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Developing a set of diagnostics and outputs for MULTIFAN-CL stock assessments WCPFC-SC16-2020/MI-IP-07

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## **Executive Summary**

Stock assessments may be performed to estimate the current and historical status of stocks for the provision of management advice, and also to condition operating models for management strategy evaluation (MSE) (e.g. Vincent et al., 2019; Tremblay-Boyer et al., 2018; Scott et al., 2020). After fitting a stock assessment model it is important to explore the fitting diagnostics and model outputs, for example, to check that the model has converged satisfactorily and that the observed data is adequately predicted by the model.

MULTIFAN-CL is used to condition the operating models for the WCPO skipjack and South Pacific albacore WCPFC harvest strategy MSE evaluations (Kleiber et al., 2019; Scott et al., 2020, 2019). SC15 discussed the need for diagnostics and model outputs for all of the conditioned models in the skipjack MSE operating model grid to be made available.

This report describes progress towards developing a set of model diagnostics and outputs to explore stock assessments performed using MULTIFAN-CL. Here, the currently available outputs are calculated for the grid of operating models in the WCPO skipjack harvest strategy MSE.

When exploring the diagnostics and outputs for all models in a grid, rather than providing a large report that contains many plots and tables, an online tool that allows exploration of the results may be useful. An example tool can be seen here. If found to be useful, further development of the tool will take place. Similar tools can be prepared in the future for exploring the outputs and diagnostics of other stock assessments.

We invite WCPFC-SC to consider the progress towards a set of diagnostics and model outputs from MULTIFAN-CL assessments. Specifically we invite SC16 to:

- Suggest further diagnostics and outputs that could be calculated;
- Consider if an online tool, such as demonstrated here, is a useful tool for exploring the outputs.

## 1 Introduction

Stock assessments may be performed to estimate the current and historical status of stocks for the provision of management advice, and also to condition operating models for management strategy evaluation (MSE) (e.g. Vincent et al., 2019; Tremblay-Boyer et al., 2018; Scott et al., 2020). After fitting a stock assessment model it is important to explore the fitting diagnostics and model outputs to check that the model has converged satisfactorily and that the observed data is adequately predicted by the model. It is also important to investigate if the estimated model is suitable for use in running future projections.

As well as inspecting the diagnostics and outputs of individual models, it can be useful to compare them across a grid of models. For example, it is useful to compare estimated selectivities from multiple models to identify the effect of different grid factors. It also allows for the identification of factors in the grid that may be redundant and can potentially be dropped. This can also help identify models that estimate noticeably different parameter values to other models and which may then require further investigation.

MULTIFAN-CL is used to condition the operating models for the WCPO skipjack and South Pacific albacore WCPFC harvest strategy MSE evaluations (Kleiber et al., 2019; Scott et al., 2020, 2019). SC15 discussed the need for diagnostics and model outputs for all of the conditioned models in the skipjack MSE operating model grid to be made available for inspection by members (WCPFC, 2019).

This report describes progress towards developing a set of model diagnostics and outputs to explore stock assessments performed using MULTIFAN-CL. Similar approaches have been developed for other stock assessment models (e.g. Cass-Calay et al., 2014).

## 2 Diagnostics and model outputs

We divide the diagnostics and outputs into five overlapping categories:

- Fitting diagnostics inspects if the model has converged satisfactorily.
- **Model consistency** inspects the internal consistency of the model and evaluates if it is appropriate to use the model for projections.
- Fits to data sources inspects how well the observed data that was used to fit the model is being predicted by the model. This can include catch and effort data; length / weight frequency data and tagging data.
- **Model outputs** inspects other parameters estimated by the model, such as selectivity and natural mortality.
- Estimates of stock status inspects metrics used for the provision of management advice, such as estimates of biomass.

The currently available outputs are described in Table 1 in the Appendix. To illustrate the outputs

they are calculated for the grid of 24 operating models in the WCPO skipjack harvest strategy MSE of relevance to the 'historical' period (Scott et al., 2020) and example plots are shown in the Appendix.

## 3 Online tool for exploring the outputs

When exploring the diagnostics and outputs for all models in a grid, rather than providing a large report that contains many plots and tables, an online tool that allows the user to explore the results may be useful. A preliminary version of such a tool (the Hierophant<sup>2</sup>) is provided here.

The current examples in the tool are based on the grid of fitted operating models in the WCPO skipjack MSE (Figure 1) (Scott et al., 2020). the grid has four factors: steepness, tag mixing period, growth model and hyperstability. Each of these factors has 2 or 3 levels, giving 24 models in total. Individual models can be selected from a drop down menu, and compared to the full grid of models. Additionally, the results can be explored by grid factor. For example, it is possible to investigate the differences in the outputs between the three levels of steepness.



Figure 1: Screenshot of the preliminary Hierophant application for exploring the outputs and diagnostics of MULTIFAN-CL model fits.

If found to be useful, further development of the tool will take place. Similar tools can be prepared in the future for exploring the outputs and diagnostics of other stock assessments.

<sup>&</sup>lt;sup>2</sup>A hierophant (Greek, *Hierophants*, "displayer of holy things"), was a chief of the ancient Greek Eleusinian cult and an interpreter of sacred mysteries and arcane principles (see here and here).

## 4 Further developments

The example model outputs and diagnostics presented here represent a preliminary set and it is anticipated that more will be added in the future, including those requested by members. Proposed future inclusions include: "jittering" to evaluate model stability, where a well behaved model should converge on a global solution across a reasonable range of input parameters (Cass-Calay et al., 2014) and hindcasts to evaluate the predictive power of the model.

## 5 Acknowledgments

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## A Summary of currently available diagnostics and outputs

Table 1: Currently available diagnostics and model outputs in the online tool. The Single and Multiple columns refer to whether the output is available to compare across multiple models, for a single model only, or both. The model type refers to to the type of output: A (fitting diagnostic), B (model consistency), C (fit to data), D (model output) and E (stock status).

Type	Output	Single	Multiple
A	Likelihood profile	Х	
А	Gradient and likelihood component table	Х	Х
В	Retrospectives	Х	
С	Effort deviates (by fishery)	Х	Х
С	Effort deviates penalties (by fishery)	Х	
С	Tag returns time (by tag recapture group)	Х	Х
$\mathbf{C}$	Tag attrition (by tagging program, model region or combined)	Х	Х
$\mathbf{C}$	Tag return proportion (by region and quarter)	Х	
С	Catch size distribution (by fishery)	Х	
С	Catch (observed - predicted) (by fishery)	Х	Х
D	Selectivity (by age class or length and fishery)	Х	Х
D	Natural mortality	Х	Х
D	Growth	Х	Х
D	Maturity	Х	Х
D	Movement rates (single models or difference between two models)	Х	Х
D	Stock Recruitment Relationship	Х	Х
D	Recruitment distribution (by model region and quarter)		Х
D	Recruitment deviates (by model region and quarter)	Х	Х
Е	$\text{Depletion } (SB/SB_{F=0})$	Х	Х
Е	Adult biomass	Х	Х
Ε	Kobe plot	Х	
Е	Majuro plot	Х	
Е	Reference points table	Х	Х

## **B** Example diagnostics and model outputs

Examples of the currently available diagnostics and model outputs are presented here. All calculations were carried out using R (R Core Team, 2020). Only limited guidance on the interpretation of the outputs is provided.

As mentioned above, the diagnostics and outputs are placed into five overlapping categories: fitting diagnostics, model consistency, fits to data sources, model outputs and estimates of stock status.

### **B.1** Fitting diagnostics

These diagnostics inspect if the model has converged satisfactorially.

### B.1.1 Likelihood profiles

The likelihood profiles show how the final likelihood changes as different variables change, similar to a sensitivity test. The relative likelihood profiles are explored one model at a time (Figure 2).



Figure 2: Likelihood profiles for a single model

### B.1.2 Gradient and likelihood components

The likelihood components and gradients can be seen in Table 2. All models, or a subset of them, can be compared. The likelihood values are more useful when compared across models as they can be used to identify models with different behaviour and that may require further inspection. However, to compare likelihoods the models should have approximately the same structure and data to ensure that they have similar likelihood functions.

The maximum gradient can be checked to see if the model has converged to within the specified limits.

Max Gradient	8.000E-04	9.539 E-04	7.366E-04	6.534E-04	7.810E-04	8.482 E-04	8.333E-04	8.876E-04	5.203 E-04	8.870E-04	9.354E-04	9.557E-04	9.831E-04	9.904E-04	7.246E-04	8.888E-04	9.532 E-04	9.335 E-04	$9.422 E_{-}04$	8.776E-04	8.149E-04	7.109E-04	9.899 E-04	7.189 E-04
Total	170378.2679	169940.8432	172122.5828	171361.5166	173187.7000	172844.6822	174784.3933	174082.1630	170378.2766	169940.8360	172142.3866	171361.5611	173187.7033	172844.6759	174822.7637	174082.1585	170378.2742	169940.8472	172142.3876	171361.5507	173187.7210	172845.7747	174784.3935	174082.1758
Tag data	27466.8110	27436.3146	25502.6217	25528.7374	24533.3690	24494.3638	22698.1421	22695.6480	27466.8132	27436.3083	25507.4098	25528.6702	24533.3428	24494.3527	22705.2073	22695.6163	27466.7841	27436.3355	25507.3642	25528.6884	24533.3292	24496.7966	22698.1726	22695.6563
Weight comp.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Length comp.	-200505.0879	-200317.6142	-200230.5391	-200095.6456	-200382.8212	-200214.2523	-200110.5754	-199964.5716	-200505.1081	-200317.6343	-200229.2582	-200095.6450	-200382.7981	-200214.2414	-200109.6374	-199964.5452	-200505.0872	-200317.6385	-200229.2305	-200095.6638	-200382.7999	-200214.1057	-200110.5807	-199964.5875
Catchability devs	116.9353	120.2885	112.5802	114.9377	120.3201	123.3578	117.1219	120.0571	116.9256	120.2831	113.1386	114.8968	120.3170	123.3807	117.4581	120.0309	116.9515	120.2839	113.1226	114.9175	120.3165	123.4248	117.1047	120.0558
Effort devs	2542.9191	2820.0185	2492.5907	3090.2898	2541.3117	2751.7318	2510.7894	3066.5752	2542.9384	2820.0567	2466.1601	3090.3508	2541.3145	2751.7149	2464.0794	3066.6103	2542.9209	2820.0217	2466.1897	3090.3423	2541.3117	2747.9919	2510.7795	3066.5703
BH Steepness	0.1546	0.1493	0.1638	0.1640	0.1205	0.1167	0.1287	0.1283	0.1544	0.1504	0.1630	0.1660	0.1206	0.1172	0.1288	0.1292	0.1564	0.1503	0.1664	0.1649	0.1217	0.1177	0.1304	0.1292
Model	A0B0C1D0E0	A0B0C1D1E0	A0B0C2D0E0	A0B0C2D1E0	A0B1C1D0E0	A0B1C1D1E0	A0B1C2D0E0	A0B1C2D1E0	A1B0C1D0E0	A1B0C1D1E0	A1B0C2D0E0	A1B0C2D1E0	A1B1C1D0E0	A1B1C1D1E0	A1B1C2D0E0	A1B1C2D1E0	A2B0C1D0E0	A2B0C1D1E0	A2B0C2D0E0	A2B0C2D1E0	A2B1C1D0E0	A2B1C1D1E0	A2B1C2D0E0	A2B1C2D1E0

Table 2: Likelihood components and maximum gradient of the models.

### B.2 Model consistency

Diagnostics for model consistency inspect the internal consistency of models and evaluate if they are appropriate to use for projections.

#### **B.2.1** Retrospective analysis

Retrospective analysis involves rerunning the assessment a number of times with successively truncated time series. If the resulting estimates of stock status show repeated bias it suggests that the model is mis-specified. In this example, estimates of depletion from five stock assessments of the same model, each missing a further a year of data, are compared to the full assessment (Figure 3). The trends and levels of depletion are similar for each assessment indicating that the model is internally consistent.



Figure 3: Retrospective analysis of estimates of SB/SBF=0, with up to five years of data being truncated.

#### **B.3** Fit to data sources

It is important to inspect how well the observed data that was used to fit the model is being predicted by the model. MULTIFAN-CL stock assessments can use a variety of different data sources including catch and effort data, length / weight frequency data and tagging data.

It is possible to inspect the difference between the predicted and observed data (sometimes known as a deviate or a residual). When the deviates are plotted against time ideally there should no time trend and they should be centred around zero. Otherwise, it suggests that the model has been mis-specified. However, perfect fits to all data sets are unlikely, and the patterns must be expertly interpreted to identify serious issues.

#### **B.3.1** CPUE and effort

**B.3.1.1 Effort deviates** MULTIFAN-CL estimates a deviate for each effort observation that is used to calculate an effective effort inside the model (Kleiber et al., 2019). It is important to inspect the effort deviates for each fishery in the model. As mentioned above, these deviates should show no time trend and be centred around zero.

It is possible to plot the effort deviates for one model with a loess smoother through the points (Figure 4), or plot them for multiple models and only show loess smoothers for each model without the points (Figure 5). Comparing the effort deviates across the models allows for identification of spurious results.



Figure 4: Effort deviates over time for fisheries receiving standardised CPUE indices for a single model.



Figure 5: Effort deviates over time for fisheries receiving standardised CPUE indices for a collection of models (model legend not shown).

**B.3.1.2 Effort deviate penalities** The effort deviate penalty is a plot of how well the model should fit the standardized CPUE index. A higher penalty means more weight is given to this observation (Kleiber et al., 2019). The effort deviate penalties of each fishery by region are plotted for a single model (Figure 6).



Figure 6: Effort deviate penalties over time by fishery and region for the index fisheries.

### B.3.2 Tag data

**B.3.2.1** Tag returns over time by tag recapture group The tag recaptures over time are plotted by tag recapture group. When plotting a single model the tag recaptures can either be plotted as time series of observed and predicted values (Figure 7) or as a time series of the difference between the observed and predicted values, scaled by the mean observed value (Figure 8). When plotting the difference a loess smoother is also shown. Ideally there should no time trend to the difference and the points should be centred around zero.



Figure 7: Predicted (black line) and observed (red points) tag returns over time for a subset of the tag recapture groups for a single model.

It is also possible to plot the tag recaptures for multiple models as time series of the scaled difference between the observed and predicted values (Figure 9). When plotting multiple models the individual points are not shown, only a loss smoother for each model.



Figure 8: Difference between observed and predicted tag returns over time (with loess smoother), scaled by the mean number of observed tags for a subset of the tag recapture groups for a single model.



Figure 9: Difference between observed and predicted tag returns over time (with loess smoother), scaled by the total number of observed tags, for a subset of the tag recapture groups for multiple models (model legend not shown).

**B.3.2.2 Tag Attrition** Tag attrition plots show the observed and predicted number of recaptured tags against period at liberty. This can be shown by recapture region, by tagging program or by all regions and programs combined.

When plotting a single model it is possible to show the time series of the observed and predicted tag returns (Figure 10), or the difference between them scaled by the mean number of observed returns (Figure 11) with a loess smoother.



Figure 10: Predicted and observed tag attrition by tagging program for a single model.

It is also possible to plot the tag attrition for multiple models. In this case only the scaled difference is shown with a loess smoother for each model and the individual points are not shown (Figure 12)



Figure 11: Difference between observed and predicted tag attrition, scaled by the mean number of observed tags by tagging program for a single model.



Figure 12: Difference between observed and predicted tag attrition, scaled by the total number of observed tags, by region for a selection of models.

**B.3.2.3** Tag recapture proportion by region The tag recapture proportion plot shows the difference between the observed and predicted proportions of tag recaptures in each recapture region and quarter, by release region for a single model (Figure 13). The difference in each quarter is shown by the points (it is also possible as a bar graph too, not shown). For a well fitted model the points should be close to the zero horizontal line.



Figure 13: Difference between the predicted and observed proportion of recaptured tags by release and recapture region, and by quarter.

### B.3.3 Size data





Figure 14: Predicted (red lines) and observed (blue bars) composite (all time periods combined) catch-at-length data for the purse seine fisheries.

### B.3.4 Catch data

**B.3.4.1 Predicted and observed catches** The catch plot shows a time series of the difference between the observed and predicted catches by fishery, scaled by the mean observed catch. If a single model is plotted the points are shown and a loess smoother is put through the points (Figure 15). If multiple models are plotted a loess smoother for each model is shown without the points (Figure 16).



Figure 15: Difference between observed and predicted catches, scaled by the mean observed catch, for the purse seine fisheries for a single model.



Figure 16: Difference between observed and predicted catches, scaled by the mean observed catch, for the purse seine fisheries for multiple models.

## B.4 Model outputs

Model outputs are estimated by the model during the fitting process. Inspecting the outputs can help determine if a model is behaving as expected and identify potential problems, particularly when comparing across multiple models.

### B.4.1 Selectivity

The estimated selectivity of each fishery can be plotted by age (Figure 17) or length (Figure 18).



Figure 17: Selectivity by age for the purse seine fisheries for all models (model legend not shown).



Figure 18: Selectivity by length for the purse seine fisheries for all models (model legend not shown).

### B.4.2 Natural mortality

Estimated natural mortality is plotted by age class for multiple models (Figure 19).



Figure 19: Natural mortality by age class for multiple models (model legend not shown).

#### B.4.3 Growth

Estimated growth is plotted by age class for multiple models (Figure 20). There are two growth models for the 24 operating models in the grid.

#### **B.4.4** Movement rates

Estimated movement rates can plotted for a single model (Figure 21), or the difference between two models (Figure 22). It is also possible to plot movement for particular age classes, or averaged across age classes. Similarly, it is possible to plot movement by season, or averaged across seasons (Figure 23).



Figure 20: Growth curve for multiple models (model legend not shown). There are two growth models for the 24 operating models in the grid.



Figure 21: Movement, averaged across ages and seasons



Figure 22: Movement averaged across ages and seasons (difference between two models)



Figure 23: Movement for age classes 1 - 4, for all seasons

#### B.4.5 Maturity

Estimated maturity can be plotted by age class (Figure 24) or length (Figure 25) for multiple models.



Figure 24: Maturity by age class for multiple models (model legend not shown).

#### B.4.6 Stock-recruitment relationship

The estimated stock-recruitment relationship can be plotted for multiple models, with and without estimated points (Figure 26).

#### B.4.7 Recruitment distribution

The proportion of total recruitment by region and quarter is plotted as a distribution across all models. It is possible to specify a year range over which to take the average (from 1982 to 2018 is used here). This can be plotted as a box plot or as a violin plot. Only the violin is shown here (Figure 27). It also possible to overlay the observed data (not shown here).

#### B.4.8 Recruitment deviates

The time series of recruitment deviates by region can be plotted for multiple models (Figure 28). A loess smoother for each model is plotted through the points. The points can be removed for clarity.



Figure 25: Maturity by length for multiple models (model legend not shown).



Figure 26: Stock-recruitment relationship for multiple models (model legend not shown).



Figure 27: Proportion of total average recruitment (1982 to 2018) by region and quarter plotted as a distribution across all models.



Figure 28: Recruitment deviates over time for multiple models.

## B.5 Estimated stock status

### B.5.1 Depletion

A time series of instantaneous depletion  $(SB/SB_{F=0})$  can be plotted annually (Figure 29), seasonally (Figure 30) and with regions separated (Figure 31) for multiple models.



Figure 29: Annual estimated depletion with an LRP 0.2 and a TRP of 0.5 for multiple models (model legend not shown).



Figure 30: Seasonal estimated depletion with an LRP 0.2 and a TRP of 0.5 for multiple models (model legend not shown).



Figure 31: Annual estimated depletion by model region for multiple models (model legend not shown).

## B.5.2 Adult biomass

Adult biomass can be plotted with the same options as the depletion plot (annually, seasonly and by region) for multiple models. Only the annual plot is shown here (Figure 32).



Figure 32: Annual estimated biomass for multiple models (model legend not shown).

## B.5.3 Biomass contributions

The regional contributions plot shows the proportion of biomass by source region for a single model (Figure 33).



Figure 33: Proportion of biomass by source region for a single model.

### B.5.4 Kobe and Majuro plots

The Kobe and Majuro plots can be plotted for a single model (Figures 34 and 35 respectively). These plot stock status over time, relative to different reference points.



Figure 34: Kobe plot for a single model. The green point indicates the start of the time series. The blue point indicates the most recent estimate.



Figure 35: Majuro plot for a single model. The green point indicates the start of the time series. The blue point indicates the most recent estimate.

### **B.5.5** Reference points

The stock status estimates and reference points can be seen in Table 3. All models, or a subset, can be compared.

Model	SBSBF0	MSY	BMSY	FMSY
A0B0C1D0E0	0.4032	554600	952000	0.2228
A0B0C1D1E0	0.3980	564300	874600	0.2187
A0B0C2D0E0	0.3626	498300	980500	0.2214
A0B0C2D1E0	0.3203	477500	966900	0.2161
A0B1C1D0E0	0.5000	688300	1185000	0.2218
A0B1C1D1E0	0.4744	682400	1081000	0.2175
A0B1C2D0E0	0.4387	579900	1175000	0.2182
A0B1C2D1E0	0.3870	550700	1135000	0.2142
A1B0C1D0E0	0.3717	576300	1305000	0.1894
A1B0C1D1E0	0.3672	584300	1221000	0.1859
A1B0C2D0E0	0.3301	526100	1330000	0.1898
A1B0C2D1E0	0.2884	507500	1325000	0.1849
A1B1C1D0E0	0.4734	703800	1568000	0.1907
A1B1C1D1E0	0.4483	696700	1455000	0.1868
A1B1C2D0E0	0.4095	601000	1542000	0.1884
A1B1C2D1E0	0.3592	573900	1504000	0.1846
A2B0C1D0E0	0.4232	554200	671600	0.2668
A2B0C1D1E0	0.4176	567200	583000	0.2652
A2B0C2D0E0	0.3835	492000	717900	0.2609
A2B0C2D1E0	0.3407	469600	697500	0.2559
A2B1C1D0E0	0.5168	692300	870800	0.2613
A2B1C1D1E0	0.4912	689200	759900	0.2585
A2B1C2D0E0	0.4569	576600	887300	0.2544
A2B1C2D1E0	0.4046	546500	848500	0.2504

Table 3: Stock status estimates.