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# **Forecasting the Abundance of Juvenile Spring-Run Chinook Salmon Outmigrants from Sacramento River Tributaries and the Mainstem Using Spawner-Outmigrant Stock-Recruit Models**

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### **Acknowledgments**

The data used in this modeling effort are rich and extensive—in some cases, data collection has been ongoing since the late 1990s. This work would not be possible without the field staff collecting daily rotary screw trap data and the data stewards that have managed these data over time. Special thanks to the following individuals for running programs and synthesizing data for the Juvenile Production Estimate Modeling Team: Jason Kindopp, Feather River; Kassie Hickey, Feather River; Ryan Revnak, Mill and Deer Creek; Casey Campos, Yuba River; Mike Shraml, Battle and Clear Creek; Natasha Wingerter, Battle and Clear Creek; and Grant Henley, Butte Creek.

We also thank the Spring-run Juvenile Production Estimate Core Team, Modeling Advisory Team, and Interagency Review Team for their useful comments and advice.

Work by Ecometric Research and FlowWest on this project was supported by California Department of Water Resources. Work by QEDA Consulting was supported by the California State Water Contractors organization.

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## Executive Summary

Spawner-juvenile outmigrant stock-recruit relationships will be used as part of a model to forecast annual juvenile production estimates (JPE) for spring-run Chinook salmon (*Oncorhynchus tshawytscha*) (spring-run) entering the Sacramento–San Joaquin River Delta (Delta). Spawner-outmigrant models were fit to rotary screw trap (RST) data collected in five Sacramento River tributaries used by spring-run, and at a site on the mainstem. A series of annual covariates for each site were calculated to represent flow or temperature conditions potentially influencing survival rates during upstream migration, spawning-incubation, and early rearing phases. Stock-recruit models included the effects of both spawner abundance and a single covariate on productivity (outmigrants/spawner). Here we describe the structure of these models and show predictions based on fits to data from Battle, Clear, Deer, Mill, and Butte creeks, Yuba River, and from Knights Landing on the mainstem Sacramento River.

We fit 16 different stock-recruit models to data from RST sites in tributaries. This included model mu (i.e., no spawner abundance or covariate effects on productivity), the null model (i.e., spawner effect only), two discrete water year type models, and 12 continuous covariate models. We fit 11 models to the data from Knights Landing RST site, which included mu and null models, two discrete water year covariate models, and seven continuous covariate models. Models were compared using a variety of statistics including fit, unexplained process error, and the magnitude and reliability of the coefficient for the covariate effect. In addition, we used a leave-one-out cross validation approach to evaluate out-of-sample predictive accuracy of outmigrant forecasts.

There was considerable variation in the sample sizes available to fit spawner-outmigrant models among tributaries. A common rule of thumb for the minimum sample size for a statistical model is 10–20 points per parameter. Thus, a two-parameter stock-recruitment model (a null model) should be fit based on a minimum of approximately 20 years of data, while covariate models would require a minimum of approximately 30 years of data. The Upper Battle and Clear creeks, Butte Creek, and Knights Landing sites had the largest sample sizes ( $n \sim 15$ –20 years) because there were many years of outmigrant estimates and considerable overlap with the years spawner data were available. However, these sample sizes were still less than recommended minimum requirements for covariate models. There were only four years with both outmigrant and reliable spawner abundance data (as redd counts) for Mill Creek, which was an inadequate sample size ( $n=4$ ) to estimate stock-recruit parameters. Sample sizes were modest for RST sites on the Yuba River ( $n=7$ ) and Deer Creek ( $n=12$ ) and were well below the recommended minimum sample sizes for both null and covariate models.

The best stock-recruitment models we fit only explained a moderate amount of variation in log outmigrants/spawner ( $r^2 \sim 0.4-0.7$ ), and had relatively high out-of-sample error in predicting outmigrant abundance (relative errors of approximately 50–100%). Surprisingly, flow- and temperature-based covariates sometimes led to only modest improvements in model fit, and in many cases did not reduce out-of-sample error in outmigrant abundance predictions. In a number of cases in Battle and Clear creeks and Knights Landing, including effects of spawner abundance on productivity did not improve out-of-sample error. The best covariate models for Battle and Clear creek sites indicated that productivity declined at higher temperatures during the spawning and incubation period, and with higher maximum flows during both spawning-incubation and rearing periods. The best models from Deer Creek and Butte Creek sites also showed negative effects of higher temperatures on productivity. Models from the Butte Creek site also showed increases in productivity with higher flows during spawning-incubation and rearing periods, and higher productivity in wet water years. These results are consistent with the hypotheses that cooler water and higher flows generally increase productivity for Chinook salmon populations.

Our analysis highlights some of the challenges of applying a stock-recruitment approach to RST sites in the mainstem Sacramento River. This requires estimates of spawner abundance from all tributaries upstream of the mainstem site in the same years (i.e., in Battle, Clear, Mill, Deer, and Butte creeks). This requirement substantially reduced the sample size of stock-recruit points for Knights Landing, forcing us to index spawner abundance based on data from only two of five contributing tributaries (at Battle and Clear creeks). Use of tributary-specific stock-recruitment relationships combined with routing predicted juvenile outmigrant abundance to the Delta via mainstem survival estimates is a more reliable approach. Outmigrant estimates from monitoring on the mainstem are still useful as an out-of-sample check on routed tributary-based outmigrant estimates.

Estimates of maximum productivity from the stock-recruit analysis can be used to calculate egg-outmigrant survival rate to determine whether productivity estimates are realistic. For example, maximum productivity for the Battle Creek model based on upstream passage for spawner abundance was 261 outmigrants/spawner. Assuming 1,500 eggs/spawner (3,000 eggs/female \* 0.5 females) results in a maximum egg-outmigrant survival rate of 17% ( $261/(1 \text{ spawner} * 1,500 \text{ eggs/spawner})$ ). The magnitude of this survival rate is plausible, which was the case at most other sites. The maximum outmigrants/spawner estimate for Knights Landing was unrealistically high, but this was expected as spawner estimates did not include spawner abundance in Mill, Deer, and Butte creeks.

The majority of uncertainty in outmigrant abundance forecasts at all sites was driven by high levels of error not explained by effects of spawner abundance and covariate values. This highlights the importance of identifying models and covariates that explain more of the variation in observed outmigrants/spawner. This

may include identifying and potentially reducing error in spawner estimates, which currently is not quantified and is contributing to an unknown portion of the out-of-sample error observed in the stock-recruit models.

The best stock-recruitment models from our study left a larger amount of unexplained variability in outmigrants per spawner, and did not produce highly accurate or precise forecasts of outmigrant abundance. These findings were not unexpected. There are many factors contributing to the net survival between egg-to-juvenile outmigration, but our models could only consider two covariates at a time (i.e., spawner abundance and one covariate). We did not evaluate models with more than one flow or temperature covariate owing to limitations in sample size. In addition, the extent of contrast in spawner abundance and covariate conditions across years was sometimes limited. Error and biases in outmigrant and spawner abundance estimates used in the analysis would also obscure stronger underlying relationships. The reliability of spawner-outmigrant models should improve over time as more years of data accumulate, and with improvements to spawner and outmigrant enumeration programs.

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## Acronyms and Abbreviations

<b>Term</b>	<b>Definition</b>
CV	coefficient of variation
JPE	juvenile production estimate
spring-run	spring-run Chinook Salmon
LOOCV	leave-one-out cross validation
PLAD	probabilistic length at date
Delta	Sacramento–San Joaquin River Delta
RST	rotary screw trap
BT-SPAS	Bayesian Temporally Stratified Population Analysis System
°C	degrees Celsius

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## 1 Introduction

Spawner-juvenile outmigrant stock-recruitment relationships will be used as part of a model to provide a juvenile production estimate (JPE) for spring-run Chinook salmon (*Oncorhynchus tshawytscha*) (spring-run) entering the Sacramento–San Joaquin River Delta (Delta). JPE predictions can be used by water managers to make operational decisions, or take other protective actions to minimize impacts.

Spawner-outmigrant models were fit to rotary screw trap (RST) data collected in Sacramento River tributaries used by spring-run, and at a mainstem site. Estimates of annual juvenile spring-run outmigrant abundance are available from the recently developed BT-SPAS-X (Chapters 4 and 5) and probabilistic length-at-date (PLAD) (Chapter 6) models. Estimates of annual spawner abundance are available from a variety of surveys, including upstream passage counts, redd counts, swim surveys of holding adults, and carcass surveys. A stock-recruitment model fit to such data describes the relationship between spawning stock abundance and the resulting freshwater juvenile production measured at an RST. This relationship describes the expected (average) juvenile outmigrant abundance for a given number of spawners. Environmental covariates, such as flow or temperature during the spawning and incubation period, can be added to the model to explain variation around the average stock-recruitment curve. A forecast of juvenile outmigration abundance at an RST can be made using estimated parameters of the stock-recruitment relationship and the observed spawner abundance in the forecast year. Predictions of environmental conditions can also be included in the model to potentially improve the accuracy of the outmigrant forecast. In the JPE model, abundance of spring-run juveniles at the Delta (the JPE) can be calculated by multiplying the forecasted abundance at the RST from spawner-outmigrant models by a survival rate between the RST and the Delta based on predictions from a survival model fit to acoustic telemetry data (Chapter 9). This procedure can be repeated across spring-run tributaries to calculate the total JPE. It is also possible to use a mainstem-based stock-recruitment relationship to directly predict a JPE.

This chapter describes the structure, fit, and predictive accuracy of spawner-outmigrant stock-recruitment models applied to the data from five tributary RST sites and one mainstem site. We summarize the effects of spawner abundance and covariates on productivity, and compare models based on fit and out-of-sample forecast error statistics.

## 2 Methods

We predicted annual juvenile outmigrant abundance at an RST site using a Ricker stock-recruit model with a covariate effect. We chose a Ricker model rather than the Beverton-Holt model because it is most commonly used for salmon stock-recruit models and more ably captures the over-compensation observed in salmon due to factors like density-dependent superimposition of redds or disease outbreaks caused by limited spawning habitat, although other model configurations could be explored in the future if warranted by the data. We used the following form of the Ricker model, which accounts for both density-dependent effects of spawner abundance and abiotic environmental effects (e.g., flow and temperature) on survival rates between spawning and juvenile outmigration (productivity).

### Equation 1.

$$R_t = S_t \cdot e^{\alpha + \beta \cdot S_t + \gamma \cdot X_t}$$

Where:

$R_t$  is the abundance of outmigrants (recruits) produced from spawners ( $S$ ) in brood year  $t$  (recruits)

$\alpha$  is the log of the maximum number of outmigrants produced per spawner when there are no density effects ( $S \rightarrow 0$ ) under average environmental conditions

$\beta$  is a density-dependent effect of spawner abundance, and

$\gamma$  is an effect of environmental covariate  $X_t$  (refer to Equation 7.7.5 of Hilborn and Walters 1992)

As  $X_t$  is a standardized ( $X_t = \frac{x_t - \mu}{\sigma}$ , where  $\mu$  and  $\sigma$  are the mean and standard

deviation of values across years and  $x_t$  are the raw covariate values), this formulation results in a base recruitment curve at the mean level of the covariate value since the standardized value would be 0 (thus  $\gamma \cdot X_t = 0$ ). At the average covariate condition, the maximum number of outmigrants produced per spawner is  $e^\alpha$  (the slope of the spawner-outmigrant curve near the origin). For example,  $\alpha = 7$  translates to a maximum productivity of approximately 1,000 outmigrants/spawner. The survival rate from the RST location (where outmigrant abundance is calculated) to adult return would need to be greater than or equal to 0.001 (0.1%) for population replacement at this level of productivity (i.e., one spawner will produce 1,000 outmigrants, which will result in one spawner returning).

Note that the product of  $\gamma$  and  $X_t$  represents the shift in  $\alpha$  in year  $t$  caused by the environmental covariate value in that year (e.g.,  $\alpha + \gamma \cdot X_t$ ). Thus, covariate effects shift this maximum rate up or down. As carrying capacity in this form of the Ricker model is proportional to  $\alpha/\beta$ , the additive covariate effect on  $\alpha$  also results in a change in carrying capacity.

The Ricker spawner-outmigrant model was fit by transforming Equation 1 into linear form following the approach of Hilborn and Walters (1992, in Equation 7.6.11):

### Equation 2a.

$$\log\left(\frac{\widehat{R}_t}{S_t}\right) = \alpha + \beta \cdot S_t + \gamma \cdot X_t + \epsilon_t$$

Where:

$\log\left(\frac{\widehat{R}_t}{S_t}\right)$  is the predicted outmigrants per spawner in log space, and

$\epsilon_t$  is a normally distributed annual random deviate drawn from a zero-centered normal distribution with a standard deviation  $\sigma_p$  ( $\epsilon_t \sim \text{normal}(0, \sigma_p)$ ).

$\sigma_p$  represents the magnitude of unexplained process error. That is, the magnitude of interannual variation in  $\log\left(\frac{\widehat{R}_t}{S_t}\right)$  that cannot be explained by density-dependent and covariate effects. Note that if spawner abundance is represented by total egg deposition, Equation 2a predicts the more intuitive log of survival from egg-to-juvenile outmigration.

Simplified versions of Equation 2a were used to quantify the potential gains in fit and predictive ability by accounting for density-dependent and covariate effects on productivity:

### Equation 2b.

$$\log\left(\frac{\widehat{R}_t}{S_t}\right) = \alpha + \epsilon_t$$

### Equation 2c.

$$\log\left(\frac{\widehat{R}_t}{S_t}\right) = \alpha + \beta \cdot S_t + \epsilon_t.$$

Equation 2b is referred to as model “mu” because the only fixed effect is the estimated mean of the log of recruits per spawner. Note that productivity does not depend on spawner abundance for this model. Equation 2c, referred to as the null model, includes the effect of spawner abundance on productivity (i.e., density-dependent effects). It is referred to as the null model because it does not include a

fixed covariate effect and can therefore be used to quantify potential improvements from adding a covariate. Finally, we also considered a discrete version of the Ricker covariate model (Equation 2a):

**Equation 2d.**

$$\log\left(\frac{\widehat{R}_t}{S_t}\right) = \alpha + \beta \cdot S_t + \gamma_{X_t} + \epsilon_t$$

Where:

$X_t$  is an index from one to the number of unique levels of  $X$ , with a specified level for each year  $t$ .

This model is used to quantify the effects of discrete variables like water year type. In Equation 2d, we fix  $\gamma_1$  to zero; thus  $\gamma$  values for higher levels (2 and 3) represent the change in log productivity for a group relative to the lowest level.

The data likelihood used to estimate model parameters is:

**Equation 3.**

$$\text{obs\_log}\left(\frac{R_t}{S_t}\right) \sim \text{normal}\left(\log\left(\frac{\widehat{R}_t}{S_t}\right), \sigma_{\text{obs}}\right)$$

Where:

$\text{obs\_log}\left(\frac{R_t}{S_t}\right)$  and  $\sigma_{\text{obs}}$  are the mean and standard deviation of the observed log of outmigrants per spawner, calculated based on posterior distributions of juvenile outmigration abundance determined from BT-SPAS-X and PLAD models, and the observed number of spawners.

Error in annual spawner estimates could not be incorporated into the calculation since they are not available. Thus, observation error is solely driven by uncertainty in the annual outmigration estimate. The use of observation error in the data likelihood allows separation of observation and process error ( $\sigma_p$ ). The magnitude of process error will be smaller after accounting for observation error effects in the data likelihood because some of the deviation between predictions and observations of  $\log(R/S)$  is recognized as coming from observation error.

Stock-recruit models were fit to data from RST sites (Figure 1) in a number of tributaries with spring-run, which included:

- Battle Creek
- Upper Clear Creek
- Mill Creek

- Deer Creek
- Butte Creek (at Parrot-Phelan Dam)
- Yuba River (at Hallwood Boulevard)
- RST site in the mainstem Sacramento River at Knights Landing

Estimates of the annual number of outmigrant (fry + smolt) spring-run at each site were calculated using BT-SPAS-X (Chapters 4 and 5) and PLAD (Chapter 6) models and were used as the measure of annual recruits. Yearling spring-run (age 1+) were excluded from outmigrant abundance estimates because outmigrant sampling at RSTs is not effective for these larger juveniles.

Fits to data from Feather River will be provided in a forthcoming analysis when results from the PLAD model predicting spring-run proportions in RST catches are available. Weekly estimates of juvenile spring-run abundance are currently not available for RST sites on the Feather River. Work is ongoing to apply the PLAD model (Chapter 6) to data from the Feather River, which is more challenging than application at other RST sites due to a more complicated run structure and to the release of large numbers of hatchery-origin spring-run juveniles upstream of the RST sites.

The spawner abundances used for the stock-recruit modeling were based on estimates from the recommended enumeration method(s) for each tributary provided by regional monitoring teams: redd counts and upstream passage for both Battle and Clear creeks, redd counts for Mill Creek, holding counts for Deer Creek, and carcass survey estimates for Butte Creek and the Yuba River. Selection of enumeration depended partly on the number of years for which each data type was available and overlapped with years for which outmigrant RST data were available, which is a requirement for use in stock-recruit modeling (refer to Table 2 and [Draft Summary of Data Used in JPE](#) for more detail on overlapping data availability).

Spawner abundance for the Knights Landing stock-recruit analysis required summing annual spawner estimates from the five tributaries with confluences upstream of Knights Landing (Figure 1). However, a consistent set of adult abundance estimates based on one method from all these tributaries was not available because upstream passage estimates in Butte, Mill, and Deer creeks were not considered reliable by regional monitoring teams. Thus, we indexed spawner abundance contributing to juvenile production at Knights Landing based on the sum of annual upstream passage estimates from Battle and Clear creeks only. This requires the assumption for the stock-recruit analysis for Knights Landing that the interannual trend in upstream passage estimates from these two tributaries adequately represents the trend in total spawner abundance from all tributaries contributing to juveniles at Knights Landing.

A series of annual covariates were calculated to represent flow or temperature conditions potentially influencing survival rates during specific life stages (Table 1). For sites in tributaries, this included the spawning and incubation phase (August–

December, denoted by prefix “si” in covariate names) and the early rearing phase from emergence to outmigration (November–July, with prefix “rr”). The hypotheses associated with each covariate are provided on the [spring-run JPE GitHub website](#). We also calculated covariates for the mainstem analysis based on temperatures in the mainstem Sacramento River during adult upstream migration (March–May, prefix “mi”), and using flow statistics during the period that fry and smolts are in the mainstem (January–July, prefix “rr”), as determined from an outmigration timing model for Knights Landing (Korman et al. 2025c). For both tributary and mainstem sites, we used water year type to demonstrate how the stock-recruit model can incorporate effects of discrete covariates. A water year’s type is determined using [multiple factors related to water availability](#); water year type in order from low to high water availability are:

- Critical (C)
- Dry (D)
- Below normal (BN)
- Above normal (AN)
- Wet (W)

In the examples presented in this chapter, we modeled discrete levels for water year type in two different ways following:

- Water year type model WY<sub>a</sub>: Level 1 for water year types C or D, level 2 for water year type BN, and level 3 for water year types AN or W
- Water year type model WY<sub>b</sub>: Level 1 for water year type C, level 2 for water year types D or BN, and level 3 for water year types AN or W

Water years extend from October of the prior calendar year to September of the current calendar year (e.g., Water Year [WY] 2020 is determined from flows between October 1, 2019 to September 30, 2020).

For modeling, water years were aligned with brood years (e.g., brood year 2020). The hypothesis behind this alignment was that the majority of inflows in a water year occur from December through May (as either rainfall or snowpack), which determines the level of reservoir storage in spring and summer, which in turn determines flow and temperature conditions for spring-run downstream of reservoirs during spawning and incubation. Note that water year type models were built partly as a placeholder to demonstrate how discrete models can be used to make a forecast of outmigrant abundance, as forecasting the value of a continuous covariate may not be possible or may be highly uncertain. Ongoing analyses are exploring the development and modeling of alternative discrete flow and/or temperature covariates based on continuous data.

Models were fit in the Stan Bayesian statistical modeling software (Stan Development Team 2023). Acceptable convergence, as assessed by the Gelman-Rubin convergence statistic (Gelman et. al., 2004,  $\hat{r} < 1.05$ ), was achieved by running three chains for 1,000 iterations. Uninformative zero-centered normal priors with standard deviations of 1,000 were used for all parameters except  $\sigma_p$ , where a uniform prior with a lower limit of 0.01 was used. Estimates of  $\beta$  were constrained so they could not exceed zero (i.e., we assume outmigrant abundance/spawner cannot increase with increasing spawner abundance).

We fit 16 different models to data from tributary RST sites. This included model mu (no effects of spawner abundance or covariates on productivity), the null model (only a spawner effect on productivity), two discrete water year type models (WYa and WYb), and 12 continuous covariate models. We fit 11 models to the data from the Knights Landing RST site, which included mu and null models, two discrete covariate models (water year type), and seven continuous covariate models.

Models were compared using a variety of statistics. Model fit was evaluated based on the square of the Pearson correlation coefficient ( $r^2$ ) calculated based on predicted and observed log(R/S), and the magnitude of the estimated unexplained process error ( $\sigma_p$ ). The reliability of covariate effects was assessed in part based on the increase in the Pearson correlation coefficient and reduction in process error for each covariate model relative to the null model. As annual covariate values were standardized, differences in the magnitude of the median of the posterior distribution of  $\gamma$  (the covariate coefficient) among models reflect differences in the magnitude of covariate effects on productivity. The certainty of  $\gamma$ , as indexed by the 95% credible interval and the coefficient of variation (CV) of the posterior distribution of  $\gamma$ , was used to determine the reliability of estimated covariate effects.

We evaluated the error in forecasts of juvenile outmigration abundance from stock-recruit models using both in-sample and out-of-sample approaches. For the in-sample approach, we generated an annual forecast of outmigration using the average historical spawner abundance as a placeholder for the observed spawner abundance in a forecast year. We assumed the forecast of the covariate was equal to the historical average covariate conditions (thus  $\gamma \cdot X[i] = 0$ ). Forecasted juvenile abundance included the effects of uncertainty in parameter estimates and simulated process error as determined from the model fit to all years of available data. Predictions are not impacted by uncertainty in the  $\gamma$  parameter because we assumed an average covariate condition in the forecast year.

We used a leave-one-out cross validation (LOOCV) approach to calculate the out-of-sample error in annual forecasts of juvenile abundance from stock-recruit models. The analysis was conducted in six steps for each RST site and model (e.g., null, covariate 1, etc.) as follows:

1. We estimated stock-recruit parameters leaving out one year of data from the full set of years available to fit the model (n years). This process was repeated for each year, resulting in n different model fits based on n-1 years of data.
2. We used the posterior distribution of model parameters for each n-1 fit to forecast juvenile outmigrant abundance in the year left out of the fitting. The observed spawner abundance in the year left out of the fitting was used as the input spawner abundance to the stock-recruit model, and if fitting a covariate model, the historical covariate value for that year was used in the forecast. Note that some covariate values would not be available at the time of a JPE forecast and the covariate value itself would need to be forecasted (e.g., covariates describing upcoming winter or spring environmental conditions that have not occurred yet). As with the in-sample analysis, predictions of outmigrant abundance included effects of process error.
3. The difference between the forecasted annual juvenile abundance and the “observed” annual abundance in the left-out year was then calculated. Note uncertainty in the “observed” estimate of spring-run juvenile abundance based on predictions from BT-SPAS-X and PLAD was included in the calculation. Given posterior distributions of both forecasted (predicted) and observed (observed) juvenile abundance in the left-out year, a posterior distribution of differences (predicted-observed) was calculated.
4. Two statistics for each left-out-year were computed from the distribution of differences calculated in Step 3): a) the median of the absolute values of differences ( $diff=abs(predicted-observed)$ ); and b) the median of the absolute value of relative differences ( $reldiff=100*abs(predicted-observed)/observed$ ). The latter statistic allows for comparisons of accuracy across RST sites and across years within sites since it is not impacted by the scale of outmigrant abundance.
5. Finally, we summarized the annual predictions of out-of-sample error by taking the across-year medians of median diff and reldiff values from Step 4.

### 3 Results

There was considerable variation in the available sample sizes to fit stock-recruitment models (Table 2). The Battle and Clear creek, Butte Creek, and Knights Landing sites had relatively large sample sizes ( $n \sim 15-20$  years) because there were many years of outmigrant estimates and considerable overlap with the years spawner data were available. A common rule of thumb to determine the minimum sample size for a statistical model is 10–20 points per parameter. Thus, a sample size of 20 years would be considered a minimum to reliably estimate the two parameters of the null stock-recruitment model ( $\alpha$  and  $\beta$ ), but would be considered insufficient to estimate the three parameters of covariate models ( $\alpha$ ,  $\beta$ , and  $\gamma$ ). There were only four years with both outmigrant and reliable spawner abundance data (redd counts) for Mill Creek, which is an inadequate sample size ( $n=4$ ) to estimate stock-recruit parameters. Sample sizes were modest for Yuba River ( $n=7$ ) and Deer Creek ( $n=12$ ) sites and well below the rule of thumb of sample size needed for both null and covariate models.

We examined the correlation among annual values of environmental covariates to help interpret differences in stock-recruitment model results and to guide further model development. Covariates with higher correlations are expected to provide similar fits and predictions of outmigrant abundance. Future development of stock-recruitment models that include more than one covariate would need to be restricted to pairs of covariates with limited covariation. Temperature-based covariates during the spawning and incubation period were often highly correlated (Pearson  $r > 0.7$ , Figure 2). There were also some high correlations among flow-based metrics both within and between spawning-incubation and rearing periods (e.g., *si\_max\_flow* vs *rr\_max\_flow*). Temperature- and flow-based covariates were sometimes negatively correlated (e.g., *si\_weekly\_max\_temp\_max* and *si\_min\_flow*). Highly correlated covariate pairs varied among RST sites the magnitude of correlations and the variables that were highly correlated (Appendix A).

Stock-recruitment models were compared based on fit statistics ( $r^2$ ,  $\sigma_p$ ), covariate effect size ( $\gamma$ ), and out-of-sample error in predicted juvenile abundance (LOOCV, Table 3). Models that fit the data better (higher  $r^2$ ) had less unexplained variation (lower  $\sigma_p$ ), and tended to have lower out-of-sample error (MAE\_rel; i.e., better predictive accuracy). Covariate models that fit the data better and had lower out-of-sample error compared to the null model (no covariate effect) had covariate effect sizes ( $\gamma$ ) with medians further from zero and were more precisely defined (lower CV, credible intervals not spanning zero). The best stock-recruitment models we estimated only explained a moderate amount of variation in log outmigrants/spawner ( $r^2 \sim 0.4-0.7$ ), and had relatively high out-of-sample error in predicting outmigrant abundance (MAE\_rel  $\sim 50-100\%$ ). Surprisingly, flow- and temperature-based covariates sometimes led to only modest improvements in

model fit, and in many cases did not reduce out-of-sample error in outmigrant abundance predictions. In a number of cases, models that included density-dependent effects on productivity did not improve out-of-sample error (models mu versus null). Summaries of site-specific results are provided below.

### Battle Creek

The best-fitting models explained moderate amounts of the variation in the log of outmigrants/spawner ( $r^2 \sim 0.4-0.5$ , Tables 3a and 3b, and Figures 3a and 3b). There was evidence for negative effects of higher temperature (si\_gdd\_spawn, si\_weekly\_max\_temp\_) on productivity for the stock-recruit model based on upstream passage. High flows during spawning and incubation (redd-based model) and rearing (upstream passage-based model) had negative effects on productivity, and some led to improvements in out-of-sample accuracy. Covariate effect sizes for the models with the highest out-of-sample accuracy were uncertain (lowest CV approximately 0.4–0.5). The mu model, which does not include effects of spawner abundance or covariates on productivity, had out-of-sample errors close to or as low as models that included spawner and covariate effects.

### Upper Clear Creek

Spawner abundance and covariates explained very little of the variation in the log of outmigrants/spawner (highest  $r^2 \leq 0.13-0.26$ ; Tables 3c and 3d, and Figures 3c and 3d). There was a very limited range in spawner abundance over the majority of years, which likely contributed to the limited utility of spawner abundance for predicting variation in productivity.

Covariate effects had means that were generally close to zero and all estimates were very uncertain. Fits were better and out-of-sample error was lower for the best models based on redd counts compared to best models based on upstream passage. The best-fitting model based on redd counts predicted a decrease in juvenile productivity with an increase in water temperature over the spawning and incubation period (si\_weekly\_max\_temp\_median). However, this model had similar out-of-sample accuracy to the mu model (MAE\_rel=67%). The best out-of-sample accuracy among mu models was based on upstream passage.

### Deer Creek

This site had some of the best-fitting stock-recruitment models and some of the best out-of-sample accuracy compared to models from most other RST sites (Table 3e and Figure 3e). Productivity increased as the day- and week-of-year when water temperature first exceeded 13 Celsius (°C) occurred later in the season (si\_above\_13\_temp\_ day or week). These covariates explained 63–69% of the variation in the log of outmigrants/spawner, and the effects sizes were well above zero and relatively precisely defined (CV = 0.32–0.38). Relative out-of-sample error in predicting outmigrant abundance was less than 50% for these models, which was

considerably lower compared to the mu (70%) and null (64%) models and the other covariate models for Deer Creek. Spawner abundance was also an important determinant of productivity. This was evident based on the lower forecast error of the null model relative to the mu model. Effects of spawner abundance on outmigrant abundance are also apparent in the estimated relationship between the covariate value and outmigrant abundance (Figure 4). Note that large outliers from the relationship had unusually low (brood years 2008 and 2023) or high (brood year 2006) spawner abundances, and that these spawner effects were well-predicted by the model (blue lines).

### Mill Creek

Stock-recruit results are not reliable for this site owing to the very limited number of years available for the analysis (n=4, Table 3f).

### Butte Creek

This site produced some of the most convincing stock-recruit models relative to other sites given the moderate sample size (n=15 compared to n=10 for Deer Creek), moderate fit for some models ( $r^2 \sim 0.6$ ), well-defined covariate effect sizes (CV approximately 0.3), and moderate levels of out-of-sample accuracy (approximately 60–75%; Table 3g and Figure 3f). Similar to Deer Creek, out-of-sample error for the best covariate models (61–67%) was considerably lower than those for mu and null models (87%). Also similar to Deer Creek, the model predicted that productivity increased with the day- and week-of-year that temperatures first exceeded 13 °C. Some flow-based models indicated that productivity increased with flow. One of the discrete water year type models (WYb, which places critical years in their own level) also had good fit and out-of-sample error statistics, and predicted considerably higher productivity in above normal and wet years compared to critical years.

### Yuba River

Results from this site are not reliable given the low sample size (n=7). The relatively good fits for some covariate models ( $r^2$  of approximately 0.555–0.75) are not surprising given that three to four parameters are used to fit seven data points. This inadequacy is reflected in the low precision of covariate effect sizes. Out-of-sample accuracy was low for all models (relative error greater than or equal to 95%; Table 3h and Figure 3g). Given the low sample size, mu and null models are likely the most reliable models for forecasting abundance at this site until more data becomes available.

## Knights Landing

Covariate models resulted in very modest improvements in fit relative to the null model ( $r^2 = 0.28$  versus 0.21), and effect sizes were very poorly defined (CV greater than 0.7; Table 3i and Figure 3h). Out-of-sample error was moderate, with the mu model having the lowest out-of-sample error (52%). Owing to the difficulty of quantifying spawner abundance for mainstem stock-recruit models (refer to Section 2), predicting outmigrant abundance based on model mu would likely be necessary.

An examination of the posterior distributions for Knights Landing's most predictive model highlights important aspects of parameter estimation for the stock-recruit models generally (Figure 5; refer to Appendix B for results for all RST sites). Posterior distributions were generally well-defined relative to their uninformative normal distributions, though the effect of the non-positive constraint on  $\beta$  was sometimes apparent (note that the upper limit of posterior at 0 for some models).

Similar to many of the stock-recruit relationships we examined, Knights Landing had a negative correlation between posterior samples of  $\alpha$  and  $\beta$ . Owing to the scatter in spawner-outmigrant data points (Figure 3h), the model can partially explain the data based on a more linear stock-recruitment curve which would show lower productivity (lower initial slope) and less density-dependence (straighter line), or vice versa (higher productivity and more density-dependence reflected by a line that is more asymptotic). The model shown for Knights Landing (Figure 5) was one of the few cases with a modest correlation between the magnitude of density-dependent ( $\beta$ ) and covariate ( $\gamma$ ) effects. That is, the model could explain variation in the observed productivity based on a weaker density-dependent effect (closer to zero) combined with a stronger covariate effect (further from zero), or vice versa.

This cause for this correlation is apparent in Figure 3h, which shows that the observation for brood year 2021 can be fit by a model with a weaker density effect combined with a stronger covariate effect (straighter black line combined with longer colored vertical lines), or the vice versa (more bend in black line with shorter vertical lines). In this example, covariate and density-dependent effects are partially confounded because the brood year with the highest spawner abundance also experienced some of the most extreme covariate conditions.

The limited range of spawner abundance for the majority of the dataset contributed to the correlation between parameters. This highlights that the reliability of stock-recruit parameters depends on the range of spawner and covariate values that are observed over the time series as well as the number of points in the time series. For example, a site with a large sample size may not provide a reliable estimate of spawner abundance effects on productivity if the range of spawner abundances over the time series is low.

Estimates of maximum productivity from the stock-recruit analysis can be used to calculate egg-outmigrant survival rates to compare with estimates from other studies to determine whether productivity estimates from the stock-recruitment models are realistic (Table 4). For example, maximum productivity ( $e^\alpha$ ) for the Battle Creek model based on upstream passage spawner estimates was 276 outmigrants/spawner. Assuming 2,572 eggs per spawner, based on data in Table G-1 from Stillwater Sciences (2012) leads to a prediction of a maximum egg-outmigrant survival rate of 11% ( $276/(1 \text{ spawner} * 2752 \text{ eggs/spawner})$ ). Egg-to-smolt survival rates for RST sites other than Yuba River and Knights Landing ranged from 11–32%. The magnitude of these survival rates are comparable to the eff-to-age 0 smolt survival rate (7%) calculated from life-stage specific survival rates used in a Yuba River spring-run life cycle model (Stillwater Sciences 2012). Maximum egg-outmigrant survival at Upper Clear Creek sites were higher than for other tributary sites, perhaps because the Upper Clear Creek RST largely captures newly emerged fry. The maximum outmigrants/spawner estimate for Knights Landing was unrealistically high, but this was expected as spawner estimates did not include escapements to Mill, Deer, and Butte creeks. Similarly, Yuba River outmigrants/spawner estimate was unrealistically high, and the cause of this is currently being investigated. The PLAD-based estimates of spring-run proportions at Knights Landing used in this chapter are biased high, which also leads to overestimation of egg-to-smolt survival rate. At Battle and Clear creeks, outmigrants/spawner was higher based on models, which used redds to index spawner abundance compared to models which used upstream passage. These differences could be driven by biases in the estimated spawner abundance (e.g., overestimation of spawner abundance from redds due to double counting, or underestimation from upstream passage due to some fish bypassing the counting facility), or by pre-spawn mortality between passage and spawning.

To better understand the factors influencing forecast error, we calculated the in-sample uncertainty in outmigrant forecasts using the most predictive models for each site. Uncertainty in forecasts for all sites except Yuba River (low sample size) was relatively low ( $CV < 0.3$ ) if forecasts only considered uncertainty in model parameters ( $\alpha$ ,  $\beta$ , and  $\gamma$ ; Table 5). In-sample CVs of outmigrant abundance forecasts increased by four- to six-fold when the effects of process error (unexplained by parameters) was included in the forecast. Thus, the majority of uncertainty in outmigrant abundance forecasts is driven by high levels of error not explained by fixed effects of spawner abundance and covariate. This highlights the importance of identifying models that explain more of the variation in the log of outmigrants/spawner.

To better understand the factors driving out-of-sample error in outmigrant abundance predictions, we plotted relative error for each out-of-sample year for the null and best covariate stock-recruit model for Deer Creek (Figure 6). The covariate model predicted higher productivity with increases in the week-of-year when water temperature first exceeded 13 °C, (Figure 4), and had a lower across-year median

of relative out-of-sample error than the null model (Figure 6). The covariate model had lower out-of-sample error compared to the null model for seven of 10 years, when covariate values were substantively lower or higher than the across-year mean value (standardized value = 0). This pattern occurred because the covariate relationship was relatively well defined (Figure 4), so dropping a year did not result in a substantive change in the covariate effect size. This in turn resulted in the covariate model outperforming the null model in years when covariate values were substantively lower or higher than the mean value across years.

## 4 Discussion

Spawner-outmigrant stock-recruitment models provided at best only moderate fits to the data, which led to relatively higher error in forecasts of outmigrant abundance. Surprisingly, flow- and temperature-based covariates only improved out-of-sample prediction error at Deer and Butte creek RST sites. The mu model, which did not include effects of spawners or covariates on productivity, had the best out-of-sample accuracy for Battle and Clear creeks and at Knights Landing.

Including the effects of spawner abundance on productivity generally led to only modest improvements in fit and predictive accuracy relative to the mu model at the other sites. One explanation here is that spawner abundance during the period the model was fit to was far from carrying capacity, resulting in negligible density-dependent effects on egg-outmigrant survival rates. It is also possible that unaccounted bias in spawner abundance estimates is obscuring its effect on outmigrant/spawner productivity.

Covariate effects varied among RST sites but were generally consistent with the hypothesis that freshwater productivity for Chinook salmon in Central Valley streams declines with warmer water temperatures, lower flows, or with high peak flows. Restricting comparisons to reliable covariate estimates (CV less than or equal to 0.5), models for Battle and Clear creeks indicated negative effects of higher temperatures during the spawning and incubation period on productivity, and negative effects of higher flows during spawning-incubation and rearing periods on productivity. Models from Deer and Butte creeks also showed negative effects of higher temperatures on productivity (productivity increased with the date when temperatures exceeded 13 °C). Models from Butte Creek showed increases in productivity with higher flows during spawning-incubation and rearing periods, and higher productivity in wet years. Flow and temperature effects on productivity were not observed at all RST sites, or were highly uncertain. It is possible that covariate effects were masked by uncertainty/biases in outmigrant and spawner estimates, or inadequate sample size or contrast in covariate values.

Predicting outmigrant abundance from stock-recruitment models requires estimates of spawner abundance and covariate conditions in the year a forecast is being made. Data to calculate flow- and temperature-based covariates during the spawning-incubation period would likely be available by early January when an initial forecast may be needed. However, flow conditions during the rearing period would need to be predicted and would likely be uncertain. With the exception of Deer and Butte creeks, the mu or null models had the best out-of-sample accuracy. One benefit of this result is that outmigrant forecasts would not require forecasts of covariate conditions. Note that the null model still requires an estimate of spawner abundance in the forecast year to predict outmigrant abundance even though spawner abundance is not needed to predict productivity (note S in Equation 1 even if the  $\beta \cdot S$  term is removed).

Our analysis highlights some of the challenges of fitting a stock-recruitment model to data from RST sites in the mainstem Sacramento River. This requires estimating spawner abundance from all tributaries upstream of the mainstem site in the same years. In our application, this requirement substantially reduced the sample size of stock-recruit points for Knights Landing, forcing us to index spawner abundance based on data from only two of five tributaries contributing to juvenile production at this site. This led to a gross overestimate of productivity, and likely impacted the reliability of estimates of spawner abundance and covariate effects on productivity.

In addition, our analysis only considered covariate effects in the mainstem. We did not attempt to create a composite of tributary-based covariate values. This would require weighting each tributary covariate value by a factor reflecting the contribution of its outmigrant abundance to the outmigrant abundance at the mainstem RST site. Ultimately, these weighting factors would depend on the relative outmigrant production from each tributary adjusted for differential survival rates in the mainstem. Forecasting such tributary-weighted covariate values would be even more problematic as the weighting factors for the forecast year would not be known. Thus, tributary-specific stock-recruitment relationships, combined with routing predicted juvenile outmigrant abundance to the Delta via mainstem survival estimates (Chapter 9), will provide a more reliable approach to predict JPEs compared to using a mainstem stock-recruitment relationship. Outmigrant estimates from mainstem RSTs will still be useful as an out-of-sample check on routed tributary-based outmigrant estimates.

Additional work on spawner-outmigrant stock-recruit modeling is required. Sample size could be substantially increased for some RST sites if missing years of spawner data are filled-in. For example, our original assessment for Mill Creek was based on 12 stock-recruit pairs. Recent quality assurance of the data revealed that eight of these years did not include one of the reaches where redds are counted. When the dataset was trimmed to exclude these years to provide a more consistent time series of spawner abundance, the sample size for the stock-recruit modeling was reduced to only four years, which was inadequate for stock-recruit analysis. In future efforts, the missing data for this reach could be infilled using a model that estimates the proportion of counts in the missing reach based on data from years when all reaches were sampled. However, there could be substantial error in the infilled estimates if the proportion of redd counts in the missing reach is highly variable over years.

Future efforts could focus on improving methodologies and analytical approaches to provide more reliable estimates of annual spawner abundance in all tributaries. The reliability of spawner abundance estimates based on redd and holding spawner counts is impacted by unknown variation in survey life and observer efficiency across years. Upstream passage estimates do not always account for negative bias related to fish bypassing counting facilities during high flows. Developing models that account for these issues should provide more reliable estimates of spawner

abundance and quantify uncertainty in estimates. State-space approaches to fit stock-recruit models have been developed to account for uncertainty in stock size (spawner) estimates to avoid bias and underestimation of uncertainty in parameters (e.g., Staton et al. 2017). We could not employ this approach in our analysis because estimates of uncertainty in annual spawner abundance estimates were not available.

The best stock-recruitment models from our study left a larger amount of unexplained variability in outmigrants per spawner, and did not produce highly accurate or precise forecasts of outmigrant abundance. These findings were not unexpected. There are many factors contributing to survival between egg-to-juvenile outmigration, but our models could only consider two covariates at a time (spawner abundance and one covariate) due to limitations in sample size. In addition, the extent of contrast in spawner abundance and covariate conditions across years was sometimes limited. The reliability of spawner-outmigrant models should improve over time as additional years of spawner and outmigrant abundance estimates become available. Reliability of stock-recruitment model inputs will also likely increase over time if adult sampling and RST programs implement improvements that increase certainty in spawner and outmigrant abundance estimates.

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## 5 Web Links

Spring-run JPE GitHub website  
([https://srjpe.github.io/SRJPEdata/articles/sr\\_covariates.html](https://srjpe.github.io/SRJPEdata/articles/sr_covariates.html))

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## 6 References

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## Tables and Figures

## Tables

**Table 1. Description of Covariates Used in the Spawner-Outmigrant Stock-Recruit Analysis**

Covariate	Description
si_gdd_spawn	Water temperature exposure during adult upstream migration, spawning, and incubation (August–December). Calculated by summing mean daily temperatures.
si_above_13_temp_day	Day of the year (1:365) when water temperature exceeds 13 °C.
si_above_13_temp_week	Week of the year (1:52) when water temperature exceeds 13 °C.
si_weekly_max_temp_max	Weekly maximum water temperature during spawning and incubation (August–December). Calculated by: 1) Calculating the maximum temperature for each day 2) Calculating the maximum weekly temperature based on a) 3) Calculating the maximum temperature between August and December based on b)
si_weekly_max_temp_mean	As for si_weekly_max_temp_max except except the mean is taken in Step 3).
si_weekly_max_temp_median	As for si_weekly_max_temp_max except except the median is taken in Step 3).
si_mean_flow	Mean flow during spawning and incubation (August–December). Calculated by taking the mean of mean daily flows.
si_max_flow	Maximum flow during spawning and incubation (August–December). Calculated by taking the maximum of mean daily flows.
si_min_flow	Minimum flow during spawning and incubation (August–December). Calculated by taking the minimum of daily maximum flows.
si_median_flow	Median flow during spawning and incubation (August–December). Calculated by taking the median of mean daily flows.
rr_mean_flow	Mean flow during juvenile rearing (November–July for tributaries, January–July for mainstem Sacramento). Calculated by taking the mean of mean daily flows.
rr_max_flow	Maximum flow during juvenile rearing (November–July for tributaries, January–July for mainstem Sacramento). Calculated by taking the maximum of mean daily flows.
rr_min_flow	Minimum flow during juvenile rearing (November–July for tributaries, January–July for mainstem Sacramento). Calculated by taking the minimum of mean daily flows.
rr_median_flow	Median flow during juvenile rearing (November–July for tributaries, January–July for mainstem Sacramento). Calculated by taking the median of mean daily flows.
WY <sub>a</sub> (C/D, BN, AN/W)	Water year classification with critical and dry years forming the first level.
WY <sub>b</sub> (C, D/BN, AN/W)	Water year classification with only critical years forming the first level.

Covariate	Description
mi_gdd_sacramento	Water temperature exposure during adult upstream migration in the mainstem Sacramento River (March–May), calculated by summing mean daily temperatures.
mi_above_13_temp_day	Week of the year (1:52) when water temperature exceeds 13 °C during the adult upstream migration in the mainstem Sacramento (March–May).
mi_above_13_temp_week	Day of the year (1:365) when water temperature exceeds 13 C during the adult upstream migration in the mainstem Sacramento (March–May).

**Table 2. Summary of Maximum Years of Data Type Availability for Stock-Recruitment Models Including Years of Overlap Between Juvenile Outmigrant and Adult Data Types**

Site	RST Outmigrant	Adult Passage	Redd Counts	Adult Holding	Adult Carcass	Outmigrant Passage Overlap	Outmigrant Redd Overlap	Outmigrant Redd Overlap	Outmigrant Carcass Overlap
Battle Creek	22	30	20			22	17		
Upper Clear Creek	18	25	24			16	17		
Mill Creek	13		16				4		
Deer Creek	12			32				12	
Butte Creek	19				24				15
Yuba River	7				24				7
Knights Landing	27					22 <sup>a</sup>			

<sup>a</sup> Based on the sum of annual upstream passage estimates for Battle and Clear creeks only.

**Table 3. Statistics for Spring-Run Chinook Salmon Spawner-Juvenile Outmigrant Stock-recruitment Relationships Fit to Data**

Statistics for spring-run Chinook salmon spawner-juvenile outmigrant stock-recruitment relationships fit to data from Sacramento River tributaries and the mainstem. 'n' and 'r<sup>2</sup>' show the number of years of data used to fit the models and the proportion of observed log outmigrants/spawner explained by the models without random effects.  $\sigma_p$  is the mean of the posterior distribution of the estimate of process error (unexplained variation in log(R/S)). Statistics for the posterior distribution of the covariate effect ( $\gamma$ ) include the lower 95% credible interval (LCI), median (med), and upper 95% credible interval (UCI), and the coefficient of variation (CV). For discrete versions of the covariate model (WY<sub>a</sub> and WY<sub>b</sub>), statistics for  $\gamma$  represent values for the last water year type (AN/W). Columns MAE and MAE\_rel show the median absolute error (abs(predicted-observed)) and median relative absolute error (100\*abs(predicted-observed)/observed) determined from LOOCV (out-of-sample error), respectively. Yellow-shaded rows identify models that have the lowest MAE\_rel values within a site-spawner data type set.

**Table 3a. Battle Creek—Redd Counts**

Yellow-shaded rows identify models that have the lowest MAE\_rel values within a site-spawner data type set; in Table 3a, those models are mu, null, si\_mean\_flow, si\_max\_flow, rr\_mean\_flow and rr\_median\_flow.

Covariate	n	r <sup>2</sup>	g-sp	g-LCI	g-med	UCI	CV	MAE	MAE_rel
mu	14	0.00	0.80	-	-	-	-	14	47%
null	14	0.12	0.78	-	-	-	-	12	49%
WY <sub>a</sub> (C/D, BN, AN/W)	14	0.29	0.80	-1.26	-0.24	0.74	2.16	19	67%
WY <sub>b</sub> (C, D/BN, AN/W)	14	0.16	0.86	-1.79	-0.24	1.34	3.25	16	60%
si_gdd_spawn	14	0.12	0.82	-0.55	-0.05	0.48	5.95	15	52%
si_above_13_temp_day	14	0.16	0.78	-0.58	-0.14	0.33	1.66	18	46%
si_above_13_temp_week	14	0.15	0.82	-0.68	-0.13	0.42	1.96	17	48%
si_weekly_max_temp_max	14	0.12	0.83	-0.54	-0.03	0.44	8.06	14	51%
si_weekly_max_temp_mean	14	0.14	0.81	-0.57	-0.11	0.35	2.1	15	53%
si_weekly_max_temp_median	14	0.12	0.83	-0.44	0.02	0.52	10.61	16	56%
si_mean_flow	14	0.43	0.64	-0.84	-0.43	0	0.49	12	43%
si_max_flow	14	0.44	0.63	-0.84	-0.45	-0.05	0.43	16	50%
si_min_flow	14	0.13	0.82	-0.52	-0.03	0.45	6.13	13	52%
si_median_flow	14	0.13	0.83	-0.59	-0.05	0.47	4.97	13	52%
rr_mean_flow	14	0.26	0.74	-0.72	-0.28	0.22	0.85	17	48%
rr_max_flow	14	0.24	0.76	-0.73	-0.28	0.2	0.91	16	51%
rr_min_flow	14	0.16	0.81	-0.31	0.17	0.68	1.35	18	52%

Covariate	n	r2	g-sp	g-LCI	g-med	UCI	CV	MAE	MAE_rel
rr_median_flow	14	0.24	0.76	-0.8	-0.27	0.19	0.88	18	48%

**Table 3b. Battle Creek—Upstream Passage**

Yellow-shaded rows identify models that have the lowest MAE\_rel values within a site-spawner data type set; in Table 3b, those models are mu, si\_gdd\_spawn, si\_weekly\_max\_temp\_mean, and rr\_max\_flow.

Covariate	n	r2	g-sp	g-LCI	g-med	UCI	CV	MAE	MAE_rel
mu	16	0.00	0.91	-	-	-	-	11	39%
null	16	0.27	0.80	-	-	-	-	10	46%
WY <sub>a</sub> (C/D, BN, AN/W)	16	0.38	0.80	-1.26	-0.17	0.92	3.15	17	66%
WY <sub>b</sub> (C, D/BN, AN/W)	16	0.28	0.88	-1.31	0.23	1.86	3	14	55%
si_gdd_spawn	16	0.40	0.73	-0.73	-0.31	0.11	0.69	10	39%
si_above_13_temp_day	16	0.30	0.80	-0.59	-0.17	0.33	1.39	11	43%
si_above_13_temp_week	16	0.29	0.81	-0.63	-0.14	0.33	1.69	11	44%
si_weekly_max_temp_max	16	0.42	0.74	-0.77	-0.34	0.13	0.67	14	50%
si_weekly_max_temp_mean	16	0.49	0.68	-0.83	-0.42	0.01	0.5	13	38%
si_weekly_max_temp_median	16	0.35	0.77	-0.72	-0.26	0.16	0.82	13	47%
si_mean_flow	16	0.42	0.74	-0.73	-0.34	0.13	0.67	13	45%
si_max_flow	16	0.50	0.68	-0.79	-0.41	-0.01	0.47	11	45%
si_min_flow	16	0.27	0.83	-0.54	0	0.53	103	11	48%
si_median_flow	16	0.27	0.82	-0.44	0.05	0.52	5.35	11	51%
rr_mean_flow	16	0.45	0.75	-0.86	-0.36	0.09	0.64	11	50%
rr_max_flow	16	0.40	0.74	-0.72	-0.3	0.16	0.73	10	37%
rr_min_flow	16	0.33	0.78	-0.18	0.25	0.68	0.92	12	51%
rr_median_flow	16	0.41	0.75	-0.79	-0.32	0.1	0.68	12	50%

**Table 3c. Upper Clear Creek—Redd Counts**

Yellow-shaded rows identify models that have the lowest MAE\_rel values within a site-spawner data type set; in Table 3c, those models are mu, si\_weekly\_max\_temp\_median, and rr\_max\_flow.

Covariate	n	r2	g-sp	g-LCI	g-med	UCI	CV	MAE	MAE_rel
mu	14	0.00	0.85	-	-	-	-	21	67%
null	14	0.13	0.93	-	-	-	-	22	71%
WY <sub>a</sub> (C/D, BN, AN/W)	14	0.00	1.06	-1.66	0.1	1.77	10.26	30	87%
WY <sub>b</sub> (C, D/BN, AN/W)	14	0.02	1.07	-1.91	0.25	2.16	4.88	30	88%
si_gdd_spawn	14	0.05	0.90	-0.88	-0.34	0.24	0.84	18	73%

Covariate	n	r2	g-sp	g-LCI	g-med	UCI	CV	MAE	MAE_rel
si_above_13_temp_day	14	0.01	0.93	-0.29	0.26	0.84	1.06	19	72%
si_above_13_temp_week	14	0.04	0.89	-0.33	0.32	0.85	0.91	18	69%
si_weekly_max_temp_max	14	0.06	0.98	-0.7	-0.1	0.49	3.2	22	80%
si_weekly_max_temp_mean	14	0.08	0.88	-0.95	-0.37	0.19	0.75	16	72%
si_weekly_max_temp_median	14	0.26	0.78	-1.07	-0.51	0	0.51	14	67%
si_mean_flow	14	0.01	0.95	-0.76	-0.2	0.34	1.39	20	81%
si_max_flow	14	0.02	0.94	-0.94	-0.26	0.27	1.06	17	77%
si_min_flow	14	0.06	0.99	-0.66	-0.08	0.5	3.62	25	77%
si_median_flow	14	0.02	0.99	-0.46	0.11	0.77	2.6	22	89%
rr_mean_flow	14	0.06	0.88	-0.94	-0.36	0.16	0.72	25	67%
rr_max_flow	14	0.16	0.84	-1.03	-0.48	0.1	0.59	23	65%
rr_min_flow	14	0.15	1.01	-0.53	0.08	0.66	3.77	24	75%
rr_median_flow	14	0.05	0.97	-0.71	-0.15	0.42	1.95	29	77%

**Table 3d. Upper Clear Creek—Upstream Passage**

Yellow-shaded rows identify models that have the lowest MAE\_rel values within a site-spawner data type set; in Table 3d, that models is mu.

Covariate	n	r2	g-sp	g-LCI	g-med	UCI	CV	MAE	MAE_rel
mu	12	0.00	0.85					20	54%
null	12	0.00	0.93					22	69%
WYa (C/D, BN, AN/W)	12	0.03	1.07	-1.37	0.62	2.47	1.6	30	79%
WYb (C, D/BN, AN/W)	12	0.03	1.07	-1.83	0.46	2.55	2.47	32	94%
si_gdd_spawn	12	0.05	0.94	-0.88	-0.28	0.34	1.16	19	81%
si_above_13_temp_day	12	0.03	0.98	-0.46	0.21	0.89	1.59	19	68%
si_above_13_temp_week	12	0.03	0.93	-0.46	0.21	0.81	1.44	20	69%
si_weekly_max_temp_max	12	0.00	1.01	-0.88	-0.16	0.64	2.51	21	79%
si_weekly_max_temp_mean	12	0.13	0.87	-0.95	-0.37	0.25	0.8	17	70%
si_weekly_max_temp_median	12	0.07	0.95	-1	-0.32	0.37	1.06	18	78%
si_mean_flow	12	0.01	0.99	-0.87	-0.17	0.46	1.85	20	75%
si_max_flow	12	0.05	0.95	-0.99	-0.29	0.34	1.12	16	73%
si_min_flow	12	0.00	1.00	-0.62	-0.04	0.7	16.5	26	76%
si_median_flow	12	0.00	1.04	-0.82	-0.05	0.6	6.71	31	71%
rr_mean_flow	12	0.00	1.05	-0.76	-0.08	0.56	3.8	24	81%
rr_max_flow	12	0.01	1.00	-0.93	-0.12	0.49	2.56	22	73%
rr_min_flow	12	0.03	0.97	-0.91	-0.2	0.55	1.91	22	79%
rr_median_flow	12	0.00	1.00	-0.58	0.02	0.69	9.74	24	84%

**Table 3e. Deer Creek—Holding Counts**

Yellow-shaded rows identify models that have the lowest MAE\_rel values within a site-spawner data type set; in Table 3e, those models are si\_above\_13\_temp\_day, and si\_above\_13\_temp\_week.

Covariate	n	r2	g-sp	g-LCI	g-med	UCI	CV	MAE	MAE_rel
mu	10	0.00	0.98	-	-	-	-	277	70%
null	10	0.07	0.98	-	-	-	-	224	64%
WYa (C/D, BN, AN/W)	10	0.44	0.87	-1.61	0.08	1.53	12.61	232	71%
WYb (C, D/BN, AN/W)	10	0.47	0.90	-0.88	1.08	3.38	0.89	305	67%
si_gdd_spawn	10	0.10	1.18	-0.84	-0.2	0.67	2.37	317	76%
si_above_13_temp_day	10	0.63	0.67	0.16	0.67	1.18	0.38	138	48%
si_above_13_temp_week	10	0.69	0.58	0.23	0.68	1.09	0.32	136	45%
si_weekly_max_temp_max	10	0.25	0.95	-1.27	-0.46	0.24	0.81	196	66%
si_weekly_max_temp_mean	10	0.15	1.06	-1.08	-0.29	0.71	1.55	282	77%
si_weekly_max_temp_median	10	0.09	1.09	-0.96	-0.13	0.64	3.12	271	75%
si_mean_flow	10	0.06	1.06	-0.74	0.1	0.93	3.91	202	73%
si_max_flow	10	0.14	1.02	-0.95	-0.2	0.56	1.89	352	83%
si_min_flow	10	0.26	0.94	-0.3	0.47	1.13	0.78	275	71%
si_median_flow	10	0.23	0.97	-0.24	0.45	1.33	0.77	288	70%
rr_mean_flow	10	0.21	1.03	-1.15	-0.36	0.42	1.06	232	65%
rr_max_flow	10	0.22	0.98	-0.97	-0.34	0.45	1.09	190	55%
rr_min_flow	10	0.19	1.00	-0.41	0.32	1.09	1.17	212	71%
rr_median_flow	10	0.08	1.04	-0.74	0.04	0.82	11.25	311	75%

**Table 3f. Mill Creek—Redd Counts**

Yellow-shaded rows identify models that have the lowest MAE\_rel values within a site-spawner data type set; in Table 3f, those models are mu, WYb (C, D/BN, AN/W), si\_gdd\_spawn, and rr\_median\_flow.

Covariate	n	r2	g-sp	g-LCI	g-med	UCI	CV	MAE	MAE_rel
mu	4	0.00	3.08	-	-	-	-	5.94	38%
null	4	0.70	2.15	-	-	-	-	8.16	140%
WYa (C/D, BN, AN/W)	4	0.69	4.36	-4.73	-0.09	4.78	74.66	6.65	83%
WYb (C, D/BN, AN/W)	4	0.94	1.49	-4.77	-0.11	4.85	60.23	5.18	38%
si_gdd_spawn	4	0.77	3.79	-3.46	-0.54	4.01	6.60	6.99	37%
si_above_13_temp_day	4	0.74	7.65	-2.90	0.03	3.28	4.23	4.80	47%
si_above_13_temp_week	4	0.79	2.96	-3.78	0.56	3.73	5.09	7.47	29%
si_weekly_max_temp_max	4	0.85	3.47	-3.92	-0.56	3.16	2.91	7.20	51%

Covariate	n	r2	g-sp	g-LCI	g-med	UCI	CV	MAE	MAE_rel
si_weekly_max_temp_mean	4	0.91	2.53	-4.05	-0.67	2.41	1.97	7.22	88%
si_weekly_max_temp_median	4	0.99	2.11	-4.01	-0.96	2.92	1.56	5.98	87%
si_mean_flow	4	0.69	3.42	-3.59	0.00	4.09	17.91	9.77	222%
si_max_flow	4	0.78	2.40	-3.00	-0.58	2.72	4.56	6.61	81%
si_min_flow	4	0.66	4.81	-4.66	-0.37	3.63	3.83	6.39	54%
si_median_flow	4	0.70	2.99	-1.81	-0.13	2.89	66.33	7.47	123%
rr_mean_flow	4	0.93	2.78	-3.84	-0.96	2.60	1.49	7.74	91%
rr_max_flow	4	0.99	2.18	-4.33	-1.89	1.44	0.78	5.51	82%
rr_min_flow	4	0.80	4.81	-3.32	0.53	3.97	3.86	7.13	113%
rr_median_flow	4	0.85	3.13	-4.74	-2.22	2.72	0.96	7.16	35%

**Table 3g. Butte Creek—Carcass Estimates**

Yellow-shaded rows identify models that have the lowest MAE\_rel values within a site-spawner data type set; in Table 3g, those models are WYb (C, D/BN, AN/W), si\_above\_13\_temp\_day, si\_above\_13\_temp\_week, si\_min\_flow, si\_median\_flow, and rr\_min\_flow.

Covariate	n	r2	g-sp	g-LCI	g-med	UCI	CV	MAE	MAE_rel
mu	15	0.00	1.38	-	-	-	-	687	87%
null	15	0.09	1.37	-	-	-	-	639	87%
WYa (C/D, BN, AN/W)	15	0.36	1.27	-0.25	1.32	3.15	0.64	673	77%
WYb (C, D/BN, AN/W)	15	0.55	1.07	0.51	2.29	4.01	0.37	718	65%
si_gdd_spawn	15	0.28	1.27	-1.34	-0.56	0.19	0.68	441	90%
si_above_13_temp_day	15	0.61	0.89	0.43	0.92	1.42	0.27	488	67%
si_above_13_temp_week	15	0.60	0.93	0.42	0.91	1.5	0.3	532	65%
si_weekly_max_temp_max	15	0.32	1.24	-1.34	-0.61	0.12	0.62	1,198	91%
si_weekly_max_temp_mean	15	0.27	1.31	-1.36	-0.56	0.22	0.71	542	91%
si_weekly_max_temp_median	15	0.17	1.36	-1.11	-0.34	0.43	1.16	771	73%
si_mean_flow	15	0.10	1.42	-0.9	-0.03	0.82	15.94	750	87%
si_max_flow	15	0.16	1.36	-1.08	-0.29	0.58	1.49	597	85%
si_min_flow	15	0.57	1.00	0.23	0.9	1.44	0.33	518	61%
si_median_flow	15	0.52	1.06	0.16	0.86	1.61	0.42	602	67%
rr_mean_flow	15	0.16	1.35	-0.46	0.29	1.03	1.32	656	90%
rr_max_flow	15	0.11	1.41	-0.67	0.17	1.02	2.52	707	87%
rr_min_flow	15	0.38	1.18	0.03	0.72	1.38	0.5	778	63%
rr_median_flow	15	0.18	1.32	-0.32	0.42	1.19	0.89	884	90%

**Table 3h. Yuba River—Carcass Estimates**

Yellow-shaded rows identify models that have the lowest MAE\_rel values within a site-spawner data type set; in Table 3h, those models are WYa (C/D, BN, AN/W), si\_above\_13\_temp\_week, si\_weekly\_max\_temp\_max, and rr\_min\_flow.

Covariate	n	r2	g-sp	g-LCI	g-med	UCI	CV	MAE	MAE_rel
mu	7	0.00	2.82	-	-	-	-	7,612	99%
null	7	0.16	2.78	-	-	-	-	8,450	99%
WYa (C/D, BN, AN/W)	7	0.74	2.03	-2.43	1.98	4.52	0.94	6,311	96%
WYb (C, D/BN, AN/W)	7	0.63	2.19	-2.64	2.22	4.83	0.98	13,365	97%
si_gdd_spawn	7	0.26	3.22	-3.53	-0.69	1.51	1.61	16,089	118%
si_above_13_temp_day	7	0.63	2.10	-0.13	1.54	3.44	0.54	12,911	95%
si_above_13_temp_week	7	0.67	2.05	-0.42	1.51	3.47	0.6	12,136	97%
si_weekly_max_temp_max	7	0.57	2.43	-3.34	-1.45	0.93	0.75	7,811	96%
si_weekly_max_temp_mean	7	0.25	3.01	-3	-0.7	2.36	1.88	21,849	202%
si_weekly_max_temp_median	7	0.18	3.45	-3.52	-0.36	2.51	3.64	20,224	179%
si_mean_flow	7	0.27	2.97	-1.99	1.16	3.93	1.27	10,217	95%
si_max_flow	7	0.20	3.01	-1.69	0.82	3.49	1.52	8,247	97%
si_min_flow	7	0.37	2.86	-1.35	1.05	3.5	1.09	13,704	98%
si_median_flow	7	0.41	2.82	-1.63	1.24	3.77	1.03	13,856	98%
rr_mean_flow	7	0.17	3.21	-2.3	0.44	3.19	3	10,089	98%
rr_max_flow	7	0.14	3.34	-2.41	0.41	3.99	3.2	9,917	100%
rr_min_flow	7	0.66	2.22	-0.34	1.64	4.08	0.61	6,113	96%
rr_median_flow	7	0.20	3.03	-1.91	0.58	3.21	1.89	9,801	98%

**Table 3i. Knights Landing—Upstream Passage (Battle and Clear)**

Yellow-shaded rows identify models that have the lowest MAE\_rel values within a site-spawner data type set; in Table 3h, those models are mu, and rr\_min\_flow.

Covariate	n	r2	g-sp	g-LCI	g-med	UCI	CV	MAE	MAE_rel
mu	22	0.00	1.27	-	-	-	-	1,730	52%
null	22	0.21	1.14	-	-	-	-	1,610	65%
WYa (C/D, BN, AN/W)	22	0.21	1.21	-1.43	-0.06	1.15	7.17	1,967	73%
WYb (C, D/BN, AN/W)	22	0.24	1.18	-1.17	0.39	1.79	1.99	1,919	66%
mi_above_13_temp_day	22	0.28	1.15	-0.91	-0.36	0.18	0.77	1,965	71%
mi_above_13_temp_week	22	0.29	1.13	-0.97	-0.39	0.17	0.74	2,093	71%
rr_mean_flow	22	0.22	1.18	-0.44	0.19	0.72	1.67	1,749	66%
rr_max_flow	22	0.22	1.17	-0.42	0.17	0.7	1.85	1,886	64%
rr_min_flow	22	0.24	1.13	-0.28	0.24	0.76	1.11	1,794	59%

Covariate	n	r2	g-sp	g-LCI	g-med	UCI	CV	MAE	MAE_rel
rr_median_flow	22	0.25	1.14	-0.3	0.3	0.97	1.04	1,577	61%
mi_gdd_sacramento	22	0.24	1.14	-0.81	-0.23	0.37	1.32	1,722	67%

**Table 4. Mean Estimates**

Mean estimates of the log of maximum productivity ( $\alpha$ ), maximum productivity ( $e^\alpha$ ), and resulting estimate of egg-fry/smolt survival rate assuming 2,752 eggs/spawner (100\* $e^\alpha$ /2752). "rd," "us," "hd," and "cs" denote redd count, upstream passage, holding count, and carcass survey methods to quantify spawner abundance, respectively.

Site-Spawner Method	Covariate	$\alpha$	Outmigrants/Spawner $e^\alpha$	Egg-Outmigrant Survival
ubc-rd	si_mean_flow	6.21	498	19%
ubc-us	rr_max_flow	5.62	276	11%
ucc-rd	si_weekly_max_temp_median	6.71	822	32%
ucc-us	si_weekly_max_temp_mean	5.95	384	15%
deer-hd	si_above_13_temp_week	6.52	679	26%
butte-cs	si_above_13_temp_week	5.66	287	11%
yuba-cs	si_above_13_temp_week	8.65	5,710	222%
knights landing-us	rr_min_flow	9.54	13,767	535%

deer = Deer Creek

yuba = Yuba River

butte = Butte Creek

UBC = Battle Creek

UCC = Upper Clear Creek

**Table 5. Error in Forecasted Juvenile Outmigrant Abundance**

Error in forecasted juvenile outmigrant abundance (in '000s) by rotary screw trap (RST) site and spawner abundance enumeration method for models with the lowest out-of-sample median error in relative abundance (MAE<sub>rel</sub> = 100\*abs(predicted-observed)/observed). In-sample forecasts are based on the average spawner abundance across available years for each site and adult data type. In-sample forecast error is quantified based on the 80% credible interval (10–90%) and the CV of the posterior distribution of the outmigrant forecast. The “parameters only” statistics (PO) are based on forecasted outmigrant abundance that only considers uncertainty in model parameters ( $\alpha$ ,  $\beta$ , and  $\gamma$ ), while “parameters & process error” (PPE) includes the effects of both parameter uncertainty and simulated annual random effects that depend on the magnitude of process error ( $\sigma_p$ ).

Site and Data Type	Covariate	PO CI_0.1	PO CI_0.9	PO CV	PPE CI_0.1	PPE CI_0.9	PPE CV	PPE MAE_rel
battle-rd	si_mean_flow	28	45	0.20	15	86	0.78	43%
battle-us	rr_max_flow	28	45	0.20	13	97	0.85	37%
upper clear-rd	si_weekly_max_temp_median	42	72	0.23	20	156	0.99	67%
upper clear-us	si_weekly_max_temp_mean	75	145	0.27	34	351	1.13	70%
deer-hd	si_above_13_temp_week	376	602	0.20	221	1,016	0.66	45%
butte-cs	si_above_13_temp_week	875	1,638	0.26	359	4,067	1.19	65%
yuba-cs	si_above_13_temp_week	4,429	33,377	1.29	706	190,475	12.44	97%
knights landing-us	rr_min_flow	2,616	4,959	0.26	804	15,377	1.58	59%

deer = Deer Creek

yuba = Yuba River

butte = Butte Creek

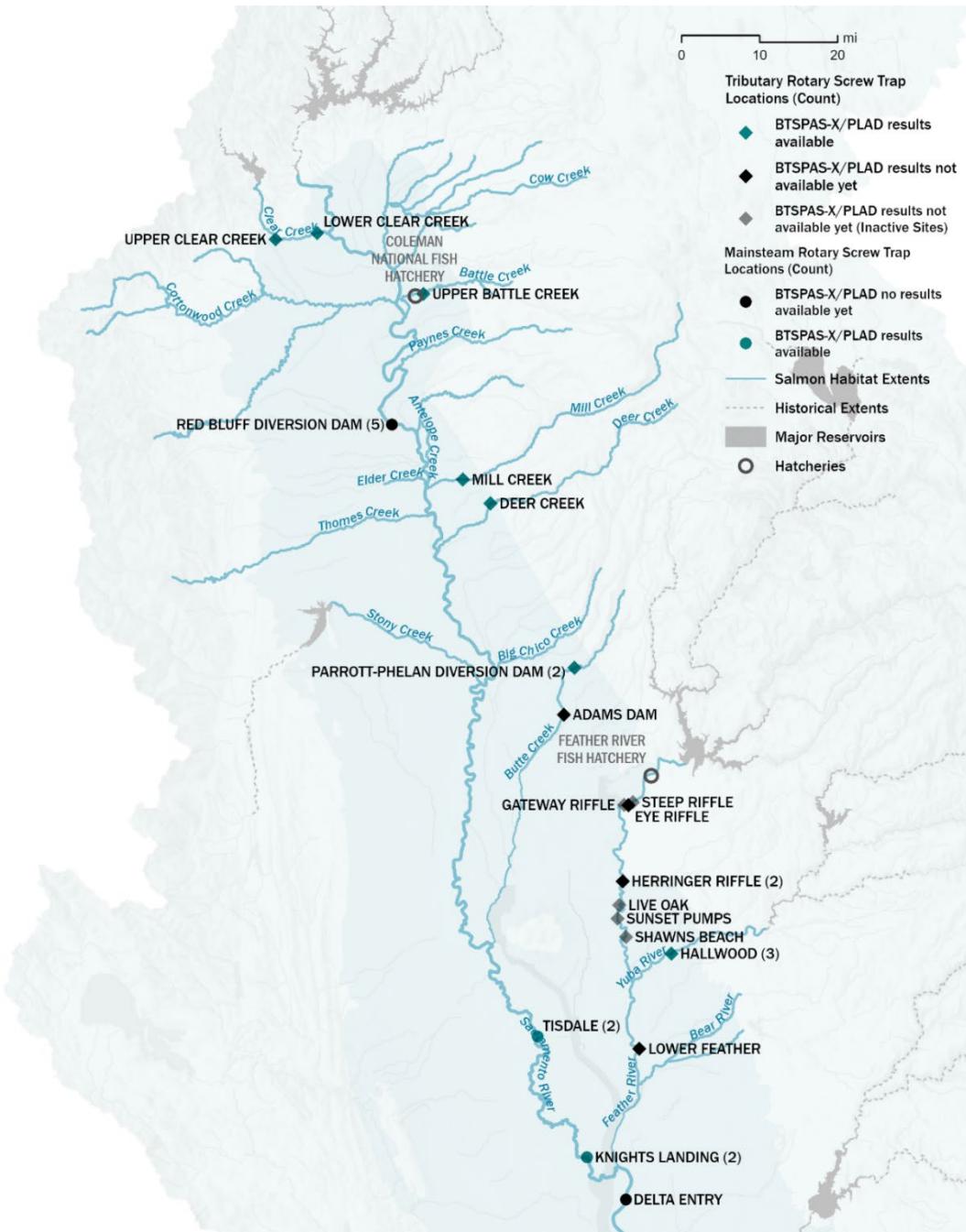
battle = Battle Creek

upper clear = Upper Clear Creek

# Figures

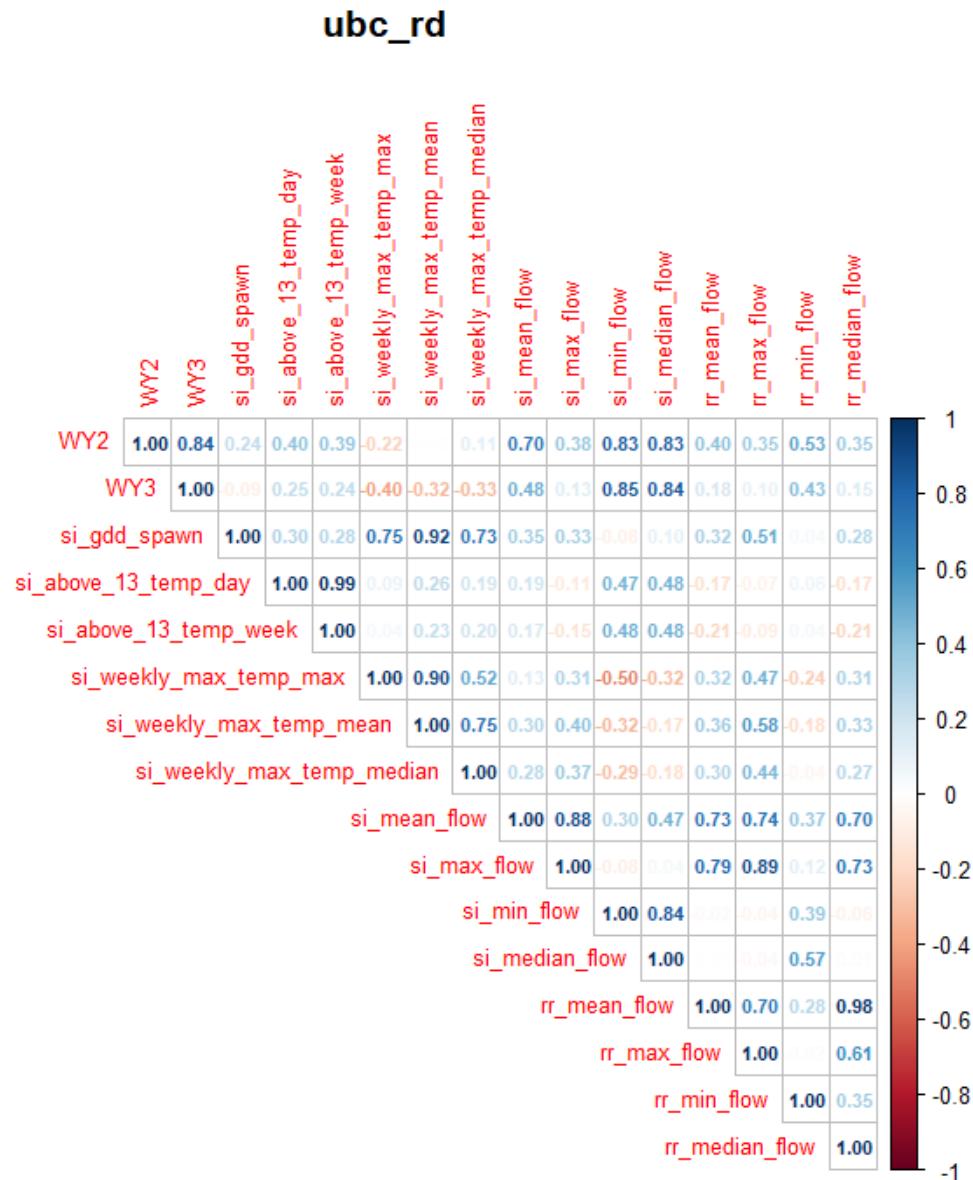
**Figure 1. Map of Sacramento River and Tributaries**

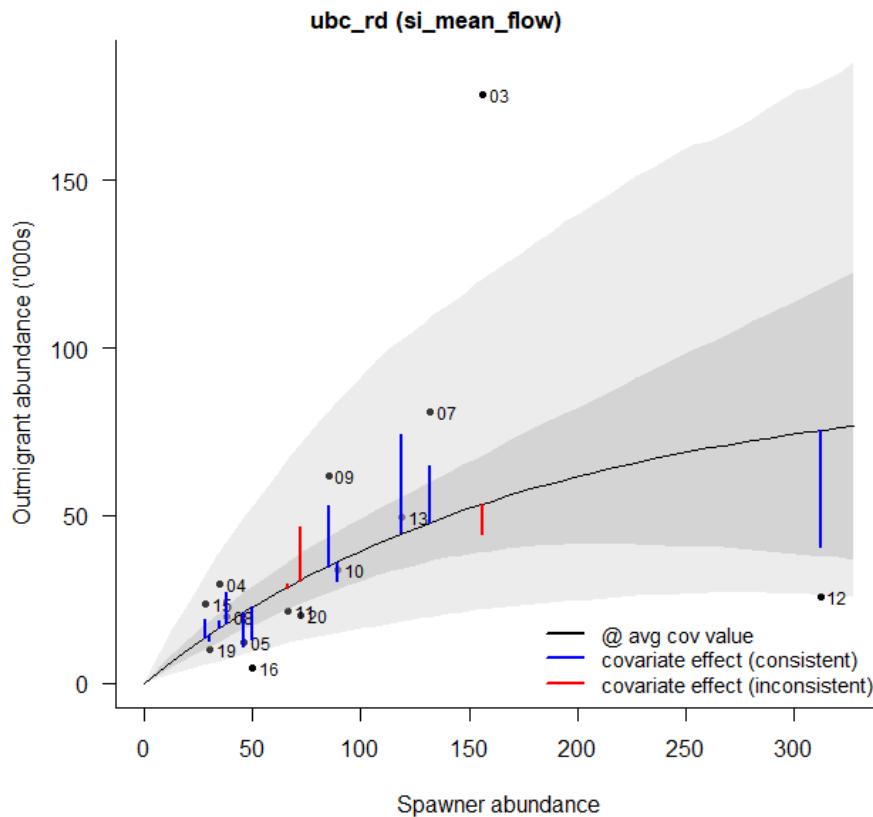
Map of the Sacramento River and tributaries showing the location of RST sites used in spring-run Chinook salmon juvenile production modeling.



## Figure 2. Pearson Correlation Coefficients Among Covariates

Pearson correlation coefficients among covariates for the Battle Creek stock-recruitment time series based on redd counts. Refer to Appendix A for similar plots for other site-spawner abundance method groups.

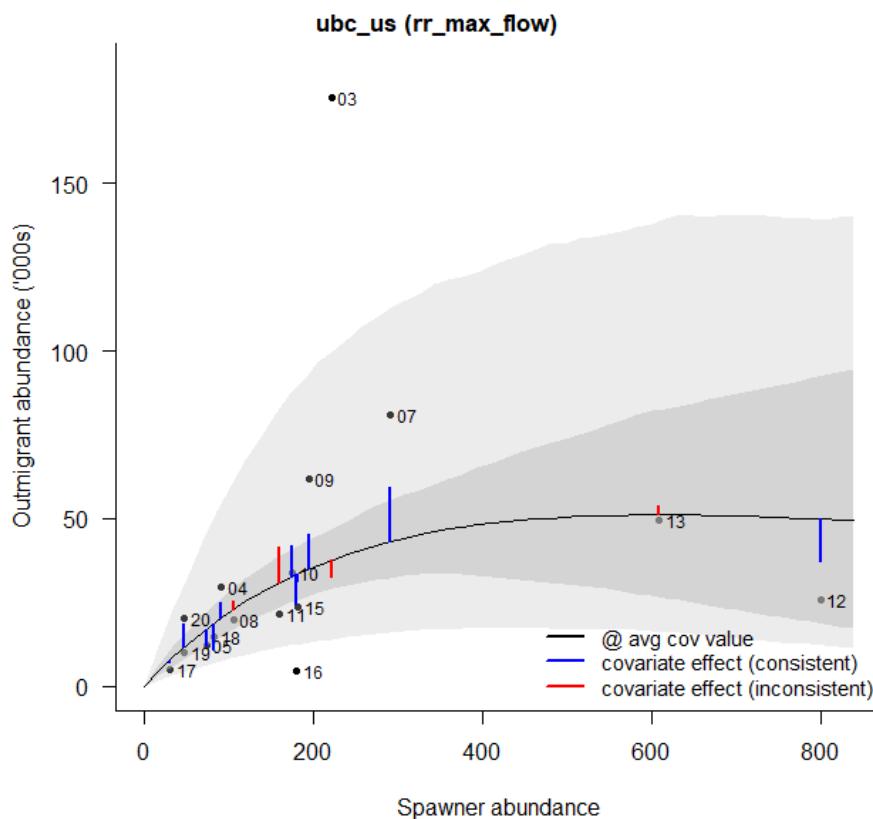


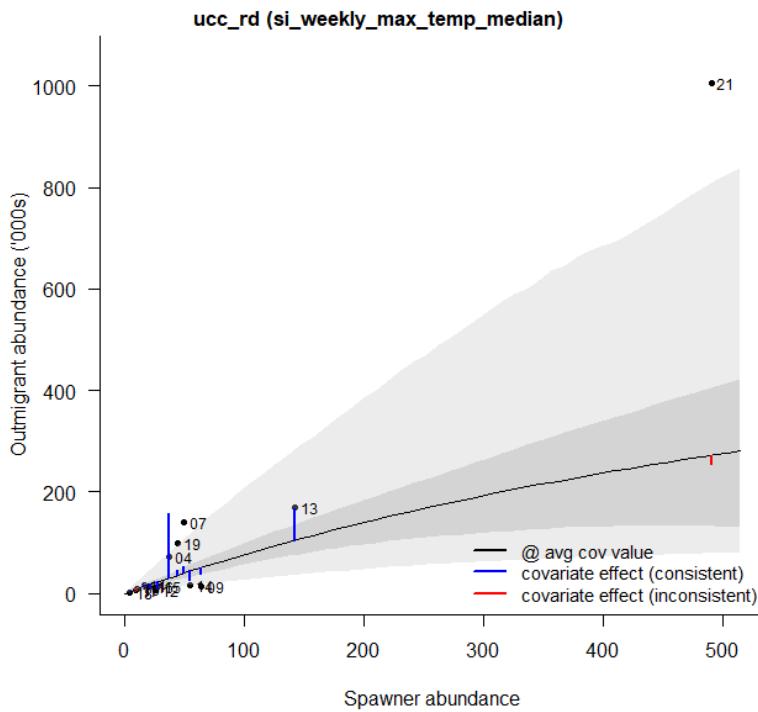
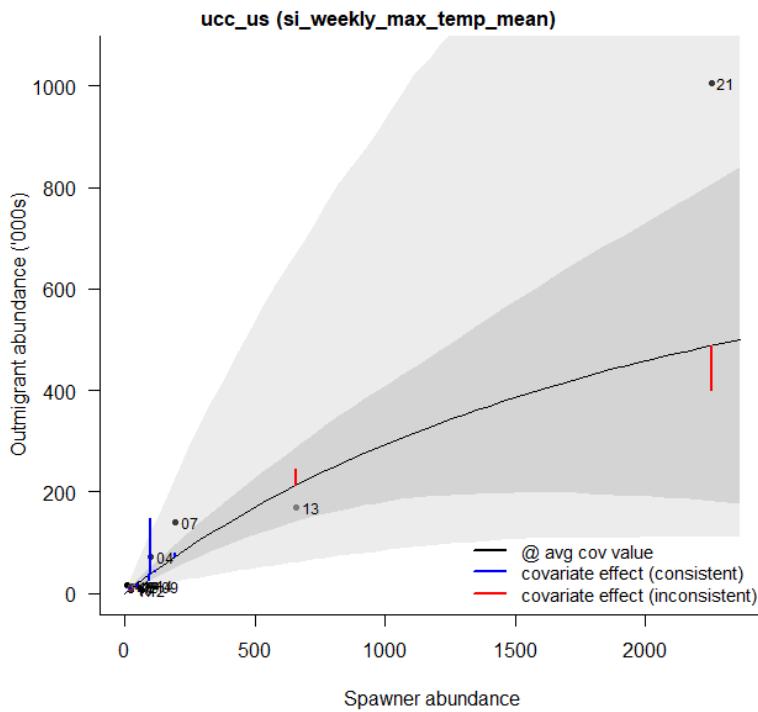
**Figure 2a. Battle Creek—Redd Count**

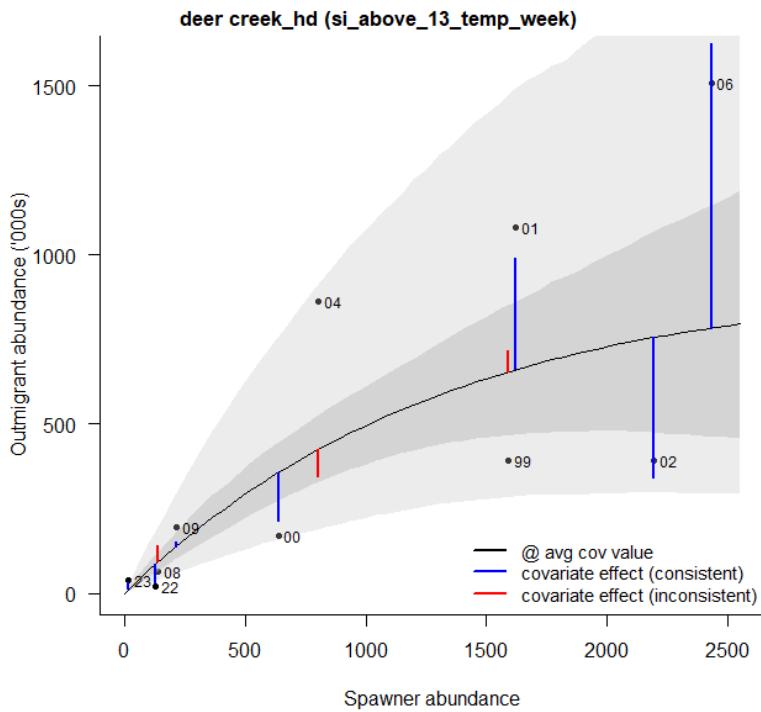
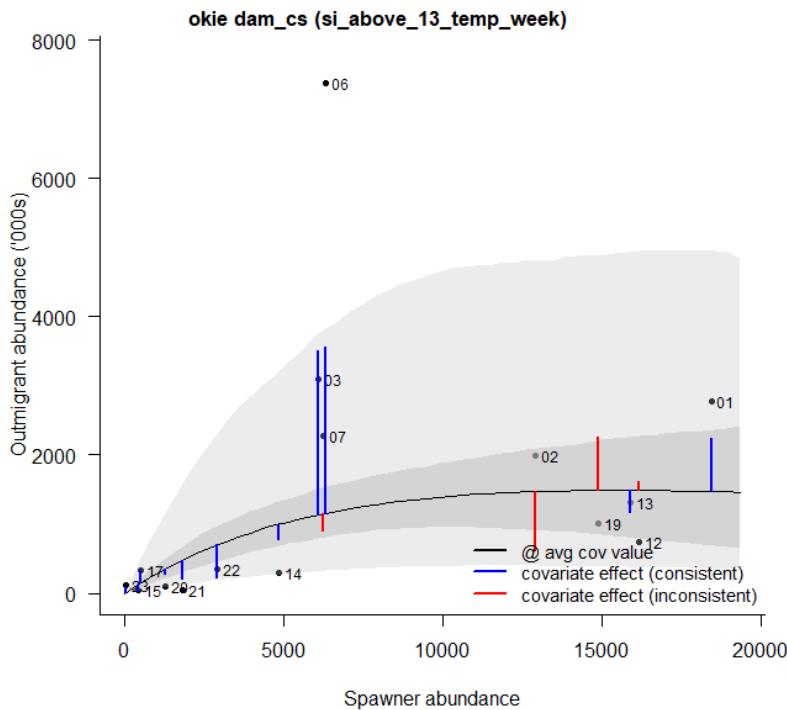
### Figure 3. Fit of Ricker Stock-Recruitment Covariate Models to Spawner Abundance: Juvenile Outmigrant Abundance Data

Fit of Ricker stock-recruitment covariate models to spawner abundance: juvenile outmigrant abundance data. The numbers beside each point represent the brood year. The black line represents the spawner-outmigrant relationship at the mean covariate value. The gray-shaded area represents the 95% credible interval of predicted outmigrants with (light gray) and without (dark gray) effects of process error. The vertical colored-lines represent the predictions of outmigrant abundance for each brood year based on the observed spawner abundance (x-position) and the annual covariate value (determining length of vertical line). Blue lines indicate that the direction of predictions is consistent with the direction of the observation (i.e., either both above or below the black line). Red lines indicate that the direction of the predictions is inconsistent with the direction of the observation. The title of each plot identifies the covariate used in the model (refer to Table 1 for definitions of covariates).

#### Figure 3a. Battle Creek—Upstream Passage



**Figure 3b. Upper Clear Creek—Redd Count****Figure 3c. Upper Clear Creek—Upstream Passage**

**Figure 3d. Deer Creek, Holding Count****Figure 3e. Butte Creek, Carcass Estimates**

### Figure 3f. Yuba River, Carcass Estimate

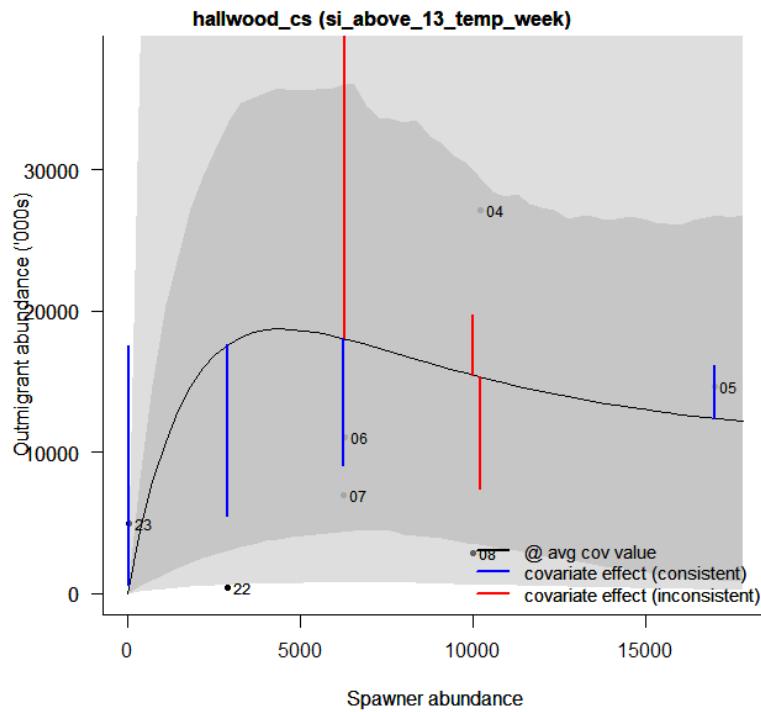
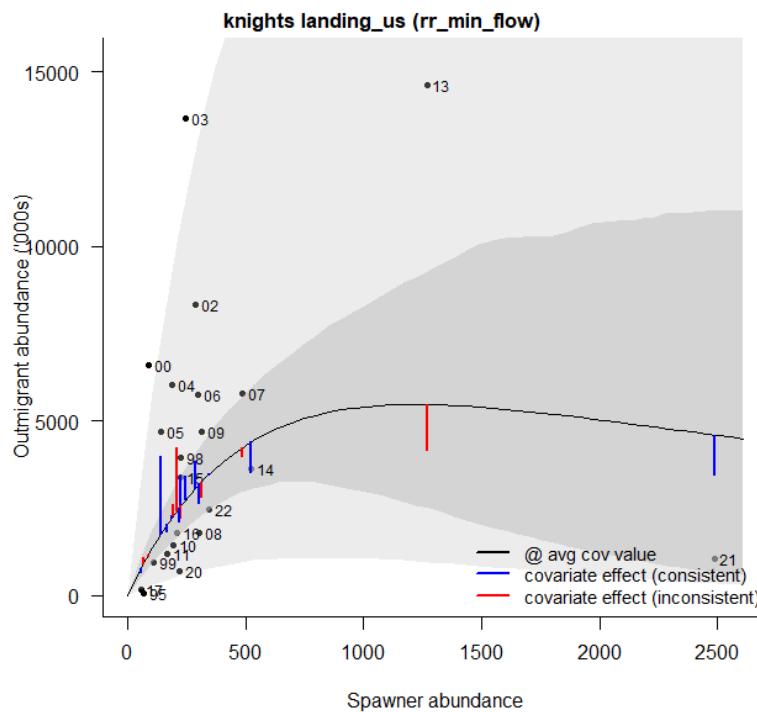
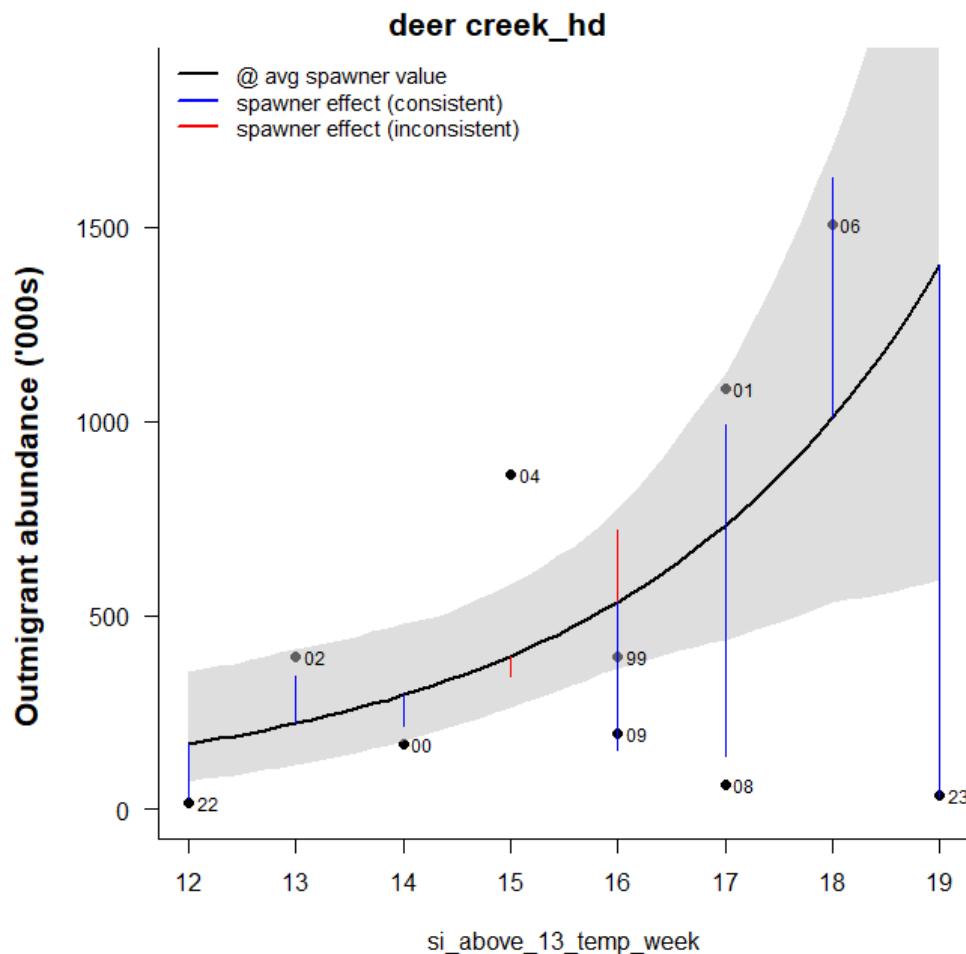


Figure 3g. Knights Landing, Upstream Passage at Battle and Clear Creeks



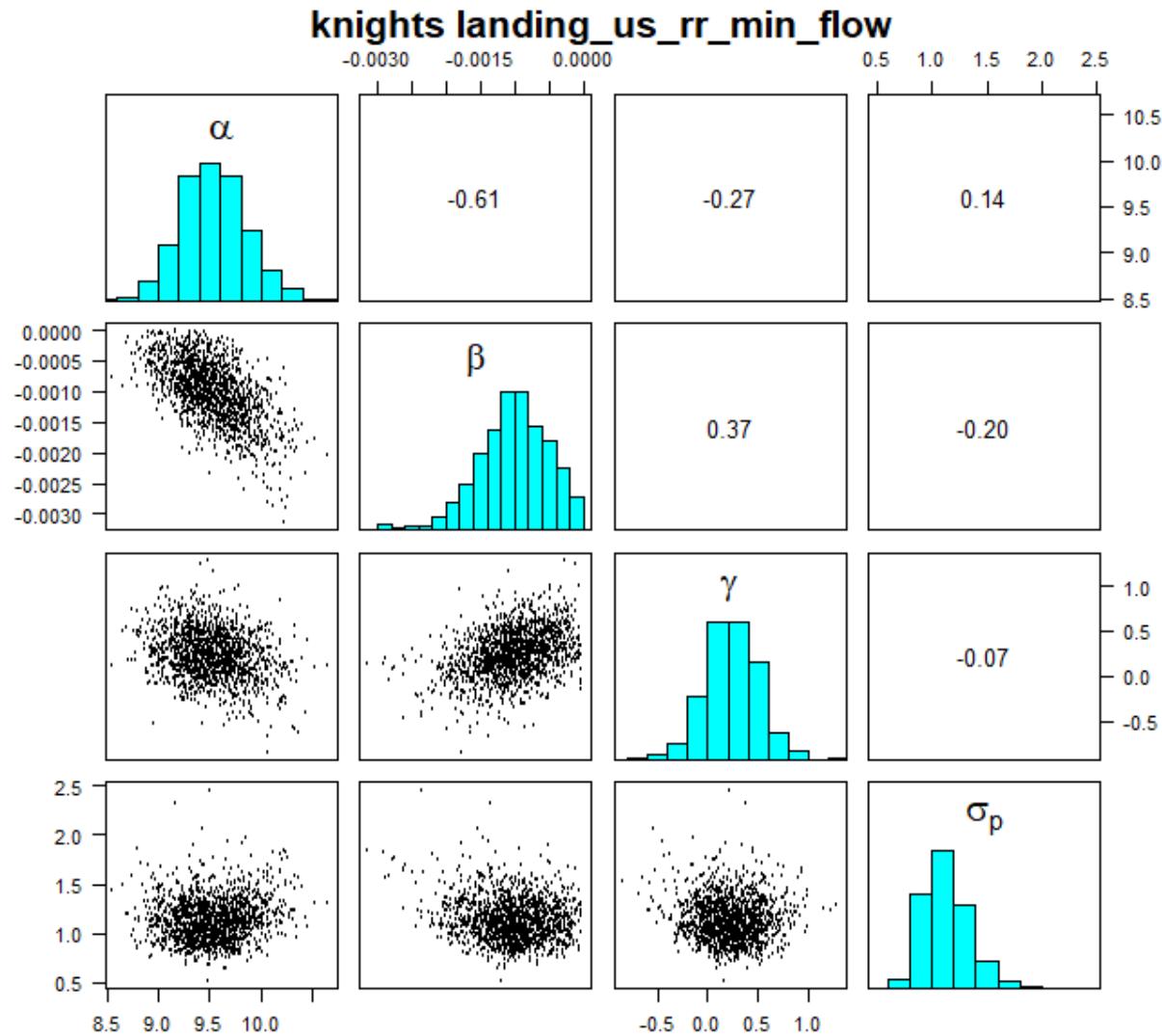
**Figure 4. Fit of a Ricker Stock-Recruitment Covariate Model to Spawner Abundance: Juvenile Outmigrant Abundance Data from Deer Creek**

Fit of a Ricker stock-recruitment covariate model to spawner abundance: juvenile outmigrant abundance data from the Deer Creek RST site (model based on holding counts to index spawner abundance). The numbers beside each point represent the brood year. The black line represents the estimated covariate-outmigrant relationship at the mean spawner abundance across years. The dark gray-shaded area represents the 95% credible interval of the mean relationship without process error. The vertical colored-lines represent the predictions of outmigrant abundance for each brood year based on the annual covariate value (x-position) and the annual spawner abundance (determining magnitude of vertical lines). Blue lines indicate that the direction of predictions is consistent with the direction of the observation (i.e., either both above or below the black line). Red lines indicate that the direction of the predictions is inconsistent with the direction of the observation.



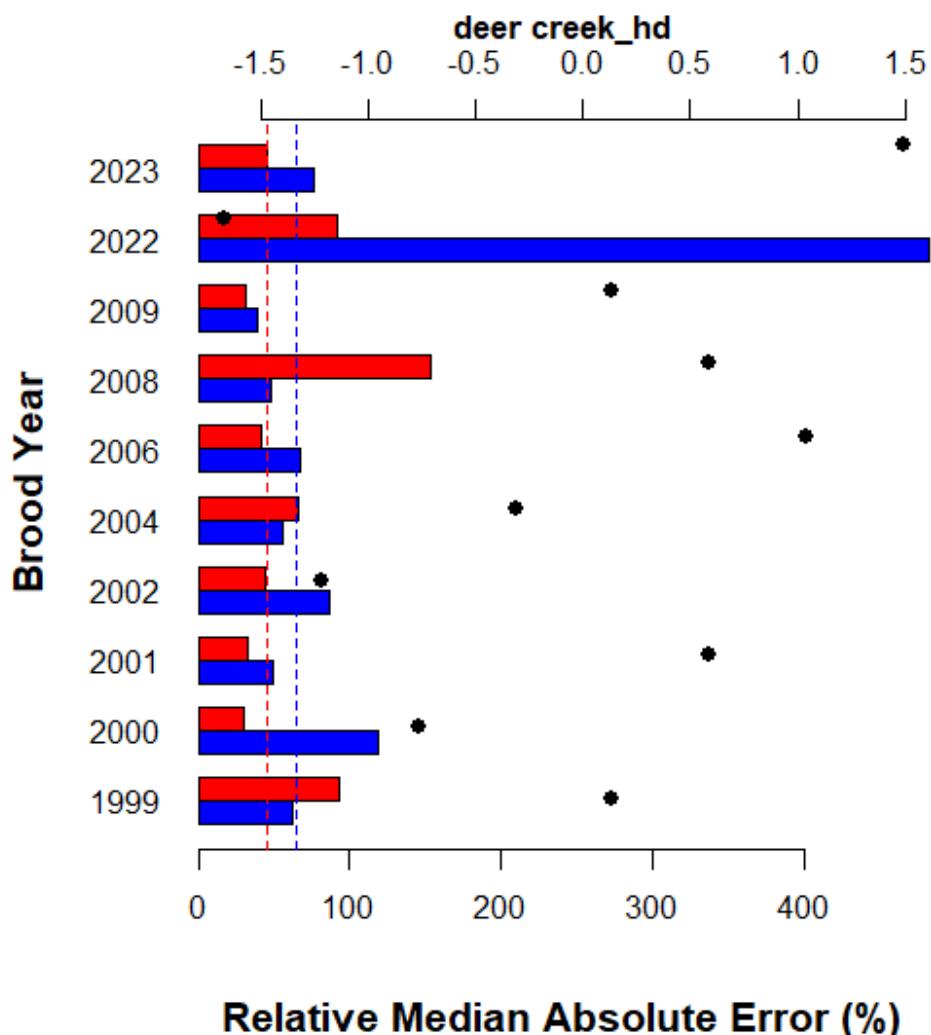
### Figure 5. Posterior Distributions and Covariation of Posterior Samples

Posterior distributions (diagonal) and covariation of posterior samples between parameters (lower diagonal) for the Knights Landing outmigrant stock-recruit model (based on upstream passage) with a covariate effect (minimum flows over the juvenile rearing-outmigration period in the mainstem). The values in the upper diagonal show the Pearson correlation coefficient for each parameter combination.



### Figure 6. Out-of-sample Relative Error in Predictions of Juvenile Outmigration Abundance

Out-of-sample relative error in predictions of juvenile outmigration abundance based on the Deer Creek stock-recruit model (based on holing counts for spawners). Errors are shown for the null (blue bars) and the si\_above\_13\_temp\_week covariate models (red bars). The black points and x-axis at the top of the panel show the standardized values of covariate values for each year. Dashed vertical lines show the across-year medians of relative error (values shown in the MAE\_rel column in Table 3e).



## A. Pearson Correlations

Pearson correlations among annual flow- and temperature-based covariates used in spawner-juvenile outmigrant abundance stock-recruit modeling (Covar\_Cor.pdf). Refer to Table 1 for definition of covariate values.

Please refer to the pdf titled “Appendix A – Pearson Correlatations.pdf.”

## B. Posterior Distributions

Posterior distributions (diagonal) and covariation of posterior samples between parameters (lower diagonal) for models with the lowest or near-lowest relative out-of-sample error in predicting juvenile outmigrant abundance (Post\_Cor.pdf). The values in the upper diagonal show the Pearson correlation coefficient for each parameter combination.

Please refer to the pdf titles “Appendix B – Posterior Distributions.pdf.”