Rules-Based Systems Modeling for Hydropower Forecasting in Multi-Objective Reservoir Systems: Application to California's Central Valley Project

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Abstract

Hydropower from large multi-objective reservoirs and water management projects constitutes the bulk of global reservoir-based generation. Yet accurate forecasting remains challenging because generation is governed not only by hydrology but by complex institutional rules, environmental regulations, and infrastructure constraints. This study demonstrates that a rules-based systems modeling approach, one that explicitly integrates water allocation institutions, operational constraints, and hydrological variability, produces significantly more accurate and financially valuable hydropower forecasts than purely statistical methods. This framework is applied to California's Central Valley Project (CVP) using CALFEWS, an open-source daily timestep rules-based model of the Central Valley, extended here to include the Trinity River Diversion System and its evolving environmental flow regulations. CALFEWS is validated against 20 years of operational hydropower data (2003–2023), achieving r^2 = 0.84 for monthly CVP hydropower generation. Herein, we develop a 12 month two-stage October–April hydropower forecasting approach, initialized with October storage conditions and historical climatology, that incorporates water year type classification in April. The resulting forecasts achieve high fidelity, nearly matching the skill of simulations with perfect inflow foresight. Compared to statistical baselines, CALFEWS reduces hydropower forecast errors by 40% (RMSE) and hydropower financial losses relative to historic baselines by 20% ($75–115 million over a decade). While demonstrated for the CVP, the framework is directly transferable to any multi-objective reservoir system where institutional rules and competing water demands govern hydropower generation, a condition common across the U.S. and globally.

Plain Language Summary

Hydropower from large dams provides flexible, low-cost renewable electricity, yet forecasting how much will be generated is difficult for a range of reasons, starting with hydrological variability. In addition, dams don't just generate hydropower, they also supply water for farms and cities, protect against floods, and maintain river habitats for fish. All of these competing demands are governed by legal rules and environmental regulations that determine when and how much water is released, which combines with water availability, to determine power generation. Statistical models often miss this complexity. This study shows that a rules-based simulation model, one that explicitly simulates water management rules and constraints can forecast hydropower generation far more accurately. This approach is applied to California's Central Valley Project, a large federal water system with nearly 2,100 MW of hydropower capacity. Using only the amount of water stored in reservoirs at the start of the water year and general information about how wet or dry the year turns out to be, the model forecasts monthly hydropower generation with high accuracy. Better forecasts translate directly to financial savings reducing forecast-related losses by 20%, or $75–115 million over a decade. This approach is applicable to any large water management system where institutional rules, not just hydrology, govern hydropower generation.

Key Points -

- Rules-based water system modeling outperforms statistical methods for forecasting hydropower in multi-objective reservoir systems.
- Ensemble forecasts initialized with October storage and water year type achieve forecast skill near that of perfect-foresight simulations.
- Rules-based forecasts reduce financial losses from hydropower forecast errors by 20% compared to purely statistical baselines.

1. Introduction

Hydropower constitutes the largest share of renewable power generation globally, with over 30 countries using hydropower to generate more than 50% of their power needs (Førsund, 2015). The United States is the fourth largest hydropower generator, where it accounts for 6% of total power generation and 28% of electricity from renewables (Uria Martinez & Johnson, 2023). However, strong spatial heterogeneity exists in hydropower generation potential, with hydropower serving as a base load resource in the Pacific Northwest (Denaro et al., 2022; Markoff & Cullen, 2008), while functioning primarily as a dispatchable peaking resource elsewhere, including in California (Amonkar et al., 2025). Additionally, hydroelectric powerplants have low marginal costs of operation and are characterized by high ramping capability (Kern et al., 2015). Beyond energy generation, hydropower provides critical grid services including ancillary services, frequency regulation, and nearly 40% of black start capacity nationwide (Chang et al., 2013; Forrest et al., 2018; Pérez-Díaz & Wilhelmi, 2010), while also supporting the integration of intermittent renewables (Chang et al., 2013). Yet hydropower generation is vulnerable to hydrologic variability, with drought-driven reductions in inflows diminishing both generation and revenues (Amonkar et al., 2025; Zeighami et al., 2023). This risk is compounded by the correlation between droughts and heatwaves which drive elevated electricity demand (AghaKouchak et al., 2014). Overall, hydropower is of critical importance to the reliable and cost-effective operation of the modern electric grid.

Multi-purpose water management reservoirs that also produce hydropower constitute the bulk of hydropower capacity in the U.S. and across the globe. The Central Valley Project (California), the Tennessee Valley Authority (U.S. Southeast), the Colorado River Storage Project (American West), the Bonneville Power Administration and the Grand Coulee Dam Complex (Pacific Northwest) all operate large-scale, multi-purpose reservoir systems that combine flood control, irrigation, and navigation with significant hydroelectric power generation. Furthermore , there has been limited development of large multi-purpose reservoirs in the 21st century, making the existing hydropower capacity extremely valuable to the electric grid operations (East & Grant, 2023; Ho et al., 2017).

Such large multi-purpose reservoirs serve multiple competing objectives, including water supply, flood control, environmental protection, recreation, while also generating hydropower (Førsund, 2015; Kern & Characklis, 2017). These competing objectives result in reduced operational flexibility, leading to lower hydropower generation or a shift in generation during a period of lower economic value. Detrimental environmental impacts due to presence of these large projects have necessitated measures such as minimum environmental flows to ensure a suitable habitat for aquatic species (Zillig et al., 2021).

Minimum environmental flows for reservoirs without downstream regulating pools limit the ramping rate and thus the operational flexibility of hydropower plants (Kern & Characklis, 2017). Flood protection measures on the other hand require maintaining a flood control pool dictated by the U.S Army Corp of Engineers, potentially resulting in releases and hydropower generation during less optimal times.

Forecasts of hydropower generation from multi-objective water management projects that require coordination across numerous reservoirs, conveyance infrastructure, pump stations, compound hydrologic uncertainty (e.g., how much water will be available for generation at a reservoir) with operational uncertainty (e.g., when will reservoir operators release water for generation). Complex interactions between environmental regulations, infrastructure capacities, and economic institutions like water rights (Womble & Hanemann, 2020) drive reservoir releases and shift hydropower generation. Agricultural water demands driven by water rights in downstream basins influence the timing of inter-basin water transfers through jointly operated conveyance systems, driving overall release schedules from upstream reservoirs and influence regional hydropower generation (Zeff et al., 2021). Rules-based models are particularly effective at simulating these highly interdependent and institutionally complex systems that govern hydropower generation in multi-objective water management systems (Haimes, 2018).

Overall, reservoir-based hydropower systems represent key interactions between water and energy systems, yet most of the academic work has focused on optimizing the available flexibility of power generation as the single priority with limited, if any, consideration of the water system (Rheinheimer et al., 2023; Yates et al., 2021, 2024). A few studies have focused on modelling hydropower generation within electric grid models incorporating various characteristics yet only at the individual reservoir level, missing the decisions made at the overall project level (Magee et al., 2022; Stark et al., 2023). This divergence in the representation of such reservoir-based hydropower optimization in energy models results in overestimation of hydropower generation potential (Rheinheimer et al., 2023). This stands in contrast, especially in California, where “water trumps power” serves as the informal policy and hydropower is a lower and often conflicting priority to other water supply management objectives. Incorporating water system constraints helps reveal the true, thought limited, state-space over which hydropower can be optimized. This manuscript develops the central argument that accurately modeling hydropower within a multi-purpose, multi-reservoir system with competing objectives requires first modeling the water system itself, including the operational constraints and institutions-based priority rules that govern reservoir releases, in order to realistically represent hydropower operations and forecast generation. California's Central Valley Project with its complex system infrastructure exemplifies precisely the type of system where this approach is most needed and where purely statistical methods are most likely to fall short. The CVP is used here as a case study, though the underlying framework and findings are broadly applicable to large multi-objective water management projects that generate hydropower.

1.1 Study Region: California's Central Valley

Hydropower is a critical component of California's electric grid providing 10-20% of California's power needs contingent on the water year type (Rheinheimer et al., 2023). Variation in annual hydropower generation, driven by variability in annual precipitation, affects electricity prices, grid reliability, and the dispatch of alternative generation sources throughout the state (Amonkar et al., 2025). During California's 2012-2016 drought, the cost of lost hydropower generation amounted to approximately $1.9 billion (Kern et al., 2020). Studies point to an enhanced hydroclimatic "whiplash" in California (Swain et al., 2018), which are increased periods of multi-year droughts interrupted by very wet periods, shown to reduce carryover capacity and hydropower generation (Facincani Dourado et al., 2024). Additionally, California has numerous small high-elevation run-of-the-river hydropower plants in the Sierra Nevada mountains, yet a small number of large, multi-purpose dams such as Shasta and Oroville account for nearly 80% of hydropower generation (California Energy Commission, 2017; Nover et al., 2019; Rheinheimer et al., 2023). It is these multi-purpose water management reservoirs and the hydropower they generate that play a disproportionately large role in electric grid operations and are a focus of this study.

California's Central Valley (Figure 1, dark brown shaded region), spread over 20,000 sq. miles and drained by the Sacramento and San Joaquin rivers, is one of the most agriculturally productive regions in the world. About 17% of the nation's and 75% of California's irrigated land is located within the Central Valley (USGS, 2022). As seen in Figure 1, a vast array of dams, diversions, and related facilities form the water management infrastructure to support water supply, flood control, environmental requirements, recreation and hydropower in this region (Zeff et al., 2021). Statewide operations are coordinated through two large water management projects, the State Water Project (SWP) and the Central Valley Project (CVP). The CVP, owned by the federal government and operated by the U.S. Bureau of Reclamation serves to transport water from Northern California to the agricultural needs in the lower part of the Central Valley, in particular the San Joaquin and Tulare River basins. The SWP is owned and operated by the state of California and helps transport water to meet municipal demands in Southern California. The two projects are themselves regulated by an complex legal framework governing environmental protection disputes and regulations including meant to address acute groundwater depletion (Scanlon et al., 2012).

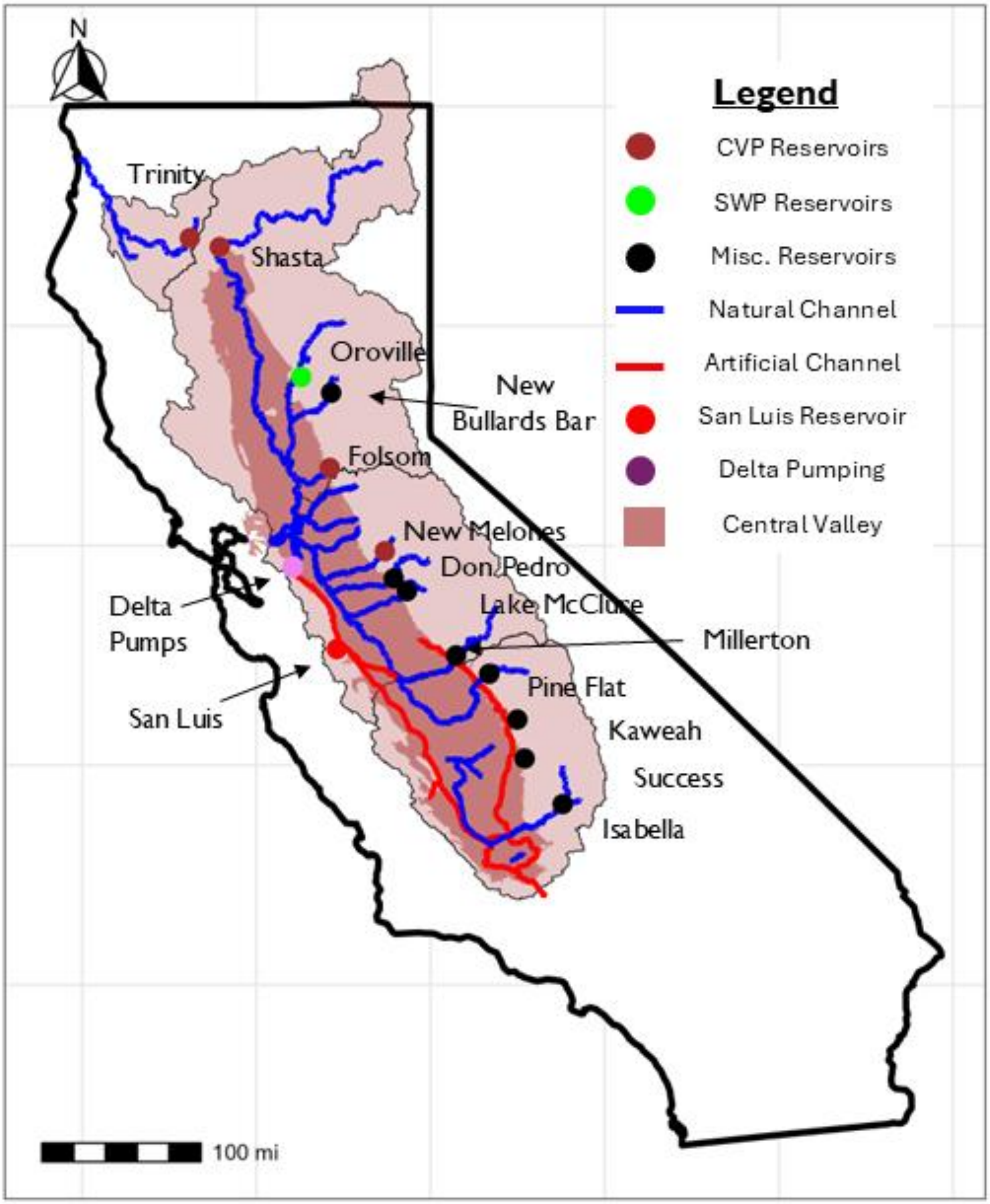

Figure 1: Map showing the study area and a subset of the included networks of main reservoirs, demand nodes, natural channels, artificial canals, hydropower plants, pumped- hydro plants and delta pumping incorporated in CALFEWS (Zeff et al (2021)).

CVP is a complex network of multi-purpose, multi-reservoir water storage and delivery projects extending hundreds of miles while also providing flood protection, environmental protection and hydropower generation (Figure 1) (USBR, 2024). The major facilities operated by the CVP are Shasta, Trinity, Folsom, New Melones, San Luis and Friant dams and reservoirs. In addition, CVP has long-term water supply agreements with over 250 contractors in the state's 29 counties. On average, CVP delivers about 5 million acre-feet (AF) of water for agriculture and about 600,000 AF for municipal and industrial uses (USBR, 2024). CVP is also a major producer of hydropower with nearly 2,100 MW of installed hydropower capacity and is a producer of hydropower in the state. Shasta powerplant is the largest of the facilities with an installed capacity of 676 MW, and Table S1 (where "S" denotes supplementary materials) displays the capacities of the eight hydropower plants operated by the CVP.

These large dams alter a river's natural streamflow (Nichols et al., 2014; Zillig et al., 2021) and block access to upstream riverine habitats, thereby endangering native fish populations, a huge concern for salmonid species in California's Central Valley (Yoshiyama et al., 2000). Furthermore, water demands from irrigation districts in the San Joaquin and Tulare basins impact the timing of water exports from the Sacramento-San Joaquin Delta, driving overall water releases schedules from Sacramento basin reservoirs and influencing statewide hydropower generation (Zeff et al., 2021). California's highly interdependent and institutionally complex water management system makes it an ideal case study for analyzing the effectiveness of rules-based models in simulating and forecasting hydropower generation.

This study uses the California Food Energy Water System (CALFEWS) model (Zeff et al. 2021), an open-source, rules-based, model of Central Valley surface water and groundwater operations, to model and forecast CVP hydropower generation. To enable this analysis, we extended the CALFEWS modeling framework with representations of the Trinity River Diversion System (See Supplemental Information for more details), including its evolving environmental flow regulations and developed bespoke hydropower generation modules for all CVP powerplants, collectively representing the first integrated rules-based simulation of CVP hydropower operations. The additions and modifications to CALFEWS needed to accurately represent CVP hydropower operations are described in the Data and Methods sections. The Results section begins with a baseline validation of CALFEWS's skill in representing CVP hydropower operations from October 1996 to September 2023, followed by a comparison of ensemble forecasting approaches using CALFEWS over multiple time horizons against purely statistical methods. Finally, financial risks associated with forecast skill are evaluated and traced to losses incurred in electricity markets. The paper concludes with a discussion of findings, conclusions, and directions for future work.

2 Data

2.1 California Data Exchange Center

The California Data Exchange Center (CDEC) a centralized repository that collects, processes, and disseminates real-time hydrologic information (precipitation, river forecasts, river stages and flow rates, snow conditions, and reservoir storage levels) contributed by various collaborative agencies throughout California, serves as the primary source of daily hydrological data utilized in this study (California DWR, 2025). Given that CALFEWS is a daily simulation model, the CDEC data serve as “ground truth” within the model and are used to inform and update hydrological states at reservoirs, flow gauges, and demand. We refer the reader to Zeff et al., 2021 for additional details on the CDEC variables and stations used throughout CALFEWS. For example, each storage node within CALFEWS is associated with a CDEC full-natural flow gauge, outflow gauge and multiple snowpack gauges.

2.2 Monthly Hydropower Generation Data

The Energy Information Administration (EIA) in its survey Form EIA-923 (previously EIA-906/920) collects annual and monthly net generation across almost all U.S. power plants, including hydroelectric plants (U.S. EIA, 2023). While about 90% of the nearly 1,500 hydroelectric plants across the U.S. report values at an annual level and are then imputed monthly (using aggregated allocation factors rather than considerations of local hydrology) (Turner et al., 2022), all the CVP owned powerplants report monthly values making the Form EIA-923 data suitable for this study. The monthly net generation across the CVP owned power plants (Table S1) are obtained from Form EIA-923 from October 2003 to September 2023 and serve as the “ground truth” for validation and assessing CALFEWS modeling and forecast skill.

2.3 Hydropower Generation Modules

Daily hydropower generation at each CVP powerplant is estimated using plant-specific generation modules developed by the Western Area Power Administration (WAPA) and further adapted for this study and incorporated within CALFEWS. These modules use higher order polynomials to estimate gross hydraulic head (the difference between tailwater and forebay elevation), power generation potential (kWh/AF of release), and total hydropower generation. Penstock flow release constraints (i.e., the volumetric limit that can be sent to the powerhouse) are also included using plant-specific penstock capacities (e.g., 34.9 Thousand Acre-Feet (TAF) per day for Shasta), with daily flows exceeding this limit treated as spill. One shortcoming of these modules is that they do not account for planned and unplanned powerplant outages or operator decisions to curtail generation when electricity prices fall below zero. Table S1 displays the installed capacity (MW), penstock capacity (TAF/day), and module performance statistics (Pearson correlation and mean-squared errors) for the CVP hydroelectric powerplants. Module validation against monthly EIA-923 reported generation is shown in Figure S1. Overall, the modules perform well, with some months of overestimation attributable to unmodeled plant shutdowns.

3 Methods

3.1 CALFEWS

CALFEWS is an open-source rules based Python/Cython simulation model of the surface water movement across California, primarily focusing on operations within the Central Valley (Zeff et al., 2021). The CALFEWS modeling framework has numerous advantages when compared to other open-source alternatives including CALVIN (Draper et al., 2003) , CALSIM (Draper et al., 2004) & CalLite (Islam et al., 2020) water resource models. The primary advantage is modeling at finer spatiotemporal resolutions without exceedingly highly computational requirements (running one year takes one minute on a regular personal computer, with parallelization also possible). CALFEWS includes distinct water demands representation (water districts & irrigation districts) while also running at a daily time step. The detailed demand representation provides CALFEWS with the unique capability to monitor how district-level decision-making affects statewide water supply projects which has importance given the large interannual hydrological variability & changing demand structure affecting the overall operations. Similarly, daily time resolution is necessary to resolve a number of environmental constraints and model the influence of transient high-flow events (e.g., atmospheric rivers) on power generation. Additionally, CALFEWS also includes representation of both the CVP and the SWP, and the coordinated operations between them. CALFEWS also employs a rules-based representation of system dynamics, unlike the mathematical optimization and programming approaches used in the previously mentioned models. For this study, we extended CALFEWS to include the Trinity River Diversion System, which accounts for nearly a quarter of total CVP installed hydropower capacity and is governed by complex, evolving environmental flow regulations including the 2000 Record of Decision (see the supplementary materials section on Trinity Diversion System for additional details). Daily reservoir releases and storage levels from CALFEWS are passed through plant-specific hydropower generation modules to estimate daily hydropower generation at each CVP powerplant. This rules-based method allows for more flexible representation of system complexities including ever-evolving regulatory landscape, adaptive operations, environmental regulations, groundwater banking arrangements, and distributed district-level decision-making. Figure 2 represents CALFEWS's overall operational and logical schematic and flow of information depicting how observed states (e.g., full-natural flow and snowpack) are used to model distributed decision-making (e.g. reservoir releases, groundwater recharge diversions) and state responses (e.g. reservoir storage, groundwater bank accounts) and finally converting to model decisions constrained by institutional capacities and regulatory constraints (Zeff et al., 2021).

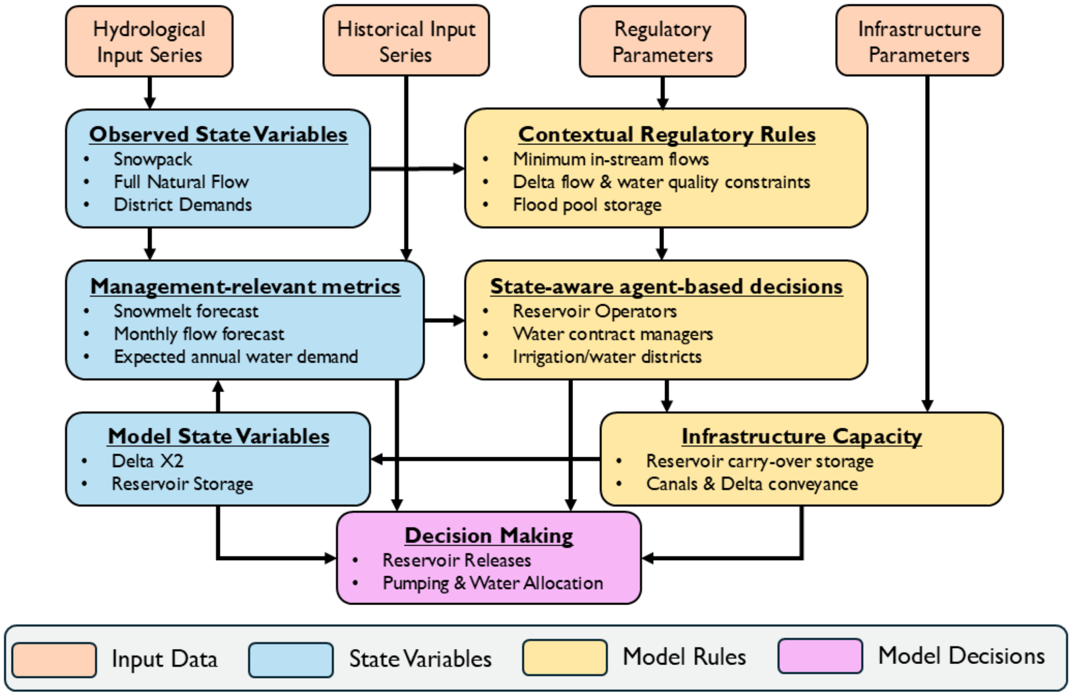

Figure 2: CALFEWS daily simulation schematic adapted from Zeff et al (2021).

The CALFEWS modeling framework allows the model to run in both validation and simulation mode. In the validation mode run from 1st October 1995 to 30th September 2023, the reservoir storage levels are initialized at the beginning of each water year (October 1st) to the "true" CDEC values and CALFEWS mimics operator decisions based on incoming (yet historic) full natural flows and the evolving regulatory constraints over the water year and the process resets again on October 1st. Whereas in the simulation period, the storage values are initialized only once at the beginning and the system can be subjected to different combinations of full natural flow inflows and regulatory regimes. While this validation run serves as a check on the ability of CALFEWS to model the historic conditions, the simulation runs allows for testing the system under different hydrological (environmental) and regulatory (institutional) regimes.

4 Results

The results are presented in three sections. First, we validate CALFEWS's ability to model hydrological operations and CVP hydropower generation from October 1995 to September 2023 while accounting for the evolving regulatory and policy structure. Second, we develop and evaluate ensemble forecasting approaches using CALFEWS across multiple lead times and compare predictive skill against purely statistical methods. Finally, we translate forecast errors into financial losses to quantify the economic value of improved hydropower forecasting.

4.1 CALFEWS Validation

The results presented in this section are based on running CALFEWS in annual validation mode, in which the system is modeled using observed data that serves as the validation dataset. Simulated reservoir storage levels generated using historical forcing data are benchmarked against observed reservoir storage levels at locations throughout the Central Valley to evaluate the fidelity with which CALFEWS reproduces historical operational behavior. The annual model validation begins on October 1st, 1995 (WY 1996) and end on September 30th, 2023 (WY 2023) representing 28 separate runs. The model runs begin at the start of each Water Year (October-1st), and “true” CDEC full natural flow data are passed through the model one-day at the time. The model makes decisions on the data available and does not “see” the entire year ahead, thereby mimicking the operations by water operators. These annual simulations can be conceptualized as CALFEWS hydropower projections under conditions of perfect inflow foresight, given that hydrological uncertainty constitutes the predominant source of variability. CALFEWS dynamically updates its representation of water rights, environmental regulations, and operational policies across the simulation period, allowing the validation to reflect the evolving regulatory and management context between WY 1996 and WY 2023. The reader is referred to Zeff et al. (2021) for a comprehensive treatment of CALFEWS performance across additional state variables.

4.1.1 Validation – Storage & Releases

The rules based operating structure within CALFEWS enables simulation of the hydrological system given daily natural flow across all reservoir nodes. For example, one reservoir node within CALFEWS is the Shasta reservoir, with a total reservoir capacity of 4.55 MAF, which serves vital functions of flood control, water supply, and maintaining environmental conditions. Similarly, Trinity reservoir captures waters from the Trinity basin and serves as the point of transfer (from Lewiston) to CVP in Sacramento (Figure 1). From the CVP perspective, Shasta and Trinity form the two largest reservoirs and are crucial in CVP operations. Figure 3 shows the ability of CALFEWS to accurately model fluctuations in reservoir storage levels from WY1996-WY2023, including capturing the dynamics during the multi-year droughts in 2014-2016 and 2020-2022. The coefficient of determination (r^2) between CDEC and CALFEWS reservoir storage values for both Shasta and Trinity are 0.95, whereas the root mean-squared error (RMSE) in modeling the monthly storage is 242 TAF and 117 TAF respectively. Storage levels at Folsom (r^2=0.82), New Melones (r^2=0.95) and San Luis (r^2= 0.82), other major CVP reservoirs with installed hydropower capacity, are also well represented within CALFEWS (Figure S3). Overall, CALFEWS shows considerable skill in modeling hydrological operations for all the reservoirs (CVP & SWP) across the Sacramento, San Joaquin and Tulare River basins, with performance best in the Sacramento and upper San Joaquin reservoirs that host the bulk of CVP hydropower installations (Figure S3).

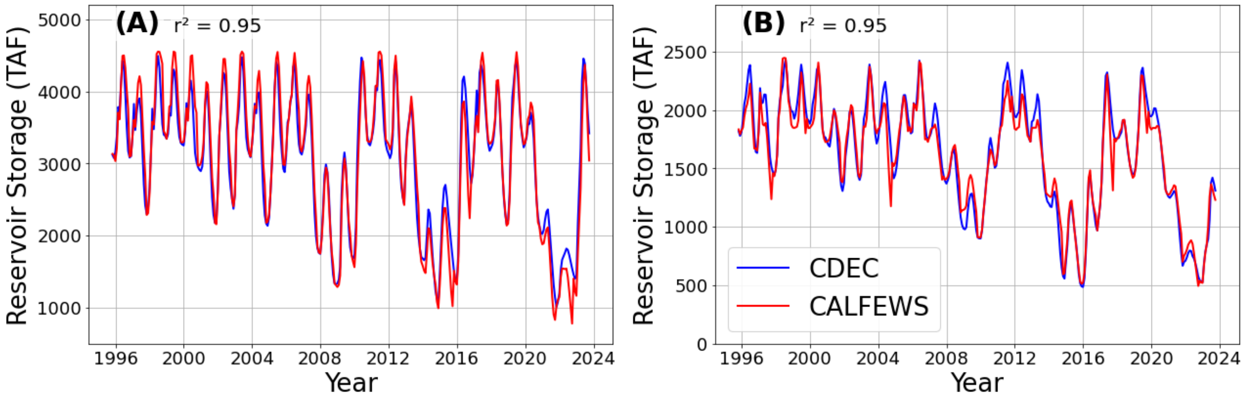

Figure 3: CALFEWS and CDEC storage values in TAF at Shasta (A) and Trinity (B) reservoirs. For each subplot, the red line denotes the mean monthly CALFEWS storage whereas the blue line denotes values as recorded in the CDEC database.

4.1.2 Validation – Hydropower

The total CVP hydropower is the sum of the hydropower generated from power plants operated as part of the CVP (Table S1). The outputs from the annual validation CALFEWS runs (i.e., daily reservoir releases and storage levels) serve as the inputs to the hydropower generation modules to estimate daily hydropower. The monthly EIA data serves as the hydropower validation dataset and daily CALFEWS modelled hydropower was aggregated at the monthly timestep to facilitate a comparison. The shorter validation period corresponds to the availability of the EIA data. Figure 4 shows the performance between observed monthly and simulated CVP hydropower during the 20-year historical period. Overall, CALFEWS captures variability in the total CVP generation across the 20-year validation period from October 2003 to September 2023. The modelled CALFEWS hydropower captures the overall trends across drought periods as well as during wet and normal years. The strong correlation $r^2 = 0.84$ between observed and simulated monthly hydropower generation indicates that the model effectively captures the majority of variability in total CVP hydropower generation, despite the sheer complexity of operations in the Central Valley. Similar plots for the individual hydropower plants are attached in the supplemental materials (Figure S4) . The monthly correlation, representing the skill of CALFEWS to capture the variability in operations, is high at Shasta, Folsom, New Melones and Trinity which form the bulk of the operations.

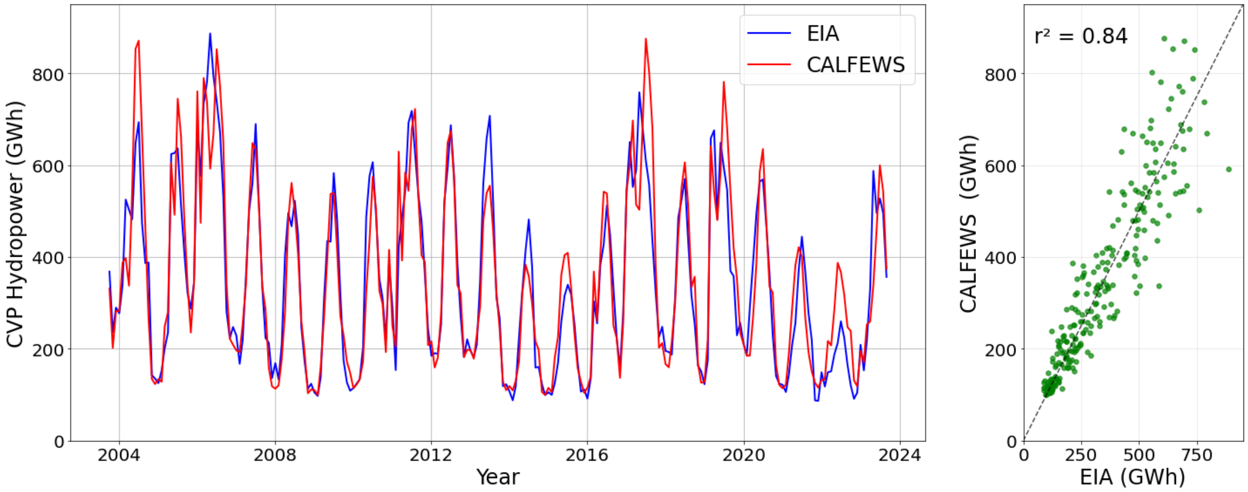

Figure 4: (Left) - Timeseries of the total monthly CVP hydropower generation as computed using the CALFEWS (red) and EIA reported values (blue). (Right) - Scatter plot of the CALFEWS vs EIA generation values for the total monthly CVP hydropower generation. The dotted black line denotes the 45-degree line.

Figure 5 illustrates the strong correspondence between CALFEWS and EIA generation at an annual timestep for each water year along with the corresponding water year type as recorded for Sacramento Valley. The largest determinant of variability in overall CVP generation is the water year type. Critical water years are associated with the lowest total generation whereas the extremely wet water year types (attributed when Trinity basin is classified to be in an extremely wet year) correspond to years with the highest generations. Furthermore, the scale of the variability from nearly 2000 - 7000 GWh/yr illustrates the true supply risk of CVP hydropower. For non-extreme water years, initial storage levels become the deciding factor in that year's generation values. For example, WY 2023 classified as a 'Wet' water year has the lowest generation total of 3850 GWh for any wet water year by a huge margin. This is caused by a low starting storage level caused by the preceding multi-year drought, which included a dry year (WY 2020) and two critical years (WY 2021 and WY 2022). Whereas WY 2006's anomalous large generation value can be attributed to the extremely high inflows along with a different regulatory regime in the Trinity River basin which allowed for greater diversions and consequently hydropower generation. The same value of inflow and storage in WY 2024 would lead to lower generation due to evolving regulations.

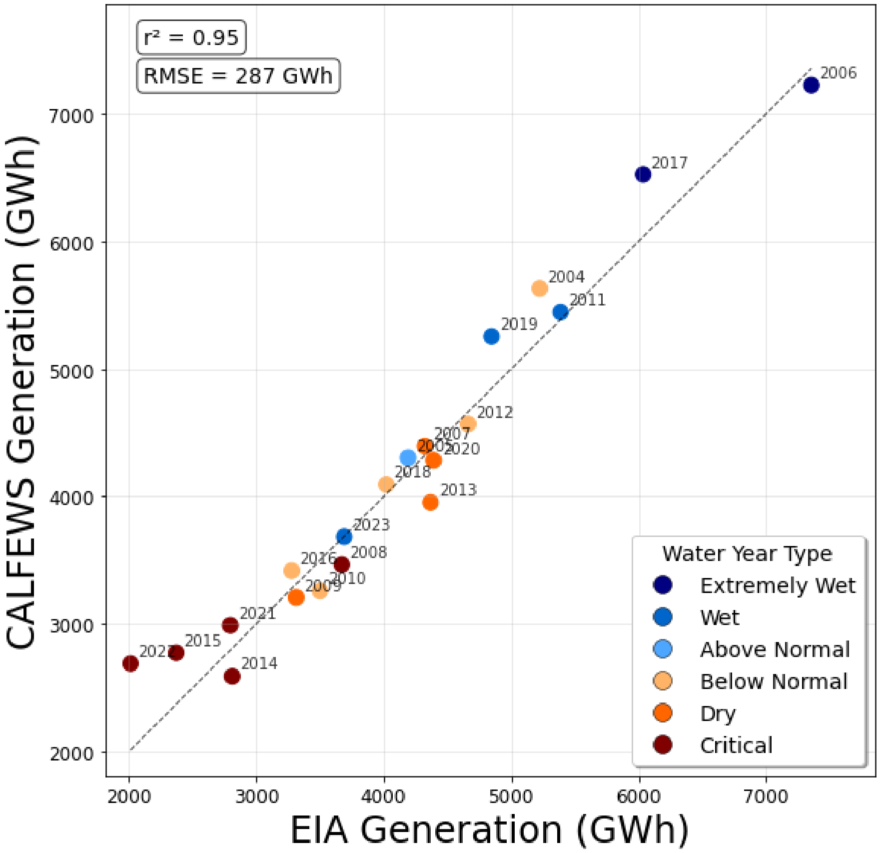

Figure 5: Scatterplot of annual CALFEWS estimated versus EIA reported CVP hydropower generation. The shaded colors denote the Water Year Types in the Sacramento River, and the numbers denote the Water Years.

Overall CALFEWS demonstrates robust validation across key hydrological metrics, capturing reservoir storage levels, hydropower generation, and CVP hydropower with high fidelity. Furthermore, the model's validation period incorporates temporal representations of regulatory and infrastructure modifications, including environmental flow mandates, delta transfer constraints, and physical infrastructure changes, all aligned with their actual implementation dates. By encompassing significant structural transitions and diverse hydrological conditions, the validation approach substantiates the CALFEWS adaptive framework and its potential to analyze future uncertainties in water resource management.

4.2 Hydropower Ensemble Forecasting

CVP hydropower serves as a peaking power resource in California. Power consumers, especially large sophisticated buyers, continuously adjust their open positions (projected demand minus power purchase agreements). Accurate hydropower generation forecasts help power consumers proactively purchase additional power and reduce market volatility exposure. Under-forecasting forces consumers to purchase power at the last minute on the spot market. Whereas over-forecasting compels consumers to pay a premium earlier to purchase power and then having to sell it at the spot market.

Hydrological variability, characterized by annual full natural flows and water year type, significantly impacts hydropower generation (Figure 5). Furthermore, the annual validation runs show that CALFEWS can accurately model and thereby forecast CVP hydropower given annual full natural flows. Yet predicting hydropower generation over longer timeframes using future inflows isn't a feasible solution. Future precipitation and streamflow are notoriously difficult to predict over longer periods, especially in California (Harrison & Bales, 2016). For example, the 365-day streamflow ensembles provided by California Nevada River Forecast Center (CNRFC) are influenced by short-term meteorological forecast information for the first few days. As forecast skill diminishes especially beyond 28 days of lead time, the streamflow traces are 100% driven by climatological meteorology (NOAA NWS, 2020). Consequently, the historical climatological data (WY 1996 – WY 2023) is used as a more reliable basis for our long-horizon hydropower ensembles. This helps circumvent the limitations of streamflow predictive models.

In the sections below we ask the question, using only initial reservoir storage conditions (information that is available in real time) and the historical climatology, can CALFEWS generate useful ensemble forecasts of CVP hydropower over multi-year time horizons beginning October 1st? This approach could be used to generate the ensemble forecasts in real time every October 1st, helping in hydropower planning and allocation.

4.2.1 Long Term Ensemble Forecasting

Figure 6 illustrates CALFEWS's hydropower ensemble forecasts over a 5-yr time horizon starting from October 1st 2018 and up to September 30th 2023. October 1st, 2018 was selected as the initialization date as it represents the start of the last complete 5-year period within the validation record (WY 1996–WY 2023). The ensemble forecasts are all initialized using October 1st 2018 reservoir storage levels across the reservoir nodes included in CALFEWS (Figure 1). Each ensemble run corresponds to a red line in Figure 6 and represents the CALFEWS response to a 5-year contiguous period forcing. We start the ensemble runs by initializing CALFEWS using October 1st 2018 storage values and forcing the daily full natural inflows as were observed from October 1st 1995 to September 30th 2000. The next ensemble run was initialized with the same October 1st 2018 storage values but input flows from October 1st 1996 to September 30th 2001, with the whole process being repeated across the entire climatological record producing a total of 23 traces. Modeled CALFEWS releases and reservoir storage levels from each run were used to compute CVP hydropower and represented as red lines in Figure 6. The red shaded region denotes the 80% ensemble probability range, representing the spread in the 10th to 90th percentiles, whereas the blue solid line denotes the EIA generation.

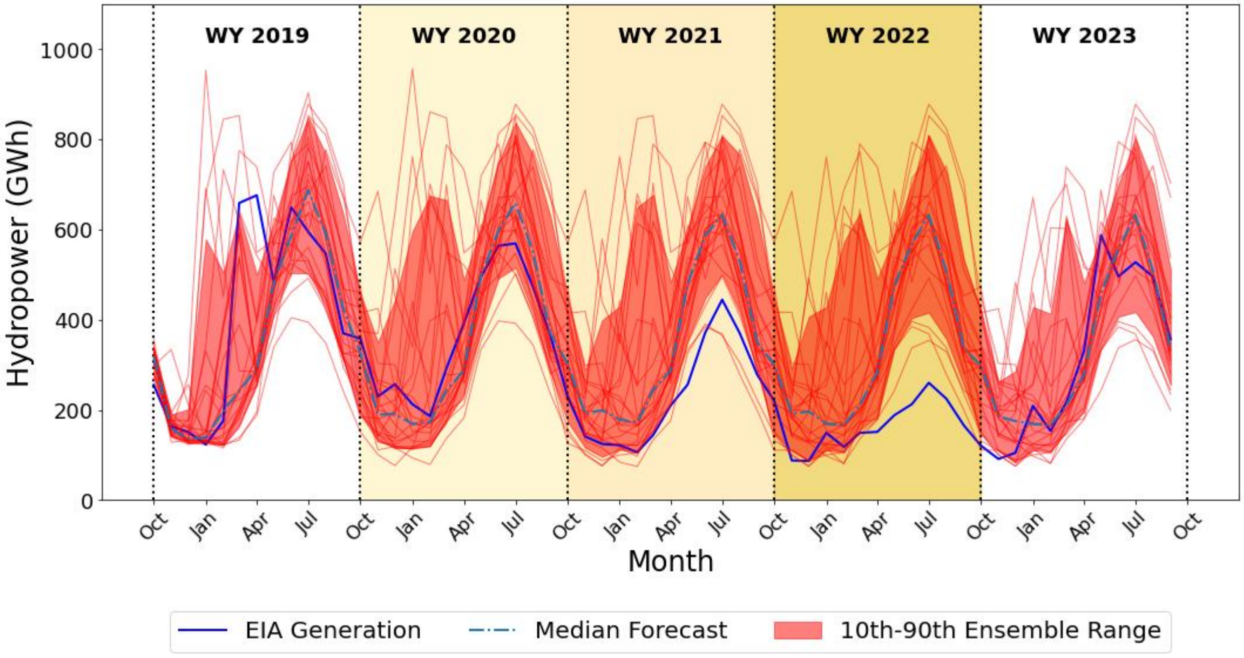

Figure 6: Monthly CVP hydropower ensemble forecasts generated using CALFEWS initiated using October 1st, 2018, storage levels . The individual red lines denote the individual runs using the 28-yr climatological record. The solid blue line denotes the EIA generation values, whereas the dotted blue line denotes the median of the ensembles. The red shaded region denotes the 80% probability range. The vertical dotted lines denote subsequent October 1st dates.

The ensemble forecast uncertainty is small during the first three months, closely bracketing observed EIA generation (Figure 6), before increasing substantially yet bracketing the true values within the 80% probability bounds except for one month during water year 2019 (Figure 6). For WY 2020, the first year of the three-year drought period (2020-2022), EIA generation remains within the 80% ensemble probability range. However, in the water year 2021 and water year 2022, EIA values significantly deviate from the ensemble forecast before returning to the ensemble range by water year 2023. This pattern is not surprising, as ensemble forecasts are designed to capture the median system behavior, making it inherently challenging to predict multi-year extremes far from the initiation point. The key takeaway from Figure 6 is not that CALFEWS predicts CVP hydropower with exceptional accuracy over five years, but that it effectively captures the plausible range of hydropower generation outcomes using readily available inputs namely, current storage levels and historical climatology.

The next step was to ascertain the influence of initial reservoir storage levels on future hydropower generation. CALFEWS was initialized at two points at the start of the water year. The first on October 1st 2011, which represents the highest initial total reservoir storage levels measured using the total storage across all CVP reservoirs (henceforth high storage). The second on October 1st 2015 (henceforth low storage) which was the lowest total reservoir storage. Both model initializations were then forced with the same historic climatology over a 5-year time horizon as described above. Figure 7 shows the computed median and ensemble spread of CVP hydropower for both the high storage and low storage level starts. The difference in hydropower generation between ensemble forecasts is large during the first few months, reflecting the period when storage conditions directly control release patterns and generation capacity. Even by the summer of the first water year, a significant difference persists in median expected generation between scenarios, though the ensemble ranges begin to show growing overlap by this point. Ensemble range overlap increases substantially by the second water year, with near convergence achieved by third water year. Figure 7 demonstrates that while initial reservoir storage conditions strongly influence annual hydropower generation, their predictive skill diminishes rapidly beyond that timeframe. At longer time scales, incoming flows (i.e., hydrology) become the primary driver of generation variability.

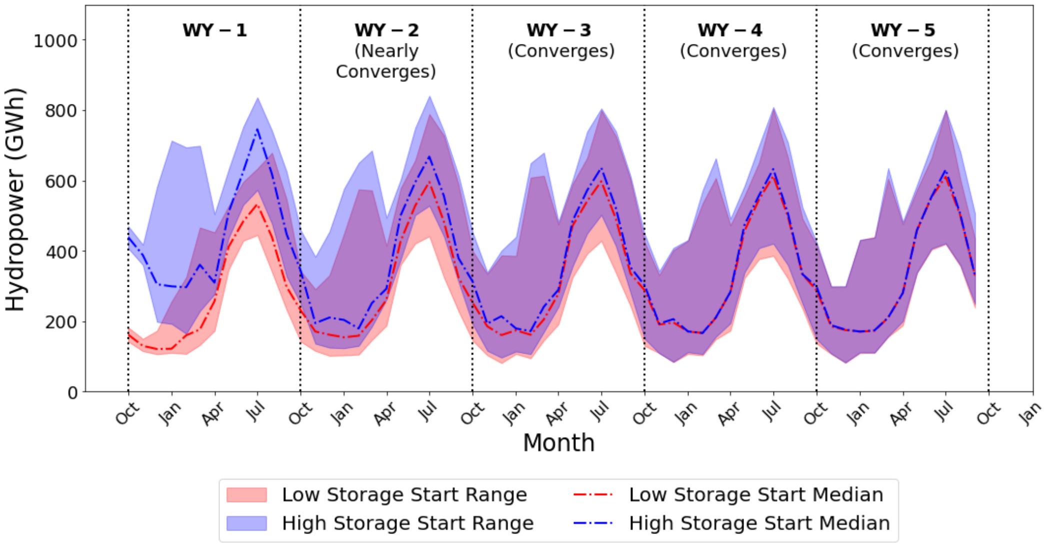

Figure 7: Monthly CVP hydropower ensemble forecasts generated using CALFEWS initiated on October 1st 2011 (high storage start) and on October 1st 2015 (low storage start). The dotted lines and shaded regions denote the median and 80% probability range for the respective ensembles. The vertical dotted lines denote subsequent October 1st dates.

4.2.2 Annual Ensemble Forecasting

CALFEWS October-April Two Stage Forecasts

This section focuses on annual hydropower forecasts for the Central Valley Project. CALFEWS is initialized every 1st October, using the recorded reservoir storage levels. The model runs are then forced with annual climatological inflows to generate an ensemble of CVP hydropower for the next 365 days. This procedure is repeated from October 1st 1995 to October 1st 2022, 28 different intializations each forced with 28 historical annual inflows, representing 784 (28 x 28) annual CALFEWS runs (Figure S5).

The next step is incorporating that year's hydrological conditions within the generated ensembles. The year's overall hydrological conditions are well represented as a single metric in the Water Year type. Furthermore the water year type is known with high confidence by April (Harrison & Bales, 2016). This helps overcome the problem of poor long-term streamflow forecasts. We refer to this forecasting approach as the CALFEWS October-April two-stage annual forecast. To augement the annual ensemble of hydropower generation using initial storage conditions and climatology that was generated on October 1st we use the following rules: Hydropower generation from October to March is assumed to be the median value of the ensemble. This represents months when future inflow conditions are not known, hence a guess of the median value. Only on April 1st is the information on the water year type included. The forecast including the entire range of ensemble values are provided on October 1st, with an additional guidance on April 1st.

Hydropower generation from April to September incorporates this single input of the water year type as additional information in the forecast. Furthermore based on the water year type we use the following ensemble percentiles for the next six months: Critical – 10th percentile, Dry – 25th percentile, Below Normal – 50th percentile, Above Normal – 75th percentile, Wet – 90th percentile and Extremely Wet – 95th percentile. Overall, the CALFEWS October-April two stage annual forecast uses October 1st reservoir storage levels to generate the entire ensemble spread for the next 365 days. Later on April 1st, additional information is incorporated to determine the ensembe exceedance threshold. Figure S6 displays this forecasting process for the different water year types and show the April classification is reflected in the ensemble.

Statistical Forecasts

The CALFEWS based forecasts are compared against statistical forecasts that use the same input information. This enables an "apples-to-apples" comparision against statistical methods that serve as proxies for current operational practices. The statistical (baseline) and statistical (ensemble) methods use regression to predict CVP hydropower generation using October 1st reservoir storage and cumulative monthly inflows as predictors. Both methods use the same fitted regression parameters (Refer the suppplemental information for details on the regression). Statistical (ensemble) uses a similar October-April two-stage forecast methodology. Hydropower predictions are made for each year using the October 1st reservoir storage levels and repeated for each cumulative monthly inflow set observed in the climatology. This generates an ensemble of hydropower predictions and we use a similar set of rules described above to decide on the monthly forecast values. Unlike CALFEWS only the 10th, 50th and 90th ensemble percentile values are used for different water year types, representing the inflow forecasts provided in Bulletin 120 by the California Department of Water Resources (California DWR, 2020). The statistical (baseline) method on the other hand, uses 10th, 50th and 90th percentile inflow exceedances based on historical climatology to make predictions. This approach use the 50th percentile inflows from October to March and the 10th, 50th or 90th percentiles if the water year is Critical or Dry; Below Normal; Above Normal, Wet or Extremely Wet respectively along with the October 1st storage as the other predictor. Refer to supplementary materials for more information.

CALFEWS skill in predicting annual CVP hydropower using the October-April two stage forecasting method is compared against statistical (baseline) and statistical (ensemble) methods in Figure 8. Water year 2014 – water year 2023, the second half of the CALFEWS model runs, represents the testing dataset. Despite being subject to a degree of forecasting bias (especially in Water year 2017), CALFEWS skillfully forecasts CVP hydropower, especially when compared to the other methods. Forecasted CVP hydropower using the CALFEWS October-April two stage method has an r^2 of 0.9, whereas the r^2 from the statistical (baseline) versus the statistical (ensemble) methods using a similar two stage method are 0.26 and 0.66 respectively.

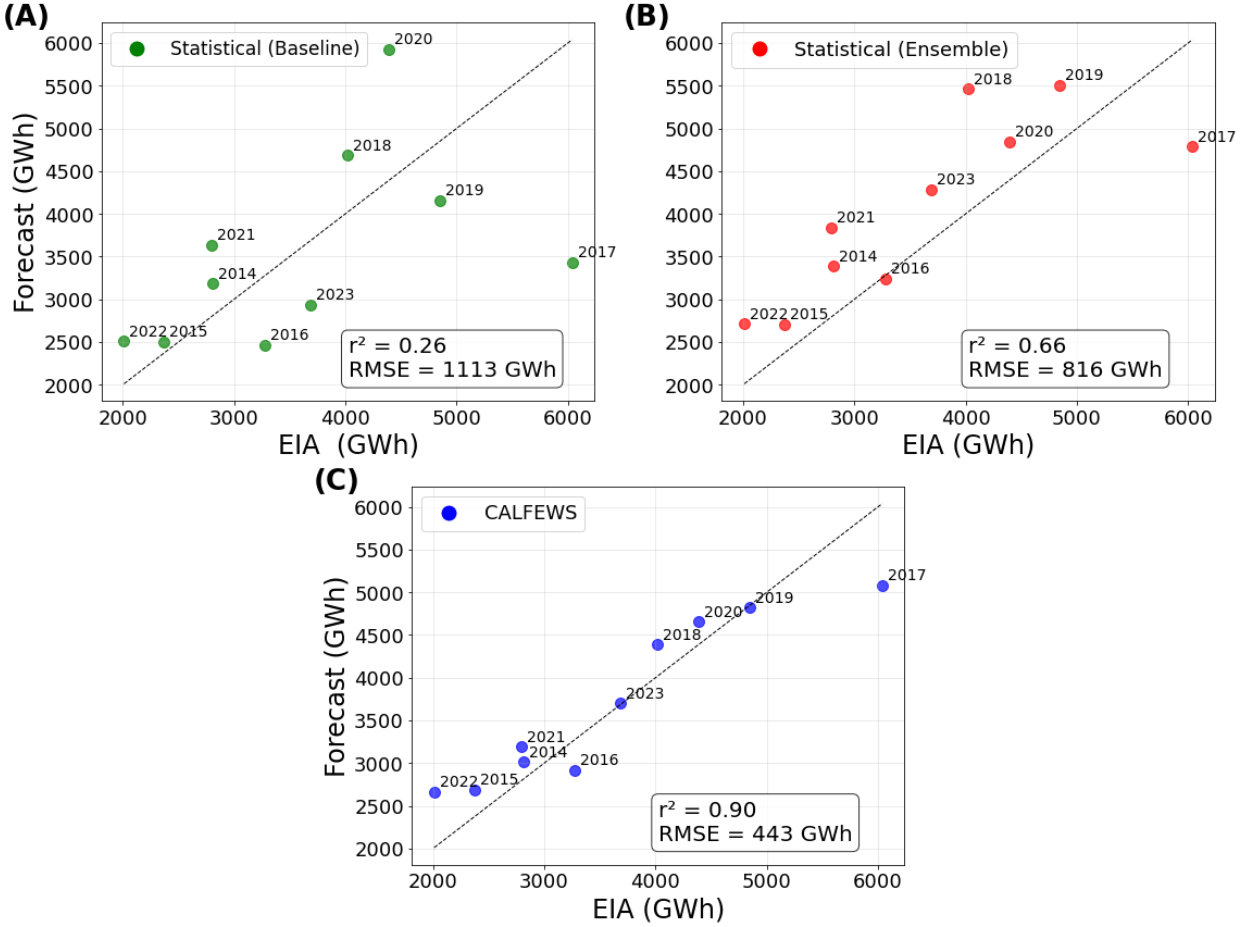

Figure 8: October-April two stage forecast estimates versus EIA generation values for the annual CVP hydropower using the statistical baseline (A), statistical ensemble (B) and CALFEWS (C) methods. Water Years are denoted besides each dot. For each method the coefficient of determination (r^2) and the root mean squared error over the testing dataset (WY 2014- WY 2023) are shown.

Similarly, the CALFEWS RMSE of 443 GWh per year is nearly half of the statistical (baseline) RMSE and represents a 40% reduction when compared to the statistical (ensemble) method. Despite the overall complexity driving system operations, the CALFEWS October-April two stage forecast skillfully forecasts hydropower using October 1st storage levels and can be made available to the necessary stakeholders in two stages on October 1st and April 1st. Operating with just October 1st storage and water year type information, the October-April two stage forecasts (r^2 = 0.9 and RMSE = 443 GWh) nearly approaches the skill of validation case (r^2 = 0.95, RMSE = 287 GWh Figure 6) where the incoming full-natural flows are known, suggesting that the water year classification and initial storage conditions constitute the primary drivers of seasonal predictability.

4.3 Financial Risks

In this section we analyze the integration of hydropower forecasts in power operations from a first principle basis and help translate uncertainty and errors in forecasts (generally communicated in r^2 and RMSE in GWh) to potential financial losses. This also helps indirectly answer the question, what is the value of a forecast and how do improvements in forecasting skill translate to better operational planning and reduced costs. Assuming the reported EIA generation values as the ground truth, the potential errors in the forecast are converted to financial losses using the monthly averaged CAISO prices. Both shortfalls and overestimations in forecasted hydropower are treated as equivalent financial risks. When actual hydropower generation falls short of forecasts, the deficit must be purchased on the spot market at prevailing prices. Conversely, when forecasts overestimate generation, this creates opportunity costs through suboptimal hedging strategies that were based on the inflated projections. To account for the evolving electricity rate structure associated with renewable energy integration and technological innovation (Kern & Characklis, 2017; Krietemeyer et al., 2021), financial losses in California were estimated using two distinct pricing frameworks: historical baseline monthly prices from October 2013 through September 2023, and current market rates represented from October 2022 through September 2023 (Water Year 2023).

The CALFEWS October-April two stage forecasts outperform statistical forecasting using the similar two stage methodology, reducing financial losses by 20% under both pricing scenarios compared to the statistical baseline (Table 1). This performance advantage is considerable, representing $75 million in avoided losses under historical pricing conditions and $115 million under Water Year 2023 rates over the decade-long evaluation period. The statistical ensemble method demonstrates negligible improvement over the baseline with only 2% reduction under historical pricing and slight deterioration (-1%) under contemporary pricing.

Table 1: Financial losses estimated using the October-April two stage forecast values for Water Year 2014 to Water Year 2023. The historical losses are computed using the historical prices from October 2013-September 2023, whereas the losses for the second case (WY 2023) are computed using monthly WY 2023 prices and forecasting erros across the 10-yrs of testing data.

	Losses (Historical)	% Reduction (Historical)	Losses (WY 2023)	% Reduction (WY 2023)
Statistical (Baseline)	$ 373 M	-	$ 611 M	-
Statistical (Ensemble)	$ 365 M	2 %	$ 615 M	-1%
CALFEWS	$ 298 M	20 %	$ 497 M	19%

The financial losses attributed to CALFEWS may be overestimated in this analysis, as the daily forecasting model's hydropower outputs are aggregated to monthly timesteps, causing even minor temporal shifts (e.g., weekly variations) to register as losses despite accurate cumulative annual production predictions. This temporal aggregation effect is evident in Water Year 2023 using the historical pricing scenario (Figure S7), where CALFEWS accurately predicted total annual generation but still incurred $35 million in estimated losses due to slight monthly timing differences, suggesting that more detailed electric system modeling is required to fully capture the true financial benefits of CALFEWS modeling capabilities. The statistical baseline and ensemble approaches, operate on monthly regressions and achieving finer temporal granularity for these statistical approaches is challenging due to limited historical data availability and the substantial increase in model parameters required when transitioning from monthly to daily resolution.

5. Discussion & Conclusion

Large multi-objective reservoir and water management projects sit at the intersection of water and energy systems, a pattern common across the U.S. and globally. Hydropower generated by these systems is among the most flexible and least expensive renewable resources available to the grid. Yet forecasting its generation remains challenging because hydropower is often one of several objectives governed by complex water allocation rules, environmental regulations, and infrastructure constraints that vary across systems and evolve over time. This study demonstrates that a rules-based systems modeling approach, one that models multiple aspects of the water system and then derives hydropower as an output, produces more accurate and financially valuable forecasts than purely statistical methods. Results show that predictability was limited to only a few months, even considering extremes in initial storage levels. Given the role of hydropower forecasts in overall power procurement strategies across large power consumer, this motivated analysis limiting the prediction horizon to one year incorporating additional mid-water year information in April. Forecast skill from CALFEWS was compared against purely statistical methods, using the same input data sources. The results show that CALFEWS forecasts of CVP hydropower have the potential to reduce financial losses by $75M over 10 years relative to more commonly used approaches.

While the rules-based forecasting approach demonstrates significant predictive skill, several limitations exist and remedying this will be the focus of future work. Codified operational rules are represented in CALFEWS but not real-time operator discretion. Decisions to deviate from standard release protocols during extreme hydrologic conditions appear to introduce variability that the model cannot currently fully represent. This limitation is not unique to CALFEWS. Any rules-based model of a multi-objective system must balance fidelity to institutional rules against the irreducible uncertainty of human decision-making. Additionally, while CALFEWS requires periodic modification to incorporate evolving regulatory constraints, infrastructure changes, and shifting climatological patterns, the modeling framework can easily accommodate these changes. This adaptability is itself a strength of the rules-based approach. Regulations such as the Trinity 2000 ROD (U.S. Department of Interior, 2000) , State Water Control Board Decision 1641 (SWRCB, 2000), and NMFS Biological Opinions (NMFS, 2009) are already incorporated directly, as can infrastructure scenarios such as raising Shasta Dam, constructing the Sites Reservoir (Randle & Linville, 2024), or groundwater banking projects (Hamilton et al., 2022). Its capacity to evaluate counterfactual regulatory and infrastructure scenarios is a key advantage over purely statistical approaches, which lack training data in this space.

The financial risk analysis in this study uses monthly resolution and assumes full spot market exposure, averaging out the short-term price extremes where hydropower's peaking value is highest. The estimated financial benefits of improved forecasting are therefore likely conservative. Integrating rules-based water system models with power dispatch models operating at finer temporal resolution (Yufei Su et al., 2020) would better characterize the true economic value of forecast skill. Such an approach is applicable wherever hydropower interacts with electricity markets. The percentile selection rules in the October-April two-stage method are based on expert judgment rather than formal optimization, calibrating these thresholds could further improve forecast skill.

This work can be extended in several directions. First, providing quarterly or monthly forecast updates integrated with short-term inflow forecasts from agencies like the California Nevada River Forecast Center (NOAA NWS, 2020). Such forecasts naturally leverage the increasing path dependency of hydrological conditions as the water year progresses. Second is extending hydropower forecasting to other multi-objective water management systems across the U.S. where similar institutional complexity governs hydropower generation.

Finally, the statistical comparison in this study uses relatively simple regression models, such as those currently used in practice, whereas CALFEWS represents a multi-year collaborative development effort across several studies (Zeff et al., 2021; Hamilton et al., 2022). More complex statistical and machine learning approaches, including random forests, LSTMs, and other deep learning architectures, could offer improved predictive skill over the regression baselines used here. However, the relevant comparison is not purely one of predictive accuracy, but of what each approach can and cannot represent. Recent advances in deep learning for hydrology have demonstrated remarkable ability to learn across hydrological boundaries and generalize across catchments (Kratzert et al., 2019). More broadly, physics-constrained AI and foundation models are increasingly being developed for earth system applications, including architectures that embed conservation laws such as energy and mass balance directly into neural network design (Beucler et al., 2021). Such models leverage the fact that the underlying physical processes governing rainfall-runoff response are universal. Variations in scaling, geography, land cover, and catchment characteristics can be learned from data. The institutional rules governing multi-objective reservoir operations do not share this universality. Institutional considerations, including environmental flow mandates, water rights hierarchies, inter-basin transfer agreements, and evolving regulatory decisions are not hydrological signals that can be learned from streamflow data. They are human decisions that are as political as they are rational. A rules-based model can be modified to directly incorporate a new regulation the day it takes effect, whereas any data-driven approach must wait for sufficient post-implementation observations to learn its impact. This distinction becomes especially critical for scenario analysis, where the goal is to evaluate system performance under regulatory or infrastructure configurations that have no historical precedent. Given the rapid pace of advances in AI, we do not discount the possibility that this hurdle may eventually be overcome. Yet we are not aware of any existing or emerging framework capable of mechanistically encoding human-enforced institutional rules while simultaneously enabling the counterfactual scenario analysis that is essential for water resource and hydropower planning.

Overall, while this analysis is focused on California's Central Valley Project, the underlying approach, modeling the water system first explicitly incorporating a broad range of rules associated with system constraints, is directly transferable to any multi-objective reservoir system where institutional and operational complexity governs generation. As grid operators increasingly rely on hydropower to balance intermittent renewables, rules-based forecasting frameworks that capture this complexity will become essential tools for managing the financial and operational risks of variable hydropower supply.

Data & Code Availability

All data used in this study are publicly available. Data and code to replicate this analysis, including instructions to download and run CALFEWS, are available at https://github.com/yashamonkar/CALFEWS_Hydro_Forecasting

Funding Acknowledgement

This material is based upon work supported by the U.S. Department of Energy (DOE), Office of Critical Minerals and Energy Innovation, Hydropower & Hydrokinetic Office. Pacific Northwest National Laboratory is operated for the DOE by Battelle Memorial Institute under Contract DE-AC05-76RL01830. Support for the research done at the University of North Carolina at Chapel Hill was provided via subcontract 725734 with Battelle Memorial Institute, Pacific Northwest Division, acting Under Prime Contract DE-AC05-76RL01830 with the U.S. Department of Energy operating the Pacific Northwest National Laboratory (PNNL).

Conflict of Interest

The authors declare no conflict of interest. The views expressed in this article do not necessarily represent the views of the Western Area Power Administration or the United States.

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Rules-Based Systems Modeling for Hydropower Forecasting in Multi-Objective Reservoir Systems: Application to California's Central Valley Project

Supplementary Materials

Table S1: The boilerplate capacity (MW) and the penstock flow capacities (AF/day) for the ten hydroelectric powerplants operated by CVP. Note: San Luis (W. R. Gianelli) O'Neill power plants are not included since they do not count as CVP generation and are settled separately.

Sr. No	Plant Name	Boilerplate Capacity (MW)	Penstock Flow Capacity (TAF/day)	Hydropower Generation Modules Validation Metrics	
				Correlation Squared (r^2)	Mean-Squared Error (GWh)
1	Shasta	676	34.9	0.97	17
2	Trinity	140	7.4	0.92	6
3	Carr	184	7.1	0.95	12
4	Spring Creek	200	8.6	0.67	16
5	Keswick	105	32	0.88	7
6	Folsom	198	13.8	0.95	7
7	Nimbus	17	10.2	0.66	2
8	New Melones	300	16.6	0.99	3

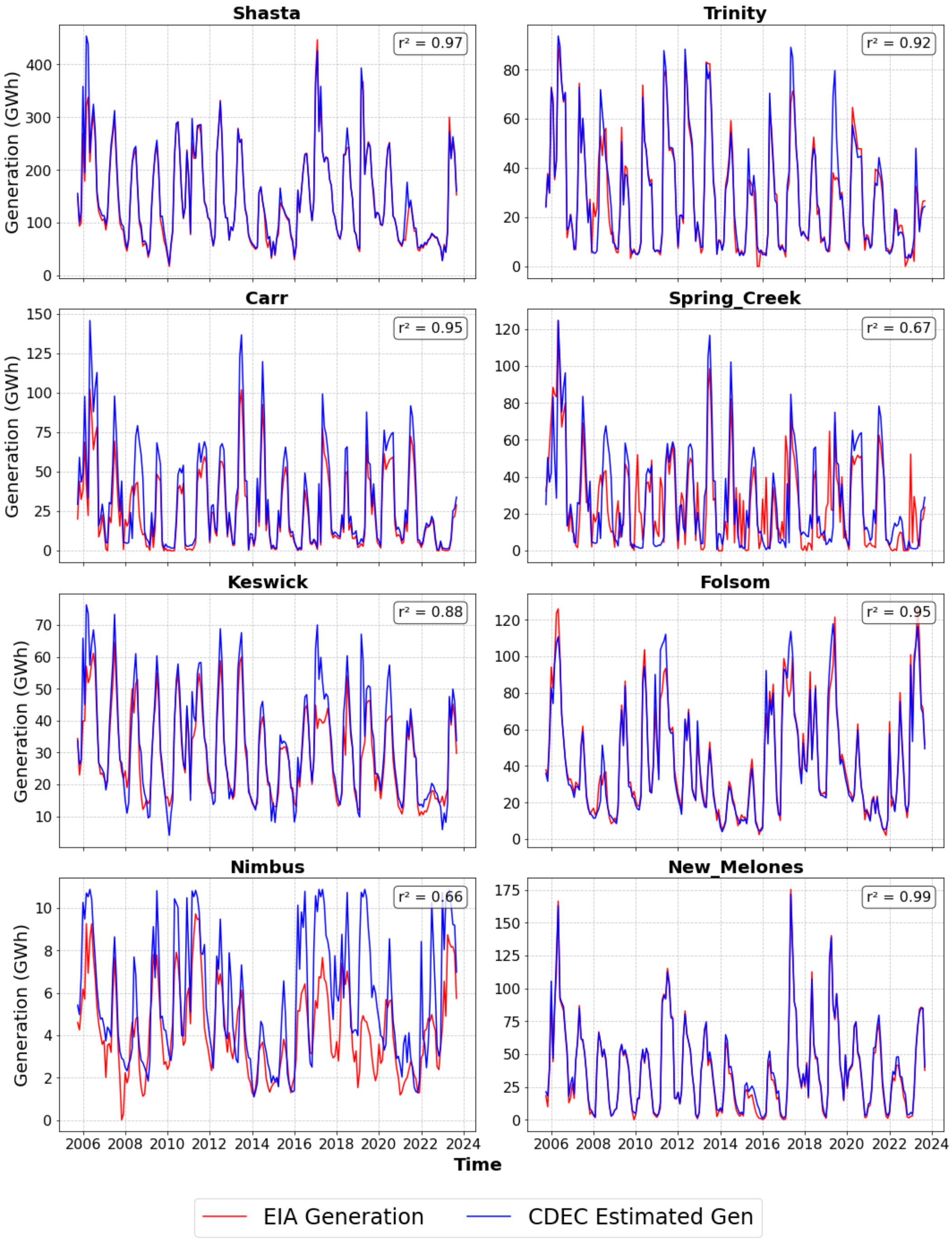

Figure S1: Monthly hydropower generation computed using the hydropower generation modules and daily CDEC data (blue) and the reported EIA values (red) for the ten hydro-electric power plants owned by the CVP.

Trinity Diversion System

The Trinity River originates in Trinity County, Northern California and naturally flows eastwards meeting the Klamath river and finally the Pacific Ocean in Oregan. The Trinity River Diversion System, authorized by an act of Congress in 1955, allowed for the total annual water export of 704 Thousand Acre-Feet (TAF) from the Trinity River Basin to the Central Valley, which was considered at that time to be surplus to the present and future needs of the Trinity River Basin (1). Currently the diversion system consists of the Trinity, Whiskeytown & Spring Creek Reservoirs; Trinity & Lewiston Dams; Clear Creek and Spring Creek Tunnels which help facilitate the export of water from the Trinity to Sacramento Basin in the Central Valley. Additionally, the diversion system is also composed of Trinity, J.F. Carr, & Spring Creek powerplants, representing nearly a quarter of the total CVP installed hydropower capacity.

The act authorizing the diversion and export of water from the Trinity to Sacramento basin also stipulated the said export shall occur "… without detrimental effect on the fishery resources" in the Trinity River and directed the Secretary of the Interior to "… adopt appropriate measures to insure the preservation and propagation of fish and wildlife" (1). Since the inception, the Trinity River Diversion System has been a subject to intense litigation to ensure that the exports are environmentally acceptable to the wishes of Congress. The last major revision was the 2000 Record of Decision by the U.S. Department of Interior (henceforth 2000 ROD) which established minimum annual water flows for the Trinity River in California, reducing water diversions to the Central Valley Project to restore the river's ecosystem and fish populations, particularly salmon (2). It allocates between 369 TAF and 815 TAF acre-feet of water annually to the Trinity River, depending on the water-year type (Table S2). Figure S2 represents the proposed daily hydrograph for flows into the Trinity River based on a variable flow regime based on 5 water year types. These flows were designed to mimic more natural flows and are important for sediment management, channel rehabilitation and salmon management. The operators can adjust the schedule for releasing water daily but have to meet the total annual flow volumes and peak values established in the 2000 ROD (Table S2).

Table S2: The total annual volumes (TAF), peak flows (CFS) and peak flow duration in days for flows into the Trinity River designated by the 2000 ROD.

Water-Year Class	Volume (Thousand Acre-Feet)	Peak Flow (cfs)	Peak Flow Duration (days)
Critically Dry	369	1,500	36
Dry	453	4,500	5
Normal	647	6,000	5
Wet	701	8,500	5
Extremely Wet	815	11,000	5

Overall, the Trinity River Diversion System and the environmental considerations which dictate the flows into the Trinity River and flows to be exported to the Central Valley are institutionally complex and governed by legal regulations rather than pure considerations of hydrology. CALFEWS with its rules-based approach provides the necessary framework to integrate such a system within the broader Central Valley Operations. Across the validation period in CALFEWS (October 1995 to September 2023), CALFEWS includes three regulatory frameworks applicable to the Trinity System. The first regulatory regime is the pre-2000 ROD flows, where 369 TAF was allocated to the Trinity River and rest exported to the Central Valley irrespective of the water-year type. The second regime included was the period from 2001-2005 when Lewiston Dam was a significant factor in the delayed implementation. The dam's release facilities needed modifications to safely handle the higher peak flows mandated by the ROD, particularly 11,000 cubic feet per second (Figure S1). The regime uses information provided in the 2000 ROD with respect to the reduced peak flows. Finally, the entire 2000-ROD regime is codified into CALFEWS for Trinity River operations post 2005. Such evolving regulatory regimes are a part of the ‘contextual regulatory rules’ within CALFEWS (Figure S1), and further evolving changes can also be included.

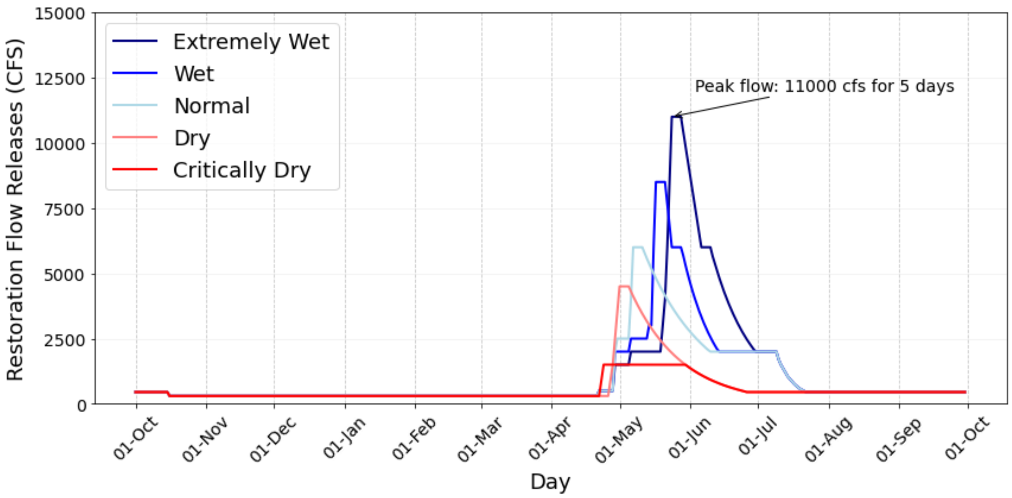

Figure S2: The Trinity River Restoration Flow Hydrographs as proposed in the 2000 Record of Decision (2000 ROD), depicting the daily flow releases into the Trinity River from Lewiston dam based on the water-year type .

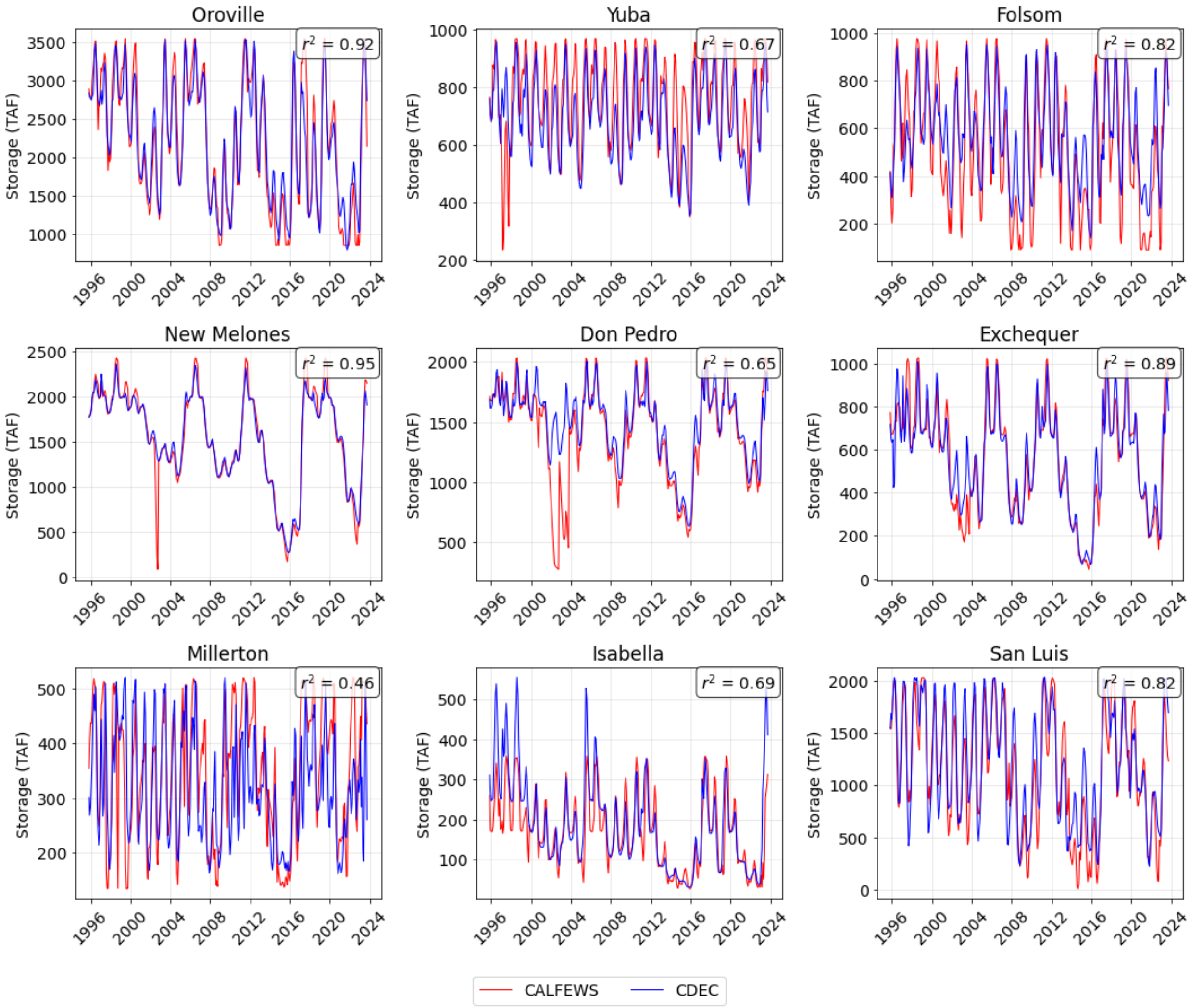

Figure S3: Modelled CALFEWS and CDEC storage values in TAF at individual reservoirs represented in CALFEWS. For each subplot, the red line denotes the mean monthly CALFEWS storage whereas the blue line denotes the same values as recorded in the CDEC database. The r^2 for each sub-plot is displayed besides the label.

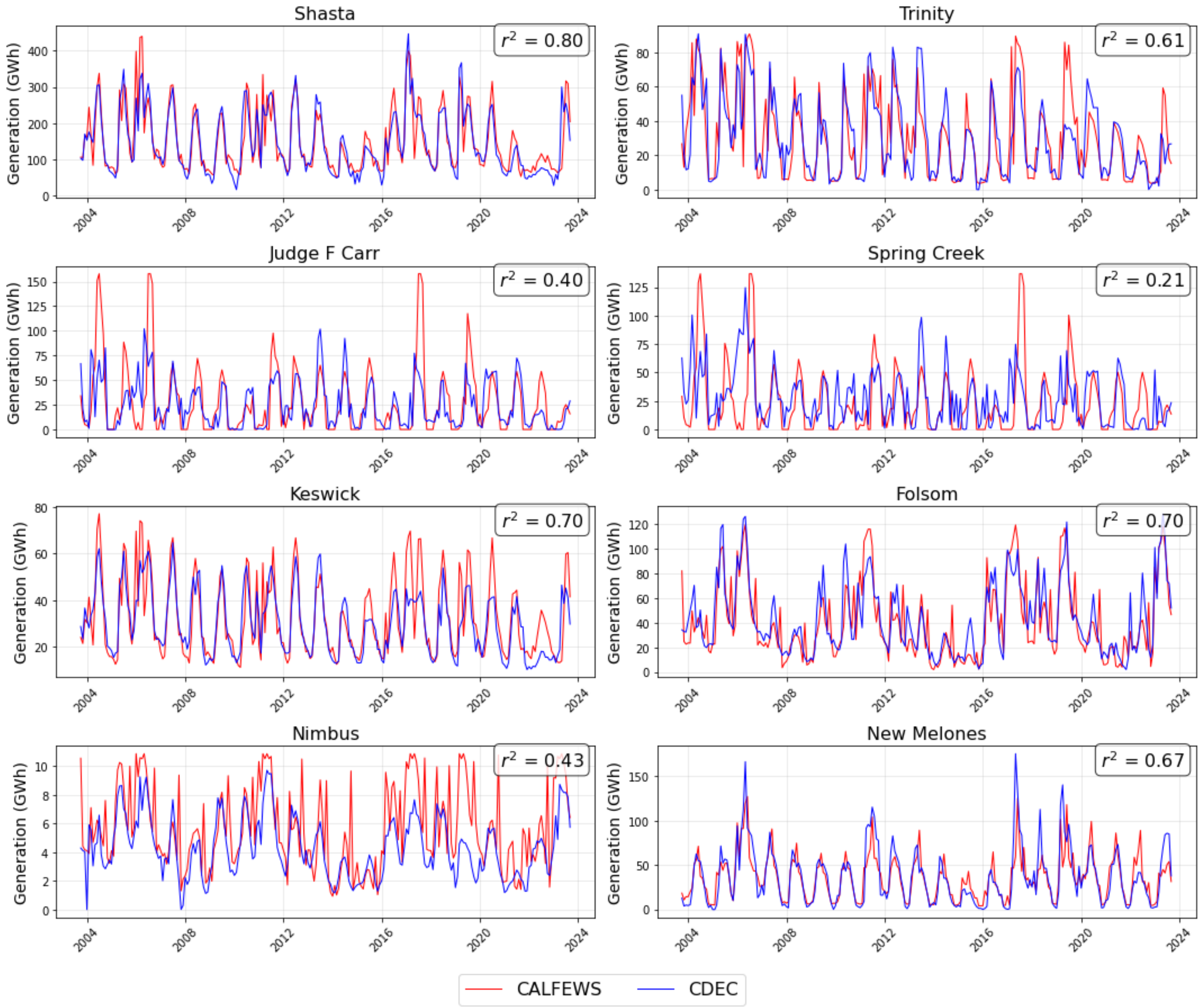

Figure S4: Timeseries of the monthly CVP hydropower generation as computed using the CALFEWS (red) and EIA reported values (blue) for individual CVP reservoirs. The r^2 for each sub-plot is displayed besides the label.

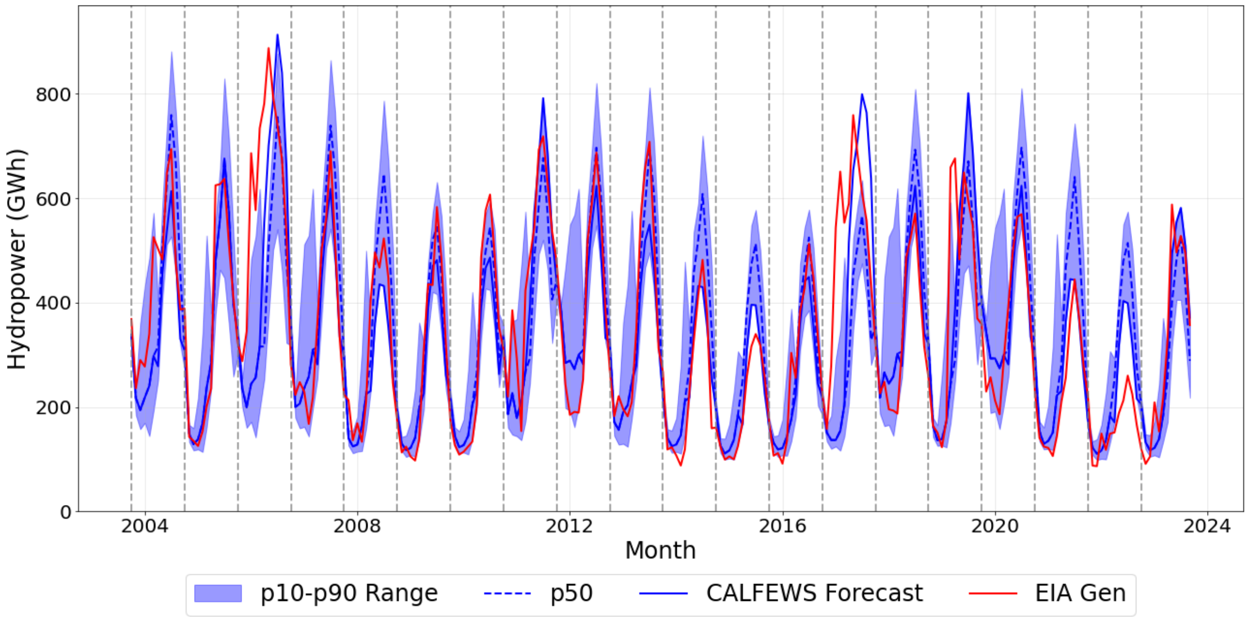

Figure S5: CALFEW derived annual ensemble forecasts using the October-April two stage forecasting method. The solid blue line denotes the monthly forecast whereas the red line denotes the EIA generation value. The blue shaded region denotes the 10th – 90th percentile ensemble range and the dotted blue line denote the ensemble mean.

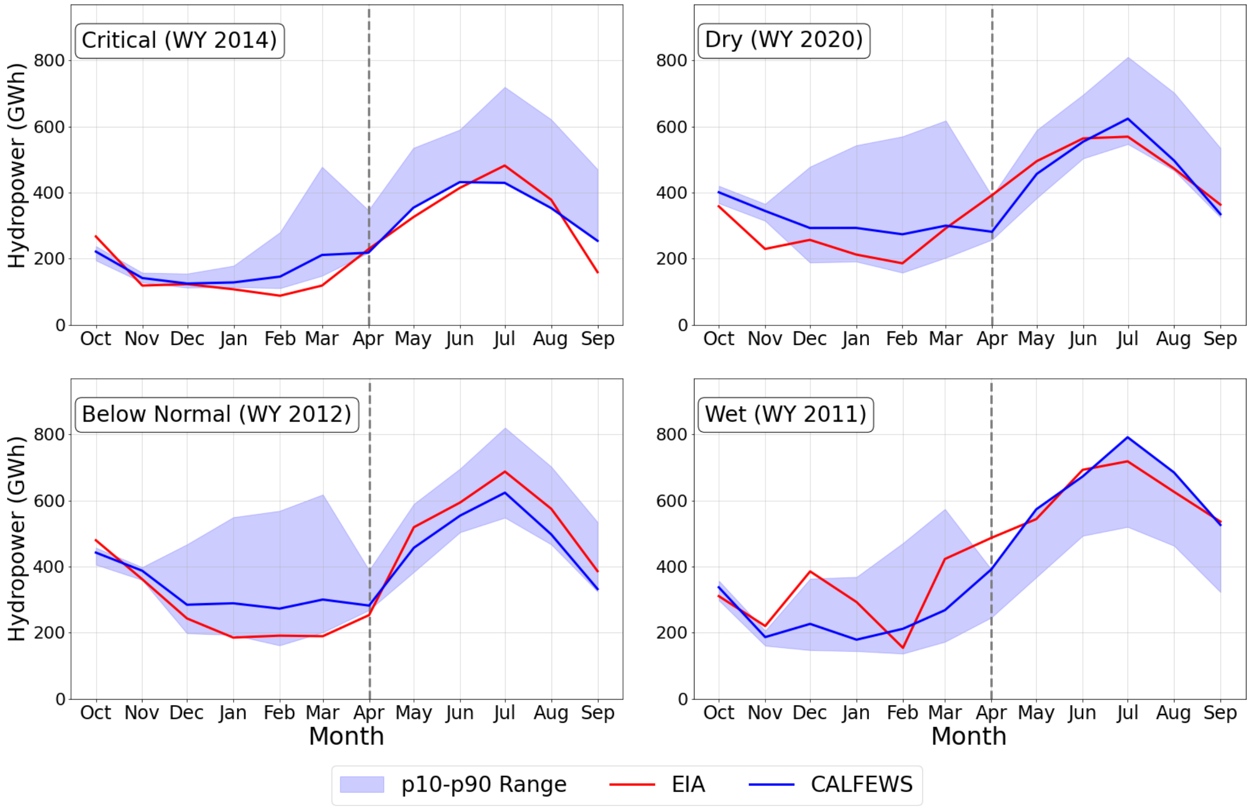

Figure S6: Schematic representation of the CALFEW derived annual ensemble forecasts using the October-April two stage forecasting method for each Water Year type. The solid blue line denotes the monthly forecast whereas the red line denotes the EIA generation value. The blue shaded region denotes the 10^{th} – 90^{th} percentile ensemble range and the dotted blue line denote the ensemble mean.

Statistical Method – Regression

Regression analysis is used for predicting CVP hydropower in both the statistical (ensemble) and statistical (baseline) method. Furthermore, both methods use the same regression fitted parameters described below. The regression is represented as,

$$CVP\_Gen_{m} = \beta_0 + \beta_1 \times Oct\ 1\ \ Storage + \beta_2 \times Cumsum\_fnf_m\ \ Storage + \beta' \times M$$

Where, CVP_Gen_{m} is the CVP generation in month m, $Oct\ 1\ \ Storage$ is the total storage across Shasta, Trinity, Folsom, New Melones and San Luis on October 1st. October 1st storage level stays constant across the entire water year and is updated next October. $Cumsum\_fnf_m$ is the total cumulative inflow across Shasta, Folsom, Trinity and New Melones in month m. M are dummy vectors denoting the months. $\beta_0, \beta_1, \beta_2, \beta'$ = [β_3, β_4, β_5, β_6, β_7, β_8, β_9, β_{10}, β_{11}, β_{12}, β_{13}] are the computed coefficient vectors. The first ten years of data (October 2003 – September 2013) are used for training whereas the next ten years (October 2013 – September 2023) are used for testing. Data from October 1995 to September 2003 were not included due to the lack of the EIA dataset which is used to compute the CVP_Gen_{m}.

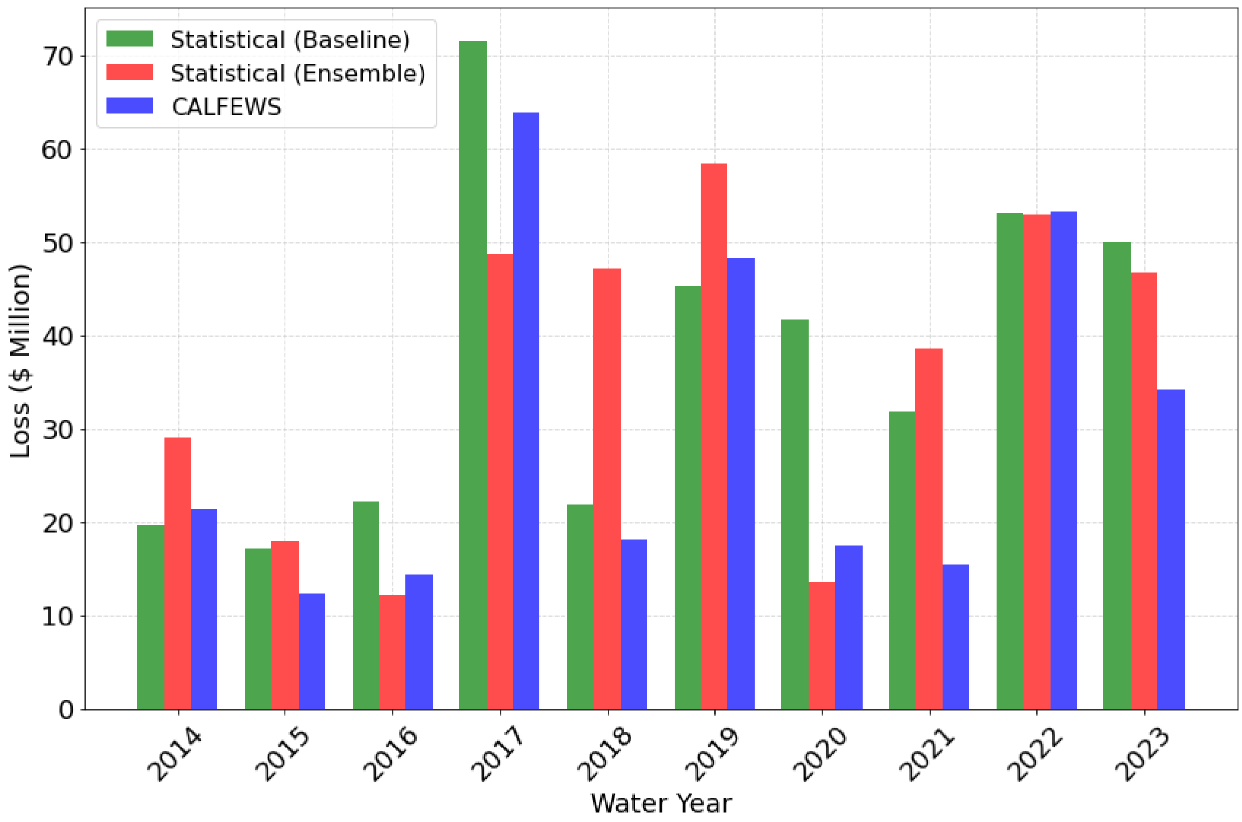

Figure S7: Annual financial losses ($ millions) estimated using the October-April two stage forecast using statistical (baseline), statistical (ensemble) and CALFEWS.

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