ISC/24/PBFWG-2/06

Consideration about a possible unseen change in catchability in the standardized CPUE for the robustness test of the PBF MSE

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December 2024

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 10 to 13 December 2024, online.

1 Introduction

Catch per unit of effort based abundance index (CPUE index) is one of the common data source for the stock assessment of fish and this is critically important in the case when the survey abundance index is not available. This is the case in Pacific bluefin tuna (PBF) assessment and the CPUE from longline fisheries have been used to inform the relative trend of large adult PBF stock for the past assessments. Given a possibility of different catchability by area, time, vessel size and so on, the CPUEs were standardized by generalized linear mixed models (Yuan et al. 2024, Tsukahara et al. 2022). The PBFWG acknowledged that those data are representative of the abundance trend of the stock and there was an internal consistency among the adult CPUE indices, recruitment index, catch time series and size composition data under certain assumptions of the population dynamics.

One of the issues using the fishery dependent CPUE index is the possible change in catchability (q) over time due to the technological and operational changes in fisheries (i.e. effort creep; Palomares and Pauly 2019, Kleiven et al. 2022). Since there are some limitations in available information to use as a covariate, some of the technological and operational developments were not always accounted in the CPUE standardization process. Misinterpretation of the trends in catchability over time will bias the stock status estimate and that bias could be amplified as the time series extends (Han et al. 2023). Hoyle et al. (2024) recommended stock assessments, particularly for the target species, to consider a range of reasonable scenarios regarding long-term catchability trends, from low to high but noting that 0% is rarely plausible.

Although the PBFWG generally considered that the current assessment model is reliable based on its good model diagnostics owing to the strong production relationship consistently appeared in the several data sources including adult abundance indices, they decided to consider the possible change in catchability of the index for one of the robustness test of the management procedure (MP) in the PBF management strategy evaluation (MSE).

This document provides some results of the population dynamics model assuming unseen catchability change in the adult abundance indices. Several scenarios of q change were prepared, and the performance of the models were compared. The purpose of this document was to provide a reasonable scenario of catchability change in terms of the choice of the index as well as the magnitude of the change.

2 Material and Method

2.1 Model and Data

A length-based age structured population dynamics model implemented to the Stock Synthesis version 3.3 (Methot and Wetzel 2013) for the 2024 PBF stock assessment was the basis of this analysis. The fishery data until 2022 fishing year were used and all of the model setting was consistent with the 2024 stock assessment. Detailed information of those input data (the catch, discard, abundance index, and size composition) is described in the stock assessment report (ISC 2024).

For testing an abundance index with unseen increase in catchability, I ad-hockly gave a linear trend to the longline indices from Japanese and Taiwanese fleets by -2% to 4% per year (Figure 1). For comparisons, 4 scenarios of fleet choice for unseen catchability change with different slopes between -2 to 4% per year were tested as below;

a. q was constant for both JpLL and TwnLL indices (base-case; 0%);
b. q improved for both JpLL and TwnLL indices (1, 2, 3, 4% per year);
c. q improved only for JpLL index (-2, -1, 1, 2, 3, 4% per year);
d. q improved only for TwnLL index (1, 2, 3, 4% per year).

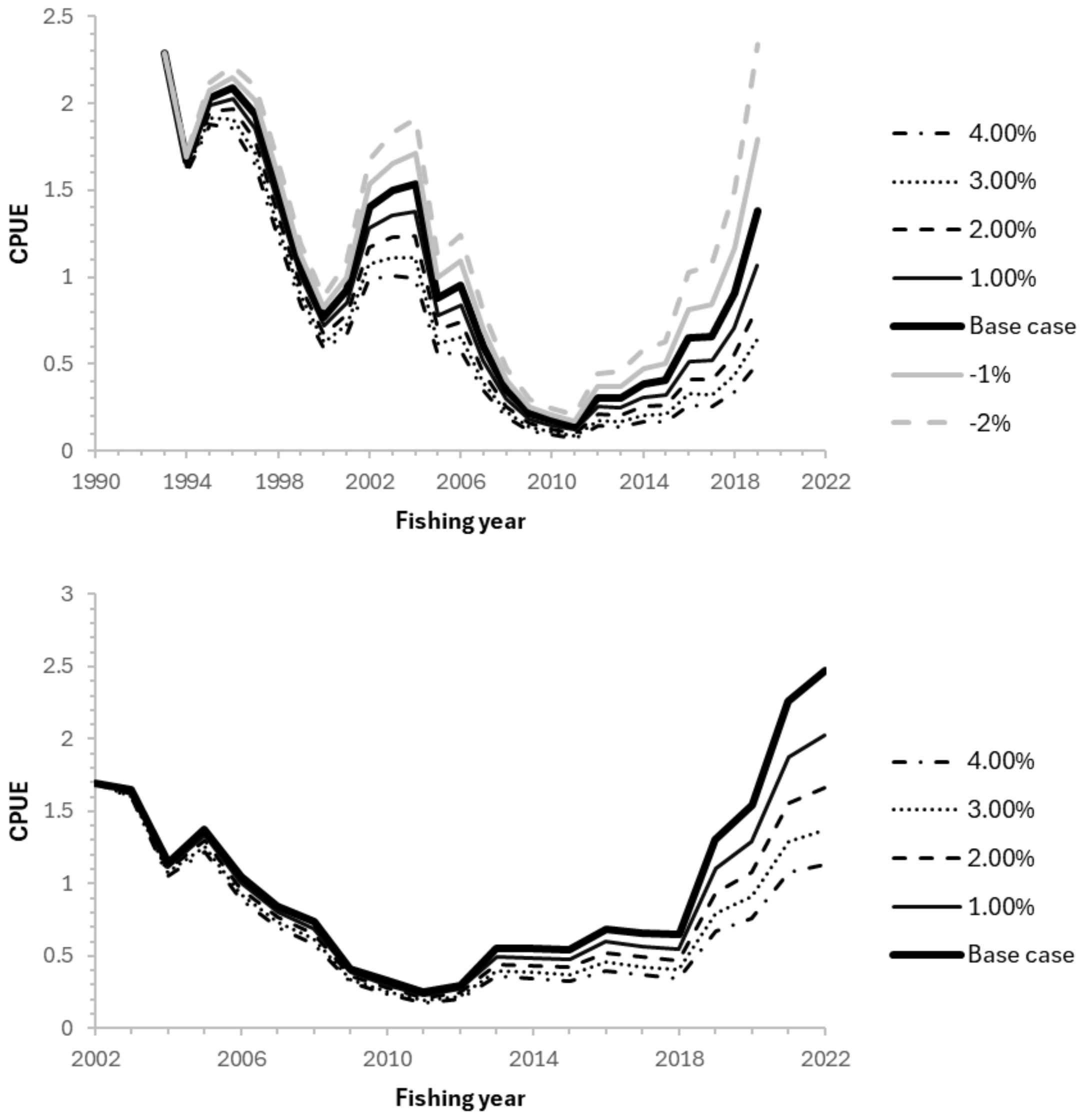

Figure 1 Japanese longline (Top) and Taiwanese longline (Bottom) CPUE indices with different unseen catchability change assumptions.

2.2 Analysis

In this document, I assumed that the catch time series is not biased and correct in a ballpark, and the recruitment index (1983-2010) provides a reliable information about the recruitment trend (Lee et al., 2020). With this precondition, I tested each index with unseen catchability change using the fully integrated model and the age structured production model with estimated recruitment variation (ASPM-R) (Table 1).

In the ASPM-R, the model was fitted to the catch time series, recruitment index, and LL indices, but the size composition data is not included in the likelihood function. The negative log likelihood of the ASPM-R for longline indices were compared to evaluate the consistency among the longline indices, catch timeseries, and recruitment index. Because ASPM-R estimated only some parameters under the given selectivity, a degraded fit to the longline indices from the base case (no q change) could be an indication of the conflicted information about the population trend.

In the later stage, I further tested the hindcasting to evaluate the prediction skill of the models, which fitted to the LL indices with different unseen q assumptions.

3 Results

3.1 Model fits for the unseen q change scenario

Table 1 shows the negative log likelihood for each data components and index of abundance. For both model structures, the scenarios b and c showed a degraded model fit from the scenario a, but the scenario d showed a better fit to the LL indices than those of the scenario a. The results suggested that the Taiwanese longline index improved consistency with the catch time series when it was assumed some unseen catchabilities increase. Among the models assuming the positive catchability change for TLL index, models with the TLL index assumed 2% y^{-1} catchability showed a better model fit to the TLL index than the rest of the models.

Although the models assuming some unseen increases in catchability in JLL showed a degraded consistency with the catch time series, the models improved its fit to the JLL index when some unseen catchability decreases (-1, -2% per year) for JLL index were assumed (Table 1). But those results just highlighted the conflicted information between the trends of the longline indices from Japanese and Taiwanese fleets and need to be carefully interpreted. Possible catchability change should be investigated from the real information of the fleet operation and observed size data in addition to this kind of model practice.

3.2 Prediction skill of the model for the unseen q change scenario

To evaluate the prediction skill of the model fitted to the index assuming the unseen catchability change, the hindcasting analysis for seven years were conducted using the fully integrated model (Fig. 2). Two models of the assessment base case and scenario d-2%, which is the model fitted to the TLL index with 2% unseen catchability increase, were compared, and the root mean square error (RMSE) during the forecasting period was used as a metrics of the prediction skill. As shown in the 2024 assessment, the base case model could depict the trend of Taiwanese longline index for 7 years forecasting period (RMSE = 0.24). On the other hand, the model of scenario d-2% overestimated the recovery trend than the observed index (RMSE = 0.37). In both models, the stock suffered in a severe situation during 1983-2010. After the introduction of the catch limit since 2011, the models expected rapid recovery of the stock based on the production function informed by the historical catch and indices. The TLL index assuming 2% y^{-1} was not matched with the stock recovery expected by the model.

On the other hand, the model with the JLL index assuming a negative catchability change (-2%) showed a higher prediction skill for both JLL and TLL indices than the base case (Table 2). In general, the unseen catchability change is discussed as an underestimation of the catchability due to the overlooking of the technological improvements of the fishing equipment such as GPS, echo-sounder, bird radar, or internet connection. The possibility of the unseen catchability decrease also needs to be carefully comprehended. However, the current Japanese longline CPUE index applied a data filtering scheme to exclude the fish smaller than a certain size by using the average body weight of the PBF in each operation (Tsukahara et al., 2020). By using the average weight for filtering, there might be a bias between the false-positive (actually large fish but filtered out because it was caught with many small fish) and false-negative (actually small fish but not filtered out because it was caught with very big fish). Given an increasing trend of the relatively small spawner due to the influx of the protected cohorts by the size-based management, the frequency of the false-positive case might be increased than before, and this could bring a negative catchability change to JLL index.

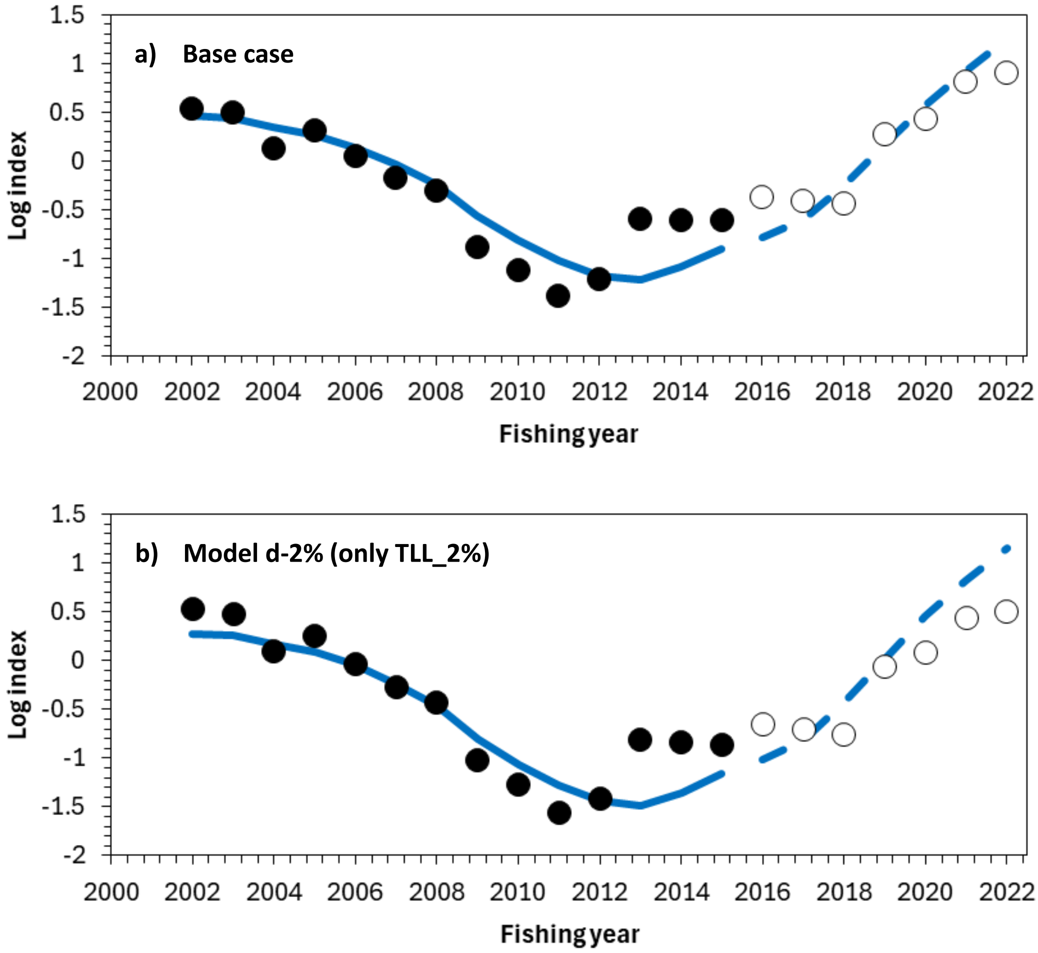

Figure 2 Result for hindcasting of the recent 7 years (2016-2022). The solid circles represent the observed Taiwanese longline (TLL) CPUE used in the model, and open circles represent the missing values for the recent 7 years. The blue solid lines were the expected TLL CPUE estimated by the fully integrated model and blue dashed lines were forecasted values based on the catch at age and the stock recruitment relationship (ASPM).

3.3 Biomass trend

Figure 3 shows comparisons of the SSB and its fraction of unfished SSB estimated by the 2024 base case and the scenario d-2%. Those models generally showed a similar biomass trend until the middle of 2010's, but there was a discrepancy after that because of assumed catchability change in the index (Fig. 1 bottom). Although the difference between those two models were not critical in this moment, the robustness test assuming unseen catchability change is still worth to conduct because the impact of the overlooking of catchability change could be evaluated by the proper conditioning process as well as the data generation process with a bias.

4 Conclusion

For both standardized JLL and TLL indices, further investigations about the possible change in catchability are needed based on the actual observations and knowledge about the fishery operation. For just a sake of the precautionality, the author recommends a scenario to assume 2% y-1 catchability increase for TLL index for the robustness test of the PBF MSE. To assume "unseen catchability change" in the OM and EM, it is necessary to make a modification in the data generation process to give a biased trend to an index for the assessment using EM. Then of course, a discrepancy between the stock dynamics (OM) and assessment results (EM) will be expanded year by year if this "unseen catchability change" continues.

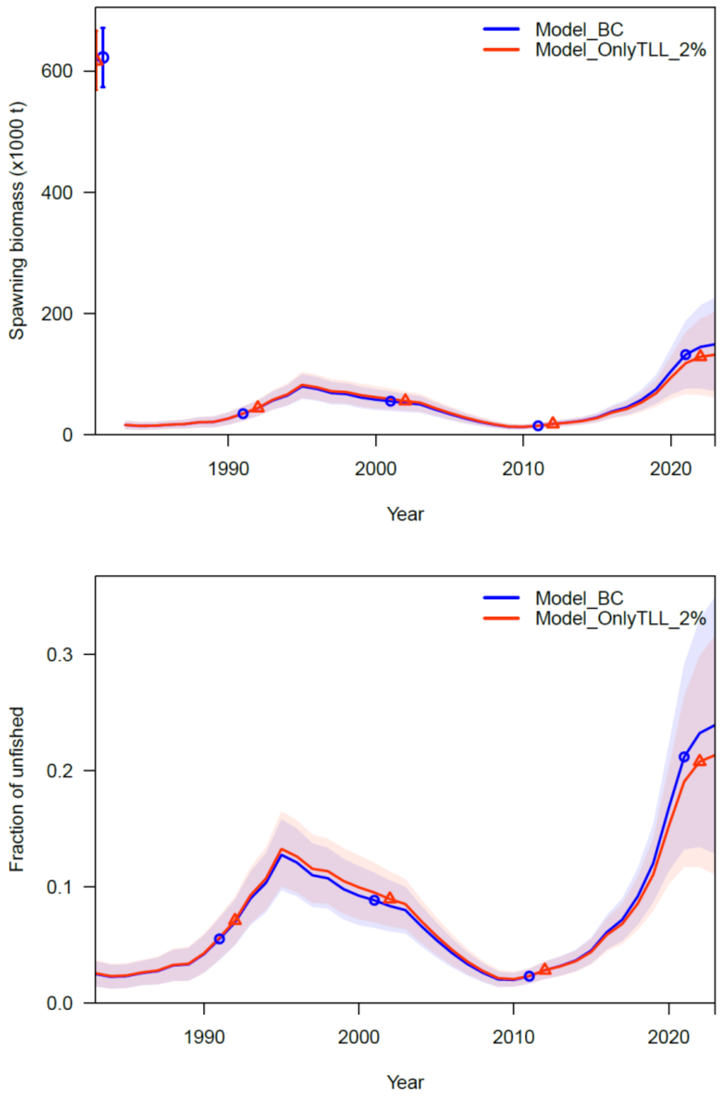

Figure 3 Trajectory of spawning stock biomass (SSB; top) and its fraction of unfished SSB (bottom) of Pacific bluefin tuna estimated from the base-case model and the model fitted to TLL index with catchability increase for 2% y^{-1}.

Table 1 Negative log-likelihood for each model fitted to the longline index with different slopes of unseen catchability change.

Integrated_model	Change in Catchability (/y)	Total LL	Catch	Survey					SizeFreq	Recruitment	InitEQ_Regime	Parm_softbounds	Parm_devs
				Total	JLL_term	JLL_early	Jtroll	TLL					
BC	0.0%	1247.7	0.3	-84.5	-16.6	-13.8	-35.2	-19.0	1309.2	-4.0	0.2	0.0	26.5
Both	1.0%	1251.8	0.3	-83.0	-15.2	-13.9	-35.3	-18.7	1311.7	-3.9	0.2	0.0	26.5
Both	2.0%	1256.5	0.3	-81.1	-13.5	-14.0	-35.3	-18.4	1314.4	-3.8	0.2	0.0	26.4
Both	3.0%	1261.9	0.3	-78.8	-11.5	-14.1	-35.2	-18.0	1317.5	-3.7	0.1	0.0	26.4
Both	4.0%	1268.1	0.4	-76.0	-9.2	-14.1	-35.0	-17.7	1320.8	-3.6	0.1	0.0	26.4
JLL_only	-2.0%	1237.7	0.2	-88.9	-20.0	-13.6	-35.0	-20.3	1303.6	-4.2	0.3	0.0	26.6
JLL_only	-1.0%	1241.9	0.2	-87.4	-18.7	-13.7	-35.1	-19.9	1306.3	-4.1	0.2	0.0	26.5
JLL_only	1.0%	1255.2	0.3	-80.5	-13.7	-13.8	-35.3	-17.6	1312.6	-3.9	0.2	0.0	26.4
JLL_only	2.0%	1264.3	0.3	-75.2	-9.9	-13.9	-35.4	-16.0	1316.3	-3.8	0.2	0.0	26.4
JLL_only	3.0%	1274.9	0.3	-68.5	-5.2	-14.0	-35.4	-13.9	1320.3	-3.7	0.2	0.0	26.3
JLL_only	4.0%	1287.2	0.3	-60.5	0.3	-14.1	-35.3	-11.5	1324.6	-3.7	0.2	0.0	26.2
TLL_only	1.0%	1245.2	0.3	-86.3	-17.7	-13.8	-35.2	-19.6	1308.4	-4.0	0.2	0.0	26.5
TLL_only	2.0%	1243.5	0.3	-87.5	-18.6	-13.8	-35.1	-20.0	1307.8	-4.0	0.2	0.0	26.6
TLL_only	3.0%	1242.7	0.3	-88.0	-19.2	-13.8	-35.1	-19.9	1307.5	-3.9	0.2	0.0	26.6
TLL_only	4.0%	1242.5	0.3	-87.9	-19.6	-13.8	-35.0	-19.6	1307.2	-3.8	0.2	0.0	26.6

ASPMR_est	Change in Catchability (/y)	Total LL	Catch	Survey					SizeFreq	Recruitment	InitEQ_Regime	Parm_softbounds	Parm_devs
				Total	JLL_term	JLL_early	Jtroll	TLL					
BC	0.0%	-82.7	0.6	-101.4	-27.1	-15.0	-40.4	-19.0		-8.6	0.2	0.0	26.5
Both	1.0%	-80.8	0.7	-99.5	-26.0	-15.0	-40.2	-18.2		-8.7	0.1	0.0	26.5
Both	2.0%	-78.2	1.0	-97.1	-24.5	-15.1	-39.8	-17.7		-8.8	0.1	0.0	26.5
Both	3.0%	-75.0	1.3	-94.1	-22.5	-15.1	-39.3	-17.2		-8.9	0.1	0.0	26.5
Both	4.0%	-71.4	1.7	-90.9	-20.6	-15.1	-38.7	-16.6		-8.8	0.1	0.0	26.5
JLL_only	-2.0%	-87.0	0.3	-105.5	-30.0	-14.9	-40.5	-20.1		-8.4	0.2	0.0	26.5
JLL_only	-1.0%	-85.6	0.4	-104.2	-28.9	-14.9	-40.5	-19.9		-8.5	0.2	0.0	26.5
JLL_only	1.0%	-78.1	0.8	-97.1	-24.3	-15.0	-40.2	-17.7		-8.6	0.1	0.0	26.5
JLL_only	2.0%	-71.9	1.2	-91.2	-20.6	-15.0	-39.8	-15.8		-8.6	0.1	0.0	26.5
JLL_only	3.0%	-64.1	1.6	-83.7	-16.3	-15.1	-39.2	-13.1		-8.6	0.1	0.0	26.5
JLL_only	4.0%	-54.6	2.0	-74.7	-10.2	-15.1	-38.7	-10.7		-8.5	0.1	0.0	26.5
TLL_only	1.0%	-84.5	0.5	-103.0	-28.3	-15.0	-40.5	-19.2		-8.6	0.1	0.0	26.5
TLL_only	2.0%	-85.5	0.5	-104.0	-29.2	-15.0	-40.5	-19.3		-8.7	0.1	0.0	26.5
TLL_only	3.0%	-85.7	0.5	-104.2	-29.5	-15.0	-40.6	-19.1		-8.6	0.1	0.0	26.5
TLL_only	4.0%	-85.3	0.5	-104.0	-29.9	-15.0	-40.7	-18.4		-8.5	0.1	0.0	26.5

Table 2 Root mean square error (RMSE) for 7 years forecasting period between the observed (but not included in the likelihood function) and predicted longline CPUEs by each model fitted to the index with different slopes of unseen catchability change.

	RMSE for forecasting 7 years	
	JLL	TLL
Base case	0.36	0.24
TLL_1%	0.38	0.31
TLL_2%	0.38	0.37
TLL_3%	0.39	0.47
TLL_4%	0.39	0.51
JLL_-1%	0.33	0.26
JLL_-2%	0.29	0.28

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