Multispecies survey design optimization for the Gulf of Alaska Groundfish Bottom Trawl Survey

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Plan Team Meeting 9/22/2021

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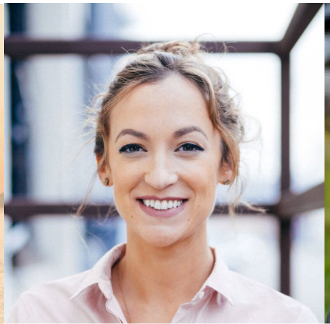


Motivation and outline

- Issue
  - Variable survey effort presents a challenge given existing design
- Goals
  - Increase flexibility and efficiency of stratified random survey design
  - Obtain accurate and precise estimates of abundance indices and their variance for most assessed stocks
- Outline of simulation approach
  - **operating model ->**
  - **survey optimization ->**
  - **expected performance**

Key current and proposed design elements

	Status quo
how many strata?	59
strata characteristics	depth, terrain, etc.
allocation criteria	Neyman: f (B, value, cost, s^2, area)
constraints	sample size

- Potential improvements in the face of survey effort fluctuations
  - Better estimates of stratum variances with fewer strata
- Why do we care about the variance of our estimates?
  - Used for data weighting within stock assessments

How to change the GOA survey design?

	Status quo	**Proposed**
how many strata?	59	5-25
strata characteristics	depth, terrain, etc.	depth, longitude
allocation criteria	Neyman: f (B, value, cost, s^2, area)	Bethel: f (σ^2, expected CV)
constraints	sample size	expected CV

- Potential improvements in the face of survey effort fluctuations
  - Better estimates of stratum variances with fewer strata
  - Quantify expected precision and tune according to needs
  - More flexibility in species prioritization

Progress to date

- Presented initial framework and results at Fall 2020 Plan Team
- General framework published, focusing on optimization methods

ICES Journal of Marine Science

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ICES Journal of Marine Science (2021), doi:10.1093/icesjms/fsab038

Incorporating spatiotemporal variability in multispecies survey design optimization addresses trade-offs in uncertainty

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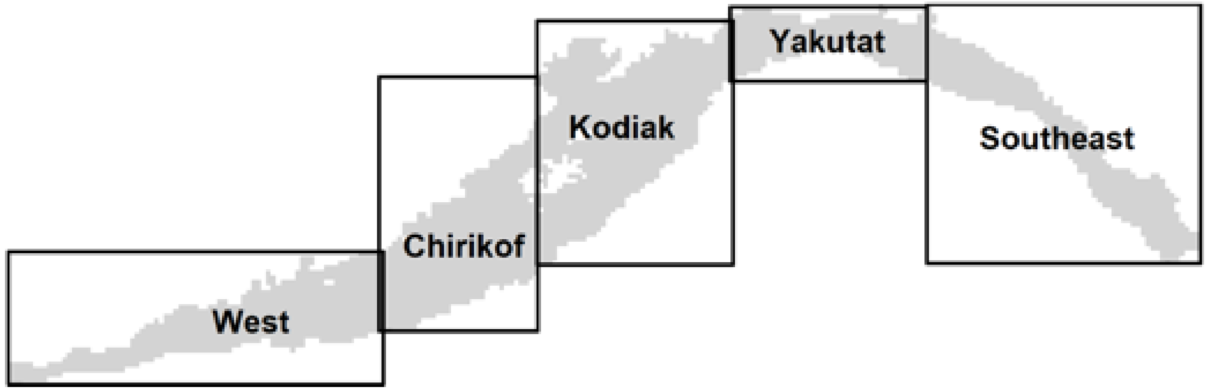
- NOAA Tech Memo in revision (focus on n=550 effort level)
    - Operating model: species-specific covariates, spatial resolution, observation and estimation error
    - Species-specific constraints
    - Extended comparison to existing survey design

Responsiveness to plan team inquiries

- Compared spatial scales of optimization to determine how to best estimate abundance at the unit of the NMFS management area
- Tested different approaches to modeling covariates (splines)
- Expanded the species set



Conditioning model: data informing operating model

- Gulf of Alaska Bottom Trawl Survey (11 survey years 1996-2019)

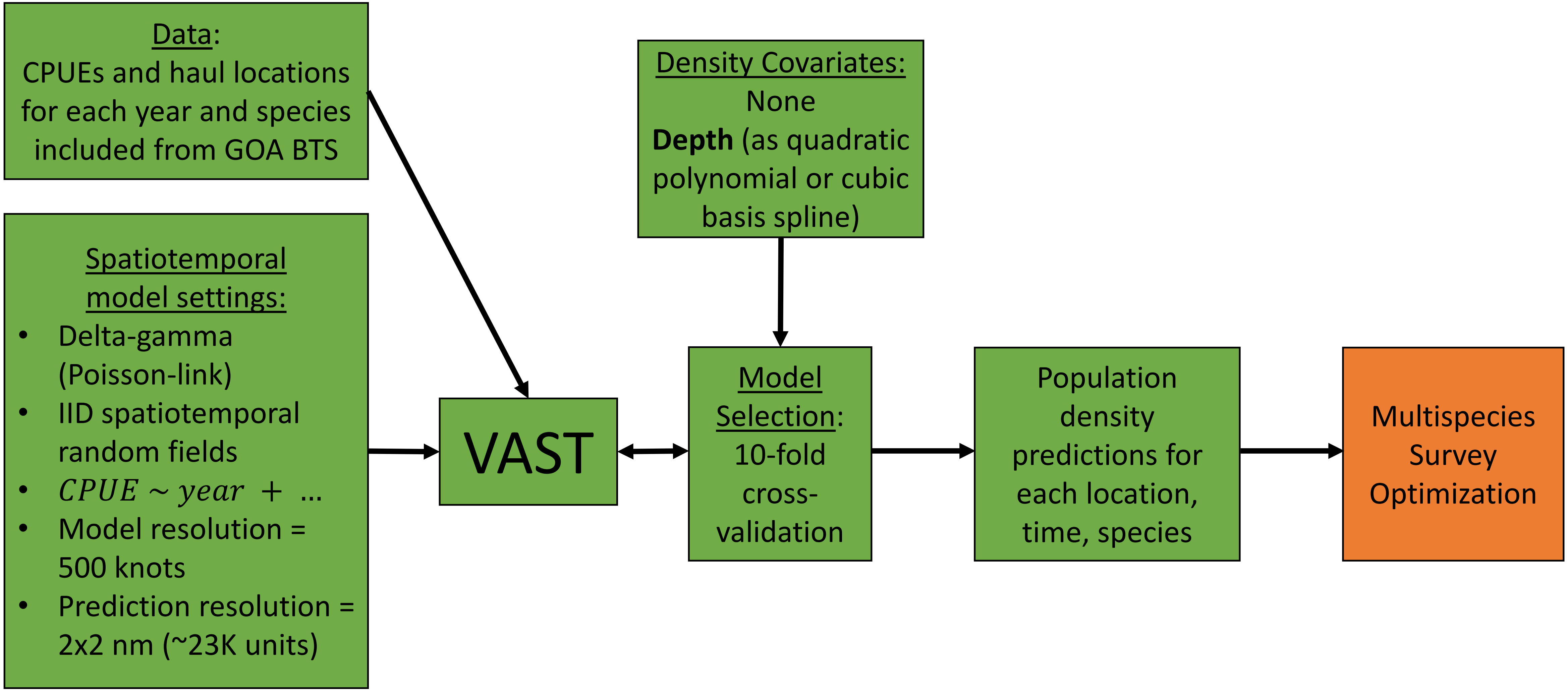
Optimize + simulate surveys

Pacific ocean perch
arrowtooth flounder
Pacific cod
walleye pollock
Pacific halibut
rex sole
flathead sole
dover sole
northern rock sole
southern rock sole
dusky rockfish
northern rockfish
rougheye/blackspotted rockfish
shortspine thornyhead
silvergray rockfish

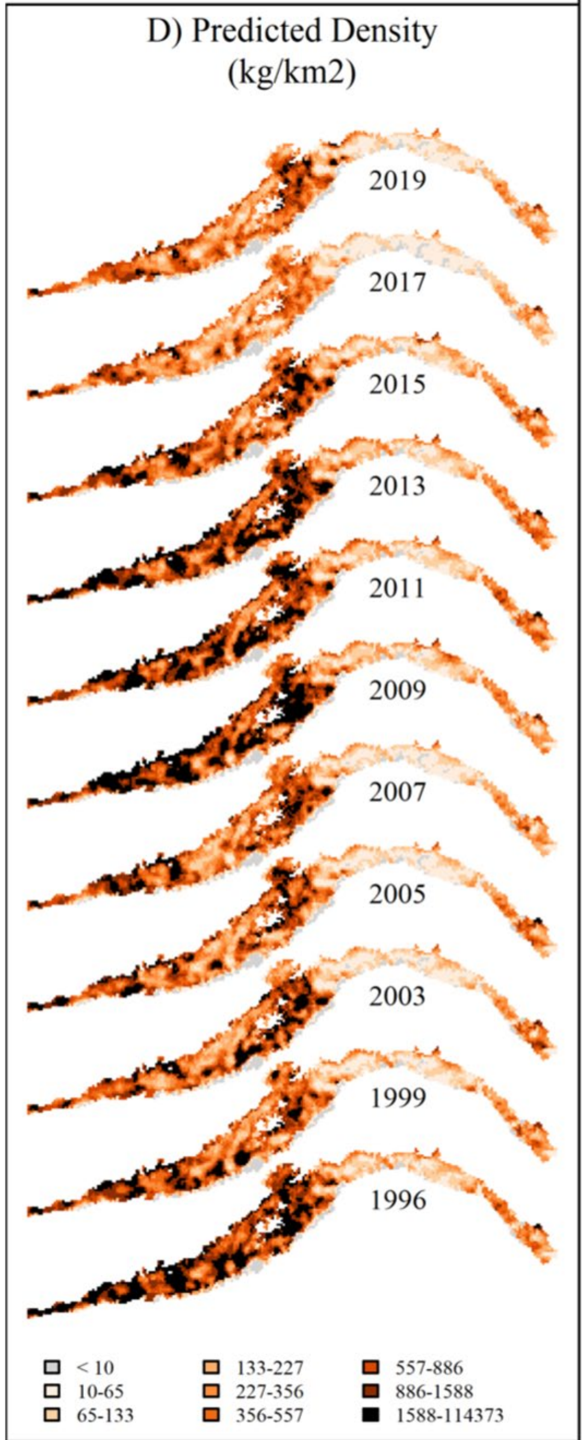
Simulate surveys only

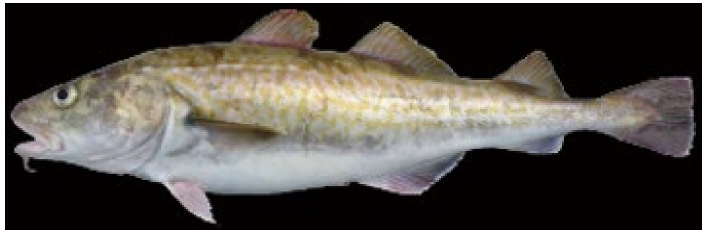
sablefish
Atka mackerel
harlequin rockfish
giant octopus
Pacific spiny dogfish
shortraker rockfish
longnose skate
big skate
yelloweye rockfish
sculpins
giant grenadier

Project overview: operating model -> survey optimization



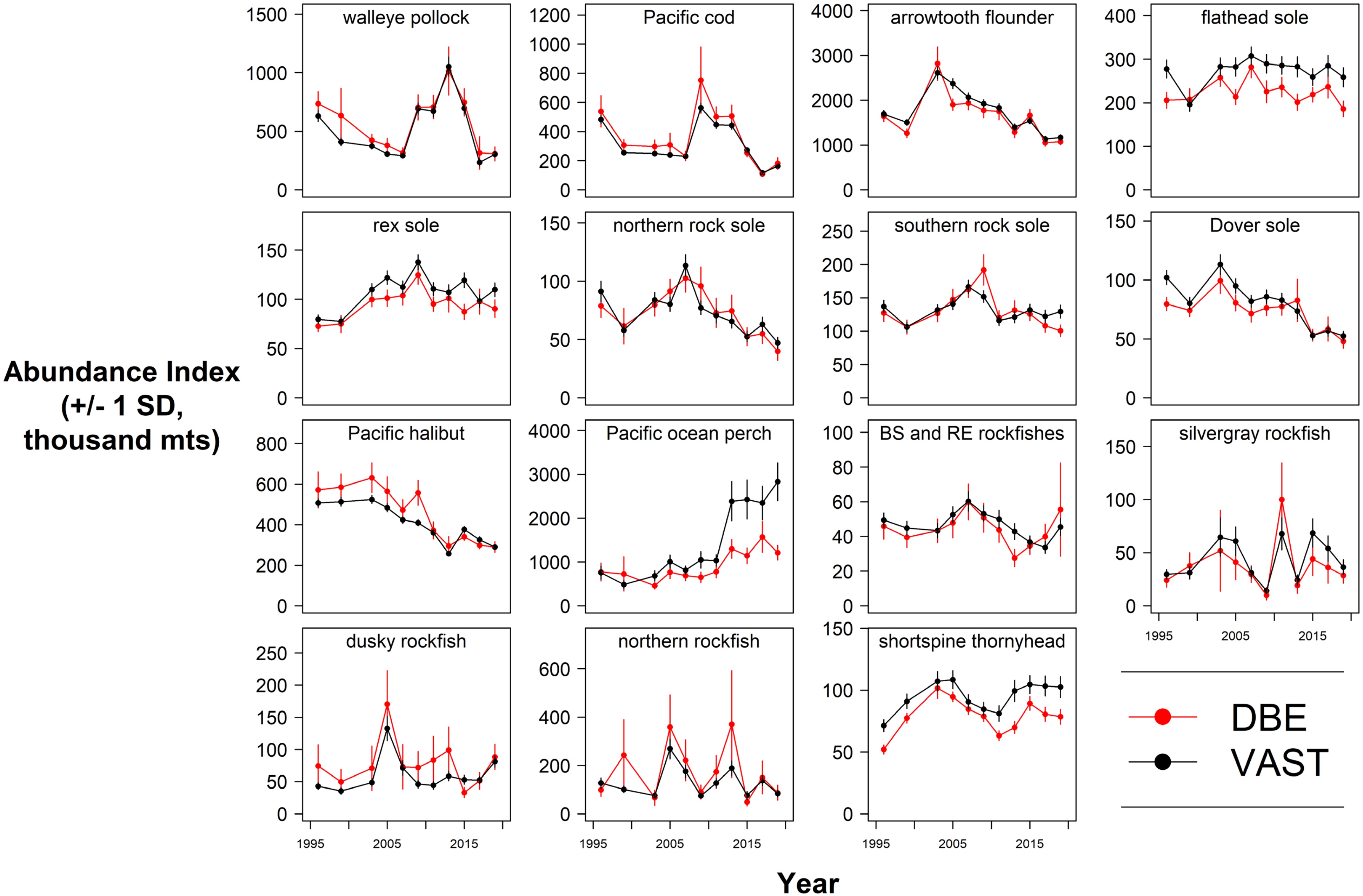
Spatiotemporal model accurately captures species distribution over time





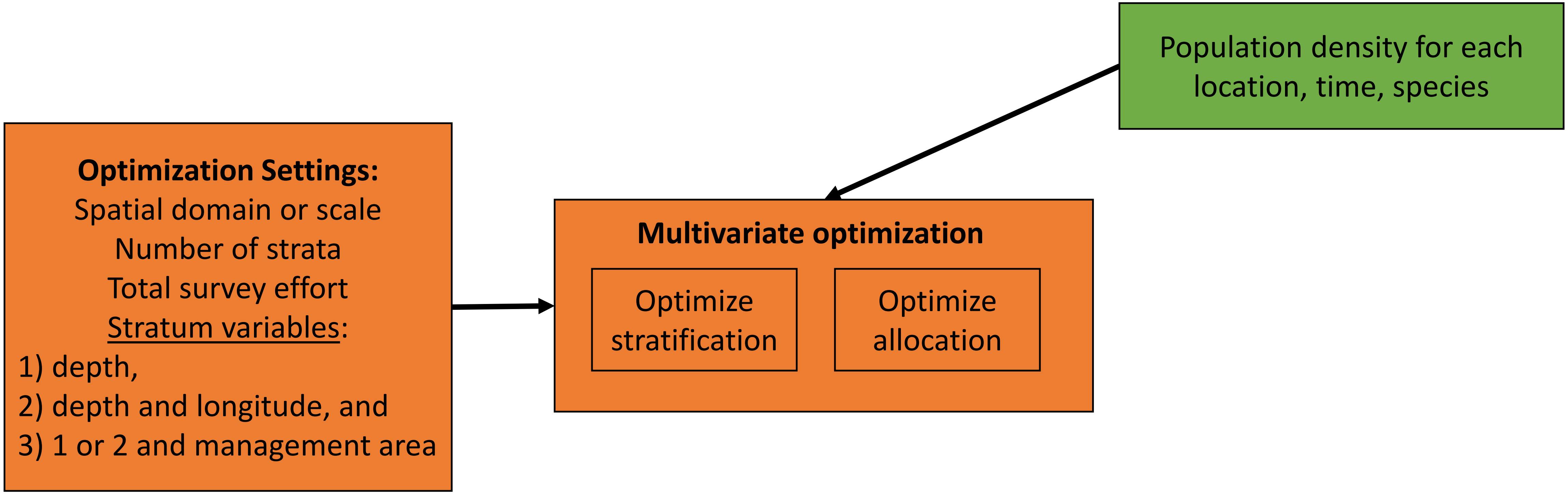
Operating model

Biomass trends are similar between design- and model- based estimates



Operating model

Project overview: operating model -> survey optimization

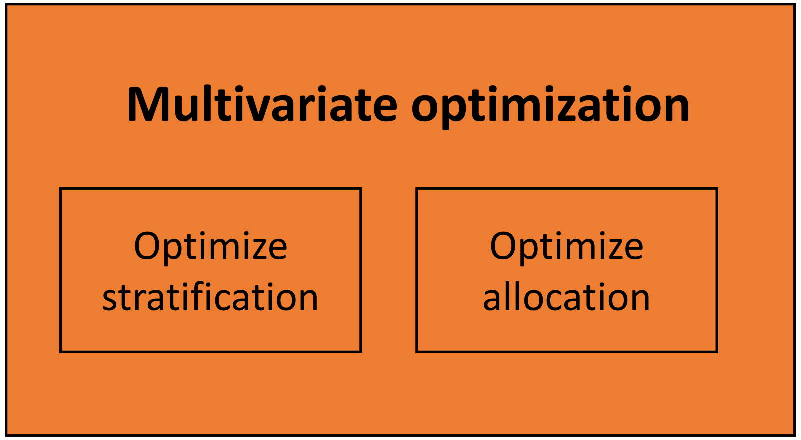


Optimization: two algorithms, three steps

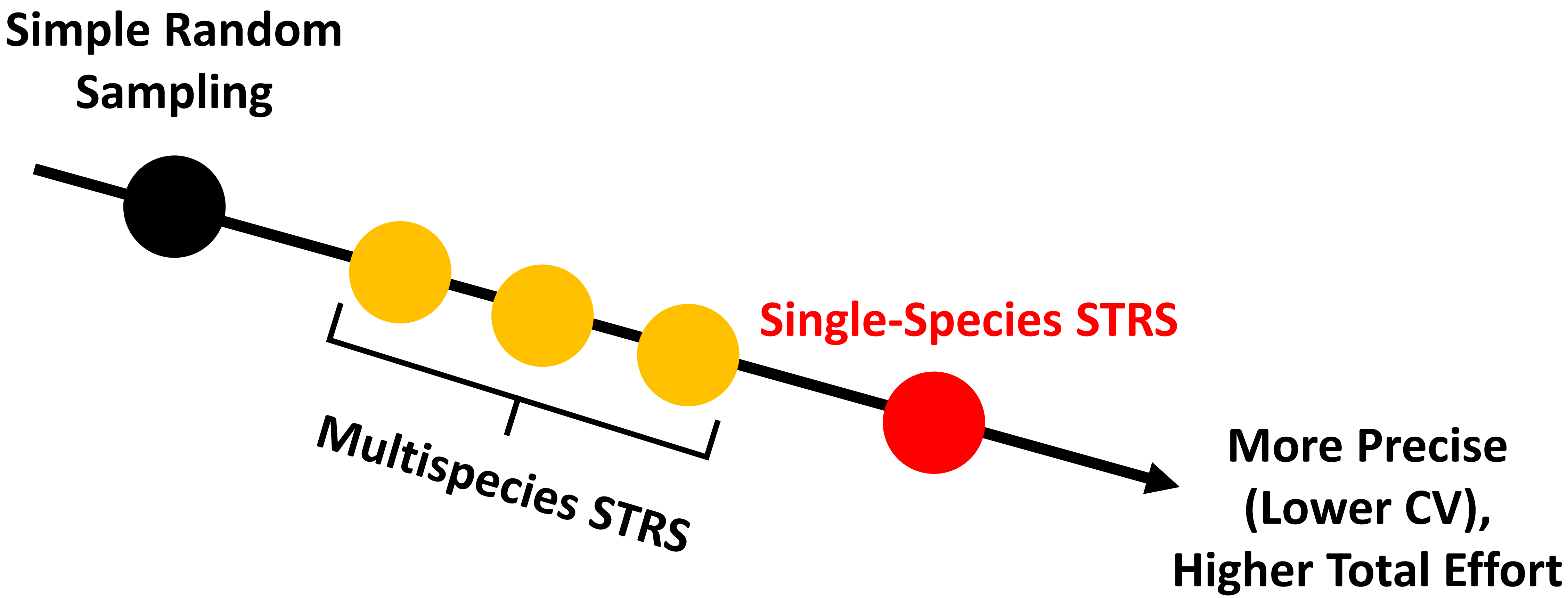
1. **Genetic algorithm**: searches for optimal stratification boundaries based on defined stratum variables

2. **Bethel algorithm**: optimizes allocation of samples across strata given user-defined upper limit on precision for each species (CV constraints)
   a) Determines which solutions advance in evolution of genetic algorithm (those with lowest sample size)

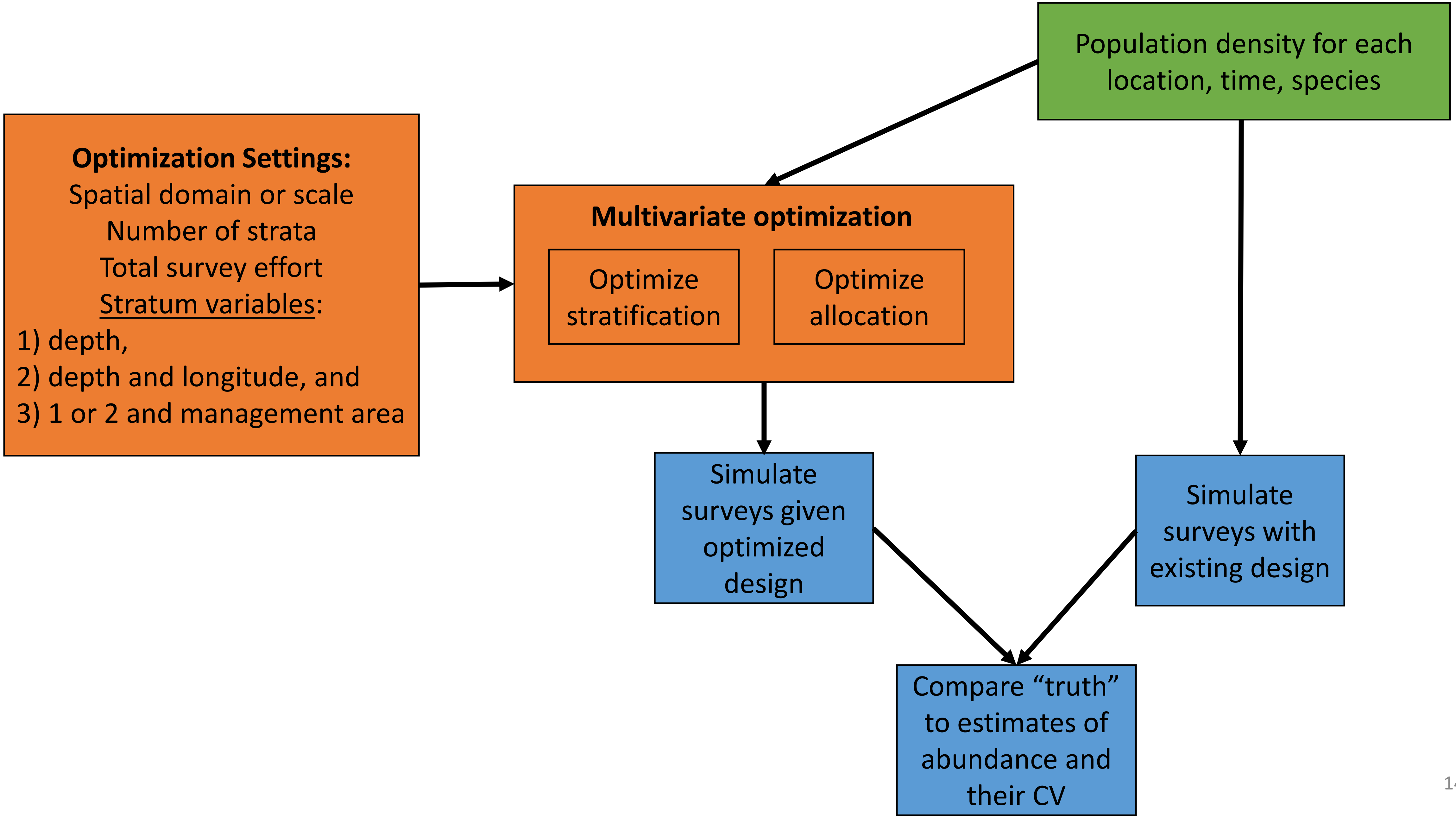
3. CV constraints are tuned to find the value obtainable given a desired sample size (total survey effort)



Bounding and tuning CV constraints



Project overview: operating model -> survey optimization -> expected performance



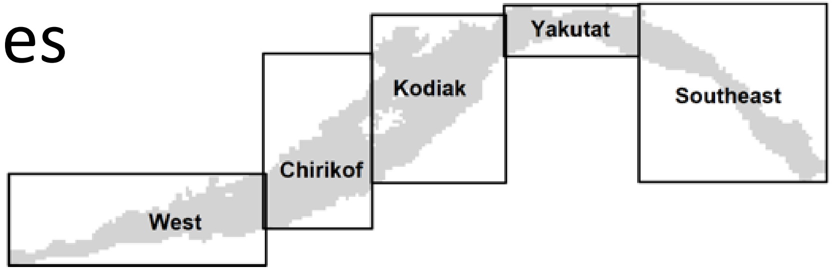
Simulating surveys to evaluate performance

Survey settings

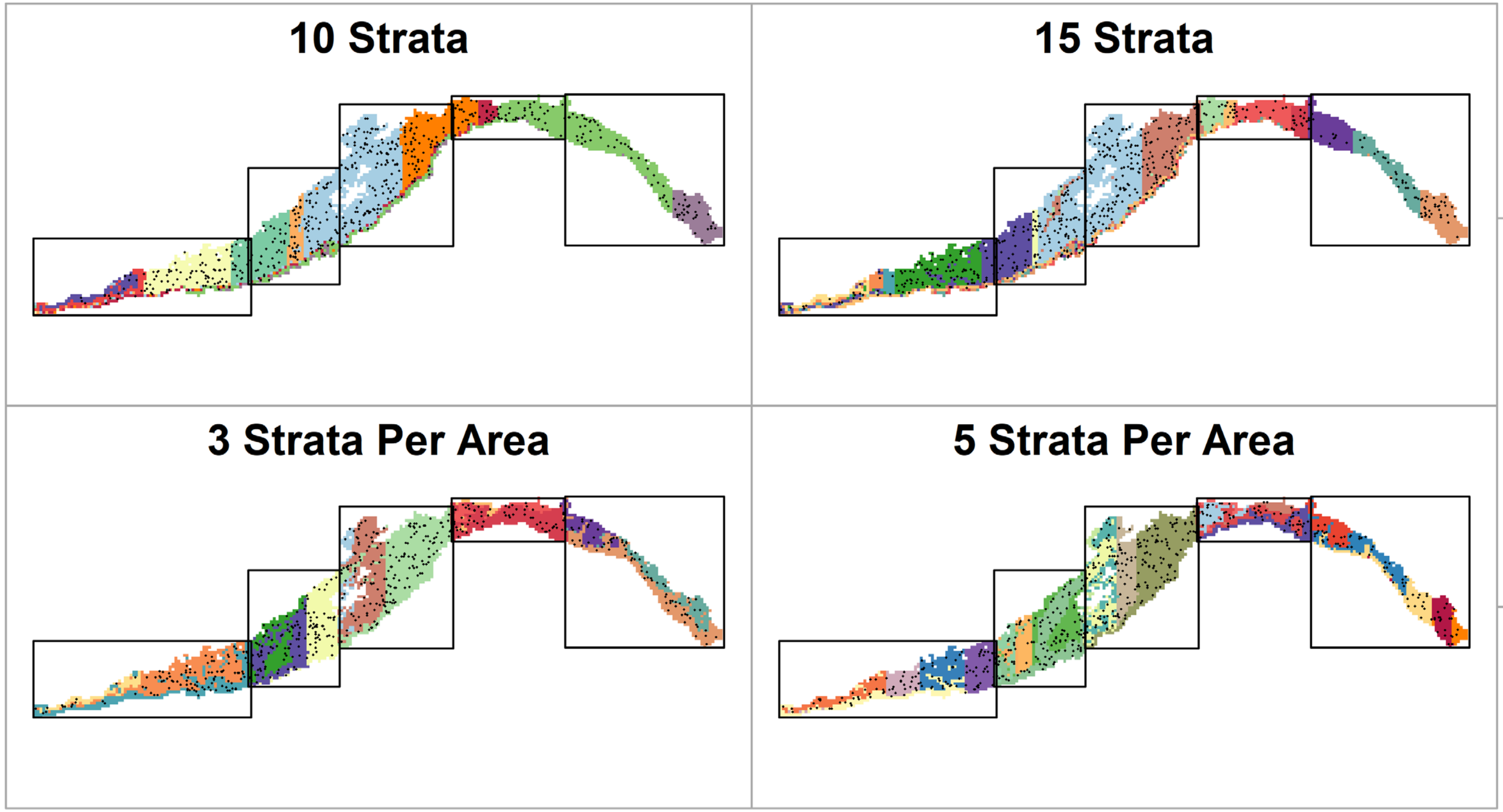
- 1000 survey replicates, each with 550 stations (2-boat survey)
- All locations assumed to be trawlable
- Performance metrics
  - Index bias, index precision, and uncertainty of precision estimate

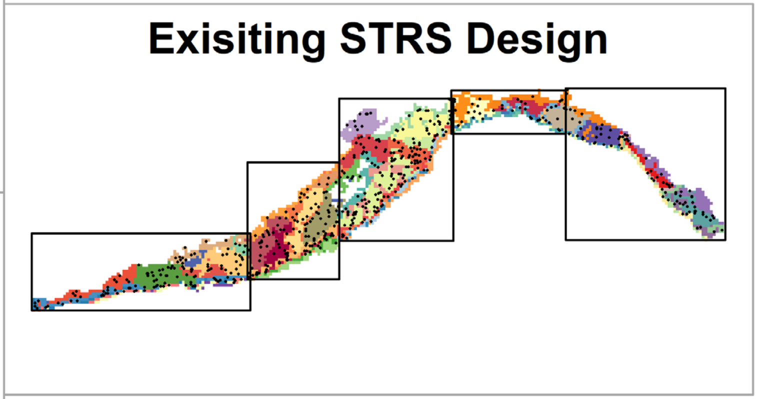
Five survey designs:

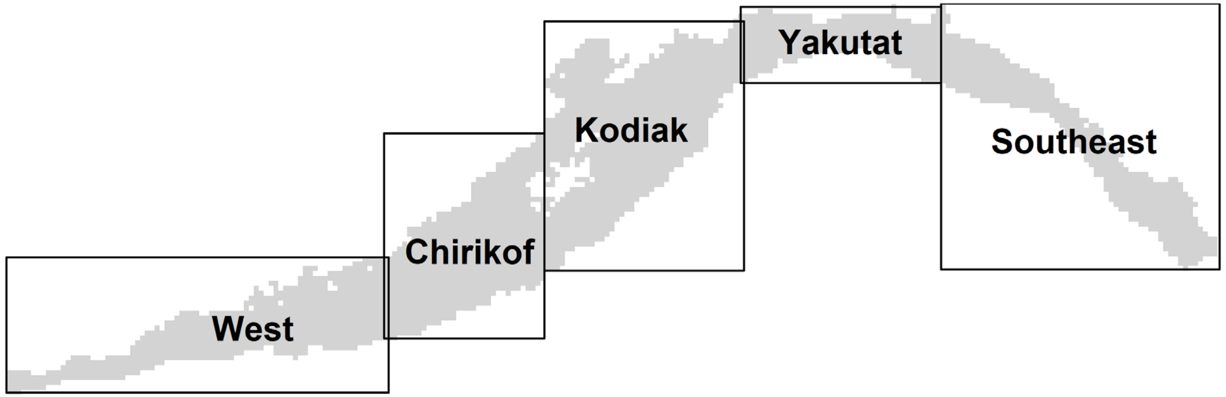
- <u>Proposed survey</u>, optimized at two spatial scales
  - *Gulf-wide*: 10 or 15 strata
  - *Management area-level*: 3 or 5 strata per area
- <u>Existing survey</u>
  - Strata > 700m are not allocated samples at this effort level



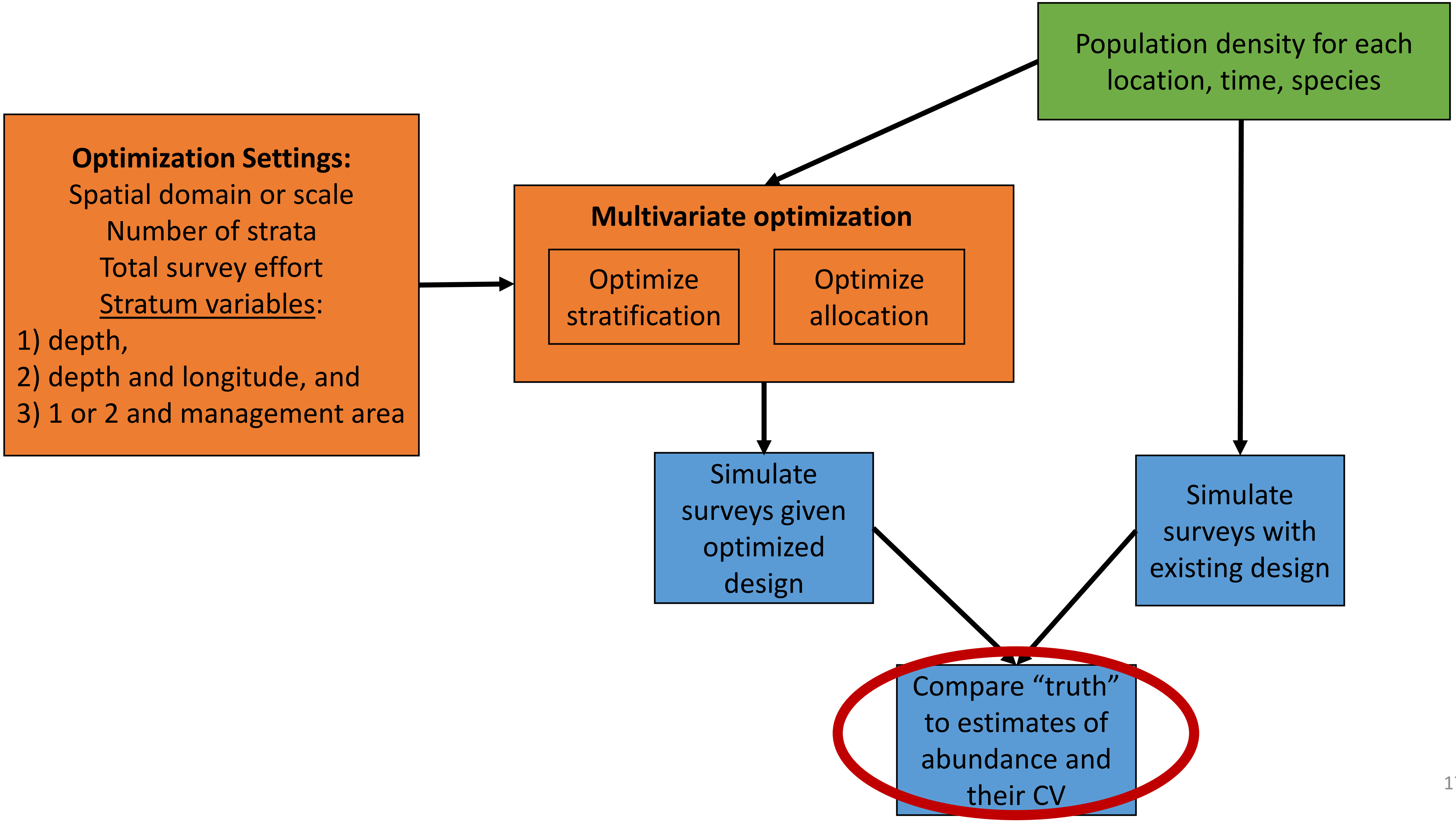
Strata boundaries differ with N strata and optimization scale



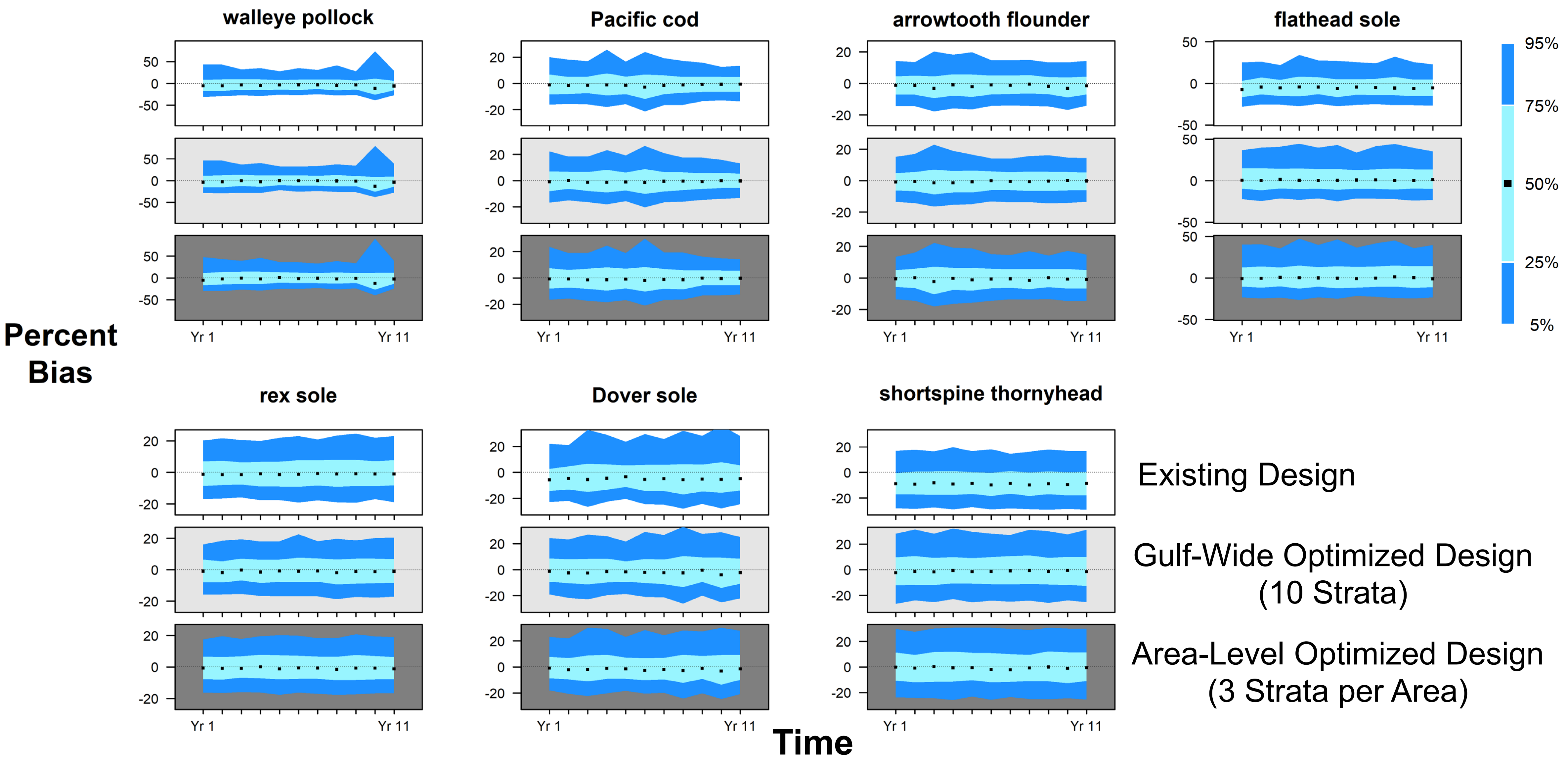




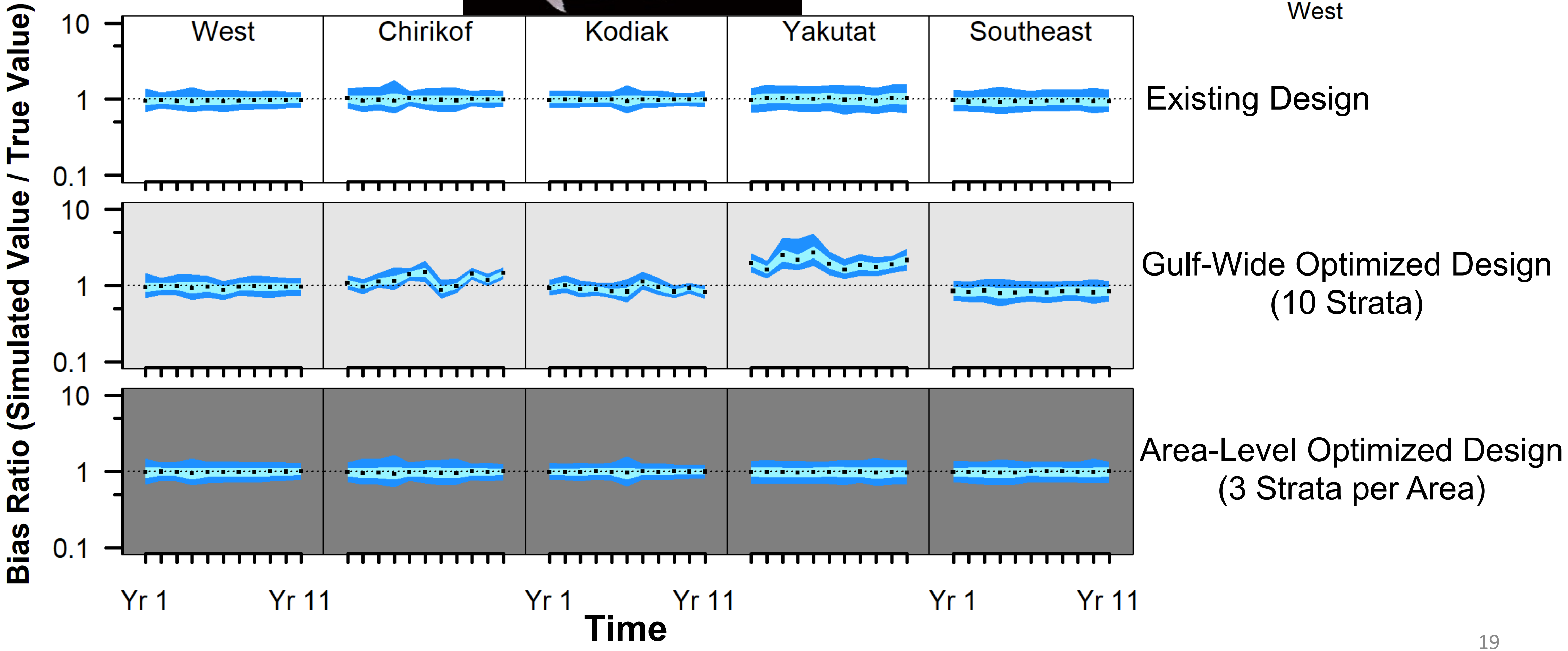
Project overview: operating model -> survey optimization -> expected performance

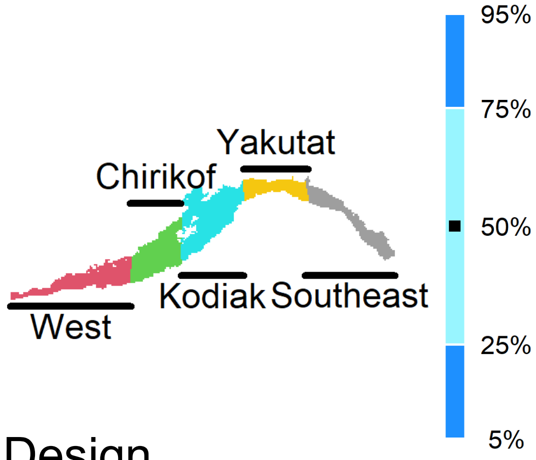


Bias in abundance is reduced by optimization

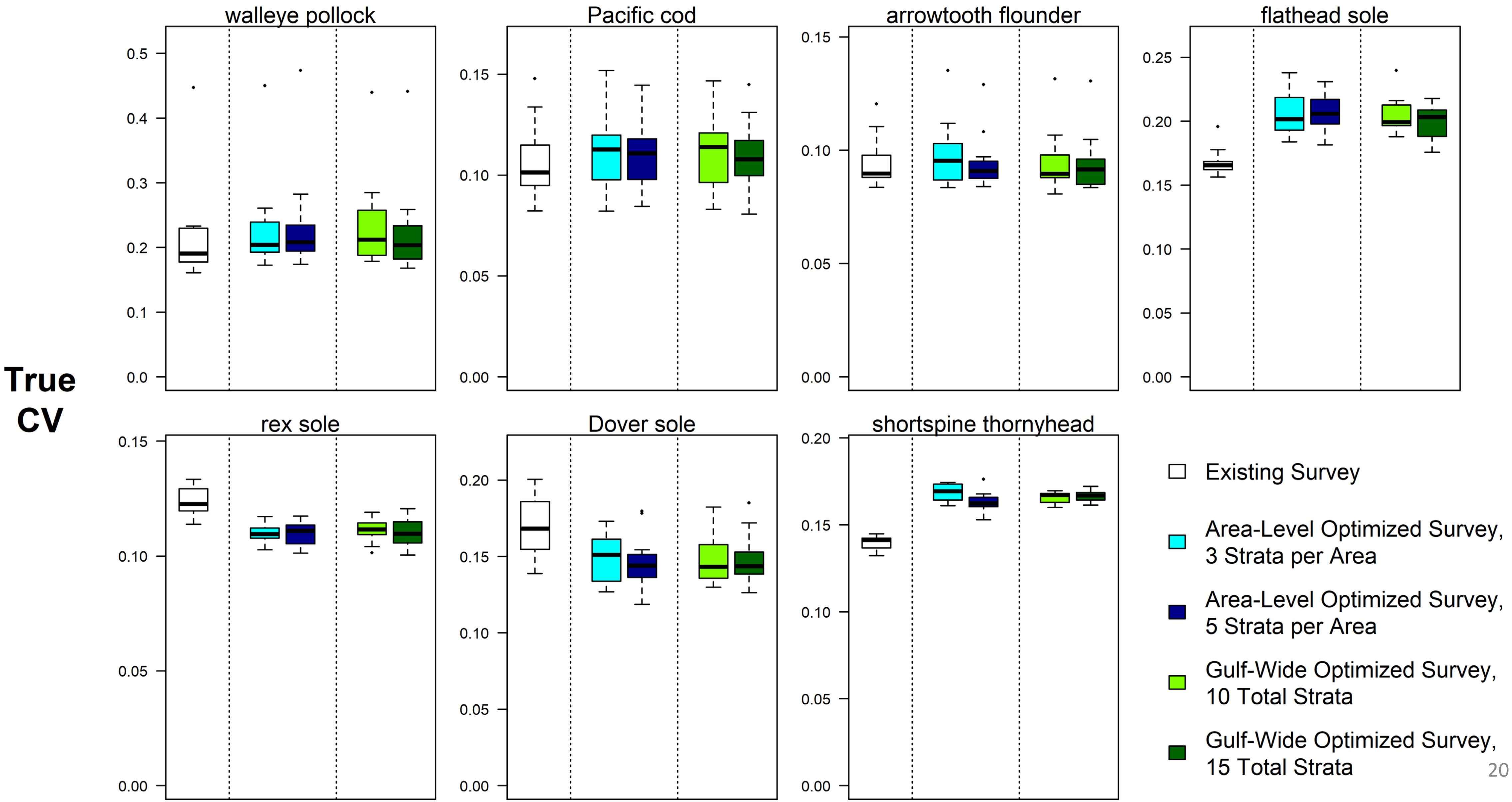


Area-level optimization eliminates bias from post-stratifying results from gulf-wide design

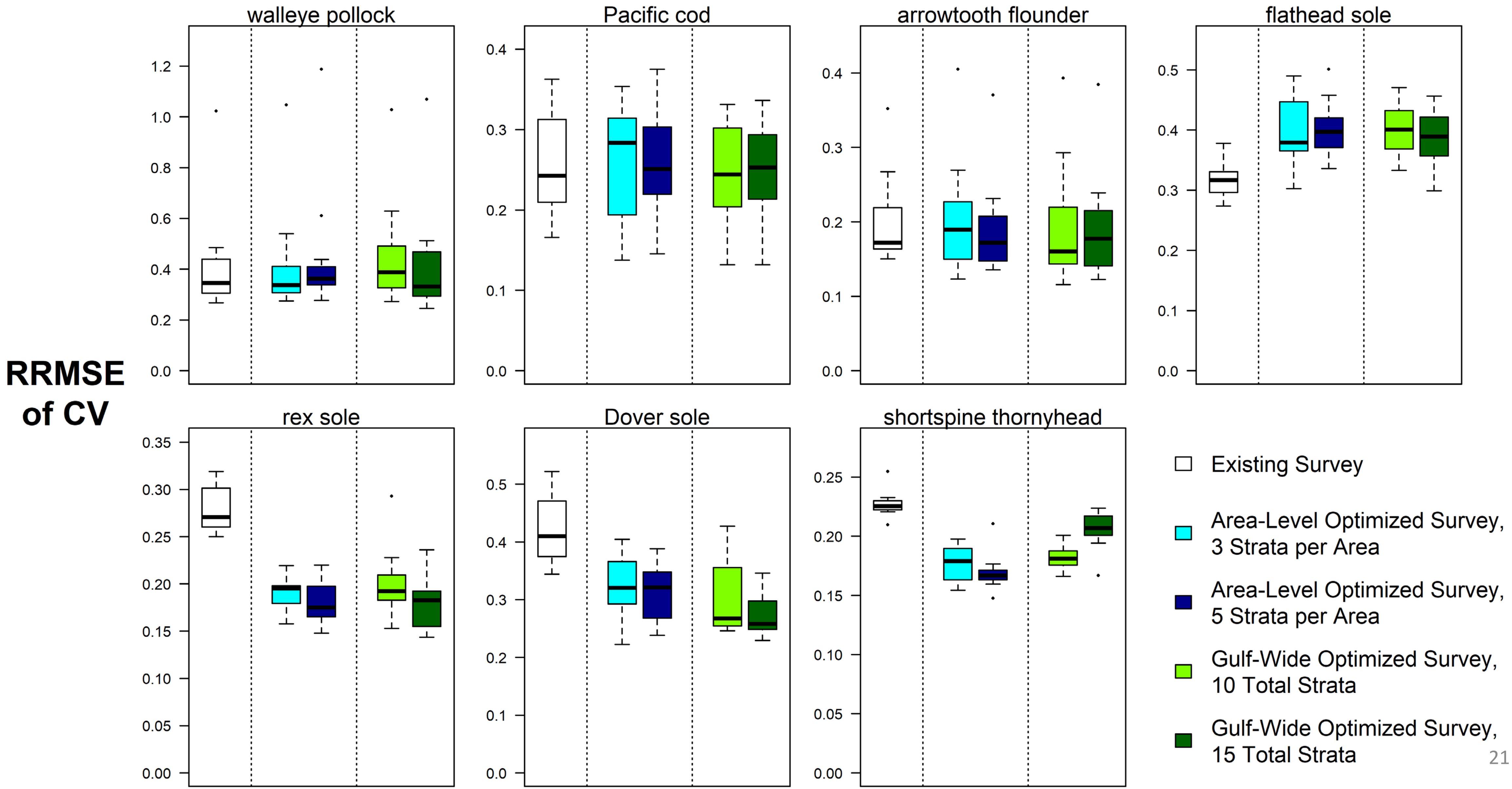




Mean precision is similar between designs, with exceptions



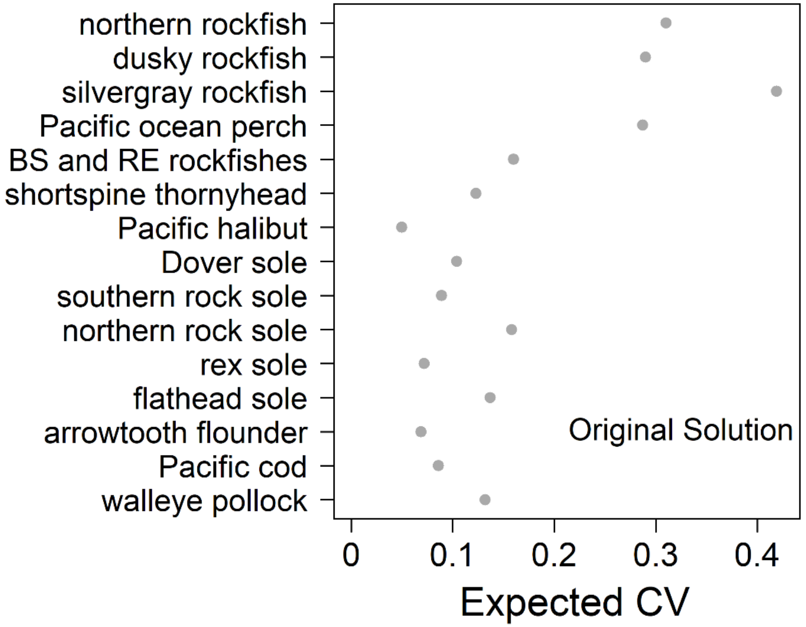
Accuracy of CV is improved more often than not

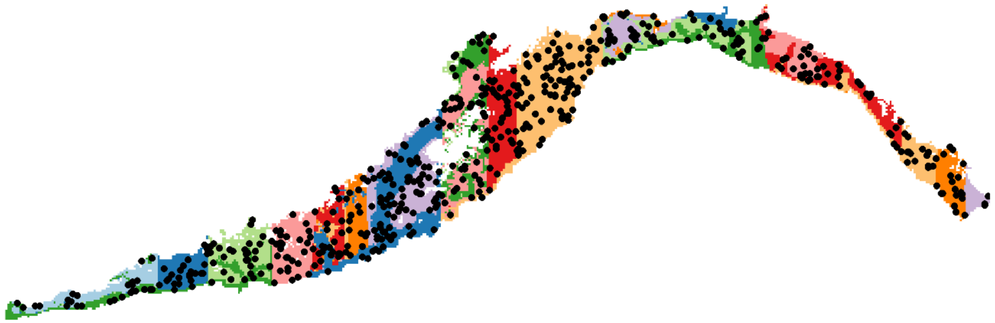


Addressing interspecific tradeoffs and species prioritization

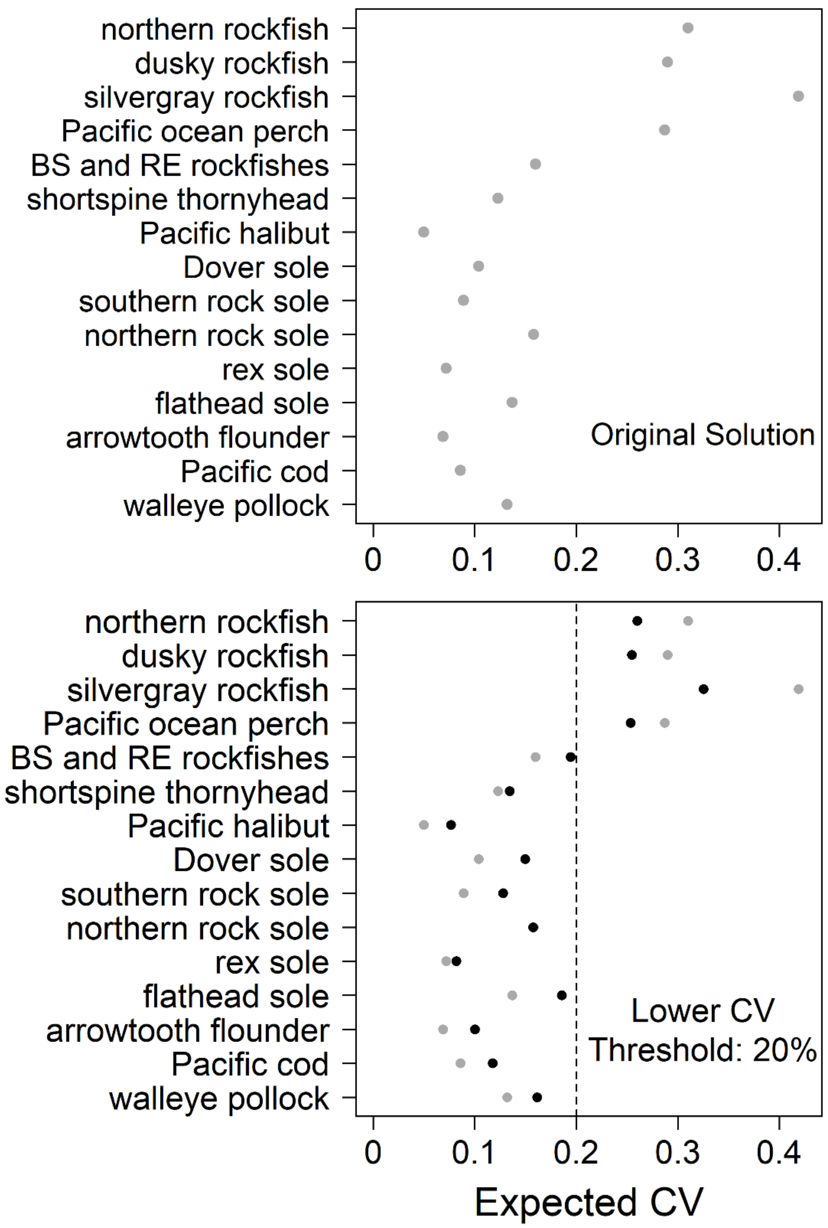
- Why?
  - Increase efficiency to obtain accurate and precise estimates for the most stocks
- Options
  1. Reduce CV constraints for all species proportionally
  2. Reduce CV constraints of stocks with greatest uncertainty
  3. Fix CV constraints at targets/limits determined by assessment authors (or via ongoing work by Spencer)

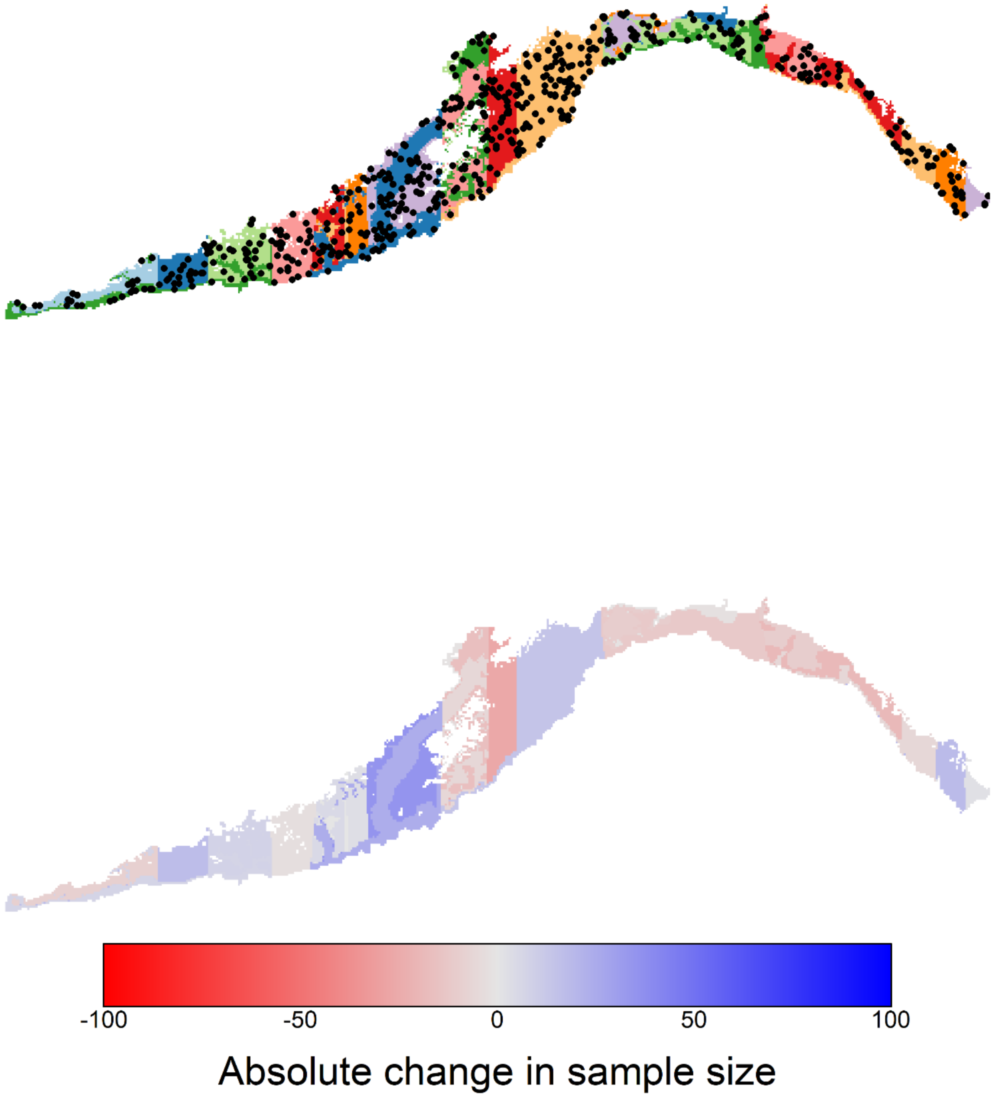
Tradeoffs of reducing uncertainty for rockfishes





Tradeoffs of reducing uncertainty for rockfishes

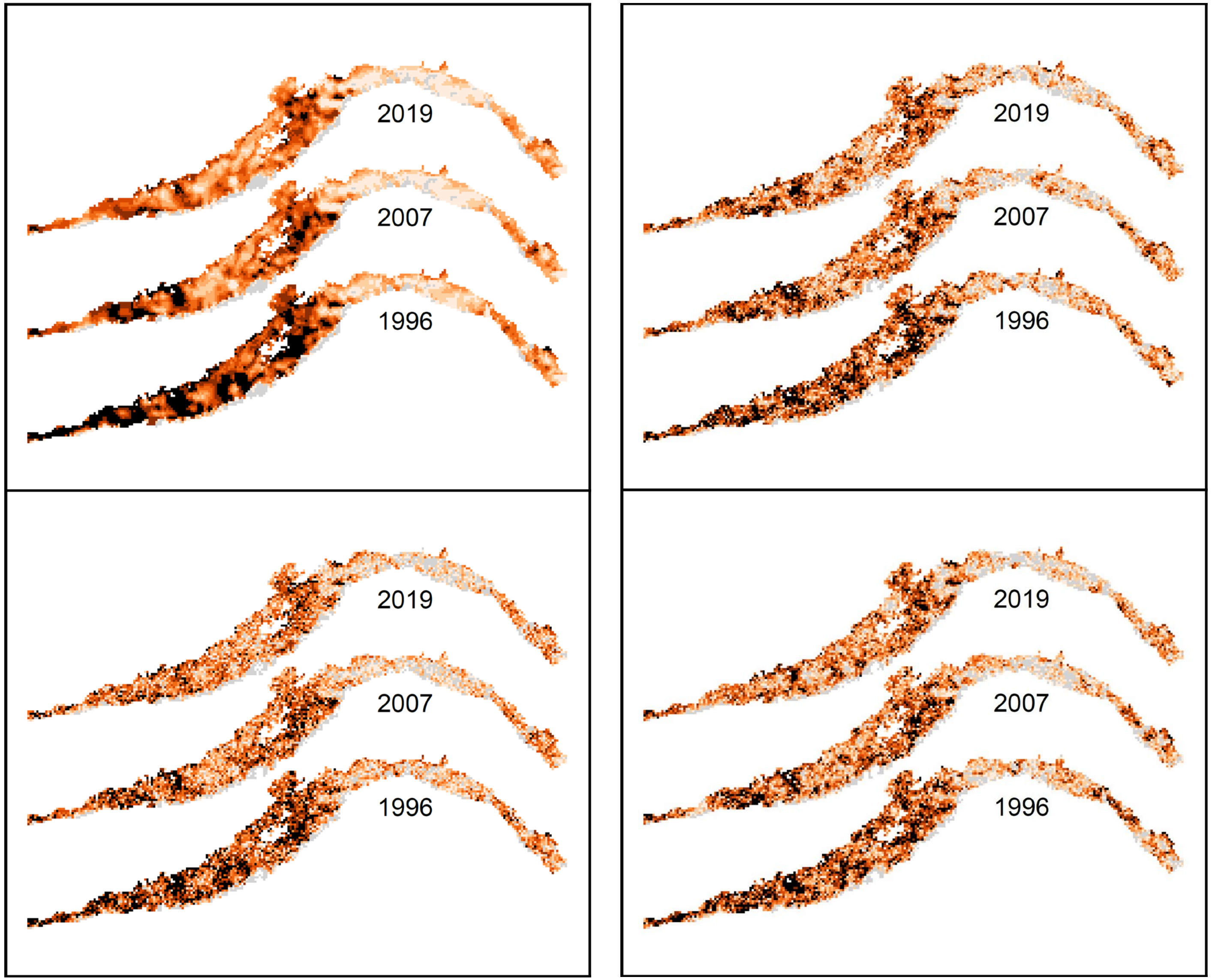




Sensitivities: Incorporating measurement and estimation error

Predicted density at MLE (conditioning model)

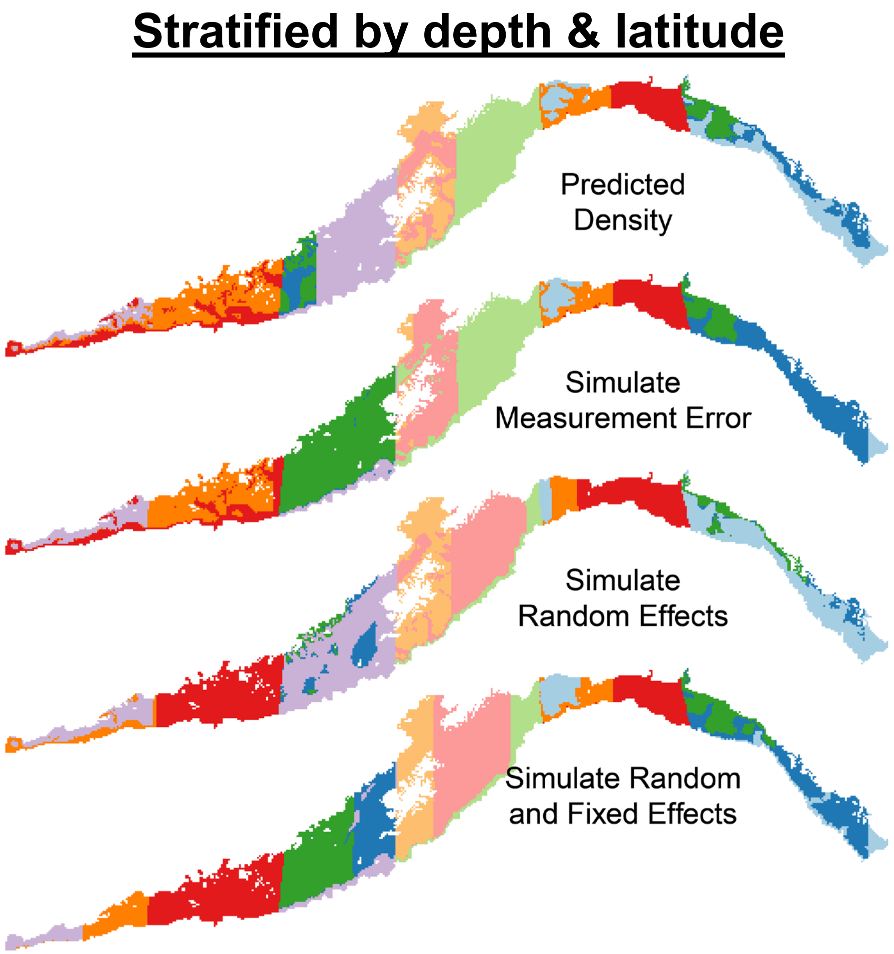
Simulated density with estimation error (random effects)

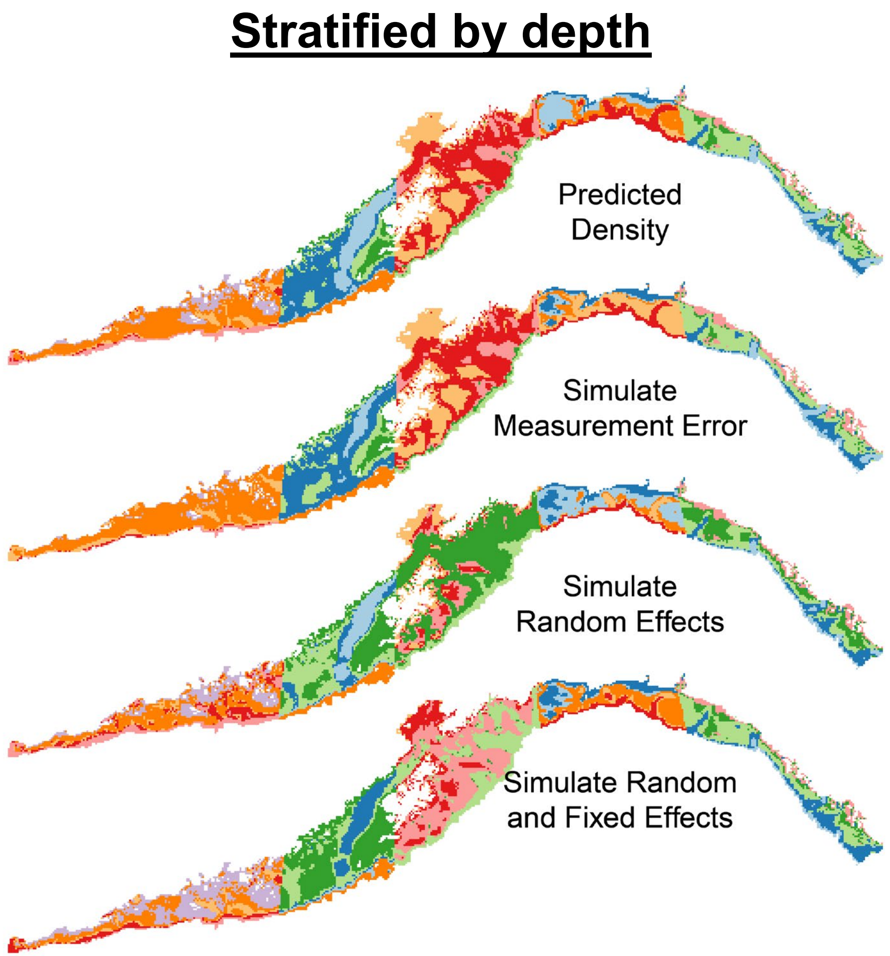


Simulated density with measurement error

Simulated density with estimation error (fixed and random effects)

Sensitivity of strata boundaries to uncertainty in density





Proposal: incorporate expert knowledge by letting survey team modify strata boundaries of base case, given alternatives from simulation draws

Summary: advantages of proposed design

- Can design a survey to meet user-specified precision constraints
- Improve abundance index estimation for some species
  - Reduce bias (important for tier 5 stocks)
  - Increase accuracy of uncertainty estimate (important for data-weighting)
  - Tailor optimization to prioritize species based on management needs
- Improved flexibility of surveys given modular approach
  - Can update and adjust operating model (update years, use different models and covariates)
  - Enabling quick, data-driven decisions on where to cut samples when necessary

Future and ongoing work

- Operating model
  - Improving predictive skill
- Optimization
  - Final decisions on species-specific CV constraints
- Tactical adjustments post hoc
  - Adjust strata based on expert knowledge or other analyses

Questions for Plan Team consideration:

1. Is this general approach acceptable?
2. How to approach species prioritization?
3. Whether/how often to update design given changes in ecosystem and management priorities?
4. What else would you like to see to inform whether/how to change the survey?

Questions for us?

Supplemental methods: performance metrics

- **Objective**: compare uncertainty and bias in abundance index for optimized and current design, across potential sampling effort levels

- **Computation**: simulate $D = 1000$ surveys, compare abundance index precision and accuracy relative to their true value, for each species and year

  - **Precision of estimated mean:**

$$CV_{true} = \frac{\sqrt{(D-1)^{-1}\sum_{d=1}^{D}(y_d - \bar{y})^2}}{Y}$$

  - **Relative bias of estimated mean:**

$$RB(y) = 100\% \frac{\sum_{d=1}^{D}(y_d - Y)}{D\ Y}$$

  - **Accuracy of uncertainty estimate:**

$$RRMSE(CV) = \frac{\sqrt{D^{-1}\sum_{d=1}^{D}(CV_d - CV_{true})^2}}{\overline{CV}}$$

Expected performance