

**MODELING THE MIGRATORY BEHAVIOR OF JUVENILE SALMON:  
WHAT PROCESSES GOVERN DOWNSTREAM MOVEMENT?**

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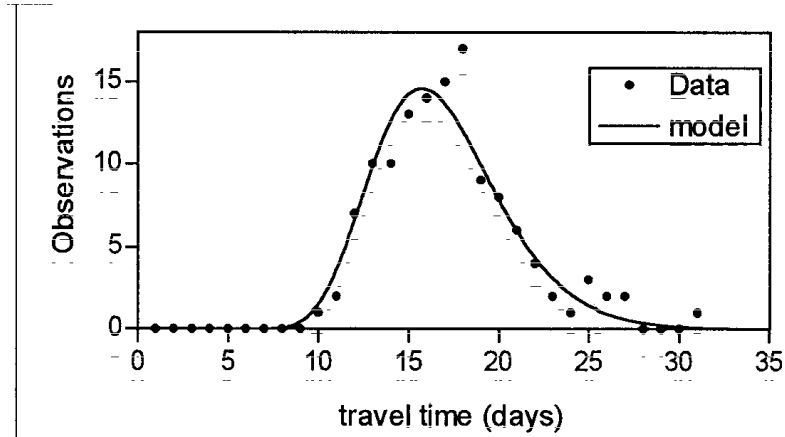
**Introduction**

In the Columbia River Basin in the northwestern United States, twelve stocks (4 different species) of anadromous Pacific salmonid have been listed as endangered under the U.S. Endangered Species Act. Recovering stocks will be challenging because each stock behaves uniquely and will respond differently to mitigation actions. Therefore, efforts to restore salmonid populations should include attempts to understand fish behavior, particularly how it varies among stocks or species and throughout life-histories. This talk will present results of modeling of migratory behavior with an emphasis on discerning individual-based behavioral variability and how this behavior evolves through the salmon life-history.

**Methods**

A model that can describe migrating fish populations is the advection-diffusion equation, which has been applied to a variety of dispersing animal populations (Okubo 1980). The advection term moves fish downstream and the diffusion term spreads the population through time. From this underlying migration equation, one can generate a distribution of travel times through a reach for a group of fish. Fitting this distribution to data requires estimating two parameters:  $r$ , downstream migration rate, and  $\sigma$ , rate of population spreading (Figure 1). Zabel and Anderson (1997) applied this equation to spring chinook

salmon migrating through a reservoir in the Snake River, a major tributary of the Columbia River.



**Figure 1.** Example of travel time model fit to data. Wild Snake River spring chinook were released at Lower Granite Dam on April 12, 1995 and observed at McNary Dam, 225 km

One of the assumptions of the basic model described above is that all fish within a population follow the same behavioral rules. This may be unrealistic in some cases, but the basic model can serve as a null model to which more complex models can be compared. Here I relaxed this assumption by relating migration rate of individuals to fish length at tagging. In addition, I included covariates flow and release date, which are common to all fish released as a group but vary through a season of releases. This allowed for the effect of individual variability to be compared to variability among release groups. To assess the importance of various factors, I developed a series of equations to model migration rate:

$$\text{Model 0: } r_i = \beta_0 \text{ (null model)}$$

$$\text{Model 1: } r_i = \beta_0 + \beta_1 \cdot \text{length}_i$$

$$\text{Model 2: } r_i = \beta_0 + \beta_1 \cdot \text{length}_i + \beta_2 \cdot \text{flow}_i$$

$$\text{Model 3: } r_i = \beta_0 + \beta_1 \cdot \text{length}_i + \beta_2 \cdot \text{flow}_i + \beta_3 \cdot \text{date}_i$$

where subscript  $i$  refers to the  $i$ th individual,  $r_i$  is migration rate, the  $\beta$ s are coefficients,  $\text{length}_i$  is the length at tagging (mm), and  $\text{flow}_i$  is the mean flow (kcfs) during the migratory period, and  $\text{date}_i$  is the release date (Julian date).

Maximum likelihood was used to fit the  $\beta$  coefficients along with the spread parameter  $\sigma$ . Akaike's Information Criterion (AIC, Akaike 1973) was used to determine which model was most supported by the data. Models 1-3 were compared directly to the null model, and the AIC value provides an indication of the importance of added factors.

The data analyzed were from PIT-tagged (Passive Integrated Transponder) juveniles. PIT tags allow for tracking of individuals as they move downstream and pass detection sites. The general experimental design is to release groups of fish from a single location and tabulate temporal passage distributions at downstream sites.

Three stocks of chinook salmon were analyzed. Wild Snake River spring/summer chinook, which migrate as yearlings, were tagged at Lower

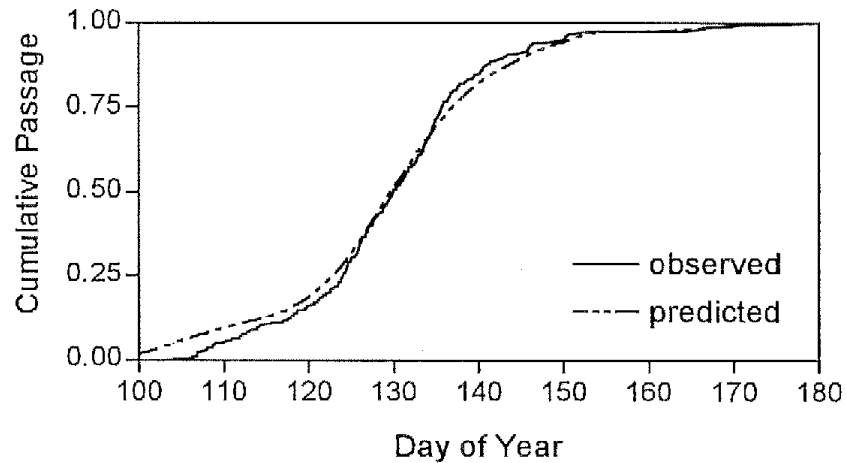
Granite Dam (1996, 1998, 1999) on the Snake River and detected at McNary Dam on the Columbia River, 225 km downstream. Run-of-the-river (mixed hatchery and wild) Columbia River fall chinook were tagged at McNary Dam (1999) on the Columbia River and detected 123 km downstream at John Day Dam. Both these stocks were tagged as active migrants. Wild Snake River fall chinook, which migrate as subyearlings, were beach-seined (1995-1999) in their rearing areas in the Snake River as pre-smolts and detected at Lower Granite Dam. Though these fish were tagged at variable locations, their migratory reach was considered to be Lower Granite Reservoir, which is 51 km long. Since these fish were not actively migrating when tagged, their “travel times” were a combination of migration and rearing.

## **Results and Discussion**

For Snake River fall chinook, fish length was the most important factor for determining migration rate. For the Columbia River fall chinook, length was clearly important, but the addition of the flow covariate substantially improved model performance. For the Snake River spring chinook, length was unimportant, while the factor river flow was most important.

As juvenile chinook salmon mature from the rearing stage to a more actively migrating stage, individual variability becomes less important in terms of predicting migration rate, while river velocity becomes more important. This probably reflects that fish must reach a certain developmental threshold (for which fish length is an indicator) before they initiate active downstream migration. As fish more actively migrate, they shift from nearshore rearing habitats to mid-river regions where they are more influenced by river velocity. Understanding the basic biology of endangered populations is crucial for developing recovery plans. While the conceptual model of behavior presented above is not necessarily new, the ability to quantify spatial and temporal patterns in migrating populations is valuable. Figure 2 demonstrates how these results can be used to predict passage distributions at specific points along the migration route, which is useful for determining when to implement management actions aimed at enhancing survival of migrating salmon.

**Figure 2.** Observed and predicted passage distributions at McNary Dam in 1999 for yearling chinook salmon PIT-tagged at Lower Granite Dam, 225 km upstream. The prediction was based on model parameters estimated from previous years' data. Note that day 100 corresponds to April 10.



PIT tags are increasingly being used to monitor fish populations world-wide. The modeling approach described here has potential for applications in many river systems where passage timing information is important in decisions on how to manage regulated rivers to improve fish survival.

### References

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