An optimised catch-only assessment method for data poor fisheries

Journal:	*Fish and Fisheries*
Manuscript ID	Draft
Wiley - Manuscript type:	Original Article
Date Submitted by the Author:	n/a

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Key terms:	biological reference points, biomass dynamics, catch-based method, production model, stock reduction analysis, Catch-MSY

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An optimised catch-only assessment method for data poor fisheries

Alternative 1: Fisheries stock assessment using catch data

Alterative 2: OCOM—a catch-based assessment method

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Suggested running title: optimised catch-only method

Abstract

Catch statistics are perhaps the easiest data to collect and are a widely available source of information for many fisheries. However, it is currently difficult to provide scientific advice for fishery managers using only catch data. We develop a catch-only method for stock assessment of data-poor fisheries. It uses time series of catches and two priors, one for the intrinsic population growth rate derived from natural mortality, and another for stock depletion based on catch trends. The method is based on a biomass dynamics model, along with an algorithm to search the possible parameter space. The utility of this method is demonstrated by applying it to 13 stocks in Australia that are assessed using Stock Synthesis—an assessment package that can make use of a variety of data sources. The estimated parameters, including carrying capacity, intrinsic population growth rate, maximum sustainable yield and depletion from the catch-only method are broadly comparable with those from the full assessments. The circumstances in which the method can perform poorly, such as longer-term changes in productivity and episodic recruitment, are highlighted.

Keyword: biological reference points, biomass dynamics, catch-based method, production model, stock reduction analysis, Catch-MSY

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INTRODUCTION

Catch statistics are the most widely available fisheries data, with catch records for most fisheries worldwide maintained by the FAO (Garibaldi 2012). However, it is difficult to estimate reference points and to assess stock status using only catch data. Even the simplest assessment methods such as surplus production (aka biomass dynamics) and depletion models require additional information, such as fishing effort, to derive catch-per-unit-effort (CPUE) indices that could be used as an index of relative biomass (Quinn and Deriso 1999). However, information on effort is not available for many fisheries, or is difficult to measure or standardize, or CPUE cannot be used as an indicator of biomass because of factors such as changes over time in efficiency, and because the distribution of fishing effort does not match that of the species of interest.

The idea of conducting stock assessments using primarily catch data was first explored by Kimura and Tagart (1982) and Kimura *et al.* (1984) using so-called Stock Reduction Analysis (SRA). In SRA, the biomass dynamics involve annual constant recruitment added to the total biomass at the start of each year less fishery catch. A set of nonlinear catch equations is solved for instantaneous fishing mortality and average recruitment, conditioning on an assumed value for the instantaneous natural mortality rate (M), initial stock size and the decline in stock size. There has been an increased interest in using SRA during the last decade. For example, Walters *et al.* (2006) used a Monte Carlo SRA method, and Dick and MacCall (2011) proposed Depletion-Based Stock Reduction Analysis (DB-SRA), which merged stochastic SRA with Depletion-Corrected Average Catch (DCAC, MacCall, 2009). Martell and Froese (2013) used similar stochastic methods to estimate MSY using catch data and "resilient" as a prior for the population growth rate in a surplus production model. This Catch-MSY method has been extended recently to estimate reference points (Froese *et al.* 2016).

A prior distribution for stock depletion (d, the proportion of biomass depleted due to fishing relative to unfished stock size (B_0) or the theoretical carrying capacity level K (i.e. $d = 1 - B_y/K$), where B_y is stock size in year y) is a necessary input parameter for these catch-only methods, but is typically assumed based on auxiliary information. Consequently, Thorson and Cope (2014) used age-composition data for recent years in a catch curve analysis to estimate fishing mortality for those years, a method they referred to as "catch-curve stock reduction analysis" (CC-SRA). Bentley and Langley (2012) included additional known information such as exploitation rates and biomass in some years to constrain the simulated stochastic stock biomass trajectories. The basic idea that underlies these approaches is similar: to reconstruct possible trajectories of stock change from the start of the fishery, given (i) informative priors on stock dynamics (e.g., on carrying capacity and population growth rate), (ii) assumed or estimated stock status (either biomass or relative depletion) in a recent year, and (iii) historical catches. Since the end point is approximately fixed in these approaches, the process of selecting the intrinsic population growth rate, r, and K to determine biomass trajectories involves "threading the needle", as discussed by Walters et al. (2006): starting from biomass in the first year, randomly choosing K and r, and ending at the predefined B_y range. Biomass trajectories in these approaches are determined by only two variables: a biomass at the start of the fishery (relative to K) and a population growth rate (for example r

in the surplus production model). Invalid trajectories, e.g. those resulting in extinction, are discarded. Combinations of valid parameters can be found that match the current biomass or current depletion by tracing back from the most recent stock status and historical removals.

Although SRA is conceptually simple, with a fixed time-series of catch there is a wide range of K and r combinations that may lead to the same range of ending stock sizes (Martell and Froese 2013). Hence, it is necessary to provide reasonable priors on carrying capacity, growth rate, depletion, as well as other parameters depending on the specific methods. However, the choice of prior distributions (for example, uniform, lognormal) and their values (range, mean, variance etc.) will affect the results. Defining and defending sensible priors is often difficult. Further, it has been shown that catch-only methods are very sensitive to the priors, particularly that for depletion (Dick and MacCall 2011; Zhou *et al.* 2013; Carruthers *et al.* 2014; Wetzel and Punt 2015), e.g. the effect of fishing on the population can be underestimated when an overly-optimistic prior for depletion is assumed and vice versa.

Recently, there have been developments in research relevant to data-poor assessment methods. For example, Zhou *et al.* (2012) derived relationships between fishing mortality-based biological reference points and life history parameters using a meta-analysis of global data-rich species. Further, Chen et al.[1] directly estimated the intrinsic population growth rate parameter in the Schaefer surplus production model using life-history parameters, specifically the natural mortality rate M. The results of these studies can be used to formulate a prior for the population growth rate parameter for use in SRA methods. In addition, a boosted regression trees (BRT) model has been developed to estimate stock depletion using only catch data (Zhou et al. in press). This BRT model is calibrated using data from the RAM

[1] Chen, Z., Zhou, S., Ye, Y., Smith, D., and Zhang, K. In review. Relationship between intrinsic rate of population increase and natural mortality in fish and invertebrates.

Legacy Database (RAMLD), and models depletion as a function of various catch trends represented by the parameters of linear regressions of scaled catch over varying time periods.

A catch-only method was recently developed and applied to several data poor stocks (Zhou and Sharma 2013; Zhou *et al.* 2013; IFOP 2014; IOTC Secretariat 2014; IOTC 2015; Martin and Robinson 2016). We use recent developments to enhance this method and refer to it as optimized catch-only method (OCOM) because it uses an optimization algorithm rather than stochastic "thread the needle" approaches. The enhancements include incorporating priors from the newly-developed $r{\sim}M$ relationship and BRT model, and an algorithm to search for feasible parameter values. We first describe the method and then apply it to 13 stocks in Australia's Southern and Eastern Scalefish and Shark Fishery (SESSF) that have been assessed using Stock Synthesis (Methot and Wetzel 2013). This modified OCOM mainly uses catch data with some basic life history parameters to derive a prior for r, to estimate key biological quantities, including virgin biomass, intrinsic population growth, annual biomass, and depletion, as well as management quantities such as MSY, B_{MSY}, and F_{MSY} (respectively the biomass and exploitation rate corresponding to MSY). Although it is not a purely catch-only method as originally developed, the modified OCOM belongs to the class of methods that focuses on catch data and does not need information required by classic methods of stock assessments (e.g., age, length, sex, maturity, gear selectivity, fishing effort), and is consequently still a catch-only assessment method (c.f. Wetzel and Punt 2015).

Materials and methods

We use the Graham-Schaefer surplus production model, as it is very simple and has been widely used:

$$B_{y+1} = B_y + rB_y\left(1 - \frac{B_y}{K}\right) - C_y \qquad (1)$$

where B_y is the biomass at the start of time step y, r is the intrinsic growth rate, K is the carrying capacity (equal to the virgin or initial biomass B_0 for a surplus production model, but K may differ from the initial biomass for a Stock Synthesis assessment), and C_y is the (known) catch during time-step y. This model has two unknown parameters, r and K. Because depletion $d = 1 - S = 1 - B_y/K$, where S is referred to as stock saturation (Zhou *et al.* in press), K in equation 1 can be solved if prior information on r and S (or d) is available.

Productivity prior *r*

A meta-analysis based on data for 245 fish species yielded the following relationships between r and the instantaneous natural mortality rate M (Zhou *et al.* 2012): $F_{MSY} = 0.87M$ (SD = 0.05) for teleosts, and $F_{MSY} = 0.41M$ (SD = 0.09) for chondrichthyans. A separate study[1] based on 189 stocks, and r values produced by the Graham-Schaefer surplus production model, led to the relationships $\bar{r} = 2.02M$ for invertebrates (SD = 0.21), $\bar{r} = 0.76M$ for elasmobranchs (SD = 0.11), and $\bar{r} = 1.72M$ for teleosts (SD = 0.09). Assuming $r = 2F_{MSY}$, which is the case for the Schaefer model, the results from these two studies are quite similar. Therefore, we assume $r \sim \text{normal}(\bar{r} = 1.72M, \text{SD} = 0.18)$ for teleosts, and $r \sim \text{normal}(\bar{r} = 0.79M, \text{SD} = 0.22)$ for chondrichthyans based on the average from these two studies. Measurement error in M is estimated to be $\sigma_M^2 = 0.23$ (Zhou *et al.* 2012). To avoid potentially negative values being sampled, we transfer the normal distributions to a lognormal distribution: $r \sim \text{lognormal}(\mu_r, \sigma^2_r)$, where $\mu_r = \log(\bar{r} - \sigma_r^2/2)$, and $\sigma_r^2 \approx \sigma_M^2$.

Natural mortality may be unavailable for many data-poor species (but not the example SESSF stocks in this study) in which case it is necessary to estimate this parameter using empirical life-history invariant equations, for example:

- $M = 4.899 t_{max}^{-0.916}$, where t_{max} is the maximum age (Then *et al.* 2014);

- $M = 4.118k^{0.73}L_{\infty}^{-0.33}$, where k and L_{∞} are Bertalanffy growth parameters (Then *et al.* 2014);
- $M = 1.82k$ (Charnov *et al.* 2013);
- $M = 1.65/t_{mat}$, where t_{mat} is maturation age (Jensen 1996).

Prior for saturation *S*

Zhou *et al*. (in press) parameterized relationships between $S_e = B_e/K$ (B_e is the biomass at the end of the time series) and catch history using the parameters of linear regressions of catch trends over various time periods based on the RAMLD. They also provided a way to construct probability distributions for B_e/K for use as a prior in data-poor assessment methods:

$S \sim sNorm(\text{mean} = S_{\text{BRT}} - 0.072, \text{SD} = 0.189, \text{skewness} = 0.763)$, when $S_{\text{BRT}} \leq 0.5$

$S \sim sNorm(\text{mean} = S_{\text{BRT}} + 0.179, \text{SD} = 0.223, \text{skewness} = 0.904)$, where $S_{\text{BRT}} > 0.5$,

where *sNorm* is a skewed normal distribution, S_{BRT} is the BRT-predicted point estimate of B_e/K, and S is the prior constrained within the range of [0, 1].

Model implementation

Model implementation involves: (i) drawing a large number (e.g., n = 10,000) of values for r and S from their priors; and (ii) deriving K in Model (1) by solving $|B_e/K - S|$ using an optimization algorithm (function "optimize" in R). For each random r and S, the algorithm finds the optimal corresponding K value. With the large number of r-S pairs, the search process identifies all corresponding K values. This approach also improves the search efficiency as every random draw ends up with a feasible K value, unlike the "thread the needle" approach where a large number of random draws may be invalid because the stochastic ending biomass does not fall within the predefined S interval (e.g., Walters *et al.* 2006; Dick and MacCall 2011; Martell and Froese 2013). The search range can be very wide, for example K between $C_{\max}$ and $300C_{\max}$, where $C_{\max}$ is the maximum catch in the time series. This part of the approach is the same as the so-called "backwards approach" developed to assess baleen whales (e.g. Butterworth and Punt 1995; Punt and Butterworth 1996). Each random sample of r and S determines the corresponding values for K and B_e.

Parameter derivation

The above steps lead to n sets of values for r, S, and K, as well as derived quantities such as MSY = $rK/4$. Summary statistics (e.g., mean, median, geometric mean, and percentiles) for these distributions are obtained from the samples. The distributions for r and S are samples from their prior distributions. Therefore, the final joint distributions for these parameters are not "posterior probability distributions" in the sense of Bayesian statistical inference, but are rather implied prior distributions for quantities derived from r and S.

Application

We applied OCOM to 13 stocks in Australia's SESSF to validate the method and compare its results with those from data-intensive "full" assessments. We used catch data (landings plus discards) from the most recent assessments, although we recognize that discard information may not be available for many data-poor species. The effect of not including discards is the same as under-reporting catch. If the ratio of under-reporting to the total catch is constant over time, the OCOM will proportionally under-estimate K and MSY, but r and S will be unaffected. OCOM requires an estimate of natural mortality in addition to catch data. We adopted the values for M in the actual assessments of these stocks (instead of estimating M using the empirical equations presented above) to avoid differences in outputs due to different input data. Many SESSF stocks have distinctive life history and catch series, and have been assessed using Stock Synthesis (SS), a stock assessment method based on an age-structured population dynamics model, which can use a broad range of data sources (Methot and Wetzel, 2013; Dichmont *et al.* 2016). The length of catch history ranged from 25 to 100 years. Fishing mortality was generally low compared to global stocks (Worm *et al.* 2009), which might lead to difficulties for catch-only methods because low fishing intensity might be insufficient to change the abundance detectable by the method. The mean fishing mortality over time, $\overline{F}$ from SS, for the 13 stocks varied between 0.031 and 0.135 y^{-1}, with an average of 0.085 y^{-1}. For SESSF stocks, the target reference point is F_{48}. The ratio $\overline{F}/F_{48}$ ranged from 0.23 for School Whiting to 3.39 for Orange Roughy, with an average value of 1.20 for all 13 stocks. Gemfish East, Orange Roughy, and Redfish have the highest values for $\overline{F}/F_{48}$ due to their high F_y in early years and low F_{48}.

Routine (not necessarily annual) stocks assessments are conducted for the stocks in the SESSF. The assessments use a range of data inputs, including landings, discards, standardized catch-rate indices, length-composition, age-composition, and sex ratio, as well as auxiliary information on natural mortality, stock-recruit steepness, maturity, etc. (Tuck 2014). The assessments estimate unfished recruitment, the deviations in annual recruitment about the stock-recruit relationship, selectivity as a function of age or length, and (in some cases) natural mortality and growth. The SS assessments also produce benchmark quantities, including unfished spawning biomass, unfished biomass for age 0+ fish, target spawning biomass and target fishing mortality rate. The target reference points are typically associated with the biomass $0.48B_0$, a default proxy value assumed to correspond to maximum economic yield MEY (Smith *et al.* 2008). Hence, the outputs from these routine assessments are MEY proxies and not directly comparable with the outputs of the Schaefer surplus production model (i.e., carrying capacity in terms of exploitable biomass, MSY, and F_{MSY}). To make the results comparable, we re-ran the assessments using the same data and computed outputs associated with MSY (the fits to the data and the estimates of the parameters of the population dynamics model were unchanged). We defined exploitable biomass as the biomass for all ages equal to that for which fishery selectivity at age was 0.5 or larger.

Because fishable age varied among fleets, the age corresponding to 0.5 selectivity was weighted by the relative fishing mortality rate by fleet for stocks that were harvested using multiple gears. This process led to values for B_0 (in units of exploitable biomass), F_{MSY}, MSY, and B_e/B_0 (= S) for each of the 13 stocks.

The results for OCOM were also compared with those from the Catch-MSY method (Martell and Froese 2013). Catch-MSY requires a "resilience" parameter, which we obtained from fishbase.org. The parameter r was defined by resilience category as: r between 0.6-1.5 for High resilience, between 0.2-1 for Medium resilience, between 0.05-0.5 for Low resilience, and between 0.015-0.1 for Very low resilience. Catch-MSY defines B_e/K based on $C_e/C_{\max}$: S between 0.3-0.7 for $C_e/C_{\max} > 0.5$, and between 0.01-0.4 for $C_e/C_{\max} \le 0.5$. The original Catch-MSY method did not attempt to estimate stock depletion. We derived stock saturation for Catch-MSY by extracting an additional parameter—the biomass at the end of the estimated time series, B_e, from equation (1), and as usual, divided by the corresponding K.

We used four statistics to evaluate model performance. For each stock, we calculated error (deviation) E, absolute error AE, relative error RE, and absolute relative error ARE:

$$E_{m,\theta} = \hat{\theta}_m - \theta_{SS}$$

$$AE_{m,\theta} = |\hat{\theta}_m - \theta_{SS}| \qquad (2)$$

$$RE_{m,\theta} = \frac{\hat{\theta}_m - \theta_{SS}}{\theta_{SS}}$$

$$ARE_{m,\theta} = \frac{|\hat{\theta}_m - \theta_{SS}|}{\theta_{SS}}$$

where $\hat{\theta}_m$ is the value from method m (OCOM or Catch-MSY) for the quantity θ (i.e., K, F_{MSY}, MSY, and S) and θ_{SS} is the maximum likelihood estimate from Stock Synthesis. We used the geometric mean to summarize the outputs from Catch-MSY as this summary statistic was recommended for this method by Martell and Froese (2013). We compared the geometric mean and median of OCOM outputs, and found they were similar so we only report results based on the median for OCOM. To compare OCOM and Catch-MSY, we used mean values of the four statistics (i.e., F_{MSY}, K, MSY, and S) across all 13 stocks, i.e., ME, MAE, MRE, and MARE. Note that these measures are relative to SS. It was difficult to directly compare results between different methods because of differences in model assumptions (e.g., whether the initial biomass is assumed to equal K and the shape of the production function). Nevertheless, comparisons with data-rich fully quantitative assessments should indicate the general reliability and potential utility of the OCOM method.

Results

Biomass series

First we compare the biomass trajectories from OCOM with the "true" results derived from SS. Figure 1 plots the time series of biomass from SS with a sample of the biomass trajectories (central 25% to 75%) from OCOM. The catch time series are also shown to help understand the behaviour of OCOM. The biomass time series from OCOM match those from SS very well, with the SS result falling mostly within the range of OCOM outputs for five stocks (Deepwater Flathead, Morwong West, Pink Ling West, Redfish, and Tiger Flathead). The biomass trends for three other stocks are similar, but the absolute levels differ considerably (Bight Redfish, Orange Roughy, School Whiting). The biomass series from the SS assessments for Blue Grenadier and Silver Warehou exhibit marked fluctuations due to episodic recruitment, and SS yields estimates of biomass higher than B_0 in some years, which OCOM does not detect (OCOM assumes that the biomass is less than K for all years). The trends in OCOM differ greatly from those provided by SS for Gemfish East and Morwong East. Specifically, OCOM overestimates biomass for Gemfish East both initially and at the end of the time series. Both Gemfish East and Morwong East are thought to have undergone longer-term changes in productivity, which are reflected in the SS results but cannot be accounted for by OCOM.

Population parameters

We now examine OCOM in terms of its ability to estimate the four parameters of interest – carrying capacity K, stock productivity represented by F_{MSY} (= 0.5r), maximum sustainable yield MSY, and stock saturation S (see Table 1 and an example of their distributions for Bight Redfish in Figure 2).

Across the 13 stocks, the average K value from SS is 25,149t compared with 32,274t from OCOM. OCOM overestimates K for about half of the stocks (seven out of 13 so unbiased in this respect) (Figure 3), but the overestimates are greater than the underestimates, resulting in an overall average overestimate of 7,125t (about 28% of the average K from SS). The relative errors range from -0.36 to +2.31, with an average of 0.38. The largest overestimate is 56,698t for Orange Roughy, and the largest relative error is +2.31 for Morwong East (note that K from SS is smaller than the initial biomass in SS; Figure 1; the difference between SS and OCOM is smaller if K from OCOM is compared with the initial biomass from SS). The mean absolute errors, MAEs, and mean absolute relative errors, MAREs, for K for OCOM (9,856t and 0.51 respectively) are correspondingly higher than the ME and MRE values (Table 3).

The average F_{MSY} value for SS for the 13 stocks is 0.43 compared with 0.16 for OCOM. There is a consistent bias for F_{MSY}, with OCOM leading to high values for F_{MSY} for only one stock (Gemfish East). Several stocks have very high negative relative errors (-0.94 for Bight Redfish, -0.86 for Morwong West, and -0.84 for Orange Roughy; note that the minimum relative error is -1). Gemfish East has the highest positive relative error, +1.78. The negative relative errors for F_{MSY} occur in part because the shape of the underlying production functions differs between SS and OCOM, with B_{MSY}/B_0 occurring at 0.5 for OCOM and at less than 0.5

(often substantially so, e.g. Bight Redfish) for SS (Figure 4). SS estimates the production function accounting for the yield-per-recruit and stock-recruitment relationships. Consequently, the yield function approximates the (often asymptotic) yield-per-recruit function when exploitable age is older than maturation age and stock-recruitment steepness is high, which is the case for Bight Redfish and Morwong West. Hence, given approximately the same MSY and B_0 values, SS must produce a larger F_{MSY} than OCOM (Figure 5).

Of more management relevance than K and F_{MSY} (or r) is MSY. For the 13 stocks, the average MSY value from SS is 1,541t. The average value for MSY from OCOM is 1,947t, about 26% higher. The extent of this discrepancy arises almost entirely from two stocks – Gemfish East and Morwong East (Table 1; Figure 3). Morwong East is estimated to have undergone a significant "regime shift" (see discussion) and the SS results reflect the more recent lower productivity regime. The SS assessment for Gemfish East also estimates very low productivity in recent years and hence a low MSY. In other respects, MSY is estimated quite well by OCOM, with approximately equal positive and negative relative errors. If the two "problem" stocks are excluded, the mean relative error drops from 0.63 to 0.02 (i.e. nearly unbiased), and the mean absolute relative error from 0.75 to 0.13.

Also of considerable management relevance are the estimates of stock saturation S. Across the 13 stocks, the average value for SS is 0.41, with an among-stock range from 0.09 to 0.78. For OCOM, the average value is 0.37, with an among-stock range from 0.10 to 0.82. Stock saturation is over-estimated for seven and under-estimated for six stocks by OCOM, and the MRE of the 13 stocks is 0. Five of the stocks have errors within the range ± 0.1, eight within ± 0.2 and ten within ± 0.3. The mean absolute error is 0.19.

The comparison between OCOM and SS in Table 1 and Fig 1 is based on OCOM using the same values for M as the SS assessments. The Supplementary Material shows that the results are robust to basing M in OCOM instead on values for M and other life-history parameters (i.e., t_{max}, k, L_{∞}, and t_{mat}) from Fishbase.

Comparison with Catch-MSY

Catch-MSY results in similar estimates of the four key parameters as OCOM (Table 2), but its mean values for all these parameters have larger errors (relative to SS) than OCOM. For example, the mean K for SS, OCOM, and Catch-MSY are 25,149t, 32,274t, and 35,653t, respectively. The mean F_{MSY} is more similar between OCOM and Catch-MSY (0.16 compared to 0.12) than SS (0.43). However, Catch-MSY yielded a narrow range of F_{MSY} values around a mean of 0.12 (range: 0.05 and 0.20). In contrast, the prior for OCOM based on M better includes extreme values for F_{MSY}, and its estimated F_{MSY} extends from 0.03 for Orange Roughy to 0.44 for School Whiting (Table 1). Using the S prior based on the BRT prediction, OCOM also yields a wider range for S than Catch-MSY, ranging from 0.10 to 0.82. In contrast, the estimates of S from Catch-MSY S fall into two narrow bands, one between 0.1 and 0.19 and the second one between 0.53 and 0.57. On average, Catch-MSY underestimates S by 43% while OCOM underestimates S by 11%. OCOM is more accurate than Catch-MSY for all parameters based on the mean error (ME) (Table 3). For the other three criteria, i.e., mean absolute error (MAE), mean relative error (MRE), and mean absolute relative error (MARE), OCOM outperforms Catch-MSY for three out of four parameters. Using mean absolute relative error and excluding the two "problem" stocks (Gemfish East and Morwong East), OCOM outperforms Catch-MSY by 9% for F_{MSY}, 29% for MSY, and 11% for S, but underperforms -4% for K. Overall, based on four statistics by four parameters, OCOM outperforms Catch-MSY by 13 to 3 (Table 3). However, due to large variability, the improvement in OCOM may not appear to be substantial for the 13 stocks tested.

Discussion

Development of data-poor methods that primarily use catch data has attracted increasing interest in recent years. We present a modified optimized catch-only assessment method that uses prior information from recent studies, adding another tool to the existing toolbox in this category. In general, our method yields reasonable estimates for most stocks we examined. Because of its limited data requirements and simplicity, the data preparation and assessment process can be very quick. Using the steps described in the Materials and Methods and written in R (R Core Team 2013), the method can produce results in minutes. The procedure can be designed for batch processing data for a large number of species. Using prior information for *r* and *S* that have been derived from data-rich stocks (Zhou et al. 2012, in press) has advantages over arbitrarily assuming a value or a range for these quantities as is the case for other data-poor methods. Unlike the "thread the needle" approach, using an optimisation algorithm also has computational advantages, which ensures little chance of missing possible viable values.

Comparing results between different assessment methods is not straightforward. For example model outputs are sensitive to various assumptions about priors, life history parameters, and the time series of data used, even for data-intensive integrated assessments (Ichinokawa *et al.* 2014). We examine potential reasons that lead to the differences between the results from SS and OCOM. The error of F_{MSY} is not symmetric: OCOM underestimates F_{MSY} for all stocks except Gemfish East. The main reason is that, unlike B_0 and MSY, F_{MSY} is model-dependent, which implies that it is not comparable between SS and OCOM. Ideally, the same surplus production model should be applied to OCOM and SS to compare them. Unfortunately, neither SS nor OCOM has such an option.

Catch-MSY also performs quite well for these 13 stocks; *K* and MSY are similar between the two simple approaches. Catch-MSY tends to be insensitive to very small or very large values, particularly for the productivity parameter r. This may be caused by its three categories of r prior using resilience. The assumed S prior has two choices: between 0.3 and 0.7, and between 0.01 and 0.4, depending on the $C_e/C_{\max}$ ratio. Hence, it is understandable that estimated S also ends in one of the two narrow bands. Catch-MSY derives a prior for r based on "resilience" found in Fishbase.org and S based on $C_e/C_{\max}$ ratio. This appears to be simpler than OCOM, where r is based on M, and S is based on the BRT model. However, because M can be derived from alternative methods and BRT modelling has been established, implementing OCOM is fully automatic with an input file containing the time series of catch data, similar to Catch-MSY.

Why OCOM cannot mimic SS – three example stocks

Assessment of the Gemfish East stock is challenging. Stock assessments since the late 1980s show a sharp decline in adult biomass during the early 1980s and weak cohorts spawned in the late 1980s (Little and Rowling 2010). Natural mortality is assumed to be 0.38yr^{-1} (Tuck 2014). However, SS yields a very low estimate of F_{MSY} (= 0.08yr^{-1}), about 20% of the M value. F_{MSY} is generally close to M (Quinn and Deriso 1999; Zhou *et al.* 2012). SS also yielded a low MSY of 540t. OCOM's estimated MSY of 3,687t is closer to the average observed catch of 2,786t during the first 30 years. Using an index of abundance, as well as age and length data, SS estimates lower productivity and a lower MSY in recent years because the productivity of Gemfish East is estimated to have dropped substantially over time with no evidence for recovery even under low removals (Punt and Smith, 1999). OCOM is unable to capture this effect because it assumes constant K and r over the entire catch history and is not able to update the prior distribution for r.

Bight Redfish is a long-lived species with a low natural mortality (M = 0.1yr^{-1}). The stock assessment using SS in recent years (between 2000 and 2015) resulted in a wide range of estimates (Haddon 2015). For example, the unfished female spawning biomass varied between 5,451t and 31,660t, depending on the time period used and assumptions regarding biological parameters. The difficulties in these assessments may partially be due to low contrast in biomass due to a history of relatively low fishing mortality rates. For example, SS results are sensitive to the assumed gear selectivity and the age range used to derive exploitable biomass (Zhou, SS sensitivity test results not included).

Recruitment of Morwong East has been below average since 1985 (Wayte 2013; Tuck 2014). The decline in recruitment is likely due to a climate-induced regime shift (Wayte 2013). SS estimates a low current B_0 of 7,693t and a low current MSY of 468t (Table 1), following the estimated regime shift in the late 1980s. This new B_0 and MSY are much lower than the estimated mean exploitable biomass of 25,556t in the first 40 years from 1914 to 1954, and the mean observed catch of 1,743t over 40 years from 1946 to 1985 (c.f. Figure 1). In contrast, OCOM uses the entire time series and results in B_0 = 25,435t and MSY = 1,374t. OCOM also yields similar estimates of F_{MSY} for the Eastern and Western stocks because it is based on the same prior. Again, OCOM is unable to detect a productivity change due to a regime shift because it assumes constant K and r over the entire catch history. This inability to detect productivity change or environmental regime shifts is a major weakness of OCOM. This simple method assumes that the population follows a certain dynamic process and is not primarily environmentally-driven. The stationary production function using an average population growth rate r and an average carrying capacity K is unable to capture long term shifts in average recruitment or highly variable population dynamics. In addition, OCOM cannot detect abrupt changes in carrying capacity and maximum sustainable yield. This is evident for Morwong East, which exhibits some of the largest differences in estimated management parameters between SS and OCOM.

The value of OCOM for management purposes

OCOM is a data-poor assessment method that mainly utilizes catch data, so should not be expected to accurately replicate assessments based on more sophisticated methods and much more data, such as SS. What can we conclude about its robustness from the comparisons presented here? The answer depends, to a large extent, on what information is being sought from such an analysis.

1. The performance in estimating MSY and S is of much more management relevance than in estimating K and F_{MSY} (or r). The latter are in a sense "nuisance" parameters that in combination may offer insights on more important parameters. For example, r and K may be poorly estimated but their product (note that MSY = $rK/4$) may be better estimated. This seems to be the case in these results.

2. In some cases, a method such as OCOM may be used to assess the status of an individual stock. In that case, considerations of both bias and variance arise, and the user would want to have some idea of just how poor a single estimate may be (and whether it is more likely to be biased high or low). In other cases, OCOM may be used to estimate management quantities across a range of stocks simultaneously, in which case the average or ensemble statistics become more important. For example, data-poor methods have been used to try to assess the status of large numbers of stocks at a time, in efforts to estimate global or regional status of fisheries (Froese *et al.* 2012; Costello *et al.* 2012, 2016).

3. Estimated management quantities may be used as the basis for harvest strategies or management procedures. Properly constructed harvest strategies (that include harvest control rules as well as estimates of stock status) can be made somewhat "robust" to uncertainties in management quantities such as MSY and S. This is an important topic not dealt with in this

paper, but now widely explored in a range of recent publications (Carruthers *et al.* 2014; Wetzel and Punt 2015).

Building on these considerations, OCOM should be used with some care in assessing and managing individual stocks. Considering MSY, it seems to perform quite well in most situations, but performed poorly where there were large temporal changes in stock productivity or episodic recruitment. Such changes have been well documented for Morwong East (Wayte 2013), and are considered plausible for Gemfish East as well (Punt and Simth 1999; Little and Rowling 2010). However, it will likely be very difficult to predict whether such changes have occurred for data-poor stocks. In the absence of such considerations, some additional level of precaution would be required in using MSY estimates to manage a fishery, particularly as MSY itself is a "limit" management quantity.

For assessing current stock status (saturation *S*), the prior from the BRT model performs reasonably well, though individual relative errors can be quite large. Estimates of *S* appear to be unbiased (very low values for ME and MRE) and mean absolute errors are tolerable (0.19). *S* is valid in the range 0 to 1, so absolute errors may be of more management interest than relative errors. Additionally, most management concern is about low stock sizes, so the ability to estimate *S* at the low end of the range may be much more important than at the high end of the range. Four of the SS stocks are estimated to be below 0.3*K* and OCOM "picked" this for three of those stocks (Gemfish East, Orange Roughy and Redfish). It also indicated lower levels of *S* for two further stocks – Morwong East, which is appropriate considering the regime change, and Tiger Flathead, which appears to be an error. Viewed overall, OCOM may perform reasonably well in estimating stock depletion for an ensemble of stocks.

Caveats and future work

OCOM requires a prior for r, which is based on natural mortality M. Accuracy in estimating M will affect the results of OCOM. It may be difficult to obtain reliable estimates of M. For School Whiting, previous SS assessments have suggested a range of values for this parameter from 0.37 to 0.90yr^{-1} (Day 2010). Using $M = 0.57$yr^{-1} in this study results in $F_{MSY} = 0.44$ and $K = 15{,}101$t. Further studies of the robustness of OCOM and its sensitivity to various inputs and assumptions are required.

Although OCOM can use catch data to estimate several key management quantities, additional information, if available, can be incorporated into the method to enhance its power. Possible information includes one or more years with estimates of absolute abundance, a relative abundance index, an estimate of fishing mortality rate, and more than one year of fishing effort data. This means that the default method can be tailored to accommodate various cases depending on data availability.

OCOM is based on a particular surplus production model and produces MSY-related reference points. Achieving MSY has been a traditional fisheries objective, and most management regimes have been built around this framework. Among the key parameters, MSY is the least biased quantity from OCOM (if Gemfish East and Morwong East are excluded). Using MSY as a reference point and catch as an indicator could be used to form a simple harvest control rule for fisheries management, particularly for data-poor stocks (Martell and Froese 2013; Carruthers *et al.* 2014). Since OCOM can also estimate annual biomass, hence fishing mortality rate F, the pair of F_y–F_{MSY} could be used for F-based management. However, further research to improve its accuracy for individual species may be needed, and the performance of harvest strategies based on OCOM-derived quantities requires careful testing using management strategic evaluation methods (Punt *et al.* 2016).

Moreover, analysis would be required to examine what properties of the catch time series themselves (length of time series, multiple peaks and troughs, error in catch data, etc.) seem to facilitate more robust estimation by methods like OCOM.

Acknowledgements

We thank J. Day, R. Little, R. Thomson G. Tuck, and J. Upston for providing the original Stock Synthesis assessments (including input data and output results) and for assistance with the assessments. We further thank R. Little and G. Tuck for their constructive comments on the earlier version of the paper. This research was co-funded by FAO and CSIRO Australia.

References

Bentley, N. and Langley, A.D. (2012) Feasible stock trajectories: a flexible and efficient sequential estimator for use in fisheries management procedures. *Canadian Journal of Fisheries and Aquatic Sciences* **69**, 161–177.

Butterworth, D.S. and Punt, A.E. (1995) On the Bayesian approach suggested for the assessment of the Bering-Chukchi-Beaufort Seas stock of bowhead whales. *Reports of the International Whaling Commission*, 303–311.

Carruthers, T.R., Punt, A.E., Walters, C.J., MacCall, A., McAllister, M.K., Dick, E.J. and Cope, J. (2014) Evaluating methods for setting catch limits in data-limited fisheries. *Fisheries Research* **153**, 48–68.

Charnov, E.L., Gislason, H. and Pope, J.G. (2013) Evolutionary assembly rules for fish life histories. *Fish and Fisheries* **14**, 213–224.

Costello, C., Ovando, D., Clavelle, T., et al. (2016) Global fishery futures under contrasting management regimes. *Proceedings of the National Academy of Sciences of the United States of America* **113**, 5215–5219.

Costello, C., Ovando, D., Hilborn, R., Gaines, S.D., Deschenes, O. and Lester, S.E. (2012) Status and Solutions for the World's Unassessed Fisheries. *Science* **338**, 517–520.

Day, J. (2010) School Whiting (Sillago flindersi): Exploration of fixed projected catches and a retrospective look at variability in recruitment estimates . 1–45.

Dichmont, C.M., Deng, R.A., Punt, A.E., et al. (2016) A review of stock assessment packages in the United States. *Fisheries Research* **183**, 447–460.

Dick, E.J. and MacCall, A.D. (2011) Depletion-Based Stock Reduction Analysis: A catch-based method for determining sustainable yields for data-poor fish stocks. *Fisheries Research* **110**, 331–341.

Froese, R., Demirel, N., Coro, G., Kleisner, K.M. and Winker, H. (2016) Estimating fisheries

reference points from catch and resilience. *Fish and Fisheries*, 1–21.
Froese, R., Zeller, D., Kleisner, K. and Pauly, D. (2012) What catch data can tell us about the status of global fisheries. *Marine Biology* **159**, 1283–1292.
Garibaldi, L. (2012) The FAO global capture production database: A six-decade effort to catch the trend. *Marine Policy* **36**, 760–768.
Haddon, M. (2015) Bight redfish (Centroberyx gerrardi) stock assessment using data to 2014/2015. Report to November 2013 GAB RAG meeting. CSIRO, Oceans and Atmosphere, Australia. 40p.
Ichinokawa, M., Okamura, H. and Takeuchi, Y. (2014) Data conflict caused by model mis-specification of selectivity in an integrated stock assessment model and its potential effects on stock status estimation. *Fisheries Research* **158**, 147–157.
IFOP (2014) Review of biological reference points in domestic fisheries. Report of the Third International Workshop Held in Viña del Mar, Chile, August 2014. Instituto de Fomento Pesquero.
IOTC (2015) Assessment of Indian Ocean kawakawa (Euthynnus affinis) using data poor catch-based methods. Indian Ocean Tuna Commission. IOTC–2015–WPNT05–21.
IOTC Secretariat (2014) Report of the Fourth Session of the IOTC Working Party on Neritic Tunas. Indian Ocean Tuna Commission. Phuket, Thailand. 29 June - 22 July 2014.
Jensen, A.L. (1996) Beverton and Holt life history invariants result from optimal trade-off of reproduction and survival. *Canadian Journal of Fisheries and Aquatic Sciences* **53**, 820–822.
Kimura, D. and Tagart, J. (1982) Stock Reduction Analysis , Another Solution to the Catch Equations. *Canadian Journal of Fisheries and Aquatic Sciences* **39**, 1467–1472.
Kimura, D.K., Balsiger, J.W. and Ito, D.H. (1984) Generalized Stock Reduction Analysis. *Canadian Journal of Fisheries and Aquatic Sciences* **41**, 1325–1333.

Little, R. and Rowling, K. (2010) 2010 Update of the Eastern Gemfish (Rexea solandri) stock assessment. 1–39.

MacCall, a. D. (2009) Depletion-corrected average catch: a simple formula for estimating sustainable yields in data-poor situations. *ICES Journal of Marine Science* **66**, 2267–2271.

Martell, S. and Froese, R. (2013) A simple method for estimating MSY from catch and resilience. *Fish and Fisheries* **14**, 504–514.

Martin, S. and Robinson, J. (2016) Assessment of Indian Ocean longtail tuna (Thunnus tonggol) using data poor catch-based methods. Indian Ocean Tuna Commission. IOTC–2016–WPNT06–17.

Methot, R.D. and Wetzel, C.R. (2013) Stock synthesis : A biological and statistical framework for fish stock assessment and fishery management. *Fisheries Research* **142**, 86–99.

Punt, A.E. and Butterworth, D.S. (1996) Further Remarks on the Bayesian Approach for Assessing the Bering-Chukchi-Beaufort Seas Stock of Bowhead Whales. *Rep. Int. Whal. Commn.* **46**, 481–491.

Punt, A.E., Butterworth, D.S., de Moor, C.L., De Oliveira, J.A.A. and Haddon, M. (2016) Management strategy evaluation: Best practices. *Fish and Fisheries* **17**, 303–334.

Punt, A.E. and Simth, A.D.M. (1999) Harvest strategy evaluation for the eastern stock of gemfish (Rexea solandri). *ICES Journal of Marine Science* **56**, 860–875.

Quinn, T.J. and Deriso, R.B. (1999) *Quantitative fish dynamics*. Oxford University Press, New York.

R Core Team (2013) R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0.

Smith, A.D.M., Smith, D.C., Tuck, G.N., et al. (2008) Experience in implementing harvest strategies in Australia's south-eastern fisheries. *Fisheries Research* **94**, 373–379.

Then, A.Y., Hoenig, J.M., Hall, N.G. and Hewitt, D.A. (2014) Evaluating the predictive performance of empirical estimators of natural mortality rate using information on over 200 fish species. *ICES Journal of Marine Science*.

Thorson, J.T. and Cope, J.M. (2015) Catch curve stock-reduction analysis: An alternative solution to the catch equations. *Fisheries Research* **171**, 33–41.

Tuck, G.N. (ed) (2014) *Stock Assessment for the Southern and Eastern Scalefish and Shark Fishery: 2013*. Australian Fisheries Management Authority and CSIRO Marine and Atmospheric Research, Hobart.

Walters, C.J., Martell, S.J.D. and Korman, J. (2006) A stochastic approach to stock reduction analysis. **223**, 212–223.

Wayte, S.E. (2013) Management implications of including a climate-induced recruitment shift in the stock assessment for jackass morwong (Nemadactylus macropterus) in south-eastern Australia. *Fisheries Research* **142**, 47–55.

Wetzel, C.R. and Punt, A.E. (2015) Evaluating the performance of data-moderate and catch-only assessment methods for U.S. west coast groundfish. *Fisheries Research* **171**, 170–187.

Worm, B., Hilborn, R., Baum, J.K., et al. (2009) Rebuilding global fisheries. *Science* **325**, 578–585.

Zhou, S., Pascoe, S., Dowling, N., et al. (2013) Quantitatively defining biological and economic reference points in data poor fisheries. Final Report on FRDC Project 2010/044. Canberra, Australia.

Zhou, S. and Sharma, R. (2013) Stock assessment of two neritic tuna species in Indian Ocean: kawakawa longtail tuna using catch-based stock reduction methods. Indian Ocean Tuna Commission. IOTC–2013–WPNT03–25.

Zhou, S., Yin, S., Thorson, J.T., Smith, A.D.M., Fuller, M. and Walters, C.J. (2012) Linking fishing mortality reference points to life history traits: an empirical study. *Canadian Journal of Fisheries and Aquatic Sciences* **69**, 1292–1301.

Table 1. Comparison of key parameters from Stock Synthesis (SS) and OCOM for 13 SESSF stocks. $S = B_e/K$, RE = relative error.

Stock			SS				OCOM				RE			
ID	Common name	Scientific name	K	F_{MSY}	MSY	S	K	F_{MSY}	MSY	S	K	F_{MSY}	MSY	S
1	Bight Redfish	Centroberyx gerrardi	7,735	1.45	611	0.63	12,537	0.08	529	0.69	0.62	-0.94	-0.13	0.09
2	Blue Grenadier	Macruronus novaezelandiae	70,993	0.22	4,435	0.78	67,203	0.14	4,650	0.34	-0.05	-0.37	0.05	-0.57
3	Deepwater Flathead	Neoplatycephalus conatus	15,164	0.29	1,257	0.47	11,482	0.18	1,061	0.31	-0.24	-0.37	-0.16	-0.34
4	Gemfish East	Rexea solandri	15,146	0.08	538	0.13	32,337	0.23	3,687	0.19	1.14	1.78	5.85	0.44
5	Morwong East	Nemadactylus macropterus	7,693	0.23	468	0.34	25,435	0.12	1,469	0.10	2.31	-0.51	2.14	-0.72
6	Morwong West	Nemadactylus macropterus	1,943	0.80	185	0.63	1,846	0.11	108	0.32	-0.05	-0.86	-0.42	-0.50
7	Orange Roughy	Hoplostethus atlanticus	81,054	0.20	2,192	0.23	137,752	0.03	2,148	0.15	0.70	-0.84	-0.02	-0.34
8	Pink Ling East	Genypterus blacodes	15,670	0.16	789	0.20	10,078	0.16	805	0.37	-0.36	-0.00	0.02	0.87
9	Pink Ling West	Genypterus blacodes	10,893	0.23	789	0.43	12,221	0.16	893	0.79	0.12	-0.29	0.13	0.82
10	Redfish	Centroberyx affinis	31,537	0.09	980	0.09	37,627	0.08	1,439	0.12	0.19	-0.19	0.47	0.30
11	School Whiting	Sillago flindersi	8,578	1.25	2,268	0.65	15,101	0.44	3,042	0.82	0.76	-0.65	0.34	0.27
12	Silver Warehou	Seriolella punctata	25,715	0.36	2,686	0.32	24,056	0.22	2,683	0.39	-0.06	-0.38	-0.00	0.22
13	Tiger Flathead	Neoplatycephalus richardsoni	34,818	0.28	2,830	0.49	31,882	0.18	2,793	0.20	-0.08	-0.37	-0.01	-0.58
	Mean		25,149	0.43	1,541	0.41	32,274	0.16	1,946.72	0.37	0.38	-0.31	0.63	-0.00

Table 2. Comparison of key parameters from Catch-MSY and from Stock Synthesis output for 13 SESSF stocks. $S = B_e/K$, RE = relative error.

	SS				Catch-MSY					RE			
Stock	K	F_{MSY}	MSY	S	K	F_{MSY}	MSY	S	Resilience	K	F_{MSY}	MSY	S
Bight Redfish	7,735	1.45	611	0.63	6,645	0.12	388	0.15	Very low	-0.14	-0.92	-0.37	-0.77
Blue Grenadier	70,993	0.22	4,435	0.78	71,682	0.12	4,192	0.19	Low	0.01	-0.46	-0.05	-0.76
Deepwater Flathead	15,164	0.29	1,257	0.47	14,930	0.12	910	0.16	Low	-0.02	-0.58	-0.28	-0.66
Gemfish East	15,146	0.08	538	0.13	55,126	0.09	2,459	0.15	Low	2.64	0.09	3.57	0.15
Morwong East	7,693	0.23	468	0.34	45,412	0.05	1,151	0.15	Low	4.90	-0.78	1.46	-0.55
Morwong West	1,943	0.80	185	0.63	1,865	0.11	105	0.10	Low	-0.04	-0.86	-0.43	-0.85
Orange Roughy	81,054	0.20	2,192	0.23	133,945	0.09	6,105	0.16	Very low	0.65	-0.53	1.79	-0.31
Pink Ling East	15,670	0.16	789	0.20	12,794	0.11	686	0.13	Low	-0.18	-0.32	-0.13	-0.36
Pink Ling West	10,893	0.23	789	0.43	8,064	0.12	489	0.19	Low	-0.26	-0.47	-0.38	-0.56
Redfish	31,537	0.09	980	0.09	29,920	0.13	2,018	0.16	Medium	-0.05	0.42	1.06	0.81
School Whiting	8,578	1.25	2,268	0.65	18,928	0.18	1,727	0.53	Medium	1.21	-0.85	-0.24	-0.18
Silver Warehou	25,715	0.36	2,686	0.32	30,669	0.17	2,651	0.53	Medium	0.19	-0.52	-0.01	0.69
Tiger Flathead	34,818	0.28	2,830	0.49	33,510	0.20	3,283	0.57	Medium	-0.04	-0.30	0.16	0.15
Mean	25,149	0.43	1,541	0.41	35,653	0.12	2,013	0.24		0.68	-0.47	0.47	-0.25

Table 3. Comparison of model performance between OCOM and Catch-MSY. ME: mean error; MAE: mean absolute error; MRE: mean relative error; MARE: mean absolute relative error. All statistics are relative to Stock Synthesis estimates.

	OCOM				Catch-MSY			
Statistics	K	F_{MSY}	MSY	S	K	F_{MSY}	MSY	S
ME	7125	-0.27	406	-0.05	11386	-0.28	518	-0.14
MAE	9856	0.29	473	0.19	13045	0.29	817	0.20
MRE	0.38	-0.31	0.63	0.00	0.68	-0.47	0.47	-0.25
MARE	0.51	0.58	0.75	0.46	0.79	0.55	0.76	0.52

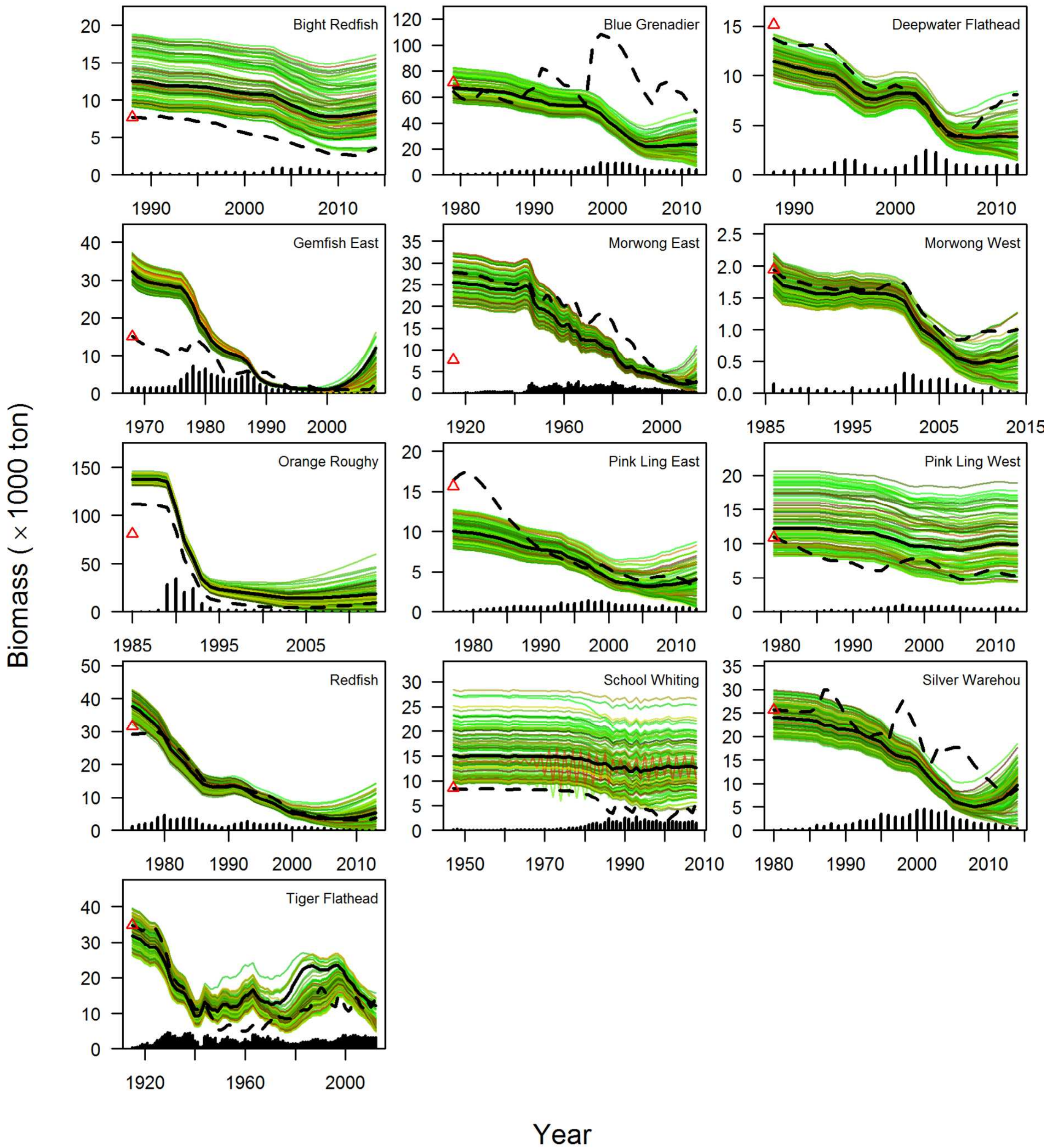

Figure 1. OCOM-estimated exploitable biomass trajectories (coloured lines) from 100 *r*-*K* pairs for 13 SESSF stocks. The solid black line is the median, the black dashed line is the "true" biomass from SS, the red triangle is estimated *K* from SS, and the vertical bars are the observed catch. Note that the start of the solid black line is the median *K* from OCOM, and the start of the dashed line is the initial biomass from SS.

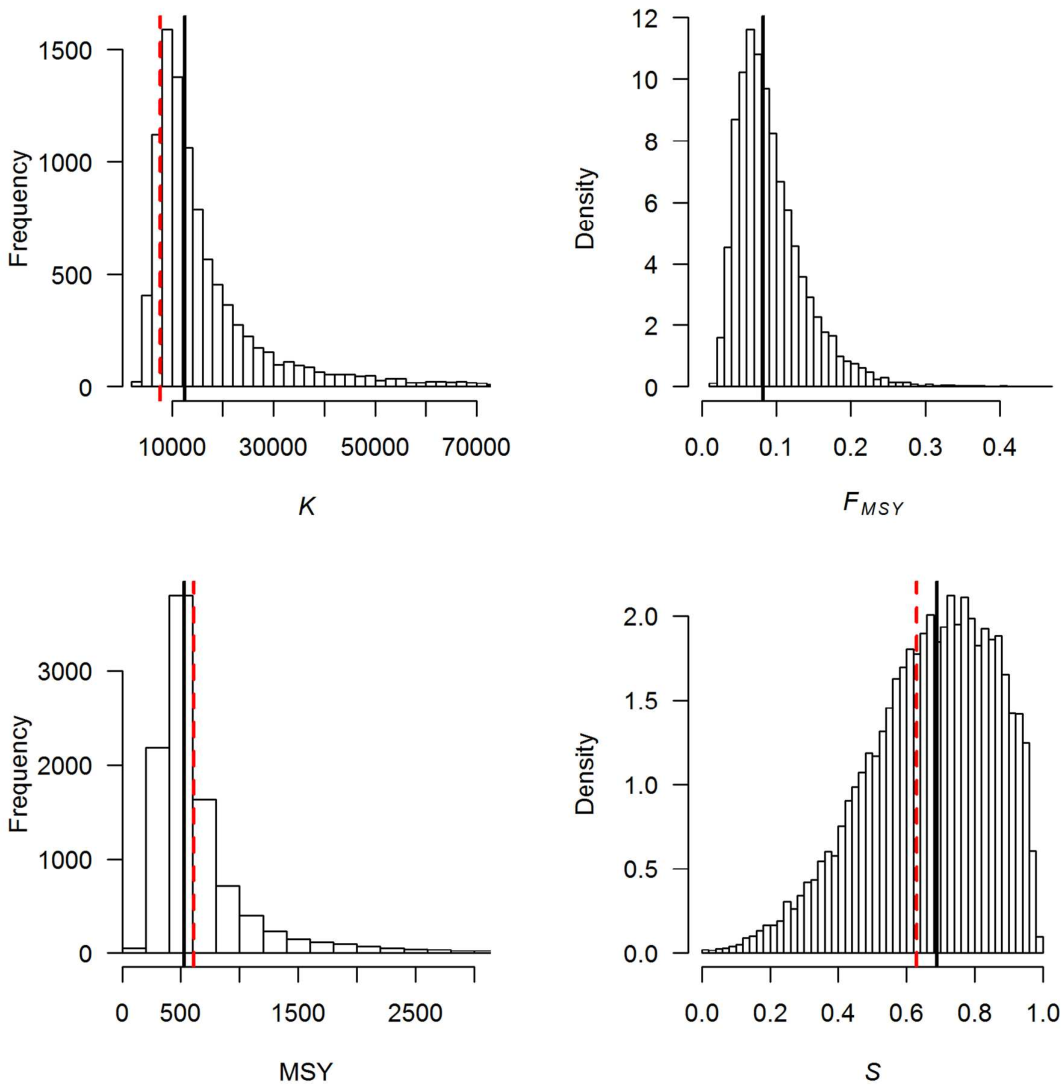

Figure 2. Distribution of four parameter outputs from OCOM for Bight Redfish. The vertical black lines are the medians, and the red lines are point estimates from Stock Synthesis. F_{MSY} = 1.45 for SS is outside of the range of values plotted.

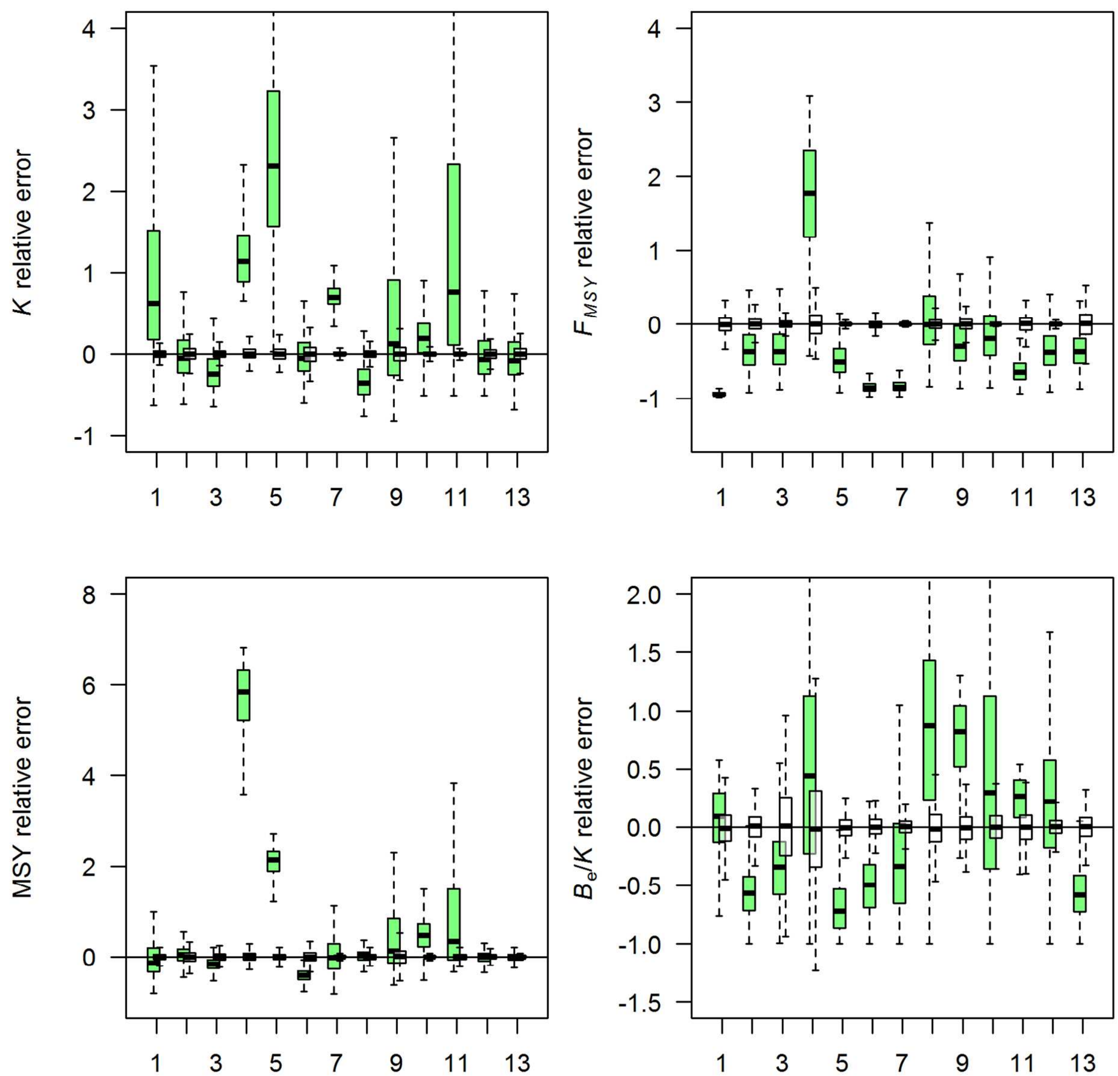

Figure 3. Comparison of four parameters between OCOM (green) and SS (white) for the 13 SESSF stocks. The boxplots for OCOM are based on 10,000 samples whereas the boxplots for SS are based on the point estimate and the (asymptotic) standard error. Stock number is the same as stock ID in Table 1 (i.e., number 4 is Gemfish East and number 5 is Morwong East).

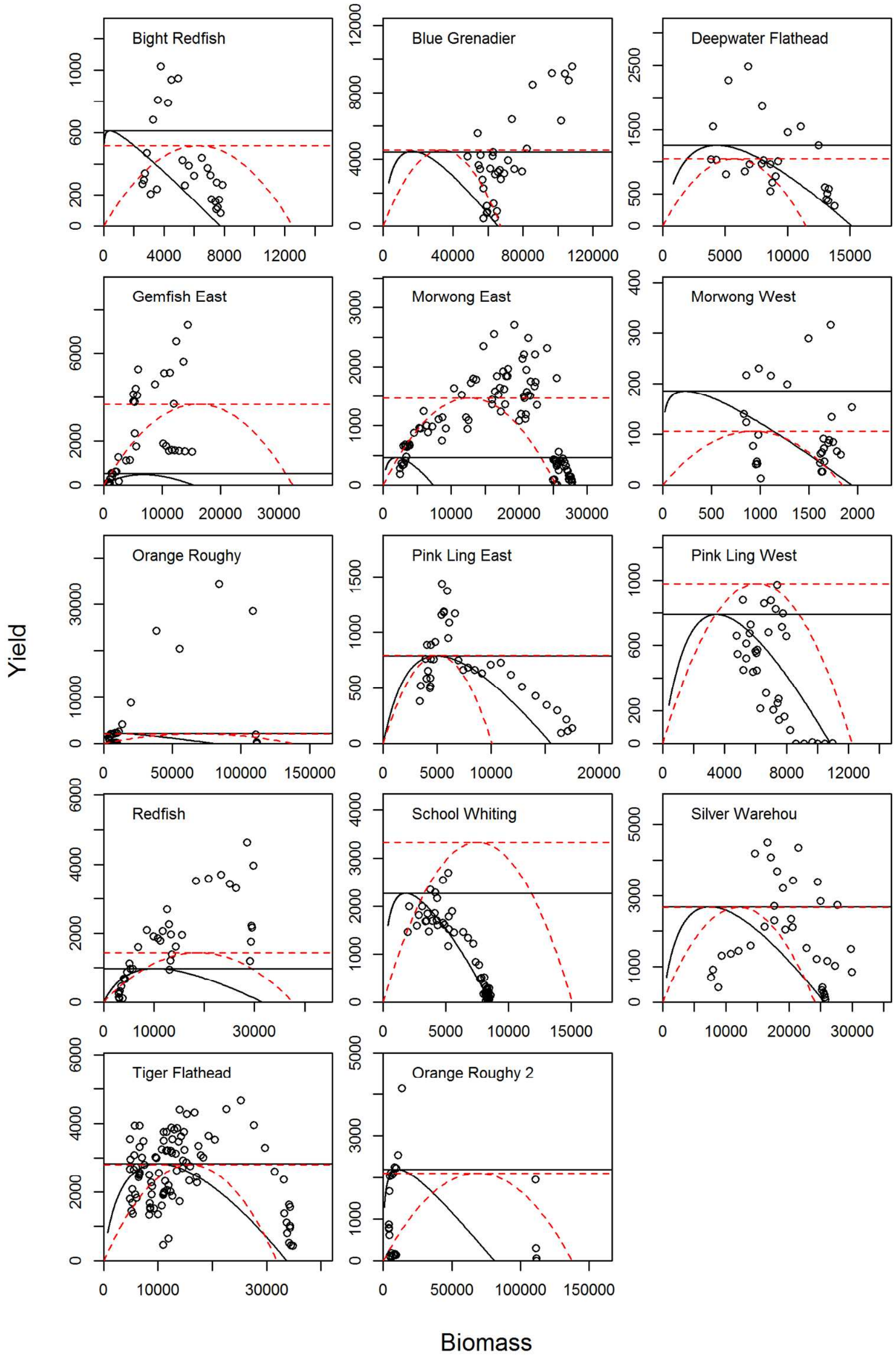

Figure 4. Equilibrium relationships between yield and exploitable biomass from SS (black solid lines) and OCOM (red dashed lines). The circles are observed catch versus SS-estimated exploitable biomass, and the horizontal lines are the estimated MSYs. The last panel repeats Orange Roughy but the bounding y-axis between 0 and 5,000t so the five large data points are not shown.

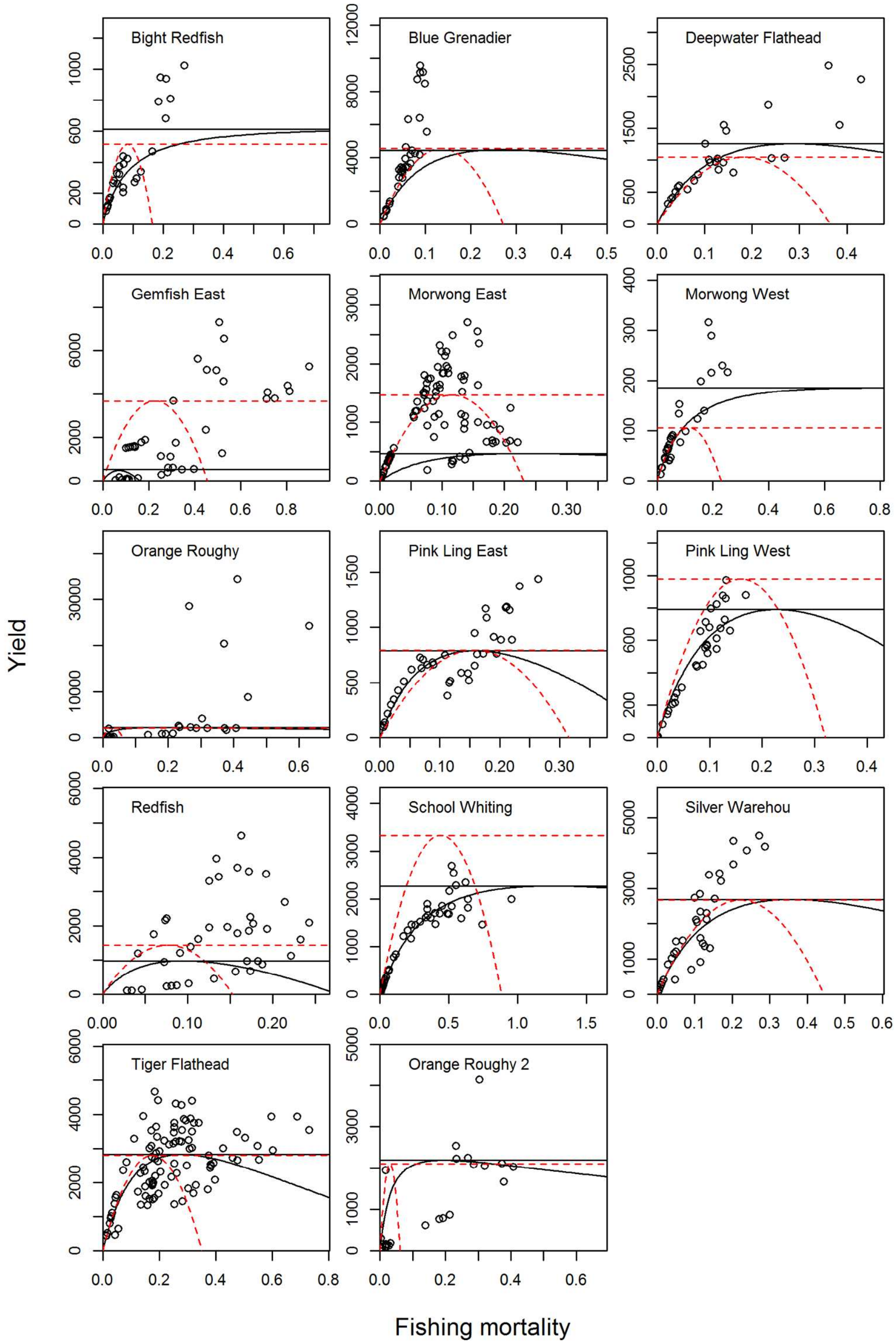

Figure 5. Equilibrium relationships between yield and fishing mortality rate based on parameters estimated by SS (black solid lines) and OCOM (red dashed lines). The circles are observed catch versus SS estimated exploitable biomass and the horizontal lines are the estimated MSY values. The last panel repeats Orange Roughy but bounding the y-axis between 0 and 5,000t so five large data points are not shown.

Supplementary material

1. Using natural mortality from Fishbase

We used the natural mortality rates that are adopted in SS to compare the results from the OCOM and SS assessments for the 13 SESSF stocks, in the main text. However, natural mortality may be unavailable for some species in other data-poor fisheries. For these species, we suggest obtaining values for natural mortality from Fishbase.org and applying four empirical equations using other life-history parameters. To see how *M* from Fishbase may affect the results, we obtained *M* or other life-history parameters directly from Fishbase for the SESSF species. Fishbase has values for *M* for four of the 11 species so we used other life-history parameters, i.e., maximum age, von Bertalanffy growth parameters, and maturation age to obtain average *M* for the remaining seven species. The biomass trajectories are very similar to those in the main text (Figure S1 vs Figure 1). Performance appears to be slightly worse for some stocks (e.g., Redfish and Silver Warehou), but better for others (e.g., Bight Redfish, Orange Roughy, and School Whiting). Overall, using *M* from Fishbase reduces relative error for *K* and F_{msy} but increases it for MSY (Table S1 vs Table 1).

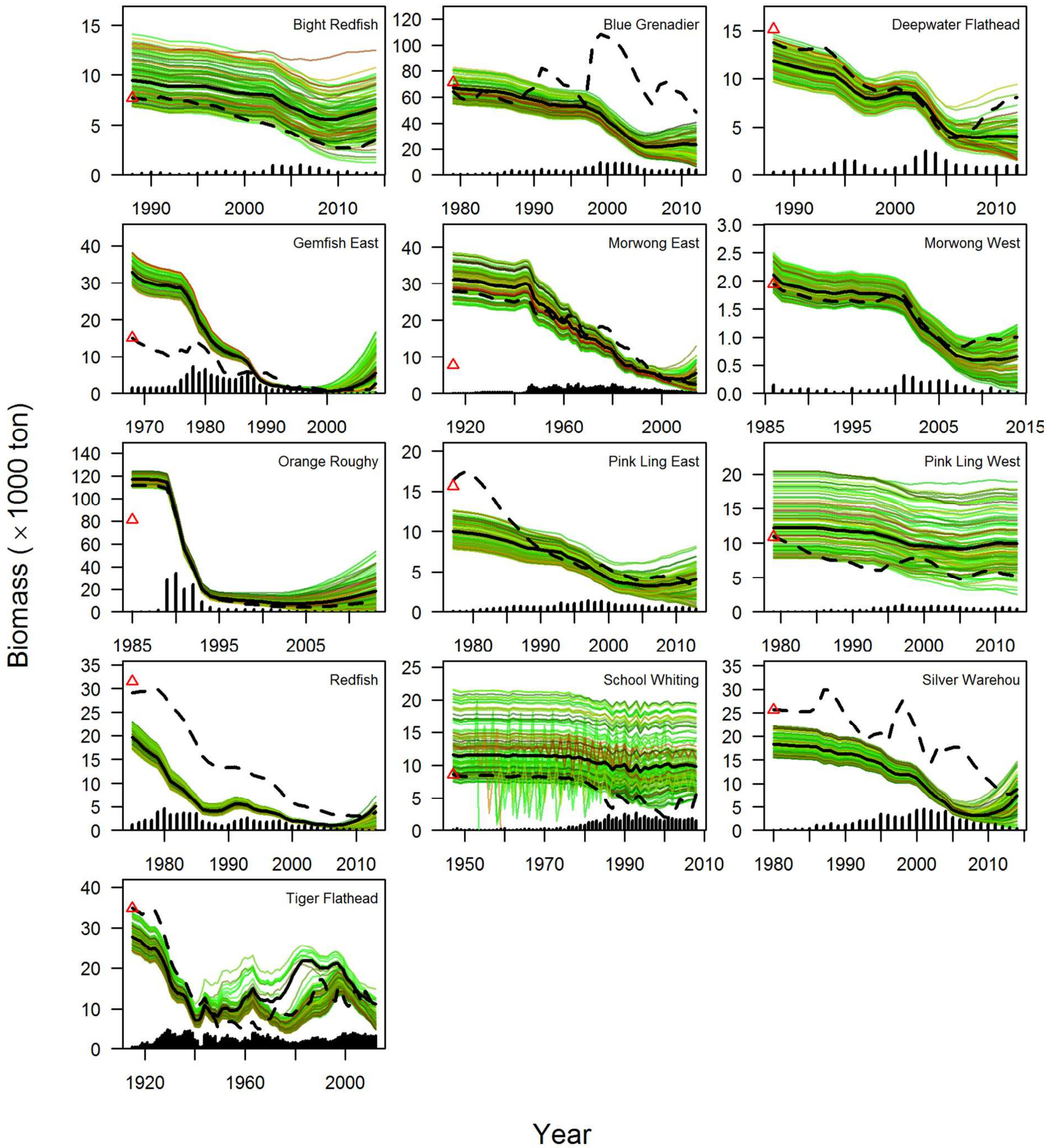

Figure S1. OCOM-estimated exploitable biomass trajectories (coloured lines) from 100 *r*-*K* pairs for 13 SESSF stocks using ***M* from Fishbase**. The solid black line is the median, the black dashed line is the "true" biomass from SS, the red triangle is estimated *K* from SS, and the vertical bars are the observed catch. Note that the start of the solid black line is the median *K* from OCOM, and the start of the dashed line is the initial biomass from SS.

Table S1. Comparison of estimates of K, F_{MSY} and MSY from Stock Synthesis (SS) and OCOM for 13 SESSF stocks. RE = relative error. M_{SS} = M used in SS. M_{fb} = M from Fishbase.

	SS			OCOM			RE				
Stock	K	F_{msy}	MSY	K	F_{msy}	MSY	K	F_{msy}	MSY	M_{SS}	M_{fb}
Bight Redfish	7,735	1.45	611	9,454	0.12	580	0.22	-0.91	-0.05	0.11	0.16
Blue Grenadier	70,993	0.22	4,435	66,843	0.14	4,672	-0.06	-0.36	0.05	0.18	0.18
Deepwater Flathead	15,164	0.29	1,257	11,862	0.17	1,044	-0.22	-0.40	-0.17	0.24	0.23
Gemfish East	15,146	0.08	538	32,866	0.22	3,651	1.17	1.70	5.78	0.38	0.36
Morwong East	7,693	0.23	468	31,156	0.09	1,374	3.05	-0.62	1.93	0.15	0.12
Morwong West	1,943	0.80	185	2,106	0.09	97	0.08	-0.89	-0.48	0.15	0.12
Orange Roughy	81,054	0.20	2,192	116,774	0.08	4,876	0.44	-0.57	1.22	0.04	0.11
Pink Ling East	15,670	0.16	789	10,028	0.16	806	-0.36	0.01	0.02	0.21	0.21
Pink Ling West	10,893	0.23	789	12,189	0.16	896	0.12	-0.28	0.14	0.21	0.21
Redfish	31,537	0.09	980	19,612	0.25	2,410	-0.38	1.59	1.46	0.10	0.37
School Whiting	8,578	1.25	2,268	11,556	0.62	3,351	0.35	-0.50	0.48	0.58	0.84
Silver Warehou	25,715	0.36	2,686	18,262	0.32	2,958	-0.29	-0.10	0.10	0.30	0.50
Tiger Flathead	34,818	0.28	2,830	27,733	0.21	2,909	-0.20	-0.25	0.03	0.27	0.37
Mean RE	25,149	0.43	1,541	28,496	0.20	2,279	0.30	-0.12	0.81		

2. R codes for OCOM

```
####################################################
##                 Optimized catch-only method function     ##
####################################################

## Predictors for BRT model
# First load the following function catchParam.
# This function derives 56 predictors based on catch history.
# It can be used for batch processing of multiple stocks.
# Data format must be 3 columns: stock, yr, catch.

require(segmented)
require(gbm)
require(dismo)
require(fGarch) # for skewed normal dist

catchParam = function(catchData) {
  sid = unique(as.character(catchData$stock))
  n.stock = length(sid)
  para = matrix(NA, n.stock, 57)
  n.ab = 7  # number of years at the beginning and ending time series
  a=b=a0=b0=matrix(0, n.stock, n.ab)
   for(i in 1:n.stock) {
    stk = sid[i]
    dat = subset(catchData, stock==stk)
         yr = dat$yr-min(dat$yr) +1
    midYr = mean(yr)
    C = dat$catch/max(dat$catch)   # regressions are based on scaled catch
    C05max = sum(C[-length(C)]>0.5)
    Cmean = mean(C)
         nyr = length(yr)
    nyrToCmax = min(yr[C==max(C)]-yr[1]+1)
    nyrToCmaxR = nyrToCmax/nyr
    nyrAfterCmax = nyr-nyrToCmax
    yr.cent = yr-midYr          # regressions are based on centred year
    line0 = lm(C~yr.cent)
    yr1.cent = yr[1:nyrToCmax]-mean(yr[1:nyrToCmax])
    line1 = lm(C[1:nyrToCmax]~yr1.cent)
    yr2.cent = yr[nyrToCmax:nyr]-mean(yr[nyrToCmax:nyr])
    line2 = lm(C[nyrToCmax:nyr]~yr2.cent)
      aa0 = summary(line0)$coeff[1]; bb0 = summary(line0)$coeff[2]    #all yr
      aa1 = summary(line1)$coeff[1]; bb1 = summary(line1)$coeff[2]    #before Cmax
      aa2 = summary(line2)$coeff[1]; bb2 = summary(line2)$coeff[2]    #after Cmax
    for (j in 1:n.ab) { # periodical regressions
      yrLast.cent = yr[(nyr-j):nyr]-mean(yr[(nyr-j):nyr])
      l.last = lm(C[(nyr-j):nyr]~yrLast.cent)               # last several years
      a[i,j] = summary(l.last)$coeff[1];
      b[i,j]=summary(l.last)$coeff[2]
      yrBegin.cent = yr[1:(j+1)]-mean(yr[1:(j+1)])
      l.begin = lm(C[1:(j+1)] ~ yrBegin.cent)               # beginning several years
      a0[i,j] = summary(l.begin)$coeff[1]
      b0[i,j] = summary(l.begin)$coeff[2] }
# segmented regression: use yr and breakpoint is between 0-1
```

```
    f = tryCatch(segmented(line0, seg.Z=~yr, psi=list(yr=median(yr))) , error=function(err) {})
    if(is.null(f)) {
          a.spline = NA; b1.spline = NA; b2.spline = NA; breakPoint = NA
        } else {
          a.spline = summary(f)$coef[1]
          b1.spline = summary(f)$coef[2]
          slp= slope(f)
          b2.spline = slp$yr[2]
          breakPoint = (round(f$psi.history[[5]],0)-yr[1] +1)/nyr
    }
 para[i,] = c(aa0, aa1, aa2, bb0, bb1, bb2, a[i,], b[i,], a0[i,], b0[i,], a.spline, b1.spline,b2.spline,
breakPoint, C[1:n.ab], C[(nyr-n.ab): nyr], Cmean, nyrToCmaxR, nyr, C05max)
   }   # end params
 colnames(para) = c('a.AllYr', 'a.BfMax', 'a.AfMax', 'b.AllYr', 'b.BfMax', 'b.AfMax',
paste('a.LsY',1:n.ab, sep=""), paste('b.LsY',1:n.ab, sep=""), paste("a.BgY", 1:n.ab, sep = ""),
paste('b.BgY', 1:n.ab, sep=""), 'a.seg', 'b1.seg', 'b2.seg','breakPoint',  paste('c.BgY',1:n.ab, sep=""),
paste('c.LsY', n.ab:0, sep=""), 'Cmean','nyrToCmaxR','nyr', 'C05max')
 para = data.frame(stock=sid, para)
 return(para)
}

#### biomass dynamics model: one parameter r, using optimize
BDM = function(K, r, S, b, C) {
    nyr = length(C)
            B = vector()
            B[1] = K*b
            for (i in 1:nyr) {
                        B[i+1] = max(min(B[i]+r*B[i]*(1-B[i]/K)-C[i], K), 0)
    }
    if (all(B[-nyr]>C) & all(B<=K)) abs(B[nyr]/K-S)  else max(K)*10^4
}

### derive S = B/K prior bwt [0,1]
Sdistrib = function(n, s_mean) {
 nv = 0 ; n.redo = 0
 while(nv < n) {
    n.redo = n.redo+1
    if(s_mean<=0.5) {
        si1 = rsnorm(n*n.redo, mean=max(s_mean,0)-0.072, sd=0.189, xi=0.763)
        si = si1[si1>0 & si1<1]
    } else if(s_mean>0.5) {
        si1 = rsnorm(n*n.redo, mean=max(s_mean,0)+0.179, sd=0.223, xi=0.904)
        si = si1[si1>0 & si1<1] }
    if(length(si)>n) si = sample(si,n);
    nv = length(si) }
 return (si)
 }

### draw biomass trajectories
drawBt = function(cdat, oc0){
    B = Bmed = vector()
    n.sim = 100
    oc1 = oc0[oc0$obj<0.01 & oc0$k>1.01*min(oc0$k) & oc0$k<0.99*max(oc0$k), c(2:5)] #
eliminate bordering effect
    oc2 = oc1[oc1$k>quantile(oc1$k, 0.25) & oc1$k<quantile(oc1$k, 0.75),]
```

```
    smp = sample(1:nrow(oc2), n.sim, replace=T)
    if(min(oc2$k)>1000) {
      k = oc2[smp,1]/1000
      C = cdat$catch/1000
    } else {
      k = oc2[smp,1]
      C = cdat$catch }
    r = oc2[smp,2]
    kmed = median(k); rmed = median(r)
    stock = cdat$stock[1]
    yr=cdat$yr; nyr = length(yr)

    plot(rep(0, nyr)~yr, type='n',  ylim=c(0, max(k)*1.2),xlab='', ylab='', las=1, yaxs='i')#
expression("B (" %*% "1000t)"), las=1)
      legend("topright", legend=stock, bty='n', cex=0.8)
    Bmed[1] = kmed
    for (j in 1:n.sim){
       B[1] = k[j]
       for(t in 1:(nyr-1)) {
         B[t+1] = (B[t])+r[j]*B[t]*(1-B[t]/k[j])-C[t]
         Bmed[t+1] = (Bmed[t])+rmed*Bmed[t]*(1-Bmed[t]/kmed)-C[t]
       }
       lines(yr, B, col=rgb(runif(1,0,j)/n.sim,(n.sim-runif(1,0,j))/n.sim, 1/(n.sim+100), alpha=0.6) )
     }
    lines(yr, Bmed, lwd=2)
    lines(C~yr, type='h', lwd=2 )

 mtext('Year', side=1, line=2, outer=T)
 if(min(oc2$k)>1000) mtext(expression('Biomass (' %*% '1000 ton)'), side=2, line=2, outer=T)
 else  mtext(expression('Biomass (ton)'), side=2, line=2, outer=T)
}


     ########################################
     #              Optimized Catch-Only Method       #
     #                     December 2016                   #
     ########################################

require(fGarch) # for skewed normal dist
require(plyr)

## Import catch and M data
## catch data must have three columns: stock, yr, catch
## natural mortality data has two coulumns: stock, M
## Example: SESS stocks in Australia
Dir =("E:/")
catchData =read.table(paste0(Dir, 'catchData.txt'), head=T)
sessM =read.table(paste0(Dir, 'sessM.txt'), head=T)

## if M is unkonwn, derive M from other life history parameters, e.g.:
M = vector()
M[1] = 4.899*Tmax^-0.916            # Tmax = max age
M[2] = 4.11*k^0.73*Linf^-0.33        # k and Linf: Bertalanffy growth parameters
M[3] = 1.82*k
M[4] = 1.65/Tmat                   # Tmax = maturation age
```

```
M = mean(M)

## derive prior for stock saturation S = B/K
## load saved BRT models: two alternative models. You can use 1 or both models.
## model 1: BRTmodelP8   (using 8 predictors )
## model 2: BRTmodelP38  (using 38 predictors)
 load(file = paste0(Dir, "BRTmodelP8.RData"))   # model 1
 load(file = paste0(Dir, "BRTmodelP38.RData"))  # model 2

## derive predictors from catch history
sessPar = catchParam(catchData)

## centering the first 37 predictors
sessParCent = scale(sessPar[,2:38], center=BRTmodelP8$parMean, scale=F)

## construct predition data
stockName = unique(as.character(catchData$stock))
nstk = length(stockName)
predDat = data.frame(stock=stockName, sessParCent, sessPar[,39:57])

## estimating saturation S
s8 = predict.gbm(BRTmodelP8$model, predDat, n.trees=BRTmodelP8$model$gbm.call$best.trees,
type="response")
s38 = predict.gbm(BRTmodelP38$model, predDat,
n.trees=BRTmodelP38$model$gbm.call$best.trees, type="response")

## Bias correction
## for model 1
slr8.a = BRTmodelP8$slr[[1]]; slr8.b = BRTmodelP8$slr[[2]];
sBC8 = (s8-slr8.a)/slr8.b
sBC8[sBC8<=0] = 0.01

## for model 2
slr38.a = BRTmodelP38$slr[[1]]; slr38.b = BRTmodelP38$slr[[2]];
sBC38 = (s38-slr38.a)/slr38.b
sBC38[sBC38<=0] = 0.01

## Output S
sessS = data.frame(stock=stockName, S8=sBC8, S38=sBC38, S = (sBC8+sBC38)/2)

    ####################################
    ########      OCOM       ######
    ####################################

n = 10000
summ = array(NA, dim=c(5,4,nstk))

for (i in 1:nstk) {  # i=1
  stk = stockName[i]
  dat = subset(catchData, stock==stk)
  C = dat$catch ;
  yr = dat$yr
## derive r prior with lognorm dist
  M = sessM$M[sessM$stock==stk]
  r_mean = M*1.72; r_var = 0.23          # for teleosts
```

```
  r_sig = sqrt(log(r_var/(r_mean)^2+1))
## r_mean = 0.79*M ; r_var = 0.23        # for chondrichthyans
  r_mu = log(r_mean)-r_sig^2/2
  ri = rlnorm(n, r_mu, r_sig)

## derive S prior btw 0 and 1
  s_mean = sessS[sessS$stock==stk, 4] # column 2 = BRTmodelP8
  si = Sdistrib(n, s_mean)

  rs = cbind(r=ri, s=si)
  k.low = max(C); k.up=max(C)*200
  opt = apply(rs, 1, function(x) { optimize(BDM, c(k.low, k.up), r=x[["r"]], S=x[["s"]], b=1, C=C) })

  ki = sapply(opt, '[[', 1)
  msy = ki*ri/4
  obji = sapply(opt,'[[',2)
  kr = data.frame(k=ki, r=ri, msy, s=si, obj=obji)
  write.csv(kr, paste0(Dir, "test/krms", i, ".csv", sep=""))

## summary
  kr2 = kr
  kr2[kr2$k<1.01*k.low | kr2$k>0.99*k.up | kr2$obj>0.01,] = NA # bordering effect
  kr2 = na.omit(kr2)
# plot(log(kr2$k), log(kr2$r), xlab="K", ylab='r')
# abline(h=mean(log(kr$r)), v=mean(log(kr$k)), lty=2, col=2)
  summ[,,i] = apply(kr2, 2, function(x) quantile(x, c(0.05, 0.25, 0.5, 0.75, 0.95)))[,1:4]
 }

## summary result
 summ2 = adply(summ, 3)
 colnames(summ2)=c('stockID', 'k', 'r', 'MSY', 'S')
 sumOut = data.frame(percent=rep(c(5, 25, 50, 75, 95),nstk), summ2)
 write.csv(sumOut, paste0(Dir, "result.csv"))

########################################
## distribution
par(mfrow=c(2,2), mai=c(.8,.8,0.1,0.1))
hist(kr2$k, xlab='K', main='', las=1); abline(v=median(kr$k), lwd=2);
hist(kr2$r, xlab='r', main='', las=1); abline(v=median(kr$r), lwd=2);
hist(kr2$msy, xlab='MSY', main='', las=1); abline(v=median(kr$msy), lwd=2);
hist(kr2$s, xlab='S', main='', las=1); abline(v=median(kr$s), lwd=2);

########################################
## draw 100 biomass trajectories

windows()
par(mfrow=c(5,3), mai=c(.2,.25,0.1,0.1), omi=c(0.5,0.5,0,0))

for (i in 1:nstk) { # i=1
   cdat = subset(catchData, stock==stockName[i])
   oc0 = read.csv(paste0(Dir,'test\\krms', i, '.csv', sep=''))
   drawBt(cdat, oc0)
}
```