. This shows the reduced sensitivity to hydrologic changes that would be expected for off-stream reservoirs, which might be a benefit for off-stream storage projects planned for the future.

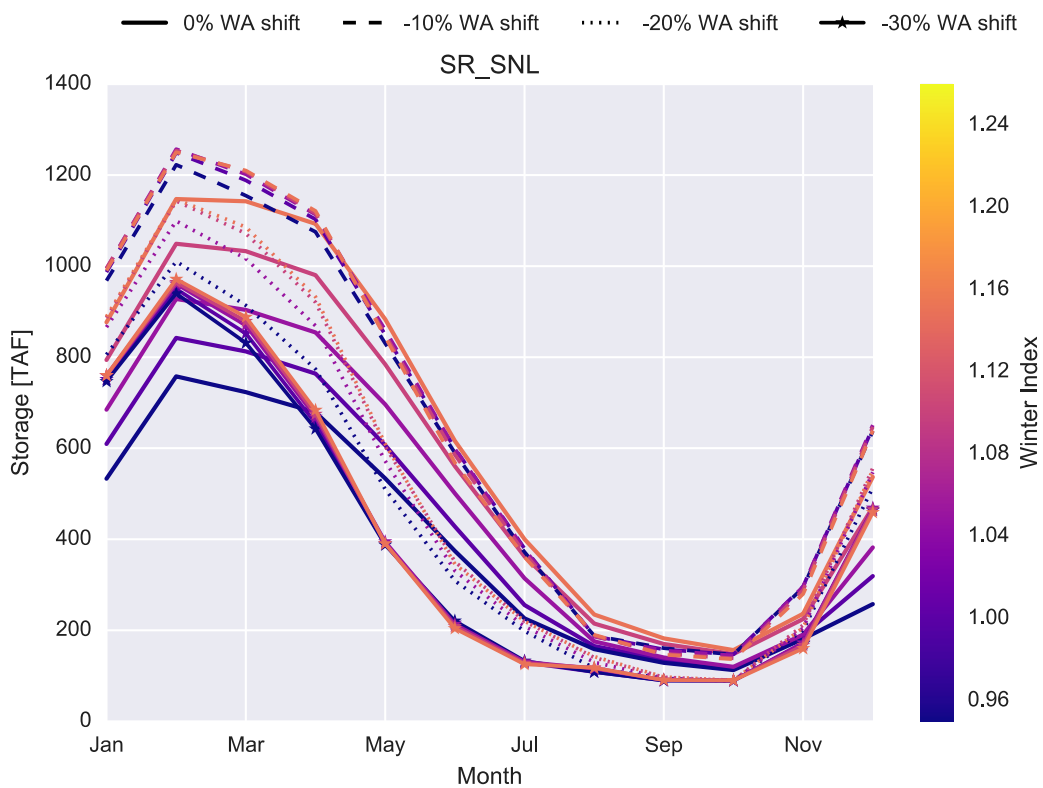

Figure 20: San Luis Reservoir average monthly storage in sampled climate scenarios

4.3.3 Environmental Flows

In the CALVIN model, minimum instream flow requirements (MIF) for environmental purposes are represented by fixed constraints, where either the lower bound and upper bound are equal for each time step, or with a nonzero lower bound and arbitrarily large upper bound. In dry scenarios, the automatic debug flow algorithm will reduce lower bounds to ensure feasibility of the solution, possibly reducing MIFs in the process. The linear programming model allows the opportunity to assign a marginal opportunity cost to environmental flow deliveries, providing information on the economic value of the water being allocated to

environmental uses if it were traded to other nodes in the network, which represents an adaptation option that might be explored under climate change scenarios.

Figure 21 shows the monthly average marginal value across scenarios for the Clear Creek MIF, one selected example of an environmental flow in the model network. The marginal value of this constraint increases significantly as water availability is reduced from -20% to -30%, primarily in the winter months. By comparison, the variation in the winter index (i.e., temperature) has negligible impact on the marginal value of this environmental flow requirement within each water availability scenario. Dual values for this constraint are zero in the summer months, representing a non-binding constraint in the model. Reservoir releases for agriculture occur primarily during the summer months, so the minimum environmental requirement is not binding.

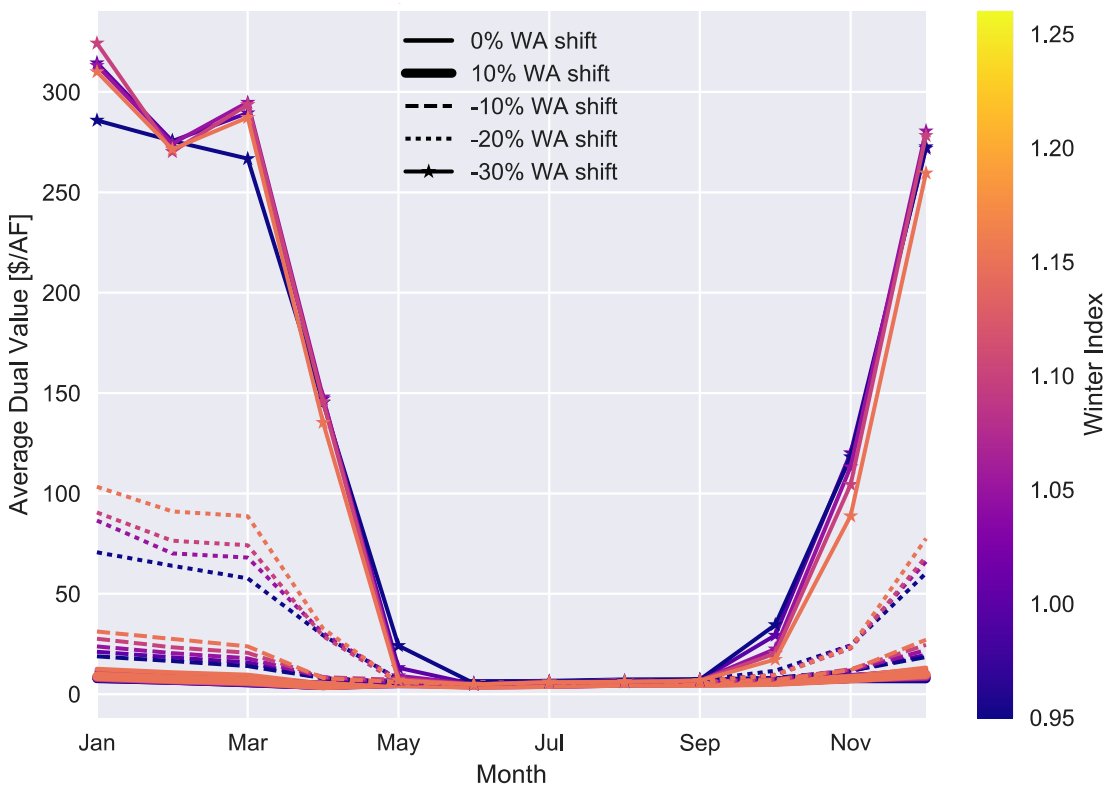

Figure 21: Average monthly marginal opportunity costs associated with the Clear Creek minimum environmental flow requirement downstream of Whiskeytown Reservoir

Table 4 contains the average yearly maximum marginal opportunity costs for environmental flows. All links in the model with marginal value greater than $100/AF / month are included. The values reflect the warmest scenario ("Warm3") at each sampled level of water availability. The average yearly maximum was chosen for analysis because the metric captures the variation due to the water availability in the month of the year when the water is most valuable. Marginal value increases with decreasing water availability, but by varying amounts at different points in

the state. Consistent with prior studies, instream flow requirements for Mono Lake and the Trinity River show high value in the driest scenarios [*Tanaka et al.*, 2006].

Table 4: Environmental flow average marginal opportunity costs with different levels of average water availability [$/AF/month]

DESCRIPTION	CALVIN LINK	+10%	0%	-10%	-20%	-30%
MONO LAKE	SR_GNT-SR_ML	876	894	975	1267	1431
TRINITY RIVER	D94-SINK	49	55	96	229	593
CLEAR CREEK	SR_WHI-D73	12	15	44	154	478
SACRAMENTO RIVER @ KESWICK RESERVOIR	D5-D73	10	13	41	150	476
CALAVERAS RIVER	C41-C42	19	24	62	186	452
SAN JOAQUIN RIVER	D616-C42	22	28	68	179	405
MOKELUMNE RIVER	SR_CMN-C38	14	20	50	144	372
SACRAMENTO RIVER @ RIO VISTA	D507-D509	6	10	40	145	350
FEATHER RIVER	C25-C31	4	6	30	109	303
AMERICAN RIVER	D9-D85	6	9	26	85	265
SACRAMENTO RIVER @ SACRAMENTO NAVIGATION CONTROL POINT	D61-C301	6	7	16	62	265
YUBA RIVER	SR_ENG-C28	13	63	39	92	214
STONY CREEK @ BLACK BUTTE DAM	SR_BLB-C9	14	17	29	56	211
BEAR RIVER	SR_CFW-C33	9	11	24	68	185
SACRAMENTO RIVER @ DELTA CROSS CHANNEL	D503-D511	7	9	22	71	181
COSUMNES RIVER	C37-C38	49	51	58	83	136
STONY CREEK @ TEHAMA-COLUSA CANAL	C9-C12	18	23	33	51	118

All of the environmental flows in Table 5 apart from Mono Lake show an approximately quadratic increase in marginal opportunity cost as water availability decreases. These values are shown in Figure 22. The quadratic relationships are to be expected, given the quadratic water demand curves for urban and agricultural nodes in the model.

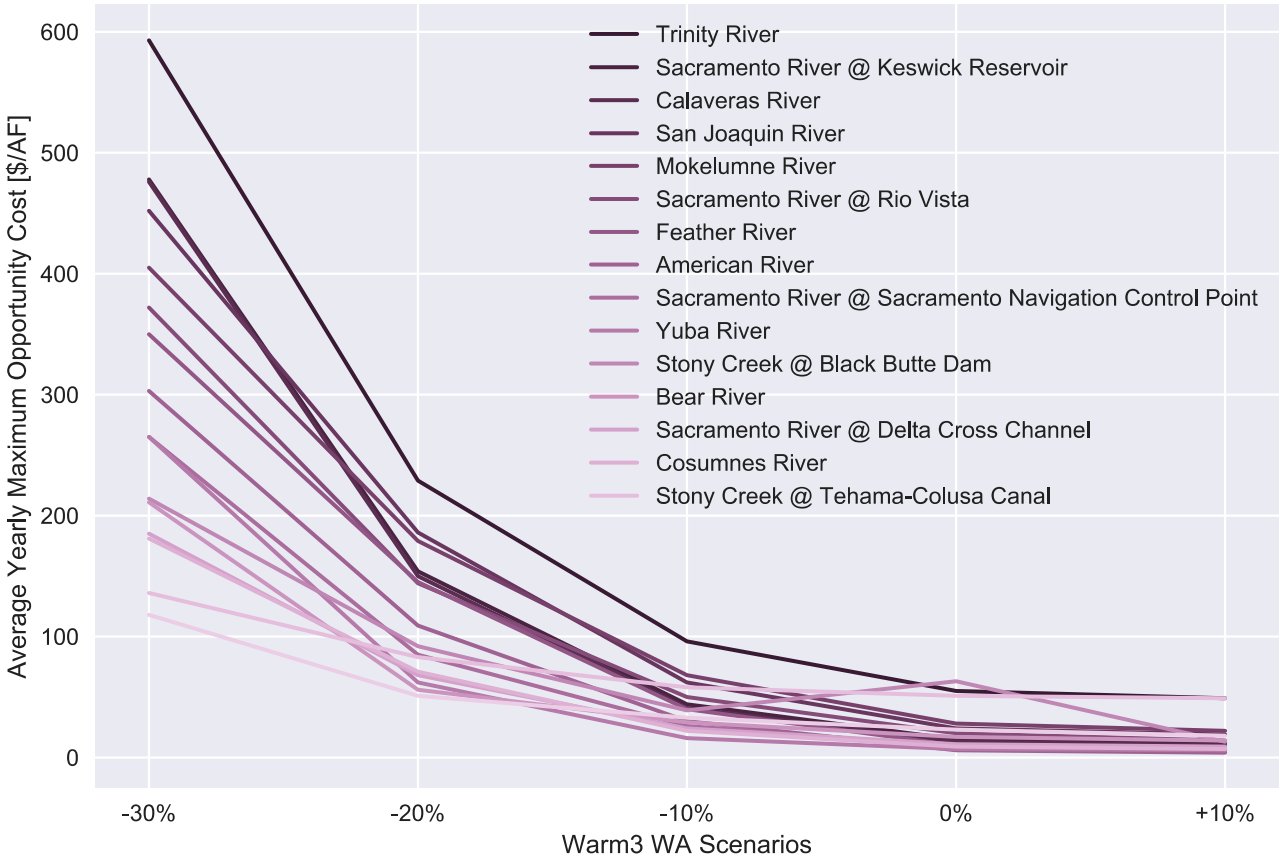

Figure 22: Quadratic increase in marginal opportunity costs of environmental flows with decreasing water availability

This analysis is not intended to assign economic value to environmental flows, as valuing nonrevenue water like environmental flows is difficult. For example, water delivered to national wildlife refuges provides no direct economic benefit but serves an important purpose in maintaining critical ecosystems and fostering biodiversity by providing habitat for endangered and threatened species. However, the model provides an implied opportunity cost for these constraints based on the value of allocating this water to meet human water demands elsewhere in the state. These opportunity costs may be useful to inform adaptation strategies under climate change—for example, if water rights could be purchased for the environment during drought, the costs shown in Table 5 and Figure 22 might serve as a guide for how water users might be incentivized to perform these trades.

These marginal opportunity costs partially depend on the extent to which the environmental flow constraints have been reduced to achieve model feasibility. The automatic "debug mode" of the model will reduce fixed lower-bound constraints, including minimum instream flow requirements, that cause the model to be infeasible. Environmental flow deliveries for the warmest scenario ("Warm3") with changing water availability are shown below in Table 5. This table shows increases in most environmental flow deliveries in the wetter scenario (+10% WA) and gradual reduction in deliveries with decreased water availability. Links with a gradual reduction generally have a linear relationship with water availability, meaning a 30% reduction in average water availability statewide resulted in a 30% reduction of the environmental

requirement. A few environmental flow locations such as Clear Creek, Trinity River, San Joaquin River at Vernalis, and Bear River have no reduction in the requirement even when statewide water availability is reduced, indicating that these constraints did not cause infeasibility. For the other environmental flows, reductions were needed to make the model feasible. These reductions occur prior to any optimization of cost—there is simply not enough water in the network in drier scenarios to meet the environmental constraints unless these constraints are reduced by the amounts shown in Table 5.

Table 5: Average environmental flow constraints with changing water availability in the warmest scenario [TAF / month]

DESCRIPTION	CALVIN LINK	+10%	0%	-10%	-20%	-30%
Clear Creek @ Sacramento River	SR_WHI-D73	135	122	123	122	122
Sacramento River @ Keswick Reservoir	D5-D73	7042	6320	5608	4886	4211
Sacramento River @ Red Bluff	D77-D75	8612	8132	6968	6210	5561
Sacramento River @ Sacramento Navigation Control Point	D61-C301	7498	6883	5608	4762	4303
Stony Creek @ Black Butte Dam	SR_BLB-C9	456	414	373	331	290
Stony Creek @ Tehama-Colusa Canal	C9-C12	344	303	275	244	227
Trinity River	D94-SINK	607	607	607	606	606
Bear River Inflow to Lake Combie/Rollins Lake	C35-SR_RLL_CMB	385	391	387	388	387
Bear River below Lake Combie/Rollins Lake	N201-N202	294	279	257	238	218
Bear River @ Camp Far West Reservoir	SR_CFW-C33	380	366	343	324	305
Bear River from DA 68	C33-C308	232	229	252	254	272
American River @ Sacramento River	D64-C8	2880	2574	2305	2037	1784
American River @ Nimbus Dam	D9-D85	2918	2639	2371	2109	1869
Calaveras River @ San Joaquin River	C41-C42	102	103	116	107	101
Feather River @ Kelly Ridge	C23-C25	661	554	568	554	547
Feather River @ Thermalito Afterbay	C25-C31	4467	4041	3649	3224	2811
Feather River @ Sacramento River	D42-D43	6522	5885	5368	4812	4256
Cosumnes River @ Dry Creek	C37-C38	389	361	325	289	253
Sacramento River @ Hood	D503-D511	17888	16446	14138	12445	11160

DESCRIPTION	CALVIN LINK	+10%	0%	-10%	-20%	-30%
Sacramento River @ Rio Vista	D507-D509	6101	12647	5252	5101	4848
Yuba River @ Englebright Dam	SR_ENG-C28	1827	1660	1494	1327	1160
Yuba River from DA 67	C83-C31	1818	1697	1490	1332	1166
San Joaquin River @ Vernalis	D616-C42	3073	3072	3073	3077	3098
San Joaquin River @Mendota	D609-D608	131	126	119	120	119
Fresno River @ Chowchilla Bypass	D624-C48	44	30	20	14	2
Merced River @ Lower Merced River	D645-D646	427	330	242	207	231
Merced River @ San Joaquin River	D649-D695	397	288	202	177	199
Stanislaus River @ Ripon	D672-D675	703	761	597	551	503
Stanislaus River @ San Joaquin River	D675-D676	821	879	714	658	597
Mokelumne River @ Camanche Dam	SR_CMN-C38	616	546	492	422	378
Tuolumne River @ New Don Pedro Dam	SR_DNP-D662	1575	1438	1277	1102	937
Tuolumne River @ Lagrange Dam	D662-D663	722	631	520	448	417
Mono Lake	SR_GNT-SR_ML	75	75	74	73	70

4.3.4 Reservoir Expansion

Expansion of infrastructure, including storage and conveyance capacity, is one possible adaptation to climate change. This study considers the marginal value of capacity expansion for the surface reservoirs in the CALVIN model. These expansions are explorations of model output and are not necessarily tied to specific plans for infrastructure expansion in the state. Also, new infrastructure plans that have been discussed, such as Sites Reservoir, are not considered here.

Because reservoir capacities are represented by upper-bound constraints in the CALVIN model, their marginal value is computed by model runs in each climate scenario. To evaluate the marginal value of reservoir expansion, the maximum dual value for each year was averaged over the 82-year dataset. California reservoirs typically only fill once per year, thus only one local maximum appears in the yearly time series. Values for each reservoir are reported in Table 6; higher values indicate reservoirs that would be more valuable to expand in each climate scenario. Table 6 includes all reservoirs with a marginal value of expansion greater than $50/AF per year from the warmest scenario ("Warm3").

Table 6: Marginal values of reservoir storage capacity expansion with decreasing water availability [$/AF/year]. Reservoirs are listed in decreasing order based on the -30% scenario, and only the fifteen reservoirs with the highest marginal values are listed.

DESCRIPTION	CALVIN NODE	+10%	0%	-10%	-20%	-30%
BLACK BUTTE LAKE	SR_BLB	19	23	44	134	348
ENGLEBRIGHT LAKE	SR_ENG	2	19	23	90	233
FOLSOM LAKE	SR_FOL	2	2	16	69	161
ROLLINS RESERVOIR/COMBIE LAKE	SR_RLL_CMB	6	8	19	67	161
CAMP FAR WEST RESERVOIR	SR_CFW	7	8	18	65	153
NEW BULLARDS BAR RESERVOIR	SR_BUL	3	20	18	58	139
LOS VAQUEROS RESERVOIR	SR_LVQ	7	8	13	40	129
THERMALITO FORE/AFTERBAY	SR_TAB	4	4	9	33	80
CLEAR LAKE/INDIAN VALLEY RESERVOIR	SR_CLK_INV	3	3	12	34	70
LAKE OROVILLE	SR_ORO	1	1	5	25	60
LOS ANGELES (TOTAL)	SR_LA	33	33	36	41	54
LAKE CROWLEY/LONG VALLEY RESERVOIR	SR_CRW	37	35	37	41	52
LAKE KAWEAH	SR_TRM	55	57	48	34	23
LAKE SUCCESS	SR_SCC	50	53	47	39	41
MILLERTON LAKE	SR_MIL	40	44	39	35	36

Most reservoirs see an increasing marginal value of expansion as the scenarios become drier. Reservoirs located in the San Joaquin Valley, such as Lake Success, Millerton Lake, and Kaweah Lake, show a decrease in the marginal value of expansion as water availability decreases, because these reservoirs reach maximum capacity less frequently than the reservoirs north of the Delta. Variation in the winter index is not shown in Table 6 because the marginal values do not increase more than 10% from the coldest to warmest scenario when holding water availability constant. Because these values are marginal, reflecting the value of one additional unit of storage—in this case, 1 TAF— and because they assume perfect foresight, the true benefit of reservoir capacity expansion requires deeper analysis. In reality, agencies would expand reservoirs by volume increments much larger than 1 TAF, such as the Santa Clara Valley Water District proposing to increase the volume of Pacheco Lake by 124 TAF [*Rogers*, 2017]. Table 6 suggests some locations in the state where further investigation of expansion might be warranted. However, additional storage is a high-cost adaptation option and would require more analysis to determine if it is worth the benefit received [*Hanak and Lund*, 2012b]. Additionally, some of the capacity expansions explored in Table 6 may not be economically or geographically feasible.

4.3.5 Conveyance Expansion

Similar to storage capacity expansion, the CALVIN model output also includes marginal values associated with conveyance expansion. The marginal values associated with the upper bound constraints of key conveyance links are shown in Table 7. Similar to Table 6, these are not necessarily planned infrastructure expansions, and some of them may not be feasible. However, the constrained optimization formulation of the model allows us to explore the marginal value of increased flow capacity on links.

Table 7: Marginal values of conveyance expansion for the warmest scenario ("Warm3") under varying levels of water availability [$/AF/month]. These values are the average of the annual maximum dual value output by the model. Conveyance links are listed in decreasing order based on the -30% scenario.

DESCRIPTION	CALVIN LINK	+10%	0%	-10%	-20%	-30%
LOS VAQUEROS TO CONTRA COSTA CANAL	C310-C70	33	34	51	123	281
SFPUC-HAYWARD INTERTIE	U209-C78	263	265	264	261	267
FOLSOM SOUTH CANAL	D9-C173	6	8	24	82	254
MADERA CANAL	C72-HSU306C72	75	83	98	109	145
FRESNO SLOUGH	C54-D608	8	13	29	59	74
CHOWCHILLA BYPASS	D609-C48	7	12	28	42	57
CONTRA COSTA CANAL	PMP_CC1-C70	52	53	50	47	45
CORNING CANAL	D77-HSU102D77	0	0	2	10	37
DELTA MENDOTA CANAL-CALIFORNIA AQUEDUCT INTERTIE	D701-D800	12	12	11	12	13
LOWER CHERRY CREEK AQUEDUCT	SR_LL_ENR-C44	5	5	5	6	8
DELTA MENDOTA CANAL	D722-D723	0.7	0.1	0.1	1.5	2.7
LA AQUEDUCT	C120-SR_LA	0.1	0.1	0.2	0.3	0.5

As expected, the marginal value of additional conveyance capacity increases as water availability decreases. In dry scenarios, the network receives more value from the ability to move more water during rare wet months to where it is needed. The monthly marginal values in Table 7 are generally much larger (if multiplied by 12) than those for annual storage capacity expansion as shown in Table 6. This suggests overall that conveyance expansion might be more valuable than storage expansion at key points in the network. The effects of changing temperature on the marginal value of conveyance capacity are small. The marginal values increased by less than 10% across temperature scenarios with a fixed water availability. Table 7 shows that the SFPUC-Hayward Intertie retains high marginal value in all scenarios, suggesting an adaptation that may yield economic benefit even under conditions similar to historical. In the model formulation, this intertie connects the East Bay and San Francisco in both directions, delivering water from the Hetch Hetchy system.

5: Conclusions and Future Work

5.1 Limited Foresight Hydroeconomic Modeling

Hydro-economic optimization models have long served as decision support tools by integrating water resources infrastructure, management policies, and economic values. For climate change assessments, hydro-economic optimization offers several advantages: water demands are represented by economic functions; marginal values of promising infrastructure and policy options are identified automatically; and operating rules can change in the future rather than remaining fixed.

Prior studies have considered perfect foresight of water availability over a decades-long planning horizon, providing an optimistic lower bound of adaptation costs by allowing the model to reduce allocations in advance of severe droughts. In reality, costs will be higher due to limited forecasting ability. This study has created a new open-source version of the CALVIN hydro-economic model for California, which allows the flexibility to investigate a limited foresight version of the model. In this approach, sequential annual optimizations were evaluated using an optimized minimum fixed constraint for carryover reservoir storage between years. Results show an average annual shortage cost of approximately three times that of the perfect foresight case. The limited foresight optimization is prone to spikes in annual shortage cost during drought years, whereas the perfect foresight is able to evenly distribute cost over the time period. The limited foresight model reflects a more realistic management policy, since accurate forecasts of drought events are not available years in advance. This effort was completed concurrently to the climate change analysis, so perfect foresight model assumptions were used for the climate scenarios. Therefore, shortage volumes and costs may be underestimated in the climate scenarios, as in prior assessments. However, the limited foresight capability has been created and tested, and is available in the open source repository for this project to be used in future studies.

5.2 Climate Scenario Uncertainty

This study evaluates a systematically sampled set of climate scenarios to reflect plausible changes to runoff magnitude and timing, representing changes to precipitation and temperature, respectively. These scenarios extend beyond the range of the Fourth Assessment scenarios derived from downscaled GCMs to create drier conditions. This approach to understanding uncertainty in climate scenarios allows vulnerabilities and adaptations to be explored without assuming a likelihood of a particular scenario occurring in the future.

The flexible operations suggested by the CALVIN model would require collaborative planning among stakeholders in the statewide water network. The results show no single “best” reservoir operating policy for all reservoirs across the state. Under drier climate scenarios, a combination of adaptation strategies yielded optimal results: some reservoirs, like Oroville, show minimal changes to operations, while reservoirs such as Trinity Lake and New Melones Reservoir steadily decreased average monthly storage levels with decreasing water availability.

With optimal statewide management, results show that a shift in the timing of inflows due to a warmer climate would have a small impact compared to shift in water availability, the effect of which is far more pronounced. In the warmer scenarios, CALVIN allocates more water to

downstream reservoirs in the winter months to account for the additional runoff beyond the capacity of the upstream reservoirs. Large reservoirs like Shasta Lake and Lake Oroville historically maintain high storage levels in winter (excluding flood pool storage) and the additional runoff appearing early in the year cannot be held at these reservoirs. Due to its role as an offstream storage reservoir, San Luis has capacity to capture this additional water and store it until it can be delivered to meet a demand. San Luis Reservoir also shows increased storage levels as the average water availability decreases from historical to -10%. Water supply vulnerabilities would be expected to increase more rapidly with decreasing water availability under the limited foresight assumption.

Both the statewide surface water storage and total shortage cost point towards a sharp increase in shortage and decrease in reservoir volumes occurring between -20% and -30% water availability. Also, significant reductions in reservoir levels exist compared to the difference between the other scenarios. Results show reservoir storage decreasing with water availability, supporting the fact that reservoir expansion will likely not be the answer to the state's water supply problems under climate change (though increasing capacity may provide additional flood protection, which is not considered in this study). Managing the state's surface storage capacity is more promising and less costly than constructing new storage facilities or expanding existing ones [*Hanak and Lund*, 2012a], a fact which is underscored by the relatively low marginal values of additional reservoir storage capacity observed in the results of this study.

5.3 Limitations and Opportunities

Climate adaptation studies have typically focused on drought and minimizing water shortage cost, but recent climate studies suggest increased precipitation and intensity of storms in California's future [*Dettinger et al.*, 2011]. To address this, existing systems models can include ways to measure flood potential and design flood management strategies. In particular, the CALVIN model's main utility lies in long-term drought and scarcity cost management based on monthly hydrologic input and does not include extensive hydrologic modeling of peak flood volume and timing on rim inflows. A model with hourly, daily, or weekly hydrologic input data would be more apt than CALVIN to explore optimal flood management.

Climate adaptation modeling is also constrained by the uncertainty of the ocean-atmospheric modeling performed. Historically, climate models have not agreed whether California will receive more or less precipitation, with predictions ranging from -11% to +28% from the historical average [*Connell-Buck et al.*, 2011b]. Recent work suggests California may receive more precipitation as a result of warming in the Pacific Ocean, similar to the El Niño phenomenon [*Allen and Luptowitz*, 2017]. Moreover, the downscaled hydrologic projections used in this study generally point to wetter futures on average, though still with multi-year droughts, as has always been the case in California. In future work it may be possible to create a two-stage optimization model, where the first stage selects optimal infrastructure capacities, and the second stage determines optimal operations.

The approach taken to design a limited foresight model in this study is based only on fixed carryover storage constraints at surface reservoirs. Groundwater storage volumes are constrained to the optimal end-of-year values from the full 82-year run with perfect foresight. It is a simplifying assumption that the large surface reservoirs would be operated for the same carryover targets as a percentage of their respective capacities. More advanced methods to assign economic value to carryover storage at individual reservoirs are presented in Draper

[2001], and Draper and Lund [2004]. Similarly, the approach to include water rights in the model focused only on urban water users in the Sacramento basin, but can be extended to the statewide water rights dataset. Groundwater representation can also be improved by including constraints on overdraft, for example representing the Sustainable Groundwater Management Act (SGMA). Initial steps in this direction are being developed in ongoing work.

Another improvement to the CALVIN model would emulate other California simulation models like CALSIM to provide a business-as-usual baseline that would include current institutional operating rules to compare to the optimized management strategies. The value of this format in CALVIN to emulate current operating procedures would show the economic benefit of cooperative management of reservoirs by identifying the reductions in shortage, shortage cost, and marginal values across the network.

While reservoir and conveyance expansion remain costly, and reduction to environmental flows faces legal concerns, adaptive operation of reservoirs statewide yields positive results to manage a variety of hydrologic scenarios. Reduced climate uncertainty through improved model representation would allow specific changes to operating rules to be designed. Flexible management of the statewide network of reservoirs controlled by various institutions requires collaborative management of water resources within California, which history has shown is a difficult task. Through continued efforts to identify vulnerabilities and develop adaptation strategies, California can adjust to drier and warmer climates by working towards collaboratively managing water at a statewide scale.

Climate change poses a significant threat to California, and adaptive water resources planning and management strategies will be required to respond to future stressors on the water network. Modeling plays a critical role in better understanding climate effects, including a combination of global circulation models and water resources planning models, to simulate or optimize operations. Furthermore, hydro-economic modeling can enlighten optimal strategies for adaptation and suggest potential operational improvements to the water supply network.

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