

FISS rationalisation

Agenda item 5.1 IPHC-2019-SRB015-06

Background

- Program of planned FISS expansions undertaken from 2014-19
- In each Regulatory Area, gaps in FISS coverage were sampled, providing data for the full geographic extent of North American Pacific halibut for the first time
- However, this full FISS footprint is too expensive to sample annually
- Need to establish a set of methods for determining annual FISS designs that meet sampling goals subject to FISS cost constraints



Summary of methods for FISS rationalisation

- Propose data quality targets
- Determine geographic sampling priorities and sampling frequency
- Test designs on simulated data sets
- Propose design options
- Estimate design costs



Precision targets

• To maintain data quality, we proposed the following targets on coefficient of variation (CV):

Management unit	O32 WPUE	All sizes WPUE	All sizes NPUE
Reg Area (all)	15%	15%	NA
Bio Regions 2, 3, 4	10%	10%	10%
Bio Region 4B	15%	15%	15%
Coastwide	NA	NA	10%



Potential for bias

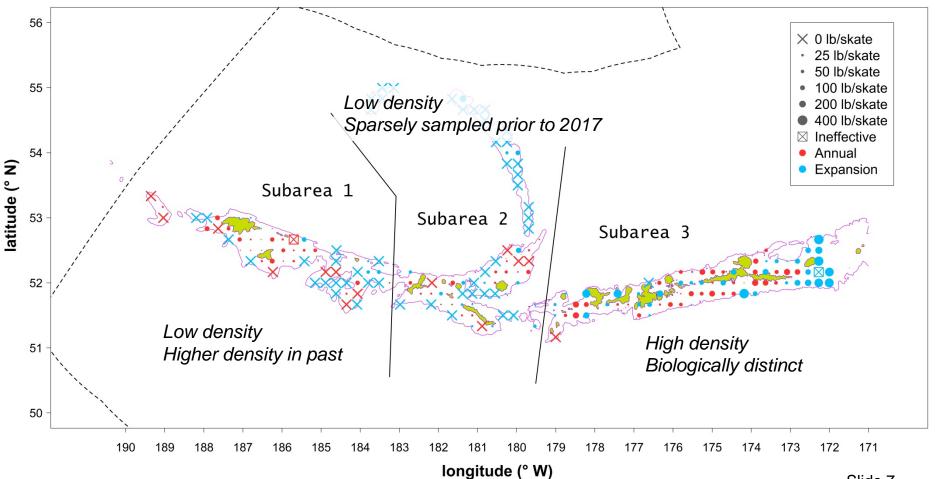
- Failure to observe and account for changes in WPUE or NPUE in an unsurveyed subarea can lead to bias
- Therefore, it is important to undertake setline surveys frequently enough to keep any bias small
- In this, we are guided by estimates of past changes



Example: Regulatory Area 4B and 2A

- At SRB014, we looked at two examples
- Regulatory Areas 4B and 2A were each divided into three subareas
 - Subareas based on historical density and biological characteristics
- Subareas were prioritised for future sampling based on recent biomass proportions and potential for bias if unsampled





Reg Area 4B sampling priorities

- 1. Subarea 3: 70-80% of biomass since 2013
- Subarea 1: Frequent changes of ≥10% of biomass % over short periods (3-4 years)
- 3. Subarea 2: Generally low and stable biomass % (but likely affected by sparse historic sampling)



Evaluation of options

- Fit models using simulated data for future years
- Models can take a long time to run: full simulation study using many data sets not practical
- Instead, for each year, single simulated sample data sets were taken from the posterior samples from the 2018 modelling



Results of simulations: are CV targets met?

Estimated CVs (%) by data input for Reg Area 4B. Target CV = 15%.

Data input	Sampled subareas	2017	2018	2019	2020	2021	2022
1993-2018 data		9	14				
+ 2019-20 simulated data	2020 Subarea 3	9	13	12	10		
+ 2019-21 simulated data	2020-21 Subarea 3	10	13	13	11	12	
+ 2019-22a simulated data	2020-22 Subarea 3	9	12	12	10	12	14
+ 2019-22b simulated data	2020-21 Subarea 3 2022 Subarea 1	9	12	12	10	11	17
+ 2019-22c simulated data	2020-21 Subarea 3 2022 Subareas 1, 2	9	11	11	9	9	14



IPHC-2019-SRB014-R

The SRB REQUESTED analysis of past prediction patterns (a type of cross-validation analysis) to help assess the proposed methods' ability to meet precision targets while maintaining low bias. This should include an examination of spatio-temporal residual patterns for the appropriateness of estimated autocorrelation.



Past prediction patterns

- Compare predictions of CVs from simulated data with observed CVs
- Undertaken for FISS year 2018
 - Models refit using simulated data (samples from 2017 posterior predictive distributions) in place of observed data for 2018
 - Undertaken for Reg Areas 4B and 2A
 - Repeated three times (i.e., using three simulated 2018 data sets) as a check for consistency



CVs (%) for 2018 O32 WPUE estimated using full 1993-2018 data series, and using simulated data for 2018

Reg Area	1993-2018 data	1993-2017 data, 2018 simulated				
		Sim 1	Sim 2	Sim 3		
2A	11.7	10.8	10.3	11.0		
4B	14.1	12.9	13.4	13.8		

- CVs estimated using simulated data consistently lower than that estimated from observed data
- Differences are small (0.3-1.4%)
 - Does not imply the use of posterior samples to predict precision should affect comparison of future design options



Posterior predictive diagnostics

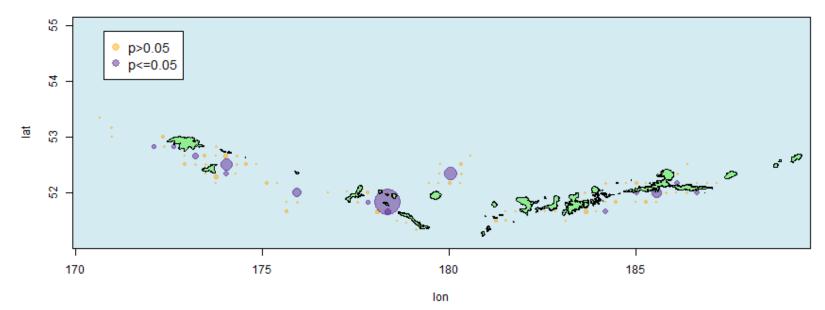
• Used discrepancy measure, *T*, to assess model fit (Cressie and Wikle, 2011):

$$T(Z_i; Y, \theta) = \frac{\left(Z_i - E(Z_i | Y, \theta)\right)^2}{\operatorname{var}(Z_i | Y, \theta)}$$

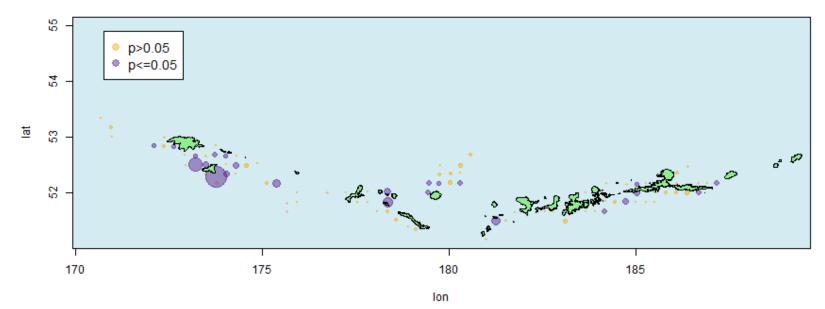
- Z_i is observed WPUE or WPUE, Y is the underlying process, and θ is the parameter vector.
- Value of *T* for each Z_i can be compared to distribution obtained by substituting the posterior samples for Z_i , denoted by $Z_{i,rep}$
- "Extremeness" of values of *T* measured using posterior predictive *p*-values:

$$P(T(Z_{i,rep}; Y, \theta) \ge T(Z_i; Y, \theta) | Z_i)$$

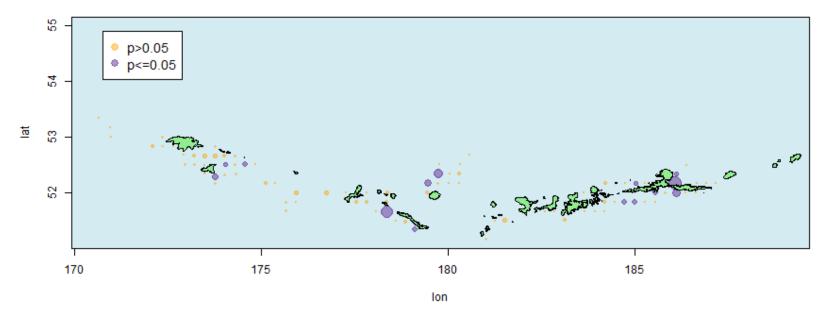




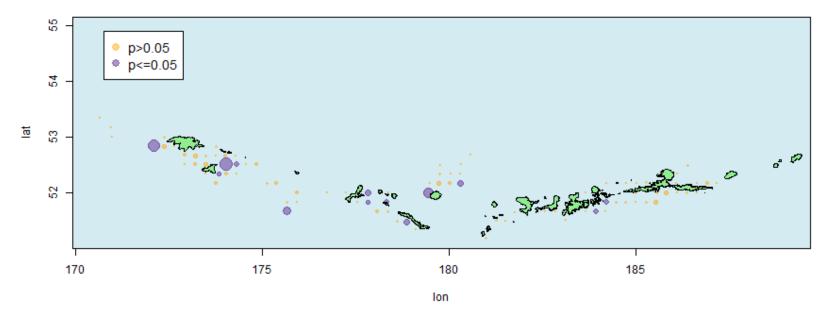




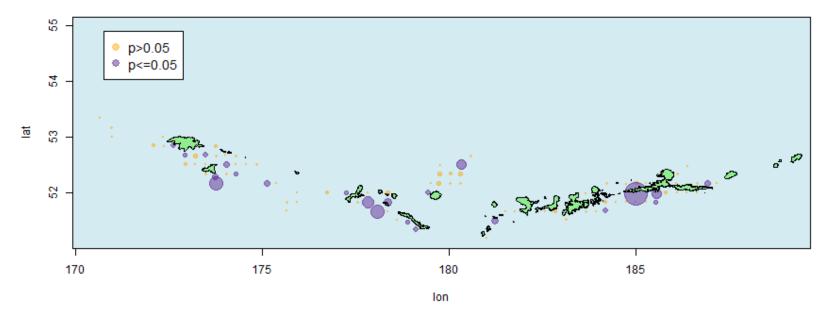




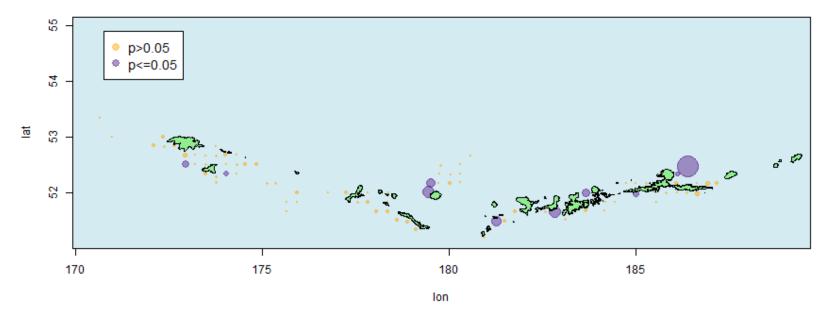






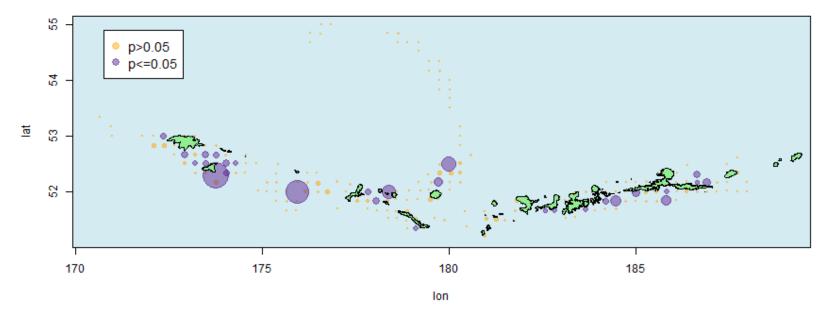






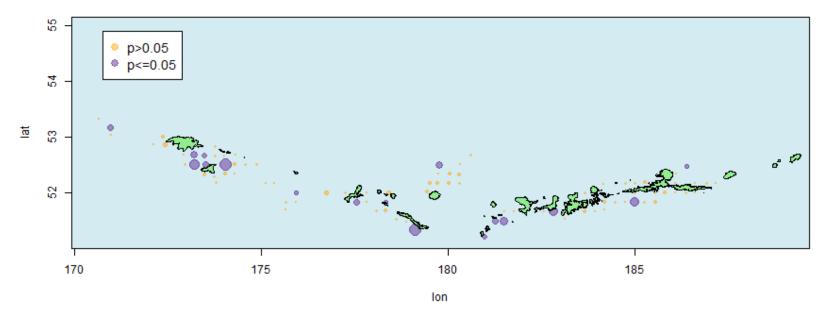


4B 2017

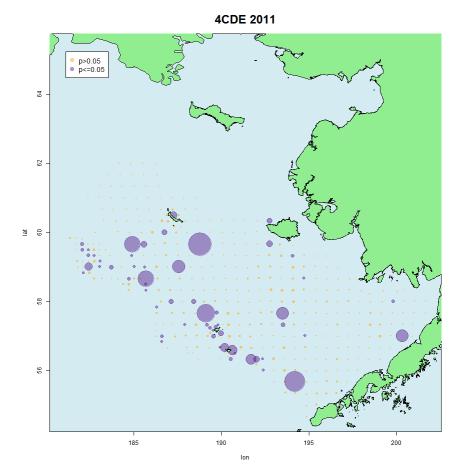




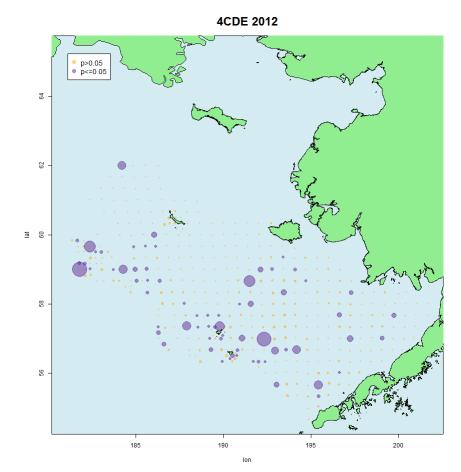




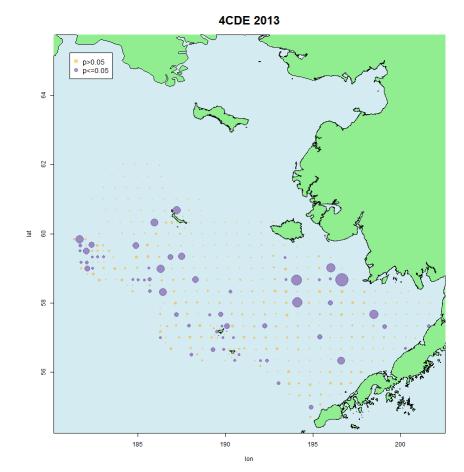


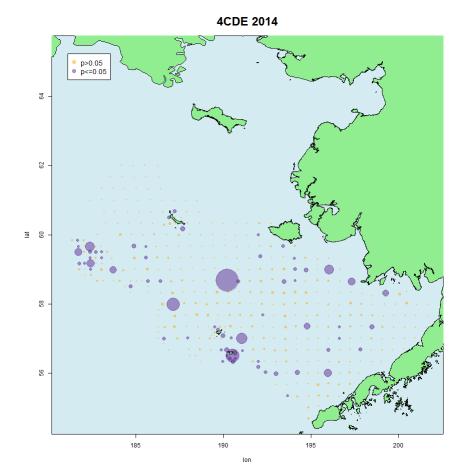




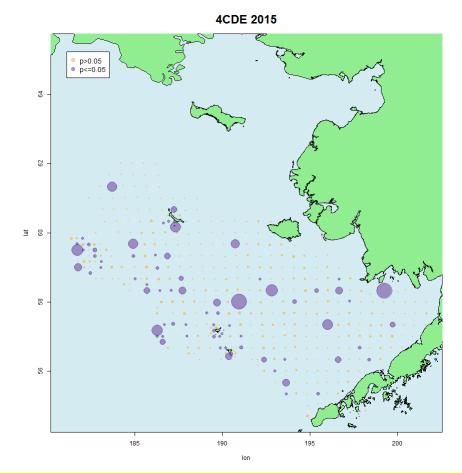


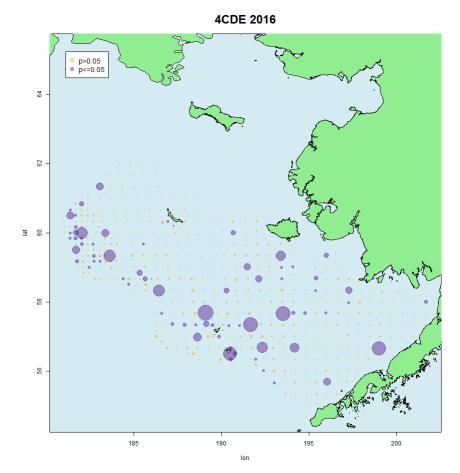






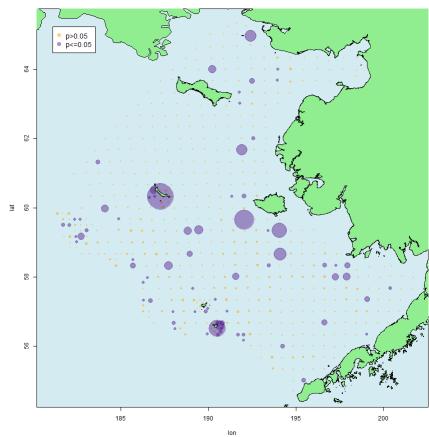






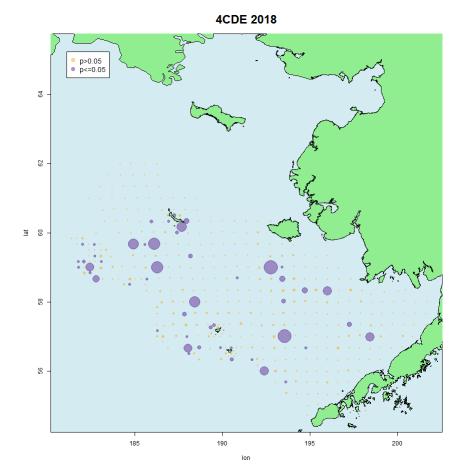


4CDE 2017





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Map summary

- Evidence for localised lack of fit in space-time model
- No clear, consistent patches of lack of fit in Reg Area 4B
- Possible clusters of high discrepancy values on Bering Sea shelf edge and around islands in most years
 - Strength of spatial dependence may vary with habitat



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