EVALUATION OF DATA POOR APPROACHES FOR EVALUATING STOCK STATUS AND TRENDS: CROSS TESTING USING INTEGRATED 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. For example although ICCAT has more than a hundred species in its statistical database only 15 Tuna and billfish stocks have been formally assessed. This is due either to lack of data, capacity or management recommendations. The lack of formal assessments may hamper progress towards Ecosystem Based Fisheries Management, we therefore evaluate the ability of data poor methods to provide robust advice on stock status and trends. We do this by conducting a cross-test using integrated stock assessments conducted by the SCRS to simulate psuedo data. These are then used to fit models based on biomass dynamics for scenarios related to quality, and priors and heuristics based on expert knowledge. Although this approach ignores many sources of uncertainty comparing the performance of data poor methods to estimates from assessment model used to provide actual advice, allows the value-of -information to be evaluated.

KEYWORDS

Catch Only; Cross-test; Data Limited; Data Poor; Ecosystem Based Fisheries Management; 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 species that may also be endangered, threatend and protected (ETP). In many cases, however, the available data are insufficient to use traditional stock assessment methods based on catch, length and indices of abundance. For example although ICCAT list over a hundred species in its database, currently only 15 tuna and billfish stocks have been formally assessed. This is due either to lack of data, capacity or management recommendations. This lack of formal assessments may hamper progress towards EBFM.

The quality of data in the ICCAT database for many species 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. The purpose of this paper is therefore 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 cross-testing procedure where estimates from integrated data rich stock assessment are used to generate data which are then used to estimate stock status uisng alternative models (Deroba et al., 2014). This provides an objective way to evaluate the impact of the different assumptions on estimates of stock trends and status and the value-of-infomation in the data, life history parameters and expert knowledge.

We therefore 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 cross-test using an Operating Model (OM) conditioned on integrated stocks assessments conducted by the SCRS. In a cross-test estimates from a model are used to simulate psuedo data. these are then used to fit alternative models and the results compared to the original estimates. Although this approach ignores many sources of uncertainty comparing the performance of data poor methods to estimates from assessment model used to provide actual advice, allows the value-of -information to be evaluated.

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 the apparent differences, the 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.

Material and Methods

The cross-test approach requires a reference set of historical estimates based on a stock assessment that is fitted to the best available input data. When testing scenarios were run for the data poor methods where various data sets and knowledge are omitted. This allows the value-of-infomation in the datasets and priors used in the data poor assessments to be evaluated. For the data rich datasets we used Stock Synthesis assessments conducted by the SCRS for *Thunnus albacares, Thunnus obesus, Xiphias gladius, Kajikia albida , and Makaira nigricans.*

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 integrated assessments. Following which the following four data poor assessment model scenarios, with different data requirements and assumptions were run:

- Same as the benchmark but the index of abundance included measurement error (log normal with 40% CV)
- Catch-only and heuristics to determine final depletion $p = B_{end}/K$ levels
- Catch-only and priors on r, K and p taken from the OM, assuming 30% CVs.
- 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 10 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 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.

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

Results

The absolute trends is abundance estimated for each stock and assessment model are shown in **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). Absolute trends in biomass for the catch only methods are highly biased and uncertain. The following results are therefore reported as biomass relative to $B_{MSY.}$

Figures 2 and 3 shows the trends estimated using the entire historical period for the entire period and last 10 years. **Figure 4** the same quantities from the short time series and **Figure 5** contrasts the two sets of results.

When an index of abundance is available then the trends are well estimated (**Figure 2**), status relative to B_{MSY} is overestimated, expect for swordfish. When the index is not available trends are poorly estimated. When the catch only methods are used with heuristics and priors the downward trend is captured but not the variability in the dynamics. Both methods overestimate final depletion. Catch-MSY fails to capture the trends and appears to overestimate final depletion.

When only 10 years of data are available the models with an index overestimate stock status relative to $B_{MSY,}$ and fail to identify when stocks are overfished, although trends are still captured in most cases. The catch only methods perform poorly, neither being able to capture trends or status.

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. It appears that the regression slope does not estimate well the recent stock trend, however the 2 over 3 rule appears to perform well even when only 10 years of data are available.

Discussion

- The assessment scenarios spanned the spectrum of biomass dynamic biomass dynamic stock assessment models, from data rich where a full time series of historical catches and an index of abundance was availble, to data poor where only 10 years of catch were available.

- When a full catch series was available catch-only methods were not able to estimate absolute abundance. However, when an index of abundance was available trends in absolute biomass was well estimated.

- Trends in biomass relative to B_{MSY} were less biased than absolute trends, however trends were poorly estimated by the catch-only methods.

- When only 10 years of data were available estimates of biomass relative to B_{MSY} were poorly estimated, although trends appeared to be well estimated.

- For the catch only method and 10 years of data results, neither trends nor status were well estimated.

Conclusions

- The cross 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.

- The 2 over 3 rule appears to perform well in identifying stock trends and could be used in a Management Proceedure as part of Management Strategy Evaluation.

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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	1.160	1.051	1.051	1.176	1.000	1.044
	bum	1.163	1.014	1.014	1.175	1.020	1.016
	swo	1.161	1.059	1.059	1.175	1.005	1.088
	whm	1.159	1.138	1.138	1.189	1.073	1.023
	yft	1.157	0.976	0.976	1.184	0.998	0.977
Regression	bet	-0.023	0.013	0.013	-0.013	-0.001	0.008
	bum	-0.027	-0.009	-0.009	-0.018	0.009	0.013
	swo	-0.025	0.036	0.036	-0.013	0.004	0.078
	whm	-0.024	0.053	0.053	-0.004	0.027	-0.010
	yft	-0.028	-0.049	-0.049	-0.003	-0.004	-0.020

10 Years

	Stock	Catch & Heuristics	Catch & Index	Catch & Index Error	Catch & Priors	CMSY	OM
2 over 3	bet	1.206	1.046	1.046	1.130	0.978	1.044
	bum	1.183	1.011	1.011	1.160	0.990	1.016
	swo	1.198	1.053	1.053	1.151	0.972	1.088
	whm	1.213	1.125	1.125	1.137	0.991	1.023
	yft	1.191	0.976	0.976	1.132	0.968	0.977
Regression	bet	0.001	0.013	0.013	-0.036	-0.010	0.008
	bum	-0.023	-0.006	-0.006	-0.023	-0.001	0.013
	swo	-0.008	0.029	0.029	-0.027	-0.007	0.078
	whm	0.002	0.046	0.046	-0.038	0.004	-0.010
	yft	-0.015	-0.042	-0.042	-0.043	-0.016	-0.020

Figures

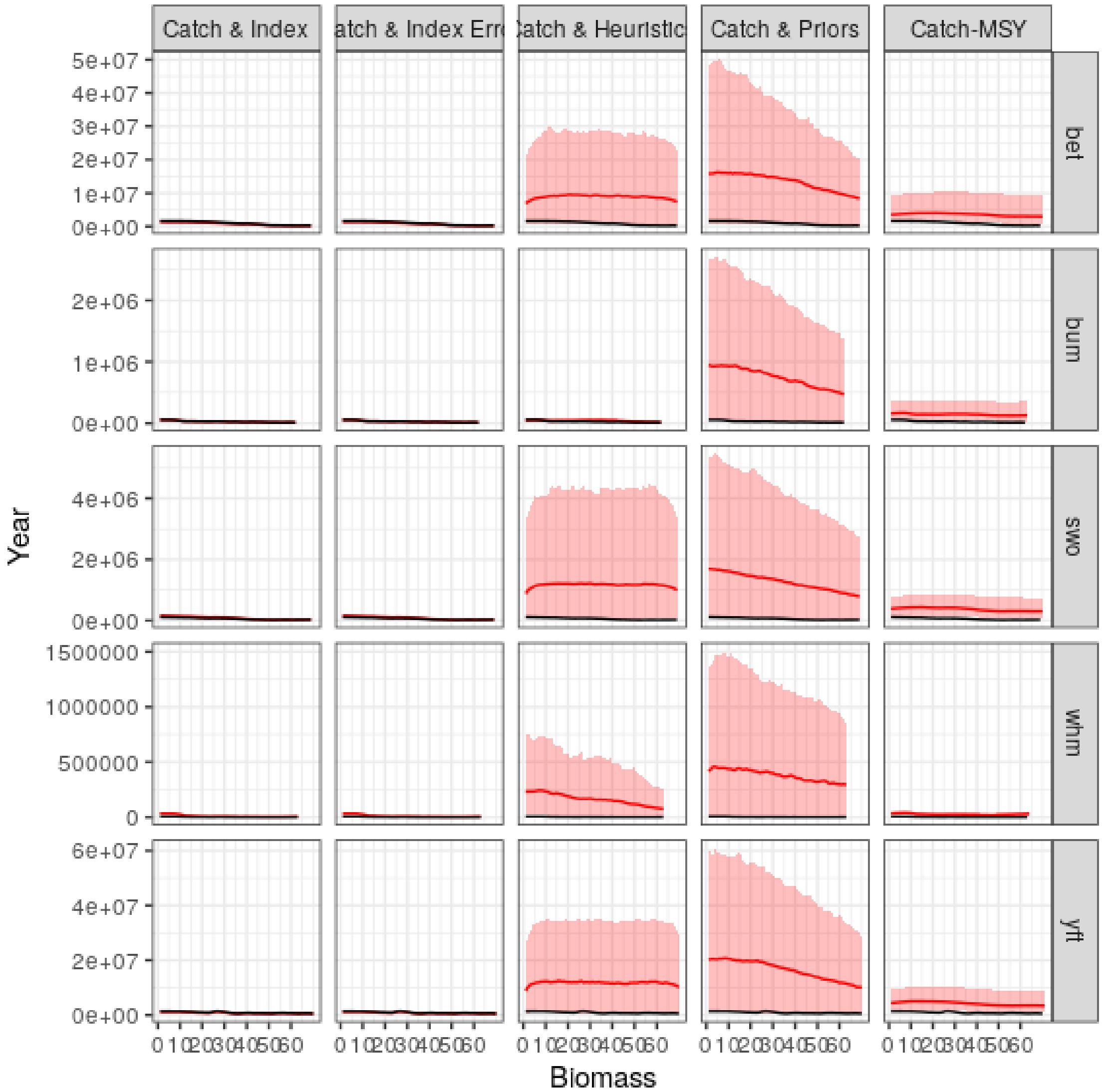

Figure 1 Absolute trends

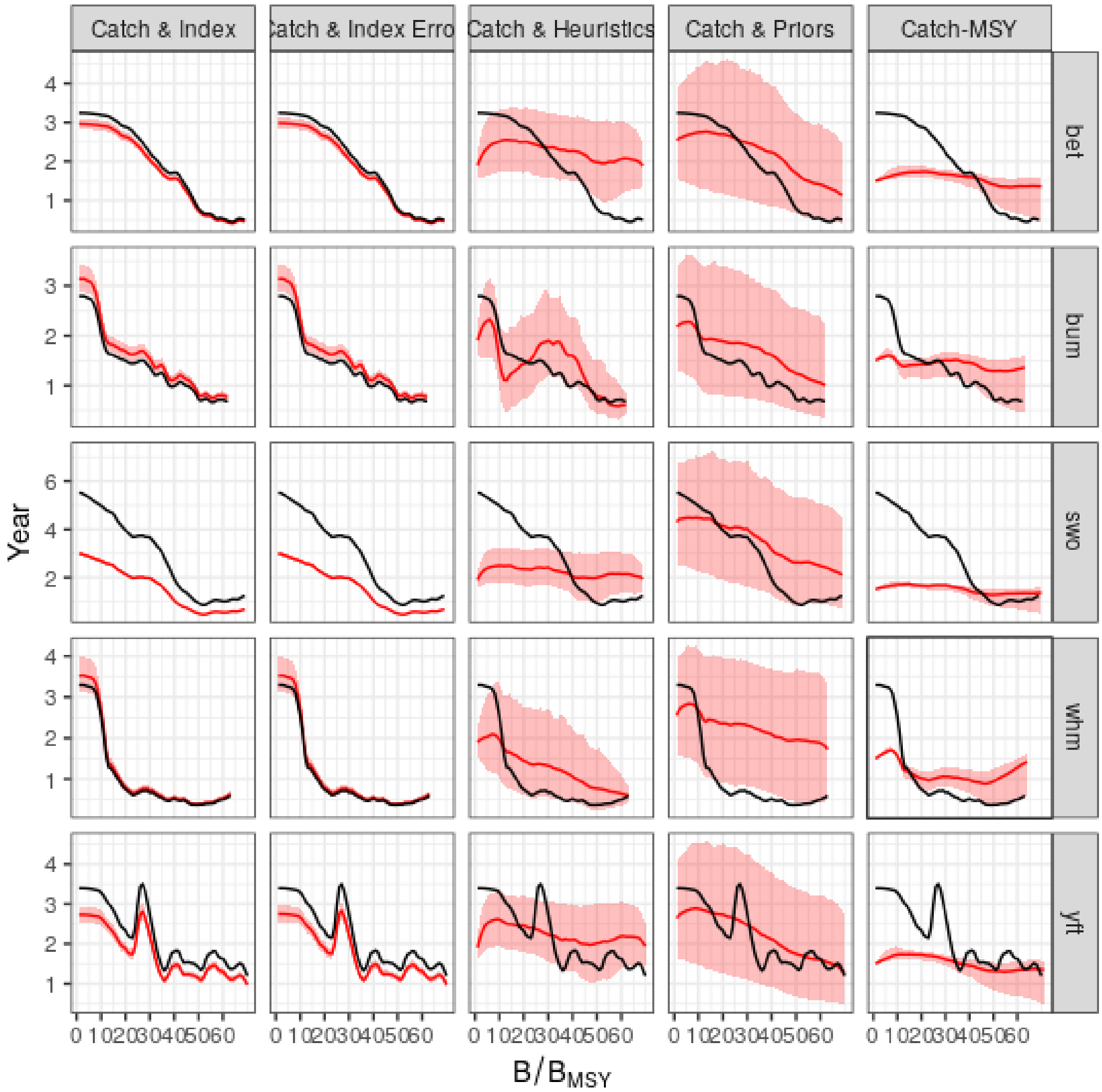

Figure 2 Trends relative to B/B_{MSY}

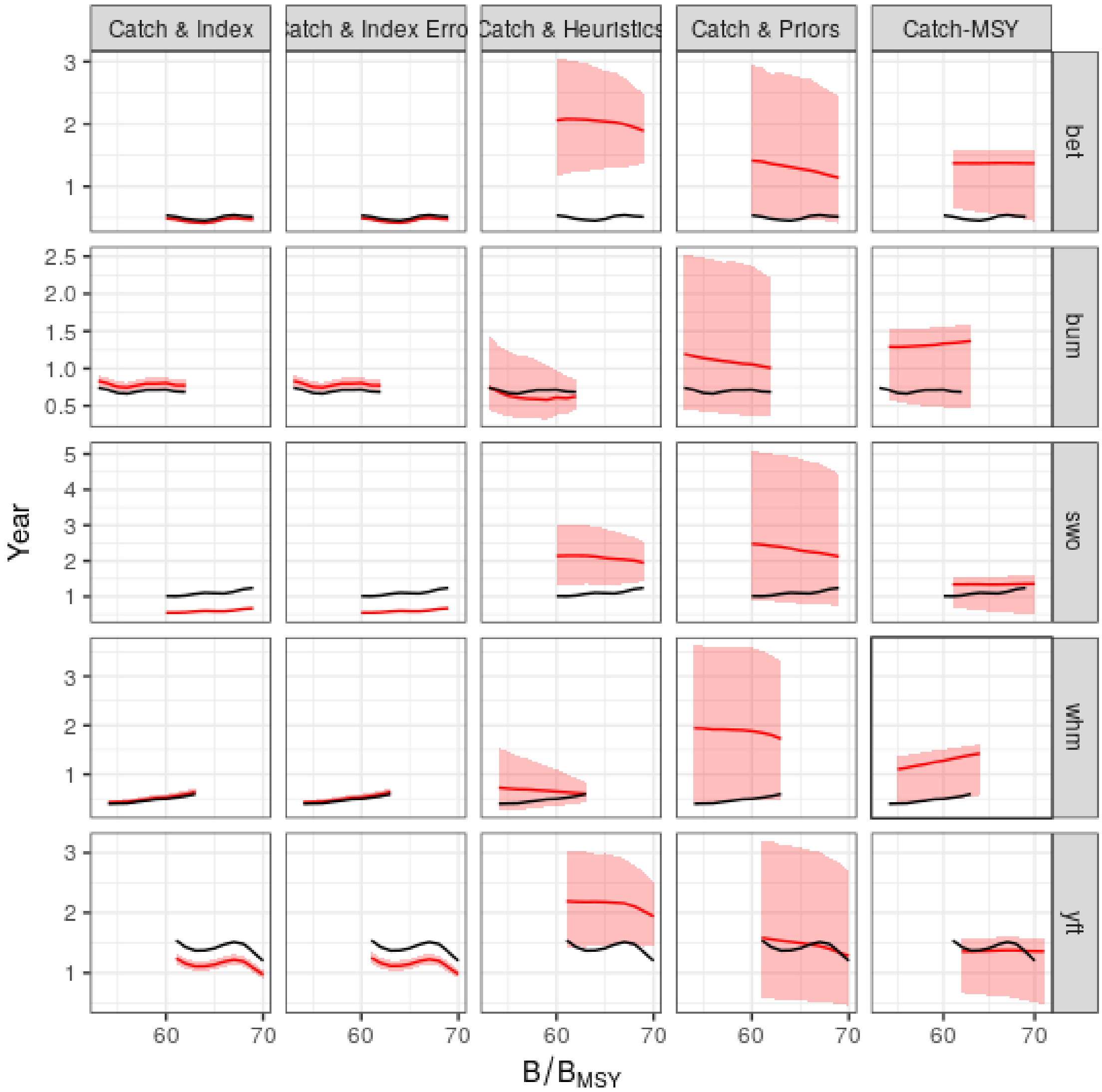

Figure 3 Trends relative to B/B_{MSY} in last 10 years.

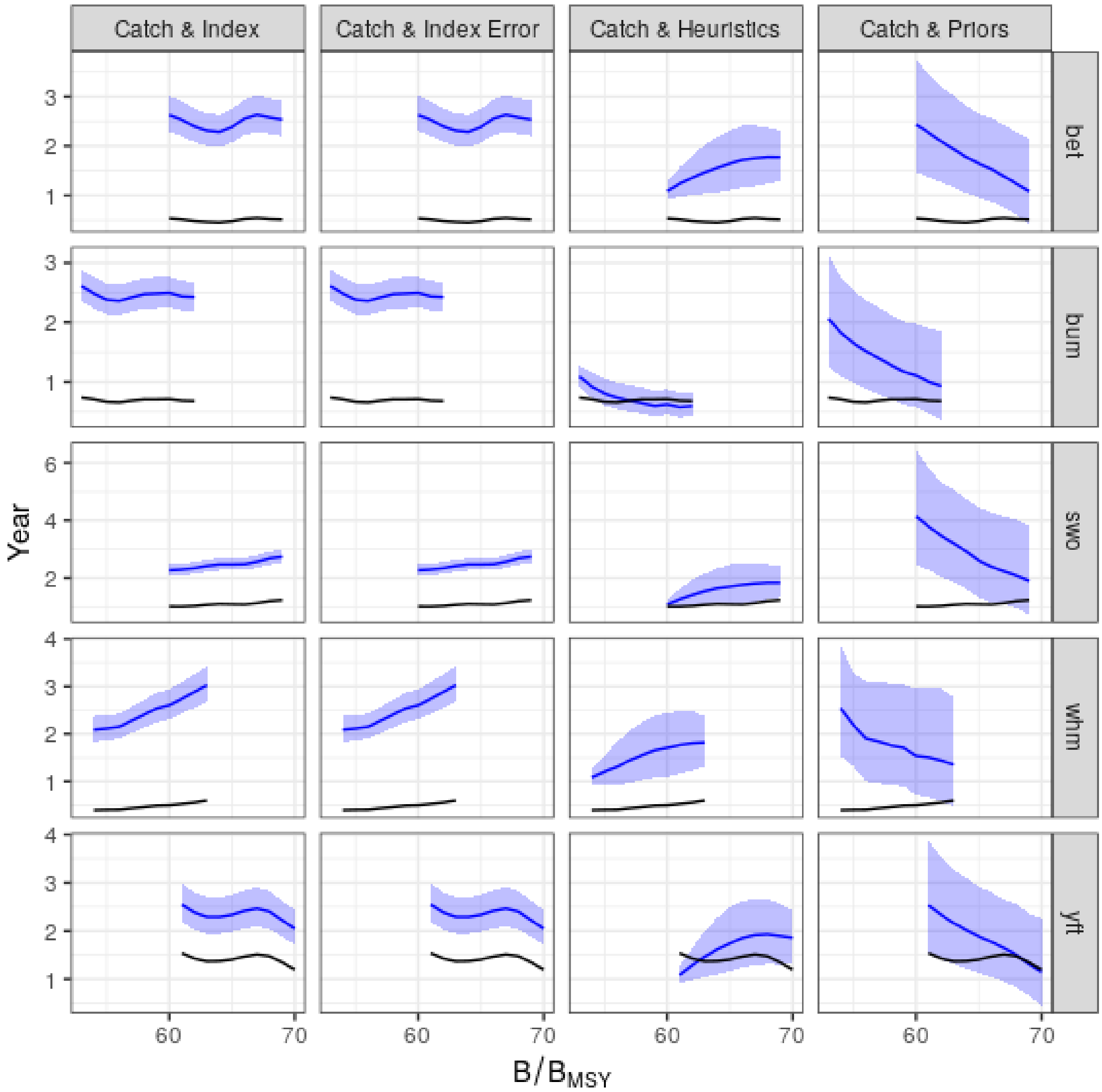

Figure 4 Trends relative to B/B_{MSY} in last 10 years using truncated data.

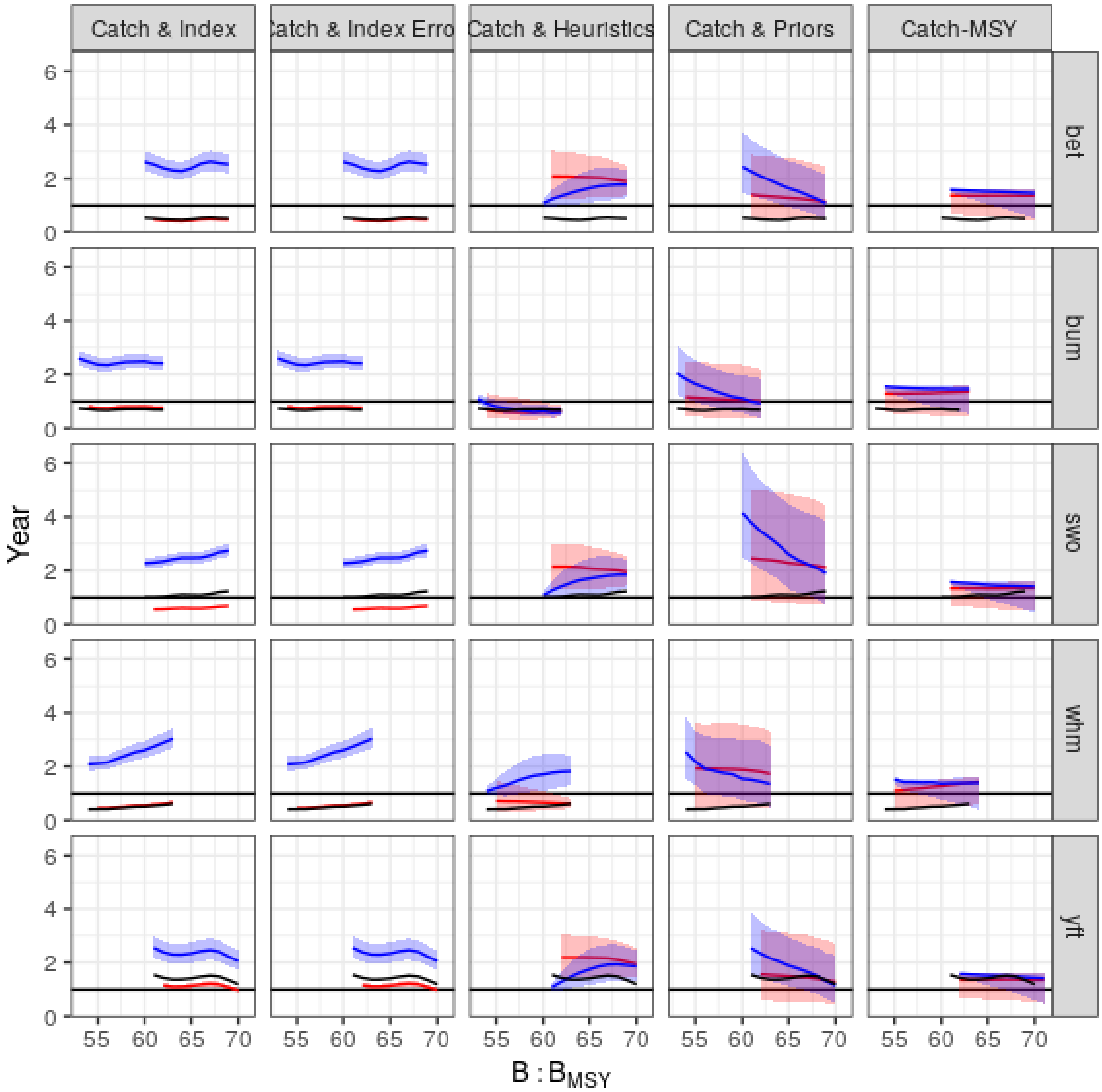

Figure 5 Trends relative to B/B_{MSY} in last 10 years compared for all and truncated datasets.

All Years

	Stock	Catch & Heuristics	Catch & Index	Catch & Index Error	Catch & Priors	CMSY	OM
2 over 3	bet	1.160	1.051	1.051	1.176	1.000	1.044
	bum	1.163	1.014	1.014	1.175	1.020	1.016
	swo	1.161	1.059	1.059	1.175	1.005	1.088
	whm	1.159	1.138	1.138	1.189	1.073	1.023
	yft	1.157	0.976	0.976	1.184	0.998	0.977
Regression	bet	-0.023	0.013	0.013	-0.013	-0.001	0.008
	bum	-0.027	-0.009	-0.009	-0.018	0.009	0.013
	swo	-0.025	0.036	0.036	-0.013	0.004	0.078
	whm	-0.024	0.053	0.053	-0.004	0.027	-0.010
	yft	-0.028	-0.049	-0.049	-0.003	-0.004	-0.020

10 Years

	Stock	Catch & Heuristics	Catch & Index	Catch & Index Error	Catch & Priors	CMSY	OM
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	bum	1.183	1.011	1.011	1.160	0.990	1.016
	swo	1.198	1.053	1.053	1.151	0.972	1.088
	whm	1.213	1.125	1.125	1.137	0.991	1.023
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	swo	-0.008	0.029	0.029	-0.027	-0.007	0.078
	whm	0.002	0.046	0.046	-0.038	0.004	-0.010
	yft	-0.015	-0.042	-0.042	-0.043	-0.016	-0.020