BAYESIAN SURPLUS PRODUCTION MODELS (JABBA) APPLIED TO THE EASTERN ATLANTIC SKIPJACK TUNA STOCK ASSESSMENT

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SUMMARY

Bayesian State-Space Surplus Production Models were fitted to Eastern Atlantic skipjack tuna catch and CPUE data using the 'JABBA' R package. The ten scenarios were based on the previous assessment and on uncertainty grid proposed during the 2022 SKJ Data Preparatory Meeting, which in summary corresponded to nine runs based on variations in growth parameters and steepness. To implement these scenarios in a Bayesian surplus production model, a Pella-Tomlinson production function was used and priors for r and $B_{MSY}/B0$ was derived using the concept called Age-Structured Equilibrium Model (ASEM). All scenarios showed similar trends for the trajectories of B/B_{MSY} and F/F_{MSY} over time.

RÉSUMÉ

Les modèles de production excédentaire état-espace de type bayésien ont été ajustés aux données de capture et de CPUE du listao de l'Atlantique Est au moyen du progiciel JABBA R. Les dix scénarios étaient basés sur l'évaluation précédente et sur la grille d'incertitude proposée lors de la réunion de préparation des données sur le listao de 2022, ce qui correspondait en résumé à neuf scénarios basés sur des variations des paramètres de croissance et de la steepness. Pour mettre en œuvre ces scénarios dans un modèle bayésien de production excédentaire, une fonction de production Pella-Tomlinson a été utilisée et des priors pour r et $B_{PME}/B0$ ont été dérivés en utilisant le concept appelé modèle structuré par l'âge en conditions d'équilibre (ASEM). Tous les scénarios ont montré une tendance similaire pour les trajectoires de B/B_{PME} et F/F_{PME} au fil du temps.

RESUMEN

Los modelos de producción excedente bayesianos de estado espacio se ajustaron a los datos de captura y CPUE de listado del Atlántico oriental utilizando el paquete R de 'JABBA'. Los diez escenarios se basaron en la evaluación anterior y en la matriz de incertidumbre propuesta durante la reunión de preparación de datos de listado de 2022, que en resumen correspondían a nueve ensayos basados en variaciones de los parámetros de crecimiento y la inclinación. Para implementar estos escenarios en un modelo de producción excedente bayesiano, se utilizó una función de producción de Pella-Tomlinson y se derivaron las distribuciones previas para r y $B_{RMS}/B0$ utilizando el concepto denominado Modelo de equilibrio estructurado por edad (ASEM). Todos los escenarios mostraron una tendencia similar para las trayectorias de B/B_{RMS} y F/F_{RMS} a lo largo del tiempo.

KEYWORDS

Skipjack, stock status, CPUE fits, hindcast, life history priors

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1. Introduction

The skipjack tuna (*Katsuwonus pelamis*) is widely distributed in the tropical and subtropical waters of the Atlantic, Indian and Pacific Oceans (ICCAT, 2006). The species has habitat preferences for an epipelagic realm, generally inhabiting open waters with optimum temperature range varying between 20 ºC and 30 ºC (ICCAT, 2006). As a function of its wide distribution, skipjack tuna has been intensively exploited by various fisheries around the world (ICCAT, 2006). For management purposes, the International Commission for the Conservation of Atlantic Tunas (ICCAT) considers two distinct stock units in the Atlantic Ocean, East and West stocks (ICCAT, 2006). In this study, we will focus on the East stock of the skipjack only. This stock is mainly exploited by purse seiners fleet (≈83% of the total catch). The baitboat fleet had subsequently contributed with 16%, and the longline fleet had contributed with less than 0.5% of the total catches.

The last East Atlantic skipjack tuna stock assessment was carried out in 2014 (ICCAT, 2014) and included outputs from two distinct models, (a) a Catch-only model, and; (b) a Bayesian Surplus Production model (BSP). All detailed descriptions and concerns about the results of each model can be observed in the Report of the 2014 ICCAT East and West Atlantic Skipjack stock assessment meeting (ICCAT, 2014). The final summary of the models shown distinct problems in convergence and difficulty for the models identify reliable MSY estimates (ICCAT, 2014).

Here, we present the 2022 preliminary stock assessment results for East Atlantic skipjack tuna stock based on the Bayesian State-Space Surplus Production Model framework, JABBA (Just Another Bayesian Biomass Assessment; https://github.com/jabbamodel/JABBA; Winker *et al.*, 2018). The JABBA model is a fully documented, open-source R package (https://github.com/JABBAmodel) that has been formally included in the ICCAT stock catalogue (https://github.com/ICCAT/software/wiki/2.8-JABBA) and has been widely applied in a number of recent ICCAT stock assessments, including: South Atlantic blue shark (ICCAT, 2016b), Mediterranean albacore (ICCAT, 2017c), South Atlantic swordfish (ICCAT, 2017a; Winker *et al.*, 2018), Atlantic shortfin mako shark stocks (south and north) (ICCAT, 2017d; Winker *et al.*, 2017, 2019a), Atlantic blue marlin (Mourato *et al.*, 2019), Atlantic bigeye tuna (Winker *et al.*, 2019b), Atlantic white marlin (Mourato *et al.*, 2020), Atlantic yellowfin tuna (Sant'Ana *et al.*, 2020), Mediterranean swordfish (Winker *et al.* 2020; ICCAT, 2017b) and South Atlantic albacore (Winker *et al.*, 2020b).

This preliminary assessment of the East Atlantic skipjack tuna stock is guided by the SCRS work plan. A grid scenario was built based on the discussions and recommendations that raised during the 2022 Skipjack Data Preparatory Meeting. In this way, extensive model diagnostics, retrospective pattern analysis and model prediction skillness were provided to evaluate the fitted models. In addition, this document explores the sensitivity of the base case scenario to the inclusion of alternative and additional standardized CPUE indices that have been made available for this assessment.

2. Material and Methods

2.1. JABBA inputs

This stock assessment is implemented using the Bayesian state-space surplus production model framework called JABBA (Winker *et al.*, 2018), which is now available as '*R package*' that can be installed from github.com/jabbamodel/JABBA. JABBA's inbuilt options include: (1) automatic fitting of multiple CPUE time series and associated standard errors; (2) estimating or fixing the process variance, (3) optional estimation of additional observation variance for individual or grouped CPUE time series, and (4) specifying a Fox, Schaefer or Pella-Tomlinson production function by setting the inflection point B_{MSY}/K and converting this ratio into a shape parameter m, (5) extensive diagnostic procedures and associated plots (e.g. residual run tests) and (6) a routine to conduct retrospective analysis. A full JABBA model description, including formulation and state-space implementation, prior specification options and diagnostic tools is available in Winker *et al.* (2018).

2.2. Fishery data

The ICCAT Secretariat provided fishery catch data for East Atlantic skipjack tuna from 1950 to 2020 (**Figure 1**). Relative abundance indices were made available, principally, in the form of joint standardized CPUE time series. These indices cover various periods and represent the distinct fishing gears and fleets that operate over the E-SKJ stock. A summary of the available indices is described below:

- EU PS VAST;
- EU Echosounder;

- AZO BB Past;
- CAN BB Past;
- DAK BB Past.

The CVs for all indices were scaled to an 0.25 average.

2.3. Model specifications

The model specifications were based on uncertainty grid defined in the Skipjack Data Preparation Meeting that resulted in nine distinct scenarios. These scenarios incorporate three variations in growth parameters as provided in Anon (2022) and three variations of steepness (0.7, 0.8, and 0.9). All models were implemented using a Pella and Tomlinson production function (**Table 1**).

The priors of K were kept uninformative similar to those used in the last assessment of the species. For K, a lognormal distribution was implemented using JABBA "range" option. Lower and upper values ranged from 290,000 t to 1,500,000 t, which resulted in an approximated mean value of 717,622 t and a CV of 43%. For r, were developed priors distribution with an associated shape parameter of a Pella-Tomlinson production function from an Age-Structured Equilibrium Model (ASEM) approach with Monte-Carlo simulations (Winker *et al.*, 2019b). The stock parameters used as inputs for the ASEM models included the uncertainty grid configuration citet before and presented in **Table 1**.

For all scenarios, the same initial depletion prior ($\varphi = B_{1952}/K$) was defined by a beta distribution with mean = 0.93 and CV of 5%. All catchability parameters were formulated as uninformative uniform priors. Even as, the process error of $\log(B_y)$ in year y for all scenarios were defined by an inverse-gamma distribution with shape parameter equal to 0.01 and rate parameter equal to 0.01.

JABBA is implemented in R (R Development Core Team, https://www.r-project.org/) with JAGS interface (Plummer, 2003) to estimate the Bayesian posterior distributions of all quantities of interest by means of a Markov Chains Monte Carlo (MCMC) simulation. The JAGS model is executed from R using the wrapper function jags() from the library r2jags (Su and Yajima, 2012), which depends on rjags R package. In this study, three MCMC chains were used. Each model was run for 30,000 iterations, sampled with a burn-in period of 5,000 for each chain and thinning rate of five iterations. Basic diagnostics of model convergence included visualization of the MCMC chains using MCMC trace-plots as well as Heidelberger and Welch (1992), Geweke (1992), and Gelman and Rubin (1992) diagnostics as implemented in the coda package (Plummer *et al.*, 2006).

2.4. Model diagnostics and sensitivity runs

To evaluate CPUE fits, the model predicted CPUE indices were compared to the observed CPUE. JABBA-residual plots were used to examine (1) colour-coded lognormal residuals of observed versus predicted CPUE indices for all fleet together with (2) boxplots indicating the median and quantiles of all residuals available for any given year; the area of each box indicates the strength of the discrepancy between CPUE series (larger box means higher degree of conflicting information), and (3) a loess smoother through all residuals aids to detect the presence systematic residual patterns. In addition, it depicts the root-mean-squared-error (RMSE) as a goodness-of-fit statistic. We conducted a runs test to quantitatively evaluate the randomness of residuals (Carvalho *et al.*, 2017). The runs test diagnostic was applied to residuals of the CPUE fit on log-scale using the function runs.test in the R package tseries, considering the 2-sided p-value of the Wald-Wolfowitz runs test. The runs test results can be visualized within JABBA using a specifically designed plot function that illustrates which time series passed or failed the runs test and highlights individual data points that fall outside the three-sigma limits (e.g. Anhøj and Olesen, 2014).

To check for systematic bias in the stock status estimates, we also performed a retrospective analysis for central reference scenario (S05: ASEM h = 0.8 Pella m), by sequentially removing one year of data at a time over a period of eight years (n = 8), refitting the model after each data removal and comparing quantities of interest (*i.e.* biomass, fishing mortality, B/B_{MSY}, F/F_{MSY}, B/B_0 and MSY) to the reference model that is fitted to full data time series. To compare retrospective bias between the models, we computed Mohn's (1999) rho (ρ) statistic, specifically the commonly used formulation defined by Hurtado-Ferro *et al.* (2014).

Although the above model diagnostics are important to evaluate the goodness of fit to the data and the consistency of benchmarking retrospectively, providing scientific advice should also involve checking that the model has prediction skill of future states under alternative management scenarios. To do this, the model-free hindcasting cross-validation (HCXval) technique by Kell *et al.* (2016) was applied, where observations are compared to their predicted future values. The HCXval algorithm has in common with retrospective analysis that requires the same two routine procedures of sequential removal the observations and re-fitting the model to the so truncated data series, but HCXval involves the additional steps of projecting ahead over the missing years and then cross-validating these forecasts against observations to assess the model's prediction skill. A robust statistic for evaluating prediction skill is the Mean Absolute Scaled Error (MASE) proposed by Hyndman and Koehler (2006), which scales the mean absolute error of prediction residuals to a naïve baseline prediction, where a 'prediction' is said to have 'skill' if it improves the model forecast when compared to the naïve baseline. A widely used baseline forecast for time series is the 'persistence algorithm' that takes the value at the previous time step to predict the expected outcome at the next time step as a naïve in-sample prediction, e.g., tomorrow's weather will be the same as today's. The MASE score scales the mean absolute error of the prediction residuals to the mean absolute error of a naïve in-sample prediction. A MASE score higher than one can then be interpreted such that the average model forecasts are no better than a random walk. Conversely, a MASE score of 0.5 indicates that the model forecasts twice as accurately as a naïve baseline prediction; thus, the model has prediction skill.

Finally, the analysis included sensitivity model runs based on forward stepwise inclusion of each index one-by-one in the model. Taking as prior indices the EU PS VAST as default indices in the small model. The general idea with this comparative analysis was to evaluate the possible effects of the inclusion of each index over estimated biomass dynamic of this stock.

3. Results and Discussion

The MCMC convergence tests by Heidelberger and Welch (1992), Geweke (1992), and Gelman and Rubin (1992) were passed by all estimable key parameters for all models. Adequate convergence of the MCMC chains was also corroborated by visual inspection of trace plots (results available on request), which showed good mixing in general (*i.e.*, moving around the parameter space).

The model fits to each of the five standardized CPUE's indices are shown in **Figure 2** for each of the nine uncertainty grid scenarios. For all scenarios, the behaviour of the model's fits appeared to be led by the pattern observed in the DAK BB Past and EU PS VAST indices more than to the others indices. Some general variations observed in the other indices tended to be not well interpreted by the distinct models fitted. As commented in the SCRS/2022/099 document, this behaviour is common when the trends observed along all time-series have poor signal, and this kind of pattern can be commonly corroborated by the presence of long and relatively flat time-series indices.

The results of the log-residuals runs tests for each CPUE and each scenario are shown in **Figure 3**. Green panels indicate CPUE indices that passed the runs test with no evidence of a non-random residual pattern ($p > 0.05$) and red panels indicating a failed runs test. In addition, the inner shaded area shows 3-sigma limits around the overall mean as proposed by Anhøj and Olesen (2014) and the red circles identify each specific year where the residuals are larger than the threshold limit. In all scenarios were observed a same pattern, with a failed behavior in the runs test diagnostic procedure for almost all indices, with expection of AZO BB Past index in all scenarios and EU PS VAST index in scenario S03 (**Figure 3**). The goodness-of-fit were comparable among all scenarios, in general, the RMSE statistics were ranging from 83.1% to 85.6% (**Figure 4**). This pattern shows some conflicting between indices. The annual process error deviation estimated for all scenarios shown a similar stochastic pattern with a constant average centered around the zero and 95% credibility intervals always covering the zero value (**Figure 5**), which suggest no evidence of structural model misspecifications.

The medians of the marginal posteriors for K ranged between 1,080,736 t (S03) and 1,699,609 t (S07) (**Table 3**). The values estimated for posterior to prior median (PPMR) and variance (PPVR) ratios estimated to K indicates that this parameter have been informed by the data for all scenarios. However, there was not observed expressive reductions in the precision of the posteriors in relation to the priors defined to this parameter. For the r, the medians of the marginal posteriors ranged between 0.397 (S07) and 1.014 (S03). The values of PPMR and PPVR estimated for r, in general, shown that the priors used have defined the behaviour of the posteriors as expected. This pattern was less evident for the scenarios S01, S02, and S03 (**Figure 6**). The initial depletion ($\varphi = B_{1952}/K$) marginal posteriors for each scenario were also similar and largely informed by the priors distributions.

The range of *MSY* median estimates were narrow between all nine scenarios, reaching the lower value in the S07 scenario (240,018 metric tons) and the higher value in the S03 scenario (340,567 metric tons) (**Table 3**). Furthermore, the marginal posterior medians for B_{MSY} varied between 453,865 (S03) and 645,927 (S07) metric tons, and estimates of F_{MSY} showed a small variation between the nine scenarios with median values varying from 0.371 (S07) to 0.769 (S03) (**Table 3**).

In general, all scenarios showed similar trends for the trajectories of B/B_{MSY} and F/F_{MSY} over time (**Figure 7**; **Figure 8**). The trajectory of B/B_{MSY} showed a slight tendency to decrease over time. On the other hand, the F/F_{MSY} trajectory showed a trend of constant increase over time (**Figure 7**; **Figure 8**). For all scenarios evaluated here, the models do not evidenced periods of overfishing ($F/F_{MSY} > 1$) or even the stock are being overfished ($B/B_{MSY} < 1$) (**Figure 7**; **Figure 8**). In general, the B/B_0 trajectory also shown a similar trend for all nine scenarios, with a slight tendency to decrease over the period evaluated (**Figure 9**).

The results of an eight year retrospective analysis applied to scenario S05 is depicted in **Figure 10**. In general, the Base Case scenario (S05) shows a negligible retrospective pattern. The estimated Mohn's rho for all stock quantities fell within the acceptable range of -0.15 and 0.20 (Hurtado-Ferro *et al.*, 2014; Carvalho *et al.*, 2017) and these results confirm the absence of an undesirable retrospective pattern (**Table 4**). The hindcasting cross-validation results for all updated indices show predictions within limits of the 95% CRI's suggesting a good prediction skills for S05 scenario (**Figure 11**). Except for the EU Echosounder index that had presented some predictions outside of the 95% CRI's limits. The mean absolute scaled error (MASE) estimated were above of the reference level (MASE > 1) for both indices evaluated, which indicates that the average model forecasts are not better than a naïve baseline prediction – like a random walk process (Carvalho *et al.*, 2021). Nonetheless, for the index with a flat trend with low variation at the end of the time series is expected that the MASE estimation will be close to reference level one.

The results of the sensitivity analysis based on forward stepwise indices in models (**Table 2**) are shown in **Figure 12**. These results shown some distinct behaviors over the general trajectories estimated in each interaction / addition of new index. The general trend and the pattern observed at the beginning of the series were similar among all models, the most specific change can be observed at the final of the time-series for all quantities (Biomass, B/B_0, B/B_{MSY} and F/F_{MSY}). The model based only in the EU PS VAST index had shown a most pessimistic trend, and the gradual inclusion of the other indices in the model tended to make the results more optimistic with each interaction. The full model presented the highest MSY values.

The Kobe biplots for all scenarios were shown in **Figure 13**. All scenarios show optimistic status with probabilities of the stock being stable on green area (**Figure 13**). Although, these results are very preliminary and they were explored during the skipjack stock assessment meeting. New runs were recommended by the group during this meeting and another pack of results will be presented and explored during an intersessional meeting.

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Table 1. Summary of the uncertainty grid scenarios for East Atlantic skipjack tuna.

Scenario	Model	r	B_{MSY}/K (m)
S01	ASEM h = 0.7 Pella m	Lognormal (0.545, 0.284)	0.40
S02	ASEM h = 0.8 Pella m	Lognormal (0.607, 0.318)	0.41
S03	ASEM h = 0.9 Pella m	Lognormal (0.668, 0.330)	0.42
S04	ASEM h = 0.7 Pella m	Lognormal (0.416, 0.148)	0.38
S05	ASEM h = 0.8 Pella m	Lognormal (0.440, 0.184)	0.37
S06	ASEM h = 0.9 Pella m	Lognormal (0.466, 0.219)	0.36
S07	ASEM h = 0.7 Pella m	Lognormal (0.366, 0.142)	0.38
S08	ASEM h = 0.8 Pella m	Lognormal (0.385, 0.172)	0.36
S09	ASEM h = 0.9 Pella m	Lognormal (0.402, 0.206)	0.35

Table 2. Summary of sensitivity analysis runs for East Atlantic skipjack tuna (*Katsuwonus pelamis*).

Scenario	Model	Type	Indices
S05	Pella m	ASEM h = 0.8	+ EU PS VAST
S05	Pella m	ASEM h = 0.8	+ EU PS VAST + EU Echosounder
S05	Pella m	ASEM h = 0.8	+ EU PS VAST + EU Echosounder + AZO BB Past
S05	Pella m	ASEM h = 0.8	+ EU PS VAST + EU Echosounder + AZO BB Past + CAN BB Past
S05	Pella m	ASEM h = 0.8	+ EU PS VAST + EU Echosounder + AZO BB Past + CAN BB Past + DAK BB Past

Table 3. Summary of posterior quantiles presented in the form of marginal posterior medians and associated the 95% credibility intervals of parameters for the Bayesian state-space surplus production models for East Atlantic skipjack tuna.

S01				S02			
Estimates	**Median**	**LCI (2.50%)**	**UCI (97.50%)**	**Estimates**	**Median**	**LCI (2.50%)**	**UCI (97.50%)**
K	1.268.825	774.129	2.230.156	K	1.127.863	692.823	1.805.619
r	0,756	0,435	1,273	r	0,915	0,507	1,496
ψ(psi)	0,940	0,815	0,991	ψ(psi)	0,940	0,813	0,991
σ_{proc}	0,104	0,056	0,171	σ_{proc}	0,099	0,054	0,171
F_{MSY}	0,636	0,366	1,072	F_{MSY}	0,730	0,404	1,194
B_{MSY}	507.507	309.637	892.022	B_{MSY}	462.485	284.095	740.402
MSY	319.010	210.781	542.690	MSY	328.488	219.064	537.318
B_{1950}/K	0,931	0,721	1,173	B_{1950}/K	0,931	0,719	1,160
B_{2020}/K	0,716	0,493	0,964	B_{2020}/K	0,717	0,493	0,951
B_{2020}/B_{MSY}	1,789	1,232	2,410	B_{2020}/B_{MSY}	1,750	1,203	2,318
F_{2020}/F_{MSY}	0,380	0,184	0,766	F_{2020}/F_{MSY}	0,378	0,192	0,753

S03				S04			
Estimates	**Median**	**LCI (2.50%)**	**UCI (97.50%)**	**Estimates**	**Median**	**LCI (2.50%)**	**UCI (97.50%)**
K	1.080.736	663.238	1.832.490	K	1.577.513	1.121.595	2.328.869
r	1,014	0,564	1,667	r	0,453	0,340	0,605
ψ(psi)	0,940	0,816	0,991	ψ(psi)	0,940	0,810	0,990
σ_{proc}	0,095	0,052	0,164	σ_{proc}	0,122	0,071	0,185
F_{MSY}	0,769	0,428	1,263	F_{MSY}	0,424	0,318	0,566
B_{MSY}	453.865	278.533	769.570	B_{MSY}	599.525	426.256	885.074
MSY	340.567	227.655	580.637	MSY	253.503	175.562	387.062
B_{1950}/K	0,929	0,731	1,155	B_{1950}/K	0,927	0,696	1,200
B_{2020}/K	0,730	0,515	0,948	B_{2020}/K	0,691	0,446	0,994
B_{2020}/B_{MSY}	1,738	1,227	2,258	B_{2020}/B_{MSY}	1,818	1,175	2,615
F_{2020}/F_{MSY}	0,367	0,179	0,719	F_{2020}/F_{MSY}	0,470	0,250	0,939

S05				S06			
Estimates	**Median**	**LCI (2.50%)**	**UCI (97.50%)**	**Estimates**	**Median**	**LCI (2.50%)**	**UCI (97.50%)**
K	1.509.670	1.036.906	2.405.568	K	1.414.773	966.329	2.266.726
r	0,507	0,355	0,732	r	0,566	0,367	0,868
ψ(psi)	0,939	0,816	0,991	ψ(psi)	0,939	0,816	0,991
σ_{proc}	0,116	0,065	0,180	σ_{proc}	0,113	0,061	0,179
F_{MSY}	0,501	0,351	0,724	F_{MSY}	0,591	0,383	0,906
B_{MSY}	558.692	383.734	890.242	B_{MSY}	509.341	347.894	816.057
MSY	280.290	191.428	452.797	MSY	302.014	202.936	486.489
B_{1950}/K	0,930	0,709	1,186	B_{1950}/K	0,928	0,711	1,174
B_{2020}/K	0,698	0,464	0,988	B_{2020}/K	0,699	0,470	0,974
B_{2020}/B_{MSY}	1,887	1,252	2,671	B_{2020}/B_{MSY}	1,941	1,305	2,707
F_{2020}/F_{MSY}	0,411	0,206	0,820	F_{2020}/F_{MSY}	0,370	0,187	0,733

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Table 3. Continued from the previous page.

S07			
Estimates	**Median**	**LCI (2.50%)**	**UCI (97.50%)**
K	1.699.609	1.205.711	2.590.927
r	0,397	0,301	0,523
$\psi_{(psi)}$	0,940	0,814	0,991
σ_{proc}	0,122	0,074	0,185
F_{MSY}	0,371	0,281	0,490
B_{MSY}	645.927	458.224	984.668
MSY	240.018	165.728	370.847
B_{1950}/K	0,926	0,702	1,191
B_{2020}/K	0,694	0,443	1,018
B_{2020}/B_{MSY}	1,826	1,165	2,680
F_{2020}/F_{MSY}	0,495	0,256	0,985

S08			
Estimates	**Median**	**LCI (2.50%)**	**UCI (97.50%)**
K	1.616.704	1.097.909	2.496.304
r	0,429	0,304	0,605
$\psi_{(psi)}$	0,939	0,816	0,990
σ_{proc}	0,120	0,070	0,185
F_{MSY}	0,448	0,317	0,631
B_{MSY}	582.039	395.265	898.709
MSY	260.666	173.535	413.629
B_{1950}/K	0,925	0,698	1,190
B_{2020}/K	0,692	0,448	0,991
B_{2020}/B_{MSY}	1,923	1,244	2,752
F_{2020}/F_{MSY}	0,434	0,221	0,887

S09			
Estimates	**Median**	**LCI (2.50%)**	**UCI (97.50%)**
K	1.585.391	1.065.949	2.469.064
r	0,472	0,314	0,715
$\psi_{(psi)}$	0,938	0,813	0,990
σ_{proc}	0,116	0,065	0,181
F_{MSY}	0,520	0,346	0,788
B_{MSY}	555.010	373.165	864.364
MSY	287.897	190.381	465.542
B_{1950}/K	0,928	0,704	1,182
B_{2020}/K	0,702	0,467	0,995
B_{2020}/B_{MSY}	2,005	1,333	2,843
F_{2020}/F_{MSY}	0,376	0,190	0,766

Table 4. Summary Mohn's rho statistic computed for a retrospective evaluation period of eight years for the S05 scenario. The more the values diverge from the zero, the stronger is the retrospective bias. Values falling between -0.15 and 0.2 are widely deemed as acceptable retrospective bias (Huerto *et al.*, 2014).

Scenario	***Stock Quantity***					
	B	***F***	***B/B$_{MSY}$***	***F/F$_{MSY}$***	***B/K***	***MSY***
S05	-0.1750	0.2194	-0.0525	-0.2719	0.0036	-0.1678

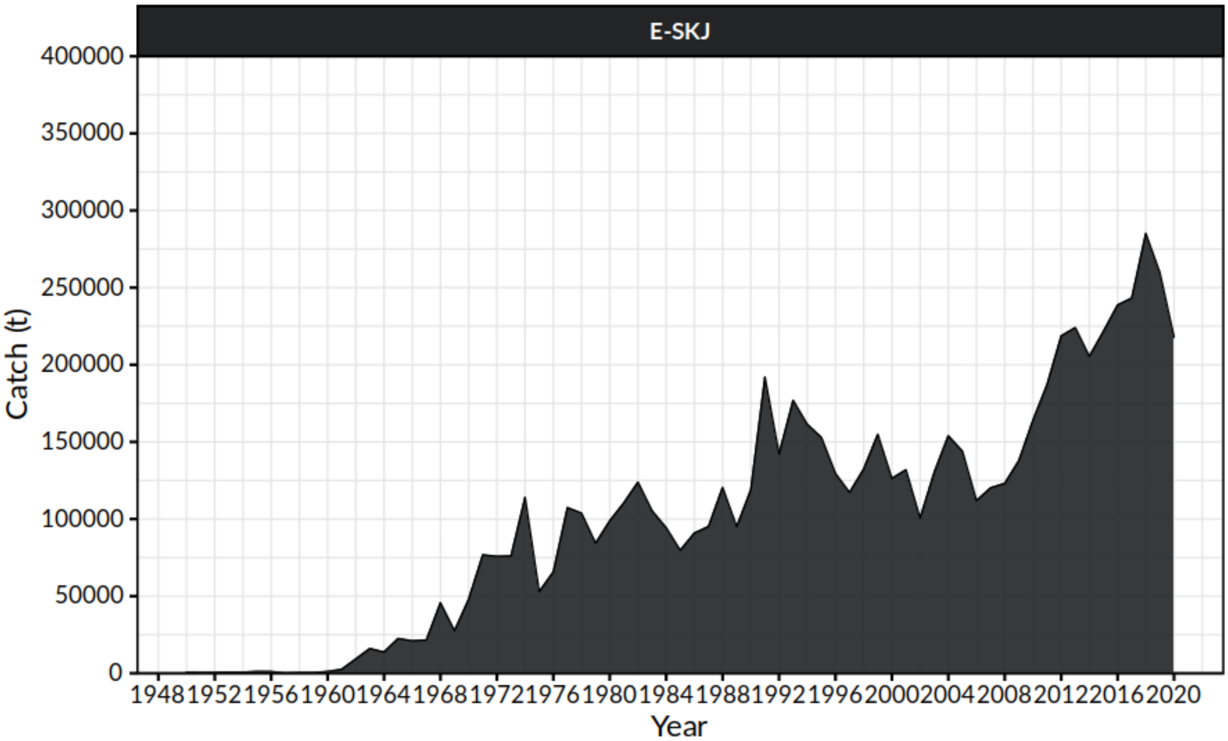


Figure 1. Catch time series in metric tons (t) between 1952 and 2020 for East Atlantic skipjack tuna.

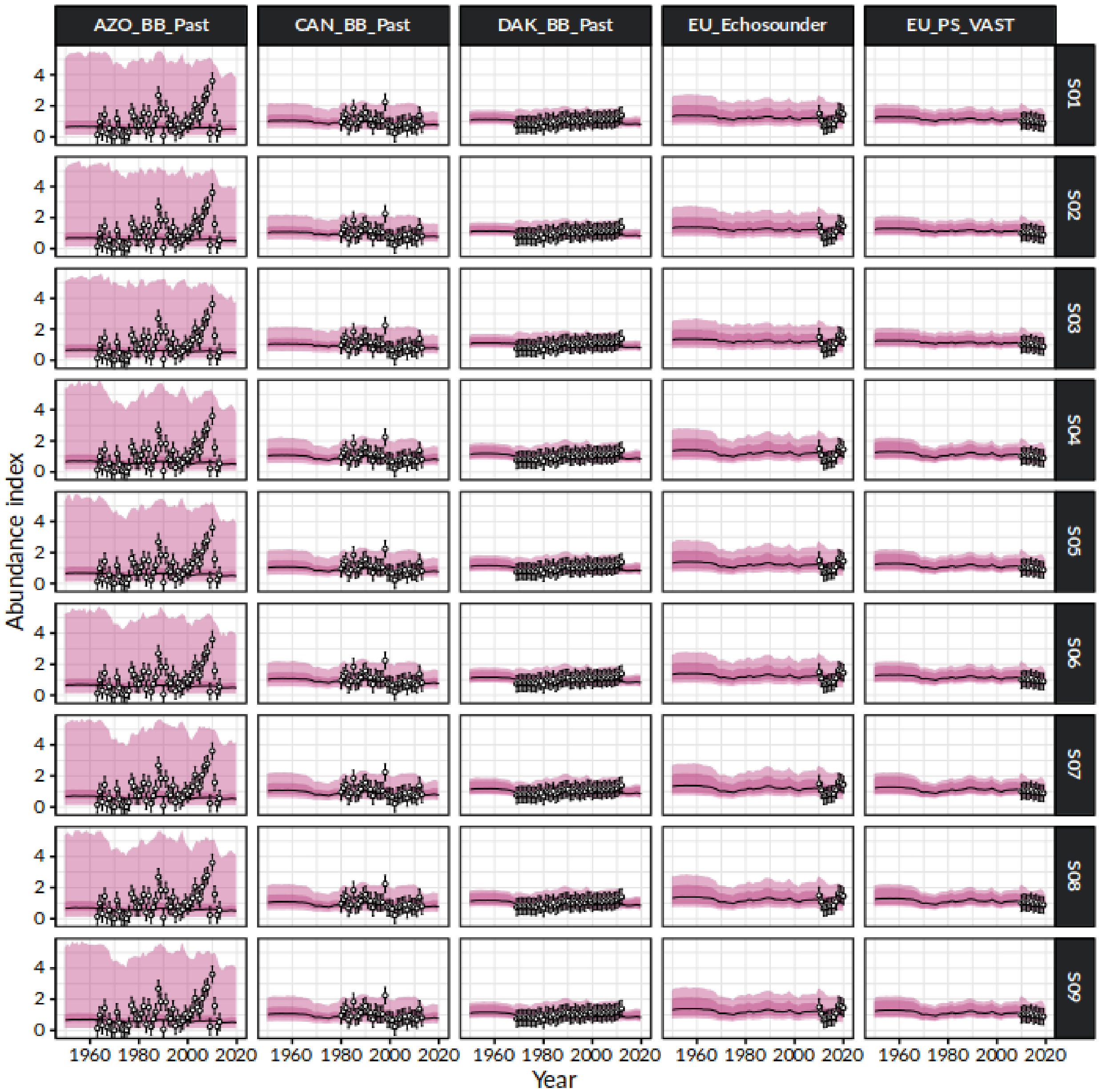


Figure 2. Time series of observed (circle) with error 95% Cis (error bars) and predicted (solid line) CPUE of East Atlantic skipjack tuna for the Bayesian state-space surplus production model JABBA for each scenario fitted. Dark shaded blue areas show 95% credibility intervals of the expected mean CPUE and light shaded blue areas denote the 95% posterior predictive distribution intervals.

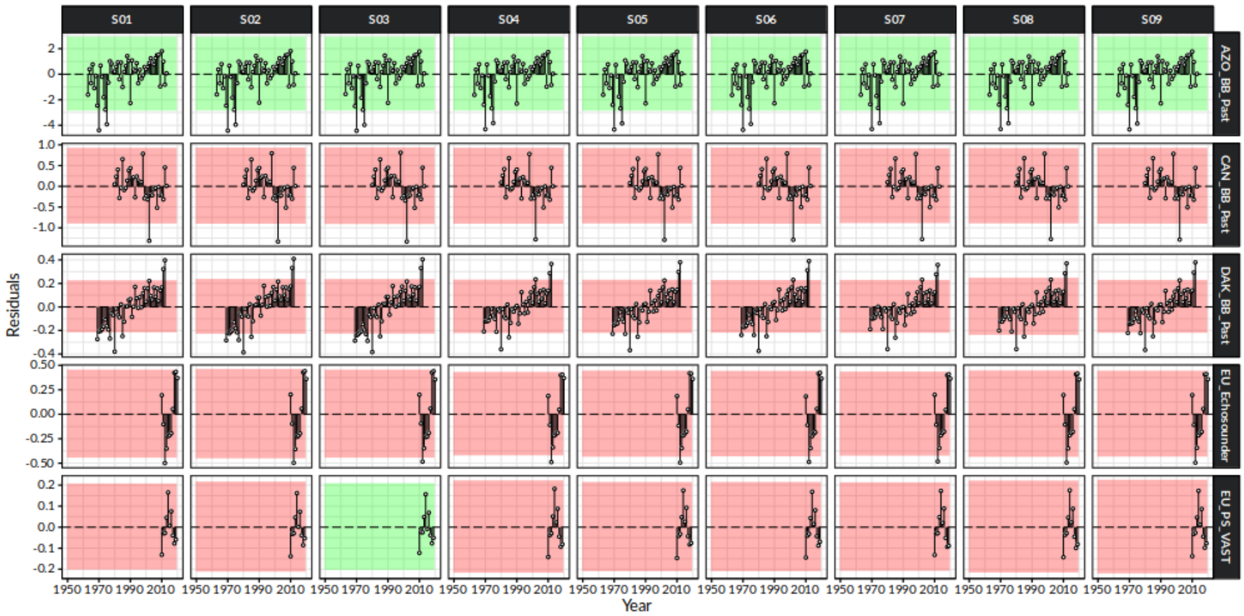


Figure 3. Runs tests to quantitatively evaluate the randomness of the time series of CPUE residuals for each scenario fitted for the West Atlantic skipjack tuna. Green panels indicate no evidence of lack of randomness of time-series residuals (p>0.05) while red panels indicate the opposite. The inner shaded area shows three standard errors from the overall mean and red circles identify a specific year with residuals greater than this threshold value (3x sigma rule).

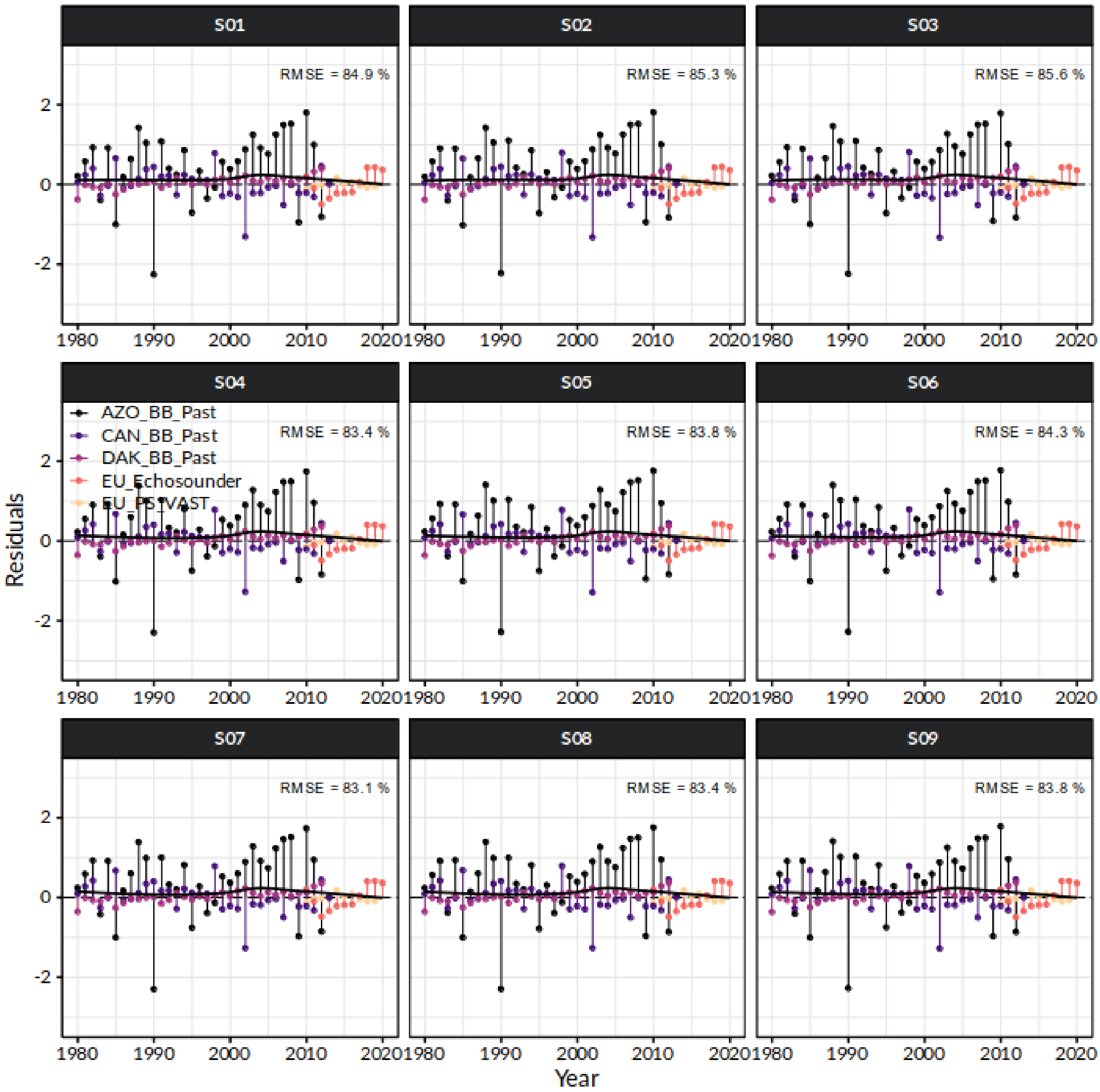


Figure 4. JABBA residual diagnostic plots for alternative sets of CPUE indices examined for each scenario fitted for the East Atlantic skipjack tuna. Solid black lines indicate a loess smoother through all residuals.

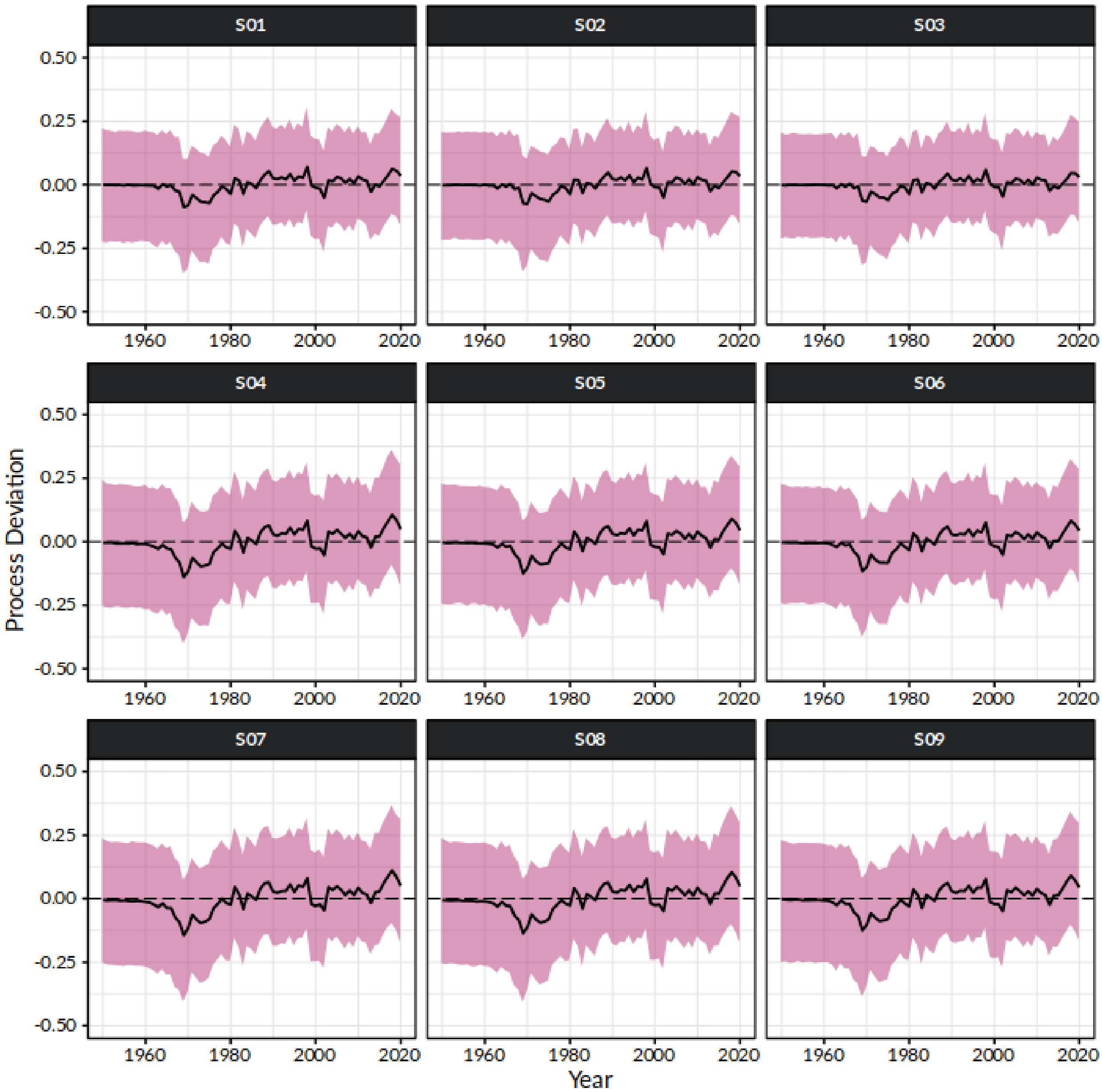
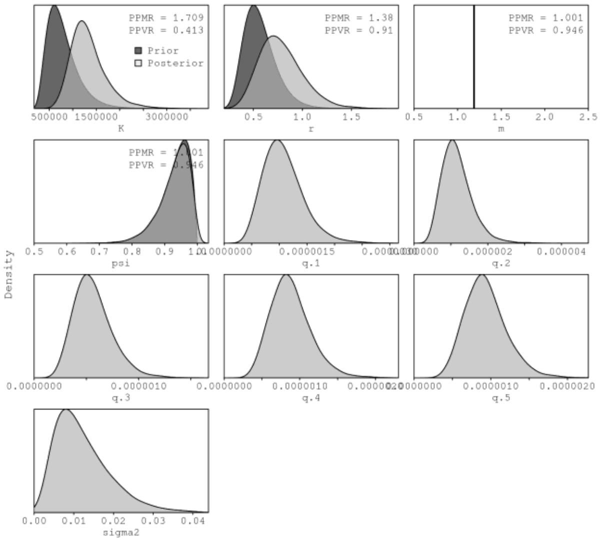
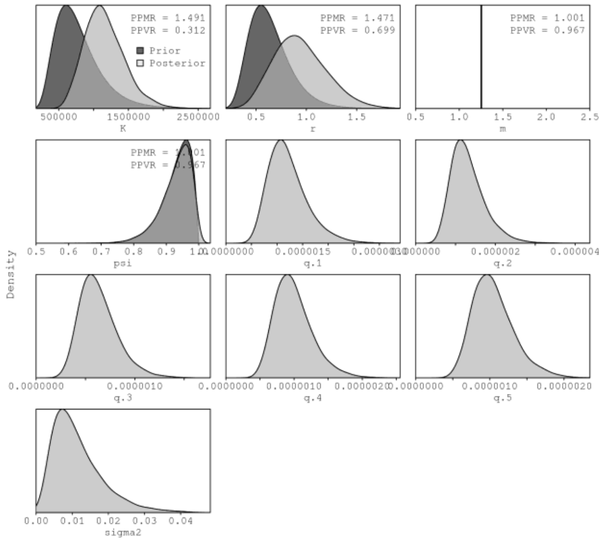


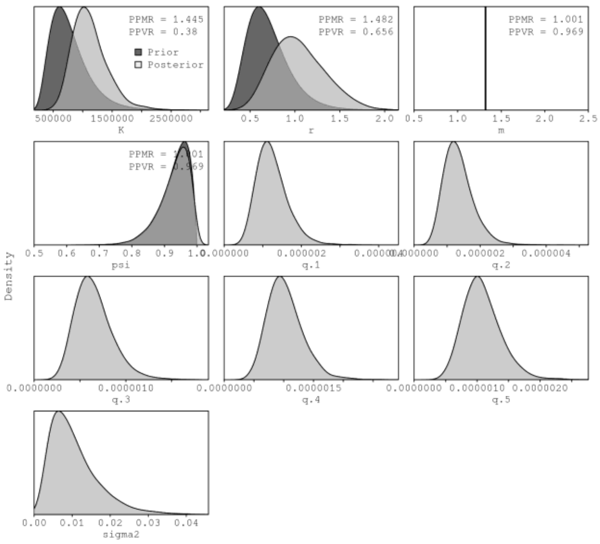
Figure 5. JABBA residual diagnostic plots for alternative sets of CPUE indices examined for each scenario fitted for the East Atlantic skipack tuna. Process error deviates (median: solid line) with shaded blue area indicating 95% credibility intervals.

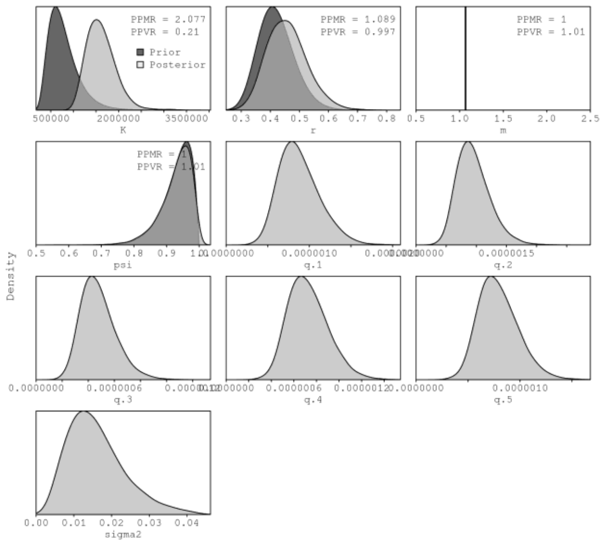
S01 **S02**





S03 **S04**





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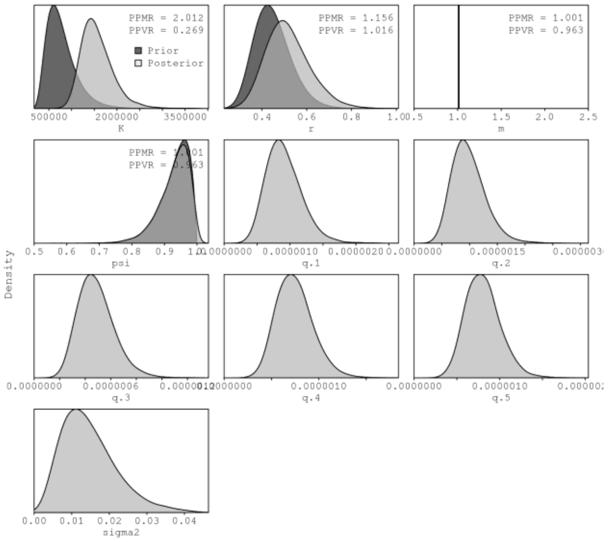
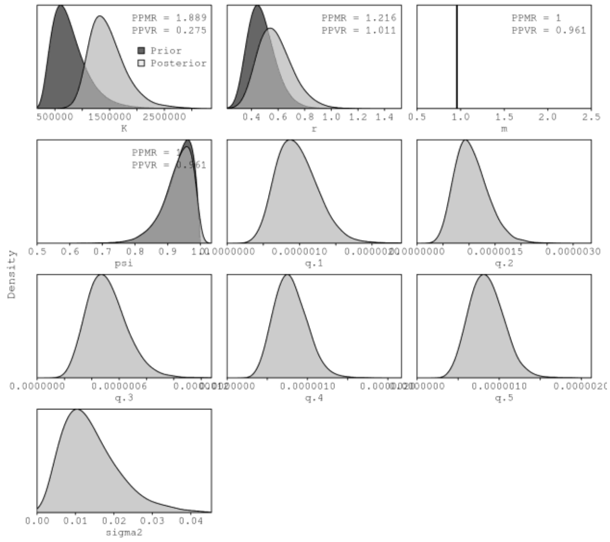
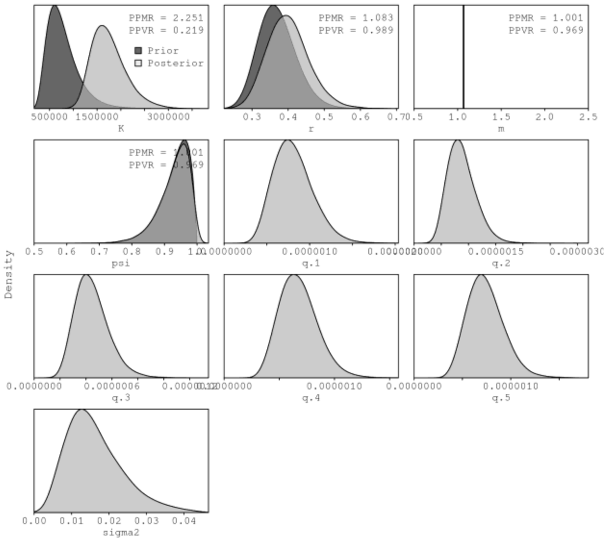
S05



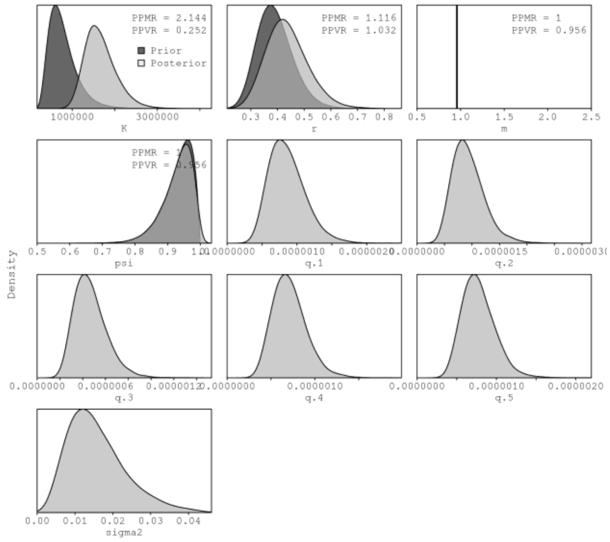
S06



S07



S08



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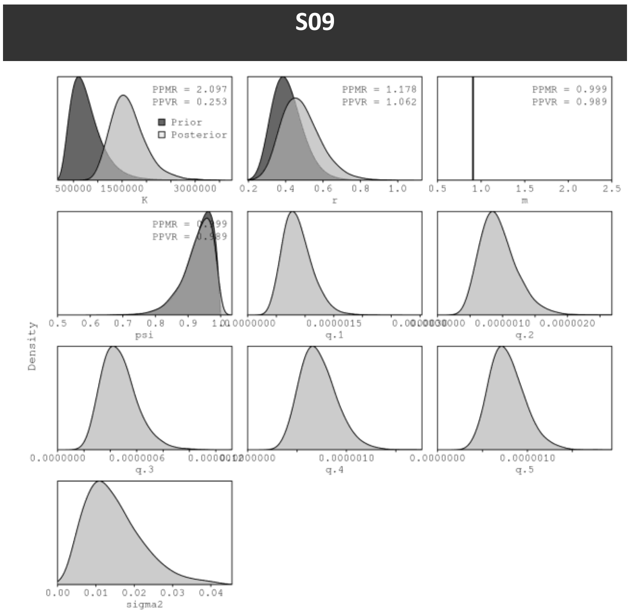

Figure 6. Prior and posterior distributions of various model and management parameters for the Bayesian state-space surplus production fitted for the East Atlantic skipjack tuna. PPRM: Posterior to Prior Ratio of Medians; PPRV: Posterior to Prior Ratio of Variances.

Figure 7. Trends in biomass relative to B_{MSY} (B/B_{MSY}) for each scenario from the Bayesian state-space surplus production JABBA model fits to East Atlantic skipjack tuna.

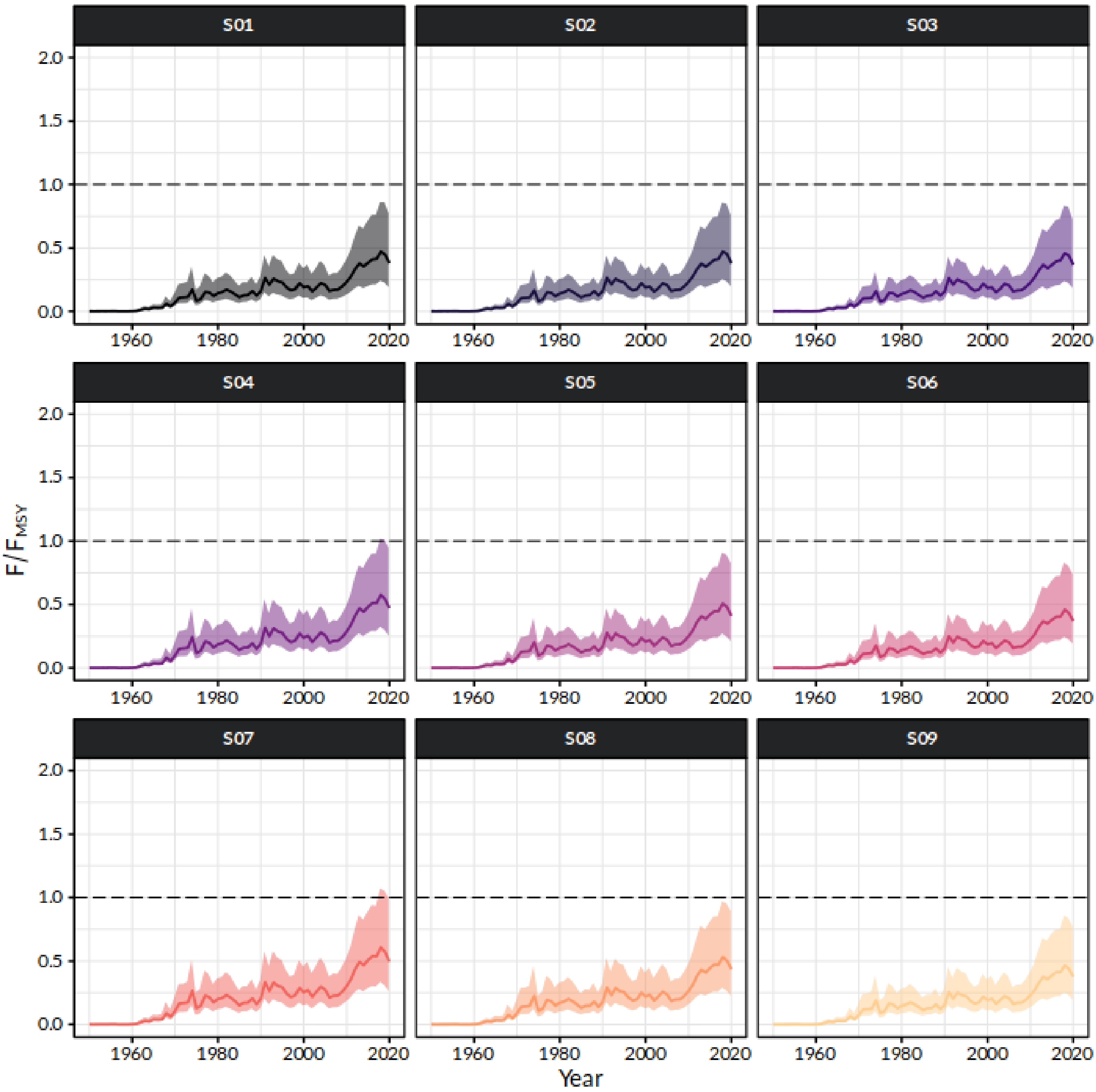

Figure 8. Trends in biomass relative to F_{MSY} (F/F_{MSY}) for each scenario from the Bayesian state-space surplus production JABBA model fits to East Atlantic skipjack tuna.

Figure 9. Trends in biomass relative to B_0 (B/B_0) for each scenario from the Bayesian state-space surplus production JABBA model fits to East Atlantic skipjack tuna.

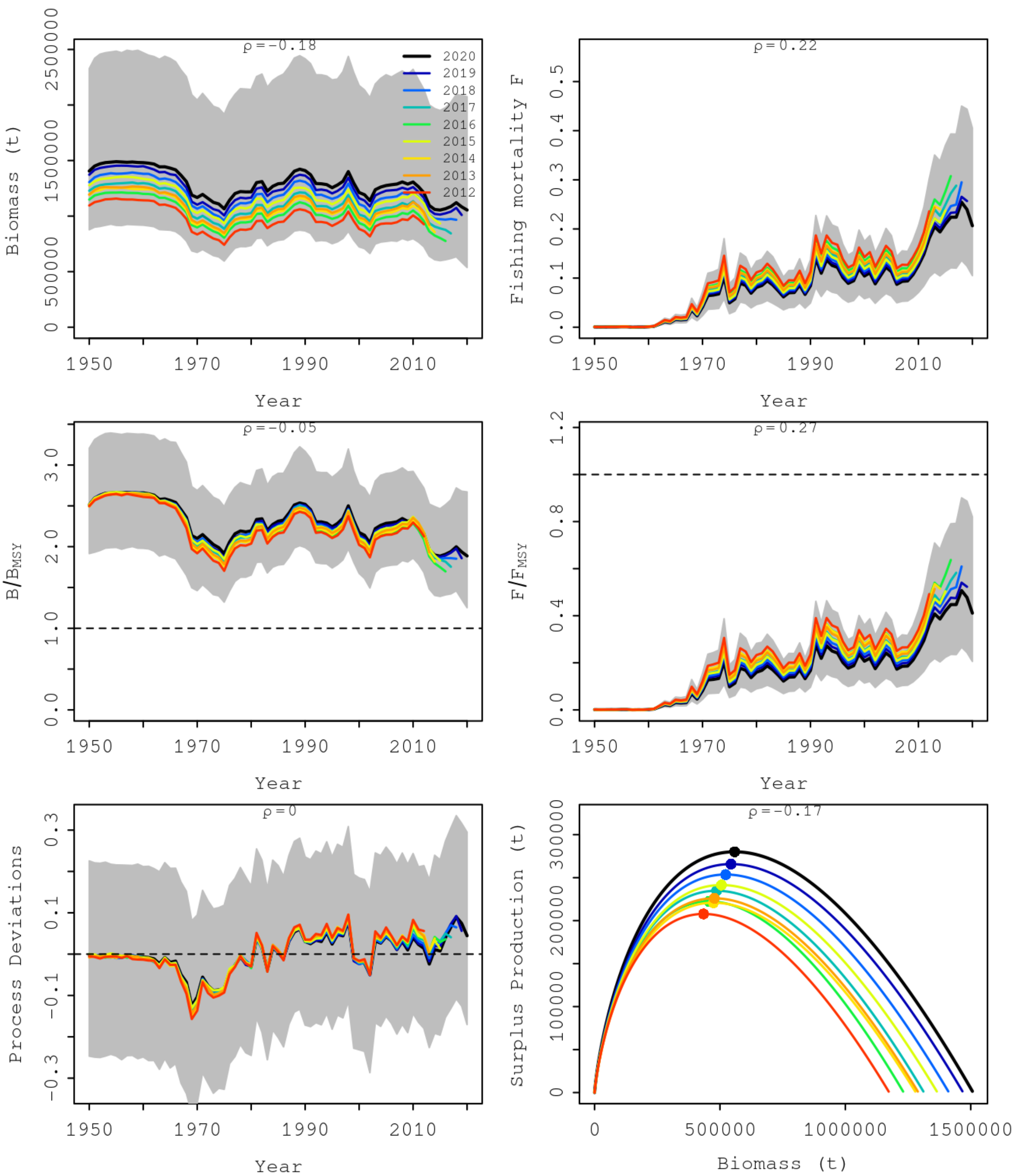

Figure 10. Retrospective analysis conducted for scenario S05 for East Atlantic skipjack tuna, by removing one year at a time sequentially (n=8) and predicting the trends in biomass and fishing mortality (upper panels), biomass relative to B_{MSY} (B/B_{MSY}) and fishing mortality relative to F_{MSY} (F/F_{MSY}) (middle panels) and process deviations and surplus production curve (bottom panels) from the Bayesian state-space surplus production model fits.

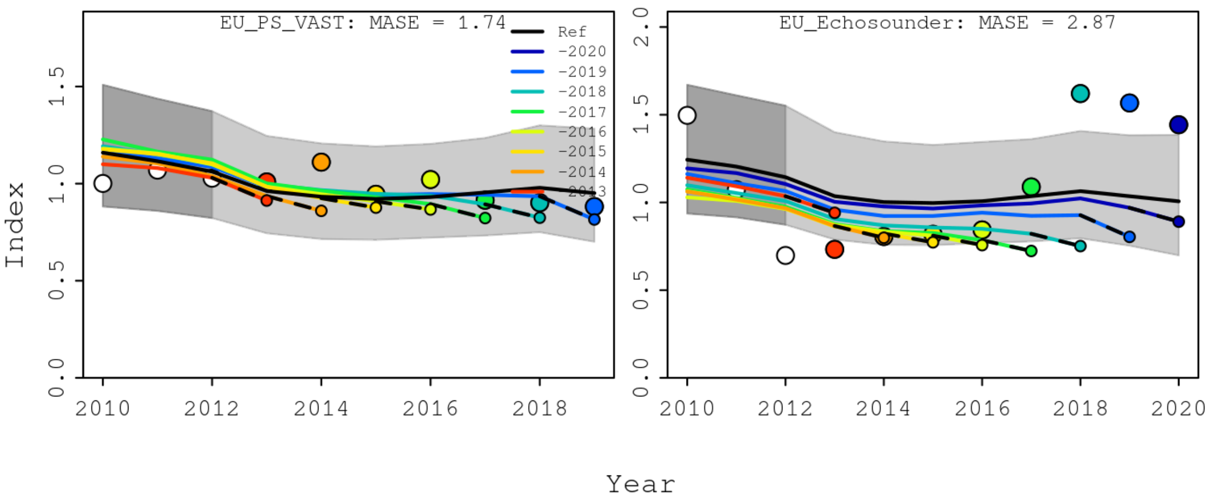

Figure 11. Hindcasting cross-validation results (HCxval) for the two scenarios S05 for East Atlantic skipjack tuna, showing one-year-ahead forecasts of CPUE values (2011-2019), performed with eight hindcast model runs relative to the expected CPUE. The CPUE observations, used for cross-validation, are highlighted as color-coded solid circles with associated light-grey shaded 95% confidence interval. The model reference year refers to the end points of each one-year-ahead forecast and the corresponding observation (i.e. year of peel + 1).

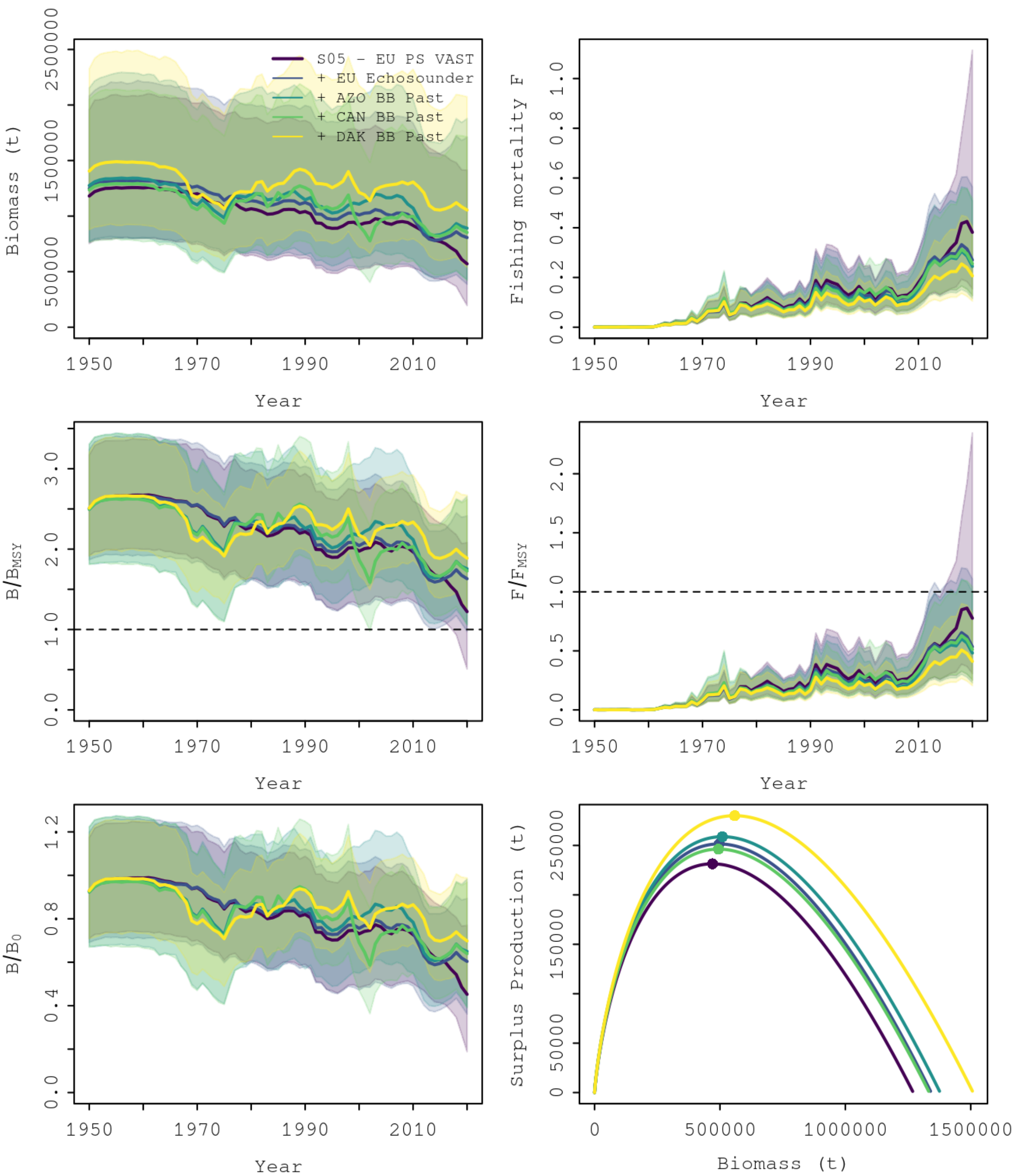

Figure 12. Sensitivity analysis performed for scenarios S05 showing the trends in biomass and fishing mortality (upper panels), biomass relative to B_{MSY} (B/B_{MSY}) and fishing mortality relative to F_{MSY} (F/F_{MSY}) (middle panels) and biomass relative to K (B/K) and surplus production curve (bottom panels) for the East Atlantic skipjack tuna.

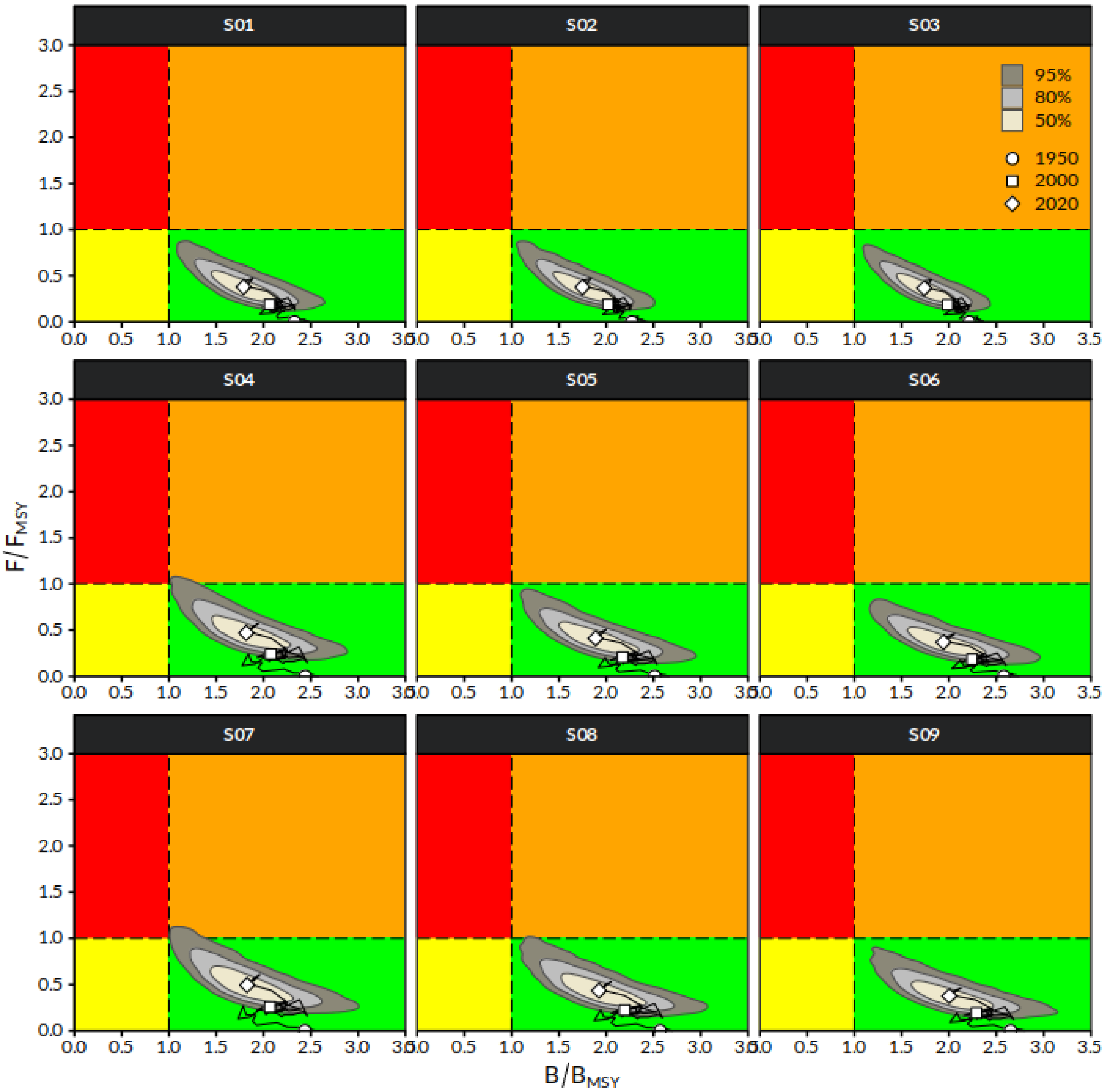

Figure 13. Kobe phase plot showing estimated trajectories (1952-2020) of B/B_{MSY} and F/F_{MSY} for the Bayesian state-space surplus production model for the East Atlantic skipjack tuna. Different grey shaded areas denote the 50%, 80%, and 95% credibility interval for the terminal assessment year. The probability of terminal year points falling within each quadrant is indicated in the figure legend.