



**Review and test for performance, robustness and pliability  
of 2018 PBF stock assessment model**

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**March 2019**

Working document submitted to the ISC Pacific bluefin tuna Working Group, International Scientific Committee for Tuna and Tuna-Like Species in the North Pacific Ocean (ISC), from 18-22 March 2019, Jeju, Korea.

## INTRODUCTION

The latest full stock assessment for the Pacific bluefin tuna (hereafter PBF) had been developed by the ISC PBF working group (PBFWG) in 2016, and the fishery data at 2015 and 2016 were updated in 2018 stock assessment (ISC PBFWG, 2018). In the report of 2016 assessment, the PBFWG acknowledged that the assessment model was substantially improved from the 2014 assessment and the model could explain the observed data fairly well, which was not the case in the past assessment model.

The main reasons why the model could reconcile the observed data would be revealed in the critical data analysis performed before the assessment as well as more detailed fishing (removal) processes than ever such as the variation in the fishery selection patterns by year/season/area. This detailed model processes made the estimation of the selectivity parameters more flexible and reduced the impact of the model misfit on the important parameter estimation. Given the base case model structure, the model performed well in terms of the consistency of the population scale estimates, model fits to the composition data and abundance indices, and retrospective errors.

Since the next full stock assessment is scheduled in the early 2020, the PBFWG will reconsider the current model assumptions for the further improvement based on their newly available data and knowledge. For the full stock assessment, it would be necessary to comprehend the traits of current assessment model. The main purpose of this document is to elucidate the behavior of the current model to the different assumptions for the area where the WG might revisit for a possible change in the 2020 stock assessment. This kind of exercise may also help future Management Strategy Evaluation work since the WG will have to consider incorporating structural uncertainty during their conditioning works for operating models.

## METHODS

In this document, the base case developed in March 2018 by ISC PBFWG was applied.

### 1.) BIOLOGICAL PARAMETERS

#### Natural Mortality

Natural mortality for the base case run were set in three levels, which were 1.6 for age 0 (M0), 0.386 for age 1 (M1) and 0.25 for age 2+ (M2+). In total, 8 sensitivity runs were carried out and these runs were categorized into 3 types. The sets SMRun1 and SMRun2 were set by increasing/decreasing  $M_{\text{young}}$  (M0 and M1) for 10%. The sets SMRun3 and SMRun4 were set by increasing/decreasing  $M_{\text{old}}$  (M2

and older) for 10%. SMRun5–SMRun8 were set by increasing/decreasing the M for all ages for 10 or 20%.

### **Maturity**

Maturity rates by age for the base case were set at 0, 0.2, 0.5 and 1 for ages 0 through 2, age 3, age 4 and age 5 and over, respectively. There were two sensitivity runs where slower maturity ogive (SRRun1) and faster one (SRRun2) assumed. The rates in SRRun1 were set at 0.15 at age 3, 0.3 at age 4 and 5, respectively, increased by 0.14 after age 5, and, subsequently, reached 1 at age 10 in SRRun1. The rates in SB2Run2, where maturity started from age 2, were set at 0.25, 0.5 and 1.0 for age 2, age 3 and over, respectively (Table 3).

### **Stock-Recruitment Relationship (SRR)**

In the base case run, Beverton-Holt SRR was expressed as Steepness parameter (h) of 0.999 and sigma R of 0.6. The values of steepness (h) in sensitivity run (SRRun3) were set in 0.99. SRRun4-7 assumed a sigma R of 0.4, 0.8, 1.0, and 2.0, respectively. And for SRRun8, a sigma R was estimated within the model.

### **Growth**

Coefficient of variation for the older fish (CV for L2 in the SS) was changed to lower and higher values for SGRun1 and 2. Also CV for L2 was estimated within the model in SGRun3.

## **2.) FISHERIES DATA**

### **CPUE time series**

In the base case model, the following CPUEs were included and fitted; Japanese longline (S1, S2 and S3), Japanese troll in Nagasaki (S5) and Taiwanese longline (S9). Sensitivity runs were set as SFRun1, SF1Run2 which excluded S1 and S9 (terminal CPUEs) from the model, respectively.

### **Data weighting**

In the base case, the observed size composition with given input sample size and abundance indices were equally weighted given the input sample size for the composition data. Sensitivity runs were set as SFRun3, SFRun4 which down-weighted relative weight of the composition data and abundance indices to the halves by setting all lambdas of corresponding fleet for 0.5.

## **RESULTS and DISCUSSIONS**

In total, 21 model runs were tested, however, 4 model runs were not considered converged since the hessian was not positive definite or there were some issues for

parameter estimation. Those issues occurred for the runs with lower  $M$  (SMrun8), slightly lower steepness (SRrun3), higher CV for L2 (SGrun2), and halved data weight for size composition component (SFrun3). Those were not the cases for the past PBF assessment model; it was considered converged even with lower steepness values (Kumagai et al., 2015). The main differences between the past and current assessment models were in the data weighting among CPUE and composition data as well as the number of parameters for its removal process; the current model required about 300 parameters estimation to depict the detailed removal process where the past model had required about 120 parameters. Note that the number of parameters and the degree of model misfit are in relation of the trade-off given the data weighting. Thanks to the detailed model process for the fisheries removal, the catch at each age estimated by the sensitivity runs were almost identical even though each run assumed different productivity or data weighting (Fig. 1). The author regarded the relatively low variability in the catch at age estimates to be a reflection of given selection parameterization imposing a very rigid model structure. However, the WG has believed that all of the observed data in the model, which had been analyzed and reviewed critically before the 2016 full assessment, were reliable, and for this reason, the additional model processes have been necessary to reconcile those observed data.

Since the runs, which failed to converge, were often seen in the scenarios for relatively lower productivity (lower  $M$  or lower  $h$ ), those models might include too high depletion rate that disable the stock sustained given the low productivity and a very rigid catch at age estimates.

As for the rest of the runs which were converged, the models showed their robustness to the alternative assumptions. The most of the test runs, which had different productivity assumptions, marked very similar total and component likelihoods with the base case (Tables 1-3). Since each test run for different  $M$  series and different maturity series has a different potential for unfished stock per single recruitment,  $R_0$  and  $SSB_0$  could be varied for each run. However, there seems to be no sign of the unacceptable negative impact of model misfits on the  $R_0$  estimates. Those results indicated that the current PBF assessment model is robust and work under the new assumptions unless it is farther from the current assumptions. Those also indicated the current model can evaluate the range of variation in the biomass estimates due to the structural uncertainty of the model appropriately.

On the other hand, the total likelihood increased from the base case when the higher  $\sigma_R$  assumed. However, the component likelihoods of CPUE and Composition marked similar values with base case (scenarios 5 to 7 in Table 2), and the recruitment

estimates also showed similar values, in particular, after 1980 when the recruitment abundance index became available (Fig. 2). Those things suggested that the recruitments during the assessment period were estimated based on the information from observed data and those were robust even though the recruitment time series were estimated at the larger assumed standard deviations in log-space. However, the  $R_0$  estimated by the models with higher  $\sigma_R$  assumptions were much higher than that of the base case or the average recruitment estimated by each test runs. Since the bias correction factor did not work appropriately for those runs with higher  $\sigma_R$ ,  $R_0$  value estimated by those runs could be biased possibly due to the strong penalty likely for the difference between log of initial recruitment and  $\log R_0$ . Further investigation is necessary to make clear this issue.

The run 1 and 2 of table 4 which tested the alternative assumptions about the terminal adult abundance indices marked similar population scales although it showed different depletion ratio at 2016 (Table 4). Those indicated that a future possible change in the adult abundance indices might not affect significantly to the population scale unless those indices give similar (but better) information to the model. It should be appreciated that the changes in the terminal abundance indices could affect to the recent stock trend.

In summary, several test runs showed the robustness of the model to the alternative assumptions. In particular, the model misfits to the abundance indices and size composition data were minimal among several tested runs, and recruitment estimates were also robust even though the different recruitment variations were assumed. Since the recruitment estimates and removal process performed well in terms of the fits to the corresponding data, and those showed certain robustness to the alternative assumptions, some of the changes of model assumption by the next full stock assessment based on the better knowledge about the biology, fishery, and modeling will likely be able to conducted without any fatal issues.

On the other hand, although it is not quite sure if the very rigid removal process imposed by given parameterization method caused the current model of losing some pliability to the alternative assumptions, the WG may want to reconsider about the method of the parameterization. Less number of parameters with the similar model performance may lead the model more pliable and can save the calculation time.

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Table 1 Scenarios of sensitivity runs for the Natural mortality and the results about population dynamics variables

Annual M	M-0	M-1	M-2	M-3	M-4	M-5	M-6	M-7	M-8	M-9	M-10	M-11+	Converge	Total Likelihood	CPUE Component	Composition Component	R0	SSB0	SSB <sub>2016</sub> /SSB <sub>0</sub>
Base Case	1.6	0.386	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25/y OK	1441	-112	1531	13,681	642,635	3.3%
Run1	1.76	0.425	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25/y OK	1442	-113	1532	15,890	611,980	3.4%
Run2	1.44	0.347	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25/y OK	1440	-112	1530	11,794	675,737	3.2%
Run3	1.6	0.386	0.275	0.275	0.275	0.275	0.275	0.275	0.275	0.275	0.275	0.275	0.275/y OK	1441	-112	1530	14,059	542,844	4.2%
Run4	1.6	0.386	0.225	0.225	0.225	0.225	0.225	0.225	0.225	0.225	0.225	0.225	0.225/y OK	1442	-113	1531	13,325	772,068	2.5%
Run5	1.76	0.425	0.275	0.275	0.275	0.275	0.275	0.275	0.275	0.275	0.275	0.275	0.275/y OK	1442	-112	1531	16,364	518,036	4.4%
Run6	1.44	0.347	0.225	0.225	0.225	0.225	0.225	0.225	0.225	0.225	0.225	0.225	0.225/y OK	1441	-112	1530	11,500	812,648	2.4%
Run7	1.92	0.463	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3/y OK	1444	-112	1533	19,694	425,120	5.7%
Run8	1.28	0.309	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2/y Hessian_negative						

Table 2 Scenarios of sensitivity runs for the Recruitment assumptions and the results about population dynamics variables

	Matur_ Age2	Matur_ Age3	Matur_ Age4	Matur_ Age5	Matur_ Age6	Matur_ Age7	Matur_ Age8	Matur_ Age9	Matur_ Age10+	Steepness	SigmaR	Converge	Total Likelihood	CPUE Component	Composition Component	R0	SSB0	SSB <sub>2016</sub> /SSB <sub>0</sub>
Base Case	0	0.2	0.5	1	1	1	1	1	1	0.999	0.6	OK	1441	-112	1531	13,681	642,635	3.3%
Run1	0	0.15	0.3	0.3	0.44	0.58	0.72	0.86	1	0.999	0.6	OK	1441	-112	1531	13,685	472,337	2.7%
Run2	0.2	0.5	1	1	1	1	1	1	1	0.999	0.6	OK	1441	-112	1531	13,667	707,012	3.7%
Run3	0	0.2	0.5	1	1	1	1	1	1	0.99	0.6	Hessian_negative						
Run4	0	0.2	0.5	1	1	1	1	1	1	0.999	0.4	OK	1448	-112	1538	12,706	596,856	3.8%
Run5	0	0.2	0.5	1	1	1	1	1	1	0.999	0.8	OK	1445	-112	1528	15,400	723,387	2.9%
Run6	0	0.2	0.5	1	1	1	1	1	1	0.999	1.0	OK	1452	-112	1527	18,002	845,621	2.5%
Run7	0	0.2	0.5	1	1	1	1	1	1	0.999	2.0	OK	1482	-112	1525	70,168	3,296,080	0.6%
Run8	0	0.2	0.5	1	1	1	1	1	1	0.999	0.576 *1	OK	1441	-112	1531	13,528	635,448	3.4%

\*1 SigmaR was estimated by Run8

Table 3 Scenarios of sensitivity runs for the Growth assumptions and the results about population dynamics variables

	L1	L2	K	CVL1	CVL2	Converge	Total Likelihood	CPUE Component	Composition Component	R0	SSB0	SSB <sub>2016</sub> /SSB <sub>0</sub>
Base Case	19.05	118.57	0.188	0.259	0.044	OK	1441.15	-112.384	1530.79	13,681	642,635	3.3%
Run1	19.05	118.57	0.188	0.259	0.025	OK	1540.63	-109.916	1630.17	14,058	657,675	4.3%
Run2	19.05	118.57	0.188	0.259	0.10	Hessian_negative						
Run3	19.05	118.57	0.188	0.259	0.043 <sup>*1</sup>	OK	1440.98	-112.159	1530.51	13,700	643,341	3.4%

\*1 CV for L2 parameter was estimated by Run 3.

Table 4 Scenarios of sensitivity runs for the Fisheries assumptions and the results about population dynamics variables

lambda	S1	S2	S3	S5	S9	Size Comps	Converge	Total Likelihood	CPUE Component	Composition Component	R0	SSB0	SSB <sub>2016</sub> /SSB <sub>0</sub>
Base Case	1	1	1	1	1	1 for All	OK	1441	-112	1531	13,681	642,635	3.3%
Run1	0	1	1	1	1	1 for All	OK	1436	-108	1520	13,785	647,545	5.8%
Run2	1	1	1	1	0	1 for All	OK	1442	-111	1531	13,634	640,453	2.7%
Run3	1	1	1	1	1	0.5 for All	Hessian_neg						
Run4	0.5	0.5	0.5	0.5	0.5	1 for All	OK	1493	-47	1518	13,699	643,498	3.9%

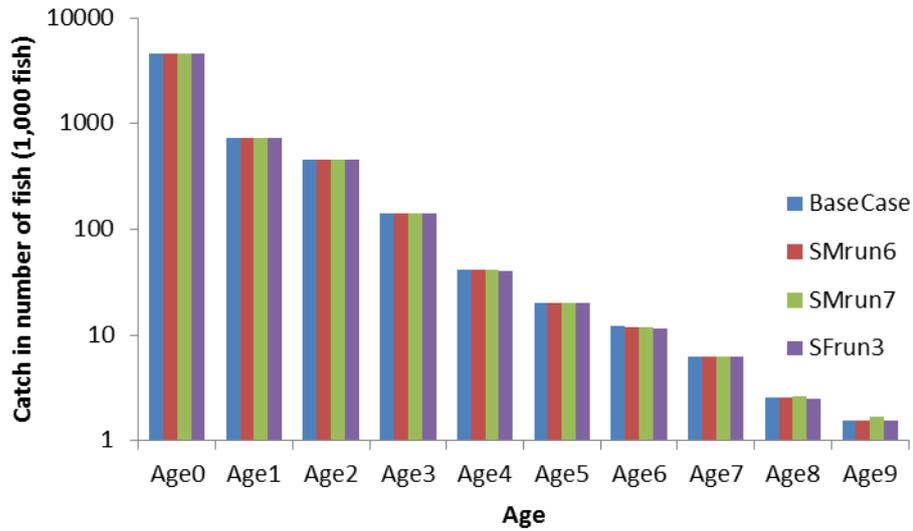


Fig. 1 Total catch in number of Pacific bluefin tuna during 2012-2015 estimated by the base case assessment model and 3 of test runs.

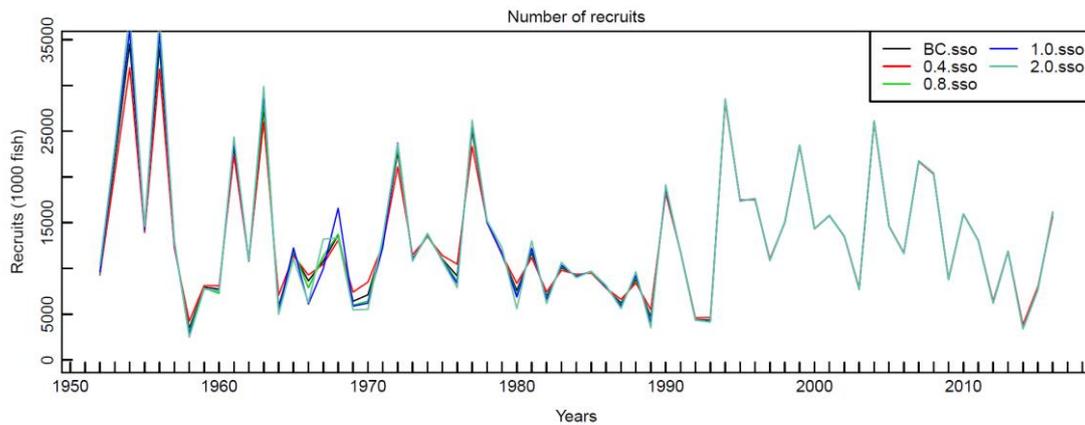


Fig. 2 Time series of estimated recruitment of PBF by the 2018 base case assessment model (Black line) and the sensitivity runs for the assumed  $\sigma_R$  (0.4, 0.8, 1.0, and 2.0 for red, green, blue and right green lines, respectively).