Comprehensive Passage (COMPASS) Model – version 1.1

Review DRAFT

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Table of Contents

1 Background and Model Overview

The Comprehensive Passage (COMPASS) model was developed by scientists from throughout the Pacific Northwest. The purpose of the model is to predict the effects of alternative operations of Snake and Columbia River dams on salmon survival rates, expressed both within the hydrosystem and latent effects which may occur outside the hydrosystem. Accordingly, the model has the following capabilities: 1) realistically simulate survival and travel time through the hydrosystem under variable river conditions; 2) produce results in agreement with available data, particularly PIT-tag data; 3) allow users to simulate the effects of alternative management actions; 4) operate on sub-seasonal time steps; 5) produce an estimate of uncertainty associated with model results; 6) estimate hydrosystem-related effects that may occur outside of the hydrosystem.

The COMPASS model simulates downstream migration and survival of juvenile salmon through the tributaries and dams of the Columbia and Snake rivers (via in-river migration and transportation) to the estuary (Figure 1). In addition, the model applies any latent mortality related to hydrosystem passage expressed outside of the hydrosystem (Figure 1). Thus, the model attempts to simulate all mortality associated with passage through the hydrosystem.

Although the COMPASS model will be used for a variety purposes, including in-season monitoring of survival and travel time, the primary function of the model is to compare hydrosystem survival across management scenarios. The three main operations that vary among management scenarios are flow (based on releases from storage reservoirs), proportion of river flow passed through the spillway, and transportation scheduling. Changes in these operations can change in-river survival and adult return rate through a variety of mechanisms (Table 1). Also, dam configurations have changed across years, notably the addition of spillway weirs, and certain management scenarios may involve further dam configurations. Additional management scenarios that may be visited at a future time include reducing reservoir elevations to increase water velocity, predator removal, and dam breaching.

COMPASS is capable of representing any salmonid population that migrates through the Snake and Columbia rivers, including the Upper Columbia River. We have currently calibrated the model for the Snake River spring/summer Chinook salmon and steelhead Evolutionarily Significant Units (ESUs). While this manual presents results for these two ESUs, we plan to expand the modeling capabilities in the future to other ESUs.

The model is supported by extensive data sets, particularly PIT-tag data, which provide information on survival and travel time. Additionally, dam passage parameters were estimated from radio-telemetry, acoustic tag, and hydroacoustic studies. The model was calibrated by fitting survival and migration rate relationships to historical data. During this calibration phase, we assembled historical data sets of river conditions (water flow, water temperature, and reservoir elevations) and dam operations (spill and transportation schedules), and we also implemented historical dam configurations.

To run the model prospectively, we needed to assemble data files of river conditions (primarily flow and temperature) that reasonably reflect the variability in future conditions. As has been implemented in past modeling efforts, we used a hydrological model (HYDSIM) that reconstructs river conditions in the hydrosystem based on historical outflows from headwaters during the years 1929-1998. The HYDSIM model also takes into account current storage reservoirs and scheduled water releases. Because temperature is an important factor in some reservoir survival relationships, we also simulated water temperatures during these years based on flow-temperature relationships. The details of this hydrological modeling are contained in Appendix 8.

For each of the "water years" described above, we produce key information on juvenile fish migration through the hydrosystem – annual survival through the entire hydrosystem, percentage of fish transported, and arrival timing below Bonneville (along with other diagnostic information). We then apply post-Bonneville mortality. For some post-Bonneville hypotheses, information from the downstream migration module – arrival timing, water travel time, percent fish transported – are incorporated into predictions of post-Bonneville survival. We present details of prospective modeling in Appendix 8.

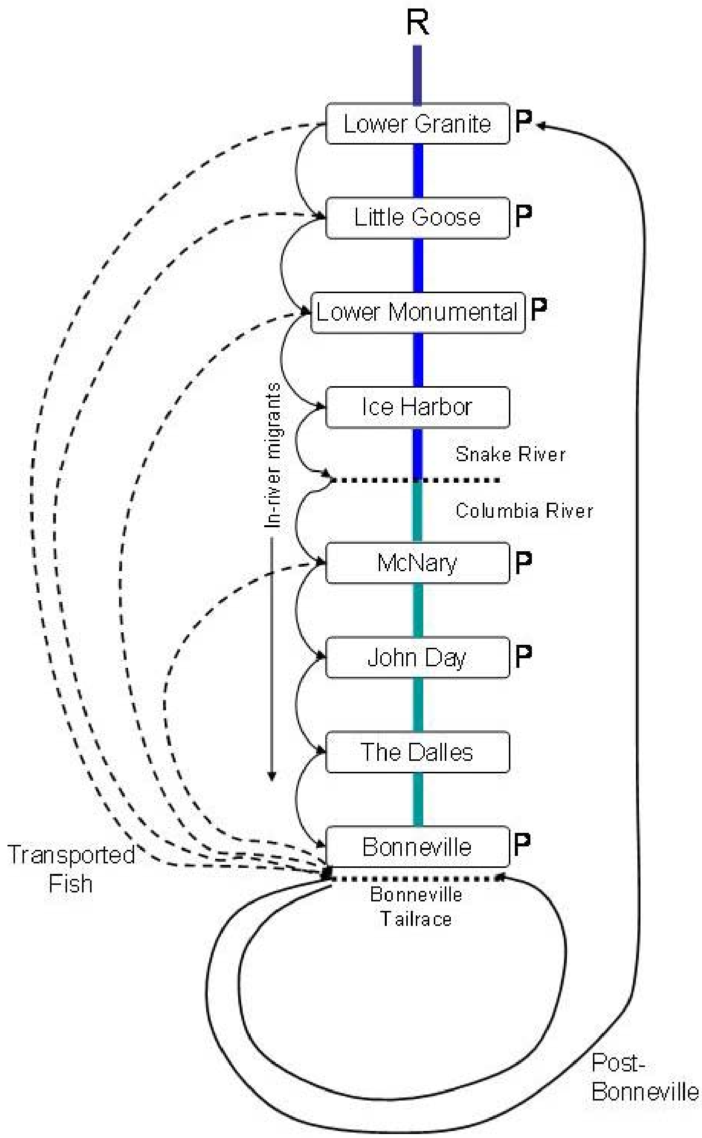

Figure 1. Features of the Snake and Columbia River hydrosystem modeled in COMPASS for Snake River fish. "R" represents the release site or the site where fish enter the hydrosystem (head of Lower Granite reservoir). Fish move downstream via in-river migration or by transportation. "P" represents PIT-tag detection sites. The post-Bonneville component of the model takes fish from the Bonneville tailrace and returns them to either Bonneville Dam or Lower Granite Dam, depending on the hypothesis.

Table 1. List of potential management actions and their effects on survival, as expressed through the model.

Action	Effect on Model	Effect on Survival
Flow Augmentation	Flow increases	Reservoir survival increases
	Temperature decreases (or increases)	Reservoir survival increases (or decreases)
	Water velocity increases	Reservoir survival increases due to decreased exposure time resulting from decreased travel time
	Water velocity increases	Increased SAR of in-river migrants due to earlier arrival in the estuary resulting from decreased travel time
Increased spill (but at or below gas cap)	More fish pass via spillway	Dam survival increases
	More fish pass via spillway	Reservoir survival increases due to relationship with spill
	Fewer fish transported	SAR increases or decreases depending on post-Bonneville survival
	Delay in dam passage decreased	In-river survival increases due to decreased travel time
	Delay in dam passage decreased	SAR of in-river migrants increases because of earlier arrival to estuary
Transportation schedule	Change timing of transportation	SAR increases or decreases depending on post-Bonneville survival
	Change timing of transportation	Overall in-river survival increases or decreases because of altered timing of in-river migrating population and consequently altered population-wide exposure to river conditions

2 Downstream Passage

2.1 Model Overview

The downstream passage component of COMPASS models downstream migration and survival of juvenile salmon populations (where population is synonymous with ESU) through the Snake and Columbia rivers. COMPASS computes daily fish passage for all river segments and dams on a release-specific basis. The model is composed of four submodels: reservoir survival, dam passage, travel time, and hydrological processes. A brief description of the submodels follows.

The structure of COMPASS allows incorporation of different algorithms to simulate hydrosystem processes for each of these models. The reservoir survival module in particular allows the substitution of different algorithms to represent different hypotheses concerning reservoir survival.

Reservoir Survival. Reservoir survival is computed as fish move through each reservoir. Reservoir survival is potentially related to river flow, river temperature, spill rate, travel time, and travel distance. The relationship varies among populations and among major river segments (e.g., Snake and Columbia rivers). The specific relationships are based on statistical analyses of PIT-tag survival data.

Dam Passage. Fish can pass dams by several passage routes: spillways, removable spill weirs, sluiceways, turbines, and fish bypass systems. Each of these routes has an associated probability of passage and survival. Day/night (diel) differences may exist in these passage and survival probabilities. Further, fish that enter the bypass systems of collector dams (Lower Granite, Little Goose, Lower Monumental, and McNary) can be diverted into trucks or barges for transportation to below Bonneville Dam.

Travel Time. The travel time submodel moves release groups downstream according to a migration rate and a rate of spreading. Migration rate is based on water velocity, date of release, water temperature, and spill passage rate. The spreading rate of a release group determines its temporal distribution as it passes through dams and reservoirs. Travel time parameters are specified by population and are based on statistical analyses of PIT-tag data.

Hydrological Processes. Daily river flow, water velocity, and water temperature are represented through a detailed hydrological submodel. Daily flows and temperatures at headwaters are either taken directly from historical data or from system hydroregulation models external to the COMPASS model.

The four submodels interact to simulate the survival and timing of release groups as they pass through a project (Figure 2). The user specifies release information, provides input parameters for survival and travel time relationships and dam passage, specifies dam operations (spill and transportation), and provides a data file for water temperature and flow. The model outputs number of fish per day entering the next downstream river segment and the number of fish transported by day.

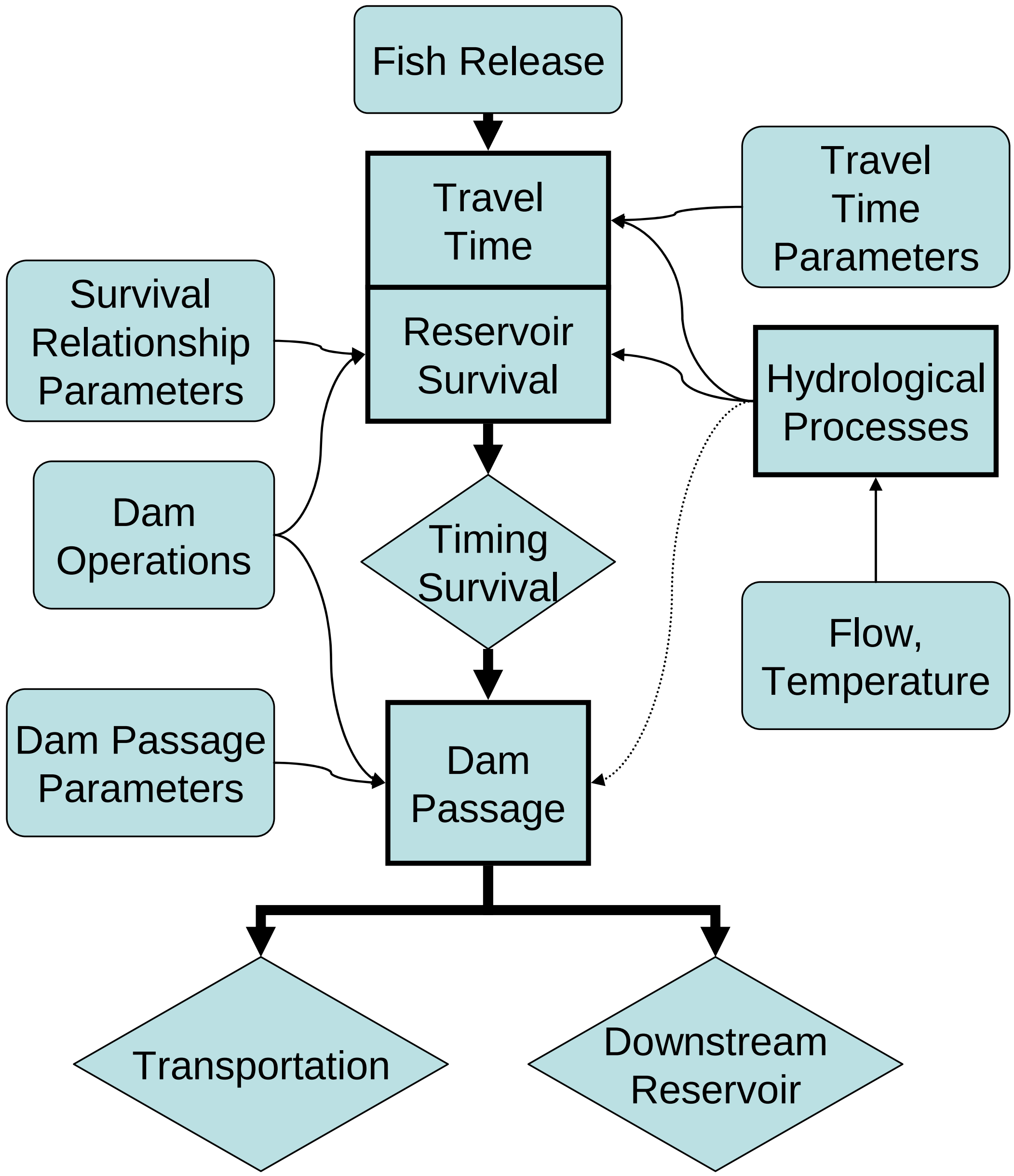

Figure 2. Schematic diagram of fish passage through a project (reservoir and dam). The rectangular boxes represent the model submodels. The boxes with rounded corners represent user inputs. The diamonds represent model outputs.

The model is initiated with a release group specified at a particular release site. Release groups may be distributed across days with varying numbers of fish per day. All fish in a release group share behavioral characteristics; that is, they have common travel time and survival parameters. The model proceeds by moving fish, in half-daily time increments, through river segments and dams following a sequence of steps (Figure 3). The first step is to take all fish released into a reservoir on a given day or all fish arriving at the top of a reservoir on a given day and distribute them at the bottom of the reservoir according to the travel time model, described in detail below. Next, reservoir survival (details below) is applied to these fish before they move to the dam passage algorithm. At the dam, arriving fish are first distributed across the day in a diel passage pattern and then distributed across passage routes according to specified passage probabilities. Route-specific survival probabilities are then applied. Surviving fish are then formed into daily release groups to enter the next downstream reservoir. Note that these daily release groups are composed of all the fish from the initial release group that arrive at a dam on the same day (but may have entered the top of the reservoir on different days). Fish that enter the bypass system at collector dams may be transported, according to specified transportation schedules.

In the future, there are two modes that COMPASS can use: a Scenario Mode that produces deterministic results, and a Monte Carlo Mode, which produces measures of uncertainty in predicted passage survival. In the latter case, the model will be run repeatedly, drawing parameters from distributions for each run, and presenting survival information as probability distributions. At present, only the deterministic mode is running, with the Monte Carlo mode under development (see Appendix 7).

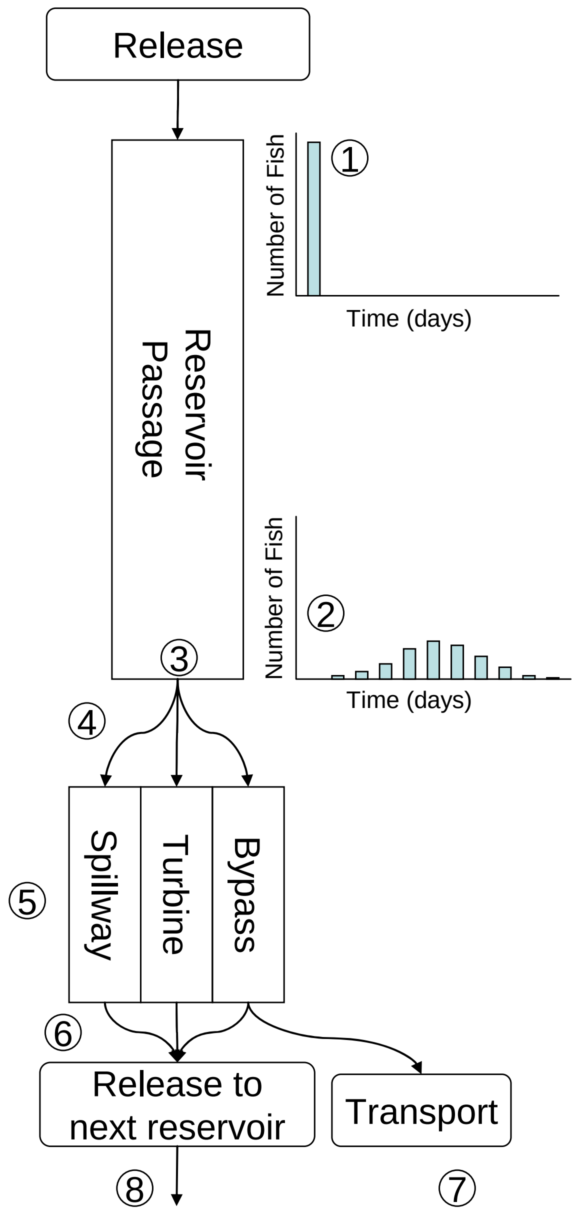

Figure 3. Passage model algorithm, features the steps taken to move a daily release of fish through a project. (1) Fish released at the top of a reservoir. (2) Fish distributed (across daily time steps) at bottom of reservoir according to travel time model. (3) Reservoir mortality applied. (4) Fish distributed into daytime and nighttime passage groups and then assigned to passage routes. (5) Dam mortality applied. (6) Surviving fish pooled to form release group for next reservoir. (7) Fish that entered bypass system may be transported. (8) Fish released, in daily increments, into next downstream reservoir; return to step (1). Note that in the final step, daily release groups are composed of all fish passing the dam on a given day, regardless of when they were released at the upstream site.

2.2 PIT-tag Data

PIT-tag data are the primary source for calibrating survival, migration rate, and dam passage parameters in COMPASS. During 1997-2007, juvenile Snake River spring/summer Chinook salmon and steelhead were captured, PIT tagged, and released at Lower Granite Dam or upstream from the dam (see Smith et al. 2004 and references cited within for details of tagging). Tagged fish were grouped into weekly cohorts based on day of release or day of passage at Lower Granite Dam (Table 2). As they migrated seaward, tagged fish potentially could be detected at 5 downstream detection sites located in juvenile bypass systems at dams (Figure 1). In addition, a small proportion of fish were detected downstream from Bonneville Dam. Because cohorts of fish spread out as they migrate downstream, we regrouped fish (of Snake River origin) at McNary Dam to form new weekly cohorts for analyses through the lower Columbia River.

We examined several issues related to these data, with details provided in Appendix 1. First, we considered whether to separate wild and hatchery fish in our analyses. We concluded that wild and hatchery fish differ substantially in survival, migration rate, and detection probability (Appendix 1), and we therefore chose to separate them in all our analyses. Unfortunately, this resulted in a loss of precision of survival estimates when comparing wild versus combined hatchery and wild cohorts (as used in the previous version of COMPASS). Regarding precision of survival estimates, Snake River spring/summer Chinook cohorts generally had more precise survival estimates than those of steelhead. Also, survival estimates for cohorts migrating through the Snake River were far more precise than those for cohorts migrating through the Columbia River. In fact, survival estimates through the lower Columbia River were so poor that we believe we were severely limited in our ability to relate survival to environmental factors in these river segments. Accordingly, we identified obtaining more precise survival estimates through the lower Columbia River as a high priority for future monitoring. As a way to partially rectify this problem, we examined whether forming cohorts over two week periods would yield better precision. Unfortunately, this did little to improve precision but substantially reduced the number of cohorts available (Appendix 1). We thus opted to continue using one-week cohorts.

Table 2: Summary of PIT-tag data used to calibrate COMPASS.

	Snake River spring/summer Chinook				Snake River steelhead			
	Lower Granite cohorts		McNary cohorts		Lower Granite cohorts		McNary cohorts	
Year	Cohorts	Released	Cohorts	Released	Cohorts	Released	Cohorts	Released
1997	14	956	--	--	10	1,755	--	--
1998	14	17,286	7	5,674	10	10,003	6	1,076
1999	11	19,276	6	10,888	11	11,267	9	2,558
2000	14	66,050	9	14,235	10	77,808	6	5,691
2001	11	18,308	6	7,567	9	15,104	5	2,105
2002	12	1,908	6	6,352	11	1,974	7	3,196
2003	17	51,491	7	14,136	10	35,540	9	3,370
2004	14	22,521	9	7,577	11	14,878	4	965
2005	12	19,100	8	7,039	12	11,971	5	2,000
2006	12	15,565	7	7,644	11	15,684	8	3,286
2007	12	20,176	8	11,573	8	11,857	5	2,592

2.3 Reservoir Survival

Foundation of Survival Modeling

A standard form for survival functions is

$$S(t) = \exp(-r \cdot t)$$

where $S(t)$ is the probability of surviving through t units of time and r is the mortality rate, which has units 1/time (Kalbfleish and Prentice 1980, Hosmer and Lemeshow 1999). The parameter r is interpreted as the instantaneous probability that an individual will die in the next short time increment given that the individual has survived to the current time (Ross 1993). Thus, as r increases survival across a time period decreases (Figure 4). If survival is measured across an extended time period during which the instantaneous mortality rate is not constant, then the rate term r can be interpreted as the mean mortality rate over the time period (Ross 1993).

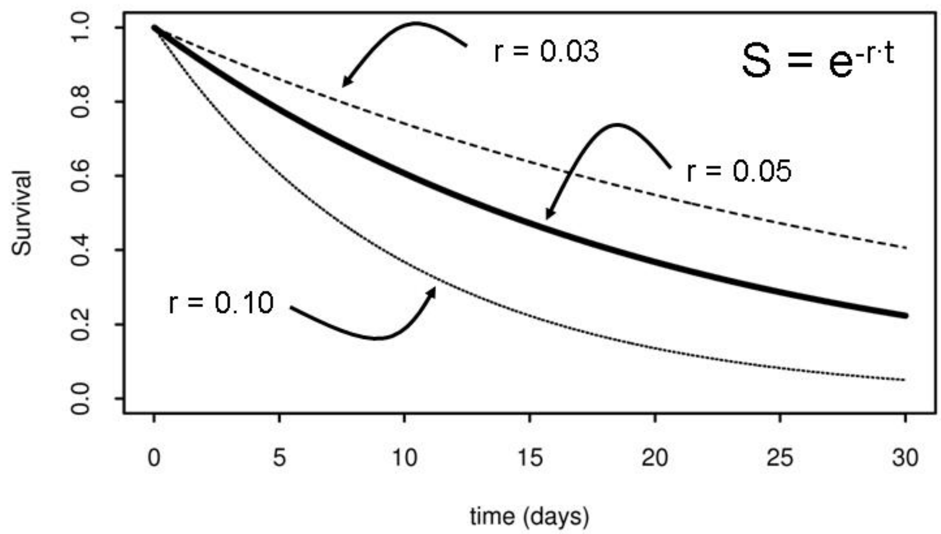

Figure 4. Exponential survival relationships as a function of exposure time for various values of the parameter *r* (instantaneous mortality). As *r* increases, survival decreases at a greater rate.

In addition to the mechanistic foundation, the exponential formulation has a number of desirable properties. Like the survival process itself, the exponential equation above begins at 1.0 when $t = 0.0$ and falls to 0.0 as t gets large (given that r is positive). Another desirable feature is that survival over a sequence of time intervals is multiplicative. That is, for example,

$$S(t_1 + t_2) = \exp(-r \cdot (t_1 + t_2)) = \exp(-r \cdot t_1) \cdot \exp(-r \cdot t_2).$$

Also, log[1] survival is additive:

$$\log(S(t_1 + t_2)) = \log(\exp(-r \cdot (t_1 + t_2))) = -r \cdot (t_1 + t_2)$$

This property is extremely useful when we want to partition survival across river segments, and we know how much time fish spent in each segment and the overall survival across all segments (for example, we have survival estimates from Lower Monumental Dam to McNary Dam, but we need to estimate, in the passage model, survival from Lower Monumental to Ice Harbor and Ice Harbor to McNary).

However, a strict exposure time model isn't consistent with the survival data, otherwise we would expect to observe stronger survival vs. travel time relationships than have been found previously (Smith et al. 2002). An alternative explanation is that survival is related

[1] Note that for here and the remainder of this document, log refers to natural log.

to distance traveled (Muir et al. 2001, Anderson et al. 2005). An exposure model also works here, but the exposure is to distance traveled,

$$S(d) = \exp(-r \cdot d)$$

This formulation also has the desirable property that survival over shorter segments can be multiplied together to give survival over a longer reach. To accommodate both types of survival process, we implemented a hybrid model where survival is a function of both travel time and distance traveled:

$$S(t,d) = \exp(-(r_t \cdot t + r_d \cdot d)),$$

or, on the log scale:

$$\log(S(t,d)) = -(r_t \cdot t + r_d \cdot d)$$

In our approach, the survival data determine the relative importance of distance versus travel time.

To relate reservoir survival to varying river conditions we modeled the instantaneous mortality rates, r_t and r_d, as functions of predictor variables. To determine which factors to include in the model and in which form, we first assumed that predation is the primary cause of mortality in the reservoir. Thus mortality rate in our model is analogous to predation rate (per unit time or distance). Predation rate is typically nonlinear in response to temperature (e.g., Vigg & Burley 1991), and thus we believe a quadratic term for temperature is justified. Evidence also exists to support the hypothesis that predation rate is negatively related to river flow, perhaps through turbidity effects (Gregory & Levings 1998). We included proportion of fish passing through the spillway as a potential predictor variable, based on the assumption that increased spill leads to increased survival in the reservoir due to a quicker and safer passage through the upstream dam. We related these covariates to both the distance and time mortality rates. Finally, we also included a "grand" intercept, which reflects any mortality that is not related to travel time or distance or any of the covariates. Taking the natural log of both sides of the exponential survival equation yields a simple linear model (Hosmer & Lemeshow 1993):

$$\log(S_{g,r}) = \gamma + (\alpha_0 + \alpha_1 \cdot Flow + \alpha_2 \cdot Temp + \alpha_3 \cdot Temp^2 + \alpha_4 \cdot Spill) \cdot d$$
$$+ (\beta_0 + \beta_1 \cdot Flow + \beta_2 \cdot Temp + \beta_3 \cdot Temp^2 + \beta_4 \cdot Spill) \cdot t + \varepsilon_{g,r}$$

where survival and the error term are referenced to a particular release group (*g*) over a particular river segment (*r*), *Spill* is the proportion of fish passing the spillway at the upstream dam, Flow and Temperature (*Temp*) are the mean across the time the fish were in the reservoir, *t* is the average travel time of the release group through the reservoir, and *d* is the length of the reservoir, and ε is the error term that is normally distributed with zero mean.

In addition to the full model above, we also considered several other model forms.

Full travel time with distance intercept:

$$\log(S_{g,r}) = \alpha_0 \cdot d + (\beta_0 + \beta_1 \cdot Flow + \beta_2 \cdot Temp + \beta_3 \cdot Temp^2) \cdot t + \varepsilon_{g,r}$$

Full travel time (no distance):

$$\log(S_{g,r}) = (\beta_0 + \beta_1 \cdot Flow + \beta_2 \cdot Temp + \beta_3 \cdot Temp^2) \cdot t + \varepsilon_{g,r}$$

CRITFC Model

$$\log(S_{g,r}) = (\beta_0 + \beta_1 \cdot Spill) \cdot t + \varepsilon_{g,r}$$

As formulated, certain combinations of parameter values can lead to predicted survival > 1.0. Because this has the effect of "creating" fish, we constrain survival to be ≤ 1.0 when the model is run is scenario mode. However, in the future, when we run the model in Monte Carlo mode, we will constrain the deterministic component of the survival prediction to be ≤ 1.0 but allow the overall survival prediction to be > 1.0. This is because a goal of the Monte Carlo mode is to reflect the uncertainty in the PIT-tag survival data, which includes a number of estimates > 1.0.

Survival Estimates

We used the standard Cormack-Jolly-Seber (CJS) model (Cormack 1964, Jolly 1965, Seber 1965) to estimate survival (and standard errors) between successive PIT-tag detection sites (Skalski et al. 1998). This method takes into account that not all fish are detected at each detection site. The approach involves estimating detection probabilities based on detections at downstream sites. These detection probabilities are then used to estimate survival by inflating the number of fish actually detected. Because of this, it is possible to generate survival estimates from these data that are > 1.0. This is particularly common in cases where true survival is close to 1.0 and sample sizes are limited.

PIT-tag survival estimates represent survival through an entire "project" (reservoir and dam), or two such projects in some cases (e.g., Lower Monumental Dam to McNary Dam, which includes Ice Harbor Dam (Figure 1)).

$$S_{PROJECT} = S_{RESERVOIR} \cdot S_{DAM}$$

When we calibrate the survival sub-model, the unit of comparison is project survival, which incorporates both dam survival and reservoir survival. The COMPASS model produces predictions of project survival that combine dam survival predictions and reservoir survival predictions. We compare model-predicted project survival to project survival estimated from PIT-tag data. Because we purposely included factors in the reservoir survival function (flow and spill) that are potentially related to dam survival, any variability in dam survival related to these is potentially captured in the overall relationship.

Model Calibration

Model calibration is the process of parameter estimation for the functional relationships that drive the fish behavioral processes (reservoir survival relationship and migration rate relationship) within the passage model. Note that the PIT tag data are also used to estimate FGE and SPE relationships at some dams (see section 2.4), but this is not part of the iterative calibration routine. The goal of the calibration routines is to ensure that model output (predicted survival and passage timing) represents the PIT-tag data as closely as possible. Accordingly, the calibration routine operates by repeatedly running the model with an optimization routine comparing model output to PIT-tag data (Figure 5). The optimization routine adjusts the free model parameters (those being fit to the data) such that the fit is optimized. COMPASS is run on a yearly basis and is supplied with data files reflecting river conditions, PIT-tag release timing and numbers, reach survival estimates, and dam operations during the year.

The calibration fitting routine uses a conjugate gradient optimization method (Press et al. 1994), with derivatives calculated numerically using a finite difference method (Gill et al 1981), to find the parameter set that results in the minimum weighted sum of squared differences between the observed and model-predicted outcome values. The weighted sum of squares (*SS*) is calculated as:

$$SS = \sum_{i=1}^{Y} \sum_{j=1}^{C_i} \sum_{k=1}^{R} w_{ijk} \left(Y_{ijk} - \hat{Y}_{ijk} \right)^2$$

where i indexes the year, Y is the total number of years, j indexes the cohort, C_i is the total number of cohorts in year i, k indexes the river segment, R is the total number of river segments, w is the weight, Y is the data, and $\hat{Y}$ is the model prediction. The fitting routine stops when the absolute value of the difference in sum-of-squares between the last and current iteration is < 0.005.

For the reservoir survival relationships, we compare model-predicted log of project survival (dam + reservoir) to the observed log survival estimates. In doing so, we fix the dam survival parameters, which are based on independent data, and allow the reservoir survival parameters to vary. This has the effect of partitioning the project survival into dam and reservoir survival components. The weight for these comparisons is inverse relative variance of survival (variance/survival^2), which is the variance of log survival (Burnham et al. 1987).

For travel time calibration, we compare model predicted migration rates to mean migration rate for a cohort. These migration rates incorporate any delay in dam passage. The weight in this comparison is the inverse variance of the estimated mean migration rate (see Zabel and Anderson 1997). In addition, we also calculated the maximum likelihood estimate of the migration "spread" rate parameter, σ^2_r, which determines the distribution of fish as they migrate downstream

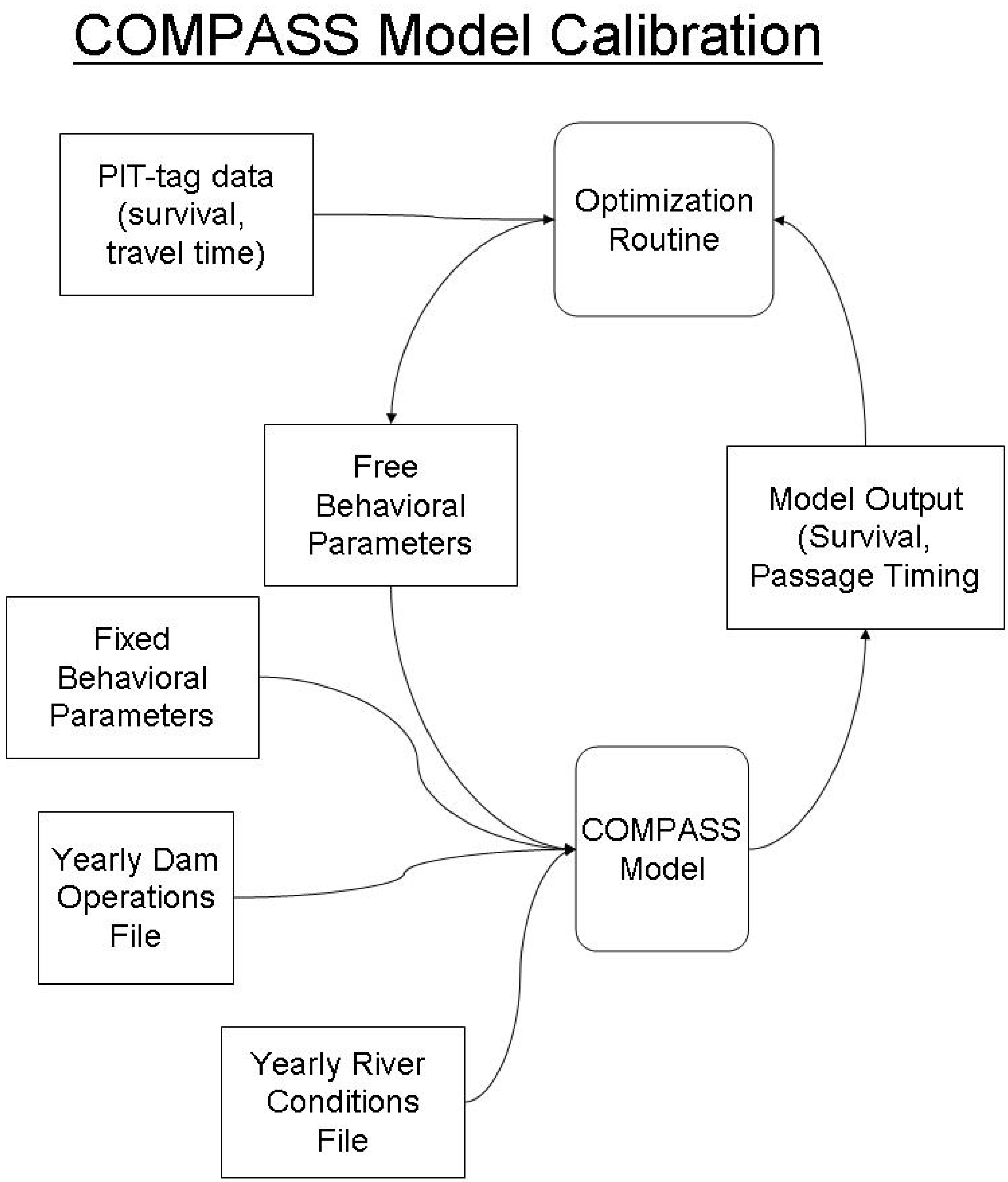

Figure 5. Schematic diagram of the model calibration routine.

We ran the travel time and survival calibrations iteratively in a sequence starting with a travel time model calibration followed by a survival model calibration until both models converge on their optimal parameter sets. The best fit parameters from the latest travel time run are fed into the next survival run, and then the best fits from that survival run are fed into the next travel time run and so on. Within each run all the parameter values for all functional relationships in the passage model are held fixed except for those of the model component being calibrated (either travel time or survival). The following steps occur within each calibration run:

Data Analysis and Model Selection

Because the survival estimates varied considerably in precision, in the analyses that follow, we weighted the survival estimates by their inverse "relative" variance (coefficient-of-variation squared) because the variance of log(S) is equal to relative variance (Burnham et al. 1987).

As mentioned above, we typically start with a full model, and then remove terms that do not contribute significantly to model fit. We used Akaike's Information Criterion (AIC) for selecting among alternative models (Burnham and Anderson 2002). The AIC balances better model fit (as measured by the likelihood function) with penalties for the number of parameters estimated from the data. The lower the AIC, the better the model fit. In contrast to other model selection criteria (e.g., likelihood ratio test), AIC can be used to compare non-nested models.

We imposed the following constraints on model selection: (1) if a quadratic term was included, the corresponding linear term was also included; (2) if a time-exposure variable was included, then an intercept term involving time was included (β_{t0}); (3) if a distance-exposure variable was included, then an intercept term involving distance was included (β_{d0}). Also, to protect against over-fitting, we imposed the following requirement: if during the model selection routine we encountered a coefficient whose sign was not consistent with the mechanisms outlined above, we did not consider the model. For example, if the coefficient for flow was negative, implying a negative relationship between survival and flow, we did not consider this model.

Since the Snake and Columbia rivers are physically different, we developed separate reservoir survival relationships for each river. To do this, we first estimated survival parameters for the lower river (McNary to Bonneville). Then, when we estimated parameters for the upper river, we applied the lower river parameters to McNary reservoir (Snake/Columbia River confluence to McNary Dam) and fit the upper river parameters from Lower Granite Dam to the confluence based on survival estimates from Lower Granite Dam to McNary Dam.

We calculated a weighted R^2 for each model fit. Although no consensus exists on how to calculate R^2 in cases of no intercept, we applied the following calculation:

$$R^2 = 1 - \frac{\sum_{i=1}^{N} w_i \cdot d_i^{\,2}}{\sum_{i=1}^{N} w_i \cdot (S_i - \bar{S})^2}$$

where *i* indexes each group/river segment survival, *N* is total number of group/river segment combinations, *w* is the weight (inverse relative variance), *d* is the deviance between observed and predicted survival, *S* is the observed survival, and $\bar{S}$ is the weighted mean of the observed survivals.

Finally, there is a trend in ecological studies toward recognizing that several alternative models can perform similarly well, and that there may not be a single "best" model (Johnson and Omland 2004). The method of AIC-weights can be used to assess how models perform relative to the "best" model:

$$w_i = \frac{\exp(-\Delta_i / 2)}{\sum_{j=1}^{M} \exp(-\Delta_j / 2)}$$

where *M* is the total number of models considered, and Δ_i is the difference in AIC between model *i* and the one with the lowest AIC (Burnham and Anderson 2002). The denominator normalizes the weights so they sum to 1.0. The weights are sometimes interpreted as estimates of the probability that any particular model is the "best" one among the suite of alternative models considered in the candidate set. We apply these weights to alternative models in Appendix 3.

Results

Details of the best fit models (based on AIC) for the "full" model are provided in Table 3. Plots of model fits for the full model are provided in Figure 6. The best fit model for Chinook had 6 parameters for the Snake River relationship and 1 parameter for the Columbia River relationship (Table 3). The best fit model for steelhead had 5 parameters in the Snake and 3 in the Columbia. Travel time was a significant factor in all best fit models, and was the only significant factor for spring/summer Chinook migrating through the Columbia River. Temperature and flow were significant factors in the three of the models. Distance and spill were significant factors in Chinook cohorts migrating through the Snake River, and distance was a significant factor for steelhead cohorts migrating through the Snake River. Diagnostics for these model fits are provided in Appendix 2.

We provide a more detailed analysis of alternative models (with AIC values and weighting). These additional analyses are provided in Appendix 3. In addition, we provide sensitivity analyses in Appendix 9.

Table 3. Regression results for log(survival) versus environmental covariates, distance and travel time. See text (Equation 5) for definitions of coefficients. Abbreviations: temp = temperature; s.e. = standard error; N = sample size (number of cohorts).

Coefficient	Variables	Value	s.e.	t-value	P-value
Chinook Salmon / Upper River			*N = 252 AICc = -256.62 R^2 = 0 .577*		
α_0	distance	-0.00281	0.000484	-5.81	< 0.0001
α_1	distance·flow	0.0000123	0.0000033	3.79	0.0002
α_4	distance·spill	0.00304	0.000546	5.56	< 0.0001
β_0	time	-0.0530	0.00952	-5.57	< 0.0001
β_2	time·temp	0.0110	0.00146	7.53	< 0.0001
β_3	time·temp^2	-0.000554	0.0000592	-9.38	< 0.0001
Chinook Salmon / Lower River			*N = 132 AICc =* 154.83 *R^2 =* 0.139		
β_0	time	-0.0210	0.00266	-7.88	< 0.0001
Steelhead / Upper River			*N = 198 AICc = -53.83 R^2 = 0.586*		
α_0	distance	-0.00420	0.00136	-3.09	0.0023
β_0	time	-0.229	0.0362	-6.33	< 0.0001
β_1	time·flow	0.000908	0.000189	4.81	< 0.0001
β_2	time·temp	0.0423	0.00618	6.85	< 0.0001
β_3	time·temp^2	-0.00240	0.000288	-8.35	< 0.0001
Steelhead / Lower River			*N = 97 AICc = 217.56 R^2 = 0.577*		
β_0	time	-0.0540	0.01659	-3.25	0.0016
β_1	time·flow	0.000440	0.0000410	10.73	< 0.0001
β_2	time·temp	-0.00977	0.00127	-7.70	< 0.0001

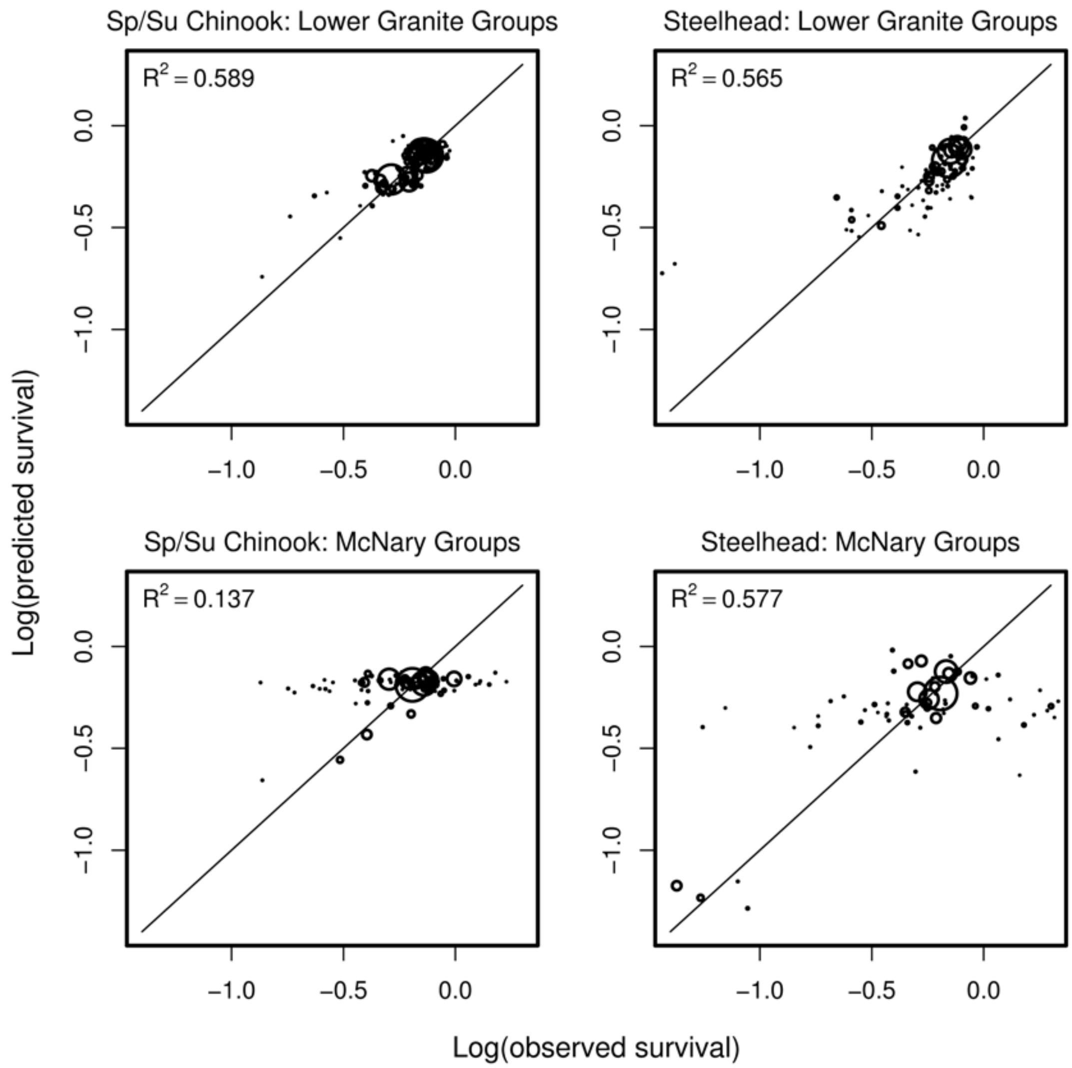

Figure 6. Log(predicted survival) versus log(observed survival) for Snake River spring/summer Chinook (left plots) and Snake River steelhead (rights plots), with survival estimates from the upper river reaches (Lower Granite to McNary, top plots) and lower river reaches (McNary to Bonneville, bottom plots). Model fits are based on the models provided in Table 3. The R^2s provided are weighted by inverse relative variance (see text for formulation). The diameter of each point reflects it weight.

2.4 Dam Passage

2.4.1 Dam Passage Algorithms

Fish are passed to the dam module from the reservoir module on a half day time step (nighttime or daytime) according to diel passage probabilities. Dam passage is represented primarily by a sequence of algebraic expressions representing passage probabilities. Most of these probabilities vary with river conditions according to passage efficiency relationships, while other passage probabilities are constant.

Constant Passage Efficiencies

Passage efficiencies represent the probability of passing through a particular passage route. Since they are probabilities, they range from 0.0 to 1.0.

At some dams, fish can pass via sluiceways or surface bypass collectors. The probability of passing through these routes is sluiceway passage efficiency (SLE).

Passage Efficiency Relationships

An "efficiency curve" describes the relationship between the proportion of fish passing through a passage route as a function of factors such as the proportion of flow passing through the route. These curves are applied to passage through a bypass system, spillway, passage through a removable spillway weir (RSW, described below), and passage through multiple powerhouses (at Bonneville Dam and Rock Island Dams).

These relationships are typically nonlinear but are constrained to pass through the points 0.0, 0.0 and 1.0, 1.0. We developed a flexible, nonlinear model to fit a variety of relationships while also satisfying the constraints. First, we define *y* as logit(*P*), where *P* is the proportion of fish passing through a passage route, where the logit transformation is defined as log(*P/*(1-*P*)). This is a common transformation for data that are probabilities. The efficiency relationship is expressed as

$$y = \beta_0 + \beta_1 \cdot x_1 + \beta_2 \cdot x_2 + \ldots.$$

where the *x*'s are explanatory variables.

In the case of spill passage efficiency, one of the predictor variables is F_{SPILL} (proportion of flow through the passage route). Since this is also in effect a probability, we also applied the logit transform to *F*. These transformations result in a flexible relationship that approaches 0.0, 0.0 as F_{SPILL} approaches 0.0 and 1.0, 1.0 as F_{SPILL} approaches 1.0 (with $\beta_1 > 0.0$) (Figure 7). In addition, we also express SPE as a function of total river flow (F_{TOTAL}), so the relationship is

$$\log it(P_{SPILL}) = \beta_0 + \log it(F_{SPILL}) + F_{TOTAL}$$

where P_{SPILL} is the proportion of fish passing via the spillway.

The equation above is easily fit to the data using simple linear regression. Appendix 4 provides details of the data analysis, estimated parameters, and plots of model fits.

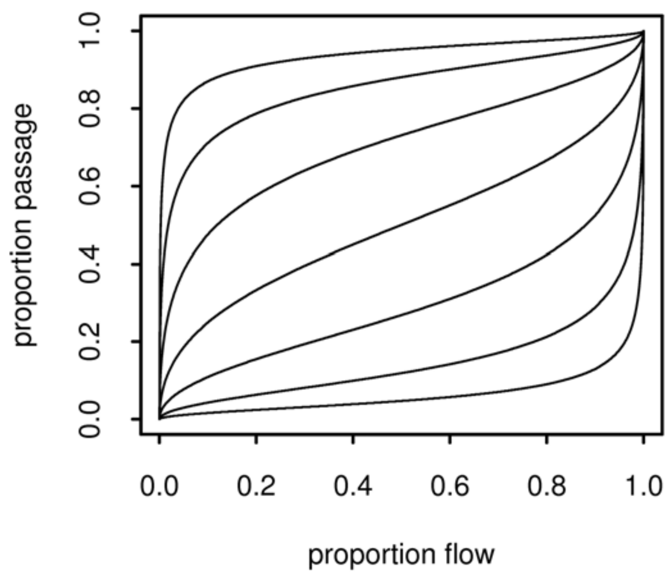

Figure 7. Examples of passage efficiency relationships. In these examples, the β_0 parameter was varied from -3 to 3 in unit increments while the β_1 parameter was fixed at 0.5. Note this plot only presents some of types of curves possible.

Removable Spill Weir (RSW) or Raised Crest Spillway devices are designed to route fish preferentially. These spillways do not exist at every project in the system, but where they do exist, they are considered to be the preferred route for fish. The efficiency of the RSW passage route is defined as the fraction of fish that are passed through this route as a function of the proportion of flow passing through the RSW relative to all flow passing through the spillway (RSW spill + normal spill). When there is RSW spill, COMPASS calculates the proportion of fish going through all spill routes with one spill efficiency equation and then the proportion going through the RSW with a second equation, then takes the difference (proportion through all spill - proportion through RSW) to get the proportion that went through normal spill routes.

The proportion of flow spilled at each dam is retrieved from data files, which are either based on historical records, or they can be generated from hydroregulation models (HYDSIM). Spill is specified for both daytime and nighttime periods.

Fish Guidance Efficiency (FGE) is defined as the proportion of fish entering the powerhouse (and thus pass via either the bypass system or turbines) that pass via the fish bypass system. FGEs can be specified for day and night at each dam, if sufficient data exist. Some dams do not have bypass systems, and in these cases, FGE = 0.0. For those dams with ample data, we developed models where FGE is a function of flow through the powerhouse (F_{PH}) and day in the season as follows:

$$\operatorname{logit}(FGE) = \beta_0 + \beta_1 \cdot F_{PH} + \beta_2 \cdot day$$

FGE can also be expressed as a function of temperature, but because day in the season and temperature are highly correlated, we used one or the other.

Calculating route-specific passage probabilities (for dams with single powerhouses)

The order of computations is (Figure 8a):

1. Proportion of fish passing through all spillway routes.
2. Proportion of fish passing through the RSW, if one exists.
3. Proportion of fish passing via the sluiceway or surface bypass collector (SLE).
4. Proportion of fish passing through the juvenile bypass system (FGE).
5. Proportion of fish passing through a Turbine.

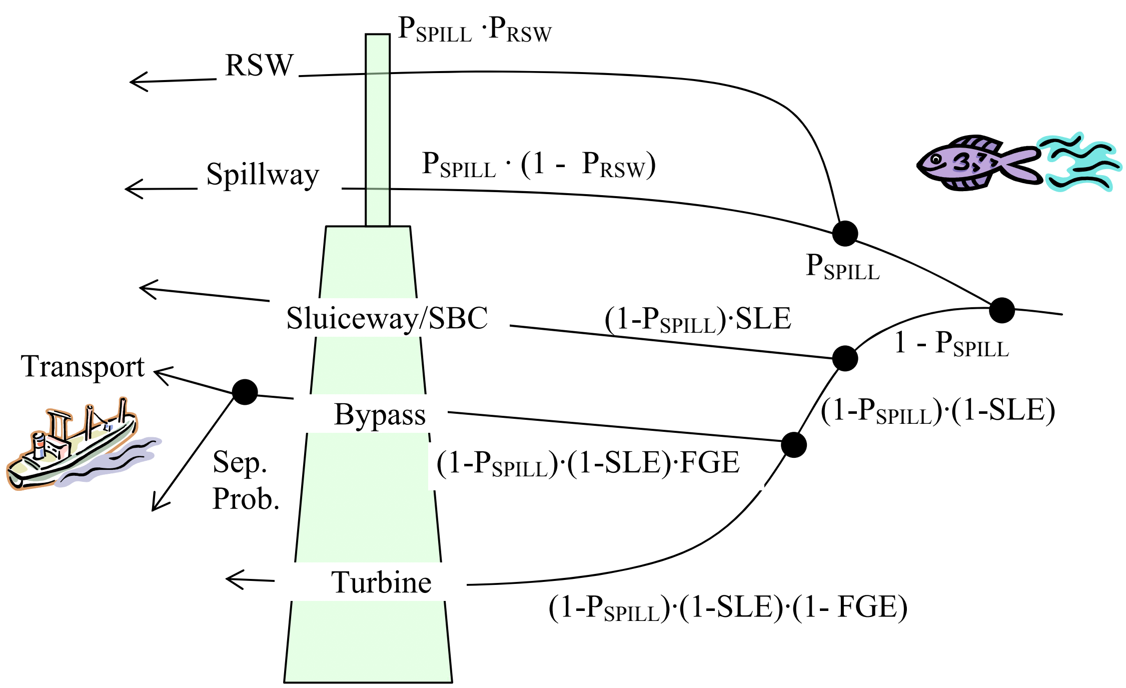

Figure 8a. Possible routings of fish at a dam. The black dots represent bifurcations of the population where there are only two possible routes. P_{SPILL} = proportion of fish

passing via the spillway, and P_{RSW} = proportion of fish passing the spillway that pass via the RSW. SLE = Sluiceway Efficiency or Surface Bypass Collector Efficiency, in COMPASS, these are equivalent. FGE = Fish Guidance Efficiency, the fraction of fish entering the powerhouse that are bypassed.

Multiple Powerhouses

Bonneville Dam and Rock Island Dam each have two powerhouses that can be operated independently to optimize survival during the fish passage season. Each project has a single spillway (Figure 8b).

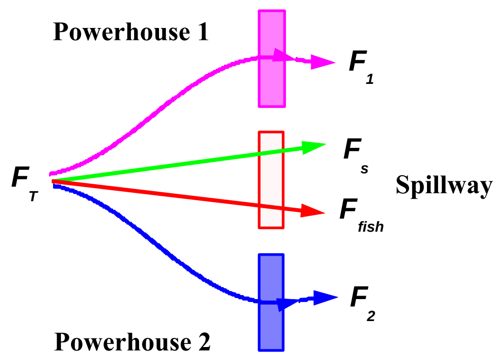

Figure 8b. Passage through multiple powerhouses. Abbreviations: F_T = total flow; F_1 = flow through powerhouse 1; F_2 = flow through powerhouse 2; F_{fish} is planned spill for fish passage; F_s = other flow through the spillway.

For multiple powerhouse dams, flow is allocated fractionally as follows:

1. Flow is first allocated to planned spill in fish passage hours.
2. Remaining flow is partitioned between the primary and secondary powerhouses and additional spill as follows:
   - operate highest priority powerhouse up to its hydraulic capacity
   - spill water up to another level called the spill threshold
   - above the threshold, use the second powerhouse
   - above the second powerhouse hydraulic capacity, spill extra flow.

Fish are passed through the spillway and the powerhouses according passage efficiency relationships (Appendix 4).

2.4.2 Dam passage survival

Each dam passage route (turbine, bypass system, spillway, RSW, etc.) has an associated survival probability that varies by species and dam. The survival probabilities are typically based on site-specific radio-telemetry studies and are contained in Appendix 5. This appendix also lists data sources for each estimate.

At this point, all dam survival probabilities are deterministic, due to insufficient data to fully characterize their distributions. However, as mentioned above, per-project survival, which contains dam survival, is derived from PIT-tag estimates. Thus, any uncertainty in dam survival estimation is contained in the overall project survival variability.

2.4.3 Delay in Dam Passage

Migrating juveniles may spend considerable time in the forebay of dams before passing. This delay in dam passage can also vary among passage routes, with fish passing via the spillway or RSW typically delaying less than fish passing other routes. To account for this, we have incorporated percentage of fish passing through the spillway as a parameter in the travel time model, described below. The effect of this is that spilled fish experience less dam delay, and thus passing more fish via the spillway leads to decreased travel times. In future versions of COMPASS, we plan to model this delay process more directly based on observations from telemetry data.

2.5 Fish Travel Time

Fish travel time through a reservoir is based on a model developed by Zabel and Anderson (1997; see also Zabel 2002) and is governed by two parameters: r, migration rate, and σ, the rate of population spread. The travel time distribution is typically right-skewed, which is consistent with the data (Figure 9). In some cases, the travel time model appears to “miss” the mode of the distribution.

The migration rate term is related to river velocity, date in the season, and water temperature, as described below. In the current version of the model, migration rate is also related to percentage of fish passing through the spillway. This accounts for the fact that spilled fish pass over dams more quickly than non-spilled fish (or, spilled fish experience less delay than non-spilled fish). We note that both the model and the data incorporate any delay experienced during dam passage.

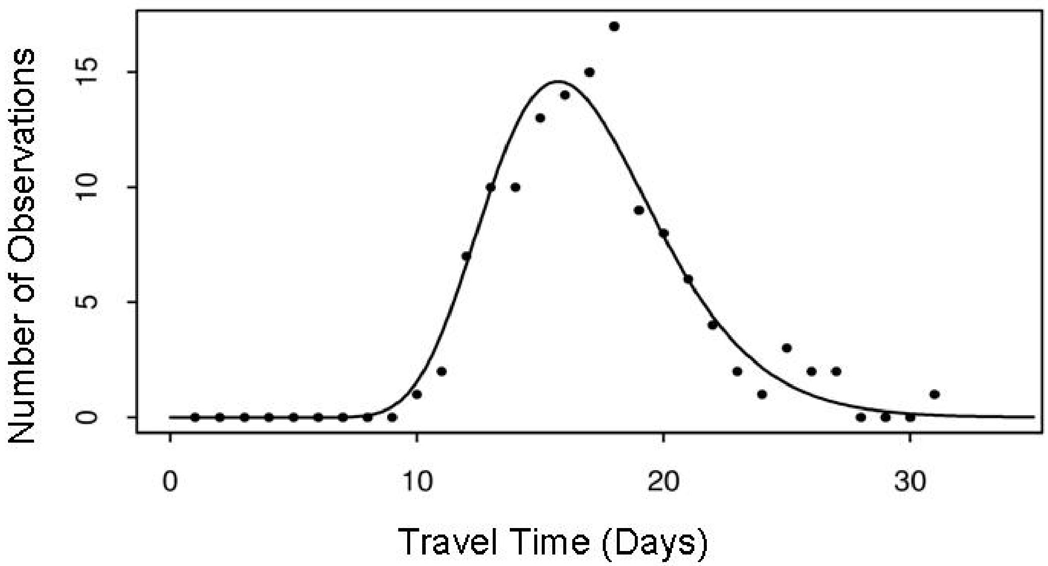

Figure 9. Fish travel time model (from Zabel 2002) for Snake River spring/summer Chinook salmon migrating from Lower Granite Dam to McNary Dam. Points represent data; solid line is model fit.

Migration Rate Models

The goal of the migration rate equation is to be flexible enough to capture a variety of migratory behaviors without requiring an excessive number of parameters to fit. Accordingly, we modified the migration rate model of Zabel et al. (1998). The equation has a term that relates migration rate to river velocity and a term that is independent of river velocity. Both terms have temporal components, with migration rate increasing through the season. In addition, we incorporated a term relating migration rate to proportion of river flow spilled to account for dam delay effects, as mentioned above.

The full migration rate model is:

$$r_i = \beta_0 + \beta_1 \cdot \left[\frac{1}{1 + \exp(-\alpha_1 \cdot (t_i - T_{RLS,i})} \right] + \beta_{FLOW} \cdot velocity_i \cdot \left[\frac{1}{1 + \exp(-\alpha_2 \cdot (t_i - T_{SEASN})} \right] + \beta_{SPILL} \cdot spill_i + \varepsilon_i$$

where r_i is the migration rate (mi/day) of the *i*th cohort, t_i is the date (expressed as day in the year) the cohort enters the top of a reservoir $T_{RLS,i}$ is the release date of cohort *i*, $velocity_i$ is mean water velocity over the migration period, T_{SEASN} is a seasonal inflection point, and $spill_i$ is the percentage of fish passing the spillway and is measured on the day the fish pass the upstream dam.

Both the flow dependent and flow independent components used the logistic equation (term in square brackets) because upper and lower bounds can be set. This eliminates the problem of unrealistically high or low migration rates that can occur outside observed ranges with linear equations. Also, for suitable parameter values, the logistic equation effectively mimics a linear relationship.

β_0 and β_1 are combined in the following way to determine the flow-independent contribution to migration rate:
$\beta_{MIN} = \beta_0 + \beta_1/2$ (minimum flow-independent migration rate at $t = T_{RLS,i}$)
$\beta_{MAX} = \beta_0 + \beta_1$ (maximum flow-independent migration rate as t gets large).

The magnitude of the flow dependence is determined by β_{FLOW}, which determines the percentage of the average river velocity that is used by the fish in downstream migration. This term has a seasonal component determined by T_{SEASN}, which has the effect of the fish using less of the flow early in the season and more of the flow later in the season.

We also considered a slightly reduced form of the migration rate equation:

$$r_i = \beta_0 + \beta_{FLOW} \cdot velocity_i + \beta_2 \cdot date_i + \beta_3 \cdot velocity_i \cdot date_i + \beta_{SPILL} \cdot spill_i + \varepsilon_i$$

As with the reservoir survival modeling, we begin with the "full" model above, and selected the best fit model based on AIC. We compared model-predicted migration rates to PIT-tag data (see Figure 10). As with the reservoir survival modeling, we developed separate relationships for the Snake and Columbia Rivers. Also, model fits were weighted by the inverse variance of the migration rate (see Zabel and Anderson 1997). Also, the spread parameter, σ, was set to its (analytical) maximum likelihood values (see Zabel and Anderson 1997).

In all cases, water velocity was a significant factor for predicting migration rate (Table 4). Spill was also a significant factor for 3 of the groups of cohorts. Seasonal effects were detected in three of the models. Plots of predicted versus observed arrival distributions are presented for all models in Appendix 2. Also, a sensitivity analysis is presented in Appendix 9.

Table 4. Regression results for fish velocity versus environmental covariates and date in the season. See text (Equation 7) for definitions of coefficients. Abbreviations: s.e. = standard error; N = sample size (number of cohorts).

Coefficient	Value	s.e.	t-value	P-value
Chinook Salmon / Upper River	*N = 434 AICc = 1001.98 R^2 = 0.818*			
β_{MIN}	0.932	0.186	5.03	< 0.0001
β_{MAX}	5.38	1.968	2.73	0.00652
α_1	0.184	0.0229	8.02	< 0.0001
β_{FLOW}	0.706	0.00828	85.26	< 0.0001
T_{SEASN}	107.98	0.612	176.51	< 0.0001
α_2	0.476	0.160	2.97	0.00311
β_{SPILL}	2.11	0.286	7.40	< 0.0001
Chinook Salmon / Lower River	*N = 132 AICc = 154.84 R^2 = 0.890*			
β_0	-5.48	0.493	-11.12	< 0.0001
β_{FLOW}	3.41	0.133	25.58	< 0.0001
T_{SEASN}	140.96	2.05	68.87	< 0.0001
α_2	0.0316	0.00179	17.59	< 0.0001
β_{SPILL}	9.17	0.121	75.64	< 0.0001
Steelhead / Upper River	*N 335 AIC = 921.03 R^2 = 0.805*			
β_0	-0.335	0.109	-3.09	0.0022
β_{FLOW}	0.288	0.0530	5.42	< 0.0001
β_3 (date x flow)	0.00225	0.000396	5.68	< 0.0001
β_{SPILL}	1.40	0.225	6.22	0.01667
Steelhead / Lower River	*N 133 AIC = 598.496 R^2 = 0.763*			
β_0	-2.31	0.754	-3.06	0.00265
β_{FLOW}	0.930	0.0512	18.17	< 0.00001

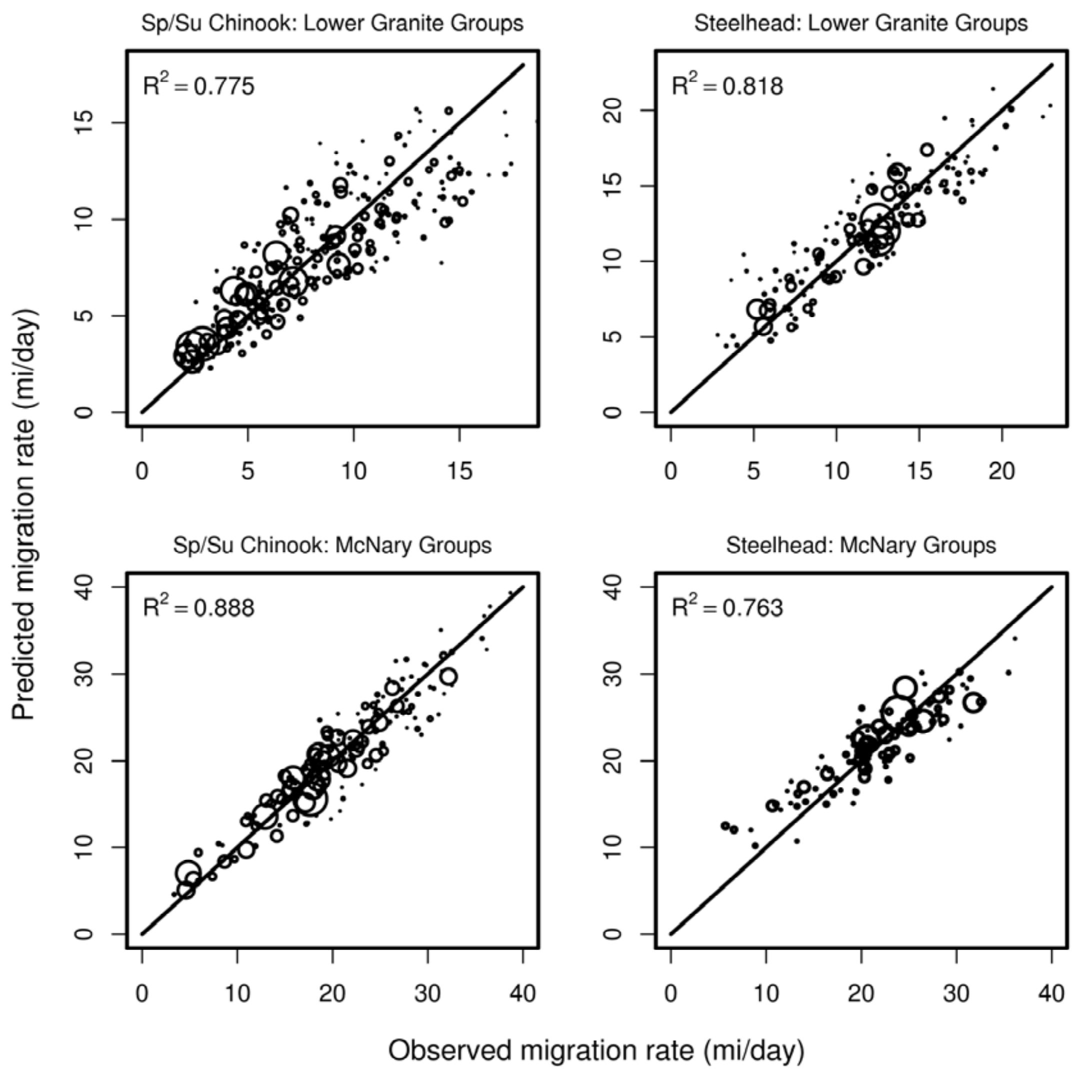

Figure 10. Predicted migration rate versus observed migration rate for Snake River spring/summer Chinook (left plots) and Snake River steelhead (rights plots), with migration rates from the upper river reaches (Lower Granite to McNary, top plots) and lower river reaches (McNary to Bonneville, bottom plots). Model fits are based on the models provided in Table 4. The R^2s provided are weighted by variance (see text for formulation). The diameter of each point reflects it weight.

2.6 Hydrological Process

The COMPASS model simulates river flow, water velocity, and water temperature throughout the hydrosystem daily (Figure 11). The model operates by reading daily headwater flows and temperatures from an input file. Headwaters are either regulated (storage reservoir upstream) or unregulated and represent the major inputs of water into the hydrosystem (Figure 11). The flows and temperatures are propagated downstream according to water movement algorithms and water mixing at confluences (see Appendix 6 for more details). Water flow is converted to water velocity based on reservoir geometry, including reservoir water depth (Appendix 6). Water flow can be adjusted at dams to account for water losses (due to evaporation or irrigation withdrawals) or additions from minor tributaries. These adjustments are typically based on measurements taken at the dams. Similarly, temperature can be adjusted at the dams to account for heating or cooling processes.

The COMPASS modeling group has relied on two sources of data for the input data. First, for calibration purposes, we have generated historical data files for the years 1997-2007. Second, for prospective modeling, to represent the effects of year-to-year variability in river conditions on survival, we used reconstructed river conditions (river flows and water temperatures) over the years 1929-1978. This involved running observed headwater flows through a hydro-regulation model that emulates river flows in the current hydrosystem configuration. The hydro-regulation model provided monthly or bi-monthly average flows. These flows were then modulated to represent daily flows (see Appendix 8-3 for details). Further, a temperature flow relationship was developed to generate daily temperatures (see Appendix 8-3 for details).

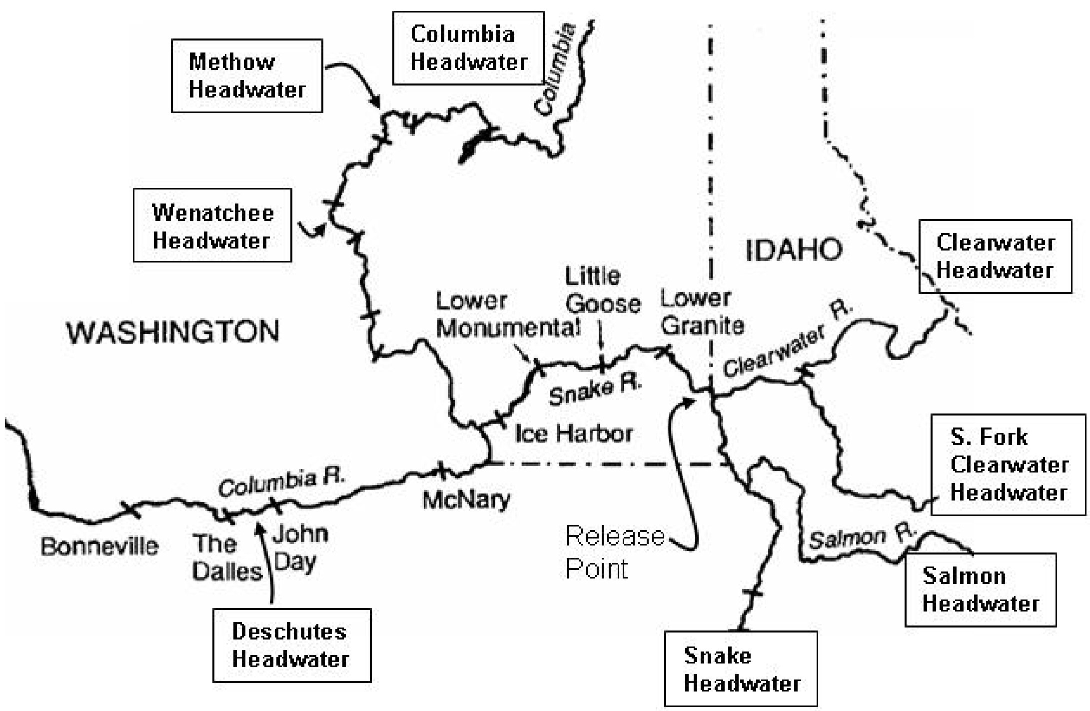

Figure 11. Map of the Columbia River basin showing the location of headwaters.

2.7 Model Uncertainty

Background

The primary reason for implementing Monte Carlo simulation mode in COMPASS is to reflect uncertainty in survival predictions. The deterministic version of COMPASS, like any deterministic model, always gives the same output for a given set of inputs. There may sometimes be a tendency for model users and consumers to overlook that even for a high quality model that matches observations very well, knowledge of the real system is never perfect. For many reasons, when working with models there is always a range of predictions that are reasonable from a given set of inputs. By implementing the Monte Carlo mode in COMPASS, our aim is to characterize that reasonable range, given the imperfect understanding represented by our model.

Uncertainty in COMPASS predictions of survival arises from several sources, including sampling error in available survival data (e.g., project survival estimates based on PIT-tag data) and environmental data (e.g., indices of exposure to environmental conditions), and uncertainty in selection of a particular regression model from among a suite of candidate models. Moreover, even if environmental indices and survival probabilities were measured without error, two cohorts of fish with the exact same exposures are not likely to have exactly the same survival probability. Such "natural variability", also known as "process error," is another important source of uncertainty in model outputs.

In the presence of process error, predictions of survival for a given set of explanatory variables represent predictions of the mean survival for cohorts with those variables, and the reasonable range of predictions must reflect the magnitude of the process error. Reservoir survival models in COMPASS were developed using PIT-tag survival estimates. Variance among these estimates depends on the environmental variables that influence expected survival, on process error, and on sampling error.

We have applied a statistical method ("random effects" modeling, also known as "variance components") to separately estimate the contribution of process error to the overall variance in PIT-tag survival estimates, simultaneously accounting for explanatory variables and sampling error. In a sense, the sampling error in the estimates represents an artifact of the data collection that has occurred in the past, while process error represents the "real" variability in the process we are modeling.

Statistical random effects modeling offers two critical advantages over weighted least squares methods. The first we have already discussed: separating components of variability into process error and sampling error allows insight into underlying processes that weighted least squares cannot provide. Our method of implementing uncertainty in COMPASS predictions makes critical use of this partitioning of total variability. The second advantage is that through the use of a general weighting matrix, random effects models explicitly account for the correlation that arises mathematically between PIT-tag survival estimates in successive reaches for a given cohort in the Cormack-Jolly-Seber model (see Figure 12). Weighted least squares methods incorporate only the variances of the individual reach estimates and improperly ignore the covariance terms.

When our estimate of the amount of variability due to process error is of sufficient quality, our goal for implementing Monte Carlo mode is to produce a range of reasonable predictions that reflect only the process error. When the model is run in Monte Carlo mode, multiple runs of the model are conducted for each set of environmental conditions. Each run has different parameter inputs to appropriately represent the uncertainty of our knowledge of the mean process. The result of these repeated runs is a distribution of values that describes the range of reasonable predictions for mean survival under the set of environmental conditions.

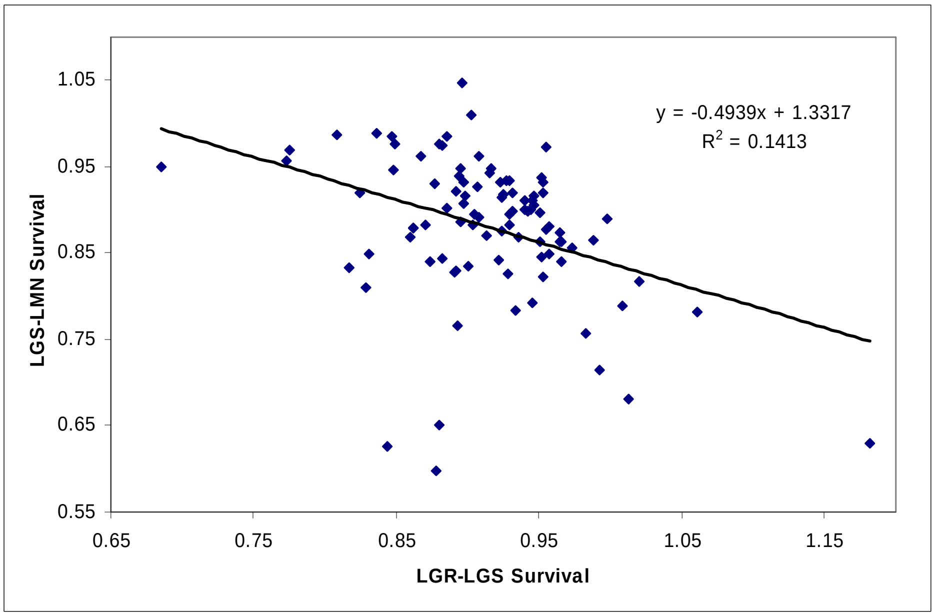

Figure 12. Negative correlation between successive project-survival estimates (each point on the graph represents two successive estimates for the same release groups) in the Snake River for Snake River spring/summer Chinook salmon.

Scale on Which to Match Uncertainty of Survival Estimates

Using data on PIT-tag detections at dams, it is possible to estimate survival probabilities for "projects" (one project is one reservoir plus one dam), but not for reservoirs and dams separately. Estimates of survival probabilities and associated estimates of sampling variability are available between successive detection sites; for the Snake and Columbia rivers this means one project (e.g., Little Goose Dam plus its reservoir, or Lower Granite Dam tailrace to Little Goose Dam tailrace) or two projects (e.g., Lower Monumental Dam tailrace to McNary Dam tailrace). Thus our approach for implementing the Monte Carlo version of COMPASS is to randomly sample parameter sets according to the scale of the data underlying the survival relationships. In other words, because survival is estimated per cohort across a project (or projects), we will draw a unique set of parameters for each cohort as it migrates through a project corresponding to the data.

More specifically, when we estimate a vector of model parameters, $\hat{\boldsymbol{\beta}}$, for the survival relationships, we can also estimate the corresponding variance-covariance matrix, $\mathbf{VC}(\hat{\boldsymbol{\beta}})$. To draw a set of parameters during a Monte-Carlo simulation, we simply draw from the following multivariate normal distribution:

$$MVN\left[\hat{\boldsymbol{\beta}}, \mathbf{VC}(\hat{\boldsymbol{\beta}})\right]$$

We then will apply the randomly sample parameter set to the appropriate cohort/river segment combination. Each iteration of the model will produce a different survival prediction, and running the model repeatedly will produce of distribution of predictions.

As mentioned above, several methods exist to estimate the variance-covariance matrix. In appendix 7, we present the "random effects" method, which accounts for sampling and process error. However, we will develop the Monte Carlo mode of COMPASS such that the user specifies $\hat{\boldsymbol{\beta}}$ and $\mathbf{VC}(\hat{\boldsymbol{\beta}})$, and thus it will accommodate any estimation method.

This component of the model is currently under development. We plan to implement it shortly. In the mean time, Appendix 7 demonstrates an application of this approach to an external set of survival estimates.

3 Post-Bonneville Survival

COMPASS has several options to model survival of fish once they have passed the hydrosystem. To standardize the discussion, we introduce the following notation (Figure 13). First, we designate survival terms using S and mortality terms using $L = 1 - S$. Terms for in-river migrants are denoted by the subscript I and terms for transported fish by the subscript T. We partition survival and mortality into the following life stages: downstream migration through the hydropower system (subscript *ds*), estuary/ocean (subscript *e/o*), and upstream migration through the hydropower system (subscript *us*). We further partition the estuary/ocean stage to reflect mortality that would occur independent of the hydropower system ($1-S_{e/o}$), and hydropower system-related latent mortality (L), which applies to both transported fish and in-river migrants. This partitioning of estuary/ocean survival reflects an assumption that for in-river fish, latent mortality is essentially entirely expressed in the estuary/ocean stage.

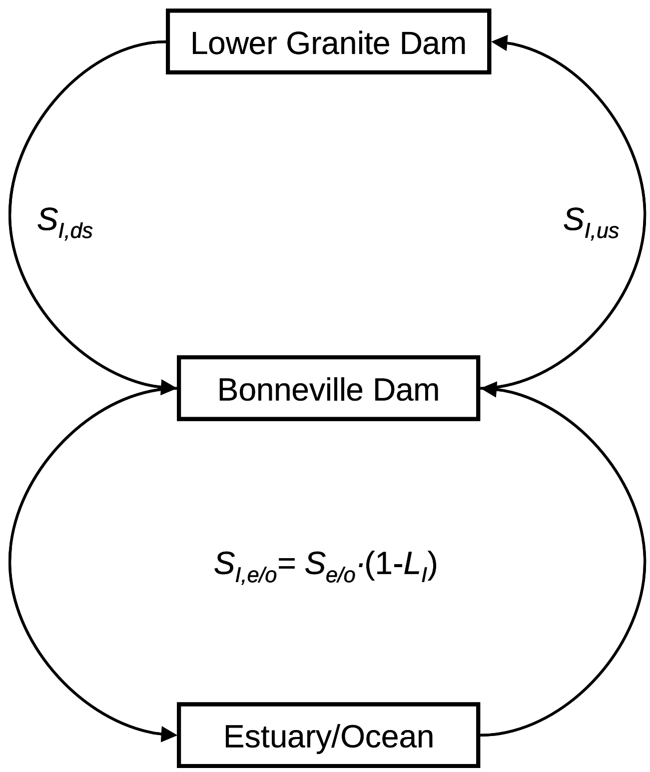

Figure 13. Survival (*S*) and mortality (*L*) affecting Snake River anadromous salmonids migrating in-river (denoted by subscript *I*) at various life stages. The life stages are downstream migration through the hydropower system (*ds*), estuary/ocean (*e/o*), and upstream migration through the hydropower system (*us*). The estuary/ocean survival is partitioned into survival that would occur in the absence of the hydropower system ($s_{e/o}$) and latent mortality associated with the passage through the hydropower system (L_I). Transported fish (denoted by subscript *T*) are affected by the same survival and mortality processes and are represented by changing the subscript *I* to *T*.

D refers to the ratio of smolt-adult survival (measured from below Bonneville Dam as juveniles to Lower Granite Dam as adults) of transported fish relative to that of in-river migrants. Using our earlier notation, the corresponding SARs are

$SAR_{T,BON\rightarrow LGR} = S_{e/o}(1-L_T)S_{T,us}$, and

$SAR_{I,BON\rightarrow LGR} = S_{e/o}(1-L_I)S_{I,us}$.

Therefore, D is simply

$$D = \frac{SAR_{T,BON\rightarrow LGR}}{SAR_{I,BON\rightarrow LGR}} = \frac{(1-L_T)S_{T,us}}{(1-L_I)S_{I,us}} .$$

Note that we assume the same natural estuary/ocean survival ($S_{e/o}$) for both in-river and transported fish. Also, we use different upstream survival terms for in-river and transported fish. Differential upstream survival for the two groups, for example, could result from latent mortality for transported fish related to impaired homing. Further, it is not necessary to delineate any latent mortality when estimating D as it is simply the ratio of SARs.

3.1 Hypotheses on post-Bonneville survival

The model user has 4 options for specifying post-Bonneville survival.

1) Third year ocean survival (S_3) is related to water travel time. This method computes mean water travel time over a specified time period (usually April and May) and over a specified river segment (usually Lower Granite Dam to Bonneville Dam). The user specifies model parameters, and the model returns survival through the third year.

2) Constant D. In this method, a user-specified D is applied to the fish arriving below Bonneville via transportation. Overall hydrosystem survival is then adjusted accordingly.

3) Latent mortality. The user specifies L_I and L_T (latent mortality for inriver and transported fish, respectively). The model produces and overall survival related to the hydrosystem.

4) Smolt-to-adult return (SAR) related to arrival timing below Bonneville. Separate relationships are specified for inriver and transported fish that relate survival from Bonneville to Lower Granite as a function of arrival date. The model produces an overall survival from Lower Granite (juvenile) to Lower Granite (adult). Details of this method are provided in Appendix 8-2.

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This appendix addresses two issues concerning PIT-tag data. First, we considered whether hatchery fish should be included with wild fish to calibrate the downstream migration component of the model. We conducted a series of analyses to determine whether hatchery fish differ significantly from wild fish in survival, detection probability, and migration rate. Second, we examined the quality of survival estimates by plotting distributions of standard errors. Because release groups formed at McNary Dam exhibit greater standard errors than those formed at Lower Granite Dam, we considered whether to form the McNary groups fish into weekly or bi-weekly cohorts.

Part1: Comparison of wild PIT-tagged juvenile fish to hatchery ones

Introduction

Each year, tens of thousands of hatchery-origin, Snake River spring/summer (SRSS) Chinook salmon and Snake River (SR) steelhead juveniles are PIT tagged and monitored during downstream migration. These hatchery fish have been used to augment sample sizes of wild fish based on the assumption that wild and hatchery fish have similar survival probabilities during migration through the hydropower system. Here, we address the question of whether hatchery fish differ from wild fish in survival, detection probability, and migration rate. The objective of this analysis is to assess whether it is appropriate to lump data from hatchery fish with wild fish to develop the COMPASS model for wild populations.

Methods

We first constructed a data set based on weekly groups of fish leaving Lower Granite Dam and McNary Dam during migration years 1997-2007. A weekly group consisted of all fish of Snake River origin that were either tagged and released at the site or were detected and returned to the river at the site during the specified 7 day period, with the seven day periods defined consistently from year to year. We separated individuals by ESU and further compiled individuals into groups corresponding to their origin: wild, hatchery, and a combined hatchery and wild group. For each Lower Granite group, we estimated survival probabilities and migration rates (mi/day) from Lower Granite to Lower Monumental Dam and from Lower Monumental to McNary Dam, and we estimated detection probabilities at Little Goose, Lower Monumental, and McNary Dams. For each McNary group, we estimated survival probabilities and migration rates from McNary to John Day Dam and John Day to Bonneville Dam, and we estimated detection probabilities at John Day and Bonneville Dam. For each estimated survival probability, migration rate, and detection probability, we also estimated its corresponding standard error.

To address whether wild fish were different from hatchery fish, we tested the following hypotheses:

H_o: $\mu_{Wild} - \mu_{Hatchery} = \mu_{Diff} = 0$

H_A: $\mu_{Wild} - \mu_{Hatchery} = \mu_{Diff} \neq 0$

where μ is mean survival probability, detection probability, or migration rate.

To test the hypotheses we used a paired, two-sided *z*-test. The test statistic is:

$$z = \frac{\overline{X}_{DIFF}}{s_{\overline{X}_{Diff}}}$$

which is assumed to be distributed as N(0,1) under the null hypothesis.

To calculate the test statistic, we first defined $\hat{X}_{Diff,i} = \hat{X}_{Wild,i} - \hat{X}_{Hatchery,i}$ as the difference between paired samples (i.e., groups from the same week and same "release" site, and the same reach or detection site). Further, we weighted each data point as follows:

$$W_i = 1/(Var(\hat{X}_{Diff,i}) = 1/(Var(\hat{X}_{Wild,i}) + Var(\hat{X}_{Hatchery,i}))$$

Thus, we calculated

$$\overline{X}_{Diff} = \frac{\sum_{i=1}^{N} W_i \cdot X_{Diff,i}}{\sum_{i=1}^{N} W_i}$$

and

$$s_{\overline{X}_{Diff}} = \sqrt{\frac{\sum_{i=1} W_i \cdot (X_{Diff,i} - \overline{X}_{Diff})^2}{(N-1) \cdot \sum_{i=1}^{N} W_i}}$$

where *N* is the sample size (number of pairs).

In addition, we calculated a weighted Pearson's correlation coefficient, ρ, for comparison purposes.

Results

In all cases below, percentage differences are expressed are expressed as absolute (not relative) difference.

Survival Probabilities

For all cases, survival probabilities of wild fish were highly significantly different from survival probabilities of hatchery fish (Table A1-1, Figures A1-1 and A1-2). For SRSS Chinook, hatchery fish had mean survival probability 1.03% and 5.53% greater than wild fish for Lower Granite and McNary groups, respectively. For SR steelhead, Lower Granite wild groups had mean survival probability 2.15% greater than their hatchery counterparts, while McNary wild groups had mean survival probability 9.4% less than their hatchery counterparts.

Detection Probabilities

Mean detection probabilities of wild fish were highly significantly greater than those of hatchery fish, except for McNary steelhead, where no significant difference existed between groups (Table A1-2, Figures A1-3 and A1-4). Lower Granite wild SRRS Chinook had mean detection probability nearly 7% greater than their hatchery counterparts, and McNary wild groups had mean detection probability 3.32% greater than their hatchery counterparts. Lower Granite wild SR Steelhead had mean detection probability 1.37% greater than their hatchery counterparts.

Migration Rates

For all cases, mean migration rates were highly significantly different between wild and hatchery fish (Table A1-3, Figures A1-5 and A1-6). Lower Granite wild SRSS Chinook migrated on average 0.415 mi/day more quickly than their hatchery counterparts, while McNary wild SRSS Chinook migrated about 1.5 mi/day more slowly on average than their hatchery counterparts. Wild steelhead from both sites migrated about 2.5 mi/day more quickly on average than their hatchery counterparts.

Discussion and Conclusions

Clear differences exist in survival probabilities, detection probabilities, and migration rates between wild and hatchery juvenile salmonids migrating through the Snake and Columbia rivers. Although in some cases differences in survival were minimal (e.g., Lower Granite groups exhibited an approximate 1% difference in mean survival, Table A1-1), the generally substantial differences in detection probabilities and migration rates between wild and hatchery groups indicates that the two groups have different experiences in dam passage and migration timing. Thus, we will treat wild and hatchery fish separately in COMPASS modeling. We have focused on wild fish in our current modeling. However, if management actions were directed at hatchery fish, we could easily develop model calibrations to accommodate hatchery fish or combined hatchery and wild.

The fact that hatchery and wild groups are often highly correlated in their survival probabilities, detection probabilities, and migration rates (Tables A1-1, A1-2, and A1-3) suggests that data from hatchery releases can potentially provide information for wild fish, and *vice versa*. In the future, we will explore the possibility of developing analyses where both hatchery and wild groups are included together, with factors distinguishing the two groups in the analysis.

The processes underlying survival, detection and migration rate are likely complex, and thus we can only speculate on the mechanisms leading to the observations described here. In general, hatchery fish are larger than wild ones, and mortality processes are often size-selective. However, the direction of size-selective mortality can vary. For example, piscivorous predators typically select smaller fish, but avian predators may select larger ones (Sogard 1997). Also, turbine mortality may increase with fish size (Ferguson et al. in press). Thus, it is not surprising that in three cases, hatchery fish had greater survival than wild fish, and the opposite occurred in one case. In all cases where a significant difference existed between wild and hatchery fish detection probabilities, the wild fish were detected at a greater rate. This is consistent with the observation of Zabel et al. (2005) that smaller fish have greater detection probabilities than smaller ones.

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Table A1-1. Mean differences (and standard errors), results from z-tests, and correlations between estimated <u>Survival Probabilities</u> of wild and hatchery fish. N refers to the number of pairs of cohorts.

	N	$\overline{X}_{Diff}$	$s_{\overline{X}_{Diff}}$	z	P		ρ
SRSS Chinook – LGR Releases	234	-0.0103	0.0035	-2.927	0.003		0.810
SRSS Chinook – MCN Releases	124	-0.0553	0.0109	-5.050	< 0.001		0.503
SR Steelhead – LGR Releases	194	0.0215	0.0054	3.947	< 0.001		0.924
SR Steelhead – MCN Releases	91	-0.0940	0.0204	-4.606	< 0.001		0.753

Table A1-2. Mean differences (and standard errors), results from z-tests, and correlations between estimated <u>Detection Probabilities</u> of wild and hatchery fish. N refers to the number of pairs of cohorts.

		$\overline{X}_{Diff}$	$s_{\overline{X}_{Diff}}$	z	P		ρ
SR S/S Chinook – LGR Releases	372	0.0697	0.0027	25.385	< 0.001		0.980
SR S/S Chinook – MCN Releases	124	0.0332	0.0051	6.495	< 0.001		0.916
SR Steelhead – LGR Releases	297	0.0137	0.0040	3.394	0.001		0.968
SR Steelhead – MCN Releases	91	-0.0108	0.0100	-1.078	0.281		0.690

Table A1-3. Mean differences (and standard errors), results from z-tests, and correlations between estimated <u>Migration Rates</u> of wild and hatchery fish. N refers to the number of pairs of cohorts.

		$\overline{X}_{Diff}$	$s_{\overline{X}_{Diff}}$	z	P		ρ
SR S/S Chinook – LGR Releases	257	0.4149	0.0659	6.295	< 0.001		0.963
SR S/S Chinook – MCN Releases	191	-1.5286	0.1029	-14.852	< 0.001		0.979
SR Steelhead – LGR Releases	210	2.5262	0.1181	21.396	< 0.001		0.939
SR Steelhead – MCN Releases	129	2.4765	0.2673	9.264	< 0.001		0.919

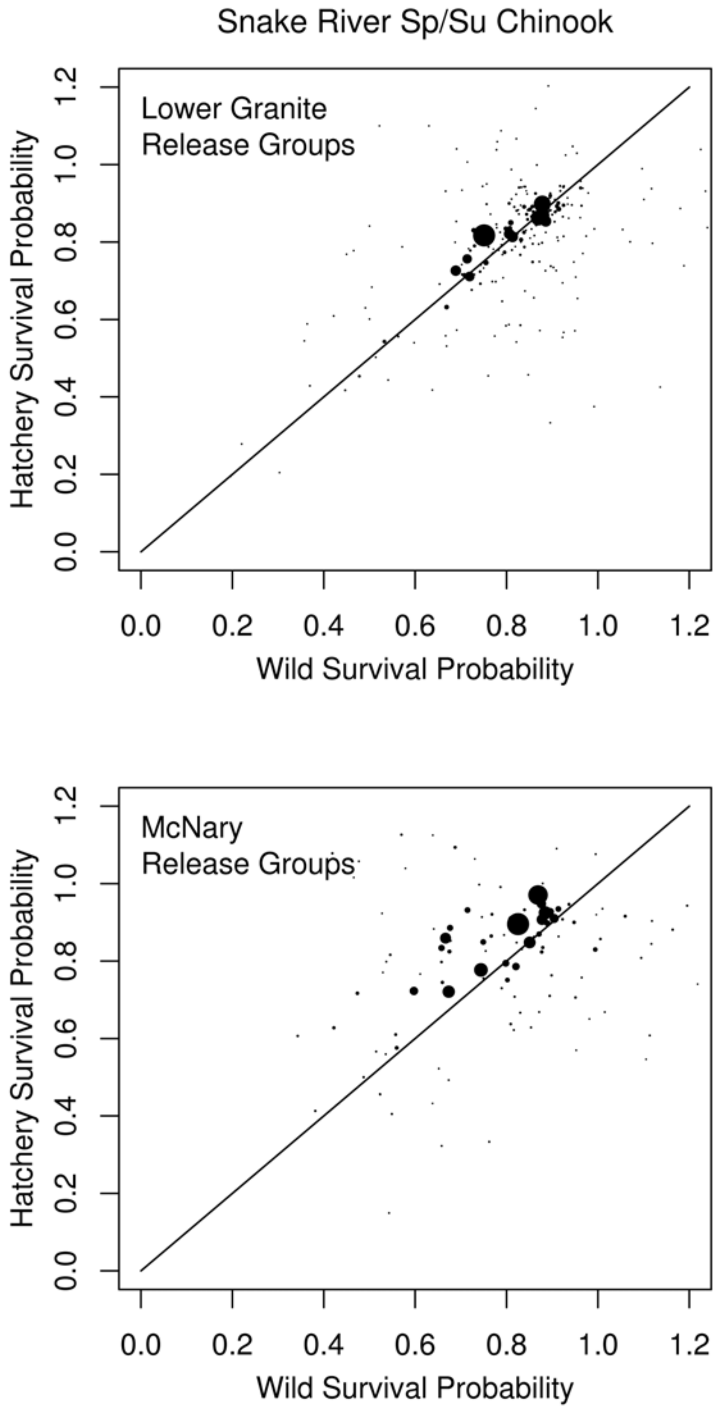


Figure A2-1. Wild survival probability versus hatchery survival probability for paired groups of Snake River spring/summer Chinook salmon released at Lower Granite (top plot) and McNary (bottom plot). The size of each point reflects its relative weight. The solid line represents points where wild and hatchery survival probability is equal.

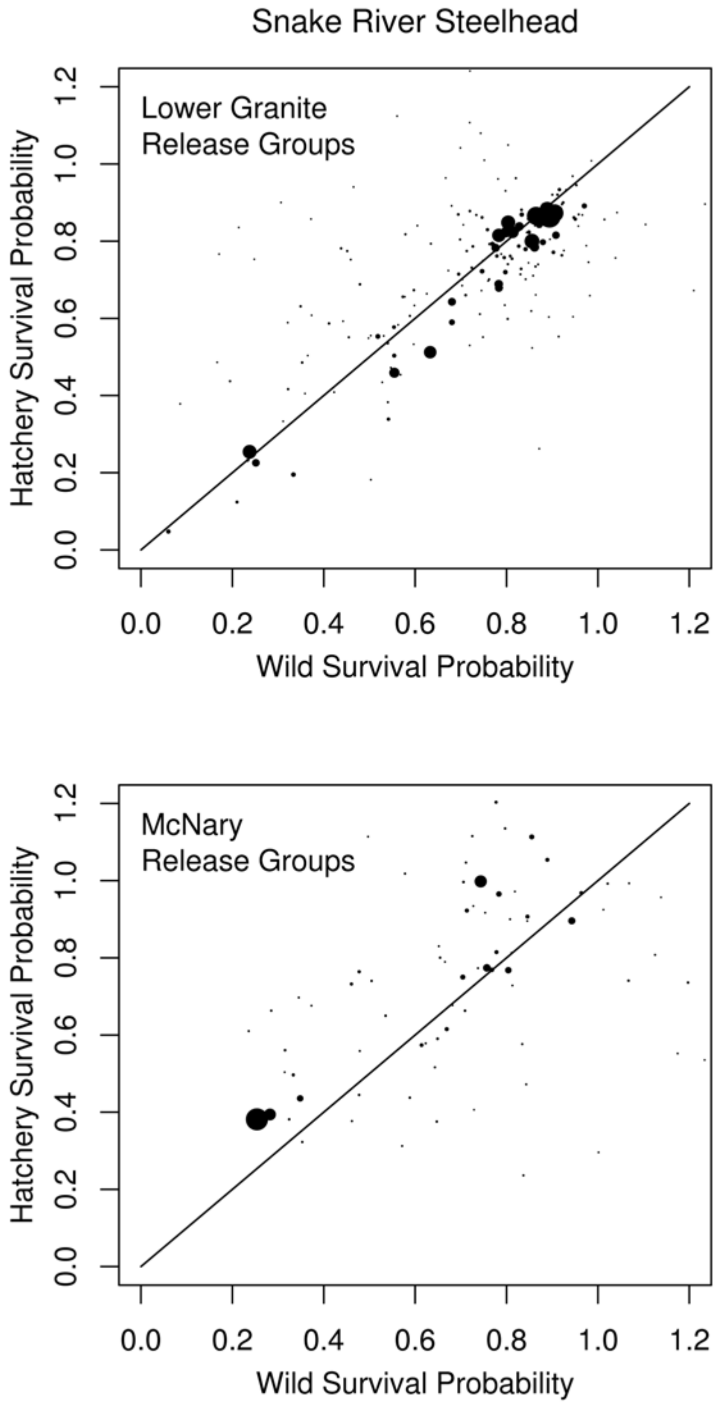


Figure A2-2. Wild survival probability versus hatchery survival probability for paired groups of Snake River Steelhead released at Lower Granite (top plot) and McNary (bottom plot). The size of each point reflects its relative weight. The solid line represents points where wild and hatchery survival probability is equal.

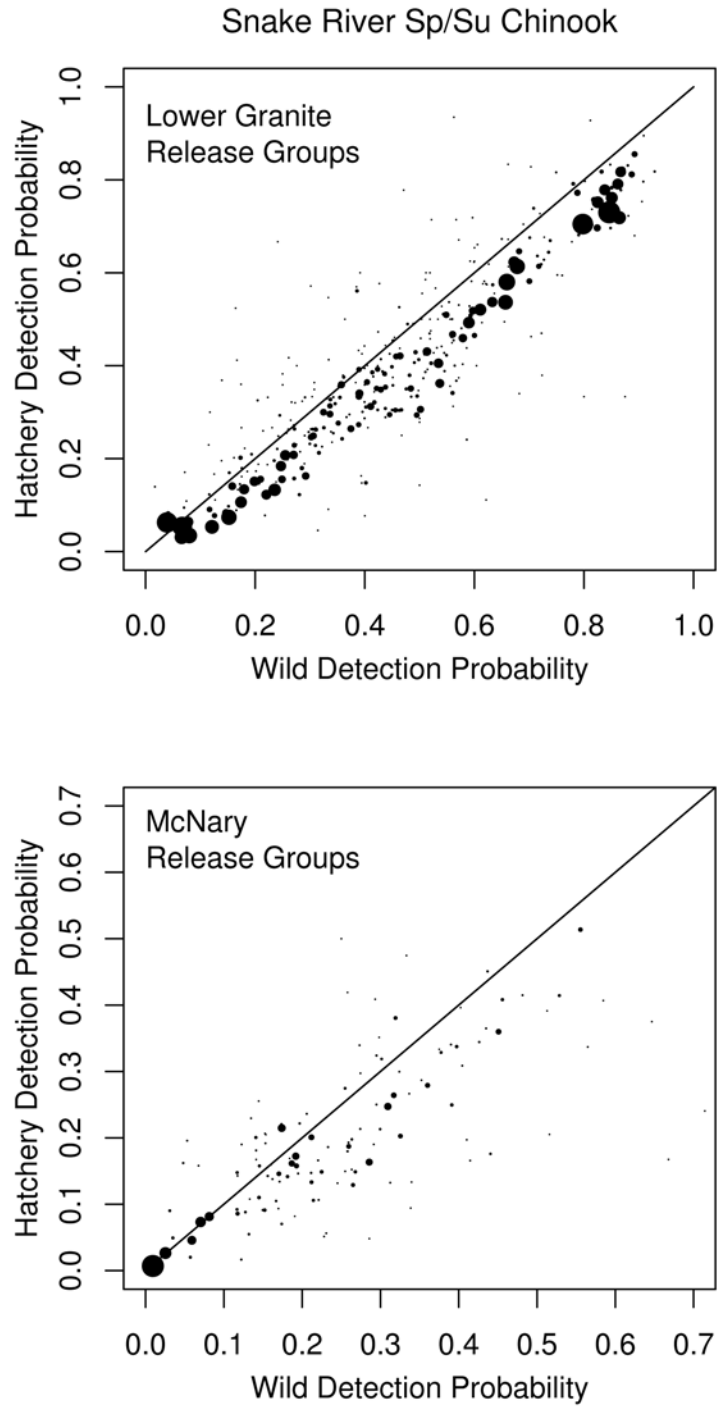
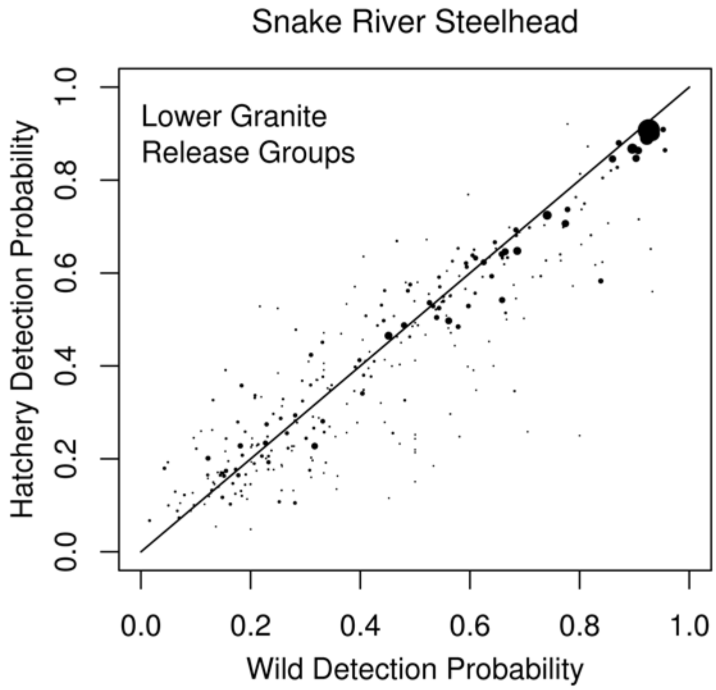


Figure A2-3. Wild detection probability versus hatchery detection probability for paired groups of Snake River spring/summer Chinook salmon released at Lower Granite (top plot) and McNary (bottom plot). The size of each point reflects its relative weight. The solid line represents points where wild and hatchery detection probability is equal.



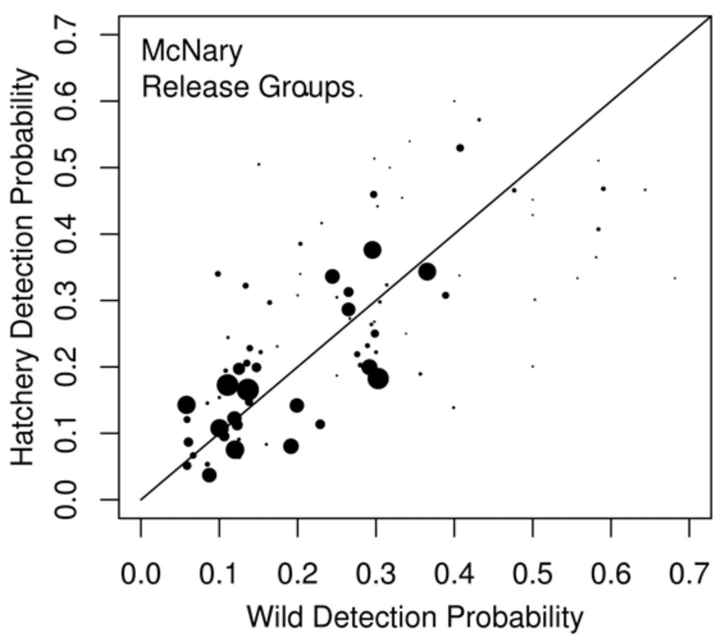


Figure A2-4. Wild detection probability versus hatchery detection probability for paired groups of Snake River Steelhead released at Lower Granite (top plot) and McNary (bottom plot). The size of each point reflects its relative weight. The solid line represents points where wild and hatchery detection probability is equal.

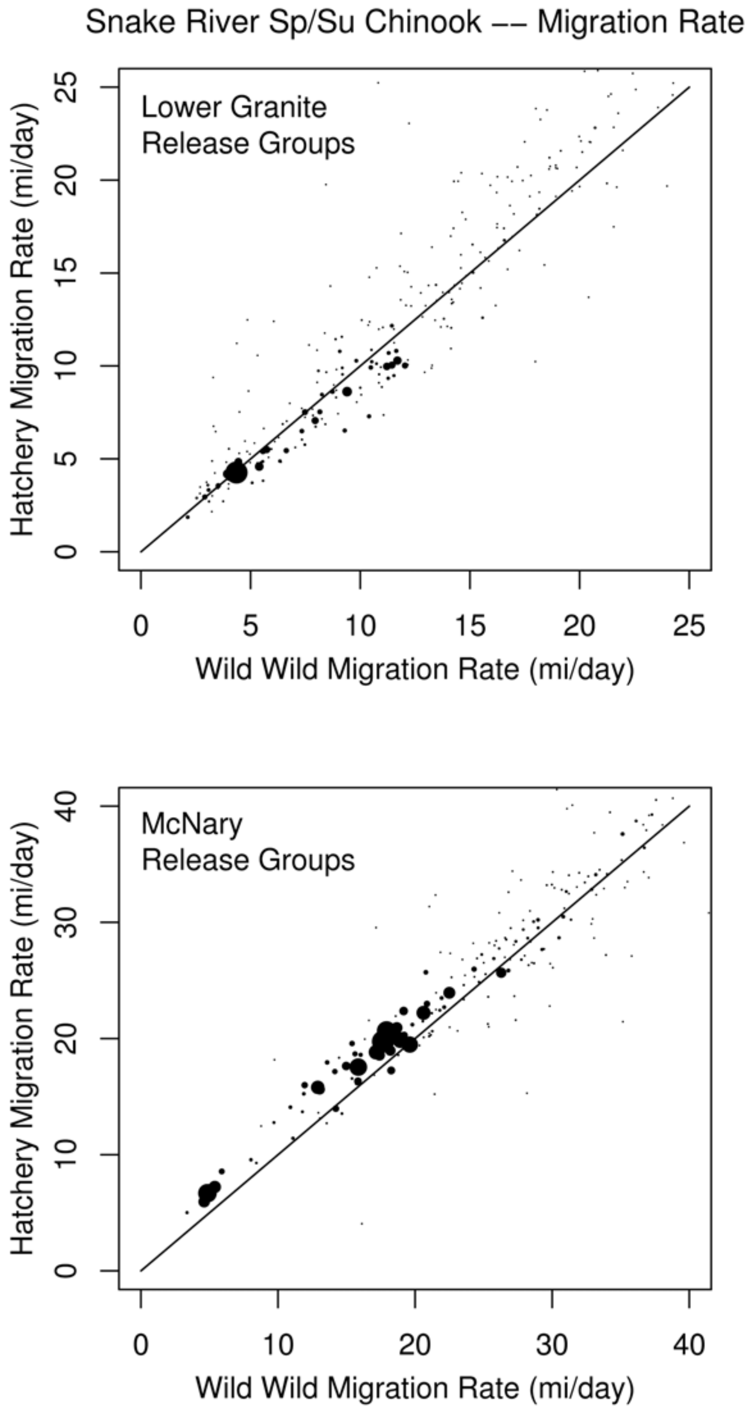


Figure A2-5. Wild migration rate (mi/day) versus hatchery migration rate (mi/day) for paired groups of Snake River spring/summer Chinook salmon released at Lower Granite (top plot) and McNary (bottom plot). The size of each point reflects its relative weight. The solid line represents points where wild and hatchery migration rate is equal.

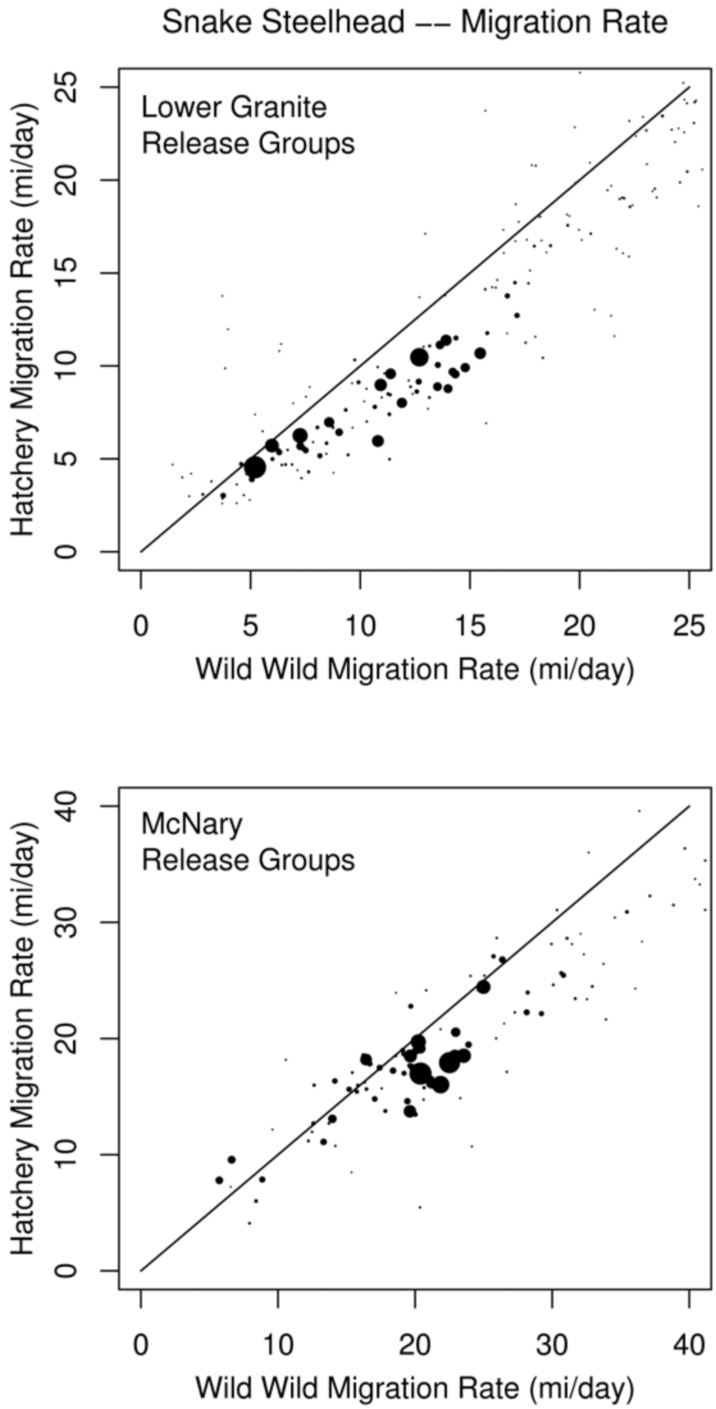


Figure A2-6. Wild migration rate (mi/day) versus hatchery migration rate (mi/day) for paired groups of Snake River steelhead released at Lower Granite (top plot) and McNary (bottom plot). The size of each point reflects its relative weight relative. The solid line represents points where wild and hatchery migration rate is equal.

Part 2: Precision of PIT-tag survival estimates

Introduction

In this appendix, we assessed the quality of the PIT-tag survival estimates by addressing several questions. First, we assessed the overall quality of the estimates by plotting distributions of standard errors and comparing spring/summer Chinook to steelhead and Lower Granite to McNary groupings. In addition, based on the conclusion from Appendix 1 part 1 that wild and hatchery fish should be treated separately, we examined the difference in precision of survival estimates based on wild, hatchery and combined groupings. Finally, because of the relatively large standard errors associated with survival estimates for the McNary groups, we compared the distribution of standard errors for one and two week groupings to determine whether the two week groupings would provide substantially more precise estimates.

Methods

We first constructed a data set based on weekly groups of fish leaving Lower Granite Dam and McNary Dam during migration years 1997-2007. The groups were formed as described in Part 1 of this appendix. In addition, for fish leaving McNary Dam, we compiled groupings based on fish detected at McNary over a two week period.

We sorted the groups according to their standard errors, ranking them from smallest to largest standard error. We then created plots of standard error versus individual group ranks. This allowed for a visual inspection of the quality of survival estimates across groupings, such as hatchery versus wild.

Results and Conclusions

In all cases, forming groups from only wild fish resulted in survival estimates with larger standard errors compared to groups formed from wild and hatchery fish combined (Figures A1 7 and A1 8). For example, for spring/summer Chinook groups formed at Lower Granite, approximately 100 wild groups had standard errors less than 0.05, while approximately 130 combined wild and hatchery groups met this criterion (Figure A1 7, top plot). In general, spring/summer Chinook had more precise survival estimates than steelhead. In addition, survival estimates for groups formed at Lower Granite were substantially more precise than those formed at McNary.

These plots demonstrate how imprecise the survival estimates are in the lower Columbia River (Figures A1 7 and A1 8, bottom plots). For wild spring/summer Chinook, fewer than 40 groups had standard errors less than 0.1, and for steelhead, the situation is even worse with fewer than 20 groups with standard errors less than 0.1. Unfortunately, hatchery and wild fish had greater differences in survival (5-10%) in the lower Columbia than in the Snake River (Table A1 1), so combining hatchery and wild fish is not prudent.

We believe that it should be a monitoring priority to have more precise survival estimates in the lower Columbia River.

Because of these imprecise estimates, we explored the option of increasing sample sizes in groups by combing fish over a two week period. Unfortunately, this resulted in fewer groups did not increase precision substantially (Figure A1 9). Thus we decided to continue using one week groupings.

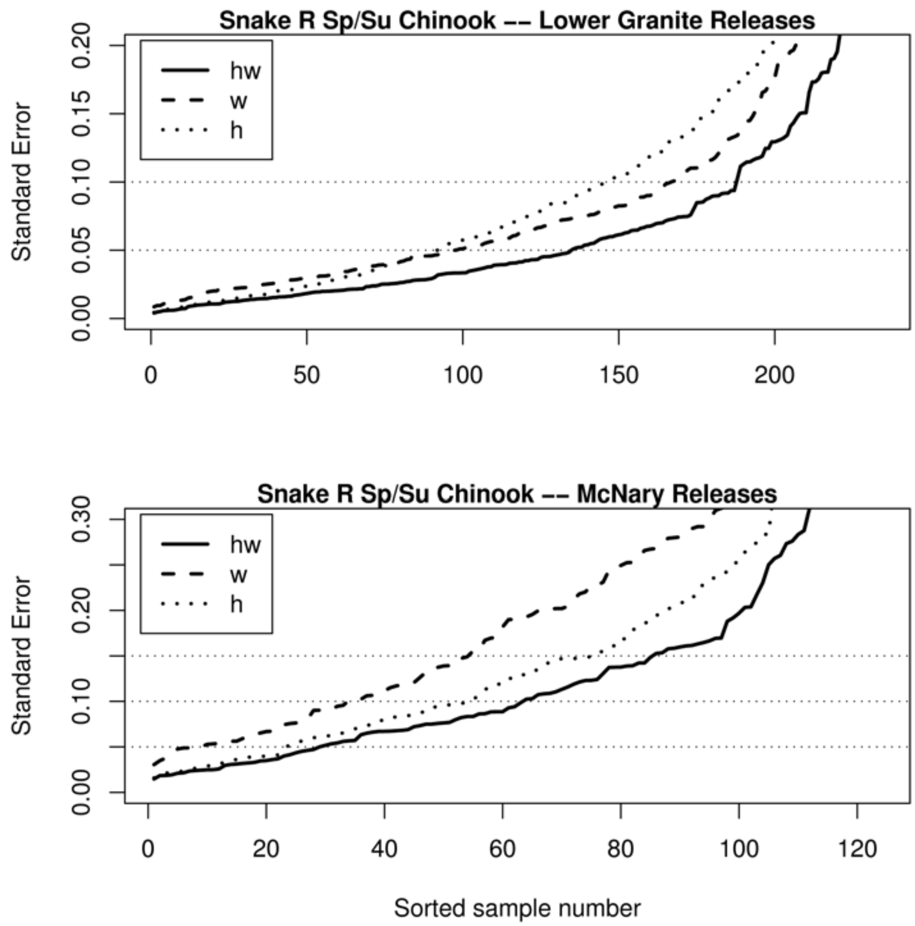


Figure A2 7. Sorted standard errors of survival estimates for Snake River spring/summer Chinook salmon released at Lower Granite Dam and McNary Dam. H = hatchery fish, W = wild fish, and HW = hatchery and wild fish combined.

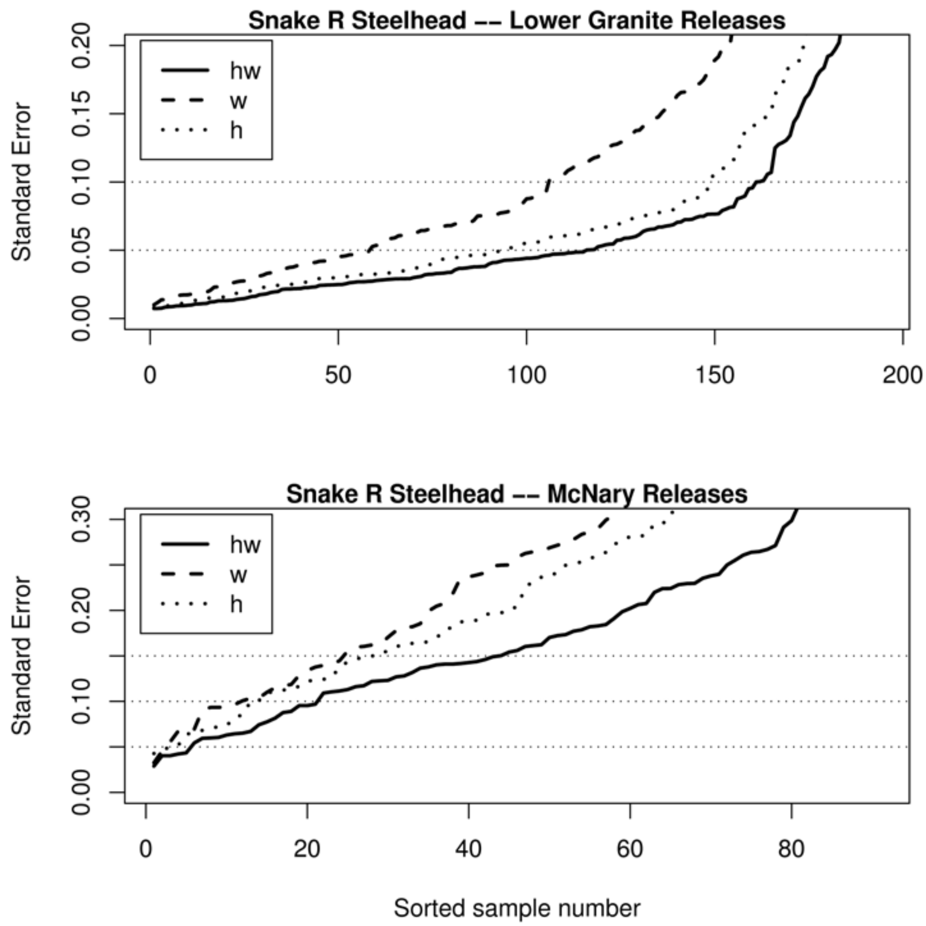


Figure A2 8. Sorted standard errors of survival estimates for Snake River steelhead released at Lower Granite Dam and McNary Dam. H = hatchery fish, W = wild fish, and HW = hatchery and wild fish combined.

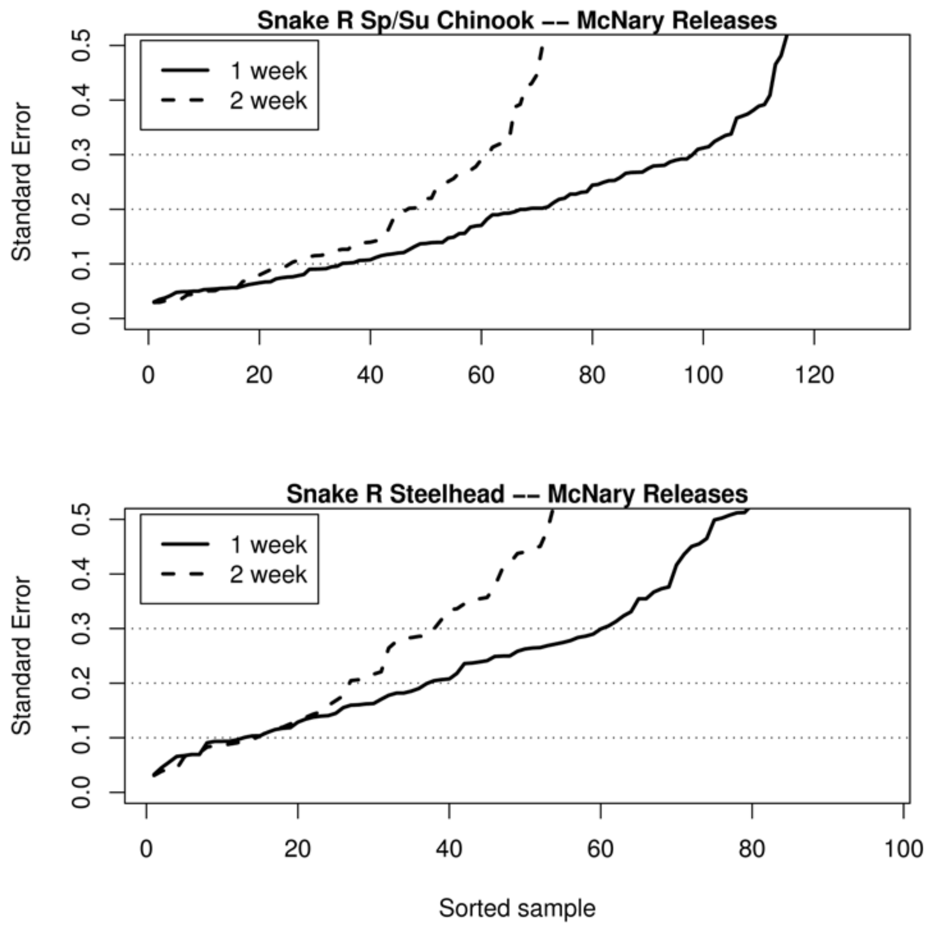


Figure A2 9. Comparison of standard errors of survival estimates for one week versus two week groups fomed at McNary Dam. Wild fish only.

This Appendix provides detailed diagnostics of the model fit to PIT-tag data. It is separated into the following sections:

Appendix 2-0 – Introduction, Methods, and Discussion for each section

Appendix 2-1 – Analysis of residuals

Appendix 2-2 – Predicted and observed survival probabilities for weekly groups

Appendix 2-3 – Predicted and observed bypass proportions for weekly groups

Appendix 2-4 – Predicted and observed passage distributions

Section 1: Analysis of residuals

In this section, we provide an analysis of residuals for the survival (Figures A2-1 1 through 4) and migration rate models (Figures A-2 5 through 8). The residuals are based on the best fit models presented in Tables 3 and 4 in the main text. For each model, we created four plots: 1) predicted versus observed estimates (replicated from Figures 6 and 10 in the main text); 2) residuals versus observed estimates; 3) residuals versus migration year; and 4) residuals versus river segment.

For the survival model, no apparent bias is revealed by plotting residuals against observed values, year, or river segment (Figures A2-1 1 through 4). Moreover, variance appears relatively homogenous compared to observed values, year, and river segment. It is clear that weighting of data points is not uniform across years or river segment. In particular, the upper river segments (Lower Granite to Lower Monumental and McNary to John Day) receive more weight than the lower reaches (Lower Monumental to McNary and John Day to Bonneville). This is unavoidable given the nature of the data.

The model fit for survival of cohorts of spring/summer Chinook migrating through the lower Columbia River (Figure A2-1 1) is relatively poor, with more variability in the predicted values compared to the observed ones. We believe this is largely due to poor quality data in these river segments (see Appendix 1-1 and the plots in section 2 of this appendix). Because of this variability, it is difficult to detect a signal.

The plots of predicted versus observed migration rates demonstrate that the model captures a great deal of variability in migration rates (Figures A-2 5 through 8). The residuals become somewhat more variable as migration rate increase, but this is not surprising because the points have increasing variance (less weight) as migration rate increases. Also, compared to the survival plots, the migration rate residuals exhibit more year to year variability. However, this is not such a concern because of the strong model fits. There is no apparent bias across river segments, and the variance appears relatively homogeneous across river segments. Also, downstream migration rates receive considerable weight.

Section 2: **Predicted and observed survival probabilities for weekly groups**

To construct these plots, we ran COMPASS with weekly cohorts reflecting those in the PIT-tag database. For each cohort, we predicted survival corresponding to PIT-tag survival estimates. The plots contain model predictions compared to the survival estimates, which are plotted with their 95% confidence intervals (Figures A2-2 1 through 22).

These plots demonstrate that when data quality is good, the model captures seasonal trends in survival. For example, Chinook survival drops off at the end of the season in some years (1998, 2000, 2001) but not in others (1999, 2005, 2006), and the model captures this.

As mentioned above, the plots demonstrate the poor quality of data in the lower Columbia River. Because the confidence intervals are so broad, the model predictions are less variable, which is expected.

Section 3: **Predicted and observed detection probabilities for weekly groups**

These plots were constructed in a similar manner to the above survival plots. In these plots we compared model-prediction proportion of fish passing the bypass system to PIT-tag detection probabilities with 95% confidence intervals (Figures A2-3 1 through 22). These plots reveal the much improved ability of the COMPASS model to capture variability in bypass proportion (see Appendix 3 for details of the methodology). As with the survival predictions, COMPASS captures seasonal variability in bypass proportion. This is important, because this proportion determines the proportion of fish transported, which strongly influences adult return rate (see Appendix 9, sensitivity analyses).

Section 4: **Predicted and observed passage distributions**

In this section, we created model release distributions equivalent to the distribution of PIT-tagged fish. We then compared model-predicted arrival distributions to arrival distributions of PIT-tagged fish (Figures A2-4 1 through 4). In nearly all cases, model-predicted distributions are within a day or two of the observed ones. These plots reveal that COMPASS realistically models the temporal distributions of migrating juvenile salmonids. This is important because many management actions (e.g., timing of spill and transportation) have a timing component.

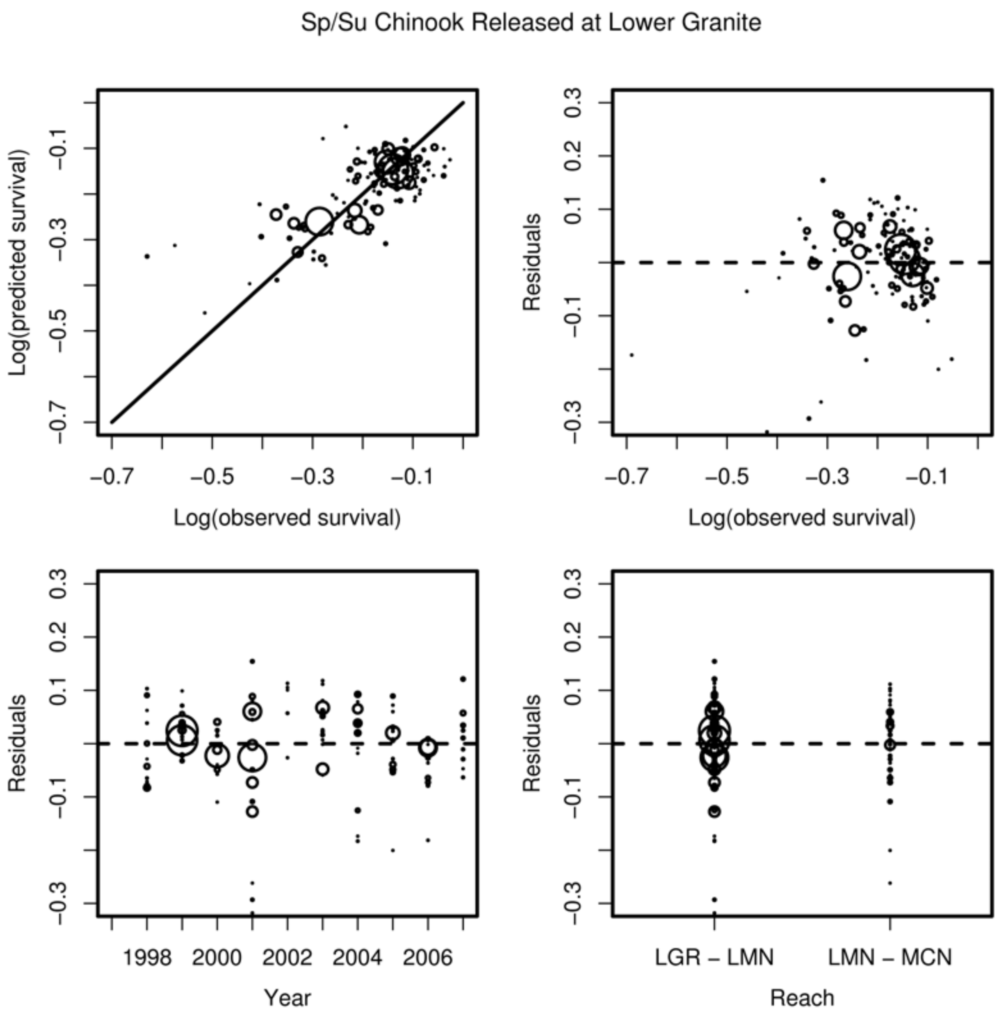


Figure A2-1 1. Diagnostics of predicted survival probabilities for Snake River spring/summer Chinook migrating from Lower Granite to McNary Dam. The diameter of the points in the plots reflects the weight assigned to the point. Abbreviations: LGR = Lower Granite Dam; LMN = Lower Monumental Dam; MCN = McNary Dam.

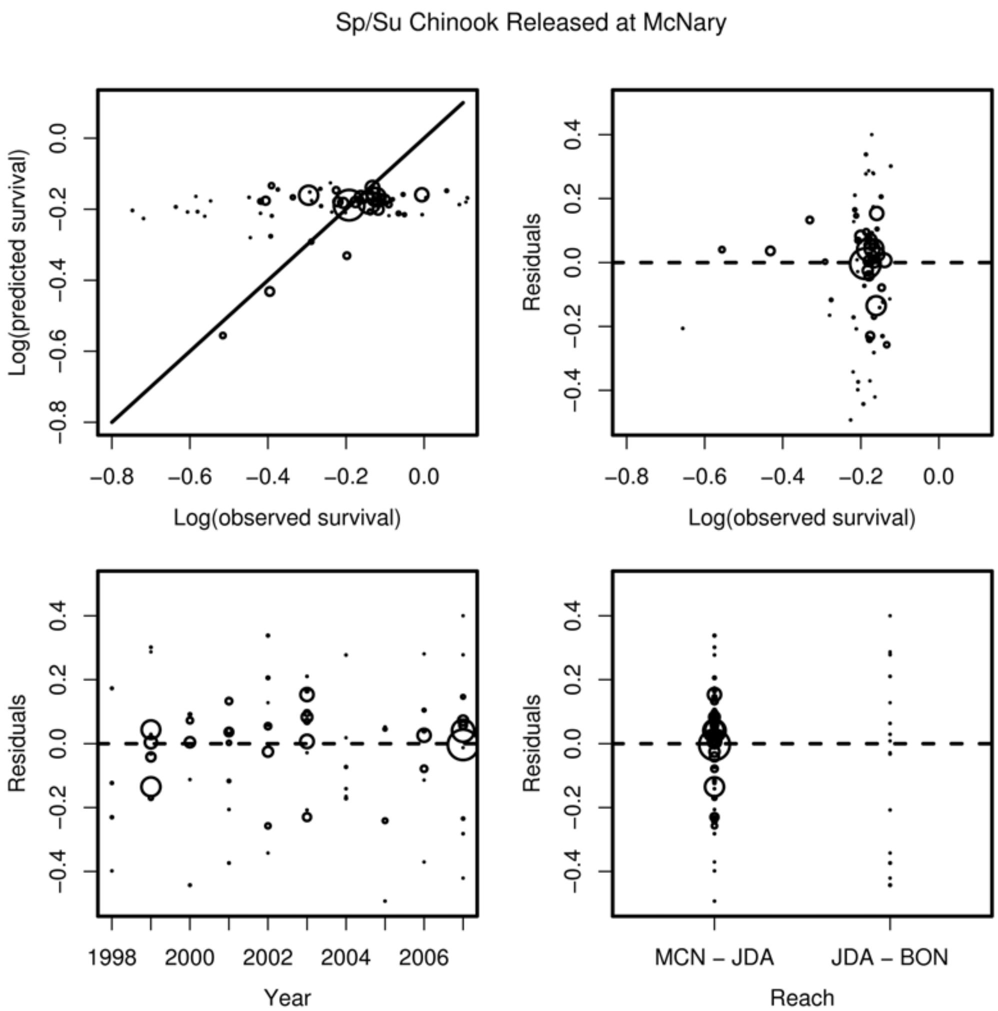


Figure A2-1 2. Diagnostics of predicted survival probabilities for Snake River spring/summer Chinook migrating from McNary Dam to Bonneville Dam. The diameter of the points in the plots reflects the weight assigned to the point. Abbreviations: MCN = McNary Dam; JDA = John Day Dam; BON = Bonneville Dam.

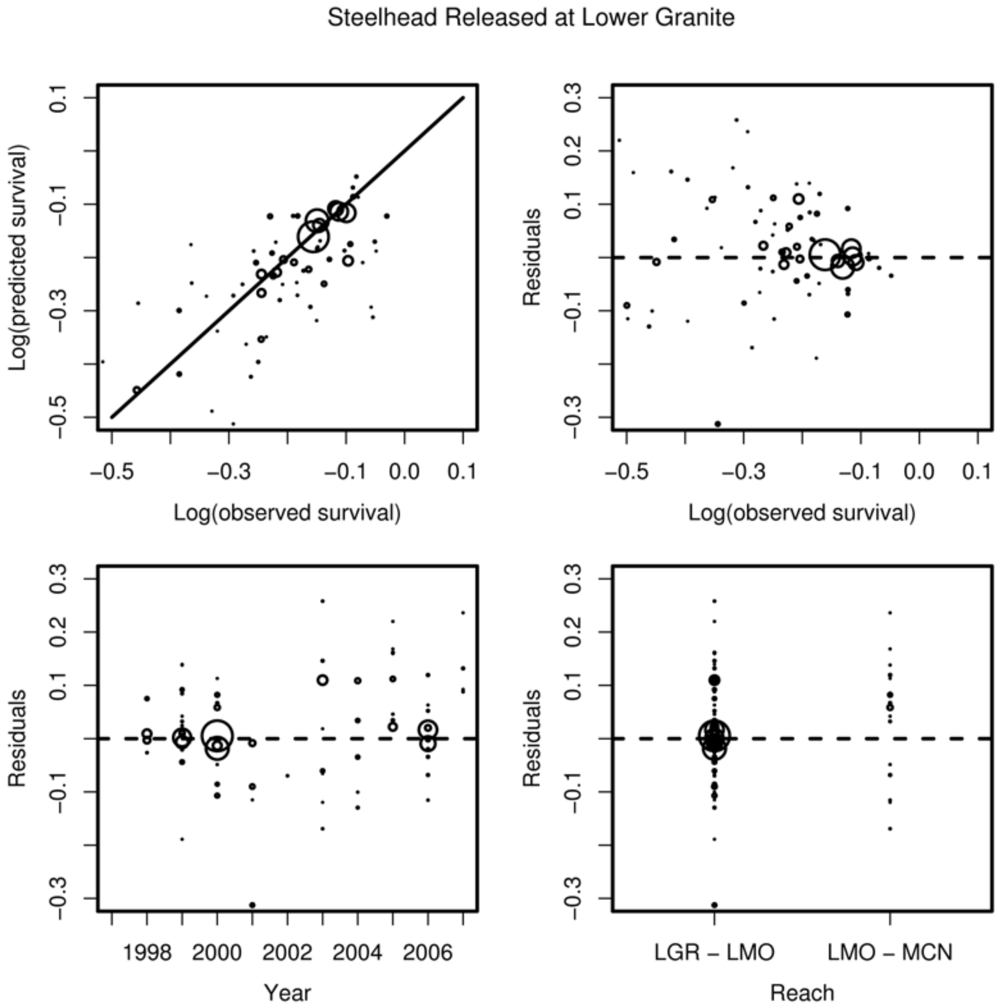


Figure A2-1 3. Diagnostics of predicted survival probabilities for Snake River steelhead migrating from Lower Granite to McNary Dam. The diameter of the points in the plots reflects the weight assigned to the point. Abbreviations: LGR = Lower Granite Dam; LMN = Lower Monumental Dam; MCN = McNary Dam.

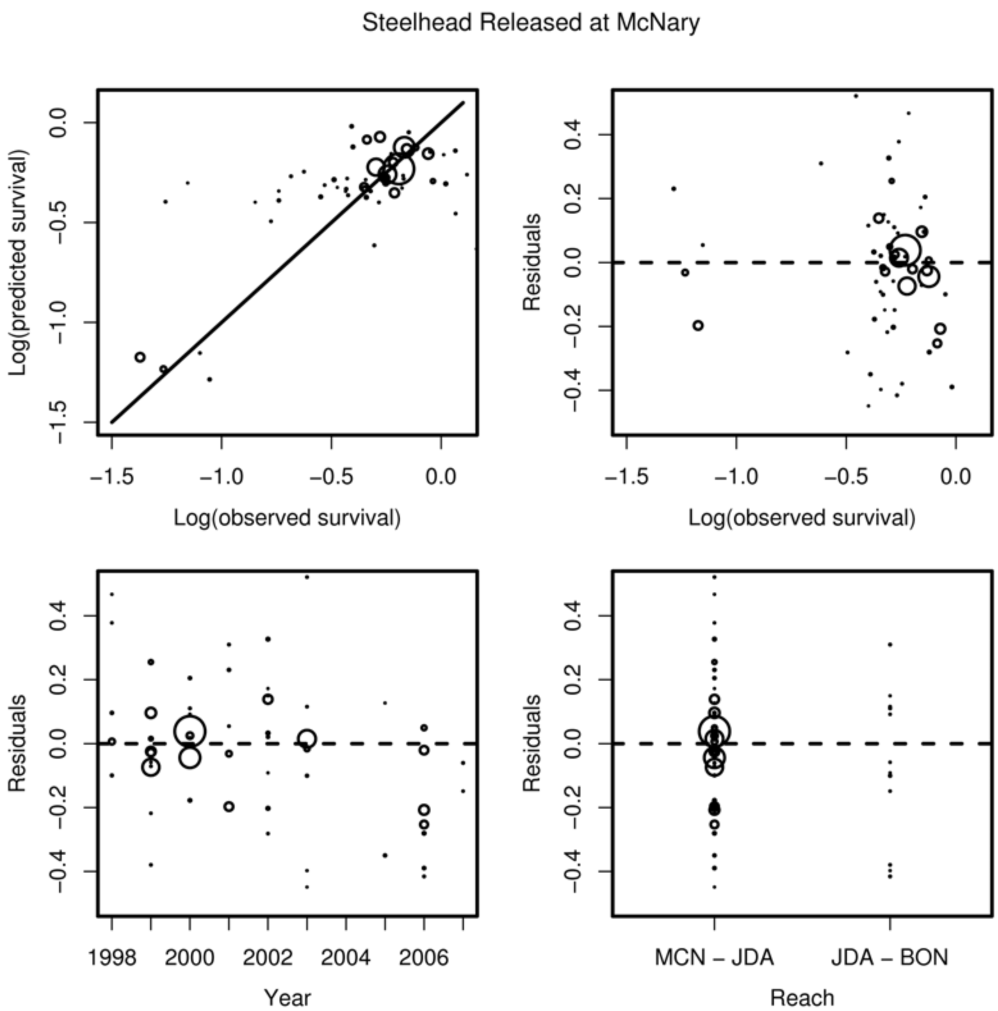


Figure A2-1 4. Diagnostics of predicted survival probabilities for Snake River steelhead migrating from McNary Dam to Bonneville Dam. The diameter of the points in the plots reflects the weight assigned to the point. Abbreviations: MCN = McNary Dam; JDA = John Day Dam; BON = Bonneville Dam.

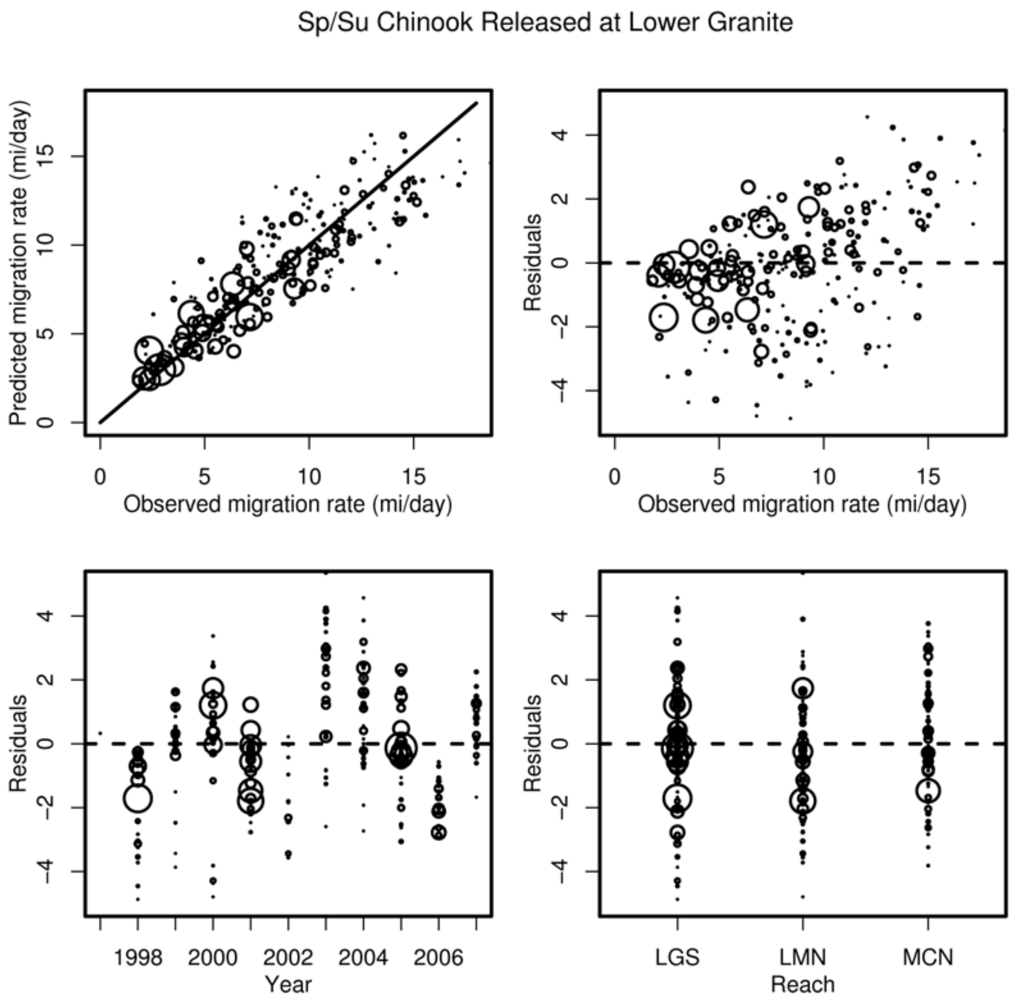


Figure A2-1 5. Diagnostics of predicted migration rates for Snake River spring/summer Chinook migrating from Lower Granite to McNary Dam. The diameter of the points in the plots reflects the weight assigned to the point. Abbreviations: LGS = Little Goose Dam; LMN = Lower Monumental Dam; MCN = McNary Dam.

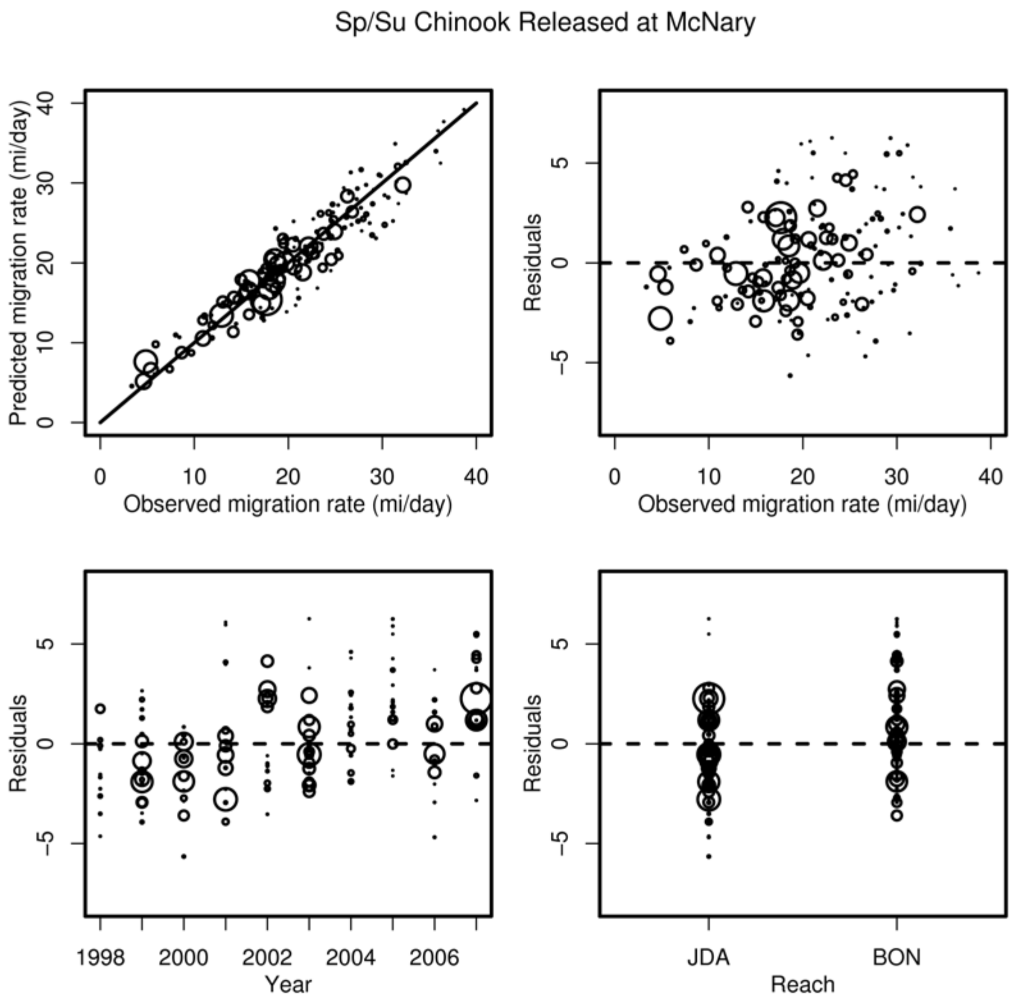


Figure A2-1 6. Diagnostics of predicted migration rates for Snake River spring/summer Chinook migrating from McNary Dam to Bonneville Dam. The diameter of the points in the plots reflects the weight assigned to the point. Abbreviations: JDA = John Day Dam; BON = Bonneville Dam.

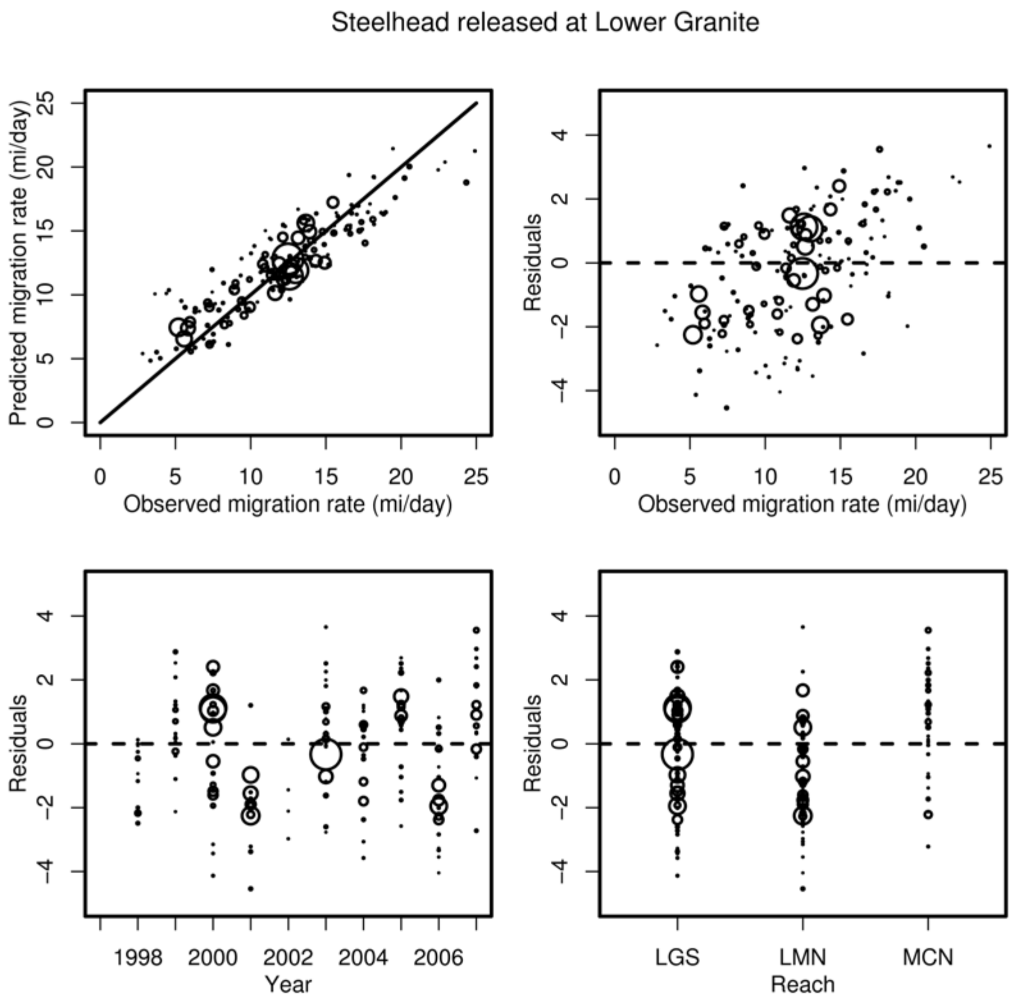


Figure A2-1 7. Diagnostics of predicted migration rates for Snake River steelhead migrating from Lower Granite to McNary Dam. The diameter of the points in the plots reflects the weight assigned to the point. Abbreviations: LGS = Little Goose Dam; LMN = Lower Monumental Dam; MCN = McNary Dam.

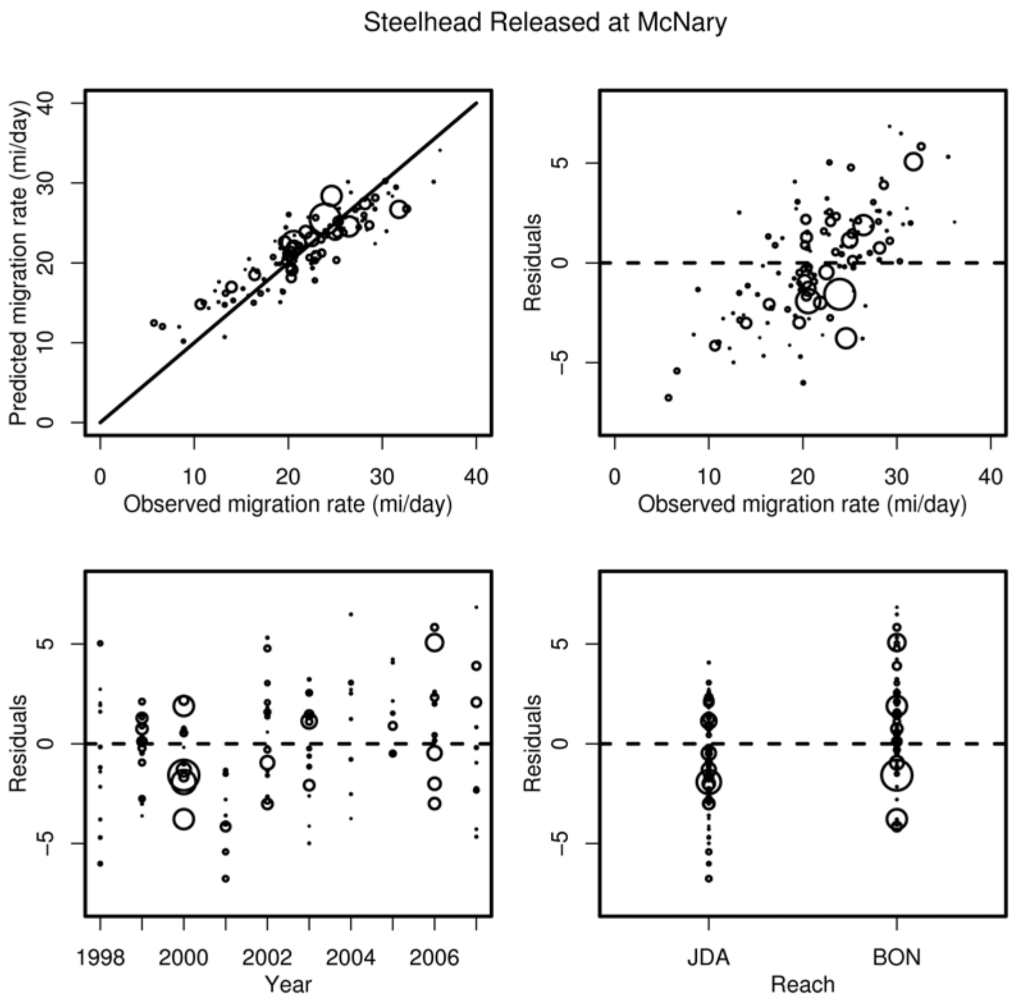


Figure A2-1 8. Diagnostics of predicted migration rates for Snake River steelhead migrating from McNary Dam to Bonneville Dam. The diameter of the points in the plots reflects the weight assigned to the point. Abbreviations: JDA = John Day Dam; BON = Bonneville Dam.

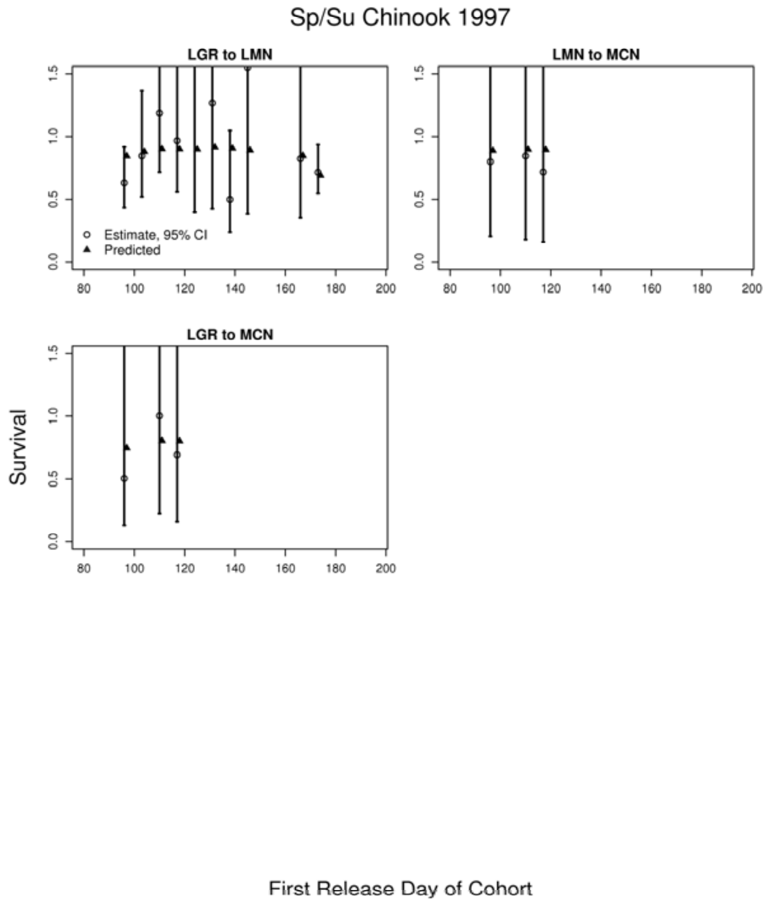


Figure A2-2 1. Survival probabilities for weekly groups of Snake River sp/su Chinook, by river segment, in 1997. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

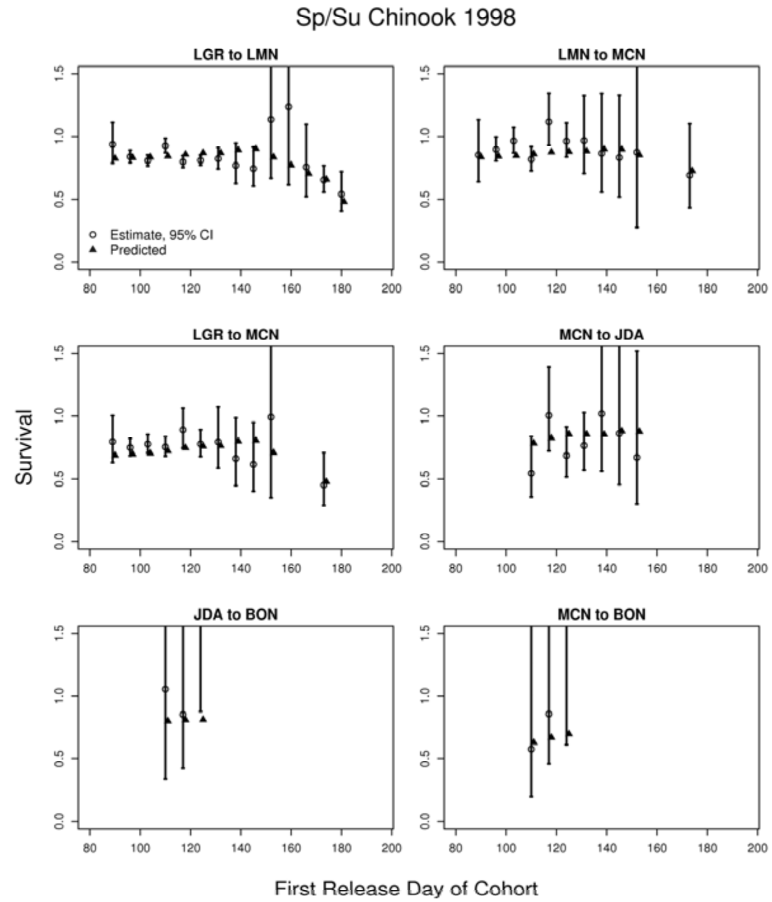


Figure A2-2 2. Survival probabilities for weekly groups of Snake River sp/su Chinook, by river segment, in 1998. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

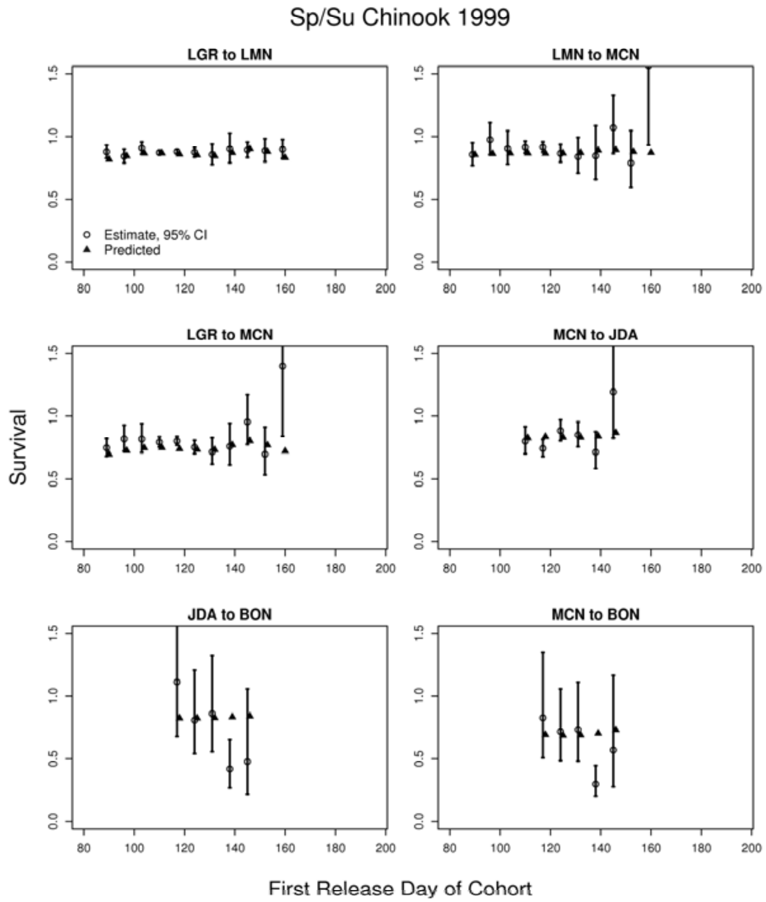


Figure A2-2 3. Survival probabilities for weekly groups of Snake River sp/su Chinook, by river segment, in 1999. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

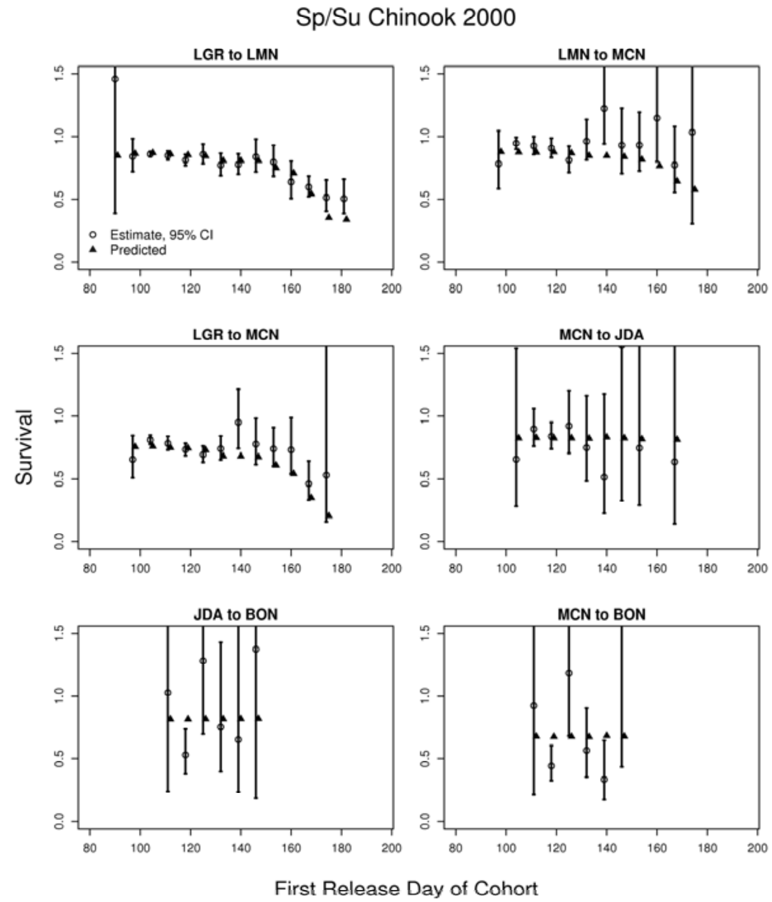


Figure A2-2 4. Survival probabilities for weekly groups of Snake River sp/su Chinook, by river segment, in 2000. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

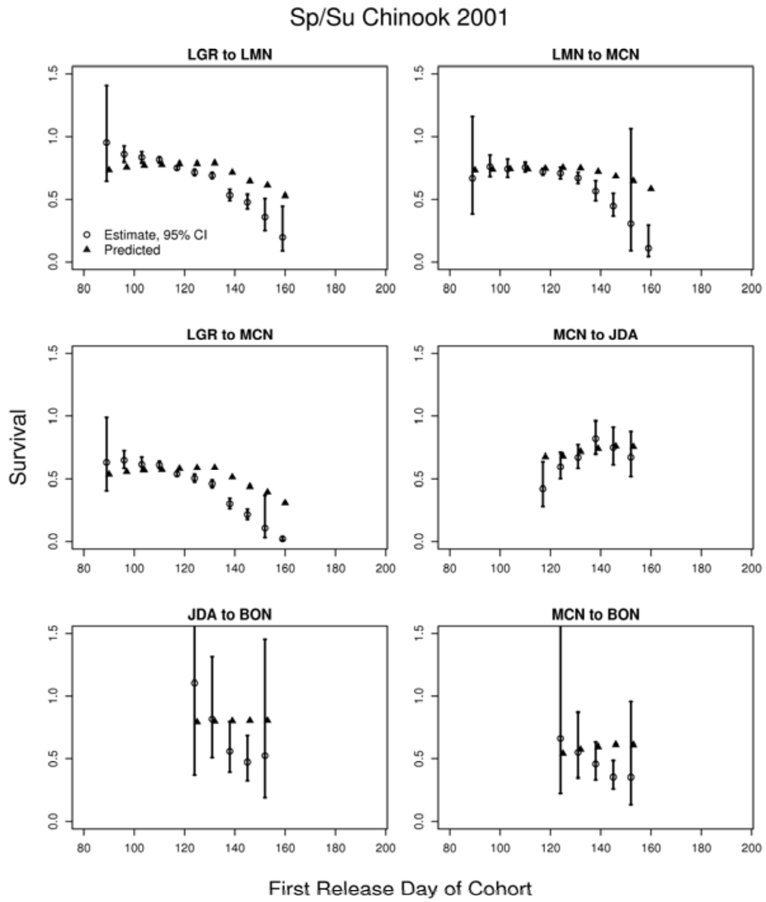


Figure A2-2 5. Survival probabilities for weekly groups of Snake River sp/su Chinook, by river segment, in 2001. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

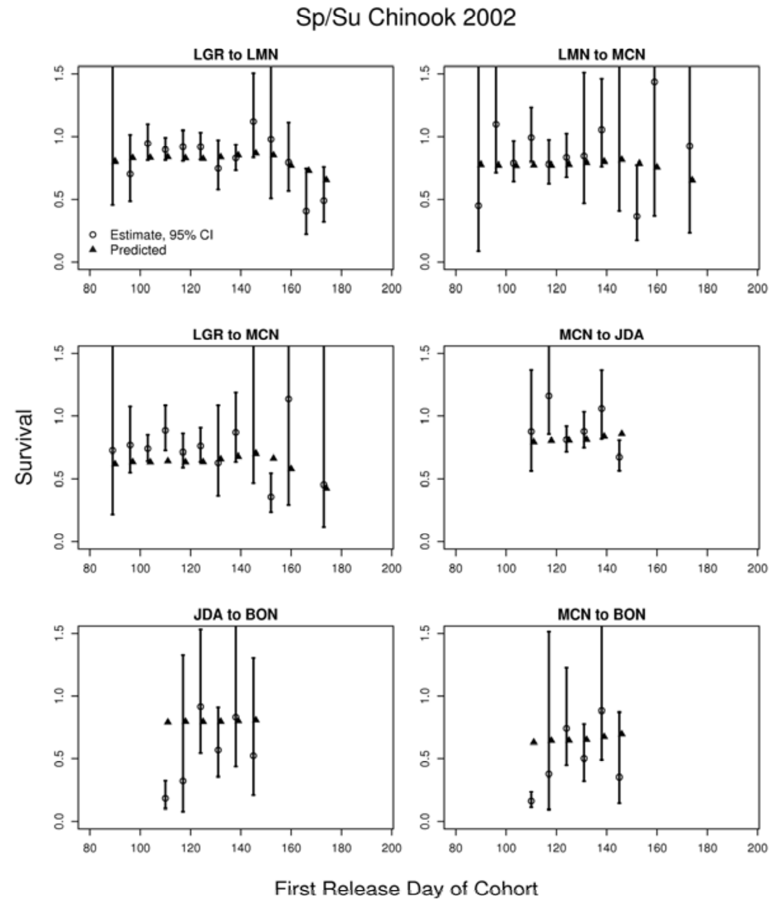


Figure A2-2 6. Survival probabilities for weekly groups of Snake River sp/su Chinook, by river segment, in 2002. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

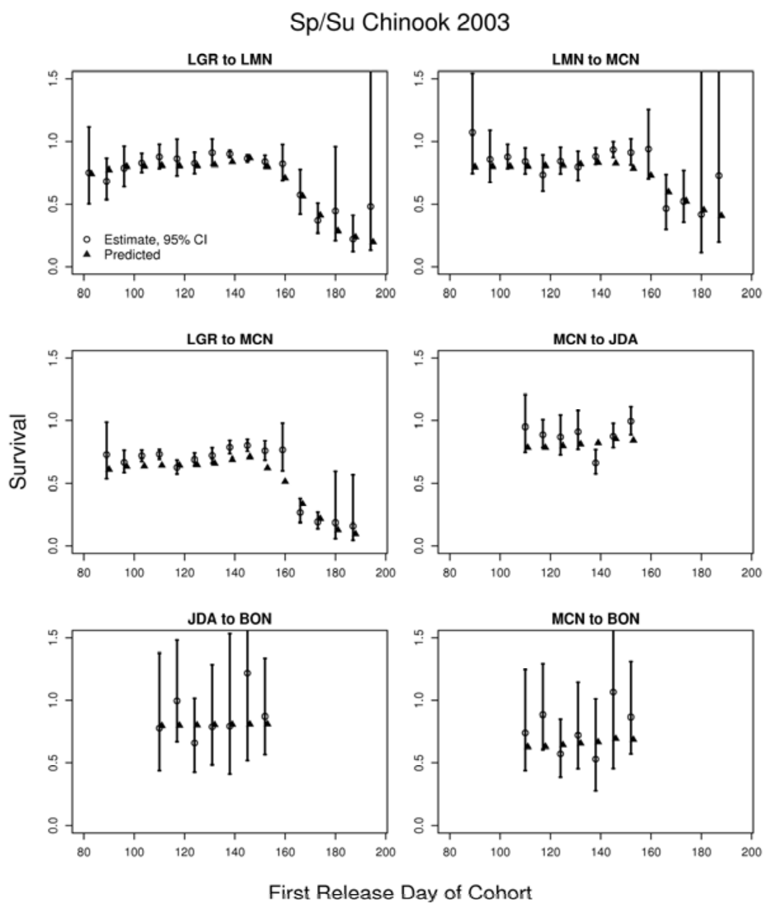


Figure A2-2 7. Survival probabilities for weekly groups of Snake River sp/su Chinook, by river segment, in 2003. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

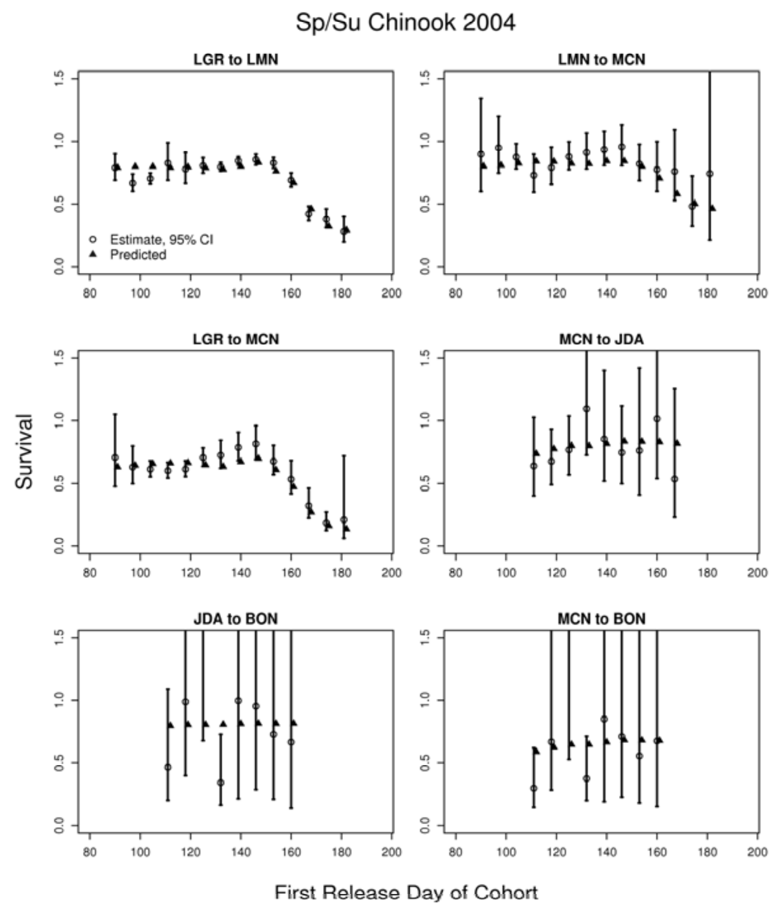


Figure A2-2 8. Survival probabilities for weekly groups of Snake River sp/su Chinook, by river segment, in 2004. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

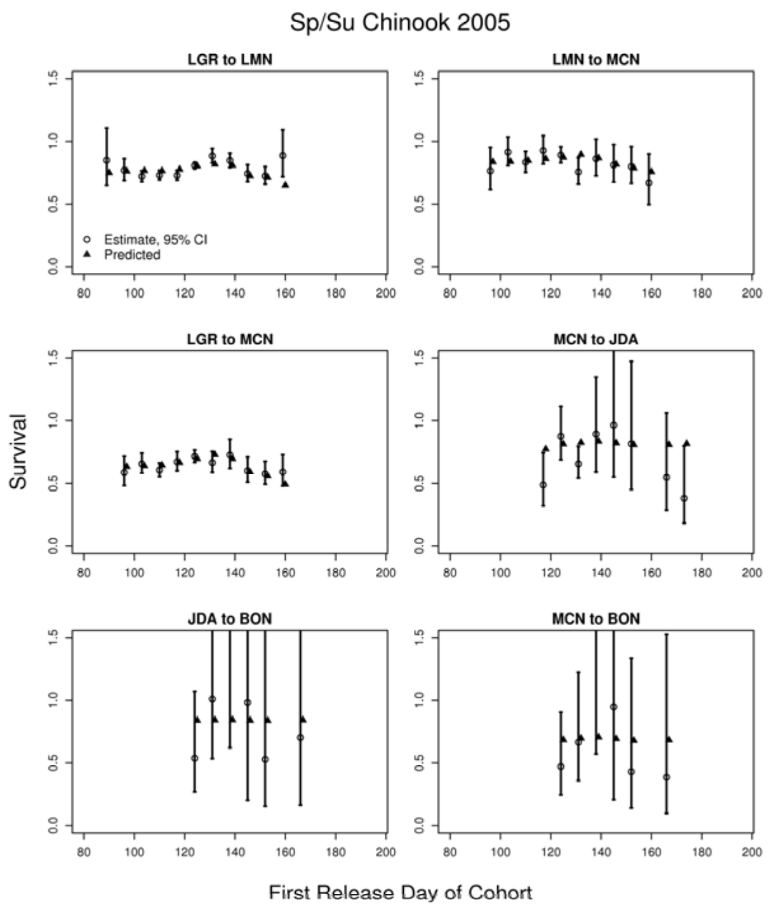


Figure A2-2 9. Survival probabilities for weekly groups of Snake River sp/su Chinook, by river segment, in 2005. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

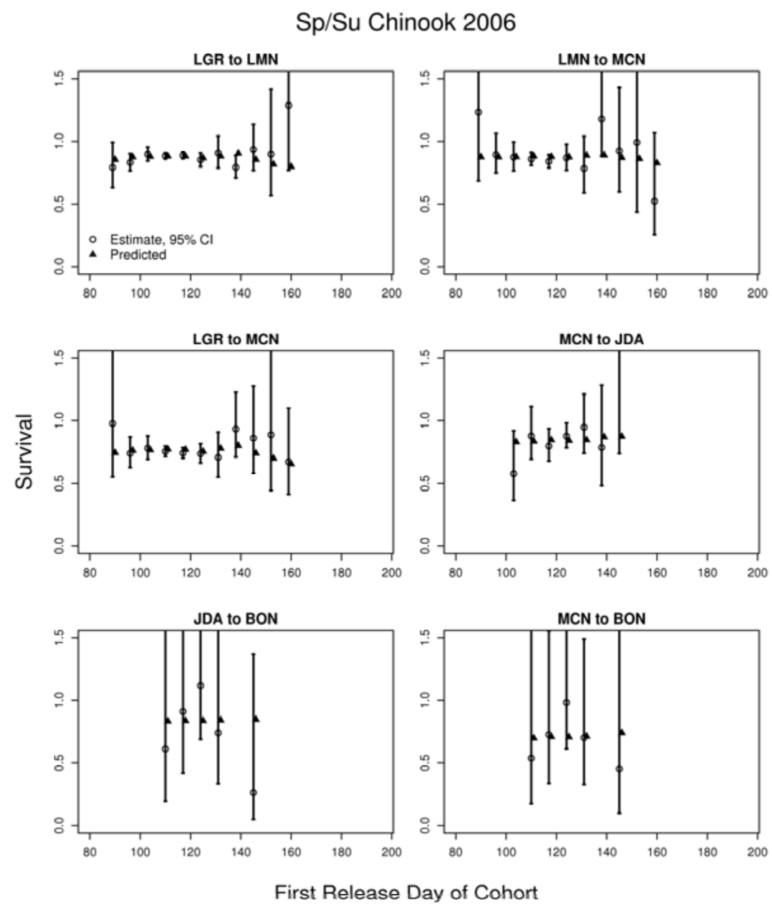


Figure A2-2 10. Survival probabilities for weekly groups of Snake River sp/su Chinook, by river segment, in 2006. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

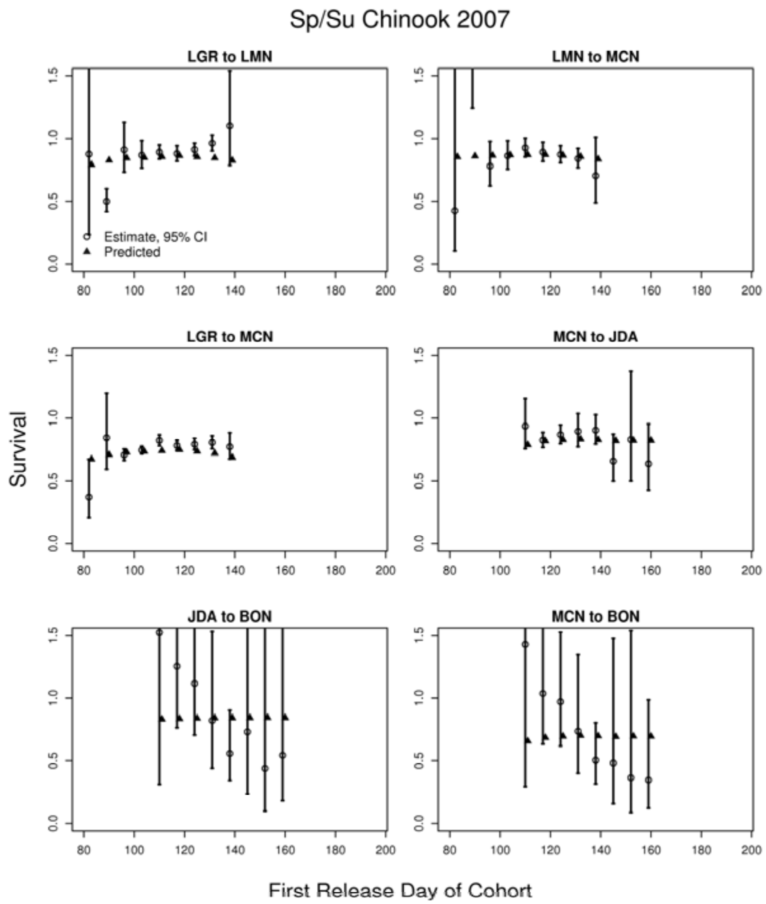


Figure A2-2 11. Survival probabilities for weekly groups of Snake River sp/su Chinook, by river segment, in 2007. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

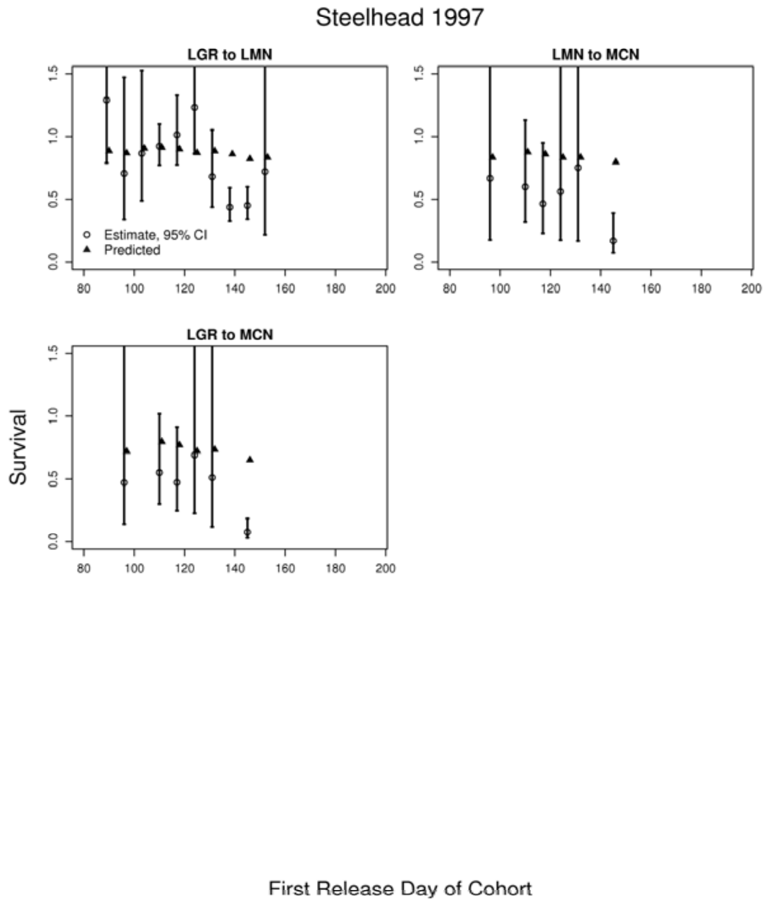


Figure A2-2 12. Survival probabilities for weekly groups of Snake River steelhead, by river segment, in 1997. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

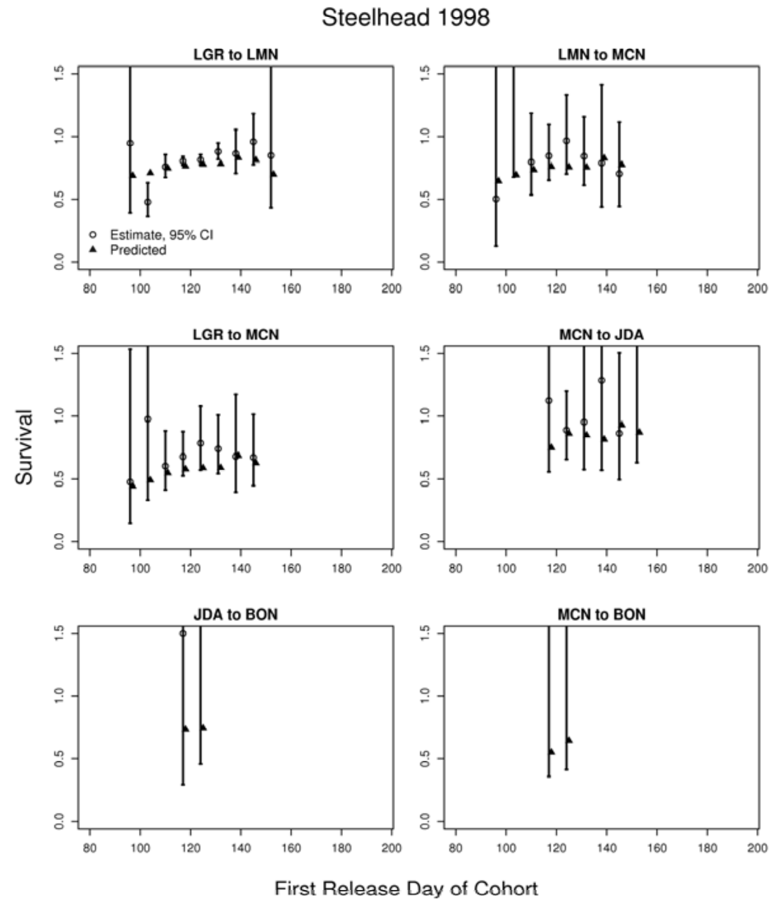


Figure A2-2 13. Survival probabilities for weekly groups of Snake River steelhead, by river segment, in 1998. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

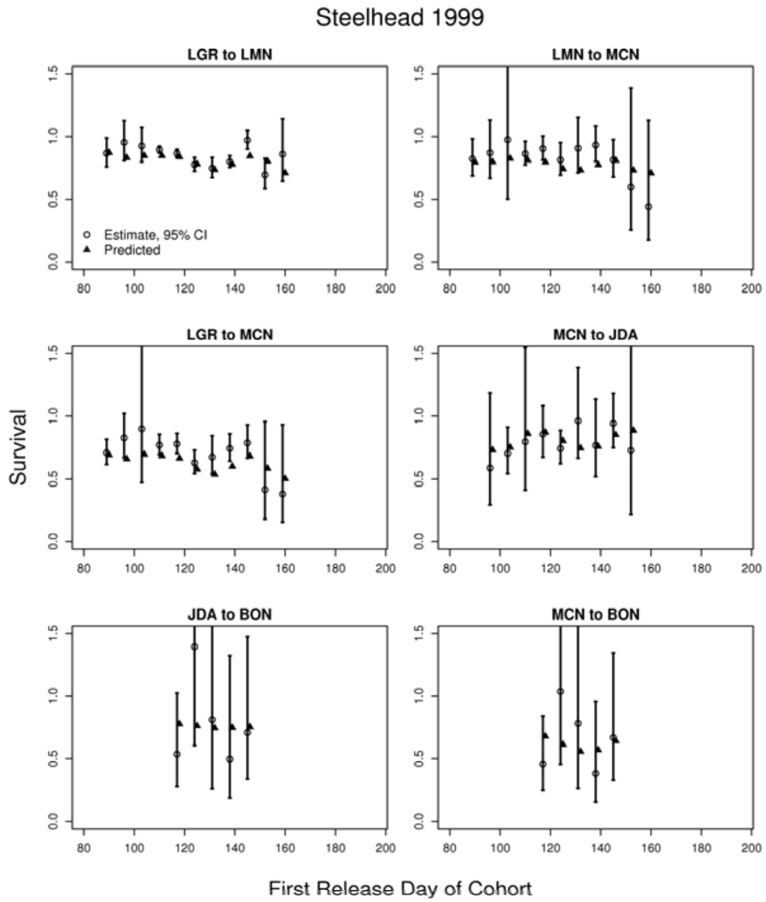


Figure A2-2 14. Survival probabilities for weekly groups of Snake River steelhead, by river segment, in 1999. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

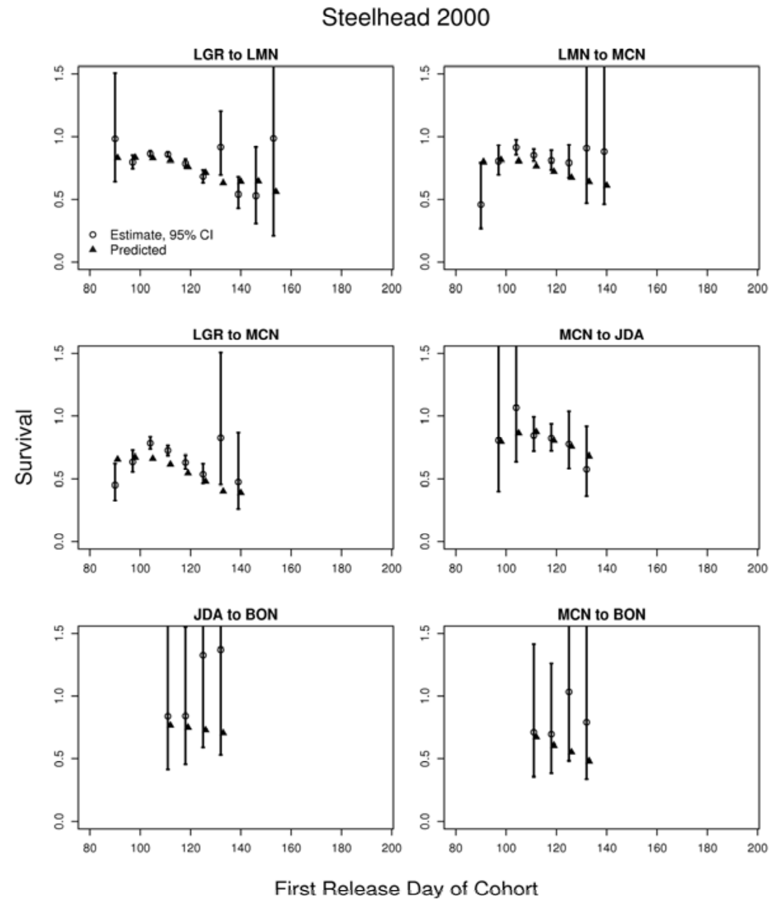


Figure A2-2 15. Survival probabilities for weekly groups of Snake River steelhead, by river segment, in 2000. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

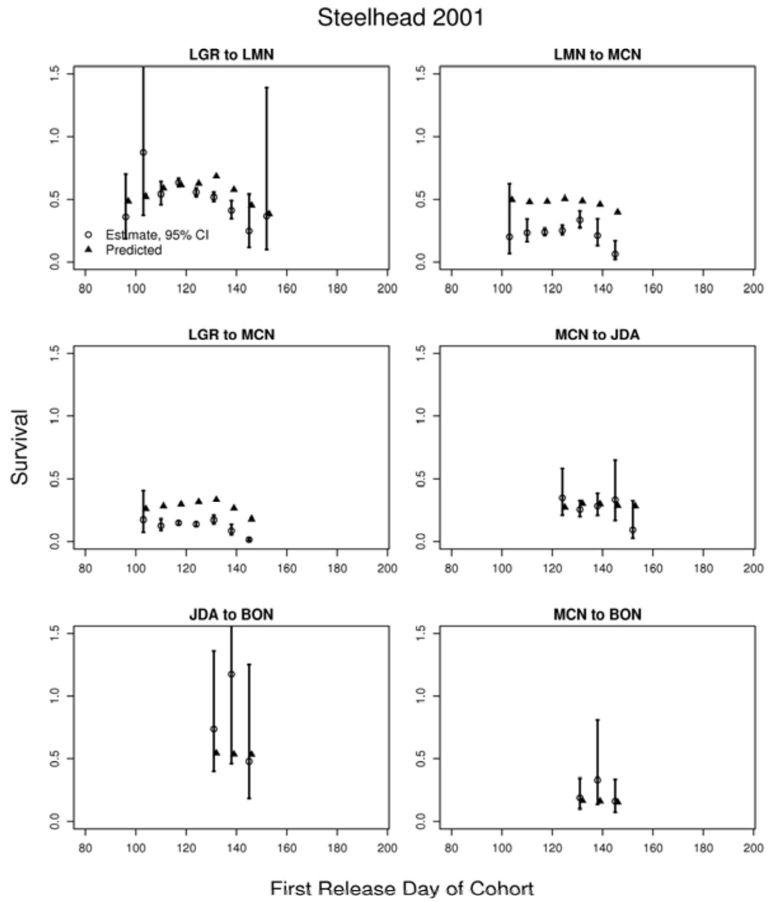


Figure A2-2 16. Survival probabilities for weekly groups of Snake River steelhead, by river segment, in 2001. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

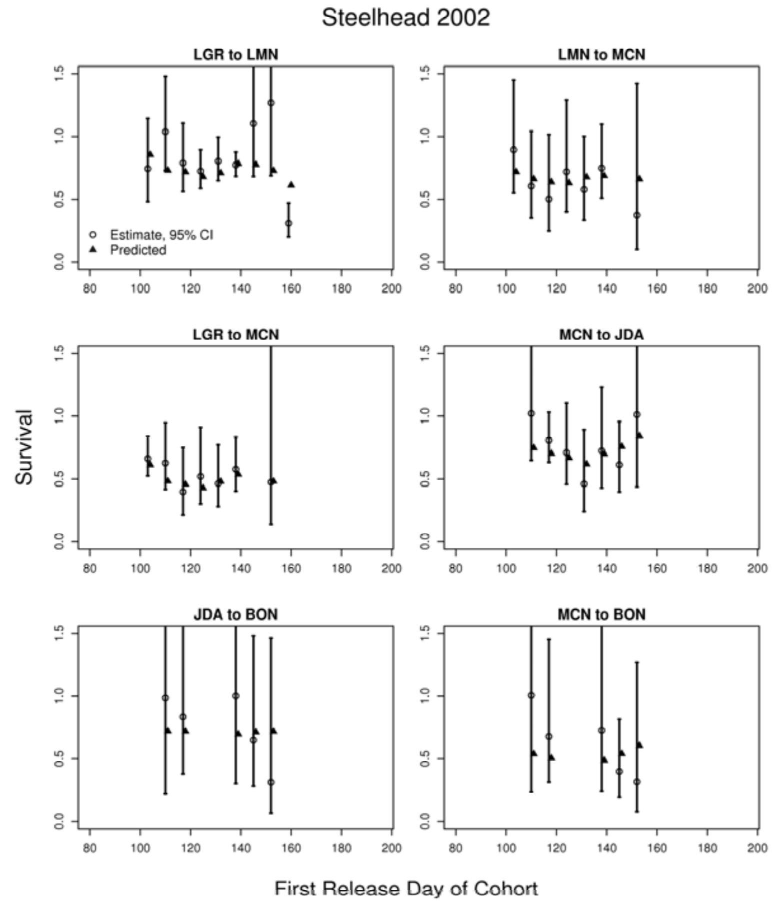


Figure A2-2 17. Survival probabilities for weekly groups of Snake River steelhead, by river segment, in 2002. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

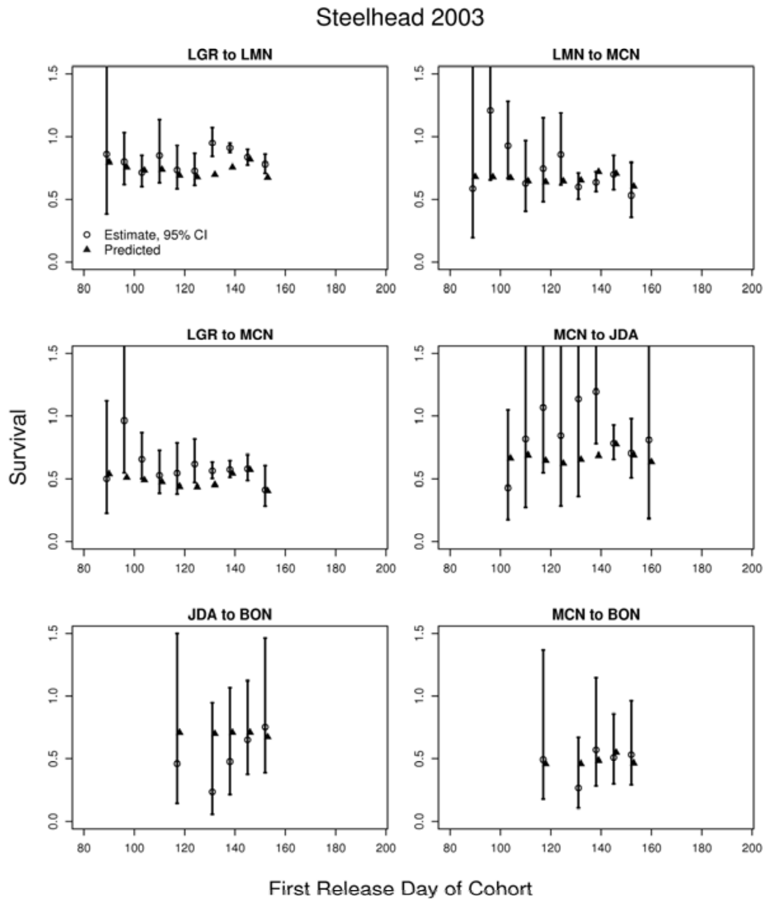


Figure A2-2 18. Survival probabilities for weekly groups of Snake River steelhead, by river segment, in 2003. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

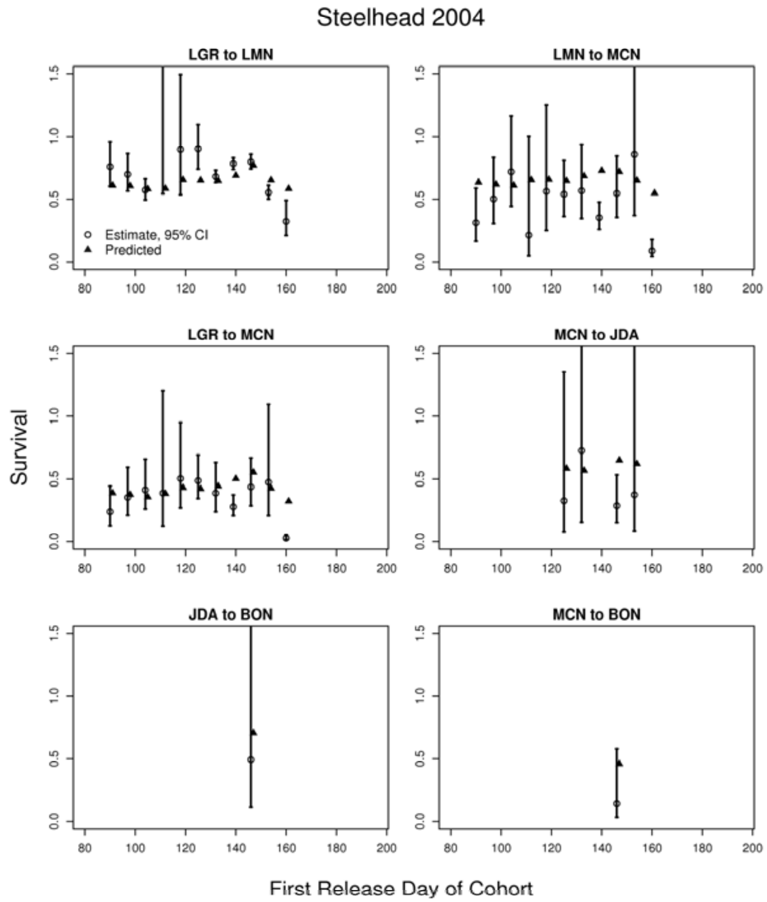


Figure A2-2 19. Survival probabilities for weekly groups of Snake River steelhead, by river segment, in 2004. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

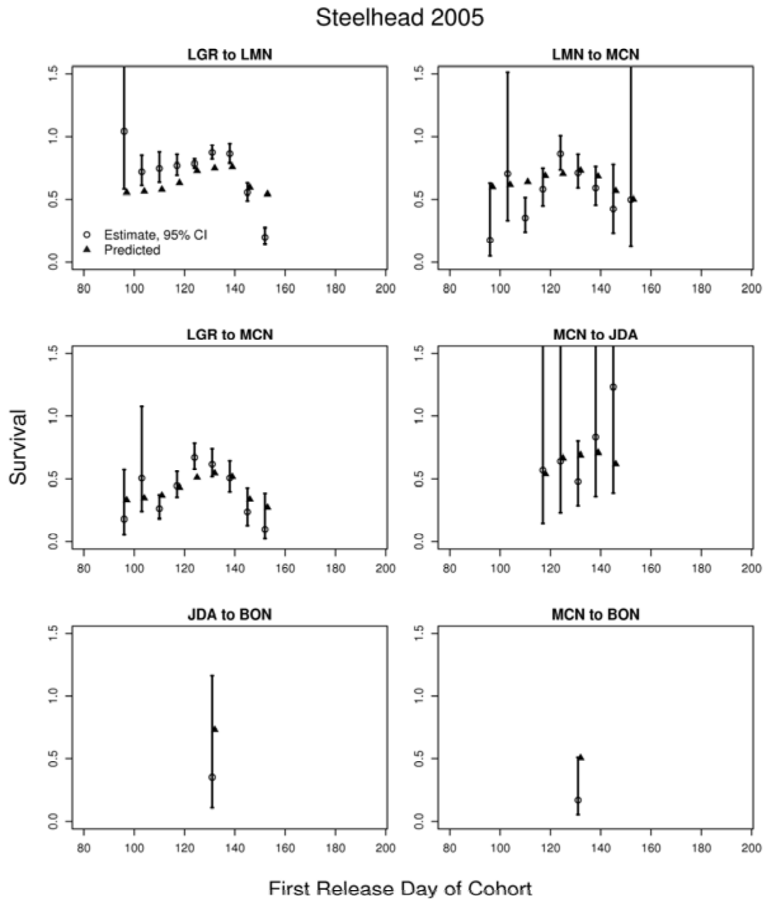


Figure A2-2 20. Survival probabilities for weekly groups of Snake River steelhead, by river segment, in 2005. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

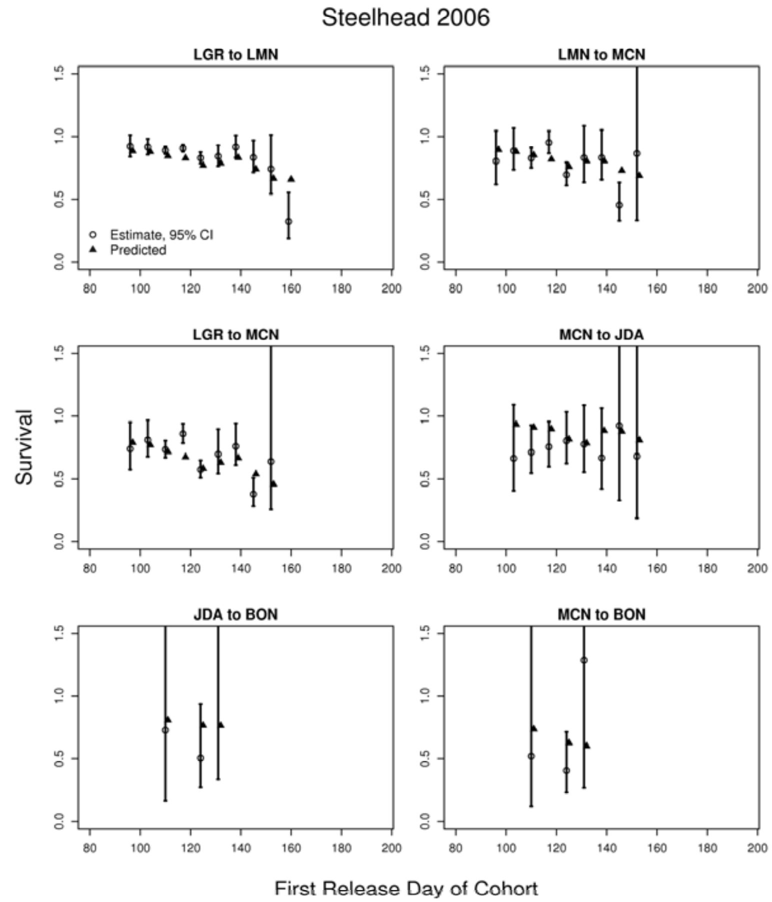


Figure A2-2 21. Survival probabilities for weekly groups of Snake River steelhead, by river segment, in 2006. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

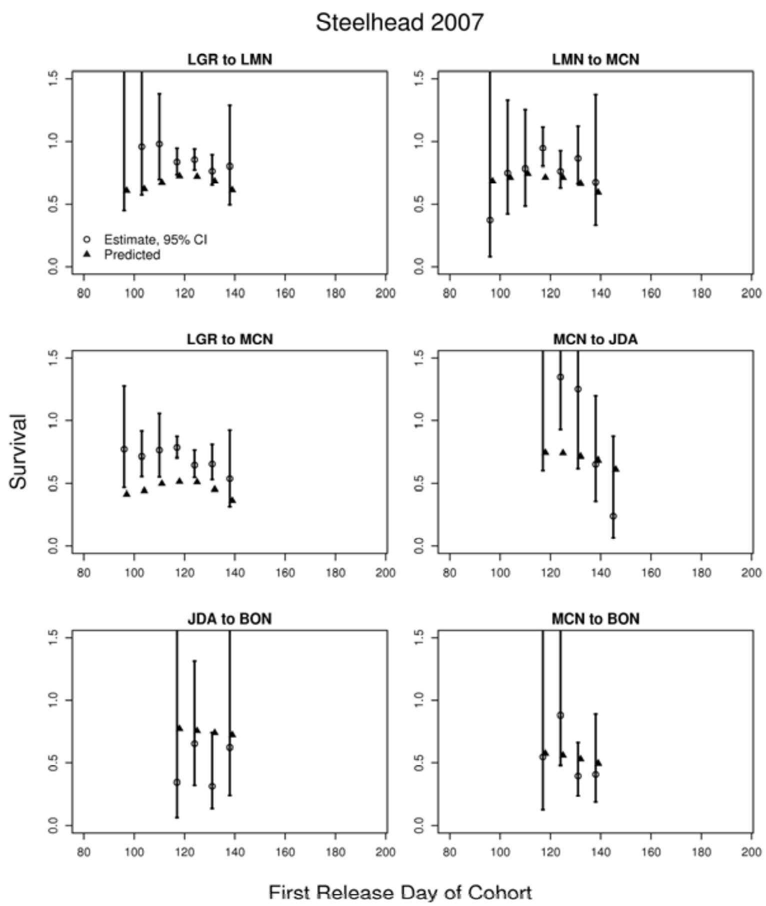


Figure A2-2 22. Survival probabilities for weekly groups of Snake River steelhead, by river segment, in 2007. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

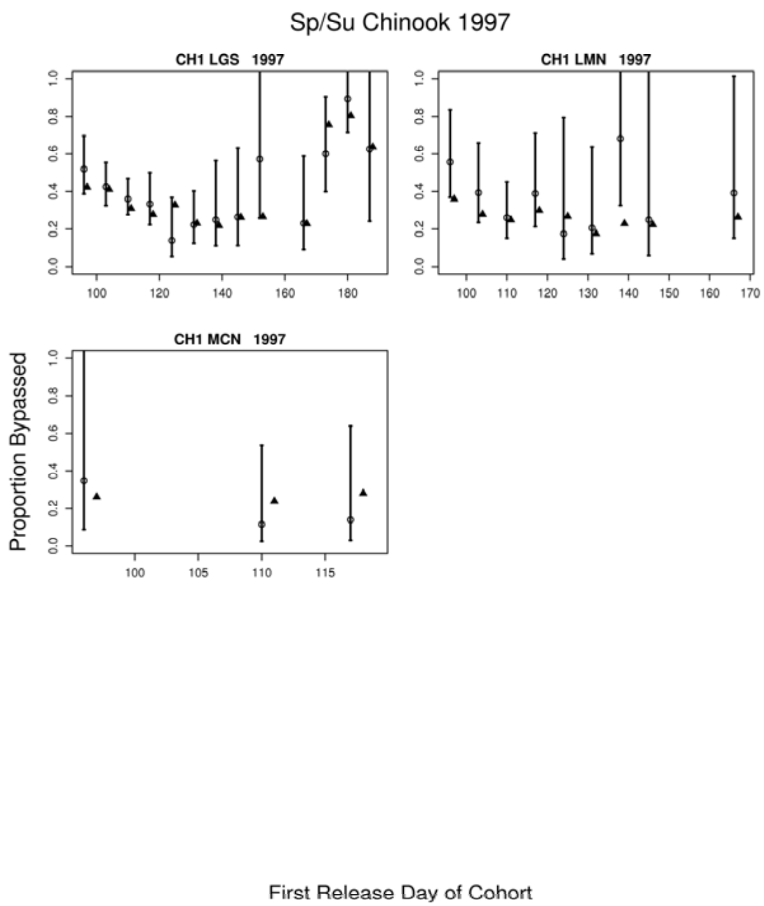


Figure A2-3 1. Proportion of Snake River sp/su Chinook passing bypass systems, by site, for weekly groups in 1997. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

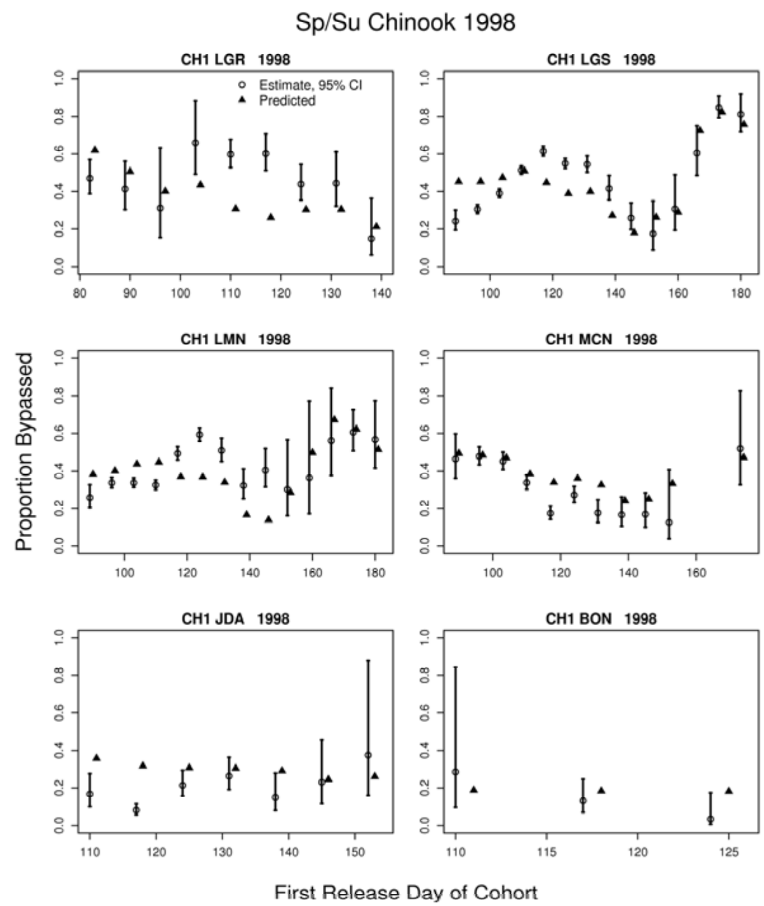


Figure A2-3 2. Proportion of Snake River sp/su Chinook passing bypass systems, by site, for weekly cohorts in 1998. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

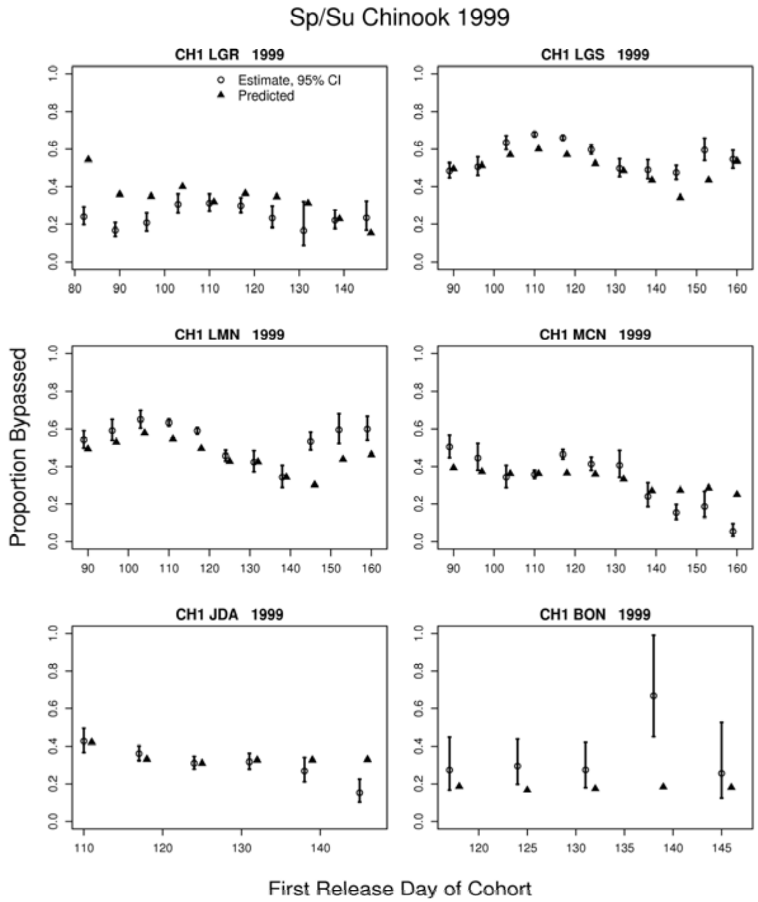


Figure A2-3 3. Proportion of Snake River sp/su Chinook passing bypass systems, by site, for weekly groups in 1999. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

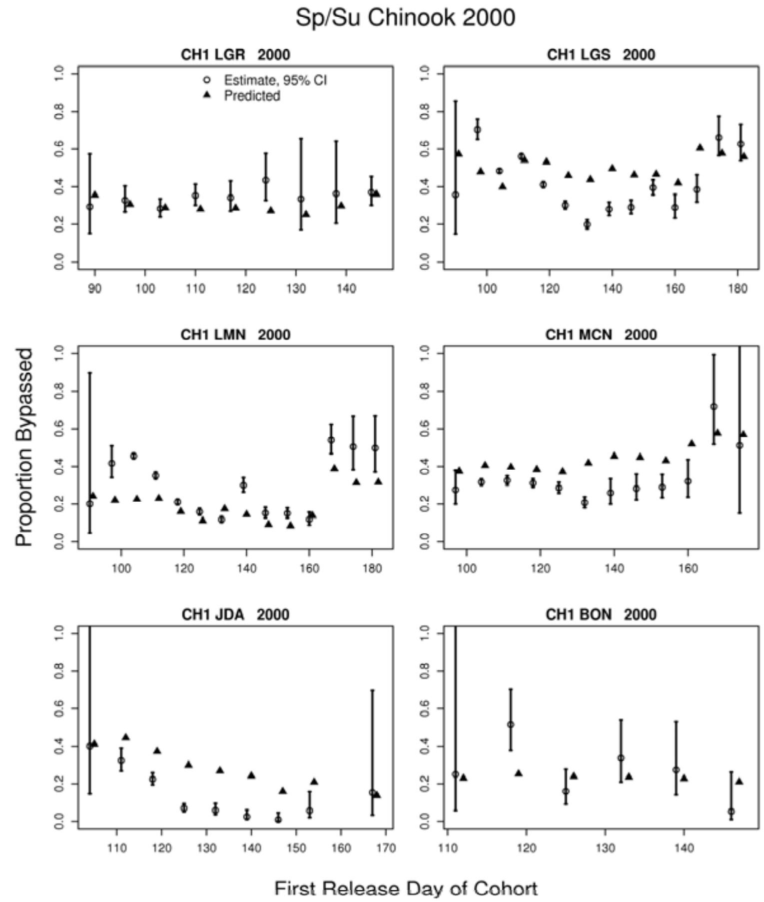


Figure A2-3 4. Proportion of Snake River sp/su Chinook passing bypass systems, by site, for weekly groups in 2000. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

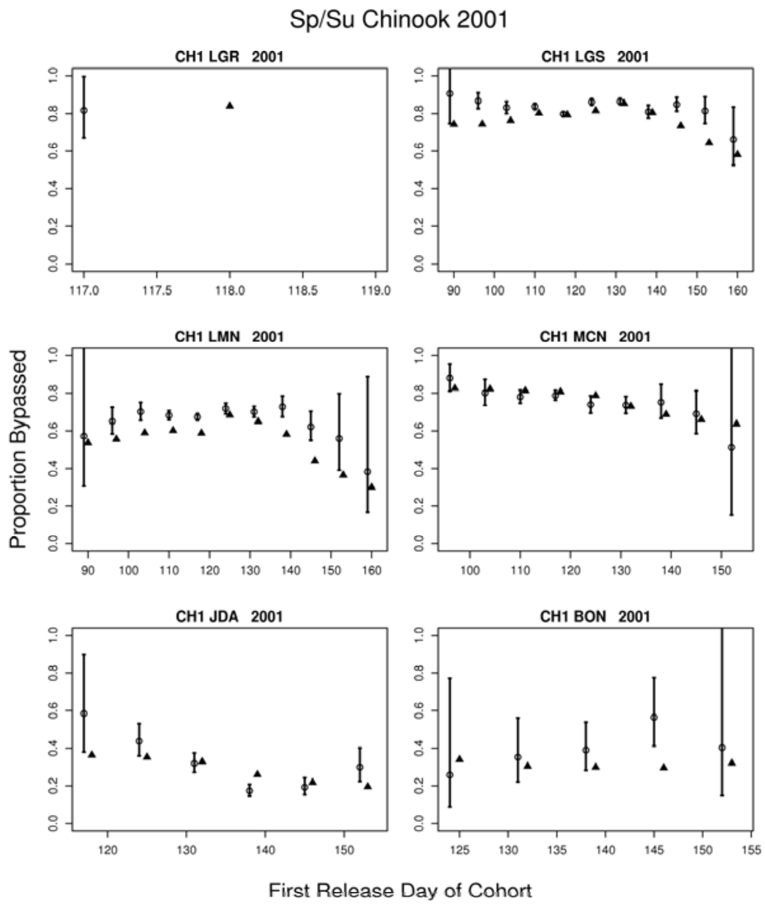


Figure A2-3 5. Proportion of Snake River sp/su Chinook passing bypass systems, by site, for weekly groups in 2001. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

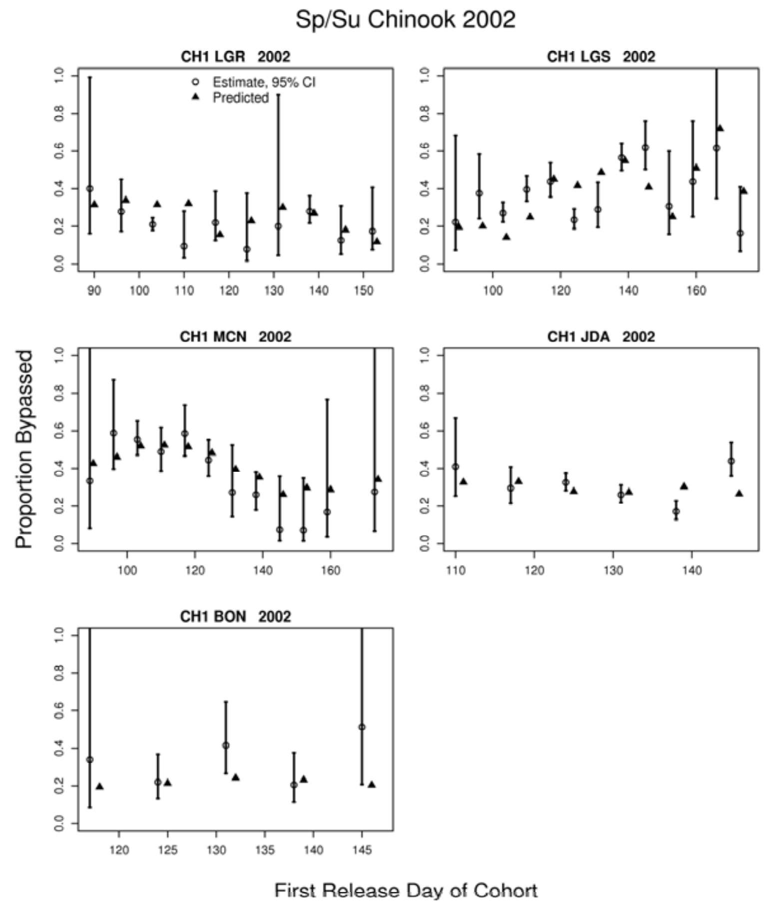


Figure A2-3 6. Proportion of Snake River sp/su Chinook passing bypass systems, by site, for weekly groups in 2002. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

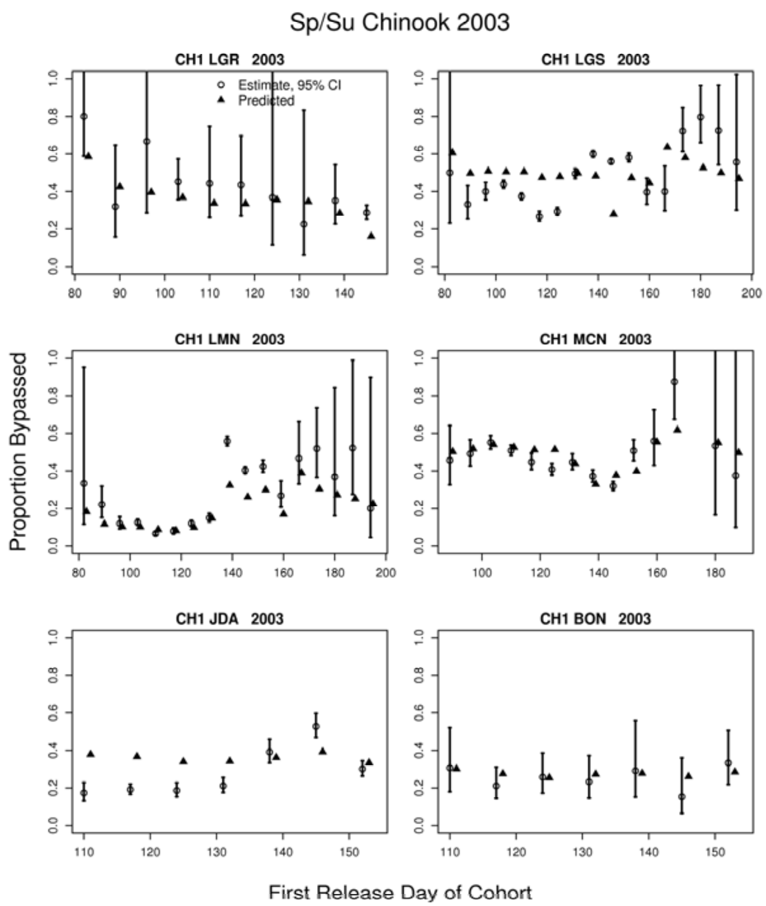


Figure A2-3 7. Proportion of Snake River sp/su Chinook passing bypass systems, by site, for weekly groups in 2003. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

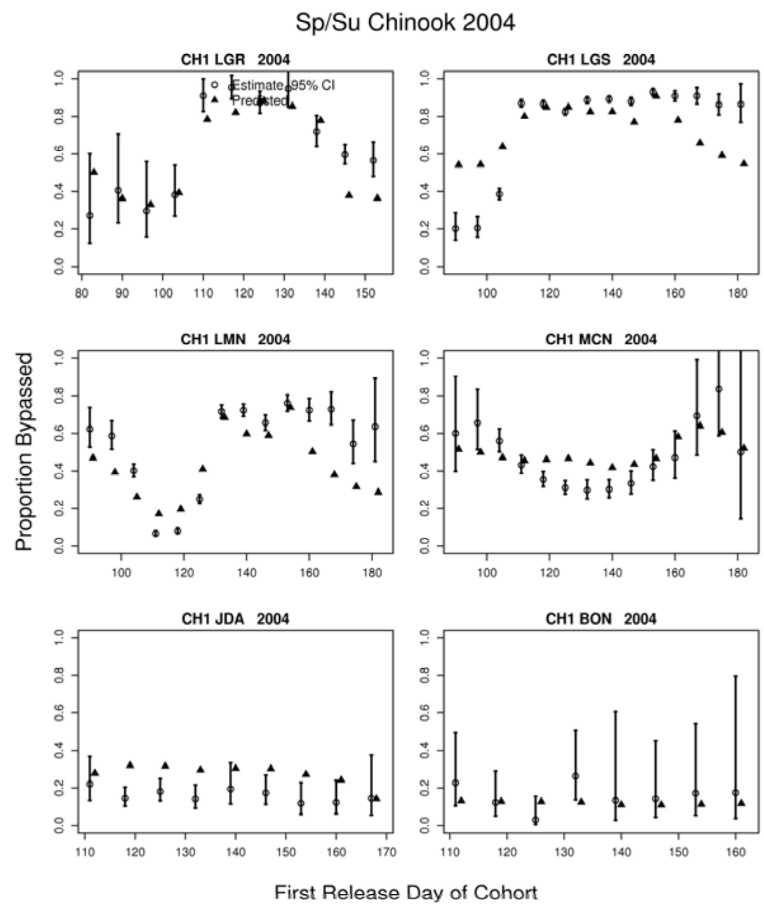


Figure A2-3 8. Proportion of Snake River sp/su Chinook passing bypass systems, by site, for weekly groups in 2004. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

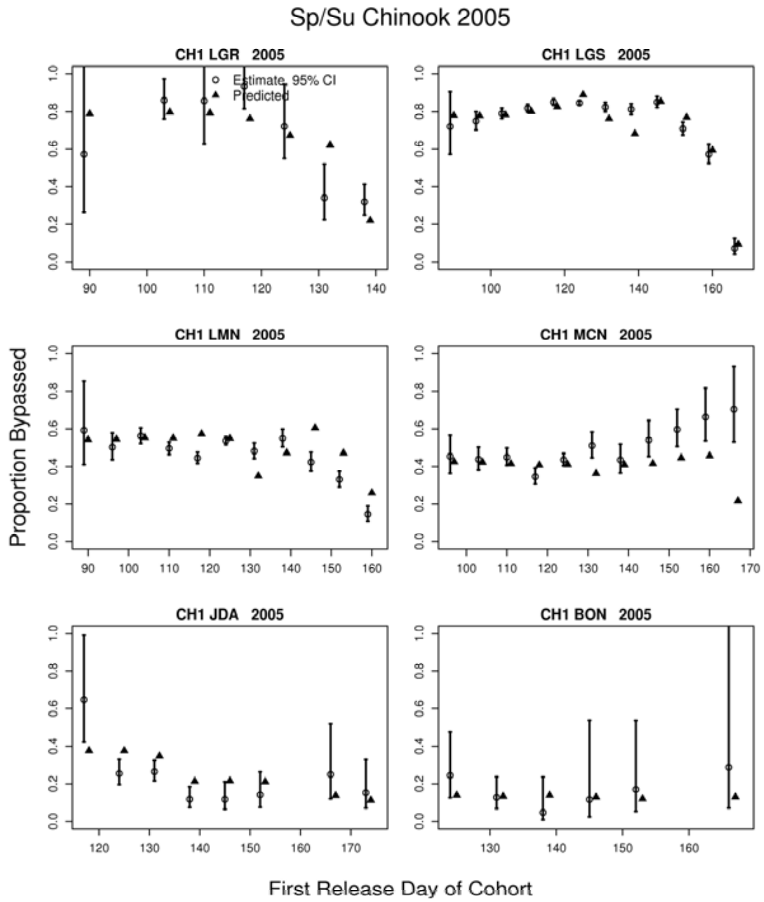


Figure A2-3 9. Proportion of Snake River sp/su Chinook passing bypass systems, by site, for weekly groups in 2005. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

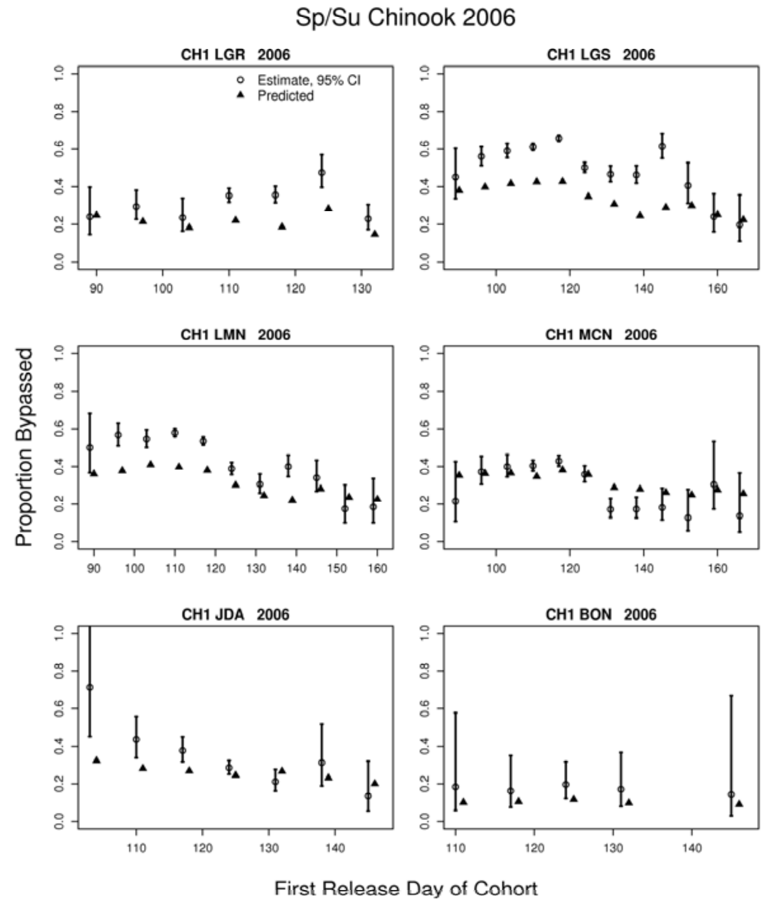


Figure A2-3 10. Proportion of Snake River sp/su Chinook passing bypass systems, by site, for weekly groups in 2006. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

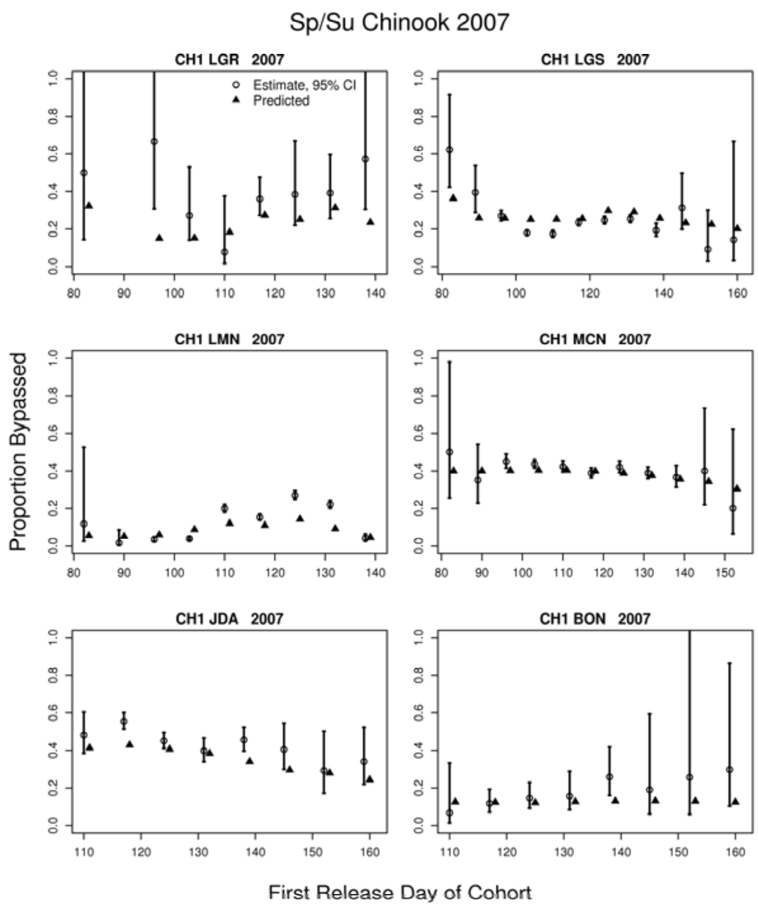


Figure A2-3 11. Proportion of Snake River sp/su Chinook passing bypass systems, by site, for weekly groups in 2007. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

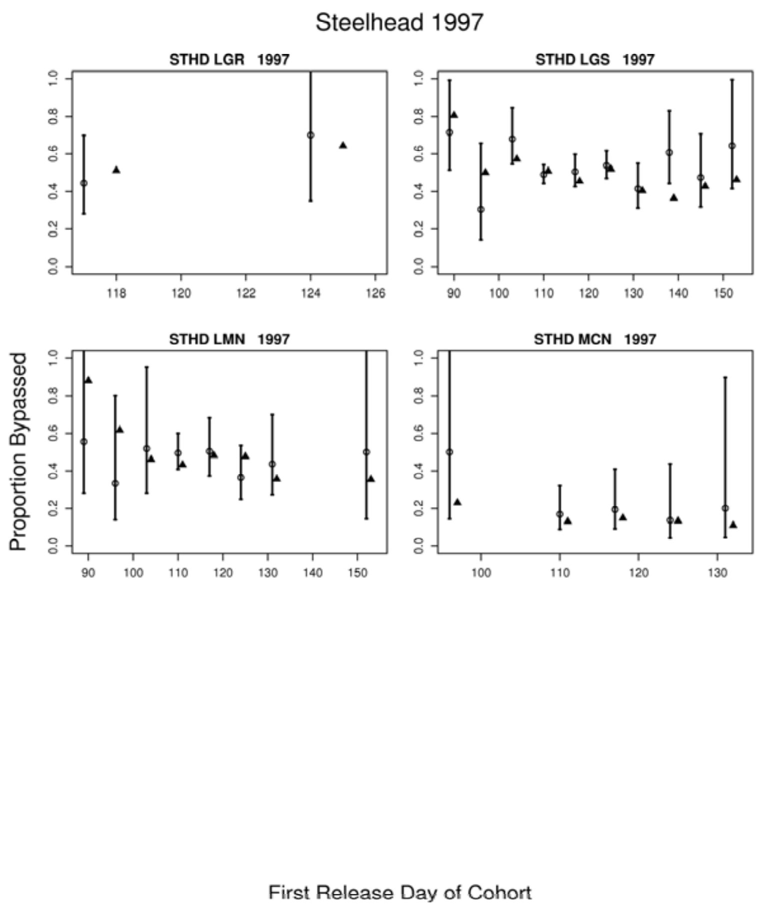


Figure A2-3 12. Proportion of Snake River Steelhead passing bypass systems, by site, for weekly groups in 1997. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

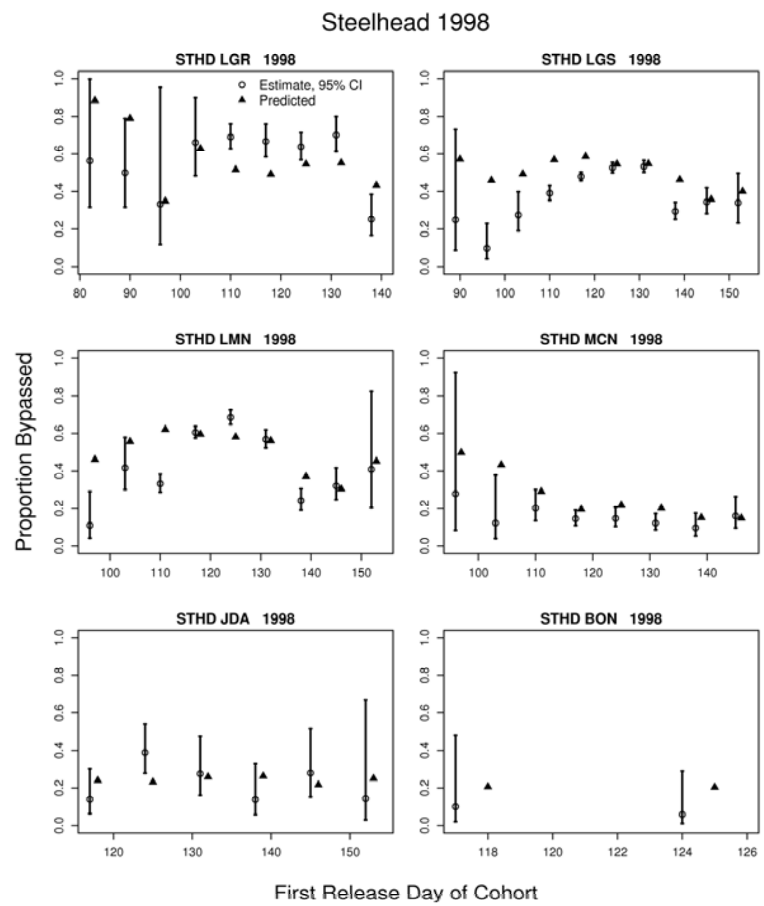


Figure A2-3 13. Proportion of Snake River Steelhead passing bypass systems, by site, for weekly cohorts in 1998. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

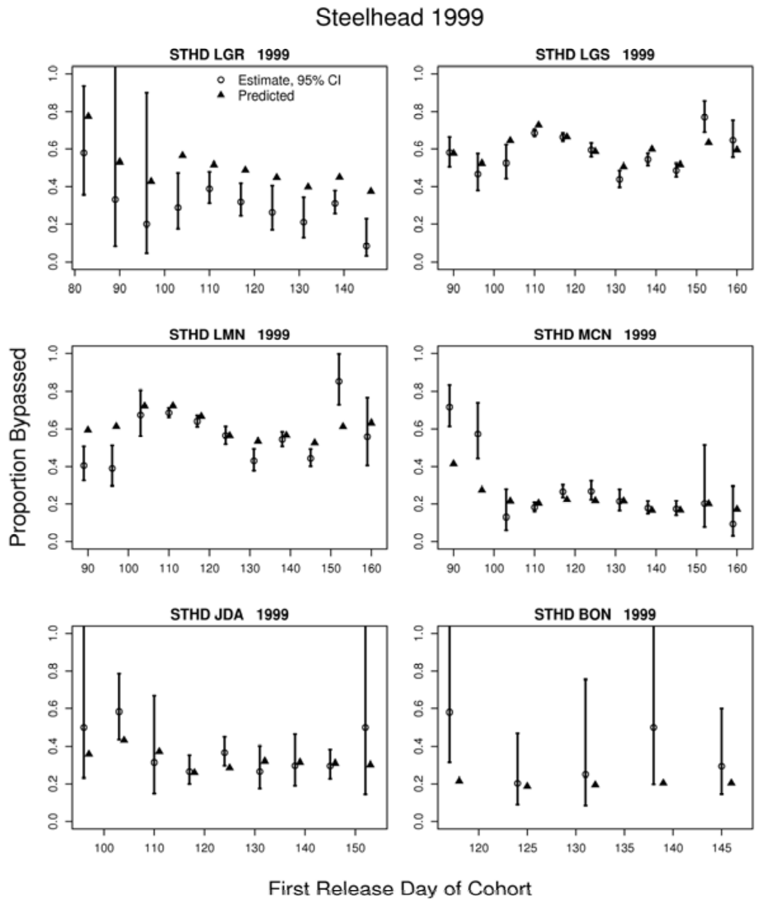


Figure A2-3 14. Proportion of Snake River Steelhead passing bypass systems, by site, for weekly groups in 1999. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

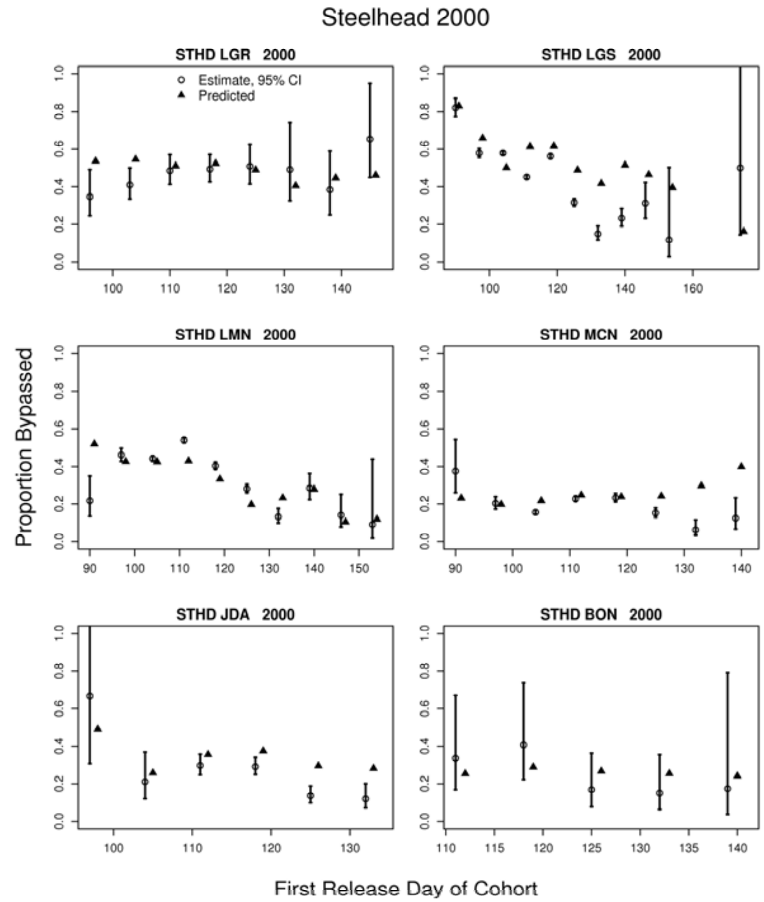


Figure A2-3 15. Proportion of Snake River Steelhead passing bypass systems, by site, for weekly groups in 2000. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

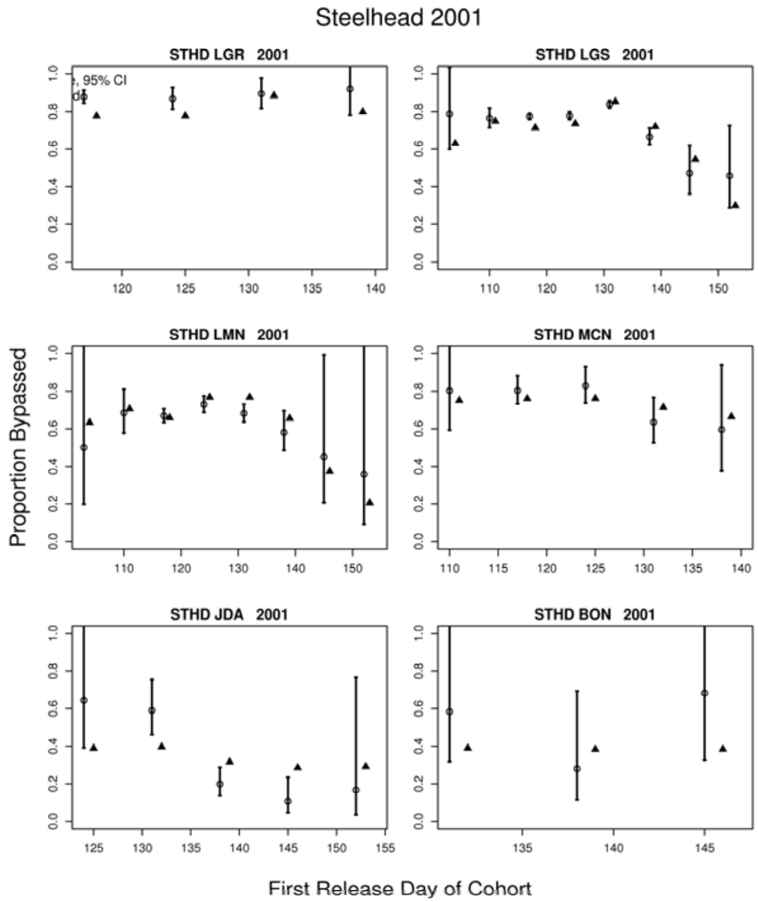


Figure A2-3 16. Proportion of Snake River Steelhead passing bypass systems, by site, for weekly groups in 2001. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

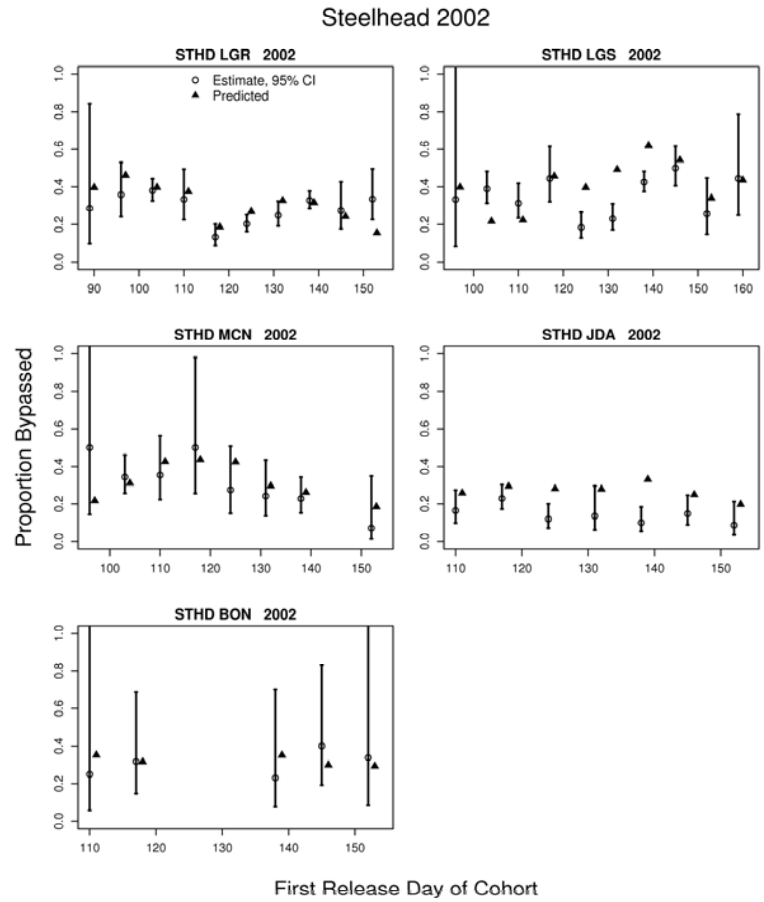


Figure A2-3 17. Proportion of Snake River Steelhead passing bypass systems, by site, for weekly groups in 2002. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

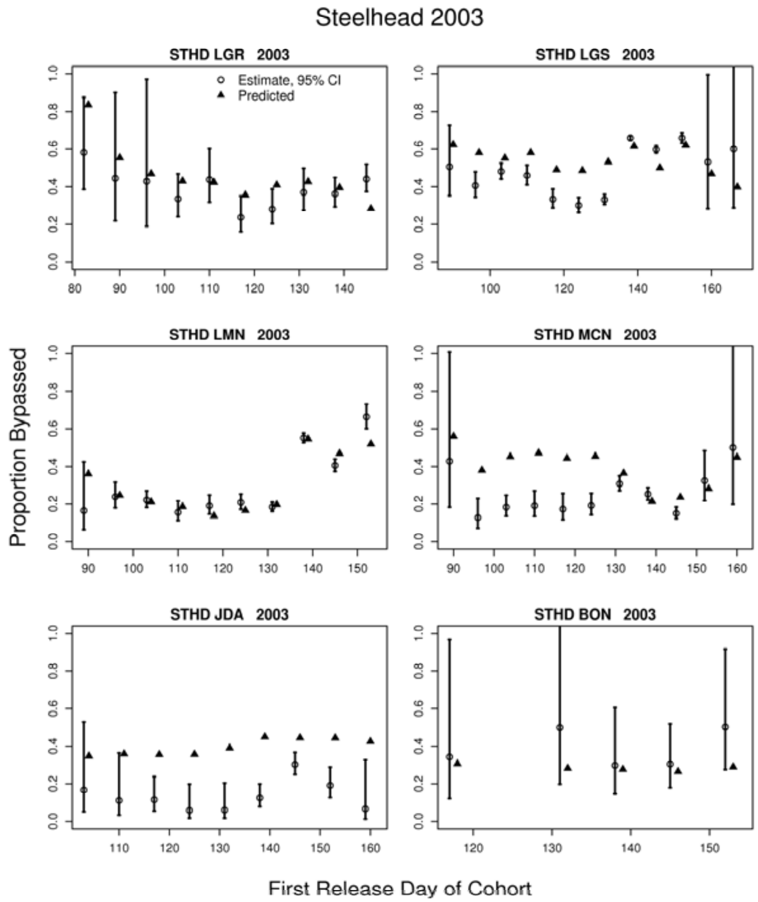


Figure A2-3 18. Proportion of Snake River Steelhead passing bypass systems, by site, for weekly groups in 2003. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

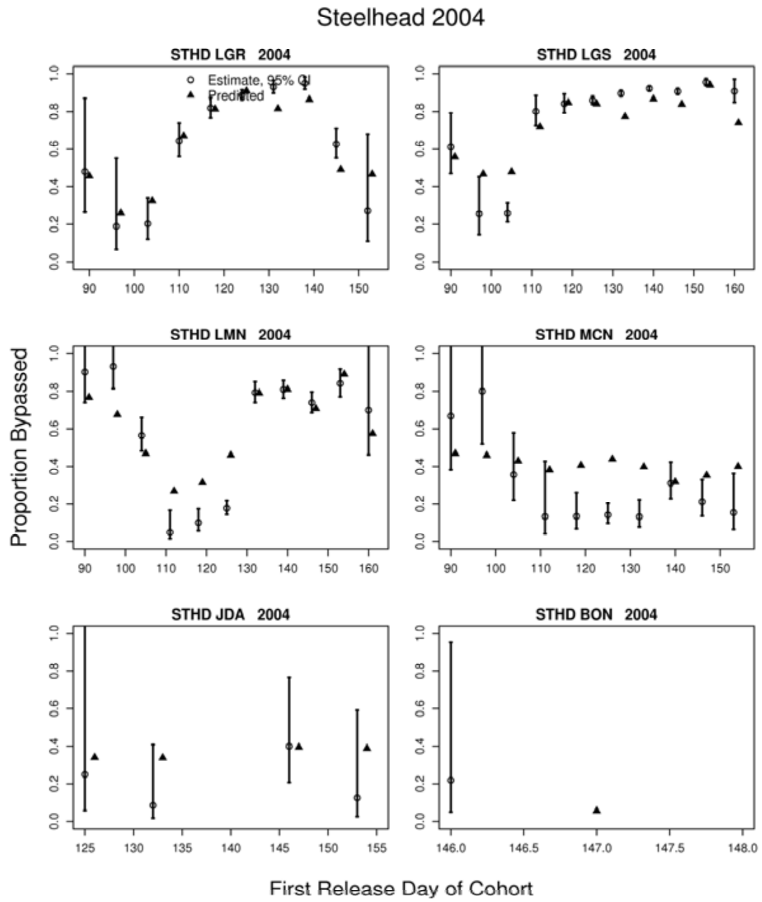


Figure A2-3 19. Proportion of Snake River Steelhead passing bypass systems, by site, for weekly groups in 2004. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

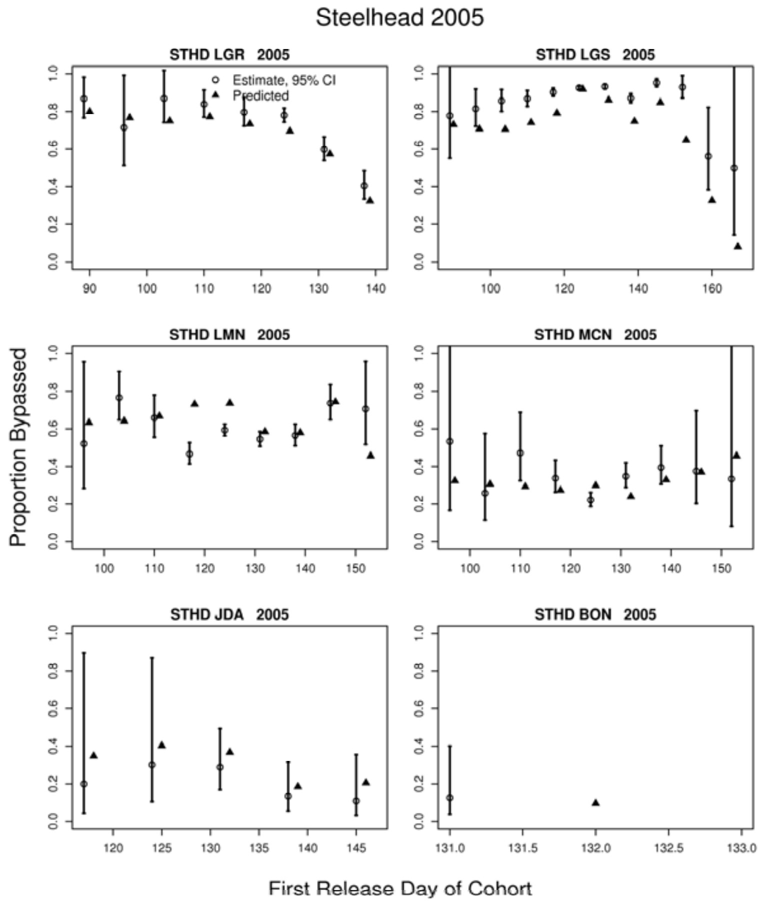


Figure A2-3 20. Proportion of Snake River Steelhead passing bypass systems, by site, for weekly groups in 2005. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

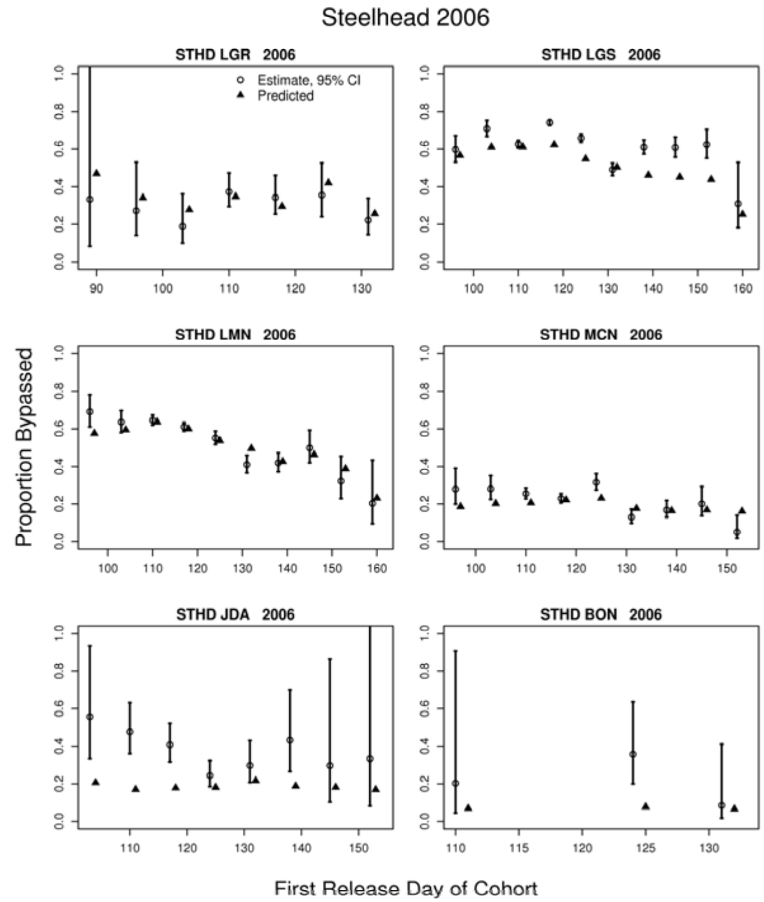


Figure A2-3 21. Proportion of Snake River Steelhead passing bypass systems, by site, for weekly groups in 2006. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

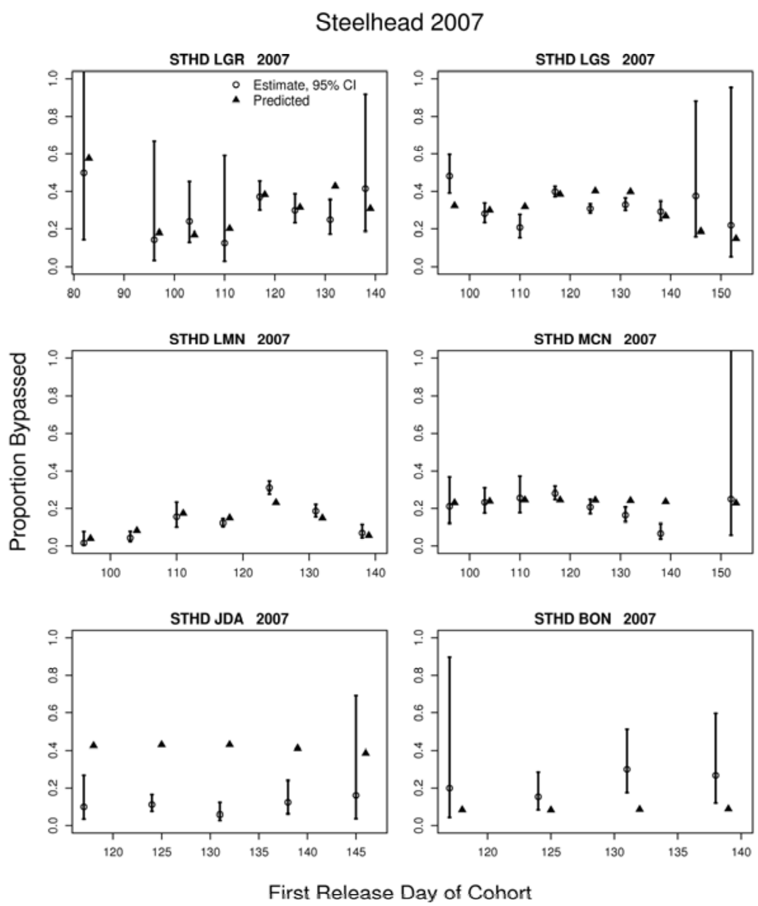


Figure A2-3 22. Proportion of Snake River Steelhead passing bypass systems, by site, for weekly groups in 2007. Triangles represent COMPASS model predictions. Points represent PIT-tag estimate, and the vertical line represent the 95% CI.

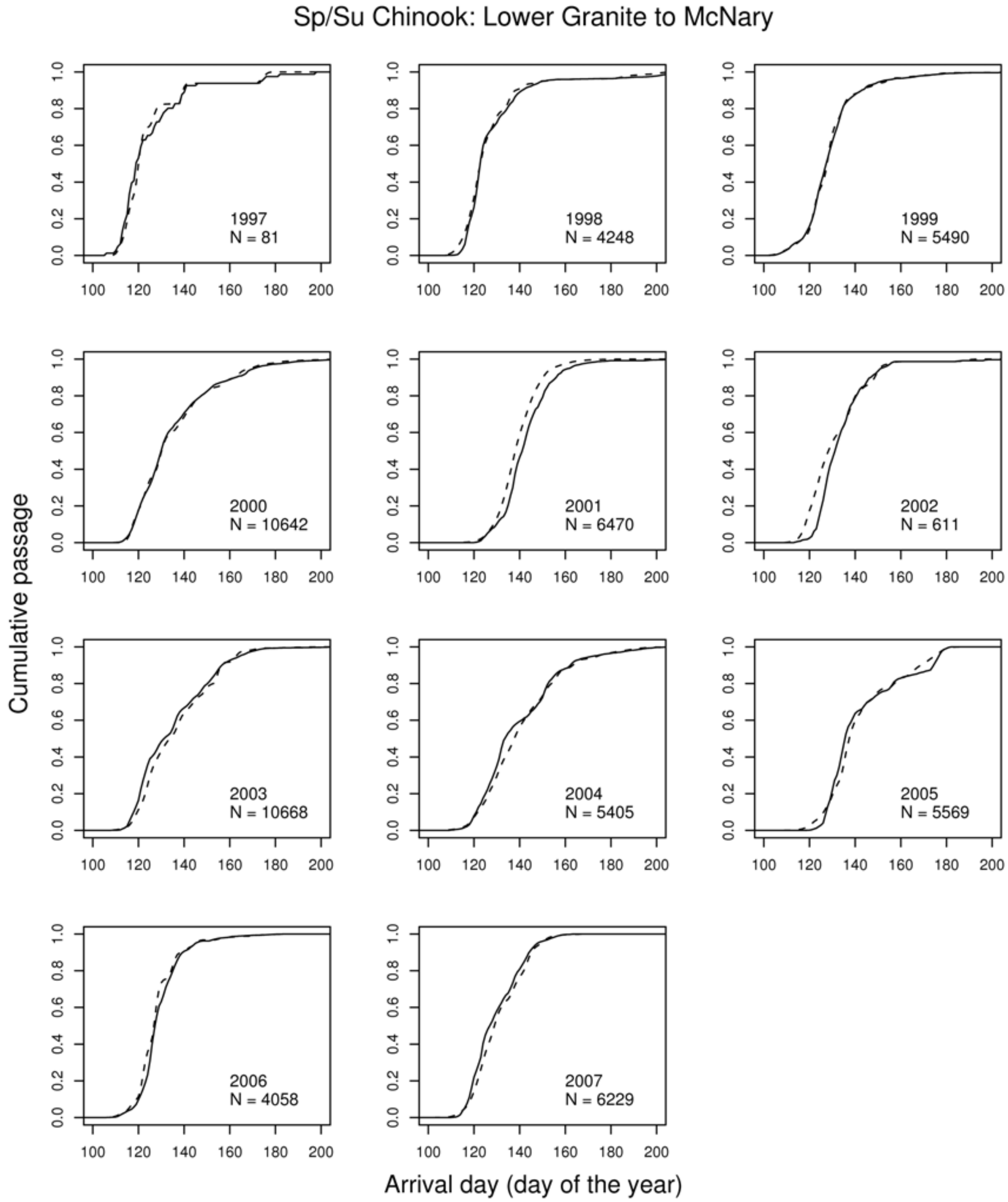


Figure A2-4 1. Predicted (dashed line) versus observed (solid line) passage distribution at McNary Dam for Snake River spring/summer Chinook grouped at Lower Granite Dam. N refers to the number of observed fish.

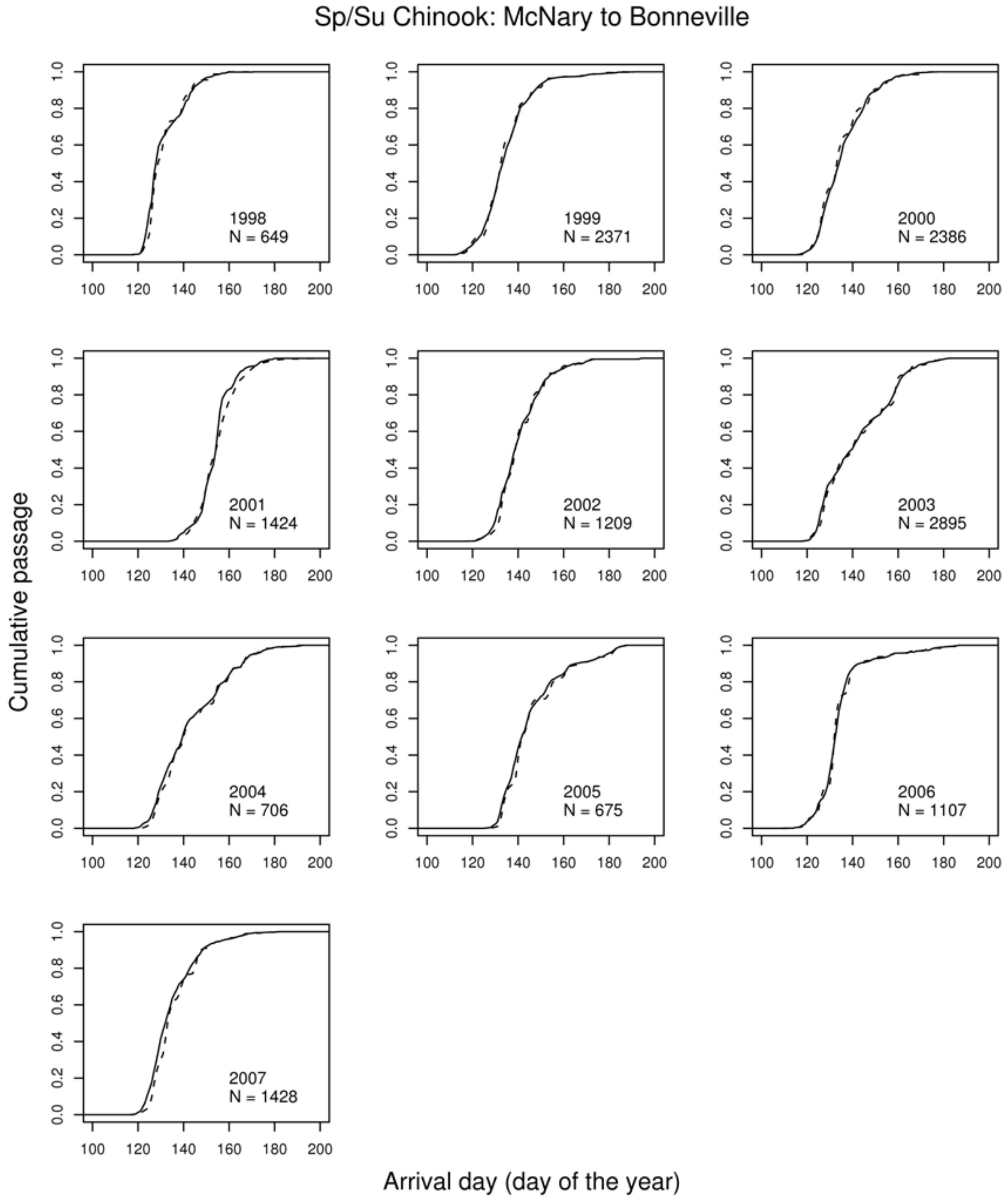


Figure A2-4 2. Predicted (dashed line) versus observed (solid line) passage distribution at Bonneville Dam for Snake River spring/summer Chinook grouped at McNary Dam. N refers to the number of observed fish.

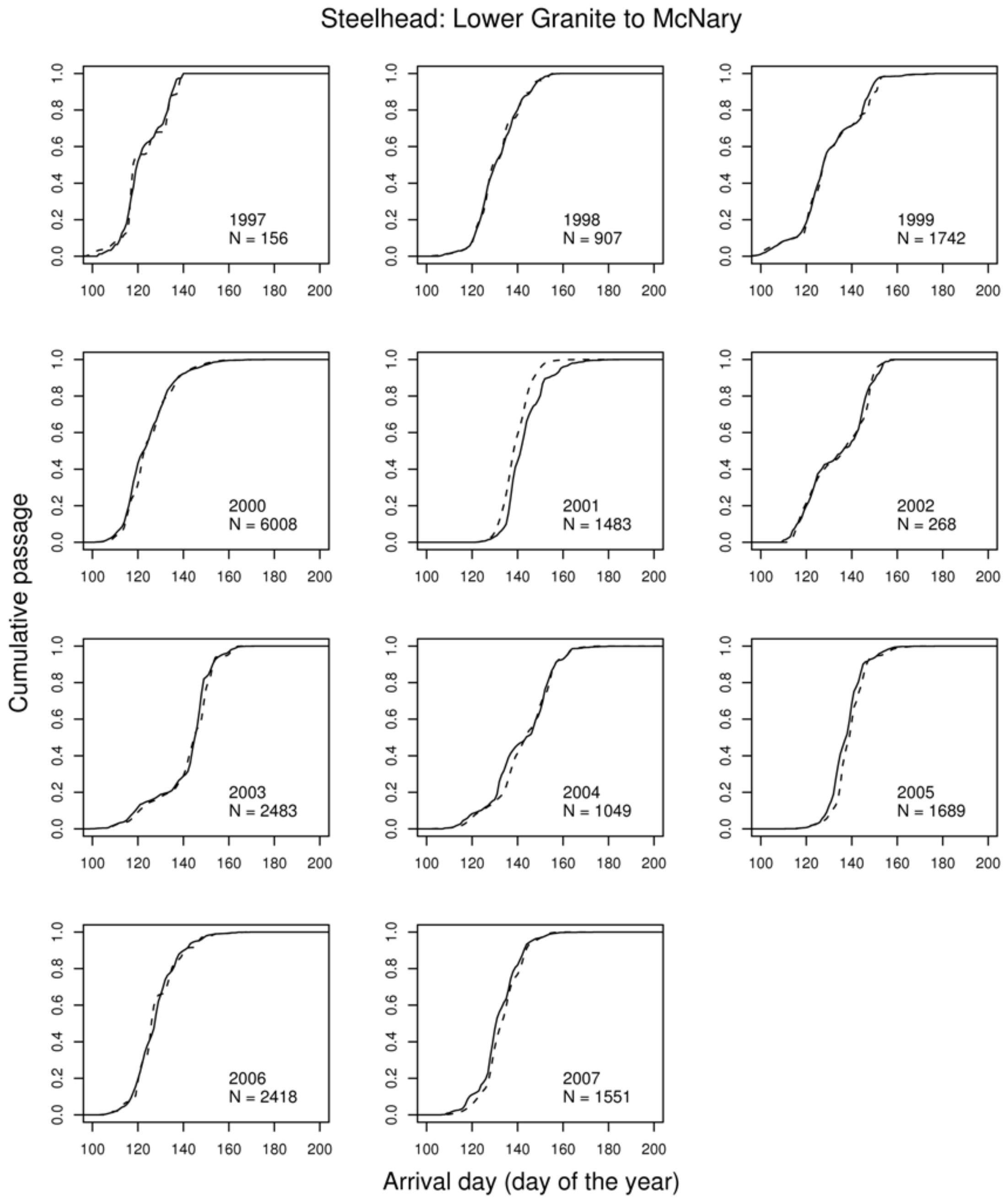


Figure A2-4 3. Predicted (dashed line) versus observed (solid line) passage distribution at McNary Dam for Snake River steelhead grouped at Lower Granite Dam. N refers to the number of observed fish.

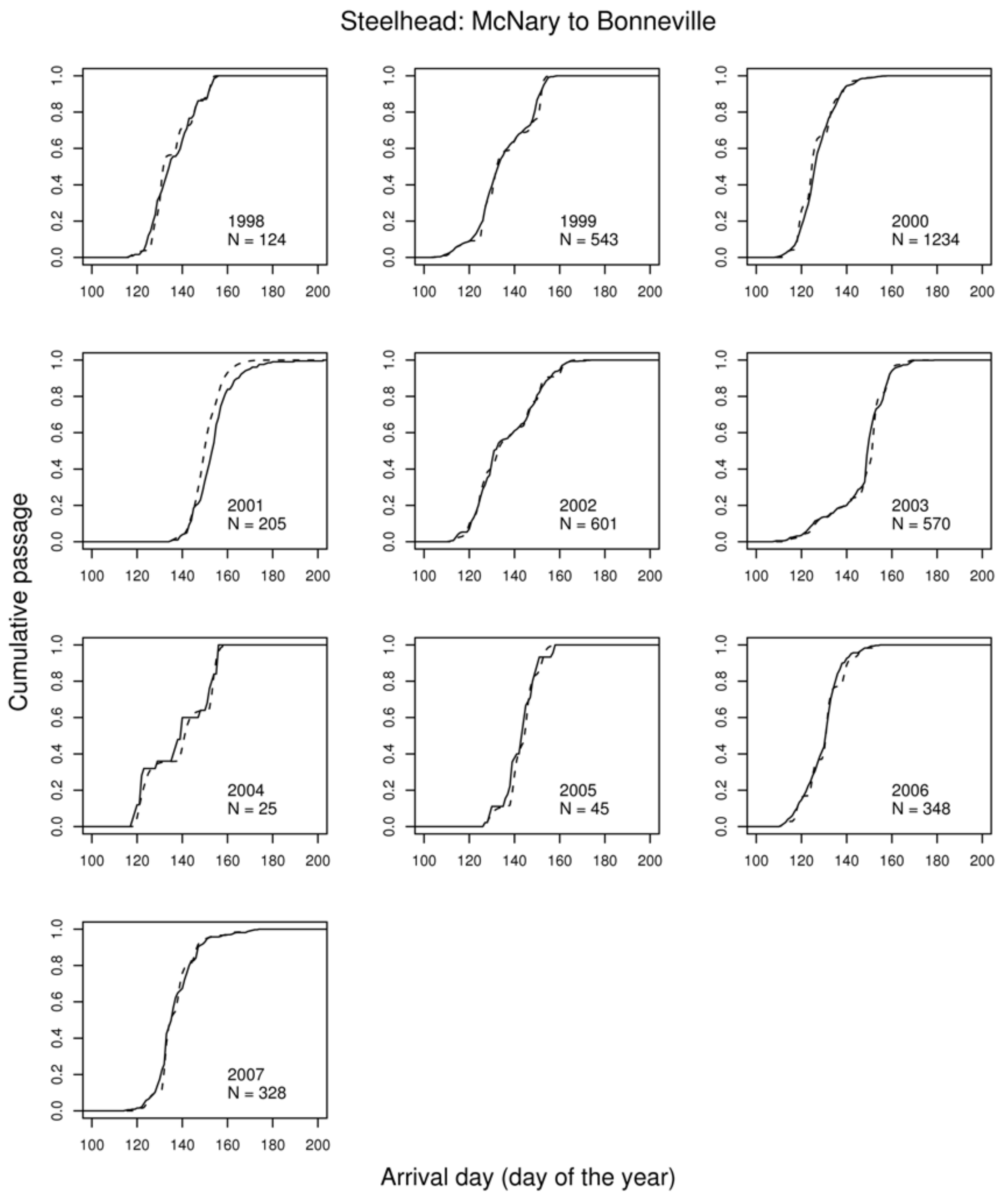


Figure A2-4 4. Predicted (dashed line) versus observed (solid line) passage distribution at Bonneville Dam for Snake River steelhead grouped at McNary Dam. N refers to the number of observed fish.

Section 1: Comparison of reservoir survival models

In this section, we compared performance among alternative reservoir survival models. The alternative model formulation and model selection routine are described in Section 2.3 of the main text. For each model, we computed AICc (AIC corrected for sample size, Burnham and Anderson 2002), ΔAICc (relative to the best fitting model), and AIC weight (see Section 2.3 of the main text for a description). The AIC weights are interpreted as estimates of the probability that any particular model is the "best" one among the suite of alternative models considered in the candidate set.

We had two primary objectives in this analysis. First, we assessed the relative performance of the best fitting models to determine whether one model was clearly best fitting or whether several models received similar weights. We included the top 5 best fitting models for each species/river segment combination in this part of the analysis. Second, we assessed the effect on model fit of removing model terms, namely distance, flow, and temperature. Here, we included the best fitting models that excluded each of these terms. To calculate the AIC weights, we included all of these models (top 5 and the three reduced models) in the candidate set. In some cases, the reduced models appeared in the top 5.

Results and discussion

In all 4 cases, the top model received the majority (at least 70%) of the model weight (Tables A3 1-4). Thus, using a single reservoir model for prospective modeling appears justified. Nonetheless, we plan to sample from alternative models according to their weight (as was done for the post-Bonneville modeling in Appendix 8-2) when we run the model in Monte-Carlo mode.

Removing flow, temperature, and distance from the reservoir survival relationship resulted in much worse fits in the Lower Granite to McNary river segments. When these terms were removed, the resulting models received little to no weight and AICc increased substantially, indicating that these terms were important to reservoir survival. The results were not as dramatic in the segments from McNary to Bonneville, but the data quality was relatively poor in these river segments (see Appendices 1 and 2), resulting in a decreased ability to detect effects.

References

Burnham, K. P., and D. R. Anderson. 2002. Model selection and inference, a practical information-theoretic approach, second edition. Springer-Verlag, New York.

Table A3 1. Model comparisons for Snake River spring/summer Chinook salmon migrating from Lower Granite Dam to McNary Dam. The category of models are Top 5 best fitting models (T5), no distance terms (ND), no flow terms (NF), and no temperature terms (NTmp). Model terms are distance (x), flow (F), temperature (T), spill (S), and travel time (t). An x or a t in front of a term means there was an interaction between the terms. In the model terms columns, a 0 means the term was not present, a 1 means the term was present, and a 2 means the temperature term was squared. ΔAICc is relative to the top model, and AIC weight is calculated as in Section 2.3 in the main text.

	Model terms										
Category	x	xF	xT	xS	t	tF	tT	tS	AICc	ΔAICc	weight
T5	1	1	0	1	1	0	2	0	-256.62	0.00	0.813
T5	1	1	0	0	1	0	2	1	-253.62	3.00	0.182
T5	1	1	2	1	0	0	0	0	-245.47	11.14	0.003
T5, NF	1	0	0	1	1	0	2	0	-244.72	11.90	0.002
T5	1	0	2	1	0	0	0	0	-240.43	16.18	0.000
ND	0	0	0	0	1	0	1	0	-220.62	35.99	0.000
NTmp	1	1	0	1	0	0	0	0	-186.78	69.84	0.000

Table A3 2. Model comparisons for Snake River spring/summer Chinook salmon migrating from McNary Dam to Bonneville Dam. The category of models are Top 5 best fitting models (T5), no distance terms (ND), no flow terms (NF), and no temperature terms (NTmp). Model terms are distance (x), flow (F), temperature (T), and travel time (t). An x or a t in front of a term means there was an interaction between the terms. In the model terms columns, a 0 means the term was not present, a 1 means the term was present, and a 2 means the temperature term was squared. ΔAICc is relative to the top model, and AIC weight is calculated as in Section 2.3 in the main text.

Category	x	xF	xT	xS	t	tF	tT	tS	AICc	ΔAICc	weight
T5,ND,NF,NTmp	0	0	0	0	1	0	0	0	154.84	0.00	0.841
T5	1	0	2	0	1	0	0	0	158.75	3.91	0.119
T5	1	1	0	0	0	0	0	0	161.48	6.64	0.030
T5	1	1	2	0	0	0	0	0	164.99	10.15	0.005
T5	1	0	0	0	0	0	0	0	165.40	10.56	0.004

Table A3 3. Table A3 1. Model comparisons for Snake River steelhead migrating from Lower Granite Dam to McNary Dam. The category of models are Top 5 best fitting models (T5), no distance terms (ND), no flow terms (NF), and no temperature terms (NTmp). Model terms are distance (x), flow (F), temperature (T), and travel time (t). An x or a t in front of a term means there was an interaction between the terms. In the model terms columns, a 0 means the term was not present, a 1 means the term was present, and a 2 means the temperature term was squared. ΔAICc is relative to the top model, and AIC weight is calculated as in Section 2.3 in the main text.

Category	x	xF	xT	xS	t	tF	tT	tS	AICc	ΔAICc	weight
T5	1	0	0	0	1	1	2	0	43.15	0.00	0.979
T5	1	0	1	0	1	1	0	0	50.81	7.65	0.021
T5, ND	0	0	0	0	1	1	2	0	61.28	18.13	0.000
T5	1	1	0	0	1	0	2	0	64.57	21.41	0.000
T5	1	0	2	0	1	1	0	0	67.19	24.04	0.000
NTmp	1	0	0	1	1	1	0	0	83.58	40.43	0.000
NF	1	0	2	0	1	0	0	0	103.81	60.66	0.000

Table A3 4. Table A3 2. Model comparisons for Snake River steelhead migrating from McNary Dam to Bonneville Dam. The category of models are Top 5 best fitting models (T5), no distance terms (ND), no flow terms (NF), and no temperature terms (NTmp). Model terms are distance (x), flow (F), temperature (T), and travel time (t). An x or a t in front of a term means there was an interaction between the terms. In the model terms columns, a 0 means the term was not present, a 1 means the term was present, and a 2 means the temperature term was squared. ΔAICc is relative to the top model, and AIC weight is calculated as in Section 2.3 in the main text.

Category	x	xF	xT	xS	t	tF	tT	tS	AICc	ΔAICc	weight
T5, ND	0	0	0	0	1	1	1	0	217.56	0.00	0.708
T5	0	0	0	0	1	1	2	0	220.31	2.75	0.179
T5	1	0	0	0	1	1	2	0	223.12	5.56	0.044
T5	1	0	1	0	1	1	0	0	223.93	6.37	0.029
T5	0	0	0	0	1	1	0	0	224.89	7.33	0.018
NTmp	1	1	0	0	1	0	2	1	224.89	7.33	0.018
NF	0	0	0	0	1	0	2	0	227.82	10.26	0.004

Section 2: Comparisons of model form

In this section, we conduct several analyses to assess relative performance of alternative model forms. In particular, we examined a log transform versus a logit transformation of the survival data and we assessed the importance of incorporating intercept terms. To simplify the comparisons, we used the "external" dataset described in the model uncertainty appendix (Appendix 7). This dataset contains project survival estimates with dam survival (based on COMPASS model runs) "backed out" to produce estimates of reservoir survival. In addition, the dataset contains median travel times of cohorts and cohort environmental exposure indices (weighted averages based on cohort passage distributions). This dataset allowed us to quickly conduct analyses to determine whether particular model forms should be included in COMPASS.

Log versus logit transformations

To compare log versus logit transforms, we compared a suite of models that included the same predictor variables (distance, travel time, flow, proportion river spilled, temperature, and temperature^2) but with different transformed dependent variables (log or logit transformations). The regressions were weighted by the variance of the survival estimates. Because we couldn't directly compare model performance with different response variables, we back transformed predicted survival and compared it to observed survival. For each transformation and model, we calculated a weighted sum of squares of predicted versus observed survival. We compared the resulting weighted sum of squares between transformed models that included identical predictor variables.

For Chinook, the back-transformed weighted sum of squares for models with the logit transformation were generally greater than those for the log transformed models (Figure A3 1). For steelhead, the logit transformation received more support (Figure A3 2). Because these results were mixed, and because of the theoretical support for and practical advantages of using the log transform, we will continue to use the log transformation in COMPASS.

Intercept terms

To this point, we have not included a grand intercept in reservoir survival models. This is because we have modeled reservoir as a rate per unit time or distance (see Section 2.3 in the main text for a description of the survival models). However, cases may exist where survival is more of an acute process, and including a grand intercept to account for this would be justified.

Using a similar approach as above, we compared models that incorporated a grand intercept to those that did not by comparing models including identical predictor variables but with or without a grand intercept term. We included the same suite of predictor variables as in the analysis above.

There was little support for including an intercept term in models of Chinook migrating from Lower Granite Dam to McNary Dam or for steelhead migrating from McNary Dam to Bonneville Dam (Figures A3 3 and 4). In addition, there was moderate support for including an intercept term in models of Chinook migrating from McNary Dam to Bonneville Dam (Figure A3 3). In contrast, there was strong support for including an intercept term for models of steelhead migrating from Lower Granite Dam to McNary Dam (Figure A3 4), with differences in AIC values between models without an intercept and those with an intercept of approximately 20-40. This indicates that models with an intercept perform substantially better than those without. We suspect that this effect is related to acute bird predation on steelhead that occurs near the confluence of the Snake and Columbia rivers. In the near future, we will incorporate models of reservoir survival that include an intercept terms into COMPASS.

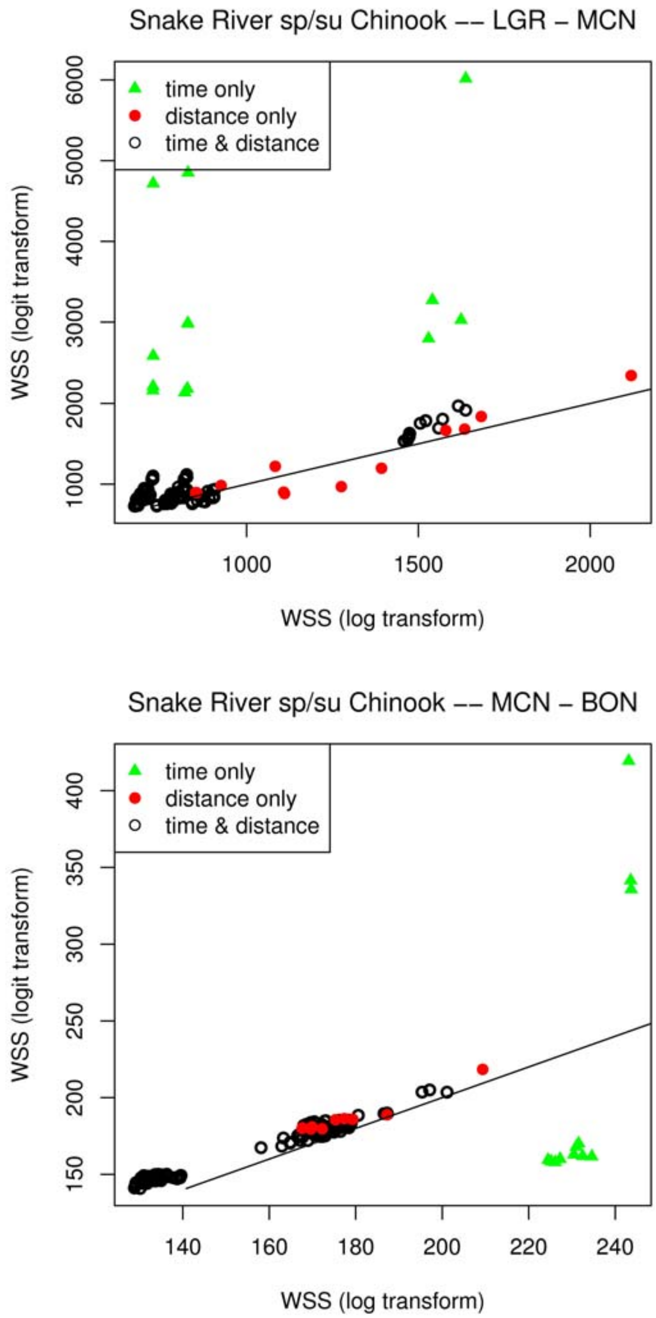
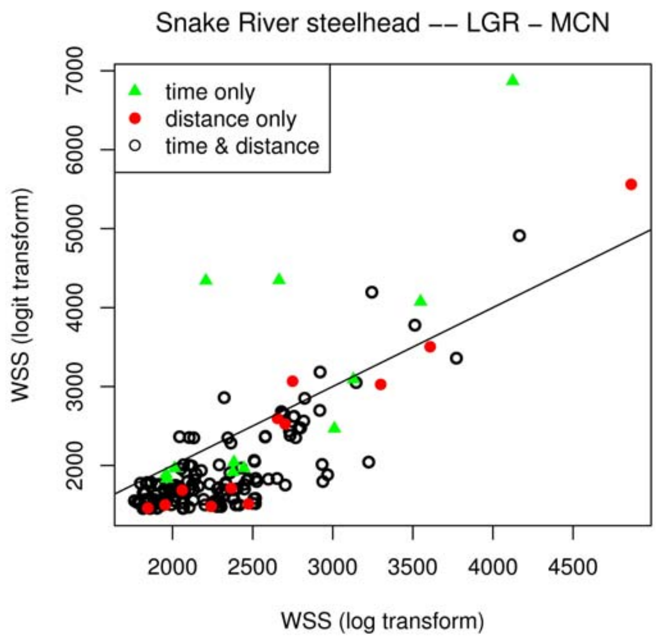


Figure A3 1. Comparison of log versus logit transformations of survival data for Snake River spring/summer Chinook migrating from Lower Granite (LGR) to McNary (MCN) dams (top plot) and from McNary to Bonneville (BON) dams (bottom plot). Each point represents the weighted sum of squares (WSS) for an equivalent model (in terms of predictor variables) but with different dependent variables. WSS is calculated from back-transformed survivals. The solid line represents points where WSS is equal under the two transformations.



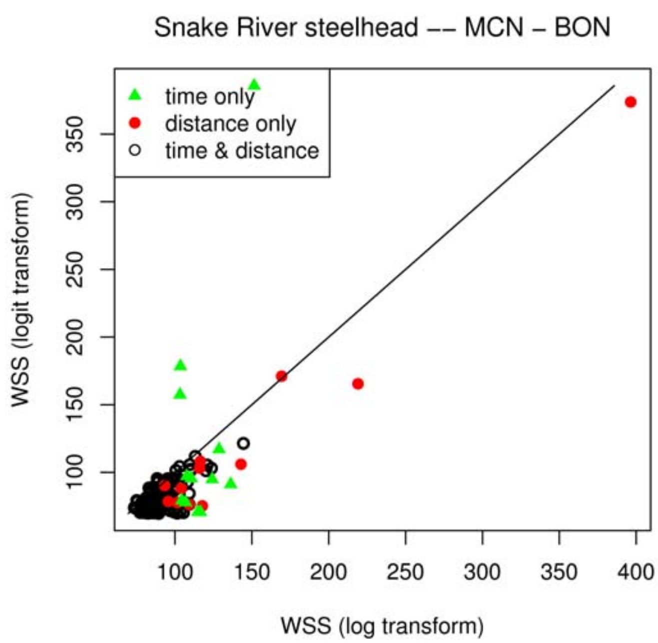


Figure A3 1. Comparison of log versus logit transformations of survival data for Snake River steelhead migrating from Lower Granite (LGR) to McNary (MCN) dams (top plot) and from McNary to Bonneville (BON) dams (bottom plot). Each point represents the weighted sum of squares (WSS) for an equivalent model (in terms of predictor variables) but with different dependent variables. WSS is calculated from back-transformed survivals. The solid line represents points where WSS is equal under the two transformations.

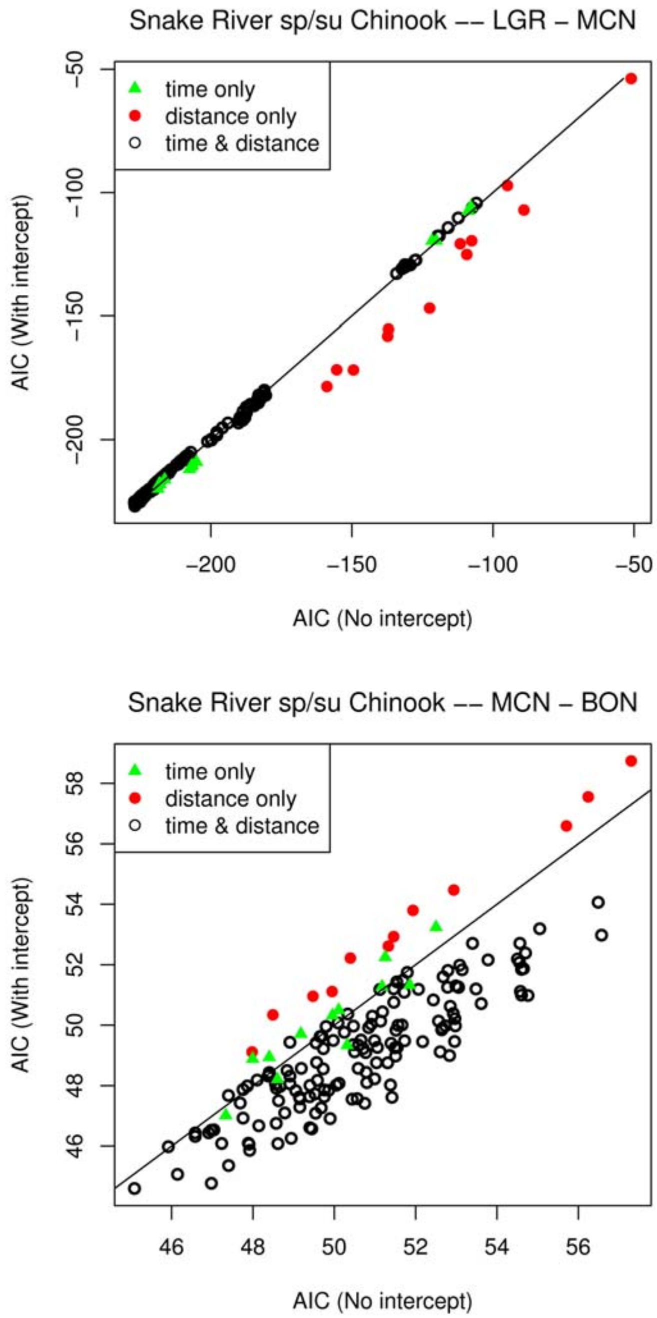
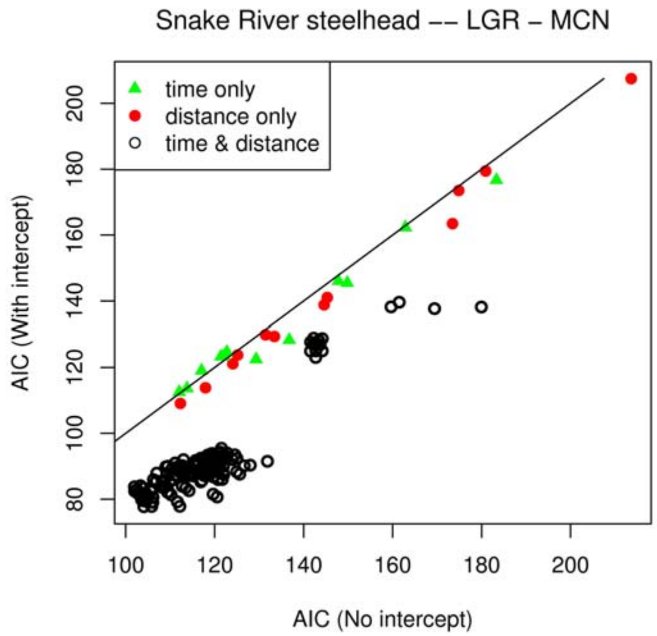


Figure A3 3. Comparison of reservoir survival models with and without intercept terms for Snake River spring/summer Chinook migrating from Lower Granite (LGR) to McNary (MCN) dams (top plot) and from McNary to Bonneville (BON) dams (bottom plot). Each point represents the AIC for an equivalent model (in terms of predictor variables) but with or without an intercept term. The solid line represents points where AIC is equal in models with and without intercept terms.



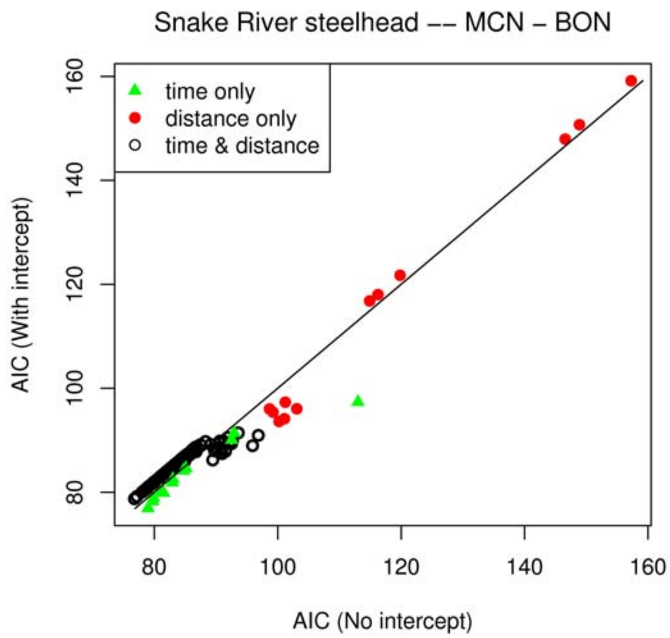


Figure A3 3. Comparison of reservoir survival models with and without intercept terms for Snake River steelhead migrating from Lower Granite (LGR) to McNary (MCN) dams (top plot) and from McNary to Bonneville (BON) dams (bottom plot). Each point represents the AIC for an equivalent model (in terms of predictor variables) but with or without an intercept term. The solid line represents points where AIC is equal in models with and without intercept terms.

Abstract

Over the past year, the methods used to parameterize dam passage in COMPASS have been substantially revised for the dams with most information from tagged fish. This section provides a condensed overview of the revisions as well as the data and methods that underlie them.

The routing of fish at dams – whether they pass via the turbines, bypass facilities in the powerhouse, or over the spillway – is important both because the routes usually have different survival rates and because bypassed fish are often transported. In earlier versions of COMPASS, estimates of these proportions, and how they change with flow and spill, were derived via expert opinion and simple regression models, both informed by numerous studies of radio-tagged (RT) smolts over the past decade. Spill passage efficiency (SPE), or the relationship between water spilled and passage via the spillway, was assumed not to vary over the season, and was estimated using binned data from RT studies. Fish guidance efficiency (FGE), the proportion passing via the powerhouse and guided into bypass systems, was assumed to be constant for a given dam, regardless of the dam's operations or the time of year.

While this was the best information available at the time, potential problems became apparent in 2007. Closer examination of the RT data, using individual detection events, suggested that the simple SPE regressions understated the complexity of the relationship between spill, turbine flow, and passage route. In addition, analysis of PIT tag detections (PIT tagged fish are detected only in the bypass systems, while RT fish are usually detected regardless of passage route) showed that FGE can vary markedly, both with dam operations, environmental conditions, and over the course of the spring passage season. Not surprisingly, the effort to compile data for these analyses confirmed our assumption that data quantity and quality varied markedly for the eight dams of interest, with the lower Snake dams having many more RT studies and PIT tag detections than the four mainstem Columbia dams. Finally, when we compared PIT tag-derived estimates of SPE (using a combination of algebra and assumptions) and FGE estimates to RT-based results, there were numerous differences between the two.

Where sufficient data are available, the dam passage portion of COMPASS have been changed to reflect these findings. In some cases, the revised model is identical to earlier versions, while in others SPE and FGE relationships differ substantially. We believe that the resulting model is both a more accurate summary of relationships apparent in the existing data, and that it now provides better predictions of the biological consequences of future hydrosystem operations.

Introduction

The COMPASS model simulates passage, and survival of migrating salmonids. To accurately estimate survival related to dam passage, it is necessary to accurately estimate the proportion of fish passing through each major passage route. Whether fish pass through the spillway, turbine, juvenile bypass system or surface passage outlet can greatly influence their probability of survival. In addition, fish entering the bypass system at some dams are collected and placed into barges for transport downstream past the downstream dams, which also influences their probability of survival. Clearly, estimating the routes by which fish pass dams is integral to the estimation of survival.

This appendix addresses the modeling of passage probabilities known as spill passage efficiency (SPE) and fish guidance efficiency (FGE). SPE is the probability of passing a dam via the spillway under a given set of conditions, the main condition being proportion of water passing the spillway. FGE is the conditional probability of a fish being guided into a juvenile bypass system given it has entered the powerhouse. If SPE and FGE relationships can be estimated with some confidence, it is possible to predict the proportions of fish passing through the spillways, turbines, and juvenile bypass routes at a dam. We also address the conditional probability of passing through a removable spillway weir (RSW) given passage over a spillway. Passage through sluiceways is not addressed in the appendix.

The modeling of route-specific passage probabilities for COMPASS has evolved over the course of model development. The availability of new data and the proposal different approaches to analyzing the data allowed us to improve predictions at some sites. However, not all dams are equal in the type, quantity, or quality of data available, so uniform methods could not be applied to all dams. The end result draws upon a combination of data sets and modeling approaches to achieve the best result for each dam. The end product is best understood following a description of the data and analyses methods used along the way and a brief description of reasoning for adopting the final combination of approaches.

The first section of this appendix gives an overview of the history of analyses used and the reasoning for using them. If you are only interested in the list of model parameters and associated figures for those models currently used in COMPASS, you can skip ahead to the Current Models Used in COMPASS section that follows the Overview of Analysis History. Those sections are followed by sections with more detailed descriptions of the analyses of the radio-telemetry (RT) data and the PIT tag data. The appendix concludes with a description of the current set of parameters for FGE and SPE models used in COMPASS.

Overview of Analysis History

Prior to the Spring of 2007, we used SPE models based on data points that were summaries of data from various RT studies. The data were pooled from various studies within set levels of spill. The binning of spill levels depended on the amount of data and the conditions of the studies. Simple regressions of the logit transformed proportion of fish passing on the logit of spill proportion were performed separately by species and dam as the available data permitted. Here the logit(x) = ln(x/(1-x)). This “logit-logit” model produces relationship between proportion of fish spilled and proportion of water spilled that naturally passes through (0,0) and (1,1). The parameter estimates resulting from those fits are shown in Table A4 1. The data available were limited to a handful of years at some sites, and there was no data at some sites for some species. If there was no data for one species at a site, then results for the available species were substituted. Drawbacks of this approach were the limited data set, the restricted values of spill imposed by binning the data, and the failure to account for uncertainty in point estimates of proportion of fish spilled.

Table A4 1. Spill efficiency model parameter estimates by dam and species (CH1 = Sp/Su Chinook, STH = Steelhead) based on original logit-logit analysis of summarized data from RT studies. Estimates are on the logit scale. Also shown are parameter estimates for probability of passing through the RSW given passage through the spillway for IHR and LGR. *Note that the parameter estimates for BON and TDA are still currently used in COMPASS.

Species	Dam	Intercept	Slope on Logit(spill)
CH1	*BON	0.139	1.005
	*TDA	1.046	0.992
	JDA	0.945	0.990
	MCN	-0.087	0.989
	IHR (RSW Off)	1.829	1.146
	IHR (RSW On)	3.638	1.023
	LMN	1.797	0.997
	LGS	0.006	0.979
	LGR (RSW Off)	0.979	1.083
	LGR (RSW On)	0.835	0.986
STH	*BON	0.040	1.007
	*TDA	1.304	0.992
	JDA	0.632	0.993
	MCN	-0.087	0.989
	IHR (RSW Off)	1.411	1.257
	IHR (RSW On)	0.946	0.992
	LMN	1.797	0.997
	LGS	0.032	0.989
	LGR (RSW Off)	1.839	1.048
	LGR (RSW On)	1.817	1.186
Conditional RSW Passage			
Species	Dam	Intercept	Slope on Logit(RSW spill)
CH1	IHR	0.493	0.989
	LGR	3.227	1.045
STH	IHR	0.898	0.987
	LGR	2.542	0.98

Table A4 2. Point estimates of fish guidance efficiency (FGE) for Spring/Summer Snake River Chinook (CH1) and Snake River Steelhead (STH) by dam and year for retrospective years (1997-2007). The estimates for Bonneville (BON) and Ice Harbor (IHR), are currently used for historic years in COMPASS. Estimates for other sites have been replaced by FGE models estimated using PIT tag data. There is no juvenile bypass system at The Dalles Dam, so no estimates of FGE are provided there. The guidance screens were not used at the Bonneville Powerhouse 1 (BON1) after 2003, so FGE there is zero during that period.

Species	Dam	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
CH1	BON1	0.38[1]	0.38[1]	0.38[1]	0.5[2]	0.45[3]	0.5[4]	0.38[1]	0	0	0	0
	BON2	0.44[1]	0.44[1]	0.44[1]	0.39[2]	0.46[3]	0.37[4]	0.505[5]	0.33[6]	0.33[7]	0.33[7]	0.33[7]
	JDA	0.64	0.64	0.64	0.64	0.64	0.64	0.64	0.64	0.64	0.64	0.64
	MCN	0.95	0.95	0.95	0.95	0.95	0.93	0.9	0.637	0.75	0.75	0.75
	IHR	0.71[1]	0.71[1]	0.71[1]	0.71[1]	0.71[1]	0.71[1]	0.71[1]	0.71[1]	0.711[8]	0.711[9]	0.711[9]
	LMN	0.817	0.817	0.817	0.817	0.721	0.817	0.817	0.817	0.817	0.817	0.817
	LGS	0.82	0.82	0.82	0.82	0.82	0.82	0.82	0.82	0.874	0.874	0.874
	LGR	0.79	0.79	0.79	0.79	0.88	0.68	0.82	0.814	0.814	0.814	0.814
STH	BON1	0.41[1]	0.41[1]	0.41[1]	0.59[2]	0.5[3]	0.75[4]	0.41[1]	0	0	0	0
	BON2	0.48[1]	0.48[1]	0.48[1]	0.55[2]	0.55[3]	0.59[4]	0.505[5]	0.4[6]	0.4[7]	0.4[7]	0.4[7]
	JDA	0.76	0.76	0.76	0.76	0.76	0.76	0.76	0.76	0.76	0.76	0.76
	MCN	0.89	0.89	0.89	0.89	0.89	0.93	0.91	0.77	0.827	0.827	0.827
	IHR	0.93[1]	0.93[1]	0.93[1]	0.93[1]	0.93[1]	0.93[1]	0.93[1]	0.93[1]	0.93[1]	0.93[1]	0.93[1]
	LMN	0.817	0.817	0.817	0.817	0.721	0.817	0.817	0.817	0.817	0.817	0.817
	LGS	0.81	0.81	0.81	0.81	0.81	0.81	0.81	0.81	0.964	0.964	0.964
	LGR	0.93	0.93	0.93	0.93	0.945	0.81	0.925	0.925	0.925	0.925	0.925

1. Ferguson et al. 2005.
2. Evans et al. 2001a. Report for 2000 RT research.
3. Evans et al. 2001b. Report for 2001 RT research.
4. Evans et al. 2003. Report for 2002 RT research (season ave.).
5. Based on expert opinion.
6. Reagan et al. 2005. Report for 2004 RT research.
7. Estimates carried over from 2004.
8. Axel G.A. et al, 2005, Letter report to COE NWW for 2005 data.
9. Estimates carried over from 2005.

The FGE estimates used were taken from a variety of studies performed at each dam over multiple years (see Table A4 2). A working group was created to review each study and compile estimates in a way that best represented the conditions and operations at each dam for chinook and steelhead between 1995 and 2005. These were the best available estimates of FGE from radio and acoustic tag studies. As one might expect, the coverage of years with available studies was not the same for each dam and species. This dictates that substitutions must be made between species when data are lacking, and that single estimates must be applied to multiple years at some dams.

To test the predictive ability of the SPE and FGE estimates described above, we compared observed capture probability estimates for weekly releases of PIT-tagged fish to COMPASS predictions of proportion of fish entering the bypass system for releases with the same cohort size and release timing as the PIT-tagged cohorts. Figures A4 1 and A4 2 show observed vs predicted plots and residuals (observed-predicted) plots by year for these comparisons for chinook and steelhead, respectively. Comparisons were made at five dams with available PIT tag estimates. The "R^2" in the plots is the weighted squared correlation between the predictions and observations. The "β" in the plots is the slope from a weighted regression of the predictions on the observations. Values close to 1.0 for both R^2 and β indicate good concordance between predictions and observations. In both cases the weights are the inverse of the estimated sampling variance of the PIT tag capture probability estimates. The size of the circles in the plots is representative of the relative size of the precision of the estimates at a dam, where larger circles represent higher precision. Predictions at Lower Granite (LGR) appeared to fit the PIT tag data fairly well, but predictions at other sites were not nearly as good.

In Spring of 2007, after concerns were expressed to us regarding the adequacy of our SPE models, we formed a working group to investigate different modeling approaches and sources of data. We decided to use the passage data collected on individual fish from radio telemetry studies to model SPE. RT studies provide route-specific passage information and time of passage for individual fish. These are the only data we have of such fine resolution. Data on individual fish allowed more precise estimates of conditions at the time of passage and provide a way to weight the data. Some drawbacks are that RT data is currently not available at all dams for both species (Sp/Su Chinook and Steelhead) and it is only available for a limited number of years and days in the season. Furthermore, the data come from a variety of studies, most of which were designed to test various operations on survival and not designed to estimate spill efficiency functions. Therefore the data represent a limited range of spill conditions at some dams, and some confounding exists between spill levels and study protocols and dams. These gaps in the data and confounding factors can make objective model selection difficult and dictate the use of simpler models. See the section on RT data analysis for further details and see Table A4 3 for a summary of the strengths and weaknesses of the RT data on individual fish.

Table A4 3. Attributes of RT data on individual fish.

Strengths	Weaknesses
Route specific passage info and time of passage for individual fish.	Less than 100% detection rate through each passage route, and varies by route, dam, and study. Route-specific detection rates generally unknown. Unequal detection rates among routes could bias estimates of route-specific passage probabilities. Numbers of fish passing some routes can be small
Fine time scale allows conditions at the time of passage to inform passage probability estimation. This allows modeling of night/day patterns and better captures responses to changes in operations within a short period of time.	The fine scale of time resolution could misrepresent conditions that influence passage route selection. Behavioral response time, quick changes in dam operations, complexities in hydrodynamics, and approach location in river can contribute to this.
Multiple years of studies available for some sites for both species.	Limited data at some dams for some species. Limited representation of years and days in season. Data mostly for hatchery fish. Range of fish sizes limited by tag type.
	Possible confounding of spill levels, study protocols and dams.

We used estimated SPE models based on RT data (from Tables A4 7-12) and used existing estimates of FGE (from Table A4 2) to create COMPASS predictions of bypass proportions for weekly cohorts as was done for earlier estimates. Figures A4 3 and A4 4 show observed vs. predicted plots and residual plots from these comparisons for Chinook and steelhead, respectively. The predicted values for bypass proportion were fairly good at LGR, but were still off from observed estimates at Little Goose (LGS), Lower Monumental (LMN), and McNary (MCN). The predictions at John Day (JDA) are essentially unchanged because the model is that from the previous approach. Investigation of capture probability estimates within season suggested that the fixed FGE values were inaccurate in some cases and that FGE was not constant through the season. In particular, under conditions of low to zero spill we observed a consistent pattern of decreasing detection probability estimates as the season progressed at several sites for both species. For example, refer to the plots of estimated detection probabilities from 2001 that are shown in Appendix 3. Since detection probability gives a direct estimate of FGE when there is no spill, this indicated that FGE was not constant. Even over periods of very low spill where FGE (detection probability) estimates appeared constant, the COMPASS predictions were off by a substantial amount in many cases (not shown in plots of Appendix 3 – what is shown is prediction based on PIT tag models). We felt that FGE was likely influenced by factors such as flow, temperature, and other factors for which day in the season might provide a surrogate, and that we could estimate models of FGE as functions of these variables.

We investigated using the RT data set for estimating FGE functions. However, there were not adequate sample sizes at each site for each species to estimate FGE. Some sites, such as LGS and LMN had only one or two seasons of data. There was also concern that unequal detection rates across routes and dams would create a bias in FGE estimation. When a fish has an unknown route of passage it is dropped from the analysis. When the incidence of unknown passage is not equal across passage routes it can create biased estimates. For example, some sites were thought to have more unknown passage events for fish that actually passed through the turbines, which would result in artificially inflated estimates of FGE for those sites. Another concern was that hatchery and wild fish behave differently at the dams, either due to size differences or inherent response patterns. The RT data set is composed mostly of hatchery fish, and is likely skewed towards larger fish due to the minimum size requirements for RT tags.

These concerns led us to investigate the PIT tag data as an additional source of data for modeling both SPE and FGE, either to stand alone or to supplement the RT data. We developed a statistical model that allowed us to estimate FGE and SPE functions simultaneously using PIT tag detection probability estimates. This approach uses CJS capture probability estimates for weekly release cohorts. The data are weighted by the estimated precision of the capture probability estimates. The PIT tag data cover multiple years at sites with PIT tag detection facilities, and they also cover multiple weeks within the migration season. Both hatchery and wild fish are represented in the PIT data and analyses can be done separately on each rearing type. The PIT tag data cover a range of years and conditions that the RT data do not. This allows us to fill in gaps where the RT data are lacking. Drawbacks to the PIT tag data are that only average conditions for a cohort are represented and fine scale operational changes are not captured. There is also a possibility for inaccurate separation of FGE and SPE contributions to capture probability. This problem is helped by having a good representation of periods with little to no spill. See Table A4 4 for a summary of the strengths and weaknesses of the PIT tag data.

Table A4 4. Attributes of PIT tag data for weekly release groups.

Strengths	Weaknesses
Detection rates in the bypass systems are essentially 100%. CJS estimators of capture probability are essentially unbiased.	Estimates only available for probability of entering the bypass system and no direct estimates for other routes. Spill-passed fish cannot be distinguished from turbine-passed fish, because neither are detected during passage. Pit detection rates can be low during high spill.
Data available for multiple years and days within a season for both species of interest.	Data only available for sites and years where PIT tag detection systems in place.

Sufficient data on both hatchery and wild fish.	
Statistical modeling methods available to separate SPE and FGE from capture probability estimates. Provides estimates for FGE and SPE for sites and conditions not possible with other data sets.	Methods to separate SPE and FGE using PIT tag data require some observations with little to no spill. Contributions from SPE and FGE model components are not 100% separable. Misrepresentation of one model component can result in overcompensation by the other.
	Estimation method for capture probabilities requires grouping of fish into cohorts. Conditions influencing passage probabilities are averaged for the cohort. Averaging causes a loss of information. Fine scale changes in operations and day/night patterns cannot be modeled.
	Conditions at time of passage only known for detected (bypass) fish. Requires assumption that average conditions at time of passage for detected fish represent those of the entire cohort.
	Timing of pit detection is dependent on timing of tagged fish moving through the system, which may differ from untagged fish

The observed vs. predicted plots and residual plots for the best set of models based on the PIT tag data are shown in Figures A4 5 and A4 6 for Chinook and steelhead, respectively. These are based on the models shown in Tables A4 15-18. There were clearly improvements made over both the original approach and the RT approach at LGS, LMN, and MCN. It is not clear whether much was gained at LGR, and the predictions at JDA were only marginally improved. One caveat is that the parameter estimates used here came from a model fit to the PIT tag data, which is the same response data used in this comparison. This not necessarily an unfair comparison, since the predictions are produced by COMPASS.

We also developed a statistical method to fit the RT data and PIT tag data simultaneously using a joint likelihood approach. This allowed us to use information from both data sets to inform estimates of FGE and SPE model parameters. We are not currently using results from this approach, but we would like to develop the method further as more data become available.

Current Models used in COMPASS

The set of models and parameters currently used in COMPASS is a combination of results from the three approaches described above. The determination of which approach is used is determined primarily by the availability of PIT tag detection or usable RT data. For Bonneville (BON) and The Dalles (TDA) we are using the FGE estimates from Table A4 2 and the original set of SPE parameters from Table A4 1. At Ice Harbor we are using the original FGE estimates from Table A4 2 and the SPE parameters from the individual RT data shown in Table A4 8. At LGR, LGS, LMN, MCN, and JDA we are using FGE and SPE models and parameter estimates from the PIT tag analyses, which are shown in Tables A4 15-18. We are using the conditional RSW passage model parameters for IHR and LGR from fits to the individual RT data shown in Table A4 12.

The following listed figures show plots of the SPE and FGE functions described in the corresponding list of tables mentioned above. Figures A4 7 and A4 8 show SPE relationships to spill proportion for the Lower Columbia River dams (MCN, JDA, TDA, and BON) for Chinook and steelhead, respectively. The RSW effect displayed in Figure A4 8 for steelhead is the effect estimated from LGR. These hypothetical RSW effects are used in prospective model runs that investigate additional RSW's that currently do not exist. Figures A4 9 and A4 10 show SPE relationships at the Snake River dams (LGR, LGS, LMN, and IHR) by RSW operation (on/off) under average flow conditions (85 kcfs) for Chinook and steelhead, respectively. Figures A4 11 (Chinook) and A4 12 (steelhead) show SPE relationships at varying levels of flow at the Snake River dams where flow was a variable in the SPE models (LGR, LGS, and LMN). Figure A4 12 for steelhead also shows the flow relationships by RSW operation. Figure A4 13 shows the conditional RSW passage efficiency as a function of the proportion of spilled water going through RSW for Chinook and steelhead at LGR and IHR. Figures A4 14 (Chinook) and A4 15 (steelhead) show FGE functional relationships to Julian day and powerhouse flow at the dams for which these functions were estimated with PIT tag data (LGR, LGS, LMN, MCN, and JDA).

Modeling Spill Efficiency with Individual Radio-Tagged Fish

Spill is one of the primary tools available for influencing fish passage conditions and survival rates at FCRPS dams. To make the most of spill as a management tool, it is necessary to have some idea how changing the spill proportion will change the distribution of fish passage. Empirical data on fish passage distributions is collected primarily by studies utilizing active (radio or acoustic) tags in fish or by using hydro-acoustics to quantify untagged fish passage. That empirical data can be examined to reveal relationships between spill and passage.

In recent usage, "Spill Passage Efficiency" (SPE) represents the proportion of migrating smolts that pass a project by spill routes (which may be generalized to include surface routes such as removable spillway weirs). The term "Spill Passage Effectiveness" (SPS) is used to represent the proportion of migrating smolts that pass a project by spill routes divided by the proportion of water passing those routes. SPE is used for describing the distribution of fish among routes. SPS is used when evaluating whether passage distribution differs from the distribution of water among routes. Spill proportion provides a better relative indication of the distribution of water across the entire project, and it has been chosen here as the basis for building relationships with SPE.
SPE changes with proportion of spill, the species of interest, and other factors such as time of day. By fitting models to the spill efficiency versus spill proportion relationships, we hope to predict the distribution of fish passage for a given project, species of interest, and spill proportion.

<u>Methods</u>

To develop spill passage efficiency relationships, it is first necessary to identify and acquire suitable passage data. Passage events must then be associated with dam operations data. Relationships can then be developed by fitting curves to passage and spill data. Similar techniques are applied to develop RSW passage efficiency relationships to determine what proportion of spill passage occurs through the RSW. Work to date by USGS and NOAA has been funded by the Walla Walla District of the Corps of Engineers focused on the Snake River Dams and McNary Dam. These techniques are applicable to any project where passage and operations data are available.

Passage Events
A passage event represents the passage of an individual radio-tagged fish. The species (and run), route of passage, and time of passage must be known for each event. Dam operations data must also be available for the time of passage to allow for further analysis. For spill analysis, each event is assigned a 1 if passage is through a spillway route (including RSWs), or a 0 if passage is through non-spill routes. For analysis of RSW passage as a fraction of spill passage, events that were assigned a 1 for spill passage are assigned an additional 1 if passage was through the RSW or a 0 if passage was through a normal spill bay.

Data

Numerous radio telemetry studies have been conducted at the dams of interest. The researchers expended considerable effort to provide data in a form that was usable for developing passage events. Most data were collected in studies performed by USGS or NMFS for the Walla Walla District of the Corps of Engineers. Tables A4 5 and A4 6 show the data that were available for analysis at the time of this writing. Note that 2002 fish passage data at Lower Granite Dam were included in the analysis despite the Behavioral Guidance Structure (BGS) operation, in an effort to increase sample size.

The quantity and distribution of data varied by species group and dam. Wild and hatchery fish of the same species and run were combined into a species group. Only two RSWs, at LGR and IHR, are currently in operation, so data with an operating RSW are more limited. In contrast, Lower Granite Dam has recently been run almost exclusively with the RSW in operation, making non-RSW data scarce for that project. It is important to recognize that data are often not nearly uniformly distributed across the range of spill proportions. An absence of data at the high or low end of the range means that curves will be extrapolated and less certain in those areas.

Table A4 5 Distribution of radio-tagged fish and spill levels across dams and RSW operation and by species (CH1 = Spring chinook, STH = Steelhead).

Species	Dam	RSW (1 on, 0 off)	Number of RT smolts	Minimum spill proportion	Mean spill proportion	Maximum spill proportion
CH1	LGR	0	470	0.157609	0.524397	0.858768
CH1	LGR	1	1994	0.074907	0.320877	0.995342
CH1	LGO	0	1589	0.050868	0.23472	0.484187
CH1	LMN	0	2011	0.064495	0.325231	0.749662
CH1	IHR	0	4898	0.316176	0.69508	0.990196
CH1	IHR	1	3326	0.28508	0.45329	0.907974
CH1	MCN	0	5137	0.001205	0.489895	0.79172
STH	LGR	0	381	0.102283	0.554184	0.794168
STH	LGR	1	2118	0.074289	0.323072	0.987635
STH	LGO	0	1338	0.05105	0.243892	0.4801
STH	LMN	0	1071	0.065618	0.27866	0.745088
STH	IHR	0	1141	0.33358	0.759446	0.945148
STH	IHR	1	2331	0.28508	0.454991	0.907974
STH	MCN	0	2048	0.003185	0.575728	0.790544

Table A4 6. Distribution of radio-tagged fish across sites and years by species and RSW operation.

Species	Dam	RSW	1999	2002	2003	2004	2005	2006	Total
CH1	LGR	Off	0	135	335	0	0	0	470
		On	0	413	582	0	379	620	1994
	LGS	Off	0	0	0	0	483	1106	1589
		On	0	0	0	0	0	0	0
	LMN	Off	0	0	0	732	0	1279	2011
		On	0	0	0	0	0	0	0
	IHR	Off	697	0	892	2315	994	0	4898
		On	0	0	0	0	1250	2076	3326
	MCN	Off	0	0	794	754	1908	1681	5137
		On	0	0	0	0	0	0	0
STH	LGR	Off	0	139	241	0	0	1	381
		On	0	470	404	0	458	786	2118
	LGS	Off	0	0	0	0	205	1133	1338
		On	0	0	0	0	0	0	0
	LMN	Off	0	0	0	0	0	1071	1071
		On	0	0	0	0	0	0	0
	IHR	Off	0	0	0	590	551	0	1141
		On	0	0	0	0	694	1637	2331
	MCN	Off	0	0	0	929	731	388	2048
		On	0	0	0	0	0	0	0
Total			697	1157	3248	5320	7653	11778	29853

Dam Operations

In most cases, dam operations data were available by passage route on a 5-minute basis. Because it is likely that operations at and prior to the passage event may influence the route of passage, several alternatives were evaluated for summarizing the operations for use in developing spill-passage relationships. Some of those alternatives for summarizing spill flow percent included:

1) Nearest 5-minute instantaneous operation
2) Average of the previous 60 minutes
3) Hourly average at the top of the hour. (e.g., 1:30 to 2:30 operations averaged for fish passing between 1:30 and 2:30)
4) Hourly average at the bottom of the hour. (e.g., 1:00 to 2:00 operations averaged for fish passing between 1:00 and 2:00)

The 5-minute operational data explained the most variation in passage route distribution in 5 of 9 comparisons (results not shown) and was selected for fitting spill passage relationships. In any case, the four measures were very highly correlated (Pearson R > 0.99), so the results are not sensitive to the spill measure employed in the analysis.

Spill Proportions and RSW operation
The ideal set of data for developing spill passage efficiency relationships would include all four dams operating across a wide range of spill proportions, with many tagged Chinook and steelhead passing when RSW's were operating and when they were not. In point of fact, only Lower Granite and Ice Harbor have RSW's, and spill proportions at Little Goose (0.05 – 0.48) have little overlap with spill proportions at Ice Harbor (0.28 – 0.99), from Table A4 5. This is very different from the PIT tag data used to develop survival and travel time relationships. It occurs in part because the data are simply more limited (30K fish and six years of data spread unevenly among projects, versus millions of fish and 11+ years for PIT tags passing all projects). Perhaps more importantly, due to both expense and logistical constraints, radio tagging has mostly been done to test the effectiveness of particular dam operational scenarios (e.g., nighttime spill vs. daytime spill, RSW's on or off), rather than as long-term trend and status monitoring addressed with PIT tags. As will be seen in the next section, this in turn imposes constraints on model development.

Model Estimation
Techniques developed to fit spill passage efficiency relationships to hydro acoustic data have used logit-transformed flow proportions and passage proportions. One benefit of the logit transformations is that the relationships are then fit with a simple linear regression. When back-transformed, those relationships are forced through the mandatory points of (0%,0%) and (100%,100%) (spill, passage). As a result, these relationships do not produce values of passage less than 0% or greater than 100%.

In previous analyses, hydro acoustic data were often grouped by 12-hour operational periods for analysis. Grouping allowed spill passage proportion and spill flow proportion to be computed for each operational period. Active tag data, such as radio or acoustic telemetry, usually include fewer passage events, and thus need to be grouped by something other than 12-hr operational periods to utilize the established curve fitting techniques. In a similar vein, for the 2006 COMPASS analyses, passage events were grouped into 10% bins of spill proportion. This allowed simple modeling techniques to function, but raised concerns about how the binning influenced the fits.

To avoid those concerns, we sought a technique that could treat the passage events as a binary comparison of passage through spill or non-spill routes. This type of count data lends itself well to binary logistic regression (on the set of passage events for individual tagged fish) with a logit link function. When spill flow proportions are represented as logit-transformed values, this method produces curves of the same (logit-logit) form that are currently incorporated into COMPASS. This method can analyze passage events as individual data points, and did not require grouping or binning. The results discussed here use a multivariate models to simultaneously fit spill efficiency relationships for multiple species (spring chinook and steelhead) and dams (Lower Granite, Little Goose, Lower Monumental, Ice Harbor and McNary) to the extent that data are available.

Because the data are obtained as a result of numerous site-specific experiments, rather than as a directed effort at developing spill efficiency relationships, we believe that there are limits to the complexity of the models that these data can support. In earlier modeling efforts we fit separate models for every dam and species. Doing so is equivalent to fitting a single complex model with multi-level interactions between dam, species, spill, and RSW. Here, we present the results of much simpler models which assume that spill passage efficiency varies by dam and species, with RSW operation, and that the influence of a dam or RSW may vary by species, but that the slope of logit (SPE) versus logit (spill proportion) will be the same across species and projects.

We fit three groups of models. The first model combines Chinook and steelhead at the Snake River dams (LGR, LGS, LMN, and IHR). The second model combines Chinook and steelhead at MCN. The third model predicts the probability of RSW passage given passage over the spillway. That model combines Chinook and steelhead at LGR and IHR. The continuous explanatory variable is the logit of the proportion of water passing over the spillway that passes through the RSW.
The logistic regression model, using individual fish passage data and a logit link function, is thus:

$$\text{logit}(\pi) = species + dam + dam * species + rsw + rsw * species + \text{logit}(spill\_proportion),$$

where

π_i = E[Y_i | $covariates_i$] = expected probability of passing the spillway (SPE) for individual fish i,

Y_i is distributed as a Bernoulli random variable with mean π_i and variance $\pi_i(1 - \pi_i)$,

species is an indicator variable for species (chinook = 0, steelhead = 1),

dam is a set of indicator variables for dam, where LGR is the reference level,

rsw is an indicator variable for RSW operation (0 = off, 1 = on),

and logit(*spill_proportion*) is the logit transformation of the proportion of water passing the dam that passes the spillway.

While some more complex models do result in improved AIC scores, etc., we believe that estimating such models is fraught with potential problems due the dam-by-dam experimental nature of the data collection process.

Results

Regression results for the Snake River model are displayed in Table A4 7. Of the 22,668 fish passing the Snake River dams, 16,466 (73%) passed via spillways or RSW's. RSW effect was significant and differed by species and dam.

Table A4 7. Parameter estimates and associated standard errors and p-values from logistic regression model for 22,668 radio-tagged Chinook and steelhead at LGR, LGS, LMN, and IHR. The reference level for indicator variables is Chinook at LGR with RSW off.

	Estimate	Std. Error	z-value	p-value
Intercept	1.13741	0.11149	10.202	<2.00E-16
Sthd	-0.51813	0.15985	-3.241	0.00119
Dam_LGS	-0.20049	0.12856	-1.559	0.11888
Dam_LMN	0.65749	0.12558	5.236	1.64E-07
Dam_IHR	0.84514	0.12618	6.698	2.11E-11
Dam_LGS_Sthd	0.18011	0.17809	1.011	0.31184
Dam_LMN_Sthd	-0.20594	0.17947	-1.148	0.25117
Dam_IHR_Sthd	0.15922	0.20911	0.761	0.44639
RSW_On	0.27263	0.12432	2.193	0.02831
RSW_On_Sthd	0.51931	0.17336	2.996	0.00274
Dam_IHR_RSW_On	-0.37901	0.14261	-2.658	0.00787
Dam_IHR_RSW_On_Sthd	-0.67909	0.22976	-2.956	0.00312
Logit_spill_prop	1.02741	0.03162	32.497	<2.00E-16

Table A4 8. Parameter estimates on the logit scale from Table A4 7 expressed as intercept and slope on logit(spill proportion) by species, dam, and RSW operation. *Note the parameters for IHR are the only ones from this table that are currently used in COMPASS.

Species	Dam	RSW	Intercept	Slope
CH1	LGR	Off	1.137407	1.027407
	LGR	On	1.410039	1.027407
	LGS	Off	0.936917	1.027407
	LGS	On	1.209549	1.027407
	LMN	Off	1.794901	1.027407
	LMN	On	2.067533	1.027407
	*IHR	Off	1.982544	1.027407
	*IHR	On	1.876163	1.027407
STH	LGR	Off	0.619281	1.027407
	LGR	On	1.411222	1.027407
	LGS	Off	0.5989	1.027407
	LGS	On	1.390841	1.027407
	LMN	Off	1.070831	1.027407
	LMN	On	1.862771	1.027407

	*IHR	Off	1.623641	1.027407
	*IHR	On	1.35748	1.027407

Although only intercepts differ among dams, spill passage efficiency relationships can appear quite different. When plotted (not shown), the curvature of the relationship between spill proportion (horizontal axis) and predicted proportion of fish spilled (vertical axis) differs substantially among dams, from nearly linear (indicating a proportionate influence of spill on passage) at McNary, to strongly curved at Ice Harbor and Lower Monumental (indicating a disproportionately large influence on passage), with Little Goose being nearly linear. See Figures A4 9-10 for the plots of the SPE relationship at IHR.

The results of the regression model at MCN are shown in Table A4 9. Species did not differ significantly in their intercepts, but since the estimated effect was small, we left species in the model.

Table A4 9. Parameter estimates and associated standard errors and p-values from logistic regression model for 8,096 radio-tagged Chinook and steelhead at MCN. The reference level for the species indicator variable is Chinook.

	Estimate	Std. Error	z-value	p-value
Intercept	0.50921	0.03015	16.888	<2e-16
Sthd	0.02047	0.05892	0.347	0.728
Logit_spill_prop	0.97067	0.03625	26.781	<2e-16

Table A4 10. Parameter estimates on the logit scale from Table A4 9 expressed as intercept and slope on logit(spill proportion) by species.

Species	Intercept	Slope
CH1	0.5092	0.97067
STH	0.5296	0.97067

The results of the regression model for conditional RSW passage are shown in Table A4 11. This model indicates that the probability of passage through an RSW given a fish is passing through the spillway differs by species and dam. The plots for these relationships are shown in Figure A4 13.

Table A4 11. Parameter estimates and associated standard errors and p-values from logistic regression model for 7,094 radio-tagged Chinook and steelhead at LGR and IHR. Model predicts conditional probability of passing through and RSW given passage through the spillway. The reference levels for indicator variables are Chinook at IHR.

	Estimate	Std. Error	z-value	p-value
Intercept	0.99189	0.06552	15.14	< 2e-16
Sthd	0.23916	0.05245	4.56	5.12e-06
Dam_LGR	0.87997	0.05583	15.76	< 2e-16
Logit(rswspill)	0.77050	0.03671	20.99	< 2e-16

Table A4 12. Parameter estimates on the logit scale from Table A4 11 expressed as intercept and slope on logit(rsw spill proportion) by species. RSW spill proportion is the proportion of water passing the spillway that passes through the RSW. Note that all of these parameters are currently used in COMPASS when an RSW is in operation.

Species	Dam	Intercept	Slope
CH1	LGR	1.87186	0.7705
	IHR	0.99189	0.7705
STH	LGR	2.1102	0.7705
	IHR	1.23105	0.7705

<u>Discussion</u>

Previous efforts to develop spill passage relationships using single dams and species, or using a complex multivariate model resulted in relationships that were implausible. An example of an implausible relationship would be one that predicted an extremely rapid increase in passage at low but increasing spill proportion, followed by a plateau of very little change in spill passage across a broad range of spill proportion, with another rapid change in spill passage as spill proportion approached 100%. It is hard to imagine a biological mechanism that would result in such large variations in the attractiveness to spill across such small ranges of spill proportion. We believe our previous approaches to developing spill passage efficiency relationships were over-fitting the available data. The simplified multivariate approach was developed to avoid such over-fitting, while still allowing the data to define the influence that dams, species, and RSWs have on spill passage efficiency.

The simplified multivariate regression approach presented here allowed spill passage efficiency relationships to be developed which reflect the influence of species, individual dam, and RSW operation and allowed the influence of dam and RSW to differ among species. The resulting spill passage efficiency relationships ranged from a gradual increase in spill passage with increasing spill proportion at McNary dam, to a rapid increase in spill passage with spill discharge proportion at Lower Monumental.

The slope of the relationship determined how sigmoidal (S-shaped) the curves appear. By requiring the relationships to have a common slope, all curves were forced to have the same S-shaped quality. Curves were allowed to be very much or very little S-shaped, but the best overall fit was achieved when the curves were not S-shaped at all. The common slope avoided relationships that produce unreasonable estimates of passage outside the range of spill proportions that occur in the existing data. Earlier efforts at fitting spill passage efficiency curves one dam and species at a time or with multivariate models that allowed slopes to vary among dams and species sometimes produced such curves that were considered implausible. No such problem has arisen with the current simplified multivariate approach.

Although this approach has provided a reasonable set of spill passage efficiency curves for incorporation into the COMPASS modeling effort, it has not eliminated all concerns about the limitations of the existing data set. Where data are clumped within high spill proportions (e.g., Ice Harbor) the influence of the relatively small proportion of RSW discharge is unlikely to be large. Unfortunately, data for operations without an RSW are scarce at Lower Granite, the only other site where an RSW currently exists.

It will be advantageous to incorporate new data as it becomes available. We expect existing data from lower river projects to be available for similar analyses soon. For future studies, releases of tagged fish across wider ranges of spill, and better balance between RSW on – RSW off, are obvious methods to help extend and strengthen the results described here. In addition, releases and detections of acoustic tagged smolts promise to be useful, perhaps extending the range of environmental and operational conditions under which fish pass the dams.

Modeling FGE and SPE Using PIT tag Data

Estimates of capture probability at a dam for cohorts of PIT-tagged fish using standard capture-recapture methods give direct estimates of the probability of entering the juvenile bypass system of that dam over the period of time that the cohort passed. Since detection of PIT tags is only in the bypass system, we cannot directly estimate the probability of passing through other individual passage routes. However, by assuming some general functional relationships between passage probabilities through non-bypass routes and a set of explanatory variables we can use the estimates of bypass (capture) probabilities to estimate parameters of the functional relationships and thereby indirectly estimate the passage probabilities through the other passage routes.

Model Description

The relationship between FGE, SPE, and the probability of entering the bypass can be described using basic rules of probability. The following example uses spillway, turbine, and bypass as the three possible passage routes at a dam. The route-specific probabilities of passage sum to 1.0.

$$P(Bypass) + P(Turbine) + P(Spillway) = 1.0$$

The probability of entering the powerhouse is

$$\begin{aligned} P(Powerhouse) &= P(Bypass) + P(Turbine) \\ &= 1.0 - P(Spillway) \end{aligned}$$

The conditional probability of entering the bypass given entry into the powerhouse is

$$P(Bypass \mid Powerhouse) = \frac{P(Bypass)}{P(Bypass) + P(Turbine)} = \frac{P(Bypass)}{P(Powerhouse)}$$

Using this relationship the probability of entering the bypass can be expressed as a function of FGE and SPE.

$$\begin{aligned} P(Bypass) &= P(Bypass \mid Powerhouse) P(Powerhouse) \\ &= P(Bypass \mid Powerhouse)(1 - P(Spillway)) \\ &= FGE * (1 - SPE) \end{aligned}$$

The FGE and SPE probabilities can be expressed as functions of some set of explanatory variables, which creates a modeling framework for prediction of bypass probability.

$$P(Bypass) = f(\underline{x})[1 - g(\underline{z})]$$

We assumed that SPE and FGE are both linear functions of sets of explanatory variables on the logit scale. The logit is a common link function used in regression modeling of probabilities. This is the same model structure used in the logistic regression modeling of SPE using the data on individual radio-tagged fish described in the previous section.

$$\text{logit}(FGE) = \theta_0 + \sum_{j=1}^{n} \theta_j X_j$$

$$\text{logit}(SPE) = \beta_0 + \sum_{k=1}^{m} \beta_k Z_k$$

Here the θ's and β's are regression parameters and the X's and Z's are explanatory variables. Note that some variables such as indicators for dam or species could be common to both equations. Putting these functions together and back-transforming to the probability scale creates a non-linear model for predicting probability of entering the bypass system.

$$P(Bypass) = \left[\frac{\exp\left(\theta_0 + \sum_{j=1}^{n} \theta_j X_j\right)}{1 + \exp\left(\theta_0 + \sum_{j=1}^{n} \theta_j X_j\right)} \right] \left[1 - \frac{\exp\left(\beta_0 + \sum_{k=1}^{m} \beta_k Z_k\right)}{1 + \exp\left(\beta_0 + \sum_{k=1}^{m} \beta_k Z_k\right)} \right]$$

In practice we take the logit of both sides of the equation to fit the model. The response variable is then the logit of bypass (capture) probability. The residuals on the logit scale are assumed to be distributed normal with mean zero and constant variance.

<u>Data</u>

We used weekly release groups of PIT-tagged fish to get estimates of capture (bypass) probabilities at dams with PIT-tag detection facilities. We used the same weekly release groups of Snake River Spring/Summer Chinook and Steelhead that were used for modeling survival from LGR to MCN to estimate capture probabilties at LGS, LMN, and MCN. We created weekly releases from the Clearwater, Grande Ronde, Imnaha, Salmon, and Snake River Traps for estimation of capture probabilities at LGR. We used the weekly release groups created for estimation of survival from MCN to estimate capture probability at JDA. The release groups were split by rearing type, which resulted in separate data sets for hatchery only, wild only, and hatchery/wild combined. The analysis presented here is for wild fish only. We used standard Cormack-Jolly-Seber capture-recapture methods to estimate capture probabilities and associated standard errors for each release group at each dam. See Tables A4 13 and A4 14 for description of number cohorts and estimates by release site, dam, and species. Note that we did not use PIT tag data from Ice Harbor Dam (IHR) in this analysis. There were only two years of data available (2006-2007) and the detection probability estimates there were very low due to high spill conditions and the estimates were relatively imprecise. We decided that data were insufficient to model dam passage at IHR.

Table A4 13. Number of weekly release cohorts of wild PIT-tagged Sp/Su Chinook and Steelhead by release site and range of years represented. Total number of tagged fish represented by the cohorts is in parentheses.

Release Site	**Years**	**Chinook**	**Steelhead**
Traps	1997-2007	367 (116,999)	332 (67,510)
LGR	1997-2007	429 (252,692)	370 (207,881)
MCN	1998-2007	73 (92,685)	64 (26,839)

Table A4 14. Number of cohort observations by species and dam.

River	**Dam**	**Chinook**	**Steelhead**
Snake	LGR	367	332
	LGS	143	114
	LMN	121	93
	Total	631	539
Columbia	MCN	120	92
	JDA	73	64
	Total	193	156

Daily measurements of temperature, flow, and spill for each dam were downloaded from the Columbia River DART website. We used those daily values to create weighted averages for each variable for each cohort at each dam. The weights were the daily number of detected fish for a cohort at a dam. By assuming that the daily distribution of passage for detected and non-detected fish within a cohort is the same, this approach allows estimation of the mean conditions the cohorts experienced at the time of passage.

Each species was modeled separately. The dams were grouped by Snake (LGR, LGS, and LMN) or Columbia (MCN and JDA) and each dam group was modeled separately. The explanatory variables used for the FGE component of the model for both river segments were indicator variables for dam, and continuous variables for mean temperature, median day of passage, and mean powerhouse flow (kcfs). Here powerhouse flow is defined as mean total flow kcfs minus mean spill kcfs. Explanatory variables used for the SPE component for Snake River dams were indicator variables for dam, an indicator for RSW on or off, mean total flow (kcfs), logit(mean spill proportion), and an interaction between RSW and flow. The indicator for RSW on/off was specified at the cohort level with the restriction that RSW was coded as on if any of the detected fish in the cohort passed the dam while the RSW was on. The SPE component for the Columbia River dams was simplified to have just an indicator for dam and logit(mean spill proportion).

We chose to model FGE as a function of dam, powerhouse flow, median day of passage, and temperature because they could be justified from a mechanistic standpoint. Each dam has its own unique structural and operational configuration and is expected to differ in fish guidance efficiency. Powerhouse flow provides an index of the amount of hydrologic force the fish experience when approaching the turbine intake. One might expect that swimming speed and maneuverability would be affected by powerhouse flow, and therefore the ability of fish to escape intake screens would likely be affected. Note that ideally we would use flow per turbine unit, but data on the daily per-unit flow was not available to us at the time of analysis. Water temperature could influence vertical distribution of smolts, which would affect FGE. Day of the migration season is intended to act as a surrogate measure for fish size and level of smoltification, both of which are expected to influence fish guidance. Day of season is also highly positively correlated with temperature. For this reason we decided not to allow temperature and day to be in the same models together.

We allowed total flow to be in the SPE component of the model because it seems reasonable that fish behavior while approaching a dam is likely influenced by the amount of flow. At lower flows we expect that spill, especially surface spill through RSW, may be more attractive than at higher flows. At high flows the fish are probably less likely to escape the force of flow or have time to select between powerhouse and spillway. We also included an indicator term that accounted for the experimental "bulk" spill pattern that occurred at LMN in 2007. This spill pattern was implemented through the majority of the migration season, so all cohorts at LMN in 2007 were coded with bulk spill.

Model Fitting and Selection

The response variable was the logit of the estimated capture probabilities. We used weighted non-linear least squares to fit the models, with weights equal to inverse of the estimated sampling variances on the logit scale.

For the Snake River dam group, the allowed combinations of explanatory variables resulted in 12 possible FGE models and 28 SPE models, for a total of 336 possible model combinations. Half of the SPE models fixed the parameter on logit(spill) to 1.0 instead of estimating it. This was done because it eliminates the possibility of an S-shaped relationship between SPE and spill proportion (see section on modeling of RT data for further discussion). Holding that parameter at 1.0 also limits the level of compensation between SPE and FGE that may result from fitting models of increasing complexity. For the Columbia River grouping there were 12 possible FGE models and only 1 SPE model, for a total of 12 models. Due to the limited number of observations and the restricted range of environmental conditions at the Columbia dams we chose to allow both JDA and MCN to have the same spill model and have the slope of the logit(spill) relationship set equal to 1.0.

We used an information-theoretic approach based on Akaike's information criterion (AIC) for model selection (e.g., Burnham and Anderson 1998). We fit all allowed combinations of models and then ranked them based on AIC score, where the lowest AIC scores correspond to the best models. We divided the set of models into those with FGE components that included median day of passage, and those that included temperature. Models that included neither of these terms were common to both sets. We assigned AIC weights based on the difference in AIC (Δ_i), from the best fitting model within each group of R models, where

$$\Delta_i = AIC_i - AIC_{min} \text{ .,}$$

and the weight for the ith model is defined as

$$w_i = \frac{\exp(-\Delta_i / 2)}{\sum_{i=1}^{R} \exp(-\Delta_i / 2)} .$$

We then used the weights to calculate model-averaged values for the parameters within each model group, where the model average of a single parameter is the weighted average of that parameter of across all possible models in a group. When a variable did not occur in a particular model, the parameter value for that variable was set to zero to remove bias in model-averaged parameters.

<u>Results</u>

The top models based on AIC contained median day of passage as a predictor of FGE. Therefore we chose to use the model-averaged parameter values for the models that did not contain temperature as a predictor of FGE.

Chinook Snake River

The top models for Chinook in the Snake River contained terms for an RSW effect and those terms were highly significant. However, the estimates of RSW effect were consistently negative for all models. The RSW effect was -0.2 on the logit scale on average. This result was consistent with some of the models fit to the RT data, where RSW effect was negative although non-significant for Chinook. We were concerned that the PIT tag data did not have fine enough resolution to capture the apparent small benefit of RSW for Chinook, so we decided to drop all models that contained RSW effects and just assume that the effect is zero rather than negative. The remaining sets of models discussed below did not include RSW effects.

The top model of the no-temperature no-RSW group was ranked number 6 among all possible models (including those with RSW and temperature) and had a ΔAIC of 14.35 compared to the overall best model. Within the no-temperature no-RSW group, the top model contained 97.9% of the AIC weight, and the top two models contained 99.9% of the weight. Despite this heavy weighting on the top model, we model averaged the parameter values over all models in the non-temperature set. The result is essentially the same as taking the top model, but one can be sure that all model outcomes were taken into account.

The model averaged FGE and SPE parameter values by dam are shown in Table A4 15. Figure A4 14 shows the FGE relationships and figures A4 9 and A4 11 show the SPE relationships.

Table A4 15. Parameter estimates on the logit scale for FGE and SPE model components by dam for Chinook at Snake River dams for model average of models with no temperature and no RSW.

	FGE				**SPE**		
Dam	**Intercept**	**P.H. Flow**	**Day**		**Intercept**	**Logit(spill)**	**Flow**
LGR	1.580764	0.026582	-0.01121		2.075128	1.003269	-0.0077
LGS	1.311993	0.026582	-0.01121		1.667248	1.003269	-0.0077
LMN	0.246391	0.026582	-0.01121		1.823091	1.003269	-0.0077

Steelhead Snake River

The top 5 models of the 224 in the no-temperature group held 99.7% of the AIC weight, so the model average is heavily influenced by those top five. Table A4 16 shows the parameter estimates for the model average. Figure A4 15 shows the FGE relationships and Figures A4 10 and A4 12 show the SPE relationships.

Table A4 16. Parameter estimates on the logit scale for FGE and SPE model components by dam for Steelhead at Snake River dams for model average of models with no temperature.

		FGE				**SPE**		
Dam	**RSW**	**Intercept**	**P.H. Flow**	**Day**		**Intercept**	**Logit(spill)**	**Flow**
LGR	Off	2.338488	0.054432	-0.03179		0.723938	0.860551	-0.00077
	On	2.338488	0.054432	-0.03179		1.272162	0.860551	-0.00204
LGS	Off	1.987525	0.054432	-0.03179		0.589293	0.860551	-0.00077
	On	1.987525	0.054432	-0.03179		1.137517	0.860551	-0.00204

LMN	Off	1.61572	0.054432	-0.03179		0.75415	0.860551	-0.00077
	On	1.61572	0.054432	-0.03179		1.302374	0.860551	-0.00204

Chinook Columbia River

Model complexity was restricted for the MCN and JDA models due to the limited range of conditions and lower precision capture probability estimates at those sites. In particular, there were very few data points with low spill and those points had low weights. Also, many of the spill percentage values at JDA were clustered around 30%. This made estimation of the separate FGE and SPE components difficult. The SPE model component was restricted to just an intercept common to both MCN and JDA, and the slope on logit(spill) was fixed to 1.0. The top model of the eight possible in the no-temperature group held 83.7% of the AIC weight, and the top two models held 99.9% of the weight. Table A4 17 shows the model averaged parameter estimates by dam. Figure A4 14 shows the FGE relationships and Figure A4 7 shows the SPE relationships.

Table A4 17. Parameter estimates on the logit scale for FGE and SPE model components by dam for Chinook at Columbia River dams for model average of models with no temperature.

	FGE				**SPE**	
Dam	**Intercept**	**P.H. Flow**	**Day**		**Intercept**	**Logit(spill)**
MCN	3.349288	0.008832	-0.02217		0.586142	1.0
JDA	1.294261	0.008832	-0.02217		0.586142	1.0

Steehead Columbia River

The same set of restricted models were used for steelhead as were for Chinook. The top model in the no-temperature group held 75% of the AIC weight, and the top four held 99.9% of the weight. Table A4 18 shows the model averaged parameter estimates by dam. Figure A4 15 shows the FGE relationships and Figure A4 8 shows the SPE relationships.

Table A4 18. Parameter estimates on the logit scale for FGE and SPE model components by dam for Steelhead at Columbia River dams for model average of models with no temperature.

	FGE				**SPE**	
Dam	**Intercept**	**P.H. Flow**	**Day**		**Intercept**	**Logit(spill)**
MCN	-0.35434	0.012169	-0.0000007		1.31122	1.0
JDA	-1.98867	0.012169	-0.0000007		1.31122	1.0

Discussion

This method allows the use of PIT tag data to jointly estimate SPE and FGE contributions to the probability of entering a bypass system. PIT tag data are available for multiple sites across several years and for multiple weeks during the migration season. This allows for a wider, if less detailed, representation of environmental conditions and dam operations than with other data types. It also allows models to be fit for dams such as LGS and LMN, which are important transportation collection sites but have limited RT data available.
The representation of years and flow levels allowed us to investigate SPE models that included flow, which we did not do with the RT models due to concerns about confounding with dams and study protocols. Flow was a strong predictor of SPE in the RT data, but we did not pursue its use. Flow was also a strong predictor of SPE in many of the PIT tag models. We believe that its inclusion in the models is warranted given its predictive ability and mechanistic rational.

One of the main objectives of using the PIT tag data was to improve our predictions of the proportion of fish entering the bypass system. Accurate prediction of bypass proportions is necessary for accurate prediction of proportion of fish transported, which can greatly influence the estimated adult returns of a model run. We were not adequately predicting proportion of fish bypassed using other methods, especially at LGS and LMN.

One of the limitations of using the PIT tag method is that FGE and SPE contributions to bypass probability are not 100% separable. When either the FGE or the SPE component is inadequately specified, there is compensation in the other component. Compensation means that fish that would pass over the spillway may be predicted to pass through the turbines, or vice versa. This misclassification of passage route becomes more important where survival probabilities differ among routes, as they often do for turbines and spillways. It becomes more difficult to estimate the FGE parameters when there are limited data points with zero spill. For these reasons, the individual FGE and SPE models produced should be used with caution, particularly when applied outside of the range of the data to which the models were fit. However, when used in combination within the range of experience of the data we believe this method provides the best predictions of bypass probabilities.

Appendix Conclusions

There is a lot of quality data from a variety of sources available for estimating SPE and FGE at Snake and Columbia River dams. However, the many gaps in the data need to be filled before strong prediction models can be developed for all dams. We have used a combination of the best available data to develop our SPE and FGE models, and we have improved our predictions by incorporating the various data types and analyses methods. However, we do believe that model development is still a work in progress and will be improved as more data become available and as our methods of analyzing the data become more refined.

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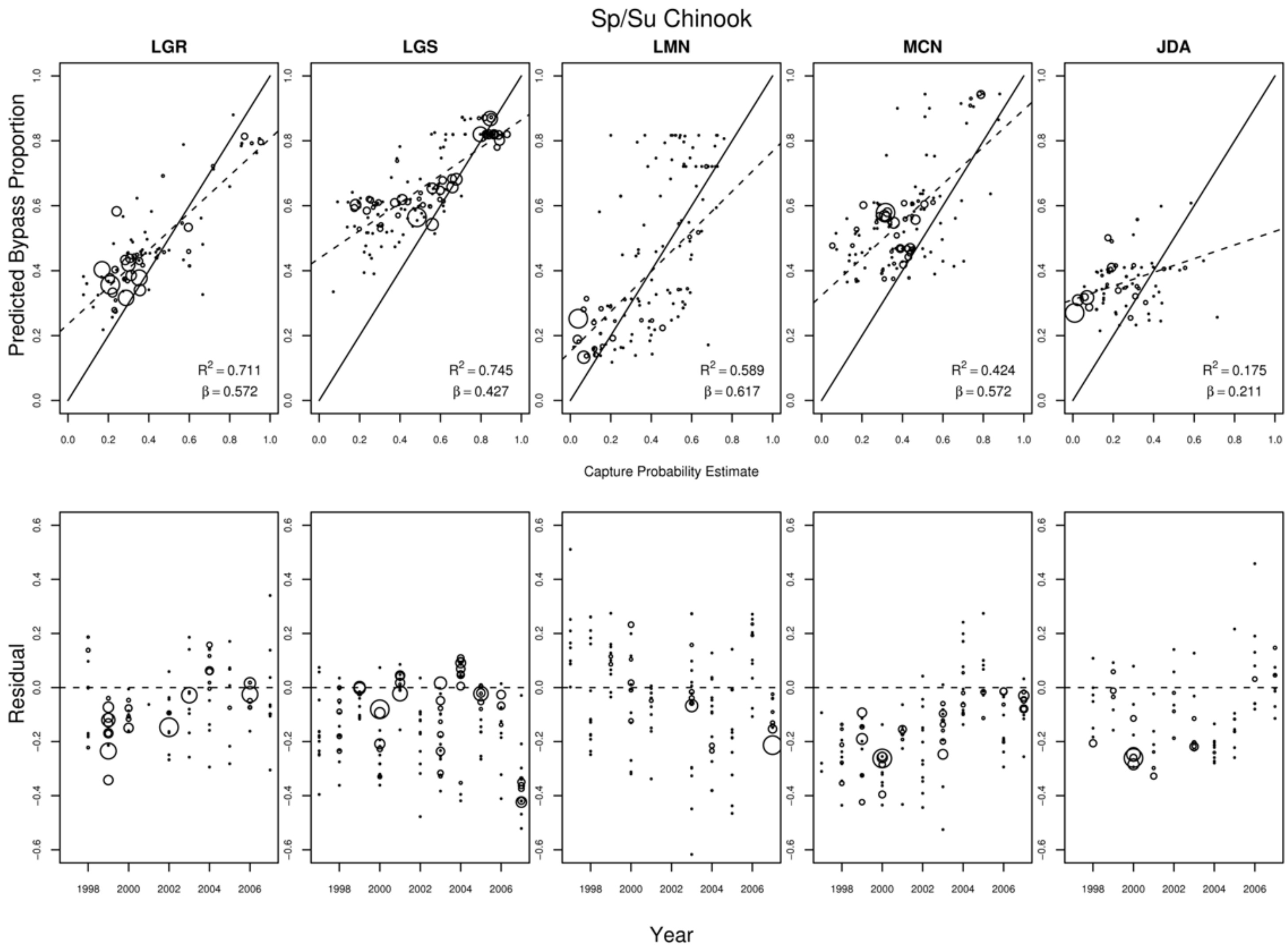

Figure A4 1. Comparison of predictions of bypass proportions from COMPASS model using original FGE estimates and SPE models versus PIT tag detection probabilities (1997-2007) for wild Snake River Sp/Su Chinook. The top row shows predicted versus observed plots and the bottom row shows residuals (observed – predicted) by year. Size of circles represents relative precision of estimates at a dam, with larger circles having higher precision. Also shown are squared weighted correlation between observed and predicted (R^2) and slope of weighted regression of predicted on observed (β).

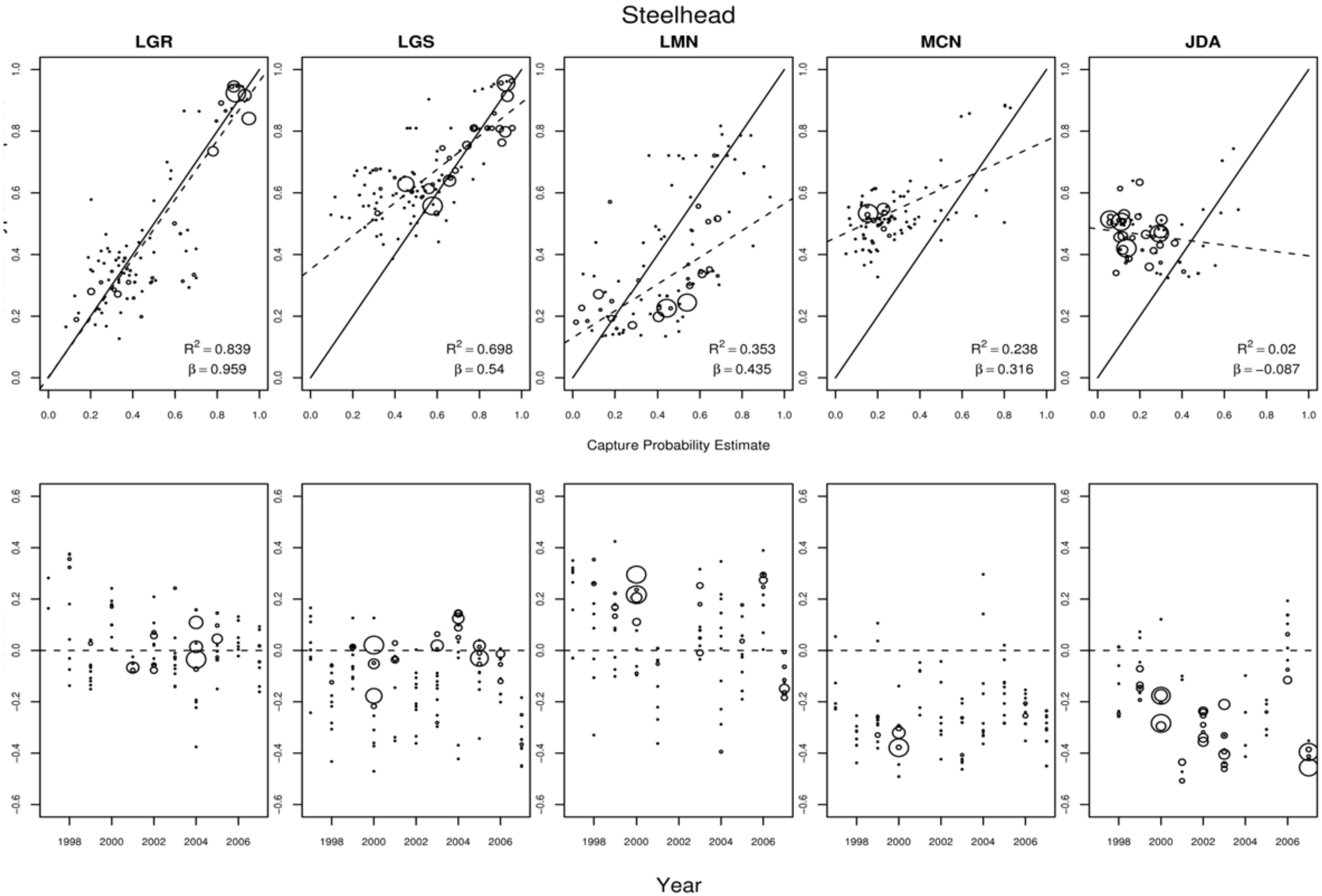

Figure A4 2. Comparison of predictions of bypass proportions from COMPASS model using original FGE estimates and SPE models versus PIT tag detection probabilities (1997-2007) for wild Snake River steelhead. The top row shows predicted versus observed plots and the bottom row shows residuals (observed – predicted) by year. Size of circles represents relative precision of estimates at a dam, with larger circles having higher precision. Also shown are squared weighted correlation between observed and predicted (R^2) and slope of weighted regression of predicted on observed (β).

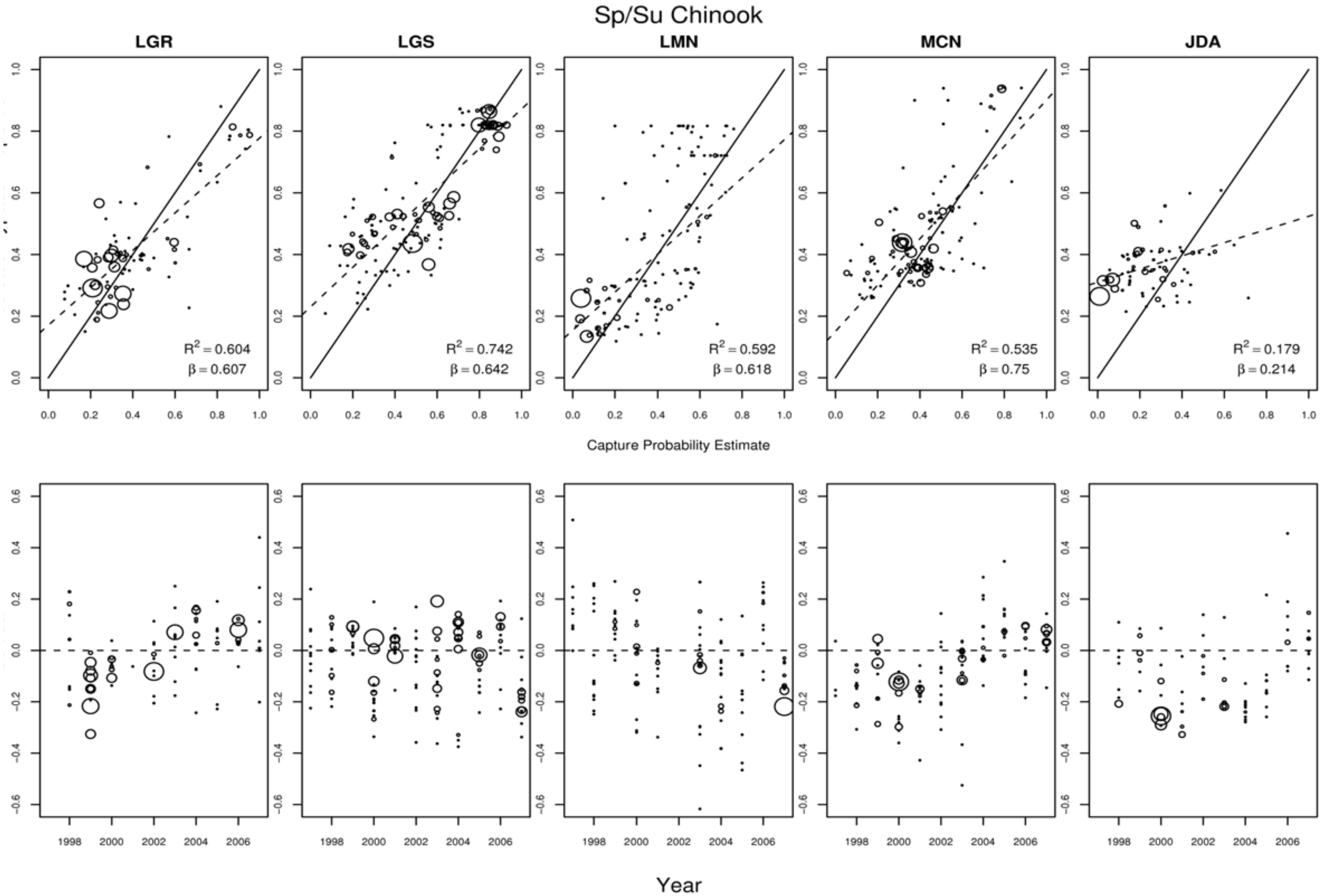

Figure A4 3. Comparison of predictions of bypass proportions from COMPASS model using original FGE estimates and RT-based SPE models versus PIT tag detection probabilities (1997-2007) for wild Snake River Sp/Su Chinook. The top row shows predicted versus observed plots and the bottom row shows residuals (observed – predicted) by year. Size of circles represents relative precision of estimates at a dam, with larger circles having higher precision. Also shown are squared weighted correlation between observed and predicted (R^2) and slope of weighted regression of predicted on observed (β).

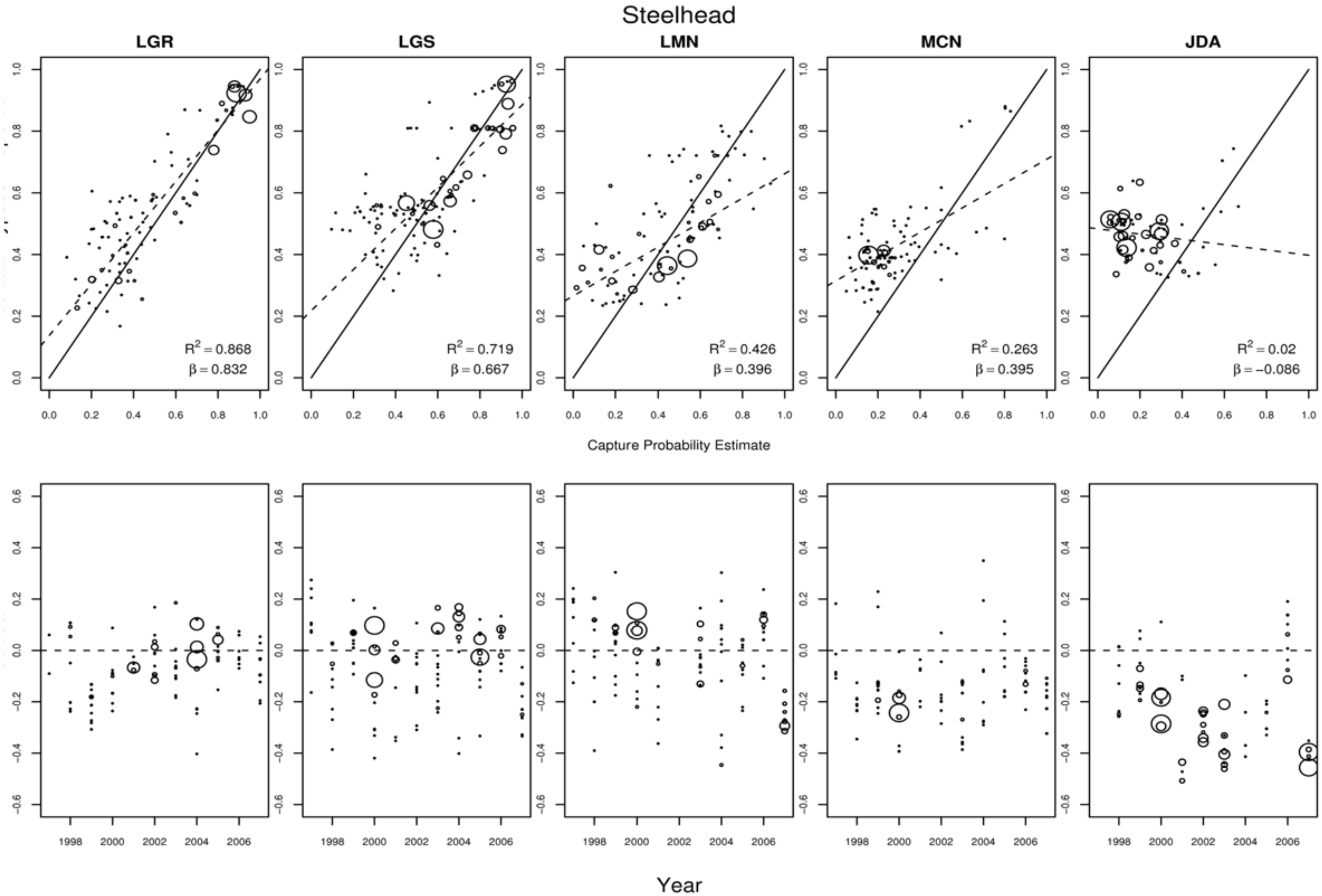

Figure A4 4. Comparison of predictions of bypass proportions from COMPASS model using original FGE estimates and RT-based SPE models versus PIT tag detection probabilities (1997-2007) for wild Snake River steelhead. The top row shows predicted versus observed plots and the bottom row shows residuals (observed – predicted) by year. Size of circles represents relative precision of estimates at a dam, with larger circles having higher precision. Also shown are squared weighted correlation between observed and predicted (R^2) and slope of weighted regression of predicted on observed (β).

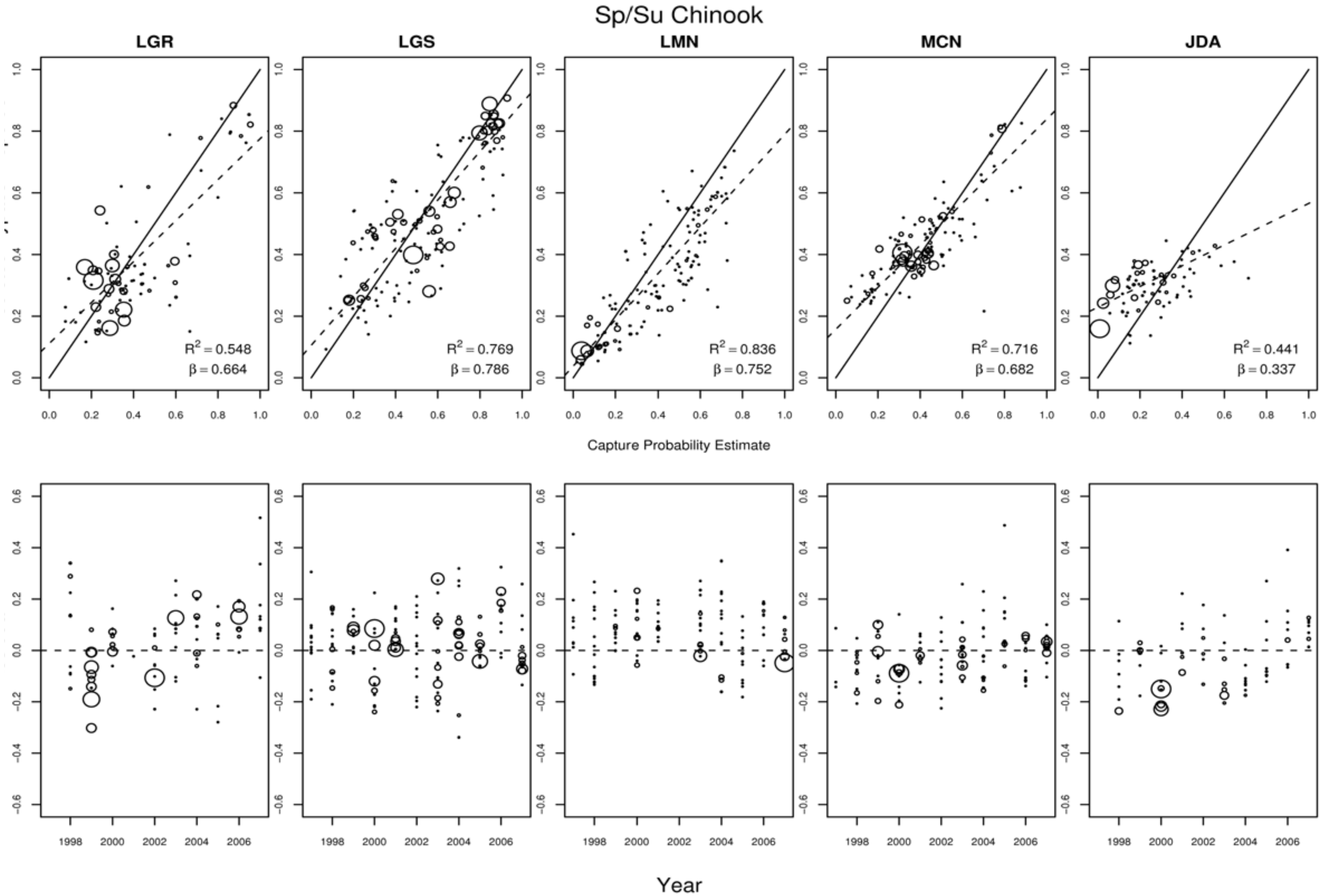

Figure A4 5. Comparison of predictions of bypass proportions from COMPASS model using FGE and SPE models estimated from PIT tag data versus PIT tag detection probabilities (1997-2007) for wild Snake River Sp/Su Chinook. The top row shows predicted versus observed plots and the bottom row shows residuals (observed – predicted) by year. Size of circles represents relative precision of estimates at a dam, with larger circles having higher precision. Also shown are squared weighted correlation between observed and predicted (R^2) and slope of weighted regression of predicted on observed (β).

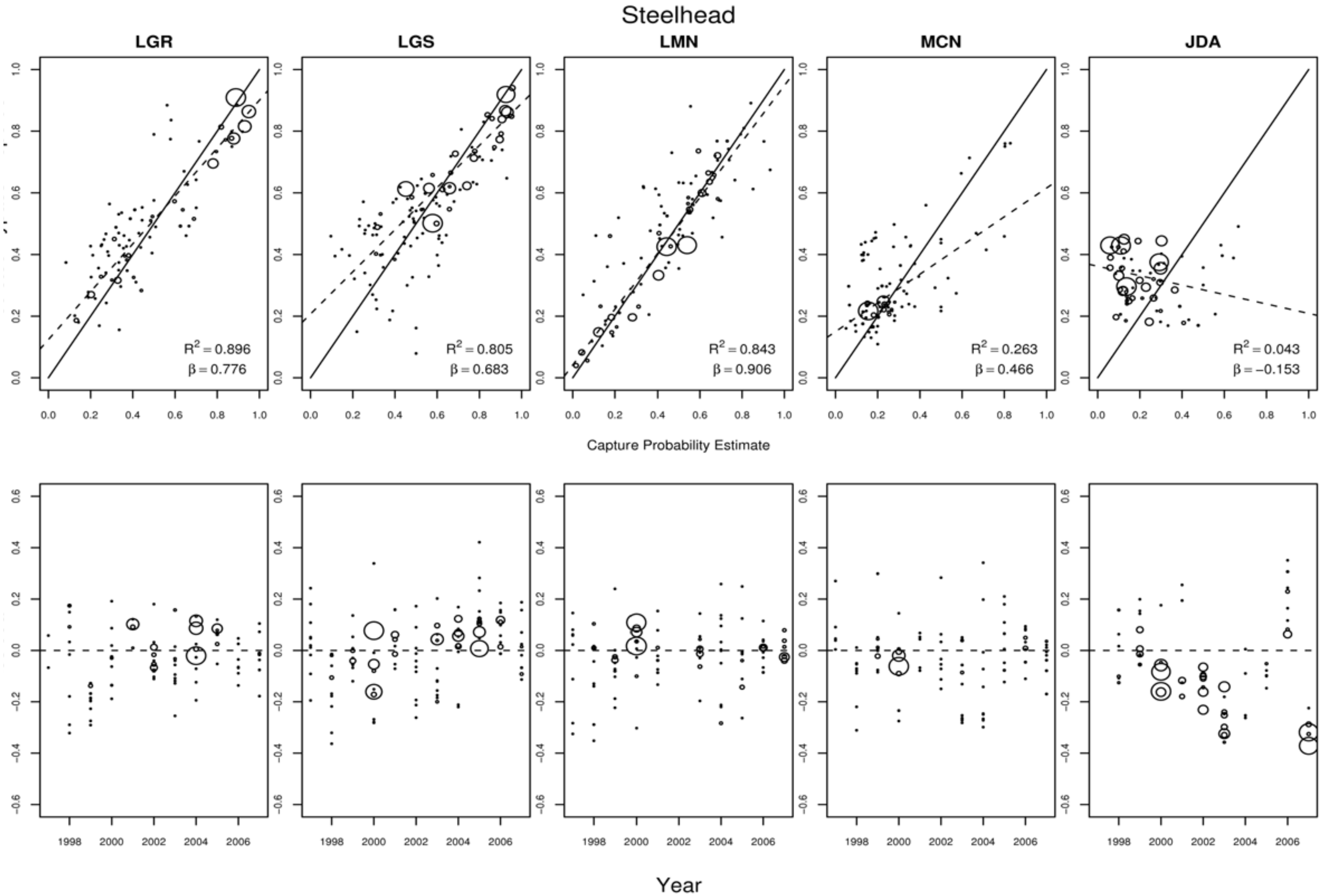

Figure A4 6. Comparison of predictions of bypass proportions from COMPASS model using FGE and SPE models estimated from PIT tag data versus PIT tag detection probabilities (1997-2007) for wild Snake River steelhead. The top row shows predicted versus observed plots and the bottom row shows residuals (observed – predicted) by year. Size of circles represents relative precision of estimates at a dam, with larger circles having higher precision. Also shown are squared weighted correlation between observed and predicted (R^2) and slope of weighted regression of predicted on observed (β).

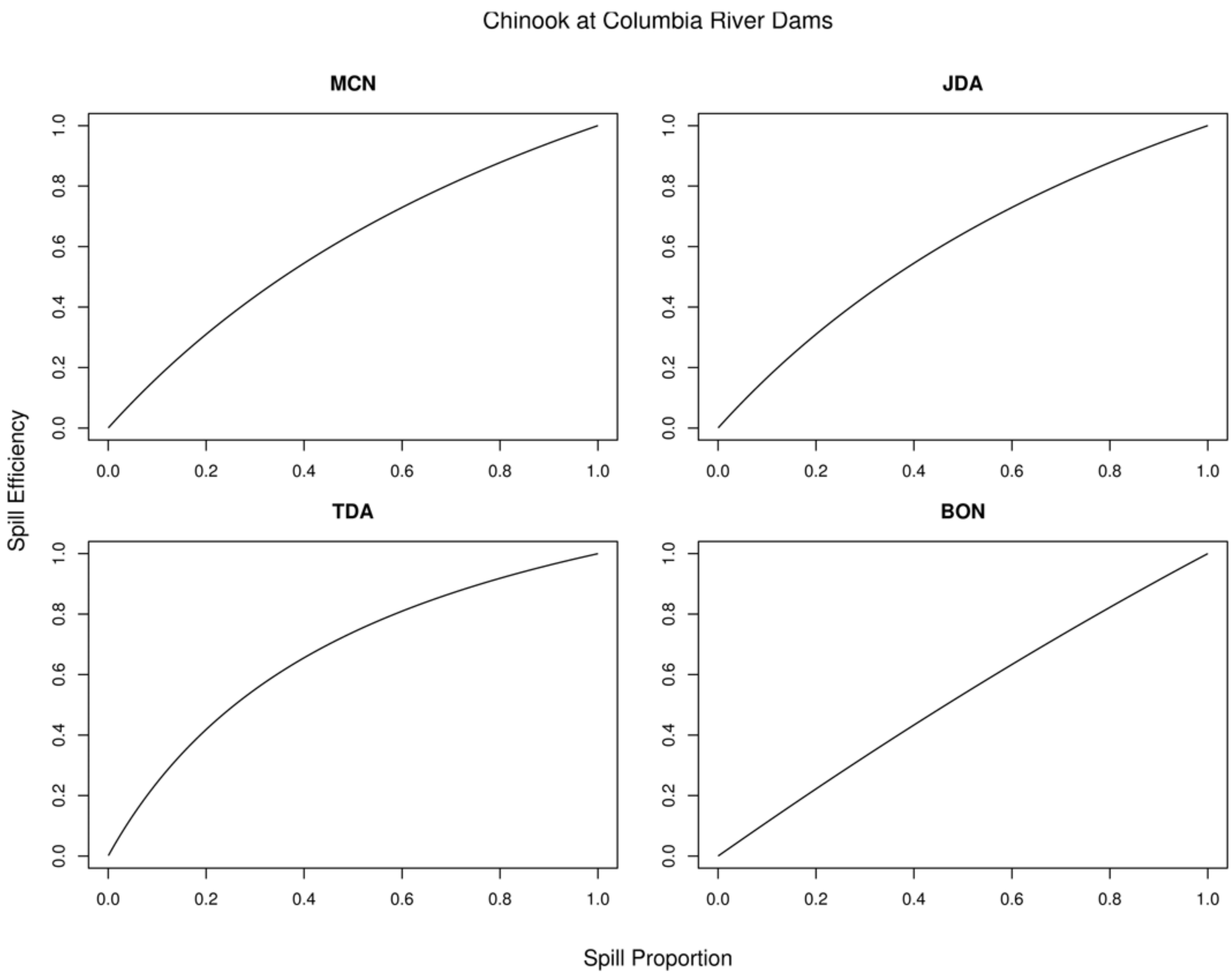

Figure A4 7. Spill Efficiency curves as currently used in COMPASS for wild Snake River Sp/Su Chinook at Columbia River dams. The MCN and JDA relationships are based on models fit to PIT tag data, and the TDA and BON relationships are based on fits to summaries of RT data.

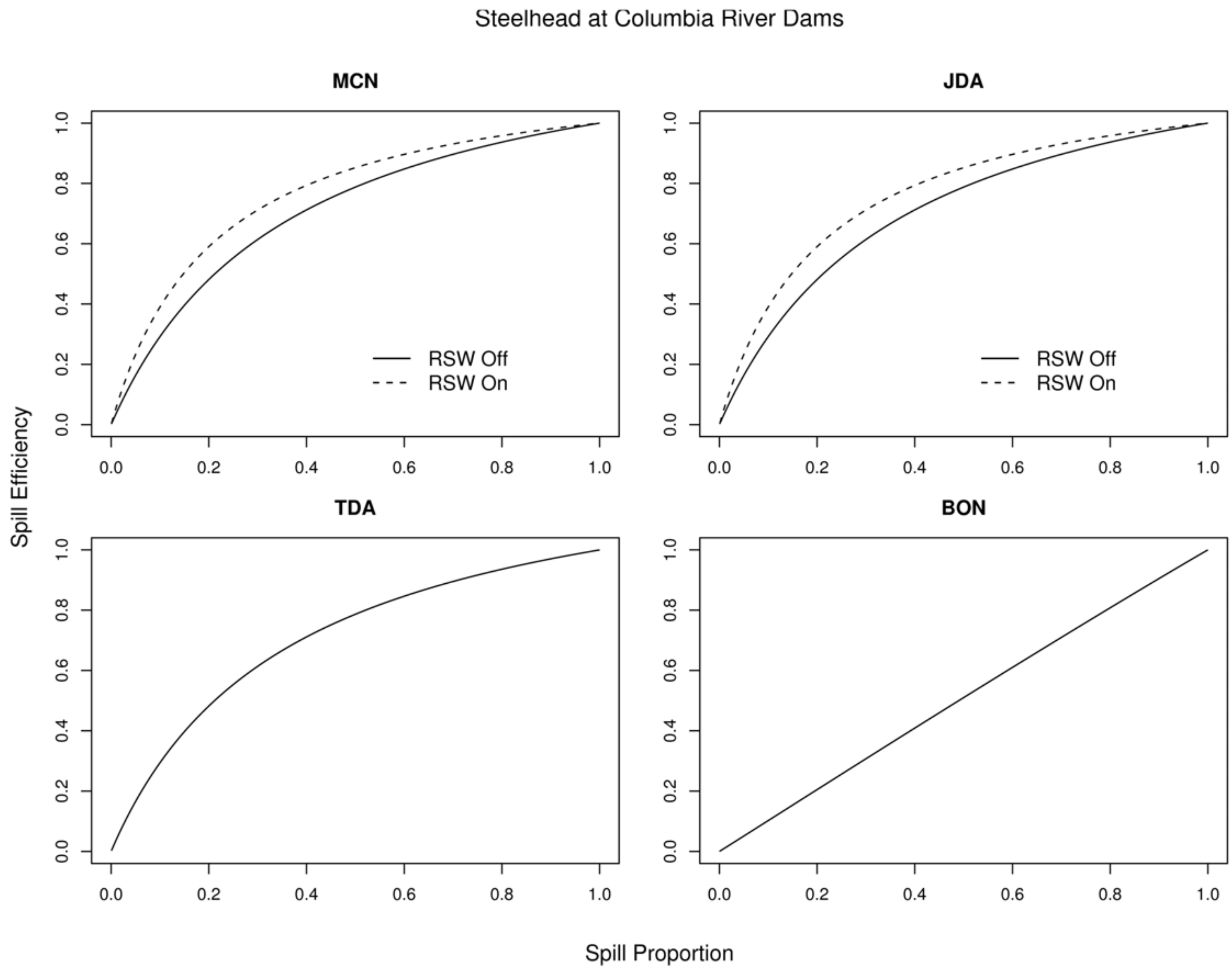

Figure A4 8. Spill Efficiency curves by RSW operation as currently used in COMPASS for wild Snake River steelhead at Columbia River dams. The MCN and JDA relationships are based on models fit to PIT tag data, and the TDA and BON relationships are based on fits to summaries of RT data. The estimate of RSW effect is taken from model for steelhead at LGR.

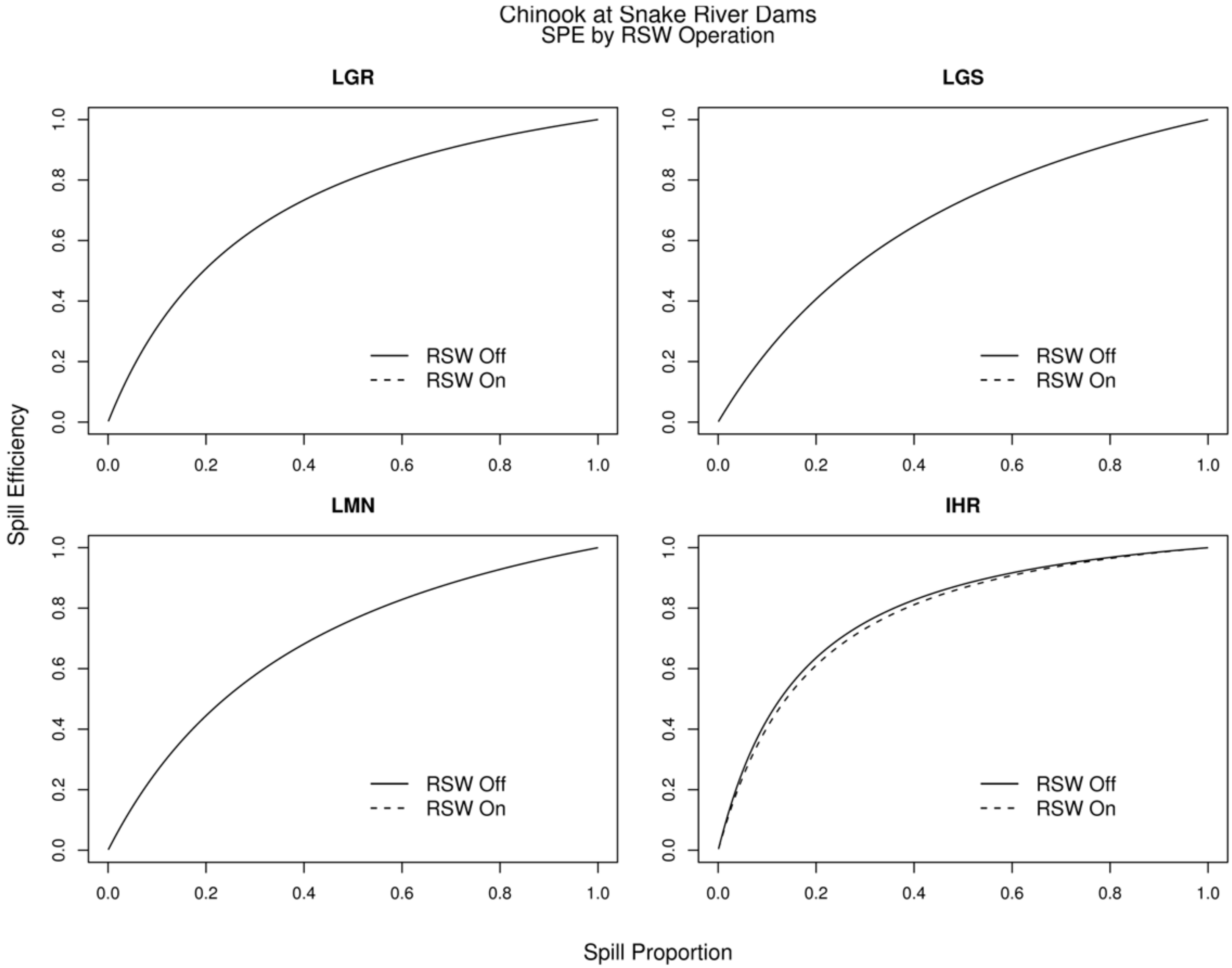

Figure A4 9. Spill Efficiency curves currently used in COMPASS for wild Snake River Sp/Su Chinook at Snake River dams. The LGR, LGS, and LMN relationships are based on models fit to PIT tag data, and the IHR relationship are based on model fit to individual RT data. Curves shown for LGR, LGS, and LMN are for an average level of flow (85 kcfs). The IHR relationship does not depend on flow.

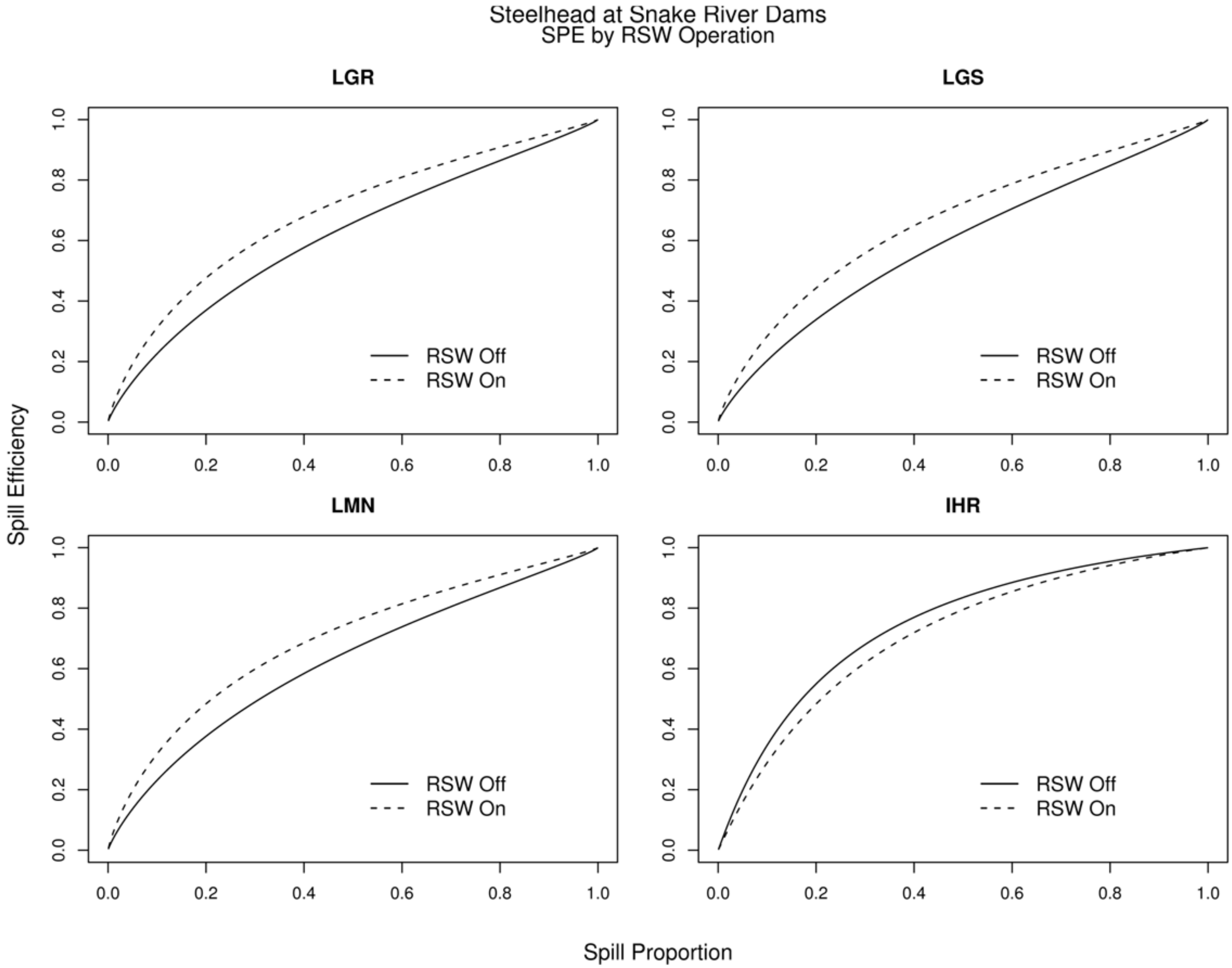

Figure A4 10. Spill Efficiency curves currently used in COMPASS for wild Snake River steelhead at Snake River dams. The LGR, LGS, and LMN relationships are based on models fit to PIT tag data, and the IHR relationship are based on model fit to individual RT data. Curves shown for LGR, LGS, and LMN are for an average level of flow (85 kcfs). The IHR relationship does not depend on flow.

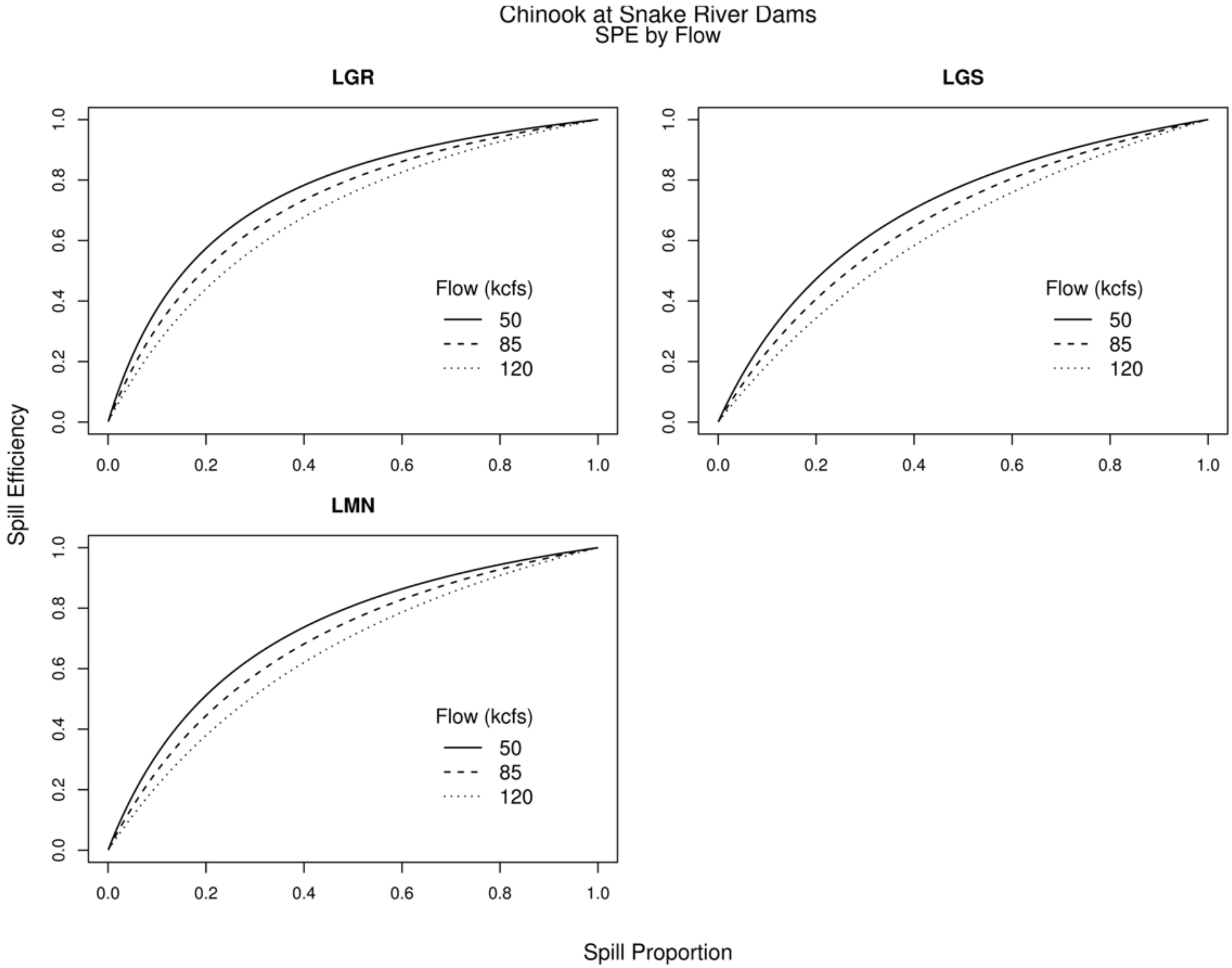

Figure A4 11. Spill Efficiency curves currently used in COMPASS for wild Snake River Sp/Su Chinook at Snake River dams. Curves show relationship at various levels of flow for dams where models including flow were fit. These relationships are derived from PIT tag data. These models for Sp/Su Chinook did not have an RSW effect.

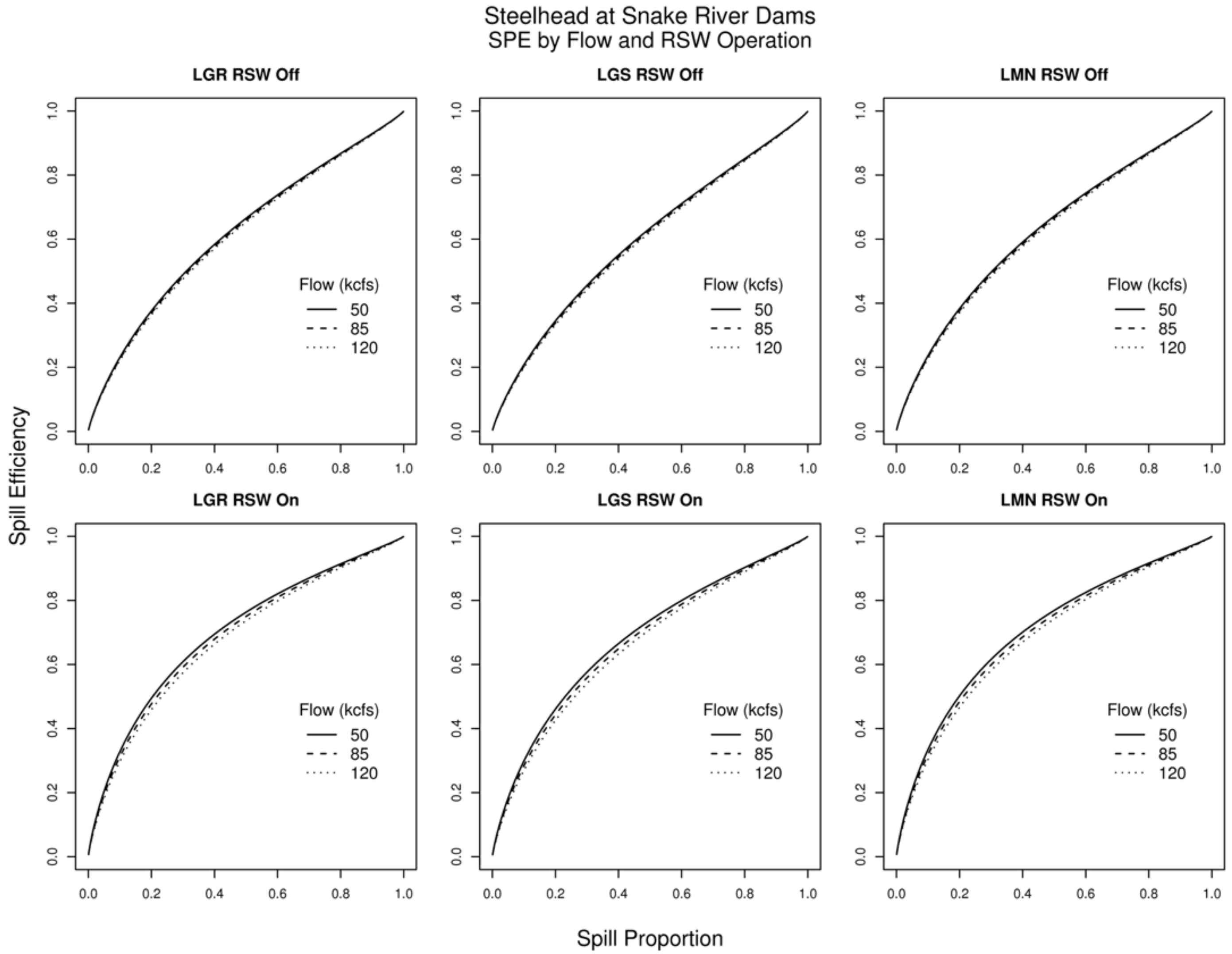

Figure A4 12. Spill Efficiency curves currently used in COMPASS for wild Snake River steelhead at Snake River dams. Curves show relationship at various levels of flow by RSW on/off for dams where models including flow were fit. These relationships are derived from PIT tag data.

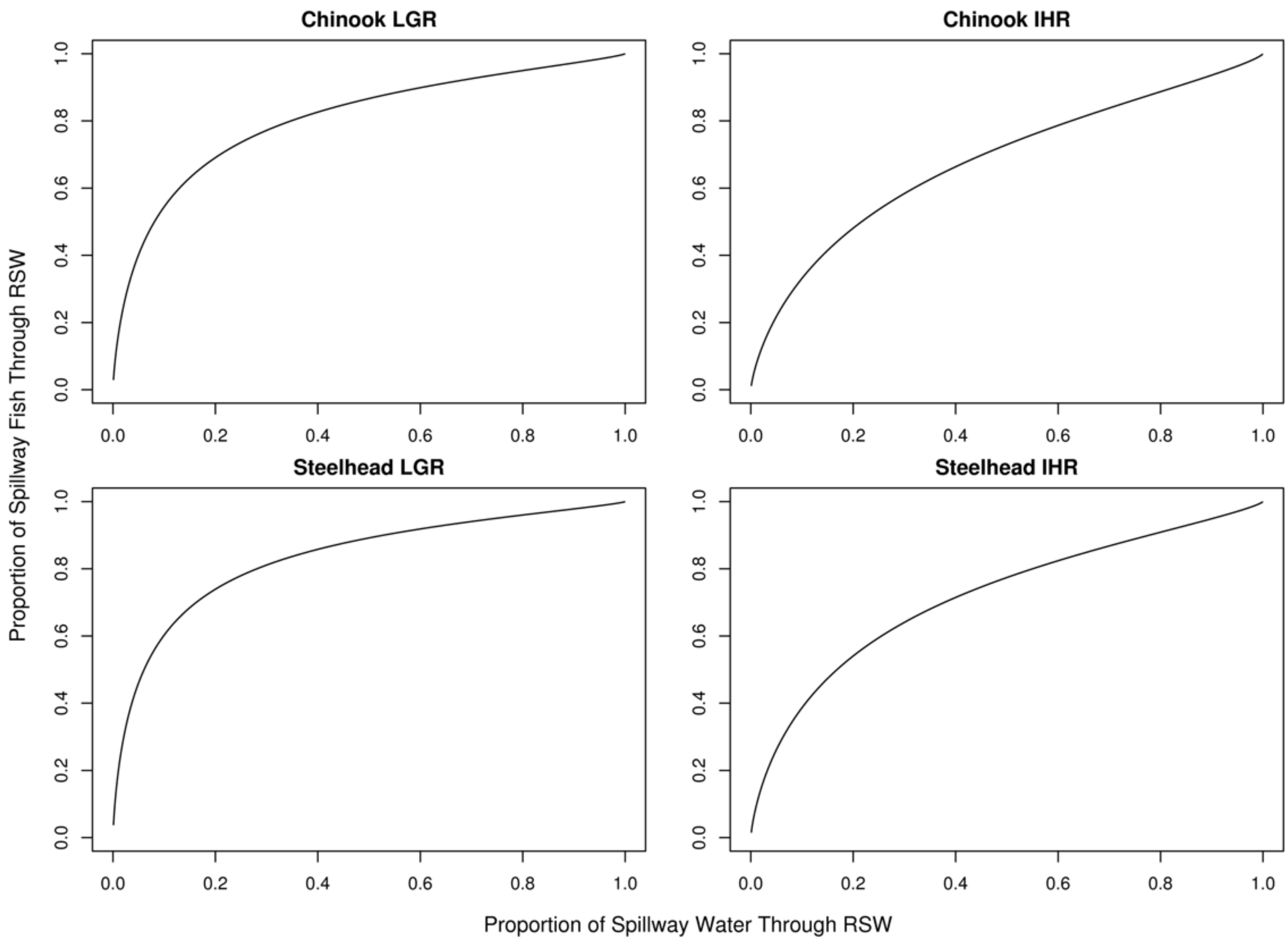

Figure A4 13. RSW Spill Efficiency as a function of proportion of spillway water passing through RSW for Snake River Sp/Su Chinook and Snake River steelhead at LGR and IHR. These relationships are currently used in COMPASS and are based on models fit to data on individual radio-tagged fish.

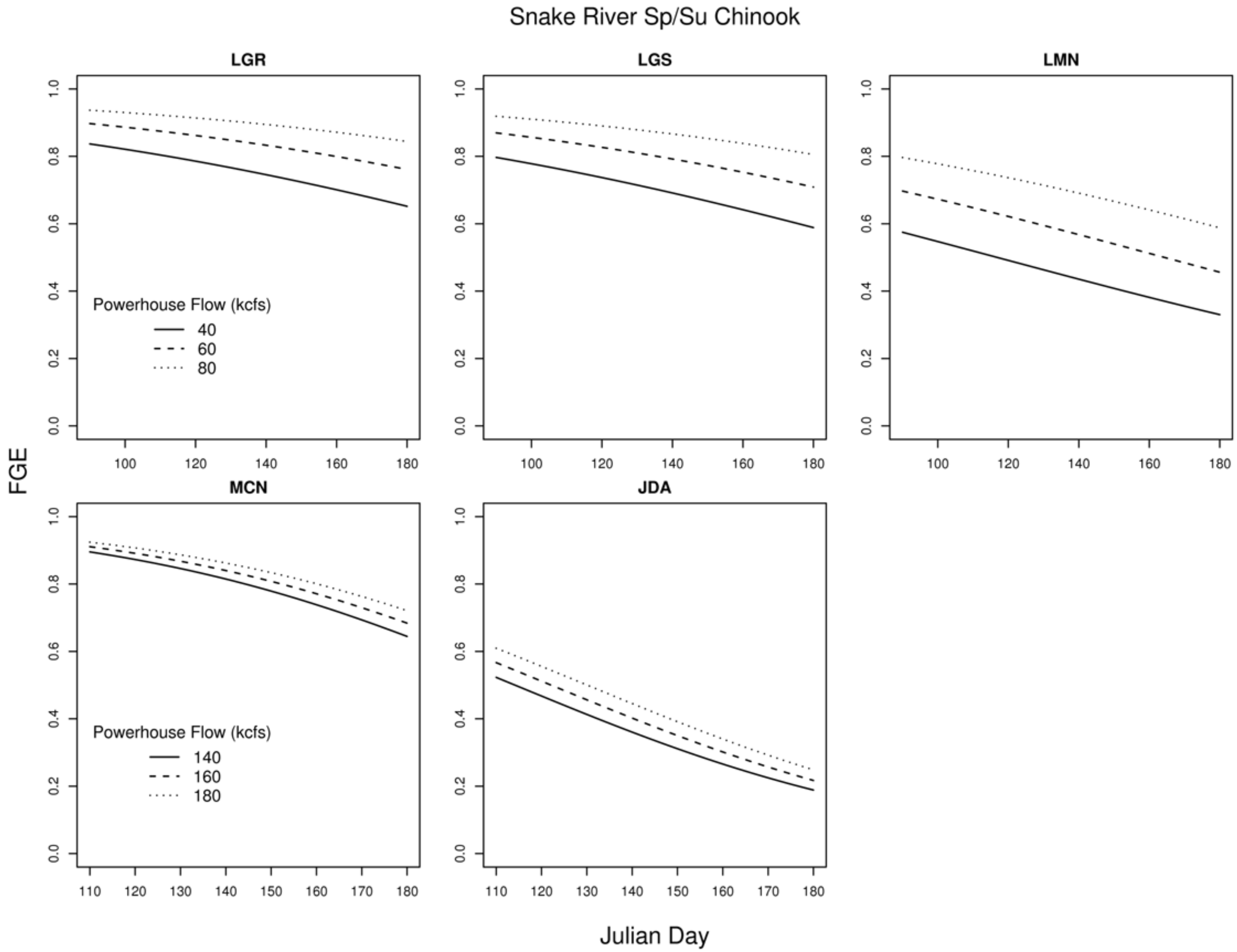

Figure A4 14. Fish Guidance Efficiency by Julian day and powerhouse flow for wild Snake River Sp/Su Chinook at all dams where FGE relationships were derived from PIT tag data. These relationships are currently used in COMPASS.

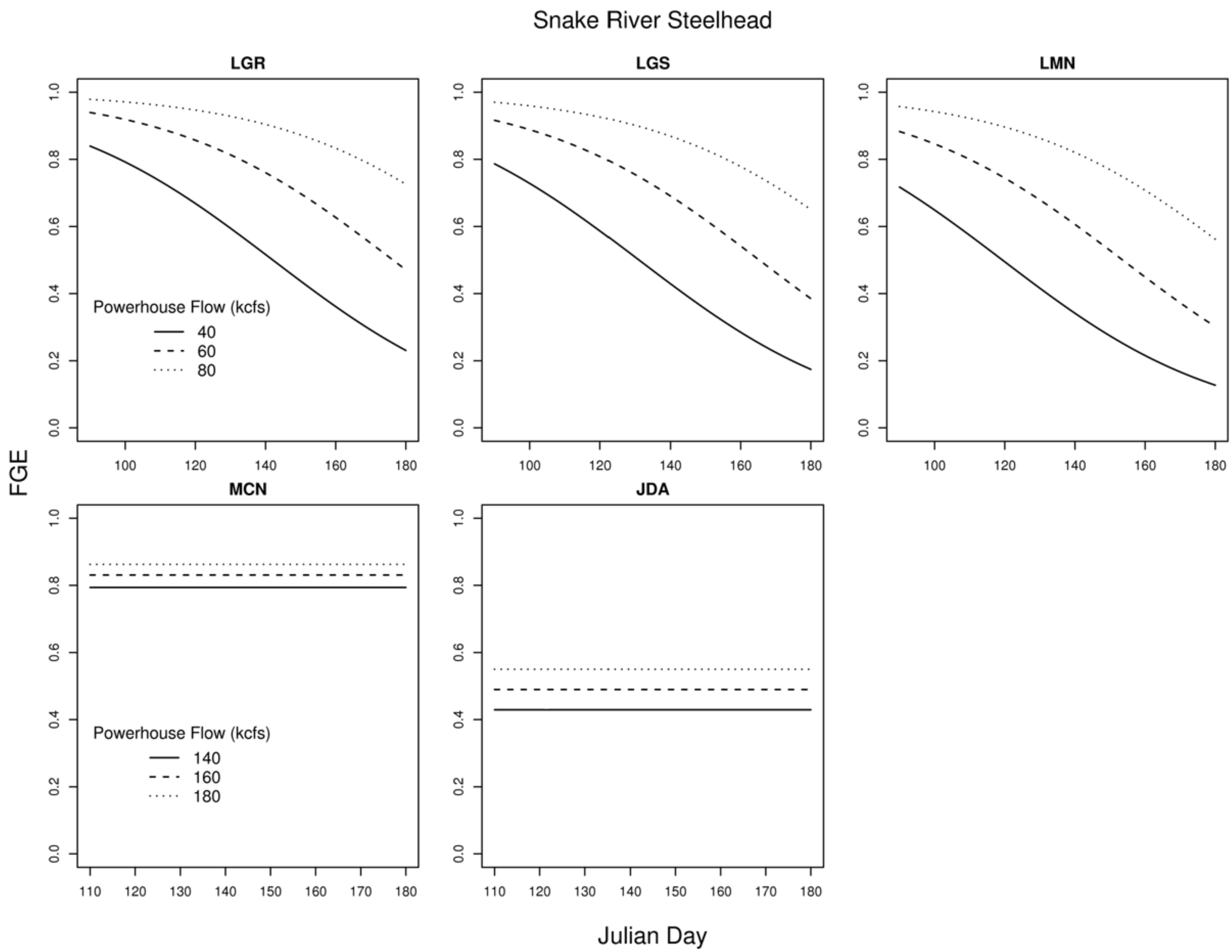

Figure A4 15. Fish Guidance Efficiency by Julian day and powerhouse flow for wild Snake River steelhead at all dams where FGE relationships were derived from PIT tag data. These relationships are currently used in COMPASS.

This appendix contains tables of dam survival and passage parameters and references.

Bonneville Dam	Species	Compass parameter	Value	Data Source
1995				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.38	Ferguson et al. 2005.
		Sluicewway/SBC_Proportion	0.44	
		Power_Priority	1	
		Turbine_Survival	0.9	Marmorek and Peters.1998. Standard PATH turbine survival.
		Spillway_Survival	0.98	Marmorek and Peters. 1998. Standard PATH spill survival parameter.
		Bypass_Survival	0.9	2000 Biological Opinion - Biological Effects Team Judgement
		Sluiceway/SBC_Survival	0.9	2000 Biological Opinion - Biological Effects Team Judgement
		Diel	0.43	
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.41	Ferguson et al. 2005.
		Sluicewway/SBC_Proportion	0.44	
		Power_Priority	1	
		Turbine_Survival	0.9	Marmorek and Peters.1998. Standard PATH turbine survival.
		Spillway_Survival	0.98	Marmorek and Peters. 1998. Standard PATH spill survival parameter.
		Bypass_Survival	0.9	
		Sluiceway/SBC_Survival	0.9	2000 Biological Opinion - Biological Effects Team Judgement
		Diel	0.505	Evans et al. 2003. Adapted from data in the Addendum 1 to the 2002 RT research report for only the 75kcfs day/TDG night spill treatments.
1996				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.38	Ferguson et al. 2005.
		Sluicewway/SBC_Proportion	0.44	
		Power_Priority	1	
		Turbine_Survival	0.9	Marmorek and Peters.1998. Standard PATH turbine survival.
		Spillway_Survival	0.98	Marmorek and Peters. 1998. Standard PATH spill survival parameter.
		Bypass_Survival	0.9	2000 Biological Opinion - Biological Effects Team Judgement
		Sluiceway/SBC_Survival	0.9	2000 Biological Opinion - Biological Effects Team Judgement
		Diel	0.43	
	Steelhead			
		rsw_spill_cap	0	

Bonneville Dam	Species	Compass parameter	Value	Data Source
		FGE	0.41	Ferguson et al. 2005.
		Sluicewway/SBC_Proportion	0.44	
		Power_Priority	1	
		Turbine_Survival	0.9	Marmorek and Peters.1998. Standard PATH turbine survival.
		Spillway_Survival	0.98	Marmorek and Peters. 1998. Standard PATH spill survival parameter.
		Bypass_Survival	0.9	
		Sluiceway/SBC_Survival	0.9	2000 Biological Opinion - Biological Effects Team Judgement
		Diel	0.505	Evans et al. 2003. Adapted from data in the Addendum 1 to the 2002 RT research report for only the 75kcfs day/TDG night spill treatments.
1997				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.38	Ferguson et al. 2005.
		Sluicewway/SBC_Proportion	0.44	
		Power_Priority	1	
		Turbine_Survival	0.9	Marmorek and Peters.1998. Standard PATH turbine survival.
		Spillway_Survival	0.98	Marmorek and Peters. 1998. Standard PATH spill survival parameter.
		Bypass_Survival	0.9	2000 Biological Opinion - Biological Effects Team Judgement
		Sluiceway/SBC_Survival	0.9	2000 Biological Opinion - Biological Effects Team Judgement
		Diel	0.43	
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.41	Ferguson et al. 2005.
		Sluicewway/SBC_Proportion	0.44	
		Power_Priority	1	
		Turbine_Survival	0.9	Marmorek and Peters.1998. Standard PATH turbine survival.
		Spillway_Survival	0.98	Marmorek and Peters. 1998. Standard PATH spill survival parameter.
		Bypass_Survival	0.9	
		Sluiceway/SBC_Survival	0.9	2000 Biological Opinion - Biological Effects Team Judgement
		Diel	0.504761905	Evans et al. 2003. Adapted from data in the Addendum 1 to the 2002 RT research report for only the 75kcfs day/TDG night spill treatments.
1998				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.38	Ferguson et al. 2005.
		Sluicewway/SBC_Proportion	0.44	
		Power_Priority	1	
		Turbine_Survival	0.9	Marmorek and Peters.1998. Standard PATH turbine survival.

Bonneville Dam	Species	Compass parameter	Value	Data Source
		Spillway_Survival	0.98	Marmorek and Peters. 1998. Standard PATH spill survival parameter.
		Bypass_Survival	0.9	2000 Biological Opinion - Biological Effects Team Judgement
		Sluiceway/SBC_Survival	0.9	2000 Biological Opinion - Biological Effects Team Judgement
		Diel	0.43	
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.41	Ferguson et al. 2005.
		Sluicewway/SBC_Proportion	0.44	
		Power_Priority	1	
		Turbine_Survival	0.9	Marmorek and Peters.1998. Standard PATH turbine survival.
		Spillway_Survival	0.98	Marmorek and Peters. 1998. Standard PATH spill survival parameter.
		Bypass_Survival	0.99	
		Sluiceway/SBC_Survival	0.9	2000 Biological Opinion - Biological Effects Team Judgement
		Diel	0.504761905	Evans et al. 2003. Adapted from data in the Addendum 1 to the 2002 RT research report for only the 75kcfs day/TDG night spill treatments.
1999				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.38	Ferguson et al. 2005.
		Sluicewway/SBC_Proportion	0.44	
		Power_Priority	1	
		Turbine_Survival	0.9	Marmorek and Peters.1998. Standard PATH turbine survival.
		Spillway_Survival	0.98	Marmorek and Peters. 1998. Standard PATH spill survival parameter.
		Bypass_Survival	0.9	2000 Biological Opinion - Biological Effects Team Judgement
		Sluiceway/SBC_Survival	0.9	2000 Biological Opinion - Biological Effects Team Judgement
		Diel	0.43	
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.41	Ferguson et al. 2005.
		Sluicewway/SBC_Proportion	0.44	
		Power_Priority	1	
		Turbine_Survival	0.9	Marmorek and Peters.1998. Standard PATH turbine survival.
		Spillway_Survival	0.98	Marmorek and Peters. 1998. Standard PATH spill survival parameter.
		Bypass_Survival	0.99	
		Sluiceway/SBC_Survival	0.9	2000 Biological Opinion - Biological Effects Team Judgement
		Diel	0.504761905	Evans et al. 2003. Adapted from data in the Addendum 1 to the 2002 RT research report for only the 75kcfs day/TDG night spill treatments.
2000				

Bonneville Dam	Species	Compass parameter	Value	Data Source
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.5	Evans et al. 2001a. Report for 2000 RT research.
		Sluicewway/SBC_Proportion	0.29	Evans et al. 2001a. Report for 2000 RT research.
		Power_Priority	1	
		Turbine_Survival	0.9	Marmorek and Peters.1998. Standard PATH turbine survival.
		Spillway_Survival	0.98	Marmorek and Peters. 1998. Standard PATH spill survival parameter.
		Bypass_Survival	0.9	2000 Biological Opinion - Biological Effects Team Judgement
		Sluiceway/SBC_Survival	0.9	2000 Biological Opinion - Biological Effects Team Judgement
		Diel	0.43	
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.59	Evans et al. 2001a. Report for 2000 RT research.
		Sluicewway/SBC_Proportion	0.44	Evans et al. 2001a. Report for 2000 RT research.
		Power_Priority	1	
		Turbine_Survival	0.9	Marmorek and Peters.1998. Standard PATH turbine survival.
		Spillway_Survival	0.98	Marmorek and Peters. 1998. Standard PATH spill survival parameter.
		Bypass_Survival	0.9	
		Sluiceway/SBC_Survival	0.9	2000 Biological Opinion - Biological Effects Team Judgement
		Diel	0.504761905	Evans et al. 2003. Adapted from data in the Addendum 1 to the 2002 RT research report for only the 75kcfs day/TDG night spill treatments.
2001				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.45	Evans et al. 2001b. Report for 2001 RT research.
		Sluicewway/SBC_Proportion	0.76	Evans et al. 2001b. Report for 2001 RT research.
		Power_Priority	2	
		Turbine_Survival	0.92	Best Professional Judgement, estimated improved survival due to MGR unit installation.
		Spillway_Survival	0.98	Marmorek and Peters. 1998. Standard PATH spill survival parameter.
		Bypass_Survival	0.9	2000 Biological Opinion - Biological Effects Team Judgement.
		Sluiceway/SBC_Survival	0.92	Best Professional Judgement, Assumed no better than PH1 turbine survival.
		Diel	0.43	
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.5	
		Sluicewway/SBC_Proportion	0.6	

Bonneville Dam	Species	Compass parameter	Value	Data Source
		Power_Priority	2	
		Turbine_Survival	0.92	Best Professional Judgement, estimated improved survival due to MGR unit installation.
		Spillway_Survival	0.98	Marmorek and Peters. 1998. Standard PATH spill survival parameter.
		Bypass_Survival	0.99	
		Sluiceway/SBC_Survival	0.92	Best Professional Judgement, Assumed no better than PH1 turbine survival.
		Diel	0.504761905	Evans et al. 2003. Adapted from data in the Addendum 1 to the 2002 RT research report for only the 75kcfs day/TDG night spill treatments.
2002				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.5	Evans et al. 2003. Report for 2002 RT research (season ave.).
		Sluicewway/SBC_Proportion	0.33	Ploskey et al. 2003. Report for 2002 HA research.
		Power_Priority	2	
		Turbine_Survival	0.92	Best Professional Judgement, estimated improved survival due to MGR unit installation.
		Spillway_Survival	0.977	Counihan et al. 2003. Draft report for 2002 research (this value reflects the average of 2 treatments).
		Bypass_Survival	0.91	Counihan et al. 2003. Draft report for 2002 research.
		Sluiceway/SBC_Survival	0.92	Best Professional Judgement, Assumed no better than PH1 turbine survival.
		Diel	0.43	
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.75	Evans et al. 2003. Report for 2002 RT research (season ave.). High Sandard error!
		Sluicewway/SBC_Proportion	0.65	
		Power_Priority	2	
		Turbine_Survival	0.92	Best Professional Judgement, estimated improved survival due to MGR unit installation.
		Spillway_Survival	0.977	Counihan et al. 2003. Draft report for 2002 research (this value reflects the average of 2 treatments).
		Bypass_Survival	0.91	
		Sluiceway/SBC_Survival	0.92	Best Professional Judgement, Assumed no better than PH1 turbine survival.
		Diel	0.504761905	Evans et al. 2003. Adapted from data in the Addendum 1 to the 2002 RT research report for only the 75kcfs day/TDG night spill treatments.
2003				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.45	Evans et al. 2001b. Report for 2001 RT research.

Bonneville Dam	Species	Compass parameter	Value	Data Source
		Sluicewway/SBC_Proportion	0.6	
		Power_Priority	2	
		Turbine_Survival	0.92	Best Professional Judgement, improved survival due to MGR unit installation.
		Spillway_Survival	0.936	Counihan et al. 2003, 2005a, 2005b. Ave of '02, '04, '05 for 75k day/TDG cap night operation.
		Bypass_Survival	0.91	Counihan et al. 2003. Draft report for 2002 research.
		Sluiceway/SBC_Survival	0.92	Best Professional Judgement, Assumed no better than PH1 turbine survival.
		Diel	0.43	
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.41	Ferguson et al. 2005.
		Sluicewway/SBC_Proportion	0.6	
		Power_Priority	2	
		Turbine_Survival	0.92	Best Professional Judgement, improved survival due to MGR unit installation.
		Spillway_Survival	0.936	Counihan et al. 2003, 2005a, 2005b. Ave of '02, '04, '05 for 75k day/TDG cap night operation.
		Bypass_Survival	0.91	
		Sluiceway/SBC_Survival	0.92	Best Professional Judgement, Assumed no better than PH1 turbine survival.
		Diel	0.504761905	Evans et al. 2003. Adapted from data in the Addendum 1 to the 2002 RT research report for only the 75kcfs day/TDG night spill treatments.
2004				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0	
		Sluicewway/SBC_Proportion	0.53	Reagan et al. 2005. Report for 2004 RT research.
		Power_Priority	2	
		Turbine_Survival	0.996	Counihan et al. 2005a. Draft report for 2004 research.
		Spillway_Survival	0.91	Counihan et al. 2005a. Draft report for 2004 research.
		Bypass_Survival	1	
		Sluiceway/SBC_Survival	0.937	Counihan et al. 2005a. Draft report for 2004 research.
		Diel	0.43	
	Steelhead			
		rsw_spill_cap	0	
		FGE	0	
		Sluicewway/SBC_Proportion	0.55	Reagan et al. 2005. Report for 2004 RT research.
		Power_Priority	2	
		Turbine_Survival	0.974	Counihan et al. 2005a. Draft report for 2004 research.
		Spillway_Survival	0.979	Counihan et al. 2005a. Draft report for 2004 research.
		Bypass_Survival	1	

Bonneville Dam	Species	Compass parameter	Value	Data Source
		Sluiceway/SBC_Survival	0.985	Counihan et al. 2005a. Draft report for 2004 research.
		Diel	0.504761905	Evans et al. 2003. Adapted from data in the Addendum 1 to the 2002 RT research report for only the 75kcfs day/TDG night spill treatments.
2005				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0	
		Sluicewway/SBC_Proportion	0.44	
		Power_Priority	2	
		Turbine_Survival	0.948	Counihan et al. 2005b. Draft 2005 research report.
		Spillway_Survival	0.93	Counihan et al. 2005b. Draft 2005 research report.
		Bypass_Survival	1	
		Sluiceway/SBC_Survival	0.919	Counihan et al. 2005b. Draft 2005 research report.
		Diel	0.43	
	Steelhead			
		rsw_spill_cap	0	
		FGE	0	
		Sluicewway/SBC_Proportion	0.44	
		Power_Priority	2	
		Turbine_Survival	0.934	Counihan et al. 2005b. Draft 2005 research report. Based on PH1 total survival estimate.
		Spillway_Survival	0.955	Counihan et al. 2005b. Draft 2005 research report.
		Bypass_Survival	1	
		Sluiceway/SBC_Survival	0.933	Counihan et al. 2005b. Draft 2005 research report. Based on PH1 total survival estimate.
		Diel	0.5	Evans et al. 2003. Adapted from data in the Addendum 1 to the 2002 RT research report for only the 75kcfs day/TDG night spill treatments.
Current				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0	
		Sluicewway/SBC_Proportion	0.44	
		Power_Priority	2	
		Turbine_Survival	0.948	Counihan et al. 2005a and 2005b. Average of 2004 and 2005 turbine survivals under low powerhouse loading.
		Spillway_Survival	0.969	Counihan et al. 2003, 2005a, 2005b. Average of 2002, 2004 and 2005 spillway survivals w/ spill near 100 kcfs (night only in 2004 and 2005).
		Bypass_Survival	1	
		Sluiceway/SBC_Survival	0.928	Counihan et al. 2005a and 2005b. Average of 2004 and 2005 sluiceway survivals under low powerhouse loading.
		Diel	0.43	
	Steelhead			

Bonneville Dam	Species	Compass parameter	Value	Data Source
		rsw_spill_cap	0	
		FGE	0	
		Sluicewway/SBC_Proportion	0.44	
		Power_Priority	2	
		Turbine_Survival	0.9535	Couninan et al. 2005a and 2005b. Average of 2004 and 2005 turbine survivals under low powerhouse loading.
		Spillway_Survival	1.0035	Counihan et al. 2005a, 2005b. Combination of 2004 and 2005 spillway survivals w/ spill near 100 kcfs (night spill levels in these years).
		Bypass_Survival	1	
		Sluiceway/SBC_Survival	0.959	Couninan et al. 2005a and 2005b. Average of 2004 and 2005 sluiceway survivals under low powerhouse loading.
		Diel	0.5	

Bonneville Dam PH2	Species	Compass parameter	Value	Data Source
1995				
	Chinook 1			
		FGE	0.44	Ferguson et al. 2005.
		Sluicewway/SBC_Proportion	0	
		Power_Priority	1	
		Turbine_Survival	0.9	Marmorek and Peters.1998. Standard PATH turbine survival.
		Spillway_Survival	1	
		Bypass_Survival	0.9	2000 Biological Opinion - Biological Effects Team Judgement
		Sluiceway/SBC_Survival	1	
		Diel	0.43	
	Steelhead			
		FGE	0.48	Ferguson et al. 2005.
		Sluicewway/SBC_Proportion	0	
		Power_Priority	1	
		Turbine_Survival	0.9	Marmorek and Peters.1998. Standard PATH turbine survival.
		Spillway_Survival	1	
		Bypass_Survival	0.9	2000 Biological Opinion - Biological Effects Team Judgement
		Sluiceway/SBC_Survival	1	
		Diel	0.504761905	Evans et al. 2003. Adapted from data in the Addendum 1 to the 2002 RT research report for only the 75kcfs day/TDG night spill treatments.
1996				
	Chinook 1			
		FGE	0.44	Ferguson et al. 2005.
		Sluicewway/SBC_Proportion	0	
		Power_Priority	1	
		Turbine_Survival	0.9	Marmorek and Peters.1998. Standard PATH turbine survival.

Bonneville Dam PH2	Species	Compass parameter	Value	Data Source
		Spillway_Survival	1	
		Bypass_Survival	0.9	2000 Biological Opinion - Biological Effects Team Judgement
		Sluiceway/SBC_Survival	1	
		Diel	0.43	
	Steelhead			
		FGE	0.48	Ferguson et al. 2005.
		Sluicewway/SBC_Proportion	0	
		Power_Priority	1	
		Turbine_Survival	0.9	Marmorek and Peters.1998. Standard PATH turbine survival.
		Spillway_Survival	1	
		Bypass_Survival	0.9	2000 Biological Opinion - Biological Effects Team Judgement
		Sluiceway/SBC_Survival	1	
		Diel	0.504761905	Evans et al. 2003. Adapted from data in the Addendum 1 to the 2002 RT research report for only the 75kcfs day/TDG night spill treatments.
1997				
	Chinook 1			
		FGE	0.44	Ferguson et al. 2005.
		Sluicewway/SBC_Proportion	0	
		Power_Priority	1	
		Turbine_Survival	0.9	Marmorek and Peters.1998. Standard PATH turbine survival.
		Spillway_Survival	1	
		Bypass_Survival	0.9	2000 Biological Opinion - Biological Effects Team Judgement
		Sluiceway/SBC_Survival	1	
		Diel	0.43	
	Steelhead			
		FGE	0.48	Ferguson et al. 2005.
		Sluicewway/SBC_Proportion	0	
		Power_Priority	1	
		Turbine_Survival	0.9	Marmorek and Peters.1998. Standard PATH turbine survival.
		Spillway_Survival	1	
		Bypass_Survival	0.9	2000 Biological Opinion - Biological Effects Team Judgement
		Sluiceway/SBC_Survival	1	
		Diel	0.504761905	Evans et al. 2003. Adapted from data in the Addendum 1 to the 2002 RT research report for only the 75kcfs day/TDG night spill treatments.
1998				
	Chinook 1			
		FGE	0.44	Ferguson et al. 2005.
		Sluicewway/SBC_Proportion	0	
		Power_Priority	1	
		Turbine_Survival	0.9	Marmorek and Peters.1998. Standard PATH

Bonneville Dam PH2	Species	Compass parameter	Value	Data Source
				turbine survival.
		Spillway_Survival	1	
		Bypass_Survival	0.9	2000 Biological Opinion - Biological Effects Team Judgement
		Sluiceway/SBC_Survival	1	
		Diel	0.43	
	Steelhead			
		FGE	0.48	Ferguson et al. 2005.
		Sluicewway/SBC_Proportion	0	
		Power_Priority	1	
		Turbine_Survival	0.9	Marmorek and Peters.1998. Standard PATH turbine survival.
		Spillway_Survival	1	
		Bypass_Survival	0.9	2000 Biological Opinion - Biological Effects Team Judgement
		Sluiceway/SBC_Survival	1	
		Diel	0.504761905	Evans et al. 2003. Adapted from data in the Addendum 1 to the 2002 RT research report for only the 75kcfs day/TDG night spill treatments.
1999				
	Chinook 1			
		FGE	0.44	Ferguson et al. 2005.
		Sluicewway/SBC_Proportion	0	
		Power_Priority	1	
		Turbine_Survival	0.9	Marmorek and Peters.1998. Standard PATH turbine survival.
		Spillway_Survival	1	
		Bypass_Survival	0.98	Marmorek and Peters. 1998. Standard PATH bypass survival parameter. Also seems a reasonable number based on Holmberg et al. (2001) post construction evaluation in 1999.
		Sluiceway/SBC_Survival	1	
		Diel	0.43	
	Steelhead			
		FGE	0.48	Ferguson et al. 2005.
		Sluicewway/SBC_Proportion	0	
		Power_Priority	1	
		Turbine_Survival	0.9	Marmorek and Peters.1998. Standard PATH turbine survival.
		Spillway_Survival	1	
		Bypass_Survival	0.98	Marmorek and Peters. 1998. Standard PATH bypass survival parameter. Also seems a reasonable number based on Holmberg et al. (2001) post construction evaluation in 1999.
		Sluiceway/SBC_Survival	1	
		Diel	0.504761905	Evans et al. 2003. Adapted from data in the Addendum 1 to the 2002 RT research report for only the 75kcfs day/TDG night spill treatments.
2000				
	Chinook 1			

Bonneville Dam PH2	Species	Compass parameter	Value	Data Source
		FGE	0.39	Evans et al. 2001a. Report for 2000 RT research.
		Sluicewway/SBC_Proportion	0	
		Power_Priority	1	
		Turbine_Survival	0.9	Marmorek and Peters.1998. Standard PATH turbine survival.
		Spillway_Survival	1	
		Bypass_Survival	0.98	Marmorek and Peters. 1998. Standard PATH bypass survival parameter. Also seems a reasonable number based on Holmberg et al. (2001) post construction evaluation in 1999.
		Sluiceway/SBC_Survival	1	
		Diel	0.43	
	Steelhead			
		FGE	0.55	Evans et al. 2001a. Report for 2000 RT research.
		Sluicewway/SBC_Proportion	0	
		Power_Priority	1	
		Turbine_Survival	0.9	Marmorek and Peters.1998. Standard PATH turbine survival.
		Spillway_Survival	1	
		Bypass_Survival	0.98	Marmorek and Peters. 1998. Standard PATH bypass survival parameter. Also seems a reasonable number based on Holmberg et al. (2001) post construction evaluation in 1999.
		Sluiceway/SBC_Survival	1	
		Diel	0.504761905	Evans et al. 2003. Adapted from data in the Addendum 1 to the 2002 RT research report for only the 75kcfs day/TDG night spill treatments.
2001				
	Chinook 1			
		FGE	0.46	Evans et al. 2001b. Report for 2001 RT research.
		Sluicewway/SBC_Proportion	0	
		Power_Priority	2	
		Turbine_Survival	0.929	Counihan et al. 2002. Report for 2001 research.
		Spillway_Survival	1	
		Bypass_Survival	0.962	Counihan et al. 2002. Report for 2001 research.
		Sluiceway/SBC_Survival	1	
		Diel	0.43	
	Steelhead			
		FGE	0.57	Evans et al. 2001b. Report for 2001 RT research.
		Sluicewway/SBC_Proportion	0	
		Power_Priority	2	
		Turbine_Survival	0.929	Counihan et al. 2002. Report for 2001 research.
		Spillway_Survival	1	
		Bypass_Survival	0.962	Counihan et al. 2002. Report for 2001 research.
		Sluiceway/SBC_Survival	1	

Bonneville Dam PH2	Species	Compass parameter	Value	Data Source
		Diel	0.504761905	Evans et al. 2003. Adapted from data in the Addendum 1 to the 2002 RT research report for only the 75kcfs day/TDG night spill treatments.
2002				
	Chinook 1			
		FGE	0.37	Evans et al. 2003. Report for 2002 RT research (season ave.).
		Sluiceway/SBC_Proportion	0	
		Power_Priority	2	
		Turbine_Survival	0.948	Counihan et al. 2002, 2005a, 2005b. Ave of 2001,04,05 PH-2 Turbine survival.
		Spillway_Survival	1	
		Bypass_Survival	0.98	Counihan et al. 2002, 2005a, 2005b. Ave of 2001,04,05 PH-2 Bypass survival.
		Sluiceway/SBC_Survival	1	
		Diel	0.43	
	Steelhead			
		FGE	0.59	Evans et al. 2003. Report for 2002 RT research (season ave.).
		Sluiceway/SBC_Proportion	0	
		Power_Priority	2	
		Turbine_Survival	0.948	Counihan et al. 2002, 2005a, 2005b. Ave of 2001,04,05 PH-2 Turbine survival.
		Spillway_Survival	1	
		Bypass_Survival	0.98	Counihan et al. 2002, 2005a, 2005b. Ave of 2001,04,05 PH-2 Bypass survival.
		Sluiceway/SBC_Survival	1	
		Diel	0.504761905	Evans et al. 2003. Adapted from data in the Addendum 1 to the 2002 RT research report for only the 75kcfs day/TDG night spill treatments.
2003				
	Chinook 1			
		FGE	0.505	
		Sluiceway/SBC_Proportion	0	
		Power_Priority	2	
		Turbine_Survival	0.948	Counihan et al. 2002, 2005a, 2005b. Ave of 2001,04,05 PH-2 Turbine survival.
		Spillway_Survival	1	
		Bypass_Survival	0.98	Counihan et al. 2002, 2005a, 2005b. Ave of 2001,04,05 PH-2 Bypass survival.
		Sluiceway/SBC_Survival	1	
		Diel	0.43	
	Steelhead			
		FGE	0.505	
		Sluiceway/SBC_Proportion	0	
		Power_Priority	2	

Bonneville Dam PH2	Species	Compass parameter	Value	Data Source
		Turbine_Survival	0.948	Counihan et al. 2002, 2005a, 2005b. Ave of 2001,04,05 PH-2 Turbine survival.
		Spillway_Survival	1	
		Bypass_Survival	0.98	Counihan et al. 2002, 2005a, 2005b. Ave of 2001,04,05 PH-2 Bypass survival.
		Sluiceway/SBC_Survival	1	
		Diel	0.504761905	Evans et al. 2003. Adapted from data in the Addendum 1 to the 2002 RT research report for only the 75kcfs day/TDG night spill treatments.
2004				
	Chinook 1			
		FGE	0.33	Reagan et al. 2005. Report for 2004 RT research.
		Sluicewway/SBC_Proportion	0.37	Reagan et al. 2005. Report for 2004 RT research.
		Power_Priority	2	
		Turbine_Survival	0.953	
		Spillway_Survival	1	
		Bypass_Survival	0.97	Counihan et al. 2005a. Draft report for 2004 research.
		Sluiceway/SBC_Survival	1.016	Counihan et al. 2005a. Draft report for 2004 research.
		Diel	0.43	
	Steelhead			
		FGE	0.4	Reagan et al. 2005. Report for 2004 RT research.
		Sluicewway/SBC_Proportion	0.74	Reagan et al. 2005. Report for 2004 RT research.
		Power_Priority	2	
		Turbine_Survival	0.889	Counihan et al. 2005a. Draft report for 2004 research.
		Spillway_Survival	1	
		Bypass_Survival	0.951	Counihan et al. 2005a. Draft report for 2004 research.
		Sluiceway/SBC_Survival	1.03	Counihan et al. 2005a. Draft report for 2004 research.
		Diel	0.504761905	Evans et al. 2003. Adapted from data in the Addendum 1 to the 2002 RT research report for only the 75kcfs day/TDG night spill treatments.
2005				
	Chinook 1			
		FGE	0.35	no data yet
		Sluicewway/SBC_Proportion	0.29	Adams, 2005. Preliminary Data - FFDRWG Handout, Noah Adams, August 3, 2005.
		Power_Priority	2	
		Turbine_Survival	0.965	
		Spillway_Survival	1	
		Bypass_Survival	1.007	Counihan et al. 2005b. Draft 2005 research report.
		Sluiceway/SBC_Survival	1.02	Counihan et al. 2005b. Draft 2005 research report.
		Diel	0.43	

Bonneville Dam PH2	Species	Compass parameter	Value	Data Source
	Steelhead			
		FGE	0.505	no data yet
		Sluicewway/SBC_Proportion	0.66	Preliminary Data - FFDRWG Handout, Noah Adams, August 3, 2005.
		Power_Priority	2	
		Turbine_Survival	0.868	Counihan et al. 2005b. Draft 2005 research report.
		Spillway_Survival	1	
		Bypass_Survival	0.956	Counihan et al. 2005b. Draft 2005 research report.
		Sluiceway/SBC_Survival	1.009	Counihan et al. 2005b. Draft 2005 research report.
		Diel	0.504761905	Evans et al. 2003. Adapted from data in the Addendum 1 to the 2002 RT research report for only the 75kcfs day/TDG night spill treatments.
Current				
	Chinook 1			
		FGE	0.35	
		Sluicewway/SBC_Proportion	0.29	
		Sluicewway/SBC_Proportion	0.33	
		Power_Priority	2	
		Turbine_Survival	0.948	Counihan et al. 2002, 2005a, 2005b. Ave of 2001,04,05 PH-2 Turbine survival.
		Spillway_Survival	1	
		Bypass_Survival	0.98	Counihan et al. 2002, 2005a, 2005b. Ave of 2001,04,05 PH-2 Bypass survival.
		Sluiceway/SBC_Survival	1.018	Couninan et al. 2005a and 2005b. Average of 2004 and 2005 corner collector survivals.
		Diel	0.43	
	Steelhead			
		FGE	0.505	
		Sluicewway/SBC_Proportion	0.66	
		Sluicewway/SBC_Proportion	0.7	
		Power_Priority	2	
		Turbine_Survival	0.8785	Counihan et al. 2005a, 2005b. Ave of 2004, 2005 PH-2 Turbine survival.
		Spillway_Survival	1	
		Bypass_Survival	0.9535	Counihan et al. 2005a, 2005b. Ave of 2004,05 PH-2 Bypass survival.
		Sluiceway/SBC_Survival	1.0195	Couninan et al. 2005a and 2005b. Average of 2004 and 2005 corner collector survivals.
		Diel	0.5	

The Dalles Dam	Species	Compass Parameter	Value	Reference
1995				

The Dalles Dam	Species	Compass Parameter	Value	Reference
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0	
		Sluicewway/SBC_Proportion	0.445	
		Turbine_Survival	0.84	Counihan et al. 2002. Absolon et al. 2002. Average of 2000 R/T and PIT spring migrant studies (YCH).
		Spillway_Survival	0.886	Dawley et al. 2000a. (survival est. for coho during 64% spill treatment in 1998).
		Bypass_Survival	1	
		Sluiceway/SBC_Survival	0.96	Dawley et al. 2000a. (survival at 30% spill for coho salmon in 1998).
		Diel	0.5	2001 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0	
		Sluicewway/SBC_Proportion	0.59	
		Turbine_Survival	0.84	Counihan et al. 2002. Absolon et al. 2002. Average of 2000 R/T and PIT spring migrant studies (YCH).
		Spillway_Survival	0.886	Dawley et al. 2000a. (survival est. for coho during 64% spill treatment in 1998).
		Bypass_Survival	1	
		Sluiceway/SBC_Survival	0.96	Dawley et al. 2000a. (survival at 30% spill for coho salmon in 1998).
		Diel	0.5	2000 Biological Opinion
1996				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0	
		Sluicewway/SBC_Proportion	0.445	
		Turbine_Survival	0.84	Counihan et al. 2002, Absolon et al. 2002. Average of 2000 R/T and PIT spring migrant studies (YCH).
		Spillway_Survival	0.871	Dawley et al. 1998. (survival for coho salmon at 64% spill in 1997).
		Bypass_Survival	1	
		Sluiceway/SBC_Survival	0.96	Dawley et al. 2000a (survival at 30% spill for coho salmon in 1998).
		Diel	0.5	2001 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0	
		Sluicewway/SBC_Proportion	0.59	
		Turbine_Survival	0.84	Counihan et al. 2002, Absolon et al. 2002. Average of 2000 R/T and PIT spring migrant studies (YCH).
		Spillway_Survival	0.871	Dawley et al. 1998. (survival for coho salmon at 64% spill in 1997).
		Bypass_Survival	1	

The Dalles Dam	Species	Compass Parameter	Value	Reference
		Sluiceway/SBC_Survival	0.96	
		Diel	0.5	2000 Biological Opinion
1997				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0	
		Sluicewway/SBC_Proportion	0.445	
		Turbine_Survival	0.84	Counihan et al. 2002, Absolon et al. 2002. Average of 2000 R/T and PIT spring migrant studies (YCH).
		Spillway_Survival	0.871	Dawley et al. 1998. (survival for coho salmon at 64% spill in 1997).
		Bypass_Survival	1	
		Sluiceway/SBC_Survival	0.96	Dawley et al. 2000a (survival at 30% spill for coho salmon in 1998).
		Diel	0.5	2001 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0	
		Sluicewway/SBC_Proportion	0.59	
		Turbine_Survival	0.84	
		Spillway_Survival	0.871	
		Bypass_Survival	1	
		Sluiceway/SBC_Survival	0.96	Dawley et al. 2000a (survival at 30% spill for coho salmon in 1998).
		Diel	0.5	2000 Biological Opinion
1998				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0	
		Sluicewway/SBC_Proportion	0.445	
		Turbine_Survival	0.84	Counihan et al. 2002, Absolon et al. 2002. Average of 2000 R/T and PIT spring migrant studies (YCH).
		Spillway_Survival	0.928	Dawley et al. 2000a (ave. survival for coho salmon at 2 ops, 30 and 64% spill in 1998).
		Bypass_Survival	1	
		Sluiceway/SBC_Survival	0.96	Dawley et al, 2000a (survival at 30% spill for coho salmon in 1998)
		Diel	0.5	2001 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0	
		Sluicewway/SBC_Proportion	0.59	
		Turbine_Survival	0.84	Counihan et al. 2002, Absolon et al. 2002. Average of 2000 R/T and PIT spring migrant studies (YCH).
		Spillway_Survival	0.928	Dawley et al. 2000a (ave. survival for coho salmon at 2 ops, 30 and 64% spill in 1998).

The Dalles Dam	Species	Compass Parameter	Value	Reference
		Bypass_Survival	1	
		Sluiceway/SBC_Survival	0.96	Dawley et al, 2000a (survival at 30% spill for coho salmon in 1998)
		Diel	0.5	2000 Biological Opinion
1999				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0	
		Sluicewway/SBC_Proportion	0.445	
		Turbine_Survival	0.84	Counihan et al, 2002, Absolon et al. 2002. Average of 2000 R/T and PIT spring migrant studies (YCH).
		Spillway_Survival	0.948	Dawley et al. 2000b (average survival for coho salmon at 2 ops, 30 and 64% spill in 1999)
		Bypass_Survival	1	
		Sluiceway/SBC_Survival	0.96	Dawley et al, 2000a (survival at 30% spill for coho salmon in 1998)
		Diel	0.5	2001 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0	
		Sluicewway/SBC_Proportion	0.59	
		Turbine_Survival	0.84	Counihan et al, 2002, Absolon et al. 2002. Average of 2000 R/T and PIT spring migrant studies (YCH).
		Spillway_Survival	0.948	Dawley et al. 2000b (average survival for coho salmon at 2 ops, 30 and 64% spill in 1999)
		Bypass_Survival	1	
		Sluiceway/SBC_Survival	0.96	Dawley et al, 2000a (survival at 30% spill for coho salmon in 1998)
		Diel	0.5	2000 Biological Opinion
2000				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0	
		Sluicewway/SBC_Proportion	0.445	
		Turbine_Survival	0.84	Counihan et al. 2002, Absolon et al. 2002. Average of 2000 R/T and PIT spring migrant studies (YCH).
		Spillway_Survival	0.94	Counihan et al. 2002. Data for yearling chinook.
		Bypass_Survival	1	
		Sluiceway/SBC_Survival	0.967	Counihan et al. 2002, Absolon et al. 2002. Average of 2000 R/T and PIT spring migrant studies (YCH).
		Diel	0.5	2001 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0	
		Sluicewway/SBC_Proportion	0.59	

The Dalles Dam	Species	Compass Parameter	Value	Reference
		Turbine_Survival	0.84	Counihan et al. 2002, Absolon et al. 2002. Average of 2000 R/T and PIT spring migrant studies (YCH).
		Spillway_Survival	0.94	Counihan et al. 2002. Data for yearling chinook.
		Bypass_Survival	1	
		Sluiceway/SBC_Survival	0.967	Counihan et al. 2002, Absolon et al. 2002. Average of 2000 R/T and PIT spring migrant studies (YCH).
		Diel	0.5	2000 Biological Opinion
2001				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0	
		Sluicewway/SBC_Proportion	0.445	
		Turbine_Survival	0.84	Counihan et al. 2002, Absolon et al. 2002. Average of 2000 R/T and PIT spring migrant studies (YCH).
		Spillway_Survival	0.897	Dawley et al. 1998, 2000a and 2000b. Average of 1997, 1998, 1999 PIT TDA spillway survival estimates for YCH and Coho
		Bypass_Survival	1	
		Sluiceway/SBC_Survival	0.993	Counihan et al. 2005. Final report for 2001 research
		Diel	0.5	2001 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0	
		Sluicewway/SBC_Proportion	0.59	
		Turbine_Survival	0.84	Counihan et al. 2002, Absolon et al. 2002. Average of 2000 R/T and PIT spring migrant studies (YCH).
		Spillway_Survival	0.897	Dawley et al. 1998, 2000a and 2000b. Average of 1997, 1998, 1999 PIT TDA spillway survival estimates for YCH and Coho
		Bypass_Survival	1	
		Sluiceway/SBC_Survival	0.993	Counihan et al. 2005. Final report for 2001 research
		Diel	0.5	2000 Biological Opinion
2002				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0	
		Sluicewway/SBC_Proportion	0.445	
		Turbine_Survival	0.85	Counihan et al. 2006a. Report for 2002 research.
		Spillway_Survival	0.88	Counihan et al. 2006a. Report for 2002 research.
		Bypass_Survival	1	
		Sluiceway/SBC_Survival	0.91	Counihan et al. 2006a. Report for 2002 research.
		Diel	0.5	2001 Biological Opinion
	Steelhead			

The Dalles Dam	Species	Compass Parameter	Value	Reference
		rsw_spill_cap	0	
		FGE	0	
		Sluicewway/SBC_Proportion	0.59	
		Turbine_Survival	0.85	Counihan et al. 2006a. Report for 2002 research.
		Spillway_Survival	0.88	Counihan et al. 2006a. Report for 2002 research.
		Bypass_Survival	1	
		Sluiceway/SBC_Survival	0.91	Counihan et al. 2006a. Report for 2002 research.
		Diel	0.5	2000 Biological Opinion
2003				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0	
		Sluicewway/SBC_Proportion	0.445	
		Turbine_Survival	0.83	Counihan et al. 2002 and 2006a. Average 2000, 2002 RT data for yearling chinook at 40% spill.
		Spillway_Survival	0.91	Counihan et al. 2002 and 2006a. Average 2000, 2002 RT data for yearling chinook at 40% spill.
		Bypass_Survival	1	
		Sluiceway/SBC_Survival	0.925	Counihan et al. 2002 and 2006a. Average 2000, 2002 RT data for yearling chinook at 40% spill.
		Diel	0.5	2001 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0	
		Sluicewway/SBC_Proportion	0.59	
		Turbine_Survival	0.83	Counihan et al. 2002 and 2006a. Average 2000, 2002 RT data for yearling chinook at 40% spill.
		Spillway_Survival	0.91	Counihan et al. 2002 and 2006a. Average 2000, 2002 RT data for yearling chinook at 40% spill.
		Bypass_Survival	1	
		Sluiceway/SBC_Survival	0.925	Counihan et al. 2002 and 2006a. Average 2000, 2002 RT data for yearling chinook at 40% spill.
		Diel	0.5	2000 Biological Opinion
2004				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0	
		Sluicewway/SBC_Proportion	0.445	
		Turbine_Survival	0.797	Counihan et al. 2006b. Report for 2004 research.
		Spillway_Survival	0.909	Counihan et al. 2006b. Report for 2004 research.
		Bypass_Survival	1	
		Sluiceway/SBC_Survival	0.981	Counihan et al. 2006b. Report for 2004

The Dalles Dam	Species	Compass Parameter	Value	Reference
				research.
		Diel	0.5	2001 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0	
		Sluicewway/SBC_Proportion	0.59	
		Turbine_Survival	0.797	Counihan et al. 2006b. Report for 2004 research.
		Spillway_Survival	0.909	Counihan et al. 2006b. Report for 2004 research.
		Bypass_Survival	1	
		Sluiceway/SBC_Survival	0.981	Counihan et al. 2006b. Report for 2004 research.
		Diel	0.5	2000 Biological Opinion
2005				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0	
		Sluicewway/SBC_Proportion	0.445	
		Turbine_Survival	0.838	Counihan et al. 2006c. Report of 2005 research.
		Spillway_Survival	0.938	Counihan et al. 2006c. Report of 2005 research.
		Bypass_Survival	1	
		Sluiceway/SBC_Survival	1.006	Counihan et al. 2006c. Report of 2005 research.
		Diel	0.5	2003 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0	
		Sluicewway/SBC_Proportion	0.59	
		Turbine_Survival	0.838	Counihan et al. 2006c. Report of 2005 research.
		Spillway_Survival	0.938	Counihan et al. 2006c. Report of 2005 research.
		Bypass_Survival	1	
		Sluiceway/SBC_Survival	1.006	Counihan et al. 2006c. Report of 2005 research.
		Diel	0.5	2000 Biological Opinion
		Bypass_Survival	1	
		Sluiceway/SBC_Survival	0.994	Counihan et al. 2006b, 2006c. Ave of point estimates from 2004 and 2005 research at 40% spill
		Diel	0.5	
Current				
	Chinook 1			
		rsw_spill_cap	0	

The Dalles Dam	Species	Compass Parameter	Value	Reference
		FGE	0	
		Sluicewway/SBC_Proportion	0.445	
		Turbine_Survival	0.818	Counihan et al. 2006b, 2006c. Ave of point estimates from 2004 and 2005 research at 40% spill
		Spillway_Survival	0.924	Counihan et al. 2006b, 2006c. Ave of point estimates from 2004 and 2005 research at 40% spill
		Bypass_Survival	1	
		Sluiceway/SBC_Survival	0.994	Counihan et al. 2006b, 2006c. Ave of point estimates from 2004 and 2005 research at 40% spill
		Diel	0.5	
	Steelhead			
		rsw_spill_cap	0	
		FGE	0	
		Sluicewway/SBC_Proportion	0.59	
		Turbine_Survival	0.818	Counihan et al. 2006b, 2006c. Ave of point estimates from 2004 and 2005 research at 40% spill
		Spillway_Survival	0.924	Counihan et al. 2006b, 2006c. Ave of point estimates from 2004 and 2005 research at 40% spill
		Bypass_Survival	1	
		Sluiceway/SBC_Survival	0.994	Counihan et al. 2006b, 2006c. Ave of point estimates from 2004 and 2005 research at 40% spill
		Diel	0.5	

John Day Dam				
1995				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.64	Ferguson et al. 2005
		Turbine_Survival	0.82	Counihan et al. 2006 and 2003 (draft). Ave point estimates for route specific survival in 2002 and 2003 w/ 0/60 spill (78 and 82%).
		Spillway_Survival	0.98	PATH Estimate is best for pre-deflector estimate.
		Bypass_Survival	0.988	Counihan et al. 2003 (draft). 2003 chinook data. 0 day, 45% night spill closest to ops for these years.

John Day Dam				
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.76	Hansel et al. 2000 (final), Beeman et al. 2003 (Final), Beeman et al (preliminary data). USGS RT data from1999, 2000, & 2002.
		Turbine_Survival	0.82	Counihan et al. 2006 and 2003 (draft). Ave point estimates for route specific survival in 2002 and 2003 w/ 0/60 spill (78 and 82%) for chinook.
		Spillway_Survival	0.98	PATH Estimate is best for pre-deflector estimate.
		Bypass_Survival	0.988	Counihan et al. 2003 (draft). 2003 chinook data. 0 day, 45% night spill closest to ops for these years.
		Diel	0.5	2000 Biological Opinion
1996				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.64	Ferguson et al. 2005
		Turbine_Survival	0.82	Counihan et al. 2006 and 2003 (draft). Ave point estimates for route specific survival in 2002 and 2003 w/ 0/60 spill (78 and 82%).
		Spillway_Survival	0.98	PATH Estimate is best for pre-deflector estimate.
		Bypass_Survival	0.988	Counihan et al. 2003 (draft). 2003 chinook data. 0 day, 45% night spill closest to ops for these years.
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.76	Hansel et al. 2000 (final), Beeman et al. 2003 (Final), Beeman et al (preliminary data). USGS RT data from1999, 2000, & 2002.
		Turbine_Survival	0.82	Counihan et al. 2006 and 2003 (draft). Ave point estimates for route specific survival in 2002 and 2003 w/ 0/60 spill (78 and 82%) for chinook.
		Spillway_Survival	0.98	PATH Estimate is best for pre-deflector estimate.
		Bypass_Survival	0.988	Counihan et al. 2003 (draft). 2003 chinook data. 0 day, 45% night spill closest to ops for these years.
		Diel	0.5	2000 Biological Opinion
1997				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.64	Ferguson et al. 2005
		Turbine_Survival	0.82	Counihan et al. 2006 and 2003 (draft). Ave point estimates for route specific survival in 2002 and 2003 w/ 0/60 spill (78 and 82%).

John Day Dam				
		Spillway_Survival	0.98	PATH Estimate is best for pre-deflector estimate.
		Bypass_Survival	0.988	Counihan et al. 2003 (draft). 2003 chinook data. 0 day, 45% night spill closest to ops for these years.
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.76	Hansel et al. 2000 (final), Beeman et al. 2003 (Final), Beeman et al (preliminary data). USGS RT data from1999, 2000, & 2002.
		Turbine_Survival	0.82	Counihan et al. 2006 and 2003 (draft). Ave point estimates for route specific survival in 2002 and 2003 w/ 0/60 spill (78 and 82%) for chinook.
		Spillway_Survival	0.98	PATH Estimate is best for pre-deflector estimate.
		Bypass_Survival	0.988	Counihan et al. 2003 (draft). 2003 chinook data. 0 day, 45% night spill closest to ops for these years.
		Diel	0.5	2000 Biological Opinion
1998				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.64	Ferguson et al. 2005
		Turbine_Survival	0.82	Counihan et al. 2006 and 2003 (draft). Ave point estimates for route specific survival in 2002 and 2003 w/ 0/60 spill (78 and 82%).
		Spillway_Survival	0.971	Counihan et al. 2002, 2006, 2003 (draft). Ave of data for 2000, 2002, and 2003.
		Bypass_Survival	0.95	Counihan et al. 2006 and 2003 (draft). Ave point estimates for route specific survival in 2002 and 2003 w/ 0/60 spill.
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.76	Hansel et al. 2000 (final), Beeman et al. 2003 (Final), Beeman et al (preliminary data). USGS RT data from1999, 2000, & 2002.
		Turbine_Survival	0.82	Counihan et al. 2006 and 2003 (draft). Ave point estimates for route specific survival in 2002 and 2003 w/ 0/60 spill (78 and 82%) for chinook.
		Spillway_Survival	0.96	Counihan et al. 2006. Survival under 0/60 spill operation in 2002.
		Bypass_Survival	0.882	Counihan et al. 2006. Paired release survival under 0/60 spill operation in 2002.
		Diel	0.5	2000 Biological Opinion
1999				
	Chinook 1			
		rsw_spill_cap	0	

John Day Dam				
		FGE	0.64	Ferguson et al. 2005
		Turbine_Survival	0.82	Counihan et al. 2006 and 2003 (draft). Ave point estimates for route specific survival in 2002 and 2003 w/ 0/60 spill (78 and 82%).
		Spillway_Survival	0.971	Counihan et al. 2002, 2006, 2003 (draft). Ave of data for 2000, 2002, and 2003.
		Bypass_Survival	0.95	Counihan et al. 2006 and 2003 (draft). Ave point estimates for route specific survival in 2002 and 2003 w/ 0/60 spill.
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.76	Hansel et al. 2000 (final), Beeman et al. 2003 (Final), Beeman et al (preliminary data). USGS RT data from1999, 2000, & 2002.
		Turbine_Survival	0.82	Counihan et al. 2006 and 2003 (draft). Ave point estimates for route specific survival in 2002 and 2003 w/ 0/60 spill (78 and 82%) for chinook.
		Spillway_Survival	0.96	Counihan et al. 2006. Survival under 0/60 spill operation in 2002.
		Bypass_Survival	0.882	Counihan et al. 2006. Paired release survival under 0/60 spill operation in 2002.
		Diel	0.5	2000 Biological Opinion
2000				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.64	Ferguson et al. 2005
		Turbine_Survival	0.805	Counihan et al. 2006. Data for 2002 research (ave of 2 operations).
		Spillway_Survival	0.962	Counihan et al. 2002. Data for 2000 research (ave of 2 operations).
		Bypass_Survival	0.951	Counihan et al. 2006. Data for 2002 research (ave of 2 operations).
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.76	Hansel et al. 2000 (final), Beeman et al. 2003 (Final), Beeman et al (preliminary data). USGS RT data from1999, 2000, & 2002.
		Turbine_Survival	0.805	Counihan et al. 2006. Data for 2002 research (ave of 2 operations) for chinook.
		Spillway_Survival	0.946	Counihan et al. 2002. Data for 2000 research (ave of 2 operations).
		Bypass_Survival	0.904	Counihan et al. 2006. Data for 2002 research (ave of 2 operations).
		Diel	0.5	2000 Biological Opinion
2001				
	Chinook			

John Day Dam				
	1			
		rsw_spill_cap	0	
		FGE	0.64	Ferguson et al. 2005
		Turbine_Survival	0.83	Counihan et al. 2006. Survival in 2002 at 30 day/30 night.
		Spillway_Survival	1	Counihan et al. 2006. Spill survival at 30/30 in 2002 (May spill 0% until end of May then ~30%).
		Bypass_Survival	0.932	Counihan et al. 2005. Report for 2001 research.
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.76	Hansel et al. 2000 (final), Beeman et al. 2003 (Final), Beeman et al (preliminary data). USGS RT data from1999, 2000, & 2002.
		Turbine_Survival	0.83	Counihan et al. 2006. Survival in 2002 at 30 day/30 night for chinook.
		Spillway_Survival	0.932	Counihan et al. 2006. Survival in 2002 at 30 day/30 night.
		Bypass_Survival	0.917	Counihan et al. 2005. Data for 2001 research.
		Diel	0.5	2000 Biological Opinion
2002				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.64	Ferguson et al. 2005
		Turbine_Survival	0.805	Counihan et al. 2006. Data for 2002 (ave of 2 operations).
		Spillway_Survival	0.997	Counihan et al. 2006. Data for 2002 (ave of 2 operations).
		Bypass_Survival	0.95	Counihan et al. 2006. Data for 2002 (ave of 2 operations).
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.76	Hansel et al. 2000 (final), Beeman et al. 2003 (Final), Beeman et al (preliminary data). USGS RT data from1999, 2000, & 2002.
		Turbine_Survival	0.805	Counihan et al. 2006. Data for 2002 research (ave of 2 operations) for chinook.
		Spillway_Survival	0.946	Counihan et al. 2006. Data for 2002, ave point estimate for two operations.
		Bypass_Survival	0.904	Counihan et al. 2006. Data for 2002 research (ave of 2 operations).
		Diel	0.5	2000 Biological Opinion
2003				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.64	Ferguson et al. 2005

John Day Dam				
		Turbine_Survival	0.79	Counihan et al. 2003. Draft data for 2003 (average over season for 2 operations).
		Spillway_Survival	0.935	Counihan et al. 2003. Draft data for 2003 (average over season for 2 operations).
		Bypass_Survival	1.004	Counihan et al. 2003. Draft data for 2003 (average over season for 2 operations).
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.76	Hansel et al. 2000 (final), Beeman et al. 2003 (Final), Beeman et al (preliminary data). USGS RT data from1999, 2000, & 2002.
		Turbine_Survival	0.805	Counihan et al. 2006. Data for 2002 research (ave of 2 operations) for chinook.
		Spillway_Survival	0.946	Counihan et al. 2006. Data for 2002, ave point estimate for two operations.
		Bypass_Survival	0.904	Counihan et al. 2006. Data for 2002 research (ave of 2 operations).
		Diel	0.5	2000 Biological Opinion
2004				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.64	Ferguson et al. 2005
		Turbine_Survival	0.82	Counihan et al. 2006 and 2003. Ave point estimates for route specific survival in 2002 and 2003 w/ 0/60 spill.
		Spillway_Survival	0.964	Counihan et al. 2006 and 2003. Ave point estimates for route specific survival in 2002 and 2003 w/ 0/60 spill.
		Bypass_Survival	0.95	Counihan et al. 2006 and 2003. Ave point estimates for route specific survival in 2002 and 2003 w/ 0/60 spill.
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.76	Hansel et al. 2000 (final), Beeman et al. 2003 (Final), Beeman et al (preliminary data). USGS RT data from1999, 2000, & 2002.
		Turbine_Survival	0.805	Counihan et al. 2006. Data for 2002 research (ave of 2 operations) for chinook.
		Spillway_Survival	0.973	Counihan et al. 2002 and 2006. Ave of 2000 and 2002 at 0 day and 60 night spill estimates.
		Bypass_Survival	0.904	Counihan et al. 2006. Data for 2002 research (ave of 2 operations).
		Diel	0.5	2000 Biological Opinion
2005				
	Chinook 1			
		rsw_spill_cap	0	

John Day Dam				
		FGE	0.64	Ferguson et al. 2005
		Turbine_Survival	0.82	Counihan et al. 2006 and 2003. Ave point estimates for route specific survival in 2002 and 2003 w/ 0/60 spill.
		Spillway_Survival	0.964	Counihan et al. 2006 and 2003. Ave point estimates for route specific survival in 2002 and 2003 w/ 0/60 spill.
		Bypass_Survival	0.95	Counihan et al. 2006 and 2003. Ave point estimates for route specific survival in 2002 and 2003 w/ 0/60 spill.
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.76	Hansel et al. 2000 (final), Beeman et al. 2003 (Final), Beeman et al (preliminary data). USGS RT data from1999, 2000, & 2002.
		Turbine_Survival	0.805	Counihan et al. 2006. Data for 2002 research (ave of 2 operations) for chinook.
		Spillway_Survival	0.973	Counihan et al. 2002 and 2006. Ave of 2000 and 2002 at 0 day and 60 night spill estimates.
		Bypass_Survival	0.904	Counihan et al. 2006. Data for 2002 research (ave of 2 operations).
		Diel	0.5	2000 Biological Opinion
Current				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.64	
		Turbine_Survival	0.799	Counihan et al. 2006 and 2003. Ave point estimates for route specific survival in 2002 and 2003 w/ 0/60 spill.
		Spillway_Survival	0.964	Counihan et al. 2006 and 2003. Ave point estimates for route specific survival in 2002 and 2003 w/ 0/60 spill.
		Bypass_Survival	0.965	Counihan et al. 2006 and 2003. Ave point estimates for route specific survival in 2002 and 2003 w/ 0/60 spill.
		Diel	0.5	
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.76	
		Turbine_Survival	0.799	Counihan et al. 2006 and 2003. Ave point estimates for RSSM in 2002 and 2003 w/ 0/60 spill for CH1.
		Spillway_Survival	0.973	Counihan et al. 2002 and 2006. Ave of 2000 and 2002 at 0 day and 60 night spill estimates.
		Bypass_Survival	0.882	Counihan et al. 2002 pt estimate at 0/60 spill for sthd.
		Diel	0.5	

McNary Dam	Species	Parameter	Value	Reference

McNary Dam	Species	Parameter	Value	Reference
1995				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.57	Krasnow, 1998. FGE estimates.
		Turbine_Survival	0.933	Perry et al. 2006b. Draft 2005 RT rept. Season 24 hr spill treatment avg.
		Spillway_Survival	0.959	Axel et al. 2004a, b, Perry et al. 2005. Ave of 2002, 03, 04 RT point estimates.
		Bypass_Survival	0.898	Axel et al. 2004a, b, Perry et al. 2006a. Ave of 2002, 03, 04 RT point estimates.
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.57	Ferguson et al. 2005.
		Turbine_Survival	0.886	Perry et al. 2006b. Draft 2005 RT rept. 24 h spill treatment
		Spillway_Survival	0.959	Axel et al. 2004a, b, Perry et al. 2006a. Ave of 2002, 03, 04 RT point estimates.
		Bypass_Survival	0.898	Axel et al. 2004a, b, Perry et al. 2006a. Ave of 2002, 03, 04 RT point estimates.
		Diel	0.5	2000 Biological Opinion
1996				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.57	Krasnow, 1998. FGE estimates.
		Turbine_Survival	0.933	Perry et al. 2006b. Draft 2005 RT rept. Season 24 hr spill treatment avg.
		Spillway_Survival	0.959	Axel et al. 2004a, b, Perry et al. 2005. Ave of 2002, 03, 04 RT point estimates.
		Bypass_Survival	0.898	Axel et al. 2004a, b, Perry et al. 2006a. Ave of 2002, 03, 04 RT point estimates.
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.57	Kransow, 1998. FGE estimates.
		Turbine_Survival	0.886	Perry et al. 2006b. Draft 2005 RT rept. 24 h spill treatment
		Spillway_Survival	0.959	Axel et al. 2004a, b, Perry et al. 2006a. Ave of 2002, 03, 04 RT point estimates.
		Bypass_Survival	0.898	Axel et al. 2004a, b, Perry et al. 2006a. Ave of 2002, 03, 04 RT point estimates.
		Diel	0.5	2000 Biological Opinion
1997				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.95	Ferguson et al. 2005.

McNary Dam	Species	Parameter	Value	Reference
		Turbine_Survival	0.933	Perry et al. 2006b. Draft 2005 RT rept. Season 24 hr spill treatment avg.
		Spillway_Survival	0.959	Axel et al. 2004a, b, Perry et al. 2005. Ave of 2002, 03, 04 RT point estimates.
		Bypass_Survival	0.898	Axel et al. 2004a, b, Perry et al. 2006a. Ave of 2002, 03, 04 RT point estimates.
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.89	Ferguson et al. 2005.
		Turbine_Survival	0.886	Perry et al. 2006b. Draft 2005 RT rept. 24 h spill treatment
		Spillway_Survival	0.959	Axel et al. 2004a, b, Perry et al. 2006a. Ave of 2002, 03, 04 RT point estimates.
		Bypass_Survival	0.898	Axel et al. 2004a, b, Perry et al. 2006a. Ave of 2002, 03, 04 RT point estimates.
		Diel	0.5	2000 Biological Opinion
1998				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.95	Ferguson et al. 2005.
		Turbine_Survival	0.933	Perry et al. 2006b. Draft 2005 RT rept. Season 24 hr spill treatment avg.
		Spillway_Survival	0.959	Axel et al. 2004a, b, Perry et al. 2005. Ave of 2002, 03, 04 RT point estimates.
		Bypass_Survival	0.898	Axel et al. 2004a, b, Perry et al. 2006a. Ave of 2002, 03, 04 RT point estimates.
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.89	Ferguson et al. 2005.
		Turbine_Survival	0.886	Perry et al. 2006b. Draft 2005 RT rept. 24 h spill treatment
		Spillway_Survival	0.959	Axel et al. 2004a, b, Perry et al. 2006a. Ave of 2002, 03, 04 RT point estimates.
		Bypass_Survival	0.898	Axel et al. 2004a, b, Perry et al. 2006a. Ave of 2002, 03, 04 RT point estimates.
		Diel	0.5	2000 Biological Opinion
1999				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.95	Ferguson et al. 2005.
		Turbine_Survival	0.933	Perry et al. 2006b. Draft 2005 RT rept. Season 24 hr spill treatment avg.
		Spillway_Survival	0.959	Axel et al. 2004a, b, Perry et al. 2005. Ave of 2002, 03, 04 RT point estimates.
		Bypass_Survival	0.898	Axel et al. 2004a, b, Perry et al. 2006a. Ave of 2002, 03, 04 RT point estimates.
		Diel	0.5	2000 Biological Opinion

McNary Dam	Species	Parameter	Value	Reference
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.89	Ferguson et al. 2005.
		Turbine_Survival	0.886	Perry et al. 2006b. Draft 2005 RT rept. 24 h spill treatment
		Spillway_Survival	0.959	Axel et al. 2004a, b, Perry et al. 2006a. Ave of 2002, 03, 04 RT point estimates.
		Bypass_Survival	0.898	Axel et al. 2004a, b, Perry et al. 2006a. Ave of 2002, 03, 04 RT point estimates.
		Diel	0.5	2000 Biological Opinion
2000				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.95	Ferguson et al. 2005.
		Turbine_Survival	0.933	Perry et al. 2006b. Draft 2005 RT rept. Season 24 hr spill treatment avg.
		Spillway_Survival	0.959	Axel et al. 2004a, b, Perry et al. 2005. Ave of 2002, 03, 04 RT point estimates.
		Bypass_Survival	0.898	Axel et al. 2004a, b, Perry et al. 2006a. Ave of 2002, 03, 04 RT point estimates.
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.89	Ferguson et al. 2005.
		Turbine_Survival	0.886	Perry et al. 2006b. Draft 2005 RT rept. 24 h spill treatment
		Spillway_Survival	0.959	Axel et al. 2004a, b, Perry et al. 2006a. Ave of 2002, 03, 04 RT point estimates.
		Bypass_Survival	0.898	Axel et al. 2004a, b, Perry et al. 2006a. Ave of 2002, 03, 04 RT point estimates.
		Diel	0.5	2000 Biological Opinion
2001				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.95	Ferguson et al. 2005.
		Turbine_Survival	0.933	Perry et al. 2006b. Draft 2005 RT rept. Season 24 hr spill treatment avg.
		Spillway_Survival	0.959	Axel et al. 2004a, b, Perry et al. 2005. Ave of 2002, 03, 04 RT point estimates.
		Bypass_Survival	0.898	Axel et al. 2004a, b, Perry et al. 2006a. Ave of 2002, 03, 04 RT point estimates.
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.89	
		Turbine_Survival	0.886	Perry et al. 2006b. Draft 2005 RT rept. 24 h spill treatment

McNary Dam	Species	Parameter	Value	Reference
		Spillway_Survival	0.959	Axel et al. 2004a, b, Perry et al. 2006a. Ave of 2002, 03, 04 RT point estimates.
		Bypass_Survival	0.898	Axel et al. 2004a, b, Perry et al. 2006a. Ave of 2002, 03, 04 RT point estimates.
		Diel	0.5	2000 Biological Opinion
2002				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.93	Axel et al. 2004a
		Turbine_Survival	0.873	Absolon et al. 2003. Paired release 2002 RT study. Hose release.
		Spillway_Survival	0.976	Axel et al. 2004a. Results for 2002 R/T study
		Bypass_Survival	0.927	Axel et al. 2004a. Results for 2002 R/T study
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.93	Axel et al. 2004. Final Report of 2002 Data. Based on Chinook data.
		Turbine_Survival	0.886	Perry et al. 2006b. Draft 2005 RT rept. 24 h spill treatment
		Spillway_Survival	0.976	Axel et al. 2004a. Results for 2002 R/T study
		Bypass_Survival	0.927	Axel et al. 2004a. Results for 2002 R/T study
		Diel	0.5	2000 Biological Opinion
2003				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.9	Axel et al. 2004b
		Turbine_Survival	0.933	Perry Et al. 2006b Draft 2005 RT rept. Season 24 hr spill treatment avg.
		Spillway_Survival	0.928	Axel et al. 2004b. Results for 2003 R/T study
		Bypass_Survival	0.865	Axel et al. 2004b. Results for 2003 R/T study
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.905	Axel et al. 2004. Final Report of 2003 Data. Average FGE of Snake River and Columbia River yearling chinook.
		Turbine_Survival	0.886	Perry et al. 2006b. Draft 2005 RT rept. 24 h spill treatment
		Spillway_Survival	0.928	Axel et al. 2004b. Results for 2003 R/T study
		Bypass_Survival	0.865	Axel et al. 2004b. Results for 2003 R/T study
		Diel	0.5	2000 Biological Opinion
2004				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.637	Perry et al. 2005. May be biased low due to detection bias.

McNary Dam	Species	Parameter	Value	Reference
		Turbine_Survival	0.872	Perry et al. 2006a. Final 2004 RT reort page xviii
		Spillway_Survival	0.973	Perry et al. 2005. Draft 2004 RT report.
		Bypass_Survival	0.902	Perry et al. 2005. Draft 2004 RT report.
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.766	Perry et al. 2005. Draft 2004 RT report.
		Turbine_Survival	0.894	Perry et al. 2006a. Final 2004 RT report. Page xviii.
		Spillway_Survival	0.996	Perry et al. 2006a. Final 2004 RT report.
		Bypass_Survival	0.976	Perry et al. 2006a. Final 2004 RT report.
		Diel	0.5	2000 Biological Opinion
2005				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.75	Perry et al. 2005 preliminary data . October 7, 2005 letter from R. Perry to Rebecca K. Seasonal ave.
		Turbine_Survival	0.933	Perry et al. 2006b Draft 2005 RT rept season 24 hour spill treatment avg.
		Spillway_Survival	0.972	Perry et al. 2006b. Draft 2005 RT rept Season 24 hr spill treatment avg.
		Bypass_Survival	0.957	Perry et al. 2006b. Draft 2005 RT rept Season 24 hr spill treatment avg.
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.827	Perry et al. 2005 preliminary data . October 7, 2005 letter from R. Perry to Rebecca K. Seasonal ave.
		Turbine_Survival	0.886	Perry et al. 2006b. Draft 2005 RT rept. 24 h spill treatment
		Spillway_Survival	0.922	Perry et al. 2006b. Draft 2005 RT rept. 24 h spill treatment
		Bypass_Survival	0.927	Perry et al. 2006b. Draft 2005 RT rept. 24 h spill treatment
		Diel	0.5	2000 Biological Opinion
Current				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.75	
		Turbine_Survival	0.903	Perry et al 2006a, b. Ave of 2004 and 2005 RT point estimates.
		Spillway_Survival	0.962	Axel et al. 2004a, b; Perry et al. 2006a,b. Ave of 2002, 03, 04, 05 RT point estimates.
		Bypass_Survival	0.913	Axel et al. 2004a, b; Perry et al. 2006a,b. Ave of 2002, 03, 04, 05 RT point estimates.
		Diel	0.5	
	Steelhead			

McNary Dam	Species	Parameter	Value	Reference
		rsw_spill_cap	0	
		FGE	0.827	
		Turbine_Survival	0.89	Average of 2004 and 2005 RT estimates from Perry et al. 2006a,b
		Spillway_Survival	0.959	Average of 2004 and 2005 RT estimates from Perry et al. 2006a,b
		Bypass_Survival	0.952	Average of 2004 and 2005 RT estimates from Perry et al. 2006a,b
		Diel	0.5	

Ice Harbor Dam	Species	Parameter	Value	Reference
1995				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.71	
		Turbine_Survival	0.871	Absolon et al. 2005. (2003 survival study direct releases PIT tag fish)
		Spillway_Survival	0.978	Eppard et al. 2002. 2000 PIT study.
		RSW_Survival	1	
		Bypass_Survival	0.95	Best professional judgement, given that the system passed fish through the sluiceway (no sluiceway survival).
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.93	Ferguson et al. 2005.
		Turbine_Survival	0.871	Absolon et al. 2005. (2003 survival study direct releases PIT tag fish)
		Spillway_Survival	0.978	Eppard et al. 2002. 2000 PIT study.
		RSW_Survival	1	
		Bypass_Survival	0.95	Best professional judgement, given that the system passed fish through the sluiceway (no sluiceway survival).
		Diel	0.5	2000 Biological Opinion
1996				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.71	
		Turbine_Survival	0.871	Absolon et al. 2005. (2003 survival study direct releases PIT tag fish)
		Spillway_Survival	0.978	Eppard et al. 2002. 2000 PIT study.
		RSW_Survival	1	
		Bypass_Survival	0.996	Axel et al. 2003. Report for 2001 research.
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	

Ice Harbor Dam	Species	Parameter	Value	Reference
		FGE	0.93	Ferguson et al. 2005.
		Turbine_Survival	0.871	Absolon et al. 2005. (2003 survival study direct releases PIT tag fish)
		Spillway_Survival	0.978	Eppard et al. 2002. 2000 PIT study.
		RSW_Survival	1	
		Bypass_Survival	0.996	Axel et al. 2003. Report for 2001 research.
		Diel	0.5	2000 Biological Opinion
1997				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.71	
		Turbine_Survival	0.871	Absolon et al. 2005. (2003 survival study direct releases PIT tag fish)
		Spillway_Survival	0.978	Eppard et al. 2002. 2000 PIT study.
		RSW_Survival	1	
		Bypass_Survival	0.996	Axel et al. 2003. Report for 2001 research.
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.93	Ferguson et al. 2005.
		Turbine_Survival	0.871	Absolon et al. 2005. (2003 survival study direct releases PIT tag fish)
		Spillway_Survival	0.978	Eppard et al. 2002. 2000 PIT study.
		RSW_Survival	1	
		Bypass_Survival	0.996	Axel et al. 2003. Report for 2001 research.
		Diel	0.5	2000 Biological Opinion
1998				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.71	
		Turbine_Survival	0.871	Absolon et al. 2005. (2003 survival study direct releases PIT tag fish)
		Spillway_Survival	0.978	Eppard et al. 2002. 2000 PIT study.
		RSW_Survival	1	
		Bypass_Survival	0.996	Axel et al. 2003. Report for 2001 research.
		Diel	0.5	2004 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.93	Ferguson et al. 2005.
		Turbine_Survival	0.871	Absolon et al. 2005. (2003 survival study direct releases PIT tag fish)
		Spillway_Survival	0.978	Eppard et al. 2002. 2000 PIT study.
		RSW_Survival	1	
		Bypass_Survival	0.996	Axel et al. 2003. Report for 2001 research.
		Diel	0.5	2000 Biological Opinion
1999				

Ice Harbor Dam	Species	Parameter	Value	Reference
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.71	
		Turbine_Survival	0.871	Absolon et al. 2005. (2003 survival study direct releases PIT tag fish)
		Spillway_Survival	0.978	Eppard et al. 2002. 2000 PIT study.
		RSW_Survival	1	
		Bypass_Survival	0.996	Axel et al. 2003. Report for 2001 research.
		Diel	0.5	2004 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.93	Ferguson et al. 2005.
		Turbine_Survival	0.871	Absolon et al. 2005. (2003 survival study direct releases PIT tag fish)
		Spillway_Survival	0.978	Eppard et al. 2002. 2000 PIT study.
		RSW_Survival	1	
		Bypass_Survival	0.996	Axel et al. 2003. Report for 2001 research.
		Diel	0.5	2000 Biological Opinion
2000				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.71	
		Turbine_Survival	0.871	Absolon et al. 2005. (2003 survival study direct releases PIT tag fish)
		Spillway_Survival	0.978	Eppard et al. 2002. 2000 PIT study.
		RSW_Survival	1	
		Bypass_Survival	0.996	Axel et al. 2003. Report for 2001 research.
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.93	Ferguson et al. 2005.
		Turbine_Survival	0.871	Absolon et al. 2005. (2003 survival study direct releases PIT tag fish)
		Spillway_Survival	0.978	Eppard et al. 2002. 2000 PIT study.
		RSW_Survival	1	
		Bypass_Survival	0.996	Axel et al. 2003. Report for 2001 research.
		Diel	0.5	2000 Biological Opinion
2001				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.71	
		Turbine_Survival	0.871	Absolon et al. 2005. (2003 survival study direct releases PIT tag fish)
		Spillway_Survival	0.893	Eppard et al. 2005a. 2002 study (PIT results, ave of day and night results).
		RSW_Survival	1	

Ice Harbor Dam	Species	Parameter	Value	Reference
		Bypass_Survival	0.996	Axel et al. 2003. Report for 2001 research.
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.93	Ferguson et al. 2005.
		Turbine_Survival	0.871	Absolon et al. 2005. (2003 survival study direct releases PIT tag fish)
		Spillway_Survival	0.893	Eppard et al. 2005a. 2002 study (PIT results, ave of day and night results).
		RSW_Survival	1	
		Bypass_Survival	0.996	Axel et al. 2003. Report for 2001 research.
		Diel	0.5	2000 Biological Opinion
2002				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.71	
		Turbine_Survival	0.871	Absolon et al. 2005. (2003 survival study direct releases PIT tag fish)
		Spillway_Survival	0.893	Eppard et al. 2005a. 2002 study (PIT results, ave of day and night results).
		RSW_Survival	1	
		Bypass_Survival	0.996	Axel et al. 2003. Report for 2001 research.
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.93	Ferguson et al. 2005.
		Turbine_Survival	0.871	Absolon et al. 2005. (2003 survival study direct releases PIT tag fish)
		Spillway_Survival	0.893	Eppard et al. 2005a. 2002 study (PIT results, ave of day and night results).
		RSW_Survival	1	
		Bypass_Survival	0.996	Axel et al. 2003. Report for 2001 research.
		Diel	0.5	2000 Biological Opinion
2003				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.71	
		Turbine_Survival	0.871	Absolon et al. 2005. (2003 survival study direct releases PIT tag fish)
		Spillway_Survival	0.938	Eppard et al. 2005b, (avg. of BiOp and 50% survival estimates for RT fish in 2003)
		RSW_Survival	1	
		Bypass_Survival	0.996	Axel et al. 2003. Report for 2001 research.
		Diel	0.5	2004 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.93	Ferguson et al. 2005.

Ice Harbor Dam	Species	Parameter	Value	Reference
		Turbine_Survival	0.871	Absolon et al. 2005. (2003 survival study direct releases PIT tag fish)
		Spillway_Survival	0.938	Eppard et al. 2005b, (avg. of BiOp and 50% survival estimates for RT fish in 2003)
		RSW_Survival	1	
		Bypass_Survival	0.996	Axel et al. 2003. Report for 2001 research.
		Diel	0.5	2000 Biological Opinion
2004				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.71	
		Turbine_Survival	0.871	Absolon et al. 2005. (2003 survival study direct releases PIT tag fish)
		Spillway_Survival	0.963	Eppard et al. 2005c (avg. of bulk and flat survival estimates for RT fish in 2004)
		RSW_Survival	1	
		Bypass_Survival	0.996	Axel et al. 2003. Report for 2001 research.
		Diel	0.5	2004 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.93	Ferguson et al. 2005.
		Turbine_Survival	0.871	Absolon et al. 2005. (2003 survival study direct releases PIT tag chinook)
		Spillway_Survival	0.977	Axel et al. 2005. 2004 RT steelhead study (95% CI from flat spill estimate since pt estimates are the same for both treatments).
		RSW_Survival	1	
		Bypass_Survival	0.996	Axel et al. 2003. Report for 2001 research. Chinook
		Diel	0.5	2000 Biological Opinion
2005				
	Chinook 1			
		rsw_spill_cap	7.9	
		FGE	0.711	data range
		Turbine_Survival	0.871	Absolon et al. 2005. (2003 survival study direct releases PIT tag fish)
		Spillway_Survival	0.965	Axel G.A. et al, 2005, Letter report to COE NWW for 2005 data (avg. of spill survival estimates for both operations)
		RSW_Survival	0.97	Axel G.A. et al, 2005, Letter report to COE NWW for 2005 data
		Bypass_Survival	0.997	Axel G.A. et al, 2005, Letter report to COE NWW for 2005 data
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	7.9	
		FGE	0.93	Ferguson et al. 2005.
		Turbine_Survival	0.871	Absolon et al. 2005. (2003 survival study direct releases PIT tag yearling chinook)

Ice Harbor Dam	Species	Parameter	Value	Reference
		Spillway_Survival	0.99	Axel G.A. et al, 2005, Letter report to COE NWW for 2005 data (avg. of spill survival estimates for both operations) Steelhead
		RSW_Survival	0.985	Axel G.A.. et al, 2005, Letter report to COE NWW for 2005 steelhead data
		Bypass_Survival	1	Axel G.A.. et al, 2005, Letter report to COE NWW for 2005 steelhead data
		Diel	0.5	2000 Biological Opinion
Current				
	Chinook 1			
		rsw_spill_cap	7.9	
		FGE	0.711	
		Turbine_Survival	0.871	Absolon et al. 2005. (2003 survival study direct releases PIT tag fish)
		Spillway_Survival	0.965	Axel G.A. et al, 2005, Letter report to COE NWW for 2005 data (avg. of spill survival estimates for both operations)
		RSW_Survival	0.97	Axel G.A. et al, 2005, Letter report to COE NWW for 2005 data
		Bypass_Survival	0.997	Axel G.A. et al, 2005, Letter report to COE NWW for 2005 data
		Diel	0.5	
	Steelhead			
		rsw_spill_cap	7.9	
		FGE	0.93	
		Turbine_Survival	0.871	Absolon et al. 2005. (2003 survival study direct releases PIT tag yearling chinook)
		Spillway_Survival	0.99	Axel G.A. et al, 2005, Letter report to COE NWW for 2005 data (avg. of spill survival estimates for both operations) Steelhead
		RSW_Survival	0.985	Axel G.A.. et al, 2005, Letter report to COE NWW for 2005 steelhead data
		Bypass_Survival	1	Axel G.A.. et al, 2005, Letter report to COE NWW for 2005 steelhead data
		Diel	0.5	

Lower Monumental Dam	Species	Parameter	Value	Reference
1995				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.817	Hockersmith et al 2005 (2004 hatchery yrlg chinook RT study)
		Turbine_Survival	0.865	Muir et al. 2001. N. Am. J. of Fish Mgmt. (PIT tagged 1993-1997 yearling chinook) Relative Survival Estimate, controls released downstream of bypass outfall, last row of table 2 & table 2-extended
		Spillway_Survival	0.956	Muir et al. 1995. Ave of 1994 estimates (0.927 and 0.984).
		Bypass_Survival	0.95	2000 Biological Opinion (ref: 2000 NMFS Passage White Paper)

Lower Monumental Dam	Species	Parameter	Value	Reference
		Diel	0.5	2001 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.817	Hockersmith et al 2005 (2004 hatchery yrlg chinook RT study)
		Turbine_Survival	0.865	Muir et al. 2001. N. Am. J. of Fish Mgmt. (PIT tagged 1993-1997 yearling chinook) Relative Survival Estimate, controls released downstream of bypass outfall, last row of table 2 & table 2-extended
		Spillway_Survival	0.956	Muir et al. 1995. Ave of 1994 estimates (0.927 and 0.984).
		Bypass_Survival	0.95	2000 Biological Opinion (ref: 2000 NMFS Passage White Paper)
		Diel	0.5	2001 Biological Opinion
1996				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.817	Hockersmith et al 2005 (2004 hatchery yrlg chinook RT study)
		Turbine_Survival	0.865	Muir et al. 2001. N. Am. J. of Fish Mgmt. (PIT tagged 1993-1997 yearling chinook) Relative Survival Estimate, controls released downstream of bypass outfall, last row of table 2 & table 2-extended
		Spillway_Survival	0.956	Muir et al. 1995. Ave of 1994 estimates (0.927 and 0.984).
		Bypass_Survival	0.95	2000 Biological Opinion (ref: 2000 NMFS Passage White Paper)
		Diel	0.5	2001 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.817	Hockersmith et al 2005 (2004 hatchery yrlg chinook RT study)
		Turbine_Survival	0.865	Muir et al. 2001. N. Am. J. of Fish Mgmt. (PIT tagged 1993-1997 yearling chinook) Relative Survival Estimate, controls released downstream of bypass outfall, last row of table 2 & table 2-extended
		Spillway_Survival	0.956	Muir et al. 1995. Ave of 1994 estimates (0.927 and 0.984).
		Bypass_Survival	0.95	2000 Biological Opinion (ref: 2000 NMFS Passage White Paper)
		Diel	0.5	2001 Biological Opinion
1997				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.721	Hockersmith et al 2005 (2004 hatchery yrlg chinook RT study)
		Turbine_Survival	0.865	Muir et al. 2001. N. Am. J. of Fish Mgmt. (PIT tagged 1993-1997 yearling chinook) Relative Survival Estimate, controls released downstream of bypass outfall, last row of table 2 & table 2-extended
		Spillway_Survival	0.956	Muir et al. 1995. Ave of 1994 estimates (0.927 and 0.984).
		Bypass_Survival	0.95	2000 Biological Opinion (ref: 2000 NMFS Passage White Paper)

Lower Monumental Dam	Species	Parameter	Value	Reference
		Diel	0.5	2001 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.817	Hockersmith et al 2005 (2004 hatchery yrlg chinook RT study)
		Turbine_Survival	0.865	Muir et al. 2001. N. Am. J. of Fish Mgmt. (PIT tagged 1993-1997 yearling chinook) Relative Survival Estimate, controls released downstream of bypass outfall, last row of table 2 & table 2-extended
		Spillway_Survival	0.956	Muir et al. 1995. Ave of 1994 estimates (0.927 and 0.984).
		Bypass_Survival	0.95	2000 Biological Opinion (ref: 2000 NMFS Passage White Paper)
		Diel	0.5	2001 Biological Opinion
1998				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.817	Hockersmith et al 2005 (2004 hatchery yrlg chinook RT study)
		Turbine_Survival	0.865	Muir et al. 2001. N. Am. J. of Fish Mgmt. (PIT tagged 1993-1997 yearling chinook) Relative Survival Estimate, controls released downstream of bypass outfall, last row of table 2 & table 2-extended
		Spillway_Survival	0.956	Muir et al. 1995. Ave of 1994 estimates (0.927 and 0.984).
		Bypass_Survival	0.95	2000 Biological Opinion (ref: 2000 NMFS Passage White Paper)
		Diel	0.5	2001 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.817	Hockersmith et al 2005 (2004 hatchery yrlg chinook RT study)
		Turbine_Survival	0.865	Muir et al. 2001. N. Am. J. of Fish Mgmt. (PIT tagged 1993-1997 yearling chinook) Relative Survival Estimate, controls released downstream of bypass outfall, last row of table 2 & table 2-extended
		Spillway_Survival	0.956	Muir et al. 1995. Ave of 1994 estimates (0.927 and 0.984).
		Bypass_Survival	0.95	2000 Biological Opinion (ref: 2000 NMFS Passage White Paper)
		Diel	0.5	2001 Biological Opinion
1999				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.817	Hockersmith et al 2005 (2004 hatchery yrlg chinook RT study)
		Turbine_Survival	0.865	Muir et al. 2001. N. Am. J. of Fish Mgmt. (PIT tagged 1993-1997 yearling chinook) Relative Survival Estimate, controls released downstream of bypass outfall, last row of table 2 & table 2-extended
		Spillway_Survival	0.956	Muir et al. 1995. Ave of 1994 estimates (0.927 and 0.984).
		Bypass_Survival	0.958	Hockersmith et al. 2000 (report for 1999 research)
		Diel	0.5	2001 Biological Opinion

Lower Monumental Dam	Species	Parameter	Value	Reference
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.817	Hockersmith et al 2005 (2004 hatchery yrlg chinook RT study)
		Turbine_Survival	0.865	Muir et al. 2001. N. Am. J. of Fish Mgmt. (PIT tagged 1993-1997 yearling chinook) Relative Survival Estimate, controls released downstream of bypass outfall, last row of table 2 & table 2-extended
		Spillway_Survival	0.956	Muir et al. 1995. Ave of 1994 estimates (0.927 and 0.984).
		Bypass_Survival	0.958	2000 Biological Opinion (ref: 2000 NMFS Passage White Paper)
		Diel	0.5	2001 Biological Opinion
2000				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.817	Hockersmith et al 2005 (2004 hatchery yrlg chinook RT study)
		Turbine_Survival	0.865	Muir et al. 2001. N. Am. J. of Fish Mgmt. (PIT tagged 1993-1997 yearling chinook) Relative Survival Estimate, controls released downstream of bypass outfall, last row of table 2 & table 2-extended
		Spillway_Survival	0.956	Muir et al. 1995. Ave of 1994 estimates (0.927 and 0.984).
		Bypass_Survival	0.958	Hockersmith et al. 2000 (report for 1999 research)
		Diel	0.5	2001 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.817	Hockersmith et al 2005 (2004 hatchery yrlg chinook RT study)
		Turbine_Survival	0.865	Muir et al. 2001. N. Am. J. of Fish Mgmt. (PIT tagged 1993-1997 yearling chinook) Relative Survival Estimate, controls released downstream of bypass outfall, last row of table 2 & table 2-extended
		Spillway_Survival	0.956	Muir et al. 1995. Ave of 1994 estimates (0.927 and 0.984).
		Bypass_Survival	0.958	2000 Biological Opinion (ref: 2000 NMFS Passage White Paper)
		Diel	0.5	2001 Biological Opinion
2001				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.817	Hockersmith et al 2005 (2004 hatchery yrlg chinook RT study)
		Turbine_Survival	0.865	Muir et al. 2001. N. Am. J. of Fish Mgmt. (PIT tagged 1993-1997 yearling chinook) Relative Survival Estimate, controls released downstream of bypass outfall, last row of table 2 & table 2-extended
		Spillway_Survival	0.956	Muir et al. 1995. Ave of 1994 estimates (0.927 and 0.984).
		Bypass_Survival	0.958	Hockersmith et al. 2000 (report for 1999 research)
		Diel	0.5	2001 Biological Opinion
	Steelhead			

Lower Monumental Dam	Species	Parameter	Value	Reference
		rsw_spill_cap	0	
		FGE	0.817	Hockersmith et al 2005 (2004 hatchery yrlg chinook RT study)
		Turbine_Survival	0.865	Muir et al. 2001. N. Am. J. of Fish Mgmt. (PIT tagged 1993-1997 yearling chinook) Relative Survival Estimate, controls released downstream of bypass outfall, last row of table 2 & table 2-extended
		Spillway_Survival	0.956	Muir et al. 1995. Ave of 1994 estimates (0.927 and 0.984).
		Bypass_Survival	0.958	2000 Biological Opinion (ref: 2000 NMFS Passage White Paper)
		Diel	0.5	2001 Biological Opinion
2002				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.817	Hockersmith et al 2005 (2004 hatchery yrlg chinook RT study)
		Turbine_Survival	0.865	Muir et al. 2001. N. Am. J. of Fish Mgmt. (PIT tagged 1993-1997 yearling chinook) Relative Survival Estimate, controls released downstream of bypass outfall, last row of table 2 & table 2-extended
		Spillway_Survival	0.956	Muir et al. 1995. Ave of 1994 estimates (0.927 and 0.984).
		Bypass_Survival	0.958	Hockersmith et al. 2000 (report for 1999 research)
		Diel	0.5	2001 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.817	Hockersmith et al 2005 (2004 hatchery yrlg chinook RT study)
		Turbine_Survival	0.865	Hockersmith et al. 2000 (report for 1999 research)
		Spillway_Survival	0.956	Muir et al. 2001. N. Am. J. of Fish Mgmt. (PIT tagged 1993-1997 yearling chinook) Relative Survival Estimate, controls released downstream of bypass outfall, last row of table 2 & table 2-extended
		Bypass_Survival	0.958	
		Diel	0.5	2001 Biological Opinion
2003				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.817	Hockersmith et al 2005 (2004 hatchery yrlg chinook RT study)
		Turbine_Survival	0.865	Muir et al. 2001. N. Am. J. of Fish Mgmt. (PIT tagged 1993-1997 yearling chinook) Relative Survival Estimate, controls released downstream of bypass outfall, last row of table 2 & table 2-extended
		Spillway_Survival	0.9	Hockersmith et al. 2004 (report for 2003 research)
		Bypass_Survival	0.958	Hockersmith et al. 2000 (report for 1999 research)
		Diel	0.5	2001 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.817	Hockersmith et al 2005 (2004 hatchery yrlg

Lower Monumental Dam	Species	Parameter	Value	Reference
				chinook RT study)
		Turbine_Survival	0.865	Muir et al. 2001. N. Am. J. of Fish Mgmt. (PIT tagged 1993-1997 yearling chinook) Relative Survival Estimate, controls released downstream of bypass outfall, last row of table 2 & table 2-extended
		Spillway_Survival	0.9	Hockersmith et al. 2004 (report for 2003 research)
		Bypass_Survival	0.958	Hockersmith et al. 2000 (report for 1999 research)
		Diel	0.5	2001 Biological Opinion
2004				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.817	Hockersmith et al 2005 (2004 hatchery yrlg chinook RT study)
		Turbine_Survival	0.881	Hockersmith et al. 2005 (report for 2004 research, 2 week test)
		Spillway_Survival	0.961	Hockersmith et al. 2005 (report for 2004 research, 2 week test)
		Bypass_Survival	0.922	Hockersmith et al. 2005 (report for 2004 research, 2 week test)
		Diel	0.5	2001 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.817	Hockersmith et al 2005 (2004 hatchery yrlg chinook RT study)
		Turbine_Survival	0.881	Hockersmith et al. 2005 (report for 2004 research, 2 week test)
		Spillway_Survival	0.961	Hockersmith et al. 2005 (report for 2004 research, 2 week test)
		Bypass_Survival	0.922	Hockersmith et al. 2005 (report for 2004 research, 2 week test)
		Diel	0.5	2001 Biological Opinion
2005				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.817	Hockersmith et al 2005 (2004 hatchery yrlg chinook RT study)
		Turbine_Survival	0.881	Hockersmith et al. 2005 (report for 2004 research)
		Spillway_Survival	0.932	Hockersmith et al. (prelim. report for 2005 research). Average of spillbays 7 (.92) & 8 (.944).
		Bypass_Survival	0.922	Hockersmith et al. 2005 (report for 2004 research)
		Diel	0.5	2001 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.817	Hockersmith et al 2005 (2004 hatchery yrlg chinook RT study)
		Turbine_Survival	0.881	Hockersmith et al. 2005 (report for 2004 research)
		Spillway_Survival	0.932	Hockersmith et al. (prelim. report for 2005 research). Average of spillbays 7 (.92) & 8 (.944).
		Bypass_Survival	0.922	Hockersmith et al. 2005 (report for 2004 research)
		Diel	0.5	2001 Biological Opinion

Lower Monumental Dam	Species	Parameter	Value	Reference
Current				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.817	Hockersmith et al 2005 (2004 hatchery yrlg chinook RT study)
		Turbine_Survival	0.881	Hockersmith et al. 2005 (report for 2004 research, 2 week test)
		Spillway_Survival	0.961	Hockersmith et al. 2005 (report for 2004 research, 2 week test)
		Bypass_Survival	0.922	Hockersmith et al. 2005 (report for 2004 research, 2 week test)
		Diel	0.5	
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.817	
		Turbine_Survival	0.881	Hockersmith et al. 2005 (report for 2004 research, 2 week test)
		Spillway_Survival	0.961	Hockersmith et al. 2005 (report for 2004 research, 2 week test)
		Bypass_Survival	0.922	Hockersmith et al. 2005 (report for 2004 research, 2 week test)
		Diel	0.5	

Little Goose Dam	Species	Parameter	Value	Reference
1995				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.57	Kransow, 1998. FGE estimates.
		Turbine_Survival	0.923	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.97	Muir et al. 1998. Steelhead PIT data.
		Bypass_Survival	0.964	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.57	Kransow, 1998. FGE estimates.
		Turbine_Survival	0.93	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.972	Muir et al. 1998. (PIT-tag hose release data from 1997).
		Bypass_Survival	0.95	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion
1996				
	Chinook			

	1			
		rsw_spill_cap	0	
		FGE	0.82	Ferguson et al. 2005.
		Turbine_Survival	0.923	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.972	Muir et al. 2001 (PIT-tag hose release data from 1997)
		Bypass_Survival	0.964	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.81	Ferguson et al. 2005.
		Turbine_Survival	0.93	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.972	Muir et al. 1998. (PIT-tag hose release data from 1997).
		Bypass_Survival	0.95	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion
1997				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.82	Ferguson et al. 2005.
		Turbine_Survival	0.923	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.972	Muir et al. 2001 (PIT-tag hose release data from 1997)
		Bypass_Survival	0.964	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.81	Ferguson et al. 2005.
		Turbine_Survival	0.93	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.972	Muir et al. 1998. (PIT-tag hose release data from 1997).
		Bypass_Survival	0.95	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion
1998				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.82	Ferguson et al. 2005.
		Turbine_Survival	0.923	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.972	Muir et al. 2001 (PIT-tag hose release data from 1997)
		Bypass_Survival	0.964	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion

	Steelhead			
		rsw_spill_cap	0	
		FGE	0.81	Ferguson et al. 2005.
		Turbine_Survival	0.93	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.972	Muir et al. 1998. (PIT-tag hose release data from 1997).
		Bypass_Survival	0.95	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion
1999				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.82	Ferguson et al. 2005.
		Turbine_Survival	0.923	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.972	Muir et al. 2001 (PIT-tag hose release data from 1997)
		Bypass_Survival	0.964	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.81	Ferguson et al. 2005.
		Turbine_Survival	0.93	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.972	Muir et al. 1998. (PIT-tag hose release data from 1997).
		Bypass_Survival	0.95	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion
2000				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.82	Ferguson et al. 2005.
		Turbine_Survival	0.923	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.972	Muir et al. 2001 (PIT-tag hose release data from 1997)
		Bypass_Survival	0.964	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.81	Ferguson et al. 2005.
		Turbine_Survival	0.93	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.972	Muir et al. 1998. (PIT-tag hose release data from 1997).
		Bypass_Survival	0.95	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion

2001				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.82	Ferguson et al. 2005.
		Turbine_Survival	0.923	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.972	Muir et al. 2001 (PIT-tag hose release data from 1997)
		Bypass_Survival	0.964	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.81	Ferguson et al. 2005.
		Turbine_Survival	0.93	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.972	Muir et al. 1998. (PIT-tag hose release data from 1997).
		Bypass_Survival	0.95	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion
2002				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.82	Ferguson et al. 2005.
		Turbine_Survival	0.923	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.972	Muir et al. 2001 (PIT-tag hose release data from 1997)
		Bypass_Survival	0.964	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.81	Ferguson et al. 2005.
		Turbine_Survival	0.93	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.972	Muir et al. 1998. (PIT-tag hose release data from 1997).
		Bypass_Survival	0.95	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion
2003				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.82	Ferguson et al. 2005.
		Turbine_Survival	0.923	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.972	Muir et al. 2001 (PIT-tag hose release data from 1997)

		Bypass_Survival	0.964	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.81	Ferguson et al. 2005.
		Turbine_Survival	0.93	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.972	Muir et al. 1998. (PIT-tag hose release data from 1997).
		Bypass_Survival	0.95	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion
2004				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.82	Ferguson et al. 2005.
		Turbine_Survival	0.923	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.972	Muir et al. 2001 (PIT-tag hose release data from 1997)
		Bypass_Survival	0.964	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.81	Ferguson et al. 2005.
		Turbine_Survival	0.93	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.972	Muir et al. 1998. (PIT-tag hose release data from 1997).
		Bypass_Survival	0.95	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion
2005				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.874	Perry, R., 7 Oct 2005 letter to R. Kalamasz. Prelim results for 2005 research
		Turbine_Survival	0.923	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.913	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research (based on 63 RT fish)
		Bypass_Survival	0.964	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.964	Perry et al, 2005 Letter Report to COE NWW. Ave of hatchery and wild.

		Turbine_Survival	0.93	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.972	
		Bypass_Survival	0.95	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion
Current				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.874	
		Turbine_Survival	0.923	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.97	Muir et al. 1998. Steelhead PIT data.
		Bypass_Survival	0.964	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.964	
		Turbine_Survival	0.93	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.972	Muir et al. 2001 (PIT-tag hose release data from 1997)
		Bypass_Survival	0.95	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	

Lower Granite Dam	Species	Parameter	Values	Reference
1995				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.57	Kransow, 1998. FGE estimates.
		Turbine_Survival	0.945	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.98	Pre RSW, Best Professional Judgement - 2000 Biological Opinion (ref: 2000 NMFS Passage White Paper)
		RSW_Survival	1	
		Bypass_Survival	0.97	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.57	Krasnow, 1998. FGE estimates.
		Turbine_Survival	0.945	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.98	2000 Biological Opinion (ref: 2000 NMFS Passage White Paper) Pre RSW, Best Professional Judgement.

Lower Granite Dam	Species	Parameter	Values	Reference
		RSW_Survival	1	
		Bypass_Survival	0.97	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion
1996				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.79	Plumb et al., 2001 (pg. 44)
		Turbine_Survival	0.945	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.98	Pre RSW, Best Professional Judgement - 2000 Biological Opinion (ref: 2000 NMFS Passage White Paper)
		RSW_Survival	1	
		Bypass_Survival	0.97	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.93	
		Turbine_Survival	0.945	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.98	2000 Biological Opinion (ref: 2000 NMFS Passage White Paper) Pre RSW, Best Professional Judgement.
		RSW_Survival	1	
		Bypass_Survival	0.97	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion
1997				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.79	Plumb et al., 2001 (pg. 44)
		Turbine_Survival	0.945	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.98	Pre RSW, Best Professional Judgement - 2000 Biological Opinion (ref: 2000 NMFS Passage White Paper)
		RSW_Survival	1	
		Bypass_Survival	0.97	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.93	
		Turbine_Survival	0.945	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research

Lower Granite Dam	Species	Parameter	Values	Reference
		Spillway_Survival	0.98	2000 Biological Opinion (ref: 2000 NMFS Passage White Paper) Pre RSW, Best Professional Judgement.
		RSW_Survival	1	
		Bypass_Survival	0.97	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion
1998				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.79	Plumb et al., 2001 (pg. 44)
		Turbine_Survival	0.945	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.98	Pre RSW, Best Professional Judgement - 2000 Biological Opinion (ref: 2000 NMFS Passage White Paper)
		RSW_Survival	1	
		Bypass_Survival	0.97	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.93	
		Turbine_Survival	0.945	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.98	2000 Biological Opinion (ref: 2000 NMFS Passage White Paper) Pre RSW, Best Professional Judgement.
		RSW_Survival	1	
		Bypass_Survival	0.97	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion
1999				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.79	Plumb et al., 2001 (pg. 44)
		Turbine_Survival	0.945	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.98	Pre RSW, Best Professional Judgement - 2000 Biological Opinion (ref: 2000 NMFS Passage White Paper)
		RSW_Survival	1	
		Bypass_Survival	0.97	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	2004 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.93	

Lower Granite Dam	Species	Parameter	Values	Reference
		Turbine_Survival	0.945	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.98	2000 Biological Opinion (ref: 2000 NMFS Passage White Paper) Pre RSW, Best Professional Judgement.
		RSW_Survival	1	
		Bypass_Survival	0.97	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion
2000				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.79	Plumb et al., 2001 (pg. 44)
		Turbine_Survival	0.945	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.98	Pre RSW, Best Professional Judgement - 2000 Biological Opinion (ref: 2000 NMFS Passage White Paper)
		RSW_Survival	1	
		Bypass_Survival	0.97	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	2004 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	
		FGE	0.93	
		Turbine_Survival	0.945	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.98	2000 Biological Opinion (ref: 2000 NMFS Passage White Paper) Pre RSW, Best Professional Judgement.
		RSW_Survival	1	
		Bypass_Survival	0.97	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion
2001				
	Chinook 1			
		rsw_spill_cap	0	
		FGE	0.88	Plumb et al., 2001 (pg 43)
		Turbine_Survival	0.945	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.98	Pre RSW, Best Professional Judgement - 2000 Biological Opinion (ref: 2000 NMFS Passage White Paper)
		RSW_Survival	1	
		Bypass_Survival	0.97	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	2004 Biological Opinion
	Steelhead			
		rsw_spill_cap	0	

Lower Granite Dam	Species	Parameter	Values	Reference
		FGE	0.94	Plumb et al., 2001 (pg 43)
		Turbine_Survival	0.945	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.98	2000 Biological Opinion (ref: 2000 NMFS Passage White Paper) Pre RSW, Best Professional Judgement.
		RSW_Survival	1	
		Bypass_Survival	0.97	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion
2002				
	Chinook 1			
		rsw_spill_cap	6.75	
		FGE	0.68	Plumb et al. 2002 (pg. 72)
		Turbine_Survival	0.945	Perry, R., 7 Oct 2005 letter to R. Kalamasz. Prelim results for 2005 research
		Spillway_Survival	0.931	Plumb et al.(2004), report on 2003 season. Based on non RSW passed fish.
		RSW_Survival	0.98	Plumb et al.(2004), report on 2003 season
		Bypass_Survival	0.97	Perry, R., 7 Oct 2005 letter to R. Kalamasz. Prelim results for 2005 research
		Diel	0.5	2004 Biological Opinion
	Steelhead			
		rsw_spill_cap	6.75	
		FGE	0.91	
		Turbine_Survival	0.945	Perry, R., 7 Oct 2005 letter to R. Kalamasz. Prelim results for 2005 research
		Spillway_Survival	0.931	Plumb et al.(2004), report on 2003 season. Based on non RSW passed fish.
		RSW_Survival	0.98	Plumb et al.(2004), report on 2003 season
		Bypass_Survival	0.97	Perry, R., 7 Oct 2005 letter to R. Kalamasz. Prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion
2003				
	Chinook 1			
		rsw_spill_cap	6.75	
		FGE	0.82	Plumb et al, 2003 (pg. 66)
		Turbine_Survival	0.945	Perry, R., 7 Oct 2005 letter to R. Kalamasz. Prelim results for 2005 research
		Spillway_Survival	0.931	Plumb et al.(2004), report on 2003 season. Based on non RSW passed fish.
		RSW_Survival	0.98	Plumb et al.(2004), report on 2003 season
		Bypass_Survival	0.97	Perry, R., 7 Oct 2005 letter to R. Kalamasz. Prelim results for 2005 research
		Diel	0.5	2004 Biological Opinion
	Steelhead			
		rsw_spill_cap	6.75	

Lower Granite Dam	Species	Parameter	Values	Reference
		FGE	0.925	
		Turbine_Survival	0.945	Perry, R., 7 Oct 2005 letter to R. Kalamasz. Prelim results for 2005 research
		Spillway_Survival	0.931	Plumb et al.(2004), report on 2003 season. Based on non RSW passed fish.
		RSW_Survival	0.98	Plumb et al.(2004), report on 2003 season
		Bypass_Survival	0.97	Perry, R., 7 Oct 2005 letter to R. Kalamasz. Prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion
2004				
	Chinook 1			
		rsw_spill_cap	6.75	
		FGE	0.814	Perry, R., 7 Oct 2005 letter to R. Kalamasz. Prelim results for 2005 research
		Turbine_Survival	0.945	Perry, R., 7 Oct 2005 letter to R. Kalamasz. Prelim results for 2005 research
		Spillway_Survival	0.931	Plumb et al.(2004), report on 2003 season. Based on non RSW passed fish.
		RSW_Survival	0.98	Plumb et al.(2004), report on 2003 season
		Bypass_Survival	0.97	Perry, R., 7 Oct 2005 letter to R. Kalamasz. Prelim results for 2005 research
		Diel	0.5	2004 Biological Opinion
	Steelhead			
		rsw_spill_cap	6.75	
		FGE	0.93	
		Turbine_Survival	0.945	Perry, R., 7 Oct 2005 letter to R. Kalamasz. Prelim results for 2005 research
		Spillway_Survival	0.931	Plumb et al.(2004), report on 2003 season. Based on non RSW passed fish.
		RSW_Survival	0.98	Plumb et al.(2004), report on 2003 season
		Bypass_Survival	0.97	Perry, R., 7 Oct 2005 letter to R. Kalamasz. Prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion
2005				
	Chinook 1			
		rsw_spill_cap	6.75	
		FGE	0.814	Perry, R., 7 Oct 2005 letter to R. Kalamasz. Prelim results for 2005 research
		Turbine_Survival	0.945	Perry, R., 7 Oct 2005 letter to R. Kalamasz. Prelim results for 2005 research
		Spillway_Survival	0.931	Perry, R., 7 Oct 2005 letter to R. Kalamasz. Prelim results for 2005 research
		RSW_Survival	0.979	Perry, R., 7 Oct 2005 letter to R. Kalamasz. Prelim results for 2005 research
		Bypass_Survival	0.97	Perry, R., 7 Oct 2005 letter to R. Kalamasz. Prelim results for 2005 research
		Diel	0.5	2004 Biological Opinion

Lower Granite Dam	Species	Parameter	Values	Reference
	Steelhead			
		rsw_spill_cap	6.75	
		FGE	0.93	
		Turbine_Survival	0.945	Perry, R., 7 Oct 2005 letter to R. Kalamasz. Prelim results for 2005 research
		Spillway_Survival	0.931	Perry, R., 7 Oct 2005 letter to R. Kalamasz. Prelim results for 2005 research
		RSW_Survival	0.979	Perry, R., 7 Oct 2005 letter to R. Kalamasz. Prelim results for 2005 research
		Bypass_Survival	0.97	Perry, R., 7 Oct 2005 letter to R. Kalamasz. Prelim results for 2005 research
		Diel	0.5	2000 Biological Opinion
Current				
	Chinook 1			
		rsw_spill_cap	6.75	
		FGE	0.814	
		Turbine_Survival	0.923	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Spillway_Survival	0.972	Muir et al. 2001 (PIT-tag hose release data from 1997)
		RSW_Survival	0.979	
		Bypass_Survival	0.964	Perry 7Oct2005 letter to Kalamasz with prelim results for 2005 research
		Diel	0.5	
	Steelhead			
		rsw_spill_cap	6.75	
		FGE	0.93	
		Turbine_Survival	0.945	Perry, R., 7 Oct 2005 letter to R. Kalamasz. Prelim results for 2005 research
		Spillway_Survival	0.931	Perry, R., 7 Oct 2005 letter to R. Kalamasz. Prelim results for 2005 research
		RSW_Survival	0.979	Perry, R., 7 Oct 2005 letter to R. Kalamasz. Prelim results for 2005 research
		Bypass_Survival	0.97	Perry, R., 7 Oct 2005 letter to R. Kalamasz. Prelim results for 2005 research
		Diel	0.5	

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The main purpose of the hydrological processes submodel is to realistically represent the environmental conditions, particularly water flow, velocity, and temperature. In the model, these conditions vary daily and across river segments. This appendix describes how water velocity is calculated from river flow and reservoir geometry.

Flow / Velocity / Elevation

The river velocity used in fish migration calculations is related to river flow and pool geometry and varies with pool elevation as a function of the volume. The pool is represented as an idealized channel having sloping sides and longitudinal sloping bottom. As a pool is drawn down, part of it may return to a free flowing stream that merges with a smaller pool at the downstream end of the reservoir. The important parameters are as follows:

- H_u = full pool depth at the upstream end of the segment
- H_d = full pool depth at the downstream end of the segment
- L = pool length at full pool
- x = pool length at lowered pool
- E = pool elevation drop below full pool elevation
- W = pool width averaged over reach length at full pool
- θ = average slope of the pool side
- F = flow through the pool in kcfs
- U_{free} = velocity of free flowing river.

Other parameters illustrated are used to develop the relationships between the parameters listed above and water velocity and pool volume. They are not named explicitly.

Pool Volume

Reservoir volume depends on elevation. Elevation is measured in terms of E, the elevation drop below the full pool level. The volume calculation is based on the assumptions that the width of the pool at the bottom and the pool side slopes are constant over pool length. As a consequence of these two assumptions, the pool width at the surface increases going downstream in proportion to the increasing depth of the pool downstream. When $E > H_u$, the drawn down elevation is below the level of the upstream end and the upper end of the segment becomes a free flowing river section that connects to a pool downstream in the segment. When $E < H_u$, the reservoir extends to the upper end of the segment and for mathematical convenience COMPASS calculates a larger volume and subtracts off the excess. The volume relationship (as a function of elevation drop for E positive measured downward) is developed below.

The total volume is defined:

(1)
$$V(E) = V_1(E) \qquad E \geq H_u$$
$$V(E) = V_1(E) - V_2(E) \qquad E < H_u$$

The equation for V_1 is developed as follows. Note that when $E = H_u$, the volume V_1 divides into two parts:

(2)
$$V_1 = 2V' + V''$$

where V' is a side volume and V" is the thalweg volume. They are defined:

(3)
$$V' = \frac{zxy'}{6} \qquad V'' = \frac{zxy''}{2}$$

where

(4)
$$x = L\frac{H_d - \mathrm{E}}{H_d - H_u} \qquad z = H_d - E \qquad y' = z\tan\theta \qquad y'' = W - (H_d + H_u)\tan\theta$$

Combining these terms, when $E \geq H_u$ it follows pool volume is:

(5)
$$V_1 = \frac{zxy'}{3} + \frac{zxy''}{2}$$

In terms of the fundamental variables in equations, this is:

(6)
$$V_1(E) = L\left[\frac{(H_d - E)^2}{H_d - H_u}\right]\left[\frac{W}{2} - \left(\frac{H_d}{6} + \frac{H_u}{2} + \frac{E}{3}\right)\tan\theta\right]$$

for $E \geq H_u$ and $x \leq L$.

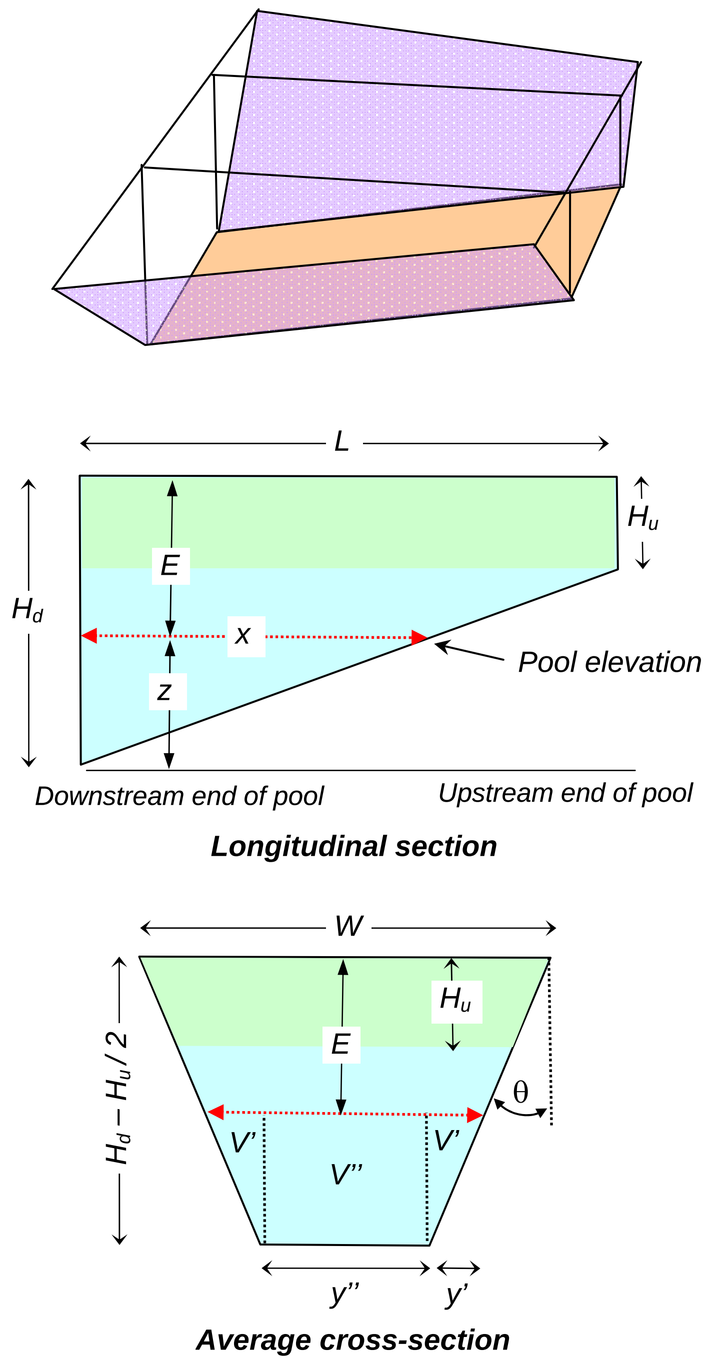


Figure 1 Pool geometry for volume calculations showing perspectives of a pool and cross-sections; the pool bottom width remains constant while the surface widens in the downstream direction. Definitions of parameters are given above. For the average cross-section the depth is $H_d - H_u/2$.

Recall from eq (1) that when the pool elevation drop is less than the upper depth (so $E < H_u$ and x = L), the pool volume is described by the equation

(7) $$V(E) = V_1(E) - V_2(E)$$

The term $V_1(E)$ is the volume of the pool extended longitudinally above the dam where the depth is H_u, so as to form the same triangular longitudinal cross- section as before. The term $V_2(E)$ is the excess volume of the portion of the pool above the dam and can be expressed:

(8) $$V_2(E) = L\left[\frac{(H_u - E)^2}{H_d - H_u}\right]\left[\frac{W}{2} - \left(\frac{H_d}{2} + \frac{H_u}{6} + \frac{E}{3}\right)\tan\theta\right]$$

Summarizing, the volume relationship as a function of elevation drop, for E positive measured downward, is:

(9) $$\begin{aligned} V(E) &= V_1(E) & E &\geq H_u \\ V(E) &= V_1(E) - V_2(E) & E &< H_u \end{aligned}$$

where

(10) $$\begin{aligned} V_1(E) &= L\left[\frac{(H_d - E)^2}{H_d - H_u}\right]\left[\frac{W}{2} - \left(\frac{H_d}{6} + \frac{H_u}{2} + \frac{E}{3}\right)\tan\theta\right] \\ V_2(E) &= L\left[\frac{(H_u - E)^2}{H_d - H_u}\right]\left[\frac{W}{2} - \left(\frac{H_d}{2} + \frac{H_u}{6} + \frac{E}{3}\right)\tan\theta\right] \end{aligned}$$

The equation for full pool volume can be expressed:

(11) $$V(0) = L\left[W\frac{H_d + H_u}{2} - \frac{\tan\theta}{3}\left(\frac{(H_d + H_u)^2}{2} + H_d H_u\right)\right]$$

When the bottom width is zero the full pool volume becomes:

(12) $$V(0) = \frac{LW}{3}\left[\frac{H_d^3 - H_u^3}{H_d^2 - H_u^2}\right]$$

Water Velocity

Water velocity through a reservoir is described in terms of the residence time T and the length of the segment L. The residence time in a segment depends on the amount of the reservoir that is pooled and free flowing.

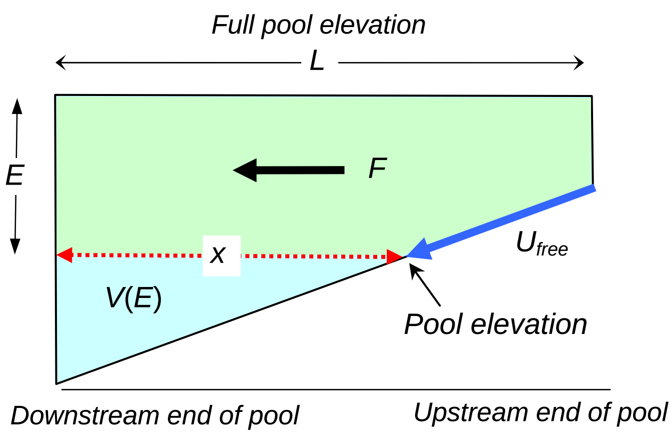


Figure 2 Reservoir with free flowing and pooled portions.

The equations for residence time are:

$$T = \frac{V(E)}{F} + \frac{L-x}{U_{free}} \qquad E \geq H_u$$
$$T = \frac{V(E)}{F} \qquad E < H_u \tag{13}$$

where

- V(E) = pool volume (ft^3) as a function of elevation drop E in feet
- F = flow in 1000 cubic feet per second (kcfs)
- L = segment length in miles
- x = pool length with units of feet
- U_{free} = velocity of water in the free stream (kfs)

  Using the John Day River, the default value is 4.5 ft./s which is 4.5 x 10-3 kfs).
- T = residence time in this calculation is in kilo seconds (ks)
- H_u = full pool depth at the upstream end of the segment.

The velocity in the segment is:

$$U = \frac{L}{T} \tag{14}$$

The velocity with the above units is in thousands of feet per second. The segment velocities are:

(15) $$U = \frac{L}{\frac{V_1(E)}{F} + \frac{L-x}{U_{free}}} \quad \text{for } E \geq H_u$$

and

(16) $$U = \frac{LF}{V_1(H_u) + V_2(E)} \quad \text{for } E < H_u$$

where

- U = average river velocity in ft/s
- U_{free} = the velocity of a free flowing stream in ft/s
- F = flow in kcfs
- E = elevation drop (positive downward) in ft
- H_u = depth of the upper end of the segment in ft
- V_1 and V_2 = volume elements

Flow / Velocity Calibration

The calibration of the volume equation requires determining the average pool slope from the pool volume. The equation is the smaller angle of the two forms:

$$\theta = \operatorname{atan}\left(\frac{3W(H_d + H_u) - 6\frac{V(0)}{L}}{(H_d + H_u)^2 + 2H_dH_u}\right)$$

or

(17) $$\theta = \operatorname{atan}\left(\frac{W}{H_d + H_u}\right)$$

where

- $V(0)$ = pool volume at full pool.

This scheme reflects the volume versus pool elevation relationship developed for each reservoir by the U.S. Army Corps of Engineers. Capacity versus elevation curves were obtained from several dams to check the accuracy of our volume model. The figures below show data points from these curves versus COMPASS's volume curve for two dams. Figure 3 illustrates Lower Granite Pool with model coefficients of H_u = 40 ft., H_d = 118 ft, θ= 80.7º, L = 53 miles, W = 2000 ft, and Wanapum Pool with model coefficients H_u = 42 ft., H_d = 116 ft, θ = 87.0º, L = 38 miles, W = 2996.1 ft.

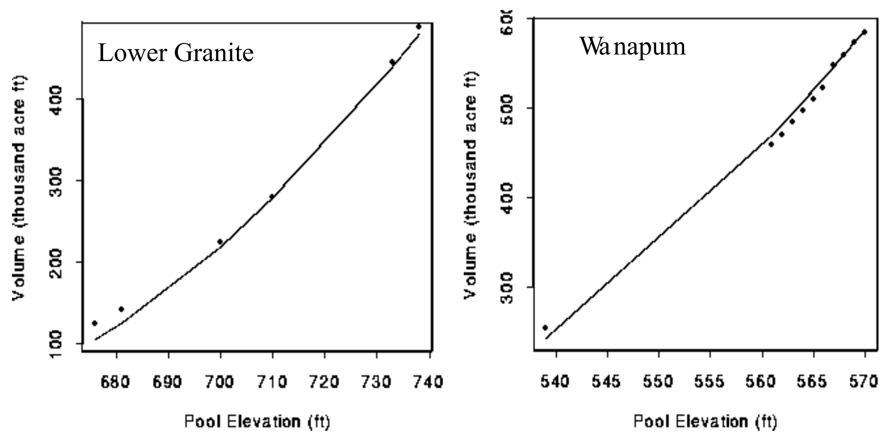


Figure 3 Pool elevation vs. volume for Lower Granite and Wanapum pools

Table 1 Geometric data on Columbia River system

Segment	*L*	Elev	MOP	*V*	A	*W*	H_u	H_d	θ
Units	miles	ft MSL	ft MSL	kaf	k ft ^{2}	Feet	feet	feet	º of arc
Bonneville	46.2	77.0	70.0	565	101.8	3643	22	93	88
The Dalles	23.9	160.0	155.0	332	114.6	3624	60	105	87
John Day	76.4	268.0	257.0	2,370	255.9	5399	34	149	86.9
McNary	61	340.0	335.0	1,350	182.6	5153	40	105	88
Hanford Reach	44	---	---	131	24.6	3213	29	29	---
Priest Rapids	18	488.0	465.0	199	91.2	3208	32	101	87
Wanapum	38	572.0	539.0	587	127.4	2996	42	116	87.0
Rock Island	21	613.0	609.0	113	44.4	982	15	44	64.4
Rocky Reach	41.8	707.0	703.0	430	84.8	1815	37	108	84.5
Wells	29.2	781.0	767.0	300	84.8	3023	91	111	86
Chief Joseph	52	956.0	930.0	516	81.9				
Ice Harbor	31.9	440.0	437.0	407	105.2	2154	18	110	83.3
L. Monumental	28.7	540.0	537.0	377	108.4	1937	42	118	81.3
Little Goose	37.2	638.0	633.0	365	80.9	2200	40	140	78.2
Lower Granite	53	738.0	733.0	484	75.3	2000	48	140	80.7

The pool volume velocity/travel time equation was tested against particle travel time calculations for Lower Granite Pool as reported by the U.S. Army Corps of Engineers in the 1992 reservoir drawdown test (Wik et al. 1993).

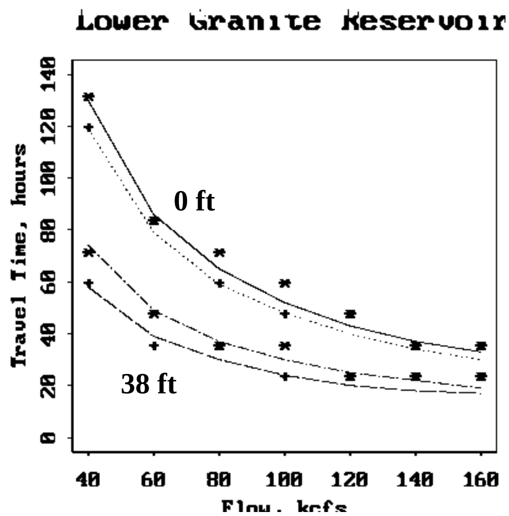


Figure 4 Water particle travel time vs. flow for COMPASS (points) and Army Corps calculations (lines) at two elevations full pool (0) and 38 ft below full pool for Lower Granite Dam

Introduction

These notes are intended to illuminate the class of models known as "random effect" models and the idea of "variance components." We illustrate the estimation of regression coefficients while simultaneously estimating variance components using a stand-alone "external analysis" of PIT-tag data (that is, not through calibration internal to the full COMPASS model). We then demonstrate how to use the variance component estimates along with the regression coefficient estimates and their associated estimated variance-covariance matrix to estimate the distribution of possible outcomes from the COMPASS model from a given set of inputs.

Eventually, we intend to implement the estimation of random-effects models through calibration methods using the full COMPASS model. Considerable effort, beyond the current scope, will be required to implement the necessary steps of the calibration routine. At this time, we have completed a variance components analysis of PIT-tag survival data separated from the rest of the model, and it is this analysis we present here.

Data

We first compiled data sets based on weekly cohorts of fish leaving Lower Granite Dam (LGR) during migration years 1997-2007 or McNary Dam (MCN) during migration years 1998-2007. A weekly cohort from LGR consisted of all PIT-tagged fish of Snake River origin that were either tagged and released at LGR or that had been released upstream from LGR and were detected and returned to the river at LGR during the specified 7 day period. Weekly cohorts at MCN were compiled similarly. For Snake River Spring/Summer Chinook salmon and for Snake River steelhead, we compiled weekly groups for wild fish alone, hatchery fish alone, and for the combined "all origin" cohort. The analysis of wild fish is presented here.

For each Lower Granite group, we estimated survival probabilities (Cormack-Jolly-Seber model) and mean travel time (days) from Lower Granite to Lower Monumental Dam and from Lower Monumental to McNary Dam, and we estimated detection probabilities at Little Goose, Lower Monumental, and McNary Dams. For each McNary group, we estimated survival probabilities (CJS model) and migration rates from McNary to John Day Dam and John Day to Bonneville Dam, and we estimated detection probabilities at John Day and Bonneville Dam. For each estimated survival probability, mean travel time, and detection probability, we also estimated its corresponding standard error.

The survival probabilities in the CJS models represent survival from the tailrace of the upstream dam to the tailrace of the downstream dam. The probabilities reflect mortality from all sources in that segment of river. Specifically, mortality that occurs during dam passage at the downstream dam or at any other dam in the river segment affects the survival estimate. Because they contain survival both at the dams in the reservoirs, we refer to the CJS-model probabilities as "project survival." PIT-tag data cannot be used to isolate reservoir survival. Instead, we used current dam-survival parameters and ran COMPASS to get estimates of dam-passage survival for all the dams passed by each weekly cohort. We divided each project survival estimate by corresponding dam-passage survival estimate(s) to obtain estimated reservoir survival for each cohort. For example, reservoir survival between the tailrace of Lower Granite Dam and tailrace of Lower Monumental Dam was obtained by dividing the PIT-tag project survival estimate by dam-passage survival at Little Goose Dam and by dam-passage survival at Lower Monumental Dam. Lower Monumental Dam-to-McNary Dam project survival includes dam-passage survival at Ice Harbor and McNary Dams. McNary Dam-to-John Day Dam includes only John Day passage, while John Day Dam-to-Bonneville Dam includes both The Dalles Dam and Bonneville Dam survival.

Finally, for each reach for each weekly cohort, we used daily data on environmental variables and passage distributions for the cohort to calculate exposure indices for flow (kcfs), proportion of water spilled at dams (0.0 to 1.0), and water temperature (^{o}C).

Within each data set the observation unit was a single reach for single cohort. For the random effects model of survival, the relevant data for each observation unit was the reservoir survival probability, the length (miles) of the reach, the mean travel time, and the flow, spill proportion, and temperature indices. Observation units were eliminated from the data set for the following reasons:

- PIT-tag detection data not sufficient to estimate survival;
- Detection probability estimate at downstream dam equal to 1.0, as corresponding survival estimates in the CJS model are biased low in this circumstance.

These conditions occur almost exclusively in extremely sparse data. Some observations had estimated reservoir survival greater than 1.0 These observations were left in the data set. This can occur because the CJS model sometimes gives project survival estimates greater than 1.0 (though almost always with large standard errors), or because the COMPASS-estimated dam-passage survival is lower than the CJS estimate of project of survival. Truncating such estimates at 1.0 or eliminating the observations from the model both would bias results.

Table A7 1 shows the number of observations in the final data set for each segment for each species each year.

Table A7 1 Number of observations in the final data set for each segment for each species each year.

	Snake River spring/summer Chinook				Snake River steelhead			
	Lower Granite Releases		McNary Releases		Lower Granite Releases		McNary Releases	
Year	LGR-LMN	LMN-MCN	MCN-JDA	JDA-BON	LGR-LMN	LMN-MCN	MCN-JDA	JDA-BON
1997	9	3	---	---	8	5	---	---
1998	14	11	7	3	9	8	6	2
1999	11	11	6	5	11	11	9	5
2000	14	12	9	6	10	8	6	4
2001	11	9	6	5	8	5	5	3
2002	13	12	6	5	8	7	7	5
2003	16	14	7	7	10	10	9	5
2004	14	14	9	8	11	10	4	1
2005	11	10	8	6	9	9	5	1
2006	11	11	7	5	10	9	8	3
2007	9	8	8	8	7	7	5	4
Total	133	115	73	58	101	89	64	33

Within the COMPASS model, LGR-LMN and LMN-MCN (to the Snake-Columbia confluence) are treated as the same "reach class," which means that the same reservoir survival model is used in both reaches. Also, MCN-JDA and JDA-BON have the same reservoir model in COMPASS. Consequently, we combined LGR-LMN and LMN-MCN observations for the external analysis, giving 248 observations for SRSS Chinook and 190 for SR steelhead. The data set for MCN-JDA and JDA-BON combined had 131 observations for SRSS Chinook and 97 for steelhead.

Basic Variance-Components Model for Grand Mean

In the sections that follow we discuss models that include a multiple regression component to explain survival. However, to introduce concepts of random effects and variance components, we begin with a model that does not include functions of covariates to explain the response. In the context of survival probabilities of cohorts of migrating salmonids, we could posit an artificial situation in which environmental conditions (or fish behavior) do not affect survival, or in which environmental conditions were identical for a series of cohorts. The key notion in a random effects model is that even in such a situation, we should not expect the true survival probability of all cohorts to be exactly the same. Rather, there is a distribution of expected (true) probabilities, and the probability for each cohort is a single realization from the distribution. Viewing the particular cohorts we happened to tag as a random sample from the distribution, we see the origin of the label "random effects."

Suppose there are ***n*** such cohorts for which the survival probabilities from Lower Granite Dam to Lower Monumental Dam and from Lower Monumental Dam to McNary Dam were known exactly. Denote the entire set of probabilities (two for each cohort) as: $S_1, S_2, \ldots, S_{2n}$.Following the usual approach for COMPASS modeling (see Chapter 2), we assume that the survival probabilities are approximately log-normally distributed, and use as our response variable the negative natural logarithm of survival: $y_i = -\log(S_i)$. The random effects model is based on the model for the population parameters:

$$y_i = -\log(S_i) = \mu + \varepsilon_i ,$$

where the ε_i are independent, identically distributed normal random variables with mean 0 and variance σ^2. The parameter σ^2 is known as the "process error."

In reality, of course, the population survival probabilities are not known exactly, but must be estimated from PIT-tag data using the CJS model. The CJS model for the n cohorts is conditional on the underlying estimable survival probabilities $S_1, S_2, \ldots, S_{2n}$ (and also on underlying detection probabilities). For a given cohort and reach, the response variable can be represented (conditionally) as:

$$\hat{y}_i = -\log(\hat{S}_i) = y_i + \delta_i ,$$

where δ_i represents the sampling error in the PIT-tag data. (Hereafter, we will drop the references to the survival probabilities S_i, and use the response variables y_i instead).

Given S_i, the large sample expected value of $\hat{y}_i$ is y_i (i.e. $E(\delta_i \mid y_i) = 0$; CJS estimates are asymptotically unbiased. Thus, considering the full vector of estimates we can say that, conditional on the vector of population parameters,

$E(\underline{\hat{y}} \mid \underline{y}) = \underline{y}$ and $\underline{\delta}$ has conditional sampling variance-covariance matrix **W,** which will be complicated function of the CJS survival probability and detection probability parameters. Assuming that the CJS model is applied independently to data from each cohort, only the two survival probabilities for the same cohort are correlated with each other. Probabilities for each cohort have zero covariance (independent) with probabilities from each other cohort, and **W** is a "block-diagonal" matrix of dimension $2n \times 2n$. The diagonal elements are 2×2 matrices representing the variance-covariance matrices for the two estimates from each of the cohorts.

Finally, assuming mutual independence of the sampling errors $\underline{\delta}$ and the process errors $\underline{\varepsilon}$, the unconditional random effects model for the transformed CJS estimates is

$$\underline{\hat{y}} = \mu + \underline{\delta} + \underline{\varepsilon} , \qquad \mathbf{VC}(\underline{\hat{\delta}} + \underline{\varepsilon}) = \mathbf{D} = \sigma^2 \mathbf{I} + E_{\underline{y}}(\mathbf{W}) \qquad (1)$$

where VC denotes a variance-covariance matrix. From the expression for the unconditional VC matrix for the estimates, the origin of the label "variance components" becomes clear. The unconditional VC matrix represents the "total variance" in the vector of estimates, and the random-effects formulation decomposes the total into components for sampling error ($E_{\underline{y}}(\mathbf{W})$) and process error ($\sigma^2\mathbf{I}$).

In the next section, we describe how the process error is estimated, in the context of a model that represents the mean μ as a multiple linear function of explanatory variables.

Variance-Components Model with Multiple Linear Regression

Much of this section is adapted from Franklin et. al. (2002). Consider now a random effects model incorporating a suite of explanatory variables; where the mean of response variable $E(y\,|\,\underline{X})$ depends on the value of $\underline{X}$ through the linear combination $\underline{X}\,\underline{\beta}$. For a single cohort, the model for the response variable is now

$$\hat{y}_i = \underline{X}_i\,\underline{\beta} + \delta_i + \varepsilon_i$$

And for the entire set of cohorts we have

$$\underline{\hat{y}} = \mathbf{X}\underline{\beta} + \underline{\delta} + \underline{\varepsilon}, \quad \text{and} \quad \mathbf{VC}(\underline{\hat{\delta}} + \underline{\varepsilon}) = \mathbf{D} = \sigma^2\mathbf{I} + E_{\underline{y}}(\mathbf{W}), \text{ as before.} \qquad (2)$$

The parameters to estimate from the data are the regression parameters $\underline{\beta}$ and the process error σ^2, the variance-covariance matrix for $\underline{\hat{\beta}}$, and an indicator of the precision of the estimated process error (a method to compute a confidence interval is available, as described below).

From generalized least squares theory, for a given value of σ^2, the best linear unbiased estimator of $\underline{\beta}$ is

$$\underline{\hat{\beta}} = (\mathbf{X}'\mathbf{D}^{-1}\mathbf{X})^{-1}\mathbf{X}'\mathbf{D}^{-1}\underline{\hat{y}}.$$

Assuming approximate normality of $\underline{\hat{y}}$ then from the same generalized least squares theory the weighted residual sum of squares $(\underline{\hat{y}} - \mathbf{X}\underline{\hat{\beta}})'\mathbf{D}^{-1}(\underline{\hat{y}} - \mathbf{X}\underline{\hat{\beta}})$ has a central chi-square distribution on *(k – r)* degrees of freedom, where *k* is the number of observations and *r* is the number of $\underline{\beta}$ parameters estimated. Therefore, a method of moments estimator of σ^2 is obtained by solving the equation

$$k - r = (\underline{\hat{y}} - \mathbf{X}\underline{\hat{\beta}})'\mathbf{D}^{-1}(\underline{\hat{y}} - \mathbf{X}\underline{\hat{\beta}}).$$

Substituting $\underline{\hat{\beta}}$ from the equation above, this equation has only one unknown, σ^2, and a unique estimate numerical solution always exists. The solution $\hat{\sigma}^2$ can be negative; in these cases we truncate at 0 (i.e., proceed with $\hat{\sigma}^2 = 0$).

The theoretical unconditional sampling variance-covariance for $\underline{\hat{\beta}}$ is

$$\mathbf{VC}(\underline{\hat{\beta}}) = (\mathbf{X'D^{-1}X})^{-1} \tag{3}$$

where, as before, $\mathbf{D} = \sigma^2\mathbf{I} + E_{\underline{y}}(\mathbf{W})$.

The central chi-square distribution of the weighted residual sum of squares is exploited again to derive a $(1-\alpha)$ 100% confidence interval by solving the following equations:

$$\chi^2{}_{df,1-\alpha/2} = (\underline{\hat{y}} - \mathbf{X}\underline{\hat{\beta}})'\mathbf{D}^{-1}(\underline{\hat{y}} - \mathbf{X}\underline{\hat{\beta}}) \text{ (lower limit)}$$

$$\chi^2{}_{df,\alpha/2} = (\underline{\hat{y}} - \mathbf{X}\underline{\hat{\beta}})'\mathbf{D}^{-1}(\underline{\hat{y}} - \mathbf{X}\underline{\hat{\beta}}) \text{ (upper limit).}$$

The lower limit can be negative. In these cases, we truncated the lower limit at 0 and used $\chi^2{}_{df,\alpha}$ in the equation to solve for the upper limit.

A practical difficulty is that we do not have formulae for the elements of $E_{\underline{y}}(\mathbf{W})$; we cannot take the exact expectations needed. An estimator of $E_{\underline{y}}(\mathbf{W})$ is needed. Franklin et al. (2002) recommend the using the negative of the matrix of second partial derivatives of the log-likelihood function, say **F**, which estimates the Fisher information matrix, and then $\hat{\mathbf{W}} = \hat{E}_{\underline{y}}(\mathbf{W}) = \mathbf{F}^{-1}$. We have used the simpler approach of using the (observed) estimated variance-covariance matrix of the log-transformed CJS survival probability estimates. As in Franklin et al., we will use Monte Carlo simulation to evaluate the inference performance of this approximation.

Model Fitting for Random Effects Models of Reservoir Survival

To illustrate the application of random effects models to our PIT-tag survival data, we selected a model for each data set that was reasonably favored by the calibration approach to model selection. We used the same predictor variables and same form of the models as in Chapter 2. Using the notation of Chapter 2, a random effects model where all predictors are present has the form:

$$\begin{aligned}-\log(\hat{S}_{g,r}) = \hat{y}_{g,r} &= (\alpha_0 + \alpha_1 \cdot Flow + \alpha_2 \cdot Temp + \alpha_3 \cdot Temp^2 + \alpha_4 \cdot Spill) \cdot d \\ &+ (\beta_0 + \beta_1 \cdot Flow + \beta_2 \cdot Temp + \beta_3 \cdot Temp^2 + \beta_4 \cdot Spill) \cdot t + \delta_{g,r} + \varepsilon_{g,r}\end{aligned} \tag{4}$$

where survival and the error terms are referenced to a particular release cohort, or group (*g*) over a particular river segment (*r*), *Spill* is the proportion of fish passing the spillway at the upstream dam, Flow and Temperature (*Temp*) are the exposure indices for the time fish from the group were in the reservoirs, *t* is the average travel time of the release group from the upstream tailrace to downstream tailrace, and *d* is the total length of reservoirs in the river segment.

The shorthand for this model is, as in the previous section:

$$\underline{\hat{y}} = \mathbf{X}\underline{\beta} + \underline{\delta} + \underline{\varepsilon}, \qquad \text{where} \quad VC(\underline{\hat{\delta}} + \underline{\varepsilon}) = \mathbf{D} = \sigma^2\mathbf{I} + E_{\underline{y}}(\mathbf{W})$$

The crucial differences between this model and the weighted least squares models of Chapter 2 are in the handling of the error terms. First, there is an additional error term to represent process error. Here, $\underline{\varepsilon}$ is the vector process error terms that are independently identically normally distributed with zero mean and variance σ^2. The second important difference is the use of the complete sampling variance-covariance matrix **W**. Whereas the weighted least squares models accounted only for the variance of survival estimates (through the weights), the random effects method explicitly accounts for the covariance between survival estimates for the same cohort in successive river segments by using the full, general, weighting matrix **W**. (The variances used in weighted least squares are, of course, the diagonal elements of **W**).

Table A7 2 shows the parameter estimates from the selected models. Each model includes an estimate of the process error variance σ^2, which represents variance in residuals of the model after accounting for the estimated predictable component $\mathbf{X}\underline{\beta}$ and sampling variance-covariance **W**. The table also includes the total variance of the response variable (negative log of PIT-tag survival estimates) and the estimated process error variance from the grand mean model (1). Comparing the total variance in the response variable to the estimated process error for the grand mean model gives an indication of the relative size of the process and sampling error components. Comparing the process error variance from the grand mean model to that of the fitted model indicates the change in estimated residual error after accounting for the linear predictor.

Table A7 2. Parameter estimates for selected random effects models of reservoir survival for Snake River spring/summer Chinook salmon and Snake River steelhead. Response variable was $-\log(\hat{S}_{g,r})$. Separate models were fit for Snake River reaches and Columbia River reaches. For reference, the total variance of the response variable is provided (which depends on both process error and sampling error), along with an estimate of process error from the grand mean model.

Parameter	Description	Sp/Su Chinook		Steelhead	
		Snake R	Columbia R	Snake R	Columbia R
Variance Information					
	$\mathrm{Var}(-\log(\hat{S}_{g,r}))$	0.0812	0.151	0.149	0.265
	Process error estimate for grand mean model (95% CI)	0.0288 (0.0215, 0.0389)	0.0116 (0.00437, 0.0259)	0.0717 (0.0542, 0.0966)	0.0568 (0.0289, 0.110)
Fitted Model					
σ^2	process error (variance)	0.00628	0.00998	0.0453	0.00198
	95% CI for σ^2	(0.00407, 0.00968)	(0.00311, 0.0240)	(0.0336, 0.0660)	(0.000, 0.0220)
α_0	distance	-0.000189		-0.0132	
α_1	Flow·distance	-0.00000372			
α_2	Temp·distance			0.00136	
α_3	Temp^2·distance				
α_4	Spill·distance	-0.000829			
β_0	time	-0.0168	0.0136	0.0450	0.0178
β_1	Flow·time			-0.000363	-0.000232
β_2	Temp·time	0.00236	0.000715		0.00778
β_3	Temp^2·time	0.0000614			
β_4	Spill·time				

Using Random Effects Models to Model Uncertainty in COMPASS Predictions

The parameters of the random effects model to be estimated are the process error variance σ^2 and the regression parameters $\underline{\beta}$. The fitted (predicted) values of a set of cohorts with covariates **X** are given by $\mathbf{X}\underline{\hat{\beta}}$. Remember that the key concept of the random effects method is that there is a distribution of expected (true) probabilities at any given value $\underline{X}_i$, and the response variable for any particular cohort is a single realization from the distribution ($\underline{X}_i \beta + \varepsilon_i$). From that point of view, the value $\underline{X}_i \underline{\hat{\beta}}$ represents the estimate of the mean of the distribution of the response variable for cohorts with covariate value $\underline{X}_i$. Because we assume the distribution is symmetric, $\underline{X}_i \underline{\hat{\beta}}$ is also our best *deterministic* prediction for any single cohort with covariates $\underline{X}_i$. Of course, the uncertainty of the prediction for a single cohort with a particular $\underline{X}_i$ is greater than the uncertainty of the prediction of the mean of all cohorts with the same value.

The uncertainty in the predicted mean $\underline{X}_i \underline{\hat{\beta}}$ is characterized by the estimated process error $\hat{\sigma}^2$, the uncertainty in that estimate, and by the uncertainty in the estimates of the regression coefficients. Before our explanation of the use of these elements to ultimately represent COMPASS predictions of reservoir and project survival, it is useful to explore the elements of uncertainty in more detail.

First, we have an imperfect knowledge of magnitude of the process error variance; $\hat{\sigma}^2$ is estimated from our observed sample data. The sampling distribution of the estimated $\hat{\sigma}^2$ is derived from the theoretical central chi-square distribution of the weighted residual sum of squares from the model $(\underline{\hat{y}} - \mathbf{X}\underline{\hat{\beta}})'\mathbf{D}^{-1}(\underline{\hat{y}} - \mathbf{X}\underline{\hat{\beta}})$. Because each value in this chi-square distribution corresponds to a unique value of σ^2 (**D** is a function of σ^2), we can translate the chi-square distribution into the distribution of $\hat{\sigma}^2$. Figure A7 1 shows the distributions for each of the four models illustrated in the previous section.

The distribution of σ^2 values for groups of steelhead released from McNary Dam stands out among the four distributions depicted in Figure A7 1 because of the large number of values truncated at zero (over a third of the distribution). The response variable for that species and river segment is extremely variable, with very large sampling error (see Table A7 2). It is very unlikely that the process error is truly zero. In this case, it is far more likely that sampling error is "swamping" process error, and the estimated process error near zero is indicative of inability to estimate accurately. We will return to the implications of this below. We are conducting simulation studies to determine the point at which sample data of poor quality makes effective estimation of variance components impossible.

Second, the unconditional sampling variance-covariance for $\underline{\hat{\beta}}$ (equation 3) is estimated by

$$\hat{\mathbf{V}}\mathbf{C}(\underline{\hat{\beta}}) = (\mathbf{X}'\hat{\mathbf{D}}^{-1}\mathbf{X})^{-1} \quad (5)$$

where $\hat{\mathbf{D}} = \hat{\sigma}^2\mathbf{I} + \mathbf{W}$. The presence of **W** in the expression for $\mathbf{VC}(\underline{\hat{\beta}})$ means that uncertainty of our estimates of regression coefficients depends on the sampling error present in the PIT-tag data. Of course, this is as it should be; the quality of any parameter estimates depends on the quality of the data used to calculate them.

However, COMPASS is designed to model the processes, not to model the imperfect measurements of the processes represented by historical sample PIT-tag data. Accordingly, to the extent possible, we would like the uncertainty in prospective COMPASS model runs to depend on our understanding of variability in the process alone. The decomposition of the matrix **D** into components for process error and sampling error suggests a method for doing this.

Because of the assumption of mutual independence of the sampling errors $\underline{\delta}$ and the process errors $\underline{\varepsilon}$, the sampling variance-covariance matrix **W** and the process error variance σ^2 are also independent. This means that if $\underline{\hat{y}}$ were measured without error (**W**=**0**) and/or if somehow we knew the value of σ^2 exactly, we could use as the variance-covariance matrix for the coefficients, a function of only the predictor variables and the process error variance: $\mathbf{VC}_P(\underline{\hat{\beta}}) = \sigma^2(\mathbf{X}'\mathbf{X})^{-1}$ where the subscript “P” denotes “process error.”

The estimation of process error separately from sampling error and the decomposition of $\hat{\mathbf{D}}$ suggests that an estimate of the process-error-only variance-covariance is given by

$$\hat{\mathbf{V}}\mathbf{C}_P(\underline{\hat{\beta}} \mid \hat{\sigma}^2) = \hat{\sigma}^2(\mathbf{X}'\mathbf{X})^{-1} \quad (6)$$

The notation of equation (6) makes explicit the fact that this expression is conditional on the particular value of $\hat{\sigma}^2$. While the parameter σ^2 is independent of sampling error, our estimate of $\hat{\sigma}^2$ is derived from data that includes sampling error, and is not independent. As we have seen, the estimate has a distribution that is derived from the central chi-square distribution of the weighted residual sum of squares. Thus, our estimate of the matrix $\hat{\mathbf{V}}\mathbf{C}_P(\underline{\hat{\beta}} \mid \hat{\sigma}^2)$ also has a “distribution,” which is derived from the distribution of $\hat{\sigma}^2$.

We have now introduced all the tools required for the proposed method for representing uncertainty in COMPASS projections of reservoir survival (and by extension project survival). Now we will illustrate the approach for a cohort of fish migrating from Lower Granite to McNary Dam. For illustration, we will use the random effects model for LGR cohorts of Chinook presented above. This model has 6 regression coefficients: distance, Flow·distance, Spill·distance, time, Temp·time, and Temp^2·time. The estimated process error variance is 0.00628, with 95% confidence interval (0.00407, 0.00968).

Essentially, the projection method relies on Monte Carlo sampling of the distributions of estimated process error $\hat{\sigma}^2$ and of estimated process-error-only variance-covariance of the regression coefficients $\hat{\mathbf{V}}\mathbf{C}_P(\underline{\hat{\beta}} \mid \hat{\sigma}^2)$. To characterize the distributions of predicted survival probabilities, we use 1000 Monte Carlo samples, each conducted through the following steps (see below for variation when process error variance is not well estimated):

A. Project reservoir survival from Lower Granite to Lower Monumental Dam

1. Randomly draw a value $\dot{\sigma}^2$ from the estimated distribution of process error variance, using the property that the weighted residual sum of squares from the fitted model is χ^2-distributed with $(k-r)$ degrees of freedom, where k is the number of observations and r is the number of $\underline{\beta}$ parameters estimated. That is, draw a random value $\dot{\chi}^2$ from the χ^2 distribution and then solve this equation for $\dot{\sigma}^2$:

$$\dot{\chi}^2 = (\underline{\hat{y}} - \mathbf{X}\underline{\hat{\beta}})'\mathbf{D}^{-1}(\underline{\hat{y}} - \mathbf{X}\underline{\hat{\beta}})$$

   where $\mathbf{D} = \sigma^2\mathbf{I} + \mathbf{W}$.

2. Randomly draw a vector of regression coefficients $\underline{\dot{\beta}}$ from the multivariate normal distribution with mean $\underline{\hat{\beta}}$ and variance-covariance equal to the process-error-only matrix $\dot{\mathbf{V}}\mathbf{C}_P(\dot{\beta} \mid \dot{\sigma}^2) = \dot{\sigma}^2(\mathbf{X}'\mathbf{X})^{-1}$.
3. For both mean and single-realization, calculate value of (mean) response variable $\dot{y} = \underline{X}_i\underline{\dot{\beta}}$ and reservoir survival probability $\dot{S}_{res} = e^{-\dot{y}}$, where $\underline{X}_i$ is the vector of covariates for LGR-LMN.
4. For single-realization, randomly draw a value for process error $\dot{\varepsilon}$ from normal distribution with mean 0 and variance $\dot{\sigma}^2$. Calculate value of single-realization of response variable $\ddot{y} = \underline{X}_i\underline{\dot{\beta}} + \dot{\varepsilon}$ and reservoir survival probability $\ddot{S}_{res} = e^{-\ddot{y}}$.
5. Multiply reservoir survival by (fixed) values of dam survival for Little Goose and Lower Monumental Dams to get project survival: $\dot{S}_{proj} = \dot{S}_{res} \cdot S_{\lg s} \cdot S_{lmn}$ and $\ddot{S}_{proj} = \ddot{S}_{res} \cdot S_{\lg s} \cdot S_{lmn}$.

B. Project reservoir survival from Lower Granite to Lower Monumental Dam.

Repeat steps 1 through 5. In step 3, $\underline{X}_i$ is the vector of covariates for LMN-MCN. In step 5, multiply by dam survival for Ice Harbor and McNary Dams.

C. Multiply LGR-LMN project survival by LMN-MCN project survival to get overall survival LGR-MCN for both mean $\dot{S}_{proj}$ and single-realization $\ddot{S}_{proj}$ distributions.

When the process error variance is not well estimated, as was the case for McNary cohorts of steelhead (see Figure A7 1), the Monte Carlo approach outlined above breaks down. If the distribution of $\hat{\sigma}^2$ contains too many zeroes, then the variability produced in both Steps 1 and 2 is insufficient. In this case, in Step 2 we will use the variance-covariance matrix for $\underline{\beta}$ based on the total variability: $\dot{\mathbf{V}}\mathbf{C}_P(\dot{\beta} \mid \dot{\sigma}^2) = (\mathbf{X}'\dot{\mathbf{D}}^{-1}\mathbf{X})^{-1}$, where $\dot{\mathbf{D}} = \dot{\sigma}^2\mathbf{I} + \mathbf{W}$. We are using simulated data to investigate the point at which the method breaks down. These investigations are not yet complete. Provisionally, we will use the process-error-only version of $\dot{\mathbf{V}}\mathbf{C}_P$ in Step 2 if at least 95% of the sampling distribution of $\hat{\sigma}^2$ is greater than 0. If more than 5% of the distribution is equal to zero, we will use the total-variance version.

Figure A7 2 shows Monte Carlo mode projections for both the project survival of a single-realization of a cohort with the same exposure indices as the weekly group of Chinook that left Lower Granite Dam during the week of April 20-26, 1998 (see Table A7 3), and the mean of the population of cohorts with those indices.

Table A7 3. Data for weekly cohort of Chinook leaving LGR April 20-26, 1998

	LGR-LMN	LMN-MCN
Distance	65.9	74.0
Flow	75.9	105.4
Spill	0.174	0.202
Time	8.81	4.90
Temperature	10.9	12.2
Flow·distance	5001.4	7799.7
Spill·distance	11.5	15.0
Temp·time	95.9	59.8
$Temp^2$·time	1044.5	731
Fitted value (deterministic prediction of response variable ($-\log(\hat{S}_{g,r})$)	0.1023	0.0486
Predicted reservoir survival probability	0.903	0.953
Dam survival in segment	0.908	0.912
Predicted project survival probability	0.819	0.869
Predicted overall survival LGR-MCN	0.712	

We applied the Monte Carlo process (1000 times) to each cohort with observations in the final data set (Table A7 1), for both SRSS Chinook and SR steelhead, and for both Lower Granite Dam and McNary Dam cohorts. We applied the method independently for each cohort. For example, we did a separate random draw of $\dot{\sigma}^2$, $\underline{\dot{\beta}} \sim MVN(\underline{\hat{\beta}}, \quad \dot{\mathbf{V}}\mathbf{C}_P(\dot{\beta} \mid \dot{\sigma}^2) = \dot{\sigma}^2(\mathbf{X}'\mathbf{X})^{-1})$, and $\dot{\varepsilon}$ for each of the 133 weekly LGR cohorts of SRSS Chinook that had PIT-tag survival estimates for the LGR-LMN segment. In all, there was a separate draw of $(\dot{\sigma}^2, \underline{\dot{\beta}}, \dot{\varepsilon})$ for each cohort in each segment, so that we had a collection of Monte Carlo samples of mean project survival proibability ($\dot{S}_{proj}$) for the $\underline{X}_i$ values for each cohort and of single realizations of project survival probability($\ddot{S}_{proj}$) for the $\underline{X}_i$ values for each cohort.

Then, for each set of cohorts representing a single year, we computed a weighted average of the predicted mean project survival probabilities for each segment. (For convenience, weights were equal to the inverse relative variance of the original PIT-tag estimates—exactly which weights are appropriate is a subject for continued research). We multiplied the annual weighted averages for LGR-LMN, LMN-MCN, MCN-JDA, and JDA-BON to derive an annual estimate of overall survival from Lower Granite Dam tailrace to Bonneville Dam tailrace.

To the extent that the exposure indices in the data set summarize the flow, spill, and temperature profiles foe each year, the distributions of predicted overall LGR-BON survival give an indication of the uncertainty in our prediction of (a) mean survival for all realizations of years with the same profiles and (b) survival for a single year with the same profile. Figure A7 3 shows distributions for SRSS Chinook for 1998, 2001, and 2007, and Figure A7 4 shows distributions for SR steelhead for the same years.

The relevance of each type of uncertainty (mean or single-realization) depends on the use to which the model is put. To predict for an upcoming migration season, one would use hydrographic models to derive the anticipated flow and water temperature profiles and also specify a spill schedule. The uncertainty in the prediction of a single upcoming season would then be characterized by the distribution of single-realization uncertainty (right-hand panels of Figures A7 3 and A7 4). On the other hand, if the objective is to evaluate the anticipated long-term differences between two management strategies, then the uncertainty of the mean is the more relevant consideration.

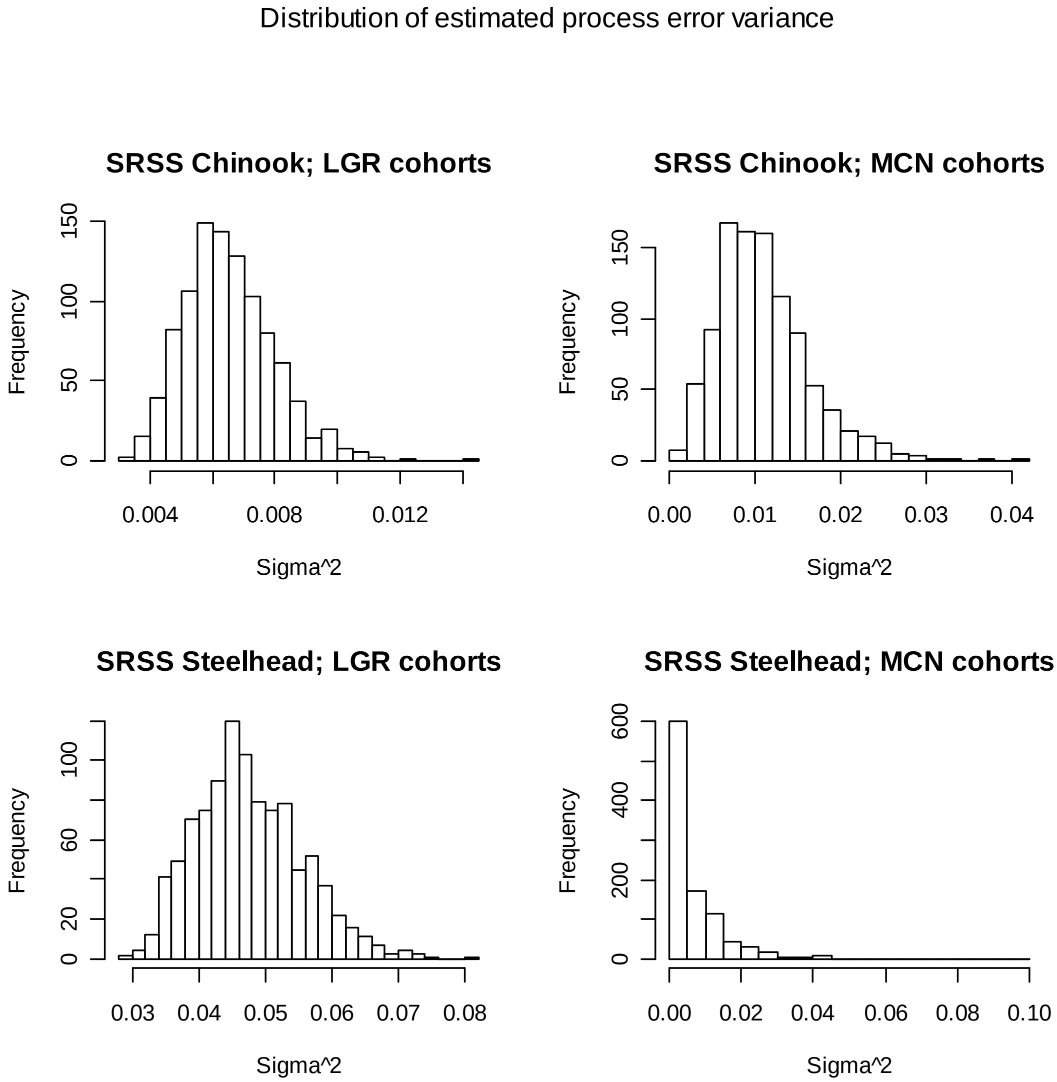


Figure A7 1. Sampling distributions of estimated process error for random effects models of reservoir survival estimates derived from PIT-tag data. Specific models are those referenced in text.

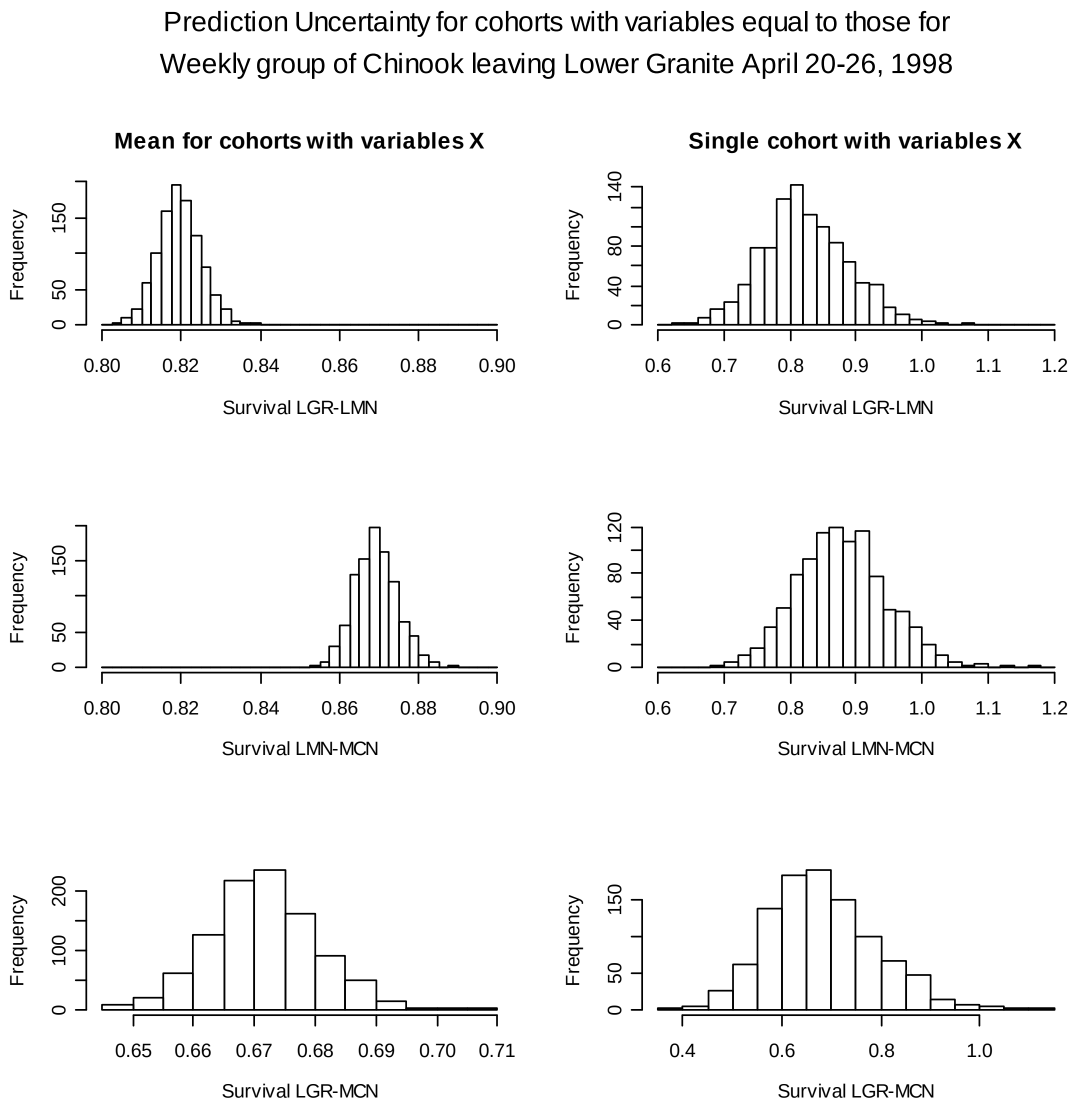


Figure A7 2. Prediction uncertainty in project survival between tailraces of Lower Granite and McNary Dams for cohorts with variables equal to those observed for weekly group of Chinook leaving Lower Granite Dam April 20-26, 1998.

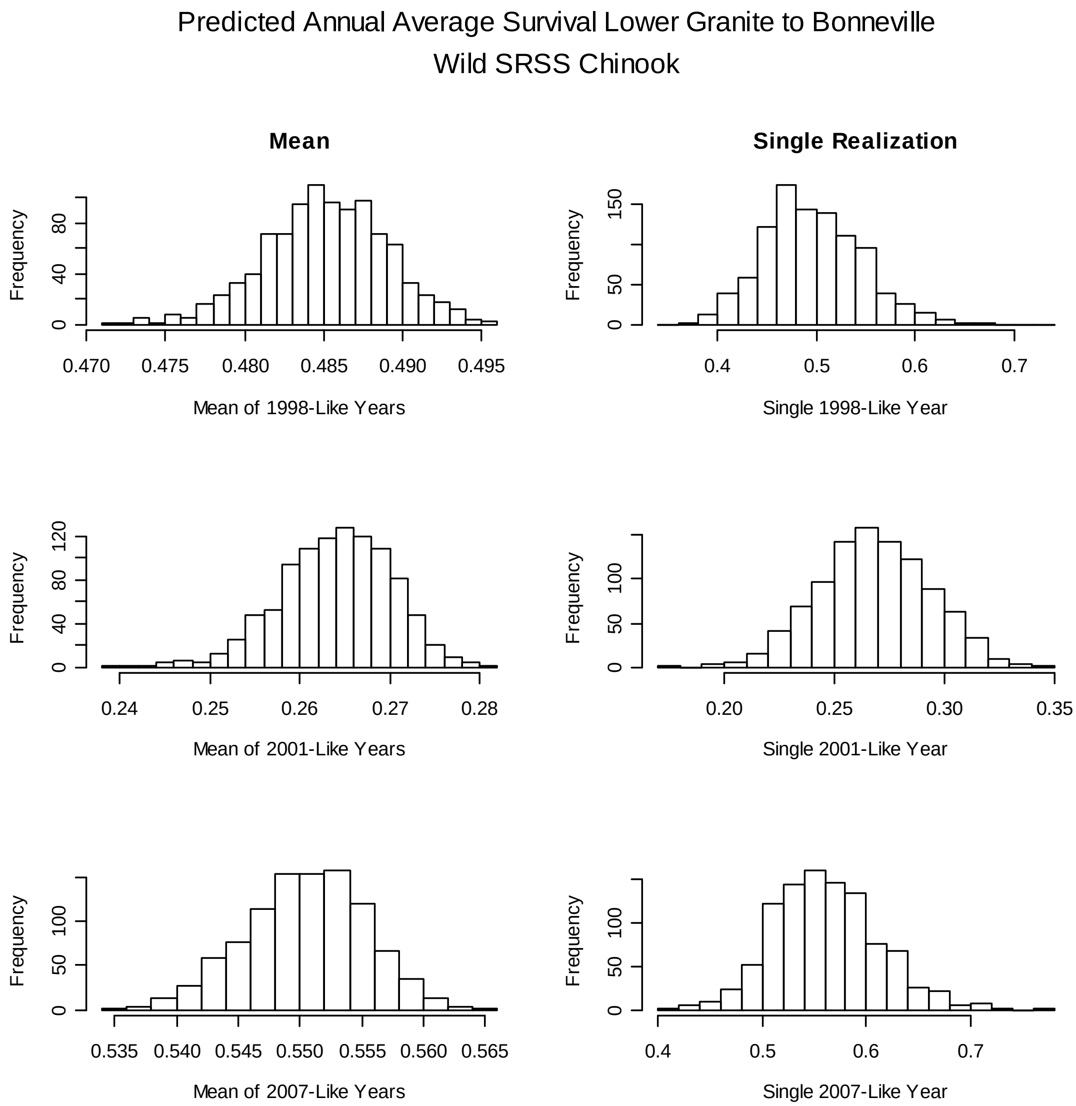


Figure A7 3. Prediction uncertainty for annual average project survival from Lower Granite Dam tailrace to Bonneville Dam tailrace for SRSS chinook. Predictions are based on weekly cohorts of fish leaving Lower Granite and McNary Dams, with flow, temperature, and spill profiles (i.e., exposure indices) equal to those in the observed data for the indicated years. Left-hand panels show uncertainty of the mean of the population of cohorts with the same profiles. Right-hand panels show uncertainty in a single realization of a year with the same profiles.

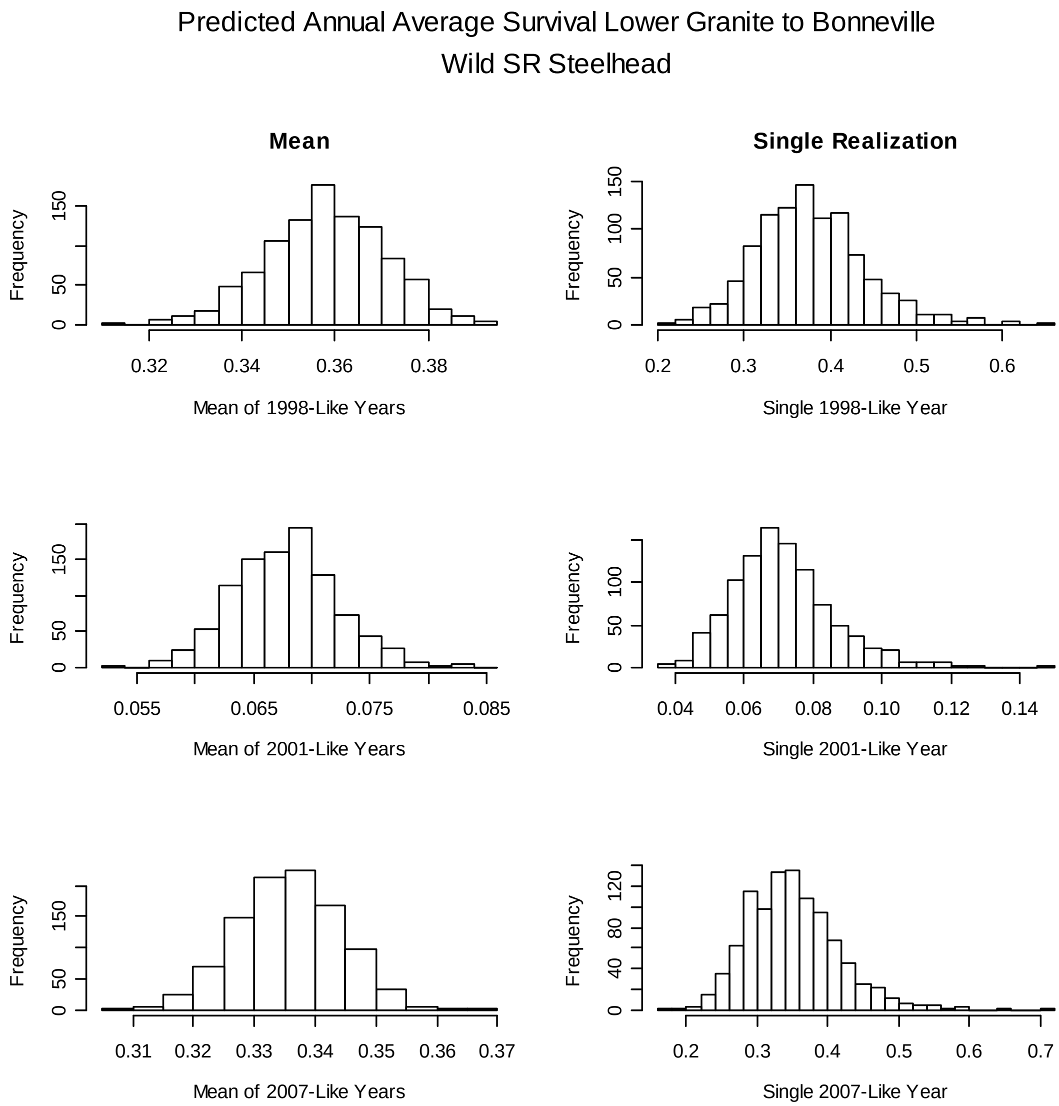


Figure A7 4. Prediction uncertainty for annual average project survival from Lower Granite Dam tailrace to Bonneville Dam tailrace for SR steelhead. Predictions are based on weekly cohorts of fish leaving Lower Granite and McNary Dams, with flow, temperature, and spill profiles (i.e., exposure indices) equal to those in the observed data for the indicated years. Left-hand panels show uncertainty of the mean of the population of cohorts with the same profiles. Right-hand panels show uncertainty in a single realization of a year with the same profiles.

Introduction

These notes are intended to illuminate the class of models known as “random effect” models and the idea of “variance components.” We illustrate the estimation of regression coefficients while simultaneously estimating variance components using a stand-alone “external analysis” of PIT-tag data (that is, not through calibration internal to the full COMPASS model). We then demonstrate how to use the variance component estimates along with the regression coefficient estimates and their associated estimated variance-covariance matrix to estimate the distribution of possible outcomes from the COMPASS model from a given set of inputs.

Eventually, we intend to implement the estimation of random-effects models through calibration methods using the full COMPASS model. Considerable effort, beyond the current scope, will be required to implement the necessary steps of the calibration routine. At this time, we have completed a variance components analysis of PIT-tag survival data separated from the rest of the model, and it is this analysis we present here.

Data

We first compiled data sets based on weekly cohorts of fish leaving Lower Granite Dam (LGR) during migration years 1997-2007 or McNary Dam (MCN) during migration years 1998-2007. A weekly cohort from LGR consisted of all PIT-tagged fish of Snake River origin that were either tagged and released at LGR or that had been released upstream from LGR and were detected and returned to the river at LGR during the specified 7 day period. Weekly cohorts at MCN were compiled similarly. For Snake River Spring/Summer Chinook salmon and for Snake River steelhead, we compiled weekly groups for wild fish alone, hatchery fish alone, and for the combined “all origin” cohort. The analysis of wild fish is presented here.

For each Lower Granite group, we estimated survival probabilities (Cormack-Jolly-Seber model) and mean travel time (days) from Lower Granite to Lower Monumental Dam and from Lower Monumental to McNary Dam, and we estimated detection probabilities at Little Goose, Lower Monumental, and McNary Dams. For each McNary group, we estimated survival probabilities (CJS model) and migration rates from McNary to John Day Dam and John Day to Bonneville Dam, and we estimated detection probabilities at John Day and Bonneville Dam. For each estimated survival probability, mean travel time, and detection probability, we also estimated its corresponding standard error.

The survival probabilities in the CJS models represent survival from the tailrace of the upstream dam to the tailrace of the downstream dam. The probabilities reflect mortality from all sources in that segment of river. Specifically, mortality that occurs during dam passage at the downstream dam or at any other dam in the river segment affects the survival estimate. Because they contain survival both at the dams in the reservoirs, we refer to the CJS-model probabilities as “project survival.” PIT-tag data cannot be used to isolate reservoir survival. Instead, we used current dam-survival parameters and ran COMPASS to get estimates of dam-passage survival for all the dams passed by each weekly cohort. We divided each project survival estimate by corresponding dam-passage survival estimate(s) to obtain estimated reservoir survival for each cohort. For example, reservoir survival between the tailrace of Lower Granite Dam and tailrace of Lower Monumental Dam was obtained by dividing the PIT-tag project survival estimate by dam-passage survival at Little Goose Dam and by dam-passage survival at Lower Monumental Dam. Lower Monumental Dam-to-McNary Dam project survival includes dam-passage survival at Ice Harbor and McNary Dams. McNary Dam-to-John Day Dam includes only John Day passage, while John Day Dam-to-Bonneville Dam includes both The Dalles Dam and Bonneville Dam survival.

Finally, for each reach for each weekly cohort, we used daily data on environmental variables and passage distributions for the cohort to calculate exposure indices for flow (kcfs), proportion of water spilled at dams (0.0 to 1.0), and water temperature (^{o}C).

Within each data set the observation unit was a single reach for single cohort. For the random effects model of survival, the relevant data for each observation unit was the reservoir survival probability, the length (miles) of the reach, the mean travel time, and the flow, spill proportion, and temperature indices. Observation units were eliminated from the data set for the following reasons:

- PIT-tag detection data not sufficient to estimate survival;
- Detection probability estimate at downstream dam equal to 1.0, as corresponding survival estimates in the CJS model are biased low in this circumstance.

These conditions occur almost exclusively in extremely sparse data. Some observations had estimated reservoir survival greater than 1.0 These observations were left in the data set. This can occur because the CJS model sometimes gives project survival estimates greater than 1.0 (though almost always with large standard errors), or because the COMPASS-estimated dam-passage survival is lower than the CJS estimate of project of survival. Truncating such estimates at 1.0 or eliminating the observations from the model both would bias results.

Table A7 1 shows the number of observations in the final data set for each segment for each species each year.

Table A7 1 Number of observations in the final data set for each segment for each species each year.

	Snake River spring/summer Chinook				Snake River steelhead			
	Lower Granite Releases		McNary Releases		Lower Granite Releases		McNary Releases	
Year	LGR-LMN	LMN-MCN	MCN-JDA	JDA-BON	LGR-LMN	LMN-MCN	MCN-JDA	JDA-BON
1997	9	3	---	---	8	5	---	---
1998	14	11	7	3	9	8	6	2
1999	11	11	6	5	11	11	9	5
2000	14	12	9	6	10	8	6	4
2001	11	9	6	5	8	5	5	3
2002	13	12	6	5	8	7	7	5
2003	16	14	7	7	10	10	9	5
2004	14	14	9	8	11	10	4	1
2005	11	10	8	6	9	9	5	1
2006	11	11	7	5	10	9	8	3
2007	9	8	8	8	7	7	5	4
Total	133	115	73	58	101	89	64	33

Within the COMPASS model, LGR-LMN and LMN-MCN (to the Snake-Columbia confluence) are treated as the same "reach class," which means that the same reservoir survival model is used in both reaches. Also, MCN-JDA and JDA-BON have the same reservoir model in COMPASS. Consequently, we combined LGR-LMN and LMN-MCN observations for the external analysis, giving 248 observations for SRSS Chinook and 190 for SR steelhead. The data set for MCN-JDA and JDA-BON combined had 131 observations for SRSS Chinook and 97 for steelhead.

Basic Variance-Components Model for Grand Mean

In the sections that follow we discuss models that include a multiple regression component to explain survival. However, to introduce concepts of random effects and variance components, we begin with a model that does not include functions of covariates to explain the response. In the context of survival probabilities of cohorts of migrating salmonids, we could posit an artificial situation in which environmental conditions (or fish behavior) do not affect survival, or in which environmental conditions were identical for a series of cohorts. The key notion in a random effects model is that even in such a situation, we should not expect the true survival probability of all cohorts to be exactly the same. Rather, there is a distribution of expected (true) probabilities, and the probability for each cohort is a single realization from the distribution. Viewing the particular cohorts we happened to tag as a random sample from the distribution, we see the origin of the label "random effects."

Suppose there are ***n*** such cohorts for which the survival probabilities from Lower Granite Dam to Lower Monumental Dam and from Lower Monumental Dam to McNary Dam were known exactly. Denote the entire set of probabilities (two for each cohort) as: $S_1, S_2, \ldots, S_{2n}$.Following the usual approach for COMPASS modeling (see Chapter 2), we assume that the survival probabilities are approximately log-normally distributed, and use as our response variable the negative natural logarithm of survival: $y_i = -\log(S_i)$. The random effects model is based on the model for the population parameters:

$$y_i = -\log(S_i) = \mu + \varepsilon_i ,$$

where the ε_i are independent, identically distributed normal random variables with mean 0 and variance σ^2. The parameter σ^2 is known as the "process error."

In reality, of course, the population survival probabilities are not known exactly, but must be estimated from PIT-tag data using the CJS model. The CJS model for the n cohorts is conditional on the underlying estimable survival probabilities $S_1, S_2, \ldots, S_{2n}$ (and also on underlying detection probabilities). For a given cohort and reach, the response variable can be represented (conditionally) as:

$$\hat{y}_i = -\log(\hat{S}_i) = y_i + \delta_i ,$$

where δ_i represents the sampling error in the PIT-tag data. (Hereafter, we will drop the references to the survival probabilities S_i, and use the response variables y_i instead).

Given S_i, the large sample expected value of $\hat{y}_i$ is y_i (i.e. $E(\delta_i \mid y_i) = 0$; CJS estimates are asymptotically unbiased. Thus, considering the full vector of estimates we can say that, conditional on the vector of population parameters,

$E(\underline{\hat{y}} \mid \underline{y}) = \underline{y}$ and $\underline{\delta}$ has conditional sampling variance-covariance matrix **W,** which will be complicated function of the CJS survival probability and detection probability parameters. Assuming that the CJS model is applied independently to data from each cohort, only the two survival probabilities for the same cohort are correlated with each other. Probabilities for each cohort have zero covariance (independent) with probabilities from each other cohort, and **W** is a "block-diagonal" matrix of dimension $2n \times 2n$. The diagonal elements are 2×2 matrices representing the variance-covariance matrices for the two estimates from each of the cohorts.

Finally, assuming mutual independence of the sampling errors $\underline{\delta}$ and the process errors $\underline{\varepsilon}$, the unconditional random effects model for the transformed CJS estimates is

$$\underline{\hat{y}} = \mu + \underline{\delta} + \underline{\varepsilon} , \qquad \mathbf{VC}(\underline{\hat{\delta}} + \underline{\varepsilon}) = \mathbf{D} = \sigma^2 \mathbf{I} + E_{\underline{y}}(\mathbf{W}) \qquad (1)$$

where VC denotes a variance-covariance matrix. From the expression for the unconditional VC matrix for the estimates, the origin of the label "variance components" becomes clear. The unconditional VC matrix represents the "total variance" in the vector of estimates, and the random-effects formulation decomposes the total into components for sampling error ($E_{\underline{y}}(\mathbf{W})$) and process error ($\sigma^2\mathbf{I}$).

In the next section, we describe how the process error is estimated, in the context of a model that represents the mean μ as a multiple linear function of explanatory variables.

Variance-Components Model with Multiple Linear Regression

Much of this section is adapted from Franklin et. al. (2002). Consider now a random effects model incorporating a suite of explanatory variables; where the mean of response variable $E(y \mid \underline{X})$ depends on the value of $\underline{X}$ through the linear combination $\underline{X}\underline{\beta}$. For a single cohort, the model for the response variable is now

$$\hat{y}_i = \underline{X}_i \underline{\beta} + \delta_i + \varepsilon_i$$

And for the entire set of cohorts we have

$$\underline{\hat{y}} = \mathbf{X}\underline{\beta} + \underline{\delta} + \underline{\varepsilon}, \quad \text{and} \quad \mathbf{VC}(\underline{\hat{\delta}} + \underline{\varepsilon}) = \mathbf{D} = \sigma^2\mathbf{I} + E_{\underline{y}}(\mathbf{W}), \text{ as before.} \qquad (2)$$

The parameters to estimate from the data are the regression parameters $\underline{\beta}$ and the process error σ^2, the variance-covariance matrix for $\underline{\hat{\beta}}$, and an indicator of the precision of the estimated process error (a method to compute a confidence interval is available, as described below).

From generalized least squares theory, for a given value of σ^2, the best linear unbiased estimator of $\underline{\beta}$ is

$$\underline{\hat{\beta}} = (\mathbf{X'D^{-1}X})^{-1}\mathbf{X'D}^{-1}\underline{\hat{y}}.$$

Assuming approximate normality of $\underline{\hat{y}}$ then from the same generalized least squares theory the weighted residual sum of squares $(\underline{\hat{y}} - \mathbf{X}\underline{\hat{\beta}})'\mathbf{D}^{-1}(\underline{\hat{y}} - \mathbf{X}\underline{\hat{\beta}})$ has a central chi-square distribution on *(k – r)* degrees of freedom, where *k* is the number of observations and *r* is the number of $\underline{\beta}$ parameters estimated. Therefore, a method of moments estimator of σ^2 is obtained by solving the equation

$$k - r = (\underline{\hat{y}} - \mathbf{X}\underline{\hat{\beta}})'\mathbf{D}^{-1}(\underline{\hat{y}} - \mathbf{X}\underline{\hat{\beta}}).$$

Substituting $\underline{\hat{\beta}}$ from the equation above, this equation has only one unknown, σ^2, and a unique estimate numerical solution always exists. The solution $\hat{\sigma}^2$ can be negative; in these cases we truncate at 0 (i.e., proceed with $\hat{\sigma}^2 = 0$).

The theoretical unconditional sampling variance-covariance for $\underline{\hat{\beta}}$ is

$$\mathbf{VC}(\underline{\hat{\beta}}) = (\mathbf{X'D^{-1}X})^{-1} \quad (3)$$

where, as before, $\mathbf{D} = \sigma^2 \mathbf{I} + E_{\underline{y}}(\mathbf{W})$.

The central chi-square distribution of the weighted residual sum of squares is exploited again to derive a $(1-\alpha)$ 100% confidence interval by solving the following equations:

$$\chi^2_{df,1-\alpha/2} = (\underline{\hat{y}} - \mathbf{X}\underline{\hat{\beta}})'\mathbf{D}^{-1}(\underline{\hat{y}} - \mathbf{X}\underline{\hat{\beta}}) \text{ (lower limit)}$$

$$\chi^2_{df,\alpha/2} = (\underline{\hat{y}} - \mathbf{X}\underline{\hat{\beta}})'\mathbf{D}^{-1}(\underline{\hat{y}} - \mathbf{X}\underline{\hat{\beta}}) \text{ (upper limit).}$$

The lower limit can be negative. In these cases, we truncated the lower limit at 0 and used $\chi^2_{df,\alpha}$ in the equation to solve for the upper limit.

A practical difficulty is that we do not have formulae for the elements of $E_{\underline{y}}(\mathbf{W})$; we cannot take the exact expectations needed. An estimator of $E_{\underline{y}}(\mathbf{W})$ is needed. Franklin et al. (2002) recommend the using the negative of the matrix of second partial derivatives of the log-likelihood function, say **F**, which estimates the Fisher information matrix, and then $\hat{\mathbf{W}} = \hat{E}_{\underline{y}}(\mathbf{W}) = \mathbf{F}^{-1}$. We have used the simpler approach of using the (observed) estimated variance-covariance matrix of the log-transformed CJS survival probability estimates. As in Franklin et al., we will use Monte Carlo simulation to evaluate the inference performance of this approximation.

Model Fitting for Random Effects Models of Reservoir Survival

To illustrate the application of random effects models to our PIT-tag survival data, we selected a model for each data set that was reasonably favored by the calibration approach to model selection. We used the same predictor variables and same form of the models as in Chapter 2. Using the notation of Chapter 2, a random effects model where all predictors are present has the form:

$$\begin{aligned} -\log(\hat{S}_{g,r}) = \hat{y}_{g,r} &= (\alpha_0 + \alpha_1 \cdot Flow + \alpha_2 \cdot Temp + \alpha_3 \cdot Temp^2 + \alpha_4 \cdot Spill) \cdot d \\ &+ (\beta_0 + \beta_1 \cdot Flow + \beta_2 \cdot Temp + \beta_3 \cdot Temp^2 + \beta_4 \cdot Spill) \cdot t + \delta_{g,r} + \varepsilon_{g,r} \end{aligned} \quad (4)$$

where survival and the error terms are referenced to a particular release cohort, or group (*g*) over a particular river segment (*r*), *Spill* is the proportion of fish passing the spillway at the upstream dam, Flow and Temperature (*Temp*) are the exposure indices for the time fish from the group were in the reservoirs, *t* is the average travel time of the release group from the upstream tailrace to downstream tailrace, and *d* is the total length of reservoirs in the river segment.

The shorthand for this model is, as in the previous section:

$$\underline{\hat{y}} = \mathbf{X}\underline{\beta} + \underline{\delta} + \underline{\varepsilon}, \qquad \text{where} \quad VC(\underline{\hat{\delta}} + \underline{\varepsilon}) = \mathbf{D} = \sigma^2\mathbf{I} + E_{\underline{y}}(\mathbf{W})$$

The crucial differences between this model and the weighted least squares models of Chapter 2 are in the handling of the error terms. First, there is an additional error term to represent process error. Here, $\underline{\varepsilon}$ is the vector process error terms that are independently identically normally distributed with zero mean and variance σ^2. The second important difference is the use of the complete sampling variance-covariance matrix **W**. Whereas the weighted least squares models accounted only for the variance of survival estimates (through the weights), the random effects method explicitly accounts for the covariance between survival estimates for the same cohort in successive river segments by using the full, general, weighting matrix **W**. (The variances used in weighted least squares are, of course, the diagonal elements of **W**).

Table A7 2 shows the parameter estimates from the selected models. Each model includes an estimate of the process error variance σ^2, which represents variance in residuals of the model after accounting for the estimated predictable component $\mathbf{X}\underline{\beta}$ and sampling variance-covariance **W**. The table also includes the total variance of the response variable (negative log of PIT-tag survival estimates) and the estimated process error variance from the grand mean model (1). Comparing the total variance in the response variable to the estimated process error for the grand mean model gives an indication of the relative size of the process and sampling error components. Comparing the process error variance from the grand mean model to that of the fitted model indicates the change in estimated residual error after accounting for the linear predictor.

Table A7 2. Parameter estimates for selected random effects models of reservoir survival for Snake River spring/summer Chinook salmon and Snake River steelhead. Response variable was $-\log(\hat{S}_{g,r})$. Separate models were fit for Snake River reaches and Columbia River reaches. For reference, the total variance of the response variable is provided (which depends on both process error and sampling error), along with an estimate of process error from the grand mean model.

Parameter	Description	Sp/Su Chinook		Steelhead	
		Snake R	Columbia R	Snake R	Columbia R
Variance Information					
	$\mathrm{Var}(-\log(\hat{S}_{g,r}))$	0.0812	0.151	0.149	0.265
	Process error estimate for grand mean model (95% CI)	0.0288 (0.0215, 0.0389)	0.0116 (0.00437, 0.0259)	0.0717 (0.0542, 0.0966)	0.0568 (0.0289, 0.110)
Fitted Model					
σ^2	process error (variance)	0.00628	0.00998	0.0453	0.00198
	95% CI for σ^2	(0.00407, 0.00968)	(0.00311, 0.0240)	(0.0336, 0.0660)	(0.000, 0.0220)
α_0	distance	-0.000189		-0.0132	
α_1	Flow·distance	-0.00000372			
α_2	Temp·distance			0.00136	
α_3	Temp^2·distance				
α_4	Spill·distance	-0.000829			
β_0	time	-0.0168	0.0136	0.0450	0.0178
β_1	Flow·time			-0.000363	-0.000232
β_2	Temp·time	0.00236	0.000715		0.00778
β_3	Temp^2·time	0.0000614			
β_4	Spill·time				

Using Random Effects Models to Model Uncertainty in COMPASS Predictions

The parameters of the random effects model to be estimated are the process error variance σ^2 and the regression parameters $\underline{\beta}$. The fitted (predicted) values of a set of cohorts with covariates **X** are given by $\mathbf{X}\hat{\underline{\beta}}$. Remember that the key concept of the random effects method is that there is a distribution of expected (true) probabilities at any given value $\underline{X}_i$, and the response variable for any particular cohort is a single realization from the distribution ($\underline{X}_i \beta + \varepsilon_i$). From that point of view, the value $\underline{X}_i \hat{\underline{\beta}}$ represents the estimate of the mean of the distribution of the response variable for cohorts with covariate value $\underline{X}_i$. Because we assume the distribution is symmetric, $\underline{X}_i \hat{\underline{\beta}}$ is also our best *deterministic* prediction for any single cohort with covariates $\underline{X}_i$. Of course, the uncertainty of the prediction for a single cohort with a particular $\underline{X}_i$ is greater than the uncertainty of the prediction of the mean of all cohorts with the same value.

The uncertainty in the predicted mean $\underline{X}_i \hat{\underline{\beta}}$ is characterized by the estimated process error $\hat{\sigma}^2$, the uncertainty in that estimate, and by the uncertainty in the estimates of the regression coefficients. Before our explanation of the use of these elements to ultimately represent COMPASS predictions of reservoir and project survival, it is useful to explore the elements of uncertainty in more detail.

First, we have an imperfect knowledge of magnitude of the process error variance; $\hat{\sigma}^2$ is estimated from our observed sample data. The sampling distribution of the estimated $\hat{\sigma}^2$ is derived from the theoretical central chi-square distribution of the weighted residual sum of squares from the model $(\hat{\underline{y}} - \mathbf{X}\hat{\underline{\beta}})'\mathbf{D}^{-1}(\hat{\underline{y}} - \mathbf{X}\hat{\underline{\beta}})$. Because each value in this chi-square distribution corresponds to a unique value of σ^2 (**D** is a function of σ^2), we can translate the chi-square distribution into the distribution of $\hat{\sigma}^2$. Figure A7 1 shows the distributions for each of the four models illustrated in the previous section.

The distribution of σ^2 values for groups of steelhead released from McNary Dam stands out among the four distributions depicted in Figure A7 1 because of the large number of values truncated at zero (over a third of the distribution). The response variable for that species and river segment is extremely variable, with very large sampling error (see Table A7 2). It is very unlikely that the process error is truly zero. In this case, it is far more likely that sampling error is "swamping" process error, and the estimated process error near zero is indicative of inability to estimate accurately. We will return to the implications of this below. We are conducting simulation studies to determine the point at which sample data of poor quality makes effective estimation of variance components impossible.

Second, the unconditional sampling variance-covariance for $\hat{\underline{\beta}}$ (equation 3) is estimated by

$$\hat{\mathbf{V}}\mathbf{C}(\underline{\hat{\beta}}) = (\mathbf{X}'\hat{\mathbf{D}}^{-1}\mathbf{X})^{-1} \qquad (5)$$

where $\hat{\mathbf{D}} = \hat{\sigma}^2\mathbf{I} + \mathbf{W}$. The presence of **W** in the expression for $\mathbf{VC}(\underline{\hat{\beta}})$ means that uncertainty of our estimates of regression coefficients depends on the sampling error present in the PIT-tag data. Of course, this is as it should be; the quality of any parameter estimates depends on the quality of the data used to calculate them.

However, COMPASS is designed to model the processes, not to model the imperfect measurements of the processes represented by historical sample PIT-tag data. Accordingly, to the extent possible, we would like the uncertainty in prospective COMPASS model runs to depend on our understanding of variability in the process alone. The decomposition of the matrix **D** into components for process error and sampling error suggests a method for doing this.

Because of the assumption of mutual independence of the sampling errors $\underline{\delta}$ and the process errors $\underline{\varepsilon}$, the sampling variance-covariance matrix **W** and the process error variance σ^2 are also independent. This means that if $\underline{\hat{y}}$ were measured without error (**W**=**0**) and/or if somehow we knew the value of σ^2 exactly, we could use as the variance-covariance matrix for the coefficients, a function of only the predictor variables and the process error variance: $\mathbf{VC}_P(\underline{\hat{\beta}}) = \sigma^2(\mathbf{X}'\mathbf{X})^{-1}$ where the subscript “P” denotes “process error.”

The estimation of process error separately from sampling error and the decomposition of $\hat{\mathbf{D}}$ suggests that an estimate of the process-error-only variance-covariance is given by

$$\hat{\mathbf{V}}\mathbf{C}_P(\underline{\hat{\beta}} \,|\, \hat{\sigma}^2) = \hat{\sigma}^2(\mathbf{X}'\mathbf{X})^{-1} \qquad (6)$$

The notation of equation (6) makes explicit the fact that this expression is conditional on the particular value of $\hat{\sigma}^2$. While the parameter σ^2 is independent of sampling error, our estimate of $\hat{\sigma}^2$ is derived from data that includes sampling error, and is not independent. As we have seen, the estimate has a distribution that is derived from the central chi-square distribution of the weighted residual sum of squares. Thus, our estimate of the matrix $\hat{\mathbf{V}}\mathbf{C}_P(\underline{\hat{\beta}} \,|\, \hat{\sigma}^2)$ also has a “distribution,” which is derived from the distribution of $\hat{\sigma}^2$.

We have now introduced all the tools required for the proposed method for representing uncertainty in COMPASS projections of reservoir survival (and by extension project survival). Now we will illustrate the approach for a cohort of fish migrating from Lower Granite to McNary Dam. For illustration, we will use the random effects model for LGR cohorts of Chinook presented above. This model has 6 regression coefficients: distance, Flow·distance, Spill·distance, time, Temp·time, and Temp^2·time. The estimated process error variance is 0.00628, with 95% confidence interval (0.00407, 0.00968).

Essentially, the projection method relies on Monte Carlo sampling of the distributions of estimated process error $\hat{\sigma}^2$ and of estimated process-error-only variance-covariance of the regression coefficients $\hat{\mathbf{V}}\mathbf{C}_P(\underline{\hat{\beta}} \,|\, \hat{\sigma}^2)$. To characterize the distributions of predicted survival probabilities, we use 1000 Monte Carlo samples, each conducted through the following steps (see below for variation when process error variance is not well estimated):

A. Project reservoir survival from Lower Granite to Lower Monumental Dam

1. Randomly draw a value $\dot{\sigma}^2$ from the estimated distribution of process error variance, using the property that the weighted residual sum of squares from the fitted model is χ^2-distributed with $(k - r)$ degrees of freedom, where k is the number of observations and r is the number of $\underline{\beta}$ parameters estimated. That is, draw a random value $\dot{\chi}^2$ from the χ^2 distribution and then solve this equation for $\dot{\sigma}^2$:

   $$\dot{\chi}^2 = (\underline{\hat{y}} - \mathbf{X}\underline{\hat{\beta}})'\mathbf{D}^{-1}(\underline{\hat{y}} - \mathbf{X}\underline{\hat{\beta}})$$

   where $\mathbf{D} = \sigma^2\mathbf{I} + \mathbf{W}$.
2. Randomly draw a vector of regression coefficients $\underline{\dot{\beta}}$ from the multivariate normal distribution with mean $\underline{\hat{\beta}}$ and variance-covariance equal to the process-error-only matrix $\dot{\mathbf{V}}\mathbf{C}_P(\dot{\beta} \,|\, \dot{\sigma}^2) = \dot{\sigma}^2(\mathbf{X}'\mathbf{X})^{-1}$.
3. For both mean and single-realization, calculate value of (mean) response variable $\dot{y} = \underline{X}_i\underline{\dot{\beta}}$ and reservoir survival probability $\dot{S}_{res} = e^{-\dot{y}}$, where $\underline{X}_i$ is the vector of covariates for LGR-LMN.
4. For single-realization, randomly draw a value for process error $\dot{\varepsilon}$ from normal distribution with mean 0 and variance $\dot{\sigma}^2$. Calculate value of single-realization of response variable $\ddot{y} = \underline{X}_i\underline{\dot{\beta}} + \dot{\varepsilon}$ and reservoir survival probability $\ddot{S}_{res} = e^{-\ddot{y}}$.
5. Multiply reservoir survival by (fixed) values of dam survival for Little Goose and Lower Monumental Dams to get project survival: $\dot{S}_{proj} = \dot{S}_{res} \cdot S_{\lg s} \cdot S_{lmn}$ and $\ddot{S}_{proj} = \ddot{S}_{res} \cdot S_{\lg s} \cdot S_{lmn}$.

B. Project reservoir survival from Lower Granite to Lower Monumental Dam.

Repeat steps 1 through 5. In step 3, $\underline{X}_i$ is the vector of covariates for LMN-MCN. In step 5, multiply by dam survival for Ice Harbor and McNary Dams.

C. Multiply LGR-LMN project survival by LMN-MCN project survival to get overall survival LGR-MCN for both mean $\dot{S}_{proj}$ and single-realization $\ddot{S}_{proj}$ distributions.

When the process error variance is not well estimated, as was the case for McNary cohorts of steelhead (see Figure A7 1), the Monte Carlo approach outlined above breaks down. If the distribution of $\hat{\sigma}^2$ contains too many zeroes, then the variability produced in both Steps 1 and 2 is insufficient. In this case, in Step 2 we will use the variance-covariance matrix for $\underline{\beta}$ based on the total variability: $\dot{\mathbf{V}}\mathbf{C}_P(\dot{\beta} \mid \dot{\sigma}^2) = (\mathbf{X}'\dot{\mathbf{D}}^{-1}\mathbf{X})^{-1}$, where $\dot{\mathbf{D}} = \dot{\sigma}^2\mathbf{I} + \mathbf{W}$. We are using simulated data to investigate the point at which the method breaks down. These investigations are not yet complete. Provisionally, we will use the process-error-only version of $\dot{\mathbf{V}}\mathbf{C}_P$ in Step 2 if at least 95% of the sampling distribution of $\hat{\sigma}^2$ is greater than 0. If more than 5% of the distribution is equal to zero, we will use the total-variance version.

Figure A7 2 shows Monte Carlo mode projections for both the project survival of a single-realization of a cohort with the same exposure indices as the weekly group of Chinook that left Lower Granite Dam during the week of April 20-26, 1998 (see Table A7 3), and the mean of the population of cohorts with those indices.

Table A7 3. Data for weekly cohort of Chinook leaving LGR April 20-26, 1998

	LGR-LMN	LMN-MCN
Distance	65.9	74.0
Flow	75.9	105.4
Spill	0.174	0.202
Time	8.81	4.90
Temperature	10.9	12.2
Flow·distance	5001.4	7799.7
Spill·distance	11.5	15.0
Temp·time	95.9	59.8
$Temp^2$·time	1044.5	731
Fitted value (deterministic prediction of response variable ($-\log(\hat{S}_{g,r})$)	0.1023	0.0486
Predicted reservoir survival probability	0.903	0.953
Dam survival in segment	0.908	0.912
Predicted project survival probability	0.819	0.869
Predicted overall survival LGR-MCN	0.712	

We applied the Monte Carlo process (1000 times) to each cohort with observations in the final data set (Table A7 1), for both SRSS Chinook and SR steelhead, and for both Lower Granite Dam and McNary Dam cohorts. We applied the method independently for each cohort. For example, we did a separate random draw of $\dot{\sigma}^2$, $\underline{\dot{\beta}} \sim MVN(\underline{\hat{\beta}}, \quad \dot{\mathbf{V}}\mathbf{C}_P(\dot{\beta} \mid \dot{\sigma}^2) = \dot{\sigma}^2(\mathbf{X}'\mathbf{X})^{-1})$, and $\dot{\varepsilon}$ for each of the 133 weekly LGR cohorts of SRSS Chinook that had PIT-tag survival estimates for the LGR-LMN segment. In all, there was a separate draw of $(\dot{\sigma}^2, \underline{\dot{\beta}}, \dot{\varepsilon})$ for each cohort in each segment, so that we had a collection of Monte Carlo samples of mean project survival proibability ($\dot{S}_{proj}$) for the $\underline{X}_i$ values for each cohort and of single realizations of project survival probability($\ddot{S}_{proj}$) for the $\underline{X}_i$ values for each cohort.

Then, for each set of cohorts representing a single year, we computed a weighted average of the predicted mean project survival probabilities for each segment. (For convenience, weights were equal to the inverse relative variance of the original PIT-tag estimates—exactly which weights are appropriate is a subject for continued research). We multiplied the annual weighted averages for LGR-LMN, LMN-MCN, MCN-JDA, and JDA-BON to derive an annual estimate of overall survival from Lower Granite Dam tailrace to Bonneville Dam tailrace.

To the extent that the exposure indices in the data set summarize the flow, spill, and temperature profiles foe each year, the distributions of predicted overall LGR-BON survival give an indication of the uncertainty in our prediction of (a) mean survival for all realizations of years with the same profiles and (b) survival for a single year with the same profile. Figure A7 3 shows distributions for SRSS Chinook for 1998, 2001, and 2007, and Figure A7 4 shows distributions for SR steelhead for the same years.

The relevance of each type of uncertainty (mean or single-realization) depends on the use to which the model is put. To predict for an upcoming migration season, one would use hydrographic models to derive the anticipated flow and water temperature profiles and also specify a spill schedule. The uncertainty in the prediction of a single upcoming season would then be characterized by the distribution of single-realization uncertainty (right-hand panels of Figures A7 3 and A7 4). On the other hand, if the objective is to evaluate the anticipated long-term differences between two management strategies, then the uncertainty of the mean is the more relevant consideration.

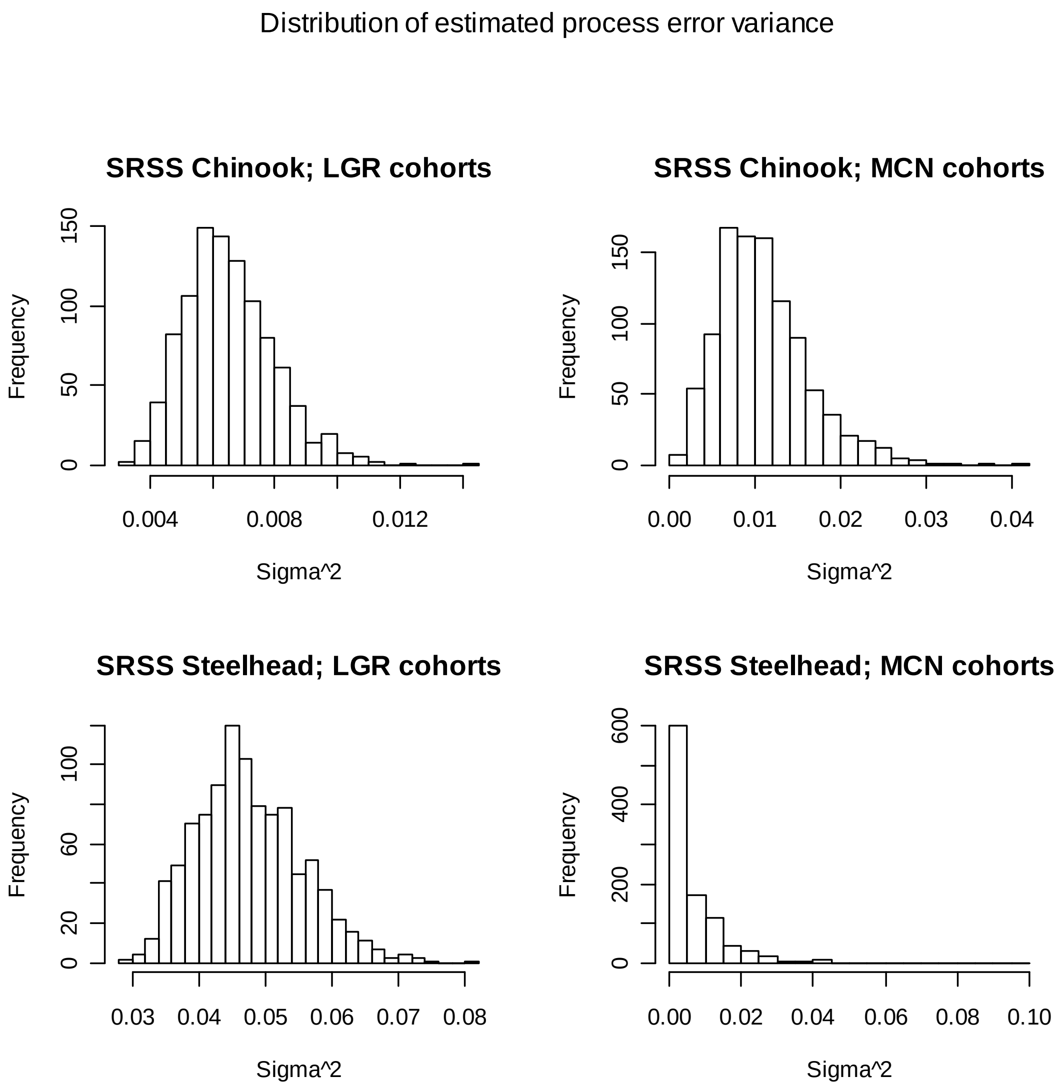


Figure A7 1. Sampling distributions of estimated process error for random effects models of reservoir survival estimates derived from PIT-tag data. Specific models are those referenced in text.

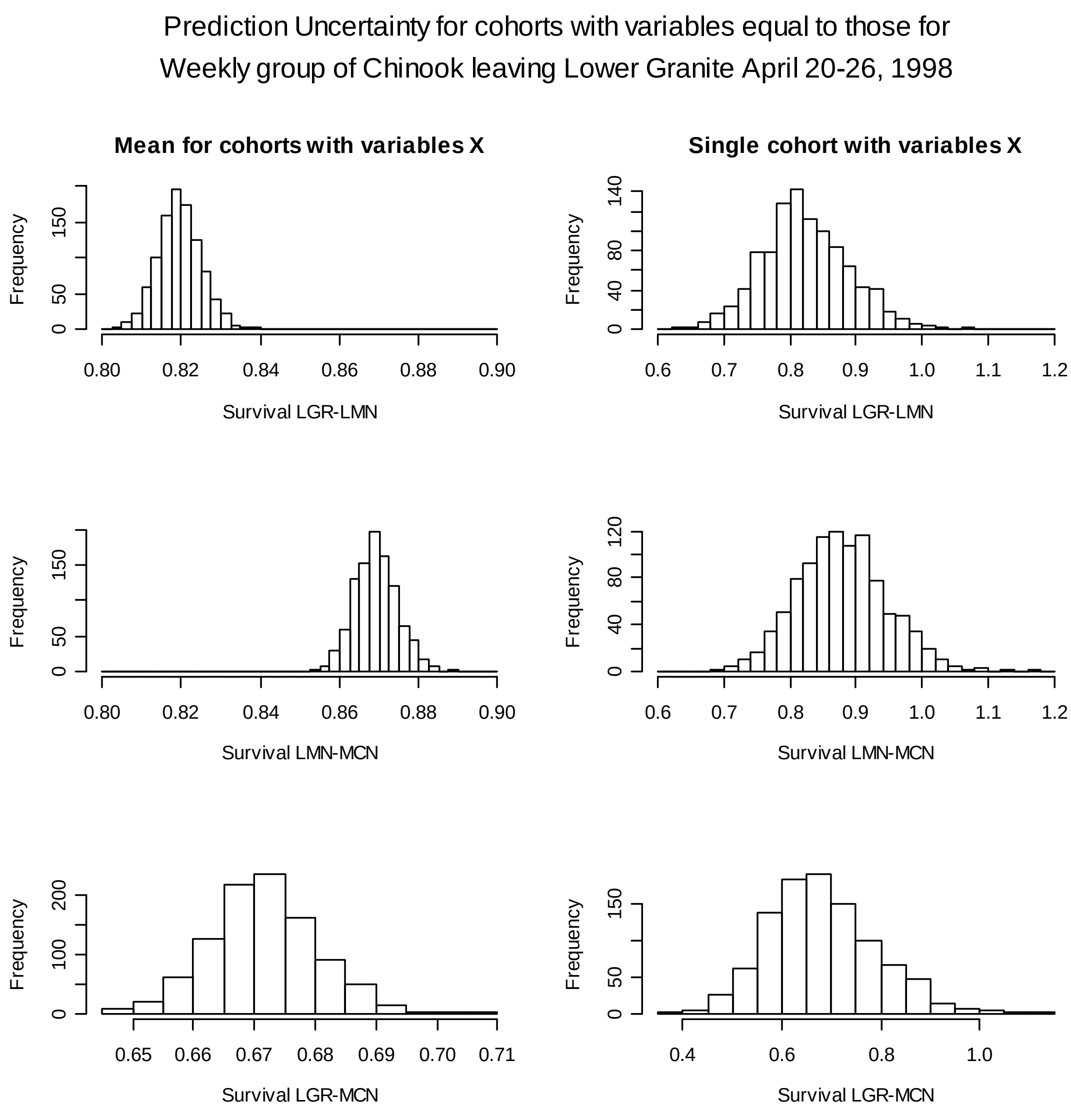


Figure A7 2. Prediction uncertainty in project survival between tailraces of Lower Granite and McNary Dams for cohorts with variables equal to those observed for weekly group of Chinook leaving Lower Granite Dam April 20-26, 1998.

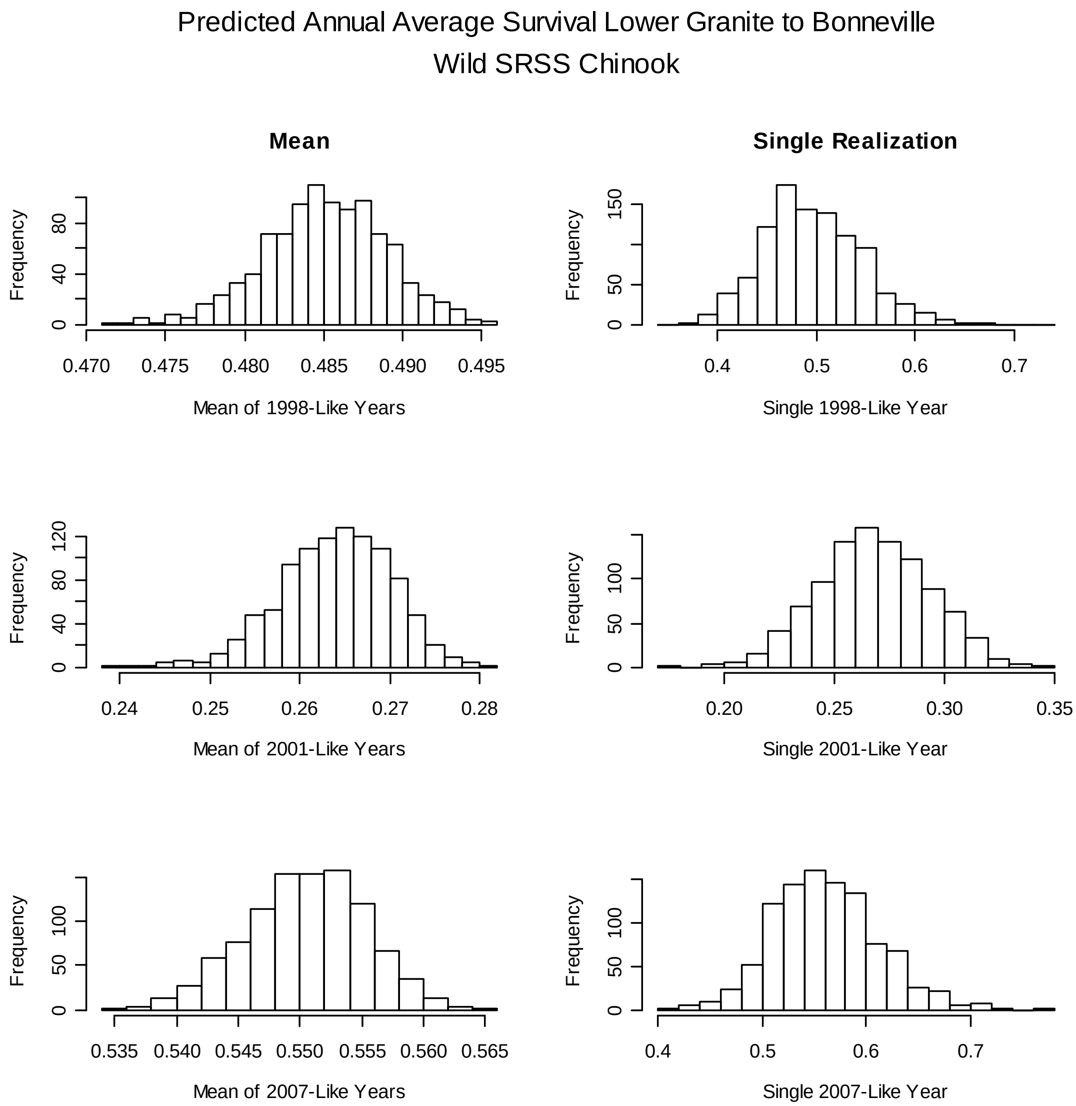


Figure A7 3. Prediction uncertainty for annual average project survival from Lower Granite Dam tailrace to Bonneville Dam tailrace for SRSS chinook. Predictions are based on weekly cohorts of fish leaving Lower Granite and McNary Dams, with flow, temperature, and spill profiles (i.e., exposure indices) equal to those in the observed data for the indicated years. Left-hand panels show uncertainty of the mean of the population of cohorts with the same profiles. Right-hand panels show uncertainty in a single realization of a year with the same profiles.

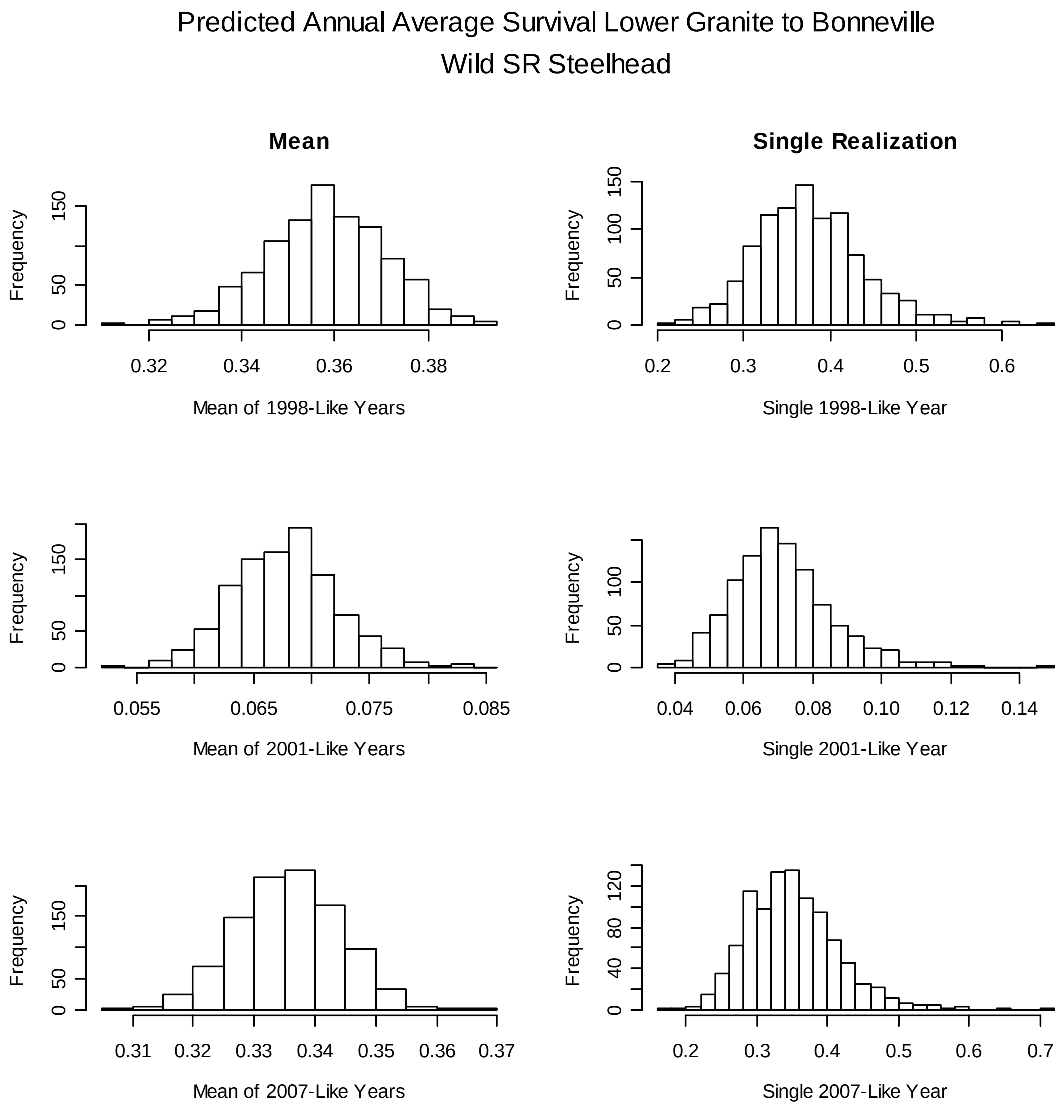


Figure A7 4. Prediction uncertainty for annual average project survival from Lower Granite Dam tailrace to Bonneville Dam tailrace for SR steelhead. Predictions are based on weekly cohorts of fish leaving Lower Granite and McNary Dams, with flow, temperature, and spill profiles (i.e., exposure indices) equal to those in the observed data for the indicated years. Left-hand panels show uncertainty of the mean of the population of cohorts with the same profiles. Right-hand panels show uncertainty in a single realization of a year with the same profiles.

Appendix 7-2: Monte Carlo simulation study of performance of random effects and traditional multiple regression models

Introduction

This appendix describes the first stages what will eventually be a very large-scale study of the performance of random effect models in the context of survival modeling for use in COMPASS. The primary tool we use is Monte Carlo simulation of the probabilistic processes of survival of migrating juvenile salmonids and detection of PIT-tagged fish as they pass dams. In this way, we create simulated data sets which have the same framework as the observed data, but for which we know perfectly (because we chose) the underlying parameters of all the processes involved. We then apply to the simulated data set the analytical methods that we used for the observed data (Appendix 7-1). By repeatedly creating and analyzing hundreds or thousands of data sets, we begin to understand how well our methods are able to estimate parameters and to model the processes.

Summary of Results

When there was no process error in the data, the random effects and weighted least squares methods were very similar in performance.

With moderate process error, random effects methods outperformed weighted least squares when sampling error was low or moderate. When sampling error was high, the two methods performed similarly.

With high process error, random effects methods substantially outperformed weighted least squares. Weighted least squares methods were considerably biased, overestimating survival probabilities.

There were no scenarios in which the weighted least squares method outperformed random effects.

The overall goal of this appendix was to present a method to predict future survival probabilities for a cohort with a certain set of predictor variables. In this regard, the random effects model performed very well; much better than weighted least squares. In most cases—except when sampling and process error variance were both large—the random effects model produced good predictions of single realizations that estimated the known underlying distribution of true survival probabilities.

In cases where distributions of predictions did not match as well, the predictions tended to be more variable than the underlying true distribution. This was when process error was moderate, but “swamped” by very large sampling error. Conservatism (greater variance) is a reasonable response to poor sample data.

Methods

Appendix 7-2: Monte Carlo simulation study of performance of random effects and traditional multiple regression models

Traditional Multiple Regression vs. Random Effects Models--In the traditional multiple linear regression model, a given observation unit with response variable Y_i and vector of predictor variables $\underline{X}_i$ is modeled as

$$Y_i = \underline{X}'_i \underline{\beta} + e_i$$

where $\underline{X}'_i \underline{\beta}$ is the expected value of the response as a linear function of the predictor variables and e_i is a random variable representing the total "statistical error" in Y_i. In this usage, statistical error includes all reasons that contribute to the failure of the observed data point to fall exactly on the straight line. These sources of error include lack of fit of the linear model (usually assumed negligible; sometimes requiring transformation of data), measurement error in Y_i ($\underline{X}_i$ is usually treated as if measured without error), effects of influential variables not explicitly included in the model, and random error due to natural variability (also known as "process error").

In the simplest and most familiar linear regression model, all error terms e_i are assumed independent and identically distributed (iid) according to the Normal distribution with mean 0 and common variance. Weighted linear regression is appropriate if the error terms are independent with unequal variance. Parameters of the linear regression models are typically estimated using least squares methods. Generalized least squares methods are available if the error terms are correlated (non-independent).

As illustrated in Appendix 7.1, the key to random effects models is the decomposition of the statistical error into one component for process error and one component for sampling error (the model is usually assumed to be well-specified, with negligible lack of fit due to non-linearity or omission of important predictors). To model the response variable Y_i, the total variance e_i is decomposed into one term for process error ε_i and one term for sampling error δ_i:

$$Y_i = \underline{X}'_i \underline{\beta} + \varepsilon_i + \delta_i .$$

Our data sets of survival estimates from the Cormack-Jolly-Seber model are well-suited for modeling using random effects because each data set consists of two correlated estimates of reach survival for each cohort and we have a reliable estimate of the sampling variance-covariance matrix. To summarize the more full development in Appendix 7.1, let our observed response variable be $\hat{y}_{g,r} = -\log(\hat{S}_{g,r})$ where $\hat{S}_{g,r}$ is the CJS survival estimate for group *g* in reach *r*. Considering the full vector of survival estimates, we have:

$$\underline{\hat{y}} = \mathbf{X}\underline{\beta} + \underline{\delta} + \underline{\varepsilon} ,$$

with variance-covariance matrix for the error terms:

$$\mathbf{VC}(\underline{\delta} + \underline{\varepsilon}) = \mathbf{D} = \sigma^2 \mathbf{I} + E_{\underline{y}}(\mathbf{W}) ,$$

assuming that the process error terms ε_i are iid N$(0,\sigma^2)$ and denoting the sampling variance-covariance matrix as **W**.

If there were no sampling error (i.e. we could somehow obtain survival estimates that were exactly equal to the true survival probabilities ($S_{g,r}$) for each group and river reach), then the model would be

$$\underline{\hat{y}} = \underline{y} = \mathbf{X}\underline{\beta} + \underline{\varepsilon},$$

where $y_{g,r} = -\log(S_{g,r})$ and process error terms $\underline{\varepsilon}$ are multivariate normal with mean $\underline{0}$ and variance-covariance matrix $\sigma^2\mathbf{I}$. This illustrates several points about the random effects model that will be important in our Monte Carlo explorations of its performance:

- For each value of $\underline{X}$, there is a distribution of possible values of y.
- The linear predictor $E\lfloor \underline{y} \rfloor = \mathbf{X}\underline{\beta}$ describes the expected values, or means, of the distributions; i.e., the vector of "true" regression coefficients $\underline{\beta}$ pertains to the means of the distributions.
- Any particular observed (or simulated) set of cohorts has true survival probabilities that are conditional on their covariates and on process error. Because of process error, ($\underline{y} \mid \mathbf{X}, \underline{\varepsilon}$) represents a random sample from the distributions of response variables and the true survival probabilities for a given simulated data set will not fall on the line describing the means.
- If there were no sampling error, the model for the true survival probabilities would be equivalent to the traditional multiple regression model with iiid Normal errors. Because of process error, even if we knew the vector of true response variables $\underline{y}$ we would not know the true regression coefficients $\underline{\beta}$ that determine the means of ($\underline{y} \mid \mathbf{X}$). We could use unweighted least squares to get a best-fit vector of estimates (we will denote these $\underline{\tilde{\beta}}$) of the true regression coefficients $\underline{\beta}$, and an estimate of the process error variance σ^2.
- Given that both sampling error and process error are present in any particular sample of survival estimates, the estimated regression coefficients ($\underline{\hat{\beta}}$) of the model fitted to the estimated response variables $\hat{y}_{g,r} = -\log(\hat{S}_{g,r})$ are conditional on the true survival probabilities, including process error: $\mathbf{X}\underline{\beta} + \underline{\varepsilon}$. Accordingly, as part of our evaluation of the performance of the random effects model, we compare the estimated coefficients $\underline{\hat{\beta}}$ to the coefficients $\underline{\tilde{\beta}}$

of the best-fit line describing the true survival probabilities in any particular Monte Carlo iteration, and not to the vector $\underline{\beta}$ that determines the means.

Fixed Elements of Simulated Data Sets--The framework of the simulated scenarios completed to date is based on the observed data set of weekly cohorts of wild Chinook salmon leaving from Lower Granite Dam (Table A7 4). Among the observed data sets for wild fish, that for wild Chinook from Lower Granite Dam is the highest quality. However, by altering the sizes of the simulated cohorts (number of fish) and the amount of process error, we can use this framework to investigate the performance of the methods in data sets of poorer quality (e.g., steelhead from McNary Dam).

Some elements were fixed for every generated data set. Each data set consisted of 115 cohorts. This is the number of observed weekly cohorts of wild Chinook salmon 1997-2007 for which PIT-tag data were sufficient to estimate reach survival in both the Lower Granite-to-Lower Monumental and Lower Monumental-to-McNary reaches. Covariate values and detection probabilities for each of the 115 simulated cohorts were set equal to those of the corresponding observed cohort. Thus, each cohort in each simulated data set corresponded directly with a unique observed cohort.

To demonstrate the performance of the random effects model, it is not necessary that the simulated data sets be tied so closely to observed data, but by doing so we have simulated specific historic conditions. Thus, observed patterns of flow, spill, and water temperature, the correlations among them, and their relationships with patterns in detection probabilities are all preserved and reflected in our simulated data sets.

Table A7 4. Elements and settings used to generate simulated data sets.

Elements that were fixed across all iterations.	
Number of cohorts	115 Chosen to be equal to the number of cohorts in the observed data set (1997-2007) that had estimates for both LGR-LMN and LMN-MCN
Covariates (Distances, travel times, indices of cohort exposure to flow, spill, temperature)	Values for each cohort in each reach are equal to those in the observed (1997-2007) data set
Detection probabilities	Set to equal the observed (estimated) detection

Appendix 7-2: Monte Carlo simulation study of performance of random effects and traditional multiple regression models

	probability estimates for the 115 cohorts (1997-2007)
Model	* Response variable is negative logarithm of survival probability * 6 predictor variables are Distance, Distance*Flow, Distance*Pspill, TTime, TTime*Temperature, TTime*Temperature^2
Regression coefficients/ Average reach survival probability	Regression coefficients were set so that average reach survival (LGR-LMN and LMN-MCN) was near 0.50 (average negative logarithm was near .693) (numeric subscripts are as in Chapter 2): $\alpha_0 = \alpha_{Distance} = 0.0077$ $\alpha_1 = \alpha_{Distance*Flow} = -0.0000012$ $\alpha_4 = \alpha_{Distance*Spill} = -0.00014$ $\beta_0 = \beta_{TTime} = -0.024$ $\beta_2 = \beta_{TTime*Temperature} = 0.0045$ $\beta_3 = \beta_{TTime*Temperature2} = -0.000017$
Elements that were varied across iterations	
Number tagged per cohort	(1) N_{obs} = number per cohort in observed data set (range from 13 to 15,369), (2) N_{obs}*10 = 10 times observed (range (130 to 153,690), or (3) N_{obs}/10 = one-tenth observed (range 1 to 1,537)
Magnitude of process error (σ^2 = process variance)	(1) $\sigma^2 = 0.007$ (estimated from observed data), (2) $\sigma^2 = 0.07$ (10 times estimated from observed data), or 93) $\sigma^2 = 0.0$ (no process error; variability in survival estimates results solely from sampling error)

Appendix 7-2: Monte Carlo simulation study of performance of random effects and traditional multiple regression models

The equation we used to generate the true reach survival probabilities for each of the 115 cohorts was (using notation of Chapter 2):

$$-\log(S_{g,r}) = y_{g,r} = (\alpha_0 + \alpha_1 \cdot Flow_{g,r} + \alpha_4 \cdot Spill_{g,r}) \cdot d_r + (\beta_0 + \beta_2 \cdot Temp_{g,r} + \beta_3 \cdot Temp_{g,r}{}^2) \cdot t_{g,r} + \varepsilon_{g,r}$$

where $S_{g,r}$ is the survival probability for a particular release cohort, or group (*g*) over a particular river reach (*r*), *Spill* is the proportion of fish passing the spillway at the upstream dam, *Flow* and Temperature (*Temp*) are the exposure indices for the time fish from the cohort were in the reservoirs, *t* is the average travel time of the cohort from the upstream tailrace to downstream tailrace, and *d* is the total length of reservoirs in the reach. This is the model illustrated in Appendix 7.1.

The process error terms $\varepsilon_{g,r}$ were independent and identically normally distributed with mean 0 and variance σ^2. Because the covariates and regression coefficients were fixed across generated data sets, the mean survival probability for a particular set of covariate values (i.e., for one particular cohort) was the same in all data sets:

$$E\left[y_{g,r}\right] = (\alpha_0 + \alpha_1 \cdot Flow_{g,r} + \alpha_4 \cdot Spill_{g,r}) \cdot d_r + (\beta_0 + \beta_2 \cdot Temp_{g,r} + \beta_3 \cdot Temp_{g,r}{}^2) \cdot t_{g,r}$$

For a particular iteration of the simulation, the negative logarithm of the true survival probability was generated by adding to the mean a randomly generated error term drawn from the N(0, σ^2) distribution. In this way, the true survival probability for a cohort and reach in each simulated data set represented a single random sample from the distribution of possible probabilities among all cohorts with that same set of covariate values.

Note that hereafter, when we wish to refer to all regression coefficients at once, both those related to distance and those related to travel time, we will use the vector notation $\underline{\beta}$ where $\underline{\beta} = (\alpha_0, \alpha_1, \alpha_4, \beta_0, \beta_2, \beta_3)$.

Table A7 2 gave values of parameters estimated using a random effects model of observed PIT-tag data. In initial Monte Carlo studies, we found that these parameter values gave mean (fitted) values of negative-log-survival for many of the cohorts that were close enough to 0.0 (i.e. survival close enough to 1.0) that adding random process variation resulted in significant numbers of cohorts with generated survival probabilities greater than 1.0. When simulating detection histories, survival probabilities greater than 1.0 are effectively truncated and treated as if they were equal to 1.0, thus decreasing the effective amount of process error. Thus, the actual realized process error variance in any particular simulated data set was a function of the (random) number of generated survival probabilities that exceeded 1.0.

As explained in the previous section, for each simulated data set, we compared our estimated regression coefficients $\underline{\hat{\beta}}$ to the coefficients $\underline{\tilde{\beta}}$ of the best-fit line describing the true survival probabilities, and the values of $\underline{\tilde{\beta}}$ varied from Monte Carlo sample to sample. Similarly, to evaluate the performance of the estimator of σ^2, it is possible to account for true process error varying from sample to sample, but we preferred to have a fixed amount of process error for a given scenario.

Accordingly, to generate survival probabilities we selected values of the regression coefficients that gave average reach survival around 0.5 (Table A7 4), so that addition of random process error almost never resulted in a cohort's true survival probability exceeding 1.0. Thus, this is one part of the Monte Carlo simulation study that does not reflect observed data. However, the values we selected for the regression coefficients do preserve both the general relationships among coefficients and the patterns of relative survival present in the observed data.

Elements of Simulated Data Sets That Varied Among Scenarios--Two elements of the data framework were varied among simulation scenarios: the number of PIT-tagged fish per cohort and the amount of process error in the survival probabilities. A total of 9 scenarios are reported here, representing the 9 combinations of 3 levels of sample sizes and 3 levels of process error.

One scenario represented the observed data (except for the adjusted values of the regression coefficient to give survival 0.5), using the observed numbers of tagged fish and a value for σ^2 (process variance on the logarithm scale) equal to 0.007, a value near that estimated for this random effects model of the observed data (see Table X2 of Appendix X). Other levels of sample size were 10 times the observed number tagged and the observed number tagged divided by 10. Other levels of process error were 0.07 (10 times the process variance estimated from data) and 0.0 (no process error at all—true survival for a particular cohort is exactly the same in all Monte Carlo samples).

We generated 1,000 data sets under each of the 9 scenarios.

Generation of detection histories--Generation of detection histories for the 115 simulated cohorts required detection probabilities for two dams (in the spirit of the realism of the scenario, these were Lower Monumental and McNary Dams), and survival probabilities for two reaches (Lower Granite-to-Lower Monumental and Lower Monumental-to-McNary). In addition, another probability is needed for the probability of detection somewhere downstream of McNary Dam (in the observed data this is the probability of being seen somewhere downstream of McNary Dam; the joint probability of surviving to and being detected at a downstream detection site).

As described above, detection probabilities used for the two dams were equal to those in the observed data, and survival probabilities for the two reaches were generated randomly. For simplicity, we used for the downstream probability the product of the average of the capture probabilities for the first two dams and the average of the survival probabilities for the first two reaches.

Once all the cohort-specific probabilities were in place, detection histories for all fish in the cohort were simulated through a series of simulated Bernoulli trials to determine how far downstream the simulated fish survived and at which sites it was detected. Each Bernoulli trial was simulated by generating a random variable from the Uniform(0,1) distribution. If the random number was less than the relevant probability the trial was a "success."

Estimation of Parameters From Simulated Data Sets-- From each Monte Carlo sample of detection histories, we used the Cormack-Jolly-Seber (CJS) model to estimate the two survival probabilities for each cohort and their variances and covariance. These estimates, combined with the covariate values, represent the data required to apply the random effects methods of Appendix 7.1. For each simulated data set, we used these methods to estimate regression parameters, their corresponding variance-covariance matrix, and the process variance σ^2.

We also estimated the regression parameters using the traditional weighted least-squares multiple regression model, using the relative variance of the survival estimates (equal to inverse variance of the negative-log survival estimate) as weights.

Covariates included in the models and corresponding estimated regression parameters were those that were used to generate the data:

Distance

Distance*Flow

Distance*Spill

TTime

TTime*Temperature

TTime*Temperature^2.

We assessed the agreement of estimated regression coefficients with the best-fit line in three ways. In each case, we compared results for random effects estimates with those for weighted least squares estimates. The three methods were:

- XY-scatterplots;
- Mean linear correlation coefficient, calculated as $\frac{\sum_{j=1}^{6} cor(\underline{\hat{\beta}}_j, \underline{\tilde{\beta}}_j)}{6}$ where $\underline{\hat{\beta}}_j$ is the vector of 1,000 estimates of the regression coefficient for the j^{th} covariate, etc.
- "Standardized distance" between $\underline{\hat{\beta}}$ and $\underline{\tilde{\beta}}$ averaged over all Monte Carlo iterations and calculated for a single iteration as $\sum_{j=1}^{6} \frac{\left(\hat{\beta}_j - \tilde{\beta}_j\right)^2}{\tilde{\beta}_j}$. In practice, we used a trimmed mean of this standardized distance, as there were some iterations that had some $\tilde{\beta}_i$ very close to zero, which in the denominator

of the term resulted in exaggerated influence on the sum. We trimmed 5% of the iterations with greatest distance, calculating the mean of the lowest 950 of 1000 distances.

Summary, Commentary, Notation, Step-by-Step Procedure for Simulations--Nine scenarios are reported here, amounting to all possible combinations of three levels of the factors Number Tagged and Process Error (Table A7 4).

The values of the following elements were the same for all scenarios (Table A7 4):

Number of cohorts.

Number of reaches/dams.

Covariates for each cohort/reach.

Detection probabilities at each of the dams.

Form of equation and values of linear coefficients ("true $\underline{\beta}$") in the equation used to generate mean survival probability for a given set of covariates.

Linear coefficients estimated.

For each of the scenarios, 1,000 data sets were simulated and then analyzed. Each time through the entire process of data simulation and model fitting is called an "iteration." The step-by-step process for each iteration (i) of the simulation was as follows:

a. Generate True Survival Probabilities

For each cohort *g*, reach *r* (covariates $\underline{X}_{g,r}$), generate survival probability $S_{g,r(i)}$ by randomly sampling a value $\varepsilon_{g,r(i)}$ from the theoretical normal distribution of the process error for the negative logarithm of the survival probability: $\varepsilon_{g,r(i)} \sim Normal(0,\sigma^2)$. Add $\varepsilon_{g,r(i)}$ to the expected value of the negative logarithm:

$$E[y_{g,r}] = (\alpha_0 + \alpha_1 \cdot Flow_{g,r} + \alpha_4 \cdot Spill_{g,r}) \cdot d_r + (\beta_0 + \beta_2 \cdot Temp_{g,r} + \beta_3 \cdot Temp_{g,r}^{\ 2}) \cdot t_{g,r}$$

Combining all cohorts and reaches gives the i^{th} Monte Carlo sample vector of true transformed survival probabilities $\underline{y}_{(i)}$. The true survival probability for simulating detection histories are given by $\underline{S}_{(i)} = e^{-\underline{y}_{(i)}}$.

b. Simulate Detection Histories

For each fish in each cohort, simulate a detection history using a series of simulated Bernoulli trials to determine how far downstream the simulated fish survived and at which sites it was detected. Simulate each Bernoulli trial by generating a pseudo-random

Appendix 7-2: Monte Carlo simulation study of performance of random effects and traditional multiple regression models

variable from the Uniform(0,1) distribution. If the random number is less than the relevant probability the trial is a "success."

c. Calculate Cormack-Jolly-Seber Survival Estimates and Corresponding Variance-Covariance Matrix

Notation for results is:

$\underline{\hat{S}}_{(i)}$ = vector of survival estimates for iteration (i);

$\mathbf{VC}(\underline{\hat{S}}_{(i)})$ = estimated sampling variance-covariance matrix for vector of survival estimates;

$\underline{\hat{y}}_{(i)} = -\log(\underline{\hat{S}}_{(i)})$ = vector of transformed survival estimates = response variable for regression models;

$\mathbf{W} = \mathbf{VC}(\underline{\hat{y}}_{(i)})$ = estimated variance-covariance matrix for response variable, calculated using delta method.

From each simulated data set, there are potentially 230 survival probability estimates (115 cohorts, 2 reaches). However, the simulated data will sometimes be insufficient to estimate survival for some reaches for some groups. For each iteration, we tallied the number of such "missing" observations, and removed them from the data set.

d. Estimate Random Effects and Weighted Least Squares Models

Use methods of Appendix 7-1 to obtain estimates for process error variance $\hat{\sigma}_{(i)}$ and regression coefficients $\underline{\hat{\beta}}_{RE(i)}$ from random effects model. Use traditional weighted least squares methods to obtain estimates of regression coefficients $\underline{\hat{\beta}}_{WLS(i)}$.

e. Calculate Coefficients of Best-Fit Line for True (Transformed) Survival Probabilities

If there were no process error, each $y_{g,r(i)}$ would equal the mean for $X_{g,r}$, so $\underline{\hat{\beta}}_{RE(i)}$ and $\underline{\hat{\beta}}_{WLS(i)}$ would be expected to estimate the underlying regression coefficients for the means $\underline{\beta}$.

However, in the presence of process error, the true response variables $\underline{y}_{(i)}$ do not fall on the regression line for the means. Even if CJS survival estimates were perfect (i.e., no sampling error, so that $\underline{\hat{y}}_{(i)} \equiv \underline{y}_{(i)}$), the regression coefficients estimated from $\underline{\hat{y}}_{(i)}$ would not be expected to estimate the coefficients describing the line for the means. Instead, for any given iteration, the estimated regression coefficients are expected to estimate the coefficients of the unweighted least squares linear regression of the true response variables on **X**:

Appendix 7-2: Monte Carlo simulation study of performance of random effects and traditional multiple regression models

$$\underline{\tilde{\beta}}_{(i)} = (\mathbf{X'X})^{-1}\mathbf{X'}\underline{y}_{(i)}$$

e. Calculate Fitted Values

As described above, because of process error the estimated regression coefficients in any particular iteration are not expected to equal the true coefficients for the means. Moreover, because of correlations among the covariates and among the estimated regression coefficients in each iteration, the average across all 1,000 iterations of the estimated regression coefficients for a particular covariate will also not be equal to the true coefficients. This is also true for the coefficients of the best-fit lines for the true response variables. This means that we cannot assess the performance of models by comparing estimated regression coefficients to a single expected value.

If the models perform well, a quantity that *is* expected to be equal to the mean is the fitted value for any particular cohort and reach (i.e., particular $X_{g,r}$). We calculated fitted values for all cohorts and reaches to compare with the true mean responses. We selected two cohorts to use for more focused attention. The covariates for the cohort that left Lower Granite Dam April 20-26, 1998 were most typical (technically, closest to the multidimensional centroid of the full covariate data set), and those for the June 1-7, 2001 cohort were most untypical (farthest from the centroid). The covariate values and expected response variables are given in Table A7 5 (note effect of adjusting regression coefficients so that typical survival probability was near 0.50).

Table A7 5. Data for LGR-LMN reach for selected weekly cohorts of Chinook leaving LGR.

	April 20-26, 1998	June 1-7, 2001	True Reg. Coefficient
Distance	65.9	65.9	0.0077
Flow	75.9	45.8	---
Spill	0.174	0.000	---
Time	8.81	20.33	0.024
Temperature	10.9	15.2	---
Flow·distance	5001.4	3020.4	0.0000012

Appendix 7-2: Monte Carlo simulation study of performance of random effects and traditional multiple regression models

Spill·distance	11.5	0.000	0.00014
Temp·time	95.9	308.1	0.0045
$\text{Temp}^2\cdot\text{time}$	1044.5	4670.2	-0.000017
Fitted value (deterministic prediction of response variable ($-\log(S_{g,r})$)	0.70231	1.32305	---
Mean reach survival probability	0.495	0.266	---

e. Generate Predictions Incorporating Uncertainty

For the final step of the Monte Carlo study, for each simulated data set, we used the methods in the final section of Appendix 7.1 (Using Random Effects Models to Model Uncertainty in COMPASS Predictions) to generate predictions based on the fitted models. The methods ensure that for any set of covariates, the mean of the distribution of predictions will be equal to the fitted value from the model, including any bias (e.g., for the weighted least squares model with high process error). Of more interest are the properties of the spread of the prediction distribution. In particular, for single realizations of each set of covariates, a perfect prediction method would be expected to produce a distribution of predictions with mean near the mean of the true distribution and variance equal to the process error variance. We evaluated predictions based on random effects models (using variance-covariance of regression parameters based on either the estimated process-error variance only or the total variance – see Appendix 7.1) and on weighted least squares models. We also reported properties of the predicted means of the true distributions, based on random effects models.

Results

Estimation of process error variance—In general, the process error variance was estimated well in most scenarios (Table A7 6; Figure A7 5). However, when sampling variability was very high relative to process error (scenarios with number tagged equal $N_{obs}/10$ and process error variance equal 0.0 or 0.007), difficulty in estimating process error was apparent (bottom row of Figure A7 5). Process error variance tended to be overestimated in these cases, and coverage was not nominal for the estimated 95% confidence interval. When sampling variability was low (number tagged equal $N_{obs}*10$), the process error variance was very well estimated, with low variability from iteration to iteration and nominal confidence interval coverage. With moderate sampling variability (number tagged equal N_{obs}), process error variance was reliably estimated. When process error was present in any magnitude the estimated variance was equal to 0.0 only when sampling variability was high, and then only 7.5% of the time. When there was no process error, the estimate was usually 0 (62%-83% of the time), and the lower limit of the 95% confidence interval was almost always 0 (94%-99.5%).

Estimation of regression coefficients—When there was no process error the true response variables for all cohorts fell exactly on the line described by $\mathbf{X}\underline{\beta}$ and the fitted values for the best-fit line are the same in all Monte Carlo iterations (i.e. $\underline{\tilde{\beta}_{(i)}} \equiv \underline{\tilde{\beta}} = \underline{\beta}$). Therefore, no linear correlation can be calculated between estimates and best-fit values. However, the standardized distance between the best-fit values and the estimates can be calculated (Table A7 7). With no process error, estimates from the random effects model and estimates from the weighted least squares model are in essentially equal agreement with the best-fit values. In our sample, the weighted least squares estimates were a bit closer when sampling error was high (number tagged was small).

With moderate process error $\left(\sigma^2 = 0.007\right)$, estimates from the random effects model were in better agreement (both correlation and standardized distance) with the coefficients of best-fit model to the true response variables, except when sampling error was high. With small numbers tagged (high sampling error), random effects and weighted least squares were in equal agreement; neither was better.

With high process error $\left(\sigma^2 = 0.07\right)$, the random effects model was considerably better than the weighted least squares model in all cases.

Appendix 7-2: Monte Carlo simulation study of performance of random effects and traditional multiple regression models

Table A7 6. Summary of estimation of process error variance for 1,000 iterations of Monte Carlo simulation of nine scenarios. First two columns identify the scenario. For each scenario information is mean number of missing survival estimates (number of 230 possible cohort/reach combinations for which data were insufficient to estimate survival); number of iterations with estimated process error variance equal to 0; mean and standard deviation of process error variance estimates; and the percentage of 95% confidence intervals for estimated process error variance that covered the true value.

Number Tagged	Process Error Variance σ^2	Mean # missing surv. est.	% iter. $\hat{\sigma}^2 = 0.0$	Mean $\hat{\sigma}^2$	Std. Dev. $\hat{\sigma}^2$	95% conf. interval coverage
N_{obs}	0	11	71.4	0.00014	0.00035	97.3
N_{obs}*10	0	1	83.1	0.00001	0.00012	99.5
N_{obs}/10	0	56	62.2	0.00151	0.00308	94.0
N_{obs}	0.007	11	0.0	0.00743	0.00194	92.5
N_{obs}*10	0.007	1	0.0	0.00705	0.00101	94.3
N_{obs}/10	0.007	56	7.5	0.00874	0.00636	86.6
N_{obs}	0.070	12	0.0	0.07072	0.00945	95.1
N_{obs}*10	0.070	1	0.0	0.06937	0.00724	95.0
N_{obs}/10	0.070	58	0.0	0.07108	0.01832	90.7

Appendix 7-2: Monte Carlo simulation study of performance of random effects and traditional multiple regression models

Table A7 7. Summary of agreement of estimated regression coefficients with best-fit line for the true survival probabilities over for 1,000 iterations of Monte Carlo simulation of nine scenarios. First two columns identify the scenario. A single "standardized distance" across all 6 coefficients is calculated for each scenario, and the mean of the 1,000 distances is given in the table. For correlation, a separate simple linear correlation was calculated across all 1,000 scenarios for each of the 6 coefficients, and the mean of 6 correlation coefficients is presented.

		Random Effects Model		Weighted L.S. Model	
Number Tagged	Process Error Variance σ^2	Mean Std. Distance $(\underline{\tilde{\beta}}, \underline{\hat{\beta}})$	Mean Correl. $(\underline{\tilde{\beta}}_i, \underline{\hat{\beta}}_i)$	Mean Std. Distance $(\underline{\tilde{\beta}}, \underline{\hat{\beta}})$	Mean Correl. $(\underline{\tilde{\beta}}_i, \underline{\hat{\beta}}_i)$
N_{obs}	0	7.0	---	7.0	---
N_{obs}*10	0	0.7	---	0.7	---
N_{obs}/10	0	128.2	---	106.4	---
N_{obs}	0.007	15.6	0.516	27.2	0.332
N_{obs}*10	0.007	3.3	0.753	20.6	0.386
N_{obs}/10	0.007	116.8	0.235	107.1	0.227
N_{obs}	0.070	38.3	0.753	359.5	0.330
N_{obs}*10	0.070	11.0	0.908	31.41	0.317
N_{obs}/10	0.070	188.7	0.456	415.0	0.287

Appendix 7-2: Monte Carlo simulation study of performance of random effects and traditional multiple regression models

Figures A7 6 through A7 8 illustrate typical XY scatterplots of estimated regression coefficients versus coefficients for the best-fit line for true response variables. We do not show scatterplots for all possible predictor variables, as they are all similar; these are for Travel Time. With moderate sampling variability (Figure A7 6, numbers tagged equal to observed), the estimated regression coefficients from the random effects model show slightly better agreement to the best-fit line (falling closer to the Y=X line) and less scatter than those from the weighted least squares model. These patterns are much more strongly apparent when sampling variability is low (Figure A7 7, numbers tagged equal to 10 times observed). They remain apparent, but much less strongly so, when sampling variability is high (Figure A7 8, numbers tagged equal to one-tenth observed).

Estimation of mean response given X (Fitted Values)—When there was no process error or moderate process error the fitted values from both random effects and weighted least squares models appeared nearly unbiased when sampling error was moderate (numbers tagged equal numbers observed) or low (10 times numbers observed) (Tables A7 8 and A7 9 and Figures A7 9 through A7 11 for two illustrative cohorts and reaches). When sampling variability was high (one-tenth numbers observed), both methods appeared to be slightly biased. Overestimating the negative logarithm of survival probability means underestimating survival.

When there was no process error the variability in fitted values across Monte Carlo iterations was similar between the two methods. When process error was moderate the fitted values from the random effects model were less variable than those from weighted least squares, unless sampling variability was high, in which case variability of fitted values was similar for the two methods.

When process error was high, the fitted values from the random effects model were substantially less variable than those from weighted least squares, at all levels of sampling variability (numbers tagged). Moreover, weighted least squares gave considerably biased fitted values. Underestimating the negative logarithm of survival probability means overestimating survival.

Table A7 10 summarizes fitted values for all 230 observational units (2 reaches for each of 115 cohorts). The table includes information for the best-fit lines to the true survival probabilities (i.e., the unobservable underlying probabilities, not including sampling error) as well as for the two methods of estimation from simulated data that include sampling error. Regardless of the amount of process error, the mean of the true response variable for a given cohort (predictor variables $X_{(i)}$) was always determined by $X_{(i)}\underline{\beta}$. Thus, for any Monte Carlo iteration, the mean of the 230 true means was the same in all scenarios; in this case equal to 0.72768.

As noted above, when there was no process error the true response variable for cohort *i* in every Monte Carlo iterations was exactly equal to the mean $X_{(i)}\underline{\beta}$. This means the best-fit line to all 230 true response variables fit perfectly, with no variation in fitted values

Appendix 7-2: Monte Carlo simulation study of performance of random effects and traditional multiple regression models

Table A7 8 Summary of fitted values (negative logarithm of survival probability) in the first reach for cohort leaving Lower Granite Dam April 20-26, 1998 over 1,000 iterations of Monte Carlo simulation of nine scenarios. First two columns identify the scenario. The true mean response variable for this cohort is 0.70231 (see Table A7.5).

		Random Effects Model		Weighted L.S. Model	
Number Tagged	Process Error Variance σ^2	Mean of Fitted Values	Std. Dev. of Fitted Values	Mean of Fitted Values	Std. Dev. of Fitted Values
N_{obs}	0	0.70524	0.00482	0.70475	0.00502
N_{obs}*10	0	0.70257	0.00223	0.70259	0.00242
N_{obs}/10	0	0.73046	0.01548	0.72386	0.01542
N_{obs}	0.007	0.70489	0.01088	0.69527	0.01523
N_{obs}*10	0.007	0.70170	0.00822	0.69225	0.01497
N_{obs}/10	0.007	0.72885	0.02029	0.71256	0.02118
N_{obs}	0.070	0.69842	0.02558	0.60229	0.05468
N_{obs}*10	0.070	0.70016	0.02398	0.59966	0.05658
N_{obs}/10	0.070	0.71453	0.03802	0.61971	0.06298

Appendix 7-2: Monte Carlo simulation study of performance of random effects and traditional multiple regression models

Table A7 9 Summary of fitted values (negative logarithm of survival probability) in the first reach for cohort leaving Lower Granite Dam June 1, 2001 over 1,000 iterations of Monte Carlo simulation of nine scenarios. First two columns identify the scenario. The true mean response variable for this cohort is 1.32305 (see Table A7.5).

		Random Effects Model		Weighted L.S. Model	
Number Tagged	Process Error Variance σ^2	Mean of Fitted Values	Std. Dev. of Fitted Values	Mean of Fitted Values	Std. Dev. of Fitted Values
N_{obs}	0	1.33472	0.02715	1.33057	0.02768
N_{obs}*10	0	1.33464	0.00822	1.32419	0.00856
N_{obs}/10	0	1.37309	0.08640	1.35284	0.08807
N_{obs}	0.007	1.33150	0.04969	1.32378	0.06503
N_{obs}*10	0.007	1.33190	0.03449	1.31510	0.06151
N_{obs}/10	0.007	1.36742	0.10417	1.34744	0.10869
N_{obs}	0.070	1.33027	0.11030	1.24815	0.21350
N_{obs}*10	0.070	1.32705	0.09878	1.24003	0.21115
N_{obs}/10	0.070	1.35551	0.15614	1.28098	0.23105

Appendix 7-2: Monte Carlo simulation study of performance of random effects and traditional multiple regression models

Table A7 10. Summary of fitted values for all 230 cohort/reach combinations over 1,000 iterations of Monte Carlo simulation of nine scenarios. First two columns identify the scenario. Statistics are given for the best-fit line to the true response variables (simple least squares fit to true values with no sampling variability) and for random effects and weighted least squares models fitted to simulated data that includes sampling variability.

			Best-Fit to True Response Fitted Values			Random Effects Model Fitted Values			Weighted L.S. Model Fitted Values		
Number Tagged	Process Error Variance σ^2	Mean of True Mean Response Var.	Mean	Mean Std. Dev	Mean Correl. w/True Mean	Mean	Mean Std. Dev	Mean Correl. w/True Mean	Mean	Mean Std. Dev	Mean Correl. w/True Mean
N_{obs}	0	0.72768	0.72768	0.0	1.0	0.73300	0.01203	0.977	0.73199	0.01249	0.997
N_{obs}*10	0	0.72768	0.72768	0.0	1.0	0.72836	0.00437	1.0	0.72827	0.00460	1.0
N_{obs}/10	0	0.72768	0.72768	0.0	1.0	0.75509	0.04122	0.954	0.75036	0.04196	0.957
N_{obs}	0.007	0.72768	0.72758	0.01224	0.998	0.73302	0.02285	0.990	0.72205	0.03249	0.982
N_{obs}*10	0.007	0.72768	0.72768	0.01226	0.998	0.72704	0.01585	0.996	0.71734	0.03036	0.984
N_{obs}/10	0.007	0.72768	0.72791	0.01230	0.998	0.75346	0.04873	0.943	0.73955	0.05165	0.948
N_{obs}	0.070	0.72768	0.72702	0.03821	0.977	0.72309	0.04934	0.958	0.62369	0.11183	0.847
N_{obs}*10	0.070	0.72768	0.72761	0.03905	0.976	0.72387	0.04184	0.971	0.61856	0.11409	0.838
N_{obs}/10	0.070	0.72768	0.72728	0.03958	0.975	0.73158	0.07508	0.885	0.64100	0.12366	0.819

Appendix 7-2: Monte Carlo simulation study of performance of random effects and traditional multiple regression models

across iterations (in the table, mean standard deviation equal 0.0), and perfect correlation between fitted values and true means (in the table, mean correlation between fitted values and true mean response equal 1.0).

With a moderate amount of process error $\left(\sigma^2 = 0.007\right)$, the fitted values for the best-fit became variable across Monte Carlo iterations (mean standard deviation 0.01227), but remained highly correlated with the true mean responses (mean correlation 0.998), indicating that the regression line through the true response variables was usually very near the line through the true mean responses, as expected. Even when process error was high $\left(\sigma^2 = 0.07\right)$, the mean correlation between fitted values and true mean responses was 0.976.

Because they are not affected by sampling error, the best-fit lines through the true response variables represent the best fit possible for the methods applied to data that include sampling error. Comparing results for random effects and weighted least squares models with fitted values for the best-fit line can indicate how much potential information is "lost" because we cannot have perfect knowledge of the true response variables (must sample and estimate using PIT tags), and whether the difference in handling sources of variation results in one method outperforming the other.

The patterns identified for the two illustrative cases above were apparent when summarizing across all units (Table A7 10):

- When there was no process error, the random effects and weighted least squares methods gave very similar results: at all levels of sampling error (numbers tagged), variability in fitted values was near equal between the two methods and fitted values were equally correlated with true mean responses.
- With high sampling error (low numbers tagged) and no process error , response variables were slightly overestimated on average (survival probabilities underestimated) by both methods.
- With moderate process error and high sampling error, the results were similar as for zero process error and high sampling error: slight overestimation of response variable and little difference between the two methods in variability of fitted values or in correlation with true mean responses.
- With moderate process error and low or moderate sampling error, both methods appeared to give unbiased fitted values. However, fitted values from the random effects method were less variable and more highly correlated with true mean responses than those from the weighted least squares method.
- With high process error, the random effects model greatly outperformed weighted least squares. Fitted values from random effects were far less variable and much more correlated with true mean response. In fact, with moderate sampling error and especially with low sampling error, the correlation with true mean responses was nearly as high as with the best-fit model to true response variables. Because fitted values were unbiased, this

means random effects accounted very well for the process error and very little information was "lost."

- At all levels of sampling error, fitted values from weighted least squares were substantially biased when process error was high (negative logarithm of survival underestimated; survival probabilities overestimated).
- There were no scenarios in which the weighted least squares method outperformed the random effects method.

Predictions with Uncertainty--For each model fit to the data set in each Monte Carlo iteration, we computed distributions of predicted future responses for each of the 230 sets of covariates in our data set. For random effects models, we computed distributions for both the mean of the distribution of responses for a given $\underline{X}$ and for a single realization from the distribution. Table A7 11 summarizes the variances of these distributions.

When process error variance was zero, predictions had distributions with non-zero variance. This occurred for two reasons: the presence of sampling error, and the truncation of estimated process error at 0.0. Zero-process-error scenarios are artificial—not likely to occur in reality. Nonetheless, in most cases the predicted distributions had very little variability.

The non-zero process error scenarios are of more interest. Table A7 11 shows that for random effects models there was very little difference in variability of predictions based on the variance-covariance matrix incorporating estimated process error only and incorporating total variance. Both estimates of variance-covariance of regression parameters resulted in prediction distributions for single realizations with variance reasonably near the actual process error variance, except when sampling error was high relative to process error (number tagged = N_{obs}/10 and σ^2 = 0.007), in which case the prediction distributions tended to have variance greater than the underlying σ^2. Variance of the single-realization prediction distributions was also greater than σ^2 when sampling variance and process error variance were both high (N_{obs}/10 and σ^2 = 0.07), though not nearly as much greater.

In all cases with moderate or (N_{obs}) low (N_{obs}*10) sampling error, variance of the single-realization prediction distributions averaged near the underlying σ^2 and variances of most of the 230 prediction distributions were within a small range of σ^2 (for example, 90% of the 230 distributions had variance in the range (0.00718, 0.00956) in the case most like observed data (numbers tagged equal to N_{obs} and σ^2 = 0.007).

Prediction distributions based on weighted least squares tended usually had too little variance (average variance of prediction distributions much lower than the underlying σ^2), and the range of values of variance was much wider, with some distributions having very little variance at all. For example, when sampling variance and process error variance were both high (N_{obs}/10 and σ^2 = 0.07), nearly 30% of the 230 prediction distributions had variance less than 0.01. Moreover, as we saw in the previous section on fitted values, the mean predictions based on weighted least squares were fairly severe biased.

Discussion

It is very likely that real-world PIT-tag survival data contain process error—cohorts with exactly the same covariates are not likely to have exactly the same survival probabilities. Moreover, we do not have perfect knowledge of the underlying survival probabilities for any given cohort—we have to estimate the probabilities using the CJS model. Estimates for a single cohort from the CJS model are correlated, not independent as assumed for the weighted least squares model, and the CJS model provides a reliable estimate of sampling variance-covariance. These circumstances make PIT-tag survival data very well-suited for analysis using the class of statistical models known as "Random Effects" or "Variance Components" models.

The Monte Carlo simulation study reported here has shown:

- Random effects model reliably estimates process error variance, as long as sampling variance is not too large.
- In the presence of process error, the linear regression component of random effects model reliably estimates the simple least-squares line that would be fit to true survival probabilities if we could measure them without sampling error.
- There were no scenarios in which weighted least squares substantially outperformed random effects. At best, the performance of weighted least squares was equal, performing equally well in the unlikely scenarios where process error was zero, and equally poorly when sampling error variance was very high in relation to process error variance. Random effects models performed much better when process error was high and when process error was moderate and sampling error was moderate or low.
- The overall goal of this appendix was to present a method to predict future survival probabilities for a cohort with a certain set of predictor variables. In this regard, the random effects model performed very well; much better than weighted least squares. In most cases—except when sampling error was very large, "swamping" the ability to estimate process error variance—the random effects model produced good predictions of single realizations that estimated the known underlying distribution of true survival probabilities. When sampling error swamped process error the predictions remained relatively unbiased, but conservative with regard to variability of the prediction (overestimated variance of the underlying distribution).

Appendix 7-2: Monte Carlo simulation study of performance of random effects and traditional multiple regression models

Limitations of the study reported here will be addressed by additional Monte Carlo investigations in the future:

- In order to hold the amount of process error constant in any given simulated data set, we chose regression coefficients that gave expected survival near 0.50, and distributions of survival that were essentially unconstrained on both sides. In reality, reach survival probabilities are closer to 1.0, and true probabilities are constrained by 1.0 (probability can't exceed 1). Scenarios with more realistic survival probabilities will investigate behavior of the models when process error is not equal in all iterations.
- In all results reported here, the model that was estimated was the "correct" model – including all of the covariates, and only those covariates, that generated the data. We will investigate the effects of estimating the "wrong model"—either overspecifying by estimating parameters for covariates that were not used to generate the data, or omitting predictors we know to be important.
- In general, the efficacy of model selection using random effects models can be studied in more depth.
- In the study reported here, predictions based on the random-effects model were very nearly the same whether we based the variance-covariance of the regression coefficients on estimated process error only or on the total variance including effect of sampling variance. This study was unable to resolve the issue of which variance-covariance to use. Further investigation is needed to determine whether this is always the case or an artifact of the limited number of scenarios we investigated here.
- We need Monte Carlo simulation of scenarios where process error is present but the estimate of process variance from random effects model is likely to be zero. This will lead to rules to use for prediction when the estimate from data is equal to or near zero, as in our observed data set for steelhead in the lower river.

Appendix 7-2: Monte Carlo simulation study of performance of random effects and traditional multiple regression models

Table A7 11. Means of variances of prediction distributions for means and single realizations across 230 cohort-reach combinations.

		Prediction Based on Random Effects Model						Prediction Based on Weighted Least Squares Model	
		Process Error Variance Only			Total Variance				
Number Tagged	Process Error Variance σ^2	Mean of Distribution	Single Realization	90% Range for Single	Mean of Distribution	Single Realization	90% Range for Single	Total Variance	90% Range
N_{obs}	0	0.00026	0.00040	(0.00013, 0.00065)	0.00052	0.00066	(0.00016, 0.00120)	0.00057	(0.00004, 0.00111)
N_{obs}*10	0	0.00003	0.00004	(0.00001, 0.00006)	0.00005	0.00006	(0.00001, 0.00011)	0.00006	(0.00001, 0.00012)
N_{obs}/10	0	0.00308	0.00458	(0.00156, 0.00722)	0.00584	0.00736	(0.00177, 0.01196)	0.00612	(0.00041, 0.01079)
N_{obs}	0.007	0.00092	0.00838	(0.00718, 0.00956)	0.00141	0.00884	(0.00719, 0.01042)	0.00224	(0.00027, 0.00401)
N_{obs}*10	0.007	0.00050	0.00751	(0.00665, 0.00822)	0.00061	0.00766	(0.00666, 0.00852)	0.00175	(0.00023, 0.00336)
N_{obs}/10	0.007	0.00432	0.01309	(0.00844, 0.01678)	0.00737	0.01610	(0.00879, 0.02234)	0.00826	(0.00065, 0.01503)
N_{obs}	0.070	0.00513	0.07573	(0.06651, 0.08179)	0.00616	0.07713	(0.06851, 0.08833)	0.02214	(0.00310, 0.04043)
N_{obs}*10	0.070	0.00399	0.07335	(0.06520, 0.07928)	0.00426	0.07382	(0.06633, 0.08097)	0.02227	(0.00337, 0.03993)
N_{obs}/10	0.070	0.01112	0.08234	(0.06832, 0.09525)	0.01551	0.08658	(0.06682, 0.10232)	0.03116	(0.00425, 0.05367)

Appendix 7-2: Monte Carlo simulation study of performance of random effects and traditional multiple regression models

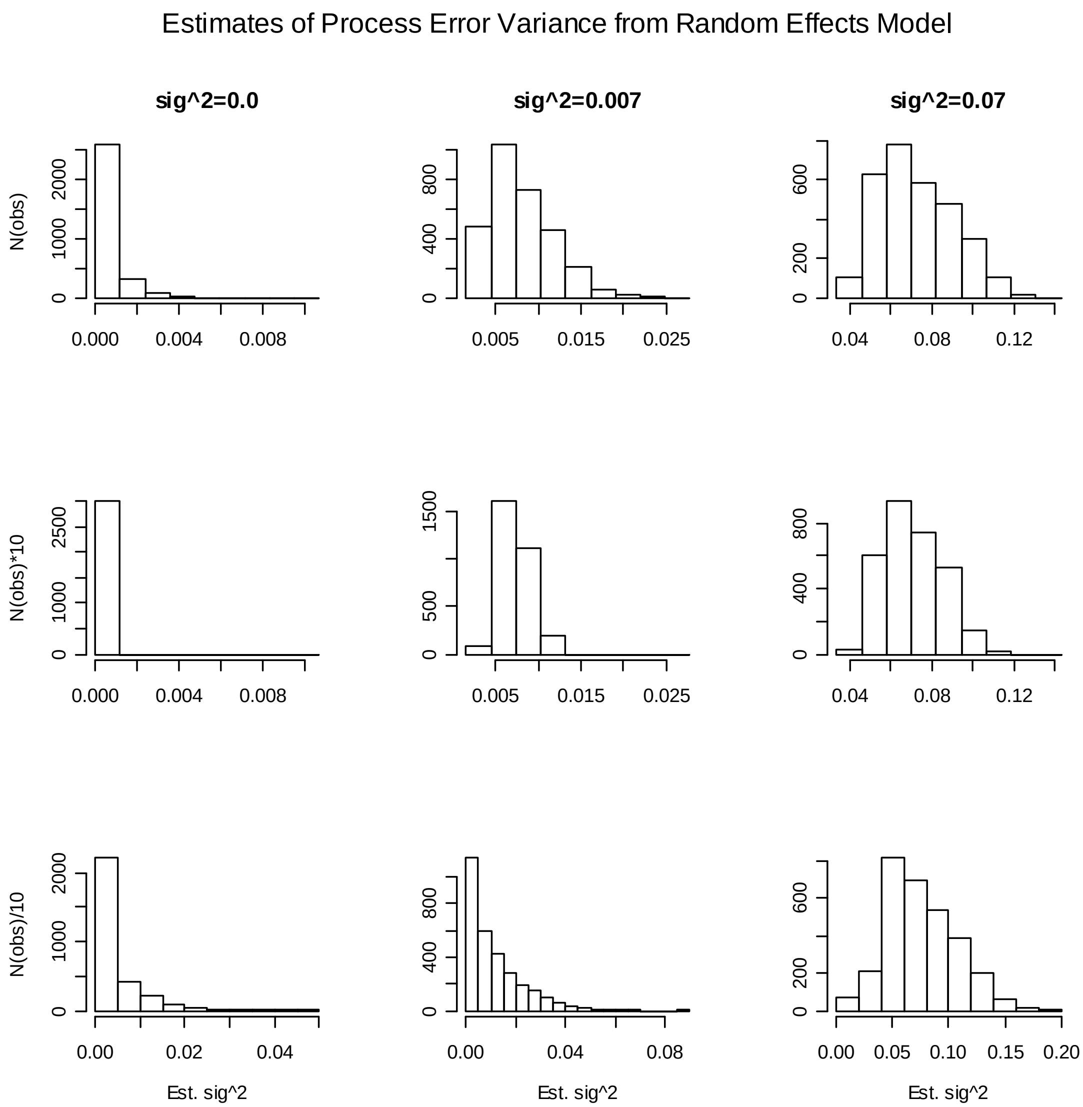


Figure A7 5. Distributions of estimated process error variance from 1,000 iterations of each of nine scenarios. Top row (number tagged = N_{obs}) and middle row (number tagged = $N_{obs}*10$) have same x-axes. Distributions in bottom row (number tagged = $N_{obs}/10$) have much greater variability and wider x-axes.

Appendix 7-2: Monte Carlo simulation study of performance of random effects and traditional multiple regression models

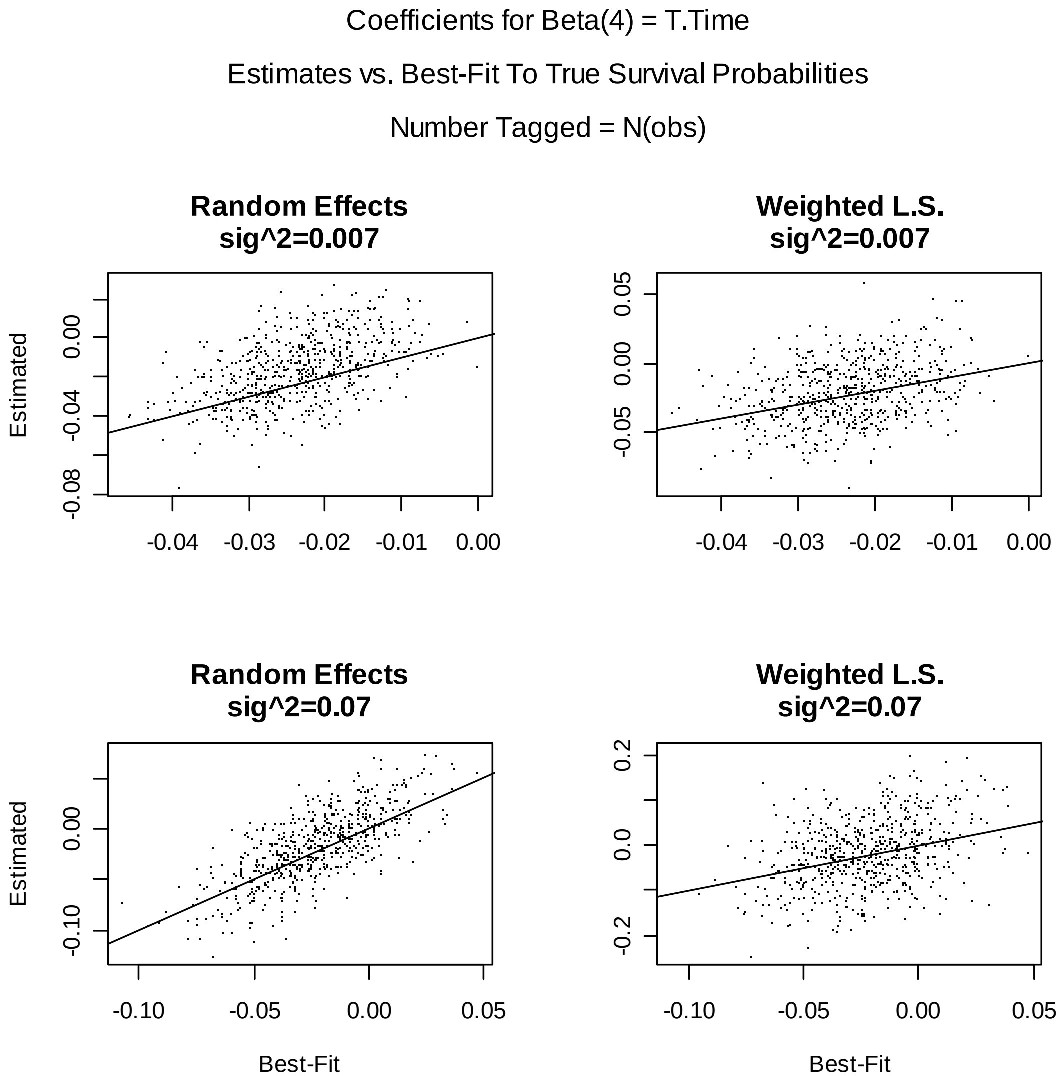


Figure A7 6. Scatterplots of estimated regression coefficient for Travel Time vs. coefficient of best-fit line to true response variables from 1,000 iterations of each of two scenarios with numbers tagged equal to the numbers tagged in the observed data set. Line indicates Y=X. Scenario with no process error is not shown because X=best-fit coefficient is the same for all Monte Carlo iterations.

Appendix 7-2: Monte Carlo simulation study of performance of random effects and traditional multiple regression models

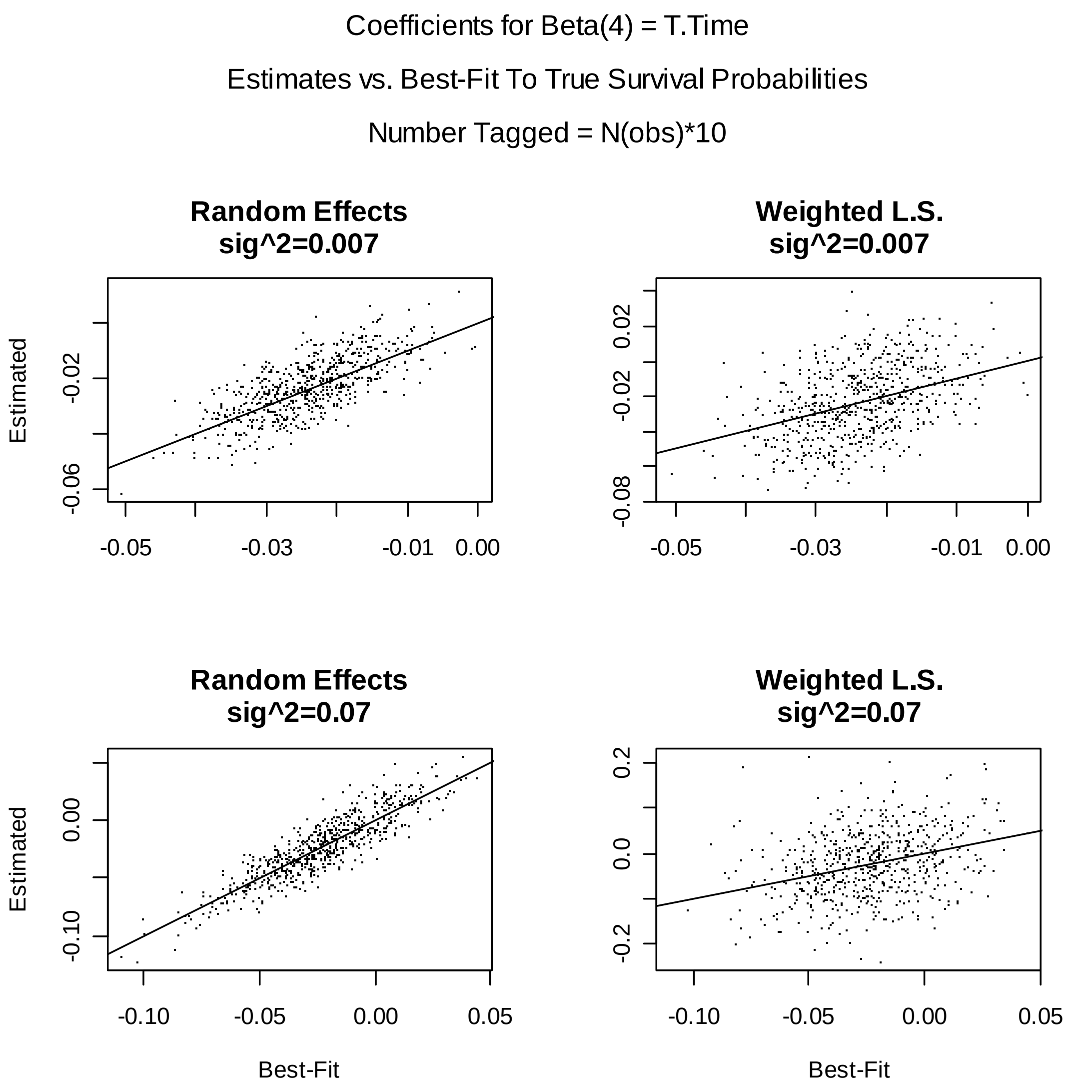


Figure A7 7. Scatterplots of estimated regression coefficient for Travel Time vs. coefficient of best-fit line to true response variables from 1,000 iterations of each of two scenarios with numbers tagged equal to 10 times the numbers tagged in the observed data set. Line indicates Y=X Scenario with no process error is not shown because X=best-fit coefficient is the same for all Monte Carlo iterations.

Appendix 7-2: Monte Carlo simulation study of performance of random effects and traditional multiple regression models

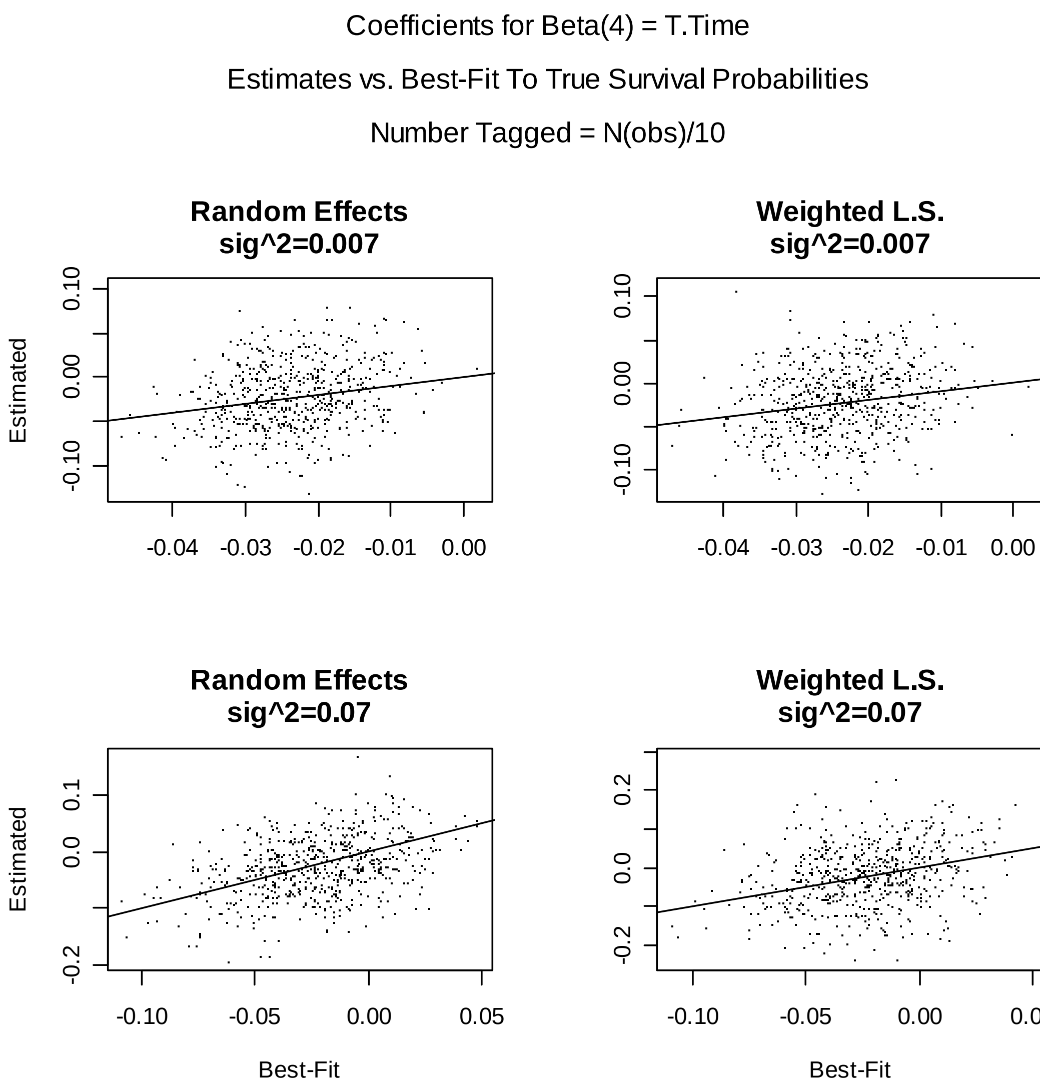


Figure A7 8. Scatterplots of estimated regression coefficient for Travel Time vs. coefficient of best-fit line to true response variables from 1,000 iterations of each of two scenarios with numbers tagged equal to one-tenth the numbers tagged in the observed data set. Line indicates Y=X. Scenario with no process error is not shown because X=best-fit coefficient is the same for all Monte Carlo iterations.

Appendix 7-2: Monte Carlo simulation study of performance of random effects and traditional multiple regression models

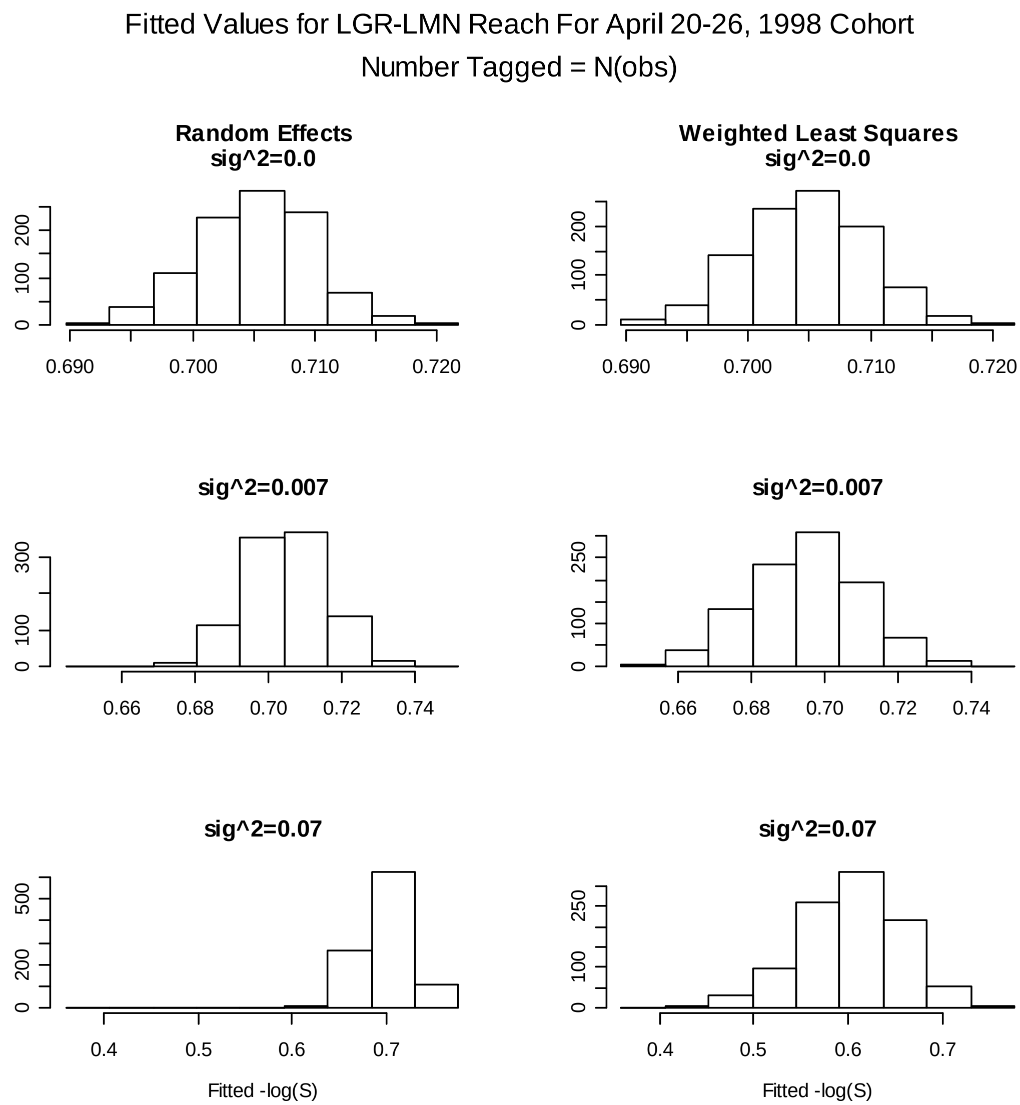


Figure A7 9. Distributions of estimated fitted values for first reach for cohort leaving Lower Granite Dam April 20-26, 1998 from 1,000 iterations of each of three scenarios with numbers tagged equal to the numbers tagged in the observed data set. Fitted values estimated from random effects model (left column) or weighted least squares model of the same Monte Carlo data set.

Appendix 7-2: Monte Carlo simulation study of performance of random effects and traditional multiple regression models

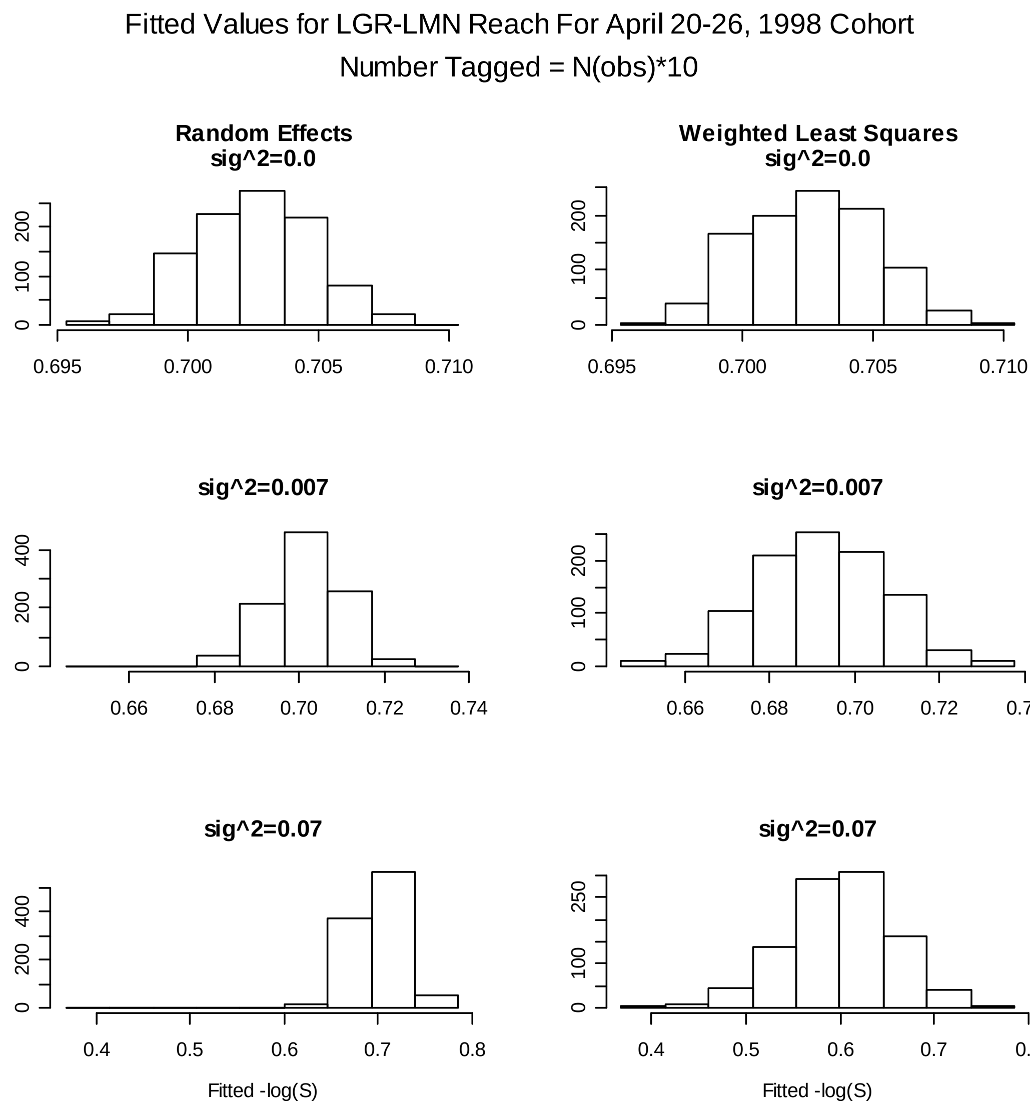


Figure A7 10. Distributions of estimated fitted values for first reach for cohort leaving Lower Granite Dam April 20-26, 1998 from 1,000 iterations of each of three scenarios with numbers tagged equal to 10 times the numbers tagged in the observed data set. Fitted values estimated from random effects model (left column) or weighted least squares model of the same Monte Carlo data set.

Appendix 7-2: Monte Carlo simulation study of performance of random effects and traditional multiple regression models

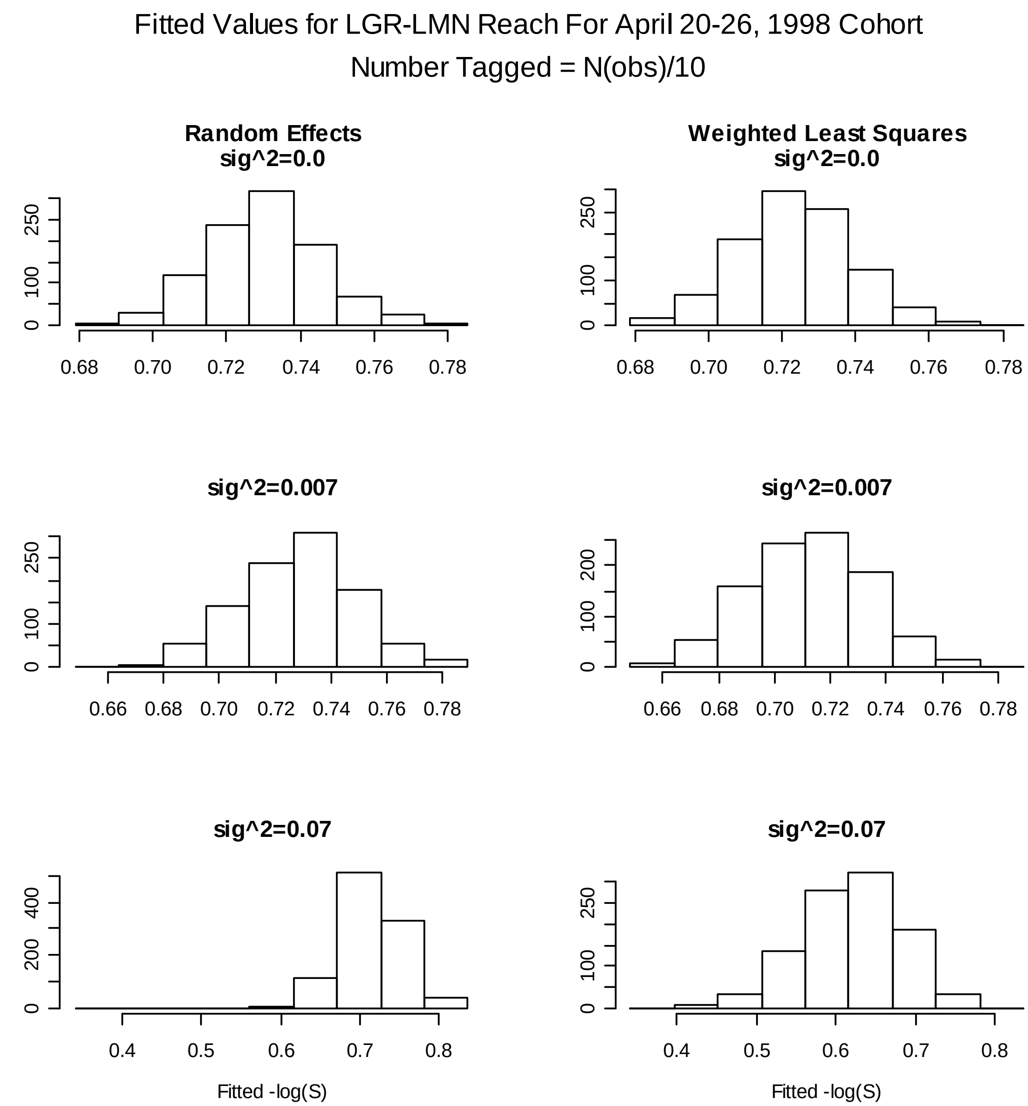


Figure A7 11. Distributions of estimated fitted values for first reach for cohort leaving Lower Granite Dam April 20-26, 1998 from 1,000 iterations of each of three scenarios with numbers tagged equal to one-tenth the numbers tagged in the observed data set. Fitted values estimated from random effects model (left column) or weighted least squares model of the same Monte Carlo data set.

Appendix 8-1: Introduction and COMPASS model results
Appendix 8-2: Post-Bonneville prospective modeling
Appendix 8-3: Prospective hydrological modeling

Introduction

In the appendix, we present results from prospective modeling conducted for the FCRPS Biological Opinion (BiOp). The purpose of the prospective modeling is to predict changes in survival (both within the hydrosystem and outside the hydrosystem) when comparing a "Base Case" scenario to the "Proposed Action" under the Biop. The Base Case is based on 2004 river operations, and the Proposed Action represents the suite of hydrosystem action proposed under the draft Biop. Relative to the Base Case, the Proposed Action has more spill and typically begins transportation later in the season. Details of the operations associated with the proposed action can be found in the draft BiOp. The final version of the Biop will likely have further modifications to the Proposed Action. Thus this section is intended to demonstrate the methodology rather than serve as a final place for results.

As described in Appendix 8-3, the modeling is based on an historic 70 year (1929-1998) water record. The natural runoffs are modified by the HYDSIM model according to storage reservoir operations to produce modeled flows that reflect current reservoir operations. The flows are further modified to project daily flows, temperatures and spill patterns according to hydrosystem operations, as described in Appendix 8-3.

For each model year, we initiated modeling with an arrival distribution at Lower Granite Dam forebay. To determine the arrival distribution for each prospective year, we developed an algorithm based on recent years' distributions. First, we estimated arrival distributions of wild fish at Lower Granite Dam based on collection count data provided by the Fish Passage Center (FPC) and estimates of daily capture probabilities from PIT tagged fish. Years with data for wild Snake River Spring/Summer Chinook were 1995 to 2006. FPC did not separate hatchery (clipped) and wild (unclipped) steelhead in their collection counts in all years. Years with data for wild Snake River steelhead where the collection started during or before the first week of April were 1990-1991, and 1995-2002. However the FPC smolt index was used for steelhead in 1990-1991 because there were no PIT tag capture probability estimates available for those years. For each species and year we calculated the median day of passage at LGR and the mean daily flow (kcfs) between April 1 and June 20 (Table 1). We regressed median passage day on mean flow to estimate prediction equations for median day of passage. Results of linear regressions are shown in Tables A8-1 2 and 3. Plots of data and regression lines are shown in Figures A8-1 1 and 2.

We used the daily passage proportions, shifted by the yearly median passage date, to calculate an average passage profile across the available years for each species. This profile reflects the spread of arrival timing across a season. To predict daily passage proportion we first predicted the median day of passage using the prediction equations from the linear regression, and then shifted the average smolt passage profile so that the median passage day matches the median predicted by regression. Figures A8-1 3 and 4 show cumulative passage plots for the results of using this method to predict daily passage in the years used in model estimation.

In this first part of the appendix, we present results for prospective COMPASS modeling. The downstream component of COMPASS utilized the "best fit" parameters contained in the main text (Tables 3 and 4). The post-Bonneville return rates were based on a mean (across 4 or 5 years) return rate versus arrival date relationship. To determine this mean, we developed yearly relationships (as described in Appendix 8-2), and calculated the mean of each of the three parameters with each year weighted equally. In Appendix 8-2, we describe how we modeled the uncertainty about the post-Bonneville relationships.

Table A8-1 1. Median passage day (julian) and mean daily flow (April 1 – June 20) for wild Snake River Spring/Summer Chinook and wild Snake River Steelhead.

		Median Day of Passage	
Year	**Mean Flow**	**Chinook**	**Steelhead**
1990	67.95	NA	128*
1991	64.40	NA	134*
1995	96.26	123	128
1996	133.79	114	124
1997	155.87	113	119
1998	110.75	121	124
1999	113.65	120	133
2000	84.09	122	NA
2001	47.47	134	NA
2002	83.44	119	NA
2003	89.99	122	NA
2004	70.13	119	NA
2005	66.31	125	NA
2006	125.30	119	NA

*Passage profile based on FPC smolt index.

Table A8-1 2. Parameter estimates and standard errors from regressions of median passage day on mean flow for Snake River Sp/Su Chinook.

	Estimate	**Std. Error**	**t-value**	**P-value**
Intercept	134.8841	3.18422	42.36	<0.0001
Flow	0.1424	0.03107	4.583	0.00101

Residual standard error: 3.197 on 10 df
R-Squared: 0.6775
F-statistic: 21.01 on 1 and 10 df, p-value: 0.001006

Table A8-1 3. Parameter estimates and standard errors from regressions of median passage day on mean flow for Snake River Sp/Su Steelhead.

	Estimate	**Std. Error**	**t-value**	**P-value**
Intercept	139.81291	5.24484	26.657	<0.0001
Flow	-0.11942	0.04748	-2.515	0.0535

Residual standard error: 3.861 on 5 DF
R-Squared: 0.5585
F-statistic: 6.325 on 1 and 5 df, p-value: 0.0535

Results of the prospective modeling

Inriver survival increased for both Chinook and steelhead when comparing the proposed action to the base case (Table A8-1 4 and Figures A8-1 4 and 5). This is primarily due to increased spill and improvements to the dams. Under both alternatives, inriver survival was quite variable from year to year, which is consistent with the data. The proposed action begins transportation later in the season compared to the base case, and the decreased proportion of fish destined for transportation under the proposed action is consistent with this. Arrival timing of transported fish was shifted later in the season under the proposed action.

Relative return rates (from Bonneville dam to Lower Granite Dam) increased for both inriver and transported Chinook under the proposed action, due to increased inriver survival and shifts in arrival timing, leading to an overall return rate increase of 7.5% (Table A8-1 5, Figure A8-1 6). However, for steelhead, although return rate of inriver fish increased substantially, the overall return rate decreased by 5.09% (Table A8-1 5 and Figure A8-1 7). This was because transported fish typically return at a greater rate than inriver fish (see Appendix 8-2 and Appendix 9), and the proposed action transported fewer steelhead.

Discussion

The proposed action resulted in a tradeoff between increased performance by Snake River spring/summer Chinook and decreased performance of steelhead, according to the COMPASS model results.

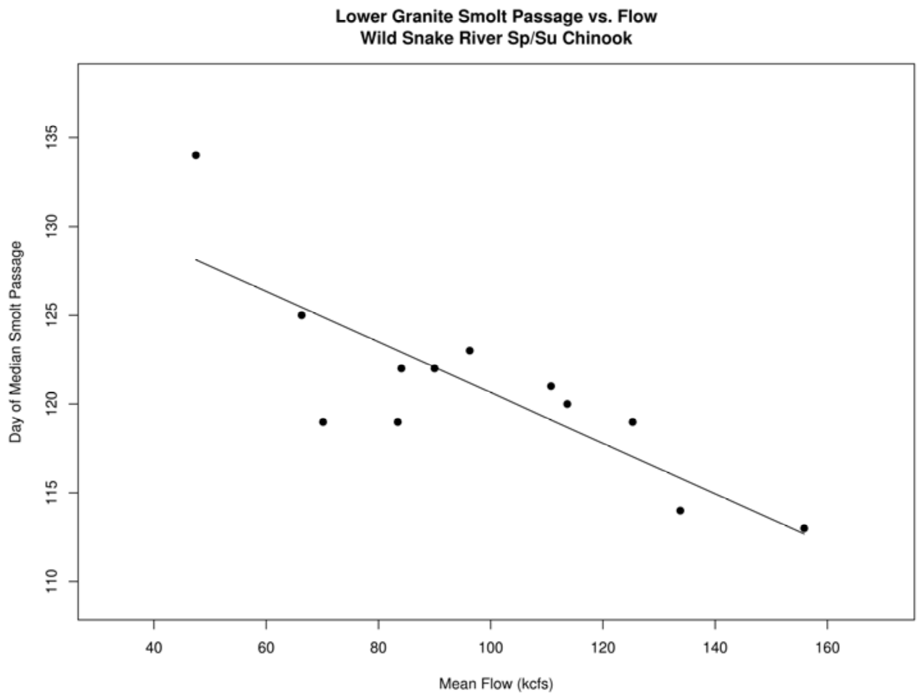
Although the method for estimating arrival distribution was relatively crude, it represented the year to year variability in arrival distribution reasonably well. This is important because arrival timing can interact with actions, such as transportation, that have a temporal aspect. In particular, fish arrive later in lower flow years, and this needs to be taken into account in devising management plans. We intend to explore these relationships more fully in the future.

Table A8-1 4. Prospective modeling results for the downstream migration component of COMPASS. Base Case reflects 2004 river operations, and Proposed Action represents operations under the draft FCRPS BiOp. These results are updated from the draft Biop with the updated COMPASS model.

	Snake River sp/su Chinook			Snake River steelhead	
	Base Case	Proposed Action		Base Case	Proposed Action
In-river Survival	0.487	0.557		0.319	0.369
Proportion destined for Transportation	0.746	0.677		0.853	0.780
Median Bonneville arrival date (in-river migrants)	141.2	141.2		138.7	137.2
Median Bonneville arrival date (transported fish)	127.6	130.9		133.3	135.1

Table A8-1 5. Prospective modeling results – relative (Proposed Action to Base Case) adult return rates. Base Case reflects 2004 river operations, and Proposed Action represents operations under the draft FCRPS BiOp. These results are updated from the draft Biop with the updated COMPASS model.

	Snake R. sp/su Chinook	Snake R. steelhead
Relative post-Bonneville return rate for in-river migrants	8.80	13.55
Relative post-Bonneville return rate for transported fish	2.63	-1.23
Relative total return rate (LGR to LGR) for all fish	7.50	-5.09



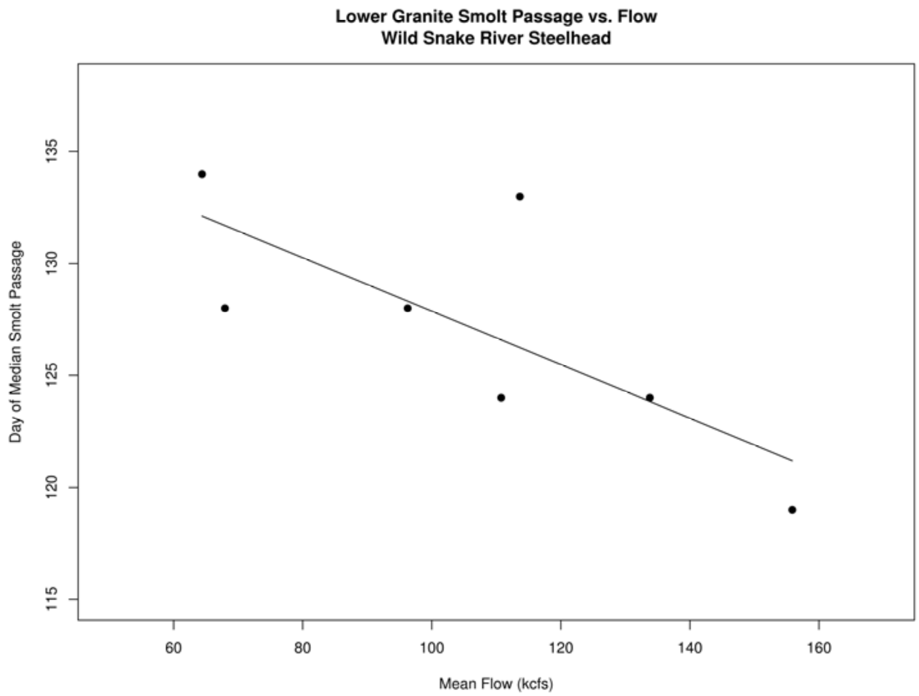


Figure A8-1 1. Median passage date at Lower Granite Dam versus mean flow for wild Snake River spring/summer Chinook (top plot) and steelhead (bottom plot).

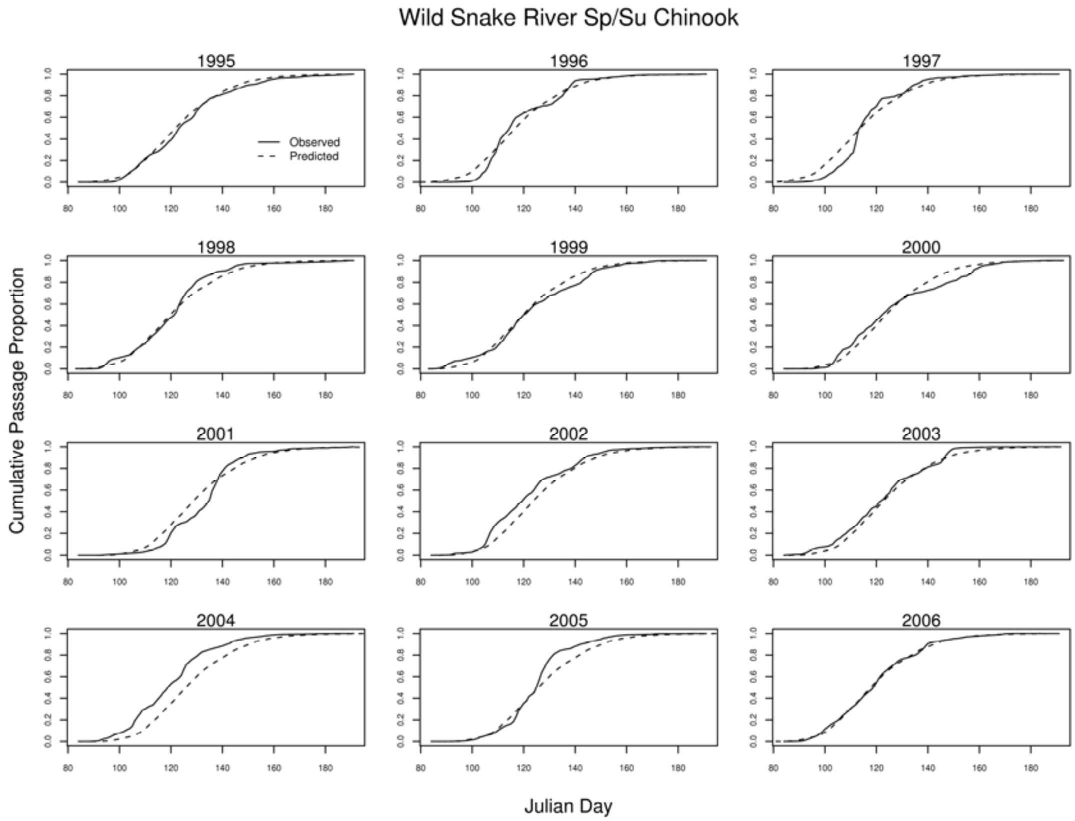


Figure A8-1 2. Estimated (dashed line) cumulative arrival distribution at Lower Granite Dam versus observed distribution (solid line) for wild Snake River spring/summer Chinook.

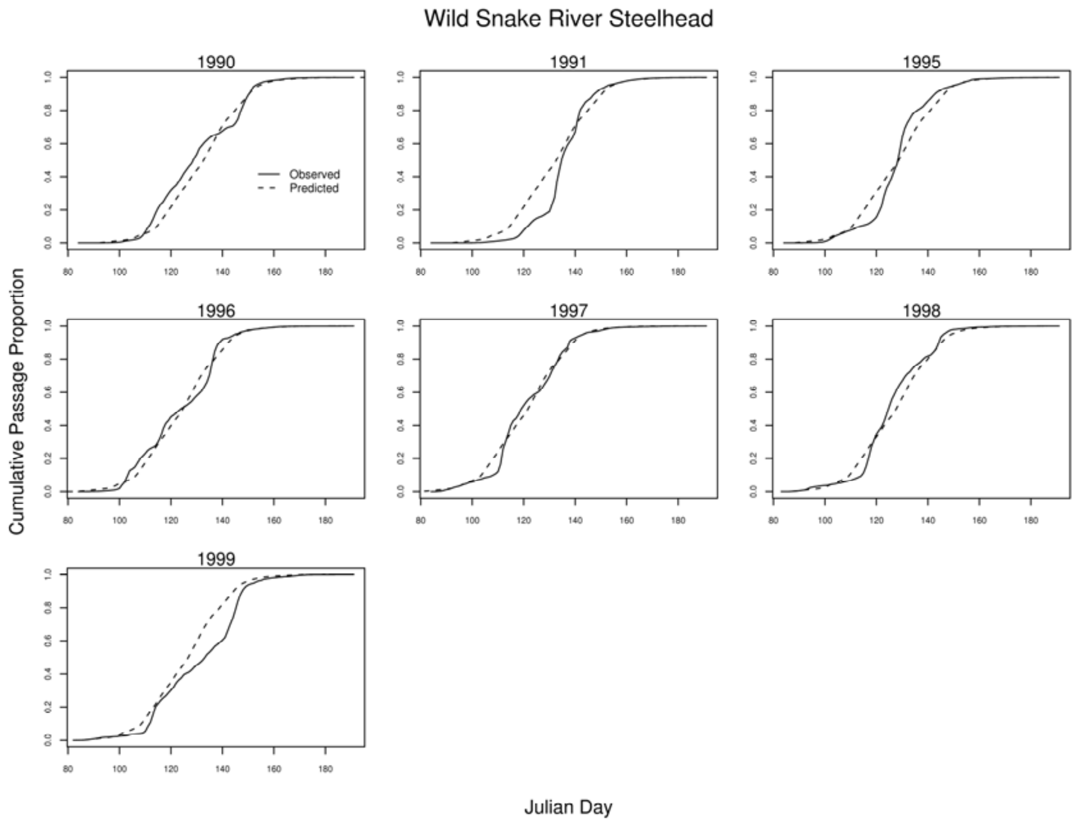


Figure A8-1 3. Estimated (dashed line) cumulative arrival distribution at Lower Granite Dam versus observed distribution (solid line) for wild Snake River steelhead.

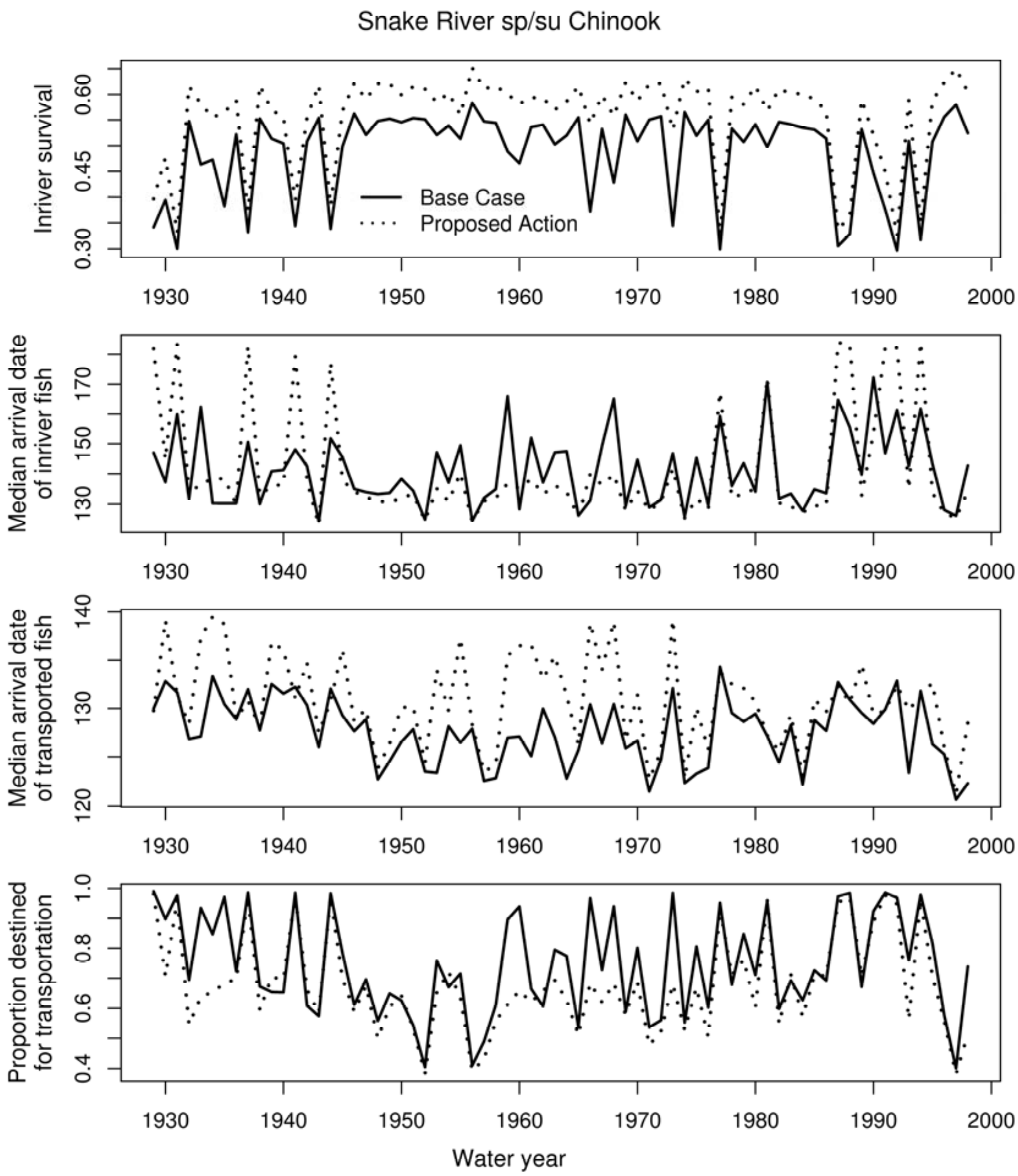


Figure 8-1 4. Prospective modeling results (juvenile downstream migration) for Snake River spring/summer Chinook salmon over the 70 year (1928-1997) water record for the 2004 Base Case (solid line) and Proposed Action (dashed line).

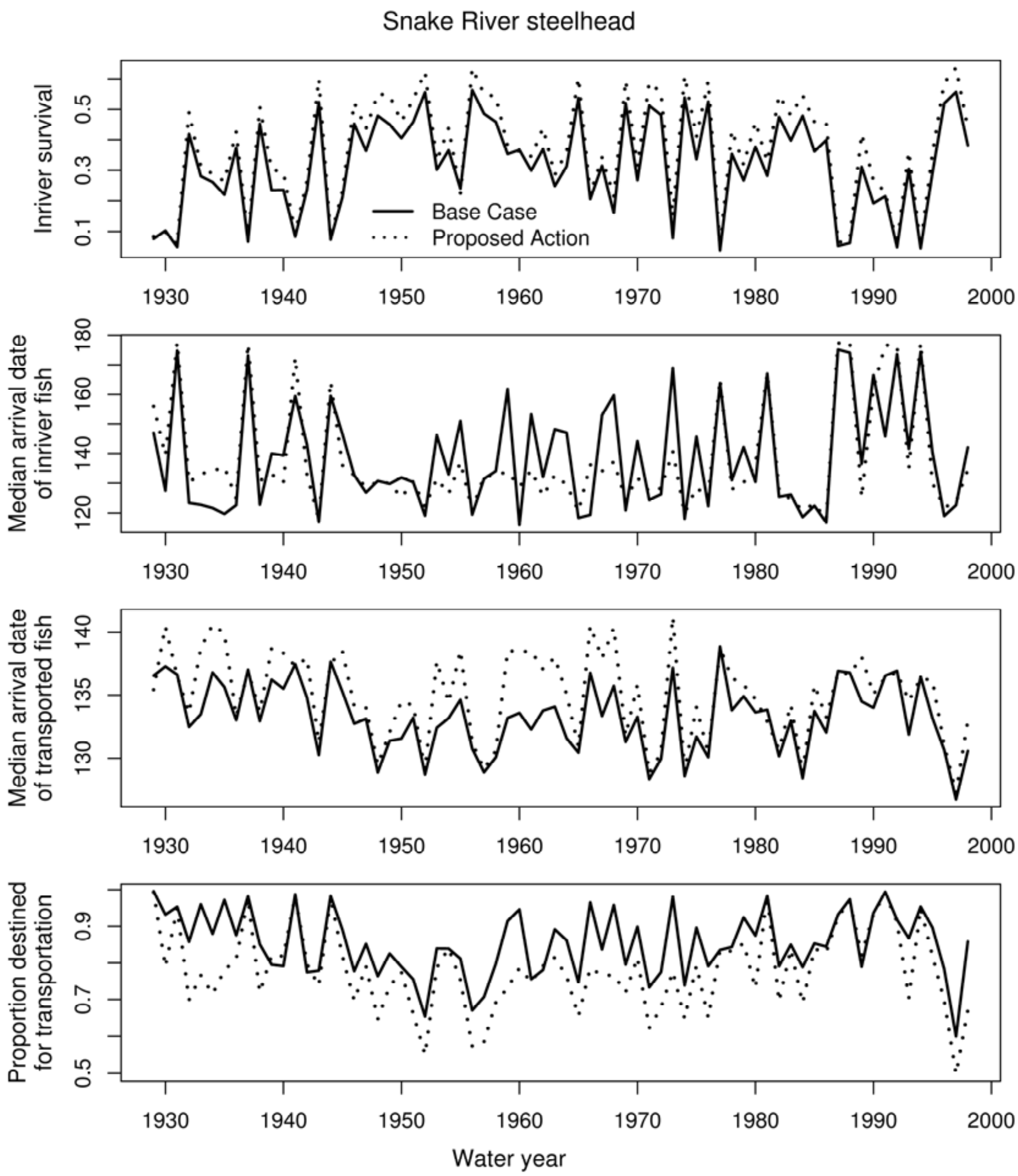


Figure 8-1 5. Prospective modeling results (juvenile downstream migration) for Snake River steelhead over the 70 year (1928-1997) water record for the 2004 Base Case (solid line) and Proposed Action (dashed line).

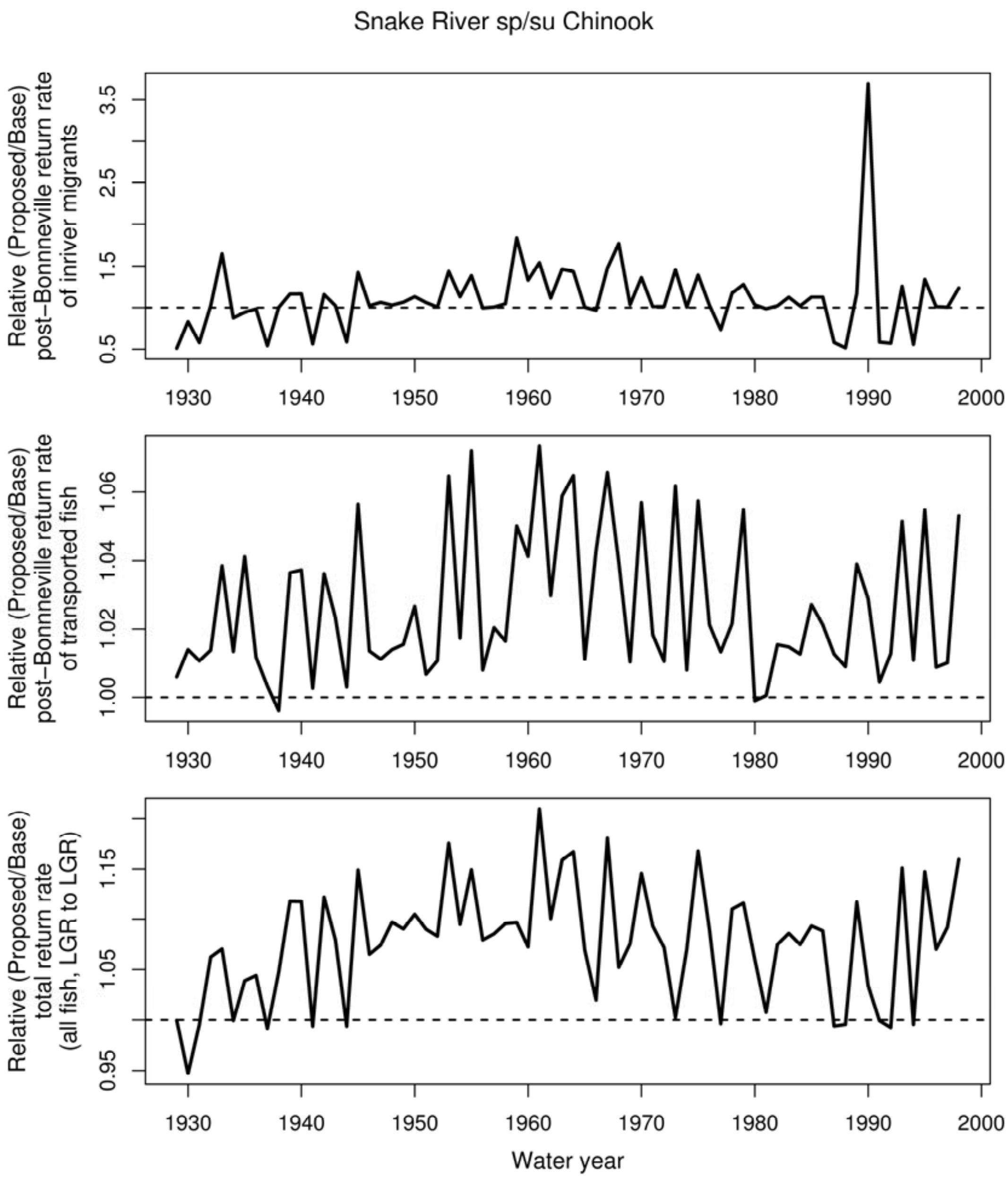


Figure 8-1 6. Prospective modeling results (post-Bonneville survival) for Snake River spring/summer Chinook salmon over the 70 year (1928-1997) water record for the 2004 Base Case (solid line) and Proposed Action (dashed line).

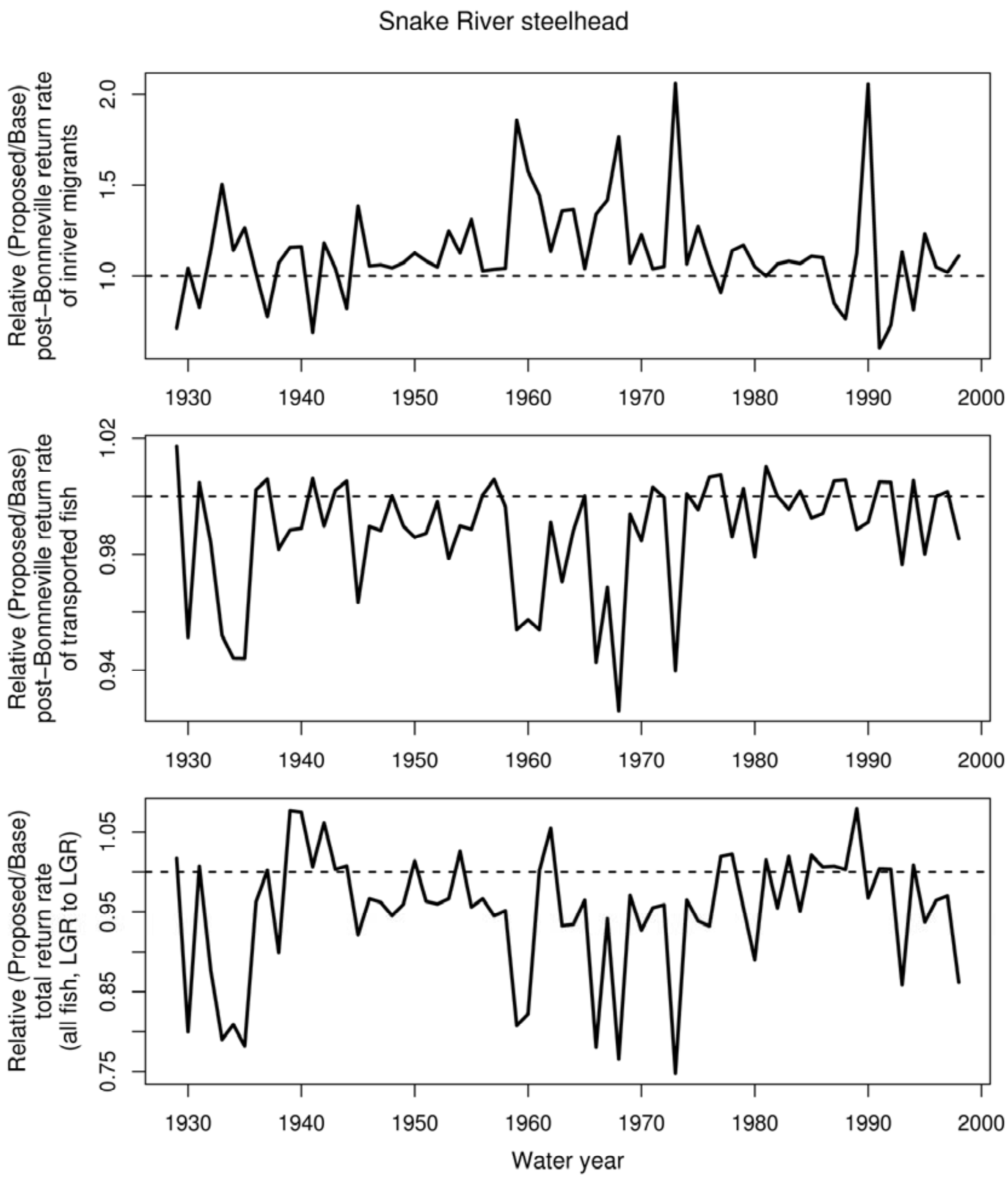


Figure 8-1 7. Prospective modeling results (post-Bonneville survival) for Snake River steelhead over the 70 year (1928-1997) water record for the 2004 Base Case (solid line) and Proposed Action (dashed line).

Introduction

In this appendix, we describe methods used to relate smolt-to-adult return rate (to Lower Granite Dam) to arrival timing below Bonneville Dam for both in-river migrants and transported fish. The analyses were based on return rates of PIT-tagged individuals that were either detected at (in-river migrants) or transported to a release point below Bonneville Dam. The analyses used four (juvenile migration) years of data for steelhead and five years for Chinook. The main goal of the modeling is to predict differences in return rates of Snake River spring/summer Chinook and steelhead corresponding to alternative hydrosystem operations that affect arrival timing.

In addition to characterizing arrival timing effects, we also characterized the uncertainty in the data. This uncertainty arose from three sources: 1) year-to-year variability in return rates and relationships; 2) uncertainty about yearly relationships; and 3) model uncertainty (i.e., uncertainty about which form of the model to use). As described below, we incorporated all three sources of uncertainty into our prospective modeling.

Before proceeding, we make the following clarifications. First, we note that the analysis is based on juveniles passing Bonneville Dam and returning to Lower Granite Dam. Thus, these analyses alone do not provide direct information on the efficacy of transportation as a function of date at the transport sites (Lower Granite Dam, Little Goose Dam, and Lower Monumental Dam). The analysis is intended to be coupled with the downstream migration component of COMPASS to address such questions. Similarly, the ratio of return rates from Bonneville for transported to inriver fish (referred to as “D”) does not directly determine the efficacy of transportation. Instead, D should be compared to the ratio of inriver migrants to the survival of fish during barging (typically assumed to be 0.98). If D is greater than this survival ratio, then transportation will return more fish than an inriver migration strategy. We illustrate this type of comparison in the analyses that follow.

Methods

Data source and classification

Data were extracted from the PTAGIS database for all wild, Snake River spring/summer Chinook salmon and steelhead PIT-tagged at or upstream of Lower Granite Dam (LGR) from migration years 1998-2003 (corresponding to adult return years 1999-2006). Transported fish were assigned an arrival date below Bonneville Dam (BON) equal to two days after they were loaded onto the barge and were assumed to have 100% survival in the barge. Arrival timing of in-river migrants was defined as the date of detection at BON. We used adult detections at LGR and assumed that their detection probability was 100%. We used years where 10 or more adults returned from both in-river and transported groups. Uncertainty about predicted relationships was too great when sample sizes were small. This resulted in 4 years of data (1999-2000 and 2002-2003) for steelhead and 5 years (1998-2000 and 2002-2003) for Chinook. Data summaries for both species are provided in Tables A8-2 1 and 2.

Model formulation, model assessment, and parameter estimation

Because all of our data are based on individually PIT-tagged fish, we treated the individual fish as the unit of comparison in our survival analyses. This greatly increased sample size over other approaches that lump fish into groups before calculating smolt-to-adult return rates for the groups. Because the data were binary, with individuals taking on a value of 1 (returned) or 0 (did not return), we used logistic regression (Hosmer and Lemeshow 2000) to investigate relationships between probability of returning as an adult and the predictor variables. The explanatory variables were year and day of arrival below Bonneville Dam (measured as number of days past April 1). We separately analyzed in-river migrants and transported fish. We used the R statistical software package to perform the analyses.

With logistic regression, the response probability *p* (i.e., probability of return) is modeled as a function of an explanatory variable, *x*, as:

(1)
$$p(x) = \frac{\exp(\beta_0 + \beta_1 \cdot x)}{1 + \exp(\beta_0 + \beta_1 \cdot x)} + \varepsilon \ .$$

Unlike standard linear regression where the error term is normally distributed, the error term is binomially distributed in the logistic regression model. Alternatively, the logit transformation, $g(x)$, yields a linear response:

(2)
$$g(x) = \ln\left[\frac{p(x)}{1 - p(x)}\right] = \beta_0 + \beta_1 \cdot x \ .$$

We considered a "full" model that included a grand mean (μ), categorical year effects (ψ_y), and the day of arrival at Bonneville (d). We included the quadratic term for day, d^2, so that the effect would not necessarily be strictly increasing or decreasing. Further, we allowed for possible interactions between year and d, and between year and d^2. Although this function applied to both species, here we drop the subscript for simplicity. Thus, for either species, our full model for a specific year (y) with all interaction terms was:

(3)
$$g_y(d) = \mu + \psi_y + (\phi + \phi_y) \cdot d + (\theta + \theta_y) \cdot d^2 \ .$$

Those parameters in the model without subscripts correspond to the earliest year of data in the analysis with all other years having an additional offset denoted by the subscript y. We tested a sequence of alternative models, refereed to in shorthand as follows:

Model 1) $g(d) = \mu$ (grand mean model)
Model 2) $g(d) = year$ (year effects model)
Model 3) $g(d) = year + date$ (year + date model)
Model 4) $g(d) = year * date$ (year/date interaction)
Model 5) $g(d) = year + date + date^2$ (year + date + date-squared)

Model 6) $g(d) = year*(date) + date^2$ (year/date interaction + date-squared)

Model 7) $g(d) = year*(date + date^2)$ (year/date and year/date-squared interactions)

The "+" means the terms were additive in the model, and the "*" means there was an interaction between terms. We always included main effects along with any interactions. For each model, we estimated all parameters and the variance-covariance matrix (***VC***) for the parameters. The uncertainty in the parameter estimates was represented using a multivariate normal distribution with mean vector equal to the parameter estimates and covariance matrix equal to the estimated ***VC***.

To assess each model, we calculated its AIC value and its ΔAIC relative to the model with lowest AIC (i.e., the best fitting model). Also, there is a trend in ecological studies toward recognizing that several alternative models can perform similarly well, and that there may not be a single "best" model (Johnson and Omland 2004). The method of AIC-weights is used to assess how models perform relative to the "best" model:

(4) $$w_i = \frac{\exp(-\Delta_i / 2)}{\sum_{j=1}^{M} \exp(-\Delta_j / 2)}$$

where M is the total number of models considered, and Δ_i is the difference in AIC between model i and the one with the lowest AIC (Burnham and Anderson 2002). The denominator normalizes the weights so their sum is 1.0. The weights are sometimes interpreted as estimates of the probability that any particular model is the "best" one among the suite of alternative models considered in the candidate set.

Implementing the model in prospective runs

For a give scenario, the downstream migration component of COMPASS produces the arrival timing below Bonneville for both in-river migrants and transported fish. For prospective modeling, we applied the post-Bonneville relationships to these arrival timing distributions to predict adult return rate under alternative hydrosystem operations. To account for uncertainty in the models, we used a Monte-Carlo approach by repeatedly (10,000 times) applying random samples of the post-Bonneville relationships and then compiling the range of results produced. Because a great deal of year-to-year variability exists in adult return rates and relationships, for each iteration we first selected a year, *y*, from the range of years available in the analyses. We applied the selected year pairwise to both the in-river group and transported groups in to reflect the large degree of correlation between return rates of in-river and transported fish within individual years. After selecting the common year, we treated in-river and transported fish separately. The next step was to select a model from the suite of models tested, as described. We randomly selected the model according to its weight; that is, we selected model *i* with probability equal to its AIC weight. Finally, given the selected year and model, we randomly drew model parameters from the estimated multivariate normal distribution of the parameters. To perform this last step, we had to reduce the parameter sets and ***VC*** matrices for the multi-year models to represent single years. For each year, we combined parameters (main effects and yearly offsets) to produce a three-parameter model describing the relationship for the given year and a corresponding 3x3 $\boldsymbol{VC}_y$. The three-parameter model is as follows:

(6) $$g_y = \beta_{1y} + \beta_{2y} \cdot d + \beta_{3y} \cdot d^2$$

Once we selected the parameters, we back-transformed the logit-transformed response variable to probability of return for fish arriving on day *d* as follows:

(5) $$p_y(d) = \frac{\exp[g_y(d)]}{1 + \exp[g_y(d)]} \ .$$

When we were specifically comparing a base-case scenario to an alternative scenario, we applied the same parameters to both scenarios in an iteration of the Monte-Carlo simulations. We then computed differences in adult return rates under identical post Bonneville conditions.

Results

The data for these analyses were extensive (Tables A8-2 1 and 2). For in-river migrating Chinook, 28,195 individuals were detected at Bonneville, and 609 adults returned to Lower Granite. For transported Chinook, 97,113 juveniles were released, and 994 returned. For in-river migrating steelhead, 17,747 juveniles were detected, and 442 of those returned as adults. For transported steelhead, 96,140 juveniles were released, and 2,398 adults returned.
We found highly significant variation in SAR (probability of return) within (dy effects) and across years (year effects) for both Chinook salmon and steelhead, whether they migrated in-river or were transported (see Scheuerell and Zabel 2006 for results). In general, return rates decreased toward the end of the migratory season. In some cases, the earliest arriving fish also performed relatively poorly (Figures A8-2 1 and 2).

In all cases, the best performing model contained a year effect and date and date^2 effects (Tables A8-2 3-6). In fact, models that did not contain these three terms had little to no weight. In all cases, models with some sort of year/date interaction received considerable weight, indicating that the nature of the relationship with date varied from year to year. In addition, strong year effects were revealed by the large decrease in AIC when comparing model 2 (year model) to model 1 (grand mean model).

To demonstrate the Monte-Carlo simulation of post Bonneville survival, we plotted 100 realizations of the simulations (Figure A8-2 3 and 4). The realizations demonstrate that the approach captures model uncertainty. We also plotted the realizations of seasonally varying "D", which is the ratio of post Bonneville survival for transported to in-river migrants. Although D is quite variable, it typically increases toward the end of the migration season.

To demonstrate the utility of these analyses for management purposes, we compared our distributions of D to the mean estimates of inriver survival from the prospective analyses presented in the preceding section. We first computed seasonally varying percentiles of the random D relationships (Figures A8-2 5 and 6) and compared these percentiles to inriver survival. We then determined the proportion of seasonally varying D relationships that were greater than inriver survival across the season. For Snake River spring/summer Chinook, before approximately May 15th, the proportion of times D was greater than inriver survival was less than 50%, implying that, on average, fish that arrived to Bonneville Dam before May 15th via inriver migration returned at a greater rate than their transported counterparts. However, after May 15th, transported fish arriving below Bonneville outperformed their inriver counterparts, and this advantage steadily increased as the season progressed. For steelhead, transported fish always outperformed their inriver counterparts by a wide margin, although this advantage decreased as the season progressed. We emphasize that these comparisons were based on when fish passed Bonneville Dam. Inriver migrants likely departed from Lower Granite Dam 2-3 weeks earlier.

When we implemented the variable post Bonneville return relationships in conjunction with COMPASS modeling of alternative hydro scenarios, it produced a 95% confidence interval of approximately ± 3% about the mean difference (across the 70 years water years) when comparing the proposed action to the base case scenario (Figure A8-2 5).

Discussion

This extensive data set revealed clear patterns of adult return rate versus time of arrival below Bonneville Dam. Several types of management actions will lead to changes in arrival timing below Bonneville Dam: flow augmentation (increases water velocity); increased spill (decreases delay at dams); installation of surface passage routes; lowering reservoir elevation (increases water velocity); and changing transportation timing. Thus the ability, demonstrated here, to account for how these actions translate into differential adult return rate is valuable for management. Further, understanding the magnitude of uncertainty associated with these predictions is also valuable information for management purposes.

To simplify the modeling, these simulations did not include two effects that were detected previously (Scheuerell and Zabel 2006). First, for transported steelhead, we detected differences in return rate depending on where the fish were transported from (not significant for Chinook). Also, for Chinook, return rate was significantly related to the number of times a fish was bypassed (not significant for steelhead). This bypass effect likely includes a size component – in general, smaller fish are bypassed at greater rates (Zabel et al. 2005) and smaller fish return at lower rates (Zabel and Williams 2002). COMPASS does not account for any size-related processes. In the future, we could include transportation site effects and bypass effects in the simulations for comparison purposes.

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Table A8-2 1. Summary of PIT-tag data for wild Snake River spring/summer Chinook salmon used in the logistic regression analyses.

	In-river		Transported	
Year	Smolts	Adult returns	Smolts	Adult returns
1998	2044	26	7829	52
1999	6619	214	11,848	268
2000	8109	267	17,956	297
2002	4785	84	25,847	290
2003	6638	18	33,633	87
Total	28,195	609	97,113	994

Table A8-2 2. Summary of PIT-tag data for wild Snake River steelhead used in the logistic regression analyses.

	In-river		Transported	
Year	Smolts	Adult returns	Smolts	Adult returns
1999	2555	39	7216	110
2000	7675	286	25,034	1119
2002	3939	86	26,604	522
2003	3308	31	21,254	275
Totals	17,747	443	96,140	2398

Table A8-2 3. Model assessment results Snake River spring/summer Chinook, in-river migrants. *w* is the AIC model weight.

Model	**ΔAIC**	***w***
mean	316.405	0.000
year	59.205	0.000
year + date	17.597	0.000
year*date	18.003	0.000
year + date + date^2	1.292	0.311
year*date + date^2	0.000	0.594
year*(date + date^2)	3.680	0.094

Table A8-2 4. Model assessment results Snake River spring/summer Chinook, transported fish. *w* is the AIC model weight.

Model	**ΔAIC**	***w***
mean	972.761	0.000
year	141.198	0.000
year + date	143.190	0.000
year*date	149.735	0.000
year + date + date^2	9.948	0.006
year*date + date^2	3.535	0.145
year*(date + date^2)	0.000	0.849

Table A8-2 5. Model assessment results Snake River steelhead, in-river migrants. *w* is the AIC model weight.

Model	**ΔAIC**	***w***
mean	115.255	0.000
year	23.469	0.000
year + date	12.284	0.002
year*date	14.298	0.001
year + date + date^2	6.701	0.031
year*date + date^2	0.000	0.875
year*(date + date^2)	4.505	0.092

Table A8-2 6. Model assessment results Snake River steelhead, transported fish. *w* is the AIC model weight.

Model	**ΔAIC**	***w***
mean	750.696	0.000
year	129.209	0.000
year + date	76.794	0.000
year*date	51.311	0.000
year + date + date^2	59.556	0.000
year*date + date^2	43.727	0.000
year*(date + date^2)	0.000	1.000

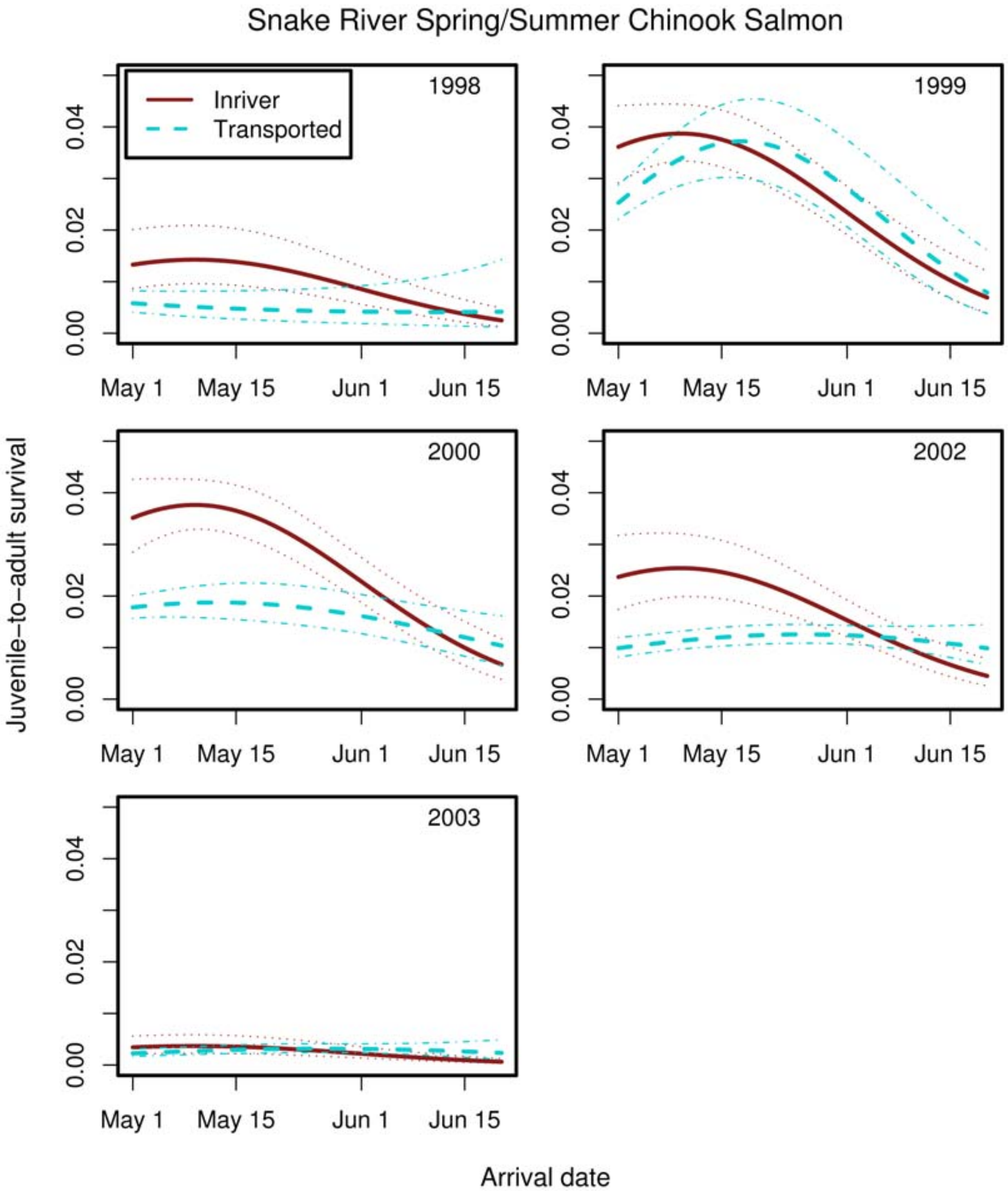

Figure A8-2 1. Relationships between juvenile-to-adult survival of Chinook salmon versus day of arrival below Bonneville Dam from 1998-2002 (minus 2001). Solid lines represent in-river migrants and dashed lines represent transported fish. Dotted lines denote the 95% C.I. about the mean response.

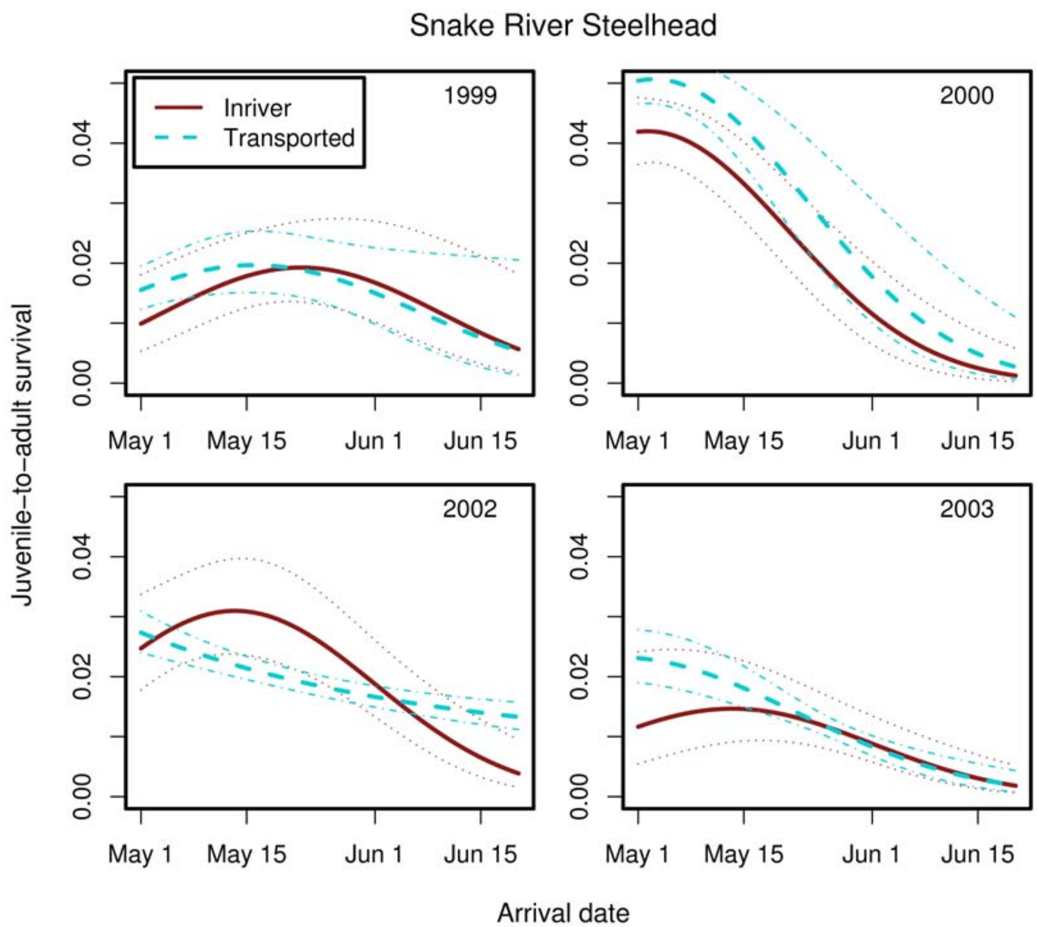

Figure A8-2 2. Relationships between juvenile-to-adult survival of Chinook salmon versus day of arrival below Bonneville Dam from 1998-2002 (minus 2001). Solid lines represent in-river migrants and dashed lines represent transported fish. Dotted lines denote the 95% C.I. about the mean response.

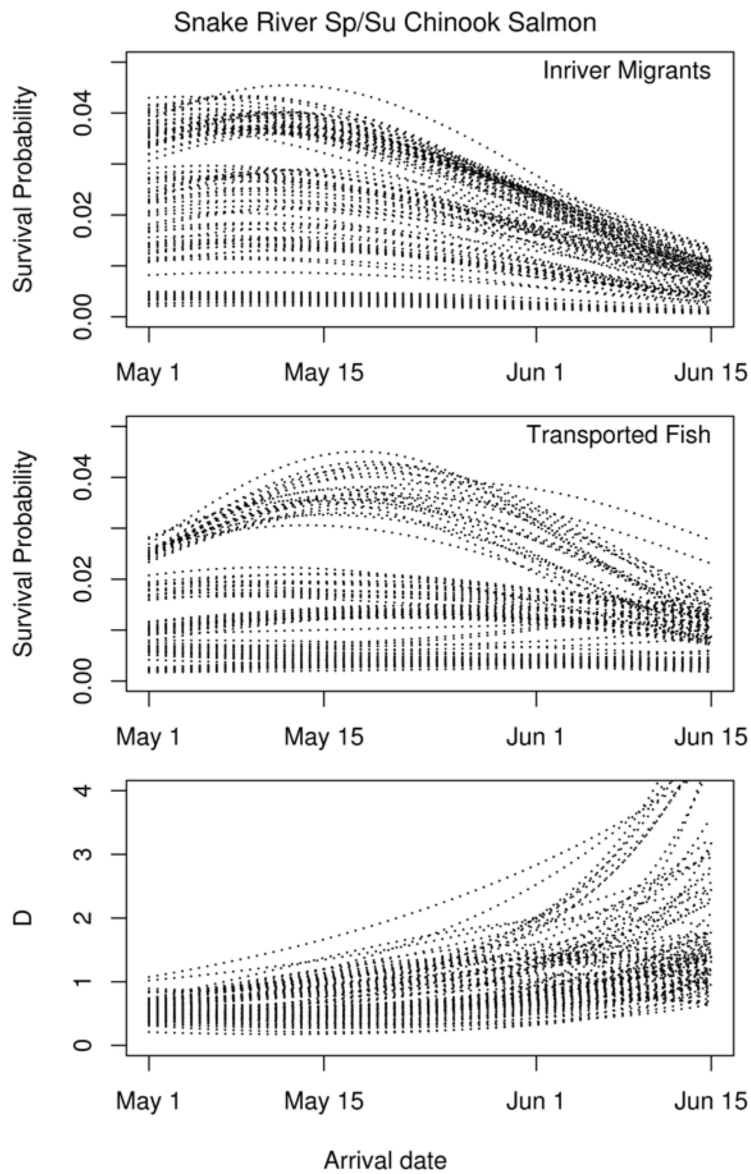

Figure A8-2 3. 100 random realizations of the post-Bonneville survival relationships for in-river migrants (top plot), transported fish (middle plot), and the ratio of post-Bonneville survival of transported fish to in-river migrants, or D (bottom plot) for Snake River spring/summer Chinook.

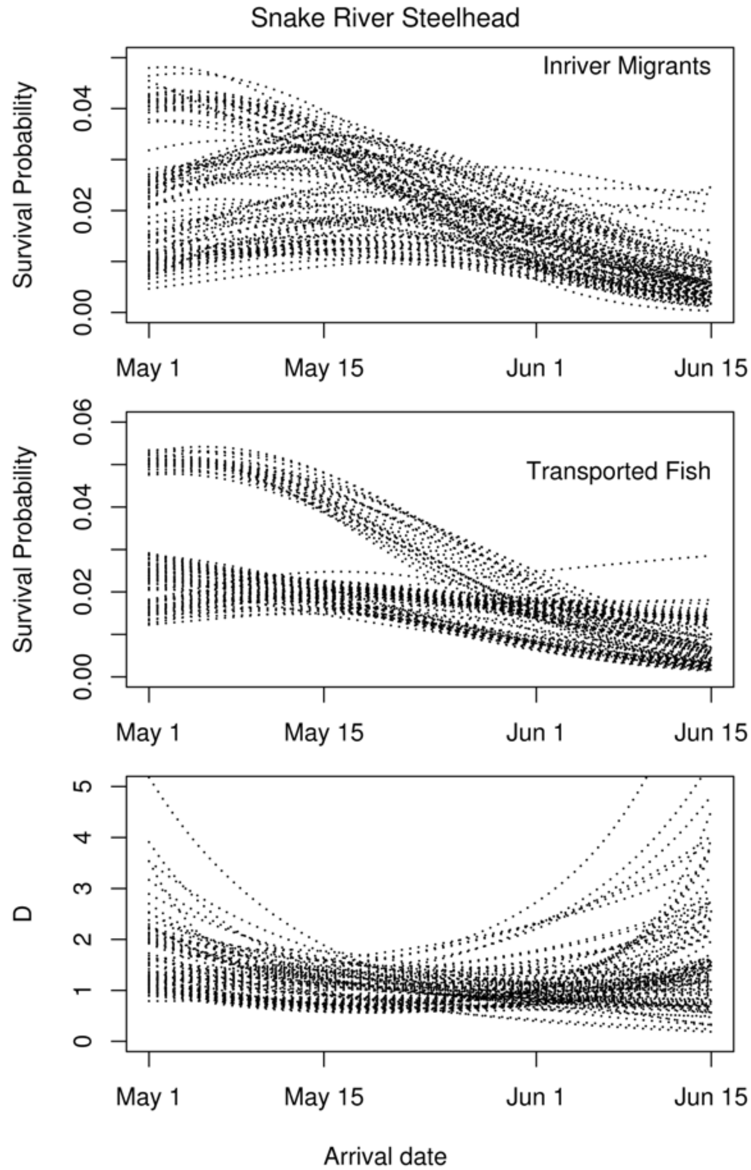

Figure A8-2 4. 100 random realizations of the post-Bonneville survival relationships for in-river migrants (top plot), transported fish (middle plot), and the ratio of post-Bonneville survival of transported fish to in-river migrants, or D (bottom plot) for Snake River steelhead.

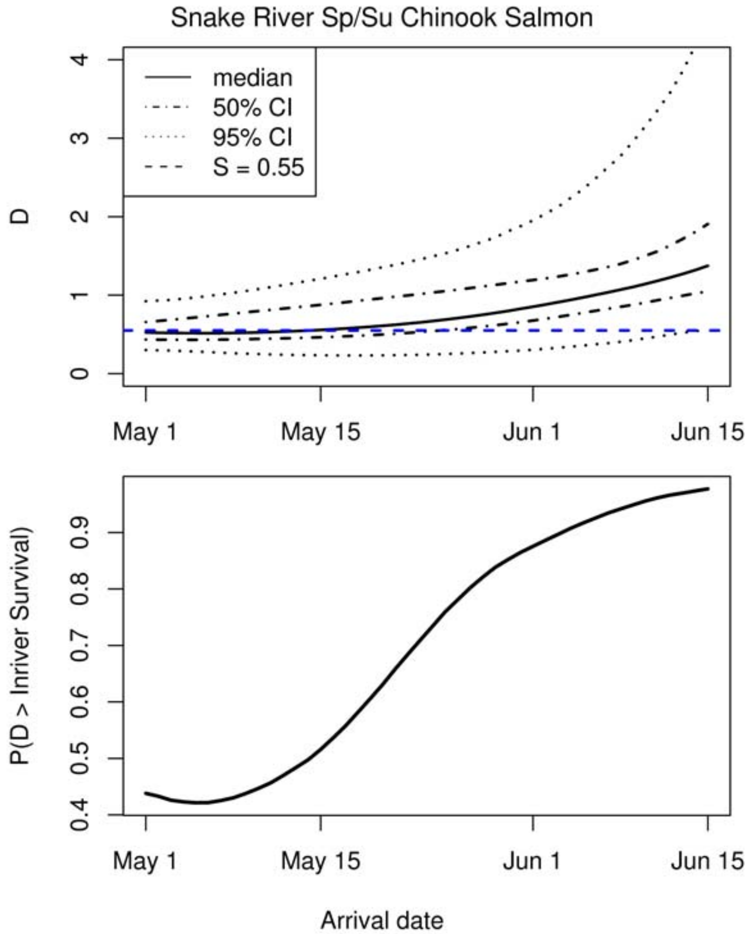

Figure A8-2 5. Top plot: median and 50% and 95% confidence intervals (CI) of the random seasonal D relationships for Snake River sp/su Chinook presented in Figure A8-2 3. The mean inriver survival from the prospective modeling (S = 0.55, dashed horizontal line) is plotted for comparison purposes. If D is greater than inriver survival, then transportation, on average, will return more fish to Lower Granite Dam than inriver migration. The bottom plot show the proportion and random realizations greater than inriver survival as a function of arrival date at Bonneville.

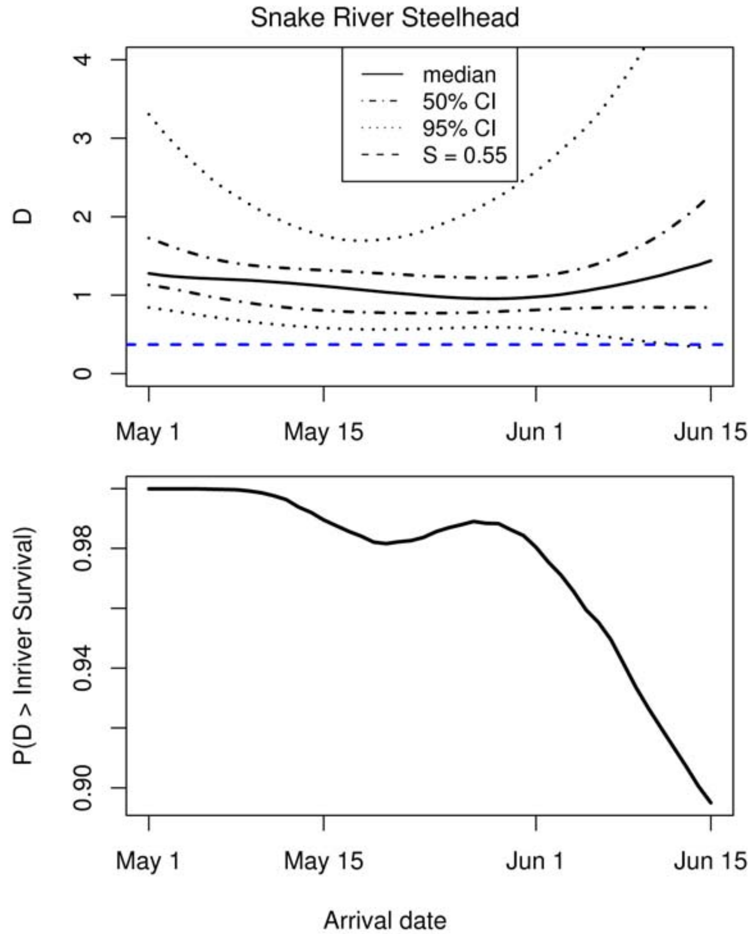

Figure A8-2 6. Top plot: median and 50% and 95% confidence intervals (CI) of the random seasonal D relationships for Snake River steelhead presented in Figure A8-2 4. The mean inriver survival from the prospective modeling (S = 0.55, dashed horizontal line) is plotted for comparison purposes. If D is greater than inriver survival, then transportation, on average, will return more fish to Lower Granite Dam than inriver migration. The bottom plot show the proportion and random realizations greater than inriver survival as a function of arrival date at Bonneville.

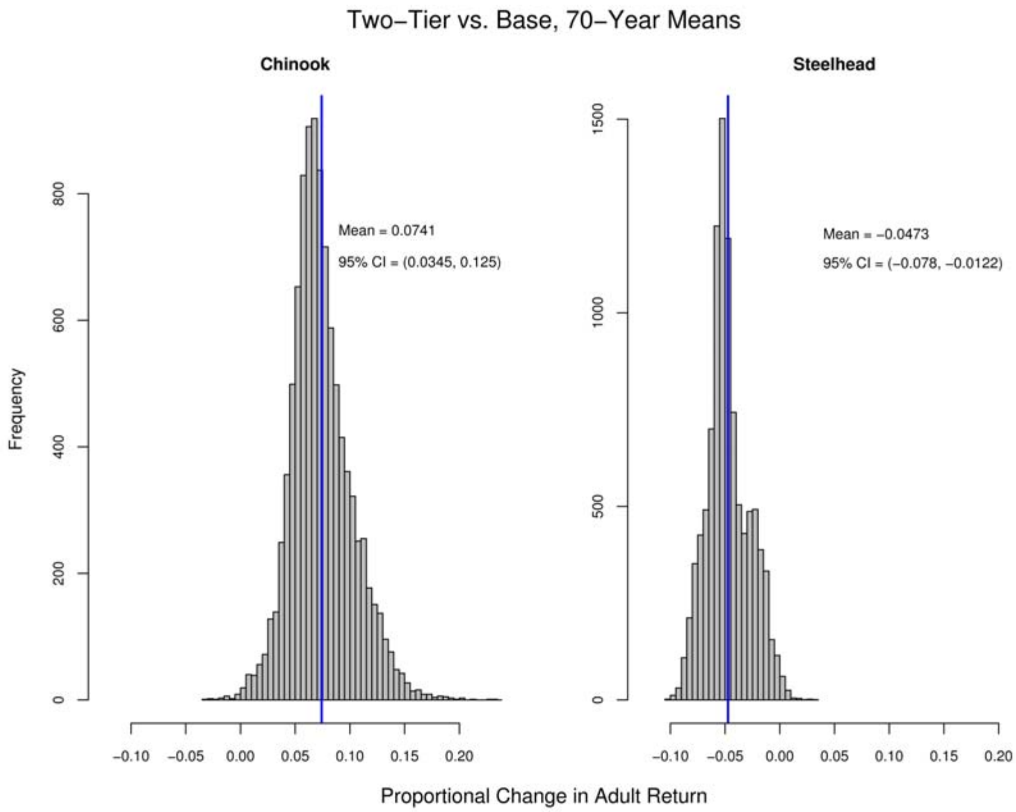

Figure A8-2 7. Distribution of mean (across the 70 simulation years) difference in predicted adult returns between proposed future operations and current operations. The distributions are based on 10,000 random realizations of the post-Bonneville survival relationships.

Introduction

HYDSIM, a hydrosystem simulation model, is used by BPA to translate flow and spill targets proposed in the BiOp into detailed hydro operations at both the eight dams passed by Snake River salmonids and many other storage and run-of-river dams throughout the Columbia Basin. With two exceptions, HYDSIM operates on a monthly time step, with April and August each split into two periods. In addition to an immense set of rules, designed to meet constraints on power supply, flood control, navigation, channel capacity, etc., it uses a 70-year water record, consisting of unregulated headwater flows for the Columbia and its tributaries, extending from 1929 to 1998. Given the rule set, unregulated flows, and physical constraints on reservoir capacities, turbine capacities, and system configuration (e.g., water flows from Lower Granite into Little Goose, but not *vice versa*), it produces monthly flow and spill at the run-of-river projects through which Snake and Upper Columbia chinook and steelhead pass from Lower Granite to Bonneville.

In contrast, COMPASS operates on a daily time step, and actual flows vary substantially from day to day (Figure 8-3 1). While one could feed COMPASS monthly flows without accounting for shorter-term fluctuations, the result would be month-long periods of constant flows with abrupt changes only occurring during the transition from one month to the next (Figure 8-3 2). Additionally, spill that was intended to start or stop within a period would only start or stop at the beginning or ending or a period.

Therefore, we developed a simple algorithm to shape monthly flows and spills into daily flows and spills that in turn are used as input for the passage model while ensuring that the COMPASS operations are consistent with the HYDSIM operations. The remainder of this memo describes requirements for the algorithm, the logic that underlies it, and back-checks performed to ensure that the requirements are in fact met in practice.

Daily shaper requirements

To be of practical use in the Biological Opinion and related analyses, the daily shaping algorithm needs to meet several requirements:

1. The monthly averages of daily total flow, spill, and turbine flow should conform to the monthly values produced by HYDSIM. This ensures that the operating strategies designed by policy makers are in fact being followed in COMPASS, and simplifies back-checking (i.e., ensuring that the flows fish see in COMPASS are those intended by the hydro modelers, on average).
2. Day-to-day flow and spill fluctuations should reflect realistic variations as seen in actual operations.
3. Daily fluctuations should apply to all projects simultaneously, to maintain a day-to-day mass balance and avoid water "piling up" behind one project while being drained away

from another. This also preserves the high correlations in flow and spill between projects (e.g., Figure 8-3 3).

4. The algorithm should be easy to apply to HYDSIM output, quickly taking the monthly flows and converting them to daily flow and spill. Furthermore, it should be reasonably easy to explain and easy to modify as policies and hydro operating strategies change over time.

Daily modulation algorithms and logic

The algorithm chosen for the draft and final Biological Opinion modeling, while not particularly elegant, appears to meet the requirements noted above. We matched the 70 HYDSIM output years to the past 11 years of actual flows based on annual April-June flow at McNary Dam (MCN) and professional judgment. We developed shaping factors in terms of percent variation from the month-average flows for each day within a period from the past 11 years' actual data. For instance, some days within a month may have had only 80% of the month average flow, while other days had 120%. The modulation ensures that the 70 water years' monthly output from HYDSIM are shaped within months to be similar to the past 11 years' actual daily operations. For each of the 70 water years, we employed these daily shaping factors to modulate monthly HYDSIM flows into realistic daily flows. We are confident that the fluctuations are reasonable because they are based on the fluctuations that actually occurred at MCN in the past 11 years. We used the same adjustment factor based on actual McNary data for all 8 projects in order to maintain a mass balance as noted in constraint (3).

Spill is characterized as forced (flow > turbine capacity); over generation (flow > required power generation at a dam); and bypass spill, intended solely to guide fish over spillways instead of through turbines. To provide daily spill amounts for COMPASS, HYDSIM's average percent spill for each period is applied to the daily modulated flows. Additionally, the period-average spill is shaped according to the type of spill and the dates to which it applies (e.g., some alternatives specify bypass spill to start and end within a month). For example, if the forced spill in a period was 10% of the total flow, the daily forced spill in that period was estimated as 10% of the daily (varying) flow. The same logic applies to over generation spill; if there was 5% period-average over generation spill, the daily over generation spill would be 5% of the daily flow. Daily fish bypass spill was estimated in a similar manner but compressed into the spill dates specified in the BiOp. Therefore, the period-average spill volume from HYDSIM would be maintained, and the fish bypass spill would occur only in the intended time interval, while other types of spill will occur throughout the month. For example, if HYDSIM indicated 40% fish bypass spill at Lower Granite in May, and the BiOp specified May fish bypass spill ended on May 15th, the spill on each day from May 1 through 14 was estimated as (40% spill) x (31 total days in May) / (14 days in May with fish bypass spill) x (daily flow). Then the different types of spill – forced, over generation, and bypass - were summed up on each day for the total daily spill input into the COMPASS model. Thus, daily spill estimates for COMPASS are realistically shaped while maintaining the volumes of spill developed from the 14-period 70-year record of the HYDSIM study.

The results appear to satisfy the design constraints, and to produce realistic daily modulations in flows. Figure 8-3 4 shows actual and HYDSIM-simulated, modulated flows at Bonneville for 1975. The correlation between the two is 0.991, and the overall patterns are generally similar. No unrealistically abrupt changes in flow between weeks or months are apparent. Back-checks show that the daily values average to within 0.1% of the monthly HYDSIM flow and spill for each dam, and month.

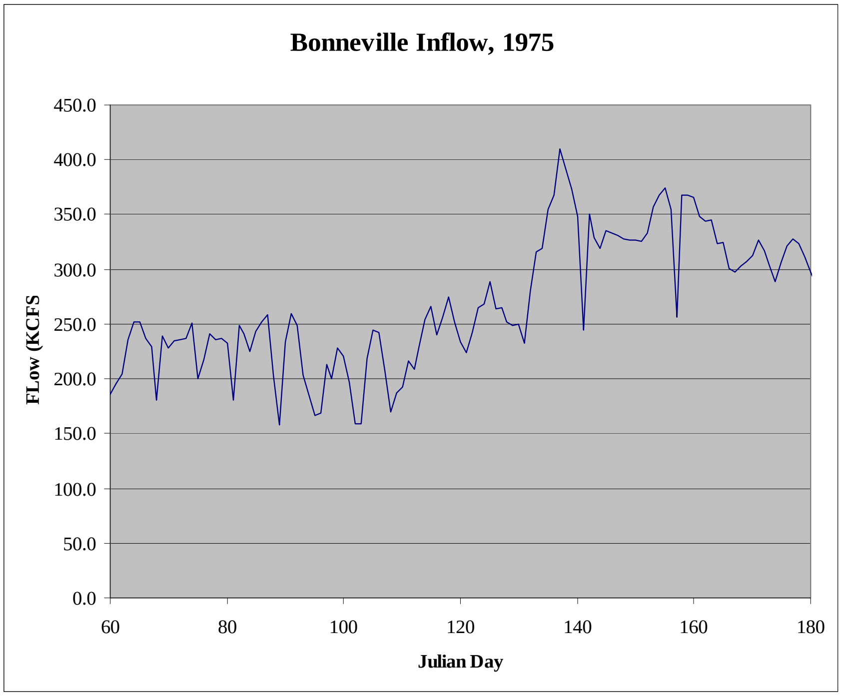

Figure 8-3 1. Daily average flows at Bonneville, 1975

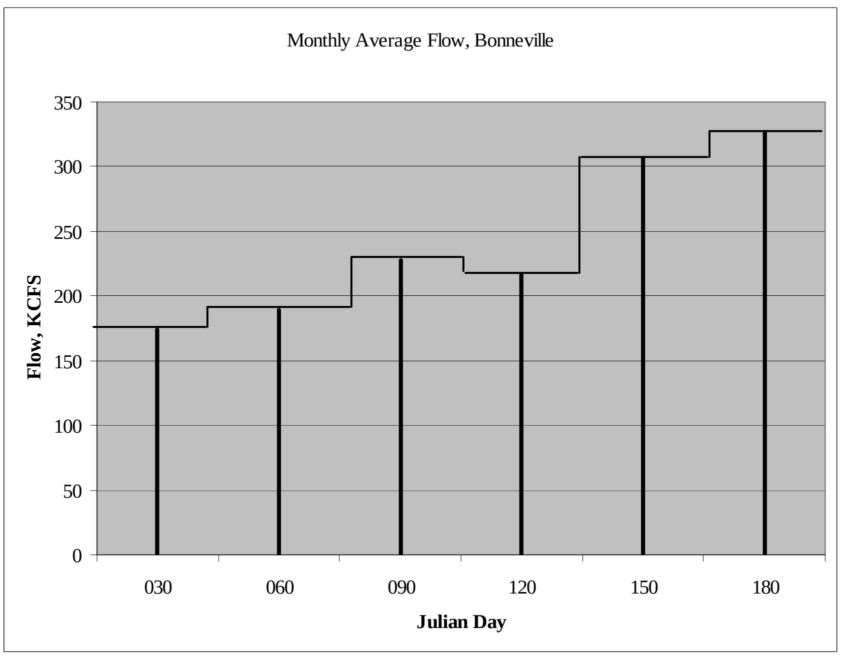

Figure 8-3 2. Month-average flows at Bonneville, 1975

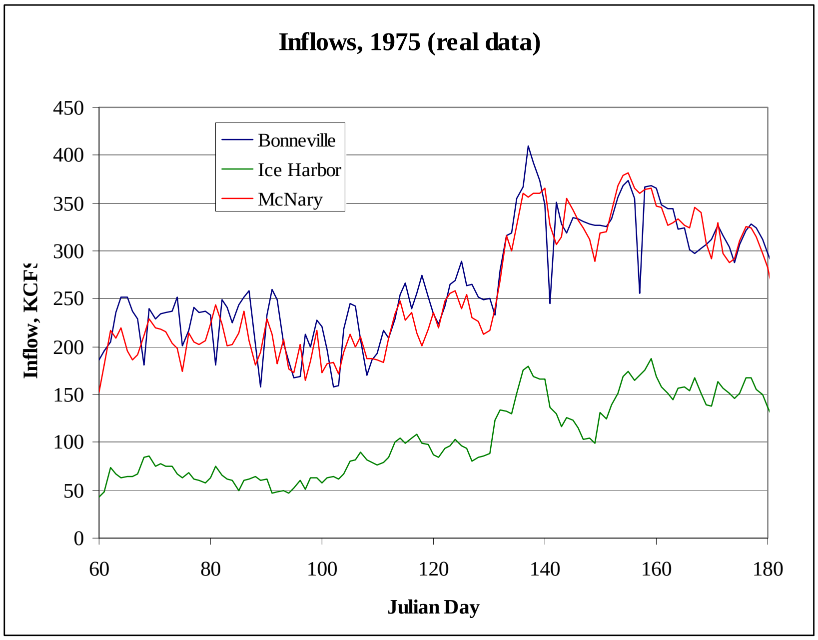

Figure 8-3 3. Inflows for Bonneville, McNary, and Ice Harbor, 1975.

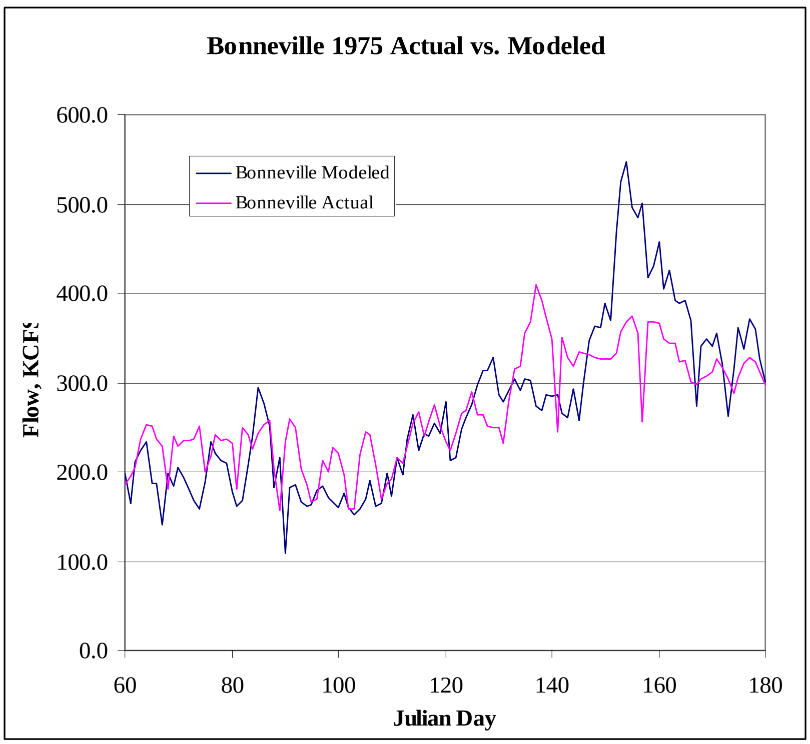

Figure 8-4 4. Actual vs. Modeled flows, Bonneville, 1975

Temperature Modeling

While the hydro simulation model (HYDSIM) will provide regulated inflows (water years 1928-1977) for COMPASS, it will not provide water temperatures, needed to drive the reservoir survival simulations. We decided to simulate water temperature on a daily time step (required by COMPASS) as a function of flow. Originally, we thought that the fastest way to proceed would be to map water years that have extensive survival estimates – 1995 to 2007 – to water years with no survival estimates, on the assumption that temperature profiles would be similar in years with similar flows. We ran DART queries (http://www.cbr.washington.edu/dart/dart.html) for temperature and flow at Lower Granite, McNary, and Bonneville for 1975 (1st year with extensive temperature monitoring) through 2005. Informal inspection of the results (e.g., Figures 8-3 5a and 5b) suggested that temperature profiles for two low-flow years were similar, but they are obviously not identical, despite having similar flow patterns.

In addition, the selection of matching years (e.g., 1975 is most like 2001) has an irreducible subjective element: different individuals examining the same data series might well arrive at different conclusions regarding how to match water years in the record. Given the importance of temperature for fish survival, we decided to make daily estimates of water temperature based on flows (from the modulated HYDSIM output) and long-term average temperatures.

The remainder of the appendix is divided into a Data section, where we discuss the historic fish, flow and temperature data used in the analysis, a Methods section describing the statistical models used to relate flow and temperature, a Results section with numerical results, and a Discussion section with some suggested next steps.

Data

Daily data for scroll case temperature and flow are available from DART from 1975, when Lower Granite was completed, through 2005 for all eight hydro projects that Snake spring-summer chinook and steelhead encounter in their downstream migration. While flow data (project inflow) is available for nearly all projects and days, temperature data are sparser. Scroll case readings, while not ideal as a surrogate for reservoir temperatures experienced by migrating smolts, extend farther back in time than other temperature data series. COMPASS uses WQM case temperatures in the calibration of reservoir survival functions. Where data are available for both, the correlation between them is very high.

We used daily flows at each project from 01/01 to 12/31 each year as our flow indicators, and relate this to daily scroll case temperature from 01/01-12/31 each year. We extracted data from Dart for daily temperatures and flow for all eight projects encountered by Snake migrants for 1975-2005 for the dates noted. In addition, we use long-term arithmetic averages of flow and temperature in the regression models.

Methods

We developed a simple model for daily temperature for each of the eight projects, as follows:

$$T_{j,n} = \alpha + \beta_1 * Q_n + \beta_2 * Q_n^2 + \beta_3 * Q_{j,n} + \beta_4 * \overline{Q}_j + \beta_5 * \overline{T}_j + \varepsilon_{j,n} \qquad \text{Eq. 8-3 1}$$

Where:

$T_{j,n}$ = Temperature, degrees C, year n, Julian day j
α = model intercept
Q_n *and* Q_n^2 are average daily flow, 1/1-12/31, and flow squared in year n,
in thousands of cubic feet per second (kcfs)
$Q_{j,n}$ = Actual daily flow at the project, Year n, Julian day j
$\overline{Q}_j$ = Average flow, 1975-2005, for day j
$\overline{T}_j$ = Average temperature, 1975-2005, for day j
β_1 *to* β_5 are estimated coefficients
$\varepsilon_{j,n}$ = error term, assumed randomly distributed with mean zero and variance σ^2.

Note that we one set of models for each of the eight dams. The model employed was selected in a stepwise regression using all combinations of the independent variables for each of the eight dams, with the difference in AIC between the full model in Eq. XX.1 and the next-best-fit, using AIC, generally > 10. This suggests that all of the independent variables in Eq. XX.1 are important, although more complex models than those considered might be supported by the data.

Results

Summary results are shown in Table 8-3 1. The models fit the scroll case temperature measurements quite well, with r-squares ranging from 0.93 to 0.97. At all eight projects, the estimated coefficient for flow, β_1, was negative and significant, while the coefficient for flow squared, β_2, was positive and significant. This suggests what while higher flows are associated with lower temperatures, there is an lower limit to this association. Actual daily flow , β_3, always had a negative coefficient, suggesting that increased flow had a short-term, negative association with temperature. Mean daily flow for each given day, β_4, always had a positive coefficient. Finally, not surprisingly, mean daily temperature, β_5, always had a coefficient near one. All coefficients across the eight projects were significantly different from zero, and, in most cases, coefficients for each independent variable had the same magnitude across projects. To implement this in COMPASS, we simply apply the estimated coefficients from Table XX.1 to the modulated flows described previously to simulate daily temperatures.

Figure 8-3 6 shows actual vs. predicted values for Bonneville; we performed but do not display similar goodness of fit, outlier, and influence diagnostics for all eight projects. The only notable problem is that roughly 5% of the temperature observations have absolute values of the residuals > 3 degrees C, which could be problematic for passage survival simulations. In some cases, examination of the data suggests data measurement or recording problems, while in others the cause is not readily apparent. We return to this problem below.

Generally, comparing actually and predicted temperatures over day (1-365) did not reveal serious problems (results not shown). The only exception to this is that in some cases the reported temperature was constant for 2-3 weeks while predicted temperature changed more rapidly. As with the residuals just noted, we suspect data entry or related problems in these cases.

Discussion

With the caveat that we are not temperature modelers by training, we think the results are encouraging for a first-round attempt. The models account for 93 to 97 percent of the variation in observed scroll case temperatures, and we suspect the fits could be improved by judicious but time-consuming quality assurance/quality control (QA/QC) of the temperature data. Preliminary discussions with Stuart McKenzie (USGS, retired) suggest that these results are reasonable, though they should be treated as the first of what may prove to be several rounds of data extraction, QA/QC, and analysis.

We would, therefore, like to suggest what those next steps might be. The first, we think, would be to "predict" temperatures for years and projects with abundant temperature data, and carefully check these against the actual data. The second, following McKenzie's suggestion, would be to convene a group of temperature modelers to review the COMPASS requirements and the existing data to select which series (e.g., scroll case at project X, WQM at project Y) data best meet our needs. Finally, someone familiar with the information would carefully QA/QC the numbers, which in turn could be used as input to a new round of regression models. These in turn could be used to estimate temperatures for a future round of COMPASS runs.

In addition, two other issues must be resolved for the future modeling. These include:

1. How to incorporate stochasticity: while the models are reasonably accurate, the r-squares are obviously < 1, so some unexplained residual variance remains.
2. How to incorporate relationships between projects: temperatures across projects are strongly correlated, but the first-round models ignore this, except insofar as the flows are correlated across projects.

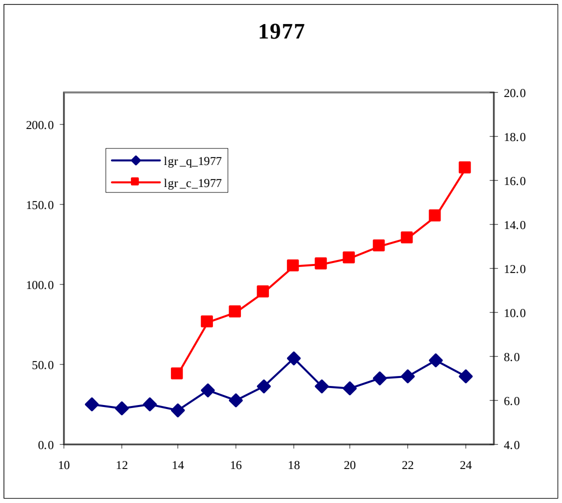

Figure 8-3 5A. Weekly average flow (blue, in kcfs, left-hand scale) and scroll case temperature (red, degrees C, right-hand scale), Lower Granite, 1977.

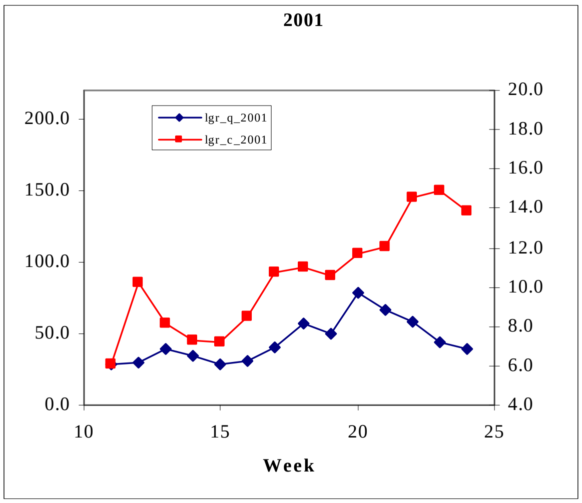

Figure 8-3 5B. Weekly average flow (blue, in kcfs) and scroll case temperature (red, degrees C), Lower Granite, 2001.

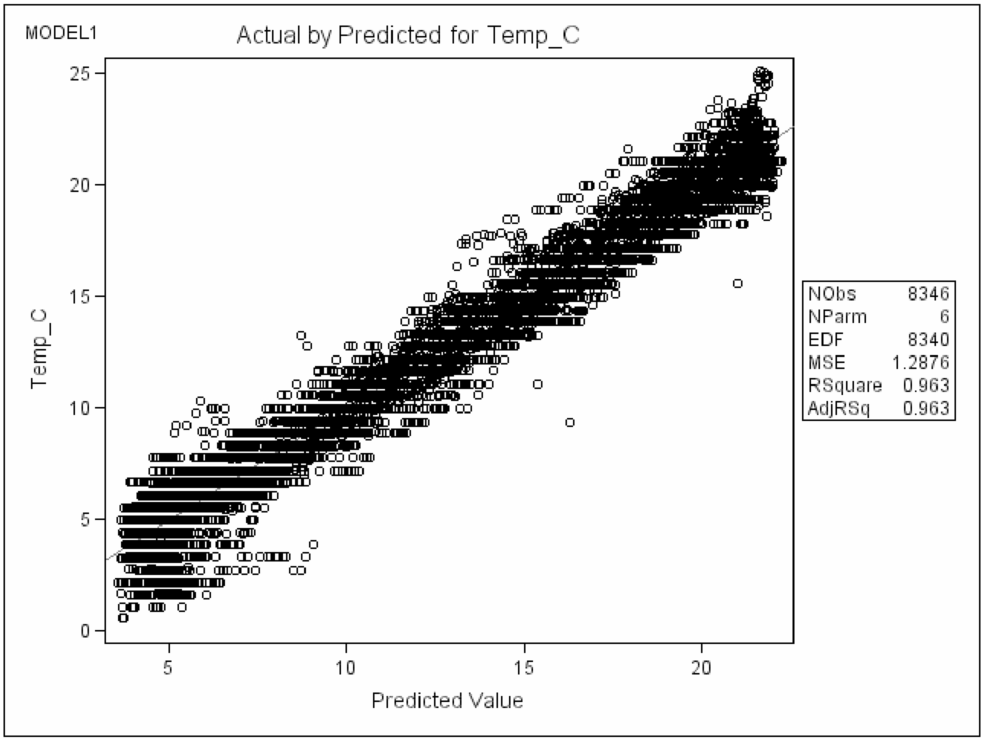

Figure 8-3 6. Actual vs. predicted temperature, Bonneville

Table 8-3 1. Parameter estimates and adjusted R-squares

Lower Granite, r-square = 0.9335				
Label	**Parameter Estimate**	**Standard Error**	**Pr > |t|**	
Intercept	1.69431	0.18275	0.0001	
Average Annual flow, kcfs	-0.06328	0.00701	0.0001	
Annual mean flow squared	0.0005415	6.647E-05	0.0001	
Actual daily project flow, kcfs	-0.01118	0.0007999	0.0001	
Project-specific long-term daily mean Q kcfs	0.01101	0.0009653	0.0001	
Project-specific long-term daily mean Temp, one per cal. Day	0.99806	0.00289	0.0001	
Little Goose, r-square = 0.9388				
Label	**Parameter Estimate**	**Standard Error**	**Pr > |t|**	
Intercept	1.24208	0.20586	0.0001	
Average Annual flow, kcfs	-0.02648	0.00755	0.0005	
Annual mean flow squared	0.0001238	7.256E-05	0.088	
Actual daily project flow, kcfs	-0.01015	0.0007969	0.0001	
Project-specific long-term daily mean Q kcfs	0.00864	0.001	0.0001	
Project-specific long-term daily mean Temp, one per cal. Day	0.98725	0.00386	0.0001	
Lower Monumental, r-square = 0.9538				
Label	**Parameter Estimate**	**Standard Error**	**Pr > |t|**	
Intercept	0.78727	0.15671	0.0001	
Average Annual flow, kcfs	-0.0264	0.00533	0.0001	
Annual mean flow squared	0.0001684	4.945E-05	0.0007	
Actual daily project flow, kcfs	-0.00688	0.0006152	0.0001	
Project-specific long-term daily mean Q kcfs	0.00711	0.0007861	0.0001	
Project-specific long-term daily mean Temp, one per cal. Day	1.00279	0.00326	0.0001	
Ice Harbor, r-square = 0.9644				
Label	**Parameter Estimate**	**Standard Error**	**Pr > |t|**	
Intercept	2.34844	0.13452	0.0001	
Average Annual flow, kcfs	-0.08042	0.00505	0.0001	
Annual mean flow squared	0.0006054	4.693E-05	0.0001	
Actual daily project flow, kcfs	-0.00601	0.0006028	0.0001	
Project-specific long-term daily mean Q kcfs	0.00591	0.0007414	0.0001	
Project-specific long-term daily mean Temp, one per cal. Day	0.99932	0.00208	0.0001	

Table 8-3 1 (concluded)

McNary, r-square = 0.9625				
Label	**Parameter Estimate**	**Standard Error**	**Pr > |t|**	
Intercept	4.64304	0.31036	0.0001	
Average Annual flow, kcfs	-0.04157	0.00328	0.0001	
Annual mean flow squared	8.808E-05	8.89E-06	0.0001	
Actual daily project flow, kcfs	-0.004	0.0003253	0.0001	
Project-specific long-term daily mean Q kcfs	0.00379	0.0004206	0.0001	
Project-specific long-term daily mean Temp, one per cal. Day	0.99203	0.00246	0.0001	
John Day, r-square = 0.9563				
Label	**Parameter Estimate**	**Standard Error**	**Pr > |t|**	
Intercept	5.28766	0.32158	0.0001	
Average Annual flow, kcfs	-0.04972	0.00327	0.0001	
Annual mean flow squared	0.0001107	8.55E-06	0.0001	
Actual daily project flow, kcfs	-0.00312	0.0003732	0.0001	
Project-specific long-term daily mean Q kcfs	0.00285	0.0004782	0.0001	
Project-specific long-term daily mean Temp, one per cal. Day	0.99371	0.00281	0.0001	
The Dalles, r-square=0.9687				
Label	**Parameter Estimate**	**Standard Error**	**Pr > |t|**	
Intercept	2.91641	0.27374	0.0001	
Average Annual flow, kcfs	-0.02605	0.00286	0.0001	
Annual mean flow squared	0.0000496	7.68E-06	0.0001	
Actual daily project flow, kcfs	-0.00173	0.0002959	0.0001	
Project-specific long-term daily mean Q kcfs	0.00188	0.0003829	0.0001	
Project-specific long-term daily mean Temp, one per cal. Day	1.00103	0.00238	0.0001	
Bonneville, r-square = 0.9630				
Label	**Parameter Estimate**	**Standard Error**	**Pr > |t|**	
Intercept	2.88159	0.27694	0.0001	
Average Annual flow, kcfs	-0.02864	0.00282	0.0001	
Annual mean flow squared	0.0000658	7.19E-06	0.0001	
Actual daily project flow, kcfs	-0.00181	0.000315	0.0001	
Project-specific long-term daily mean Q kcfs	0.00197	0.0004096	0.0001	
Project-specific long-term daily mean Temp, one per cal. Day	1.00149	0.00222	0.0001	

Introduction

We assessed the sensitivity of COMPASS passage model outputs to input levels of river environment and river operation variables. Two sets of sensitivity scenarios were run. The first set focused on the effects of varying levels of flow, temperature, and spill on dam survival, inriver survival, and travel time. The second set focused on the effects of varying transportation start date and levels of spill on adult return rate and proportion of fish transported. All scenarios were run for both yearling Chinook and steelhead.

Methods

<u>Set 1 - Survival and Travel Time</u>

Set 1 focused on the response of inriver survival, dam survival, and travel time to varying inputs of flow, temperature, and spill proportion. Inriver survival included both dam and reservoir survival and was defined as the cumulative survival from the forebay of Lower Granite Dam (LGR) to the confluence of the Snake and Columbia rivers and from the confluence to the tailrace of Bonneville Dam (BON). Dam survival included the survival at individual dams, and the cumulative dam survival for LGR through BON. Travel time was the median time of passage between LGR and the confluence and between the confluence and BON. Flow, temperature, and spill proportion were the input variables used because these are the three input variables for the migration rate and reservoir survival models that can be directly manipulated as daily inputs. Spill proportion also affects dam survival.

Daily river environment data collected at Lower Granite Dam (LGR) and McNary Dam (MCN) from 1995-2006 were used as a guide for setting input levels of flow, temperature, and spill proportion. Daily river environment data were taken from the Columbia River DART website (http://www.cbr.washington.edu/dart/dart.html).

The Scenarios were constructed using continuous and categorical levels of input variables. Each level of a continuous variable was assessed at each combination of the categorical levels for the remaining two variables. Table A9 1 shows continuous and categorical levels of inputs used to construct the scenarios.

Table A9 1. Input levels for sensitivity scenarios in Set 1.

	Continuous Levels Range (step)	Categorical Levels
Flow (kcfs)		
Snake	20 - 200 (20)	50, 100, 150
Columbia	118 - 462 (38)	175, 270, 365
Temperature (°C)	4 - 24 (1)	6, 12, 18
Spill proportion	0.00 - 0.80 (0.10)	0.00, 0.25, 0.50, 0.75

Not all combinations of input levels were observed in the historic data. We wanted to keep the model inputs within the experience of the observed data to which the model was calibrated. Therefore, if a combination was outside the bounds of the observed data, that scenario was dropped from the sensitivity analysis. For example, temperatures of 18° C or greater were not observed when flow exceeded 160 kcfs at LGR (385 kcfs at MCN). Another example is spill percentages of 30% or less were not observed at MCN when flow was 340 kcfs or greater. This resulted in a total of 311 scenarios run in Set 1. Note, however, that some combinations used here might never occur in real operations (e.g., 80% spill at all dams simultaneously).

For each scenario in Set 1, input data values for sensitivity variables were set constant across every day in the year. All river segments had the same temperature value and every dam had the same spill proportion. All Snake River segments had the same constant Snake River flow level and all Columbia River segments had the same constant Columbia River flow level.

The parameter values used the reservoir survival equations and the migration rate equations were those specified in Tables 3 and 4, respectively, in the COMPASS Manual. The parameter values used for dam passage (route-specific passage and survival probabilities, spill efficiencies, etc.) were those specified in Appendices 4 and 5.

For all scenarios, fish were released into the forebay of LGR using the same release profile. The release profiles for Chinook and steelhead were based on average smolt passage distributions at LGR for wild fish. The first day of release for both chinook and steelhead was March 24th.

<u>Set 2 - Transportation</u>

We investigated the effect of transportation start date and proportion of water spilled on adult return rate and proportion of fish destined for transportation. The proportion of fish destined for transportation takes into account the mortality incurred during migration to lower transportation sites.

The continuous and categorical input levels for transportation start day and spill proportion are shown in Table A9 2.

Table A9 2. Input levels for sensitivity scenarios in Set 2.

	Continuous Levels Range (step)	Categorical Levels
Transportation Start Day	84 - 184 (4)	NA
Spill Proportion	NA	0.00, 0.25, 0.50, 0.75

We investigated two spill scenarios. Scenario 1 applied the specified spill proportion to every day in the year at each transport dam. Scenario 2 applied the specified spill proportion to every day up until the start of transportation, at which point spill was set to

0.0 at all transport dams. The various levels of transportation start day, spill proportion, and spill scenario resulted in a total of 378 scenarios run for Set 2.

We used the river environment data (temperature and flow) for four water years from the prospective modeling (Appendix 8). Spill proportions used at non-transporting dams were those observed the base case. We used the dam passage parameters, migration rate parameters, reservoir survival parameters, and release profiles used in Set 1. Post-Bonneville return rate was based on the mean return rate (i.e., mean parameter values across all realizations of the relationships) of the relationships described in Appendix 8.

Results

The inriver survival of both Snake River spring/summer Chinook and steelhead was sensitive to varying levels of flow, water temperature, and proportion river spilled (Figure A9 1-6). Comparatively, Chinook were more sensitive to spill, and steelhead were more sensitive to flow. The survival of both Chinook and steelhead was strongly sensitive to water temperature, with both species exhibiting a nonlinear response. Chinook were not sensitive to temperature during migration through the Columbia River.

Dam survival was responsive to proportion spill (Figure A9 7), although the response varied across dams. Overall, dam survival increased by approximately 15 percent as spill proportion varied from zero to eighty percent. Also, dam survival of steelhead was slightly greater than that of Chinook.

The travel time of both Chinook and steelhead was strongly sensitive to river flow (Figure A9 8). Steelhead were more sensitive to proportion spill, with total travel time varying by several days across levels of spill.

Adult return rate was strongly influenced by transportation start date (Figures A9 9-12), but the patterns differed between the species. Chinook typically had a unimodal response, with a peak return when transportation was initiated in early May. Also, in scenario 1 (spill turned off at transport sites when transportation was initiated) Chinook return rate responded to spill level, but the response was diminished at higher spill levels. For Chinook, scenario 2 (spill during the entire season at transport site) was clearly less beneficial than scenario 1. The return rate of steelhead dropped precipitously after transport start dates in late April to early May. Also, return rate of steelhead was comparatively less responsive to spill level. For steelhead, scenario 1 was clearly more beneficial than scenario 2. In scenario 2, increased spill levels led to decreased proportion transported (see Figures A9 13-16) and consequently decreased return rates.

As expected, transportation start date strongly influences the proportion of fish transported (Figures A9 13-16). Also, in scenario 2 (spill during the entire season), the proportion of flow spilled at transport sites greatly influences proportion of fish transported.

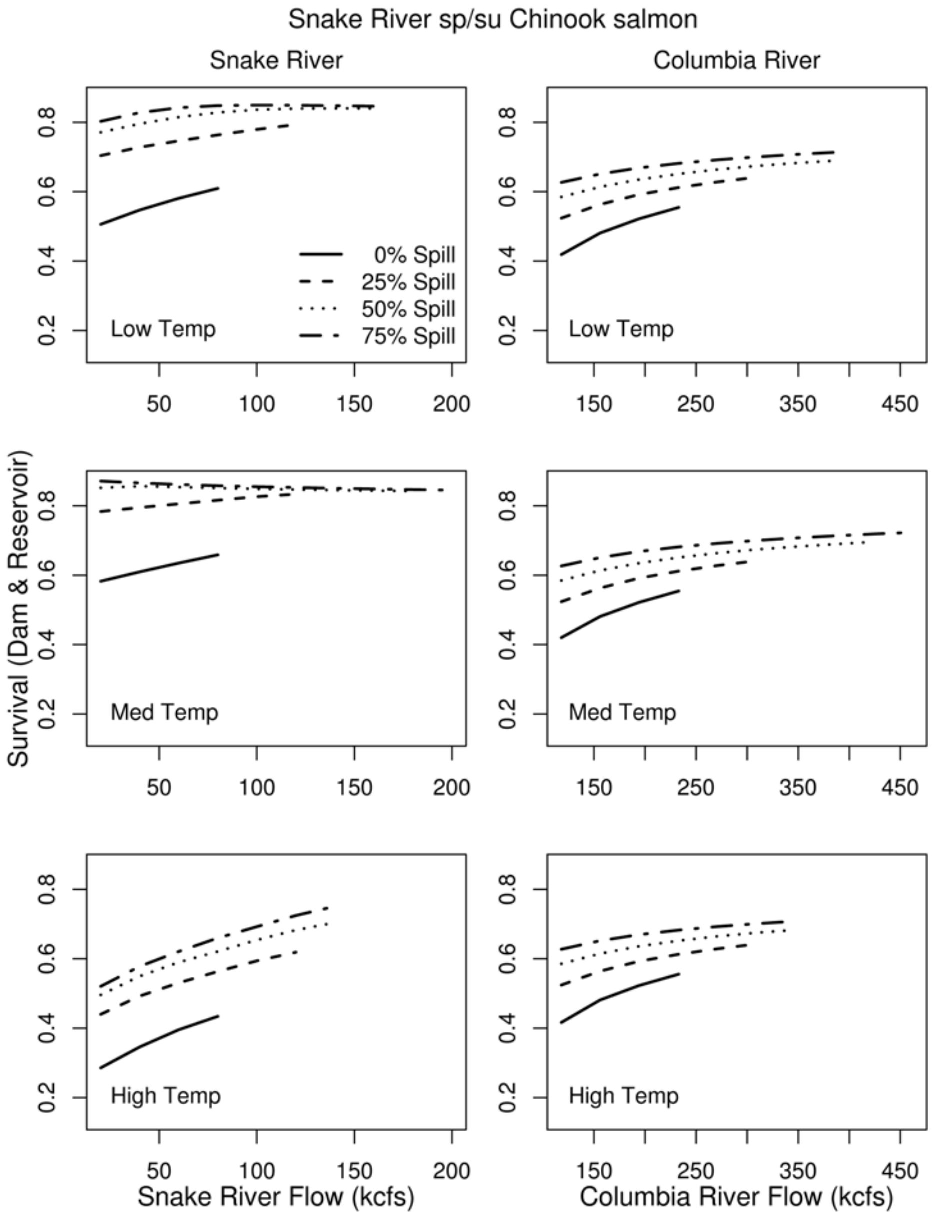

Figure A9 1. Sensitivity of overall survival (dam and reservoir) through the Snake (Lower Granite forebay to the mouth) and Columbia (mouth of the Snake River to Bonneville tailrace) as a function of river flow for Snake River spring/summer Chinook. Sensitivities were performed for three levels of temperature and four levels of spill.

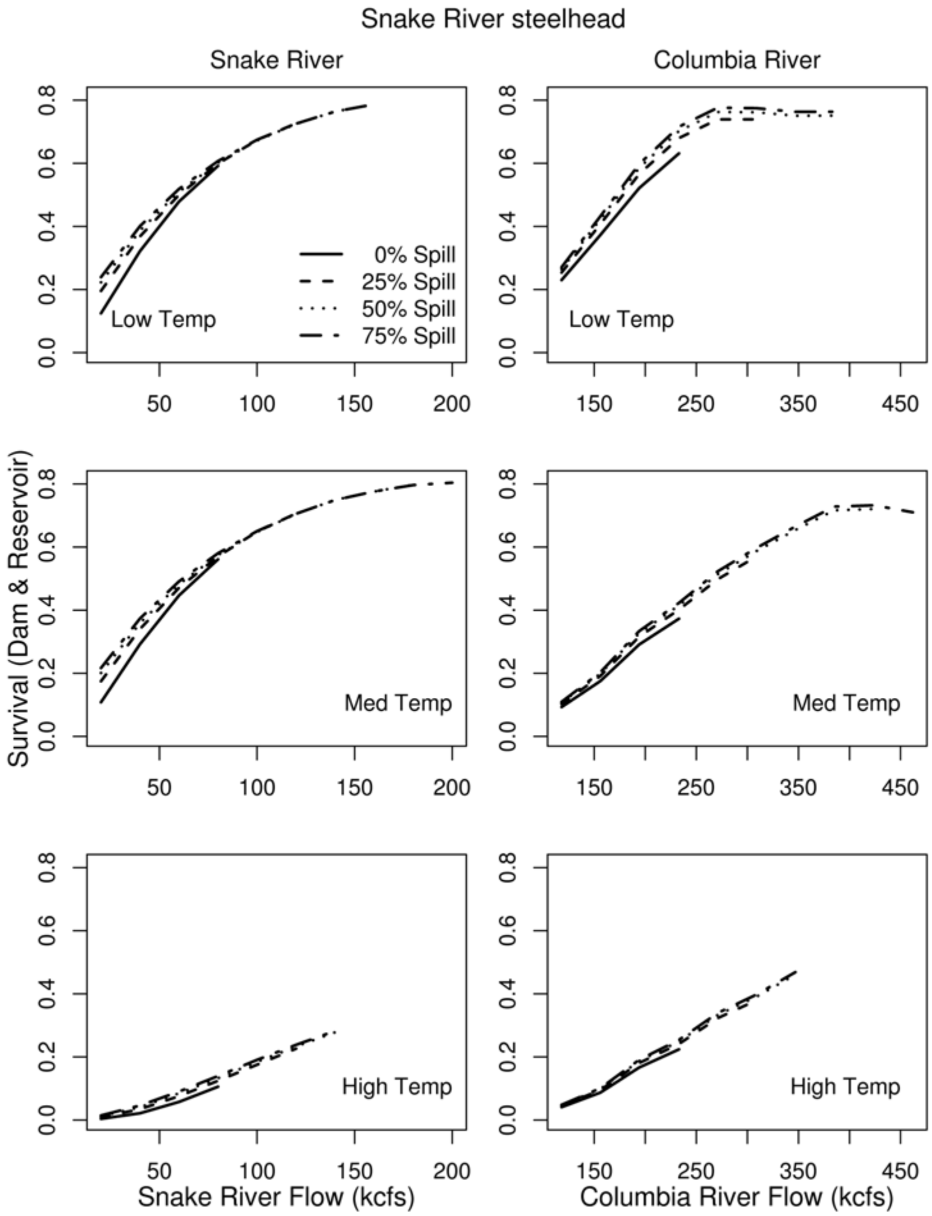

Figure A9 2. Sensitivity of overall survival (dam and reservoir) through the Snake (Lower Granite forebay to the mouth) and Columbia (mouth of the Snake River to Bonneville tailrace) as a function of river flow for Snake River steelhead. Sensitivities were performed for three levels of temperature and four levels of spill.

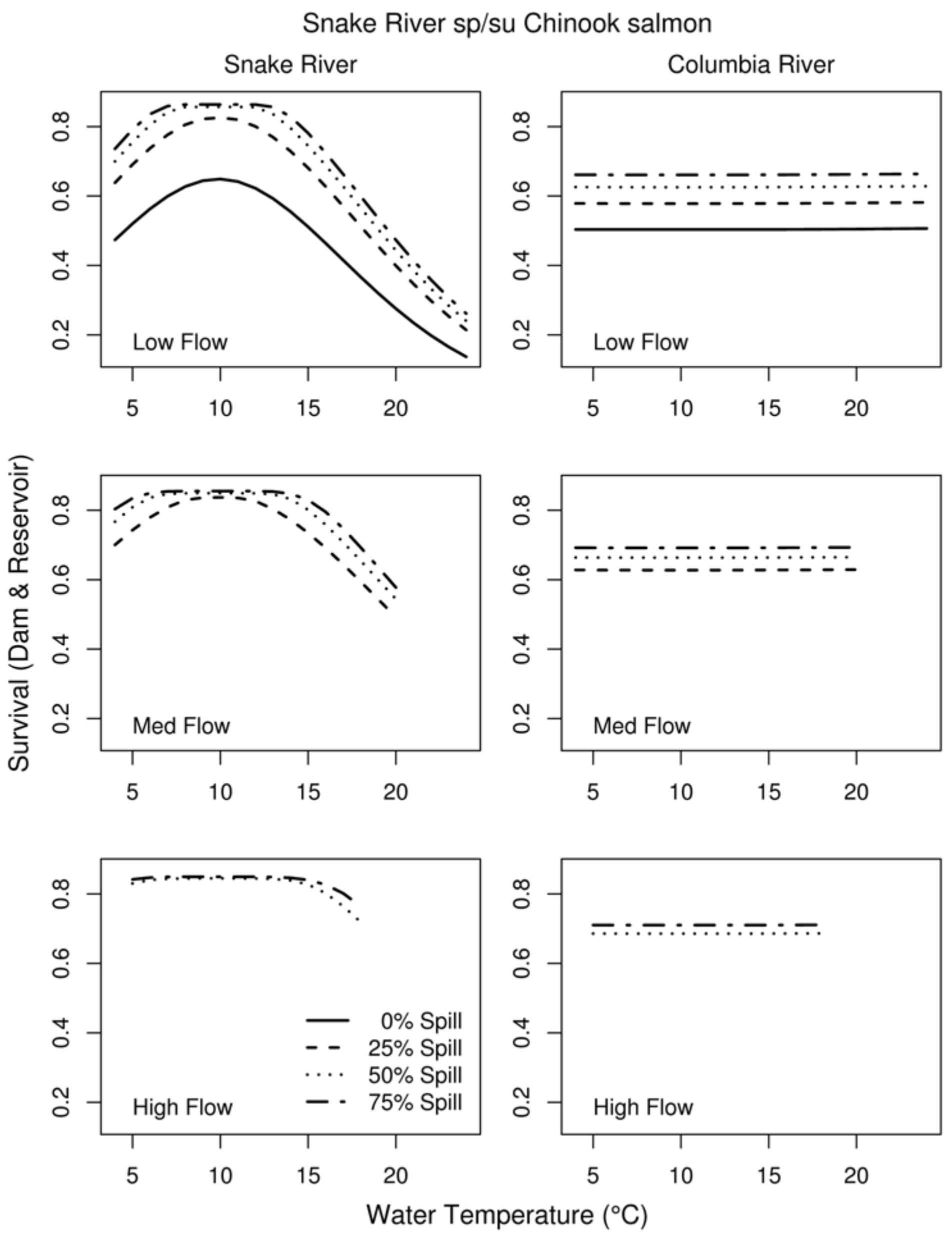

Figure A9 3. Sensitivity of overall survival (dam and reservoir) through the Snake (Lower Granite forebay to the mouth) and Columbia (mouth of the Snake River to Bonneville tailrace) as a function of water temperature for Snake River spring/summer Chinook. Sensitivities were performed for three levels of flow and four levels of spill.

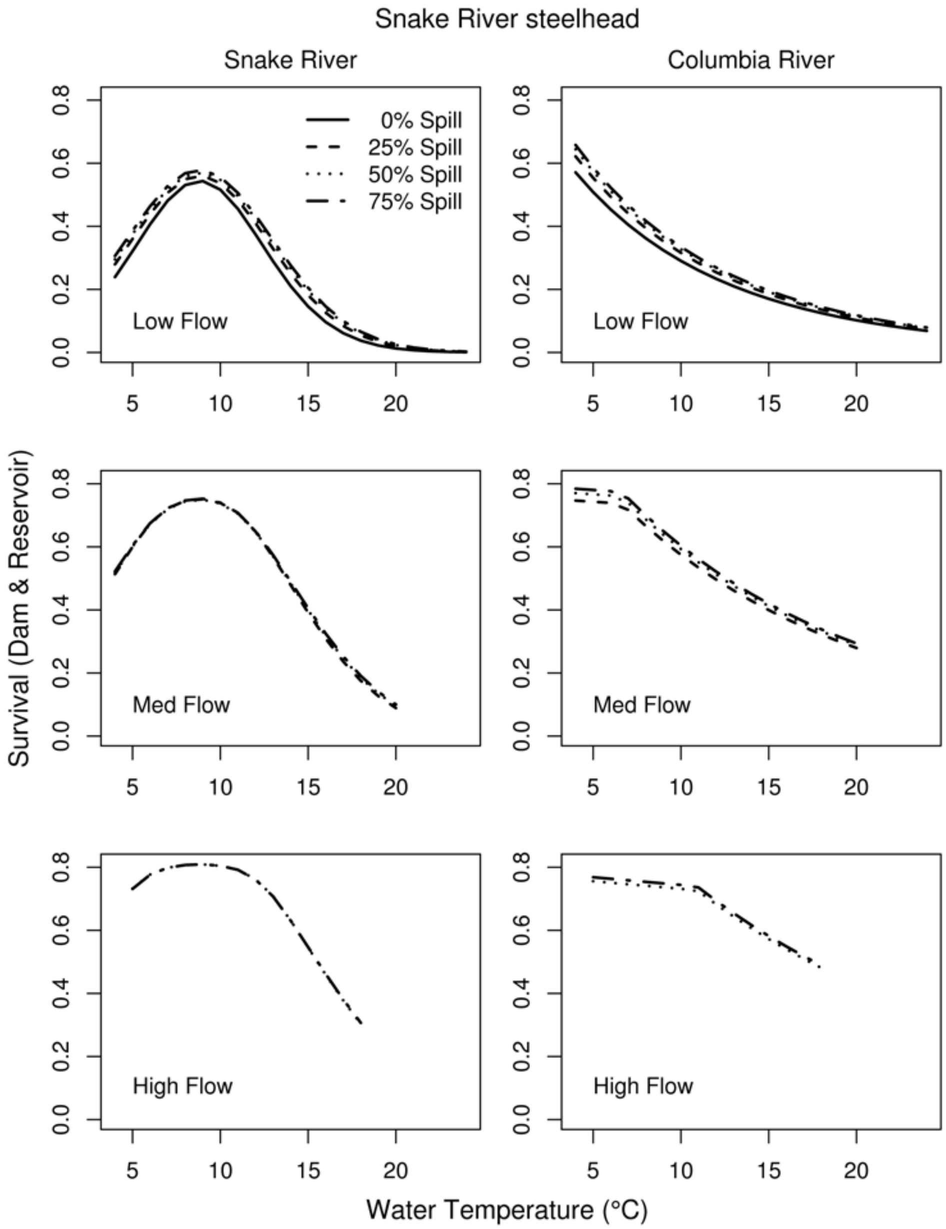

Figure A9 4. Sensitivity of overall survival (dam and reservoir) through the Snake (Lower Granite forebay to the mouth) and Columbia (mouth of the Snake River to Bonneville tailrace) as a function of water temperature for Snake River steelhead. Sensitivities were performed for three levels of flow and four levels of spill.

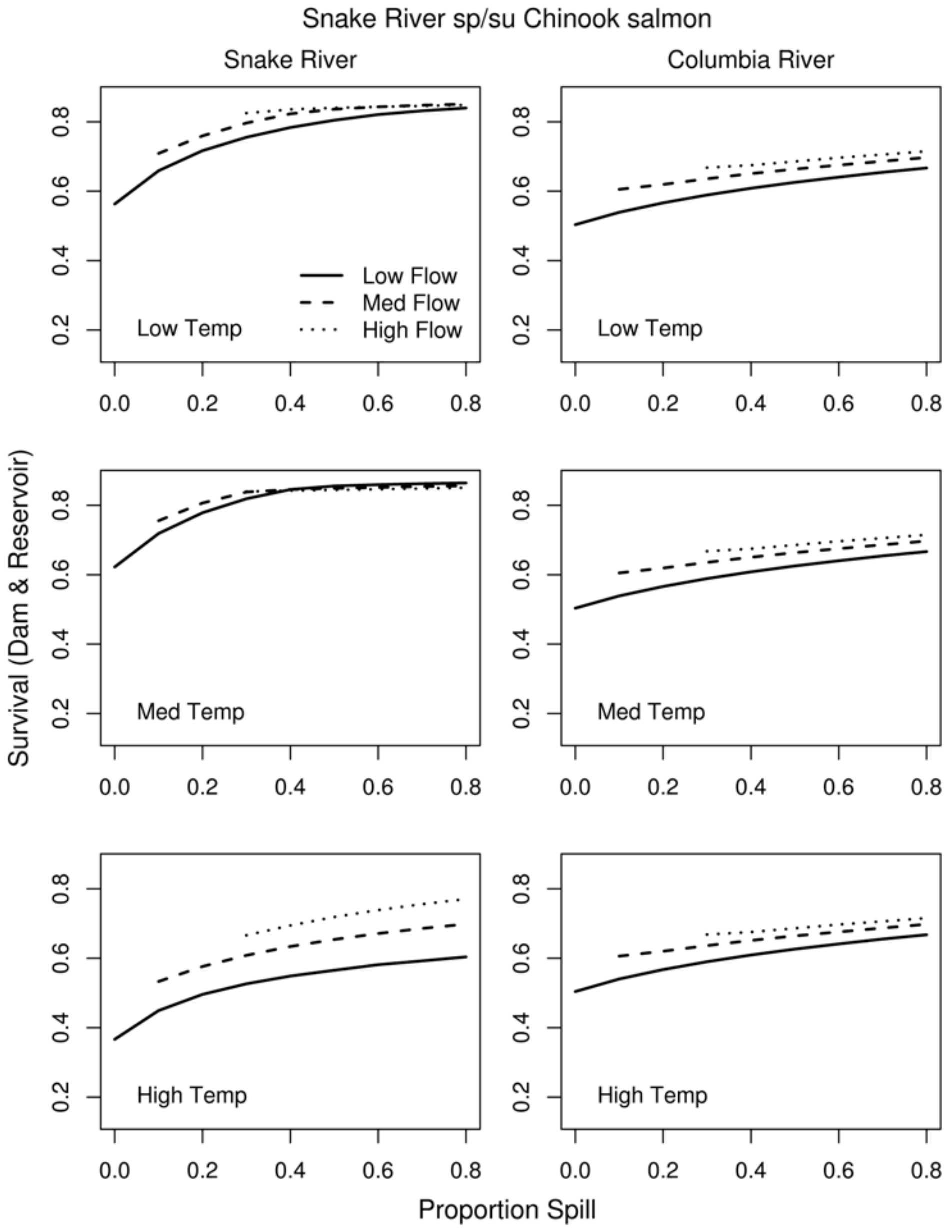

Figure A9 5. Sensitivity of overall survival (dam and reservoir) through the Snake (Lower Granite forebay to the mouth) and Columbia (mouth of the Snake River to Bonneville tailrace) as a function of proportion spill for Snake River spring/summer Chinook. Sensitivities were performed for three levels of flow and three levels of temperature.

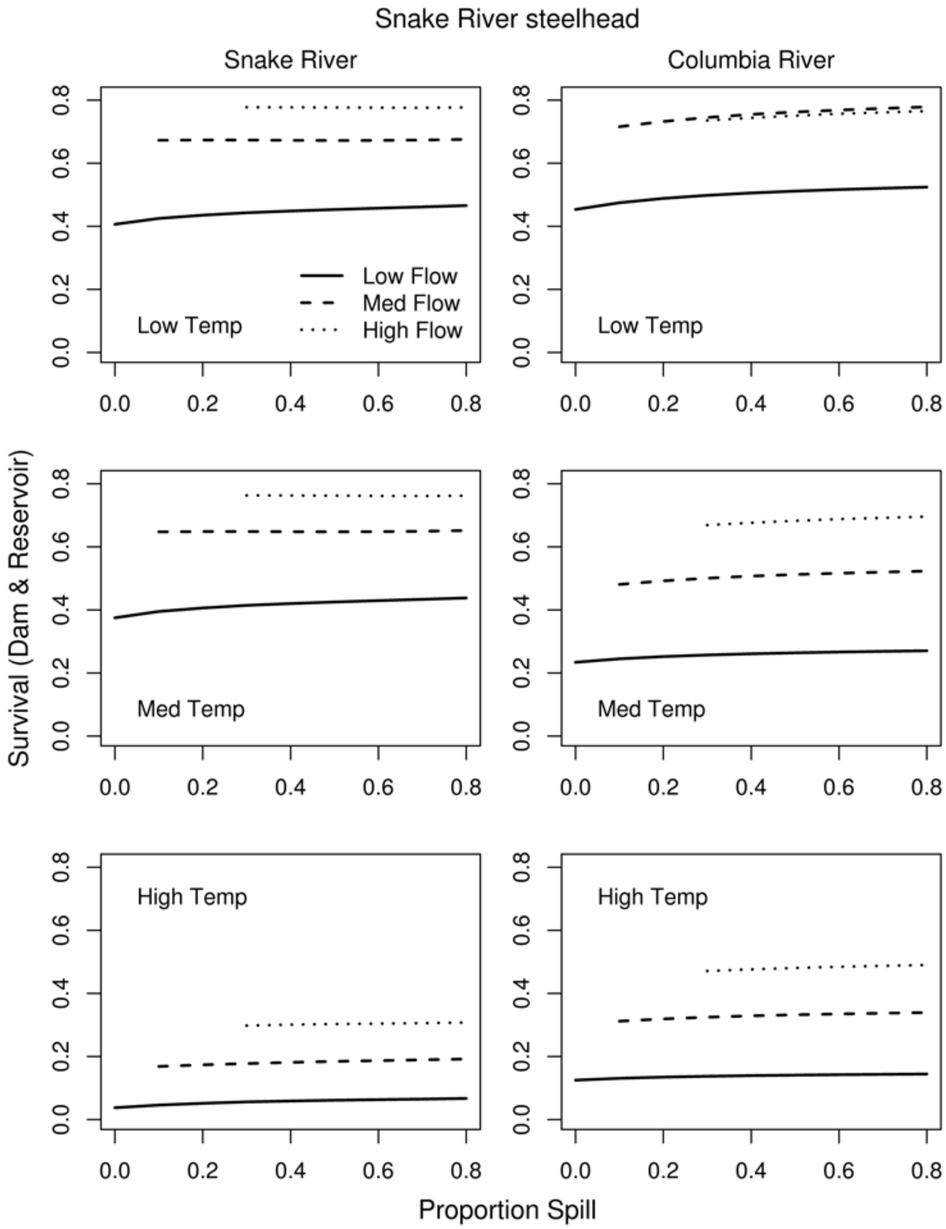

Figure A9 6. Sensitivity of overall survival (dam and reservoir) through the Snake (Lower Granite forebay to the mouth) and Columbia (mouth of the Snake River to Bonneville tailrace) as a function of proportion spill for Snake River steelhead. Sensitivities were performed for three levels of flow and three levels of temperature.

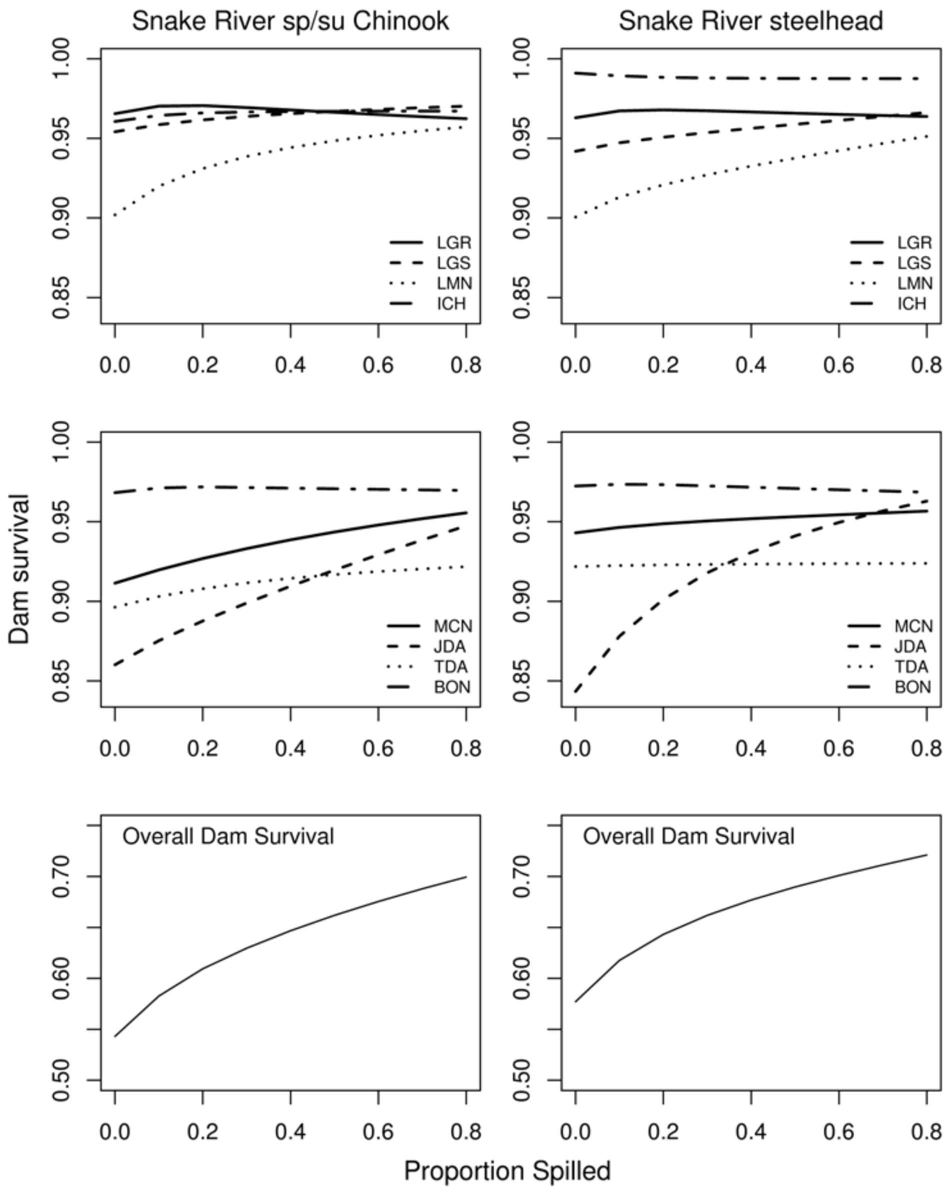

Figure A9 7. Sensitivity of dam survival through the Snake (Lower Granite forebay to the mouth) and Columbia (mouth of the Snake River to Bonneville tailrace) as a function of proportion flow spilled for Snake River spring/summer Chinook and steelhead.

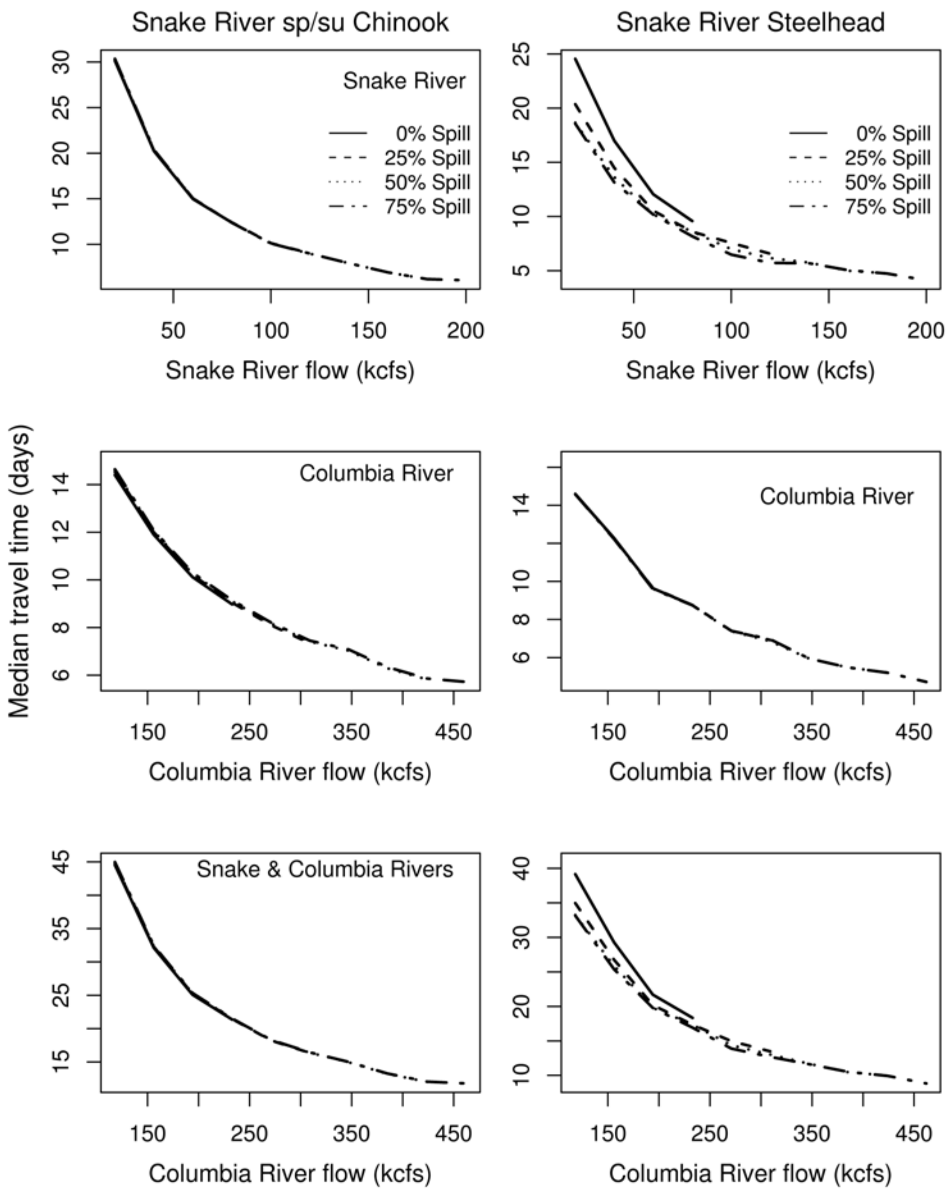

Figure A9 8. Sensitivity of travel time through the Snake (Lower Granite forebay to the mouth) and Columbia (mouth of the Snake River to Bonneville tailrace) as a function of river flow for Snake River spring/summer Chinook and steelhead.

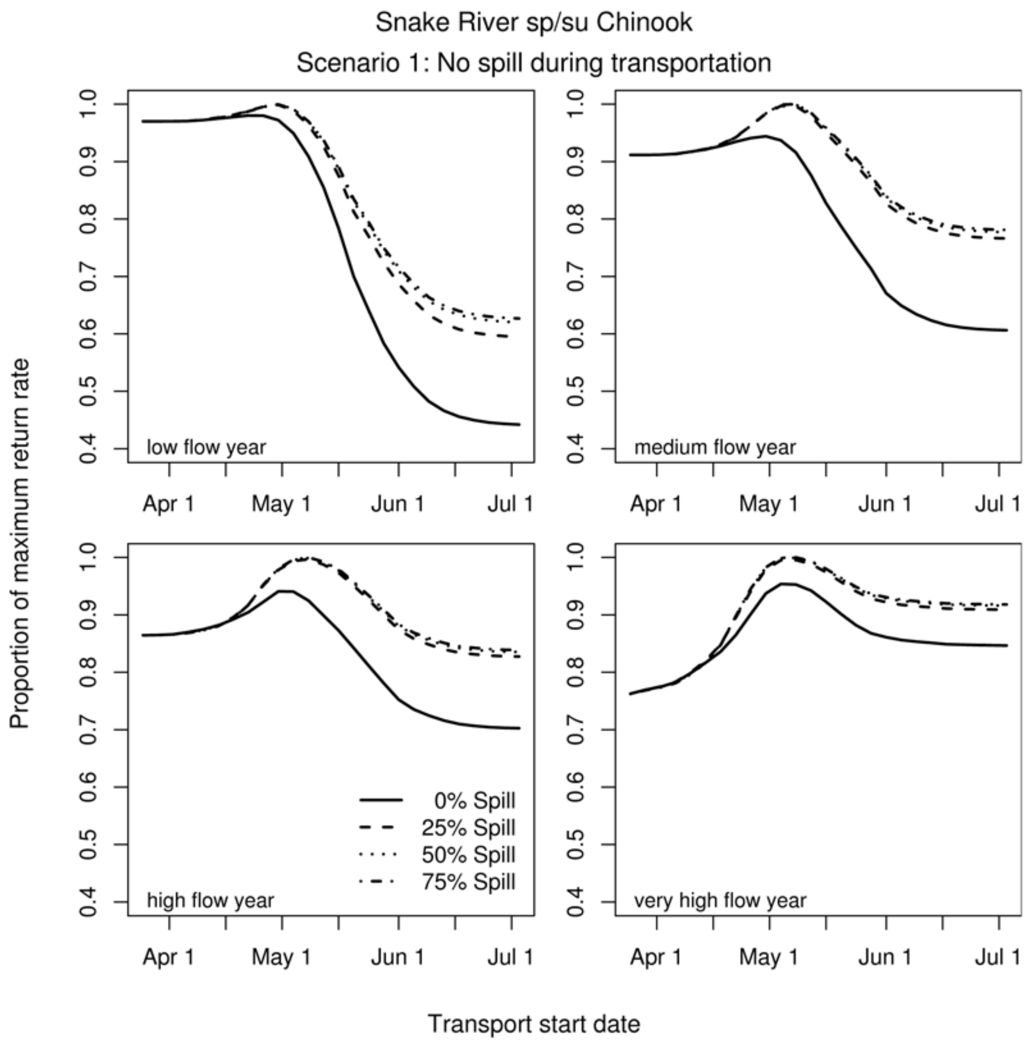

Figure A9 9. Sensitivity of proportion of maximum return rate of Snake River sp/su Chinook versus transportation start date for several levels of spill. Under scenario 1, fish spill is set to zero once transportation is initiated. The proportion return rate is relative to the maximum return rate for a given water year under both scenarios 1 and 2.

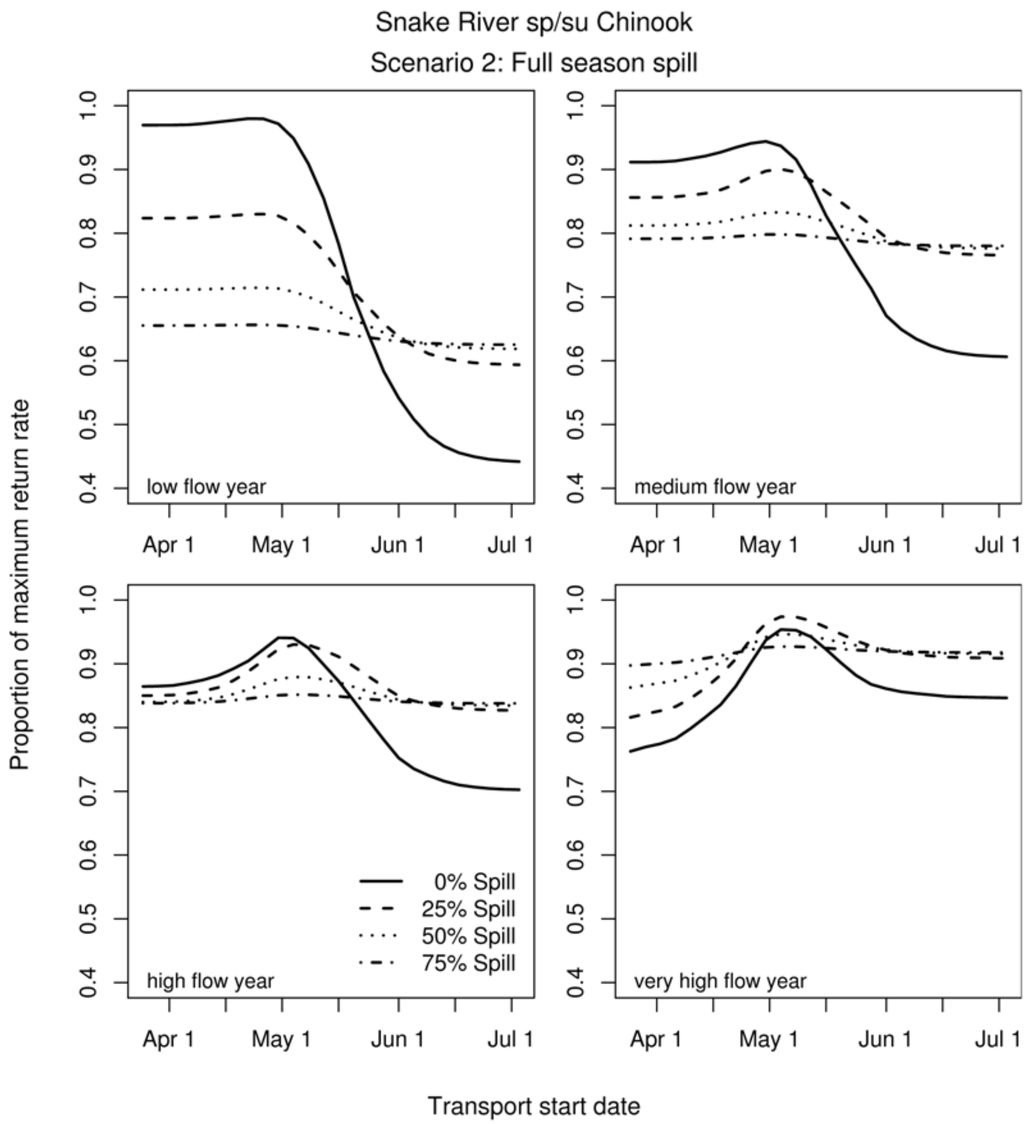

Figure A9 10. Sensitivity of proportion of maximum return rate of Snake River sp/su Chinook versus transportation start date for several levels of spill at transport dams. Under scenario 2, fish spill at transport dams is maintained at a constant level throughout the season. The proportion return rate is relative to the maximum return rate for a given water year under both scenarios 1 and 2.

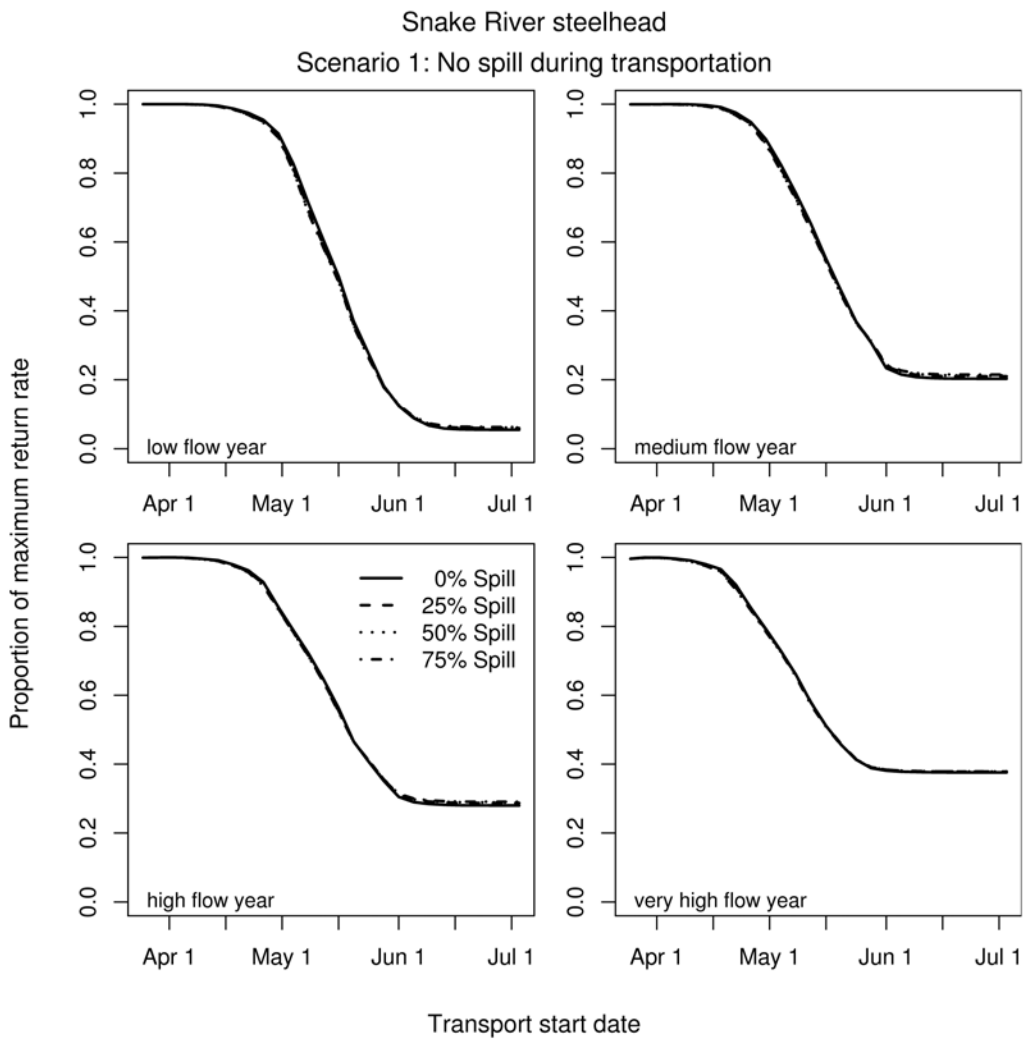

Figure A9 11. Sensitivity of proportion of maximum return rate of Snake River steelhead versus transportation start date for several levels of spill. Under scenario 1, fish spill is set to zero once transportation is initiated. The proportion return rate is relative to the maximum return rate for a given water year under both scenarios 1 and 2.

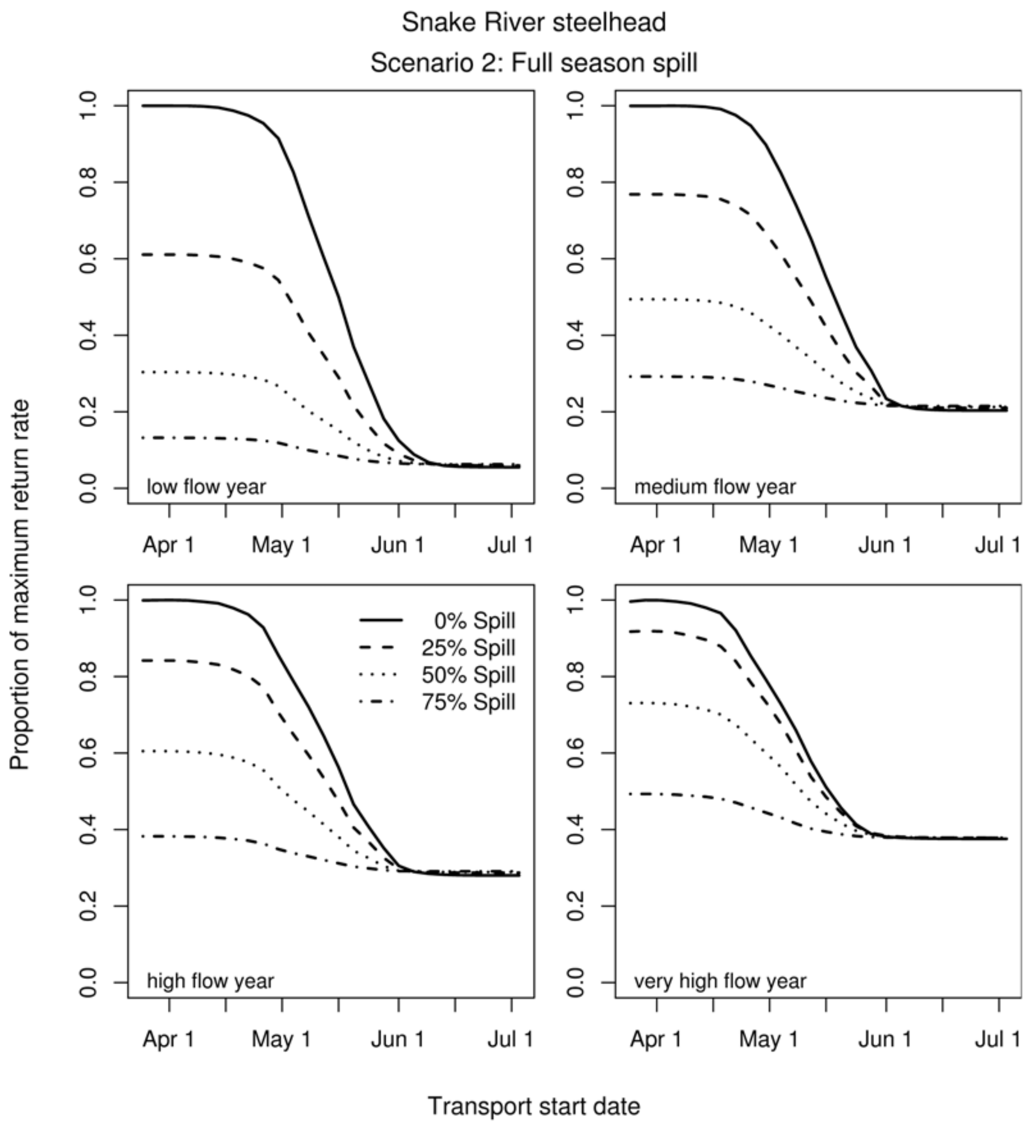

Figure A9 12. Sensitivity of proportion of maximum return rate of Snake River steelhead versus transportation start date for several levels of spill. Under scenario 2, fish spill is maintained at a constant level throughout the season. The proportion return rate is relative to the maximum return rate for a given water year under both scenarios 1 and 2.

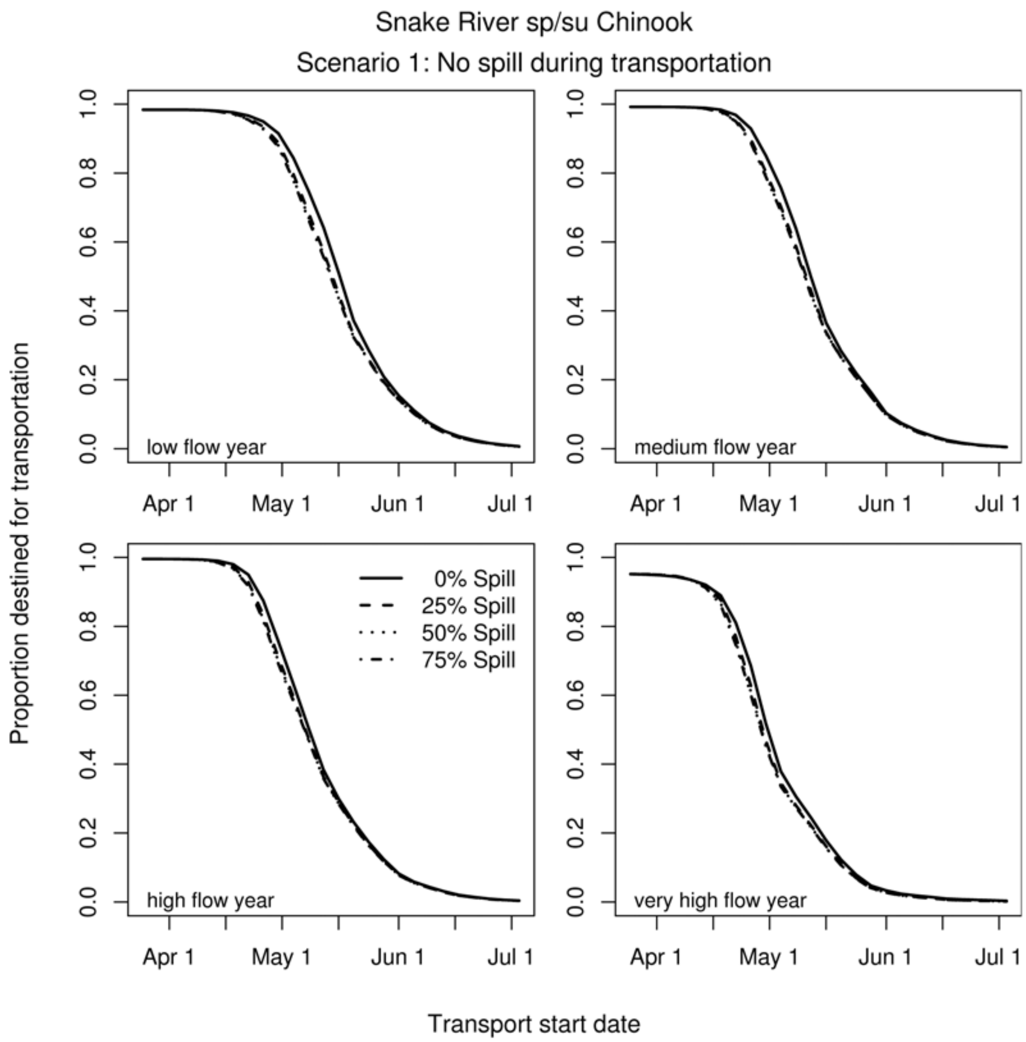

Figure A9 13. Sensitivity of proportion of Snake River sp/su Chinook destined for transportation versus transportation start date for several levels of spill at transport dams. Under scenario 1, fish spill is set to zero at transport dams once transportation is initiated.

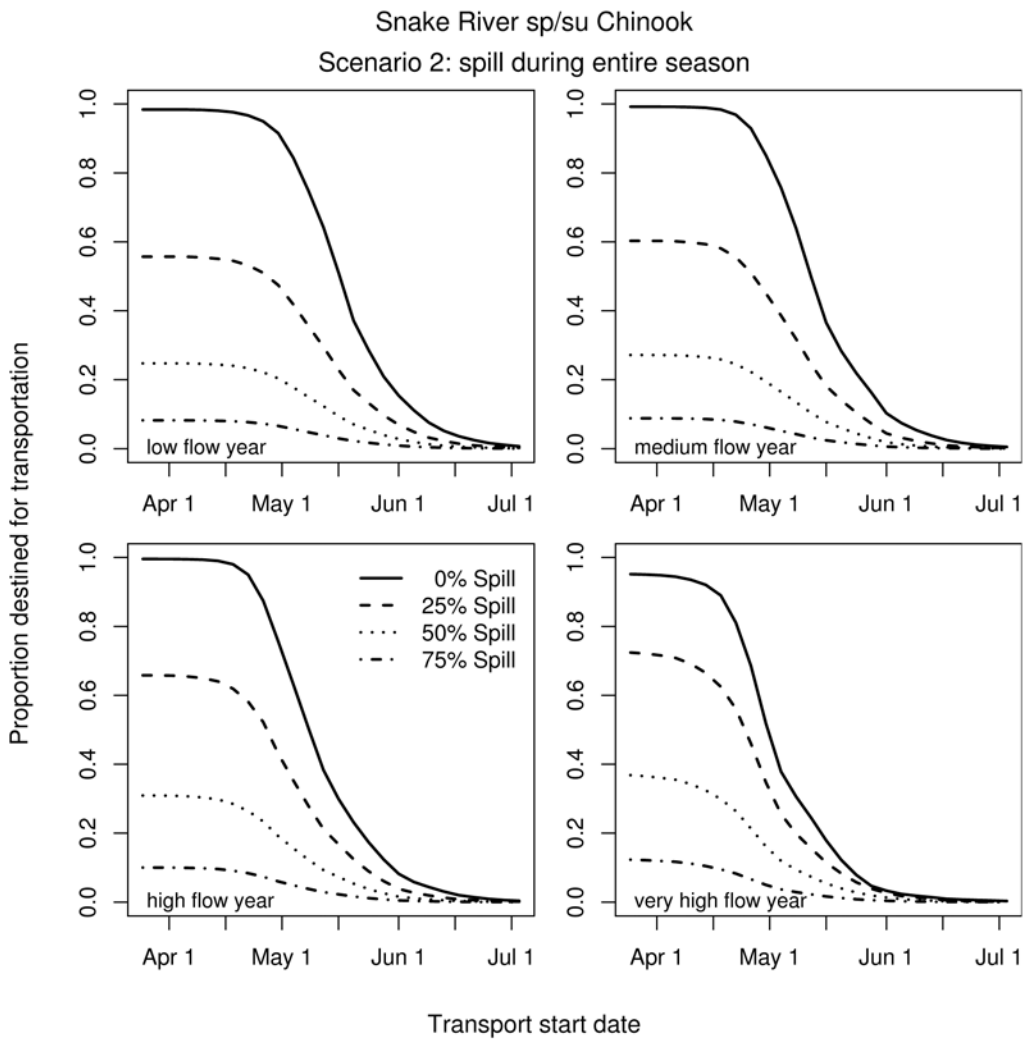

Figure A9 14. Sensitivity of proportion of maximum return rate of Snake River sp/su Chinook versus transportation start date for several levels of spill at transport dams. Under scenario 2, fish spill at transport dams is maintained at a constant level throughout the season. The proportion return rate is relative to the maximum return rate for a given water year under both scenarios 1 and 2.

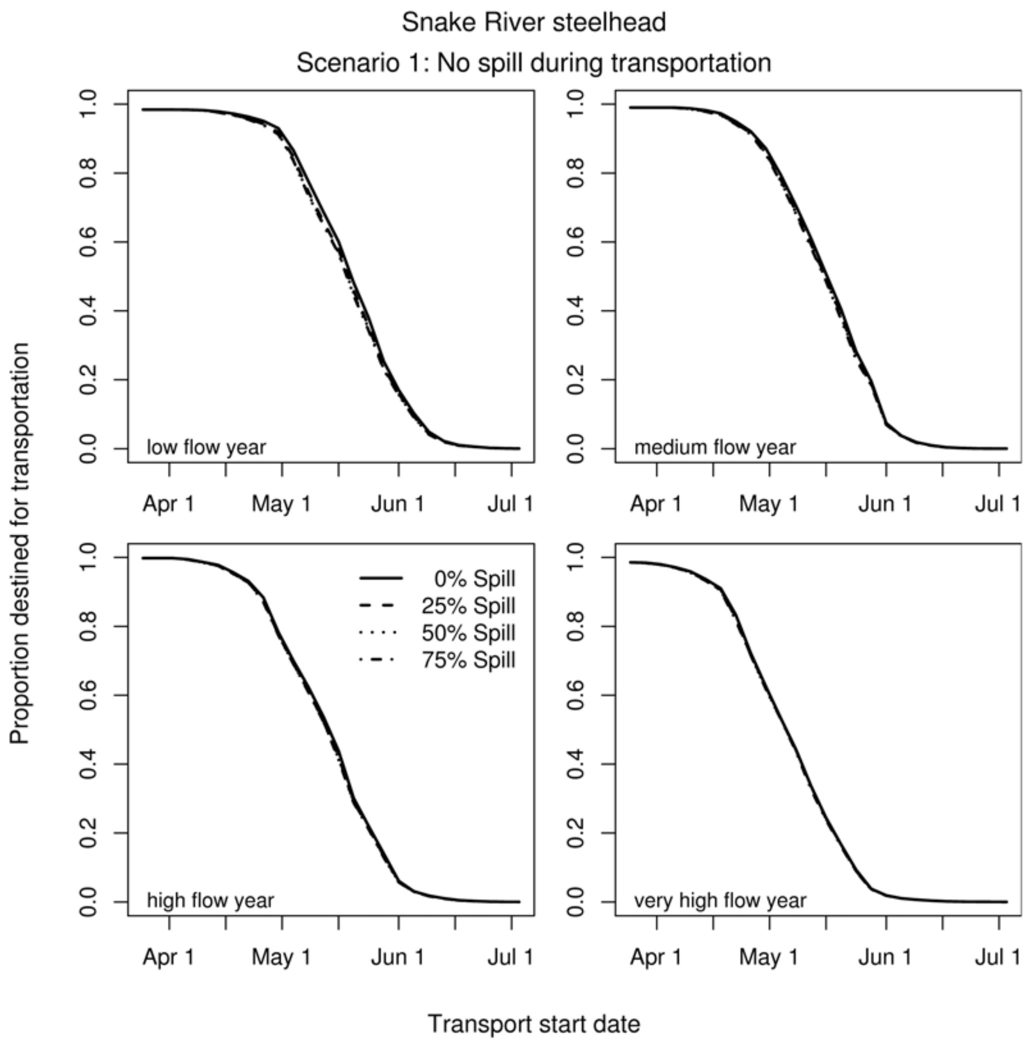

Figure A9 15. Sensitivity of proportion of maximum return rate of Snake River steelhead versus transportation start date for several levels of spill at transport dams. Under scenario 1, fish spill at transport dams is set to zero once transportation is initiated. The proportion return rate is relative to the maximum return rate for a given water year under both scenarios 1 and 2.

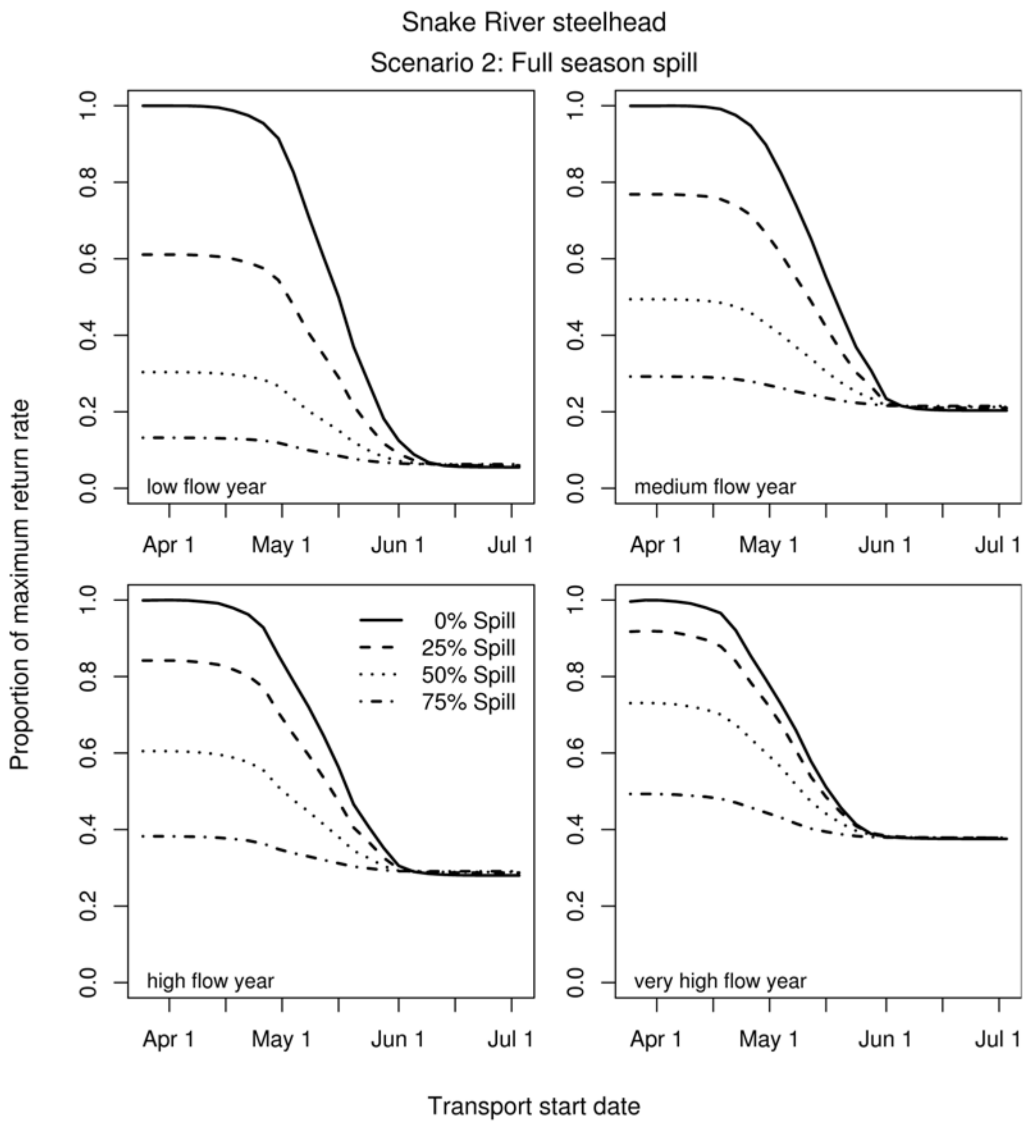

Figure A9 16. Sensitivity of proportion of maximum return rate of Snake River steelhead versus transportation start date for several levels of spill at transport dams. Under scenario 2, fish spill at transport dams is maintained at a constant level throughout the season. The proportion return rate is relative to the maximum return rate for a given water year under both scenarios 1 and 2.