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WESTERN ATLANTIC SKIPJACK TUNA MSE: UPDATES TO THE OPERATING MODELS AND INITIAL EVALUATION OF THE RELATIVE PERFORMANCE OF PRELIMINARY MANAGEMENT PROCEDURES

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SUMMARY

The present analysis aimed to update the initial operating models (OMs) for the management strategy evaluation for Western Atlantic skipjack tuna. The OMs were conditioned using the same fleet structure agreed during the ICCAT Data Preparatory for Skipjack tuna meeting in February 2022, with the catch time series spanning from 1952 to 2020, CPUEs, and length compositions from five different fleets. During the data preparatory meeting, several sources of uncertainty were identified for growth and natural mortality. Therefore, a set of 11 OMs, covering much of the discussions on life-history parameter uncertainty, was explored in the present analysis. The analysis also included the initial trials of the closed-loop simulation of the management strategy evaluation for the western Atlantic skipjack tuna stock by evaluating the relative performance of pre-selected management procedures across an initial set of performance metrics.

RÉSUMÉ

La présente analyse visait à actualiser les modèles opérationnels (OM) initiaux pour l'évaluation de la stratégie de gestion du listao de l'Atlantique Ouest. Les OM ont été conditionnés en utilisant la même structure de flottille que celle convenue lors de la réunion de préparation des données de l'ICCAT pour le listao en février 2022, avec les séries temporelles de capture s'étendant de 1952 à 2020, les CPUE et les compositions par taille de cinq flottilles différentes. Au cours de la réunion de préparation des données, plusieurs sources d'incertitude ont été identifiées pour la croissance et la mortalité naturelle. Par conséquent, un ensemble de 11 OM, couvrant une grande partie des discussions sur l'incertitude des paramètres du cycle vital, a été exploré dans la présente analyse. L'analyse a également inclus les premiers essais de la simulation en boucle fermée de l'évaluation de la stratégie de gestion pour le stock de listao de l'Atlantique Ouest en évaluant la performance relative des procédures de gestion présélectionnées sur un ensemble initial de paramètres de performance.

RESUMEN

El presente análisis tenía como objetivo actualizar los modelos operativos (OM) iniciales para la evaluación de estrategias de ordenación del listado del Atlántico occidental. Los OM se condicionaron utilizando la misma estructura de flotas acordada durante la reunión de preparación de datos de ICCAT para el listado en febrero de 2022, con las series temporales de capturas que abarcan desde 1952 hasta 2020, las CPUE y las composiciones de tallas de cinco flotas diferentes. Durante la reunión de preparación de datos, se identificaron varias fuentes de incertidumbre para el crecimiento y la mortalidad natural. Por lo tanto, en el presente análisis se exploró un conjunto de 11 OM, que cubren gran parte de las discusiones relacionadas con la incertidumbre sobre los parámetros del ciclo vital. El análisis también incluyó las pruebas iniciales de la simulación en bucle cerrado de la evaluación de estrategias de ordenación para el stock de listado del Atlántico occidental, evaluando el desempeño relativo de los procedimientos de ordenación preseleccionados a través de un conjunto inicial de mediciones del desempeño.

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KEYWORDS

Management strategy evaluation, stock assessment, performance metrics, closed-loop simulation, harvest strategy

1 Introduction

The work on developing the western Atlantic skipjack MSE began in 2020 through a collaboration between Brazilian scientists with scientists who developed the openMSE R Package (Open-Source Software for Management Strategy Evaluation https://openmse.com/; Hordyk *et al*., 2021). This collaboration resulted in the presentation of the document SCRS/2020/140 (Huynh *et al*., 2020) at the ICCAT Tropical Tunas Species Group meeting in September 2020. It included a demonstration MSE framework with operating model (OM) conditioning for the western Atlantic Skipjack. However, this preliminary MSE exercise considered the southwestern Atlantic portion as a single stock using catches from the Brazilian bait boat and handline fleets.

During the Tropical Tuna Species Group meeting in 2021 (ICCAT, 2021), it was agreed that the following steps on the development of western Atlantic Skipjack MSE must consider the current hypothesis of stock structure and should include data from all western fisheries, such as the Venezuelan and the US, in conformity with the stock structure used in the last western Atlantic Skipjack stock assessment.

Taking into consideration the agreement made by the Tropical Species Group in 2020, the present analysis updates the initial operating models by including data from other fishing fleets from different CPCs. In addition, during the ICCAT Skipjack Data Preparatory meeting (ICCAT, 2022), several sources of uncertainty were identified for growth and natural mortality; therefore, a set of operating models covering much of the discussions on life history parameter uncertainty were explored in the present analysis, including an extra scenario that incorporated environmental factors for estimating the standardized CPUEs for the purse seine and bait boat fleets from Venezuela and Brazil. We also explored the AOTTP and tagging ICCAT data bases to assess the movement patterns of the western Atlantic Skipjack stock and inform the operating model spatial parameters. Finally, the analysis includes the relative performance of pre-selected management procedures across an initial set of performance metrics. It was done by conducting the initial trials of the closed-loop simulation of the management strategy evaluation for the western Atlantic skipjack tuna stock. These initial trials also included a specific scenario to evaluate the impact of climate change on the stock future projections.

2 Methods

2.1 Fleet structure and fisheries data

ICCAT estimates catch for many fleets and nations based on the reported catch by contracting and non-contracting parties submitted to the ICCAT Secretariat. The operating models were conditioned using the same fleet structure agreed during the ICCAT Data Preparatory for Skipjack tuna meeting in February 2022. **Table 1** shows the details and combinations of fleets, fishing gears, size, and CPUE data available. The operating models were conditioned using five different fleets with the catch time series spanning from 1952 to 2020 (**Figure 1**). The standardized CPUE series covers most of the fishing fleets operating in the western Atlantic Ocean, which include surface fleets (bait boat, BB and purse seine, PS), handline (HL), longline (LL), and a larvae index from the Gulf Mexico (GOM larvae) (**Figure 2**). In addition, an operating model with two additional CPUE series that incorporate environmental factors (**Figure 2**) for estimating the standardized CPUEs for the purse seine and bait boat fleets from Venezuela and Brazil was included (see details in **Appendix A**). This specific operating model (see details in the section 2.3) was built to consider the impact of climate change on the western Atlantic Skipjack tuna stock. For the length composition data that was included in the MSE operating models, the information was compiled by the ICCAT secretariat which covered most of the fishing fleets operating in the western Atlantic Ocean.

2.2 Life History parameters

During the ICCAT Data Preparatory for Skipjack tuna meeting in February 2022, the group reviewed the available data on skipjack biology. It made a set of decisions regarding the inputs for the different assessment models. The operating models were conditioned following the same recommendations and encompass two significant sources of uncertainty concerning the growth pattern and its consequences in estimating natural mortality at age vector. For the specific coefficients of the length-weight relationship, we used the same that was used in the assessment in 2014 (a = 7.48E-6 and b = 3.253). Size-at-maturity was also the same used in the 2014 assessment, an L50 of 42 cm FL and an L95 of 53 cm FL.

Growth curve scenarios

Given the uncertainty of growth for skipjack, the group decided to build a simulation framework for estimating a plausible range of growth curves. This simulation was based on studies about the growth of skipjack tuna carried out worldwide, but excluding the ones based on spines and vertebrae age readings. **Figure 3** shows the simulation results that were considered for the operating model conditioning. The estimated VB growth parameters (median and associated 25th-75th quantiles) were:

- Linf: 76 cm (67-86 cm)
- K: 0.53 (0.54-049)
- t0: -0.31 (-0.09--0.49)

After an exploratory analysis, it was noted that the estimated growth curve based on the 25th quantile does not provide a reliable growth pattern for this species, noting that Linf is about half of the largest observed specimen (~ 150 cm FL). Also, it was noted that the estimated length-at-age using the 25th quantile scenario resulted in an underestimation of size (less than 5 cm, see the red line in **Figure 3**) for the age group "0+". For this reason, the operating models conditioning exercise only considered the median and 75th quantile (scenarios "med" and "up", respectively) for the hypothesis of the growth pattern for the western Atlantic Skipjack tuna.

Natural Mortality scenarios

During the ICCAT Data Preparatory for Skipjack tuna in February 2022, the Group decided that the M-at-length vector should be estimated using the Gaertner (2015) scaling approach. In the past assessment, this approach was used to estimate the M-at-age vector using the three growth curve assumptions described in the above section. Also, the group noticed that the estimated M-at-age vector (Gaertner, 2015) resulted in a significant impact on the predicted M, characterized by high values, on age 0, 1, and 2 fish, primarily if the low growth curve scenario (25th quantile) was used (**Figure 4**). Given the high uncertainty on M, we also explored alternative approaches for estimating a plausible range of M-at-age vectors for operating model conditioning. One possible solution is to use the "half length-at-age" vector for estimating the M vector, which is essentially the use of 0.5-6.5 instead of 0-6 age groups for estimating the M-at-age (scenarios "LowM" and "M", respectively). We also explored alternative methodologies, such as Lorenzen (1996) and Gislason (2010) (**Figure 4**). The exploratory analyses showed that scenarios "LowM" (half age vector) with Lorenzen's method provided the most reliable predicted age compositions (results not shown). Therefore, the combination of "med" and "up" growth curves scenarios with the "LowM" and Lorenzen method was considered to explore the alternative steepness values (0.7, 08, and 0.9). See the set of operating models on the section on “Uncertainty grid”.

2.3 Uncertainty grid and operating model conditioning

It is difficult to incorporate all major uncertainties into a single operating model. An initial set of OMs was described in Huynh *et al*. (2020) which included alternative assumptions about selectivity, growth, natural mortality, and steepness. In the present analysis, we explored a new set of operating models covering much of the discussions on life history parameter uncertainty during the ICCAT Skipjack Data Preparatory meeting (ICCAT, 2022). **Table 2** discriminate the list of operating models, including a description of the main parameters and methods for the assumptions regarding growth and natural mortality (described in the above sections).

We used a multi-fleet Stock Reduction Analysis (SRA; Walters *et al*., 2006) for operating model conditioning through the R package openMSE framework. The openMSE is an umbrella R package for building operating models, analyzing fishery data, and conducting management strategy evaluation for fisheries systems (*Hordyk et al.*, 2021). It includes the R core packages, MSEtool, DLMtool, and SAMtool (see https://openmse.com/; Hordyk *et al.*, 2022; Carruthers *et al.*, 2022; Huynh *et al.*, 2022). The stock reduction analysis for operating models conditioning is available through the RCM function accessible in the SAMtool R package. The stock reduction analysis is a useful tool in the absence of stock assessment models to parameterize operating models and it is comparable to statistical catch-at-age (SCA) models (see Huynh *et al*., 2020). The SRA model can estimate a range of plausible stock depletion levels by reconstructing the historical fishing mortality and recruitment levels that could have generated the observed data. More details about the structure of this model and the mathematical description can be found in: https://openmse.com/tutorial-rcm-eq/.

The MSEtool uses a two-box spatial model (see details in https://openmse.com/object-stock/7-spatial-movement/) and requires input parametrization for important parameters regarding spatial movements and exchange among the Atlantic Skipjack tuna stocks (west and east). For this reason, we also analyzed the AOTTP and tagging ICCAT data bases to assess the movement patterns of the western Atlantic Skipjack stock and inform the operating models. A detailed analysis can be accessed in **Appendix B**. We used the output from this analysis to guide the parameterization regarding the probability of individuals staying in each stock, by setting the slots “prob_staying”, “Size_area_1” and “Frac_area_1” at 0.5. This value-level allows some exchanges (migrations) between western and eastern stocks.

Each operating model contained 100 stochastic replicates that incorporated uncertainty in the estimates of recruitment, including the unfished recruitment parameter (R_0) and annual recruitment deviates. From a single SRA fit, the variance-covariance matrix was re-sampled 100 times. The annual multinomial sample size for the length compositions was taken to be the natural logarithm of the nominal sample size. The Beverton-Holt model was used to describe the stock-recruitment relationship and the parameter SigmaR was set at 0.4 for all operating models. The selectivity was constant within operating model as estimated in the SRA and was set to be flat-topped for the longline fleets (LL_USMX and LL others), while for the surface fleets (PS west, BB west and HL_RR) the dome-shape function was considered.

2.4 MSE simulation

The projection period for this initial exercise of the closed-loop MSE simulation was 40 years with 100 replicates and considered a data lag of two years (e.g., in 2022, the TAC for 2023 is set with data up to 2020). Projected catches were assumed to be perfectly known without any error and in full compliance with the established TACs. The selectivity is based on the F-at-age in the terminal year of the historical period (e.g. 2020). A coefficient of variation of 0.4 and the autocorrelation based on the operating model conditioning was used as the model's error structure.

A set of management procures based on constant catches, index-slope, and assessment model scenarios were initially pre-selected for the MSE evaluation over the reference set of operating models. The constant catch management procedures were based on setting a fixed TAC, as follows:

- ***CC_15kt*** (fixed TAC of 15 thousand tonnes)
- ***CC_20kt*** (fixed TAC of 20 thousand tonnes)
- ***CC_25kt*** (fixed TAC of 25 thousand tonnes)
- ***CC_30kt*** (fixed TAC of 30 thousand tonnes)
- ***CC_35kt*** (fixed TAC of 35 thousand tonnes)
- ***CC_40kt*** (fixed TAC of 40 thousand tonnes)

Index-slope management procedures adjust the TAC up and down as the CPUE increases and decreases, respectively. Three index-slope management procedures were evaluated: ***Iratio***, ***Islope***, and ***GBslope*** (see Huynh *et al*., 2020). We also tested a 40-10 harvest control rule (HCR) management procedure by associating the output of the assessment models for obtaining the reference points, as follows:

- ***SP_4010*** - A surplus production model with a 40-10 control rule.
- ***SCA_4010*** - A statistical catch-at-age model with a 40-10 control rule.

A management procedure that establishes no fishing (***NFref***) and the current fishing effort management (***curE***) was also considered. Both allow an assessment of the rebuilding time of a collapsed stock and evaluate a *status quo* approach (projecting the current fishing mortality) (see Huynh *et al.*, 2020).

Four preliminary performance metrics (PMs) were used to compare the pre-selected management procedures (see Huynh *et al.*, 2020):

- ***40% B0*** **–** the probability (mean over 100 replicates) that the spawning depletion is greater than 40% during the projection period.
- ***STC30*** (short term catch) – the probability that the catch exceeds 30 kt in the first decade of the projection period.
- ***LTC30*** (long term catch) – the probability that the catch exceeds 30 kt in the second decade of the projection period.
- ***AAVC*** (average annual variability in catch) – the probability that the interannual catch variability is less than 20% during the projection period.

To consider possible impacts of climate changes in the management strategy evaluation analysis, the operating model "*OM_med_Lorenzen_LowM_h09_env*" that incorporates environmental covariates on the CPUE time series from Venezuelan purse seiners and Brazilian bait boat fisheries were used to create a robustness test by increasing the recruitment variability in the future projections (e.g., increased sigmaR to 0.9, see **Figure 5**). This allowed us the initial and preliminary assessment of the possible impacts of the climate changes in the MSE through the robustness testing from different OM scenarios.

We used the R package ggmse (https://github.com/pbs-assess/ggmse) to generate many of the figures and outputs from the operating model conditioning and the evaluation of the initial exercise of the closed-loop MSE simulation.

3 Results and Discussion

3.1 Operating model conditioning

In this document, the main operating models outputs are described, as well as, most of the figures for the OM scenario "OM_growth_med_Lorenzen_LowM_h09". The complete detailed output for all individual operating models can be accessed, and a summary of all operating models results at https://github.com/ICCAT/wskj-mse.

The historical trajectories of spawning biomass (SSB) and SSB depletion for most of the fitted operating models show similar trends, with the SSB falling in the early 1980s followed by a general stable trend up to 2020 (**Figure 6** and **7**). However, for the OM scenario that includes the GOM larvae CPUE ("OM_med_Lorenzen_LowM_h09_larvae") these trajectories were different, and it shows an increasing trend after the decline observed in the early 1980s (**Figure 6** and **7**). Also, for the OM scenario that includes environmental factors on CPUE time series, these trajectories seem to be more pessimistic with levels oscillating close to or below 40% of virgin spawning biomass (SSB0) (**Figures 6** and **7**). After the late 1970s, the shape of trajectories is mostly driven by the CPUE time series (**Figure 8,** see https://github.com/ICCAT/wskj-mse) in conjunction with the catch time series. The decline observed in the early 1980s coincides with the peaks of catches and the apical fishing mortality (the maximum annual fishing mortality) (**Figure 9**).

For all scenarios, the effective selectivity for the projection period is a dome shape, with the age of full selection being estimated to be age 2 and fully maturity was set at age 2 (**Figure 10**). The effective selectivity was obtained using the terminal year F-at-age, which is informed by the estimates of fleet selectivity from fitting to the length data (**Figure 11 - 15**). While maturity and selectivity are unchanged, the spawning biomass is expected to be very close to the exploitable biomass.

One crucial point for all scenarios is the difficulty of estimating MSY reference points. **Figure 16** shows the yield curves by apical F. As the apical F increases, and the yield curves tend to be flat but do not reach an optimum level. Therefore, MSY reference points might not be a good choice for the management of this stock. Here, we proposed 40% depletion as a proxy for BMSY and build this proxy into the performance metrics (see Huynh *et al.*, 2020).

The results of an eight-year retrospective analysis applied to all scenarios show that the estimated Mohn's rho statistics for biomass, apical F and recruitment fell within the acceptable range of -0.15 and 0.20 (Hurtado-Ferro *et al.* 2014; Carvalho *et al.* 2017) (**Table 3**) and confirm the absence of an undesirable retrospective pattern in the trajectories (**Figure 17**, see https://github.com/ICCAT/wskj-mse).

3.2 Management procedures evaluation

In all OMs there was a clear trade-off between keeping the SSB above 40% depletion and achieving high catches (CC_35kt, CC_40kt), with higher values associated with the STC30 and LTC30 (**Table 4**). Trade-off plots show that a set of candidate MPs with a higher probability of being above 40% depletion also have lower chances of exceeding 30,000 t in the first decade of the projection period (**Figure 18**). The MPs with constant catch TACs higher than 30,000 t show higher probabilities of STC30 but oscillate around 50% for the performance metric 40% depletion (**Figure 18**). For OMs with steepness less than 0.9, it was noted that the 40% depletion probability is even lower, around 30% (**Figure 18**).

From the radar plots (**Figure 19**), the CC_35kt and CC_35kt MPs often had the highest STC30, LTC30, and AAVY but lower '40% B0'. The CC_25kt and SP_4010 seem to be good options for managing the western Atlantic Skipjack tuna, with both presenting high probabilities for '40% B0', and low values for STC30 and LTC30. Although the statistical catch-at-age model MP (SCA_4010) presented satisfactory for biomass performance metric, it failed in AAVY with low probabilities in all OMs (**Figure 19**).

The projected depletion and catches time series is presented for the OM scenario "OM_growth_med_Lorenzen_LowM_h09" (**Figure 20**). In general, CC_35kt and CC_40kt MPs resulted in a decline of biomass in the future, while the rest of the MPs show a relatively stable trend, with few exceptions, such as GBslope and SCA_4010 that resulted in an increase of biomass in the projection period (**Figure 20**). A summary of MSE simulation results including additional plots can be accessed at https://github.com/ICCAT/wskj-mse

Overall, short-term catch performance (STC30) was similar to the long-term catch performance (LTC30). As expected, for the MSE simulations that incorporate environmental factors and climate change ("OM_med_lorenzen_LowM_env" and "OM_med_lorenzen_LowM_env_sigmaR09"), the MPs were less likely to achieve the conservation performance metric with lower '40% B0' compared to the other 10 OMs. In all OMs, catches of at least 30 kt were not likely to be achieved with any MP (except CC_35kt and CC_40kt), consistent with the yield curve calculations from the OM conditioning (**Figure 16**).

The present analysis updates the initial operating models presented by Huynh *et al.* (2020) by including data from other fishing fleets from different CPCs, covering the current hypothesis of stock structure for Atlantic Skipjack tuna in the Atlantic Ocean. We explored a set of OMs including different life-history parameter uncertainty assumptions, including an initial closed-loop evaluation of pre-selected MPs and a presentation of relevant performance metrics. The results demonstrate that the uncertainty in natural mortality, growth parameters, and alternative steepness values are most consequential in predicting stock dynamics. With guidance from the ICCAT Tropical Tunas MSE Technical Group, additional axes of uncertainty that improve the characterization of core assumptions for western Atlantic Skipjack stock can be explored for the operating model conditioning. After the upcoming Atlantic Skipjack tuna assessment meeting, this process might include the operating model reconditioning with the assessment model outputs (i.e., SS model). Additional management procedures and performance metrics can also be explored in future MSE simulations.

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Table 1. Fleet structure for the management strategy evaluation of the western Atlantic Skipjack stock

Fleet Name	Description	Gear	Catch (Flag name or fleet code ICCAT)	Size Fleet code	CPUE available
PS West	Purse seine	PS	All PS flags (mainly VEN, USA)	USA, VEN	PS Venezuela: 1987-2020
BB West	Baitboat	BB	All BB flags (BRA, VEN, CUB, JPN, PAN)	BRA, VEN, CUB, JPN, PAN	Brazil BB: 2000-2021 Historic Brazil BB: 1981 - 1999
LL USMX	Longline USA, Mexico and Canada	LL	All LL flags except JPN, CTP	MEX	USA LL: 1993-2020
LL Others	Longline Japan and Chinese-Taipei	LL	JPN, CTP LL Add catch other gears	JPN, TAI	GOM larvae: sensitivity only
HL_RR	Handline Brazil Rod & Reel USA	HL+RR +SP	BRA, USA	BRA, USA	Brazil HL: 2010-2016

Table 2. Operating model scenarios for the management strategy evaluation of the western Atlantic Skipjack stock

OM scenario	Name	*Linf*	*K*	*t0*	*h*	M at age scenario	Fisheries data (CPUE)
1	OM_growth_med_Gaertner_M_h09	76	0.53	-0.31	0.9	Gaertner (2014)	PS_VEN, BB_BRA, LL_USA, HL_BRA, BB_BRA_hist
2	OM_growth_med_Gaertner_LowM_h09	76	0.53	-0.31	0.9	Gaertner (2014) & LowM	PS_VEN, BB_BRA, LL_USA, HL_BRA, BB_BRA_hist
3	OM_growth_med_Lorenzen_M_h09	76	0.53	-0.31	0.9	Lorenzen (1996)	PS_VEN, BB_BRA, LL_USA, HL_BRA, BB_BRA_hist
4	OM_growth_med_Lorenzen_LowM_h09	76	0.53	-0.31	0.9	Lorenzen (1996) & LowM	PS_VEN, BB_BRA, LL_USA, HL_BRA, BB_BRA_hist
5	OM_growth_up_Lorenzen_LowM_h09	86	0.49	-0.49	0.9	Lorenzen (1996) & LowM	PS_VEN, BB_BRA, LL_USA, HL_BRA, BB_BRA_hist
6	OM_growth_med_Lorenzen_LowM_h08	76	0.53	-0.31	0.8	Lorenzen (1996) & LowM	PS_VEN, BB_BRA, LL_USA, HL_BRA, BB_BRA_hist
7	OM_growth_up_Lorenzen_LowM_h08	86	0.49	-0.49	0.8	Lorenzen (1996) & LowM	PS_VEN, BB_BRA, LL_USA, HL_BRA, BB_BRA_hist
8	OM_growth_med_Lorenzen_LowM_h07	76	0.53	-0.31	0.7	Lorenzen (1996) & LowM	PS_VEN, BB_BRA, LL_USA, HL_BRA, BB_BRA_hist
9	OM_growth_up_Lorenzen_LowM_h07	86	0.49	-0.49	0.7	Lorenzen (1996) & LowM	PS_VEN, BB_BRA, LL_USA, HL_BRA, BB_BRA_hist
10	OM_med_Lorenzen_LowM_h09_env	76	0.53	-0.31	0.9	Lorenzen (1996) & LowM	same but including environmental factors (BRA_BB and PS_VEN)
11	OM_med_Lorenzen_LowM_h09_larvae	76	0.53	-0.31	0.9	Lorenzen (1996) & LowM	same but including USA_GOM larvae

Table 3. Estimated Mohn's rho statistic values for the retrospective analysis of the main trajectories of the operating model outputs

	Mohn's rho statistic										
	OM_1	**OM_2**	**OM_3**	**OM_4**	**OM_5**	**OM_6**	**OM_7**	**OM_8**	**OM_9**	**OM_10**	**OM_11**
Fishing mortality of PSwest	0.164	0.132	0.138	0.153	-0.036	0.187	0.159	0.187	0.159	0.408	0.057
Fishing mortality of BBwest	0.154	0.126	0.136	0.164	-0.032	0.187	0.17	0.187	0.17	0.417	0.056
Fishing mortality of LL_USMX	0.23	0.198	0.203	0.244	0.002	0.281	0.25	0.281	0.25	0.314	0.066
Fishing mortality of LL_others	0.228	0.196	0.201	0.24	0.001	0.278	0.246	0.278	0.246	0.279	0.069
Fishing mortality of HL_RR	0.187	0.154	0.161	0.185	-0.028	0.22	0.191	0.22	0.191	0.378	0.061
Apical F	0.157	0.128	0.139	0.166	-0.033	0.19	0.172	0.19	0.172	0.407	0.057
Spawning biomass	-0.14	-0.124	-0.131	-0.135	0.057	-0.164	-0.143	-0.164	-0.143	-0.084	-0.08
Spawning depletion	-0.084	-0.084	-0.075	-0.102	0.031	-0.121	-0.108	-0.121	-0.108	-0.073	-0.076
Recruitment	0.152	0.18	0.159	0.192	0.295	0.167	0.18	0.167	0.18	0.335	0.138

Table 4. Performance metrics for each MP in the 12 MSE simulations. The color gradient spans blue to white to light orange, corresponding to values of 0, 0.5, and 1, respectively, for each performance metric.

	OM_growth_med_Gaertner_LowM_h09				OM_growth_med_Gaertner_M_h09				OM_growth_med_Lorenzen_LowM_h07			
	40% B0	STC30	LTC30	AAVY	40% B0	STC30	LTC30	AAVY	40% B0	STC30	LTC30	AAVY
NFref	>0.99	<0.01	<0.01	0.04	>0.99	<0.01	<0.01	0.02	0.99	<0.01	<0.01	0.04
SCA_4010	0.98	<0.01	<0.01	0.19	0.99	0.01	0.02	0.25	0.98	<0.01	<0.01	0.12
Islope	0.98	0.01	<0.01	>0.99	0.99	0.01	<0.01	>0.99	0.97	0.01	<0.01	>0.99
CC_15kt	0.98	<0.01	<0.01	>0.99	0.99	<0.01	<0.01	>0.99	0.97	<0.01	<0.01	>0.99
Iratio_	0.97	0.06	0.07	<0.01	0.98	0.04	0.06	0.01	0.97	0.05	0.06	<0.01
GBslope	0.97	<0.01	0.03	0.04	0.98	<0.01	0.02	0.03	0.96	<0.01	0.03	0.05
CC_20kt	0.94	<0.01	<0.01	>0.99	0.96	<0.01	<0.01	>0.99	0.92	<0.01	<0.01	>0.99
curE	0.91	0.24	0.27	0.01	0.94	0.24	0.27	0.01	0.88	0.24	0.27	0.01
CC_25kt	0.85	<0.01	<0.01	>0.99	0.90	<0.01	<0.01	>0.99	0.81	<0.01	<0.01	>0.99
CC_30kt	0.71	0.02	0.02	0.97	0.81	<0.01	<0.01	0.98	0.65	0.02	0.03	0.97
CC_35kt	0.56	0.79	0.75	0.85	0.70	0.83	0.80	0.90	0.49	0.78	0.74	0.80
CC_40kt	0.45	0.76	0.72	0.50	0.60	0.81	0.77	0.64	0.37	0.76	0.70	0.45
SP_4010	0.78	0.18	0.17	0.84	0.50	0.70	0.66	0.07	0.76	0.16	0.13	0.78

	OM_growth_med_Lorenzen_LowM_h08				OM_growth_med_Lorenzen_LowM_h09				OM_growth_med_Lorenzen_M_h09			
	40% B0	STC30	LTC30	AAVY	40% B0	STC30	LTC30	AAVY	40% B0	STC30	LTC30	AAVY
NFref	0.99	<0.01	<0.01	0.04	0.99	<0.01	<0.01	0.04	>0.99	<0.01	<0.01	0.03
SCA_4010	0.98	<0.01	<0.01	0.12	0.98	<0.01	<0.01	0.26	0.99	<0.01	0.01	0.37
Islope	0.97	0.01	<0.01	>0.99	0.97	0.01	<0.01	0.99	0.98	0.01	<0.01	>0.99
CC_15kt	0.97	<0.01	<0.01	>0.99	0.98	<0.01	<0.01	>0.99	0.99	<0.01	<0.01	>0.99
Iratio_	0.97	0.05	0.06	<0.01	0.97	0.04	0.06	<0.01	0.98	0.04	0.06	<0.01
GBslope	0.96	<0.01	0.03	0.05	0.97	<0.01	0.03	0.07	0.98	<0.01	0.03	0.02
CC_20kt	0.92	<0.01	<0.01	>0.99	0.93	<0.01	<0.01	>0.99	0.96	<0.01	<0.01	>0.99
curE	0.88	0.24	0.27	0.01	0.89	0.24	0.27	0.01	0.94	0.25	0.28	0.01
CC_25kt	0.81	<0.01	<0.01	>0.99	0.84	<0.01	<0.01	>0.99	0.89	<0.01	<0.01	>0.99
CC_30kt	0.65	0.02	0.03	0.97	0.70	0.02	0.03	0.97	0.79	0.01	0.01	0.98
CC_35kt	0.49	0.78	0.74	0.80	0.56	0.77	0.75	0.78	0.67	0.84	0.81	0.91
CC_40kt	0.37	0.76	0.70	0.45	0.45	0.75	0.72	0.50	0.56	0.81	0.77	0.65
SP_4010	0.76	0.16	0.13	0.78	0.78	0.17	0.15	0.84	0.80	0.30	0.23	0.86

	OM_growth_up_Lorenzen_LowM_h07				OM_growth_up_Lorenzen_LowM_h08				OM_growth_up_Lorenzen_LowM_h09			
	40% B0	STC30	LTC30	AAVY	40% B0	STC30	LTC30	AAVY	40% B0	STC30	LTC30	AAVY
NFref	0.99	<0.01	<0.01	0.04	0.99	<0.01	<0.01	0.04	0.98	<0.01	<0.01	0.10
SCA_4010	0.98	<0.01	0.01	0.12	0.98	<0.01	0.01	0.12	0.92	0.01	0.02	<0.01
Islope	0.97	0.01	<0.01	>0.99	0.97	0.01	<0.01	>0.99	0.89	0.01	<0.01	>0.99
CC_15kt	0.97	<0.01	<0.01	>0.99	0.97	<0.01	<0.01	>0.99	0.93	<0.01	<0.01	>0.99
Iratio_	0.96	0.04	0.07	0.02	0.96	0.04	0.07	0.02	0.90	0.04	0.04	0.01
GBslope	0.96	<0.01	0.03	0.09	0.96	<0.01	0.03	0.09	0.89	<0.01	0.01	0.08
CC_20kt	0.93	<0.01	<0.01	>0.99	0.93	<0.01	<0.01	>0.99	0.81	<0.01	<0.01	>0.99
curE	0.89	0.24	0.27	0.01	0.89	0.24	0.27	0.01	0.56	0.24	0.28	0.01
CC_25kt	0.82	<0.01	<0.01	>0.99	0.82	<0.01	<0.01	>0.99	0.62	<0.01	<0.01	0.98
CC_30kt	0.66	0.02	0.03	0.97	0.66	0.02	0.03	0.97	0.47	0.01	0.02	0.54
CC_35kt	0.50	0.80	0.75	0.82	0.50	0.80	0.75	0.82	0.39	0.36	0.42	0.14
CC_40kt	0.38	0.77	0.71	0.49	0.38	0.77	0.71	0.49	0.34	0.34	0.40	<0.01
SP_4010	0.77	0.15	0.14	0.83	0.77	0.15	0.14	0.83	0.55	0.11	0.08	0.68

	OM_med_Lorenzen_LowM_h09_env				OM_med_Lorenzen_LowM_h09_env_sigmaR09				OM_med_Lorenzen_LowM_h09_larvae			
	40% B0	STC30	LTC30	AAVY	40% B0	STC30	LTC30	AAVY	40% B0	STC30	LTC30	AAVY
NFref	0.98	<0.01	<0.01	0.04	0.97	<0.01	<0.01	<0.01	>0.99	<0.01	<0.01	0.16
SCA_4010	0.95	<0.01	0.01	0.33	0.76	0.04	0.04	0.04	0.98	0.01	0.01	0.26
Islope	0.92	0.04	0.03	0.83	0.80	0.02	0.04	0.37	0.98	0.01	<0.01	>0.99
CC_15kt	0.94	<0.01	<0.01	>0.99	0.78	<0.01	<0.01	>0.99	0.98	<0.01	<0.01	>0.99
Iratio_	0.91	0.10	0.15	<0.01	0.80	0.06	0.09	<0.01	0.98	0.04	0.06	<0.01
GBslope	0.92	<0.01	0.06	<0.01	0.80	<0.01	0.02	0.03	0.97	<0.01	0.02	0.09
CC_20kt	0.87	<0.01	<0.01	>0.99	0.67	<0.01	<0.01	0.84	0.95	<0.01	<0.01	>0.99
curE	0.40	0.44	0.48	<0.01	0.32	0.34	0.32	<0.01	0.97	0.18	0.19	0.02
CC_25kt	0.72	<0.01	<0.01	>0.99	0.58	<0.01	<0.01	0.27	0.87	<0.01	<0.01	>0.99
CC_30kt	0.56	0.03	0.03	0.96	0.50	0.08	0.06	0.04	0.75	0.02	0.02	>0.99
CC_35kt	0.43	0.62	0.64	0.55	0.45	0.49	0.45	<0.01	0.63	0.87	0.83	0.98
CC_40kt	0.34	0.59	0.61	0.21	0.40	0.47	0.43	<0.01	0.52	0.84	0.80	0.74
SP_4010	0.67	0.13	0.10	0.81	0.56	0.13	0.14	0.09	0.92	0.02	0.02	0.89

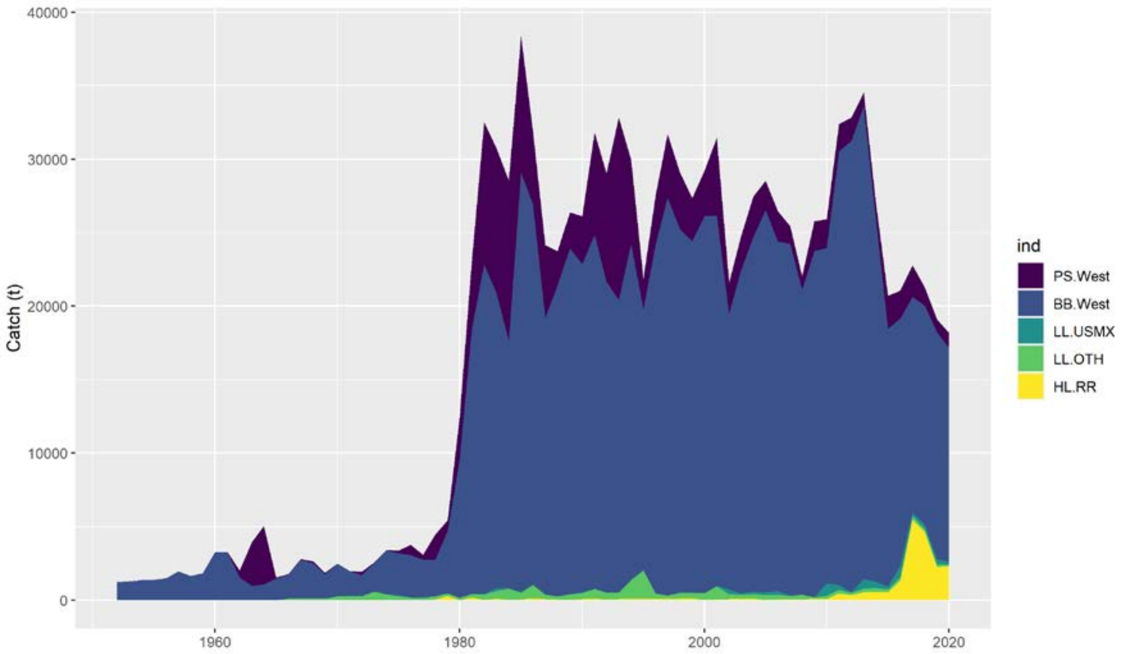

Figure 1. Catches (t) of the western Atlantic Skipjack stock by fleet between 1952 and 2020.

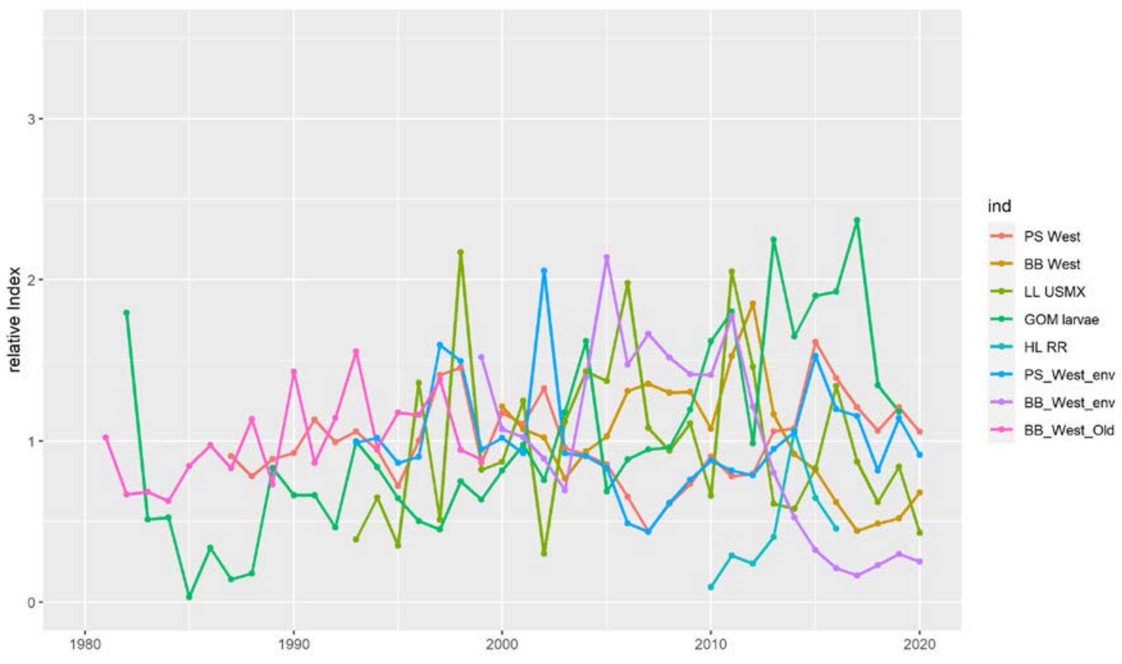

Figure 2. Available abundance indices of the western Atlantic Skipjack stock.

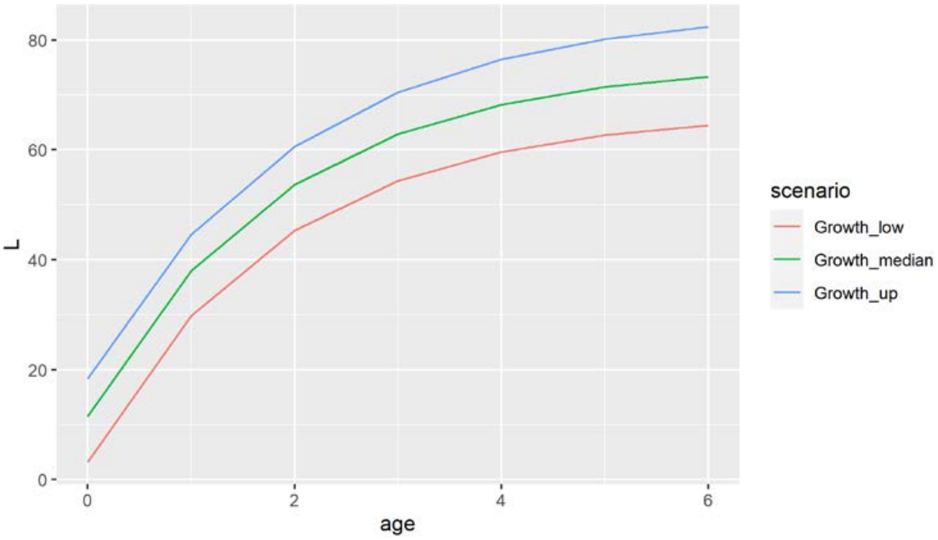

Figure 3. Estimated Von Bertalanffy growth parameters (median and associated 25th-75th quantiles) of the western Atlantic Skipjack stock.

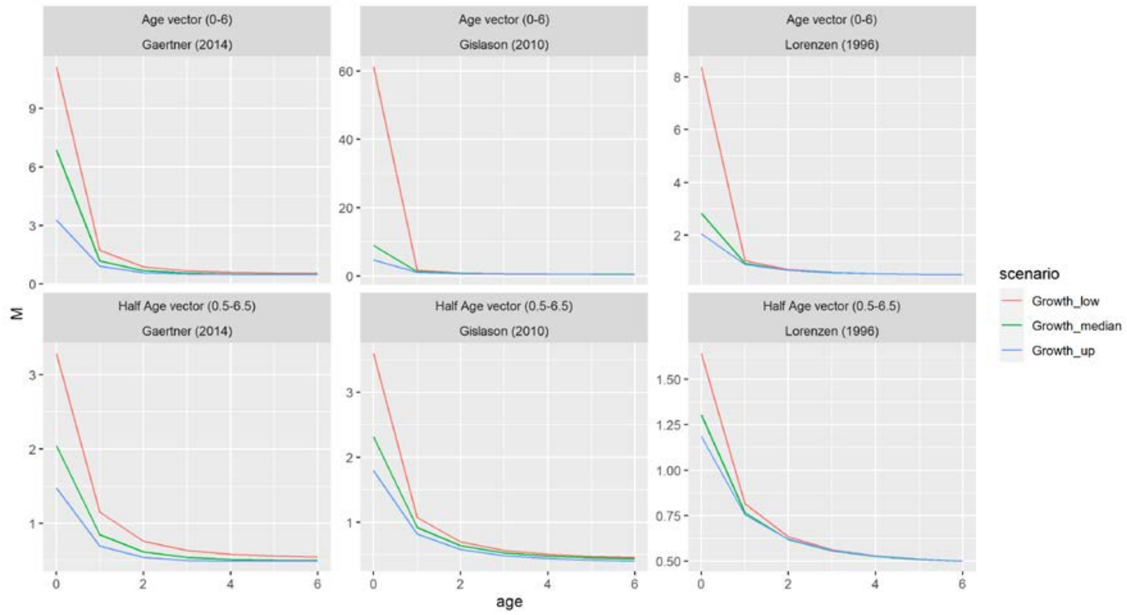

Figure 4. Estimated natural mortality at age by growth scenario (median and associated 25th-75th quantiles) and method of the western Atlantic Skipjack stock.

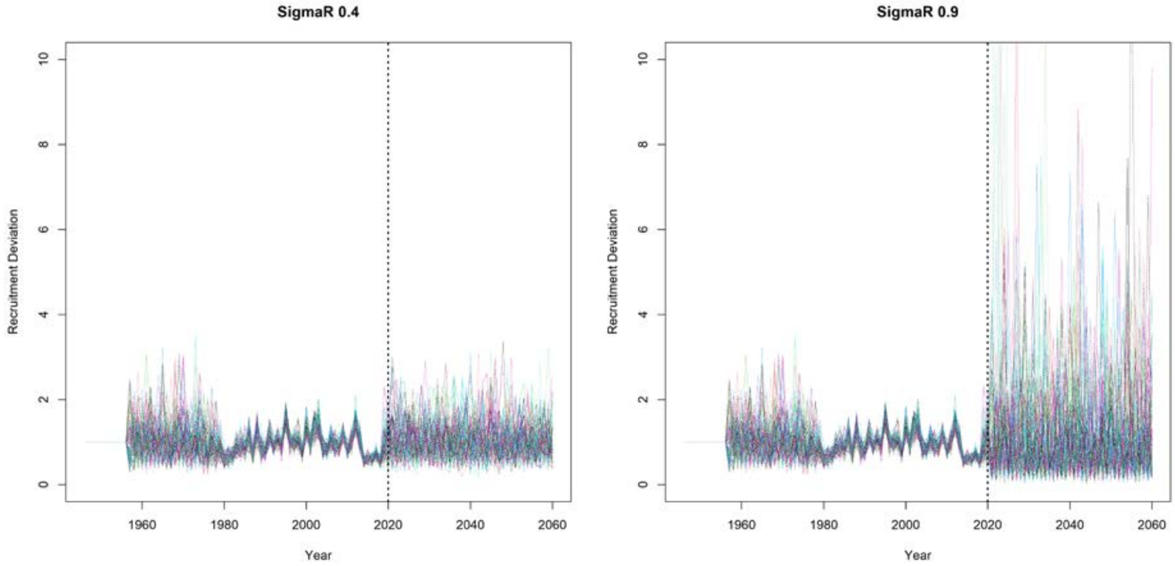

Figure 5. Recruitment deviates for the historical and projection periods of the western Atlantic Skipjack stock, based on the operating model "OM_med_Lorenzen_LowM_h09_env".

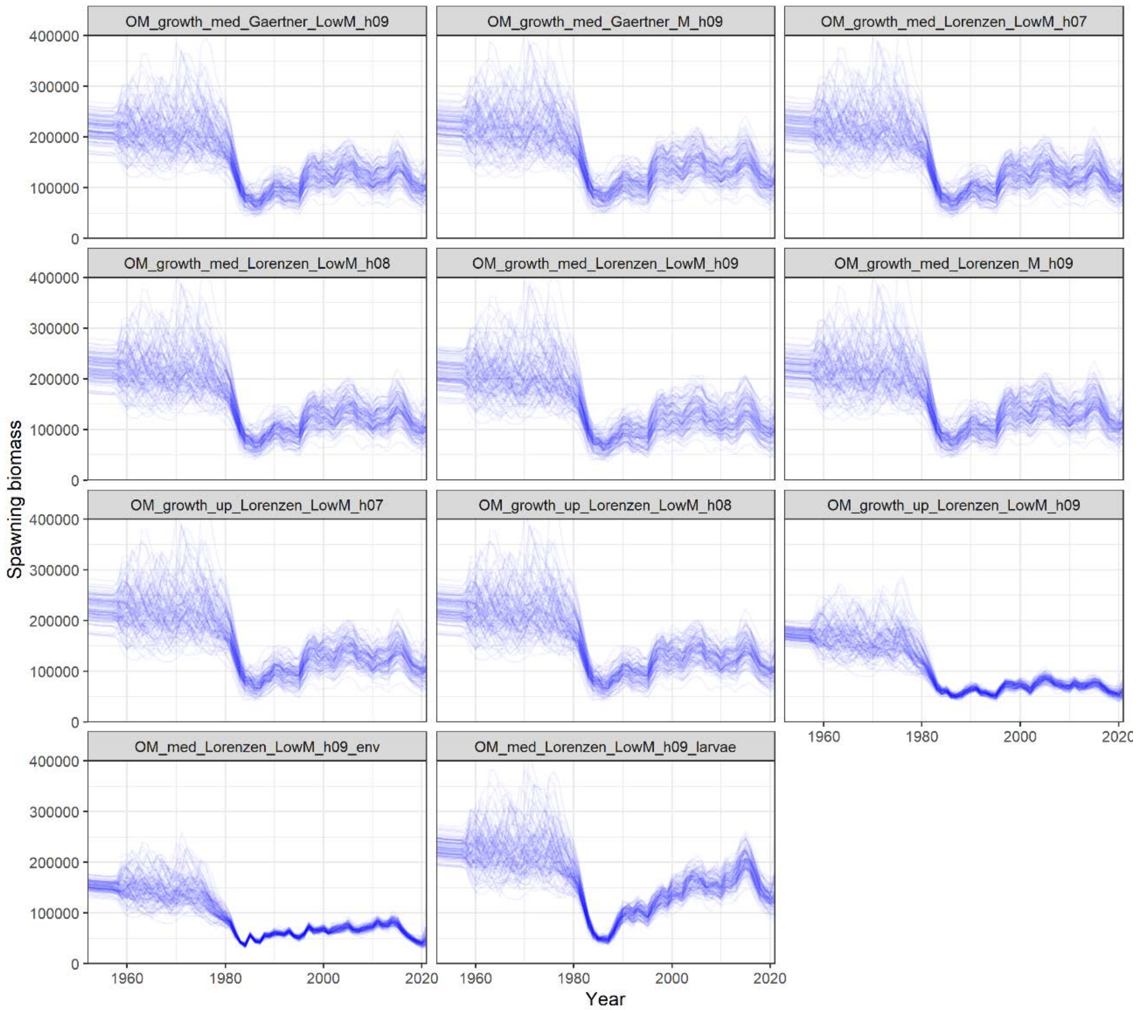

Figure 6. Predicted spawning biomass (tonnes) for the 11 operating models in the historical period of the western Atlantic Skipjack stock.

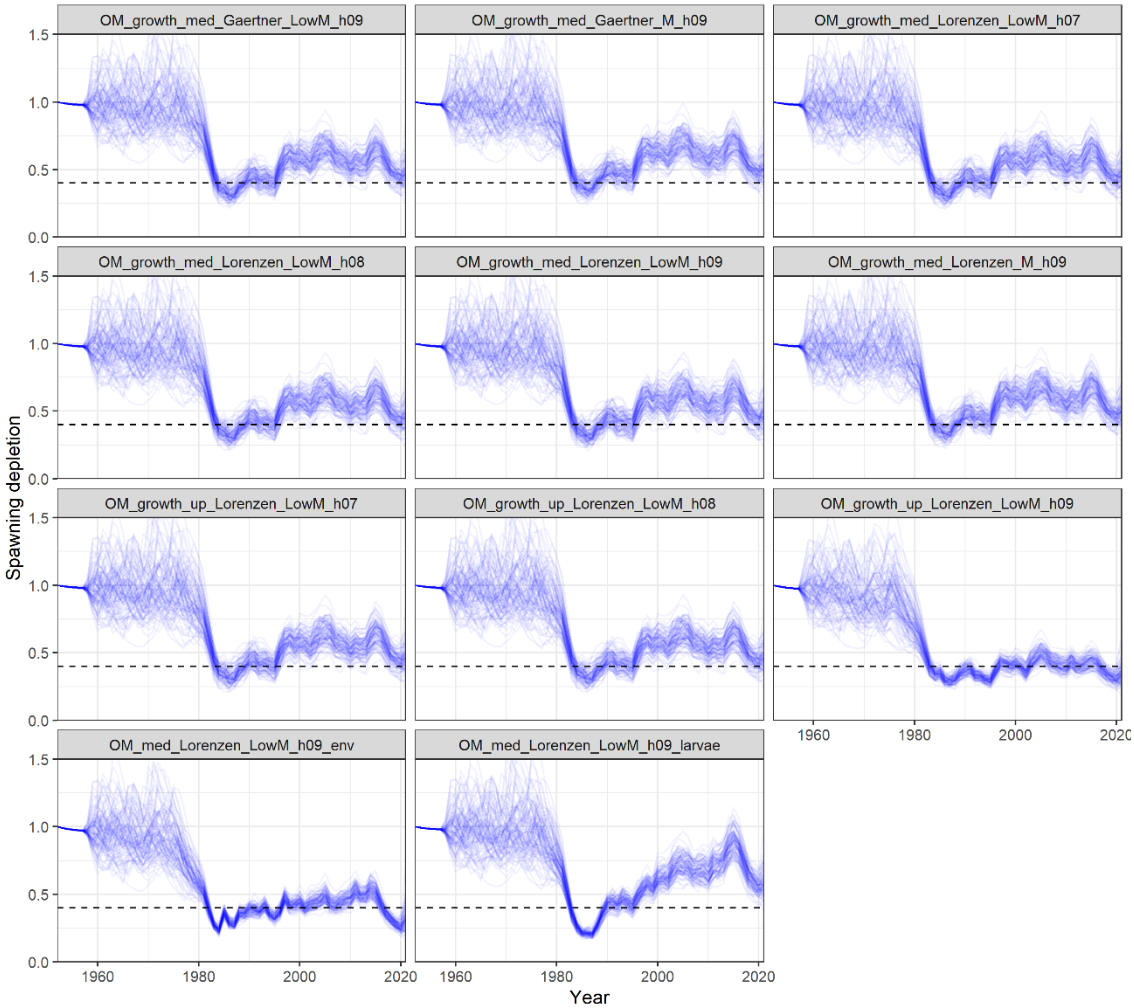

Figure 7. Predicted spawning biomass depletion for the 11 operating models in the historical period of the western Atlantic Skipjack stock.

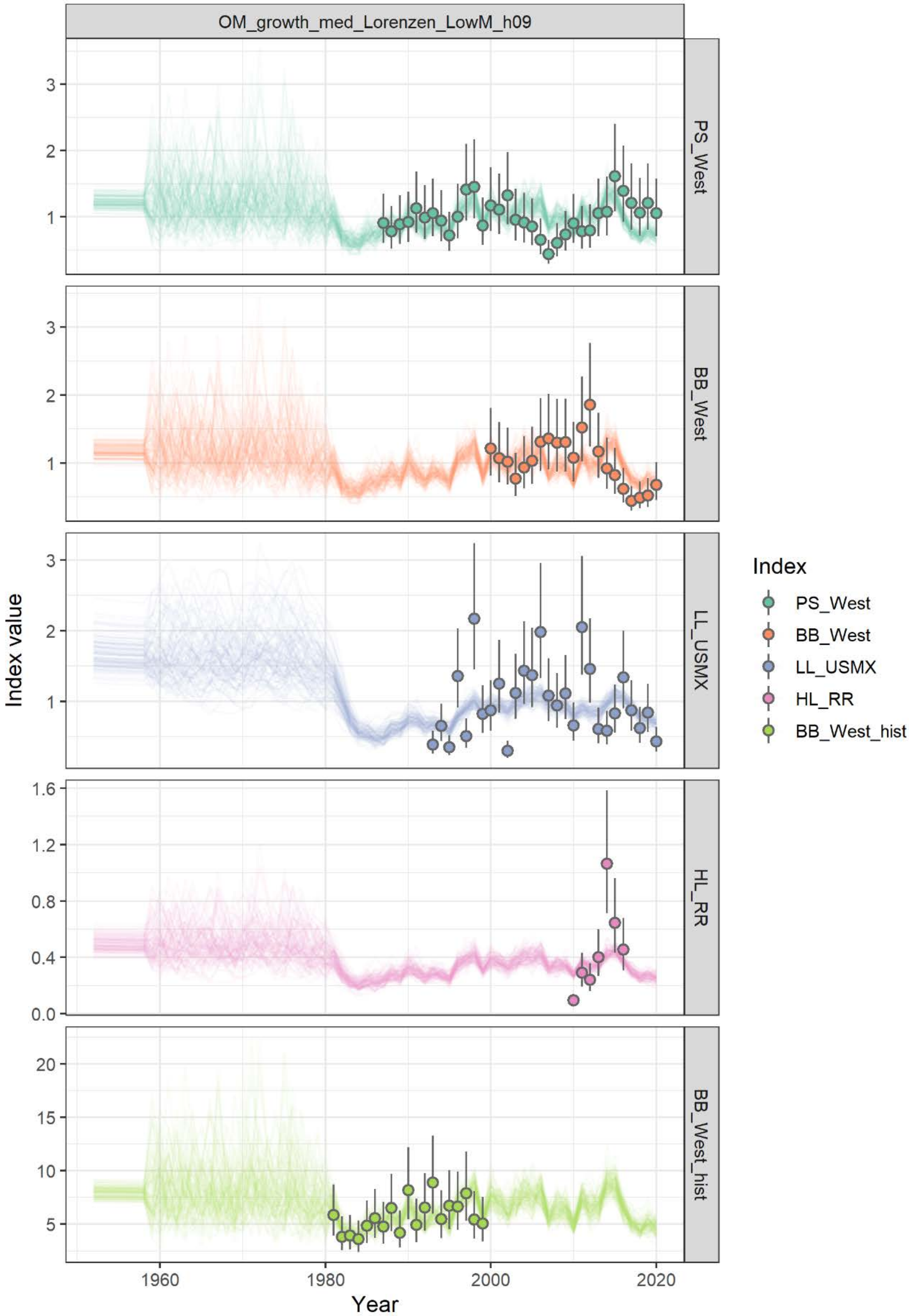

Figure 8. Observed (dots, with confidence intervals in vertical red lines) and predicted CPUE (color lines) by fleet of the western Atlantic Skipjack stock, based on the operating model "OM_growth_med_Lorenzen_LowM_h09".

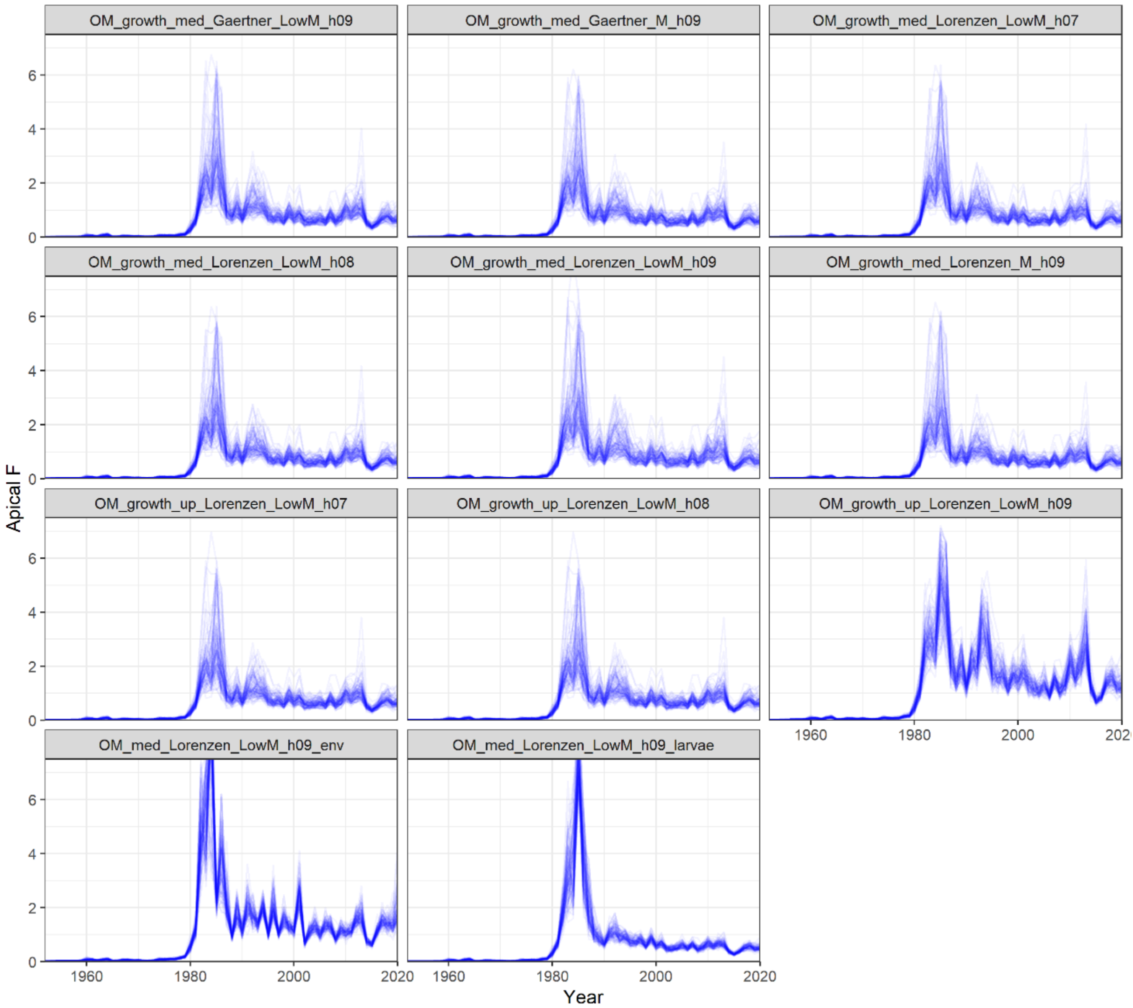

Figure 9. Apical instantaneous fishing mortality rates (per year) for the 11 operating models in the historical period of the western Atlantic Skipjack stock,

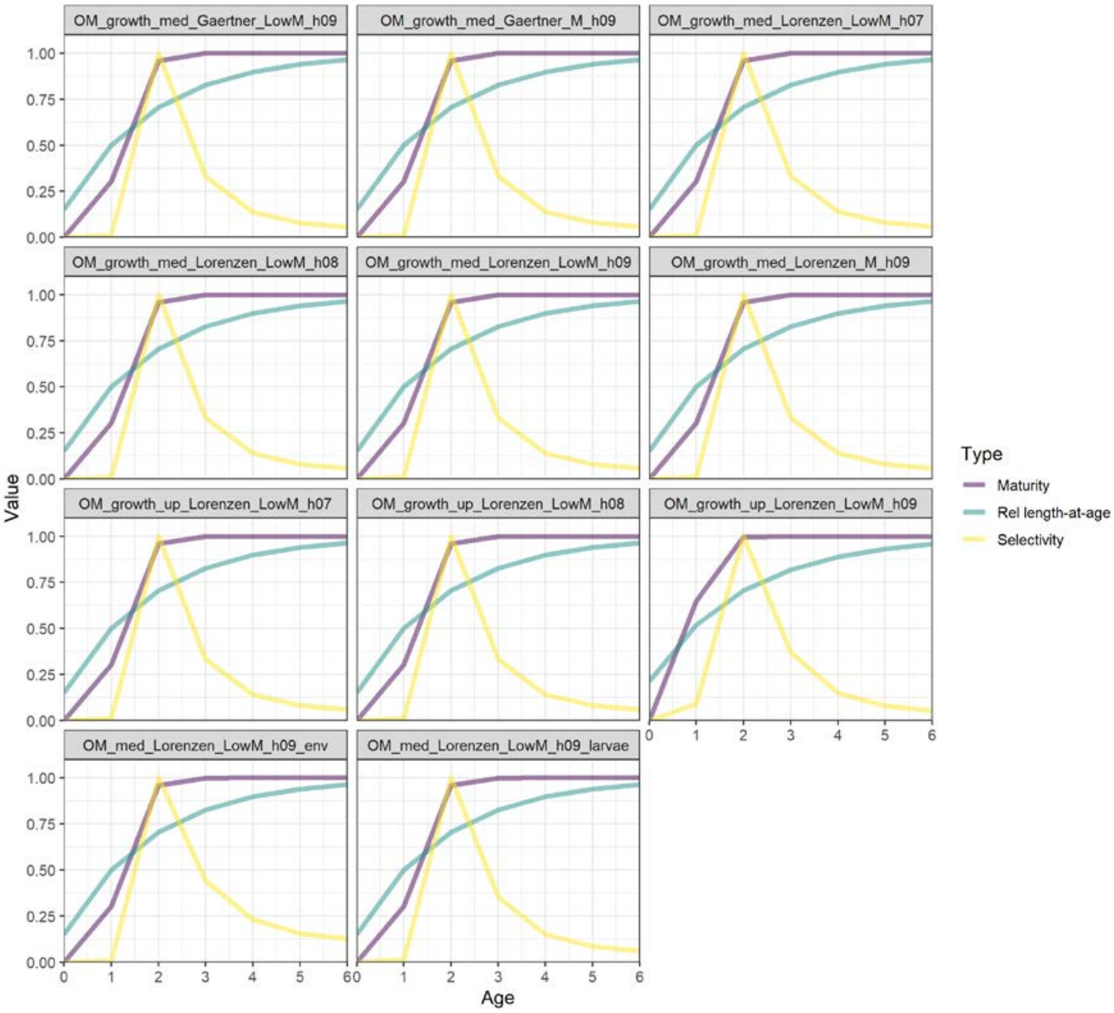

Figure 10. Effective selectivity (from the terminal year F-at-age) in the projection period relative to maturity-at-age for the 11 skipjack operating models. Length-at-age relative to Linf is shown.

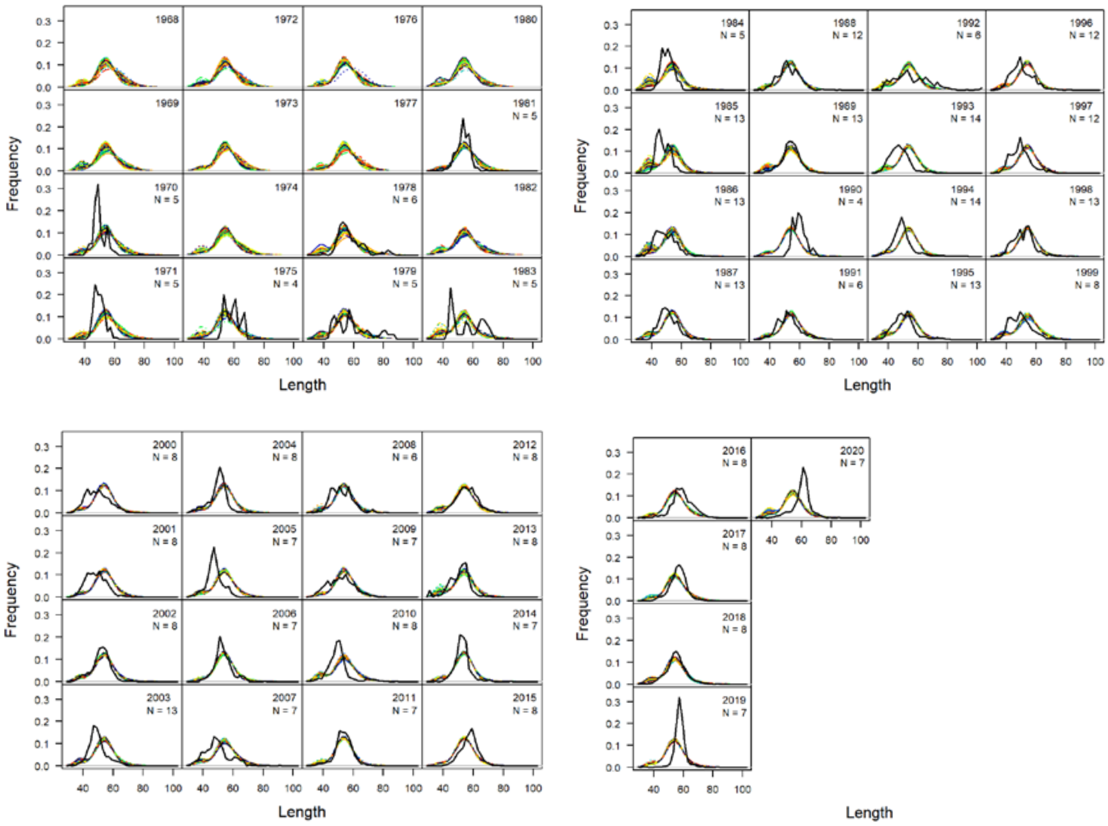

Figure 11. Observed (black lines) and predicted (color lines) length compositions for the PS west fleet.

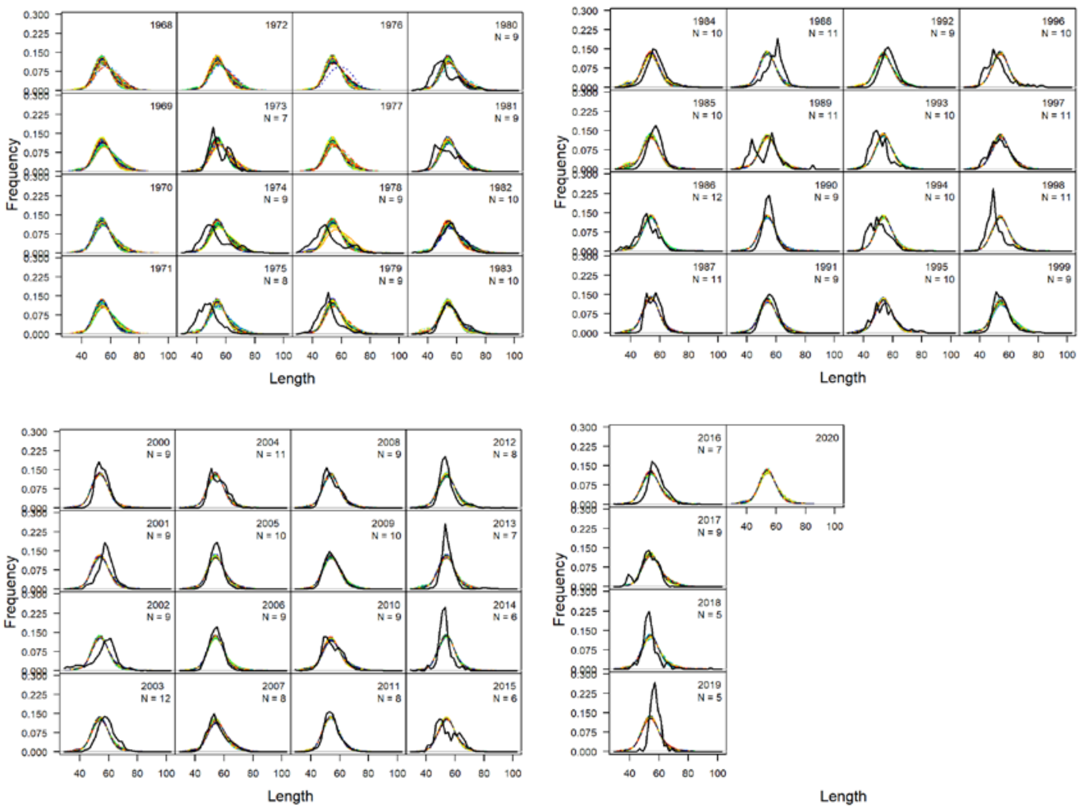

Figure 12. Observed (black lines) and predicted (color lines) length compositions for the BB west fleet.

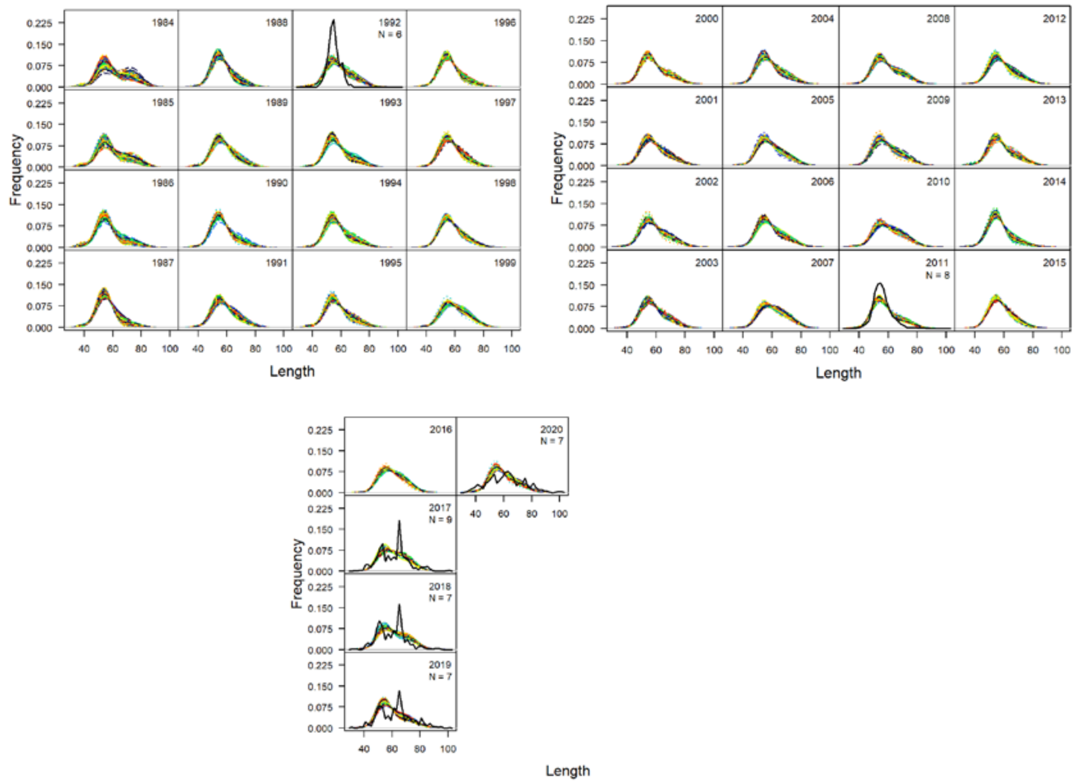

Figure 13. Observed (black lines) and predicted (color lines) length compositions for the LL USMX fleet.

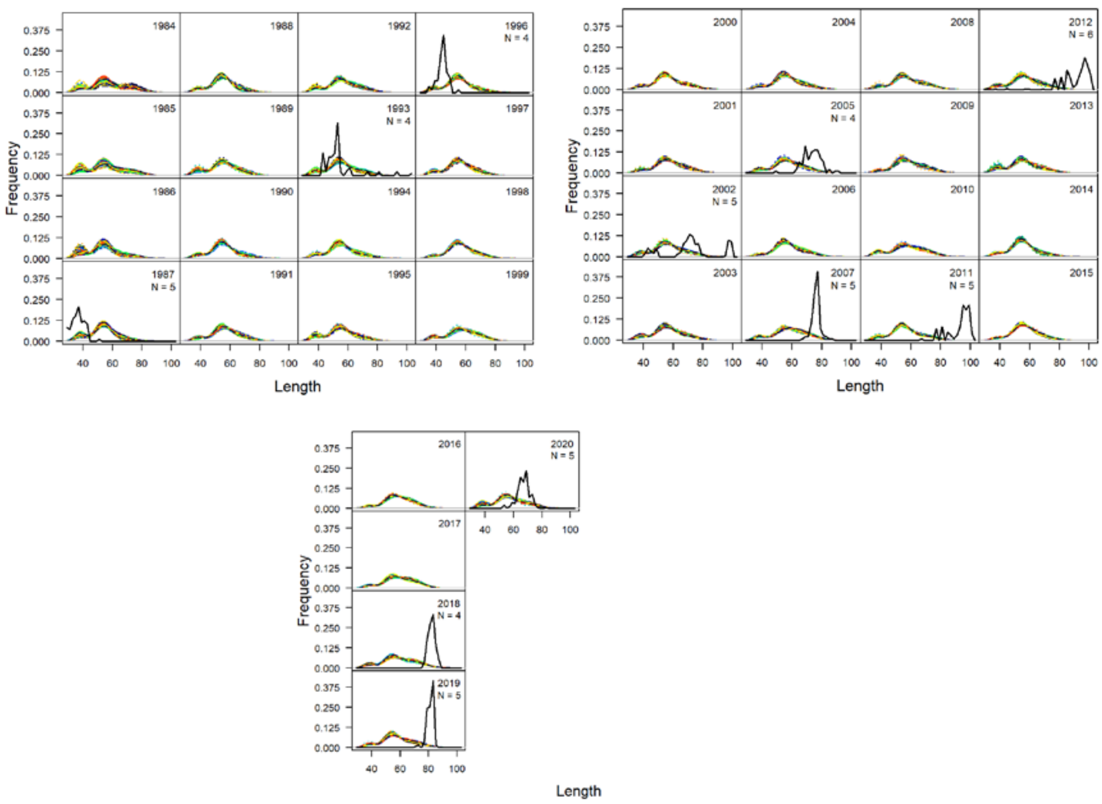

Figure 14. Observed (black lines) and predicted (color lines) length compositions for the LL others fleet.

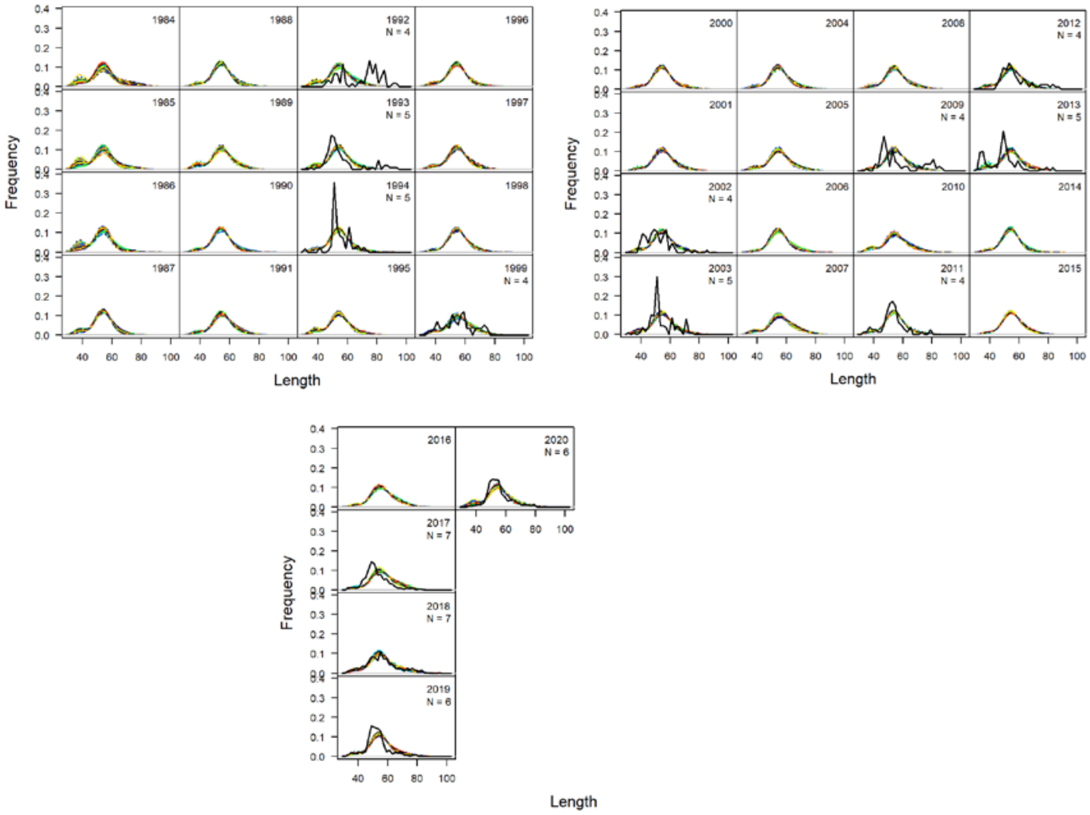

Figure 15. Observed (black lines) and predicted (color lines) length compositions for the HL_RR fleet.

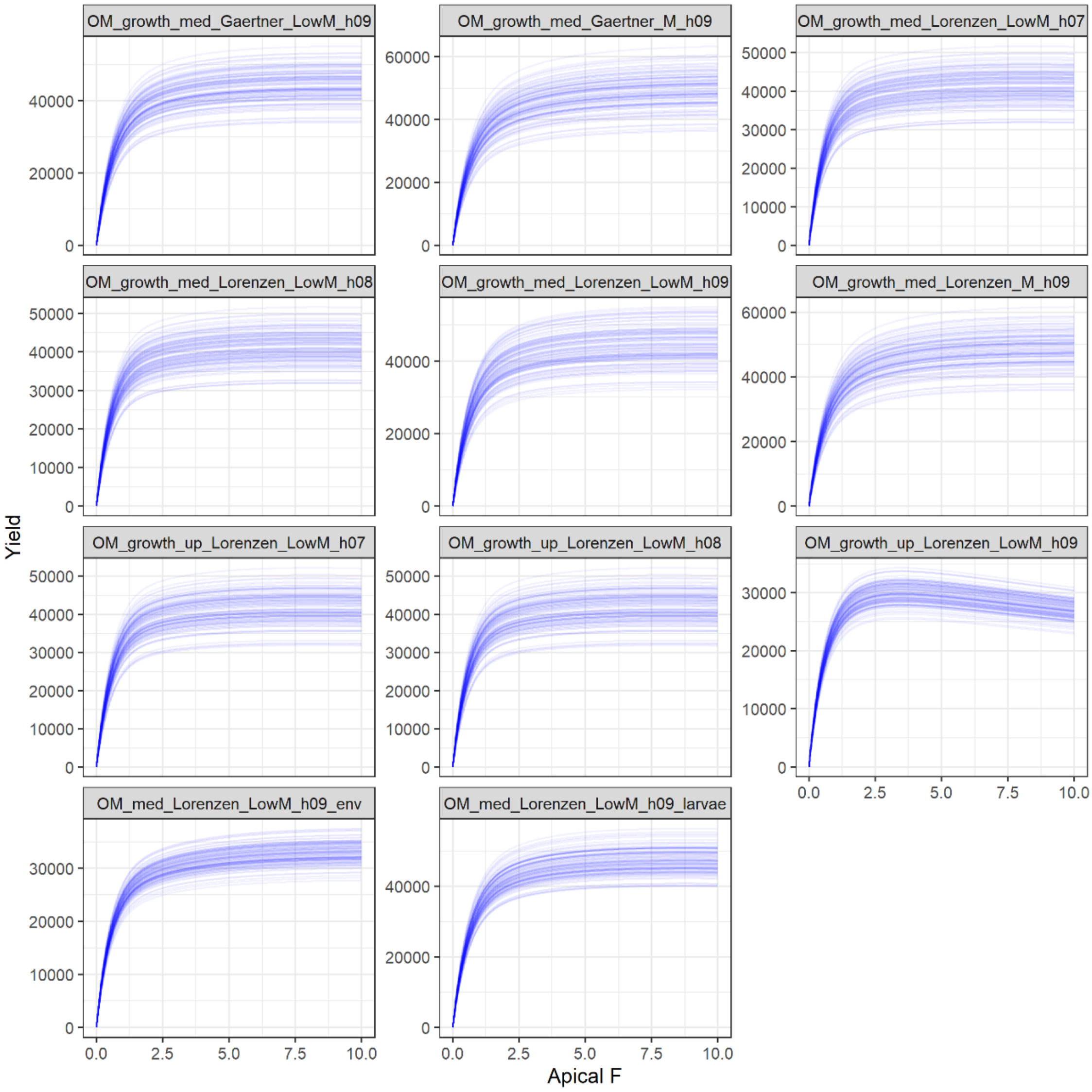

Figure 16. Yield curve by Apical instantaneous fishing mortality rates for the 11 operating models in the historical period of the western Atlantic Skipjack stock,

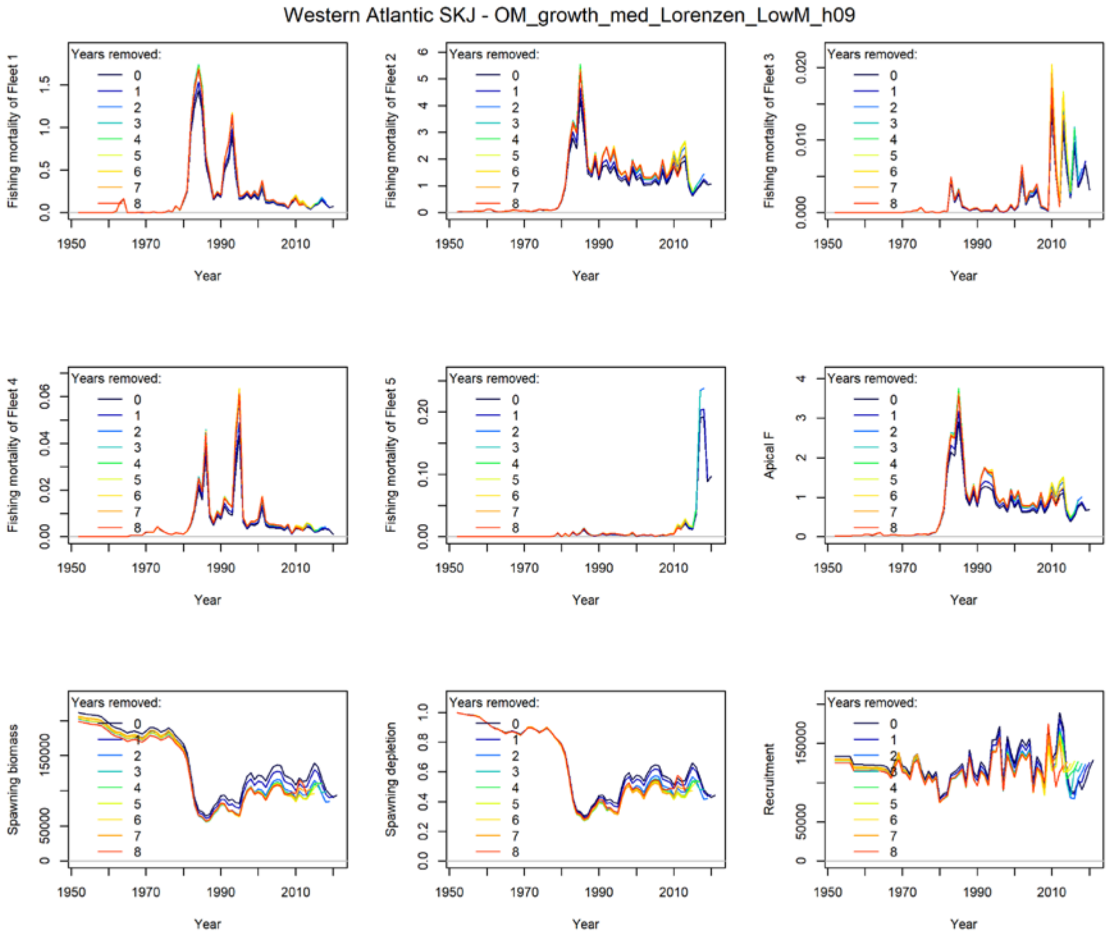

Figure 17. Retrospective analysis for the main trajectories outputs of the western Atlantic Skipjack stock, based on the operating model "OM_growth_med_Lorenzen_LowM_h09".

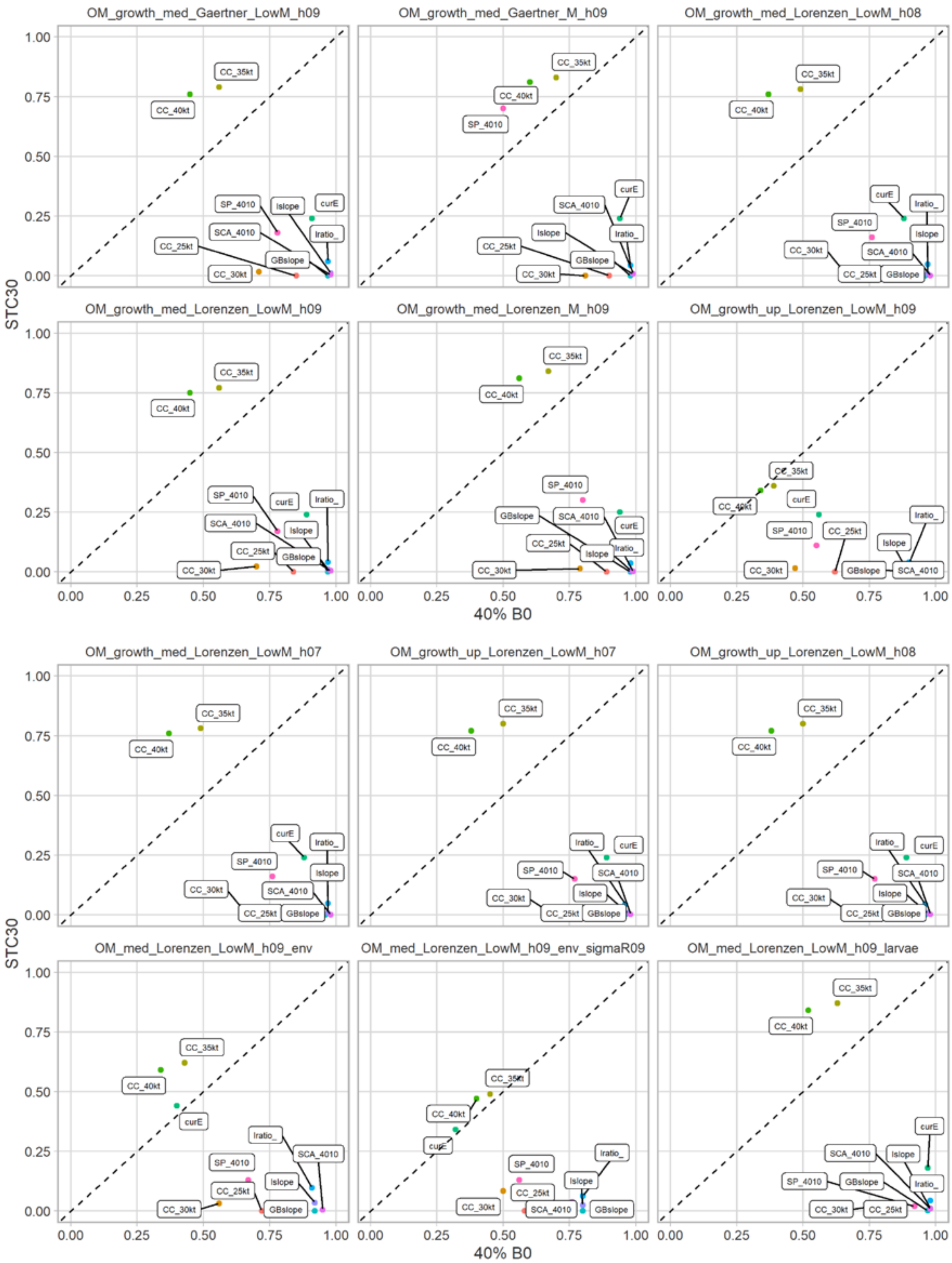

Figure 18. Trade-off plots between '40% B0' and STC30 for the 12 MSE simulations of the western Atlantic Skipjack stock.

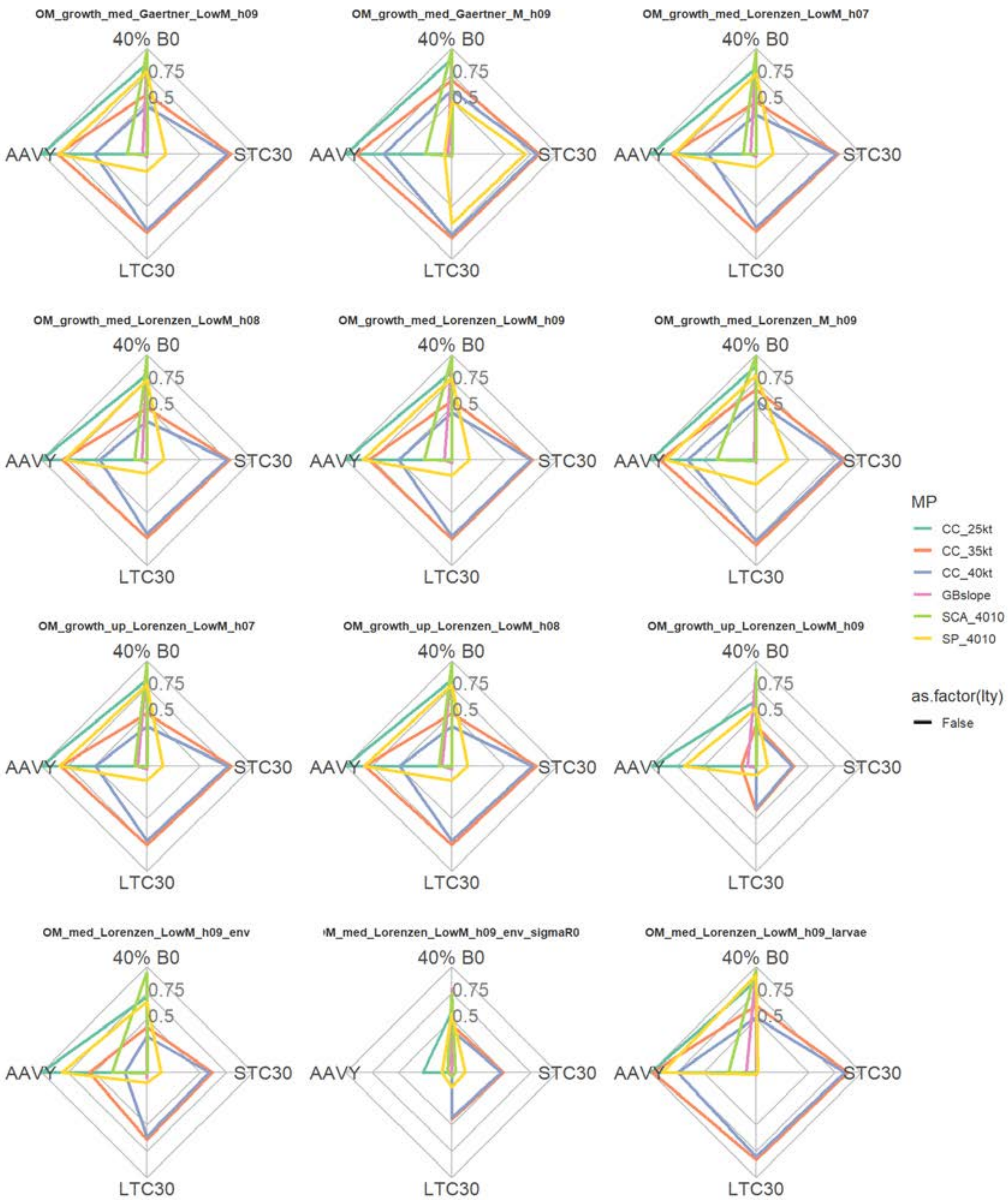

Figure 19. Radar plots between '40% B0' and STC30 for the 12 MSE simulations of the western Atlantic Skipjack stock.

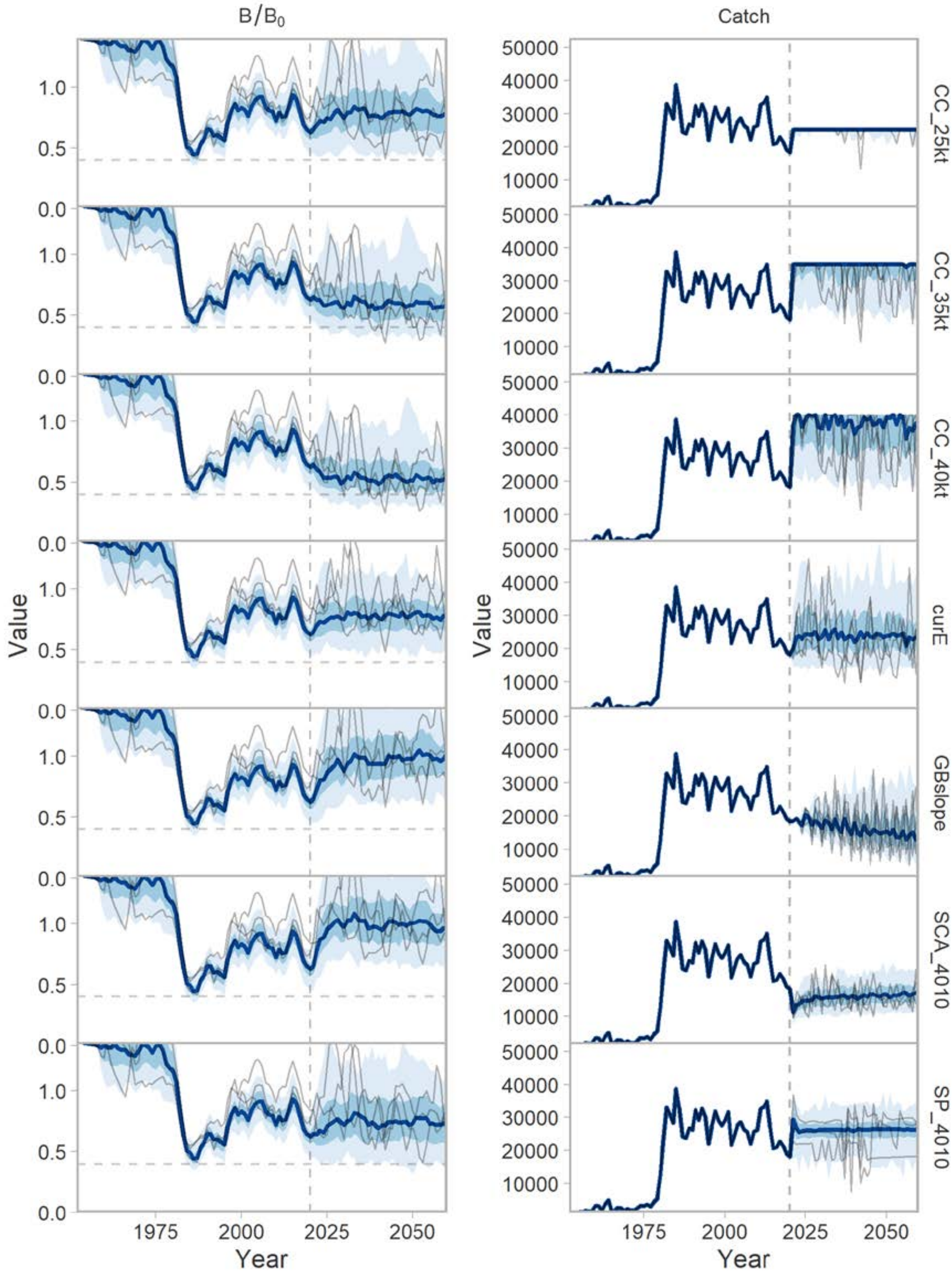

Figure 20. Spawning depletion (left column) and catches (right column) from the closed-loop simulation for a selection of MPs (rows) in the operating model "OM_growth_med_Lorenzen_LowM_h09". Dashed, horizontal lines for spawning depletion indicate a value of 0.4. Dashed, vertical lines separate the historical and projection periods of the operating model. The dark blue line indicates the median from 100 simulation replicates, while lighter blue bands represent the interquartile range and 95% confidence intervals. Solid, grey lines plot 3 individual simulations.

Appendix A

CPUE STANDARDIZATION OF SKIPJACK TUNA (*Katsuwonus pelamis*) CAUGHT BY BRAZILIAN BAITBOAT FLEET IN SOUTHWESTERN ATLANTIC OCEAN INCLUDING ENVIRONMENTAL VARIABLES

Methodology

Data from fishing effort and skipjack tuna caught in the southwest Atlantic Ocean by the Brazilian baitboat fleet used here was provided by fisheries landings monitoring projects conducted by the Universidade do Vale do Itajaí (http://pmap-sc.acad.univali.br/). This database is composed of fishing effort and catches information collected between the years 2000 and 2021. The information was collected by interviews conducted with each skipper at the end of each cruise, logbooks completed and provided by the fishing skippers also at the end of each cruise and/or from data collected onboard the vessels through historical official observer monitoring programmes and recently scientific observer programmes.

More than 2,000 fishing trips were analyzed, the information corresponds to 57.7% of all fishing trips conducted by the Brazilian baitboat fleet during the period between 2000 and 2021. The baitboat fleet have been fishing offshore of Brazil since 1981, unfortunately, the information available for the models for the early period between 1981 and 1999 do not have the same spatial coverage and general detailing required here. The spatial resolution was 0.5º x 0.5º. The reports of skipjack catch equal to zero are scarce, less than 1.6%.

The E.U. Copernicus Marine Service Information was accessed in a way to compile the environmental variables that were considered for the models fitted in this study. In this sense, data from Sea Surface Temperature (SST, in degree Celsius), Chlorophyll-α (Chl, in mg.m^{-3}) and Mixed Layer Depth (MLD, in m) for the southwestern Atlantic ocean, between 2000 and 2021, were downloaded and included in the standardization models.

Data cleaning and preparation for the analysis were based on the approaches proposed by Hoyle et al. (2015), Hoyle *et al*. (2016) and Hoyle *et al*. (2018). All analyses were carried out in R version 4.1.0 (R Core Team, 2021). During the cleaning process, in the first step, vessels that had never caught a skipjack tuna before were removed from the dataset.

For the CPUE standardization of the skipjack caught in the southwest Atlantic Ocean, Hierarchical Bayesian models were used, structured through the Integrated Nested Laplace Approximations (INLA) (Rue et al., 2009; Lindgren et al., 2011). This approach allows understanding the spatial, temporal and seasonal trends in the abundance index estimated for a species. In this sense, effects that may be contained and directly related to spatial-temporal or even seasonal variations can be minimized due to this model structuring format. Thus, providing a cleaner view of the behavior of the abundance index of the species being evaluated. Similarly to Generalized Linear Models, this type of model assumes that the response variable belongs to the exponential distribution families, here used as a Lognormal distribution and that its parameters (θ) are linked to the linear predictor addictive structure (η) through a logarithmic canonic connection function g(.), such as g(θ) = η (Agresti, 2002; Cosandey-Godin et al., 2014). The model differs from the traditional linear component specification $x_i^T\beta$ due the inclusion of the term *f*(.), so that:

$$\eta_i = g(\mu_i) = \beta_0 + \sum_{j=1}^{J} \beta_j x_{ij} + \sum_{k=1}^{K} f_k(\, z_{ik})$$

where η_i is the linear predictor; $g(\mu_i)$ is the link function for the expected values of the *i* observations ($E(y_i)$); β_0 is the intercept of the model; the coefficients $\beta = \{\beta_1, \ldots, \beta_j\}$ quantify the fixed effect of some covariates $x = (x_1, \ldots, x_j)$ on the response; and $f = \{f_1(.), \ldots, f_k(.)\}$ is the collection of functions defined in terms of a set of covariates $z = (z_1, \ldots, z_k)$. The terms $f_k(.)$ can assume different forms such as smooth and nonlinear effects of covariates, environmental and oceanographic effects, random intercepts and slopes as well as temporal or spatial random effects (Blagiardo and Cameletti, 2015). These components define the latent field as $\theta = \{\beta_0, \beta, f\}$, where β and f are the covariates and smooth functions and/or random effects included in the linear predictor with their appropriate prior distributions (ψ).

Similar to Generalized Additive Model (GAM), the f_k are semi-parametric functions defining the spatial, temporal and random effects included in the models. Distinct criteria were used to compare the performance of the different models: (*i*) reduction in deviance; (*ii*) Watanabe-Akaike Information Criteria (WAIC) (Watanabe, 2010); (*iii*)

Deviance Information Criterion (DIC) (Spiegelhalter et al., 2002) and (*iv*) Conditioning Predictive Ordinate (CPO) (Roos and Held, 2011). Additionally, as a measure of diagnostic, the Probability Integral Transform (PIT) was used (Schrödle and Held, 2011). Thus, the variable selection process and structure for the random effect for each covariate were based on the same four criteria. As proposed by Cosandey-Godin et al. (2014), the process was conducted in three hierarchical steps: (1) the structure was evaluated for temporal, seasonal and environmental covariates; (2) the contribution of each covariate with structure defined in the last step including the random effect (IID) for the covariate boat was evaluated, and; (3) finally, were evaluated the combination of all covariates with the respective structure pre-defined in the earlier steps.

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SKJ PS VEN - STANDARDIZED CATCH RATE – MODELING APPROACH: GAM, INCLUDING ENVIRONMENTAL VARIABLES

Methodology

The data used in this study came from the INSOPESCA statistics collection database of purse seiners logbooks (1993-2020), which covers between 90-100% of total catch. Environmental data was available since 1993, for this reason the standardization model only used the 1993-2020 fishery data (although fishery CPUE data is available since 1987). Also, CPUE data records for which environmental data was missing (NA), were excluded from the analysis. A total of 9901 fishing sets were analyzed, of which 5120 sets were positives for SKJ catch.

Factors included in the analysis were year, season (Jan-Mar, April-Jun, Jul-Sep and Oct-Dec), area of fishing (Caribbean and western Atlantic), association with whales (associated or not), association with whale shark (associated or not), seiner category (small-medium seiners and large seiners) according to Gaertner *et al.* (1998) classification. Environmental variables considered for the model were sea surface temperature, chlorophyll *a* ($mg.m^{-3}$) and mixed layer depth (m), downloaded from E.U. Copernicus Marine Service Information. Catch rates were calculated as tons of skipjack tuna caught per set.

Relative indices of abundance for skipjack tuna were estimated by Generalized Additive Modeling approach (Hastie and Tibshirani 1990) assuming a delta lognormal model distribution (Arocha *et al.* 2010). This method involves the fitting of two models; modeling the records for which the catch is non-zero, and modeling the probability of non-zero catch (Lo *et al.* 1992; Ortiz and Arocha 2004). Catch rates for the lognormal model were transformed to log (CPUE+10%mean) prior to the analysis (Arocha *et al.* 2008). For the positive catch rates lognormal error distribution was assumed, and binomial error distribution for the proportion of positive observations (positive sets/total sets). Deviance analysis was used to select explanatory factors and variables considering the relative percent of deviance explained by adding each one of them in the evaluation (those that explained more than 5% were selected) and the Chi-squared significance (McCullagh and Nelder 1989). Selection of the final model was based on the Akaike's Information Criterion (AIC), the Bayesian Information Criterion (BIC), and a $\chi 2$ test of the difference between the [–2 loglikelihood] statistic of a successive model formulations (Littell *et al*. 1996).

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Appendix B

CROSSING POLITICAL BORDERS WITHOUT VISA: THE ATLANTIC SKIPJACK

Introduction

The skipjack tuna (SKJ) (*Katsuwonus pelamis*) is the main tuna species in terms of landed biomass in the Atlantic Ocean. The Standing Committee on Research and Statistics (SCRS) of the International Commission for the Conservation of Atlantic Tunas (ICCAT) has historically considered the existence of two distinct stocks of SKJ in the Atlantic Ocean; the western and eastern stocks.

Tagging release and recovery efforts from several nations and research agencies constructed the ICCAT and the Atlantic Ocean Tropical Tuna Tagging Programme (AOTTP) tagging database for several species in the Atlantic and the Mediterranean Sea. Tagging data provides essential knowledge of the populations' structure and has been used to support the best scientific advice on the definition of the management units for ICCAT species.

This document aims to add information for the discussion on the stock structure and particularly on the individual exchange between the two Atlantic SKJ stocks. For this, the current information on conventional tagging was summarized and presented in a preliminary analysis focusing on the movements of skipjack in the eastern and western stocks and between them. We have also provided the same analysis considering different scenarios of stock boundaries. The tagging information is the collection of multiple tagging programs carried out by ICCAT, some of them based on a scientific research plan, but others were more opportunistic (Ortiz, 2017). As such, results and conclusions from the analysis need to be considered with caution.

Data

Over 136,000 skipjack tunas were tagged and released from 1961 to 2020. The ICCAT database accounted for over 95,000 releases, while the AOTTP accounted for 40,000 releases (Figure 1). Most tag releases occurred from 2016 to 2020 through the AOTTP program period (Figure 1). The individuals were released from several fishing gears (Figure 2a), mainly by the bait boat. Over 12,000 recaptures were reported from the released individuals, mainly by the Purse seine and Bait Boat (Figure 2b). Table 1 summarizes the number of individuals tagged and recaptured by the fishing fleet and the overall tagged and released SKJ. The overall percentage of recapture was 8.82%.

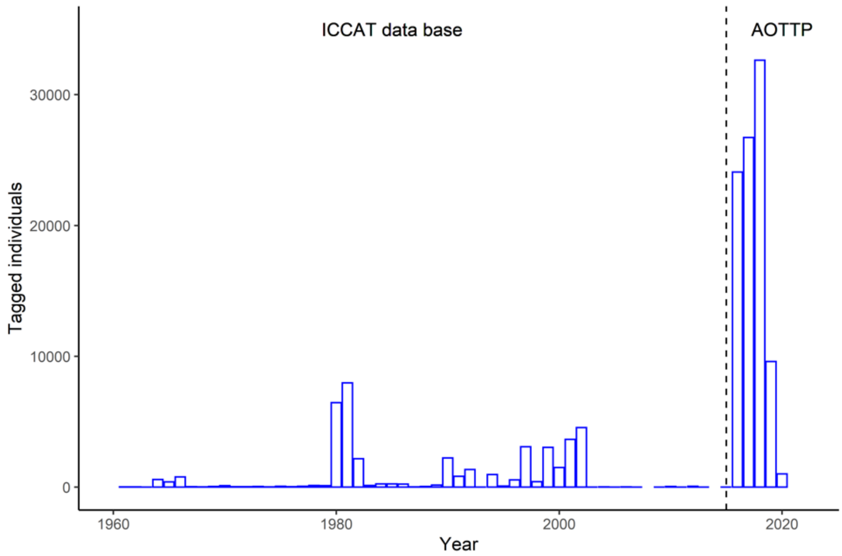

Figure 1. Tagged individuals per year from 1961 to 2020 from ICCAT and AOTTP data bases.

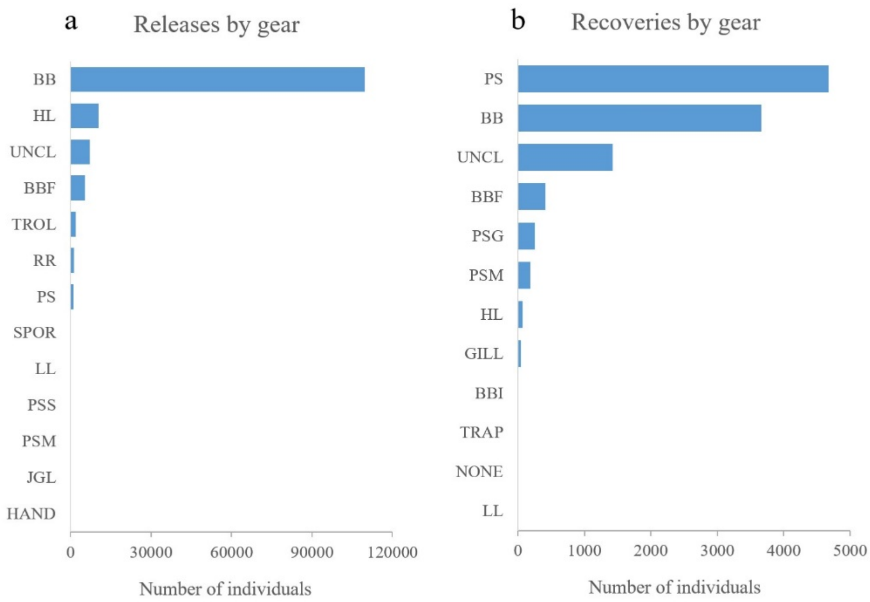

Figure 2. Number of SKJ individuals released (a) and recovered (b) by fishing gear.

Figure 3 shows the overall spatial distribution of SKJ tag releases and recaptures. Most tagging activities occurred upon the Eastern stock at the West African coast from Congo in the south to Marocco in the north. Nonetheless, some SKJ were tagged and released in the western stock area, in the southwestern Atlantic along the Southern Brazilian coast, in the equatorial west Atlantic along the north Brazilian coast, and in the northwest Atlantic along the southeastern US coast. The recovery locations were more spread-out than the releases, but followed the same general pattern of numbers of individuals by area. The recoveries spread over a broader region on the western African coast, with fish recovered in places far from the coast compared to where they were released. It was noticeable the low number of recoveries in the northwestern Atlantic along the US coast.

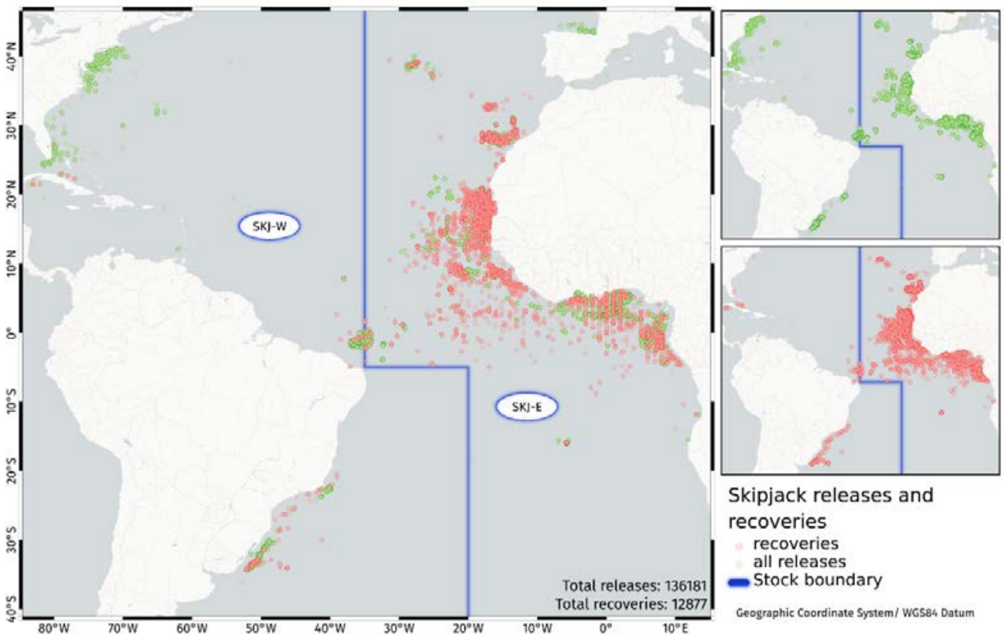

Figure 3. Spatial distribution of the released (green dots) and recovered SKJ (red dots) in the Atlantic Ocean.

The longest time at liberty for a tagged SKJ was 1068 days (Figure 4), almost three years for a fish tagged off the Southern Brazilian coast in April 2018, measuring 49 cm FL when released and 50 cm FL when recaptured. The median time at liberty was 24 days. 56% of the tagged fish were recovered in the first month, 73% in the second, and 82% until the third month. Until the first year, 98% of the tagged fish were recaptured. A slight variation of time at liberty was observed concerning the releasing gear, with a median of 24 days for the fishes released by the Bait boat, 22 days by those released by the Hand line, and 31.5 days by those released by the Bait boat freezer.

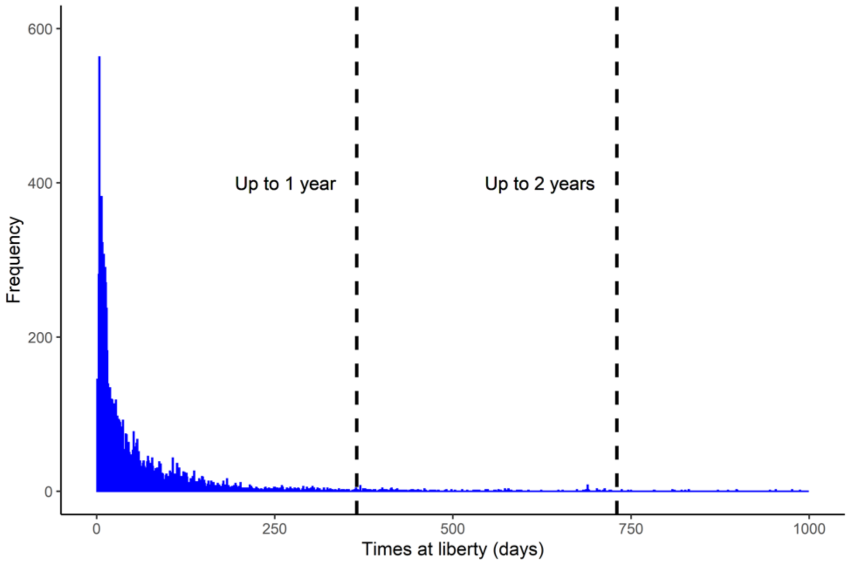

Figure 4. Times at liberty between the day the fish was tagged and released until the day the tag was recovered.

Methods

The location of release and recapture were available for each fish tagged, released, and recaptured. The displacement distances were estimated in km as the geodesic shortest distance between two points on an ellipsoid using the WGS84 and earth radius of 6378137 m (Karney 2013).
The linear displacement distances of each tagged and recovered individual were shown in different ways to highlight: 1) The gears of releasing and recovering; 2) The individuals who crossed and did not cross the ICCAT SKJ stock boundaries, and 3) Different groups of times at liberty. The same charts were constructed considering two alternative scenarios for stock boundaries, displacing the northern boundary of the stock 2.5 and 5 degrees to the east, respectively.

The rate of tagged individuals crossing the current stock boundaries was estimated with all the data. Considering the high numbers of individuals who crossed the stock boundaries in the western equatorial Atlantic, we calculated the crossing rate for two restricted data sets: 1) considering only the releases and recoveries performed between 10°N and 10°S, and 2) considering only the releases and recoveries performed between 10°N and 10°S of latitude and west of 30 and east of 40 degrees of longitude.

All the calculations were performed using R version 4.0.3. (R Core Team, 2020).

Results and Discussion

Table 2 presents the number of individuals crossing the ICCAT SKJ stock boundaries considering the different datasets selected and the alternative scenarios of stock boundaries. Overall, the proportion of fish crossing the stock boundary decreased as the northern boundary was displaced further east (Table 2). Considering all the recovery data set, 0.33% of the SKJ crossed the current stock boundary (Figure 5), with fish crossing mainly from West to East. If the northern stock boundary were 2.5 degrees of latitude further east, 0.18% of recovered fish would have crossed the border (Figure 6), with fish crossing mainly from West to East. If the northern stock boundary were 5 degrees of latitude further east, 0.13% of recovered fish would have crossed the boundary (Figure 7), with fish crossing mainly from East to West.

Limiting the release and recovery data for fish tagged between 10°N and 10°S of latitude, the crossing frequency increased for 1.04% with the current stock boundaries and for 0.6% and 0.36% considering the two alternative stock boundaries scenarios, respectively (Table 2). When considering the fish tagged and recovered only between 10°N and 10°S of latitude and 30 and 40° West of longitude, the crossing frequency increased abruptly for 53.3% with the current stock boundaries and for 18.56% and 8.49% considering the two alternative stock boundaries scenarios, respectively (Table 2).

Table 2. Number of individuals which crossed the current ICCAT SKJ stock boundary and the alternative scenarios of northern stock boundary displacement towards east for different data sets.

Recovery data	Northern stock boundary	Did not cross	Crossed	Crossing frequency	W-->E	E-->W
All	Current	10458	26	0.25%	22	4
All	2.5 east	10467	17	0.16%	11	6
All	5 east	10475	9	0.09%	3	6
10N-10S	Current	3264	26	0.80%	22	4
10N-10S	2.5 east	3273	17	0.52%	11	6
10N-10S	5 east	3282	8	0.24%	3	5
10N-10S & 30-40W	Current	49	25	51.02%	22	3
10N-10S & 30-40W	2.5 east	58	16	27.59%	6	10
10N-10S & 30-40W	5 east	68	6	8.82%	0	6
10-35S & 20-55W	Current	145	0	0%	0	0

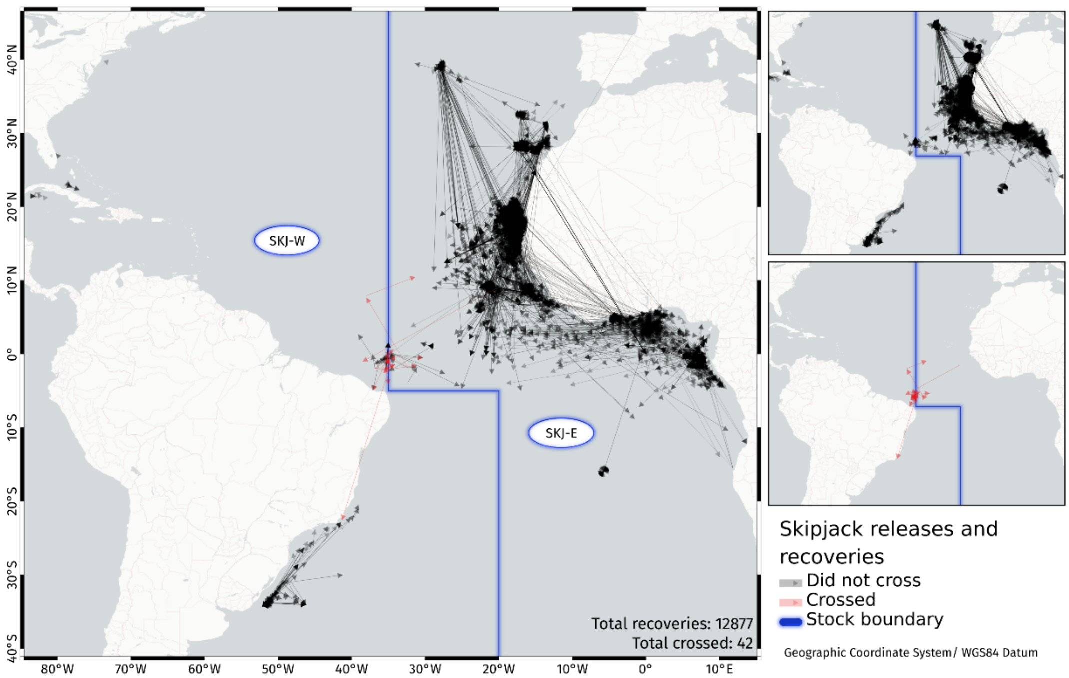

Figure 5. Skipjack releases and recoveries in the Atlantic Ocean highlighting the fish which crossed (red arrows) the current ICCAT stock boundaries (in blue).

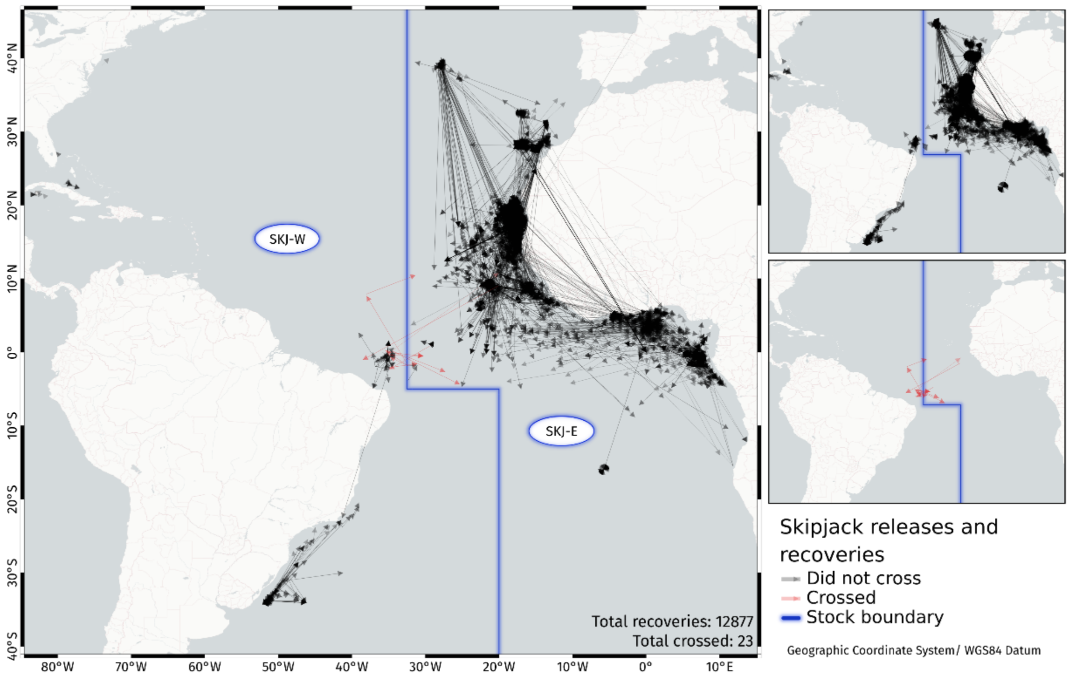

Figure 6. Skipjack releases and recoveries in the Atlantic Ocean highlighting the fish which would have crossed (red arrows) an alternative stock boundary displaced 2.5° further east (in blue).

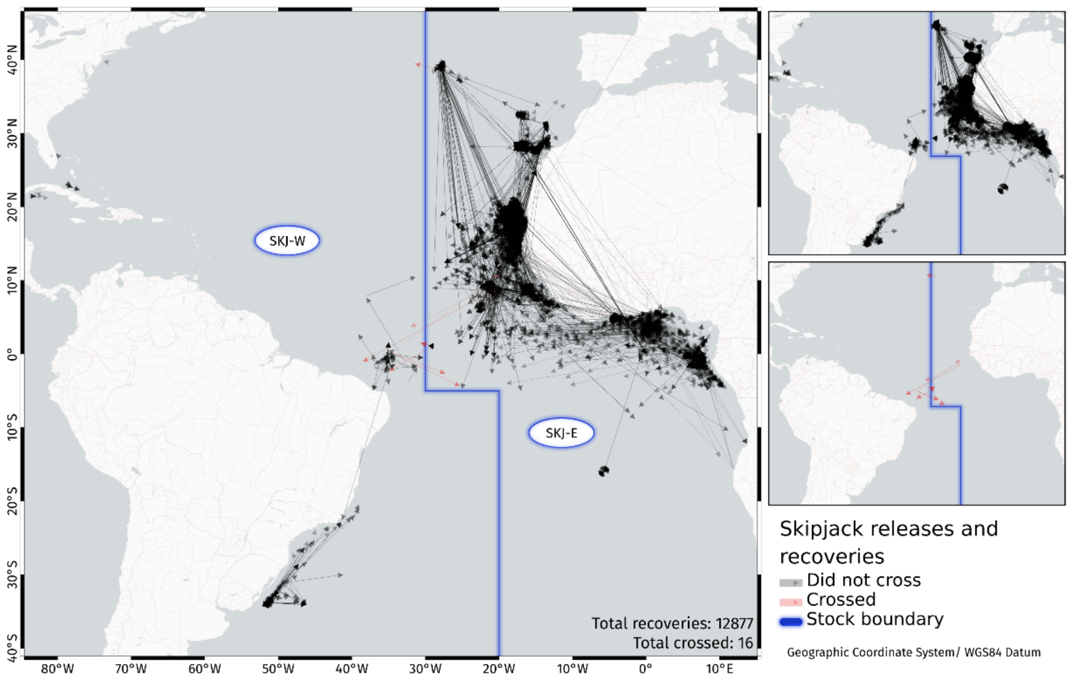

Figure 7. Skipjack releases and recoveries in the Atlantic Ocean highlighting the fish which would have crossed (red arrows) an alternative stock boundary displaced 5° further east (in blue).

The days at liberty do not influence the movement patterns observed for SKJ (Figure 8). In other words, the general movement patterns raised from releases and recoveries data were similar among fish despite the time it remained with the tag until being recaptured. Furthermore, there is no apparent relationship between the distance between the release and recovery locations and the time at liberty (Figure 9). The long-term permanence in specific areas of the Atlantic Ocean by the fish that remained with the tags for more than a half year may be seen as evidence of solid stock structuration across the sampled area.

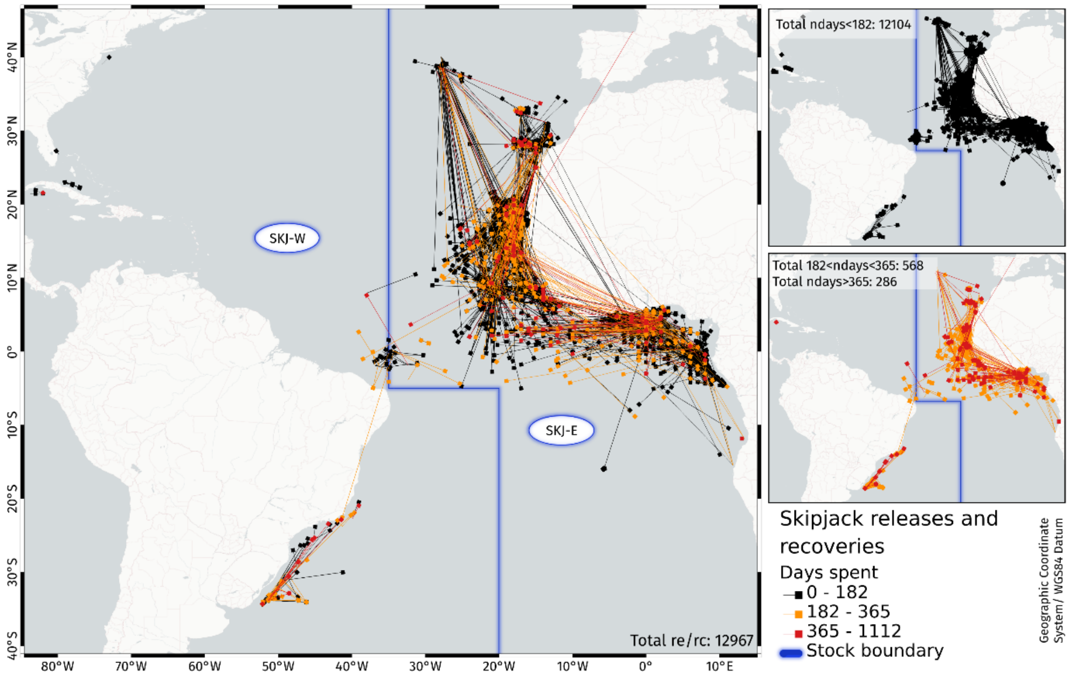

Figure 8. Skipjack releases and recoveries in the Atlantic Ocean grouped into fish that remained between 0 and 182 days at liberty, between 182-365 and > than 365.

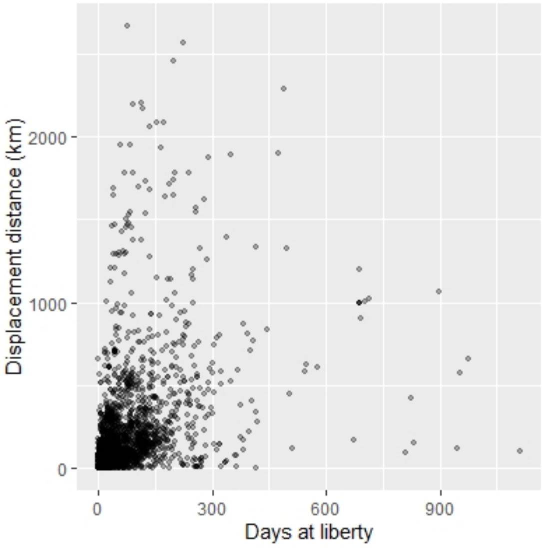

Figure 9. Displacement distances and days at liberty data for released and recovery Skipjack in the Atlantic Ocean.

Concluding remarks

The results achieved in this study help to understand better the stock structuration of SKJ in the Atlantic Ocean. The data allowed us to observe an intense fish movement through all of the eastern Atlantic from Africa's southwestern coast to the mid North Atlantic area around the Azores islands. This strong exchange indicates a stock unit in the east of the Atlantic. There is an area with a high rate of fish exchanges in the equatorial Atlantic near Brazil's northeastern coast between the currently defined east and west stock boundary. When considering only the fish recovered in that area, the rate of individuals that cross the stock borders can attain more than 50%. In hypothetic scenarios where the northern boundary of the stock was displaced further east, the crossing rates decreased substantially. On the other hand, little exchange was observed between the northern and southern portions of the western stock along the south of the Brazilian coast. However, it is crucial to recognize that the spatial coverage of the tag and recovery data is related to the fishing areas; thus, the results and conclusions presented in this study should be used carefully.

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