Candidate base cases for the stock assessment of chub mackerel in Northwest Pacific Ocean in 2025

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Summary

- A state-space age-structured (assessment) model (SAM) was used to conduct a stock assessment of the chub mackerel stock in the Northwestern Pacific.
- Two candidate base case scenarios (exclude/include the abundance indices in 2024).
- Two candidate base cases showed almost identical results.
- The estimated total biomass and spawning stock biomass had two booms, in 1970s and 2010s.
- After 2020, the total biomass and spawning stock biomass decreased rapidly.
- The most recent spawning stock biomass was 16% of the last peak. This was near the historical lowest.
- The retrospective analysis showed a positive patterns in total biomass and recruitment, and there is room for further improvement on these issues.
- The retrospective bias was smaller when 2024 data was included.

Introduction

- Chub mackerel is a commercially important small pelagic fish, and its stock assessment is important for providing scientific management advice.
- Through the simulation testing for stock assessment model selection, it has been agreed that the state-space stock assessment model (SAM) be used in the Technical Working Group for Chub Mackerel Stock Assessment (TWG CMSA) in NPFC (TWG CMSA 2023).
- This year, the TWG CMSA has almost determined the data to be used.
- Last year, the TWG CMSA set a base case scenario for the SAM and conducted the first stock assessment.
- Since this is the second time stock assessment, no large modifications to the model were made.

Modifications

Some minor modifications were made this time.

- 1. Inclusion of Russian trawl CPUE as an abundance index
- 2. One year update of the input data
- 3. Estimation of process errors for the number of age 1–6+ fish
 - -> How to restrict the process errors were determined by the model selection
 - -> Later slide

- 4. Setting of the selectivities:
 - -> Later slide

Brief description of the data used



- SAM uses age-specific data on catch numbers, stock weight, and maturity in each fishing years.
- The TWG CMSA has prepared these data from the 1970 fishing year (FY1970) to FY2023 by aggregating data from Members (China, Japan and Russia).
- In the base case run, there are seven abundance indices from China, Japan, and Russia.

Model structure – population number

$$\log(N_{0,y}) = \log[f(SSB_y)] + \eta_{0,y}, \qquad (1)$$

$$\log(N_{a,y}) = \log(N_{a-1,y-1}) - F_{a-1,y-1} - M_{a-1,y-1} + \eta_{a,y}, \qquad 1 \le a \le 5$$
(2)

 $\log(N_{6+,y}) = \log(N_{5,y-1}e^{-F_{5,y-1}-M_{5,y-1}} + N_{6+,y-1}e^{-F_{6+,y-1}-M_{6+,y-1}}) + \eta_{6+,y}, \qquad a = 6+$ (3)

$$f(SSB_y) = \frac{\alpha \times SSB_y}{1 + \beta \times SSB_y}, \qquad (4)$$

$$SSB_{y} = \sum_{a=0}^{6+} g_{a,y} w_{a,y} N_{a,y} .$$
(5)

- Beverton-Holt stock-recruitment relationship
- Sum-product of maturity-, weight- and number-at-age

- Beverton-Holt stock-recruitment relationship was used according to the last stock assessment
- The number of each cohort decreases by fishing and natural mortality and process error

Model structure— fishing mortality

F at age

 $\log(F_y) = \log(F_{y-1}) + \xi_y ,$

where $F_y = (F_{1,y}, ..., F_{A+,y})^T$, $\xi_y \sim MVN(0, \Sigma)$, and Σ is the variance-covariance matrix of multivariate normal distribution (MVN).

- Its multivariate normal random walk allows smooth changes in F-at-age and selectivity at age
- The diagonal elements of matrix Σ were σ²_a, while off-diagonal elements represent covariance of F process errors between age classes
- The simple function of age difference (ρ^{|a-a'|}) is used as a correlation coefficient of the MVN matrix (estimated ρ)

Model structure— observation for catch-at-age

Catch at age

• Baranov equation

$$\hat{C}_{a,y} = \frac{F_{a,y}}{F_{a,y} + M_{a,y}} (1 - \exp(-F_{a,y} - M_{a,y})) N_{a,y}.$$

• Lognormal error

$$\log(C_{a,y}) = \log(\hat{C}_{a,y}) + \varepsilon_{a,y}, \qquad \varepsilon_{a,y} \sim N(0, \tau_a^2)$$

Model structure— observation for abundance index

The predicted value of abundance index $\hat{I}_{k,y} = a$

$$q_k \left[\sum_{a=0}^{6+} (\chi_{a,y,k} N_{a,y}) \right]^{b_k} \qquad \text{lognormal error} \\ \log(I_{k,y}) \sim N(\log(\hat{I}_{k,y}), \nu_k^2)$$

1. Relative number of age 0 fish from the summer survey by Japan γ

2. Relative number of age 0 fish from the autumn survey by Japan \int

- 3. Relative number of age 1 fish from the autumn survey by Japan $\longrightarrow \chi_{a,y,k} = \begin{cases} 1, \\ 0. \end{cases}$
- 4. Relative SSB from the egg survey by Japan
- 5. Relative SSB from the dip-net fishery by Japan
- Relative vulnerable stock biomass from Chinese light purse-seine fishery → next page
- 7. Relative vulnerable stock biomass from Russian trawl fishery \rightarrow next page

$$\chi_{a,y,k} = \begin{cases} 1, & a = 0\\ 0, & otherwise \end{cases}$$

$$\bigg\} \qquad \chi_{a,y,k} = g_{a,y} w_{a,y}$$

Product of maturity and weight

Model structure— observation for abundance index

The predicted value of abundance index

$$\hat{I}_{k,y} = q_k \left[\sum_{a=0}^{6+} (\chi_{a,y,k} N_{a,y}) \right]^{b_k}$$

lognormal error $\log(I_{k,\nu}) \sim N(\log(\hat{I}_{k,\nu}), \nu_k^2)$

- 6. Relative vulnerable stock biomass from Chinese light purse-seine
- 7. Relative vulnerable stock biomass from Russian trawl
 - $\rightarrow \chi_{a,y,k} = \hat{s}_{a,y,k} W_{a,y,k}$,

Estimated selectivity for these fleets



The method of this fitting was proposed and agreed upon at the 2nd intersessional meeting



List of mathematical notations for SAM

Symbol	Туре	Description			
<i>a</i>	Index	Age class (from 0 to 6+)			
у	Index	shing year (from 1970 to 2022)			
<i>k</i>	Index	et ID for abundance index (from 1 to 6)			
C _{a,y}	Data	Observed catch number at age a in a year y			
W _{a,y}	Data	Stock weight at age a in a year y (also used as catch weight for simplicity)			
$g_{a,y}$	Data	Maturity at age a in a year y			
M _{a,y}	Data	Natural mortality coefficient at age a in a year y			
N _{a,y}	RE	Number at age a in a year y			
$F_{a,y}$	RE	Fishing mortality coefficient at age a in a year y			
ω_a	FE	SD for the process error in number at age a			
σ_a	FE	SD for the process error in F at age a			
ρ	FE	Correlation coefficient in MVN of F random walk between adjacent age classes			
$ au_a$	FE	SD for the measurement error in catch at age a			
q_k	FE	Catchability coefficient for abundance index k			
ν_k	FE	SD for the measurement error in abundance index k			
b_k	FE	Nonlinear coefficient for abundance index k			
α	FE	Slope of stock-recruitment relationship at the origin			
β	FE	Strength of density dependence in stock-recruitment relationship			
$\hat{C}_{a,y}$	DQ	Predicted catch number at age a in a year y			
$\hat{s}_{a,y}$	DQ	Selectivity at age a in a year y			

RE: random effect, FE: fixed effect, DQ: derived quantity

Estimation methods using TMB

- The parameters are estimated to maximize the marginal likelihood of summing process-error components and observation error components.
- The marginal likelihood is computed by the numerical integration using the Laplace approximation via Template Model Builder (TMB: Kristensen et al., 2016).
- We applied a generic bias-correction estimator for derived quantities calculated as a nonlinear function of random effects (e.g., $N_{a,y}$ is a derived quantity calculated from the random effect of $log(N_{a,y})$), which is implemented in TMB (Thorson and Kristensen, 2016).
- Estimation uncertainties including standard errors (SEs) were computed from the delta method in TMB.
- In this stock of chub mackerel, the period from July to the following June is treated as a fishing year (NPFC-2024-TWG CMSA09-WP01), and the estimated abundance is that at the beginning of the fishing year (i.e., July).

Natural mortality

- age-specific M (0.80, 0.60, 0.51, 0.46, 0.43, 0.41, and 0.40 for age 1–6+, respectively)
- This M-at-age have been determined according to the natural mortality estimator using biological parameters from different areas (Convention Area and Japanese EEZ) (Ma et al. 2024; Nishijima et al., 2021).
- It is assumed that the M-at-age is time-invariant throughout all years.



Scenarios



- Without 2024 indices: S01-InitBase
- Use 2024 indices: S02-Index24_1
- Biological Parameters in 2024 were assumed to be their averages over 2016–2023
- The proportion of Russian catch number in 2024, necessary to fit the Russian trawl index, was assumed to be the average over 2021-2023
- Results of sensitivity analysis on these assumptions on 2024 will be presented after this presentation

Avoiding overparameterization

- We set restrictions for the magnitude of CAA observation error, the F process error, and the N process error
- We set restrictions for the nonlinearity for the abundance indices
- Using a stepwise model selection approach

Model-selection approach— 1st step

- Choose which age to change the magnitude of the CAA observation error, the F process error, and the N process error based on AIC by a step-wise approach
- the N process error breakpoints were not placed between ages 2 and 3.
- This is because the maturities for ages 2 and 3 recently have declined to 0 and 0.3, respectively,
- SSB index does not have sufficient recent information for these ages.

stage	AIC	var	which	model
0	1245.35	-	-	selected
1	1234.05	varC	6	selected
2	1214.75	varC	2	selected
3	1211.54	varF	2	selected
4	1210.43	varC	4	selected
5	1210.22	varC	1	selected
6	1209.36	varF	3	best
7	1210.68	varC	5	selected

Example of the S01-InitBase dataset

The selected restriction



The same model configuration was selected for S02-Index24_1

Model selection approach— 2nd step

Indexes are divided into 5 types, each calculated for the case of estimating nonlinear coefficients

- 1. Summer trawl survey for age 0, and autumn trawl survey for ages 0 and 1 by Japan
- 2. Egg survey for SSB by Japan
- 3. Dipnet fishery CPUE for SSB by Japan
- 4. Light purse-seine fishery CPUE by China
- 5. Trawl fishery CPUE by Russia

Filtered out

- 1. Models without convergence
- 2. Models that did not output SE (non-positive definite of Hessian matrix)
- 3. Very large SE (>10)

Among models meeting these criteria, the simplest model with $\Delta AIC < 2.0$ was selected as the setting for each scenario

Model selection results

Rank	Trawl_jpn	EggSurv_jpn	Dipnet_jpn	PS_chin	TR_russ	AIC	ΔΑΙϹ	diagnosis	maxSE
S01-Initl	Base								
1	е	f	f	f	f	1172.22	0	\checkmark	2.34
2	е	f	f	f	е	1173.11	0.89	\checkmark	2.39
3	е	е	f	f	f	1173.32	1.1	\checkmark	2.33
4	е	f	е	f	f	1174.05	1.83	\checkmark	2.36
5	е	f	f	е	f	1174.21	1.99	\checkmark	2.35
6	е	е	f	f	е	1174.31	2.09	\checkmark	2.37
S02-Inde	ex24_1								
1	е	f	f	f	е	1187.47	0	\checkmark	2.32
2	е	f	f	f	f	1188.16	0.69	\checkmark	2.31
3	е	е	f	f	е	1188.91	1.44	\checkmark	2.31
4	е	f	е	f	е	1189.04	1.57	\checkmark	2.35
5	е	е	f	f	f	1189.39	1.92	\checkmark	2.30
6	е	f	f	е	е	1189.46	1.99	\checkmark	2.33
7	е	f	е	f	f	1189.79	2.32	\checkmark	2.33

'e' and 'f' indicate 'estimated' and 'fixed at 1', respectively.

Estimating nonlinear coefficients only for Japan's trawl surveys yield the simplest model with $\Delta AIC < 2$

The same model was selected for the S02-Index24_1

Fixed-effect (FE) parameters

FE	MLE	SE	Gradient	Unlinked value	Unlinked value
logQ (JPN summer survey)	-15.66019	2.3408706	-8.65E-06	1.58E-07	2.31E-07
logQ (JPN autumn survey age 0)	-14.744235	2.30258077	4.41E-07	3.95E-07	9.77E-07
logQ (JPN autumn survey age 1)	-10.648674	1.60682097	-2.57E-05	2.37E-05	2.94E-05
logQ (JPN egg survey)	-0.2271382	0.12698076	-6.61E-06	0.79681068	0.80295615
logQ (JPN dipnet)	-2.4437991	0.1570056	2.53E-05	0.08683035	0.08752557
logQ (CHN purse sein)	-5.4764757	0.14196201	-7.95E-06	0.00418405	0.00430581
logQ (RUS trawl)	-4.0759971	0.24502031	-3.99E-07	0.01697528	0.01724802
logB (JPN summer survey)	0.86570013	0.12158874	- 0.0001603	2.37666948	2.34247171
logB (JPN autumn survey age 0)	0.82683531	0.1235896	-5.72E-06	2.28607257	2.18820389
logB (JPN autumn survey age 1)	0.56916294	0.12307821	- 0.0001382	1.76678752	1.75197034
logσ (age 0–1)	-0.711492	0.18336391	-1.94E-05	0.49091123	0.40909281
$\log\sigma$ (age 2)	-0.9952621	0.19313847	3.00E-05	0.36962655	0.30817531
logσ (age 3–)	-1.2750514	0.17011628	-1.50E-05	0.27941662	0.77895517
$\log \omega$ (age 0)	-0.2612567	0.12744292	5.00E-07	0.77008321	0.2972536
$\log \omega$ (age 1–)	-1.1696498	0.13795139	-2.19E-05	0.31047565	0.48144348
$\log \tau (\text{age } 0)$	-0.240506	0.13625482	-3.34E-05	0.78622997	0.23419627
$\log \tau$ (age 1)	-0.6449846	0.16902655	1.82E-06	0.52467061	0.62989388
log7 (age 2–3)	-1.5971847	0.32853356	-1.52E-05	0.20246572	0.27327995
$\log \tau (\text{age } 4-5)$	-0.9197831	0.13817615	4.23E-06	0.39860547	0.4001481
$\log \tau$ (age 6+)	-0.1209851	0.13153698	6.82E-06	0.88604714	0.84711823
logv (JPN summer survey)	-0.2678933	0.25517752	9.16E-07	0.76498942	0.7126411
logv (JPN autumn survey age 0)	-0.4479691	0.30906346	-2.71E-05	0.63892443	0.71420766
logv (JPN autumn survey age 1)	-0.4688911	0.24698986	1.68E-05	0.62569573	0.53366485
logv (JPN egg survey)	-1.0239682	0.18603686	-1.02E-05	0.35916687	0.37476015
logv (JPN dipnet)	-0.5300865	0.16761127	8.21E-06	0.58855408	0.57301314
logv (CHN purse sein)	-1.2363837	0.2621174	-5.52E-06	0.29043261	0.27109477
logv (RUS trawl)	-0.5614886	0.26075444	-2.03E-06	0.57035938	0.54899224
loga	-4.3455321	0.19242052	-2.71E-05	0.01296461	0.01263028
logβ	-8.277446	1.58715382	2.64E-06	0.00025419	0.00023633
logit ρ	4.07762693	0.84481291	-3.91E-06	0.9833348	0.97611767

These are the results for S01-InitBase, but almost the same results were obtained for S02-Index24_1

All FE parameters has final gradients that are close to zero

All SEs are sufficiently small

Correlation between FE parameters

S01-InitBase

logit_rho-0.0+0.010.01-0.060.050.060.050.010.01-0.01 <mark>0.34</mark> 0.090.12 <mark>-0.02 0.1 0.24</mark> 0.020.010.01 <mark>0.18</mark> 0.01-0.030.0+0.01 0 0 0	010.030.06
rec_logb0.1-0.070.030.040.030.050.030.090.070.03 0 -0.020.020.010.05-0.020.02-0.020.030.02-0.040.020.01-0.010.01-0.014	01 <mark>0.77</mark>
rec_loga -0.080.060.02 <mark>0.090.07</mark> 0.040.060.080.030.010.060.03-0.01 0 -0.020.020.020.020.020.020.020.020.020.0	
logSdLogObs12 - 0 0.010.01-0.030.020.040.030.01-0.01-0.010.01 0 -0.01 0 -0.020.01-0.010.01 0.020.01-0.010.01-0.01-0.010.01 0.02	
logSdLogObs11 -0.030.040.070.010.01-0.05 0 -0.040.050.080.060.05-0.020.03-0.070.01-0.040.080.050.01-0.020.020.060.050.02	
logSdLogObs10 -0.020.040.060.050.030.01 0 -0.020.030.050.030.03-0.010.020.02 0 -0.040.070.01-0.020.020.010.020.01	
logSdLogObs9 -0.040.030.040.060.040.090.050.040.030.040.010.030.07 0 0.006 0 0.01-0.030.020.020.02 0 0	
logSdLogObs8 -0.010.080.150.030.020.030.030.010.08-0.140.070.060.010.02-0.190.03-0.030.030.090.02.0.11-0.12	
logSdLogObs7 -0.050250.01-0.030.02 0 -0.010.04-0.250.01-0.020.01 0 0.080.07-0.160.030.030.030.01-0.35	
logSdLogObs6 -0.16-0.180.020.01 0.01-0.03 0 -0.150.180.020.040.020.01-0.130.210.150.030.080.080.01	
logSdLogObs5 -0.010.020.010.060.040.040.030.010.020.01 0.110.05-0.110.01-0.030.07-0.060.080.02	
logSdLogObs4 -0.030.07 0 0.030.030.010.020.020.06 0 0.2 0.17-0.080.01-0.37 0.1 0.140.04	
logSdLogObs3 -0.080.130.120.090.070.090.050.090.130.13-0.280.44-0.1-0.180.340.080.26	
logSdLogObs2 -0.07-0.1-0.11 0 0 0.02 0 0.080.11 0.11-0.280.230.05-0.150.110.01	
logSdLogObs1 -0.060.170.05 0 0 -0.020.010.060.170.050.190.120.03-0.150.13	
logSdLogN2 -0.120.240.11-0.080.060.040.050.11-0.23-0.1 -0.1-0.080.040.15	
logSdLogN1 -0.170.250.140.010.01-0.030.01-0.180.260.150.040.01-0.05	
logSdLogFsta3 -0.010.020.010.080.060.080.050.010.010.010.010.350.46	
logSdLogFsta2 -0.02 0 0.05-0.01-0.05-0.01-0.080.01-0.080.04	1.0
logSdLogFsta1 -0.02 0 0.05-0.01-0.01-0.03-0.01-0.03-0.01-0.07	
logB30.3,07310,990.080.030.170.070.310.32	
logB2 -0.5+0.990.310.070.050.180.090.52	0.5
logB1 -0.990.510.290.070.04 0.2 0.09	
logQ7 - 0.029-060.040.380.290.39	0.0
logQ6 -0.150.130.12 <mark>0.480.36</mark>	
logQ5 -0.0+0.020.01 0.43	0.5
logQ4 -0.030.030.01	-0.5
logQ3 -0.290.31	
logQ2 -0.51	-1.0
	66,00
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~	60/
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~	-
10,40,40, 10,40,40,40,40,40,40,40,40,40,40,40,40,40	

S02-Index24_1



Strong positive correlation between the two stock-recruitment parameters (α , β)

Strong negative correlation between nonlinear coefficient and proportionality constant

These two parameters correspond to slope and intercept in the linear regression: $\log(I_{k,y}) = \log(q_k) + b_k \log(N_{a,y}) + \varepsilon_{k,y}$ When $\log(N_{a,y})$ is large, these two parameters are likely to be correlated

Relationship between abundance and index



S01-InitBase result

The Japan's trawl survey indices for age-0 and age-1 fish show the tendency of hyperdepletion (*b*>1)

Time series of abundance estimates

Scenario - S01-InitBase - S02-Index24_1



- The two scenarios obtained almost identical results.
- Stock levels were high in the 1970s, but declined in the 1980s, and stock levels were maintained at fairly low levels from the 1990s to the early 2000s
- Stock levels gradually recovered in the late 2000s and increased rapidly after the occurrence of the strong year classes in 2013.
- Total biomass and SSB during the most recent 10year period (2013-2022) did not reach the same high level as in the 1970s.
- Exploitation rate (estimated catch biomass / total biomass) and mean F remained constant, with some fluctuations, until the 2000s, but decreased thereafter, then increased to the average level in 2020s.

Abundance estimates in recent years



Scenario - S01-InitBase - S02-Index24_1

- In recent years, SSB had increased and had a peak in 2017, then has declined.
- The increase in SSB was due to the strong year class 2013.
- Another strong year class 2018 disappeared.
- Most recent spawning stock biomass was 16% of the peak in 2017. This was near the historical lowest.

Comparison to the previous assessment

Scenario - S01-InitBase -- S02-Index24 - S28-ProcEst(SA2024) - S34-ProcEst23(SA2024)



The inclusion of 2023 indices revised the recent Biomass, SSB, and Recruitment downward.

The past estimates of the biomass, SSB, Recruitment, and Exploitation rate were almost consistent between current and previous assessments.



Stock-recruitment relationship



- Slightly convex SRR was observed.
- SD were 0.78 and 0.80 for S01-InitBase and S02-Index24_1, respectively.
- SD was 0.80 for S28-ProcEst (the base case last year)

Residual plots for catch-at-age



S01-InitBase result

- Observation errors were largest for young and old age groups and smallest for intermediate age groups
- The time-series trend of the residuals was weak

Residual plots for abundance indices

S01-InitBase result



• Observation error was large in the Russian trawl fishery indices, relative to other indices

Process errors for log(N) and log(F)



- The process errors in log(*N*) for age-0 fish fluctuated strongly and has been positive after 2020
- A large positive process error was
 observed in age 2 in 2015
- Process errors for log(F) were larger in ages 0 and 1 than in the other ages
 - The pattern of random walks for each age was very similar (correlation coefficient of 0.98 between the closely adjacent ages)

Deviance of abundance







The deviances were calculated by $\widehat{N}_{a,y} \times w_{a,y} \times [\exp(\widehat{\eta}_{a,y}) - 1]$

Age 0

- The large positive process error in age 2 in 2015, resulted in a large positive deviance
- Perhaps CAA of age 2 in 2015 was very high
- And because this age group was not well covered by either Japanese trawl surveys or SSB indices
- Nevertheless, the number of age 2 in 2015
 decreased from the number of age 1 in 2014.



Retrospective analysis

S01-InitBase



S02-Index24_1

- Biomass and Recruitment showed positive retrospective patterns
- As a result, total biomass and F tended to be over- and underestimated, respectively
- The positive retrospective pattern diminished in S02-Index24_1
- Mohn's rho values for SSB were close to zero

Retrospective forecasting

S01-InitBase



S02-Index24_1

- One-year-ahead forecasting was conducted in the retrospective analysis (retrospective forecasting)
- The positive retrospective patterns in the forecasted dynamics were larger than those in the retrospective analysis

Likelihood profiling for varying M



Added M - -0.3 - -0.2 - -0.1 - 0 - 0.1 - 0.2 - 0.3

- The change in log likelihood was examined by adding M values of -0.3 to 0.5 simultaneously from the M values in the two base case scenarios.
- The negative log-likelihood monotonically decreases (i.e., the likelihood increases) as M is decreased.
- This suggests that it is difficult to estimate M from these data.
- Higher values of M resulted in higher values of total biomass, SSB, and recruitment, especially for the recent decade

Likelihood profiling for stock-recruit parameters



- Examined the negative log-likelihood (NLL) when the parameters were varied around the estimate to evaluate model convergence and parameter uncertainty
- A convex shape with the MLE as the smallest was found when the parameters related to the stock-recruitment relationship were varied, the objective function (negative log-likelihood)
- The parameter β has a smaller range of change in the NLL than α and the SD of recruitment variability, suggesting that there is a large uncertainty in the density-dependent parameter

Likelihood profiling for proportionality constant q



- A convex shape with the MLE as the smallest was found when the parameters of proportionality constants for abundance indices were varied
- This suggests that the model converged, and the indices had the information of abundance

Leave-out-out (LOO) index analysis

S01-InitBase

SSB Biomass 4000 750 3000 500 2000 250 1000 0 0 Recruitment Exploitation_rate 0.20 15 0.15 10 0.10 5 0.05 0.00 0 2022 2012 2014 2016 2018 2020 2012 2014 2016 2018 2020 2022 Year

-3

Scenario - full -- -1 -- -2

- The abundance and exploitation rate did not change much regardless of which index was removed, indicating that the estimates are robust
- The influence of the Russian trawl CPUE was small

Conclusions

- All inputs were updated for one year
- Russian trawl CPUE was newly included
- Two candidate base cases, without and with the indices in 2024
- Although retrospective biases were detected for the total biomass and recruitment, no other serious problems were found.
- The retrospective bias was smaller in S02-Index24_1, WITH the 2024 indices.
- SSB increased since the occurrence of the strong year class in 2013, but then has declined to the historical low level from the last peak.
- The stock has shown a continued downward trend, and the most recent spawning stock biomass was 16% of the recent peak of. This was near the historical lowest.

Age - 0 - 1 - 2 - 3 · · 4 · - 5 - 6+















