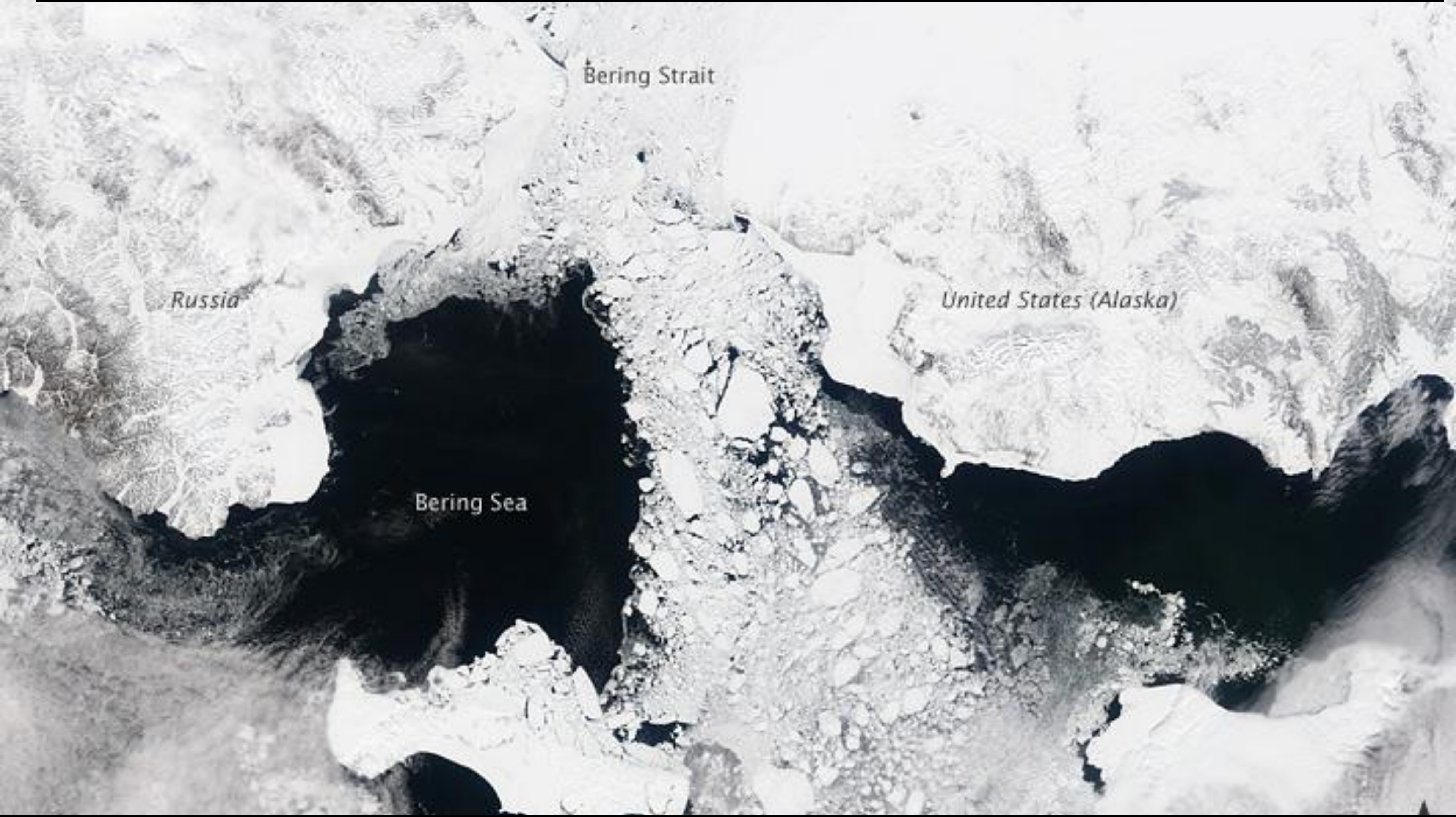
James Thorson



Benefits, drawbacks, and proposed terms-of-reference for using VAST in 2019 SAFE reports

Habitat and Ecosystem Process Research (HEPR)

Mission:

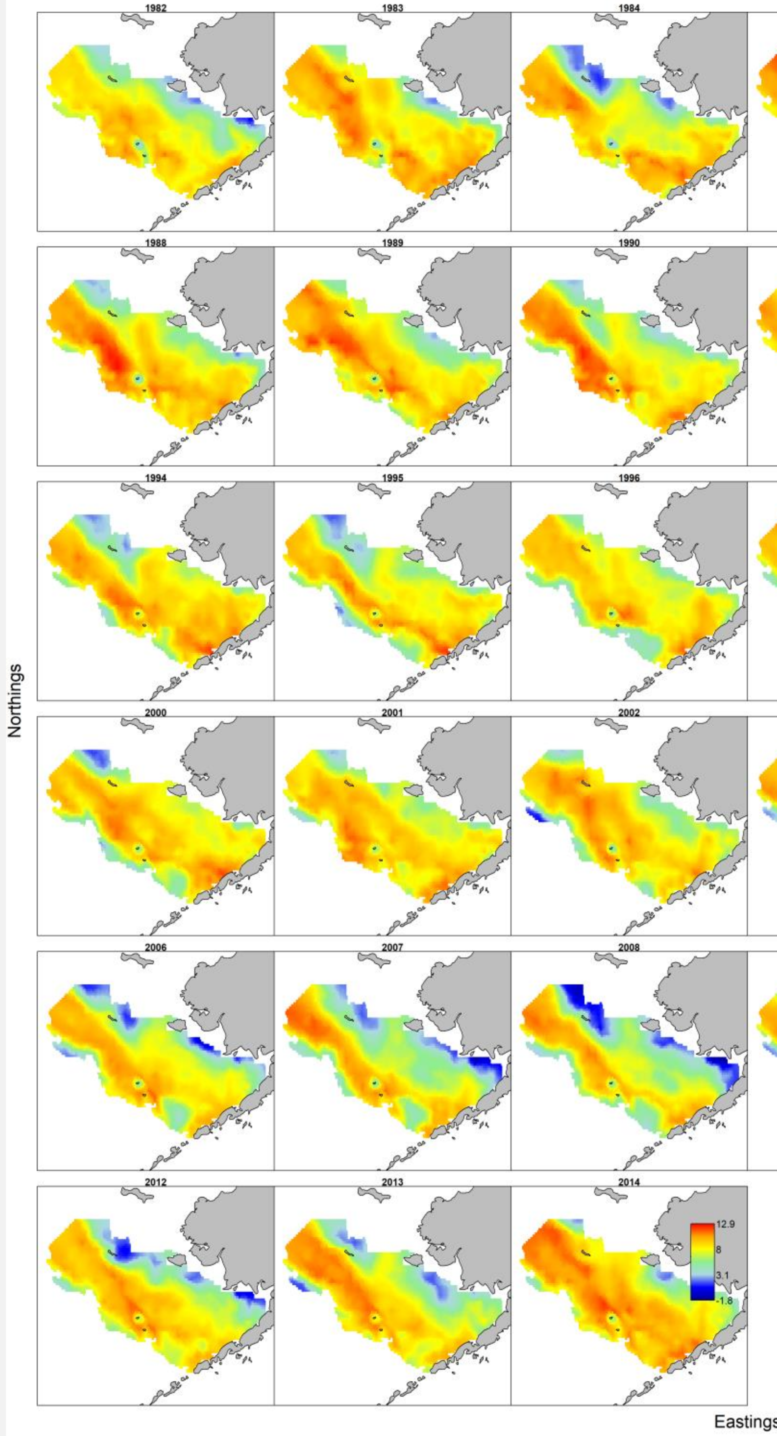
- Generate/facilitate cross-divisional activities
- Coordinate multi-divisional responses
- Provide vision for core programs

Core programs

- Loss of Sea Ice
- Essential fish habitat
- Ocean Acidification (Tom Hurst is Program Lead)

Advisory roles

- Ecosystem-based research (IEA, RPA, FATE, etc.)
- Deep-sea coral research
- Equity analysis committee



Walleye pollock density in Eastern Bering Sea

(ln kg. per square km.)

Model structure

Delta-model for observations

$$\Pr(B = b) = \begin{cases} 1 - \gamma(s,t) & \text{if } B = 0 \\ \gamma(s,t) \times g(B; \lambda(s,t)) & \text{if } B > 0 \end{cases}$$

– Where $\gamma(s,t)$ is the probability of encountering the species
– $g(B;\lambda(s,t))$ is a distribution for positive catches

Spatio-temporal variation in encounter probability

$$\underbrace{logit(\gamma(s,t))}_{encounter\ probability} = \underbrace{\alpha_\gamma(t)}_{Annual\ intercept} + \underbrace{\omega_\gamma(s)}_{Spatial\ variation} + \underbrace{\varepsilon_\gamma(s,t)}_{Spatio-temporal\ variation}$$

– $\alpha_\gamma(t)$ is the intercept for each year
– Where $\boldsymbol{\omega}_\gamma$ and $\boldsymbol{\varepsilon}_\gamma(t)$ follow a spatial distribution
– $\boldsymbol{\varepsilon}_\gamma(t)$ represents spatial patterns from year to year

Spatio-temporal variation in density

$$\underbrace{\log(\lambda(s,t))}_{encounter\ probability} = \underbrace{\alpha_\lambda(t)}_{Annual\ intercept} + \underbrace{\omega_\lambda(s)}_{Spatial\ variation} + \underbrace{\varepsilon_\lambda(s,t)}_{Spatio-temporal\ variation}$$

– Where parameters are defined similarly to $\gamma(s,t)$

Used to predict local density

$$\underbrace{\hat{d}(s,t)}_{\substack{Predicted\\ density}} = \underbrace{\hat{\gamma}(s,t)}_{\substack{Predicted\\ encounter\ probability}} \times \underbrace{\hat{\lambda}(s,t)}_{\substack{Predicted\\ positive\ catch\ rate}}$$

– Where $\hat{\gamma}(s,t)$ and $\hat{\lambda}(s,t)$ are predictions conditioned on data

Model structure

Characteristics:

1. Exchangeable among years
   – Given standard settings, you can re-order the year labels and results are identical

$$\boldsymbol{\varepsilon}(\cdot, t) \sim Multivariate.Normal(\mathbf{0}, \boldsymbol{\Sigma})$$

   – Avoids shrinking years towards adjacent years

Model structure

Characteristics:

2. Autoregressive spatio-temporal variation when fitting northern Bering Sea data

- When fitting spatially unbalanced data, I use a first-order autoregressive term for spatio-temporal variation

$$\boldsymbol{\varepsilon}(\cdot, t+1) \sim Multivariate.Normal(\rho\boldsymbol{\varepsilon}(\cdot, t), \boldsymbol{\Sigma})$$

- its important to estimate hotspots that persist even when sampling doesn't occur

Model structure

Characteristics:

3. Extends easily to a multivariate model
   - Add subscript c for category
     - Represents age-class from 1 to the plus-group
   - Treats every spatial and spatio-temporal term independently for every age-class

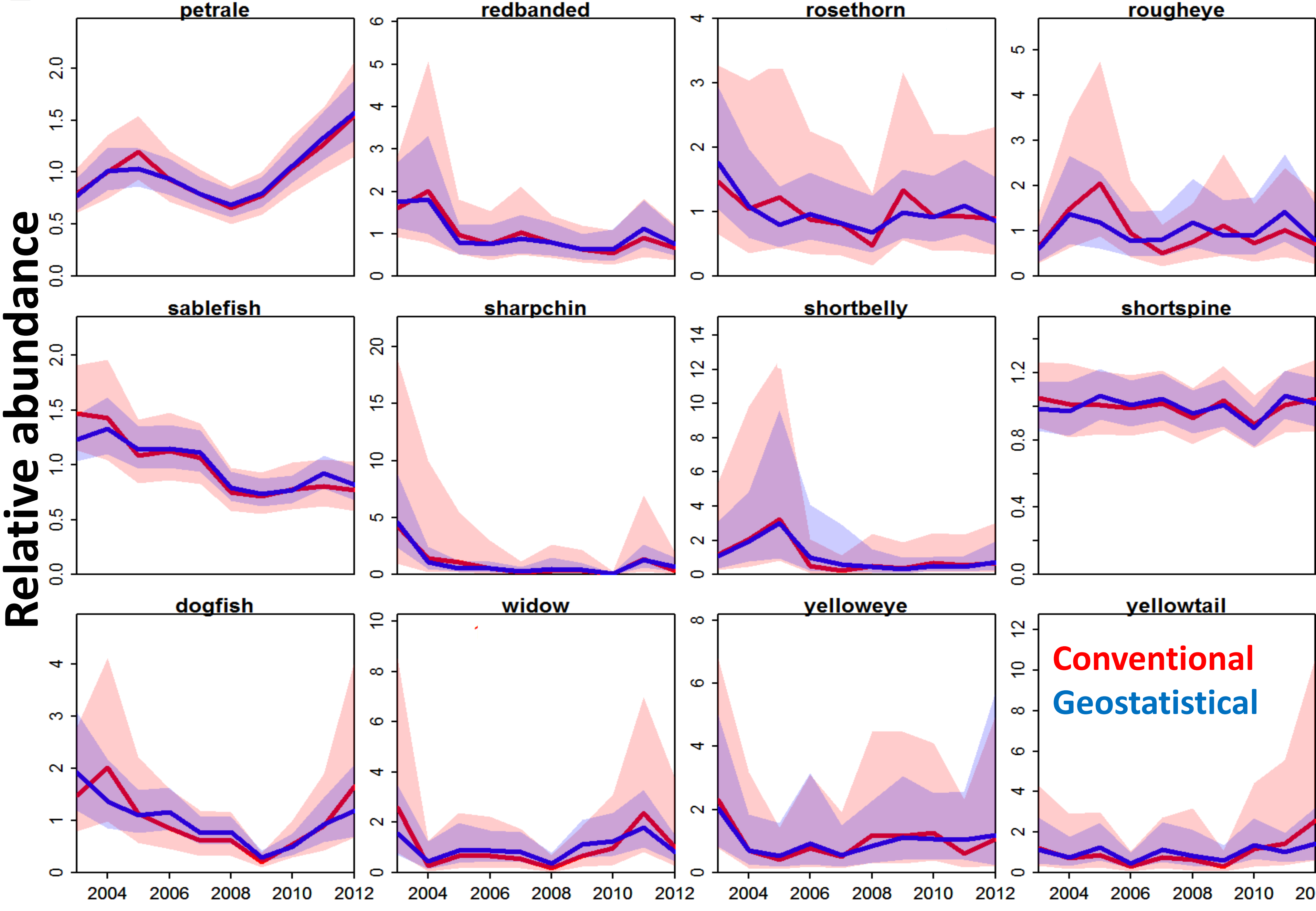
$$\boldsymbol{\varepsilon}(\cdot, c, t) \sim Multivariate.Normal(\mathbf{0}, \boldsymbol{\Sigma})$$

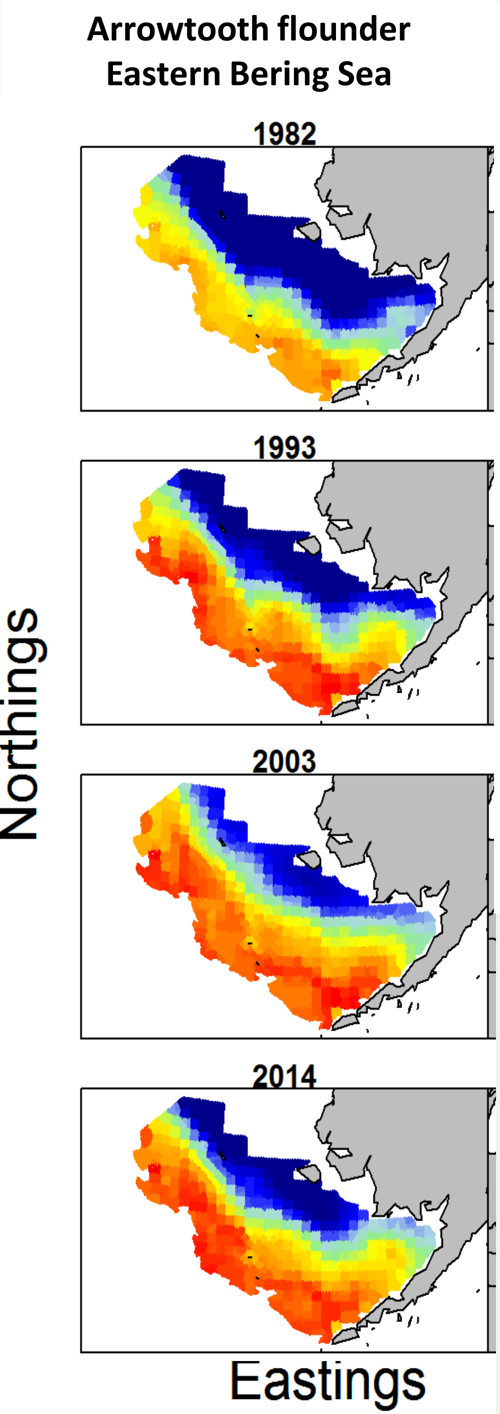
or

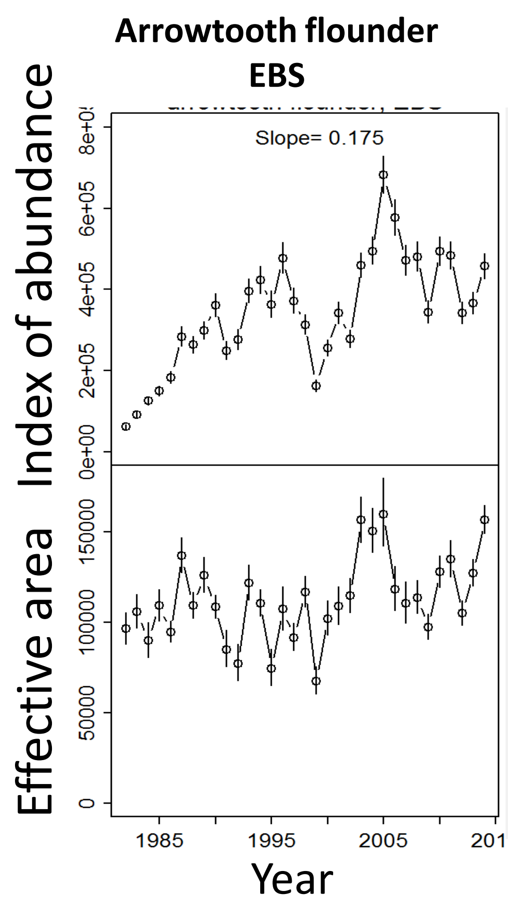
$$\boldsymbol{\varepsilon}(\cdot, c, t+1) \sim Multivariate.Normal(\rho\boldsymbol{\varepsilon}(\cdot, c, t), \boldsymbol{\Sigma})$$

depending on whether fitting to the northern Bering Sea or not.

Abundance indices







Thorson, Rindorf, Gao, Hanselman, and Winker. 2016. Density-dependent changes in effective area occupied for sea-bottom-associated marine fishes. Proc R Soc B **283**(1840).

Density-dependent habitat selection

- Do populations shrink their range when abundance is low?
- Average
  - Small contraction in range
  - Greatest in Eastern Bering Sea

Usage to date

Assessments (base model)

1. North Pacific FMC: 2 assessments 2015-2018
   - Dusky rockfish 2015
   - Northern rockfish 2018
2. Pacific FMC: 10 assessments 2015-2017
3. Secretariat of the Pacific Commission: 1 assessment 2018
4. New England FMC: 1 assessment 2018
5. Western and Central Pacific Fisheries Commission: 1 assessment 2019
6. ICES: 1 assessment 2019

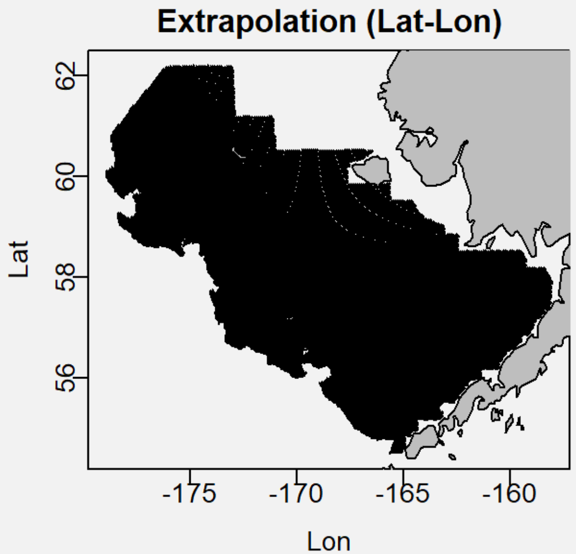
Assessments (exploratory)

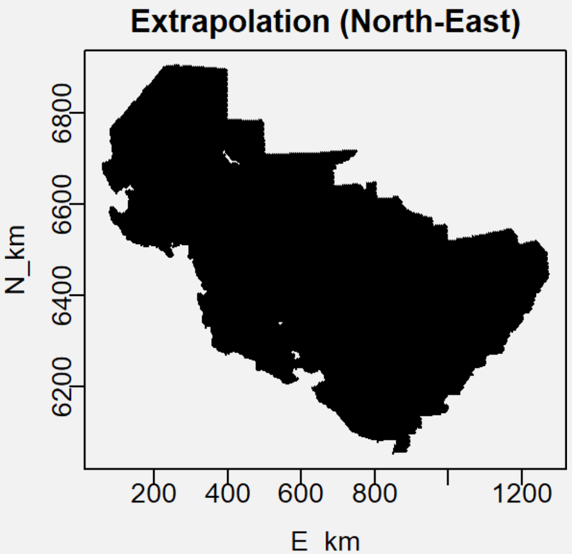
1. North Pacific FMC: 4 assessments 2016-2018
   - EBS pollock 2016
   - EBS arrowtooth 2017
   - EBS pollock 2018
   - St. Matthews Blue King Crab 2017
2. Pacific FMC: 1 assessment 2017
3. South Africa: 12 species 2017

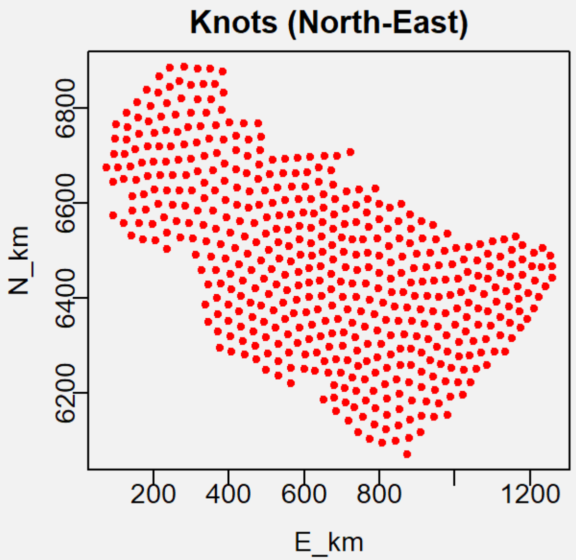
Ecosystem Status Report / Integrated Ecosystem Assessment

1. North Pacific FMC: 3 regional, annual reports 2017-2018

Diagnostics



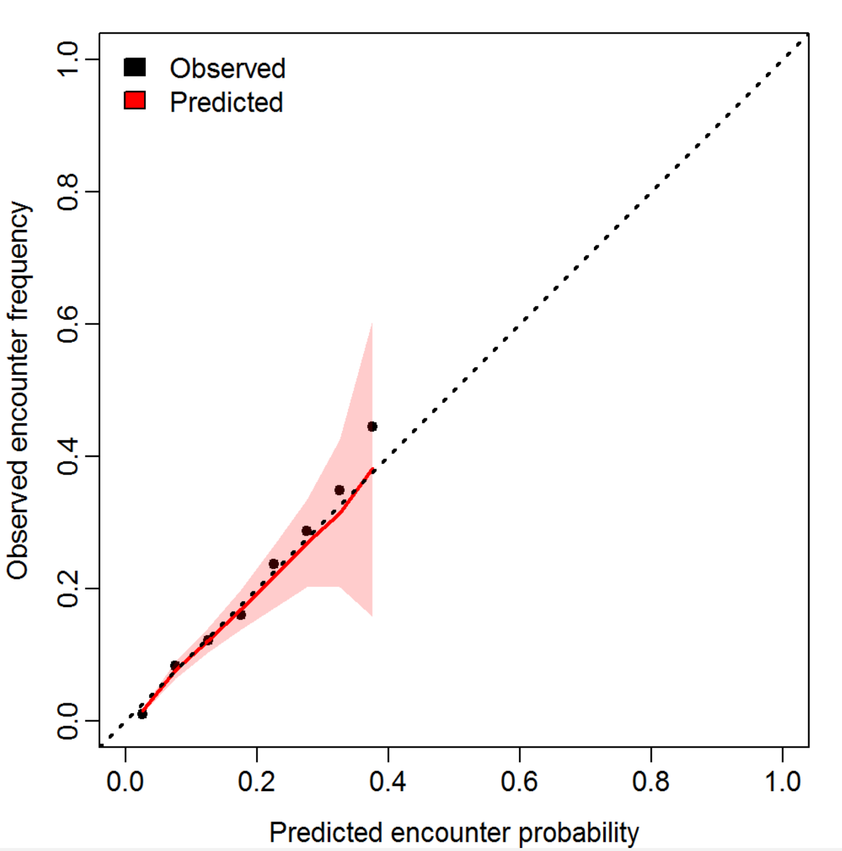




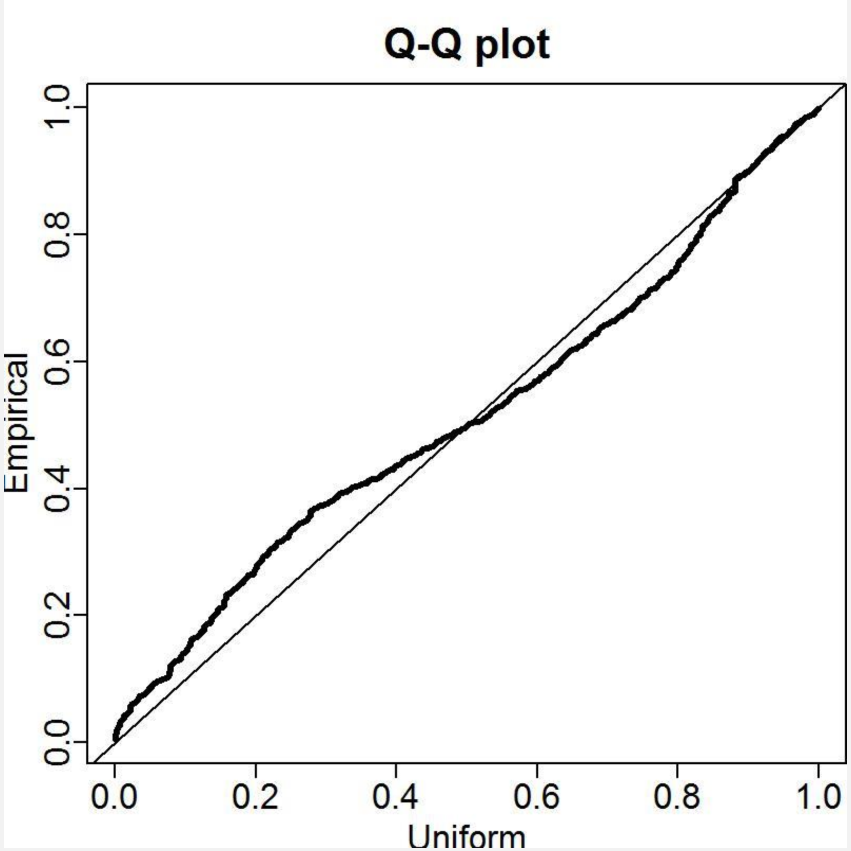
Advice: Inspect extrapolation footprint and knots

Diagnostics

Encounter probability vs. frequency



Quantile-quantile plot for positive catch rates



Benefits and drawbacks of VAST

Benefit (ranked large to small)
Combine multiple data streams (to avoid bias arising from differences in area-sampled)
Disciplined approach to spatially unbalanced data (propagates variance without "ignoring" missing data)
Account for portion of variance associated with randomized sample location
Improve "statistical efficiency" (decrease standard errors) for limited data
Improved communication and intuition using downscaled density and indices of spatial ecology

Drawback	Response to drawback
Potential to introduce bias	Simulation suggests that bias in trend and scale are small
Results are model-based (so affected by user decisions)	Pre-define terms of reference (TOR)
Comparison with design-based approach requires greater consideration of data weighting	Recommend inspecting data-weighting standards across species
Complicated to use and explain	Simplified user-interface in progress

Benefit #1: Combine data and account for spatially unbalanced data

Benefit #1: Combine data and account for spatially unbalanced data

What to do with northern Bering Sea data?

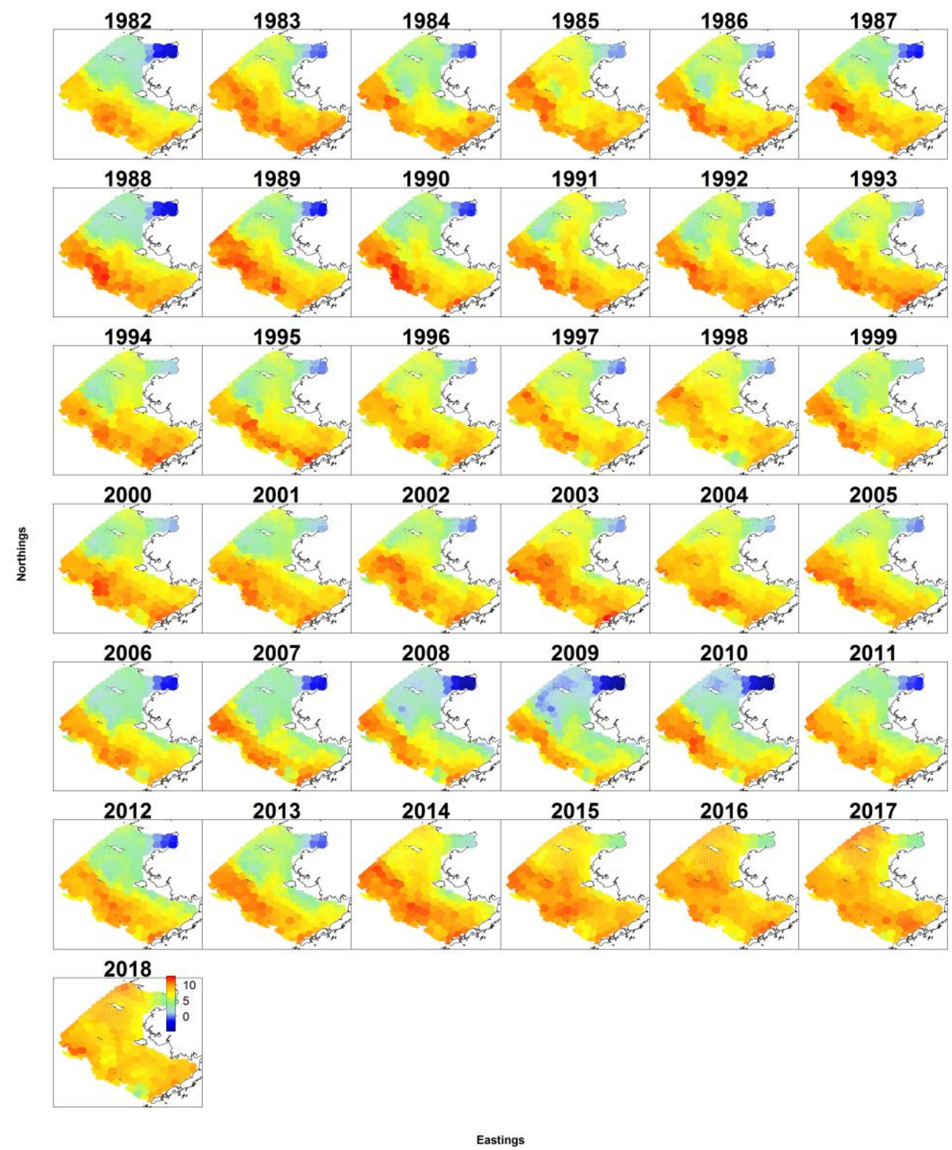
1. Ignore northern Bering Sea data
2. Assessment model with two strata (“2-box model”) and movement
3. Assessment model with one stratum (“1-box model”), using EBS data in some years, and adding NBS+EBS data when both are available
4. 1-box model with separate indices and annual estimate of availability to EBS
5. 1-box model with model-based indices and comps

Benefit #1: Combine data

Methods

1. Fit with spatial and spatio-temporal variability
2. Use Poisson-link delta model
3. Use AR1 process on spatio-temporal variation
   – Hotspots persist from one year to the next
4. Calculate multiple indices using estimated density:
   – EBS
   – NBS
   – both combined

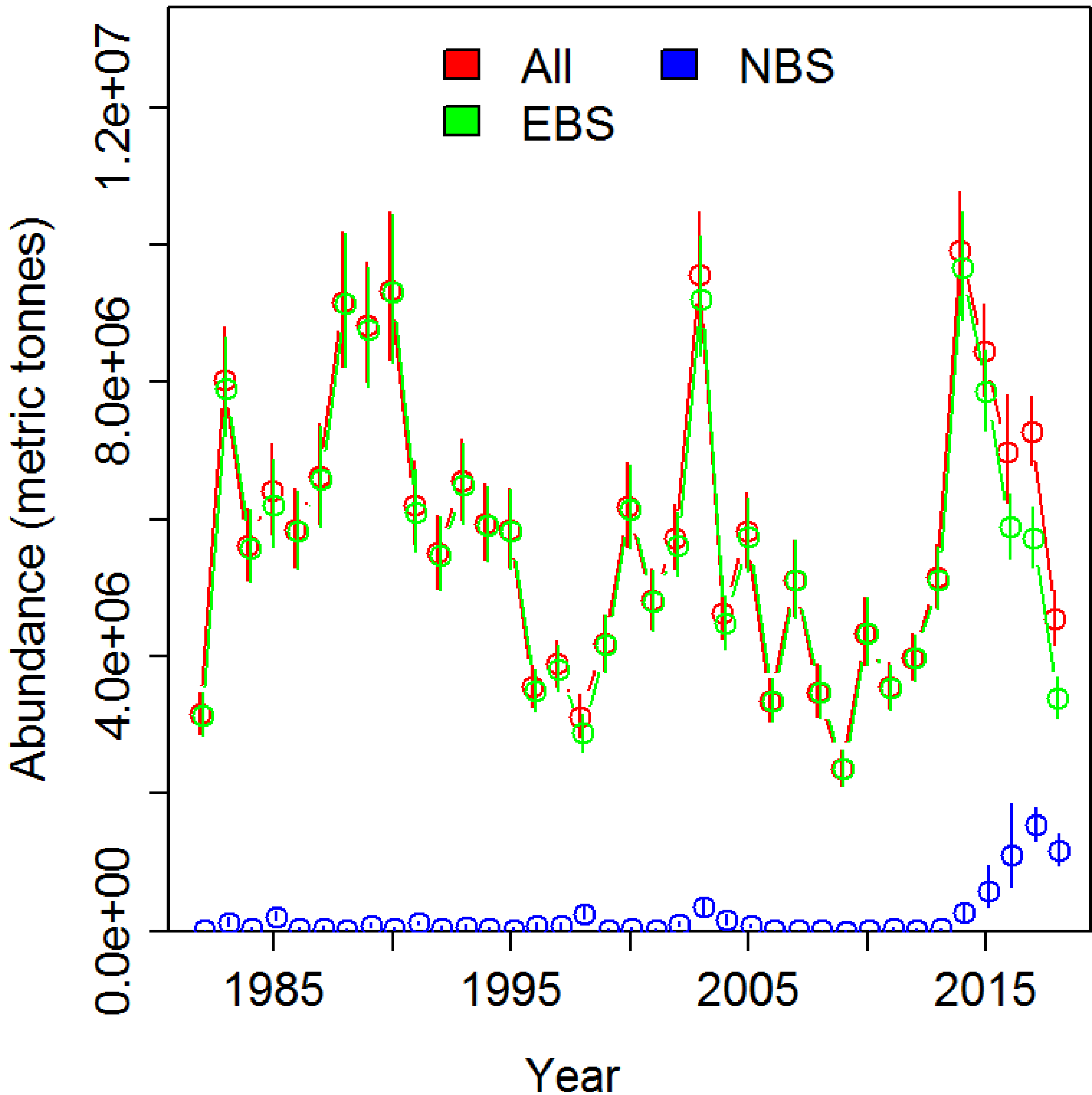
Without temperature



Benefit #1: Combine data

Conclusions

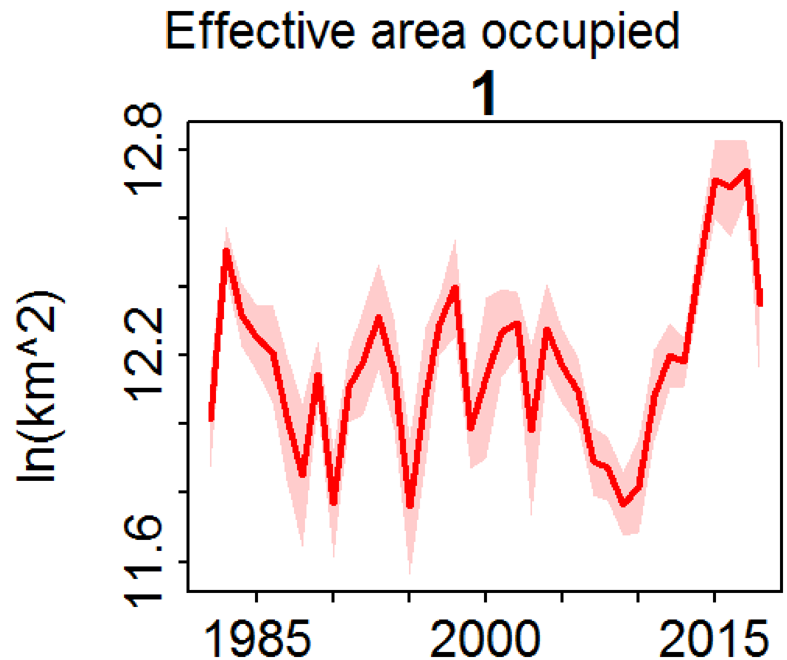
1. An increasing proportion in Northern Bering Sea
2. Important to account for shifts in distribution in assessment for fishery with >$300 million dockwide value per year



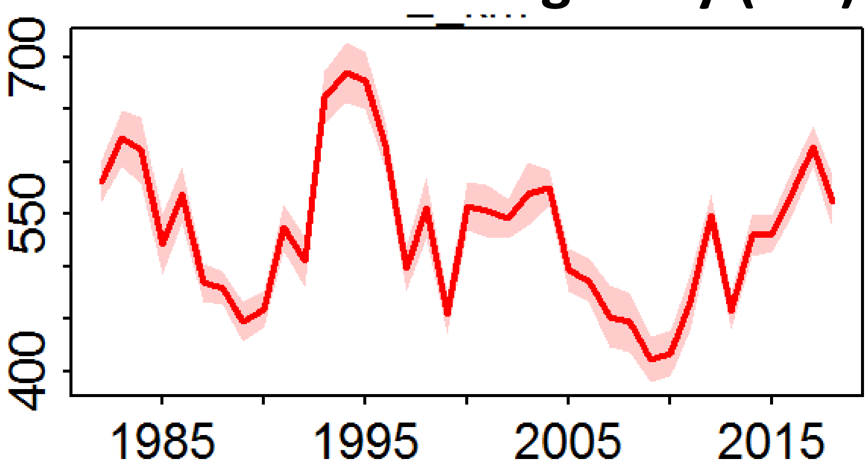
Benefit #1: Combine data

Conclusions

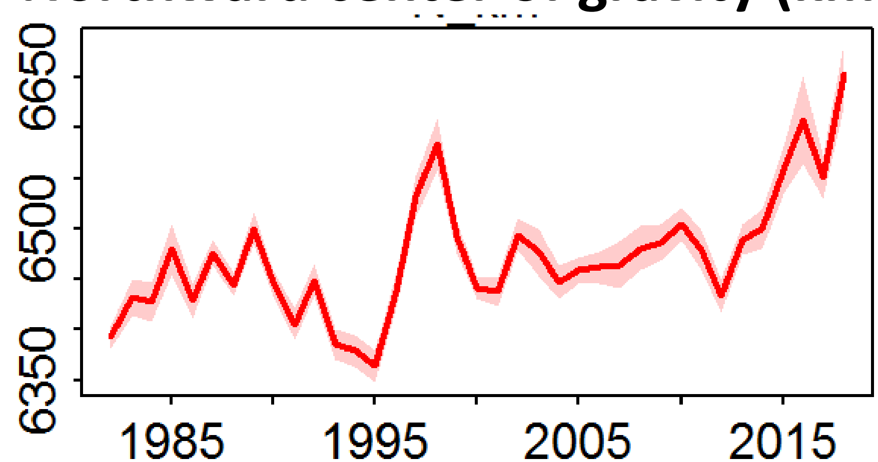
1. Has moved >300 km north from 1995-2018
2. Nearly 200 km north from 2012-2018
3. Increase 250% in area occupied since 2010



Eastward center of gravity (km)



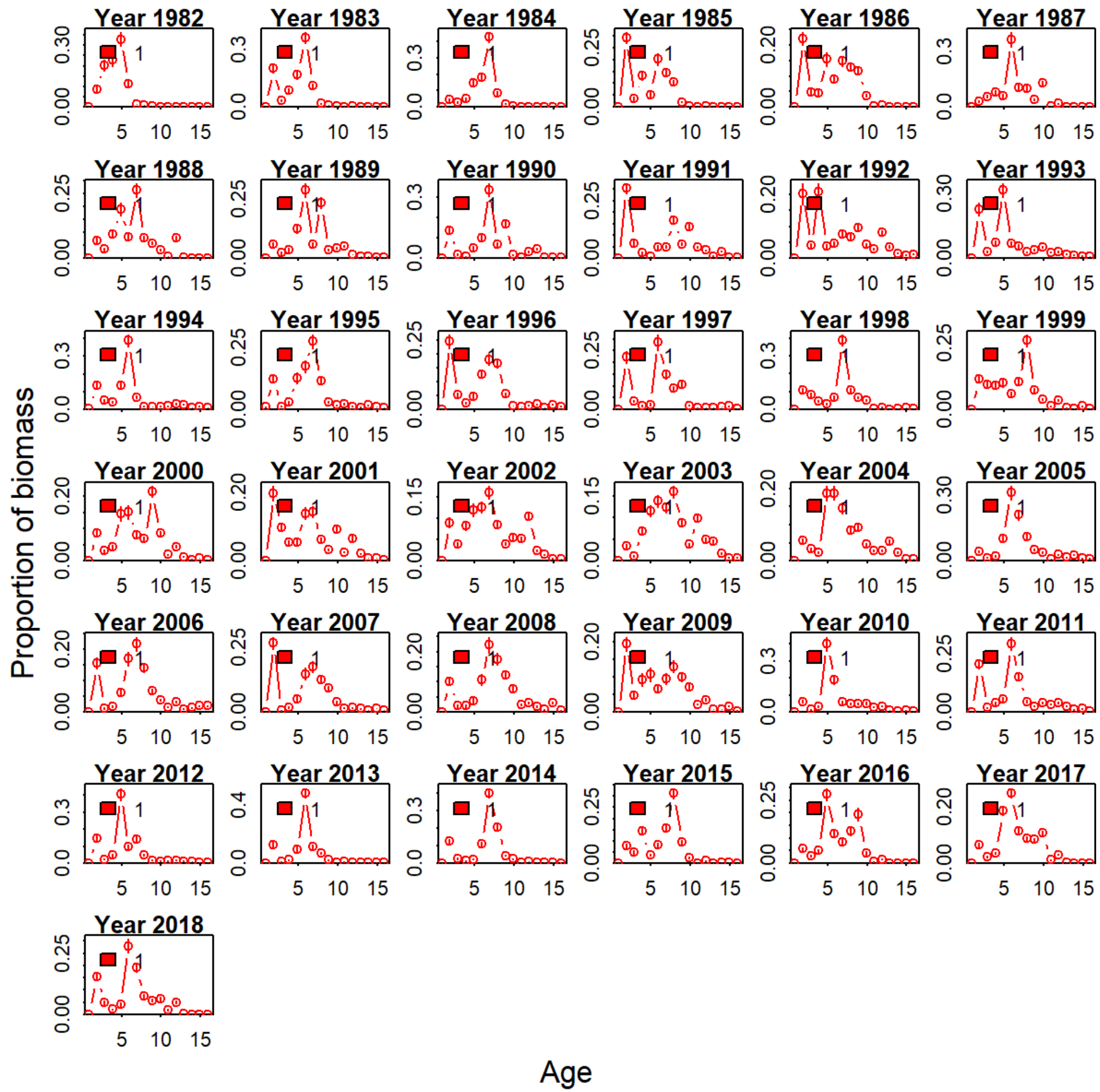
Northward center of gravity (km)



Benefit #1: Combine data

Expanding age-composition data

- Fit to catch by age
  - Used age-length key to expand from subsampled lengths to predicted ages
- Used coarse spatial resolution
  - 50 knots



Benefit #1: Combine data and account for spatially unbalanced data

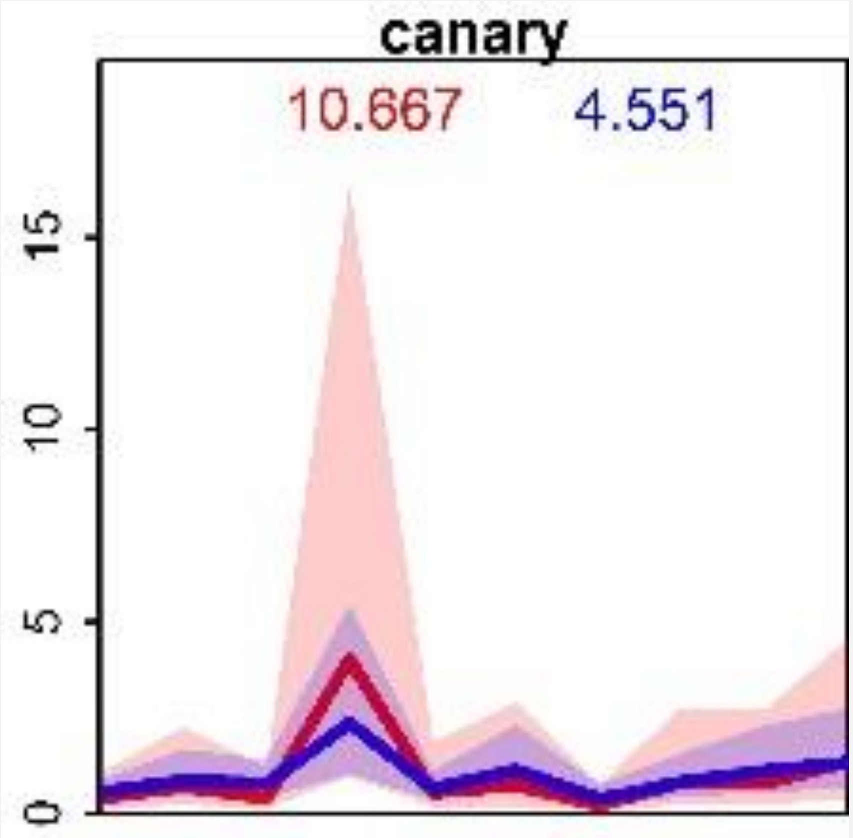
What to do with northern Bering Sea data?

My response:

- Keep sampling as often as we can
- Assimilate data while accounting for spatially-unbalanced design

Benefit #2: Improve statistical efficiency given limited data

What to do with outlier indices?



Benefit #2: Improve statistical efficiency given limited data

What to do with outlier indices?

Approach #1: Fit indices with equal weighting among years

- Results in large influence for index in anomalous years
  - High index -> caused by “extreme catch events”
  - Low index -> caused by random sampling design locating samples in poor habitat

Benefit #2: Improve statistical efficiency given limited data

What to do with outlier indices?

Approach #2: Weight index by variance in each year

- Often results in small log-standard error for anomalously low years
- Results in stronger leverage for years with negative residuals

Benefit #2: Improve statistical efficiency given limited data

What to do with outlier indices?

Approach #3: Model-based indices

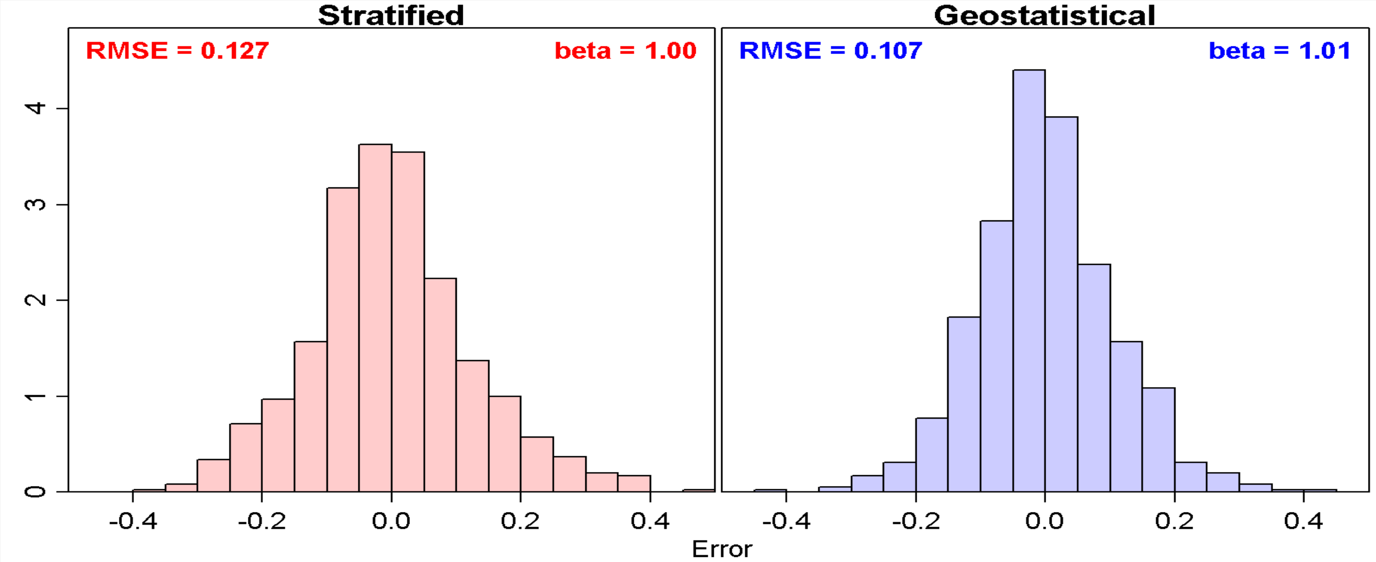
- Typically results in more similar standard errors among years
  - Results in more uniform weighting of index across years
- Accounts for poor ability for design-based methods to estimate standard errors (Kotwicki and Ono 2019, https://doi.org/10.1111/faf.12375)
- Typically results in lower statistical leverage for outliers
  - Years with all samples in poor habitat are "accounted for"
  - Observations with anomalously high catch are assigned lower leverage

Drawback #1: Potential to introduce bias

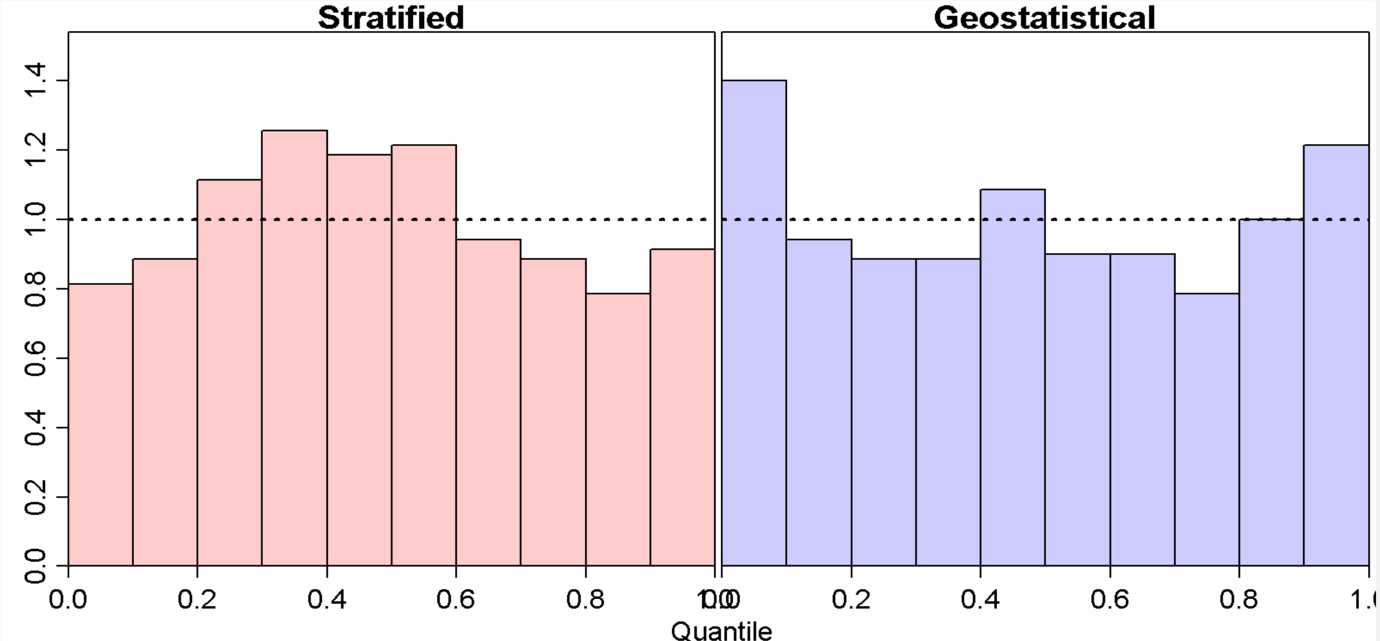
Response: Simulation-testing for bias:

1. Thorson et al. 2015 ICES JMS
   – Simulation testing for estimating indices of abundance
2. Thorson et al. 2017 CJFAS
   – Simulation testing for fishery-dependent standardization
3. Thorson and Haltuch 2018 CJFAS
   – Simulation testing for estimating age/length composition data
4. Grüss et al. 2019 Fish. Res.
   – Blinded experiment with independently made operating model
5. Brodie et al. In press Ecography
   – Biologically motivated operating model, comparing VAST, random forest, and GAMs
6. Johnson et al. 2019 Fish. Res.
   – Simulation experiment comparing model performance for VAST when missing covariates

VAST estimates abundance indices precisely



Neither model has badly calibrated intervals



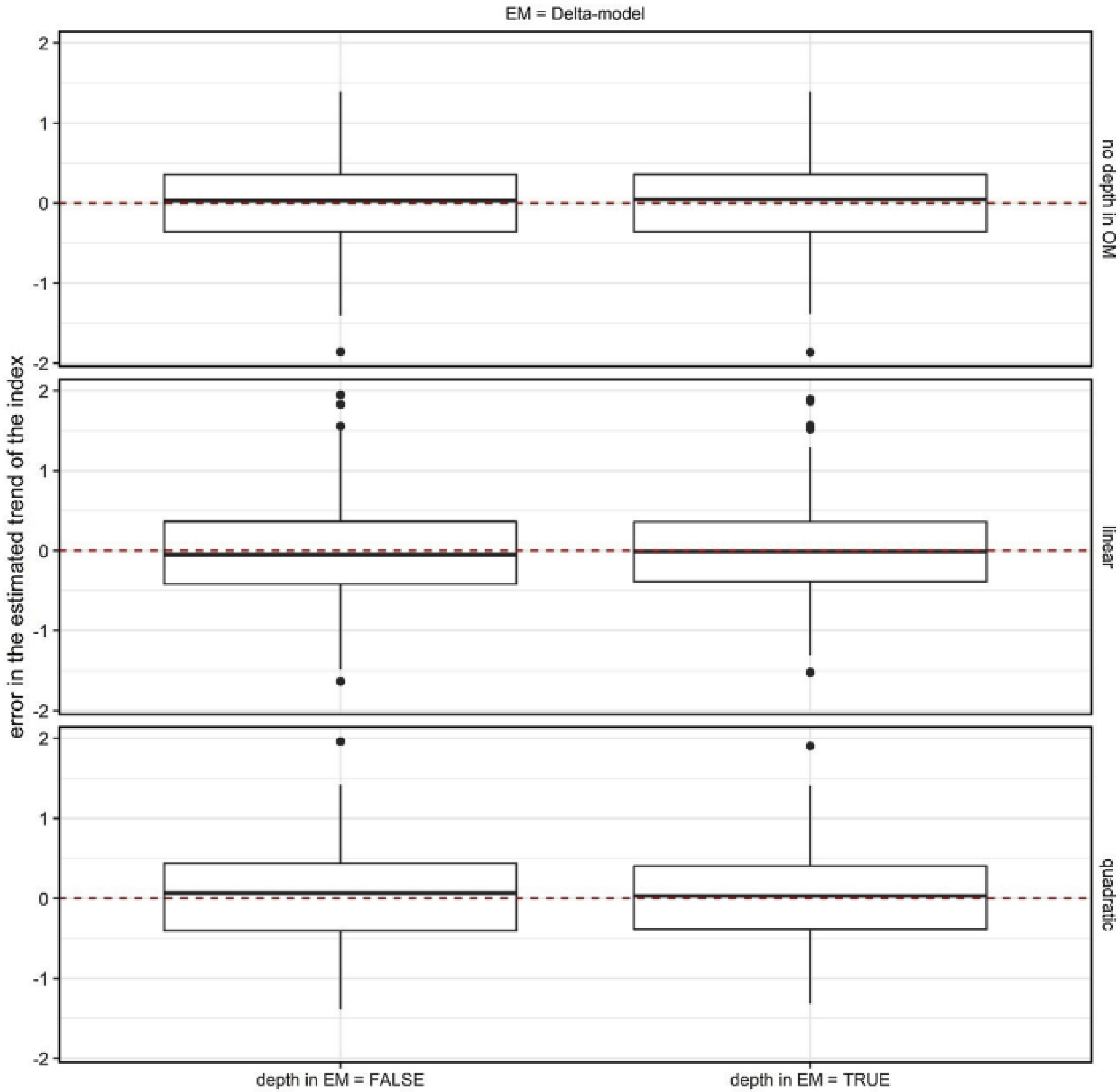
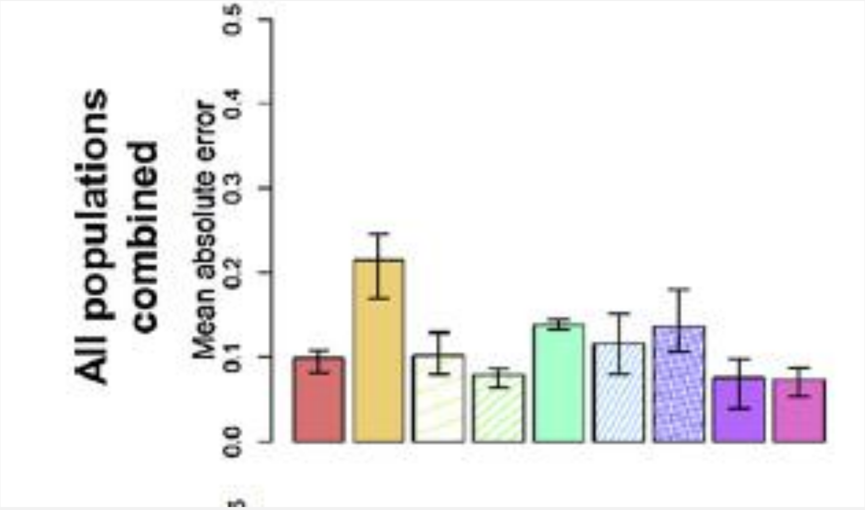
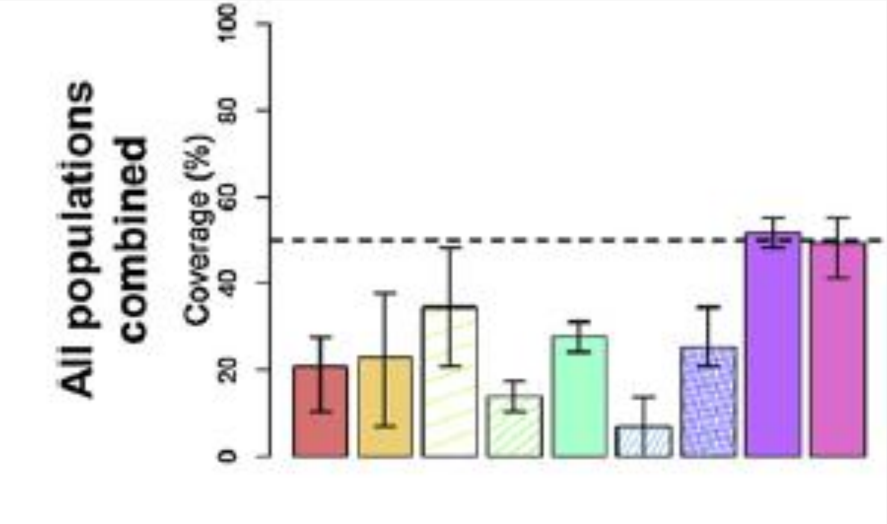


Fig. 6. Boxplots of the error in the log ratio of the first and last years of the index of abundance from two estimation methods (EMs), one that did not include depth (left column) and one that estimated quadratic depth (right column). Dynamics of the true system (rows; operating model, OM) were modelled in the following three ways: not governed by depth (top row) or governed by linear (middle row) or quadratic depth (bottom row). The red, dashed line indicates the location of unbiased estimates. Whiskers span 1.5 times the first and third quartiles, and points indicate outliers. For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.

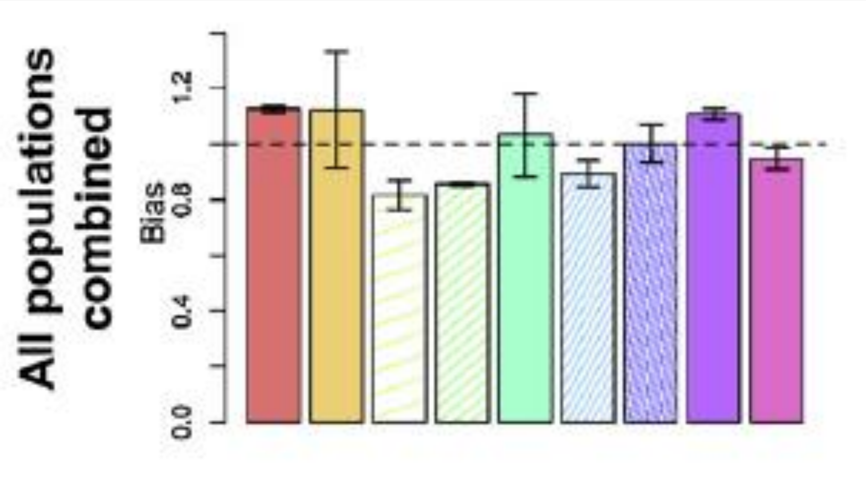
Mean absolute error (low is good)

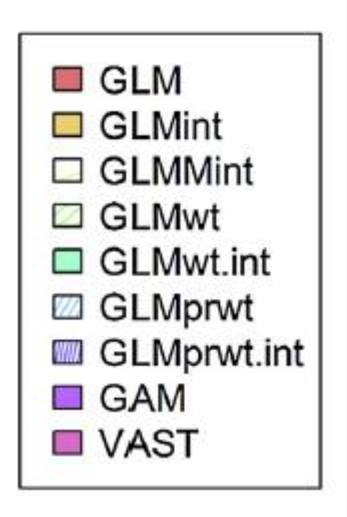


Confidence interval coverage (50% is good)

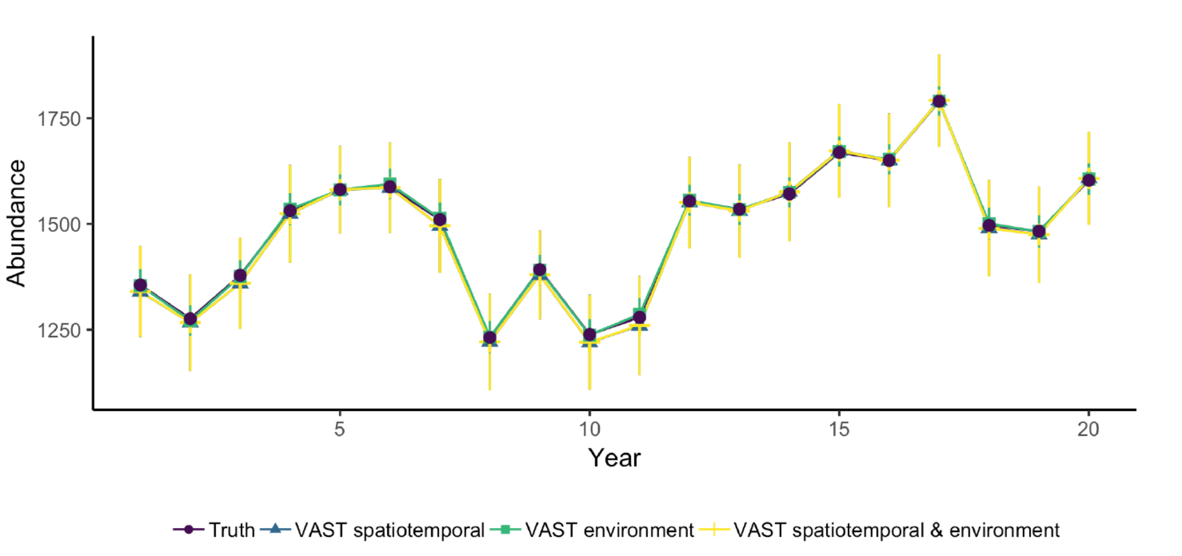


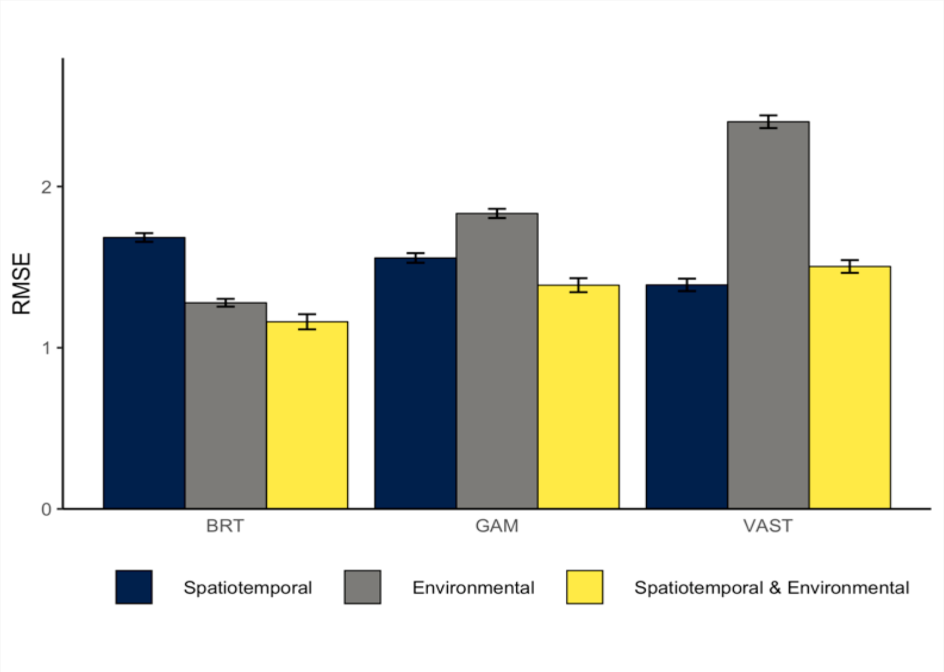
Slope between log(true) and log(estimated) index (1.0 is good)





Grüss, Walter, Babcock, Forrestal, Thorson, Lauretta, & Schirripa. (2019). Evaluation of the impacts of different treatments of spatio-temporal variation in catch-per-unit-effort standardization models. *Fisheries Research*, *213*, 75–93. https://doi.org/10.1016/j.fishres.2019.01.008





Brodie, Thorson, Carroll, Hazen, Bograd, Haltuch, … Selden. (In press). Pattern or Process: considering space, time, and the environment in species distribution models. *Ecography*.

Drawback #2: Results are model based, so people could “shop for the answer they want”

Response: Define terms of reference

Index standardization

- For all models
  - Ensure results are computationally feasible across machines
    - Eastern Bering Sea: 100 knots in spatial mesh
    - Gulf of Alaska / Aleutian Islands: 250 knots
  - Use existing extrapolation grids
  - Use “fine_scale=TRUE” for bilinear interpolation between knots
  - Use “bias.correct=TRUE” for epsilon-bias correction method
  - Use Poisson-link delta model
- For spatially balanced data:
  - Include spatial variation,
  - Include spatio-temporal variation that is independent in each year
- For spatially unbalanced data
  - Include spatial variation,
  - Include spatio-temporal variation that includes an autoregressive term
  - Include a spatially-varying response to cold-pool extent

Drawback #2: Results are model based, so people could "shop for the answer they want"

Response: Define terms of reference

Compositional expansion

- To ensure results are computationally feasible across machines
  - 50 knots in spatial mesh
  - Use existing extrapolation grids
  - Use "fine_scale=FALSE" for piecewise-linear interpolation
  - Use "bias.correct=TRUE" for epsilon-bias correction method
  - Use conventional delta-lognormal model
- For spatially balanced data:
  - Include spatial variation,
  - Include spatio-temporal variation that is independent in each year
- For spatially unbalanced data
  - Include spatial variation,
  - Include spatio-temporal variation that includes an autoregressive term

Drawback #3: Requires new consideration of data weighting

Example: Decreased standard errors could lead to overfitting model-based indices, unless additional variance (from catchability) is included

Response: Estimate additional variance for model-based inputs

Drawback #4: Difficulties communicating method

Example: fishing industry may not trust results

Response: Make plan to improve communication of methods

- Need input from public participants

Proposed process for next 1-2 years

Timeline

- April
  - Define list of stocks for model-based indices
  - Identify stocks needing model-based comp-data
  - Define terms-of-reference for that year
    - Balance of computational power, staff time, and model resolution
- May
  - Initial run of model-based indices and comps
- Sept
  - Updated run of indices and comps using updated data from that year

Responsibilities

1. Assessment team will provide model-based indices
2. Assessment scientists are free to use them or not
   - Permitted to re-run code and justify departure from terms-of-reference

Proposed process for next 1-2 years

Good practices

- Follow terms-of-reference (or justify departures)
- Present standard diagnostics
  - Q-Q plot for encounter and positive catch rates
  - Maps of Pearson residuals
- If using model-based indices, compare results with design-based indices
  - Justify data-weighting and impact on model
- If using model-based indices, justify use of model-based or design-based age/length comps
  - Goal is to use similar method for both