Quantifying the Impacts of Everglades Restoration by Connecting Inshore Nurseries with Offshore Reefs

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Background

This project explores the dynamics and linkages among the multi-billion-dollar Everglades restoration project, Florida Bay habitat and fish community, and inshore-offshore connectivity with the Florida Keys Reef Tract.

- Fish species undergo ontogenetic shifts and use multiple habitat types throughout their life cycle
- Climate change is altering the distance and quality of essential fish habitat patches[1]
- Restoring water quality and nursery habitats creates refugia, facilitating the transition of juvenile and subadult fish to offshore habitats[2]
- Machine learning (ML) approaches can overcome limitations of traditional statistics[3]

1. **Can inshore juvenile population-community trends predict offshore adult population-community trends?**
2. **Can the effects of Everglades restoration on the offshore reef fish community be quantified?**

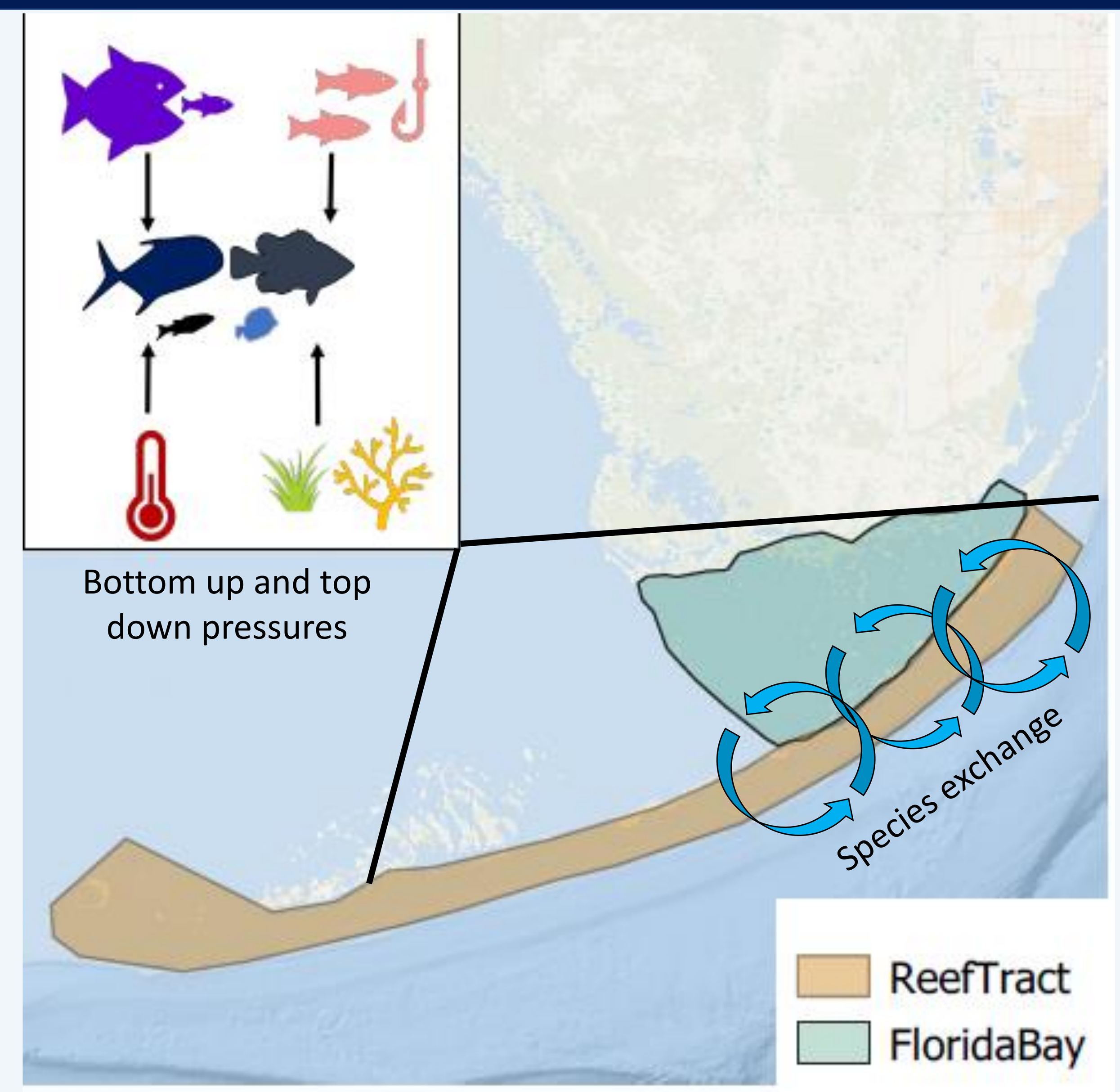


Figure 1: Map of study region and subregions. Arrows indicate species connectivity and exchange among regions. Inset panel highlights top-down and bottom up stressors driving fish communities.

Methods

Fish community and abiotic sampling has been conducted in both Florida Bay (2006-Present) and the Florida Keys Reef Tract (2000-Present) by Florida Fish and Wildlife Conservation Commission, NOAA, and D.Lewis. The machine learning models are trained with a subset of empirical abundance and water quality data (i.e., training data). Next, a different subset of data (i.e., test data) are compared to the model output to assess the predictive power of the model[3-5] (Fig 2).

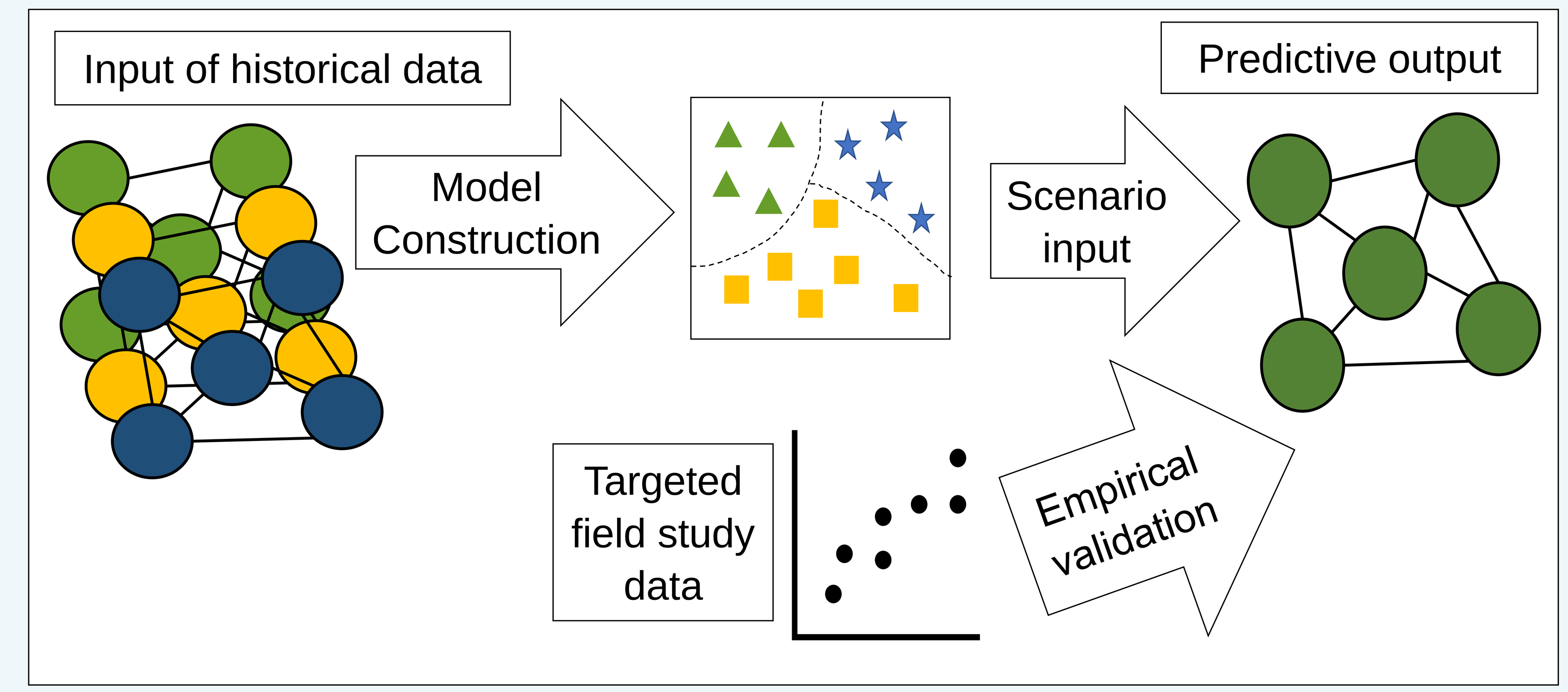


Figure 2: Machine learning workflow for predicting shifts in community dynamics using empirical data and forecasted environmental conditions.

Preliminary Results- ML model

Machine learning techniques were used to predict species abundance based on environmental parameters. These models were able to detect spikes in fish abundance given temperature, salinity, dissolved oxygen, and pH parameters (Fig 3).

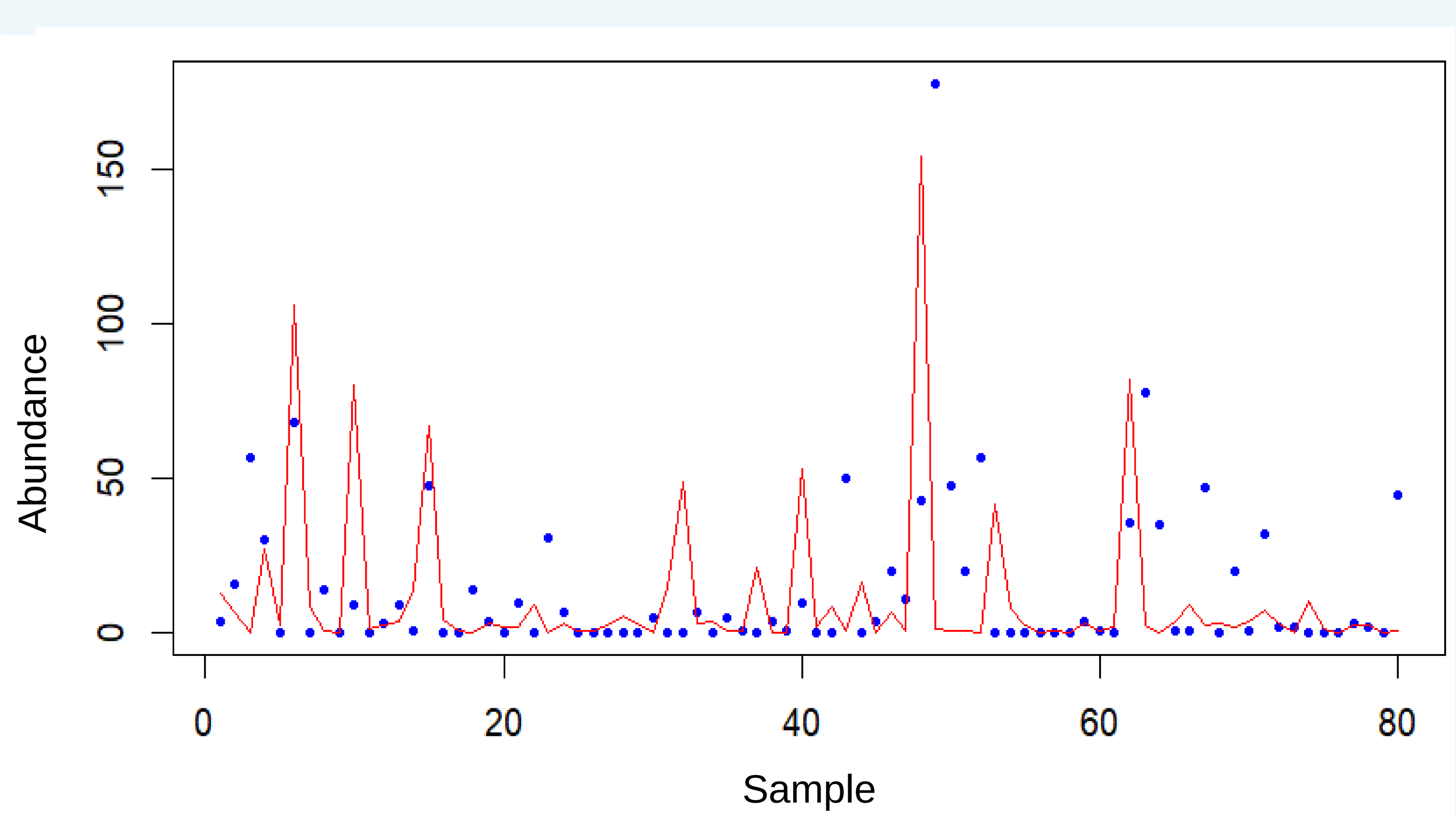


Figure 3: Extreme gradient boosted model predicting Florida Bay Mojarra abundance (mean= 19.7, SD=45.4) using water quality parameters (RMSE=37.7).

Preliminary Results- nMDS

There are clear differences in community composition between the Reef Tract and the Bay. However, 52 fish species inhabit both the reef and the bay for all or part of their life cycles (Fig 4).

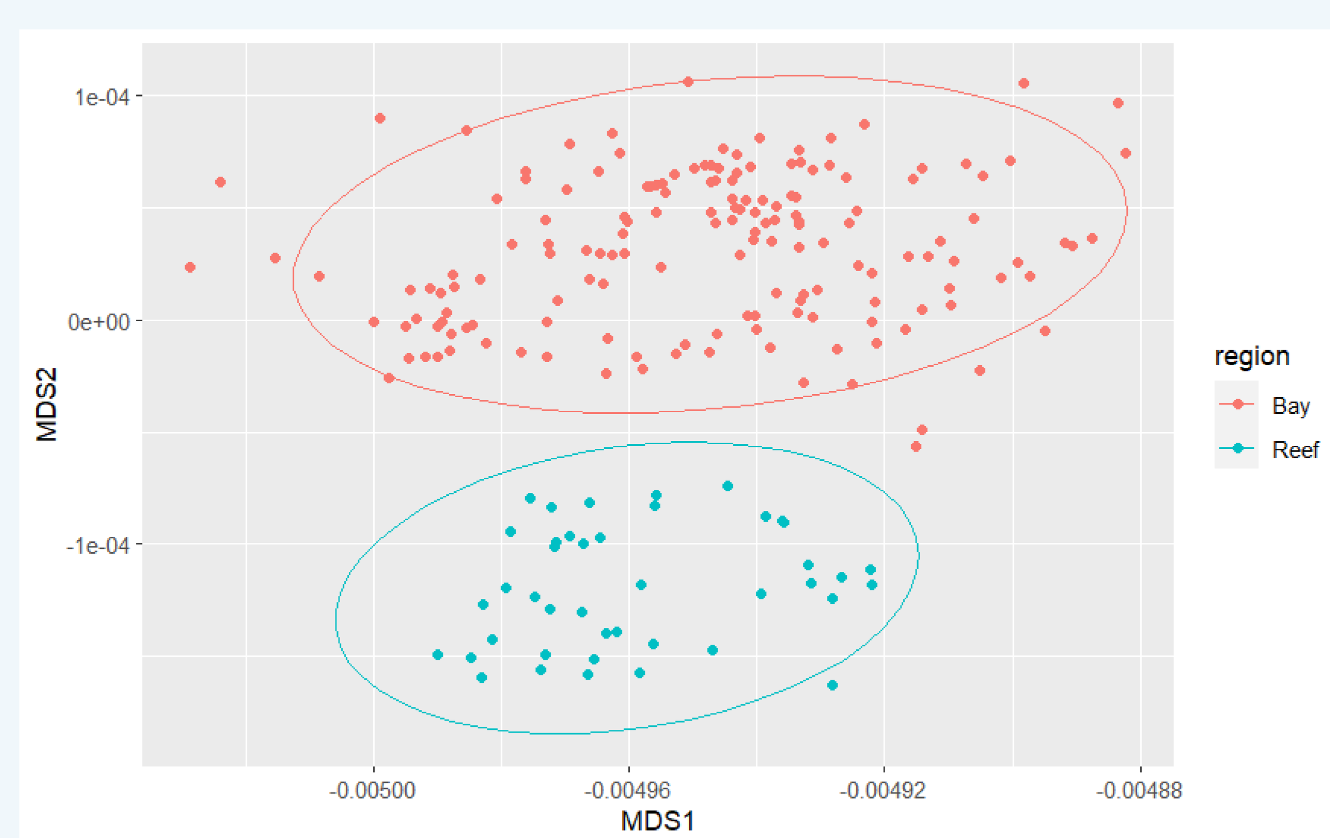
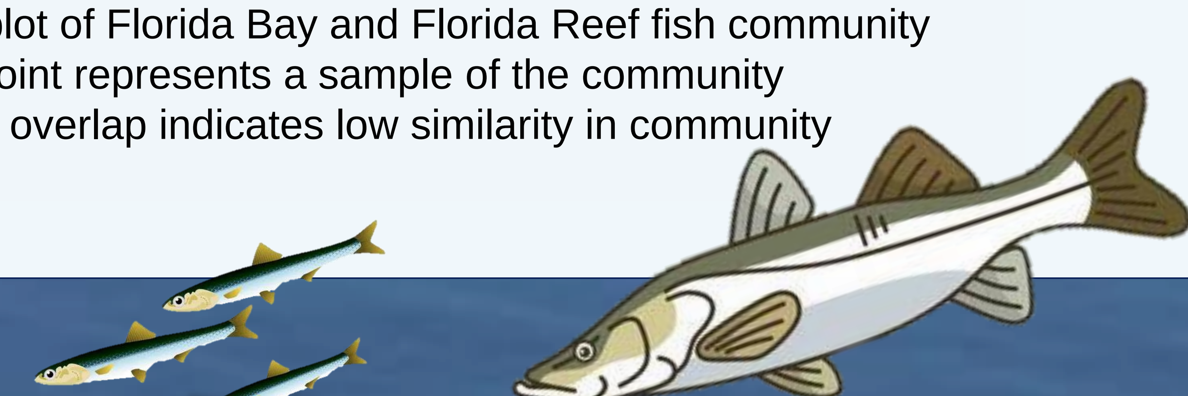


Figure 4: nMDS plot of Florida Bay and Florida Reef fish community from 2022. Each point represents a sample of the community (stress<0.01). Low overlap indicates low similarity in community composition.



Highlights & Future Directions

- **Fifty-two species of fish** utilize both the **Florida Bay and the Florida Keys Reef Tract** for all or part of their life cycles
- Novel **ML** models were able **to predict peaks in fish abundance** under various environmental conditions
- **ML** approaches can identify **nonlinear patterns** and predict relationships between **fish abundance and the environment**
- **Next Steps- 2022 and 2023 data** will be **integrated** into ML models to assess **factors driving community structure**
- **Finally, forecasted environmental conditions will be incorporated to estimate long-term effects of Everglades restoration and climate change on community dynamics**

Affiliations & Acknowledgements

Funding for this research was provided **by The Everglades Foundation** and the **Patrick P. Lee Foundation**. Additional funding was provided by the **National Defense Science and Engineering Graduate Student Fellowship** and **Forage Fish Research Program**.

Literature Cited

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