Trading joules for fish? Opportunity costs in the adaptive management of regulated rivers

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Abstract

Forgoing the traditional economic benefits of dam management to utilize designer flows—ecologically motivated releases of water into highly regulated river segments—can be an effective but costly approach to conserving threatened species. In this paper, we perform an integrated assessment of designer flow implementation at the Glen Canyon Dam on the Colorado River. In this prominent and representative example, designer flows can be used to control nonnative species that disadvantage endemic threatened species. Our analysis of this system suggests that the cost of designer flows remains too high to justify implementation. The lack of cost effectiveness of designer flows stems from the high value of foregone hydropower, the delay in benefits for downstream threatened species, and the uncertainty in designer flow effectiveness. Our results inform an ideal course of conservation action in other regulated river systems based on the presence or absence of these critical features.

Keywords: designer flows, hydropower, Glen Canyon Dam, Colorado River, integrated assessment, adaptive management, value of information, population viability, chance-constrained dynamic programming (JEL: C61, Q25, Q47, Q57)

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1 Introduction

Understanding the trade-offs associated with managing dam-regulated rivers is increasingly important due to the growing number of obstructions on large rivers (Zarfl et al., 2014) and increasing recognition of the values of resources within rivers (Jackson et al., 2008). While dams can provide considerable economic benefits, such as hydropower electricity generation and reliable water supply, they can also disturb ecosystem function and services, threaten freshwater species diversity, and facilitate the establishment of nonnative species (Schmidt et al., 1998; Vörösmarty et al., 2010; Liermann et al., 2012; Ziv et al., 2012). A pervasive challenge in regulated river management is operating dam infrastructure in a way that balances economic and conservation objectives.

Designer flows are a promising approach for balancing these objectives (Schmidt et al., 1998; Poff et al., 2016). A designer flow manipulates the downstream hydrological conditions of a river through prescribed water releases from a dam (Acreman et al., 2014). For example, the release of water can be timed to dewater—and thus control—populations of nonnative fish species downstream (Giardina et al., 2024). The evaluation of designer flows is now commonplace (e.g. Sabo et al., 2017), and there are several instances where designer flows have been used on large regulated rivers to improve ecosystem function and services (Watts et al., 2011; Olden et al., 2014; Deemer et al., 2022).

Despite evaluating the ability of designer flows to meet multiple objectives, previous studies have not considered the opportunity cost of designer flows in terms of the foregone benefits that would have been prioritized in the absence of designer flows, e.g., from hydropower generation, agricultural production, or natural flow mimicry. Further, the benefits of experimentation when the effectiveness of designer flows is uncertain have not been considered. These lacunae are due to the scarcity of formal integrated assessment models considering economic outcomes, conservation objectives, and opportunities for active adaptive management to integrate learning into implementation (Hermoso et al., 2012). Without considering the opportunity cost of designer flows and the value of information through experimentation, managers cannot ensure that conservation objectives are being met at the lowest expected cost, or that designer flow implementation is justified.

In this paper, we perform an integrated assessment of designer flows for achieving conservation goals with an application to a large dam-regulated ecosystem downstream of the Glen Canyon Dam on the Colorado River in the Southwest United States. Using the recent development of shadow value viability (SVV; Donovan et al., 2019; Donovan and Springborn, 2022), we consider management to achieve a viable population of a threatened native species using the least costly combination of conservation actions. Optimal management using SVV ensures that species viability is maintained with a given level of confidence while considering the opportunity cost of designer flows in terms of the foregone economic value of hydropower electricity generation. Our framework provides an integrated assessment that considers conservation outcomes, the economic opportunity cost of management actions, and the value of information from designer flows.

In our study, two management actions are available to dam regulators. First, designer flows reduce the recruitment of a nonnative species, rainbow trout (*Oncorhynchus mykiss*), in the tailwater immediately downstream from the dam by manipulating flows to strand juveniles on higher elevation gravel bars (Giardina et al., 2024). Second, a nonflow action (electrofishing) is available to control adult nonnative trout populations further downstream, where a threatened native species, humpback chub (*Gila cypha*), is impacted by competition and predation (Yackulic et al., 2018b). The opportunity cost of designer flows is the economic value foregone by deviating from a release schedule that maximizes the value of hydropower. Thus, the cost of designer flows is more sensitive to external factors (i.e., electricity prices) than the nonflow action. Optimal management entails employing neither, either, or both actions to maintain threatened species viability at minimal cost.

Our conclusions are fourfold. First, designer flows are a prohibitively expensive management tool when rainbow trout are the focus of designer flows in the system. The optimal policy does not frequently use designer flows to control rainbow trout when nonflow action is available because the benefit to the humpback chub accrues only after two years—the interval over which juvenile trout grow and migrate downstream before posing a viability threat—and downstream removal actions can be safely delayed until there is a sufficient threat posed to the humpback chub. Thus, a policy favoring the nonflow action generates the lowest present-valued cost of management without loss of threatened species viability.

Second, the optimal designer flow policy is highly sensitive to the recruitment of juvenile rainbow trout—the share of juveniles that reach maturity and successfully migrate downstream of Glen Canyon Dam—but this information is costly to obtain and not required for downstream nonflow action. Even if rainbow trout recruitment observation is undertaken, the management advantage that designer flows earn relative to the nonflow action only occurs in rare cases when recruitment is exceptionally high while downstream conditions are favorable for the humpback chub (which eases the need for immediately impactful downstream removals). Thus, obtaining this recruitment information has very little impact on long-run expected costs.

Third, our designer flow policy is sensitive to the biological traits of the nonnative species and the nature of interspecific interactions. For example, a much more piscivorous predator, brown trout (*Salmo trutta*), increased in the study area starting around 2015 (Runge et al., 2018; Yackulic et al., 2020; Healy et al., 2023). While brown trout carrying capacity is expected to be lower than for rainbow trout, they are expected to have a greater per capita effect on humpback chub if they reach high abundances downstream of Glen Canyon Dam tailwater. Extending our model to consider a more effective predator reduces the prior preference for the nonflow action, chiefly due to a combination of brown trout's effect on the humpback chub and higher natural survival rate (which increases the duration of this higher per capita effect). Early designer flow action is preferred given that repeated years of high downstream brown trout abundance pose a serious threat to the humpback chub.

Fourth, we find that an adaptive management regime can reduce electricity generation opportunity costs at Glen Canyon Dam. We employ a form of active adaptive management where a manager has the option to implement a short-run program of increased designer flow use to reduce uncertainty in flow efficacy before determining an optimal management plan for the long-run. Our manager can choose to implement no learning, or one of two short-run learning regimes that differ in their aggressiveness. The two learning regimes arrive at more precise information over different expected time horizons due to their differing intensity. We demonstrate that the decision to experiment is highly sensitive to future energy costs. Our main result is as follows: if energy costs are not expected to increase dramatically, the less aggressive learning regime generates a net benefit relative to a policy that does not employ learning.

While our conclusions are specific to the Colorado River downstream of Glen Canyon Dam, our study illustrates how detailed knowledge of management objectives, ecosystem functions, opportunity costs, and active learning opportunities can be integrated to assess the performance of conservation actions. By explicitly modeling the mechanisms that drive system outcomes, we are able to demonstrate the sensitivity of conservation and learning decisions to critical features of our setting, such as opportunity costs and the interactions of downstream aquatic species. Our results can thus inform an ideal course of conservation action in other regulated river systems based on the presence or absence of these critical features.

In the next section, we lay out the three components of our integrated assessment model. First, Section 2.1 presents the bioeconomic model and solution method. Sections 2.2 and 2.3 then specify the opportunity cost of designer flows and our adaptive management strategy, respectively. Section 3 explores the value of designer flows with simulated results from several numerical exercises including our baseline model (3.1), incorporating more detailed ecosystem monitoring (3.2), considering a more piscivorous predatory species (3.3), and adaptive management (3.4), respectively. Section 4 concludes with further discussion regarding external validity, designer flow experimentation, and integrated assessment research.

2 Integrated assessment model

In this section, we present our integrated assessment framework for evaluating the cost-effectiveness of designer flows for the Glen Canyon Dam in achieving conservation goals for a threatened humpback chub population. We begin with a biological model that depicts the dynamics and interspecific interactions of trout and humpback chub populations in the Colorado River downstream of the Glen Canyon Dam. We then introduce an environmental manager's program, which is to minimize the expected cost of trout-reducing actions (mechanical removals and designer flows), subject to an objective of maintaining (probabilistically) the humpback chub population above a viability threshold. The cost of undertaking trout-reducing actions includes the opportunity cost of implementing a designer flow, which we characterize as the forgone economic value of energy generation when dam releases deviate from those that meet energy generation objectives. We present a hydropower optimization model that determines the hourly flow that maximizes the economic value of hydropower. The opportunity cost of designer flows is the difference in the optimal economic value of hydropower generation with and without designer flow constraints. Finally, we extend the environmental manager's problem to include an element of active adaptive management, which provides an opportunity to learn the true efficacy of designer flows in the future through short-run experimentation.

2.1 Species viability model and solution method

The Colorado River downstream of Glen Canyon Dam is habitat for both an economically valuable nonnative rainbow trout (trout) sport fishery and for the threatened native humpback chub (chub) (Bair et al., 2016; Yackulic et al., 2014). Contemporary operation of the dam facilitates a self-reproducing population of rainbow trout in Glen Canyon, which periodically migrates downstream into Marble and Grand Canyons, especially following large recruitment events (Korman et al., 2015). A population of chub occurs around the confluence of the Colorado River and Little Colorado River in Grand Canyon National Park, 125 km below Glen Canyon Dam. Chub spawn in the Little Colorado River and a portion of juveniles disperse into the mainstem of Colorado River, where they are vulnerable to competitive and predatory pressure from adult trout (Yackulic et al., 2014, 2018b).

Figure 1 shows a map of the study area.

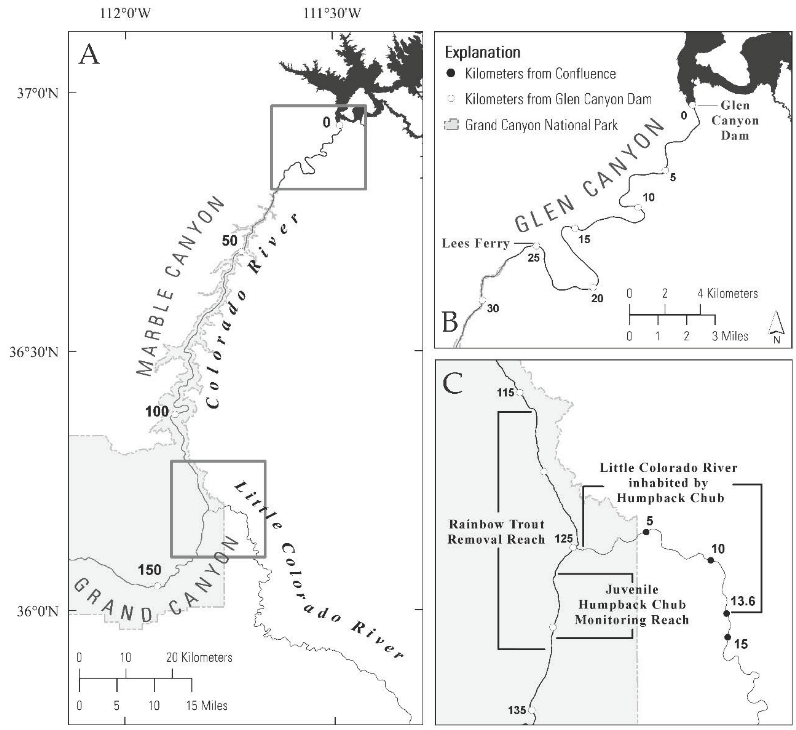

Figure 1: Map of (A) the study area in the Colorado River ecosystem, with detail of (B) the tailwater below Glen Canyon Dam, and (C) chub monitoring and trout removal reaches near the confluence of the Colorado River and Little Colorado River.

Our biological model is adapted from previous bioeconomic analyses of this system (Bair et al., 2018; Donovan et al., 2019), and parameterizations (numerical values in Appendix A) are derived from past population modeling efforts (Yackulic et al., 2014; Korman et al., 2015; U.S. Department of the Interior, 2016; Yackulic et al., 2018b).

Adult population dynamics for each species are modeled at an annual timestep t and given by

$$W_{t+1} = (W_t - x_t + w_t) \cdot \gamma_w,\ W_t \geq 0, \tag{1}$$

$$X_{t+1} = (X_t + x_t) \cdot s_x(A_t) \cdot \gamma_x,\ X_t \geq 0, \tag{2}$$

$$Y_{t+1} = \left\{ \begin{array}{rl} y_t \cdot s_y(X_t) + Y_t \cdot \gamma_y, & \text{if } Y_t > \overline{Y} \\ \overline{Y}, & \text{if } Y_t \leq \overline{Y}, \end{array} \right\}, \tag{3}$$

where W, X, and Y denote stocks of adult trout upstream in Marble Canyon, adult trout downstream in the Juvenile Humpback Chub Monitoring Reach, and adult chub within the same monitoring reach, respectively. Adult population levels are given by uppercase letters and new recruits to the adult stocks (either juveniles or incoming migrants) by the same letter in lowercase. The natural annual survivorship share for stock i is denoted as γ_i. Adult trout in the monitoring reach face additional mortality from nonflow removals, A_t, as specified by the survival function $s_x(A_t)$. Juvenile chub face additional mortality via the predation pressure from adult trout, given by $s_y(X_t)$. A chub population that falls below the viability threshold $(\overline{Y})$ is considered "collapsed"—an irreversible state that triggers a different decision-making regime beyond the scope of this model.

Recruitment to each stock via new juveniles (w, y) or migrants (x) is given by

$$w_t = \psi_w \cdot \exp\left(\varepsilon_{w,t-1}\right) \cdot s_w(F_{t-1}) \qquad \varepsilon_{w,t} \overset{\text{iid}}{\sim} \text{unif}(\alpha_w, \kappa_w)\,\forall t \tag{4}$$

$$x_t = \psi_x \cdot W_t \tag{5}$$

$$y_t = \psi_y \cdot \varepsilon_{y,t-1} \qquad \varepsilon_{y,t} \overset{\text{iid}}{\sim} \text{unif}(\alpha_y, \kappa_y)\,\forall t\ , \tag{6}$$

where the ψ terms govern the share of a given sub-population that out-migrate (ψ_w additionally accounts for 1-year juvenile survival). Trout and chub recruitment are stochastic processes, with variance driven by the distributions of the ε terms. Trout recruitment is subject to additional pressure from designer flow-induced mortality, captured by $s_w(F_{t-1})$. From these dynamic equations, it takes an average of two years for Glen Canyon trout recruits to arrive at the monitoring reach (via Marble Canyon), and are thus potentially exposed to both control actions (A, F) at different life stages. Both action variables are binary and represent a single within-period implementation.

There are three survival functions, including post-designer flow survival of trout recruitment in Glen Canyon, post-removal survival of trout in the monitoring reach, and survival of juvenile chub as a function of the monitoring reach trout abundance,

$$s_w(F_t) = 1 - \theta_F \cdot F_t \tag{7}$$

$$s_x(A_t) = 1 - \theta_A \cdot A_t \tag{8}$$

$$s_y(X_t) = \left(\text{logit}^{-1}(\mu + \lambda \cdot X_t)\right)^{12}\ , \tag{9}$$

where the θ and λ parameters specify the strength of these mortality impacts. In our model, θ_F is taken to be an unknown parameter with a given uniform distribution to reflect the current state of knowledge concerning designer flow efficacy—obtained through expert elicitation and recent hypsometric analysis (Runge et al., 2015; Giardina et al., 2024).

We are concerned with the cost-effective reduction of trout competition and predation on juvenile chub in the monitoring reach that maintains the adult chub population (Y) above a viability threshold $(\overline{Y})$ over a given time horizon (T) with some level of confidence (Δ). The optimal policy minimizes the expected present cost of trout-reducing actions (removals A and designer flows F) such that our viability goal is continually satisfied for the next T years,

$$\min_{A_t, F_t} E\left[\sum_{t=0}^{\infty} \beta^t \cdot C(A_t, F_t)\right] \tag{10}$$

$$\text{s.t. } P\left(\bigcap_{s=t}^{t+T} Y_s > \overline{Y}\right) \geq \Delta,\ t = 0, 1, \ldots\infty\ , \tag{11}$$

and is subject to the dynamics in Equations 1-9. Within-period cost is given by

$$C(A_t, F_t) = c_A \cdot A_t + c_F \cdot F_t\ , \tag{12}$$

where c_A is the cost of removal and c_F is the cost of conducting a designer flow, the latter of which is determined by a model of future energy costs described in the next section. Removals and designer flows are restricted to one implementation per year so that $A_t, F_t \in \{0, 1\}$. Delaying action lowers costs in present-valued terms via the discount factor β.

An environmental manager's viability horizon of T years is nested in an infinite horizon optimization problem since, in each year t, we are concerned with survivorship over the next T years. This "rolling window" constraint cannot be recast as something like $Y_t > \overline{Y},\ \forall t$ because no policy can support this constraint indefinitely due to the stochasticity in the underlying dynamics (Donovan and Springborn, 2022). Similarly, the time horizon of the cost minimization problem cannot be restricted to T years, because this incentivizes a reduction in care for a threatened species in later periods that would cause regret once the manager extends their program beyond the first T years (Donovan and Springborn, 2022). Thus, the rolling horizon is the correct representation of the viability goal, and solving the above objective generates a dynamically consistent policy.

The manager's problem can be equivalently cast as solving for the fixed point of a Bellman equation. Let $Z = [W, X, Y]$ denote the vector of state variables, $G(Z)$ represent the population dynamics specified in Equations 1-9, and ζ_t capture additional "shock" variables with no path-dependence (such as the recruitment of trout, w_t). Then the optimal policy $\{A(Z, \zeta),\ F(Z, \zeta)\}$ satisfies

$$V(Z_t) = \min_{A_t, F_t}\ C(A_t, F_t) + \beta \cdot E_\varepsilon[V(Z_{t+1}) | A_t, F_t, Z_t, \zeta_t] \tag{13}$$

$$\text{s.t. } P\left\{\bigcap_{s=t}^{t+T} Y_s > \overline{Y}\right\} \geq \Delta \tag{14}$$

$$\text{and } Z_{t+1} = G(Z_t)\ . \tag{15}$$

Given the joint chance constraint imposing the viability requirement in Equation 14, the problem specified above does not maintain the Markov property required by standard dynamic programming solution techniques. To address this, we use a dynamic programming algorithm specified by Donovan et al. (2019) which entails imposing an estimable penalty (Ω) that is incurred by the manager if the chub population falls to $\overline{Y}$, which is treated as irreversible. This provides a virtual incentive for the manager to avoid states that approach the threshold and penalty by taking on costly management action. Given this penalty, a solution to the problem above—without the viability constraint—is found via value function iteration (Judd, 1998), and the joint chance constraint is checked after the optimization step. We iterate over penalty levels to find the lowest penalty that induces the manager to meet (or exceed) the viability goal everywhere in the state-space it is feasible to do so. This feasible region is referred to as the viability kernel, $\{Z\}_k$ (Donovan et al., 2019; De Lara and Doyen, 2008; Oubraham and Zaccour, 2018).

In summary, we solve Program 16:

$$\min\{\Omega\} \text{ s.t. } P\left\{\bigcap_{s=t}^{t+T} Y_s > \overline{Y} \,\middle|\, A^{\Omega}, F^{\Omega}, Z_t \in \{Z\}_k\right\} \geq \Delta, \tag{16}$$

where $\{A^{\Omega}, F^{\Omega}\}$ solve the following cost-minimization problem conditional on Ω:

$$V^{\Omega}(Z_t) = \min_{A_t, F_t}\left\{C(A_t, F_t) + \beta \cdot E_{\varepsilon}\left[V^{\Omega}(Z_{t+1}) \mid A_t, F_t, Z_t, \zeta_t\right]\right\} \tag{17}$$

$$\text{s.t. } V^{\Omega}(W_t, X_t, \overline{Y}) = \Omega \tag{18}$$

$$\text{and } Z_{t+1} = G(Z_t)\ . \tag{19}$$

After solving for $V^{\Omega}(Z_t)$ and the optimal policy $\left\{A^{\Omega}(Z_t, \zeta_t), F^{\Omega}(Z_t, \zeta_t)\right\}$, we can recover $V(Z_t)$ directly by calculating the expected present costs of the optimal policy (Donovan and Springborn, 2022).

2.2 Opportunity cost of designer flows

The reach of the Colorado River running through Glen, Marble and Grand Canyons is regulated by Glen Canyon Dam (GCD). Annual releases from GCD are allocated to meet Upper Colorado River Basin water deliveries to the Lower Colorado River Basin, while monthly and daily regulation is driven by hydropower and other downstream resource objectives (U.S. Department of the Interior, 2016). Hydropower generation at GCD is utilized in the Western Interconnection, a power grid encompassing the western United States and parts of Canada and Mexico. Given the low marginal cost of hydropower, GCD is used as a load-following facility that adjusts output throughout the day to maximize the value of energy generated as demand changes, allowing avoidance of alternative high-cost electricity generation from other sources during peak demand periods.

Designer flows result in dam releases that deviate from those that meet energy generation objectives. At GCD, dam operators choose to implement an annual designer flow cycle, which consists of three separate designer flows in the months of May, June, and July (U.S. Department of the Interior, 2016). The opportunity cost of a designer flow cycle is the unrealized economic value of energy generation when deviating from the river flow that meets energy generation objectives. To estimate this foregone economic value, we model energy generation under a dam operator selecting hourly flow through GCD to optimize the economic value of energy subject to operational constraints, with and without designer flows. The difference in the optimal economic value of energy generation with and without designer flows informs c_F in Equation 12.

To begin, we model hydropower production (in MWh) generated at GCD as a function of flow Q_h (in cfs) through power-generating turbines and reservoir elevation L (feet above mean sea level) (Waldo et al., 2021),

$$M(Q_h, L) = \sigma \cdot Q_h \cdot \left(L - \overline{L}\right) \ . \tag{20}$$

Q_h is assumed to be constant over an hourly time step h. Because hourly flow through the GCD is assumed to have negligible impact on reservoir elevation, L is exogenous to the contemporaneous hourly flow rate Q_h. L is further assumed to be constant within a month, as elevation varies within tenths of a percent over this timeframe (Bureau of Reclamation, 2024). Energy generation is proportional to reservoir elevation above the tailwater $\overline{L}$. Consequently, σ converts reservoir height to hydraulic pressure, which ensures the full calculation produces a measure of energy (hydraulic pressure × total flow volume).

To identify optimal hourly energy generation over the planning horizon, we utilize the following hydropower optimization model which follows Harpman (1999). Within each month, an operator's objective is to maximize the economic value of hydropower,

$$\max_{Q_1,\ldots,Q_H} \sum_{h \in H_m} p_h \cdot M\left(Q_h, L\right), \tag{21}$$

subject to several operational constraints,

$$
\begin{array}{rll}
\sum_{h\in H_m} Q_h \leq & \text{max monthly volume (cfs),} & \text{for } m \in \{\text{May, June, July}\} \\
Q_{h=j} \geq & \text{min off-peak flow,} & \text{for } j \in \text{off-peak hours} \\
Q_{h=i} \geq & \text{min on-peak flow,} & \text{for } i \in \text{on-peak hours} \\
Q_h \leq & \text{max flow} & \\
Q_{h-1} - Q_h \leq & \text{max down ramp} & \\
Q_h - Q_{h-1} \leq & \text{max up ramp} & \\
|Q_h - Q_{h-k}| \leq & \text{max flow change in 24 hours,} & \text{for } k \in \text{24 hour period.}
\end{array}
\tag{22}
$$

where p_h is the predicted hourly price (\$/MWh) during each hour h within a given monthly window (H_m). Since hydropower generated from the GCD constitutes less than 2% of the generating capacity in the regions of the Western Electricity Coordinating Council where it's marketed, we assume the operator is a price-taker and considers the predicted prices p_h to be exogenous (EIA, 2023). We use historical Palo Verde hub prices to construct a representative weekly price vector for May, June, and July, resulting in a range of hourly prices for each month in which designer flows could take place.

Each designer flow in each month results in three consecutive days of high water releases, followed by an abrupt decline to very low levels for six hours. When designer flows are implemented, Equation 21 is thus subject to

$$
Q_h = \left\{ \begin{array}{ll} 20000 \text{ cfs}, & \text{if } h \in H_{hf} \\ 5000 \text{ cfs}, & \text{if } h \in H_{lf}, \end{array} \right\}. \tag{23}
$$

where H_{hf} is the collection of "high flow" hours spanning 8:00 AM - 8:00 AM on the first three weekdays of each month, and H_{lf} is the six hour "low flow" period following each three day high flow event in each month. This "go high then low" strategy completes a designer flow cycle, stranding trout on higher elevation gravel bars (Giardina et al., 2024). This schedule contrasts a flow schedule prioritizing maximum energy value, which would instead follow demand through the day, subject to operation constraints, maximizing flow during early morning and late evening and minimizing flow during high renewable generation mid-day and lower night time demand.

We solve for the optimal release schedule with and without designer flow constraints. The economic cost of implementing a designer flow is then the difference between the economic value of hydropower generation under the optimal schedule with no designer flow and the optimal schedule subject to designer flow constraints. Because peak energy demand occurs in August—outside of the proposed designer flow schedule—additional generation capacity is available on the grid during designer flow implementation. Thus, we characterize the opportunity cost of a designer flow as short-run, i.e., from paying another available generator to supply the forgone energy generation rather than from building new energy generation capacity.

2.3 Adaptive management and experimentation

The use of designer flows to manage nonnative fish species is a recent innovation in river management, and their efficacy is not well-studied in the Colorado River ecosystem. Utilization of this tool will not only manage the system under study, but provide useful information that can inform more efficient flow designs, reducing future program costs.

We extend our base model in Section 2.1—where beliefs about the designer flow efficacy θ_F follow a given uniform distribution—to allow the true value of θ_F to be learned at a date in the near future. We consider an active adaptive management strategy that begins with a targeted learning procedure in the short term and then switches to a new optimal policy conditional on newly-learned information concerning designer flow efficacy. The cost of this adaptive management program can then be compared to the costs of the optimal policy in the non-adaptive program that has no learning. The population viability objective is still reached under the adaptive management program because it employs action more frequently than is necessary for short-run management. Thus, the only meaningful difference between the two programs is their cost.

During the short-run learning phase, designer flows are used according to a predetermined learning regime (described below), and the nonflow action (removals) is not used. This is sufficient to meet the viability objective, though at a higher cost than could be achieved with a mix of the two control options. Upon discovery of the true designer flow efficacy—stylized as a random draw from the θ_F distribution described in Section 2.1—the learning-savvy environmental manager calculates the optimal policy for the next management phase by solving Program 16. The total program cost, given new information arriving in year T_L, is

$$C(T_L) = \sum_{t=0}^{T_L} \beta^t \cdot c_F F_t + \beta^{T_L+1} \cdot C_L, \tag{24}$$

where the summation captures total costs during the learning stage and the second term provides the present discounted value of future costs, C_L, i.e., the expected costs of an updated optimal program from year T_L that accounts for the new information. The continuation value C_L is calculated using iterated expectations. That is, we first calculate the expected long-run costs of the post-learning optimal policy under each potential true value of θ_F that the manager could observe, then calculate the expectation of these conditional expected costs over the θ_F distribution.

We consider two types of learning regimes, indexed by R: (1) a designer flow is implemented only in select high trout recruitment years (defined as an event above the $1 - \phi$ percentile; $R = select$), or (2) a designer flow is implemented in all years ($R = annual$). The probability of a high recruitment event, ϕ, defines a threshold recruitment event size, above which the signal from a single designer flow experiment is notably stronger (Yackulic et al., 2018a). The probability of learning the true value of θ_F each year a designer flow is implemented is denoted by π. We consider this as the probability that stakeholders find that a given experiment establishes sufficient confidence in the current estimate of θ_F, which we take to be the inverse frequency of past experimental efforts (Yackulic et al., 2024).

The viability objective is met under both of these learning regimes, but the more aggressive *annual* flow regime results in higher chub abundances and lower trout abundances over a similar period of implementation. The less aggressive *select* regime that utilizes fewer experiments is less costly in the learning phase on average, but the lower number of observed designer flows results in slower learning and later adoption of an informed policy post-learning.

The expected cost of the learning program, conditional on ϕ, T_L and R, is

$$\begin{aligned} C(T_L|R) &= \sum_{t=0}^{T_L} \beta^t \cdot \phi^{\mathbb{1}(R=select)} \cdot c_F + \beta^{T_L+1} \cdot C_L \\ &= \phi^{\mathbb{1}(R=select)} \cdot \frac{1-\beta^{T_L+1}}{1-\beta} \cdot c_F + \beta^{T_L+1} \cdot C_L, \end{aligned} \tag{25}$$

which assumes that under the *select* regime the chance of a designer flow in each period is independent of previous decisions (i.e., that recruitment is not an autocorrelated process).

The learning stage continues until the true designer flow efficacy is discovered. The likelihood of learning (successful discovery) in a single period is given by

$$p_R = \phi^{\mathbb{1}(R=select)} \cdot \pi \; . \tag{26}$$

The probability that the manager learns for the first time in year T_L is determined by calculating the likelihood of failing to learn in every year before T_L, multiplied by the likelihood in learning in period T_L:

$$P(T_L|R) = (1-p_R)^{T_L} \cdot p_R\ . \tag{27}$$

With either learning strategy, the time to learning is distributed geometrically, and the expected learning time will be longer for the $R = \textit{select}$ regime. If the continuation value C_L is not state-dependent (which we relax in Section 3.4), the expected cost of the learning program is

$$\begin{aligned} E\left[C(T_L|R)|R\right] &= \sum_{T_L=0}^{\infty} P(T_L|R) \cdot C(T_L|R) \\ &= \frac{\phi^{\mathbb{1}(R=select)} \cdot c_F}{1-\beta} - \frac{p_R \cdot \beta}{1-\beta+p_R \cdot \beta} \cdot \left(\frac{\phi^{\mathbb{1}(R=select)} \cdot c_F}{1-\beta} - C_L \right)\ . \end{aligned} \tag{28}$$

Equation 28 illustrates that, regardless of the learning regime, the expected cost above equals the perpetuity cost of staying in the learning phase forever, minus the expected discounted long-run savings from leaving it.

3 The value of designer flows

In this section, we identify optimal management for the Colorado River ecosystem to achieve a population viability goal under multiple scenarios. In our baseline model (Section 3.1), the manager observes only adult chub and trout populations and does not observe juvenile chub and trout recruitment or designer flow efficacy. In this case, designer flows are rarely used due to (1) uncertainty in their efficacy given the unknown contemporary level of trout recruitment and (2) the delayed effect of designer flows on downstream trout recruitment in subsequent years.

We then make two changes to the biological model to understand whether the initial undesirability of the designer flow action is robust. First, we allow the manager to observe trout recruitment via monitoring (Section 3.2). As expected, we find that designer flow use is highly sensitive to the level of current trout recruitment. Further, the use of designer flows is preferred to nonflow action in periods of heavy trout recruitment and low immediate predation pressure on chub downstream. The allowance for informed designer flow use lowers total costs, although not dramatically, as designer flows are still infrequently prescribed. Second, we adjust the model to account for a new, more effective predator (Section 3.3). We demonstrate that the designer flow policy (and prior preference for the nonflow action) is sensitive to the specifics of the invading species' demography and the strength of interspecific interactions.

Finally, we evaluate the gains from active adaptive management. In the above simulations, θ_F is an unknown parameter with a given distribution. In Section 3.4, we allow this parameter to be determined with perfect precision after an uncertain number of experimental designer flow regimes. We show that employing a learning strategy that facilitates short-run designer flow experimentation yields potential improvements in long-run cost-effectiveness over the no-learning scenario, conditional on future energy prices.

3.1 Designer flow use is rarely a cost-effective choice without trout recruitment monitoring

In our baseline scenario, our manager observes and responds to adult populations of both chub and trout, and recruitment of either species is not observed. By happenstance, both the designer flow and nonflow management actions have similar contemporary per-action costs in practice (Table A1). In Figure 2, we show the policy function, which, conditional on adult trout abundances upstream (vertical axes) and downstream (horizontal axes), presents the adult chub abundance threshold below which it is optimal to use designer flows (2A) and/or the nonflow action (2B). In the white (non-shaded) region, it is never optimal to employ the management action; that is, there is no chub population above the chub viability threshold (4,000) for which it is optimal to take the action. Darker shades indicate that even for high chub abundances, action is still optimal. Lighter shades imply a more stringent threshold for action (i.e., the chub population falling below a smaller level). For example, in the top right corner—at maximum abundances of both upstream and downstream adult trout—it is optimal to employ the nonflow action whenever chub abundance falls below 9,500 and, in addition, designer flows when chub abundance dips under 6,000. As might be expected, chub thresholds are lower when trout abundances are lower and higher when trout abundances are higher.

The impact of any designer flow action is not immediately known in the baseline scenario. Without the monitoring of trout recruitment—the sub-population impacted by designer flows—the timing of designer flows cannot be selectively implemented when they would have maximum impact (in high recruitment years) and avoided when they would have minimum impact (in low recruitment years). Because of this, nonflow actions are predominantly used instead of designer flows (Figure 2), as the nonflow action is sufficient for maintaining chub viability on its own (Appendix B). Designer flows are entirely avoided except in dire situations and are always accompanied by nonflow action, showing that they are not cost-effective to apply on their own. The optimal policy illustrates

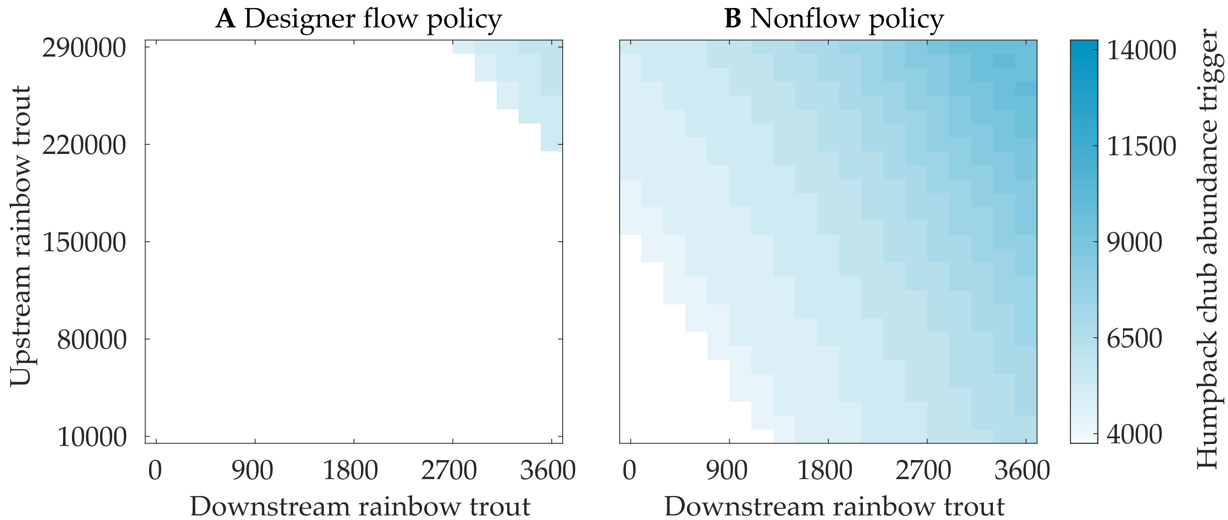

Figure 2: Optimal control policy representing the threshold chub abundance (shading) below which (A) designer flows and (B) nonflow actions are used, as a function of the adult trout abundances upstream (vertical axes) and downstream (horizontal axes). The shading indicates the highest chub population where action is undertaken.

that designer flows only contribute to cost-effective chub viability when the chub abundance is very low and the trout abundance is very high. However, as we show next, such a situation is quite unlikely to occur if a manager is operating under this optimal policy.

Figure 3 shows the probability mass function for adult chub, upstream adult trout, and downstream adult trout populations after $T = 20$ years under optimal management. The chub population persists in numbers well above the population viability target threshold ($\overline{Y} = 4,000$), and trout abundance is relegated to relatively low levels. The primary implication of Figure 3 is that under optimal management, both actions are infrequent—particularly designer flows, as mentioned above. For example, even for high trout populations, designer flows aren't employed until the chub population falls below an abundance of 6,000 (Figure 2A). This occurs rarely under optimal management, less than seven percent of the time (Figure 3A). Ultimately, this result is driven by the large and lasting impact that either management action has on chub and trout populations. Once action is undertaken, it takes several years, on average, before the next action is warranted.

While designer flows alone are sufficient for achieving viability (Appendix B), they are rarely employed relative to the nonflow action because of the uncertainty in their efficacy without monitoring and their delayed conservation effect on the downstream chub population. As such, the availability of designer flows does not generate a meaningful decrease in operating costs, as the rarely-visited states that use designer flows do not contribute significantly to the expected present cost calculation. However, pairing designer flows with

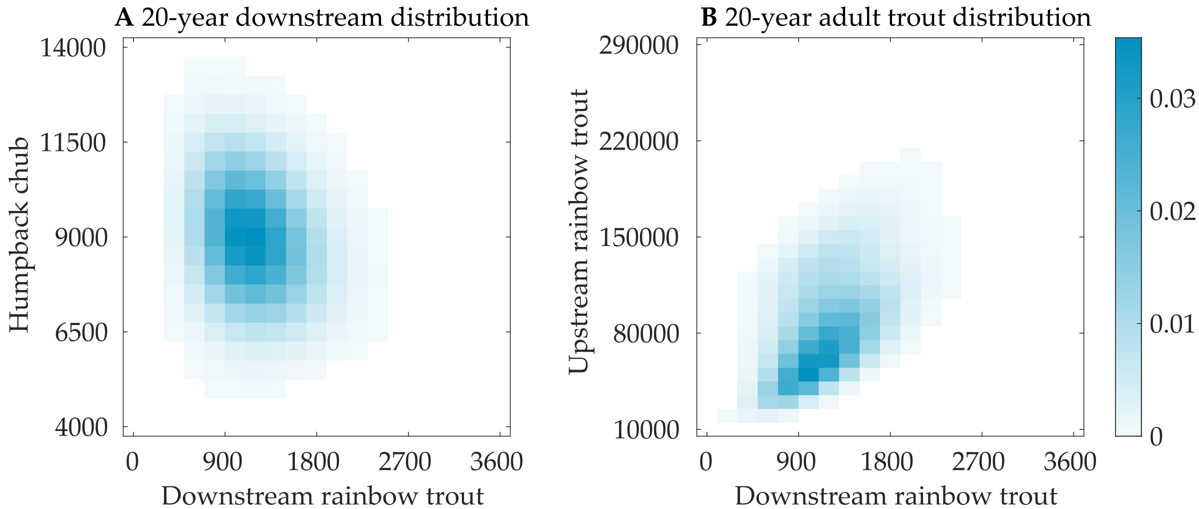

Figure 3: Probability mass function resulting from the optimal policy in the baseline scenario for (A) chub and downstream trout and (B) upstream and downstream trout. The omitted state variable in either panel is held at its 20-year modal value.

trout recruitment monitoring or improvements in design flow efficiency have the potential to qualify these conclusions. The next two sections extend the baseline model to account for these two features to determine if a savvier manager could make more effective and frequent use of designer flows.

3.2 Designer flow use is highly sensitive to trout recruitment

Without monitoring trout recruitment, our manager lacks important ecological information when determining whether designer flows will be effective in a given year, thereby eschewing this tool in most circumstances. Our study system exhibits large variability in trout recruitment, which can be monitored with dedicated agency effort. When monitoring is available in our model, these observations result in a designer flow policy that is highly sensitive to recruitment and used across a much wider range of species abundance circumstances, thus improving conditions downstream in future years and reducing the need for nonflow actions.

When informed by trout recruitment monitoring, our policy becomes a function of four state variables, including trout recruitment, upstream adult trout, and downstream adult trout and chub. The recruitment-naïve planner in our baseline model faced a distribution of recruitment outcomes which only resolved once adult trout populations were observed in subsequent years upstream and downstream. In contrast, the recruitment-informed manager is able to leverage trout recruitment abundance information one full year earlier while designer flows can still have an impact on the recruits.

We show the recruitment-informed designer flow policy in Figure 4, which has been modified from the policy function in Figure 2 to account for the extra state variable. Figure 4 shows the policy for two different levels of chub while the response to the new state variable, trout recruitment, is given by the color shading. When trout recruitment is above the level indicated by the color bar, designer flows are optimal.

The designer flow policy is highly sensitive to trout recruitment: when designer flows are optimal, recruitment is typically quite high, and this recruitment threshold decreases as the adult trout population increases or the chub population decreases, all else equal. Lighter colors signify that action is needed even after low recruitment events. The gray region of the state space shows where recruitment does not trigger a flow, given the state of the other three populations.

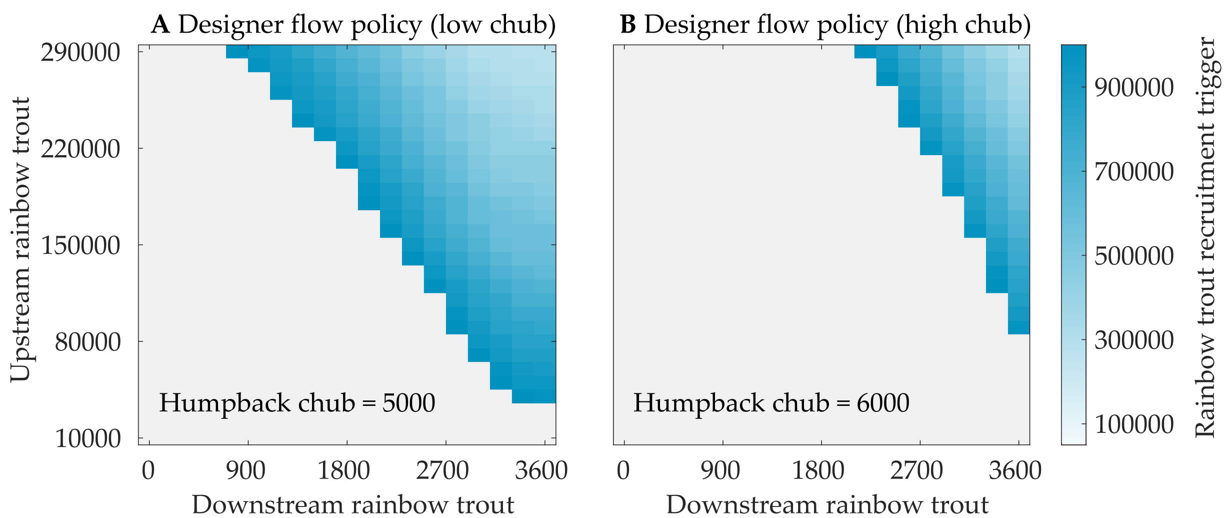

Figure 4: Optimal designer flow policy when trout recruitment is observed.

We find that the policy in Figure 4 results in the same abundance density as Figure 3. This implies that the recruitment-informed manager still uses designer flows at a very low rate. Further, the recruitment-informed nonflow policy responds only slightly to recruitment information (Appendix C). This is not surprising given that observations of the adult nonnative population in later years embody all of the relevant information from an earlier recruitment event. Because the nonflow policy does not noticeably relax, even in periods with low immediate survival pressure on the chub population and extraordinary trout recruitment (the case least addressed by the nonflow action), the expected operating costs are not meaningfully lowered with the inclusion of upstream trout recruitment monitoring. If we were to relax our assumption that monitoring costs are negligible, the net value of monitoring would fall further.

While the recruitment information facilitates the selective use of designer flows, downstream actions can still be delayed for several years and produce similarly effective control, thereby reducing the present value of operational costs through a discounting effect. Further, the nonflow action impacts both established trout populations downstream as well as new migrants. Therefore, the nonflow action can be delayed until predation pressure becomes too large to ignore, while the designer flow option loses its efficacy the moment trout migrate away from the reach immediately downstream of the dam.

Next, we consider two extensions under which designer flow use might become more favorable. The first extension addresses a recent and substantial increase in predation pressure on the chub population from a nonnative brown trout population (Section 3.3). The second involves improving the designer flow schedule through active adaptive management, whereby a costly short-run learning regime reveals the true designer flow efficacy parameter and can potentially discover a more cost-effective designer flow schedule (Section 3.4).

3.3 Anticipated changes to predation pressure in the ecological system will promote use of designer flows

Changing environmental conditions in the Colorado River have led to the establishment and recruitment of a nonnative brown trout population. Despite their lower numbers, brown trout are much more piscivorous, with approximately a seven-fold greater per-capita impact on the chub population relative to rainbow trout (Runge et al., 2018; Yackulic et al., 2018a). This section tests the sensitivity of the above results to a critical new development in the ecology of the Colorado River.

We make three changes to our model. First, we replace rainbow trout with brown trout. Second, brown trout recruitment is only 10% as large as that of rainbow trout, leading to lower populations all along the river. Third, brown trout have a higher survival rate each year, which means increases in the adult population persist longer without active management. It is assumed that designer flow efficacy, movement rates, and nonflow capture probability for brown trout are similar to that of rainbow trout.

Figure 5 summarizes the optimal policy and long run population abundances resulting from this updated brown trout management policy under the assumption of upstream recruitment monitoring (which is currently active for brown trout). Panels A through D exhibit some of the same management patterns as seen previously: the designer flow policy reacts strongly to brown trout recruitment, while the nonflow policy does not. However, we see that the nonflow policy has been reduced in cases where designer flows have been prescribed. This is due to the increased natural survival of brown trout, which reduces the power of the nonflow delay option described in Section 3.2. Therefore, there is a shift towards earlier reduction of brown trout compared to rainbow trout. Panel E shows that the resulting density for the humpback chub is similar to before, which is to be expected given that the viability objective has not changed. Panels E and F together imply that designer flows are used much more frequently relative to the rainbow trout-dominated system, about every other year.

3.4 Designer flow experimentation may be profitable, conditional on efficacy improvements and favorable energy cost projections

As designer flows are an emerging management strategy in our system under study, we have limited knowledge concerning their true efficacy. Experimentation in the short-run allows a manager to determine their efficacy with greater confidence. This section integrates the adaptive management model in Section 2.3 with the bioeconomic model in Section 2.1 and determines the economic conditions necessary to justify a short-run experimental regime to develop a better understanding of designer flow efficacy. We apply this adaptive management approach to the brown trout-dominated system with recruitment monitoring, which has a greater need for contemporary designer flow use that may justify experimentation with the promise of future program efficiency gains.

Under active adaptive management, the manager now has the option to employ one of two short-run learning strategies: a more aggressive approach that simply implements an experiment (designer flow) every year and a less aggressive approach that implements an experiment only when the strength of the designer flow effect signal is highest (which occurs when brown trout recruitment is high). In either case, we assume that the nonflow action is suspended during the learning stage (due to a budget constraint, for instance). Each experiment poses an opportunity to gain sufficient confidence about the true efficacy, and upon such a realization, the learning stage ends, and a new optimal schedule is designed using the new information. Total costs are calculated by summing the expected costs during the learning stage and the expected continuation costs over the distribution of the true designer flow efficacy (θ_F) and the population state density at the beginning of the post-learning stage given the number of designer flows implemented in the learning stage. This admits a time-sensitive and state-dependent continuation cost, C_L, which allows us to compare the total costs of the two learning regimes.

Given the significant increase in energy prices in recent years, we consider how this

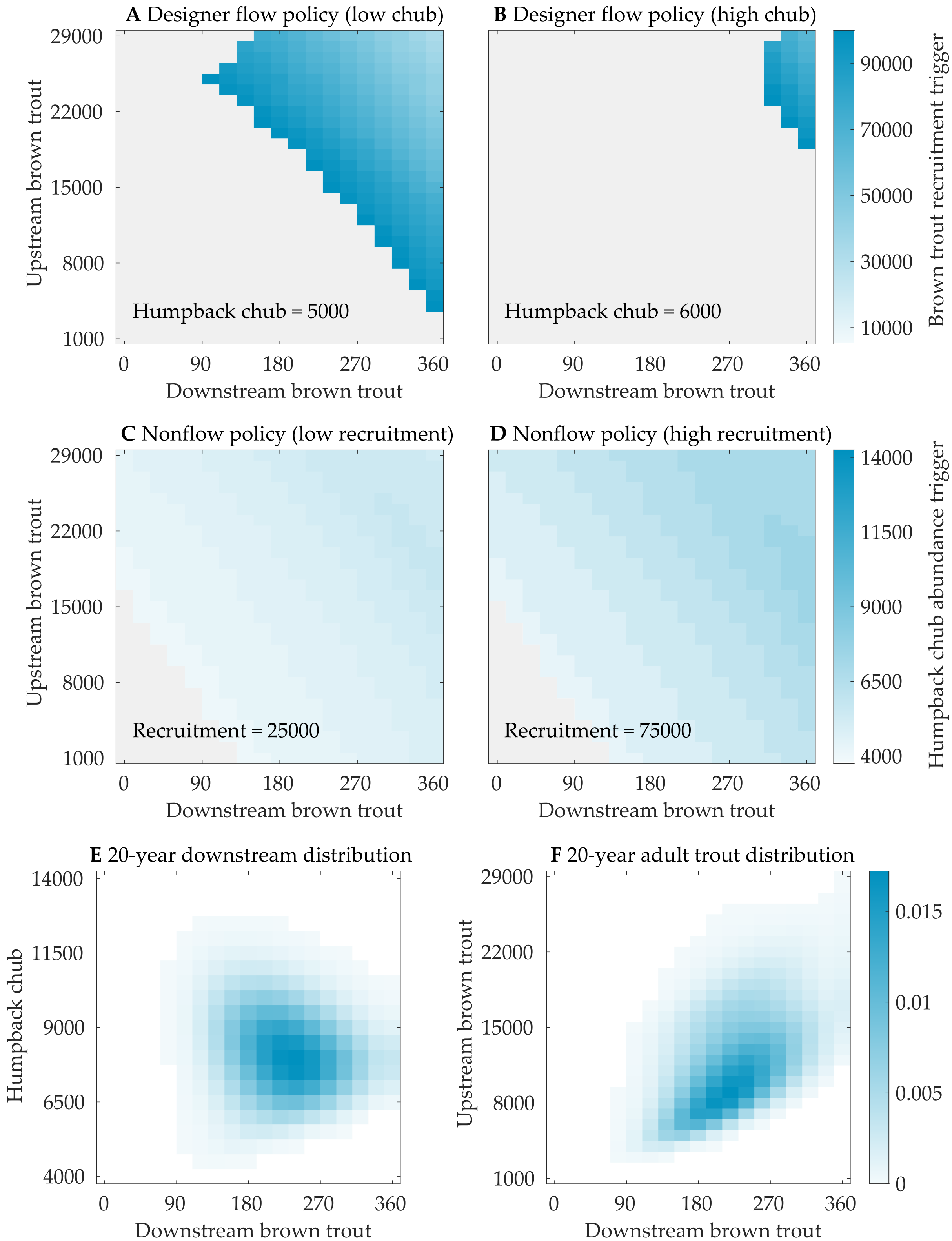

Figure 5: Optimal policies and resulting population densities for the case of brown trout.

value of information changes with respect to changing opportunity costs of hydropower. For example, relative to 2020, energy prices at the Palo Verde hub were 162% and 256% higher in 2021 and 2022, respectively, for the months of May-July (California Independent System Operator, 2024). We use this range of prices to determine a range of plausible opportunity costs of implementing designer flow experiments.

Figure 6 presents the expected program costs for the non-learning scenario, the less aggressive "high recruitment" experimental regime, and the more aggressive "annual flow" experimental regime. Here, there is significant sensitivity to the opportunity costs of designer flows, and energy costs must fall to 2020 levels in order for the learning regime to produce positive expected net benefits. On this low end of the future energy cost range ($250-350k), the less aggressive experimental regime can promote early adoption of designer flows even when a management plan with lower short-run costs under current and fixed information (the non-learning approach) is available. For all regimes, these lower opportunity costs result in higher designer flow use, which begins to lower the management costs even in the non-learning case. However, lower opportunity costs have a greater effect on the learning regimes, owing to the reduction of the immediate cost of experimentation.

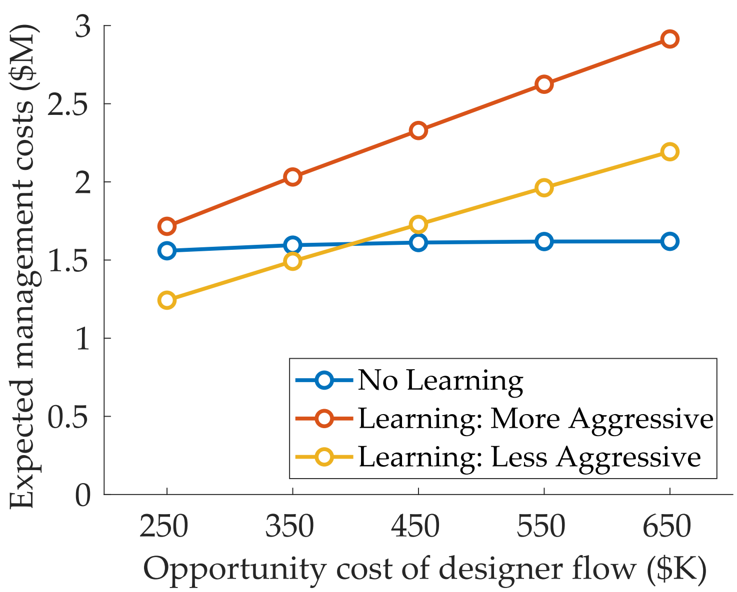

Figure 6: Expected management costs as a function of designer flow opportunity costs under the no learning program and two alternative learning programs.

We find, trivially, that aggressive learning produces a net loss in all scenarios considered, although for the lowest flow cost, this loss is approaching zero. This is because the additional designer flow activity in the learning stage is excessive, as earlier experiments have already brought the system into a state that is favorable to the manager. Thus, further experimentation does not lower continuation costs because this provides minimal ecological benefit in the post-learning stage. Because urgent, repeated contemporary management is not needed during the learning stage, and because both regimes will produce similarly low present-valued continuation costs (given liberal application of designer flows in either case), the high upfront costs of the more aggressive regime are not justified.

In summary, only the less aggressive learning regime that waits for periods of high brown trout recruitment before employing experimental designer flows can be justified: if future energy costs are not expected to increase dramatically, the less aggressive learning regime generates a net benefit relative to a policy that does not employ learning. The optimal contemporary program that manages brown trout costs \$1.6M in present valued terms, and potential cost savings from the less aggressive learning regime are 7.5% and 23% of this figure when per flow cycle opportunity costs are \$350k and \$250k, respectively. These gains are relatively large, but small in absolute terms (and relative to the cost of any one management action) due to the lasting impact of a single designer flow. These results suggest that the learning regime could be pursued for little-to-no additional cost relative to the non-learning policy. Given that designer flow efficacy knowledge is useful for ongoing management—and potentially for other systems—these results suggest that an experimental learning regime would be valuable.

4 Discussion

Designer flows are a promising and increasingly utilized approach to improve ecosystem function and services in dam-regulated rivers, yet we still have a limited understanding of their tradeoffs when attempting to balance economic and conservation objectives. One prominent omission from previous studies is the opportunity cost of designer flows, i.e., the foregone benefits that would have been achieved in their absence. Another is the value of new information on the efficacy of designer flows in a given environment generated by active experimentation. While including such elements is critical for understanding whether, when, and how designer flows should be implemented, they are difficult to evaluate given the complexities of formulating integrated assessment models that consider economic and conservation objectives, the ecosystem functions of downstream rivers, and the value of information from active learning through experimentation.

In this article, we demonstrate how to perform an integrated assessment of designer flow implementation for achieving a conservation objective in a shadow value viability (SVV) framework. To our knowledge, this application to the Glen Canyon Dam on the Colorado River is the first economic analysis of designer flows to incorporate the opportunity costs of foregone hydropower electricity generation. We also show how the SVV approach can be extended to explore adaptive management to address the fact that uncertainty and learning over time are key realities of natural resource management.

Our baseline model results (without monitoring or learning) show that designer flows are prohibitively expensive for managing rainbow trout populations when other nonflow actions, such as downstream trout removal, are available. This occurs, in part, due to the delayed and thus discounted benefits of designer flows, but also due to three other model features, which we explore further. First, implementing rainbow trout recruitment monitoring facilitates targeting designer flows to high recruitment years, boosting effectiveness and thus the range of conditions in which this action is efficient to use. Second, when the need arises to control a much more piscivorous predator (brown trout), this elevated threat to vulnerable humpback chub warrants expanded use of designer flows. Finally, we show that as long as the flow costs from forgone energy generation are not too high, an active adaptive management strategy of experimentation in high recruitment years to learn about designer flow efficacy is preferred to a non-learning approach.

Our approach demonstrates how essential economic and ecosystem features can be combined to evaluate conservation actions in dam-regulated rivers. We have identified several critical system characteristics for predicting whether there may be a benefit of designer flow implementation in other settings. However, new prescriptions will still be context-specific and require a detailed understanding of the fundamental mechanisms that drive system behavior. Our study draws from considerable experience working with managers, scientists, and stakeholders of the Glen Canyon Dam system. Successfully adapting our approach for environmental decision-making in other dam-regulated systems will largely depend on the meaningful involvement of stakeholders and their recognition of the value of the modeling effort (Horne et al., 2016).

Future changes to the Colorado River will continue to shape optimal dam management. Nonstationarities in both climate and economic systems present new challenges for the river's ecology. For example, if federal hydropower shifts to a larger role in balancing electricity sector grid resources, our results suggest that the designer flow option may become cost-prohibitive. This possibility strengthens the need to consider environmental flows and power capacity expansion objectives jointly along with other regional-scale socio-economic values. The change may require the consideration of co-benefits, such as those derived from sediment transport or recreational fishery improvements, to justify designer flow use.

The operational flexibility of dams provides a unique opportunity to respond to otherwise deleterious developments (Bair et al., 2019). For example, smallmouth bass (*Mi-*

cropterus dolomieu), a warm-water nonnative species, have proliferated upstream of Glen Canyon Dam. Lower reservoir elevations due to historically low flows in the Colorado River have allowed this species to migrate through the hydropower inlets at Glen Canyon Dam (Eppehimer et al., 2024), however, thoughtful departures from normal operation of the dam can protect the health of downstream species. Dam operators have the option to send a share of downstream water allocations through bypass tubes—which do not generate electricity or facilitate smallmouth bass migration. This process also reduces downstream temperatures which inhibits smallmouth bass growth. While this alternative flow design comes at great opportunity cost to hydropower generation, it can strengthen environmental protection within the socio-ecological system as drought conditions become more common and hydrological variability increases.

Designer flows show significant promise. Indeed, dam infrastructure on regulated rivers is constructed for several reasons unrelated to ecosystem viability, including hydropower electricity generation, reduced flood risk, and consistent water supply. While large dams have already caused significant changes to the world's river basins in pursuit of meeting these objectives, their creative and flexible operation can provide a cost-effective tool for maintaining ecosystem viability.

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A Numerical specification of the bioeconomic model

Table A1: Parameter definitions with values and sources.

Parameter	Description	Value	Source
α_w, κ_w	stochastic trout recruitment bounds	11,14	(Korman et al., 2012)
α_y, κ_y	stochastic chub recruitment bounds	4000, 35000	(U.S. Department of the Interior, 2016)
ψ_x	trout movement rate: MC to JCMR	0.009	(Korman et al., 2015)
ψ_y	share of chub recruits to JCMR	0.1	(Yackulic et al., 2014)
ψ_w	share of trout recruits to MC	0.1735	(Korman et al., 2015)
γ_x, γ_w	adult trout survival after natural mortality	0.61 (0.69)	(Korman et al., 2015)
γ_y	adult chub survival after natural mortality	0.83	(Yackulic et al., 2014)
c_A	cost of [five] trout removal trips	\$450K	(Bair et al., 2018)
c_F	cost of designer flow	\$250K-\$650K	Modeled
θ_A	nonflow action efficacy	0.28	(Korman et al., 2012)
θ_F	designer flow efficacy bounds	0.1 - 0.5	(Korman et al., 2012)
μ, λ	trout viability effects (monthly)	5, -0.0009 (-0.0063)	(Yackulic et al., 2018b)
T	viability time horizon	20 years	(U.S. Department of the Interior, 2016)
σ	energy conversion factor	0.0000744 $MWh/cfs \cdot ft$	(Waldo et al., 2021)
$\underline{L}$	reservoir elevation	3575 ft	(Waldo et al., 2021)
$\overline{L}$	tailwater elevation	3177 ft	(Waldo et al., 2021)
ϕ	probability of high trout recruitment	0.25	(Yackulic et al., 2018a)
π	probability of learning event	0.33	Chosen
β	discount factor	0.97	(Donovan et al., 2019)
$\overline{Y}$	lower abundance limit of chub	4000	(Donovan et al., 2019)
Δ	viability confidence	0.90	(Donovan et al., 2019)

Notes: Where rainbow and brown trout dynamics differ, we place the brown trout parameter in parentheses. In our non-learning simulations, designer flow costs are \$450,000. π, β, $\overline{Y}$, and Δ are policy parameters chosen to reflect stakeholder concerns and knowledge. The discount factor and viability goal parameters are chosen to be consistent with (Donovan et al., 2019).

B Substitutability of designer flow and nonflow actions

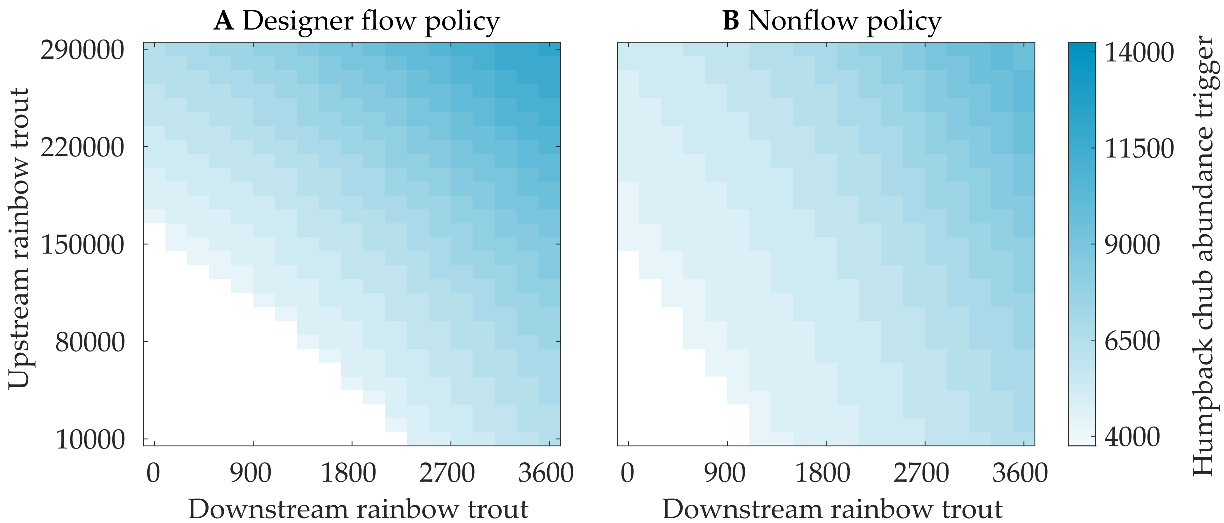

Figure A1: A: designer flow policy when non-flow action isn't available. B: nonflow policy when designer flows aren't available. Either policy is sufficient on its own for achieving the joint abundance distribution in Figure 3, although the designer flow policy is more costly (and thus not chosen in Figure 2).

C Nonflow policy response to upstream monitoring

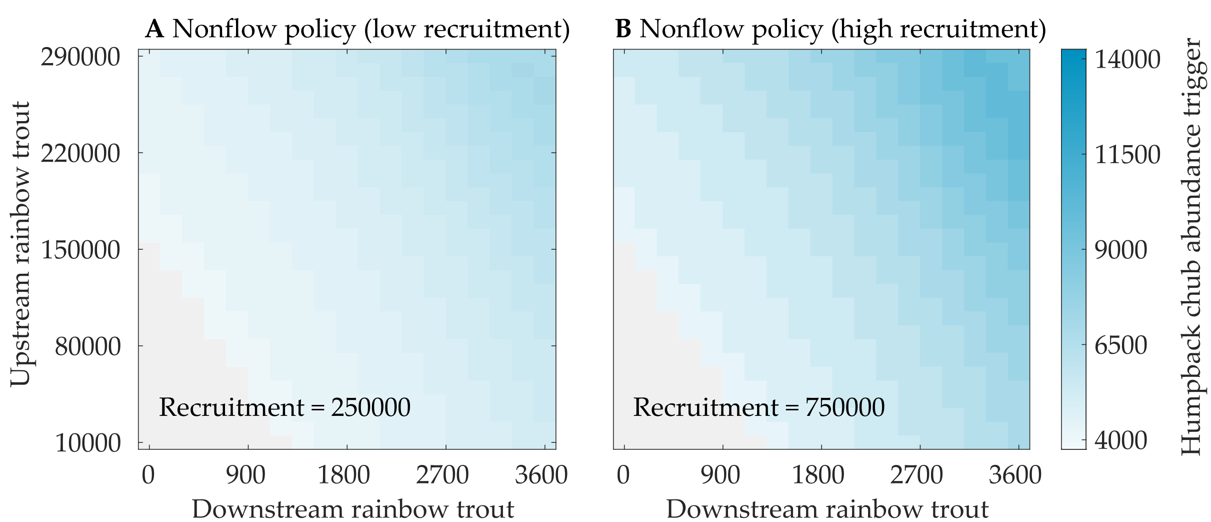

Figure A2: Nonflow policy conditional on the observation of upstream trout recruitment.