

Stock assessment for Atlantic yellowfin tuna based on extended surplus production model considering life history

Zhipan Tian¹, Fei Wang⁴, Siqun Tian^{1, 2, 3}, Qiuyun Ma^{1, 2, 3*}

¹ College of Marine Sciences, Shanghai Ocean University, Shanghai 201306, China

² National Distant-water Fisheries Engineering Research Center, Shanghai 201306, China

³ Key Laboratory of Sustainable Exploitation of Oceanic Fisheries Resources, Ministry of Education, Shanghai 201306, China

⁴ Fisheries College, Zhejiang Ocean University, Zhoushan 316022, China

Received 4 March 2021; accepted 12 May 2021

© Chinese Society for Oceanography and Springer-Verlag GmbH Germany, part of Springer Nature 2022

Abstract

The modern fishery stock assessment could be conducted by various models, such as Stock Synthesis model with high data requirement and complicated model structure, and the basic surplus production model, which fails to incorporate individual growth, maturity, and fishery selectivity, etc. In this study, the Just Another Bayesian Biomass Assessment (JABBA) Select which is relatively balanced between complex and simple models, was used to conduct stock assessment for yellowfin tuna (*Thunnus albacares*) in the Atlantic Ocean. Its population dynamics was evaluated, considering the influence of selectivity patterns and different catch per unit effort (CPUE) indices on the stock assessment results. The model with three joint longline standardized CPUE indices and logistic selectivity pattern performed well, without significant retrospective pattern. The results indicated that the stock is not overfished and not subject to overfishing in 2018. Sensitivity analyses indicated that stock assessment results are robust to natural mortality but sensitive to steepness of the stock-recruitment relationship and fishing selectivity. High steepness was revealed to be more appropriate for this stock, while the fishing selectivity has greater influence to the assessment results than life history parameters. Overall, JABBA-Select is suitable for the stock assessment of Atlantic yellowfin tuna with different selectivity patterns, and the assumptions of natural mortality and selectivity pattern should be improved to reduce uncertainties.

Key words: population dynamics, selectivity, tropical tuna, fishery management

Citation: Tian Zhipan, Wang Fei, Tian Siqun, Ma Qiuyun. 2022. Stock assessment for Atlantic yellowfin tuna based on extended surplus production model considering life history. *Acta Oceanologica Sinica*, 41(8): 41–51, doi: 10.1007/s13131-021-1924-x

1 Introduction

Yellowfin tuna (*Thunnus albacares*) is one of the most valuable species in the global marine fisheries with the production worth tens of billions of dollars each year (Galland et al. 2016). In the Atlantic Ocean, the yield of yellowfin tuna has reached 140 kt (ICCAT, 2019a). The main tuna fisheries contain longline, purse seine, bait boat and other surface small-scale fisheries, while the purse seine fishery yields about 70% of the total catch in the Atlantic Ocean (ICCAT, 2019a). Fishing selectivity and landings vary by gears in yellowfin tuna fishery, for example, longline fishery tends to catch bigger fish than purse seine and bait boat. Therefore, the exploitable biomass of yellowfin tuna are not constant among different fisheries with the same spawning biomass (Langley, 2019; Walter, 2019).

The Atlantic yellowfin tuna stock is managed by the International Committee and Conservation of Atlantic Tunas (ICCAT). To improve the accuracy and precision of stock assessment results, multiple models are encouraged for Atlantic yellowfin tuna stock assessment, including A Stock Production Model Incorporating Covariates (ASPIC) (Matsumoto and Satoh, 2017), Age Structured Production Model (ASPM) (Satoh et al., 2017), Virtual Population Analysis (VPA) (Tropical Tunas Species Group, 2012),

Just Another Bayesian Biomass Assessment (JABBA) (Sant'Ana et al., 2020), Surplus Production Model (SPM) (Merino et al., 2019) and Stock Synthesis III (SS3) (Walter, 2019). In 2019, management strategy was defined according to integrated results of JABBA, SPM and SS3 (ICCAT, 2019b). However, selectivity variations were not considered in the stock assessment of Atlantic yellowfin tuna, which may hinder the understanding of population and fishing dynamic, and impact its management (ICCAT, 2019b).

Since the data limit occurs frequently for marine pelagic species (Costello et al., 2012; Carruthers et al., 2014), SPMs are the preference source for Regional Fishery Management Organizations (RFMOs) when it comes to routine stock assessment for such species, or to provide more information for comparison with other complicated models (Chang et al., 2015; Punt et al., 2015; Rankin and Lemos, 2015; Omori et al., 2016; Kolody et al., 2019). SPMs are among the least data and parameter demanding population models that can produce estimates of maximum sustainable yield (MSY) and associated fisheries reference points. The shape of production function depends on biological parameters and age-specific selectivity of the fishery, without consideration in SPMs (Pella and Tomlinson, 1969; Maunder, 2002;

Foundation item: The Fund of National Key R&D Programs of China under contract No. 2019YFD0901404; the China Postdoctoral Science Foundation under contract No. 2019M651475.

*Corresponding author, E-mail: qyma@shou.edu.cn

Wang et al., 2014). Contrasts to SPMs, ASPMs also consider the spawning biomass besides exploitable biomass (Restrepo and Legault, 1998), which is the portion of the biomass that is made up of mature fish (or females) in the population. This allows ASPMs to account for age-specific processes into the fishery, to track the propagation of cohorts, and to explicitly account for the effects of selective fishing, even in the absence of reliable size or age data.

Process and observation errors are important in fishery stock assessment model, corresponding to the errors from fish population dynamics and fishing behavior, respectively. However, these two errors could not be estimated simultaneously in traditional SPMs, which affects the precision and accuracy of stock assessment (Xu et al., 2019). With Markov Chain Monte Carlo (MCMC) techniques, Bayesian methods with informative prior distributions can simulate the unconditional likelihood function of the parameter in the stochastic model, with precise parameter estimates and reduced bias (Punt and Hilborn, 1997; McAllister et al., 2001; Lewy and Nielsen, 2003). State-space approach allows stock assessment model to simultaneously account for both process and observation errors for random variability in the data and annual biomass dynamics of a stock (Millar and Meyer, 2000). Thus, by overcoming SPMs' shortcomings, Bayesian state-space model facilitates the model fitting and reduces uncertainties of stock assessment.

There are many applications of Bayesian state-space surplus production model in the stock assessments, such as JABBA (Winker et al., 2018), Bayesian state-space surplus production model (BSM) (Froese et al., 2017) and a generalized Bayesian surplus production stock assessment software (BSP2) (McAllister, 2014). Among them, JABBA-Select (Winker et al., 2020) was formulated to incorporate life history and fishery selectivity, considering different selectivity and associates fishing mortality over time and across different fleets. Moreover, the inclusion of life-history parameters enables its ability to distinguish between exploited biomass and spawning biomass, thus making its results directly comparable to those of ASPMs.

Besides the fishing behavior, fish population dynamics is highly affected by many biological and environmental factors, such as predators, preys, sea surface temperature, sea current, North Atlantic Oscillation index, etc. These factors influence the growth, maturity, fecundity, and natural mortality in fish life history, which introduce much uncertainties to life history estimation. These uncertainties in both fishing dynamics and life history would definitely affect the stock assessment results and biological reference points estimations. To improve the effective conservation and management for Atlantic yellowfin tuna, it's important to evaluate the influence of these uncertainties.

In this study, we applied this alternative method, JABBA-Select, to assess the stock of Atlantic yellowfin tuna. The objectives of this study are (1) to evaluate the state of Atlantic yellowfin tuna's stock; (2) to explore the influences of different selectivity patterns and life history parameters on stock assessment results and fishery management for Atlantic yellowfin tuna.

2 Materials and methods

We assumed that the yellowfin tuna species in the whole Atlantic Ocean belongs to a single stock which is acknowledged by ICCAT, and the population size in 1950 is the unexploited biomass, equal to the carrying capacity (K).

2.1 Data sources

Catch and standardized catch per unit effort (CPUE) indices used in this study, are derived from ICCAT (ICCAT, 2019a; Hoyle et al., 2019; Narvaez, 2020; Guéry, 2020) (Figs 1 and 2). The CPUE series were calculated from five fleets, including French purse

seine (FR-PS), joint longline of three regions (tropical, north, and south temperate area, represented by JLL-R1, JLL-R2 and JLL-R3, respectively, with borders of about 15°N and 15°S) and Venezuela longline (VEN-LL). Considering different trends and fleets of these CPUE series, multiple scenarios were established in the preliminary experiments to compare model fitting and performance (Table 1). All scenarios use the same life-history parameters (Table 1) and logistic selectivity patterns for both longline and purse seine fishery (LLL-PSL) (Fig. 3a). The catches of longline, bait boat and other small-scale fisheries were assumed to follow longline selectivity, while catches of PS followed purse seine selectivity.

Some life-history traits and fishery dynamics information are required to establish JABBA-Select for Atlantic yellowfin tuna, including the growth parameters of von Bertalanffy growth function, length-weight relationship parameters, natural mortality, Beverton and Holt spawner recruitment relationship, maturity, and fisheries selectivity (Table 2).

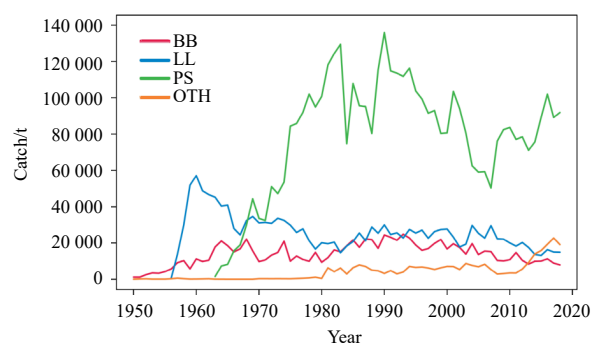


Fig. 1. The catch of Atlantic yellowfin tuna among different fisheries from 1950 to 2018. OTH means small-scale fisheries except for longline (LL), purse seine (PS) and bait boat (BB).

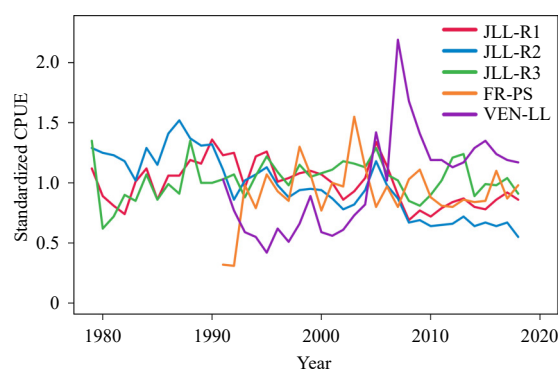


Fig. 2. Available standardized catch per unit effort (CPUE) series for Atlantic yellowfin tuna from 1979 to 2018.

Table 1. Configuration of Scenarios S1-S6 considering different catch per unit effort (CPUE) in the JABBA-Select model for Atlantic yellowfin tuna

Scenarios	CPUE	RMSE/%	DIC
S1	JLL-R1, JLL-R2, JLL-R3, VEN-LL, FR-PS	27.8	-361.1
S2	JLL-R1, JLL-R2, JLL-R3, FR-PS	21.4	-403.7
S3	JLL-R1, JLL-R2, JLL-R3	15.4	-425.4
S4	JLL-R1, JLL-R2, FR-PS	22.8	-392.4
S5	JLL-R1, JLL-R3, FR-PS	20.8	-383.0
S6	JLL-R2, JLL-R3, FR-PS	23.1	-316.8

Note: RMSE is the abbreviation of root mean square error; DIC, deviation information criteria.

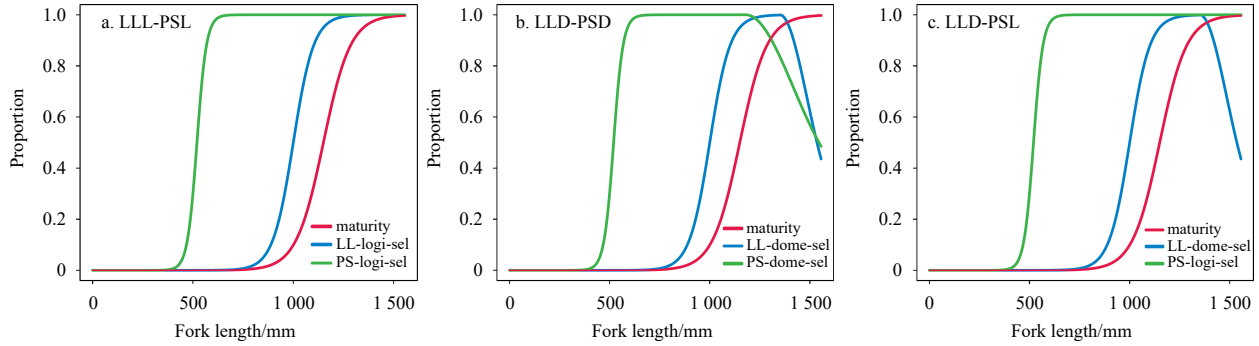


Fig. 3. Maturity and assumed selectivity patterns in the JABBA-Select model for Atlantic yellowfin tuna fisheries. LL-logi-sel and PS-logi-sel represent logistic longline and purse seine selectivity, respectively; LL-dome-sel and PS-dome-sel represent dome-shaped longline and purse seine selectivity, respectively.

Table 2. Summary of life history and selectivity parameters for Atlantic yellowfin tuna used in the JABBA-Select

Parameters	Symbol	Values	Sources/References
Maximum length/cm	L_∞	155.7	ICCAT (2019a)
Growth rate/a ⁻¹	k	0.443	ICCAT (2019a)
Theoretical age at zero-length/a	t_0	0.014 8	ICCAT (2019a)
Scaling coefficient for the weight at length/(kg·cm ⁻³)	a	2.15×10 ⁻⁵	ICCAT (2019a)
Shape parameter for the body form	b	2.976	ICCAT (2019a)
Minimum age/a	t_{\min}	0	ICCAT (2019a)
Maximum age/a	t_{\max}	18	ICCAT (2019a)
Natural mortality	M	0.35	ICCAT (2019a)
Steepness in the spawner recruitment relationship	h	0.8	ICCAT (2019a)
Length at 50% maturity/cm	mat_{50}	115	Diaha et al. (2015)
Length at 95% maturity/cm	mat_{95}	135	Diaha et al. (2015)
Length at 50% selectivity of longline/cm	$L_{LL,50}$	100	Walter (2019)
Length at 95% selectivity of longline/cm	$L_{LL,95}$	115	Walter (2019)
Length at 50% selectivity of purse seine/cm	$L_{PS,50}$	52	Walter (2019)
Length at 95% selectivity of purse seine/cm	$L_{PS,95}$	59	Walter (2019)

2.2 JABBA-Select model

Based on the life history parameters and fishery’s selectivity, the age-structured equilibrium model (ASEM) (Winker et al., 2020) defined in JABBA-Select, generates parameters of r and m for surplus production function. Detailed information and formula of ASEM are provided in Winker et al. (2020) (see its Fig. 2).

The generalized form of the process equation is given by

$$SB_y = SB_{y-1} + SP_{y-1} - \sum_s C_{s,y-1}, \quad (1)$$

where SP_y is surplus production in year y ; $C_{s,y}$ is the catch in year y with selectivity s ; and SB_y is spawning biomass. The surplus production is assumed as function of spawning biomass (Thorson et al., 2012):

$$SP = \frac{r}{m-1} SB \left(1 - \left(\frac{SB}{SB_0} \right)^{m-1} \right), \quad (2)$$

where r is the intrinsic rate of population increase; SB_0 is SB when the stock was unfished; and m is a shape parameter that determines at which SB/SB_0 ratio of the maximum surplus production is attained.

With the definitions that H_{MSY} is the harvest rate at MSY, and P_y is the ratio of SB_y to SB_0 , (i.e., $H_{MSY} = MSY/SB_{MSY}$ and $P_y = SB_y/SB_0$). Equations (1) and (2) could be combined and trans-

ferred to the full process equation in JABBA-Select:

$$P_y = \begin{cases} \psi e^{\eta_y - 0.5\sigma_\eta^2}, & y = y_{\text{init}}, \\ \left(P_{y-1} + \frac{\sum_s \gamma_{s,y-1} H_{MSY_s}}{1-m^{-1}} P_{y-1} (1 - P_{y-1}^{m-1}) - \frac{\sum_s C_{s,y-1}}{SB_0} \right) \psi e^{\eta_y - 0.5\sigma_\eta^2}, & y > y_{\text{init}}, \end{cases} \quad (3)$$

where y_{init} is the initial fishery year (1950); ψ is scaling for initial biomass depletion P_1 with $\psi \sim \text{Lognormal}(1, 0.3)$. And η_y is the process error term with $\eta_y \sim \text{Normal}(0, \sigma_\eta^2)$; and $\sigma_\eta^2 \sim \text{Lognormal}(0.08, 0.2)$. The $\gamma_s = C_{s,y} / \sum_s C_{s,y}$ is used as a multiplier to weight H_{MSY_s} relative to catch taken with selectivity s , while SB_0 is assumed with mean equal to 2 500 000 t and coefficient of variation equal to 2. The biomass reference point was set to be $SB_{MSY}/SB_0 = 0.4$ (Thorson et al., 2012; Punt et al., 2014b).

The exploitable biomass (EB) is expressed as the product of SB_y :

$$EB_{s,y} = SB_y \left(v_{1s} + (v_{2s} - v_{1s}) \frac{1 - e^{-v_{3s}(P_y - P_{1s})}}{1 - e^{-v_{3s}(P_{2s} - P_{1s})}} \right), \quad (4)$$

where $v_{1s} - v_{3s}$ are the externally derived parameters to approximate the ratio $EB_{s,y}/SB_y$. The observation equation defined in

JABBA-Select is given by

$$\ln(I_{s,y}) \sim N\left(\ln(q_i EB_{s,y}), \sigma_{\epsilon,y,i}^2\right), \quad (5)$$

where $I_{s,y}$ is the standardized CPUE; q_i is the catchability coefficient for CPUE i ; and $\sigma_{\epsilon,y,i}^2$ is the total observation variance, which is given by

$$\sigma_{\epsilon,y,i}^2 = \sigma_{\text{est},i}^2 + \sigma_{\text{fix}}^2, \quad (6)$$

where $\sigma_{\text{est},i}^2$ is the estimated portion in model running; σ_{fix}^2 is fixed at 0.1 for addressing over-precise in fitting (Winker et al., 2013).

2.3 Model diagnostics

The goodness of fitting among different models or scenarios was evaluated by root mean squared error (RMSE) and deviation information criteria (DIC). RMSE aims to quantitatively evaluate the randomness of model residuals, and DIC is particularly useful in Bayesian model selection where the posterior distributions of the models have been obtained by MCMC simulation. Lower DIC and RMSE values indicate better performance.

For all scenarios, convergences of the posterior distribution for parameters were judged by the Geweke (1991) and Heidelberger and Welch (1983) diagnostic tests. A total of 450 000 iterations per scenario was performed, with a burn-in period of 150 000 for every 3 chains, and subsequently saving every 10th step to attain a joint posterior of 90 000 saved values.

The retrospective problems need much concern in the stock assessment, which might relate to data inconsistencies and/or unaccounted for changes in population processes (i.e., growth, natural mortality, or fishery selectivity) over time and may lead to biased management advice (Mohn, 1999; Stewart and Martell, 2014). Retrospective patterns were quantified using the formulation proposed by Hurtado-Ferro et al. (2015) to calculate Mohn's ρ :

$$\rho = \frac{\bar{X}_{Y-y,p} - X_{Y-y,\text{ref}}}{X_{Y-y,\text{ref}}}, \quad (7)$$

where X is the parameter for which Mohn's ρ was calculated; Y is the final year of the assessment period; y is the last year of a given peel p ; and ref is the reference peel, i.e., the most recent assessment. In this study, Mohn's ρ is presented with the last year (2018) as the ref year and calculates Mohn's ρ for 7 a backwards from 2017 to 2011. Most yellowfin tuna has a life span of 6 a to 7 a and its maximum age change from 11 a to 18 a. In ICCAT, the stock assessment for yellowfin tuna is conducted every 3 a. Therefore, 7 a was used for retrospectively analysis, covering the recruitment period, half generation and two assessment intervals.

2.4 Sensitivity analysis

There are many uncertainties for the estimation of natural mortality (M) and the spawner-recruitment relationship. The ratio of the average unfished recruitment when spawning biomass is reduced to 20% of unfished levels, was defined as steepness, h . Both M and h are essential information of population dynamics. Thus, several sensitivity analyses were conducted to evaluate the sensitivity of stock assessment results to life history parameters M and h . The base value of M was set to be 0.55 which is also applied in 2016 ICCAT yellowfin tuna stock assessment, and 0.45 and 0.25 were assumed to be the highest and lowest values, respectively, compared to the base value of 0.35 (ICCAT, 2016). The

highest value for h was set to be 0.9 recommended by ICCAT SCRS, and 0.7 as the lowest value relative to the base value of 0.8 (ICCAT, 2019b).

Selectivity is the most important parameter in fishing dynamics, with substantial influence on the stock assessment results. Therefore, more selectivity patterns were assumed in the sensitivity analysis, which are dome-shaped selectivity for longline and purse seine fishery (LLD-PSD) (Fig. 3b), and dome-shaped for the longline fishery with logistic for purse seine fishery (LLD-PSL) (Fig. 3c). Additionally, we also conducted 3 scale factors (0.9, 1.1 and 1.2) to length at 50%/95% selectivity of longline/purse seine in the sensitivity analysis to explore potential risks of model setting.

2.5 Projections

Since there is no limit or target reference points for yellowfin tuna in the management of yellowfin tuna by ICCAT, MSY-based reference points were used for the determination of stock status and total allowable catch (TAC) was used for management strategy. To evaluate the management performances of the TAC, projections relied on the base case model were estimated for Atlantic yellowfin tuna. Based on ICCAT's recommendation of TAC (110 000 t) for Atlantic yellowfin tuna (ICCAT, 2019b), eight projections were made with catch set at the level of 88 000–165 000 t, by 11 000 t intervals, while the catch in 2019 was assumed to be same as 2018 catch (133 900 t). Projection period was set to 14 a (2020–2033), which was about the whole generation time for Atlantic yellowfin tuna.

In this study, all analyses were conducted by the R software (v4.0.0) (R Core Team, 2013) and R code of JABBA-Select (<https://github.com/JABBAmodel/JABBA-Select>).

3 Results

3.1 Model diagnostic and caveats

The first scenario (S1) including all CPUE indices provided evidence that VEN-LL was characterized by high variations and inharmonious (Fig. 4). Scenarios of S2, S4–S6 which included FR-PS also revealed noticeable conflicts with the overall trend in some periods. The quantitative fits to the standardized CPUE provided a direct way for scenario selection (Table 1). The third scenario S3 was revealed to perform best, with the lowest RMSE and DIC values, chosen as the base case model for the stock assessment of Atlantic yellowfin tuna.

3.2 Assessment results

The posterior densities of model parameters from the base case showed good convergences with a symmetric distribution of all parameters (Fig. 5). The base case model estimated the median and 95% confidence interval for unfishing spawning biomass (SB_0), and population growth rate r (mean value of $r1$ and $r2$) to be 1.67×10^6 t (confidence interval from 0.92×10^6 t to 3.65×10^6 t) and 0.232 (confidence interval from 0.134 to 0.396), respectively (Table 3). The catchability q for Atlantic yellowfin tuna longline fishery was about 8×10^{-7} (Fig. 5).

3.3 Stock status

Harvest rate H increased continuously in 1950–1980 with the consistent decrease of the spawning biomass SB , then both H and SB fluctuated but still did not violate the reference points (H_{MSY} and SB_{MSY}) (Fig. 6). Kobe plot showed that the Atlantic yellowfin tuna's stock in 2018 has 71.8% in the green zone, with 7.3% and 20.9% in the yellow and red zones, respectively (Fig. 6), in-

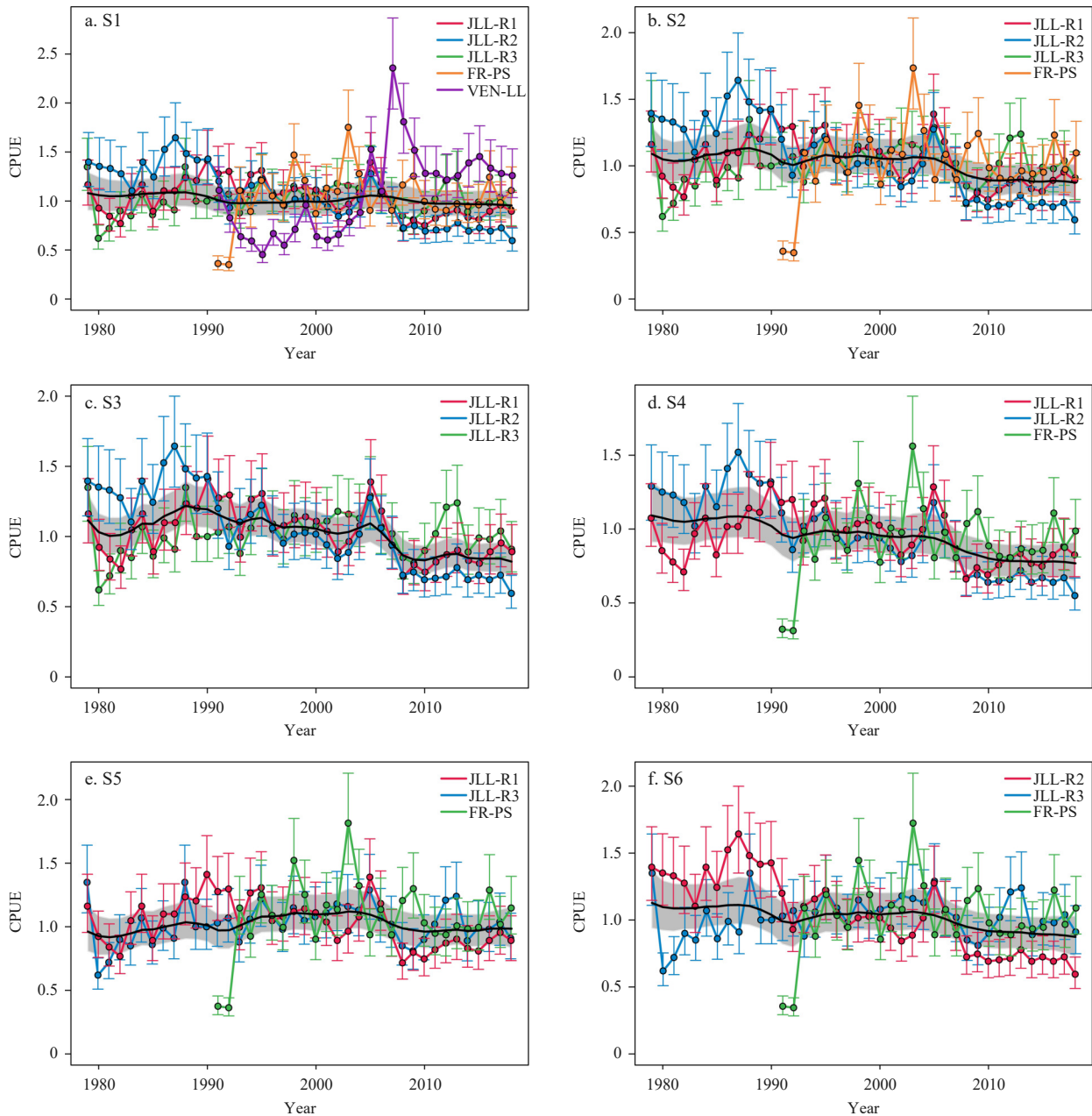


Fig. 4. The CPUE series (in color lines with dots) and expected CPUE (in black lines with grey shade for 95% confidence interval) of six scenarios (S1–S6) in the JABBA-Select model for Atlantic yellowfin tuna.

dicating that Atlantic yellowfin tuna is neither overfished nor subject to overfishing.

3.4 Sensitivity analysis

Results of the sensitivity analyses indicated that SB_{2018}/SB_{MSY} , H_{2018}/H_{MSY} and MSY were more stable than H_{MSY} and SB_{MSY} in a1–a5, and these three estimators were more sensitive to h and robust to M in Scenarios a1–a5 (Table 4). When M value was set to be higher, MSY and H_{MSY} increased, but SB_{MSY} decreased, with relative stable SB_{2018}/SB_{MSY} and H_{2018}/H_{MSY} indicating better stock status. The high h scenario (a4) was much stable than the low h scenario (a5) while both had good stock status (Table 4). Biomass trends of Scenarios a1–a5 are close to Scenario S3 except for Scenario a5 ($h=0.7$) (Fig. 7), and all estimators in Scenario a5 are more different with Scenario S3 compared with Scenarios a1–a4 (Table 4). Biomass trend were more sensitive to fish-

ing selectivity (Scenarios b1–b5) than life history parameters changing (Scenarios a1–a5) (Fig. 7). Additionally, all the biological reference points estimates were sensitive to the different assumptions of fishing selectivity for Atlantic yellowfin tuna, with irregularity in ascending fishing selectivity scenarios (Scenarios b3–b5) and similar variations tendency in changing fishing selectivity scenarios (Scenarios b1–b2) (Table 4).

Retrospective analyses showed that H/H_{MSY} and H were slightly overestimated, SB/SB_{MSY} and SB were underestimated (Fig. 8), but no significant retrospective pattern was revealed, with mean values of Mohn ρ are -0.27 , -0.08 , 0.03 and 0.09 , respectively.

3.5 Projection

Projection of biomass depletion rate in 2020–2033 (Fig. 9) showed that all TAC (0.8–1.5 times relative to 110 000 t) will lead

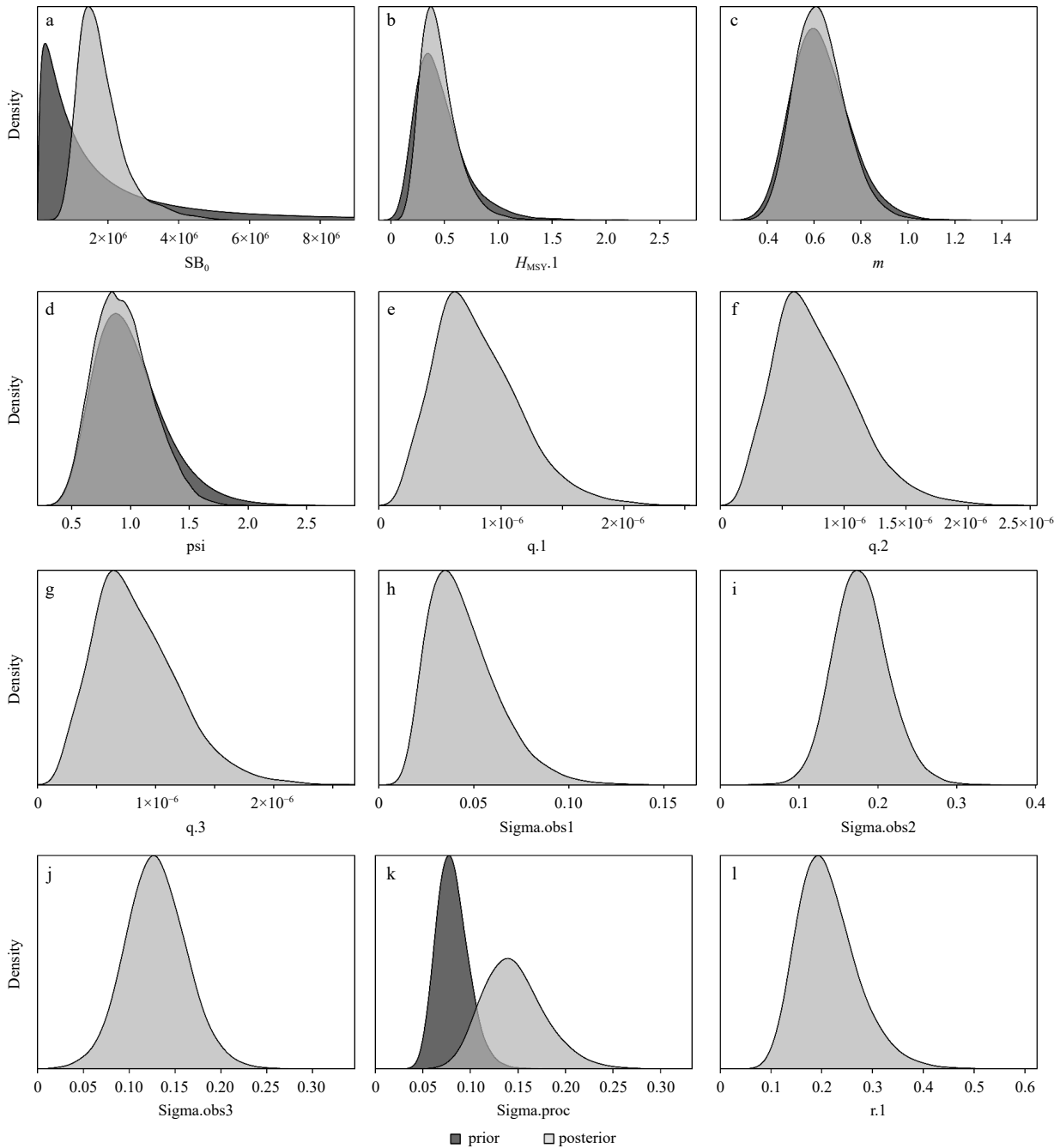


Fig. 5. Parameters' prior and posterior distributions of base case (Scenario S3) in the JABBA-Select model for Atlantic yellowfin tuna. SB_0 : the unfishing spawning biomass; $H_{msy.1}$: the harvest rate that produces maximum sustainable yield from the corresponding spawning biomass equilibrium SB_{MSY} ; m : the shape parameter; ψ : the initial depletion of SB_1/SB_0 ; $q.1$, $q.2$, and $q.3$: catchability coefficients of catch per unit efforts (CPUEs) from JLL-R1, JLL-R2 and JLL-R3, respectively; σ_{obs1} , σ_{obs2} , and σ_{obs3} : observation errors of CPUEs from JLL-R1, JLL-R2 and JLL-R3, respectively; σ_{proc} : the process error; $r.1$: the intrinsic rate of population increase.

to increase in abundance, and the probabilities of $SB > SB_{MSY}$ for all TAC were high (at least 64.8%). When the catch was set to be 4 000 t higher than the catch in 2018, Atlantic yellowfin tuna would not be overfished, with 80.7% probability of $SB > SB_{MSY}$ in 2024.

4 Discussion

This research explored six scenarios using JABBA-Select for Atlantic yellowfin tuna. The base case model showed that At-

lantic yellowfin tuna stock is neither undergoing overfishing nor being overfished, which is consistent with current ICCAT stock assessment (ICCAT, 2019b). The estimated MSY (217 179 t) far exceeds the 2018 catch (133 900 t) with $SB_{2018}/SB_{MSY} > 1$ and $H_{2018}/H_{MSY} < 1$. Projections indicated that stock will remain steady suffering the current catch pressure. It should be noted that the result of this study was based on 2019 catch, fixed at 133 900 t, given that ICCAT's setting was 131 042 t (ICCAT, 2019b), indicating better resilience of the stock. As per ICCAT's recommenda-

Table 3. Parameters and biological reference points estimates (median and 95% confidence interval (CI)) of base case (Scenario S3) in the JABBA-Select model for Atlantic yellowfin tuna

Parameter	Median	Lower CI (2.5%)	Upper CI (97.5%)
r_1	0.259	0.150	0.441
r_2	0.205	0.118	0.350
m	0.534	0.344	0.826
SB_0/t	1 667 588	918 141	3 653 741
MSY_1/t	190 685	130 525	435 825
MSY_2/t	150 544	101 675	343 324
H_{MSY_1}	0.419	0.198	0.876
H_{MSY_2}	0.331	0.156	0.694
H_{2018}/H_{MSY}	0.734	0.218	1.913
SB_{2018}/SB_{MSY}	1.171	0.602	1.844

Note: Exploitable biomass related indicator has 2 estimates since the model has 2 different selectivity patterns (for example, MSY1 and MSY2).

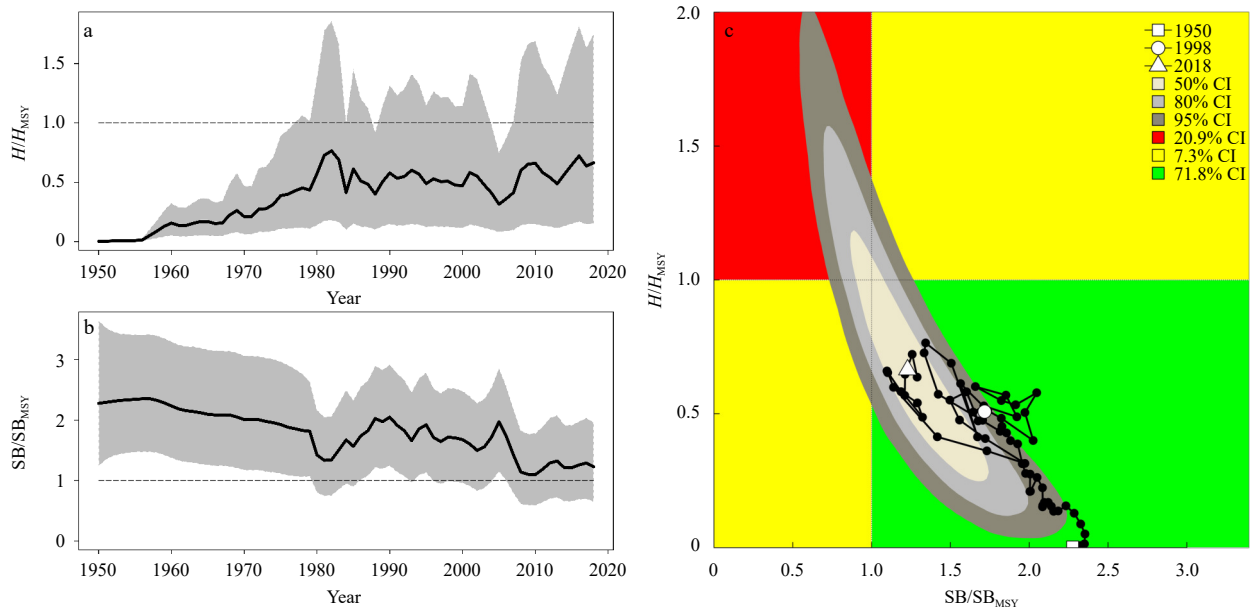


Fig. 6. Harvest rate (a) and biomass (b) trends with 95% confidence interval (CI) and Kobe plot (c) of base case (Scenario S3) in the JABBA-Select model for Atlantic yellowfin tuna.

Table 4. Percentage changes of biological reference points (BRPs) in the sensitivity analysis of natural mortality (M), steepness (h) and selectivity of base case (Scenario S3) in the JABBA-Select model for Atlantic yellowfin tuna

Scenario	Assumption	SB_{2018}/SB_{MSY}	H_{2018}/H_{MSY}	MSY	H_{MSY}	SB_{MSY}
a1	$h=0.8, M=0.25, LLL-PSL$	2%	0%	0%	-21%	24%
a2	$h=0.8, M=0.45, LLL-PSL$	6%	-12%	9%	13%	-4%
a3	$h=0.8, M=0.55, LLL-PSL$	3%	-11%	10%	24%	-11%
a4	$h=0.9, M=0.35, LLL-PSL$	0%	-1%	5%	13%	-7%
a5	$h=0.7, M=0.35, LLL-PSL$	10%	-16%	6%	-18%	28%
b1	$h=0.8, M=0.35, LLD-PSD$	6%	-16%	16%	11%	6%
b2	$h=0.8, M=0.35, LLD-PSL$	6%	-18%	18%	13%	2%
b3	$h=0.8, M=0.35, 0.9*(LLL-PSL)$	19%	-30%	21%	5%	14%
b4	$h=0.8, M=0.35, 1.1*(LLL-PSL)$	9%	-18%	12%	13%	-2%
b5	$h=0.8, M=0.35, 1.2*(LLL-PSL)$	27%	-34%	18%	-11%	27%

Note: Exploitable biomass related indicator has 2 estimates since the model has 2 different selectivity patterns, so MSYs are mean values of MSY1 and MSY2, with the same for H_{MSY} . LLL-PSL means logistic selectivity for longline and purse seine fishery; LLD-PSD, dome-shaped selectivity for longline and purse seine fishery; LLD-PSL, dome-shaped selectivity for longline fishery and logistic selectivity for purse seine fishery. Values of each estimator are percentage changes compared to those values of Scenario S3. The values of BRPs in S3 are 1.17, 0.73, 170 615 t, 0.38 and 473 348 t of SB_{2018}/SB_{MSY} , H_{2018}/H_{MSY} , MSY, H_{MSY} , and SB_{MSY} , respectively.

tion, catches below the 120 000 t are expected to maintain healthy stock biomass through 2033 (ICCAT, 2019a).

A noticeable difference between the previous stock assessment (Walter and Sharma, 2017) and this study for Atlantic yel-

lowfin tuna is that CPUE index used is much more distinct: three joint longline CPUE series by region rather than by fleets (ICCAT, 2016, 2019c). This change in CPUE index leads to obvious changes in the whole CPUE trends than the previous stock as-

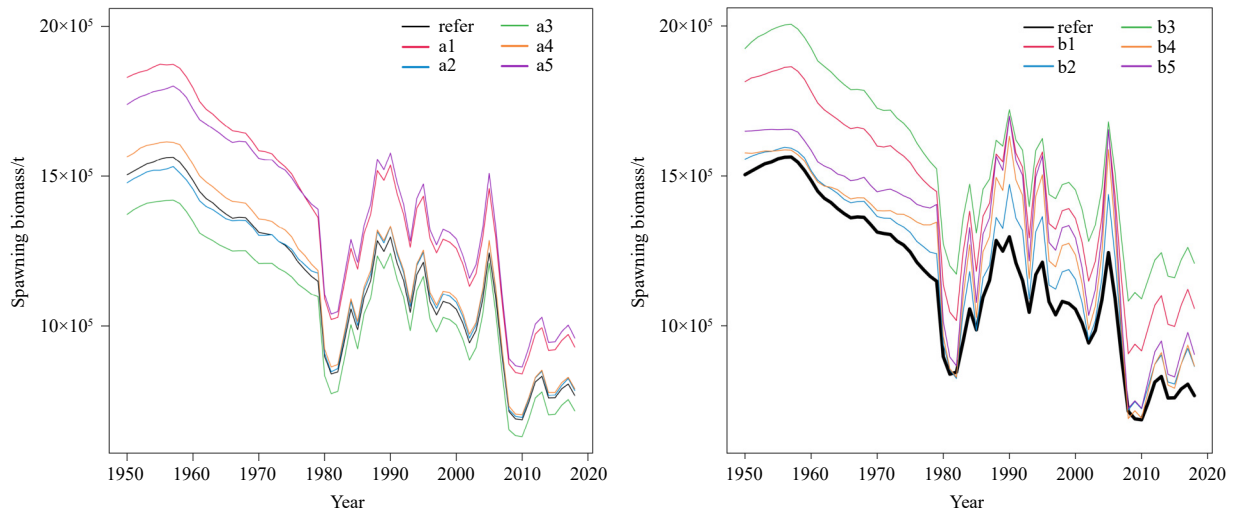


Fig. 7. Biomass of base case (Scenario S3) and different sensitivity scenarios in the JABBA-Select model for Atlantic yellowfin tuna.

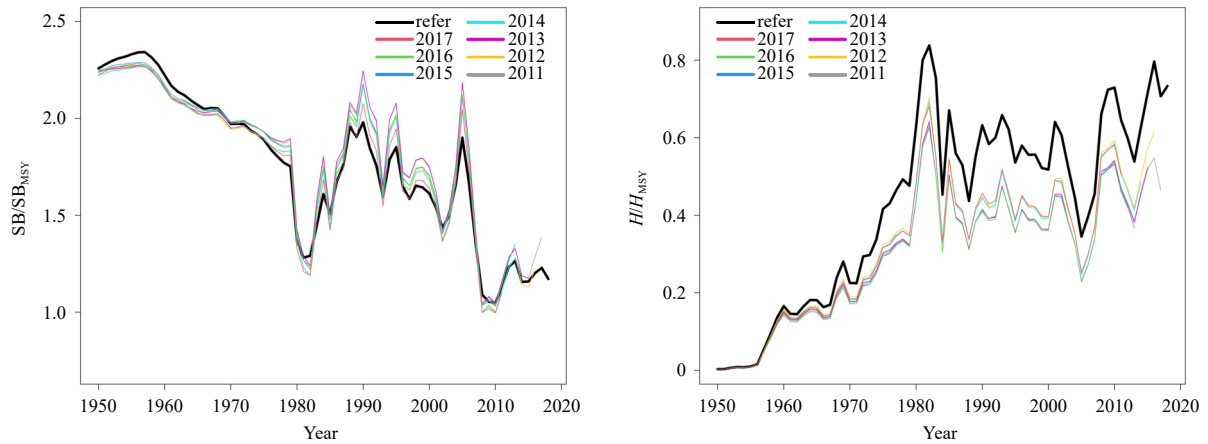


Fig. 8. Retrospective analysis of SB/SB_{MSY} and H/H_{MSY} of base case (Scenario S3) in the JABBA-Select model for Atlantic yellowfin tuna.

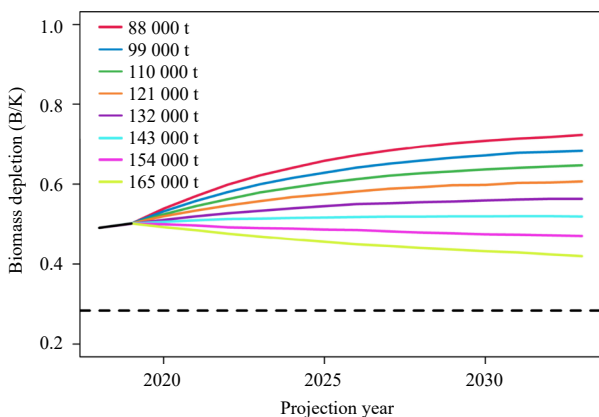


Fig. 9. Projection of biomass depletion rate of base case (Scenario S3) in the JABBA-Select model for Atlantic yellowfin tuna. B/K represent biomass/carrying capacity.

assessment, and caused fluctuated SB/H trajectory and a disordered Kobe plot. The selected base case model includes three longline CPUE series, while the purse seine CPUE was excluded. The CPUE standardization process is difficult to conduct for purse seine fishery, failing to represent the trend of actual abundance. The model performing and comparison results are also

consistent with the general characteristics of CPUE from purse seine fishery.

The results of base case model show that the estimated median intrinsic rate $r=0.24$, similar with (Sant’Ana et al. 2020) (range 0.156–0.290) but lower than that information from Fishbase (0.57), while the estimated carrying capacity K and MSY are much higher (Walter and Sharma, 2017). This information indicates that there might be data misspecification or inappropriate assumption for selectivity (Butterworth et al., 2014).

Impact of selectivity-dependent distortion to stock showed that EB/SB becomes increasingly disproportionate towards lower biomass levels as age-at-selectivity generally diverges from age-at-maturity. Logistic and dome-shaped selectivity can generate great difference on estimates of fishing mortality, absolute abundance, and stock status (Punt et al., 2014a), which was also revealed by the results of sensitivity analyses. More complex dome-shaped selectivity is worth to explore in the future research when related information is available, but not limit to the logistic selectivity in this study. Furthermore, considering that largest size classes of fish are not fully retained by the gear, non-parametric or semi-parametric may be more fit to Atlantic yellowfin tuna compared to the parametric model for selectivity (Thorson and Taylor, 2014).

Intuitive visual figures and near to zero values of Mohn ρ in-

indicated that base case model doesn't have retrospective problems basically. The slightly changes observed in H/H_{MSY} and SB/SB_{MSY} may be caused by large variations of catch data in recent years, especially for the model that backwards to 2017. The time slicing possibly reduce retrospective patterns (Guan et al., 2012), but due to limited information about selectivity changes, subjective modelling might lead to high uncertainty and produce biased management quantities (Butterworth and Punt, 1990, Szuwalski et al., 2018). Additionally, allowing natural mortality to vary may reduce retrospective patterns (Szuwalski et al., 2018).

Most stock assessment models assume natural mortality and steepness constant, considering the high difficulty for M estimation and moderate-low precision and moderate-high bias of h estimation (Lee et al., 2012; Hurtado-Ferro et al., 2015). Sensitivity analyses towards the assumptions of M and h are conducted in this research by JABBA-Select. The results showed that base case model is robust to h but sensitive to M , and the current relative values (SB_{2018}/SB_{MSY} and H_{2018}/H_{MSY}) are more stable than absolute quantities (MSY etc.). Scenarios with relative high h (0.8, 0.9) or wild-range M (0.25, 0.35, 0.45, 0.55) generate similar spawning biomass with Scenario S3, indicates high robustness of stock assessment for Atlantic yellowfin tuna. In this case, the precision of

input M needs improvement when conducting stock assessment and providing management advice for Atlantic yellowfin tuna. Considering the variations in fish population dynamics (Hurtado-Ferro et al., 2015; Thorson et al., 2019), time-varying M and h could be explored to reduce bias and to better reflect the uncertainties in the future research (Szuwalski et al., 2018).

Posterior and prior densities of parameters showed that posterior and prior of SB_0 have a big difference, indicating that data input provides sufficient information for the Bayesian analysis. On the other hand, the prior used was informative for H_{MSY} and m , revealing that H_{MSY} and m generated from ASEM were precise enough for Atlantic yellowfin tuna (Winker et al., 2020).

Formulation of a multivariate normal (MVN) prior and Monte-Carlo simulations (Fig. 10b) showed that H_{MSY} and m have logarithmic negative correlations which verify the consequence of specifying a Beverton-Holt stock recruit function (Winker et al., 2020). Since both H_{MSY} and m are generated from ASEM that incorporated all life-history parameters, it's difficult to recognize which parameter is more influential. It is important to improve the accuracy of these input parameters, in order to have a smooth model estimation process and to constrain the production function in JABBA-Select (Winker et al., 2020).

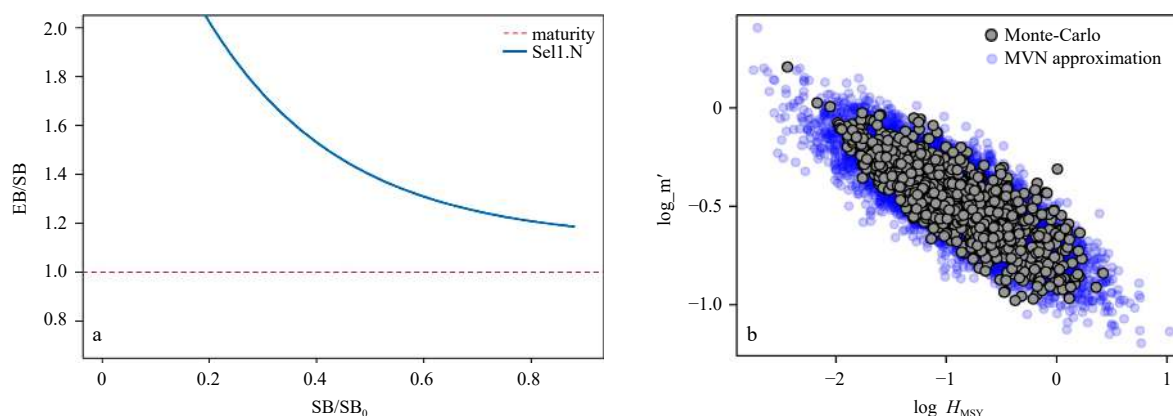


Fig. 10. Selectivity-dependent distortion in the EB/SB over a wide range of SB/SB_0 and multivariate normal (MVN) approximation of $\log_{H_{MSY}}$ and $\log_{m'}$, random deviates generated from the ASEM via Monte-Carlo simulations.

Compared to traditional SPMs, JABBA-Select could estimate the exploitable biomass and spawning biomass separately, which could be directly compared with the results from age-structured assessment model like SS3 (Fig. 49 in Walter, 2019), which is not commonly used for many tuna species in RFMOs. JABBA-Select performed at least as well as the ASPM in terms of point estimation and outperformed ASPM in terms of quantifying uncertainty. Considering available data of Atlantic yellowfin tuna, SS3 incorporate multiple-source data (fishery data and tagging data from Atlantic Ocean Tropical Tuna Tagging Programme) covering different regions. Therefore, too much difficulties exist during the process of SS3, with more uncertainties (Lee et al., 2020; Hilborn, 2001). The management of Atlantic yellowfin tuna is conducted with TAC, and JABBA-Select is more efficient to meet the needs. Furthermore, the ASEM constructed in the JABBA-Select provides an alternative way to derive informative prior distribution of shape parameter m and intrinsic rate r instead of other complex methods like meta-analysis, but it requires additional information about M and h (Foss-Grant et al., 2016). Meanwhile, uncertainty about M may also indirectly produced by growth, maturation, and longevity in the form of the H_{MSY} prior variance. Therefore, extending ASEM to incorporate uncertainty about

more life history parameters as well as selectivity should be considered in future research.

In conclusion, the stock status of Atlantic yellowfin tuna is healthy and the current TAC is going to achieve ICCAT's conservation goal. Given the fishery data, life history parameters and selectivity information, JABBA-Select provided substantial assessment results and referable information for the conservation and management of Atlantic yellowfin tuna. Overall, based on the tested scenarios, observed performances, time efficiency and ease to operate (Winker et al., 2020), we recommend JABBA-Select as an alternative compromise approach between SPMs and age-structured models in future stock assessment and scientific fishery management.

Acknowledgements

We appreciate ICCAT's supporting for data sharing, and gratefully thank Kindong Richard and Dongyan Han for their efforts to improve the manuscript.

References

Butterworth D S, Punt A E. 1990. Some preliminary examinations of the potential information content of age-structure data from

- Antarctic minke whale research catches. Reports-International Whaling Commission, 40: 301–315
- Butterworth D S, Rademeyer R A, Brandão A, et al. 2014. Does selectivity matter? A fisheries management perspective. *Fisheries Research*, 158: 194–204, doi: [10.1016/j.fishres.2014.02.004](https://doi.org/10.1016/j.fishres.2014.02.004)
- Carruthers T R, Punt A E, Walters C J, et al. 2014. Evaluating methods for setting catch limits in data-limited fisheries. *Fisheries Research*, 153: 48–68, doi: [10.1016/j.fishres.2013.12.014](https://doi.org/10.1016/j.fishres.2013.12.014)
- Chang Yi-Jay, Brodziak J, O'Malley J, et al. 2015. Model selection and multi-model inference for Bayesian surplus production models: a case study for Pacific blue and striped marlin. *Fisheries Research*, 166: 129–139, doi: [10.1016/j.fishres.2014.08.023](https://doi.org/10.1016/j.fishres.2014.08.023)
- Costello C, Ovando D, Hilborn R, et al. 2012. Status and solutions for the world's unassessed fisheries. *Science*, 338(6106): 517–520, doi: [10.1126/science.1223389](https://doi.org/10.1126/science.1223389)
- Diaha N C, Zudaire I, Chassot E, et al. 2015. Present and future of reproductive biology studies of yellowfin tuna (*Thunnus albacares*) in the eastern Atlantic Ocean. *Collective Volume of Scientific Papers ICCAT*, 71(1): 489–509
- Foss-Grant A P, Zipkin E F, Thorson J T, et al. 2016. Hierarchical analysis of taxonomic variation in intraspecific competition across fish species. *Ecology*, 97(7): 1724–1734, doi: [10.1890/15-0733.1](https://doi.org/10.1890/15-0733.1)
- Froese R, Demirel N, Coro G, et al. 2017. Estimating fisheries reference points from catch and resilience. *Fish and Fisheries*, 18(3): 506–526, doi: [10.1111/faf.12190](https://doi.org/10.1111/faf.12190)
- Galland G, Rogers A, Nickson A. 2016. *Netting Billions: A Global Valuation of Tuna*. Washington: The Pew Charitable Trust
- Geweke J. 1991. Evaluating the accuracy of sampling-based approaches to the calculation of posterior moments. Minneapolis: Federal Reserve Bank of Minneapolis
- Guan Wenjiang, Gao Feng, Lei Lin, et al. 2012. Retrospective problem in fishery stock assessment. *Journal of Shanghai Ocean University*, 21(5): 841–847
- Guéry L. 2020. SCRS/2019/066. Accounting for fishing days without a fishing set in the CPUE standardization of yellowfin tuna in free schools for the EU purse seine fleet operating in the eastern Atlantic Ocean during the 1993–2018 PERIOD. *Collective Volume of Scientific Papers ICCAT*, 76(6): 294–320
- Heidelberger P, Welch P D. 1983. Simulation run length control in the presence of an initial transient. *Operations Research*, 31(6): 1109–1144, doi: [10.1287/opre.31.6.1109](https://doi.org/10.1287/opre.31.6.1109)
- Hilborn R. 2001. Calculation of biomass trend, exploitation rate, and surplus production from survey and catch data. *Canadian Journal of Fisheries and Aquatic Sciences*, 58(3): 579–584
- Hoyle S D, Lauretta M, Lee M K, et al. 2019. Collaborative study of yellowfin tuna CPUE from multiple Atlantic Ocean longline fleets in 2019. *Collective Volume of Scientific Papers ICCAT*, 76(6): 241–293
- Hurtado-Ferro F, Szuwalski C S, Valero J L, et al. 2015. Looking in the rear-view mirror: bias and retrospective patterns in integrated, age-structured stock assessment models. *ICES Journal of Marine Science*, 72(1): 99–110, doi: [10.1093/icesjms/fsu198](https://doi.org/10.1093/icesjms/fsu198)
- ICCAT. 2016. Report of the 2016 ICCAT Yellowfin Tuna Data Preparatory Meeting. San Sebastian: International Committee and Conservation of Atlantic Tunas
- ICCAT. 2019a. Report of the Standing Committee on Research and Statistics (SCRS). Madrid: International Committee and Conservation of Atlantic Tunas
- ICCAT. 2019b. Report of the 2019 ICCAT Yellowfin Tuna Stock Assessment Meeting. Grand-Bassam: International Committee and Conservation of Atlantic Tunas
- ICCAT. 2019c. Report of the 2019 ICCAT Yellowfin Tuna Data Preparatory Meeting. Madrid: International Committee and Conservation of Atlantic Tunas
- Kolody D S, Eveson J P, Preece A L, et al. 2019. Recruitment in tuna RFMO stock assessment and management: a review of current approaches and challenges. *Fisheries Research*, 217: 217–234, doi: [10.1016/j.fishres.2018.11.031](https://doi.org/10.1016/j.fishres.2018.11.031)
- Langley A. 2019. Stock assessment of albacore tuna in the Indian Ocean using Stock Synthesis for 2019. IOTC-2019-WPTmT07 (AS)-11. <https://iotc.org/sites/default/files/documents/2019/07/IOTC-2019-WPTmT07AS-11.pdf>[2019-07-09/2021-03-05]
- Lee Q, Lee A, Liu Zunlei, et al. 2020. Life history changes and fisheries assessment performance: a case study for small yellow croaker. *ICES Journal of Marine Science*, 77(2): 645–654, doi: [10.1093/icesjms/fsz232](https://doi.org/10.1093/icesjms/fsz232)
- Lee Hui-Hua, Maunder M N, Piner K R, et al. 2012. Can steepness of the stock-recruitment relationship be estimated in fishery stock assessment models?. *Fisheries Research*, 125–126: 254–261
- Lewy P, Nielsen A. 2003. Modelling stochastic fish stock dynamics using Markov Chain Monte Carlo. *ICES Journal of Marine Science*, 60(4): 743–752, doi: [10.1016/S1054-3139\(03\)00080-8](https://doi.org/10.1016/S1054-3139(03)00080-8)
- Matsumoto T, Satoh K. 2017. Stock assessment for Atlantic yellowfin tuna using a non-equilibrium production model. *Collective Volume of Scientific Papers ICCAT*, 73(2): 451–474
- Maunder M N. 2002. The relationship between fishing methods, fisheries management and the estimation of maximum sustainable yield. *Fish and Fisheries*, 3(4): 251–260, doi: [10.1046/j.1467-2979.2002.00089.x](https://doi.org/10.1046/j.1467-2979.2002.00089.x)
- McAllister M K, Pikitch E K, Babcock E A. 2001. Using demographic methods to construct Bayesian priors for the intrinsic rate of increase in the Schaefer model and implications for stock rebuilding. *Canadian Journal of Fisheries and Aquatic Sciences*, 58(9): 1871–1890
- Merino G, Urtizberea A, Murua H, et al. 2019. Stock assessment for Atlantic yellowfin using a biomass production model. IOTC-2019-WPTT-49. <https://iotc.org/sites/default/files/documents/2019/10/IOTC-2019-WPTT21-49.pdf>[2019-10-10/2021-05-10]
- Millar R B, Meyer R. 2000. Non-linear state space modelling of fisheries biomass dynamics by using Metropolis-Hastings within-Gibbs sampling. *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, 49(3): 327–342, doi: [10.1111/1467-9876.00195](https://doi.org/10.1111/1467-9876.00195)
- Mohn R. 1999. The retrospective problem in sequential population analysis: an investigation using cod fishery and simulated data. *ICES Journal of Marine Science*, 56(4): 473–488, doi: [10.1006/jmsc.1999.0481](https://doi.org/10.1006/jmsc.1999.0481)
- Narvaez M. 2020. SCRS/2019/123. Standardized catch rates for yellowfin tuna (*Thunnus albacares*) from the Venezuelan pelagic longline fishery in the Caribbean Sea and adjacent waters of the western central Atlantic for the period of 1991–2018. *Collective Volume of Scientific Papers ICCAT*, 76(6): 662–673
- Omori K L, Hoenig J M, Luehring M A, et al. 2016. Effects of underestimating catch and effort on surplus production models. *Fisheries Research*, 183: 138–145, doi: [10.1016/j.fishres.2016.05.021](https://doi.org/10.1016/j.fishres.2016.05.021)
- Pella J J, Tomlinson P K. 1969. A generalized stock production model. *Inter-American Tropical Tuna Commission Bulletin*, 13(3): 416–497
- Punt A E, Hilborn R. 1997. Fisheries stock assessment and decision analysis: the Bayesian approach. *Reviews in Fish Biology and Fisheries*, 7(1): 35–63, doi: [10.1023/A:1018419207494](https://doi.org/10.1023/A:1018419207494)
- Punt A E, Hurtado-Ferro F, Whitten A R. 2014a. Model selection for selectivity in fisheries stock assessments. *Fisheries Research*, 158: 124–134, doi: [10.1016/j.fishres.2013.06.003](https://doi.org/10.1016/j.fishres.2013.06.003)
- Punt A E, Smith A D M, Smith D C, et al. 2014b. Selecting relative abundance proxies for B_{MSY} and B_{MEY} . *ICES Journal of Marine Science*, 71(3): 469–483, doi: [10.1093/icesjms/fst162](https://doi.org/10.1093/icesjms/fst162)
- Punt A E, Su Nan-Jay, Sun Chilu. 2015. Assessing billfish stocks: a review of current methods and some future directions. *Fisheries Research*, 166: 103–118, doi: [10.1016/j.fishres.2014.07.016](https://doi.org/10.1016/j.fishres.2014.07.016)
- R Core Team. 2013. R: a language and environment for statistical computing. In: R Foundation for Statistical Computing. <http://www.R-project.org/>[2017-06-30/2021-04-28]
- Rankin P S, Lemos R T. 2015. An alternative surplus production model. *Ecological Modelling*, 313: 109–126, doi: [10.1016/j.ecolmod.2015.06.024](https://doi.org/10.1016/j.ecolmod.2015.06.024)
- Restrepo V R, Legault C M. 1998. A stochastic implementation of an age-structured production model. *Fishery Stock Assessment Models*, AK-SG-98-01: 435–450
- Sant'Ana R, Mourato B, Kimoto A, et al. 2020. Atlantic yellowfin tuna stock assessment: an implementation of Bayesian state-space surplus production model using JABBA. *Collective Volume of*

- Scientific Papers ICCAT, 76(6): 699–724
- Satoh K, Yokoi H, Nishida T, et al. 2017. SCRS/2016/111. Stock assessment for Atlantic yellowfin tuna using age structured production model. *Collective Volume of Scientific Papers ICCAT*, 73(2): 577–631
- Stewart I J, Martell S J D. 2014. A historical review of selectivity approaches and retrospective patterns in the Pacific halibut stock assessment. *Fisheries Research*, 158: 40–49, doi: [10.1016/j.fishres.2013.09.012](https://doi.org/10.1016/j.fishres.2013.09.012)
- Szuwalski C S, Ianelli J N, Punt A E. 2018. Reducing retrospective patterns in stock assessment and impacts on management performance. *ICES Journal of Marine Science*, 75(2): 596–609, doi: [10.1093/icesjms/fsx159](https://doi.org/10.1093/icesjms/fsx159)
- Thorson J T, Cope J M, Branch T A, et al. 2012. Spawning biomass reference points for exploited marine fishes, incorporating taxonomic and body size information. *Canadian Journal of Fisheries and Aquatic Sciences*, 69(9): 1556–1568, doi: [10.1139/f2012-077](https://doi.org/10.1139/f2012-077)
- Thorson J T, Rudd M B, Winker H. 2019. The case for estimating recruitment variation in data-moderate and data-poor age-structured models. *Fisheries Research*, 217: 87–97, doi: [10.1016/j.fishres.2018.07.007](https://doi.org/10.1016/j.fishres.2018.07.007)
- Thorson J T, Taylor I G. 2014. A comparison of parametric, semi-parametric, and non-parametric approaches to selectivity in age-structured assessment models. *Fisheries research*, 158: 74–83, doi: [10.1016/j.fishres.2013.10.002](https://doi.org/10.1016/j.fishres.2013.10.002)
- Tropical Tunas Species Group. 2012. SCRS/2011/205. Alternative virtual population analyses of yellowfin tuna (*Thunnus albacares*), 1970–2010. ICCAT, 68(3): 1044–1059
- Walter J. 2019. SCRS/2019/121. Stock synthesis model for Atlantic yellowfin tuna. ICCAT, 76(6): 558–639
- Walter J, Sharma R. 2017. Atlantic Ocean yellowfin tuna stock assessment 1950–2014 using stock synthesis. *Collective Volume of Scientific Papers ICCAT*, 73(2): 510–576
- Wang Shengping, Maunder M N, Aires-da-Silva A. 2014. Selectivity's distortion of the production function and its influence on management advice from surplus production models. *Fisheries Research*, 158: 181–193, doi: [10.1016/j.fishres.2014.01.017](https://doi.org/10.1016/j.fishres.2014.01.017)
- Winker H, Carvalho F, Kapur M. 2018. JABBA: just another Bayesian biomass assessment. *Fisheries Research*, 204: 275–288, doi: [10.1016/j.fishres.2018.03.010](https://doi.org/10.1016/j.fishres.2018.03.010)
- Winker H, Carvalho F, Thorson J T, et al. 2020. JABBA-Select: incorporating life history and fisheries' selectivity into surplus production models. *Fisheries Research*, 222: 105355, doi: [10.1016/j.fishres.2019.105355](https://doi.org/10.1016/j.fishres.2019.105355)
- Winker H, Kerwath S E, Attwood C G. 2013. Comparison of two approaches to standardize catch-per-unit-effort for targeting behaviour in a multispecies hand-line fishery. *Fisheries Research*, 139: 118–131, doi: [10.1016/j.fishres.2012.10.014](https://doi.org/10.1016/j.fishres.2012.10.014)
- Xu Luoliang, Li Bai, Chen Xinjun, et al. 2019. A comparative study of observation-error estimators and state-space production models in fisheries assessment and management. *Fisheries Research*, 219: 105322