DECEMBER 2018

SAN FRANCISCO ESTUARY & WATERSHED SCIENCE

Sponsored by the Delta Science Program and the UC Davis John Muir Institute of the Environment

RESEARCH

Alternative Juvenile Production Estimate (JPE) Forecast Approaches for Sacramento River Winter-Run Chinook Salmon

Michael R. O'Farrell*[1], William H. Satterthwaite[1], Albert N. Hendrix[2], and Michael S. Mohr[1]

Volume 16, Issue 4 | Article 4
https://doi.org/10.15447/sfews.2018v16iss4art4

* Corresponding author email: *michael.ofarrell@noaa.gov*

1 Fisheries Ecology Division
Southwest Fisheries Science Center
National Marine Fisheries Service
National Oceanic and Atmospheric Administration
Santa Cruz, CA 95060 USA

2 QEDA Consulting, LLC
Seattle, WA 98103 USA

ABSTRACT

Sacramento River winter-run Chinook Salmon are listed under the Endangered Species Act as Endangered, and there are substantial efforts to estimate, predict, and limit mortalities at various stages of their life cycle. One such effort is the annual forecast of the number of juvenile winter-run entering the Sacramento–San Joaquin Delta. The natural-origin juvenile production estimate (JPE) is defined as the number of winter-run juveniles produced from natural spawning areas that enter the Delta, and its forecast is used to determine the allowable level of winter-run incidental take at the state and federal pumping facilities located in the South Delta. Current monitoring programs in the Sacramento River basin do not allow the JPE to be directly estimated, and thus various methods have been used to forecast this value annually. Here, we describe three alternative methods for forecasting the natural-origin JPE. The methods range from the status quo approach (Method 1), which expresses the JPE forecast only as a point estimate, to two other methods that account for forecast uncertainty to various degrees. A comparison of JPE forecasts for 2018 across the three methods indicates that relative to Method 1, Methods 2 and 3 result in lower JPE forecasts, by 24% and 18%, respectively, primarily because of lower forecasts of the fry-to-smolt transition and the smolt survival rate that occurs downstream of Red Bluff Diversion Dam. Because post hoc estimates of juvenile winter-run abundance at the entrance to the Delta do not currently exist, we are unable to evaluate forecast skill among the three methods.

KEY WORDS

Chinook Salmon, Sacramento River, winter-run, juvenile production estimate, forecast, incidental take

INTRODUCTION

Management of fish and wildlife populations relies upon data generated from monitoring programs and analytical tools that use these data to inform decisions. For imperiled species, the need for robust monitoring and models is particularly acute because management actions can significantly affect population persistence, extinction risk, and the potential for recovery. One such imperiled species is Sacramento River winter-run Chinook Salmon (hereafter winter-run), which has been listed as Endangered under the Endangered Species Act (ESA) since 1994 (Fed Regist 1994). Native to the headwaters of the Sacramento River basin in northern California, nearly all winter-run spawning habitat was blocked by the construction of Shasta and Keswick dams on the Sacramento River, and currently the species exists as a single population that spawns in the mainstem Sacramento River near the terminus of fish passage. Maturing winter-run leave the ocean for the Sacramento River in winter, where they hold until spawning in the summer. Juveniles emerge in late summer and early fall, and ultimately enter the ocean in the following winter/spring (Fisher 1994). Winter-run persist in the Sacramento River outside of their historic range only because releases from Shasta Dam can be maintained at cool enough temperatures in most years to allow for successful spawning and egg incubation during the summer months (Fisher 1994; Yoshiyama et al. 1998; Lindley et al. 2007).

Currently, there are substantial efforts to enumerate and predict winter-run abundance and survival across several life stages, as well as recent recommendations for improvement and augmentation of the existing monitoring network (Johnson et al. 2017; Windell et al. 2017). Most of these monitoring and research efforts are focused on informing water and fisheries management decisions. The juvenile production estimate (JPE) is a forecast of the number of juvenile winter-run entering the Sacramento–San Joaquin Delta that relies on existing monitoring and research projects occurring in the Sacramento River. We refer to the JPE as a forecast because it is a forward projection rather than an estimate of a current or past state. The National Marine Fisheries Service (NMFS) makes this forecast annually, and provides it to the U.S. Bureau of Reclamation generally in January or February. (In 2018, this occurred on January 29 [NMFS 2018].) The JPE is used to determine the annual allowable level of incidental take of ESA-listed (endangered) winter-run at the state and federal pumping facilities in the South Delta. Separate natural-origin and hatchery-origin JPE forecasts are made—and origin-specific incidental take levels are established—based on these JPE forecasts.

The methods used to forecast the JPE have varied over time. In recent years, a variety of methods have been presented, with a preferred method identified. In 2017 and 2018, the method chosen for the natural-origin JPE was termed the "JPI" (juvenile production index) method because it relied on an estimate of the number of natural-origin winter-run juveniles, in fry-equivalent units[1], that passed the Red Bluff Diversion Dam (RBDD) (Voss and Poytress 2017). The JPI method, for natural-origin fish n, was defined as

$$\widehat{\mathrm{JPE}}_{n,t} = \widehat{\mathrm{JPI}}_{t-1} \times \hat{f} \times \hat{s}_n, \quad (1)$$

where $\hat{f}$ is a forecast of the fry-to-smolt survival rate, and $\hat{s}_n$ is a forecast of the smolt survival rate of natural-origin fish from RBDD (more precisely, Salt Creek, which lies 3 miles downstream of RBDD) to the Delta entrance (Tower Bridge in Sacramento). The JPI estimate from calendar year t–1 is used for the year t JPE forecast because most of the fry passage at RBDD occurs in the fall and winter of the calendar year before the year t JPE. We refer to the $\widehat{\mathrm{JPI}}_{t-1}$ as an estimate because it is a characterization of the fry abundance in year t–1. The terms $\hat{f}$ and $\hat{s}_n$ are referred to as forecasts because they represent a projection of quantities for which year-specific data are not yet available.

For hatchery-origin fish,

$$\widehat{\mathrm{JPE}}_{h,t} = \mathrm{P}_t \times \hat{s}_h, \quad (2)$$

where P_t is the number of hatchery-origin pre-smolts released in year t in the upper Sacramento River (typically at Caldwell Park in Redding), and $\hat{s}_h$ is a forecast of the survival rate of hatchery-origin fish from release to the Delta entrance. For both the natural- and hatchery-origin JPEs, $\hat{s}$ was forecast based on data from acoustically tagged hatchery-origin fish in previous years; year t estimates of $\hat{s}_n$ and $\hat{s}_h$ are not available in time to forecast the year t JPE.

A review of past JPE forecast methods (Anderson et al. 2014) led to a number of recommendations. Most

1 The relative proportions of winter-run fry and pre-smolts passing Red Bluff Diversion Dam varies annually. Production is therefore standardized to the fry stage to facilitate comparisons across years.

relevant to the development of a new JPE forecasting approach were recommendations to develop better estimates of the egg-to-fry survival rate, and to commit more resources to developing improved estimates of winter-run survival below RBDD (see Anderson et al. 2014, p. 23). The recommendation to develop better estimates of the egg-to-fry survival rate may not be warranted because fry-equivalent passage of natural-origin winter-run past RBDD is routinely estimated, and thus it is possible to use these year-specific abundance estimates directly, in lieu of multiplying estimates of egg production by a survival rate estimated from previous years' data. The recommendation to develop improved estimates of winter-run survival below RBDD has, therefore, become a central focus of our analysis.

In this paper, we present three alternative methods for forecasting the natural-origin JPE. Method 1 is the most current JPE forecast method. Following current practices for forecasting the JPE, the components of Equation 1 are expressed as point estimates, and thus the JPE forecast is itself a point estimate with no associated expression of uncertainty. Method 2 follows the same basic model structure as Method 1 but (1) introduces a new approach for forecasting the fry-to-smolt survival rate ($\widehat{f}$), (2) uses external survival estimates to forecast the smolt survival rate ($\hat{s}_n$), and (3) quantifies observation error for the model components and thus the JPE itself. Observation error represents the error in estimation for a particular year; it is the variation between the true value and its estimate. Method 3 accounts for observation error in the JPI estimate and uses the same approach to forecast $\widehat{f}$ as Method 2, but uses a Bayesian approach to forecasting $\hat{s}_n$ that accounts for both observation and process error. Process error is the variation in true abundances or rates (not their estimates) across years from endogenous or exogenous forces. Both observation and process error can be important when making forecasts.

For the three methods, we forecast the 2018 natural-origin JPE and compare their results. We end with a discussion of the relative merits and drawbacks of the three methods, and describe the data deficiencies that limit the current options available for forecasting the JPE.

METHOD 1

Method 1 is the approach to forecasting the natural-origin JPE that has most recently been used in practice (NMFS 2018). This method uses Equation 1 for the forecast, with its three component quantities estimated or forecast as described below.

The $\widehat{\mathrm{JPI}}_{t-1}$ was a point estimate of the number of fry-equivalent juveniles that pass RBDD, and the preliminary estimate for 2017 was $\widehat{\mathrm{JPI}}_{2017} = 545{,}132$ (2018 email from B. Poytress to M. O'Farrell, unreferenced, see "Notes"). Juvenile passage at RBDD is standardized to the fry stage by summing (1) the estimated fry passage and (2) the estimated number of smolts and pre-smolts that pass RBDD, which are converted to fry-equivalents by applying the inverse of the fry-to-smolt survival rate $\widehat{f}^{-1}$ (Poytress et al. 2014). The fry-to-smolt survival rate value used to estimate $\widehat{\mathrm{JPI}}_{t-1}$ and forecast $\widehat{\mathrm{JPE}}_{n,t}$ was set at 0.59, an estimate attributed to work by Hallock (undated). Smolt survival from RBDD to the Delta entrance was forecast to be $\hat{s}_n = 0.5129$. This was based on a variance-weighted mean of survival rates estimated from acoustic tagging studies performed on hatchery-origin winter-run conducted over 2013–2017 (NMFS 2018), where the weights are inversely proportional to the estimated variance of the corresponding survival rate estimate (Table 1). This approach used a binomial model to estimate annual survival rates and the associated variances (Cochran 1977), treating the estimated number of tagged fish that pass Salt Creek as the number of "attempts," and the estimated number of tagged fish that pass Tower Bridge as the number of "successes" (Table 1). Because the variance calculations do not directly account for detection probabilities, they understate the uncertainty associated with each estimate, and do so by varying amounts, depending on the detection probability for that year.

Using Method 1, the 2018 natural-origin JPE forecast is $\widehat{\mathrm{JPE}}_{n,2018} = 545{,}132 \times 0.59 \times 0.5129 = 164{,}963$.

METHOD 2

For Method 2, the variance associated with observation error is estimated for each of the components on the right side of Equation 1. These error variances are then used to derive a variance

https://doi.org/10.15447/sfews.2018v16iss4art4

Table 1 Acoustic tag-derived estimates of hatchery-origin winter-run passage, survival rates, variances of the survival rates, and weights used to forecast $\hat{s}_n$ under Method 1. Passage estimates at the two locations represent tagged fish detected by receivers at those locations, as well as tagged fish that were not detected at those locations but detected further downstream. When there were multiple releases within a year, the passage estimates were pooled for that year. Passage estimates were provided by A. Ammann (2017 email from A. Ammann to M. O'Farrell, unreferenced, see "Notes").

	Passage				
Release year	**Salt Creek**	**Tower Bridge**	**Survival rate**	**Variance**	**Weight**
2013	137	21	0.1533	0.0009473612	0.1260
2014	325	135	0.4154	0.0007472007	0.1598
2015	471	269	0.5711	0.0005200450	0.2296
2016	538	288	0.5353	0.0004623658	0.2582
2017	400	279	0.6975	0.0005274844	0.2264

estimate for the overall forecast JPE that results from uncertainty in the mean level of each component of the forecast, assuming that the observation error in each component is independent. Note, however, that the variance in the forecast JPE does not include uncertainty associated with year-to-year variation in the survival rates $\hat{f}$ and $\hat{s}_n$, nor does it account for the covariance between them, in part because of the lack of data adequate to characterize annual variability in $\hat{f}$ (see "Discussion"). Method 2 can be implemented either in a spreadsheet or using a computer programming language, for example, R (R Core Team 2018).

The forecast natural-origin JPE in year t is calculated as the product of $\widehat{\mathrm{JPI}}_{t-1}$, the estimated fry-to-smolt survival rate $\hat{f}$, and the estimated smolt survival rate $\hat{s}_n$ from RBDD to the Delta entrance (Equation 1). Assuming that these three terms are statistically independent, the variance associated with this product may be estimated as (Gray 1999):

$$\widehat{V}\left(\widehat{\mathrm{JPE}}_{n,t}\right)=\left[\widehat{\mathrm{JPI}}_{t-1}^{2}-\widehat{V}\left(\widehat{\mathrm{JPI}}_{t-1}\right)\right] \tag{3}$$

$$\left[\hat{f}^{2}\widehat{V}\left(\hat{s}_n\right)+\hat{s}_n^{2}\widehat{V}\left(\hat{f}\right)-\widehat{V}\left(\hat{f}\right)\widehat{V}\left(\hat{s}_n\right)\right]+\hat{f}^{2}\hat{s}_n^{2}\widehat{V}\left(\widehat{\mathrm{JPI}}_{t-1}\right).$$

Method 2 uses a new approach to forecasting $\hat{f}$. A zero-intercept linear model was fitted to estimates of hatchery-origin juvenile survival rates $\hat{j}_h$, and estimates of natural-origin juvenile survival rates $\hat{j}_n$, from the same year, with the estimated slope representing $\hat{f}$ (Figure 1). Hatchery-origin juvenile survival rates (spanning the period of time from release as pre-smolts to the end of age-2 in the ocean) are estimated using cohort reconstruction methods applied to coded-wire-tag recovery data (O'Farrell et al. 2012). The structure of the cohort reconstruction model does not allow observation error for the hatchery-origin juvenile survival rates to be estimated. We estimated natural-origin juvenile survival rates (spanning fry-equivalent passage at RBDD to the end of age-2 in the ocean) using a Bayesian state–space population dynamics model (Winship et al. 2014). Although this forecast of $\hat{f}$ is not a direct measure of fry-to-smolt survival, we note that the differences in the hatchery- and natural-origin juvenile survival rates represent different durations in the *river* environment but similar durations in the *marine* environment (Winship et al. 2014). The slope of the linear model was estimated using the ratio of means estimator

$$\hat{f}=\frac{\mathrm{mean}\left\{\hat{j}_n\right\}}{\mathrm{mean}\left\{\hat{j}_h\right\}} \tag{4}$$

and its associated variance estimator

$$\widehat{V}\left(\hat{f}\right)=\frac{1}{T\left[\mathrm{mean}\left\{\hat{j}_h\right\}\right]^{2}}\frac{\Sigma_{i=1}^{T}\left(\hat{j}_{n,i}-\hat{f}\,\hat{j}_{h,i}\right)^{2}}{T-1} \tag{5}$$

(Cochran 1977), where mean$\{\cdot\}$ denotes the arithmetic mean of the respective survival rate estimates, and T is the number of years with paired $\hat{j}_n$ and $\hat{j}_h$. Over the period of record (brood years 1998–2013), this yielded $\hat{f}=0.4725$ and $\widehat{V}\left(\hat{f}\right)=0.01104971$.

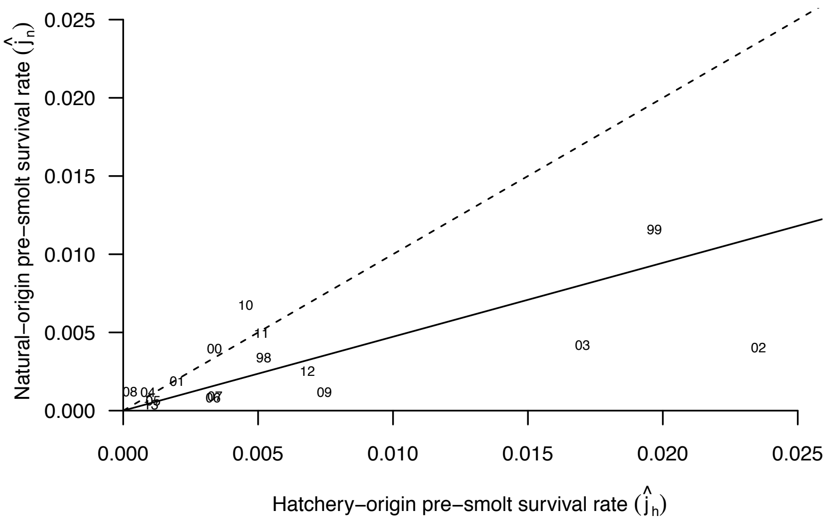

Figure 1 Relationship between hatchery-origin and natural-origin survival rates. Solid line is the fitted zero-intercept model, and the dashed line is the 1:1 line. Numbers denote brood years.

The estimated $\widehat{\mathrm{JPI}}_{2017}$ for Method 2 differs from Method 1 because the different forecasts of $\hat{f}$ result in a change in the factor used to convert pre-smolt passage to fry-equivalent units ($\hat{f}^{-1}$). Given $\hat{f} = 0.4725$, $\widehat{\mathrm{JPI}}_{2017} = 606{,}039$ (2018 email from B. Poytress to M. O'Farrell, unreferenced, see "Notes"). The variance associated with $\widehat{\mathrm{JPI}}_{2017}$ was specified by squaring the product of $\widehat{\mathrm{JPI}}_{2017}$ and the coefficient of variation (CV) for the JPI estimates, $\widehat{\mathrm{CV}}\left(\widehat{\mathrm{JPI}}_{t-1}\right)$, averaged over the previous 5 years. This approximation of the variance estimate was necessary because at the time of this writing, the estimated observation error variance for $\widehat{\mathrm{JPI}}_{2017}$ was unavailable (and may not be available in time for annual forecasting of the $\widehat{\mathrm{JPE}}_{n,t}$). For $t = 2013–2017$, mean $\left\{\widehat{\mathrm{CV}}\left(\widehat{\mathrm{JPI}}_{t-1}\right)\right\} = 0.2185$ and $\widehat{\mathrm{JPI}}_{2017} = 606{,}039$ yielding an estimated variance of $\hat{V}\left(\widehat{\mathrm{JPI}}_{2017}\right) = 17{,}535{,}056{,}400$.

We forecast the smolt survival rate $\hat{s}_n$ by taking the variance-weighted mean of estimated annual survival rates (Table 2). Annual survival rates were estimated using the Cormack-Jolly-Seber model for live recapture, as described in Michel et al. (2015), and the estimated variance of the rates was obtained by squaring the model-estimated standard errors. Note that annual survival rate estimates reported in Table 1 differ from those reported in Table 2. These differences are the result of the Cormack–Jolly–Seber model accounting for detection probabilities in the estimation of annual survival rates; no such accounting occurs under Method 1.

Each study year is assigned a weight $w_i \propto \hat{V}\left(\hat{s}_{n,i}\right)^{-1}$. That is,

$$w_i = \frac{\frac{1}{\hat{V}\left(\hat{s}_{n,i}\right)}}{\sum_{k=1}^{T} \frac{1}{\hat{V}\left(\hat{s}_{n,k}\right)}} \tag{6}$$

where T is the set of all years under study (this also follows Meier [1953]). The mean survival rate over the study period of record is then estimated as the weighted average,

$$\hat{s}_n = \sum_{i=1}^{T} w_i \hat{s}_{n,i} \tag{7}$$

with variance

$$\hat{V}\left(\hat{s}_n\right) = \frac{1}{\sum_{i=1}^{T} \frac{1}{\hat{V}\left(\hat{s}_{n,i}\right)}}. \tag{8}$$

Table 2 Hatchery-origin winter-run survival rate estimates, variances and weights used to forecast $\hat{s}_n$ under Method 2. Survival rates and standard errors (from which the variances were computed) were provided by C. Michel (2018 email from C. Michel to M. O'Farrell, unreferenced, see "Notes").

Release year	Survival rate	Variance	Weight
2013	0.1686	0.0010901817	0.1697
2014	0.4175	0.0008083331	0.2289
2015	0.4765	0.0009904364	0.1868
2016	0.5366	0.0004707077	0.3930
2017	0.6369	0.0085626337	0.0216

https://doi.org/10.15447/sfews.2018v16iss4art4

The variance $\widehat{V}\left(\hat{s}_n\right)$ reflects the uncertainty in the estimated mean survival. It does not reflect the amount of year-to-year variability in smolt survival from RBDD to the Delta entrance, and implicitly assumes (as does the variance-weighted mean approach the NMFS adopted previously) that the variability in survival across years is negligible. Given the data from releases in 2013–2017, $\hat{s}_n = 0.4378$ and $\widehat{V}\left(\hat{s}_n\right) = 0.000185004$. The forecast of $\hat{s}_n$ for Method 2 differs from the variance-weighted mean approach applied in Method 1 because the standard errors (and thus the variances) estimated from the mark–recapture model are larger, especially in years with low detection probabilities, such as 2017. This results in a substantial down-weighting of the 2017 estimate, and thus the Method 2 approach generates a smaller forecast of $\hat{s}_n$ relative to Method 1.

Thus, for Method 2, $\widehat{\text{JPE}}_{n,2018} = 606{,}039 \times 0.4725 \times 0.4378 = 125{,}378$ and $\widehat{V}\left(\widehat{\text{JPE}}_{2018}\right) = 1{,}505{,}106{,}006$, yielding a 95% confidence interval of 49,339 to 201,418 using a normal approximation.

METHOD 3

As with the two previous methods, JPE forecast Method 3 has the same basic structure defined in Equation 1; however, each of the components on the right side of Equation 1 are expressed as probability distributions. Taking the product of samples from the component distributions results in a distribution of $\widehat{\text{JPE}}_{n,t}$, from which the mean, credible intervals, and other measures can be obtained. Under Method 3, a hierarchical Bayesian model that accounts for both observation and process error is used to forecast a posterior predictive distribution of $\hat{s}_n$. Method 3 is implemented in R (R Core Team 2018), with the forecast of $\hat{s}_n$ performed in JAGS (Plummer 2016).

To account for observation error associated with fry abundance, we drew values of $\widehat{\text{JPI}}_{t-1}$ from a Lognormal$(\hat{\mu}, \hat{\sigma}^2)$ distribution where $\hat{\mu}$ is the estimated log-scale bias-corrected mean,

$$\hat{\mu} = \log\left(\widehat{\text{JPI}}_{t-1}\right) - \frac{\hat{\sigma}^2}{2}, \qquad (9)$$

and $\hat{\sigma}^2$ is the estimated log-scale variance of $\widehat{\text{JPI}}_{t-1}$

$$\hat{\sigma}^2 = \log\left(1 + \frac{\widehat{V}\left(\widehat{\text{JPI}}_{t-1}\right)}{\widehat{\text{JPI}}_{t-1}^2}\right) \qquad (10)$$

(Newman and Lindley 2006). For forecasting the 2018 JPE, $\widehat{\text{JPI}}_{2017} = 606{,}039$ and $\widehat{V}\left(\widehat{\text{JPI}}_{2017}\right) = 17{,}535{,}056{,}400$, as noted in the description of Method 2.

The fry-to-smolt survival rate is estimated in the same manner as described for Method 2. To account for observation error, values of f were drawn from a Normal$(\hat{\mu}, \hat{\sigma}^2)$ distribution with $\hat{\mu} = \hat{f} = 0.4725$ and $\hat{\sigma}^2 = \widehat{V}\left(\hat{f}\right) = 0.01104971$.

The distribution used for $\hat{s}_n$ accounts for both observation and process error, and was developed using a Bayesian hierarchical model as follows. For computational tractability, the number of acoustically tagged fish estimated to enter the Delta—relative to the number passing the upstream detector—was modeled as a binomial random variable

$$R_t \sim \text{Binomial}\left(N_t, s_{n,t}\right) \qquad (11)$$

where N_t is the number of tagged fish that pass Salt Creek in year t, R_t is the number of fish that pass Tower Bridge at Sacramento in year t, and $s_{n,t}$ is the survival probability. The values used for N_t and R_t (Table 3) are not raw count data, but instead were generated based on the estimated survival probabilities and associated standard errors from the mark–recapture model. For each year, a set of counts was generated for N_t and R_t that, when modeled as a binomial process, yielded a mean and standard error as close as possible to the mean and standard error generated by the mark–recapture model (see Appendix A for details). This resulted in effective sample sizes with information content similar to the outputs of the mark–recapture model. This approach greatly increased the computational efficiency and tractability of the Bayesian model, and is conceptually similar to the tuning of effective sample sizes for age- or size-composition data frequently used in integrated stock assessments of West Coast groundfish and coastal pelagic species (Francis 2011). We accounted for process error by modeling the annual survival probability itself as a random variable. We assumed the logit-transformed survival probability for year t, $\text{logit}\left(s_{n,t}\right) = \log\left[s_{n,t} / \left(1 - s_{n,t}\right)\right]$, to be equal to a mean survival rate across years, α, plus a year-specific random effect, ε_t,

$$\text{logit}\left(s_{n,t}\right) = \alpha + \varepsilon_t \qquad (12)$$

where $\varepsilon_t \sim \text{Normal}(0, \sigma_\varepsilon^2)$. We used the logit transformation to ensure that the resulting random variable $s_{n,t}$ was bounded by 0 and 1.

We specified Bayesian prior distributions for the two model parameters as $\alpha \sim \text{Normal}(0, 1.6)$ and $\sigma_\varepsilon \sim \text{Gamma}(1,1)$ (Figure 2). We chose the prior distribution for α because it is relatively uninformative on the arithmetic scale (Figure 2). We thought the prior distribution for σ_ε was a reasonable representation of the year effect standard deviation, though we considered other forms and parameterizations (see "Discussion"). We generated a posterior predictive distribution of $\hat{s}_n$ by (1) taking a

Table 3 Derived numbers of fish passing Salt Creek and Tower Bridge, which yield a mean and standard error nearly equivalent to those estimated by the mark–recapture model

	Passage	
Release year (t)	**Salt Creek (N_t)**	**Tower Bridge (R_t)**
2013	120	18
2014	301	125
2015	248	142
2016	529	283
2017	25	17

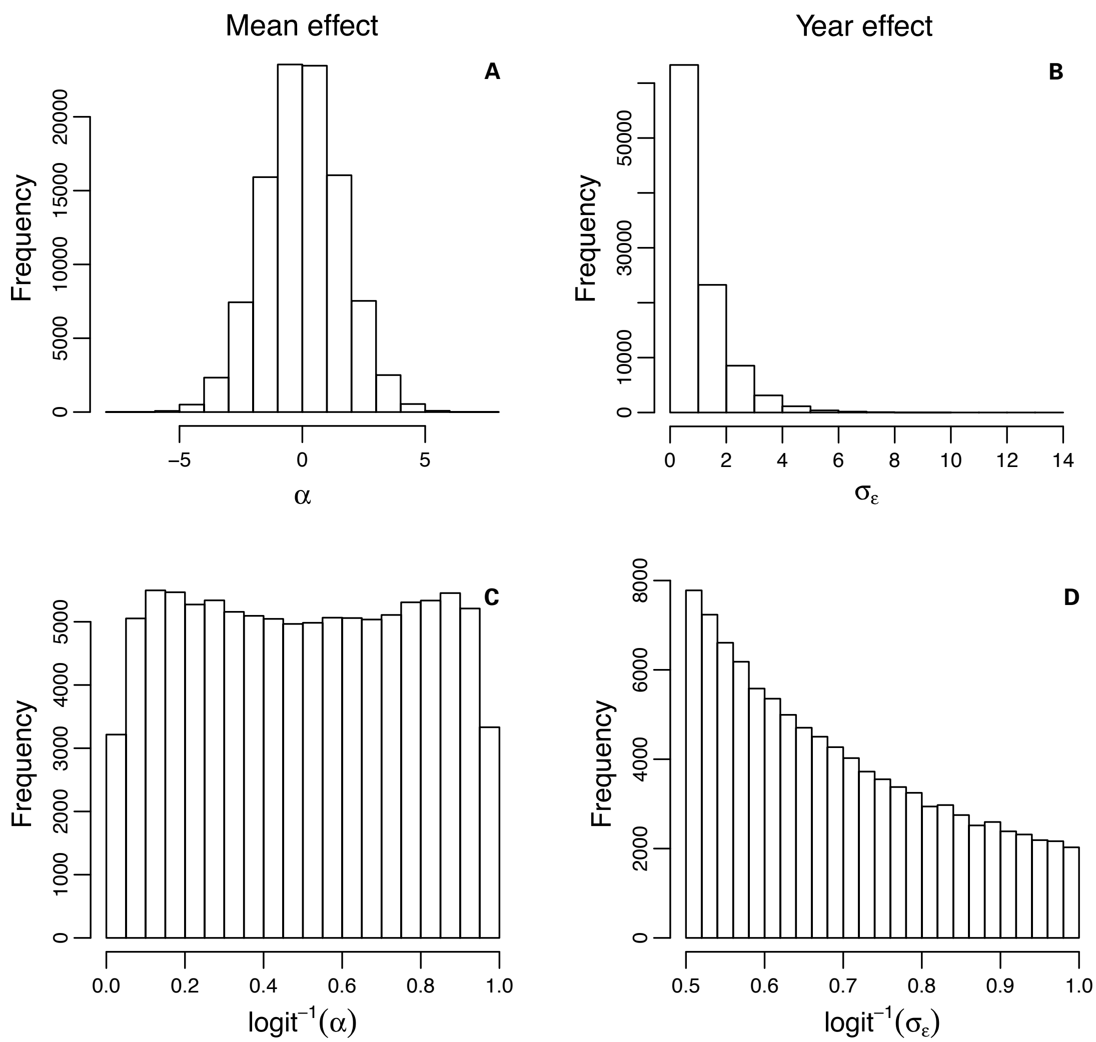

Figure 2 Prior distributions for the mean effect (α) and the year effect standard deviation (σ_ε). Plots in the top row (**A, B**) display the prior distributions on the logit scale, while plots in the bottom row (**C, D**) display these distributions on the arithmetic scale. Distributions were generated by making 100,000 random draws from the respective distributions of α and σ_ε.

https://doi.org/10.15447/sfews.2018v16iss4art4

draw from the posterior distribution of α, (2) taking a draw from $\mathrm{Normal}(0,\sigma_\varepsilon^2)$, where σ_ε is itself a draw from the posterior distribution of the year effect standard deviation, (3) taking the sum of these draws, and (4) performing a back transformation from the logit scale to the arithmetic scale. This procedure is repeated many times to generate the posterior predictive distribution of $\hat{s}_n$. The mean, credible intervals, and other measures can then be estimated from the posterior distribution, if desired.

Figure 3 displays the distributions of $\widehat{\mathrm{JPI}}$, $\hat{f}$, and $\hat{s}_n$. The JPE forecast distribution is the product of these random quantities, following Equation 1, and is determined by taking the product of random samples from the component distributions. The mean of the JPE forecast distribution was $\widehat{\mathrm{JPE}}_{n,2018} = 135,472$, with a 95% credible interval of 19,848 to 318,201. We note, however, that other distributional metrics, such as the median, could be considered as an alternative measure of central tendency for $\widehat{\mathrm{JPE}}_{n,t}$. Because the distribution of $\widehat{\mathrm{JPE}}_{n,2018}$ is positively skewed, the mean of the distribution exceeds the median.

The Method 3 approach accounts for annual variation in $\hat{s}_n$, but as currently implemented does not fully characterize JPE forecast uncertainty that results from annual variability, because it accounts neither for annual variability in $\hat{f}$ nor the covariance between $\hat{s}_n$ and $\hat{f}$.

RESULTS

Table 4 summarizes the $\widehat{\mathrm{JPI}}_{2017}$, $\hat{f}$, $\hat{s}_n$, and $\widehat{\mathrm{JPE}}_{n,2018}$ forecast under the three methods. Relative to Method 1, Methods 2 and 3 result in lower JPE forecasts by 24% and 18%, respectively. The disparity between Method 1 and Methods 2 and 3 are partly due to lower forecasts of the fry-to-smolt transition. However, the largest difference between the methods concerns $\hat{s}_n$. Method 2 results in the lowest $\hat{s}_n$ and $\widehat{\mathrm{JPE}}_{n,2018}$ forecasts among the three approaches.

DISCUSSION

In this paper, we present three methods for forecasting the JPE that have the same general form but differ in complexity and their quantification of uncertainty. Method 1 makes no attempt to quantify uncertainty. Method 2 accounts for observation error but not process error, and therefore underestimates true forecast uncertainty since survival probabilities f and s_n likely vary substantially across years.[2] Method 3 accounts for uncertainty in $\hat{s}_n$ more comprehensively than Method 2 because it incorporates both observation and process error.

2 In theory, variance in the annual estimates of sn could be partitioned into within- versus across-years components using a random effects ANOVA approach (Gelman et al. 2004, p. 131–139), but the point estimate of annual variability would be highly uncertain with only 5 years of data.

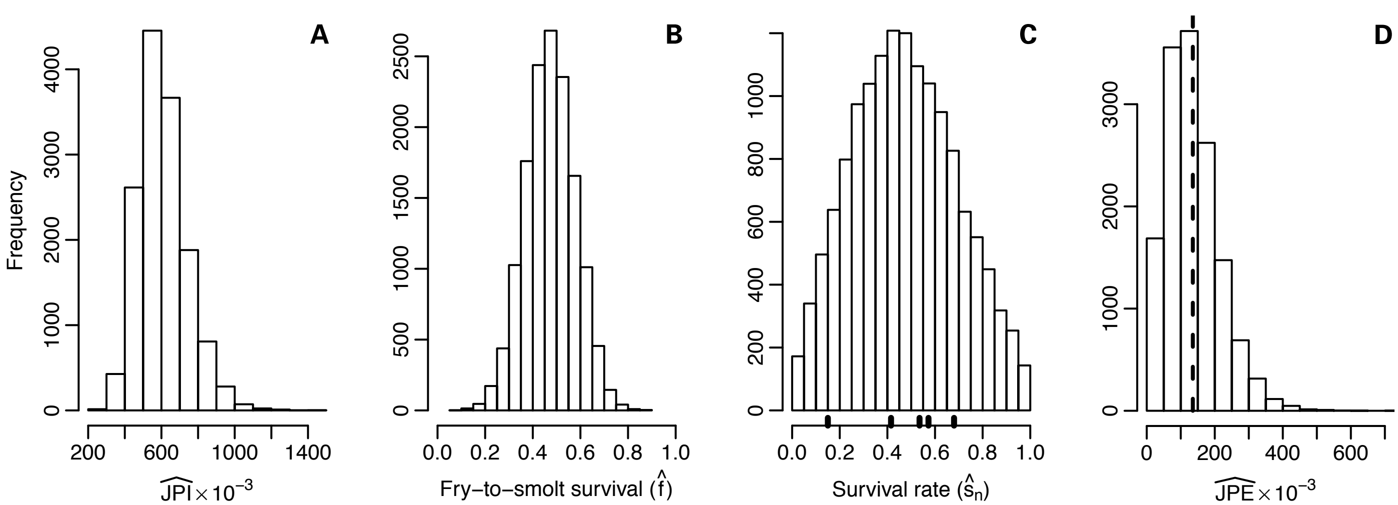

Figure 3 Distributions of the components of the JPE and the 2018 JPE forecast under Method 3. Vertical lines below the survival rate ($\hat{s}_n$) distribution represent point estimates from the 5 years of acoustic tag data. The vertical dashed line represents the mean of the $\widehat{\mathrm{JPE}}_{n,2018}$ distribution.

Table 4 Point estimates used to make the 2018 JPE forecast. For Method 3, the point estimates are means of the respective distributions.

	Method		
	1	2	3
$\widehat{\text{JPI}}_{2017}$	545,132	606,039	606,794
$\hat{f}$	0.5900	0.4725	0.4733
$\hat{s}_n$	0.5129	0.4378	0.4721
$\widehat{\text{JPE}}_{n,2018}$	164,963	125,378	135,472

We note, however, that the modeled uncertainty in $\hat{f}$ for Method 3, like Method 2, only accounts for uncertainty in the estimated mean value and not the year-to-year variation in f. Additionally, neither method accounts for covariation between s_n and f.

There are substantial difficulties in accounting for the year-to-year variation in the forecast of $\hat{f}$. In particular, the ratio of natural-origin to hatchery-origin survival rates is not a true estimate of a survival rate, but rather an indirect method of approximating fry-to-smolt survival in the apparent absence of data that could be used to estimate this rate directly. The limitations of this approach are evident in that the ratio of natural-origin to hatchery-origin survival rate estimates exceeds 1.0 in 4 of 16 years (Figure 1). Yet, the approach may be an improvement on the forecast of $\hat{f}$ used in Method 1 because it is fully documented, reproducible, is based entirely on winter-run data, and can accommodate new data going forward.

The $\hat{f}$ forecast is used both in the estimate of $\widehat{\text{JPI}}_{t-1}$ and the forecast of $\widehat{\text{JPE}}_{n,t}$. Estimates of $\widehat{\text{JPI}}_{t-1}$ are used in other aspects of winter-run management aside from the application discussed here, and for many years the standardization to fry-equivalents has assumed $\hat{f} = 0.59$, attributed to work performed by Hallock. A change to the methods used to convert total RBDD passage to fry-equivalent units should thus be considered carefully, because it may raise consistency issues with other winter-run management efforts.

Some logistical issues with implementation of Methods 2 and 3 will need to be considered carefully. Both methods require an estimate of the variance of the JPI estimate. However, at the time the JPE is to be forecast, the JPI estimate is preliminary. To date, the USFWS has provided the preliminary estimate to the JPE Project Work Team as a point estimate, and estimates of the variance have not been provided at that time (2017 in-person conversation between B. Poytress and M. O'Farrell, unreferenced, see "Notes"). It may be infeasible to obtain preliminary estimates of the JPI variance in time to make the JPE forecast. A solution to this issue, applied here, was to use historical estimates of the CV, derived from past estimates of the JPI and its error variance, and assume that the average of past CVs represent the current year CV. Such an approach would be less tenable if substantial annual changes in the CV were to occur in the future.

Method 3 uses a Bayesian approach to estimating the distribution of the survival rate based on past data, and thus prior distributions for the model parameters must be specified. We specify minimally informative prior distributions for the example provided here, but recognize that these priors can substantially influence the parameter estimates, given the small amount of acoustic telemetry data currently available. To investigate how sensitive the estimates were to the prior distribution on the year effect standard deviation, we fitted the model to simulated data sets that ranged in length from 5 to 50 years. We found that there was little sensitivity to the prior once there were approximately 10 years of data (unpublished analysis). Hence, as data accumulate, the influence of the prior distributions will be expected to diminish, and overall uncertainty will decrease. Of course, additional data will accumulate slowly, and that accumulation will depend on continued funding of the acoustic tagging and monitoring program.

Each method described here employs survival rate data for hatchery-origin fish as a proxy for natural-origin fish, which can be problematic for several reasons. First, there are out-migration timing differences because hatchery-origin fish are usually released in February while peak passage of natural-origin fish at RBDD is frequently in October. Furthermore, hatchery-origin fish that pass RBDD are generally larger than the natural-origin fish that pass RBDD. This condition has required the use of a fry-to-smolt survival rate that is not based on winter-

https://doi.org/10.15447/sfews.2018v16iss4art4

run data. We introduced an approach that indirectly estimates the fry-to-smolt survival rate, yet cannot verify its accuracy. Natural-origin survival from RBDD to Sacramento could perhaps be estimated by implanting acoustic tags in natural-origin fish captured at RBDD earlier than the date of hatchery release. This would obviate the need to estimate fry-to-smolt survival, and allow for more direct estimates of s_n. We understand that tags have recently decreased in size such that they could be implanted in fish smaller than the pre-smolts currently released from Livingston Stone Hatchery (though tag size is likely still too large to be implanted in winter-run fry). There is also a potential issue with the current practice of timing hatchery releases to target flow pulses. This practice may cause the relationship between hatchery and natural-origin survival to change over time.

A number of challenges exist for forecasting the JPE. Current monitoring in the Sacramento River does not allow the number of winter-run juveniles that enter the Delta to be estimated. Johnson et al. (2017) identified this data gap, and recommended that steps be taken to allow for annual estimations. Without estimates of winter-run passage at Sacramento, we cannot make comparisons between JPE forecasts and observed (estimated) values. As such, assessment of forecast skill for the alternative methods is currently not feasible. In theory, we could evaluate the skill of proposed forecast models for s_n. However, with only five annual estimates of $s_{n,t}$ from winter-run currently available, it would be difficult to verify the statistical significance of any apparent relationships identified. This situation could slowly improve through time as more data accumulate.

Anderson et al. (2014) recommended considering “trickle” rather than “batch” releases of tagged fish to increase the statistical power of future survival analyses. Although this could help the effects of environmental conditions at the time of fish migration to be better understood, it does not solve the problem that any forecast of $\hat{s}_n$ to inform the JPE forecast would need to be made before those environmental conditions were known. Because acoustically tagged, hatchery-origin fish are typically released after the JPE is forecast, and environmental conditions at the time of release are not yet known, we did not attempt to include environmental covariates into our forecasts of $\hat{s}_n$.

CONCLUSIONS

Given the current winter-run management setting and the available data, we recommend use of Method 2 to forecast the JPE. The use of annual smolt survival rates estimated from a mark–recapture model allows variation in detection probabilities to be accounted for, thus better characterizing the variances that inform the weighted mean approach to forecasting s_n. Method 2 has several advantages over Method 1, including the accounting for observation error, the use of a fry-to-smolt survival rate forecast that is reproducible and documented, and the aforementioned use of smolt survival rates and their variances estimated by a mark–recapture model. We do not recommend the use of Method 3 at this time because the “tuning” of the juvenile passage estimates is somewhat ad hoc, and the Bayesian model used to forecast s_n is highly sensitive to prior distributions given the few years of data currently available. In addition, further development of this approach would ideally include characterization of annual variation in f as well as the covariance between f and s_n, which are not possible now, given the currently available data. As data accumulate, Method 3 may become a more viable alternative. Regardless of the JPE forecast method used in the future, we recommend collection of data that will enable the number of juvenile winter-run that enter the Delta to be estimated (Johnson et al. 2017), so that performance of these and potentially new JPE forecast approaches can be rigorously assessed.

ACKNOWLEDGMENTS

We thank A. Ammann and C. Michel of the Fisheries Ecology Division, Southwest Fisheries Science Center, National Marine Fisheries Service, for providing acoustic telemetry-based estimates used in this paper. Members of the winter-run JPE Project Work Team provided valuable feedback on the methods described here. We would also like to thank Cyril Michel and two anonymous reviewers for their comments. Funding for this work was provided by the NMFS’s California Central Valley Office.

REFERENCES

Anderson JJ, Gore JA, Kneib RT, Monsen NE, Nestler JM, Van Sickle J. 2014. Independent review panel (IRP) report for the 2014 long-term operations biological opinions (LOBO) annual science review. [cited 2017 October 31]. [Sacramento (CA)]: Delta Science Program. Available from: http://deltacouncil.ca.gov/sites/default/files/2014/12/2014-12-11-LOBO-2014-Report- Panel-Final.pdf

Cochran WG. 1977. Sampling techniques. 3rd ed. [New York (NY)]: Wiley & Sons.

Federal Register. 1994. Endangered and threatened species; status of Sacramento River winter-run Chinook Salmon, final rule. Tuesday, January 4, 1994. Rules and regulations. [cited 2017 October 31]. Fed Regist 59(2):440–450. Available from: https://www.federalregister.gov/documents/1994/01/04/93-31089/endangered-and-threatened-species-status-of-sacramento-river-winter--run-chinook-salmon

Fisher FW. 1994. Past and present status of Central Valley Chinook Salmon. Conserv Biol 8(3):870–873. https://doi.org/10.1046/j.1523-1739.1994.08030863-5.x

Francis RICC. 2011. Data weighting in statistical fisheries stock assessment models. Can J Fish Aquat Sci 68(6):1124–1138. https://doi.org/10.1139/f2011-025

Gelman A, Carlin JB, Stern HS, Rubin DB. 2004. Bayesian data analysis. 2nd ed. [London (UK)]: Chapman & Hall/CRC.

Gray G. 1999. Covariances in multiplicative estimates. Trans Am Fish Soc 128(3):475–482. https://doi.org/10.1577/1548-8659(1999)128<0475:CIME>2.0.CO;2

Hallock RJ. undated. The status of inland habitat and factors that adversely affect salmon resources; Sacramento River system King salmon population models.

Johnson RC, Windell S, Brandes PL, Conrad JL, Ferguson J, Goertler PAL, Harvey BN, Heublein J, Israel JA, Kratville DW, et al. 2017. Science advancements key to increasing management value of life stage monitoring networks for endangered Sacramento River winter-run Chinook Salmon in California. San Franc Estuary Watershed Sci 15(3). https://doi.org/10.15447/sfews.2017v15iss3art1

Lindley ST, Schick RS, Mora E, Adams PB, Anderson JJ, Greene S, Hanson C, May BP, McEwan DR, MacFarlane RB, et al. 2007. Framework for assessing viability of threatened and endangered Chinook Salmon and Steelhead in the Sacramento–San Joaquin Basin. San Franc Estuary Watershed Sci 5(1). Available from: https://doi.org/10.15447/sfews.2007v5iss1art4

Meier P. 1953. Variance of a weighted mean. Biometrics 9(1):59–73. Available from: https://www.jstor.org/stable/3001633

Michel CJ, Ammann AJ, Lindley ST, Sandstrom PT, Chapman ED, Thomas MJ, Singer GP, Klimley AP, MacFarlane RB. 2015. Chinook Salmon outmigration survival in wet and dry years in California's Sacramento River. Can J Fish Aquat Sci 72(11):1749–1759. https://doi.org/10.1139/cjfas-2014-0528

Newman KB, Lindley ST. 2006. Accounting for demographic and environmental stochasticity, observation error, and parameter uncertainty in fish population dynamics models. N Am J Fish Manag 26(3):685–701. https://doi.org/10.1577/M05-009.1

[NMFS] U.S. National Marine Fisheries Service. 2018. Letter dated January 29, 2018 to Mr. Jeff Rieker, U.S. Bureau of Reclamation. Letter provides the U.S. Bureau of Reclamation with the estimated number of juvenile Sacramento River winter Chinook Salmon expected to enter the Sacramento–San Joaquin Delta during water year 2018. Available from: https://www.westcoast.fisheries.noaa.gov/publications/Central_Valley/Water%20Operations/Delta%20Operations%20for%20Salmonids%20and%20Sturgeon/DOSS%20WY%202018/winter-run_juvenile_production_estimate__jpe__for_brood_year_2017_-_january_29__2018__1_.pdf

O'Farrell MR, Mohr MS, Grover AM, Satterthwaite WH. 2012. Sacramento River winter Chinook cohort reconstruction: analysis of ocean fishery impacts. [cited 2017 October 31]. NOAA Technical Memorandum NMFS-SWFSC-491. Available from: https://swfsc.noaa.gov/publications/TM/SWFSC/NOAA-TM-NMFS-SWFSC-491

Plummer M. 2016. JAGS: A program for analysis of Bayesian graphical models using Gibbs sampling. Version 4.2.0. [cited 2017 October 31]. Available from: http://mcmc-jags.sourceforge.net/

https://doi.org/10.15447/sfews.2018v16iss4art4

Poytress WR, Gruber JJ, Carrillo FD, Voss SD. 2014. Compendium report of Red Bluff Diversion Dam rotary trap juvenile anadromous fish production indices for years 2002–2012. [cited 2017 October 31]. [Red Bluff (CA)]: U.S. Fish and Wildlife Service. Available from: *https://www.fws.gov/redbluff/MSJM%20Reports/RST/Juvenile%20Anadromous%20Fish%20Monitoring%20Compendium%20Report%20(2002-2012).pdf*

R Core Team. 2018. R: a language and environment for statistical computing. [Vienna (Austria)]: R Foundation for Statistical Computing. [cited 2018 March 06]. Available from: *https://www.r-project.org/*

Voss SD, Poytress WR. 2017. Brood year 2015 juvenile salmon production and passage indices at Red Bluff Diversion Dam. [cited 2017 October 31]. [Sacramento (CA)]: U.S. Fish and Wildlife Service. 57 p. Available from: *https://www.fws.gov/redbluff/MSJM%20Reports/RST/Brood%20Year%202015%20Juvenile%20Salmonid_FINAL_Annual_Report_100417.pdf*

Windell S, Brandes PL, Conrad JL, Ferguson JW, Goertler PAL, Harvey BN, Heublein J, Israel JA, Kratville DW, Kirsch JE, et al. 2017. Scientific framework for assessing factors influencing endangered Sacramento River winter-run Chinook Salmon (*Oncorhynchus tshawytscha*) across the life cycle. [cited 2017 October 31]. U.S. Department of Commerce, NOAA Technical Memorandum NMFS-SWFSC-586. 49 p. *http://doi.org/10.7289/V5/TM-SWFSC-586*

Winship AJ, O'Farrell MR, Mohr MS. 2014. Fishery and hatchery effects on an endangered salmon population with low productivity. Trans Am Fish Soc 143(4):957–971. *https://doi.org/10.1080/00028487.2014.892532*

Yoshiyama RM, Fisher FW, Moyle PB. 1998. Historical abundance and decline of Chinook Salmon in the Central Valley region of California. N Am J Fish Manag 18(3):487–521. *https://doi.org/10.1577/1548-8675(1998)018%3C0487:HAADOC%3E2.0.CO;2*

NOTES

Ammann A. 2017. Email communication to Michael O'Farrell from A. Ammann (National Marine Fisheries Service) regarding winter-run acoustic tagging data.

Michel C. 2018. Email communication from Cyril Michel (University of California, Santa Cruz) to Michael O'Farrell regarding winter-run survival rates estimated from acoustic tagging data.

Poytress B. 2017. Telephone conversation between Michael O'Farrell and B. Poytress (U.S. Fish and Wildlife Service) on the annual timing of final winter-run fry-equivalent JPI estimates.

Poytress B. 2018. Email communication to Michael O'Farrell from B. Poytress (U.S. Fish and Wildlife Service) regarding preliminary JPI estimates for 2017.