# Passage to Spawner (P2S) model: Predicting Chinook Salmon Spawner Abundance from Upstream Passage Estimates in the Sacramento River Valley

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## Introduction

A spring-run chinook salmon (SRCS) juvenile production estimate (JPE) was commissioned in 2020 to inform operation of the State Water Project run by the California Department of Water Resources so as to minimize take of SRCS.

Monitoring programs exist to collect data at different points of the SRCS lifecycle, and several of these were used to inform development of the JPE. Monitoring programs included juvenile salmon outmigration monitoring using rotary screw traps (RSTs), spawning adult surveys (redd surveys, holding surveys, and carcass surveys), and upstream passage monitoring via video systems. RST data and associated efficiency trials provide estimates of juvenile abundance. Spawning adult surveys provide estimates of the spawning adult population, though survey types collect data at different points in the adult life stage. Upstream passage data is used to estimate the abundance of adult escapement, or adults returning upstream to spawn. Each tributary collects these data differently, in different formats, and with different assumptions informed by the variable habitat, institutional knowledge, and geographic variation.

These data were aggregated, documented, and standardized across tributaries to be used in the JPE. The JPE model system consists of several submodels that describe relationships at key points in the SRCS lifecycle (Figure 1). To take advantage of the multiple data types available, a submodel was created to model the relationship between upstream passage and spawner abundance. The Passage to Spawner (P2S) submodel explicitly models prespawn mortality for four key tributaries and uses this relationship to predict spawner abundance from upstream passage (Figure 2).

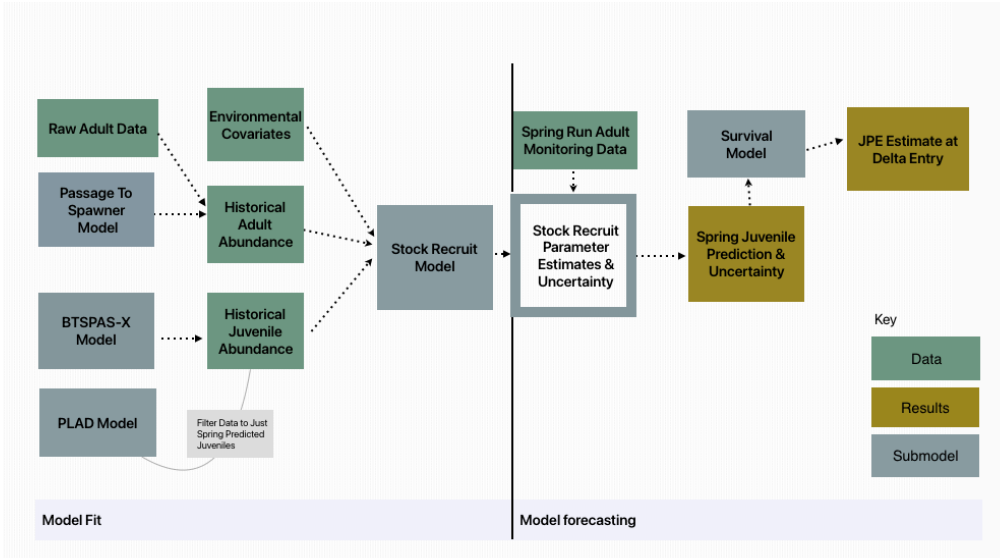


*Figure 1. A conceptual model outlining the relationships between potential submodels and data in a Spring Run JPE.*

As part of the JPE model system, the P2S model provides resiliency for years where data may be missing (i.e. for years where upstream passage data was collected but spawner surveys were not conducted), provides an estimate of prespawn mortality, and utilizes all possible data. However, the P2S relies on upstream passage data which, by itself, is considered by monitoring programs to be inaccurate. Using the P2S in any river system should be informed by these sources of error, as well as key assumptions detailed below.

## Methods

*Data Collection*

Three categories of data were accessed and aggregated for this study: upstream passage, spawner abundance, and environmental data. Detailed methods describing monitoring programs in each tributary, the aggregation of those data, and evaluation of data types can be found in Appendix A. There were four tributaries for which upstream passage and a spawner survey were recommended for use in development of the JPE: Battle Creek, Clear Creek, Deer Creek, and Mill Creek. Butte Creek, Feather River, and Yuba River either did not have those data at the time of development or had limitations that precluded those data from use in the P2S model (Appendix A). Deer Creek and Mill Creek data are in the process of QA/QC and were included in these analyses. However, not all of these tributaries are precluded from being used in the P2S in the future: Yuba River has begun to collect upstream passage data and Butte Creek has the necessary data but will require more documentation of drawbacks and specifics of the system. The sample sizes for Battle and Clear Creek were determined by the number of years where upstream passage overlapped with spawner abundance and range from 20 to 21 years (Table 1).

*Environmental covariate selection*

Several environmental variables thought to be associated with prespawn mortality were assessed in the model: flow, water temperature and water year type. Temperature data were collected from gauges located as close to the sampling sites as possible. Flow was collected from gauges operated in some cases at the RSTs. Water year type was accessed from DWR and standardized into a binary variable. Data were downloaded from the source using APIs. Passage timing was considered; however, limited data reduced the sample size of the datasets for some tributaries so much as to remove them from candidacy for the model due to lack of statistical power. Several forms of available environmental variables were considered and tested for inclusion in P2S models (see Appendix B). The covariates that we ended up using were maximum flow during holding and spawning months, sum of days over a threshold of 20 degrees Celsius during holding and spawning months (source), and water year type. All continuous environmental variables (flow and temperature) were standardized and centered within streams before performing any analyses so that the scale of the data did not affect results. Water year type was coded as a binary variable for wet (wet, above normal) vs. dry (below normal, dry, critical).

Full code and documentation of this process are available on the SRJPEdata package Github.

*Passage to Spawner (P2S) Model*

The model predicts spawner abundance $\hat{S}_y$ a function of annual observed passage $P_y$ and the annual conversion rate of upstream passage counts to spawner counts $R_y$.

$$(1)\ \hat{S}_y = P_y * R_y$$

The likelihood function assumes the error between $\hat{S}_y$ and observed spawner count $S_y$ is poisson-distributed (Eq. 2).

$$(2)\ S_y \sim P(\hat{S}_y)$$

The conversion rate $R_y$ was modeled as a function of the selected environmental covariate $X_y$, the conversion rate fixed effect parameter $\beta_1$, and a log-scale random year effect $\beta_{0_y}$ (Eq. 3, Figure 3).

$$(3)\ R_y = exp\left(\log\left(\beta_{0_y}\right) + \beta_1 * X_y\right)$$

$X_y$ is a standardized value:

$$(4)\ X_y = \frac{x_y - \mu}{\sigma}$$

Where $x_y$ is the actual annual value for that covariate. Year-specific random effects $\beta_{0_y}$ were modeled as lognormally distributed around a mean $\mu_{\beta_0}$ and standard deviation $\sigma_{\beta_0}$, hyperparameters that determine the distribution of $\beta_0$ across years:

$$(5)\ \log\left(\beta_{0_y}\right) \sim N\left(\mu_{\beta_0}, \sigma_{\beta_0}\right)$$

$\beta_{0_y}$ is estimated on a log scale to restrict to positive values but allow for values over 1, and that the distribution of $\beta_{0_y}$ is lognormal as determined by hyperparameters $\mu_\delta$ and $\sigma_\delta$.

The key output of the model is the conversion rate $R_y$ for each year and the estimated effect of the environmental covariate, captured in the parameter $\beta_1$. Important to note is that this model makes several assumptions about sex ratio in our spawner count data: the sex ratio was assumed to be 0.5, and for redds specifically (which were used for both Battle and Clear Creeks), each female was assumed to create one redd. Our parameter $\beta_{0_y}$, which is a random year effect for the intercept of the model predicting conversion rate, acts as a catch-all term for many year-specific sources of variation and factors like sex ratio, redds-per-female and error in redd counts (for streams using redd count), and snorkeler detection (for snorkel surveys).

*Estimation*

The model was fit to each tributary separately in two phases. The first phase was to identify, through the model, the environmental covariate with the most statistical power to predict spawner abundance. The model was fit with flow, temperature, water year type, and a "null" covariate (coded as 0). Before comparing these models, datasets were truncated only to those years where every covariate was available. Model output for a tributary was compared across each environmental covariate for accuracy and precision to identify a) whether flow, temperature, or water year type improved the accuracy of the model over the null model, and b) if so, which covariate provided the best fit. Criteria for selecting the best fit was as follows:

- Proportion of variance in predicted spawners explained by fixed effect $\beta_1$ - measured as the proportion of variance explained by the fixed effect ($R^2$)
- Greater effect of the fixed effect $\beta_1$ - measured as the magnitude of the posterior mean of the fixed effect $\beta_1$
- Least variance in estimate of the fixed effect $\beta_1$ - measured as the magnitude of the posterior standard deviation of the fixed effect $\beta_1$
- Least variance in forecasted spawner abundance - magnitude of the posterior standard deviation of each spawner abundance forecast
    - For continuous environmental variables, the two forecasts use the mean value and the mean value + 1 standard deviation
    - For water year type, the two forecasts use dry (0) and wet (1) years.

The second phase was to evaluate performance of the model in forecasting and conversion rate. Because for all continuous environmental variables the forecast would rely on modeled future temperature and flow which have high uncertainty, further analyses were based on results from fitting each tributary's data to the model using the only discrete variable: water year type.

The STAN model is a mixed-effects model and as such is expected to produce predicted spawner counts that closely match observed spawner counts, with either the fixed effect or random effects absorbing much of the error. To assess the suitability of the model's fixed effect (which can be forecasted using environmental covariate data), we looked at the predicted vs. spawner counts for each stream and the R squared value of that relationship, and we plotted the conversion rate (which incorporates the fixed effect) and random year effect parameter estimate for each year and stream to assess their magnitude.

## Results

*Environmental covariate selection*

Battle and Clear Creek, when run with the null covariate, produced an $\hat{R}$ statistic above 1.05 for $\beta_1$, indicating non-convergence for the model (Table 2). The best environmental covariate, based on the magnitude of variance explained by the fixed effect, was water year type for Battle Creek and growing degree days for Clear Creek.

By criteria of the highest median estimate of $\beta_1$, water year type was the best performing covariate for Battle and Clear Creek (0.149 and 0.519, respectively). By criteria of the least variance around this parameter, growing degree days was the best performer for Battle Creek (standard deviation of 0.111) and maximum flow for Clear Creek (standard deviation of 0.219).

The variables for Battle and Clear Creek that showed the least variance in forecasting at average conditions were growing degree days for Battle (standard deviation of 53.8) and passage index for Clear Creek (standard deviation of 309). Forecasts across all variables showed high uncertainty.

*Model fit and performance*

The predicted spawner counts very closely matched the observed spawner counts (Figure 7). The $R^2$ of a linear regression of predicted vs. observed spawner counts was 0.9999. Inspection of univariate distributions of draws from the MCMC chains showed even univariate normal distributions for the key parameters $\beta_1$ and $\mu_\delta$ and bivarariate distributions (Figure 8 and Figure 9). Trace plots of MCMC draws for those same parameters showed a random and even distribution around 0 (Figure 10 and Figure 11).

*Conversion rates*

The relationship between conversion rates and water year type variable was generally positive with a wet year indicating a higher conversion rate (Figure 4). This is because the random year effect $\beta_{0_y}$, by design, absorbs much of the error not accounted for by the fixed effect parameter $\beta_1$. Key diagnostic parameters and their estimated value are in Table 2.

*Forecasts*

All covariates performed similarly for forecasting for Battle Creek, with temperature having slightly less variability around forecasts than the other covariates. Water year type showed high variability for predicting wet years, and the least variability using passage index (Figure 6).

## Results in the context of the SRJPE

The results show that the model is able to fit and forecast using a discrete forecasting variable (water year type) and estimate a conversion rate where streams have the necessary data. In years where a stream has upstream passage data but no spawner survey (i.e. either early in the season, before the spawner survey, or circumstances meant that no spawner survey could be performed that year) the P2S model could be used to forecast spawner counts. Further, in instances where monitoring data is incomplete, the P2S can be used to predict spawner abundance and fill in those data gaps. There are several such years for Battle and Clear Creek, and for Battle Creek the model performs well enough that we could fill in those data with P2S estimates (Table 4). However, for Clear Creek we would want to adjust the model to better account for years where spawner count exceeds passage estimates before implementing this method. Finally, our conversion rate can be used to support analyses of prespawn mortality or lifecycle modeling in the future.

The model is sensitive to years where upstream passage exceeds spawner count, which can happen when upstream passage data collection is affected by high flows and/or other processes that cause fish to be missed. Clear Creek is a good example of this: spawner counts don't always exceed upstream passage counts and so the estimated conversion rate is above 1 (Figure 4 and Figure 5).

There are several potential pathways to better understanding and incorporating observation error (i.e. error in upstream passage estimates) into the model. Some streams in the SRJPE use a generative additive model (GAM) to interpolate upstream passage estimates and produce confidence intervals; however, these are not included for every stream and documentation and methods are not available for each stream. If we can access confidence intervals or a measure of error (standard deviation) for each year of upstream passage data for a stream, we can easily modify the P2S to account for error in the predictor variable of upstream passage via a state-space model framework. This requires additional data; however, it is a potential pathway to reducing the impact of anomalous years on P2S performance.

Other future improvements include running the model on Deer and Mill Creeks when the data are ready.

# Figures

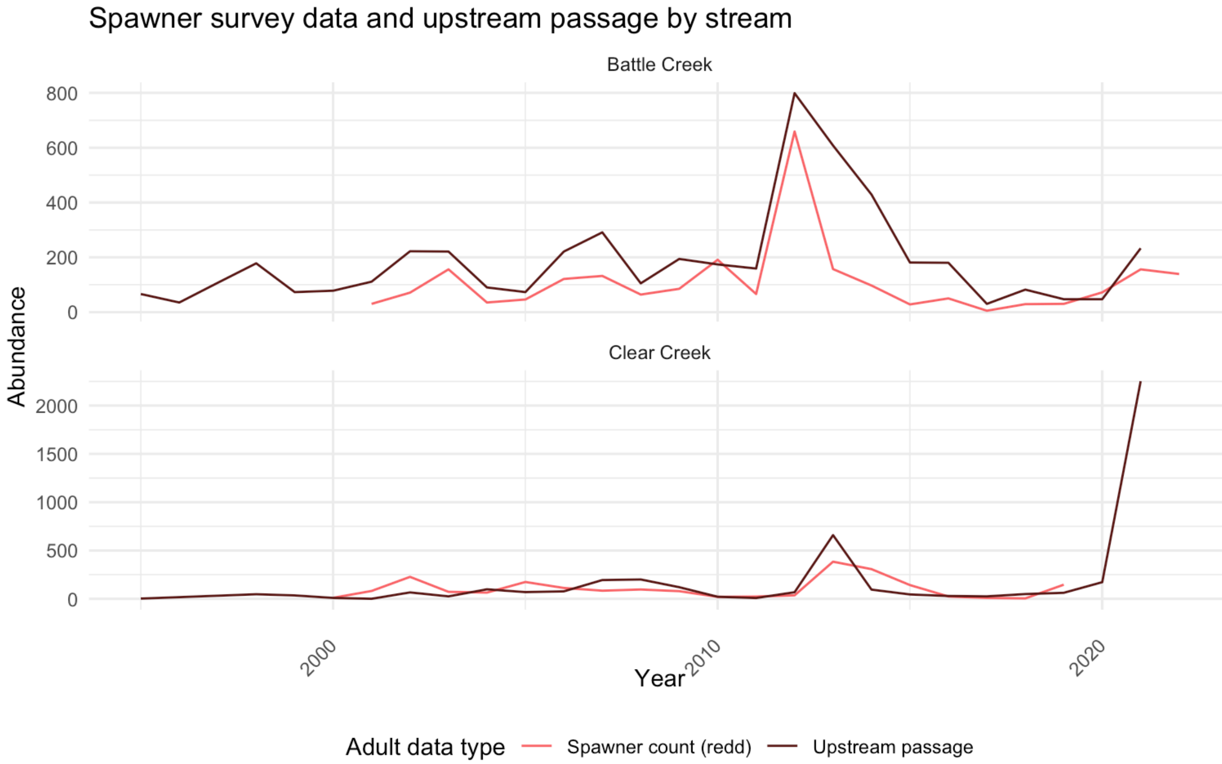


*Figure 2. Observed annual spring-run Chinook salmon spawner counts (redd surveys for Battle and Clear Creeks) and upstream passage counts for three streams on the Sacramento River.*

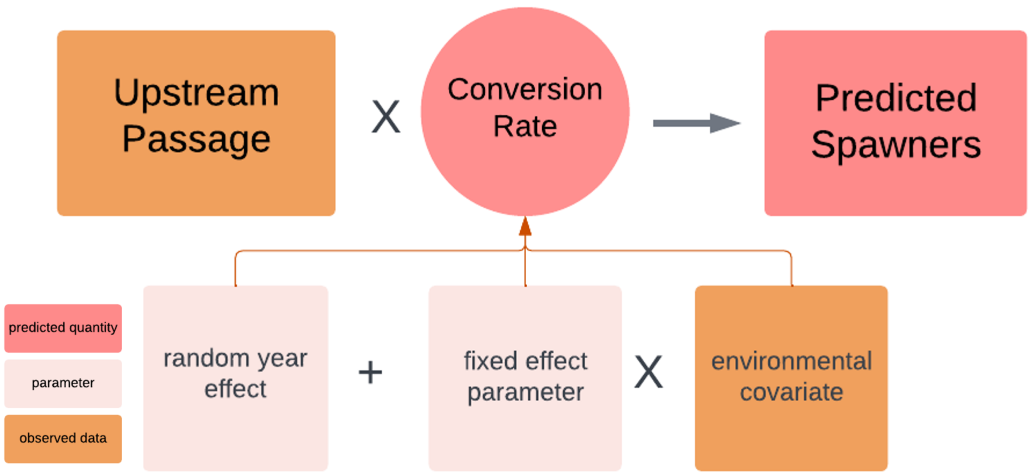


*Figure 3. Parameter structure used in the model. The conversion rate of upstream passage to spawner count is composed of a fixed effect, an environmental covariate, and a random year effect.*

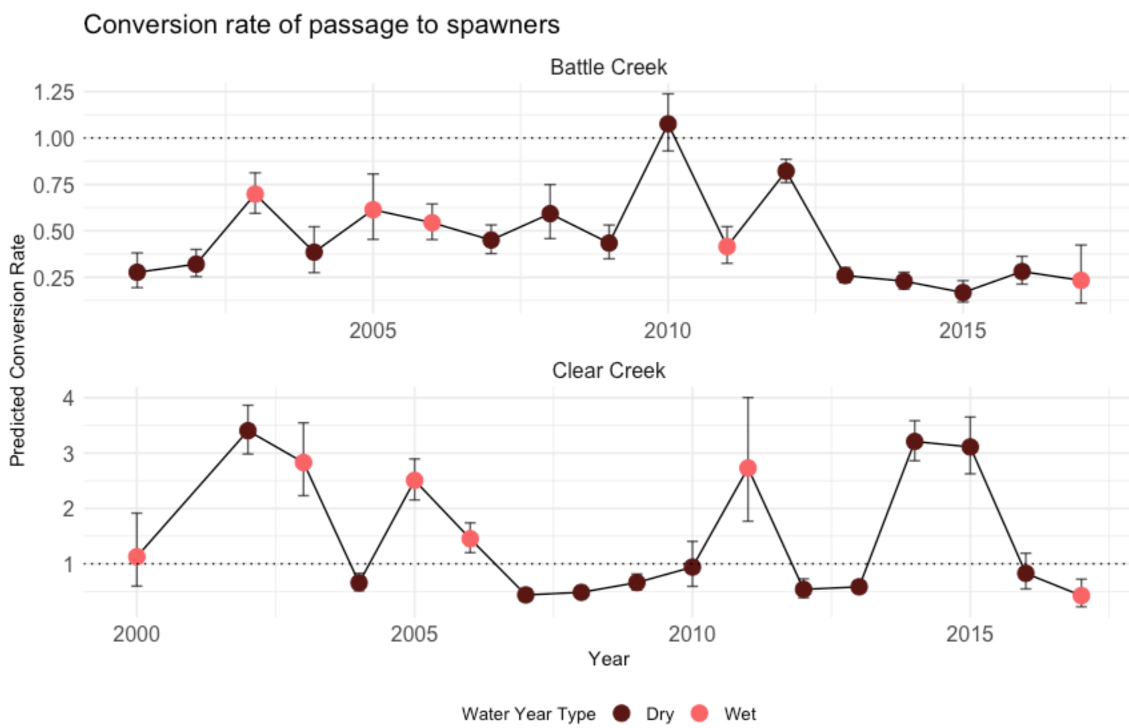


*Figure 4. Conversion rates plotted by stream, with points colored by water year type (dry vs. wet).*

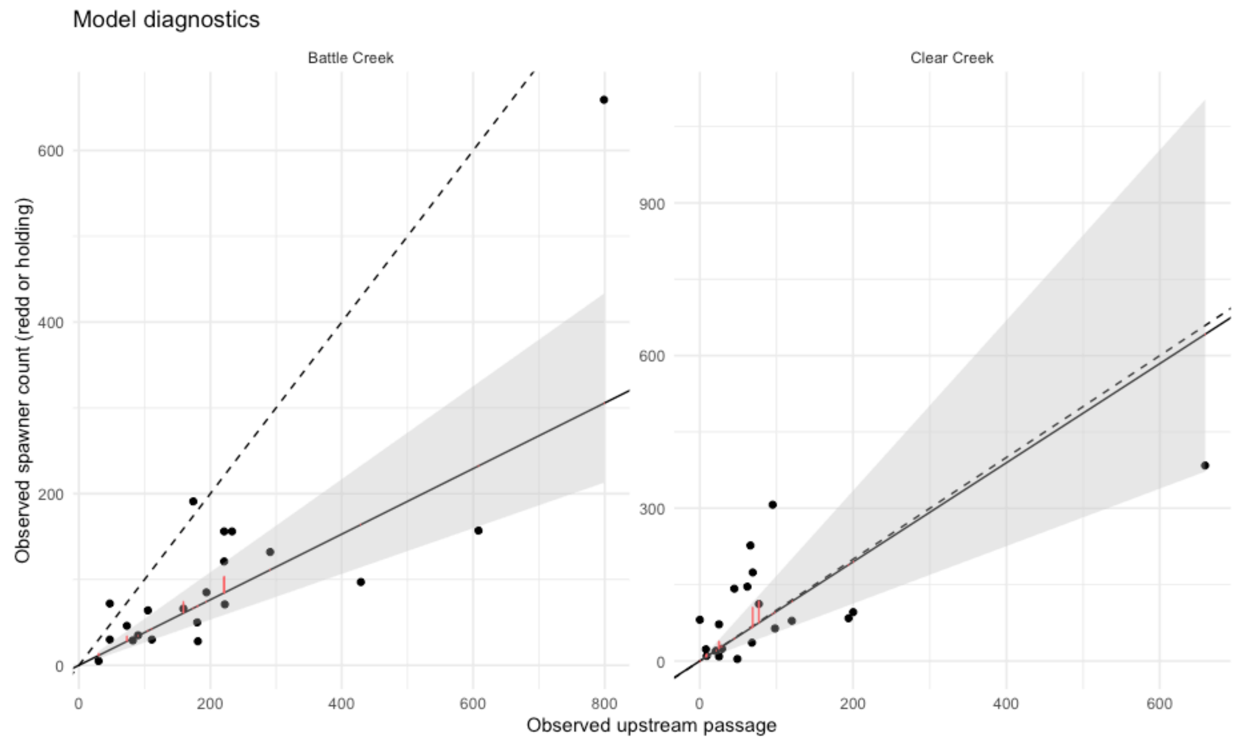


*Figure 5. Relationship between upstream passage abundance and spawner abundance as indexed by redd counts of snorkel swims (holding) for battle creek. The points represent the data used in the model. The black solid line is the conversion rate from passage-spawners under average covariate conditions (water year type = 0 or 1 for dry and wet classes, respectively). The shaded grey area is the 95% credible interval of that average conversion rate. The red vertical lines represent predictions of spawner abundance from the model. In this example the red lines only show up for the wet year type, as the dry year type is coded as 0. The black dashed-line is the 1:1 line (upstream passage = spawners).*

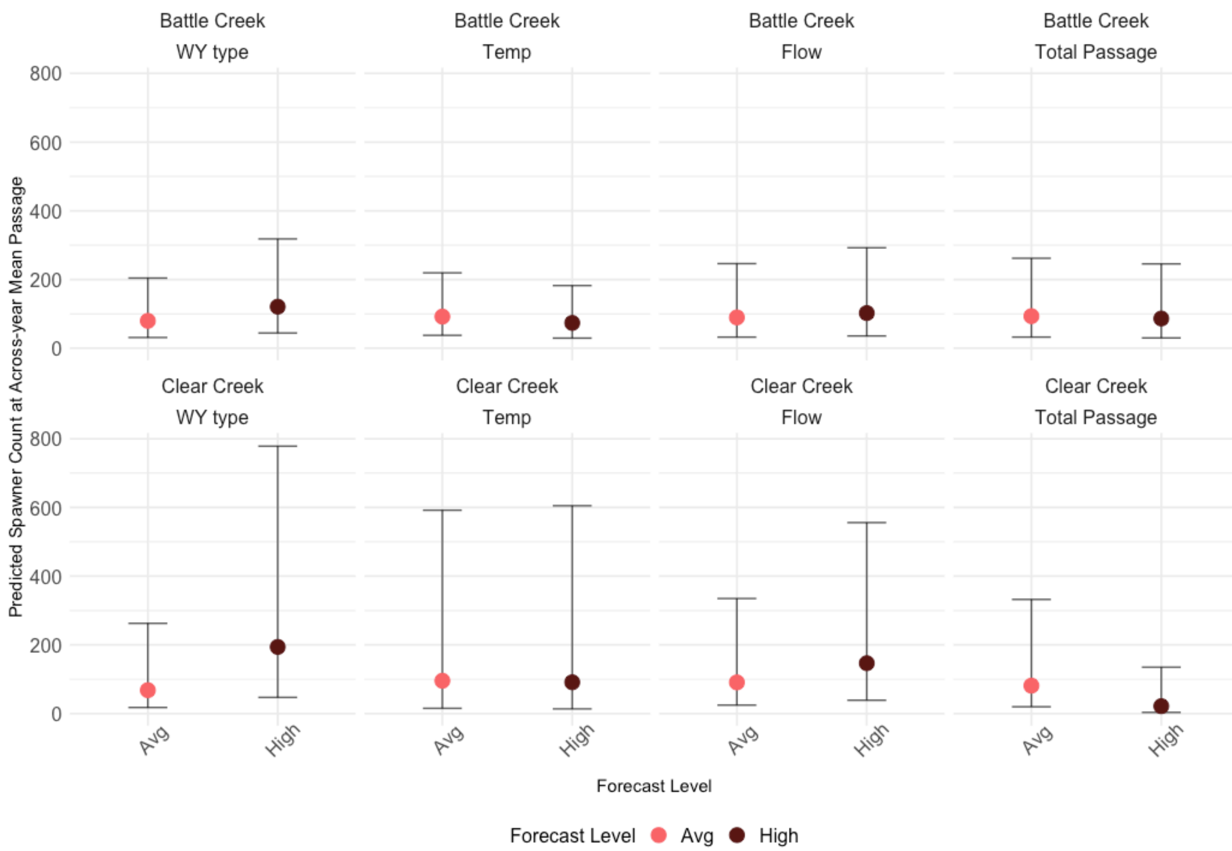


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*Figure 6. Forecasting for water year type, temperature, and flow. The dot shows the predicted spawner count using across-year mean upstream passage; the error bars show 95% confidence intervals of the prediction. The null model did not converge for any stream.*

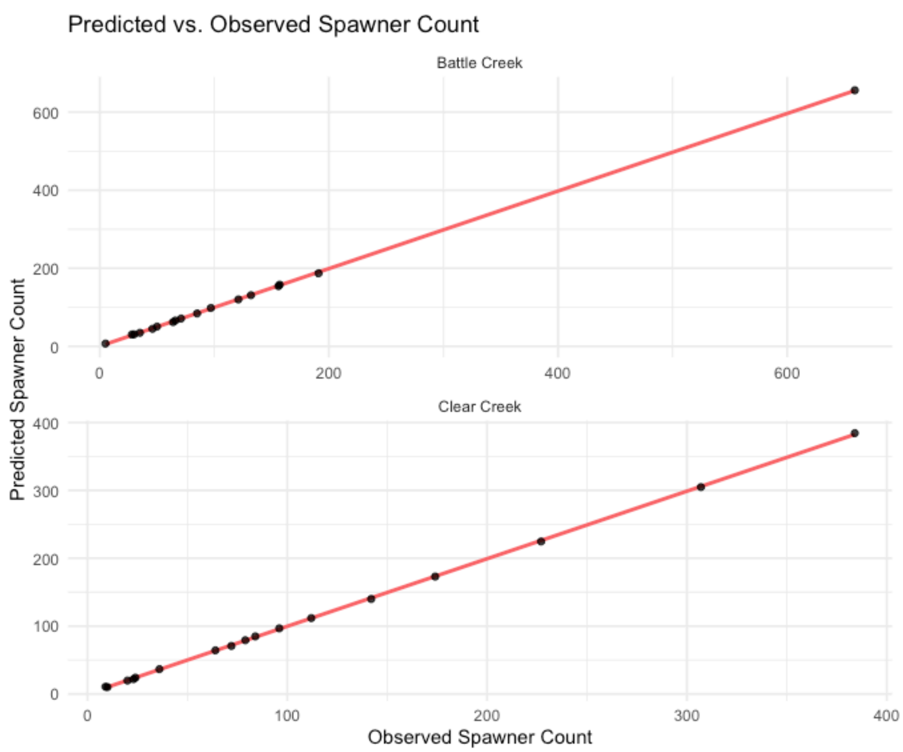



*Figure 7. Predicted vs. observed spawner counts.*

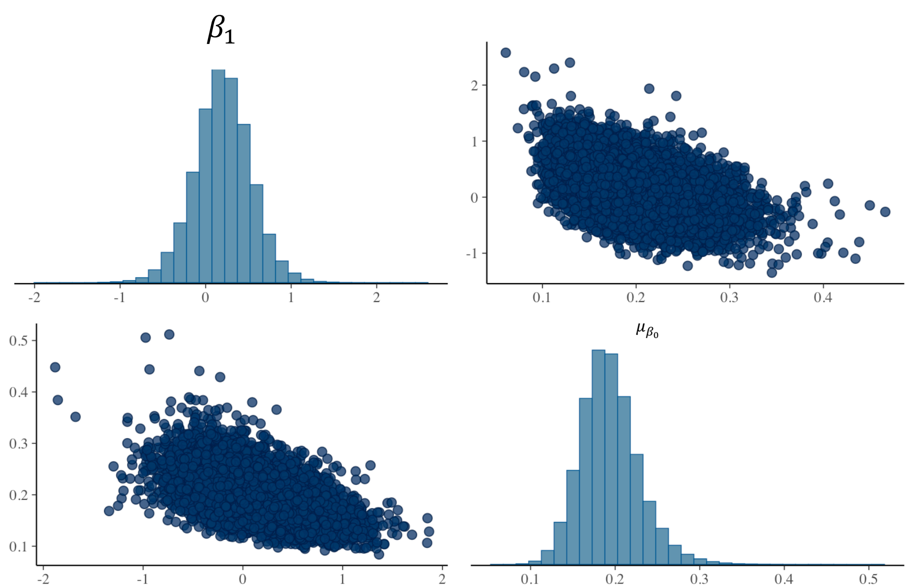



*Figure 8. Plot matrix showing univariate marginal distributions for the fixed effect parameter $\beta_1$ and mean random year effect parameter $\mu_{\beta 0}$ for Battle Creek in top left and bottom right. Top right and bottom left show bivariate distributions as scatterplots. Model was fit using water year type as the environmental covariate.*

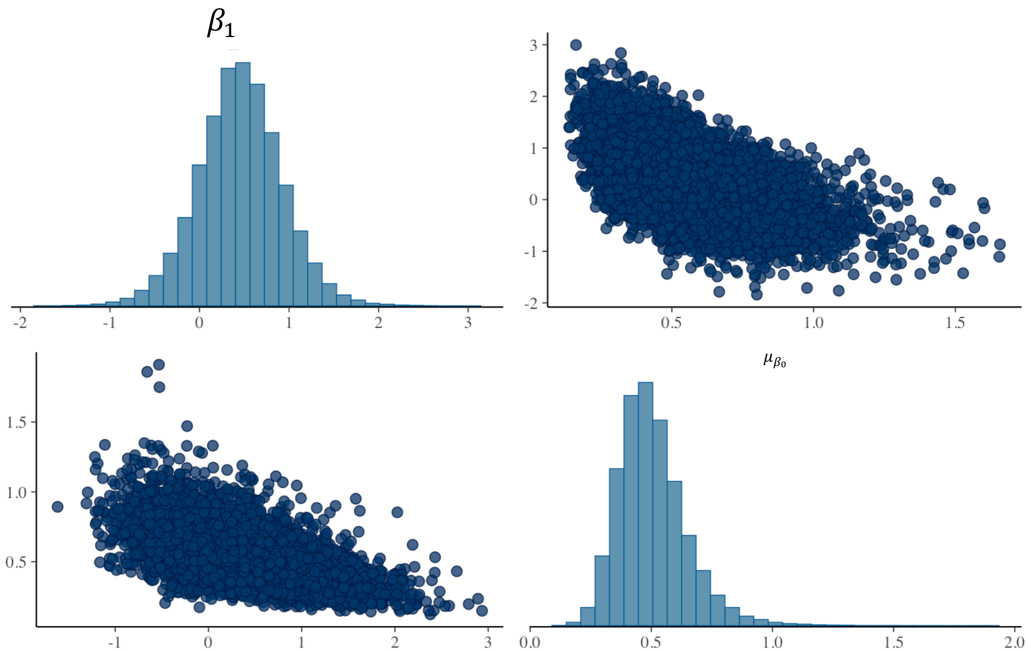



*Figure 9. Plot matrix showing univariate marginal distributions for the fixed effect parameter $\beta_1$ and mean random year effect parameter $\mu_{\beta 0}$ for Clear Creek in top left and bottom right. Top right and bottom left show bivariate distributions as scatterplots. Model was fit using water year type as the environmental covariate.*

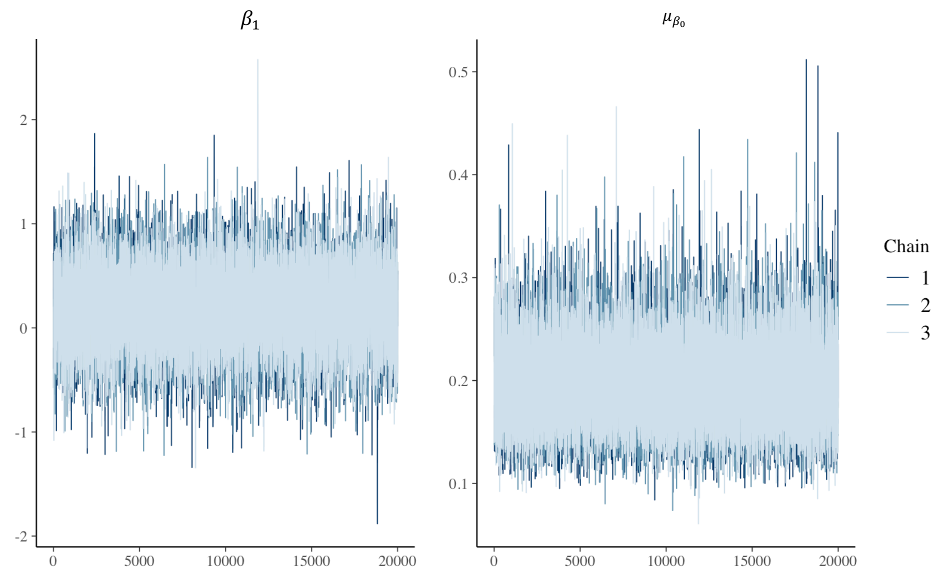



*Figure 10. Trace plots of Monte Carlo Markov Chain (MCMC) draws for fixed effect parameter $\beta_1$ and mean random year effect parameter $\mu_{\beta 0}$ on Battle Creek. Model was fit using water year type as the environmental covariate.*

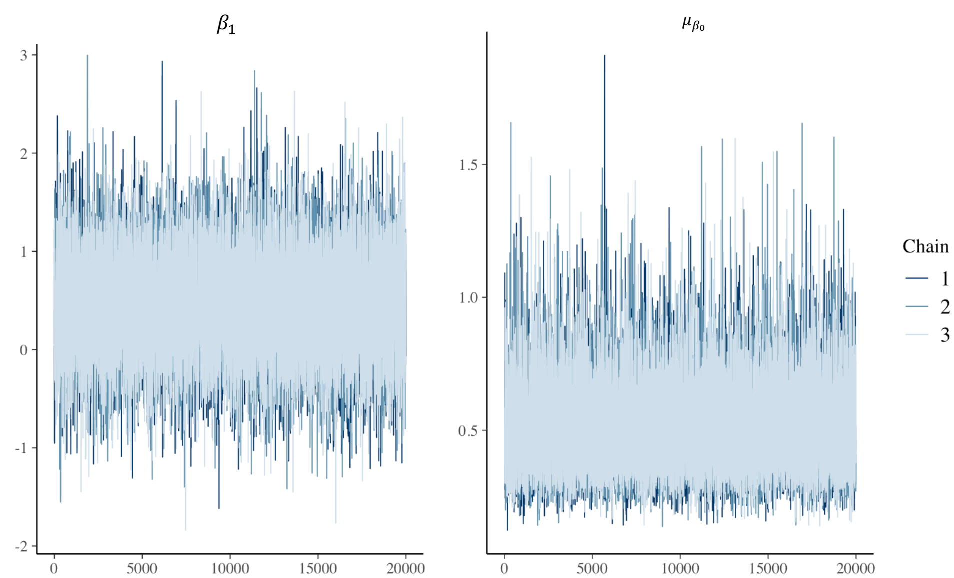



*Figure 11. Trace plots of Monte Carlo Markov Chain (MCMC) draws for fixed effect parameter $\beta_1$ and mean random year effect parameter $\mu_{\beta 0}$ on Clear Creek. Model was fit using water year type as the environmental covariate.*

## Tables

Table 1: Sample size of datasets for use in the Passage-to-Spawner model for four tributaries. The sample size column refers to the number of years where upstream passage and a redd data are both available.

| Stream | Sample Size |
|---|---:|
| Battle Creek | 21 |
| Clear Creek | 20 |

Table 2: Parameter estimates produced by fitting the passage to spawner STAN model to all combinations of streams and covariate types ($X_y$). The model was fit to each stream with a null covariate for comparison, but these models did not converge by the $\hat{R}$ statistic ($\hat{R}$ > 1.05). Only parameter used to assess the impact of an environmental covariate on the conversion rate are reported here: the proportion of variance explained by the fixed effect ($R^2$), the fixed effect covariate ($\beta_1$), and the forecasted spawner abundance. This forecast is produced using the average environmental covariate (or a dry year for water year type) or using the average plus one standard deviation (or a wet year for water year type) in the prediction.

| Parameter | Stream | Mean | Median | Standard deviation | 25% CI | 95% CI | Covariate |
|---|---|---|---|---|---|---|---|
| $R^2$ of fixed effects | Battle Creek | 0.54 | 0.56 | 0.21 | 0.14 | 0.89 | Water year type |
| $R^2$ of fixed effects | Battle Creek | 0.52 | 0.54 | 0.2 | 0.14 | 0.87 | Maximum flow |
| $R^2$ of fixed effects | Battle Creek | 0.52 | 0.55 | 0.19 | 0.13 | 0.84 | Growing degree days |
| $R^2$ of fixed effects | Battle Creek | 0.53 | 0.55 | 0.21 | 0.14 | 0.88 | Passage index |
| $\beta_1$ | Battle Creek | 0.15 | 0.15 | 0.37 | -0.6 | 0.87 | Water year type |
| $\beta_1$ | Battle Creek | 0.01 | 0.01 | 0.2 | -0.39 | 0.42 | Maximum flow |
| $\beta_1$ | Battle Creek | -3.90E-01 | -3.90E-01 | 1.10E-01 | -6.10E-01 | -1.70E-01 | Growing degree days |
| $\beta_1$ | Battle Creek | 0.04 | 0.04 | 0.15 | -0.25 | 0.35 | Passage index |
| $\mu_{\beta_0}$ | Battle Creek | 0.21 | 0.2 | 0.04 | 0.13 | 0.3 | Water year type |
| $\mu_{\beta_0}$ | Battle Creek | 0.21 | 0.21 | 0.04 | 0.15 | 0.3 | Maximum flow |
| $\mu_{\beta_0}$ | Battle Creek | 0.21 | 0.21 | 0.02 | 0.17 | 0.26 | Growing degree days |
| $\mu_{\beta_0}$ | Battle Creek | 0.21 | 0.21 | 0.04 | 0.14 | 0.3 | Passage index |
| $\sigma_{\beta_0}$ | Battle Creek | 0.63 | 0.6 | 0.15 | 0.4 | 0.99 | Water year type |
| $\sigma_{\beta_0}$ | Battle Creek | 0.64 | 0.61 | 0.15 | 0.41 | 1 | Maximum flow |
| $\sigma_{\beta_0}$ | Battle Creek | 0.39 | 0.37 | 0.11 | 0.24 | 0.65 | Growing degree days |
| $\sigma_{\beta_0}$ | Battle Creek | 0.63 | 0.61 | 0.16 | 0.41 | 1.01 | Passage index |
| Forecasted Spawner Abundance - average | Battle Creek | 127.3 | 100.64 | 122.65 | 26.09 | 389.58 | Water year type |
| Forecasted Spawner Abundance - average | Battle Creek | 133.39 | 105.52 | 120.73 | 27.17 | 400.19 | Maximum flow |

| | | | | | | |
|---|---|---|---|---|---|---|
| Forecasted Spawner Abundance - average | Battle Creek | 116.61 | 107.14 | 53.83 | 45.72 | 244.24 | Growing degree days |
| Forecasted Spawner Abundance - average | Battle Creek | 136.53 | 103.68 | 1339.34 | 26.27 | 398.24 | Passage index |
| Forecast Spawner Abundance - average + 1 sd | Battle Creek | 150.69 | 116.98 | 143.69 | 27.65 | 475.91 | Water year type |
| Forecast Spawner Abundance - average + 1 sd | Battle Creek | 138.55 | 107.44 | 134.39 | 25.79 | 434.67 | Maximum flow |
| Forecast Spawner Abundance - average + 1 sd | Battle Creek | 79.21 | 72.07 | 38.18 | 29.84 | 170.43 | Growing degree days |
| Forecast Spawner Abundance - average + 1 sd | Battle Creek | 145.66 | 108.04 | 2021.49 | 27.44 | 423.45 | Passage index |
| $R^2$ of fixed effects | Clear Creek | 0.48 | 0.46 | 0.1 | 0.33 | 0.74 | Water year type |
| $R^2$ of fixed effects | Clear Creek | 0.47 | 0.47 | 0.08 | 0.33 | 0.67 | Maximum flow |
| $R^2$ of fixed effects | Clear Creek | 0.48 | 0.48 | 0.07 | 0.34 | 0.64 | Growing degree days |
| $R^2$ of fixed effects | Clear Creek | 0.47 | 0.46 | 0.09 | 0.32 | 0.72 | Passage index |
| $\beta_1$ | Clear Creek | 0.52 | 0.52 | 0.5 | -0.48 | 1.51 | Water year type |
| $\beta_1$ | Clear Creek | 0.28 | 0.28 | 0.22 | -0.16 | 0.71 | Maximum flow |
| $\beta_1$ | Clear Creek | 4.40E-01 | 4.40E-01 | 5.40E-01 | -6.30E-01 | 1.52E+00 | Growing degree days |
| $\beta_1$ | Clear Creek | -0.85 | -0.86 | 0.68 | -2.18 | 0.5 | Passage index |
| $\mu_{\beta_0}$ | Clear Creek | 0.51 | 0.49 | 0.15 | 0.28 | 0.85 | Water year type |
| $\mu_{\beta_0}$ | Clear Creek | 0.58 | 0.57 | 0.14 | 0.35 | 0.89 | Maximum flow |
| $\mu_{\beta_0}$ | Clear Creek | 0.68 | 0.65 | 0.2 | 0.37 | 1.15 | Growing degree days |
| $\mu_{\beta_0}$ | Clear Creek | 0.52 | 0.51 | 0.13 | 0.31 | 0.83 | Passage index |
| $\sigma_{\beta_0}$ | Clear Creek | 0.9 | 0.87 | 0.2 | 0.6 | 1.38 | Water year type |
| $\sigma_{\beta_0}$ | Clear Creek | 0.89 | 0.86 | 0.2 | 0.6 | 1.35 | Maximum flow |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| $\sigma_{\beta_0}$ | Clear Creek | 0.92 | 0.89 | 0.2 | 0.62 | 1.4 | Growing degree days |
| $\sigma_{\beta_0}$ | Clear Creek | 0.88 | 0.85 | 0.2 | 0.58 | 1.35 | Passage index |
| Forecasted Spawner Abundance - average | Clear Creek | 181.18 | 109.52 | 451.37 | 16.09 | 753.33 | Water year type |
| Forecasted Spawner Abundance - average | Clear Creek | 202.17 | 127.03 | 395.18 | 19.74 | 803.74 | Maximum flow |
| Forecasted Spawner Abundance - average | Clear Creek | 248.6 | 145.94 | 1558.34 | 20.91 | 1031.17 | Growing degree days |
| Forecasted Spawner Abundance - average | Clear Creek | 180.39 | 113.7 | 308.73 | 17.92 | 732.58 | Passage index |
| Forecast Spawner Abundance + 1 sd | Clear Creek | 316.9 | 183.9 | 787.67 | 24.71 | 1369.33 | Water year type |
| Forecast Spawner Abundance + 1 sd | Clear Creek | 274.87 | 168.1 | 686.14 | 24.89 | 1116.57 | Maximum flow |
| Forecast Spawner Abundance + 1 sd | Clear Creek | 544.64 | 225.21 | 12563.55 | 21.39 | 2456.03 | Growing degree days |
| Forecast Spawner Abundance + 1 sd | Clear Creek | 111.41 | 48.33 | 581.28 | 4.44 | 546.59 | Passage index |

Table 3: Parameter estimates from fitting the model to water year type for each tributary.

| Parameter | Stream | Mean | Standard Error (mean) | Standard deviation | 2.5% | 50% | 97.5 % |
|---|---|---|---|---|---|---|---|
| $\mu_{\beta_0}$ | Battle Creek | -0.96 | 0.001 | 0.18 | -1.32 | -0.96 | -0.61 |
| $\sigma_{\beta_0}$ | Battle Creek | 0.58 | 0.001 | 0.13 | 0.39 | 0.56 | 0.89 |
| $\beta_1$ | Battle Creek | 0.20 | 0.003 | 0.33 | -0.47 | 0.20 | 0.86 |
| $R^2$ of fixed effects | Battle Creek | 0.55 | 0.001 | 0.21 | 0.14 | 0.58 | 0.89 |
| $\mu_{\beta_0}$ | Clear Creek | -0.03 | 0.002 | 0.27 | -0.57 | -0.03 | 0.51 |
| $\sigma_{\beta_0}$ | Clear Creek | 0.87 | 0.001 | 0.19 | 0.59 | 0.84 | 1.33 |
| $\beta_1$ | Clear Creek | 0.45 | 0.004 | 0.47 | -0.49 | 0.45 | 1.38 |
| $R^2$ of fixed effects | Clear Creek | 0.47 | 0.000 | 0.10 | 0.32 | 0.46 | 0.74 |

Table 4: Years in adult monitoring timeframe where data is missing and P2S could be used to fill in abundance estimates.

| **Stream** | **Year** | **Data Type** | **Reason for Exclusion** |
|---|---|---|---|
| Battle Creek | 2004 | Redd survey | Missing reaches 1, 5 and 6 |
| Battle Creek | 2015 | Redd survey | Missing reaches 3, 5, and 6 |
| Battle Creek | 2017 | Redd survey | Missing reaches 2, 3, 5, and 6 |
| Battle Creek | 2018 | Redd survey | Missing reaches 3, 5, and 6 |
| Clear Creek | 2018 | Upstream passage | Missing March/April |
| Clear Creek | 2019 | Upstream passage | Missing March/April |
| Clear Creek | 2000 | Redd survey | Missing reach 3, 6, and partial coverage on 5 |
| Clear Creek | 2020 | Redd survey | Only sampling reach 6 and 7 |

## Appendix A: Data Aggregation and Criteria

Data completeness, quality, and availability varied across streams. The P2S model could conceivably be applied to Battle Creek, Clear Creek, Mill Creek, and Deer Creek because they had robust spawner count data (redd surveys for Battle, Clear, and Mill; holding surveys for Deer) and upstream passage data. However, Deer and Mill Creek survey data are in the final stages of QA/QC and so for the purposes of model development and model review, only Battle and Clear Creek are included in P2S analyses here.

For the remaining streams in the JPE, other methods were used to get an estimate of spawner abundance. Butte Creek and Feather River both had high quality carcass surveys and spawner abundances were estimated using a Cormack Jolly-Seber mark-recapture model. Yuba River had upstream passage data and performs carcass surveys but only had CJS estimates for four years (2014, 2015, 2019, and 2020). Because of these limitations, Yuba River spawner abundances were estimated directly from upstream passage data - to account for potential failures in the video capture systems, the Yuba River monitoring teams used a generalized additive model (GAM) to produce estimates for each year.

The CJS and GAM were conducted by the stream monitoring programs themselves and results of the CJS model and upstream passage estimates were provided by staff directly for Butte Creek, Feather River, and Yuba River. The specific methods applied in these streams are available (Butte and Feather: unpublished reports; Yuba: Poxon, B., P. Bratovich. 2020. Lower Yuba River Vaki Riverwatcher Chinook Salmon Passage and Run Differentiation Analyses. HDR).

# Appendix B: P2S Covariate Construction

This appendix describes the process used to select the form of each environmental covariate used in P2S alternative models from among various possible configurations for each environmental variable available for modeling. Differences between this first round of covariate construction and the second round of alternative model building and selection are described in Table 1.

*Table 1. Description of analyses performed to explore and select covariates for use in the P2S model.*

| **Round** | **Model** | **Metrics** | **Covariate structure** | **Response variable** |
|---|---|---|---|---|
| 1 | Linear regression | $R^{2,}$ visual inspection of linear regression plots | Many different approaches to summarizing flow, temperature, passage, etc. | Simple pre-spawn survival (spawner/passage abundance ratio) |
| 2 | P2S Bayesian | $R^2$ (fixed effects), magnitude of estimate of $\beta_1$ (fixed effect covariate), variation in predicted spawner abundance | One approach to summarizing flow, temperature, passage, etc. | Modeled passage to spawner conversion rate ($R_y$) |

### *Calculating Prespawn Survival*

Prespawn survival, or the proportion of adults that survived from upstream passage to spawn, was calculated as spawner count divided by upstream passage estimate. When we were using redd counts as spawner count, we assumed a 50/50 sex ratio and multiplied redd count by 2 to get a full spawner count. Generally, one redd per female is a reasonable assumption although the P2S model left the possibility open for more than one redd per female (Murdoch et al., 2009). This produced values of prespawn survival that exceeded 1 for some years on some streams, which could be attributed to error in upstream passage estimates.

### *Environmental Covariates*

Candidate covariates were derived from five general variables that were available from monitoring programspredict prespawn survival: flow, temperature, water year type, upstream passage timing, and upstream passage index (i.e. the magnitude of fish escapement, which serves as a proxy for density-dependent effects, habitat availability, etc.). We identified these general variables based on a literature review and suggestions from the SRJPE Modeling Advisory Team (MAT).

For most of these variables, we constructed multiple summary statistics for potential use as covariates in the P2S models:

- Temperature
  - Proportion of days exceeding a temperature threshold – calculate the proportion of days within migratory (March-May) and holding (May-July) months that exceed a threshold of 20 degrees C (Marine & Cech 2004, Keefer et al., 2018). Temperature data were pulled from the mainstem for migratory calculations and the tributaries for holding.
  - Growing Degree Days (GDD) – subtract a "base" temperature of 20 degrees C from the temperature measured in the mainstem (migratory, March-May) or tributary (holding, May-August) and then sum that value across all days within the period. Then sum across migratory and holding data to obtain a total GDD value. This accounts for the cumulative exposure to thermal stress over a threshold of 20 degrees C (Keefer et al., 2018).
- Flow
  - Mean and maximum flow over migratory (March-May) and holding (May-August) periods.
- Upstream passage timing
  - Median, mean, and minimum week of passage timing for each tributary and year.
- Water year type (wet or dry)
  - Wet includes "wet" and "above normal" years; dry includes "below normal", "dry", and "critical".
- Passage magnitude ("Passage index")
  - The total number of upstream passage estimated for each year

### *Statistical Importance of Covariates*

To determine which form of variables to use in P2S modeling, we used simple linear regressions of candidate environmental covariates against prespawn survival calculated as described above. We found we did not have enough data points for each stream to test multivariate regressions and instead we fit a single linear regression of prespawn survival and each predictor variable and compared adjusted $R^2$ values, where the highest $R^2$ would indicate the strongest fit among multiple forms of each environmental covariate.

## *Results*

Passage timing produced the highest $R^2$ in linear regression against prespawn survival for both Battle (minimum passage timing) and Clear (median passage timing) Creeks, followed by growing degree days for Battle Creek and proportion of days exceeding temperature threshold for Clear Creek (Table 2). However, $R^2$ for Clear Creek were low across all covariates indicating a weak relationship as can also be seen in the figures. We selected one summarization method for each environmental covariate type for testing in the P2S models. Because Clear Creek had more anomalous years than Battle (years where spawner counts exceeded upstream passage), and because the $R^2$ were low for all values, we based these selections on $R^2$ and data availability with respect to Battle Creek. This resulted in the following covariates: growing degree days (for temperature), maximum flow (for flow), water year type (for a discrete variable), and passage index. Though passage timing had the highest $R^2$ value, data was very limited because for many years and streams passage data was provided summarized at the yearly level, and so we did not use it in the next round of analyses.

## *References*

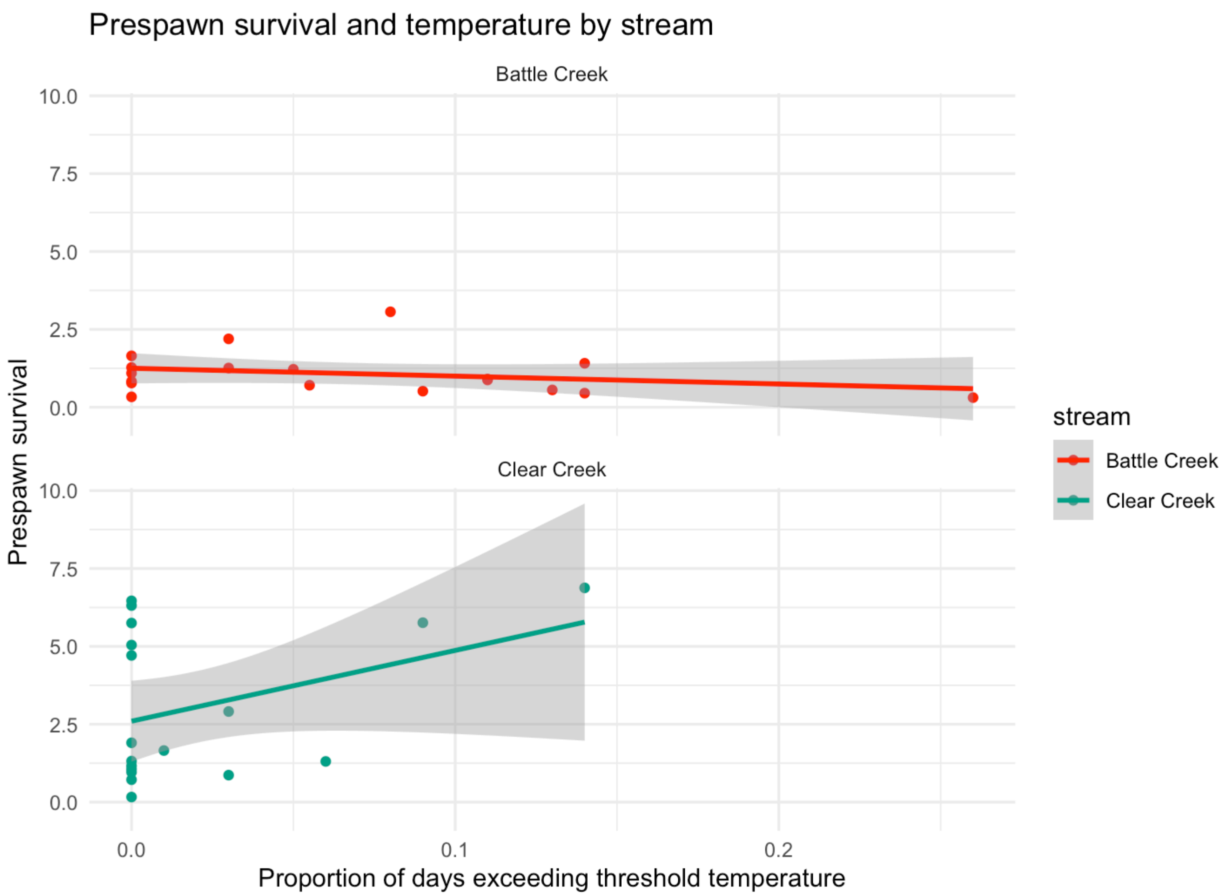
Keefer, Matthew L., Clabough, Tami S., Jepson, Michael A., Johnson, Eric L., Peery, Christopher A., Caudill, Christopher C. (2018). *Thermal exposure of adult Chinook salmon and steelhead: Diverse behavioral strategies in a large and warming river system.* PLoS ONE 13(9).

Marine, Keith R. & Cech, Joseph J. Jr. (2004). *Effects of High Water Temperature on Growth, Smoltification, and Predator Avoidance in Juvenile Sacramento River Chinook Salmon*. North American Journal of fisheries Management 24:198-210.

Murdoch, Andrew R., Pearsons, Todd N., Maitland, Travis. (2009). *The Number of Redds Constructed per Female Spring Chinook Salmon in the Wenatchee River Basin.* North American Journal of Fisheries Management 29(2): 441-446.

## *Figures*

Temperature



Prespawn survival and temperature by stream
Battle Creek
Clear Creek
10.0
7.5
5.0
2.5
0.0
Prespawn survival
0.0
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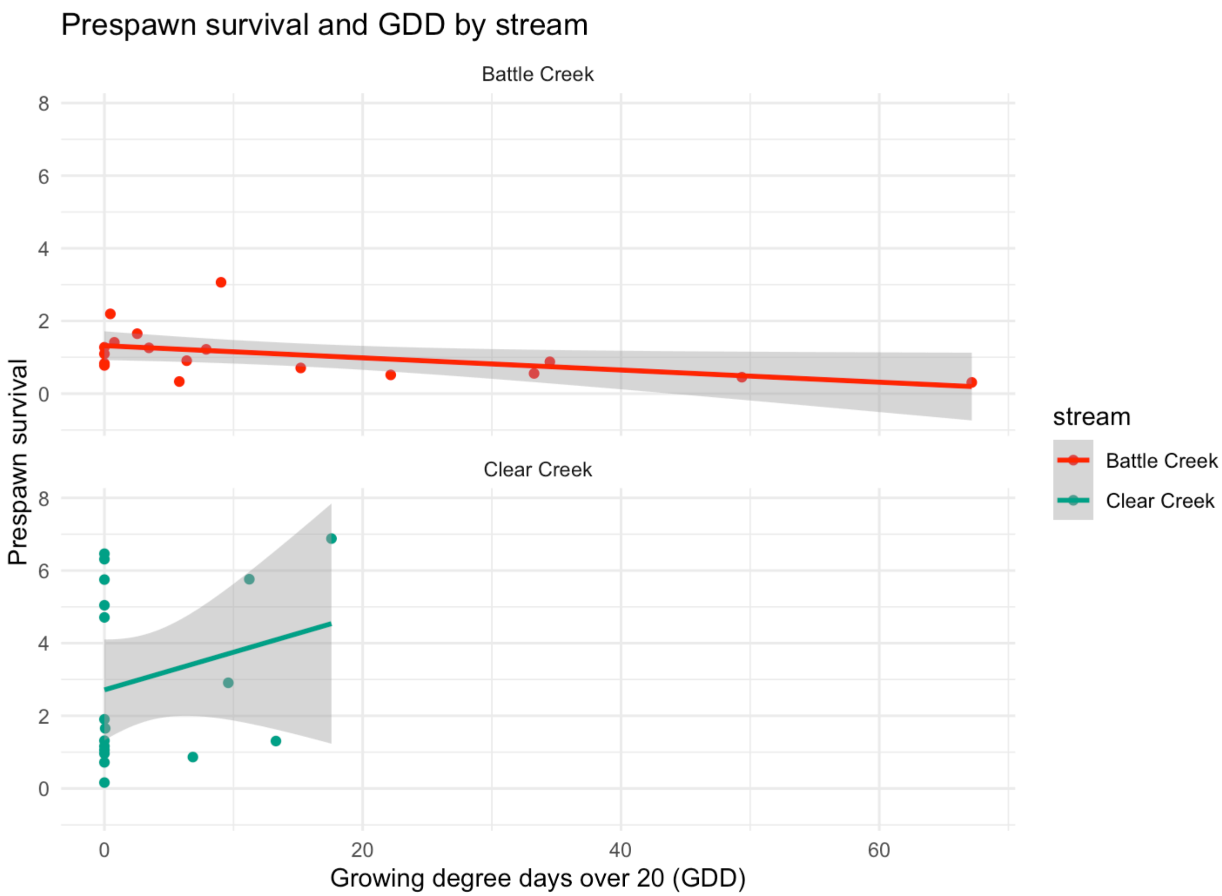
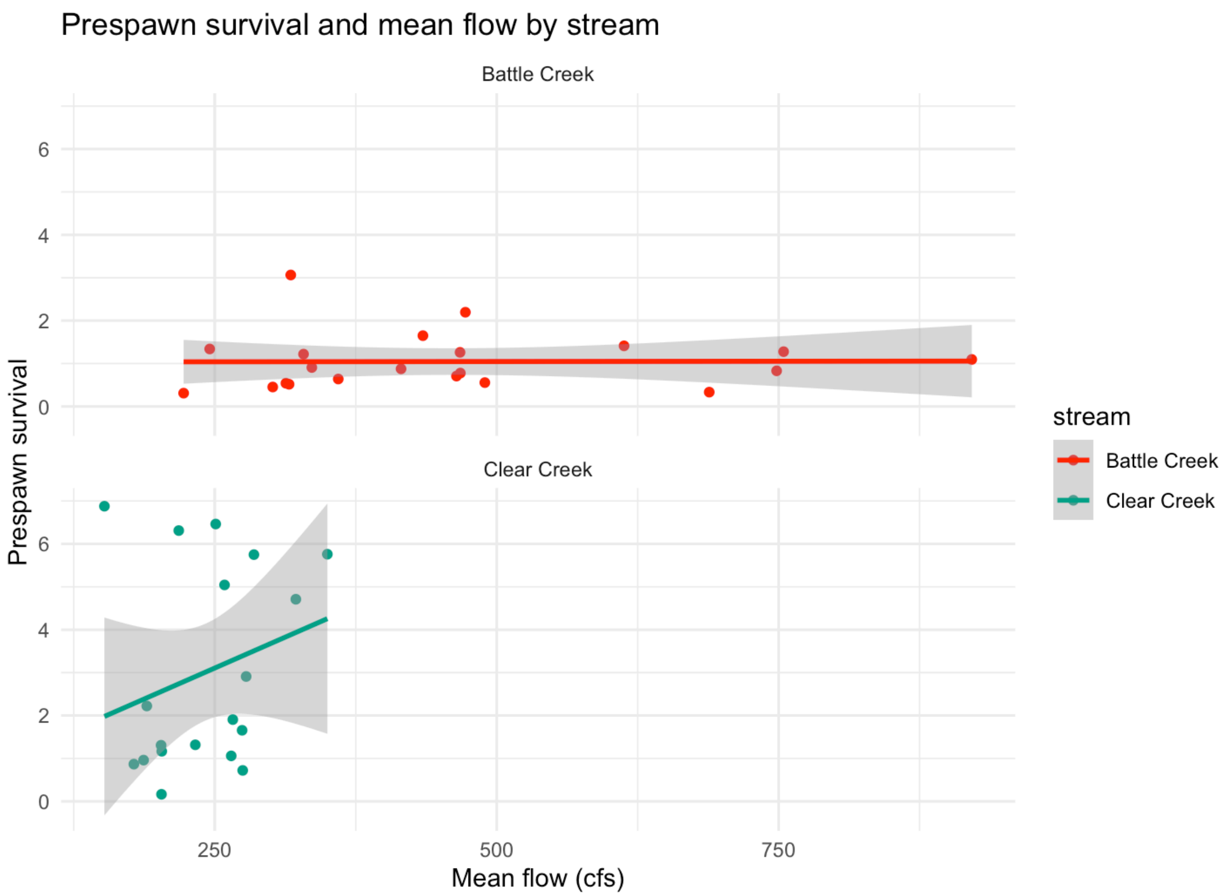
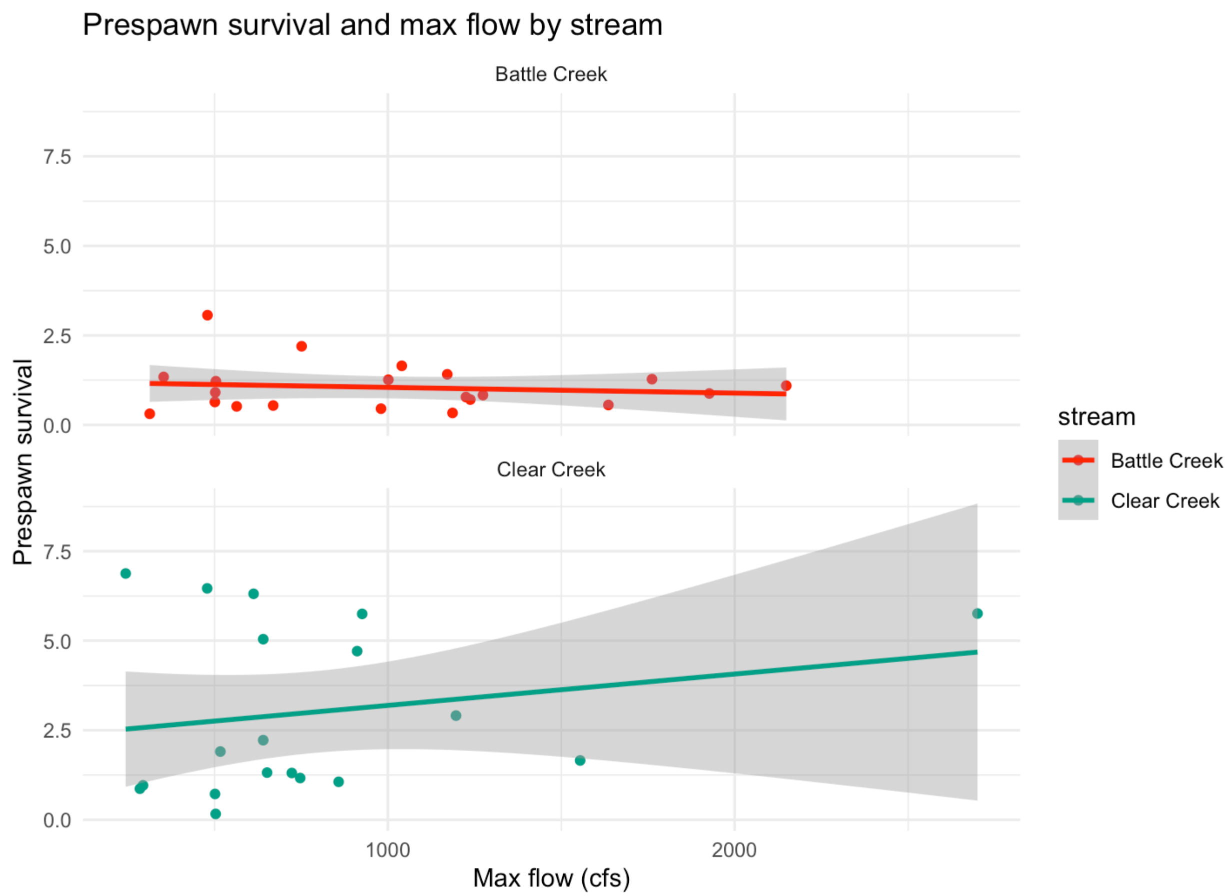
Proportion of days exceeding threshold temperature
stream
Battle Creek
Clear Creek


383

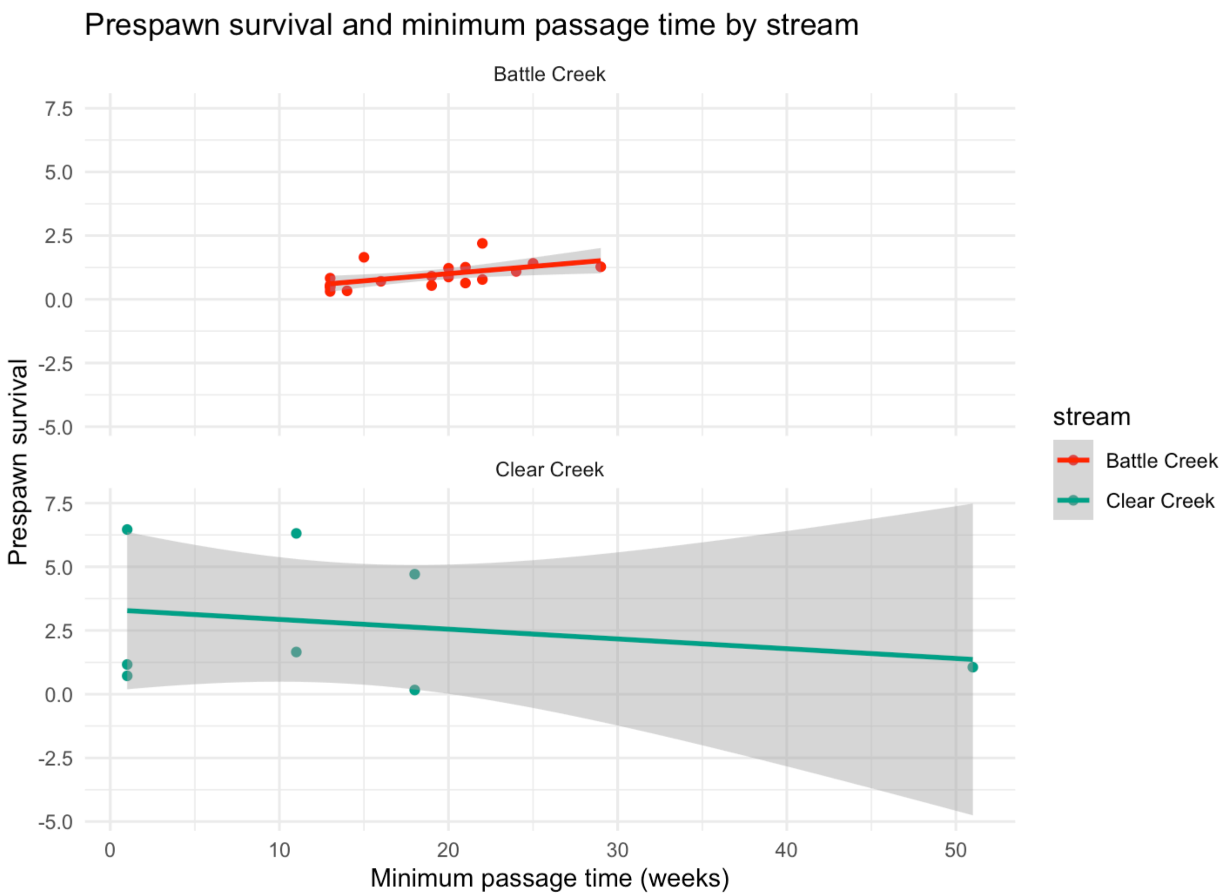

Prespawn survival and GDD by stream
Battle Creek
Clear Creek
Prespawn survival
Growing degree days over 20 (GDD)
stream
Battle Creek
Clear Creek
8
6
4
2
0
0
20
40
60

Flow

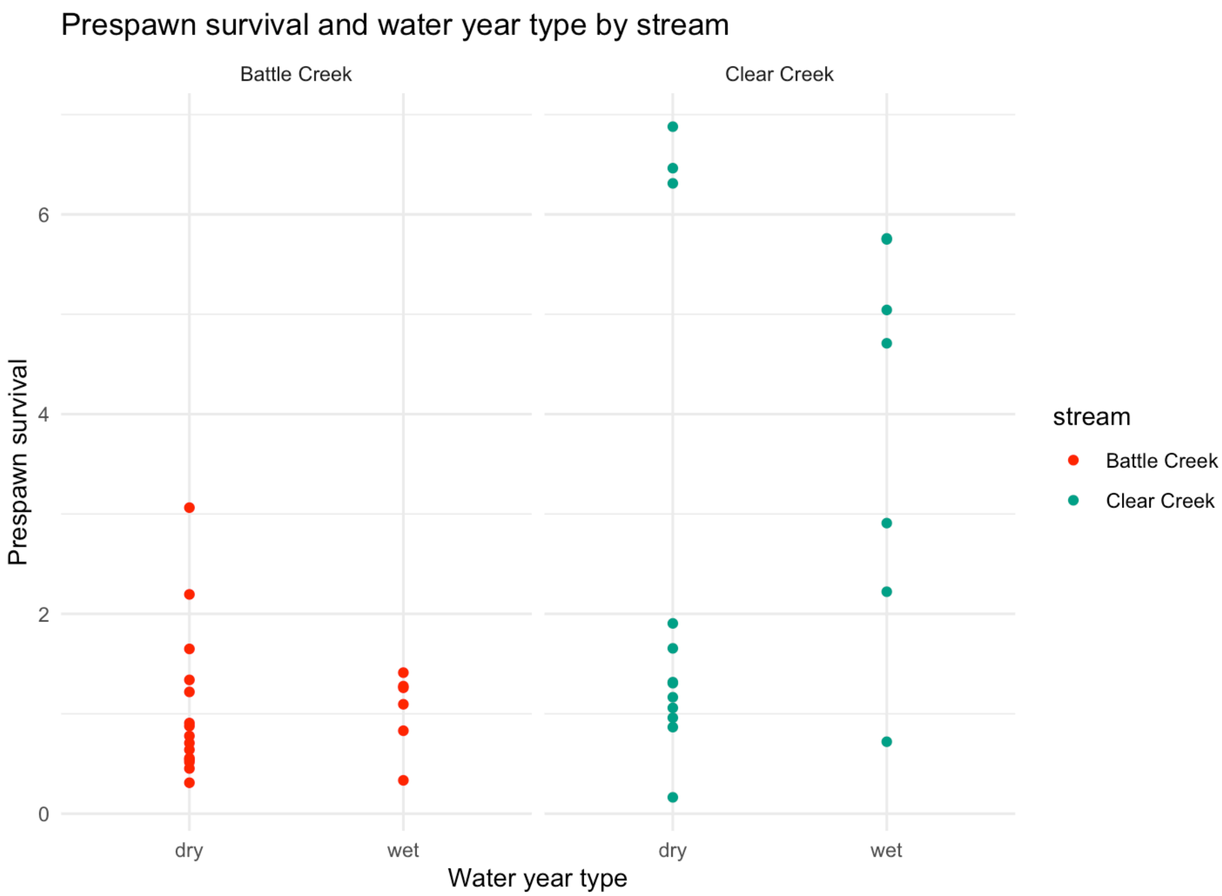

Prespawn survival and mean flow by stream
Battle Creek
Clear Creek
Prespawn survival
Mean flow (cfs)
0
2
4
6
250
500
750
stream
Battle Creek
Clear Creek



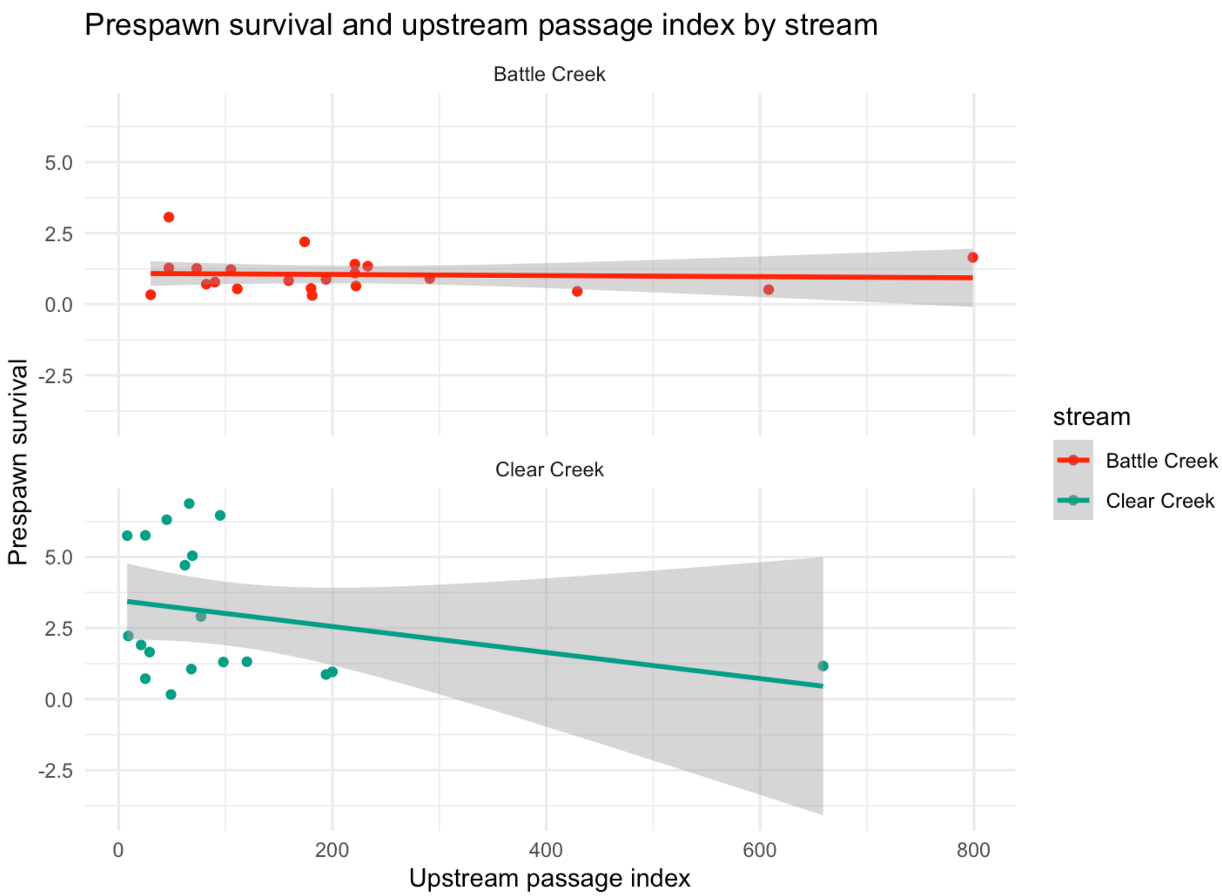

## Passage timing




Water Year Type

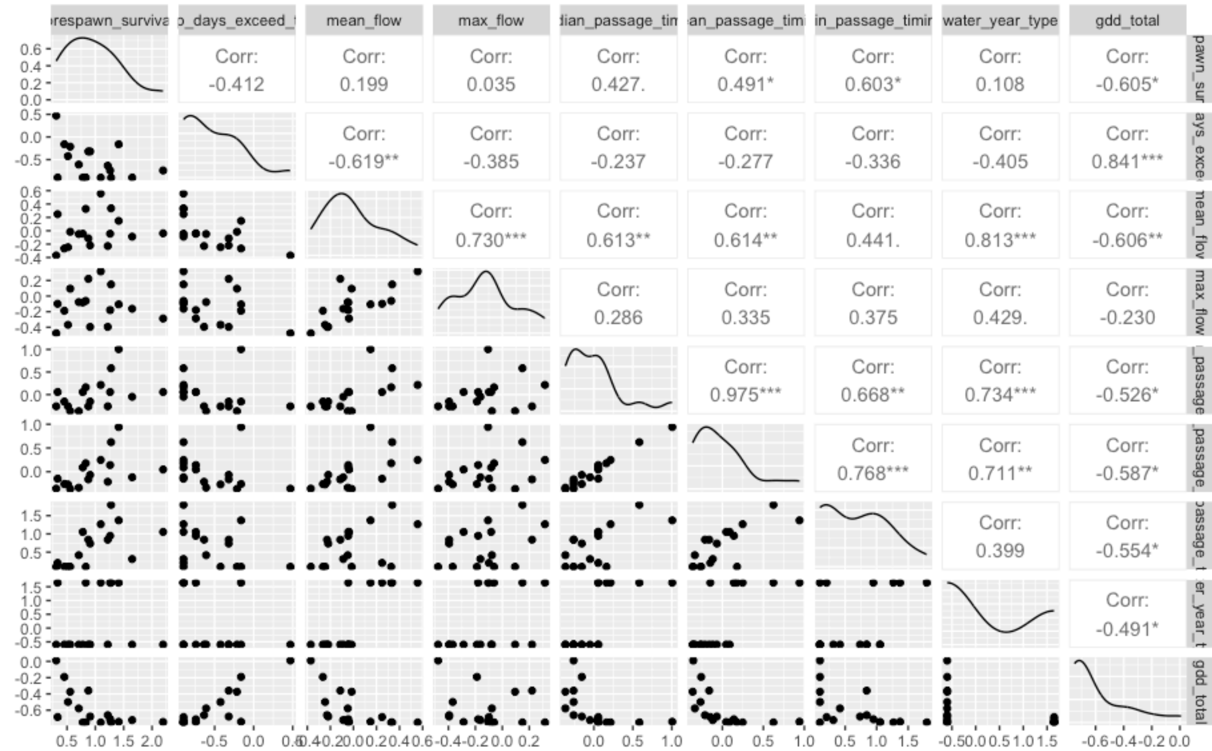



Passage Index




*Pairs Plots*

Battle Creek



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gdd_total
Corr: -0.412
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Corr: 0.427.
Corr: 0.491*
Corr: 0.603*
Corr: 0.108
Corr: -0.605*
Corr: -0.619**
Corr: -0.385
Corr: -0.237
Corr: -0.277
Corr: -0.336
Corr: -0.405
Corr: 0.841***
Corr: 0.730***
Corr: 0.613**
Corr: 0.614**
Corr: 0.441.
Corr: 0.813***
Corr: -0.606**
Corr: 0.286
Corr: 0.335
Corr: 0.375
Corr: 0.429.
Corr: -0.230
Corr: 0.975***
Corr: 0.668**
Corr: 0.734***
Corr: -0.526*
Corr: 0.768***
Corr: 0.711**
Corr: -0.587*
Corr: 0.399
Corr: -0.554*
Corr: -0.491*
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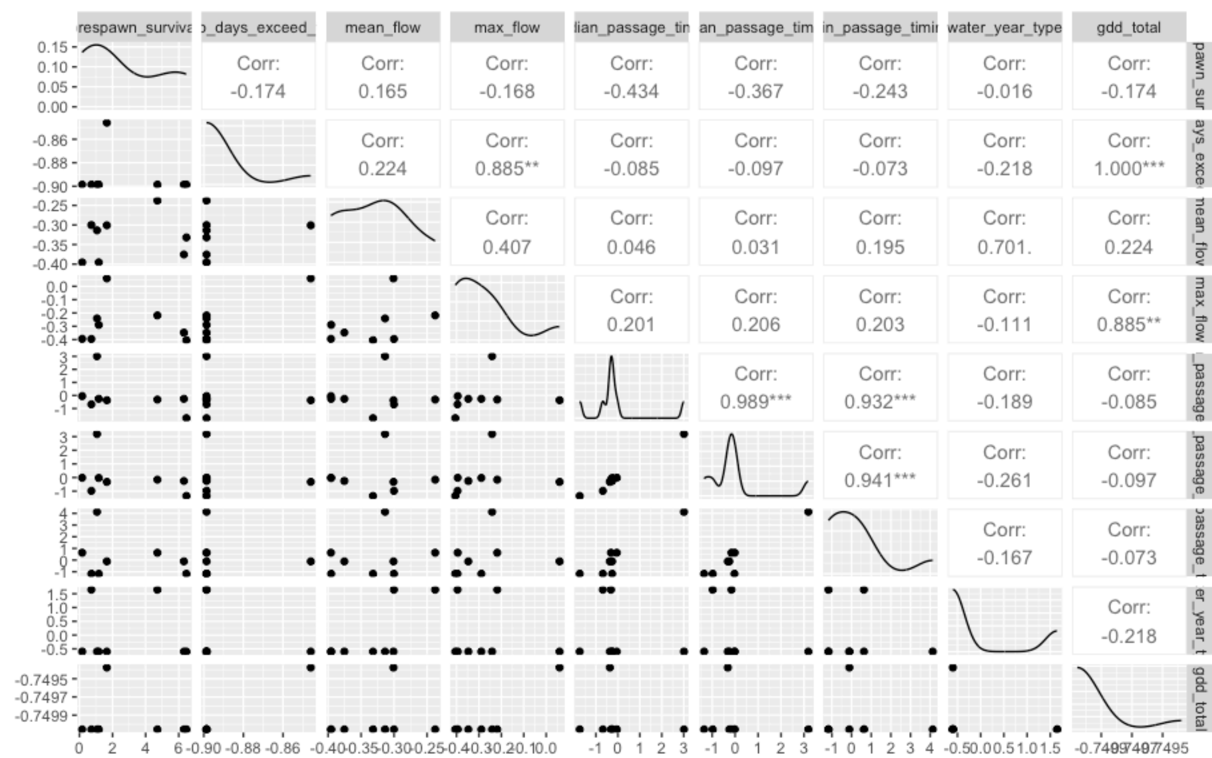
## Clear Creek



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Corr: -0.174
Corr: 0.165
Corr: -0.168
Corr: -0.434
Corr: -0.367
Corr: -0.243
Corr: -0.016
Corr: -0.174
Corr: 0.224
Corr: 0.885**
Corr: -0.085
Corr: -0.097
Corr: -0.073
Corr: -0.218
Corr: 1.000***
Corr: 0.407
Corr: 0.046
Corr: 0.031
Corr: 0.195
Corr: 0.701.
Corr: 0.224
Corr: 0.201
Corr: 0.206
Corr: 0.203
Corr: -0.111
Corr: 0.885**
Corr: 0.989***
Corr: 0.932***
Corr: -0.189
Corr: -0.085
Corr: 0.941***
Corr: -0.261
Corr: -0.097
Corr: -0.167
Corr: -0.073
Corr: -0.218
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gdd_total

*Table 2: Adjusted $R^2$ values*

| | $R^2$ (against prespawn survival) | |
|---|---|---|
| **Covariate** | **Battle Creek** | **Clear Creek** |
| Minimum passage timing | 0.309 | 0.059 |
| Growing degree days | 0.222 | 0.061 |
| Mean passage timing | 0.168 | 0.135 |
| Median passage timing | 0.151 | 0.188 |
| Proportion days exceeding threshold | 0.067 | 0.137 |
| Maximum flow | 0.017 | 0.044 |
| Water year type | 0.000 | 0.084 |
| Mean flow | 0.000 | 0.064 |

# Appendix C: Leave One Out (LOO) analysis

*LOO cross-validation summary*

LOO and widely applicable information criterion (WAIC) estimate "pointwise out-of-sample prediction accuracy from a fitted Bayesian model" (Vehtari et al 2016). Using the LOO R package, we calculate the Pareto-smoothed importance sampling (PSIS) LOO for Battle and Clear Creek Passage to Spawner models fit to all environmental covariates (Vehtari et al 2024). These analyses were performed in response to feedback about out-of-sample prediction accuracy of the Passage to Spawner model in the context of the Spring Run Juvenile Production Estimate and to supplement environmental covariates selection. We present here two analyses addressing these points:

We used LOOIC to compare covariates for Battle and Clear Creek and found that in all instances, water year type performed better than a null covariate, but continuous covariates (temperature, flow, passage index) weren't consistently better or worse than null or water year type across streams. To compare covariates, datasets had to be truncated for years where all covariates were available, which reduced the sample size for Clear Creek for continuous comparisons to five years (restricted by the availability of median passage timing data). Covariate selection also needed to consider data availability (i.e. if we used that environmental covariate, how many years of data would be available to feed into the model?) and forecasting in the SRJPE (i.e. a discrete variable like water year type has far fewer assumptions than using a forecasted continuous variable, like temperature, to then predict spawner count).

We also fit Battle and Clear Creek models using water year type for the full dataset (21 data points for Battle, and 19 data points for Clear). For these models, we present expected differences in predicted values and effective parameter sizes, which allows for analysis of specific years in the LOO framework and evaluation of model specification (effective parameter size). This adds additional context to our understanding of anomalous years (years where our data show spawner count being greater than upstream passage count) and their influence on predictive accuracy of the model. Our results suggest that improving modeling of those anomalous years will improve the predictive capacity of P2S.

*Details*

Cross validation re-fits the model to different data training sets. Traditional LOO uses importance sampling but is noisy; PSIS LOO allows for calculating importance weights that might otherwise be inappropriate by fitting a Pareto distribution to the upper tail of the importance weight distribution. PSIS LOO is "more robust in the finite case with weak priors or influential observations" (Vehtari et al 2016) compared to WAIC. The expected log predictive density (elpd), or prediction accuracy, for a new dataset, the effective number of parameters (p_loo), and the leave-one-out information criteria (LOOIC) are all reported alongside standard errors. In a model comparison framework, a lower LOOIC means that has better prediction accuracy for a new dataset.

We used LOO to compare performance of the models fit to Battle and Clear Creeks for water year type, median passage timing, growing degree days, maximum flow, passage index, and a null variable (all zeros). For all models to be fit to comparable datasets, we truncated the dataset to where we had data for each covariate, which reduced the sample size to 7 years of data for Clear Creek and 17 years for Battle Creek.

We also report pointwise (for each data point, or year) prediction accuracy and effective parameter size for the model fit to Battle and Clear Creeks using water year type as an environmental covariate. These statistics allow for more in-depth analysis of each data point's contribution to prediction accuracy – i.e. if the data point from 2004 is left out for Battle Creek, what is the model's ability to predict that data point accurately?

### *Results*

The table below shows the LOOIC (or prediction accuracy) calculated for each covariate for Battle and Clear Creeks. Based on this statistic, the model with the best out-of-sample prediction fit is growing degree days for Battle and water year type for Clear Creek, though considering standard error (SE in the table) reduces the distinction between the different covariates. Out of the full dataset for Battle Creek, growing degree days has 18 years of data compared to 21 years of data for water year type. Continuous variables perform better than water year type for both streams which makes sense because they are a more direct measure of environmental conditions than a discrete variable like water year type, though again the SE values show that there is minimal distinction between covariates when incorporating uncertainty in LOOIC values. However, if the P2S model were to be approved for forecasting in the SRJPE, forecasted continuous environmental variables would need to be used which would introduce more error. For both Battle and Clear Creeks water year type performed better (a lower LOOIC) than the null model, and a discrete variable like water year type would introduce less error in a forecasting context, if proposed. All models performed very similarly for Clear Creek.

| **Battle Creek (n = 17)** | | |
|---|---|---|
| **Covariate** | **LOOIC** | **SE** |
| Growing degree days | 144.35 | 4.88 |
| Water year type | 145.91 | 4.21 |
| Median passage timing | 146.11 | 4.74 |
| Passage index | 146.73 | 4.54 |
| Maximum flow | 147.59 | 5.03 |
| Null | 147.66 | 4.85 |
| **Clear Creek (n = 7)** | | |

| | | |
|---|---|---|
| Water year type | 58.82 | 4.80 |
| Median passage timing | 58.96 | 4.63 |
| Passage index | 59.02 | 5.04 |
| Maximum flow | 59.57 | 4.32 |
| Null | 59.79 | 4.70 |
| Growing degree days | 60.11 | 4.78 |

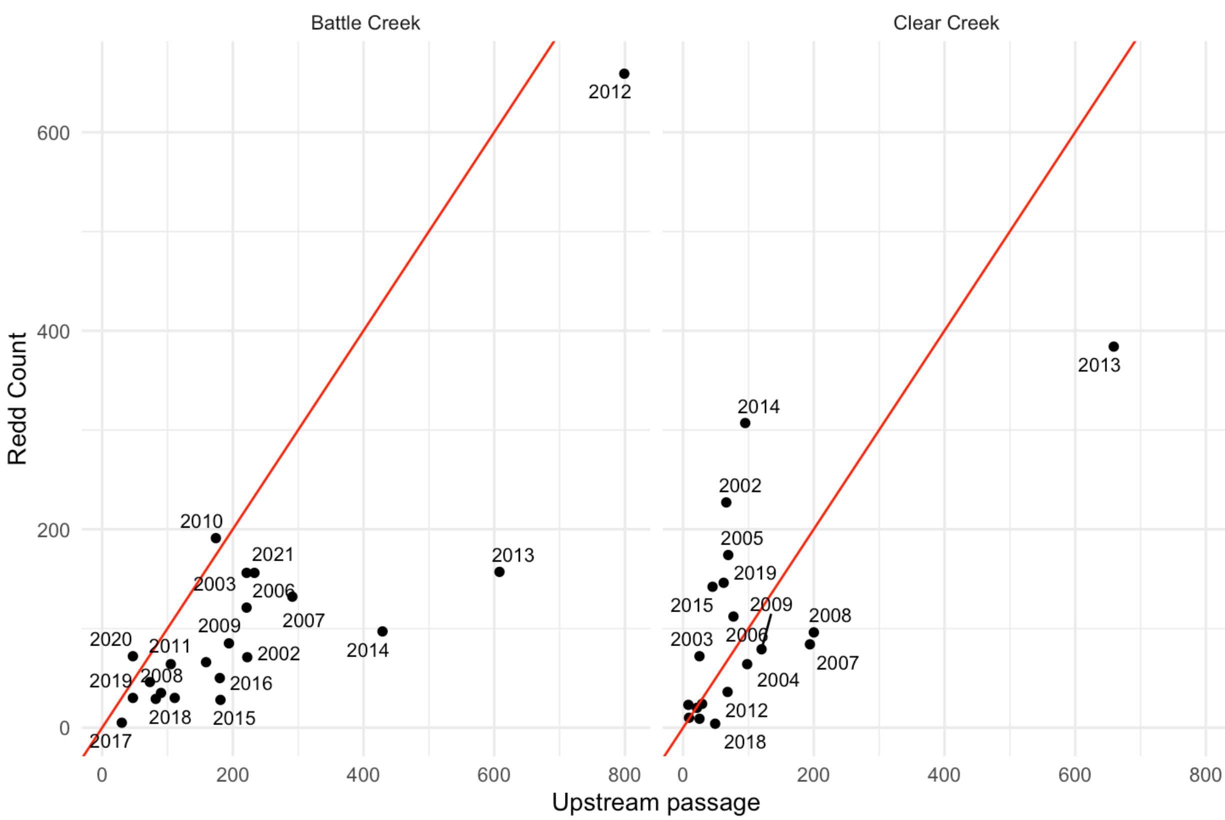
The table below shows pointwise expected log predictive density (theoretical expected error between the predicted and true value), the Monte Carlo standard error (MCSE), and the LOOIC (which is the -2 * ELPD) for each data point (year) for Battle and Clear Creek.

| **Battle Creek (n = 21)** | | | | **Clear Creek (n = 19)** | | | |
|---|---|---|---|---|---|---|---|
| **Year** | **ELPD** | **ELPD MCSE** | **LOOIC** | **Year** | **ELPD** | **ELPD MCSE** | **LOOIC** |
| 2001 | -3.72 | 0.08 | 7.44 | 2000 | -3.03 | 0.05 | 6.05 |
| 2002 | -4.14 | 0.06 | 8.28 | 2002 | -4.98 | 0.14 | 9.97 |
| 2003 | -4.76 | 0.09 | 9.52 | 2003 | -4.34 | 0.11 | 8.67 |
| 2004 | -3.81 | 0.12 | 7.62 | 2004 | -4.14 | 0.07 | 8.28 |
| 2005 | -3.91 | 0.05 | 7.82 | 2005 | -4.86 | 0.13 | 9.71 |
| 2006 | -4.48 | 0.06 | 8.97 | 2006 | -4.49 | 0.08 | 8.98 |
| 2007 | -4.55 | 0.09 | 9.1 | 2007 | -4.56 | 0.19 | 9.11 |
| 2008 | -4.3 | 0.14 | 8.59 | 2008 | -4.45 | 0.13 | 8.9 |
| 2009 | -4.24 | 0.07 | 8.49 | 2009 | -4.22 | 0.07 | 8.44 |
| 2010 | -5.03 | 0.14 | 10.06 | 2010 | -3.69 | 0.14 | 7.37 |
| 2011 | -4.29 | 0.15 | 8.58 | 2011 | -3.73 | 0.12 | 7.46 |
| 2012 | -5.36 | 0.06 | 10.73 | 2012 | -3.97 | 0.14 | 7.93 |
| 2013 | -4.6 | 0.08 | 9.21 | 2013 | -5.1 | 0.08 | 10.2 |
| 2014 | -4.66 | 0.22 | 9.32 | 2014 | -5.06 | 0.08 | 10.12 |
| 2015 | -4.25 | 0.12 | 8.5 | 2015 | -4.8 | 0.15 | 9.61 |
| 2016 | -3.98 | 0.06 | 7.96 | 2016 | -3.59 | 0.07 | 7.18 |
| 2017 | -3.42 | 0.08 | 6.84 | 2017 | -3.54 | 0.12 | 7.08 |
| 2018 | -3.65 | 0.09 | 7.31 | 2018 | -3.87 | 0.17 | 7.75 |
| 2019 | -3.86 | 0.1 | 7.72 | 2019 | -4.66 | 0.07 | 9.32 |
| 2020 | -5.02 | 0.23 | 10.05 | | | | |
| 2021 | -4.7 | 0.12 | 9.39 | | | | |

Some years have a higher LOOIC than others. For Clear Creek, almost all the years with a LOOIC over 9 (highlighted in grey) are “anomalous years”, or years where spawner count exceeds upstream count, indicating these could be years that reduce the prediction accuracy of the model. 2008 and 2013 are the only years with higher LOOICs (highlighted in grey) for Clear Creek that are not anomalous. For Battle Creek, 2010, 2012, and 2020 have the highest LOOICs where 2010 and 2020 are anomalous and 2012 is much higher for both upstream and redd counts compared to the rest of the dataset.

For years where survey data is inconsistent, the passage to spawner model could be utilized to “fill in the gaps” – i.e. predict spawner counts where we have passage estimates. For example, in some years for Battle Creek some reaches were not surveyed. These years (2004, 2015, 2017, and 2018) are shown in the table above with their LOOIC values, showing that the theoretical expected predictive accuracy is not as high as the “anomalous” years indicating relatively better accuracy.

See the figure below for raw data for both streams (a 1:1 line is shown in red):




Finally, the table below shows the effective parameter number (p_loo) for Battle and Clear Creeks. The number of parameters in the model is 24 for Battle and 22 for Clear (a random year effect for each year in the model, which is 21 for Battle and 19 for Clear), the intercept, the standard deviation of the random year effect, and the fixed effect parameter. For both Battle and Clear Creeks and across all covariates, the effective parameter number is less than the total number of parameters used (24 or 22).

| | Battle Creek | | Clear Creek | |
|---|---|---|---|---|
| **Covariate** | **p_loo** | **SE** | **p_loo** | **SE** |
| Water year type | 15.36 | 0.74 | 6.32 | 0.15 |
| Maximum flow | 16.24 | 0.73 | 6.70 | 0.34 |
| Growing degree days | 14.23 | 1.24 | 6.96 | 0.40 |
| Median passage timing | 15.45 | 0.86 | 6.39 | 0.23 |
| Passage index | 15.82 | 0.48 | 6.43 | 0.20 |
| Null | 16.26 | 0.96 | 6.80 | 0.29 |

*References*

Vehtari A, Gabry J, Magnusson M, Yao Y, Bürkner P, Paananen T, Gelman A (2024). "**loo: Efficient leave-one-out cross-validation and WAIC for Bayesian models.**" R package version 2.8.0, https://mc-stan.org/loo/.

Vehtari, A., Gelman, A., Gabry, J. (2016). **Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC**. *Statistics and Computing*.