NOAA FISHERIES
Alaska Fisheries
Science Center

# Report of the September 2019 BSAI Groundfish Plan Team meeting

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October 2, 2019

# Meeting overview

- Dates: September 17-18
- Place: AFSC Seattle lab
- Leaders: Grant Thompson, Steve Barbeaux (co-chairs); Steve MacLean (coordinator)
- Participation: 14 Team members present, plus numerous AFSC and AKRO staff and members of the public
- Documents and presentation files available on the Team agenda site
  - Link provided on Council agenda (under item C5)

# Agenda (action items in red)

- Administrative
- EBS Pacific cod
- Model averaging
- EBS pollock
- BS/RE rockfish
- AI Pacific cod
- Atka mackerel
- Northern rockfish
- Skates BMSY proxy
- Harvest specifications

# EBS Pacific cod (1 of 38)

- Jim Thorson added as coauthor this year
- Authors responded to 10 Team and 11 SSC comments
- In the interest of brevity, only those comments that are referenced again later in this presentation are shown on the next three slides
  - Three others will be taken up under the “Model averaging” item

# EBS Pacific cod (2 of 38)

- BPT7: “For next year’s assessment, the Team recommended that the author considers an ensemble of models using the three hypotheses discussed above to address the structural uncertainty resulting from these hypotheses, as well as additional uncertainties captured by various models. The three hypotheses are 1) P. cod in the NBS are insignificant to the managed stock, 2) P. cod in the NBS are simply the same stock as in the EBS and should be managed as one stock, and 3) P. cod in the NBS and EBS are from the same stock and should be managed as one stock, but P. cod in the NBS should be modeled separately within one model with separate catchability and selectivity to capture differences observed in the fish in that area. *Response*: In addition to the base model, six new models are presented here, spread across the Team’s three hypotheses (specifically, two new models per hypothesis)

# EBS Pacific cod (3 of 38)

- SSC3: “The SSC recommends that future efforts focus on treatment of the Northern Bering Sea data prior to adding to the assessment – via summation of the components (as in model 16.6i) or through model-based approaches that can estimate contributions of unsampled areas (such as developed for EBS walleye pollock). However, the SSC noted that many requested changes made in development of the 17.x and 18.x series of models represent improvements over the 16.x models. These improvements include inclusion of fishery age composition data, the prior on natural mortality, composition data weighted by the number of hauls, and harmonic mean composition weights. Other changes continue to be worthy of evaluation, but may not be clear improvements, such as time-varying selectivity and catchability. The SSC recommends bringing these branched model series back together either in the form of one model, or an ensemble of models for 2019.”
- (Response on next slide)

# EBS Pacific cod (4 of 39)

- *Response to SSC3*: Results from Model 16.6i, which uses simple summation of the design-based survey estimates, are again reported here, along with results from six new models, two of which use VAST estimates of survey abundance and age composition. All of the new models include fishery age composition data and initial weighting of compositional data by the number of hauls (in either absolute or relative terms), and three of the new models include reweighting of compositional data and time-varying selectivity and catchability.
- SSC8 (part 1): "The SSC strongly supported the PT approach of organizing alternative models around explicit hypotheses regarding the assessment structure or population dynamics. This approach was very helpful to make clear where the need for additional research was most important, and also provided a logical framework for developing an ensemble of models corresponding to each hypothesis...."
  *Response*: See response to BPT7

# EBS Pacific cod (5 of 38)

- Base model:
  - Model 16.6i was adopted last year as the new base model
  - Its main structural features are as follow:
    - One fishery, one gear type, one season per year
    - Logistic age-based selectivity for both the fishery and survey
    - External estimation of time-varying weight-at-length parameters and the standard deviations of ageing error at ages 1 and 20
    - All parameters constant over time except for recruitment and $F$
    - Internal estimation of $M$, $F$, $Q$, recruitment, and all length at age, ageing bias, and selectivity parameters
  - The only difference between Model 16.6i and Model 16.6 is the inclusion in Model 16.6i of data from the NBS survey, which were incorporated by simple summation with the EBS survey data

# EBS Pacific cod (6 of 38)

- Alternative models:
  - Six alternative models are presented, in addition to the base model
  - These constitute a factorial design involving the Team's three hypotheses regarding treatment of the NBS (Comments BPT7 and SSC8) and the SSC's desire to explore multiple ranges of possible enhancements to the structure of the base model (Comment SSC3)
  - Reprising the Team's three hypotheses:
    1. Pacific cod in the NBS are insignificant to the managed stock, so the assessment should include data from the EBS only
    2. Pacific cod in the EBS and NBS comprise a single stock, and the EBS and NBS surveys can be modeled in combination
    3. Pacific cod in the EBS and NBS comprise a single stock, but the EBS and NBS surveys should be modeled separately

# EBS Pacific cod (7 of 38)

- Alternative models, continued:
  - Relative to the base model, two ranges of structural modifications are featured among the alternative models
  - More specifically, two models are presented for each hypothesis, one of which contains a certain set of structural modifications, and the other of which contains a second, larger, set of structural modifications
  - The two sets of structural modifications are the same across hypotheses, except that an additional set of survey parameters is required for Hypothesis 3
  - In addition to structural differences, the models for the various hypotheses also involve different data

# EBS Pacific cod (8 of 38)

- Alternative models, continued:
  - The first (smaller) set of structural modifications is as follows:
    - Set input $N$ for compositional data equal to no. hauls, rescaled to an average of 300 for each component (Model 16.6i sets input $N$ equal to the no. *observations*, rescaled to a mean of 300 for each component)
    - Include fishery age composition data (Model 16.6i ignores those)
    - Use age-based, double-normal selectivity, potentially dome-shaped for the fishery but forced asymptotic for the survey (Model 16.6i uses age-based, logistic selectivity for both fleets)
    - Tune the input $\sigma$ of log-scale recruitment deviations ($\sigma_R$) to match the square root of the variance of the estimates plus the sum of the estimates' variances (Model 16.6i estimates $\sigma_R$ internally)
    - Use size-based maturity (Model 16.6i uses age-based maturity)

# EBS Pacific cod (9 of 38)

- Alternative models, continued:
  - The second (larger) set of structural modifications is as follows:
    - Set input sample size for compositional data equal to raw number of hauls rather (than rescaled to an average of 300)
    - Reweight compositional data internally using the Dirichlet-multinomial distribution (Thorson et al. 2017)
    - Use size-based double-normal selectivity rather than age-based (but keeping the assumption of asymptotic survey selectivity)
    - Allow ageing bias at ages 1 and 20 to differ between the pre-2008 and post-2007 periods to compensate for a change in criteria
    - Allow yearly variation in survey selectivity (two parameters), with the input $\sigma$ of the deviations tuned to set the variance of the estimates plus the sum of the estimates' variances equal to unity
    - (continued on next slide)

# EBS Pacific cod (10 of 38)

- Alternative models, continued:
  - The second (larger) set of structural modifications (continued):
    - Allow yearly random variation in survey catchability, with the input $\sigma$ of the deviations tuned to set the variance of the estimates plus the sum of the estimates' variances equal to unity
    - Allow yearly random variation in mean length at age 1.5, with the input $\sigma$ of the deviations tuned to set the variance of the estimates plus the sum of the estimates' variances equal to unity, in order to address the significant amount of time-variability in growth documented by Puerta et al. (2019)
    - Allow yearly random variation in fishery selectivity (three parameters), with the input $\sigma$ of the deviations tuned to set the variance of the estimates plus the sum of the estimates' variances equal to unity

# EBS Pacific cod (11 of 38)

- Alternative models, continued:
  - Referring to models conforming to the first set of structural modifications as "simple" and models conforming to the second (larger) set of structural modifications as "complex," the set of alternative models can be summarized as follows:

| Hypothesis: | 1: EBS only | | 2: Combine EBS and NBS | | 3: Separate EBS and NBS | |
|---|---|---|---|---|---|---|
| Structure: | Simple | Complex | Simple | Complex | Simple | Complex |
| Name: | M19.1 | M19.2 | M19.3 | M19.4 | M19.5 | M19.6 |

  - Bridging analyses are presented in the document for:
    - Transition from M16.6i (base) to M19.3 (closest 19.x analogue)
    - Transition from M19.3 (simple) to M19.4 (complex)
  - These are not included here, in the interest of brevity

# EBS Pacific cod (12 of 38)

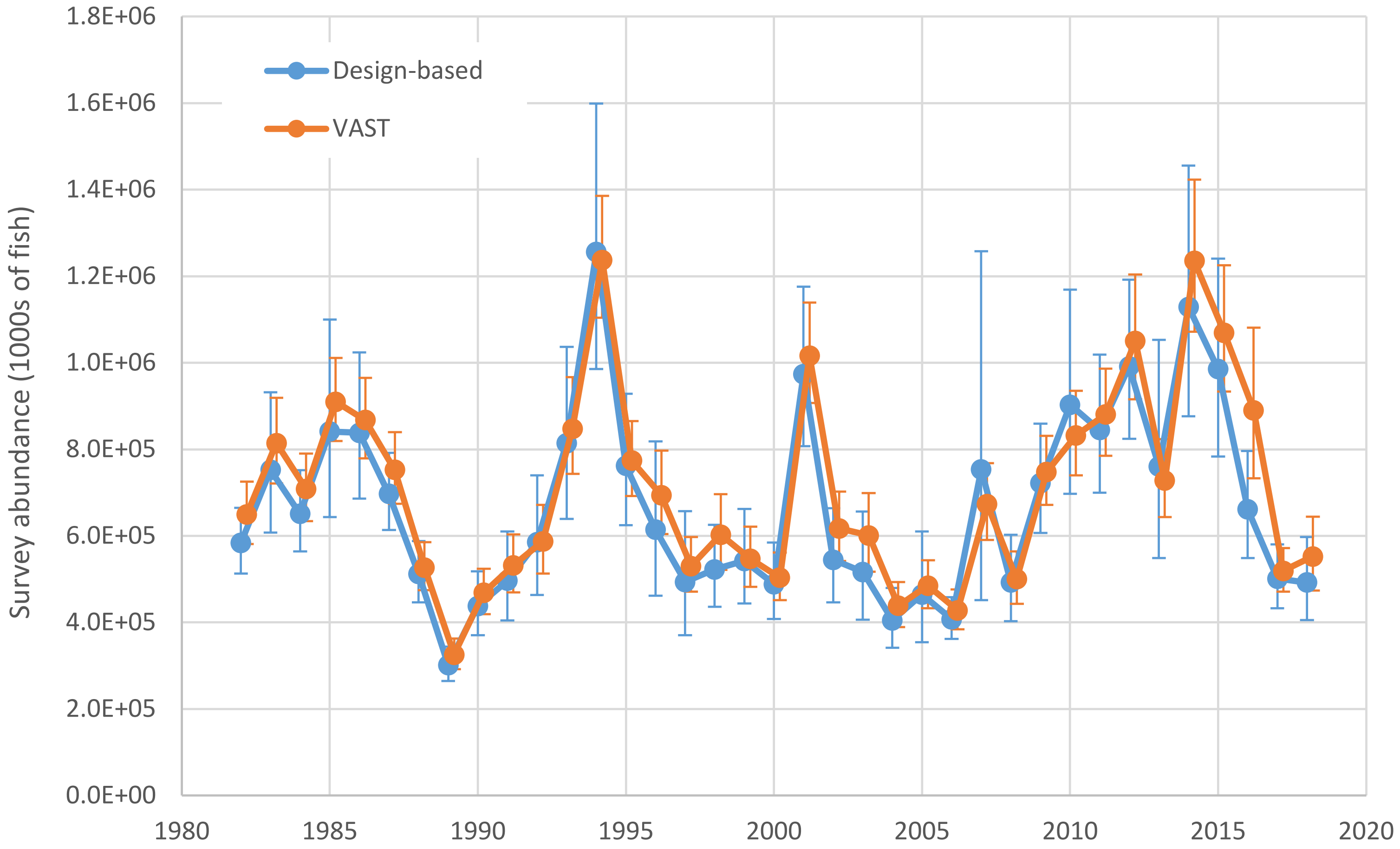
- Features explored but not included:
  - Use of VAST survey index estimates without the cold pool covariate
  - Use of VAST estimates of survey abundance without bias correction
  - Internal estimation of a time-invariant “extra” survey standard error
  - Allowing yearly random variation in the Brody growth coefficient ($K$)
  - Internal estimation of a parameter expressing cohort-specific growth
  - External re-weighting of compositional data components
  - Survey catchability fixed (i.e., not estimated statistically) at 1.0
  - Exponential-logistic fishery selectivity
  - Exponential-logistic survey selectivity
  - Different sets of selectivity parameters subject to random variation
  - Allowing survey selectivity to be dome-shaped

# EBS Pacific cod (13 of 38)

- The design-based EBS+NBS survey estimates used in Model 16.6i were replaced by:
  - Design-based EBS-only survey estimates in Models 19.1 and 19.2 (Hypothesis 1)
  - VAST estimates for the combined surveys in Models 19.3 and 19.4 (Hypothesis 2)
    - Bias-corrected, with cold pool covariate
    - Settings followed the recommendations given by Thorson (2019)
    - Of the 34 years in which the EBS was surveyed but the NBS was not, the VAST EBS+NBS estimate exceeds the design-based EBS-only estimate by more than 10% only 7 times
  - Area-specific design-based estimates for the EBS and NBS surveys in Models 19.5 and 19.6 (Hypothesis 3)

# EBS Pacific cod (14 of 38)

- VAST vs. design-based EBS+NBS index



# EBS Pacific cod (15 of 38)

- Main results: management quantities

| EBS/NBS hypothesis: | Combine | EBS only | | Combine | | Separate | |
|---|---|---|---|---|---|---|---|
| Model structure: | Base | Simple | Complex | Simple | Complex | Simple | Complex |
| Model | M16.6i | M19.1 | M19.2 | M19.3 | M19.4 | M19.5 | M19.6 |
| ADSB | 0.090 | 0.323 | 0.255 | 0.106 | 0.573 | 0.100 | 0.351 |
| Mohn's ρ | 0.207 | 0.093 | 0.679 | 0.337 | 0.741 | 0.558 | 0.736 |
| B(2019) | 290205 | 96355 | 190394 | 303532 | 322998 | 221920 | 201524 |
| B(2020) | 246467 | 118012 | 169236 | 244208 | 266750 | 194879 | 176107 |
| maxABC(2019) | 181431 | 12191 | 108116 | 200978 | 218243 | 135217 | 120504 |
| maxABC(2020) | 137364 | 17707 | 81106 | 142515 | 169733 | 98986 | 87074 |
| B(2019)/B100% | 0.44 | 0.11 | 0.32 | 0.47 | 0.50 | 0.35 | 0.34 |
| B(2020)/B100% | 0.38 | 0.13 | 0.28 | 0.38 | 0.42 | 0.31 | 0.29 |
| maxFABC(2019) | 0.31 | 0.05 | 0.30 | 0.34 | 0.37 | 0.30 | 0.32 |
| maxFABC(2020) | 0.29 | 0.07 | 0.27 | 0.31 | 0.37 | 0.26 | 0.28 |

# EBS Pacific cod (16 of 38)

- Main results: key parameters

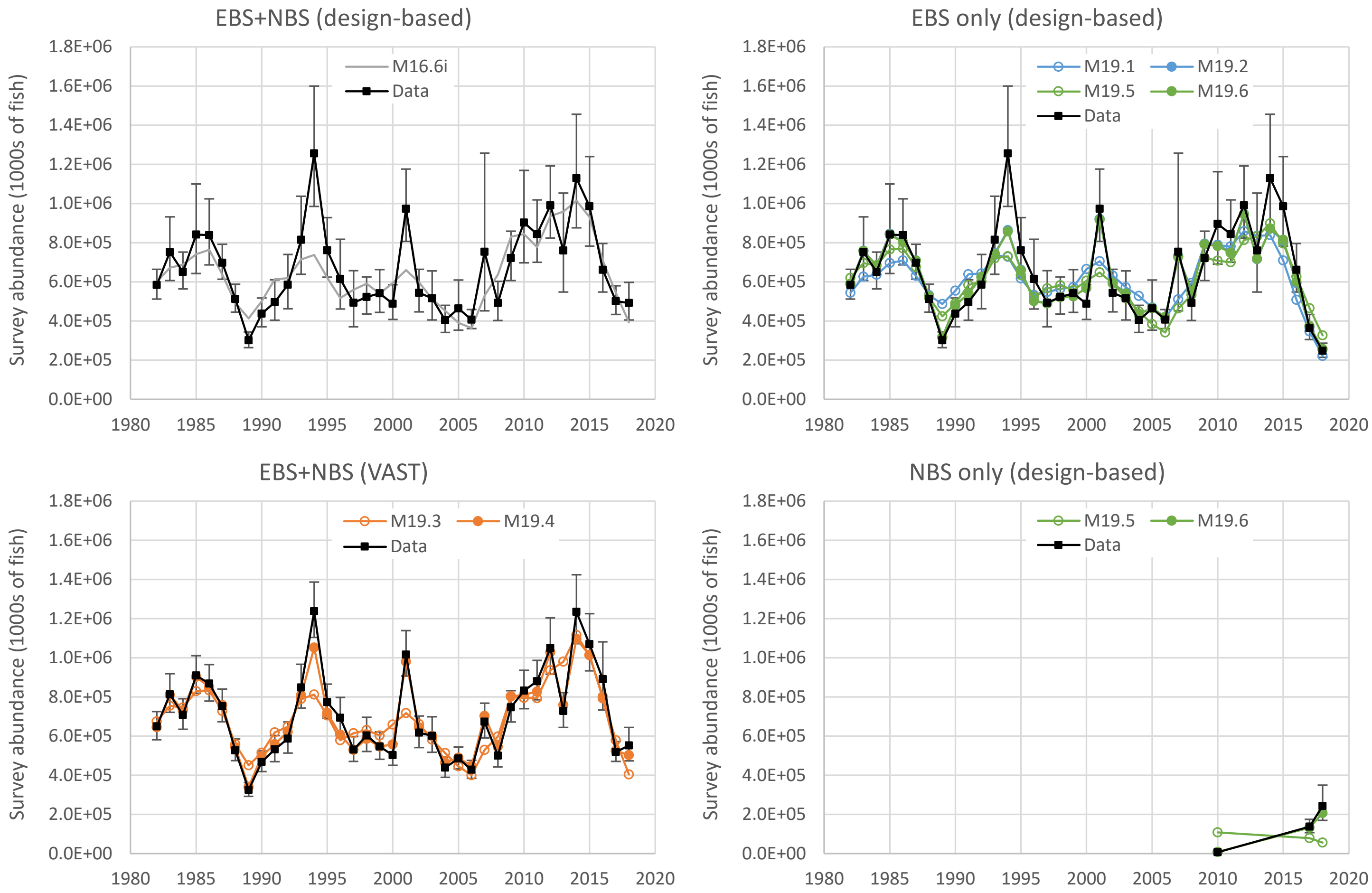
| Treatment of EBS and NBS surveys:[a] | Combined | | EBS only | | | | Combined | | | | Separated | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Model: | Model 16.6i | | Model 19.1 | | Model 19.2 | | Model 19.3 | | Model 19.4 | | Model 19.5 | | Model 19.6 | |
| Reweighted, size select., time-varying: | No | | No | | Yes | | No | | Yes | | No | | Yes | |
| Parameter | Est. | SD | Est. | SD | Est. | SD | Est. | SD | Est. | SD | Est. | SD | Est. | SD |
| Natural mortality rate | 0.340 | 0.012 | 0.265 | 0.013 | 0.382 | 0.012 | 0.363 | 0.017 | 0.372 | 0.013 | 0.366 | 0.017 | 0.380 | 0.012 |
| Length at age 1.5 | 16.377 | 0.088 | 16.673 | 0.090 | 15.205 | 0.406 | 16.425 | 0.091 | 15.128 | 0.408 | 16.530 | 0.093 | 15.177 | 0.395 |
| Asymptotic length | 100.619 | 1.955 | 139.565 | 5.677 | 104.772 | 1.203 | 102.426 | 1.898 | 104.071 | 1.138 | 104.061 | 2.149 | 104.797 | 1.194 |
| Brody growth coefficient (K) | 0.195 | 0.012 | 0.083 | 0.008 | 0.178 | 0.007 | 0.197 | 0.011 | 0.180 | 0.007 | 0.185 | 0.011 | 0.178 | 0.007 |
| Richards growth coefficient | 1.039 | 0.047 | 1.449 | 0.033 | 1.118 | 0.034 | 0.992 | 0.045 | 1.120 | 0.034 | 1.019 | 0.046 | 1.121 | 0.034 |
| SD(length at age 1) | 3.456 | 0.058 | 3.501 | 0.053 | 3.430 | 0.061 | 3.478 | 0.060 | 3.456 | 0.061 | 3.529 | 0.061 | 3.447 | 0.061 |
| SD(length at age 20) | 9.532 | 0.272 | 9.877 | 0.250 | 9.150 | 0.205 | 8.497 | 0.271 | 9.087 | 0.203 | 8.907 | 0.282 | 9.119 | 0.205 |
| Mean ageing bias at age 1[b] | 0.335 | 0.012 | 0.188 | 0.024 | 0.343 | 0.016 | 0.325 | 0.014 | 0.332 | 0.017 | 0.320 | 0.015 | 0.343 | 0.016 |
| Mean ageing bias at age 20[b] | 0.157 | 0.145 | -0.520 | 0.095 | 0.754 | 0.221 | -0.267 | 0.130 | 0.888 | 0.233 | -0.256 | 0.132 | 0.743 | 0.222 |
| Mean ageing bias at age 1 (post-2007) | | | | | 0.011 | 0.026 | | | 0.024 | 0.026 | | | 0.012 | 0.026 |
| Mean ageing bias at age 20 (post-2007) | | | | | -2.163 | 0.341 | | | -2.223 | 0.362 | | | -2.149 | 0.342 |
| ln(mean post-1976 recruitment) | 12.984 | 0.097 | 12.377 | 0.089 | 13.233 | 0.104 | 13.142 | 0.124 | 13.218 | 0.110 | 13.161 | 0.125 | 13.219 | 0.102 |
| SD(log-scale recruitment) | 0.656 | 0.067 | 0.618 | _ | 0.592 | _ | 0.687 | _ | 0.563 | _ | 0.685 | _ | 0.586 | _ |
| ln(pre-1977 mean recruitment offset) | -1.158 | 0.201 | -1.336 | 0.050 | -1.187 | 0.190 | -0.993 | 0.204 | -1.130 | 0.182 | -0.985 | 0.205 | -1.179 | 0.188 |
| Pre-1977 mean fishing mortality rate | 0.190 | 0.075 | 1.827 | 0.657 | 0.261 | 0.094 | 0.142 | 0.047 | 0.226 | 0.076 | 0.147 | 0.050 | 0.259 | 0.092 |
| ln(catchability) for EBS survey[c] | 0.030 | 0.059 | 0.356 | 0.041 | -0.054 | 0.069 | 0.101 | 0.059 | 0.007 | 0.072 | -0.016 | 0.061 | -0.058 | 0.068 |
| ln(catchability) for NBS survey | | | | | | | | | | | -1.686 | 0.117 | -1.564 | 0.352 |

# EBS Pacific cod (17 of 38)

- Key to figure colors and symbols:
  - Colors distinguish hypotheses
    - Blue = Models 19.1 and 19.2 (Hypothesis 1)
    - Orange = Models 19.3 and 19.4 (Hypothesis 2)
    - Green = Models 19.5 and 19.6 (Hypothesis 3)
    - Gray = Model 16.6i (base)
  - Symbols distinguish levels of complexity
    - Open circles = simple (Models 19.1, 19.3, and 19.5)
    - Solid circles = complex (Models 19.2, 19.4, and 19.6)
    - No circles = base (Model 16.6i)

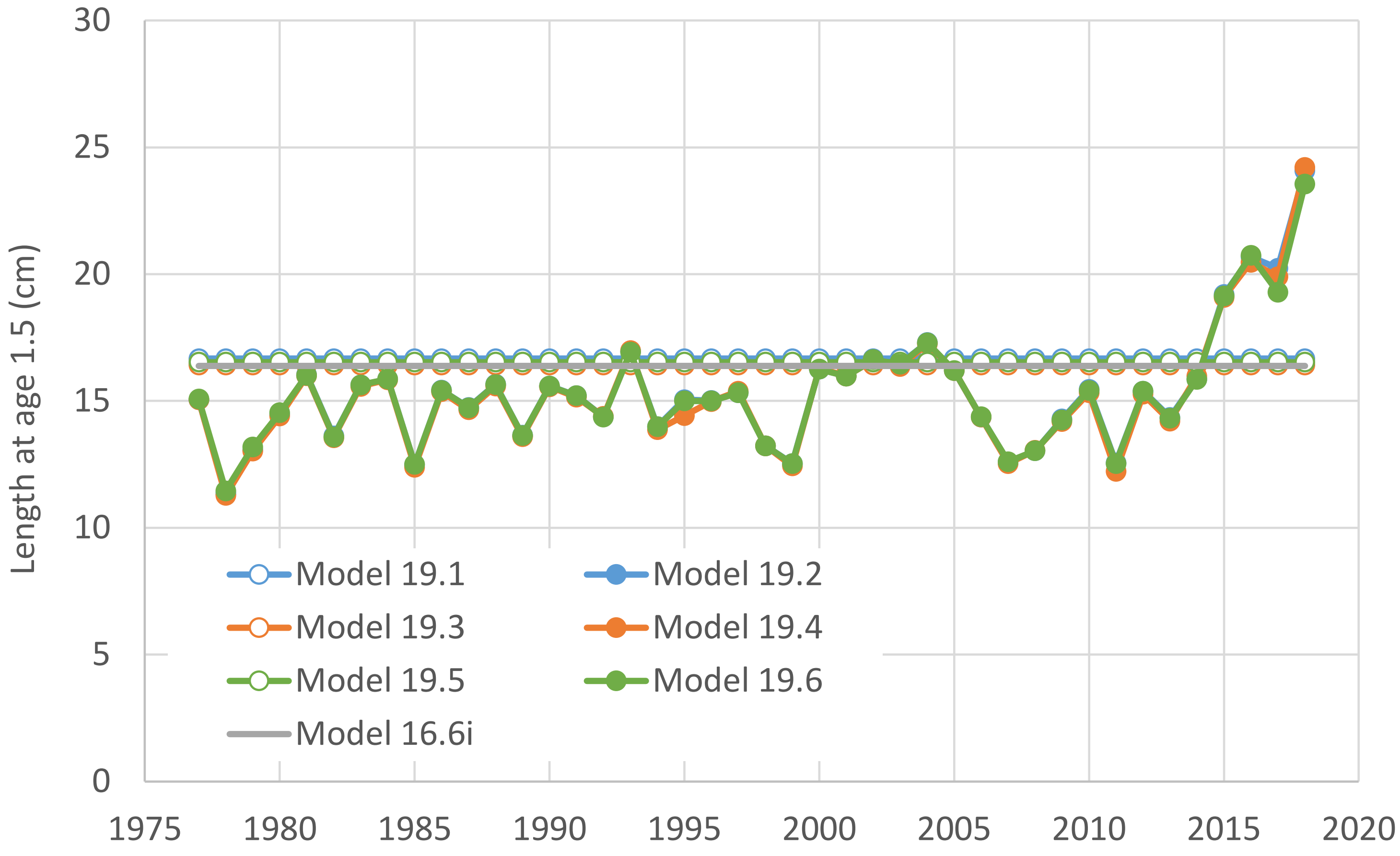
# EBS Pacific cod (18 of 38)

- Fit to survey indices



# EBS Pacific cod (19 of 38)

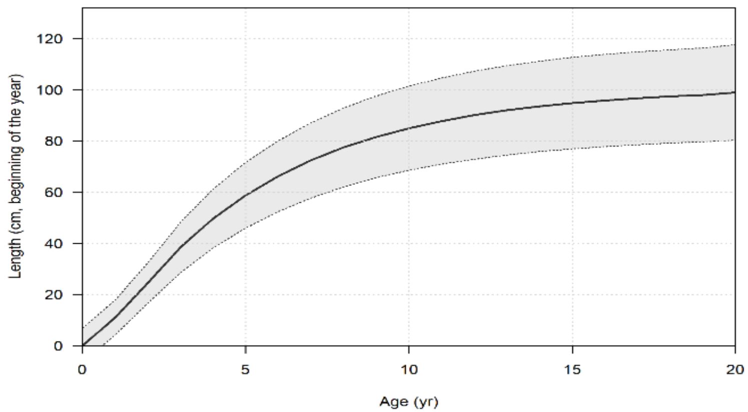
- Length at age 1.5



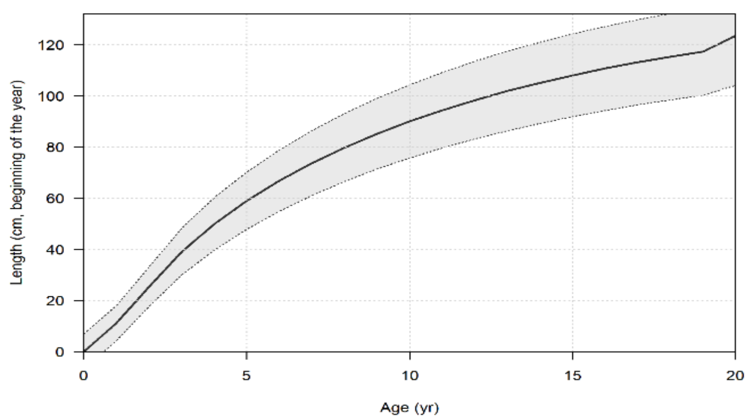
# EBS Pacific cod (20 of 38)

- Length at age (Models 16.6i and 19.1-19.2)

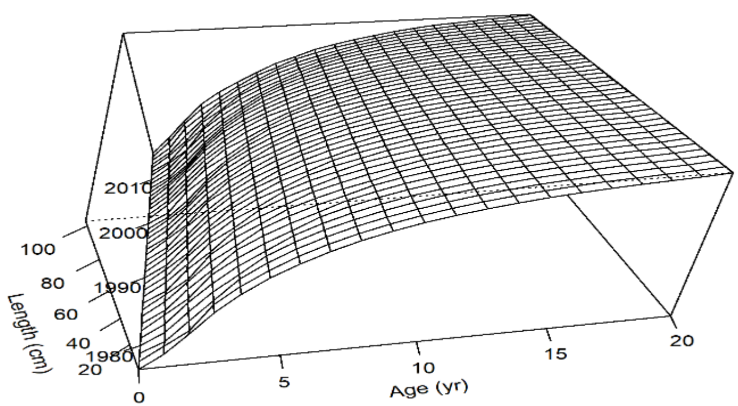
Model 16.6i




Model 19.1



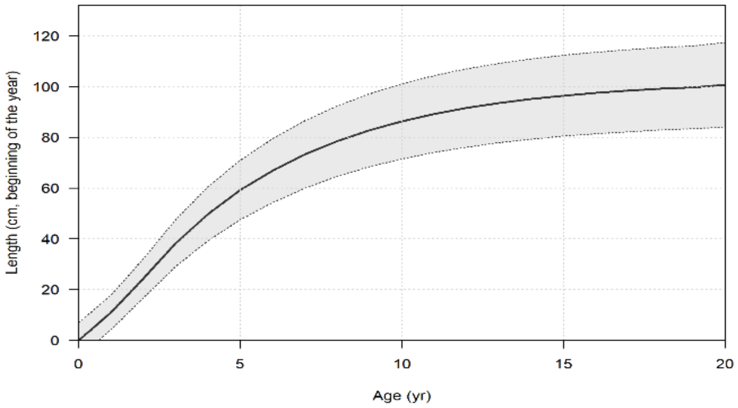

Model 19.2



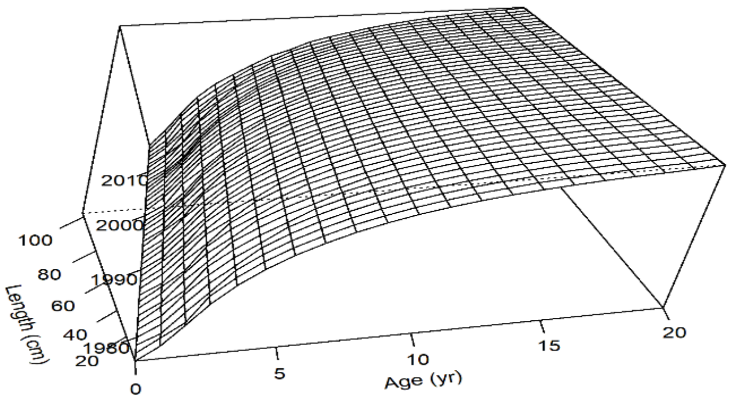
# EBS Pacific cod (21 of 38)

- Length at age (Models 19.3-19.6)

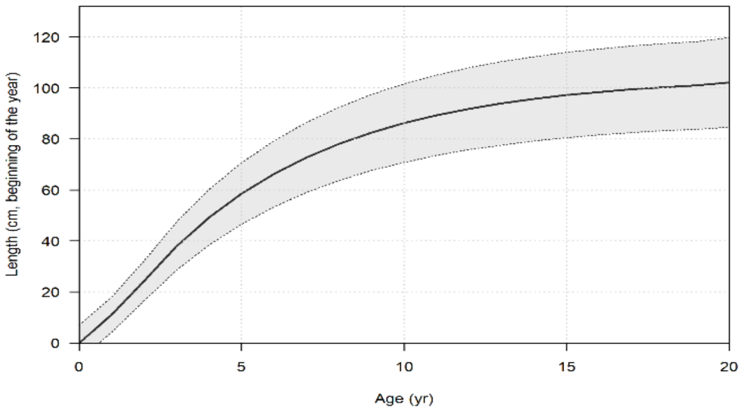
Model 19.3



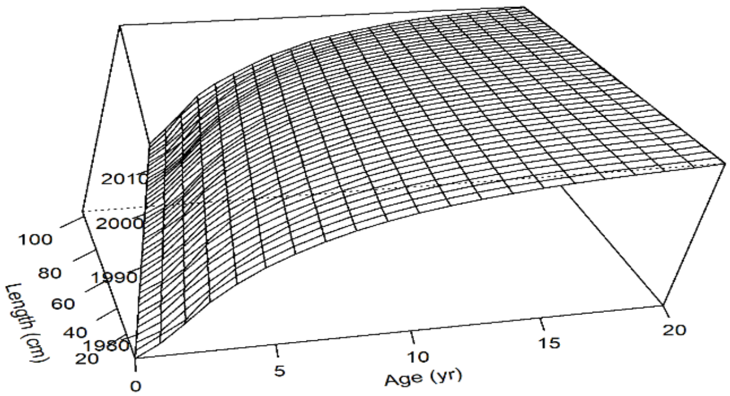

Model 19.4




Model 19.5

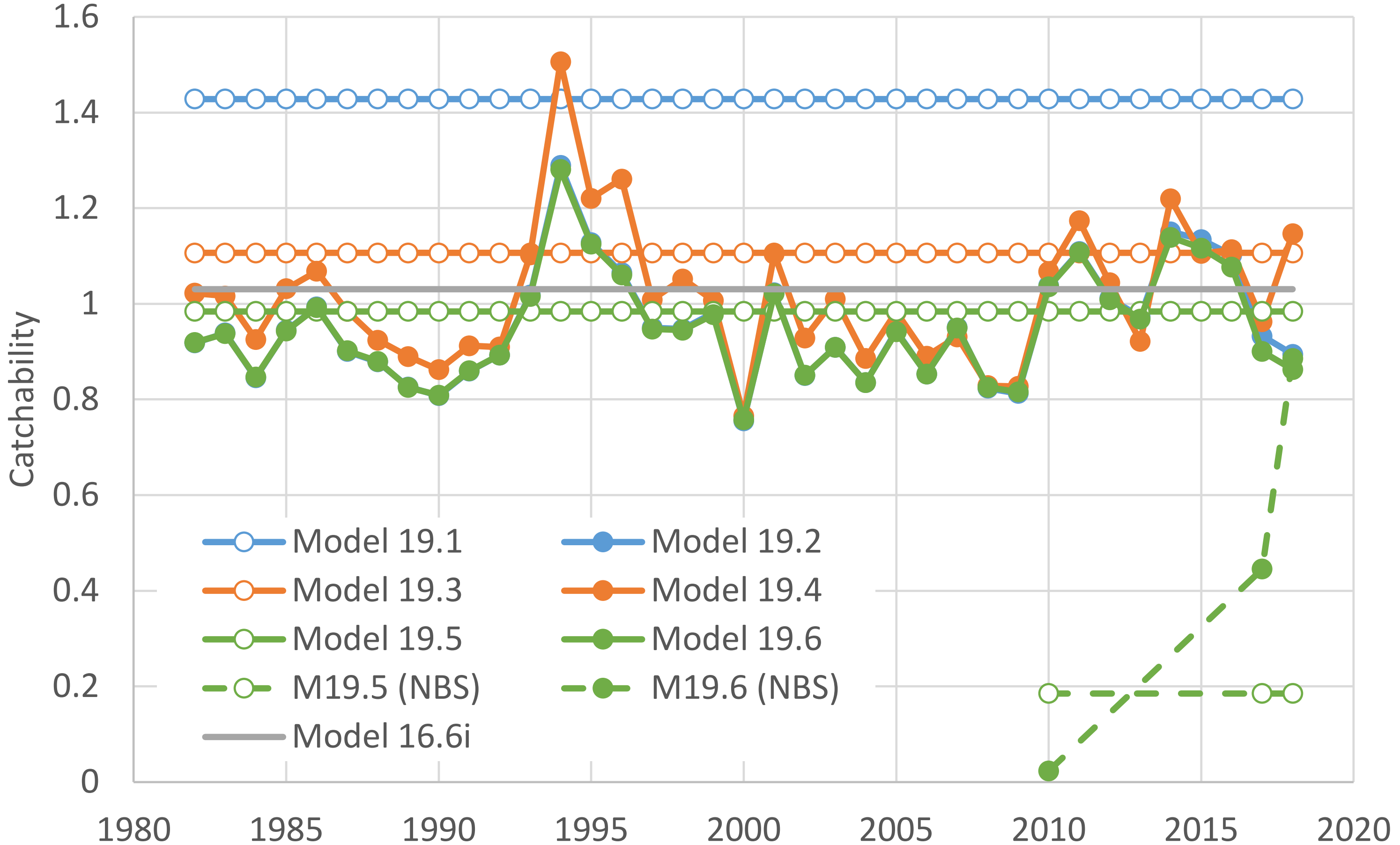



Model 19.6



# EBS Pacific cod (22 of 38)

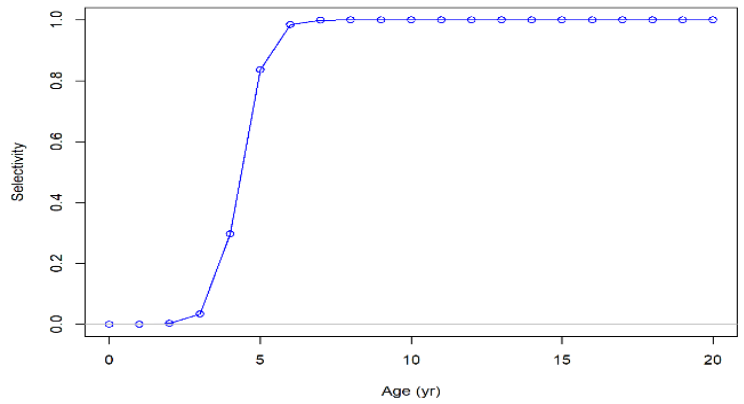
- Catchability



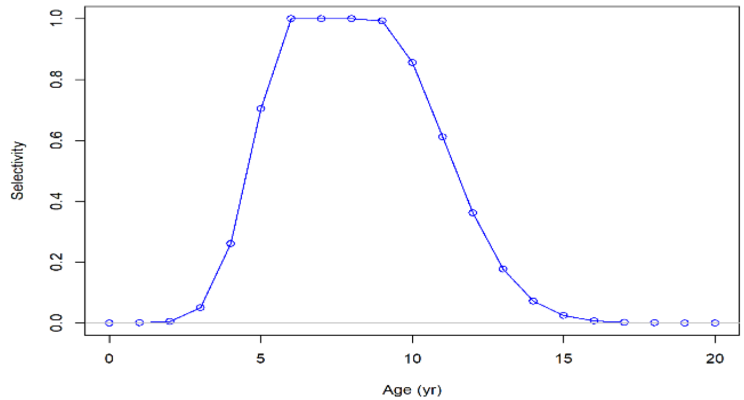
# EBS Pacific cod (23 of 38)

- Fishery selectivity (Models 16.6i and 19.1-19.2)

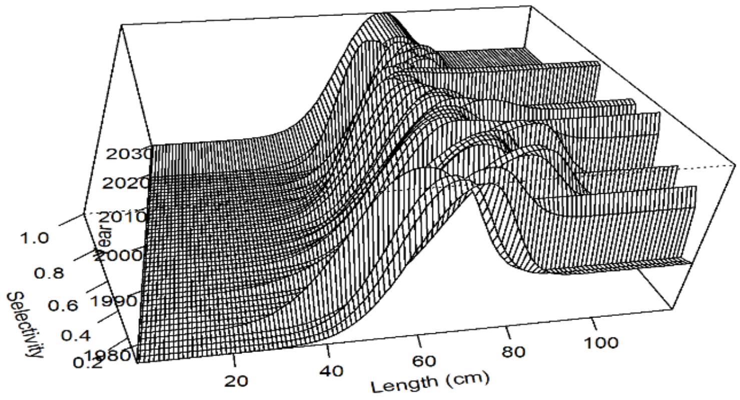
Model 16.6i




Model 19.1



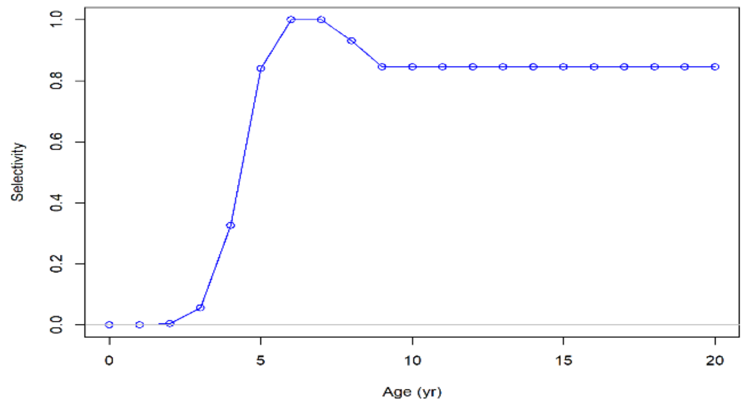

Model 19.2



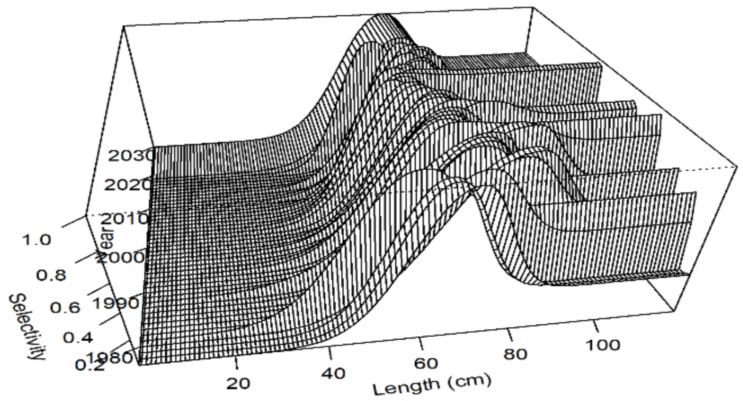
# EBS Pacific cod (24 of 38)

- Fishery selectivity (Models 19.3-19.6)

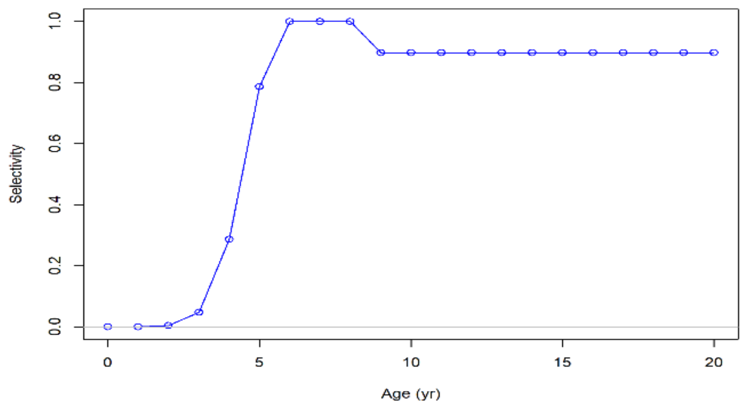
Model 19.3



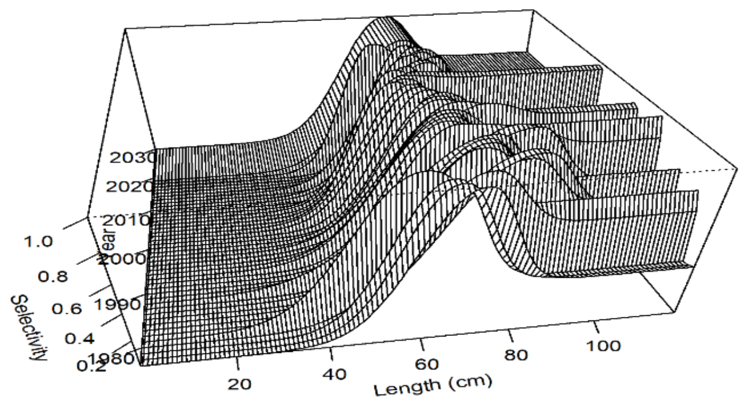

Model 19.4




Model 19.5



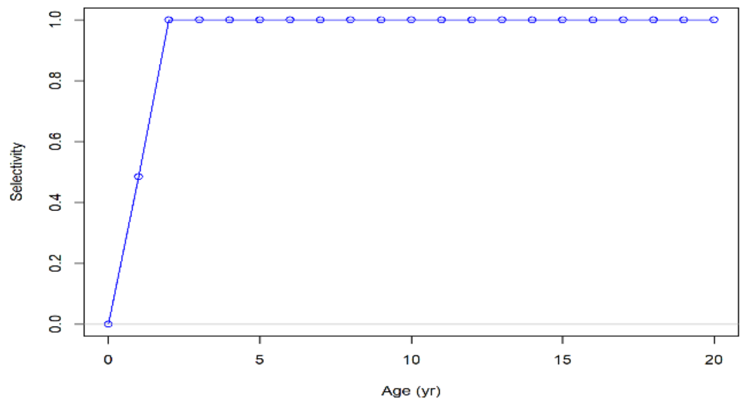

Model 19.6



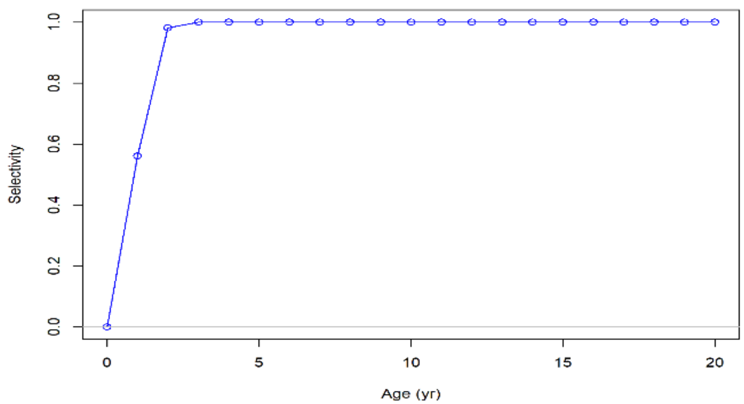
# EBS Pacific cod (25 of 38)

- Survey selectivity (Models 16.6i and 19.1-19.2)

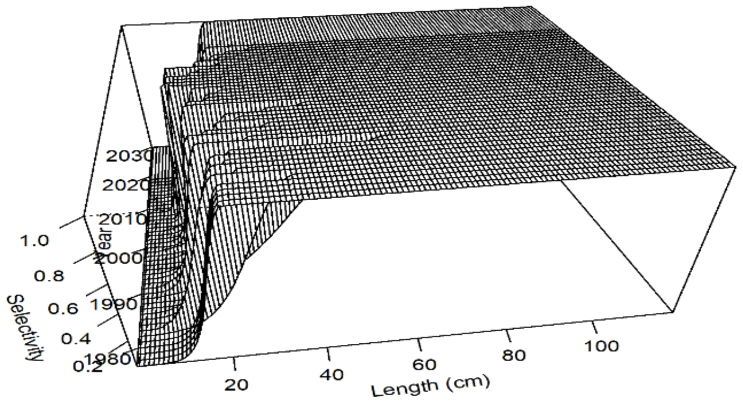
Model 16.6i




Model 19.1



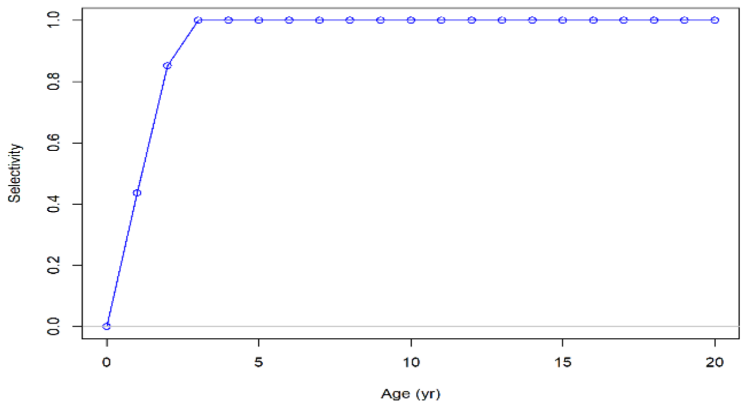

Model 19.2



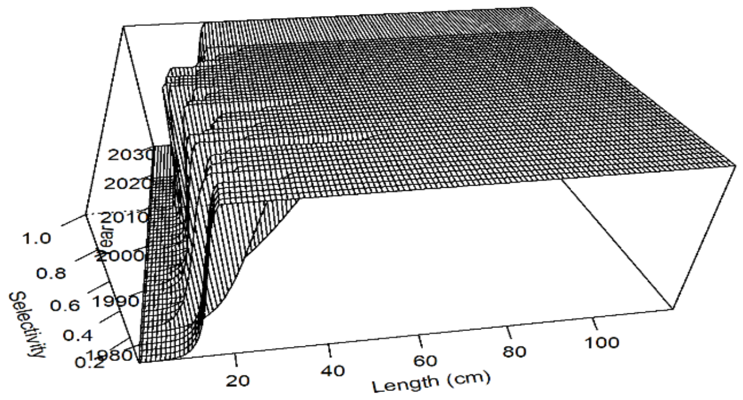
# EBS Pacific cod (26 of 38)

- Survey selectivity (Models 19.3-19.6)

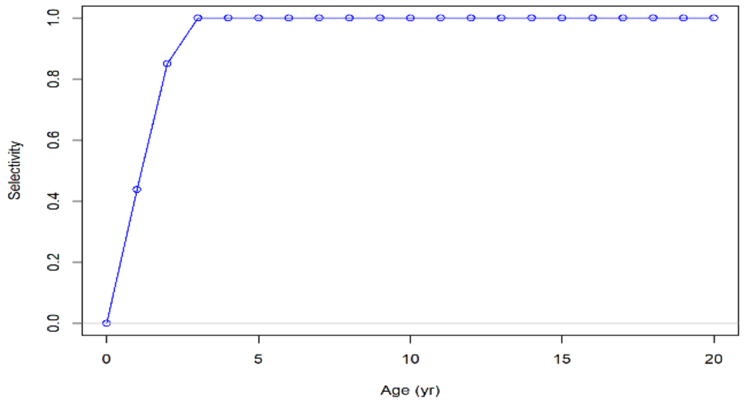
Model 19.3



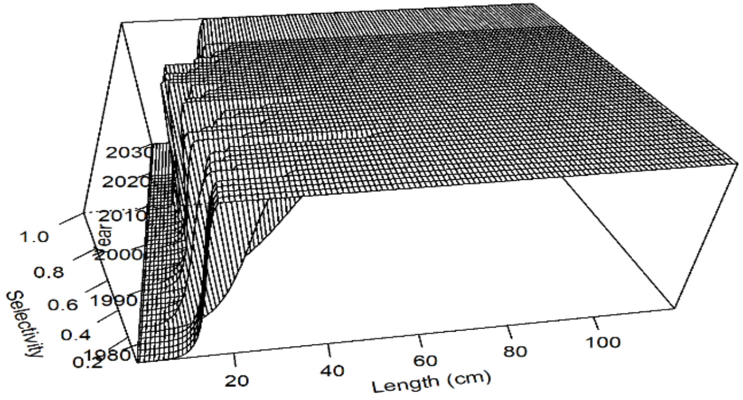

Model 19.4




Model 19.5



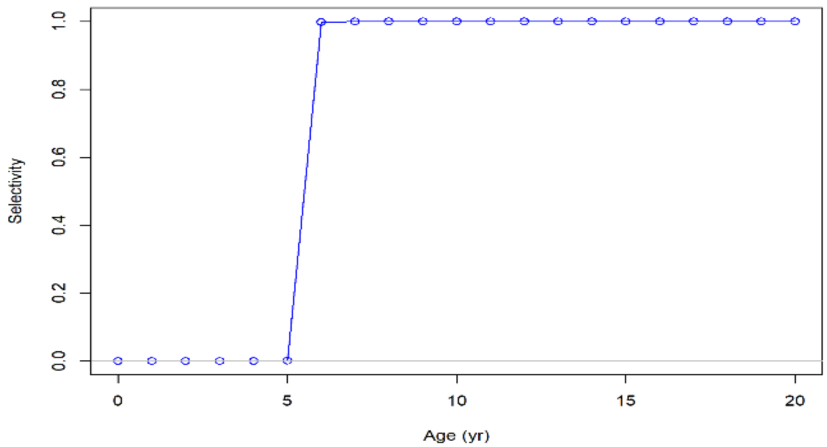

Model 19.6



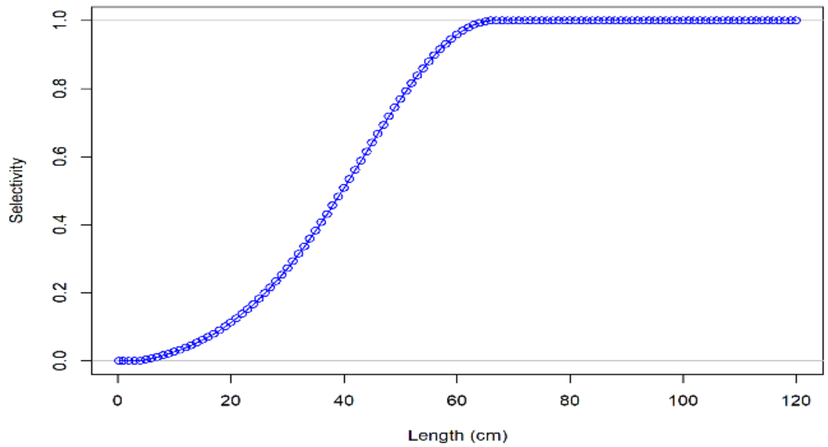
# EBS Pacific cod (27 of 38)

- NBS survey selectivity (Models 19.5-19.6)

Model 19.5

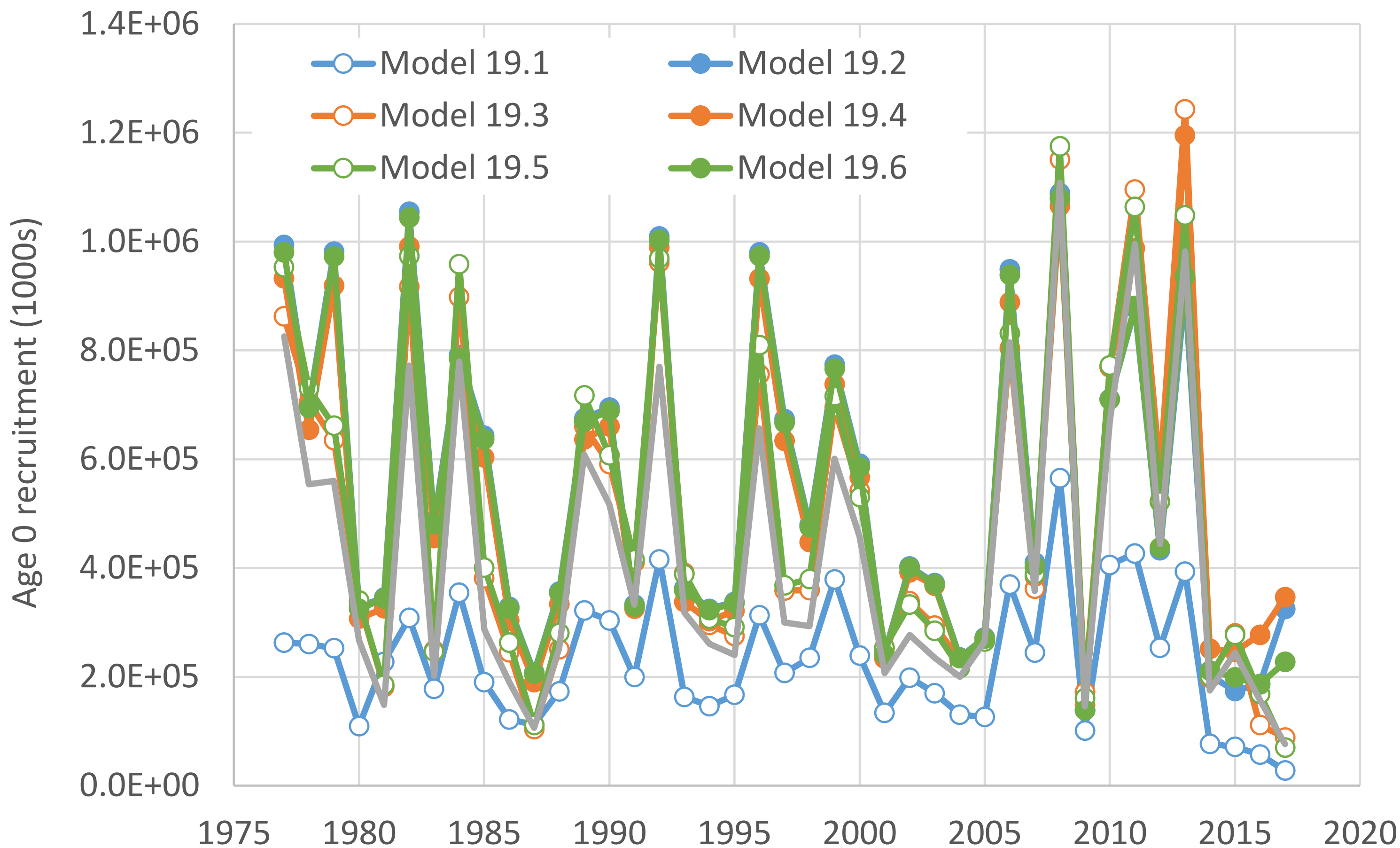



Model 19.6



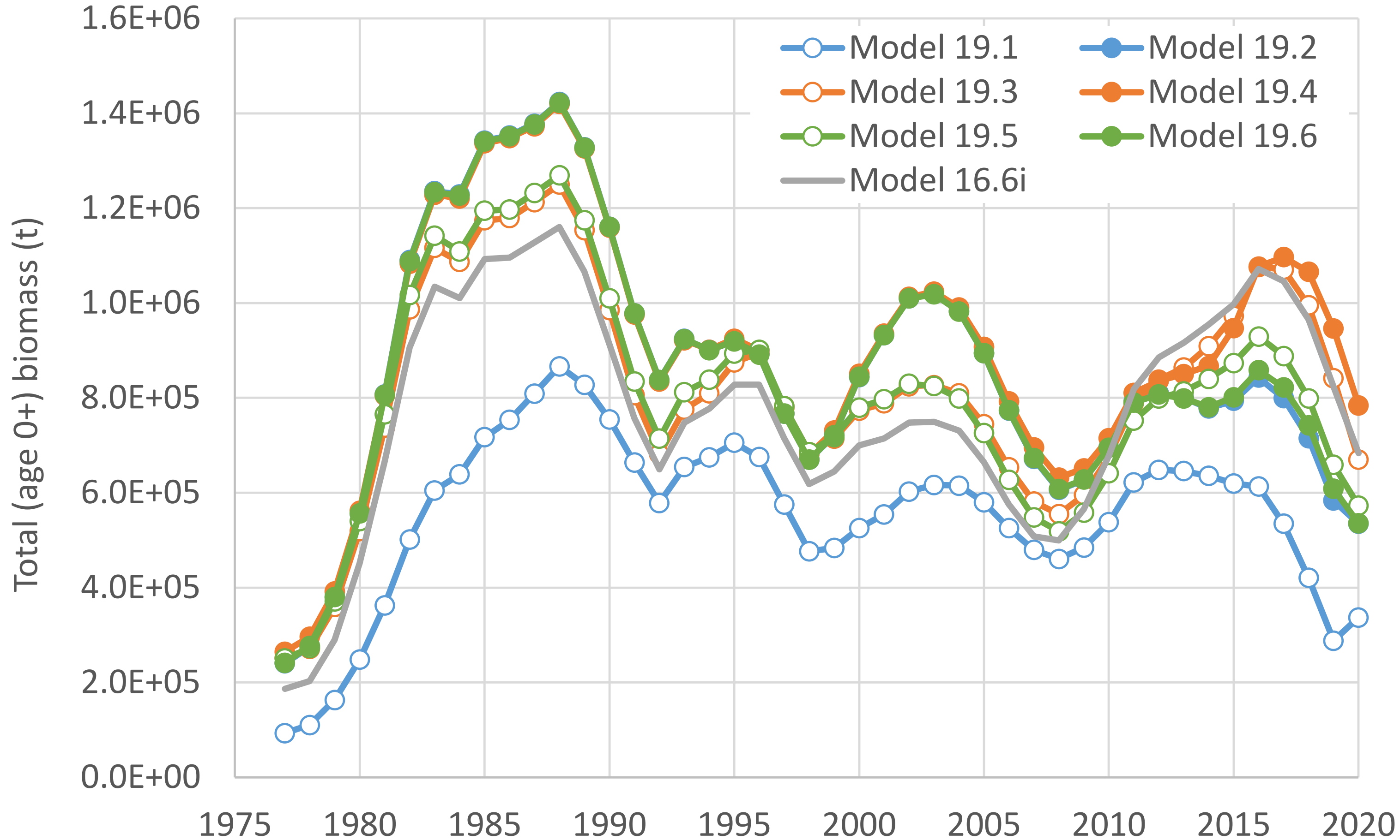
# EBS Pacific cod (28 of 38)

- Recruitment



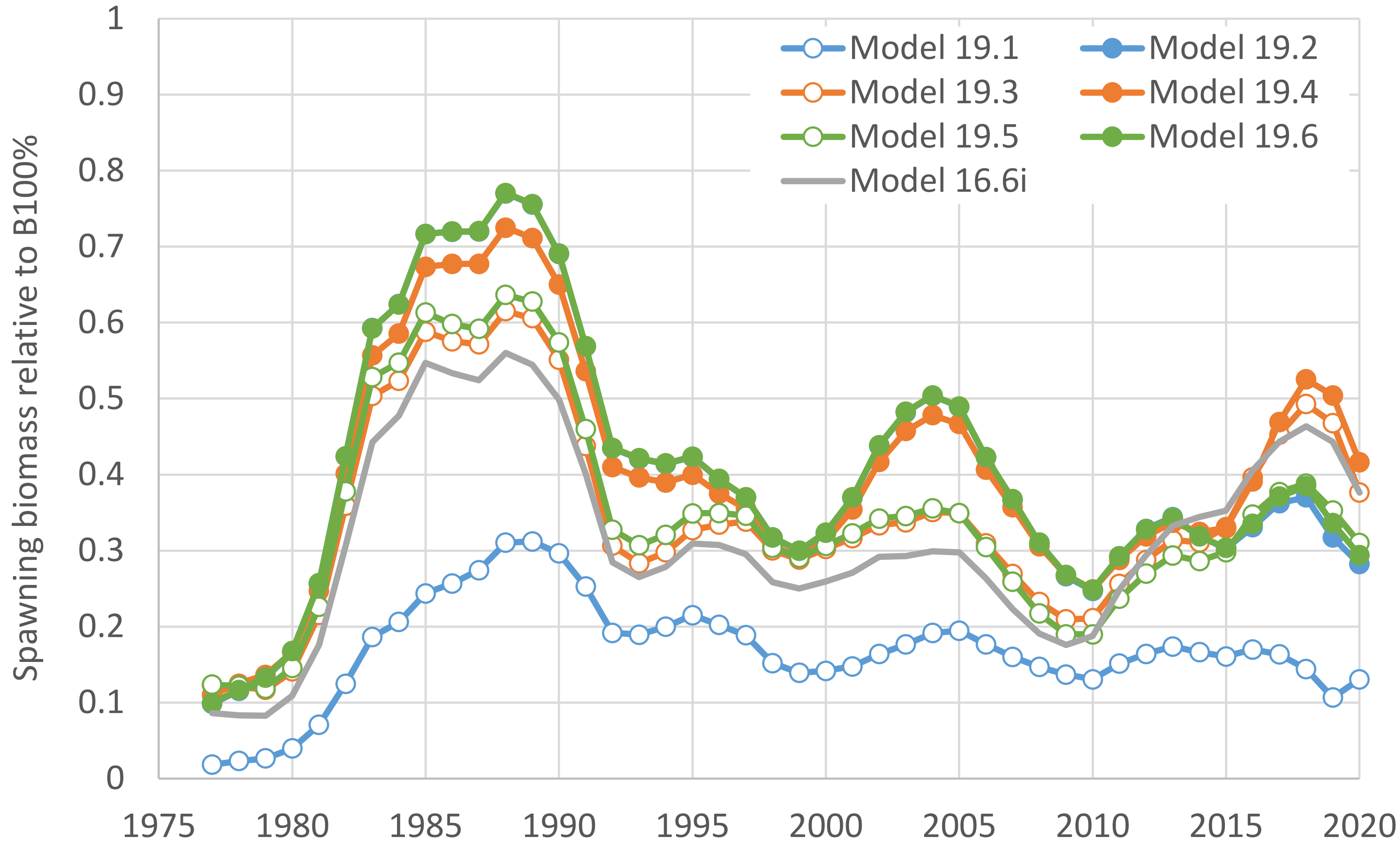
# EBS Pacific cod (29 of 38)

- Total (age 0+) biomass, with projections



# EBS Pacific cod (30 of 38)

- Relative spawning biomass, with projections



# EBS Pacific cod (31 of 38)

- Team discussion of models (1 of 5):
  - A bridging analysis was performed to show the effect of sequentially adding or changing data or an assumption, with the caveat that the order of the steps may influence the perception of important changes
  - Bridging from 16.6i to 19.3 showed a large change when adding fishery age-compositions, but subsequently became more similar to 16.6i as selectivity changes were made
  - Bridging from 19.3 (simple) to 19.4 (complex) showed a large change when weighting the data but again approached 19.3 with the inclusion of additional specifications
  - The fits to survey data improved greatly when estimating yearly random variation in catchability
  - Retrospective plots would be useful to determine if large $\rho$ values were influenced by a single peel where a significant portion of the data were removed (e.g., the few recent NBS observations)

# EBS Pacific cod (32 of 38)

- Team discussion of models (2 of 5):
  - Last year, Team members suggested that values of $Q \geq 1.0$ for both the EBS and NBS (in the same year) might be justified if the survey were simply following the fish northward
    - However, independent analyses of fishery CPUE by the author, Alan Haynie, and Allen Chen did not support this hypothesis
  - There was concern that the truncated survey area for the NBS survey in 2018 could cause an overinflation of the 2018 survey estimates
    - This is a benefit of VAST, as it will tend to smooth between the 2017 and 2019 estimates
    - It would be useful to compare the design-based NBS estimates to the model-based estimates of abundance for only the NBS area
    - Additionally, it would be useful to see the VAST estimates without the cold-pool variable

# EBS Pacific cod (33 of 38)

- Team discussion of models (3 of 5):
  - Why should selectivity be time-varying, given standardization of the gear and inclusion of time-varying catchability?
    - Statistically, there was support to estimate time-varying selectivity and catchability for the survey
    - Also, the annual deviations in water temperatures nearshore could be changing the distribution of fish in the surveyed area
  - There was some discussion on the use of the ageing bias correction in the model and how growth can be confounded with ageing bias estimation in Stock Synthesis
    - Authors had explored annually varying $K$ and $L_{1.5}$, but their relation to ageing bias within the model was not explored, except to note that the mean bias at age 1 was virtually constant across models, regardless of whether $L_{1.5}$ was allowed to vary

# EBS Pacific cod (34 of 38)

- Team discussion of models (4 of 5):
  - Mohn's ρ may not be a useful diagnostic unless accompanied by retrospective plots
  - Looking at these model predictions retrospectively involves comparing across the 6 models as well as datasets and hypotheses
  - It does not appear to be appropriate to penalize a model that is attempting to predict movement in and out of the NBS with observations available only for several recent years
  - Further, the Team was concerned that specific parameters might be driving the retrospective pattern; looking at the retrospective results for specific parameters can aid in interpreting Mohn's ρ
  - Mohn's ρ was used as a formal justification for model selection last year, but this does not seem appropriate to use across these model-data combinations for model selection this year across hypotheses

# EBS Pacific cod (35 of 38)

- Team discussion of models (5 of 5):
  - Can Hypothesis 1 (EBS only) be removed, given that:
    1. another year of NBS and EBS survey data are now available,
    2. young fish are present in the NBS,
    3. genetics are similar between the areas, and
    4. the longline fishery has been operating in the NBS?
  - Given concerns regarding uncertainty in the connection with Russian waters and the possibility that young fish could have moved into the survey area as a result of warm water nearshore in the NBS, Hypothesis 1 is still useful
  - Funding is in place for a 2020 NBS survey, and support for Hypothesis 1 may be considered again in the future
  - Hypothesis 1 could be downweighted if there is less support for it than for the others

# EBS Pacific cod (36 of 38)

- The Team recommends that:
  - The authors break out the NBS VAST vs empirical in November. (Show separate indices for EBS and NBS using VAST and design-based estimators, along with the combined estimates)
  - The simple and complex versions of models associated with the three developed hypotheses should move forward
  - If possible, the authors leave out areas of the NBS (for 2017-2019) for cross-validation of VAST models 19.3 and 19.4 and areas of the EBS. Specifically, leaving out the northern portion could be valuable, dependent on the time available.
  - (continued on next slide)

# EBS Pacific cod (37 of 38)

- The Team recommends that (continued):
  - The 6 19.X models be brought forward in November and the author choose an ensemble if time allows along with appropriate weighting
    - If time does not allow, bring back six 19.X models and an equal weighting average may be attempted by the Team during the Plan Team meeting with the set or a subset of the available models (using code developed for SS ensemble averaging developed by Allan Hicks)
    - Team recommends that author provide measures of uncertainty for all models so that it would be possible to select ensemble elements and integrate them into a single assessment model
  - Present retrospective estimates of specific parameters that show retrospective patterns
    - Steve Barbeaux may help by providing a script to assist with this

# EBS Pacific cod (38 of 38)

- A question for the SSC from the senior author:  Should last year's model evaluation criteria (below) be modified and, if so, how?
  1. Are catchability estimates plausible?
  2. Is retrospective performance acceptable?
  3. Are changes in the complexity of model structure justified?
     - SSC (6/18): "...Assessments should be periodically evaluated for 'complexity creep' and consistency with similar assessments."
  4. Are changes in model structure appropriately incremental?
     - SSC (6/12): "…The SSC encourages the authors to evaluate changes in one or a few structural elements at a time."
     - SSC (6/13): "...The SSC recommends that model changes be kept to a minimum...."
     - SSC (12/15): "...The SSC has repeatedly stressed the need to incrementally evaluate model changes...."

# Model averaging (1 of 14)

- Grant Thompson presented a proposal for model averaging by cross-conditional decision analysis (CCDA)
- This was, in part, a response to a pair of Team and SSC requests:
  - BPT8: “For next year’s assessment, the Team recommended that ... the author considers bringing forward an ensemble of models to capture structural uncertainty with a justifiable weighting....”
  - SSC8 (part 2): “...Moving forward, weighting of models for an ensemble may be developed based on the relative plausibility of each model hypothesis. The SSC recommends further efforts in developing this approach.”
- It appears that the Team wants weighting to be objective and the SSC wants weighting to be subjective (see also SSC 10/17 minutes)
  - Objective: weights are computed statistically
  - Subjective: weights are assigned based on relative believability

# Model averaging (2 of 14)

- Problem #1: ensembles require weighting (equal weighting is an option)
  - Basic steps in a Bayesian approach:
    - Choose a quantity of interest
    - Calculate the posterior distribution of the quantity of interest
    - Choose a loss function
    - Integrate the product of the posterior pdf and the loss function
    - Minimize the integral (the expected loss; i.e., the risk)
  - Step 2 in the above list becomes complicated when dealing with an ensemble (i.e., a set of models), because the posterior distribution will be an average of the *model-specific* posterior distributions, but there is yet no consensus on how this average should be computed

# Model averaging (3 of 14)

- Previous solutions to problem #1:
  - Many authors suggest that the weights should ideally consist of Bayesian posterior probabilities
  - However, computation of such probabilities can be difficult and, more importantly, requires that the same data be used to fit all of the models in the ensemble
  - Although some studies have successfully produced fully Bayesian probabilities for the models in an ensemble, most have defaulted to approximations (e.g., purely subjective “plausibility weighting” or weights based on importance sampling, Akaike Information Criterion, Bayesian Information Criterion, Deviance Information Criterion, bootstrapping, cross-validation, or retrospective analysis) or assumed equal weighting.
  - (continued on next slide)

# Model averaging (4 of 14)

- Previous solutions to problem #1, continued:
  - The “superensemble” approach, introduced originally by Krishnamurti et al. (1999) in the fields of weather and climate forecasting and recently applied to fisheries management by Anderson et al. (2017) and Rosenberg et al. (2018), provides another alternative, in which weights are estimated statistically so as to minimize an objective function (here, the expected loss)
  - These two major alternatives, weights that *reflect probability* and weights that *maximize performance*, are not mutually exclusive
  - Both can be used simultaneously, as they serve different purposes
  - The former are necessary to *compute* the expected loss, whereas the latter can be used to *minimize* the expected loss

# Model averaging (5 of 14)

- Problem #2: unobservable quantity of interest
  - When $ofl$ is the quantity of interest and an ensemble is involved, the methods that have been used for optimizing performance-based weights in other disciplines are typically not applicable
  - This is because, in other disciplines such as weather forecasting, a time series of true values for the primary quantity of interest exists (e.g., precipitation is routinely measured with negligible error) and can be used to estimate ("train") the optimal weights, but in fishery management, no time series of "true" $ofl$ values exists
  - One possibility is to optimize the weights by training on data that *are* observed, such as a survey index time series (as suggested by Stewart and Martell 2015), but there is no guarantee that an ensemble tuned to fit something other than the quantity of interest will be good at estimating the quantity of interest

# Model averaging (6 of 14)

- This is where conditioning comes in:
  - Reasons why we do not have a time series of true OFLs:
    1. We do not know the structure of the true model
    2. We have only one realization of the data used by any given model
  - Both of these problems can be addressed by treating each model, one at a time, *as though* it were the true model ("conditioning")
    - Conditional parametric bootstrapping $\rightarrow$ distribution of OFL estimates $\rightarrow$ optimal OFL estimate for the respective model
    - The optimal OFL estimate is still not the "true" OFL, but we have always acted as though the best point estimate is the true OFL, so why not do so here as well (where we "know" the true model)?
  - But what do we do with the other models in the ensemble while a particular model is taking its turn as the conditionally true model?

# Model averaging (7 of 14)

- This is where cross-conditioning comes in:
  - As each model is taking its turn as the conditionally true model (the “pivot” model), all of the other models are also fit to the bootstrap data sets generated by the pivot model (“cross-conditioning”)
  - For each pivot model, a conditional expected loss is computed by comparing the weighted average OFLs from the full set of models to the optimal OFL for the pivot model and averaging across all bootstrap data sets for that pivot model
  - An overall expected loss is then obtained by multiplying each conditional expected loss by the probability that the respective pivot model is the true model, then summing over all pivot models
  - The optimized OFL pdf for the ensemble is obtained by adjusting the weights (not the probabilities) so as to minimize the expected loss, then using those weights to average the model-specific OFL pdfs

# Model averaging (8 of 14)

- "Decision analysis" is just another name for "decision theory," which the author has been advocating for the last 30+ years, with few successes:
    - Tier 1 buffer (an approximation)
    - PSEIS alternative 3b (another approximation)
- Reason for so few successes: full optimization is hard!
    - Full optimization requires being able to measure the physical impacts of various fishing mortality rates (e.g., the impacts on long-term yield resulting from fishing too much or too little)
- CCDA, on the other hand, addresses a much simpler problem:
    - CCDA requires only a subjective assessment of the relative undersirability of various OFL overestimates or underestimates

# Model averaging (9 of 14)

- The following loss function is assumed:

$$loss(y|\hat{y},ra) = \left(\frac{y^{1-ra} - \hat{y}^{1-ra}}{1-ra}\right)^2 \text{, where:}$$

  - $y$ is the quantity of interest,
  - $\hat{y}$ is intended to approximate the true-but-unknown value of $y$, and
  - $ra$ is the level of risk aversion, where:
    - any value of $ra > 0$ implies true risk aversion
    - the special case of $ra = 0$ implies risk neutrality, and
    - any value of $ra < 0$ implies risk proclivity
      - Here, "risk aversion" means that any underestimate is preferred to an overestimate of the same magnitude

# Model averaging (10 of 14)

- The procedure is fairly general, and should be applicable to a wide range of choices as to the quantity of interest, with two constraints:
  - the quantity of interest cannot take negative values, and
  - if any value of $ra$ other than $0$ is chosen, the scaling of the quantity has to be consistent with the meaning of risk aversion
- Risk is defined as the expected loss (i.e., the sum of the product of the pdf or pmf and the loss function)
- The risk-minimizing value of $\hat{y}$ is the $y$ mean of order $1{-}ra$, defined as the $(1{-}ra)$th root of the $(1{-}ra)$th noncentral moment of the $y$ pdf.

$$m_y(1-ra)=\left(\int_0^{\infty} g_y(y)y^{1-ra}dy\right)^{1/(1-ra)}$$

- If $ra{=}0$, solution is arithmetic mean; if $ra{=}2$, solution is harmonic mean

# Model averaging (11 of 14)

- Using CCDA to produce harvest specifications:
  - For OFL:
    1. Optimize each conditional OFL using a risk-neutral loss function
    2. Optimize the ensemble OFL pdf using a risk-neutral loss function
    3. Optimize the ensemble OFL using a risk-neutral loss function
    4. Set OFL = risk-neutral ensemble OFL
  - For ABC:
    1. Optimize each conditional OFL using a risk-averse loss function
    2. Optimize the ensemble OFL pdf using a risk-averse loss function
    3. Optimize the ensemble OFL using a risk-averse loss function
    4. Compute the average control rule ABC using risk-averse weights
    5. Set ABC = min(risk-averse ensemble OFL, control rule ABC)

# Model averaging (12 of 14)

- ABC in the NS1 guidelines:
  - 2016 NS1 guidelines (proposed rule):
    - "The North Pacific Council expressed interest in using a decision theoretic approach, which is similar in concept but is not the same as the probabilistic approach"
  - 2016 NS1 guidelines (final rule):
    - ABC "is a level of a stock or stock complex's annual catch, which is based on an ABC control rule that accounts for the scientific uncertainty in the estimate of OFL, any other scientific uncertainty, and the Council's risk policy"
    - "The Council's risk policy could be based on an acceptable probability (at least 50 percent) that catch equal to the stock's ABC will not result in overfishing, but other appropriate methods can be used"

# Model averaging (13 of 14)

- Some issues with the approach:
  - Different from the common $p*$ approach
  - Nothing like this is done for any NPFMC stocks currently
  - Requires specifying each model's probability of being "true"
    - Compare to SSC request for weighting based on "plausibility"
  - Requires specifying a level of risk aversion (for $abc$)
    - Compare to need for specifying $p*$
  - Complicated!
  - Time-consuming ($nmod \times nsim \times nmod$ runs required)!
  - Very small amount of testing to date
  - Dirichlet-multinomial distribution not yet implemented in the SS routine for generating bootstrap data sets

# Model averaging (14 of 14)

- Team discussion of CCDA:
  - Team and author agreed that there are likely too many issues to resolve in order to utilize CCDA in this year's assessment
  - Given the infeasibility of using CCDA in November, the Team discussed alternative means of creating a model ensemble
  - The Team noted that the largest struggle has been selecting among 2-3 relatively equally feasible models
  - Thus, maintaining the ability to equally weight a subset of models in an ensemble is very appealing for choosing the best model(s)
- The Team recommends continuing investigation of the CCDA model averaging method, realizing it is unlikely to be implemented this year. The Team is very enthusiastic about this approach. The Team will discuss with the author whether additional input would be useful in further testing and developing the method.

# Model averaging: author's concerns (1 of 7)

- The CCDA approach differs significantly from the approaches recommended by the Team and SSC:
  - BPT8: "...All model outputs in the ensemble that are management related should be averaged, and the ABC should be determined from those averaged outputs (i.e., the application of the control rule to averaged biological reference values"
  - SSC2: "...The combining of model output should occur on the basic estimates from the assessment (biomass, F, etc.) and not the reference points themselves"
- The steps involved in implementing the Team and SSC approaches are listed on the next 2 slides

# Model averaging: author's concerns (2 of 7)

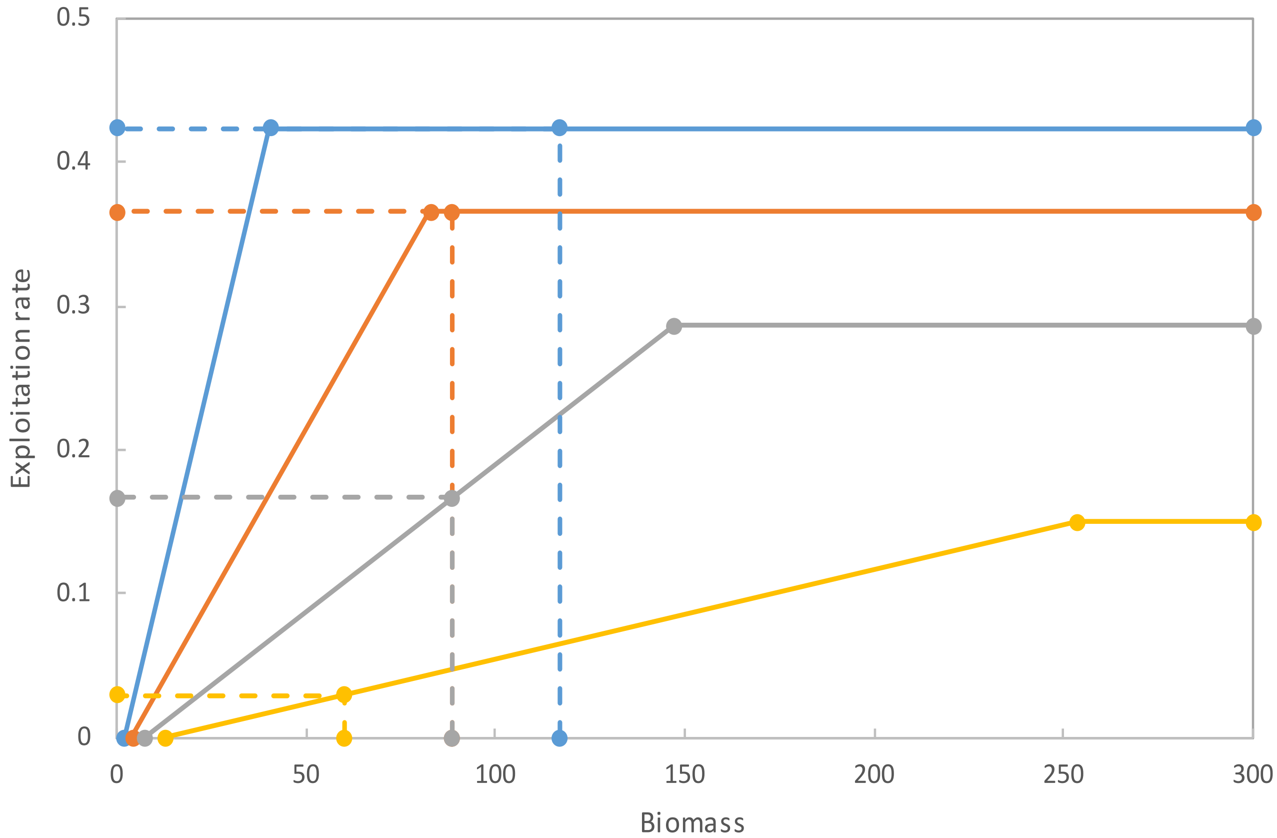
- Team's approach:
  - Compute averages of model-specific natural mortality rates, maturity-at-age vectors, selectivity-at-age vectors, and weight-at-age vectors
  - Compute averages of model-specific $F_{40\%}$ and $B_{40\%}$ estimates
  - Use the averages computed in step 2 to parameterize an "average" *maxABC* harvest control rule
  - Compute average of model-specific projected spawning biomasses; then insert that average into the "average" *maxABC* harvest control rule constructed in step 3 to obtain an "average" *maxFABC*
  - Use averages computed in step 1 and "average" *maxFABC* value obtained in step 4 to compute an "average" *maxABC* at each age
  - Compute the "average" *maxABC* as the sum (across ages) of the model-specific "averages" computed in step 5

# Model averaging: author's concerns (3 of 7)

- SSC's approach:
  - All steps are the same as in the Team's approach, except for step 2, which is replaced by the following:
  - Do not average the model-specific $F_{40\%}$ and $B_{40\%}$ reference points as in step 2 of the Team's approach, but instead use the averages computed in step 1 to compute an "average" $F_{40\%}$ value; then compute the average of the model-specific mean recruitments and use that average along with the averages computed in step 1 to compute an "average" $B_{40\%}$ value

# Model averaging: author’s concerns (4 of 7)

- Legend: blue = Model 2, orange = SSC, gray = Team, yellow = Model 1
- Team maxABC = 18.974, SSC maxABC = 41.577.



# Model averaging: author’s concerns (5 of 7)

- The problem of nonlinearity:
  - Both the harvest control rule, and the models themselves, result in $abc$ values that are nonlinear transforms of the parameters that are actually involved in minimizing the objective function.
    - Note that biomass is *not* one of the “basic estimates from the assessment;” it is a *function* of the estimated parameters.
  - Analogy: which is the better way to estimate average sample weight?
    - average the weights of the fish in the sample, or
    - fit a weight-at-length model, then average the lengths of the fish in the sample, then insert that average length into the model?
- (continued on next slide)

# Model averaging: author's concerns (6 of 7)

- The problem of nonlinearity (continued):
- As was stressed repeatedly at last year's Team workshop on model averaging and *abc* reductions, it is impossible to produce an "internally consistent" ensemble when nonlinearities are present
- Note the following Team recommendation (9/18, SSC endorsed 10/18):
  - "Assuming that some sort of model averaging is involved, an ensemble model should be treated the same as any other model (i.e., an ensemble is a 'model' and should be treated as such in reference to the existing language in the FMP and SAFE report guidelines)"
  - That is, rather than trying to reverse-engineer a single model that matches the behavior of the ensemble, the ensemble itself should be as "the" model
- (continued on next slide)

# Model averaging: author's concerns (7 of 7)

- The problem of nonlinearity (continued):
  - The solution is simple:
    - If an optimal estimate of $F_{40\%}$ is desired, compute the ensemble estimate of $F_{40\%}$
    - If an optimal estimate of current biomass is desired, compute the ensemble estimate of current biomass
    - If an optimal estimate of the $ofl$ distribution is desired, compute the ensemble estimate of the $ofl$ distribution
    - Etc.
  - The set of resulting estimates will not map into any single assessment model, but they *will* be consistent with the Team/SSC advice to treat the ensemble as a model, and they *will* be optimal

# Blackspotted/rougheye rockfish (1 of 2)

- Diana Stram and Mary Furuness presented the issue of spatial management of blackspotted/rougheye (BSRE) rockfish in the AI
- This stock is managed with a combined Western and Central AI ABC and a Maximum Subarea Species Catch (MSSC) in the WAI and CAI
- In all but one year since MSSC has been provided, the catches in the WAI have exceeded the MSSC, and in 2019 the WAI catch has exceeded 100 t whereas the MSSC is 37 tons
- The Team has expressed “strong concern” regarding stock structure, based largely on stock status and demographic information
- Further genetic research with advanced methods may help elucidate spatial population connectivity
- The Team discussed reviewing subarea ABCs in the future in response to the SSC request to no longer include this analysis (SSC minutes, 12/18)

# Blackspotted/rougheye rockfish (2 of 2)

- The Team recognized that the AKRO already prohibits directed fishing for the species in the WAI/CAI when the TAC is reached and a WAI ABC could serve to increase discards, but potentially not reduce catch
- Catches are generally retained at high levels, but discards increased this year due to large catches of fish that are too small to process
- The Team expressed concerns that the use of MSSC is inconsistent with other species where conservation concerns exist and that the use of MSSC has not resulted in achieving its stated purpose
- The Team also expressed concerns over the choice between MSSC and subarea ABC prioritizing economics over conservation concerns
- The author and industry pointed out that fishery data collection methods have changed and may provide improved information for the assessment
- The Team recommends that BSRE stock structure research, specifically the planned genetics work outlined in the AFSC Genomics Activity Plan, be highlighted in the Council's Research Priorities

# AI Pacific cod (1 of 19)

- Ingrid Spies presented a preliminary age-structured model for AI Pcod
- From 2012 through the preliminary 2016 draft, a total of 22 unique age-structured models were fully vetted in the assessments of AI Pcod
- However, none of them were accepted by either the Team or SSC for the purpose of recommending harvest specifications
- Given that there were so many outstanding issues with respect to the assessments of Pcod in both the EBS and AI as of Sept/Oct 2016, the Team and SSC recommended suspending efforts to develop an age-structured model of the AI stock until such time as the issues with respect to the EBS assessment had been resolved
- In December of 2018, the SSC requested "that an age-structured model be developed" for the AI stock, which prompted Ingrid's current efforts

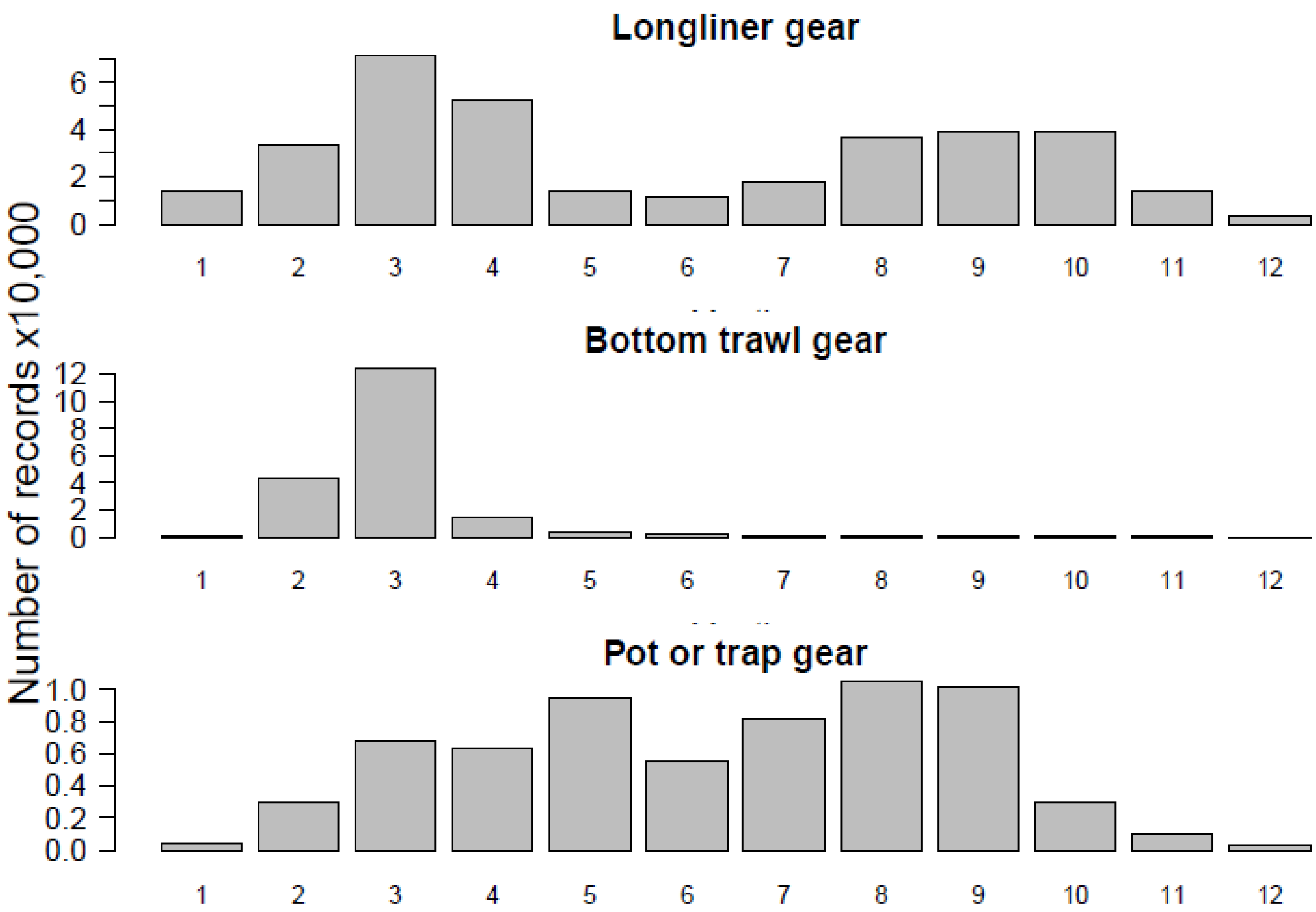
# AI Pacific cod (2 of 19)

- Data used

| Source | Type | Years |
|---|---|---|
| Fishery | Catch biomass | 1990-2018* |
| Fishery | Size composition | 1990-2018 |
| AI bottom trawl survey | Biomass estimate | 1991, 1994, 1997, 2000, 2002, 2004, 2006, 2010, 2012, 2014, 2016, 2018 |
| AI bottom trawl survey | Age composition | 1991, 1994, 1997, 2000, 2002, 2004, 2006, 2010, 2012, 2014, 2016 |

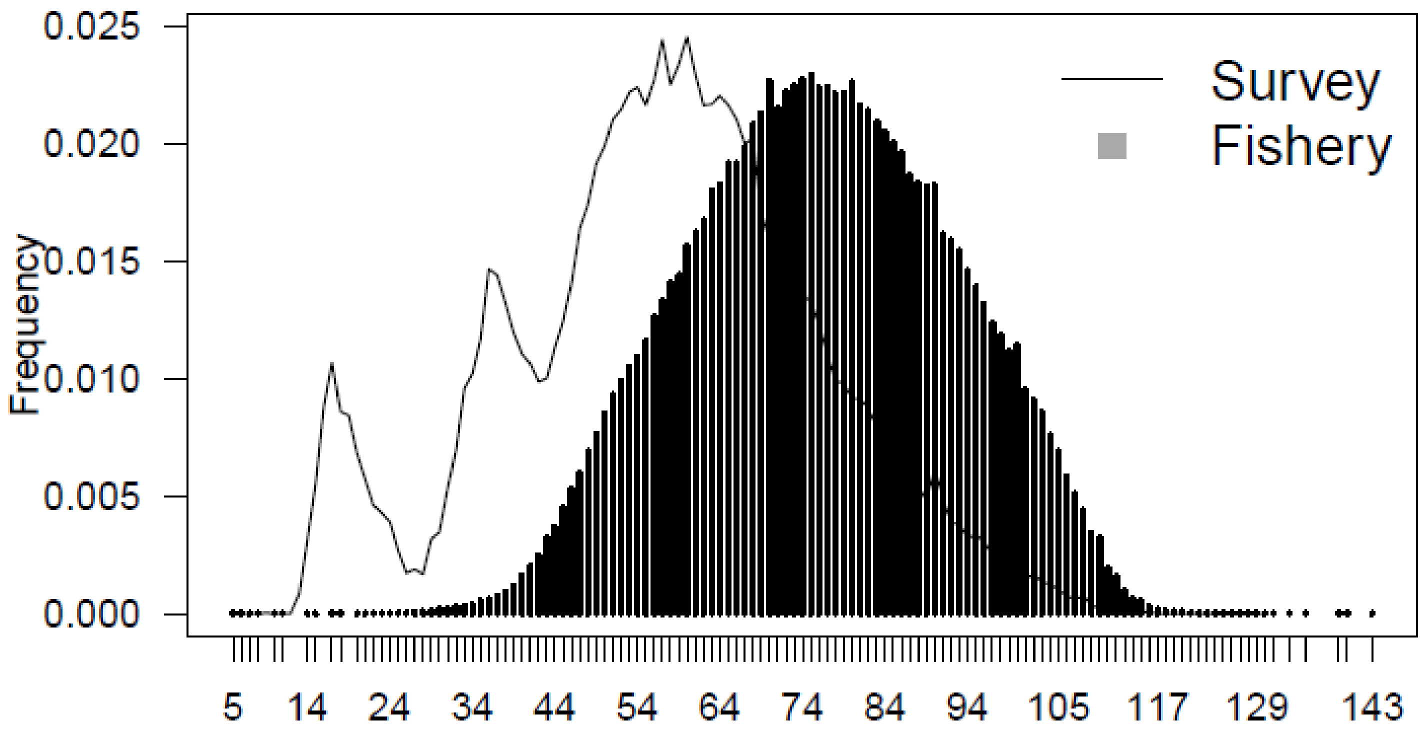
# AI Pacific cod (3 of 19)

- Distribution of length samples by gear and month



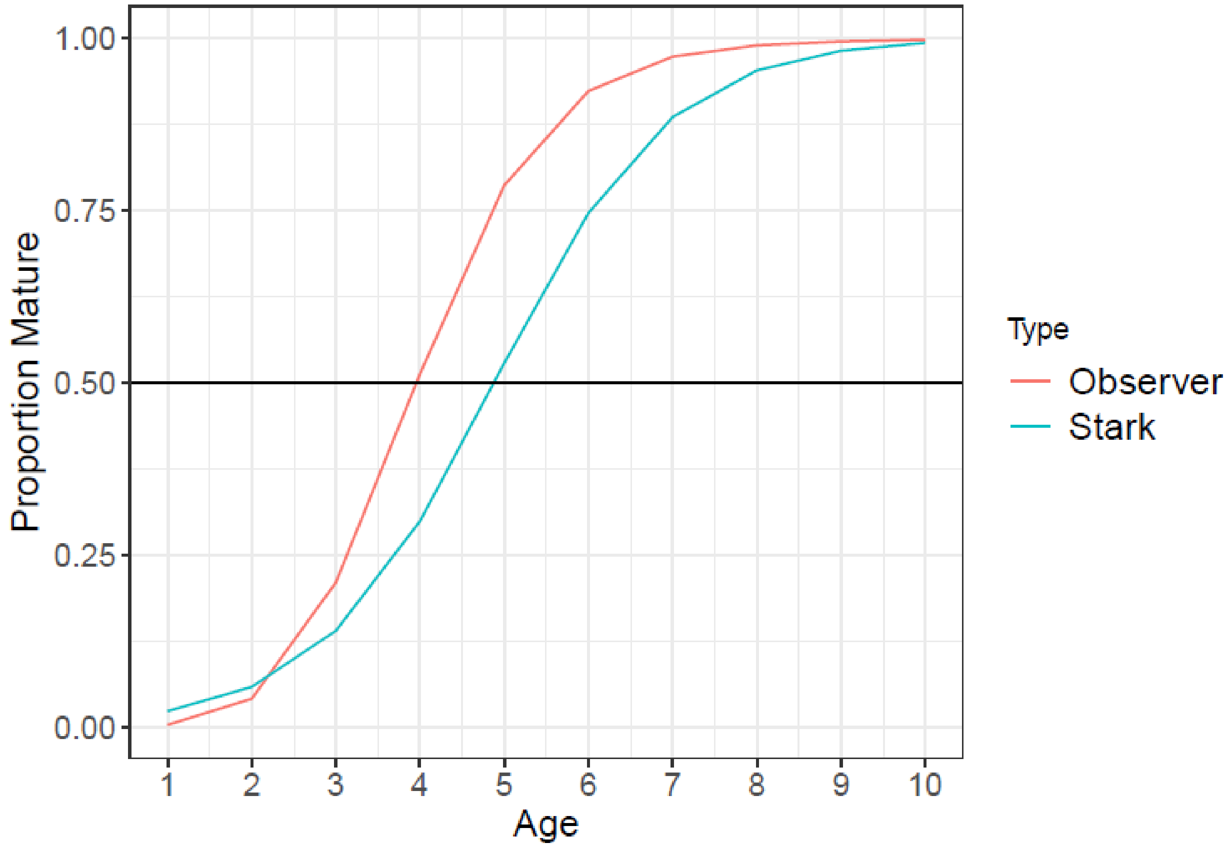
# AI Pacific cod (4 of 19)

- Long-term size (cm) compositions in the survey and fishery



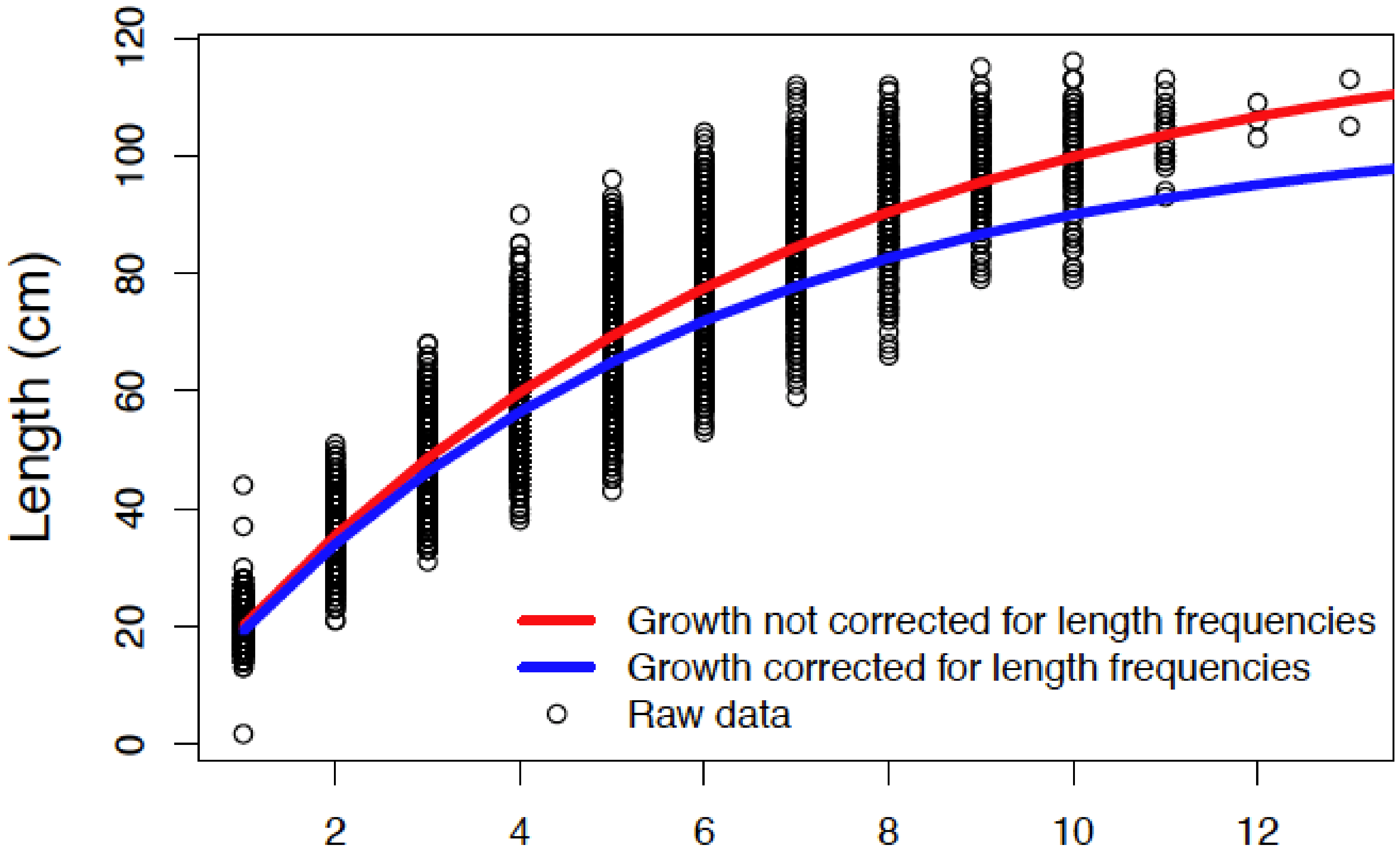
# AI Pacific cod (5 of 19)

- Maturity curves (author chose the curve based on observer data)



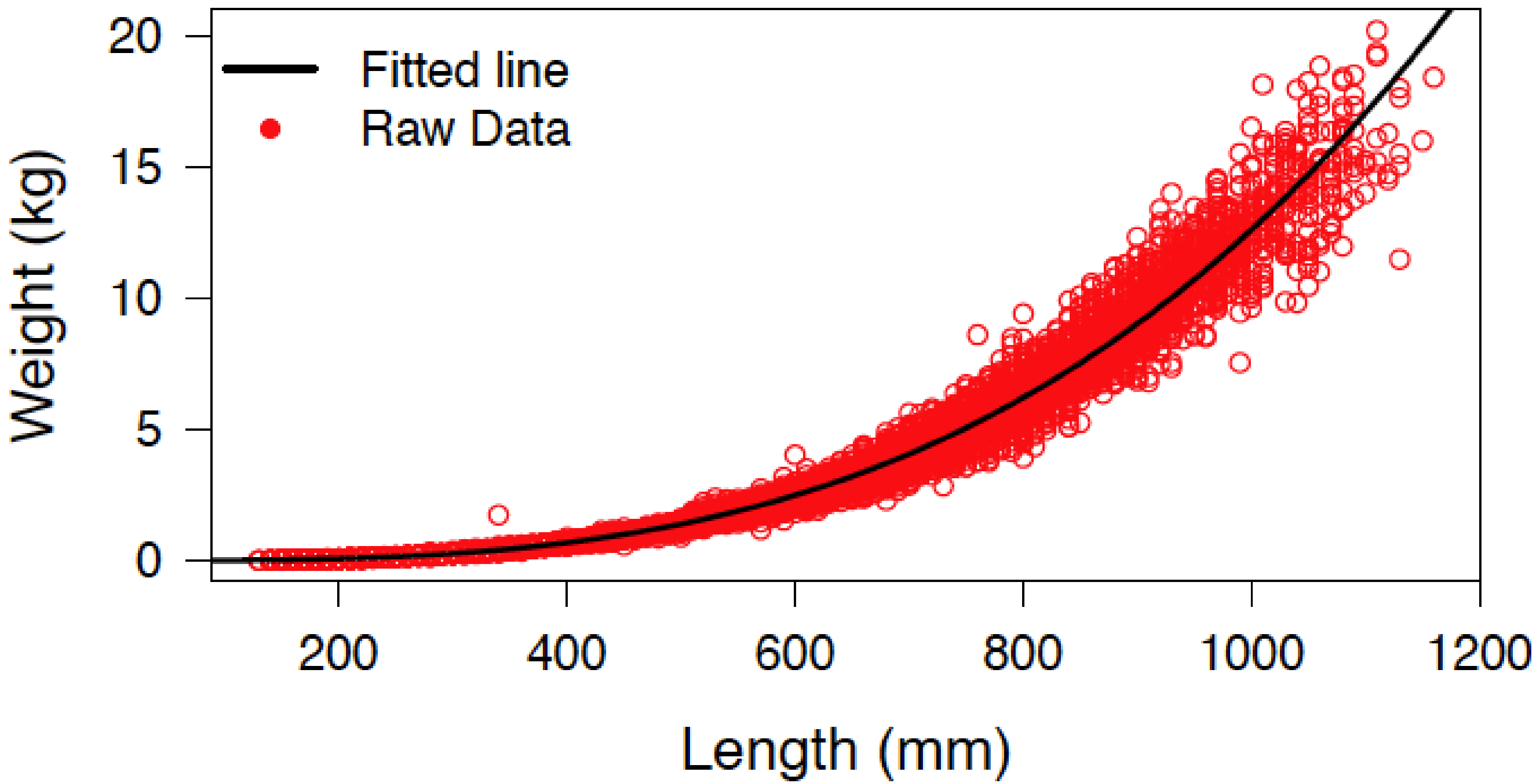
# AI Pacific cod (6 of 19)

- Length at age (author chose the “uncorrected” curve)



# AI Pacific cod (7 of 19)

- Weight at length

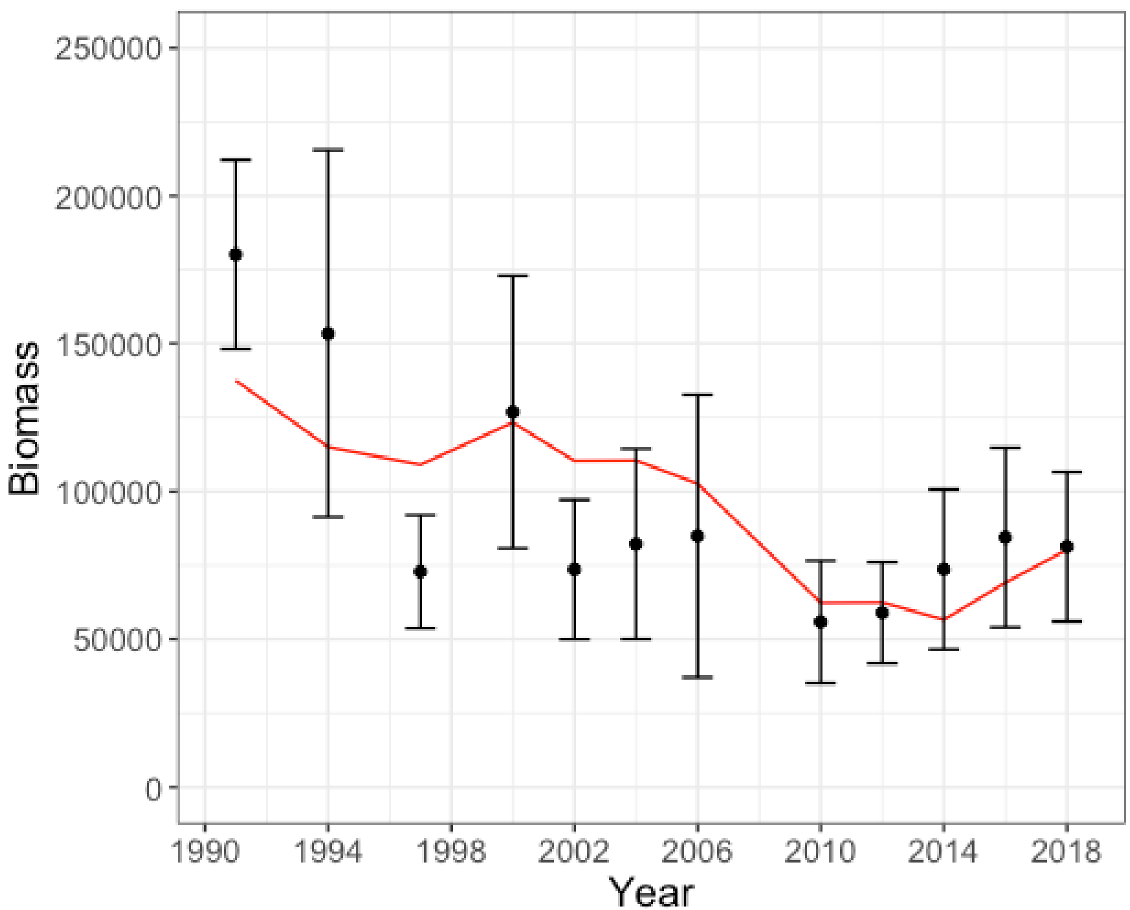


# AI Pacific cod (8 of 19)

- Model features:
  - One fishery, one gear type, one season per year
  - Combined-sex model, with 1:1 male:female ratio
  - Logistic age-based selectivity for both the fishery and survey
  - External estimation of length at age and weight at age
  - Ageing error matrix for ages 1 through 10
  - All parameters constant except for recruitment and fishing mortality
  - Internal estimation of $F$, catchability, and selectivity parameters
  - Recruitment estimated as a mean with normally distributed deviations
  - $M$ fixed at 0.40, informed by likelihood profiles

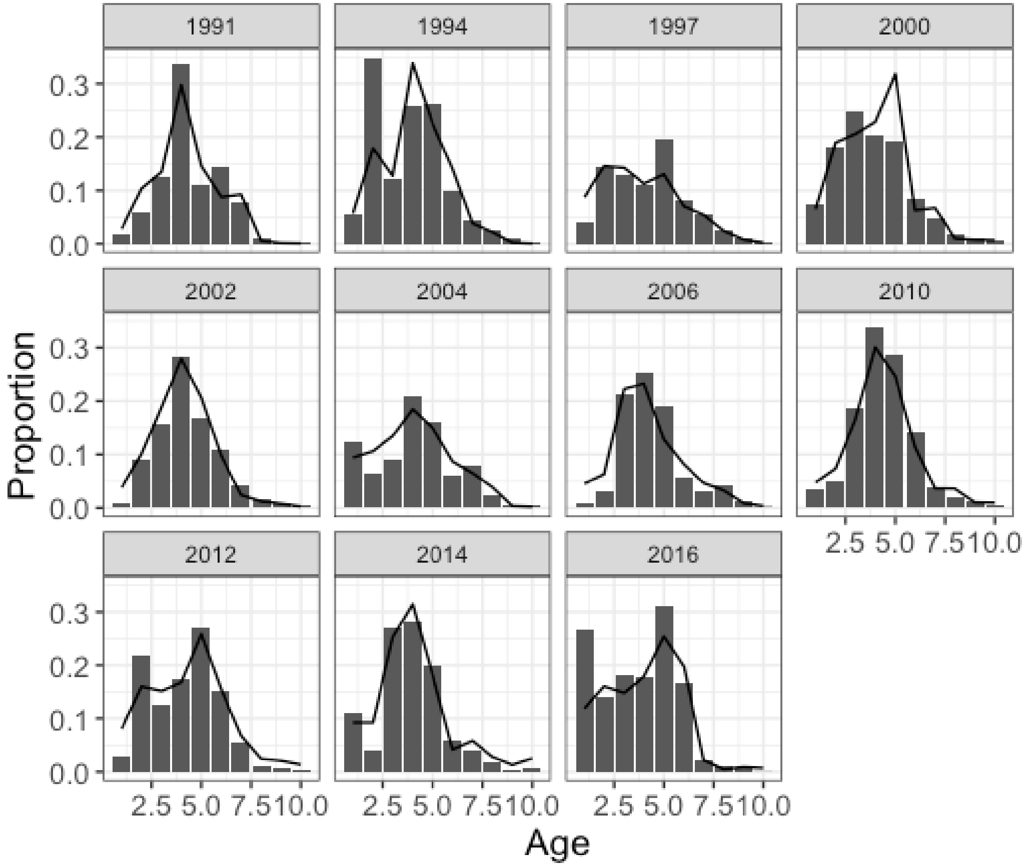
# AI Pacific cod (9 of 19)

- Fit to survey biomass (not in document)



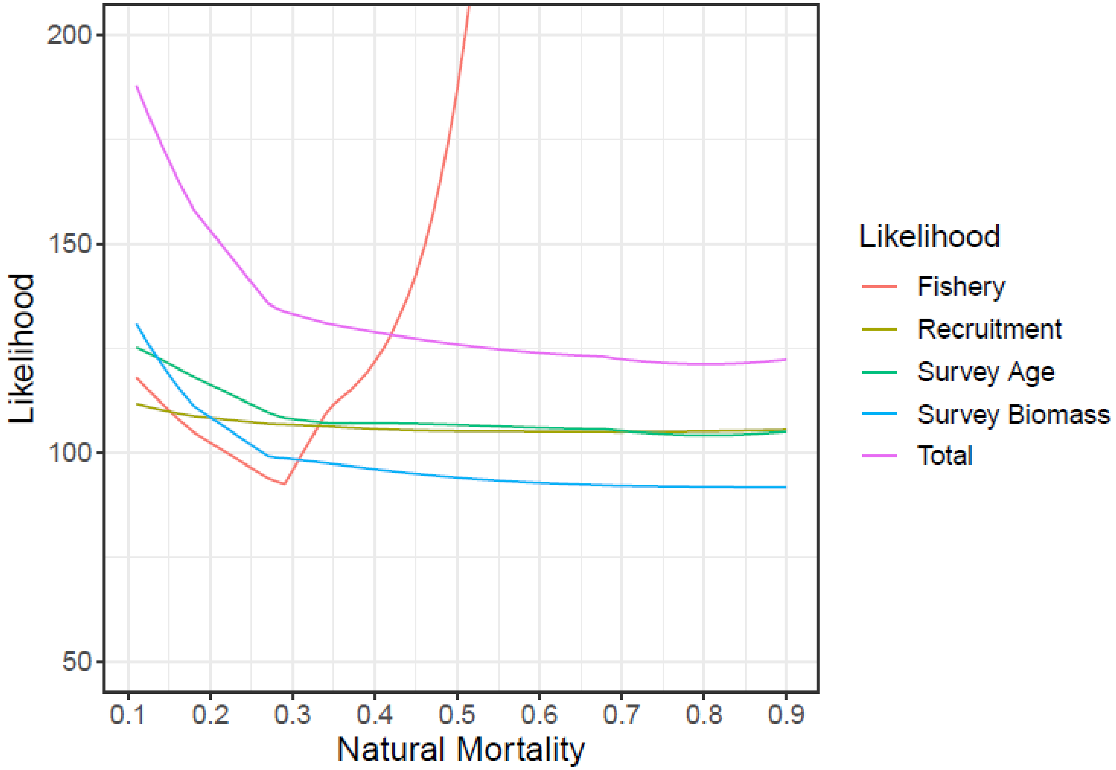
# AI Pacific cod (10 of 19)

- Fit to age composition data (not in document)



# AI Pacific cod (11 of 19)

- Likelihood profiles over $M$




- "To balance the different likelihood components and consider the values for $M$ used in other assessments, the value $M = 0.4$ was selected."

# AI Pacific cod (12 of 19)

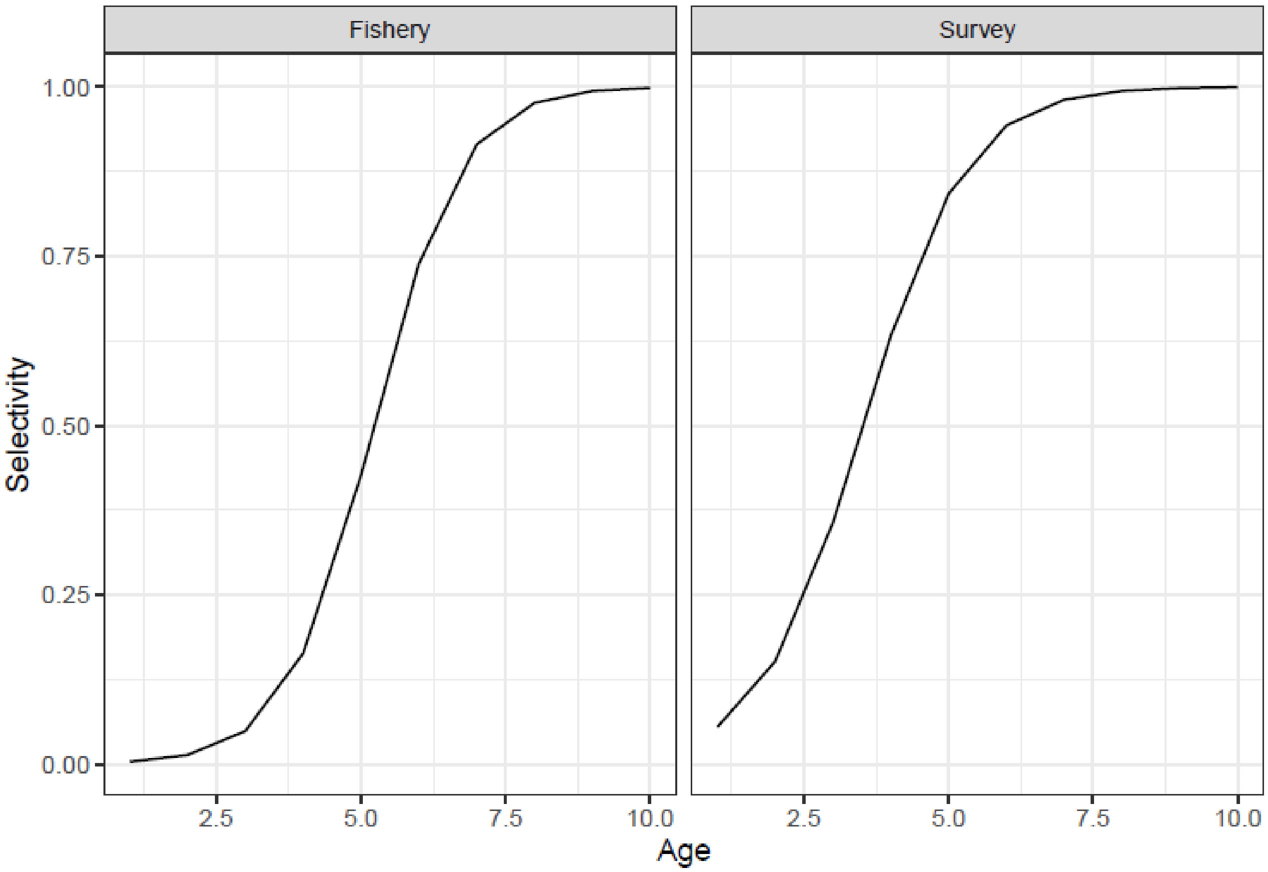
- Estimates of time-invariant parameters

| | Value | Lower Confidence Interval | Upper Confidence Interval |
|---|---|---|---|
| Catchability | 0.91940 | 0.6557800 | 1.1830200 |
| Mean log recruitment | 10.54000 | 10.4444735 | 10.6355265 |
| Log average fishing mortality | -0.65799 | -0.9780776 | -0.3379024 |
| Survey selectivity slope | 1.13220 | 0.9956213 | 1.2687787 |
| Survey selectivity a50 | 3.52110 | 3.0692612 | 3.9729388 |
| Fishery selectivity slope | 1.33620 | 0.4394020 | 2.2329980 |
| Fishery selectivity a50 | 5.22230 | 4.3312448 | 6.1133552 |

- Compare catchability estimate to Nichol et al. (2007) value of 0.916

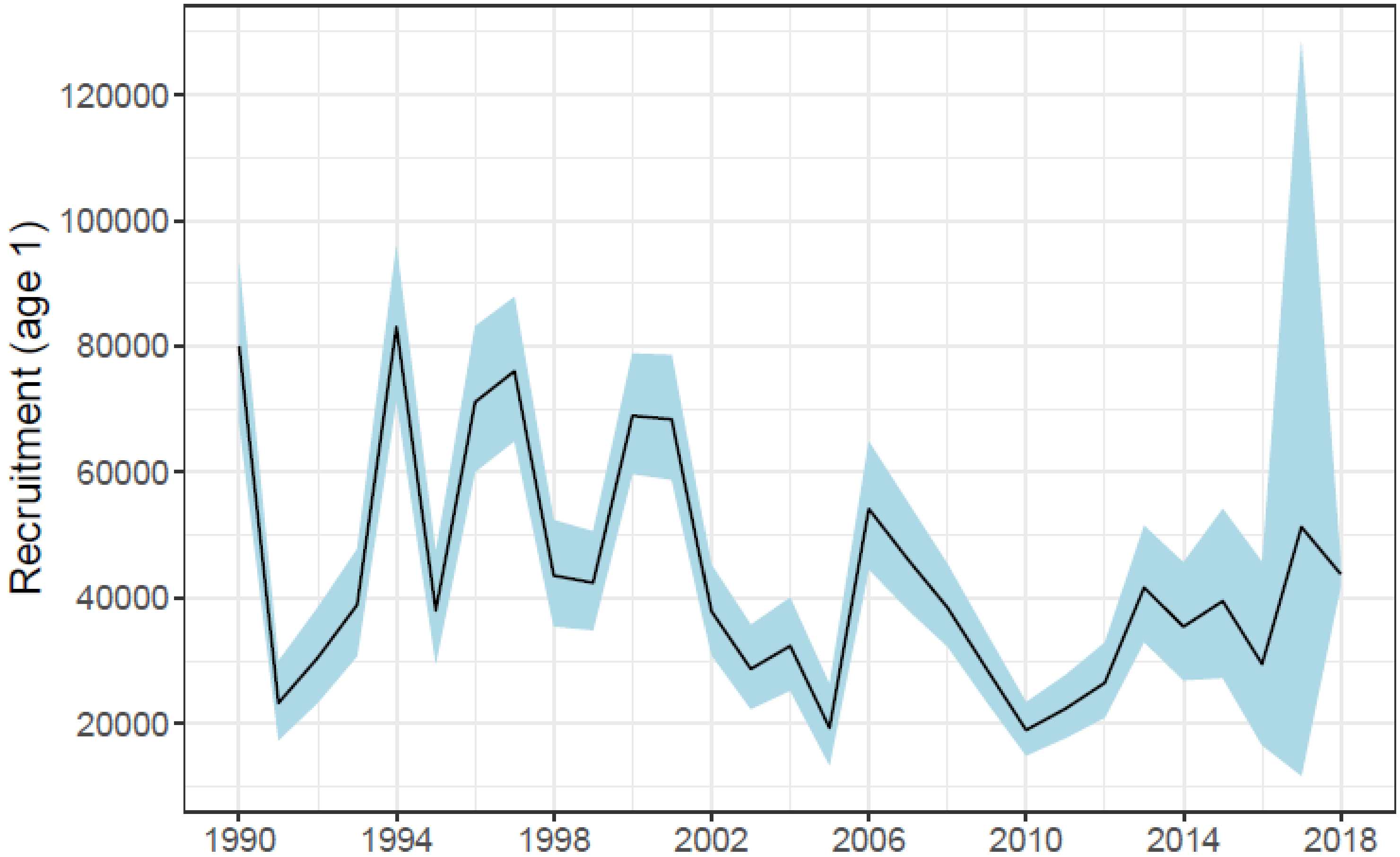
# AI Pacific cod (13 of 19)

- Selectivity in the fishery and survey



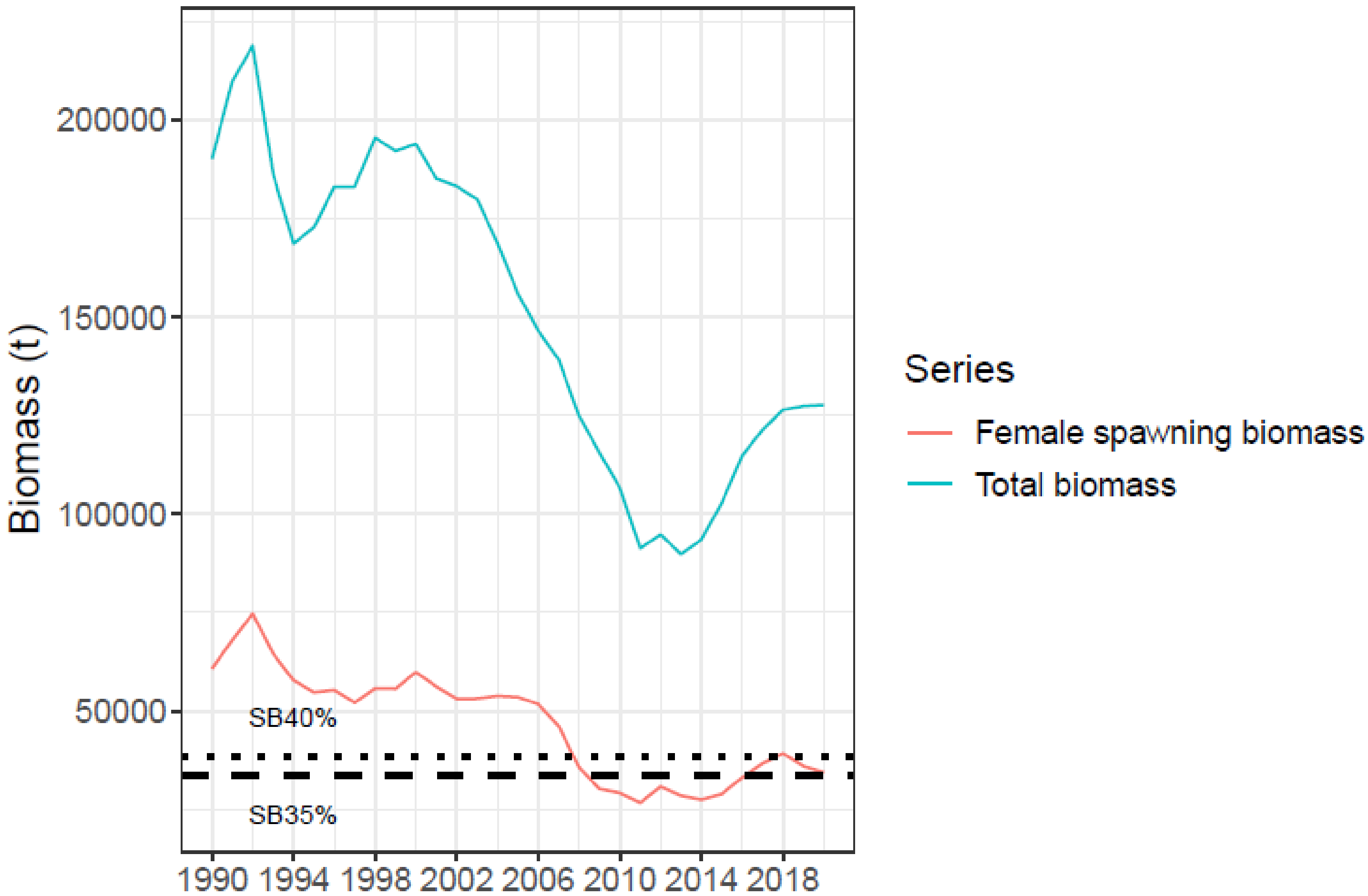
# AI Pacific cod (14 of 19)

- Recruitment time series



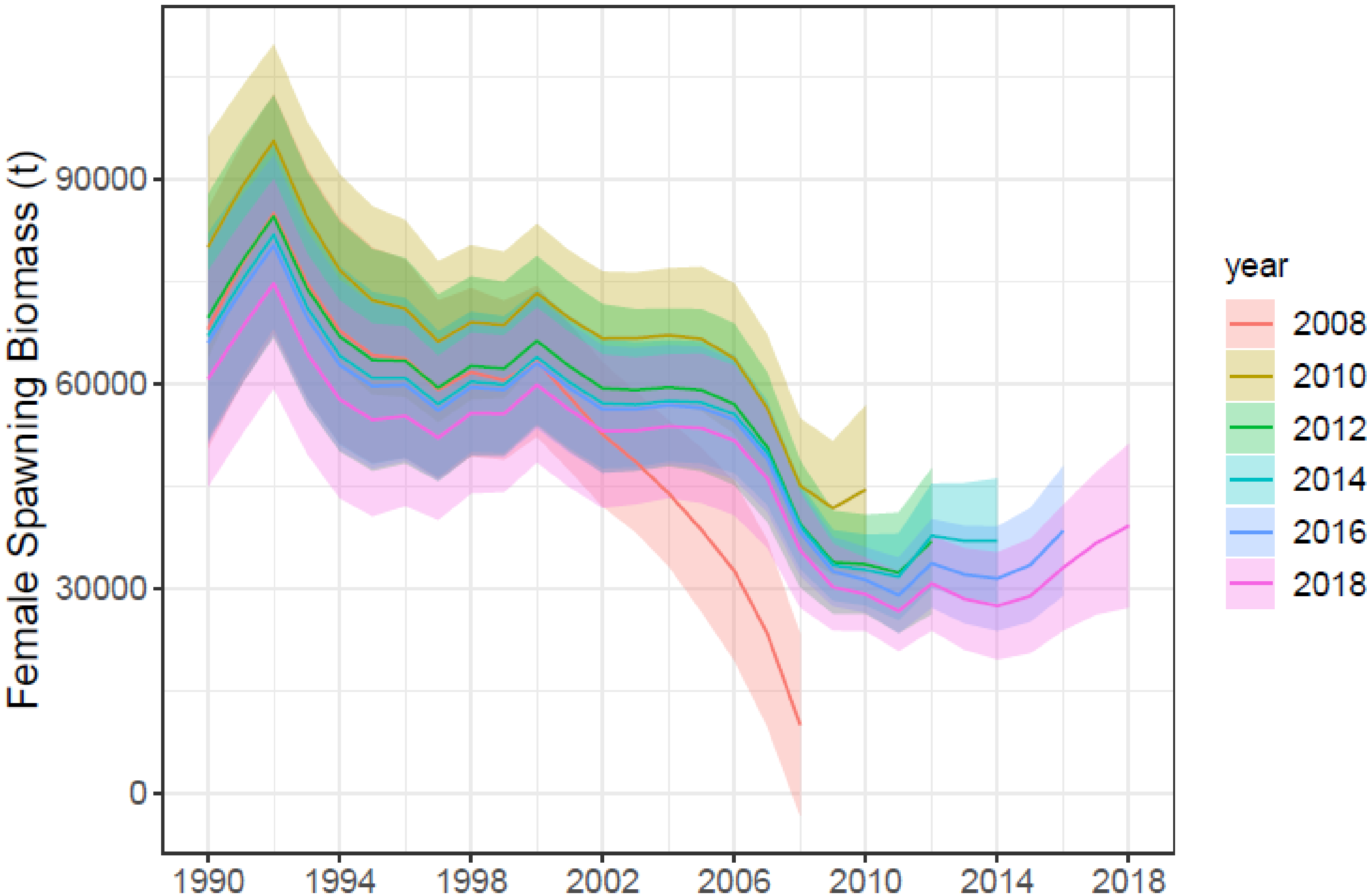
# AI Pacific cod (15 of 19)

- Biomass time series



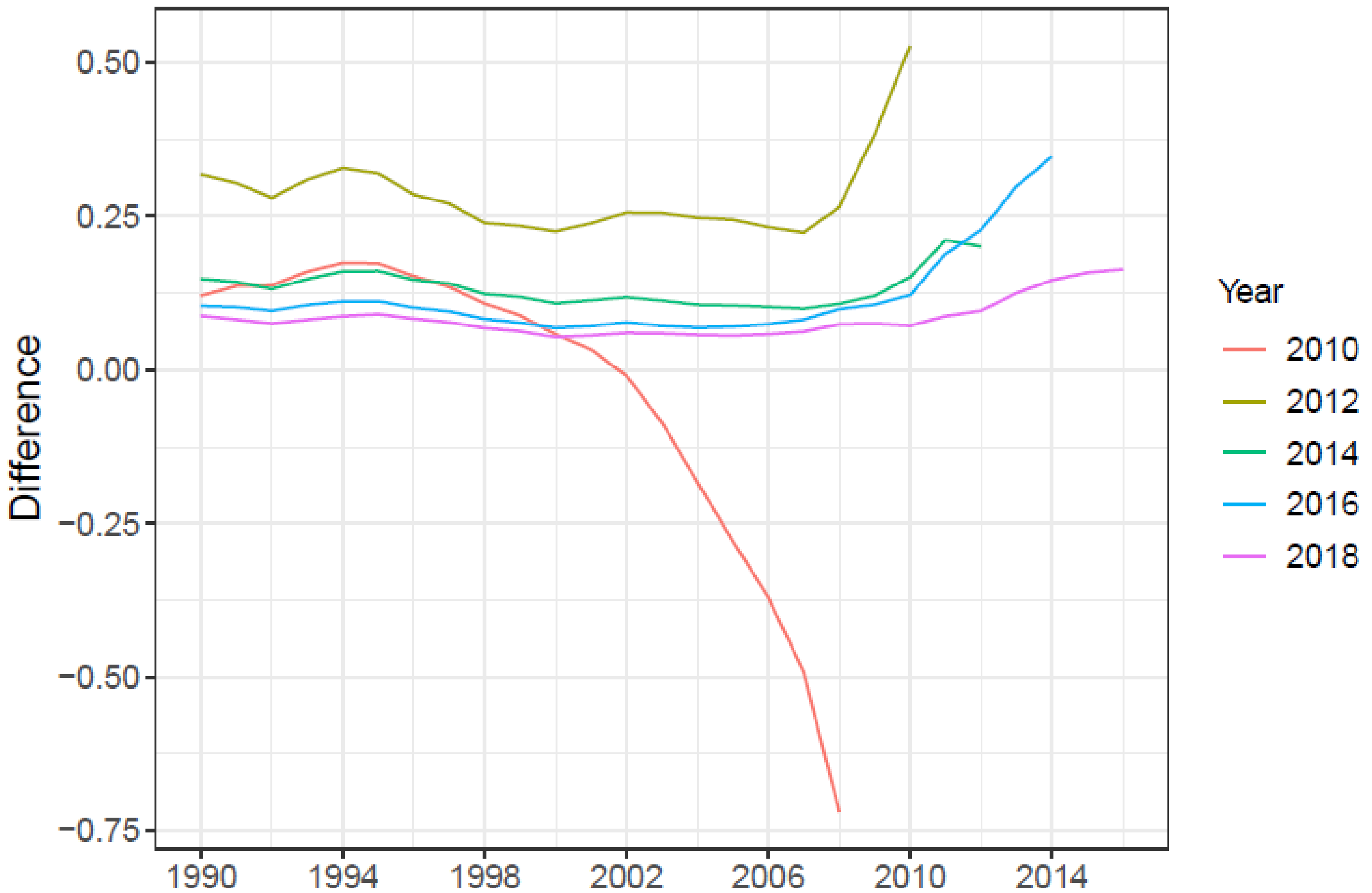
# AI Pacific cod (16 of 19)

- Retrospective analysis ($\rho = 0.10$), slide 1 of 2



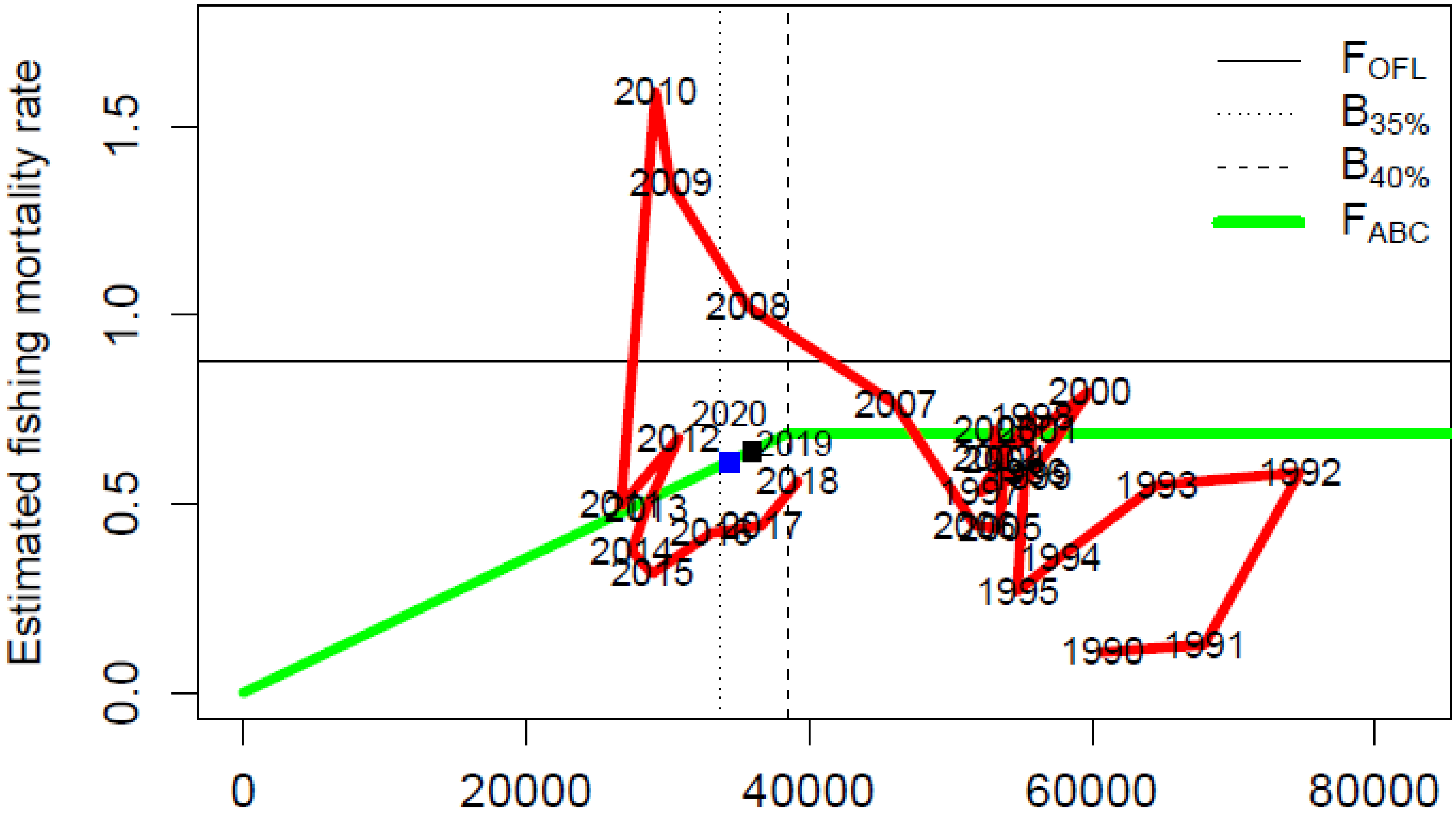
# AI Pacific cod (17 of 19)

- Retrospective analysis ($\rho$ = 0.10), slide 2 of 2



# AI Pacific cod (18 of 19)

- Phase plane



# AI Pacific cod (19 of 19)

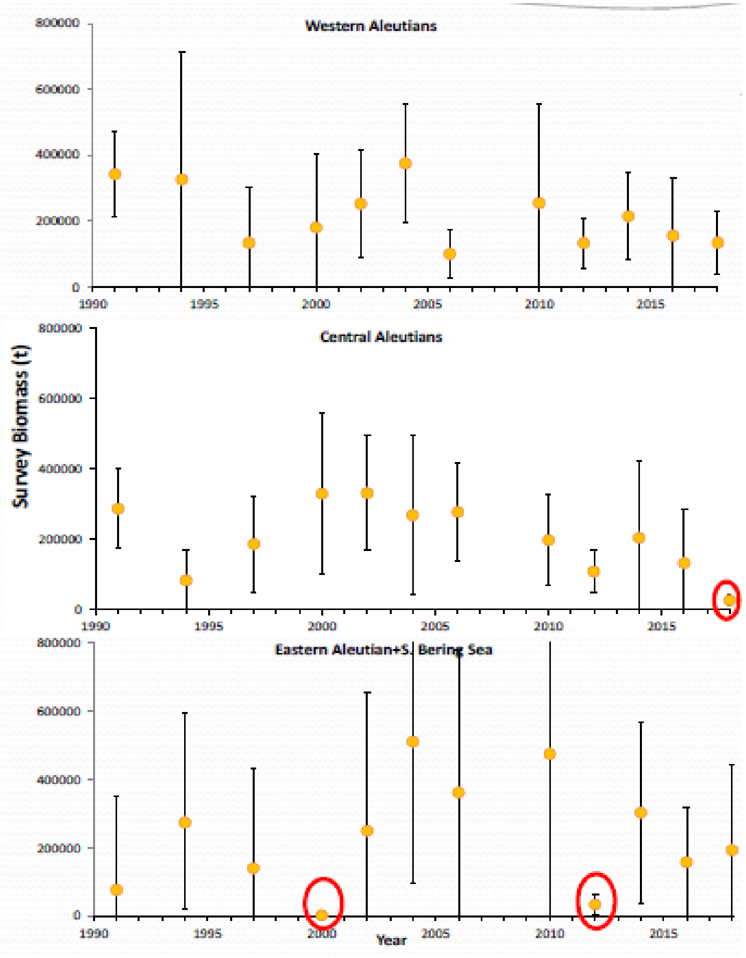
- The Team discussed possible alternative values of $M$, for example:
  - $M = 0.66$ in CEATTLE for age 1
  - $M$ could be fixed at some statistic associated with the prior distribution used in last year's EBS Pcod assessment
- Team recommends that the authors report the fit of the maturity curve
- Team recommends that the authors report an exploration of how different reasonable $M$ values impact reference points
- Team recommends that the authors report the general results of an existing model that was run without fishery lengths
- Team recommends that the authors report quantitative goodness of fit statistics
- Team recommends that the authors communicate with Cindy Tribuzio of AFSC to obtain IPHC survey indices and cod lengths for possible inclusion in future years

# Atka mackerel (1 of 7)

- Sandra Lowe presented a proposal for using fishery independent and dependent indices for apportionment estimation of BSAI Atka mackerel
- For 2018 the stock assessment used the 2018 AI bottom trawl survey data that showed a 21% decrease in biomass for the overall survey area since the 2016 survey, including an 80% drop in biomass for the CAI
- Since 2015, the standard Tier 5 RE model had been fit to the bottom trawl survey to determine apportionments for the three AI areas
- This would have reduced the CAI from 35% in 2018 to 10% in 2019
- The fishery catch was not consistent with the survey decrease in the CAI
- The 2019 apportionments were instead based on the approach used prior to 2016, consisting of an 8:12:18:27 weighted average of the four most recent survey estimates, resulting in a CAI apportionment of 21%
- The SSC and Team requested that the author investigate alternatives

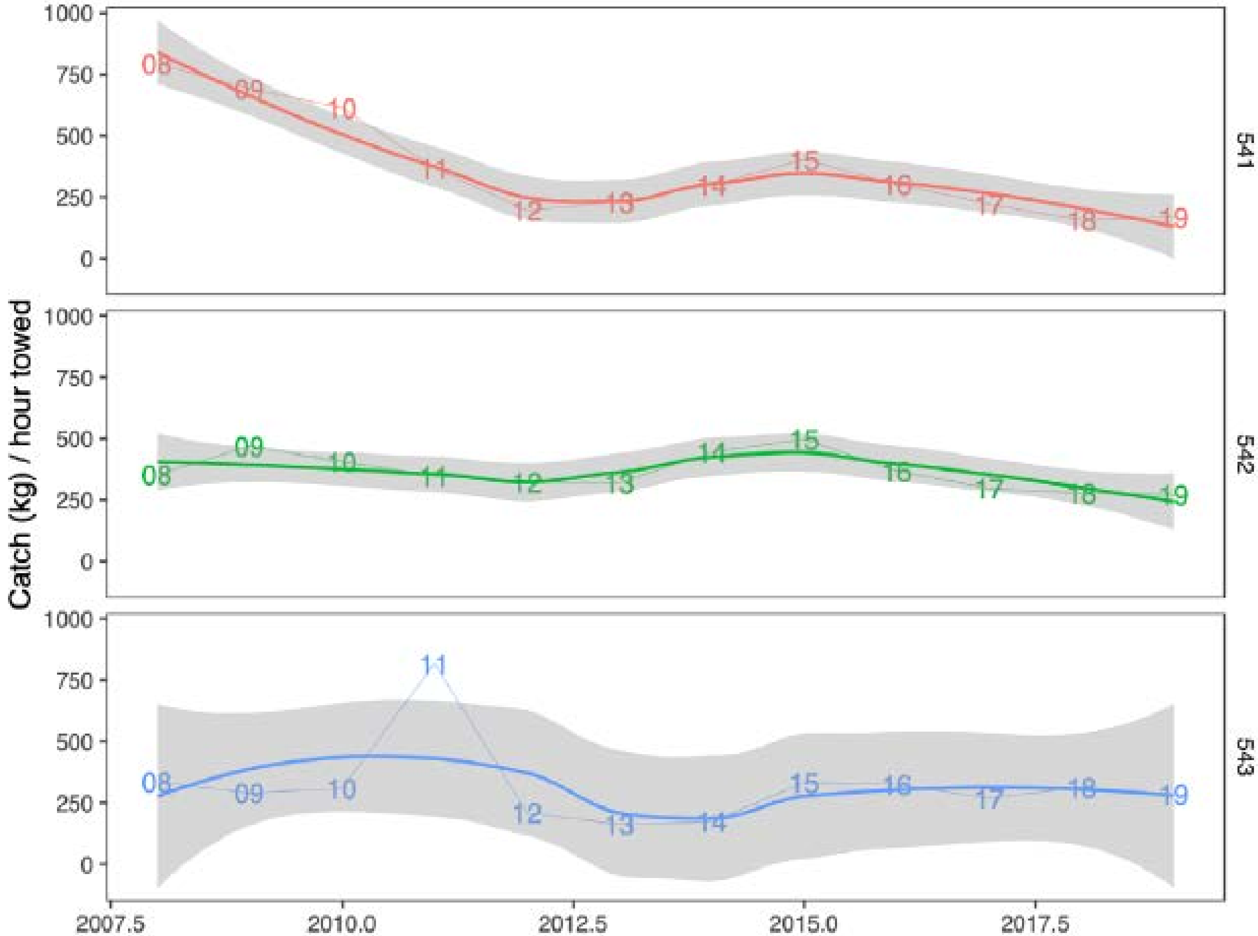
# Atka mackerel (2 of 7)

- Survey biomass time series, by area



# Atka mackerel (3 of 7)

- Mean nominal fishery CPUE time series, by area



# Atka mackerel (4 of 7)

- The authors' proposed approach uses a RE model following Hulson et al. (in prep), which applies a common process error across regions, allows for multiple indices, with user-specified weighting of the indices
- In this application, the indices consist of the survey biomass estimates and mean fishery CPUE
- Five alternative weightings presented (fishery relative to survey):
  1. zero weight
  2. half the weight of the survey index
  3. equal weight to the survey index
  4. double the weight of the survey index
  5. all the weight given to the fishery CPUE data
- This resulted in a range for the CAI of 10% (no weight on the fishery CPUE index) to 26% if using only the fishery CPUE data

# Atka mackerel (5 of 7)

- Apportionments resulting from the five weighting options:

| CPUE weight | Eastern | Central | Western |
|---|---|---|---|
| 0.0 | 49.6% | 9.3% | 41.1% |
| 0.5 | 43.8% | 17.0% | 39.2% |
| 1.0 | 40.8% | 20.4% | 38.7% |
| 2.0 | 38.0% | 22.8% | 39.2% |
| 100 | 32.7% | 26.2% | 41.1% |

# Atka mackerel (6 of 7)

- Relative to the four-survey average with between-year weights fixed at the pre-2016 levels, the proposed approach has the advantage that the between-*year* weights are estimated statistically rather than fixed *a priori*
- Potential disadvantages are the need to specify the between-*index* weights and diluting the impact of the survey index with an alternative index that may not be a good measure of relative biomass
- Depending on the between-index weighting, the two approaches can calculate similar apportionments
- When it becomes available, another approach would be to use VAST
  - Currently, VAST has some challenges for Atka mackerel in the AI (interpolation across islands; see “VAST” section in Joint minutes)

# Atka mackerel (7 of 7)

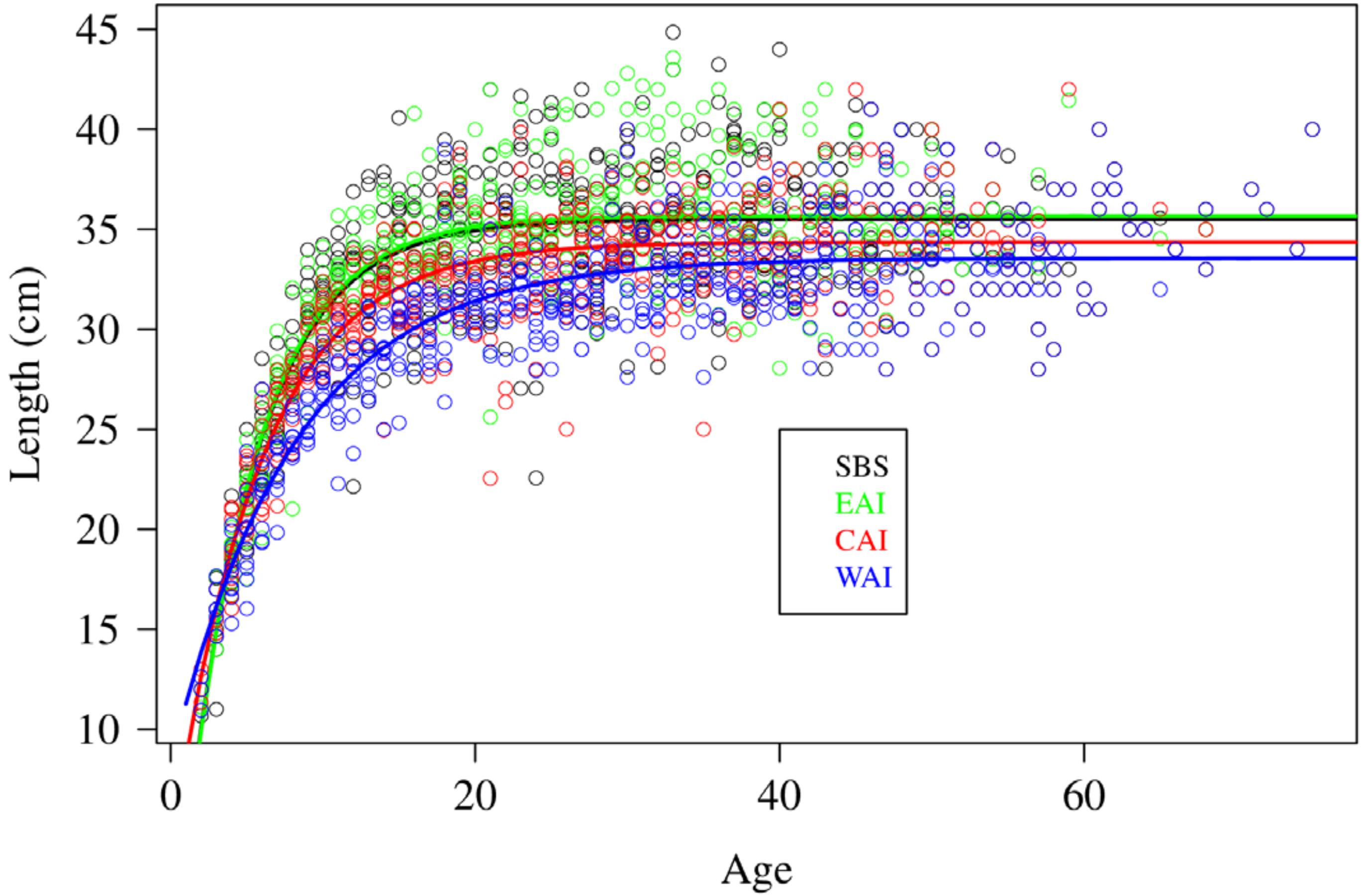
- A Team member noted that the authors' proposed approach was previously applied to AI Pacific cod in 2015 (with the IPHC survey comprising the alternative index), and that neither the author, Team, nor SSC were enthusiastic about the approach at that time
- The Team recommends that the authors investigate the application of median smoothers, the potential for hyperstability within the Atka mackerel fishery to impact this method, the available trip length data, and the potential to develop an objective weighting for the new approach

# Northern rockfish (1 of 5)

- Paul Spencer presented methods for calculating length at age for northern rockfish
- Current methods do not abundance-weight the otolith data (i.e, they are weighted by sample size), yet there are strong spatial patterns in length at age and abundance:
  - WAI fish are smallest and get larger for a given age eastward, meanwhile most of the population abundance is in the WAI
- There were not large differences within an area among years for length-at-age or length-weight relationships, so Paul fit von Bertalanffy curves within each region and combined the abundance-weighted curves to derive global length-at-age values
- The Team noted that, while curves were similar between years, length at age 0 did differ by +/- ~10 cm
  - Paul pointed out that this may be due to lack of data for young ages

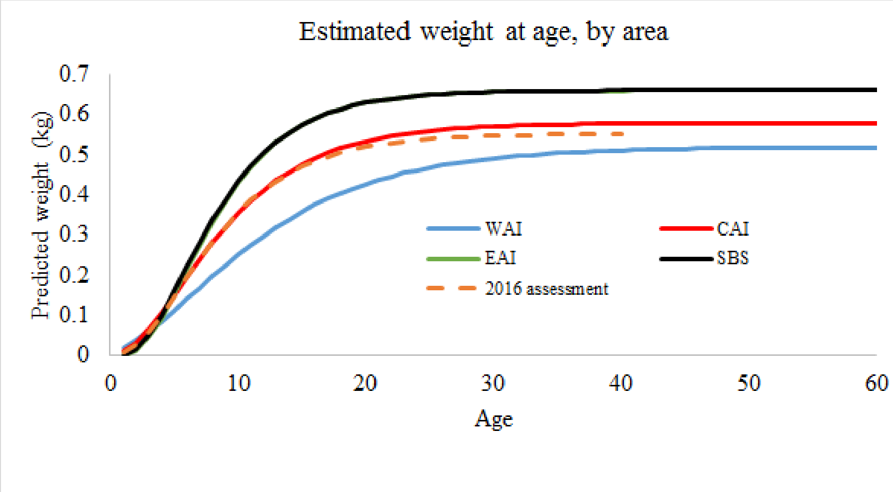
# Northern rockfish (2 of 5)

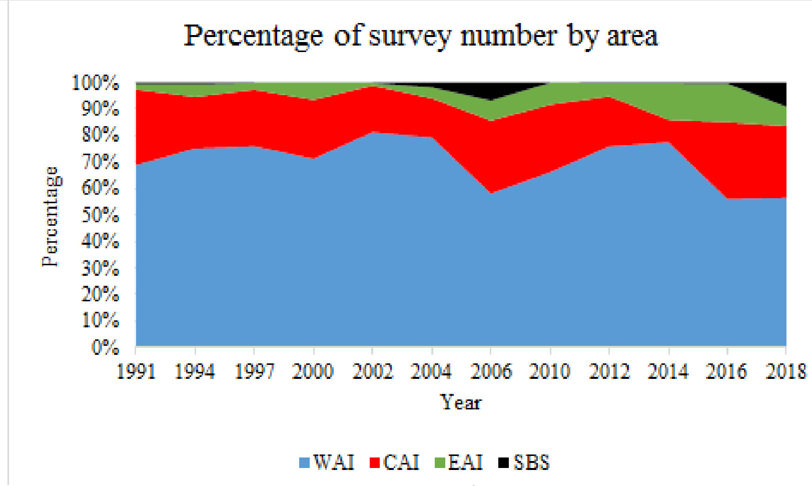
- Length at age, by area (all years)

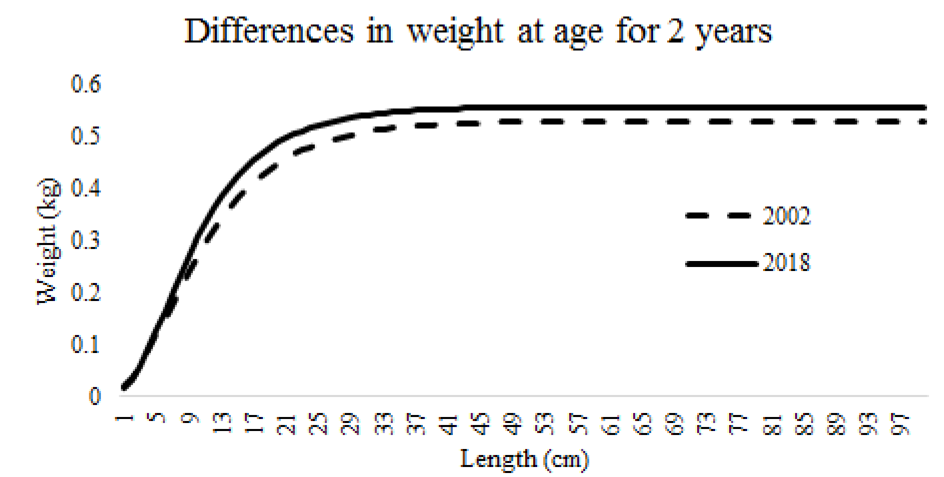


# Northern rockfish (3 of 5)

- Effect on weight at age (two examples)

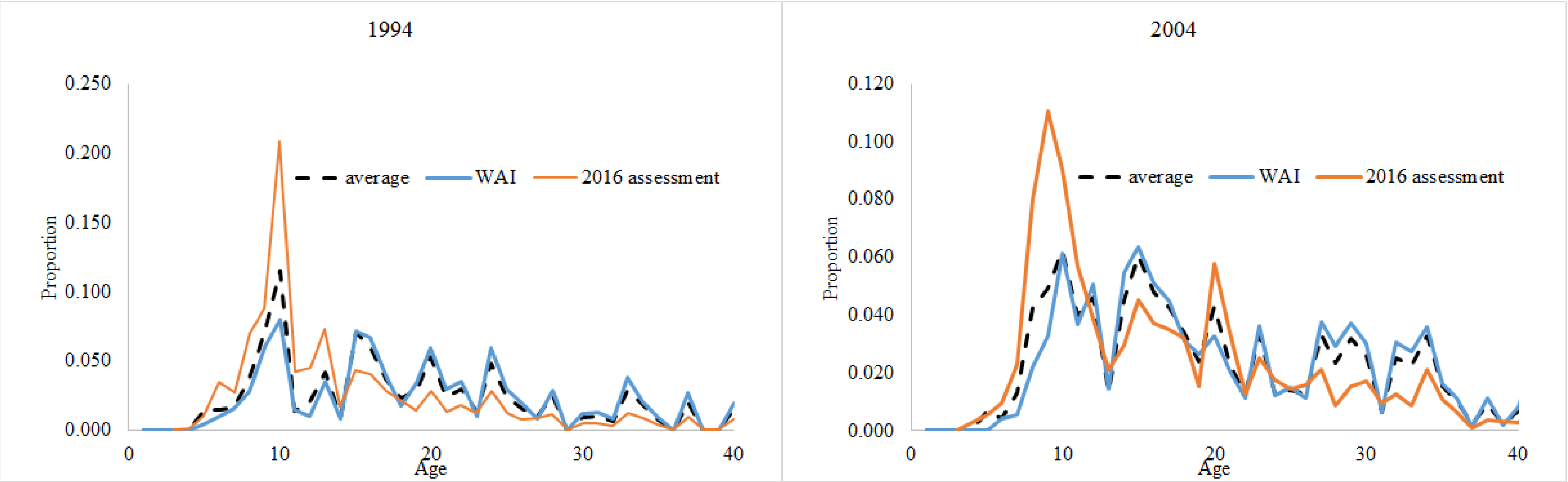


# Northern rockfish (4 of 5)

- Effect on age composition (two examples)



# Northern rockfish (5 of 5)

- The Team recommends that Paul use the abundance-weighted lengths at age
- For next September, the Team requests that the BS and AI survey groups at AFSC present their methods for computing age composition and mean length and weight at age (e.g., is a global mean provided to authors, or is biomass or abundance weighted by area mean?)

# Skates BMSY proxy (1 of 2)

- Olav Ormseth presented a discussion of the appropriateness of the $B_{MSY}=B_{35\%}$ assumption for Alaska skate
- This was planned as part of last year's presentation, but was not given then due to time constraints
- Elasmobranchs are equilibrium strategists (i.e., late maturity, low fecundity and high pup survival), which generally have reduced compensatory ability
- Thus, species utilizing this life history strategy often have $B_{MSY}$ values greater than the $B_{MSY}=B_{35\%}$ assumption used for Tier 3 species
- The author explored a range of $B_{MSY}$ proxies, from 35%-80%, as well as three catch scenarios:
  1. catch set to the maximum ABC
  2. constant F set at the average from 2014-2018
  3. constant catch set equal to 2018 catch

# Skates BMSY proxy (2 of 2)

- The author noted that Alaska skate catch is highly correlated with Pacific cod catch, and the constant $F$ scenario is likely the most relevant
- The realized average $F$ for Alaska skate is approximately $F_{50\%}$
- At this rate, the spawning biomass is currently above $B_{MSY}$ and projections in the constant catch scenario decrease the spawning biomass to $B_{MSY}$ and then trend along the $B_{MSY}$ value
- While the $B_{MSY}=B_{35\%}$ assumption is likely inaccurate for this species, current catch rates and biomass suggest that it is not problematic
- It is also unlikely that the true $B_{MSY}=B_{80\%}$, or anywhere close to that value, because current biomass has been relatively stable
- If the true $B_{MSY}$ were closer to the upper extreme value, the assessment would already be showing substantial declines in spawning biomass
- The Team requests that the author include this analysis as an appendix in the next full assessment

# Harvest specifications (1 of 2)

- The Team recommends adoption of the 2020 BSAI final OFLs and ABCs published in the harvest specifications (84 FR 9000, March 13, 2019) for the proposed 2020/2021 BSAI OFLs and ABCs for the purpose of notifying the public of potential final harvest specifications
- The Team noted that the Joint Teams recommended that the authors bring forward two alternatives for OFL in November: (1) combine the BS and AI and (2) combine OFL Alaska-wide

# Harvest specifications (2 of 2)

**Table 1. Proposed Plan Team recommended OFL, ABC, and TAC for Groundfish in the Bering Sea/Aleutian Islands (metric tons) for 2020-2021.**

9/12/2019

| Species | Area | 2018 OFL | 2018 ABC | 2018 TAC | Catch as of 12/31/2018 | 2019 OFL | 2019 ABC | 2019 TAC | Catch as of 9/7/2019 | Plan Team Proposed 2020/2021 OFL | Plan Team Proposed 2020/2021 ABC | Plan Team Proposed 2020/2021 TAC |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Pollock | EBS | 4,797,000 | 2,592,000 | 1,364,341 | 1,379,306 | 3,914,000 | 2,163,000 | 1,397,000 | 1,237,975 | 3,082,000 | 1,792,000 | |
| | AI | 49,289 | 40,788 | 19,000 | 1,860 | 64,240 | 52,887 | 19,000 | 1,453 | 66,981 | 55,125 | |
| | Bogoslof | 130,428 | 60,800 | 450 | 14 | 183,080 | 137,310 | 75 | 117 | 183,080 | 137,310 | |
| Pacific cod | BS | 238,000 | 201,000 | 188,136 | 186,702 | 216,000 | 181,000 | 166,475 | 121,981 | 183,000 | 137,000 | |
| | AI | 28,700 | 21,500 | 15,695 | 14,719 | 27,400 | 20,600 | 14,214 | 12,459 | 27,400 | 20,600 | |
| Sablefish | BSAI | na | na | na | na | na | na | na | na | 10,438 | 4,682 | |
| | BS | 2,887 | 1,464 | 1,464 | 1,598 | 3,221 | 1,489 | 1,489 | 2,820 | n/a | 1,994 | |
| | AI | 3,917 | 1,988 | 1,988 | 660 | 4,350 | 2,008 | 2,008 | 465 | n/a | 2,688 | |
| Yellowfin sole | BSAI | 306,700 | 277,500 | 154,000 | 131,544 | 290,000 | 263,200 | 154,000 | 100,656 | 284,000 | 257,800 | |
| Greenland turbot | BSAI | 13,148 | 11,132 | 5,294 | 1,835 | 11,362 | 9,658 | 5,294 | 2,831 | 10,476 | 8,908 | |
| | BS | n/a | 9,718 | 5,125 | 1,672 | n/a | 8,431 | 5,125 | 2,663 | n/a | 7,777 | |
| | AI | n/a | 1,414 | 169 | 163 | n/a | 1,227 | 169 | 168 | n/a | 1,131 | |
| Arrowtooth flounder | BSAI | 76,757 | 65,932 | 13,621 | 7,002 | 82,939 | 70,673 | 8,000 | 6,840 | 83,814 | 71,411 | |
| Kamchatka flounder | BSAI | 11,347 | 9,737 | 5,000 | 3,108 | 10,965 | 9,260 | 5,000 | 4,195 | 11,260 | 9,509 | |
| Northern rock sole | BSAI | 147,300 | 143,100 | 47,100 | 28,275 | 122,000 | 118,900 | 47,100 | 24,720 | 147,500 | 143,700 | |
| Flathead sole | BSAI | 79,862 | 66,773 | 14,500 | 11,061 | 80,918 | 66,625 | 14,500 | 12,652 | 83,190 | 68,448 | |
| Alaska plaice | BSAI | 41,170 | 34,590 | 16,100 | 23,342 | 39,880 | 33,600 | 18,000 | 13,861 | 37,860 | 31,900 | |
| Other flatfish | BSAI | 17,591 | 13,193 | 4,000 | 5,984 | 21,824 | 16,368 | 6,500 | 3,539 | 21,824 | 16,368 | |
| Pacific Ocean perch | BSAI | 51,675 | 42,509 | 37,361 | 34,749 | 61,067 | 50,594 | 44,069 | 32,562 | 59,396 | 49,211 | |
| | BS | n/a | 11,861 | 11,861 | 9,635 | n/a | 14,675 | 14,675 | 6,219 | n/a | 14,274 | |
| | EAI | n/a | 10,021 | 9,000 | 8,946 | n/a | 11,459 | 11,009 | 8,191 | n/a | 11,146 | |
| | CAI | n/a | 7,787 | 7,500 | 7,312 | n/a | 8,435 | 8,385 | 8,264 | n/a | 8,205 | |
| | WAI | n/a | 12,840 | 9,000 | 8,856 | n/a | 16,025 | 10,000 | 9,888 | n/a | 15,586 | |
| Northern rockfish | BSAI | 15,888 | 12,975 | 6,100 | 5,767 | 15,507 | 12,664 | 6,500 | 8,549 | 15,180 | 12,396 | |
| Blackspotted/Rougheye Rockfish | BSAI | 749 | 613 | 225 | 238 | 676 | 555 | 279 | 371 | 868 | 715 | |
| | EBS/EAI | n/a | 374 | 75 | 66 | n/a | 351 | 75 | 67 | n/a | 448 | |
| | CAI/WAI | n/a | 239 | 150 | 173 | n/a | 204 | 204 | 304 | n/a | 267 | |
| Shortraker rockfish | BSAI | 666 | 499 | 150 | 250 | 722 | 541 | 358 | 283 | 722 | 541 | |
| Other rockfish | BSAI | 1,816 | 1,362 | 845 | 987 | 1,793 | 1,344 | 663 | 1,066 | 1,793 | 1,344 | |
| | BS | n/a | 791 | 275 | 212 | n/a | 956 | 275 | 564 | n/a | 956 | |
| | AI | n/a | 571 | 570 | 775 | n/a | 388 | 388 | 502 | n/a | 388 | |
| Atka mackerel | BSAI | 108,600 | 92,000 | 71,000 | 70,393 | 79,200 | 68,500 | 57,951 | 46,873 | 73,400 | 63,400 | |
| | EAI/BS | n/a | 36,820 | 36,500 | 36,085 | n/a | 23,970 | 23,970 | 13,113 | n/a | 22,190 | |
| | CAI | n/a | 32,000 | 21,000 | 20,889 | n/a | 14,390 | 14,390 | 14,319 | n/a | 13,310 | |
| | WAI | n/a | 23,180 | 13,500 | 13,419 | n/a | 30,140 | 19,591 | 19,441 | n/a | 27,900 | |
| Skates | BSAI | 46,668 | 39,082 | 27,000 | 31,207 | 51,152 | 42,714 | 26,000 | 14,801 | 48,944 | 40,813 | |
| Sculpins | BSAI | 53,201 | 39,995 | 5,000 | 5,109 | 53,201 | 39,995 | 5,000 | 4,484 | 53,201 | 39,995 | |
| Sharks | BSAI | 689 | 517 | 180 | 103 | 689 | 517 | 125 | 114 | 689 | 517 | |
| Squids | BSAI | 6,912 | 5,184 | 1,200 | 1,736 | 0 | 0 | 0 | 0 | 0 | 0 | |
| Octopuses | BSAI | 4,769 | 3,576 | 250 | 290 | 4,769 | 3,576 | 400 | 193 | 4,769 | 3,576 | |
| Total | BSAI | 6,235,729 | 3,779,809 | 2,000,000 | 1,947,838 | 5,340,955 | 3,367,578 | 2,000,000 | 1,655,860 | 4,491,785 | 2,967,269 | |

Sources: 2018 OFLs, ABCs, and TACs and 2019 OFLs and ABCs are from harvest specifications adopted by the Council in December 2017 and December 2018, respectively; 2018 catches through December 31, and 2019 catches through September 7, 2019 from AKR Catch Accounting.