Estimating stock status from relative abundance and resilience

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Abstract

The Law of the Sea as well as regional and national laws and agreements require exploited populations or stocks to be managed such that they can produce maximum sustainable yields. However, exploitation level and stock status are unknown for most stocks, because the data required for full stock assessments are missing. This study presents a new method (AMSY) that estimates relative population size when no catch data is available, using time series of catch-per-unit-of-effort or other relative abundance indices as main input. AMSY predictions for relative stock size were not significantly different from the "true" values when compared with simulated data. Also, they were not significantly different from relative stock size estimated by data-rich models in 88% of the comparisons within 140 real stocks. Application of AMSY to 38 data-poor stocks showed the suitability of the method and led to the first assessments for 23 species. Given the lack of catch data as input, AMSY estimates of exploitation come with wide margins of uncertainty which may not be suitable for management. However, AMSY seems to be well suited for estimating productivity as well as relative stock size and may therefore aid in the management of data-poor stocks.

Introduction

The Law of the Sea (UNCLOS 1982) commits its signatories to manage the exploitation of fish and invertebrates such that these populations are large enough to generate maximum sustainable yields (MSY). National and regional implementations of this MSY framework have made it clear that for risk-avoidance and economic benefits, biomass (*B*) of stocks must be above the *MSY* level (B_{msy}) or proxies thereof (CFP 2013; HSP 2018) and fishing pressure (*F*) must be below the *MSY* level (F_{msy}) (UNFSA 1995; MSA 2007). However, exploitation level and stock status are unknown for most exploited populations or stocks, because the data required for full stock assessments are missing. Methods that make best use of available data combined with general knowledge and Monte Carlo approaches have recently been developed on the basis of previous work in fish population dynamics (Graham 1933, 1935; Beverton and Holt 1957; Schaefer 1954, 1957; Ricker 1975), such as CMSY (Froese et al. 2017) for catch data and LBB (Froese et al. 2018, 2019) to estimate relative biomass levels from length frequency data. This study applies a similar approach to observed trends in the relative abundance of exploited species and thus complements CMSY and LBB.

Fisheries-independent surveys carried out, year after year, with standardized gear and in a random or stratified fashion produce time series of indices of fish abundance also referred to as catch-per-unit-of-effort (CPUE), conventionally in units of catch in numbers or weight per duration of gear deployment or per swept area. CPUE obtained from such standardized research surveys is a good indicator of abundance (see, e.g. Silliman and Gutsell 1958 for experimental confirmation). Abundance estimates (relative or absolute) can also be obtained using hydroacoustic methods, as practiced e.g. for half a century for the stock of Peruvian anchoveta (*Engraulis ringens*; see Pauly et al. 1987). Time series of abundance are useful in that they allow trend analyses such as comparing current CPUE to the average of previous years (e.g. ICES 2017). However, it is often unclear whether such abundance trajectories refer to a stock fluctuating around unexploited stock size, or around a stock size close to collapse, or somewhere in between. If reliable catch data are available, this ambiguity is best addressed by combining CPUE trends with catch data, e.g. in surplus production models (Schaefer 1954; Fox 1970; Pella and Tomlinson 1969; Froese et al. 2017; Pedersen and Berg 2017; Winker et al. 2018).

If no reliable data are available for the total catch taken from a stock, as is often the case in migratory species, widely dispersed stocks, in by-catch species or in species with high discard rates, independent assessments of relative stock size can be used as priors for modelling, such as derived from expert opinion or preferably from other data sources such as length-frequency data (LBB, Froese et al. 2018, 2019). One must be conscious, however, that such use of independent assessments of relative stock size to present the observed CPUE in an MSY framework fully depends on the quality of the independent assessment and is not informed by the CPUE data. This study aims to overcome this limitation by performing a joint analysis of abundance trends, independent stock size information, and readily available information on the resilience or productivity of the respective species.

Material and Methods

Theoretical background

For stocks that lack information on age, natural mortality or recruitment, but have reliable time series of catch and abundance, surplus production models are the method of choice for estimating stock status and exploitation. Based on Graham (1935), the Schaefer (1954) model estimates surplus production or equilibrium Yield (Y) from biomass (B), maximum intrinsic rate of population increase (r, sometimes called r_{max}) and carrying-capacity (k) (Equation 1).

$$Y = B\, r\, (1 - \frac{B}{k}) \qquad \text{Equation 1}$$

The difference form of the Schaefer model predicts the biomass in the next year (B_{t+1}) from the current biomass (B_t) plus surplus-production or yield (Y_t), minus catch (C_t) (Equation 2).

$$B_{t+1} = B_t + Y_t - C_t = \ B_t + B_t\, r \left(1 - \frac{B_t}{k}\right) - C_t \qquad \text{Equation 2}$$

Note that the expression ($1 – B_t/k$) describes the linear decline with relative biomass of the applicable fraction of r, resulting in a factor of 1 when $B_t = 0$ and zero when $B_t = k$.

In surveys that deploy a standard gear in a random or stratified fashion across an area, CPUE is usually assumed to be directly proportional to the abundance or biomass of the target species in that area. The relation between CPUE and biomass is then determined by the catchability-coefficient q (Arreguin-Sanchez 1996; Maunder and Punt 2004), which is here assumed to be constant over the considered time period (but see below for exceptions) (Equation 3), such that:

$$CPUE_t = \ B_t\, q \qquad \text{Equation 3}$$

Multiplying both sides of Equation 2 with q and replacing $B_t\, q$ with $CPUE_t$ gives Equation 4.

$$CPUE_{t+1} = CPUE_t + CPUE_t \ \ r \left(1 - \frac{B_t}{k}\right) - C_t\, q \qquad \text{Equation 4}$$

Solving Equation 3 for B_t and inserting in Equation 4 gives Equation 5 (Froese et al. 2017).

$$CPUE_{t+1} = CPUE_t + CPUE_t \ \ r \left(1 - \frac{CPUE_t}{k\, q}\right) - C_t\, q \qquad \text{Equation 5}$$

For the purpose of estimating relative exploitation and stock status it is not necessary to know the absolute values of C_t, B_t, k and q. One can instead treat $C_t\, q$ as relative catch $C_{q\,t}$ and $k\, q$ as relative carrying capacity k_q or the CPUE one would obtain if there were no commercial fishing (Equation 6).

$$CPUE_{t+1} = CPUE_t + CPUE_t \ \ r \left(1 - \frac{CPUE_t}{k_q}\right) - C_{q\,t} \qquad \text{Equation 6}$$

Equation 6 can be rearranged to predict relative catch C_q, up to the second last year in the time series:

$$C_{q\,t} = CPUE_t + CPUE_t\ r\left(1 - \frac{CPUE_t}{k_q}\right) - CPUE_{t+1}$$ Equation 7

In the Schaefer model, the maximum sustainable catch (*MSY*) is obtained at half of *k* and half of *r* with *MSY* = *r*/2 * *k*/2. A similar expression is obtained in Equation 8.

$$MSY_q = \frac{r}{2}\frac{k_q}{2} = \frac{r\,k_q}{4}$$ Equation 8

where MSY_q is the maximum sustainable value of relative catch C_q and therefore the ratio C_q/MSY_q is the same as the ratio *C/MSY*. This logic, which is very similar to the matter covered in Ricker (1975, p. 316), also means that the relative catch predicted from Equation 7 can be presented in an MSY framework.

Similarly, since k_q represents the expected value of CPUE in the absence of fishing, the ratio $CPUE_t/k_q$ is the same as the ratio B_t/k and therefore CPUE can be presented as relative biomass within an MSY framework.

Finally, in the Schaefer model, the fishing mortality *F* is equal to the ratio of catch to biomass C_t/B_t, which is identical to the ratio $C_{q\,t}/CPUE_t$. Hence, the fishing mortality that corresponds to *MSY* is F_{msy} = 0.5 *r* and therefore relative exploitation can be presented within an MSY framework (Equation 9).

$$\frac{F}{F_{msy}} = \frac{\frac{C_{q\,t}}{CPUE_t}}{r/2} = \frac{2\,C_{q\,t}}{r\,CPUE_t}$$ Equation 9

The Abundance-MSY (AMSY) approach

A time series of CPUE and prior ranges for *r* and relative stock size B_t/k in a given year are required input data for AMSY. A prior range for k_q is derived from B_t/k and $CPUE_t$ as described below. With this information, the time series of CPUE can be placed within a preliminary MSY framework where half of the end points of the k_q range are used as ranges for B_{msy_q} (Figure 1 (a)). A multivariate log-normal random sample or *r*-k_q pairs is then created based on the correlation matrix shown in Table 1, where the prior log ranges of *r* and k_q are assumed to represent four standard deviations and variance is standard deviation squared. The *r*-k_q covariance in log space is obtained from the empirical correlation between log *r* and log k_q obtained as median = -0.607 across 140 stocks (Froese et al. 2018) analyzed with a Bayesian Schaefer model (Froese et al. 2017), and from the prior standard deviations (SD) of log *r* and log k_q, such that covariance log *r*-k_q = -0.607 * SD log(*r*) * SD log(k_q) (see cloud of grey dots in Figure 1).

Table 1. Covariance matrix for multivariate normal distribution of r and k_q in log-space

variance log *r*	covariance log *r*-k_q
covariance log *r*-k_q	variance log k_q

As shown in the simulations in Appendix 1 and the upper panel of Figure 1, this procedure will result in a predicted central *r*-k_q pair in the middle of the prior *r*-k_q log space, with approximated confidence limits as wide as that space. In order to better accommodate "true" *r*-k_q pairs that are off the center and to reduce the amount of uncertainty, AMSY applies filters to exclude *r*-k_q pairs that would give unreasonable results when combined with the priors and CPUE data. For example, the relative catch predicted from Equation 7 may not become negative or exceed CPUE anywhere in the time series, because it is unlikely that a fishery catches all fish in a given year. Only *r*-k_q pairs that fulfill these and additional conditions (see below) are considered 'viable' and are retained and used by AMSY to determine the most likely r-k_q pair, with approximate confidence limits (see examples in Appendix 2 and the lower panel of Figure 1).

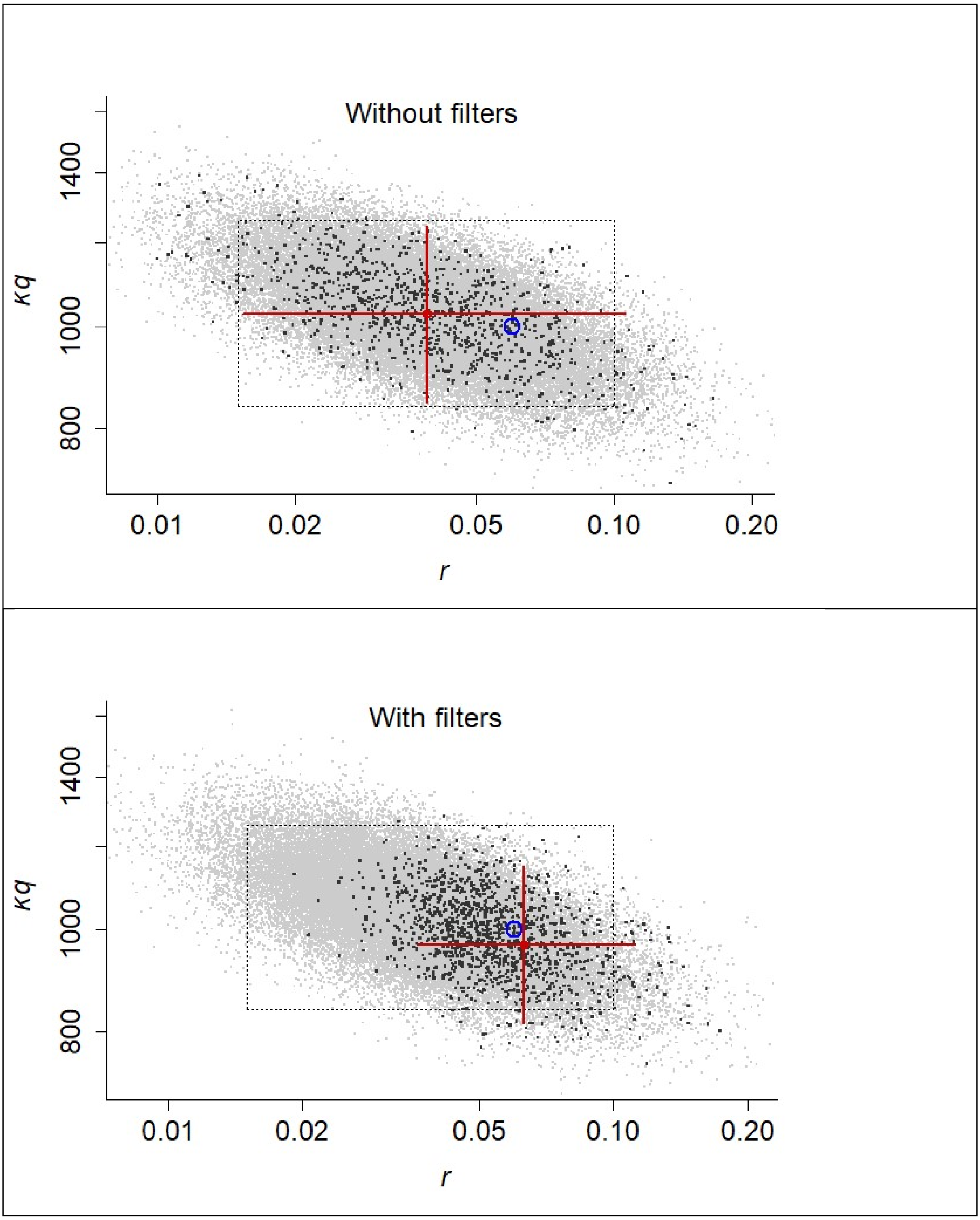

Figure 1. AMSY analysis of simulated data for a stock with very low productivity and low biomass. The grey dots are a random sample of 50,000 points drawn from a multivariate distribution of r and k_q in log space. The dotted rectangle indicates the prior ranges of r and k_q and contains 95% of the random points. The black dots are 'viable' r-k_q pairs with the red cross indicating the most probable value with approximate 95% confidence limits. The blue circle indicates the "true" r-k_q pair used in the simulations. In the upper panel, no logical filters are applied and the most probable r-k_q pair falls in the

center with confidence limits about equal to the prior ranges. In the lower panel, logical filters are applied to the selection of 'viable' r-k_q pairs, with a central value much closer to the true one and much narrower confidence limits which slightly exceed the prior range.

Priors for *r*, k_q and F/F_{msy}

Priors for *r* were derived from FishBase (www.fishbase.org, Froese and Pauly 2019) for fish and from SeaLifeBase (www.sealifebase.org, Palomares and Pauly 2019) for invertebrates, from the section on the species summary page entitled "Estimates of some properties based on models", either as lognormal distributions based on previous assessments or as qualitative indications of resilience from very low to high (Table 2). Resilience was then translated into uniform prior ranges as described in Froese et al. (2017) and reproduced here for easy reference.

Table 2. Translation of resilience categories in FishBase or SeaLifeBase into ranges of r.

Resilience	Lower limit	Upper limit
Very low	0.015	0.1
Low	0.05	0.5
Medium	0.2	0.8
High	0.6	1.5

A prior for relative biomass *B/k* can be derived from experts who are asked how stock size in a year of their choice compared to past stock size when there was little fishing of the species. For example, if the stock was only lightly fished in the beginning of the time series, it is reasonable to assume that stock size was more than half of the unexploited level in those years. Such qualitative assessment is then translated into *B/k* ranges as indicated in Table 3. Alternatively, and preferably, a quantitative assessment of *B/k* or B/B_{msy} is derived from a previous assessment or from independent data such as length frequencies analyzed with methods such as LBB (Froese et al. 2018, 2019, see examples in Appendix 4). The year for which the B/k prior is provided depends on the available data, i.e. a year with a good length-frequency sample or unanimous expert opinion. For example, if fishing was very light at the beginning of the time series, experts are likely to agree that stock size was close to unexploited, giving a *B/k* prior of e.g. 0.75 – 1.0.

Table 3. Translation of qualitative stock size information into prior ranges of B/k.

B/k	Lower limit	Upper limit
Very small	0.01	0.2
Small	0.15	0.4
About half	0.35	0.65
More than half	0.5	0.85
Close to unexploited	0.75	1.0

A prior range for k_q is derived from *B/k* as $k_q = CPUE_t/(B_t/k)$. If the lower bound of k_q resulting from this exercise is less than maximum CPUE in the time series, max(CPUE) is used as lower k_q bound because abundance of an exploited species is unlikely to exceed carrying capacity. Also, in order to avoid unrealistically narrow or wide ranges, the upper bound of k_q is set to at least 30% larger than the lower bound but not further away than 3 times the lower bound. In other words, the *B/k* prior together with population dynamics and scaling considerations is used to put the observed CPUE into a preliminary MSY framework. This placement is then refined by the Monte Carlo filtering described below.

AMSY Monte Carlo filtering

Based on the prior knowledge of *B/k*, a time series of CPUE can be presented in a preliminary MSY-framework, with the CPUE range that is capable of producing MSY_q given by $CPUE_{msy} = CPUE_t / (B_t/k)$, using the lower and upper limits of *B/k* (see Fig. 1a). Pairs of *r-kq* are then randomly selected from their respective prior ranges and the time series of relative catch C_q corresponding to the time series of CPUE is calculated from Equation 7 (see Fig. 1b-e).

To account for reduced recruitment and thus reduced productivity or surplus production at very small stock sizes, Equation 7 is combined with a hockey-stick recruitment function (Barrowman and Myers 2000; Froese et al. 2016, 2017). Thus, if relative stock size at the end of the time series is smaller than half of B_{msy} or 0.25 CPUE/k_q, a linear reduction of surplus production with declining biomass is assumed (similar to the MSY $B_{trigger}$ rule in ICES 2016) (Equation 10).

$$C_{q\,t} = CPUE_t + CPUE_t \ r\left(1 - \frac{CPUE_t}{k_q}\right)\left(4\ \frac{CPUE_t}{k_q}\right) - CPUE_{t+1} \quad | \ \frac{CPUE_t}{k_q} < 0.25 \qquad \text{Equation 10}$$

AMSY applies a state-space model formulation with an annual multiplicative lognormal random process error exp(η_t) and observation error exp(ε_t) terms with $\eta_t \sim N(0, \sigma_\eta^2)$ and $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$, respectively. For CPUE observation error, the default σ_ε was set to 0.3 and for surplus production process error σ_η was set to 0.05, 0.07, 0.1, or 0.15, depending on the productivity of the stock from very low to high. These error terms were not shown in the above equations for the sake of simplicity. The chosen values are preliminary but worked well for the purpose of this proof-of-concept study.

For cases where CPUE stems not from surveys but from commercial fisheries and where efficiency of commercial fishing may increase with time, an effort-creep correction can be applied by AMSY based on the average percentage of increase in catching efficiency, as provided by the user (Equation 11).

$$CPUE_{cor\,t} = CPUE_t\ (1-p)^{t-t_0} \qquad \text{Equation 11}$$

where $CPUE_{cor}$ is the corrected *CPUE*, *t* is a year in the time series, *p* is the percentage of average increase of efficiency as a decimal (e.g. 0.02 for 2%, Palomares and Pauly 2019) and t_0 is the first year in the time series.

Filters used to find *r-k* pairs compatible with the provided CPUE and priors

Note: Numerical settings or multipliers for the filters are derived from preliminary test runs against the simulated data. They were accepted as sufficient for the purpose of this presentation and proof-of-concept of AMSY and are expected to be further refined, also against real data, in subsequent research.

(1) **Exclusion of *r-k$_q$* pairs if predicted relative catch is negative.** By definition, catch is an extraction of fish from the population and may become zero but not negative. Thus, combinations of productivity and carrying capacity that, in combination with the CPUE time series, predict negative relative catches in any given year can be excluded as unrealistic. However, periods of close to zero relative catches are realistic scenarios especially during recovery phases of species with low or very low resilience, and during such periods, negative predictions of relative catch may result from the uncertainty and corresponding error terms

used in the modelling. Therefore, during such periods a negative relative catch of 2-6% of k_q (for low or very low productivity) is allowed by AMSY.

(2) **Exclusion of *r-k*$_q$ pairs if predicted catch in a given year exceeds biomass.** It is unlikely that a fishery catches all fish of a stock in a given year. Thus, r-k_q pairs that in combination with the CPUE time series predict relative catches above the available cpue appear unrealistic. However, looking at Equation 7, the term r(1-CPUE/kq) determines the amount of surplus production, and it may exceed 1.0 if e.g. r > 1.2 and CPUE/kq < 0.2, i.e., predicted annual catches may exceed biomass in species with high productivity and depleted stock size. AMSY accounts for this dependence on productivity by using empirical multipliers for the CPUE value not to be exceeded by relative catch, from 1.4 for high to 0.25 for very low productivity. This filter is skipped if at any point in the time series CPUE approaches zero (CPUE < 0.1 max(CPUE)), because under those circumstances catch may exceed mean biomass.

(3) **Exclusion of *r-k*$_q$ pairs if predicted catch strongly exceeds MSY**. While it is possible for fisheries to catch more than MSY for a few years, the degree of such overfishing is inversely correlated with the $MSY/k = r/4$ ratio: in species with very low productivity, MSY is only a small fraction of carrying capacity and can be easily exceeded several fold. In contrast, in species with high productivity, MSY is a quarter or more of carrying capacity and is unlikely to be overshot by more than MSY. Accordingly, a multiplier for maximum predicted relative catch was set from 10 times MSY_q for very low productivity to 2 times MSY_q for high productivity.

(4) **Exclusion of *r-k*$_q$ pairs if F/F_{msy} is negative or unrealistically high**. If the time series of F/F_{msy} ratios predicted by AMSY contains highly unrealistic values, such as less than -25 or more than 12, then that combination or r-k_q with its specific error patterns is excluded from the analysis. Note that while negative F/F_{msy} ratios require negative catches and thus are not possible in the real world, periods of very low or zero catches are realistic scenarios especially during recovery phases of species with low or very low resilience, and during such periods, predictions of negative F/F_{msy} ratios may result from the uncertainty and corresponding error terms used in the modelling.

(5) **Exclusion of *r-k*$_q$ pairs if modeled CPUE/*k*$_q$ is outside the prior *B/k* range.** If the relative CPUE ($CPUE/k_q$) in the year specified for prior B/k falls outside of that prior range, then the r-k_q pair is discarded.

Note that all r-k_q pairs are tested multiple times with different random error settings for surplus production and CPUE and are only excluded from further processing if all of these runs fail to pass the filters. This processing leads to a modelled CPUE time series slightly different from the observed CPUE, as peaks, troughs and slopes that would lead to unrealistic catches or unrealistic productivity are smoothed.

Finding the most likely values for r, k_q, F/F_{msy} and B/B_{msy}

The r-k_q pairs that passed the filters described above were considered as viable. Median values of viable r and k_q were considered to be the most likely estimates, and 2.5th and 97.5th percentiles were taken as approximate confidence limits, respectively. The time series of relative catch predicted by the viable r-k_q pairs in combination with cpue were stored and a proxy for median F_t was obtained by dividing the median predicted catch by the median of cpue. An estimate of recent F/F_{msy} was obtained by dividing F_t by the median estimate of $r/2$, with t set to the second last year. Approximate 95% confidence limits were obtained similarly from the 2.5th and 97.5th percentiles of predicted catch. The time series of modelled $CPUE_t$ were stored and a proxy for recent B/B_{msy} was derived by dividing median $CPUE_t$ by median $k_q/2$ and setting t to the last year. Approximate 95% confidence limits were obtained similarly from the 2.5th and 97.5th percentiles of modelled CPUE.

Simulated data

To assess the performance of AMSY, simulated catch and CPUE data were created so that the "true" simulated parameter values and stock status estimates were known and could be used for comparisons. For convenience, k_q was set to 1000 and r was set at 0.06, 0.25, 0.5 and 1.0 to represent species with Very Low (VL), Low (L), Medium (M) and High (H) resilience, respectively (c.f. Table 2). For time series of 50 years, biomass patterns of continuously high (HH), continuously low (LL), high to low (HL), low to high (LH), low-high-low (LHL) and high-low-high (HLH) biomass were created. From an "Above half" (0.5 – 0.85 k) or "Small" (0.15 – 0.4 k) start biomass in the first year, the desired pattern was produced by inserting high or low catches into Equation 6 and calculating the biomass in subsequent years. These first year ranges of relative biomass were used as prior for AMSY to reduce the influence of the prior on the estimated relative biomass 50 years later. If relative biomass fell below 0.25 k_q in any given year, surplus production was reduced as described in Equation 10 to account for potentially reduced recruitment. A catchability-coefficient q = 0.001 was assumed to turn biomass, catch and k into the desired values of CPUE, C_q and k_q, respectively. The simulated data and the spreadsheet used to produce them are part of the Supplementary Material.

Real data

For the evaluation of AMSY estimates against real data, 140 stocks from the Northeast Atlantic, the Mediterranean and Black Seas were used, as a subset of the 397 stocks used by Froese et al. (2018) (see Appendix 3). Criteria for stock selection were uninterrupted time series of catch and abundance (CPUE, indices, or predicted biomass) for at least 15 years. These data were then analyzed with a Bayesian implementation of the Schaefer model (BSM) which is part of the CMSY package (Froese et al. 2017). AMSY and BSM used the same CPUE time series and the same priors for productivity and relative stock size in the first year of the time series, the only difference being that BSM in addition had time series of catch as input. The BSM results for the 140 stocks were also used to derive the median correlation between r and k_q in log space, as required for construction of a correlation matrix (Table 1). The data and the results of the BSM analysis are part of the Supplementary Material.

First assessments of data-limited stocks

To test the usefulness of AMSY for its intended purpose, 38 data-limited stocks were analyzed first with LBB (Froese et al. 2018, 2019) to obtain objective prior information on relative stock size from length-frequencies, and then with AMSY to derive estimates of r, F_{msy}, F/F_{msy} and B/B_{msy} from CPUE data.

All appendices, data, spreadsheets and R-code used in this study are available as Supplementary Material from http://oceanrep.geomar.de/47135/. The version of LBB (33a) used in this study is available from http://oceanrep.geomar.de/43182/.

Results

Verification against simulated data

AMSY predictions of population dynamic parameters (r, k_q, MSY_q), fishing pressure (F/F_{msy}) and stock status (B/B_{msy}) at the end of the time series were compared with the "true" values used to produce the simulated data. In order to better understand the influence of the priors and of the Monte Carlo filtering on the results, the simulated data were analyzed twice by AMSY, first without and then with the Monte Carlo filters described above.

Without the filters, all r-k_q pairs of the multivariate distribution are 'viable', the central values of predicted r and k_q are in the center of the prior log space, and the respective approximate 95% confidence limits are wide and equivalent to the respective prior ranges. By design, the "true" values of r and k_q were within the prior ranges and thus fall within the approximate 95% confidence limits of the predictions. Similarly, all "true" values of MSY_q, F/F_{msy} and B/B_{msy} fall within the approximate 95% confidence limits of the respective estimates.

With Monte Carlo filtering, numerous r-k_q pairs are excluded because of unrealistic predictions, and consequently the estimated central values of r and k_q may move away from the center of the prior log space and their approximate 95% confidence limits get narrower and may exceed the original prior bounds (see Figure 1 and more examples in Appendix 2). With one exception (estimate of k_q in LHL_VL, see Appendix 2), "true" values of all parameters still fall within the narrower approximate 95% confidence limits. Table 4 shows a comparison of the estimated central values relative to true values and of relative lower confidence limits for AMSY runs without and with Monte Carlo filtering. All medians with filters are closer to 1 for the estimate/true ratios and narrower for the lower confidence limits of the estimates (except for B/B_{msy}, where the median central value and lower confidence limit are about same, with and without filters).

Table 4. Comparison of estimated central values relative to true values and of relative lower confidence limits for AMSY runs without and with Monte Carlo filtering, where est=estimated value, true=true value used in the simulation, and lcl=lower approximate 95% confidence limit of the estimate.

Comparison	Median without filters	Median with filters
r: est/true	0.72	1.04
r: (est–lcl)/est	0.55	0.36
k_q: est /true	1.08	1.07
k_q: (est—lcl)/est	0.24	0.18
F/F_{msy}: est/true	1.45	1.19
F/F_{msy}: (est—lcl)/est	1.42	0.89
B/B_{msy}: est/true	0.94	0.93
B/B_{msy}: (est—lcl)/est	0.44	0.44

Evaluation against real data

AMSY predictions for 140 real stocks were compared with those of a Bayesian implementation of a regular Schaefer model (BSM). AMSY estimates of r were similar to those of BSM (Figure 1), with 128 (91.4%) BSM estimates included in the approximate 95% confidence of AMSY. AMSY predictions of relative biomass (B/B_{msy}) in the last year included the BSM estimate in their approximate 95% confidence limits in 122 stocks (87.1%). AMSY predictions of exploitation (F/F_{msy}) included the BSM estimate in their approximate 95% confidence limits in 123 stocks (87.9%). Note, however, that AMSY confidence limits for F/F_{msy} estimates were often wide. The median ratios of AMSY versus BSM predictions for r (0.92), final F/F_{msy} (1.16) and final B/B_{msy} (0.99) were used to summarize deviations and detect potential biases. Thus, AMSY predictions were, on average, 8% lower for r, 16% higher for F/F_{msy} and 1% lower for B/B_{msy}. Note that these are not entirely fair comparisons, because catchability q is not estimated by AMSY and this may cause part of the observed deviations. A spreadsheet [EU_ StocksResults_2.xls] with the detailed results for every stock is part of the Supplementary Material.

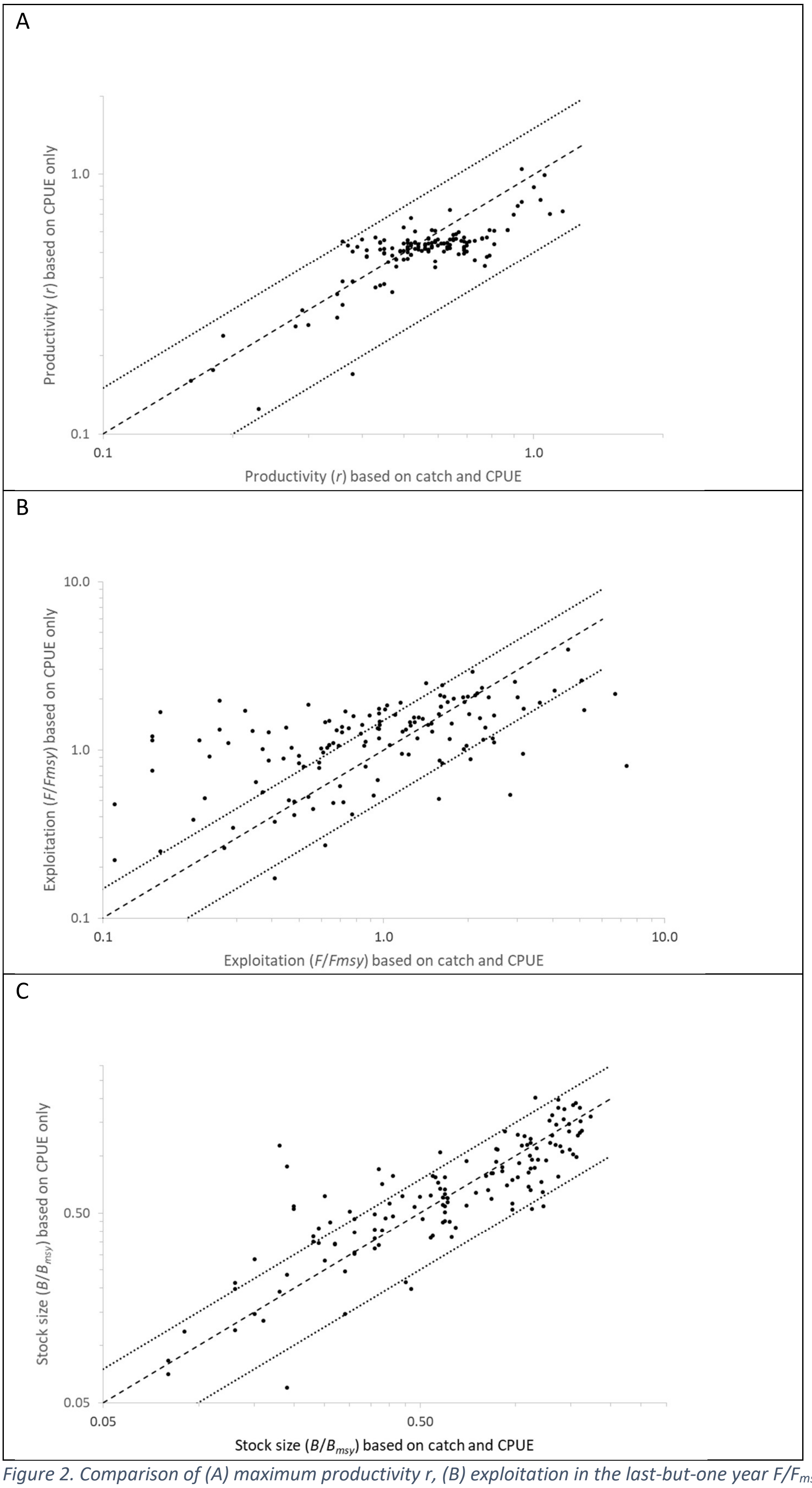

Figure 2. Comparison of (A) maximum productivity r, (B) exploitation in the last-but-one year F/F_{msy}, and (C) relative stock size in the last year (B/B_{msy}), between estimates of BSM (x-axis) based on catch and CPUE and AMSY (y-axis) based on CPUE only, for 140 real stocks. The dashed lines indicates identical predictions and the dotted lines indicate deviations of +/- 50%.

Application to data-limited stocks

Application of AMSY to data-limited stocks without reliable catch data produced the first MSY-level assessments for 38 stocks of mostly by-catch species (Table 5). This includes 23 species for which these are the first assessments globally (marked bold in Table 5). The details of these assessments are presented in Appendix 3 in Supplementary Material. Note there the overall very good agreement of relative biomass trends between LBB (Froese et al. 2018, 2019) based on length frequencies, and AMSY based on CPUE. There is also general good agreement between current and retrospective analyses, i.e., AMSY runs where data from the last 1, 2 or 3 years were omitted from the analyses. In two North Sea stocks (syc.27.3a47d, rjc.27.3a47d) the retrospective analysis indicated a substantial deviation of predicted relative biomass estimates (B/B_{msy}) if the respective last years were included, because these years suggested a strong increase in biomass. These increases were accepted for the purpose of this study but may turn out to be fluctuations once data for the subsequent years become available.

Predictions of exploitation (F/F_{msy}) in the second-to-last year indicate that 24 stocks (63%) were subject to overfishing, but note the wide margins of uncertainty. Predictions of relative biomass (B/B_{msy}) in the last year indicate that only 9 stocks (24%) were above the biomass level required by UNCLOS (1982) and 21 stocks (55%) were smaller than half of that level, suggesting that successful reproduction may be endangered. Margins of uncertainty for relative biomass are mostly less than 50% with regard to the relevant lower confidence limit and thus similar to assessments with more input data.

Table 5. Exploitation and stock status relative to MSY-levels (F/F_{msy}, B/B_{msy}) for 38 stocks comprising 35 species. For 23 of these species (marked bold) this is the first stock assessment globally. Results are arranged alphabetically by stock identifier within regions.

Region	Stock	Species	Name	Years	F/F_{msy}	B/B_{msy}
Adriatic Sea	Ille_coi_AD	*Illex coindettii*	Shortfin squid	2001-2017	0.67 0.07 - 1.71	1.14 0.64 - 2.05
	Micr_pou_AD	*Micromesistius poutassou*	Blue whiting	1994-2017	1.53 0.51 - 2.84	0.73 0.40 - 1.32
	Octo_vul_AD	*Octopus vulgaris*	Common octopus	1995-2017	0.94 0.29 - 1.74	1.01 0.56 - 1.81
Aegean Sea	ANN_GSA22 DIPL.ANN	*Diplodus annularis*	Annular seabream	1994-2016	0.89 0.11 - 2.38	0.23 0.13 - 0.42
	BOC_GSA22 CAPO.APE	*Capros aper*	Boarfish	1994-2016	1.30 0.21 - 2.90	0.61 0.34 - 1.09
	BRF_GSA22 HELI.DAC	*Helicolenus dactylopterus*	Blackbelly rosefish	1994-2016	0.76 0.07 - 1.88	1.14 0.63 - 2.15
	CIL_GSA22 CITHMAC_AEGEAN	***Citharus linguatula***	Spotted flounder	1994-2016	1.55 0.31 - 3.36	0.45 0.25 - 0.80
	HYS_GSA22 HYMEITA_AEGEAN	***Hymenocephalus italicus***	Glasshead grenadier	1994-2016	1.07 0.11 - 3.05	0.26 0.15 - 0.47
	SNQ_GSA22 SCORNOT_AEGEAN	***Scorpaena notata***	Small red scorpionfish	1994-2016	1.68 0.26 - 4.03	0.23 0.13 - 0.41
Cyprus	MERL_MER_CY	*Merluccius merluccius*	European hake	2005-2017	0.79 0.07 - 2.35	0.22 0.15 - 0.33
	SEPIOFF_CY	*Sepia officinalis*	Common cuttlefish	2005-2017	0.58 0.04 - 1.57	1.26 0.71 - 2.27
North Sea	Agonus cataphractus	***Agonus cataphractus***	Hooknose	1983-2017	1.90 0.59 - 3.68	0.49 0.27 - 0.86

	Amblyraja radiata	***Amblyraja radiata***	Starry ray	1983-2017	1.04 -0.84 - 3.99	0.21 0.12 - 0.39
	Buglossidium luteum	***Buglossidium luteum***	Solenette	1983-2017	2.16 0.69 - 4.09	0.42 0.23 - 0.76
	Callionymus lyra	***Callionymus lyra***	Dragonet	1983-2017	1.12 0.12 - 3.15	0.31 0.17 - 0.56
	Callionymus maculatus	***Callionymus maculatus***	Spotted dragonet	1983-2017	1.23 0.19 - 2.71	0.79 0.44 - 1.43
	Chelidonichthys cuculus	***Chelidonichthys cuculus***	Red gurnard	1984-2017	0.86 0.13 - 1.88	1.09 0.61 - 1.94
	Echiichthys vipera	***Echiichthys vipera***	Lesser weever	1983-2017	1.46 0.27 - 3.03	0.60 0.33 - 1.06
	Enchelyopus cimbrius	***Enchelyopus cimbrius***	Fourbeard rockling	1983-2017	1.91 0.45 - 4.29	0.25 0.14 - 0.46
	Lumpenus lampretaeformis	***Lumpenus lampretaeformis***	Snake blenny	1983-2017	1.19 0.14 - 2.88	0.45 0.25 - 0.82
	Lycodes vahlii	***Lycodes vahlii***	Vahl's eelpout	1983-2017	2.36 0.81 - 4.64	0.23 0.13 - 0.43
	Myoxocephalus scorpius	***Myoxocephalus scorpius***	Shorthorn sculpin	1983-2017	1.93 0.61 - 3.63	0.52 0.29 - 0.91
	Myxine glutinosa	***Myxine glutinosa***	Atlantic hagfish	1991-2017	1.16 -0.32 - 3.50	0.70 0.38 - 1.25
	rjc.27.3a47d	*Raja clavata*	Thornback ray	1983-2017	0.68 -0.20 - 2.36	1.25 0.70 - 2.25
	rjm.27.3a47d	*Raja montagui*	Spotted ray	1983-2017	1.26 -0.05 - 3.10	0.92 0.51 - 1.62
	syc.27.3a47d	*Scyliorhinus canicula*	Lesser spotted dogfish	1983-2017	0.83 -0.09 - 2.41	1.11 0.60 - 2.01
	Trisopterus luscus	***Trisopterus luscus***	Pouting	1983-2017	1.80 0.46 - 3.83	0.32 0.18 - 0.58
Baltic Sea	Ench_cim22-24	***Enchelyopus cimbrius***	Fourbeard rockling	1991-2018	2.43 1.01 - 4.38	0.29 0.16 - 0.52
	Eut_gurn_Balt	*Eutrigla gurnardus*	Grey gurnard	2002-2018	0.88 0.10 - 2.25	0.67 0.37 - 1.22
	Myox_scor_22-24	***Myoxocephalus scorpius***	Shorthorn sculpin	2000-2017	2.64 1.10 - 4.87	0.27 0.15 - 0.48
	Zoar_vivi_Balt	***Zoarces viviparus***	Eelpout	1999-2018	5.80 2.89 - 10.6	0.03 0.01 - 0.05
Northwest Atlantic	Little skate Eastern Canada	***Leucoraja erinacea***	Little skate	1970-2018	1.05 -0.62 - 4.05	0.35 0.19 - 0.62
	Smooth skate Laurentian Scotian	***Malacoraja senta***	Smooth skate	1970-2018	1.51 -0.32 - 4.20	0.37 0.21 - 0.67
South Africa	HELDAC	*Helicolenus dactylopterus*	Jacopever	1987-2017	0.84 0.07 - 2.53	0.15 0.08 - 0.27
	PNSK	***Cymatoceps nasutus***	Black musselcracker	1987-2017	0.73 -0.25 - 2.62	1.08 0.60 - 1.95
	STKB	***Argyrosomus thorpei***	Squaretail kob	1987-2017	1.00 0.12 - 2.70	0.26 0.15 - 0.47
	TBSK	***Raja straeleni***	Biscuit skate	1991-2017	1.60 -0.41 - 4.78	0.31 0.17 - 0.56
	WSTM	***Rhabdosargus globiceps***	White stumpnose	1987-2016	0.89 0.11 - 2.03	1.03 0.57 - 1.85

Discussion

Selection of Schaefer versus Fox or Pella-Tomlinson

Several types of surplus production models are used in fisheries, with Schaefer (1954), Fox (1970) and Pella-Tomlinson (1969) being the most common ones. Of these three, only the Schaefer model is derived from ecological principles, implementing the sigmoid population growth that has been observed in many animal populations (Hjort et al. 1933; Graham 1939; Hairston et al. 1970; Smith 1994; Yoshinaga et al. 2001). The Fox model is a logarithmic transformation of the Schaefer model, resulting in MSY being obtained at 37% of carrying capacity rather than at 50% as in the Schaefer model. This results in the Fox model predicting higher equilibrium yields for a given biomass at small stock sizes, implying that the Schaefer model is more precautionary in the proposed biomass necessary for producing MSY and in the sustainable catch that a given biomass can support (Cadima 2003; Fig A1 in Appendix 1 of Froese et al. 2011; Tsikliras and Froese 2019). The Pella-Tomlinson model is a mathematical generalization introducing a shape parameter p for the sigmoid curve, corresponding to the Schaefer model if $p = 1$ and to the Fox model if p approaches zero. For AMSY, the Schaefer (1954) model was chosen over the Fox model to err on the precautionary side and over the Pella-Tomlinson (1969) model to avoid estimation of a third parameter in a data-poor situation.

Performance of AMSY

The key point of this study is to explore whether a model that only has a time series of CPUE as input can produce similar results as a model that, in addition, has a time series of catch data as input, everything else being equal. AMSY uses CPUE data combined with independent prior knowledge about the resilience or productivity of the species and prior perceptions or estimates of stock status for the year with the best available estimate. It applies surplus production modelling with randomly selected parameters for r and k_q to predict catches that are compatible with the CPUE time series and the priors. AMSY aims to improve the precision and plausibility of stock status estimates by applying a set of filters to exclude r-k_q pairs that result in, e.g., negative catches or unrealistic exploitation values.

To better understand the respective influence of the priors and the filters on the results, AMSY was run against simulated data with and without filters. If no filters were used, the priors determined the central r-k_q values with 95% confidence limits about equal to the prior ranges and with already reasonable fits of predicted versus “true” time series of relative catch and stock size, albeit with wide margins of uncertainty (Figure 1 a-c). The addition of the filters moved the estimates of r and k_q closer to the “true” values and reduced the confidence limits for all estimates except B/B_{msy}, which remained about unchanged (Table 4).

In other words, if the relation between abundance and catch follows the logic of a surplus production model and if the priors for productivity and relative stock size include the “true” values, then AMSY predictions of r, F/F_{msy} and B/B_{msy} are not significantly different from the “true” values in simulated data covering a wide range of productivity and relative stock size. The question then is how well these assumptions are met in real world data.

For this purpose, 140 European stocks, from the Barents Sea to the Black Sea, including invertebrates from shrimp to octopus and fish from anchovy to halibut (see EU_Stocks_ID_8.csv in Supplement Material), were analyzed with a Bayesian implementation of a full Schaefer model (BSM) with time series of catch and CPUE as input, and with AMSY with only CPUE as input. Both models used the same priors for productivity and for relative stock size at the beginning of the time series.

Results from both models showed good agreement for *r*, F/F_{msy} and B/B_{msy}, with more than 87% of the BSM central estimates included in the approximate 95% confidence limits of the AMSY estimates, thus being not significantly. AMSY predictions for relative exploitation (F/F_{msy}) in the penultimate year had, however, wide margins of uncertainty and thus deviations in predictions could be substantial. Note also that BSM estimates are not free of error and some of the largest differences were found where the filters applied by AMSY prevented it from predicting extreme values of exploitation (compare Figure 2).

Application of AMSY to selected data poor stocks from the North Atlantic, the Mediterranean and South Africa, provided the first MSY-level assessments of exploitation and stock status for 38 stocks and 35 species (Table 4). The stocks were chosen such that they had no previous MSY-level assessments and no reliable or no catch data, but length frequencies as well as CPUE data available. The species range from by-catch, such as eel-pout (*Zoarces viviparus*) in the Baltic, to highly commercial species such as common octopus (*Octopus vulgaris*) in the Adriatic Sea. Note that for all these stocks, objective prior information on relative biomass depletion was provided from the analysis of length-frequency data (LBB, Froese et al. 2018, 2019). The wide margins of uncertainty for predictions of relative exploitation (F/F_{msy}, Table 5) are not surprising, given that no information on catch was available for these stocks. Therefore, these predictions of exploitation should be used with caution. In contrast, the margins of uncertainty for predictions of relative stock size are within usual ranges and therefore suitable for management advice. With few exceptions, the predicted relative biomass B/B_{msy} was below the level that can produce maximum sustainable yields and about half of the stocks were so small that successful reproduction may be endangered. While the selection of stocks was not random and therefore not representative of non-assessed species in general, the results underline the need for MSY-level assessments and management of data-poor stocks.

Properties and assumptions of AMSY

The Schaefer (1954) surplus-production function used by AMSY captures in only two parameters the interplay among somatic growth, reproduction, and natural mortality. AMSY is implemented within state-space modelling framework (Meyer and Miller, 1999; Froese et al. 2017; Winker et al. 2018) to account for process error due to the real-world variability in size-structure, species interactions, natural mortality and recruitment and observation error resulting from sampling error and variations in catchability. This allows the predicted biomass trajectories to deviate from the deterministic expectations resulting from equations 6 and 7, while keeping the trajectories within plausible biological limits by the productivity prior, the associated process variance and the filters imposed to identify viable *r*-*k* pairs. This means that the time series pattern of the predicted relative abundance (B/B_{msy}) may differ from the pattern of the CPUE provided as input to the model, in the bounds determined by the error terms for process and observation, which can be set by the user.

AMSY assumes that there is a direct relationship between CPUE and exploited biomass. However, catch rates in commercial and survey fisheries may be influenced by factors such as fishing vessel type, where and when fishing occurred, the gear used, the depth of fishing, and whether fishing occurred during day or night. There are also cases of reduced catch rates because of depredation e.g. on longlines by various predators (Söffker et al. 2015) or because of predator avoidance behavior by fishers shifting into less optimal CPUE areas (Haddon 2018). Management regulations such as size or catch limits or closed areas or seasons may also impact CPUE. These factors, and any changes therein over time, may obscure the inter-annual changes in CPUE resulting from changes in stock size, which are the focus of AMSY (e.g. Sporic and Haddon 2018).

As shown with the simulated data, predictions of AMSY come with high margins of uncertainty in stocks with very low resilience and periods of very low exploitation. Also, predictions of exploitation (F/F_{msy}) come with wide margins of uncertainty and may be especially misleading during phases of low exploitation (Figure 2 B).

When deriving management advice from CPUE, it is important to consider situations where the catch per unit of effort may be significantly biased, potentially resulting in biased advice. One such bias is the continuing increase in the efficiency of fishers to catch a certain species. This is often a combination of increase in experience about when and where target species are likely to be found, and an improvement in technology ranging from more efficient navigation (GPS, autopilots) to more efficient sonars to more efficient gear. Palomares and Pauly (2019) found this "effort creep" to increase efficiency in commercial fisheries by 1-5% per year, with 2% per year being a reasonable assumption if no better information is available. AMSY provides a correction for commercial CPUE depending on the percentage value provided by the user (Equation 11). CPUE from standardized surveys should not be affected by this.

Another potential bias in commercial CPUE data is known as 'hyperstability', where CPUE remains stable while abundance is declining, leading to overestimation of biomass and underestimation of fishing mortality (Quinn and Deriso, 1999; Harley et al. 2001). This may be caused by a fishery expanding into previously less-fished areas or depth-zones (Kleisner et al. 2014; Morato et al. 2006) with the new catches masking the overall decline. It may also be caused by aggregating behavior of the target species, when the center of the aggregation is fished primarily and the density there remains high even if overall density is declining, as occurred prior to the collapse of Northern cod (*Gadus morhua*) in Canada (Hutchings 1996), or when the spawning aggregations typical of some tropical species are exploited (see Sadovy de Mitcheson *et al.* 2008 and www.scrfa.org). In contrast, 'hyperdepletion' (Quinn and Deriso, 1999) describes a situation where CPUE declines faster than overall stock abundance. This occurred, for example, at the onset of some tuna fisheries, where fishers targeted rapidly declining accumulations of old tuna, but whose biomass was not representative of the entire, more resilient population (Ahrens and Walters 2005). While 'hyperdepletion' will lead to overly pessimistic assessment of stock status, the damage would be limited as fish not caught because of too conservative exploitation will increase remaining biomass and future catches (Froese et al. 2016). CPUE from standardized surveys should not be affected by either 'hyperstability' or 'hyperdepletion'.

Conclusion

The purpose of this study was to explore whether a standard population dynamics model can approximate regular predictions if given only one instead of two time series of input data, everything else (base model and priors) being equal. This is shown to be the case. The question then is the availability of independent priors representative of the "true" values. For the required prior on productivity, this is solved through online databases which contain such priors for practically all commercial species, based either on previous assessments or on life history traits. For the other required prior on relative stock size, it is either derived from expert knowledge or better from typically available independent data such as length frequencies, as shown here for 38 data-limited stocks.

Summarizing the results of this proof-of-concept study, AMSY seems to be well suited for estimating productivity *r* and thus F_{msy} = ½ *r* as well as relative stock size B/B_{msy}. Estimates of relative exploitation F/F_{msy} may come with wide margins of uncertainty and may be less suitable for management, especially at low levels of exploitation. As a first application of AMSY, the first MSY-level stock assessments are presented for 38 data poor stocks for which no reliable catch data are available.

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