Rio Grande Silvery Minnow Hydrobiological Analysis: Draft Results

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Rio Grande silvery minnow

- Endemic species adapted to historical, dynamic habitat

- Floodplain rearing habitats

- Hydrologic and geomorphic changes limit availability of these habitats
Rio Grande silvery minnow

- Population declines and range contraction drive ESA listing
- Federal water management projects require assessment of potential impacts to RGSM
How can we manage water resources to conserve/restore RGSM?

• How does the MRG population of RGSM respond to hydrologic changes?
2016 Biological Opinion HBO Analyses

- Explored relationships between RGSM catch per unit effort (CPUE) and hydrology
- CPUE positively related to flood metrics, negatively related to low flow metrics
- Used to predict RGSM response to future conditions
- USU contracted to review HBO analyses and provide suggestions for improvements
Suggestions from USU 2019 Review of HBO Analyses

- Account for correlated predictors
- Disaggregate catch data
- Reach-specific responses to hydrologic conditions
- Different indices of drying and flooding conditions
- Account for temporal autocorrelation
- Alternative model structures to produce realistic catch values
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Incorporating suggested analytical changes

• How does RGSM distribution and abundance change under different hydrologic conditions?
  • What hydrologic conditions drive RGSM distribution/abundance?

• How likely are recovery goals to be met under different hydrologic conditions?
  • Single year
Broad Approach

• Generate composite metric of flooding intensity

• Generate more responsive drying metric

• Generate metric of flood timing

• Compare multiple models incorporating different hydrologic metrics
Accounting for correlated predictors with a new, integrated flood index

• Highly correlated hydrologic metrics
Accounting for correlated predictors with a new, integrated flood index

• Highly correlated hydrologic metrics
• Principal components analysis (PCA) finds dominant axes of variation
• PC1 explains 78% of variance in data
• Index of flood magnitude/duration*
  • Also incorporates low flow information

![PCA plot](image)
More responsive drying Index

• RiverEyes data

• Mile-days dry
  • 24 miles dry for 10 days = 240 mile-days dry

• Predict mile-days dry from summer channel acres to fill in data gaps

Note non-linear axis
Disaggregating catch data

- Pooled seine hauls by sample site
- Demonstrates variance in catch rates
- Years with large average CPUE are driven by few very large catch events
Modeling framework

• Predict site-specific presence and CPUE of RGSM
• Predict presence, then if present, predict CPUE
• Allow populations to respond uniquely to hydrologic conditions in each reach
• Account for temporal autocorrelation
• Account for theoretical carrying capacity
CPUE Model Structure

• Hurdle Model (two-step)
  1. **Probability of non-zero catch**
  2. Predicted CPUE given it is greater than zero

• Reach specific baseline probability of presence, $\alpha_r$ (logit scale)

• Latent trend (unobserved driver), $w_y$

$$logit(p_{ry}) = \alpha_r + \beta_p \varphi_{ry} + w_y$$

$$\alpha_r \sim N(\mu_\alpha, \sigma_\alpha^2)$$

$$w_y \sim N(w_{y-1}, 1)$$

$$I(C_{ry} > 0) \sim Bernoulli(p_{ry})$$
CPUE Model Structure

• Hurdle Model (two-step)
  1. Probability of non-zero catch
  2. Predicted CPUE given it is greater than zero

• Gompertz relationship

\[ C_{ry} = K_r e^{-\beta_o} e^{-\beta_c \delta_y} \]
CPUE Model Structure

• Hurdle Model (two-step)
  1. Probability of non-zero catch
  2. Predicted CPUE given it is greater than zero

• Gompertz relationship

• Reach specific “carrying capacity”, $K_r$

• Gamma distributed errors
  • Continuous, positive values

\[
C_{ry} = K_r e^{-\beta_o} e^{-\beta_c \delta_y}
\]

\[
K_r \sim N(\mu_K, \sigma_K^2)
\]

\[
\sigma_{ry} = cv \times C_{ry}
\]

\[
\gamma_{ry} = 1 + \theta_{ry} C_{ry}
\]

\[
\theta_{ry} = \frac{C_{ry} + \sqrt{C_{ry} + 4\sigma_{ry}^2}}{2\sigma_{ry}^2}
\]

\[
(C_{ry}|C_{ry} > 0) \sim \Gamma(\gamma_{ry}, \theta_{ry})
\]
CPUE Model Structure

• Hurdle Model (two-step)
  1. Probability of non-zero catch
  2. Predicted CPUE given it is greater than zero

\[
\text{logit}(p_{ry}) = \alpha_r + \beta_p \varphi_{ry} + w_y \\
w_y \sim N(w_{y-1}, 1) \\
\alpha_r \sim N(\mu_\alpha, \sigma_\alpha^2) \\
I(C_{ry} > 0) \sim \text{Bernoulli}(p_{ry}) \\
\]

\[
C_{ry} = K_r e^{-\beta_o} e^{-\beta c \delta_y} \\
K_r \sim N(\mu_K, \sigma_K^2) \\
\sigma_{ry} = cv \times C_{ry} \\
\gamma_{ry} = 1 + \theta_{ry} C_{ry} \\
\theta_{ry} = \frac{C_{ry} + \sqrt{C_{ry} + 4\sigma_{ry}^2}}{2\sigma_{ry}^2} \\
(C_{ry}|C_{ry} > 0) \sim \Gamma(\gamma_{ry}, \theta_{ry}) \\
\]

\[
E(C_{iry}) = I(C_{ry} > 0) \times (C_{ry}|C_{ry} > 0) 
\]
Models explored

• Presence model
  \( p(\text{metric}) \)

• Catch model
  \( C(\text{metric}) \)

• Metrics
  • PC1
    • PCA axis 1
    • Flood magnitude, duration, summer flows
  • Flood peak timing
  • Mile-days dry

<table>
<thead>
<tr>
<th>Presence Component</th>
<th>Catch Component</th>
</tr>
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<tbody>
<tr>
<td>1 PC1</td>
<td>PC1</td>
</tr>
<tr>
<td>2 Timing</td>
<td>Timing</td>
</tr>
<tr>
<td>3 Mile-days dry + PC1</td>
<td>PC1</td>
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<tr>
<td>4 Mile-days dry</td>
<td>Timing</td>
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<tr>
<td>5 Mile-days dry</td>
<td>PC1</td>
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Model comparison

<table>
<thead>
<tr>
<th>Presence Component</th>
<th>Catch Component</th>
<th>WAIC</th>
<th>ΔWAIC</th>
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<tbody>
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<td>2 Timing</td>
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<tr>
<td>5 Mile-days dry</td>
<td>PC1</td>
<td>15667</td>
<td>9190</td>
</tr>
</tbody>
</table>

- Model with flood magnitude predicting both presence and catch fits data MUCH BETTER than all other models.
Predicted CPUE

- Distributions of predicted catches capture >95% of observations
- Struggles to capture rare high catches
- Higher predicted catches in years with large floods
- Higher, more variable catches in San Acacia than Isleta or Angostura

\[ E(C_{ry}) = I(C_{ry} > 0) \times (C_{ry} | C_{ry} > 0) \]
Parameter Estimates
- Presence

• Increased probability of capture in years with larger floods

• San Acacia has greatest baseline probability of catching RGSM at any given site
  • Less flooding required to increase probability of capture in San Acacia

\[
\text{logit}(p_{ry}) = \alpha_r + \beta_p \rho_{ry} + w_y
\]
Parameter Estimates
- Presence

• Increased probability of capture in years with larger floods

• San Acacia has greatest baseline probability of catching RGSM at any given site
  • Less flooding required to increase probability of capture in San Acacia

$logit(p_{ry}) = \alpha + \beta_p \varphi_{ry} + w_y$
Parameter Estimates – Presence – Latent Trend

- Periodic pattern in catch probability not captured by drying conditions

- Accounting for one or more unobserved drivers of variation, possibly including:
  - Prior year’s distribution carrying over?
  - Large-scale climatic conditions?
    - PDO
    - ENSO

$$\text{logit}(p_{ry}) = \alpha_r + \beta_p \varphi_{ry} + w_y$$

$$w_y \sim N(w_{y-1}, 1)$$
Predicted probability of presence

• Lower in years with small floods

• Periodic pattern – driven by latent trend

\[ \text{logit}(p_{ry}) = \alpha_r + \beta_p \varphi_{ry} + w_y \]
Parameter Estimates – Catch

• Larger floods increase the mean expected catch at a given sampling site

• San Acacia has highest predicted carrying capacity
  • Large uncertainties

\[ C_{r_{y}} = K_{r}e^{-\beta_{o}e^{-\beta_{c}y}} \]
Parameter Estimates – Catch

- Larger floods increase the mean expected catch at a given sampling site

- San Acacia has highest predicted carrying capacity
  - Large uncertainties

- San Acacia has greatest expected catch

\[ C_{ry} = K_r e^{-\beta o e^{-\beta c \delta y}} \]
Simulation Experiment

• What is the probability of meeting recovery goal CPUE given different flood conditions?
  • Proportion of simulated CPUEs greater than 5 RGSM per 100m²
  • Single year!
  • Useful tool for exploring alternative management options
Effect of Drying - Presence

• Model had less support by WAIC than PC1 model
  • Remember: PC1 incorporates flood and low flow information

• Demonstrates strong support for negative effect of summer drying on RGSM presence
  • San Acacia has greatest baseline probability of catching RGSM at any given site
    • Model suggests more drying required to reduce catch probability in San Acacia

\[
\text{logit}(p_{ry}) = \alpha_r + \beta_p \varphi_{ry} + w_y
\]
Implications

• Larger floods increase productivity of RGSM
  • Increases abundance and distribution

• Contemporary hydrologic backdrop can provide suitable conditions *periodically*
  • Frequency needs to be increased for recovery
    • Habitat restoration?
    • Managed flood flows?

• Summer drying extent appears less important as predictor of RGSM, but it is related to flooding
  • Minimizing drying will be beneficial

• Model provides a tool for exploring performance of alternative management approaches under uncertain future hydrologic conditions
Next Steps

• What is driving the latent trend?
  • Spawning biomass
  • Large-scale climatic indices (PDO, ENSO, etc.)

• Management strategy evaluation to inform adaptive management

• Explore trade-offs with other water management objectives
Acknowledgments

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• Fish Ecology Lab at USU
• Lake Ecology Lab at USU
• Ecology Center at USU
Predicted CPUE

a) Angostura, Isleta, San Acacia, Total

b) Angostura

c) Isleta

d) San Acacia