EVALUATION OF DATA POOR APPROACHES FOR EVALUATING STOCK STATUS AND TRENDS: SELF TESTING USING BIOMASS BASED ASSESSMENT MODELS.

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SUMMARY

Ecosystem Based Fisheries Management is challenged by fishing impacts not just on the main target stocks but also on by caught, threatened and endangered species, and the associated ecological communities. Although ICCAT's statistical database includes more than a hundred stocks, only 15 teleost stocks are formally assessed. This is due either to lack of data, capacity or management recommendations. We therefore evaluate the ability of data poor methods, fitted to total catch and indices of abundance, to determine stock trends and status. To do this, we conduct a self test based on assessments conducted by the SCRS to evaluate the Value-of-Infomation. In a self test a model is first fitted to data and then used to simulate-pseudo data. We then refit the model for scenarios where data or expert knowledge are omitted and compare the estimates obtained to the original estimates. Although this approach ignores many sources of uncertainty, if the methods do not perform well when the assessment model assumptions are the same as the original assessment, then they are unlikely to perform well in more complex situations.

KEYWORDS

Catch Only; Data Poor; Ecosystem Based Fisheries Management; Self-Test; Simulation, Stock Assessment; Value-of-Infomation.

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Introduction

As part of Ecosystem Based Fisheries Management (EBFM) Regional Fisheries Management Organisations (RFMOs) increasingly have to assess not only the main target species but also bycaught Endangered, Threatend and Protected (ETP) species. In many cases, however, the available datasets are insufficient to use traditional stock assessment methods based on catch and indices of abundance. For example although ICCAT list over a hundred species in its database, currently only 15 tuna and billfish species are assessed. This is due either to lack of data, capacity or management recommendations. This lack of formal assessments may hamper progress towards EBFM.

A variety of data poor methods have been developed to model biomass dynamics given a time series of total catches and a variety of assumptions based on life histories and final depletion to estimate biomass trends and reference points. These include Stock Reduction Analysis (SRA; Kimura and Tagart 1982; Kimura et al. 1984), which has been extended to replace strong assumptions about the final biomass depletion by an integrated catch-curve analysis of compositional data (Thorson and Cope 2015). Further extensions include incorporation of stochastic variability in population dynamics (Stochastic-SRA; Walters et al. 2006), a flexible shape for the production function (Depletion-Based SRA; Dick and MacCall 2011), prior information regarding resilience and population abundance at the start of the catch time series (Catch-Maximum Sustainable Yield, Catch-MSY; Martell and Froese 2013), Bayesian approaches (CMSY, Froese et al. 2017), and even age-structured population dynamics (Simple Stock Synthesis, SSS; Cope 2013).

Despite their differences, this family of catch-only models share a common dependence on prior assumptions about final stock depletion. Simulation testing has previously indicated that these methods perform well only when assumptions regarding final relative abundance are met (Wetzel and Punt 2015). Unsurprisingly, because final stock depletion is a prior assumption, the methods perform differently under different stock depletion levels (i.e. highly depleted or slightly depleted stocks, Walters et al. 2006) or under different harvest history or catch trends.

The quality of data in the ICCAT database for many species, however, is largely insufficient to use even these data poor methods, since data on total catch and life history characteristics for many species are not routinely collected. Tthe purpose of this paper is to evaluate the minimum information requirements to assess trends and status for stock impacted by ICCAT fisheries but currently unassessed by the SCRS. To do this we applied a self-testing procedure where the results from biomass dynamics stock assessment are used to generate data which are then used in the same model or family of model to estimate stock status (Deroba et al., 2014). This provides an objective way to evaluate the impact of the different assumptions

Material and Methods

We evaluate the Value-of-Information, i.e. the improvement in performance derived from better quality data, life history priors, and expert knowledge, for the family of data poor methods based on biomass dynamics. We do this by performing a self-test using an Operating Model (OM) conditioned on biomass dynamic stocks assessments conducted by the SCRS. Although this approach ignores many sources of uncertainty if the methods evaluated do not perform well when the assessment model assumptions are the same as the OM then they are unlikely to perform well in more complex situations.

The self-test approach requires a reference OM based on a stock assessment that is fitted to the best available input data. which are then omitted when testing the data-poor methods. For this purpose, we used the SCRS JABBA assessments for Thunnus albacares (Sant'Ana et al., 2019), Thunnus obesus (Winker et al., 2019), Xiphias gladius (Winker et al., 2018), Kajikia albida (Mourato et al., 2019), and Makaira nigricans (Mourato et al., 2018).

The analysis was performed in R using FLR (Kell et al., 2012) and SRA+a R package at the most "data limited" end of the stock assessment spectrum (Ovando et al., 2019). SRA+ approximates the behaviour of Catch-MSY (Martell and Froese 2013), sampling from prior distributions to obtain parameter values that given a catch history do not crash the population and satisfy supplied priors on initial and final depletion. At the most data-rich end the model can be fit to an abundance index or catch-per-unit-effort (CPUE) data, while incorporating priors on recent stock status based on Fisheries Management Index scores or swept-area ratio data. We also used Catch-MSY as an example of how different software packages, such as those implemented in fishmethods[4] can be included in the testing procedure.

As a benchmark we first fitted SRA configure as a data-rich assessment model using the reported catch and an index of abundance based on the estimated biomass (B) from the JABBA reference models. Following which the followingfour assessment model scenarios with different data requirements and assumptions were run:

1. Same as the benchmark but the index of abundance included measurement error (log normal with 40% CV)
2. Catch-only and heuristics to determine final depletion $p = B_{end}/K$ levels
3. Catch-only and priors on r, K and p taken from the OM, assuming 30% CVs.
4. Catch-MSY, with default settings.

The heuristics for SRA are that, if catch in the first year is less than 20% of maximum catch, initial depletion is assumed to be between 50% and 90% of carrying capacity, otherwise it is assumed to be between 20% and 60% For final depletion, the heuristic assumes that if final catch is greater than 50% of max catch, final depletion is between 30%-70%, 1%-50% otherwise.

The assessment procedures were run using all the data (the long time series) and a truncated time series comprising the last 15 years. The later scenario reflected the fact that in data poor situations complete catch time series, representative of the entire exploitation history are often unavailable and was also

4 https://cran.r-project.org/web/packages/fishmethods/index.html

intended to evaluate the benefits of improved monitoring.

Often in data poor situations trends in the most recent period are used to inform management. For example ICES uses the "2 over 3" rule (ICES, 2012), where the average of the last two years is divided by the average of the preceding 3 years, or alternatively the slope of a regression of recent abundance with respect to time could be used.

Results

Absolute trends in biomass for the catch only methods are highly biased (**Figure 1**); the OM (black lines i.e. as assessed by the SCRS) to the assessed trends (shaded areas show the 89th percentiles and the thick line the medians). The main results are therefore reported as biomass relative to B_{MSY}.

Figures 2 and 3 shows the trends estimated using the entire time series for the entire historical period and the last 5 years. **Figure 4** the same quantities from the short time series and **Figure 5** contrasts the two sets of results.

In order to evaluate the ability to detect recent trends, the slopes of a linear regression fitted to the last five years and the 2 over 3 rule were tabulated in **Table 1** using the fits to the long-time series and in **Table 2** to the truncated data.

Discussion

- The catch only methods were unable to estimate absolute abundance.
- For the long time series, estimates of final depletion from the catch only methods, SRA+ with priors and catch MSY, overlapped the true value but the credibility/confidence intervals were large.
- SRA+ with heuristics performed poorly.
- For the short time series, the catch and index methods were highly biased, however, the deterioration in performance of the catch only method was less, possibly because the fits were poor.
- SRA+ does fairly well if it has informative data on abundance.
- Catch only methods perform well in estimating relative trends if reliable life history priors are available. This illustrates the value of information, either on better data on abundance, or better data on life history priors r and K as estimated through a production function.

Conclusions

- The self test is a useful approach for comparing the performance of alternative formulations within a family of models, and for identifying information and data requirements, i.e. the value-of-information.
- The next step is to evaluate under what conditions catch only methods perform sufficiently well to be used for management advice, i.e. could unbiased, informative priors for r and K or initial

and current depletion lead to reliable stock status classification

- Cross-testing can also be used to evaluate length-based methods and compare their performance with catch only methods, which would, however, require performing the cross tests conditioning Operating Models based on available stock synthesis assessments to generate length data as input. Such age-structured can be equally used for further cross tests of SRA+ an other Catch-Only methods..

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Tables

Table 1 & 2. Trends in final estimates

All Years

	Stock	Catch & Heuristics	Catch & Index	Catch & Index Error	Catch & Priors	CMSY	OM
2 over 3	bet	1.165	1.043	0.900	1.159	1.009	1.044
	bum	1.157	1.017	0.849	1.173	1.030	1.016
	swo	1.153	1.088	0.953	1.168	1.030	1.088
	whm	1.171	1.026	0.870	1.161	1.039	1.023
	yft	1.159	0.977	0.837	1.163	1.000	0.977
Regression	bet	-0.031	0.008	-0.097	-0.019	0.002	0.008
	bum	-0.017	0.014	-0.168	-0.020	0.013	0.013
	swo	-0.026	0.077	-0.020	-0.022	0.015	0.078
	whm	-0.018	-0.007	-0.168	-0.021	0.015	-0.010
	yft	-0.028	-0.019	-0.165	-0.031	-0.004	-0.020

10 Years

	Stock	Catch & Heuristics	Catch & Index	Catch & Index Error	Catch & Priors	CMSY	OM
2 over 3	bet	1.217	1.040	0.855	1.126	1.126	1.044
	bum	1.160	1.015	0.835	1.137	1.171	1.016
	swo	1.205	1.074	0.873	1.152	1.153	1.088
	whm	1.210	1.026	0.843	1.147	1.178	1.023
	yft	1.177	0.977	0.812	1.140	1.129	0.977
Regression	bet	0.009	0.008	-0.189	-0.046	0.042	0.008
	bum	-0.033	0.010	-0.189	-0.036	0.058	0.013
	swo	-0.003	0.065	-0.129	-0.028	0.060	0.078
	whm	0.000	-0.006	-0.211	-0.036	0.060	-0.010
	yft	-0.017	-0.018	-0.214	-0.038	0.041	-0.020

Figures

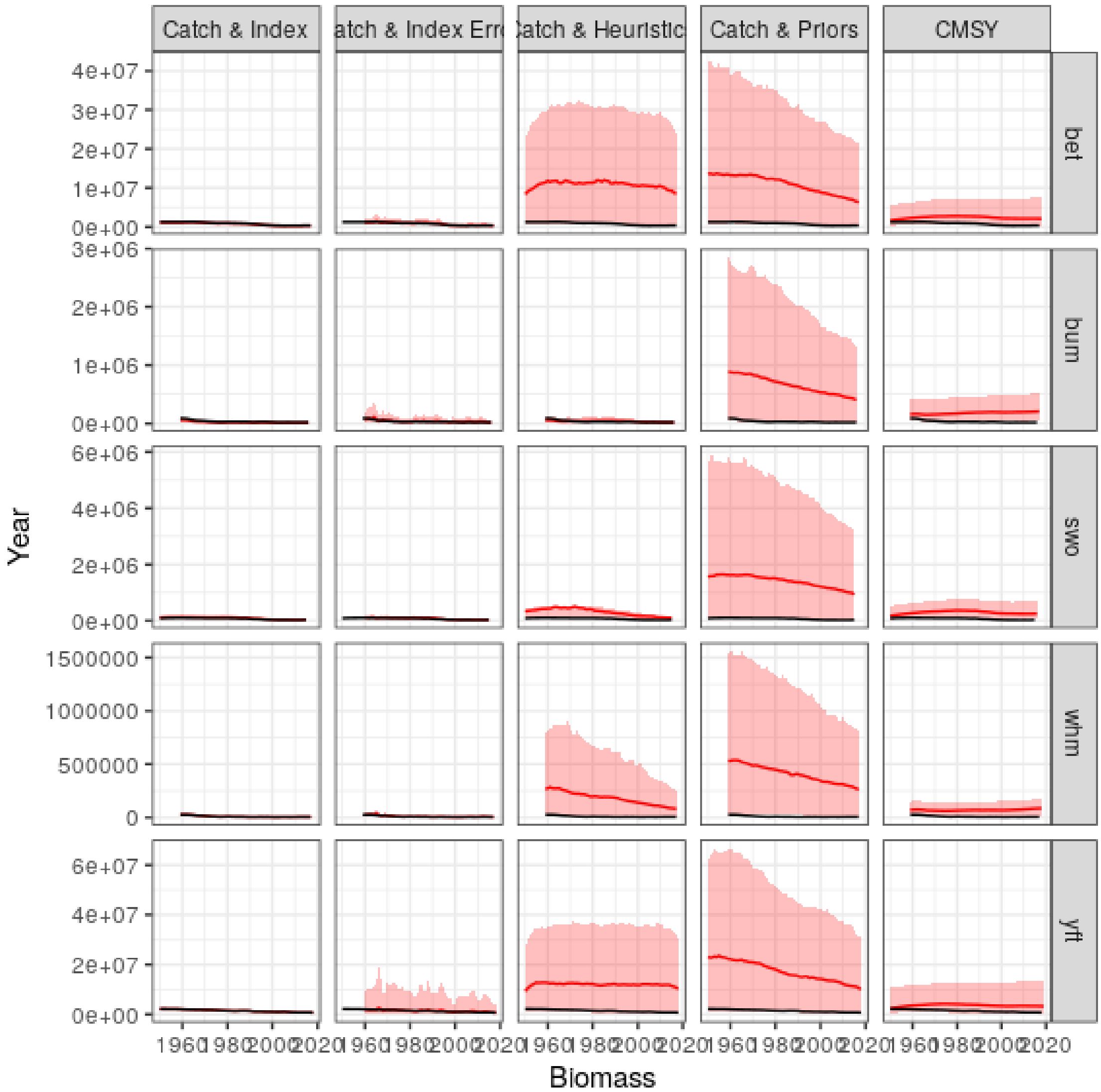

Figure 1 Absolute trends in abundance for all stocks and methods (black line are the true values).

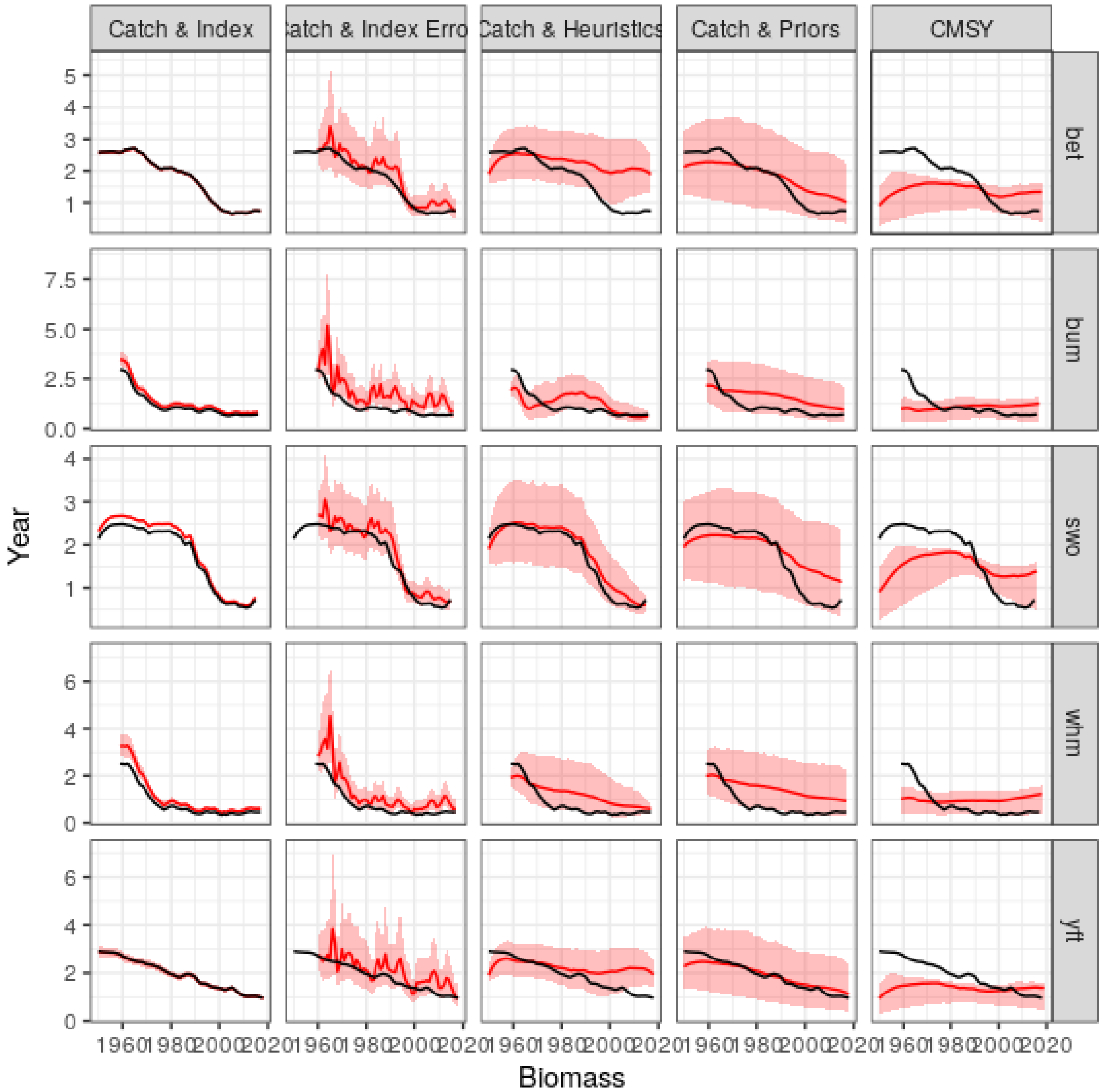

Figure 2 Trends in abundance relative to B/B_{MSY} for all stocks and methods (black line are the true values).

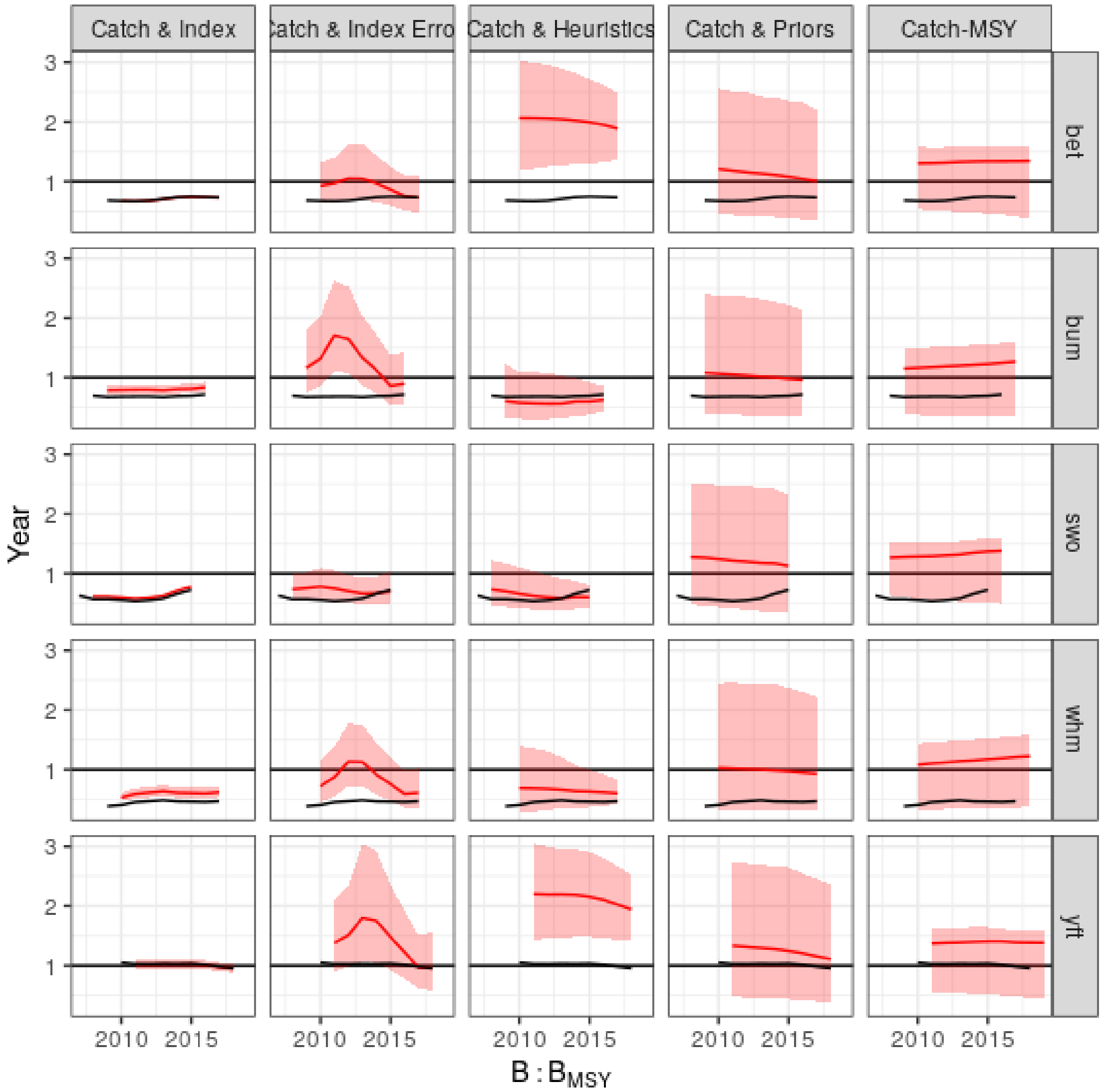

Figure 3 Trends relative to B/B_{MSY} in last 10 years using all the data.

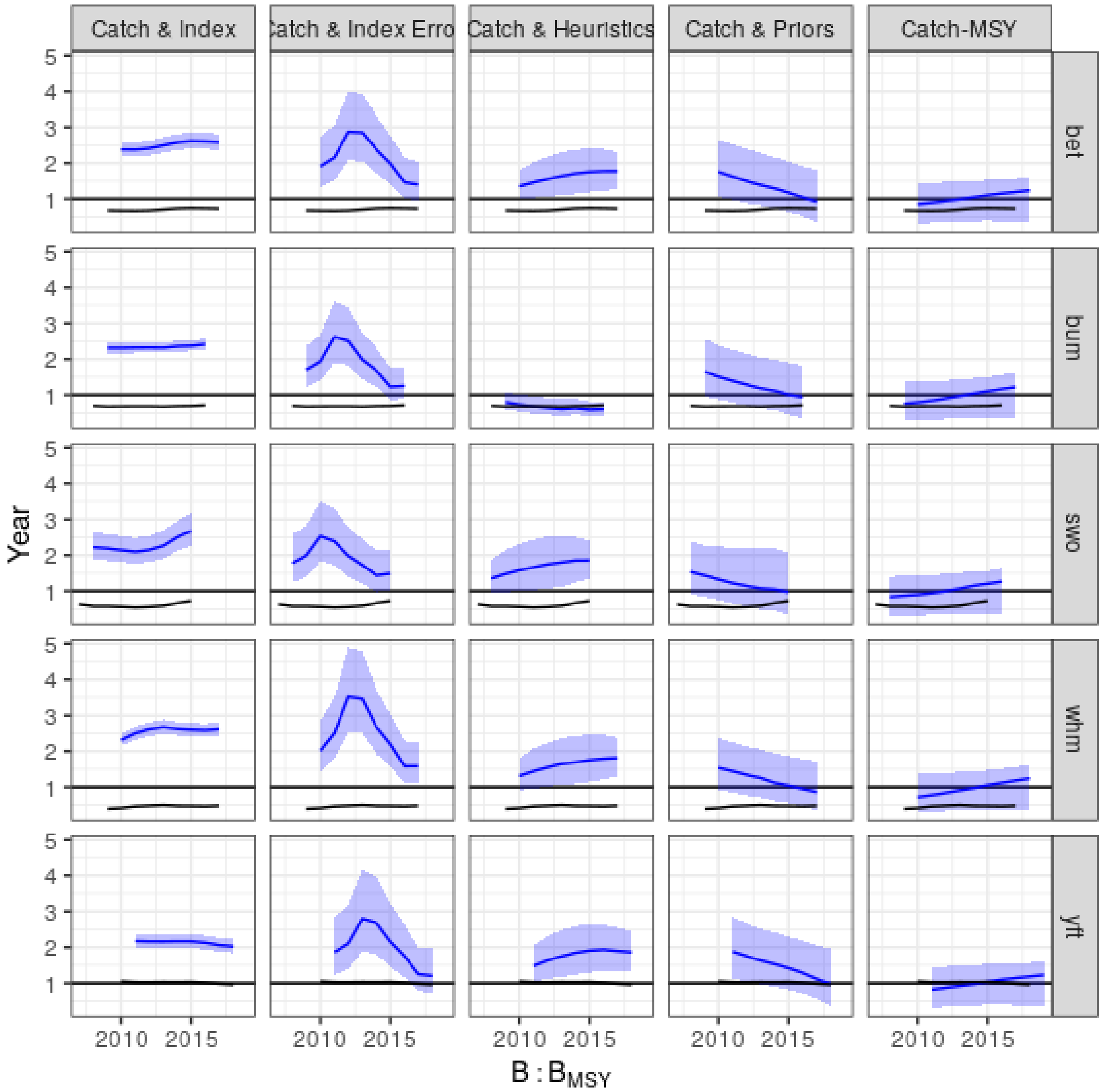

Figure 4 Trends relative to B/B_{MSY} in last 5 years using 15 years of truncated data.

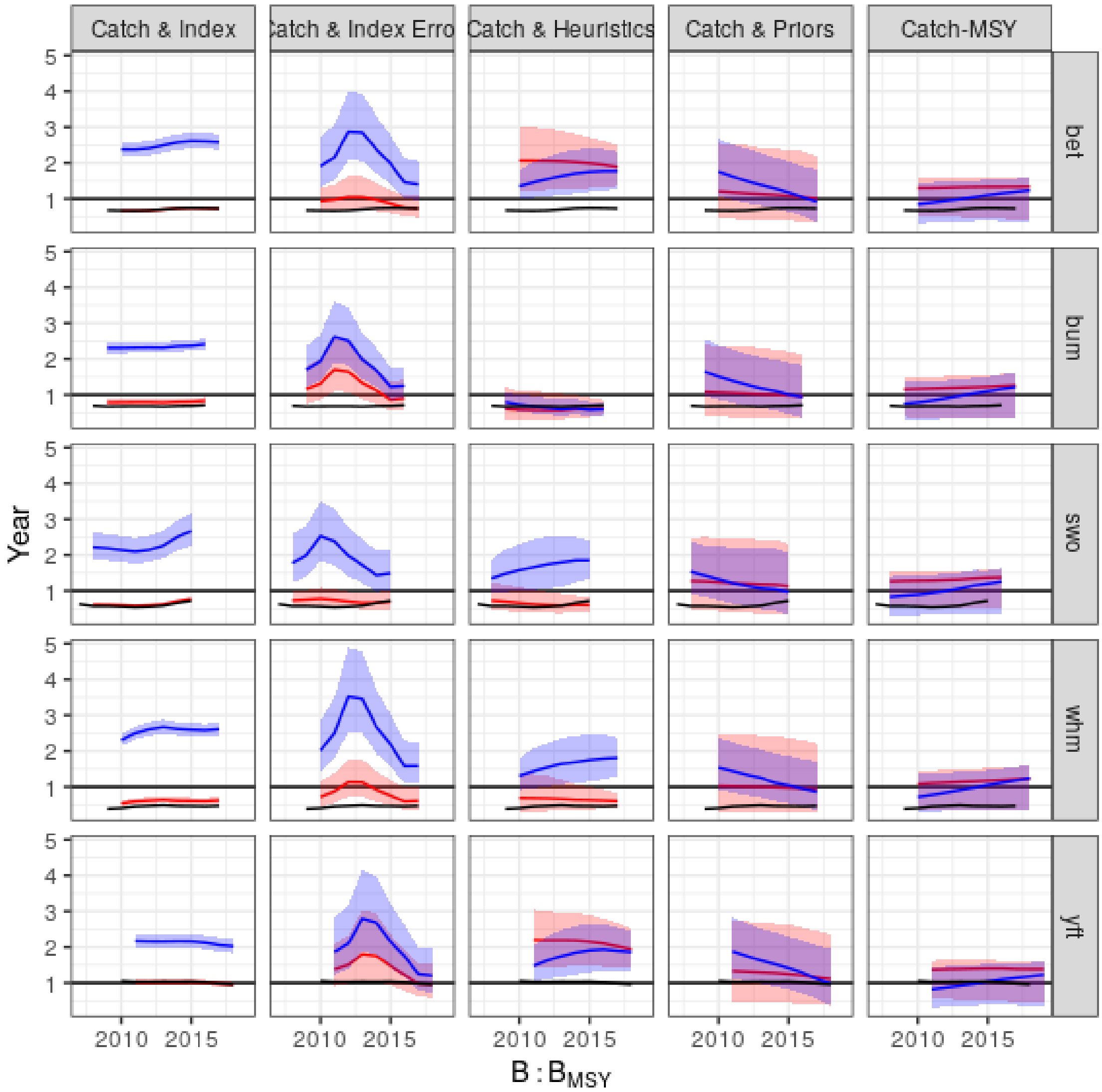

Figure 5 Trends relative to B/B_{MSY} in last 5 years compared for all data and 15? years.

I would delete Figs. 3-4 and instead add the full B/Bmsy time series across the 15 years.

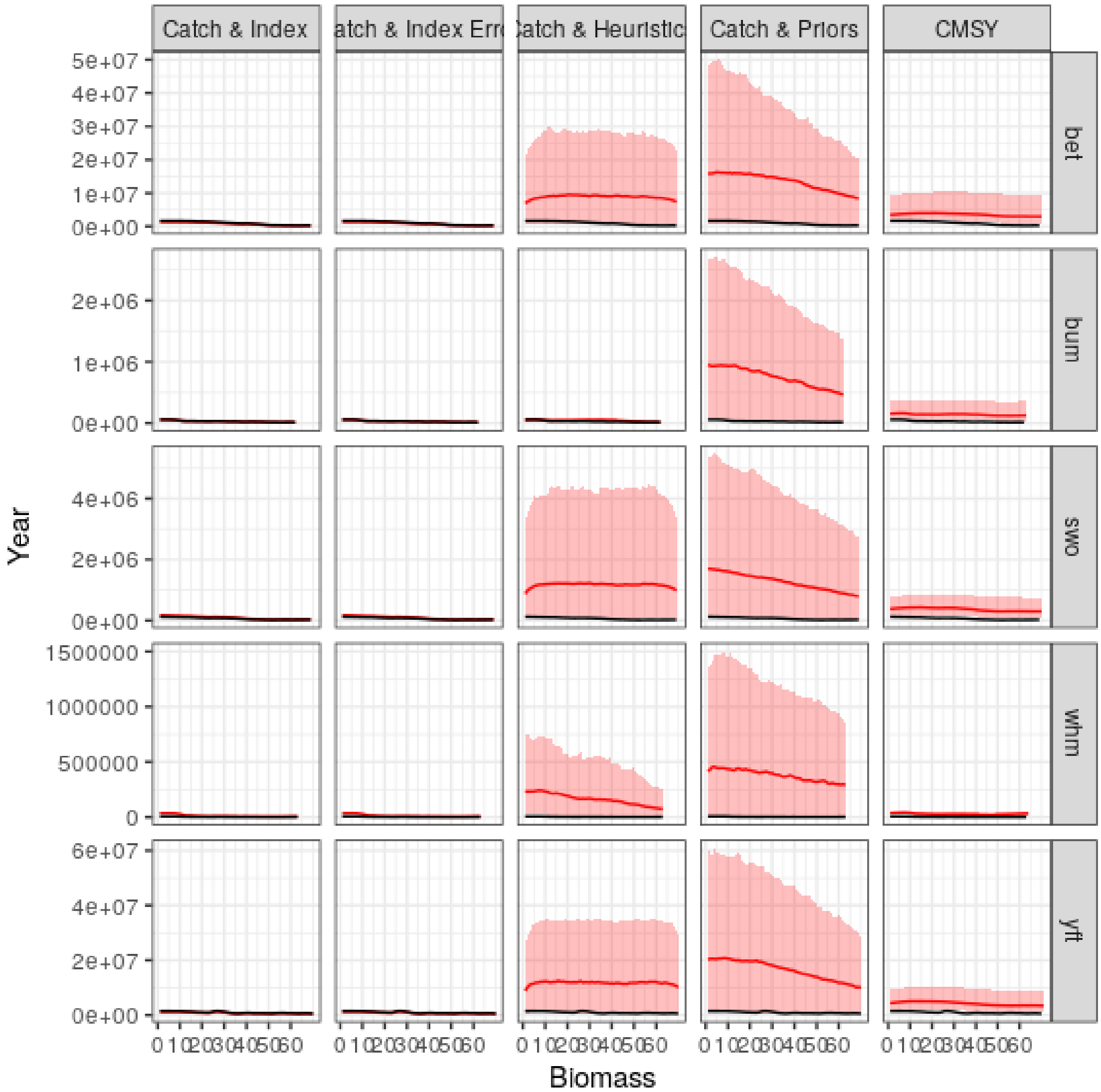

Figure 6 Absolute trends using stock synthesis based on age-structures SS3 OMs (a different model structure estimated by SRA+).

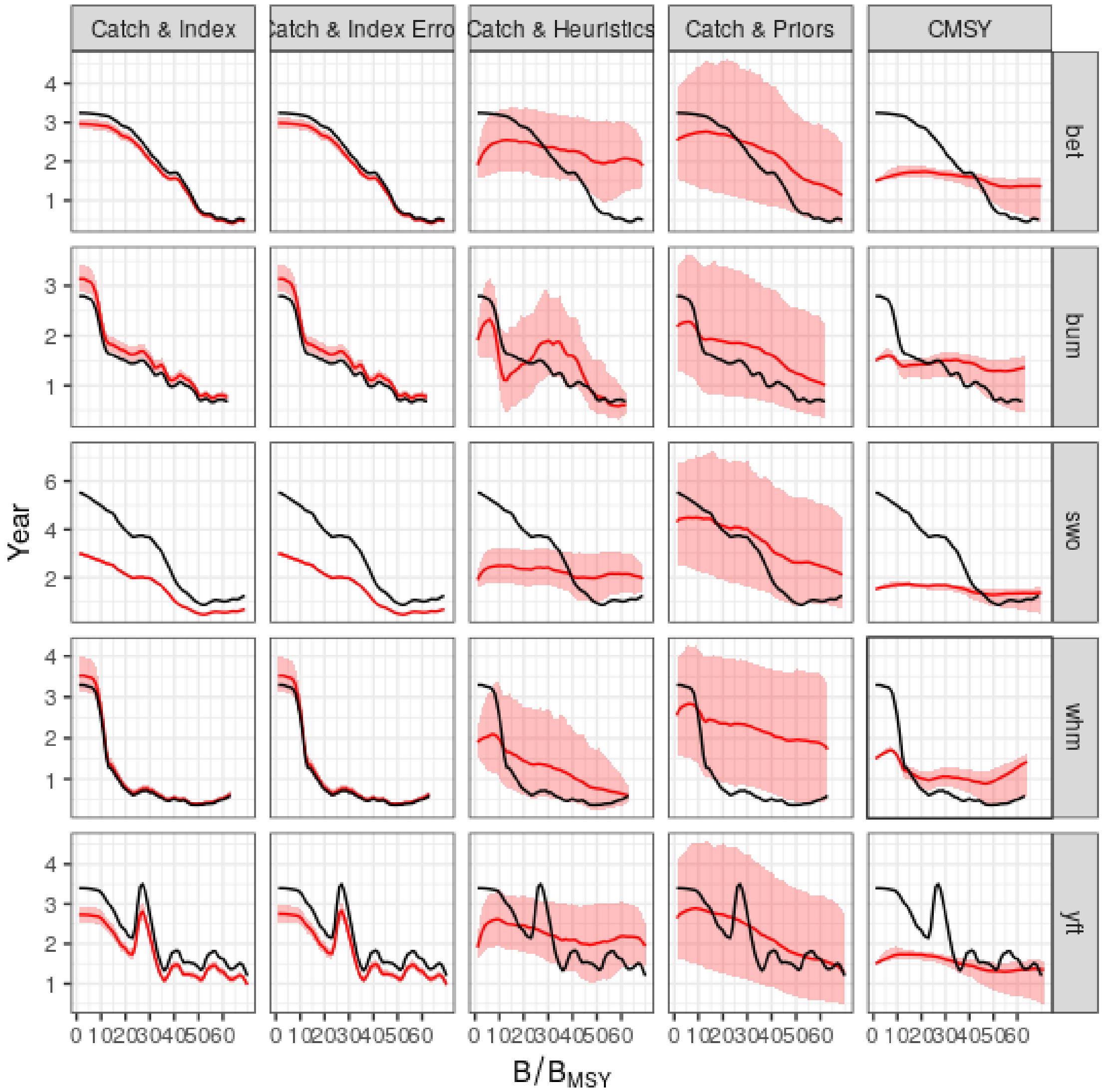

Figure 7 Trends relative to B/B_{MSY} using alternative model structures for the OM.

I think you have forgotten to add the error in the Catch & Index Error...looks the same as catch & index?

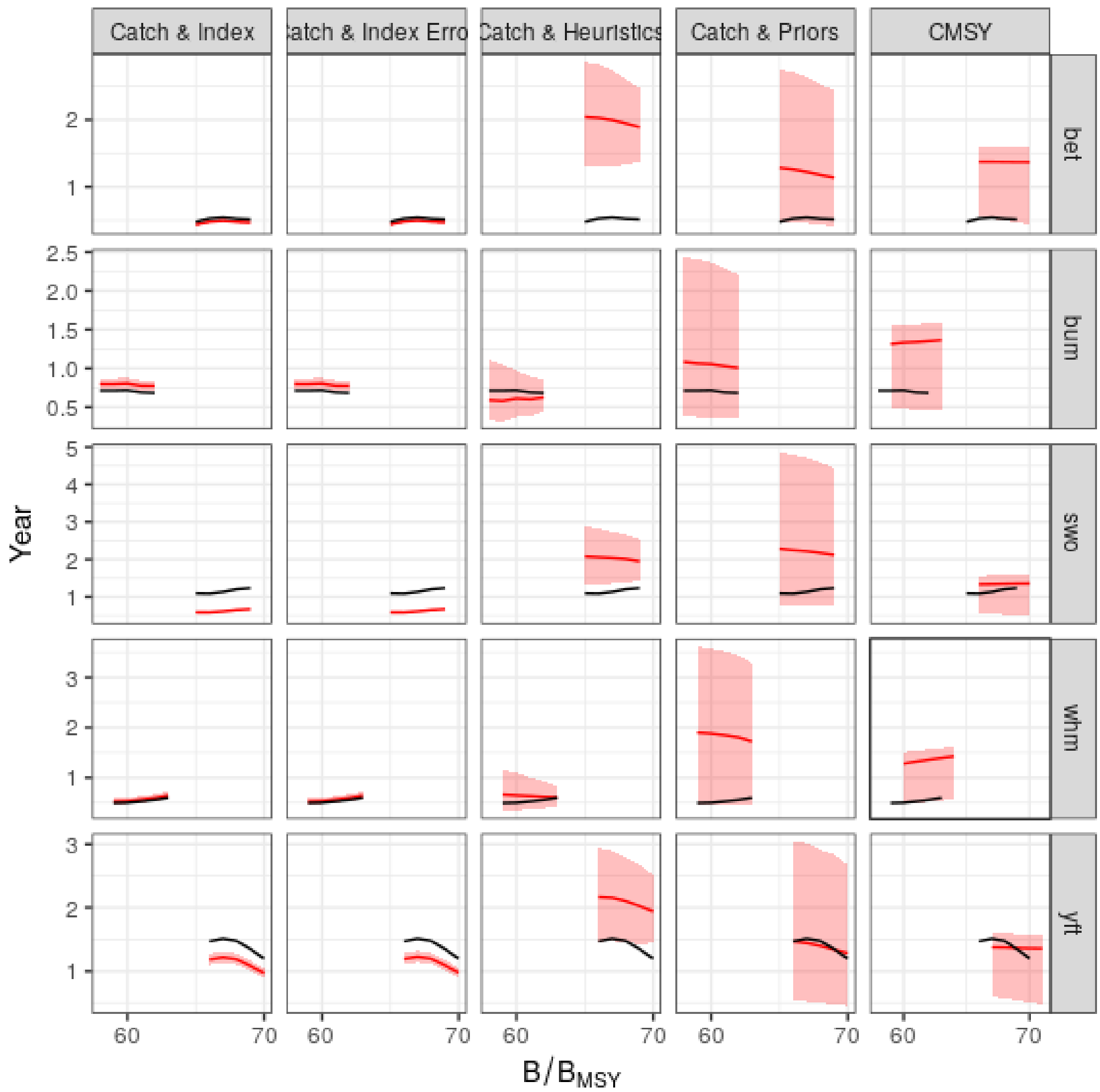

Figure 8 Trends relative to B/B_{MSY} in last 5 years using an alternative model structure

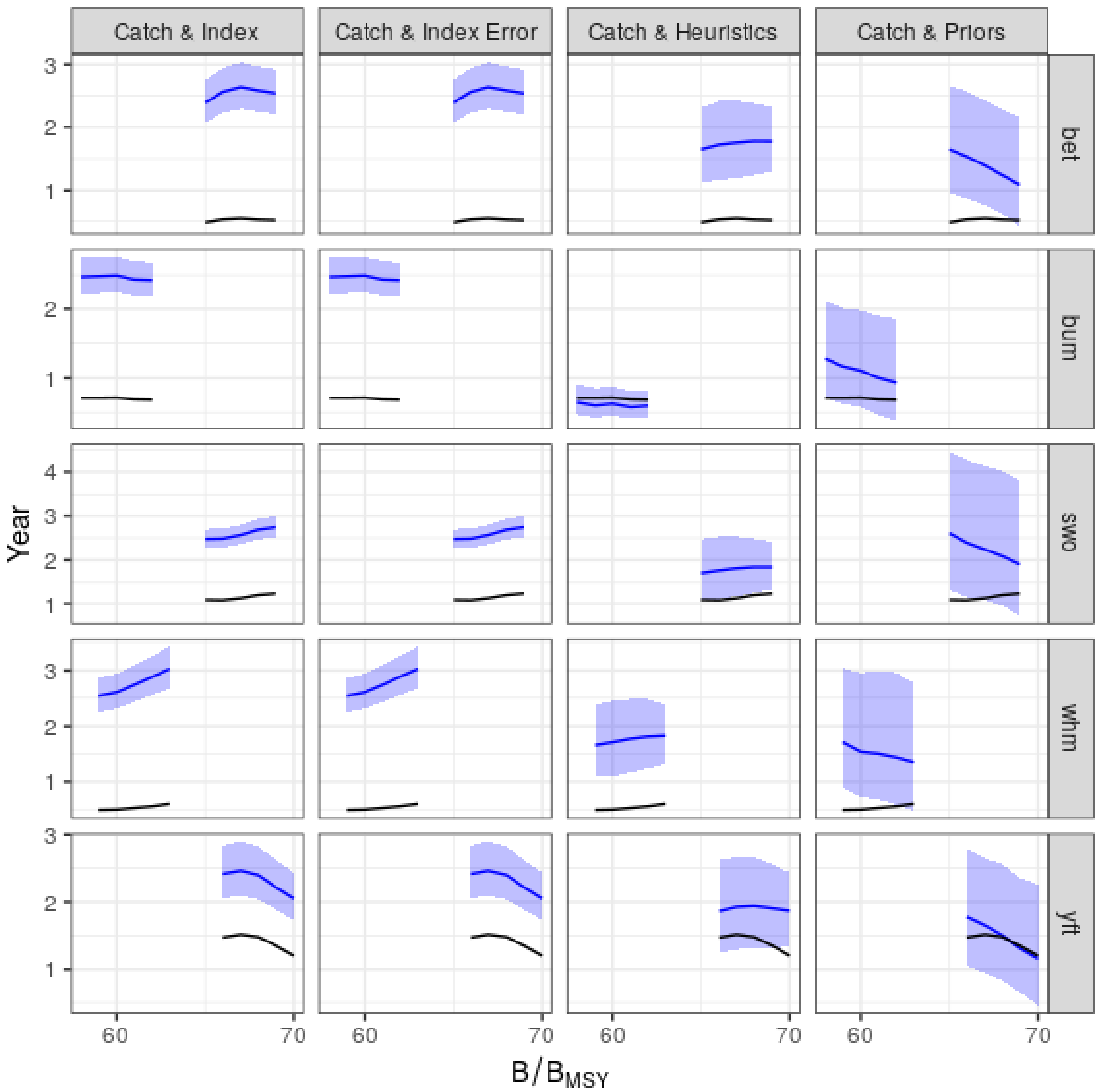

Figure 9 Trends relative to B/B_{MSY} in last 5 years using truncated data using alternative OM based on integrated model Stock Synthesis.

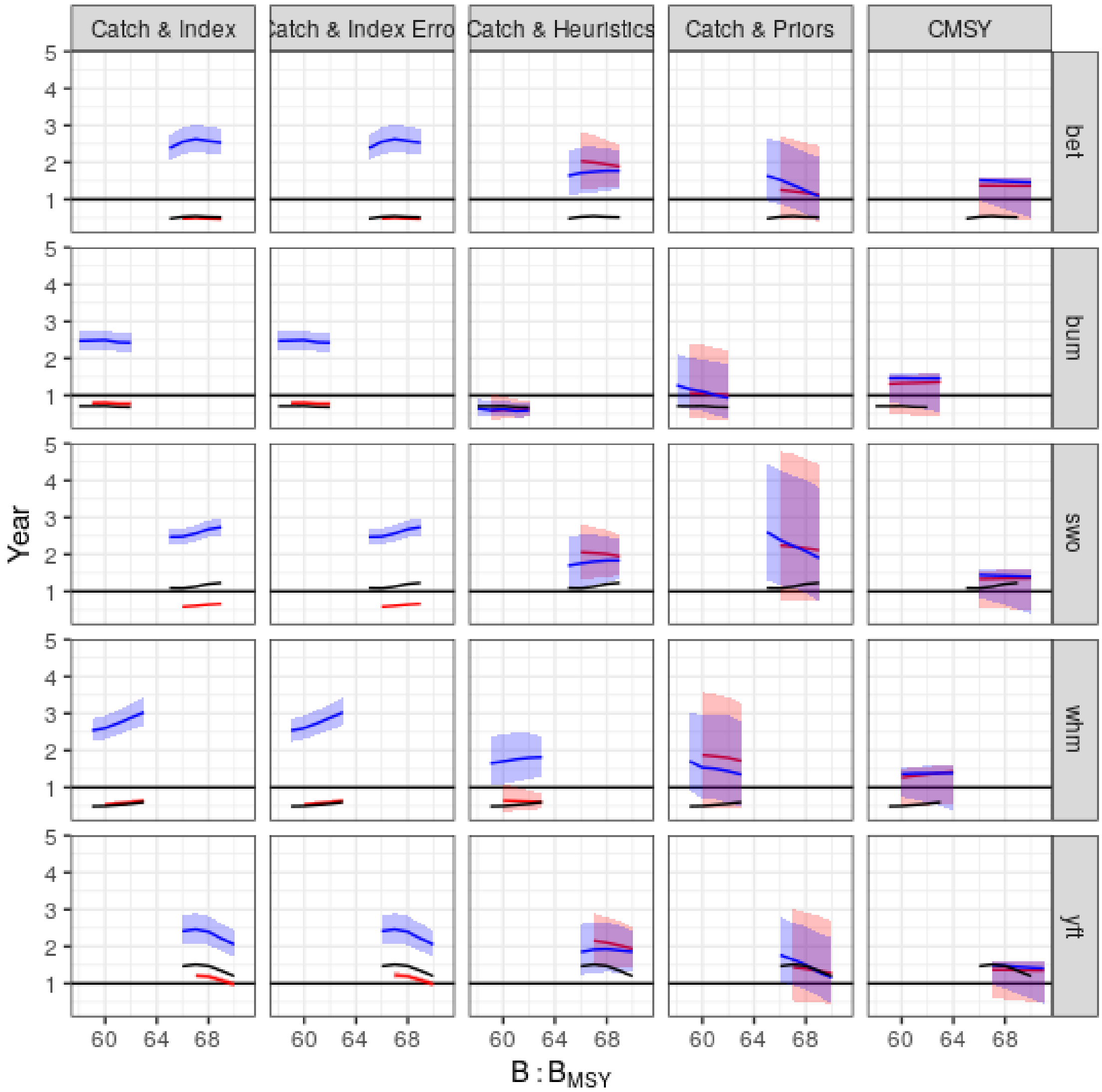

Figure 10 Trends relative to B/B_{MSY} in last 5 years compared for all data and 10 years using alternative OM based on integrated model Stock Synthesis.