Rio Grande Silvery Minnow Hydrobiological Analysis:

Draft Results

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U.S. Bureau of Reclamation, Albuquerque Office

Rio Grande silvery minnow

- Endemic species adapted to historical, dynamic habitat
- Floodplain rearing habitats
- Hydrologic and geomorphic changes limit availability of these habitats

Photo: fws.gov

Photos from: Medley and Shirey (2013) Ecohydrology, Volume: 6, Issue: 3, Pages: 491-505, First published: 04 March 2013, DOI: (10.1002/eco.1373)

Rio Grande silvery minnow

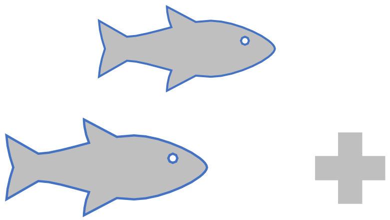
- Population declines and range contraction drive ESA listing

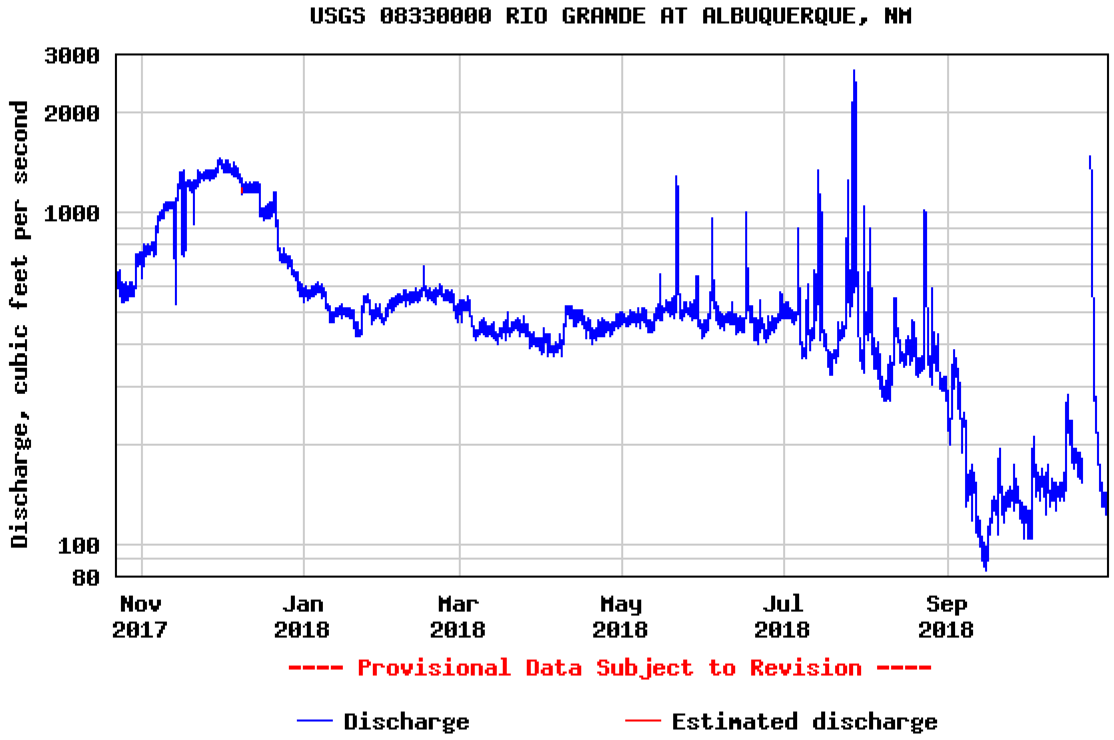
- Federal water management projects require assessment of potential impacts to RGSM

Photos from: Medley and Shirey (2013) Ecohydrology, Volume: 6, Issue: 3, Pages: 491-505, First published: 04 March 2013, DOI: (10.1002/eco.1373)

How can we manage water resources to conserve/ restore RGSM?

- How does the MRG population of RGSM respond to hydrologic changes?





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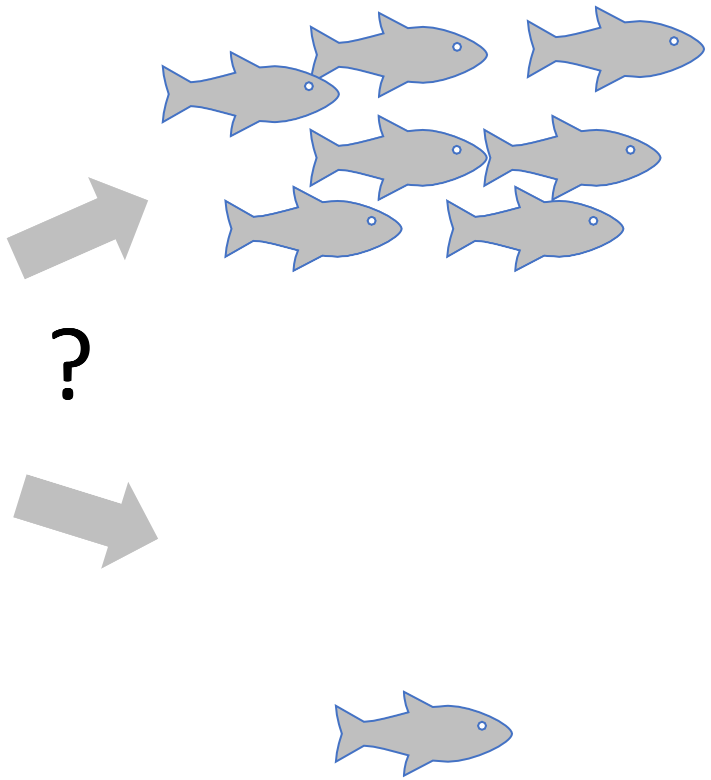
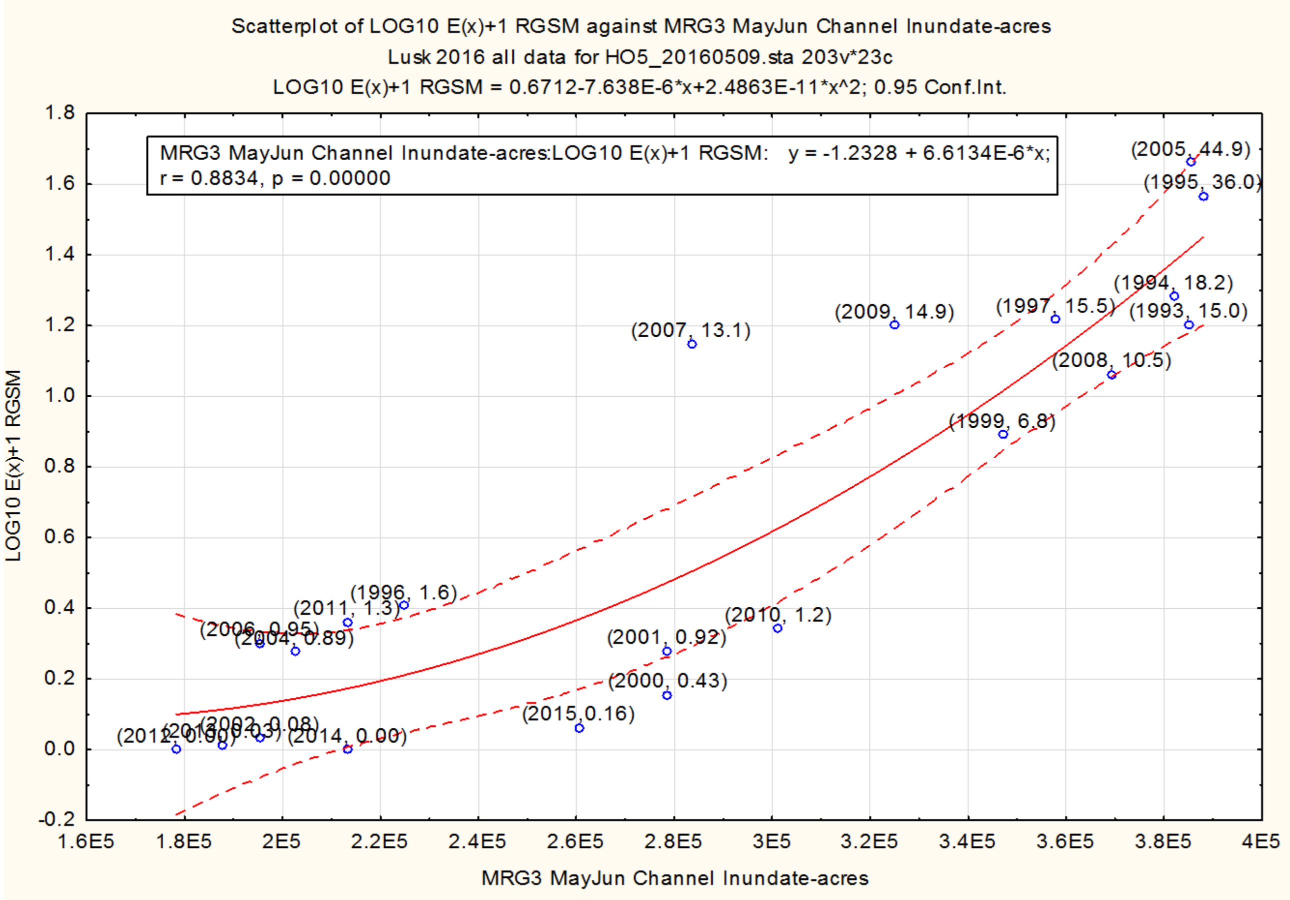


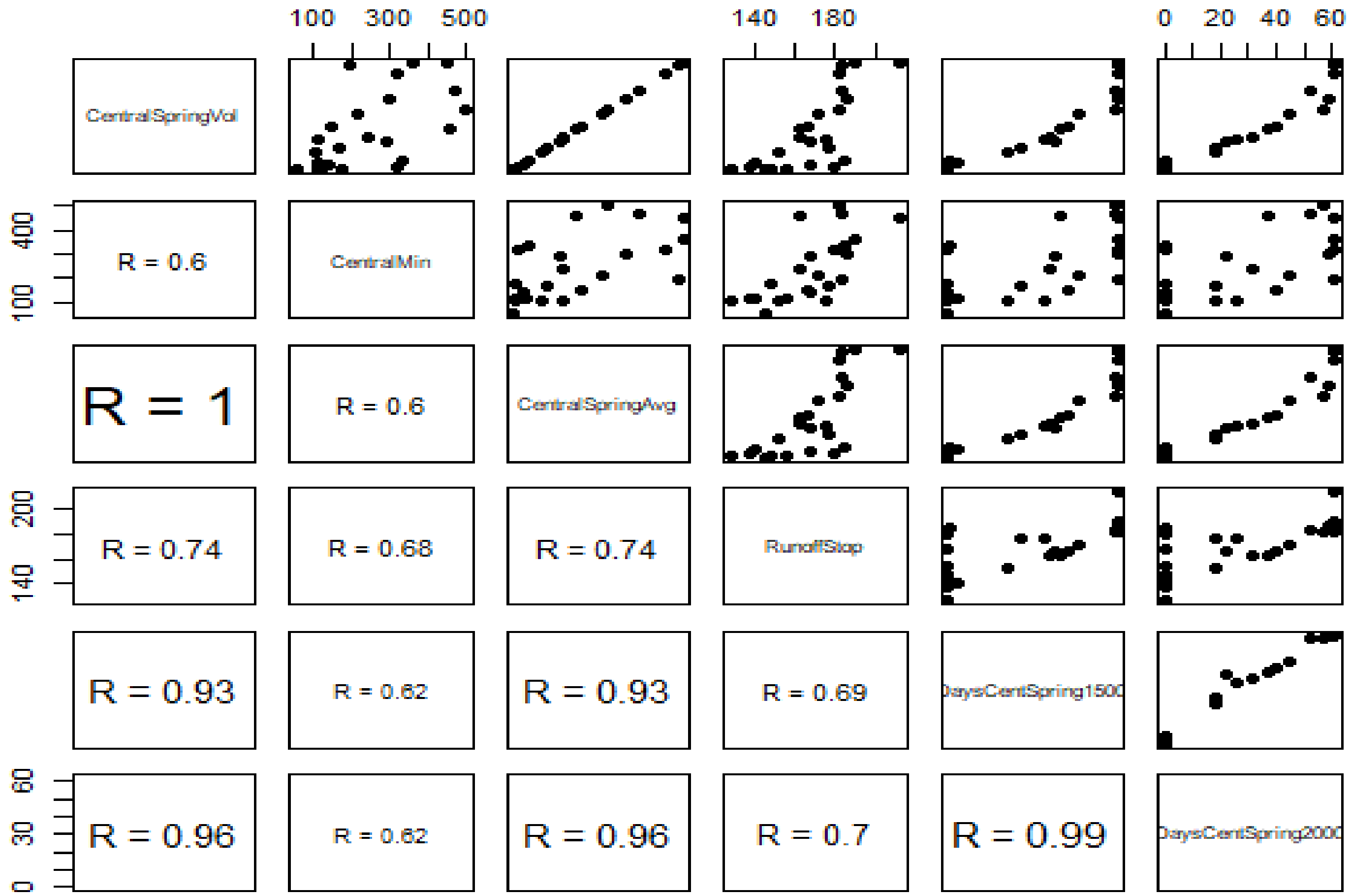
2016 Biological Opinion HBO Analyses

- 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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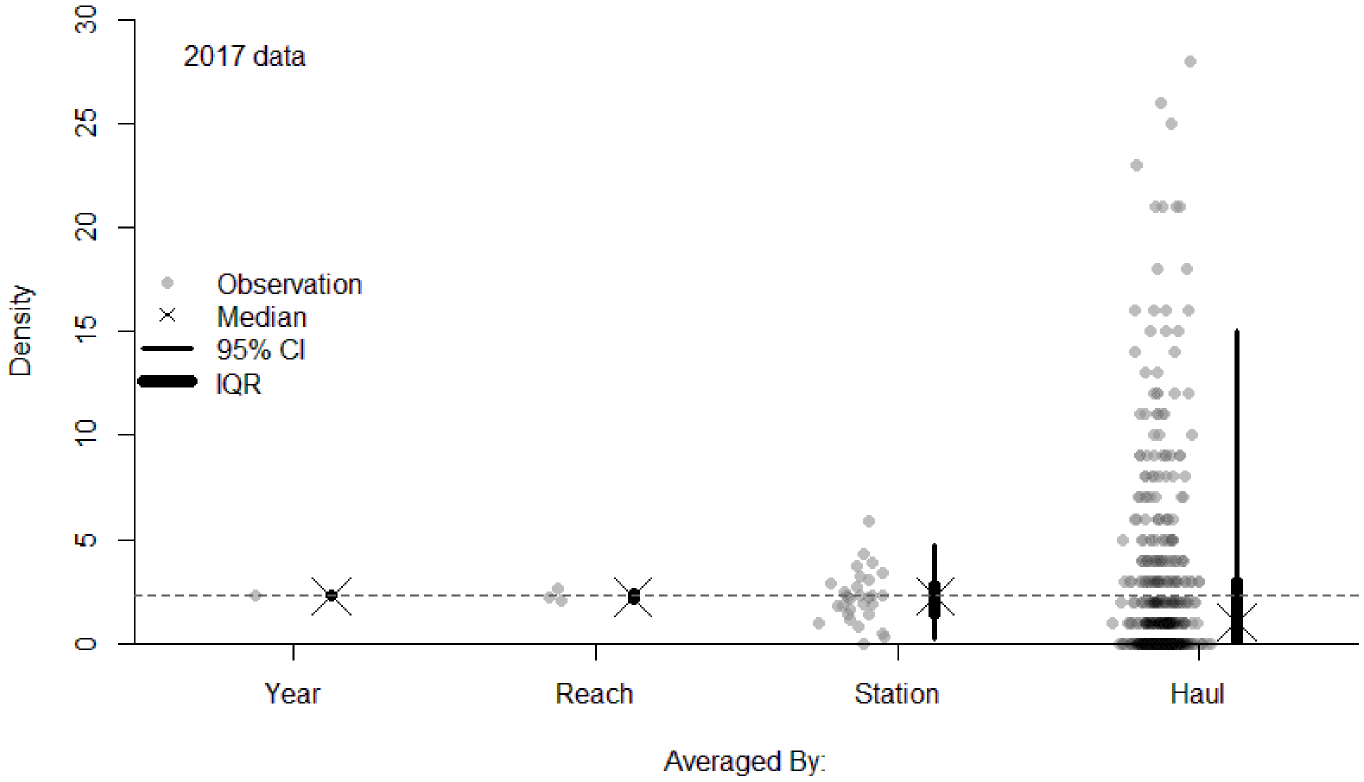

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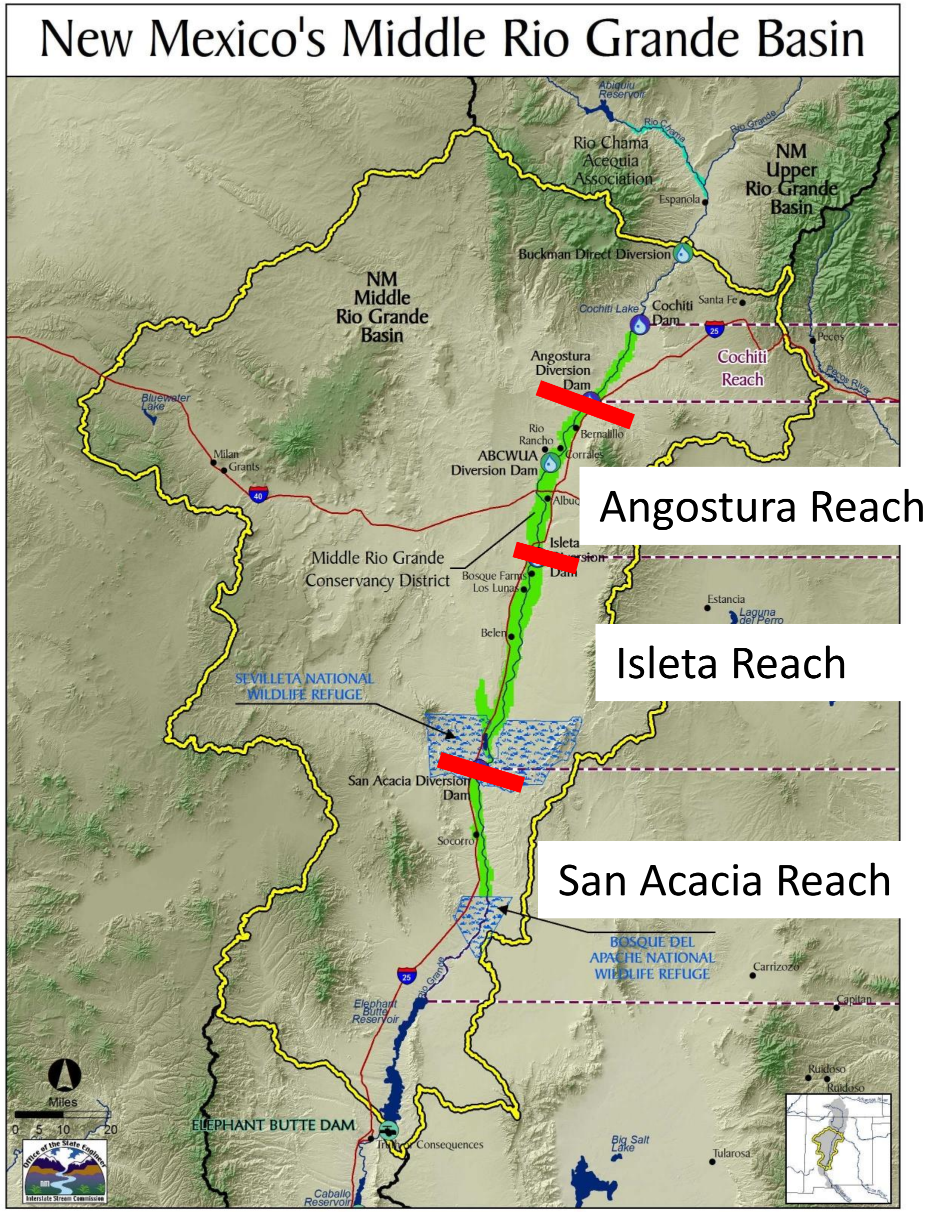

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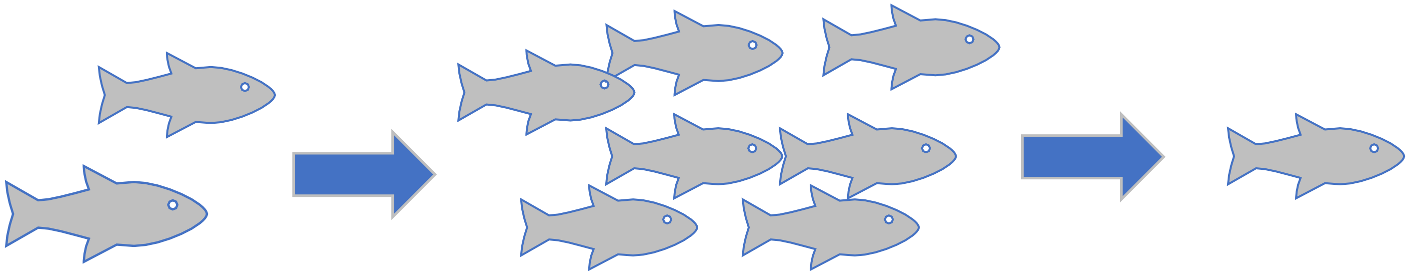

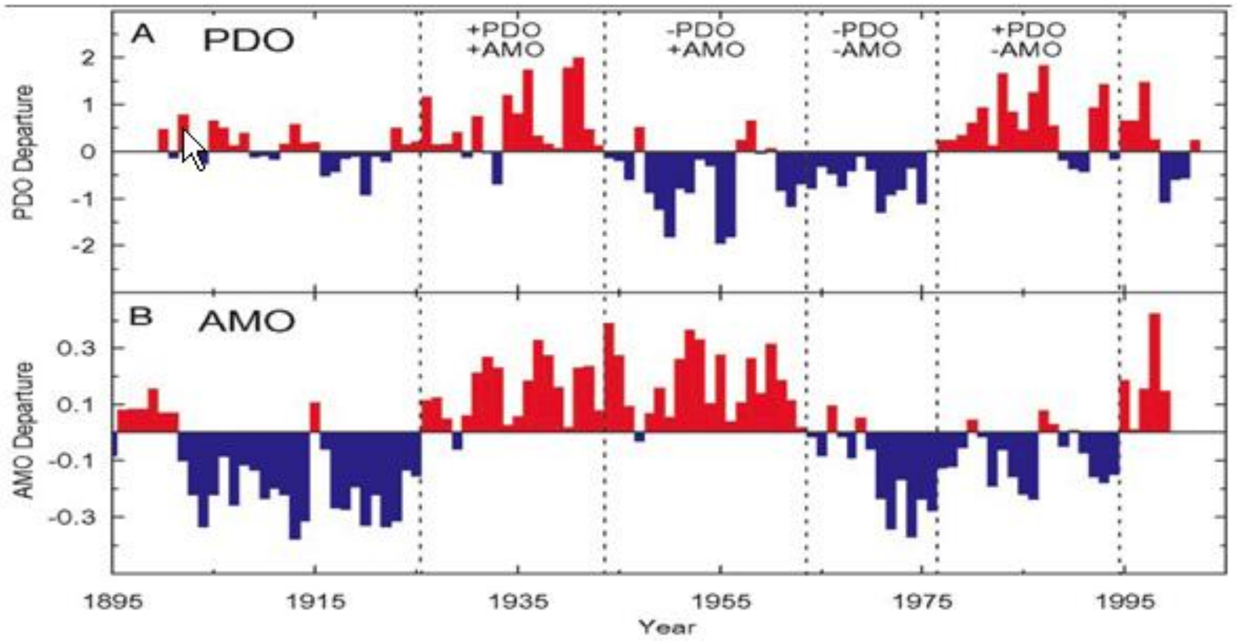

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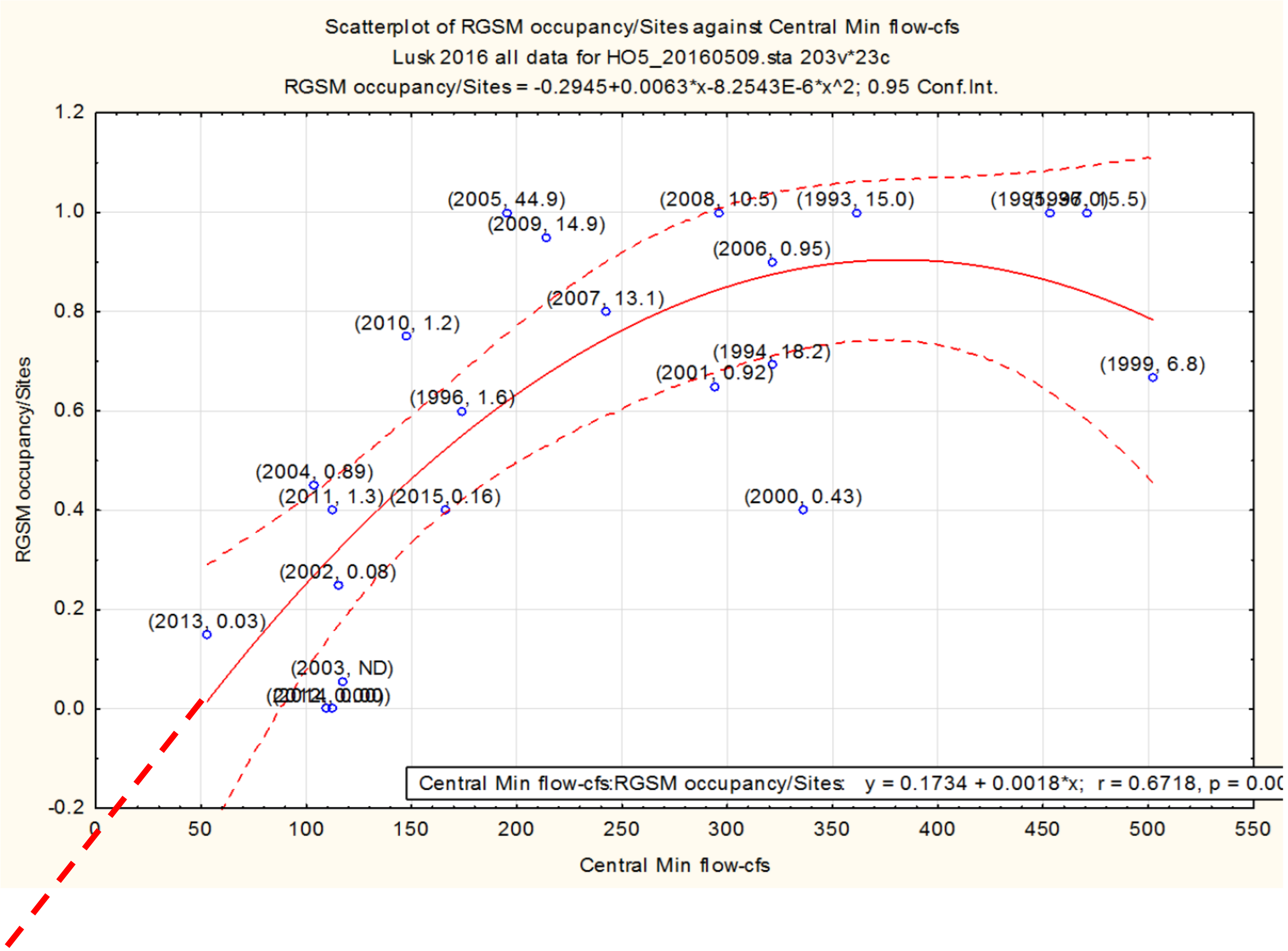

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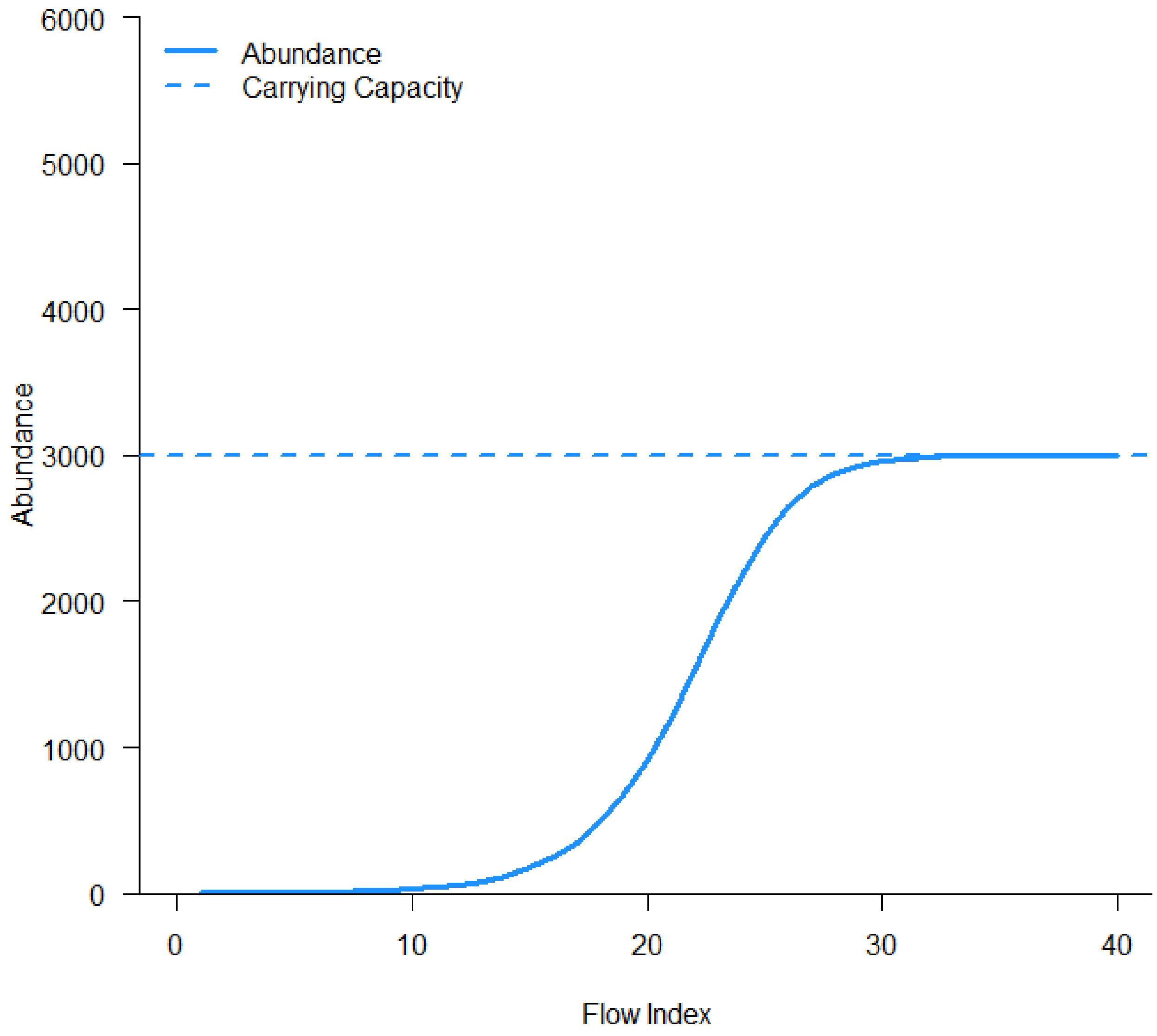


Incorporating suggested analytical changes

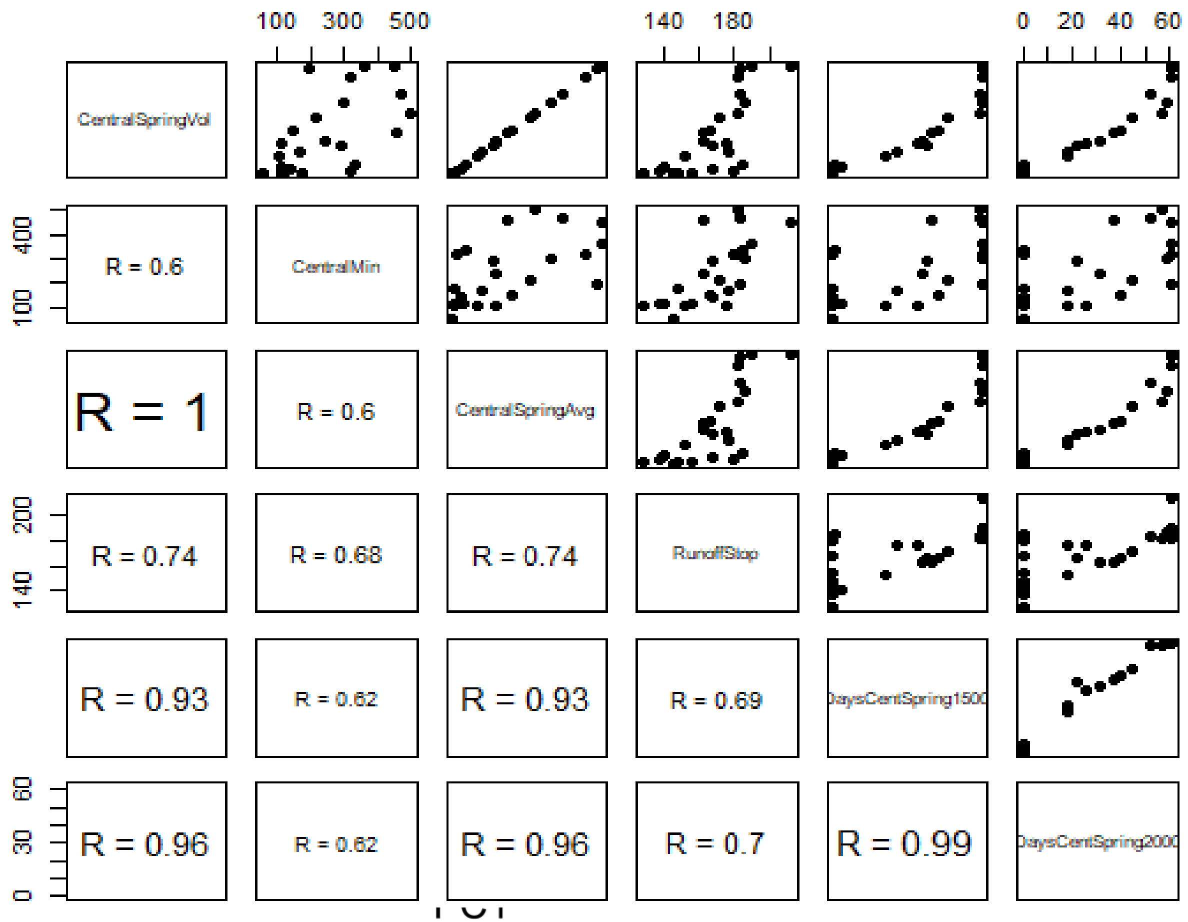
- How does RGSM distribution and abundance change under different hydrologic conditions?
  - What hydrologic conditions drive RGSM distribution/abundance?
- How likely are recovery goals to be met under different hydrologic conditions?
  - *Single year*

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

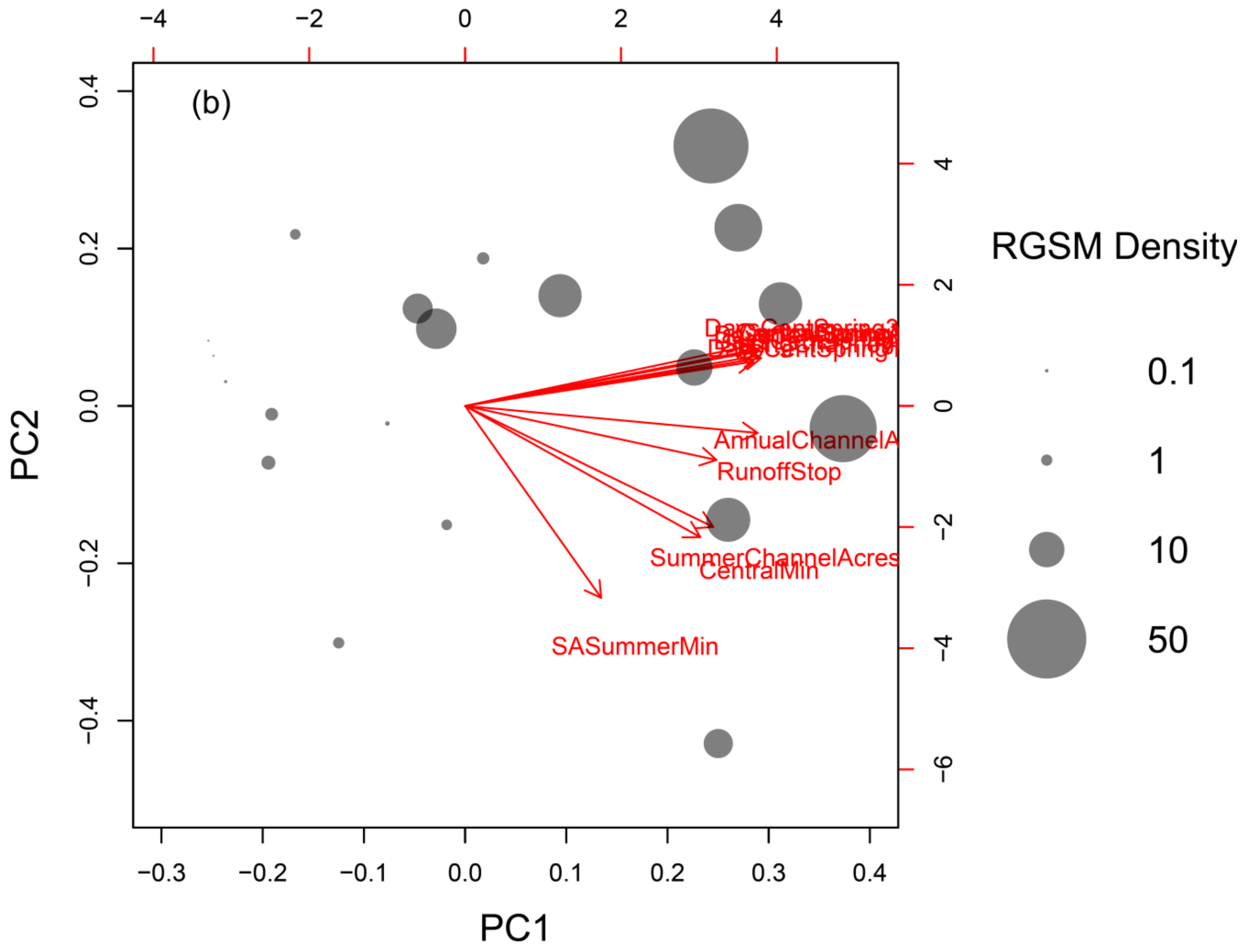
Accounting for correlated predictors with a new, integrated flood index

- Highly correlated hydrologic metrics



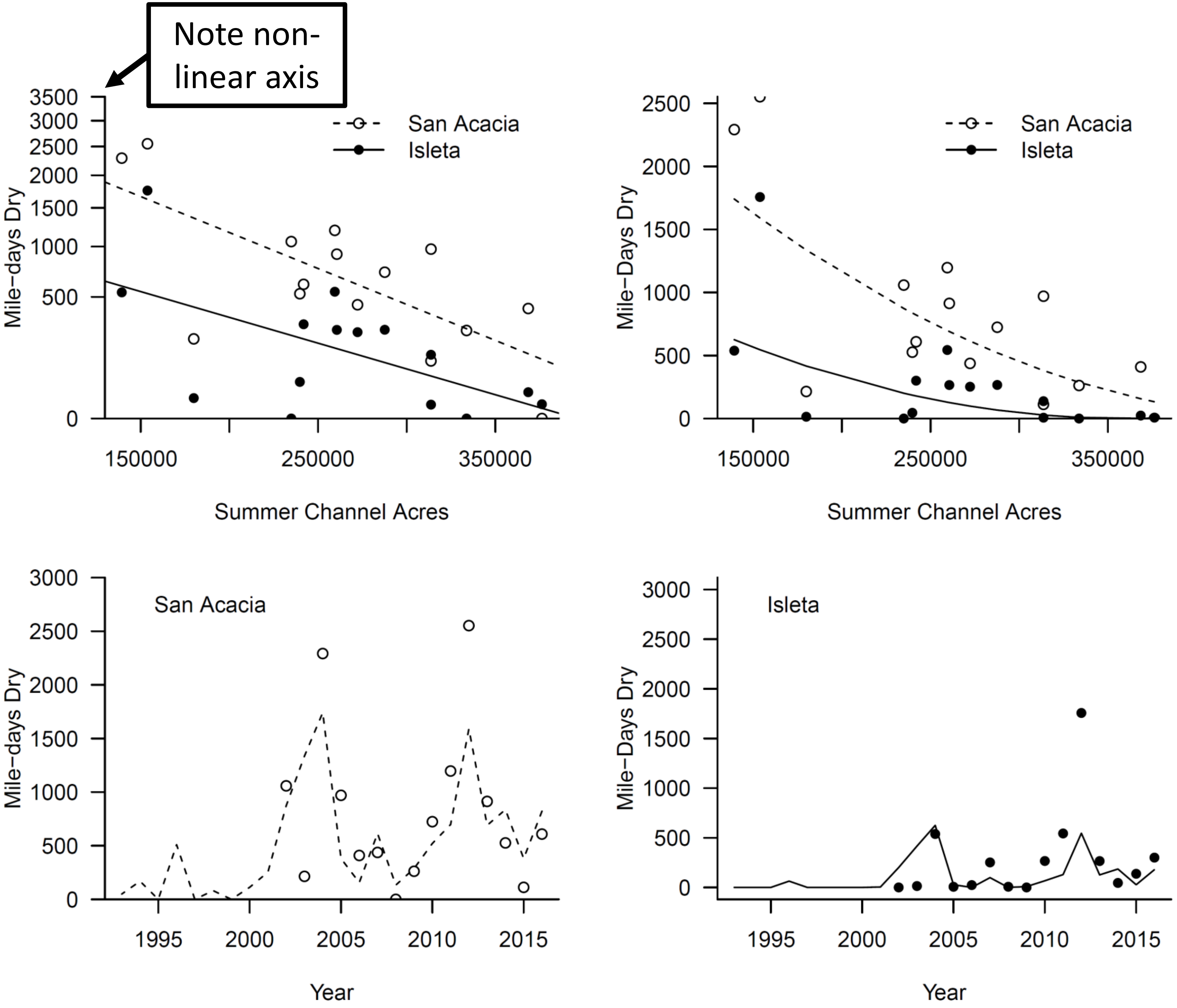
Accounting for correlated predictors with a new, integrated flood index

- 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



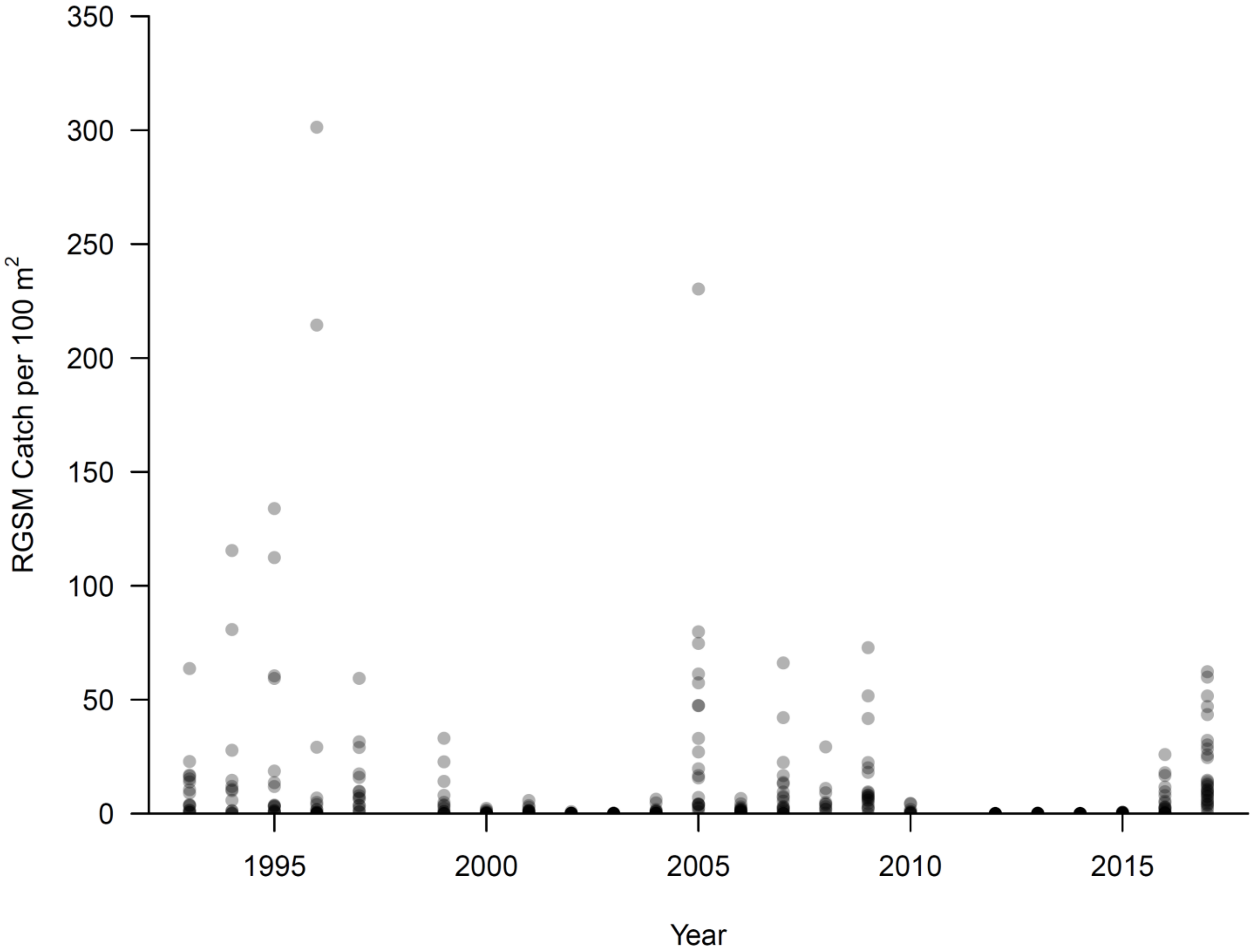
More responsive drying Index

- 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



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. $\boxed{\text{Probability of non-zero catch}}$
  2. Predicted CPUE given it is greater than zero

- Reach specific baseline probability of presence, α_r (logit scale)

- Latent trend (unobserved driver), w_y

$$logit(p_{ry}) = \alpha_r + \boldsymbol{\beta}_p \boldsymbol{\varphi}_{ry} + w_y$$

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

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

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

CPUE Model Structure

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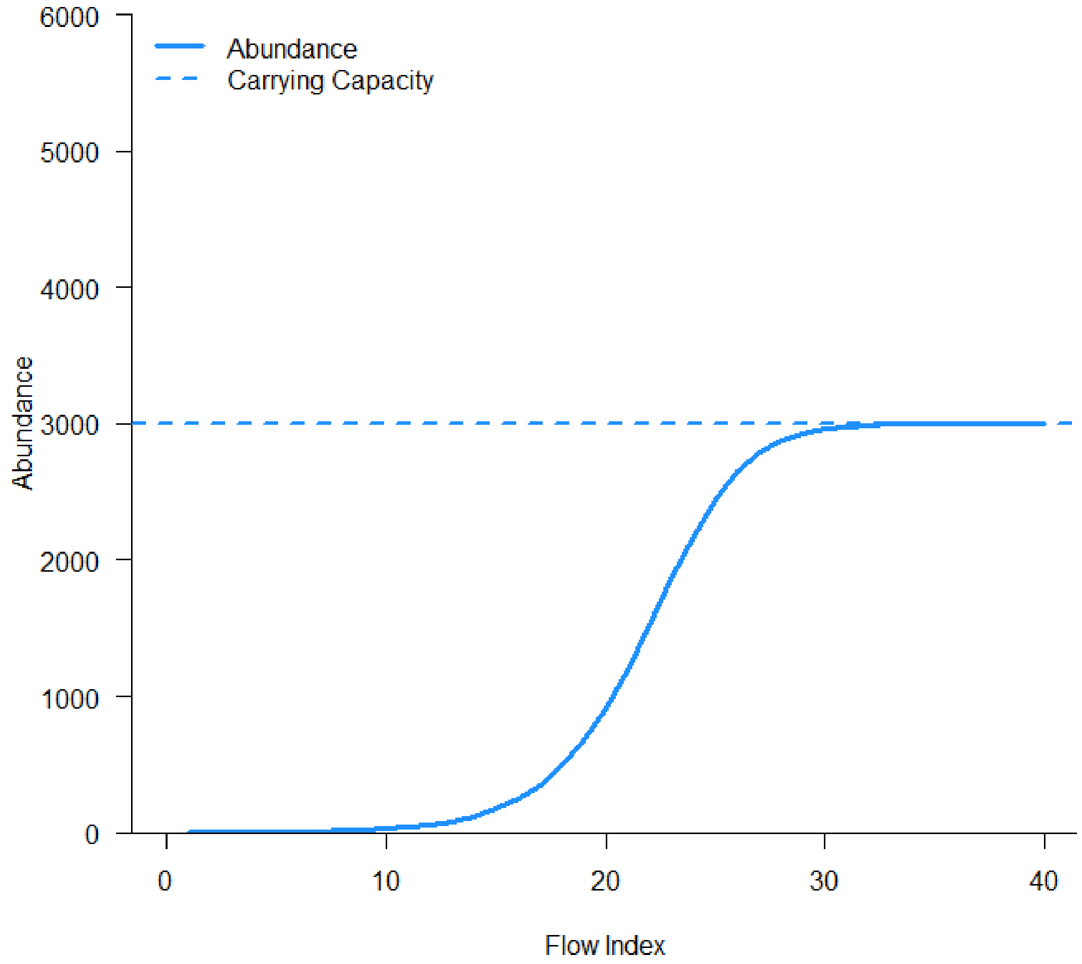
- Gompertz relationship

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



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

$$C_{ry} = K_r e^{-\beta_o e^{-\beta_C \delta_y}}$$

$$K_r \sim N(\mu_K, \sigma_K^2)$$

$$\sigma_{ry} = cv \times C_{ry}$$

$$\gamma_{ry} = 1 + \theta_{ry} C_{ry}$$

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

$$(C_{ry} | C_{ry} > 0) \sim \Gamma(\gamma_{ry}, \theta_{ry})$$

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$$(C_{ry} | C_{ry} > 0) \sim \Gamma(\gamma_{ry}, \theta_{ry})$$

$$E(C_{iry}) = \boxed{I(C_{ry} > 0)} \times \boxed{(C_{ry} | C_{ry} > 0)}$$

Models explored

- Presence model
  p(*metric*)

- Catch model
  C(*metric*)

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

	Presence Component	Catch Component
1	PC1	PC1
2	Timing	Timing
3	Mile-days dry + PC1	PC1
4	Mile-days dry	Timing
5	Mile-days dry	PC1

Model comparison

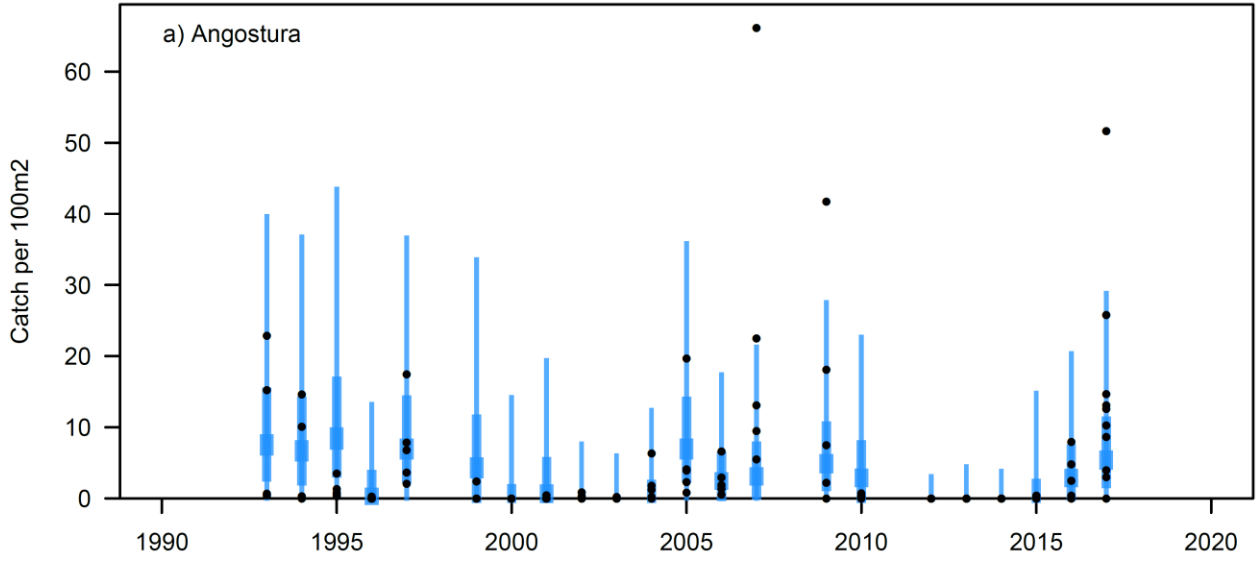
	Presence Component	Catch Component	WAIC	ΔWAIC
1	PC1	PC1	6477	0
2	Timing	Timing	10493	4016
3	Mile-days dry + PC1	PC1	15601	9124
4	Mile-days dry	Timing	15618	9141
5	Mile-days dry	PC1	15667	9190

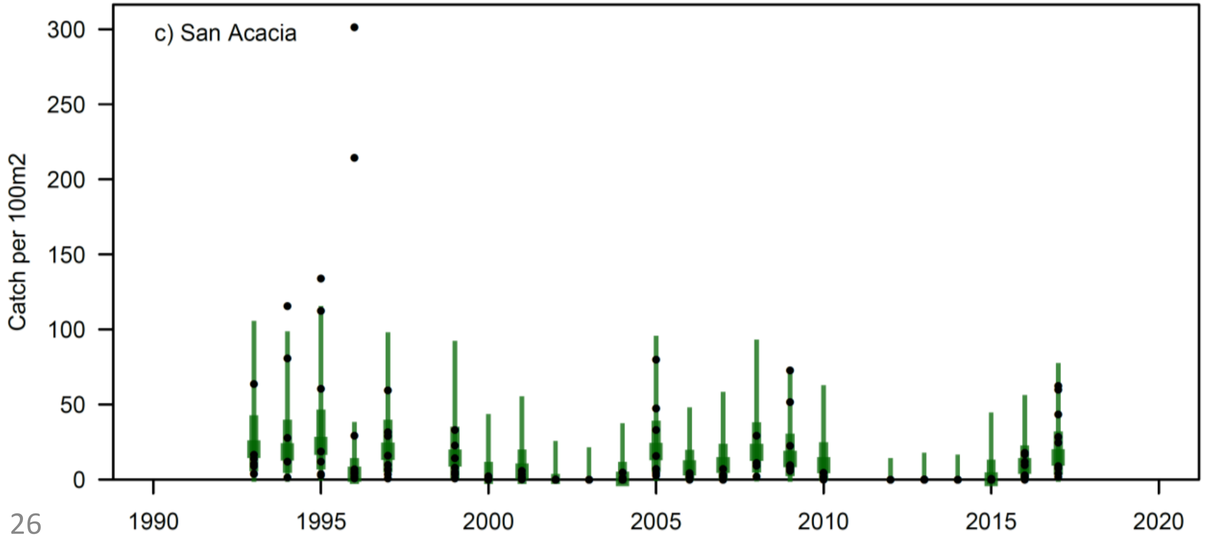
- Model with flood magnitude predicting both presence and catch fits data MUCH BETTER than all other models.

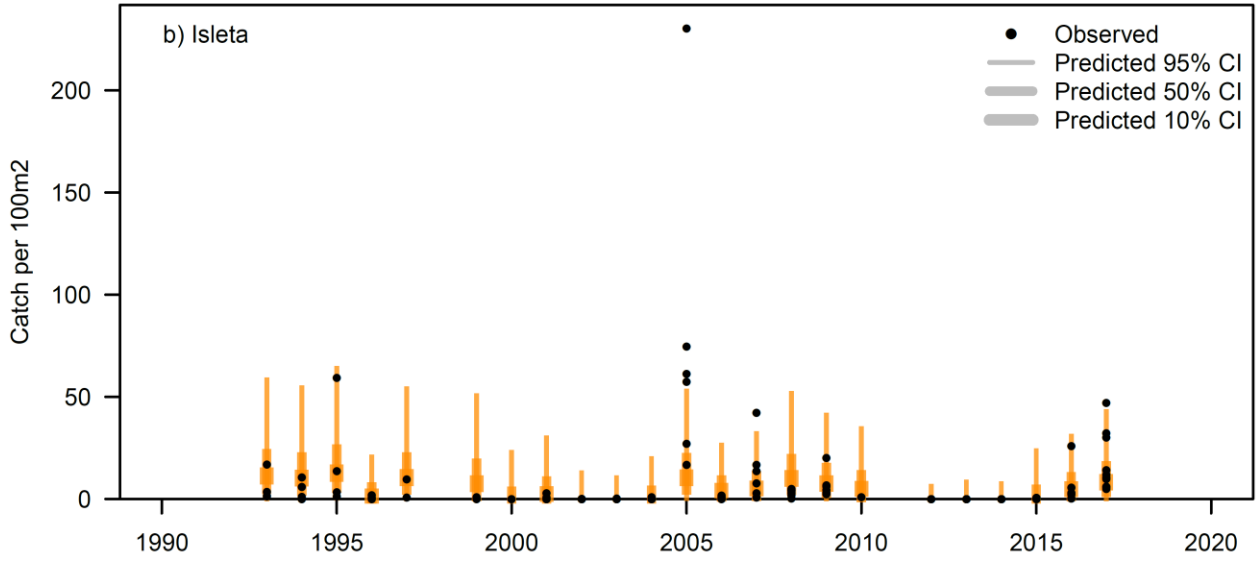
$$E(C_{ry}) = I(C_{ry} > 0) \times (C_{ry} | C_{ry} > 0)$$

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



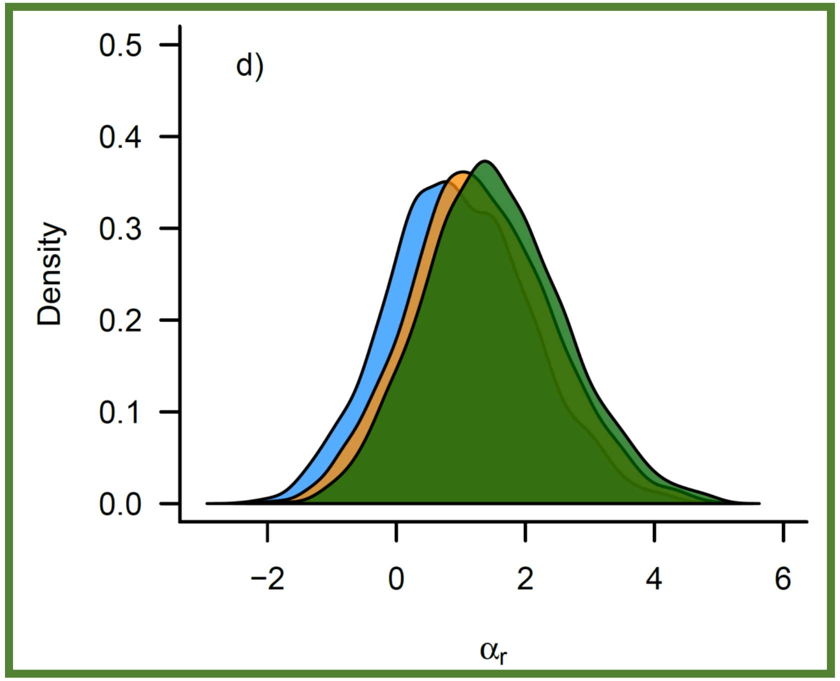




Parameter Estimates - Presence

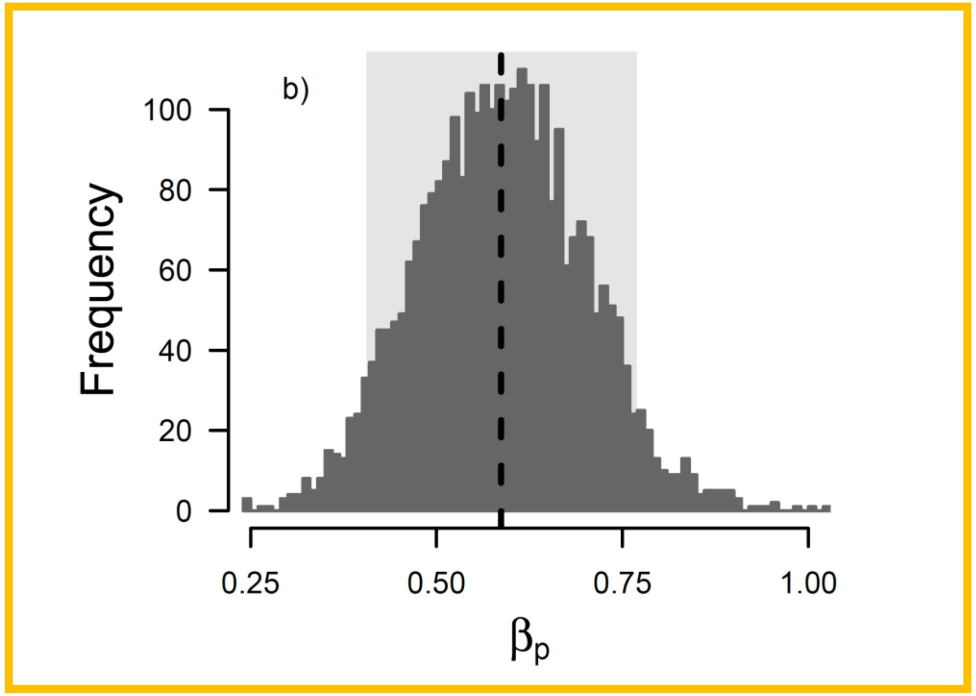
- Increased probability of capture in years with larger floods

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



Angostura
Isleta
San Acacia

$$logit(p_{ry}) = \boxed{\alpha_r} + \boxed{\boldsymbol{\beta}_p} \boldsymbol{\varphi}_{ry} + w_y$$



Parameter Estimates - Presence

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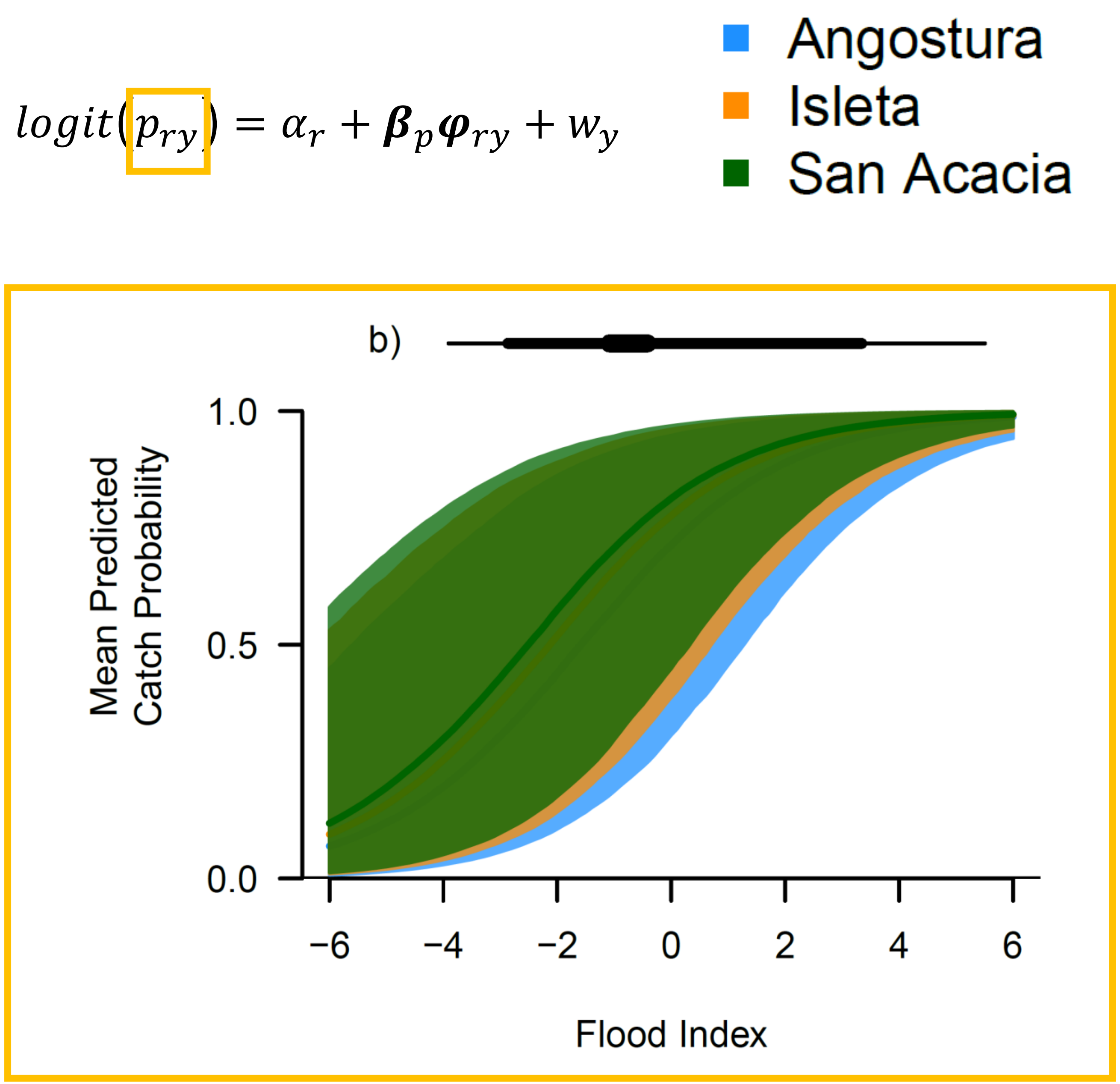


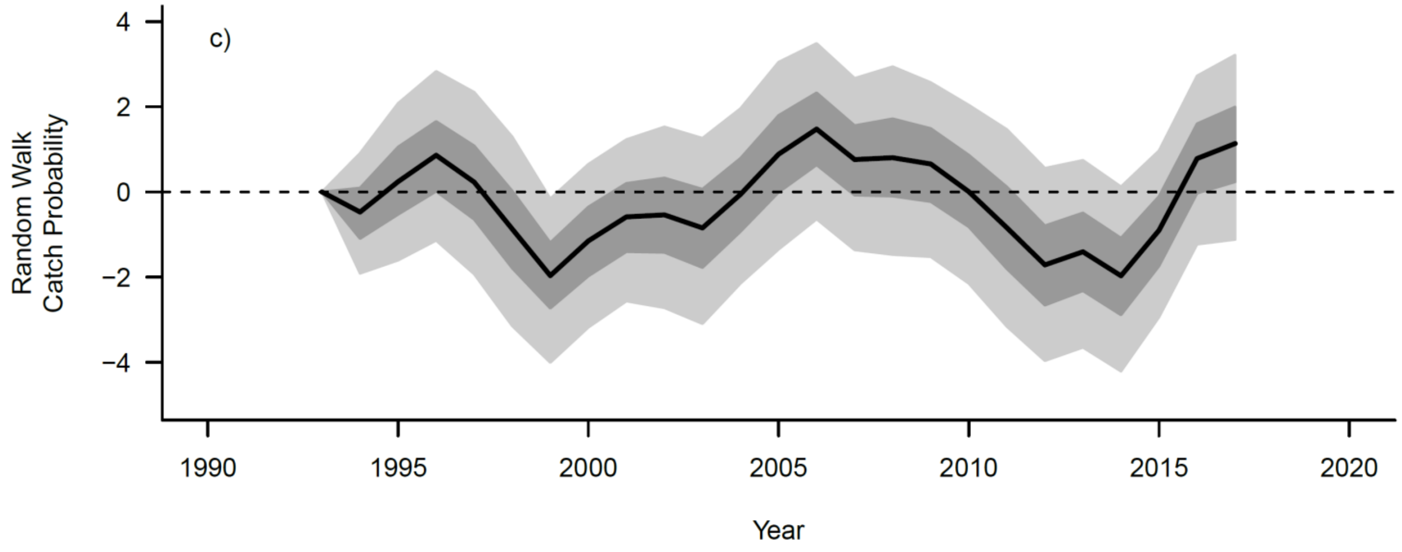
Parameter Estimates – Presence – Latent Trend

$$logit(p_{ry}) = \alpha_r + \boldsymbol{\beta}_p \boldsymbol{\varphi}_{ry} + \boxed{w_y}$$

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

- Periodic pattern in catch probability not captured by drying conditions

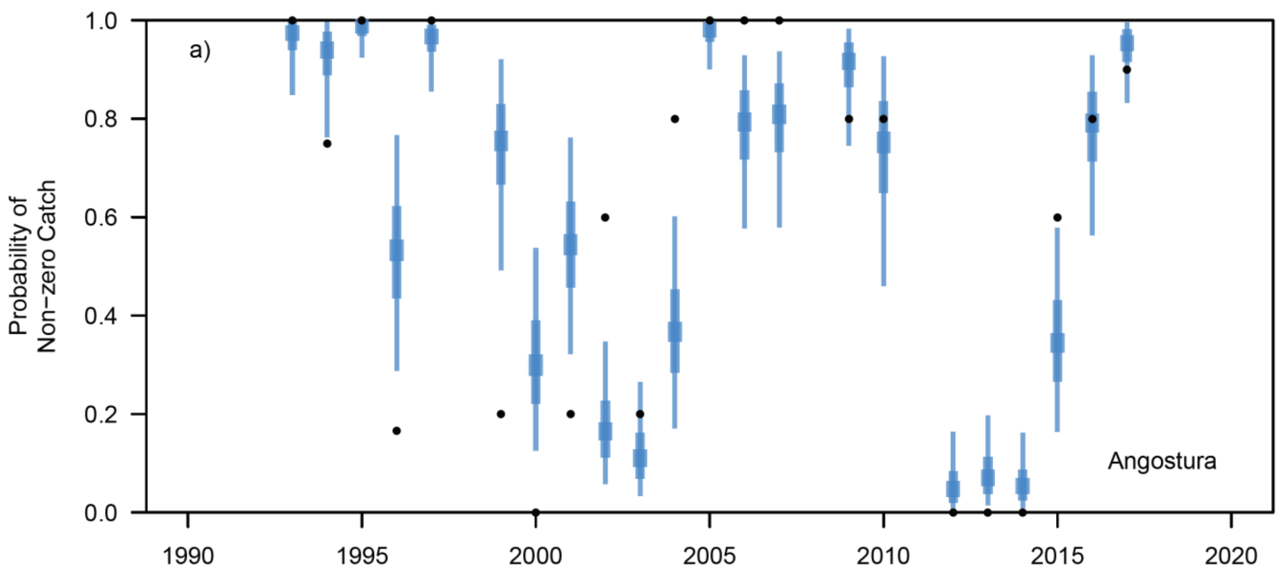
- Accounting for one or more unobserved drivers of variation, possibly including:
  - Prior year's distribution carrying over?
  - Large-scale climatic conditions?
    - PDO
    - ENSO

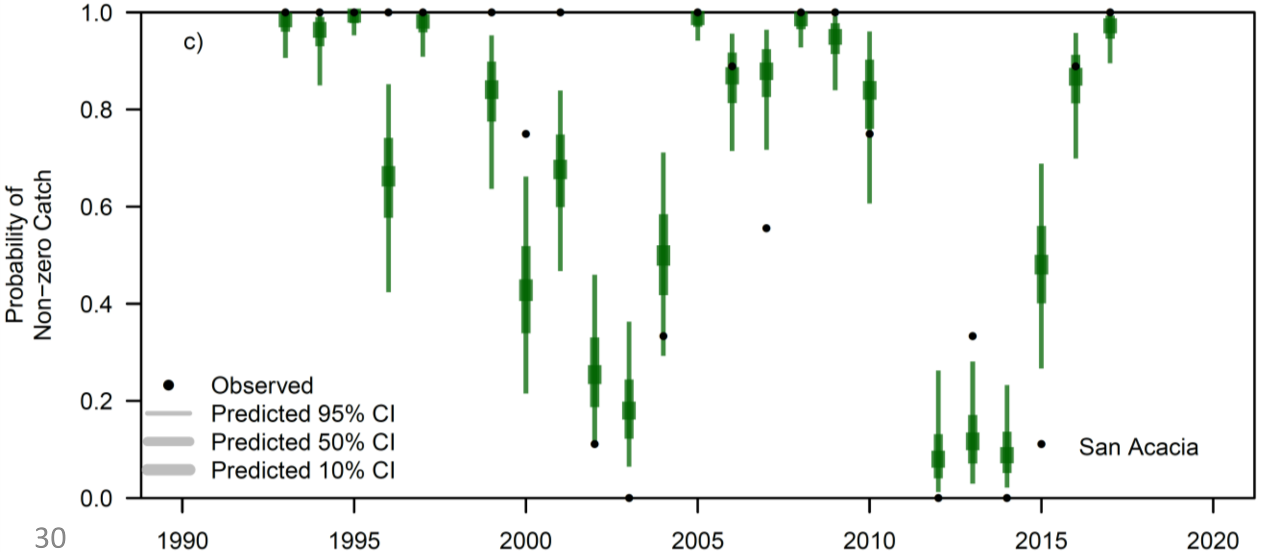


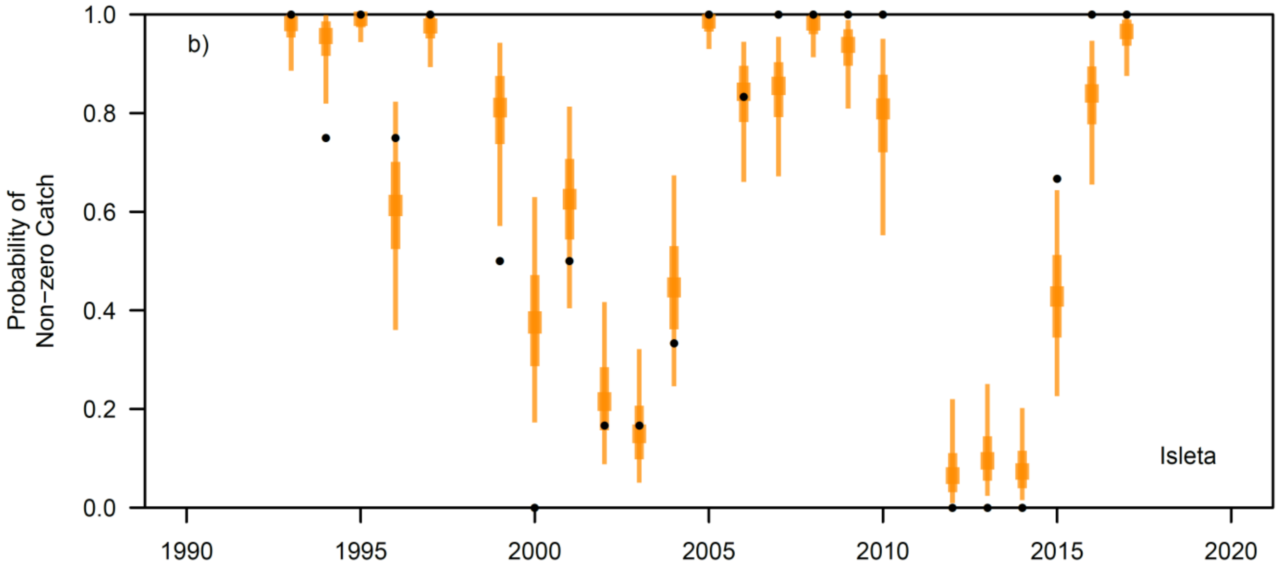
Predicted probability of presence

$$logit(p_{ry}) = \alpha_r + \boldsymbol{\beta}_p \boldsymbol{\varphi}_{ry} + w_y$$

- Lower in years with small floods
- Periodic pattern – driven by latent trend



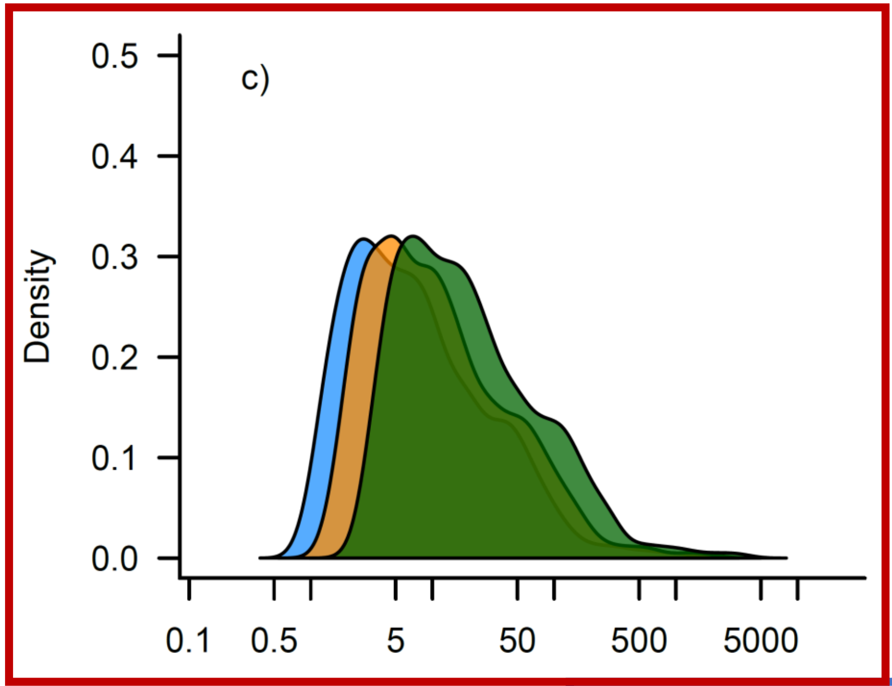




Parameter Estimates – Catch

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

- San Acacia has highest predicted carrying capacity
  - Large uncertainties



Angostura
Isleta
San Acacia

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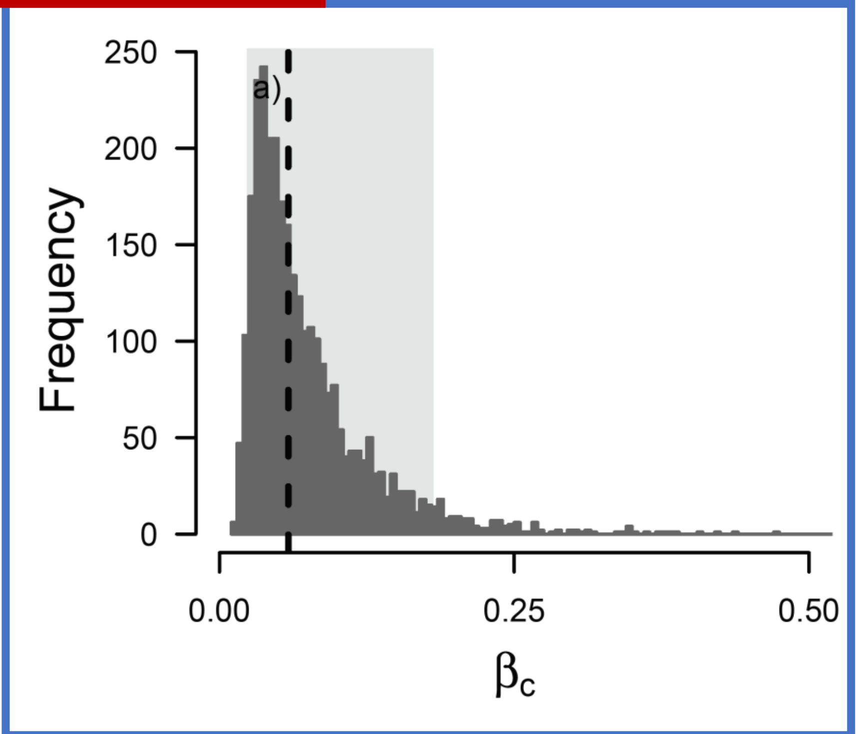

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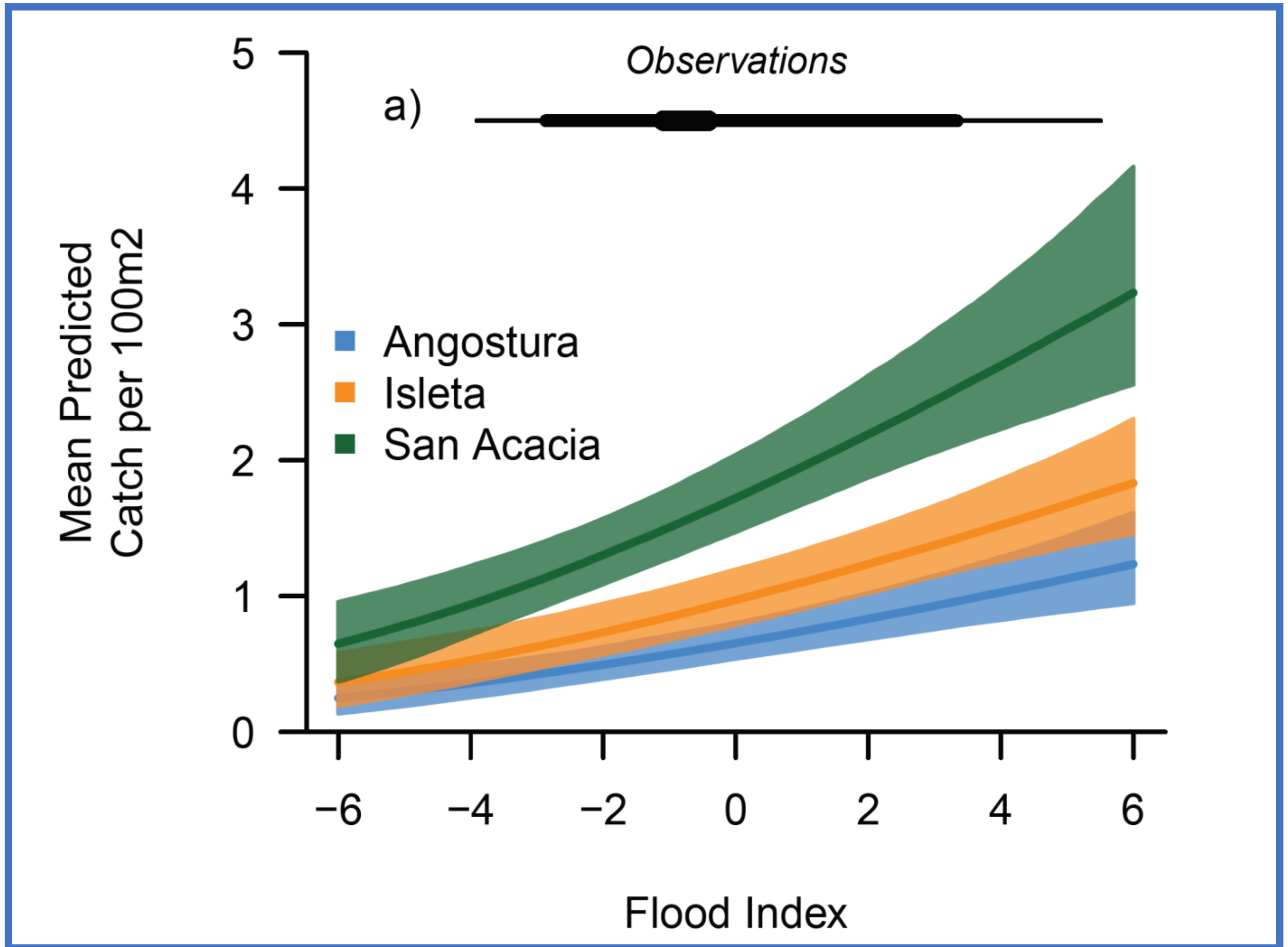
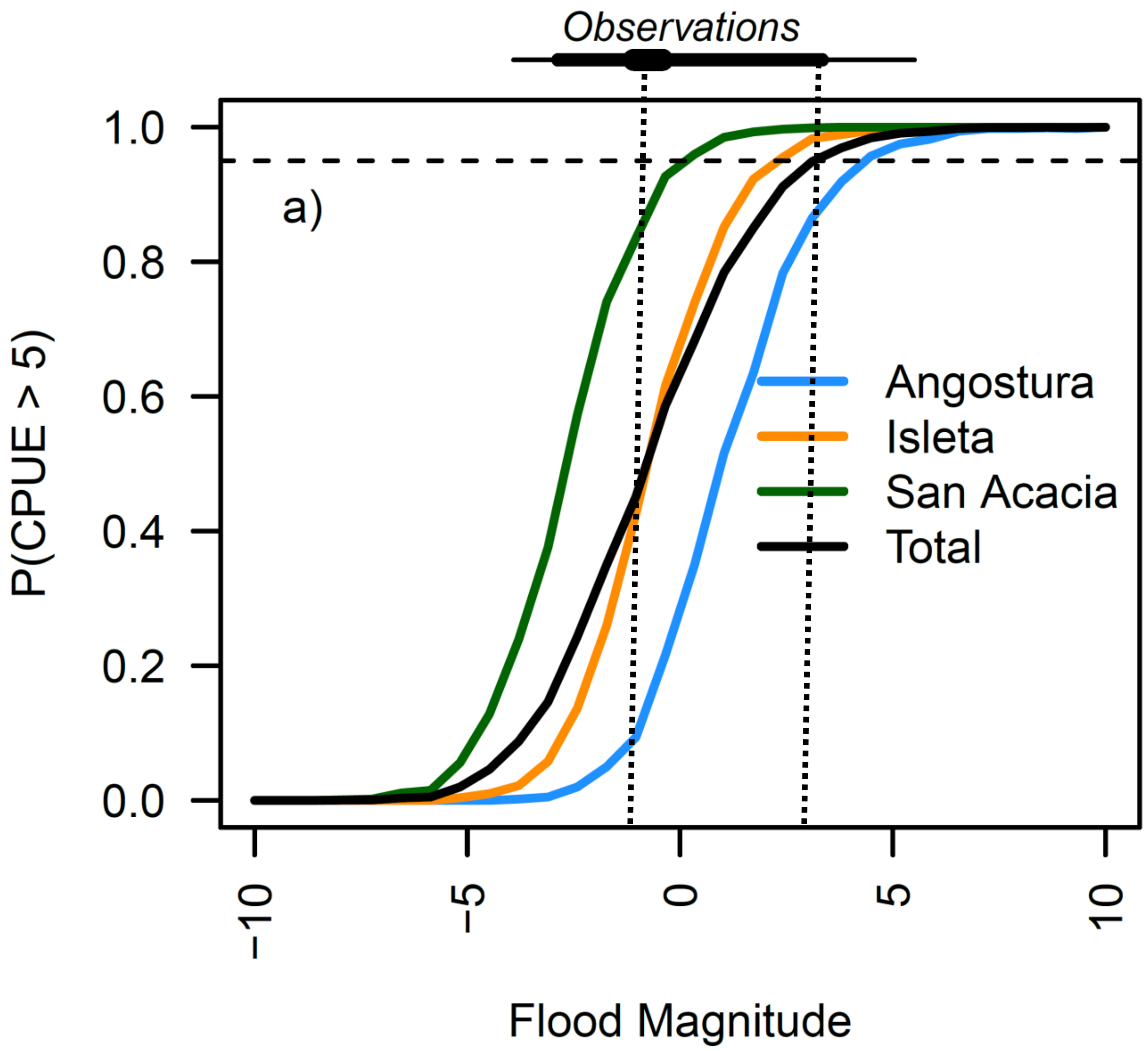
Angostura
Isleta
San Acacia

- 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



Simulation Experiment

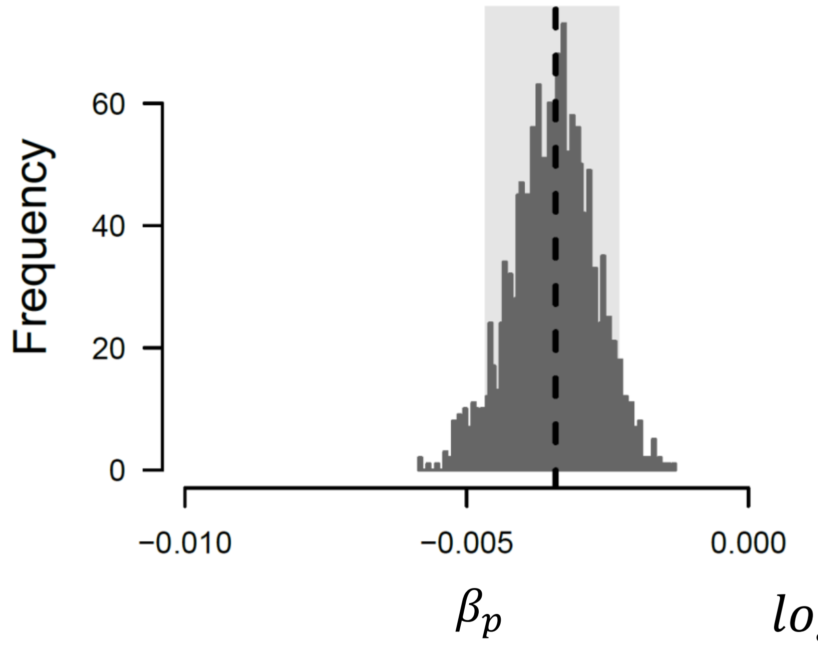
- What is the probability of meeting recovery goal CPUE given different flood conditions?
  - Proportion of simulated CPUEs greater than 5 RGSM per 100m^2
  - Single year!
  - Useful tool for exploring alternative management options



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



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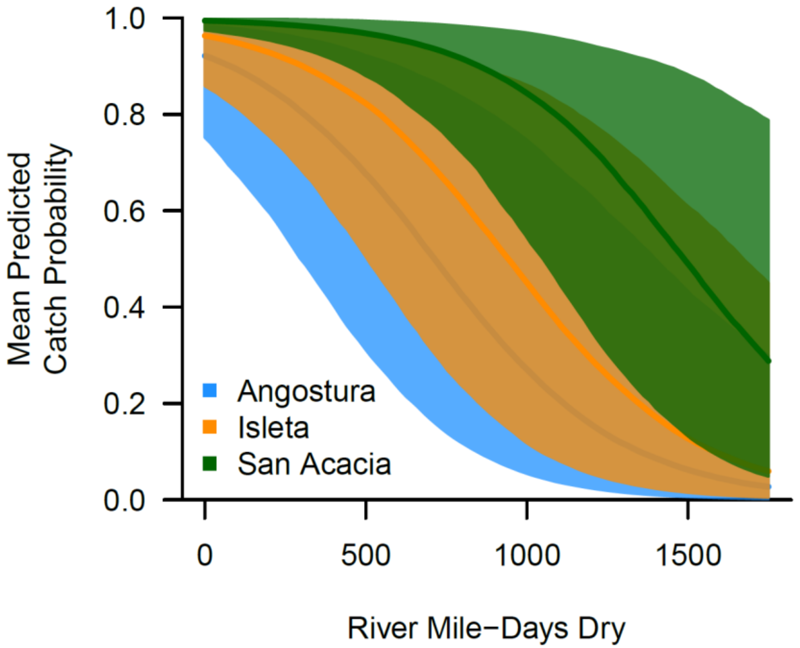
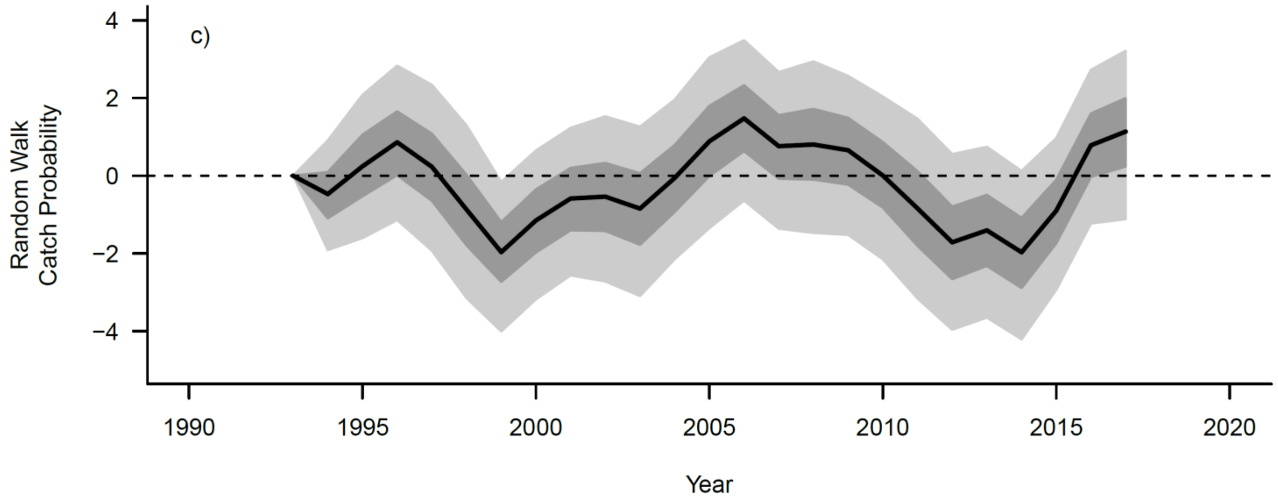


Implications

- 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

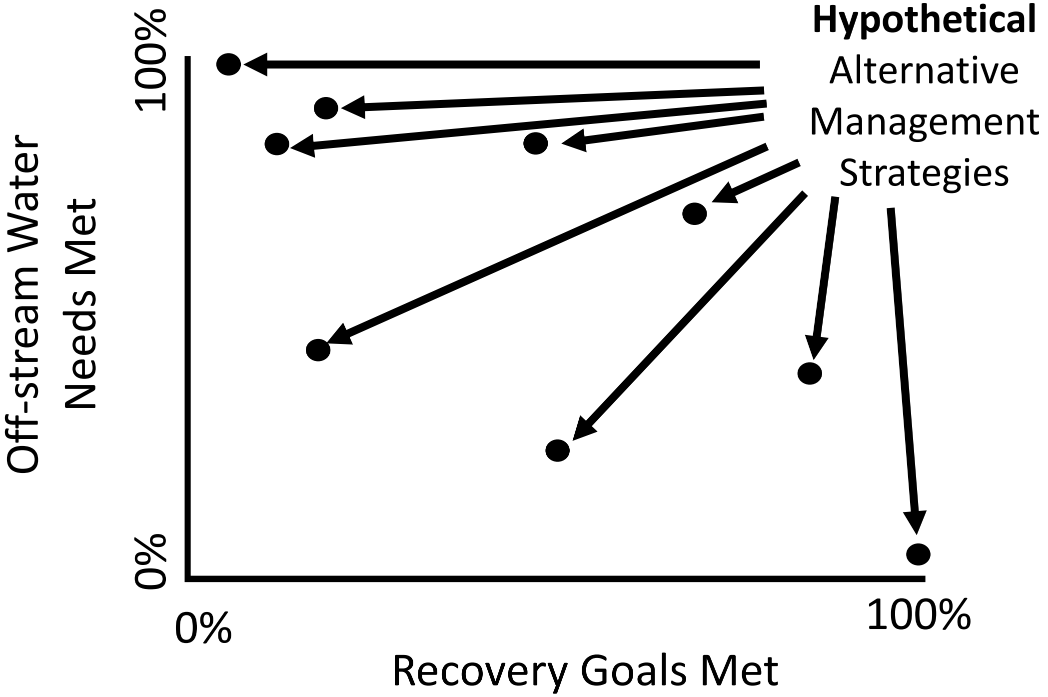
Next Steps

- 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



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- Lake Ecology Lab at USU
- Ecology Center at USU

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Predicted CPUE