Update on Plan Team and SSC requests for the BSAI Pacific ocean perch stock assessment, with preliminary model runs

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Introduction

In the 2022, the Bering Sea/Aleutian Islands Plan Team and the Statistical and Scientific Committee of the North Pacific Fisheries Management Council made several recommendations regarding the BSAI Pacific ocean perch (POP) assessment model:

(BSAI Plan Team, September 2022) *Of these CIE recommendations, the author recommended the following changes to be brought forward in November 1) fitting the model to survey abundance instead of biomass, 2) exploring stochastic initial age compositions, and 3) for equilibrium initial age composition, explore mortality rates other than that currently used in the model.*

(BSAI Plan Team, November 2022). *The Team discussed investigating the mortality rates by age particularly for the plus group as there were poor fits to this group in the eastern Bering Sea (EBS) slope survey. The Team noted that time blocks could be explored for the plus group or consider time-varying selectivity as there were younger fish in the AI BTS than the EBS slope survey.*

(BSAI Plan Team, November 2022). *The Team also discussed the relative proportion of the EBS slope survey information into the future and encouraged the author to look at alternatives for estimating the apportionment on the EBS slope and comparing where the different surveys match up in the past for determining what the proportion should be moving forward.*

(SSC, December 2022). *The SSC concurs with the BSAI GPT suggestion to pursue time-varying survey selectivity for the AI bottom trawl survey and supports the BSAI GPT's other suggestions for model improvements*

The purpose of this report is to address the items above that concern the BSAI POP stock assessment and its input data, and present potential options for the 2024 assessment. Given that the fit to the AI survey has been a concern in this assessment (and other Alaska rockfish assessment), this fit is used as a criterion in evaluating potential modeling options.

The models considered in this report are:

Model	Description
Model 16.3	Accepted model from the 2022 assessment, which freely estimates the AI and EBS survey catchability coefficients without prior distributions
Model 24.1	Model 16.3, but with estimation of the recruitment for the initial numbers at age as stochastic variables
Model 24.2	Model 16.3, but with the penalty for the dome-shapedness in the bicubic spline used for fishery selectivity increased from 10 to 30, and a lognormal prior on the AI survey catchability (mean=1, CV=0.15)
Model 24.3	Model 24.2 but with selectivity for the AI and EBS trawl survey modeled with time-varying double normal curves

1) CIE recommendations for fitting survey abundance, and initial numbers at age

Fitting the AI survey abundance estimates instead of the biomass estimates was evaluated in the 2022 assessment, and did not substantially improve the residual pattern in the fit the AI survey estimates.

Estimated initial numbers at age for the 2022 model (16.3) and a model with stochastic initial numbers at age (24.1) are shown in Figure 1. The start year of the model is 1960, and the estimated age-3 recruits in 1960 is estimated as a stochastic recruitment estimate. In model 16.3, the ages 4 to 40+ are estimated as from an equilibrium unfished population, and show a gradual decline in number at age with an accumulation of fish in the plus group. In contrast, estimation of stochastic numbers at age results in a strong estimated year class for 9 year old fish (1954 year class), and a lower number at age for the plus group, relative to model 16.3. Additionally, the estimates of age 3 fish in 1960 is smaller in model 24.1 relative to model 16.3, but the estimated number of age 4 fish is larger.

The aggregated age and length composition fits are nearly identical between models 16.3 and 24.1, for both the age (Figure 2) and the length (Figure 3) compositions. The fits to the AI survey index between these two models are also relatively similar, with very minor improvements in the fit to the 2010 – 2016 survey biomass indices (Figure 4).

The estimated total biomass is smaller in model 24.1 than in model 16.3 (Figure 5). This is largely due to survey catchability coefficients being larger in model 24.1, and the estimated natural mortality being smaller (Table 1).

In models 16.3 and 24.1, the survey catchability coefficients are estimated freely without prior distributions, whereas the natural mortality parameter was estimated with normal distribution prior distribution, with both the mean and CV set at 0.05.

Model 16.3 estimates the initial numbers at age as being in equilibrium with an unfished population at the estimated natural mortality. Mortality estimates ranging from 0.5 to 1.5 the estimated natural mortality were also considered to estimate the equilibrium initial age composition, and resulted in changes in the number of the initial population in the plus group. As expected, with lower mortality rates the proportion of the initial population in the plus group increased (Figure 1). The fits to the composition data, and the AI survey biomass index, are relatively unchanged with these alternative values of mortality (not shown). However, the AI survey catchability coefficient does change substantially to account for the change in the number of plus group fish, from 0.58 with equilibrium mortality at 0.5M to 1.25 with 1.5M. These exploratory models runs that alter the mortality rate for the initial year equilibrium population are not considered further in the assessment.

Model 24.1 does provides estimates of recruitment strength for the cohorts in the initial year that differ from those obtained with the equilibrium assumption in the current model. However, this appears to have little effect on the fit the composition data (based on the aggregated plots) and the fit to the AI survey index, which are two of the main problematic issues for this assessment. Additionally, model 24.1 estimates a large AI survey catchability coefficient of 1.51, suggesting that the AI trawl survey biomass substantially overestimates the true biomass, which seems unlikely (in part, because the AI survey does not account for the fish in the EBS portion of the stock area). Finally, we hypothesize that one reason the various modeling options for the initial year has little effect on the aggregated fits to the composition data is the long period between the initial year (1960) and the start of the fishery and AI survey age compositions (1981 and 1991, respectively). Given these issues, we recommend continuing to use the equilibrium population assumption for estimating the initial numbers at age.

Finally, in recent assessments the estimated time-varying fishery selectivity (estimated from a bicubic spline) shows an unusual multimodal distribution across ages in recent years, which is difficult to explain (Figure 6). The extent to which selectivity decreases with age in dome-shaped patters is controlled by penalty applied to the rate of selectivity decrease (i.e., the first difference), which is set to 10 in the current model. In model 24.2, we increase this penalty to 30. Additionally, this model also restores the use of a prior distribution (used in historical POP assessments) for AI survey catchability, with a mean of 1 and a CV of 0.15. The use of a prior distribution for the survey catchability is supported from field work conducted by Jones et al. (2021) that compared rockfish densities in trawlable and untrawlable grounds in the Gulf of Alaska. Jones et al. (2021) found that the survey catchability for POP was 1.15, but this would be somewhat lower in this assessment because the portion of the population in the EBS is unavailable to the AI trawl survey.

The estimated fishery selectivity for 2022 from models 16.3 and 24.2 are shown in Figure 7. Model *24.2* still has a bimodal pattern across ages for recent fishery selectivity, but the pattern is less pronounced than in model *16.3*, particularly for ages ≥ 35 years.

2) Fits to the plus group, and time-varying survey selectivity

The Pearson residuals give an indication of the temporal pattern in the fits to the age compositions, and are shown in Figures 8 - 10 for the model 16.3. This model consistently underfits the plus group for the AI survey (10 of 12 surveys) and the EBS survey (5 of 6 surveys), but overfits the plus group for the fishery age compositions (16 of 21 years).

The BSAI Plan Team noted the poor fits to the EBS survey age composition plus group in their November 2022 comment, and suggested evaluating time-varying selectivity. The SSC further suggested that time-varying survey selectivity be explored for the AI survey selectivity.

Model 24.3 has the features of model 24.2, and additionally has time-varying selectivity for both the AI and EBS trawl surveys that is modeled in time blocks. We modeled survey selectivity with the double normal equation, which can take on a wide variety of sigmoidal and dome-shaped patterns. The double normal equation for selectivity is incorporated into BSAI rockfish assessment modeling code, but has not been operationally used. The equation for the double normal equation is

$$s_a = \begin{array}{cc} e^{\frac{-(a-\mu)^2}{2\sigma_1^2}} & for\ a < \mu \\ 1 & for\ \mu < a < \mu + d \\ e^{\frac{-(a-(\mu+d)^2}{2\sigma_2^2}} & for\ a > \mu + d \end{array}$$

The double normal joins two normal distributions, with the means of the two distributions defined by μ and $\mu + d$, respectively. The slopes of the ascending and descending portions of the survey are controlled by σ_1 and σ_2, respectively, and selectivity for ages between the two means is set to the maximum value (i.e., 1 for this application). Sigmoidal shapes can be obtained by setting the parameter d (the distance between the two means) to a value larger than the maximum age, which results in maintaining the selectivity for older ages at 1.

Blocks of 4 years were used for each of the AI and EBS surveys, which begin in 1991 and 2002, respectively. After the model start year of 1960, new selectivity time blocks are initiated in 1996, 2000, 2004, 2008, 2012, 2014, and 2020. For the EBS survey, new time blocks are initiated in 2004, 2008, and 2012 (the last year for the EBS survey was 2016). Between the blocks, each of the 4 parameters (μ, σ_1, σ_2, and d) are allowed to change, subject to penalties. Specifically, the deviations from the average parameter value was modeled with a normal distribution with a mean of 0 and a standard deviation of 0.8.

The estimated time-varying AI and EBS show sigmoidal rather than dome-shaped patterns, with slight variations between the blocks with respect to the slope and location of the ascending portion of the curve (Figures 11 and 12, respectively). The Pearson residual plots for model 24.3 largely shows the same pattern in fitting to the plus group as model 16.3, namely underfitting the plus group in the survey age compositions but overfitting the fishery age composition plus group. Fits to the aggregated composition data sets and the AI survey index show similar properties to those from model 24.2, and seem to be little affected by allowance of time-varying survey selectivity.

The total biomass for 2022 was similar between models 24.2 and 24.3, but throughout most of the time series model 24.3 estimated a lower biomass than model 24.2. The use of a prior distribution for AI survey catchability results in lower estimates for this parameter in models 24.2 and 24.3 than in model 24.2.

Conclusions and recommendations for fall, 2024 assessment

Exploratory models that investigated options for modeling the initial numbers at age, and time-varying survey selectivity, have not resolved the poor residual patterns with the fits to the AI survey biomass time series, or the age and length compositions. However, these exploratory models often differ in the scale of total biomass, as the current model does not use a prior distribution on AI survey catchability.

We recommend model 24.2 be considered in the fall 2024 assessment. This model restores the prior distribution on the AI survey catchability (a feature that existed in historical BSAI POP assessments), and this prior distribution is consistent with field work conducted by Jones et al. (2021). Additionally, this model increases the penalty on domed-shapeness for fishery selectivity across ages, resulting in more stability in fishery selectivity across ages.

References

Jones, D.T., C.N. Rooper, C.D. Wilson, P.D. Spencer, D.H. Hanselman, and R. Wilborn. 2021. Estimates of availability to bottom trawls for select rockfish species from acoustic-optic surveys in the Gulf of Alaska. Fisheries Research 236:105848

Table 1. Estimates of natural mortality and survey catchability coefficients for the models considered in this report.

Parameter	Model 16.3	Model 24.1	Model 24.2	Model 24.3
Natural morality (M)	0.056	0.044	0.054	0.054
AI survey catchability	1.00	1.51	1.16	1.21
EBS survey catchability	0.25	0.37	0.30	0.31

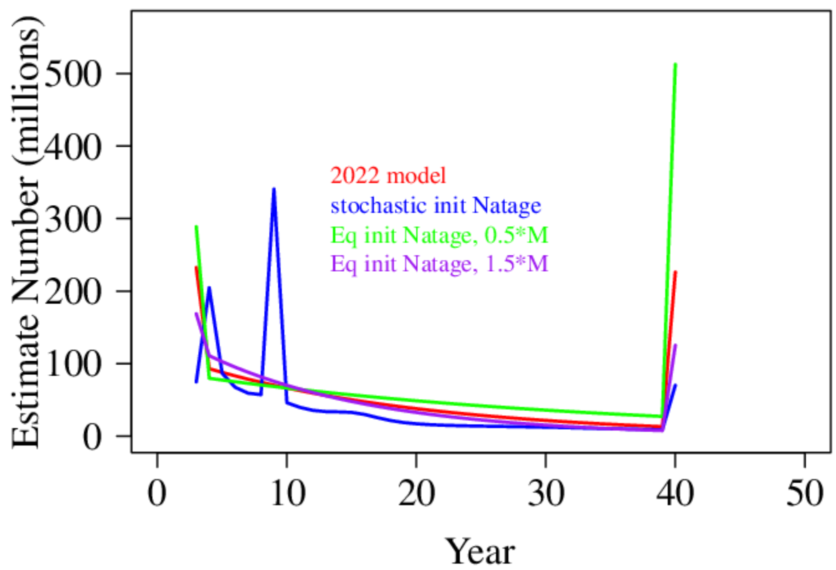

Figure 1. Estimated numbers at age from models 16.3 and 24.1, and two alternative models that estimate an equilibrium initial number at age at different mortality rates.

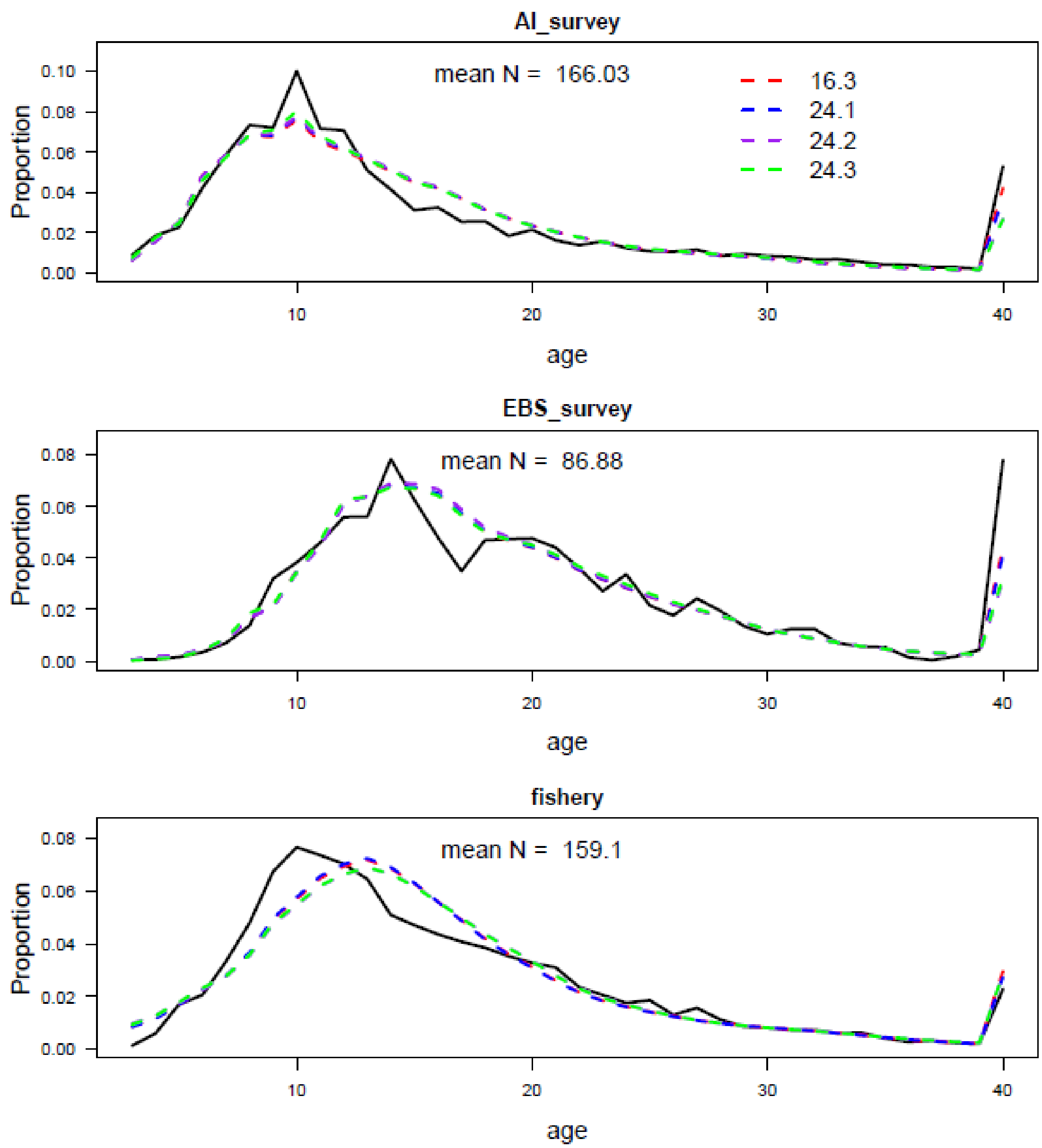

Figure 2. Aggregated age composition data and fits from the 4 models considered in this report. Years within a data type were weighted by the year-specific sample size.

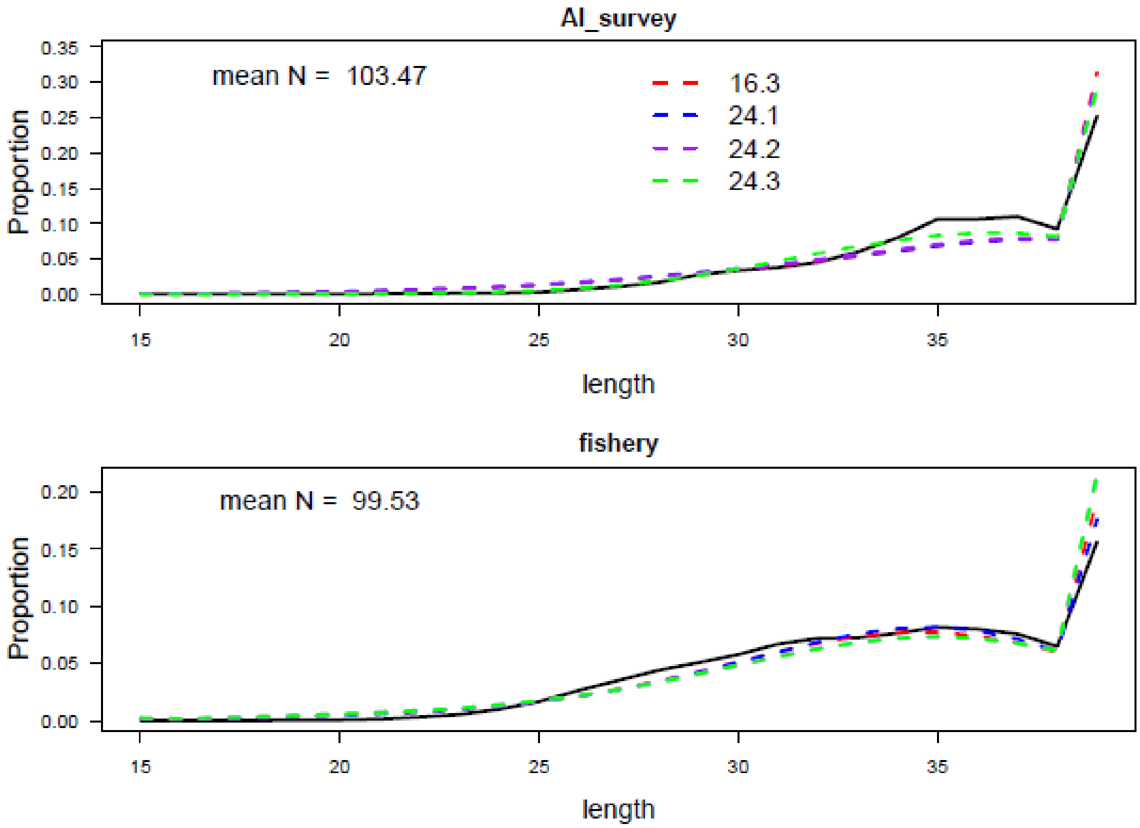

Figure 3. Aggregated length composition data and fits from the 4 models considered in this report. Years within a data type were weighted by the year-specific sample size.

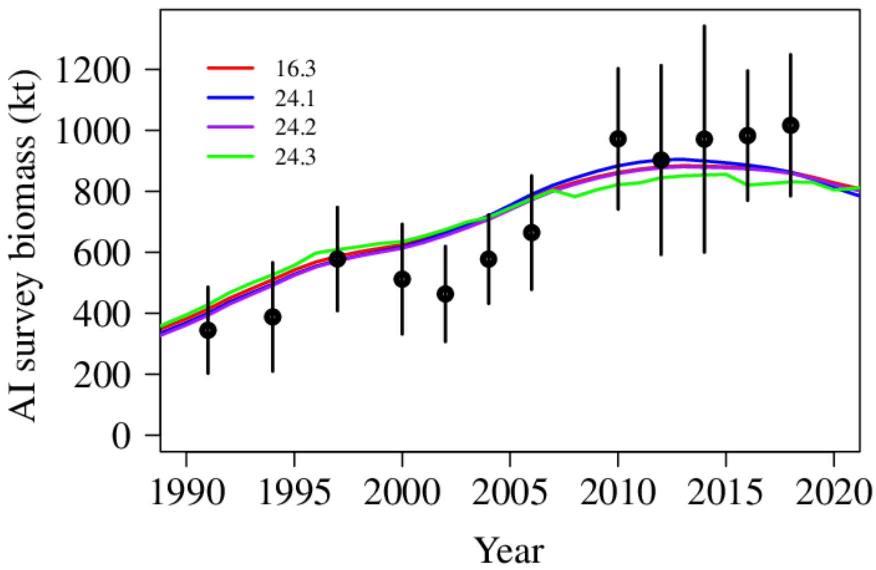

Figure 4. Fit to the AI survey biomass index from the 4 models considered in this report.

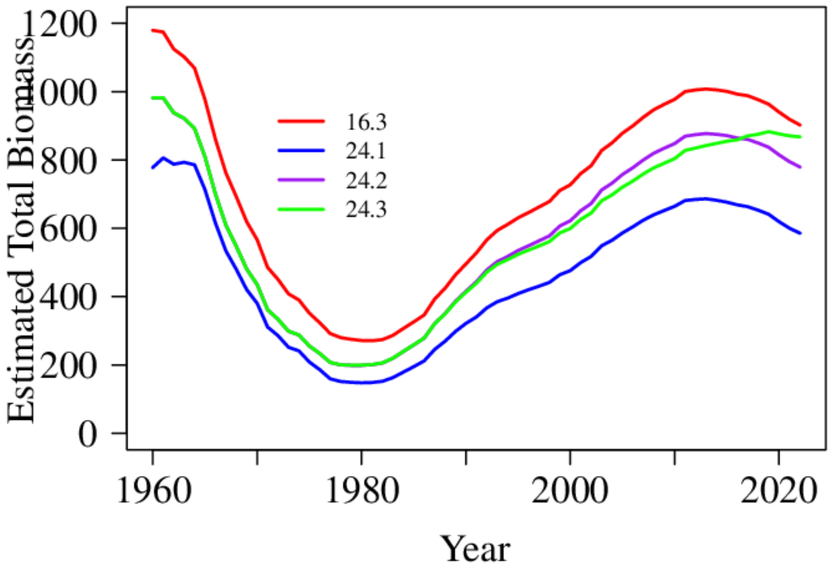

Figure 5. Estimated total biomass from the 4 models considered in this report.

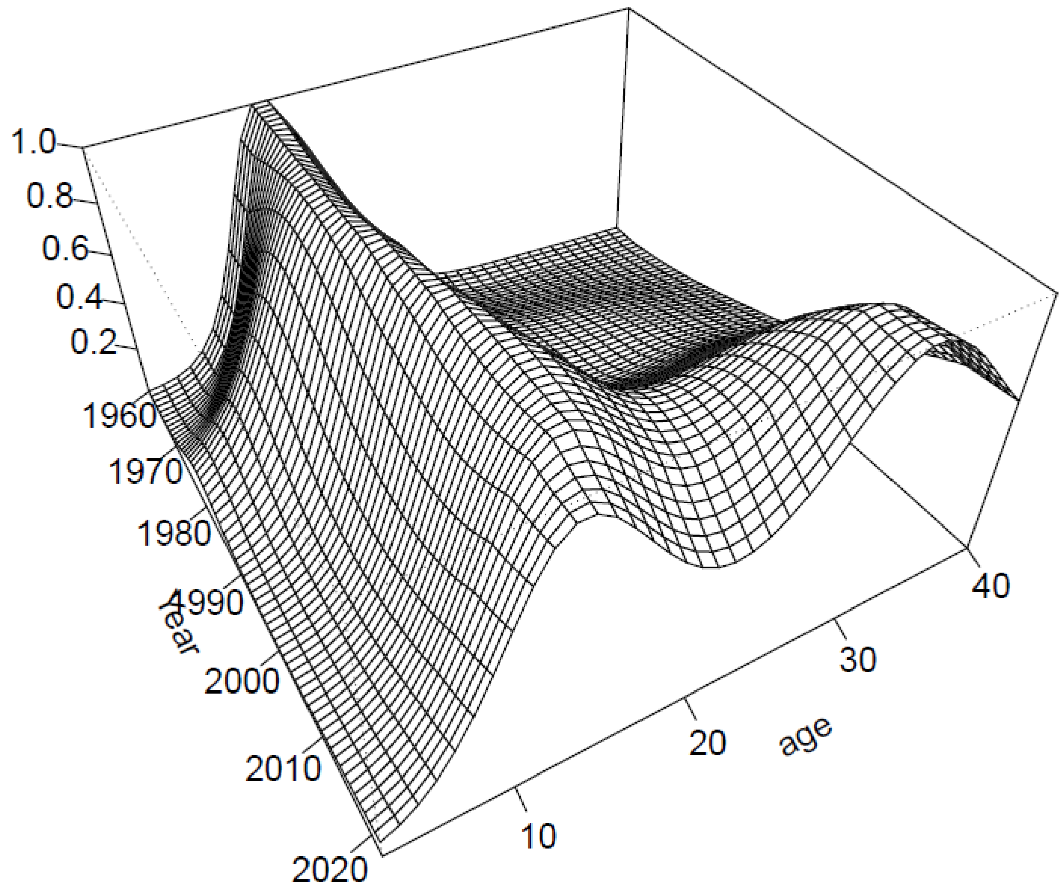

Figure 6. Estimated fishery selectivity from the 2022 model (16.3); note the bimodal selectivity in recent years.

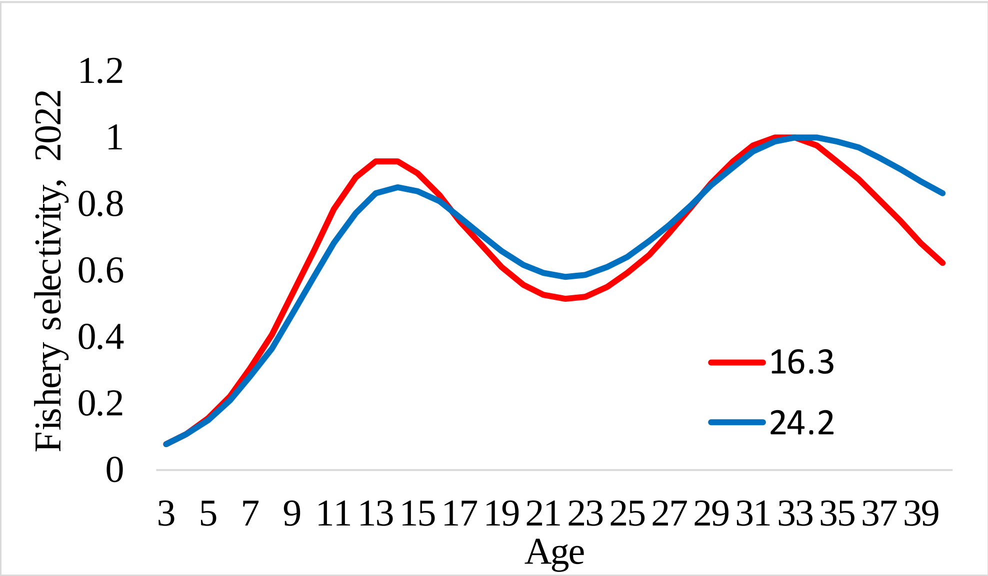

Figure 7) Estimated fishery selectivity for 2022 from models 16.3 and 24.2.

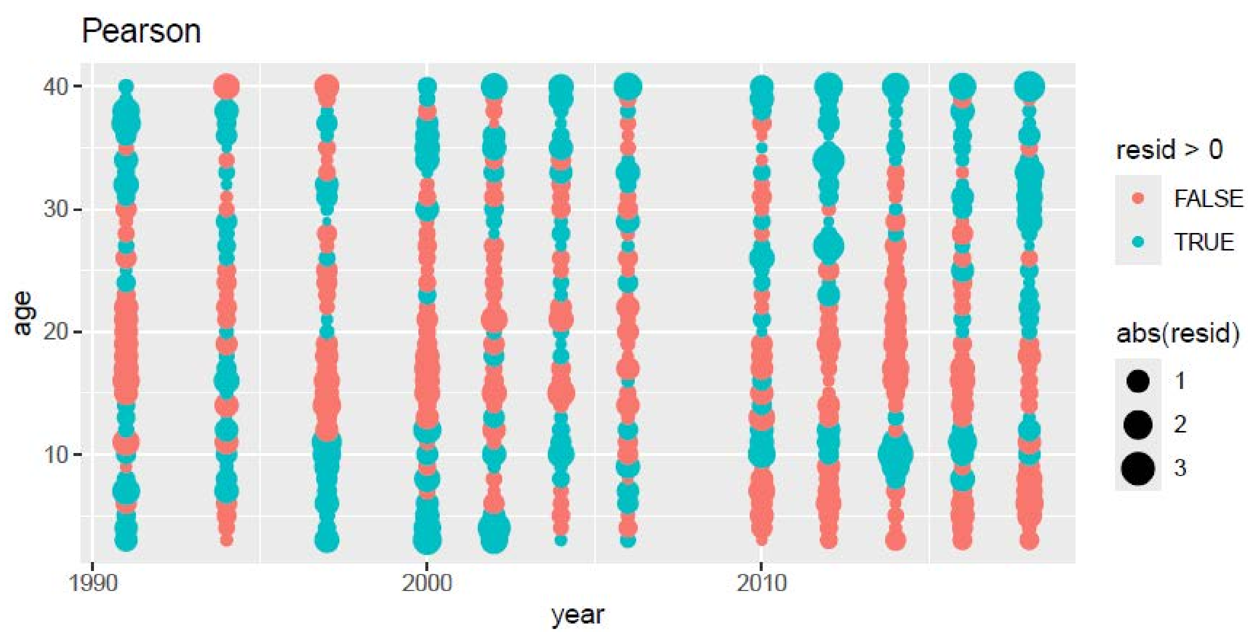

Figure 8) Pearson residuals for the AI survey age composition data, model 16.3.

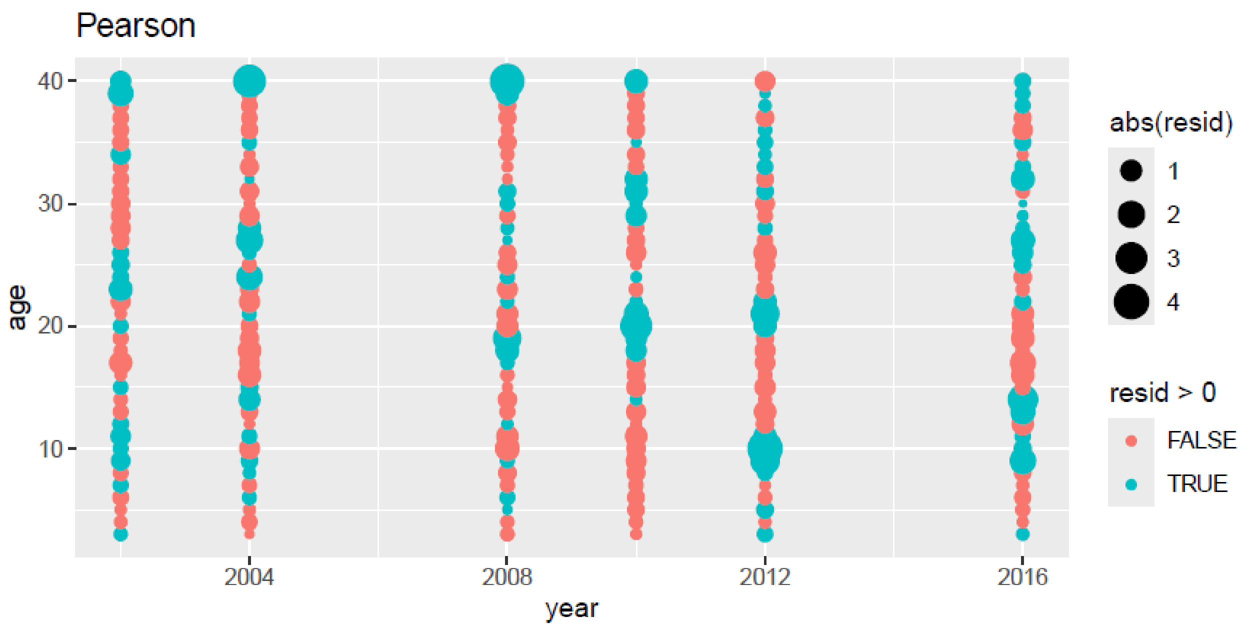

Figure 9) Pearson residuals for the EBS survey age composition data, model 16.3.

Figure 10) Pearson residuals for the fishery age composition data, model 16.3.

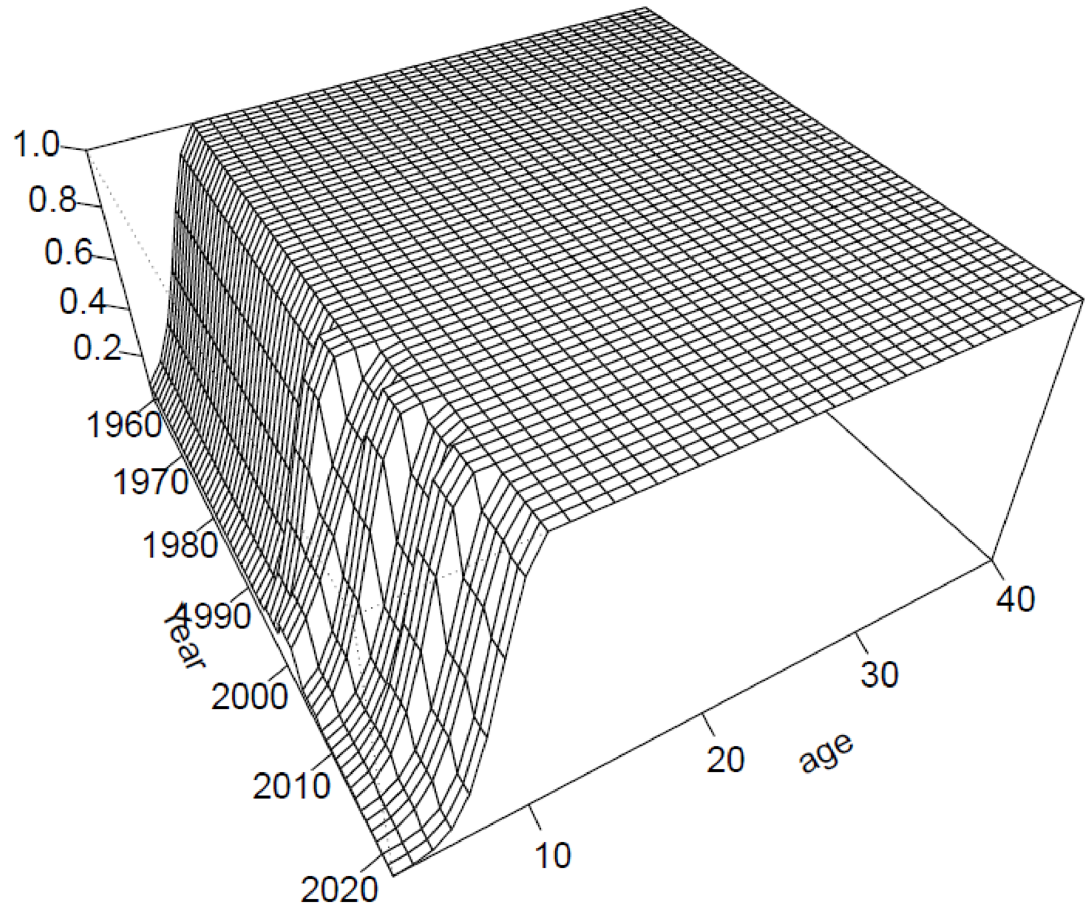

Figure 11) Estimated time-varying AI survey selectivity, model 24.3.

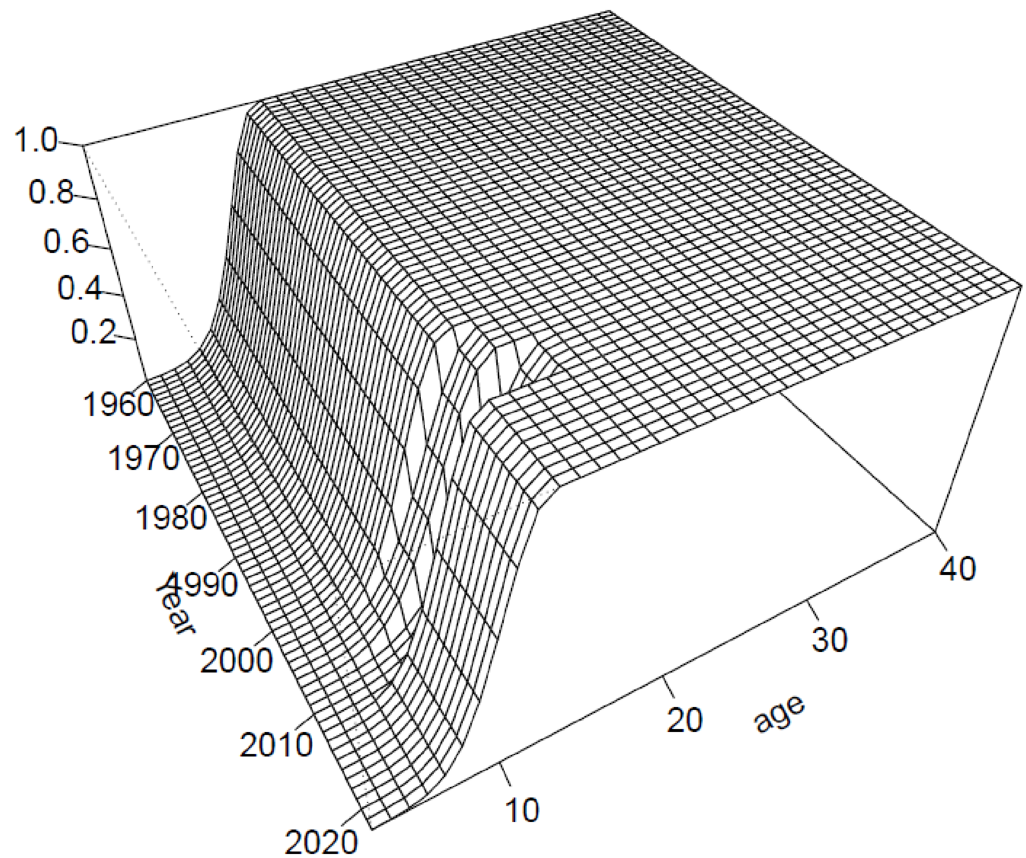

Figure 12) Estimated time-varying EBS survey selectivity, model 24.3.

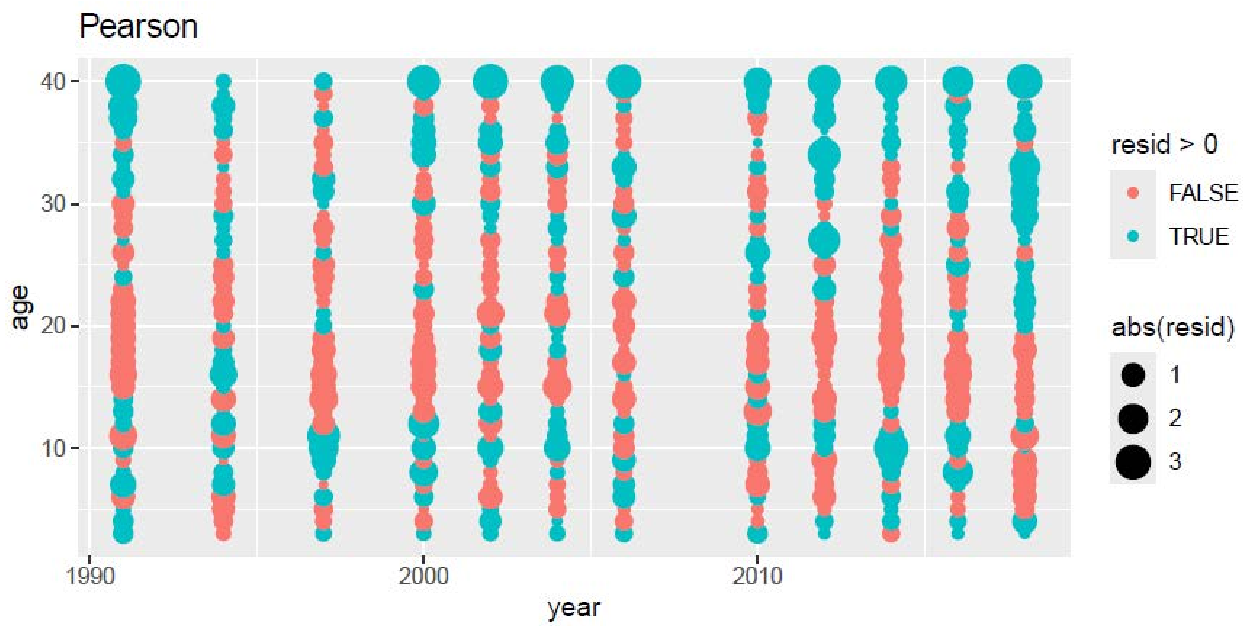

Figure 13) Pearson residuals for the AI survey age composition data, model 24.3.

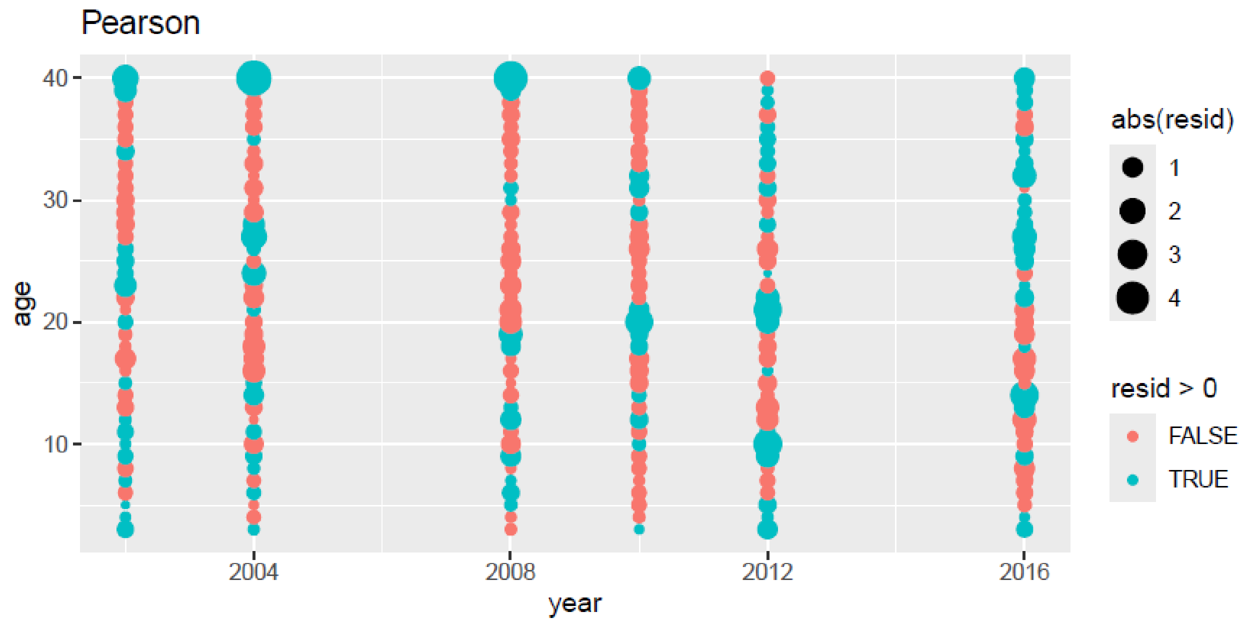

Figure 14) Pearson residuals for the EBS survey age composition data, model 24.3.

Figure 15) Pearson residuals for the fishery age composition data, model 24.3.