Optimized Reservoir Management for Downstream Environmental Purposes

by
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Dissertation

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Abstract

In regulated rivers, reservoir operation decisions largely determine downstream river temperature and flow. Computational methods can minimize the risk and uncertainty of decisions with regrettable long-term outcomes and aid operations planning and performance prediction. Mathematical modeling in particular can optimize the timing and magnitude of reservoir release decisions for downstream benefits while accounting for seasonal and inter-annual uncertainty in the weather, water storage impact, and competing water demands. This dissertation uses optimization and modeling techniques, modifying traditional optimization modeling to include temporal correlation in outcome variables and incorporating long-term planning and risk management into prescribed reservoir operations. The proposed method is implemented in one case, a) with a state variable that tracks outcome benefits over time (fish population size) and, in another case, b) with a maximin stochastic dynamic program solution algorithm that maximizes net operational benefit and minimizes worst-case outcomes (for cold water habitat delivery). This method is particularly useful for environmental flow management, when the water quality and quantity of the river and reservoir in one time step affect the environmental outcomes in the reservoir and the river for later periods. Better solutions with these methods internalize risk and hedge releases early in an operating season to maximize downstream benefit and reduce the probability of catastrophe for the season and future years. Maximizing the minimum cold-water habitat area over months of a season or multiple years, or maximizing a river indicator variable explicitly, could likely help, for example, maximize an out-migrating salmon smolt population downstream. The method is demonstrated with a case study optimizing environmental releases from Folsom Dam and another optimizing temperature management from Shasta Dam in northern California. These results inform general rules for environmental flow management and temperature management of reservoirs, with specific policy recommendations for both Folsom and Shasta reservoirs. In both cases, the added value from employing hedging rules is predicted to help reservoir operations minimize the risk of environmental catastrophe and conserve storage both within an operating season and across years. The mathematics and logic of this optimization method can be related more directly and conventionally to reservoir hedging for any long-term benefit, including water supply, hydropower, drought management, and flood control.

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Chapter Summary

Chapter 1 introduces this dissertation.

Chapter 2 develops a reservoir operations rule structure and method to maximize downstream environmental benefit while meeting human water supply targets. The result is a general approach for hedging downstream environmental objectives. A multi-stage stochastic mixed integer nonlinear program with Markov Chains, identifies optimal "environmental hedging" releases to maximize environmental benefits subject to probabilistic seasonal hydrologic conditions, current, past, and future environmental demand, human water supply needs, infrastructure limitations, population dynamics, drought storage protection, and the river's carrying capacity. Fish population size is a state variable that tracks environmental outcome benefits over time. Environmental hedging "hedges bets" for drought by reducing releases for fish, sometimes intentionally killing some fish early to reduce the likelihood of large fish kills and storage crises later. This approach is applied to Folsom reservoir in California to support survival of fall-run Chinook salmon in the lower American River for a range of carryover and initial storage cases. This chapter was published in Water Resources Research as "Environmental hedging: A theory and method for reconciling reservoir operations for downstream ecology and water supply."

Chapter 3 compares methods and develops a framework for managing temperature in reservoirs. A generalizable selective withdrawal modeling and optimization framework for managing temperature in reservoirs is proposed. To derive optimized temperature control policy with this framework, several objective functions and solution algorithms for finding optimized release schedules are compared. A new method for a maximin stochastic dynamic program solution algorithm maximizes net operational benefit and minimizes worst-case outcomes (for seasonal cold water habitat delivery) is introduced. The new algorithm uses a maximin operator to minimize the risk of environmental catastrophe and conserve storage, both within seasons and across years. This approach, unlike previous models, restricts releases by temporal persistence and consistency in benefits. Although previous studies have explored the value of characterizing uncertainty in model inflow, both with respect to capturing temporal persistence and non-stationarity, no studies have developed methods or tested the value of modeling temporal persistence in downstream outcome variables (storage depletion, river habitat availability). Applications of this method are useful for managing river temperature and avoiding regrettable mistake of releasing storage and creating unsustainable downstream cold water habitat. Maximizing the minimum cold-water habitat area over months in a year or a season should help maximize the out-migrating salmon smolt population in a river but minimize the chance that maximizing fish now damages the ability to do so in the future. With this approach, operations hedge to sustain benefits, similar to hedging more broadly for other reservoir purposes, such as economic gain from hydroelectric power production, or water delivery to agricultural uses, and, avert damage, similar to hedging for flood management or water delivery to municipal drinking water supply. Here, we uniquely do both. We maximize to sustain river flow and temperature throughout time and minimize to avert the risk of making lethal or stressful releases for the downstream ecosystem. For river management, this is imperative; water quality and quantity of the river and reservoir in one time step affect future quantity and quality in both the reservoir, the river and ecosystem populations. This provides a method for prioritizing long-term ecosystem performance, which is often sacrificed by maximizing short-term performance. This method could be useful for other purposes for which it is preferable to hedge against risk now and in the future when the performance of one time-step affects the next.

Chapter 4 applies the methods of Chapter 3 to build OTM2, an Optimized Temperature Management Model, a model that optimizes reservoir operations for temperature control management. The model is applied to optimize temperature control for the Sacramento River below Shasta Dam. The value of deriving the optimized solution with different river temperature targets, solution algorithms, and objective functions under different delivery curtailment scenarios and weather forecasts were compared over one and many operational seasons. Solvers were created in R with dynamic programming. Computational burden was reduced by aggregating the model's state, action, and outcome spaces and approximating state variables based on physical and statistical principles. Solving the problem with a maximin dynamic program improved the ability of the reservoir to meet downstream temperature goals more often and consistently, for one and multiple years, with greater and more consistent total and cold water storage availability for each state of each stage as well as for the converged operations policy. General rules for improving temperature management at Shasta reservoir were formulated as well as event-based insights,

such as when to abandon temperature management for a year or month. Hedging for temperature management at Shasta Dam could improve temperature management of Shasta reservoir as well as other large reservoirs, particularly in drought.

Chapter 5 offers some concluding remarks for the dissertation.

Chapter 6 summarizes the dissertation as a policy memo for United States reservoir operators responsible for temperature management of Shasta Dam and others.

1 Introduction to the Dissertation

In regulated rivers, reservoir operation decisions largely determine downstream river temperature and flow. Computational methods can minimize the risk and uncertainty of decisions with regrettable long-term outcomes and aid operations planning and performance prediction. Mathematical modeling in particular can optimize the timing and magnitude of reservoir release decisions for downstream benefits while accounting for seasonal and inter-annual uncertainty in the weather, water storage impact, and competing water demands. This dissertation uses optimization and modeling techniques, modifying traditional optimization modeling to include temporal correlation in outcome variables and incorporating long-term planning and risk management into prescribed reservoir operations. The proposed method is implemented in one case, a) with a state variable that tracks outcome benefits over time (fish population size) and, in another case, b) with a maximin stochastic dynamic program solution algorithm that maximizes net operational benefit and minimizes worst-case outcomes (for cold water habitat delivery). This method is particularly useful for environmental flow management, when the water quality and quantity of the river and reservoir in one time step affect the environmental outcomes in the reservoir and the river for later periods. Better solutions with these methods internalize risk and hedge releases early in an operating season to maximize downstream benefit and reduce the probability of catastrophe for the season and future years. Maximizing the minimum cold-water habitat area over months of a season or multiple years, or maximizing a river indicator variable explicitly, could likely help, for example, maximize an out-migrating salmon smolt population downstream. The method is demonstrated with a case study optimizing environmental releases from Folsom Dam and another optimizing temperature management from Shasta Dam in northern California. These results inform general rules for environmental flow management and temperature management of reservoirs, with specific policy recommendations for both Folsom and Shasta reservoirs. In both cases, the added value from employing hedging rules is predicted to help reservoir operations minimize the risk of environmental catastrophe and conserve storage both within an operating season and across years. The mathematics and logic of this optimization method can be related more directly and conventionally to reservoir hedging for any long-term benefit, including water supply, hydropower, drought management, and flood control.

2 Environmental Hedging

2.1 Introduction: Reservoir Operations for Downstream Environmental Management

Typical reservoir operations regulate downstream flows based on infrastructure limitations, water availability, water demands, and economic concerns [*Klemes*, 1977; *Loucks et al.*, 1981: *Yeh*, 1985; *Lund and Ferriera*, 1996; *ReVelle*, 1999; *Labadie*, 2004; *Harou et al*., 2009; *Lund et al*., 2017]. Separate release targets for downstream ecological needs [*Arthington*, 2012] are generally based on: a) habitat extent and suitability [*Sale et al*., 1982], b) downstream modeled fish populations [*Cardwell et al.*, 1996*; Cioffi and Gallerano*, 2012; *Jager*, 1997; *Jager and Rose*, 2003; *Null and Lund*, 2011], and/or c) environmental goals based on specified hydraulic, hydrologic, water quality or political metrics [*Tharme*, 2003]. Resulting flow regimes may approximate the 'natural' flow regime [*Palmer and Snyder*, 1985; *Poff*, 1997; *Harman and Stewardson*, 2005; *Suen and Eheart*, 2006; *Vogel et al*., 2007; *Richter and Thomas*, 2007; *Wang et al*., 2016] or may be developed using a more biophysical-social-hydrologic approach [*Poff et al*., 2010]. Habitat and population modeling can help specify release schedules to maximize habitat capacity to improve species (usually fish) survival at each of several life history stages. To meet environmental goals, a typical reservoir operation strategy releases available water until an environmental target goal, such as a minimum instream flow, is met. Making releases that mimic the natural flow regime assumes that fish and other wildlife are adapted to the local natural flow pattern so any alterations are assumed to harm the native ecosystem. All of these modeling approaches rely on expert opinion and empirical data when developing target release goals, validating modeling results, or measuring effectiveness of modeling recommendations.

Environmental flow operations often are modeled with simulation or optimization methods. Most modeling studies represent environmental goals as a constraint on operations, usually as a minimum instream flow requirement [*Homa*, 2005]. These models constrain releases to account for (a) water availability from storage and inflow from the current and previous period, (b) flood control needs, and (c) storage needs for minimum drought and carryover (e.g. human and economic) requirements. *Waddle* [1992] augments these approaches with an equation that remembers changes in fish population size between modeled release periods. *Sale et al.*, [1982], *Cardwell et al.*, [1996], and *Cioffi and Gallerano*, [2012] advanced optimization approaches by using stochastic reservoir inflow rather than using fixed water year types. Release decisions for both simulation and optimization models are typically made monthly over a water year. *Jager and Rose* [2003], instead, model two-week time steps. The natural flow regime literature simulates release decisions with calculations of hourly, daily, or weather-event periods, depending on the concern. Some models explicitly employ environmental goals as a single objective [*Sale*, 1982; *Jager and Rose*, 2003; *Null and Lund*, 2011], while others represent environmental goals within a multi-objective optimization model [*Cardwell et al*, 1996; *Cioffi and Gallerno*, 2012], maximizing for one or more biologic life stages.

Here we develop a method and theory to optimize the timing and magnitude of seasonal reservoir releases for downstream environmental benefits. The environmental benefit function is defined as the ideal environmental flow regime which could be developed using any environmental flow method. In our case study we define the benefit function to be the seasonal flow requirements of each life history stage of a keystone species of fish (salmon). Operation time steps are discretized by life histories and hydrologic seasons. Consequent reservoir release schedules maximize downstream environmental benefit while considering seasonal tradeoffs among hydrologic seasons and life cycle stages for a range of water storage and probabilistic and conditional hydrologic conditions. This method incorporates environmental flow objectives to show when reservoir releases might best be reduced for early life stages in order to improve populations of later life stages. The environmental benefit function, a persistence constraint that remembers environmental benefit over time, and a drought protection constraint, constrains reservoir operations that minimize environmental damage and maximize environmental benefit.

We employ a multi-stage stochastic mixed-integer non-linear program for a range of forecasted hydrologic states to produce optimal release schedules. Markov Chains transition forecasts of predicted inflows, as well as the contingencies for errors in these forecasts. We assume some downstream targets for human water supply (i.e. hydropower, municipal/agricultural/industrial water supply, and flood control) have higher priority than environmental demand, so decisions for the environment occur without making these other users worse off. The overall result is a general approach to maximize downstream goals: in this case, to balance downstream biological success with seasonal uncertainty and other water demands. The results sometimes involve "environmental hedging" operations which conserve water in dry times by reducing early releases to improve success in later times, given future drought probabilities and minimum storage needs for the environment and other uses. Releases avoid flood in wet times with spill. Releases hedge for past conditions by being constrained to not exceed flows for current downstream fish population size, given the 'memory' of the earlier fish population size. This strategy may force some early damage

(i.e., small fish kills in early life stages, most notably early in the scheduling period), in order to reduce the risk of storage crises and crises (i.e., fish extirpation) during extreme events.

2.2 Environmental Hedging Method

The timing and magnitude of strategic environmental release and curtailment decisions are outlined below. An objective function, six constraints, and hydrologic and ecological forecasting are the components of the environmental flow hedge method. With this method, reservoir operations deviate from standard linear operating policy with strategic hedges. A multi-stage stochastic mixed-integer non-linear program operationalizes environmental hedging theory for reservoir operations and planning practice.

The model explicitly quantifies downstream environmental impacts of release decisions with the assumption that some environmental damage (e.g. fish mortality) is sometimes inevitable, but larger damage levels (i.e. population or species extirpation) should be avoided. The optimized contingent release decisions hedge and adapt as the water year's hydrologic and ecologic uncertainty diminishes with time. In this particular case, the first stage release decision is made (based on expected fall inflow and initial storage) before observing any outcome of random "actualized" inflow for the fall or future time stages. Decisions in later stages are made within system constraints based on the realization of inflow acquired during earlier stages, without observing future inflows. Environmental benefits (e.g. fish populations) from the release decision for each possible hydrologic condition in each time period is carried forward for each time period's state into the following period. The decision tree branches combinatorially based on the number of possible inflow states and stages considered. In our case, the environmental benefit function is based on empirical observation and expert opinion of native anadromous fish (e.g. Chinook salmon) requirements. Native anadromous fish are sensitive indicators of environmental flow needs for reasons that are economic, ecological, practical, genetic, aesthetic, and moral (Moyle, 2002). Native fishes evolved with the native hydrograph. A number of species could have been used. However, we applied the model to predict survival of three freshwater life-history stages of fall –run Chinook salmon in the lower American River of California, because they require high water quality, are a species in decline, and are well-studied (Williams, 2001). Although the river flow regime is characterized by a Mediterranean climate, the principles and mathematics of the model can be modified and applied to other species or downstream goals (e.g. groundwater recharge) in other regulated rivers and climates.

2.2.1 Timing of releases

Reservoir releases $R_{y_t,t}$ are made to support each discrete life-history stage for each possible hydrologic state *y* of time duration *t*, y_t. The number of distinct operational time periods *t* coincide with the fish's riverine life stages (such as eggs or fry) and the distinct hydrologic seasons (such as fall and spring), for all hydrologic states *y* (from driest to wettest) (Figure 1). Discretizing time by meaningful fish life stages and hydrologic seasons gives flexibility in scheduling bulk water releases to account for seasonal and ecological variability. Time is aggregated by months because most water supply operations are planned with a monthly timescale. Decisions are made for all time steps and contingent conditions to maximize fish populations.

Model Decision Stage	1	2	3.1		3.2	Minimum Carryover Storage Requirement		
Time Discretization	1	2	3	4	5	6	7	8
Months	Oct, Nov, Dec	Jan, Feb, Mar, Apr	May, Jun	Jul, Aug, Sept	Oct, Nov, Dec	Jan, Feb, Mar, Apr	May, Jun	Jul, Aug, Sept
Fish year class g	A					B		
Water year h	1					2		
Hydrologic Season	Wet Season		Dry Season		Wet Season		Dry Season	
			Snowmelt	Baseflow			Snowmelt	Baseflow
Fish Development Period	Egg	Fry	Smolt	None	Egg	Fry	Smolt	None
Fish Release Decision $R_{y_t,t}$	$R_{y_1,1}$	$R_{y_2,2}$	$R_{y_3,3}$	$R_{y_4,4}$	$R_{y_5,5}$			

Figure 1: Example discretization of time periods *t* used to develop a release schedule to support two cohorts of anadromous fish downstream of a reservoir under uncertain hydrologic conditions. Release decisions vary with hydrologic states y (e.g. very wet, median, and abnormally dry).

2.2.2 Magnitude of releases

Objective Function The operator is responsible for maximizing environmental benefit below the dam. For this example, in maximizing the survival of anadromous fish, the dam operator is responsible for two cohorts over all

hydrologic conditions: one developing cohort (e.g. salmon that survive growing from eggs laid to smolts migrating to the ocean; (cohort A) and a second cohort of adults returning after several years at sea to spawn (cohort B). The objective (Equation 1) is to maximize the average weighted sum of both cohorts (N^A and N^B), across the range of seasonal hydrologic conditions (y) which occur with probability (p). The second fish cohort (g=B) is weighted with a constant ($\propto$) to capture trade-offs between cohorts. Maximizing final water storage at the end of the final period of the model (S^F) is included as added value to the objective function with weighting constant (β) to penalize present releases lacking fish benefit and to save water for fish and other water uses in the future. In another system dominated by non-migratory fish the objective function could be re-written as the sum of the probability of fish survival for every fish life history stage over the full range of hydrologic states.

$$max(z) = \left[\sum_y p_{y_{T-1},T-1} N^A_{y_{f-1},T-1} + \alpha \sum_y p_{y_T,T} N^B_{y_T,T}\right] + \beta \sum_y p_{y_T,T} S^F_{y_T,T} \quad (1)$$

where z is the net expected downstream fish population; y_t is the hydrologic/inflow state (i.e. wet, dry, very dry) of inflow for each time period t; g is the fish cohort (i.e. fish cohort A or B); T is the final time step t for future fish population (i.e. time period 5 for cohort B); t is the indexed time step expressed in aggregated months. (Time step durations can differ for each fish development and hydrologic stage.) $p_{y_t,t}$ is the probability of predicted hydrologic state y for time period t; $N^g_{y_t,t}$ is the fish surviving population in each predicted hydrologic state y of time duration t for fish cohort g; $\propto$ is the relative weighting of cohorts; β is the relative weighting of final storage; and $S^F_{y_T,T}$ is the final storage volume for final time period t = T.

Hydrologic Forecasting Each season's release decision is the sum of a base release decision and an incidental spill decision (Equation 3d). The base release decision is determined before the period has begun, for planning, based on the period's predicted inflow state $p^{q'}_{y_t,t} q'_{y_t,t}$ (Supplement S1, S2). Base release decisions hedge releases based on expected inflow to guarantee water storage during drought. Each period's spill release is made after the period has begun, based on a range of expected period inflow states $p^q_{y_t,t} q_{y_t,t}$ (S1, S2) that represent a range of actualized inflow states that could happen given the inflow of the previous stage. Spill decisions are made every period to avoid overtopping the reservoir; like hedging for drought, sometimes spill is hedged between time periods to avoid environmental damage. A range of modeled seasonal hydrologic conditions y adjusts releases to forecast and actual inflow so the release schedule has inter-annual variability. Conditional probabilities forecast seasonal predicted inflow (S1). A Markov Chain based on exceedance probabilities of the historical inflow record forecast seasonal actualized inflow. Depending on the statistical relationship between seasonal inflows (S2), predicted inflow for each hydrologic state y in each time period t can be conditional (e.g. between wet seasons), dependent (e.g. snowmelt following a wet season), or independent (e.g. at the beginning of the water year) of the previous season inflow. Building a model that forecasts both predicted (before the release) and future actualized (after the release) inflow allows for error and regret analysis for adaptive operations, explicitly modeling the likely probability that a seasonal forecast is wrong. Uncertainty narrows as the water year develops and more inflow information is known.

Decision Tree The objective function is written in terms of $N^g_{y_t,t}$ and $S^F_{y_t,t}$ as this seems the most direct model conceptualization. The decision variables, reservoir releases $R_{y_t,t}$, (including the base release decision $R^{min}_{y_t,t}$ to avoid a fish kill and a spill decision $P_{y_t,t}$) do not appear in the objective function but enter via constraints. The outcome of the release decisions is measured in terms of fish survival $N^g_{y_t,t}$ at each stage t.

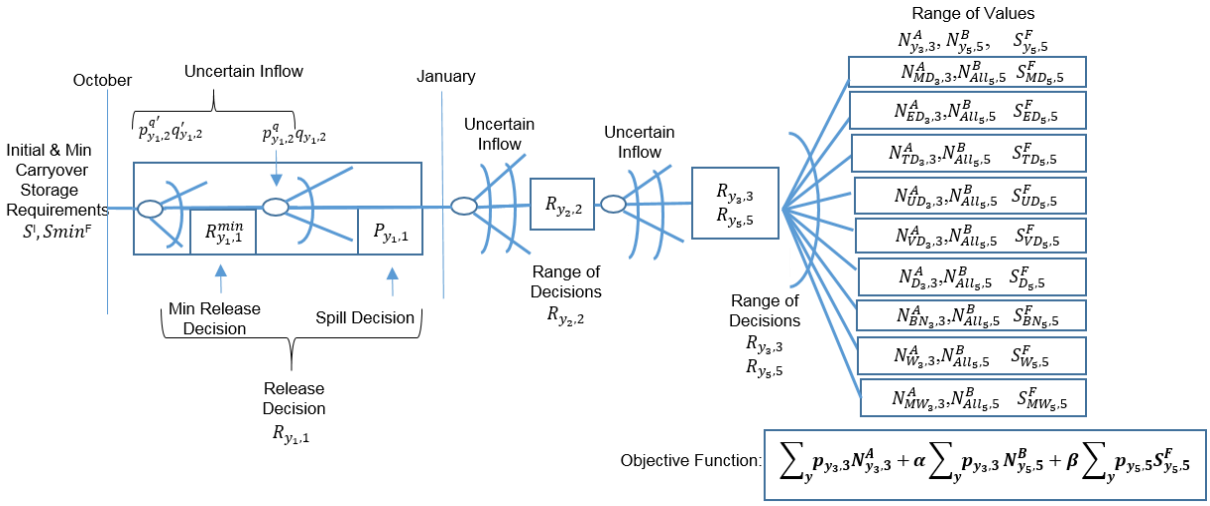


Figure 2: Decision Tree for a three-stage optimization model for maximizing fish survival. Each release decision $R_{y_t,t}$ includes a drought management decision $R^{min}_{y_t,t}$ and a flood management decision $P_{y_t,t}$.

Constraints Six constraints support reservoir releases for each time step *t*. Releases are physically constrained to fall within a) water availability, b) dam infrastructure capacities, and c) minimum streamflow requirements. Releases also are guided by d) environmental benefit functions, e) a persistence constraint, and f) a drought protection constraint.

- **Water Availability**

Releases cannot exceed available water at any time (Equation 2). Water availability includes the period's initial storage plus expected inflow minus higher priority diversions.

$$R_{y_t,t} \leq a_{y_t,t} \quad \forall \quad y \in t \quad (2)$$

$$a_{y_t,t} = S^I_{y_t,t} + q'_{y_t,t} - \ d_t \quad \forall \quad y \in t \quad (2a)$$

where $R_{y_t,t}$ is the reservoir release for each hydrologic state y of time period *t;* $a_{y_t,t}$ is the water availability each hydrologic state y of time period *t;* $S^I_{y_t,t}$ is the incoming stored water for each hydrologic state y of time period t; $q'_{y_t,t}$ is the predicted reservoir inflow for each hydrologic state y of time period t; and d_t is diversions with higher priority than fishes, such as domestic water use, for each time period t.

- **Reservoir Infrastructure Limitations**

Water storage must always equal or exceed deadpool storage dp but cannot exceed reservoir storage capacity rc (Equations 3a and 3b). Releases also cannot exceed the maximum reservoir outlet capacity moc. Releases are the total of the base required release R^{min} and the reservoir spill release P.

$$S^F_{y_t,t} \geq \ dp \quad \forall \ \ y_t \in t \quad (3a)$$

$$S^F_{y_t,t} \leq \ rc \quad \forall \ \ y_t \in t \quad (3b)$$

$$R_{y_t,t} \leq \ moc \quad \forall \ \ y_t, \ t= f \quad (3c)$$

$$R_{y_t,t} = \ R^{min}_{y_t,t} + P_{y_t,t} \quad \forall \ \ y_t, \ t= f \quad (3d)$$

where dp is the deadpool storage requirement for the reservoir; rc is the reservoir capacity; moc is the maximum reservoir outlet capacity; $R^{min}_{y_t,t}$ is the base release planned for each hydrologic state y of each time period t given the

period and hydrologic state's expected water availability *a;* and $P_{y_t,t}$ is the spill release for each hydrologic state y of time period *t.*

- **Minimum Streamflow Requirement**

Releases must meet a minimum streamflow threshold (e.g., the flow required to save at least 10% of the target fish population during the juvenile stage). Beyond this threshold the ecosystem has been pushed to the limits of resiliency and will shift to an undesirable new ecological state.

$$R^{min}_{y_t,t} \geq emin_t \quad \forall \text{ y in t} \quad (4)$$

where $emin_t$ is the minimum downstream streamflow requirement for the months of time period *t*).

- **Stored Water**

Water stored for the future offers the ability to hedge for dry times. Actualized inflow plus water storage from the previous period (less last period's diversions and releases) determine the incoming storage for the next time period (Equation 5).

$$S^F_{y_t,t} = ((S^I_{y_t,t} = S^F_{y_{t-1},t-1}) - R_{y_{t-1},t-1} + q_{y_{t-1},t} - d_{t-1}) \ \forall \ \text{y} \in \text{t} \quad (5)$$

where $q_{y_t,t}$ is the actualized inflow to the reservoir for each hydrologic state y of time period t.

- **Environmental Benefit Function**

This equation links streamflow to environmental benefit for each hydrologic state of each time period. The linkage can be based on any environmental flow methodology (e.g. expert interviews and/or mechanistic models that index environmental need based on hydraulic, hydrologic, water quality, and ecological indicators). In using fish species as indicators of environmental health, for example, fish population size (N) is limited by spawning and rearing area, such as the flow required to keep temperatures below the maximum at which the fish species can survive.

$$N_{y_t,t} \leq f(R_{y_t,t}) \quad \forall \ \text{y} \in \text{t} \quad (6)$$

- **Population Dynamics and Persistence Constraint**

Current period ecological and biological abundance is based on natural mortality and curtailments from the environmental support capacity of the previous period. For example, the fish population (N) for any life stage during any time period t has been reduced by the fish's natural mortality rate (k) and fish death in the previous period from releasing spill or curtailing the environmental benefit function (Equation 3) i.e. if the natural mortality rate (k) of eggs to fry is 30%, and egg incubation period releases are curtailed to 50% of ideal, then the largest population possible in the current period is only 35% of the target. This population dynamics constraint carries the memory of environmental conditions from one time period to the next. Strategic releases are hedged, when necessary, to meet but not exceed the requirements of the current population size rather than that for ideal population size.

$$N_{y_t,t} \leq (1-k)N_{y_t,t-1} \ \forall \ \text{y} \in \text{t} \quad (7)$$

where k is the expected mortality occurring between time step t-1 and t.

- **Drought Storage Protection**

Stored water at the end of the modeled period $S^F_{y_T,T}$ provides some drought protection for future years. This end of modeled period storage must exceed the sum of deadpool storage dp, minimum carryover storage requirements $Smin^F$, and the storage to meet the high priority diversions and minimum streamflow requirements for each season's driest hydrologic state y_D.

$$S^F_{y_T,T} \geq Smin^F_{y_T,T} + dp + d_T + emin_T - \quad \forall \quad t \in (\text{y} = \text{D}) \quad (8)$$

where $S^F_{y_T,T}$ is stored water for each hydrologic state *y* in the final modeled period *T*; $Sfmin^F_{y_T,T}$ is the minimum carryover storage requirement for the reservoir after the final modeled period; D_t is the driest expected (D) hydrologic state y of time period t; and is expected future actualized inflow for each time period t of the driest hydrologic state D.

2.3 Environmental Hedging Theory

Environmental hedging helps to manage uncertain water supply availability for downstream release and to balance near-term environmental benefit with long-term environmental resilience. The hedging selects whether or not to kill a small number of fish now in order to reduce the likelihood of killing more later if supply is limited or will cause a damaging flood. Environmental hedging applies the same logic as water supply hedging [*Draper and Lund*, 2004; *You and Cai*, 2008; *Hui and Lund*, 2015] for which "it is sometimes economical to accept a small current deficit in output so as to decrease the probability of a more severe water or energy shortage [or flood] later in the drawdown-refill cycle [*Bower et al*., 1962]." As water availability increases (from A $->$ F in Figure 3a) six types of hedges bind each period's release decision based on current, future and past biologic and water availability (displayed alphabetically in Figure 3a). The hedging effects (e.g. diminished fish populations and flow needs) of decisions in one time period persist into future time periods. Releases can be further hedged over time (Figure 3b) under drier conditions, or greater releases and spill can occur in anticipation of, or after, wetter conditions.

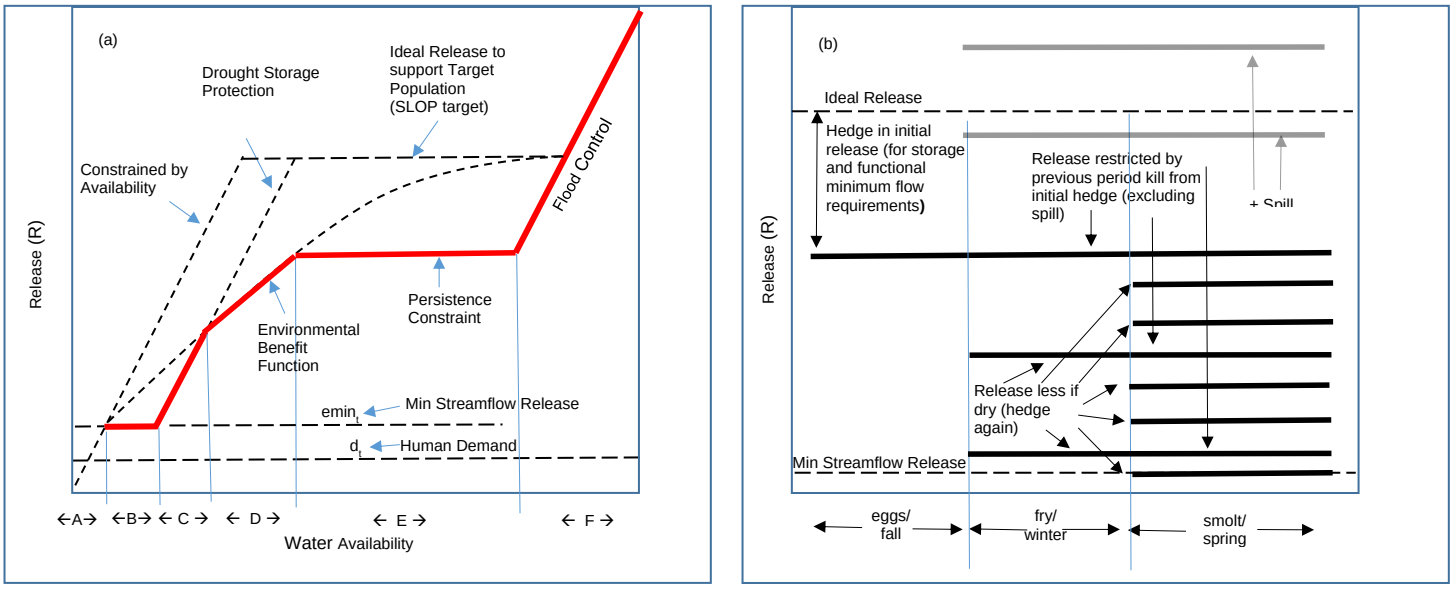


Figure 3 (a): Environmental hedging for one time period. The optimal release policy (environmental hedging) follows the thick red line for time period t. Dashed lines are release constraints. **(b):** Environmental hedging across time periods. Each line is the optimal decision per stage for each possible hydrologic condition.

Environmental Hedging method hedges along the standard linear operating policy for seven reasons. Within one time period, six reasons make up the hedge (and are displayed alphabetically in Figure 3a). Depending on the system, the order of the hedge could change. A) Water Availability, Equation 2: Water is not released beyond current water availability. B) Minimum Streamflow Requirement, Equation 4: A lower bound restricts a lower release by the minimum streamflow requirement. C) Drought Storage Protection, Equation 8: Releases are hedged to meet both water availability and drought storage constraints for the driest expected current and future seasons. D) Environmental Benefit Function, Equation 6: Releases are hedged along the slope of the environmental benefit E) Population Dynamics Persistence Constraint, Equation 7: Releases are constrained to not exceed the water needs of the current population (considering population losses from the previous period). F) Spill, Equations 3b:3d: Releases are made to avoid overtopping the reservoir, even if the spill inflicts major environmental damage downstream. Hydrologic forecasting is the reason for hedging over time (Figure 3b). The model will hedge with predicted inflow in anticipation of extreme events at each time period.

2.4 Environmental Operation of California's Folsom Dam

Environmental hedging was applied to Folsom Dam in central California to maximize the downstream Chinook salmon population that can be supported by releases to the lower American River. Environmental conditions for the 30 miles downstream from Folsom Dam to the Sacramento River confluence are determined largely by Folsom releases. Fall-run Chinook salmon are a key species for the lower American River. The hydrologic needs of the fall-run Chinook track the natural hydrograph.

Time is discretized by hydrologic season and the three distinct periods for which cohort A is in the stream: egg, fry, and smolt (t = 1, 2, 3, respectively), followed by the spawning and egg period of cohort B (t=5) (see Figure 1). October through December is the period when fall-run Chinook salmon return from the ocean to spawn and lay eggs, January through April is the period when eggs mature to fry, and May through June is when young salmon, or "smolts" migrate to the ocean where they stay for 2-5 years before returning to spawn. Each fish life stage has different instream water needs. For fall-run Chinook the hydrology and fish life cycle stages are synchronized. Cohort B is included to represent the value of flows and storage towards the end of the water year.

Hydrologic forecasting for Folsom reservoir considers the region's two distinct hydrologic periods: wet season precipitation (October – April) and dry (May – September). Wet season inflow is highly variable, so operations must consider both droughts and floods. Seasonal inflows were estimated for each time period from the river's 113 years of historical record of unimpaired from the California Data Exchange Center's Full Natural Flow at Fair Oaks station. Wet season inflow is modeled by two fish development periods: the egg stage (October through December) and fry stage (January through April) (Figure 1). Egg and fry period inflows correlate weakly with a correlation coefficient of 0.35 (p-value of 0.12×10^{-6}). The egg stage includes adult migration to spawn the eggs. The May and June spring snowmelt season coincides with smolt out-migration and with inflows correlated with wet season snowpack (r = 0.6 with a p-value of 0.75×10^{-11}); wet egg (winter) and fry (fall) seasons tend to beget wet smolt (spring) seasons. Dry season baseflow between July through September correlate strongly with the next period's wet season inflow (r = 0.83 and a p-value of 0.22×10^{-15}) and is modeled here as deterministic, so streamflow is modeled with conditional probabilities. Predicted and actualized future inflow events and the transition probability matrix between inflows for the lower American River are in Table S1 and S2. Here, the egg (fall) season inflow lacks prior inflow information at the beginning of the water year so it is predicted initially to be 919 cfs, median historical seasonal inflow. Fry (winter) and smolt (spring snowmelt) predictions and future inflow are conditional on inflow of previous wet and dry season inflow. Snowmelt and dry season inflow at the end of the water year are determined by inflow (precipitation) received earlier in the year.

Hydrologic states y_t are discretized by the quantiles of the cumulative distribution function of each state's historical record (S2). The range of selected exceedance probabilities for the lower American River, w = {0.01, 0.025, 0.05, 0.1, 0.2, 0.3, 0.4, 0.5 and 0.75, 1}, includes floods, but emphasizes dry times for drought operations planning [California SWRCB, 2015]. More fish suffer and die during drought, although some life-history stages (e.g., egg incubation) suffer from floods.

The water availability and infrastructure constraints are bound by Folsom Reservoir's 1 million acre-foot storage capacity, 90 TAF deadpool storage requirement and 1150,00 cfs outlet capacity (BOR, 2016). The 325 TAF/year

released [*NOAA*, 2011] for downstream human diversion is always met. The minimum streamflow requirement allocates water to support 5% of fish from each of the two cohorts, thereby avoiding extirpation.

The environmental benefit function is modeled with fish survival $N^{g}_{y_t,t}$ as a function of reservoir releases $p_{y_t,t}R_{y_t,t}$ for each stage (combined fish life-stage and hydrologic season). The magnitude of the fall-run Chinook-streamflow functions may have error, but the shape of the function describing the need of each fish flow, is correct. The fall-run Chinook egg survival-flow relationship is an inverse quadratic survival function (Figure 4). Survival greatly increases with flow initially, and then less so, until finally high flows scour gravel bars and redds where eggs are laid [*USFWS*, 2003; *Jager and Rose*, 2003; *Jager et al*., 1997; *Null and Lund*, 2011]. More flow creates more fry habitat [*Jager and Rose*, 2003; *Jager et al*., 1997] until the river's carrying capacity is reached. Therefore the fry survival-flow function is the linear slope-intercept between the fry minimum and maximum fish flow requirements. Smolts need pulse flows, so the smolt-flow relationship for the lower American River is pulsed [*Jager and Rose*, 2003; *Sykes et al*., 2009; *Jager*, 2014] to simulate spring snowmelt peaks that cue smolts to migrate downstream to the ocean. One pulse of 1,500 cfs is assumed to initiate outmigration for at least 75% of smolts. Releases that mimic baseflow between pulses are assumed to maintain cold temperatures. Fish population optimization results in at least two, but no more than five "snowmelt pulses" because 5 pulses that each move 70% of the smolts out, will save roughly 100% of the smolt population. Pulses are modeled as mixed-integer variables in the model. The exact timing of pulse releases within the smolt period is not allocated so the operator can flexibly synchronize American River pulse releases with Sacramento River pulses. Pulse water is not allocated in the winter because it is assumed that fish will out-migrate with the natural pulse they receive from overland flood flow. Flow of 300 cfs in May and 600 cfs in June are released between pulses to ensure minimum fall-run Chinook temperature requirements of 65ºF [*Jones and Stokes*, 1997; *US Dept of Interior*, 2008].

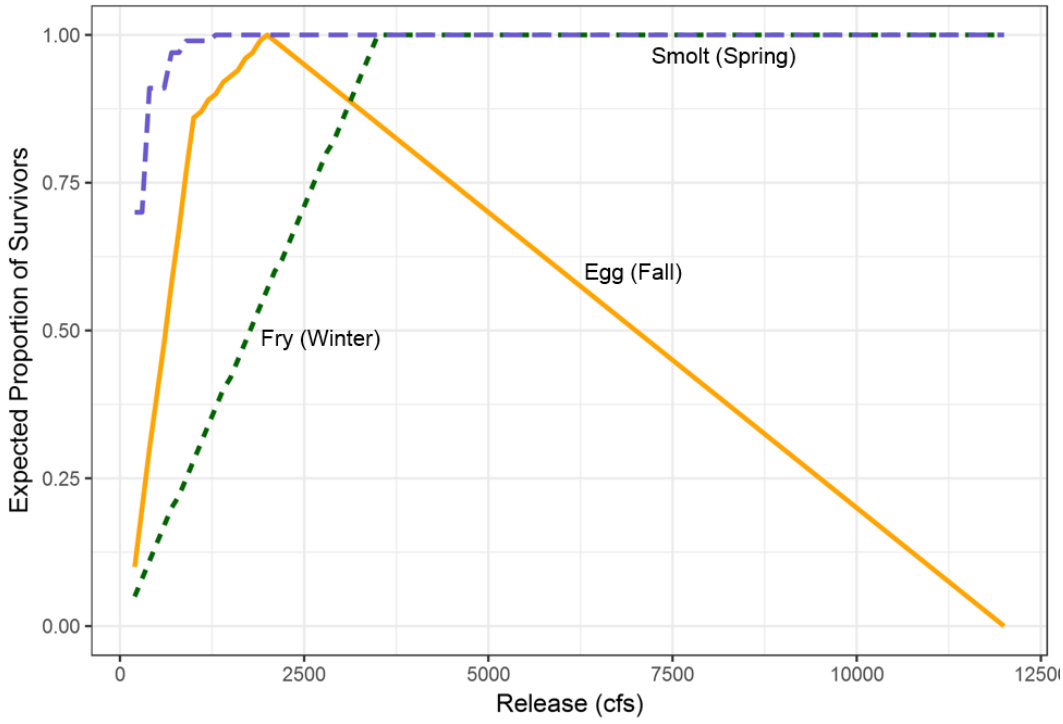


Figure 4: Maximum survival of fall-run Chinook for different releases to the lower American River. Survival rates from authors, *Bradford*, 1995; *SWRI*, 2001; *Williams*, 2006. Fish population size-streamflow curves developed from authors, *Jager et al*., 1997; *Jones and Stokes*, 1997; *Jager and Rose*, 2003; *USFWS*, 2003; *US Dept of Interior*, 2008; *Sykes et al*., 2009; *Null and Lund*, 2011; and *Jager*, 2014.

Minimum fish flow requirements for eggs and fry are 190 cfs (California SWRCB, 1958), the flow assumed to save 10% of eggs and 5% of fry. Smolts have a minimum release requirement of 123 cfs, or 33 TAF, the storage volume required to support two May pulses of 1,500 cfs with 5 days of 300 cfs and baseflow in between, which is assumed to

save at least 70% of smolt. Below these minimum fish flow requirements the population is considered extirpated because current fragmentation of the Sacramento River system prohibits fish from coping with the drought naturally by moving to another river or finding refuge in cold pools. Maximum flow requirements are assumed to support the ideal target fish population, set in the 1992 Central Valley Project Improvement Act's Anadromous Fish Restoration Plan for the wettest water year type (2,500 cfs between September to February and 4,500 cfs between March to June) which are currently used for Folsom operations [*Williams*, 2001].

The persistence of the Chinook salmon population under ideal conditions results in an average returning adult population of 160,000 [*USFWS*, 2001]. We assume female fall-run Chinook salmon (approximately 50% of the population) lay an average of 4,300 eggs [*Bradford*, 1995], about 15% of which successfully bank into redds, resulting in about 51,600,000 eggs, on average. We then assume about 10% of these eggs survive to become fry and about 70% of juveniles survive to become smolt [*Bradford*, 1995]. Including hatchery releases, about 5% of smolts survive the ocean and return to spawn [*Williams, 2006]*; even with ideal river conditions only about 7% of young salmon survive from egg to smolt.

Folsom reservoir was operated with environmental hedging for 28 combinations of initializing (i.e. at start of the model) and minimum carryover storage conditions. For these cases, minimum carryover storage requirements were discretized to 0, 50, 100, 150, 200, 250 and 300 TAF and initial storage conditions at the beginning of water year one are 250, 500 (Folsom average), 750 and 1000 TAF.

The Pareto frontier of optimal release schedules were found for each storage case by running the environmental hedging model with a range of weights between 0 and 1 for the α penalty for allocating water to cohort B and β, the penalty for allocating water to final storage. This set of efficient solutions was then plotted to analyze the tradeoffs in expected fish survival resulting from optimal allocation between the two cohorts (Figure 6a) as well as between releasing water for fish survival or storing it for the future over the range of α and β (Figure 6b). Expected fish survival for each case is the surviving percentage of the total population. These percentages exclude natural mortality to isolate the effect of water scarcity (and the consequent effects of water scarcity like habitat loss and warm temperatures).

Finding the globally optimal release schedule for each storage case required producing a subset of each case's set of efficient solutions four times. The first subset retains only solutions that produce the maximum average survival of cohorts. Maximum average survival is considered the globally optimal solution because both cohorts are equally important. Maximum average survival was normalized as the proportion of the sum of the target population supported by the release decision of each hydrologic condition weighted by the probability of that hydrologic condition. The second subset retained solutions that produced the largest final stored water volume, a less, but still important, goal. The third subset retained solutions with the smallest alpha and of those, the smallest beta to minimize computation time. For all storage cases, the optimal beta is 0.25. The optimal alpha is always 0.1 except when available stored water (initial less minimum carryover storage requirements) exceeds 600 TAF, in which case alpha is 0.05.

2.5 Results

2.5.1 Tradeoffs between Cohorts and Final Storage

A Pareto curve highlights tradeoffs between allocating water for cohort A or B (Figure 6a,b), found by selecting different values of alpha and beta, the objective function priority weights for cohort B and final storage (Equation 1). Each line in Figures 6a is an interpolation of all model runs with a range of weights for each of the initial stored water volume and carryover storage requirements. Total population maximizing solutions (displayed as circles in Figure 6a) produce the maximum average allocation to cohort A and cohort B across all water year types.

Because of spill, the small human demand below Folsom, and the small probability of drought, expected survival of cohort A is often quite high. Because of the hedge in the first period for drought protection and the population dynamics constraint, cohort A has an upper bound cap, regardless of the choice of alpha or beta. After supporting the cohort A population, surplus water is available to support cohort B and final storage requirements. Depending on the choice of alpha and beta penalties, a wide range of cohort B survival is possible.

2.5.2 Tradeoffs between Storing Water or Releasing it for Fish Survival

The relationship between salmon survival and stored water is both complimentary and competitive, particularly with environmental hedging. Depleting water reserves is needed to save fish but because fish later depend on stored water (particularly in drought), depletion is not in the best interest of later life stages. Likewise, with greater initial storage and/or inflow is greater, both stored water and releases (and consequently fish survival for both cohorts) is also greater because more initial storage can increase releases for cohort A eggs in the first stage with greater impact on improving the objective function than other life stages. However, some competition between releases and storage also exists – minimum carryover storage requirements increase at expense of the fish population.

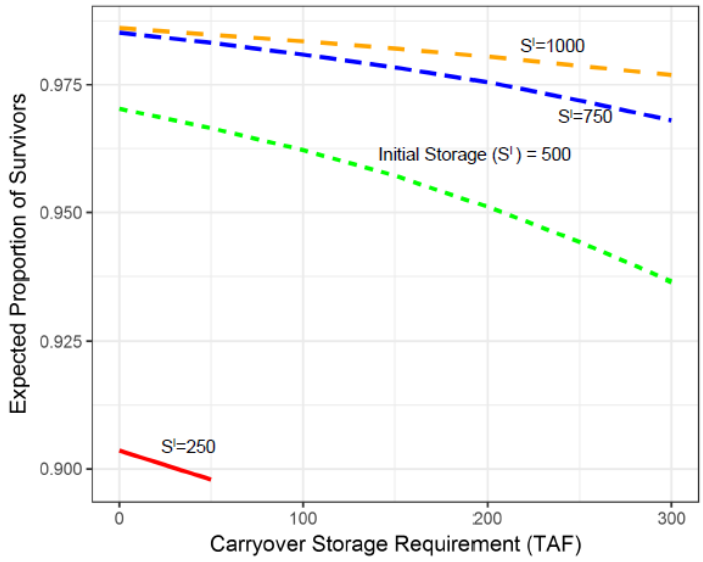


Figure 5: Maximum fish cohort survival for the range of minimum carryover and initial storage (start of model) requirements.

Within the set of efficient solutions, solutions vary negligibly with final storage penalty beta unless beta imposes a strong final storage penalty (of approximately 0). Final trade-offs among releasing water for cohort A or cohort B, or saving water in storage for the final time period, are more influenced by the choice of alpha. Strong alpha penalties (i.e. less than 0.01) tend to curtail a greater proportion of ideal releases to cohort B. In those cases, not enough water is available to improve cohort A, resulting in more fish death than is hydrologically necessary. Alpha choices above 0.01 produce the curve in the Pareto front between cohort A and B (Figure 6a). These choices exaggeratedly curtail ideal allocation to cohort A and instead save water for cohort B until all of cohort B is supported.

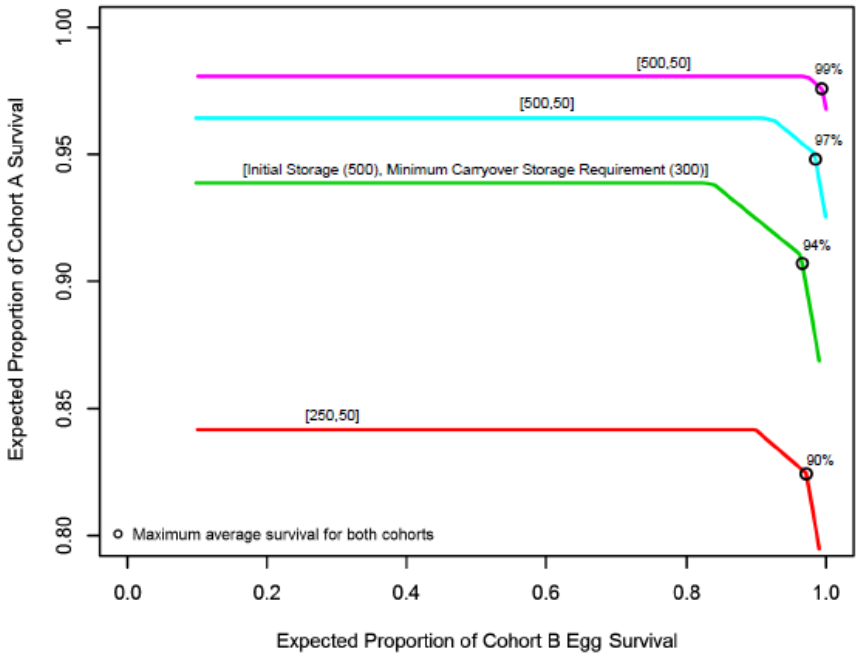


Figure 6 (a): Average fish survival of cohorts A and B for a range of initial and minimum carryover storage requirements.

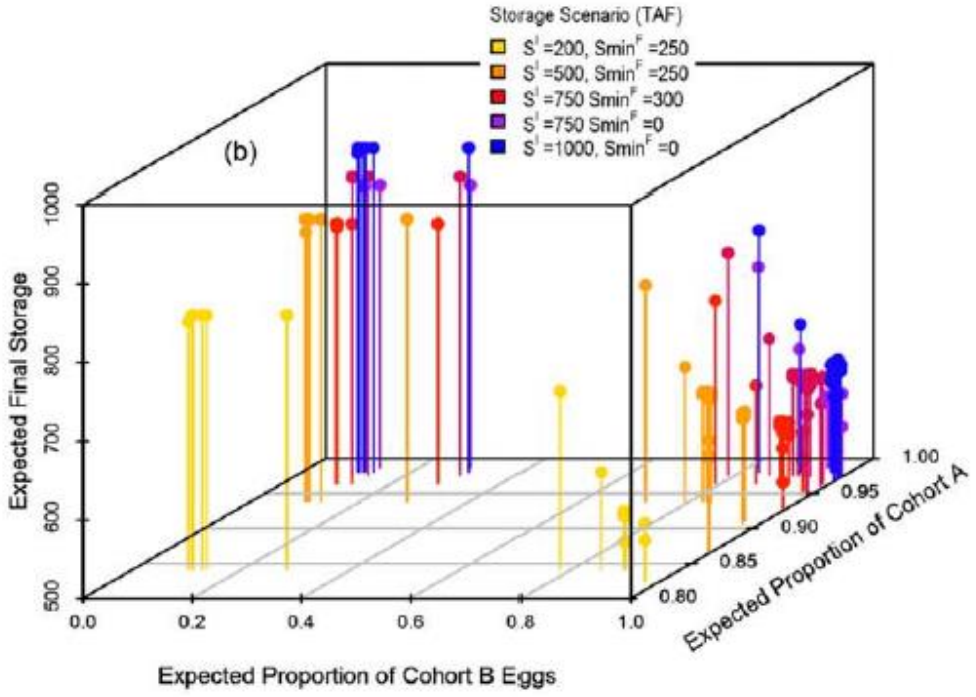


Figure 6 (b): Expected water in final storage and cohort A and B survival fish survival for a range of alpha, beta, minimum carryover storage requirements and initial water in storage conditions.

To meet all constraints, initial storage conditions at the beginning of the model at Folsom must exceed 194 TAF and the minimum carryover storage requirement be at least 194 TAF less than initial water storage conditions. Within these boundary conditions, enough stored water is available to support the minimum fish population (5%) of cohort A and B (Equation 5), as well as meet minimum carryover storage requirements – therefore avoiding the crises of fish extirpation and draining the reservoir.

2.5.3 Operating Rule Curves

Planning rule curves (Figure 7), a rule tableau (S3), and operations rule curves (Figure 8) communicate guidance for optimal release decision choices for each hydrologic condition for each time period. Planning rule curves are generated by running the model to exclude spill decisions. Operational curves include spill and communicate total releases to operators for each hydrologic condition and time period.

In figure 7, each line (or for t=1, each point) of each time period's planning rule curve follows the recommended base release per expected water availability for each stage and water storage condition. Second and third period releases are constrained by forecasted water availability, fish losses from the previous period, and stored water requirements for future releases. First and fifth period releases are similarly constrained, although because these periods occur at the start of new water years, forecast water availability is independent of the previous period. Third and fourth period inflows are known snowmelt quantities distinguished only in that the third period is when the fall-run Chinook out-migrate and the fourth period has little to no fall-run Chinook activity. Therefore, only third period releases are modeled although third period releases are required to meet third and fourth period human requirements. The infrequent non-monotonic relationship between seasons (i.e. a wetter egg season is infrequently followed by a drier fry season), are smoothed in the rule curve with non-parametric local regression (LOESS curve fitting) using the LOESS R package.

Each row of the rule table (S3) provides guidance for release decisions for each of the four time periods for which environmental release decisions are needed, for each of the 28 storage cases. Release rules are made for the range of expected inflow and incoming stored water for each time period. As the water year develops more inflow information is known so the branches of the release decisions increase (Figure 2). When plotted (Figure 7), each expected inflow (column $q'_{y,t}$ of S3) for each storage case is plotted as a line guiding the operating rule curve. Figure 8c plots the range of recommended releases for the full range of expected inflow for each modeled time period for specific initial storage conditions and minimum carryover storage requirements. Curtailments and augmentations to the environmental benefit function occur strategically. For example, releases, above 364 TAF are avoided during the egg stage because of damage to redds (i.e., the inverse quadratic fish-streamflow relationship). There are either positive or no consequences of additional water during juvenile and smolt stages, so flood releases are made during juvenile and smolt stages, when possible, instead of the egg stages.

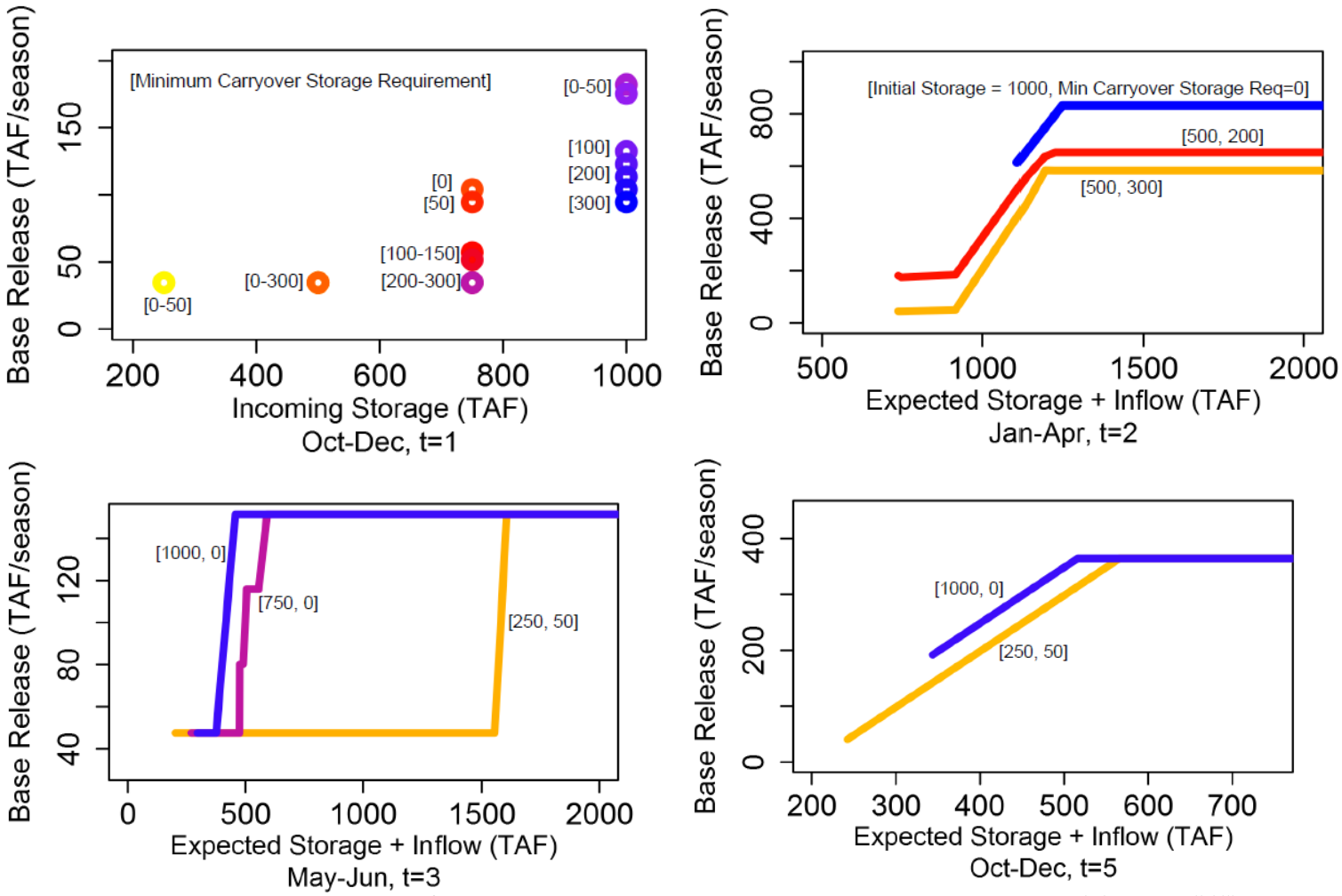


Figure 7: Each line (or point as in the case of t=1) is a base release planning schedule with the optimized release policy given each period's water availability (Equation 2) for each of 28 initial and carryover storage cases.

Each line of Figures 8a,b,and c represent a possible water year. Figure 8c plots the same information as Figure 8a, but releases are normalized as a proportion of the target release achieved over time. Figure 8b is with Figure 8c is without including flood releases. Figures 8b and 8c show the effect of the hedging: the first period is hedged when needed. The second period is hedged again as needed. The third period is also hedged, but because of the discrete releases options from the smolt pulse releases sometimes the magnitude of the release appears larger than is needed. The fifth period starts a new water year and is not hedged.

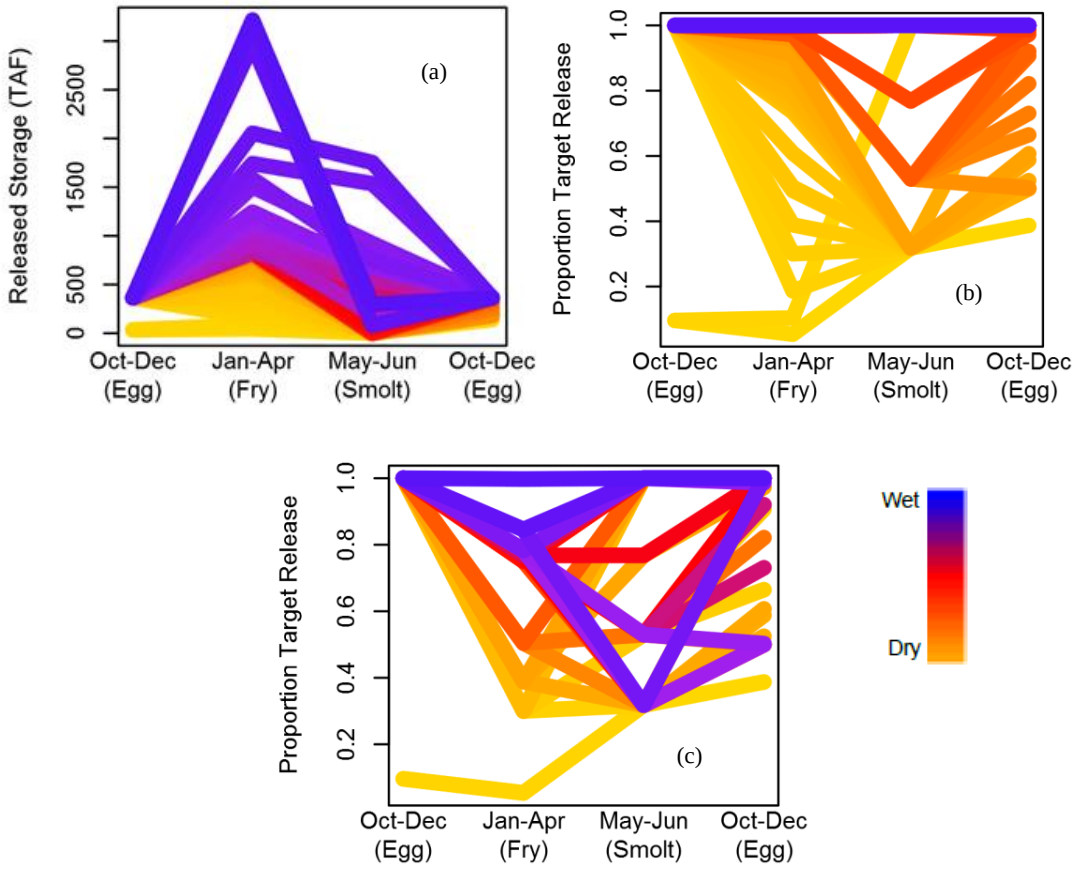


Figure 8: Each line represents expected releases over time for a range of inflow states (a) as a proportion of the release target with (b) and without spill (c), over time, with initializing model storage conditions of 500 TAF and minimum carryover storage requirements of 200 TAF. Planning release schedules exclude spill.

2.6 Discussion

Expected survival over time of fall-run Chinook salmon was compared (Figure 9a) with several alternative operating approaches: 1) this environmental hedging model, 2) standard linear operating reservoir policy (SLOP) with and without minimum carryover storage and minimum streamflow requirements, 3) a simulation that mimics the natural flow regime, 4) an incomplete environmental hedging that omits the persistence and population dynamics constraint, and 5) historical annual fall-run Chinook production (average of 134,753 adult salmon/year) measured below Folsom Dam [*Azat*, 2016]. System performance [*Hashimoto et al*., 1982; *Bayazit and Ünal*, 1990] for each approach was assessed (Figure 9b) in terms of a) the fish population expected value; b) the frequency of meeting minimum streamflow requirements and avoiding a fish kill; the probability of system failure (e.g. c) draining or d) overtopping the reservoir); e) the frequency of failing to meet the minimum carryover storage requirement; and f) the frequency of time water storage exceeds Folsom flood storage capacity (610 TAF).

The cumulative distribution function plots of fish survival (Figure 9a) were created for each reservoir operation policy for the range of hydrologic states. Since historical data was measured only for out-migrant smolts, only survival of out-migrating smolts (cohort A) were compared.

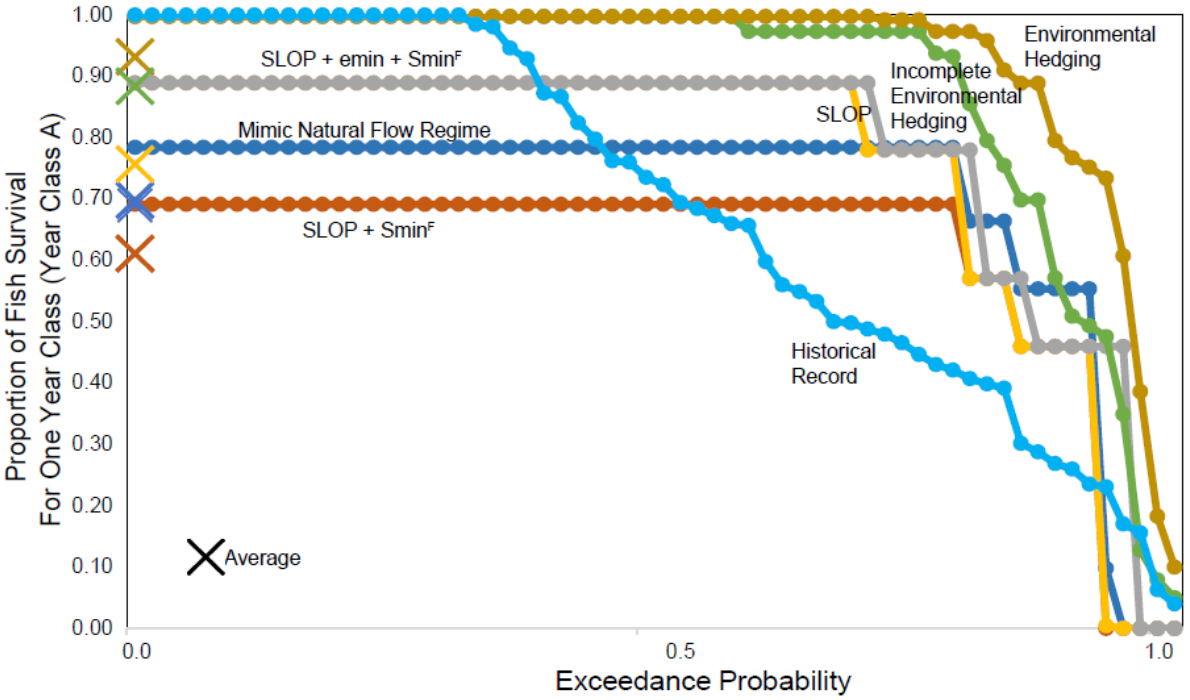


Figure 9 (a): Fish survival probability for each of six modeled operating strategies and historical operating strategy with initial model storage of 500 TAF and minimum carryover storage requirement of 200 TAF.

(b)

Initial Storage = 500 TAF
Minimum Carryover Storage Req = 200 TAF

	Frequency of…					
	Fish Survival	Fish Extirpation	Draining the Reservoir	Failing to Meet Minimum Carryover Storage	Water Storage in exceedance of Flood Capacity	Overtopping the Reservoir
Fish Hedging *	86	0	0	0	67	0
Incomplete Fish Hedging	77	0	0	0	36	0
SLOP + Min Eco Release (emin)+ Min Carryover Req (Sminᶠ)*	83	7	0	0	95	87
Mimic Natural Flow Regime *	72	6	12	2	87	65
Historical Data	72	0	0	n/a	50	0
SLOP	48	8	51	100	0	69
SLOP + Min Carryover Req (Sminᶠ)	40	70	13	1	0	61

Excellent — Poor

* Pareto efficient

Figure 9 (b): Reservoir operations performance for cohort A with six re-operation policies and historical operating policy with initial water in storage of 500 TAF and minimum carryover storage requirements of 200 TAF.

In general, fish survival is higher in wet years and lower in dry years. In wet and normal years (i.e., low and middle exceedance probabilities) all the reservoir operation approaches performed well. In near-dry and dry years all the operating approaches had more performance variation. Historical Folsom reservoir operations have the most variable success, performing well in wet years, but poorly in normal and most dry years. Perhaps most importantly, only historical Folsom operations and modeling strategies that employ optimization did not fail in very dry years. Optimization models leverage the Markov Chains and specific constraints so proposed releases best fit overall fish needs. Notable improvements in fish survival result with environmental hedging when stored water is not unnecessarily released without considering water demand from the current period's fish population size.

Non-optimized rule-based simulations (operating with SLOP or mimicking natural flow) did not consider the future. Water is allocated less efficiently and consequently saves less fish and storage than optimization models, particularly in dry times. Were fish-flow relationships strictly increasing, including the egg period, then simulation models of SLOP and the natural flow regime approach would have outperformed the optimization models in wet conditions. Environmental hedging saves all fish in wet years even though it hedges because of spill. Simulation models do not leverage past and future information and therefore just implement specified release rules over time. The advantages of SLOP in wet times are outweighed by fish kills and draining the reservoir in dry times, without hedging.

Environmental hedging had the highest average modeled survival of cohort A (86%) compared with other methods (Figure 9b). Environmental hedging also always avoided reservoir drainage and overtopping, met minimum carryover storage requirements, and performed well with respect to fish survival while meeting water supply requirements and leaving enough water in final storage for future human and fish uses.

Environmental hedging also has limitations. The current model could be improved to include evaporative losses, bed load movement and other factors affecting fish development stage survival, climate change, fish-ocean dynamics, and ecological uncertainty [*Jager and Smith*, 2008]. For the lower American River, environmental hedging also could include flow requirements of the Sacramento-San Joaquin Delta, flow requirements of the diverse fish assemblage in the Lower American River, including the summer streamflow requirements of steelhead. The model could also include groundwater interaction and banking opportunities, and multi-reservoir operation to hedge among several reservoirs to improve water supply efficiency. Extending the model to include a multi-year extreme event could provide insight into the intensity of hedging needed to maximize environmental benefits during extreme drought and flood. In short, a more comprehensive definition of Lower American River environmental benefits could also result in hedging with different timing and intensity.

Implementing environmental hedging in practice can have barriers. If environmental flow laws are more stringent than the minimum streamflow needs of the fish population, or are inflexible and prevent hedging, releases will be forced to meet regulatory requirements, even if they tend to cause fish kills in late dry years. Without hedging, forced early releases can deplete available storage and harm overall fish survival in dry years. Sufficient water is available in Folsom to meet high priority human demand and environmental demand without violating the minimum streamflow constraint. However, in a more constrained system, or at a daily time step, water availability may be insufficient for environmental hedging and a multi-objective framework that curtails both economic and environmental goals is needed (e.g. Yang and Cai, 2011).

2.7 Conclusions

Sometimes the ideal is the enemy of the good. Developing an environmental benefit function and using this environmental hedging optimization approach provides a support tool with which to set and curtail environmental releases optimally in drier periods. Killing some fish early to preserve water in storage for later use effectively ‘hedges bets’ for the worst case low hydrologic conditions and can help to avoid later and larger fish kills. Curtailing releases in early stages can enhance survival of future life stages by increasing water in storage and lessening fish-water demand for the future by diminishing current fish population size. Both functions can be particularly important in drought.

Compared to other operating policies, environmental hedging can help improve environmental performance without draining the reservoir while still meeting minimum carryover storage requirements and producing additional storage. The fish survival-streamflow environmental benefit function enables operational decisions to consider releases to support biological objectives, and to weigh trade-offs among storing or releasing water for different cohorts for different water year types and different storage limits. The hydrologic forecasting in the model can allow for realistic decisions based on long-term planning of an unknown future and short-term planning with adaptation as inflow information becomes known.

Environmental hedging provides an adaptable framework for optimizing downstream releases for environmental benefits. The environmental benefit function could be based on different environmental flow methodologies using different biological or downstream targets such as habitat, insect and bird survival, groundwater recharge, or even a multi-objective model to benefit multiple species and/or ecological goals. However, the environmental hedging principles and mathematics would remain the same.

Because any initial hedging reduces releases for all later seasons, augmenting releases during the first period (which for fall-run Chinook in the lower American River is during the egg season (better redd than dead!)) has the greatest potential for saving more fish and water in storage than later seasons. Furthermore, since water storage is in effect hedged for the driest year, which has a low probability, excess water in storage often is available at the end of wet and even normal hydrologic seasons. Banking wet season surplus water in groundwater could offer additional reserves for human demand and free water supply to augment first period environmental releases.

This paper quantifies the potential benefits and trade-offs of hedging reservoir operations for fish and other downstream environmental objectives. Environmental hedging has the potential to outperform other operating strategies for a range of cases using diverse fish population and water supply performance metrics. It is highly likely it would outperform traditional reservoir operating policy, such as historical operation of Folsom Reservoir. For example, saving stored water for later, and releasing less when it is known that some of the fish population has already suffered mortality can ultimately result in water allocations that save more fish and increase storage over an operating year cycle.

2.8 Bibliography

Arthington, A. (2012). *Environmental Flows. Saving Rivers in the Third Millennium.* University of California Press.

Azat, J. (2016). *California Central Valley Chinook Population Database Report.* California Department of Fish and Wildlife. *http://casalmon-update.webvanta.com/PDFs/Chinookprod_CompleteDraft2014Reports5.20.15.pdf*

Bayazit, M., & Ünal, N. E. (1990). Effects of Hedging on Reservoir Performance. *Water Resources Research*, 713–719.

Bower, B. T., Hufschmidt, M. M., & Reed, W. W. (1962). Operating Procedures: Their Role in the Design of Water-Resources Systems by Simulation Analyses. In A. Maass, M. M. Hufschmidt, R. Dorfman, H. A. Thomas Jr, S. A. Marglin, & G. M. Fair, *Design of Water-Resources Systems* (pp. 443-458). Cambridge, MA: Harvard University Press.

Bradford, M. J. (1995). Comparative Review of Pacific Salmon Survival Rates. *Canadian Journal of Fisheries and Aquatic Sciences*, 1327-1338.

Bureau of Reclamation. (2016). Folsom Dam Details. *https://www.usbr.gov/projects/index.php?id=74.*

California Data Exchange Center. (2015). *California Department of Water Resources.*

California State Water Resources Control Board (SWRCB). (1958, March 21). Decision on Major Applications to Appropriate Water from American River Systems, Decision D 893.

California State Water Resources Control Board (SWRCB). (2015, January 15). *Central Valley Project and State Water Project Drought Contingency Plan January 2015 - September 2015.*

Cardwell, H., Jager, H. I., & Sale, M. J. (1996). Designing Instream Flows to Satisfy Fish and Human Needs. *Journal of Water Resources Planning and Management*, 356-363.

Cioffi, F., & Gallerano, F. (2012). Multi-objective Analysis of Dam Release Flows in Rivers Downstream from Hydropower Reservoirs. *Applied Mathematics Modeling*, 2868–2889.

Draper, A., & Lund, J. (2004). Optimal Hedging and Carryover Storage Value. *Optimal Hedging and Carryover Storage Value*, 83-87.

Harman, C., & Stewardson, M. (2005). Optimizing dam release rules to meet environmental flow targets. *River Research and Applications*, 113–129.

Harou, J. J., Pulido-Velazquez, M., Rosenberg, D. E., Medellín-Azuara, J., Lund, J. R., & Howitt, R. E. (2009). Hydro-economic Models: Concepts, Design, Applications, and Future Prospects. *Journal of Hydrology*, 627–643.

Hashimoto, T., Stedinger, J. R., & Loucks, D. P. (1982). Reliability, resiliency, and vulnerability criteria for water resource system performance evaluation. *Water Resources Research*, 14–20.

Homa, E. S., Vogel, R. M., Smith, M. P., Apse, C. D., Huber-Lee, A., & Sieber, J. (2005). An Optimization Approach for Balancing Human and Ecological Flow Needs . *EWRI 2005 World Water and Environmental.* Anchorage: ASCE.

Hui, R. & Lund, J. L. (2015). Optimal Flood Pre-releases – Flood Hedging for A Single Reservoir. World Environmental and Water Resources Congress 2015: 2192 Floods, Droughts, and Ecosystems, 2192 – 2201.

Jager, H. (2014). Thinking outside the channel: Timing pulse flows to benefit salmon via indirect pathways. *Ecological Modelling*, 117-127.

Jager, H. I., & Rose, K. A. (2003). Designing Optimal Flow Patterns for Fall Chinook. *North American Journal of Fisheries Management*, 1-21.

Jager, H., Cardwell, H. E., Sale, M. J., Bevelheimer, M. J., Coutant, C. C., & Van Winkle, W. (1997). Modelling the linkages between flow management and salmon recruitment in rivers. *Ecological Modelling*, 171-191.

Jones and Stokes, A. (1997). *East Bay Utility District Supplemental Water Supply Project.* Sacramento, California: East Bay Municipal Utility District and U.S. Bureau of Reclamation.

Klemeš, V. (1977). Value of Information in Reservoir Operation. *Water Resources Research* , 837–850.

Labadie, J. W. (2004). Optimal operation of multireservoir systems: State-of-the-art review. *Journal of Water Resources Planning and Management*, 93–111.

Loucks, D. P., Stedinger, J. R., & Haith, D. A. (1981). *Water Resource Systems Planning and Analysis.* Englewood Cliffs, N.J.: Prentice-Hall.

Lund, J., & Ferreira, I. (1996). Operating Rule Optimization for Missouri River Reservoir System. *Journal of Water Resources Planning and Management*, 287-295.

Lund, J., Hui, R., Escriva, A., Porse, E., Adams, L., Connaughton, J., . . . Yi, S. (2017). Reservoir operation design. In V. Singh, *Handbook of Applied Hydrology* (p. Chapter 130). McGraw-Hill Education.

Moyle, Peter (2002). *Inland Fishes of California.* University of California Press.

NOAA. (2011). *Magnuson-Stevens Fishery Conservation and Management Act: Long-Term Operations of the Central Valley Project and State Water Project: EFH Conservation Recommendations.*

Null, S. E., & Lund, J. R. (2011). Fish Habitat Optimization To Prioritize River Restoration Decisions. *River Research and Applications*.

Palmer, R. N., & Snyder, R. M. (1985). Effects of instream flow requirements on water supply reliability. *Water Resources Research*, 439–446.

Poff, N. L., Allan, J. D., Bain, M. B., Karr, J. R., Prestegaard, K. L., Richter, B. D., . . . Stromberg, J. C. (1997). The Natural Flow Regime. *BioScience*, 769-784.

Poff, N.L., Richter, B.D., Arthington, A.H., Bunn, S.E., Naiman R.J., Kendy, E., Acreman, M., Apse, C., Bledsoe, B.P., Freeman M.C., Henriksen, J., Jacobson, R.B., Kennen, J.G., Merrittt, D.M., O'Keefe, J.H., Olden, J.D., Rogers, K., Tharme, R.E., Warne, A. (2010). The Ecological Limits of Hydrologic Alteration (ELOHA): A New Framework for Developing Regional Environmental Flow Standards. *Freshwater Biology, 147-170.*

ReVelle, C. (1999). *Optimizing Reservoir Resources: Including a New Model for Reservoir Reliability.* John Wiley and Sons.

Richter, B. D., & Thomas, G. A. (2007). Restoring Environmental Flows by Modifying Dam Operations. *Ecology and Society*.

Sale, M. J., Brille, E. D., & Herricks, E. E. (1982). An Approach to Optimizing Reservoir Operation for Downstream Aquatic Resources. *Water Resources Research*, 705–712.

Section 5930 (Fish and Game Code September 1992).

Suen, J.-P., & Eheart, J. W. (2006). Reservoir Management to Balance Ecosystem and Human Needs: Incorporating the paradigm of the ecological flow regime. *Water Resources Research*.

SWRI. (2001). *Aquatic Resources of the Lower American River: A Baseline Report.* Lower American River Fisheries And Instream Habitat.

Sykes, G. E., Johnson, C. J., & Shrimpton, J. M. (2009). Temperature and Flow Effects on Migration Timing of Chinook Salmon Smolts. *Transactions of the American Fisheries Society*, 1252–1265.

Tharme, R. E. (2003). A Global Perspective on Environmental Flow Assessment: Emerging Trends in the Development and Application of Environmental Flow Methodologies for Rivers. *River Research and Applications*, 397–441.

U.S. Dept of Interior. (2008). *Central Valley Project and State Water Project Operations Criteria and Plan Biological Assessment.*

USFWS, U. (2003). *Comparison of PHABSIM and 2-D Modeling of Habitat for Steelhead and Fall-run Chinook Salmon Spawning in the Lower American River.* Sacramento: USFWS.

USFWS, United States Fish and Wildlife Service. (2001). *Final Restoration Plan for the Anadromous Fish Restoration Plan.*

Vogel, R., Sieber, J., Archfield, S. A., Smith, M. P., Apse, C. P., & Huber-Lee, A. (2007). Relations among Storage, Yield and Instream Flow. *Water Resources Research*.

Waddle, T. (1992). A Method for Instream Flow Water Management. (p. 278). Fort Collins, Colorado: PhD Dissertation.

Wang, Y., Rhoads, B. L., & Wang, D. (2016). Assessment of the Flow Regime Alterations in the Middle reach of the Yangtze River associated with Dam Construction: Potential Ecological implications. *Hydrological Processes*, 30: 3949-3966.

Williams, J. G. (2001). Chinook Salmon in the Lower American River, California's Largest Urban Stream. *Fish Bulletin 179: Contributions to the biology of Central*.

Williams, J. G. (2006). Central Valley Salmon: A Perspective on Chinook and Steelhead in the Central Valley of California. *San Francisco Estuary and Watershed Science*.

Yang, Y. and Cai, X. (2011). Reservoir Operation for Fish Ecosystem Restoration using Daily Inflows: A Case Study of Lake Shelbyville. J. of Wat. Resource Plan. Managt. 137 (6).

Yeh, W. W.-G. (1985). Reservoir Management and Operations Models: A State-of-the-Art Review. *Water Resources Research*, 1797–1818.

You, J.-Y., & Cai, X. (2008). Hedging rule for reservoir operations: 1. A theoretical analysis and 2. A numerical model. *Water Resources Research*

3 Temperature Management in Reservoirs

3.1 Introduction to Temperature Management in Reservoirs

Dams impound the water of rivers thereby creating reservoirs for water storage, in which the water typically stratifies, with the colder, higher density water on the bottom. This results in dramatic changes to the flow and thermal regime of the impounded river. If warm water is released from the upper part of the reservoir, it will result in a river that is likely warmer than under the historic flow regime. If the water is released from the lower part of the reservoir, it is likely to be much colder than under pre-dam flows. Under either release location, the composition of the assemblage of species below the dam will be affected. Temperature has strong effects on survival, reproduction, development, and growth of each species. resulting in shifts in species assemblages that can change the function and structure of the river's ecosystem [Dallas, 2008]. The changes are often undesirable from the perspective of ecosystem health and production of desirable species. That is why managing reservoir releases for environmental purposes often is as much about water quality, particularly temperature, as water quantity.

Thermal impacts from dams can be managed by: a) exploiting vertical temperature stratification in the reservoir by selective water withdrawals (Figure 3.1) through vertically staggered outlet structures, or b) artificially destratifying the reservoir prior to discharging water from the dam [Olden and Naiman, 2010]. The most common means of controlling dam release temperatures is selective withdrawal with a multi-level intake structure (also known as a Temperature Control Device). Thermal impacts from dams can be managed by: a) exploiting vertical temperature stratification in the reservoir by selective water withdrawals (Figure 3.1) through vertically staggered outlet structures, or b) artificially destratifying the reservoir prior to discharging water from the dam [Olden and Naiman, 2010]. The most common means of controlling dam release temperatures is selective withdrawal with a multi-level intake structure (also known as a Temperature Control Device).

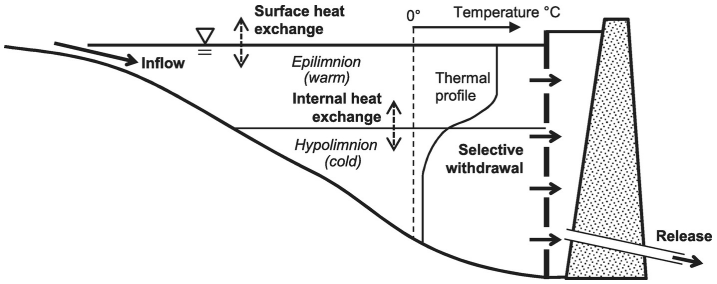


Figure 3.1: Selective withdrawal structure. Reprinted from [Fontane et al., 1981].

A Temperature Control Device can extract water from selected depths of a thermally stratified reservoir to produce more desirable water release temperatures [Price and Meyer, 1992]. Release temperatures are increased by selecting warm epilimnetic water from the surface, or decreased by drawing cold hypolimnetic water from below the thermocline [Olden and Naiman, 2010]. Despite the capital costs of installing multi-level intakes, these structures provide a flexible means to modify downstream water temperatures, even at low to medium release volumes [Sherman, 2000]. Controlling the opening and closing of shutter gates on a Temperature Control Device controls coldwater availability in a reservoir, and, based on the timing and magnitude of releases from each intake, the temperature and flow of the river downstream of the dam. Our research investigates operation policies that take advantage of this flexibility.

3.2 Literature Review

A wealth of literature describes reservoir operations modeling objectives and policy performance metrics [Loucks et al., 1981; Labadie, 2004]. Operations modeling for temperature control optimizes releases from selective withdrawal intake structures [Fontane et al., 1981; Houghtalen and Loftis, 1989; Olivares, 2008; Giuliani et al., 2014; Rheinheimer et al., 2014; Weber et al., 2017; Chaves and Kojiri, 2007; Soleimani et al., 2016; Castelletti et al., 2013]. In these models, the selection of intakes for release during the stratified

season of a density stratified (e.g., holomictic) lake determines downstream temperature. If temperature and volume are decoupled, then linear programming can find optimized temperature control releases [Rheinheimer et al., 2014]. Coupled water quality-quantity models require non-linear modeling. Dynamic programming often is used to solve the coupled models [Fontane et al., 1981; Carron and Rajaram, 2001; Castelletti et al., 2013; Giuliani et al., 2014; Olivares, 2008]. Most of these analyses focus on the computational approach for approximation and/or aggregation in dynamic programming (DP) to reduce computational burden [Fontane et al., 1981; Olivares, 2008; Castelletti et al., 2013; Giuliani et al., 2014]. Fontane (1982) developed an objective-spaced DP connected with a 1-D reservoir thermal simulation model. Olivares (2008) solved a two-pool reservoir model with constant cold temperature and a nested optimization routine within a multi-objective stochastic DP to optimize temperature releases during a stratified summer season. To simplify the computation, Olivares (2008) discretized the outcome, state, and action variables with Chebyshev approximation. Giuliani et al., (2014) and Casteletti et al., (2013) applied and designed an optimal control policy for water quality and quantity optimization from selective withdrawal systems with a batch-mode reinforcement learning algorithm, with the recursive solution of the Bellman equation approximated with a series of non-linear equations (Fitted Q-Iteration method) to derive an optimal rule set for Tono reservoir ($12.4 * 10^6 m^3$) in Japan. These models developed insight, particularly computational insight, and optimized temperature policy for one or more dams. None of these methods present the basic components of the temperature control problem, and none of them optimize releases to support temporal persistence in river ecology.

3.3 Approach

We propose a generalizable selective withdrawal modeling and optimization framework for managing temperature releases from reservoirs and a new method for optimized long-term reservoir operations for temperature or other water management concerns. Several new and traditional objective functions and solution algorithms for finding optimized release schedules for temperature management are compared. Traditional methods explored include determinisitc and stochastic dynamic programming and new methods are explored with maximin dynamic programming. A maximin solution algorithm maximizes seasonal downstream temperature benefit and minimizes the risk of environmental catastrophe via storage conservation, both within seasons and across years with a maximin operator. Unlike previous models, the maximin operator restricts releases to support temporal persistence and consistency in benefits. Although previous studies have explored the value of characterizing uncertainty in model inflow, with respect to both capturing temporal persistence [Tejada-Guibert et al., 1995] and non-stationarity [Hui et al., 2018; Milly et al., 2008], no studies have developed methods or tested the value of modeling the value of temporal persistence in downstream performance (storage depletion, river habitat availability). This method can be useful for managing river temperature to avoid the regrettable releases from storage and creating unsustainable downstream cold water habitat. Maximizing the minimum cold-water habitat area over months in a year or a season should help maximize the number of out-migrating salmon smolt in a river, but minimize the chance that maximizing fish population size now damages fish populations in the future. With this approach, operations hedge to sustain benefits, similar to hedging more broadly for other reservoir purposes like economic gain from hydroelectric power production or water delivery to agricultural uses, and, avert damage, similar to hedging for flood management or water delivery to municipal drinking water supply. Here, we uniquely do both. We maximize to sustain river flow and temperature throughout time and minimize to avert the risk of making lethal or stressful releases for the downstream ecosystem. For river management, this is imperative; water quality and quantity of the river and reservoir in one time step affects future quantity and quality in the reservoir, the river, and the ecosystem populations. A numerical example finds benefit in hedging operations with a maximin approach. This provides a method for prioritizing long-term ecosystem performance, which is often sacrificed by maximizing short-term performance. This method could be useful for any purpose for which it may be preferrable to hedge against risk now and in the future, both for flood and drought.

3.4 Model Formulation

The generic problem is to maintain enough cold water pool and total storage at each time step and throughout the summer to provide cold habitat downstream of the dam to support ecosystem function for the season and future years. Like others modeling selective withdrawal optimization, dynamic programming is used as the solver for this non-linear, multi-stage, dynamic allocation problem with cumulative benefits.

Here, we outline the basic model components and present model formulations here with a deterministic outcome benefit and a recursive benefit function. Time-steps are monthly or sub-seasonal stages (**S**) that maintain cold water below the dam, which often requires maintaining the reservoir's cold water pool throughout the summer. Temperature and flow are controlled by a set of decisions (**A**) that choose a release volume (R^n) from each selective withdrawal intake (n). The state of the temperature (T^m) and volume (V^m) at each reservoir layer (m) for each stage (S) given the stage's decisions, exogenous changes, and constraints is modeled. Exogenous conditions (**W**) change the state of the system. Exogenous conditions could be climatic from air temperature (T^a) and inflow (Q), reservoir infrastructure limitations like the reservoir's dead pool (d) and carrying capacity (k), a proxy for heat exchange between the thermal layers (e^m), and/or downstream ecosystem temperature thresholds (T^Z). Local complexity can be added as needed. Conservation of mass and energy govern storage and temperature flux between layers, stages, and states such that state transitions obey the laws of physics:

$$\begin{aligned} \text{Mass is conserved} &: V_{S+1} = f(A_S, W_S) \\ \text{Energy is conserved} &: T_{S+1} = g(A_S, W_S) \end{aligned} \tag{1}$$

3.4.1 Model Components

Basic model components of the temperature control problem help operators decide how much water of different temperatures to release (decision variables) each month (stage) given the quantity of storage available in the reservoir (state variables) for each stage's disturbances and constraints from exogenous information (weather forecasts and reservoir infrastructure limitations) to produce an optimal temperature management solution (Table 3.1). Needed details are provided for the Shasta Reservoir - Sacramento River system. An operational-scale model for the Shasta Reservoir-Sacramento River system can be found in Chapter 4.

Model Variable	Definition	Variable Name
Stage	time (month)	t
State	warm storage & cold storage volumes	V^c, V^w
Decision	warm and cold reservoir release volumes	R^c, R^w
	release volume	R
Exogenous information	weather event probability	p
	inflow volume	Q
	climate conditions (e.g., ambient temperature)	T^a
	reservoir infrastructure	d, k
	warm and cold pool temperatures	T^w, T^c
	release temperature	R^T
	initial cold and warm pool storage	$V^w_{t=initial}, V^c_{t=initial}$

Table 3.1: System Components for optimizing temperature control on large dams.

Stage (S) = t. Each modeled time-step is one month, the length of a typical reservoir operation planning period.

State (K) = { V^c, V^w }. The state (volume) of incoming cold water pool storage V^c_t and warm water pool storage V^w_t at the beginning of each stage t.

Decisions (A) = { R^c, R^w, R^T }. Cold and warm reservoir storage release volumes $R_t^{c,w}$ are chosen to optimize the overall objective for each state K of each stage t. Total release volume is the sum of the warm and cold pool volume release $R = R^c + R^w$. Spill is included when needed.

Exogenous Variables (W)

- $\{p_t, Q_t, T_t^a\}$. Monthly weather is predicted from the joint probability p of historical reservoir inflow (Q) and air temperature (T^a) time series measurements such that $p_t = \int p_t^Q * p_t^{T^a}$.
- $\{d, k\}$. Reservoir volume must exceed the deadpool storage volume (d) but be less than the storage capacity (k).
- $\{V^w_{t=initial}, V^c_{t=initial}\}$. Optimal policies were formulated for the range of feasible initial cold and warm pool storage volumes ($0 \leq \{V^c, V^w\} \leq K$) for a range of initial planning months (e.g., January, February, April and May) given the limitations of reservoir capacity and deadpool storage.
- $\{T^w, T^c = f(V^c, V^w)\}$. Reservoir pool temperature correlates with reservoir volume for Shasta Reservoir so temperatures are modeled as an alias of volume from a lookup table, rather than as an additional state variable (see Chapter 4 for details). Without this correlation, warm and cold pool reservoir temperatures would need to be modeled as additional state variables.

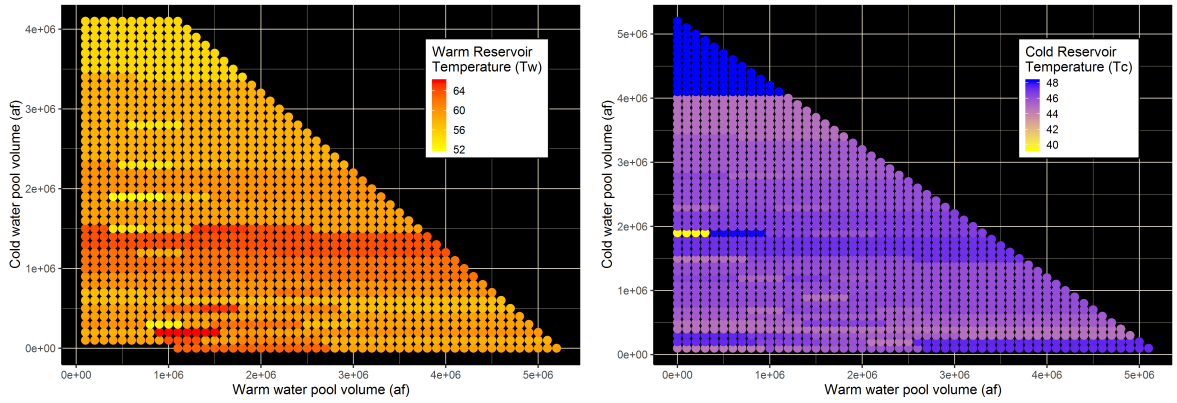
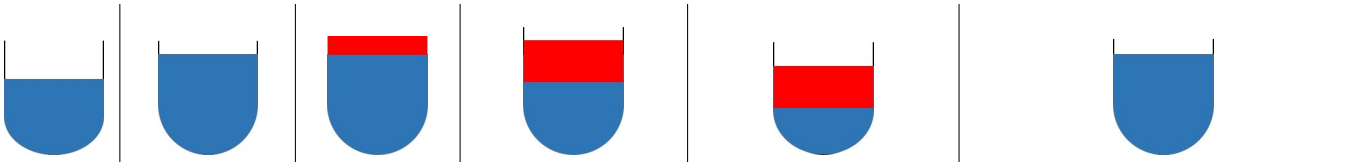


Figure 3.2: Average warm pool (left) and cold pool (right) temperatures for each combination of Shasta Dam warm and coldpool storage (af/month) when the historical record of observations is discretized by 10^5 af.

- $\{R^T\}$. Release temperature T^R is the flow-weighted temperature of the releases [Rheinheimer et al., 2014] from the reservoir's cold and warm pools $R^T = \frac{R^c * T^c + R^w * T^w}{R}$.
- $\{P\}$. Spill is released when necessary to avoid floods.
- $\{V^c_{t=initial}, V^w_{t=initial}\}$. are initial cold and warm pool volumes for the model's first stage.

State Transitions Conservation of mass and energy regulate state transitions from the incoming states of warm V^w and cold V^c pool volume storage to the end of period states of warm and cold pool storage of each stage. For the Sacramento River-Shasta Reservoir system, state transition equations (storage accumulation) vary both by lake season (e.g., overturn, stratified, mixed) and climatic season (e.g., summer, winter). The reservoir model blends two-pool and vertical layer modeling approaches to discriminate cold and warm pool volumes. The cold, mixed season's accumulated storage is based on a regression equation decomposed from historical time series of pre-Temperature Control Device (1946 - 1993) measurements with a Principal Components Analysis. Variables considered were the previous monthly reservoir and bypass releases, reservoir storage, inflow and outflow, reservoir and air temperature, the Pacific Decadal and El Niño-Southern Oscillation [Nickel et al., 2004].

State	Winter	Early Spring	Late Spring	Summer	Fall	Overturn
Months	Dec,Jan	Feb, Mar	Apr,May	Jun,Jul,Aug,Sept	Oct	Nov
State Transition Equations						
Inflow	Cold		Warm		Cold	
End period cold pool volume	$V^c_{t+1} = V^c_t + \Delta V^c_t - R^c_t$		$V^c_{t+1} = V^c_t - R^c_t$		$V^c_{t+1} = V^c_t - R^c_t + Q_t$	$V^c_{t+1} = V^c_t - R^c_t + V^w_t - R^w_t + Q_t$
End period warm pool volume	$V^w_{t+1} = 0$		$V^w_{t+1} = V^w_t + Q_t - R^w_t$		$V^w_{t+1} = V^w_t - R^w_t$	$V^w_{t+1} = 0$
Air Temperature	Cold	Warming		Warm	Cooling	

V^w_t = warm pool lake storage volume (af)
V^c_t = cold pool lake storage volume (af)
R^w_t = warm pool monthly reservoir releases (af)
R^c_t = cold pool monthly reservoir releases (af)

Basic Constraints
{Reservoir Volume Capacity Constraint}.$d \leq V^c, V^w \leq k$ Total lake volume at the beginning and end of each period must be within the reservoir capacity.
{ Conservation of Mass constraint for each reservoir temperature pool }. Conservation of mass and energy govern storage and temperature flux in the reservoir and the river within periods $V^c \geq R^c + \Delta V^c$ and $V^w \geq R^w + \Delta V^w$ and between end of period V_t^c = beginning of period V_{t+1}^c.

3.5 Solution Algorithms

Three types of solution algorithms to optimize temperature control operation of large dams are compared starting with the most simple, a standard operating policy, and then a more complex, with two variants of dynamic mathematical programs (Table 3.2). The three solution algorithms consider immediate, or immediate and future, or immediate, future and multiple benefits, by defining objective functions differently - based on a combination of ranked net benefit, or net benefit, or direct habitat benefit. Increasing levels of precision hedge on more factors and increase computational requirements. Trade-offs between the different algorithms include choices between complexity and computational requirements. Each algorithm produces the set of optimized decisions for each possible state of each stage that maximizes the objective. These algorithms are solved at a discrete set of points, but we describe them without reference to the discretization eventually employed. Benefits (B) are defined as the length of cold river habitat (x, e.g., for the Sacramento River system, the river mile count below Keswick Dam below the temperature threshold)(Equation 2).

$$x_t = B_t \tag{2}$$

where x_t is the river-miles of suitable habitat below the target.

Dynamic programs developed here employ backwards-solving dynamic programming. From the set of optimized decisions, the optimal policy O for each initial storage condition for each solution algorithm is approximated with a forward-looking algorithm. The forward-looking algorithm travels through optimal release decisions per state of each stage and grabs the optimal cold and warmpool release choice combination for the stage's expected incoming storage. With this expected 'best', or optimized solution, for each incoming April storage state, we compare optimized policies among solution algorithms. We also compare each solution algorithm's converged stationary schedule, or in other words, the converged set of decisions and expected states that maximize benefits across stages.

	Model Objective	**Solution Algorithm**	**Benefit**	**Exogenous Variable (Weather Forecasting)**
1a	Max. each sequential month's habitat (greedy & myopic)	Deterministic Greedy Standard Operating Policy	Direct Benefit	Perfect
1b	Max. each sequential month's habitat (greedy & myopic)	Stochastic Greedy Standard Operating Policy	Direct Benefit	Limited
2a	Max sum of monthly habitat values	Determinstic Dynamic Program (DDP)	Net Benefit	Perfect
2b	Max sum of monthly habitat values	Stochastic Dynamic Program (SDP)	Net Benefit	Limited
3a	Maximin - worst month limits success	Maximin DDP	Ranked Net Benefit	Perfect
3b	Maximin - worst month limits success	Maximin SDP	Ranked Net Benefit	Limited
3c	Maximin with drought penalty	Drought Weighted Maximin SDP or DDP	Ranked Net Benefit	Limited or Perfect
3d	Maximin - worst month limits success	Maximin SDP for Managing Multiple Resources	Ranked Net Benefit for Multiple Resources	Limited

Table 3.2: Developed and compared model objectives, with their solution algorithms, forecasts, and value- approximated benefit functions, for temperature control in reservoirs.

3.5.1 Greedy Operating Policy

The first operating method presented here is the most elementary solution algorithm. A greedy algorithm takes the minimum release volume that maximizes immediate benefits, without a direct concern for the future. This method is not a dynamic program, but rather a proxy for representing a standard operating policy that includes temperature management; this method is a baseline for comparing the other two methods. The benefit of each release is a function of the reservoir's incoming cold and warm pool storage volumes, releases, weather, and the downstream temperature and distance objective (policy goal) (Equation 3). When the standard operating policy model is formulated as a deterministic model, the state at the next stage is completely determined by the release decision at the current stage. The resulting objective function is solved deterministically for each of several water year types y_t to maximize release decisions (R^w, R^c) given volume availability from cold and warm pool storage (V^c, V^w), and inflow Q and air temperature T^a, with downstream distance x^Z and temperature goals T^Z.

$$B_t(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^w}, \mathbf{R_t^c}) = \max_{\min R_t^c, R_t^w} \sum_t B_t(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^w}, \mathbf{R_t^c}, x^Z, T^Z, Q_t, T_t^a, month_t) \vee y_t \tag{3}$$

Extending this approach, the expected benefit $\mathbb{E}\{\}$ from the stochastic standard operating policy implicitly models the range of cold and warm drought and flood water year types. With the stochastic model, the state and release decision of each stage is not completely determined by the state of the current stage; the states in the next stage result from a probability distribution of uncertain weather in the current stage (Equation 4).

$$\mathbb{E}\{B_t(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^w}, \mathbf{R_t^c})\} = \max_{\min R_t^c, R_t^w} \mathbb{E} \sum_t p^{QT_t^a}[B_t(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^w}, \mathbf{R_t^c}, x^Z, Q_t, T_t^a, T^Z, month_t)] \tag{4}$$

Maximizing only immediate benefits either with limited (probabilistic/stochastic) or perfect (deterministic) weather forecasting, is myopic, but nonethless can provide rough insight into optimized policy schedules with lower computational requirements.

3.5.2 Dynamic Programming

The basic dynamic program, solved with a backwards-solving Bellman's equation, chooses monthly release decisions at each stage expected to maximize net benefits - the direct immediate benefit of that release and the benefit implications from release and storage decisions of the future. The net benefit (z) is the sum of the current stage's immediate downstream benefit B_t and the accumulated habitat benefits from optimizing all later time periods, $\max_A B_{t+1}^*(A_t, x_t, W_t)$. The immediate benefit maximizes the benefit of a decision made now, the accumulative benefit maximizes decisions that maximize the chain of direct benefits from each state of each stage given this period's decision. With the dynamic program, knowledge accumulates with time. Model formulation could be stochastic or deterministic; here we display the deterministic (Equation 5).

$$z = \sum_t \max_A (B_t + B_{t+1}^*(A_t, x_t, W_t)). \tag{5}$$

For the stochastic dynamic program, we employ an implicit stochastic dynamic program with uncertain inflow and ambient temperatures rather than an adaptive control model with an explicit hydrologic variable approximated by Bayes' Theorem with a first-order Markov Chain because we are concerned with seasonal planning goals, e.g., how much cold pool storage to release over an entire stratified season, an ideal October carry-over storage target, or an ideal April beginning of season target, rather than specific release targets in any given month. Risk is distributed and, with the recursion function, releases are allocated and curtailed when benefits are greatest. Net benefit accumulates with time so this objective ultimately maximizes the sum of monthly habitat values across stages such that:

$$\mathbb{E}\{B_t(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^w}, \mathbf{R_t^c})\} = \max_{\min R_t^c, R_t^w} \mathbb{E} \sum_t \Bigg(\underbrace{p^{QT_t^a}[B_t(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^w}, \mathbf{R_t^c}, x^Z, T^Z, month_t)]}_{\text{Immediate Benefit}} + \tag{6}$$

$$\underbrace{p^{QT_{t+1}^a} B_{t+1}^* \begin{Bmatrix} V_{t+1}^c = f(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^w}, \mathbf{R_t^c}, month_t, p_t^{QT_t^a} Q_t T_t^a), \\ V_{t+1}^w = f(\mathbf{V_t^w}, \mathbf{R_t^w}, month_t, p_t^{QT_t^a} Q_t T_t^a) \end{Bmatrix}}_{\text{Future Benefit}} \Bigg)$$

This standard stochastic dynamic program formulation is not formally constrained by temporal correlation in the state of the outcome variables (e.g., providing cold river habitat). It assumes the resource availability of the outcome variable (cold water habitat) is infinite and renewable at each time-step such that overall outcomes can be summed across months in a season, independently of the state of the ecosystem in the previous stage. While this is often the method used to solve temperature control problems, it has shortcomings. With the exception of systems for which drought is a non-issue, and/or if somewhere a river exists for which temporal correlation is unimportant (there is almost no system in the world for which this is true), this unconstrained version of the temperature control problem, with this standard dynamic program, with or without forecasting, is likely sufficient.

3.5.3 Maximin Dynamic Programming

For most reservoirs, storage is limited and the state of an ecosystem is related over time. There are at least five reservoir conditions for which a standard dynamic program falls short because it does not adequately capture long-term ecosystem health. Therefore a new method was developed that explicitly addresses these concerns, specifically, for temperature control, with respect to:

- cold water pool scarcity
- total storage scarcity
- a small reservoir capacity that can not sustain warm water inflow without dumping significant cold water reserves during the stratified season of a wet year;
- undefined downstream (temperature and distance) targets resulting in impossible to sustain large releases, or ineffectual small releases;
- failure to consider correlation in ecosystem health between time steps (e.g., stressing an ecosystem with inconsistent ecosystem support).

Four of these five circumstances are drought-related, when water storage is often a limitation; all five are most pressing during extreme flood or drought years, or worse, years when flood and drought alternate. The best approach may be formulations that, in addition to finding good policy behavior over time (as with the general dynamic programming approach) may hedge explicitly to manage inter-annual reservoir shortages with stronger ecosystem performance (temporal correlation) across months. The maximin approach addresses these issues. The maximin approach hedges releases to maximize the minimum suitable habitat area existing across all months. Worst-case outcomes are ordered to the beginning of time to eliminate regrettable decisions over the longer-term (e.g., avoiding storage depletion and poor temperature months). The standard dynamic program is modified to both minimize storage release decisions that lead to larger future temperature problems and maximize sustainable benefits with a maximin objective function. Method execution is a three step maximin process (Equations 7 - 9). First, unlike standard dynamic programs, immediate benefits can not exceed sustainable future benefits. The first step takes the minimum of the immediate and future benefits of each choice of each state. The value of the release in this period cannot exceed the expected value of the optimized release made in the future period with this period's outgoing storage (Equation 7).

$$\mathbb{E}\{B_t(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^w}, \mathbf{R_t^c})\} = \min\Big(\mathbb{E}\sum_t \Bigg(\underbrace{p^{QT_t^a}[B(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^w}, \mathbf{R_t^c}, x^Z, T^Z, Q_t, T_t^a, month_t)]}_{\text{Immediate Benefit}}, \tag{7}$$

$$\underbrace{\mathbb{E}\sum_t p^{QT_{t+1}^a} B_{t+1}^* \begin{Bmatrix} V_{t+1}^c = f(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^w}, \mathbf{R_t^c}, month_t, p_t^{QT_t^a} Q_t T_t^a), \\ V_{t+1}^w = f(\mathbf{V_t^w}, \mathbf{R_t^w}, month_t, p_t^{QT_t^a} Q_t T_t^a) \end{Bmatrix}}_{\text{Future Benefit}}\Bigg)\Big)$$

Next, because there is no sense in creating temperature habitat in any one month that cannot be sustained in future life stages (wasting stored water), if the benefits from the accumulated objective function (future benefit) are less than the immediate benefit, current releases are reduced (hedged) to meet the lesser benefit of the next period (except for a need to spill), saving cold water to improve future conditions, given that the hedged release decision is feasible within the reservoir's capacity constraint and expected weather conditions (Equation 8).

$$R_t^{c*}, R_t^{w*} = \begin{cases} R_t^c, R_t^w & \text{if Immediate Benefit} \leq \text{Future Benefit} \\ R_t^c, R_t^w & \text{else if infeasible } \; R_t^c, R_t^w = R_{t+1}^{c*}, R_{t+1}^{w*} | B_{t+1}^*(V_{t+1}^c, V_{t+1}^w) \\ R_{t+1}^{c*}, R_{t+1}^{w*} & \text{otherwise} \end{cases} \tag{8}$$

The final benefit (equation 7) for the current period then, is the maximum of the minimum expected benefit of each state for each stage, with the set of monthly release decisions (Equation 8) for a range of considered disturbances.

$$\mathbb{E}\{B_t(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^w}, \mathbf{R_t^c})\} = \max_{\min R_t^{c*}, R_t^{w*}} \Big(\min\Big(\mathbb{E}\sum_t \Bigg(\underbrace{p^{QT_t^a}[B(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^{w*}}, \mathbf{R_t^{c*}}, x^Z, T^Z, Q_t, T_t^a, month_t)]}_{\text{Immediate Benefit}}, \tag{9}$$

$$\underbrace{\mathbb{E}\sum_t p^{QT_{t+1}^a} B_{t+1}^* \begin{Bmatrix} V_{t+1}^c = f(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^w}, \mathbf{R_t^c}, month_t, p_t^{QT_t^a} Q_t T_t^a), \\ V_{t+1}^w = f(\mathbf{V_t^w}, \mathbf{R_t^w}, month_t, p_t^{QT_t^a} Q_t T_t^a) \end{Bmatrix}}_{\text{Future Benefit}}\Bigg)\Big)\Big) =$$

$$\max_{\min R_t^{c*}, R_t^{w*}} \mathbb{E}\sum_t p^{Q_t T_t^a}[B_t(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^{w*}}, \mathbf{R_t^{c*}}, x^Z, T^Z, month_t)]$$

This new approach caters to temporal persistence in the outcome variable and hedges against regettable release decisions. By comparing it to a standard dynamic program, similar to [Tejada-Guibert et al., 1995], who test the value of correlated temporal persistence in inflow, we test the effect of correlated temporal persistence in outflow, and the value of developing operational models to conserve storage when temporal persistence is violated, with respect to quantity and quality. We propose that hedging to release only when temporal persistence can be preserved will improve river management. With this approach, releases hedge to meet the best expected seasonal outcome across monthly stages and avoid the worst (Equation 8). When necessary, releases are hedged to meet but not exceed the benefits of the worst month, starting with the worst-performing month. In a practical sense, ordered hedging, until the worst has passed, conserves stored water until cold water habitat can be sustainably provided through the end of a season. With this approach we meet current downstream needs for the longest duration possible, without exceeding storage capacity or the ability to meet future needs. Cold pool storage is released and reduced for the short-term, but not if it will result in long-term scarcity. The logic of this mathematical sequence maximizes seasonal benefits and the likelihood of providing cold river habitat, and minimizes the likelihood of having an empty reservoir and inter-annual risk. Optimized policy solutions solved with the maximin objective function, when iterated over the range of feasible initial cold pool storage conditions, finds the largest initial cold water storage pool volume (e.g., of April of year 1) for which the reservoir can remain operational. Without the use of the maximin objective function, an inflexible carryover storage constraint could rigidly force inter-seasonal conservation, but building a model with this rigid constraint prevents learning about the worst-case conditions.

Alternative hedging formulations could include a 'worst case' state variable (x^{WC_n}), or, a state variable that represents the current state of an outcome variable (e.g., cold water habitat) given the variable's performance in the previous period, without the maximin solution algorithm ([Adams et al., 2017]). Each worst case cold water habitat benefit, n, (e.g., n=2 river miles) could be compared against the immediate and current benefit. When the worst-case state variable performs worse than the current and immediate benefit, the release is constrained to meeting the needs of the worst-case. Since the worst case state variable does not represent additional exogenous information, including a worst case outcome state variable and a maximin solution algorithm wastes computation time calculating infeasible options by exploring sub-optimal results in which a theoretical worst-case is worse than the actual worst-case. Operating for this scenario would needlessly over-constrain the system and could result in potential flooding; it also wastes computation time. Nonetheless, we outline this formulation for which each stage's minimum would be the minimum of equation 7 and this worst case state variable (equation 10).

$$\mathbb{E}\{B_t^{WC_n}(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^w}, \mathbf{R_t^c}, \mathbf{WC_t^n})\} = \min\Big(\mathbb{E}\sum_t \Bigg(\underbrace{p^{QT_t^a}[B_t(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^w}, \mathbf{R_t^c}, x^Z, T^Z, Q_t, T_t^a, month_t)]}_{\text{Immediate Benefit}}, \tag{10}$$
$$\underbrace{\mathbb{E}\sum_t p^{QT_{t+1}^a} B_{t+1}^* \begin{Bmatrix} V_{t+1}^c = f(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^w}, \mathbf{R_t^c}, month_t, p_t^{QT_t^a} Q_t T_t^a), \\ V_{t+1}^w = f(\mathbf{V_t^w}, \mathbf{R_t^w}, month_t, p_t^{QT_t^a} Q_t T_t^a) \end{Bmatrix}}_{\text{Future Benefit}}, \underbrace{x^{WC_n}}_{\text{Worst Case Benefit}}\Bigg)\Big)$$

Releases would be adjusted with equation 8, and then final benefit would be adjusted again with these hedged releases, like in equation 7, and then the maximum computed:

$$\mathbb{E}\{B_t^{WC^n}(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^w}, \mathbf{R_t^c}, \mathbf{WC^n})\} = \max_{\min R_t^{c*}, R_t^{w*}}\Big(\min\Big(\mathbb{E}\sum_t \Bigg(\underbrace{p^{QT_t^a}[B(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^w}, \mathbf{R_t^c}, x^Z, T^Z, Q_t, T_t^a, month_t)]}_{\text{Immediate Benefit}}, \tag{11}$$
$$\underbrace{\mathbb{E}\sum_t p^{QT_{t+1}^a} B_{t+1}^* \begin{Bmatrix} V_{t+1}^c = f(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^w}, \mathbf{R_t^c}, month_t, p_t^{QT_t^a} Q_t T_t^a), \\ V_{t+1}^w = f(\mathbf{V_t^w}, \mathbf{R_t^w}, month_t, p_t^{QT_t^a} Q_t T_t^a) \end{Bmatrix}}_{\text{Future Benefit}}, \underbrace{x^{WC_n}}_{\text{Worst Case Benefit n}}\Bigg)\Big)\Big) =$$
$$\max_{\min R_t^{c*}, R_t^{w*}} \mathbb{E}\sum_t p^{Q_t T_t^a}[B_t^{WC^n}(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^{w*}}, \mathbf{R_t^{c*}}, \mathbf{WC^n}, x^Z, T^Z, month_t)]$$

Since the worst-case state variable (x^{WC_n}) is not based on additional exogenous information, the worst possible case given the system constraints is already captured by the minimization function of the current and future benefits. For example, if the benefit is cold water habitat miles, than the worst case would be a vector of feasible cold habitat miles outcomes. However, the system already solved for worst-case cold water habitat miles for each decision variable, given the system constraints, so constraining the system by a set of worst-case state variables is redundant - the worst-case cold water habitat will be captured by the system constraints and the current and future benefits. Specifically, computation time is wasted for those computations in the new action space for which:

$$\underbrace{x^{WC_n}}_{\text{Worst Case Benefit}} < \min\Big(\mathbb{E}\sum_t \Bigg(\underbrace{p^{QT_t^a}[B_t(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^w}, \mathbf{R_t^c}, x^Z, T^Z, Q_t, T_t^a, month_t)]}_{\text{Immediate Benefit}}, \tag{12}$$
$$\underbrace{\mathbb{E}\sum_t p^{QT_{t+1}^a} B_{t+1}^* \begin{Bmatrix} V_{t+1}^c = f(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^w}, \mathbf{R_t^c}, month_t, p_t^{QT_t^a} Q_t T_t^a), \\ V_{t+1}^w = f(\mathbf{V_t^w}, \mathbf{R_t^w}, month_t, p_t^{QT_t^a} Q_t T_t^a) \end{Bmatrix}}_{\text{Future Benefit}}\Bigg)\Big)$$

Similarly, having a state variable that serves as a proxy for the outcome variable (cold water habitat) and the maximin solution algorithm is also redundant, optimized cold water habitat reach is already optimized

with the maximin formulation, which already constrains the releases on the objective function. This dissertation characterizes long-term operations with two methods - an additional state variable or a maximin objective function - but avoids redundancy by avoiding implementation with both at once.

Maximin Dynamic Programs for Extreme Drought When severe drought is of significant concern and the benefit function is convex with negligible flood damage potential, as in a protracted drought, then extreme hedging can be warranted. In these cases, the likelihood of scarcity is so high the reservoir is operated exclusively for drought, either with the stochastic dynamic program with hedging formulation (Equations 7 - 9) that considers only dry - extreme drought year water types, or with the determinstic maximin dynamic program with hedging formulation with a water-year type of extreme drought. The stochastic version would use the hedging procedures outlined in equations 7 - 9, but equation 7 would be replaced with the below equation focused on dry times (wetter years omitted or assigned small probabilities).

$$\mathbb{E}\{B_t(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^w}, \mathbf{R_t^c})\} = \min \Bigg(\underbrace{\mathbb{E} \sum_t p^{QT_t^a} [B(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^w}, \mathbf{R_t^c}, x^Z, T^Z, Q_t, T_t^a, month_t)]}_{\text{Immediate Benefit}}, \tag{13}$$

$$\underbrace{\mathbb{E} \sum_t p^{QT_{t+1}^a} B_{t+1}^* \begin{Bmatrix} V_{t+1}^c = f(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^w}, \mathbf{R_t^c}, month_t, p_t^{QT_t^a}, Q_t, T_t^a), \\ V_{t+1}^w = f(\mathbf{V_t^w}, \mathbf{R_t^w}, month_t, p_t^{QT_t^a}, Q_t, T_t^a) \end{Bmatrix}}_{\text{Future Benefit}} \Bigg) \vee \text{extreme drought} \leq y_t \leq \text{drought}$$

Maximin Dynamic Programs Managing Multiple Resources Sometimes a specific downstream demand may be particularly high priority such that the objective function of temperature control is insufficiently characterized by cold water habitat. In these cases, the objective function becomes a multi-objective function to include additional exogenous conditions. This additional information could be anything, including fish population size, agricultural shortage, or any number of other hydraulic, biophysical, spiritual, cultural, or economic non-renewable or renewable objectives (F) with specific monthly river requirements $\mathbf{x_t^F}$ (Equation 14). Release decisions are then made in conjunction with cold water habitat goals. The additional objective becomes an additional state variable and a component of the objective function. The expected benefit of this additional state are modeled in two ways, depending on whether this additional information will consider temporal persistence. A period's fish population size depends on the fish population size of the previous period, for example, or a farm's profit from agricultural production (crop acreage) is likely dependent on agricultural production of the previous period.

$$x_t^F = \begin{cases} \sum_t p^{QT_t^a} B_t(\mathbf{N^F}_t, \mathbf{N^F}_{t+1}, Q_t, T_t^a) & \text{if temporal persistence matters} \\ \sum_t p^{QT_t^a} B_t(\mathbf{N^F}_t, Q_t, T_t^a) & \text{otherwise} \end{cases} \tag{14}$$

Expected benefits (Equation 15), and consequently releases (Equation 8) are limited by the cold water habitat demand of additional demand priority (e.g., fish population size/natural mortality) in addition to the the cold water habitat afforded and demanded by the immediate and future benefit like the single-objective maximin algorithm (Equation 7).

$$\mathbb{E}\{B_t(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^w}, \mathbf{R_t^c}, \mathbf{N_t^F})\} = \min \Bigg(\underbrace{\mathbb{E} \sum_t p^{QT_t^a} [B_t(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^w}, \mathbf{R_t^c}, x^Z, T^Z, Q_t, T_t^a, month_t)]}_{\text{Immediate Benefit}}, \quad (15)$$

$$\underbrace{\mathbb{E} \sum_t p^{QT_{t+1}^a} B_{t+1}^* \begin{Bmatrix} N_{t+1}^F = f(\mathbf{N_t^F}), \\ V_{t+1}^c = f(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^w}, \mathbf{R_t^c}, month_t, p_t^{QT_t^a}, Q_t, T_t^a), \\ V_{t+1}^w = f(\mathbf{V_t^w}, \mathbf{R_t^w}, month_t, p_t^{QT_t^a}, Q_t, T_t^a) \end{Bmatrix}}_{\text{Future Benefit}},$$

$$\underbrace{x_t^F}_{\text{Resource Benefit}} \Bigg)$$

Like single-objective maximin hedging, to avoid making regrettable unsustainable release decisions, if the benefits from the accumulated objective function (future benefit) or the resource benefit function are less than the immediate benefit, we constrain (hedge) current releases to meet the lesser more sustainable benefit, given that the adjusted release is feasible within the reservoir's capacity constraint and conservation of mass, with equation 8.

The final benefit is a function of these hedged releases - hedged for the future, the past, cold water habitat needs, storage, inflow, ambient conditions, the policy outcome goals, and this external consideration (e.g. fish mortality, Equation 16).

$$B_t(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^w}, \mathbf{R_t^c}, \mathbf{N_t^F}) = \max_{\min R_t^{c*}, R_t^{w*}} \sum_t p^{QT_t^a} [B_t(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^{w*}}, \mathbf{R_t^{c*}}, \mathbf{N_t^F}, x^Z, T^Z, Q_t, T_t^a, month_t)] \quad (16)$$

For this additional state variable to add value, fish population information needs to be available in time for adaptive decision making (e.g., incoming adult population from the ocean or the precise location of redds downstream). Without this added information, it could be argued, that like assigning weapons to targets in military applications [Castanón and Wohletz, 2002], assigning water to fish below a dam is an unreliable discrete resource problem. The precise outcome is unknown (which targets will be successfully hit, where in the river the fish will naturally die or spawn) - and the lag time in receiving fish population information exceeds the time at which information is needed for adaptive decision making. In this case, it would make sense to maximize cold river habitat to the extent water is available (the current logic of the maximin approach) as a single-objective problem to give the fish a greater chance of success, and because the computational burden of additional state variables is expensive. So, if the information needed for the addiitonal state variable, e.g., fish population size, is available, adding an additional state variable to the objective function can provide additional internal slack upon which to hedge (e.g., negligible incoming population size could lead to reducing or delaying cold releases for returning adults or a negligible redd population count a distance downstream of the dam could result in diminished temperature and flow releases) - all of which would result in reduced storage demand, otherwise this additional state variable is unnecessary.

Other examples of multi-objective problems (Equation 16) could be for the economic cost of shortage to agricultural production (agricultural profit is mostly a function of flow and location - although, sometimes water is so cold it hinders agricultural production) or to add a state variable for downstream salinity requirements. Hedging water deliveries for economic as well as environmental benefits would likely be operationally beneficial.

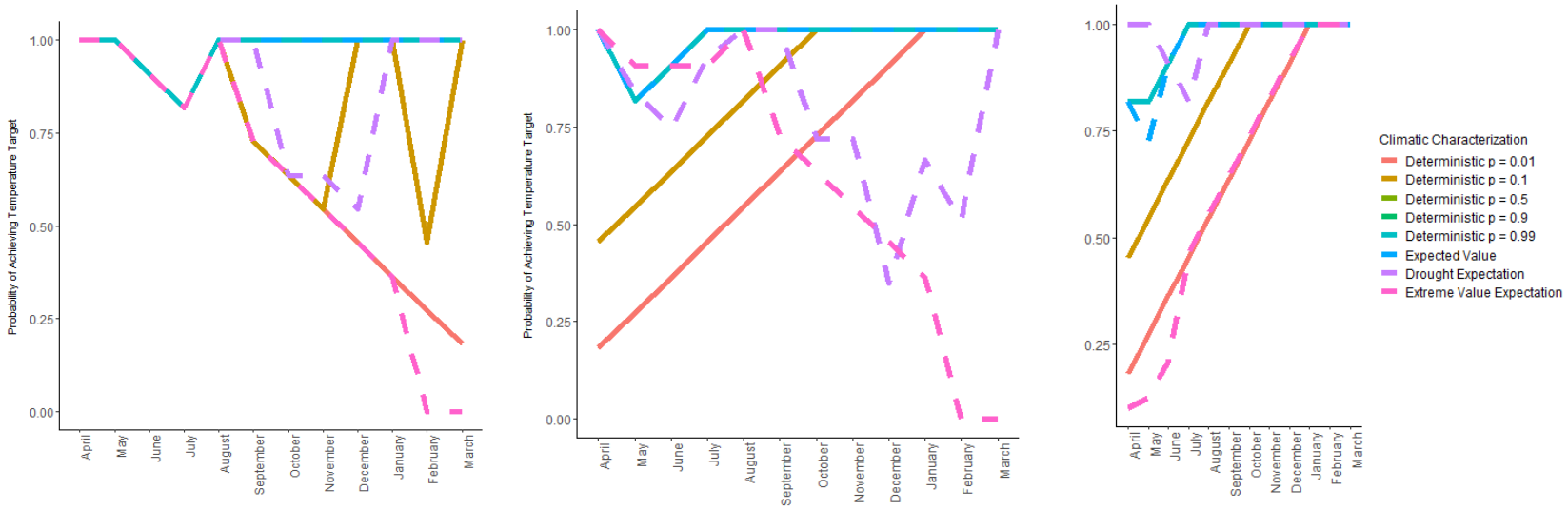
3.6 Numerical Examples

We present results from solving the temperature management problem in reservoirs with the three solution algorithm approaches (Figure 3.3) proposed here: a greedy standard operating policy (SOP), dynamic programming (DP) and maximin dynamic programming (Maximin).

3.6.1 A Range of Weather Conditions

Results were solved with a range of perfectly forecasted deterministic weather types (with joint probability of ambient temperature and inflow from the historical record of p = 0.01, 0.1, 0.5, 0.9, and 0.99), and stochastic expectations of weather types (expected value, drought weighted, and extreme weather (drought and flood) weighted) highlight patterns, strategy, and success in meeting temperature targets for each month for each of the solution algorithms.

- The greedy standard operating policy (Figure 3.3a) meets river temperature requirements early in the stratified operating season (April), but often runs out of cold and total water before the end of the year, potentially causing ecosystem collapse for one year and potentially failure to carry over storage for multiple years (a multi-year failure).
- The stochastic dynamic program (Figure 3.3b) operates to maximize net benefits, which means sometimes the program hedges early in the year and sometimes not. Sometimes running out of water later in the year is optimal, other times hedging and intentionally missing downstream targets early in the stratified season is optimal - because the function maximizes net benefits, but does not force an order on the benefits, so they sometimes occur later and other times earlier, within an operating season.
- The maximin dynamic program (Figure 3.3c) hedges to maximize net benefits like the dynamic program, but will order failures at the beginning of the year, thereby conserving stored water, in particular cold water. Risk is taken at the beginning of the season to minimize seasonal, yearly, or multi-year failure. The recommended April release curtailment to meet the long-term goal also tion of how an operator could prepare for a worst case, the expected carryover storage at the end of a season, and how low the reservoir total and cold pool storage could be before it becomes impossible to sustain one year-class of fish.



(a) Greedy standard operating policy operations.

(b) Dynamic programming operations.

(c) Maximin dynamic programming operations.

Figure 3.3: Probability of meeting temperature thresholds with three different operating policy approaches (a,b,c). Each approach is solved with several different weighting approaches without foresight (extreme weather, drought, and expected value) and with perfect foresight (e.g., probability of joint occurence of air temperature and inflow has exceedance probability of 0.01), when following the optimized monthly release schedule. Results were generated with variable temperature goal below Keswick Dam until Clear Creek (13 River Miles) with best operating policies for a range of initial April storage conditions and a resolution of 400 taf/month (6,700 cfs).

3.6.2 Worst-case Scenarios

Next, comparisons are made under dire conditions with a) low initial April storage conditions and a forecast of extreme dry and hot drought (Figure 3.4), b) low April incoming storage and limited forecasting (probabilistic/stochastic) of extreme weather (Figure 3.5) and c) all incoming April storage possibilities with limited forecasting (probabilistic/stochastic) of extreme weather (Figure 3.6) Extreme weather is modeled as a 90% chance of drought and a small expectation of extreme flood. This captures difficult drought conditions as well as the worst of the worst cases, in which an operator expects significant wet, cold inflows (and lowers reservoir levels for floods) but instead receives dry inflows (potentially intensifying a drought down river). Because of the intensified draw-down, this worst-case scenario could result in potentially worse performance than operating with perfect foresight for a drought. Our numerical example for Shasta reservoir creates cold water habitat below Keswick Dam with a coarse resolution scale (grid size = 400 taf/6,700 cfs). With this coarse resolution, release choices are large and consequential. For example, to make minimum monthly releases (independently of the temperature of those releases) between April and March, requires 4.8 maf - an extremely impactful volume of water relative to that required, for example, to meet minimum monthly releases, for example, with a grid scale of 10^6 af - 1.2 maf. Moreover, in an extreme drought year Shasta reservoir receives only about 2.8 maf. Therefore, in a drought, with this coarse resolution, some monthly failure is inevitable. In a sense, these different solution algorithms, like all optimizing solution algorithms, optimize the timing and the magnitude of that failure. A bottleneck occurs for all approaches between May and July when temperature targets are most difficult to meet. Details of finer resolution results for optimizing Shasta releases for the Sacramento river as well as Sacramento river temperature requirements are in Chapter 4.

Low Incoming April Storage with perfect (deterministic) hydrologic and temperature forecasting knowledge of extreme drought Likely annual release and end storage volumes (taf) for the Shasta Dam - Sacramento River system operated with perfect foresight of an extreme drought (exceedance probability p = 0.01) and initial April storage condition at the beginning of the planning cycle of 1.2 maf. Model results are coarsely gridded, at a scale of 400 taf, to illustrate and compare methods and general concepts and trends - not for operations.

Solution Algorithm	Seasonal Cold pool Storage Depletion (April 1 - Oct 31)	Total Annual Releases	Annual (Apr - Mar) Cold Pool Releases	Average End of Year (March) Storage (All Cold)
Greedy SOP	1200	2000	1200	0
DP	0	2000	1600	400
Maximin DP	0	2000	1600	400

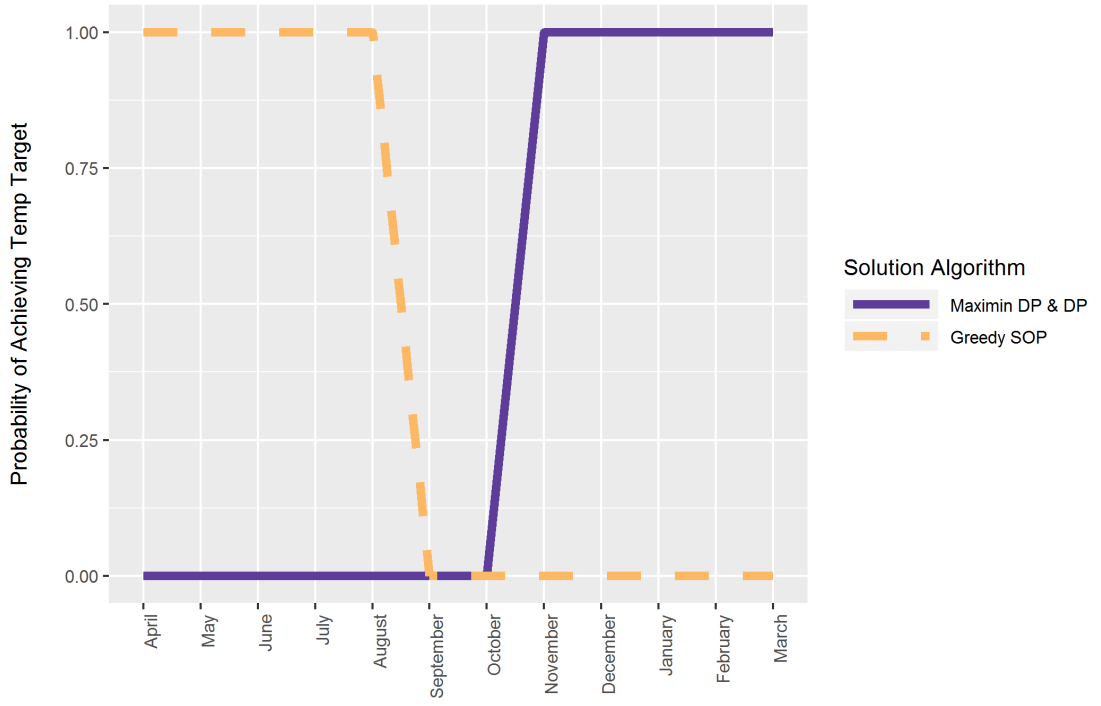


Figure 3.4: Probability of meeting the monthly temperature target for the Shasta Dam - Sacramento River system operated with perfect foresight of extreme drought (exceedance probability p = 0.01) and initial April storage condition at the beginning of the planning cycle of 1.2 maf with a greedy standard operating policy (SOP), dynamic program (DP), and maximin dynamic program (Maximin DP). Model results are coarsely gridded, at a scale of 400 taf/6,700 cfs.

With this scenario, the same result is prescribed by the dynamic program and maximin dynamic program; significant hedging at the beginning of the planning cycle must occur to avoid long-term collapse. Both the dynamic program and the maximin result in end of year cold storage because they hedge early since more net months can have high cold water habitat length if releases are conserved at the beginning of the year.

Low Incoming April Storage with limited forecasting of extreme weather Here we model the same incoming storage for April of 1.2 maf, but with limited forecasting (stochastic). Forecasting for this illustration is weighted heavily towards the expectation of extreme drought (joint probability of hot and dry weather with p = 0.9) or flood (joint probability of a smaller cold and wet flood p = 0.01) or extreme flood (p = 0.09).

Solution Algorithm	Seasonal Cold pool Storage Depletion (April 1 - Oct 31)	Total Annual Releases	Annual (Apr - Mar) Cold Pool Releases	Average End of Year (March) Storage (All Cold)
Greedy SOP	1200	2000	1200	0
SDP	0	2000	1200	0
MaximinSDP	0	2000	1600	400

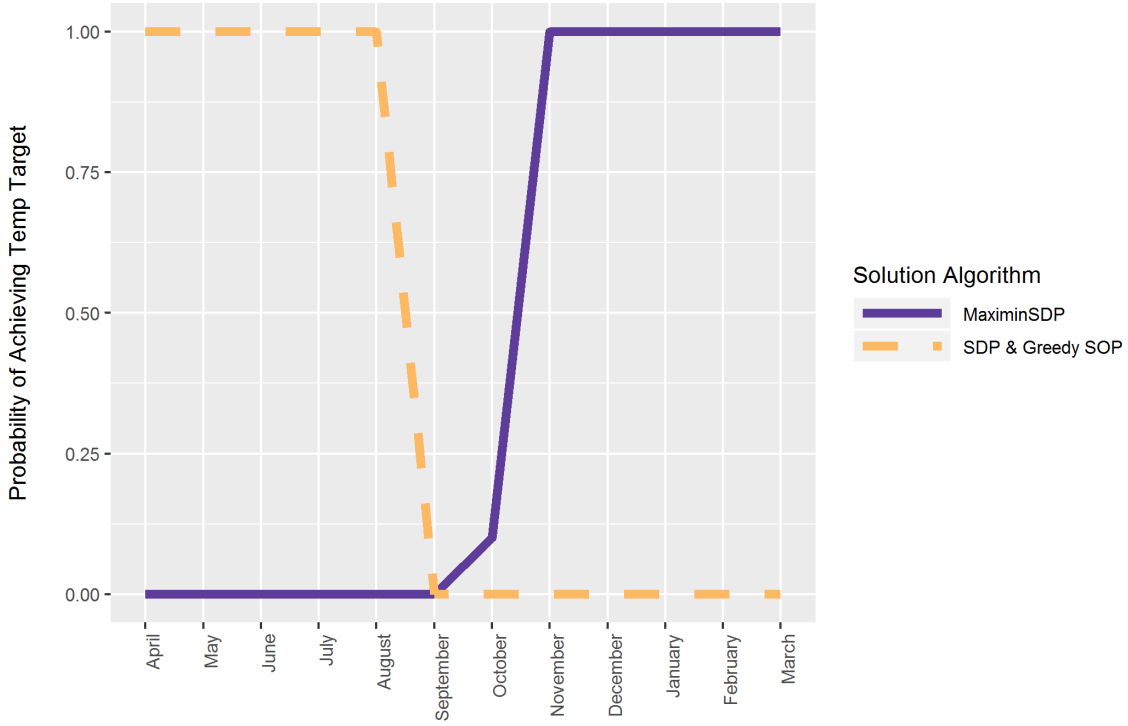


Figure 3.5: Probability of meeting the monthly temperature target for the Shasta Dam - Sacramento River system with limited forecasting of an extreme event - likely an extreme drought (with exceedance probability of p=0.9 from dry and hot), with initial April storage of 1.2 maf with a greedy standard operating policy (Greedy SOP), stochastic dynamic program (SDP) and maximin stochastic dynamic program (MaximinSDP). Model results are coarsely gridded, at a scale of 400 taf/6,700 cfs.

Even though all three solution algorithms meet the temperature target with the same frequency, the maximin dynamic program uses less cold pool storage and ends with more cold pool storage than the greedy standard operating policy algorithm and the dynamic program. Having end of period cold pool storage helps prevent multi-year problems. Here, only the maximin conserved cold water pool, the dynamic program releases early for the big flood benefits, regardless of long-term consequence.

All incoming April storage possibilities with limited forecasting knowledge of extreme weather Likely storage and end volumes (af) for the Shasta Dam - Sacramento River system for a range of weather conditions with higher weight given to extreme drought (p=0.9 to dry and hot) and the remaining probability for extreme flood, for the full range of initial April storage conditions (0 to full capacity) at the beginning of the seasonal planning cycle. Model results are coarsely gridded at a scale of 400 taf/6,700 cfs.

Solution Algorithm	Seasonal Cold pool Storage Depletion (April 1 - Oct 31)	Total Annual Releases	Annual (Apr - Mar) Cold Pool Releases	Average End of Year (March) Storage (All Cold)
Greedy SOP	1850	3200	2400	0
SDP	1850	3200	2400	0
Maximin SDP	730	3160	2550	440

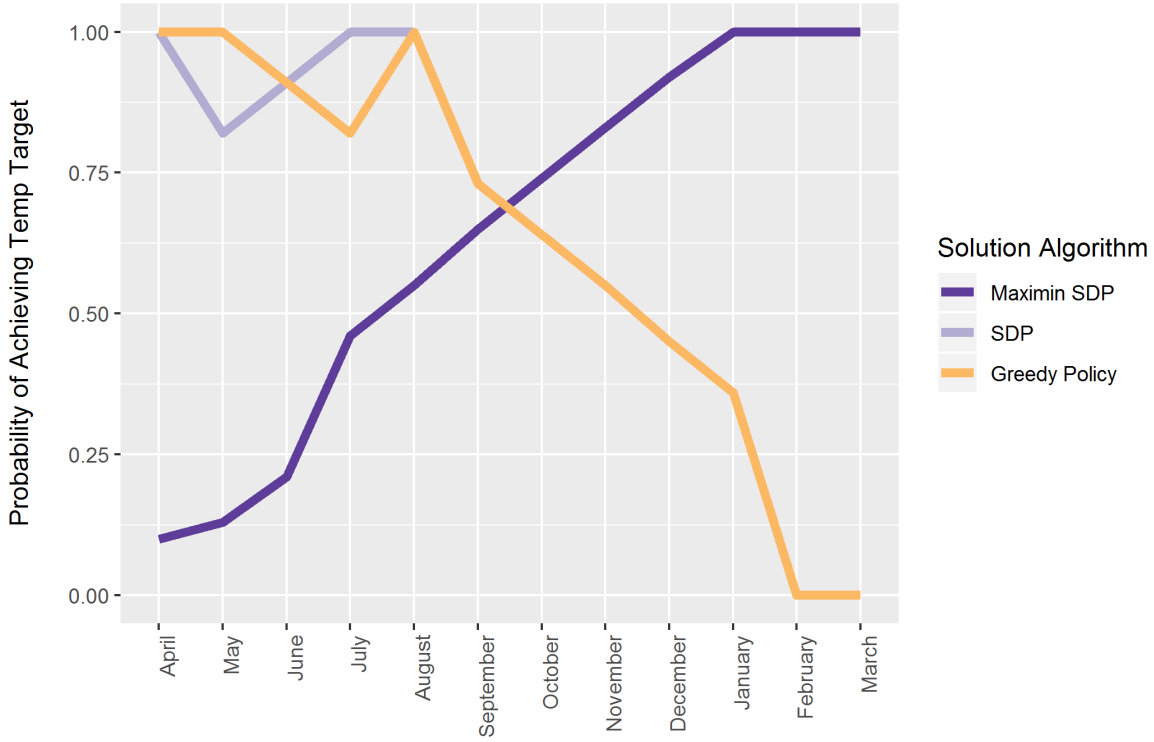


Figure 3.6: Probability of meeting the monthly temperature target for the Shasta Dam - Sacramento River system for a range of weather conditions with higher weight given to extreme drought (p=0.9 to dry and hot) for the full range of initial April storage conditions (0 to full capacity), at the beginning of the planning cycle at a scale of 400 taf/6,700 cfs.

Here, the value of ordering risk makes a difference; the maximin dynamic program outperforms the dynamic program and the standard operating policy.

Value to Fish and other Wildlife Because the maximin solution algorithm hedges against inter-annual risk and does not make releases unless the value of the release is better or equal to expected future releases; ideal cold water habitat conditions are only provided for fish if they can be sustained over time. For anadromous fish, such as the Winter-run Chinook in the Sacramento river, this means that without hedging (with the greedy standard operating policy), if unsustainable volumes of water are released for all delivery purposes, including temperature, early in the season (May - July), there might not be enough water to sustain the large population saved earlier in the year as they develop into juveniles, and then for the next year, should a multi-year drought occur. When looking at results when releases are made with this large grid size, it seems that this could be what happened in 2014-2016 during California's recent drought. "Flows released early in the season (May-June), encouraged adults to spawn over a wide area below the dam. However, flows then abruptly decreased in July and August because of the depleted cold-water pool in the reservoir, resulting in extremely high mortality rates of developing embryos, presumably from a combination of warmer temperatures and reduced hyporheic flow, reducing oxygen delivery to embryos (Martin et al. 2017). An additional impact of Shasta and Keswick Dams has been coarsening of the substrate in spawning areas from large releases from the dam. Such releases move spawning gravel downstream, while preventing new gravel inputs from upstream (Stillwater 2006). This has decreased available spawning habitat over time and requires continuous gravel augmentation in the reaches below the dams for spawning habitat [Moyle et al., 2017]." Here, we simulate fish flow releases at a coarse grid-scale for the illustrative purposes for the Sacramento River below Shasta Dam.

	Expected Fish Survival (% population)		Expected Cold Storage (maf)		Expected Total Storage (maf)	
month	SOP	Maximin DP	SOP	Maximin DP	SOP	Maximin DP
April	100	18	2.4	2.4	2.4	2.4
May	100	18	2.4	2.4	2.4	2.7
June	91	18	2.1	2.3	2.4	3.0
July	82	18	1.8	2.1	2.0	2.9
August	82	18	1.5	2.1	1.7	2.7
September	73	18	1.3	2.1	1.3	2.5
October	64	18	1.0	1.9	1.0	2.2
November	55	18	0.8	1.7	0.8	1.9
December	45	18	0.5	1.6	0.5	1.6
January	36	18	0.4	1.2	0.4	1.2
February	27	18	0.2	0.8	0.2	0.8
March	18	18	0.1	0.4	0.1	0.4
EXPECTED FINAL	18	18	0.1	0.4	0.1	0.4

Table 3.3: Expected proportion of fish population to survive (based on frequency with which temperature and flow targets are achieved) and expected cold and total reservoir storage (maf), per month. Fish population is proportional to the minimum success of meeting the temperature and flow target, over the course of the year.

In a drought, without hedging, releases can save many eggs (May - July), but deplete water to sustain the fish as juveniles (September - February), such that the fish die. Early cold water releases, in effect, were "wasted," which affected fish and other water users downstream from curtailments and storage depletion. Because of these trade-offs, "management of the cold water releases from Shasta Dam was among the most controversial of all water issues in the state [Moyle et al., 2017]." In policy terms, saving fish, because of their legal status, can be expensive. Here, the same proportion of the fish population is saved but less storage is required to save the fish with the maximin dynamic program than with the standard operating policy.

3.7 Discussion

The logic of the mathematical models used here is similar to the logic of financial hedging, a risk management technique used to offset substantial financial losses and gains in exchange for stability. Hedging can occur with many different methods on many different factors. In reservoir operations, hedging policies have been analytically and numerically demonstrated beneficial for managing flood damage[Hui et al., 2018] and increasing economic benefit [Draper and Lund, 2004; You and Cai, 2008a,b], energy production [Tejada-Guibert et al., 1995], and downstream environmental benefit [Adams et al., 2017], particularly when shortage and scarcity are of concern. In each case, hedging incurs a small certain loss now to reduce larger future risks, e.g., intentionally releasing small floods to avoid large ones, or conserving some storage and causing some immediate shortage to avoid deeper drought. We borrowed from this literature and adapted two traditional operational conditions that encourage reservoir hedging:

- A1. a concave function of (approximated) release benefits [Draper and Lund, 2004]; and
- A2. substantial probability of persistent drought [Klemeš, 1977].

We further define the advantages of different formulations of the benefits function for temperature management in reservoirs with:

- B1. defined policy goals (e.g., a monthly distance and temperature threshold that designate cold water habitat);

and add one variant that encourages hedging not just for benefits and against difficult weather, but also to avoid inter-annual risk from storage depletion or failure to meet seasonal temperature goals:

- B2. maximin behavior, that maximizes monthly downstream benefit and minimizes the possible loss of the worst-case month.

(B1) turns the policy goal into a function of the diminishing margin of cold habitat river length over time, given release temperature and flow. Optimizing release decisions to meet this concave function (A1) hedges seasonally available cold water pool so that benefits are allocated when release value (cold habitat length) is greatest and curtailed release value (cold water habitat) is least. Reducing wet-cold releases to conserve storage supports both seasonal and inter-annual operations, should persistent drought occur (A2). Implementation of one or more of these approaches, with one of the three solution algorithms outlined in this paper, results in hedging on different factors and time-scales (Table 3.4). Of the three solution algorithms, only the maximin (B2) avoids regrettable decisions and hedges not just with weather and release flow and temperature, but also orders all risk to the beginning, encouraging the system to further hedge inter-annually, thereby reducing large multi-year catastrophes. Therefore, the maximin performs best with respect to long-term storage and river management goals.

	Operating Approach		Timing			
Solution Algorithm	**Cold Habitat Distance & Temp**	**Weather**	**Seasonal**	**Inter-annual**	**Multiple Objectives**	**Fish**
Deterministic Greedy Operating Policy	✓	✓				✓
Stochastic Greedy Operating Policy	✓					✓
Determinstic Dynamic Program (DDP)	✓	✓	✓			✓
Stochastic Dynamic Program (SDP)	✓		✓			✓
Maximin DDP	✓	✓	✓	✓		✓
Maximin SDP	✓		✓	✓		✓
Drought Penalized Maximin SDP or DDP	✓	✓	✓	✓		✓
Maximin SDP for Managing Multiple Resources	✓		✓	✓	✓	✓

Table 3.4: Comparison of factors upon which different solution algorithms hedge.

The greedy standard operating policy makes releases to meet the current value of the benefit function (here, cold habitat distance and temperature) given water availability from weather and incoming conditions. The dynamic programs try to meet this current target, but also hedge against risk by maximizing net benefits across the duration of the year. The maximin approach hedges for current yearly net benefits like the dynamic program. The maximin hedges further for inter-annual benefits by reducing monthly performance so no month exceeds expected performance of any month. In some sense, all of these algorithms hedge for fish (and therefore other ecosystem benefits): they support fish-specific habitat distance and temperature requirements, weather conditions, and flow and temperature goals both seasonally, inter-annually, and within year-classes.

3.8 Limitations

Model results are coarse in this chapter; chapter 4 addresses this limitation. This study could benefit from an analytical derivation of the cost-to-go functions of the dynamic programs and the greedy algorithm for this temperature control problem. Sensitivity analysis is expensive in dynamic programming, but could provide insights.

3.9 Conclusions

Current literature on reservoir operations and environmental flows neglect temporal persistence in outcome variables (here, cold water habitat miles and ecological conditions) even though ecosystems have memory and reservoir storage and wildlife survival processes are almost always correlated across time steps. If one month's reservoir releases make a river uninhabitable and deplete river species, or if a large cold release is made that depletes cold water reservoir storage, future ecological outcomes and reservoir operational flexibility will be affected. Behavioral economics describes managing this problem as "regret avoidance" for which an agent's current decisions have a backward looking component that "avoids information which threatens to cast a past decision into an unfavorable light [Krähmer and Stone, 2005]" such that "you should choose the option that minimizes the regret you will feel at the end [Halpern and Leung, 2016]." We adapt this idea to reservoir operations - that an operator will "regret" "wasting" cold water from storage if later period releases have less benefit. To avoid regrettable decisions, we apply a maximin operator to the objective function. We maximize the minimum of the intermediate and future benefit. We minimize releases, specifically targeting cold water releases, required to obtain the maximum benefit.

Operating with regret avoidance conserves cold pool storage as well as total storage until releases can be made with outcomes that are likely sustainable over time. Hedging storage and releases is predicted to improve cold water habitat be making it consistently available for longer seasonal and inter-annual time periods. The methods developed here will provide a natural variation in temperature below a dam (with the benefit function), a river that flourishes when it can be sustained (Equations 7 - 9), adaptive management guidelines to support choosing an optimal cold and warm pool volume release decisions for any cold and warm reservoir state of any month (Equation 8), and a means by which to approximate a critical threshold for abandoning operations of a year, a season, or a month (when the prescribed optimal release is zero because releasing any incoming storage cannot be sustained for the long-term). This method leverages the certainty that a release will have a downstream effect, rather than focusing exclusively on uncertainty in weather or human decisions (reservoir release choice). Implementation of this method may require courage. Although in principal it is risk averse and minimizes the probability that an operator will make a regrettable release decision, it is a novel approach that deviates from the greedy standard operating policy and incurs some immediate losses. The mathematics and logic of such cold water hedging operations can be related more directly and conventionally to reservoir hedging for water supply, hydropower, drought management, and flood control.

References

Adams, L. E., Lund, J., Moyle, P., Quiñones, R., Herman, J., and O'Rear, T. (2017). Environmental hedging: Theory and method for reconciling reservoir operations for downstream ecology and water supply. *Water Resources Research*.

Carron, J. C. and Rajaram, H. (2001). Impact of variable reservoir releases on management of downstream water temperatures. *Water Resources Research*, 37(6):1733–1743.

Castanón, D. A. and Wohletz, J. M. (2002). Model predictive control for dynamic unreliable resource allocation. In *Decision and Control, 2002, Proceedings of the 41st IEEE Conference on*, volume 4, pages 3754–3759. IEEE.

Castelletti, A., Yajima, H., Giuliani, M., Soncini-Sessa, R., and Weber, E. (2013). Planning the optimal operation of a multioutlet water reservoir with water quality and quantity targets. *Journal of Water Resources Planning and Management*, 140(4):496–510.

Chaves, P. and Kojiri, T. (2007). Deriving reservoir operational strategies considering water quantity and quality objectives by stochastic fuzzy neural networks. *Advances in Water Resources*, 30(5):1329–1341.

Dallas, H. (2008). Water temperature and riverine ecosystems: An verview of knowledge and approaches for assessing biotic responses, with special reference to south africa. *Water Sa*, 34(3):393–404.

Draper, A. J. and Lund, J. R. (2004). Optimal hedging and carryover storage value. *Journal of Water Resources Planning and Management*, 130(1):83–87.

Fontane, D. G., Labadie, J. W., and Loftis, B. (1981). Optimal control of reservoir discharge quality through selective withdrawal. *Water Resources Research*, 17(6):1594–1602.

Giuliani, M., Galelli, S., and Soncini-Sessa, R. (2014). A dimensionality reduction approach for many-objective markov decision processes: Application to a water reservoir operation problem. *Environmental modelling & software*, 57:101–114.

Halpern, J. Y. and Leung, S. (2016). Minimizing regret in dynamic decision problems. *Theory and Decision*, 81(1):123–151.

Houghtalen, R. J. and Loftis, J. C. (1989). Improving water delivery system operation using training simulators. *Journal of Water Resources Planning and Management*, 115(5):616–629.

Hui, R., Herman, J., Lund, J., and Madani, K. (2018). Adaptive water infrastructure planning for nonstationary hydrology. *Advances in Water Resources*.

Klemeš, V. (1977). Value of information in reservoir optimization. *Water Resources Research*, 13(5):837–850.

Krähmer, D. and Stone, R. (2005). Regret in dynamic decision problems. Technical report, SFB/TR 15 Discussion Paper.

Labadie, J. W. (2004). Optimal operation of multireservoir systems: state-of-the-art review. *Journal of water resources planning and management*, 130(2):93–111.

Loucks, D. P., Stedinger, J. R., and Haith, D. A. (1981). Water resource systems planning and analysis.

Milly, P. C. D., Betancourt, J., Falkenmark, M., Hirsch, R. M., Kundzewicz, Z. W., Lettenmaier, D. P., and Stouffer, R. J. (2008). Stationarity is dead: Whither water management? *Science*, 319(5863):573–574.

Moyle, P., Lusardi, R., Samuel, P., and Katz, J. (2017). State of the salmonids: Status of californias emblematic fishes 2017.

Nickel, D. K., Brett, M., and Jassby, A. (2004). Factors regulating shasta lake (california) cold water accumulation, a resource for endangered salmon conservation. *Water Resources Research*, 40(5).

Olden, J. D. and Naiman, R. J. (2010). Incorporating thermal regimes into environmental flows assessments: modifying dam operations to restore freshwater ecosystem integrity. *Freshwater Biology*, 55(1):86–107.

Olivares, M. A. (2008). *Optimal hydropower reservoir operation with environmental requirements*. PhD thesis, University of California Davis.

Price, R. E. and Meyer, E. B. (1992). Water quality management for reservoirs and tailwaters. report 2. operational and structural water quality enhancement techniques. Technical report, Army Engineer Waterways Experiment Station Vicksburg MS Hydraulics Lab.

Rheinheimer, D. E., Null, S. E., and Lund, J. R. (2014). Optimizing selective withdrawal from reservoirs to manage downstream temperatures with climate warming. *Journal of Water Resources Planning and Management*, 141(4):04014063.

Sherman, B. (2000). *Scoping options for mitigating cold water discharges from dams*. CSIRO Land and Water Canberra.

Soleimani, S., Bozorg-Haddad, O., Saadatpour, M., and Loáiciga, H. A. (2016). Optimal selective withdrawal rules using a coupled data mining model and genetic algorithm. *Journal of Water Resources Planning and Management*, 142(12):04016064.

Tejada-Guibert, J. A., Johnson, S. A., and Stedinger, J. R. (1995). The value of hydrologic information in stochastic dynamic programming models of a multireservoir system. *Water Resources Research*, 31(10):2571–2579.

Weber, M., Rinke, K., Hipsey, M., and Boehrer, B. (2017). Optimizing withdrawal from drinking water reservoirs to reduce downstream temperature pollution and reservoir hypoxia. *Journal of Environmental Management*, 197:96–105.

You, J.-Y. and Cai, X. (2008a). Hedging rule for reservoir operations: 1. a theoretical analysis. *Water Resources Research*, 44(1).

You, J.-Y. and Cai, X. (2008b). Hedging rule for reservoir operations: 2. a numerical model. *Water Resources Research*, 44(1).

4 Temperature Management of the Shasta Reservoir-Sacramento River System

4.1 Introduction to Temperature Management of the Shasta Reservoir - Sacramento River system.

Shasta Reservoir is California's largest reservoir ($4.55x10^6af/5.5km^3$). Since construction of the dam was completed in 1945, it has impounded water from the 6,650 mi^2 (17,224 km^2) catchment of the upper Sacramento, McCloud, and Pit rivers. Shasta Reservoir has a maximum depth of $445ft$ ($136m$) and water residence times of 0.3 to 1.3 years, depending on reservoir level and inflow. Shasta Reservoir is classified as a warm monomictic lake [Rettig and Bortleson, 1983; Bartholow et al., 2001] with cold and mixed winter and early spring seasons followed by a summer with warm inflows, warming air temperatures and a stratified warm and cold pool. In the fall, inflow is again cold; the colder, denser, fall inflow sinks in the lake causing "overturn" which the lake mixes to become fully cold for winter. The tributaries to the Sacramento River (the Sacramento, McCloud, and Pit Rivers) are cold snowpack and glacial-fed rivers. Inflow to Shasta reservoir, while not insignificant during summer, is mostly from winter rain and spring snowmelt between November and May; by April, the reservoir has received almost all expected inflows. This change in temperature regime and flow, from the creation of this large lake, had significant impact downstream and for California in general, including on the California water economy.

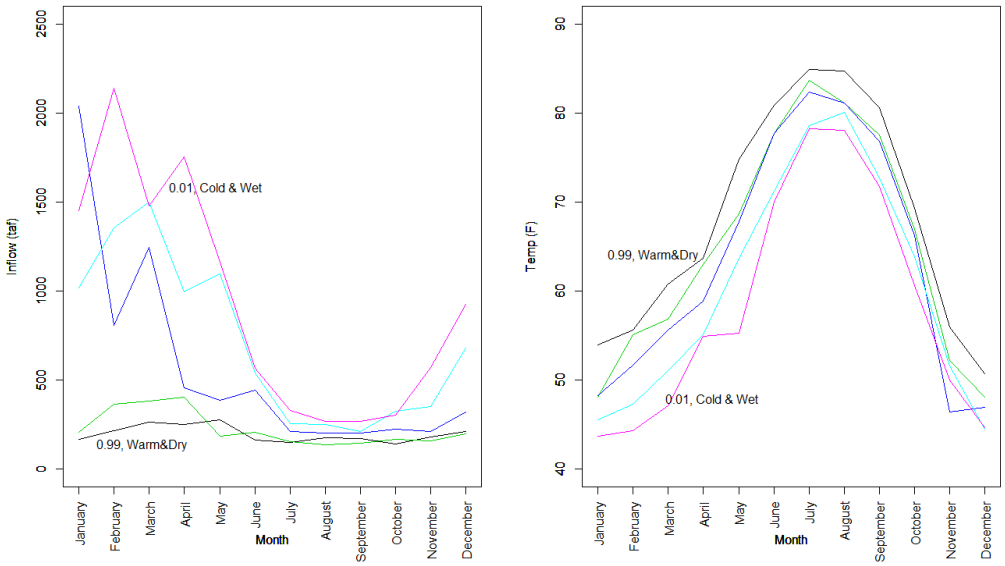


Figure 4.1: Shasta reservoir inflow (taf/month) and ambient temperatures (F) with a joint probability that is exceeded (inflow) and deceeded (temperature) with frequency of 0.99 (black), 0.9 (green), 0.5 (royal blue), 0.1 (light blue), and 0.01 (pink).

Construction of Shasta Dam severed migratory access and river connectivity between the upstream tributaries and the lower mainstem of the Sacramento river. This affected many migratory species; denying access to historic spawning ground above the dam and reducing the abundance of four thriving salmon runs. To compensate, Shasta Dam operations are legally obligated to replace historical spawning and rearing habitat that was above the dam, below the dam, so that fish downstream of the dam are in good condition [NOA, 2016] and water is supplied downstream for Delta salinity repulsion. Monitoring for this mandate occurs at several downstream locations (Figure 4.2).

To support this legal mandate and to improve fish and wildlife conditions below the dam, a selective withdrawal intake structure (temperature control device) was installed at Shasta Dam in 1997 for $80 million. The temperature control device has 18 water intakes at five elevations so water can be pulled from multiple combinations of heights along the lakes temperature profile to better regulate temperature and flow downstream in the Sacramento River when the lake is stratified in summer and early fall. The temperature control device has improved river habitat for fish, but problems still exist in drier years. In summer 2014 95% of California's Winter-run Chinook salmon died below Shasta Dam [Vogel, 2016] due to low reservoir inflows, instrument failure, and high temperature releases [NOA, 2016]. Financial and political will support improvement of the situation. The Winter-run Chinook are a federally listed Endangered Species, and (under the 1973 Endangered Specie Act), receive highest priority protection [act, 1973]. To support this endangered species and reduce their water supply demands (potentially avoiding month-long irrigation water curtailments to support fish-flows), the Glen Colusa Irrigation District spent $300,000 on a fish habitat enhancement project [GCID, 2016]. Congress appropriated $20 million in March, 2018 of an estimated $1.3 billion project to raise Shasta Dam to enlarge cold water storage capacity [Lochhead, 2018] for Winter-run Chinook below Shasta Dam.

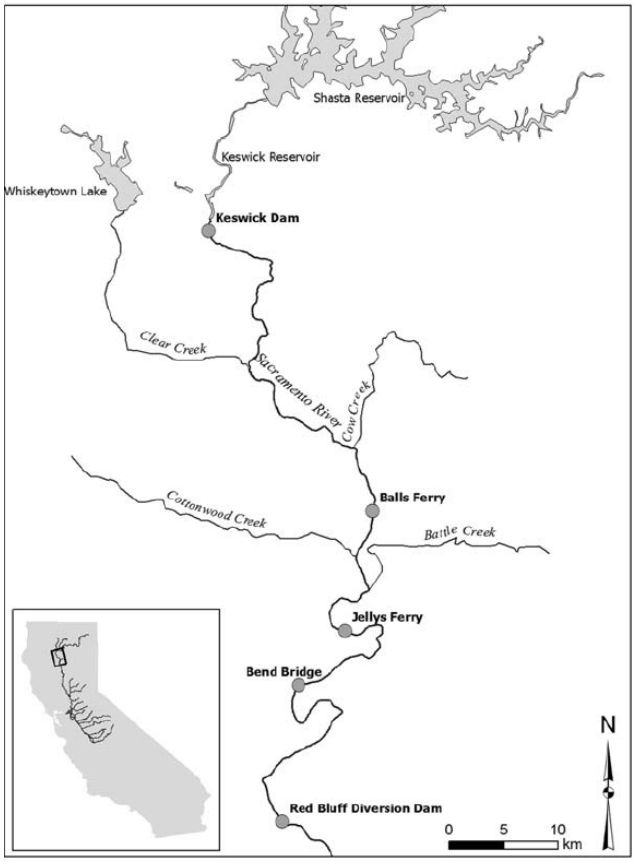


Figure 4.2: The Sacramento river below Shasta reservoir. Dots are Sacramento River Temperature Gauge Locations. An additional gauging station exists at the confluence of Clear Creek and the Sacramento River. Figure reprinted with permission from [Pike et al., 2013].

4.2 Approach

We use optimization to build rules and release schedules with this new temperature operations model, OTM2 (Optimized Temperature Management Model), to determine how much cold water should be released and stored throughout the year from Shasta reservoir to support downstream Sacramento river environmental objectives and reduce water curtailments for all downstream diverters including for agriculture, bird sanctuaries, and the Delta. Different operational approaches (e.g., downstream temperature, distance, solution algorthm and objectve function) were compared over one and many operational seasons (a "season" often refers to one water year, because temperature concern occurs mainly in the stratified season of a year) for the Shasta Dam-Sacramento River system. Computational burden for this large and complex problem was reduced by aggregating the model's state, action, and outcome spaces and approximating state variables based on physical and statistical principles. Results provide insight into different dynamic programming methods and different policy objectives for selective withdrawal systems. Release decisions were constrained so no month performed better (on average) than the previous month to hedge against catastrophe for one and many year-classes of Winter-run salmon. Resulting monthly operational management policies can hedge downstream river temperature and storage between and within time steps, seasons, and years. Results offer

an application of methods and theory for temperature management in reservoirs (see Chapter 2 for details) demonstrate the value of hedging with a maximin objective function and offer some policy, regulatory, and operational insight for Shasta reservoir and Sacramento river management.

4.3 Temperature Modeling

Most temperature withdrawal system research to date is descriptive, not prescriptive - describing the effects of using temperature control devices rather than prescribing desirable temperature control. Simulation models are employed to predict the effects of different factors such as aquatic biogeochemistry of lakes on temperature management within or below a reservoir [Beard and Willey, 1970; Price and Meyer, 1992; Nandalal and Bogardi, 1995; Hanna, 1999; Bartholow et al., 2001]. In these cases, management of selective reservoir withdrawal involves jointly managing releases and storage for three sub-systems: the reservoir water (storage and temperature), the river (temperature, flow, and downstream ecosystem function and targets), and operations modeling of release decisions (timing, magnitude, and intake). For a review of the optimization literature on selective withdrawal systems, see Chapter 3.

Reservoir Modeling Temperature modeling of the reservoir and the river can be physical, empirical, or a mix of empirical and physical approaches. In all cases, however, the modeling strategy is based on conservation of energy (Equations 1 - 2). In a mixed lake, heat exchange with the atmosphere and from incoming waterflow dictate temperature. In a well-mixed stratified lake atmospheric heat exchange governs the temperature during the stratified season as well as contributions from the hypolimnion and incoming flows.

$$\text{Accumulation} = \text{Sources - Sinks} \tag{1}$$

$$\text{Accumulation} = \text{Inflow - Outflow} \pm \text{Surface Heat Exchange} + \text{Vertical Transport}$$

$$\underbrace{V^w \rho C_\rho \frac{dT^w}{dt}}_{\text{accumulation}} = \underbrace{q_\rho^{in} C_\rho T^{in}(t)}_{\text{inflow}} - \underbrace{q^{in} \rho C \rho T^w}_{\text{outflow}} \pm \underbrace{JA^s}_{\text{surface heat exchange}} + \underbrace{v_t A^L \rho C_\rho (T^c - T^w)}_{\text{vertical transport}} \tag{2}$$

C^ρ = specific heat (cal/g $^\circ$C)
ρ = density (g/km^3)
A^s = surface area of the lake (km^2)

Quantifying each of the terms of the surface heat flux J:

$$\underbrace{J_t}_{\text{surface heat flux}} = \underbrace{J_t^{sn} + J_t^{an} - (J_t^{br}}_{\text{radiation terms}} + \underbrace{J_t^c + + J_t^e)}_{\text{nonradiation terms}} \tag{3}$$

J_t^{sn} = net solar radiation
J_t^{an} = net atmospheric longwave radiation
J_t^{br} = longwave back radiation from the water
J_t^c= conduction
J_t^e = evaporation

with net atmospheric longwave radiation:

$$J_t^{an} = \sigma(T_t^a + 273)^4(A + 0.031ea_t^{\frac{1}{2}})(1 - D) \tag{4}$$

where
σ = Stefan-Boltzmann constant = $4.9x10^{-3}\ J(m^2dK^4)^{-1}$
A=a coefficient (0.5 to 0.7) (e.g., 0.6)
ea_t = vapor pressure in overlying air (mmHg) = $0.6(4.596e^{\frac{17.27*T_t^w}{237.3+T_t^w}})$
D = reflection coefficient = 0.03

longwave back radiation:

$$J_t^{br} = \epsilon\sigma(T_t^w + 273)^4 \tag{5}$$

ϵ =emissivity of water (approx 0.97)

conduction:

$$J_t^c = c_1 f(U_t)(T_t^w - T_t^a) \tag{6}$$

c_1 =Bowen's coefficient = $0.47mmHgC^{-1}$
$f(U_t) = 19.0 + 0.95U_t^2$ with U_t =wind speed (ms^{-1}) at a fixed distance (e.g., 7m) above water surface

evaporation:

$$J^{e_t} = f(U_t)(es_t - ea_t) \tag{7}$$

es_t =$4.596e^{\frac{17.27*T_t^w}{237.3+T_t^w}}$

Within the literature, the empirical approach builds a conceptual two-pool model and the physical approach models more physical processes with more layers. The two-pool approach simplifies the reservoir into two completely mixed thermal layers; a lower hypolimnion (cold pool) with constant temperature and an upper epilimnion (warm pool) with either constant temperature [Rheinheimer et al., 2014] or an externally driven warming rate [Olivares, 2008]. When included, the metalimnion (the layer that transfers heat between the cold and warm pools) is a constant based on historical observations [Olivares, 2008; Rheinheimer et al., 2014]. In contrast, when modeling a many-layered system, the model is usually a vertical profile calibrated with a computationally and scientifically intense 1-D model such as DYRESM [Nandalal and Bogardi, 1995; Giuliani et al., 2014; Weber et al., 2017] or WESTEX [Fontane et al., 1981], with 2-D hydrodynamic and water quality software such as CE-QUAL-W2 [Bartholow et al., 2001; Soleimani et al., 2016], or with 1-D hydrodynamic-ecological software, such as DYRESM-CAEDYM Castelletti et al. [2013]. In all cases temperature and water volume are coupled.

Downstream Ecosystem Goals The fate and heat transport of temperature in a river are described by a three-dimensional advection-diffusion equation.

$$\frac{\partial T}{\partial t} + u_x\frac{\partial T}{\partial t} + u_y\frac{\partial T}{\partial t} + u_z\frac{\partial T}{\partial t} = \frac{\partial}{\partial x}(D_x\frac{\partial T}{\partial x}) + \frac{\partial}{\partial y}(D_y\frac{\partial T}{\partial y}) + \frac{\partial}{\partial z}(D_z\frac{\partial T}{\partial z}) + \frac{JA^s}{\rho C_\rho V_x} \tag{8}$$

Because of the large width to depth ratio of rivers downstream of a dam with selective withdrawal intake structures, and the long time-scale over which selective withdrawal temperature problems are analyzed, it can often be assumed that temperature in the river is fully-mixed in the vertical and lateral directions. Then the river modeling problem needs to consider only the one-dimensional transport of temperature down the river, i.e., changes in riverflow temperature depend largely on the net heat flux of the air-water interface J and the advection of the temperature as it moves downstream $\partial T/\partial x$.

$$\frac{\partial T}{\partial t} + \underbrace{u_x\frac{\partial T}{\partial x}}_{\text{longitudinal diffusion}} = \underbrace{\frac{JA^s}{\rho C_\rho V_x}}_{\text{net heat flux}} \tag{9}$$

For selective withdrawal optimization models, river temperature goals are often modeled as constant targets at the point of release. Deviations from these targets are penalized [Fontane et al., 1981; Castelletti et al., 2013; Rheinheimer et al., 2014]. Rheinheimer et al. (2015) and Carron (2001) extend these targets to include riverflow. Rheinheimer et al., (2015) developed flow networks and penalized cost-weighted deviations of streamflow release at each river reach for each time step. The targets of Rheinheimer (2015) are the constant minimum and maximum habitat temperature requirements of the rivers indicator species. Carron (2001) built a one-dimensional, nonlinear, unsteady representation of river hydraulics and stream temperature that can forecast the system state and forcing variables to manage river temperature downstream of the reservoir with 1-2 days warning time. A Principal Components Analysis developed by Guiliani (2014) maximizes ten socio-ecological objectives of a multi-objective model in both the reservoir and downstream including temperature, irrigation, reservoir level, sedimentation and algal blooms.

4.4 Methods

Previous literature and approaches were extended to model the three components of the Shasta Dam-Sacramento River system: lake temperature (Shasta Lake), river temperature (the Sacramento River), and operation decisions (Shasta/Keswick Dam operations) to develop optimized temperature management policy and insight.

4.4.1 Solution Algorithm

We solve the temperature control problem to explicitly allow hedging against the risk of catastrophic failure - by failing to deliver cold water habitat and intentionally causing small damage now to avoid depleting the reservoir and causing long-term environmental and economic damage. To achieve this goal, we built a maximin dynamic program to allocate downstream temperature and flow with a low risk strategy. See Chapter 3 for mathematical formulation and further details. As the season progresses, optimized release decisions from the maximin dynamic program provide downstream cold water habitat in equal or worse proportion than expected future cold water habitat - but not better. With this approach, the worst-case situation dominates, the system hedges for risk, and catastrophes, especially drought-related catastrophes, are reduced. Hedging releases with the maximin approach is a three step maximin process (Equations 10 - 12)(See Chapter 3 for details). The first step takes the minimum of the immediate and future benefits of each choice of each state. The value of the release in this period cannot exceed the expected value of the optimized release made in the future period with this period's outgoing storage (Equation 10).

$$\mathbb{E}\{B_t(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^w}, \mathbf{R_t^c})\} = \min\Big(\mathbb{E}\sum_t \Bigg(\underbrace{p^{QT_t^a}[B(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^w}, \mathbf{R_t^c}, x^Z, T^Z, Q_t, T_t^a, month_t)]}_{\text{Immediate Benefit}}, \tag{10}$$

$$\underbrace{\mathbb{E}\sum_t p^{QT_{t+1}^a} B_{t+1}^* \begin{Bmatrix} V_{t+1}^c = f(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^w}, \mathbf{R_t^c}, month_t, p_t^{QT_t^a} Q_t T_t^a), \\ V_{t+1}^w = f(\mathbf{V_t^w}, \mathbf{R_t^w}, month_t, p_t^{QT_t^a} Q_t T_t^a) \end{Bmatrix}}_{\text{Future Benefit}}\Bigg)\Big)$$

Next, because there is no sense in creating temperature habitat in any one month that cannot be sustained in future life stages (wasting stored water), if the benefits from the accumulated objective function (future benefit) are less than the immediate benefit, current releases are reduced (hedged) to meet the lesser benefit of the next period (except for a need to spill), saving cold water to improve future conditions, given that the hedged release decision is feasible within the reservoir's capacity constraint and expected weather conditions (Equation 11).

$$R_t^{c*}, R_t^{w*} = \begin{cases} R_t^c, R_t^w & \text{if Immediate Benefit} \leq \text{Future Benefit} \\ R_t^c, R_t^w & \text{else if infeasible } R_t^c, R_t^w = R_{t+1}^{c*}, R_{t+1}^{w*} | B_{t+1}^*(V_{t+1}^c, V_{t+1}^w) \\ R_{t+1}^{c*}, R_{t+1}^{w*} & \text{otherwise} \end{cases} \tag{11}$$

The final benefit (equation 10) for the current period then, is the maximum of the minimum expected benefit of each state for each stage, with the set of monthly release decisions (Equation 11) for a range of considered disturbances.

$$\mathbb{E}\{B_t(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^w}, \mathbf{R_t^c})\} = \max_{\min R_t^{c*}, R_t^{w*}} \Big(\min \Big(\mathbb{E} \sum_t \Bigg(\underbrace{p^{QT_t^a}[B(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^{w*}}, \mathbf{R_t^{c*}}, x^Z, T^Z, Q_t, T_t^a, month_t)]}_{\text{Immediate Benefit}}, \tag{12}$$

$$\underbrace{\mathbb{E} \sum_t p^{QT_{t+1}^a} B_{t+1}^* \begin{cases} V_{t+1}^c = f(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^w}, \mathbf{R_t^c}, month_t, p_t^{QT_t^a} Q_t T_t^a), \\ V_{t+1}^w = f(\mathbf{V_t^w}, \mathbf{R_t^w}, month_t, p_t^{QT_t^a} Q_t T_t^a) \end{cases}}_{\text{Future Benefit}} \Bigg) \Big) \Big) =$$

$$\max_{\min R_t^{c*}, R_t^{w*}} \mathbb{E} \sum_t p^{Q_t T_t^a} [B_t(\mathbf{V_t^c}, \mathbf{V_t^w}, \mathbf{R_t^{w*}}, \mathbf{R_t^{c*}}, x^Z, T^Z, month_t)]$$

4.4.2 Computation Time

Dynamic resource allocation problems, like this temperature control problem, are a type of dynamic program that suffers from all three "curses of dimensionality": dimensionality in the action space (decision variable), state space, and outcome space [Powell, 2007], so model computation is intensive and required approximate dynamic programming (Table 4.1). Computation time was reduced by narrowing the problem definition to a level of sophistication suitable for policy objectives, empirically modeling hydraulic, temperature, and ecological processes, and employing approximate dynamic programming to coarsen the state, stage, and decision variables. These approaches reduced the modeling requirements by a factor of about $6,272^L$ per stage, with L being the count of discretized choices of state variables (state and decision variables, and consequently outcome variables, were approximated by discretization; continuous state and action spaces were replaced with a grid.) Given the capacity of Shasta reservoir (approximately 4.6 maf) with an operationally relevant discretization of 100 taf, L = 46; these approximated steps reduced computational requirements by a factor of $6,272^{46}$/stage. State variables were reduced by 2^L because reservoir temperatures were found to be well-characterized as a well-correlated alias of pool volume, rather than as explicit additional state variables, and another $(n-2)^L$ because releases were from a two-pool (cold and warm pool), not a many-layered (n) pool reservoir model (e.g., HEC-5Q). River temperature was statistically imputed with a Generalized Linear Model rather than computed from state variables, which reduced the computational time by a further factor of at least 2^L. Lookup tables for climate (air temperature and inflow based on exceedance probability and month) and cold and warm pool temperature (and consequently release temperature given storage cold and warm pool volume), coupled with the river temperature GLM approximate the value of release choices (cold water habitat miles) and operationalize these approximations and aggregations. Modeling releases as a function of volume, with two choices of either warm or cold pool, without specifying exactly from which shutter gate from which an optimal release should come - in part because some shutter gates on Shasta Dam are partially stuck - reduced model demands by another factor of $(16-2)^L$. Final release therefore, is the sum of two release choices not 16, and release temperature is the weighted average of two choices not 16, reducing the model by another 28^M with M being the count of discretized release choices of M = discretization of L, 100 taf.

The continuous state and decision spaces of this reservoir problem were aggregated into a smaller number of discrete approximations at several grid sizes. Grid size choice can affect results; larger grid cells result in more extreme storage fluctuation and larger releases; spill occurs more often, and minimum releases cause larger storage deficits. Grid size is particularly impactful in flood years, for years with an expectation of both flood and drought, and years that receive either large volumes of rain but little snow, and years that expect a flood but actually receive a drought, because of the positive skew in inflow expectations. Nonetheless, a coarse model with the largest discretization size (one maf) was used to explore policy objectives and build the code. The historical minimum reservoir release (1987 - 2017) was 2,554 af/mo (43 cfs); 4,431,537 af/mo (74,605 cfs) was the maximum. The bulk of historical monthly releases exceed one maf. The final model has a discretization size of 100 taf, which is less than most monthly release records from Shasta, and sufficient for monthly planning.

Decision space dimensions vary by month; some months have fewer options, e.g., winter months have no warm water and no warm water releases. State variables represent beginning of period conditions. Releases occur at the end of each period. State variables were limited to include only feasible options. Decision variables include spill. The season with the largest grid of discretized release options is fall. Fall inflow is cold but incoming fall storage is any combination of warm and cold, therefore fall turnover had the greatest number of cold and warm release options and states of all the months. Fall season computations, therefore, have the largest memory requirement of any month. Finer discretizations allow for more operating flexibility but require more computational time. Memory requirements are a function of the grid size requirement from the fall turnover matrix - (e.g., for a bin size of 5,000 af/mo there are 415,416 states, 2,316,673 decisions and, for the stochastic model runs, 5 hydrologic conditions, each requiring 8 bytes of memory = 38,495 GB of memory)(Table 4.1). After simplifying the problem, memory was the limiting factor in reducing computation time.

The stochastic version of the program is stochastic both in the benefit and the indirect recursive benefit function. Considering the probability distribution of expected weather types y for both of these functions increases program computational time by a factor of y (here y = 5) from the deterministic version that weighs probablistic outcomes with just the current benefit. A different weighting priority is assigned contingent on management preferences, i.e., to a "drought management" (release decisions heavily weighted toward drought management), an "extreme weather" (release decisions heavily weighted towards extreme drought and flood events), or an "expected value" outcome that assigns weights according to the joint probability of that particular hydrologic condition.

	Maximin Stochastic Dynamic Program		Maximin Deterministic Dynamic Program	
Bin Size (taf)	Memory Reqs (GB)	Run Time (min)	Memory Reqs (GB)	Run Time (min)
1,000	0.8∗10−4	2	1.5*10−5	< 1
400	0.7∗10−2	17	1.5*10−3	3
100	0.3	3586	5.5*10−2	720
5	38,495	np	7,700	

Table 4.1: System requirements for running the stochastic and deterministic dynamic programs with hedging in R. np is not possible with available computing power. Discretizations smaller than 10 taf/mo are likely smaller than those needed for operational purposes. These computational requirements are for one season with 15 stages as well as the forward-looking algorithm that approximates the stationary schedule for each possible incoming storage state.

Were the dynamic program modeled with explicit stochastic methods, than the computational requirements for each decision M of each state L of each time step t are that of Y, with Y being the chain of probabalistic outcomes for each possible combination of water year types. Here, for one year of 12 months, for example, with 5 hydrologic conditions, $Y = 5^{(12-1)} = 48{,}828{,}125$. To run a multi-year temperature control problem to convergence, for example, should convergence take 3 years, requires $Y = 5^{35}$ computations, which is an intractable increase of $5^{35} - 5 * 36 \approx 5^{35}$. Future research could formulate a feasible method for solving the explicit stochastic version of the temperature control problem. Here, all functions were vectorized in R to reduce computation. Binary user-inputs select the solution algorithm and other reservoir characteristics (e.g., capacity, grid size, exogenous information time series). The model and its components can be found on github account leladams.

4.4.3 Reservoir Temperature

For Shasta reservoir, monthly cold and warm pool reservoir temperatures are alias' of monthly warm and cold pool storage volumes. We built a reservoir temperature model based on a two-pool model conceptualization [Olivares, 2008; Rheinheimer et al., 2014]. The volume of each 50' stratified layer was computed with a hyposgraphic curve relating Shasta's temperature and reservoir elevation and then re-discretized to the grid size at which the model was being run. Mean warm and cold pool temperatures of each pool (the mean of the sum of each pool's layers) are significantly predicted by the volume of each pool. Monthly temperature

observations were aggregated from two-week measurements recorded for pre-Temperature Control Device Shasta Lake (1950 -1951, 1960-1974, 1976, and 1988 - February 1997) every 50' [Nickel et al., 2004]. Monthly layers were re-discretized to the selected model grid size and then each layer sorted into 'warm' or 'cold' water pools by a temperature partition of 52°F. Warm and cold pool temperatures are the average of the pool's layers (layers are aggregated before they are released from the Temperature Control Device). Layers lacking observations were interpolated from nearest-neighbors to create a lookup table from which cold and warm pool temperatures are approximated based on cold and warm pool volumes (Figure 4.3).

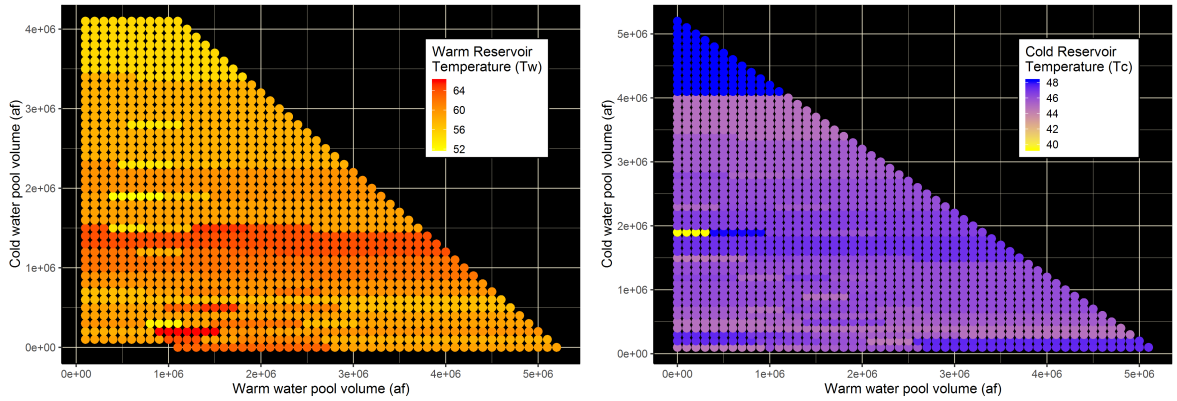


Figure 4.3: Average warm pool (left) and cold pool (right) temperatures for each combination of Shasta Dam warm and coldpool storage (af/month) when the historical record of observations is discretized by 10^5 af.

Cold pool temperatures have low variability; the temperature is almost always the same, regardless of pool volume. Within the range of available data, excluding the winter of 1985-1986, and three other months before installation of the Temperature Control Device for which cold pool temperatures were below 40°F, the average cold pool temperature of the raw data is 45.9°F with variability was less than 2% of the mean, 1.2 °F. The average cold pool temperature of all observations is 46.1°F with variability of 0.8°F, which is not statistically different than observed data: (Wilcox Test of the means (p=0.003) and F - test of the variances ($p < 0.5 * 10^-5$)), even though it significantly predicts it (p=0.005). Average warm pool temperatures have greater variability than average cold pool temperatures and depend on paired volumes of both the cold and warm pools. Warm and coldpool volumes have strong negative covariance ($-3.5 * 10^{11}$) as well as large standard deviations ($9 * 10^5$) and ($6.5 * 10^5$), respectively, resulting in a negative correlation (r = -0.6). Together the warm and cold pool predict warm pool temperatures for the historical data (p=1.2∗10^−5). Warm pool temperatures decrease most when the cold pool is largest, and to a lesser extent, when warm pool is large, or both cold and warm pool are small. Average warm pool temperatures include the epilimnion and metalimnion and are warm when cold pool is diminishing, between 0.5 and 1.5 maf of cold pool, which usually happens in mid- to late-summer of a dry year; warm pool is also slightly higher when the ratio of warm to cold pool is high and the cold volume is low. Using volume as a proxy for temperature also acts as a proxy for time of year, only certain combinations of pool volumes occur in certain months; with one exception between rare large end of summer cold pool storage and small very warm warm pools and large early spring cold pool storage with colder warm pools. An additional state variable for month would capture this difference, but, for this problem, not at the expense of additional computation time. Historically, the stratified season usually (with 67% frequency) starts in April and ends (with 77% frequency) with fall overturn in November, rather than December; consequently we model an April - October stratification season with November destratification for fall-overturn.

Based on these empirical relationships between cold and warm pool and cold and warm temperatures, a statisical data binning program was written to group each combination of warm and cold pool reservoir volumes. For the Shasta reservoir temperature problem, the continuous observations of warm and cold pool volumes were discretized into increments of 10^5 af between zero and Shasta reservoir capacity. The median temperature of each bin's observations represents that bin's cold and warm pool temperature. Historical

temperatures were significantly predicted from the lookup table approximations based on cold and warm pool volumes with $p < 2.2 * 10^{-}16$. Since not every reservoir volume has an observation, temperatures of bins lacking observations were generically imputed by bringing last or fist observation's forward, depending on the ordered position of reservoir volume according to neighbors and available data using R's generic locf function.

4.4.4 Release Temperature

Release temperature is the weighted average of the release temperatures from available cold and warm pool volumes. Available cold and warm pool is different than beginning of period cold and warm pool (V^c, V^w) since the pools include accumulated (e.g., $V^c + \Delta V^c$ and $V^w + \Delta V^w$). When available storage exceeds the reservoir capacity, then spill must occur. If the monthly available storage is less than the capacity of the reservoir, then the warm and cold temperatures are looked up from the cold and warm pool lookup table. If not, then if the warm or cold availability is greater than the capacity, the temperature of that volume is set to the maximum historical temperature; if the warm or cold availability is less than capacity, the temperature of that volume is found in the lookup table as the temperature assigned to that volume and its compliment. If the cold or warm pool volume is zero, than the temperature is zero; code improvements are required such that the temperature of only that volume is zero. Code for the release temperature lookup can be found on github account leladams.

4.4.5 River Benefits

The explicit benefit that is within control of reservoir operating decisions is release temperature, which consequently, in corroboration with geomorphology, creates cold water habitat to save wildlife, usually fish. For the Sacramento River-Shasta Reservoir system, the goal is to maximize the length of cold river habitat x below Keswick Dam, the after-bay impoundment of Shasta Dam across all stages. We define the temperature threshold for a "cold river" in two ways, and the "habitat" available at three downstream distances. We compared the consistency and frequency of achieving these targets, and the extent to which they are ecologically significant. Comparisons were developed with a stochastic standard operating policy built from a range of historical weather conditions.

Policy Goals for different Operating Approaches	
Temperature Goal	**Downstream Location of Goal (river miles (RM) below Keswick Dam)**
Monthly-Varying Constant	Clear Creek (13 RM) Ball's Ferry (26 RM) Jelly's Ferry (36 RM)

Table 4.2: Approaches for defining cold water habitat goals.

4.4.5.1 The Value of Monthly-varying Targets for Ecosystem Function

Current operating policy regulates the Sacramento River temperature threshold below Keswick Dam at a constant 13.3°C/ 56°F, although during a drought, e.g., during 2014-2016, the target temperature was raised to 56.75°F and even 58°F [sac, 2017]. We compared the success of two policy approaches, one with fixed temperature threshold targets (T^Z)(e.g., to create a perennial artificial coldwater river below Keswick Dam) and another with a monthly variable downstream temperature (T_t^Z) goal based on a monthly-varying ecological value. We selected a variable target to more closely mimic the natural thermal regime to benefit the downstream ecosystem in general, but specifically for the Winter-run Chinook (Figure 4.4).

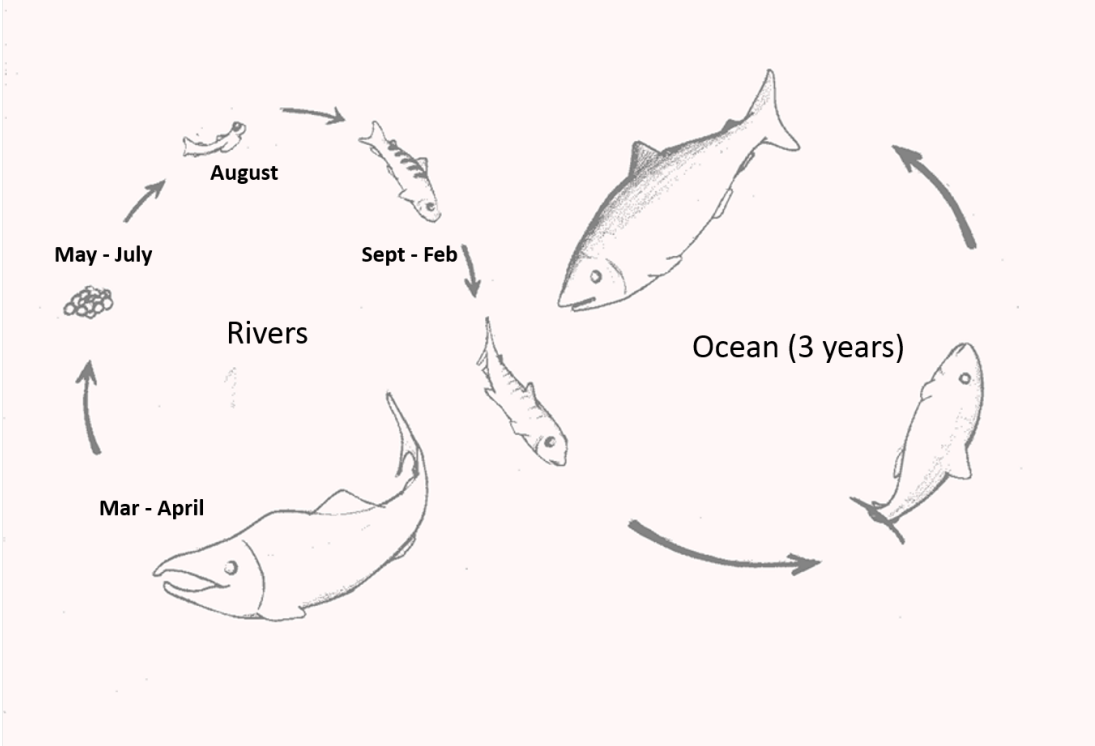


Figure 4.4: The life cycle of the Winter-run Chinook in the Sacramento River. Rendered by (Quiñones, 2013)

The Winter-run Chinook are not a perfect indicator of the river's status, but, in addition to having federal legal protection, they also indicate broader ecological health downstream. In that sense, the Winter-run Chinook are a flagship native fish that naturally evolved in the Sacramento River watershed and its natural temperature regime (cold spring-fed baseflow with cold snowmelt pulses in spring and warm summer rains). Temperature targets are focused on supporting the variable temperature demands of each life-history stage of the Winter-run Chinook (Table 4.3).

Fish Life History Stage	Months	Variable Temperature Threshold	Constant Temp Target
Returning Adults	March-April	18°C/ 64°F	13.3°C/ 56°F
Embryo Incubation	May- July	13°C/55°F	13.3°C/ 56°F
Emergents	August	20°C/68°F	13.3°C/ 56°F
Outmigrating Juveniles	September - February	19°C/66°F	13.3°C/ 56°F

Table 4.3: Variable thermal tolerances of Winter-run Chinook in California's Central Valley [Moyle, 2017][McCullough, 1999]. Constant thermal tolerances are the current operational temperature target.

Supporting the Winter-run Chinook, the variability of the Winter-run Chinook temperature needs (Table 4.3) offers more operational flexibility and potentially greater ecological welfare than meeting a constant temperature requirement.

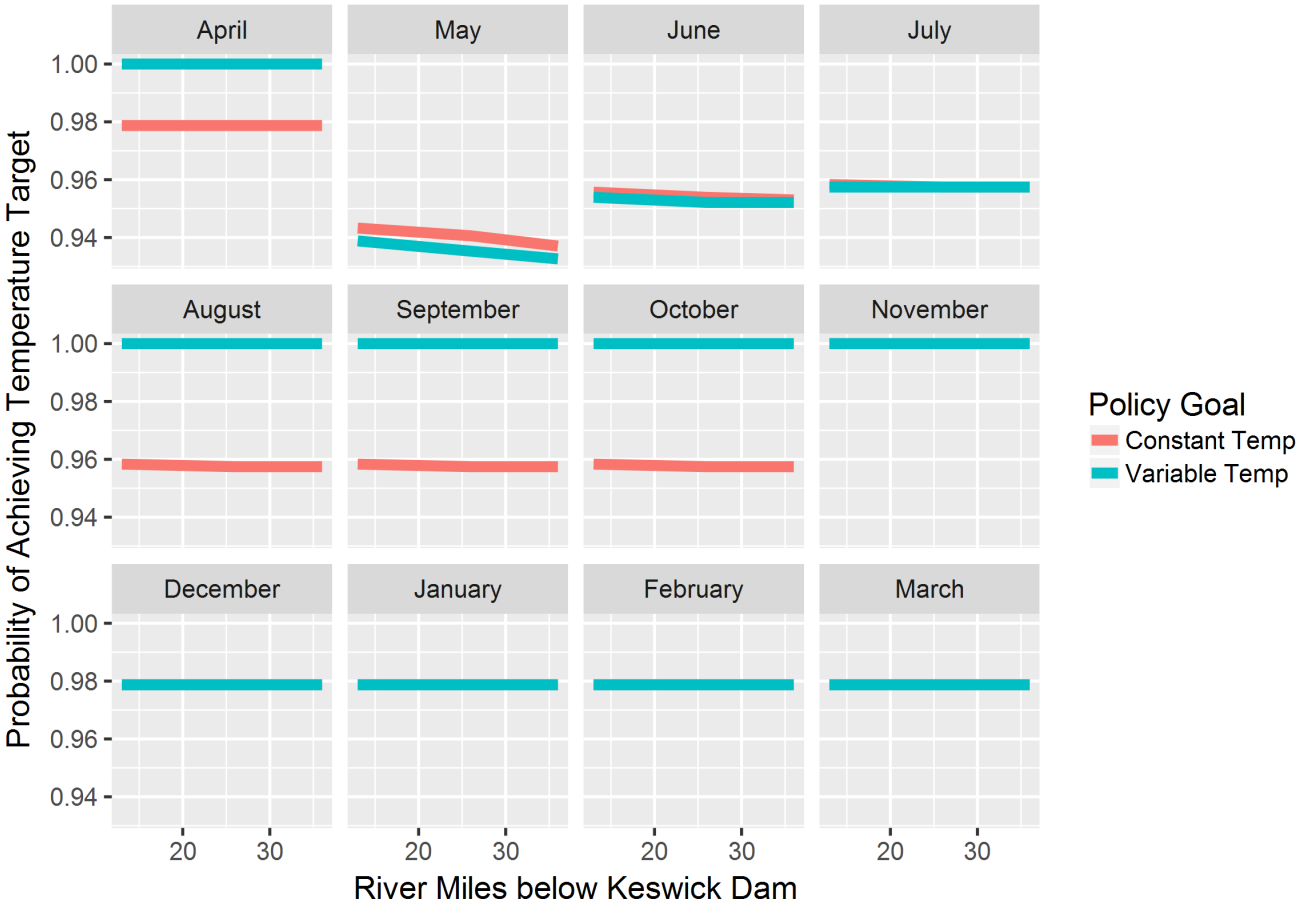


Figure 4.5: Probability of meeting temperature thresholds with constant and variable temperature goals per distance target for all possible states. Results were generated with a greedy operating strategy releasing water with resolution of 10^5 af/month (~1,500 cfs).

With the modeled results, both monthly-varying and constant temperature goals met their targets frequently, failing for only about 6% of years (a failed year is equivalent to the worst-performing month of all the year's months - failing in one month causes long-term consequences because of the memory of the river ecosystem). Any one month, however, is expected to fail only 0 - 6% of the time. Both temperature target types fail when the cold pool volume has been depleted or is tiny relative to the warm pool volume, particularly in May, if the incoming storage state is nearly all warm water.

Expected inflows are larger in May than the rest of the summer, so heavy warm May rains spill more often than June or July, and June more than July, causing more failures in May than June or July. Monthly-varying temperature goals are met more reliably than constant goals; particularly when the variable goal is less stringent than the constant goal, between August and October, and in April. Meeting the variable temperature target requires less storage and therefore offers more system flexibility. For example, the most conservative volume of cold water release required to meet each temperature target is:

$$\int_t (\min R_t^c | T_t^Z - \min R_t^c | T^Z) dt \tag{13}$$

during the stratified season, between April and October at 300 taf/season (with a grid size of 100 taf) with the variable target and 800 taf/season with the constant temperature target. The variable temperature target approach uses less stored water. And although the monthly-varying approach eliminates Winter-run Chinook that can spawn in August, it is also more meaningful from the Winter-run Chinook perspective. The constant temperature goal is too hot for embryos in early summer and unnecessarily cold during the rest of the stratified season, often providing water beyond Winter-run Chinook demand, and other times underproviding for their temperature needs. Ignoring the temperature requirements of the priority river species wastes cold water that could be saved for next year's cohort or later seasonal contingencies. The remainder of this paper employs a variable temperature target approach.

4.4.5.2 River Miles of Cold River Habitat

Current Shasta Reservoir operating policy also states that the location where temperature thresholds must be achieved changes every two-weeks to either Ball's Ferry (26 miles downstream of Keswick) or Clear Creek (13 miles downstream of Keswick) depending on which location seems most attainable at the beginning of each two-week period [sac, 2017]. Effectively, this makes the goal Ball's Ferry, although that can change if a two-week forecast indicates that it is better to hedge the target to Clear Creek. Hedging to meet a stationary downstream location could prevent the short-term benefit of large cold water releases when cold water storage is abundant, but at the expense of storing the abundance for times of cold water scarcity and consequently consistent delivery of cold river water goals. Although Winter-run chinook have spawned as far downstream as Red Bluff Diversion Dam [Martin et al., 2001], we compare policy outcomes with three downstream targets (Clear Creek, Ball's Ferry, and Jelly's Ferry (36 miles downstream of Keswick) since the vast majority (an average of 95%) of fish spawn above Clear Creek ([Calfish, 2018]). Outcome variables are continuous so intermediate target distances can be met in addition to the final distance goal (e.g., possible to meet Ball's Ferry when aiming for Jelly's Ferry).

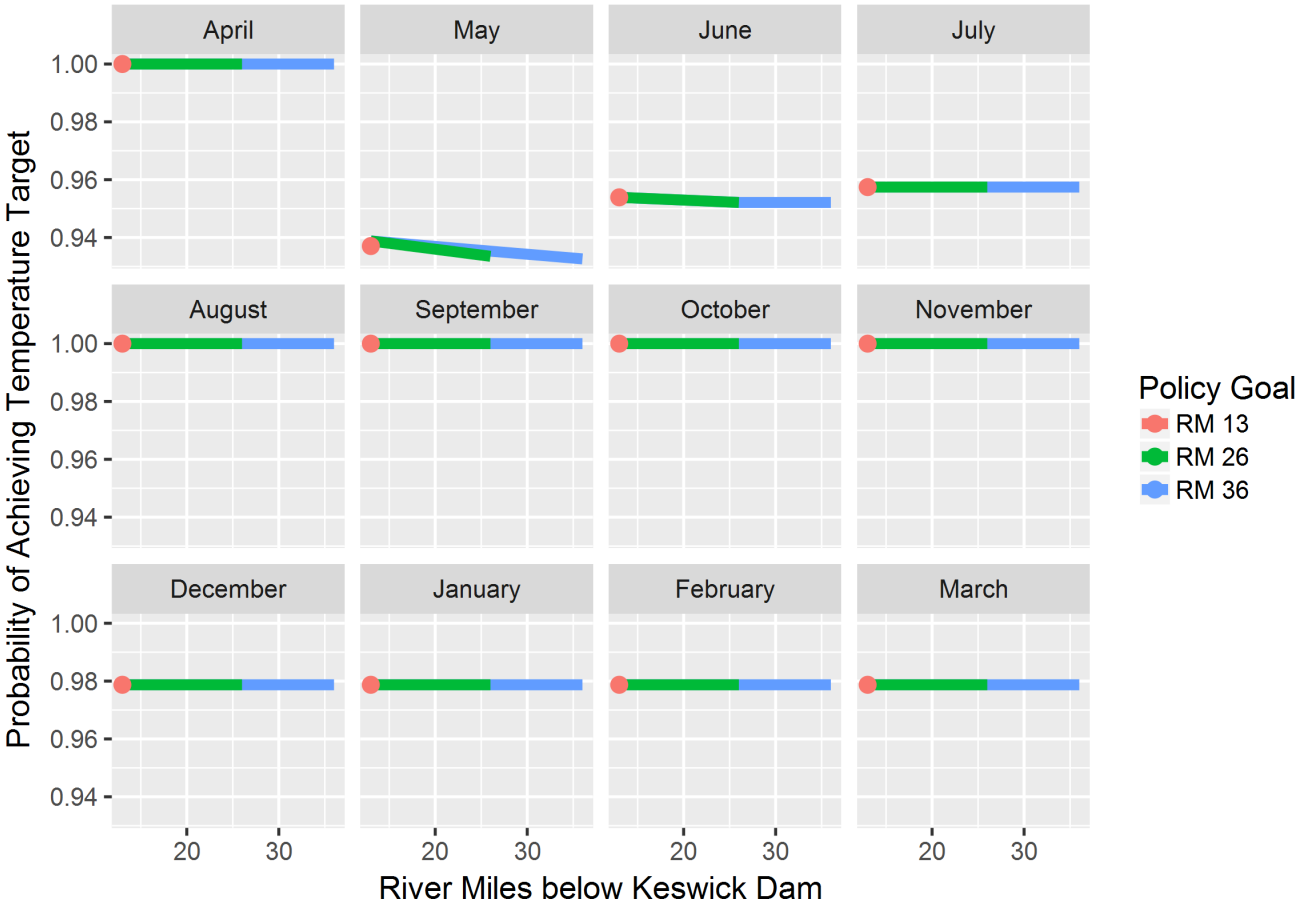


Figure 4.6: Probability of meeting temperature thresholds with variable temperature goals for each of the three target locations (Clear Creek, Ball's Ferry, and Jelly's Ferry, 13, 26, and 36 miles, respectively, from Keswick Dam) for all possible states in the immediate period. Results were generated with a standard operating policy releasing water with resolution of 100 taf/month (about 1,500 cfs).

We found that downstream targets have the same minimum annual cold water storage requirement,

$$\int_t x_t | \min R_t^c | T_t^Z \, dt \tag{14}$$

Results indicate that target location has little influence on providing cold water habitat for each month. Each location still requires 300 taf/season of cold pool storage, 100 taf in each of May - July, and none otherwise. Perhaps more importantly, few Winter-run chinook spawn below Clear Creek, so operating for temperature above Clear Creek is the priority. For the remainder of the chapter we use a distance target of 13 river miles and a monthly-varying temperature operating approach because it uses less storage, targets the specific ecological problem and requires less computation time than further downstream targets.

4.4.6 Temperature Management Release Requirements

Optimized cold and warm pool release schedules for each possible combination of warm and cold pool states requires more water with a constant temperature approach during the stratified summer months of May - September than with a monthly-varying temperature approach, independent of the downstream location target.

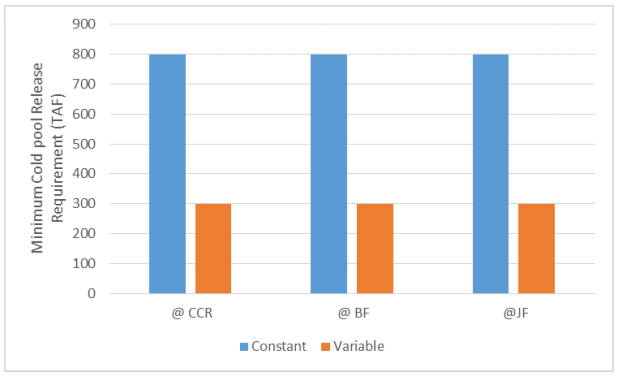


Figure 4.7: Minimum cold pool requirement for a constant versus a monthly-varying temperature goal, excluding spill at Clear Creek (CC), Jelly's Ferry (JF) and Ball's Ferry (BF).

4.4.7 River Temperature Modeling

Statistical regression, rather than a physical-process based model, was used to predict downstream temperatures based on Shasta Dam release temperature because of the high correlation between monthly air and water temperatures [Benyahya et al., 2007], because surface heat-flux effects are often negligible for large monthly time-scales, and because statistical regression is more computationally efficient (and sometimes more accurate) than more physically based models. A first-cut full statistical model was built to predict the maximum Sacramento River length under a defined temperature threshold given Shasta Dam release temperature, release flow, release month, and monthly air temperature. The final functional form of the selected Generalized Linear Model reduces the number of control variables for this problem as much as possible; all final models significantly predict river temperature by release temperature alone. Details are in the Appendix.

4.5 Results

We apply our method to temperature control for the Shasta Dam-Sacramento River system for an expected probability distribution of weather conditions (based on the joint probability of inflow and ambient temperatures of the historical record) and the range of incoming April storage conditions, including even below empty until capacity. We solve the problem for Shasta Dam with i) the maximin stochastic dynamic program developed in Chapter 3, ii) a greedy stochastic standard operating policy, and iii) a stochastic dynamic program. Results here differ from Chapter 3 because they use a finer computational discretization (100 taf). The greedy standard operating policy emulates the current policy approach to temperature management, generally speaking, and maximizes current benefits, irrespective of the future or past. The dynamic program maximizes net benefits including from the future and the past, but irrespective of the order of poor outcomes or avoiding a worst-case outcome (see Chapter 3 for further details and model formulation) and the maximin dynamic program minimizes possible loss and maximizes net benefit for both the short- and long-term.

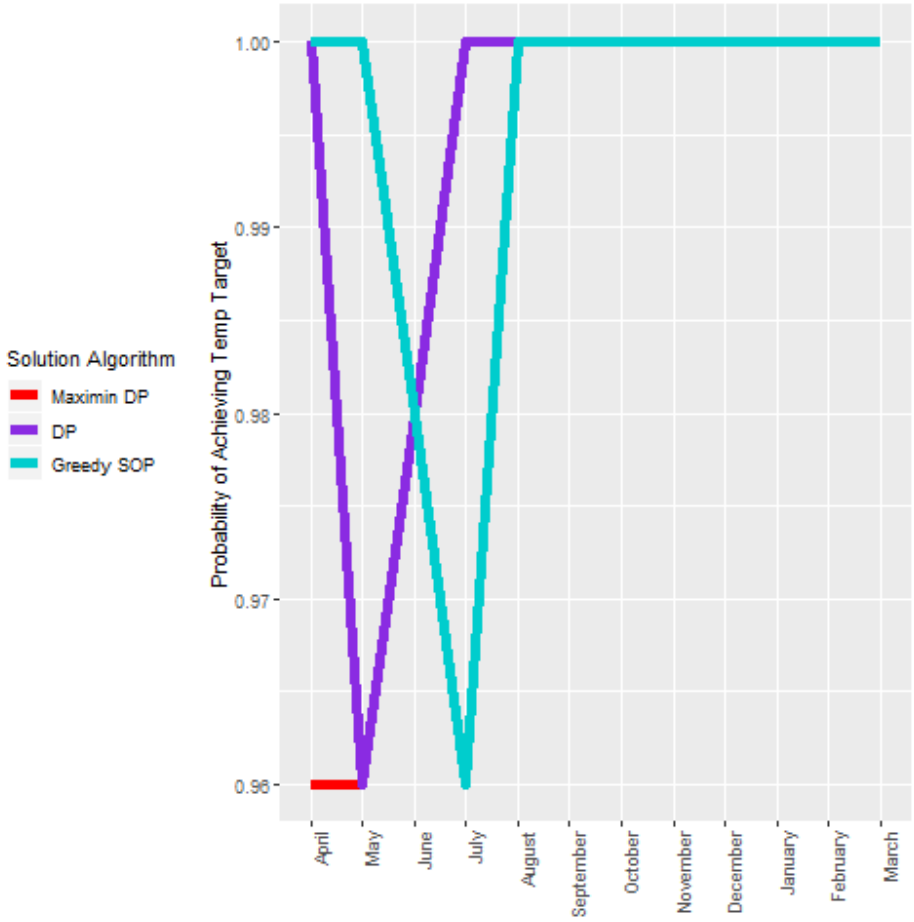


Figure 4.8: Probability of meeting temperature thresholds for each optimal policy approach with a stochastic range of weather conditions for each of three solution algorithms that optimize release temperature and volume from Shasta reservoir for the Sacramento River. Monthly-varying temperature goals were set for Clear Creek, 13 miles downstream of Keswick Dam, for all possible states in the immediate period. Results were generated for each incoming storage state of a resolution of 100 taf/month (about 1,500 cfs) between empty and a full reservoir capacity. Results are different than those of Figures 5 and 4.5 because this compares only optimal policy schedules for each incoming April storage state, Figures 5 and 4.5 are based on all possible states of each month, regardless of whether or not they are part of an optimized annual policy.

Meeting monthly-varying downstream temperature targets until Clear Creek, for an expected value of historical weather conditions, requires the same volume of water for all three solution algorithms to find the optimized release schedules - although the monthly timing of failures differ. All solution algorithms met downstream cold water habitat requirements for all months for 96% of all (0 to capacity) incoming April storage conditions, and consistently at the end of the year. Failures occurred for all three strategies for some months during the embryo stage between April and July when incoming April storage is less than 300 taf - less than non-operational deadpool storage at Shasta reservoir (550 taf). The standard operating policy operates only for the immediate benefit and consequently fails near the end of embryo season from running out of water - potentially wasting April and May storage on unsustained cold river miles. The policies with the recursive function, the stochastic dynamic program, or the maximin stochastic dynamic program, hedge for temperature in April and May to conserve storage. The maximin hedges to avoid long-term risk, in flow or temperature, and consequently hedges in April, so benefits are hedged over time and no water is spent on unsustainable cold water habitat. The stochastic policy does not hedge in April since sufficient water is available.

4.5.0.1 Hedging for Weather

Cold water pool management must be managed throughout drought, particularly when the expectation of drought is uncertain or could likely span multiple years.

Stochastic Solutions Optimized release schedules were produced with drought-weighted forecasting (p = 0.5, 0.25, 0.15, 0.05, 0.05 for joint probabilities of inflow and temperature with extreme drought, drought, mean, wet, extreme wet, respectively) and extreme drought and weather-weighting (p= 0.9, 0, 0, 0.09, 0.01) for all incoming April storage conditions. Weights were assigned to skew management and release decisions to favor drought risk management and storage conservation. Drought weights help address the flood bias in release schedules from the positive skew of the magnitude of expected inflows from wet-cold years. For Shasta reservoir, drought weighted cold water habitat provision results do not vary from expected value results (Figure 4.8). Weather forecasting did not affect temperature management decisions because there is always enough water to manage for temperature control in the Sacramento River, even during drought. Uncertainty in weather is not significant enough to affect meeting downstream cold habitat requirements alone.

Deterministic Solution Optimizing operational decisions for the worst-case set of system inputs - for inflow and air temperature with a joint exceedance probability of 1%, fails to meet cold water habitat requirements with the same probability distribution as all the stochastic model runs. Extreme drought was synthetically produced from the joint probability of inflow and temperature of the historical record (Figure 4.4).

	April	May	June	July	August	September	October	November	December	January	February	March
Inflow (taf)	200	300	200	100	200	200	100	200	200	200	200	300
Air Temperature (F)	63.7	74.8	81.5	84.9	84.7	80.6	69.3	55.9	50.7	54	55.5	60.8
Year of Record	1990	1992	2014	2014	2012	1991	2015	1991	1989	2014	1991	2015

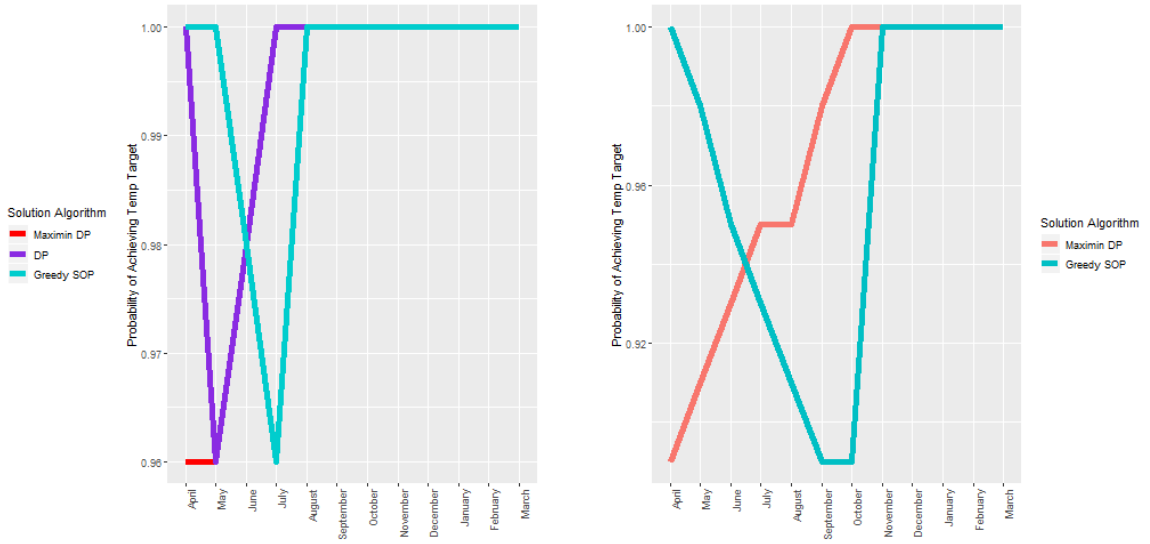
Table 4.4: Years and observations of joint exceedance probability of inflow and ambient temperatures for 1% extreme drought (1985-2016).

The fish require low volumes of water (when coupled with intentional fish habitat). Even during a synthetically produced extreme drought, more extreme than seen to date with the historical record - the minimum required monthly release to meet temperature control delivery requirements is less than expected inflow (less atmospheric losses). Each month, minimum water demand is 100 taf - either of cold or warm pool storage (although more than 100 taf can still meet temperature requirements too, e.g., releasing 500 taf of cold and 100 taf of warm from storage conditions of 3.5 maf of cold pool storage and 200 taf of warm pool storage). A minimum of 300 taf of cold water pool storage (with cold and warm pool separated at 52°F) is required between May and July for the redds; the demands of the other months are met with warm

pool alone. In April and between August and October (water demand of 400 taf) inflow between April and October (e.g., snowmelt and spring flow) exceed demand by 500 taf in an extreme drought - which is enough to sustain between November and March (demand of an additional 500 taf). Therefore, when isolating temperature control operations, with this proposed monthly-varying temperature goal to Clear Creek, Shasta reservoir only fails to meet cold water habitat requirements when initial conditions are below deadpool - not because of weather conditions. Should future weather conditions become drier and hotter than those synthetically produced here, with available summer inflow (inflow less atmospheric demand) less than 900 taf, for example, then weather could become a barrier for providing cold water habitat downstream of Shasta reservoir.

4.5.0.2 Hedging for a River Temperature Goal

While the choice of weather forecasting does not affect results, there is a difference, both in the ability to meet downstream temperature targets as well as in the storage requirements of meeting these targets, between the monthly-varying temperature policy proposed here (monthly-varying temperature goals from Keswick Dam until Clear Creek, Figure 4.9a) and the more stringent cold water habitat requirements intended to reflect current Shasta reservoir operations (with a constant temperature goal of 13.3°C/ 56°F from Keswick Dam until Jelly's Ferry, Figure 4.9b). Optimized release policies solved for the monthly-varying approach met river temperature targets for 96% of incoming storage conditions (2/46 incoming storages: 100 and 200 taf); the constant approach met its downstream temperature objective 89% of the time.



(a) Monthly-varying temp goal until Clear Creek.

(b) Constant temperature goal until Jelly's Ferry.

Figure 4.9: Probability of optimized policies meeting downstream temperature target with two different downstream temperature goals modeled with a probabilistic expectation of a range of weather forecasts.

The constant temperature operating approach fails more often than the monthly-varying approach because it is more stringent and requires more storage. Assuming an expectation of a stochastic range of incoming weather conditions, the constant temperature approach requires incoming April storage of 500-600 taf to avoid failure whereas the monthly-varying temperature approach requires only 300 taf. While this difference shows an advantage of the monthly-approach, in practice the difference is mostly meaningless; the dam cannot operate below deadpool. Even though the constant approach provides colder water in fall and the variable approach in early spring, both operational strategies essentially always meet their operational goals as long as Shasta reservoir storage is above deadpool. The discernable difference between these choices, therefore, is their biological basis (which temperature choices are appropriate) and their storage requirements (which matters most inter-annually) and not their ability to achieve downstream temperature targets.

4.5.0.3 Hedging for Storage Conservation

The advantages of the maximin algorithm (over the greedy algorithm) and the monthly-varying target at Clear Creek (over the constant target at Jelly's Ferry) are that they both optimize release schedules to provide cold water habitat downstream within a season, and, by conserving storage, between years. In Shasta reservoir, enough water is always available to meet cold water habitat requirements (with initial storage conditions above deadpool) when cold water habitat requirements are considered in isolation, without other water release demands, even with a forecast of extreme drought, regardless of operational approach (e.g., solution algorithm, downstream target).

The Converged Schedule for the Expected Value Stochastic Maximin Dynamic Program With the expected value of the maximin solution algorithm, which considers all expected weather conditions, the stationary operating policy converged after 1.5 years. After convergance, expected cold pool storage always exceeds 2.1 maf (Figure 4.10). As anticipated, warm pool storage grows from April to November before all the warm pool becomes cold when the reservoir flips and mixes in November or December. Cold pool storage diminishes throughout the summer and builds again during the cold winter and early spring. With optimized schedules, cold releases never exceed 100 taf during the summer after the schedule has converged. Releases in general are much larger during the winter.

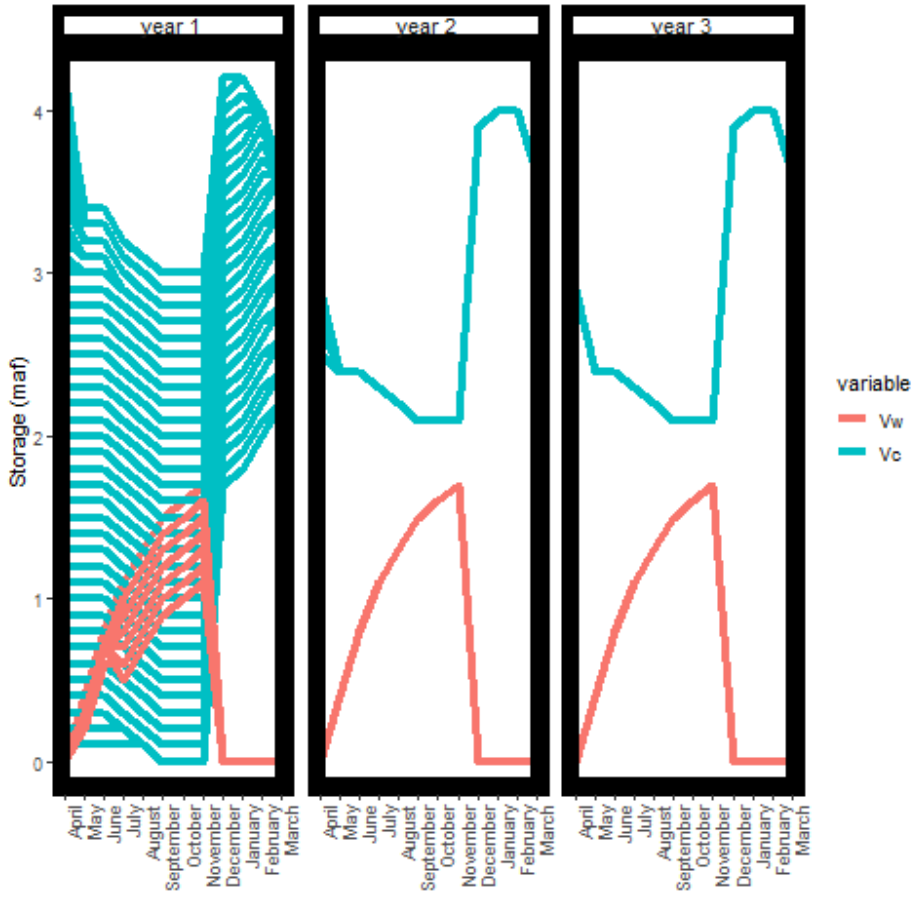


Figure 4.10: Expected cold (Vc) and warm (Vw) pool storage for the range of possible initial April cold storage conditions when operating with optimal policy. Results were created with discretization of 100 taf with variable temperature and Clear Creek downstream goal with a drought weighted objective function and the maximin solution algorithm. Model convergence occurred after 1.5 years.

Expected final storage volume with the converged schedule ranges between 2.2 and 2.8 maf - well within the range of historical average monthly carryover storage conditions.

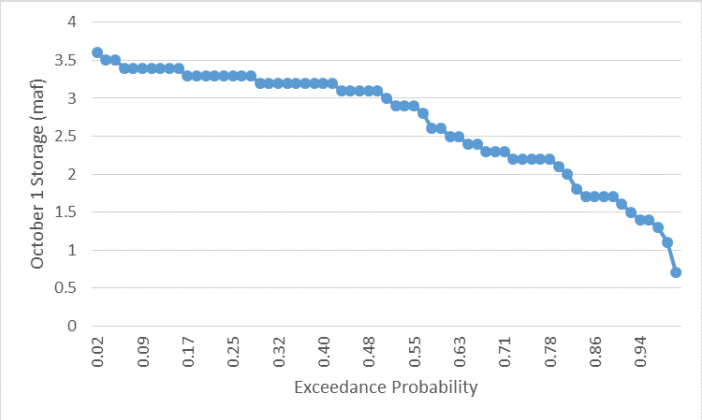


Figure 4.11: Historical incoming October storage conditions.

Drought forecasted Deterministic Policy Schedules Even with multi-year predictions of extreme drought, operating the reservoir only for temperature did not fail, even after multiple years, as long as year one initial storage exceeds deadpool - although storage depletion was less with the monthly-varying than with the constant temperature targets (Figure 4.12).

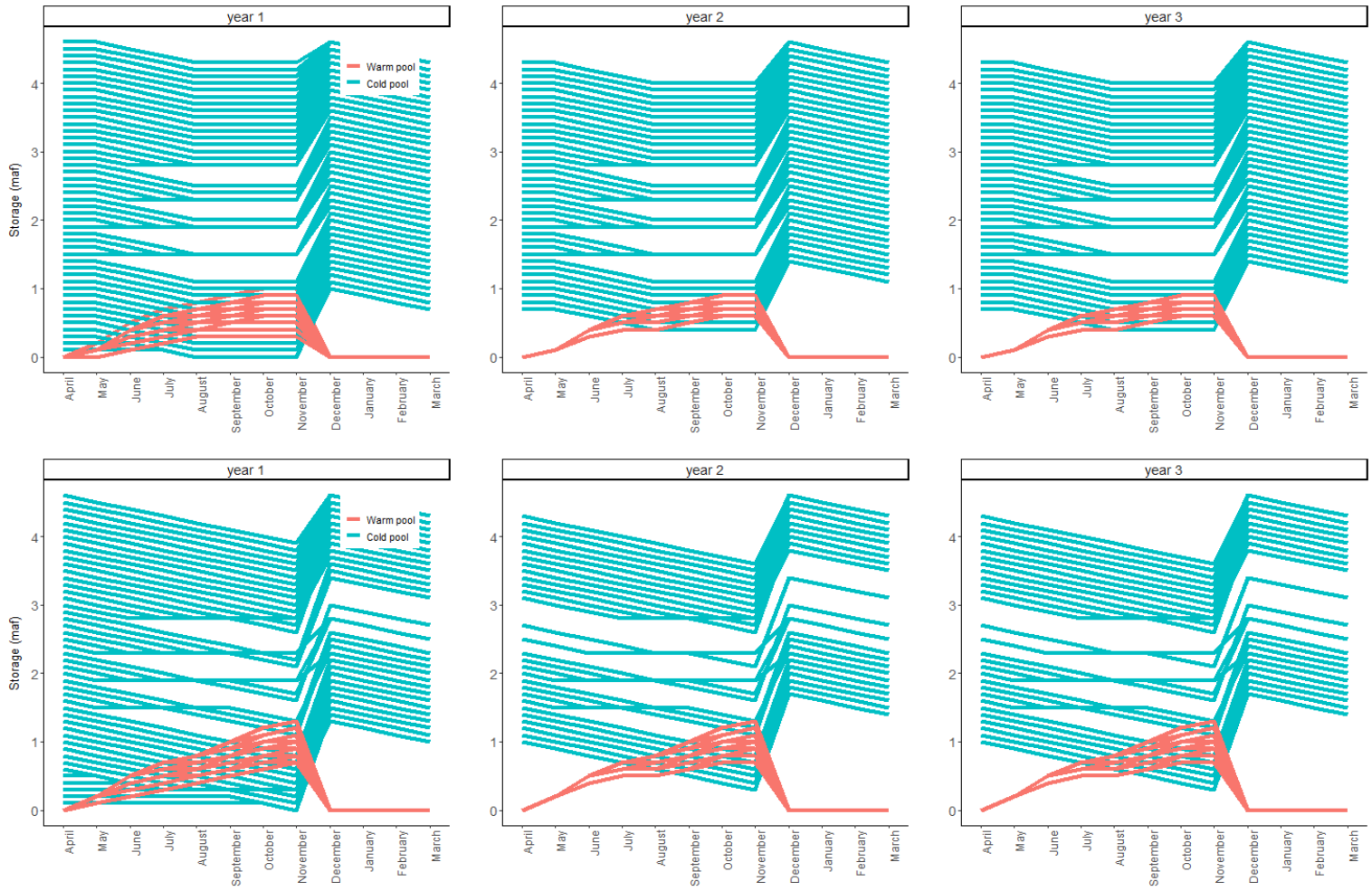


Figure 4.12: Expected storage of cold pool (V^c) and warm pool (V^w) with an optimized release schedule solved with a deterministic maximin dynamic program for a range of incoming April storage conditions (range zero to capacity) and an expectation of extreme drought to meet a (top) monthly-varying temperature requirement or (bottom) a constant temperature requirement, at Clear Creek. Downstream delivery demand excluded.

4.5.0.4 Hedging for Competing Purposes

Including water deliveries for non-habitat purposes in this temperature control model is vital for finding an optimal temperature control solution. The magnitude of delivery requirements often exceeds inflow (Figure 4.13). Between April and June expected delivery demand exceeds incoming expected wet year inflows and in late summer expected delivery demand exceeds inflow of even a cold-wet flood year with exceedance probability of 99%. Monthly delivery requirements meet or exceed downstream temperature demand volumes in all months.

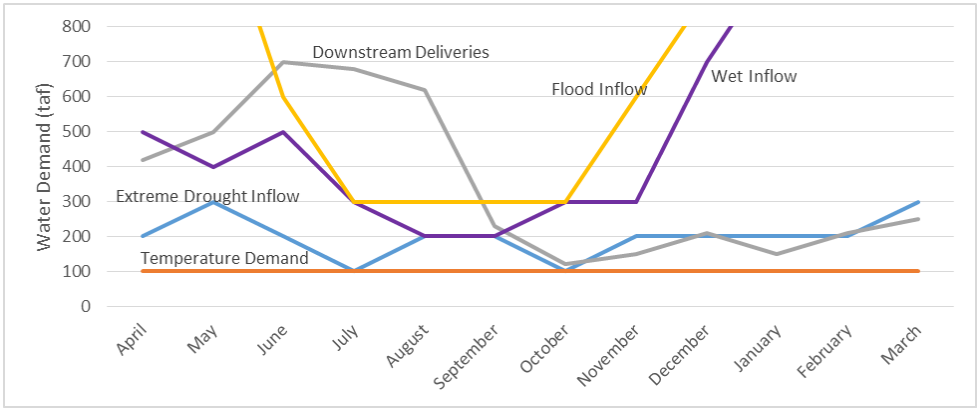
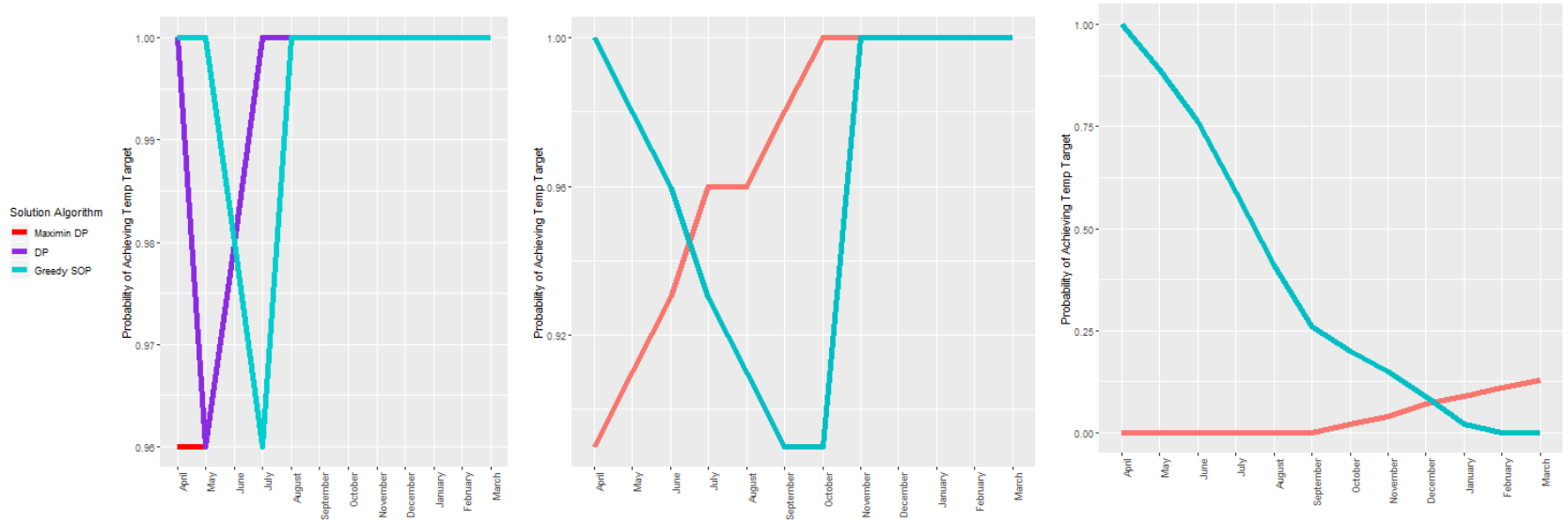


Figure 4.13: Expected inflow to Shasta reservoir during an extreme drought, the minimum monthly storage requirement to meet downstream temperature goals, and expected delivery requirements below Shasta Dam. Demand volumes are provided independently of their required temperature.

Diversions are modeled as constraints, not as part of the objective function. Release decisions prioritize diversions for other water supply purposes (e.g., agriculture, Delta outflow) over (downstream) temperature based environmental flow. Diversions are allocated from the warm and then the cold pool, according to storage availability. Deliveries are modeled as mean monthly Shasta releases before the Endangered Species Act was put into place requiring temperature-specific flows (CDEC, 2018). We compare the probability of meeting cold water habitat temperature goals for increasingly difficult-to-achieve targets with the maximin and greedy solution algorithms for (a) the monthly-varying temperature goals to Clear Creek, (b) constant temperature goals to Jelly's Ferry, and (c) constant temperature goals and delivery goals to Jelly's Ferry. Modeling inflow as a deterministic time series of extreme drought isolates weather conditions to focus results on the highest priority concern situation.



(a) The probability of meeting monthly-varying temperature requirements at Clear Creek.

(b) The probability of meeting constant temperature requirements at Jelly's Ferry.

(c) The probability of meeting all water supply delivery goals and constant temperature requirements at Jelly's Ferry.

Figure 4.14: Expected likelihood of meeting monthly temperature requirements with an optimized release schedule for a range of incoming April storage conditions (range zero to capacity) with an expectation of extreme drought with three different goals (a,b, and c).

With a greedy algorithm larger cold pool volume conditions provide more cold water habitat; 1 maf gives 2 months of cold water habitat, 2 maf gives 4, and 3 maf provides 5 months. But even when the reservoir is filled to capacity, insufficient storage is available to meet cold water habitat requirements for all consecutive months of a year (April to March), in extreme drought. With the maximin dynamic program algorithm enough storage is available to provide cold habitat from April to March only when incoming April storage is near or at capacity. Regarardless of the solution algorithm or policy choice, with full water demands and an expectation of extreme drought the reservoir always fails by the second year and does not recover (Figure 4.15).

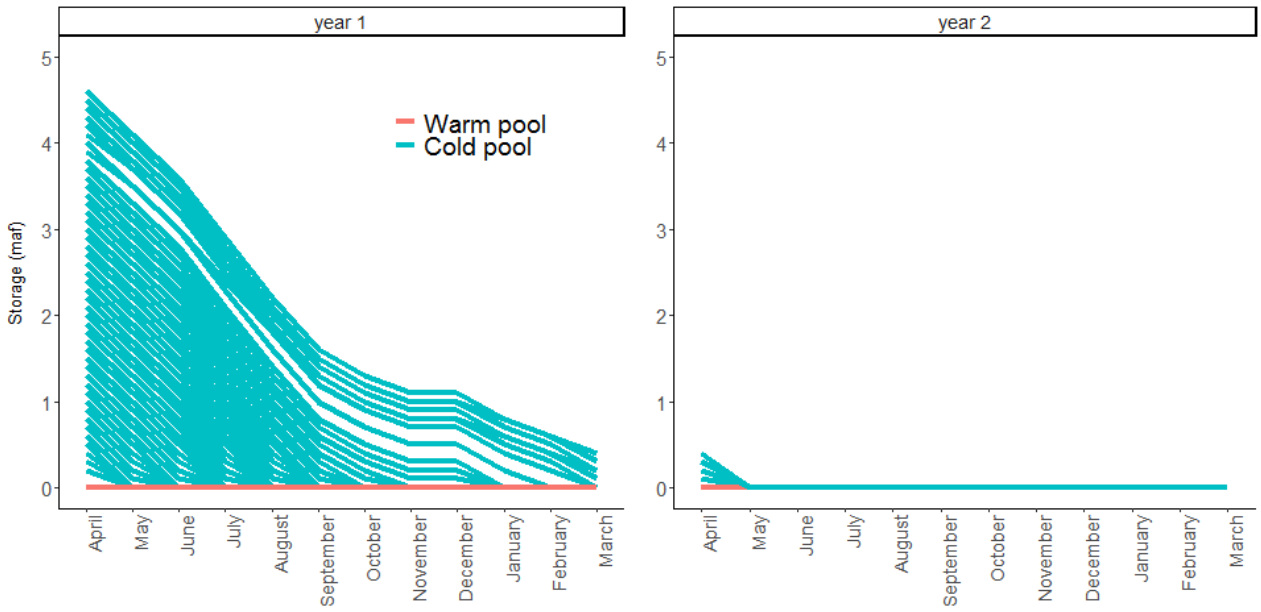


Figure 4.15: Expected storage of cold pool (Vc) and warm pool (Vw) with an optimized release schedule solved with a deterministic maximin dynamic program for a range of incoming April storage conditions (range zero to capacity) and an expectation of extreme drought to meet a monthly-varying temperature requirement at Clear Creek when meeting downstream delivery demand and temperature demand.

To stay above deadpool and meet temperature control requirements during an extreme drought, some delivery curtailment is required. Curtailing deliveries during extreme drought is part of expected regulatory protocol. Larger curtailments afford meeting one season of downstream temperature targets more often.

For multi-season analyses, however, even with curtailments of at least 50%, the reservoir fails by the end of year 2. Missing downstream fish temperature targets is not a function of fish demand, but rather of meeting downstream water delivery demand - and potentially trying to keep higher flows that meet delivery demands cold enough for fish.

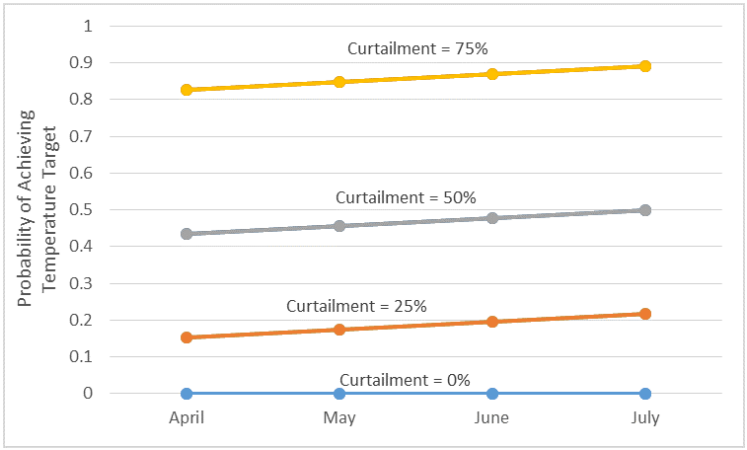


Figure 4.16: The probability of meeting the temperature target when operating with the maximin dynamic program and a monthly-varying temperature threshold to Clear Creek, with different percentages of curtailment.

When operating during extreme drought with delivery curtailments of 75% and the maximin algorithm, we also start to see the value of operating with a hedging philosophy compared with operating with a greedy philisophy (Figure 4.17). The greedy algorithm performs better than the maximin approach when incoming storage is large and worse than the maximin when incoming storage is small. In exchange for the success at the large volumes, operating with the maximin dynamic program offers stability and long-term reliability. With the monthly-varying approach and drought curtailments of 75% on diversions (Figure 4.17), however, the system can sustain multi-year drought. With the greedy algorithm, incoming storage below 800 taf depletes the reservoir by year 1, 1.6 maf depletes by year 2, and 2.6 maf depletes by year 3. With the maximin algorithm, in contrast, storage is completely depleted for all three years when incoming storage of year 1 is below 200 taf, which is anyway non-operational since it is below deadpool.

Further curtailments and knowledge of a forecast for wetter, colder weather (e.g., less intense drought or average conditions), or lfor adaptive forecasting (explicit stochastic forecasting) could also make it easier to meet both cold water habitat requirements and downstream deliveries more frequently.

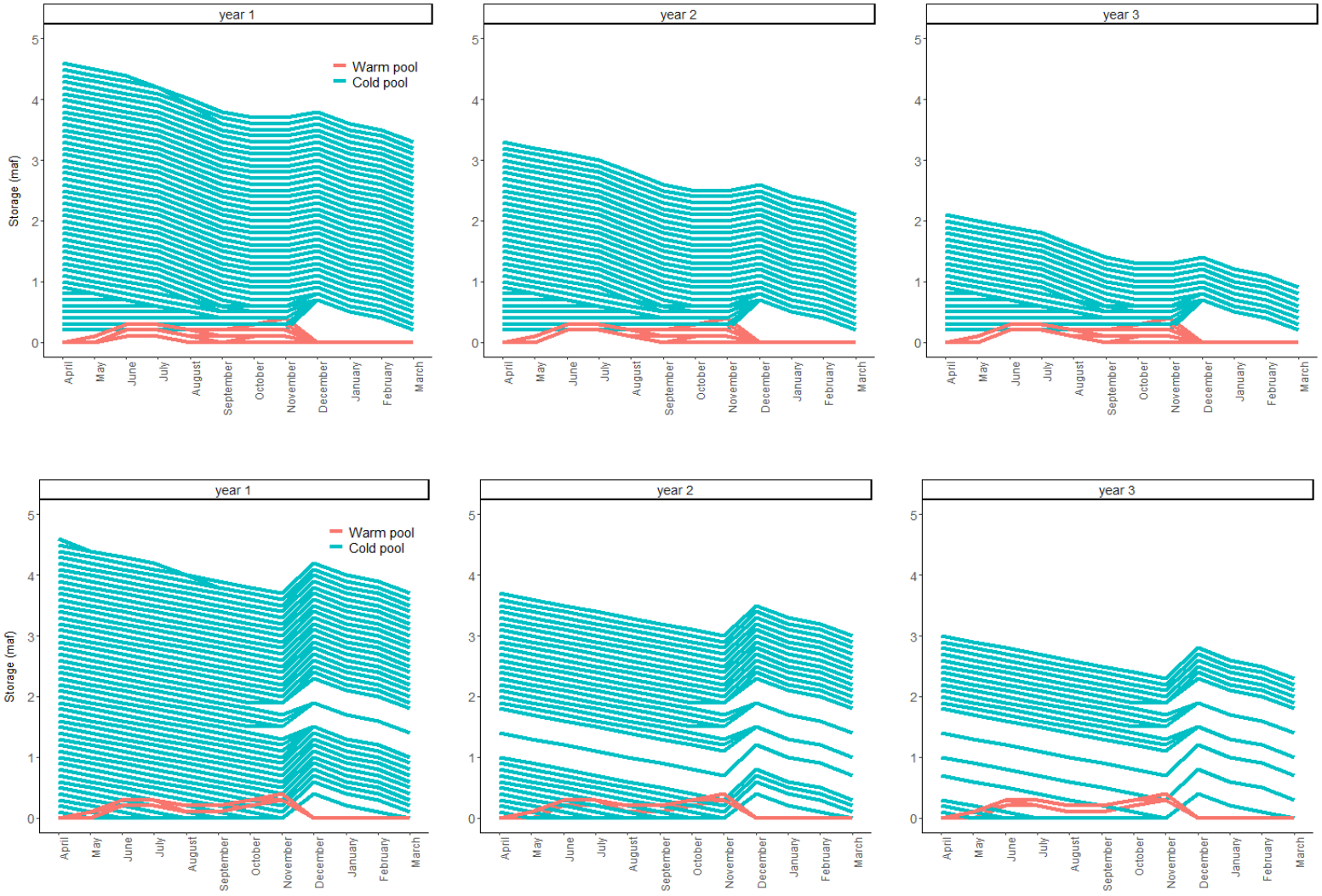


Figure 4.17: Expected storage of cold (V^c) and warm (V^w) pools with an optimized release schedule solved with a (top) maximin dynamic program and (bottom) a greedy standard operating policy for a range of incoming April storage conditions (range zero to capacity) and an expectation of extreme drought to meet a monthly-varying temperature requirement at Clear Creek and meeting 25% of downstream delivery demand.

4.5.0.5 Hedging for Risk

Risk, by definition, is the probability of failure multiplied by the damage from that failure. Failure in temperature control is often from storage depletion, or as measured here, failure to provide cold water habitat length - but in some cases, failure also could be measured in a species-specific indicator, such as fish mortality. Here, we post-process expected fish mortality from operating with the maximin dynamic program versus the greedy operating policy for each of the three downstream goals: a monthly-varying temperature goal, a constant temperature goal, and a monthly-varying temperature goal with deliveries. Expected monthly fish population information is from 2003-2017 surveys of carcasses of chinook adult. Adults are predominantly observed to finish spawning (deposit new redds) in July, and die after they spawn.

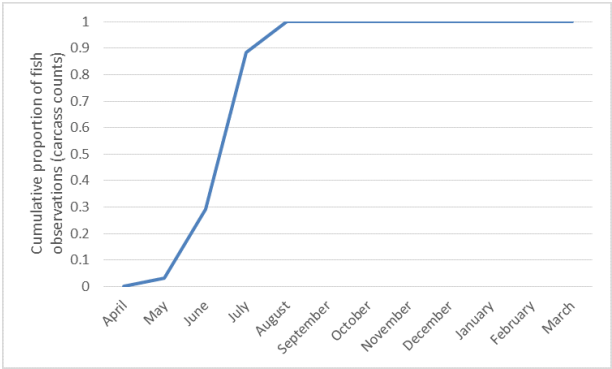


Figure 4.18: Expected cumulative monthly fish population density [Calfish, 2018].

The probability of the system failing from failure to deliver cold water habitat depends on the fish population presence and cold water habitat availability of this period $p_t^{fish} * \int_{t-1} p^{failure}$, based on weighted expectation of the proportion of the fish population p_{t-1}^{fish} by the probability of failure of the previous period $\int_{t-1} p^{failure}$.

$$p_{t-1}^{fish} * \int_{t-1} p^{failure} + p_t^{fish} * \int_t p^{failure} \tag{15}$$

With the greedy algorithm, fish are sometimes "saved" temporarily that can not be sustained for the entire year, wasting stored water. This is particularly the case when optimizing to meet full deliveries and downstream temperature goals. When meeting full downstream deliveries during drought, for example, no fish will ultimately be saved, but the greedy policy uses storage to try and save them temporarily (and sometimes futilely). The greedy policy will temporarily grow and then kill about 1,500 fish. The maximin dynamic program, in contrast, under dire conditions, recognizes the impending doom, saves no fish, and conserves storage for next year.

When solving the temperature control problem at Shasta reservoir with the maximin solution algorithm for extreme drought and delivery curtailments of 75%, enough water is available to meet river temperature goals and save some fish. Here we see the logic of operating with hedging for temperature control. With a greedy policy, more fish are expected to be saved early in the season, but as the reservoir depletes, populations decline. In contrast, with the maximin solution algorithm, the expected population of Winter-run Chinook saved in early months is sustained throughout the season, through all fish development stages, to migrate out to the ocean around March (Figure 4.19). By conserving storage, the maximin performs better for both expected water storage and fish population size.

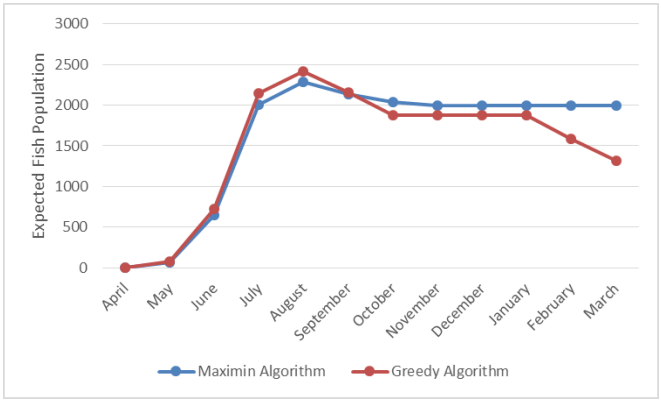


Figure 4.19: Expected fish population for cold water habitat allocation decisions made with maximin and greedy operating strategies for extreme drought. Each scenario must first allocate water supply for other users before allocating for temperature. Temperature goals for the maximin are monthly-varying for 13 river miles, to Clear Creek, and for the greedy alogorithm, a greedy 36 miles to Jelly's Ferry. Fish population surveys are from [Calfish, 2018].

The United States Congress is potentially willing to pay $1.3 billion to raise Shasta Dam for the Winter-run Chinook [Lochhead, 2018]. Surveys estimate about 2,500 Winter-run Chinook per year below Keswick Dam - this implies a value of avoiding damage to Winter-run Chinook of $500,000 per fish. The cost of operating Shasta Dam with the hedged maximin dynamic program and the current Winter-run Chinook hatchery below Keswick Dam is less than 1% of the cost of the Shasta Dam raise (about $1 per fish [dam, 2016]), and still a significant population are expected to survive, even in extreme drought.

4.5.1 When to Hedge

Temperature management schedules developed with a maximin solution algorithm find the global solution for every state of each stage. This means the program produces optimized release decisions (Chapter 2, Equations 7-9) that benefit not just the optimal policy over time, but the contingent policy too - for when operators find themselves at the beginning of a month with an unanticipated storage state. This is important because the non-stationarity of human decision making and natural events (e.g., forest fire, weather) often leaves a reservoir in an unpredicted, or even sub-optimal state. For this reason, analysis of the fraction of states of each stage for which a solution meets stakeholder performance expectations (in this case, cold water habitat), or in other words, the fraction of satisficed states [Herman et al., 2014] (which includes sub-optimal states) is potentially more useful than analyzing the fraction of stationary schedules that meet stakeholder performance expectations.

Here, we visualize the expected present value (cold habitat river length) of operations with the greedy standard operating policy and the maximin policy. Here, the visualization is both a release guide (communicates the value of each warm and cold pool release choice combination for each warm and cold pool state) and a means of communicating when hedging occurs with the optimized release schedule (maximin solution algorithm instead of greedy standard operating policy). With the maximin solution algorithm all solutions for each state of each stage (e.g., the minimum release with the maximum value) are satisficing, with the greedy algorithm and the dynamic program, they are not. Within the displays, each colored dot is a feasible release for a feasible incoming warm and cold pool storage state for each month. Blanks indicate either a) releases not within the set of discrete state and release combinations we model here, or, b) the release decision is infeasible for a given state, the release demand is too large and exceeds water availability. Spill is built into the program, which avoids situations for which releases are too small and would cause a flood. Only feasible states are displayed; the sum of cold and warm pool storage is always less than reservoir capacity; the maximum cold and warm release choices are less than that historically available from a full reservoir and a heat budget. Results for the solution of a stochastic standard operating policy (Figure 4.20) solved with a monthly-varying temperature goal at Clear Creek for one possible incoming cold pool storage

state (1.6 maf) for one stage (May) must include results for the range of feasible warm pool options (0 - 2.8 maf) for all feasible releases of all combinations of cold (0 - 72 cfs) and warm (0 - 78 cfs). Results are shown for a large grid size (400 taf) so axis labels are legible.

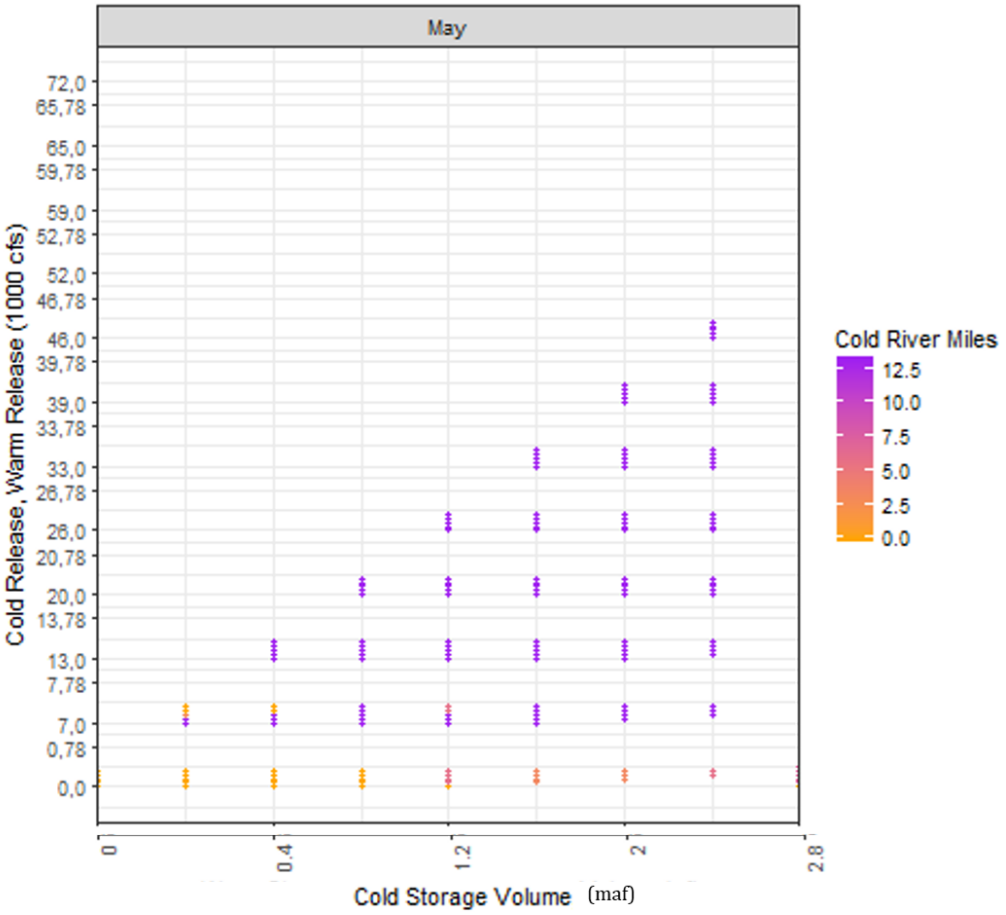


Figure 4.20: Display of stage table for the range of cold pool storage for one state of warm pool storage (1.6 maf) with an initial cold pool April storage volume of 2 maf. The value of each point is the value of the release (y-axis) of both cold and warm water, given available cold and warm pool storage volumes (x-axis) with a non-operational discretization of 400 taf. The value of the release is the number of cold river miles that result from the release's temperature and flow combination when the operational guidance follows the solution from a standard operating policy.

The value of releases is the length of cold river habitat (0-13 miles). For this displayed range of cold:warm ratios and volumes in the reservoir, a release with no cold water is too warm to create the full 13 miles of river habitat, so the value is lower and the color more yellow than purple. Cold or warm water releases that exceed water availability are also impossible, such as releasing more than 7 cfs of cold water in May with less than 200 taf of storage. Other storage and release combinations produce sub-optimal results because of the release temperature from the ratios and volumes of warm and cold pool storage and release (see Appendix for details). The solution of the stochastic standard operating policy for one stage (May) displays expected cold water habitat for each combination of cold and warm pool volume releases (y-axis) for each combination of incoming cold and warm storage states. Warm pool volume steadily increases along the x-axis. Cold pool releases steadily increase along the y-axis.

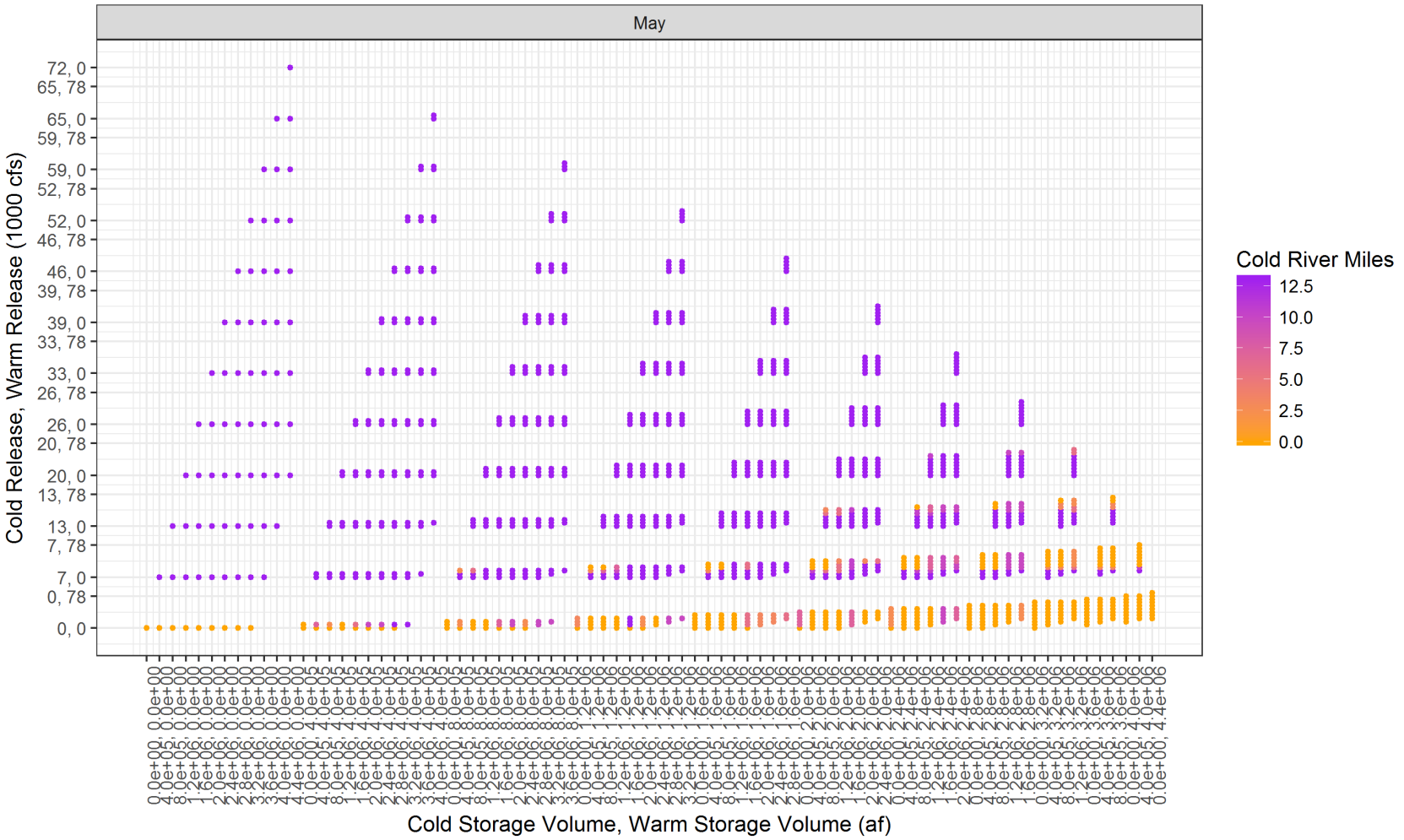


Figure 4.21: Display of stage table for one stage's (May) benefits. The value of each point is the value of the release (y-axis) of both cold and warm water, given available cold and warm pool storage volumes (x-axis) with a non-operational discretization of 400 taf. The value of the release is the number of cold river miles that result from the dam release with standard operating policy considering a probabilistic range of future weather (inflow and ambient temperature) conditions.

Still, when cold pool releases are not large enough (independently of the volume of warm released) the release has no downstream value (the line of yellow low-value releases when cold releases are zero or near zero). Or, as the ratio of warm to cold pool increases, the value of the release decreases, because the release is hotter (the cluster of yellow low-value releases from a mostly warm pool reservoir in the right lower corner).

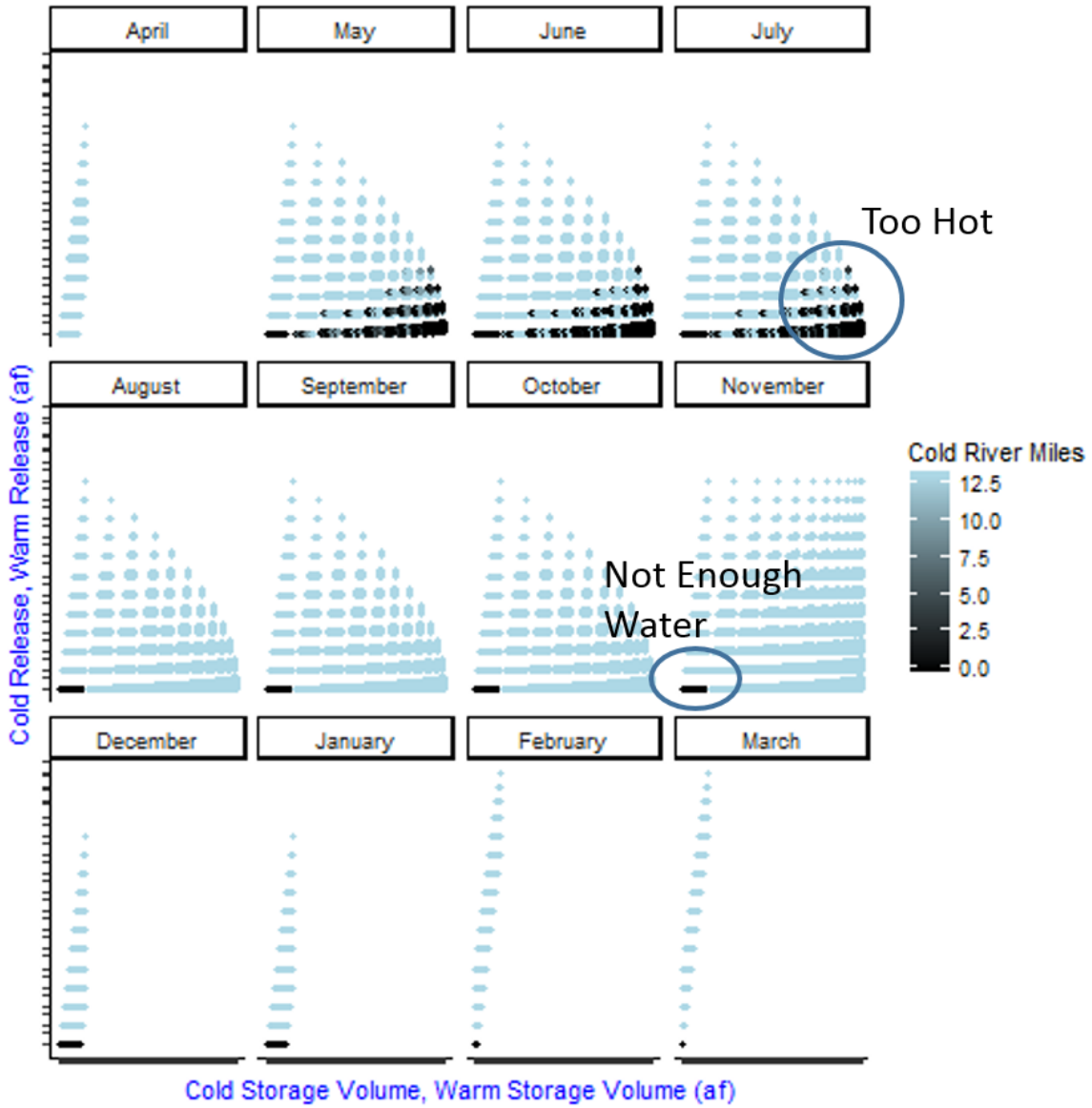


Figure 4.22: Value of all possible release decisions for all possible warm and cold pool storage combinations. Expected monthly value generated with discretizations of 400 taf for each water year type (extremely wet, wet, normal, dry, and extremely dry) as well as with a range of weights with a stochastic dynamic program, without regret avoidance/hedging (standard operating policy).

With the greedy operating policy, the full goal of cold water habitat (13 miles) provided from each cold and warm release combination given the full range of incoming warm and cold storage volumes for each month is almost always achieved with a few exceptions: when there is not enough cold water in May - July during the embryo stage when cold water demands are highest and for any month with low initial storage conditions.

Next, the problem is solved with a maximin solution algorithm. Figure (4.23) shows those releases for which the expected future benefit is less than that of the immediate benefit. The value shown in this figure is the future benefit, rather than the immediate benefit, or in other words, those releases with a number of river miles that will be "lost" should they be chosen. Decisions are regrettable because they deplete cold pool and/or total storage such that insufficient cold water is available to last until the next November when stratification ends.

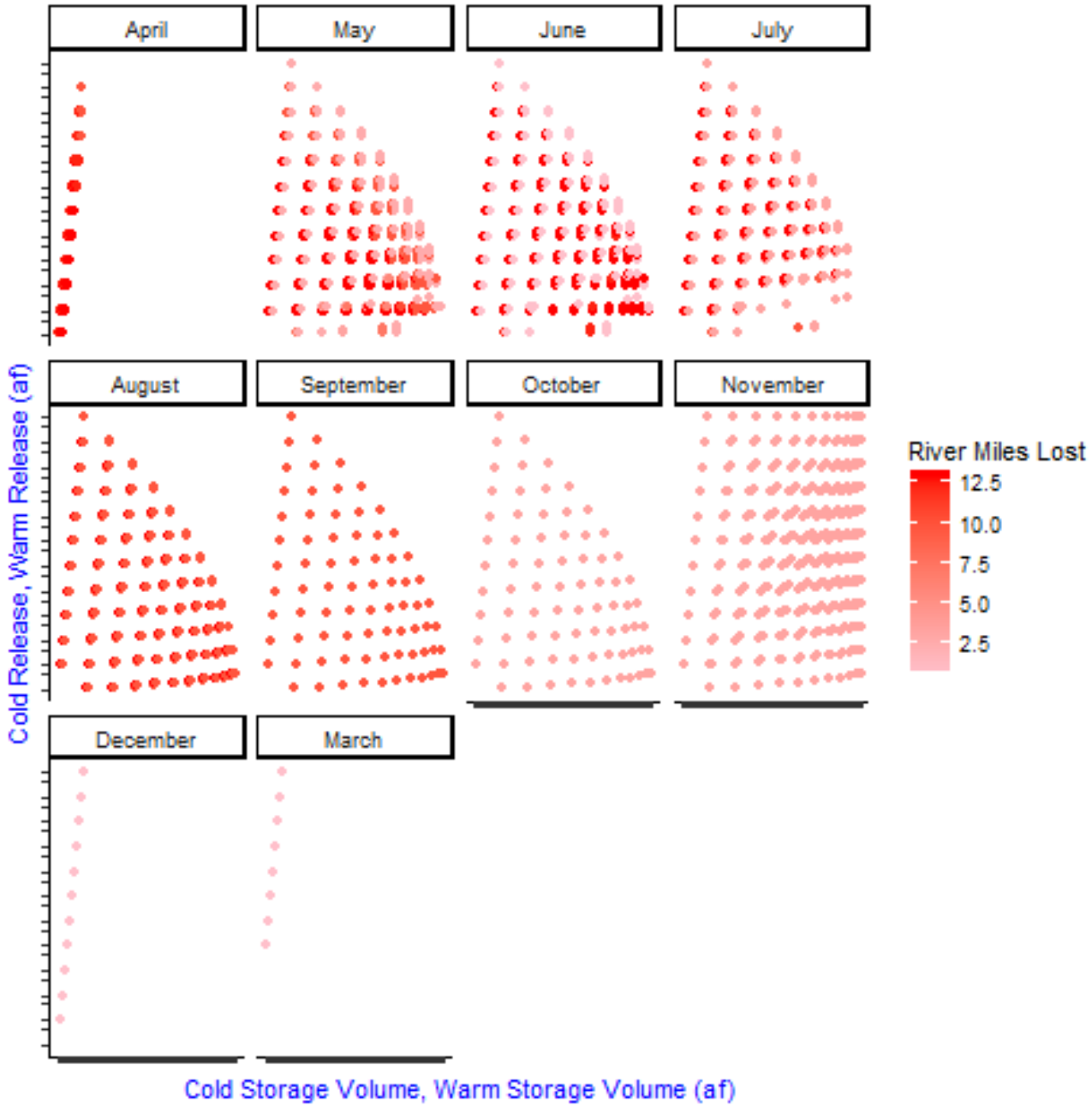


Figure 4.23: Value lost (in number of river miles) from decisions an operator would regret making for each storage state of each month were the operator to follow a prescription formulated with standard operating policy without hedging.

Finally, we show results from the results of the full maximin stochastic dynamic program (Figure 4.24). This shows the value of the optimized releases with the maximin logic, so releases are optimally hedged, at coarse resolution (400 taf). The value of a release in the maximin solution *is not* the value of the release in the current period - rather it represents the minimum value that that release will have over the course of a full year. That is why it is often *lower* than the value of the same release when solved with the standard operating policy. The standard operating policy is just current benefit - the maximin is the maximun of the minimum of current and long-term benefit.

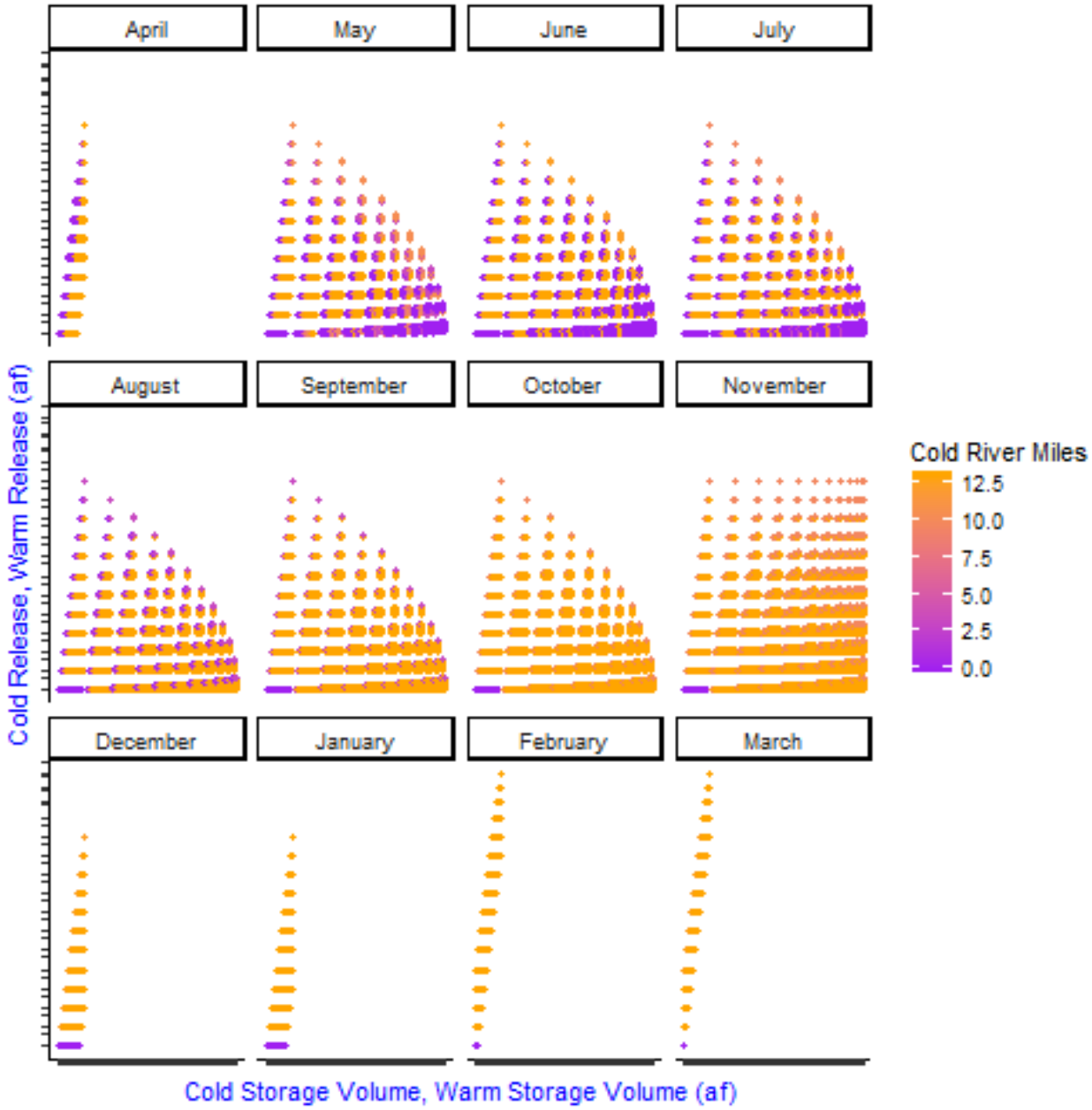


Figure 4.24: Value of each release decisions for every combination of warm and cold pool storage combinations. Expected monthly value generated with discretizations of 400 taf for each water year type (extremely wet, wet, normal, dry, and extremely dry) as well as with a range of weights with a maximin stochastic dynamic program.

Hedged decisions only occur between April and December, and in March. In May and June, the model hedges against releasing too much cold water relative to how much total and warm water is in the reservoir - because if the cold water does not last until July it is not worth releasing it anyway (the Winter-run Chinook eggs can not move). In April, the model hedges hard against releasing all its cold water - the optimal schedule hedges against a full release to a preference of releasing nothing. November and December and March hedge slightly, it is less optimal to release all available cold water, or, in November, total available water, although the loss from doing so is not catastrophic. Starting in July all hedging is to avoid draining the reservoir; the temperature threshold of the release is difficult to exceed.

4.5.2 Optimized Release Schedules for Temperature Management

At the resolution needed for Shasta releases (100 taf), we show the results of one stage (although again, the values here are the maximum of the minimum values of the releases for current and the long-term future). Labels on Figure 4.25, one month's optimized release guide, indicate the type of hedging needed for optimal operations. Optimized reservoir operating could be summarized into five types of storage-based hedging rules. By hedging with these rules (i.e., making optimized release decisions), release choice for each state of each stage is satisficing. Release rule curves for each month are in the Appendix.

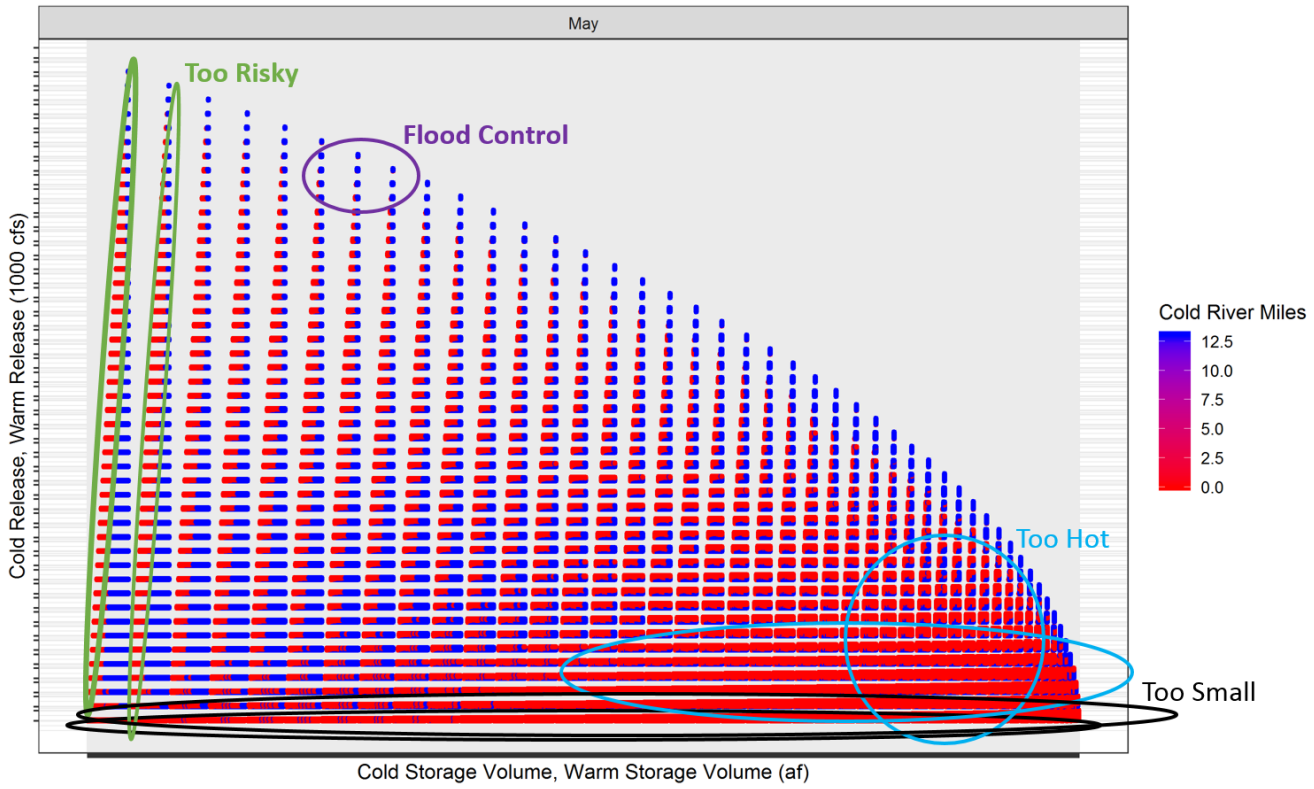


Figure 4.25: Display of stage table for one stage's (May) benefits with hedging. The value of each point is the value of the release (y-axis) of both cold and warm water, given available cold and warm pool storage volumes (x-axis) with an operational discretization of 100 taf. The value of the release is the number of cold river miles that result from the dam release. The release value is the maximum of the minimum of the current (this month) and long-term value (future months).

- **Too Risky** Releases that deplete storage to unsustainable levels and cause future damage.
- **Flood Control** Releases that must include spill to avoid flood damage.
- **Infeasible** Releases that exceed water availability are impossible.

- **Too Small** Releases for which total or cold pool storage availability are too small to meet the downstream target.
- **Too Hot** Releases for which water availability is too hot to meet downstream temperature targets.

Optimized cold and warm pool release decisions for each warm and cold pool storage combination release more cold pool in May and June, and slightly more cold pool in April, September, November and January - March when non-temperature deliveries are included. Lesser curtailments require more volume which can have consequences for long-term temperature and volume management.

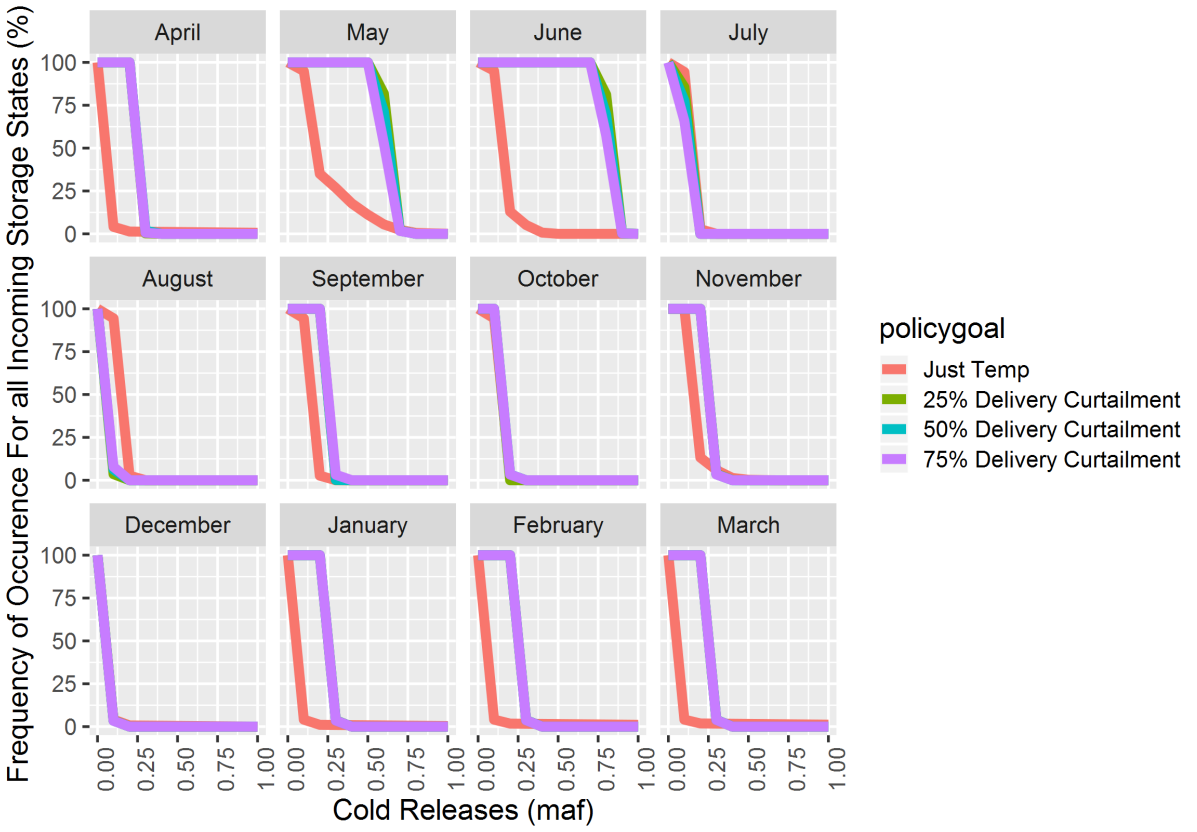


Figure 4.26: Optimized cold water pool release curves to optimize temperature management of the Shasta reservoir-river system focused on the section that highlights changes from delivery.

Optimal May and June releases can vary by up to 200 taf depending on curtailment intensity.

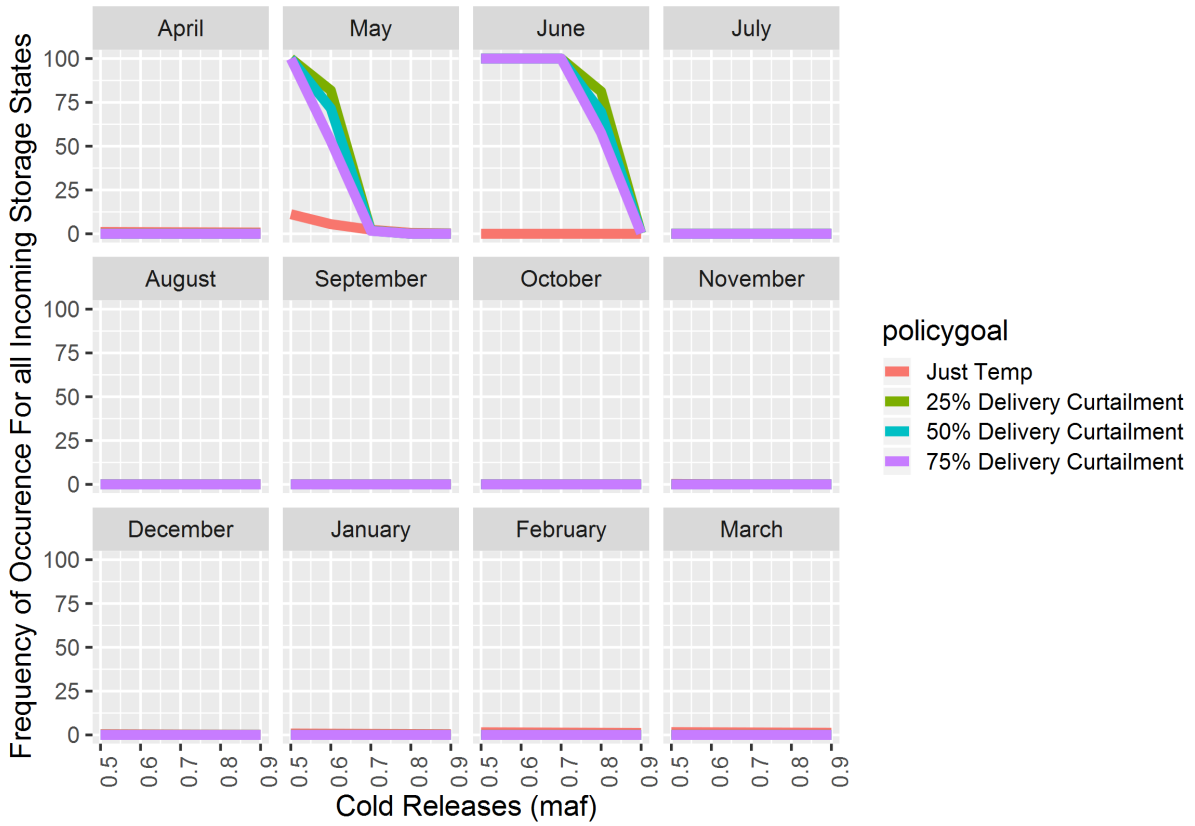


Figure 4.27: Optimized release curves to optimize temperature management of the Shasta reservoir-river system.

4.6 Discussion

4.6.1 General Drought and Temperature Management Operating Rules

Several general strategies detailed in this chapter are available that could be helpful to avoid temperature-related reservoir failures. Managing for temperature in reservoirs has similiarities to drought management in reservoirs. Both actively manage uncertainty. Both often employ benefit from hedging.

General Strategies for Temperature Management in Reservoirs		
Strategy	Why it helps	Shasta Reservoir Application
Drought hedging (Seasonal river temperature hedging) (Annual volume hedging and curtailments for downstream deliveries)	Hedges against worst-case high temperature & low inflow events Hedges against storage depletion Hedges against unsustainable provision of cold water habitat Hedges against economic and ecological collapse	Hedge releases with optimized results from Maximin Dynamic Programming Curtail deliveries about 25% in extreme drought
Monthly-varying temperature targets	Mimicks fish demand and the natural regime Saves storage	Use temperature thresholds based on fish demand (e.g., Table 4.3)
Annually-varying temperature location targets	Conserves surplus storage with constant, achievable, & ecologically consistent	Target Clear Creek Rarely fish spawn below Clear Creek

Optimal solutions follow these general strategies. These strategies could be helpful for preparing and operating for drought with contingency for non-drought conditions. Operating consistently with this hedging philosophy may offer a clear operations strategy to communicate to water users, which could help build trust and dialogue. Models operating with these strategies result in several outcomes:

- Fewer large seasonal temperature-based failures
- Fewer large seasonal volume-based failures
- Fewer multi-year volume-based failures
- Avoids greedy mistakes
- Reduces ecological collapse
- Reduces storage depletion

4.6.2 Event-based Drought and Temperature Management Operating Rules

In some months and years there is not enough incoming cold or total storage to support ecosystem function. It may be better to "hedge hard" against uncertainty and perhaps abandon some months or years under some dire conditions - to conserve their stored water for the future.

Curtailing for temperature management Releases with the maximin dynamic program algorithm are optimized for weather, storage conservation, river temperature, competing purposes, and risk. This set of optimized release rules guides when to release in full, release in full plus spill, hedge, or abandon a month. With the maximin solution algorithm, hedging is the greatest at the beginning of the season, to ensure storage availability for the season and later years. Here, April and May release decisions are critical; during these months the operator must decide how much to release, often before that month's weather is known. Releasing too much results in unsustainable ecological outcomes. For April, for example, when excluding deliveries, the derived rules are: a) when coldpool storage in the reservoir exceeds 3.1 maf, release available cold pool less 3 maf, otherwise do not release any cold pool storage; b) when cold pool storage is 0.3 to 2.9 maf, release 0.1 maf/month of warm pool; and c) when cold pool storage exceeds 3 maf, release 0.2 maf/month. For May, no cold releases are made unless cold pool storage is at least 0.3 maf. Warm May releases increase as warm water availability increases.

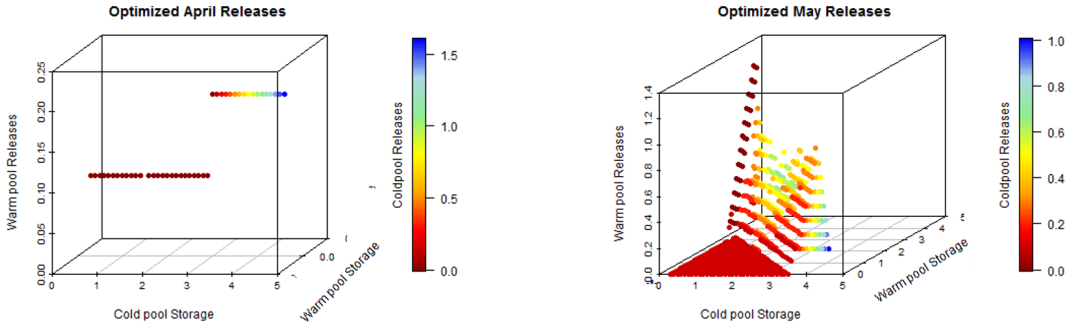


Figure 4.28: Optimized cold and warm release decisions for each feasible storage state of April and May. Results were generated with a variable temperature goal below Keswick Dam until Clear Creek (13 River Miles) with best operating policies with a maximin operating policy, extreme weather weights, and a resolution of 100 taf/month (≈1,500 cfs).

Since providing cold habitat downstream is largely independent of weather in April and May, it could be advisable to develop a policy where no cold water habitat is provided when incoming April storage is below 300 taf (deadpool), since it is impossible to sustainably deliver cold water habitat when incoming storage is that low.

Abandoning a year Stationary solutions of the maximin stochastic dynamic program and the deterministic maximin dynamic program for extreme drought approximated that the policy conditions (incoming April 1 storage level) under which to abandon a year, even with extreme drought, is when incoming April storage is below 300 taf. Below this level it may be better to allow a yearly kill-off and conserve available cold water because cold pool for this year is insufficient to support the entire year. Conservation for the future may bring benefit, even if some cold pool is lost to internal lake processes. In practical terms, this means abandoning when levels are below deadpool; when they must be abandoned anyway.

Assuming that deliveries are curtailed to afford temperature releases, the maximin dynamic program suggests, even with extreme drought, the system is operational above deadpool, even over three years. However, with the greedy policy, incoming storage above 2.1 maf is needed to sustain operations during drought, even with 75% delivery curtailments.

Abandoning a month Abandoning months could occur for three reasons: a) insufficient cold or total water available for that period, b) a likelihood of insufficient cold or total water for future periods, or c) insufficient fish present to merit cold habitat conditions. These first two reasons are incorporated into the hedged releases from the maximin dynamic programming solution. With the third option, when an incoming adult population returning from the ocean is small or non-existent, it could make sense to conserve cold water releases and storage until they arrive in May or June. It may even be advisable to always curtail releases in April for temperature management for the long-term. Between 2003 - 2018, Winter-run Chinook fish count surveys only found an average of 3 fish in April below Shasta Dam.

4.7 Limitations

The most pressing limitation of this study is the computational requirement of running the maximin dynamic program. Some additional model changes could improve result precision and insight. First, deadpool storage is already in the script, it must be turned on and analyses re-run so operations are limited by deadpool rather than being empty. Second, some details of the physical system were excluded as negligible, but it could be useful to include more details such as vertical diffusivity between the hypolimnion and the epilimnion, surface radiation, or explicit population dynamics. We assumed that residence time in Shasta reservoir is large enough and releases sufficiently distributed (with the Temperature Control Device) that lake temperature is unaffected by releases; that assumption could be tested. Disaggregating goals into daily or weekly, not monthly goals could offer the opportunity to consider daily attenuation [Lowney, 2000], which may offer additional hedging opportunities (although with great computational burden). Each month's release could be disaggregated into daily releases $t^{'}_{y_t,t}$. With this approach the problem would be solved from a Eulerian perspective. Each day's temperature change cumulates from the previous day's temperature change. The distance the streamflow travels each day is assumed constant. The change in temperature for each day is calculated with the sink term of the heat transport equation.

$$\frac{\Delta T}{\Delta t} = \underbrace{\frac{JA^s}{\rho C_\rho V_x}}_{\text{net heat flux}} \tag{16}$$

Downstream release temperature T^t is the weighted sum of the releases from the cold and warm pools. The total number of days n in the month t the streamflow travels before it exceeds the target temperature T^Z is counted. The distance x_t covered by the release R^E_t below the threshold temperature is estimated.

$$\frac{R^E_t n_t}{A^s_t} = x_t \tag{17}$$

Running the greedy algorithm and maximin dynamic program with California's 2012-2016 drought inflow and ambient temperature data, could quantify, in policy-terms, the value of the maximin algorithm and the monthly-varying temperature goal logic. Formulating the model as a multi-objective optimization model with cost-weighted delivery shortage penalties and cold water habitat goals, rather than as a single-objective river temperature model with water deliveries as a hard constraint, could better identify trade-offs in delivery curtailment and cold water habitat shortage. Applying weighted penalities to allocate warm or cold pool to satisfy delivery requirements could produce release schedules that result in greater storage conservation by meeting temperature targets more easily; although likely this is inherently covered in the model. Simplified release rules based on water availlability (inflow and warm and cold pool beginning of month storage) could simplify the logic of this dissertation for operational purposes. Regression models could use the results of this dissertation to impute storage goals based on the frequency with which river temperature targets are met at different river locations [Young, 1966].

4.8 Conclusion

In terms of operating rule development, Shasta reservoir is not limited to make releases for temperature by weather; with a constant temperature operating policy (13.3°C/ 56°F to Jelly's Ferry) or monthly-varying

temperature policy to Clear Creek, operation for cold water habitat provision alone will fail only when incoming storage is below deadpool, even for multiple years. When operating to also meet downstream deliveries, however, it is impossible to meet Shasta temperature goals during drought without delivery curtailments. A maximin dynamic program provides a method to build optimized release schedules that support more efficient tradeoffs of these objectives, and protect against failure. Operating with a monthly-varying schedule further supports long-term reservoir management goals. The maximin dynamic program, in concert with delivery curtailment and a monthly-varying temperature goal to Clear Creek, could likely improve reservoir operations for the Sacramento river below Shasta Dam as well as other large dams faced with managing drought, temperature, and long-term risk. Developing reservoir release schedules with sometimes curtailing deliveries and downstream temperature goals could likely hedge the risk of drought and unsustainable delivery of cold water habitat for temperature management in reservoirs. The model developed here, OTM2 (Optimized Temperature Management Model), could provide support for achieving long-term drought and temperature management. Looking to this re-operation approach before making major infrastructure changes such as dam expansion or new off-site storage might save resources, time, water, and fish.

References

(1973). *United States Code, Endangered Species Act*.

(2016). *Shasta Dam Tour*. Bureau of Reclamation.

(2016). *Species in the Spotlight, Priority Actions: 2016-2020, Sacramento River, Winter-run Chinook Salmon, Oncorhynchus tshawytscha*. National Oceanic and Atmospheric Administration.

(2017). *Sacramento River Temperature Task Group Annual Report of Activities*. Sacramento River Temperature Task Group.

Bartholow, J., Hanna, R., Saito, L., Lieberman, D., and Horn, M. (2001). Simulated limnological effects of the shasta lake temperature control device. *Environmental Management*, 27(4):609–626.

Beard, L. R. and Willey, R. (1970). An approach to reservoir temperature analysis. *Water Resources Research*, 6(5):1335–1345.

Benyahya, L., Caissie, D., St-Hilaire, A., Ouarda, T. B., and Bobée, B. (2007). A review of statistical water temperature models. *Canadian Water Resources Journal*, 32(3):179–192.

Calfish (2018). *Winter-run Chinook Salmon Monitoring*.

Carron, J. C. and Rajaram, H. (2001). Impact of variable reservoir releases on management of downstream water temperatures. *Water Resources Research*, 37(6):1733–1743.

Castelletti, A., Yajima, H., Giuliani, M., Soncini-Sessa, R., and Weber, E. (2013). Planning the optimal operation of a multioutlet water reservoir with water quality and quantity targets. *Journal of Water Resources Planning and Management*, 140(4):496–510.

Fontane, D. G., Labadie, J. W., and Loftis, B. (1981). Optimal control of reservoir discharge quality through selective withdrawal. *Water Resources Research*, 17(6):1594–1602.

GCID (2016). Painter's riffle anadromous fish habitat enhancement projectl. Technical report, Glenn-Colusa Irrigation District, Willows, CA.

Giuliani, M., Galelli, S., and Soncini-Sessa, R. (2014). A dimensionality reduction approach for many-objective markov decision processes: Application to a water reservoir operation problem. *Environmental modelling & software*, 57:101–114.

Hanna, R. B. (1999). Model-derived guidelines for'effective'tcd operations for target temperatures below shasta dam and the resulting changes in the coolwater pool in shasta lake.

Herman, J. D., Zeff, H. B., Reed, P. M., and Characklis, G. W. (2014). Beyond optimality: Multistakeholder robustness tradeoffs for regional water portfolio planning under deep uncertainty. *Water Resources Research*, 50(10):7692–7713.

Lochhead, C. (2018). White house, congress side with california growers over raising shasta dam.

Lowney, C. L. (2000). Stream temperature variation in regulated rivers: Evidence for a spatial pattern in daily minimum and maximum magnitudes. *Water Resources Research*, 36(10):2947–2955.

Martin, C., Gaines, P., and Johnson, R. (2001). Estimating the abundance of sacramento river juvenile winter chinook salmon with comparisons to adult escapement. *Red Bluff Research Pumping Plant Report Series*, 5.

McCullough, D. (1999). *A Review and Synthesis of Effects of Alterations to the Water Temperature Regime on Freshwater Life Stages of Salmonids, with Special Reference to Chinook Salmon.* United States Environmental Protection Agency.

Moyle, P. (2017). Chinook salmon thermal tolerances in fresh water. Technical report, UC Davis.

Nandalal, K. and Bogardi, J. J. (1995). Optimal operation of a reservoir for quality control using inflows and outflows. *Water Science and Technology*, 31(8):273–280.

Nickel, D. K., Brett, M., and Jassby, A. (2004). Factors regulating shasta lake (california) cold water accumulation, a resource for endangered salmon conservation. *Water Resources Research*, 40(5).

Olivares, M. A. (2008). *Optimal hydropower reservoir operation with environmental requirements.* PhD thesis, University of California Davis.

Pike, A., Danner, E., Boughton, D., Melton, F., Nemani, R., Rajagopalan, B., and Lindley, S. (2013). Forecasting river temperatures in real time using a stochastic dynamics approach. *Water Resources Research*, 49(9):5168–5182.

Powell, W. B. (2007). *Approximate Dynamic Programming: Solving the curses of dimensionality*, volume 703. John Wiley & Sons.

Price, R. E. and Meyer, E. B. (1992). Water quality management for reservoirs and tailwaters. report 2. operational and structural water quality enhancement techniques. Technical report, Army Engineer Waterways Experiment Station Vicksburg MS Hydraulics Lab.

Rettig, S. A. and Bortleson, G. C. (1983). Limnological study of shasta lake, shasta county, california, with emphasis on the effects of the 1977 drought. *US Geological Survey Water-Resources Investigations*, pages 82–4081.

Rheinheimer, D. E., Null, S. E., and Lund, J. R. (2014). Optimizing selective withdrawal from reservoirs to manage downstream temperatures with climate warming. *Journal of Water Resources Planning and Management*, 141(4):04014063.

Soleimani, S., Bozorg-Haddad, O., Saadatpour, M., and Loáiciga, H. A. (2016). Optimal selective withdrawal rules using a coupled data mining model and genetic algorithm. *Journal of Water Resources Planning and Management*, 142(12):04016064.

Vogel, D. (2016). Evaluation of annual estimates of winter-run chinook salmon early life stage survival/mortality with particular focus on 2014 and 2015. Technical report, Natural Resource Scientists.

Weber, M., Rinke, K., Hipsey, M., and Boehrer, B. (2017). Optimizing withdrawal from drinking water reservoirs to reduce downstream temperature pollution and reservoir hypoxia. *Journal of Environmental Management*, 197:96–105.

Young, G. K. (1966). *Techniques for Finding Reservoir Operating Rules.* PhD thesis, Harvard University.

4.9 Appendix

4.9.1 River Temperature Modeling

Temperature records were pulled for all California Data Exchange Center stations (1994 - 2017) and for each of the ten stations in the Sacramento river below Shasta with time series records (river miles from mouth of Sacramento to Keswick Dam, the first impenetrable wildlife barrier in the Sacramento River), air temperature observations from NOAA (1943-2017) and CDEC flow measurements for Keswick Dam and Shasta Dam releases (1994-2017): Emmaton (6), Greens (37), Hood (39), Red Bluff Diversion Dam (243), Bend Bridge (256), Jelly's Ferry Bridge (266), Ball's Ferry (276), Clear Creek (289), Keswick (302) and Shasta (311). Observations were retained for gauging stations that were not significantly influenced by other dams or rivers for which the temperature of Shasta Dam releases likely still affected local river temperature, and for which sufficient data was available: Jelly's Ferry Bridge (266), Ball's Ferry (276), Clear Creek (289), Keswick (302) and Shasta (311).

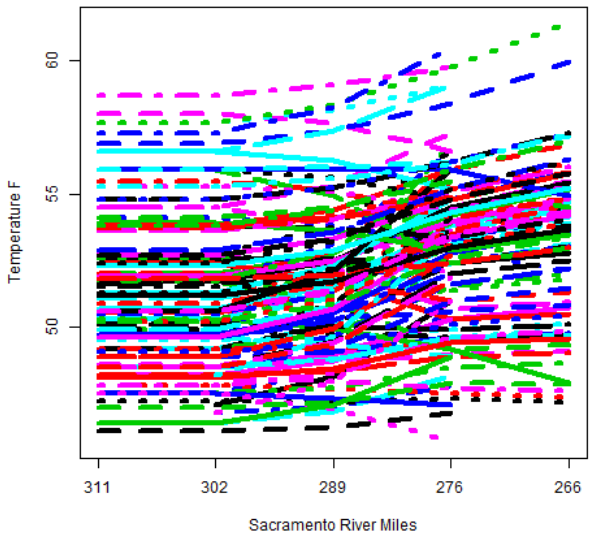


Figure 4.29: Sacramento River monthly temperature measurements per Sacramento River Mile (CDEC, 2017). Each line is a different month's measurements at each of several locations.

The full dataset, including these interpolated values, was 133 observations of monthly river temperature observations. Missing observations were interpolated from the least number of nearby gauging stations necessary. Clear Creek was found to be best interpolated from Keswick and Ball's Ferry observations ($p < 2.2 * 10^{-16}$) and Jelly's Ferry from Ball's Ferry ($p < 2.4 * 10^{-16}$).

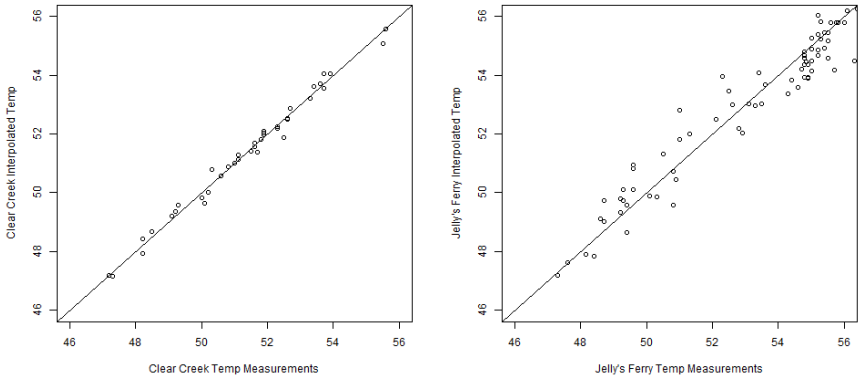


Figure 4.30: Interpolated Clear Creek and Jelly's Ferry observations.

Release volume (log of total release volume) is not a significant predictor of river temperature, either alone or in combination with other variables. Month is a proxy for air temperature and a plug-in solution for the omitted surface heat flux variables (Figure 4.1); month predicted air temperature with significant coefficients ($p < 2e-16$ and $p = 9 * 10^{-14}$, for the intercept and air temperature, respectively) having small standard errors (0.3 and 0.02, respectively). Scatterplots of observed Shasta Dam release temperature and river temperature are slightly curved for Ball's Ferry and Jelly's Ferry (Figure: 4.33), which indicated that a polynomial model could be the best fit. A positive correlation between month and downstream temperature was visualized with the raw monthly Sacramento River temperature and Shasta Dam release temperature observations (Figures 4.31 and 4.32).

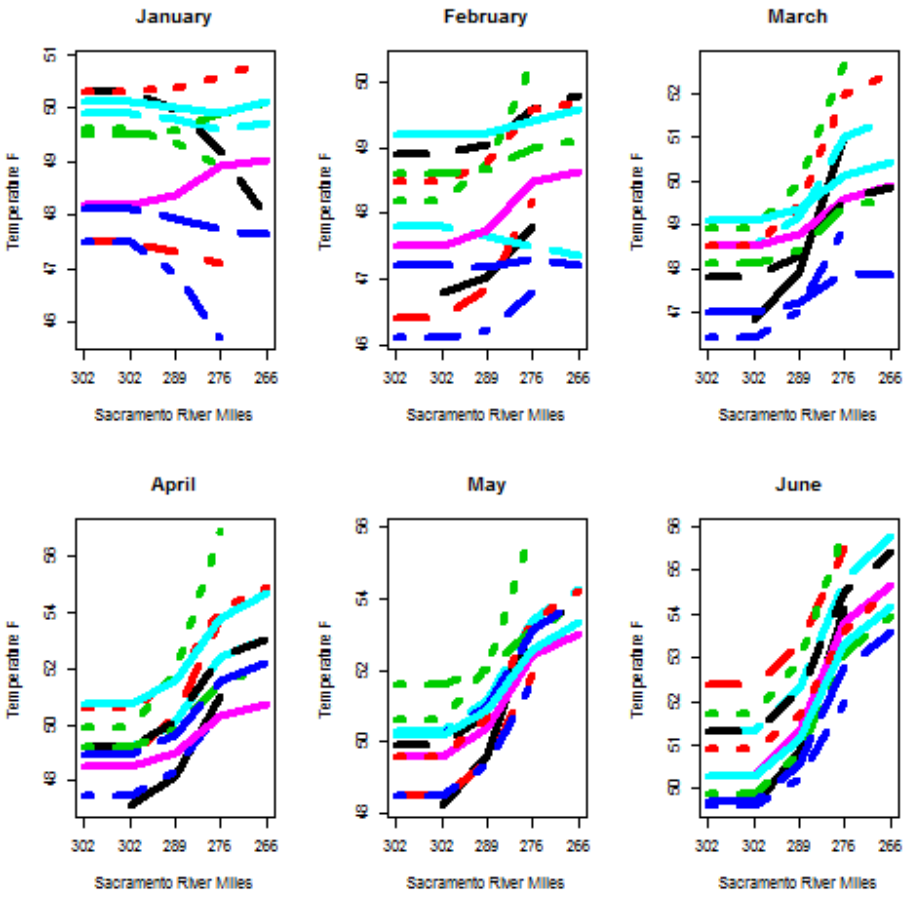


Figure 4.31: Sacramento River Temperature Measurements per Sacramento River Mile (CDEC, 2017). Each line is a year of observation.

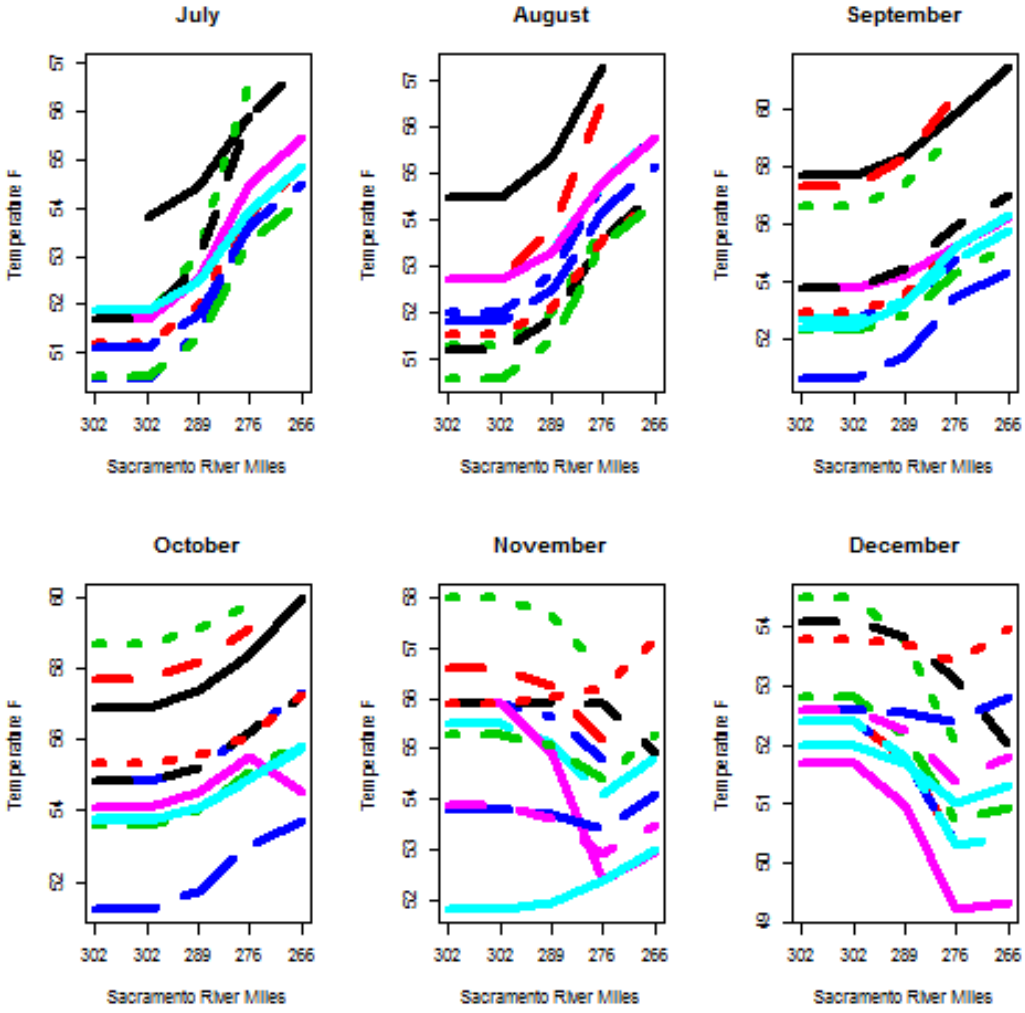


Figure 4.32: Sacramento River Temperature Measurements per Sacramento River Mile (CDEC, 2017). Each line is a year of observation.

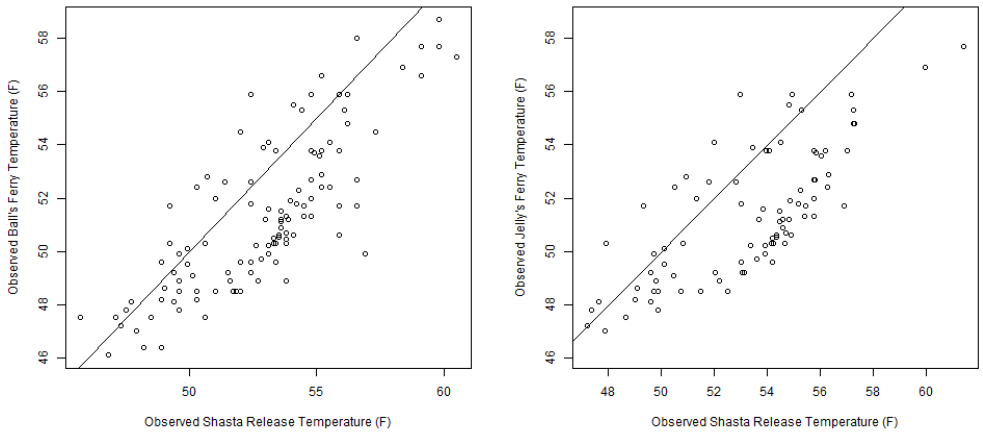


Figure 4.33: Sacramento River Temperature Measurements at Ball's Ferry (river mile 276) and Jelly's Ferry (river mile 266) given Shasta Dam release temperature (river mile 311) (CDEC, 2017). Each point is a month of observation.

With a Generalized Linear Model the square of the numeric month (e.g., January =1) and Shasta Dam release temperature predicted downstream location temperature with a large (107) and significant ($p < 2.2 * 10^{-}16$) F-statistic. Coefficients' t-values (how many standard deviations the coefficients are away from zero) are all significant, they are unwieldy (5, 11 and 3, for the intercept, temperature and month, respectively). The linear model predicting the temperature at each gauging location based on month and Shasta release temperature was less significant with significantly lesser adjusted correlation (0.09) and even larger, more unwieldy, coefficients. Explaining downstream river temperatures exclusively by Shasta release temperature, and not month and temperature, was the selected method because predicting downstream temperatures solely from release temperature lost no model explanatory power and gained savings in computational time requirements.

The relationship between Shasta temperature release and Keswick temperature (not flow-weighted temperature releases) is essentially a perfect 1:1 fit ($p < 2.2 * 10^{-16}$). Clear Creek temperature is predicted by Shasta Dam release temperature significantly with and without month in the Generalized Linear Model; both have a small residual error (0.5 °F) and very strong positive correlation (adjusted r=0.96).

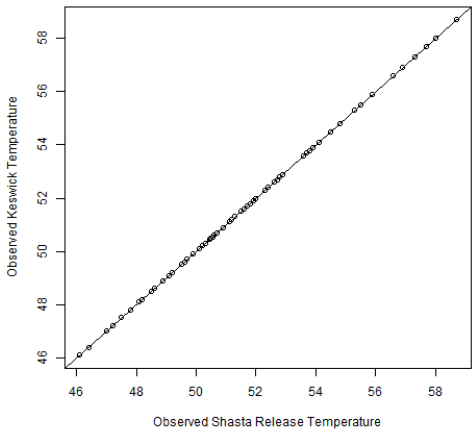


Figure 4.34: Sacramento River Temperature Measurements at Keswick Dam (river mile 302)given Shasta Dam release temperature (river mile 311) (CDEC, 2017). The lines are the true regression line.

For Ball's Ferry, the adjusted r-square value and residual standard error remain the same as when month is included as a control variable. The result has a positive correlation of 0.6 and a residual error of 1.8 °F. With just temperature, the F-statistic also doubles and remains significant ($p < 2.2 * 10^{-16}$), with coefficients that have significant t-values. Jelly's Ferry is similarly explained by just release temperature rather than month and release temperature. The residual standard error is 1.9 °F, the adjusted r=0.6, and the model significant, with or without month. Not only does it make sense statistically to rely only on release temperature to estimate downstream temperature, but it also makes sense conceptually. Shasta release temperature is a function of release flow and release temperature, which both depend on reservoir volume temperature and volume, all of which endogenously capture month (certain volume combinations and warm pool temperatures only occurs in certain months), even though no statistical or computational power is gained by including month exogenously.

Plots of residuals at each location indicate that each of these Generalized Linear Models are accurate.

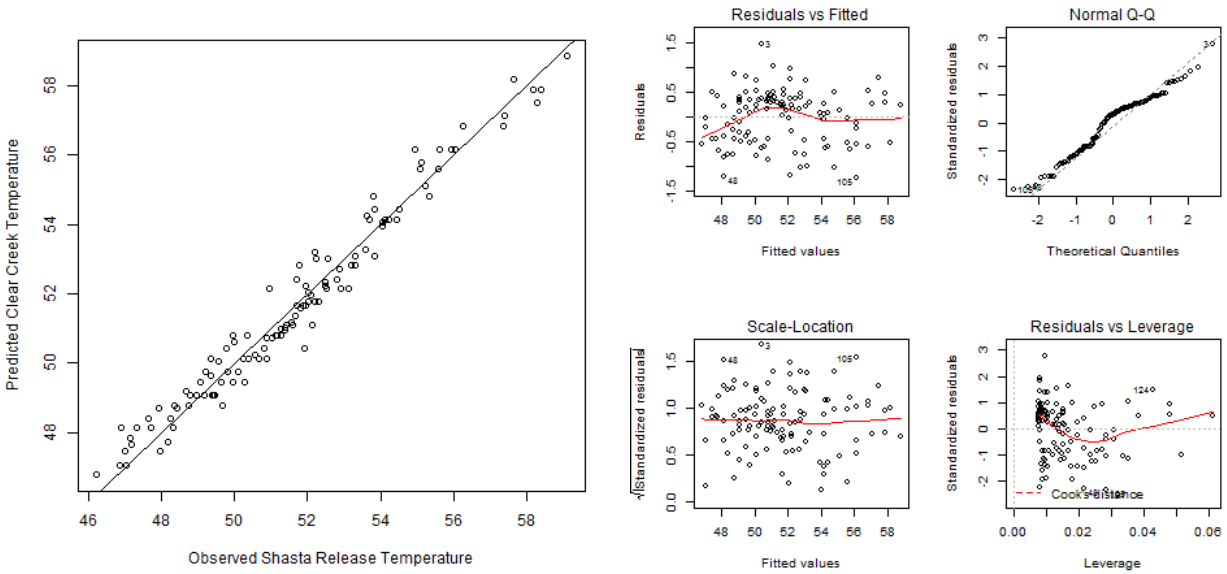


Figure 4.35: Residuals and analysis of the residuals from predicting Clear Creek river temperature given Shasta Dam release temperature.

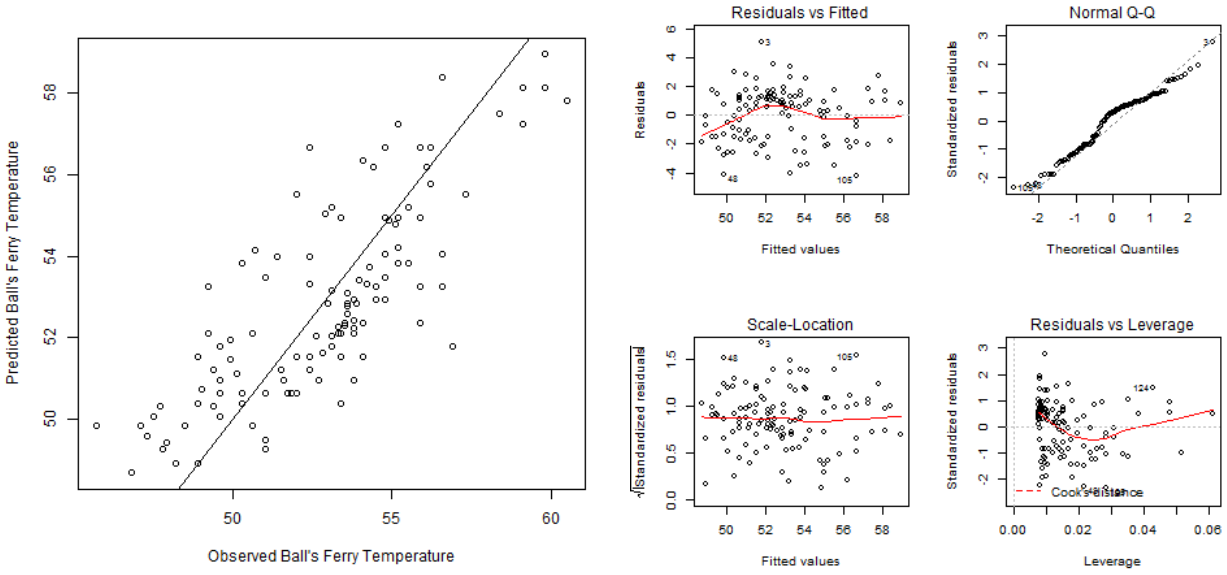


Figure 4.36: Residuals and analysis of the residuals from predicting Ball's Ferry river temperature given Shasta Dam release temperature.

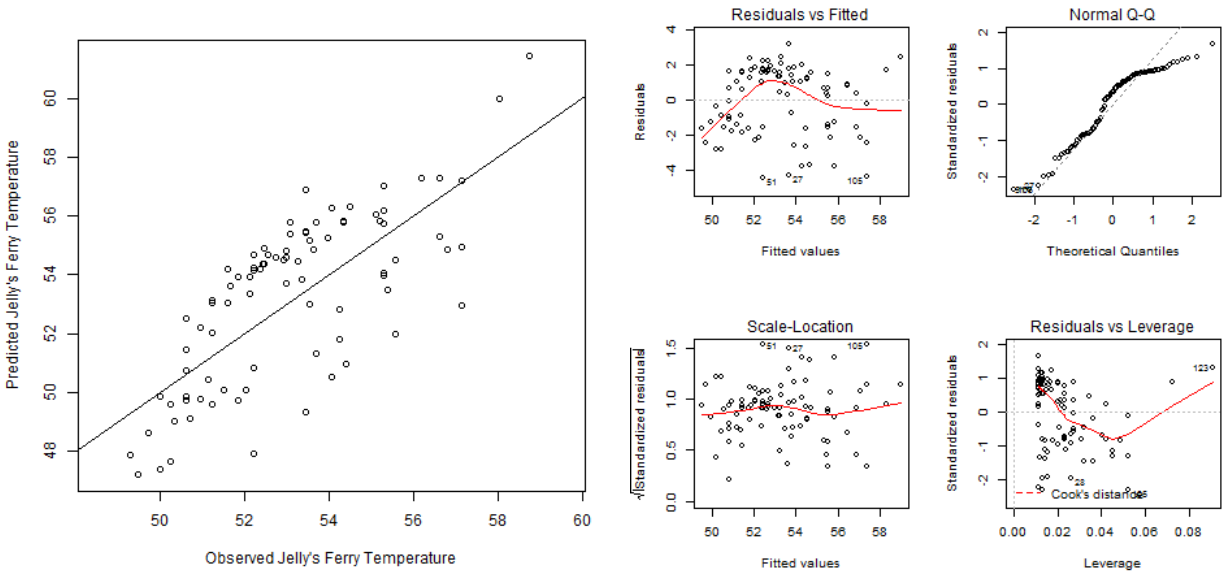


Figure 4.37: Residuals and analysis of the residuals from predicting Jelly's Ferry river temperature given Shasta Dam release temperature.

4.9.2 Monthly optimized Release Guides

Release plots were created for each combination of warm and cold pool releases per month with curtailment levels of 30%, 50%, and 75% at the operational scale of 100 taf. The list of cold and warm pool combinations during the stratified season, moving from left to right along the x-axis, is below the figures. Optimized release schedules all generated with initial storage conditions of 100 taf of only cold pool at the beginning of April. With this initial condition, with curtailments of 75%, all optimized release choices result in achieving long-term full cold habitat goals of 13 river miles for the full April - March planning cycle. With 50% or 25%, all release choices result in achieving long-term habitat 0 miles of cold river habitat over the long-term. This means that the volume of cold water released during March is less likely to achieve a downstream temperature target with lower curtailments *for the long-term not for just that month alone.* That is why if the temperature goal reads as "0" in March for one set of curtailments, and "13" for another, with the exact same release choice - because the long-term effect of these release choices is different. With high curtailments many release choices drain the reservoir in February and March, and to a lesser but still meaningful extent, May, June and July. Conserving storage throughout the fall months to prepare for February likely will bring large conservation benefits, for the long-term.

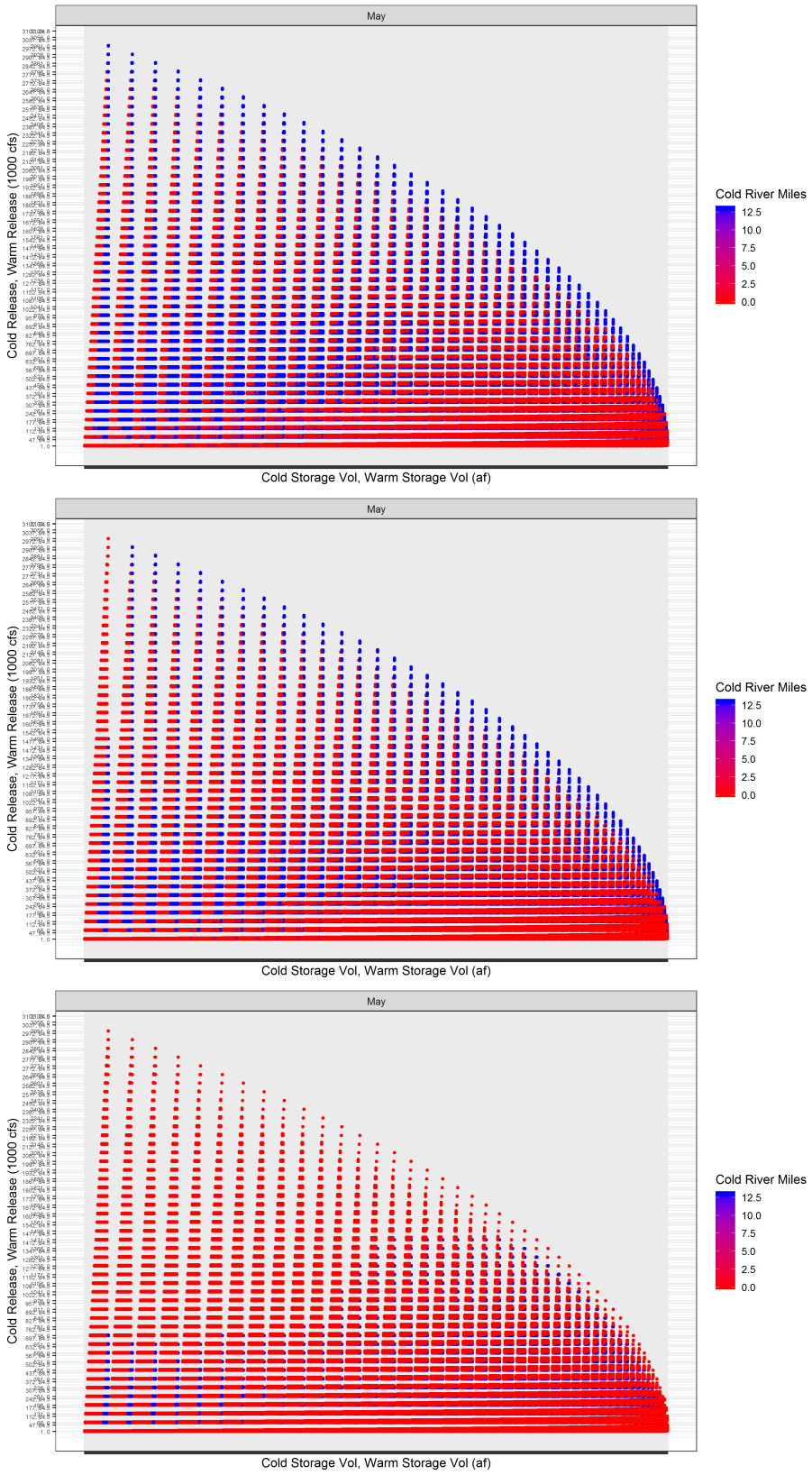


Figure 4.38: Cold river miles achieved over the long-term with optimized release schedules in May with 75%, 50%, and 30% (top, middle, and bottom, respectively) curtailment on deliveries.

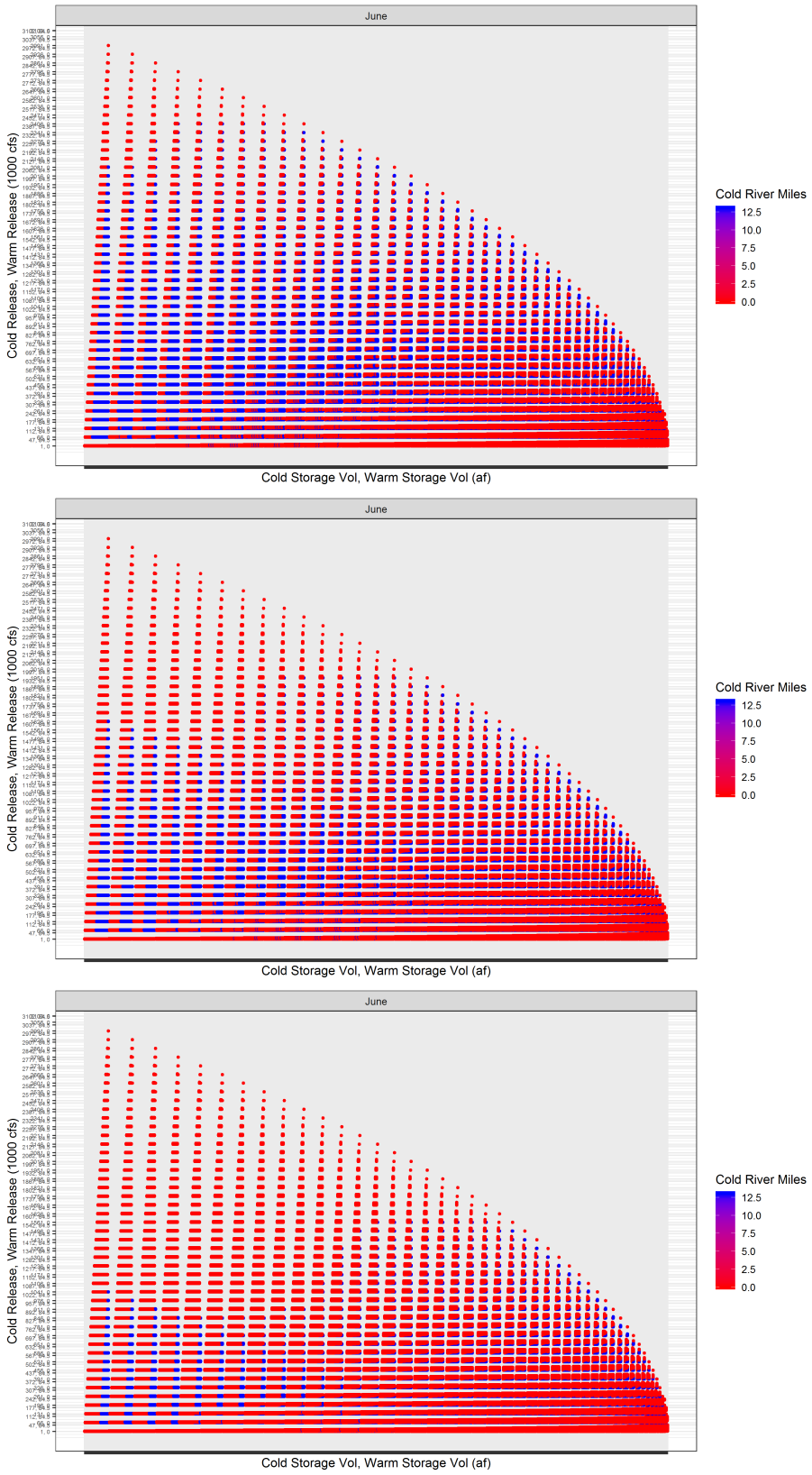


Figure 4.39: Cold river miles achieved over the long-term with optimized release schedules in June with 75%, 50%, and 30% (top, middle, and bottom, respectively) curtailment on deliveries.

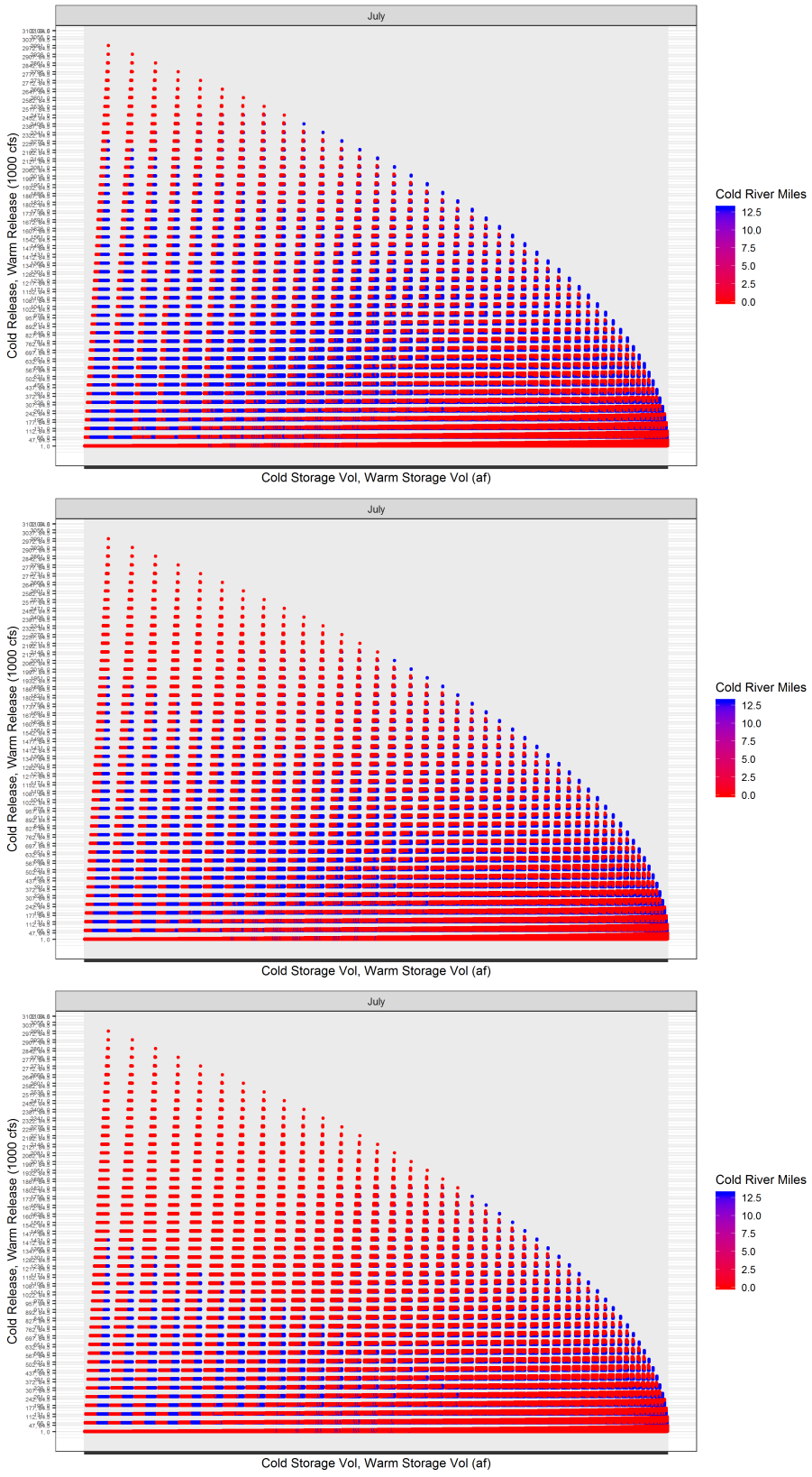


Figure 4.40: Cold river miles achieved over the long-term with optimized release schedules in July with 75%, 50%, and 30% (top, middle, and bottom, respectively) curtailment on deliveries.

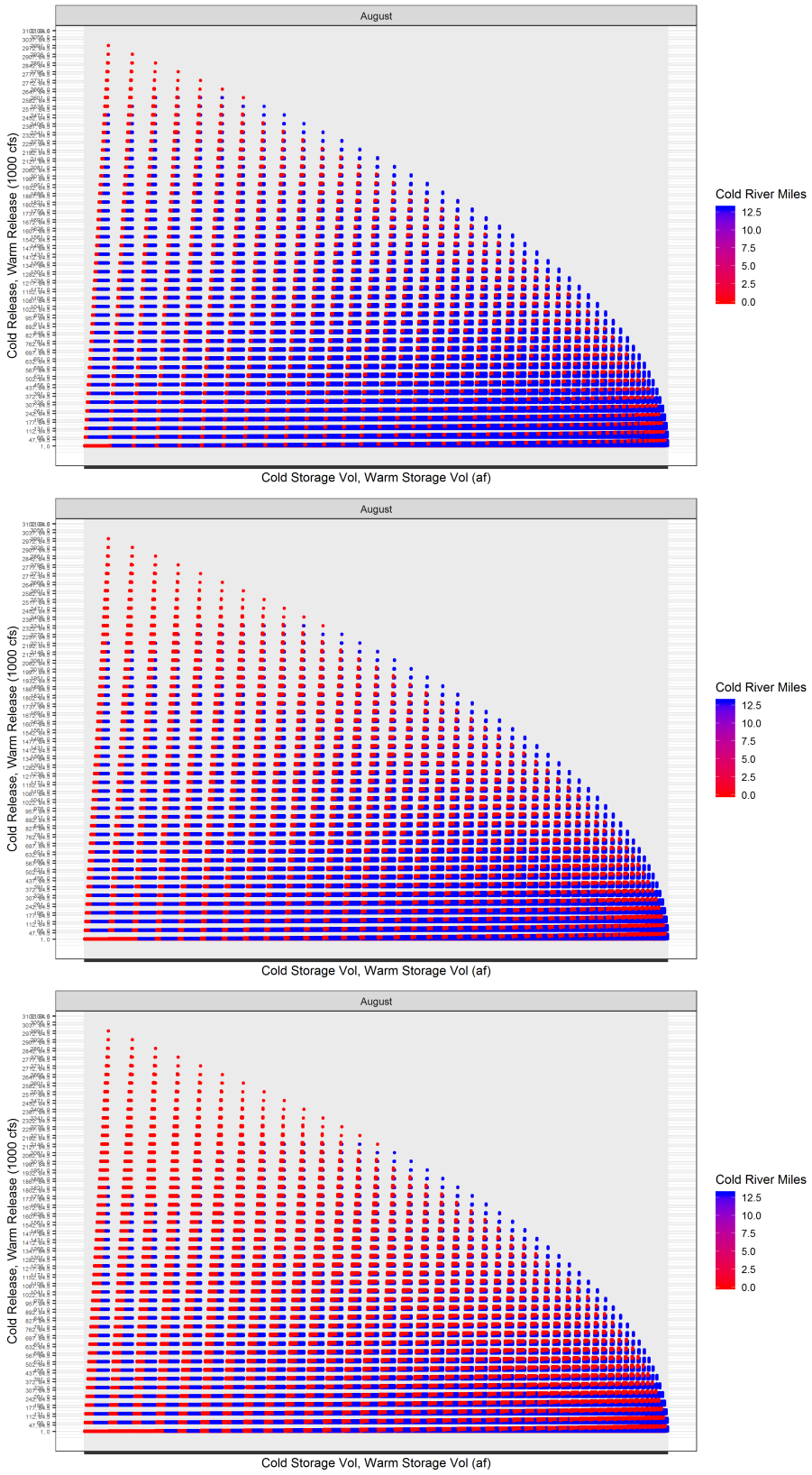


Figure 4.41: Cold river miles achieved over the long-term with optimized release schedules in August with 75%, 50%, and 30% (top, middle, and bottom, respectively) curtailment on deliveries.

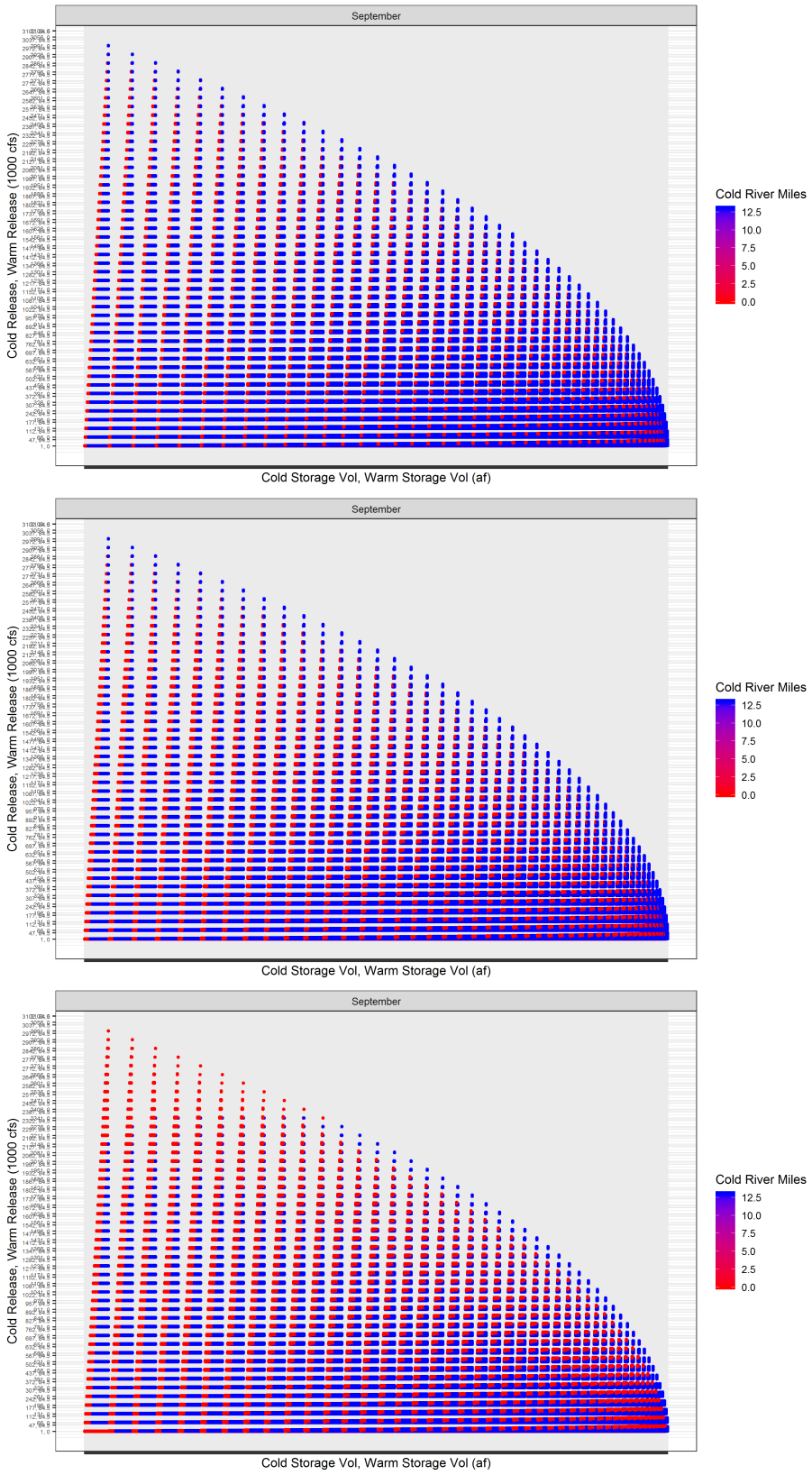


Figure 4.42: Cold river miles achieved over the long-term with optimized release schedules in September with 75%, 50%, and 30% (top, middle, and bottom, respectively) curtailment on deliveries.

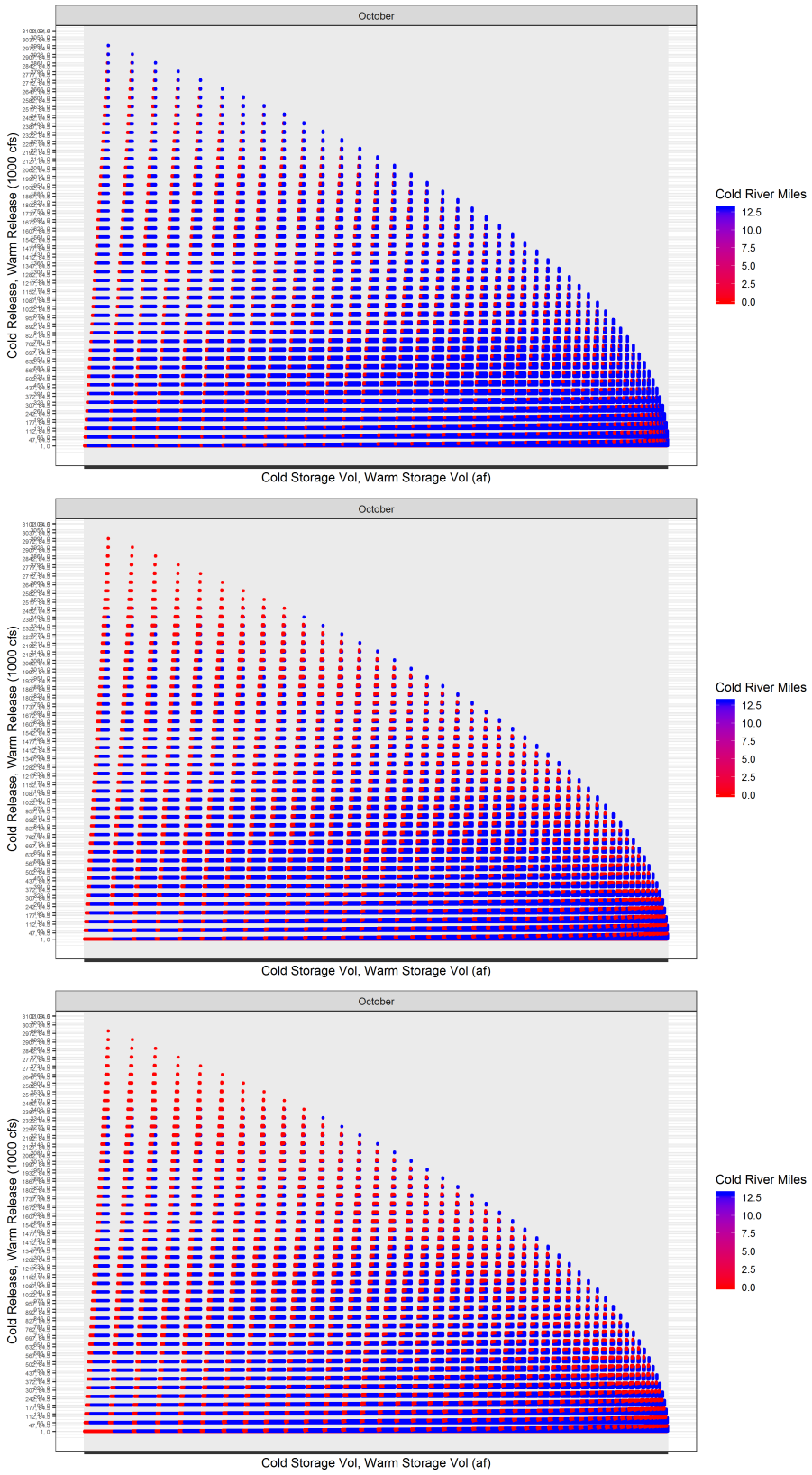


Figure 4.43: Cold river miles achieved over the long-term with optimized release schedules in October with 75%, 50%, and 30% (top, middle, and bottom, respectively) curtailment on deliveries.

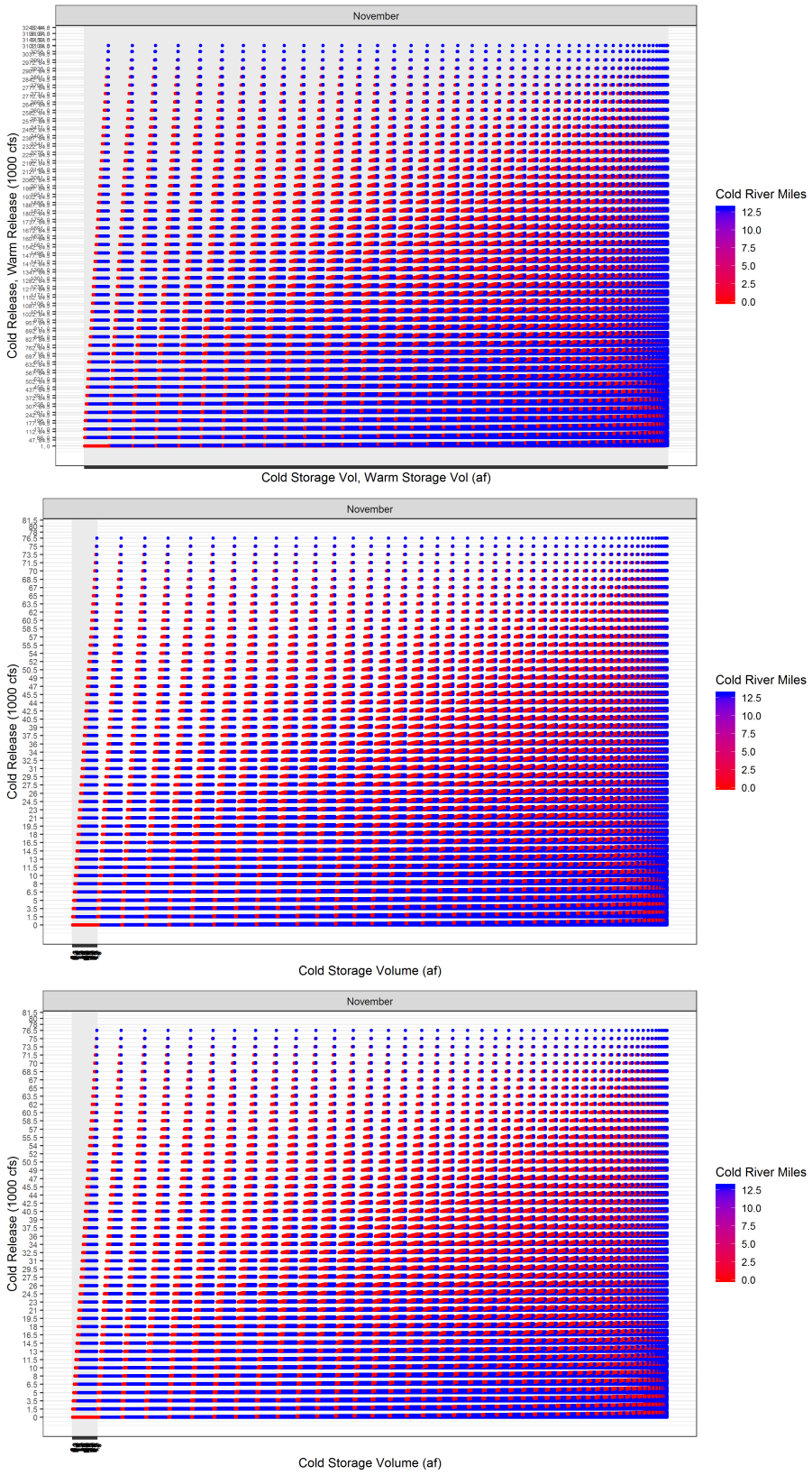


Figure 4.44: Cold river miles achieved over the long-term with optimized release schedules in November with 75%, 50%, and 30% (top, middle, and bottom, respectively) curtailment on deliveries.

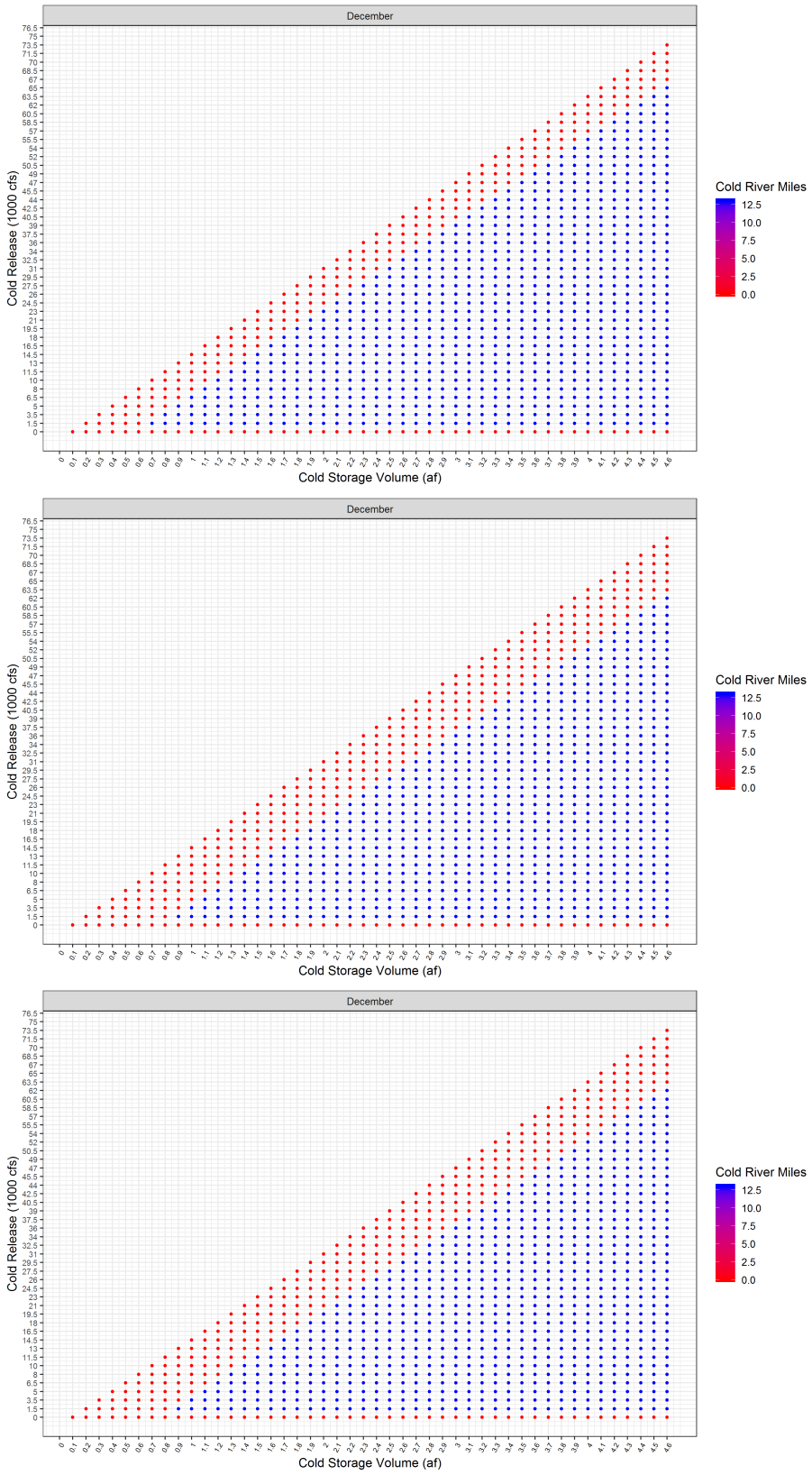


Figure 4.45: Cold river miles achieved over the long-term with optimized release schedules in December with 75%, 50%, and 30% (top, middle, and bottom, respectively) curtailment on deliveries.

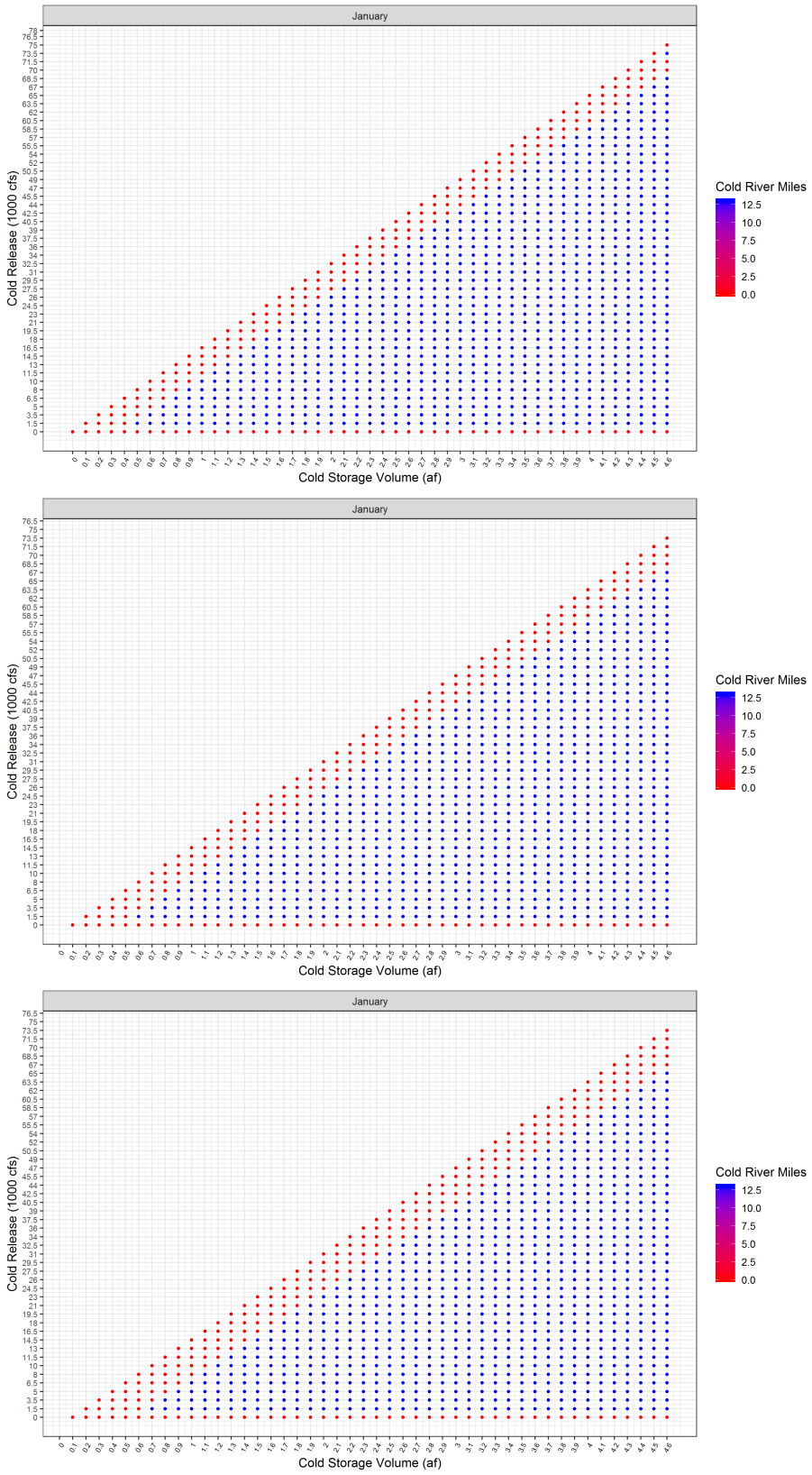


Figure 4.46: Cold river miles achieved over the long-term with optimized release schedules in January with 75%, 50%, and 30% (top, middle, and bottom, respectively) curtailment on deliveries.

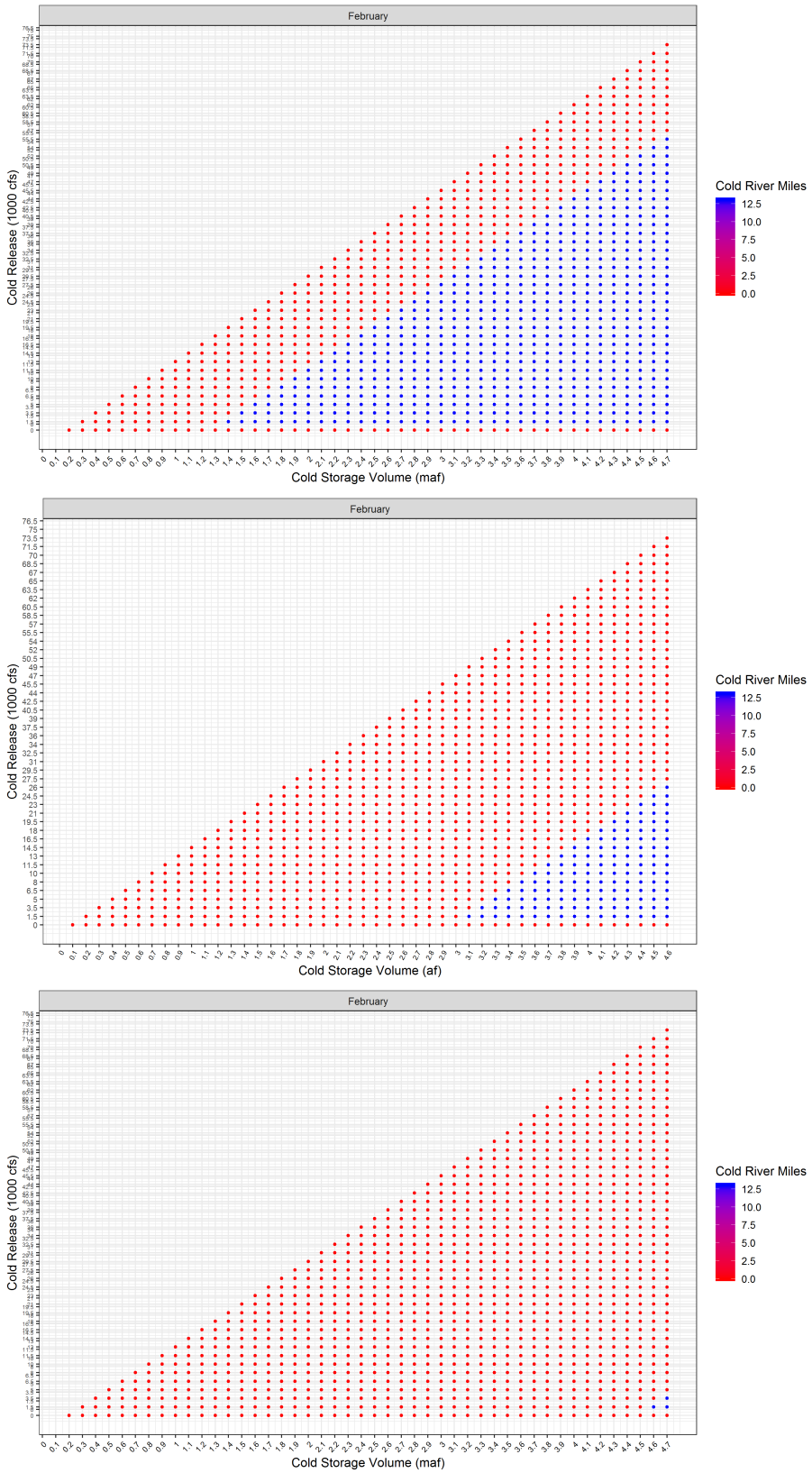


Figure 4.47: Cold river miles achieved over the long-termwith optimized release schedules in February with 75%, 50%, and 30% (top, middle, and bottom, respectively) curtailment on deliveries.

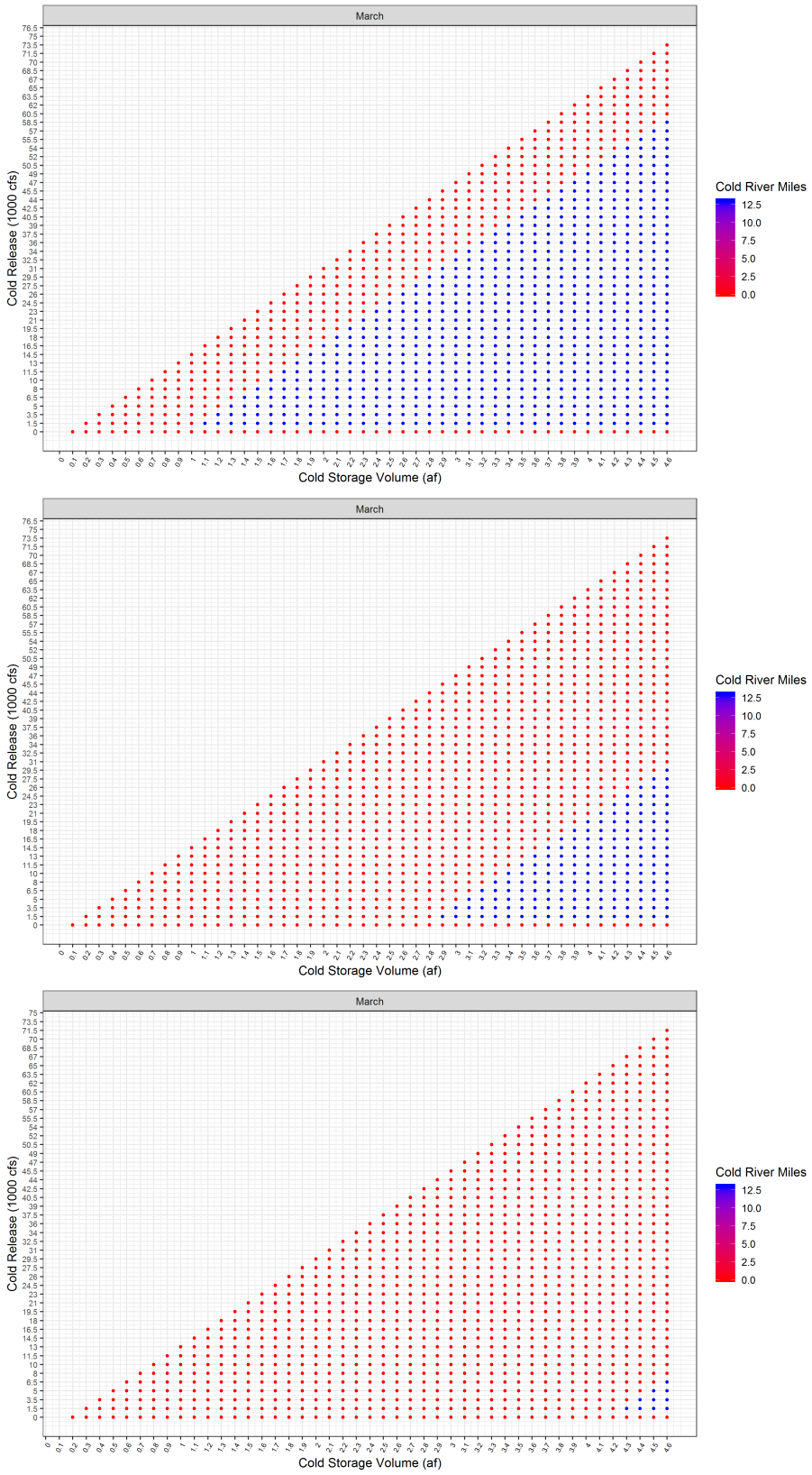


Figure 4.48: Cold river miles achieved over the long-term with optimized release schedules in March with 75%, 50%, and 30% (top, middle, and bottom, respectively) curtailment on deliveries.

5 Dissertation Conclusion

Current literature on reservoir operations and environmental flow neglect temporal persistence in outcome variables (e.g., cold water habitat) even though ecosystems often have memory and reservoir storage and wildlife survival almost always involve correlated processes across time steps. If, one month's reservoir releases make the river uninhabitable and deplete storage, or if a large cold release leaves no cold water in the reservoir, future ecological outcomes will be harmed. Behavioral economics describes managing this problem as "regret avoidance" for which an agent's current decisions have a backward looking component that "avoids information which threatens to cast a past decision into an unfavorable light [Krähmer and Stone, 2005]" such that "you should choose the option that minimizes the regret you will feel at the end [Halpern and Leung, 2016]." We adapt this idea to reservoir operations - that an operator will "regret" "wasting" water from storage if later period releases have less benefit. To avoid regrettable decisions, two approaches are taken: a) apply a maximin operator to the objective function and maximize downstream temperature benefit while minimizing worst-case outcomes, and b) add an environmental state variable to the objective function (like fish population) and optimize releases to maximize this benefit (e.g., fish population size). The environmental benefit function could be based on different environmental flow methods using different biological or downstream targets such as habitat, insect and bird survival, groundwater recharge, or even a multi-objective model to benefit multiple species and/or ecological goals: the environmental hedging principles and mathematics across time steps would remain the same.

Operating with environmental hedging logic maximizes system river benefit, but minimizes the risk of storage depletion and multi-year failure. For monthly environmental flow releases, it enables operational decisions to consider releases for biological objectives, and to weigh trade-offs among storing or releasing water for different cohorts for different water year types and different storage limits. The hydrologic forecasting in the model can allow for realistic decisions for long-term planning of an unknown future and short-term planning with adaptation as inflow information becomes known. Operating with the regret avoidance logic for temperature control requires maximizing delivery of cold water habitat and other water supply deliveries, but minimizing multi-year storage depletion or unsustainable monthly cold water releases. A maximin dynamic program, in concert with delivery curtailment and a monthly-varying temperature goal to a constant downstream location, implement this logic. When applied to Shasta reservoir, it could improve reservoir operations for the Sacramento river below Shasta Dam as well as other large dams faced with managing drought, temperature, and long-term risk. With the environmental hedging algorithm, it is likely that more Fall-run Chinook could be saved below Folsom Dam, with less water. Developing reservoir release schedules with the logic of sometimes curtailing deliveries and downstream temperature and/or riverflow goals now, to maximize net deliveries and temperature goals for the long-term, could likely hedge the risk of drought and unsustainable delivery of cold water habitat for temperature management in reservoirs. Looking to this re-operational approach before making major infrastructural changes such as dam expansion or new off-site storage could save resources, time, water, and fish. The mathematics and logic of such cold water hedging operations can be related more directly and conventionally to reservoir hedging for water supply, hydropower, drought management, and flood control.

References

Halpern, J. Y. and Leung, S. (2016). Minimizing regret in dynamic decision problems.

Krähmer, D. and Stone, R. (2005). Regret in dynamic decision problems.

6 Summarized Dissertation as a Policy Memo

To: Central Valley Operations Unit, Bureau of Reclamation

Regarding: **Temperature Management in Reservoirs with an illustrative example of Shasta Reservoir Temperature Management**

From: Lauren Adams, Center for Watershed Sciences, University of California-Davis & Planning Division MP-700, Bureau of Reclamation

A strategy is proposed for optimizing short and long-term temperature management in reservoirs. Similar to financial hedging, hedging for temperature management reduces the likelihood of large losses and gains by avoiding greedy operations and by carefully incurring small losses. Model results found that hedging releases for temperature and flow management of Shasta reservoir might protect against long- and short-term drought-driven reservoir depletion and ecosystem catastrophe. These results stem from exploratory model runs done for my dissertation; more research is needed.

Drought Hedging: A Strategy for Long-Term Temperature Management in Reservoirs

Five operating strategies make up "drought hedging," for temperature management.

- **Seasonal river temperature hedging** reduces early season releases to ensure sufficient cold and total water availability late in the season.
- **Annual river flow hedging** hedges releases to provide consistent downstream delivery and curtails releases in early drought years to save stored water for a potentially long drought
- **Monthly-varying downstream temperature targets** conserves storage and mimics biological, e.g., fish, downstream demand and the natural regime to make more ecologically effective use of cold water
- **Annually-varying downstream temperature target locations** conserves surplus storage with constant, achievable and ecologically-consistent downstream targets
- **Abandon hopeless causes** abandons months and years for which the ecosystem almost certainly lost, e.g., there is a negligible fish population size, or there is not enough incoming cold or total storage to support short and long-term downstream demand and ecosystem function

Operating with drought hedging math and philosophy differs from a greedy operating policy. A greedy operating policy maximizes current temperature benefits but not seasonal or over-year benefits.

Drought Hedging versus Greedy Policy

A numerical example demonstrates the value of operating reservoirs with drought hedging versus operating with a greedy operating policy. Hedged reservoir operation results were modeled with a maximin stochastic dynamic program (maximizing worst-month performance for consistency). Greedy policy operations are modeled with a greedy stochastic algorithm (maximizing average immediate benefits).

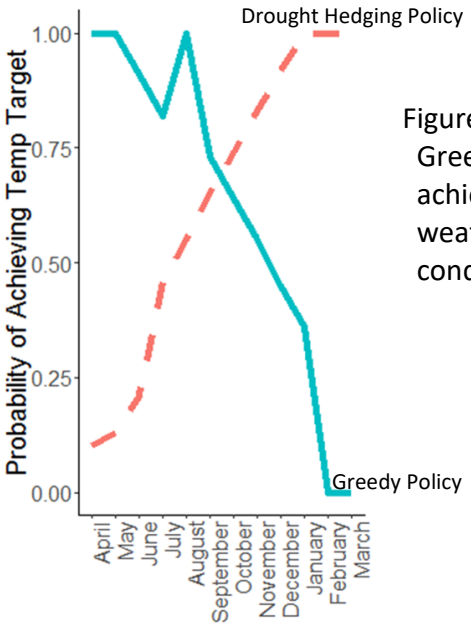


Figure 1: Example comparison of Temperature Performance with Greedy and Hedging Operations for Drought. Probability of achieving a downstream cold habitat target for a range of weather conditions and a full range of initial April storage conditions (empty to full capacity).

A Temperature Management Strategy for Shasta Reservoir

- Hedge seasonal river temperature and annual river flow to maximize the minimum monthly habitat consistently with a maximin stochastic dynamic program.
- Create habitat to support ecological function, particularly for the federally protected Winter-run Chinook.
- Operate to meet monthly-varying downstream temperature targets that mimic temperature requirements of each life history stage of the Winter-run Chinook.
- Operate to meet a consistent, achievable downstream target at Clear Creek. On average, ninety-five percent of Winter-run Chinook spawn above Clear Creek. Providing cold water habitat until Clear Creek requires the same volume as meeting Ball's Ferry or Jelly's Ferry cold water location targets: 300 TAF of cold pool and 500 TAF of warm pool volume of water.
- Curtailing downstream deliveries early in drought is highly effective for avoiding flow and temperature habitat failures, and storage depletion. When early curtailments are made, there are no years when abandoning operations is needed, even with the expectation of extreme drought.
- Abandon months when insufficient cold or total water storage is available for that season, or insufficient fish are present to merit cold habitat conditions.
- It may be advisable to always curtail releases in April for temperature management for the long-term; between 2003-2018 Winter-run Chinook fish count surveys only found an expected 3 spawning fish in April below Shasta Dam.
- Avoid a greedy strategy. Greedy policies often put downstream temperature habitat at risk. A greedy strategy for Shasta reservoir would maximize current but not long-term river and reservoir benefits. Cold water habitat length and temperature would be maximized to Jelly's Ferry with a constant cold water temperature to incubate eggs for the entire stratified season, independently of the existing fish population size. Months or years would never be abandoned for any reason.

Expected Shasta Reservoir Temperature Management Results
When Shasta reservoir is operated for temperature control and downstream delivery objectives, the system always fails under drought requirements unless deliveries are curtailed. **With enough delivery curtailments and operating with a hedging strategy, even with extreme drought, the system is operational and achieves temperature targets when initial storage is above deadpool, for multiple years.** With the greedy policy, incoming storage above 2.1 million acre feet is required to sustain operations during a three-year drought, even when curtailing deliveries by 75%.

Without downstream deliveries, **there is always enough cold and total water in Shasta reservoir to achieve downstream long-term temperature targets unless initial April storage is below deadpool,** so it does not matter whether a drought policy or greedy policy is selected.

In a year of extreme drought, operating with a hedging strategy is expected to save about 2,000 Winter-run Chinook, which is about 130% more than operating with a greedy policy.

Employing a drought hedging strategy could save the system from requiring additional reservoir capacity, either off-site or with a raise, for temperature management of the Sacramento River.

The research, conclusions and findings here come from Lauren Adams' dissertation research at the University of California-Davis, Department of Civil and Environmental Engineering. Now Lauren Adams is employed as a Modeler/Civil Engineer with the Planning Division at the Bureau of Reclamation, MP-700, Sacramento Office, phone number: 916.978.5064.