Ecological Modelling 471 (2022) 110058

Contents lists available at ScienceDirect

Ecological Modelling

journal homepage: www.elsevier.com/locate/ecolmodel

# Integrating monitoring and optimization modeling to inform flow decisions for Chinook salmon smolts

Patti J Wohner[a,*], Adam Duarte[b,c], John Wikert[d], Brad Cavallo[e], Steven C Zeug[e], James T Peterson[f]

[a] Oregon Cooperative Fish and Wildlife Research Unit, Department of Fisheries, Wildlife, and Conservation Sciences, Oregon State University, 104 Nash Hall, Corvallis, Oregon, United States
[b] U.S.D.A. Forest Service, Pacific Northwest Research Station, 3625 93rd Ave. SW, Olympia, Washington, United States
[c] Department of Fisheries, Wildlife, and Conservation Sciences, Oregon State University, 104 Nash Hall, Corvallis, Oregon, United States
[d] U.S. Fish and Wildlife Service, Anadromous Fish Restoration Program, 850 S. Guild Avenue, Suite 105, Lodi, California, United States
[e] Cramer Fish Sciences, Modeling, Analysis, and Synthesis Lab, 13300 New Airport Road., Suite 103, Auburn, California, United States
[f] U.S. Geological Survey, Oregon Cooperative Fish and Wildlife Research Unit, Department of Fisheries, Wildlife, and Conservation Sciences, Oregon State University, 104 Nash Hall, Corvallis, Oregon, United States

ARTICLE INFO

*Keywords:*
Chinook salmon
San Joaquin river
River flows
Monitoring data
Optimization modeling
California central valley

ABSTRACT

Monitoring is usually among the first actions taken to help inform recovery planning for declining species, but these data are rarely used formally to inform conservation decision making. For example, Central Valley Chinook salmon were once abundant, but anthropogenic activities have led to widespread habitat loss and degradation resulting in significant population declines. Monitoring data suggest survival through the southern Sacramento-San Joaquin River Delta, in particular, may be a limiting factor for juvenile Chinook salmon outmigrating from the San Joaquin River and its tributaries. However, survival and routing monitoring data have not been formally used to inform water management in a decision analytic framework. Here, we illustrate how estimates derived from disjunct monitoring data can be used to inform water management and as a basis for adaptively managing flows. We aggregated a meta-analysis of Chinook salmon smolt survival and routing estimates through the south Delta with other sources of data to develop a survival and routing simulation model to estimate optimal flows for the San Joaquin River during smolt outmigration from February–May. We found that large flow pulses at predictable times during the spring are projected to be optimal for increasing Chinook salmon smolt survival to the San Francisco Bay and that optimal scenarios differed somewhat with water year type. Sensitivity analysis revealed temperature and smolt outmigration timing are driving optimal pulse distribution and that water allocation changes little with parameter uncertainty. This case study highlights the utility of the decision-analytic framework for solving conservation problems.

## 1. Introduction

Monitoring data are often collected on sensitive species with the objective of informing management for conservation (Nichols and Williams, 2006; Lyons et al., 2008). Indeed, these efforts can result in years of abundance, survival, movement, and habitat quality data, sometimes in excess of twenty years. These data are rarely used formally for the purpose of informing management (Nichols and Williams, 2006). In many situations, managers and biologists believe their data are insufficient for making informed management decisions and believe more monitoring data are needed (Wright et al., 2020). The decoupling of monitoring from natural resource management decision making is inefficient and potentially wasteful if resources are expended for increased monitoring but the monitoring results lie idle (Nichols and Williams, 2006). A better approach incorporates monitoring data into a quantitative decision-support framework to evaluate the potential effectiveness of management alternatives on valued resource objectives, such as species recovery, while maintaining a flow of information to reduce uncertainty and increase predictive performance (i.e., adaptive resource management; Nichols and Williams, 2006; Lyons et al., 2008; Williams, 2011; Conroy and Peterson, 2013; Wright et al., 2020). Although adaptive resource management has demonstrated success

* Corresponding author at: Fisheries and Wildlife, Oregon State University, Nash Hall, 2820 SW Campus Way, Corvallis, OR 97330, United States.
*E-mail address:* wohnerp@oregonstate.edu (P.J. Wohner).

https://doi.org/10.1016/j.ecolmodel.2022.110058
Received 7 September 2021; Received in revised form 13 June 2022; Accepted 19 June 2022

when applied to conservation problems, it remains relatively underutilized in practice.

An example of the decoupling of monitoring from management is in the management of water flows to support migration of anadromous salmonids in the Central Valley of California. Hydrological modifications and habitat degradation have, in part, resulted in substantial declines of populations of Central Valley Chinook salmon and other anadromous fish (Smith et al., 2003; Myrick et al., 2004; Perry et al., 2018). An extensive system of dams, reservoirs, diversions and aqueducts supports agricultural (flood control and irrigation) and municipal uses (power generation and water supply) throughout the Central Valley (Smith et al., 2003; Poff et al., 2007, 2010; Perry et al., 2018; Zimmerman et al., 2018). These modifications have blocked salmon access to historical spawning habitat, and have greatly reduced the seasonal and interannual streamflow variability of rivers; altered the timing and magnitude of river discharge; and changed the temperature and turbidity of river water (Smith et al., 2003; Lund et al., 2007; Poff et al., 2007; Richter and Thomas, 2007; Singer, 2007; Brown and Bauer, 2010; Shenton et al., 2012; Perry et al., 2018; Zimmerman et al., 2018; Sturrock et al., 2020). In addition, physical habitat has been hardened and simplified to facilitate human navigation and flood control (Lehman et al., 2019) and myriad non-native species have become established resulting in dramatic changes in species assemblage structure (Dill and Cordone, 1997; Feyrer and Healey, 2003).

Chinook salmon use ocean, freshwater, and estuarine habitats to fulfill their life history needs, but observations of low survival ($<0.05$; Buchanan et al., 2018a, 2018b; Perry et al., 2018; Buchanan and Skalski, 2020) for juveniles outmigrating through the Sacramento-San Joaquin River Delta (hereafter, Delta), and the importance of this region for water management, has made the Delta a research priority (Sommer et al., 2001; Limm and Marchetti, 2009; Michel et al., 2013; 2015). Every natural-origin juvenile must pass through the Delta to successfully reach the ocean (Newman and Brandes, 2010; Perry et al., 2018; Buchanan and Skalski, 2020). However, the Delta is also the core of California's water delivery system, diverting water through a network of channels and canals (Grantham, 2013; Luoma et al., 2015; Healey et al., 2016; Perry et al., 2018; Buchanan and Skalski, 2020). The Delta has undergone an almost complete transformation from historical conditions (Whipple et al., 2012; Michel et al., 2013). Juvenile salmon navigate through multiple potential pathways in the highly modified Delta where route-specific survival is highly variable (Perry et al., 2010; 2018; Singer et al., 2013; Brown and Bauer, 2010).

Juvenile fall-run Chinook salmon can disperse from natal tributaries in early spring as smaller fry and achieve considerable growth for multiple weeks in non-natal waters prior to ocean entry, or they can rear in natal tributaries and leave as larger smolts later in the spring (Limm and Marchetti 2009; Merz et al., 2013; Zeug et al., 2014; Sturrock et al., 2020; Nobriga et al., 2021). Historically, the Delta was dominated by floodplains and wetlands that could support large numbers of rearing fry, and provide predator and thermal refugia for later outmigrating smolts (Sommer et al., 2001). However, $<3\%$ of these habitats remain today and salmon that emigrate early from natal tributaries as fry have low survival (Sturrock et al., 2020). Salmon emigrating later as smolts also have low survival due to increased water temperature ($>20\,^{\circ}$C) that corresponds with increases in bioenergetic demands of introduced predatory fish (e.g., largemouth bass [*Micropterus salmoides*]) and a reduction in salmon swimming performance (Lehman et al., 2017; Buchanan et al., 2018a,2018b).

Freshwater input into the Delta is influenced primarily by the San Joaquin River in the south and is dominated by the Sacramento River in the north (Buchanan et al., 2018a, 2018b; Perry et al., 2018). In the south Delta, multiple decades of coded wire tag releases of juvenile Chinook salmon have been used to develop models relating hydrologic conditions to salvage at the state and federal exports facilities (Zeug and Cavallo, 2014), smolt survival (Newman, 2008; Zeug and Cavallo, 2013), and movement through the Delta (Baker and Morhardt, 2001). More recently, acoustic tagging of individual smolts has allowed more precise estimation of individual smolt routing (movement) and survival in the south Delta (Holbrook et al., 2009; SJRGA, 2010, 2011, 2013; Buchanan et al., 2015, 2016, 2018a, 2018b). These multiple years of acoustic data can facilitate identification of flow regimes for the San Joaquin River that would maximize the survival of outmigrating salmon smolts through the various possible routes in the south Delta.

Our objectives were to show how to leverage currently available long-term monitoring datasets to develop decision-support tools that can directly inform management decisions without the need for waiting on additional monitoring data. For purposes of illustration, we assumed a decision context of "what is the best timing and volume of water to release for migrating salmon?" with the objective of maximizing juvenile Chinook salmon survival through the south Delta from Durham Ferry to Chipps Island. The objective could also have been e.g., minimize the probability that survival is below some threshold or maximize emigration timing diversity. The important concept is that different (or multiple) formulations of objectives could have been used for optimization and we selected "maximize survival" to demonstrate the decision-analytic framework.

To this end, we aggregated estimates from various datasets from the south Delta to develop a salmon smolt survival and movement simulation model that estimates the number of smolts that survive along the various routes in the Delta for a given flow regime. This included a meta-analysis of Chinook salmon smolt survival and routing probability estimates available from summary reports through years of monitoring that we related to environmental variables, i.e., flow, temperature, water exports, and tide. We then used optimization modeling to determine the flow regimes that maximize survival during smolt outmigration. We also used our simulation model to compare the outcome of flow decisions in previous years to model-optimized flow and conducted a sensitivity analysis to help prioritize further data and monitoring needs.

## 2. Methods

### 2.1. Management system

The California Central Valley watershed is composed of two main drainage systems encompassing 160,000 km$^2$, the Sacramento and San Joaquin basins. The Central Valley experiences a Mediterranean climate with historical flow regimes driven by winter storm events, late spring snow melt, and a hot, dry summer (Dettinger et al., 2011; San Joaquin River Group Authority (SJRGA, 2011; Yarnell et al., 2015; Hestir et al., 2016). Seasonal variation in flows is substantial (Hestir et al., 2016) with approximately 80% of average annual flow occurring in six months of the year, with peak flows generally occurring in the late spring (Whipple et al., 2012). The Sacramento and San Joaquin Rivers join to form the Delta at the eastern portion of the largest estuarine system on the West Coast of the Americas (Whipple et al., 2012). The Delta then feeds into San Pablo, Suisun, and San Francisco Bays to the west, and then to the Pacific Ocean.

The region of focus for this paper is the southern portion of the Delta from Durham Ferry in the south to Chipps Island in the northwest and bounded by the San Joaquin and Old River (Fig. 1; Buchanan and Skalski, 2020). The primary source of freshwater in this region is the San Joaquin River, and tides increasingly dominate hydrology downstream of the Head of Old River Junction (Baker and Morhardt, 2001; Cavallo et al., 2015; SST, 2017). The Central Valley Project (CVP) and State Water Project (SWP) pump water from the south Delta for agricultural and municipal uses through a series of channels, seasonal barriers, and gates (Perry et al., 2010; Hestir et al., 2016; Munsch et al., 2019). Water exports from CVP and SWP alter the hydrology in the Old-Middle River corridor and juvenile Chinook salmon can be entrained along with diverted water. Both the CVP and SWP salvage fish from diverted water and truck them to the west Delta where they are released. Greater

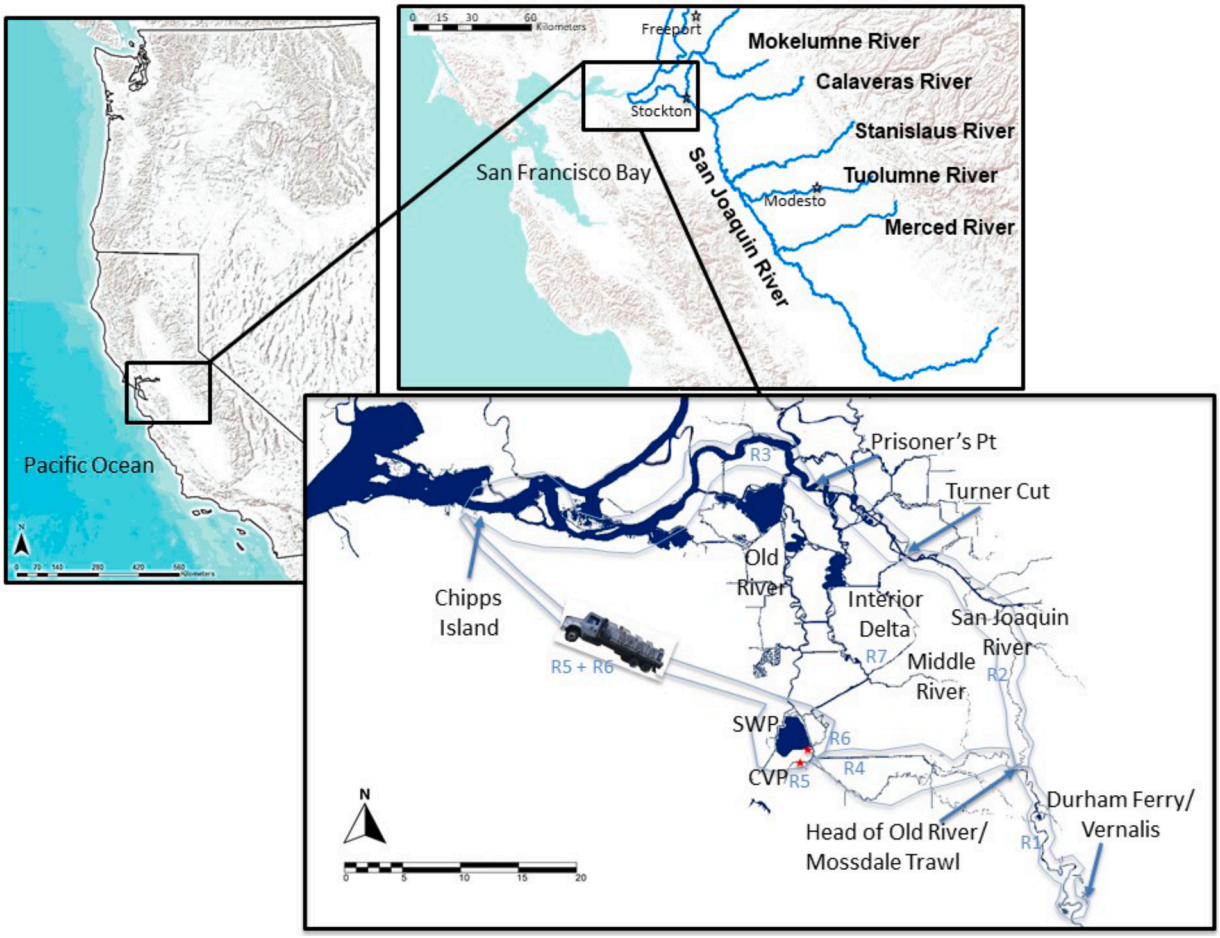


**Fig. 1.** Map of south Delta with major junctions (blue arrows) and labeled regions (blue R1–R7) (bottom), San Joaquin River watershed with major tributaries (top right), and map of California. (top left). SWP = State Water Project, CVP = Central Valley Project. Red stars indicate SWP radial gates at Clifton Court Forebay (upper star) leading to fish salvage facilities and CVP fish salvage facilities (lower star). Truck denotes trucking to the finish line from Regions 5 and 6 to Chipps Island. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

numbers of Chinook salmon are salvaged as diversion rates increase but entrainment may not increase total population mortality under most conditions (Kimmerer, 2008; Zeug and Cavallo, 2014; Buchanan et al., 2018a). In some years, a temporary fish barrier is constructed to prevent fish outmigrating from the San Joaquin River routing to these pumping facilities (Buchanan et al., 2018a, 2018b). Low river flows also affect salmon survival by altering the location of the tidal transition zone (Perry et al., 2010; Cavallo et al., 2013).

Water through the south Delta is managed based on water year type and a variety of regulatory measures that are in place to protect special-status fishes (e.g., steelhead trout [*Oncorhynchus mykiss]*, delta smelt [*Hypomesus transpacificus*]), and water quality. Water year types are complex water management classifications generally based on the amount of unimpaired runoff from October to July and the previous year's index, and are updated monthly during the rainy season (California Data Exchange Center, 2021b). We therefore modeled survival based on water year type and used the San Joaquin 60–20–20 water year hydrological classification index that varied during our timeframe of interest (2008–2018) from least amount of water available to the most: Critical water years, 2008 and 2013–2015; Dry water years, 2012 and 2016; Below Normal years, 2009 and 2018; Above Normal year, 2010; and Wet years, 2011 and 2017 (California Data Exchange Center, 2021a).

### 2.2. *Meta-analysis of survival and routing studies in the south delta*

We conducted a meta-analysis of the acoustic telemetry-based survival and routing probability estimates for hatchery-raised Chinook salmon smolts collected in the south Delta for regions where enough fish survived to include in the meta-analysis (Holbrook et al., 2009; SJRGA, 2010, 2011, 2013; Buchanan et al., 2015, 2016, 2018a, 2018b). The monitoring objectives set by the above referenced fish studies were to relate environmental variables to survival and routing of Chinook salmon smolts through the south Delta each year. The data were collected using smolt-sized (>100 mm FL) hatchery fish and tag detection arrays that were deployed in the south Delta from April through June 2008–2015. Survival, routing, and detection probabilities were estimated using multistate mark–recapture models (Brownie et al., 1993; Nichols et al., 1994; Lebreton and Pradel, 2002) for various routes through the south Delta each year beginning at release points on the San Joaquin River at Durham Ferry and ending at Chipps Island, after which surviving salmon smolts entered saltwater environments. We extracted the estimated survival and routing probabilities and their standard errors from annual reports of the hatchery fish studies (Holbrook et al., 2009; SJRGA, 2010, 2011, 2013; Buchanan et al., 2015; 2016, 2018a, 2018b) and entered estimates into a database.

We divided the south Delta into seven regions based on the locations of acoustic tag detection arrays from previous studies (2008–2015) of salmon survival and routing (Holbrook et al., 2009; SJRGA, 2010, 2011, 2013; Buchanan et al., 2015, 2016, 2018a, 2018b). We used survival

estimates from these reports for four of the seven regions for which enough fish survived, as the basis of four separate survival meta-analyses and four separate routing meta-analyses. Region 1 begins on the San Joaquin River at the release site for acoustic telemetry hatchery fish, Durham Ferry, and continues downstream to the Head of Old River (HOR; Fig. 1). Region 2 continues along the San Joaquin River from the junction with HOR to the junction at Turner Cut. Region 3 continues downstream on the San Joaquin River to Chipps Island, which is where juvenile salmon enter the brackish waters of the San Francisco Estuary on their way to the Pacific Ocean (Munsch et al., 2019). Region 4 picks up at the HOR and heads down the Old River to the CVP and SWP facilities. Regions 5 and 6 represent entrainment, pre-screen mortality, screen efficiency, salvage and trucking to Chipps Island from SWP and CVP (see Fig. 2 from Zeug and Cavallo, 2014 for more information). Region 5 begins at the trash rack for the CVP and ends with trucking to Chipps Island (Fig. 1). Region 6 begins at the radial gates at the entrance to Clifton Court Forebay for the SWP and ends with trucking to Chipps Island (Fig. 1). Region 7 represents survival of any fish routing through the interior Delta. This includes fish that route through Old River North routes for fish making it past the pumping facilities and fish routing into the interior Delta at Turner Cut. Region 7 ends therefore, with fish routing through the interior and surviving to Chipps Island. We did not conduct survival meta-analyses for Region 5, 6 or 7 and instead used estimates based on other research (Supplement 1; Gingras, 1997; Karp et al., 2017). The regions we identify here sometimes included two segments that were used in the acoustic telemetry studies (Holbrook et al., 2009; SJRGA, 2010, 2011, 2013; Buchanan et al., 2015, 2016, 2018a, 2018b) because locations of tag detection arrays varied through time. In instances where survival estimates were reported for two river segments that were within a single region, we estimated the survival for the larger region as the product of the estimated survival for the two segments and standard errors using the delta method (Williams et al., 2002). We excluded much of the 2008 and 2014 data that had poor transmitter battery survival and too few fish observed in downstream regions for reliable estimates, but we included estimates from upstream sections.

We calculated the mean of the environmental variables from the start and end dates of each release to relate to each release's survival and routing estimates. We downloaded daily flow ($m^3s^{-1}$) and water temperature ( °C) data from U.S. Geological Survey (USGS) stream gages on the San Joaquin River and the Sacramento River (USGS, 2021), SWP and CVP water exports from California Department of Water Resources,

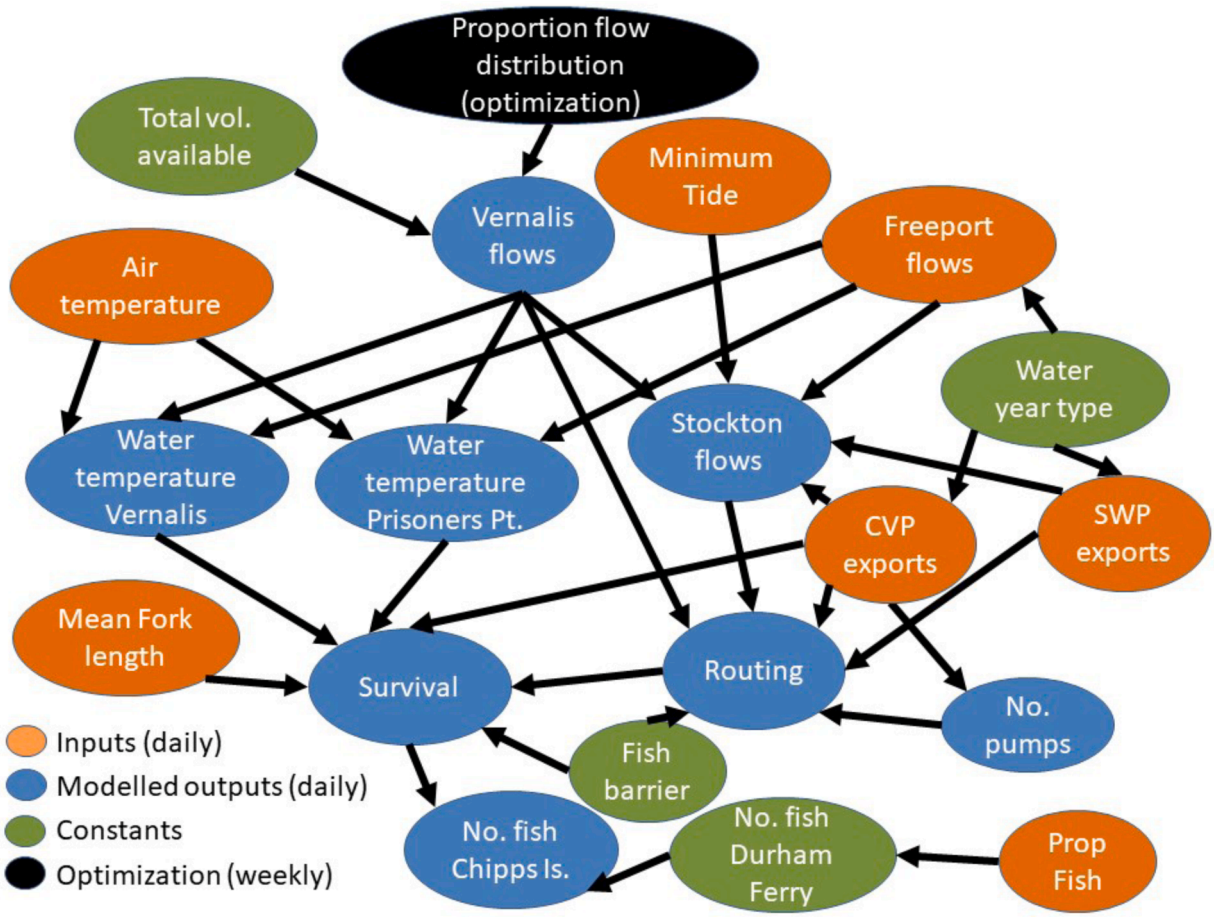


**Fig. 2.** Conceptual diagram for the decision support simulation model of juvenile Chinook salmon outmigrating through the south Delta, Central Valley California. Included are daily inputs to the model (orange ellipses), the modeled daily outputs (blue ellipses), user-defined constants (green ellipses), and the proportional flow to be optimized on a weekly basis (black ellipse). Prop Fish = proportion of smolts entering the model, vol = volume. Briefly, the user defines the minimum water volume target at Vernalis and the amount of water available to pulse which gets optimized on total survival through the south Delta. The user must also define the water year type, whether or not there is a fish barrier at Head of Old River, and how many fish start at the initialization of the survival and routing model. Inputs to the survival and routing model are drawn from random distributions based on variation from observed data and determine flows at Stockton, and water temperature at Vernalis and Prisoners Point which are then used to estimate survival and routing in the seven regions (combined here in this Fig.). Finally, the proportion of fish that are routed to each region and subsequently survive to Chipps Island is summed and then multiplied by the user specified number of fish that started. The optimized flow proportions by week for each simulation are saved and returned. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

California Data Exchange Center (2020), and minimum and maximum tide height data from the National Oceanic and Atmospheric Administration (2018) for Stockton for the same dates that the survival and routing studies were conducted. We used flow data from the USGS Vernalis stream gage 11,303,500, Prisoner's Point stream gage 11,313,460, Stockton stream gage 11,304,810, Old River stream gage 11,313,315, and water temperature data from USGS Vernalis and Prisoner's Point stream gages.

We conducted meta-regression on survival and routing data which is a type of powerful meta-analysis common in natural sciences. Meta-analysis synthesizes effect sizes from the mean values and variance estimates and weights each (mean) contribution by the inverse of the associated standard errors (Steward and Schmid, 2015; Lortie and Filizzola, 2020). Here we assumed the estimates were logit-normally distributed and used logit transformed survival and routing probabilities and their standard errors from the hatchery fish studies in our meta-analyses (Holbrook et al., 2009; SJRGA, 2010, 2011, 2013; Buchanan et al., 2015, 2016, 2018a 2018b). We assessed the additive and interaction effects of environmental variables on survival and routing probabilities. The model formulation is as follows:

$$logit\ (y_i) = X_i\beta + \epsilon_i,\ i = 1, \ldots, m,$$
$$\epsilon_i \sim N\ (0,\ S_i)$$

Where $y_i$ are the survival or routing estimates from the respective region, $m$ is the number of estimates from each region, $X_i\beta$ defines the matrix of environmental covariates that represent the population-averaged outcomes in terms of p unit-level meta-predictors in the design matrix $X_i$, with fixed-effects coefficients $\beta$ (Sera et al., 2019). The vector $\epsilon_i$ defines the unit-level sampling errors, i.e., standard errors for each fish release (Sera et al. 2019).

We did not use correlated environmental variables ($|r| > 0.7$) in the same models (Moore and McCabe, 2005). Water exports and the water export–flow ratio are linearly associated ($r = 0.83$; Newman and Brandes, 2010) so we did not use the water export-flow ratio as an environmental variable to avoid multicollinearity. During the survival and routing studies, there was a temporary physical barrier in place in 2012, 2014, and 2015 and a non-physical barrier (bio-acoustic fish fence) was tested in 2010 to prevent fish from entering the Old River (SJRGA, 2011; Buchanan et al., 2018a, 2018b). Thus, we also included the presence of the non-physical or physical HOR barrier (HORB; i.e., yes=1, no=0) as a variable in candidate models of routing at HOR. Survival meta-regression models were fit for each of the four regions separately using the mean and SE from each release. Similarly, routing probability for four of the regions was modeled separately at each junction. The best approximating meta-regression model for each of the four regions and four junctions was selected using Akaike Information Criterion with small sample bias adjustment ($AIC_c$; Burnham and Anderson, 2002). We used the R package *mixmeta* (Gasparrini et al., 2012; Sera et al., 2019) and R statistical software version 4.0.2 (R Core Team, 2020) to conduct meta-analyses where we used the logit survival or routing probability from the hatchery studies as the response, the environmental variables as covariates, and standard error from the hatchery studies as the estimate for standard error.

To estimate survival and entrainment at the CVP facility (Region 5), we used estimates from release-recapture experiments of acoustically tagged juvenile Chinook salmon conducted at the Tracy Fish Collection Facility (TFCF; Fig. 1) in March and May 2013 (Karp et al., 2017). Karp et al. (2017) evaluated smolt-sized salmon (>105 mm FL) entrainment and subsequent survival in front of and within the TFCF under a range of normal facility flows during a drought year. The months chosen for testing were when wild juvenile salmonids were typically entrained by the water pumps (Karp et al., 2017). In general, there tends to be an increase in facility salvage efficiency as the number of pumps in operation at the C.W. "Bill" Jones Pumping Plant (JPP) increases from one to five. We used the data in Karp et al. (2017) to refit models relating the number of pumps operating to the capture and survival at the CVP facility using logistic regression. This prevented the estimated probabilities from being less than zero and greater than one as could occur with the linear regression equations reported in Karp et al. (2017).

### 2.3. Decision support simulation model development

We used the results of the survival, routing, and entrainment meta-analysis and estimates based on published research to develop a quantitative Chinook salmon smolt survival and routing simulation model for the south Delta. The model operates on a daily time step and tracks the number of user-specified smolts that start at Durham Ferry and ends at Chipps Island. Fish survive from Durham Ferry to HOR (Region 1) as a function of average daily flow and water temperature at the USGS Vernalis stream gage and the effect of fish size (Table 1). Fish size was added to all survival models as a constant based on Perry et al. (2018). At HOR, surviving fish remain in the San Joaquin River as a function of whether there is a barrier (HORB) in place, average daily flow at Vernalis, and their interaction (Table 1). Fish remaining in the San Joaquin River travel down to Turner Cut (Region 2) and survive as a function of average daily flow at Vernalis and fish length (Table 1). At Turner Cut, fish remain in the San Joaquin River as a function of average daily flow at the USGS Stockton stream gage (Table 1). The survival of fish remaining in the San Joaquin River to Chipps Island (Region 3) is a function of average daily water temperature at the USGS Prisoner's Point stream gage and fish size (Table 1). At HOR, fish that enter Old River travel down toward the export facilities (Region 4) and survive as a function of average daily water temperature at Vernalis and fish size (Table 1). Entrainment at the CVP facility was a function of the number of water pumps operating (Table 1). Survival of entrained fish at the CVP that were then trucked to Chipps Island (Region 5) was modeled as a function of the number of water pumps operating. Fish that were not entrained at the CVP facility could then be entrained at the SWP facility as a function of average daily water exports (Table 1). The survival of these SWP entrained fish that were salvaged and trucked to the end point at Chipps Island (Region 6) was a constant 13.25% as estimated by Gingras (1997). The survival of fish to Chipps Island that entered the interior via the Old River and were not entrained in the CVP or SWP facilities or that entered the interior Delta via Turner Cut on their way to Chipps Island (Region 7) was modeled as a constant 1% (Table 1) based on observations of acoustically tagged salmon having very poor survival in this region (SJRGA, 2011; 2013).

Smolt survival is often related to size (Sogard, 1997; Perry et al., 2018; Sturrock et al., 2020), however we did not have data specifically for Chinook salmon outmigrating through the south Delta in winter/spring. Thus, we used the fork length (FL)-survival relationship from Perry et al. (2018) from hatchery fish outmigrating through the north Delta from release sites in the Sacramento River in December and January to link fish size to survival probability. Although smolts were from a different run, age, basin, were released earlier, and FL at the time of tagging was smaller in the acoustic telemetry studies (80–140 mm, 2014 $\bar{x} = 98.9$ mm to 2013 $\bar{x} = 115.3$ mm; Buchanan et al., 2020) than those used in Perry et al. (2018; >140 mm FL), the FL-survival relationship likely holds true across varying scenarios (R. Perry personal communication, 2021).

### 2.4. Decision support simulation model inputs

We developed three regression models to be able to link daily environmental inputs upstream to environmental variables downstream that are associated with routing and survival probabilities to use as inputs in the decision support simulation model (Fig. 2). This allowed us to create inputs for variables known to affect survival and routing from the meta-analysis that are related to user-specified upstream inputs. We included environmental variables that are typically included by water managers in Central Valley hydrologic simulation models to show how these models can be integrated with biological models in the future (Klipsch

**Table 1**
Parameter estimates, SE, and upper and lower 95% confidence intervals for juvenile Chinook salmon routing and survival probabilities from Vernalis to Chipps Island based on meta-regression analysis of tagging studies from 2008 to 2015 for Regions 1–4 and literature for Regions 5–7. Constants for Regions 6 and 7 were assumed values based on literature and were not estimated by fitting meta-regression models. All parameters are on a logit scale except constants. Freeport and Vernalis flows were log transformed, SWP exports were square root transformed and minimum tide at Stockton was transformed with the formula log (minimum tide + 1). CVP = Central Valley Project and SWP = State Water Project. Random effects are the between-study standard deviations. Note natural survival excludes salvaged fish being trucked from the facilities to Chipps Island. See Supplement 1 for additional details and Supplement 4 Table 1 for sample sizes.

| Survival and Routing Estimates and Constants | Estimate | SE | Lower 95% | Upper 95% |
|---|---|---|---|---|
| Survival Durham Ferry to Head of Old River (Region 1) | | | | |
| Intercept | 5.7750 | 3.1957 | -0.4885 | 12.0385 |
| Average daily flow at Vernalis | 0.0082 | 0.0032 | 0.0020 | 0.0144 |
| Average daily temperature SJR at Vernalis | -0.3281 | 0.1616 | -0.6447 | -0.114 |
| Standardized fork length | 0.1520 | | | |
| Random effect | 1.0954 | | | |
| Survival Head of Old River to Turner Cut (Region 2) | | | | |
| Intercept | -2.9033 | 0.5323 | -3.9466 | -1.8600 |
| Average daily flow at SJR at Vernalis | 0.0112 | 0.0033 | 0.0047 | 0.0177 |
| Standardized fork length | 0.1520 | | | |
| Random effect | 1.2117 | | | |
| Probability of remaining in SJR at Head of Old River | | | | |
| Intercept | -0.7591 | 0.2228 | -1.1958 | -0.3224 |
| Physical barrier: yes | 1.7202 | 0.7374 | 0.2749 | 3.1655 |
| Average daily flow at SJR Vernalis | 0.0036 | 0.0011 | 0.0014 | 0.0058 |
| Barrier × Average daily flow at SJR Vernalis | 0.0272 | 0.0104 | 0.0068 | 0.0476 |
| Random effect | 0.3516 | | | |
| Probability of remaining in SJR at Turner Cut | | | | |
| Intercept | 5.8313 | 1.0210 | 3.8301 | 7.8325 |
| Average daily flow at SJR Stockton | -0.0377 | 0.0126 | -0.0624 | -0.0130 |
| Random effect | 2.3308 | | | |
| Survival SJR Turner Cut to Chipps Island (Region 3) | | | | |
| Intercept | 13.4184 | 7.1815 | -0.6573 | 27.4941 |
| Average daily temperature at SJR at Prisoners Pt | -0.9007 | 0.3993 | -1.6833 | -0.1181 |
| Standardized fork length | 0.1520 | | | |
| Random effect | 1.4395 | | | |
| SurvivalinOldRiverfrom Headto CVP(Region 4) | | | | |
| Intercept | 2.1603 | 1.7435 | -1.2570 | 5.5776 |
| Average daily temperature SJR at Vernalis | -0.2050 | 0.0966 | -0.3943 | -0.0157 |
| Standardized fork length | 0.1520 | | | |
| Random effect | 0.6287 | | | |
| Probability of entrainment at CVP (Karp et al., 2017) | | | | |
| Intercept | -3.9415 | 1.9744 | -7.8113 | -0.0717 |
| Number pumps operating | 2.8012 | 1.6169 | -0.3679 | 5.9703 |
| Number pumps operating$^2$ | -0.3558 | 0.2646 | -0.8744 | 0.1628 |
| Residual error | 1.2220 | | | |
| Survival through CVP (Region 5, Karp et al., 2017) | | | | |
| Intercept | -3.1320 | 1.6199 | -6.3070 | 0.0430 |
| Number pumps operating | 1.8486 | 1.3266 | -0.7515 | 4.4487 |
| Number pumps operating$^2$ | -0.2235 | 0.2171 | -0.6490 | 0.2020 |
| Residual error | 1.0030 | | | |
| Probability of entrainment at SWP | | | | |
| Intercept | -1.0957 | 0.2342 | -1.5547 | -0.6367 |
| Exports from SWP | 0.0011 | 0.0029 | -0.0046 | 0.0068 |
| Random effect | 0.2909 | | | |
| Survival through SWP (Region 6, Gingras, 1997) | | | | |
| Constant (probability) | 0.1325 | | | |
| Survival(natural)Interior to Chipps Island (Region 7, SJRGA, 2013) | | | | |
| Constant (probability) | 0.0100 | | | |

and Hurst, 2007). Specifically, we developed the first regression model for estimating average flow at Stockton as a function of flow at Vernalis and Freeport, minimum tide, SWP and CVP water exports, and their interactions (Table 2). We developed a second regression model for estimating water temperature at Prisoner's Point as a function of flow at Vernalis and Freeport, air temperature and the quadratic effect of air temperature at Prisoner's Point, and the interaction of flow at Vernalis and air temperature at Prisoner's Point. Lastly, we developed a regression model to estimate water temperature at Vernalis as a function of flow at Vernalis and Freeport, air temperature and the quadratic effect of air temperature at Vernalis, and the interaction of flow and air temperature at Vernalis. In the Vernalis temperature model, we included Freeport flows that do not reach Vernalis because it is plausible that Freeport flows could be a possible mechanism due to regional weather patterns, coordinated reservoir releases in the Sacramento and San Joaquin rivers, or a possible external mechanism that is correlated with Freeport flows that we did not capture with our other covariates such as negative flows, maximum tides, etc.

We used $AIC_c$ (Burnham and Anderson, 2002) and Akaike weights ($w_i$) to identify the best predicting model. Water managers use Sacramento river flows to model conditions in the Delta as part of regular water management operations. However, to justify using Sacramento River flows in Stockton flow and Prisoner's Point temperature models (i.e., locations on the San Joaquin River), we evaluated the predictive ability of our model by estimating the out-of-sample error. We therefore completed 500 iterations of 10-fold cross validation (Breiman and Spector 1992) on the Stockton and Prisoners Point models with and without Freeport flows in the model. The out-of-sample predictive accuracy as measured by the root mean squared error (RMSE; mean across iterations) was 20.6 and 35.5 for Stockton discharge models with and without Freeport discharge, respectively. Similarly, RMSE of the Prisoners Point temperatures was 1.95 and 2.07 with and without Freeport

**Table 2**
Parameter estimates, SE, and upper and lower 95% confidence intervals from regression models that estimate downstream environmental conditions. CVP = Central Valley Project and SWP = State Water Project.

| Estimates | Estimate | SE | Lower 95% | Upper 95% |
|---|---|---|---|---|
| Flow at Stockton ($R^2$= 0.9132; residual error = 20.83) | | | | |
| Intercept | 806.54 | 15.46 | 776.23 | 836.86 |
| log(Flow at Freeport) | -157.01 | 2.93 | -162.76 | -151.27 |
| log(Flow at Vernalis) | -205.33 | 3.30 | -211.79 | -198.87 |
| log(Minimum tide + 1) | 131.36 | 17.42 | 97.20 | 165.52 |
| sqrt(SWP exports) | 4.79 | 0.46 | 3.90 | 5.69 |
| CVP exports | -0.316 | 0.043 | -0.40 | -0.23 |
| log(Flow at Vernalis) * log(Flow at Freeport) | 40.66 | 0.60 | 39.49 | 41.83 |
| log(Flow at Vernalis) * log (minimum tide + 1) | -32.10 | 4.39 | -40.71 | -23.50 |
| log(Flow at Vernalis) * sqrt (SWP_exports) | -1.09 | 0.11 | -1.31 | -0.87 |
| log(Flow at Vernalis) * log (CVP_exports) | 0.091 | 0.011 | 0.068 | 0.11 |
| Watertemperature at Prisoner's Point ($R^2$ = 0.90; residual error = 2.036) | | | | |
| Intercept | 3.97 | 0.57 | 2.86 | 5.08 |
| log(avg flow at Freeport) | -0.63 | 0.083 | -0.80 | -0.47 |
| log(avg flow at Vernalis) | 0.69 | 0.122 | 0.45 | 0.93 |
| avg air temp Prisoner's Point | 1.32 | 0.040 | 1.24 | 1.40 |
| avg air temp Prisoner's Point$^2$ | -0.012 | 0.00095 | -0.014 | -0.01 |
| log(avg flow Vernalis) × avg air temp PP | -0.050 | 0.0061 | -0.06 | -0.038 |
| Watertemperature atVernalis($R^2$= 0.90; residual error = 1.644) | | | | |
| Intercept | -0.39 | 0.44 | -1.24 | 0.46 |
| log(Flow at Freeport) | 0.317 | 0.067 | 0.19 | 0.45 |
| log(Flow at Vernalis) | 0.68 | 0.096 | 0.50 | 0.87 |
| Avg air temp Vernalis | 1.46 | 0.03 | 1.40 | 1.52 |
| Avg air temp Vernalis$^2$ | -0.011 | 0.00075 | -0.012 | -0.0092 |
| log(Flow at Vernalis) * avg air temp Vernalis | -0.11 | 0.0048 | -0.12 | -0.10 |

discharge, respectively. In fact, the expected error in the discharge model is 42% lower and temperature 6% lower when Freeport flows are included, thus, we chose to use the more accurate flow and temperature models that included Freeport.

We developed the three regression models using daily air temperature at National Weather Service stations at Modesto Airport (GHCND: USW00023258), at Vernalis and Stockton (GHCND: USW00023237), at Prisoners Point, and average daily flow at the USGS stream gages at Vernalis and Freeport for 2008–2018. We log-transformed Freeport and Vernalis flow, square root transformed SWP exports and transformed minimum tide at Stockton with the formula log (minimum tide + 1) for use in the regression models. We used the R package *MuMIn* (Barton, 2020) and R statistical software version 4.0.2 (R Core Team, 2020) to conduct model selection and develop model selection tables. We did not use correlated environmental variables ($|r| > 0.7$) in the same models (Moore and McCabe, 2005). We report candidate models within $AIC_c w_i < 10\%$ of the model with the largest weight to evaluate strength of evidence (Royall, 1997), and provide estimates from the top model if the top model had $AIC_c w_i > 0.8$.

We used fish monitoring data collected by the Mossdale trawl (2012–2020; USFWS, 2020) to estimate the mean and standard deviation for daily FL of smolts entering the south Delta from February 1 through May 30. We also used the Mossdale trawl data to estimate the proportion of the entire outmigration over the study period of Chinook salmon smolts that passed through Vernalis (located near Durham Ferry fish release site) each day (Hearn et al., 2014; Munsch et al., 2019). The Mossdale trawl samples open water habitats and avoids shallow edge habitats and is therefore more efficient at collecting (larger) smolts and much less efficient at collecting smaller rearing fry (Mahardja et al., 2021). Consequently, few juveniles of fry size are captured in February and March. In addition, early emigrating fry survival is relatively low for fry rearing in the south Delta (Sturrock et al., 2020; Nobriga et al., 2021); thus, our south Delta model likely underestimates the effects of Delta flows on smaller, fry-sized fish.

We used a generalized additive model (GAM; R package *mgcv*; Wood, 2017) with the smooth term (knots = 10) to model the proportion of smolts entering the south Delta each day from Mossdale trawl mean daily and total fish numbers. The resulting function, i.e., smooth terms = 10, had a relatively high coefficient of determination ($p < 0.0001$, $r^2 = 0.61$). Because the proportion of fish entering the Delta each day across the migration window must sum to one, we normalized the predicted values from the GAM to sum to one when using these values in the simulation model.

Although survival and routing estimates were from telemetry experiments conducted from April and May, we wanted to assess flow optimization across the entire period when smolts could be outmigrating including February and March (Limm and Marchetti, 2009; Merz et al., 2013; Zeug et al., 2014). To avoid making predictions using covariate data outside the range of the data used to develop the model, we constrained environmental variables within the range of values used in the meta-analysis during the simulations described below (Supplement 2). We used measured mean daily flow and mean daily temperature at the same USGS stream gages to quantify mean daily flows in February–May for each water year type.

Existing managed flow regimes on the San Joaquin River through Vernalis are partly determined from Decision 1641 (D-1641; State Water Resources Control Board, 2000), which was implemented in 1999 before studies relating Chinook salmon survival to flows were initiated (Supplement 3). D-1641 defines minimum flow targets and any extra water available beyond that minimum is available for flow pulses or for reshaping the hydrograph. In particular, for a given volume of water available, use of the upper rather than lower minimum flow objective results in having less extra water available to allocate to flow pulses. These flow targets have been used to shape flows and determine the Biological Opinion and Conference Opinion on the long-term operations of the CVP and SWP (NMFS, 2009), the Biological Assessment for the California Water Fix (NMFS, 2016), and the Biological Opinion on Long-term Operation of the Central Valley Project and the SWP (NMFS, 2019). For the purposes of demonstrating our model, we chose to use the upper and lower D-1641 flow targets at Vernalis to calculate the volume of water available at Vernalis for a given water year type (Supplement 3). In recent years, the spring pulse (typically April 15 – May 15) has been shaped to maximize flow variability (Zeug et al., 2014), inundate floodplains for rearing habitat, and manage water temperatures.

### 2.5. Simulation-optimization procedure

We wanted to determine the optimal flow regime for Chinook salmon smolts outmigrating through the south Delta in late winter through late spring. The D-1641 targets are set for minimum flows from February through June with a specified flow pulse to occur April 15 to May 15 and vary by water year type (Supplement 3). Using the flow rate targets, we calculated total volume of water available, using average daily flow rate ($m^3s^{-1}$) as a substitute for volume, from February through May by water year type by multiplying the rate by the number of days in the simulation (119). We partitioned this period into seventeen one-week periods and distributed the total volume of water available for each period after subtracting the amount needed to maintain established minimum flows according to D-1641 (Supplement 3). We determined optimal distributions of water above minimum flows among these weekly periods using a simulation-optimization approach (Conroy and Peterson, 2013). The objective was to maximize the number of smolts that survived to Chipps Island. Constraints were needed to ensure that only 100% of the available volume of water was used over the simulation time period, thus we used nonlinear optimization with constraints to solve this problem. Parameters and model inputs were drawn from statistical distributions (as described below) and the optimal distribution of water was estimated. This simulation-optimization process was repeated 10,000 times and the mean water distribution for the seventeen one-week time periods was calculated. We initiated simulations with 500,000 juvenile salmon at Durham Ferry that were randomly distributed across the 17-weeks using a multinomial distribution with probability of emigrating derived from the normalized GAM predicted values from the Mossdale trawl. We ran all comparisons with HORB = 0 (no barrier) because the physical barrier is no longer used. We checked for convergence on all solver solutions and plotted mean flow with 95% confidence intervals for 17 weeks from February through May. All optimization procedures were conducted using R package *NlcOptim* (Chen and Yin, 2019) and R statistical software version 4.0.2 (R Core Team, 2020). Briefly, this package solves optimization problems with nonlinear constraints and nonlinear objective functions based on the augmented Lagrange multiplier method for problems with parameters in the form of a matrix (see Chen, 2016).

We included stochasticity in the simulation-optimization procedure. Average daily inputs for air temperature at Prisoner's Point and Vernalis were sampled from a normal distribution and were based on average daily air temperatures from February through May with a mean monthly standard deviation from the 1999–2020 data (1.0, 0.319 SD for Prisoner's Point and Vernalis respectively). Minimum tides are cyclic, do not vary with water year type, and follow the same trend year after year, therefore, we used a randomly chosen year (2013) to represent the cyclic nature of the minimum tide and accounted for variation with an overall mean daily standard deviation from years 2008–2018. Daily inputs for average flow at Freeport, CVP water exports, and SWP water exports do vary with water year type so we derived these environmental variables from the mean and standard deviations from 1999 to 2020 data by water year type. Values were sampled from a gamma distribution each day by converting their respective mean and standard deviation to shape and scale parameters using R package *ConnMatTools* (Kaplan, 2020). FL was also sampled from a gamma distribution accounting for more variation in the data ≤Day 89 (i.e., March 30) and less variation >Day 89. Variability in the proportion of smolts outmigrating was sampled from a

multinomial distribution with probabilities of outmigration as described above. Parameter estimates of survival and routing probabilities were sampled from a normal distribution using the residual errors as the random effects.

In water resource management, system dynamics cannot be completely controlled by management due to external drivers (e.g., precipitation) that affect the ability to implement management actions as planned. This is known as partial controllability (Conroy and Peterson, 2013). Thus, in practice, managers recalculate flow releases each month from February–June that alter the volume of water available for flow management from what was initially predicted. We included 20% variation on the lower and upper minimum and pulse targets from the D-1641 table using a uniform distribution to evaluate the effects of partial controllability on the optimal flow distribution in the south Delta.

### 2.6. Hindcast scenarios

We also used our decision support simulation model to compare the outcome of flow decisions in previous years with model-optimized flow. For this exercise, we used measured environmental data (i.e., flows, temperatures, water exports, etc.), rather than predicted values from our regression models, for the 119-day period from February–May 2010–2013 and 2016–2018. We omitted 2014–2015 because the measured environmental data were incomplete. Due to a lack of data for many days in most years, a separate distribution for fish FL and proportion of fish entering the south Delta for each year was not possible. Thus, we used the mean distribution of fish and FL for inputs as described previously.

We used measured Vernalis total flows from February through May and assumed the April/May pulse targets by water year type from D-1641 to calculate the minimum flow and the amount of water available to pulse for each year. We omitted two of the Critical and Dry years (2012, 2016) that did not have enough water for upper minimum flow targets because our aim was to evaluate managed flow releases in excess of minimum flow thresholds. We then conducted year-specific simulation-optimization procedures detailed above to determine the optimal flow regime for that year constraining the amount of water available to equal the observed values. We also used the routing and survival model to predict the cumulative survival of fish reaching Chipps Island under the observed flow and temperature regimes (as measured at the gages) and under the optimal flow regime using observed water temperatures and the flows at Freeport. We also compared our modeled total survival to Chipps Island to estimated total survival reported in the annual reports, to determine how reliable our modeled survival under the observed conditions was.

### 2.7. Sensitivity analysis and value of information

We used one-way sensitivity analysis to identify the simulation model parameters (i.e., intercepts and slopes from the meta-regression analysis) and model inputs (i.e., developed from environmental variables) that had the greatest influence on estimated smolt survival from Durham Ferry to Chipps Island (Conroy and Peterson, 2013). Using the lower target from the Below Normal water year type water availability and minimum flows (Supplement 3), we varied the values of parameters and inputs throughout their 95% confidence intervals one at a time while keeping the other values unchanged, and reran the optimization procedure 10,000 times. For the survival and routing probability parameters, we varied the parameters from the 5$^{th}$ percentile to the 95$^{th}$ percentile of a normal distribution by increments of 5%. For the parameters without estimates of variability (e.g., standard errors from regression parameters), we varied the parameter +/- 50% of the mean value by 5% increments to represent the variability we found in parameters with estimates of variability, i.e., a mean difference from their 95% confidence intervals of 51% ± 14.4 SD (Peterson and Duarte, 2020). For example, for the survival intercept (0.1325) for the SWP export facilities, i.e., Region 6, we used a lower bound of 0.06625, and an upper bound of 0.19875. For environmental inputs to the model, we varied the values from the 10,000 simulations of the Below Normal water year type from the 5$^{th}$ to 95$^{th}$ percentile of a normal distribution by 5% increments. We then recorded the estimated total number of smolts surviving through the south Delta and plotted minimum (i.e., 5$^{th}$ percentile) and maximum survival (i.e., 95$^{th}$ percentile) in a tornado diagram to examine the sensitivity of the model predictions to both parameters and inputs (Conroy and Peterson, 2013). We included both intercepts and slopes because they have different interpretations. For example, the slope is the relationship between the survival or routing parameter and the environmental variable and indicates if the environmental variable itself is important in the model and the intercept is the mean of the survival or routing value at a chosen value of environmental variable and indicates if the survival or routing parameter is influential. Therefore, sensitivity analysis of both intercepts and slopes should be important to managers.

In addition to the one-way sensitivity analysis, we conducted a response profile sensitivity analysis and calculated the expected value of perfect information (EVPI). Calculating EVPI was a slow process, therefore, to illustrate the methodology, we calculated EVPI of the parameters most influential to survival as indicated by the one-way sensitivity analysis. A response profile sensitivity analysis differs from a one-way sensitivity analysis in that the focus is to evaluate how the optimal decision changes across a range of parameter values (Conroy and Peterson, 2013). Here, we used the results from the one-way sensitivity analysis of varying the parameters one at a time between the 5$^{th}$ and 95$^{th}$ percentile by 5% increments from the 10,000 iterations of the simulation optimization as described above. We plotted these nineteen flow regimes to evaluate how the distribution of water varied with the parameter. We estimated the relative value of improving knowledge of the top four parameters by calculating the expected value of perfect information (EVPI; Conroy and Peterson, 2013). The EVPI is the expected increase in a decision maker's objective (i.e., proportion of smolts surviving to Chipps Island) if the uncertainty regarding a parameter value were completely eliminated.

## 3. Results

### 3.1. Model-fitting

The meta-analysis of survival and routing probabilities was based on 16–24 hatchery fish releases from 2008 to 2015 (Table 1). Meta-analysis indicated survival probability progressively declined downstream from Durham Ferry to HOR (0.66 ± 0.03), HOR to Turner Cut (0.26 ± 0.04), HOR to CVP (0.22 ± 0.07), and Turner Cut to Chipps Island (0.06 ± 0.06). Probability of fish staying in SJR at HOR was lower (0.57 ± 0.04) than at Turner Cut (0.85 ± 0.07). We compared various meta-analysis models with San Joaquin River flows and temperatures for explaining smolt survival and routing through four of the regions for which we had enough data. Model selection results indicated that survival from Durham Ferry to the HOR (Region 1) was positively related to average daily flow at Vernalis, whereas it was negatively related to water temperature at Vernalis (Supplement 4, Table 1, and Fig. 1). Survival from HOR to Turner Cut (Region 2) also was positively related to average daily flow at Vernalis. Survival from Turner Cut to Chipps Island (Region 3) was negatively related to average daily temperature at Prisoner's Point and survival from HOR to CVP (Region 4) was negatively related to average daily temperature at Vernalis (Supplement 4, Table 1, and Fig. 1).

The probability of remaining in the San Joaquin River at HOR was positively related to the presence of the HOR barrier, average daily flow from Vernalis, and an interaction between the two (Supplement 4, Table 1, and Fig. 2). The probability of fish remaining in the San Joaquin River at Turner Cut was negatively related to average daily flow at

Stockton (Supplement 4, Table 1, and Fig. 2). The probability of fish becoming entrained at SWP was positively related to SWP exports (Table 1).

The Mossdale trawl analyses were based on from 1,059 fish in 2019 to 6,334 fish caught in 2013 (mean = 3,324.1, SD = 1,859.2). The daily proportion of smolts entering the south Delta had two peaks indicating few outmigrants in February/ March and had a bimodal trend of smolt outmigration with peaks in mid-April and mid-May (Fig. 3A). Fork length represented earlier migrations of smaller fish in February and March and later migrations of larger fish in April and May (Fig. 3B).

Model selection indicated regression models for predicting model inputs downstream had many variables and complex interactions (Supplement 5) and had high adjusted $R^2$ (i.e., 0.90–0.92) indicating good predictive ability (Table 2). None of the transformed variables used in the downstream input regression models were correlated at $|r| > 0.7$.

### 3.2. Simulated optimal flow regimes

In the simulated water year examples, the optimal flow regime for smolts differed among water year types (e.g., Critical, Wet) but all had patterns consisting of two periods of pulsed flows that coincided with peak outmigration through the south Delta, one in April and one in May with a much bigger pulse allocated to May (Fig. 4). Aside from the Critical water year type, February, March, and April air temperatures were similar among water year types, while the Critical year type was warmer in all months (Table 3). May monthly air temperatures at Vernalis and Prisoner's Point were generally higher for the drier water year types than wetter water year types (Table 3). In Critical, Dry, Below Normal, and Above Normal water years when water was available to pulse, it was optimal to allocate extra water (i.e., when going from the lower to upper target) about equally to the April and May peak outmigration periods (Fig. 4). As minimum flows and available pulse water increase in Wet water years, the strategy again was to pulse most of the water in May but when moving from the lower to the upper target, more water was distributed to the trailing end of peak migration through the south Delta in May. Smolts predicted by the model to have survived through the south Delta with optimal pulsing of water varied substantially among water years and was five times higher in Wet years (0.13 ± 0.040) than Critical years (0.026 ± 0.017).

### 3.3. Hindcasting

The optimal flow regimes calculated using historical water availability and temperatures were similar to our water year-specific optimization, with two large pulses of water that coincided with the two outmigration peaks in April and May (Fig. 5). However, in most water years except 2016 (Dry water year), the highest optimal pulse coincided with the peak in April-outmigrating fish with a lower optimal pulse corresponding with the beginning of the peak of May-outmigrating fish (Fig. 5). In 2016, the largest pulse was allocated for May-outmigrating fish. This may be related to the fact that 2016 had the highest average daily water temperature at Prisoner's Point and among the lowest average daily flows at Stockton in April during that time period (Supplement 6A and B). The main difference between observed flows and simulated hindcast optimal flows was that simulated pulses were allocated when the largest proportion of smolts were estimated to be migrating through the south Delta during April and May. In contrast, the observed flows were distributed more evenly over a longer time frame and do not correspond well with estimated peak migrations through the south Delta. In general, more smolts were predicted to survive to the ocean by saving more water to pulse in April when fish are outmigrating through the south Delta as opposed to having a higher minimum flow (Fig. 5). As opposed to the simulations based on inputs from the previous section, small hindcast pulses are allocated to February. This is likely due to the measured temperature inputs being allowed <15 °C whereas we imposed constraints on temperature in February and March for the simulations based on inputs due to our model being based on hatchery fish survival studies from April and May where temperatures did not go below 15 °C.

Our simulation model suggests that optimizing flows can increase cumulative survival through the south Delta. In this example, predicted survival with optimal hindcast flows was on average 1.3 times greater than under the observed flows and temperatures (Fig. 5). The difference in cumulative survival between hindcast and optimal flows was lowest for the Dry and Critical water years (survival under optimal 1–1.65 times greater [S increase = 0–0.015]) that had the least amount of water available to manage. Interestingly, the differences in cumulative survival between the optimal and observed regimes were greatest for the Below and Above Normal water years (optimal 1.47–1.67 times greater [S increase = 0.027–0.035]) and not the Wet years (optimal 1.22–1.31 greater [S increase = 0.08]). These counterintuitive non-linear results

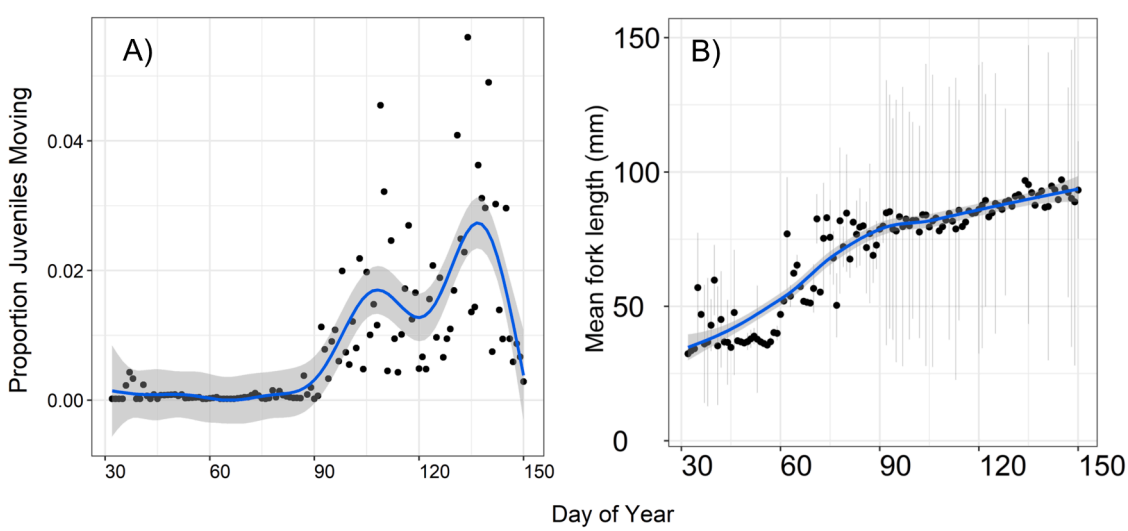


**Fig. 3.** Relationship between A) the mean daily proportion of juvenile Chinook salmon captured by the Mossdale Trawl and day of year, 2012–2021, and B) mean fork length of juvenile Chinook salmon captured by the Mossdale Trawl and day of year, 2012–2021; error bars show daily standard deviations truncated (when no. fish >1) at 5- and 150-mm. Day of Year is from February (Day of Year 32) through May (Day of Year 150). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

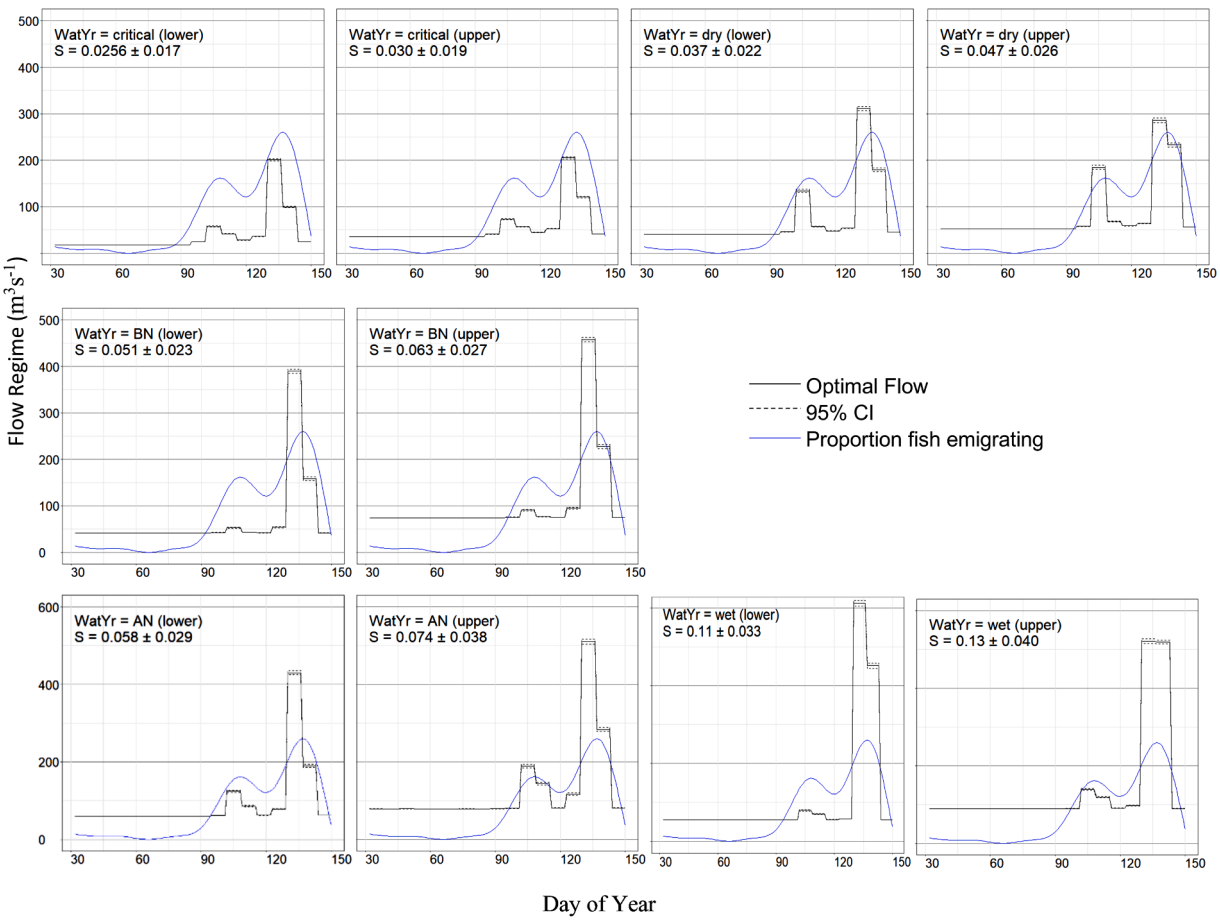


**Fig. 4.** Hydrographs of simulated optimal flow from February through May, based on target values from the Decision 1641 (D-1641; State Water Resources Control Board, 2000) table (Supplement 3) with minimum flow and pulse targets at lower and upper values for water year type (adjacent to each other) and with 0.20 partial controllability. WatYr = water year type, AN = Above Normal water year type, BN = Below Normal year, $S$ = modeled survival based on simulations using 500,000 fish ± standard deviation. Note blue line for fish emigration is not proportional to flow and is meant to indicate relative emigration and is the mean of all years. Day of Year is from February (Day of Year 32) through May (Day of Year 150). Note y-axis on different scales. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

**Table 3**
Mean, standard deviation and range (in parentheses) of average daily air temperature at Vernalis and Prisoner's Point by month and water year type.

| Water year type | Month<br>Feb | Mar | Apr | May |
|---|---|---|---|---|
| Vernalis | | | | |
| Critical | 11.5, 2.49<br>(6 - 18) | 15.5, 2.58<br>(8 - 22) | 17.5, 3.42<br>(9 - 25) | 21.0, 3.15<br>(14 - 30) |
| Dry | 11.1, 2.63<br>(6 - 18) | 13.9, 3.17<br>(6 - 21) | 16.6, 3.77<br>(8 - 27) | 21.2, 3.39<br>(14 - 30) |
| Below Normal | 10.4, 3.95<br>(6 - 15) | 13.4, 2.99<br>(8 - 19) | 15.6, 3.41<br>(10 - 26) | 21.0, 3.67<br>(13 - 31) |
| Above Normal | 10.8, 2.05<br>(6 - 15) | 12.3, 2.51<br>(8 - 18) | 15.0, 3.78<br>(7 - 22) | 18.6, 3.45<br>(12 - 27) |
| Wet | 10.9, 2.90<br>(4 - 17) | 13.1, 2.69<br>(7 - 20) | 16.2, 2.8<br>(8 - 25) | 19.6, 3.64<br>(12 - 29) |
| Prisoners point | | | | |
| Critical | 10.8, 2.44<br>(6 - 16) | 14.5, 2.73<br>(8 - 21) | 16.4, 3.23<br>(8 - 24) | 19.7, 3.12<br>(14 - 29) |
| Dry | 10.7, 2.55<br>(5 - 17) | 13.1, 2.82<br>(6 - 19) | 15.8, 3.61<br>(7 - 24) | 20.3, 3.33<br>(13 - 31) |
| Below Normal | 10.3, 2.47<br>(6 - 15) | 12.7, 2.95<br>(7 - 19) | 14.7, 3.23<br>(9 - 24) | 19.8, 3.48<br>(13 - 29) |
| Above Normal | 10.5, 2.01<br>(6 - 16) | 11.7, 2.39<br>(7 - 17) | 14.4, 3.55<br>(7 - 22) | 18.0, 3.47<br>(11 - 28) |
| Wet | 10.5, 2.83<br>(4 - 16) | 12.6, 2.64<br>(6 - 19) | 15.5, 2.74<br>(8 - 24) | 18.8, 3.30<br>(11 - 27) |

may have been difficult to verify without an optimization model.

For three years for which we had total survival estimates from the hatchery fish releases from Mossdale to Chipps Island, and we had enough environmental data to run the survival optimization model to make comparisons (2010, 2012, 2013), our survival estimates were exactly the same as in the reports (SJRGA, 2011, 2013; Buchanan et al., 2016) indicating our optimization model reliably estimates smolt survival through the south Delta for a range of water year types.

### 3.4. Sensitivity analysis and value of information

The one-way sensitivity analysis indicated that the simulation model estimates were most sensitive to survival parameters, particularly the effect of temperature on survival (Fig. 6). In contrast, the routing parameters were much less influential as were the parameters related to the CVP and SWP. The four most influential parameters on estimated smolt survival through the south Delta were survival from HOR to the CVP facility intercept and temperature at Vernalis and survival from Turner Cut to Chipps Island intercept and temperature at Prisoner's Point (Fig. 6). Export parameters were generally insensitive between the 5$^{th}$ to 95$^{th}$ percentiles (Fig. 6). Model inputs were much less influential than model parameters on juvenile survival. Of the model inputs, the most influential on survival were flows at Freeport and air temperature at Prisoner's Point and Vernalis (Fig. 6).

Response profile analysis of the top four parameter slope estimates

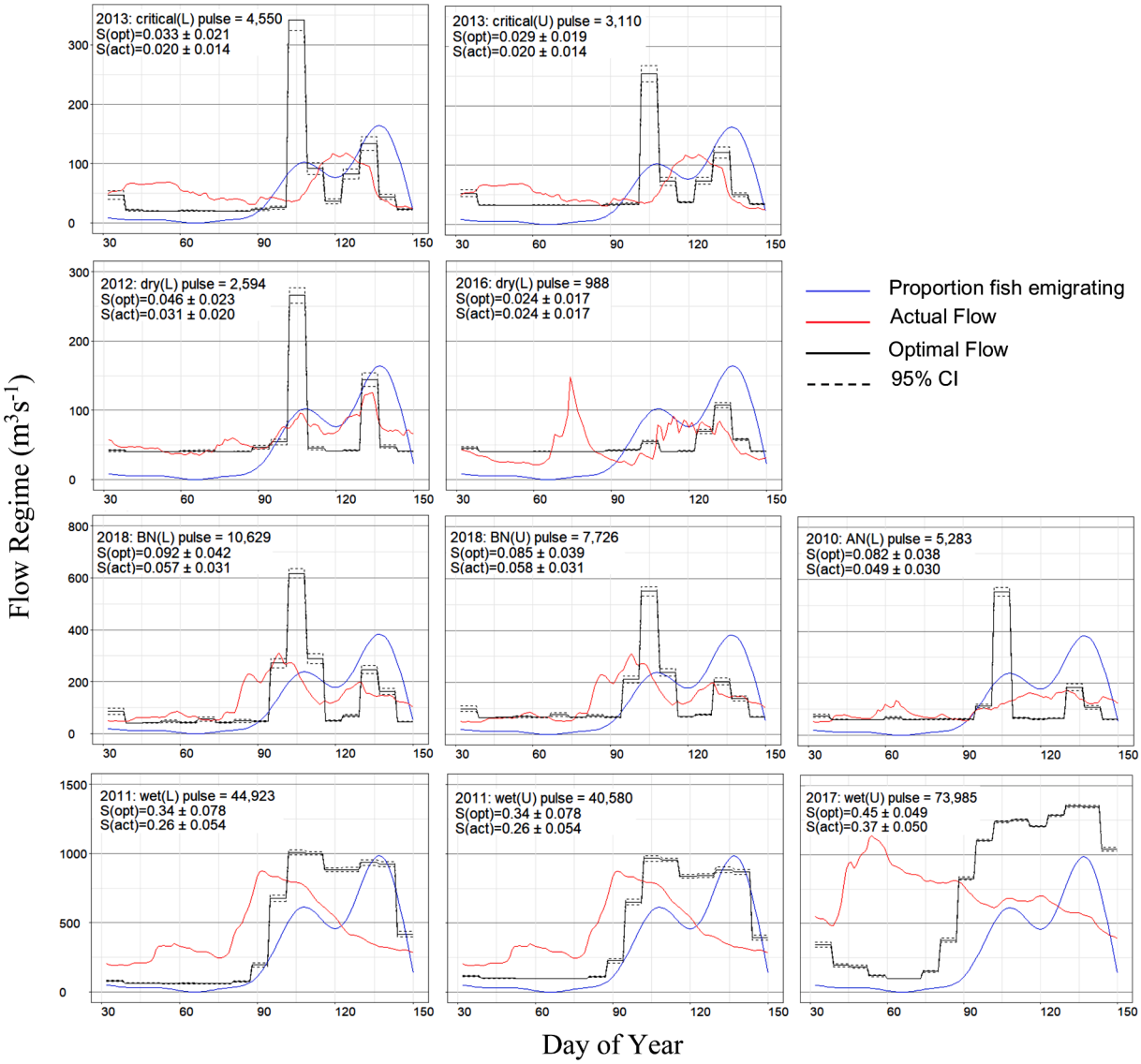


**Fig. 5.** Comparison of optimal flows predicted by model and historical managed flows for seven years from February (Day = 30) through May (Day = 150), 2010–2018 using selected Decision-1641 lower (L) and upper (U) targets by water year type; AN = Above Normal water year type, BN = Below Normal water year (Supplement 3), pulse = total water left to partition after minimum target flow deducted ($m^3s^{-1}$), S(opt) = modeled survival based on simulations using 500,000 fish ± standard deviation under optimal flows, S(act) = modeled survival under measured flows. Note y-axis on different scales/ row; blue line for fish emigration is not proportional to flow and is meant to indicate relative emigration and is the mean of all years. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

indicated the hydrographs would generally keep the same shape throughout the range of the 5$^{th}$ to 95$^{th}$ percentile of a normal distribution by increments of 5% with only a re-distribution of water over the April and May pulses (Fig. 7). With lower values of the survival model intercepts and Vernalis temperature parameter estimates, water would be allocated to the April pulse and with larger values of the parameter slope estimates, water would be allocated to the interval after the usual May peak pulse with water in the most extreme upper ends of the parameter CI being allocated to the intervals between the April and May pulses. For Turner Cut to Chipps Island parameter estimates, any change in the parameter estimates results in redistribution of water within the May peak. The EVPI for all parameters was similar, averaging +0.038 overall survival (Fig. 7). This suggests that reducing uncertainty of these parameters would improve flow management such that it would result in up to 1.57 times greater juvenile survival in Below Normal water years using the lower target (mean under uncertainty = 0.051 compared to mean with perfect information = 0.089).

## 4. Discussion

It is commonly thought that one of the major impediments to developing management strategies through quantitative modeling is the paucity of data on the linkages between habitat modification and biological responses (Pringle et al., 2000; Arthington et al., 2006; Murchie et al., 2008; Brown and Bauer, 2010). In our case study, we were able to synthesize a large number of disconnected south Delta studies and incorporate meta-analysis techniques to develop a decision support simulation model to link managed flows (i.e., habitat modifications) to Chinook salmon smolt survival and movement (i.e., biological responses). We then solved the model using optimization and evaluated the relative effect of uncertainty on management objectives; in our case smolt survival through the south Delta, to be able to demonstrate how models like these can be used to prioritize future research and monitoring efforts.

Given the inherent limitations of any decision support simulation

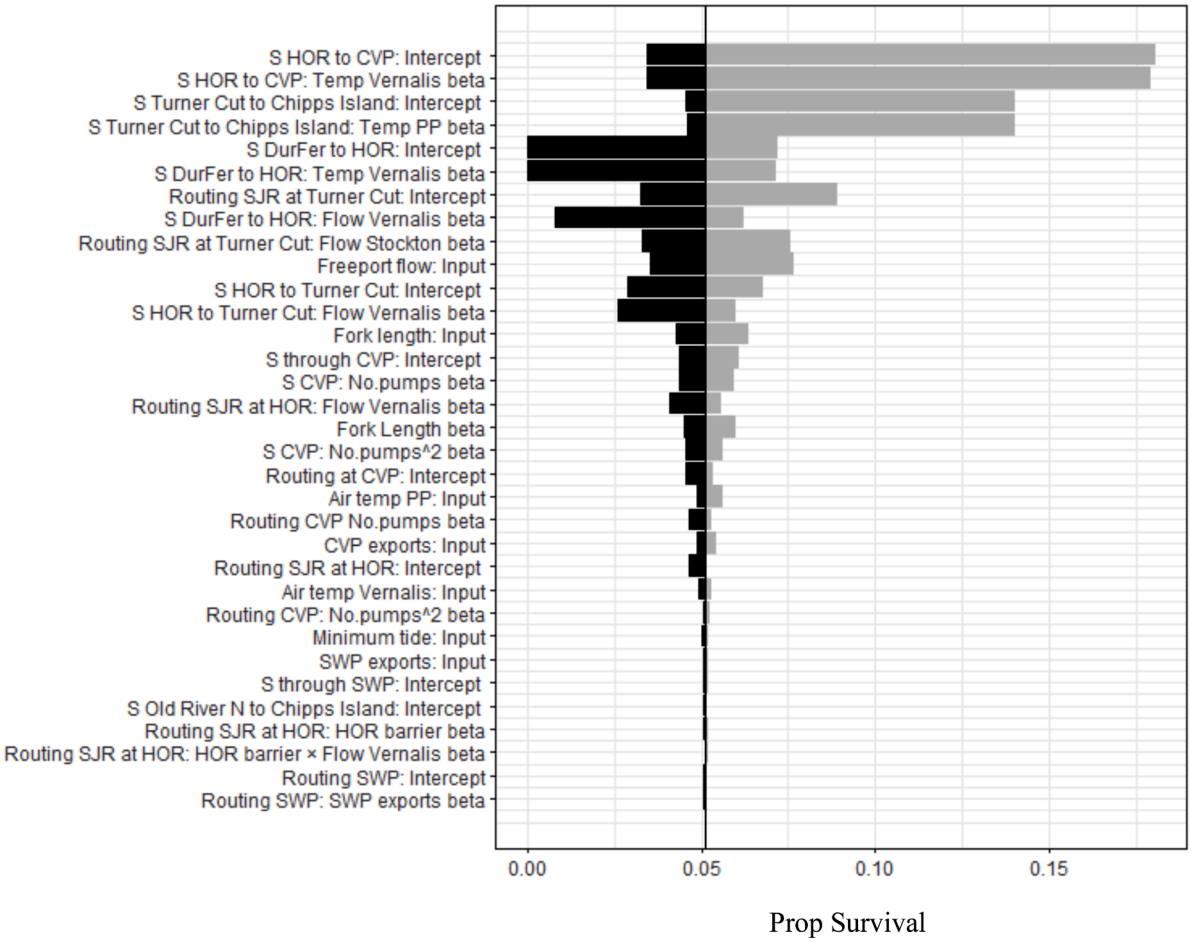


**Fig. 6.** Tornado diagram of one-way sensitivity analysis of optimization model inputs (see Section 2.7 for details) and parameters (slopes [referred to as beta] and intercepts; y-axis) on predicted fish survival through the south Delta, CA. The x-axis is the proportion of fish that survived through the south Delta relative to the baseline (before changing inputs and parameters) resulting from varying the value of the parameter slope and intercept estimates and inputs by 95% upper and lower confidence intervals. Mean fish survival (10,000 iterations) of the unaltered model for water year type Below Normal (lower) was 0.051. Black = lower bound and gray = upper bound.

model, such tools will never be a replacement for human decision-makers, particularly where real-world management strategies frequently must address economic or social considerations, not just biological outcomes. Undeniably, these tools are often best used to identify general patterns that may then be translated into real world management rulesets and provide hypotheses for directed studies to test predicted benefits. A management ruleset for smolts gleaned from our case study is to allocate increased flows in May when larger smolts are entering the south Delta. Furthermore, when more water is available for flow pulses, the optimal strategy is to spread the additional water to adjacent intervals after peak water pulses. Interestingly, even in very low water years the model suggests it is optimal to have large pulses in May when most smolts are entering the south Delta.

Decision support simulation models can provide insights into management tradeoffs that may be counterintuitive when not formally integrating information from disparate sources. (Peterson and Duarte, 2020). For example, results of our simulation modeling indicate pulses allocated in April do not follow a smooth progression from Critical to Wet years, but that in Below Normal years, it is more beneficial to allocate most of the water above the minimum target to May. Another example is that our results consistently support a flow pulse in May when water temperatures can be lethal to salmon (Kjelson et al., 1982; Smith et al., 2003; Perry et al., 2010, 2018; Vogel, 2010; Cavallo et al., 2013; Lehman et al., 2017; Buchanan et al. 2018a, 2018b), but flow pulses at this time are generally discouraged by managers. However, the potential for elevated flows to decrease water temperatures enough to increase Chinook salmon smolt survival in the south Delta in May has yet to be formally evaluated largely because of resistance to releasing the amount of water necessary to achieve temperature reduction in the various regions of the south Delta. Our results suggest that implementing flow pulses in May has the potential to increase survival of later-migrating larger smolts. If true, this management strategy may provide a longer window in which successful outmigration is possible, which could minimize competition, decrease predation risk, and promote diverse life-history strategies (Munsch et al., 2019; Sturrock et al., 2020). Similar to other analyses of the South Delta acoustic tagging studies partially relied upon in our model (Dauble et al., 2010), we found no negative effect of exports on salmon smolts. This suggests elevated river flows can benefit smolt survival even if water diversions from the South Delta are increased, which further supports implementing pulse flows during May. An adaptive resource management framework could be used to pair the implementation of increased flows in May with physical modeling and strategic monitoring to evaluate hypotheses on how flows, temperature, and diversions affect juvenile survival during this time period.

It should be noted that survival studies that informed our optimization modeling are limited in their temporal scope (April and May) and life history stage (smolt only) relative to the entire period Chinook salmon are in the south Delta. Additionally, we only used the timing of Chinook salmon smolts entering the Delta while there is some evidence

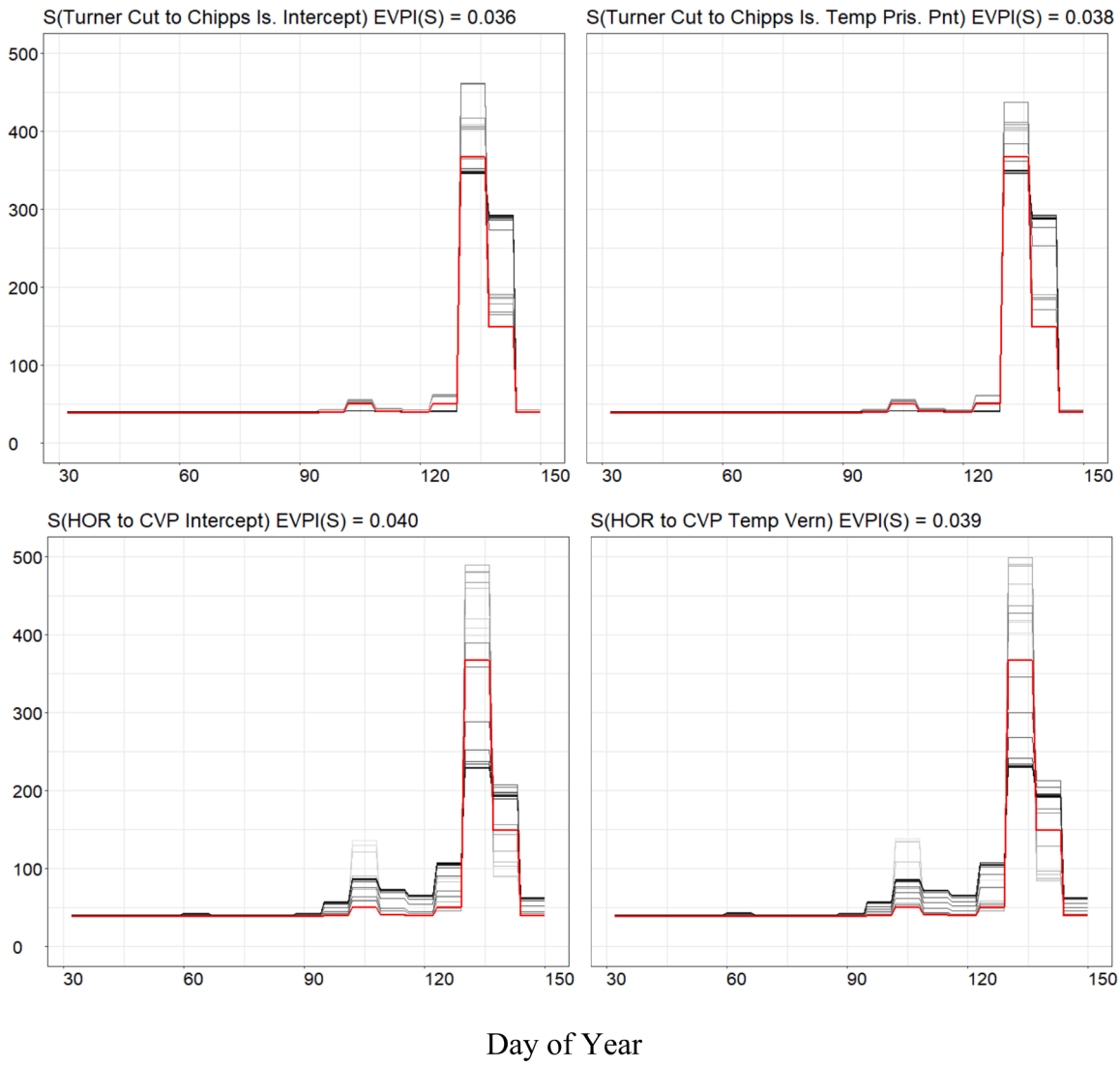


**Fig. 7.** Response profile of top four parameters from one-way sensitivity analysis with expected value of perfect information (EVPI) for survival. EVPI can be taken to mean how much survival would improve if the value of the parameter was known with certainty. Red line is modeled optimal flow regime. Quantiles of the parameter distributions estimated from the mean and standard deviation increase from interval 5 to 10 (light gray lines) up to 90 to 95 (dark gray lines).

that the proportion of juveniles migrating as fry, parr, or smolts is linked with hydrology (Brandes and McLain, 2001; Zeug et al., 2014). Adding dynamic entry timing based on flow pulses and life history stages and integrating new survival studies may change the optimal pulse strategy suggested by our example application. Thus, it would be worthwhile to evaluate management rulesets similar to that suggested by the decision support simulation model through adaptive resource management. For example, one could incorporate a sub-model that predicts the proportion of fry, parr, and smolt emigrating through the south Delta as a function of flow. We would then update our understanding of system dynamics with the revised parameter estimates to make better management decisions each year based on monitoring or directed research.

Deciding how to allocate resources among management, monitoring, and research efforts can be difficult even in some of the most well-funded management programs. Using decision analysis techniques, we can leverage existing information to evaluate the influence of various uncertainties using a common currency: typically, the currency of the management objective(s). In our example, we found the temperature – survival relationships from Turner Cut to Chipps Island and from HOR to CVP had the largest influence on cumulative smolt survival through the south Delta. Specifically, we found the expected cumulative smolt survival increased by up to 1.57 times for Below Normal water year types by improving flow management due to reduced uncertainty in smolt survival estimates from these two regions using EVPI. In other words, improved management of Below Normal water year flows, made possible by reducing uncertainty in our parameter estimates, is expected to result in a cumulative smolt survival similar to an Above Normal water year (under uncertainty). This would be equivalent to having more than twice as much water for target minimum flows (i.e., moving from 40.2 $m^3s^{-1}$ to 96.8 $m^3s^{-1}$) and 1.5 times more water to pulse (i.e., 5964 $m^3s^{-1}$ in an Above Normal water year vs 3925 $m^3s^{-1}$ in a Below Normal water year). Thus, reducing uncertainty in these parameters might mean managers can maximize the biological objective (in this case cumulative smolt survival) to the same degree for less water, potentially leaving more water that can be used for other objectives if survival is already at an acceptable level (e.g., floodplain rearing habitat).

Uncertainties can be used to design future modeling efforts. In our smolt example, the sensitivity analyses indicated the interval for preferred flow pulses (i.e., April and May) was invariant to changes in either slopes or intercepts of the parameters with the largest uncertainties, but matched with smolt outmigration patterns through the

south Delta. This indicates resources may potentially be wasted attempting to reduce uncertainty in meta-regression parameters linked to survival and routing if this knowledge does not change the predicted optimal action. The finding that the optimal intervals for flow pulses matches outmigration patterns suggests that a better understanding of the timing of smolt migration through the south Delta may be needed to inform flow management in this region. As the smolt arrival timing monitoring data came with limitations such as missing data, biased detection rates, and high variation in estimates, future monitoring efforts should focus on the variation in smolt timing to evaluate the robustness of the management rulesets that seem to be emerging with the current model. Had the pulse interval changed with varying the parameters with the largest uncertainties, i.e., survival intercept for Turner Cut to Chipps Island and slope with Prisoner's Point temperature, managers would then consider trying to reduce the uncertainty in both the survival estimate and the effect of temperature on that survival estimate. The intercept (and residual error for that matter) may include factors important to survival that we didn't account for in this model, so determining where those sources of uncertainty in the intercept occur as well as the slope would both be important in this alternate case.

Although the hydrographs were invariant to change in survival and routing parameters with the largest range of survival outcomes in this model, varying the temperature parameter values at Vernalis for survival from Durham Ferry to Head of Old River allowed us to see that survival includes zero in the range of survival outcomes. A risk-averse manager may be more concerned with the uncertainty that includes zero smolts surviving than an uncertainty that spans somewhat low and very high survival (i.e., temperature – survival relationships from Turner Cut to Chipps Island and from HOR to CVP). Satisfying the apprehensions of a risk averse manager to encourage them to implement an alternative, but potentially beneficial strategy, could mean we redefine the objective to minimizing survival to be less than a certain value (e.g., 0.025) as opposed to maximizing survival. In addition, the effects of temperature at Vernalis on survival from Durham Ferry to HOR as a priority in the monitoring framework could be added into the same adaptive management plan suggested previously for learning how increased pulses in May affect juvenile survival. As this parameter had high uncertainty in how it would affect survival, narrowing that uncertainty through additional research would be helpful for assuring the risk averse manager the new management has low probability of a zero survival result. Incorporating objectives for risk aversion can be done easily at the beginning of a structured approach to the decision-making process (Conroy and Peterson, 2013).

Managing ecological systems can be difficult, particularly when some of the factors influencing the decision are outside of the decision maker's control. This partial controllability can sometimes deter managers from using decision support simulation models because it can be viewed that the system is too complex to model. In our example, we demonstrated how uncertainty in seasonal amounts of water availability can be incorporated directly into decision support simulation models that link hydrological flow and ecological response models. This allowed the model to be solved using optimization while accounting for the real-world uncertainty in seasonal water availability. Still, it is often the case that the projected water amounts are updated in near real time as the season progresses (State Water Resources Control Board, 2000). Thus, a natural extension of this case study would be to incorporate an adaptive in-season flow management plan that uses migrating fish capture data (e.g., trawl or rotary screw trap data), the newly predicted amount of water available (e.g., water year type), and temperature trends to feed into the decision support simulation model and inform within-season flow management using the most up-to-date information.

The call for more data, rather than using what data are available to develop decision support simulation models and evaluate tradeoffs in management actions as we did, likely stems from biologists and managers knowing the limitations of their data and wanting to avoid using biased information to inform decisions. For example, our flow analysis incorporated meta-analysis of survival and routing of tagged hatchery-raised smolts, which likely have reduced survival when compared to natural-origin smolts (Del Real, 2012). Additionally, we used a size-survival relationship from smolts from a different basin, timing, and life stage which while positive, may have a different effect size. Furthermore, the acoustic tagging studies were observational and did not occur when temperatures were lower than 15.5 °C and when average daily flows were 175–275 $m^3s^{-1}$, environmental conditions that exist during the smolt outmigration window but for which we do not have tagging data. Although we certainly agree that not all monitoring data are collected in a way that makes them suitable to inform decision making, it is worth noting that all ecological data are compromised to some extent and that this does not mean they do not provide useful information. That is, imperfect data do not prevent effective evaluation of tradeoffs in management actions. When uncertainty in a particular parameter does not influence the management objective, biologists and managers need not be as concerned with the related data limitation. For example, we were able to evaluate the effect of parametric uncertainty on the management objective in a transparent way. One parameter included in our model, CVP entrainment, may have had increased uncertainty because we only had estimates from releases within one year (Karp et al., 2017). However, we did not find much of an effect of varying this parameter through its confidence interval on survival. We also found varying the parameters with the most uncertainty did not change how water volume would be distributed. On the other hand, if uncertainty in a particular set of parameters governs which decision is most effective (e.g., optimal flows were to change from April and May to February and March), this would highlight the parameter(s) that managers and biologists would benefit most from in reducing uncertainty.

The south Delta optimization model we developed could be built upon for general use by water managers. For example, an application could be made for managers to explicitly evaluate which management "knobs" to turn relative to their expected outcome and cost. In the south Delta, the main "knobs" available to managers include changing the ratio of water imports into the Delta (e.g., via dam manipulations) to water exports via the CVP or SWP export facilities, forgoing water exports, reshaping the hydrograph of available water, increasing flows to reduce temperatures, and restoring more historical habitats that favor native over non-native species. Some of these factors affect rearing habitat and therefore survival before emigrating fish even reach the south Delta. Therefore, adding upstream tributary sub-models would incorporate optimizing flows for the varying portfolios of fry, parr, and smolts important for diversifying outmigration strategies (Sturrock et al., 2020). In an upstream tributary sub-model, the weekly time step used in our south Delta model could be adapted to a daily time step to account for flow variability that cues fry outmigration from natal tributaries (Zeug et al., 2014; Sturrock et al., 2020).

The results from our south Delta smolt model are directly related to the management objective we considered (i.e., optimizing cumulative survival of smolts through the south Delta). Managers must manage the system for other, sometimes competing, biological objectives such as the number of adult fish that return to spawn, fry outmigration, floodplain rearing habitat, other species of concern such as Steelhead trout, salinity, and dissolved oxygen (Luoma et al., 2015; Horne et al., 2018; Peterson and Duarte, 2020). These objectives are relatively easy to incorporate into our modeling framework using multi-criteria decision analysis (Horne et al., 2018). Such an effort would probably be best implemented within a structured decision-making process, where complicated problems are broken down into discrete steps through a series of stakeholder driven workshops (Conroy and Peterson, 2013; Horne et al., 2018).

## 5. Conclusions

As the human population grows and the climate becomes warmer, conserving wild populations that depend on water will require a more

focused level of commitment, technical effort, and investment in conservation (Lackey et al., 2006; Naiman et al., 2008; Hanak et al., 2011; Katz et al., 2012; Luoma et al., 2015). We suggest using tools and data that we currently have to help solve complex problems despite far from perfect knowledge about how systems will respond (Webb et al., 2018). We demonstrated how to use advanced decision-analytic modeling techniques to provide the direct link between monitoring, optimization modeling, and management, using Chinook salmon smolts in the south Delta as an example. We were able to use less than perfect long-term monitoring data on Chinook salmon smolt survival and routing to develop an optimization model to predict salmon smolt survival based on environmental covariates. We then used the optimization modeling to determine flow hydrographs that optimize Chinook salmon smolt survival through the south Delta for varying water year types. We were also able to identify future monitoring priorities based on sensitivity analysis. This type of decision-support framework can be used for a wide array of conservation problems throughout the world to link biological responses to management alternatives via an adaptive process.

## Author contributions

JTP, AD conceived and designed the approach; JTP conducted the meta-analysis for the survival and routing models; JTP, AD, BC, SZ provided advice and parameters for the development of the routing and survival models; AD wrote the optimization code; PJW, AD modified and calibrated the models; JW provided expert information, PJW, JTP, AD developed the optimal flow policies; PJW, AD conducted simulations and sensitivity analyses; PJW, JTP, AD participated equally in writing the manuscript; PJW, JTP, AD, JW, BC, SZ edited the manuscript.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data Availability

Data will be made available on request.

## Acknowledgements

We appreciate the efforts of several California Central Valley and San Francisco Bay-Delta experts consulted for their input and suggestions. Support for the meta-analysis and model development was provided by the U.S. Bureau of Reclamation and U.S. Fish and Wildlife Service. We used data from reports that analysed millions of dollars' worth of telemetry data. These authors designed studies, collected data and analyzed data funded by U.S.F.W.S., U.S.G.S.-Sacramento, CDWR, U.S. B.R., University of Washington, and included R. Buchanan, D. Barnard, P. Brandes, K. Towne, J. Ingram, K. Nichols, J. Israel, M. Marshall, D. LaPlante, J. Scott Foott, C. M. Holbrook, and the San Joaquin River Group Authority. A. Duarte would also like to acknowledge support from the U.S.D.A. Forest Service, Pacific Northwest Research Station. The Oregon Cooperative Fish and Wildlife Research Unit is jointly sponsored by the U.S. Geological Survey, the U.S. Fish and Wildlife Service, the Oregon Department of Fish and Wildlife, Oregon State University, and the Wildlife Management Institute. Any use of trade, product, or firm names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

## Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ecolmodel.2022.110058.

## References

Arthington, A., Bunn, S.E., Poff, N.L., Naiman, J., 2006. The challenge of providing environmental flow rules to sustain river ecosystems. Ecol. Appl. 16, 1311–1318.
Baker, P.F., Morhardt, J.E., 2001. Survival of Chinook salmon smolts in the Sacramento-San Joaquin delta and pacific ocean. In: Brown, R.L. (Ed.), Contributions to the Biology of Central Valley Salmonids. Fish Bulletin, p. 19, 179.
Barton, K., 2020. MuMIn: multi-model inference. R Package Version 0.12.2/r18. http://R-Forge.R-project.org/projects/mumin/.
Brandes, P.L., McLain, J.S., 2001. Juvenile Chinook salmon abundance, distribution, and survival in the Sacramento-San Joaquin Estuary. In: Brown, R.L. (Ed.), Contributions to the Biology of Central Valley Salmonids. Fish Bulletin, p. 100, 179.
Breiman, L., Spector, P., 1992. Submodel selection and evaluation in regression. The X-random Case. International statistical review/revue internationale de Statistique, pp. 291–319.
Brown, L.R., Bauer, M.L., 2010. Effects of hydrologic infrastructure on flow regimes of California's central valley rivers: implications for fish populations. River Res. Applic. 26, 751–765.
Brownie, C., Hines, J.E., Nichols, J.D., Pollock, K.H., Hestbeck, J.B., 1993. Capture-recapture studies for multiple strata including non-Markovian transitions. Biometrics 49, 1173–1187.
Buchanan, R., Brandes, P., Marshall, M., Foott, J.S., Ingram, J., LaPlante, D., Israel, J., 2015. 2012 South Delta Chinook Salmon Survival Study. U.S. Fish and Wildlife Service, Lodi, CA.
Buchanan, R., Brandes, P., Marshall, M., Nichols, K., Ingram, J., LaPlante, D., Israel, J., 2016. 2013 South Delta Chinook Salmon Survival Study. U.S. Fish and Wildlife Service, Lodi, CA.
Buchanan, R., Brandes, P., Ingram, J., Marshall, M., Nichols, K., LaPlante, D., Barnard, D., Towne, K., 2018a. 2014 South Delta Chinook Salmon Survival Study. U. S. Fish and Wildlife Service, Lodi, CA.
Buchanan, R., Barnard, D., Brandes, P., Towne, K., Ingram, J.M., Nichols, K., 2018b. 2015 South Delta Chinook Salmon Survival Study. U.S. Fish and Wildlife Service, Lodi, CA.
Buchanan, R.A., Skalski, J.R., 2020. Relating survival of fall-run Chinook salmon through the San Joaquin Delta to river flow. Environ. Biol. Fish. 103, 389–410.
Burnham, K.P., Anderson, D.R., 2002. Model Selection and Multimodel inference: a Practical Information-Theoretic Approach, 2nd edition. Springer, New York.
California Department of Water Resources, California Data Exchange Center, 2021. California Department of Fish and Wildlife's. www.dfg.ca.gov/delta/apps/salvage (accessed March 5 2021,).
California Department of Water Resources, California Data Exchange Center, 2021. Water Year Hydrologic Classification Indices. http://cdec.water.ca.gov/reportapp/javareports?name=WSIHIST/ (accessed Jan 30 2021).
California Department of Water Resources, California Data Exchange Center, 2020. https://data.cnra.ca.gov/dataset/dayflow.
Cavallo, B., Merz, J., Setka, J., 2013. Effects of predator and flow manipulation on Chinook salmon (Oncorhynchus tshawytscha) survival in an imperiled estuary. Environ. Biol. Fishes 96 (2–3), 393–403. https://doi.org/10.1007/s10641-012-9993-5.
Cavallo, B., Gaskill, P., Melgo, J., Zeug, S.C., 2015. Predicting juvenile Chinook salmon routing in riverine and tidal channels of a freshwater estuary. Environ. Biol. Fishes 98, 1571–1582.
Chen, X., 2016. Nonlinear Constrained Optimization in R and Its Application For Sufficient Dimension Reduction and Variable Selection. PhD Dissertation, University of Georgia, Athens.
Chen, X., Yin, X., 2019. NlcOptim: Solve nonlinear optimization with nonlinear constraints https://cran.r-project.org/web/packages/NlcOptim/index.html (accessed April 27 2021,).
Conroy, M.J., Peterson, J.T., 2013. Decision Making in Natural Resource management: a structured, Adaptive Approach. Wiley-Blackwell, Sussex, U.K.
Dauble, D., Hankin, D., Pizzimenti, J.J., Smith, P., 2010. The Vernalis adaptive management program: report of the 2010 review panel. Prepared for the Delta Science Program. May 13, 2010.
Del Real, S.C., Workman, M., Merz, J., 2012. Migration characteristics of hatchery and natural-origin Onchorhynchus mykiss from the lower Mokelumne River. California. Environ Biol Fish 94 (2), 363–375.
Dettinger, M.D., Ralph, F.M., Das, T., Neiman, P.J., Cayan, D.R., 2011. Atmospheric rivers, floods, and the water resources of California. Water (Basel) 3, 445–478. https://doi.org/10.3390/w3020445 dx.doi.org/.
Dill, W.A., Cordone, A.J., 1997. History and status of introduced fishes in California, 1871–1996. California Dep. Fish and Game Fish Bullet. 178, 1–414.
Feyrer, F., Healey, M.P., 2003. Fish community structure and environmental correlates in the highly altered southern Sacramento-San Joaquin Delta. Environ. Biol. Fishes 66, 123–132.
Gasparrini, A., Armstrong, B., Kenward, M.G., 2012. Multivariate meta-analysis for non-linear and other multi-parameter associations. Stat. Med. 31 (29), 3821–3839.
Gingras, M., 1997. Mark/recapture experiments at Clifton Court forebay to estimate pre-screening loss to entrained juvenile fishes: 1976–1993. IEP Technical Report No. 55. http://iep.water.ca.gov/report/reports.html. (accessed March 5 2021,).
Grantham, T.E., 2013. Use of hydraulic modelling to assess passage flow connectivity for salmon in streams. River Res. Appl. 29 (2), 250–267.
Hanak, E., Lund, J., Dinar, A., Gray, B., Howitt, R., Mount, J., Moyle, P., Thompson, B., 2011. Managing California's water: from Conflict to Reconciliation. Public Policy Inst Calif, San Francisco.

Healey, M., Goodwin, P., Dettinger, M., Norgaard, R., 2016. The state of bay–delta science 2016: an introduction. San Francisco Estuary and Watershed Sci. 14 (2) https://doi.org/10.15447/sfews.2016v14iss2art5.
Hearn, A.R., Chapman, E.D., Singer, G.P., Brostoff, W.N., LaCivita, P.E., Klimley, A.P., 2014. Movements of out-migrating late-fall run Chinook salmon (Oncorhynchus tshawytscha) smolts through the San Francisco Bay Estuary. Environ. Biol. Fish. 97, 851–863.
Hestir, E.L., Schoellhamer, D.H., Greenberg, J., Morgan-King, T., Ustin, S.L., 2016. The effect of submerged aquatic vegetation expansion on a declining turbidity trend in the Sacramento-San Joaquin River Delta. Estuaries and Coasts 39 (4), 1100–1122.
Holbrook, C.M., Perry, R.W., Adams, N.S., 2009. Distribution and Joint Fish-Tag Survival of Juvenile Chinook salmon Migrating Through the Sacramento–San Joaquin River Delta, 2008. U.S. Department of the Interior, U.S. Geological Survey. Biological Resources Discipline Report to San Joaquin River Group Authority.
Horne, A.C., Szemis, J.M., Webb, J.A., Kaur, S., Stewardson, M.J., Bond, N., Nathan, R., 2018. Informing environmental water management decisions: using conditional probability networks to address the information needs of planning and implementation cycles. Environ. Manag. 61, 347–357.
Kaplan, D.M., 2020. T ools for working with connectivity data. R package version 0.3.5. https://cran.r-project.org/web/packages/ConnMatTools/ConnMatTools.pdf (accessed March 2021).
Karp, C.B., Wu, J., Kumagai, K., 2017. Juvenile Chinook salmon, steelhead, and adult striped bass movements and facility efficiency at the tracy fish collection facility. Tracy technical bulletin 2017-1. Bureau of Reclamation, Mid-Pacific Region 81. https://www.usbr.gov/mp/TFFIP/docs/tracy-reports/ttb-2017-1-juvenile-chinook.pdf (accessed March 5 2021,).
Katz, J., Moyle, P., Quiñones, R.M., Israel, J., Purdy, S., 2012. Impending extinction of salmon, steelhead and trout (Salmonidae) in California. Environ. Biol. Fish. https://doi.org/10.1007/s10641-012-9974-8.
Kimmerer, W.J., 2008. Losses of Sacramento River Chinook salmon and Delta smelt to entrainment in water diversions in the Sacramento-San Joaquin Delta. San Francisco Estuary and Watershed Science 6 (2). http://www.escholarship.org/uc/item/7v92h6fs/.
Kjelson, A.M., Raquel, P.F., Fisher, F.W., 1982. Life history of fall run Chinook salmon Onchorhynchus tshawytscha. In: Kennedy, V.S. (Ed.), the Sacramento-San Joaquin Estuary. Estuarine comparisons. Academic, New York, pp. 393–411.
Klipsch, J.D., Hurst, M.B., 2007. HEC-ResSim reservoir system simulation user's manual version 3.0. Davis, CA, US Army Corps of Engineers 512. In: https://acwi.gov/hydrology/mtsconfwkshops/conf_proceedings/3rdFIHMC/7E_Klipsch.pdf.
Lackey, R.T., Lach, D., Duncan, S., 2006. Salmon 2100: the Future of Wild Pacific salmon. American Fisheries Society, Bethesda, Maryland, p. 629.
Lebreton, J.-.D., Pradel, R., 2002. Multistate recapture models: modelling incomplete individual histories. J. Appl. Stat. 29, 353–369.
Lehman, B.M., Gary, M.P., Demetras, N.J., Michel, C.J., 2019. Where Predators and Prey meet: Anthropogenic contact Points Between Fishes in a Freshwater Estuary. San Francisco Estuary and Watershed Science. https://doi.org/10.15447/sfews.2019v17iss4art3 doi.org/.
Lehman, B., Huff, D., Hayes, S., Lindley, S., 2017. Relationships between Chinook salmon swimming performance and water quality in the San Joaquin River, California. Trans. Am. Fish. Soc. 146 (2), 349–358.
Limm, M.P., Marchetti, M.P., 2009. Juvenile Chinook salmon (Oncorhynchus tshawytscha) growth in off-channel and main channel habitats on the Sacramento River, CA using otolith increment widths. Environ. Biol. Fishes 85, 141–151.
Lortie, C.J., Filizzola, A., 2020. A contrast of meta and metaphor packages for meta-analyses in R. Acad. Practice in Ecol. Evolution 10, 10916–10921.
Lund, J., Hanak, E., Fleenor, W., Howitt, R., Mount, J., Moyle, P., 2007. Envisioning Futures For the Sacramento-San Joaquin Delta. Public Policy Institute of California, San Francisco.
Luoma, S.N., Dahm, C.N., Healey, M., Moore, J.N., 2015. Challenges facing the Sacramento–San Joaquin Delta: complex, chaotic, or simply cantankerous? San Franc Estuary Watershed Sci. 13 (3) https://doi.org/10.15447/sfews.2015v13iss3art7 dx.doi.org/.
Lyons, J.E., Runge, M.C., Laskowski, H.P., Kendall, W.L., 2008. Monitoring in the context of structured decision-making and adaptive management. J. Wildl. Manag. 72 (8), 1683–1692.
Mahardja, B., Mitchell, L., Beakes, M., Johnston, C., Graham, C., Goertler, P., Barnard, D., Castillo, G., Matthias, B., 2021. Leveraging Delta smelt monitoring for detecting juvenile Chinook salmon in the San Francisco Estuary https://escholarship.org/uc/item/9sp7r7q4.
Merz, J.E., Workman, M.L., Wikert, J.D., Cavallo, b., 2013. salmon lifecycle considerations to guide stream management: examples from california's Central Valley. San Francisco Estuary and Watershed Sci. 11 jmie_sfews_13365. http://www.escholarship.org/uc/item/30d7b0g7 (accessed 5 Feb 2021).
Michel, C.J., Ammann, A.J., Chapman, E.D., Sandstrom, P.T., Fish, H.E., Thomas, M.J., Singer, G.P., Lindley, S.T., Klimley, A.P., MacFarlane, R.B., 2013. The effects of environmental factors on the migratory movement patterns of Sacramento River yearling late fall run Chinook salmon (Onchorhynchus tshawytscha). Env. Biol. Fish 96 (2–3), 257–271.
Michel, C.J., Ammann, A.J., Lindley, S.T., Sandstrom, P.T., Chapman, E.D., Thomas, M.J., Singer, G.P., Klimley, A.P., MacFarlane, R.B., 2015. Chinook salmon outmigration survival in wet and dry years in California's Sacramento River. Can. J. Fish. Aquat. Sci. 72 (11), 1749–1759. https://doi.org/10.1139/cjfas-2014-0528.
Moore, D.S., McCabe, G.P., 2005. Introduction to the Practice of Statistics, 5th ed. W.H. Freeman and Company, New York.
Munsch, S.H., Greene, C.M., Johnson, R.C., Satterthwaite, W.H., Imaki, H., Brandes, P.L., 2019. Warm, dry winters truncate timing and size distribution of seaward-migrating salmon across a large, regulated watershed. Ecol. Appl. 29 (4), e01880. https://doi.org/10.1002/eap.1880 doi.org/.
Murchie, K.J., Hair, K.P.E., Pullen, C.E., Redpath, T.D., Stephens, H.R., Cooke, S.J., 2008. Fish response to modified flow regimes in regulated rivers: research methods, effects, and opportunities. River Res. Appl. 24, 197–217.
Myrick, C.A., Cech, J.J., 2004. Temperature effects on juvenile anadromous salmonids in California's central valley: what don't we know? Rev. Fish Biol. Fish. 14, 113–123.
Naiman, R.J., Latterell, J.J., Pettit, N.E., Olden, J.D., 2008. Flow variability and the biophysical vitality of river systems. Comptes Rendus Geoscience 340, 629–643.
National Marine Fisheries Service (NMFS), 2009, Biological opinion and conference opinion on the long-term operations of the central valley project and state water project, NOAA's national marine fisheries service, southwest region: 2008/0902 https://www.fisheries.noaa.gov/resource/document/biological-opinion-and-conference-opinion-long-term-operations-central-valley (accessed March 18 2021,).
National Marine Fisheries Service (NMFS), 2016. Biological assessment for the california water fix, NOAA's national marine fisheries service, southwest region: WCR-2016-5506 https://www.fisheries.noaa.gov/west-coast/endangered-species-conservation/california-waterfix (accessed March 18 2021,).
National Marine Fisheries Service (NMFS), 2019. Biological opinion on long-term operation of the central valley project and the state water project, NOAA's national marine fisheries service, southwest region, https://repository.library.noaa.gov/view/noaa/22046 (accessed March 19 2021,).
National Oceanic and Atmospheric Administration, 2018. Tides and currents. https://tidesandcurrents.noaa.gov/stationhome.html (Accessed March 2018).
Newman, K.B., 2008. An Evaluation of Four Sacramento-San Joaquin Delta juvenile Salmon Survival Studies. United States Fish and Wildlife Service, Stockton, CA. March 31, 2008.
Newman, K.B., Brandes, P.L., 2010. Hierarchical modeling of juvenile Chinook salmon survival as a function of Sacramento-San Joaquin Delta water exports. North Am. J. Fisheries Manag. 30 (1), 157–169.
Nichols, J.D., Hines, J.E., Pollock, K.H., Hinz, R.L., Link, W.A., 1994. Estimating breeding proportions and testing hypotheses about costs of reproduction with capture-recapture data. Ecology 75, 2052–2065.
Nichols, J.D., Williams, B.K., 2006. Monitoring for conservation. Trends in Ecol. Evolution 21 (12), 668–673. https://doi.org/10.1016/j.tree.2006.08.007.
Nobriga, M.L., Michel, C.J., Johnson, R.C., Wikert, J.D., 2021. Coldwater fish in a warm water world: implications for predation of salmon smolts during estuary transit. Ecol. Evol. 11, 10381–10395.
Perry, R.W., Brandes, P.L., Sandstrom, P.T., Ammann, A., MacFarlane, B., Klimley, A.P.J., Skalski, R., 2010. Estimating survival and migration route probabilities of juvenile Chinook salmon in the Sacramento-San Joaquin River Delta. North Am. J. Fisheries Manag. 30, 142–156.
Perry, R.W., Pope, A.C., Romine, J.G., Brandes, P.L., Burau, J.R., Blake, A.R., Ammann, A.J., Michel, C.J., 2018. Flow-mediated effects on travel time, routing, and survival of juvenile Chinook salmon in a spatially complex, tidally forced river delta. Canadian J. Fisheries and Aquatic Sci. 75, 1886–1901.
Peterson, J.T., Duarte, A., 2020. Decision analysis for greater insights into the development and evaluation of Chinook salmon restoration strategies in California's central valley. Restoration Ecol. 28 (6), 1596–1609.
Poff, N.L., Olden, J.D., Merritt, D.M., Pepin, D.M., 2007. Homogenization of regional river dynamics by dams and global biodiversity implications. Proceedings of the Nat. Acad. Sci. 104, 5732–5737.
Poff, N.L., Zimmerman, J.K., 2010. Ecological responses to altered flow regimes: a literature review to inform the science and management of environmental flows. Freshw. Biol. 55 (1), 194–205.
Pringle, C.M., Freeman, M.C., Freeman, B.J., 2000. Regional effects of hydrologic alterations on riverine macrobiota in the new world: tropical– temperate comparisons. Bioscience 50, 807–823.
Core Team, R., 2020. R: a Language and Environment For Statistical Computing. R foundation for statistical computing, Vienna, Austria. https://www.rproject.org.
Richter, B.D., Thomas, G.A., 2007. Restoring environmental flows by modifying dam operations. Ecol. Soc. 12, 12. www.ecologyandsociety.org/vol12/iss1/art12/.
Royall, R.M., 1997. Statistical evidence: a Likelihood Paradigm. Chapman and Hall, London, UK.
Salmon Scoping Team, 2017. Effects of Water Project Operations On Juvenile Salmonid Migration and Survival in the South Delta. Vol. 1: Findings and Recommendations. Prepared for the Collaborative Adaptive Management Team, California Department of Water Resources, Sacramento, CA, p. 140.
San Joaquin River Group Authority (SJRGA), 2010. 2009 Annual technical report: On implementation and monitoring of the San Joaquin river agreement and the vernalis adaptive management plan (VAMP). www.waterboards.ca.gov/waterrights/water_issues/programs/bay_delta/docs/cmnt091412/sldmwa/sjrga_2010.pdf (accessed March 4 2020,).
San Joaquin River Group Authority (SJRGA), 2011. 2010 Annual technical report: on implementation and monitoring of the San Joaquin river agreement and the vernalis adaptive management plan (VAMP): Prepared for California water resource control board.
San Joaquin River Group Authority (SJRGA), 2013. 2011 annual technical report: on implementation and monitoring of the San Joaquin river agreement and the vernalis adaptive management plan (VAMP). Prepared for the California water resources control board.
Sera, F., Armstrong, B., Blangiardo, M., Gasparrini, A., 2019. An extended mixed-effects framework for meta-analysis. Stat. Med. https://doi.org/10.1002/sim.8362.
Shenton, W., Bond, N.R., Yen, J.D.L., Mac Nally, R., 2012. Putting the "ecology" into environmental flows: ecological dynamics and demographic modelling. Environ. Manag. 50 (1), 1–10.

Singer, M.B., 2007. The influence of major dams on hydrology through the drainage network of the Sacramento River basin. California. River Res. Appl. 23, 55–72.
Singer, G.P., Hearn, A.R., Chapman, E.D., Peterson, M.L., LaCivita, P.E., Brostoff, W.N., Bremner, A., Klimley, A.P., 2013. Interannual variation of reach specific migratory success for Sacramento river hatchery yearling late-fall run Chinook salmon (Onchorhynchus tshawytscha) and steelhead trout (Onchorhynchus mykiss). Environ. Biol. Fish 96 (2–3), 363–379.
Smith, S.G., Muir, W.D., Hockersmith, E.E., Zabel, R.W., Graves, R.J., Ross, C.V., Connor, W.P., Arnsberg, B.D., 2003. Influence of river conditions on survival and travel time of Snake River subyearling fall Chinook salmon. N. Am. J. Fish. Manag. 23 (3), 939–961. https://doi.org/10.1577/M02-039.
Sogard, S.M., 1997. Size-selective mortality in the juvenile stage of teleost fishes: a review. Bull. Mar. Sci. 60 (3), 1129–1157.
Sommer, T.R., Nobriga, M.L., Harrell, W.C., Batham, W., Kimmerer, W.J., 2001. Floodplain rearing of juvenile chinook salmon: evidence of enhanced growth and survival. Canadian J. Fisheries and Aquatic Sci. 58 (2), 325–333.
State Water Resources Control Board, 2000. Revised water right decision 1641 in the matter of: implementation of water quality objectives for the San Francisco Bay/ Sacramento-San Joaquin Delta Estuary; A petition to change points of diversion of the central valley project and the state water project in the southern delta; and a petition to change places of use and purposes of use of the central valley project December 29, 1999. Sacramento, CA. https://www.waterboards.ca.gov/waterrights/board_decisions/adopted_orders/decisions/d1600_d1649/wrd1641_1999dec29.pdf (accessed March 18 2021,).
Stewart, G.B., Schmid, C.H., 2015. Lessons from meta-analysis in ecology and evolution: the need for trans-disciplinary evidence synthesis methodologies. Res. Synth. Methods 6, 109–110. https://doi.org/10.1002/jrsm.1152 doi.org/.
Sturrock, A.M., Carlson, S.M., Wikert, J.D., Heyne, T., Nusslé, S., Merz, J.E., Sturrock, H. J.W., Johnson, R.C., 2020. Unnatural selection of salmon life histories in a modified riverscape. Glob. Chang. Biol. 26 (3), 1235–1247.
U.S. Fish and Wildlife Service (USFWS), 2020. Delta juvenile fish monitoring program. https://www.fws.gov/lodi/juvenile_fish_monitoring_program/jfmp_index.htm (accessed March 5 2021,).
United States Geological Survey (USGS), 2021. National water information system: web interface, https://waterdata.usgs.gov/nwis/inventory/ (accessed Dec 2018).
Vogel, D.A., 2010. Evaluation of Acoustic-Tagged Juvenile Chinook salmon Movements in the Sacramento–San Joaquin Delta during the 2009 Vernalis Adaptive Management Program. Natural Resource Scientists, Inc., Red Bluff, California, 63 pp.
Webb, J.A., Watts, R.J., Allan, C., Conallin, J.C., 2018. Adaptive management of environmental flows. Environ. Manag. 61, 339–346.
Whipple, A.A., Grossinger, R.M., Rankin, D., Stanford, B., Askevold, R.A., 2012. Sacramento–San Joaquin Delta Historical Ecology investigation: Exploring Pattern and process. Prepared for the California Department of Fish and Game and Ecosystem Restoration Program. A report of SFEI–ASC's Historical Ecology Program, Publication #672, Richmond (CA): San Francisco Estuary Institute– Aquatic Science Center. https://www.sfei.org/sites/default/files/biblio_files/Delta_HistoricalEcologyStudy_SFEI_ASC_2012_lowres.pdf (accessed March 5 2021,).
Williams, B.K., 2011. Adaptive management of natural resources—Framework and issues. J. Environ. Manage. 92 (5), 1346–1353.
Williams, B.K., Nichols, J.D., Conroy, M.J., 2002. Analysis and Management of Animal Populations. Academic press, San Diego, CA.
Wood, S.N., 2017. Generalized Additive Models: an Introduction With R, 2nd edition. CRC.
Wright, A.D., Bernard, R.F., Mosher, B.A., O'Donnell, K.M., Braunagel, T., DiRenzo, G.V., Fleming, J., Shafer, C., Brand, A.B., Zipkin, E.F., Campbell Grant, E.H., 2020. Moving from decision to action in conservation science. Biol. Conserv. 249, 1–11. doi.org/10.1016/j.biocon.2020.108698.
Yarnell, S.M., Petts, G.E., Schmidt, J.C., Whipple, A.A., Beller, E.E., Dahm, C.N., Viers, J. H., 2015. Functional flows in modified Riverscapes: hydrographs, habitats and opportunities. Bioscience 65 (10), 963–972.
Zeug, S.C., Cavallo, B.J., 2013. Influence of estuary conditions on the recovery rate of coded wire tagged Chinook salmon (Oncorhynchus tshawytscha) in an ocean fishery. Ecol. Freshw. Fish 22, 157–168.
Zeug, S.C., Cavallo, B.J., 2014. Controls on the entrainment of juvenile Chinook salmon (Oncorhynchus tshawytscha) into large water diversions and estimates of population-level loss. PLoS ONE 9 (7). https://doi.org/10.1371/journal.pone.0101479.
Zeug, S.C., Sellheim, K., Watry, C., Wikert, J.D., Merz, J., 2014. Response of juvenile Chinook salmon to managed flow: lessons learned from a population at the southern extent of their range in North America. Fish. Manag. Ecol. https://doi.org/10.1111/fme.12063.
Zimmerman, J.K.H., Carlisle, D.M., May, J.T., Klausmeyer, K.R., Grantham, T.E., Brown, L.R., Howard, J.K., 2018. Patterns and magnitude of flow alteration in California. Freshw. Biol. 63, 859–873. doi.org/10.1111/fwb.13058.