Fisheries Research 171 (2015) 12–19

Contents lists available at ScienceDirect

Fisheries Research

journal homepage: www.elsevier.com/locate/fishres

Harvest control rules for data limited stocks using length-based reference points and survey biomass indices

Ernesto Jardim[a,b,*], Manuela Azevedo[a,1], Nuno M. Brites[a,c,1,2]

[a] IPMA, Instituto Português do Mar e da Atmosfera, Av. Brasília, 1449-006 Lisboa, Portugal
[b] European Commission, Joint Research Centre, Institute for the Protection and Security of the Citizen, Maritime Affairs Unit, TP 051, 21027 Ispra, VA, Italy
[c] Departamento de Matemática, Centro de Investigação em Matemática e Aplicações, Instituto de Investigação e Formação Avançada, Universidade de Évora, Rua Romão Ramalho, 59, 7000-671 Évora, Portugal

ARTICLE INFO

Article history:
Received 22 April 2014
Received in revised form
18 November 2014
Accepted 20 November 2014
Handling Editor A.E. Punt
Available online 24 December 2014

Keywords:
Data limited stocks
Risk
Survey indices
Length frequencies
Harvest control rules
Life History

ABSTRACT

There are a large number of commercially exploited stocks lacking quantitative assessments and reliable estimates of stock status. Providing MSY-based advice for these data-limited stocks remains a challenge for fisheries science. For many data-limited stocks, catch length composition and/or survey biomass indices or catch-per-unit effort (cpue) are available. Information on life history traits may also be available or borrowed from similar species/stocks. In this work we present three harvest control rules (HCRs), driven by indicators derived from key monitoring data. These were tested through simulation using two exploitation scenarios (development and over-exploitation) applied to 50 stocks (pelagic, demersal, deep sea species and *Nephrops*). We examine the performance of the HCRs to deliver catch-based advice that is risk adverse and drives stocks to MSY. The HCR with a biomass index-adjusted *status quo* catch, used to provide catch-based advice for several European data-limited stocks, showed the poorest performance, keeping the biomass at low or very low levels. The HCRs that adjust the *status quo* catch based on the variability of the biomass index time series was able to drive most of the stocks to MSY, showing low to moderate biological risk. The recovery of biomass required asymmetric confidence intervals for the biomass index and larger decreases in *status quo* catch than increases. The HCR based on length reference points as proxies for the F_{SQ}/F_{MSY} ratio was able to reverse the decreasing trend in biomass but with levels of catch below MSY. This HCR did not prevent some of the stocks declining when subject to over-exploitation. For data-limited stocks, the empirical HCRs tested in this work can provide the basis for catch advice. Nevertheless, applications to real life cases require simulation testing to be carried out to tune the HCRs. Our approach to simulation testing can be used for such analysis.

© 2014 Elsevier B.V. All rights reserved.

1. Introduction

The majority of worldwide commercially exploited fish and shellfish stocks do not have a formal stock assessment, due to insufficient data to estimate stock sizes and fishing mortality (Rosenberg et al., 2014). In the Northeast Atlantic, more than half of the 200 stocks for which ICES provides advice lack a quantitative assessment and estimates of stock status (ICES, 2013a). These stocks are classified by ICES as data-limited stocks (ICES, 2012a). In the absence of estimates of stock status, providing quantitative MSY-based advice remains a challenge for fisheries science, while for management bodies it continues to be a key topic for increasing the sustainable harvesting of marine resources (Anon., 2013, 2008, 2007, 2006).

The last five years have seen an increase in the development and testing of assessment methods to estimate sustainable yields and harvest levels for data-limited stocks (Rosenberg et al., 2014; Martell and Froese, 2013; Wetzel and Punt, 2011; MacCall, 2009). The category of data-limited stocks, in the sense of stocks without an analytical assessment, includes stocks with a considerable amount of information, although not always available or compiled. For example, life history parameters exist for most stocks exploited commercially (see fishbase.org), length frequencies of landings are cheap to collect, and scientific surveys catch more species than those for which abundance indices are traditionally derived. In such

* Corresponding author at: European Commission, Joint Research Centre, Institute for the Protection and Security of the Citizen, Maritime Affairs Unit, TP 051, 21027 Ispra, VA, Italy. Tel.: +39 0332 785311.
E-mail addresses: ernesto.jardim@jrc.ec.europa.eu (E. Jardim), mazevedo@ipma.pt (M. Azevedo), brites@uevora.pt (N.M. Brites).
[1] Tel.: +351 213 027 000.
[2] Tel.: +351 266 745 370.

http://dx.doi.org/10.1016/j.fishres.2014.11.013
0165-7836/© 2014 Elsevier B.V. All rights reserved.

cases the problem tends to be related to the difficulty to evaluate the quality of the data, and/or the costs of processing the information, and/or the short time series available. In European waters, all stocks caught by European fleets are covered by the European Data Collection Framework (Council Regulation (EC) No 199/2008) and, hence, such information exists. Moreover, data sets are growing every year, which will contribute to moving stocks upwards in the level of information available.

Geromont and Butterworth (2014) used simulation testing to check the robustness to uncertainties about resource dynamics, of simple empirical TAC-based harvest control rules (HCRs). These authors considered two data-poor scenarios for data availability: a data-limited scenario in which the stock had historical catch data and information on the mean length of the catch, and a data-moderate scenario where a direct index of abundance was also available for the stock. The empirical management procedures investigated by Geromont and Butterworth (2014) set future TACs by adjusting the previous year's TAC upwards or downwards, depending on whether the recent mean length is above or below a target mean length. In the case of the data-moderate stocks, the TAC adjustment was based on the recent slope of the abundance series (cpue) and on the difference between the recent cpue and a target level.

Since 2012, ICES has applied a framework to provide catch advice for the European data-limited stocks (ICES, 2013a) within a precautionary approach. For stocks where historical catch data and surveys or other relative abundance indices are available, catch advice is based on the application of an HCR using biomass or abundance index adjusted *status quo* catches (ICES, 2012b). Within this HCR, it is quite common to adopt a comparison of the averages of the two most recent index values with the three preceding ones, although the number of years to be used to compute these averages may vary among stocks, in order to account for inter-annual variability of surveys or cpue series. Simulation testing has shown that this HCR does not ensure conservative catch advice when a stock is over-exploited, while it's performance deteriorates when a well-managed stock becomes over-exploited (ICES, 2013b).

The work presented here has three main objectives: (i) to develop and test generic HCRs for stocks for which the amount and quality of data is insufficient to perform quantitative assessments; (ii) to understand the mechanisms that drive the performance of these HCRs; and (iii) to suggest a simulation procedure based on Management Strategies Evaluation (MSE; Butterworth et al., 1997; Cooke, 1999; Butterworth and Punt, 1999; Kell et al., 2005; Punt and Donovan, 2007) to be used for data limited stocks.

The simulation procedure and the HCRs proposed here provide a framework for designing and testing management plans for data limited stocks. However, when dealing with a real-life application, it is important to tune the candidate HCRs to the specific stock and fishery (not attempted here) and test its implementation with simulations.

2. Methods

Two alternatives to the harvest control rule set by (ICES, 2012a) were developed. One uses survey information and the statistical characteristics of the biomass index, while the other uses catch length compositions and life history parameters. These HCRs were developed taking into account common indicators derived from fisheries monitoring programmes and in themselves define different levels of data limitation. Survey information is independent of the fishery and constitutes a direct observation of the trends in biomass. It's an expensive type of information, but also a good source about the trends in biomass, if the survey is performed following the good practices of data collection and the index derived with sound statistical methods. On the other hand, the length distributions of the catch is fishery-dependent information. It is cheaper to collect than survey information, and once a link is established between an exploited stock's expected length composition and its spawning potential ratio (Hordyk et al., 2014) it constitutes an indirect observation of the stock status. Due to their data requirements, these HCRs can be applied to a wide range of stocks with distinct levels of data limitations, standing between catch-only type approaches (Martell and Froese, 2013) and full analytical approaches.

The simulation procedure uses life history parameters and information about the fishery's selectivity to create a simulation environment for testing HCRs. Although some assumptions are required, these simulations can provide insight into the relative effect of different HCRs and their robustness to common uncertainties, like those about stock recruitment relationships, implementation error, etc.

2.1. Simulations and MSE

The stocks used in the current study were simulated based on life history traits that loosely represent the biology of the species (Table 1), covering a wide range of life history characteristics. There were 50 stocks: 3 pelagic stocks (2 species: Herring and Sandeel), 36 demersal stocks (17 species: Cod, Haddock, Whiting, Pollack, Megrim, Anglerfish, Plaice, Sole, Striped red mulet, Lemon sole, Brill, Dab, Redfish, Golden redfish, Greenland halibut, Turbot and Witch), 6 deep sea stocks (4 species: Ling, Blue ling, Greater silver smelt and Roundnose grenadier) and *Nephrops* in the shellfish grouping (Table 1). The life history M/K ratio of the simulated stocks ranged from 1.09 to 4.20, with the exception of the deep sea stock 'rng-comb' that presented a high M/K ratio of 8.98 (Table 1 and Fig. 1).

An age-structured population dynamics model with recruitment governed by the Beverton–Holt stock-recruit function with steepness, h, of 0.75 (to simulate stocks with medium productivity) and virgin biomass, Bv, of 1000 t was adopted. The h value was adapted from Myers et al. (1999), who indicated a median of 0.71. Natural mortality for each stock was computed following Gislason et al. (2010) and was assumed to be time-invariant. Fish growth was modeled with the von Bertalanffy function, with parameter's given by ICES (2012b). Fleet selectivity was modeled with a double normal distribution (Hilborn et al., 2003) with the mode equal to the the age of 50% maturity, while survey selectivity was modeled with an asymptotically flat top curve with maximum retention at age 10. Fig. 2 shows an example for a stock with age of 50% maturity of 5.4 years. Both selectivity functions were set constant over time.

Simulations were performed for two distinct trends in fishing mortality to test the HCR's performance in 'development' and 'over-exploitation' fishery scenarios. For the 'development' phase the stocks were subject, during years −14 to 0, to a linear increasing fishing mortality from $F=0$ to $2F_{MSY}$. The 'over-exploitation' phase was obtained by keeping fishing mortality at $2F_{MSY}$ for 25 years (years: −24 to 0), although only the last 15 (years: −14 to 0) were used for the simulation study. In both cases, the HCRs were applied for 25 years (years: 1–25).

Uncertainty was introduced in:

- the operating model conditioning, through catch-at-age and the stock-recruitment relationship;
- the observation error model, through the observation of the index or the ratio M/K;
- the implementation error model, through the realized catches, making it differ from the advised catch.

Table 1
Life history parameters used to simulate stocks. a and b: length-weight relationship parameters; $a50$: age of 50% retention; a_0, K, L_∞: von Bertalanffy growth function parameters; F_{MSY}: fishing mortality that produces MSY catches and M: natural mortality.

Stock code	Group	a	b	a50	a_0	K	L_∞	F_{MSY}	M
ang-78ab	Demersal	0.00001	3.000	5.680	−0.100	0.121	162.000	0.095	0.217
ang-ivvi	Demersal	0.00001	3.000	4.320	−0.100	0.160	150.000	0.121	0.261
arg-comb-exVa	Deep	0.01000	3.000	3.569	−0.100	0.220	42.400	0.219	0.348
arg-comb-Va	Deep	0.01000	3.000	4.586	−0.100	0.170	47.900	0.165	0.324
bli-comb	Deep	0.00116	3.273	5.379	−0.100	0.130	140.000	0.089	0.302
bll-2232	Demersal	0.02470	2.930	2.837	−0.100	0.270	50.100	0.263	0.502
cod-coas	Demersal	0.01000	3.000	5.035	−0.100	0.140	130.000	0.097	0.351
cod-ewgr	Demersal	0.00750	3.040	5.924	−0.100	0.117	150.000	0.068	0.485
cod-farb	Demersal	0.00001	3.000	4.594	−0.100	0.156	110.000	0.124	0.280
cod-iceg	Demersal	0.01000	3.000	4.692	−0.100	0.150	128.000	0.115	0.303
cod-rock	Demersal	0.00001	3.000	3.483	−0.100	0.200	132.000	0.151	0.312
cod-wgr-in	Demersal	0.01025	2.979	6.491	−0.100	0.107	150.000	0.065	0.376
dab-2232	Demersal	0.00001	3.000	1.980	−0.100	0.400	32.000	0.497	0.792
dab-nsea	Demersal	0.00500	3.140	1.954	−0.100	0.400	36.000	0.455	0.777
GHL-DIS	Demersal	0.00333	3.249	9.757	−0.100	0.073	120.000	0.043	0.308
had-iris	Demersal	0.00001	3.000	4.697	−0.100	0.160	68.000	0.142	0.330
her-31	Pelagic	0.00360	3.039	2.322	−0.100	0.360	21.000	0.468	0.573
her-nirs	Pelagic	0.00360	3.039	2.510	−0.100	0.320	31.000	0.334	0.655
lem-nsea	Demersal	0.07560	3.142	2.608	−0.100	0.300	40.000	0.295	0.512
lin-comb in Subareas I-II	Deep	0.00390	3.074	5.446	−0.100	0.128	150.000	0.097	0.227
lin-comb other areas	Deep	0.00390	3.074	5.225	−0.100	0.136	119.000	0.102	0.309
meg-4a6a	Demersal	0.00001	3.000	6.455	−0.100	0.120	54.000	0.116	0.299
mut-comb	Demersal	0.00440	3.351	4.204	−0.100	0.183	53.340	0.124	0.620
nep-25	Shellfish	0.00001	3.000	4.683	−0.100	0.160	70.000	0.141	0.328
nep-2627	Shellfish	0.00001	3.000	4.931	−0.100	0.150	80.000	0.128	0.301
nep-2829	Shellfish	0.00001	3.000	3.726	−0.100	0.200	70.000	0.176	0.373
nep-30	Shellfish	0.00001	3.000	4.761	−0.100	0.160	60.000	0.145	0.345
nep-31	Shellfish	0.00001	3.000	4.899	−0.100	0.150	85.000	0.126	0.298
ple-2232	Demersal	0.01000	3.000	4.287	−0.100	0.180	52.000	0.169	0.391
ple-7b-c	Demersal	0.00001	3.000	6.978	−0.100	0.110	59.400	0.103	0.275
ple-89a	Demersal	0.00001	3.000	1.572	−0.100	0.470	54.576	0.605	0.702
ple-celt	Demersal	0.00001	3.000	6.983	−0.100	0.110	59.000	0.104	0.280
ple-eche	Demersal	0.00001	3.000	3.542	−0.100	0.211	68.500	0.178	0.397
ple-iris	Demersal	0.00001	3.000	4.360	−0.100	0.165	100.000	0.134	0.302
pol-89a	Demersal	0.00001	3.000	3.844	−0.100	0.190	85.600	0.159	0.342
pol-nsea	Demersal	0.00001	3.000	3.928	−0.100	0.186	85.600	0.156	0.342
rng-comb	Deep	0.21360	2.987	23.962	−0.100	0.035	28.700	0.015	0.314
san-ns4	Pelagic	0.00001	3.000	1.891	−0.100	0.436	22.000	0.670	0.916
smn-arct	Demersal	0.00001	3.000	2.945	−0.100	0.261	49.000	0.248	0.502
smn-con	Demersal	0.00001	3.000	2.945	−0.100	0.261	49.000	0.253	0.284
smn-dp	Demersal	0.00001	3.000	15.483	−0.100	0.051	49.000	0.051	0.196
smr-5614	Demersal	0.00001	3.000	12.886	−0.100	0.060	59.000	0.062	0.183
sol-7b-c	Demersal	0.00001	3.000	6.003	−0.100	0.130	49.800	0.120	0.327
sol-8c9a	Demersal	0.00001	3.000	6.978	−0.100	0.110	59.400	0.103	0.275
tur-nsea	Demersal	0.00001	3.132	2.576	−0.100	0.290	61.200	0.257	0.385
whg-7e-k	Demersal	0.00001	3.000	3.441	−0.100	0.218	65.000	0.188	0.401
whg-89a	Demersal	0.00001	3.000	3.928	−0.100	0.190	70.000	0.167	0.363
whg-rock	Demersal	0.00001	3.000	1.241	−0.420	0.483	45.000	0.864	0.676
whg-scow	Demersal	0.00001	3.000	7.019	−0.100	0.110	56.300	0.105	0.282
wit-nsea	Demersal	0.00170	3.390	2.970	−0.100	0.260	47.000	0.220	0.505

For all cases independent log-normal errors with a CV of 20% were used and 250 simulations ran for each case (combination of stock, scenario and HCR).

2.2. Harvest control rules

The Harvest Control Rules tested in this paper take the form:

$$C_{y+1} = C_{y-1} \cdot \alpha$$

where C are catches in weight and y indexes years.

Different forms for α, the catch multiplier, lead to alternative HCRs. Three rules were tested, one based on short term trends in surveys (used frequently by ICES to provide catch advice for data-limited stocks); an alternative that uses the confidence interval of the mean abundance of the survey, to take into account long term information; and a third that uses length-based reference points.

The rule based on short term changes in abundance, hereafter referred to as HCR1, compares the two most recent index values with the three preceding values and takes the following form:

$$\alpha = \frac{\sum_{i=y-2}^{y-1} I_i/2}{\sum_{i=y-5}^{y-3} I_i/3},$$

where I refers to the stock biomass or abundance index and i indexes years.

The rule based on survey confidence intervals, named HCR2, sets α as:

$$\alpha = \begin{cases} \alpha_l & \text{if } I_{y-1} < \mu_I + z_{low}\dfrac{\sigma_I}{\sqrt{n_I}} \\ 1 & \text{if } \mu_I + z_{low}\dfrac{\sigma_I}{\sqrt{n_I}} \le I_{y-1} \le \mu_I + z_{upp}\dfrac{\sigma_I}{\sqrt{n_I}} \\ \alpha_u & \text{if } I_{y-1} > \mu_I + z_{upp}\dfrac{\sigma_I}{\sqrt{n_I}}, \end{cases}$$

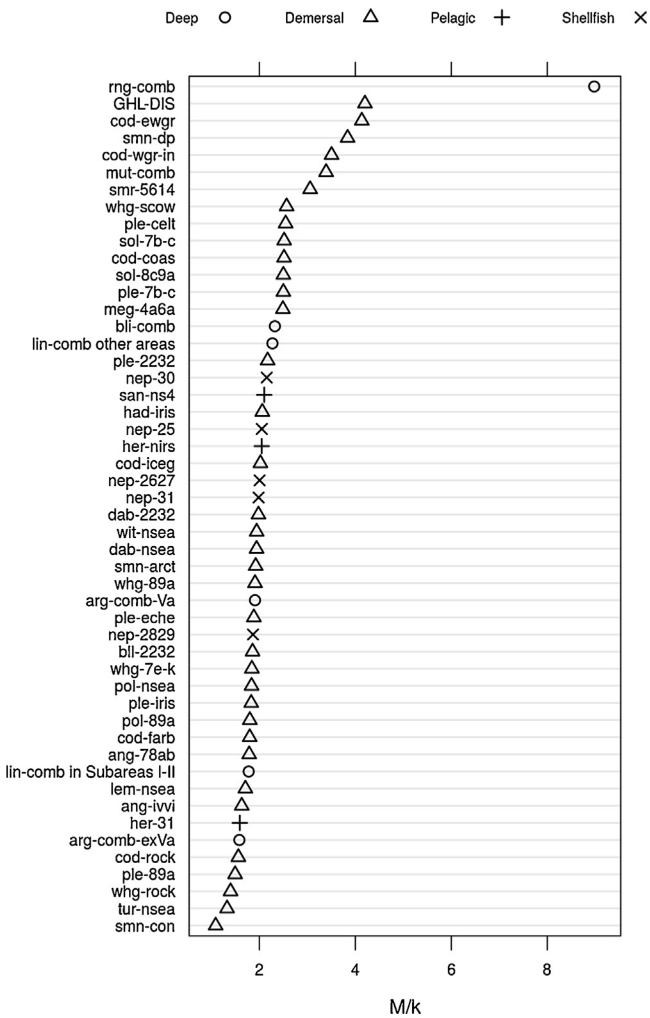

Fig. 1. Life history invariant M/K for the stocks used in this study.

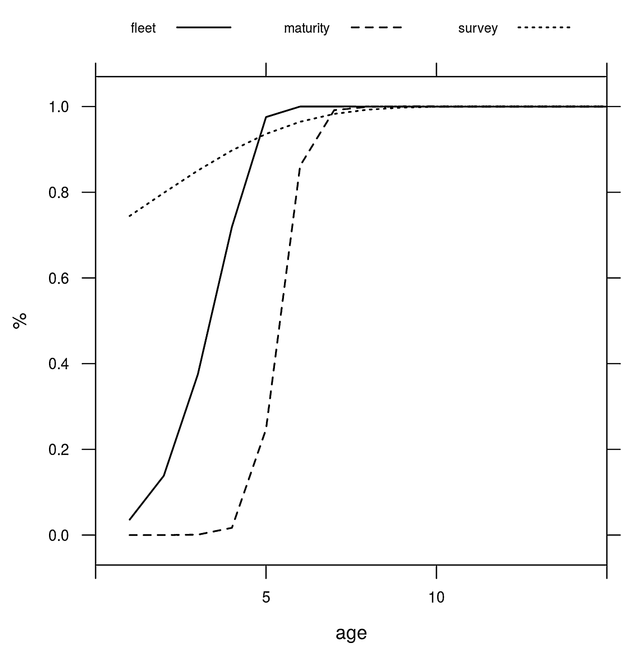

Fig. 2. Maturity, fleet selectivity and survey selectivity models by age used in this study. Fleet selectivity was modeled with a double normal distribution with the mode equal to the age of 50% maturity. Survey selectivity was modeled as an asymptotically flat curve with maximum retention at age 10. Both were held constant over time. Example shown for a stock with age of 50% maturity of 5.4 years.

with μ_I the mean index abundance, σ_I the index's standard deviation, n_I the length of the index time-series, and z_x the z-statistic from the standard normal distribution for which $P[Z \leq z_x] = x$. z_{low} and z_{upp} define the confidence interval limits, which don't have to be symmetric, and α_l and α_u the catch multipliers when the index is outside the lower or upper confidence interval, respectively. Note that in this rule the length of the index increases with time, as new data becomes available, which in theory means that the precision of the index mean, μ_I, will increase with new data.

HCR2 was parametrized using an asymmetric confidence interval, with $z_{low} = z_{0.33} = -0.44$ and $z_{upp} = z_{0.974} = 1.96$, and asymmetric changes in TAC, with $\alpha_l = 0.75$ and $\alpha_u = 1.05$. For comparison purposes HCR2 was also ran with symmetric confidence intervals, referred to as 'HCR2.sym', where $z_{low} = z_{0.025} = -1.96$ and $z_{upp} = z_{0.975} = 1.96$, and symmetric changes in TAC, $\alpha_l = 0.75$ and $\alpha_u = 1.25$.

The rule based on length-based reference points, named HCR3, has the following form for α:

$$\alpha = \frac{L_{SQ}}{L_{F=M}}$$

where F is the fishing mortality rate, M the natural mortality rate, L refers to individual length, and L_{SQ} the *status quo* (current) mean length in the catch, which is given by:

$$L_{SQ} = \frac{\sum_{a=1}^{A} C_{a,y} L_a}{\sum_{a=1}^{A} C_{a,y}}$$

with a indexing ages. $L_{F=M}$ refers to the mean length in the catch that sets fishing mortality at the same level as natural mortality (Beverton and Holt, 1957), given by:

$$L_{F=M} = 0.75 L_c + 0.25 L_\infty \tag{1}$$

with L_c, the mean length at first capture, defined by:

$$L_c = L_{a_c} = L_\infty (1 - e^{-K(a_c - a_0)})$$

where L_∞, K and a_0 are the von Bertalanffy growth model parameters, and a_c the age of first capture, which was set at the age of 25% maturity.

The length-based reference points L_{SQ} and $L_{F=M}$ were used, respectively, as proxies of current fishing mortality, F_{SQ}, and the fishing mortality at MSY, F_{MSY} (ICES, 2012c). Thus, $L_{SQ}/L_{F=M} \approx F_{SQ}/F_{MSY}$, and ratios different from 1 should drive the fishery to MSY. Appendix A presents a generalized form of this proxy where F can be set to any proportion of M.

The application of the HCRs within the management procedure was performed ignoring the parameters used in the simulation, to maximize the independence of the decision making process with respect to the simulations. In particular, the length based HCR used the common life history invariant, $K = 2M/3$, although the populations were simulated with their own estimates of these parameters. This approach tries to replicate the most frequent options taken by assessment working groups, while at the same time adding observation error to the indicator used for HCR3.

Computations were carried out with R (http://r-project.org) and FLR (http://flr-project.org; Kell et al., 2007). The code and data can be made available upon request to the first author.

3. Results

Fig. 3 shows the median SSB trajectories for each stock over 40 years by HCR and exploitation scenarios (development and overexploitation, named 'dev' and 'hi', respectively). Biological risk, computed as the ratio of SSB over virgin biomass in years 16-20, was categorized by iteration as 'low' when $SSB > 0.30B_v$, 'medium' when $0.10B_v \leq SSB \leq 0.30B_v$ and 'high' when $SSB < 0.10B_v$. The

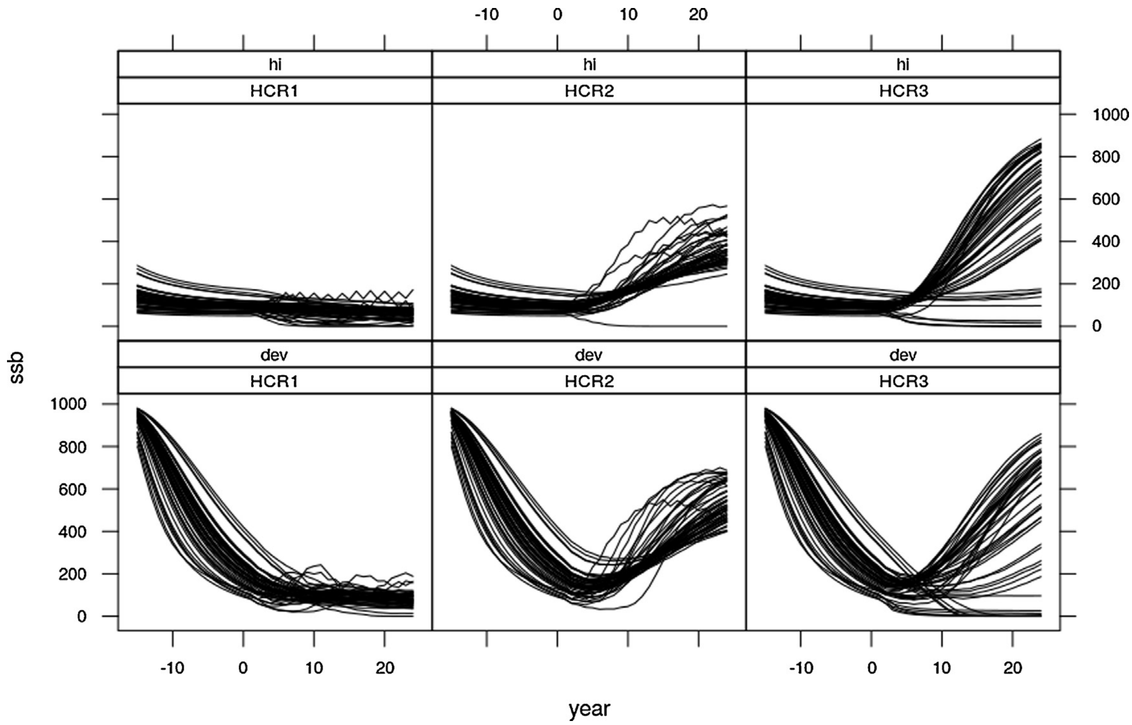

Fig. 3. Median spawning stock biomass (ssb) trajectories by stock, scenario and harvest control rule (HCR). Scenarios are labeled 'dev' for development, or 'hi' for over-exploited.

percentage of simulations (*i.e* of 50 stocks by 5 years by 250 iterations) in each category reflects the biological risk by HCR and exploitation scenario (Table 2). To evaluate the performance of the HCRs in relation to yield, the distribution of the ratio catch/MSY for the year 20, by scenario and HCR was computed (Fig. 4).

The results show that HCR1 is not able to recover the biomass in both scenarios (Fig. 3). The rule resulted in a high biological risk for the majority of the stocks (79% of the simulations in the 'hi' scenario and 69% in the 'dev' scenario; Table 2). HCRs 2 and 3 showed better performance in terms of SSB recovery and biological risk for both exploitation scenarios. HCR2 shows only 11% of the simulations in the 'hi' scenario and 5% in the 'dev' scenario with high risk, while HCR3 shows 16% of the simulations in the 'hi' scenario and 27% in the 'dev' scenario with high risk.

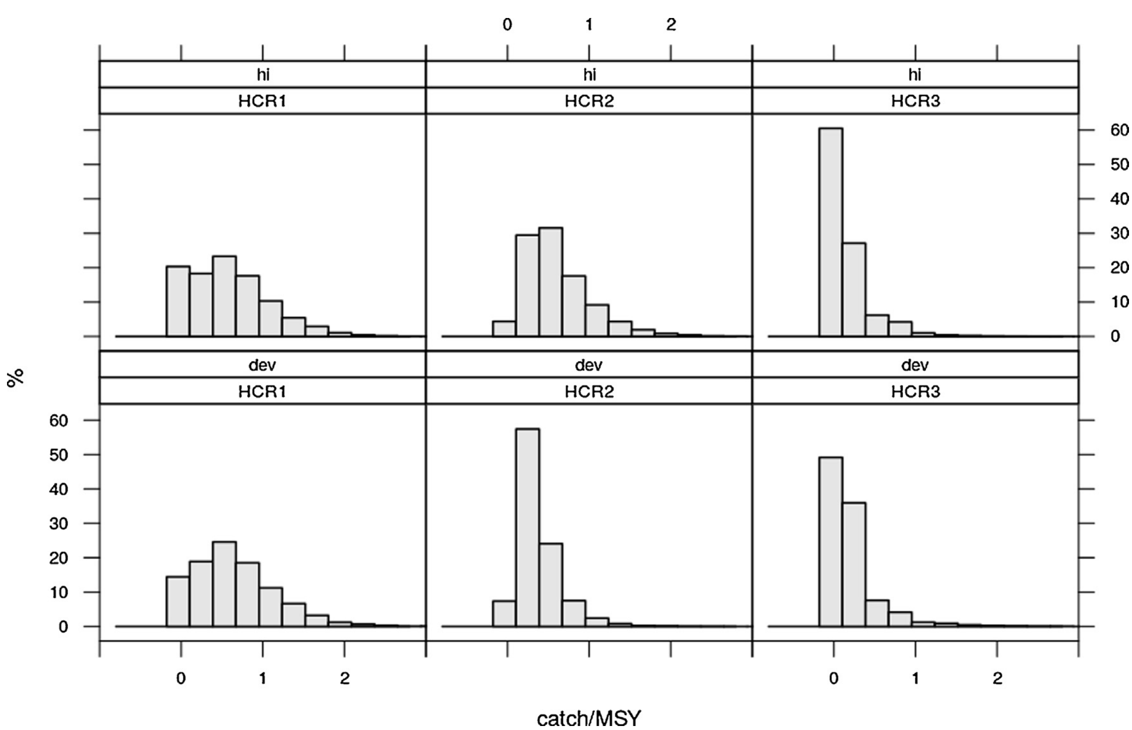

Fig. 4. Distribution of the catch over MSY ratio in year 20, by scenario and harvest control rule (HCR). The distributions are computed from the simulations (250) performed for each stock (50). Scenarios are labeled 'dev' for development, or 'hi' for over-exploited.

Table 2
Biological risk, between year 16 and 20, by scenario and harvest control rule (HCR), computed as the proportion of simulations (*i.e.* proportion of 50 stocks by 5 years by 250 iterations) in each category of biomass to virgin biomass (*Bv*) ratio. The categories are: high: < 10% *Bv*, med: 10–30% *Bv*, low: > 30% *Bv*.

Scenario	Biological risk	HCR1	HCR2	HCR3
dev	low	≪0.01	0.48	0.49
dev	med	0.31	0.47	0.24
dev	high	0.69	0.05	0.27
hi	low	0.00	0.18	0.61
hi	med	0.21	0.71	0.23
hi	high	0.79	0.11	0.16

Table 3
Probability of stocks breaking the inter-annual catch constraint (IACC) of 25%, between year 16 and 20, by scenario and harvest control rule (HCR), computed as the proportion of simulations (*i.e.* proportion of 50 stocks by 5 years by 250 iterations) above, below or within the 25% catch range in relation to the previous year's catch.

scenario	IACC	HCR1	HCR2	HCR3
dev	below	0.39	0.36	0.38
dev	within	0.24	0.24	0.32
dev	above	0.37	0.40	0.30
hi	below	0.41	0.37	0.36
hi	within	0.23	0.23	0.32
hi	above	0.36	0.40	0.32

Fig. 4 shows that all HCRs drive most fisheries to levels of catches below MSY, although in the case of HCR1 it is due to low levels of biomass, while for HCR2 and HCR3 this effect is related to low levels of fishing mortality, which reflects the more precautionary approach of these rules. HCR2 seems to behave better, showing a lower number of very small catch/MSY ratios.

Table 3 presents the probability of violating an inter-annual catch constraint of 25% for years 16-20. All HCRs have similar results, although HCR3 shows slightly better results regarding inter-annual catch stability. Note that in the case of HCR2 these results reflect the uncertainty in catches introduced through the implementation error, given the fact that this rule has the catch limits embedded in its parameters. Additionally, the HCRs operate with a two year lag on one single year catch ($C_{y+1} = C_{y-1} \cdot \alpha$); replacing C_{y-1} by an average catch over a recent period may smooth the catch variability.

To further investigate the reasons for the poor performance found in some cases, we selected two stocks of herring (in Bothnian Bay, area 31, coded 'her-31'; and in the Irish Sea, coded 'her-nirs') with similar life history parameters but which performed differently. Fig. 5 shows SSB, catch in weight and the catch multipliers (α). In the case of HCR1 the multiplier increases as soon as the biomass increases, which results in an increase in catches keeping the biomass at low levels. This rule clearly stabilizes the biomass at levels similar to the most recent observed ones. HCR2 identifies correctly that both stocks are over-exploited, but catches are not reduced quickly enough initially to recover the biomass of her-31. This rule has a fixed catch reduction of 25%. The opposite happens for her-nirs and biomass increases as well as the multiplier, yielding an increase in catches. HCR3 shows α above 1 for her-31, which results from wrongly identifying the stock as being under-exploited. This situation is due to a lower L_∞ (21 cm for her-31 compared to 31 cm for her-nirs), and a lower length of 50% mature, which is indirectly defining the age of first capture, a_c. Both effects result in a lower $L_{F=M}$ for her-31 which, in this particular case, sets the ratio with the *status quo* length above 1.

Fig. 6 shows a comparison between the parametrization used for HCR2 in this study and a fully symmetric parametrization (named 'HCR2.sym'), with a 0.05% confidence interval and the α multipliers of 0.75 and 1.25, applied to the stock of plaice in Iberian waters. SSB, catch and the α multiplier are shown. The most important difference between the two is the stabilization of SSB after recovering in the case of asymmetry, while the symmetric HCR drives SSB back to low levels. This effect results from the higher values of α, that this

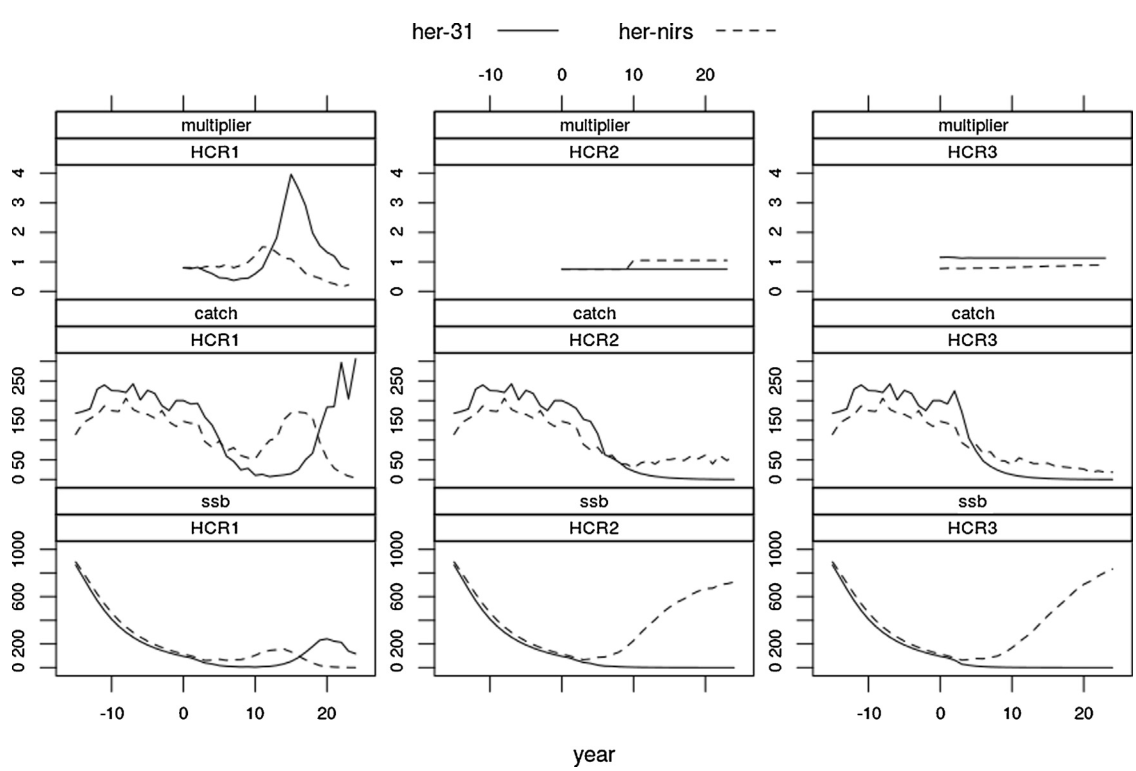

Fig. 5. Trends in spawning stock biomass (ssb), catch and catch multiplier (α in the formulations), which defines the multiplier to the catch in year $y-1$ that derives the catch advice for year $y+1$, for the stocks of herring in the Bothnian Bay, area 31 ('her-31'), and in the Irish Sea ('her-nirs'). Results are for the 'dev' scenario.

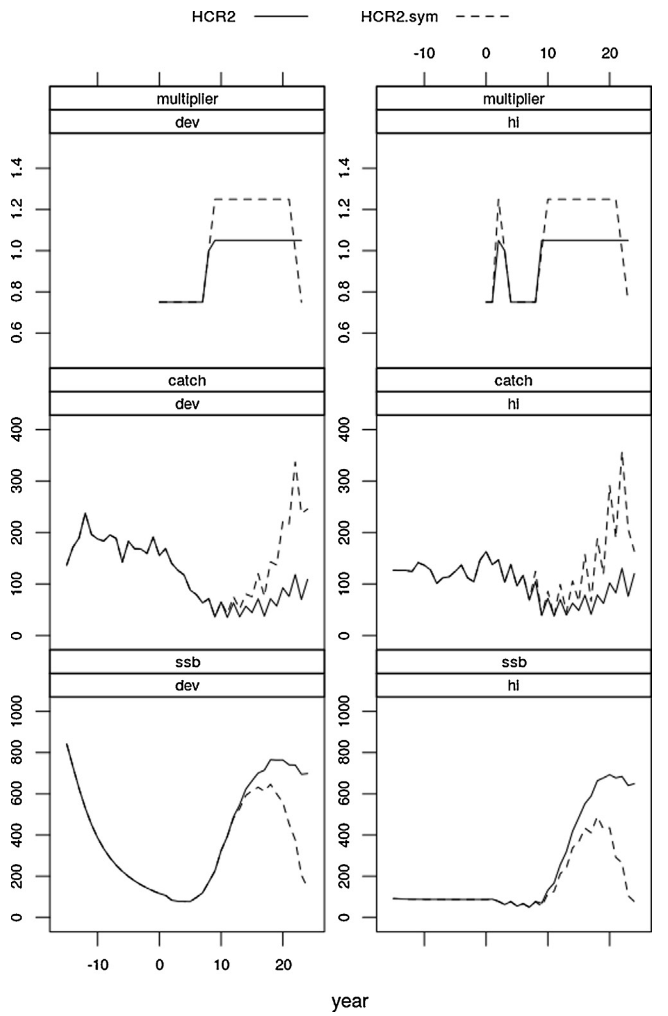

Fig. 6. Trends in spawning stock biomass (ssb), catch and catch multiplier (α in the formulations), which defines the multiplier to the catch in year $y-1$ that derives the catch advice for year $y+1$, for the stock of plaice in Iberian waters by scenario. 'HCR2.sym' reflects a different parametrization of HCR2, with a symmetric confidence interval of 5% and multipliers of 0.75 and 1.25.

parametrization holds, which provides higher catches but also risks for SSB. The example shows that there is a wide range of options for parameterizing this HCR, which, in a real life situation, should be done using MSE analysis.

4. Discussion

In this study we investigated the performance of three simple HCRs, in view of their potential application to data-limited stocks, with different data situations regarding the amount and quality of information. HCR1 and HCR2 can be used to provide catch advice if survey data exists, while HCR3 can be used in more severe data limited cases where only catch length compositions are available. If both information sources exist, combinations of these HCRs can be explored.

The HCRs tested were not able to steer simultaneously all stocks to optimal exploitation, with SSBs and fishing mortalities around values that provide MSY. Such results are expected, considering it is unlikely that a single parametrization can cope with the diversity in population life histories. In real-life situations, these HCRs should be tuned to the specificities of the stock and fisheries subject to management. Nevertheless, HCR2 with the current parametrization was much more efficient than HCR1 in approaching MSY levels, failing in one case only. HCR3 was able to drive SSB to safe levels in most cases but left the fisheries with low catches, most likely due to a poor approximation to F_{MSY} by $L_{F=M}$. As in the case of HCR2, it was more efficient than HCR1 at keeping the stocks within safe levels. Klaer et al. (2012) explored the performance of rules similar to HCR3 and also found a wide range of results, with cases where the SSB was driven to very high levels in relation to virgin biomass and others where this ratio was very low. The authors justify these results with the disparity between the natural mortality assumed by the assessment method and the real natural mortality. In our study we didn't explore this effect.

Note that HCR3 uses indirect information about the status of the stock and life history parameters to compute proxies to F_{MSY}. It is a rule that can be applied to stocks that have more severe data limitations than HCR1 and HCR2, but shows performance limitations, although with the advantage of steering the stock to safe biological levels instead of stabilizing SSB at their recent levels, like HCR1. As in any other HCR, add-hoc adjustments can be included to improve its performance, *e.g.* in the form of additional tuning parameters.

The approach to simulation testing used can provide the necessary framework to tune data limited HCRs. Depending on the information available, the operating model will be a better or worse representation of the real system. Nevertheless, our approach allows studying the robustness of the HCR to a set of common uncertainty factors, such as stock-recruitment relationships, growth, fleet selectivity, implementation error, etc.

Analysing the results obtained in more detail, one can conclude that HCR1, which was designed to provide status quo catch advice adjusted by the biomass index ratio, showed the poorest performance, decreasing or keeping SSB at low levels and catches mostly below the MSY target. This rule adjusts the catch based on short-term changes in biomass, which proves efficient at stabilizing the catches and the biomasses at recent levels, but is unable to implement the necessary catch reduction that would steer SSB to sustainable levels. Improved performance of the rule may be achieved by replacing the denominator by a biomass index target, or including a penalizing term accounting for the over-exploitation of the stock. These tweaks require assumptions to be made about the relationship between the index and the state of the stock. Such assumptions may be possible, if the survey time series covers a known period of moderate exploitation, but will be of limited interest if the survey time series is short or only covers a period when the stock was already over-exploited.

HCR2, that adjusts the *status quo* catch based on the variability of the biomass index time series, showed the best overall performance in both scenarios. However, to obtain such results, it was necessary to apply an asymmetric confidence interval combined with larger decreases in *status quo* catch (0.75) than increases (1.05). The need to parametrize this HCR may be a limitation to its applicability. The rule of thumb is that if the stock is likely to be over-exploited, then an asymmetrical parametrization will be more precautionary than one that is symmetrical. The level of asymmetry that will increase the chances of steering the fishery to MSY must be found through simulation testing, although the parametrization provided here appeared to be precautionary.

HCR3 uses the mean length in the catch (L_{SQ}) as a proxy for current fishing mortality and the mean length when fishing mortality equals natural mortality ($L_{F=M}$) as a proxy for F_{MSY}. The rule is designed to adjust the *status quo* catch downwards or upwards when the mean length in the catch is below or above the target ($L_{F=M}$), respectively. The simulations showed that for the majority of the stocks, HCR3 resulted in a reduction of F to below F_{MSY}, which had the effect of driving catches of these stocks below MSY (Fig. 4). In these cases, $L_{F=M}$ was a poor approximation to F_{MSY}, resulting in a catch multiplier (α) well below one. A common feature of the stocks for which HCR3 showed a poor performance was that exploitation (length at first capture, L_c) starts well below the length of first maturity ($L_{50\%}$). In fact, for the stocks failing with HCR3, the ratio $L_c/L_{50\%}$ was below 0.25. Moreover, SSB recovery was weaker or stock depletion more severe, for stocks with late maturity, *i.e* when the length at first maturity is closer to maximum length. Further simulation testing is required to investigate modifications of HCR3 that align the target mean length in the denominator, which depends on L_c and L_∞, with the exploitation and life-history characteristics of the stocks, in order to reduce the advised catch and promote the rebuilding of the stock. One possibility worth exploring is to add a correction factor to $L_{F=M}$ linked to the L_c, $L_{50\%}$ and L_∞ for the given stock to improve the yield/risk trade-off. In spite of the low catches, HCR3 was able to reverse, relatively quickly, the decreasing trend in SSB in the 'dev' scenario and to increase the low SSB levels in the 'hi' scenario, resulting in low biological risks.

Finally, the approach presented here does not replace analytical assessments. The information provided by these methods is more limited than the information given by an analytical method. It is important to avoid the "data-poor trap", where due to the fact that catch advice is being given for these stocks, the collection of data is seen as unnecessary (Bentley, 2014). Moving the stocks up on the "data level" is an important objective that should be kept in management policies.

Acknowledgements

The authors would like to thank the thorough reviews of two anonymous reviewers. Part of this work was carried out within GesPe Project (Planos de Gestao Pesqueira, PROMAR 31-03-01-FEP-0017, EU co-financed).

Appendix A. Generalizing the length based HCR

Note that an interesting development about HCR3 can be made. From Beverton and Holt (1957) the mean length fish in the annual catch is defined by

$$\bar{L}_y = L_\infty \left[1 - \frac{(F+M)(1-e^{-\lambda(F+M+K)})}{(F+M+K)(1-e^{-\lambda(F+M)})} e^{-K(a_c-a_0)} \right].$$

Considering $\lambda = a_\lambda - a_c$ the fishable life-span, then setting $\lambda \to +\infty$ in the equation above results in

$$\bar{L}_y = L_\infty \left[1 - \frac{(F+M)e^{-K(a_c-a_0)}}{F+M+K} \right]. \tag{A.1}$$

From $L_y = L_\infty(1-e^{-K(a-a_0)})$ and taking into account that $a = a_c \Rightarrow L_y = L_c$, we obtain

$$L_c = L_\infty(1-e^{-K(a_c-a_0)}),$$

which can be written as

$$e^{-K(a_c-a_0)} = \frac{L_\infty - L_c}{L_\infty}. \tag{A.2}$$

We can now substitute Eq. (A.2) into Eq. (A.1) to obtain

$$\bar{L}_y = \frac{KL_\infty + FL_c + ML_c}{F+M+K}.$$

Setting $F = \gamma M$, with $\gamma > 0$ and $K = \theta M$ results in

$$L_{F=\gamma M, K=\theta M} = \frac{\theta L_\infty + L_c(\gamma+1)}{\theta + \gamma + 1}. \tag{A.3}$$

Which is a generalized form that allows setting the proxy for F_{MSY} at any level of natural mortality and not only $F = M$. Eq. (1) holds if we set $\gamma = 1$ and $\theta = 2/3$ in Eq. (A.3).

References

Anon., 2006. Magnuson-Stevens Fishery Conservation and Management Reauthorized Act. Public Law 109-479. NOAA http://www.nero.noaa.gov/sfd/MSA_amended_20070112_FINAL.pdf

Anon., 2007. Commonwealth Fisheries Harvest Strategy: Policy and Guidelines. Australian Government, Department of Agriculture, Fisheries and Forestry http://www.daff.gov.au/__data/assets/pdf_file/0004/397264/hsp.pdf

Anon., 2008. Harvest Strategy Standard for New Zealand Fisheries. New Zealand Ministry of Fisheries. Circular No. 1086 http://www.fish.govt.nz/NR/rdonlyres/487988D0-F768-4297-ADDE-B5E1DFA53404/0/harveststrategyfinal.pdf

Anon., 2013. Regulation (EC) no 1380/2013 of the European Parliament and of the Council of 11 December 2013 on the Common Fishery Policy. European Commission. Official Journal of the European Union http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2013:354:0022:0061:EN:PDF

Bentley, N., 2014. Data and time poverty in fisheries estimation: potential approaches and solutions. ICES J. Mar. Sci., http://dx.doi.org/10.1093/icesjms/fsu023.

Beverton, R.J.H., Holt, S.J., 1957. On the Dynamics of Exploited Fish Populations, vol.19. Springer-Science + Business Media, B.V. Fish and Fisheries.

Butterworth, D.S., Cochrane, K.L., De Oliveira, J.A.A., 1997. Management procedures: a better way to manage fisheries ? The South African experience. In: Pikitch, E.K., Huppert, D.D., Sissenwine, M.P. (Eds.), Global Trends: Fisheries Management. American Fisheries Society, Bethesda, MD, pp. 83–90.

Butterworth, D.S., Punt, A.E., 1999. Experiences in the evaluation and implementation of management procedures. ICES J. Mar. Sci. 56, 985–998.

Cooke, J.G., 1999. Improvement of fishery-management advice through simulation testing of harvest algorithms. ICES J. Mar. Sci. 56, 797–810.

Geromont, H.F., Butterworth, D.S., 2014. Generic management procedures for data-poor fisheries: forecasting with few data. ICES J. Mar. Sci., http://dx.doi.org/10.1093/icesjms/fst232.

Gislason, H., Daan, N., Rice, J.C., Pope, J.G., 2010. Size, growth, temperature and the natural mortality of marine fish. Fish. Fish. 11, 149–158.

Hilborn, R., Maunder, M., Parma, A., Ernst, B., Payne, J., Starr, P., 2003. COLERAINE: A Generalized Age-Structured Stock Assessment Model. University of Washington, School of Aquatic and Fisheries Science http://fish.washington.edu/research/colerain/pdf/coleraine.pdf

Hordyk, A., Ono, K., Sainsbury, K., Loneragan, N., Prince, J., 2014. Some explorations of the life history ratios to describe length composition, spawning-per-recruit, and the spawning potential ratio. ICES J. Mar. Sci., http://dx.doi.org/10.1093/icesjms/fst235.

ICES, 2012a. ICES implementation of advice for data-limited stocks in 2012 in its 2012 advice (ICES CM 2012/ACOM:68), 42 pp.

ICES, 2012b. Report of the workshop on the development of assessments based on life-history traits and exploitation characteristics (WKLIFE) , 13–17 February, Lisbon, Portugal (ICES CM 2012/ACOM:36), 140 pp.

ICES, 2012c. Report of the workshop to finalize the ICES data-limited stock (DLS) methodologies documentation in an operational form for the 2013 advice season and to make recommendations on target categories for data-limited stocks (WKLIFE II) , 20–22 November, Copenhagen, Denmark (ICES CM 2012/ACOM:79), 46 pp.

ICES, 2013a. General Context of ICES Advice. In Report of the ICES Advisory Committee (Book 1).

ICES, 2013b. Report of the working group on methods for fish stock assessment (WGMG) , 30 September–4 October, Reykjavik, Iceland (ICES CM 2013/SSGUE:09), 130 pp.

Kell, L.T., Mosqueira, I., Grosjean, P., Fromentin, J.-M., Garcia, D., Hillary, R., Jardim, E., Mardle, S., Pastoors, M.A., Poos, J.J., Scott, F., Scott, R.D., 2007. Flr: an open-source framework for the evaluation and development of management strategies. ICES J. Mar. Sci. 64 (4), 640–646.

Kell, L.T., Pilling, G.M., Kirkwood, G.P., Pastoors, M., Mesnil, B., Korsbrekke, K., Abaunza, P., Aps, R., Biseau, A., Kunzlik, P., Needle, C., Roel, B.A., Ulrich-Rescan, C., 2005. An evaluation of the implicit management procedure used for some ICES roundfish stocks. ICES J. Mar. Sci. 62, 750–759.

Klaer, N.L., Wayte, S.E., Fay, G., 2012. An evaluation of the performance of a harvest strategy that uses an average-length-based assessment method. Fish. Res. 134–136, 42–51.

MacCall, A.D., 2009. Depletion-corrected average catch: a simple formula for estimating sustainable yields in data-poor situations. ICES J. Mar. Sci. 66, 2267–2271.

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

Myers, R.A., Bowen, K.G., Barrowman, N.J., 1999. Maximum reproductive rate of fish at low population sizes. Can. J. Fish. Aquat. Sci. 56 (12), 2404–2419.

Punt, A.E., Donovan, G.P., 2007. Developing management procedures that are robust to uncertainty: lessons from the International Whaling Commission. ICES J. Mar. Sci. 4 (64), 603–612.

Rosenberg, A.A., Fogarty, M.J., Cooper, A.B., Dickey-Collas, M., Fulton, E.A., Gutiérrez, N.L., Hyde, K.J.W., Kleisner, K.M., Kristiansen, T., Longo, C., Minte-Vera, C., Minto, C., Mosqueira, I., Osio, G.C., Ovando, D., Selig, E.R., Thorson, J.T., Ye, Y., 2014. Developing new approaches to global stock status and fishery production potential of the seas, Tech. Rep. Circular No. 1086. FAO http://www.fao.org/docrep/019/i3491e/i3491e.pdf

Wetzel, C.R., Punt, A., 2011. Model performance for the determination of appropriate harvest levels in the case of data-poor stocks. Fish. Res. 110, 342–355.