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MEMORANDUM

TO: Fish Passage Advisory Committee

FROM: Fish Passage Center

DATE: May 15, 2018

SUBJECT: Passage Indicator: An Interactive Application for Passage Progress Assessment of Adult Spring/Summer Chinook

The Fish Passage Center (FPC) has developed a monitoring method (i.e. passage indicator) that predicts adult salmon passage rates based on regression models using PIT-tags and adult count data. Passage indicator compares current observations of adult passage to model predictions in real time, and provides an objective assessment of passage progress.

The intention of FPC in developing passage indicator is to provide users the convenience of having multiple methods to assess adult passage progress in one interactive environment. As a good investigator considers multiple aspects and evaluates numerous lines of evidence before reaching a conclusion; similarly, a project management team goes through the exercise to consider hydraulic conditions, water summary, weather forecast, and fish passage progress while planning project operations. Thus, we encourage users of passage indicator to consider a diverse analytic perspective while assessing adult passage progress. It is important for fisheries and operation managers to minimize interruptions during adult upstream passage. At the same time, it can be just as important from the perspective of salmon life cycle, to consider the potential harmful effects of a spill reduction that can direct more juvenile migrants through the powerhouse of an in-river project. The following highlight the key points of our methods and precautions that should be taken before drawing conclusions:

- Predicted adult counts by passage indicator incorporate the variations in observed adult counts for the spring/summer Chinook run-at-large.
- Passage indicator predicts adult spring/summer Chinook travel time and the conversion from Ice Harbor to Lower Granite dam, accounting for seasonality, river flow, water temperature, tagging origin, and juvenile transport history.
- In addition to model predictions, passage indicator compares observed fish travel time with historical fish travel time from Lower Monumental to Little Goose dams, and from Ice Harbor to Lower Granite dam.

- Predictions by passage indicator can be unreliable during early migration season due to small sample sizes.
- Users of passage indicator should consider multiple assessments while monitoring adult passage progress. Assessments should all predominantly agree with one another, and users should investigate conflicting evidence before taking any management actions that may be detrimental for other life stages.

Background

Fishery and project operations management had raised concerns regarding disruptions of adult spring/summer Chinook upstream passage caused by the tailrace hydraulic conditions creating a turbulent environment where adult passage entrances could not be easily found, especially at Little Goose (LGS) dam. The Fish Passage Center believed that we were in a qualified position to address this concern because of our extensive research on passage related issues (see FPC, 2009; FPC, 2011a; FPC, 2011b; FPC, 2017; FPC, 2018b). Expanding from our past analyses, the FPC developed a set of assessment methods that would identify expected adult salmon passage rates. Mainly, we utilized regression models on dam counts (FPC, 2018a) and dynamics between fish travel time and its biological and environmental drivers (FPC, 2018c). To monitor adult passage, we would simulate passage progress based on model predictions, and compare the simulations with the observed passage progress in real time[1]. The assumption was that models would predict "average outcomes" of passage progress, and a slower than usual passage would be apparent in comparison.

Our assessment method involved four main components. We utilized the *shiny* package (Chang et al., 2017) in R to develop an application that allowed users to monitor adult spring/summer Chinook passage progress and consider multiple assessments under one interactive, web-based environment. The first component, located on the top left panel of the passage indicator dashboard (Figure 1), was based on adult counts of spring/summer Chinook run-at-large between Lower Monumental (LMN) and LGS dams. We used a regression model to predict LGS adult counts in real time based on LMN counts. In the second component, located on the top right panel, we predicted the cumulative conversion from Ice Harbor (IHR) to Lower Granite (LGR) dam based on a regression model for travel time expressed in terms of velocity. In the third component, located on the bottom left panel, we compared the LMN to LGS travel time distributions between current and historical observations. In the fourth component, located on the bottom right panel, we compared the IHR to LGR travel time distributions between current and historical observations. Also in the fourth component, we provided the option to compare the distributions between observed and predicted. Regression model predictions accounted for the effects of biological and environmental conditions on passage progress.

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[1] It takes few days for PIT-tag and dam counts data to be processed and sent to FPC database; therefore, "in real time" for our passage indicator would actually be few days behind the current observation date.

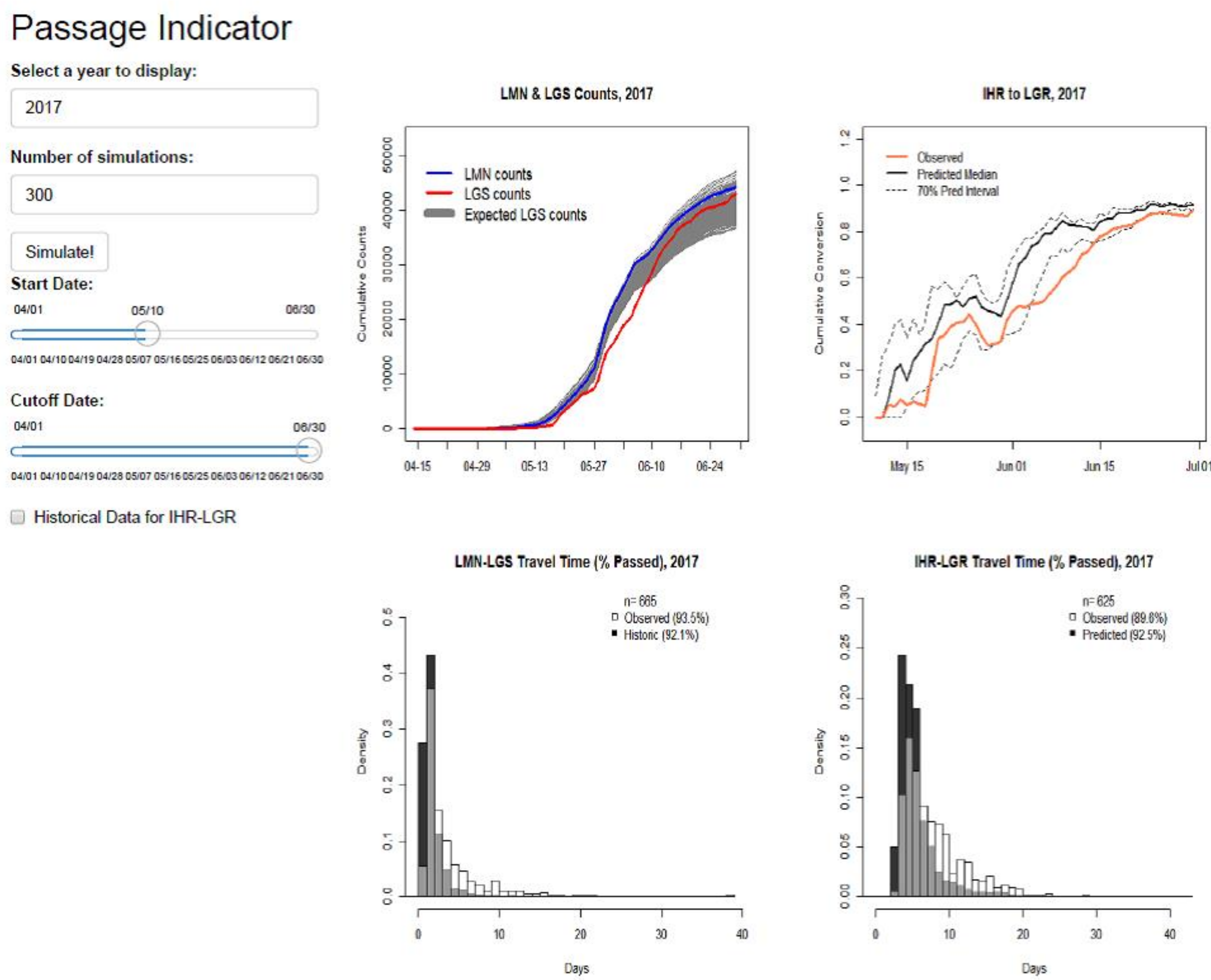

Figure 1: A screenshot of the passage indicator dashboard shows the four panels for passage progress assessment.

Passage Assessment Process

We programmed passage indicator to update and summarize adult count and PIT-tags data twice a day (7:45 AM and 15:00 PM) during spring/summer Chinook upstream migration season. It would be prudent for users to pay close attention to the sample sizes, especially during early season before significant portions of the return are observed. With a small sample size, a few slow fish might bring down the average travel time and give a misleading impression of a possible passage issue. We had observed a few "false flag" scenarios with fluctuating adult counts, mostly during early season when sample sizes were small.

Passage indicator would be more effective in predicting passage progress as more spring/summer Chinook arrived for the upstream migration season. Users might start by checking component 1, located at the upper left panel on the passage indicator dashboard, to get an overall idea on the upstream passage progress for the run-at-large. Component 1 plotted the LMN and LGS cumulative adult counts as soon as we (FPC) received updates on the adult counts. The rule of thumb was that the observed LGS counts would fall within the area of predicted LGS counts (grey lines). If the observed LGS counts ventured below the predicted area, results would suggest a *slower than expected* passage progress based on adult counts.

Even when an apparent passage issue was identified by component 1 (adult counts), it should be confirmed by other components of passage indicator before drawing conclusions. Components 2 and 4, located on the right side of the passage indicator dashboard, were based on PIT-tags detection from IHR to LGR. As such, the results from components 2 and 4 were a few days behind LMN and LGS adult counts data due to the extra time needed for fish to travel between LGS and LGR. Still, users should allow some extra time for fish to catch up on the passage progress; in the past, we had observed passage progress slowing down, and then subsequently catching back up after few days, without modifications of spill operations.

In case of a legitimate issue for passage progress, patterns of slowing down observed in adult counts would also manifest in conversion between IHR and LGR. Component 2 compared observed conversion with the model predicted conversion. And when the observed conversions fell below the predicted area, it suggested a *slower than expected* passage progress.

Components 3 and 4 compared the distributions of fish travel time between observed and the historical data, for the reach between LMN and LGS (component 3) and between IHR and LGR (component 4). The panels for components 3 and 4 displayed the overlapping histograms that represent the standardized distributions. Users could adjust the start and end/cutoff dates to zoom in on a specific date range. The rule of thumb was that during a slowdown in passage progress, users would notice the current status of passage at LGS or LGR being lower compared to the historical status of the same time period. "Percent passed," or conversion, referred to the proportion of PIT-tagged fish detected at both LMN and LGS (for component 3) or at both IHR and LGR (for component 4) within the specified time period.

Once the fish with longer travel time started to pass LGS (and eventually LGR), the observed distributions would have a higher proportion of fish with longer travel time compared to the historical data of the same time period. That is, users might see the observed distributions with taller bars in the sections of long travel time, compared to the historical distributions.

Keep in mind that comparison between current observations and historical data did not account for seasonality, river flow, temperature, tagging origin, or juvenile transport history. Therefore, we provided the option to compare current observations with model predictions in component 4. The rule of thumb for assessing passage progress was the same as the comparison between observed and historical data, but with the added advantage of accounting for environmental and biological variability.

Statistical Models and Simulation Methods

Component 1: Adult Counts Model

We summarized daily counts data for spring/summer Chinook adults and jacks that were seen at LMN and LGS Dams during April, May, and June in return years 2009 to 2016. We excluded return years 2010, 2011, and 2017 due to known passage or adult counts issues. In general, adult fish counts at LGS follow the patterns of adult fish counts at LMN, given a lag time for fish to travel between the two dams. That is, LMN counts could be used to predict LGS counts, after accounting for some travel time. Based on our previous analysis, a one-day lag between LMN and LGS counts resulted the best fitting model (FPC, 2018a).

We fitted a linear mixed effects model using daily LGS adult counts as the response variable and lagged LMN adult counts as the explanatory variable. We also included random year effects that allowed a varying intercept and a varying slope for each return year. To focus our analysis on days with adequate counts, we limited the data to records where the lagged LMN count was greater than 100 fish. We transformed the LGS and LMN counts using a natural logarithmic function to improve approximating normality of the model residuals, and the log-log form of LGS and LMN counts measured the percentage changes in their relationship instead of absolute changes. The model was specified as follows:

$$ln(LGS_i) = \beta_0 + \beta_{LMN} \cdot ln(LMN_i) + \gamma_{yr[i]} + \delta_{yr[i]} \cdot ln(LMN_i) + \epsilon_i,$$

where i the ith observation, yr represents return years 2009, 2012 to 2016, γ_{yr} and δ_{yr} are the random intercepts and slopes,

$\begin{pmatrix} \gamma_{yr} \\ \delta_{yr} \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_\gamma^2 & \rho\sigma_\gamma\sigma_\delta \\ \rho\sigma_\gamma\sigma_\delta & \sigma_\delta^2 \end{pmatrix}\right)$, and $\epsilon_i \sim N(0, \sigma^2)$ is the residual.

We fitted the linear model using `lmer()` function from the *lme4* package (Bates et al. 2015) in R.

To estimate passage progress, we simulated LGS adult counts predictions based on current observations at LMN using `sim()` function from the *arm* package (Gelman & Su, 2016) in R. The `sim()` function automated the simulation process by creating specified number of random simulations of the coefficient vector $\boldsymbol{\beta}^{rep}$ and the simulated residual standard deviation σ^{rep}. For each draw:

1. Simulate $\sigma^{rep} = \hat{\sigma}\sqrt{(n-k)/X}$, where X is a random draw from the χ^2 distribution with $n-k$ degree of freedom. n is the number of observations in the data, and k is the number of parameters.

2. Given the random draw of σ^{rep}, simulate $\boldsymbol{\beta}^{rep} = \begin{pmatrix} \beta_0^{rep} \\ \beta_{LMN}^{rep} \end{pmatrix}$ from a multivariate normal distribution with mean $\hat{\boldsymbol{\beta}} = \begin{pmatrix} \hat{\beta}_0 \\ \hat{\beta}_{LMN} \end{pmatrix}$ and variance matrix σV_β. V_β is the unscaled estimation covariance matrix from the model.

3. Calculate predicted LGS counts for all observed LMN counts. Let LGS_i^{rep} be the ith predicted LGS counts. And for an average year, $LGS_i^{rep} = e^{(\beta_0^{rep} + \beta_{LMN}^{rep} \cdot ln(LMN_i))}$. Plot the cumulative predicted LGS counts up to the observation day.

To plot the model uncertainty for LGS counts, we repeated steps 1 to 3 for specified iterations (default is set at 300). Finally, we plotted the cumulative counts for the observed LMN and LGS counts for comparison (Figure 2).

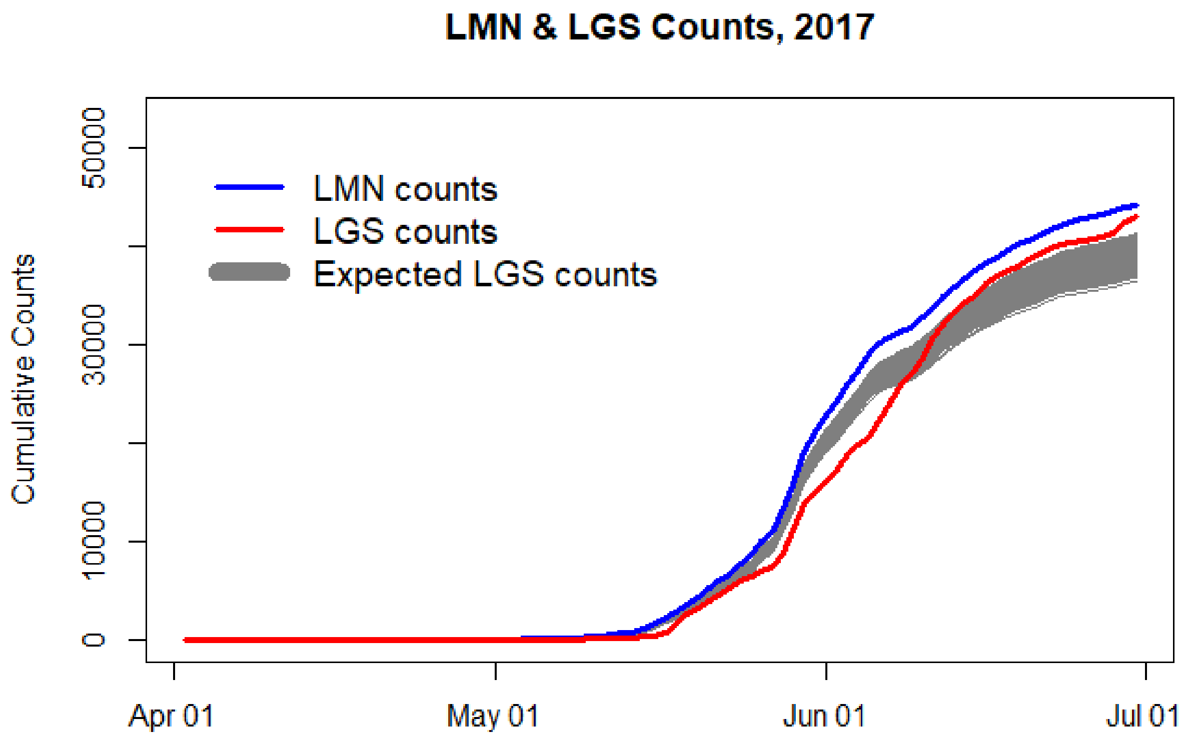

Figure 2: Component 1 shows the cumulative counts for LMN and LGS. Grey lines are model uncertainties for predicted LGS counts.

Component 2: Travel Velocity Model

To fit a travel velocity model, we included in our dataset PIT-tagged adult spring/summer Chinook that were first detected at IHR during April, May, and June, between years 2005 to 2016. Return years 2011 and 2017 were excluded from our analysis due to unusual spill operations or known passage issues. We referred to this dataset as the historical data. We only kept the fish that were PIT-tagged above LGR as juveniles, and excluded uncertain origins[2] such as the ones that were tagged at Clearwater Trap, Grande Ronde River Trap, Imnaha Trap, and Snake Trap.

For each fish, we included the time and dates of PIT-tag detection at IHR and LGR. We summarized environmental and biological information such as Julian date of detection at IHR, flow (Kcfs) at IHR (upon detection), tailrace temperature (°C) at IHR (upon detection), distance (km) to tagging site (from LGR), and juvenile transport history.

Past analyses suggested that the distribution of fish travel time was often right skewed and required transformation of the response to better approximate normality of the residuals and

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[2] Fish tagged at these traps originate from areas located far above the traps. Therefore, distance to origin is unknown for these fish.

reduce heteroscedasticity (Chapter 3 in McCann et al., 2017) or utilizing a generalized linear model with the appropriate link function (FPC, 2018c). We also noticed that transforming travel time into velocity (by dividing distance between IHR and LGR dams, 157 km, by travel time) would yield a centered, bell-shaped distribution and a superior model fit than a logarithmic transformation or utilizing a GLM with inverse-Gaussian link.

We fitted a linear mixed effects model to assess the relationship between fish travel velocity and its biological and environmental conditions. For the model, the response variable was fish travel time (FTV, km/days) between IHR and LGR dams. The fixed effects explanatory variables were Julian date, flow, tailrace temperature, distance to tagging site from LGR dam, and juvenile transport history. The random effects explanatory variable was return year. The model was specified as follows:

$$FTV_i = \beta_0 + \beta_{Jday} \cdot JulianDate_i + \beta_{Flow} \cdot Flow_i + \beta_{km} \cdot Distance_i + \beta_{Temp} \cdot Temperature_i + \beta_{MigHis} \cdot Transport_i + \gamma_{yr[i]} + \epsilon_i,$$

where i is individual PIT-tagged fish, yr represents return years 2005 to 2010 and 2012 to 2016, $Transport_i$ is an indicator variable, $\gamma_{yr} \sim N(0, \sigma_{yr}^2)$ is the random year intercept, and $\epsilon_i \sim N(0, \sigma^2)$ is the residuals.

We standardized all continuous variables in the model to improve fit. We fitted the model using `lmer()` function in the *lme4* package in R.

We plotted the observed vs. predicted conversion to assess passage progress (Figure 3). The steps to simulate predictions were as follows:

1. Simulate fish travel velocity predictions based on current observations. Let FTV_i^{rep} be the predicted fish travel time for the *i*th individual fish detected at IHR dam. And for an average return year, $FTV_i^{rep} = \hat{\beta}_0 + \hat{\beta}_{Jday} \cdot JulianDate_i + \hat{\beta}_{Flow} \cdot Flow_i + \hat{\beta}_{km} \cdot Distance_i + \hat{\beta}_{Temp} \cdot Temperature_i + \hat{\beta}_{MigHis} \cdot Transport_i + \epsilon_i^{rep}$, where $\hat{\boldsymbol{\beta}}$ are the model estimates of coefficient values. And we simulate ϵ_i^{rep} by randomly draw from a $N(0, \hat{\sigma}^2)$ distribution, where $\hat{\sigma}$ is the estimated residual standard error from the model. We use `rnorm()` function in R to perform the random drawing of ϵ_i^{rep}. We then back-transform travel velocity, FTV_i^{rep}, to travel time for the *i*th individual.

2. Predict conversion from IHR to LGR. To adjust for apparent mortality[3], we assign each fish a survival status by randomly draw from a $Bernoulli(0.96)$ distribution (`rbinom()` function in R). For each individual with a survival status of 1 (alive), we project a LGR passage date by adding the predicted travel time (from step 1) onto the IHR detection date.

[3] Our travel velocity model did not account for apparent mortality; therefore, model prediction without adjusting for mortality would tend to overestimate conversion. To mitigate overprediction due to apparent mortality, we first estimated the mean conversion (0.96) between IHR and GRA with a logistic regression model using the same PIT-tag dataset, then adjusted our conversion prediction accordingly.

After assigning a projected LGR passage date for each individual, we then summarize the portion that has arrived LGR since April 1st to the day of observation.

3. Create a prediction interval. Steps 1 and 2 are repeated numerous times (default is 300) to create a range of model predictions. We obtain the prediction median and a 70% interval by taking the 15th and 85th percentiles of model predictions.

4. Plot the predicted cumulative conversion by repeating steps 1 through 3 every day until the end of the season, or June 30th. The observed cumulative conversion is also plotted to assess the passage progress.

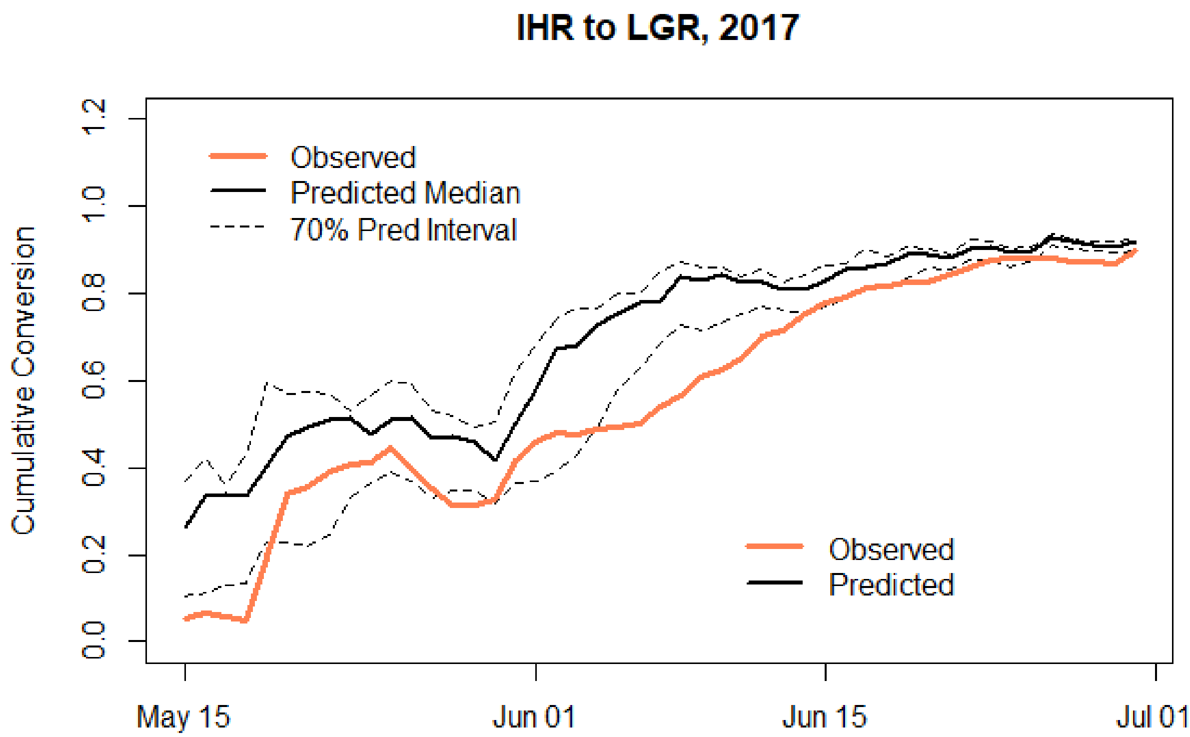

Figure 3: Component 2 shows the cumulative conversion for IHR to LGR.

Component 3: Travel Time Distribution (LMN to LGS)

We plotted LMN to LGS travel time distributions of PIT-tagged spring/summer Chinook for the historical data (2014 to 2016) and the current observations (Figure 4). We did not include return year 2017 in the historical data because 2017 was not considered as an "average" year for upstream passage. Fish in the historical data were truncated on the observation date. That is, the distribution plotted included only fish with LGS arrival date equal or earlier than the observation date. We plotted the distributions in histograms with one-day bins. The sum of the densities for all bins was equal to the conversion for LMN to LGS (labelled as "% Passed").

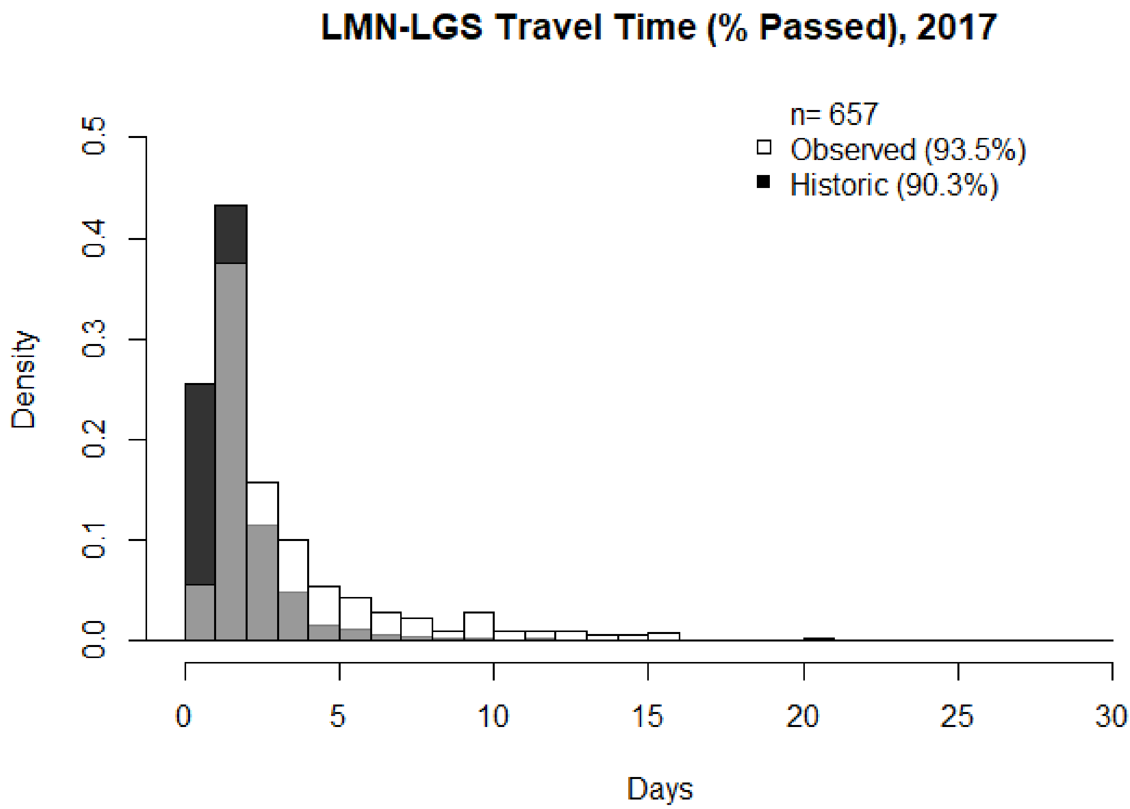

Figure 4: Component 3 compares LMN to LGS fish travel time distributions between the observed and historical data.

Component 4: Travel Time Distribution (IHR to LGR)

We included in this component the option to compare travel time distributions between observed and predicted, in addition to comparison between observed and historical. To compare distributions between observed and predicted fish travel time, we plotted the model predictions for IHR to LGR travel time from the travel velocity model (component 2) and the current observations (Figure 5).

To compare distributions between observed and historical data, we plotted the IHR to LGR travel time distributions of PIT-tagged spring/summer Chinook for 2005 to 2016 and the current observations. We did not include return years 2011 nor 2017 in the historical data due to abnormal spill operations and known passage issues. We plotted the distributions with the same procedures as in component 3.

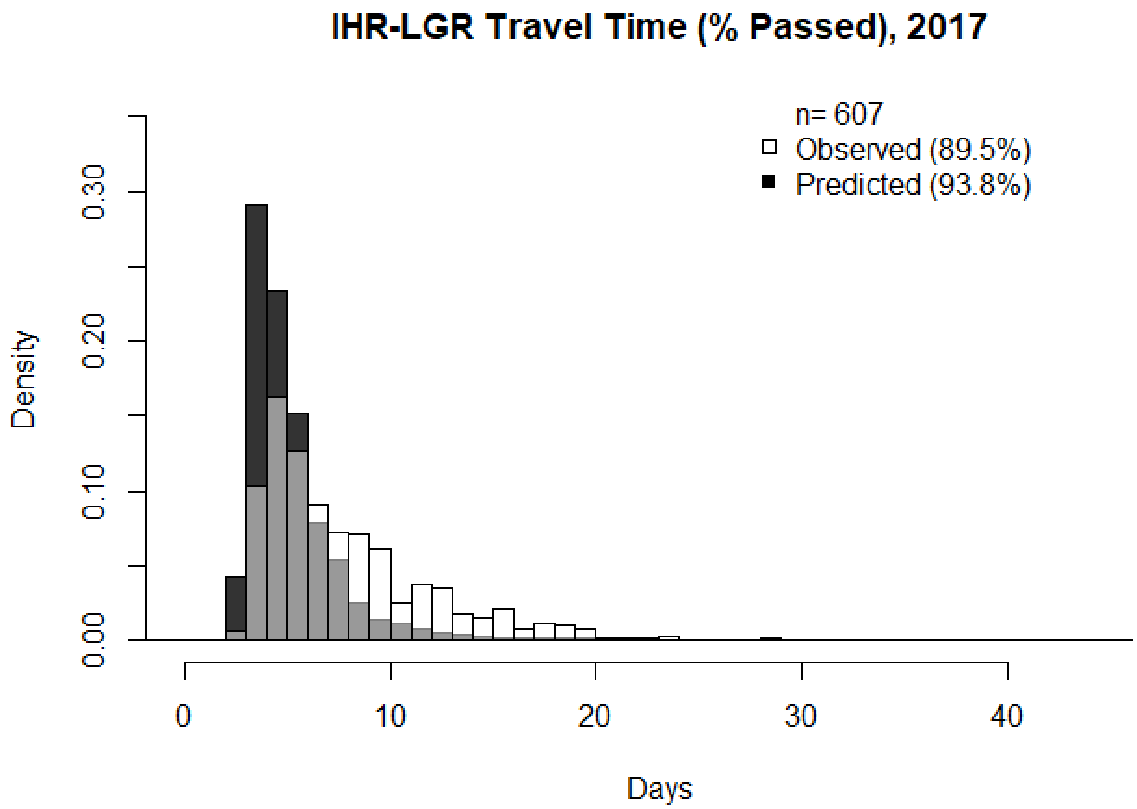

Figure 5: Component 4 compares IHR to LGR fish travel time distributions between the observed and the predicted. Passage indicator app has the option to display comparison between the observed and historical data.

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