Optimizing age-reading efforts

Goal:

Optimally allocate age-reading efforts across samples and species

Approach:

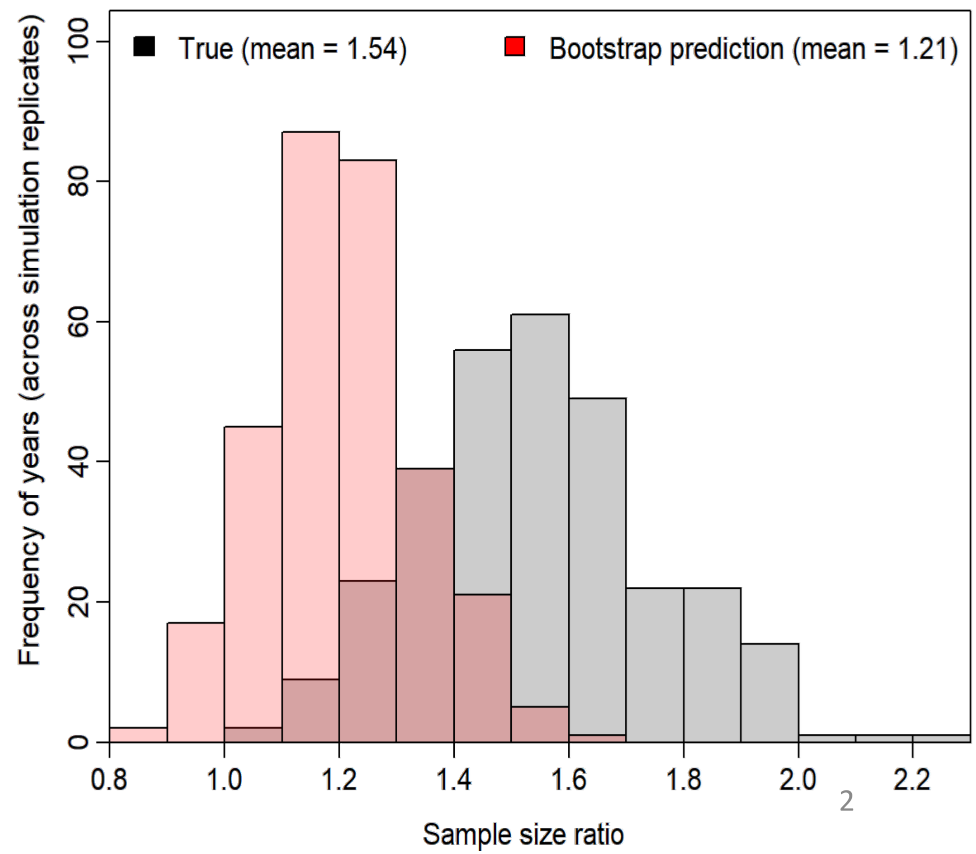
- Break pipeline into four pieces
  1. Number of ages $n_{nominal}$ to input sample size n_{input}
  2. n_{input} affects effective sample size, $n_{effective}$
  3. $n_{effective}$ affects stock-assessment variance $Var(X)$
  4. $Var(X)$ affects management performance
- Bootstrap simulation for step #1
  - Simulation-test using age-structured operating model
- Theoretical result for step #2
  - Simulation-test using population-dynamics model

Thorson, Bryan, Hulson, Punt. 2020. Simulation testing a new multi-stage process to measure the effect of increased sampling effort on effective sample size for age and length data. ICES Journal of Marine Science 77:1728–1737.

Optimizing age-reading efforts

Step #1 approach – Simulation evaluation

- Fit age-structured spatio-temporal model to walleye Pollock and use as operating model
- Simulate proportions using operating model
- Sample age-reads and calculate input-sample size
- Bootstrap with twice as many ages per tow, and use as predicted change
- Compare with true value when sampling twice as many age-reads



Optimizing age-reading efforts

Step #2 approach – Theoretical relationship

1. Based on “linear” Dirichlet-multinomial approach to weighting age/length data

$$n_{effective}(t) = \frac{1}{1+\theta} + n_{input}(t)\frac{\theta}{1+\theta}$$

2. Decompose variance into model and sampling error

$$Var_{total} = Var_{sampling} + Var_{model\,mis-specification}$$

… and plug in estimates…

$$\frac{c}{n_{effective}} = \frac{c}{n_{input}} + \sigma^2_{model}$$

… and predict effective sample size $n^*_{effective}$ under a new input sample size n^*_{input}

$$\frac{c}{n^*_{effective}} = \frac{c}{n^*_{input}} + \sigma^2_{model}$$

3. Predict effective sample size $n^*_{effective}$ given new input sample size n^*_{input}

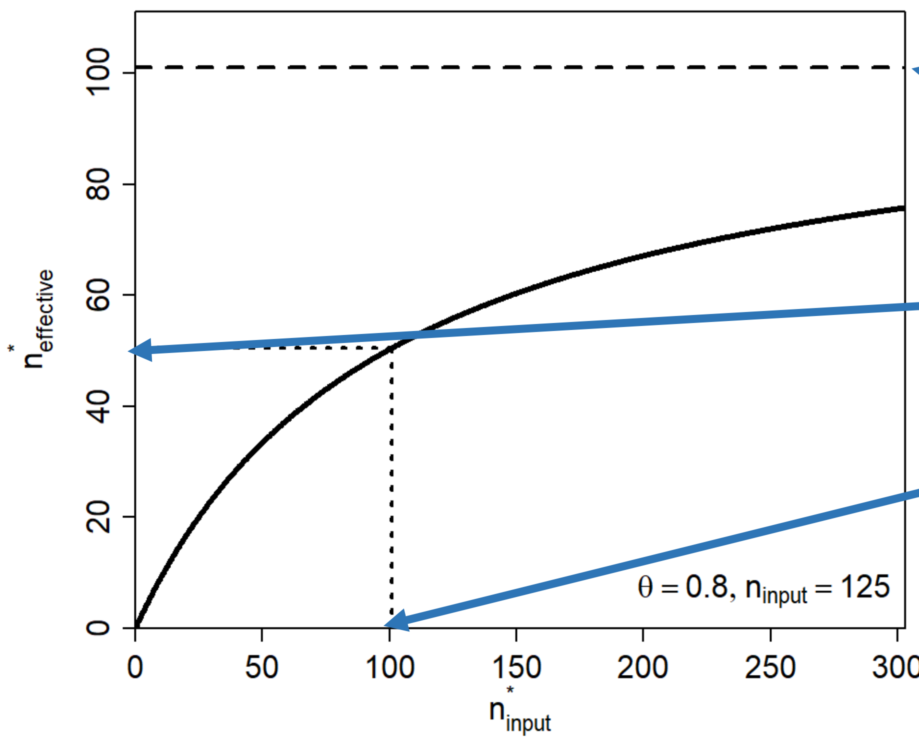
$$n^*_{effective}(t) = \frac{n^*_{input}(t)(1+\theta n_{input}(t))}{n^*_{input}(t) + \left(1+\theta n_{input}(t)\right)}$$

Optimizing age-reading efforts

Step #2 approach – Theoretical relationship

$$n^*_{effective}(t) = \frac{\alpha n^*_{input}(t)}{n^*_{input}(t) + \beta}$$

- a.k.a. Michaelis-Menten relationship with saturation and half-saturation constant $\alpha = \beta = 1 + \theta n_{input}(t)$



Saturation constant $(1 + \theta n_{input})$, i.e., maximum possible effective sample size

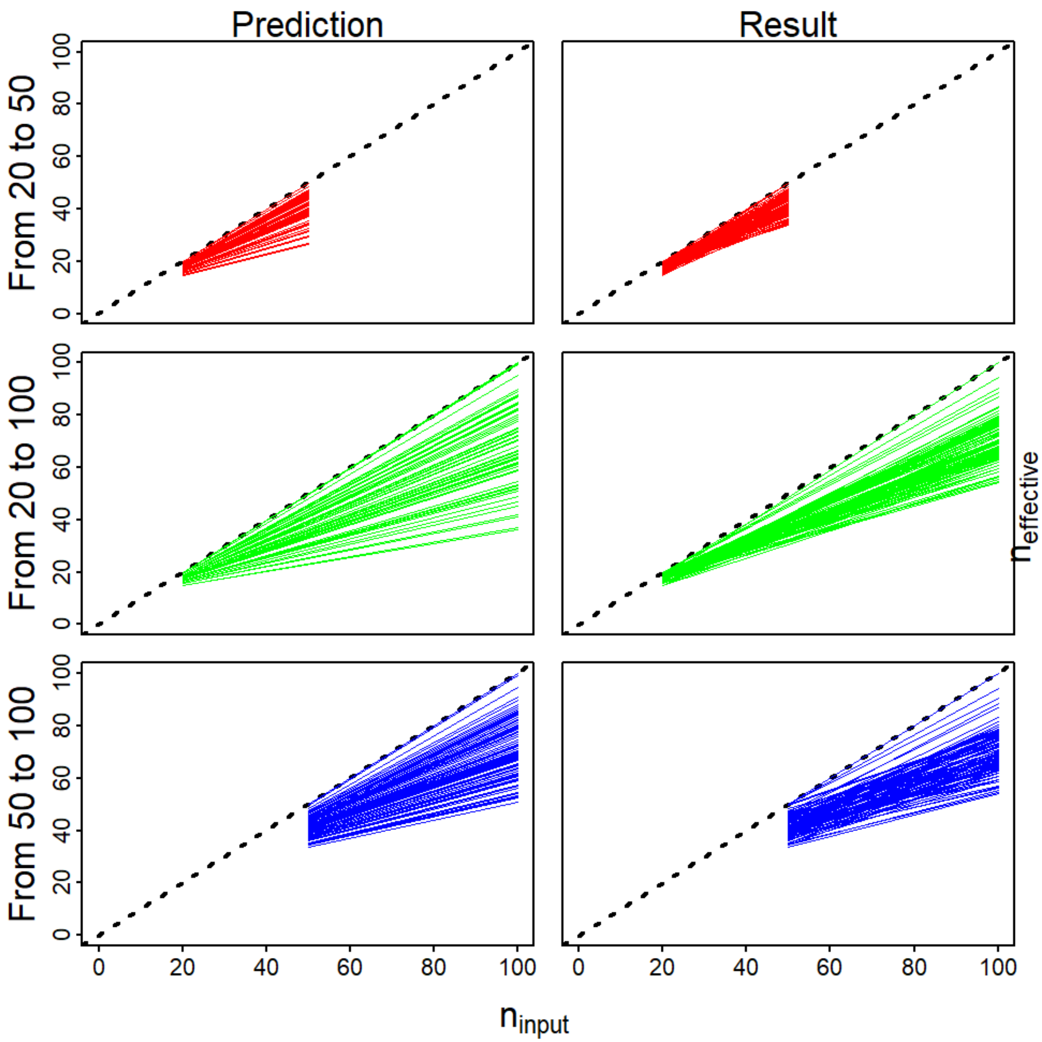
Half-saturation

Input sample size resulting in half-saturation

Optimizing age-reading efforts

Step #2 approach – Simulation evaluation

- Simulate age-structured dynamics with age-and-time varying selectivity
- Fit age-structured model with Dirichlet-multinomial and constant selectivity
  - Age data downweighted due to model mis-specification
- Predict change in effective sample size
- Compare with effective sample size given larger input sample size



The impact of changes to otolith field-sampling and ageing effort on input sample sizes and catch recommendation uncertainty

Project Team
- Jim Thorson
- Andre Punt
- Pete Hulson
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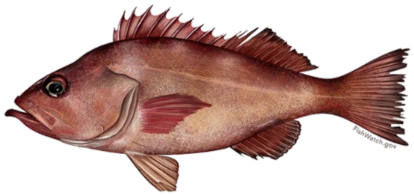
- Meaghan Bryan

Dusky Rockfish



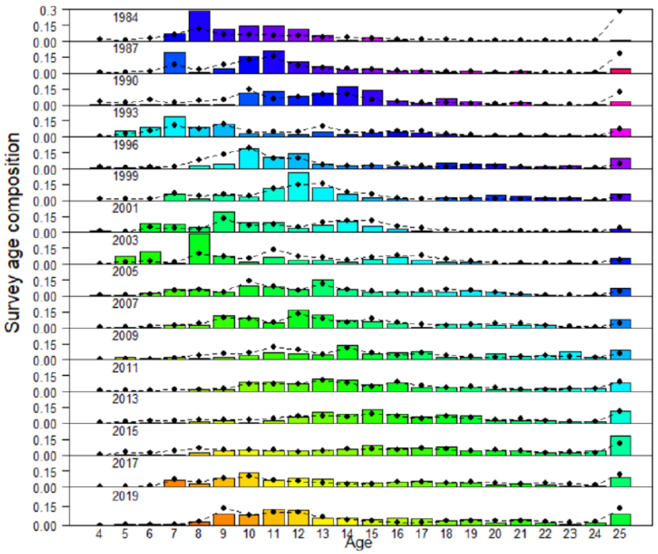
Pacific Ocean Perch

Walleye Pollock

Questions for plan team:
- Important EBS stocks to apply this to?
- Is it useful to have this type of analysis become a routine part of assessments?
- Should AFSC have a formal process to evaluate which stocks need more/less ageing effort?

Future research questions:
- Corroborate w/ model-based approach to generate N_{Input}
- How does reduction in tows affect designed-based index generation? What is this effect relative to age comps?

Background



Dusky Rockfish; Fenske et al. (2020)

- Can otolith sampling efforts be redistributed across species w/o increasing survey effort or catch recommendation uncertainty?
  - What are the tradeoffs re: sampling cost & revenue?
- How would changes to sampling affect data weighting?
  - Multinomial vs. Dirichlet-Multinomial (D-M) likelihood
  - Multinomial typically paired w/ iterative tuning
  - D-M provides similar estimates of N_{Eff} w/o iterative process
    - Estimate θ (governs ratio of N_{Input} & N_{Eff})

Sample Sizes

- **Nominal (NomSS)**: # of otoliths collected & aged
- **Input (N_{Input})**: initial relative weighting of comps data in model; upper bound on D-M weighting
- **Effective (N_{Eff})**: estimated weighting based on fit of comps data in model

Dirichlet Multinomial

$$\mathcal{L}(\tilde{\boldsymbol{\pi}}_t; \boldsymbol{\pi}_t, \theta, n_t) = \frac{\Gamma(n_t + 1)}{\prod_{i=1}^{n_i} \Gamma(n_t \tilde{\pi}_{a,t} + 1)} \frac{\Gamma(\theta n_t)}{\Gamma(n_t + \theta n_t)} \prod_{a=1}^{n_a} \frac{\Gamma(n_t \tilde{\pi}_{a,t} + \theta n_t \pi_{a,t})}{\Gamma(\theta n_t \pi_{a,t})}$$

Objectives

1. Identify the effect of re-distributing otolith sampling & ageing efforts among data-rich, data-moderate, and data-poor species on N_{Input} calculations

2. Associate a monetary cost to changes in otolith sampling & ageing efforts; define relationship between cost & uncertainty in catch recommendations from stock assessment models

3. Determine potential changes in revenue as a function of changing catch recommendation uncertainty across sampling rate scenarios

Work Flow

Bootstrap Estimator

- Generate new datasets of age data
- Sample & change number of tows or otoliths
- Resample tows & otoliths
- Calculate input sample size (N_{Input})

Conduct Stock Assessment

- Use age compositions generated from new datasets
- Use calculated N_{Input}
- Dirichlet-Multinomial distribution & ϑ-based N_{Eff} calculation
- Run assessment models

Ageing Cost & Uncertainty

- Calculate ageing cost using nominal sample size & per-otolith cost
- Calculate among-bootstrap uncertainty in OFL
- Relate cost to uncertainty in OFL across sampling rate scenarios

Predicting Changes in Revenue

- Define ABC/OFL buffer
- Use OFL uncertainty to predict changes in ABC across sampling rates scenarios, retaining buffer
- Translate changes in ABC to changes in revenue

- **Bootstrap Sampling Methods**:
  - Changing the number of otoliths for each tow (‘Otoliths Changed’)
  - Changing the number of tows (‘Tows Changed’)
- **Bootstrap Sampling Scenarios**:
  - ± 0%, ± 33%, ± 67%

Bootstrap Estimator

NRC Research Press

ARTICLE

Bootstrapping of sample sizes for length- or age-composition data used in stock assessments

Ian J. Stewart and Owen S. Hamel

Pull length data for survey

Sample tows with replacement

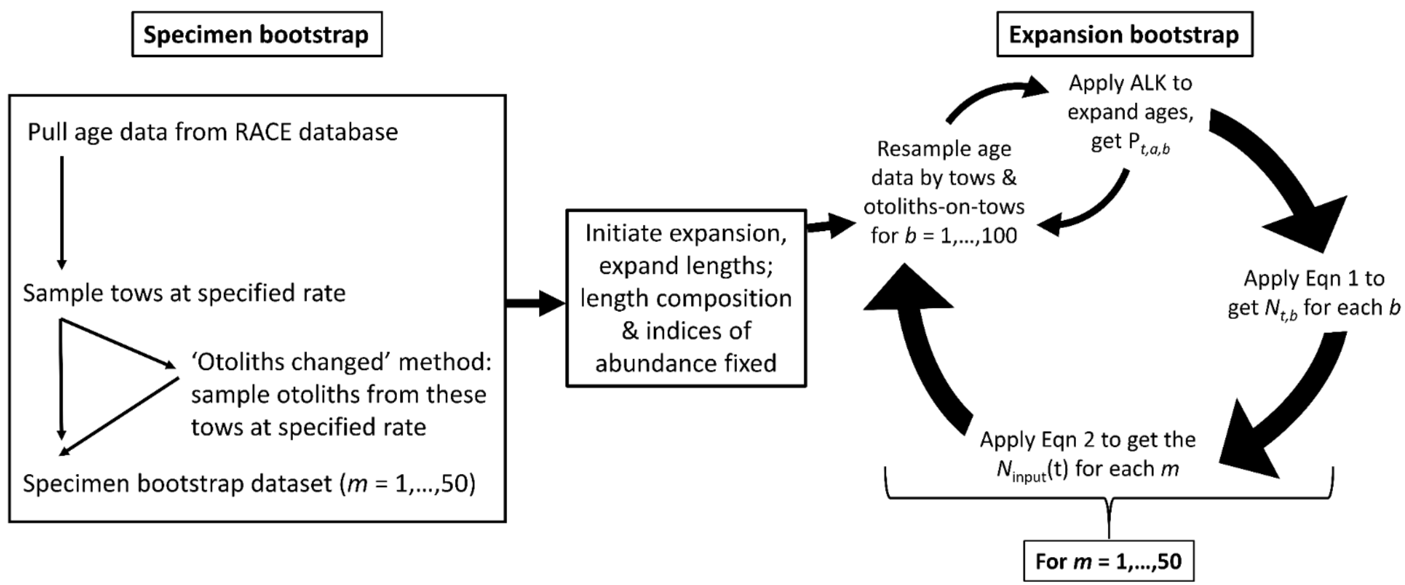
Sample lengths from these tows, keep sample size

Expand length data for each bootstrap replicate

Calculate input sample size for each bootstrap replicate of length comps (B_b)

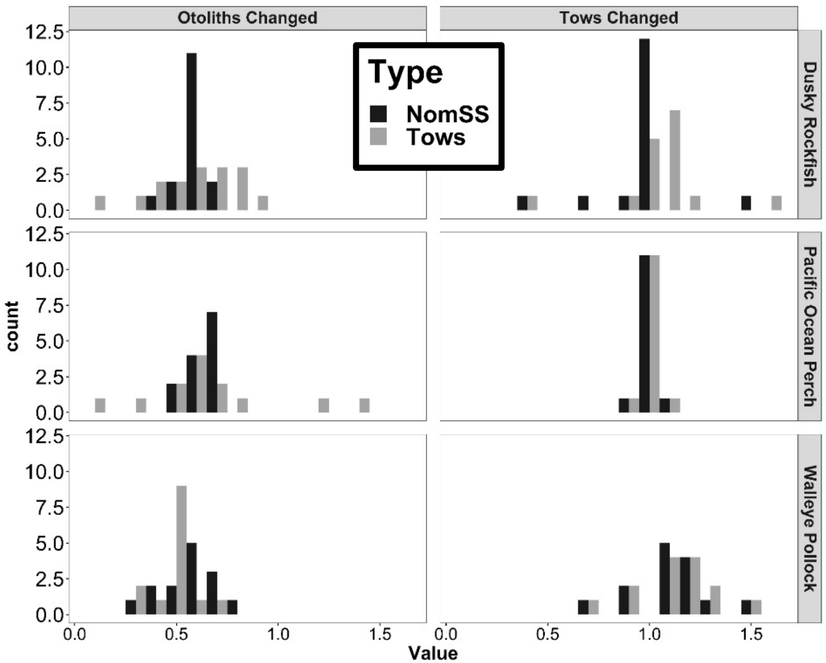
$$R = \frac{\sum_b (P_b \cdot (1 - P_b))}{\sum_b (P_b - B_b)^2}$$

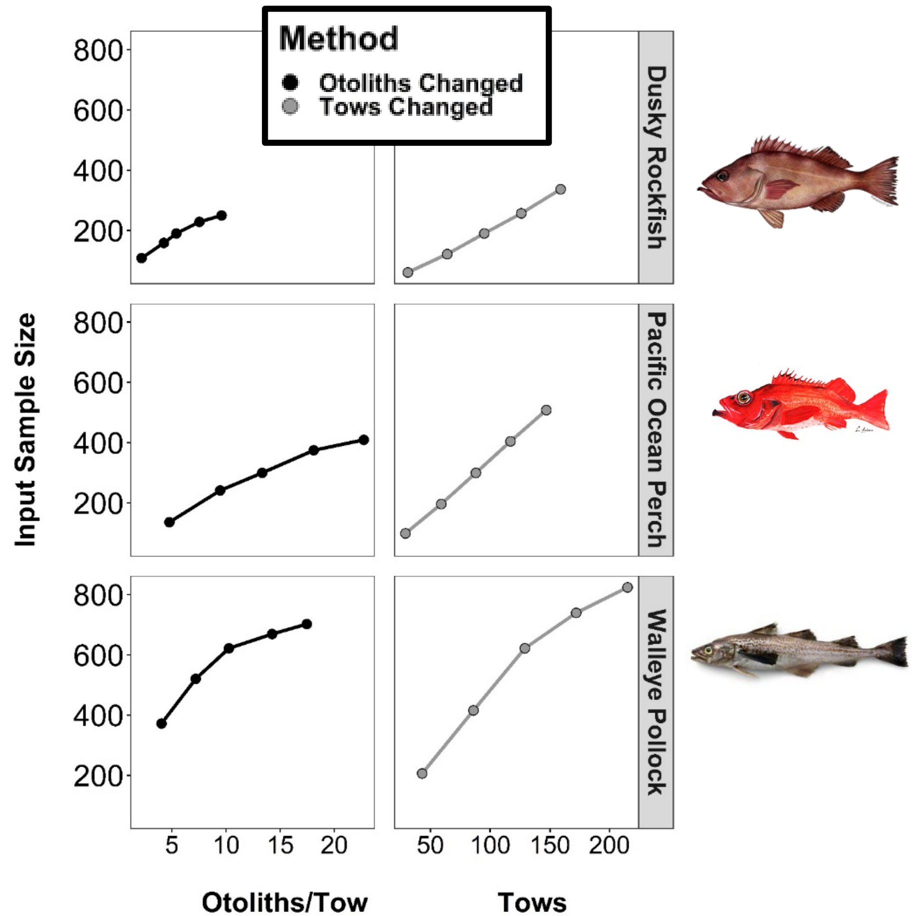
Bootstrap Estimator



Equation 1	$N_{t,b} = \frac{\sum_{a=1} \mathrm{P}_{t,a,b} \times (1 - \mathrm{P}_{t,a,b})}{\sum_{a=1} (\mathrm{P}_{t,a,b} - \widehat{\mathrm{P}}_{t,a})^2}$	Variance in bootstrapped comps
Equation 2	$N_{\mathrm{Input}}(t) = \left(\frac{\sum_{b=1} N_{t,b}^{-1}}{100}\right)^{-1}$	Harmonic mean

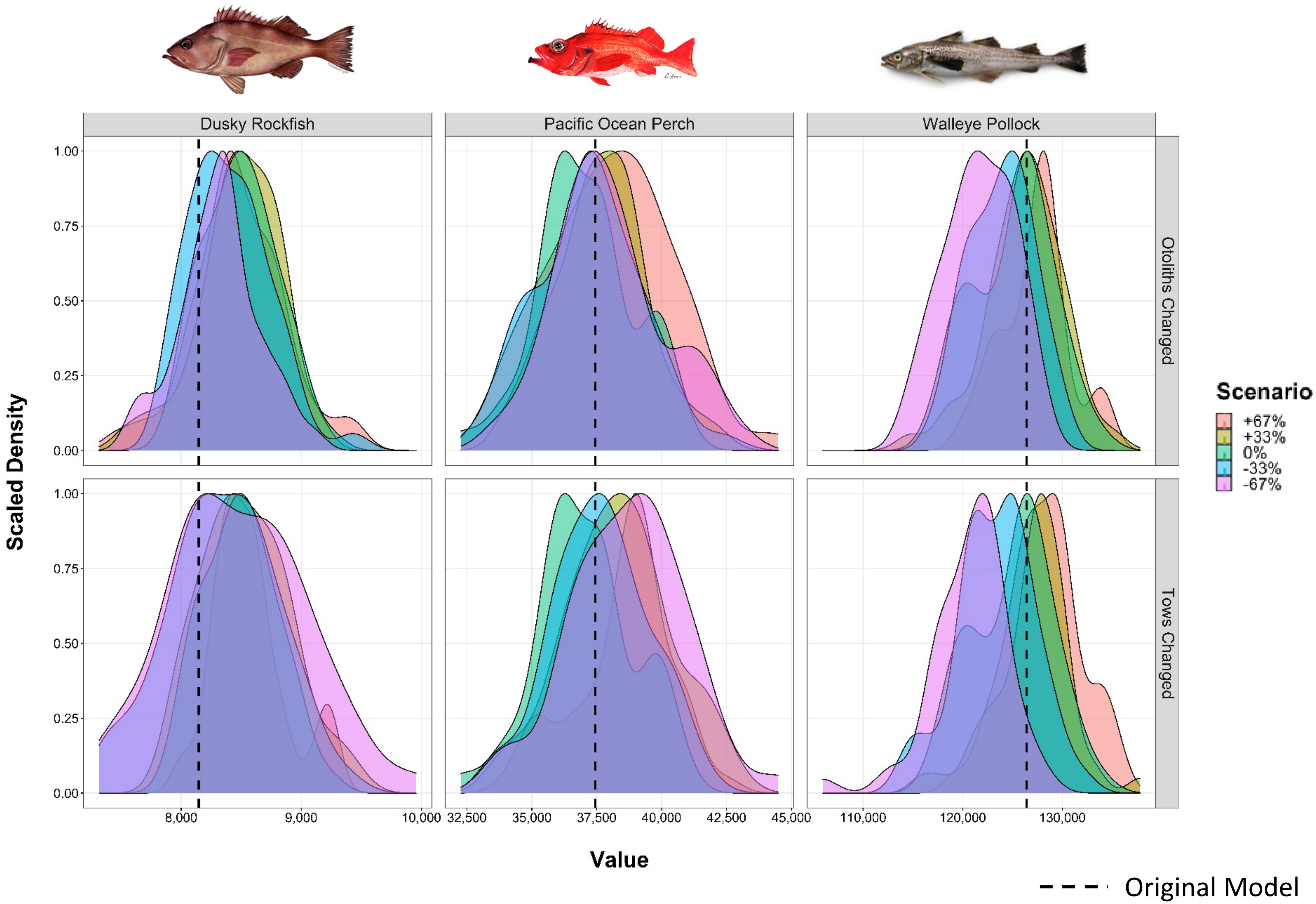
Bootstrap Estimator





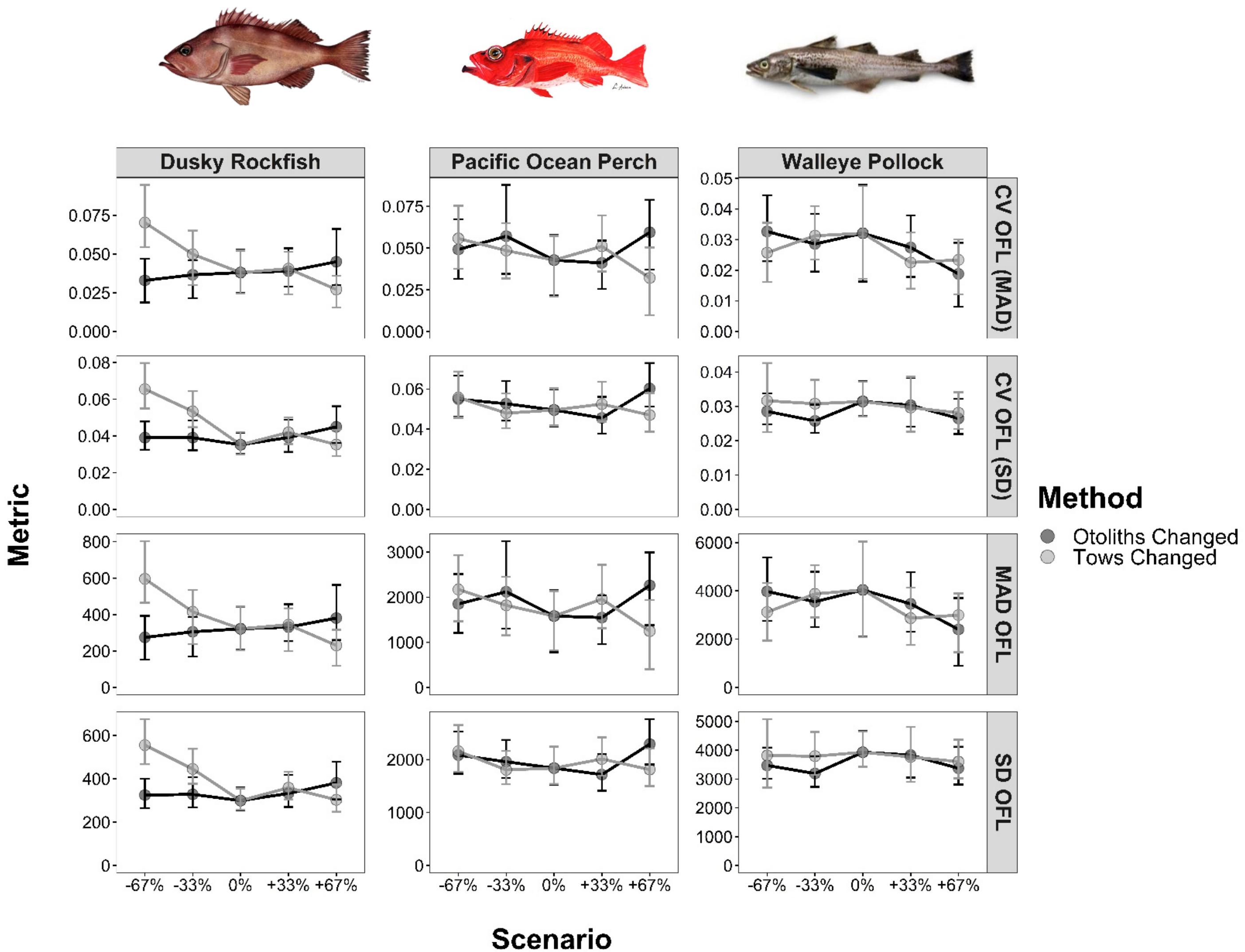
Model Output (OFL):

- Model runs cycled through
  - $\mathbf{N}_{Input}(t)$ from bootstrap estimator
  - All bootstrap replicates of $\mathbf{P}_{t,a,b}$



Uncertainty in OFL

- 0% scenario is just resampled



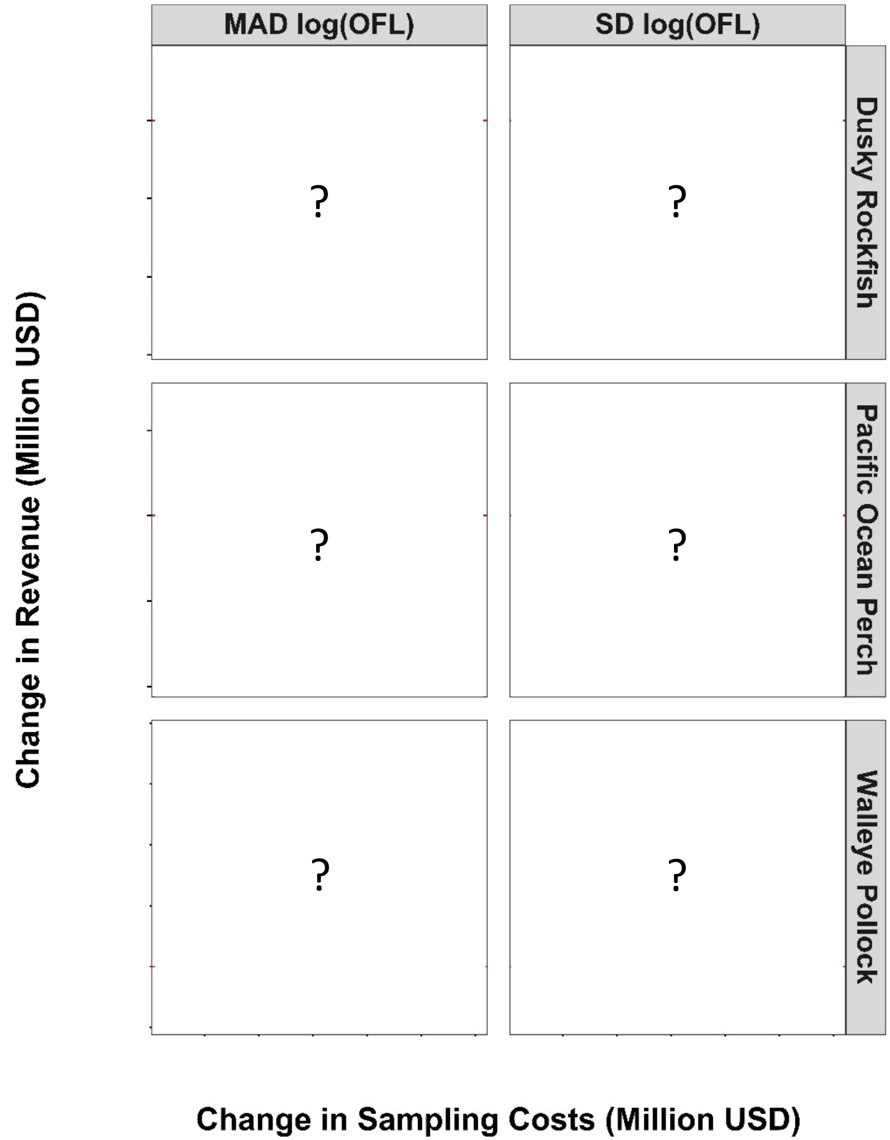
Cost-Revenue

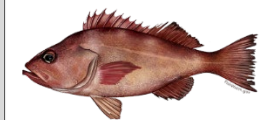
Species	$USD/lb	$USD/mt	$USD millions
Dusky rockfish	0.442	974.4	0.94
Pacific ocean perch	0.196	432.1	10.18
Walleye pollock	0.138	304.2	36.12

P-star approach:

- Define log(ABC/OFL) buffer
- Among-bootstrap OFL uncertainty
- Reported $USD/mt revenue
- Calculate new ABCs for each sampling scenario based on buffer & OFL uncertainty
- Per-otolith sampling cost applied to # of otoliths from each ±% sampling scenario

Method
- Otoliths Changed
- Tows Changed





Jim’s Acknowledgements

Co-authors

- Meaghan Bryan, Pete Hulson, Haikun Xu, André E. Punt

Reviewers

- Tom Helser, Ian Stewart, Jim Ianelli

Alaska Fisheries Science Center program support

- Chris Lunsford, Tom Helser, Anne Hollowed, Stan Kotwicki

Journal input

- Shijie Zhou (editor) and two anonymous reviewers

Funding

- HEPR-MESA-SSMA activity plan on age reductions

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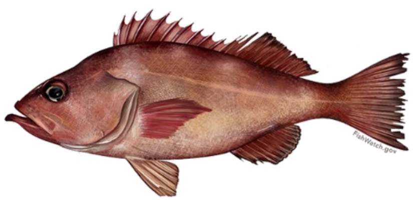

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