Identifying priority watersheds for freshwater biodiversity conservation and drivers of biodiversity decline.

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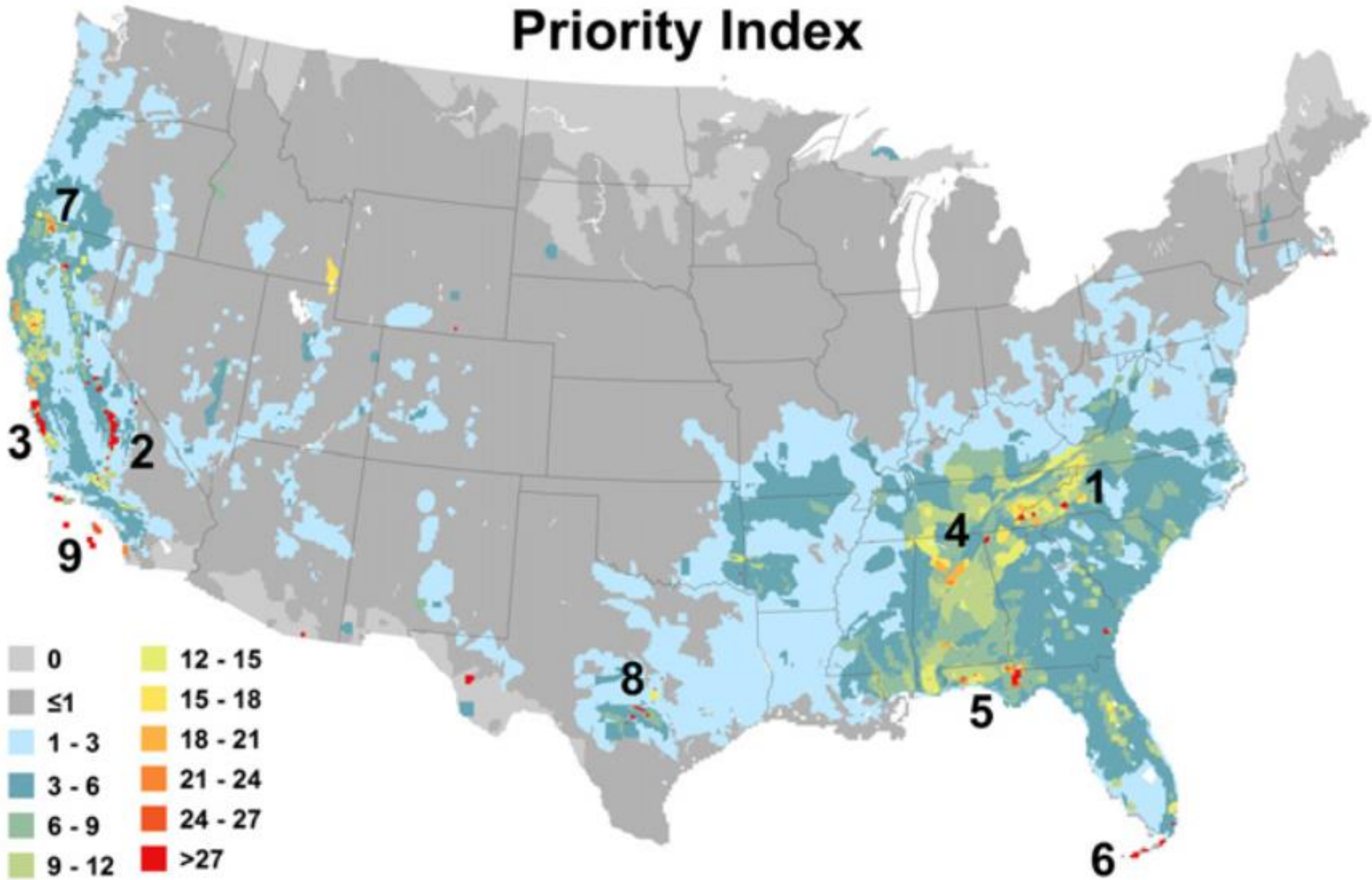
Outline

I. Integrating the distribution of non-native aquatic species into a watershed level priority assessment of freshwater biodiversity

II. Drivers of freshwater native species declines

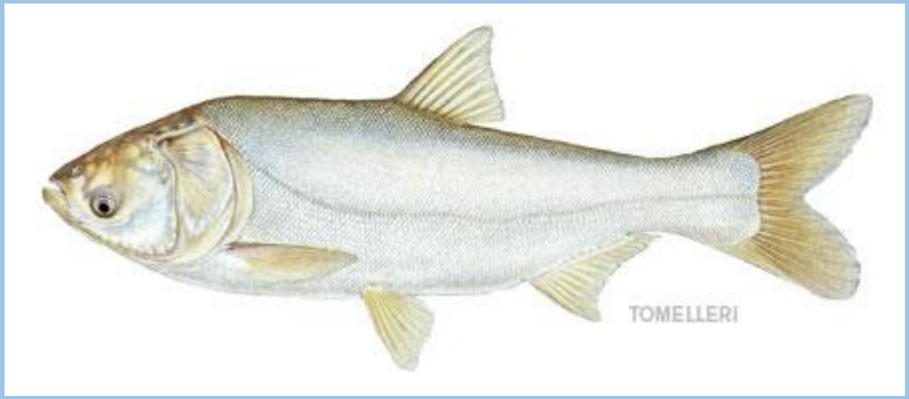


Jenkins et al. 2015

Previous priority maps have focused on where vulnerable native freshwater species are located

Background Question Methods Results Conclusion

Non-native species have negative impacts to native species.



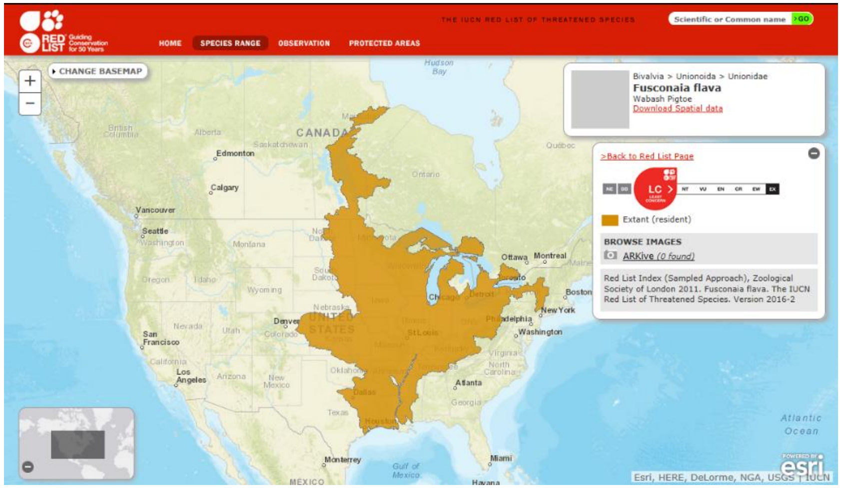
Silver carp (above), zebra mussels (right).

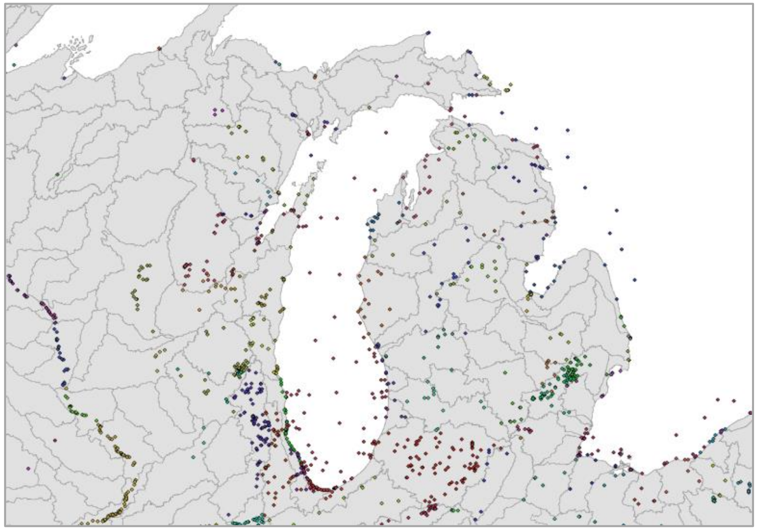
Goal

- Provide a continental scale assessment identifying priority watersheds for conservation based on the spatial overlap of vulnerable native taxa with non-native species.

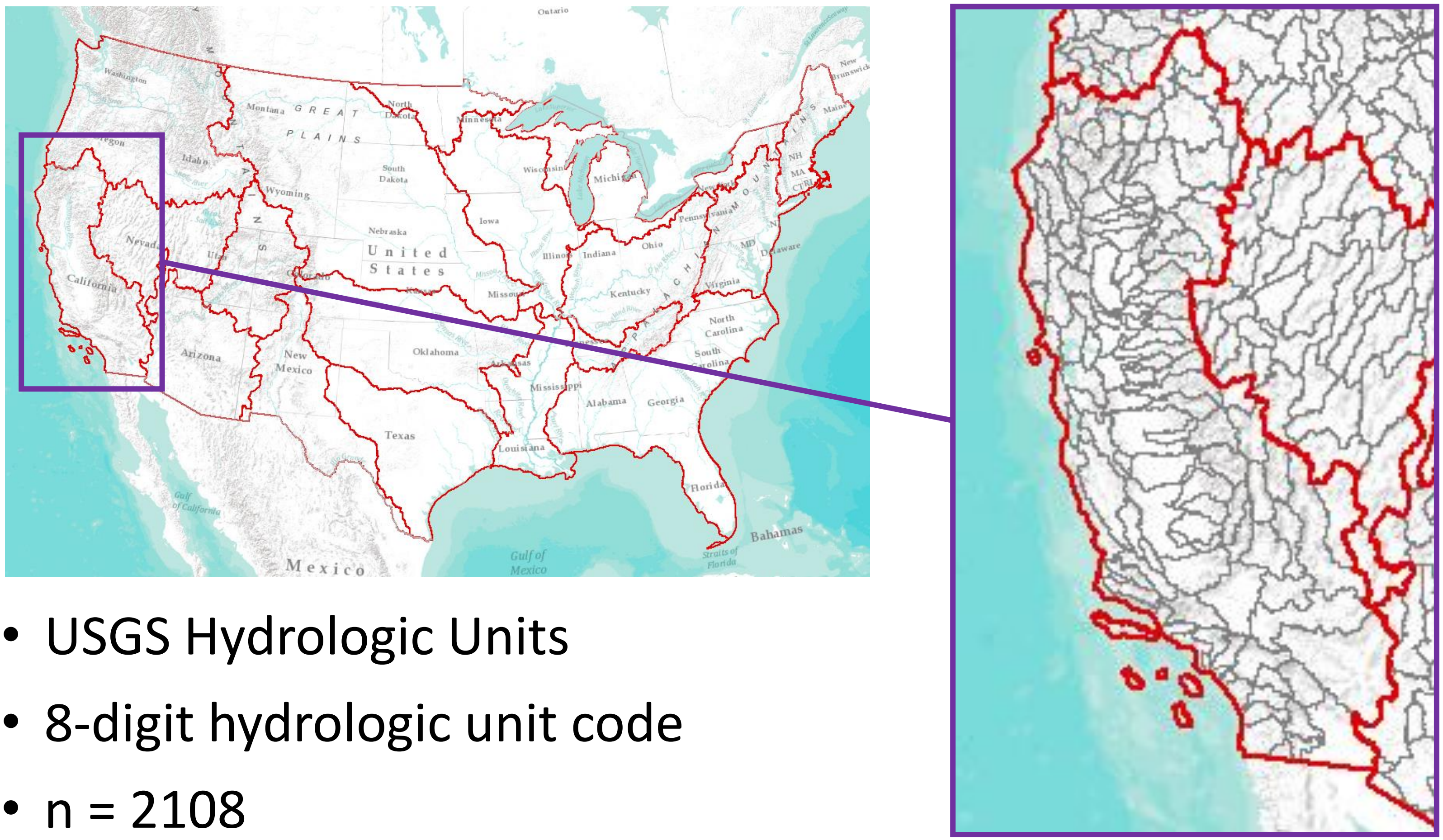
Data Sources

- Native species- IUCN
  - Fish n = 755
  - Amphibians n = 255
  - Invertebrates
    - Mollusk n = 169
    - Shrimp n = 12
    - Crayfish m = 272
  - Turtles n = 47
- Non-native species
  - USGS NAS
  - BiSON
  - EddMaps
  - Plants n = 157
  - Animals n = 287





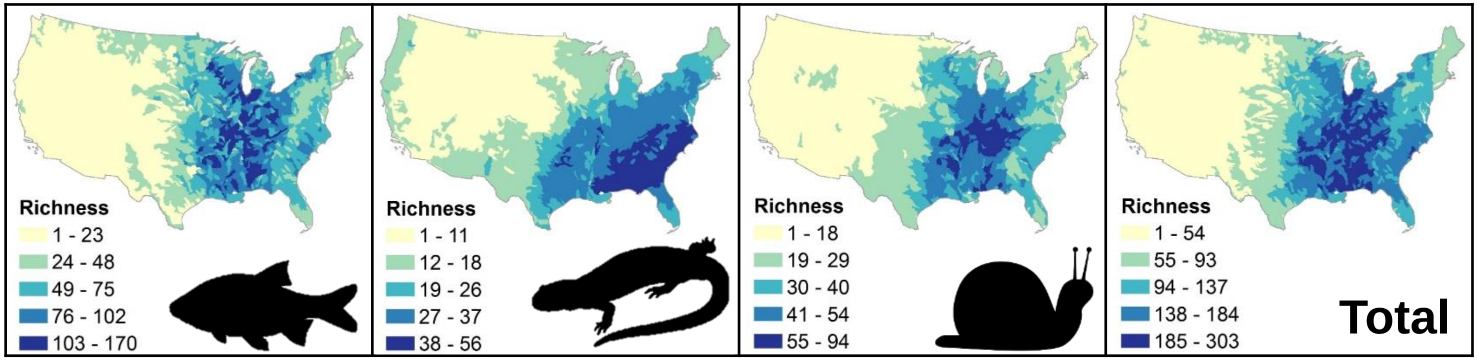
Unit of Analysis



- USGS Hydrologic Units
- 8-digit hydrologic unit code
- n = 2108

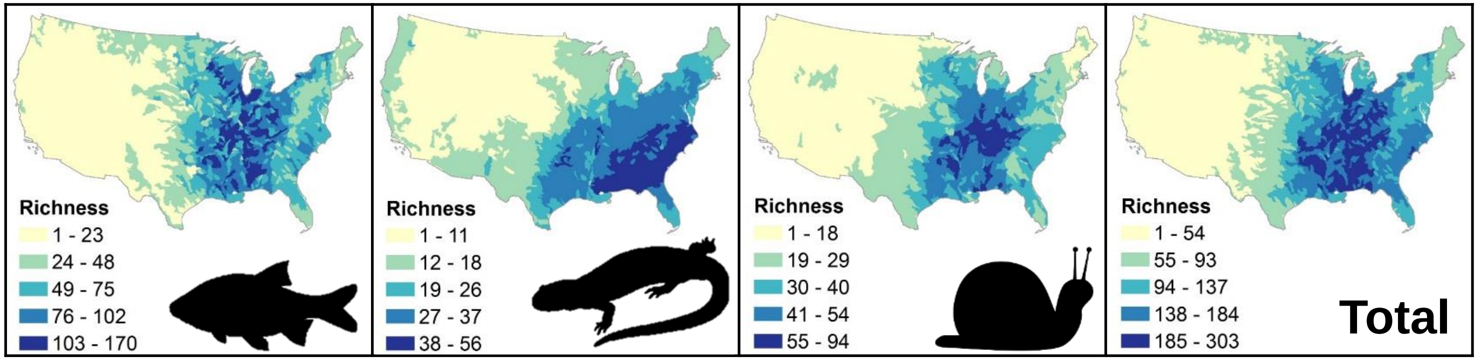
Native Metrics

Species Richness

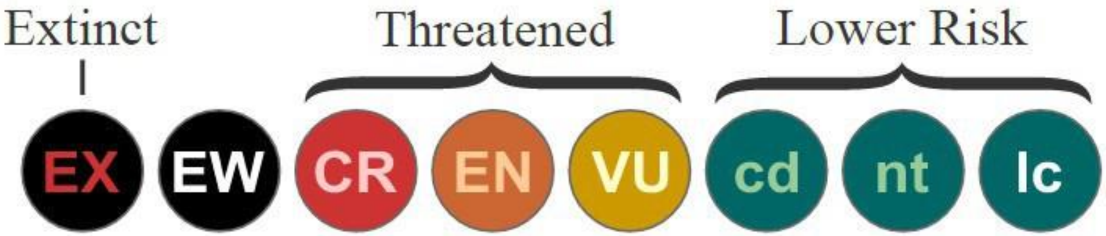


Native Metrics

Species Richness



Count of Threatened & Endangered Species



Critically Endangered

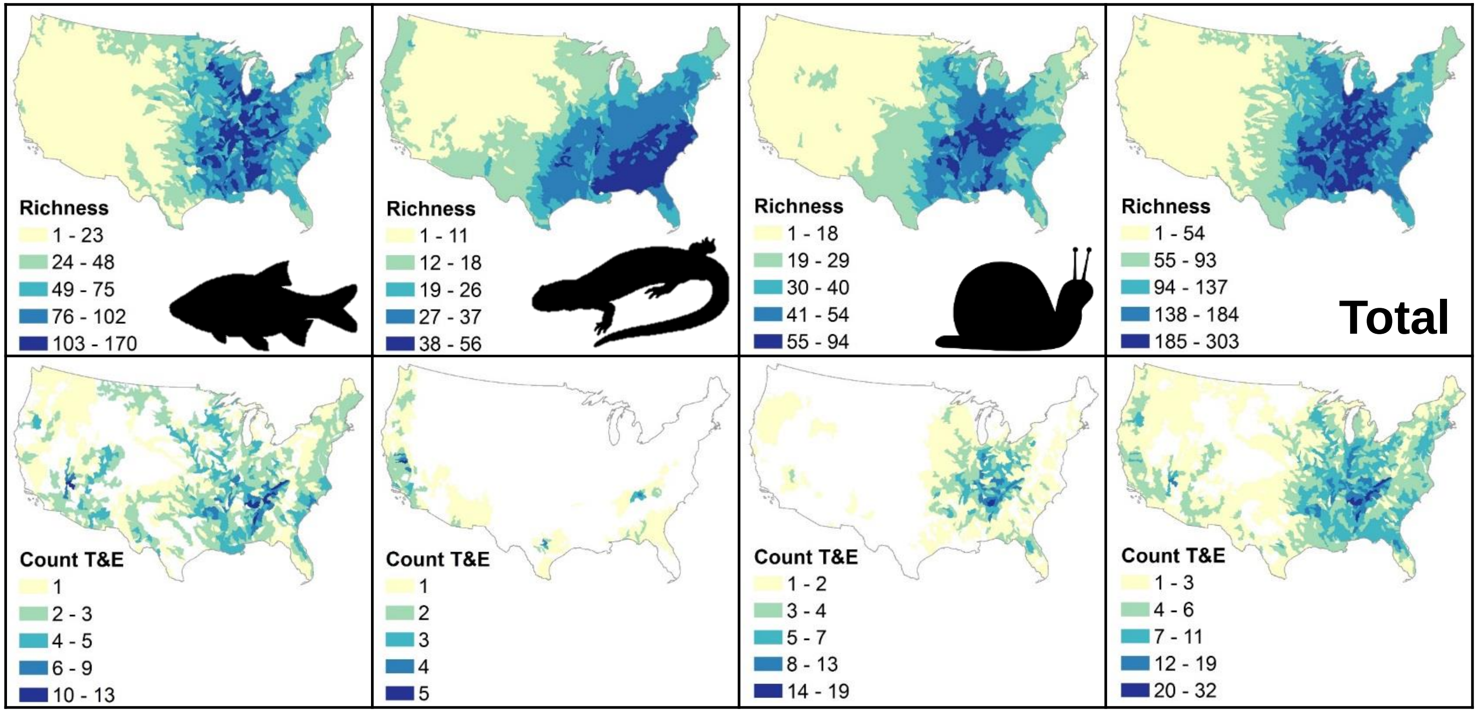
Endangered

Vulnerable

Native Metrics

Species Richness

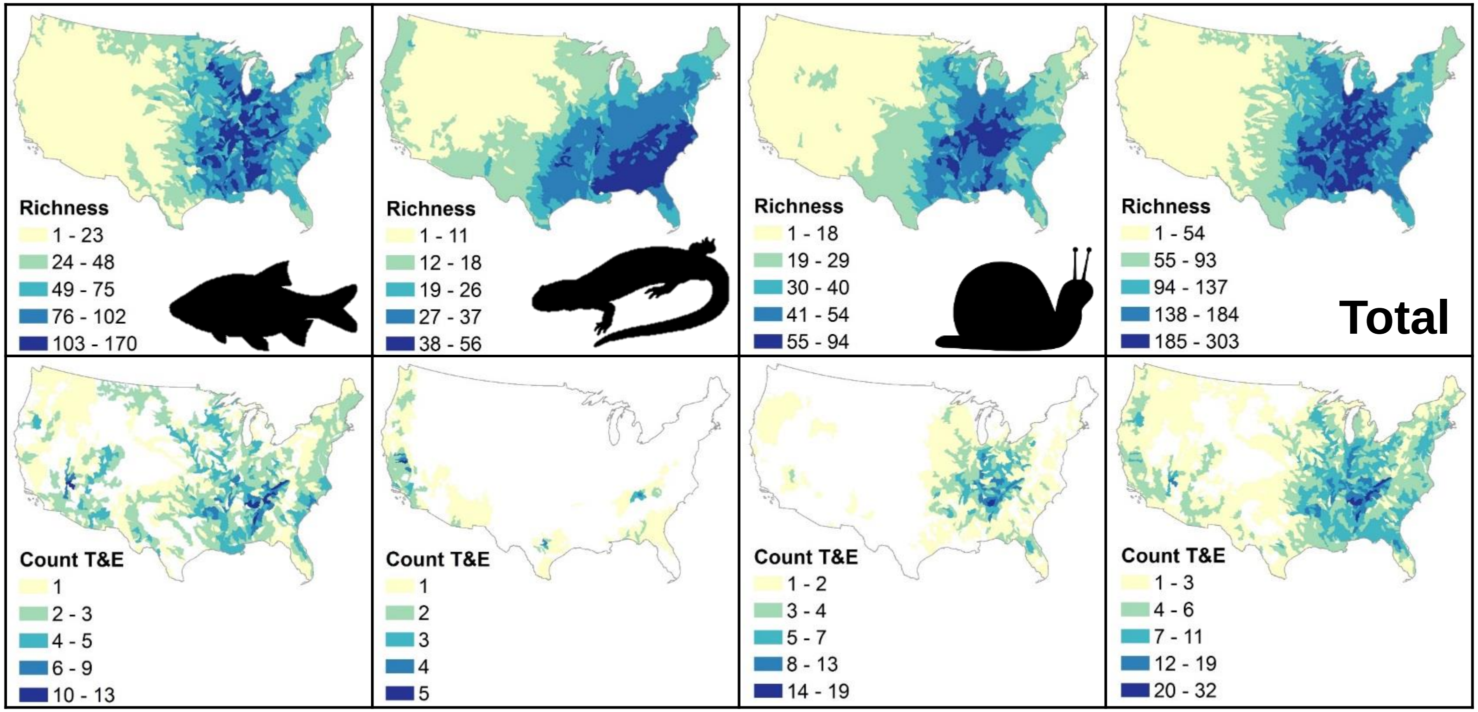
Count of Threatened & Endangered Species



Native Metrics

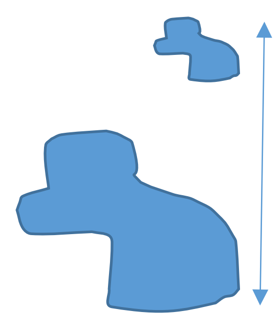
Species Richness

Count of Threatened & Endangered Species



Rarity Index

R package: Rarity
Rarity weights based on range size
Average across species per HUC 8



Most rare: 1

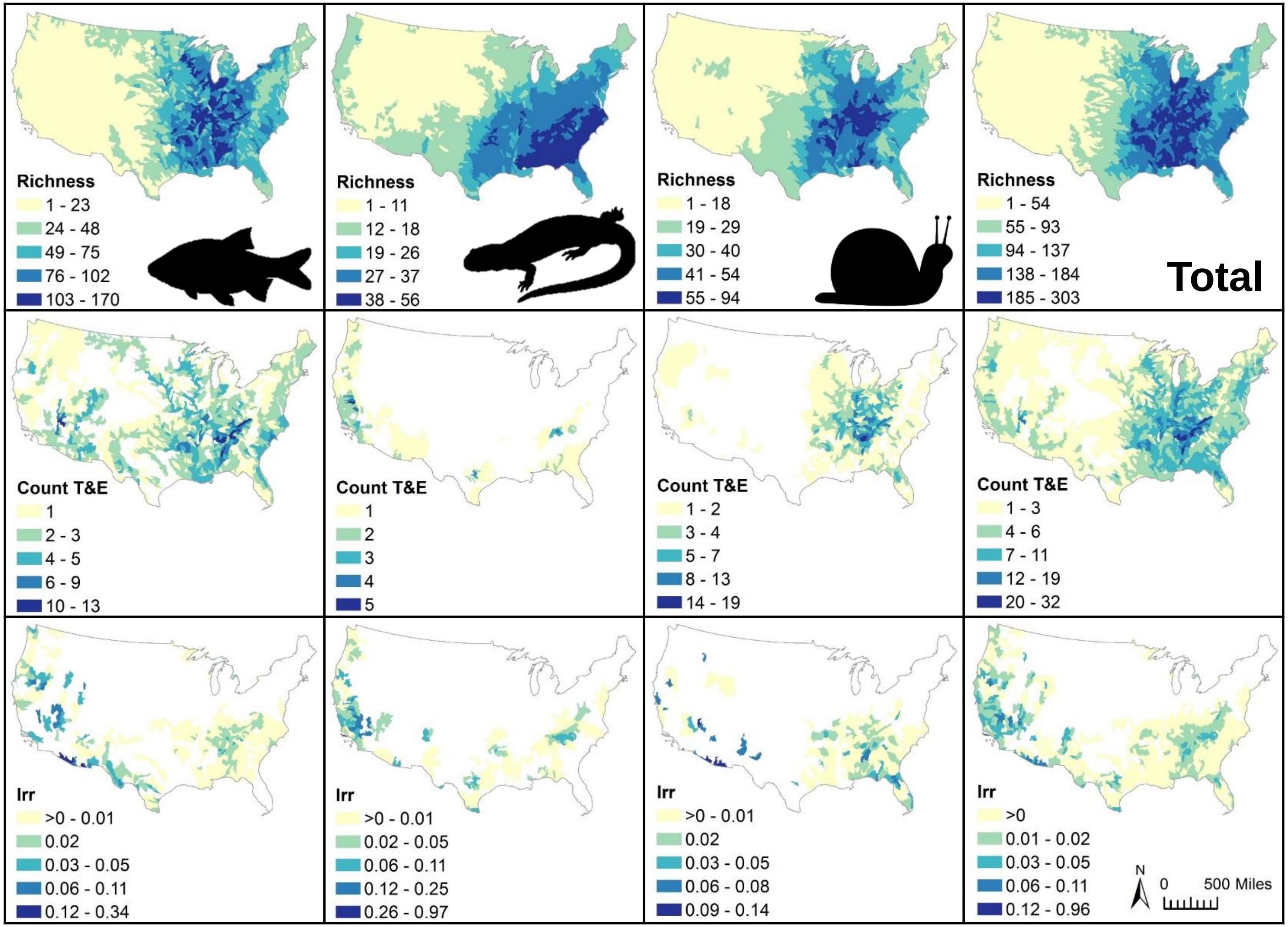
Common: 0

Native Metrics

Species Richness

Count of Threatened & Endangered Species

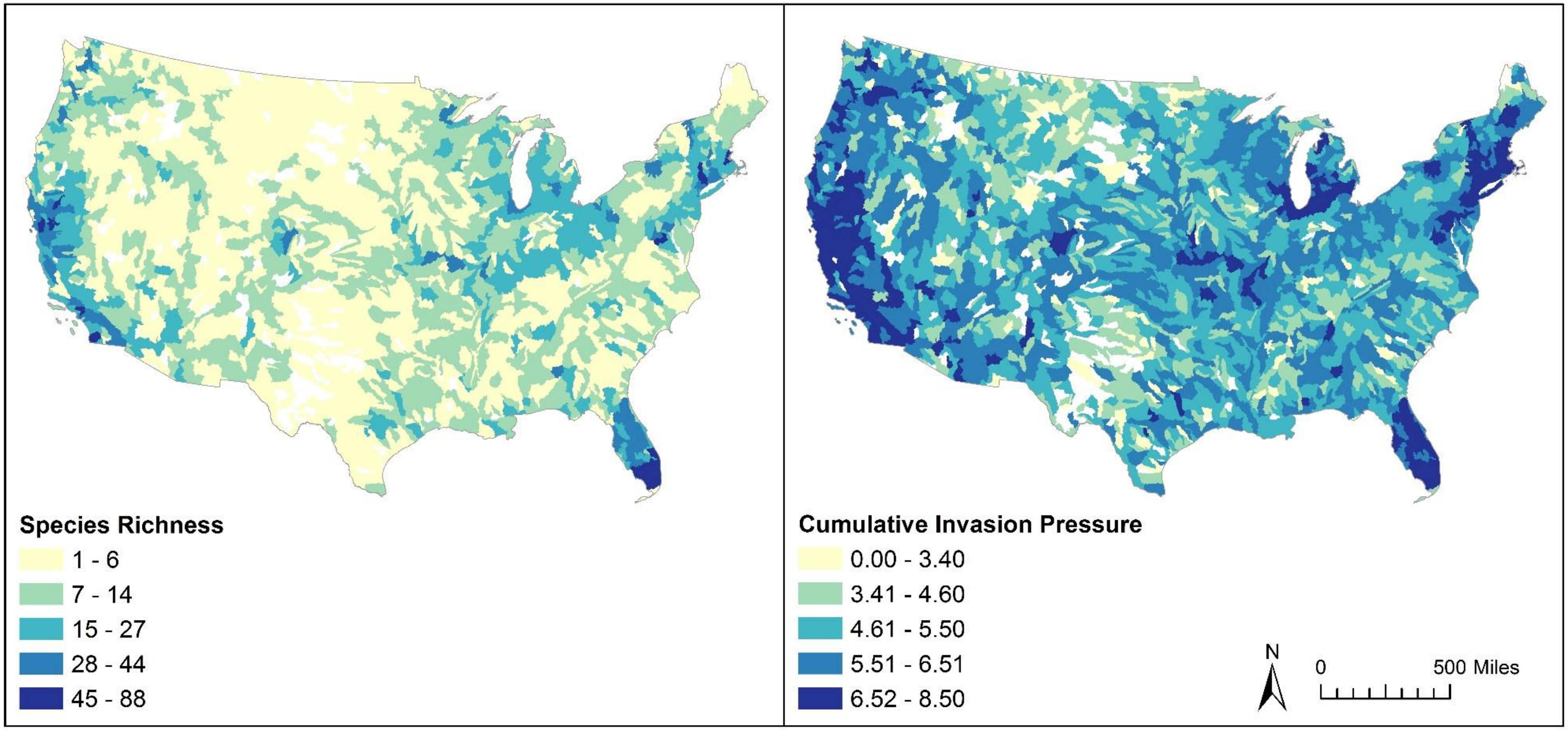
Rarity Index



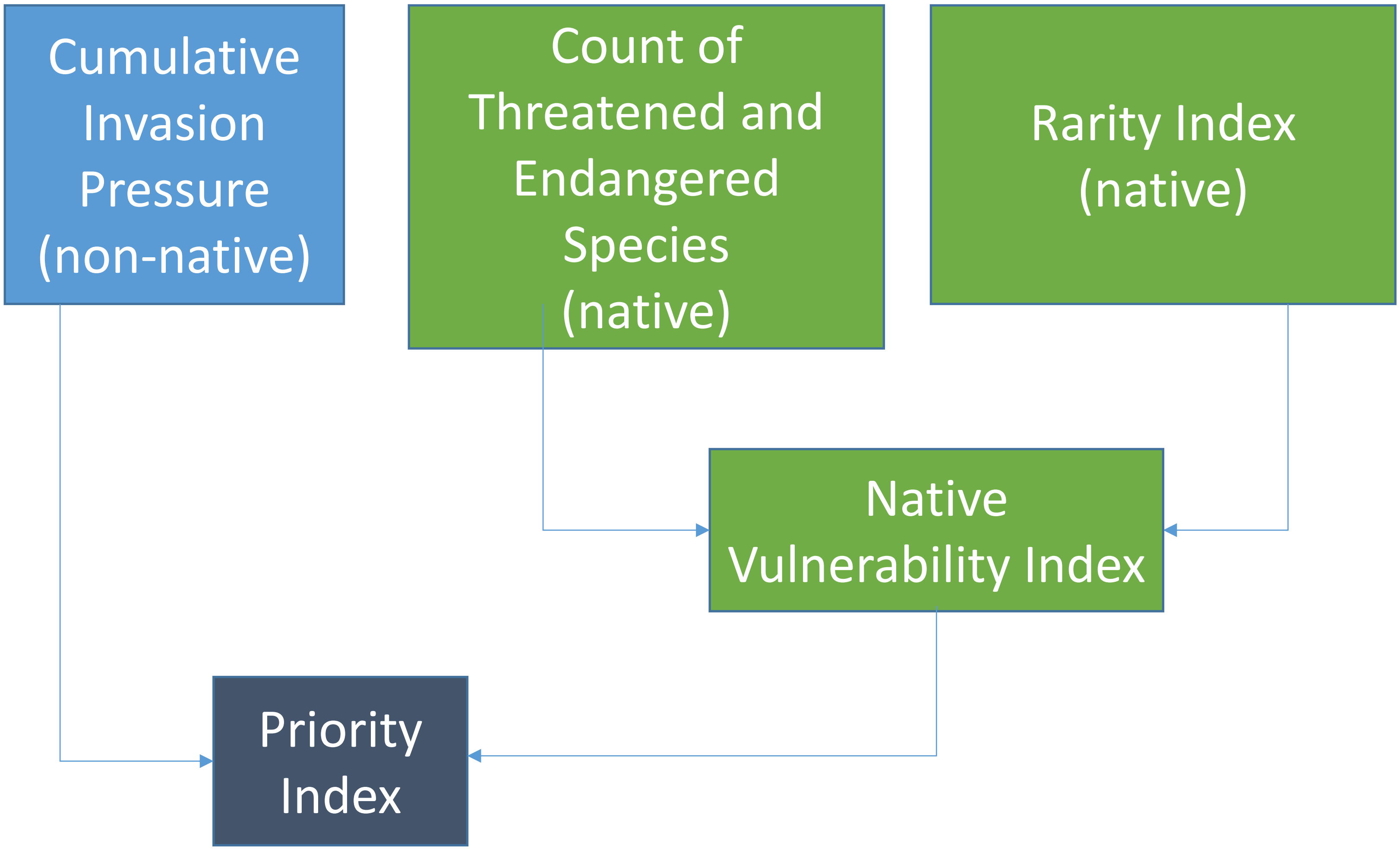
Invasion Pressure

$$CIP = \log \Sigma\,(species years)$$

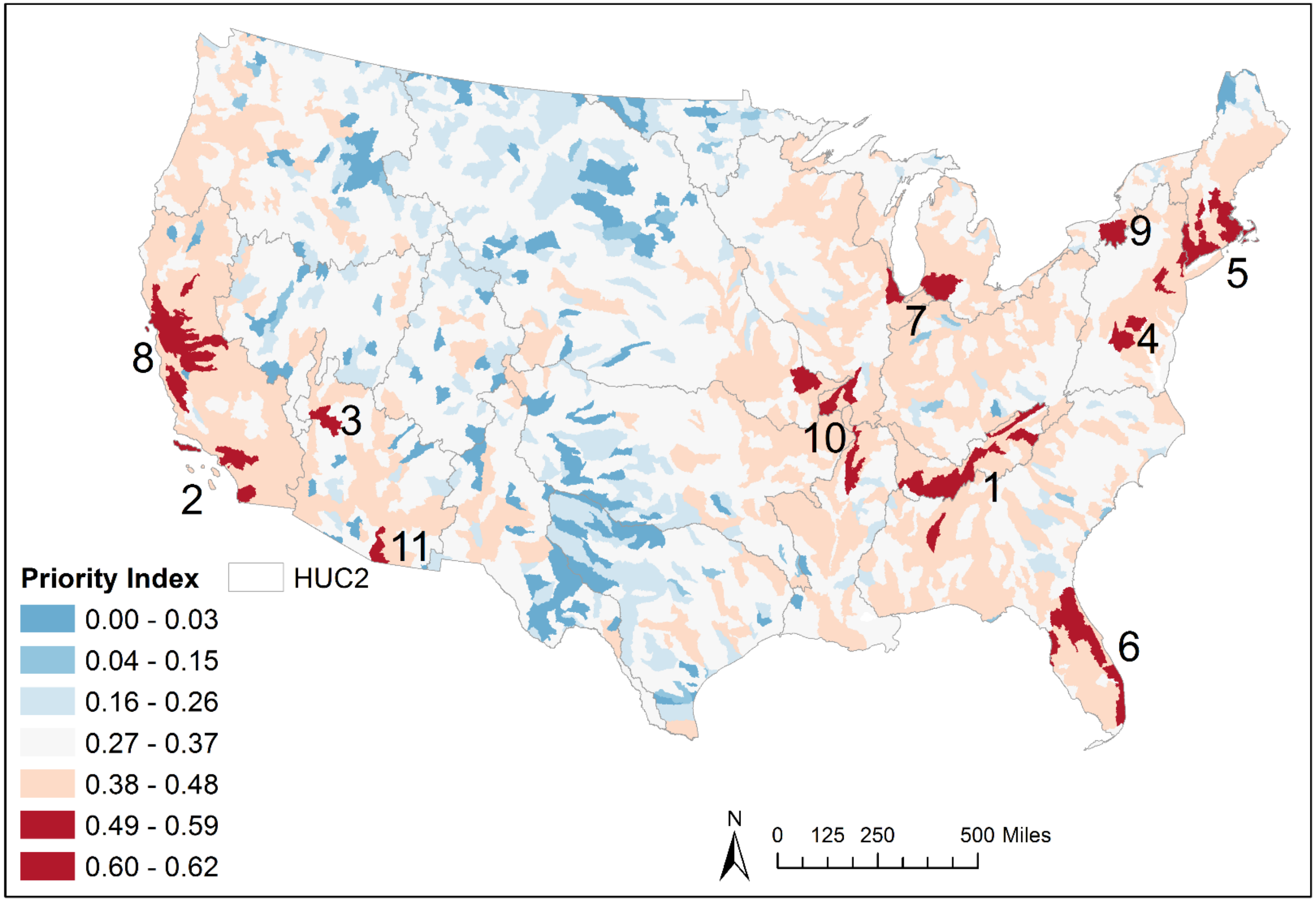
- Plants n=157, Animals n = 176



Priority Index



Priority Index



Background Question Methods **Results** Conclusion

Conclusions

- Our method can be used to expose conflict areas between vulnerable native species and invasion pressure
- Different picture emerges when including threat of non-native species in priority assessments

Part II: Drivers of freshwater native species declines

- Species data are inconsistently collected across space, time and taxa
- Missing data!! Out of an estimated ~37,000 freshwater species globally 5, 167 species have been assessed (IUCN)

Research questions

1. What are the variables associated with the reported declines in freshwater biodiversity?

2. Can we predict which watersheds are likely to have declining species?

Response variable

Presence/absence of any IUCN reported declining species or species extinction in a watershed



Drivers of freshwater native species declines

Examined the following classes of predictors using machine learning:

- Climate
- Habitat
- Landcover
- Landcover change history
- Hydrologic alteration
- Nutrient enrichment
- Non-native species
- Other human stressors: population density, fishing
- Spatial

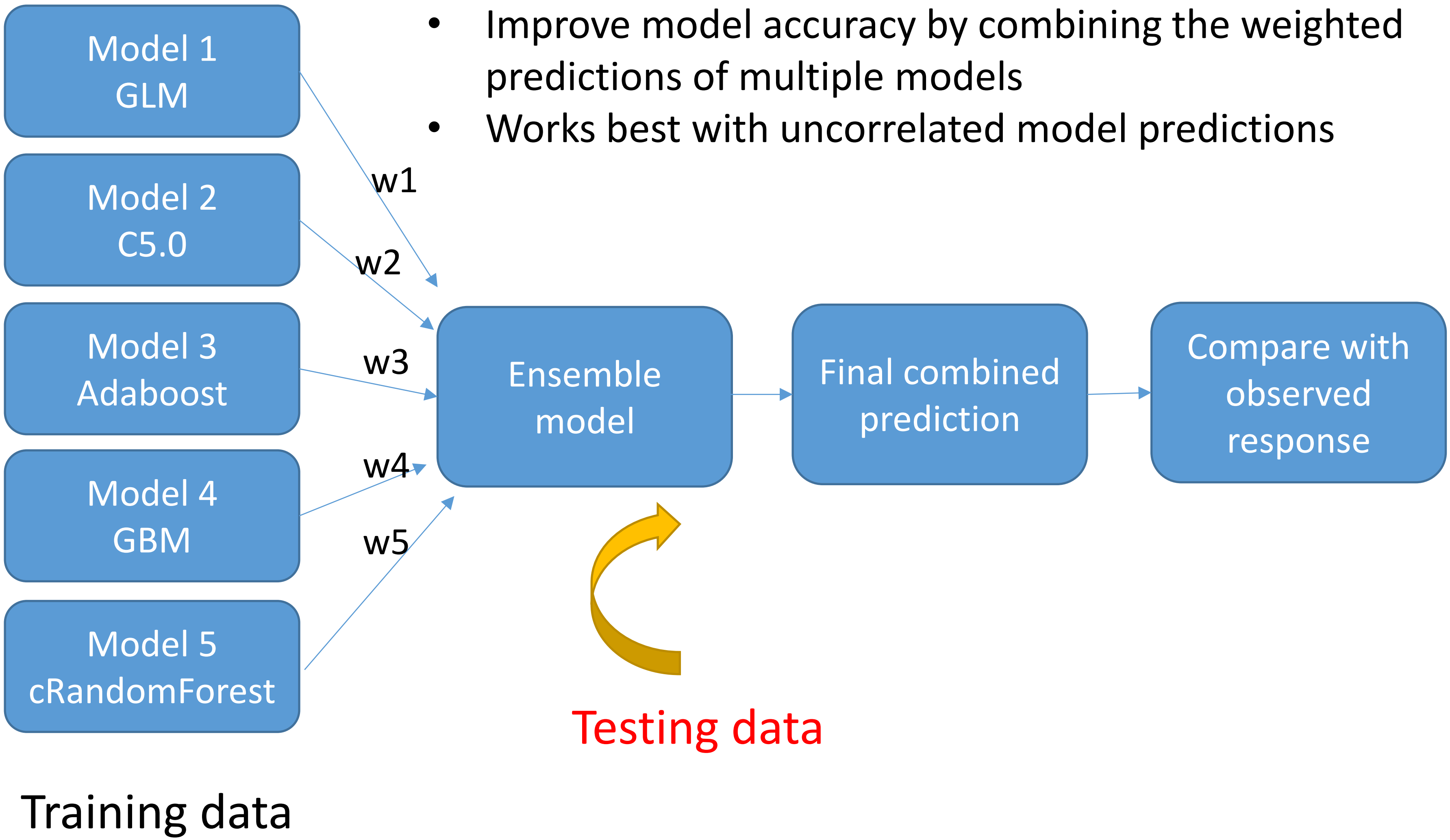
Engelbright dam, Yuba River. US Army Corp

Machine learning

- Computer learns how to classify the data correctly without being explicitly programmed via
  - **Gradient Boosting-** making weak classifiers progressively stronger by weighting the wrongly classified data
  - **Bagging**- reduces bias and overfitting by repeated samples with replacement and taking an average of the samples

Ensemble modeling

- Improve model accuracy by combining the weighted predictions of multiple models
- Works best with uncorrelated model predictions



Model accuracy assessment for ensemble model using testing data

Metric	Value
AUC	0.88
Accuracy	0.8
Omission	0.19
Commission	0.21

Top predictors from ensemble model

Importance	Predictor	Predictor Class
1	**Max. Temperature 30 yr avg**	Climate
2	**Latitude**	Space
3	**Longitude**	Space
4	**Port force of invasion**	Invasion pressure
5	**Total annual nitrogen deposition (kg/ha)**	Nutrient enrichment
6	Area of aquatic habitat	Habitat
7	Change in wetland area from 1946-1966	Landcover change
8	Percent wetland	Habitat
9	Percent agriculture on hydric soil	Landcover/Hydrologic alteration
10	Annual wet deposition of reduced nitrogen (kg/ha)	Nutrient enrichment

Top predictors from ensemble model

Importance	**Predictor**	**Predictor Class**
11	Percent cropland	Landcover
12	Annual wet deposition of oxidzed nitrogen (kg/ha)	Nutrient enrichment
13	Dam density	Hydrologic alteration
14	Change in natural land cover from 1946-1966	Landcover change
15	Total annual dry deposition of sulfur	Nutrient enrichment
16	Total annual sulfur deposition (kg/ha)	Nutrient enrichment
17	Stream length (km)	Habitat
18	Percent agriculture in areas of high water accumulation	Nutrient enrichment
19	Synthetic nitrogen fertilizer application (kg N/ha/yr)	Nutrient enrichment
20	Change in water cover from 1946-1966	Landcover change

Conclusions

1. Although, as expected each model ranked the same set of predictor differently, the top 5 predictors were consistently selected: max. temp., lat., lon., port force of invasion and N deposition.

2. Given the predictive success of our model, our results suggest that extrinsic factors drive biodiversity declines rather than species traits

Thank you!

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