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Stock assessment of Indian Ocean bigeye tuna using integrated model - implication of considering bias in catch data

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Summary

Bigeye tuna (BET), Thunnus obesus distributes in the tropical and subtropical waters of Indian Ocean. Because of a variety of fishing gears and fishing fleet structures, there remain statistical biases in the historical nominal catches of the Indian Ocean BET. However, the impact of this bias on stock assessment has been neglected in recent years' assessments. This paper investigated the impacts of observation error and statistical bias of catch on the stock assessment of Indian Ocean BET, using Age Structured Assessment Program (ASAP) based on fishery-specific catch, catch-at-age, and standardized catch-per-unit-effort data. The results showed that the current stock of BET was not overfished and overfishing was not likely occurring at the beginning of 2015 (base case model). However, the results of base model and sensitivity analysis models showed that both the observation error and the statistical bias associated with catch data can have impacts on assessment results, with the latter being more influential. Thus, this study highlights the importance of considering both the assumptions of observation error and statistical bias in catch data for tuna fishery stock assessment, with the latter often being neglected.

1 Introduction

Bigeye tuna (BET), *Thunnus obesus* is an important commercial species distributed in tropical and subtropical waters of Indian Ocean. Its stock status has been the focus of regional tuna fisheries management organizations. Recently, stock assessments of Indian Ocean BET have been conducted using ASPIC (A Stock-Production Model Incorporating Covariates) (Matsumoto, 2016), SS (Stock Synthesis) (Langley *et al*, 2013a), ASPM (Age structured production model) (Nishida & Iwasaki, 2013), and ASAP (Age Structured Assessment Program) (Zhu, 2016). Because of a variety of fishing gears and fishing fleet structures, there remain some statistical biases in the historical nominal catches (under-reported or over-reported) of the Indian Ocean BET, and they are often neglected in recent stock assessments. The objective of this paper is to investigate the impacts of observation error and statistical bias of catch on the stock assessment of Indian Ocean BET, using Age Structured Assessment Program (ASAP) based on fishery-specific catch, catch-at-age, and standardized catch-per-unit-effort data.

2 Material and Methods

2.1 Fisheries data

In this paper, Indian Ocean BET are assumed to be subject to 7 fisheries, i.e., Deep longline fishery (LL), Purse seine fishery of free-school (PSFS), Purse seine fishery of associated-school (PSLS), Pole-and-line and small seine fisheries (BB), Fresh longline fishery (FL), Line fishery (LINE), and Other fishery (OTHER), according to the available datasets provided by the IOTC Secretariat for 18th WPTT. The data sets included in the stock assessment were fishery-specific catch, standardized longline CPUEs, and catch-at-age data for 1979-2015. The standardized longline CPUE using joint fishery data from the main longline fleets were used as abundance indices for fitting the model. Two abundance index series were available, i.e., the index series for northwest (R1) and northeast (R2) waters in the Indian Ocean (**Figure 1**).

2.2 Biological parameters and assumptions

Genetic studies have suggested that there is only one population of bigeye tuna in the Indian Ocean (Appleyard *et al*., 2002; Chiang *et al*., 2008). Thus, a single stock was assumed in this study. We used classical Von Bertalanffy growth function to model BET growth (Laslett *et al*, 2008). The weight-fork length (*W-L*) relationship is $W = 3.661 * 10^{-5} L^{2.901}$. Beverton-Holt stock-recruitment relationship (*S-R*) was assumed and the steepness (*h*) parameter was assumed to be 0.8 for the purpose of this investigation.

2.3 Model and parameter estimates

In this paper, we used ASAP (a program for statistical age-structured catch-at-age analysis) (NOAA Fisheries Toolbox, 2014) as assessment model. The ASAP model is a formal stock assessment model and has been used for assessing many commercially exploited stocks, e.g., red grouper, yellowtail flounder, Pacific sardine, Greenland halibut, Gulf of Maine cod, Florida lobster (see NOAA Fisheries Toolbox at http://nft.nefsc.noaa.gov).

ASAP is an age-structured model that uses forward computations assuming separability of fishing mortality into year and age components to estimate population sizes, given observed catches, catch-at-age, and indices of abundance data. The objective function in parameter estimate is the sum of a number of model fits and two penalties. The model parameters are estimated by using maximum likelihood. There are two types of error distributions in the calculation of likelihood function: multinomial and lognormal. The multinomial distribution is assumed for catch-at-age data, with effective sample size (*ESS*) iteratively adjusted based on initial model runs. The lognormal error distribution is assumed for annual catch (in weight), abundance indices and stock-recruitment relationship (recruitment deviation). And the main impact factor of lognormal likelihood function is the standard deviation of the log-transformed error distribution. In the ASAP model, the coefficient of variation (*CV*) instead of standard deviation needs to be assumed and adjusted. The multinomial likelihood function is calculated as

$$-ln(L) = -ln(ESS!) + \sum ln(C_i!) - ESS \sum p_i \, ln(predp_i) \qquad (1)$$

where $\ln(L)$ denotes log likelihood, C_i denotes the i-year-old catch, p_i denotes the observed proportion of i-year-old catch, and $predp_i$ denotes the predicted proportion of i-year-old catch. The lognormal likelihood function is calculated as

$$-ln(L) = 0.5\, ln(2\pi) + \sum ln(obs_i) + ln(\sigma) + 0.5 \sum \frac{[ln(obs_i) - \ln(pred_i)]^2}{\sigma^2} \qquad (2)$$

where obs_i and $predp_i$ denote the observations and model estimations of the i-th data, σ denotes the standard deviation. The objective function of bigeye tuna ASAP model is calculated as

$$\text{objective function} = \lambda_j \sum [-\ln(L)]_j \qquad (3)$$

Where λ_j denotes the j-th weight coefficient of likelihood function. The parameters that need to be estimated in the ASAP model include recruitment in each year from 1979 through 2015 (*CV*=0.6 for log-tranformed recruitment deviations), catchability coefficients (*q*, constant over time) for the abundance indices, selectivity curves for the 7 fisheries, effective sample size (*ESS*) for catch-at-age for each fishery, initial population size, and fully recruited fishing mortality (*Fmult*) for each fishery for the first year and deviations for *Fmult* for the remaining years. The parameters assumed to be known included the length-at-age, weight-at-age, age-specific maturity, age-specific natural mortality rates, deviation for indices of abundance, and steepness of the stock-recruitment relationship.

2.4 Uncertainty quantification of catch and scenario design

In this study we investigated the impacts of *CVs* and statistical (reporting) bias of annual catch data on the results of stock assessments. The *CV* for annual catch data in the initial model run was assumed to be 0.1 (base case) for each of seven fisheries and constant for the whole time period. Adjustment was made according to the diagnostic results for the residual pattern and root mean square error (RMSE). The statistical bias in the annual catch could be under-reported or over-reported, based on the catch reporting analysis conducted by the IOTC secretariat. Thus, to address the potential impact derived from this error, we adjusted the catch data by increasing or decreasing by a percentage of the original catch. In total, we designed 13 models including 1 base case and 12 sensitivity analysis models (**Table 1**).

3 Results and discussion

3.1 Impact of catch error on model fit

In the 13 models, 9 models were converged. Convergence was the first signal to perceive if the model might be mis-specified. For the following analysis, we only considered converged models. Model fit diagnostics was done by looking at the residual patterns of abundance index, catch, and effective sample size. The base case model showed that the model fit the longline CPUE indices well, except for the early years (1979-1982) (**Figure 2**). The residuals between observed and estimated longline CPUE indices are shown in **Figure 3 and 4**. The index of Northwest fit better than the index of Northeast (**Figure 2**). This is possibly because the northwest Indian Ocean is the main longling fishing area for BET. The observed and predicted catch for the base case was shown in **Figure 5**. The model fit summaries are shown in **Table 2**. Overall, it seemed that the differences in catch error did not significantly impact the fit quality of abundance indices.

3.2 Impact of catch error on estimates of *F* and *SSB*

The estimated fishing mortality for each model was shown in **Figure 6**. By comparing the fishing mortality between the 8 sensitivity analysis models and the base case model, it is found that the fishing mortalities of all models were in the same trend. The fishing mortality increased gradually from 1979 to early 1990s, followed by a steep increase during the mid- and late-1990s. The fishing mortality since 2000 stayed at a relative high level, with slight annual variations. In the cases of CV = 0.05 and CV = 0.15, the estimated values of fishing mortality were very close to the values of base case model, and the trend was basically the same. However, the fishing mortality of Model 8 since 1983 was much lower than that of other models. This needs to be further investigated. Overall, the catch observation error and reporting bias seemed not to be impacting the fishing mortality estimates significantly, except for Model 8.

The estimated spawning stock biomass (*SSB*) for each model was shown in **Figure 7**. The *SSB*s of all models have the same trend. In contrast to the fishing mortality trend, the *SSB* has been declining since 1980s, although there was a short-term increase from 1979 to the mid-1980s. Except for Model 9, the *SSB* in 2015 was lower than the level of *MSY*. In the cases of CV = 0.05 and CV = 0.15, there was no obvious difference in the *SSB* between the sensitivity analysis models and the base case model. The *SSB* was the lowest when the reporting bias in catch is reduced by 15% (Model 9). Overall, the estimates of *SSB* were more impacted by the reporting bias than the observation error in the catch data.

3.2 Impact of catch error on BRPs and stock status determination

The biological reference points and related quantities from each assessment model were shown in **Table 3**. From the base case model (Model 2), F_{2015}/F_{MSY} was estimated to be 1.0, C_{curr}/MSY was estimated to be 1.02, and SSB_{2015}/SSB_{MSY} was estimated to be 1.18. Thus it is indicated that the current stock of BET in the Indian Ocean was not overfished and overfishing was not likely occurring at the beginning of 2015.

For the observation error of catch, by comparing the Models 1-3, it was found that the change of *CV* in the observation error of catch had obvious impacts on the *MSY* and the associated reference points. When the *CV* increased or decreased, the reference point *MSY*, F_{MSY}, SSB_{MSY} reduced and the C_{curr}/MSY and F_{curr}/F_{MSY} increased. The estimate of SSB_0 increased with the increase of *CV*. A comparison of F_{curr}/F_{MSY} and SSB_{curr}/SSB_{MSY} (Model 1-3) showed that when *CV* increases or decreases, the current resource status was determined to be overfishing.

For the statistical bias of catch, higher increases in catch resulted in greater MSY estimates. When the statistical bias was assumed to be 15%, the assessment results are basically consistent with the base case model. The values of F_{curr}/F_{MSY} indicated that the stock tended to be overfishing if the level of statistical bias was assumed to be 20% (**Table 3)**. While under the other assumptions (10%, 15%, -15%), the results of the stock assessment did not change significantly, compared with the base case model. To further investigate the impacts of statistical bias, we also adjusted the catch by 16%, 17%, 18%, 19% and found that the stock was also not overfishing for each of these adjustment levels. Therefore, the statistical bias of less than 20% will not impact the determination of stock status in terms of overfishing.

However, when considering stock status using Kobe plots (**Figure 10**), it can be seen that both observation error and statistical bias of catch have obvious impacts on the overall determination of stock status in terms of overfishing and/or overfished. Thus, this study highlights the importance of considering both the assumptions of observation error and statistical bias in catch data for tuna fishery stock assessment, with the latter often being neglected.

4 Future works

The purpose of this study is only to show the potential impacts of catch error on stock assessment. However, the ground truth of the underlying population dynamics is unknown. In the future analysis, we will use simulation approach to explore the impact of catch error on stock assessment of BET. The operating model can be developed using POPSIM or other related models, and conditioned on the recent stock assessment. The goal is to understand when and how the mis-specifications of uncertainties in catch data can impact the stock assessment for stocks like bigeye tuna, and to develop management advice robust to this source of uncertainty.

Acknowledgement

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References

Appleyard SA, Ward RD, Grewe PM. Genetic stock structure of bigeye tuna in the Indian Ocean using mitochondrial DNA and microsatellites. Journal of Fish Biology, 2002, 60(3):767-770.

Adam L. Stock assessment of bigeye tuna (*Thunnus obesus*) in the Indian Ocean for 2016.IOTC – 2016– WPTT18-20, 2016:66-69.

Chiang HC, Hsu CC, Wu GC, et al. Population structure of bigeye tuna (*Thunnus obesus*) in the Indian Ocean inferred from mitochondrial DNA. Fisheries Research, 2008, 90: 305–312.

Hoyle SD, Kim D, Lee S, et al. Collaborative study of tropical tuna CPUE from multiple Indian Ocean longline fleets in 2016. IOTC–2016–WPTT18–14, 2016.

IOTC. Review of the statistical data and fishery trends for tropical tuna. IOTC-2016- WPTT18-07, 2016:6-13.

Langley A, Herrera M, Sharma R. Stock assessment of bigeye tuna (*Thunnus obesus*) in the Indian Ocean for 2012. IOTC–2013–WPTT15–30, 2013.

Laslett GM, Eveson JP, Polacheck T. Growth of tropical tunas using the Laslett, Polacheck and Eveson (LEP) method. IOTC-2008-WPTT-09, 2008.

Motomura T. Stock and risk assessments of bigeye tuna in the Indian Ocean based on ASPIC. IOTC-2016-WPTT18-17, 2016.

Nakatani T, Kimball DF, Larson LE, et al. Stock assessment of bigeye tuna (*Thunnus obesus*) resources in the indian ocean by the age structured production model(ASPM) analyses.IOTC, 2001, 5(3): Proceedings.

Nishida T, Rademeyer R. Stock and risk assessments on bigeye tuna (*Thunnus obesus*) in the

Indian Ocean based on AD Model Builder implemented Age-Structured Production Model (ASPM). IOTC-2011-WPTT-42, 2011.

Nishida T, Iwasaki K. Stock and risk assessment of bigeye tuna (*Thunnus obesus*) in the Indian Ocean by Age-Structured Production Model (ASPM). IOTC-2013-WPTT15-31,2013.

NOAA Fisheries Toolboxathttp://nft.nefsc.noaa.gov.

Shono H, Satoh K, Okamoto H, et al. Updated stock assessment for bigeye tuna (*Thunnus obesus*) in the Indian Ocean up to 2008 using Stock Synthesis III (SS3). IOTC-2009-WPTT-20, 2009.

Zhu JF, Guan WJ, Tian SQ, et al. Stock assessment of bigeye tuna (*Thunnus obesus*) in the Indian Ocean using ASAP. IOTC–2013–WPTT15–28, 2013.

Zhu JF. Stock assessment of Indian Ocean bigeye tuna (*Thunnus obesus*) using Age-Structured Assessment Program. IOTC-2016-WPTT18-14, 2016:11-13.

Table 1. Base case model and sensitivity models for bigeye tuna

Model	*CV*	Time perid of catch	Adjust level for catch	Yes for converged
Model 1	0.05	1979-2015	--	Yes
Model 2 (Base case)	0.1	1979-2015	--	Yes
Model 3	0.15	1979-2015	--	Yes
Model 4	0.1	1979-2015	10%	Yes
Model 5	0.1	1979-2015	15%	Yes
Model 6	0.1	1979-2015	20%	Yes
Model 7	0.1	1979-2015	-15%	Yes
Model 8	0.1	1979-1983	-10%	Yes
		1984-1995	15%	
		1996-2012	20%	
		2013-2015	-10%	
Model 9	0.1	1979-1983	10%	Yes
		1984-1995	15%	
		1996-2012	20%	
		2013-2015	-10%	
Model 10	0.2	1979-2015	--	No
Model 11	0.25	1979-2015	--	No
Model 12	0.1	1979-2015	-10%	No
Model 13	0.1	1979-2015	-20%	No

Table 2. Model fit summary

Lambda		Objective function	Catch	Index	Age comps	Recruit devs	Penalty
		--	7	2	--	1	1000
CV	Model 1	5765.3	1703.7	54.1	3552.9	454.6	0
	Model 2	5725.7	1887.7	31.5	3352.7	453.8	0
	Model 3	6024.9	1995.8	37.3	3537.2	454.7	0
Catch	Model 4	5961.2	1912.6	44.6	3545.4	458.6	0
	Model 5	5972.8	1924.1	44.7	3543.9	460.2	0
	Model 6	5774.3	1937.9	38.2	3338.2	460.1	0
	Model 7	5883.4	1845.9	44.8	3543.7	448.9	0
	Model 8	6731.7	1920.2	59.4	4300.4	451.7	0
	Model 9	5979.4	1923.5	46.7	3547.8	461.4	0

Table 3. Biological reference points and related quantities from each assessment model

Model	MSY(t)	$Ccurr/MSY$	F_{MSY}	$Fcurr/F_{MSY}$	SSB_{MSY}(t)	$SSBcurr/SSB_{MSY}$	SSB_0(t)	$SSBcurr/SSB_0$
Model 1	88506	1.05	0.145	1.08	621982	1.16	1967740	0.37
Model 2	**91208**	**1.02**	**0.146**	**1.00**	**629187**	**1.18**	**1974170**	**0.38**
Model 3	89439	1.04	0.145	1.04	628136	1.20	1983010	0.38
Model 4	98871	0.94	0.145	1.04	695959	1.20	2200580	0.38
Model 5	103442	0.90	0.145	1.04	727117	1.20	2298140	0.38
Model 6	106374	0.87	0.146	1.06	735084	1.18	2311650	0.38
Model 7	76441	1.21	0.145	1.04	537153	1.19	1697510	0.38
Model 8	126710	0.73	0.178	0.56	633599	1.23	1902070	0.41
Model 9	105637	0.88	0.144	0.75	744251	1.24	2355170	0.39

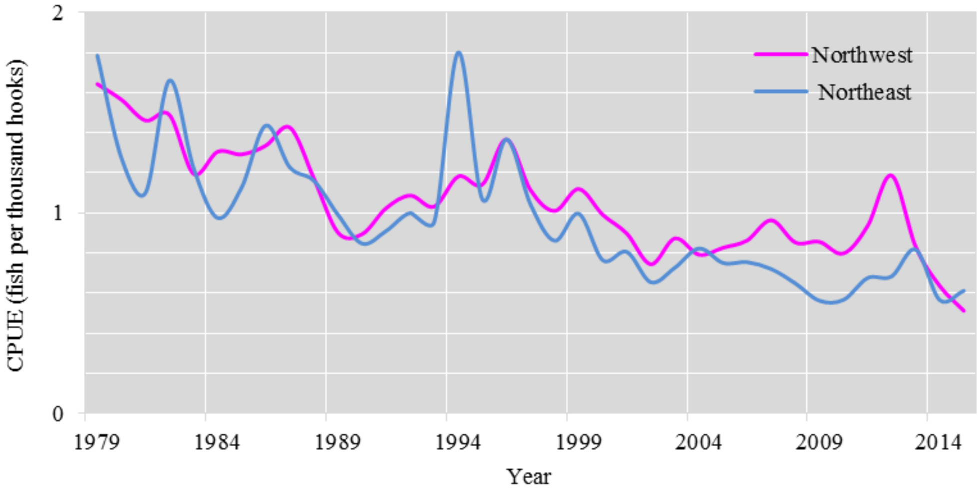

Figure 1. Standardized CPUEs of Indian Ocean bigeye tuna (1979-2015)

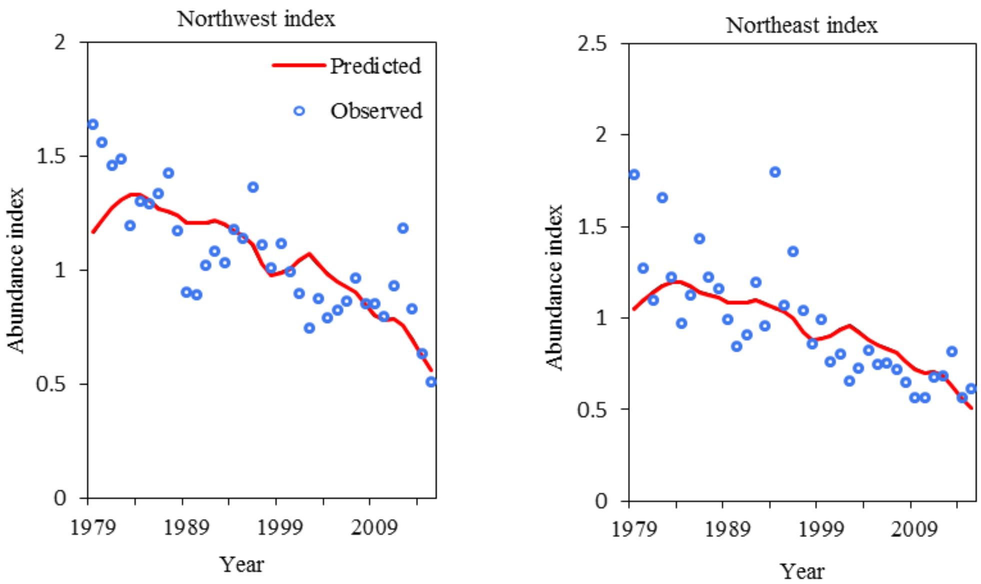

Figure 2. Observed and predicted abundance indices of Indian Ocean bigeye tuna (base case model)

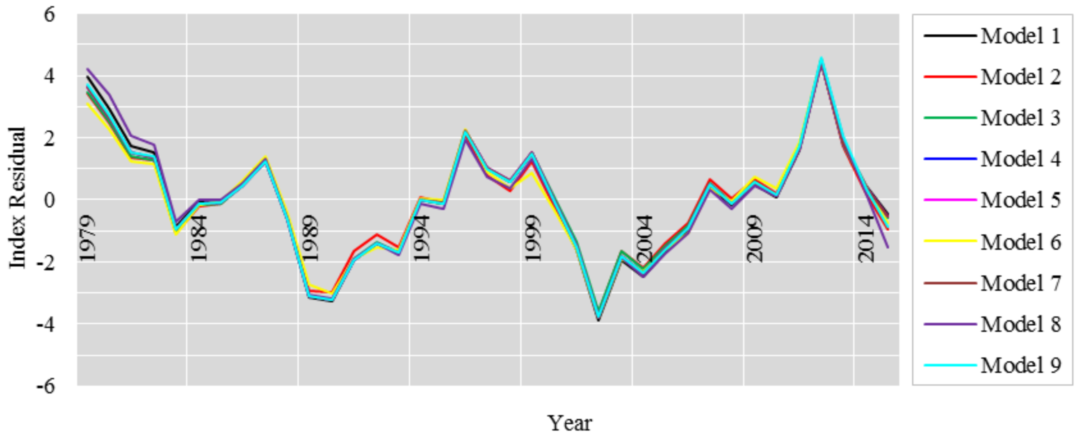

Figure 3. Residuals between observed and estimated abundance indices of Indian Ocean bigeye tuna (northwest index)

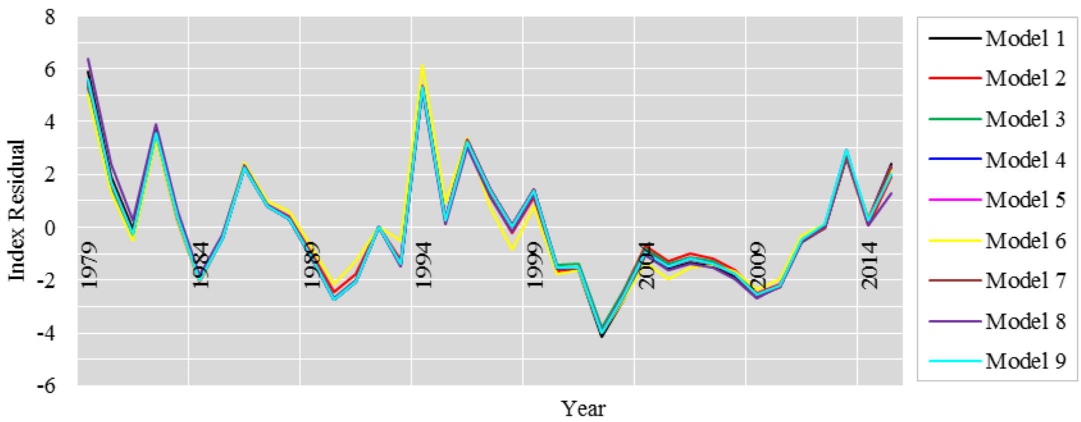

Figure 4. Residual between observed and estimated abundance index of Indian Ocean bigeye tuna (Northeast index)

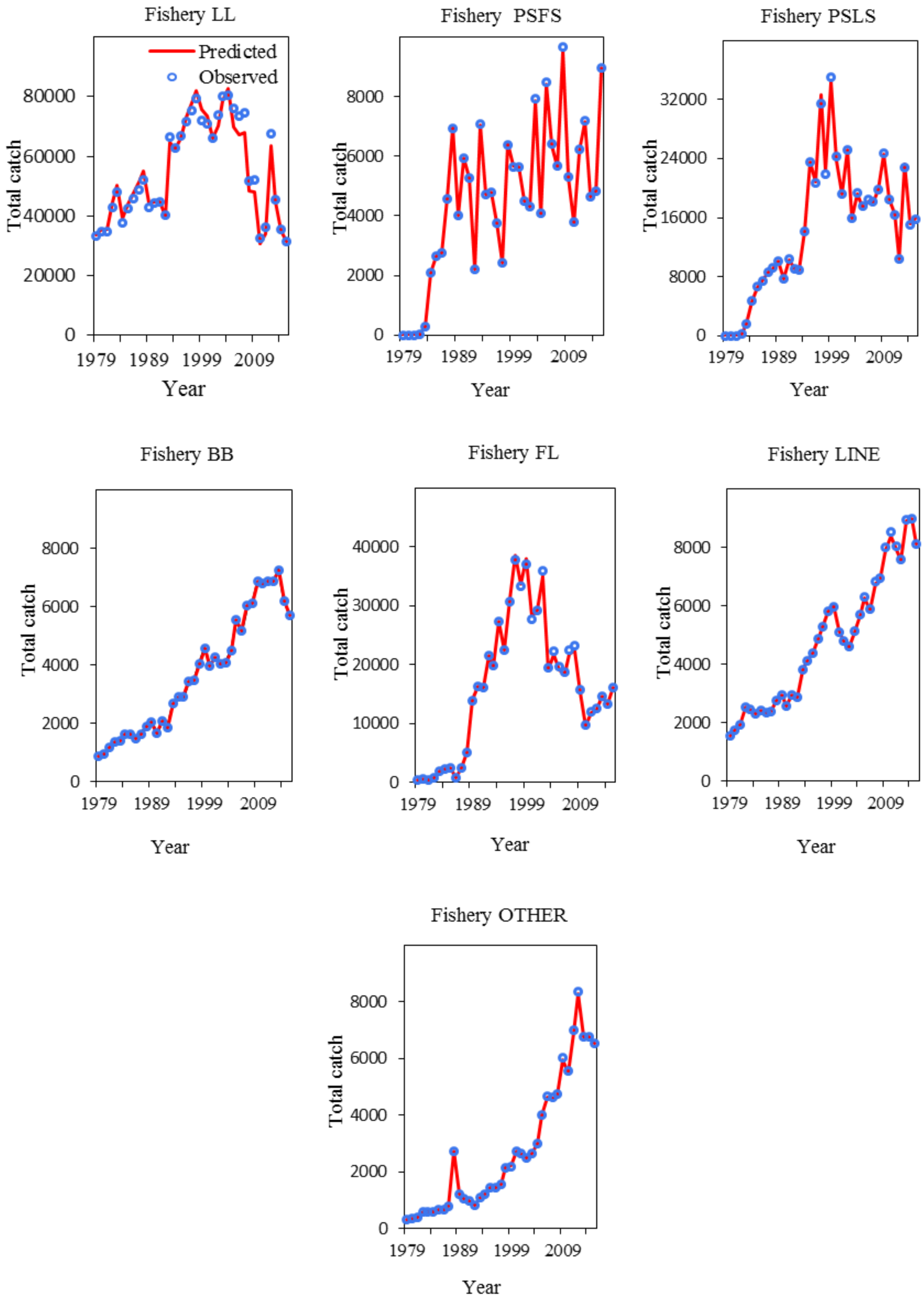

Figure 5. Observed and predicted annual catch of bigeye tuna in the Indian Ocean (base case model

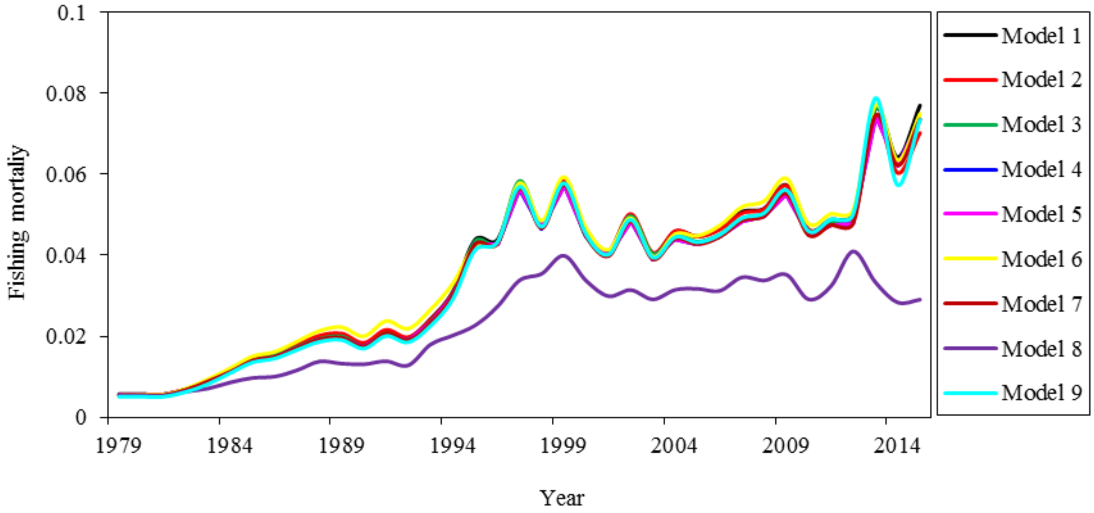

Figure 6． Estimated fishing mortality of bigeye tuna in the Indian Ocean

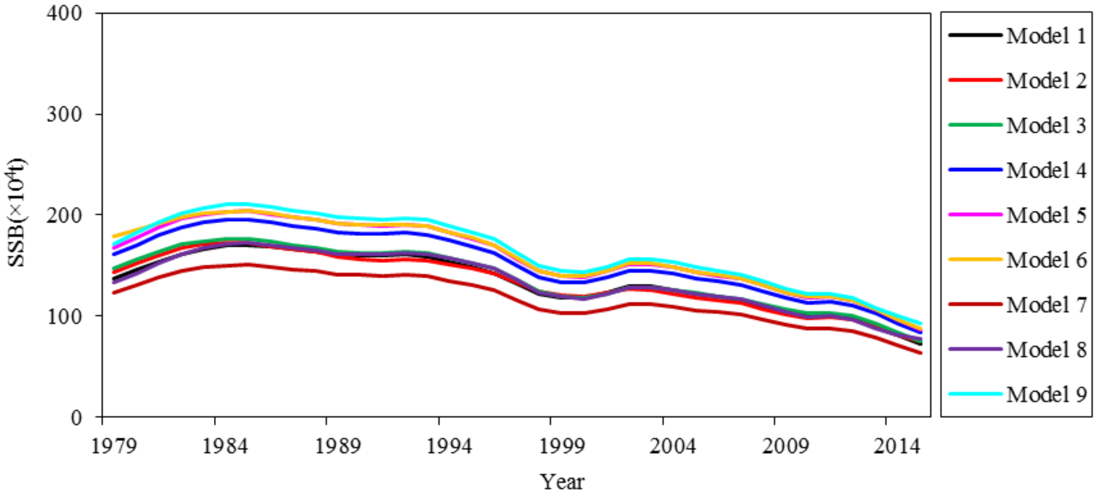

Figure 7． Estimated spawning stock biomass (SSB) of bigeye tuna in the Indian Ocean

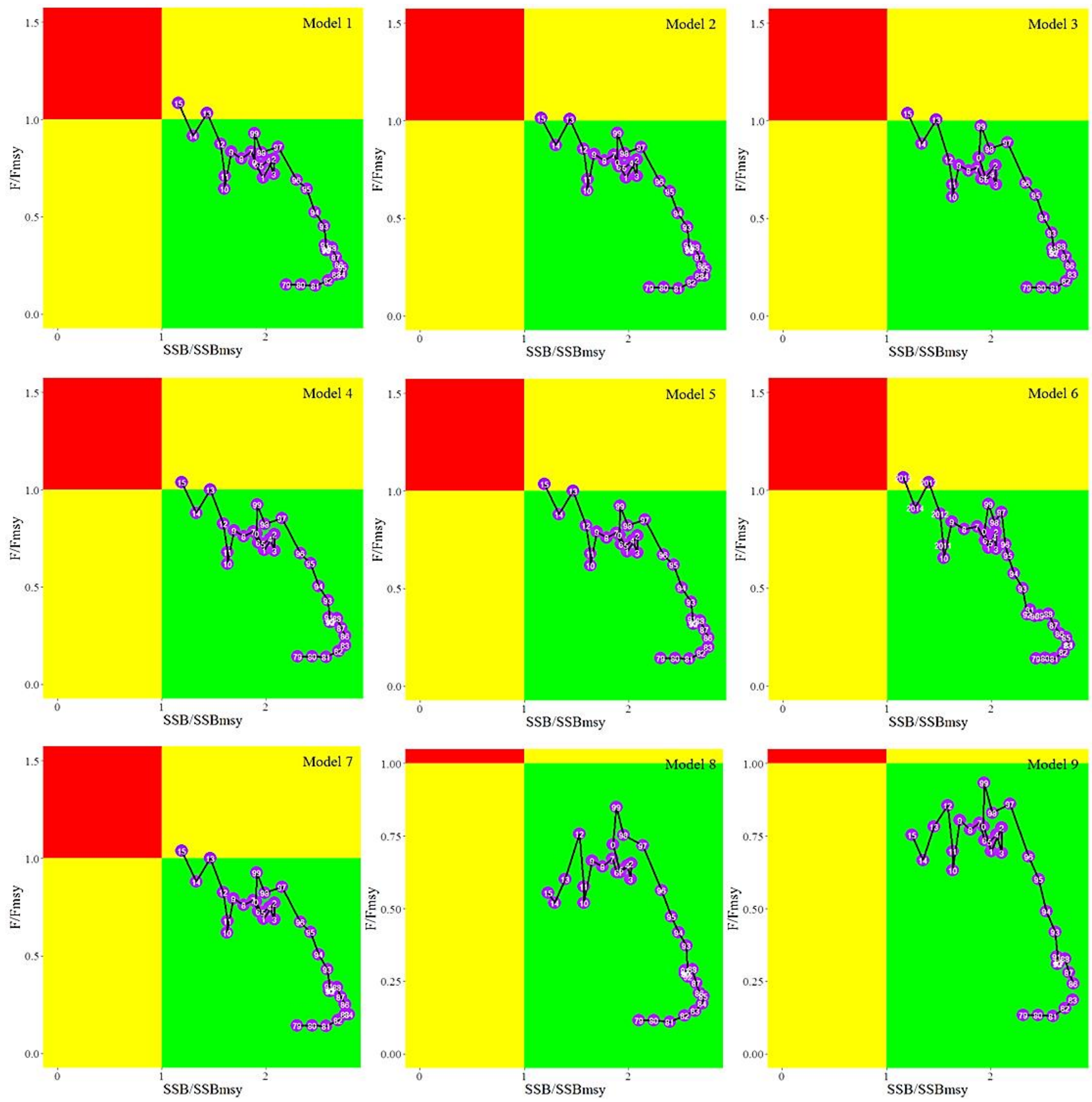

Figure 8. Kobe plots for the BET assessment in the Indian Ocean