Designing for change: the impact of altering sampling design and density on survey indices

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Background

Survey effort may be reduced or altered within a time-series for various reasons:

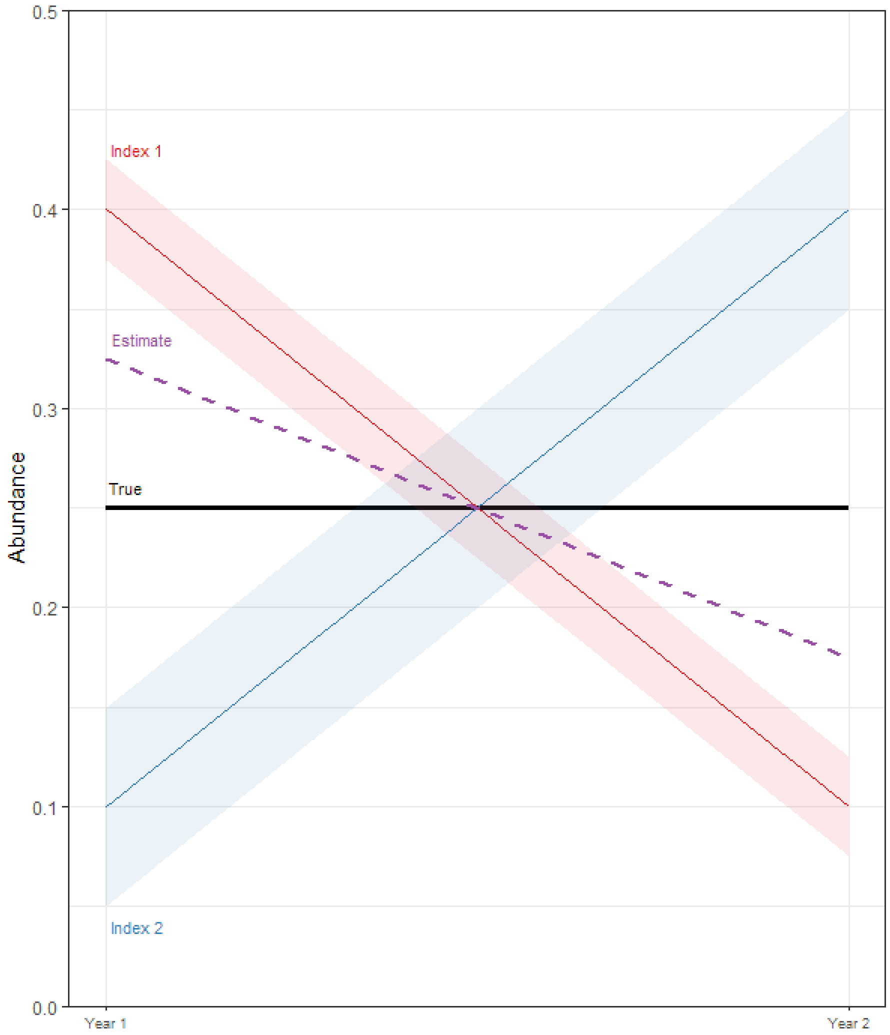
- Insufficient funding
- Logistical challenges including black swan events
- Shifts in species distributions
- Evolving management concerns

Estimation of Precision

Simple Example: Aggregating 2 Indices

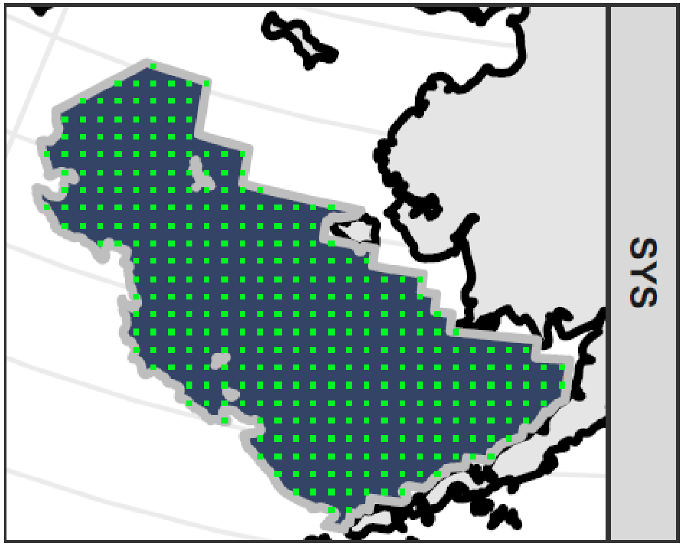
- True = no change in abundance (black line) between Years 1 and 2
- 2 indices (red and blue lines) detecting opposing trends in abundance
- If the variances of the indices are equal, the resulting trend would be the same as the true trend
- However, Index 1 has 50% of the variance of Index 2 (error ribbons), therefore the resulting trend (purple dashed line) shifts toward Index 1

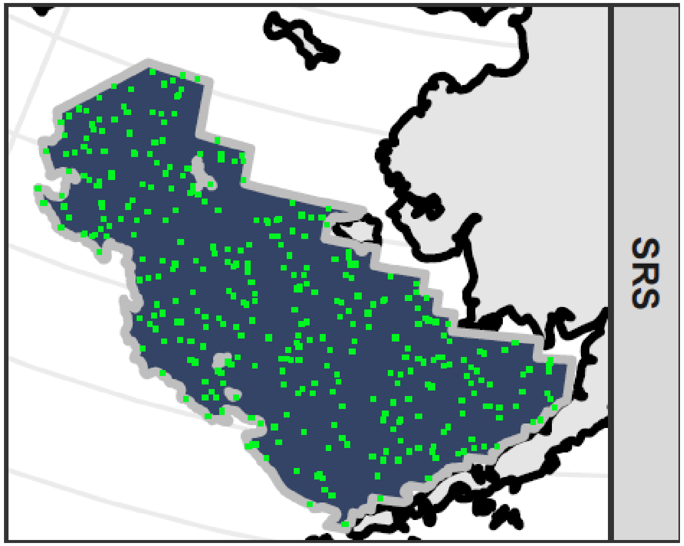
How accurate are the estimates of variance for each index?

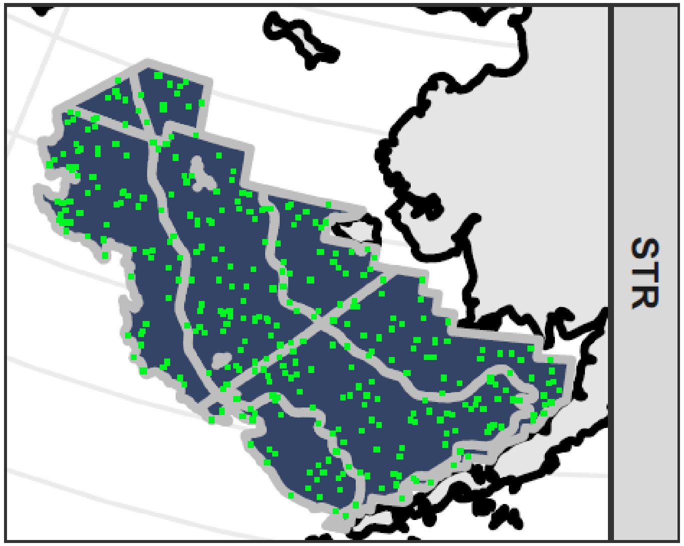


Simulated Sampling Designs

- Simple Random Sampling (SRS)
- Stratified Random Sampling (STR)
- Systematic Sampling (SYS) - Current







Systematic Sampling Overview

- Logistically less expensive
- Can be more precise than random designs if assumptions are met – specifically, that the population does not vary at the frequency of sampling
- There is no unbiased estimator for the variance of the mean (Cochran 1977)

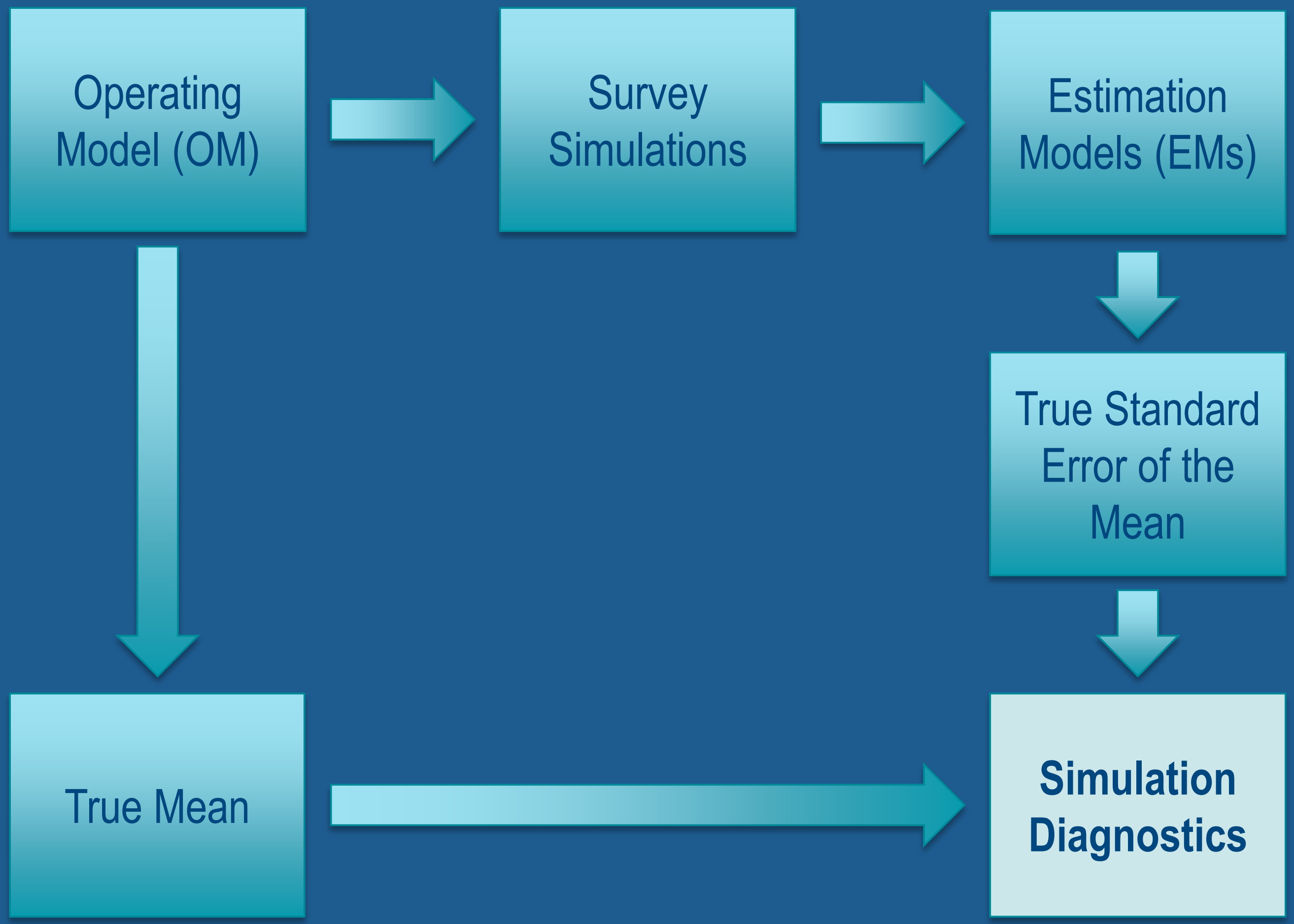
Systematic Sampling Variance

- Variance of the mean is often estimated using the estimator for simple random sampling.
  - known to likely overestimate the true variance of the mean (Strand 2017)
- CIE review of the Bering Sea bottom trawl survey in 2012 recommended exploration of alternative estimators
  - Zinger (1980) estimator – requires supplemental random samples
  - D'Orazio (2003) estimators – local variance in 2 dimensions, post-stratified

Sampling Density

- 350 – Present sample size, 132 vessel-days
- 263 – Sampling reduced to 88 vessel-days
- 175 – Sampling reduced to 66 vessel-days
- 525 – Sampling increased to 198 vessel-days

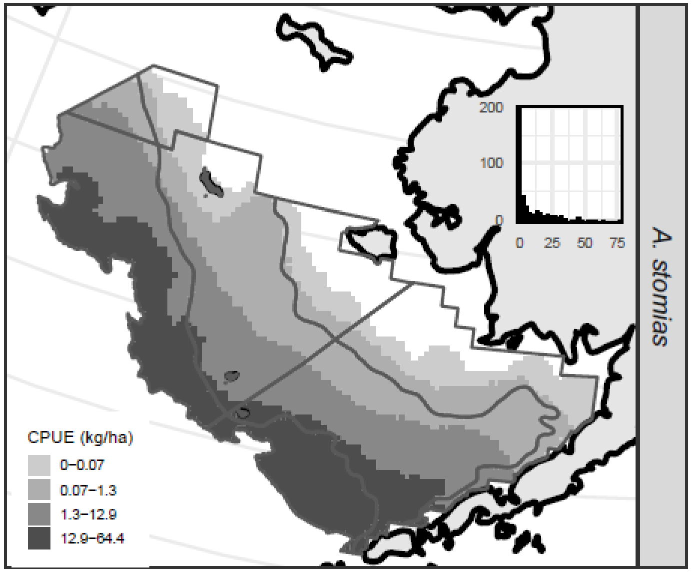
Methods

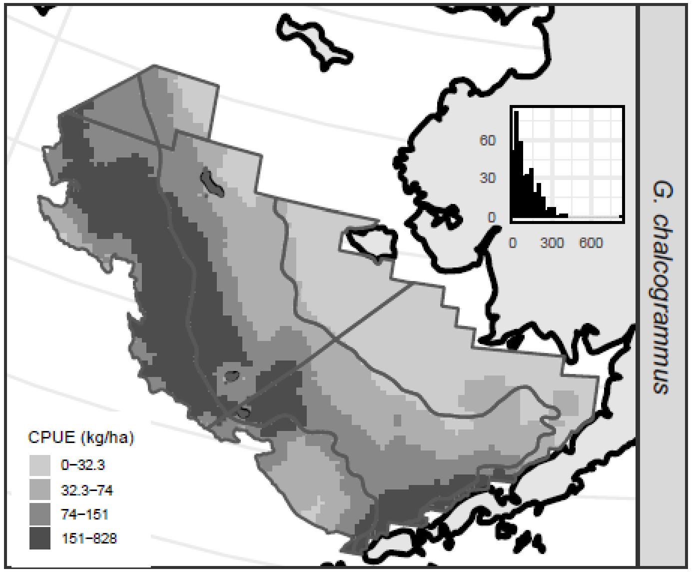


Operating Model (OM)
Survey Simulations
Estimation Models (EMs)
True Standard Error of the Mean
True Mean
Simulation Diagnostics

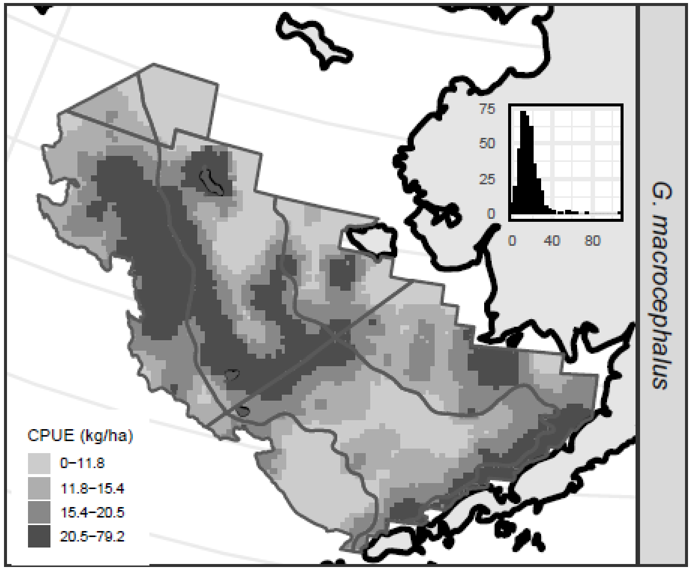
Study Cases

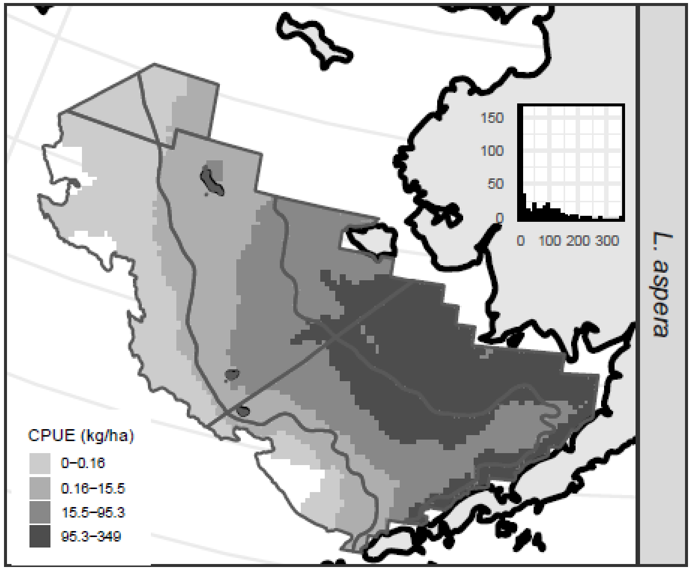
- Arrowtooth flounder (*Atheresthes stomias*)
  - affinity for depths greater than 100 m
- Walleye pollock (*Gadus chalcogrammus*)
  - strongly dependent on bottom temperature
- Pacific cod (*Gadus macrocephalus*)
  - dependent on bottom temperature, present at most stations
- Yellowfin sole (*Limanda aspera*)
  - strong affinity for depths shallower than 50 m





Typical Distributions of Study Species



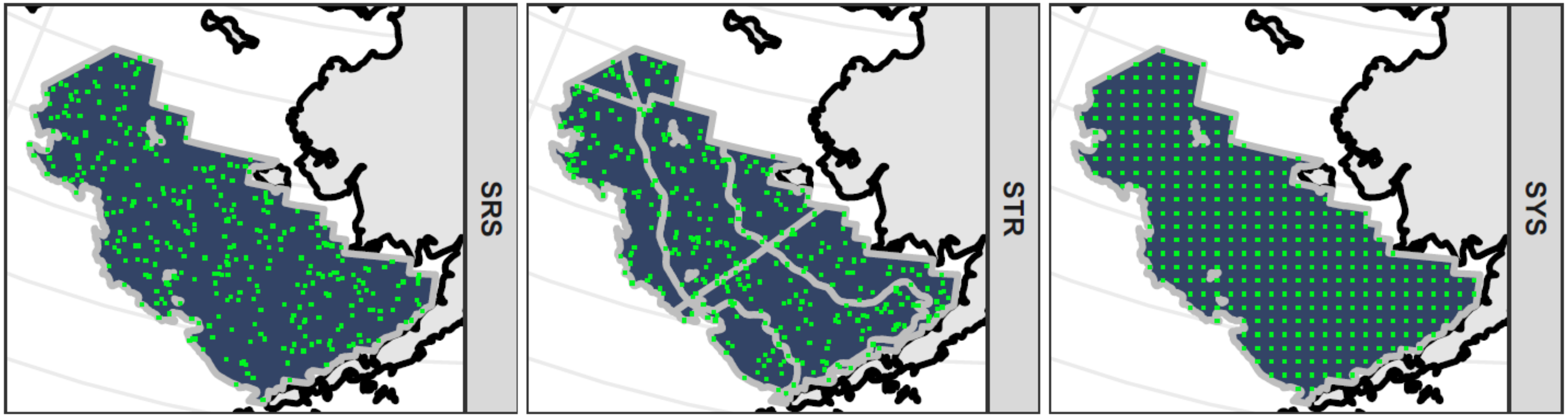


Spatiotemporal Operating Model

- Developed by Kotwicki and Ono (2019)
- Delta-GLM model
  - occurrence - binomial with logit link
  - abundance - Gaussian with log link
- Spatial/temporal dependencies included through the use of Mátern covariance function and a first-order autoregressive process (AR1)
- Covariates – depth, surface temperature, bottom temperature
- Implemented using R-package INLA
- Realized distributions produced by 10 MCMC samples from the joint posterior distribution of the model parameters for each year mapped to 4 km^2 raster

Survey Simulations

- 4 Species
- 3 Designs
- 4 Sample Densities
- 100 surveys per year (N=35), for each MCMC sample (N=10)



Parameters - “True” Values

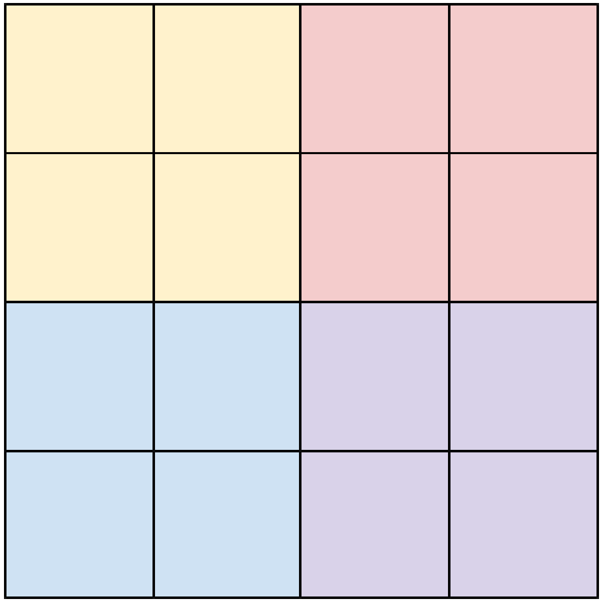
- True mean CPUE is the arithmetic mean of all values (N=68,744) from an MCMC sample per year
- True standard error of mean CPUE (SEM) is the standard error of simulated survey mean CPUEs (N=100) per each MCMC (N=10) and year (N=35)

Estimators

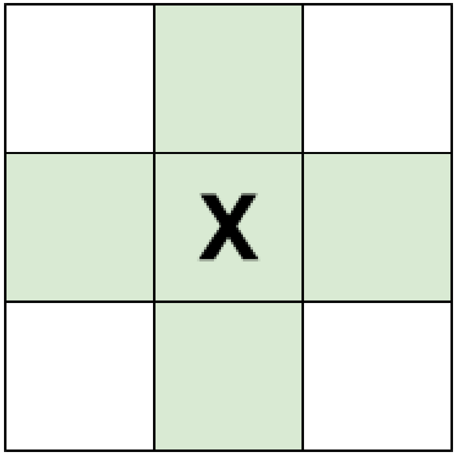
- Mean CPUE
  - SRS & SYS – arithmetic mean of samples
  - STR – area-weighted stratified mean of samples
- SEM of CPUE
  - SEM_{SRS} & SEM_{STR} – prescribed estimators for standard error of the mean
  - SEM_{SYS} – “borrowed” estimator SEM_{SRS} (Current)
  - SEM_{ST4} – local SEM, non-overlapping strata of 4 stations
  - SEM_{LO5} – local SEM, overlapping strata of station and 4 nearest stations

Alternative SEM Estimators

SEM_{ST4}



SEM_{LO5}



Diagnostics per Realized Distribution

- Relative Bias (RB)

$$\text{RB} = \frac{\left(\sum_{i=1}^{R} Y_i^{estimated}/R\right) - Y^{true}}{Y^{true}}$$

- Relative Estimation Error (REE)

$$\text{REE} = \frac{\sqrt{\left(\sum_{i=1}^{R} (Y_i^{estimated} - Y^{true})^2/R\right)}}{Y^{true}}$$

i = a survey simulation
R = number of survey iterations (N=100)

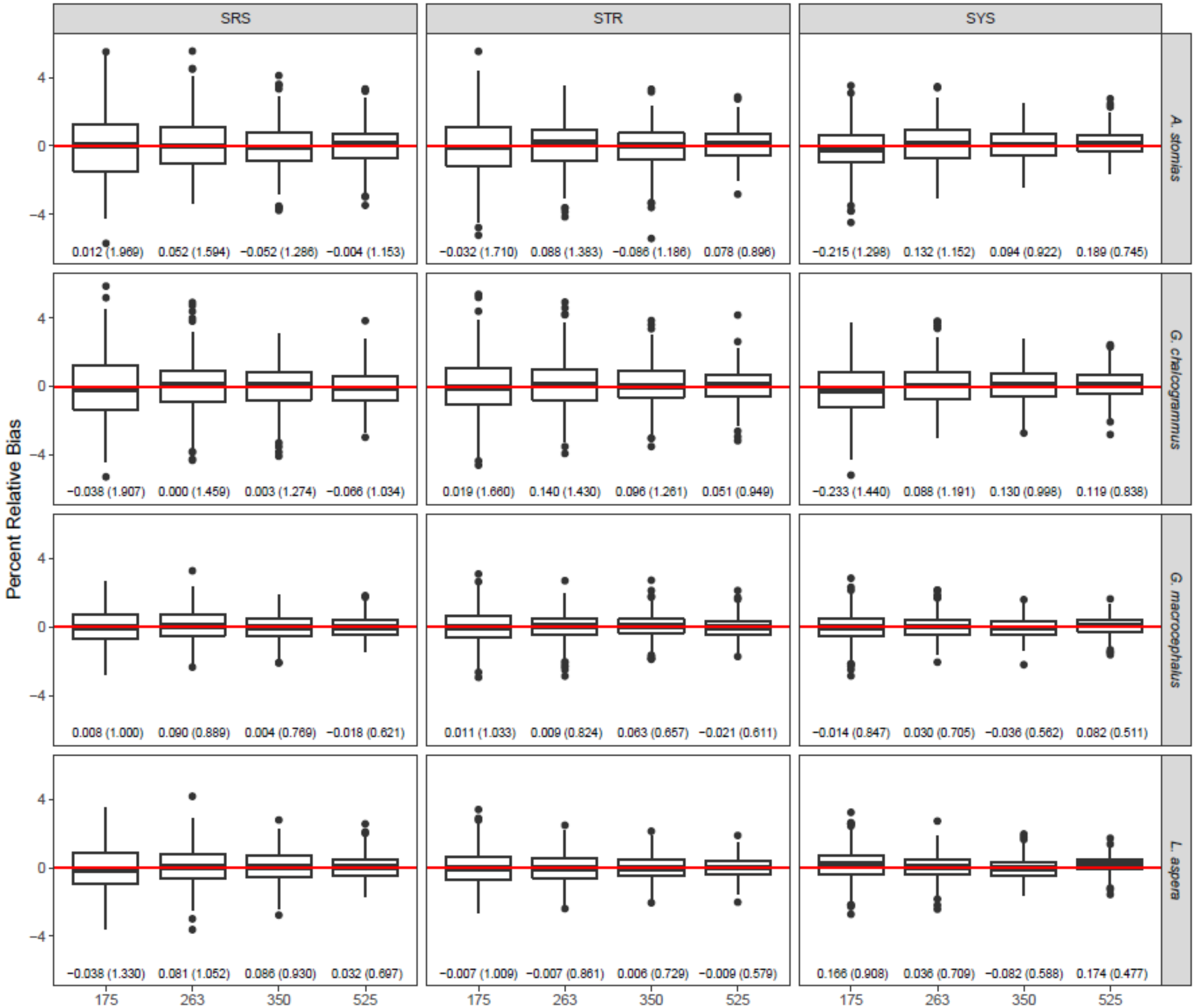
From Liu *et al.* 2009

Results

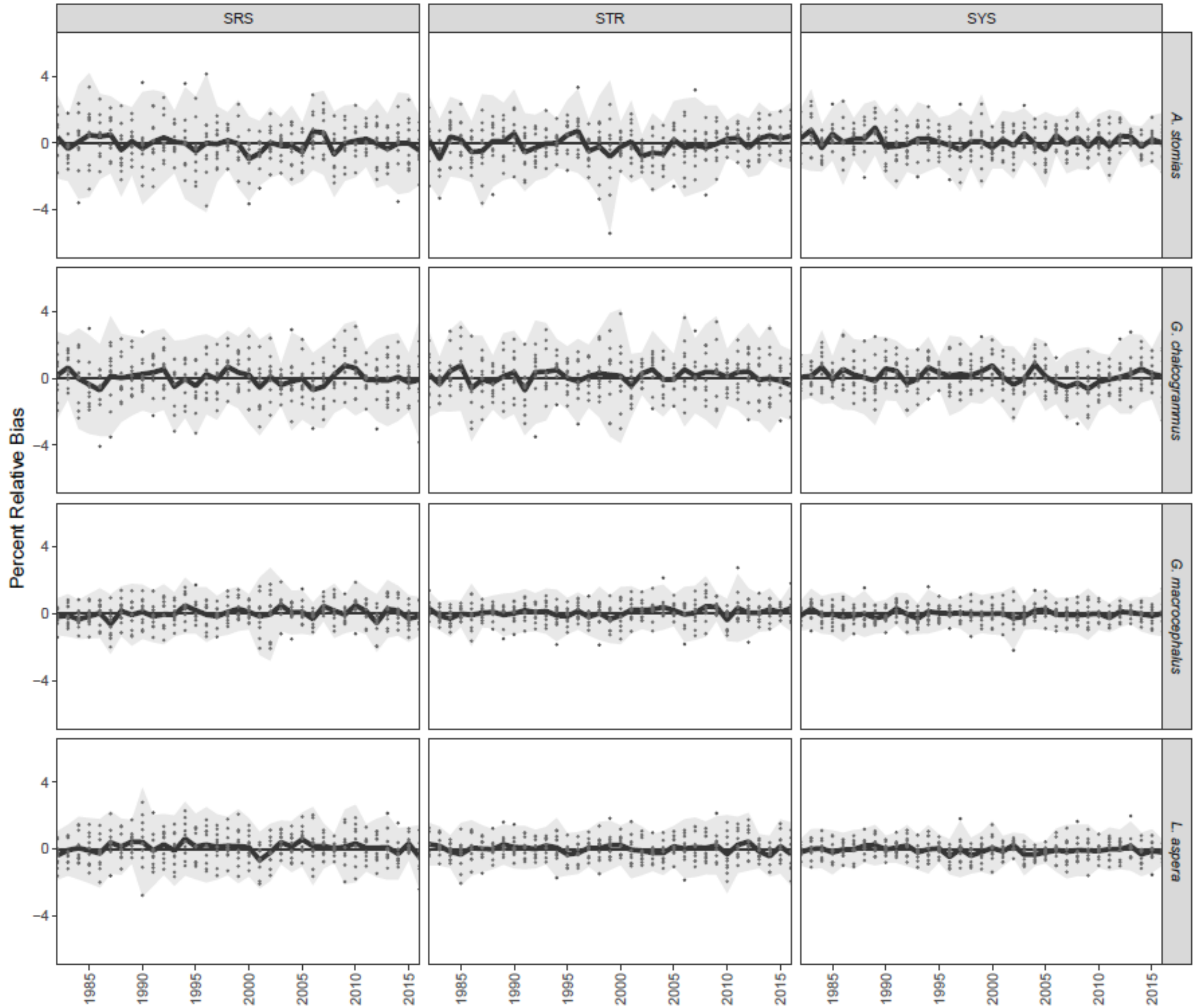
Summary

- Point estimates are accurate for all species, designs and densities, and relative bias is small and consistent over time
- SEM_{SYS} shows considerable positive relative bias
- SEM_{LO5} and SEM_{ST4} have error distributions similar to random sampling designs
- The SYS design studied (random start) yields more precise point estimates than random sampling designs

Aggregate RB of Mean CPUE - Accuracy

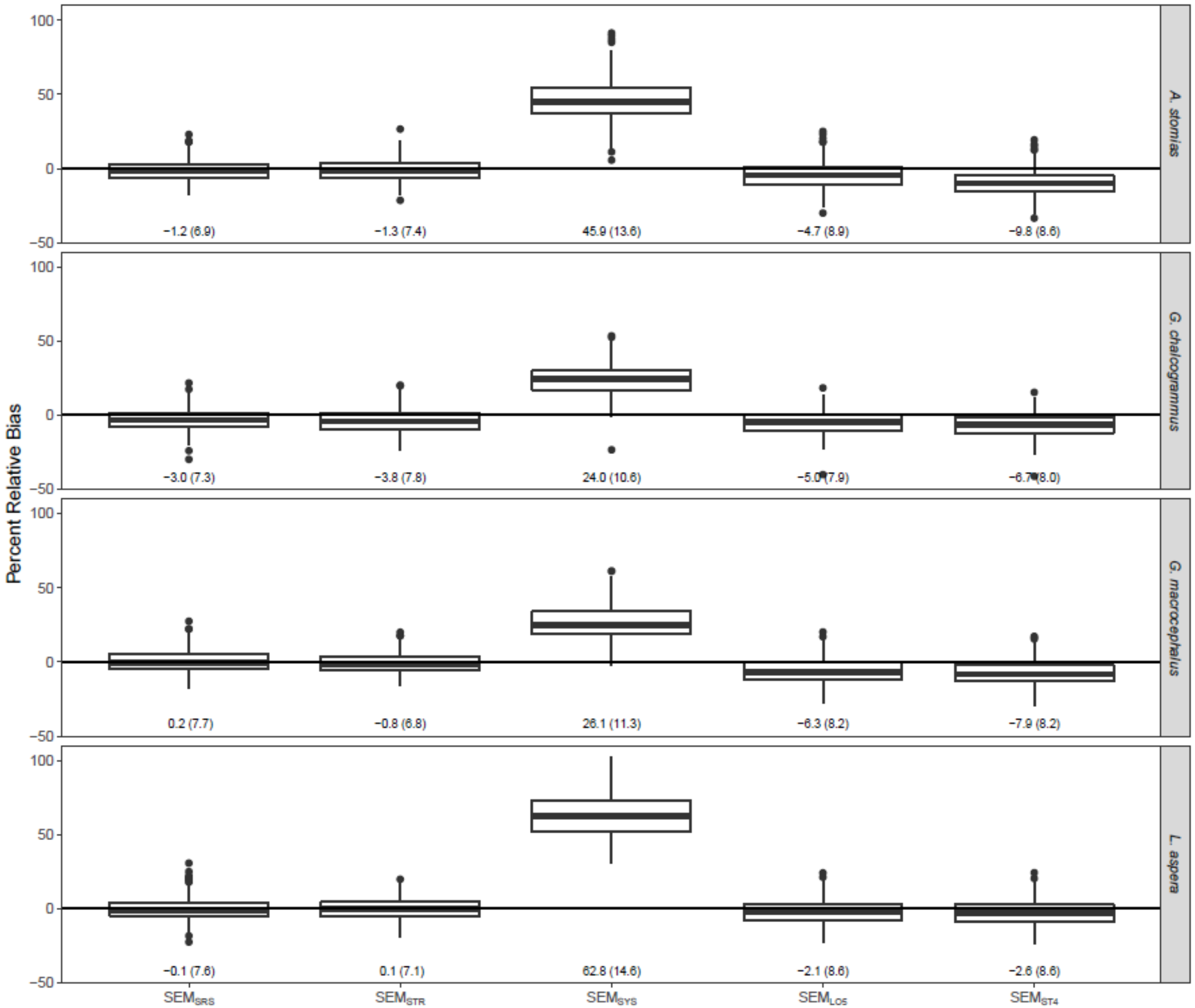


RB of Mean CPUE per Year - Accuracy



Sampling density = 350. Trend line is similar at each sampling density

RB of the SEM - Precision



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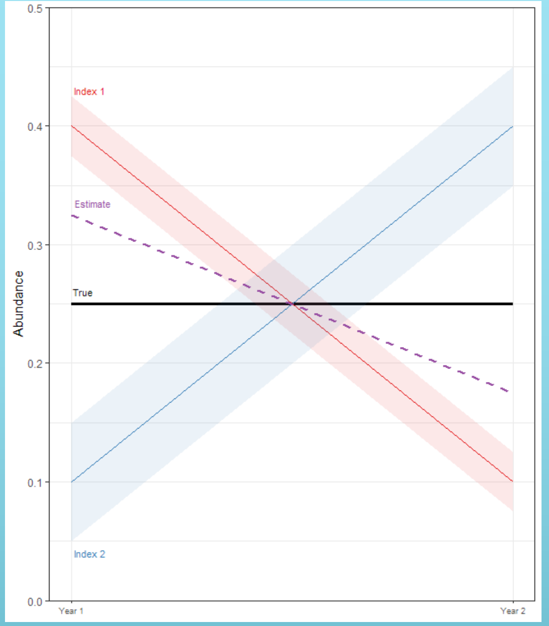
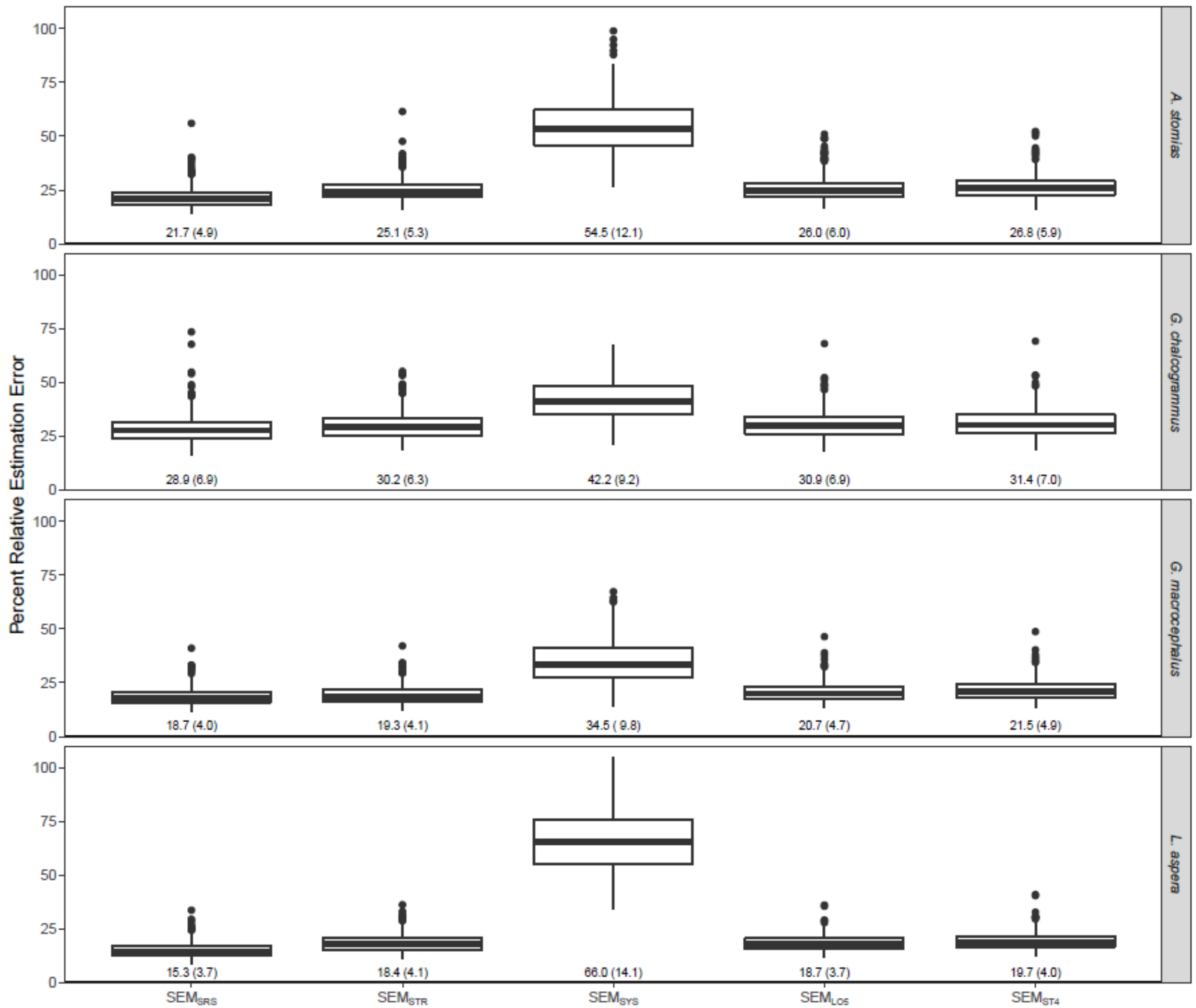


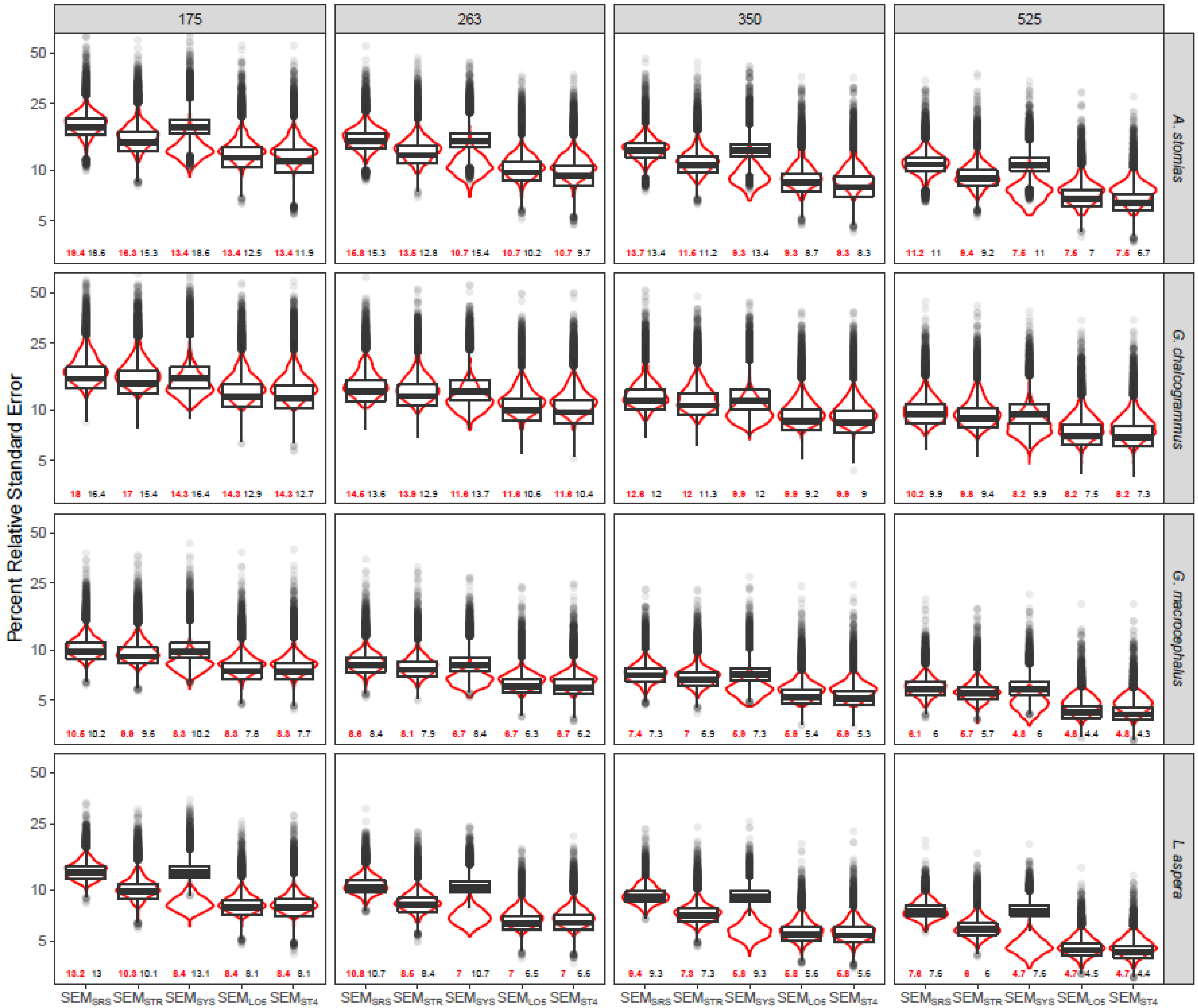
Recall the simple scenario where a stock assessment model aggregates 2 indices. If Index 2 represents the current SEM_{SYS} estimate, the resulting trend will be shifted to other indices.

REE of the SEM – Accuracy and Precision



Sampling density = 350. Trend is similar at each sampling density

Percent Relative Standard Error (aka CV)



Conclusions

- Appropriate to continue SYS survey design
- Current strata increases precision for random designs
- Simulations can approximate the increase in error with reduced sampling
- If the assumptions of the OM are viable, then it would be appropriate to accept an SEM estimator that is less-biased than the currently employed SRS estimator

Plan Team Questions

1. What would the Plan Team require to adopt an alternative estimator for the variance of the mean in a stock assessment?
2. Would the Plan Team recommend investigating bias correction for these estimators?
3. What does the Plan Team consider an acceptable range of CVs for survey indices?
4. Should GAP consider adopting a random-start systematic design in the Bering Sea? (requires a new simulation study)

References

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Supplemental Slides

Systematic Sampling Details

Target Sampling Density	Distance Between Stations (km)	Systematic Realizations	Random Realizations	Range of Sampling Densities
175	53.065	729	2.34×10^{21}	169 - 180
263	43.3	484	1.37×10^{22}	256 - 271
350	**37.53**	**361**	$\mathbf{3.58 \times 10^{22}}$	**344 - 355**
525	30.64	256	6.90×10^{22}	517 - 532

- Dimensions of square systematic sampling grids for each target sampling density.
- The number of realizations is the same as the number of sampling units within each grid cell.
- The standard sampling density for the BTS is 350 stations.

RB of SEM per Year