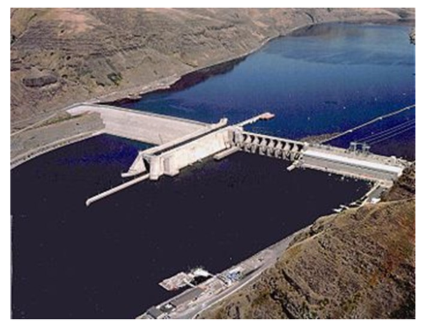
Modeling Route-Specific Passage Probabilities of Migrating Juvenile Salmonids at Hydroelectric Dams Using Detections of PIT Tags in Juvenile Bypass Systems



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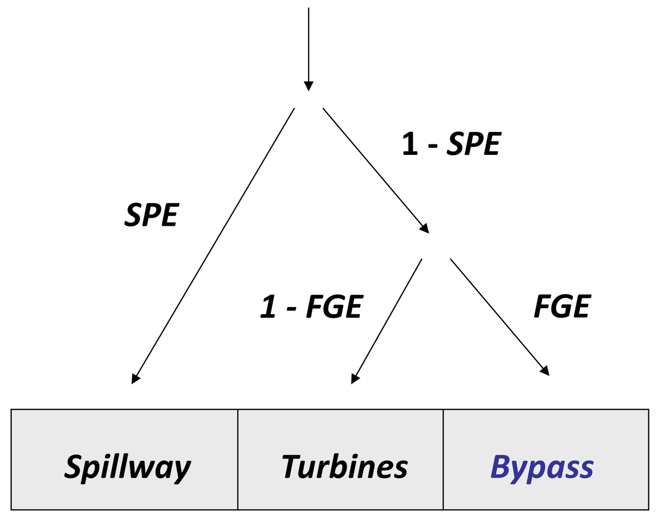
Background

Management of endangered salmon in the Columbia River Basin depends in part on knowledge of passage behavior of migrating juveniles at hydroelectric dams. The relative rates of passage among various routes depend on dam operations, environmental conditions, and individual fish characteristics. Data from acoustic or radio tags can provide a known time and route of passage for each individual fish, but studies using active tags are limited in number and scope, and often represent a narrow range of conditions. PIT-tagged fish offer an alternative data source available for multiple species, years, environmental conditions, and dams, but with the limitation that time and route of passage are only known for fish that enter juvenile bypass systems. A modeling approach was needed that could utilize PIT tag data and estimate functions that would predict passage probabilities through all routes. These models would then be used as part of a larger passage model (COMPASS model) used for predicting juvenile survival, travel time, and transportation rates.

Objective

To obtain separate models for spill efficiency (SPE) and fish guidance efficiency (FGE) using detection probabilities from a bypass system and a set of covariates.

Model Description



SPE = probability enter spillway

P(*Powerhouse*) = *P*(*Turbines*) + *P*(*Bypass*) = 1 - *SPE*

FGE = probability enter bypass given entered powerhouse

P(*Bypass*) = (1 – *SPE*)**FGE*

By letting *SPE* be a function of spill proportion and possibly other variables, the *FGE* and *SPE* components can be separately estimated.

P(*Bypass*) = (1 – *f*(**x**))**g*(**z**)

Use the logit function to constrain *f* and *g* outputs to interval (0,1).

Let $h(y)$ = logit(y) = log[y / (1 - y)], then a linear predictor function for the mean of *FGE* on the logit scale is:

$$h(\mu_F) = \eta_F = \beta_{F,0} + \sum_i \beta_{F,i} X_i$$

and a linear predictor for the mean of *SPE* on the logit scale is:

$$h(\mu_S) = \eta_S = \beta_{S,0} + \sum_j \beta_{S,j} Z_j$$

where the X_i and Z_j are explanatory variables and the β's are parameters.

Then the predictor function for the expected bypass probability for a given set of explanatory variables is a nonlinear function:

$$P(Bypass) = \mu_B = h^{-1}(\eta_F)\left[1 - h^{-1}(\eta_S)\right]$$
$$= \mu_F(1 - \mu_S)$$

The response given the predictor function is assumed to follow a Beta distribution parameterized such that $Y \sim \text{Beta}(\mu, \phi)$ and $E(Y) = \mu$ and $\text{Var}(Y) = \mu(1 - \mu)/(\phi + 1)$.

The detection probability estimates $\hat{p}$ have sampling variance estimates associated with them, which can be accounted for and used to estimate remaining process variance.

$$\text{Var}_{total} = \text{Var}_{process} + \text{Var}_{sampling}$$

$$\text{Var}(\hat{p}) = \text{Var}(p) + \text{Var}(\hat{p} \mid p)$$

$$\text{Var}(p) = \frac{\mu_B(1 - \mu_B)}{\phi_P + 1}$$

$$\phi_T = \frac{\mu_B(1 - \mu_B)}{\text{Var}(p) + \text{Var}(\hat{p} \mid p)} - 1$$

In practice the true sampling variances are not known, so estimates are used. The probability density function for a single observation is then

$$f(y_i \mid \mu_{B,i}, \phi_{T,i}) = \frac{\Gamma(\phi_{T,i})}{\Gamma(\mu_i \phi_{T,i})\Gamma[(1 - \mu_{B,i})\phi_{T,i}]} y^{\mu_{B,i}\phi_{T,i} - 1}(1 - y_i)^{(1 - \mu_{B,i})\phi_{T,i} - 1}$$

It follows that the likelihood for a sample of size *n* is then

$$L(\boldsymbol{\beta}, \phi_P \mid \boldsymbol{y}) = \prod_{i=1}^{n} f(y_i \mid \mu_{B,i}, \phi_{T,i})$$

where the y_i are the detection probability estimates ($\hat{p}_i$), the μ_B are functions of the vector of the regression parameters $\boldsymbol{\beta}$, and the ϕ_T are functions of the process precision parameter ϕ_P and the individual sampling variance estimates.

Methods

- Response data were Cormack-Jolly-Seber (CJS) estimates of detection probabilities at Lower Granite Dam for weekly release groups of run-of-river steelhead released from 5 separate smolt traps from 1997-2011 (n = 426).
- Explanatory variables were associated measures of water temperature, water velocity, spill proportion (logit-transformed), usage of removable spillway weir (RSW), and day of year.
- Matched 3 possible FGE models and 8 possible SPE models for 24 total models.
  - Possible FGE models: (1) intercept only, (2) intercept + day, (3) intercept + temperature.
  - Fullest SPE model: intercept + RSW + logit(spill) + velocity + RSW*velocity + logit(spill)*velocity
- Used maximum likelihood to fit models to data for 1997-2010 (n = 400) and used AIC selection to rank the models.
- Used best model (lowest AIC) to predict bypass probabilities for 2011 (n = 26).

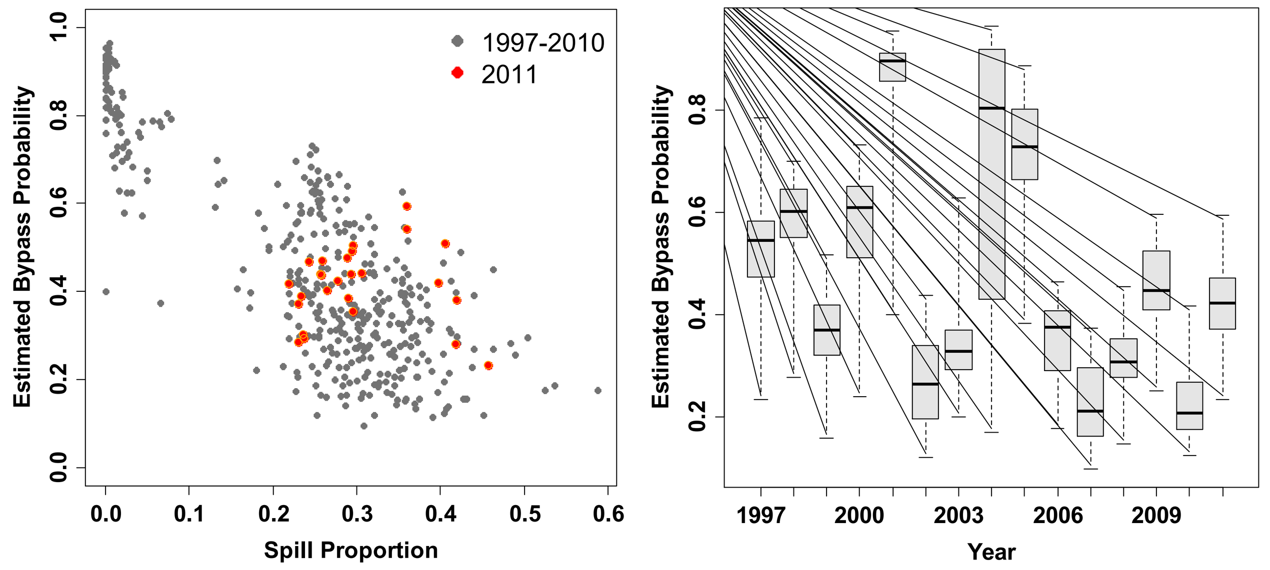


Fig. 1. CJS detection (bypass) probability estimates by spill proportion (left) and by year (right).

Results

Table 1. Top five models by AIC ranking.

FGE	SPE	Np	AICc	ΔAICc	AIC.Wt	CumWt
I + T	I + R + Sp + V + R*V + R*Sp	9	-863.7	0.0	0.854	0.85
I + D	I + R + Sp + V + R*V + R*Sp	9	-859.2	4.5	0.090	0.94
I	I + R + Sp + V + R*V + R*Sp	8	-858.3	5.4	0.056	1.00
I + T	I + R + Sp + V + R*Sp	8	-828.5	35.2	0	1
I	I + R + Sp + V + R*Sp	7	-824.2	39.5	0	1

I = intercept, T = temperature (°C), D = day of year, R = average daily proportion RSW on, Sp = logit transformed spill proportion, V = water velocity (km/day).

- The top three models accounted for nearly 100% of the cumulative AIC weight, with the only differences between models being in the FGE component (Table 1). All three had the fullest model for SPE.
- Observed versus predicted plot for the best model (Fig. 2) indicates decent correlation but there is still a substantial amount of unexplained variation.
- The FGE function for the best model was a decreasing function of temperature (Fig. 3). Temperature and day are highly correlated, but temperature performed better than day (the day term in model 2 was also not significant).
- SPE was greater when RSW was on, but the effect of RSW was greatest under lower water velocities (Fig. 4). The importance of the velocity*RSW interaction is evidenced by the large decrease in AIC when it is added to the model (Table 1).

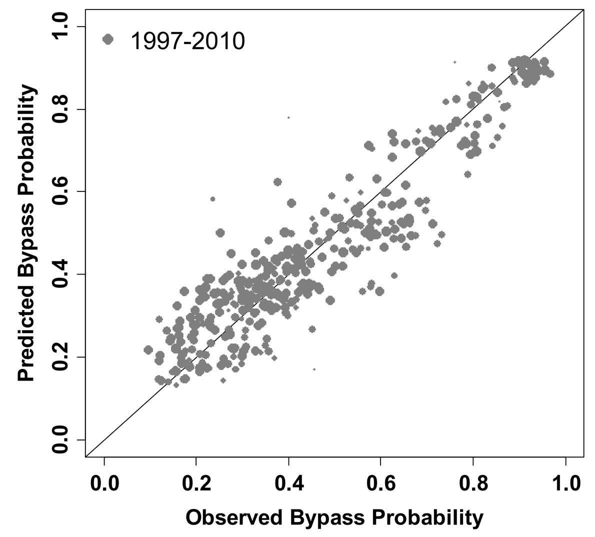


Fig. 2. Observed vs. predicted plot for model fit to 1997-2010 data for steelhead at Lower Granite Dam.

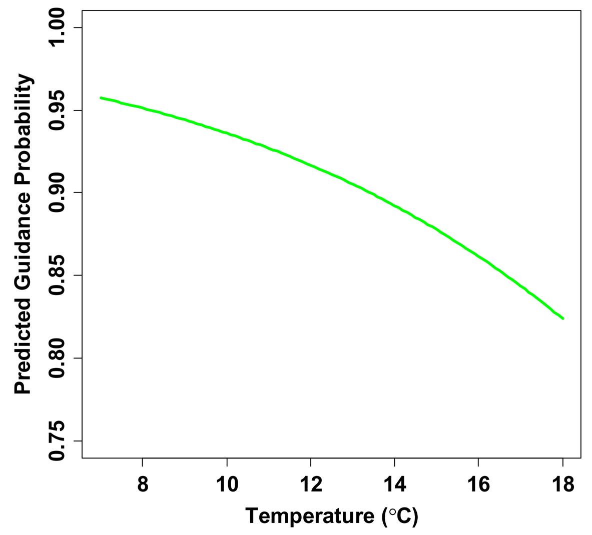


Fig. 3. FGE function for best fitting model, where FGE is a function of water temperature.

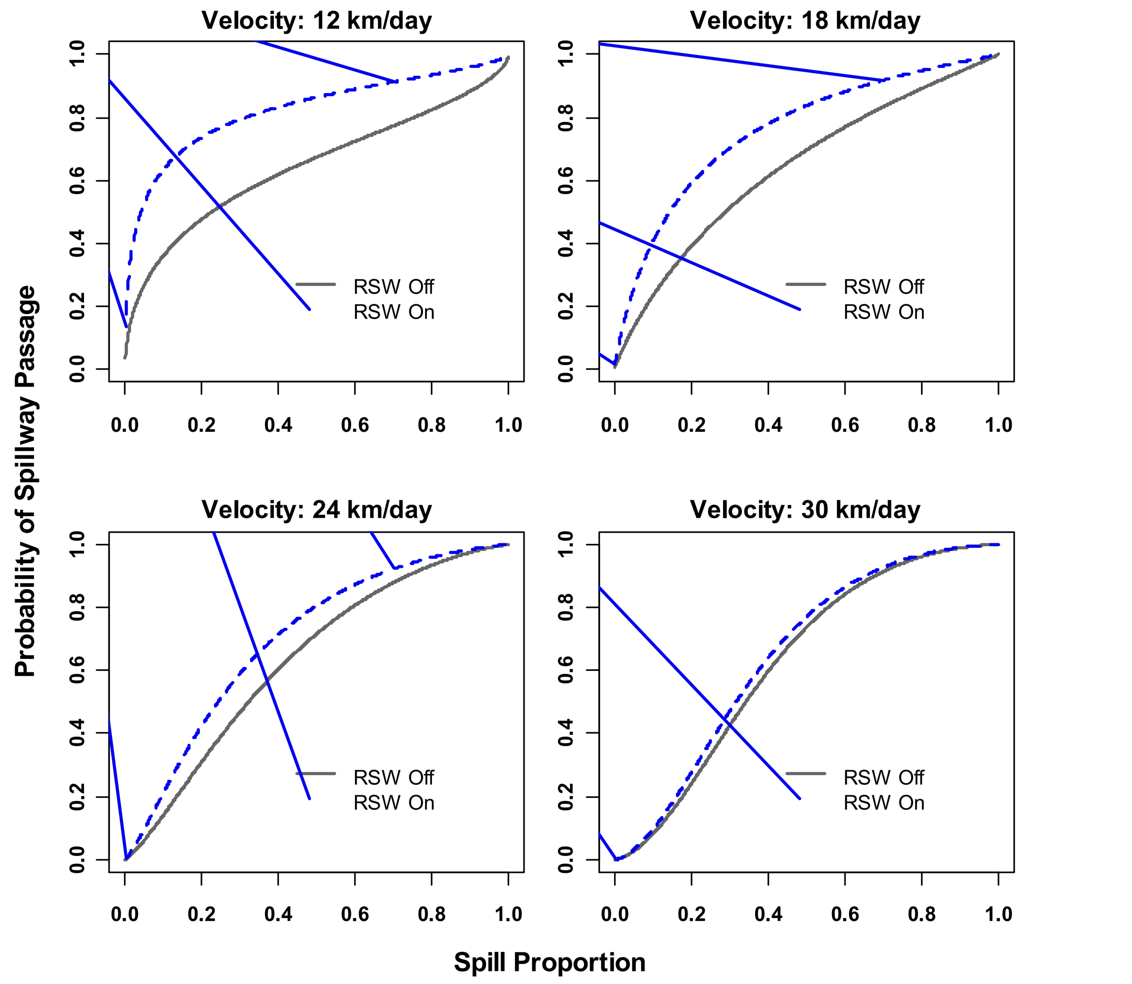


Fig. 4. Predicted SPE functions for steelhead at Lower Granite Dam for RSW on or off under various levels of water velocity.

Prediction

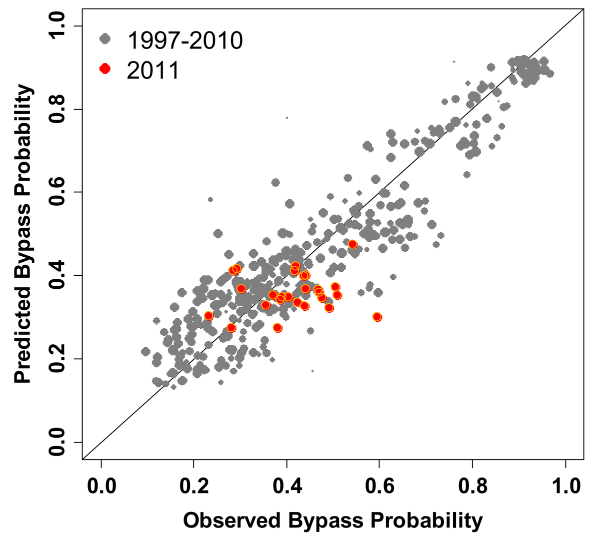


Fig. 5. Observed vs. predicted plot for model fit to 1997-2010 data with predictions for 2011 overlaid.

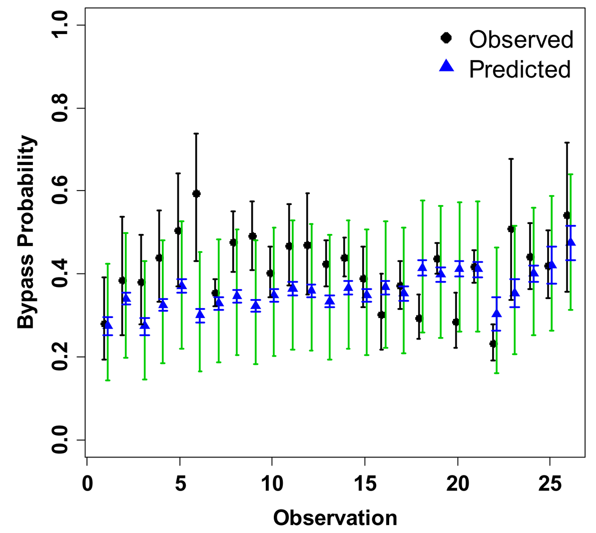


Fig. 6. Observed bypass probability estimates with 95% CI's (black) with model predictions (blue) with both 95% CI's for means (blue) and 95% prediction intervals (green).

Model predictions for 2011 data were consistently low early in the season but most observations were still within the prediction error bands.

Conclusions

- Modeling separate functions for SPE and FGE is possible with PIT tag data, but model complexity should be minimized. This method works best when there are a wide range of spill values and there are periods of low or zero spill in the data.
- Beta regression is flexible and allows modeling of variances. Process variance can be estimated, but it cannot be estimated separately for FGE and SPE.
- Will need to further validate the method with data from active tag studies and computer simulations. Will also apply this method to data for Chinook and steelhead at other dams.