Steelhead Overshoot Update

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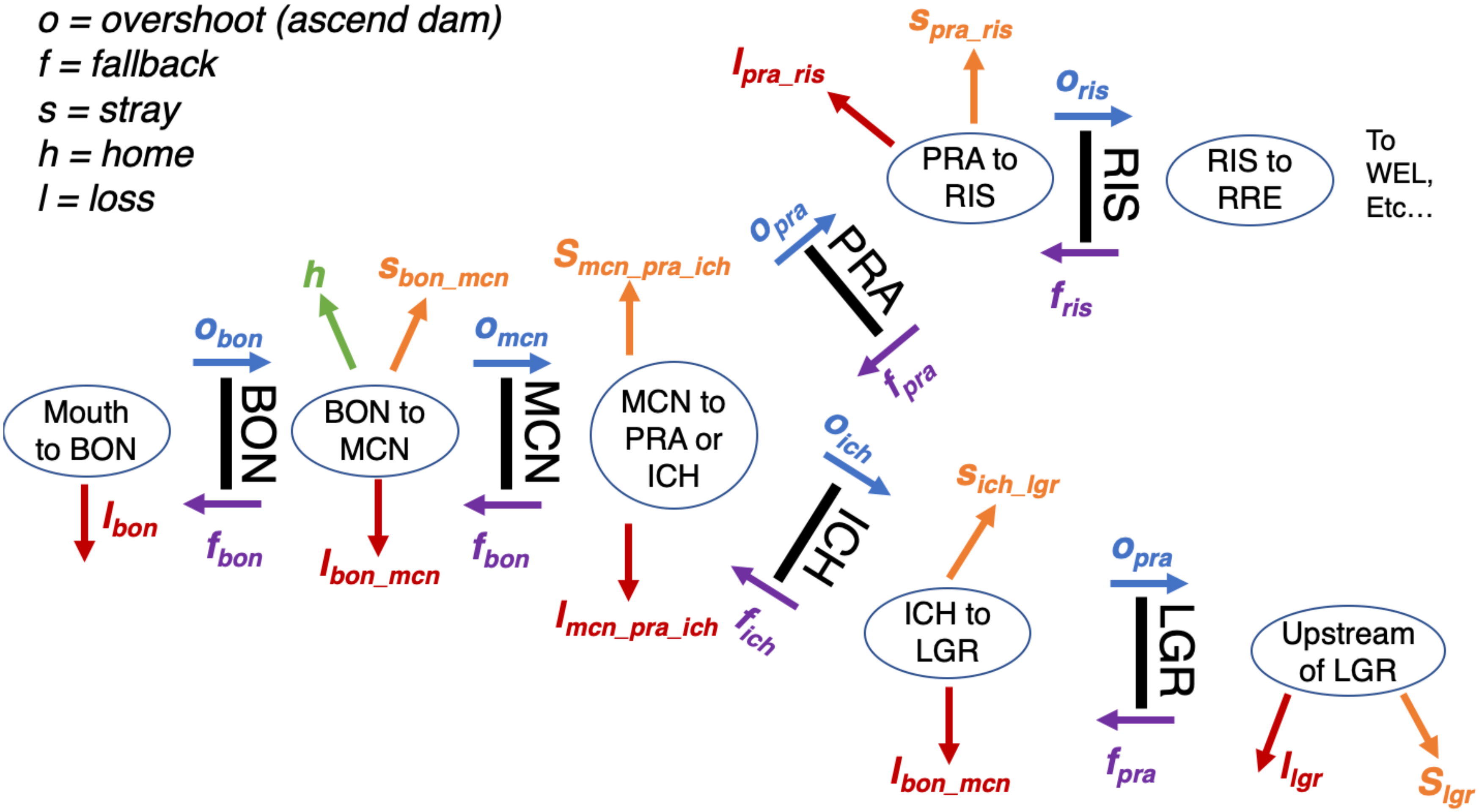
Model setup

Modeling overview

- Data still John Day River wild Steelhead, 2005-2015
- MLE form, implemented in optim()
- **Bayesian form, implemented in JAGS**

Model setup

o = overshoot (ascend dam)
f = fallback
s = stray
h = home
l = loss



Constraining movement probablities in each state to sum to 1

Two options:

1. Dirichlet prior (e.g., Waterhouse et al. 2020)

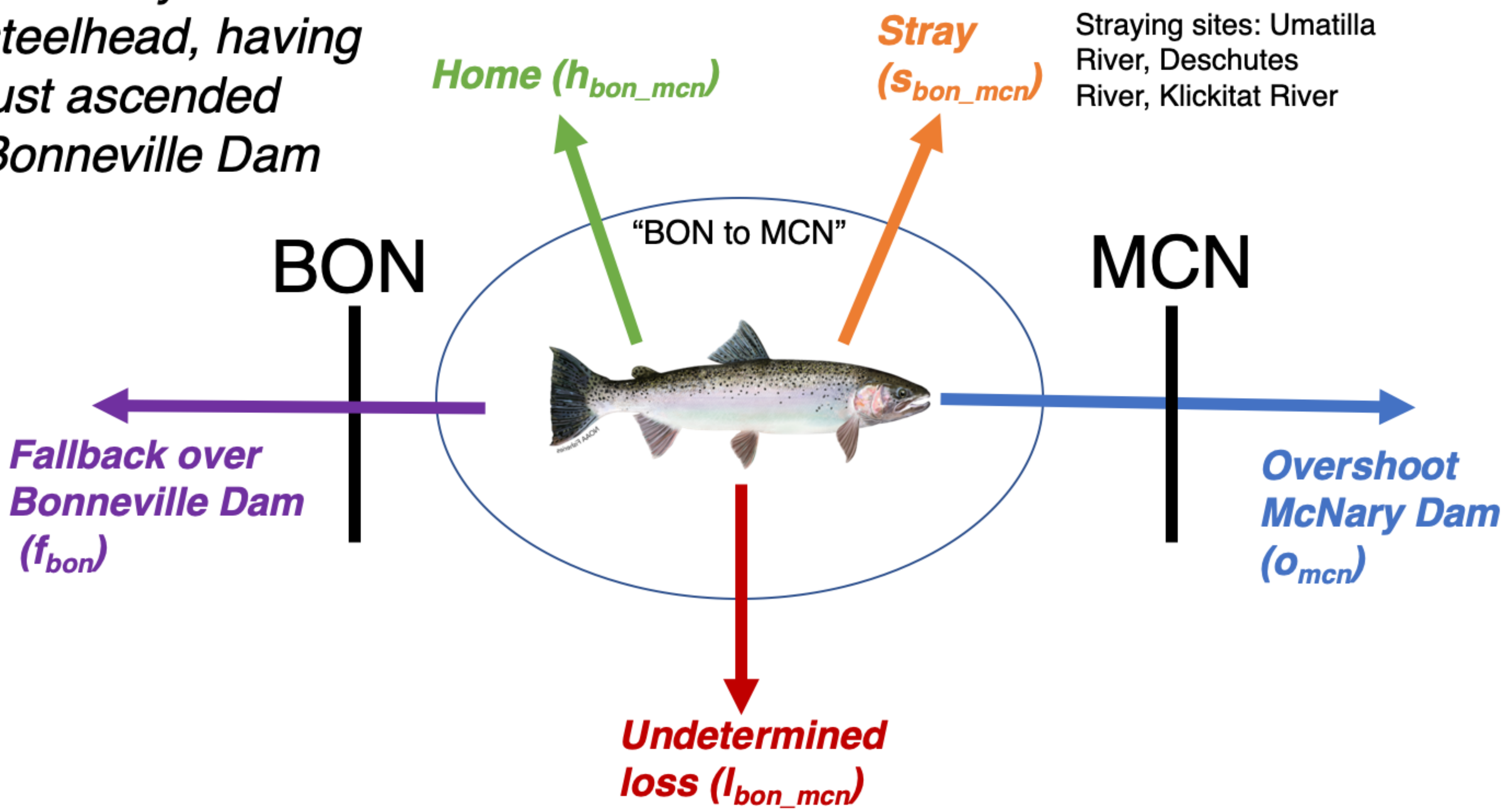
```
p <- 1 - q - r
c(p, q, r) ~ ddirch(c(1, 1, 1))
```

2. Additive log-ratio (what I chose to implement):

- Used to transform (redefine) parameters that lie on the interval [0,1] to the interval [-Inf, Inf]
- Choose one parameter to serve as reference (denominator)

Additive log-ratio: Example

John Day River wild steelhead, having just ascended Bonneville Dam



Additive log-ratio: Example

$$
\begin{aligned}
a_2 &= log(o_{mcn}/l_{bon\_mcn}) \\
b_2 &= log(s_{bon\_mcn}/l_{bon\_mcn}) \\
c_2 &= log(h_{bon\_mcn}/l_{bon\_mcn}) \\
d_2 &= log(f_{bon}/l_{bon\_mcn})
\end{aligned}
$$

$$
\begin{aligned}
o_{mcn} &= \exp(a_2)/(1 + \exp(a_2) + \exp(b_2) + \exp(c_2) + \exp(d_2)) \\
s_{bon\_mcn} &= \exp(b_2)/(1 + \exp(a_2) + \exp(b_2) + \exp(c_2) + \exp(d_2)) \\
h_{bon\_mcn} &= \exp(c_2)/(1 + \exp(a_2) + \exp(b_2) + \exp(c_2) + \exp(d_2)) \\
f_{bon} &= \exp(d_2)/(1 + \exp(a_2) + \exp(b_2) + \exp(c_2) + \exp(d_2)) \\
l_{bon\_mcn} &= 1/(1 + \exp(a_2) + \exp(b_2) + \exp(c_2) + \exp(d_2))
\end{aligned}
$$

Priors

- Vague priors - normal with precision of 0.01 (equals SD of 10)

```
a2 ~ dnorm(0, 0.01)
b2 ~ dnorm(0, 0.01)
c2 ~ dnorm(0, 0.01)
d2 ~ dnorm(0, 0.01)
```

- All parameters received these priors
- Currently 14 states in the model, so we have a1 - a14, and b, c, and/or d for the states that have more than two possible movements

Multinomial likelihood

- Get a vector of probabilities *p* with length *K*, where *K* is the number of unique observed detection histories
- In this dataset, *K* = 169 (169 unique detection histories)
- Example:

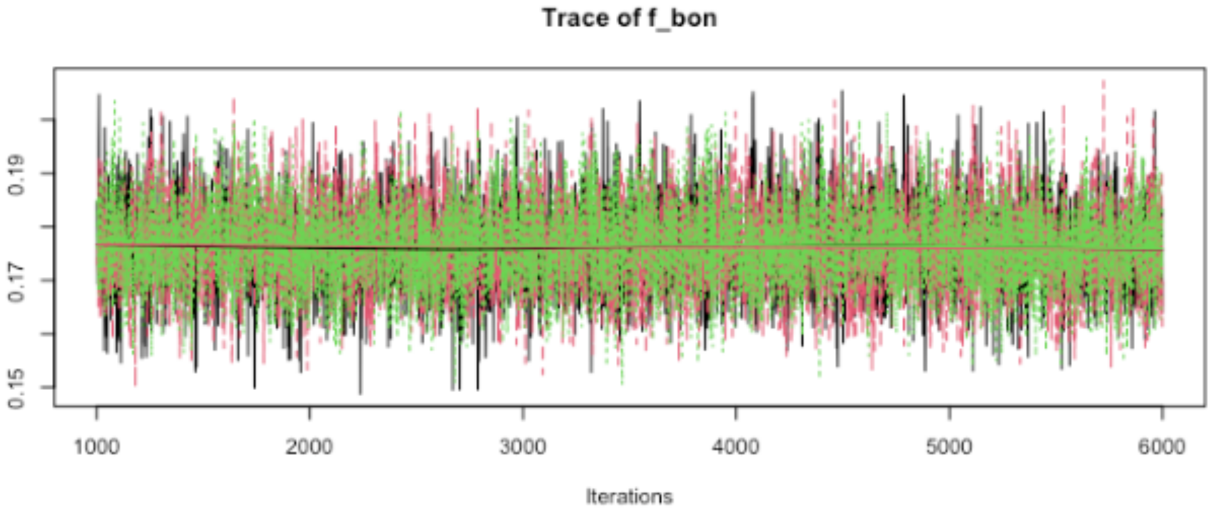
$$n_7 = f_{bon} * o_{bon} * f_{bon} * o_{bon} * h_{bon\_mcn} * l_{nat\_trib}$$
$$p[7] = n_7$$

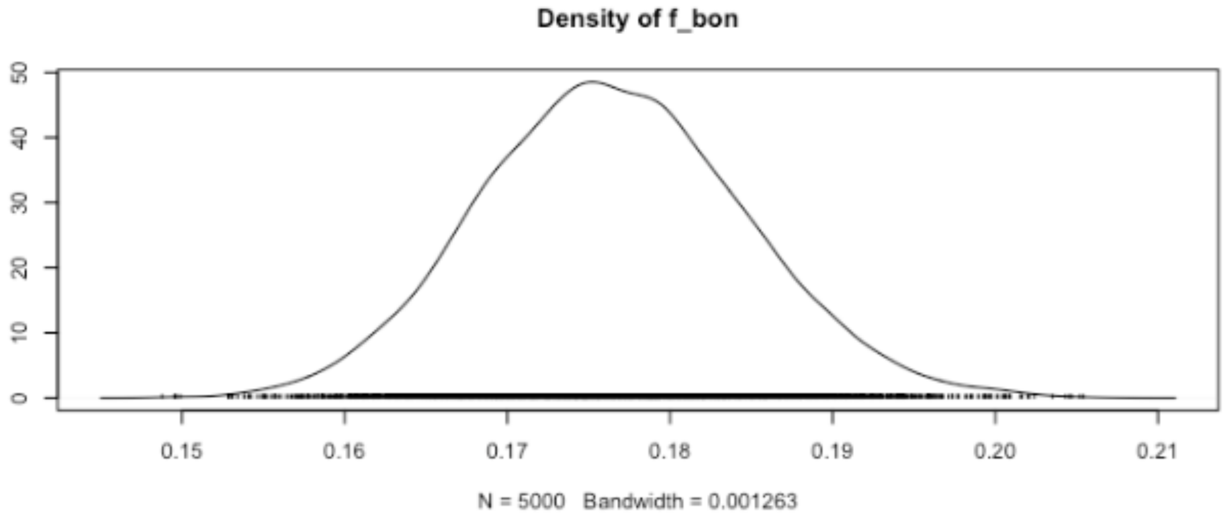
Evaluate multinomial likelihood

```
p <- c(n1, n2, n3, ... n169)

# Evaluate counts, where y are the counts of
# the number of times each of the unique detection
# histories was observed

# 2121 are the number of fish
y[1:N] ~ dmulti(p[1:N], 2121)
```

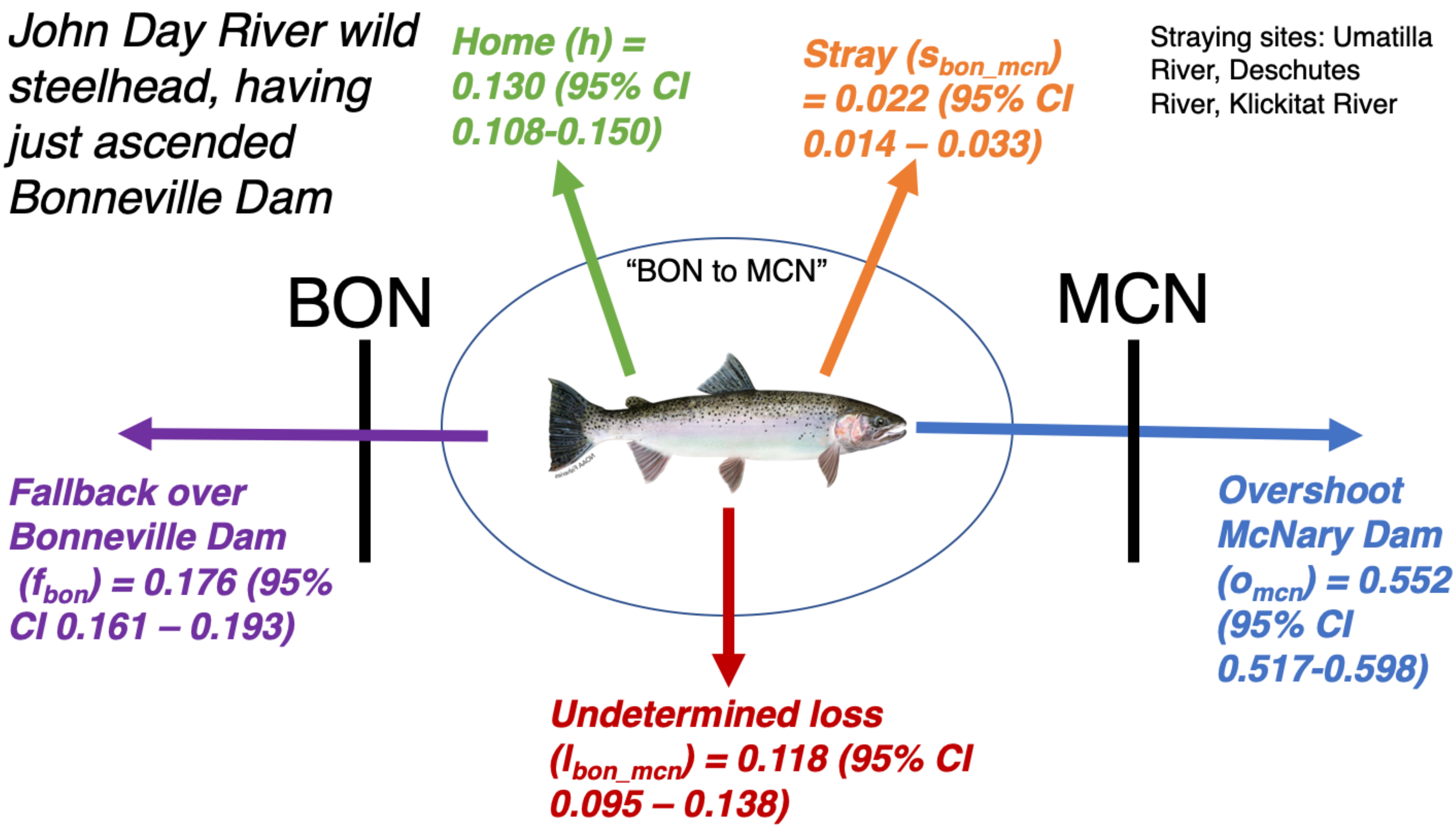
- 36 parameters monitored

Example plots





Example model outputs



Next steps

Expanding dataset

- 14 (?) natal tributaries
- 2005 onwards
- Would have to build a new model for each new arrangement of operational PIT tag arrays - i.e., would have to build a new model for 2018 onwards, when the John Day adult fishway PIT tag detectors came online

Adding complexity (via covariates, or different parameters)

1. Run year
2. Natal origin
3. Temperature
4. Spill
5. Juvenile history
6. Harvest (loss parameter?) - use WDFW data, summarize by river reach/state to align with model
7. Memory (overshoot?)

Detection probability

- Implicit movements could be considered not detected
- For example, an individual with consecutive detections in the McNary adult fishways:

$$o_{mcn} * p_{o_{mcn}} * f_{mcn} * (1 - p_{f_{mcn}}) * o_{mcn} * p_{o_{mcn}}$$

Would this help us estimate detection probabilities and thus unobserved fallback?

Informative priors

- What are sources of information for priors?