Assessing small pelagic fish trends in space and time using piscivore diet data

ICES PICES Small Pelagic Fish Symposium
Session 5
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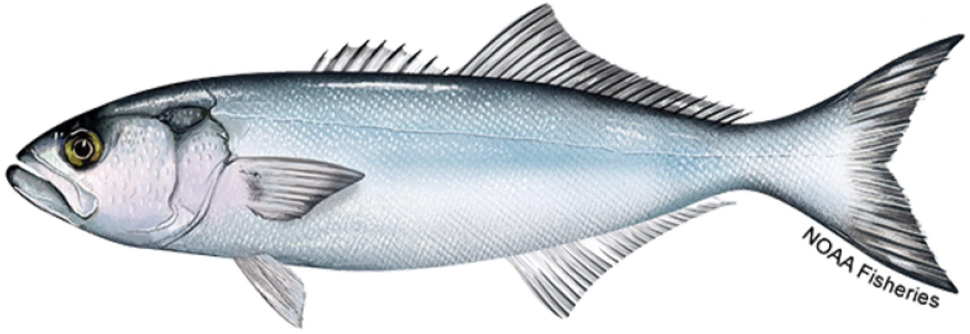
Does prey drive availability of bluefish?

Bluefish, *Pomatomus saltatrix*

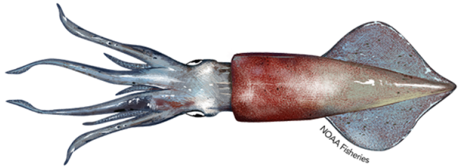


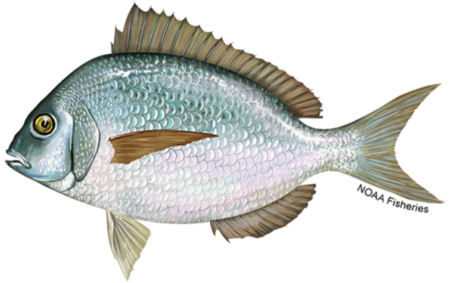
"... it is perhaps the most ferocious and bloodthirsty fish in the sea, leaving in its wake a trail of dead and mangled mackerel, menhaden, herring, alewives, and other species on which it preys." (Collette et al., 2002)

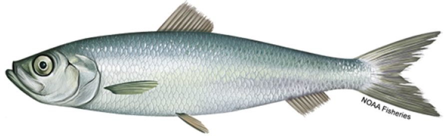
"From Raritan Bay to Rockaway Inlet, we have had a phenomenal bluefish year with lots of bunker and other bait, ultimately leading to an abundance of bluefish." Mid-Atlantic Bluefish Fishery Performance Report, 2021

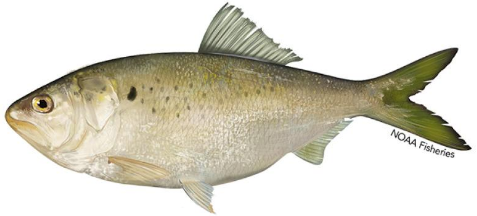
Can localized predator-prey observations scale to coastwide assessment and management?

Bluefish diet in the Northeast US: a mix of managed and unmanaged small pelagics



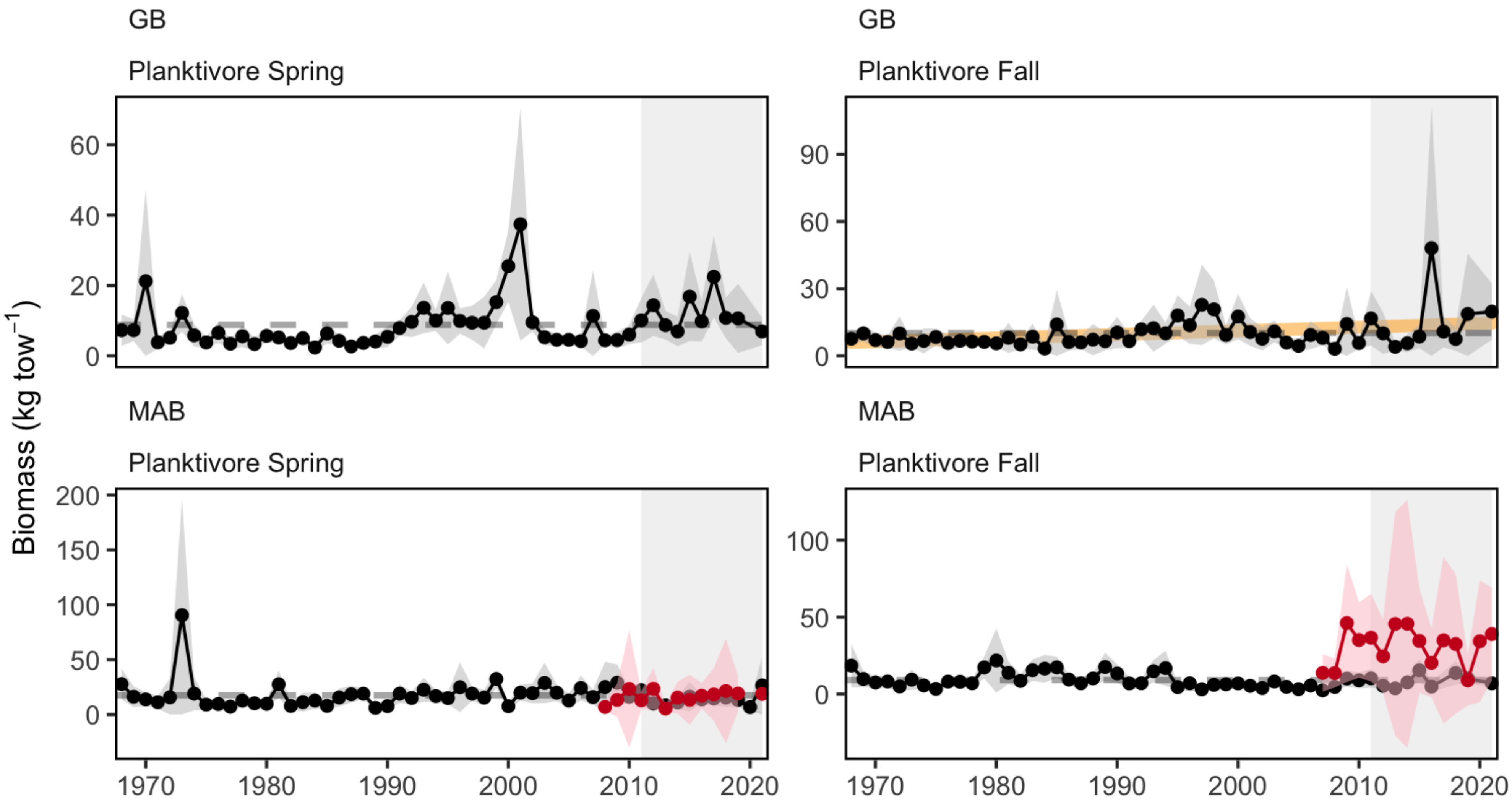






Northeast Fisheries Science Center Diet Data Online: https://fwdp.shinyapps.io/tm2020/

Bottom trawl survey small pelagics abundance estimates (Northeast US Ecosystem Reports)



Fish stomach contents → Atlantic herring biomass estimates (Ng et al., 2021)

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Predator stomach contents can provide accurate indices of prey biomass

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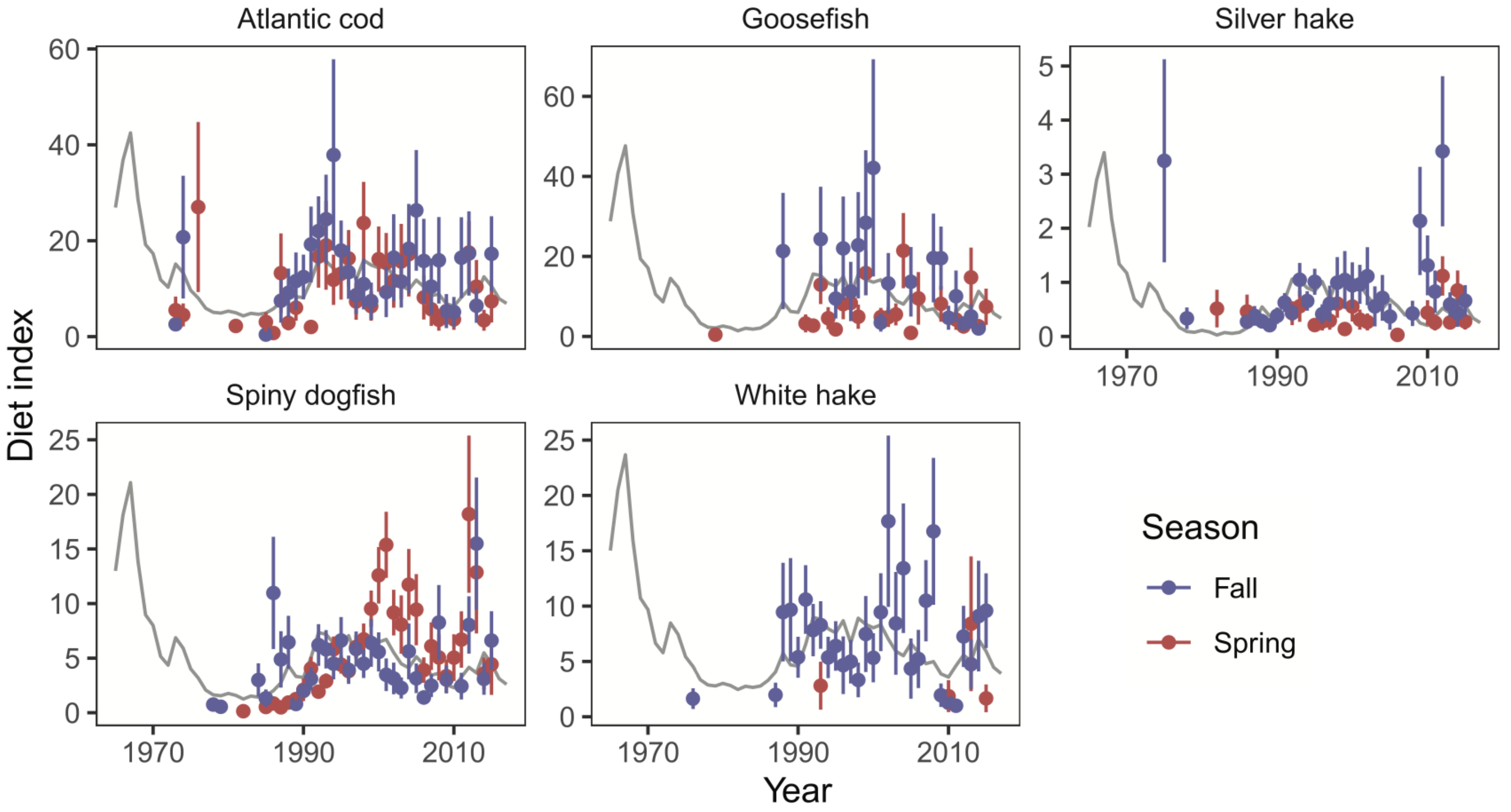


Figure 4. Diet-based annual biomass index estimated with spatio-temporal models from Atlantic herring mass in predator stomachs and controlling for predator length. Models were fit to predator diet data separately for each season. Estimated mean values are shown ± one standard error. Grey line indicates estimated Atlantic herring spawning stock biomass from stock assessment, scaled the mean and standard deviation of the diet index in each panel.

Vector Autoregressive Spatio-Temporal (VAST) modeling (Thorson et al., 2017; Thorson, 2019)

VAST models two linear predictors for an index: 1. encounter rate, and 2. positive catch (amount in stomach)

A full model for the first linear predictor ρ_1 for each observation i can include:

- fixed intercepts β_1 for each category c and time t,
- spatial random effects ω_1 for each location s and category,
- spatio-temporal random effects ε_1 for each location, category, and time,
- fixed vessel effects η_1 by vessel v and category, and
- fixed catchability impacts λ_1 of covariates Q for each observation and variable k:

$$\rho_1(i) = \beta_1(c_i, t_i) + \omega_1^*(s_i, c_i) + \varepsilon_1^*(s_i, c_i, t_i) + \eta_1(v_i, c_i) + \sum_{k=1}^{n_k} \lambda_1(k) Q(i, k)$$

The full model for the second linear predictor ρ_2 has the same structure, estimating β_2, ω_2, ε_2, η_2, and λ_2 using the observations, categories, locations, times, and covariates.

We modeled aggregate small pelagic prey as a single category, and apply a Poisson-link delta model to estimate expected prey mass per predator stomach as in (Ng et al., 2021).

VAST model code and documentation: https://github.com/James-Thorson-NOAA/VAST

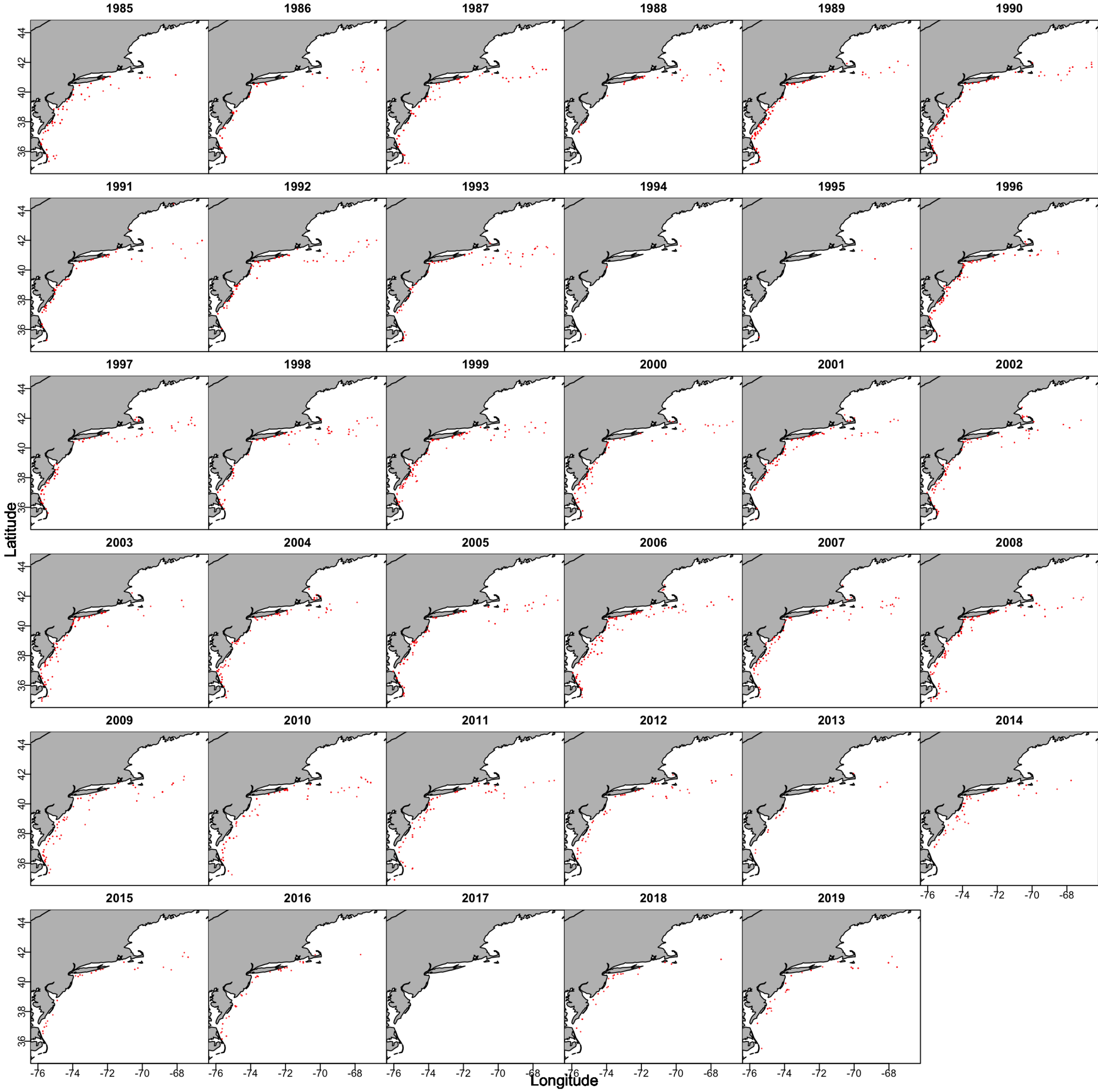
Bluefish stomachs only?

Due to uneven "sampling" of Atlantic herring by predators, (Ng et al., 2021) recommended aggregating across predators to improve the diet-based Atlantic herring biomass index.

Between 1985-2021 there were:

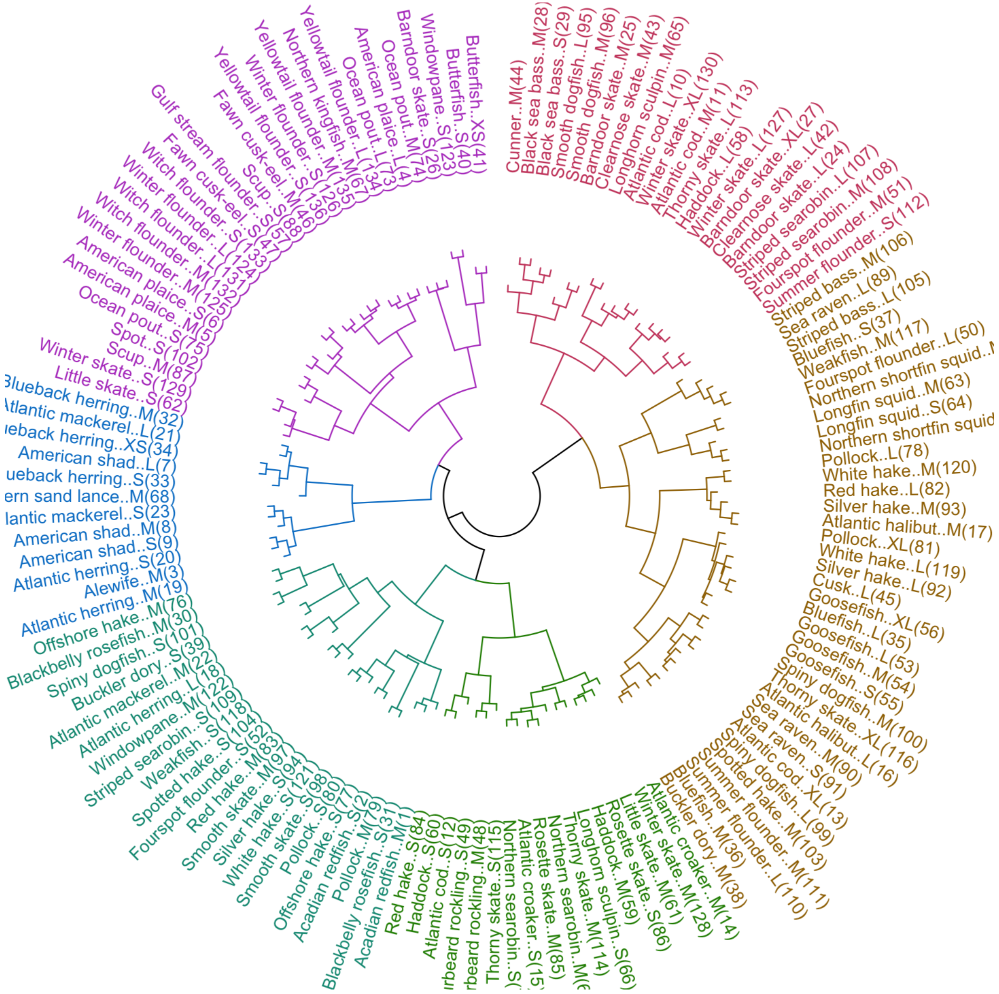
- 25634 survey stations with diet collections.
- 22751 survey stations with piscivore diets.
  - 9027 piscivore stations with bluefish prey;
  - 40% of piscivore stations have bluefish prey.
- 1814 survey stations with bluefish diets.
  - 905 bluefish stations with bluefish prey;
  - 50% of bluefish stations have bluefish prey.

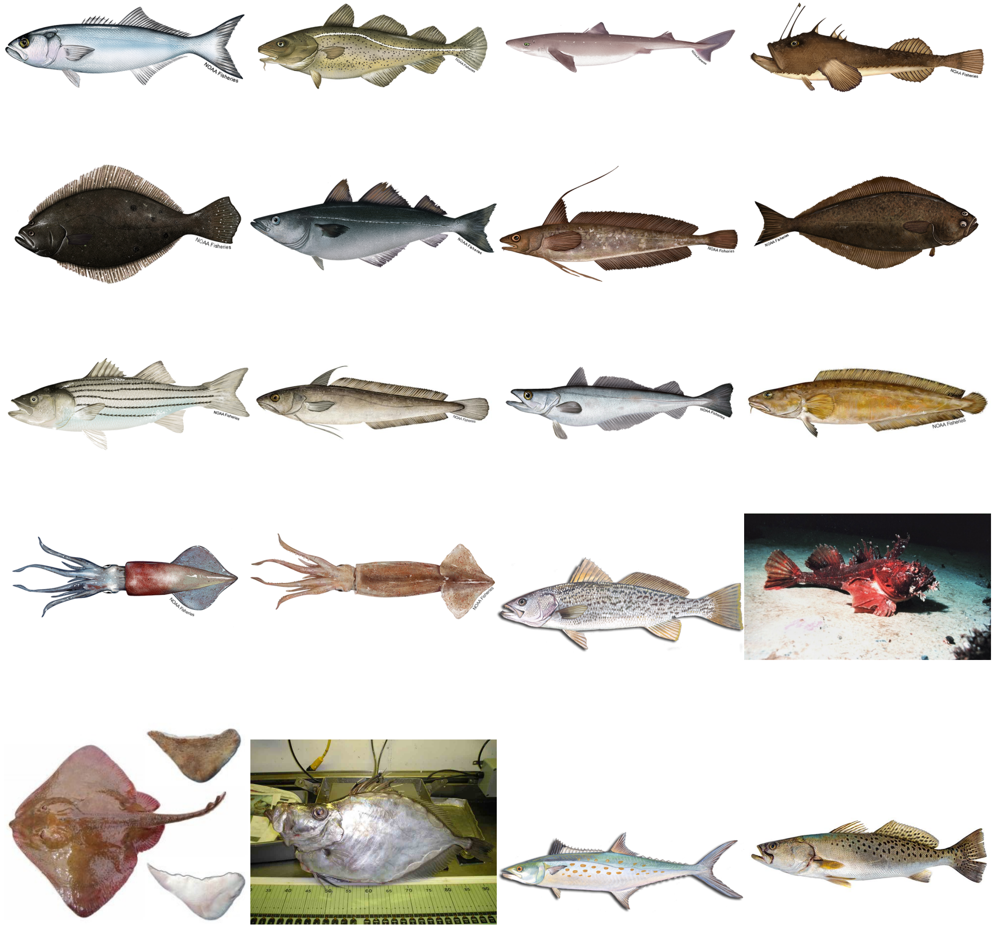
For this index combining multiple small pelagic prey, aggregating across predators most similar to bluefish both increases sample size and reduces sampling variability due to different predator availability to surveys.



Bluefish diet collection stations, fall Northeast Fisheries Science Center surveys

Aggregating predators: diet similarity to bluefish





"Catchability" covariates for aggregate predator samplers at a location

Number of predator species → likely to affect *encounter rate*

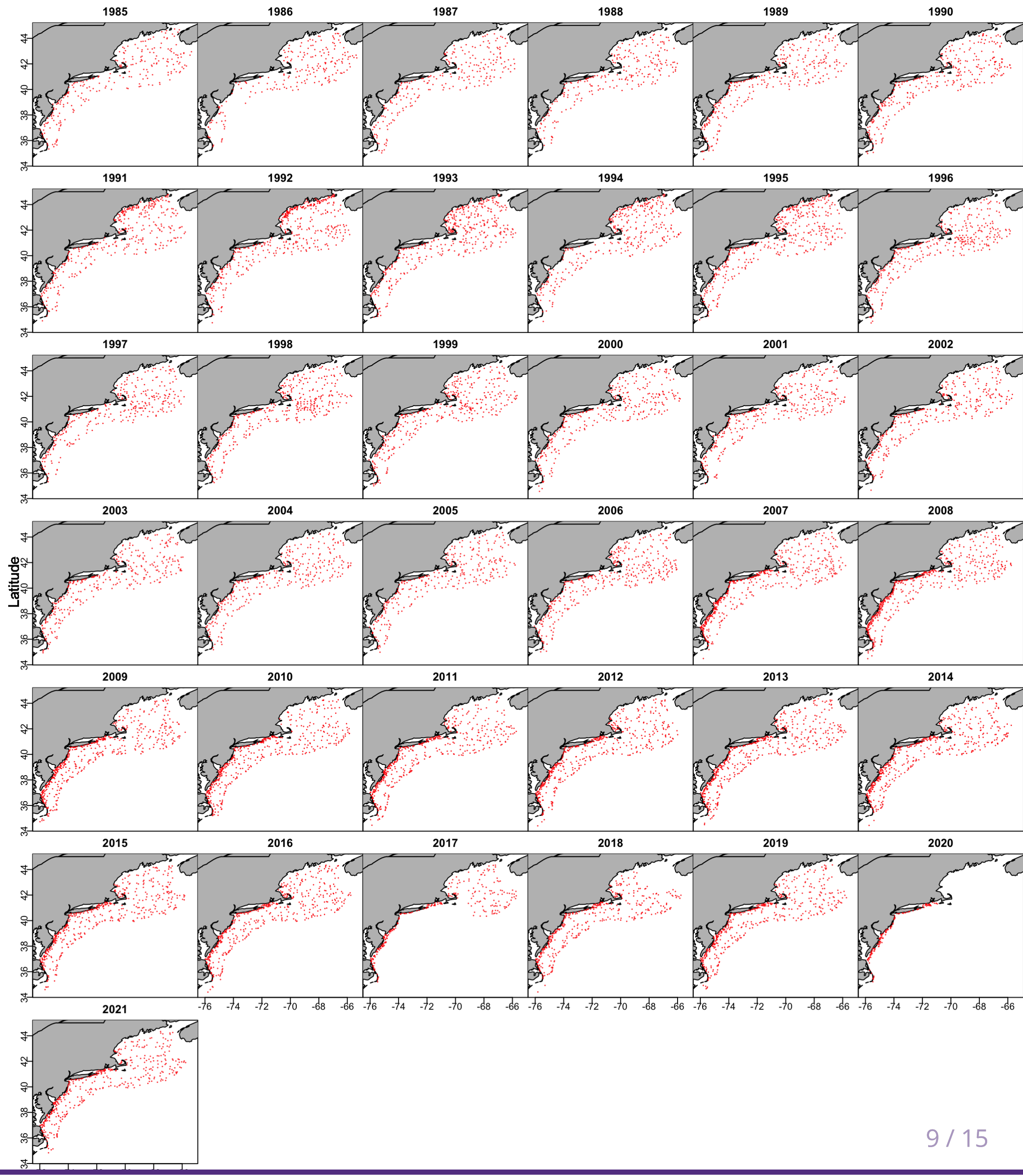
Mean size of predators → likely to affect *amount of prey* (Ng et al., 2021)

Sea surface temperature (SST) → likely to affect predator activity and feeding rate *encounter rate and amount of prey*

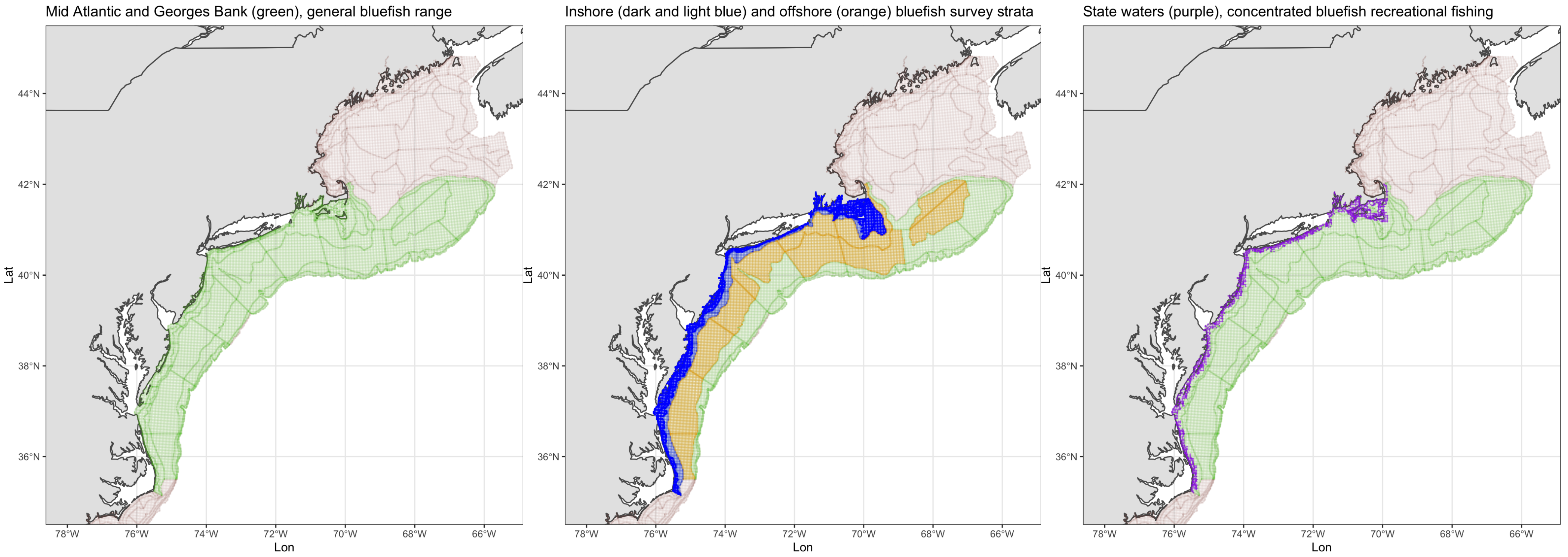
- Many missing SST measurements for surveys before 1991
- NOAA OI SST V2 High Resolution Dataset (Reynolds et al., 2007) filled gaps

Model selection consistently included number of predator species, mean predator size, and SST as covariates using fall, spring, and annual datasets

All piscivore diet collection stations, fall Northeast Fisheries Science Center surveys →



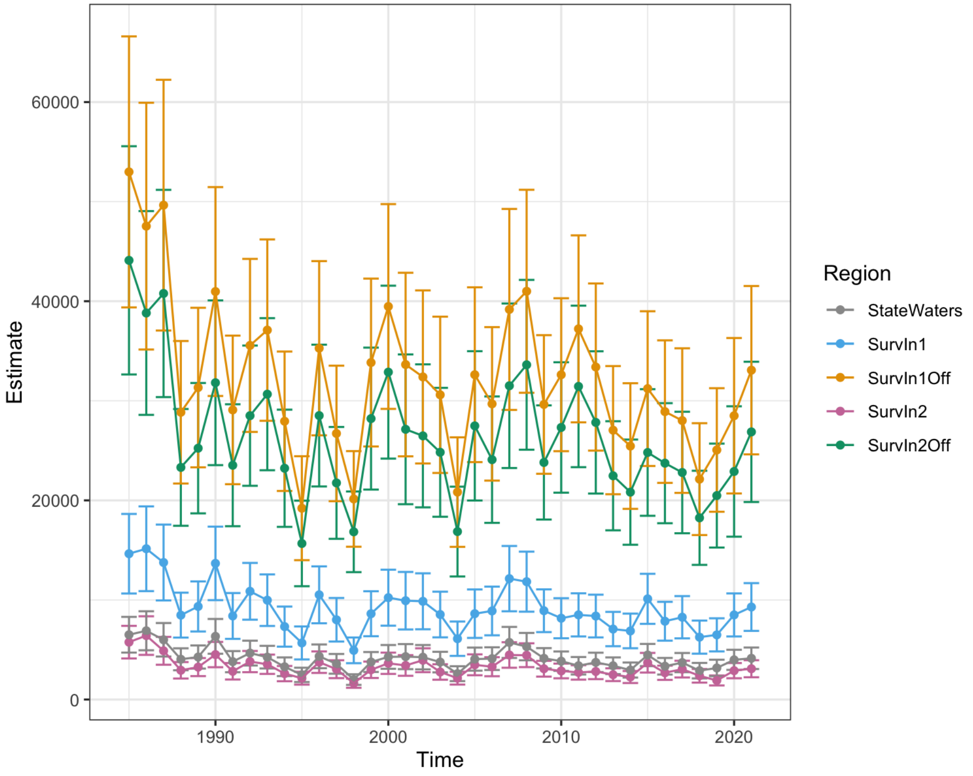
Spatial partitioning: examining small pelagics trends at multiple scales



Maps of key areas for Bluefish assessment indices. The full VAST model grid is shown in brown.

Indices for aggregate small pelagics from piscivore stomachs can be calculated for any subset of the full model domain. Bias correction of the resulting indices is then applied (Thorson et al., 2016).

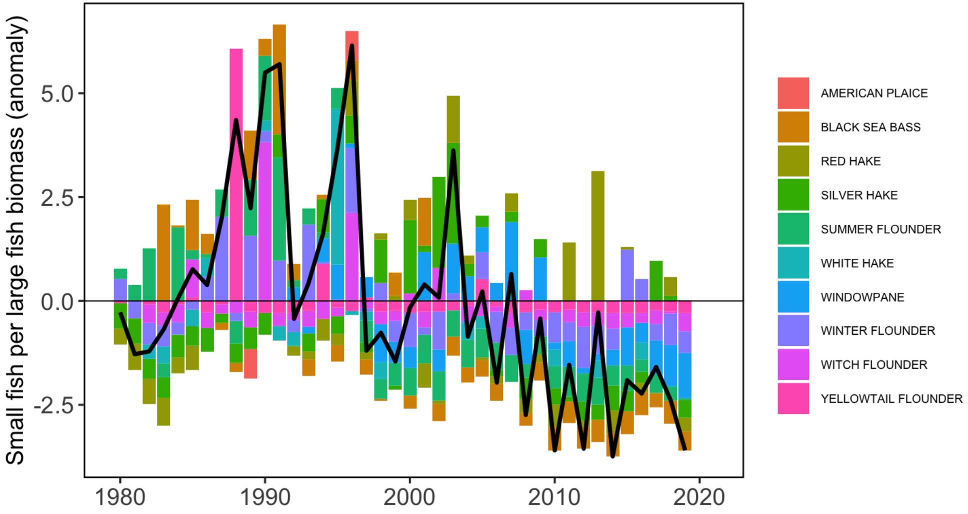
Results: Fall Forage Index

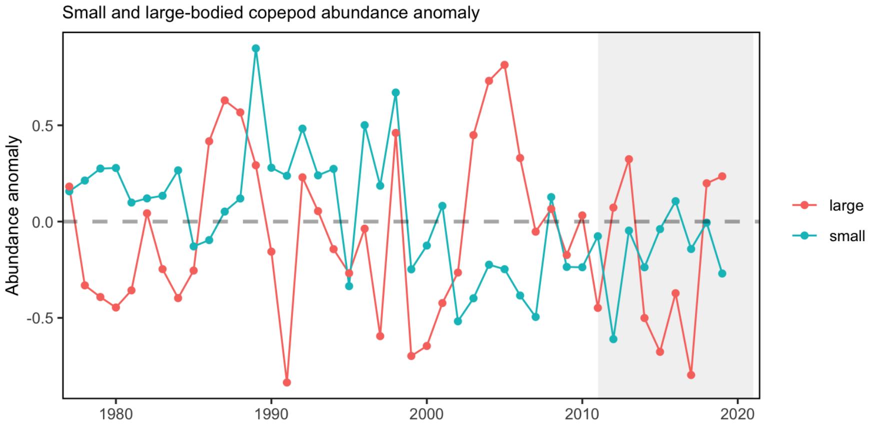


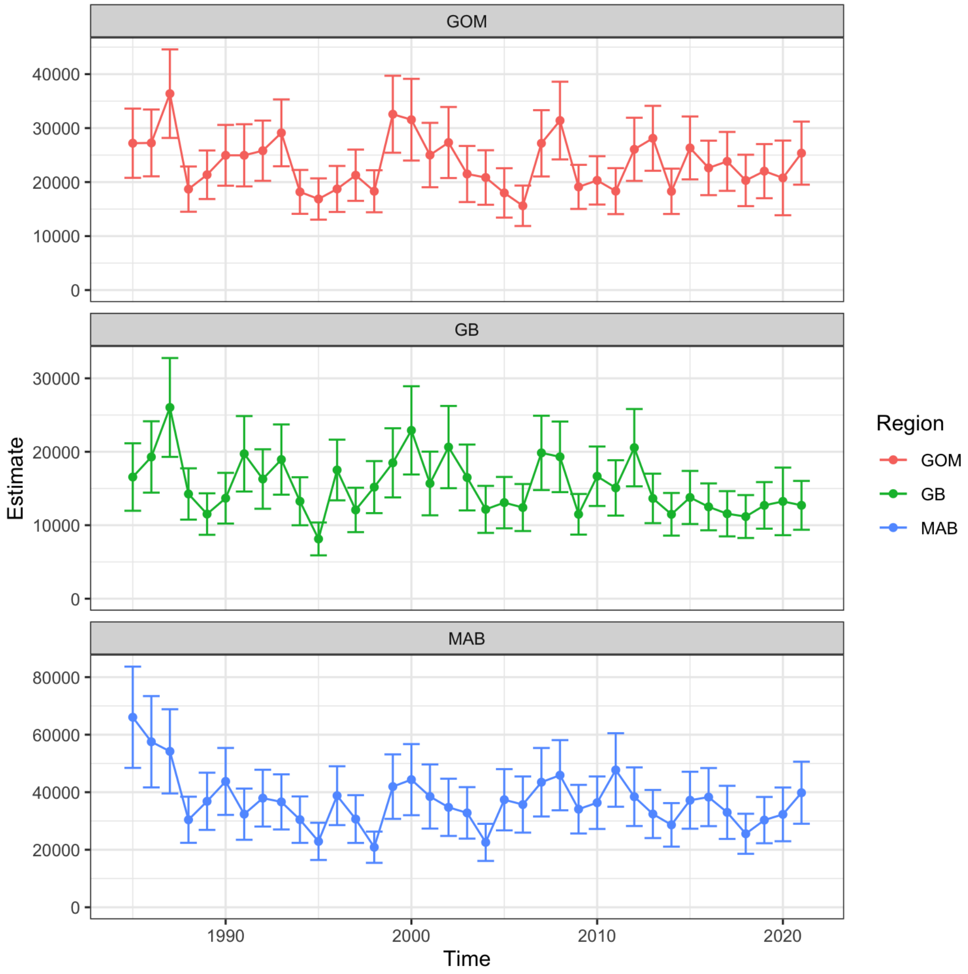
Time series of VAST estimated fall forage indices for input into the bluefish assessment, 1985-2021

VAST estimated Fall forage biomass density →

Ecosystem reporting: Can forage indices link zooplankton and fish productivity?





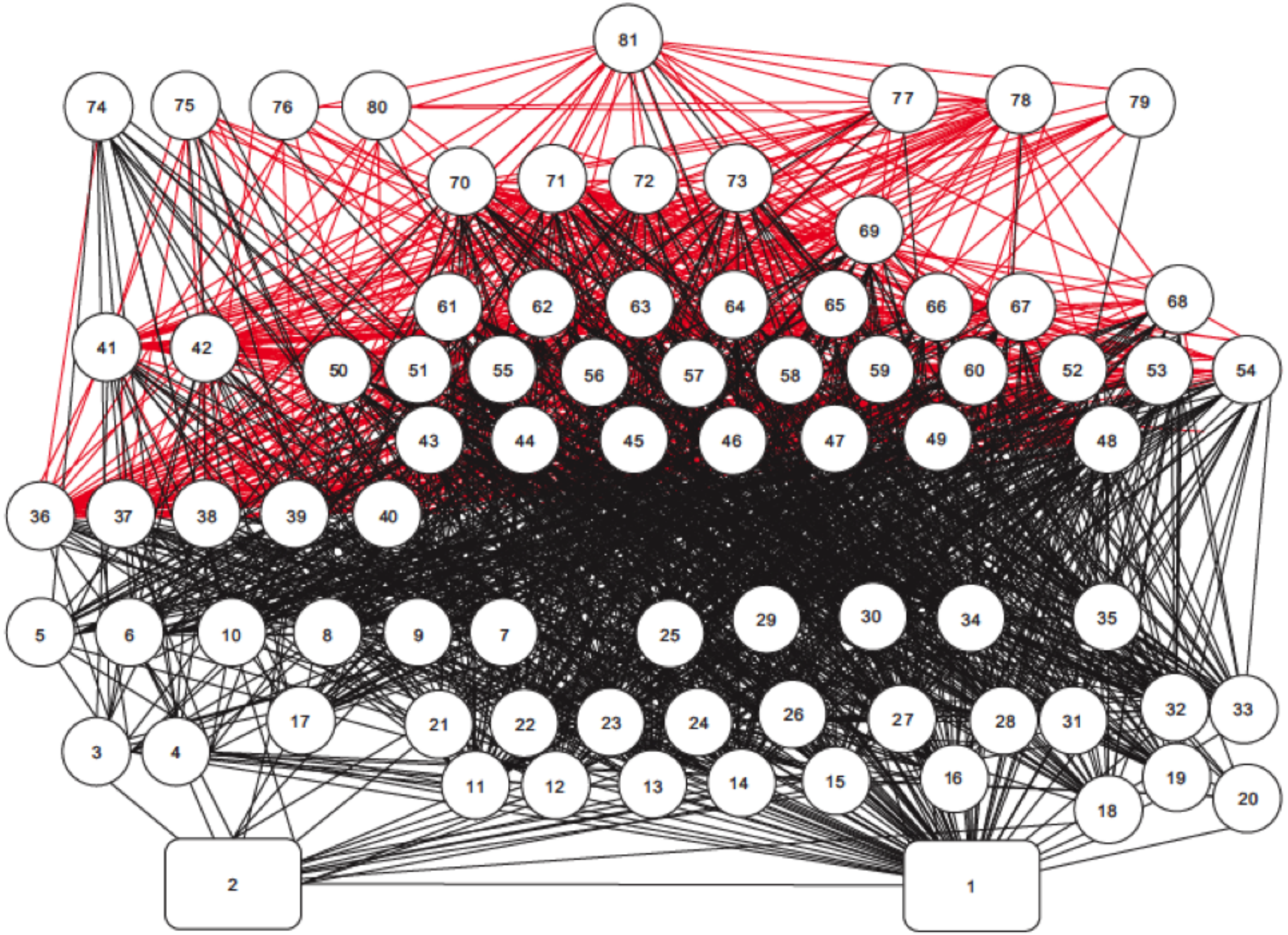


Time series of VAST estimated fall forage indices for the 2023 State of the Ecosystem report

What have we learned? New England Atlantic Herring as forage (Deroba et al., 2018).

Complex food web, generalist predators

- Weak individual predator response to many herring harvest control rules
- (Stronger predator response to changing herring growth)
- Herring is one of several important prey (36-40 in plot)
- Assessing multiple prey together will likely show stronger effects on predators



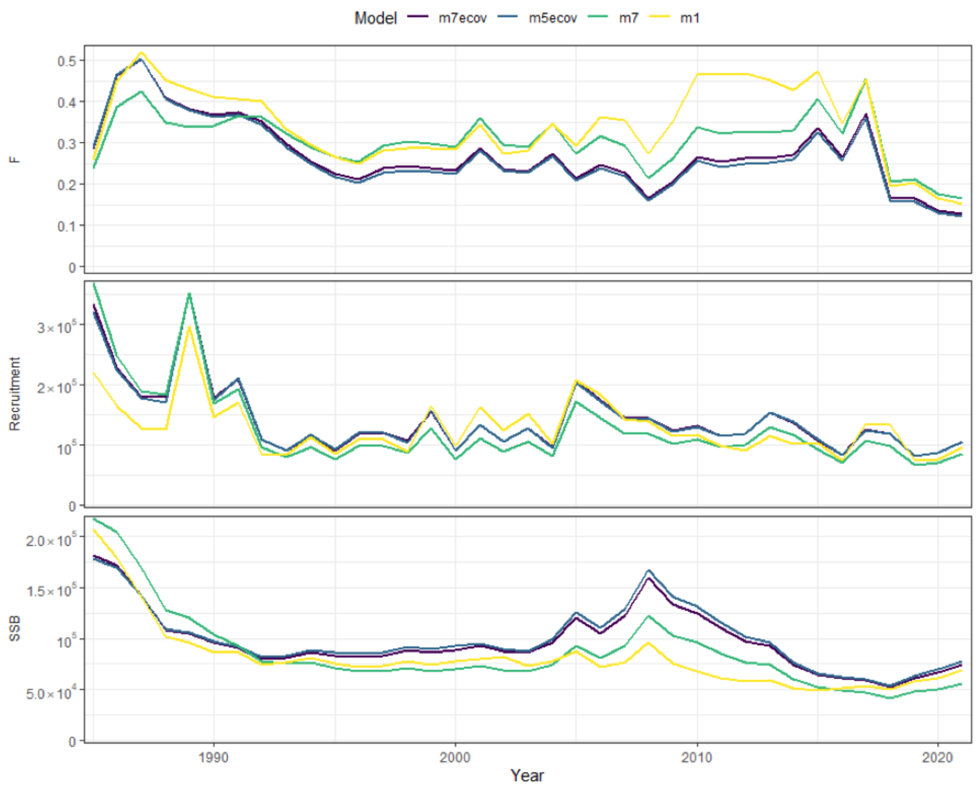
The original "horrendogram" (Link, 2002)

Do prey affect bluefish availability? Depends on the index. *Preliminary results...Review in December*

A new bluefish stock assessment was implemented using the Woods Hole Assessment Model (WHAM) (Stock et al., 2021).

Forage fish indices were explored as covariates on catchability for the fishery independent bottom trawl surveys, but either did not improve the assessment, or the exploratory models did not converge.

However, the application of the forage fish index to the recreational catch per angler catchability was successful when implemented as an autoregressive process over the time-series with WHAM estimating the standard error. **The inclusion of the forage fish index improved the fit of all models.**



The use of the forage fish index as a covariate on catchability led to an overall decreasing trend in catchability over time. The recreational index is important in scaling the biomass results, and the lower availability at the end of the time-series led to higher biomass estimates from the assessment including forage fish.

Thank you! References

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Additional resources

Northeast US State of the Ecosystem Reports

Slides available at https://noaa-edab.github.io/presentations
Contact: Sarah.Gaichas@noaa.gov