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Estimating stock status from relative abundance and resilience

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The Law of the Sea and regional and national laws and agreements require exploited populations or stocks to be managed so 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 [abundance maximum sustainable yields (AMSY)] that estimates relative population size when no catch data are available using time series of catch-per-unit-effort or other relative abundance indices as the 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.

Keywords: Common Fisheries Policy, cpue, data-poor stocks, MSFD, stock assessment, surplus production models, UNCLOS

Introduction

The Law of the Sea (UNCLOS, 1982) commits its signatories to manage the exploitation of fish and invertebrates so 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, 1935; Schaefer, 1954, 1957;

Beverton and Holt, 1957; Ricker, 1975), such as CMSY (Froese *et al.*, 2017) for catch data and LBB (Froese *et al.*, 2018a, 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-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 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, 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; Pella and Tomlinson, 1969; Fox, 1970; 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, bycatch species, or 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.*, 2018a, 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 the 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):

$$Y = B\,r\left(1 - \frac{B}{k}\right). \tag{1}$$

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):

$$B_{t+1} = B_t + Y_t - C_t = B_t + B_t r\left(1 - \frac{B_t}{k}\right) - C_t. \tag{2}$$

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 relationship between cpue and biomass is then determined by the catchability coefficient q (Arreguín-Sánchez, 1996; Maunder and Punt, 2004), which is here assumed to be constant over the considered time period (see below for exceptions) such that:

$$\text{cpue}_t = B_t q. \tag{3}$$

Multiplying both sides of (2) with q and replacing $B_t q$ with cpue_t gives:

$$\text{cpue}_{t+1} = \text{cpue}_t + \text{cpue}_t r\left(1 - \frac{B_t}{k}\right) - C_t q. \tag{4}$$

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

$$\text{cpue}_{t+1} = \text{cpue}_t + \text{cpue}_t r\left(1 - \frac{\text{cpue}_t}{kq}\right) - C_t q. \tag{5}$$

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_{qt} and kq as relative carrying capacity k_q, or the cpue one would obtain if there were no fishing:

$$\text{cpue}_{t+1} = \text{cpue}_t + \text{cpue}_t r\left(1 - \frac{\text{cpue}_t}{k_q}\right) - C_{qt}. \tag{6}$$

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

$$C_{qt} = \text{cpue}_t + \text{cpue}_t r\left(1 - \frac{\text{cpue}_t}{k_q}\right) - \text{cpue}_{t+1}. \tag{7}$$

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

$$\text{MSY}_q = \frac{r}{2}\frac{k_q}{2} = \frac{rk_q}{4}, \tag{8}$$

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 (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; therefore, cpue can be presented as the relative biomass within an MSY framework.

Finally, in the Schaefer model, fishing mortality F is equal to the ratio of catch to biomass C_t/B_t, which is identical to the ratio

C_{qt}/cpue$_t$. Hence, the fishing mortality that corresponds to *MSY* is $F_{MSY} = 0.5r$; therefore, relative exploitation can be presented within an MSY framework:

$$\frac{F}{F_{MSY}} = \frac{\frac{C_{qt}}{\text{cpue}_t}}{r/2} = \frac{2C_{qt}}{r\ \text{cpue}_t}. \tag{9}$$

The abundance MSY 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 the abundance MSY method (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 endpoints of the k_q range are used as ranges for B_{MSY_q}. A multivariate lognormal random sample or of r–k_q pairs is then created based on the variance–covariance matrix (VCM) shown in (10), where the prior log ranges of r and k_q are assumed to represent four standard deviations (*SD*), and variance is *SD* squared. The r–k_q covariance in log space was obtained from an empirical correlation between log r and log k_q obtained as median $= -0.607$ across 140 stocks (EU_Stocks_BSM_Results.xls, Froese *et al.*, 2018b) analyzed with a Bayesian Schaefer model (Froese *et al.*, 2017), and from the prior *SD* of log r and log k_q, such that covariance log r–k_q $= -0.607 \times SD\ \log(r) \times SD\ \log(k_q)$ (see cloud of grey dots in Figure 1):

$$\text{VCM}_{\log(r),\ \log(k_q)} = \begin{Bmatrix} \sigma^2_{\log(r)} & \text{cov}_{\log(r),\ \log(k_q)} \\ \text{cov}_{\log(r),\ \log(k_q)} & \sigma^2_{\log(k_q)} \end{Bmatrix}. \tag{10}$$

As shown in the simulations in Section 1 of the Supplementary material and in Figure 1a, 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. To better accommodate "true" r–k_q pairs that are off the centre 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 (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 fulfil 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 Section 2 of the Supplementary material and in Figure 1b).

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, 2019a) 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 1). Resilience was then translated into uniform prior ranges as described in Froese *et al.* (2017) and reproduced here for easy reference.

A prior for relative biomass B/k can be derived from experts who are asked how stock size was 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 2. 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.*, 2018a, 2019; see examples in Section 3 of the Supplementary material). 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.

A prior range for k_q is derived from B/k as $k_q = \text{cpue}_t/(B_t/k)$. If the lower bound of k_q resulting from this exercise is less than the maximum cpue in the time series, max(cpue) is used as the lower k_q bound because abundance of an exploited species is unlikely to exceed carrying capacity. Also, to avoid unrealistically narrow or wide ranges, the upper bound of k_q is set at least 30% larger than the lower bound, but not farther away than threefold 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 $\text{cpue}_{MSY} = \text{cpue}_t/(B_t/k)$, using the lower and upper limits of B/k. Pairs of r–k_q 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 (7).

To account for reduced recruitment and thus reduced productivity or surplus production at very small stock sizes, (7) is combined with a hockey stick recruitment function (Barrowman and Myers, 2000; Froese *et al.*, 2016a, 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):

$$C_{qt} = \text{cpue}_t + \text{cpue}_t r\left(1 - \frac{\text{cpue}_t}{k_q}\right)\left(4\frac{\text{cpue}_t}{k_q}\right) - \text{cpue}_{t+1} \mid \frac{\text{cpue}_t}{k_q} < 0.25. \tag{11}$$

AMSY applies a state-space model formulation with an annual multiplicative lognormal random process error $\exp(\eta_t)$ and observation error $\exp(\varepsilon_t)$ terms with $\eta_t \sim N\left(0, \sigma^2_\eta\right)$ and $\varepsilon_t \sim N\left(0, \sigma^2_\varepsilon\right)$, 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 are not shown in the equations for the sake of simplicity. The chosen values are preliminary but worked well for the purpose of this proof-of-concept study.

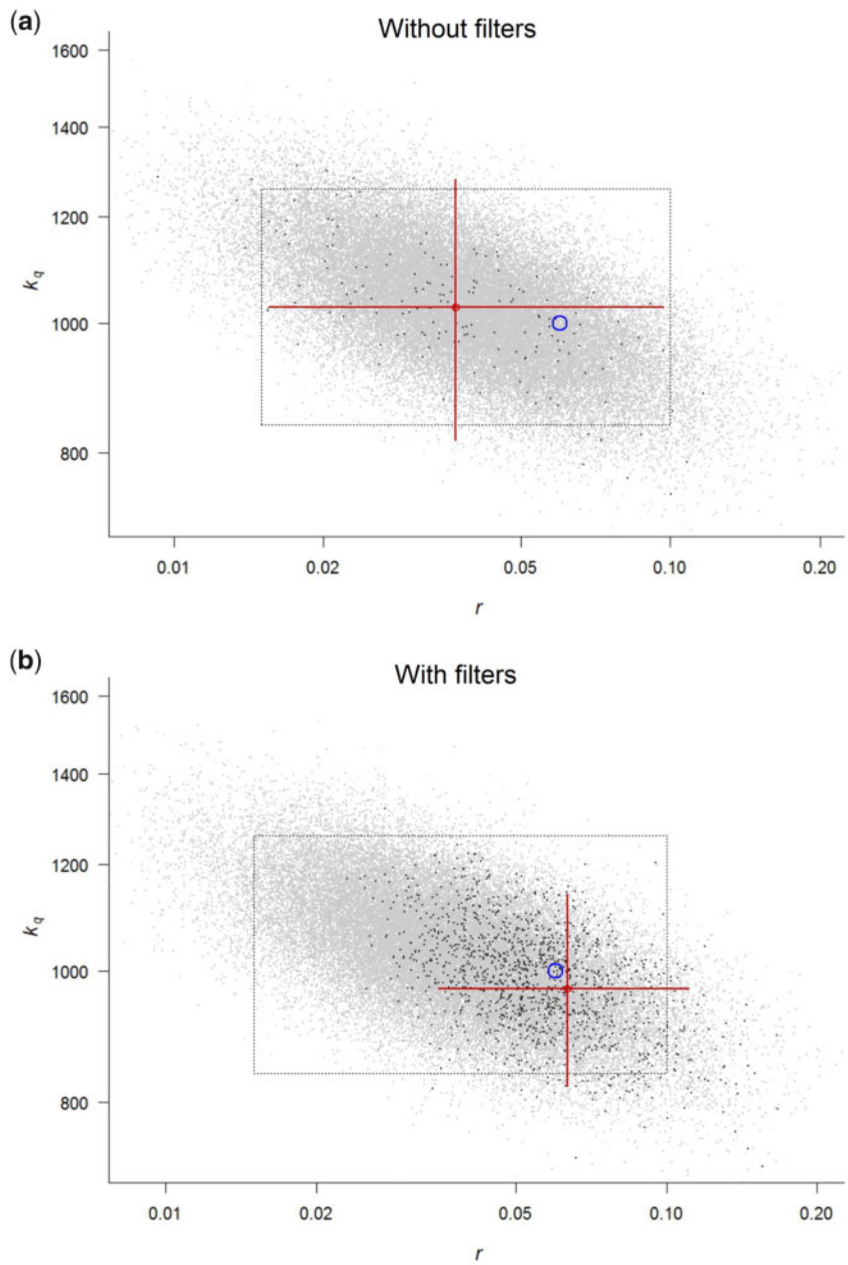

Figure 1. AMSY analysis of simulated data for a stock with very low productivity and low biomass. The grey dots are a random sample of 50 000 points drawn from a multivariate distribution of r and k_q in log space. The dotted rectangle indicates the prior ranges of r and k_q and contains 95% of the random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

For cases where cpue stems not from standardized 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:

$$\text{cpue}_{\text{corr}\,t} = \text{cpue}_t \ (1 - p)^{t-t_0}, \tag{12}$$

where $\text{cpue}_{\text{corr}}$ 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, 2019a), 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

The following 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

Table 1. Translation of resilience categories in FishBase or SeaLifeBase into ranges of r (year^{-1}).

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

Table 2. 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

expected to be further refined, also against real data, in subsequent research.

(i) **Exclusion of r–k_q pairs if predicted relative catch is negative.** By definition, catch is an extraction of fish from the population and thus may become zero but not negative. Therefore, 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 relative catches close to zero are realistic scenarios especially during recovery phases of species with low or very low resilience; 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.

(ii) **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 (7), the term $r(1 - \text{cpue}/k_q)$ determines the amount of surplus production and it may exceed 1.0 if e.g. $r > 1.2$ and $\text{cpue}/k_q < 0.2$, 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 productivity to 0.25 for very low productivity. This filter is skipped if, at any point in the time series, cpue approaches zero [$\text{cpue} < 0.1 \max(\text{cpue})$] because catch may exceed mean biomass under those circumstances.

(iii) **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 $\text{MSY}/k = r/4$ 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 tenfold MSY_q for very low productivity to twofold MSY_q for high productivity.

(iv) **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. Thus, during such periods, predictions of negative F/F_{MSY} ratios may result from the uncertainty and corresponding error terms used in the modelling.

(v) **Exclusion of r–k_q pairs if modelled 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 was 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-to-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 was 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 year^{-1} to represent species with very low (VL), low (L), medium (M), and high (H) resilience, respectively (c.f. Table 1). 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) were created. From an "above half" (0.5–0.85k) or "small" (0.15–0.4k) starting biomass in the first year, the desired pattern was produced by inserting high or low catches into (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 0.25k_q in any given year, surplus production was reduced, as described in (11) 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 the Black Sea were used as a subset of the 397 stocks analyzed by Froese *et al.* (2018b). 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 variance-covariance matrix (10). 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.*, 2018a, 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 of the sections in the Supplementary material, 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. 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 prior distribution are "viable", the central values of predicted r and k_q are in the centre of the 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.

Table 3. Comparison of MARE and MRLCL of the predictions for 24 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 (AMSYSimNoFil_5.xls and AMSYSimFil_7.xls).

	Without filters		With filters	
Estimate	**MARE**	**MRLCL**	**MARE**	**MRLCL**
r	0.28	0.55	0.07	0.36
k_q	0.09	0.24	0.10	0.18
F/F_{MSY}	0.45	1.42	0.20	0.89
B/B_{MSY}	0.08	0.44	0.10	0.44

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 centre 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 Section 2 of the Supplementary material). With one exception (estimate of k_q in LHL_VL, see Section 2 of the Supplementary material), "true" values of all parameters still fall within the narrower approximate 95% confidence limits. Table 3 shows a comparison of median absolute relative error [MARE = abs(true − estimate)/true] and of median relative lower confidence limits [MRLCL = (estimate − lcl)/estimate] for 24 AMSY runs without and with Monte Carlo filtering. In the runs with filters, MAREs are substantially reduced for r and F/F_{MSY} and only slightly increased for k_q and B/B_{MSY} and MRLCLs are substantially reduced for all estimates except B/B_{MSY}.

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 2), with 128 (91.4%) BSM estimates included in the approximate 95% confidence limits 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 vs. 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.

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 bycatch species (Table 4). This includes 23 species for which these are the first assessments globally (marked bold

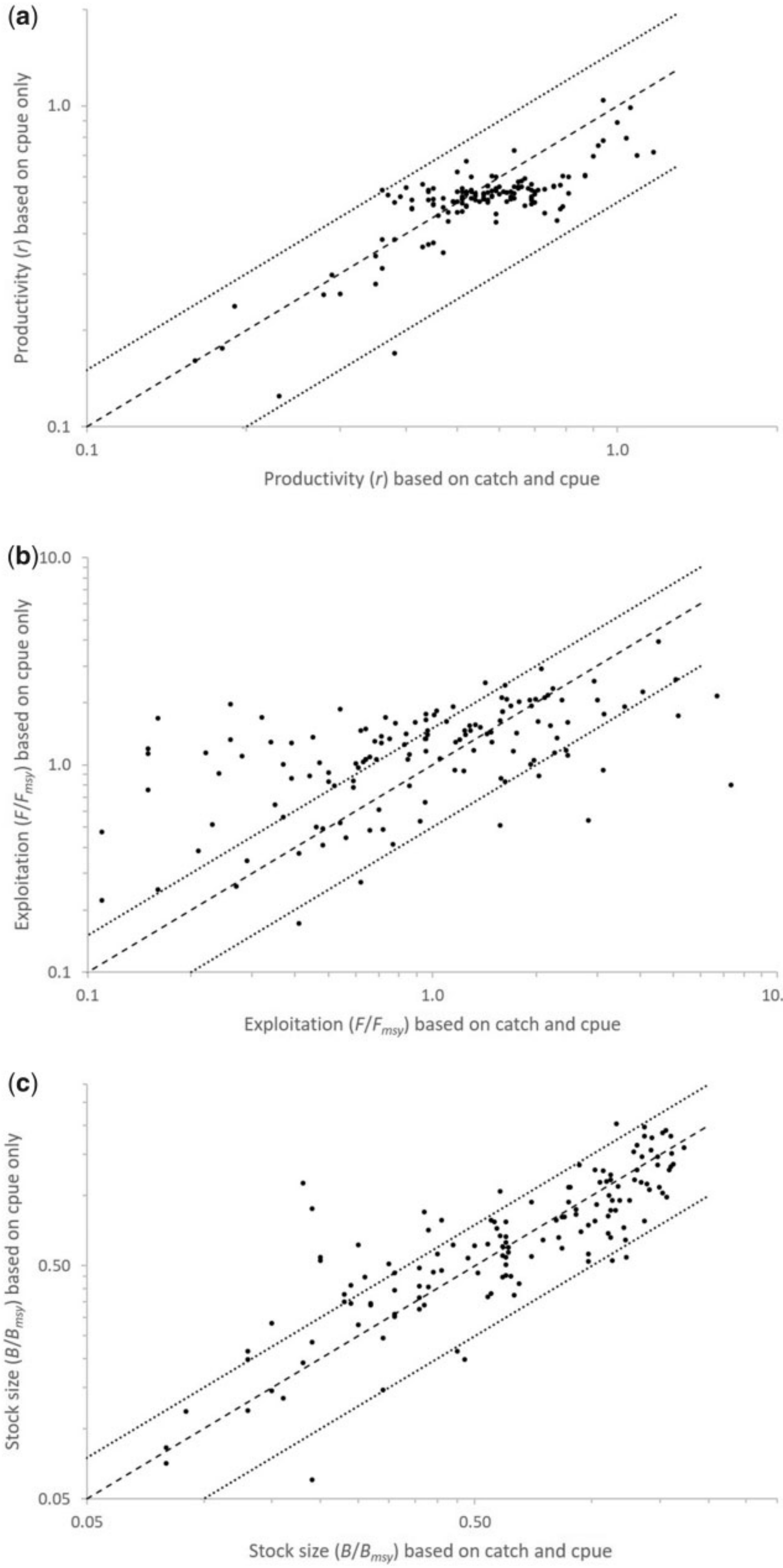

Figure 2. Comparison of (a) maximum productivity *r*, (b) exploitation in the last but one year F/F_{MSY}, and (c) relative stock size in the last year (B/B_{MSY}) between estimates of BSM (*x*-axis) based on catch and cpue and AMSY (*y*-axis) based on cpue only for 140 real stocks. The dashed lines indicate identical predictions, and the dotted lines indicate deviations of ±50% (EU_StocksResults_3.xls).

Table 4. Exploitation and stock status relative to MSY levels (F/F_{MSY}, B/B_{MSY}) for 38 stocks comprising 35 species.

Region	Stock	Species	Name	Years	F/F_{MSY}	B/B_{MSY}
Adriatic Sea	Ille_coi_AD	*Illex coindetii*	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_GSA22HYMEITA_ AEGEAN	***Hymenocephalus italicus***	Glasshead grenadier	1994–2016	1.07/0.11–3.05	0.26/0.15–0.47
	SNQ_GSA22SCORNOT_ 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 radiate	***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

For 23 of these species (marked bold), this is the first stock assessment globally. Results are arranged alphabetically by stock identifier within regions [AMSY_68y.R, Appendix 3].

in Table 4). The details of these assessments are presented in Section 3 of the Supplementary material. We found overall very good agreement of predicted relative biomass trends between LBB (Froese *et al.*, 2018a, 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 (Figure 2c) and, thus, similar to assessments with more input data.

Discussion

Choice of Schaefer vs. Fox or Pella–Tomlinson

Several types of surplus production models are used in fisheries, with Schaefer (1954), Fox (1970), and Pella and Tomlinson

(1969) being the most common. 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; Figure 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 (Pella and Tomlinson, 1969; Cadima, 2003), or with a shape parameter defined as m, such that $m=2$ for the Schaefer model and m approaching 1 for the Fox model in later implementations (e.g. Pedersen and Berg, 2017; Winker *et al.*, 2018). Beverton and Holt (1957) have shown that the biomass that can produce MSY is actually a function of fishing pressure and selectivity, reaching about half of the unexploited stock size if F is close to natural mortality M and length at first capture is close to the optimum length (see Figure 2b in Froese *et al.*, 2016b). For AMSY, the Schaefer (1954) model was chosen over the Fox (1970) model to err on the precautionary side and over the Pella and 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 vs. 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 vs. "true" time series of relative catch and stock size, albeit with wide margins of uncertainty (Figure 1a). 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 3).

In other words, if the relationship 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 much 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 and including invertebrates from shrimp to octopus and fish from anchovy to halibut (see EU_Stocks_ID_8.csv in the Supplementary 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 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. 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, 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 because 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 bycatch, such as eelpout (*Zoarces viviparus*) in the Baltic, to commercially important 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.*, 2018a, 2019). The wide margins of uncertainty for predictions of relative exploitation (F/F_{MSY}, Table 4) 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, are suitable for management advice. With few exceptions, the predicted relative biomass B/B_{MSY} was below the level that can produce MSY, and about half of the stocks were so small that successful reproduction may be endangered. While the selection of stocks was not random and was, 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 with only two parameters the interplay among somatic growth, reproduction, and natural mortality. AMSY is implemented within a state-space modelling framework (Meyer and Millar, 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 (6) and (7), while keeping the trajectories within plausible biological limits through the use of 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, within 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 proportionality 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, gear used, 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 behaviour by fishers shifting into less optimal cpue areas (Haddon, 2018). Management regulations such as size and catch limits or closed areas and seasons may also impact cpue. These factors, and any changes therein over time, may obscure the interannual 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 2b).

When deriving management advice from cpue, it is important to consider situations where the cpue 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 an 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 (2019b), based on a comprehensive review of published cases, 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 (12). 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 the 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 (Morato *et al.*, 2006; Kleisner *et al.*, 2014) with the new catches masking the overall decline. It may also be caused by aggregating behaviour of the target species, when the centre 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 the remaining biomass and future catches (Froese *et al.*, 2016b). 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 reasonable priors. For productivity, this is solved through online databases, which offer such priors for practically all commercially important species based either on previous stock assessments or on life history traits. The priors on relative stock size can be derived either 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, $F_{MSY} = (1/2)r$ 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.

Supplementary data

Supplementary material is available at the *ICESJMS* online version of the manuscript.

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