Canadian Journal of Fisheries and Aquatic Sciences
Journal canadien des sciences halieutiques et aquatiques

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Journal:	<i>Canadian Journal of Fisheries and Aquatic Sciences</i>
Manuscript ID	cjfas-2015-0318.R3
Manuscript Type:	Article
Date Submitted by the Author:	04-Dec-2015
Complete List of Authors:	Sethi, Suresh; US Fish and Wildlife Service, Bradley, Catherine; US Fish and Wildlife Service, Fisheries and Ecological Services
Keyword:	fisheries management, interpolation, phenology, SALMON < Organisms, weir

Statistical arrival models to estimate missed passage counts at fish weirs

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Draft

Abstract

Missed counts are commonplace when enumerating fish passing a weir. Typically connect-the-dots linear interpolation is used to impute missed passage; however, this method fails to characterize uncertainty about estimates, and cannot be implemented when the tails of a run are missed. Here, we present a statistical approach to imputing missing passage at weirs which addresses these shortcomings, consisting of a parametric run curve model to describe the smoothed arrival dynamics of a fish population and a process variation model to describe the likelihood of observed data. Statistical arrival models are fit in a Bayesian framework and tested with a suite of missing data simulation trials and against a selection of Pacific Salmon (*Oncorhynchus* spp.) case studies from the Yukon River drainage, Alaska, U.S.A. When compared against linear interpolation, statistical arrival models produced equivalent or better expected accuracy and a narrower range of bias outcomes. Statistical arrival models also successfully imputed missing passage counts for scenarios where the tails of a run were missed.

Keywords: fisheries management, interpolation, missing data, phenology, salmon

28 Introduction

29 Fish which migrate en masse along river systems during part of their life history provide
30 opportunity to census populations by directly counting passage at a weir. Weirs are relied upon
31 heavily in harvested salmonid systems to provide information for run reconstruction and to guide
32 fishery management decisions, with weir sites typically sighted in upper reaches of river
33 networks and providing estimates of adult spawning escapement after passing through a harvest
34 gauntlet down river (e.g. Fleischman et al. 2013). While typically used to assess adult fish
35 migrating into river systems, they can also be used to assess the abundance of out-migrating
36 juvenile fish such as Pacific Salmon smolts (*Oncorhynchus* spp.; Bradford 1999).

37 In theory, weirs produce complete enumeration of a fish run passing a point in space,
38 providing a gold standard for accurate enumeration data. In practice, field crews contend with
39 myriad challenges in successfully installing and operating a weir—high water can blow a weir
40 out or make it unsafe to operate, woody debris can overwhelm weir structures, river ice can delay
41 the installation of weirs or require their early removal, and bears can vandalize weirs or harass
42 weir operators (Figure 1). Thus, missing data at weirs are a common occurrence leading to
43 partial enumeration of fish populations.

44 Attempts to impute missing data at weirs typically involve a “connect-the-dots” linear
45 interpolation scheme (e.g. Gewin et al. 2005; Johnson et al. 2007). This approach is attractive in
46 that it is simple to implement; however, linear interpolation requires a passage observation
47 before and after a missing datum and thus is not an option to impute missing data in the tails of a
48 run when weirs are installed late or pulled early. Furthermore, linear interpolation does not
49 produce estimates of uncertainty for imputed missing passage counts, potentially communicating
50 false precision to users of the data. Another, less frequently adopted, approach to imputation

which can be implemented with standard spreadsheet software utilizes an expectation-maximization algorithm to combine run information across years to impute passage at specific dates, including in the tails of the run (e.g. Van Alen 2000). The expectation-maximization algorithm based approach asserts run dynamics from observed years to dates with missed passage. As such, the approach necessitates multiple years of data and requires the restrictive assumption that the proportion of a run that passes on a given date is constant across years.

An alternative to linear interpolation or expectation-maximization algorithm based imputation is to take an arrival model based approach and implement a statistical framework with which to make inference about passage counts at a weir. Several related efforts have been developed for estimating abundance of fish in streams associated with periodic ground-based stream surveys (e.g. Hilborn et al. 1999; Su et al. 2001). These applications explicitly model the arrival of fish in streams and the “decay” dynamics as fish exit a stream (i.e., become unavailable for detection) through depredation by predators, decomposition, or emigration. The decay model is necessary to avoid double counting of previously observed fish. Subsequently, a probability model is asserted to describe variability of observations about the underlying arrival and decay models describing fish presence in the stream, providing a likelihood for observed fish counts. Total stream abundance enters the model framework as a scalar on the arrival and decay processes and is estimated using the likelihood for the observed data. Hilborn et al. (1999) implemented the approach using maximum likelihood estimation, and Su et al. (2001) extended the approach into a hierarchical Bayesian framework allowing for analysis of multiple years of data in manner which captures across-year correlation in stream arrival and decay processes. While these approaches deal with stream surveys on Pacific Salmon with an additional complexity of needing to correct observations for the fact that fish persist in stream for some

variable amount of time, much of the underlying approach is applicable to imputation of missing data at weirs.

Conceptually, weir-based fish counts are simpler than ground-based stream surveys because weir passage is a unidirectional, one-time event. As such, an arrival model can be specified to describe the passage of a run of fish at the weir; however, a decay model which corrects for potential double counting of previously observed fish is unnecessary. Once fit, the arrival model and assessment of variability of realized passage counts about the smooth underlying arrival model can be used to estimate passage counts for missing dates. For example, the arrival model of fish at a weir could be specified as following a cumulative Normal distribution-shaped curve, and the deviations about the smooth arrival model specifying actual weir passages could be modeled as Negative Binomial random variables. Subsequently, the Negative Binomial likelihood model can be used to inform best fitting parameters describing the arrival curve for a dataset of daily passage counts, and ultimately make predictions about missing passage dates. Because the approach is based upon a statistical framework, uncertainty about missing passage estimates can be assessed, for example by providing confidence (or credibility) intervals for missed passage estimates.

In this article, we introduce a parametric statistical approach based upon fitted run arrival models in order to impute missing data and estimate total passage at weirs. Models are fit in a Bayesian framework, providing a straightforward means to summarize uncertainty about total run size estimates, arrival model characteristics (e.g. peak run date), and estimates of predicted passage counts on missing-observation dates. Subsequently, information-theoretic model selection is used to assess strength of evidence for different proposed arrival models and observation processes. Estimator performance is tested by simulating weir data modeled after

Pacific Salmon run dynamics under a suite of missing data scenarios including missing tails, missing peak run days, and data collection efforts of only 5 days a week (the “take weekends off” scenario). Performance of parametric run models is compared against a simple linear interpolation, “connect-the-dots” scheme. Finally, the parametric run curve approach is illustrated on observed weir data for Pacific Salmon runs in the Yukon River, Alaska, drainage. We find that statistical arrival models can be successfully applied to particularly ill-behaved datasets (e.g. missing observations from the tails of the run curve) where linear interpolation can fail dramatically. Furthermore, parametric models provide statistical estimates of arrival dynamics parameters informative for assessing fish phenology.

Methods

The statistical framework implemented to estimate missing data at weirs requires specification of two key processes: *i*) an underlying run curve model that governs fish arrival dynamics at the weir, and *ii*) an error model that governs the noise about the smooth arrival model exhibited by a realized fish run and which serves as the likelihood model for the observed weir counts. Subsequently during model fitting, the parameters specifying the shape of the arrival model, a total run size scalar for the arrival model (see below), and the parameters specifying the error process model are estimated. Statistical arrival models are implemented in a Bayesian framework, providing a means to directly estimate missing data while accounting for uncertainty by treating missing daily passage counts as derived parameters for which posterior summaries are generated. The key parameter of interest, total run size, is defined as a derived parameter equal to the sum of all estimated missing daily passage counts plus the known (i.e. observed) passage counts.

Statistical models

Passage dynamics at the weir are specified by a run arrival curve model that describes the cumulative proportion, p_t , of the run that has passed the weir at time step, t . In what follows, we define a time step as a 24 hour day; any choice of time step may be implemented, however, passage counts need match the specified time step and daily counts are the most commonly recorded weir data. We implemented three candidate arrival models: a run curve described by the function for a Normal cumulative distribution,

$$p_t = F_N(t \mid \mu, \sigma) = \int_{-\infty}^t \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx \quad \text{eq. 1,}$$

a left or right skewed run curve described by the function for a skew-Normal cumulative distribution (Azzalini 1985),

$$p_t = F_{SN}(t \mid \xi, \omega, \alpha) = \frac{2}{\omega} \phi\left(\frac{(t - \xi)}{\omega}\right) \Phi\left(\alpha \frac{(t - \xi)}{\omega}\right) \quad \text{eq. 2,}$$

and a fat-tailed symmetric run curve described by the function for a Student's t cumulative distribution,

$$p_t = F_{St}(t \mid \delta, \gamma, \nu) = \int_{-\infty}^t \frac{\Gamma(\frac{\nu+1}{2})}{\Gamma(\frac{\nu}{2})\gamma\sqrt{\pi\nu}} \left[1 + \frac{1}{\nu} \left(\frac{x-\delta}{\gamma}\right)^2\right]^{-(\nu+1)/2} dx \quad \text{eq. 3,}$$

where F_N , F_{SN} , and F_{St} are notation for the Normal, skew-Normal, and Student's t cumulative distribution functions, respectively, μ is the location parameter and σ is the scale parameter for the Normal distribution arrival model, ξ is the location parameter, ω is the scale parameter α , is the shape parameter (describing skewness) for the skew-Normal distribution, ϕ is the standard normal density function, and Φ is the standard Normal cumulative distribution function, δ is the location parameter, γ is the scale parameter, and ν the shape (degrees of freedom) for the Student's t distribution. Subsequently, daily passage counts under the arrival model, c_t , are calculated by taking the proportion of the run that arrives over a preceding time step multiplied by a total run size scalar, S :

$$c_t = S \times (p_t - p_{t-1}) \quad \text{eq.4.}$$

To avoid confusion, it is worth emphasizing that the cumulative distribution functions used to specify arrival dynamics do not represent probability models for weir passage counts; they are merely convenient mathematical functions to describe the shape of the arrival curve of fish at a weir.

Next, a likelihood for the observed passage counts is specified by asserting a probability model for the process variation about passage counts predicted under the arrival model. We considered both a Normal and Negative Binomial probability model for an observed passage count, c_t^o :

$$c_t^o \sim \text{Normal}(c_t, \tau) \quad \text{eq. 5,}$$

or

$$c_t^o \sim \text{NegativeBinomial} \left(\lambda = \frac{\theta}{(\theta + c_t)}, \theta \right) \quad \text{eq.6,}$$

where the specified parameterization of the success probability parameter, λ , in the Negative Binomial model produces an expectation of c_t^o (i.e. observed passage) equal to c_t (i.e. passage under the smooth arrival curve) as a function of the dispersion parameter θ (e.g. Ntzoufras 2009). The Normal process variation model implies that variability in realized passages about the smooth underlying arrival curve is constant across the run, whereas the Negative Binomial model assumes that passage count variability scales positively with the magnitude of passage. We considered white noise process variation models (eqs. 5-6) and those with lag-1 autoregressive (AR(1)) and moving average (MA(1)) serially correlated process variation (e.g. Greene 2008). Normal and Negative Binomial probability models for observed passages with AR(1) process variation are represented as, respectively:

$$c_t^o \sim \text{Normal}(c_t + \rho_{AR(1)} c_{t-1}^*, \tau) \quad \text{eq. 7,}$$

or

$$c_t^o \sim \text{NegativeBinomial} \left(\lambda_{AR(1)} = \frac{\theta}{(\theta + c_t + \rho_{AR(1)} c_{t-1}^*)}, \theta \right) \quad \text{eq.8,}$$

where $\rho_{AR(1)}$ is the AR(1) serial correlation coefficient, $c_{t-1}^* = c_{t-1}^o$ if passage was observed on date $t - 1$, else $c_{t-1}^* = c_{t-1}$, i.e. the predicted passage count at time $t - 1$. Similarly, Normal and Negative Binomial models for observed passages with MA(1) process variation are, respectively:

$$c_t^o \sim \text{Normal}(c_t + \rho_{MA(1)}(c_{t-1}^* - c_{t-1}), \tau) \quad \text{eq. 9,}$$

or

$$c_t^o \sim \text{NegativeBinomial}\left(\lambda_{MA(1)} = \theta / (\theta + c_t + \rho_{MA(1)}(c_{t-1}^* - c_{t-1})), \theta\right) \quad \text{eq.10,}$$

where $\rho_{MA(1)}$ is the MA(1) serial correlation coefficient and with c_{t-1}^* defined as above. A key difference between the forms of serial correlation, is that imputed missing passage counts in an AR(1) model contain lagged influence from all earlier observed passage counts in the data set, whereas imputed missing passage counts in the MA(1) model contain influence only from observed passage counts one time step earlier if such an observed passage count is available (otherwise the prediction is simply that as predicted by the fitted smooth underlying arrival curve). Depending on the specified arrival model and process error model combination, likelihoods of observed counts, $L(\mathbf{c}^o | \boldsymbol{\beta})$ are conditional upon four to six parameters, $\boldsymbol{\beta}$ (Supplement 1, Supplementary Materials).

Model fitting

Arrival models were fit in a Bayesian framework using Markov Chain Monte Carlo algorithms as implemented in the WinBUGS software platform (Lunn et al. 2000) and run from the R statistical programming environment (RDCT 2014) using the package R2WinBUGS (Sturtz et al. 2005). Example code is provided in Supplement 2 of the Supplementary Materials. Diffuse priors were specified for fitted parameters (Table 1). WinBUGS treats missing daily passage counts as parameters to be estimated and thus returns a posterior distribution for the passage estimate for each missing date. The sum of all observed passages and of all estimated passages for missing dates was treated as a derived parameter, returning a posterior distribution for the estimated total run size. Because observed passage counts are known quantities, this estimate of total run only incorporates uncertainty about estimated missing passage counts. WinBUGS does not have native skew-Normal or Student's *t* cumulative distribution functions. Thus, we implemented a numerical integration routine within WinBUGS models to approximate these cumulative distribution functions following equations 2-3 (Supplement 2, Supplementary Materials).

To improve model fitting, we included additional prior information when fitting statistical arrival models by including two dates approximately one month before the start of the run and two dates approximately one month after the end of the run with zero passage counts. Preliminary analyses indicated that inclusion of known zero passage dates improved estimation of arrival models, particularly when observed data was missing for the tails of the run as may occur when a weir begins operation after the commencement of a run or is pulled before the close of a run. The timing of these dates were selected to be far enough before and after the run such that there is high confidence they represent true zero passage dates; these represent a form of prior knowledge because a priori, the timing of the fish run to be modeled isn't known,

however, analysts typically have enough information about the timing of a run to propose dates early enough and late enough to be true zero passage days. We conducted simulations to test the sensitivity of estimation results to the number and placement of known zero passage dates and found total run size estimates to be robust (Supplement 3, Supplementary Materials).

Performance testing

We compared the performance of the statistical arrival models against a suite of trials in which we simulated fish runs modeled after Pacific Salmon data from the Yukon River (Table 2). The basic approach to performance testing involved three phases: *i*) assert “true” fish run arrival dynamics and simulate realized fish runs with process variation, *ii*) implement observed fish runs which include missing passage counts (e.g. the initial 15% of the run went unobserved), and *iii*) estimate missing passage counts and summarize performance.

Simulation trials included several plausible scenarios weir operations might experience in the field (Table 2), including scenarios where the peak of the run was missed (± 2 days about peak run day), scenarios where tails of the run were missed (initial 15% of run missed), and a scenario of sampling five days a week with weekends off. White noise, AR(1), and MA(1) serially correlated process variation was simulated. In order to constrain the number of simulation scenarios, a selection of Normal and skew-Normal arrival dynamics were simulated; models with Student’s *t* distribution arrival dynamics were not used in performance testing but were fit to case study data (see below).

Simulated daily and total passage counts were calculated by asserting a smooth arrival process and then adding process variation noise, following the approach outlined above: latent daily passage counts are calculated as the proportion of an asserted arrival curve that passes on a

given date multiplied by a total run size scalar, and subsequently, realized daily passages are drawn from probability distributions with expectations equivalent to the latent passage count. We fixed the total run size scalar at 10000 fish for each simulated data set, but because realized true daily passages included process noise, realized total run size typically differed from 10000. Accordingly, subsequent performance of estimators for run size with missing passage counts was assessed relative to the realized true run size for a given simulated data set.

Salmon data from Yukon River weirs suggests that daily passage variability scales positively with passage magnitude (e.g. Figure 2), therefore simulated data scenarios incorporated Negative Binomial process variation about a given arrival model. The amount of process variation specified for simulated fish runs was chosen to reflect variation observed in actual Yukon River Pacific Salmon data, and was fixed at $\theta = 7.0$. Model fits to Yukon River Pacific Salmon datasets which supported lag-1 serially correlated process variation indicated a wide range of positive serial correlation coefficients centered about 0.5. Lag-1 serially correlated process variation was included in a selection of data simulations, setting the serial correlation coefficient, $\rho = 0.5$, reflecting a moderate amount of positive autocorrelation.

For each simulated fish run, the parameters describing the arrival model functions were randomly drawn from probability distributions, such that each simulated fish run had a unique shape and timing. Location parameters for both Normal and skew-Normal arrival models were drawn from a Normal distribution with a mean of day 185 (i.e. Julian date corresponding to July 4 in non leap years) and standard deviation of 2.5 days. Scale parameters for both Normal and skew-Normal arrival models were drawn from a log-Normal distribution with a mean of $\ln(7.5)$ and standard deviation of $\ln(1.1)$. Skewness aside, these distributions for fish run arrival timing (location parameters) and fish run compression (scale parameters) result in runs of approximately

40 days in length with a peak around July 4. Finally, for simulation scenarios with skew-Normal arrival curves, the shape parameter describing skewness was fixed at a magnitude of 2.0 with the direction of skew randomly chosen for each simulated run (i.e. α is either -2.0 or 2.0), providing a moderate amount of skewness to simulated fish runs (Figure 2c). Note, because the direction of skew was randomly chosen, simulation scenarios representing late-entry of weirs where the initial 15% of the run was missed are implemented for both left- and right-skew runs.

For each simulated data set with white noise process variation, we fit four statistical models with serially independent process variation—a Normal arrival curve with Normal deviates or with Negative Binomial deviates, and a skew-Normal arrival curve with Normal deviates or with Negative Binomial deviates—to the simulated observed data and estimated missing data following Bayesian implementation detailed above (Table 2). For simulations to examine the implication of lag-1 serially correlated process variation, we fit six statistical models—Normal arrival curve with serially independent, AR(1), and MA(1), Negative Binomial deviates, and skew-Normal arrival curve with serially independent, AR(1), and MA(1), Negative Binomial deviates (Table 2). Preliminary model analyses indicated Markov chains converged quickly. Subsequently, two parallel chains each with a 5000 iteration burn in period, a thin rate of 10 iterations, and 1000 posterior parameter draws stored were implemented for each model fit. Model convergence was assessed using the Gelman-Brooks-Rubin $\hat{R}$ statistic (Brooks and Gelman 1998) for the key parameter of interest, derived total run size estimate (i.e. observed passages plus the sum of imputed missing passage counts).

In addition to statistical arrival models, we implemented a “connect the dots” linear interpolation estimator commonly used to impute missing data at weirs. The “connect the dots” approach is attractive because of its simplicity to implement, however the approach does not

characterize the uncertainty about estimates of missing passage counts. With this estimator, missing passage day are estimated using the slope, m , of a straight line between the observed passage count days nearest to a missing day or sequence of missing days:

$$\hat{m}_{t_a,t_b} = (c_{t_b}^o - c_{t_a}^o) / |t_b - t_a| \quad \text{eq. 10,}$$

$$\hat{c}_t = c_{t_a}^o + (t - t_a) \hat{m}_{t_a,t_b} \quad \text{eq. 11,}$$

where “ $\hat{}$ ” indicates an estimated quantity, t_a is the nearest date with an observed passage count preceding a given missing-observation passage day, and t_b the nearest date with an observed passage count following a given missing-observation passage day. The “connect the dots” estimator requires dates with observed passage counts both before and after a given missing date, and thus cannot directly interpolate missing tails of the run without additional assumptions. We were unable to identify a standard approach to linearly impute missing data in the tails of runs from published literature. Therefore, we implemented an approach whereby the slope parameter for linear imputation is estimated by drawing a straight line from the maximum observed passage day (as an empirical estimate of the peak of the run) to the first observed passage day in cases when the initial tail of the run is missing, or to the last observed passage day in cases where the terminal tail of the fish run is missing. Subsequently, cumulative passage in the missing tail, $\hat{c}_{tail}$, is estimated by taking the area of the triangle formed by extrapolating the estimated slope to a point of zero passage before (after) the first (last) observed passage date when the initial (terminal) tail of the run is missing:

$$\hat{m}_{tail} = (c_{max}^o - c_{t^*}^o) / |t_{max} - t^*| \quad \text{eq. 12,}$$

$$\hat{c}_{tail} = (c_{t^*}^o)^2 / 2\hat{m}_{tail} \quad \text{eq. 13,}$$

323

324 where c_{max}^o is the maximum observed passage count which occurs on date t_{max} , and $c_{t^*}^o$ is the
 325 first (last) observed passage count on date t^* when cumulative passage in the initial (terminal)
 326 tail of the run is to be estimated.

327 A total of 150 data sets were generated for each simulation scenario (Table 2). Simulated
 328 datasets for which one or more of the fitted statistical models resulted in $\hat{R} > 1.2$ for the total run
 329 size estimate, or for which the linear interpolation estimator failed (see below), were dropped
 330 from consideration. Estimator performance was measured as average percent bias, interquartile
 331 range in percent bias, and root mean squared error relative to the true realized run size. In
 332 addition, for statistical estimators implemented in a Bayesian approach, we report the median
 333 95% highest posterior density intervals (HPDI) for the derived estimate of the total run. Finally,
 334 we used DIC-based model selection (Spiegelhalter et al. 2002; Celeux et al. 2006) to assess
 335 whether the “correct” statistical model which matched the simulated arrival and process noise
 336 model was identified as the best fitting model. We calculated the model complexity penalty in
 337 DIC using one half the variance of the posterior deviance, following an approach outlined in
 338 Gelman et al. (2004; Section 6.7).

339

340 *Case studies*

341 Preliminary model runs indicated that the degrees of freedom parameter for Student’s t
 342 arrival models were poorly identified, insofar that posterior distributions looked very similar to

343 prior distributions and were sensitive to specification of prior distributions; subsequently,
344 Student's t arrival dynamics were fit with the degrees of freedom parameter fixed to 2.0 (heavy
345 leptokurtosis). A suite of 18 statistical estimators for all combinations of 3 arrival models
346 (Normal, skew-Normal, and Student's t with $\nu = 2.0$), 2 process variation models (Normal and
347 Negative Binomial), and 3 forms of serial correlation (white noise, AR(1), and MA(1)), and the
348 linear imputation approach to estimating missing data at weirs were tested against a selection of
349 Pacific Salmon data sets with missing passage dates from resistance board weirs operated by the
350 U.S. Fish and Wildlife Service on the Gisasa and East Fork Andreafsky rivers in the Yukon
351 River drainage, Alaska, USA, during 1998 and 2000 (Tables 2-3; data publicly available from
352 the U.S. Fish and Wildlife Service, email: ak_fisheries@fws.gov). Yukon River salmon were
353 selected as a study system because weir operations in this high latitude, large river system often
354 experience challenges with blowouts from high water and difficulty in installing (maintaining)
355 weirs early (late) in the season due to ice. Furthermore, salmon in these systems follow the
356 typical unimodal arrival curve for migrating Pacific Salmon (Figure 2). Case study datasets were
357 chosen to represent a selection of missing data scenarios, run sizes, and Pacific Salmon species
358 (Chinook: *O. tshawytscha*; Chum: *O. keta*; Coho: *O. kisutch*; Pink: *O. gorbuscha*) datasets were
359 selected prior to completion of simulation analyses. *A priori* placement of zero passage days
360 (Table 3) were made based on the shape of the arrival curve or, in the instance where one or both
361 tails were unobserved, by referencing data collected in previous years from a given system.
362 Sensitivity analyses indicated total run size estimates for case studies were robust to zero passage
363 day placements. Two parallel chains each with a 7500 iteration burn in period, a thin rate of 10
364 iterations, and 1500 posterior parameter draws stored were implemented for model fits. The

same uninformative priors and convergence diagnostics used to fit statistical arrival models for data simulations (above) were also used for case study data (Table 1).

Results

Simulations: white noise process variation

Total run size estimation performance varied across models and simulation scenarios with white noise process variation; however, in most cases missing passage estimates could be imputed with accuracy and reasonable precision. The ‘Weekends Off’ scenario resulted in accurate and precise missing passage imputation estimates across all estimators with either Normal or skew-Normal arrival dynamics (Table 4; “Weekends off (SN)” and “Weekends off (SN)” scenario). In these scenarios, maximum average bias was only -1.1% of true run size for the *SN-N* estimator fit to *SN-NB* arrival dynamics. Statistical estimators indicated precise total run size estimates with 95% HPDI half widths on the order of ± 14 -19% of total missed passage (± 4 -5% of total run size). DIC support was strongest for the statistical arrival model – process variation combination that matched that from the data generating process. In the case of the Normal arrival dynamics “Weekends off” scenario, DIC support was indicated for a *SN-NB* model in 30% of the trials; however, the average difference in DIC between the *N-NB* model and the *SN-NB* model in these cases was 0.04 DIC units, indicating that the two models were comparably supported by the data (data not shown but available from the authors).

Imputation of missing passage counts on scenarios with missed peak run days was generally successful for both the Normal and skew-Normal arrival curve data generating processes simulated. Accuracy and precision of total run estimates were comparable for data simulated under the Normal and skew-Normal arrival models. For example, expected bias of the

DIC-preferred model (*N-NB*) under the Normal arrival curve scenario was -0.3% with a HPDI half-width of approximately $\pm 19\%$ of total missed passage, and the DIC-preferred model (*SN-NB*) under the skew-Normal arrival curve scenario resulted in slightly larger expected bias of -2.6% with HPDI half-width of approximately $\pm 24\%$ of total missed passage (Table 4; “ ± 2 days about the peak missed” scenarios). In both scenarios, DIC-based model selection identified the correct approximating model the majority of time. Linear interpolation imputation estimators had performance within the range observed for statistical arrival curve estimators; however, the former was never the best estimator in terms of expected bias, range in bias, and RMSE.

Simulation scenarios for which the initial 15% of the run was missed—representing, for example, late installation of a weir in the field—presented a greater range in estimator performance and lower precision when compared against scenarios with missing passage dates within the interior of arrival curves. Accuracy was generally higher for missing tail scenarios with Normal arrival dynamics, resulting in expected biases ranging from 0.5 to 11.4% across estimators, as compared to missing tail scenarios with skew-Normal arrival dynamics, which resulted in expected biases ranging from 6.3 to 17.4 %. DIC-based model selection performed well for the Normal arrival curve scenario, correctly identifying the *N-NB* model as the best fit model in over 80% of trials (Table 4; “First 15% missed (Normal)” scenario); however, DIC-based model selection in the case of skew-Normal arrival dynamics indicated ambiguity, supporting both the *N-NB* and *SN-NB* as preferred models (Table 4; “First 15% missed (skew-Normal)” scenario). Because of the good performance of the *SN-NB* model for missing-tail data scenarios for both Normal and skew-Normal arrival dynamics and the potential for a skew-Normal model to accommodate both skewed and symmetric run shapes (i.e. shape parameter $\alpha = 0$), in cases of ambiguous DIC-based model support we recommend implementing the *SN-*

NB model when handling real data with missed passage counts for tails of unimodal-shaped runs such as for Pacific Salmon enumeration as examined herein. Finally, linear interpolation estimators produced average percent bias comparable to the best fit statistical models for missing tail scenarios; however, linear interpolation could result in very large positive bias outcomes with maximum percent bias of 176.6% in the case of Normal arrival dynamics and maximum bias of 930% in the case of skew-Normal dynamics (Table 4).

Simulations: serially correlated process variation

Arrival models fit to simulation scenarios for which the initial 15% of the run was missed and which included serially correlated process variation performed comparably in terms of bias to equivalent simulation scenarios with white noise process variation, enjoying good expected accuracy and a relatively tight range in bias outcomes (Table 5). Highest posterior density interval widths for models fit with serially correlated process variation were greater than equivalent arrival models fit with white noise process variation, indicating that naïve reliance on white noise models when serial correlation is present in a given data set may result in an underestimation of the uncertainty about imputed missed passage (Table 5). While DIC-based model selection produced high success in identifying the correct arrival curve model under data simulated with white noise process variation (e.g. Table 5 scenario “First 15% missed (N-WN)”), DIC based model selection performed more poorly with serially correlated simulation data, indicating comparable support for white noise and serially correlated process variation models (e.g. Table 5 scenario “First 15% missed (N-AR(1))”). That said, practical differences in bias performance and HPDI widths were small across the AR(1) versus MA(1) forms of serially correlated process variation. Furthermore, arrival curves fit with serially correlated process

variation to data simulated with white noise process variation (Table 5 scenario “First 15% missed (N-WN)”) indicated comparable bias performance as the “correct” white noise model, and the inflation in subsequent highest posterior interval widths was slight. In such cases when candidate models with serially correlated process variation were fit to data simulated with white noise process variation (i.e. Table 5 scenario “First 15% missed (N-WN)”), serial correlation coefficients were correctly estimated as close to 0.0 (Table S2). Thus, when faced with ambiguous DIC support for white noise versus serially correlated process variation, we recommend erring on the side of caution and implementing models with serial correlated process variation on the grounds of comparable expected bias performance, and conservative characterization of uncertainty about imputed passage counts.

The performance gap between statistical arrival models and linear interpolation widened with inclusion of serially correlated process variation when considering simulation scenarios for which the initial 15% of the run was missed. Both expected bias and maximum observed bias across simulation trials increased substantially for the linear interpolation estimator when faced with AR(1) or MA(1) serially correlated process variation and a missing tail scenario. In some cases, the proposed rule of thumb for linearly interpolating tails of runs produced bias outcomes of over 10,000% (e.g. Table 5 scenario “First 15% missed (N-MA(1))”).

Simulations: arrival curve attributes

While not a focus of the present simulation trials, statistical arrival models performed well in reconstructing underlying run curve characteristics (see summary of full results in Supplementary Materials, Table S1-S2). Arrival curve location and spread parameters were estimated with high accuracy, with expected bias for peak run date estimated to within ± 1 day

and spread parameters to within $\pm 5\%$ of the true estimate for DIC-preferred models. Arrival curve skew, which was constrained to 2.0 or -2.0 during simulations, was accurately estimated with average absolute bias of 0.1 for the *SN-NB* model applied to the missing peak days scenarios with skew-Normal arrival and white noise Negative Binomial process variation, and average absolute bias of 0.3 for the *SN-NB* model applied to missing 15% initial tail scenario with skew-Normal arrival. Similarly, *SN-NB* models fit to missing data scenarios with Normal arrival dynamics and white noise Negative Binomial process variation produced average skewness estimates close to zero (average absolute value of shape parameter ranged from 0.3 to 0.6 across missing data scenarios; Table S1). Finally, expected estimates of the degree of serial correlation in the process variation models were accurate for white noise (average $\rho \approx 0.0$), as well as AR(1) and MA(1) serially correlated Negative Binomial process variation models (average $\rho \approx 0.5$; Table S2).

Case Studies

The *SN-NB* was the DIC-preferred model in all but one case study, indicating substantial left and right skew in 4 of 5 of the case studies (Table 6; Figure 2d-h). In one case, Student's *t* distribution with two degrees of freedom was DIC preferred (Table 6, "2000 East Fork Andreafsky River Pink Salmon). A mix of both white noise and serially correlated process variation was supported, depending on the case study. Based upon total run size from the DIC-preferred statistical arrival model, imputed passage counts ranged from 15-31% of the total run (Table 6). Precision of total run estimates varied, and was not strongly related to the amount of missing passage imputed or the shape of the run. For example, the *SN-NB-MA(1)* statistical arrival estimator indicated 26% of the Chum salmon run on the Gisasa River in 1998 went

unobserved, producing a precise total run estimate with a 95% HPDI half width of $\pm 7.7\%$ of the estimated run size ($\pm 29\%$ of the total imputed missing passage). In contrast, data from the 2000 East Fork Andreafsky Chum salmon run indicated 17% of the run went unobserved, producing a less precise total run size estimate from the DIC-preferred *SN-NB-MA(1)* model with a 95% HPDI half width of $\pm 20.4\%$ of the estimated run size ($\pm 118\%$ of the total imputed missing passage). The lowest precision total run estimate occurred with the 1998 East Fork Andreafsky Coho Salmon run ($\pm 34.8\%$ of the total run estimate; $\pm 112\%$ of the total imputed missing passage), which exhibited high passage count variability, strong skewness, and missing data in a tail of the run (Figure 2f).

The statistical arrival model total run estimates and those from linear interpolation agreed closely for the case study runs that exhibited relatively smooth and symmetric arrival dynamics (1998 Gisasa Chum and 1998 Gisasa Chinook; Figure 2d-e; Table 6); however, the linear interpolator agreed less closely in cases with missing data near peak runs with high passage variability. For example, the maximum observed count for 1998 East Fork Andreafsky Coho (1,104 fish in a run where the total observed count equaled 5,417 fish) was followed by an observed 0 passage day and subsequently observations ceased. Owing to a lack of observations in the remainder of the run, linear imputation for the tail based upon the ad hoc rule outlined above resulted in a 0 fish estimate and underestimate of the run size relative to the DIC-preferred *SN-NB-WN* statistical arrival model estimate (Table 6).

Discussion

Simulation results demonstrated that in many cases missing data at weirs can be accurately and precisely imputed for unimodal fish runs. For example, under the simulated

process variation modeled after Pacific Salmon runs in Alaska, a weekends-off monitoring schedule (a repeated schedule of 5 days of monitoring followed by 2 days of missing data) produced little loss in accuracy for estimated total run size, while still allowing for estimation of phenological run characteristics such as peak run date.

DIC-based model selection indicated support for Negative Binomial process variation for all case studies, indicating that variability in daily passage counts for Pacific salmon may scale positively with passage. Skewed arrival curve dynamics were supported for all but the 2000 East Fork Andreafsky River Pink Salmon case study. The *SN-NB* arrival model – process variation model combination was the most flexible model estimated, requiring only one additional parameter than models with Normal arrival curves. The skew-Normal arrival model reduces to a Normal arrival model under a shape parameter of zero, but also has flexibility to accommodate single-tail fatness through skewness. Furthermore, the Negative Binomial process model allows for overdispersion in count models, but can also reduce to a pure Poisson count process model if the overdispersion parameter is zero. Thus, while we recommend fitting a suite of plausible statistical arrival models and subsequent DIC-based model selection, the *SN-NB* model may be a reasonable choice to apply to real data for those wishing to avoid fitting large suites of models.

Simulations indicated DIC-based model selection could produce ambiguous results in discriminating between white noise or serially correlated process variation in some scenarios. In cases of ambiguous DIC support for models with different process variation autocorrelation structures, we recommend implementing models with serially correlated process variation to err on the side of caution; simulation results indicate no expected loss in bias performance, and while credibility intervals about imputed passage may be inflated by fitting serially correlated

process variation models to data for which process variation is in reality white noise, the degree of uncertainty inflation may not be great.

Statistical arrival model estimators outperformed linear interpolation in most simulation trials; however, the performance gap was not always great, particularly when faced with data with white noise process variation (Table 4). With white noise process variation simulation scenarios, the proposed rule of thumb for implementing linear interpolation when the tails of a fish run were missed yielded average total run estimates quite close to model-based estimates; however this estimator led to a wider range in bias outcomes and occasionally led to very poor estimation outcomes across simulation trials (Table 4). When faced with data simulated with serially correlated process variation, the performance gap between statistical arrival models and linear interpolation widened, and the proposed rule of thumb for linearly interpolating missed tail areas could fail dramatically.

The comparable performance of linear interpolation against fitted arrival models begs the question as to whether the statistical complication is worth the trouble when imputing missing passages at weirs? For simple applications with only a few missing passage counts occurring at non-peak passage dates, linear interpolation is likely sufficient, producing an accurate estimate of total run size. The model-based framework implemented in a Bayesian framework does, however, present several advantages over linear interpolation. First, particularly in data scenarios exhibiting serially correlated process variation, linear interpolation can fail dramatically, whereas arrival models may produce more stable imputation results. Second, uncertainty estimates about missing passages are produced, providing transparency about the precision of total run size. For example, the total run size estimates from the linear interpolation estimator (7179) and the *SN-NB-WN* statistical arrival model (7876) for the 1998 East Fork

Andreafsky Coho Salmon were similar, differing by 697 fish; however, the statistical arrival model fit indicates considerable uncertainty with a total run size 95% HPDI ranging from 6497 to 11990 fish (Table 6). Third, Bayesian implementation allows for inclusion of prior information into model estimates in a unified framework, which may facilitate estimates for scenarios with substantial missing-data (although there is a limit to what can be asked of a dataset). If multiple years' data are available for a given fish passage project, statistical arrival models could be cast in a hierarchical framework, potentially improving the precision about the run arrival curve parameters, and possibly improving performance of imputation by sharing information across years (e.g. Hilborn and Liermann 1998; Su et al. 2001). We caution, however, that in such meta-analytic approaches, care need be taken to account for potential temporal or spatial trends in run timing phenology or other confounding influences on run arrival dynamics when combining datasets for hierarchical inference (e.g. Thorson et al. 2013). Finally, the model-based framework provides statistical estimates of biologically relevant information on run arrival dynamics, where the median of the fitted arrival models represents the date at which 50% of the run has passed the weir, the mode represents the peak run day after which fishery managers can expect declining passage counts, and the spread of the arrival model provides information about fish run compression. For example, Sethi and Tanner (2014) characterized annual variability in run dynamics of Chinook Salmon on the Togiak River in the Bristol Bay region of Alaska, by comparing estimates of peak run date and run compression at a resistor board weir across a suite of years using methods similar to the statistical arrival model approach outlined above.

While data simulations and case studies herein focused on missed passage counts through weirs, the statistical arrival model approach to imputation could also be applied to other fish

enumeration techniques which produce counts that follow the underlying arrival dynamics of a target fish population. Example fish counting projects include counting towers (Anderson 2000), hydroacoustic enumeration (e.g. Enzenhofer et al. 1998), or test fisheries (Flynn and Hilborn 2004). A key requirement for such applications is that passage counts need either completely enumerate all fish present on observation days, or need represent a consistent index of passage on observation days (e.g. with constant or controllable “catchability”).

Acknowledgements

We thank R. Brown (USFWS) and A. Martin (USFWS) for assistance with data for this project. R. Brown also contributed to the conception of this project. J. Reynolds (USFWS), CJFAS editorial staff and peer reviewers provided helpful comments which improved an earlier draft of this piece. S. Fleischman (ADFG) is thanked for comments related to serially correlated process variation. Any potential errors in the article are solely attributable to the authors. The findings and conclusions in this article are those of the authors and do not necessarily represent the views of the U.S. Government.

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Table 1. Prior specifications^a.

Parameter description	Prior
Run size scalar	$\log(S) \sim \text{Normal}(\mu_S = 7.5, \sigma_S = 2.0)$
Location parameter of the Normal arrival model	$\mu \sim \text{Uniform}(150, 300)$
Scale parameter of the Normal arrival model	$\sigma \sim \text{Uniform}(1, 50)$
Location parameter of the skew-Normal arrival model	$\xi \sim \text{Uniform}(150, 300)$
Scale parameter of the skew-Normal arrival model	$\omega \sim \text{Uniform}(1, 50)$
Shape parameter of the skew-Normal arrival model	$\alpha \sim \text{Uniform}(-10, 10)$
Location parameter of the Student's t arrival model	$\delta \sim \text{Uniform}(150, 300)$
Scale parameter of the Student's t arrival model	$\gamma \sim \text{Uniform}(1, 50)$
Scale parameter for the Normal process error model	$\tau \sim \text{Uniform}(0.1, 1000)$
Dispersion parameter for the Negative Binomial process error model	$\theta \sim \text{Gamma}(0.1, 0.1)$
Autocorrelation coefficient for lag-1 serially correlated process variation	$\rho \sim \text{Uniform}(-1, 1)$

^aArrival models are parameterized in terms of a daily time step. For example, the prior specification for the Normal arrival model constrain the peak run date, μ , to lie between Julian day 150 and day 300.

Table 2. Simulation and model fitting scenarios^a.

Observation scenario	Arrival model	Candidate models
<i>Simulations: white noise process variation</i>		
Weekends off: observe 5 days, miss 2 days, ...	<i>N, SN</i>	<i>N-N-WN,</i>
Run peak missed: a 5-day period (+/- 2 days)		<i>N-NB-WN,</i>
about the run peak is missed		<i>SN-N-WN,</i>
Late installation: first 15% of arrival curve is missed		<i>SN-NB-WN,</i> <i>LI</i>
<i>Simulations: AR(1) and MA(1) serially correlated process variation</i>		
Late installation: first 15% of arrival curve is missed	<i>N</i>	<i>N-NB-WN,</i> <i>N-NB-AR(1),</i> <i>N-NB-MA(1),</i> <i>SN-NB-WN,</i> <i>SN-NB-AR(1),</i> <i>SN-NB-MA(1),</i>
<i>Case studies: Yukon River Pacific Salmon (Oncorhynchus spp.)</i>		
	<i>N, SN, t(d.f. = 2)</i>	<i>All combinations (18 models)</i>

^aAbbreviations: AR(1) = lag-1 autoregressive, MA(1) = lag-1 moving average, NB = Negative Binomial, N = Normal, SN = skew-Normal, t = Student's t distribution.

Table 3. Case study data summary.

Run	Observed dates (Julian day)	Description of missing data	<i>A priori</i> zero passage count placement (Julian day)
1998 Gisasa River Chum Salmon	172-214	Neither tail fully observed; sequence of missing observations preceding the run peak	158-160; 225-227
1998 Gisasa River Chinook Salmon	175-214	Sequences of missing days in both tails of the run	168-170; 225-227
1998 East Fork Andreafsky River Coho Salmon	203-255	Sequence of missed observations after run commencement; terminal tail missed	198-200; 270-272
2000 East Fork Andreafsky River Chum Salmon	182-216	Initial tail missed; sequence of missed days after the run peak	168-170; 230-232
2000 East Fork Andreafsky River Pink Salmon	182-262	Sequences of missed days after the run peak	168-170; 270-272

Table 4. Simulation trial performance summaries for statistical arrival models and linear interpolation under white noise Negative Binomial process variation^a.

Scenario (arrival model)	Fitted model	DIC preferred (%)	Total run size estimate percent bias				RMSE	Median proportion of total passage observed (%)	Median 95% HPDI width (% missing passage prediction)
			Average (%)	Minimum (%)	Maximum (%)	IQR (%)			
Weekends off (N)	<i>N-N</i>	0	<0.1	-11.3	9.6	5.7	435.5	71.6	28.6
	<i>N-NB</i>	70.0	<0.1	-10.7	10.3	5.8	426.8		33.7
	<i>SN-N</i>	0	0.1	-11.0	10.3	5.6	440.7		30.3
	<i>SN-NB</i>	30.0	0.2	-10.6	10.5	5.8	429.8		33.0
	<i>LI</i>	.	0.4	-11.4	12.1	5.8	501.0		.
Weekends off (SN)	<i>N-N</i>	0	-0.8	-15.5	14.5	8.1	554.6	71.2	26.1
	<i>N-NB</i>	1.3	-1.0	-13.3	13.5	7.9	563.6		59.4
	<i>SN-N</i>	0	-1.1	-17.2	16.7	9.9	634.3		26.7
	<i>SN-NB</i>	98.7	-0.8	-14.1	14.0	8.2	540.9		38.8
	<i>LI</i>	.	-0.4	-13.8	23.2	8.9	672.4		.
±2 days about the peak missed (N)	<i>N-N</i>	0	0.6	-18.7	20.1	9.6	668.5	74.1	25.9
	<i>N-NB</i>	61.3	-0.3	-20.3	17.2	7.2	604.9		37.2
	<i>SN-N</i>	0	0.4	-18.4	20.2	9.0	661.8		27.5
	<i>SN-NB</i>	38.7	<0.1	-18.4	16.9	6.9	585.6		37.3
	<i>LI</i>	.	-2.5	-24.6	20.5	11.7	885.3		.
±2 days about the peak missed (SN)	<i>N-N</i>	0	-2.4	-29.6	42.6	15.0	1144.3	63.1	30.6
	<i>N-NB</i>	0	-10.5	-37.6	14.1	10.7	1400.6		61.6
	<i>SN-N</i>	0	-1.2	-34.0	31.4	14.8	1170.4		31.3
	<i>SN-NB</i>	100.0	-2.6	-26.3	23.2	9.7	897.8		46.9
	<i>LI</i>	.	-6.5	-37.7	25.2	15.6	1339.0		.
First 15% missed (N)	<i>N-N</i>	0	2.8	-10.9	50.6	8.6	978.5	87.1	190.7
	<i>N-NB</i>	80.6	1.4	-7.5	16.2	7.3	512.8		140.8
	<i>SN-N</i>	0	11.4	-12.2	56.0	24.5	2043.1		323.8
	<i>SN-NB</i>	19.4	0.5	-10.2	14.4	7.4	544.4		181.3
	<i>LI</i>	.	0.5	-14.8	176.6	11.7	2335.8		.
First 15%	<i>N-N</i>	0	6.3	-13.4	74.3	15.9	1873.7	89.0	229.1

missed (SN)	<i>N-NB</i>	54.1	12.4	-13.0	106.0	31.1	2662.7	170.4
	<i>SN-N</i>	0	17.4	-13.8	105.2	34.5	3016.2	307.3
	<i>SN-NB</i>	45.9	6.3	-13.0	172.6	12.0	1953.5	308.8
	<i>LI</i>	.	8.8	-14.1	930.0	10.8	8072.9	.

^aThe true run size scalar for simulated fish runs is 10000 in all cases. Performance summaries for arrival model scenarios only include data sets for which all four statistical arrival model fits converged and for which a linear interpolation estimate could be generated (see Methods); number of datasets for arrival scenarios, top to bottom = 150, 150, 129, 122, 150, and 149. Abbreviations: DIC = Deviance Information Criterion, HPDI = highest posterior density interval, IQR = inner quartile range, LI = linear interpolation, NB = Negative Binomial, N= Normal, RMSE = root mean squared error, SN = skew-Normal.

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Table 5. Simulation trial performance summaries for statistical arrival models and linear interpolation under white noise and lag-1 serially correlated Negative Binomial process variation^a.

		Total run size estimate percent bias						Median proportion of total passage observed (%)	Median 95% HPDI width (% missing passage prediction)
Scenario (arrival model)	Fitted model	DIC preferred (%)	Average (%)	Minimum (%)	Maximum (%)	IQR (%)	RMSE		
First 15% missed (N-WN)	<i>N-NB-WN</i>	72.1	1.4	-7.5	16.2	7.3	512.8	87.2	140.8
	<i>N-NB-AR(1)</i>	3.9	1.5	-7.9	16.4	7.3	479.8		154.5
	<i>N-NB-MA(1)</i>	4.7	1.5	-7.8	16.1	7.1	485.7		149.7
	<i>SN-NB-WN</i>	1.9	0.5	-10.2	14.4	7.4	544.4		181.3
	<i>SN-NB-AR(1)</i>	0	0.5	-11.4	15.8	7.6	474.3		208.2
	<i>SN-NB-MA(1)</i>	0	0.4	-11.7	16.2	6.7	484.9		198.5
	<i>LI</i>		0.5	-14.8	176.6	11.7	2335.8		.
First 15% missed (N-AR(1))	<i>N-NB-WN</i>	40.8	0.8	-16.5	35.0	10.3	1702.3	81.8	139.2
	<i>N-NB-AR(1)</i>	4.8	0.8	-13.3	32.6	10.0	1568.4		207.4
	<i>N-NB-MA(1)</i>	29.2	0.9	-12.8	31.5	9.6	1536.3		198.3
	<i>SN-NB-WN</i>	24.5	-4.7	-24.5	21.1	9.5	1734.0		193.5
	<i>SN-NB-AR(1)</i>	0	-3.3	-24.5	20.6	10.7	1720.9		418.1
	<i>SN-NB-MA(1)</i>	0.7	-3.9	-24.4	17.8	11.3	1749.4		420.1
	<i>LI^b</i>		51.3	-25.5	7394.7	12.4	113472.5		.
First 15% missed (N-MA(1))	<i>N-NB-WN</i>	36.7	4.7	-21.6	71.4	19.7	1695.3	79.0	153.2
	<i>N-NB-AR(1)</i>	3.6	4.4	-20.2	56.4	18.9	1345.7		235.1
	<i>N-NB-MA(1)</i>	30.9	4.5	-19.7	52.6	16.6	1311.5		222.3
	<i>SN-NB-WN</i>	26.6	-4.0	-23.6	49.7	14.1	1268.5		237.7
	<i>SN-NB-AR(1)</i>	0	-1.0	-21.6	39.4	18.8	1195.7		537.6
	<i>SN-NB-MA(1)</i>	2.2	-2.1	-23.9	33.1	16.8	1099.2		534.6
	<i>LI^b</i>		125.6	-34.6	16362.7	19.3	129134.6		.

^aThe true run size scalar for simulated fish runs is 10000 in all cases. Performance summaries for arrival model scenarios only include data sets for which all six statistical arrival model fits converged and for which a linear interpolation estimate could be generated (see Methods); number of datasets for arrival scenarios, top to bottom = 129, 147, and 139. Abbreviations: AR(1) = lag-1 autoregressive,

DIC = Deviance Information Criterion, HPDI = Highest Posterior Density Interval, IQR = inner quartile range, LI = linear interpolation, MA(1) = lag-1 moving average, NB = Negative Binomial, N= Normal, RMSE = root mean squared error, SN = skew-Normal, WN = white noise.

^bCatastrophic failure (>500% bias in the total run size estimate) of the linear interpolation estimate occurred in a small number of datasets generated with serial correlated process error under the scenario of a missing tail ($n=2$ for the AR(1) scenario and $n=3$ for the MA(1) scenario). In these cases, the difference in the first observed passage count and the maximum observed passage count is small and the first observed passage count is large (>500) resulting in a relatively small slope for the interpolated tail and an extremely large estimate for the run size. Removing these occasions, the average bias for the linear interpolation is -3.5% and -3.7% for the AR(1) and MA(1) scenarios, respectively; the maximum bias for each is 251.3% (AR(1)) and 204.9% (MA(1)). The RMSE for the two scenarios after removing these occasions are similarly reduced (5645.2 for the AR(1) scenario and 2654.1 for the MA(1) scenario).

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Table 6. Case study results^a.

Run	Observed passage	Linear interpolation run size estimate	DIC preferred statistical model	Statistical model run size estimate	Lower 95% HPDI limit	Upper 95% HPDI limit	95% HPDI width	Statistical model imputed passage
1998 Gisasa River Chum Salmon	13225	17796	SN.NB.MA	18010	16630	19430	2800	4785
1998 Gisasa River Chinook Salmon	1942	2361	SN.NB.WN	2297	2246	2357	111	355
1998 East Fork Andreafsky River Coho Salmon	5417	7179	SN.NB.WN	7876	6497	11990	5493	2459
2000 East Fork Andreafsky River Chum Salmon	22625	25089	SN.NB.MA	27365	25070	36260	11190	4740
2000 East Fork Andreafsky River Pink Salmon	37069	43500	t.NB.AR	44195	40820	50970	10150	7126

^aAbbreviations: “DIC” = Deviance Information Criterion, “HPDI” = highest posterior density interval, “SN” = skew-Normal, “NB” = Negative Binomial, t = Student’s t distribution (d.f.=2), AR(1) = lag-1 autoregressive, MA(1) = lag-1 moving average, WN = white noise.

Figure Captions

Figure 1. Weir failures. Left panel: high water tops a resistor board weir on the Killey River, Alaska, June 2013 (credit: A. Waldo). Right panel: high water destroys a resistor board weir on the Gisasa River, Alaska, July 2014 (credit: J. Mears).

Figure 2. Simulated (a-c) and observed (d-h) Pacific Salmon runs. Arrival curves are constructed with posterior medians of estimated parameters from best fitting candidate models. Simulated runs include serially independent Negative Binomial process.

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Figures

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Figure 2.
159x117mm (300 x 300 DPI)