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RESEARCH

# Improving Multi-Objective Ecological Flow Management with Flexible Priorities and Turn-Taking: A Case Study from the Sacramento River and Sacramento–San Joaquin Delta

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**Jagger's Law**

You can't always get what you want
But if you try sometimes, well you just might find
You get what you need

—*Jagger and Richards, 1969*

## ABSTRACT

Management of the Sacramento River and Sacramento–San Joaquin Delta (SRD) is one of California's greatest challenges, requiring trade-offs between valued components that serve a multiplicity of conflicting purposes. Trade-offs do not signal a failure to create clever enough models, or scenarios that find a single optimal solution. Rather, an optimal solution that meets multiple objectives does not exist. We demonstrate an improved method for multiple-objective allocation of water: "turn-taking" optimization (TTO) within a multi-model cloud computing framework. We apply TTO to an array of physical hydrologic models that are linked with the Ecological Flows Tool (EFT): a multi-species decision support framework to evaluate how specific components of the flow regime promote and balance favorable habitat conditions for 15 representative species and 31 indicators within the SRD. Applying the TTO approach incorporates the existing modelled representation of socio-economic water management criteria, priorities, and constraints—and optimizes water-release patterns each water year using a dynamically shifting set of EFT indicators. Rather than attempting to optimize conditions for all ecological indicators every year, TTO creates flexibility and opportunities for different indicators to be successful in different years, informed by the frequency with which each species' ecological needs should be met. As an individual EFT indicator is successful in a particular year, its priority in one or more subsequent years is reduced (and vice versa). Comparing TTO to a Reference Case scenario based on current management practices, 12 EFT indicators are improved, 14 show no change, and 5 show a reduction in suitability. When grouped into nine species and life-history groups, performance improved in four (late-fall-run Chinook, winter-run Chinook, spring-run Chinook, and Fremont cottonwood), did not change in four (fall-run Chinook Salmon, Delta Smelt, Splittail, and Longfin Smelt), and was worse in one group (Steelhead).

## KEY WORDS

Multi-objective optimization, endangered species, trade-offs, ecological effects analysis, Sacramento–San Joaquin Delta, environmental flow, real-time, turn-taking.

## INTRODUCTION

Developing greater awareness of the value of flexibility to manage ecosystem trade-offs among multiple objectives—and providing approaches that enable this flexibility in a real-world setting—is urgently needed. Flexibility begins with emphasizing holistic, integrated ecosystem-based management, monitoring the state of continuously fluctuating systems over relevant scales, and adjusting short-term priorities accordingly. This, in turn, requires managers to adopt a mindset focused on adaptability and learning (Christensen et al. 1996; Schindler and Hilborn 2015). Water-allocation dilemmas can be found both globally (Perrone and Hornberger 2014; Zeng et al. 2017) and locally in the Sacramento River and Sacramento–San Joaquin Delta (hereafter, the SRD). Well before the 2012–2016 drought, the SRD had been widely characterized as being in crisis because of an inability to reconcile and balance competing objectives and resource demands (Hanak et al. 2013; Lund 2016). In a recent analysis of Bay Delta Conservation Plan (BDCP, renamed California WaterFix) development scenarios, Alexander et al. (2014) clearly illustrate the impossibility of achieving multiple ecosystem flow objectives each and every year. With winners and losers depending on hydrologic conditions and priorities each year, water managers constantly face meeting irreconcilable demands, and generally lack the tools to weigh these trade-offs. Current management relies largely on deterministic models in which priorities and objectives are decided in advance—an approach which, at best, yields a narrow set of solutions with limited emphasis on—or insight into—what the potential trade-offs might be (Martin et al. 2016; Poff et al. 2016). Failure to reconcile these trade-offs is not the result of a failure to create a clever enough model that will find the optimal solution. Rather, a single optimal "all-years and all-values" solution does not exist (Alexander et al. 2014).

Ecological flow management is widely recognized as an important tool that can promote the resilience and recovery of native species. Many river-dependent plants and animals are strongly influenced by—and have adapted to—natural variation in flow, and many fish and riparian species possess traits that allow them to tolerate or exploit certain flow conditions. Although not the only stressor, the alteration of river flow regimes and habitat losses associated with dam, diversion, and other water-supply operations is one of the leading causes of declines in imperiled aquatic ecosystems (Arthington et al. 1992, 2006; Richter et al. 1996, 1997; Stanford et al. 1996; Poff et al. 1997, 2010; Annear et al. 2004; Postel and Richter 2003; Tharme 2003; Petts 2009; Carlisle et al. 2010; Fleenor et al. 2010; Poff and Zimmerman 2010; NRC 2012; Hanak et al. 2013; Null et al. 2014).

At odds with more naturally variable river flows, the management of many engineered systems like the SRD is based on complex layers of inter-agency rules and regulations intended to ameliorate competing demands for water—biological opinions (NMFS 2009) being one example. Within ecosystem objectives themselves, endangered species' legal requirements focus attention toward individual species management, a focus that tends to partition the world into "winners and losers," and hampers the development of a more balanced ecosystem and adaptive management approach (Christensen et al. 1996; Pikitch et al. 2004; Schindler and Hilborn 2015). Over time and as regulations become more layered, elaborate, and codified, the ability to mimic naturally variable river flows becomes ever more constrained, making it hard to adjust flow operations in ways that promote multiple ecosystem functions (the focus of the Ecological Flows Tool [EFT]). Moreover, because of the premium placed on achieving unrealistically high mechanistic certainty of aquatic species' responses to alternative flows before actions are implemented (Schindler and Hilborn 2015), opportunities for adaptive learning are even further constrained.

Finally, achieving more naturally variable river flows is also complicated by the myriad separate agencies and programs responsible for interrelated (and often overlapping) aspects of flow management and riparian restoration. In the SRD, the California Department of Fish and Wildlife (CDFW), National

Oceanic and Atmospheric Administration (NOAA), National Marine Fisheries Service (NMFS), U.S. Fish and Wildlife Service (USFWS), State Water Resources Control Board (SWRCB), California Department of Water Resources (CDWR), U.S. Bureau of Reclamation (USBR), and the U.S. Army Corps of Engineers (USACE) all have some level of jurisdiction over parts of the system.

The EFT is a comprehensive, linked, integrative decision-support framework for evaluating how specific components of the SRD flow regimes can be "specialized" to promote favorable habitat conditions for 15 representative species (TNC et al. 2008; Alexander et al. 2014) (Figure 1). Since the beginning of the EFT's development in 2004, the majority of advice from over 70 participating scientists, managers, and disciplinary experts has been to adopt a multi-species, multi-indicator approach, thus avoiding the paralysis caused by too broad a sphere of concern or too much detail on any one species. The EFT includes 25 functionally distinct life-history indicators for both listed and non-listed riparian and aquatic species and habitats. Its habitat and species sub-models are informed by existing conceptual models that were used to help select the EFT's key indicators (Table 1). These indicators are driven by relevant physical measures of flow, water temperature, channel migration, salinity and/or river stage at a daily (or finer) time-scale (ESSA 2011, 2013; Alexander et al. 2014). Although the EFT was designed to work with any physical model(s) capable of producing daily resolution results at required locations, in this study, those inputs are provided by a standard suite of hydrological tools (described later) for evaluating Shasta Dam operations and Delta conveyance and water export alternatives. The EFT is further linked to models of channel migration, soil erosion, and sediment transport (ESSA 2011, 2013). This broad and unique coupling of multiple models enables synthesis evaluations of the potential benefits, not only of flow modification, but also of riprap removal and gravel augmentation (Larsen and Greco 2002; Larsen 2007; Wohl et al. 2015).

Our quest for improved flow management options for the SRD is motivated by the pressing need for greater flexibility and agility in discovering and applying operational rules for the benefit of multiple species. A key premise of our research is that preferred flow characteristics for a given species or habitat are not required every single year. It is both impractical and unnecessary to pick a single best flow regime, because a flow regime favorable to one species (or even to a single life-history stage) may be unfavorable to another (Alexander et al. 2014). We also recognize that natural selection and evolution confer on many species the ability to survive and persist during sub-optimal habitat conditions (Southwood 1977; Poff and Ward 1990; Tollrian and Harvell 1999; Gabriel et al. 2005; Eliason et al. 2011). Although these adaptive capabilities have limits (e.g., continuous poor habitat conditions year after year can lead to extirpation), species resiliency affords practical opportunities for flexibility. As examples of natural flexibility in the SRD, four Chinook Salmon run-types are each adapted to a different season and habitat; adult spawners can return from age 2 to age 6, and juveniles may choose to find refuge in cold water habitat or migrate immediately to the ocean.

We hypothesize that a more agile, adaptive state-dependent approach is needed to manage SRD flows—an approach that can systematically evaluate many alternative flow regimes on an appropriate time-scale and dynamically alter priorities among ecological objectives, depending on both current hydrologic conditions and the recent history of outcomes for these same objectives. The two complementary concepts that underpin this approach are "turn-taking" between ecological indicators at biologically appropriate frequencies, and multi-objective optimization across all ecological indicators over time. Together, we call these concepts Turn-Taking Optimization (TTO). Our approach allows past ecological benefits to be "remembered" in the optimization, so that, for example, if a species' ecological indicator target (however defined) has been achieved in water year $t$-1 or earlier, its priority can be downgraded for an ecologically appropriate period of time, allowing different ecological indicators to have a higher priority. In this first demonstration of turn-taking benefits, our optimization efforts focus on two fundamental attributes of SRD hydrosystem management: (1) monthly average water release targets for Shasta Dam, and (2) monthly average maximum reverse flows in the Old and Middle rivers in the Delta. These maximum reverse-flow targets


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influence water exports into state (the Harvey O. Banks pumping plant the CDWR operates as part of the State Water Project) and federal (the Tracy pumping plant Reclamation operates as part of the Central Valley Project) facilities in the Delta. More complex water-transfer schemes are possible and feasible, but for this first demonstration of TTO with EFT we focus, for now, on these two major attributes of the SRD hydrosystem.

## METHODS

We use coupled eco-hydrologic simulation models to compare how a flexible turn-taking approach meets the flow needs of multiple ecological indicators relative to the current management paradigm. We use a baseline Reference Case scenario to compare the results of the TTO model. Below, we describe the hydrosystem-management actions we considered, the ecological indicators we used to evaluate how these actions performed, the underlying eco-hydrologic simulation models used, and the Reference Case scenario. Finally, we present in more detail the logic that underlies the proposed flexible TTO model itself.

### Study Area

The study area comprises two linked eco-regions within the SRD hydrosystem: (1) the upstream main stem of the Sacramento River between Keswick and Colusa; and (2) the Delta estuary downstream of Fremont Weir, including the Yolo Bypass, Grizzly Bay, and Suisun Bay (Figure 1). The EFT model (ESSA 2011, 2013) was developed for key habitat and species indicators within these two eco-regions.

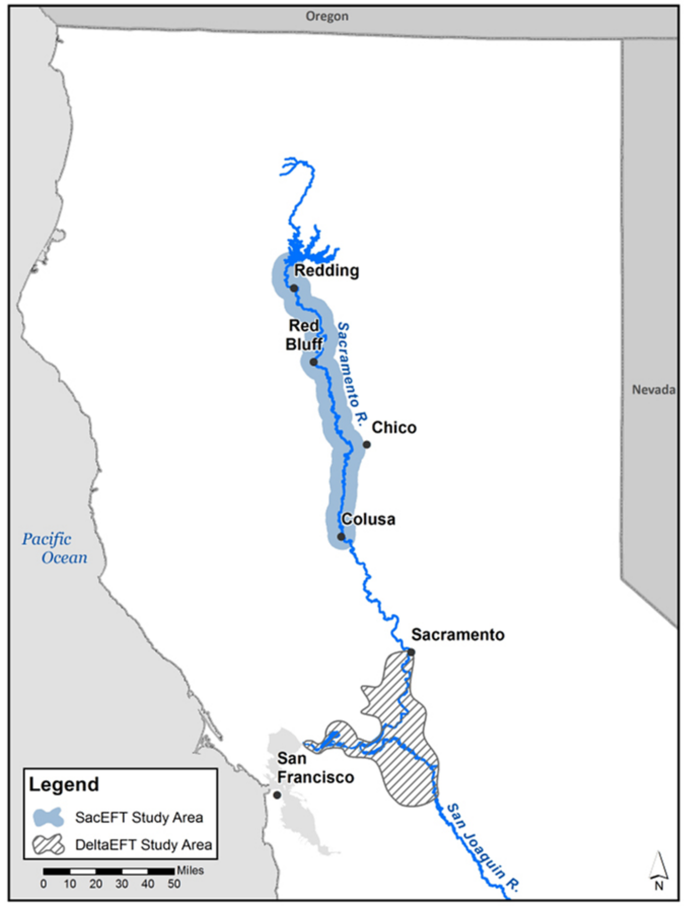


**Figure 1** The two eco-regions included in the study: an upstream region from Keswick to Colusa, and an estuarine region downstream of Fremont Weir

### Management Actions Evaluated

The study considers how to flexibly optimize 31 ecological performance indicators (Table 1) over multiple years using a 12-month management cycle (October 1 to September 30). Each year, two management actions are evaluated: (1) a monthly schedule for target releases from Shasta Dam, and (2) monthly average maximum reverse flow (MRF) targets in the Old and Middle rivers (which influence water exports from the Tracy and Banks pumping plants). Many other potential management actions exist for the SRD, such as water transfers between reservoirs and groundwater banking; but Shasta Dam releases and Delta exports affect flows the most overall, and are sufficient to demonstrate the possibilities of the TTO approach. It is also important to recognize that the implementation of these management actions using the physical models described below is subject to other objectives, values, and constraints. Often, the target Shasta Dam releases and target MRF are not achieved in various years because of the interacting effect of the priority weights placed on these other objectives (e.g., rule-sets that represent Water Right Decision 1641 [D–1461] in CalSim 2).

**Table 1** Ecological indicators defined by the Ecological Flows Tool, with abbreviated EFT codes in parentheses. For salmonids, the indicators are repeated for each of five groups: fall, late-fall, winter, and spring Chinook Salmon and Steelhead. A subset of 31 indicators considered in the optimization study are marked with '+.' Those marked with '–' note the reason for exclusion.

| Ecological Indicator | Present | Rationale for Exclusion |
|---|---|---|
| **Upper Sacramento River Eco-region** | | |
| Salmonid run types: fall, late-fall, winter, spring, Steelhead | | |
| WUA spawning (CS1) | + | |
| WUA rearing (CS2) | + | |
| Egg-to-fry survival (CS3) | – | Negligible range of variation |
| Juvenile stranding (CS4) | + | |
| Redd scour (CS5) | – | Negligible range of variation |
| Redd dewatering (CS6) | + | |
| Fremont cottonwood | | |
| Initiation success (FC1) | + | |
| Scour risk (FC2) | – | Sporadic |
| Bank Swallow | | |
| Habitat potential (BASW1) | – | Negligible range of variation |
| Inundation/sloughing risk (BASW2) | – | Meander simulation unavailable |
| Western pond turtle | | |
| Large woody debris (LWD1) | – | Meander simulation unavailable |
| Green Sturgeon | | |
| Egg development (GS1) | – | Negligible range of variation |
| **Sacramento Delta Eco-Region** | | |
| Salmonid run types: fall, late-fall, winter, spring, Steelhead | | |
| Growth in Yolo Bypass (CS7) | – | Included through smolt temperature stress |
| Passage time (CS9) | – | Included through smolt temperature stress |
| Smolt temperature stress (CS10) | + | |
| Delta Smelt | | |
| Spawning success index (DS1) | + | |
| Habitat quality index (DS2) | + | |
| Entrainment risk (DS4) | + | |
| Splittail | | |
| Yolo Bypass spawning habitat (SS1) | + | |
| Longfin Smelt | | |
| Abundance Index (LF1) | + | |
| Invasive deterrence | | |
| *Egeria* suppression (ID1) | – | Requires large floods |
| *Corbula* suppression (ID2) | – | Requires large floods |
| *Corbicula* suppression (ID3) | – | Requires large floods |
| Tidal wetland habitat | | |
| Brackish (TW1) | – | Digital Elevation Model (DEM) simulation unavailable |
| Freshwater (TW2) | – | Digital Elevation Model (DEM) simulation unavailable |


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## Multiple Ecological Flow Needs and Ecological Indicators

The 31 ecological indicators used in this study are a flow-sensitive subset of a larger set the EFT simulated (Table 1). These 31 EFT indicators represent important facets of the life-history needs of nine focal species and salmonid run-types, for both listed and non-listed riparian and aquatic species. The development of each EFT indicator was based on a logical progression of steps that began with the development of cause-and-effect conceptual models that link physical regime to representative life-history habitat and the related survival needs of the focal species (ESSA 2011, 2013). Candidate species and indicators were vetted through a review of existing conceptual models in the literature as well as expert design input and review during several workshops (see ESSA 2011, 2013).

Each ecological indicator's output depends on functional relationships that can include flow, water temperature, river stage, and salinity at a daily time-scale at relevant locations within the SRD (see Appendix H in Alexander et al. 2014). The EFT creates two broad classes of output across a range of spatial and temporal scales. The first class consists of continuous-value variables such as "square feet of spawning habitat." The second class consists of categorical versions of the continuous variables using a three-level suitability rating (Good, Fair, or Poor) based on one of three general methods (see Table 2.10 and Appendix G in Alexander et al. 2014). Continuous and categorical measures provide complementary ways to characterize improvement and degradation of the EFT indicators.

## Comparing Against a Reference Case Scenario

We used the 2011 Delivery Reliability Report (DRR) study (CDWR 2012a, 2012b) as our Reference Case scenario, comparing its ability to meet ecological needs against the TTO approach our study advocates. The Reference Case scenario provides a contemporary and publicly available snapshot of current management and operational practices for the Sacramento River and Delta. The simulation period available for comparing the benchmark DRR scenario with the TTO approach was restricted to the 16-year period from water year 1976 to 1991—a constraint introduced by the calibration period of the Delta Simulation Model II (DSM2) model described below.

## Linked Eco-Hydrologic Models

The Reference Case scenario and the turn-taking algorithm described later both depend on a group of five physical models that provide the inputs the EFT used to compute the 31 ecological indicators for this study. We briefly describe these five component models below. By definition, the cumulative assumptions and uncertainties present in these driving physical models of flow, water temperature, river stage, and salinity are carried forward to affect the analysis results the EFT generates. Our use of these models and the EFT itself emphasizes comparative findings among multi-year scenario alternatives rather than focusing on absolute predictions during specific years, months, or days. An accounting of the limitations, weaknesses, and strengths of these physical models, although a fundamental consideration, is beyond the scope of this paper. Readers interested in learning more are directed to Ferreira et al. (2005) and Ford et al. (2006) and other references that immediately follow below.

### *CalSim 2*

CalSim 2 is a generalized reservoir–river basin simulation model commonly used for planning studies related to SWP and CVP operations. The model is based on input priorities, targets, and a variety of constraints, and determines monthly river flows and diversions, Delta flows and exports, reservoir storage, and deliveries to project and non-project users (CDWR 2000: Draper et al. 2004: USBR 2008a). Other inputs to CalSim 2 include system connectivity and capacity information and regulatory requirements, as well as water diversion requirements (demands), stream accretions and depletions, rim basin inflows, irrigation efficiencies, return flows, non-recoverable losses, and groundwater operations. CalSim 2 produces monthly outputs for river flows and diversions, end-of-month reservoir storage volumes, and Delta flows and exports. CalSim 2 results are commonly used as inputs to determine water quality, hydrodynamics, and particle-tracking in the DSM2 model (described below). Using a proprietary Mixed Integer Linear Programming solver, CalSim 2 normally operates on a monthly time-scale over the water year 1922–2003 period. Much of the model's input and output is carried out through Data Storage System (DSS) files (USACE 2009). Because the solver is proprietary, our implementation of the optimization system places CalSim on the desktop computer that houses the solver license, although conceptually it is more appropriate to consider it a component of the optimization "particles" described below.

### *USRDOM*

The Upper Sacramento River Daily Operations Model (USRDOM) models the flows and related operations in the Upper Sacramento River from Keswick to Knights Landing on a daily time-scale, down-scaling the monthly time-step of CalSim 2 to a daily scale. The USRDOM was developed using the HEC-5 software. A detailed description of the USRDOM and the temporal down-scaling process can be found in CH2M Hill (2011).

### *USRWQM*

The Upper Sacramento River Water Quality Model (USRWQM) was also developed using HEC-5A software to simulate (using 6-hour meteorology) mean daily reservoir and river temperatures at key locations on the Sacramento River as far downstream as Knights Landing, using daily flows from USRDOM as input. A more detailed description of USRWQM and the temporal downscaling process is included in a Resource Management Associates (RMA) calibration report (RMA 2003), and further background on USRWQM can be found in USBR (2008b).

### *DSM2*

The Delta Simulation Model version 2 (DSM2) is a one-dimensional hydrodynamic simulation model used to simulate hydrodynamics, water quality, and particle-tracking in the SRD (USBR 2008c). The model has three interacting sub-models—HYDRO, QUAL, and PTM—that simulate, respectively, velocities and water surface elevations; the fate and transport of conservative and non-conservative water quality constituents including salts; and transport of neutrally buoyant particles.

### *EFT*

The EFT is a multi-species decision-support framework for evaluating how specific components of the flow regimes can be "specialized" to promote and balance favorable habitat conditions for 15 representative species within the SRD (Alexander et al. 2014). The EFT incorporates simulated (and historical) output from the preceding suite of hydrologic models, which together provide combinations of daily flow, water temperature, salinity, and river stage. Salinity and river stage are used only downstream of Knights Landing in the Delta. The EFT predicts up to 61 ecological indicators for 15 species and salmonid run-types in the Upper Sacramento River and Delta (ESSA 2011, 2013; Alexander et al. 2014). Consolidating the salmonid run-types, the EFT includes 25 functionally distinct ecological indicators. In the application described in this paper, we performed our TTO simulations for nine focal species and used 31 EFT indicators rather than the full set of 61 (Table 1).

## Turn-Taking Optimization (TTO)

### *Recurrence Frequency and Turn-Taking*

The two central ideas behind TTO are recurrence frequency and turn-taking. Recurrence frequency (RF) recognizes that most species are adapted to variable flows (periods of drought and flood) and do not require ideal or desired conditions every year to sustain a viable population (Tollrian and Harvell 1999; Gabriel et al. 2005; Eliason et al. 2011). As a result, most aquatic and riparian species will be successful provided the population experiences favorable life-history events at an appropriate frequency. In our simulations, RF is defined for each EFT indicator (e.g., "species indicator *j* should achieve a favorable or 'Good' outcome in at least 2 out of 4 years") and these rules are used by the TTO algorithm to adjust indicator priority weights each year. The "appropriate frequency" for RF is an important assumption, and may not always be constant through time. Table 2 shows the RF criterion (a customizable value) for each EFT indicator used in our simulations.

Turn-taking refers to the notion that once an indicator's RF has been met, that indicator is not targeted for optimization in the immediate future


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**Table 2** Recurrence frequencies (RF) for ecological indicators from the upper Sacramento and Delta eco-regions. In any given year, a given indicator's RF is met if it has the required number of Good years in the moving window of current and previous years.

| Ecological Indicator | Good years | Moving window (years) |
|---|---|---|
| **Upper Sacramento River Eco-Region** | | |
| Salmonid run types: fall, late-fall, winter, spring, Steelhead | | |
| Spawning WUA | 2 | 4 |
| Rearing WUA | 2 | 4 |
| Juvenile stranding | 2 | 4 |
| Redd dewatering | 2 | 4 |
| Fremont cottonwood | | |
| Initiation success | 1 | 8 |
| **Sacramento Delta Eco-Region** | | |
| Salmonid run types: fall, late-fall, winter, spring, Steelhead | | |
| Smolt temperature stress | 1 | 3 |
| Delta Smelt | | |
| Spawning success index | 1 | 2 |
| Habitat quality index | 1 | 1 |
| Entrainment risk | 1 | 1 |
| Splittail | | |
| Yolo Bypass spawning habitat | 4 | 10 |
| Longfin Smelt | | |
| Abundance Index | 4 | 10 |

year(s) until the RF period expires. In this way, different EFT indicators take turns being prioritized for optimization, providing flexibility for various indicators to receive greater consideration in the intervening years. Thus, the potential solutions identified by the optimization algorithm depend on the hydrologic properties of individual water years as well as the recent history and record of successes for each ecological indicator. We note that an ecological indicator can achieve a Good outcome without being explicitly assigned a high priority for optimization if the hydrologic conditions happen to be favorable for that indicator in a given simulation year and solution. The TTO paradigm includes this notion of incidental success so that indicators are deemed successful if they receive a favorable indicator rating and/or RF is met.

Figure 2 demonstrates through a hypothetical example the integration of ecological indicator performance with the RF concept: the rule of achieving RF and/or receiving a categorical Good score is met in 10 of 13 of the TTO solution scenario years, and 8 of 13 of the Reference Case scenario years, indicating that the TTO model's water release solution is an overall improvement.

### *The Optimization System—Particle Swarm Optimization*

The value of a computationally based optimization algorithm is clear given both the large number of species and indicators (ESSA 2011, 2013) and the non-linear relationships that exist between these indicators and their driving physical variables (daily flow, water temperature, river stage, and salinity). We used a Particle Swarm Optimization (PSO) with Crowding Distance (Raquel and Naval 2005) to traverse the high-dimensional EFT search space to discover sets of optimal solutions (defined below) for each year's prioritized set of EFT indicators.

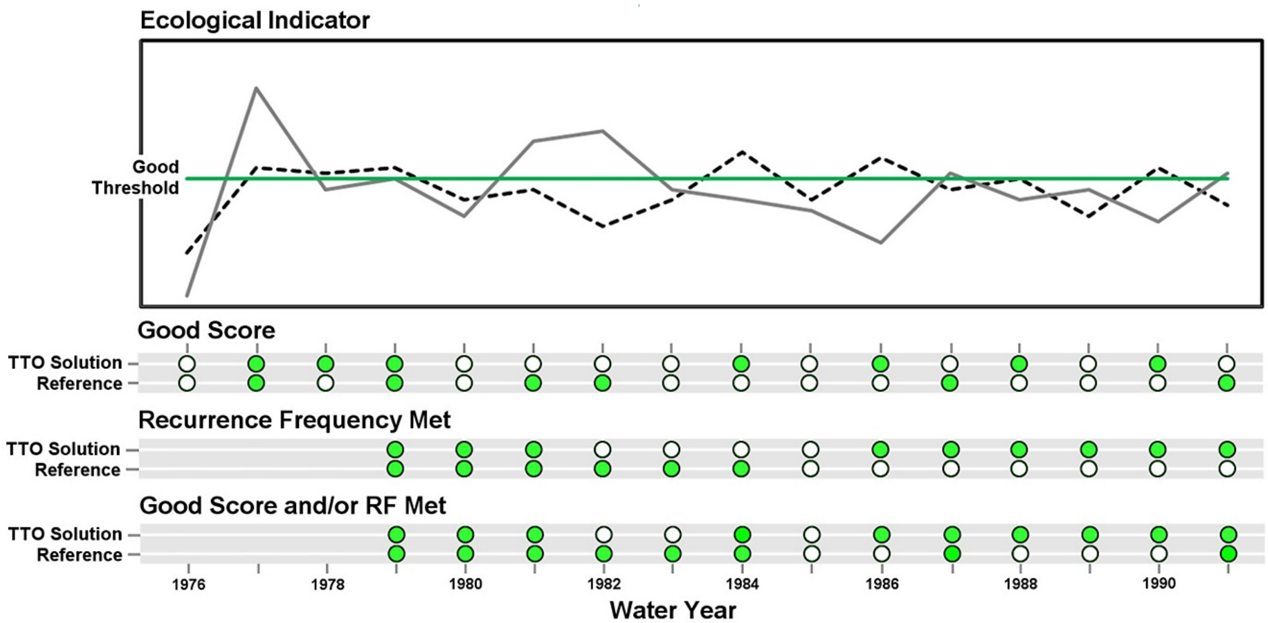


**Figure 2** Example of the recurrence frequency (RF) concept, beginning with a continuous-value ecological indicator (top panel) under two hypothetical scenarios: TTO Solution (dashed line) and Reference Case (solid line). Given the ecological indicator's suitability threshold value (green 'Good Threshold'), some annual results receive a Good categorical score (filled circles). In this example, RF is computed using a rule in which the indicator's RF is met if it has two Good years in a 4-year moving window (the rule used for salmonids in this study). Filled circles (bottom set) represent years where a categorical Good score and/or RF is met; with open circles otherwise. In this hypothetical example, the Reference Case scenario (solid line) receives a categorical Good score and/or meets RF in 8 of 13 years, compared to 10 of 13 years for the TTO solution (dashed line). Note: by definition, RF is not computable for the first 3 years.

PSO is inspired by the social biological phenomena of bird flocking and fish schooling (Kennedy and Eberhart 1995), with the underlying hypothesis that the social sharing of information among conspecifics increases the fitness of individuals. In PSO parlance, an individual is called a "particle" (Raquel and Naval 2005). Driven by search rules, groups of particles move in a multi-dimensional search space in which every location represents a simulation that produces a solution to some specified problem.

Particles work cooperatively to search for locations that correspond to better solutions to the problem (collections of Good conditions for EFT indicators), ultimately converging upon a few locations that represent alternative optimal solutions. The set of equally viable solutions among objectives is called a Pareto front (Raquel and Naval 2005). Over repeated sets of simulations, a high-dimensional Pareto-optimal response surface is probed and quantified, and these optimal solutions are identified. When optimizing for multiple objectives, the model can find many such solutions, each of which may achieve the same overall value for the objective, indicating that trade-offs may exist among the values of each of the objectives (Raquel and Naval 2005).

Unlike biological systems, where fitness is defined as an individual's ability to propagate, PSO theory uses the term more liberally, with fitness defined as the value of the objective function. In our case, the objective function consists of Good conditions for the 31 EFT indicators, and changes each year as RF is met and priorities shift. Each EFT indicator contributes to the objective function, and each indicator's value depends in unique ways on daily flow, water temperature, river stage, and salinity (Table 1)—with functional forms that range from linear to non-linear and discontinuous relationships.

In the PSO algorithm, information sharing among particles is the key feature that distinguishes PSO from approaches such as Genetic Algorithms (GA), which operate using processes analogous to natural


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selection: selecting strategies (the equivalent of PSO particles) that have the highest fitness (Axelrod 1997; Forrest 1993). We chose PSO over GA for two reasons. First, PSO performs better at exploring the entire solution space compared to a GA search (Raquel and Naval 2005). Second, the R statistical computing software (R Development Core Team 2014) for MOPSO-CD (Multi Objective PSO with Crowding Distance) (Naval 2013), had a readily available package that extends PSO in two ways: by including multiple objectives and by having particles avoid "crowding" around solutions, which leads to better exploration of the search space.

The goal of a Multiple-Objective Particle Swarm Optimization (MOPSO) search is, therefore, twofold: first, finding solutions that are close to the true Pareto front and approximate the Pareto optimal set; and second, ensuring that the search is well distributed across the front (Raquel and Naval 2005). One of the major obstacles of both simulation and analytical optimization algorithms is the convergence of solutions to local optima that are not truly global optima. For PSO algorithms, this crowding is addressed by "over-shooting" optima using mutation operators to explore unknown regions of the search space (Kennedy and Eberhart 1995; Naval 2013).

### *Setting Parameters for TTO*

The optimization system we developed is based on the pre-existing EFT linked to the hydrologic simulation models that are in common use in the study area—all embedded within the MOPSO algorithm described above. All these simulation components are customized so they work within a single simulation year rather than in the multi-decadal period. Our customization of the physical models considerably increased their agility, but otherwise adhered to the same system-operation rules as the DRR 2011 Reference Case scenario.

Each particle in our MOPSO algorithm stores 24 parameters that represent management actions: monthly targets for the Shasta release schedule, and monthly MRF targets in the Old and Middle rivers (which constrain Delta exports). At the start of a simulation, each MOPSO particle is assigned a suite of 12 monthly Shasta releases from a uniform random distribution between 3,250 and 11,000 cubic feet per second (cfs). The lower bound for releases is based on the absolute minimum in-stream flow limit for the Sacramento River, and the upper limit is based on a review of the preferred flow ranges for the ecological indicators. We took twelve monthly initial MRF values from a uniform random distribution between 0 and 15,000 cfs, limits based on the full range of pumping options for the Tracy and Banks pumping facilities.

### Implementing the TTO Model

After considering computing costs, we performed the simulations using 20 particles. In our comparative tests of MOPSO algorithms, we saw no demonstrable change performance across a range of 20 to 100 particles (a finding consistent with advice in Bratton and Kennedy 2007).

We used the Good/Fair/Poor categorical outcomes the EFT produced as the basis for each ecological indicator (see Alexander et al. 2014, Section 2.7). In preliminary tests, we found that the EFT's Good/Fair/Poor three-level categorical measures, simplified to Good and Not-Good, provided much faster convergence within a reasonable time-frame than the EFT's continuous measures (e.g., "weighted useable area of spawning in square feet"), which often did not converge at all. In addition to faster convergence, binary response is more consistent with the concept of turn-taking after a target biological suitability threshold (i.e., a Good score) has been achieved.

The iterative search for improvements to a given year's prioritized subset of 31 ecological indicators is termed a "generation," and is made through changes to each particle's monthly schedule. After the initial randomly-generated set of release/MRF schedules, each subsequent generation produces an updated set of results for our 31 categorical indicators, which are used to create the next generation of 20 release/MRF monthly targets provided to each particle. Following the MOPSO paradigm, the specific values for each particle's release/MRF target are based on the collective previous searches of all the particles, as the 31 ecological indicators vary in response to the set of release/MRF inputs. Particles with a release/MRF target that gives a higher value for the objective function retain their existing target; other particles generate new release/MRF targets based on the

MOPSO algorithm conditions. This process is repeated until convergence is achieved, at which point the water year simulation time-step is completed.

We defined convergence as seeing no change in the number of the multi-objective optima for five successive generations. For example, if by the sixth generation three unique and equally viable solutions were discovered and the solution set did not change for the next five generations, then we judged convergence to have been reached in the eleventh generation. Based on preliminary simulation tests, we set an upper bound of 20 generations to reach convergence, but this boundary was never reached. Typically, a solution set was discovered in seven generations. After an annual water year simulation time-step, if the MOPSO algorithm finds multiple equally viable solutions, the historical release target from each of these solutions is given equal probability of being selected as the release/MRF target for the following water year.

We executed each particle simulation using cloud-based Amazon EC2 Windows 2008R2 servers, dramatically reducing overall processing time by running simulations in parallel. We scheduled the computing activities of the cloud-based servers through interaction with a single batch run control (BRC) server housed with the MOPSO optimization software. The cloud-based server implementation employed Cygwin Unix emulation software (*http://www.cygwin.com*) and custom shell scripts to provide programmatic control over the various components, allowing them to run unattended. An individual particle simulation required about 5 minutes. Each server operated continuously and autonomously—requesting, locking, and processing work units, ultimately providing EFT results to the BRC and the optimization engine. Operating with 20 servers, the 16-year simulation took about 26 hours.

Figure 3 shows the main features of the overall optimization system. Optimization is driven by two agents: (a) the MOPSO algorithm and software, linked to (b) a supervisory BRC server that schedules the remote simulation engines, among other simulation-management tasks. Over the course of iterative generations, the optimization engine proposes a set of monthly releases and MRF targets that are provided (1, 2) to CalSim 2 via the BRC database. CalSim 2

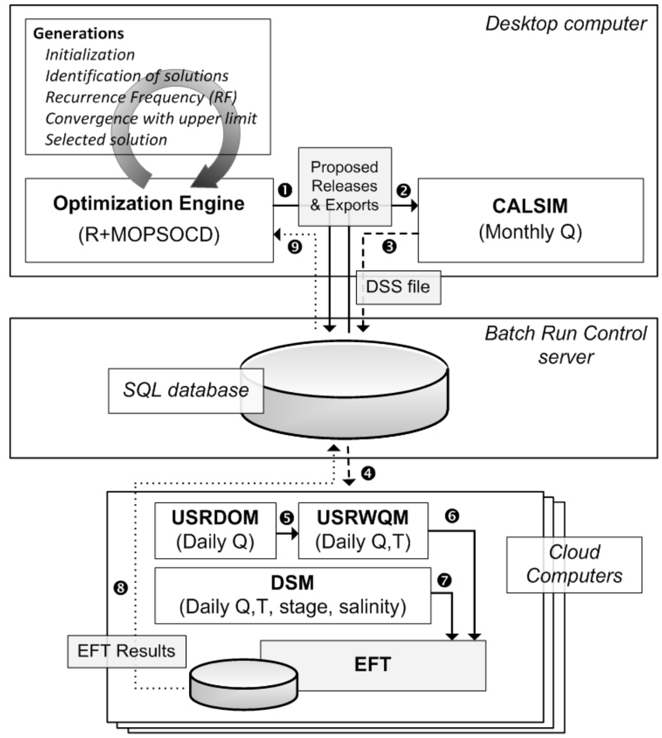


**Figure 3** Overview of the optimization system. Numbered steps show the sequence of information flow that takes place during each generation step, every water year. See text for further details.

produces a schedule for monthly hydrosystem operation targets that is passed (3, 4) through the database to an available cloud server. On the cloud servers, USRDOM downscales the CalSim 2 output from monthly to daily flow for the Upper Sacramento River, passing that information (5) to USRWQM, which simulates water temperatures. In a separate task, the CalSim 2 output for the Delta is processed for running DSM2. Finally, both Sacramento and Delta hydrologic output are passed to the EFT (6, 7), which simulates the ecological consequences for the nine focal species and 31 indicators for the water year. The EFT output is passed through the database (8) to the optimization engine (9), which tracks recurrence frequency for indicators with Good scores, updates the priorities amongst EFT species and indicators, and searches for sets of optimal solutions. The iterative search for solutions ends at convergence, or when the maximum number of generations has been reached.


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## RESULTS

### Ecological Performance

Cumulative performance measures for each indicator across all study years indicate that the TTO solutions tended to outperform the Reference Case scenario solutions. Of the 31 EFT indicators, 12 improved, 14 were unchanged, and 5 performed worse using TTO (Table 3). Figure 4 shows the cumulative performance of each indicator over water years for the Reference Case scenario and two equally viable TTO solutions.

When grouped by focal species, four of nine species improved (more improved indicators than worsened indicators): late-fall Chinook, winter Chinook, spring Chinook, and Fremont cottonwood. Within the salmonid indicators, there is also an indication that some ecological indicators (e.g., see salmonid juvenile stranding, Figure 7) succeed or fail as a group. The only species that performed consistently worse under TTO was Steelhead, which experienced improved performance for one indicator, no change for two indicators, and worse performance for two indicators (Table 3). Fall-run Chinook, Delta Smelt, Splittail, and Longfin Smelt all performed approximately the same as the Reference Case scenario.

In some cases, EFT indicator worsening may be tied to those indicators that have a temporal window spanning the October 31 water year boundary. For example, the temporal window for Steelhead weighted usable area [WUA] rearing spans the entire water year, peaking between July and October. Since the indicator cannot be completely evaluated based on the flow in one water year only, it becomes insensitive to the optimization process. A further explanation for some worsened indicators is found in tightly bound negative correlations. For example, fall Chinook WUA rearing is maximized at flows of about 4,000 cfs, while fall Chinook juvenile stranding is minimized at about 5,000 cfs. In this case, any optimization search will not be able to find flows that reconcile the different requirements—an instance of Jagger's Law.

**Table 3** Comparison of MOPSO and Reference Case solutions for 1976–1991 based on data shown in Figure 4, grouped by species for Sacramento River and Delta (SRD) eco-regions

| Indicator | Number | TTO relative to Reference Case | | |
|---|---|---|---|---|
| | | Improved | Same | Worse |
| Fall Chinook | 5 | 2 | 1 | 2 |
| Late-fall Chinook | 5 | 1 | 4 | |
| Winter Chinook | 5 | 5 | | |
| Spring Chinook | 5 | 2 | 2 | 1 |
| Steelhead | 5 | 1 | 2 | 2 |
| Fremont cottonwood | 1 | 1 | | |
| Delta Smelt | 3 | | 3 | |
| Splittail | 1 | | 1 | |
| Longfin Smelt | 1 | | 1 | |
| Total | 31 | 12 | 14 | 5 |

### Hydrosystem Effects of Re-Operation

Our analysis of TTO solutions indicates it does not introduce any egregious effects on hydrosystem performance in terms of draw-down of Shasta Reservoir. But, not surprisingly, release and export timing changes. Figure 5 shows the consequence of TTO on discovering and choosing solutions from 1976 to 1991 for key flow metrics for the two equally viable solutions relative to the Reference Case scenario. The differences in the time-series include modest differences between the Reference Case scenario and the TTO solutions (Figure 5).

To characterize the hydrosystem effects, we calculated monthly release, storage, and export statistics for the Reference Case scenario and the final two 1991 solutions over the 16-year simulation period using a paired $t$-test; we also compared standard deviations (Table 4). The results for the two final TTO solutions are similar, and show that the TTO solutions have lower average releases from Shasta Reservoir ($P<0.01$), slightly higher Shasta Reservoir storage ($P<0.01$) and higher average positive flows in the Old and Middle rivers compared to the Reference Case scenario ($P<0.01$ and $P<0.01$, respectively). Variability within the MOPSO solutions was also lower compared to the Reference Case, with standard deviations that are 90%, 86%, and 81% of the Reference Case scenario for release, storage, and exports, respectively.

Although Shasta Reservoir releases, Shasta storage, and Old and Middle river flows show broadly similar seasonal patterns over the 16-year simulation period, the timing of changes at shorter time-scales differs

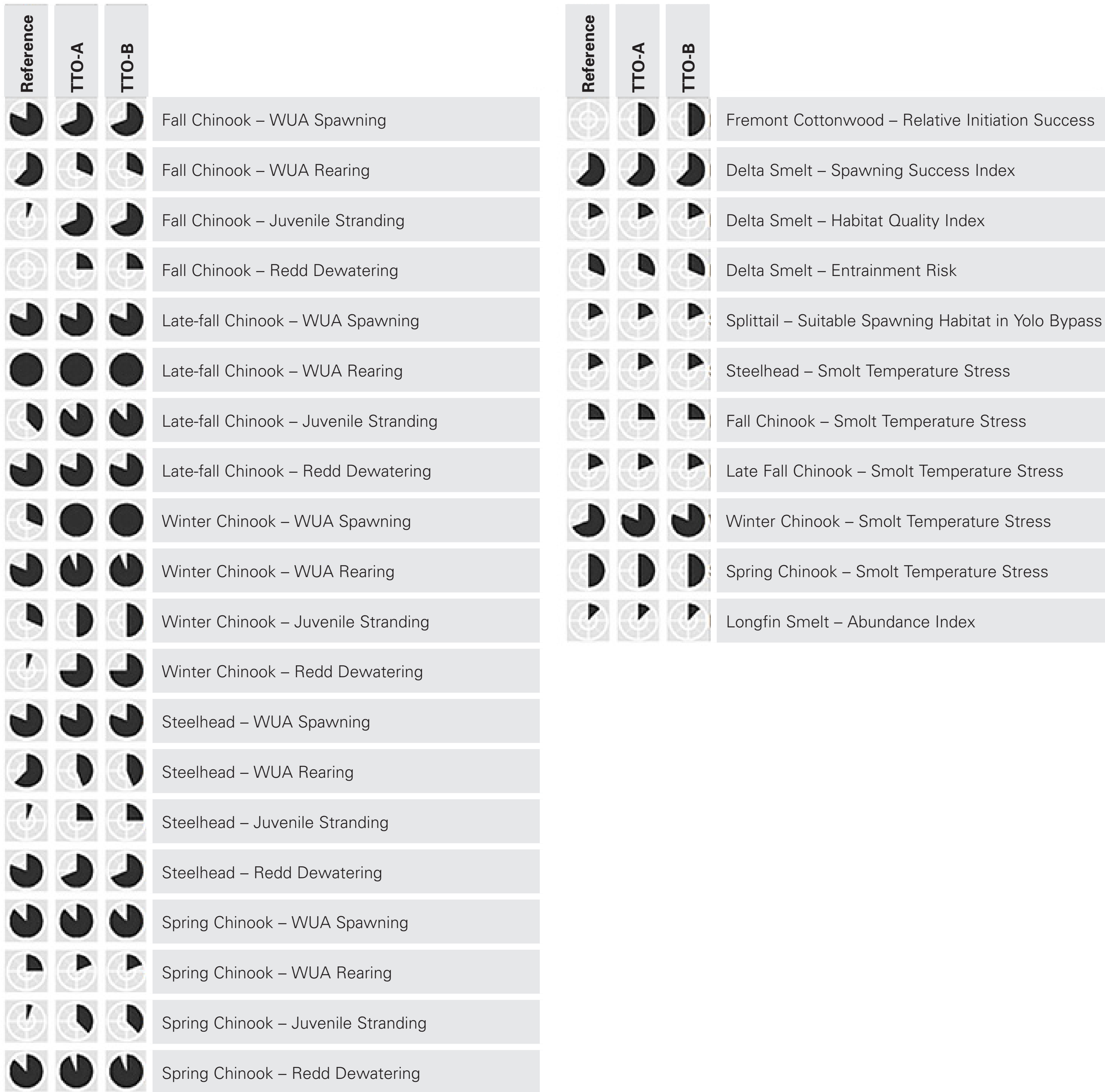


**Figure 4** Proportion of years receiving a categorical Good score and/or achieving RF target for 31 ecological indicators, for the final two TTO solutions compared with the Reference Case. Filled circles indicate a 100% score in the indicator-specific moving window from 1976 to 1991.



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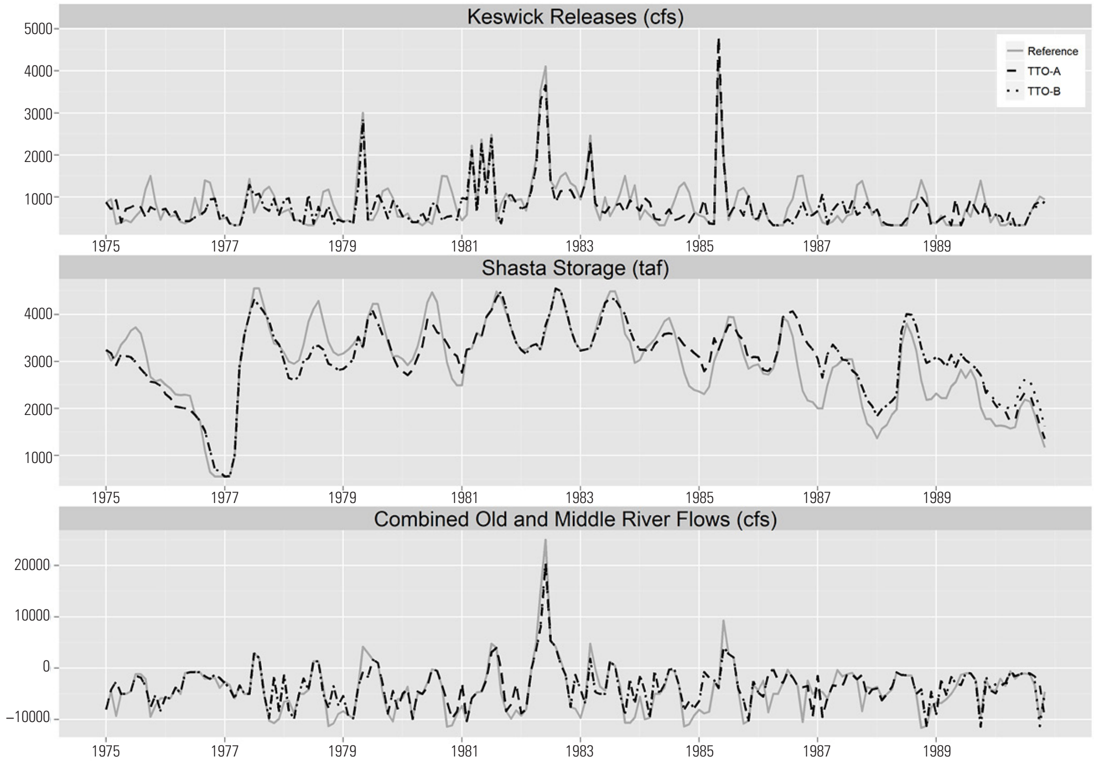


**Figure 5** Selected flow characteristics of the full 16-year simulation. The Reference Case is shown with a solid line; TTO solutions are shown with broken lines. Shasta Reservoir releases (monthly CalSim 2 inputs) are shown in the upper panel, Shasta Reservoir storage in the middle panel, and maximum reverse flow (MRF) targets (monthly CalSim 2 inputs) in the lower panel. Releases are generally less extreme in the TTO model simulations; seasonal storage patterns are broadly similar, with notable differences in specific years. In the final year (1991), the two ending solutions (TTO-A, TTO-B) are shown.

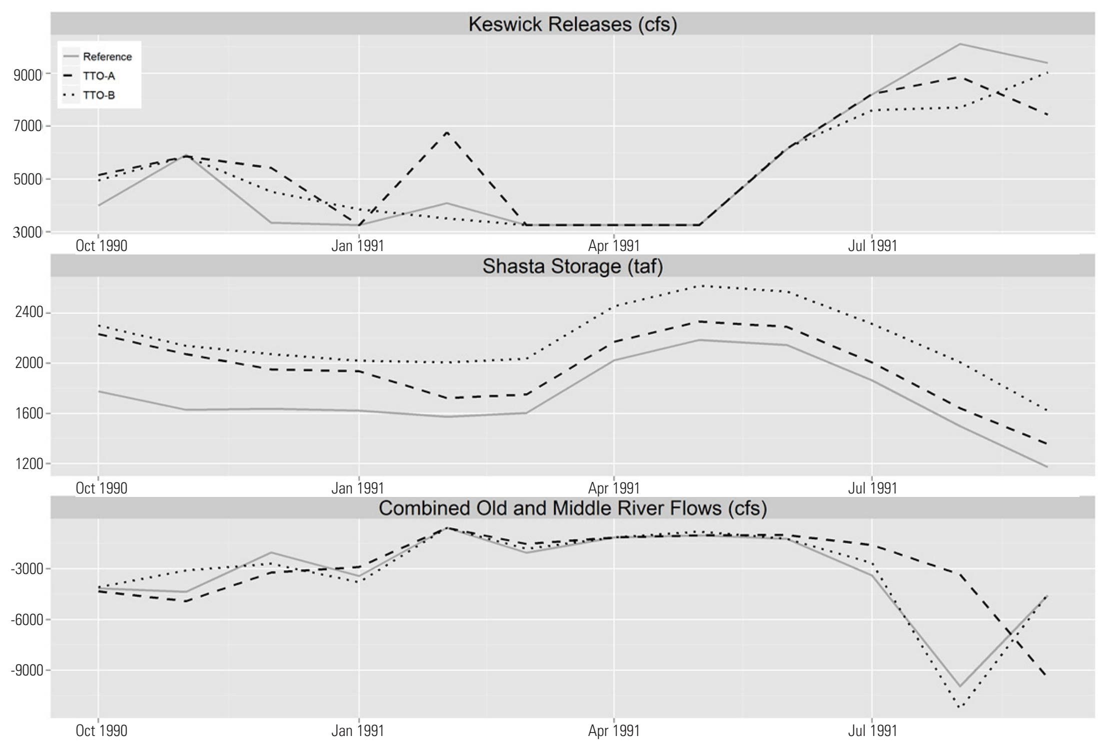


**Figure 6** Selected flow characteristics of the 1991 water year simulation. The Reference Case scenario is shown with a solid line; TTO solutions are shown with broken lines. Shasta Reservoir releases (monthly CalSim 2 inputs) are shown in the upper panel, Shasta storage in the middle panel, and maximum reverse flow (MRF) targets (monthly CalSim 2 inputs) in the lower panel. Shasta Reservoir releases are higher during winter and lower in summer for both TTO solutions, compared to the Reference Case. Shasta Reservoir storage remains consistently lower for the Reference Case, with declining storage in this year for both the Reference Case and TTO solutions.

**Table 4** Upper two rows show difference (TTO - Reference) between monthly average metrics for TTO and Reference Case solutions, 1976–1991. Positive values indicate that the TTO solution exceeds the Reference Case solution. All differences are significant at $P < 0.01$. Bottom three rows show standard deviations.

| Solution | Shasta release ($ft^3 s^{-1}$) | Shasta storage (TAF) | Old and Middle River flows ($ft^3 s^{-1}$) |
|---|---|---|---|
| Difference from reference | | | |
| A | –712 | 82 | 645 |
| B | –733 | 97 | 640 |
| Standard deviation | | | |
| Reference | 6185 | 894 | 4790 |
| A | 5586 | 776 | 3861 |
| B | 5594 | 756 | 3877 |

notably. For example, the upper panel of Figure 5 shows that, in most years, Shasta release patterns found by the TTO model found are generally less extreme than the Reference Case scenario—usually with higher spring and lower summer flows compared to the Reference Case. A more detailed example from 1991 is shown in Figure 6. In this example, the key timing differences can be seen in the form of higher early winter releases and lower releases in late summer for all TTO solutions compared to the Reference Case. Higher Shasta storage profiles for the TTO solutions are a consequence of simulations in previous years that set the initial conditions for the 1991 water year, and that are maintained throughout the year. It was beyond the scope of this first demonstration of the TTO approach to determine whether these timing shifts would be acceptable to individual water users awaiting deliveries.

Over the 16 years we simulated, the number of equally viable solutions generated by the MOPSO algorithm ranged from one to four, with no indication that these high-level differences relate to the CDEC water year type (SWRCB 1995). An example for water year 1991 is shown in Figure 7. In this year, the MOPSO algorithm identified two equally viable solutions, each consisting of a different combination of 15 ecological indicators that achieved a Good score or met the Recurrence Frequency (RF; see below), compared to the Reference Case, which


**Figure 7** Circles show ecological indicators (rows) which have a categorical Good score and/or achieve their RF for each of the optimal solutions identified by the MOPSO search, compared to the Reference Case scenario. These results are for the 1991 water year, with 15 indicators meeting the criteria for each of the two MOPSO solutions, compared to 13 for the Reference Case.

achieved a Good score and/or achieved RF for 13 indicators. Fourteen indicators (e.g., WUA spawning for fall-run Chinook) achieved a Good score and/or achieved RF across both TTO model solutions. We have not expressed the count of ecological indicators as proportions because some species have more ecological indicators associated with them than others. If expressed as proportions, this leads to unequal weighting of species to the overall value, which could be misleading.



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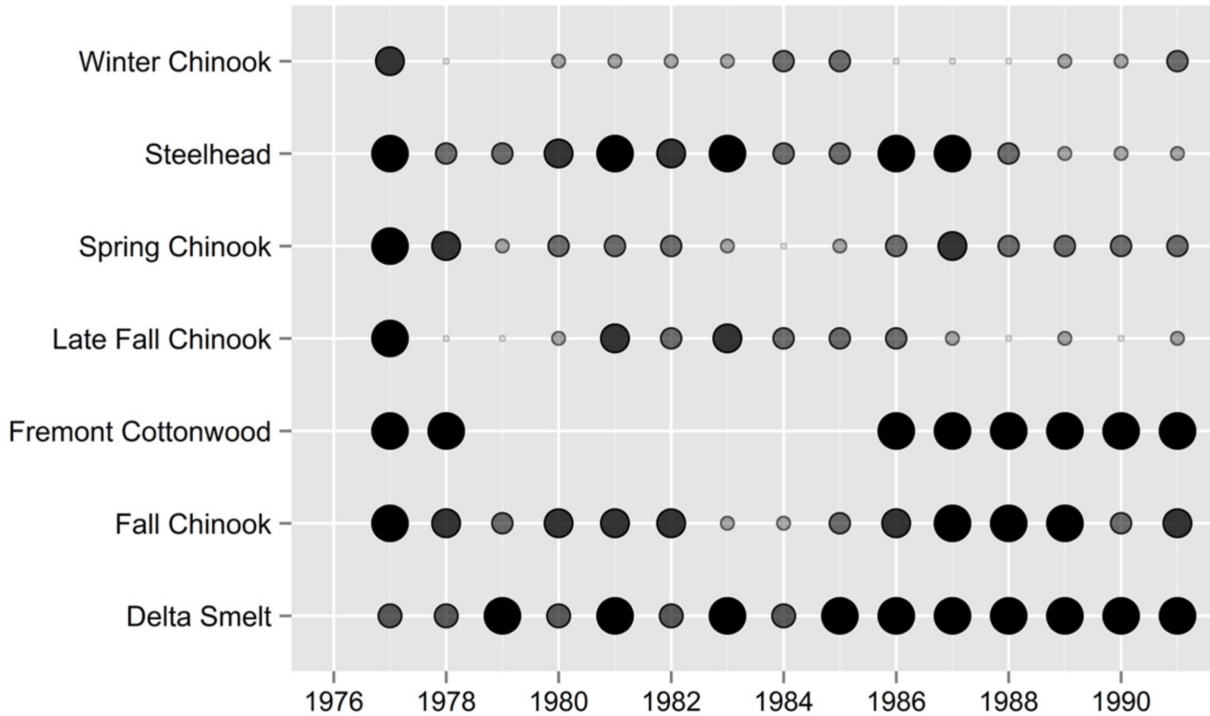


**Figure 8** Circles show changing priorities from 1976 to 1991. For presentation purposes, rows represent the average priority for groups of ecological indicators: one for Fremont cottonwood, three for Delta Smelt, and five for salmonids, using dot size and transparency to indicate priority. Ecological indicators that show no change over the entire period have been omitted.

### Increased Flexibility through Turn-Taking

The implementation of turn-taking via the concept of RF shows that the ecological indicators prioritized for optimization can change over time, as they encounter appropriate conditions over a moving window of years (Table 2). Figure 8 shows that Fremont cottonwood was a priority in 1977 and 1978. Since it received a Good categorical score in 1978, it was not a priority for the next 7 years, which allowed other ecological indicators to have a greater influence in the TTO model search for viable solutions. A more complex example of turn-taking can be seen for winter-run Chinook and Steelhead (upper two rows of Figure 8), each of which met RF for two of five indicators in 1984 and 1985. In contrast, in 1986 and 1987, four of five winter-run Chinook indicators met their RF, compared to zero of five indicators for Steelhead. This change effectively switches priorities from winter-run Chinook indicators to Steelhead indicators, creating additional flexibility to meet Steelhead objectives.

## DISCUSSION

Developing greater awareness of the value of flexibility to manage ecosystem trade-offs over time is a pressing need. California's native fish and riparian species have adapted to the state's widely variable climate, and these evolutionary adaptations have helped species persist during extended droughts and other forms of extreme water fluctuation. This feature of species life-history adaptation can, within reason, be exploited to develop state-dependent priorities and turn-taking rules (RFs), allowing more species to "win" more often. This investigation illustrates that operation of the California water system can be changed by using TTO to time releases from reservoirs and water exports to benefit a wider range of species without (1) arbitrarily constraining the number of species and indicators considered, (2) over-simplifying ecological flow targets, or (3) having major adverse consequences on storage and water exports.

**Table 5** Number of ecological indicators that have a categorical Good score and/or meet their RF in multiple water years, with the Reference Case for comparison. Labels (A, B) denote equally viable solutions in a water year. Annual CDEC water year types are shown in the Type column: W=Wet, AN=Above Normal, BN=Below Normal, D=Dry, C=Critically Dry (SWRCB 1995).

| Year | Water year type | Reference | Solution | |
|---|---|---|---|---|
| | | | TTO-A | TTO-B |
| 1976 | C | 10 | 16 | 14 |
| 1977 | C | 13 | 17 | 17 |
| 1978 | AN | 15 | 19 | |
| 1979 | BN | 14 | 18 | |
| 1980 | AN | 17 | 16 | |
| 1981 | D | 12 | 15 | |
| 1982 | W | 18 | 23 | |
| 1983 | W | 16 | 23 | 23 |
| 1984 | W | 15 | 20 | |
| 1985 | D | 15 | 20 | |
| 1986 | W | 10 | 15 | |
| 1987 | D | 12 | 14 | 15 |
| 1988 | C | 13 | 13 | 14 |
| 1989 | D | 13 | 15 | |
| 1990 | C | 12 | 15 | |
| 1991 | C | 13 | 15 | 15 |

Based on current management practices embodied by the Reference Case, using TTO improved conditions for twelve indicators; fourteen showed no change, and five showed reduced suitability. When the nine groups are grouped by species and life-history, four show improved performance (late-fall-run Chinook, winter Chinook, spring Chinook, and Fremont cottonwood), four show no change (fall-run Chinook, Delta Smelt, Splittail and Longfin Smelt), and one group shows worse performance (Steelhead, which experienced improved performance in one indicator, no change in two, and worse performance in two). Both listed species (winter Chinook and Delta Smelt) performed better or the same when TTO rather than the current management paradigm was used, demonstrating the promise of this approach. However, despite these significant improvements over the Reference Case scenario, our results—and Jagger's Law—indicate that there are always a few "losers."

Traditional model studies using CalSim 2 aim to find a single solution that works best over an extended 82-year period (or for specific water-year types). This approach is intrinsically less agile than TTO, which considers each year on its own and dynamically adjusts priorities from one year to the next. In three previous examples studied—BDCP, NODOS, and Shasta—the differences in ecological performance among scenarios were usually unimpressively small (Alexander et al. 2014). In our study, we show that TTO can improve about twice as many ecological indicators as the traditional approach of optimizing over a long period of record.

Although this case study focuses on the application of the EFT in California, TTO provides a flexible framework to better balance multiple values for key objectives that can be generalized to any jurisdiction. The objectives, RF assumptions, and other rules can be revised and TTO applied to other linked decision-support tools. Within the California hydrosystem context, although the EFT currently leverages existing generally-preferred physical models for the SRD—CalSim 2, USRDOM, USRWQM, and DSM2 (ESSA 2011, 2013)—TTO and the EFT are not intrinsically tied to these specific models and could be implemented with any hydrosystem model(s) able to appropriately resolve temporal and spatial data inputs. Furthermore, although we have implemented a daily time-scale approach appropriate to the SRD, other levels of resolution that involve coarser or finer time-scales, or different geographical scales, are equally feasible, depending on the needs of the ecological models and the availability of physical data.

Our case study implementation of TTO using the EFT did not directly optimize social and economic indicators because CalSim 2 is responsible for this function. Balancing human factors and the ecological needs of focal species is essential to modern decision-making (Yang 2011; Tsai et al. 2015). Although CalSim 2 represents vitally important aspects of water deliveries and flood protection, many of these important characteristics are currently considered to be fixed model constraints, and effectively "inaccessible" to our TTO approach. Future analyses could be adapted to explore trade-off outcomes derived from application of TTO to both socio-economic objectives and multiple ecological objectives. For example, the Water Evaluation and


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Planning (WEAP) model (Sieber and Purkey 2015) has been identified as an alternative hydrologic simulation system, recently customized for use in California (Rayej 2012; SWRCB c2017), that might be more amenable for use with TTO and the EFT. The Sacramento WEAP implementation includes representation of groundwater sources and sinks, and finer spatial resolution on agricultural and community water-delivery requirements.

To facilitate convergence, we used categorical Good scores as the criteria to optimize ecological indicators rather than continuous values, lowering the resolution of the objective function by simplifying the problem to a binary (yes/no) search result for each of the 31 indicators. Future work could examine whether an increase in the number of categories (e.g., Very Good, Good, Moderate, Poor, Very Poor) would improve model performance or identify other optimal solutions. Although our modeling did not alter the overall default priority and constraint scheme inherent in CalSim 2, we nevertheless recommend future investigations that use TTO to confirm that CalSim's (or other model's) representation of allowable departures of time-period-specific water deliveries are observed to a satisfactory degree. This would require additional consultation with professionals knowledgeable about the negotiating space available for water deliveries, a fundamental step beyond the scope of this paper.

Refinement of the TTO model could also include finer-scale priority setting among indicators. Currently, priority weights are assigned a value of zero or one (off/on), but this could be modified to incorporate higher values (e.g., zero to 10) that emphasize indicators (that some may feel are) more important to optimize (e.g., listed species). However, we anticipate movement in this direction would constrain multi-species ecological benefits that are prized by the EFT and TTO. Refinements might also include widening the temporal span of each simulation year so ecological indicators that span the water year boundary (e.g., Steelhead) are better optimized.

Additionally, future refinements could expand optimization to include releases from other reservoirs within the SRD system, which could provide additional temporal flexibility in water allocation.

## FUTURE DIRECTIONS

To best leverage the value of TTO, it should be developed within a true real-time modelling context. In our opinion, a disproportionate amount of effort is devoted to water planning models in California, but not enough attention to real-time operational tools to support environmental needs. Planning models like CalSim 2 and DSM2 (and their cousins) do not and cannot capture inflow forecasting uncertainties—the behavioral uncertainty of real-world operators—nor can they represent the true operational flexibility that exists. For example, Mount et al. (2013) were concerned that some of the modeled flow operations for certain BDCP scenarios would not actually occur in real operations. Indeed, the degree to which actual operations follow simulated operations can vary substantially (especially because most planning models have a monthly resolution) (Hyatt et al. 2015).

More fundamentally, real-time modeling tools that operators use day to day affect actual on-the-ground, real-life decisions far more (see Hyatt et al. 2015). If real-time operational tools do not exist that adequately build in ecological flow guidelines and targets derived from related modeling (such as indicators like those in the EFT or from other studies), much of the advice emerging from planning studies and their tools will remain academic. Further, the sheer number of objectives, locations, indicators, and considerations real-world managers face are too complex for "rules of thumb," which partly explains the current situation of highly simplified environmental targets.

For these reasons, we see considerable value in creation of a real-time decision engine that incorporates inflow forecasting information, ecological indicators like those in the EFT, and automatically runs TTO on a regular (daily or weekly) interval to determine a small package of equally optimal water release and export decisions. The real-time decision engine would also keep track of the recent history of success in achieving different ecological objectives, thereby further automating the establishment of shifting priorities for focal species each year. Using results from the decision engine, water operators would then be presented with two to five alternative water release and export scenarios that are recommended from an environmental perspective, and, using their judgment, weigh the value of incorporating this information to modify traditional coordinated operations. A functioning, ecological water-operations management team informed by both (1) the proposed automated decision engine (a package of appropriate integrated decision support tools structured to take advantage of TTO), and (2) a rigorous adaptive management program would be a giant step forward in routinely doing multiple objective trade-off decision-making.

## CONCLUSION

This study demonstrates that adopting a water-allocation approach that incorporates shifting priorities and optimization of ecological indicators across years can lead to overall multi-species benefits in the SRD. The approach presented in this paper relies on the concept of "turn-taking," a flexible approach that takes advantage of the frequency with which different species indicators should experience favorable conditions, along with prevailing flow conditions to optimize the widest range of ecological needs being achieved. As the ecological needs of an indicator are met, its priority weight is temporarily reduced, and other ecological indicators receive higher priority (i.e., the needs of ecological indicators take turns being met). Further, if water managers have real-time tools that enable them to rapidly evaluate many alternative flow regimes, they will be able to devise more flexible water-management approaches that will enable the needs of multiple ecosystem functions and species to be met over time. Although a water-management paradigm that embraces TTO will not solve every trade-off, if it were tried, managers just might find that more values and objectives get what they need.

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