

Acoustic-Trawl Survey Uncertainty

NPFMC Groundfish Plan Team Meeting, 22 September 2023

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Acoustic-trawl surveys of Alaska pollock in EBS







- Currently, estimate relative error using 1D geostatistics
- Typical coefficient of variation: 4-8%
- Seems too precise, so inflated to 20% for stock assessment

Acoustic

500

• What is it really?

Estimating uncertainty is a challenge for acoustic-trawl surveys

A few more-comprehensive estimates elsewhere:

- Newfoundland cod (Rose et al. 1999)
- Antarctic krill (Demer 2004)
- New Zealand hoki (O'Driscoll 2004)
- Norwegian herring (Løland et al. 2007)
- ...And for pollock at AFSC:
 - 2007: Walline, "Geostatistical simulations of EBS walleye pollock..."
 - 2016: Woillez et al., "Evaluating total uncertainty..."
 - 2020-present: myself

Why this is a hard problem



- Multiple steps between acoustics/ trawls and numbers/biomass
- Combining two datasets with:
 - Unique uncertainties/biases
 - Very different spatial scales
- Acoustic data are *extremely* non-Gaussian





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- Resampling/simulation for each step of calculations
- Mirrors standard MACE survey analysis
- Computationally fast and stable
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 - Conditional geostatistical simulation
 - Randomized spatial assignment

Conditional (non-) Gaussian geostatistical simulation



- Standard routine for Gaussian data
 - Variogram defines covariance matrix **Q** of desired simulated data *x*
 - Uses "Cholesky trick," a.k.a. "Lower-upper Gaussian simulation," LUGS
 - If Q = LL', then x = L z, where $z \sim i.i.d$. Normal(0, 1)
- Non-Gaussian data: can transform it, but complicated and/or biased
- But...turns out, z doesn't have to be normal! Just need var(z) = 1
 - Lower-upper non-Gaussian simulation: LUNGS
 - Choose z from {Gamma, Inv. Gamma, Inv. Gaussian, Lognormal} based on KLD of x from observed backscatter



Conditional simulations on 10 x 10 km grid

Randomized acoustic-trawl assignment

- Trawl composition gives us species, sizes, target strengths
- Each acoustic interval scaled by nearest trawl
- Are these scaling factors representative of area?
- Randomly assign each grid cell to a trawl, probability ~ distance⁻¹







Apply random "calibration error" from normal distribution with standard deviation of 0.1 dB (about 2.4% in linear terms).

Based on variability in past calibrations and acoustic theory.



Spatial sampling error: simulate backscatter field, conditional on variogram model and data observed along transects.





Choose random trawl selectivity curve.

Based on models fit to pocket-net data by Kresimir Williams et al.





Resample catch (individual fish) in each trawl with replacement.

Calculate species/length composition, corrected for selectivity using function from prior step.



Drop one trawl at random.

Assign each grid cell to a trawl, with probability inversely related to distance.





Generate random length-TS function for pollock. TS uncertainty is 0.14 dB, about 3% in linear terms (Lauffenburger et al 2023).

For all other species, assume ± 3 dB uncertainty (100 % in linear terms–being conservative).



Resample age data (otolith reads) from survey to get age composition.

Use to parameterize standard Gaussian mixture model for age-length key.



Resample fish measured during survey with replacement.

Generate length-weight function based on resampled measurements (De Robertis and Williams 2008).

Total pollock abundance and biomass 2007-2022





Median new CV / old CV:

- 1.57 for numbers
- 1.27 for biomass





Contributions of individual uncertainty sources



- Re-analyzed all surveys, turning on one component at a time
- Largest individual sources, on average:
 - Spatial sampling error
 - TS models
 - Echosounder calibration
 - Trawling-related sources (mostly for abundance)
- Some differences year-to-year
- EBS is homogenous-trawling likely more important in GOA

Caveats

- A few sources of uncertainty remain unaccounted for:
 - Acoustic classification errors
 - Near-bottom acoustic dead zone
 - Survey domain/geographic availability
 - Fish movement
 - Some remaining questions about calibration and TS
- Currently, ignoring bottom 3 meters of water column (~25% of biomass)
- Uncertainty of absolute biomass vs. relative index
- Results may vary in other ecosystems, but...

Works in GOA too: Shelikof Strait, Winter 2023



Conclusions

- Total biomass uncertainty for MACE EBS pollock surveys is typically 5-11%
 - \circ For individual age classes, 10-30%
- Spatial sampling error, TS, and calibration are main sources
 - For less abundant age classes/species, uncertainty may be higher/have different drivers
 - More transects = less uncertainty
- On average 1.9 and 1.5 x 1D geostatistical estimates for numbers and biomass
- 2-4 times smaller than assumed in stock assessment
- Framework can be used to think about effort allocation/reduction

Questions?

0-000-07

State State State

Thanks to the Oscar Dyson crews and everyone in MACE. Especially the calibrators!

LUNGS details and the "Cholesky trick"

- Normal "lower-upper Gaussian simulation" (LUGS):
 - Use data + variogram model to define mean (μ_x) and covariance (Q) for simulation locations
 - Cholesky (LU) decomposition of covariance matrix $Q = L L^{-1}$
 - If the vector z is i.i.d standard normal, product x = L z will have covariance Q
 - $\circ \quad Q = \operatorname{cov}(x) = \mathsf{E}[x \ x']$
 - $\circ \quad \operatorname{cov}(z) = E[z \ z'] = I$
 - $\circ \qquad Q = L \, L' = L \, I \, L' = L \, E[z \, z'] \, L' = E[(L \, z) \, (L \, z)']$
 - From definition of covariance, cov(L z) = Q
- But, z does not have to be normal—as long as var(z) = 1.0, cov(Lz) = Q
 - Get means to match: $\mu_z = L^{-1} \mu_x$
 - Know required mean and variance (1.0) for each element of *z*, can then translate into parameters for whatever non-negative distribution you want

Trawl shuffle details

- Randomly assign each acoustic cell to a trawl
- Inverse distance weighted: 1 / d^a
- Exponent a set so average pixel has 50/50 chance of getting nearest trawl when ½ distance to nearest neighbor



Individual error contributions through time



Coefficients of variation over time



Separating backscatter into "scaling strata"



Scaling Stratum 2 (small, dense schools)

Scaling Stratum 1 (continuous near-bottom backscatter)



-70 -63 -56 -48 -41 -34 S_v (dB re 1 m⁻¹)