

Investigating Climate Impacts in the Gulf of Mexico with Dynamic Bayesian Networks

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Motivation

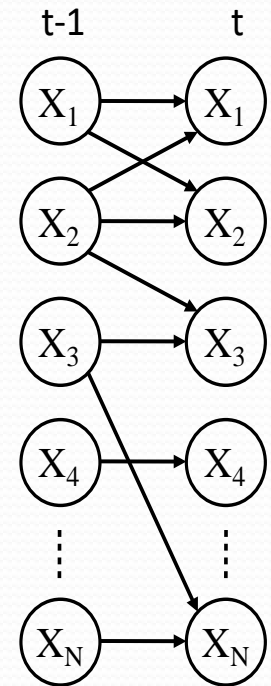
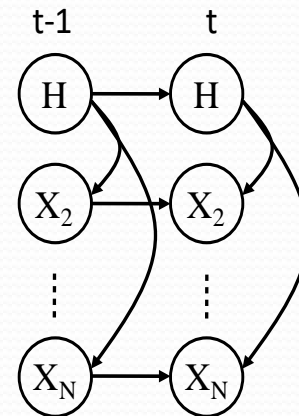


- Gulf of Mexico is an ecologically and economically important dynamic ecosystem
- Interactions with natural and anthropogenic factors
- Application of explorative, data-driven techniques
- Evaluation and implementation
- Potential response of the system to pressure
- Sustainability and management



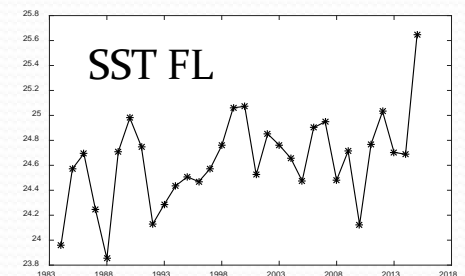
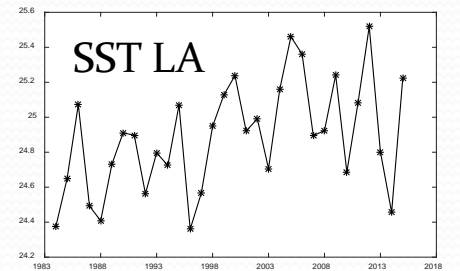
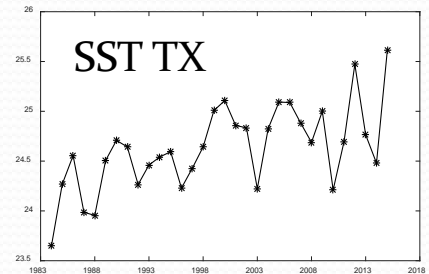
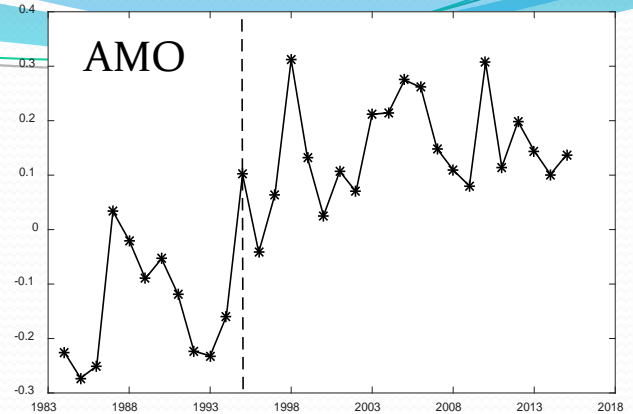
Bayesian Networks for Classification & Feature Selection & Forecasting

- Nodes that can represent class labels or variables at “points in time”
- Also hidden variables via EM
- Inter and Intra slice connections
- Predict future observations given all the observations up to the present time: $y_{1:t} = (y_1, \dots, y_t)$



Data

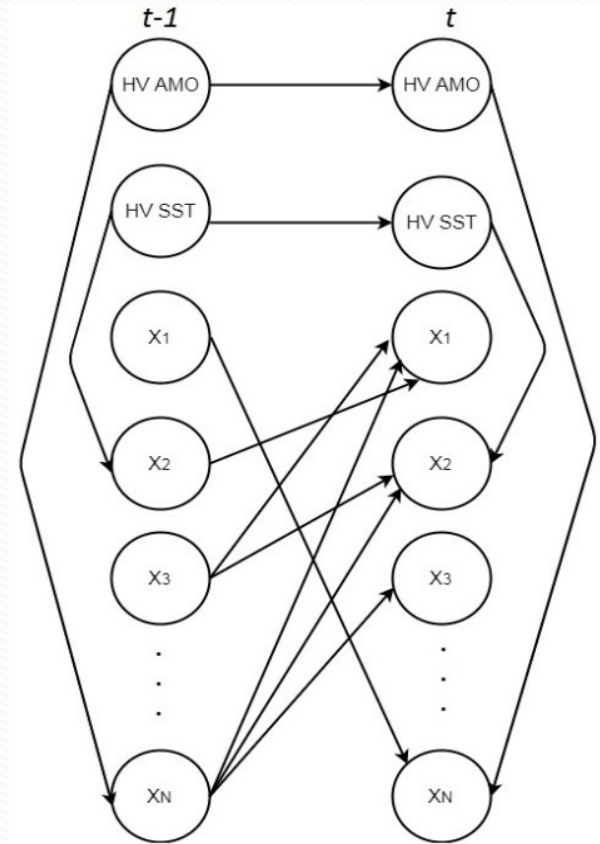
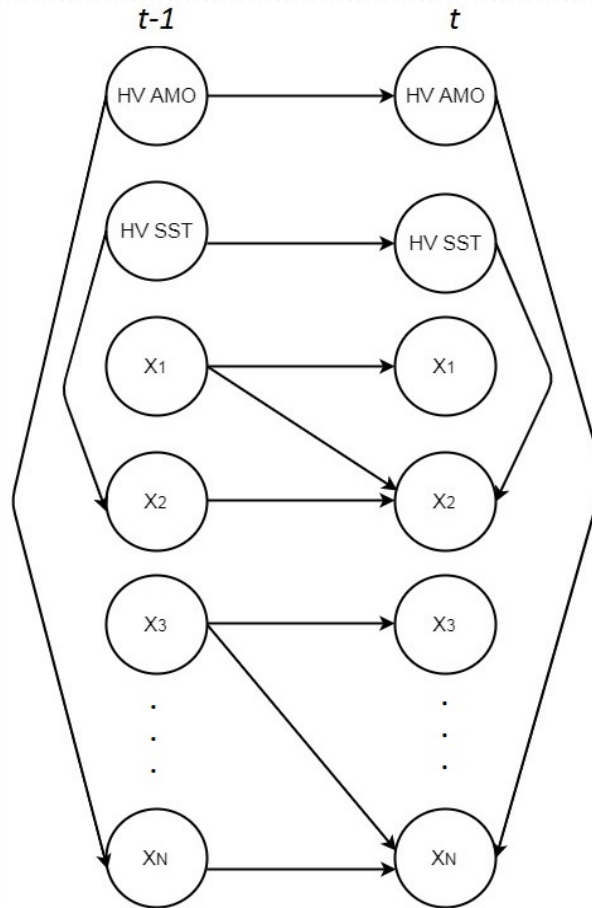
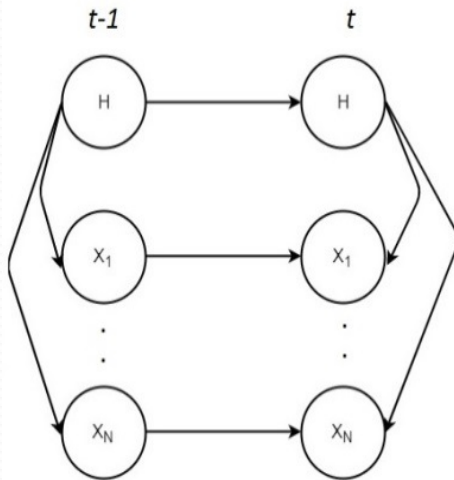
- Temporal data: 1984-2015
- Climate drivers: AMO and SST
- Physical pressures: Hypoxia
- Primary productivity
- Spring and fall zooplankton
- Shrimp recruitment estimates
- Fish recruitment deviations

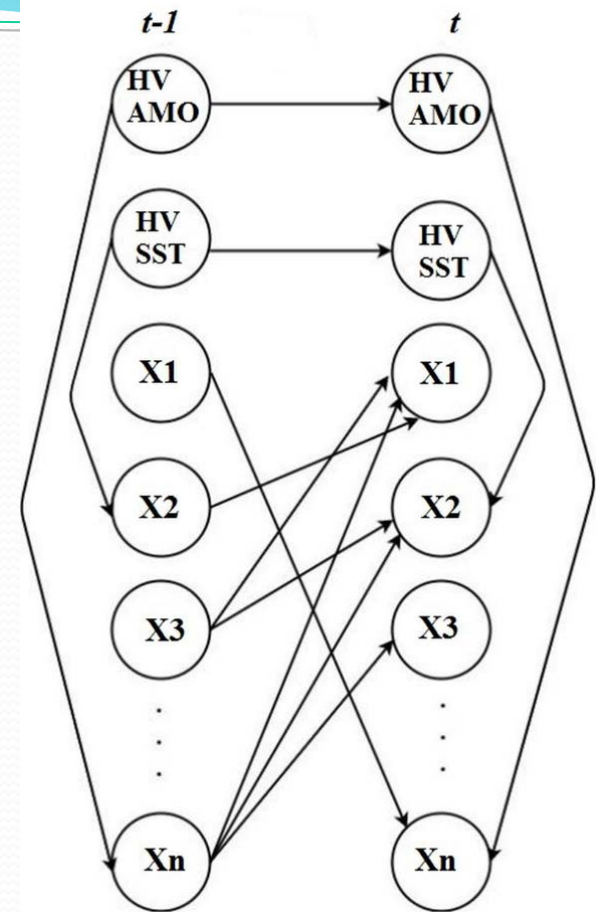
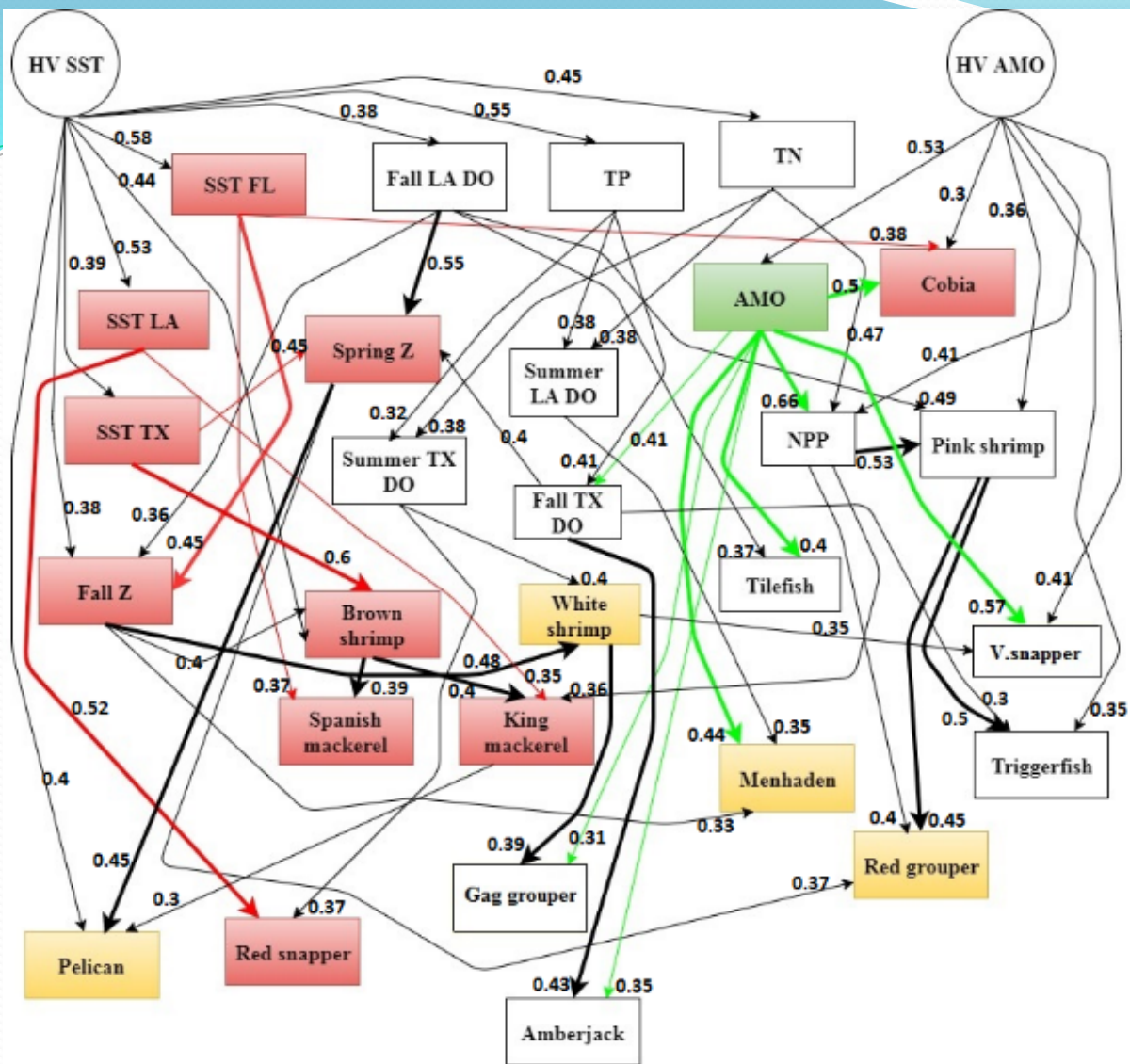


Learning Bayesian Networks

- Hill-climb optimization technique
- The learned BN links represent dependence, these are relationships that are predictive in an informative, not causal aspect
- The Bayesian Information Criterion was used for scoring candidate networks: $BIC = \log P(\Theta) + \log P(\Theta|D) - 0.5k \log(n)$

Model Comparison



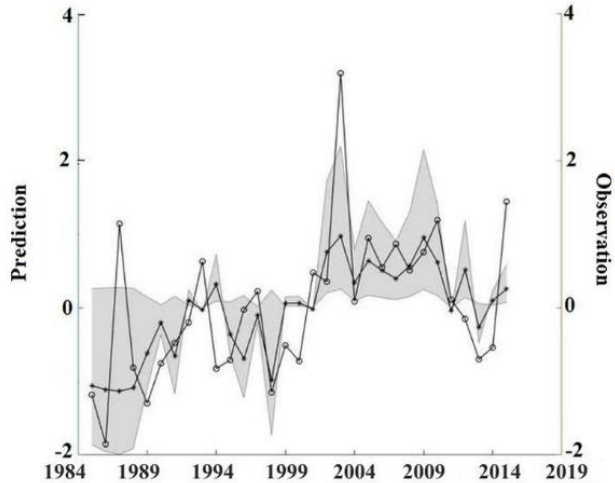


- *Data-driven dynamic BN*
- Nodes- ecosystem states

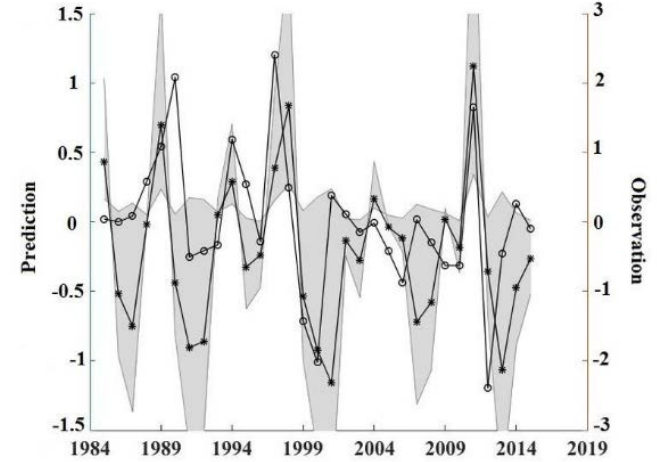
- Links- potential interactions
- Multiple associations and their changes over time

Spring zooplankton

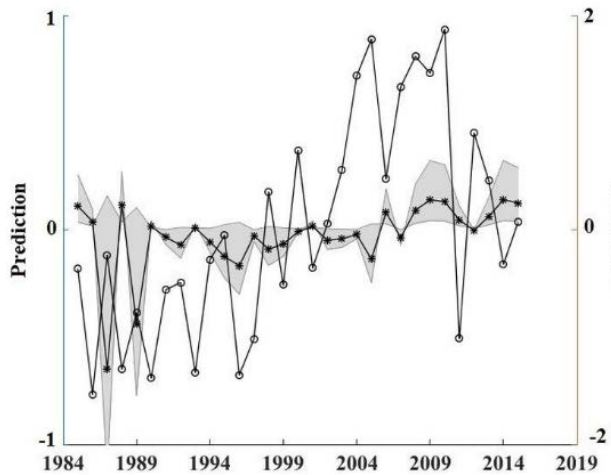
Baseline model (*) vs Original data (o)



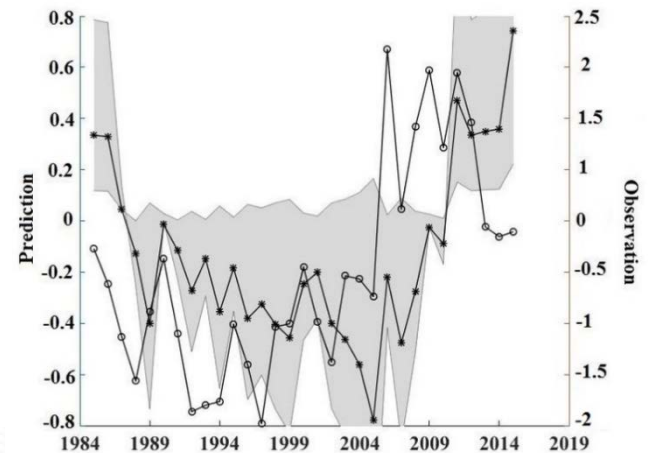
Fall zooplankton



White shrimp



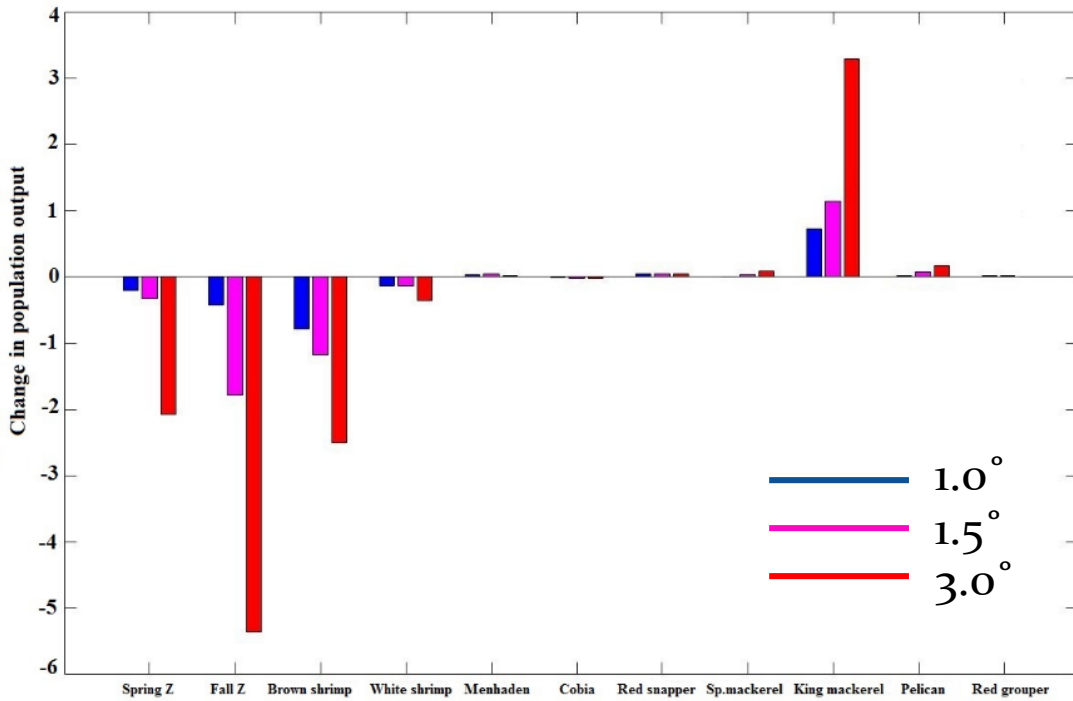
Brown shrimp



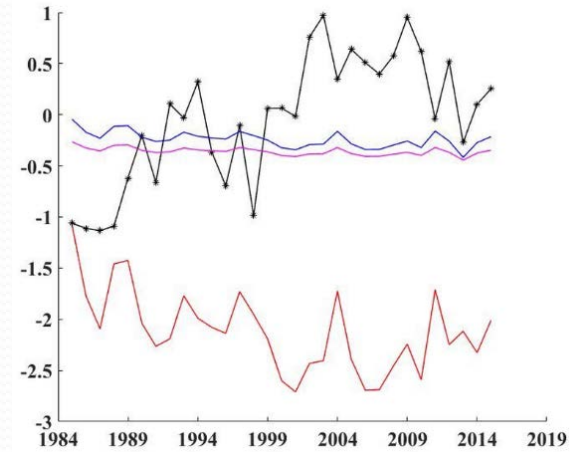
SST Scenarios and Generating Predictions

- *Baseline* model vs SST scenarios: 1.0°C, 1.5°C and 3.0°C
- Given a graphical structure, BNs naturally perform prediction using inference
- $X[t]$ where $X = X_1 \dots X_n$ are the n variables observed along time t
- Non-parametric bootstrap (re-sampling with replacement from the training set) was applied 250 times
- The hidden variables were parameterised using the EM algorithm

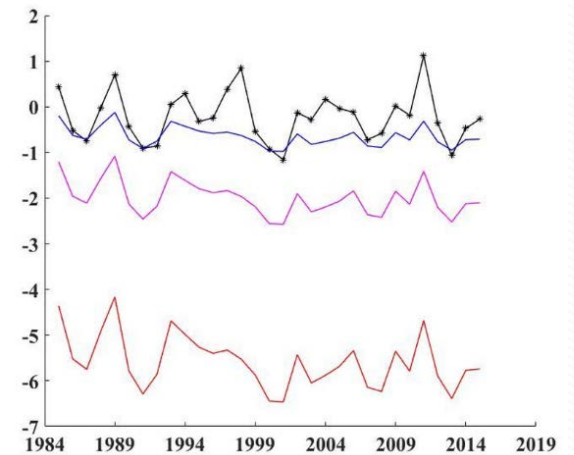
Temperature scenarios



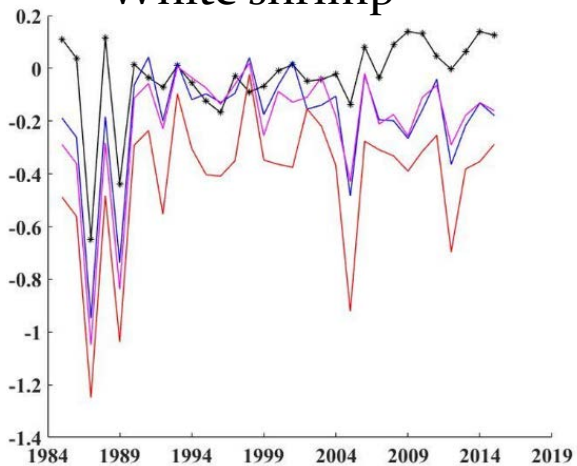
Spring zooplankton



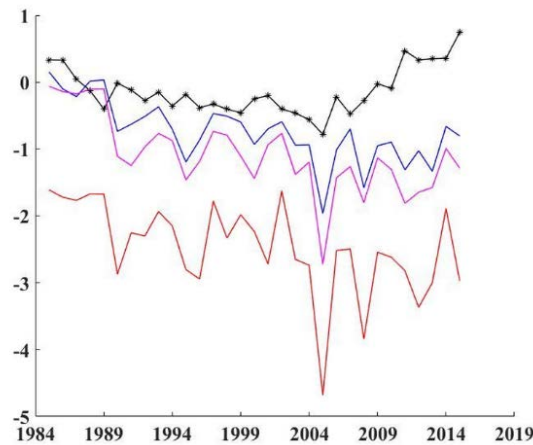
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White shrimp



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Summary

- Relationships are not causal, but model outputs are groundwork for new hypotheses that can be tested
- The data-driven approach provides contrast to other climate prediction methods that are predicated on assumed climate-fish relationships (e.g. NMFS climate vulnerability analysis)
- Variance in inputs can be directly extrapolated through network and into future climate predictions
- Network could easily be expanded to include other components of ecosystem (e.g., protected species)

Acknowledgments

- Gulf of Mexico Integrated Ecosystem Assessment Program
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