Performance of harvest control rules in a variable environment

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Brunel, T., Piet, G. J., van Hal, R., and Röckmann, C. 2010. Performance of harvest control rules in a variable environment. – ICES Journal of Marine Science, 67: 1051–1062.

Population dynamic models used for fisheries management assume that stocks are isolated entities, ignoring the influence of environmental factors on stock productivity. An operating model parameterized for North Sea cod, plaice, and herring is developed, in which the link between recruitment and environment is assumed to be known and described by generalized additive models. This tool is used to compare the performance of harvest control rules (HCRs) when recruitment is independent of the environment or when recruitment is affected by an environment varying according to different scenarios. The first HCR exploited the stock with a fixed fishing mortality (F) corresponding to maximum sustainable yield, and in the second HCR, F was set equal to the precautionary approach F (i.e. F_{pa}), but reduced from F_{pa} when stock biomass fell below B_{pa}. The performance of the HCRs altered only slightly in a randomly varying environment compared with a constant one. For a detrimental change in the environment, however, no HCR could prevent a massive decrease in stock size. The performance of the HCRs was also influenced by the stock characteristics, such as recruitment variability or the shape of the stock–recruitment relationship. The performance of "environmental" HCRs (eHCRs), in which F varies depending on environmental conditions, was compared with that of conventional HCRs. The gain in using the eHCR was small, except for a detrimental change in the environment, where the eHCR performed markedly better than a conventional HCR. The benefits of using the eHCR were the greatest for the stock with the strongest environment–recruitment relationship.

Keywords: environment–recruitment relationship, management strategy evaluation, North Sea, reference points, simulation.

Received 21 July 2009; accepted 13 December 2009; advance access publication 2 February 2010.

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Introduction

With the development of an ecosystem approach to environmental management (UN, 1992; EC, 2002), fisheries research broadened its approach. Fish are recognized as functioning within a wider ecosystem and are dependent on complex and dynamic interactions with their environment. One of the key processes that needs to be integrated for an ecosystem approach is the influence of the variability of environmental conditions on a fish stock's productivity, particularly on recruitment. After almost a century since Hjort's (1914) pioneering work studying recruitment variability, many of the processes linking recruitment to the environment have been understood, and several general recruitment hypotheses synthesizing these processes have been developed (see Houde, 2008, for a recent review). Despite this, for a vast majority of stocks, we are still unable to provide reliable recruitment predictions; most environment–recruitment models explain only a small part of the variability, and they generally fail when retested with updated data (Myers, 1998). Although the importance of environmental effects on recruitment is increasingly acknowledged by the stock-assessment community, the lack of a formal recruitment model to integrate these effects makes it difficult to incorporate environmental factors in stock assessment methodologies and management procedures. Consequently, stock assessment and management methods for many stocks still rely on the assumption that fish stocks are isolated entities whose dynamics are determined by fishing mortality alone.

For most stocks, management is based on measures of the state of the stock (e.g. spawning-stock biomass, SSB) and the level of exploitation (e.g. fishing mortality, F), the standard outputs of stock assessments. Management procedures aim to keep the stock within safe biological limits, which are represented by reference values for SSB and F. Management operates following so-called harvest control rules (HCRs), which are essentially formalized decision rules defining the level of F that can be applied to the stock in the future, given the current position of SSB and F relative to their reference values. The likely benefits of designing management procedures that take environmental variability into account have been explored (e.g. Planque *et al.*, 2003; Kell *et al.*, 2005; MacKenzie *et al.*, 2008), but in practice, the assumption is still that environmental variability does not seriously affect the productivity of a stock. However, HCRs defined under such an assumption of no environmental effect may not be appropriate if the dynamics of the stock are indeed affected by environmental variability. A simulation approach for the walleye pollock (*Theragra chalcogramma*) fishery in Alaska, in which an environment–recruitment relationship is explicitly modelled, indicated that under different scenarios of future climate change, the management strategy currently used performed poorly, both in terms of keeping the stock within safe biological limits and in achieving high and stable yields (A'Mar *et al.*, 2009). Those authors proposed an alternative management strategy accounting for environmental variability, which performed considerably better than the conventional one.

There are two ways in which environmental information could be incorporated in stock management (Basson, 1999): (i) using an environment-based recruitment forecast for short-term stock projections and (ii) varying reference points according to prevailing environmental conditions. Making short-term predictions of the state of the stock and catches 2 years ahead, under a range of different values of F, is a standard practice in ICES stock assessments. For lack of a reliable predictive model for recruitment, the assumption of constant recruitment is generally made and the geometric mean over a long period tends to be used. Occasionally, recruitment is predicted from a stock–recruitment (SR) model. In both cases, only crude estimates of future recruitment are used, a source of uncertainty for short-term stock projections. If recruitment is strongly linked to the environment, such uncertainty could be reduced using an environment–stock–recruitment relationship (referred to as eSR hereafter) to forecast future recruitment (MacKenzie *et al.*, 2008). However, this would require that the environmental conditions affecting recruitment can be either measured before the stock assessment working group meets or forecast accurately, neither of which may be possible. Pacific sardine (*Sardinops sagax*) off the US west coast is currently the only stock in the world for which such an approach is used for management (PFMC, 2007). Adjusting the reference points according to the prevailing environmental conditions is the other way to incorporate environmental information in stock management. Environmental variability is responsible for long-term trends in recruitment of fish (Brunel and Boucher, 2007) or of sudden switches from one regime to another (Beaugrand, 2004; Alheit *et al.*, 2005). Adaptive management through environment-driven changes in F reference points is a way to tune the level of exploitation to the current level of productivity of the stock (ICES, 2006).

Basson (1999) investigated both these approaches and concluded that using environmental information for short-term recruitment predictions did not improve the performance of management. However, using environmental information to adjust the fishing mortality reference points could improve management if the link between recruitment and the environment is strong enough.

Simulation is routinely used to evaluate the performance of management strategies (Schnute *et al.*, 2007), and it has also proved useful in exploring the likely benefits and feasibility of incorporating environmental factors in management procedures (Basson, 1999; Kell *et al.*, 2005; A'Mar *et al.*, 2009). In the current study, simulation was used to evaluate the performance of two HCRs to (i) compare the performance of management strategies when recruitment is affected by the environment and when it is not and (ii) investigate whether incorporating environmental effects in management procedures would improve management. To that end, we created eSR models and developed a method to revise management reference points when there is a major change in the prevailing environmental conditions. With these tools, we evaluated the performance of the two HCRs specifically contrasting conventional HCRs with a so-called environmental HCR (eHCR). This evaluation is based on three case studies with different life histories and recruitment dynamics: herring (*Clupea harengus*), plaice (*Pleuronectes platessa*), and cod (*Gadus morhua*) in the North Sea.

Material and methods

An operating model representing the dynamics of the three stocks was used to investigate the performance of two HCRs (and the corresponding eHCRs). The operating model can be configured to simulate either North Sea herring, plaice, or cod using stock-specific biological and exploitation parameters. Historical environmental and SR data were used to determine the eSR relationships for the three stocks individually. These were then used in the operating model to represent recruitment. The model was used to simulate the development of the stocks over a 50-year period, considering the two HCRs and the two eHCRs that regulate the exploitation under four different environmental scenarios. The simulations generated data that were used to produce a set of diagnostics on the performance of the HCRs.

Operating model

Basic model

A simple, age-structured population model was used to represent the dynamics of the stocks, including fishing mortality, selectivity-at-age, natural mortality, and growth and recruitment parameters. Fishing mortality for each age group in a given year ($F_{a,y}$) is the product of an annual fishing mortality F_y, fixed according to the HCR, and a selectivity-at-age vector. For the selectivity-at-age of each stock, the average of the historical selection pattern, as estimated by the ICES stock assessment working groups, was used for herring (ICES, 2007a), cod, and plaice (ICES, 2007b). Natural mortality was also taken from these ICES reports.

Growth was modelled by a von Bertalanffy equation with constant parameters (Table 1) throughout the simulation period, with an additional stochastic component representing interannual variability:

$$W_{a,y} = W_a + \varepsilon_g(a, y), \tag{1}$$

where W_a is the weight-at-age a from the von Bertalanffy model, and $\varepsilon_g(a, y)$ is white noise generated according to a normal distribution $N(0, \sigma^2_{g,a})$. Both parameters of the von Bertalanffy equation and the temporal variability in weight-at-age ($\sigma^2_{g,a}$) were estimated for each stock from the weight-at-age data given in the ICES reports.

Recruitment was modelled as the sum of the prediction from the eSR relationship (see below) according to the SSB and environmental factors in the previous year and of a lognormal stochastic component representing the variability in recruitment not explained by stock or environment variations:

$$R_y = R_{\text{pred}}(\text{SSB}_{y-1}, \text{env}_{y-1}) + \varepsilon_R(y), \tag{2}$$

where $\varepsilon_R(y)$ is a stochastic component having a lognormal distribution $\log N(0, \sigma^2_R)$. The variance σ^2_R is equal to the difference between the variance of the historical recruitment time-series and the variance explained by the eSR model.

Environment–SR relationships

The eSR relationships for the three species were mixtures of SR relationships and environment–recruitment relationships. For each stock, three SR models were fitted (Ricker, Beverton and

Table 1. Biological characteristics of the three stocks simulated.

Parameter	Cod	Plaice	Herring
Maturity			
A_{50} (years)	3.73	3.50	1.80
Slope (year^{-1})	1.62	2.13	4.27
Growth			
K (year^{-1})	0.27	0.19	0.41
W_{inf} (kg)	16.4	1.10	0.32
$CV(W)$	0.12	0.16	0.11
Recruitment			
$CV(R)$	1.21	0.69	0.64
R^2env	0.19	0.53	0.14
R^2SR	0.15	0.00	0.19
R^2eSR	0.26	0.53	0.39
Biomass			
B_{MSY} (t)	275 576	404 040	2 191 920
B_{pa} (t)	150 000	230 000	1 300 000
B_{lim} (t)	70 000	160 000	800 000
MSY (t)	544 785	171 304	716 515
Mortality			
Natural mortality (M)	0.8, 0.35, 0.25, 0.2 (ages 1, 2, 3, 4+)	0.1	1, 0.3, 0.2, 0.1 (ages 0–1, 2, 3, 4+)
ICES reference points			
F_{pa}	(age 2–4) 0.65	(age 2–6) 0.60	(age 2–6) 0.25
F_{lim}	0.86	0.74	Not defined
Calculated reference points			
F_{MSY}	0.86	0.25	0.21
F_{pa}	1.08	0.39	0.33
F_{lim}	1.29	0.46	0.50

A_{50} and slope are the age at which 50% of the fish are mature and the slope of the maturity ogive, respectively; K and W_{inf} are the growth coefficient and the asymptotic weight from the von Bertalanffy growth curve, respectively; $CV(W)$ is the average over all age classes of the coefficients of variation in weight-at-age; $CV(R)$ is the coefficient of variation in recruitment; and R^2env, R^2SR, and R^2eSR are the proportion of recruitment variance explained by the GAM of the environment–recruitment relationship, the SR model, and the eSR relationship, respectively. The F reference points are calculated using the eSR relationship for environmental conditions corresponding to the constant scenario using the method described in the text, and the values of M, B_{pa}, and B_{lim} are taken from ICES stock assessment reports.

Holt, and segmented regression), and the best was selected based on the lowest AIC (Akaike Information Criterion, where AIC $= 2k - 2\log L$, with k and L being the number of parameters and the likelihood of the model, respectively). The SSB and recruitment data for the three species were taken from the ICES working group reports. The best-fitting SR models are the segmented regression for herring and the Ricker model for cod and plaice.

The environment–recruitment relationships were investigated using generalized additive modelling (GAM). This method calculates the response variable (recruitment) as the sum of non-parametric functions (represented by a penalized regression spline) of the explanatory variables (environmental factors); it has been used in several studies to investigate the effects of the environment on recruitment (e.g. Daskalov, 1999; Cardinale and Arrhenius, 2000; van Deurs *et al*., 2009).

The environmental factors considered here were the North Atlantic Oscillation (NAO) index and various measures of temperature and salinity, the last two taken from a three-dimensional coupled biophysical model of the North Sea (ECOSMO model; Schrum *et al*., 2006). Monthly values of temperature and salinity were averaged over the relevant periods of the year and spatial areas to produce indices of the conditions experienced by the fish at different stages of their life cycle (e.g. bottom temperature during the spawning season in a specific spawning area). An exploratory analysis was first performed to select a relevant set of environmental factors and to avoid redundancy. The selection of the "best" GAM for each species was made based on the lowest AIC.

For herring, the best model included the effect of the September–November average of bottom salinity on the spawning grounds around the Orkney Islands (right panels of Figure 1). For cod, recruitment was influenced by the average temperature during the first half of the year (Figure 1, left panels). For plaice, recruitment was significantly related to the winter NAO index 1 year before spawning, the May–September average bottom temperature on the feeding grounds in the northern North Sea, and the annual minimum bottom temperature over the spawning grounds in the southern North Sea (Figure 1, centre panels).

The eSR model was then constructed by multiplying the SR relationship by the environment–recruitment relationship:

$$R_{\mathrm{pred}}(\mathrm{SSB}_{y-1}, \mathrm{env}_{y-1}, \ldots) = f_{\mathrm{SR}}(\mathrm{SSB}_{y-1}) \times f_{\mathrm{GAM}}(\mathrm{env1}_{y-1}, \ldots), \qquad (3)$$

where R_{pred} is the recruitment predicted from the eSR relationship as a function of SSB of the previous year and environmental conditions, f_{SR} the stock effect component (modelled by the segmented regression or Ricker SR model), and f_{GAM} the environmental effect component (predictions from the GAM centred on 0 by subtracting the mean of the historical recruitment time-series).

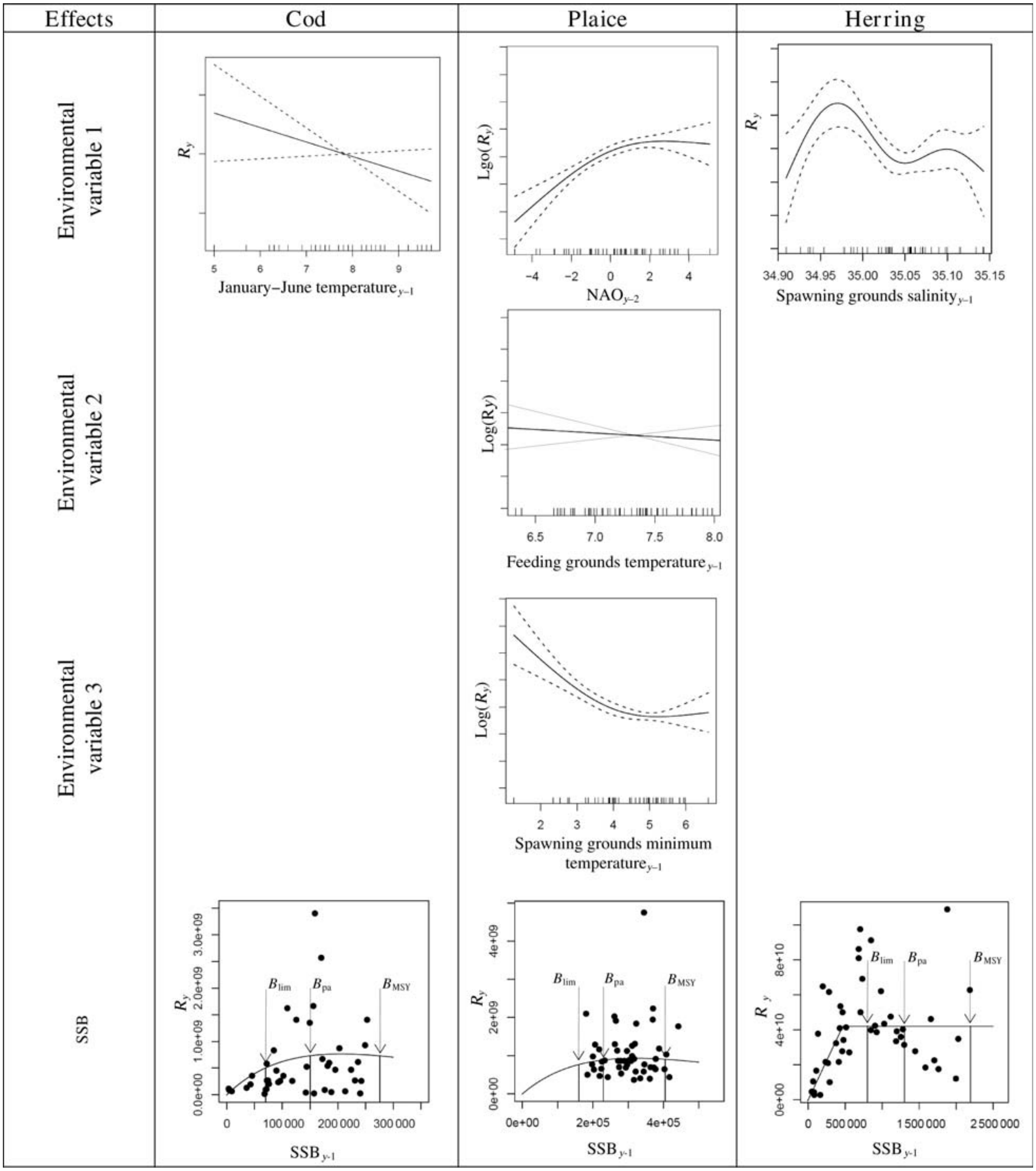

Figure 1. eSR relationships for the three stocks. The effect of environmental factors on recruitment is represented by the GAMs (top three panels) and the effect of stock size is represented by the SR curves (bottom panels).

The focus of this study was not to provide the exact mechanism through which environmental factors influence the recruitment of the three stocks. Although we attempted to find the best eSR relationship for each stock to make this exercise as realistic as possible, the eSR relationships presented here may not be robust. They should not, therefore, be used in a management context or to describe the likely effects of climate change on these three stocks. Therefore, the population models used here should not be viewed as a representation of reality, but rather as a tool for comparing how different HCRs perform under different environmental scenarios.

Evaluation of HCRs in the context of a varying environment

HCRs tested

The HCRs investigated here are based on reference points for the state of the stock and for its exploitation. Reference points here were defined according to ICES standards (ICES, 2007c). Limit reference points represent the biomass threshold below which there is an increased probability of impaired recruitment (B_{lim}), and the fishing mortality (F_{lim}) leading to B_{lim} at equilibrium. The precautionary reference point B_{pa} represents the stock level above which the risk that the stock falls below B_{lim} is low, considering the uncertainties in the assessment, and F_{pa} is the fishing mortality leading to B_{pa} at equilibrium. The biomass B_{MSY}, at which the maximum sustainable yield (MSY) is achieved, is currently not used to manage fish stocks in the ICES Area, but given the increasing political commitment towards managing all fish stocks to achieve MSY (FAO, 2003; CEC, 2007), this reference point is also considered here. The values of the B_{pa} and B_{lim} biomass reference points were taken from ICES reports. The value of B_{MSY} and the F reference points were calculated from the model (see below).

The performance of the two HCRs was investigated (Table 2). The first (HCR1) consisted of exploiting the stock with constant F equal to F_{MSY}, the fishing mortality leading to MSY in an equilibrium situation. The second (HCR2) was similar to the management strategy currently in use for North Sea herring and cod. At SSB above B_{pa}, fishing mortality was set equal to F_{pa}. When SSB fell below B_{pa} but remained above B_{lim}, fishing mortality decreased from F_{pa} to a lowest possible F-value, F_{min}, proportional to $(B_{pa} - \text{SSB})/(B_{pa} - B_{lim})$. If SSB was below B_{lim}, then fishing mortality was set to F_{min}. The values of F_{min} used by the herring and cod assessment working groups are derived from complex simulation studies. The ratio between the values F_{min} and F_{pa} used by ICES is 0.4 for herring and 0.5 for cod. As no HCR such as HCR2 is used for the management of North Sea plaice, we arbitrarily chose to use the ratio 0.4 to calculate F_{min} from F_{pa} for that stock.

We use the convention that the HCR2 in this study would determine the level of exploitation for the coming year $(y+1)$ based on the state of the stock observed in the present year (y), which is a simplification of what is done in practice by ICES. To take account of the uncertainty in the estimates of SSB produced by the assessment method, the estimated state of the stock in year y ($\hat{\text{SSB}}_y$) was sampled in a normal distribution of mean SSB_y, the true state of the stock in year y, and of $CV = 8.5\%$ (value taken from the report of the herring assessment working group). Therefore, $F_{y+1} = \text{HCR2}(\hat{\text{SSB}}_y)$, with $\hat{\text{SSB}}_y$ sampled in $N(\mu = \text{SSB}_y, \sigma = 0.085 \times \text{SSB}_y)$.

Finally, the eHCRs, eHCR1 and eHCR2, are the variants of HCR1 and HCR2, but with the reference points F_{MSY} and F_{pa}, respectively, changing in time according to the environmental conditions, as detailed below.

F_{pa} was calculated as the fishing mortality leading to B_{pa} at equilibrium under the environmental condition prevailing at the start of the simulation. To do so, a value of recruitment at B_{pa} (R_{pa}) was required and predicted from the eSR relationship, using B_{pa} as the input value of SSB, and the average over the first 5 years of the simulation for the environmental variable(s). To estimate B_{MSY} and F_{MSY}, the value of SSB at equilibrium and the corresponding catch were calculated for a range of values of F, and the values of SSB and F for which the highest catch was observed were taken as B_{MSY} and F_{MSY}.

For HCR1 and HCR2, the F_{MSY} and F_{pa} reference points were defined at the start of the simulation period and were constant in time. For eHCR1 and eHCR2, the value of F_{MSY} and F_{pa} changed in time according to environmental conditions; if the environment deteriorated, then F_{MSY} and F_{pa} were reduced, and vice versa. The method used to determine F_{pa} (the same applies for F_{MSY}) was based on the eSR relationship (Figure 2). Setting $\text{SSB} = B_{pa}$, the environment–recruitment function was predicted using a set of 1000 equally spaced values of the environmental variables, ranging from the lowest to the highest value observed (Figure 2a). These recruitment values were divided into three

Table 2. Description of the four HCRs investigated.

HCR	Description
HCR1	F constant at F_{MSY}
HCR2	F constant at F_{pa} if $\text{SSB} \geq B_{pa}$ F constant at F_{min} if $\text{SSB} \leq B_{lim}$ $F = F_{min} + (F_{pa} - F_{min})(B_{pa} - \text{SSB})/(B_{pa} - B_{lim})$ if $B_{lim} < \text{SSB} < B_{pa}$
eHCR1	As for HCR1, but with F_{MSY} varying according to environmental conditions
eHCR2	As for HCR2, but with F_{pa} varying according to environmental conditions

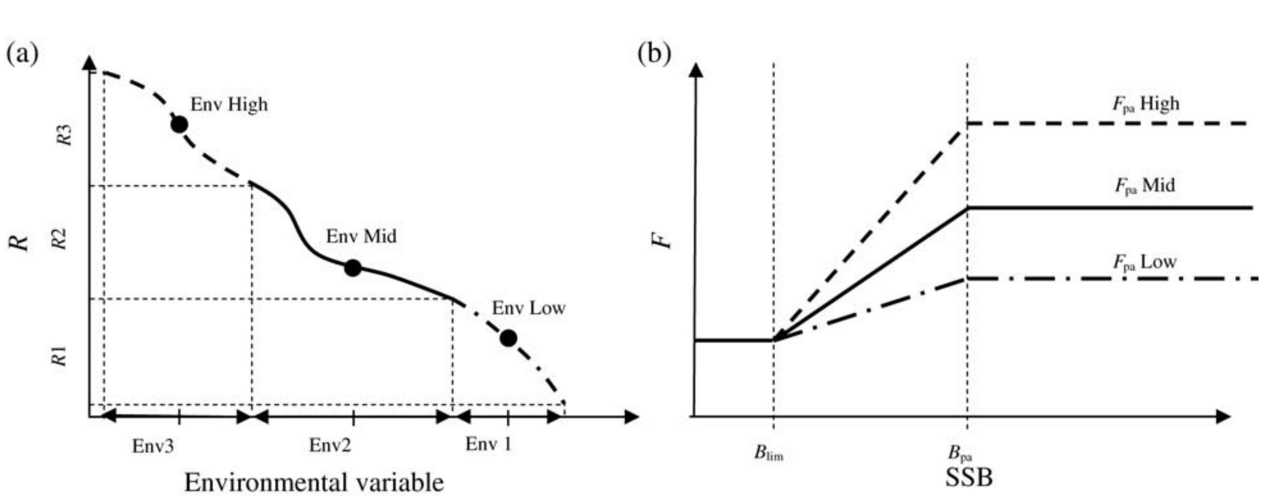

Figure 2. HCR integrating the changes in the environment (eHCR2). (a) The response function of recruitment to environment (illustrative example) is used to define three possible states of the environment. (b) Three different SSB–F relationships can be used to set the F reference point according to SSB, depending on the state of the environment.

classes of equal size (R1, R2, and R3), and based on these three recruitment classes, three environmental classes were created (Env1, Env2, and Env3, respectively, which do not necessarily have to be the same size). The median values (Env High, Mid, and Low) of these three environmental classes were used to calculate the corresponding levels of F_{pa} (F_{pa} High, Mid, and Low, respectively), which were used to determine the three SSB–F relationships that represented the eHCR2 for each environmental condition (Figure 2b). For each year, the median value of the environmental variable(s) over the previous 8 years was calculated, and depending on the class of environmental conditions to which it belonged, the state of the environment and the corresponding SSB–F function was determined. This function is the basis of the eHCR2 used for that year's (y) management that determines the level of exploitation for the following year.

Environmental scenarios tested

Unlike studies modelling the effect of future climate change on fish stocks (Kell *et al*., 2005; Röckmann *et al*., 2007; A'Mar *et al*., 2009), we decided not to use realistic climatic scenarios (e.g. that of the International Panel on Climate Change, IPCC), but generated four environmental scenarios for which the range of variation in the environmental factors was approximately the same as observed in the historical data. The rationale for this exercise was that extrapolation of recruitment produced by the GAM-based eSR relationship for values of the environmental factors outside the observed range is questionable.

The scenarios used to evaluate the HCRs consisted of 50-year time-series of the environmental factor affecting recruitment (Figure 3). In the constant scenario (C), the environmental variable used for the simulation was constant over time, equal to the mean of its observed values. That scenario aimed to test the behaviour of the stock not affected by environmental variation, with recruitment varying only because of random noise. For the random scenario (R), the value of the environmental factor was generated by sampling from a normal distribution with the same mean and variance as the actual time-series, i.e. without any trend or change over the longer term. The scenarios trend-unfavourable (TU) and trend-favourable (TF) represented a gradually changing environment, i.e. respectively, from a favourable (Env High) to an unfavourable (Env Low) state, and the reverse. For these two last scenarios, a white noise of variance equal to the variance of the actual time-series minus the variance in the long-term trend was added to the trend. By doing so, the variance of the environmental factors in scenarios R, TU, and TF was roughly equal to the variance of the actual environmental time-series.

Evaluation of HCR performance

For the three stocks, the performance of the two HCRs and the two eHCRs was tested for all four environmental scenarios by running the model 200 times with an identical model setting, i.e. in terms of biological and exploitation parameters. These 200 runs were used to investigate the variability in stock behaviour resulting from the stochastic components in the growth and recruitment models. From the 200 runs, the following diagnostics were calculated: (i) Yield, the sum of the annual yields taken from the stock for each run over the 50 years of the simulation (in tonnes), (ii) F_{bar}, the average fishing mortality over the 50 years of simulation, and (iii) Below B_{pa} and Below B_{lim}, the percentages of the years in each run for which the stock was below B_{pa} and B_{lim}, respectively.

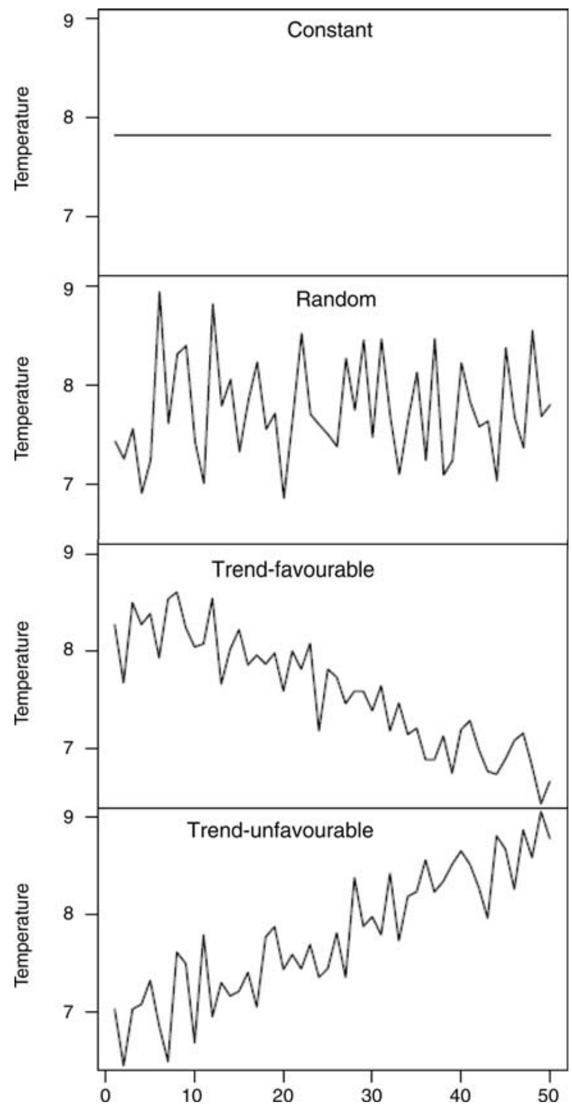

Figure 3. Visual representation for the four environmental scenarios. This is an example used for North Sea cod, where only one environmental variable (temperature) influences recruitment.

A well-performing HCR was defined as an HCR resulting in (i) a low risk for the stock (i.e. low Below B_{pa} and Below B_{lim}), (ii) a maximized catch (high Yield), and (iii) a low impact of the fishery on the stock and the ecosystem (low F_{bar}).

Results

Performance of the HCRs

In general, the four HCRs performed well in preventing the stocks from attaining levels where they would have been at risk (Below B_{lim} was almost always equal to zero in Figures 4–6). Stock collapse (defined as SSB <1% of pristine) was observed for none of the stocks (results not shown). The MSY HCRs (HCR1 and eHCR1) were always more precautionary (lower Below B_{pa}) and resulted in lower fishing pressure (F_{bar} lower by 17% for cod and 58% for herring in the constant scenario) and, generally, resulted in a higher cumulative yield than HCR2 and eHCR2 (from 5% in herring to 14% in plaice in the constant scenario).

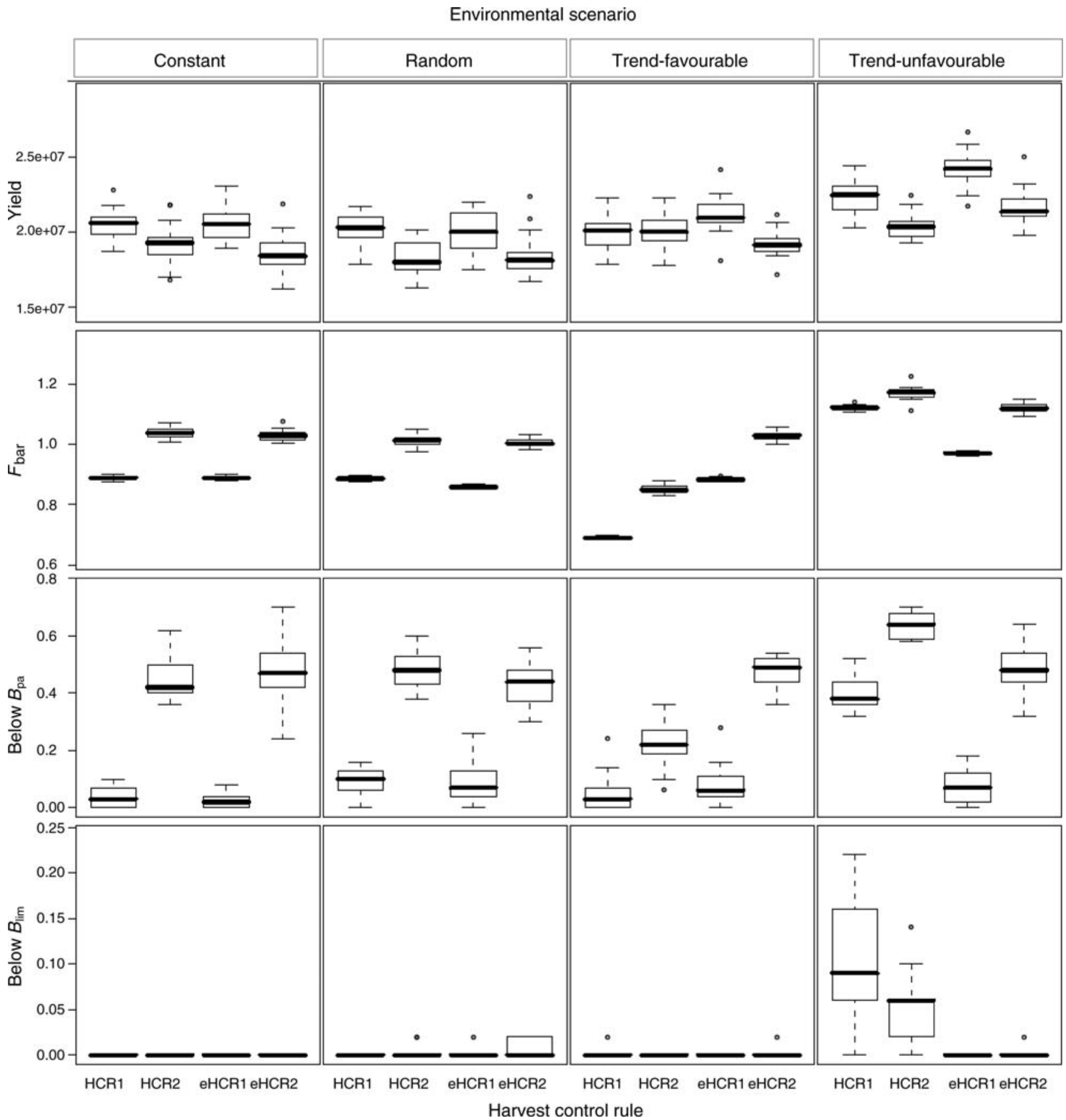

Figure 4. Performance of the four HCRs for North Sea cod for four environmental scenarios. For each environmental scenario (presented in columns), the boxplots show the distribution of the four performance diagnostics of the HCRs (in rows) for the 200 stocks simulated for each of the four HCRs tested.

The effect of environmental variability

Our first aim was to compare the performance of the conventional HCRs (HCR1 and HCR2) when the environment is constant and when it varies. There were relatively few differences in the performance of the two HCRs in a randomly varying environment compared with that in the constant-environment scenario. The main difference was a sensibly lower yield (of about 5–10%) in the random scenario compared with the constant one (except for HCR1 for cod). The average *F* was always unchanged. The time spent below B_{pa} increased in the random scenario, only slightly for HCR1 (except for cod), but more significantly for HCR2 (about 0.1 for the three species). The time spent below B_{lim} always remained at zero.

Differences in the performance of the HCRs were more pronounced between the constant scenario and the two scenarios with a trend in the environmental variables. For a favourable trend, yield was unchanged (cod) or lower (plaice and herring) than in the constant scenario for HCR1, whereas for HCR2, yield was unchanged (plaice and herring) or higher (cod). Always (except herring for HCR1), average *F* was substantially

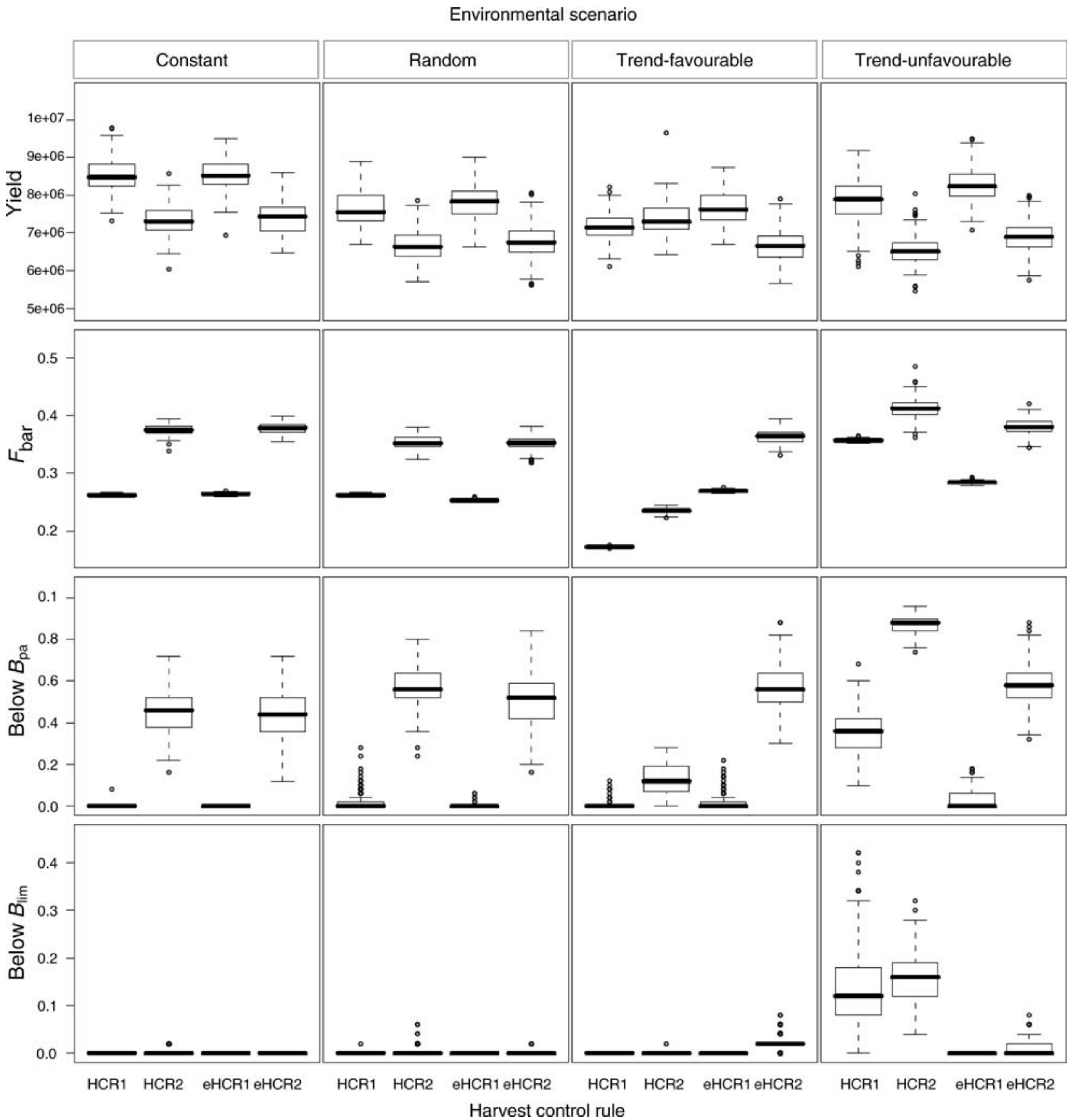

Figure 5. Performance of the four HCRs for North Sea plaice for four environmental scenarios (see Figure 4 for explanation).

lower for the favourable trend scenario than for the constant one. The time spent below B_{pa} in the TF scenario was unchanged for HCR1, but was much lower than in the constant scenario for HCR2. Again, the time spent below B_{lim} always remained at zero.

The TU scenario resulted in a higher cumulative yield for cod and herring and a lower yield for plaice, for both HCRs. Average F was always much higher than in the constant scenario (except HCR1 for herring). The time spent below B_{pa} increased dramatically (also except HCR1 for herring), reaching high values for HCR2 for cod and plaice (Below $B_{pa} > 0.6$). Plaice and cod also spent a substantial part of the time below B_{lim} with both HCR1 and HCR2.

Comparison of HCRs and eHCRs

Our second aim was to investigate whether the use of reference points varying according to environmental conditions (eHCR1 and eHCR2) instead of being fixed (HCR1 and HCR2) improved management performance. For the three stocks, HCR1 and HCR2 performed well independent of the environmental scenario, so using the eHCRs only resulted in relatively marginal improvements.

For the constant and random environmental scenarios, the eHCRs performed equally well as their conventional counterparts. For a favourable change in the environment, eHCR1 led to an improvement in the cumulative yield compared with HCR1

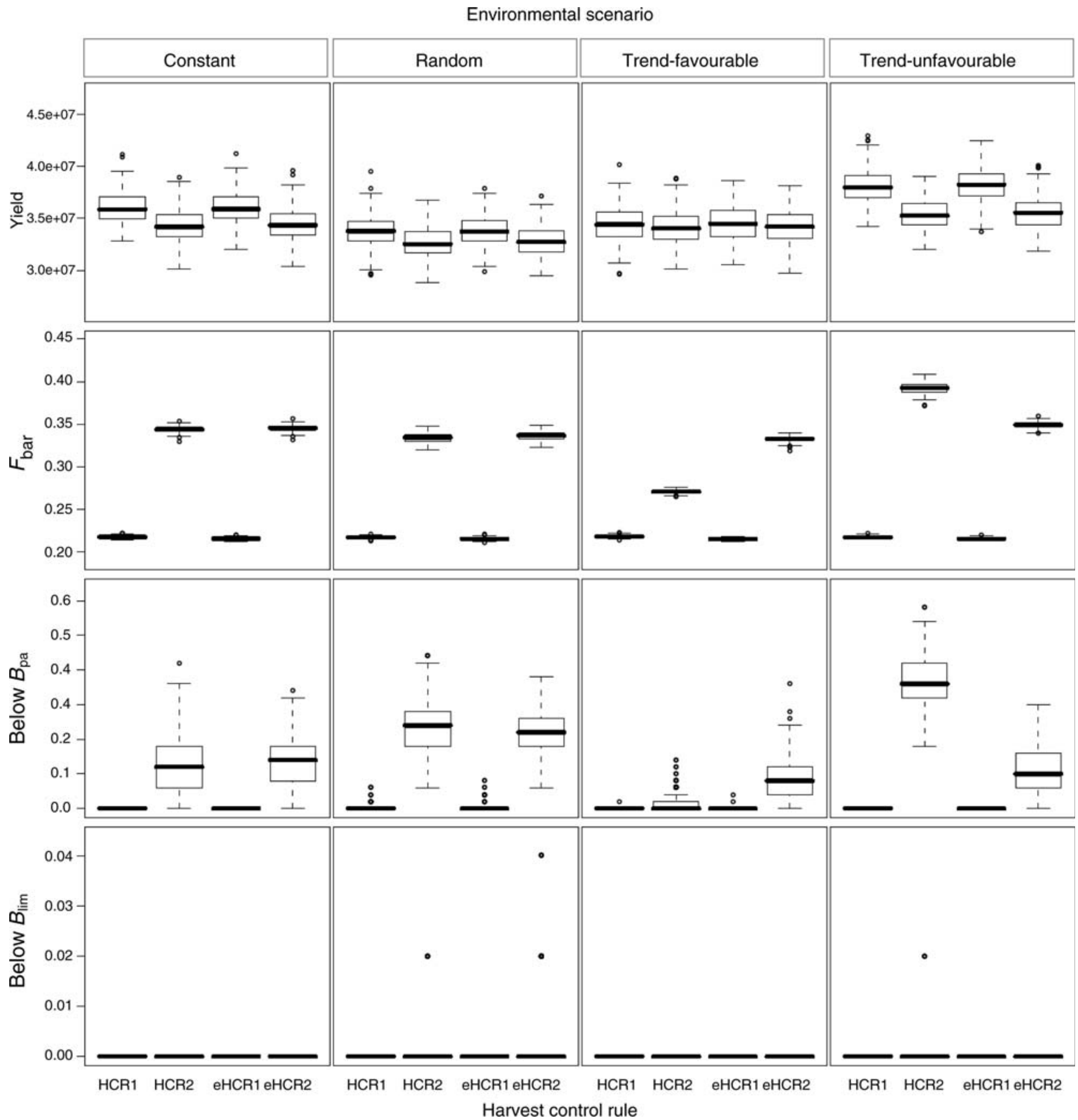

Figure 6. Performance of the four HCRs for North Sea herring for four environmental scenarios (see Figure 4 for explanation).

(plaice and cod), with no significant change in Below B_{pa} and Below B_{lim}, but with a markedly higher average F. eHCR2 also resulted in a higher average F compared with HCR2, but with a much larger proportion of time spent below B_{pa}, and a decrease in the cumulative yield. The only case for which eHCRs performed clearly better than the conventional HCRs was for an unfavourable change in the environment, for which the eHCRs resulted in higher yield than the conventional HCRs, lower average F, a decrease in the time spent below B_{pa}, and a reduction in the time spent below B_{lim}, at almost zero.

Discussion

Unlike other management-strategy-evaluation studies (Clark *et al.*, 2003; Kell *et al.*, 2005; A'Mar *et al.*, 2009), our study did not aim to produce state-of-the-stock projections of the state of the stock managed with a given procedure and based on realistic environmental scenarios. Instead, we used fictional scenarios, covering a range of environmental changes. For the sake of convenience, simplifications were made and compared with reality. These simplifications were made to create a generic tool that aimed to compare the performance of a set of eHCRs under various environmental scenarios and for different types of species in a standardized framework. First, our simulation tool did not include any stock-assessment module, so the uncertainty linked to the stock assessment method was not directly integrated in our model. However, an artificial error component of *CV* equal to 8.5% was applied to SSB_y to take account of this uncertainty in testing the performance of the HCRs. Then the way the decision on future F is taken is simplified; here, F_{y+1} is a function of SSB_y, whereas in reality, e.g. North Sea herring, F_{y+1} is decided based on SSB_{y+1}, which was not observed at the time of the assessment but projected under assumptions on the current F_y. As there is uncertainty associated with the projection, this could add noise in the management procedure and may result in a decrease in performance. However, for North Sea herring, the imprecision on the projection of SSB 1 year ahead is very low (on average 4%; M. Dickey-Collas *et al.*, pers. comm.). Moreover, the dependence of HCR on SSB_{y+1} makes it possible to incorporate the most recent information on the stock, e.g. the number of juveniles in present year y that will become mature in year $y+1$. Consequently, the real HCR implemented for North Sea herring is probably more reactive and hence performs better than the HCR2 tested here. Finally, the stock is exploited in our model exactly with the F_y value set by the HCR, whereas in practice it could differ, e.g. scientific advice not followed by the managers, quota under/overshooting. This situation is observed for many stocks and is a major cause of ineffective management (Cardinale and Svedäng, 2008). However, as the present study focused only on the performance of the HCRs, not of the whole management system, trying to integrate in the model the discrepancy between the advised and the realized F was beyond our scope.

To the current exercise, we created eSR relationships using GAMs, a method that has already been used with the same aim, but which may be criticized in terms of the lack of underlying theory for the shape of the relationships observed. The choice of the SR model used was also critical, because it affects the relationship between F and SSB at equilibrium and, hence, the estimation of the F reference points. The F reference points calculated were different from those determined by ICES for the three species (Table 1), but the difference was very small for plaice and herring. For cod, however, the F reference points estimated from our model were twice the values used by ICES. This discrepancy may be because ICES reference points were calculated in 1998, and therefore based on stock and recruitment data 10 years shorter than the time-series used here and probably using a different method. However, because of the lack of documentation on calculating North Sea cod reference points, we could not check the source of this discrepancy rigorously.

The first conclusion of this study was that, although the performance of the two conventional HCRs was not altered in a randomly varying environment compared with a constant one, this was not the case for a favourable environmental change, for which the yield dropped with HCR1, or for an unfavourable environmental change, for which neither HCR could prevent the stock from declining below B_{lim}. For a favourable trend, HCR1 still performed better than HCR2 in minimizing both the time spent below B_{pa} and B_{lim}, and the fishing pressure, but was no longer optimal in terms of yield. As the environment became more favourable, stock productivity increased and MSY moved to higher stock size and levels of F. Applying the HCR1 using F_{MSY} calculated at the start of the simulation period, therefore, resulted in a stock becoming steadily underexploited. The situation was the opposite for HCR2, for which the F_{pa} calculated at the start of the period moved gradually closer to MSY as this parameter moved towards higher levels as a result of environment change.

For an unfavourable trend in the environment, HCR1 outperformed HCR2 in terms of yield, but resulted in a proportion of the time spent below B_{lim} equal to or higher than HCR2. The unfavourable environmental change decreased stock productivity, and the F_{MSY} calculated at the start of the period corresponds to overexploitation at the end of the period, explaining why the stocks fell below B_{lim}. For HCR2, the F_{pa} level also led to overexploitation, but as F decreased proportionally to SSB, the stock only spent a limited proportion of time below B_{lim}. The extent to which the stock was affected by the unfavourable change in the environment was related to the shape of the SR curve. For cod and plaice, owing to the shape of the Ricker curve, recruitment declined when the stock fell below B_{pa}, which accentuated the unfavourable effect of environmental change. For herring, however, owing to the flat shape of the segmented regression curve, recruitment was unchanged when SSB fell below B_{pa}, and even below B_{lim} (down to about 500 000 t). Some other differences in performance of the HCRs were also observed between the three species. HCR1, exploiting the stock with a constant F equal to F_{MSY}, resulted in an average annual yield of 98 and 99% of MSY in the constant scenario for plaice and herring, respectively. For cod, however, the yield was just 76% of MSY. Cod recruitment is twice as variable as the other two stocks, and much of the variability is stochastic, i.e. not explained by the eSR relationship. Such a variability in recruitment is probably responsible for the variability in SSB, which prevented the stock from remaining exactly at MSY; the stock would vary around MSY, so resulting in catches not being maximal. This seems to be the case too in a randomly varying environment for the three stocks, which all had yields significantly lower than MSY (ranging from 85% in herring to 75% in cod).

Designing management procedures that integrate the effect of the environment on stock productivity is one of the most challenging tasks for fisheries science. One of the major impediments to achieving this goal is the difficulty in representing, in a formal mathematical model, the complexity of the mechanisms through which environmental factors can affect recruitment. The three eSR relationships used here were based only on an empirical GAM approach and had no other purpose than to serve as examples of the functional relationship linking recruitment to SSB and environmental conditions. These eSR relationships allowed us to propose and test two eHCRs in which the F reference points change according to the status of the environment.

The benefits of using eHCRs rather than conventional HCRs were different among the environmental scenarios. In the random scenario, interannual fluctuations in environmental conditions were filtered by the 8-year moving median, and the F reference points were unchanged throughout the simulation period. The eHCRs therefore behaved like the conventional ones. Using the eHCRs was clearly beneficial in the event of an unfavourable change in the environment. The decrease in F_{MSY} and F_{pa} as the environment deteriorated prevented a stock from falling below B_{lim}, which was not the case with conventional HCRs. As a consequence of the higher levels of biomass maintained, the eHCRs also yielded higher catches than the HCRs. However, although eHCR1 still performed better than HCR1 in the TF scenario, this was not the case for eHCR2, which resulted in lower Yield and higher Below B_{pa} (and higher Below B_{lim} for plaice) than HCR2. One would have expected that increasing F_{pa} with eHCR2 as conditions became more favourable would allow one to take advantage of the increased productivity of the stock, with no increase in risk. For that scenario, however, HCR2 maintained F_{pa} at a lower level, allowing stock biomass to increase to a point that later resulted in better catches and reduced risk.

Plaice was the species for which the difference in performance between HCRs and eHCRs was greatest. The GAM model explained 53% of the variability in plaice recruitment, whereas for herring and cod, it explained a lesser part of recruitment variability. The greater benefits of using the eHCR in the case of plaice, therefore, stem from the stronger link between the environment and recruitment in our model for that species. This would confirm the findings of Basson (1999) that the gain by incorporating environmental factors into management procedures depends on the strength of the environment–recruitment relationship.

The eHCRs proposed here were relatively simple and similar to the "level" approach developed by Basson (1999). Environmental conditions were classified into three groups corresponding to three different levels of recruitment productivity, with these three levels used to define three F–SSB relationships. In this "level" approach, the F_{MSY} and F_{pa} reference points could each take three values, corresponding to good, average, and poor environmental conditions.

There are several explanations for the relatively limited improvement provided by the eHCRs. First, because the choice of which of the three levels of F_{MSY} and F_{pa} should be used in a given year is based on environmental conditions over the past eight years, this eHCR acts with a delay to the environmental changes. Because of this delay, an inappropriate level of F can be maintained for several years during which the stock may be suboptimally exploited. Using a shorter moving window to determine the state of the environment would make the eHCRs react more quickly when there is a significant environmental change, but would also make them too sensitive to interannual variability in the environment. Alternatively, eHCRs could be improved by using forecasts of future variations in environmental factors, then basing the choice of F on a 5-year median of the predicted environment (Basson, 1999). Planque *et al.* (2003) showed that it was possible to forecast temperature in the North Sea using a statistical model, given the observed temperature, and to forecast cod recruitment accurately based on these predictions. However, in that study, temperature was only predicted several months ahead, and no weather forecast model is currently able to give accurate predictions at a 5-year horizon.

The second limitation of the "level" approach is that it does not permit fine tuning F_{pa} to the exact level of stock productivity. The eHCRs react to environmental change by threshold response; as long as the median of past environmental conditions remains in a given environmental class, F reference points are unchanged, and as soon as the class changes, F reference points switch to another level. It would have been theoretically possible to calculate for each year the exact value of F_{MSY} and F_{pa} corresponding to the observed environmental conditions, and to use them instead of the three levels approach. This would have resulted in more reactive eHCRs, in which F reference points change annually and can have an infinite number of possible values. This, however, may be an issue in the practical application of such eHCRs in a management context and in terms of its acceptance by stakeholders. A pragmatic alternative could be to revise reference points only when a significant environmental change has occurred, which is what the current eHCRs do.

Actual implementation of the eHCRs is hampered by a lack of robust eSR models. A purely statistical description of the relationship between recruitment and environmental factors (such as our eSR relationships), unless it is supported by a convincing explanation of the underlying biological mechanisms, cannot be considered sufficiently robust to be used for managing a stock. Besides, considering the reality of a changing climate, we would expect conditions in future that have not been observed in the past, and for which the validity of the eSR relationships established based on historical observations remains to be proven. Therefore, before eHCRs can be implemented, further work is needed to develop eSR models that not only describe the dynamics of year-class strength, but are also built on an understanding of the mechanisms through which environmental factors influence recruitment.

Acknowledgements

We thank two anonymous reviewers for useful comments on the manuscript, and J.A. Bogaards and N. Hintzen for participating in developing the operating model. The study was funded by the EU project INEXFISH (Incorporating extrinsic drivers into fisheries management).

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doi:10.1093/icesjms/fsp297