

PREDICTING ECOLOGICAL NETWORKS

CONTEXT

Empirically characterizing complex ecological interactions networks is a challenging task under the best of conditions. Network-level descriptors are thus largely ignored for practical applications even though we recognize the importance of considering the reticulated nature of complex networks. Significant insights can however be gleaned through the combined study of biotic (*i.e.* biotic interactions) and abiotic (*i.e.* environmental factors) constraints effecting the distribution and structure of communities.

OBJECTIVE

Predict the spatial structure of interactions networks structuring ecological communities

STRATEGY

Integrated niche concept¹:

- Probability of interaction and co-occurrence between two taxa in a given environment
- Combine:
 - Hierarchical Modeling of Species Communities (HMSC)² to predict cooccurrence
 - Machine learning algorithm (iEat)³ to predict interactions

EMPIRICAL DATA

- Catalogue of empirical pairwise trophic interactions^{4,5,6,7,8}
- Taxa occurrence: Annual trawl survey of northern gulf of St. Lawrence, eastern Canada
- Environmental covariables (*e.g.* temperature, salinity, depth)^{9,10}

METHODS

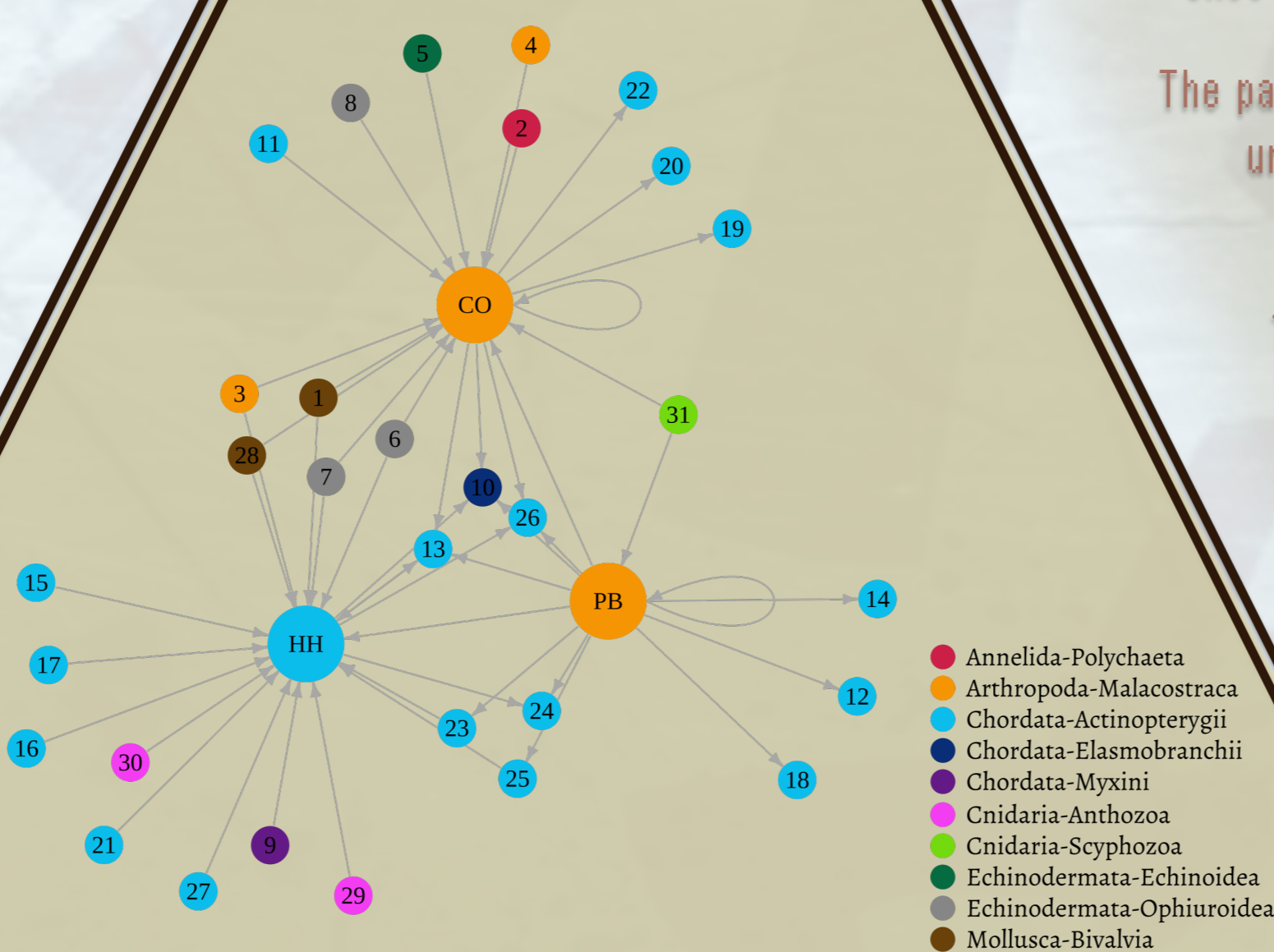
Predicting interactions (iEat)³:

- Caveat: Similar taxa are more likely to share consumers and resources
- Machine learning algorithm predicting biotic interactions
- Predictions informed by empirical biotic interactions catalogue
- Similarity parameters: taxonomy and diet
- Output: food web matrix



Figure 1. Subset of predicted metaweb using iEat and centered on Atlantic halibut (*Hippoglossus hippoglossus*; HH), northern prawn (*Pandalus borealis*; PB) and snow crab (*Chionoecetes opilio*; CO). Metaweb link density = 2.69; connectance = 0.02 (124 taxa).

INTERACTIONS



Long ago, in the beautiful kingdom of Canada surrounded by vast oceans, legends told of an omnipotent Golden Ecologist charged with the protection of its borders. Many conquerors aggressively sought to enter this kingdom and for a while laid waste to its natural resources.

At the behest of Canada's rulers, the Golden Ecologist sealed the gate to the kingdom. The seals should have endured.

But, when these events were obscured by the mists of time and became legend, the conquerors entered the kingdom once more, only to find weakened seals...

The path to destruction is once more open, unless the full might of the seals can once again be unleashed.

The descendants of the Golden Ecologist must now protect the kingdom of Canada.

But pieces of the puzzle are missing.

Wake up.. It's time to fulfill your destiny...

PREDICT NETWORK

LINK DENSITY

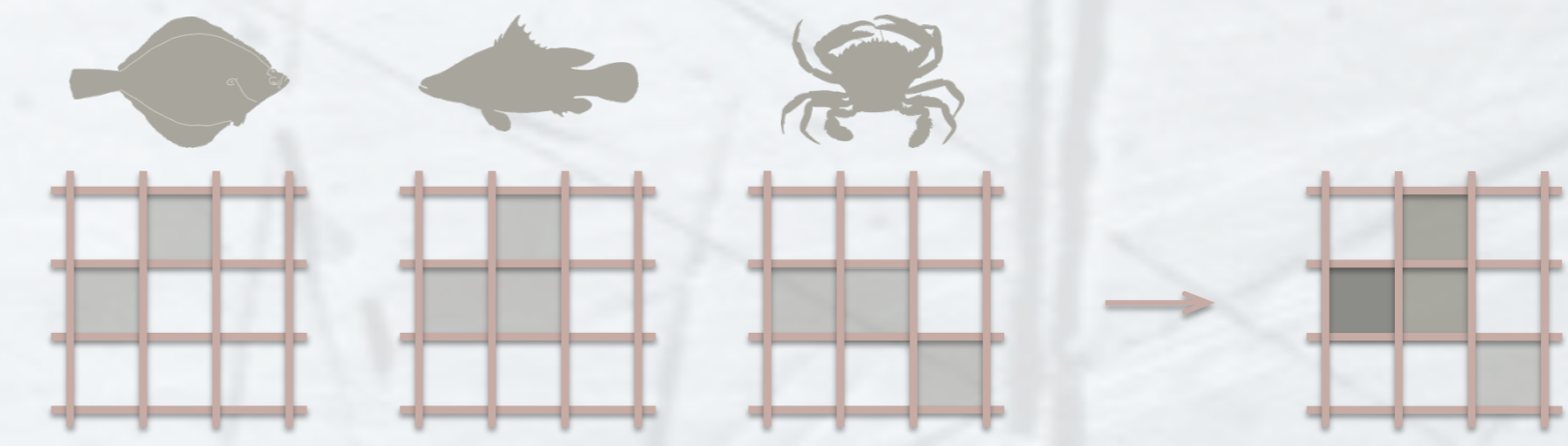


Figure 3. Prediction of the spatial distribution of link density between 124 taxa in the estuary and gulf of St. Lawrence in eastern Canada. Predictions are performed using a combination of iEat and HSMC.

METHODS CONT'D

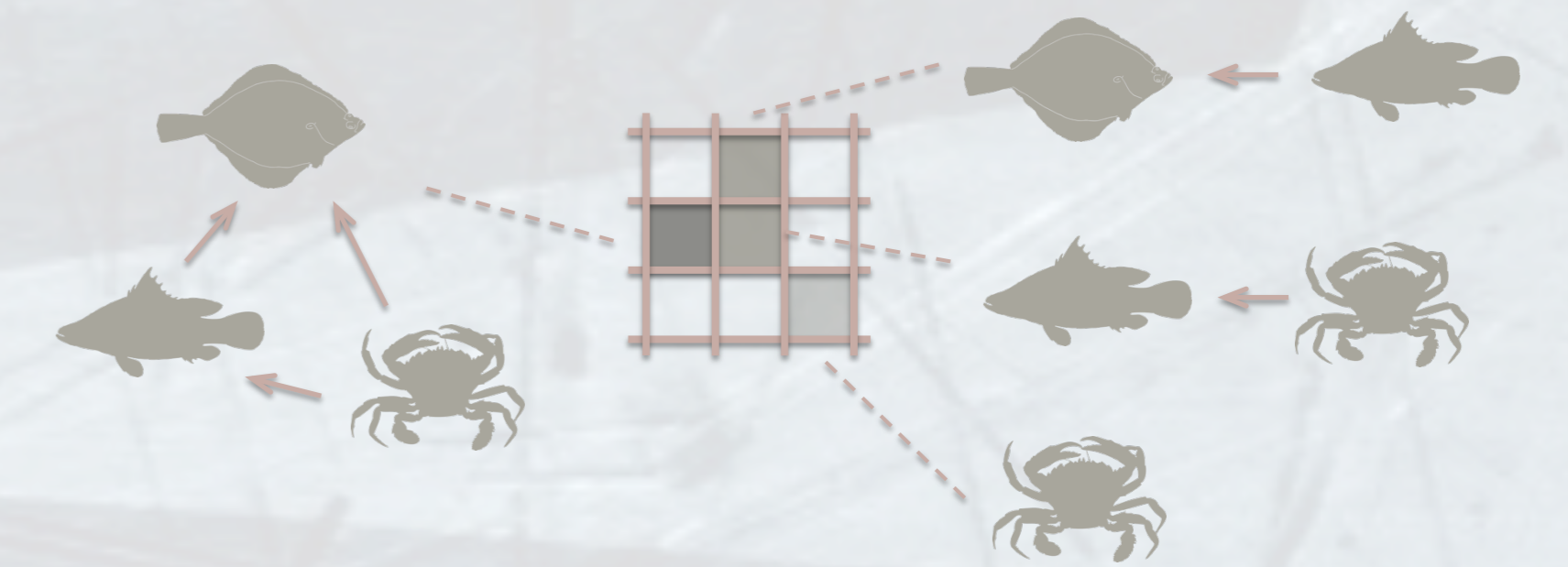
Predicting cooccurrence (HMSC)²:

- Hierarchical Bayesian joint species distribution model
- Taxa occurrence ~ environmental covariables (*e.g.* depth and salinity)
- Predicts the spatial structure of communities
- Output: distribution probability



Predicting ecological network spatial structure (predict Network):

- Predict taxa cooccurrence using HSMC model parameters posterior distribution
- Predict interactions between cooccurring taxa in with iEat



COOCCURRENCE

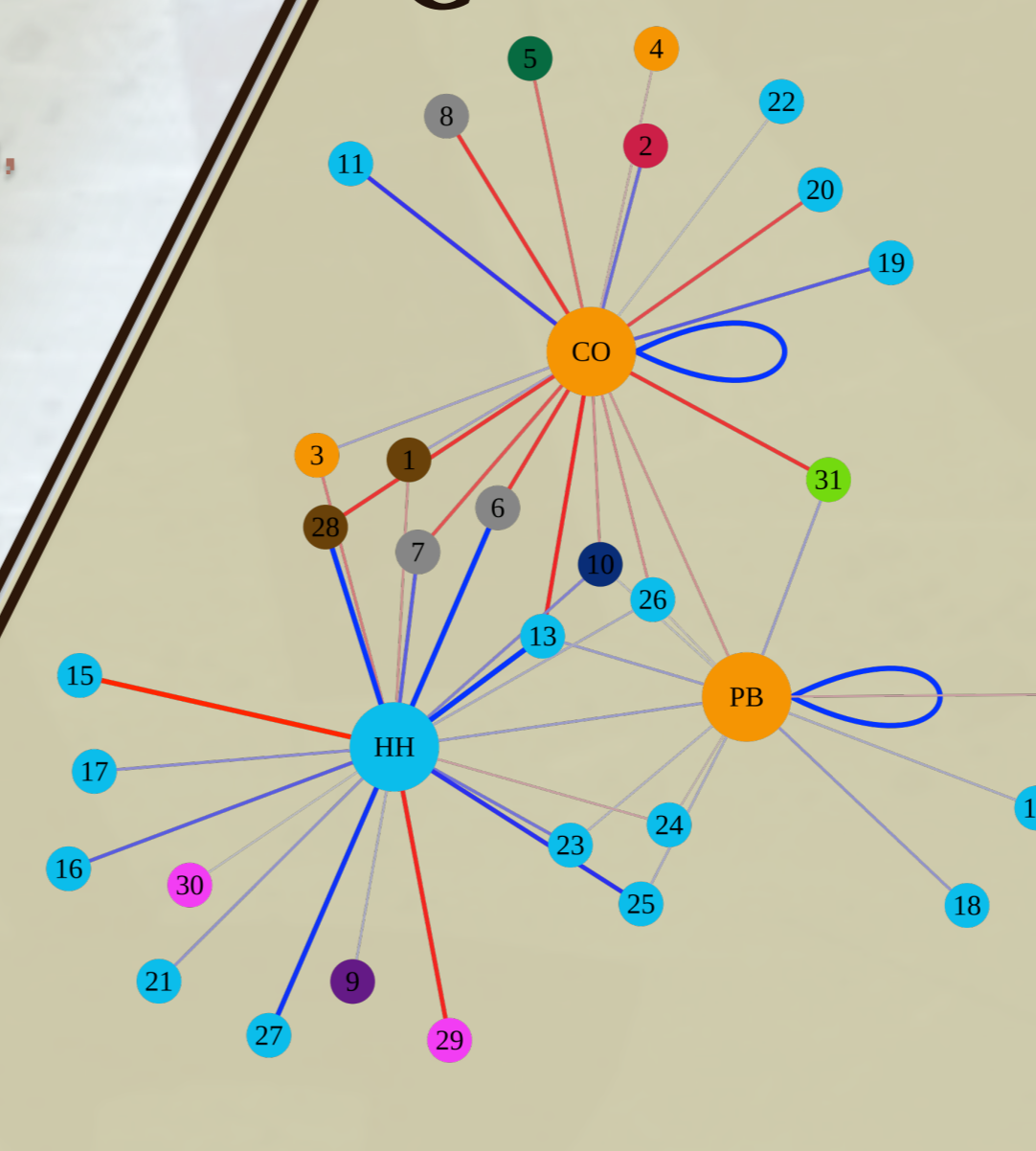


Figure 2. Positive (blue) and negative (red) spatial association between species interacting with Atlantic halibut, northern prawn and snow crab. The size of the link is proportional to the strength of the correlation. HMSC model mean t_{jkr} 's $R^2 = 0.32 \pm 0.18$; mean AUROC = 0.86 ± 0.09 (124 taxa).

DISCUSSION

- iEat has been shown to be efficient in predicting pairwise interactions³ (figure 1)
- HMSC model do not fully capture the structure of biotic interactions (figure 2)
- Biotic and abiotic constraints considered in predicting the structure of network (figure 3)

NEXT STEPS

- Incorporate other empirical occurrence datasets in analysis
- Validate predicted interactions with stomach content data in the St. Lawrence
- Evaluate the vulnerability of networks to multiple stressors
- Evaluate cumulative impacts on the network of the St. Lawrence

1-Astarte; 2-Polynoidae; 3-Pagurus; 4-Munidopsis curvirostra; 5-Strongylocentrotus; 6-Ophiopholis aculeata; 7-Ophiura; 8-Ophiacantha bidentata; 9-Myxine glutinosa; 10-Amblyraja radiata; 11-Mallotus villosus; 12-Boreogadus saida; 13-Gadus morhua; 14-Enchelyopus cimbrius; 15-Phycis chesteri; 16-Urophycis tenuis; 17-Merluccius bilinearis; 18-Sebastes; 19-Gymnocanthus tricuspid; 20-Myoxocephalus; 21-Aspidophoroides monoptyerygius; 22-Liparis gibbus; 23-Anarhichas lupus; 24-Scomber scombrus; 25-Hippoglossoides platessoides; 26-Reinhardtius hippoglossoides; 27-Ammodytes; 28-Megayoldia thraciaciformis; 29-Pennatula grandis; 30-Halipterus finmarchica; 31-Periphylla periphylla; PB-Pandalus borealis; CO-Chionoecetes opilio; HH-Hippoglossus hippoglossus

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