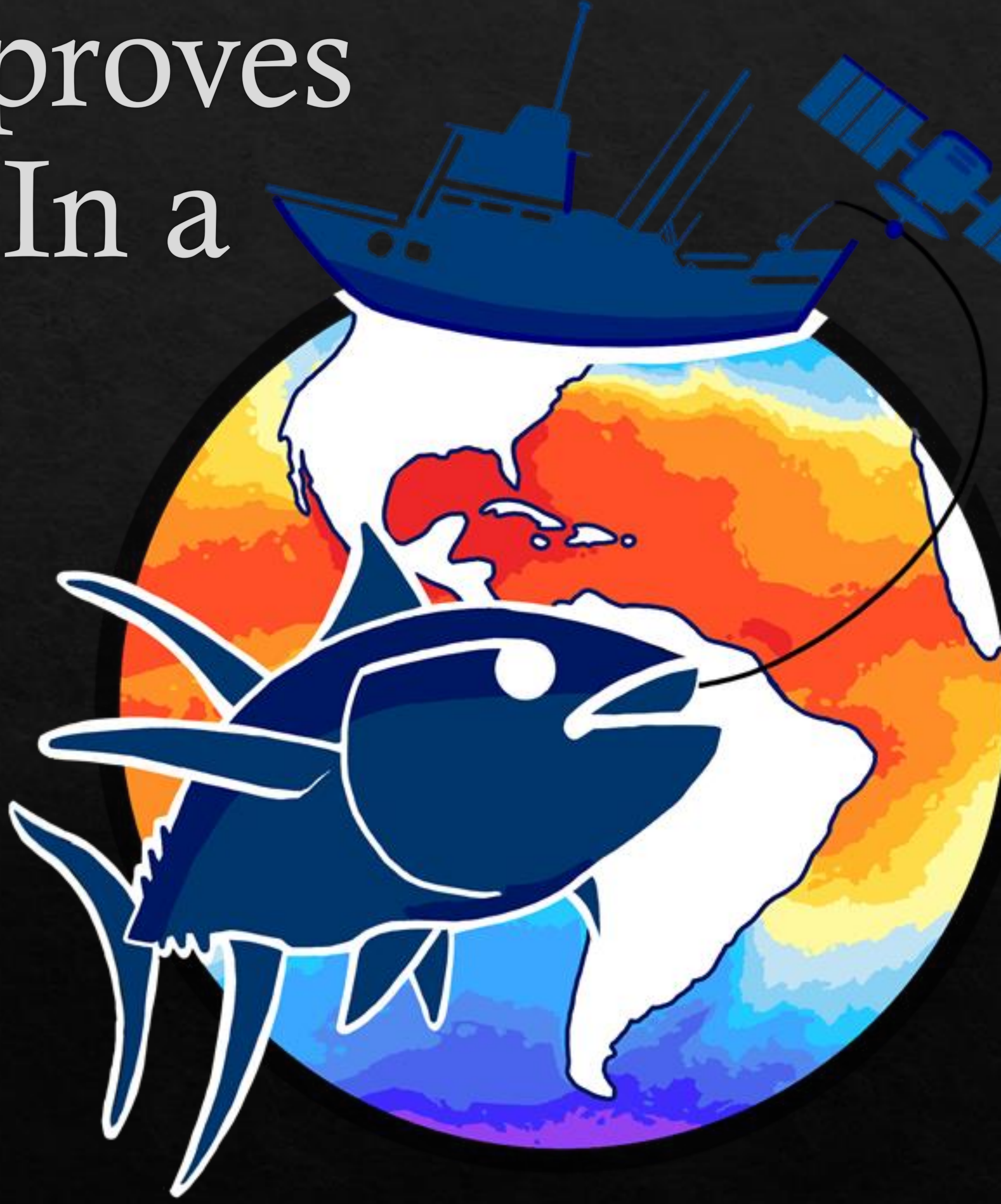
Data Integration Improves Model Performance In a Changing Climate



Nima Farchadi, Camrin D. Braun, Martin C. Arostegui, Barbara A. Muhling, Elliott L. Hazen, Andrew J. Allyn, Kiva L. Oken, Rebecca L. Lewison

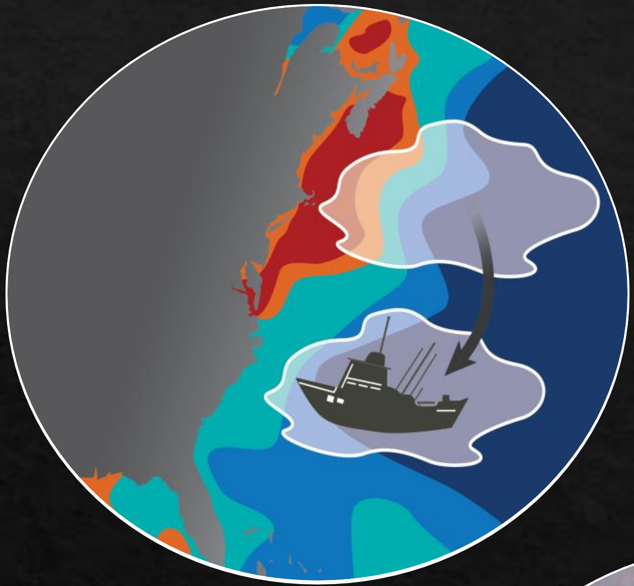
SDSU

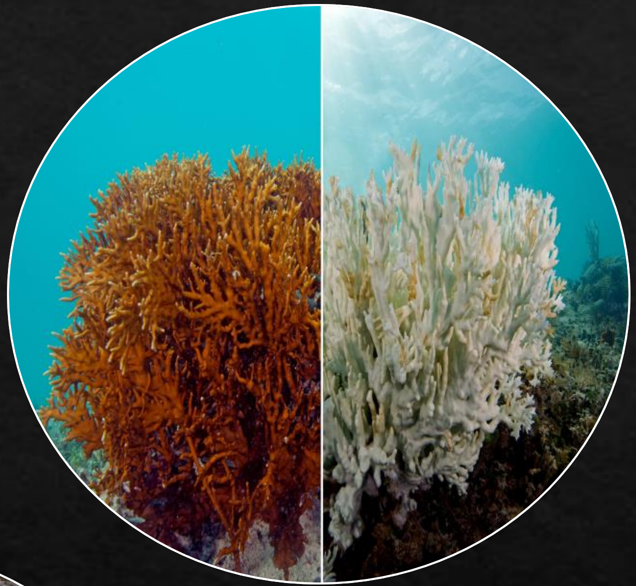
Woods Hole Oceanographic Institution 1930

NOAA National Oceanic and Atmospheric Administration U.S. Department of Commerce

Gulf of Maine Research Institute

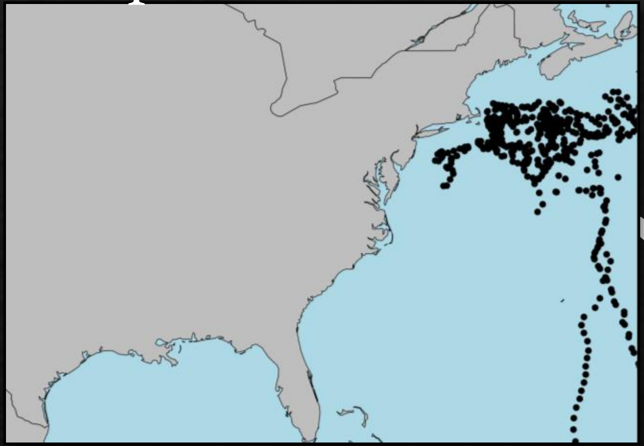
Society increasingly faces novel conditions





Species distribution models (SDMs)

Species locations



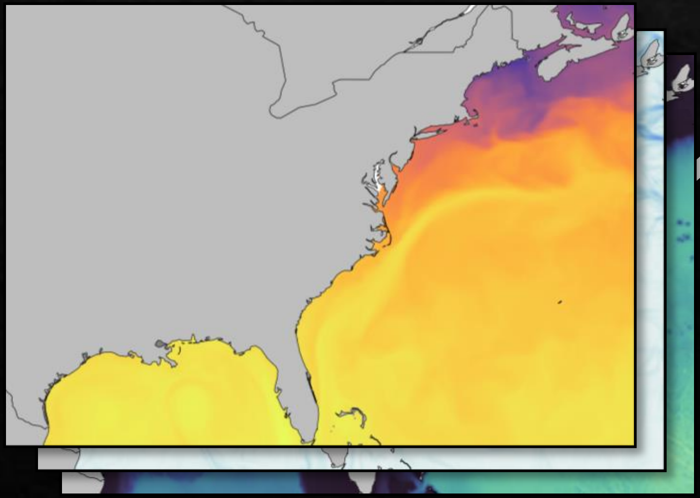
Fishery-dependent = fishing catch data

Fishery-independent = surveys, tagging data

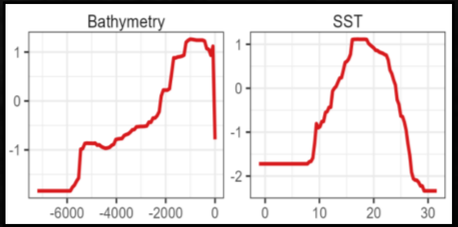
Fit

Statistical Model

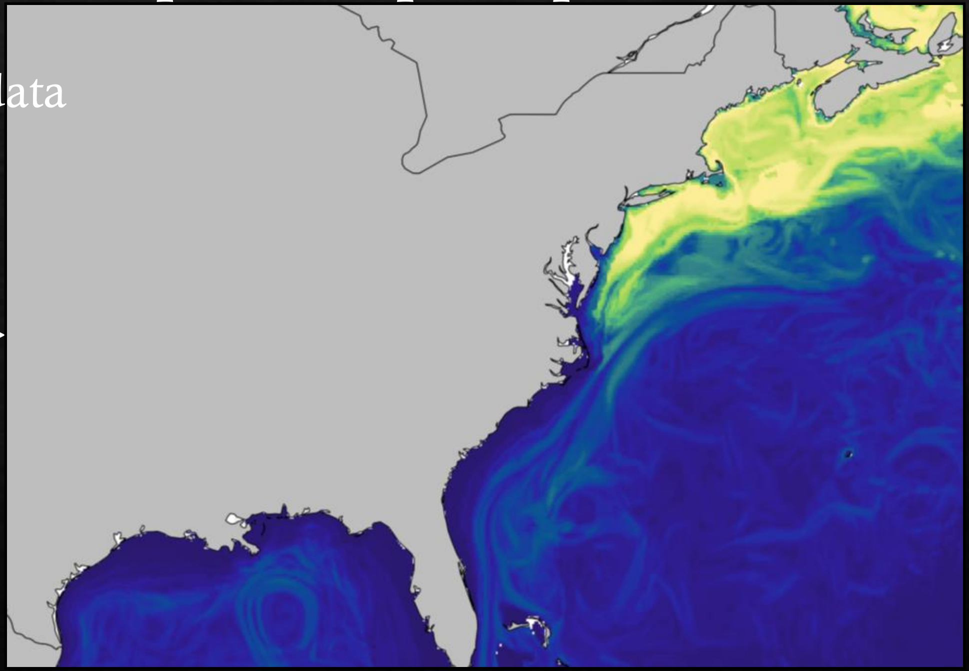
Environmental variables



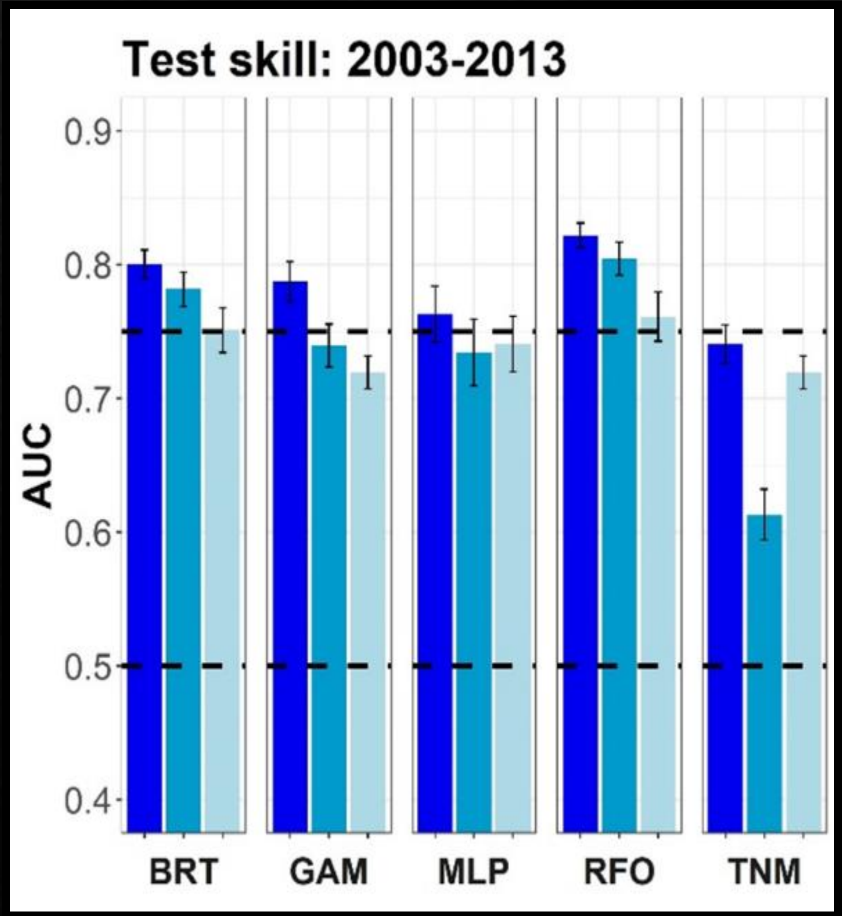
SST, SSH,
MLD, Chla, etc.



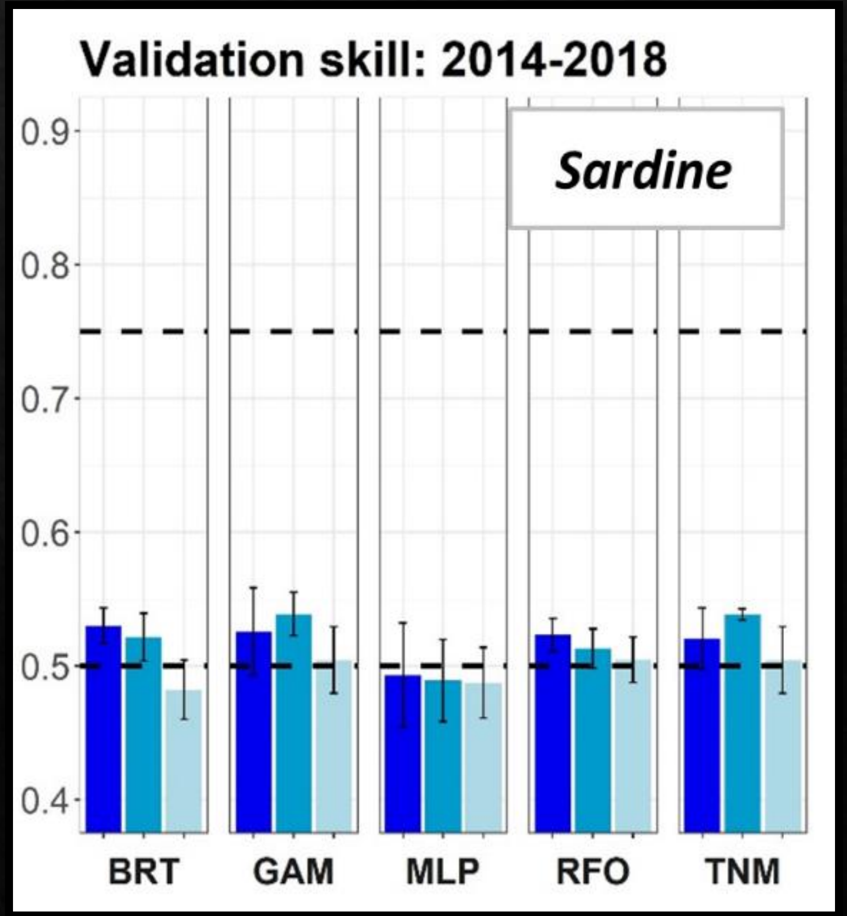
Spatiotemporal predictions



Poor forecasts under novel conditions



Sardine SDMs

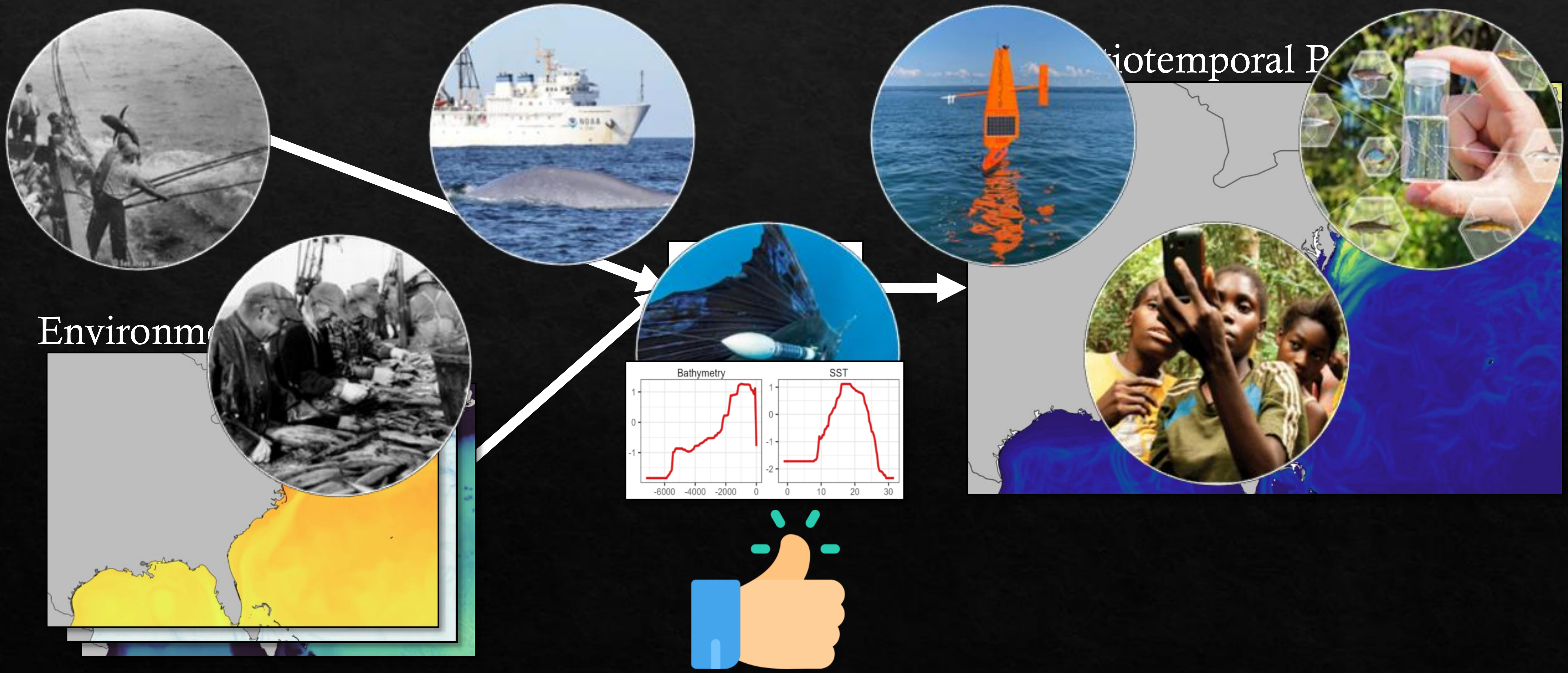


Muhling et al. 2020

Data is rapidly changing

Rarely leverage various data

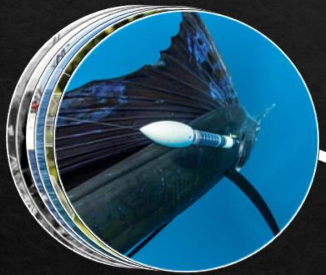
Spatial locations



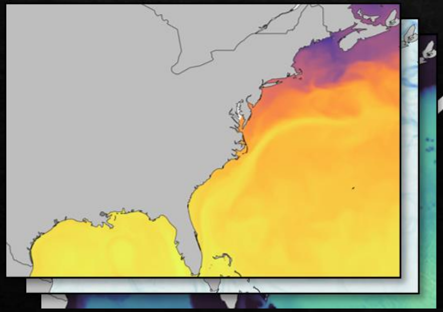
Can integration improve forecasts?

hindcasts nowcasts forecasts

Spatial locations



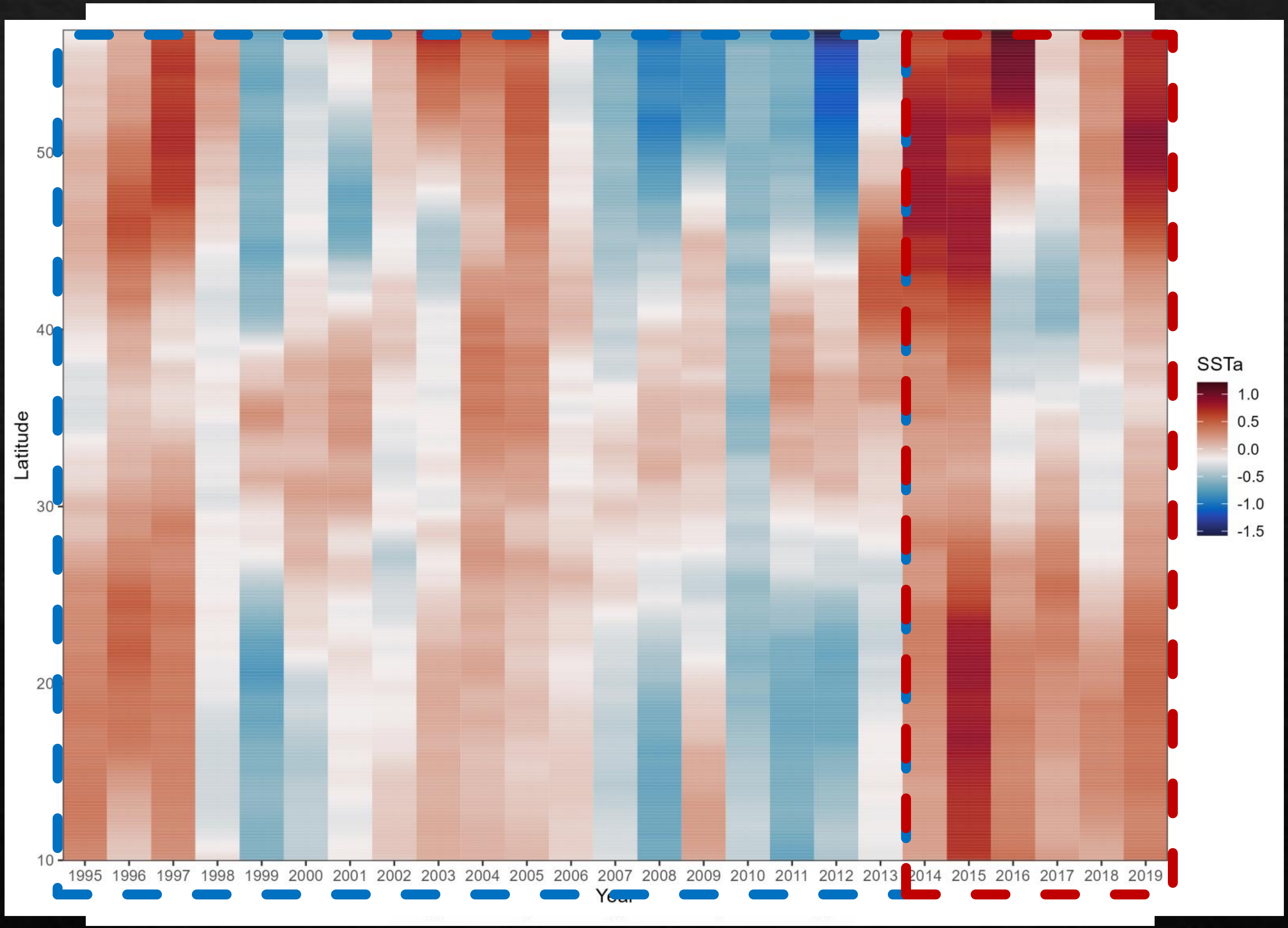
Environmental variables

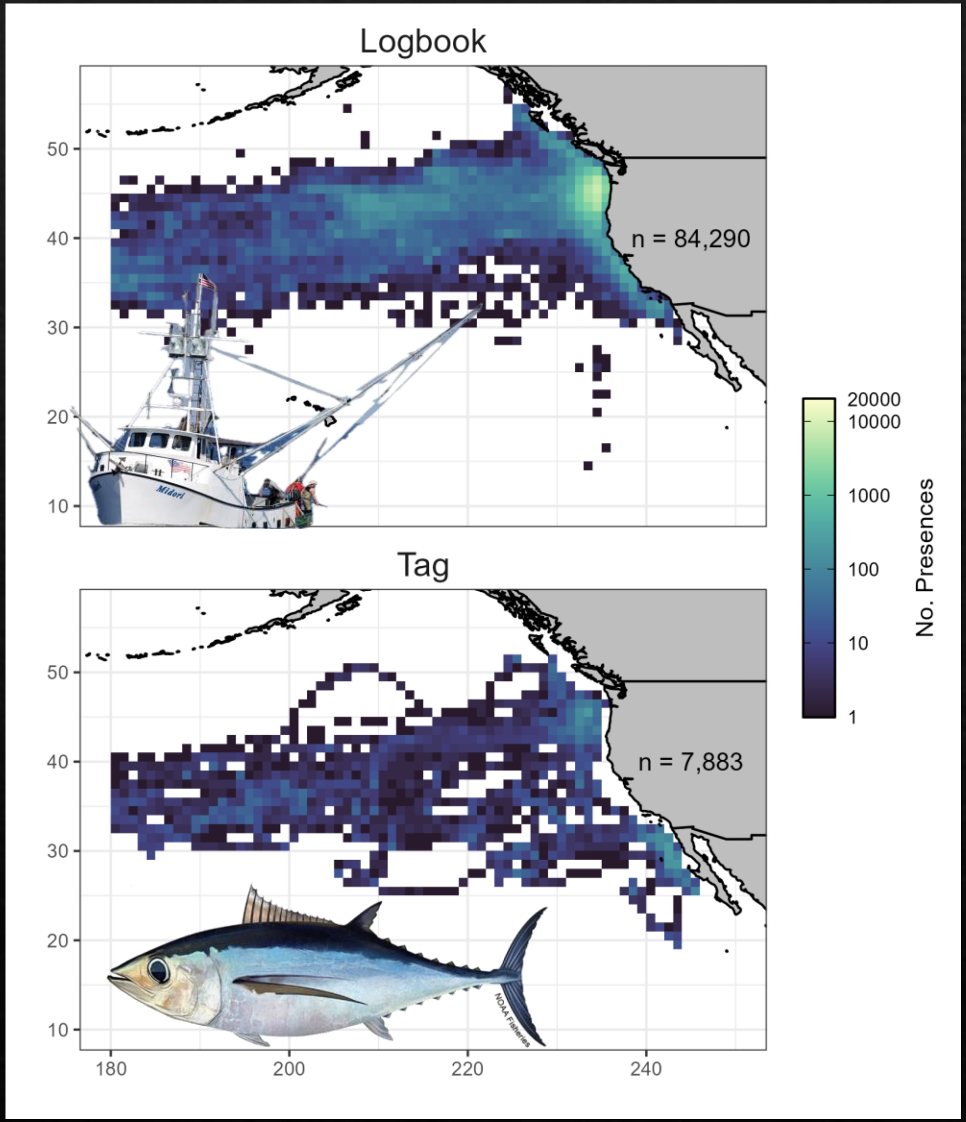


SDM

Forecast under novel conditions

Marine heatwaves (MHWs) in the North Pacific





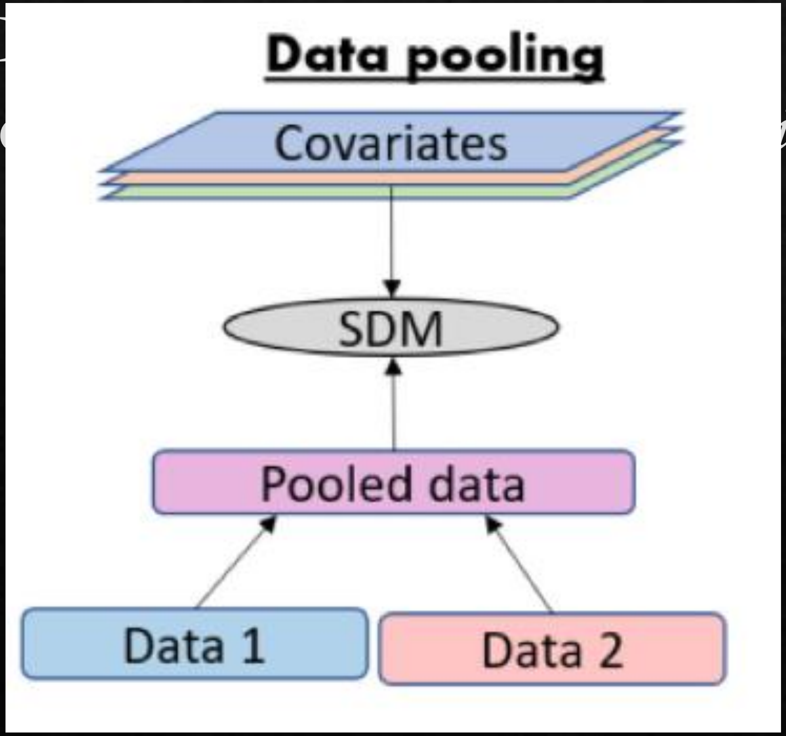
Albacore Tuna

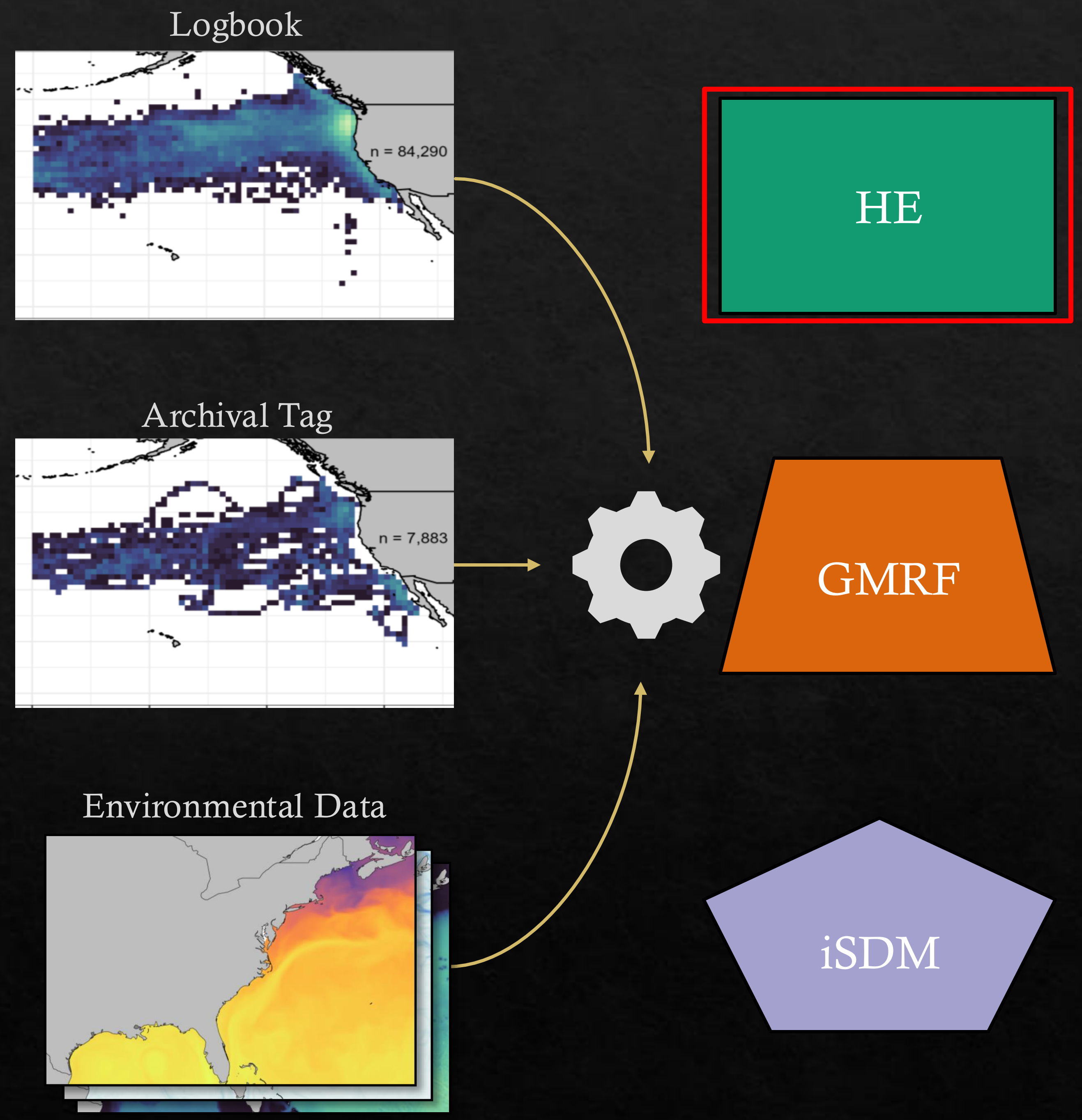
- Fishery-dependent data
    1. Vessel logbook (Troll & pole-and-line fleet)
- Fishery-independent data
    2. Archival Tags

Temporal extent: 1995 - 2019

Habitat envelope model (HE)

- Pooling approach





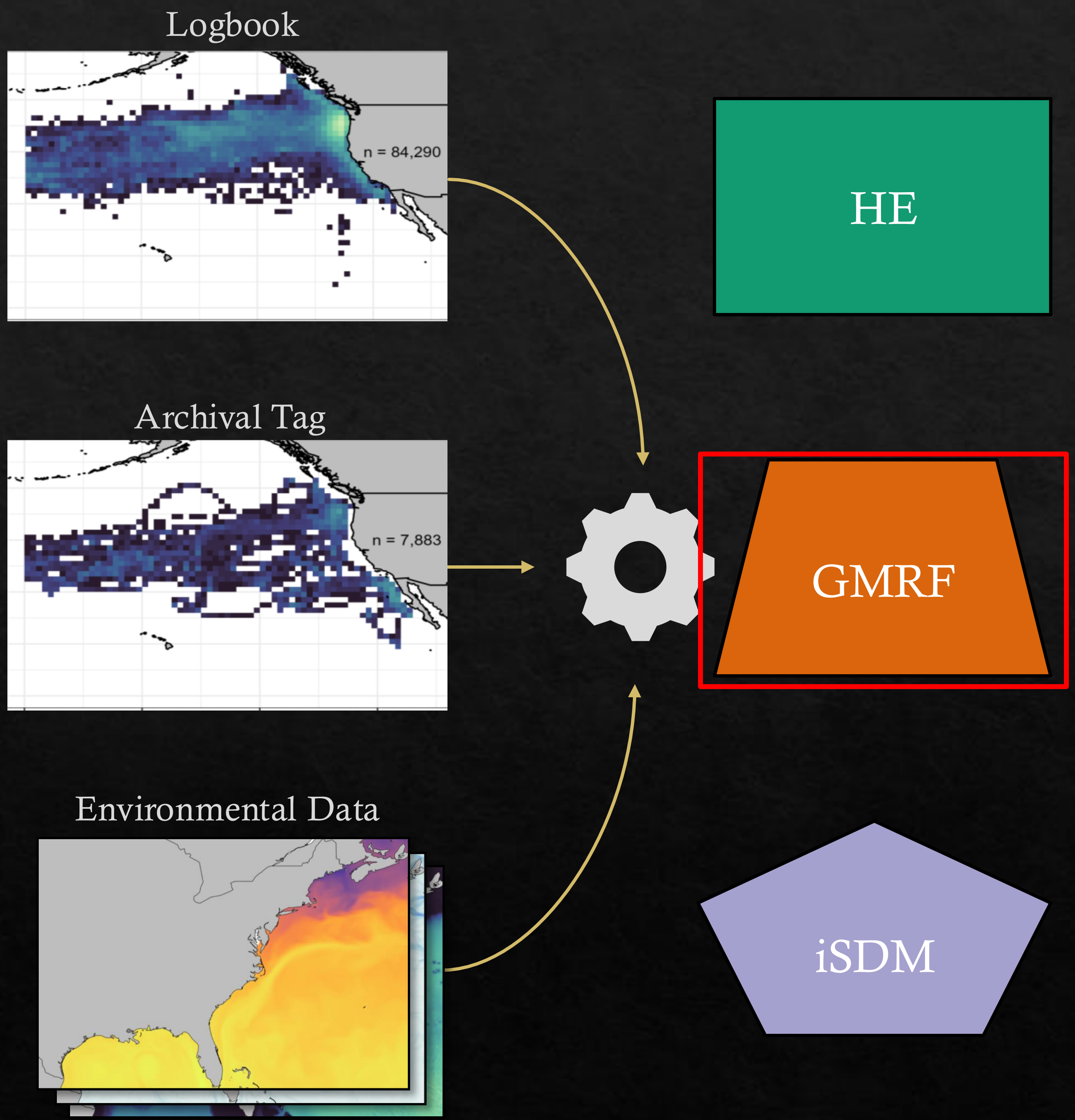
Gaussian markov random field model (GMRF)

- Pooling approach
- <u>Seasonal</u> random spatial fields
    - i.e. *spatially explicit*

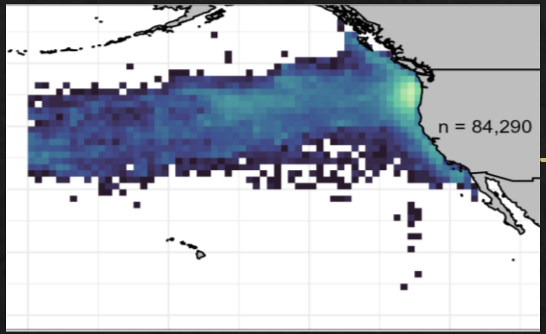
Environmental covariates

$$y = x\beta + \omega_{winter} + \omega_{spring} + \omega_{summer} + \omega_{fall} + \epsilon$$

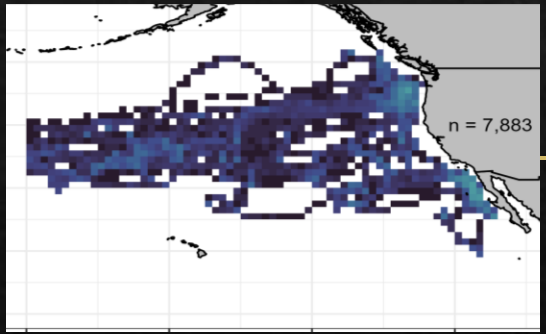
Seasonal random spatial field

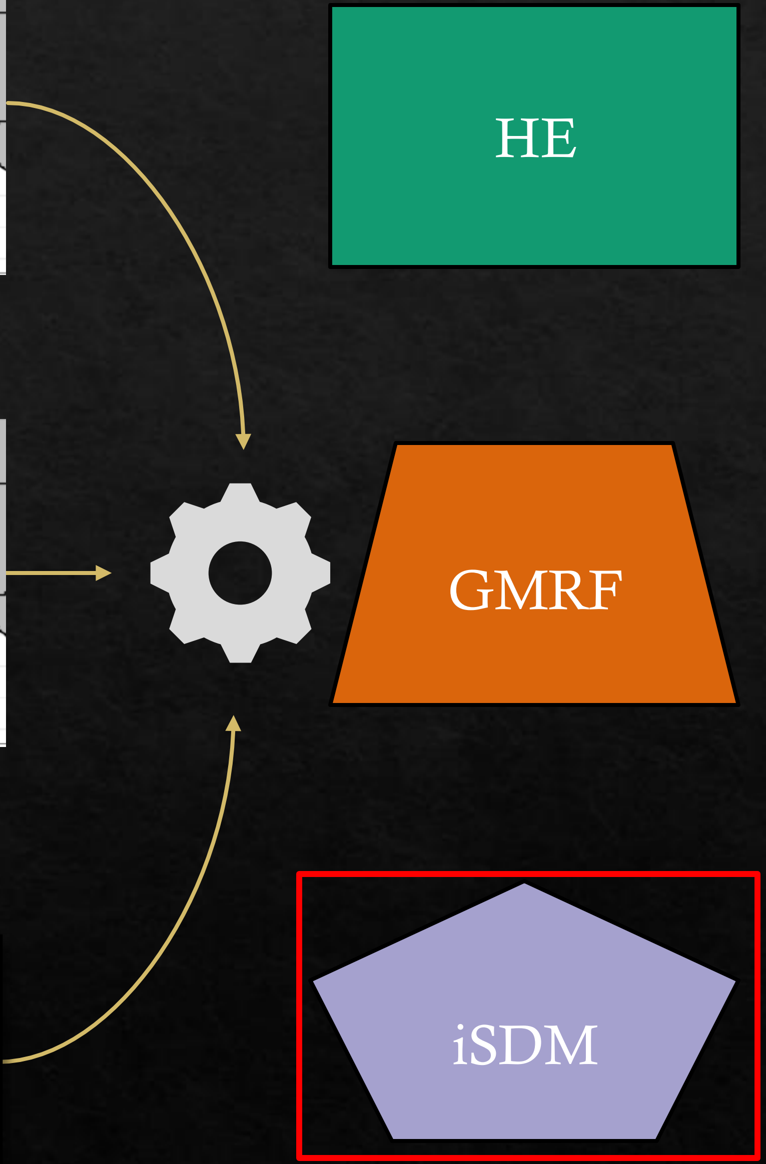


Logbook



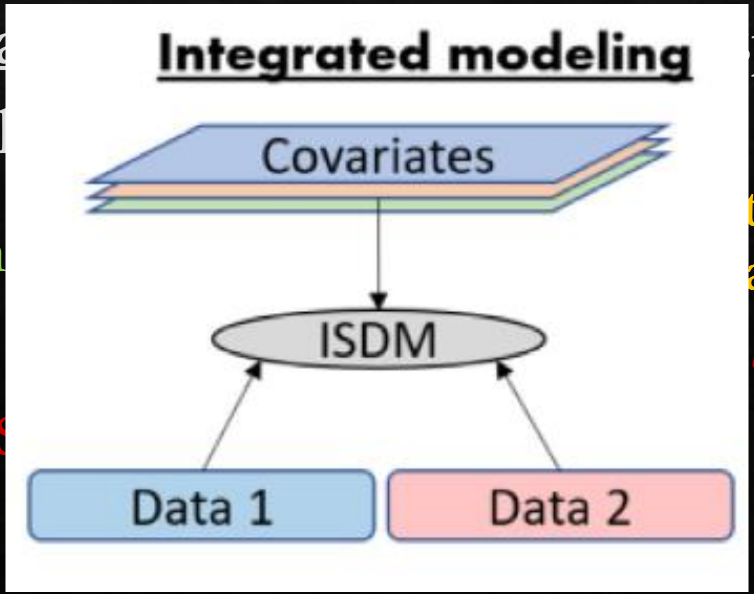
Archival Tag





integrated species distribution model (iSDM)

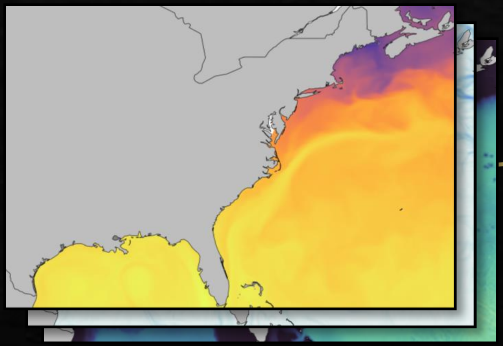
- Jointly estimated environmental parameters
- Sea … spatial fiel…



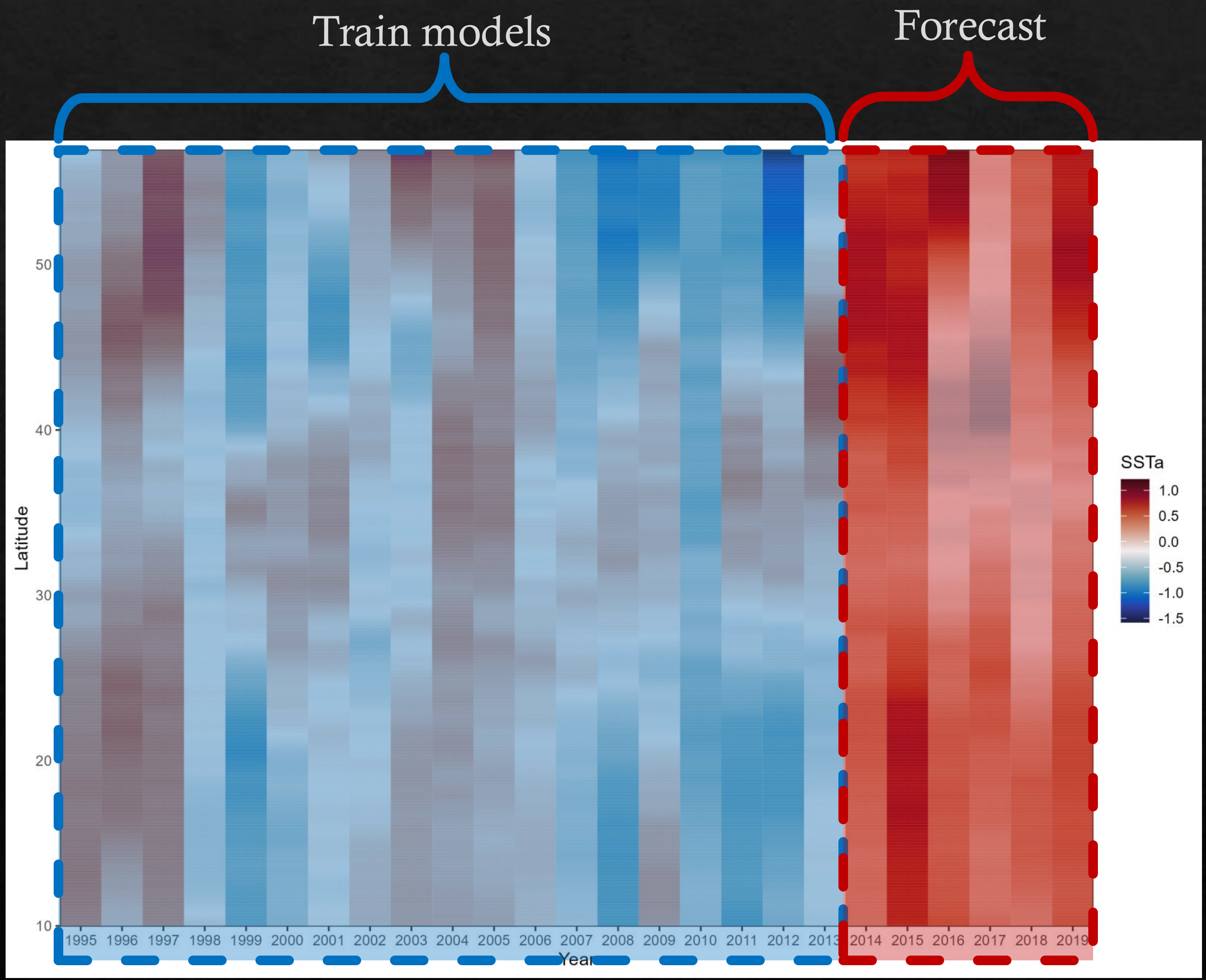
Environ… …tant random …atial field

$y = x\beta + \ldots + \varphi + \epsilon$

Environmental Data

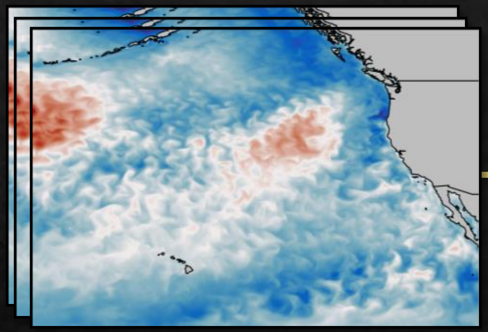


Retrospective forecasts

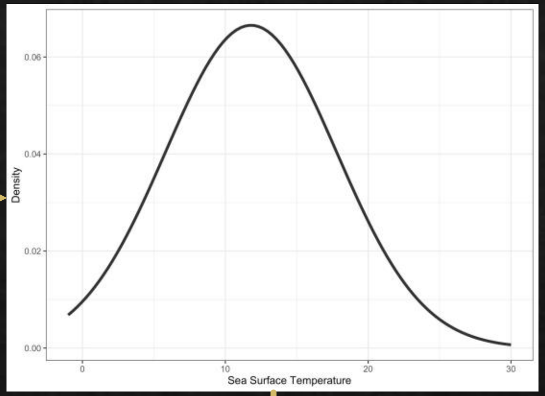


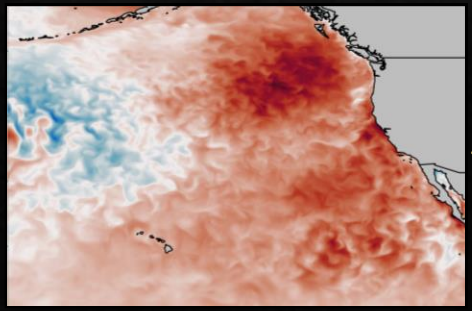
1995 to 2013

Quantifying environmental novelty

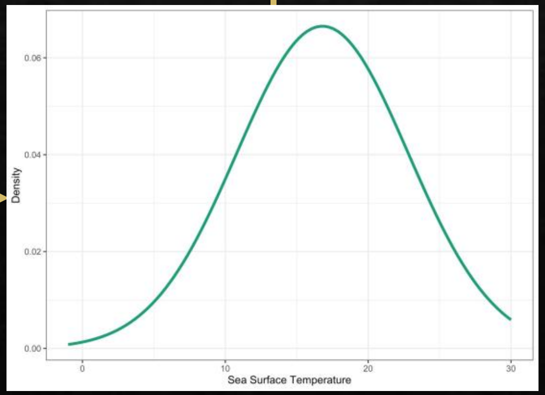


SSTs the model learned from (1995 – 2013)



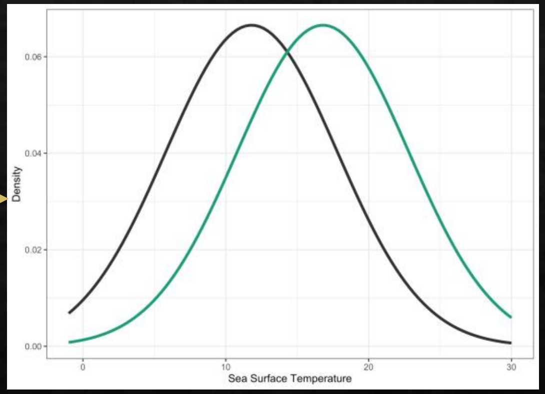


Prediction target SST



<u>Hellinger Distance</u>

Difference between two distributions

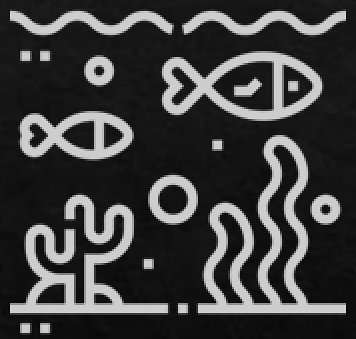


2 Dimensions of performance

Predictive Skill

How well can the model predict at new locations?

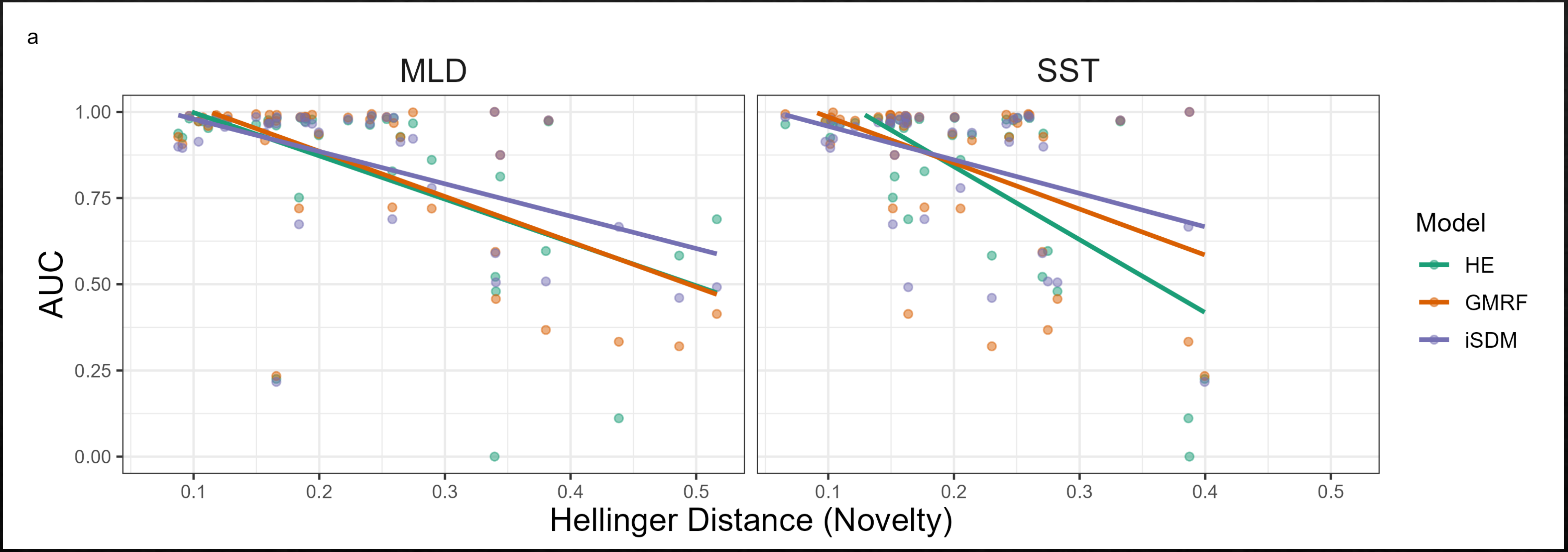
Ecological Realism



How well do model-predicted habitat suitabilities align with the data?

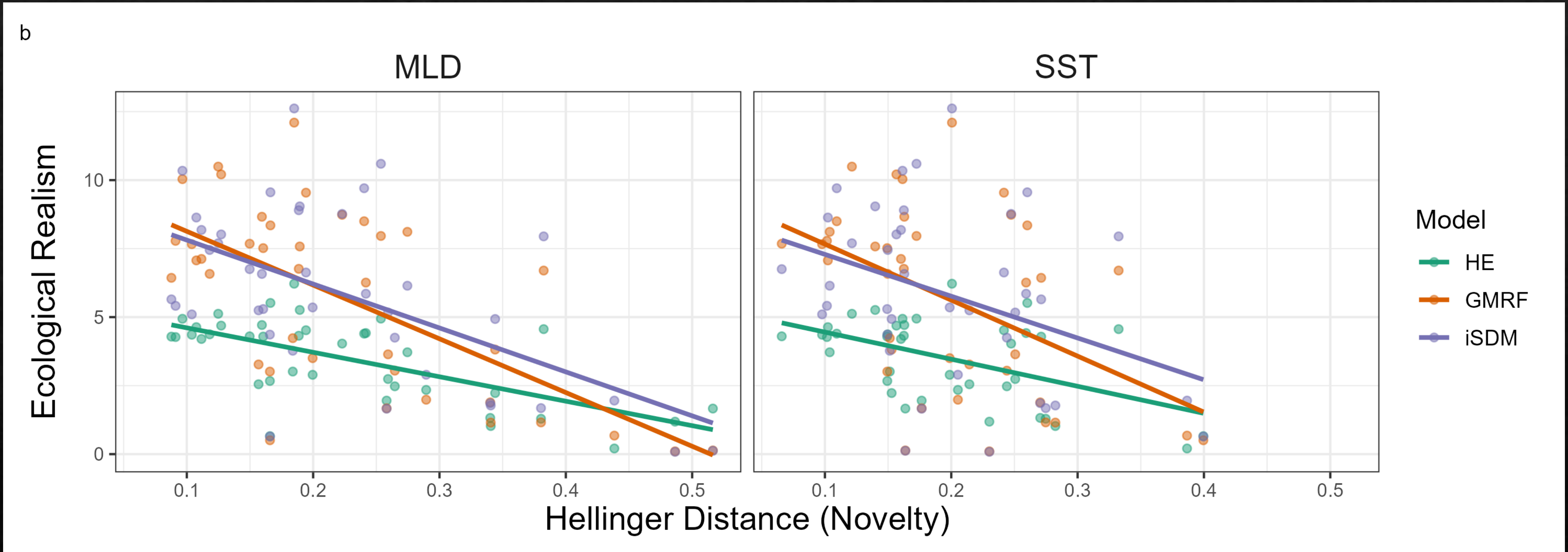
Predictive skill and environmental novelty

Better Predictive Skill



Greater Novelty

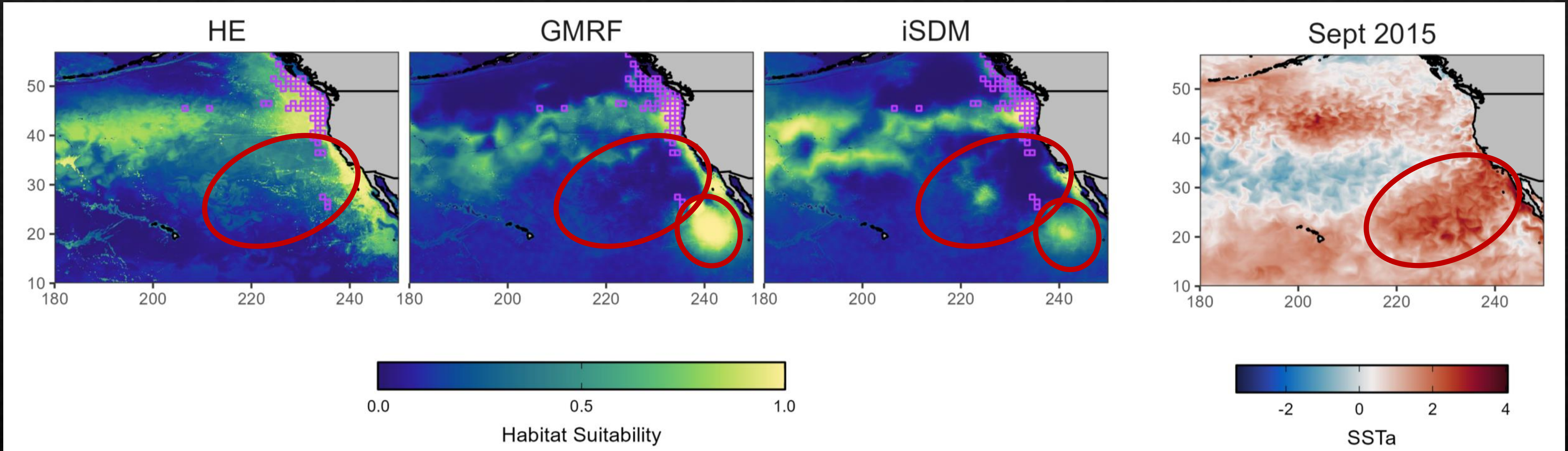
Ecological realism and environmental novelty



More Ecologically Realistic

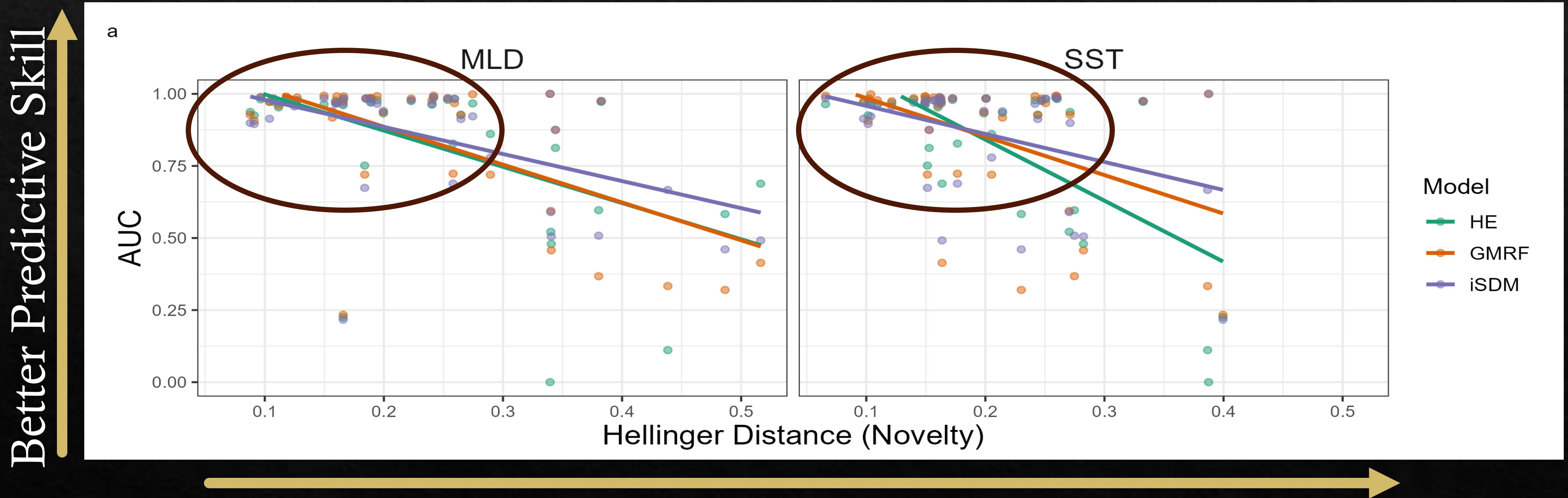
Greater Novelty

Ecological realism and environmental novelty



Lessons learned

1. *All models do well under low degrees of novelty*



Lessons learned

1. *All models do well under low degrees of novelty*

2. *iSDMs mitigate issues that are broadly attributed to a model's forecast ability*
   a. Overfitting
   b. Accounting for biases for each data source

Future directions

1. *Utility of iSDMs as foundational tools for proactive management and conservation*

2. *Exploring iSDM performance in other applications*
    a. Pair with operational forecasts products (e.g. SST)
    b. Long-term projections
    c. Data poor species
    d. Transferability across geographical space

Acknowledgements

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- Andrew Allyn
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- FaCeT Team

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