DTU Library

Implementing the precautionary approach into fisheries management: Biomass reference points and uncertainty buffers

Mildenberger, Tobias K.; Berg, Casper W.; Kokkalis, Alexandros; Hordyk, Adrian R.; Wetzel, Chantel; Jacobsen, Nis S.; Punt, André E.; Nielsen, J. Rasmus

Published in:
Fish and Fisheries

Link to article, DOI:
10.1111/faf.12599

Publication date:
2022

Document Version
Peer reviewed version

Citation (APA):
Mildenberger, T. K., Berg, C. W., Kokkalis, A., Hordyk, A. R., Wetzel, C., Jacobsen, N. S., Punt, A. E., & Nielsen, J. R. (2022). Implementing the precautionary approach into fisheries management: Biomass reference points and uncertainty buffers. *Fish and Fisheries*, *23*(1), 73-92. https://doi.org/10.1111/faf.12599

Contents

Implementing the precautionary approach into fisheries management: Biomass reference points and uncertainty buffers

Tobias K. Mildenberger[1,*], Casper W. Berg[1], Alexandros Kokkalis[1], Adrian R. Hordyk[2], Chantel Wetzel[3], Nis S. Jacobsen[1], André E. Punt[4], J. Rasmus Nielsen[1]

[1] National Institute of Aquatic Resources, Technical University of Denmark, Kemitorvet, 2800 Kgs. Lyngby, Denmark

[2] Blue Matter Science, 2150 Bridgman Ave, North Vancouver, V7P 2T9, Canada

[3] Fishery Resource Analysis and Monitoring Division Northwest Fisheries Science Center National Marine Fisheries Service, NOAA 2725 Montlake Boulevard East Seattle, Washington 98112-2097, USA

[4] School of Aquatic and Fishery Sciences, University of Washington, Box 355020, Seattle, Washington 98195-5020, USA

∗ corresponding author: t.k.mildenberger@gmail.com

Running title: Precautionary fisheries management

Abstract

The precautionary approach to fisheries management advocates for risk-averse management strategies that include biological reference points and account for scientific uncertainty (i.e., process, model, and observation uncertainty). In this regard, two approaches have been recommended: (i) biomass reference points to safeguard against low stock biomass, and (ii) uncertainty buffers that reduce the catch limit as a function of the scientific uncertainty. This study compares the effectiveness of these two precautionary approaches in recovering over-exploited fish stocks. We evaluate the performance of more than 80 harvest control rules (HCRs) within a stochastic management strategy evaluation (MSE) framework for three stocks with contrasting life-history parameters and under various levels of scientific uncertainty. The results show that both approaches reduce the risk of overfishing at the expense of expected yield. This risk-yield trade-off strongly depends on the HCRs, life-history parameters of the species, as well as the level of the scientific uncertainty. Nevertheless, some combinations of biomass threshold and limit reference points as well as uncertainty buffers lead to a more favourable risk-yield trade-off than other rules. This study elucidates the multiple factors affecting the effectiveness of management strategies and highlights key features of HCRs for precautionary fisheries management.

Keywords

harvest control rules (HCRs); management procedures; management strategy evaluation (MSE); risk assessment; scientific uncertainty;

Contents

Introduction

Fisheries management success is challenged by high levels of uncertainty inherent to ecosystems and the management process (Garcia, 2000). Uncertainty is defined as the "incompleteness of knowledge about the state or process (past, present, and future) of nature" (FAO, 1995) and can arise from natural variability in the system, observation error in the data collection process, and the practical implementation of management policies (Francis & Shotton, 1997; Rosenberg & Brault, 1993). Uncertainty translates directly into risk in the fisheries management process (Fogarty et al., 1996), such as the probability of low stock biomass. For this reason, most fisheries management systems refer to the precautionary principle in their guidelines (e.g., Department of Agriculture and Water & Resources, 2018; DFO, 2009; EU, 2013; U.S. Office of the Federal Register, 2009). The precautionary approach to fisheries management recognises the potential negative consequences associated with high uncertainty and advocates among others for the use of predefined decision rules and conservative management actions (FAO, 1995). In light of the precautionary principle, one of the key objectives of sustainable fisheries management is maximising expected returns (e.g., measured as the expected catch or revenue) from fisheries while minimising risks, such as the probability of low stock biomass (Dowling et al., 2013; Punt et al., 2001). This risk-yield trade-off predicts that expected returns associated with management tactics increase with the managers' willingness to take risks (Little et al., 2016). However, larger yields are also linked to higher variability in yield from one year to the next (May et al., 1978). Borrowing the concept of effective portfolios from finance science (Pilbeam, 2005) and based on the risk-yield-variability trade-off, we define a management strategy as 'effective' if there are no alternative strategies with: (i) the same or higher expected return and a lower risk, or (ii) the same risk and a higher or equal expected return. This study compares the effectiveness of various decision rules and conservative management actions in light of the precautionary approach to fisheries management.

Fisheries management can be implemented in many ways, including total allowable catch (TAC) limits, limits on the amount of fishing effort, restrictions in the fishing gear that can be used, temporal closures to certain areas to fishing, and socio-economic incentives (e.g., co-management, certification, or transferable fishing rights) (Selig et al., 2017). Similarly, biological reference points such as the fishing mortality rate (F_{MSY}) and biomass (B_{MSY}) corresponding to the maximum sustainable yield (MSY) remain key components of HCRs and concepts in precautionary fisheries management (Garcia, 1996; Punt, 2010). Apart from empirical HCRs that might be independent of any stock status indicator, HCRs usually link an indicator of stock abundance, for example, the estimated stock status relative to biological reference points (e.g., B/B_{MSY}), to specific management actions such as a total allowable catch (TAC) (Punt, 2010). The stock status and reference points cannot be observed but are estimated using stock assessment methods and are therefore subject to estimation uncertainty. Estimation uncertainty includes not only the uncertainty associated with natural states and processes (process uncertainty) and the measurement thereof (observation uncertainty), but also uncertainty due to structure of the estimation model (model uncertainty) (Francis & Shotton, 1997). These three sources of uncertainty are collectively referred to as scientific uncertainty (e.g., Punt & Donovan, 2007). To some extent, stochastic estimation models allow the scientific uncertainty associated with current and future stock status to be quantified as probability or likelihood distributions. Two quantitative approaches for including the precautionary approach into fisheries management have been recommended and are explored in this study: (i) Biomass (threshold and limit) reference points to safeguard against low stock biomass in the face of high uncertainty (e.g., Da-Rocha et al., 2016), and (ii) uncertainty buffers that reduce the catch limit, such as the overfishing limit (OFL) or TAC, as a function of quantified or derived scientific uncertainty of current or future stock status (e.g., Dankel et al., 2016; Shertzer et al., 2008; Wiedenmann et al., 2017).

Threshold and limit reference points, in particular those related to stock biomass, play an important role in optimal harvesting theory (e.g., Lande et al., 2001) and are the foundation for escapement strategies, where the survival ('escapement') of a certain stock biomass size is desired (Beddington & May, 1977; Getz et al., 1987; Lett & Doubleday, 1976). When predicted biomass falls below the threshold (B_{T}) fishing effort is reduced, and terminated when biomass falls below the limit (B_{L}). The absolute values and the definition of these reference points vary widely. For example, B_{T} can be defined based on an inflection point in the stock-recruitment relationship, on estimated historical biomass, or as a fraction of B_{MSY} (e.g., $0.5B_{\mathrm{MSY}}$) (ICES, 2018). Similarly, the definitions for B_{L} vary and might, for example, be based on estimated historical minimum biomass or a fraction of virgin biomass or B_{MSY} (e.g., $0.2B_0$ and $30\%B_{MSY}$, respectively) (Dichmont et al., 2017; ICES, 2018). This study evaluates the effect of various biomass threshold and limit levels defined as a fraction of B_{MSY} on the performance of the HCR.

HCRs with uncertainty buffers quantify scientific uncertainty and reduce the catch limit (Prager & Shertzer, 2010). The buffer can, for example, be derived by defining the acceptable risk (or probability) that predicted fishing mortality is above or below biological reference points (Caddy & McGarvey, 1996). This method is formally known as the P^* method, and was later refined to include the uncertainty of the reference points (Prager et al., 2003) and to be used on the predicted catch distribution rather than the fishing mortality rate (Prager & Shertzer, 2010). The distribution for the different quantities can be estimated within the assessment method, by means of simulation (Privitera-Johnson & Punt, 2020), or be a predefined measure of the uncertainty based on stock characteristics such as the amount and quality of available data. For instance, Ralston et al. (2011) provides measures of the scientific uncertainty (standard deviations in log-space) associated with current spawning stock biomass derived from a meta-analysis. We build upon previous studies (e.g., Dankel et al., 2016; Wiedenmann et al., 2017), by applying the uncertainty buffer to all components of the HCR, using assessment-based uncertainty, and combining the two above described precautionary approaches.

Based on the risk-yield-variability trade-off, we evaluate the effectiveness of various HCRs focusing on (i) the comparison between biomass reference points and the uncertainty buffer, (ii) the effect of scientific uncertainty on the HCRs, and (iii) the combination of the biomass reference points and uncertainty buffers. We use an MSE framework to compare the performances of the HCRs. MSEs simulate populations as well as the feedback between the population and the successive applications of management strategies in a closed loop (Punt et al., 2016; Smith, 1994). We use a stochastic age-based operating model to determine the population dynamics of three stocks with different life history traits. Then, we employ a stochastic production model to estimate both stock status and biological reference points with associated uncertainty. The HCR recommends a TAC based on estimated stock status that is used in the operating model to project the stock forward, i.e. closed-loop simulation framework. We identify the most effective HCRs (i.e. HCRs leading to high yield and low risk) for shorter- and longer-lived species as a HCR that combines specific biomass reference points with uncertainty buffers leading to high and stable yield while minimising the risk of overfishing.

Methods

Operating model

The operating models were based on the life history characteristics of three marine fish stocks from different geographical regions in the North Atlantic: (i) anchovy (*Engraulis encrasicolus*, Engraulidae; ICES stock code: ane.27.8) in the Bay of Biscay, representing a short-lived species (ICES, 2020b), (ii) haddock (*Melanogrammus aeglefinus*, Gadidae; ICES stock code: had.27.7.b-k) in the Celtic Sea, representing a species with intermediate life-history parameters (ICES, 2019a), and (iii) Greenland halibut (*Reinhardtius hippoglossoides*, Pleuronectidae; ICES stock code: ghl.27.1-2) in the Northeast Arctic, representing a long-lived species (ICES, 2020a). We simulated the population dynamics of the three stocks using an age-structured population model described in detail in the Supplementary Section A. The model is defined with a semiannual time step for anchovy with spawning occurring in the middle of the year (ICES, 2020b) and a yearly time step for haddock and Greenland halibut. Figure 1 shows the maturity, selectivity, natural mortality by age and the production curves for the three stocks. Spawning was assumed to occur at the beginning of each year for haddock and Greenland halibut, and in the beginning of the second semester for anchovy. We assumed an age at recruitment (to population) of zero and the Beverton and Holt stock-recruitment relationship with steepness (h) equal to 0.75 and 0.9 for all stocks (Mace & Doonan, 1988). Further, we assume auto-correlated log-normally distributed recruitment deviations with standard deviations (SD) between 0.64 and 0.77

(Supplementary Tables A1 and A2) (Thorson et al., 2014). Additionally, we evaluate the effect of lower and higher recruitment deviations by varying SDs ±50%.

FIGURE 1

We initialised the MSE with 35 years of data referred to as the historical period, which reflects the amount of relevant and standardised data available for many stocks (e.g., ICES, 2019b). We assumed that fishing effort was increasing over time and calculated the fishing mortality rate that would lead to stock biomass of approximately $0.5B_{\mathrm{MSY}}$ at the end of the historical period given process uncertainty and fishing effort during the historical period (Supplementary Figure A1). The over-exploited state allows an evaluation of the ability of the HCR to recover stocks, and amplifies the differences among HCRs. We evaluate the sensitivity of the results to the depletion level in the last historical year using an additional scenario representing an under-exploited conditions with the biomass around $2B_{\mathrm{MSY}}$ for all stocks. We added bias-corrected noise with log-normally distributed deviations to the historical fishing mortality rate: $\log(\epsilon_y^{\mathrm{F}}) \sim \mathcal{N}(-\frac{\sigma_{\mathrm{F}}^2}{2}, \sigma_{\mathrm{F}}^2)$ with $\sigma_{\mathrm{F}} = 0.15$ (Carruthers et al., 2014). Finally, we ran the projection period of 35 years, which is equal to the historical period and exceeds the maximum age of the longest lived of the three stocks (Greenland halibut: 27 yr).

Assessment model

The HCRs evaluated in this study require the quantification of stock status (relative to fishery reference points) and thus the application of a stock assessment method. In line with previous studies investigating probability-based HCRs (Caddy & McGarvey, 1996; Prager et al., 2003; Prager & Shertzer, 2010), we applied a production model to estimate reference points and stock status. In particular, we used the stochastic production model in continuous time (SPiCT; Pedersen & Berg, 2017) recommended and commonly used by ICES (ICES, 2017). SPiCT is a state-space re-parameterised version of the Pella-Tomlinson surplus production model (Fletcher, 1978; Pella & Tomlinson, 1969), i.e. quantifies uncertainty in the observation and process equations. Thus, SPiCT has the potential to derive the probability distributions of the three quantities important to fisheries management and that are part of the HCR: fishing mortality rate relative to F_{MSY} at the start of the management year (F_y/F_{MSY}), the predicted biomass relative to B_{MSY} at the start (B_y/B_{MSY}) or end of the management year (B_{y+1}/B_{MSY}), and the predicted catch during the management year C_{y+1}. The predicted catch in year y is estimated by:

$$\log(C_y) \;=\; \log\left(\int_{t=y}^{y+1} B_t\, F_t\, dt\right) + \epsilon_y^{\mathrm{C}} \tag{1}$$

where C_y is the predicted annual catch, B_t and F_t are the exploitable biomass and fishing mortality rate at time t, respectively (Supplementary Table A6), and the observation error is $\epsilon_y^{\mathrm{C}} \sim \mathcal{N}(0, \sigma_{\mathrm{C}}^2)$. SPiCT approximates continuous time by means of the Forward Euler scheme (Iacus, 2009), i.e., using small time-steps within a single year (Pedersen & Berg, 2017). All model parameters (9 fixed effect parameters, Supplementary Table A7) are estimated by maximum likelihood and the Laplace approximation using automatic differentiation, as implemented in Template Model Builder (TMB; Kristensen et al., 2016). The uncertainties of all quantities of SPiCT are estimated using the delta method assuming asymptotically normal distributions in log space (Kristensen et al., 2016; Pedersen & Berg, 2017). In line with the recommended default model configuration (Pedersen & Berg, 2017), we used two vague prior distributions (i.e., SD $\geq$ 2) for the hyper parameters $\log(\alpha) \sim \log(\beta) \sim \mathcal{N}(0, 2^2)$, corresponding to the ratios of the standard deviations of observation to process noise terms: $\alpha = \frac{\sigma_\mathrm{I}}{\sigma_\mathrm{B}}$ and $\beta = \frac{\sigma_\mathrm{C}}{\sigma_\mathrm{F}}$ (c.f. Supplementary Table A6 and A7). In addition, we used a prior for the parameter n defining the shape of the production curve as the average value pooled over all taxonomic groups in the meta-analysis by Thorson et al. (2012) ($\log(n) \sim \mathcal{N}(\log(1.478), 0.57^2)$). For computational reasons, we decreased the number of time steps of the Forward Euler scheme from the default 16 per year to 4 per year. We evaluated the sensitivity to the assumed prior distributions, the decreased number of Euler time steps, and the assessment model. In cases, where the SPiCT did not converge, we applied a status quo HCR, i.e., HCR that recommends TAC $= C_{y+1} = C_y$.

In addition to SPiCT, we used a 'simulated assessment' approach, where estimated TAC is based on the true stock status (B/B_MSY and F/F_MSY) of the operating model. We assume log-normally distributed TAC (Ralston et al., 2011) with a SD = 0.3 and biases for the stock status (B/B_MSY and F/F_MSY) of $\pm 50\%$ relative to the true values. This approach allows us to derive conclusions independent of the assessment model and quantify model uncertainty.

Data simulation

Required input data for a SPiCT assessment consist of a time series of landings or catches (i.e., landings and discards) and a relative abundance index (Pedersen & Berg, 2017). We simulated annual catches for the whole (35 yr) historical time period and two time-series of abundance indices for the last 35 and 17 years of the historical time period. For anchovy, annual catch observations were calculated as the sum of the semestral catches in weight (Supplementary Equation A12). The abundance indices correspond to the exploitable stock biomass, i.e., the part of the total stock biomass that is vulnerable to the commercial fishing gear. This assumption reflects the correction of the abundance index by the commercial gear selectivity which requires some information about the age or length composition of the fishery-dependent and fishery-independent data. While this type of information might not be available for very data-limited fish stocks, it is common practice for the application of SPiCT within ICES (ICES, 2021). The length and timing of the two surveys at the start of the year (1^{st} quarter) and mid-year (3^{rd} quarter) correspond to the ICES International Bottom Trawl Surveys (IBTS) in the North Sea (ICES, 2012). We simulated lognormal observation noise for the annual catches ($\log(\epsilon_y^\mathrm{C}) \sim \mathcal{N}(0, \sigma_\mathrm{C}^2)$) and the abundance indices ($\log(\epsilon_y^\mathrm{I}) \sim \mathcal{N}(0, \sigma_\mathrm{I}^2)$) with $\sigma_\mathrm{C} = \sigma_\mathrm{I} = 0.3$

(Supplementary Equations A15 and A16). We evaluated the effect of different levels of observation noise on the performance of the HCRs with σ_{C} and σ_{I} equal to 0.15 and 0.6 (Carruthers et al., 2014; Wiedenmann et al., 2017). Additionally, we explored the effect of implementation uncertainty by simulating log-normally distributed deviations on the realised fishing mortality rate as sensitivity scenarios. The SD of 0.15 is within the range of implementation uncertainty assumed by other studies (0.1 - 0.2) (Fischer et al., 2020; Nieland et al., 2008; Walsh et al., 2018).

Harvest control rules

This study assumes that advice is given annually for the next fishing period (year $y+1$) based on a stock assessment at the start of the same year using catches and survey data from all previous years (until the end of year y). In fact, many management systems include an intermediate year or assessment year, i.e., advice is given for year $y+1$ based on an assessment in year y using data up until year $y-1$ (abundance indices or seasonal catches might be available at the start of the assessment year y; c.f. timeline in Supplementary Fig A3) (e.g., ICES, 2019b). In this case, assumptions about fishery and biological processes during the assessment year y are required to perform a short-term forecast and predict the catch in the management year $y+1$. We explored the effect of intermediate years and two assumptions about the catch herein (continuation of the F-process or catch equals TAC of previous year) as sensitivity scenarios.

We defined the recommended TAC for any period (here year $y+1$) as a fractile of the catch distribution predicted by the assessment model given a target fishing mortality rate for that period (F^{τ}_{y+1}):

$$\mathrm{TAC} = \Phi^{-1}_{(C_{y+1}|F_{y+1}=F^{\tau}_{y+1})}(f^{\mathrm{C}}), \tag{2}$$

where $\Phi^{-1}(f^{\mathrm{C}})$ is the inverse distribution function of the predicted catch given the target fishing mortality rate and $f^{\mathrm{C}} \leq 0.5$ is the fractile for the predicted catch distribution. Note, that the fractile (f^{C}) is identical to the P^* value of the P^* method, whereas P^* does not indicate which quantity it is used for, e.g., predicted catch or relative fishing mortality. Only fractiles less than 0.5 are considered as they are more precautionary than the median and take the estimated uncertainty into account. The target fishing mortality rate F^{τ}_{y+1} is defined by

$$F^{\tau}_{y+1} = F_y \; \frac{\min\left[1, \max\left(0, \Phi^{-1}_{((B_y-B_{\mathrm{L}})/(B_{\mathrm{T}}-B_{\mathrm{L}}))}(f^{\mathrm{B}})\right)\right]}{\Phi^{-1}_{(F_y/F_{\mathrm{MSY}})}(1-f^{\mathrm{F}})}, \tag{3}$$

where B_{L} is the biomass limit and B_{T} the biomass threshold reference points and $f^{\mathrm{B}} \leq 0.5$ and $f^{\mathrm{F}} \leq 0.5$ are the fractiles of the distributions of the relative biomass and fishing mortality rate, respectively. Note that the fractile for $\frac{F}{F_{\mathrm{MSY}}}$ is $1-f^{F}$ (Eq. 3), i.e. a smaller risk fractile implies a larger fractile for this distribution. We defined the inverse distribution function for all quantities in log space. In words, this rule implies that the TAC is based on fishing at F_{MSY} when $B_y \geq B_{\mathrm{T}}$ and 0 when $B_y < B_{\mathrm{L}}$. When $B_{\mathrm{L}} \leq B_y < B_{\mathrm{T}}$, the target fishing mortality ($\mathrm{F}^{\tau}{}_{\mathrm{y+1}}$) is set to $\frac{F_{\mathrm{MSY}}(B_y - B_{\mathrm{L}})}{B_{\mathrm{T}} - B_{\mathrm{L}}}$. A wide range of HCRs are nested within this HCR formulation: 'Fishing at F_{MSY}' is obtained by setting the numerator to 1 and $f^{\mathrm{C}} = f^{\mathrm{F}} = 0.5$, i.e., the median of all distributions is used. The HCRs currently considered for management based on production models by ICES are obtained using the median of all distributions ($f^{\mathrm{C}} = f^{\mathrm{B}} = f^{\mathrm{F}} = 0.5$) and defining the biomass threshold B_{T} as $0.5B_{\mathrm{MSY}}$ and $B_{\mathrm{L}} = 0$ (ICES, 2017) as well as $B_{\mathrm{L}} = 0.3B_{\mathrm{MSY}}$ (ICES, 2021). Furthermore, the formulation can also define probability-based HCRs (Prager et al., 2003), by using any fractile (f^{C}, f^{B}, f^{F}) smaller than 0.5.

FIGURE 2

For the purpose of this study, we defined more than 80 HCR variations based on equations 2 and 3. Besides fishing at F_{MSY}, we defined 18 HCRs with various biomass thresholds (B_{T}) and limits (B_{L}; Fig. 2), for which the biomass reference points are expressed as fractions or multiples of B_{MSY}. The notation $B_{\mathrm{T}} = 0.5$ is used to refer to a biomass threshold equal to $0.5B_{\mathrm{MSY}}$. Furthermore, we defined 18 HCRs without biomass reference points but with uncertainty buffers based on fractiles of the catch distribution ($f^{\mathrm{C}} \in [0.01, 0.45]$), the distributions of F/F_{MSY} and B/B_{MSY} ($f^{\mathrm{B,F}} \in [0.01, 0.45]$), and distribution of all quantities in the HCR ($f^{\mathrm{C,B,F}} \in [0.01, 0.45]$). Lastly, we defined more than 50 combinations of various biomass reference points and uncertainty buffers (e.g., $B_{\mathrm{L}}0.3, B_{\mathrm{T}}0.5, f^{\mathrm{C,B,F}}0.35$).

Performance metrics

We evaluated the performance of the HCRs based on the following four metrics.

1. Risk of overfishing (Prop($B < B_{\mathrm{lim}}$)), defined as the average proportion of replicates in which the true biomass (i.e., B of the operating model) at the end of the stock-specific management period is below the limit reference biomass B_{lim} (ICES, 2013b), where we define B_{lim} as the biomass corresponding to surplus production = 50% MSY (ICES, 2013a). The 95% intervals for the average risk were estimated by using the Wilson score interval method for Binomial proportions (Wilson, 1927). Note that we assign another symbol for the biomass limit defined in the operating model B_{lim} rather than B_{L} used before to emphasise the difference between the biomass limit specified in the HCR and that used in the operating model and used for the calculation of risk.

2. Relative yield, defined as the median annual catch relative to the yield obtained when fishing with true F_{MSY} over the stock-specific management periods and over replicates. The 95% intervals of total and average annual yield were calculated by using the modified Cox method (Olsson, 2005).

3. Absolute interannual variability in yield (AAV), defined as the median annual differences in yield during the stock-specific management periods over replicates (Punt, 2003):

$$\mathrm{AAV} = \frac{\sum_y |C_y - C_{y-1}|}{\sum_y C_y}, \tag{4}$$

where C_y is the catch during year y.

4. Median stock status in terms of B/B_{MSY} and F/F_{MSY} at the end of the stock-specific management periods.

We define a HCR most effective as a rule that reaches a more desirable location in the risk-yield space, meaning higher yield for same risk or same yield with lower risk. To improve the comparability between stocks we calculated all performance metrics based on stock-specific management periods corresponding to the maximum age of each species, i.e., 4, 8, and 27 years after start of the management for anchovy, haddock, and Greenland halibut, respectively. We conducted 500 replicates for each stock and evaluated the stability of all performance metrics against the number of replicates; results indicated that the number of replicates for each stock was sufficient.

Results

In the following, we will present the performance of the HCRs by focusing on (i) the comparison between biomass reference points and uncertainty buffers, (ii) the effect of scientific uncertainty, (iii) the combination of the two precautionary approaches, and (iv) the sensitivity of the results to the assumptions of the simulation framework.

Biomass reference points and uncertainty buffers

Biomass reference points and uncertainty buffers reduce the risk of overfishing defined as Prop($B < B_{\mathrm{lim}}$) in comparison to fishing at F_{MSY}. The absolute risk reduction depends on the stock, B_{L} and B_{T} as well as on the uncertainty buffer. For instance, higher biomass thresholds and limits as well as larger buffers (smaller fractiles) lead to lower risk levels. Fishing at F_{MSY} implies a relatively high risk of $B < B_{\mathrm{lim}}$ of $0.32, 0.18$, and 0.1 for anchovy, haddock, and Greenland halibut, respectively. These high risk levels can be explained by the highly fluctuating population dynamics for anchovy and haddock especially due to recruitment variability with a high inherent risk as well as the combination of the over-exploited conditions at the start of the management (year 35) and the slow recovery rate for Greenland halibut. In comparison, using a biomass threshold equal to 4 times B_{MSY} or an uncertainty buffer defined by the 1$^{\mathrm{st}}$ fractile of the predicted catch distribution ($f^{\mathrm{C}} = 0.01$) reduces risk by $56-81\%$ to levels below 0.07, 0.07, 0.04 for anchovy, haddock, Greenland halibut, respectively. At the same time, however, the greater level of precaution comes at the expense of loss in expected yield. While fishing at F_{MSY} leads to a relative yield of 0.8 for anchovy, 1 for haddock and Greenland halibut, the loss in yield lies between $34\% - 57\%$ for the previously mentioned HCRs and the three stocks in comparison to fishing at F_{MSY} (Supplementary Tables B1-B3). Interestingly, this risk-yield trade-off is not linear proportional, but up to certain biomass reference points and uncertainty buffers risk can be reduced without any or only minor loss in expected yield in comparison to fishing at F_{MSY} (upper row in Fig. 3). In fact, for haddock and Greenland halibut, HCRs with $B_{\mathrm{T}} \leq 1$ (with and without B_{L}) reduce risk up to 50% with only a minor expected loss in yield ($< 5\%$). While overall, the risk-yield trade-off trajectory described by the HCRs with increasing B_{T} is similarly independent of $B_{\mathrm{L}} \in \{0, 0.1, 0.2, 0.3, 0.5\}$ for haddock and Greenland halibut, for anchovy, HCRs with a lower B_{L} are more effective than higher biomass limits (Fig. 3).

FIGURE 3

Uncertainty buffers defined by fractiles on the predicted catch distribution (f^{C}) describe a similar risk-yield trade-off to biomass reference points, but are slightly less effective for haddock and Greenland halibut (Fig. 3). While, the uncertainty buffers based on different quantities (f^{C}, $f^{\mathrm{B,F}}$, and $f^{\mathrm{C,B,F}}$) lead to the same relative risk-yield trade-offs, the absolute effect of the fractile (e.g. 25^{th}) depends on the quantities considered (Supplementary Fig. B1). In this study, the trade-off is most precautionary when considering all quantities ($f^{\mathrm{C,B,F}}$) and similarly for f^{C} and $f^{\mathrm{B,F}}$. This means, for instance, that the $f^{\mathrm{C,B,F}} = 0.35$ rule leads to a similar risk as the $f^{\mathrm{C}} = 0.25$ and $f^{\mathrm{B,F}} = 0.25$.

In terms of the yield-variability trade-off, uncertainty buffers outperform biomass reference points for all stocks (middle row in Fig. 3). While AAV continuously decreases with increasing uncertainty buffers, biomass reference points can lead to high AAV. The results indicate that the variability is larger the steeper the slope of the hockey-stick HCR is, i.e. the closer B_{L} and B_{T}, and the higher B_{L}.

Another fundamental difference between biomass reference points and uncertainty buffers lies in the temporal characteristics of the effect on TAC recommendations. While biomass reference points apply markedly low fishing mortality right after the start of the management when stock biomass is low (around $0.5B_{\mathrm{MSY}}$), uncertainty buffers apply fishing mortality consistently lower than estimated F_{MSY} throughout the whole projection period (Supplementary Figures B2-B4). The lower TAC using biomass reference points at the start of the projection period leads to both a faster stock recovery and also higher catches later. This is most pronounced for Greenland halibut, which requires a longer time to recover from the over-exploited conditions. At the same time, the time series plots also indicate that the variability in yield and biomass is larger for biomass threshold reference points than uncertainty buffers (Supplementary Figures B2 and B3).

Fishing at F_{MSY} is close to the expected center of the Kobe plot indicating optimal exploitation for all stocks after the stock-specific evaluation periods (4, 8, 27 years for the three stocks, respectively; bottom row in Fig. 3). Nevertheless, all stocks are slightly over-exploited in terms of biomass ($0.6 \geq B/B_{\mathrm{MSY}} \leq 0.7$), and haddock and Greenland halibut additionally in terms of F ($1.1 \geq F/F_{\mathrm{MSY}} \leq 1.2$).

The results indicate that both higher biomass reference points and uncertainty buffers affect the exploitation status and lead to lower F and higher biomass (Fig. 3).

Scientific uncertainty

An important component of scientific uncertainty is process uncertainty, here expressed in terms of log-normally distributed recruitment deviations. For haddock, larger process uncertainty increases the risk of overfishing and decreases expected yield relative to fishing at F_{MSY}. HCRs with high biomass limits $B_{\mathrm{L}} \geq 0.5$ can lead to a substantial and increasing loss in expected yield with increasing process uncertainty (Fig. 4).

FIGURE 4

The patterns are similar for the other two stocks. However, for anchovy, already biomass limits of $B_{\mathrm{L}} \geq 0.3$ can lead to larger and increasing loss in expected yield (Supplementary Fig. B5), and for Greenland halibut, the loss in yield due to increasing process uncertainty is less pronounced, but makes a significant jump when considering $B_{\mathrm{T}} >= 2$ (with or without B_{L}; Supplementary Fig. B6).

Another component of scientific uncertainty is observation uncertainty, here defined as log-normally distributed variability around catch and abundance index observations. Larger observation uncertainty increases the risk of overfishing and leads to similar or lower expected yield for all stocks. However, similar to process uncertainty, uncertainty buffers and biomass reference points decrease risk across all observation uncertainty levels, while only larger buffers or reference points lead to substantial loss in yield for all stocks (Fig. 5 and Supplementary Figures B7 and B8). In addition, larger uncertainty buffers reduce the sensitivity to observation uncertainty (corresponding to a lower slope of lines in Fig. 5). The same is true for high biomass reference points for Greenland halibut. Similar to process uncertainty, HCRs with high biomass threshold ($>= 2B_{\mathrm{MSY}}$) show a jump in expected yield to lower levels across various observation uncertainty levels for Greenland halibut and haddock (Supplementary Fig. B8). Across all stocks, the effect of observation uncertainty is largest for Greenland halibut, for which the risk increases by 317% when fishing at F_{MSY}.

FIGURE 5

Model uncertainty is another important component of scientific uncertainty. In this study, model uncertainty is expressed as differences between the operating and assessment model, which lead to biased estimates of stock status from the assessment model (Table 1). While for Greenland halibut, the bias in estimated stock status is below 23% across all scenarios, B/B_{MSY} is underestimated with biases up to -52% and -34% and F/F_{MSY} is over- and underestimated with biases up to 54% and -15% across all scenarios for anchovy and haddock, respectively. The bias does not only vary between stocks, but also between the assumptions of observation and process uncertainty (Table 1). For anchovy, both increasing observation and process uncertainty increase the bias in estimated stock status substantially. For haddock, the bias in B/B_{MSY} increases and the bias in F/F_{MSY} decreases with higher uncertainty.

For halibut, the bias in F/F_{MSY} is relatively consistent across all levels of uncertainty, but the bias in B/B_{MSY} decreases with higher uncertainty. While for anchovy, the bias remains throughout the whole time series, the bias in fishing mortality and biomass decreases over time for haddock (Supplementary Fig. B4).

TABLE 1

The framework with simulated assessments confirms previously described findings that both precautionary approaches reduce the risk of overfishing at the expense of expected yield. Furthermore, the results show that across all stocks, biomass reference points describe a more effective risk-yield trade-off. In fact, specific combinations of thresholds and limits minimise the risk close to 0 without any loss in expected yield. The results indicate that the optimal B_{T} and B_{L} combinations correlate with the life-history parameters of the species, with higher values for shorter-lived and smaller values for longer-lived species (Supplementary Figures B9-B14). Moreover, the framework reveals that the trade-offs also depend on the bias in estimated stock status. While overestimated F/F_{MSY} leads to low risk and low expected yield for all rules, underestimated F/F_{MSY} leads to high risk, but uncertainty buffers and biomass reference points reduce the risk at the expense of expected yield. Bias in B/B_{MSY} does not affect the performance of the uncertainty buffers (which do not use biomass reference points). By contrast, the performance of biomass reference points is highly sensitive to over and underestimation of B/B_{MSY} (Fig. 6). For anchovy, for instance, given underestimated F/F_{MSY}, $B_{\mathrm{T}} = 1$ and $B_{\mathrm{L}} \leq 0.5, B_{\mathrm{T}} = 0.5$ are the most efficient rules when assuming an -50% bias in B/B_{MSY}. However, when assuming an +50% bias in B/B_{MSY}, the risk associated with these rules can be almost as high as when fishing at F_{MSY} (upper row in Fig. 6). In turn, the most effective rules under overestimated B/B_{MSY} lead to largely reduced yield when B/B_{MSY} is underestimated. This pattern is also evident for haddock and Greenland halibut (Supplementary Figures B15 and B16).

FIGURE 6

Combining biomass reference points and uncertainty buffers

So far, we only presented results of HCRs that consider either one of the two precautionary approaches. However, biomass reference points and uncertainty buffers can also be combined. Figure 7 reveals that the combination of low biomass threshold (and limit) reference points with uncertainty buffers outperforms uncertainty buffers by themselves and is as or more effective than HCRs with high biomass reference points but without uncertainty buffers. Additionally, the combined rules also lower the high AAV associated with some biomass reference points. This effect is largest for anchovy and less pronounced for Greenland halibut.

As described for the uncertainty buffers above, also for the combined rules, absolute risk and catch reduction depends on the fractile as well as the quantities considered (order in terms of risk reduction: $f^{\mathrm{C,B,F}} > f^{\mathrm{B,F}} > f^{\mathrm{C}}$). While overall the various fractiles (f^{C}, $f^{\mathrm{B,F}}$, $f^{\mathrm{C,B,F}}$) describe similar relative risk-yield trade-offs, $f^{\mathrm{B,F}}$ rules are slightly more effective than the other rules. At the same time, f^{C} rules are more effective in terms of the yield-variability trade-off (Fig. 7).

FIGURE 7

Moreover, the combination of the two precautionary approaches offers a solution to sensitivity of biomass reference points to the accuracy of B/B_{T} (and B/B_{L}). For anchovy, for instance, the expected yield of the $B_{\mathrm{T}} = 0.5, f^{\mathrm{C}} = 0.25$ rule is only 18% smaller than the yield of the $B_{\mathrm{T}} = 0.5$ rule, independent of the bias in B/B_{MSY}. At the same time, the additional uncertainty buffer has the same risk when B/B_{MSY} is underestimated and almost half the risk of the rule without the buffer when B/B_{MSY} is overestimated (bottom row in Fig. 6). The same holds for haddock and Greenland halibut (Supplementary Figures B15 and B16).

Sensitivity scenarios

The results of the sensitivity scenarios confirm that the risk-yield-variability trade-off is generally not sensitive to the Euler time step in the assessment model, the assumptions regarding the intermediate year, or the implementation uncertainty for any of the stocks. Even though, implementation uncertainty (SD = 0.15) leads to slightly larger AAV in comparison to the baseline scenario without an intermediate year or implementation uncertainty for Greenland halibut (Supplementary Figures B21-B23).

In contrast, the prior distributions as well as the quality and quantity of available data largely affects the results. Assuming a wide prior on the shape of the production curve (parameter n) around 2 (corresponding to a Schaefer-like production model) leads to slightly higher risk for all stocks and slightly lower yield for anchovy and haddock (upper row in Fig. 8). Removing all priors shows the same trend but more pronounced, in particular for Greenland halibut. Higher risk and lower yield can be explained by the lower percentage of converged assessments. In fact, only around 23% of the assessments converge when all priors are removed for Greenland halibut (Supplementary Table B9). While the median bias in estimated stock status is similar for different prior assumptions for anchovy and haddock, then removing priors substantially affects the bias in B/B_{MSY} (-24%) and F/F_{MSY} (-37%) for Greenland halibut (Supplementary Table B10). For haddock and anchovy, the effect of the prior is larger for the precautionary rules than for fishing at F_{MSY}, which can be explained by a lower convergence rate for these rules (Supplementary Table B9).

Similarly, the quality and quantity of available data affects the risk-yield trade-off for all stocks (bottom row in Fig. 8). A shorter time series and only one abundance index (scenario "20yr") leads to higher risk, lower yield, and higher variability in yield for all stocks. The effect of available data is also reflected in frequent low convergence rates of 58%, 72%, and 85% for anchovy, haddock, and Greenland halibut, respectively, and in increasing median bias in estimated stock status for haddock and Greenland halibut (Supplementary Tables B9 and B10). In comparison, lacking fishery-independent information but using catch and effort data over the whole time series shows similar results for anchovy and haddock, but an even less effective trade-off for Greenland halibut (scenario "Effort" in Fig. 8), which can be explained by the low convergence rate of 24% for this scenario for Greenland halibut.

FIGURE 8

The patterns for the two precautionary approaches are not only present in the recovery of highly over-exploited stocks, but also for under-exploited stocks, i.e. for stocks with a decreasing fishing effort pattern during the historical time period and under-exploited conditions in the last historical year (around $2B_{\mathrm{MSY}}$), even though the overall risk is lower for the under-exploited than for the over-exploited stock (Supplementary Fig. B24). Besides larger AAV for HCRs with biomass reference points, the performance of the HCRs is similar between the two scenarios for Greenland halibut. For haddock, on the other hand, the overall risk is low for all rules and higher biomass reference points and uncertainty buffers only reduce the yield for the under-exploited scenario. For anchovy, biomass reference points and uncertainty buffers still reduce risk, however, the risk-yield-variability trade-off is more effective for uncertainty buffers than biomass reference points (Supplementary Fig. B24). Similarly to the over-exploited scenario, rules with both precautionary approaches combined allow to reduce risk without substantial loss in yield and largely reduce the AAV (Supplementary Fig. B25).

Assuming a steepness of the stock-recruitment relationship equal to 0.9 (in comparison to 0.75), shows the same relative risk-yield-variability trade-off for all stocks. The only apparent difference is the higher absolute risk levels for all HCRs and stocks (Supplementary Figures B26 and B27).

Despite the sensitivity of the results to the prior assumptions, available data, and the exploitation history in absolute terms, the overall patterns between HCRs remain and the precautionary approaches individually and combined are more precautionary than fishing at F_{MSY}.

Discussion

The precautionary principle is a central component of modern fisheries management (e.g. Department of Agriculture and Water & Resources, 2018; DFO, 2009; EU, 2013; U.S. Office of the Federal Register, 2009). Although, the guidelines and recommendations regarding its implementation vary between management systems, predefined harvest control rules together with target, threshold and limit reference points and uncertainty buffers are the main recommended approaches for the implementation of the precautionary approach into fisheries management (e.g. DFO, 2009; Link et al., 2021; Punt, 2010). We evaluated the performance and effectiveness of biomass reference points and uncertainty buffers individually and combined in terms of the trade-off between risk of overfishing, expected yield, and variability in yield for three stocks with contrasting life history traits and under a wide range of scientific uncertainties.

Biomass reference points and uncertainty buffers

Both precautionary approaches reduce the risk of overfishing and lead to faster stock recovery for over-exploited stocks than HCRs without a precautionary approach such as fishing at F_{MSY}. While overall the risk reduction comes at the expense of a loss in expected yield, some values and combinations of biomass thresholds, limits and uncertainty buffers reduce risk without substantial loss in yield. This finding is in line with previous studies demonstrating that biomass-based and probability-based control rules can maintain high average yield while reducing risk of low biomass (Benson et al., 2016; Irwin et al., 2008; Punt et al., 2008; Wiedenmann et al., 2017).

Biomass threshold and limit reference points reduce the risk of overfishing by reducing or terminating fishing mortality if biomass falls below a threshold or limit. Our results show that biomass reference points are highly effective in recovering over-exploited stocks as they imply fishing below F_{MSY} if the stock biomass is low and return high expected yield as they imply fishing close to F_{MSY} if the stock is recovered or abundant in general. Small biomass thresholds and/or limits can reduce the risk of overfishing substantially without any loss in expected yield, in particular, for long-lived species. On the downside, biomass thresholds and limits can lead to large variability in expected yield, especially for stocks that exhibit fluctuating population dynamics. Results indicate that the variability correlates positively with (i) the steepness of the ascending part of the hockey-stick rule (i.e. distance between B_{L} and B_{T}) and (ii) the level of the biomass limit. In other words, a high biomass limit or the threshold and limit being close to each other can lead to large variability in yield. While from an ecological perspective, high variability in yield is not concerning and has in fact been shown to be a major component contributing to effective and adaptive management (Charles, 1998), from a social and economic standpoint, it is more problematic for many reasons. For example, fishers might not have an alternative source of income and some running costs of the fishing vessels and production facilities are independent of the yield. Furthermore, it can lead to inconsistent TAC advice in multi-species fisheries due to flow-on effects on biomass (Little et al., 2009). Another disadvantage of biomass reference points is that they add another layer of dependency on the accuracy associated with the estimation of the biomass reference points. The findings showed that overestimated B/B_{MSY} can lead to high risk and underestimated B/B_{MSY} to low expected yield of otherwise effective and precautionary reference points.

Overall, our results confirm the findings of Punt et al. (2008), that a wide range of biomass reference points lead to low risk levels and pretty good yield (80% of MSY; Hilborn, 2010). In fact, some rules with intermediate uncertainty buffers or thresholds showed a higher expected yield than fishing at f_{MSY}, a pattern which was also found by Wiedenmann et al. (2017). The results indicate that the bias in estimated stock status is likely to be one of the main factors contributing to the higher yield of more conservative rules, as fishing at F_{MSY} gives the highest expected yield for the under-exploited scenario that does not show the same bias in estimated stock status (Supplementary Fig. B24). Furthermore, the results indicate that higher biomass thresholds show a similar performance as biomass limits and might even be more effective, in particular for short-lived species, such as anchovy. High biomass thresholds and limits, on the other hand, are likely to lead to a substantial loss in yield, in particular for long-lived species, such as Greenland halibut.

Alternative definitions of biomass thresholds and limits independent of B_{MSY} are likely to be between 0 and $4B_{\mathrm{MSY}}$ and thus accounted for in this study to some extent. While definitions for B_{T} and B_{L} other than as a fraction or multiple of estimated B_{MSY} might be independent of the performance of the assessment model, they have to be based on some model as they refer to a derived quantity (biomass). Thus, there might be an advantage of the approach used here as the use of the relative quantity eradicates the problem of absolute scale which is linked to a higher uncertainty (e.g.

Mildenberger et al., 2020; Pedersen & Berg, 2017; Punt et al., 2018).

Another promising precautionary approach is the use of uncertainty buffers defined as fractiles of the quantities used in the HCR. This approach quantifies and propagates uncertainty into management advice and leads to a consistent reduction in risk and variability in yield across stocks and levels of scientific uncertainty. While, uncertainty buffers are less effective than biomass reference points, in particular for longer-lived stocks, they still reduce risk without substantial loss in expected yield. For shorter-lived species, uncertainty buffers were as effective or even more effective than biomass reference points. This finding can likely be attributed to the fluctuating population dynamics of the shorter-lived species. Large fluctuations in stock size due to the large recruitment deviations as well as the age-composition of the population challenge the deterministic concept of MSY (Lande et al., 2001; Sæther et al., 1996), at least in terms of target reference points (Punt, 2010). Thus, a fishing mortality lower than F_{MSY} over a wide range of biomass as implied by uncertainty buffers or a high B_{T} might be an important component of precautionary fisheries management for shorter-lived species. Along the same lines, uncertainty buffers interpret F_{MSY} as a target only if uncertainty approximates zero, contributing to the notion of F_{MSY} as limit reference point (Mace, 2001; Wiedenmann et al., 2017). Thus, uncertainty buffers lead to the incentive to reduce the observation uncertainty, e.g. by improving data sampling programs (Punt & Donovan, 2007). Regarding uncertainty buffers individually, there were only minor differences between the trade-offs associated with the distributions of the different quantities in the HCR. The absolute differences could be accounted for by using a smaller fractile when only considering the predicted catch distribution and considering a larger fractile when considering all quantities (Supplementary Fig. B1).

Uncertainty in fisheries management

Process uncertainty arising from natural variability, e.g., in the recruitment process, affects the performance of all HCRs, with higher process uncertainty leading generally to higher risk and lower yield. This is not surprising as increasing process uncertainty leads to larger variability in stock size and thus directly translates into the definition of risk used in this study ($\mathrm{Prob}(B < B_{\mathrm{lim}})$) as well as lower predictability of future states (Charles, 2001). Moreover, process uncertainty is reflected in the distribution of predicted catch estimated using the assessment method. In fact, for anchovy, estimated standard deviation (SD) of the predicted catch (C_{y+1}) increases from 0.42 to 0.74, and for haddock from 0.39 to 0.49, from the scenario with the lowest to the one with the highest process uncertainty (Supplementary Table B5). For Greenland halibut, the SD remains constant for these scenarios (0.38). These differences also explain why the risk reduction by uncertainty buffers is larger for anchovy and lesser for Greenland halibut.

The definition of B_{lim} as the biomass where surplus production = 50% MSY leads to values close to $50\%B_{\mathrm{MSY}}$ commonly assumed in fisheries management guidelines in the EU (ICES, 2017), the US (e.g., Hilborn & Stokes, 2010), and Australia (Department of Agriculture and Water & Resources, 2018; Rayns, 2007), and accounts for the shape of the production curve. Future research should compare the implications of various ratios (surplus production/MSY) for the definition of B_{lim} as well as other risk definitions.

Similarly, increasing observation uncertainty arising from the data collection process increases the uncertainty and bias of estimated quantities, and thus generally increases the risk of overfishing and reduces expected yield. However, both biomass reference points and uncertainty buffers lead to low risk across a wide range of observation uncertainty in line with findings by Dankel et al. (2016). For Greenland halibut, biomass reference points can even lead to lower risk levels while maintaining higher expected yield. Although, we covered a wide range of observation uncertainty (SD $= 0.15 - 0.6$) as assumed by Carruthers et al. (2014) and by Wiedenmann et al. (2017), the information-content of the data also depends on the quantity of available data (Bentley & Stokes, 2009) and the contrast in the data in terms of periods of high and low biomass levels (Hilborn & Walters, 1992; Ono et al., 2012; Punt & Szuwalski, 2012). Reducing available data from a 35-year time series to 20 years and assuming only one abundance index reduces the performance of all HCRs (higher risk and/or lower yield). In this case, the shorter time series does not only reduce the number of data points, but also its contrast, as the shorter time series lacks information about the historical period of typical low exploitation rate and high stock biomass (Supplementary Fig. A2). Despite the higher non-convergence rate and higher biases, the precautionary HCRs still outperforms fishing at F_{MSY} with only 20 years of one abundance index or without any fishery-independent data. If the data quality and quantity do not allow the estimation of the uncertainty buffer based on a quantitative stock assessment as presented here, alternative uncertainty buffers based on pre-defined tier-based values could be considered (Ralston et al., 2011).

Model uncertainty describes the incomplete knowledge of nature's processes and states, and in an MSE context, is defined by the structural differences between the operating and assessment model. The operating model in this study is a discrete-time age-based model while the assessment model is a surplus production model in continuous time without any length or age structure. Among others, these structural differences lead to differences in simulated and estimated stock status and perception over time. Overall, the median bias is largest for anchovy and lower for haddock and Greenland halibut. While the median biases for anchovy remain throughout the projection period, the bias decreases over time for haddock (Supplementary Figures B2-B4). While these results might indicate a general tendency for the relation of the accuracy of SPiCT estimates to the life history parameters, the biases are specific to the assumptions of this study and based only on three stocks. The biases can not only be attributed to the fundamental differences between the operating and assessment model (age-based vs. biomass-pool model, auto-correlated recruitment deviations in the operating model, fixed exploitation pattern vs. random walk process for F, density-dependence, etc.), but also to high observation uncertainty. Future research is needed to confirm the potential correlation between the accuracy of the stock status estimated with SPiCT and life-history parameters of the stock. Nevertheless, the results of this study do not show systematic biases for SPiCT as found by Bouch et al. (2020). By contrast, both F/F_{MSY} and B/B_{MSY} are both over and underestimated across stocks and scenarios with various levels of scientific uncertainty. The systematic and non-precautionary bias found by Bouch et al. (2020) might have been caused by various factors, such as using biomass indices that correspond to the biomass that is vulnerable to the scientific gear rather than the commercial gear. In comparison, this study uses an exploitable biomass index, i.e., survey index that does not include the smaller individuals that are not part of the exploitable biomass, in line with common practice of stock assessments using SPiCT (ICES, 2021). The findings indicate that the reduction of fishing mortality by high biomass thresholds and uncertainty buffers protects against potentially underestimated F/F_{MSY} as well as overestimated B/B_{MSY}. At the same time, uncertainty buffers and biomass reference points might also lead to an additional loss in yield when F/F_{MSY} is overestimated or B/B_{MSY} underestimated, respectively. Although these precautionary HCRs might buffer against model uncertainty, they do not replace careful model selection and rigorous model validation (e.g, Kell et al., 2021; Thygesen et al., 2017).

Model uncertainty is also apparent in terms of non-converged assessments. Although, the overall convergence rate is quite high (around 95-98%), poor quality and quantity of available data can reduce the convergence rate substantially (22-85%; Supplementary Table B9). The results also showed the significance of priors in that respect. For instance, for Greenland halibut only 19-23% of the assessments converged when no priors were assumed. Priors might also affect the distributions used for the estimation of the uncertainty buffer by the fractile approach. Even though priors did not affect the estimated distributions markedly (Supplementary Table B11), future research should further explore the effect of priors on the performance of SPiCT specifically and probability-based HCR generally.

Another important type of uncertainty in fisheries management systems arises from the effectiveness of management decisions that are designed to ensure that catch limits are not exceeded, also called implementation uncertainty. This uncertainty might not only have large negative implications on the performance of the management strategy, but it is also generally underrepresented in fisheries related papers (Fulton et al., 2011; Nielsen et al., 2018). Although we excluded implementation uncertainty in the main analysis to isolate the performance of the HCRs rather than the management of a specific stock, i.e., the actual catch corresponds to the recommended TAC, we explored the effect of unbiased log-normally distributed implementation noise ($SD = 0.15$) in the sensitivity analysis. The results did not indicate significant differences in the risk-yield trade-off. However, implementation uncertainty affected the variability in yield, with larger uncertainty leading to larger variability, in particular for Greenland halibut.

Combining precautionary approaches

Biomass reference points are an important component of precautionary fisheries management (FAO, 1995; Punt et al., 2008) and are incorporated into fisheries guidelines worldwide. By contrast, uncertainty buffers are uniformly not yet incorporated into management, even though recommended by several scientists (e.g., Link et al., 2021; Privitera-Johnson & Punt, 2020; Ralston et al., 2011). While small biomass reference points can lead to a large risk reduction, in particular for longer-lived species, the use of higher thresholds and limits has been recommended in the face of high scientific uncertainty (Da-Rocha et al., 2016) and might particularly useful for populations with fluctuating population dynamics. However, high biomass reference points are likely to lead to larger variability in yield. Moreover, high biomass reference points might lead to high levels of forgone yield, in particular in the short-term and when biomass reference points are overestimated or biomass underestimated. This increased sensitivity to the accuracy of estimated biomass reference points is problematic as they are among the most uncertain quantities in fish stock assessment (e.g., van Deurs et al., 2021). This study demonstrates the value of combining biomass reference points and uncertainty buffers. The combined rules make use of the effectiveness of both precautionary approaches while reducing the potentially large AAV and accounting for model uncertainty in B/B_{MSY}. The combined rules outperform the individual precautionary approaches and show consistently effective trade-offs for short-lived and long-lived stocks.

While the trade-off of the uncertainty buffers individually did not depend on the quantity considered for the fractile approach (f^{C}, f^{F}), the trade-offs for the combined rules show larger differences between the quantities considered. This is likely due to the effect of the f^{B} fractile, that comes only into effect when the HCR includes a biomass reference point. The results indicate that the f^{B} fractile amplifies the effect of the biomass thresholds and limits. The results revealed that the uncertainty of the predicted catch, fishing mortality and biomass distribution depends on the life-history parameters, as well as the process and observation uncertainty (Supplementary Table B5). Therefore, it might be meaningful to consider the uncertainty of all quantities of the HCR. Nevertheless, the effect of the f^{B} fractile might differ for alternative definitions or estimations of the biomass reference points. Given the uncertainty surrounding the stock status in terms of absolute and relative biomass as well as biomass reference points, future research is needed regarding the f^{B} fractile.

Although, the main drawback of the precautionary approach, forgone yield (Little et al., 2016), remains for the combined rules, the results indicate that the risk-yield trade-off of the combined rules is not proportional. By contrast, the additional uncertainty buffer is likely to reduce the risk of overfishing without a substantial loss in yield, in particular if B/B_{MSY} is overestimated.

The optimal harvest control rule

Ultimately, the definition and choice of the HCR depends on management objectives as well as the managers' risk tolerance and, thus, is a policy decision. Ideally, and if expertise and resources allow, stock assessors should present the trade-offs between risk, yield, and AAV for a range of HCRs with different biomass reference points and uncertainty buffers to stake-holders and managers. Nevertheless, based on the results from this study, a list of recommendations can be compiled guiding the selection and implementation of the optimal HCR:

1. The HCR should be determined from stock-specific MSE using realistic levels of scientific uncertainty and in light of specific management objectives.

2. The HCR should include both biomass reference points and an uncertainty buffer.

3. The biomass threshold (B_{T}) should be between 0.5 and 2 B_{MSY} and rather higher ($\geq B_{\mathrm{MSY}}$) for short-lived species.

4. The biomass limit (B_{L}) and threshold (B_{T}) should depend on each other (fraction, multiple) or be defined on a common reference point or quantity (here: B_{MSY}).

5. The uncertainty buffer should be based on a specific risk fractile for the predicted catch distribution (f^{C}) within the range of 0.15 to 0.45 or for all distributions used in the HCR (here: $f^{\mathrm{C,B,F}}$) within the range of 0.25 to 0.45.

6. A probability-based HCR should never lead to more risk-prone management decisions (prone to overfishing) than alternative deterministic rules, i.e. that the risk fractile should not exceed 0.5 as mandated by the U.S. MagnussonStevens Fishery Conservation and Management Act and National Standards (U.S. Office of the Federal Register, 2009).

Acknowledgements

This work was mainly funded by the EMFF project "ManDaLiS - Improving the management basis for Danish data-limited stocks" (Ref 33113-B-16-085) and "RoMA - Robust management procedures and advice for data limited stocks" (Ref 33113-B-20-183), which are funded by the European Maritime and Fisheries Fund and the Danish Fisheries Agency. TKM received financial support from the University of Washington School of Aquatic and Fishery Sciences, the Otto Mønsted Foundation, and the Idella Foundation. The authors would like to express their gratitude to all participants of the ICES workshops "WKLife VII - IX" for comments on the methodology and interpretation of the results of previous simulations during the workshops, and to Ian Taylor and Owen Hamel for comments on an earlier version of this manuscript. The authors are grateful for the comments from the editor Paul Hart and two anonymous reviewers that improved this manuscript substantially.

Data Availability Statement

The code for the operating model is available at https://github.com/tokami/iamse/tree/pubFF. The code for the assessment model is available at https://github.com/tokami/spict/tree/pubFF. Additional R scripts supporting this study are available at https://github.com/tokami/pubs/tree/master/pubFF.

References

Beddington, J. R., & May, R. M. (1977). Harvesting Natural Populations in a Randomly Fluctuating Environment. *Advancement Of Science*, *197*, 463–465.

Benson, A. J., Cooper, A. B., & Carruthers, T. R. (2016). An evaluation of rebuilding policies for U.S. fisheries. *PLoS ONE*, *11*, 1–15.

Bentley, N., & Stokes, K. (2009). Contrasting Paradigms for Fisheries Management Decision Making: How Well Do They Serve Data-Poor Fisheries? *Marine and Coastal Fisheries*, *1*, 391–401.

Bouch, P., Minto, C., & Reid, D. G. (2020). Comparative performance of data-poor CMSY and data-moderate SPiCT stock assessment methods when applied to data-rich, real-world stocks. *ICES Journal of Marine Science*, *78*, 264–276.

Caddy, J. F., & McGarvey, R. (1996). Targets or Limits for Management of Fisheries? *North American Journal of Fisheries Management*, *16*, 479–487.

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

Charles, A. T. (1998). Living with uncertainty in fisheries: Analytical methods, management priorities and the Canadian groundfishery experience. *Fisheries Research*, *37*, 37–50.

Charles, A. T. (2001). *Sustainable Fishery Systems*. Blackwell Science Ltd.

Dankel, D. J., Vølstad, J. H., & Aanes, S. (2016). Communicating uncertainty in quota advice: a case for confidence interval harvest control rules (CI-HCRs) for fisheries. *Canadian Journal of Fisheries and Aquatic Sciences*, *73*, 309–317.

Da-Rocha, J. M., Garcia-Cutrin, J., & Gutierrez, M. J. (2016). Harvesting Control Rules that deal with Scientific Uncertainty. *University Library of Munich, Germany.*

Department of Agriculture and Water, & Resources. (2018). *Guidelines for the Implementation of the Commonwealth Fisheries Harvest Strategy Policy* (tech. rep.). Canberra, June. CC BY 4.0.

DFO. (2009). A Fishery Decision-Making Framework Incorporating the Precautionary Approach.

Dichmont, C. M., Fulton, E. A., Gorton, R., Sporcic, M., Little, L. R., Punt, A. E., Dowling, N., Haddon, M., Klaer, N., Smith, D. C., Little, R. L., Punt, A. E., Dowling, N., Haddon, M., Klaer, N., & Smith, D. C. (2017). From data rich to data-limited harvest strategies-does more data mean better management? *ICES Journal of Marine Science*, *74*, 670–686.

Dowling, N. A., Dichmont, C. M., Venables, W., Smith, A. D. M., Smith, D. C., Power, D., & Galeano, D. (2013). From low- to high-value fisheries: Is it possible to quantify the trade-off between management cost, risk and catch? *Marine Policy*, *40*, 41–52.

EU. (2013). *Regulation (EU) no 1380/2013 of the European Parliament and of the Council of 11 December 2013 on the Common Fisheries Policy.* (tech. rep.).

FAO. (1995). Precautionary approach to fisheries. Part 1: guidelines on the precautionary approach to capture fisheries and species introductions. *Fao fisheries technical paper no. 350.*

Fischer, S. H., De Oliveira, J. A. A., & Kell, L. T. (2020). Linking the performance of a data-limited empirical catch rule to life-history traits. *ICES Journal of Marine Science*, *77*, 1914–1926.

Fletcher, R. I. (1978). On the Restructuring of the Pella-Tomlinson System. *U.S. Fisheries Bulletin*, *76*, 515–534.

Fogarty, M. J., Mayo, R. K., O'Brien, L., Serchuk, F. M., & Rosenberg, A. A. (1996). Assessing uncertainty and risk in exploited marine populations. *Reliability Engineering and System Safety*, *54*, 183–195.

Francis, R. I., & Shotton, R. (1997). "Risk" in fisheries management: a review. *Canadian Journal of Fisheries and Aquatic Sciences*, *54*, 1699–1715.

Fulton, E. A., Smith, A. D. M., Smith, D. C., & Van Putten, I. E. (2011). Human behaviour: the key source of uncertainty in fisheries management. *Fish and Fisheries*, *12*, 2–17.

Garcia, S. M. (1996). The precautionary approach to fisheries and its implications for fishery research, technology and management: an updated review. *FAO (Food and Agriculture Organization of the United Nations) Fisheries Technical Paper*, *350*(2), 1–75.

Garcia, S. M. (2000). The precautionary approach to fisheries: progress review and main issues (1995-2000). In M. N. Nordquist & J. N. Moore (Eds.), *Current fisheries issues and the food and agriculture organization of the united nations* (pp. 479–560). Center for Oceans Law.

Getz, W. M., Francis, R. C., & Swartzman, G. L. (1987). On managing variable marine fisheries. *Canadian Journal of Fisheries and Aquatic Sciences*, *44*, 1370–1375.

Hilborn, R. (2010). Pretty Good Yield and exploited fishes. *Marine Policy*, *34*, 193–196.

Hilborn, R., & Stokes, K. (2010). Defining Overfished Stocks: Have We Lost the Plot? *Fisheries*, *35*, 113–120.

Hilborn, R., & Walters, C. J. (1992). *Quantitative fisheries stock assessment: Choice, dynamics and uncertainty.* Kluwer Academic Publishers.

Iacus, S. (2009). *Simulation and Inference for Stochastic Differential Equations: With R Examples.* Springer, New York, NY.

ICES. (2012). *Manual for the International Bottom Trawl Surveys* (tech. rep.). Series of ICES Survey Protocols. SISP 1-IBTS VIII. 68 pp.

ICES. (2013a). *Report of the Benchmark Workshop on Greenland Halibut Stocks (WKBUT), 2629 November 2013, Copenhagen, Denmark.* (tech. rep.). ICES CM 2013/ ACOM:44. 367 pp.

ICES. (2013b). *Report of the Workshop on the Development of Quantitative Assessment Methodologies Based on LIFE history Traits, Exploitation Characteristics, and Other Key Parameters for Data-limited Stocks (WKLIFE III), 28 October - 1 November 2013.* (tech. rep.). ICES CM 2013/ACOM:35. 98 pp.

ICES. (2017). *Report of the Workshop on the Development of the ICES approach to providing MSY advice for category 3 and 4 stocks (WKMSYCat34), 6-10 March 2017, Copenhagen, Denmark.* (tech. rep.). ICES CM 2017/ ACOM:47. 53 pp.

ICES. (2018). *Advice basis: General context of ICES advice* (tech. rep.). Report of the ICES Advisory Committee 2018. ICES Advice 2018. 13 pp.

ICES. (2019a). *Working Group for the Celtic Seas Ecoregion (WGCSE)* (tech. rep.). ICES Scientific Reports. 1:29. 1604 pp.

ICES. (2019b). *Working Group on the Assessment of Demersal Stocks in the North Sea and Skagerrak (WGNSSK)* (tech. rep.). ICES Scientific Reports. 1:7. 1271 pp.

ICES. (2020a). *North Western Working Group (NWWG)* (tech. rep.). ICES Scientific Reports. 2:51. 431 pp.

ICES. (2020b). *Report of the Working Group on Southern Horse Mackerel, Anchovy and Sardine (WGHANSA)* (tech. rep.). ICES Scientific Reports. 2:41. 655 pp.

ICES. (2021). *Benchmark Workshop on the development of MSY advice for category 3 stocks using Surplus Production Model in Continuous Time; SPiCT (WKMSYSPiCT)* (tech. rep.). ICES Scientific Reports. 3:20. 316 pp.

Irwin, B. J., Wilberg, M. J., Bence, J. R., & Jones, M. L. (2008). Evaluating alternative harvest policies for yellow perch in southern Lake Michigan. *Fisheries Research*, *94*, 267–281.

Kell, L. T., Sharma, R., Kitakado, T., Winker, H., Mosqueira, I., Cardinale, M., & Fu, D. (2021). Validation of stock assessment methods: is it me or my model talking? *ICES Journal of Marine Science.*

Kristensen, K., Nielsen, A., Berg, C. W., Skaug, H., & Bell, B. (2016). TMB: automatic differentiation and Laplace approximation. *Journal of Statistical Software*, *70*, 1–21.

Lande, R., Sæther, B. E., & Engen, S. (2001). Sustainable exploitation of fluctuating populations. In J. D. Reynolds, G. M. Mace, K. H. Redford, & J. G. Robinson (Eds.), *Conservation of exploited species* (pp. 67–86). Cambridge University Press.

Lett, P. F., & Doubleday, W. G. (1976). The Influence of Fluctuations in Recruitment on Fisheries Management Strategy. *ICNAF Selected Papers*, *1*, 171–93.

Link, J. S., Werner, F. E., Werner, K., Walter, J., Strom, M., Seki, M. P., Schwing, F., Rusin, J., Porch, C. E., Osgood, K., Moline, K., Methot, R. D., Lynch, P. D., Lipton, D., Koch, K., Howell, E. A., Hare, J. A., Foy, R. J., Detlor, D., … Cabana, N. (2021). A NOAA fisheries science perspective on the conditions during and after covid-19: Challenges, observations, and some possible solutions, or why the future is upon us. *Canadian Journal of Fisheries and Aquatic Sciences*, *78*, 1–12.

Little, L. R., Punt, A. E., Dichmont, C. M., Dowling, N., Smith, D. C., Fulton, E. A., Sporcic, M., & Gorton, R. J. (2016). Decision trade-offs for cost-constrained fisheries management. *ICES Journal of Marine Science*, *73*, 494–502.

Little, L. R., Punt, A. E., Mapstone, B. D., Begg, G. A., Goldman, B., & Williams, A. J. (2009). An agent-based model for simulating trading of multi-species fisheries quota. *Ecological Modelling*, *220*(23), 3404–3412.

Mace, P. M., & Doonan, I. J. (1988). *A generalised bioeconomic simulation model for fish population dynamics* (tech. rep.). New Zealand Fishery Assessment Research Document 88/4. Fisheries Research Centre, MAFFish, POB 297, Wellington, NZ.

Mace, P. M. (2001). A new role for MSY in single-species and ecosystem approaches to fisheries stock assessment and management. *Fish and Fisheries*, *2*, 2–32.

May, R. M., Beddington, J. R., Horwood, J. W., & Shepherd, J. G. (1978). Exploiting natural populations in an uncertain world. *Mathematical Biosciences*, *42*, 219–252.

Mildenberger, T. K., Berg, C. W., Pedersen, M. W., Kokkalis, A., & Nielsen, J. R. (2020). Time-variant productivity in biomass dynamic models on seasonal and long-term scales. *ICES Journal of Marine Science*, *77*, 174–187.

Nieland, J. L., Hansen, M. J., Seider, M. J., & Deroba, J. J. (2008). Modeling the sustainability of lake trout fisheries in eastern Wisconsin waters of Lake Superior. *Fisheries Research*, *94*, 304–314.

Nielsen, J. R., Thunberg, E., Holland, D. S., Schmidt, J. O., Fulton, E. A., Bastardie, F., Punt, A. E., Allen, I., Bartelings, H., Bertignac, M., Bethke, E., Bossier, S., Buckworth, R., Carpenter, G., Christensen, A., Christensen, V., Da-Rocha, J. M., Deng, R., Dichmont, C., … Waldo, S. (2018). Integrated ecological-economic fisheries models - Evaluation, review and challenges for implementation. *Fish and Fisheries*, *19*, 1–29.

Olsson, U. (2005). Confidence Intervals for the Mean of a Log-Normal Distribution. *Journal of Statistics Education*, *13*.

Ono, K., Punt, A. E., & Rivot, E. (2012). Model performance analysis for Bayesian biomass dynamics models using bias, precision and reliability metrics. *Fisheries Research*, *125-126*, 173–183.

Pedersen, M. W., & Berg, C. W. (2017). A stochastic surplus production model in continuous time. *Fish and Fisheries*, *18*, 226–243.

Pella, J. J., & Tomlinson, P. K. (1969). *A Generalized Stock Production Model* (tech. rep.). Inter-Amarican Tropical Tuna Commission, 13, 421-488.

Pilbeam, K. (2005). Portfolio Analysis: Risk and Return in Financial Markets. *Finance and financial markets* (pp. 156–187). Macmillan Education UK.

Prager, M. H., Porch, C. E., Shertzer, K. W., & Caddy, J. F. (2003). Targets and Limits for Management of Fisheries: A Simple Probability-Based Approach. *North American Journal of Fisheries Management*, *23*, 349–361.

Prager, M. H., & Shertzer, K. W. (2010). Deriving Acceptable Biological Catch from the Overfishing Limit: Implications for Assessment Models. *North American Journal of Fisheries Management*, *30*, 289–294.

Privitera-Johnson, K. M., & Punt, A. E. (2020). Leveraging scientific uncertainty in fisheries management for estimating among-assessment variation in overfishing limits. *ICES Journal of Marine Science*, *77*, 515–526.

Punt, A. E. (2003). Evaluating the efficacy of managing West Coast groundfish resources through simulations. *Fishery Bulletin*, *101*, 860–873.

Punt, A. E. (2010). Harvest control rules and fisheries management. In R. Q. Grafton, R. Hilborn, D. Squires, M. Tait, & M. Williams (Eds.), *Handbook of marine fisheries conservation and management* (pp. 582–594). Oxford University Press.

Punt, A. E., Day, J., Fay, G., Haddon, M., Klaer, N., Little, L. R., Privitera-Johnson, K., Smith, A. D., Smith, D. C., Sporcic, M., Thomson, R., Tuck, G. N., Upston, J., & Wayte, S. (2018). Retrospective investigation of assessment uncertainty for fish stocks off southeast Australia. *Fisheries Research*, *198*, 117–128.

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

Punt, A. E., & Donovan, G. P. (2007). Developing management procedures that are robust to uncertainty: Lessons from the International Whaling Commission. *ICES Journal of Marine Science*, *64*, 603–612.

Punt, A. E., Dorn, M. W., & Haltuch, M. A. (2008). Evaluation of threshold management strategies for groundfish off the U.S. West Coast. *Fisheries Research*, *94*, 251–266.

Punt, A. E., Smith, T., & Smith, A. D. M. (2001). The gospel of maximum sustainable yield in fisheries management: birth, crucifixion and reincarnation. In J. Reynolds, G. Mace, K. Redford, & J. Robinson (Eds.), *Conservation of exploited species,* (pp. 41–66). Cambridge University Press.

Punt, A. E., & Szuwalski, C. (2012). How well can F_{MSY} and B_{MSY} be estimated using empirical measures of surplus production? *Fisheries Research*, *134-136*, 113–124.

Ralston, S., Punt, A. E., Hamel, O. S., Devore, J. D., & Conser, R. J. (2011). A meta-analytic approach to quantifying scientific uncertainty in stock assessments. *Fishery Bulletin*, *109*, 217–231.

Rayns, N. (2007). The Australian government' s harvest strategy policy. *ICES Journal of Marine Science*, *64*, 596–598.

Rosenberg, A., & Brault, S. (1993). Choosing a management strategy for stock rebuilding when control is uncertain. In S. Smith, J. Hunt, & D. Rivard (Eds.), *Risk evaluation and biological reference points for fisheries management* (pp. 243–249). Canadian Special Publications of Fisheries Aquatic Sciences.

Sæther, B.-E., Engen, S., & Lande, R. (1996). Density-Dependence and Optimal Harvesting of Fluctuating Populations. *Oikos*, *76*, 40–46.

Selig, E. R., Kleisner, K. M., Ahoobim, O., Arocha, F., Cruz-Trinidad, A., Fujita, R., Hara, M., Katz, L., McConney, P., Ratner, B. D., Saavedra-Díaz, L. M., Schwarz, A. M., Thiao, D., Torell, E., Troëng, S., & Villasante, S. (2017). A typology of fisheries management tools: using experience to catalyse greater success. *Fish and Fisheries*, *18*, 543–570.

Shertzer, K. W., Prager, M. H., & Williams, E. H. (2008). A probability-based approach to setting annual catch levels. *Fishery Bulletin*, *106*, 225–232.

Smith, A. D. M. (1994). Management strategy evaluation: the light on the hill. *Population dynamics for fisheries management*, 249–253.

Thorson, J. T., Cope, J. M., Branch, T. A., & Jensen, O. P. (2012). Spawning biomass reference points for exploited marine fishes, incorporating taxonomic and body size information. *Canadian Journal of Fisheries and Aquatic Sciences*, *69*, 1556–1568.

Thorson, J. T., Jensen, O. P., Zipkin, E. F., & Rose, K. (2014). How variable is recruitment for exploited marine fishes? A hierarchical model for testing life history theory. *Canadian Journal of Fisheries and Aquatic Sciences*, *71*, 973–983.

Thygesen, U. H., Albertsen, C. M., Berg, C. W., Kristensen, K., & Nielsen, A. (2017). Validation of ecological state space models using the Laplace approximation. *Environmental and Ecological Statistics*, *24*, 317–339.

U.S. Office of the Federal Register. (2009). *Magnuson-Stevens Act Provisions; Annual Catch Limits; National Standard Guidelines* (tech. rep.). Federal Register 74: 31783213.

van Deurs, M., Brooks, M. E., Lindegren, M., Henriksen, O., & Rindorf, A. (2021). Biomass limit reference points are sensitive to estimation method, time-series length and stock development. *Fish and Fisheries*, *22*, 18–30.

Walsh, J. C., Minto, C., Jardim, E., Anderson, S. C., Jensen, O. P., Afflerbach, J., Dickey-Collas, M., Kleisner, K. M., Longo, C., Osio, G. C., Selig, E. R., Thorson, J. T., Rudd, M. B., Papacostas, K. J., Kittinger, J. N., Rosenberg, A. A., & Cooper, A. B. (2018). Trade-offs for data-limited fisheries when using harvest strategies based on catch-only models. *Fish and Fisheries*, *19*, 1130–1146.

Wiedenmann, J., Wilberg, M., Sylvia, A., & Miller, T. (2017). An evaluation of acceptable biological catch (ABC) harvest control rules designed to limit overfishing. *Canadian Journal of Fisheries and Aquatic Sciences*, *74*(7), 1028–1044.

Wilson, E. E. B. (1927). Probable Inference, the Law of Succession, and Statistical Inference. *Journal of the American Statistical Association*, *22*, 209.

Table 1: Median bias [%] in B/B_{MSY} and F/F_{MSY} for fishing at F_{MSY} over stock-specific periods of 4, 8, and 27 years after start of the management for anchovy, haddock, and Greenland halibut, respectively.

Quantity	Species	Baseline	Low proc noise	High proc noise	Low obs noise	High obs noise
B/B_{MSY}	Anchovy	-34	-19	-49	-32	-52
B/B_{MSY}	Haddock	-26	-13	-34	-24	-34
B/B_{MSY}	Greenland halibut	10	22	-2	14	6
F/F_{MSY}	Anchovy	19	-1	54	15	42
F/F_{MSY}	Haddock	-6	-15	5	-10	2
F/F_{MSY}	Greenland halibut	-17	-18	-15	-18	-17

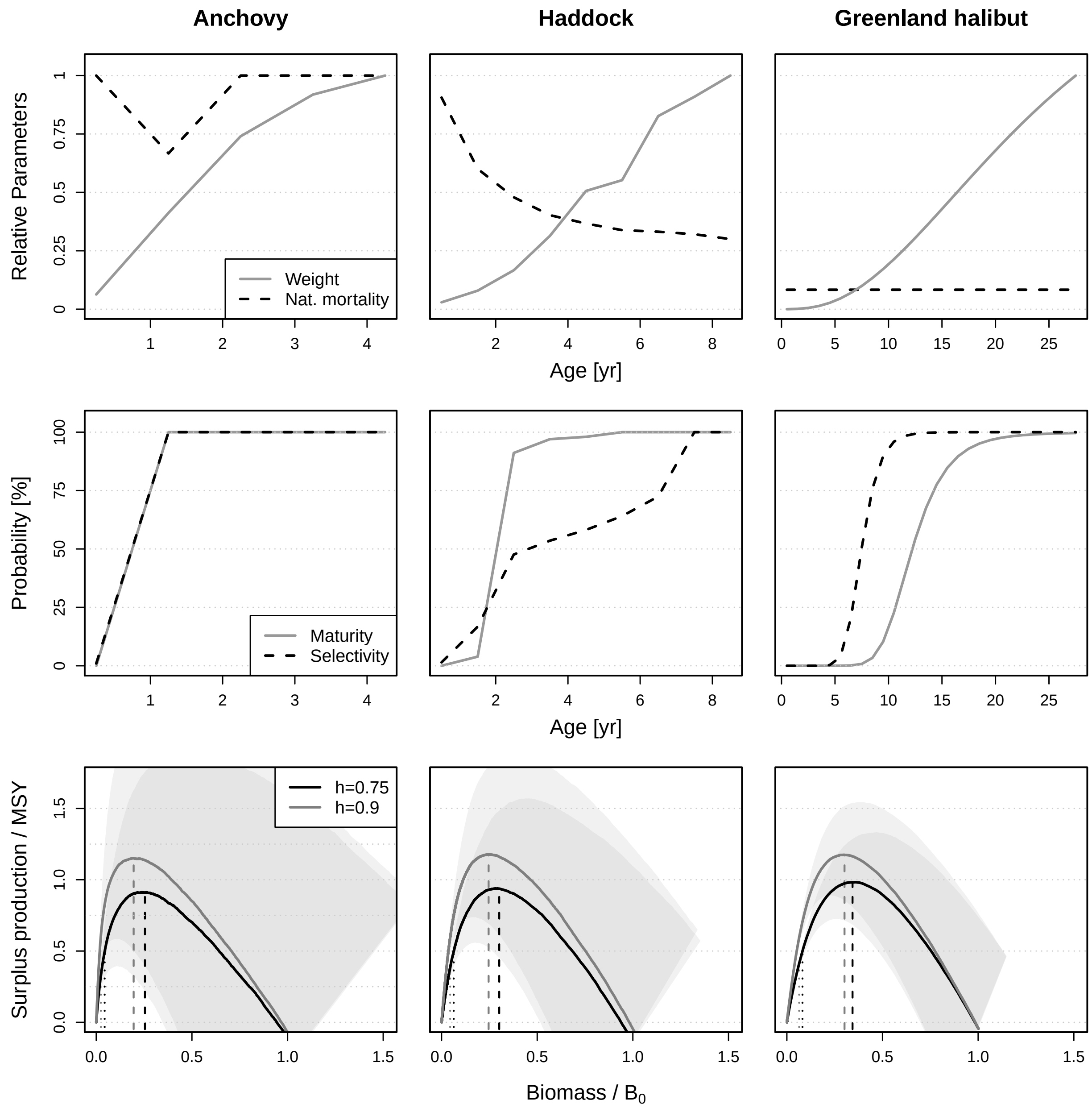

FIGURE 1

Life-history parameters for three stocks (columns). Top row shows weight-at-age relative to the maximum of each stock (solid line) and natural mortality rate by age relative to overall maximum mortality rate of anchovy (1.2yr^{-1}; broken line). Middle row shows maturity by age (solid line) and gear selectivity by age (broken line). Bottom row shows stochastic production curves, i.e. total stock biomass relative to the median virgin biomass (B_0) against the surplus production relative to the median MSY. Production curves are based on simulated equilibrium biomass given process uncertainty for a range of fishing mortality values (Supplementary Section A). The solid lines represent the median relationships, the vertical dashed lines indicate the total stock biomass with the highest surplus production relative to the virgin biomass (i.e. B_{MSY}/B_0), and the vertical dotted lines represent the risk level (B_{lim} = biomass where surplus production = 50% MSY, relative to the virgin biomass, i.e. B_{lim}/B_0)

for the scenario with steepness (h) of the stock-recruitment relationship equal to 0.75 (black lines) and equal to 0.9 (grey lines), respectively. The shaded areas extend from the 10th to the 90th percentile for the two production curves.

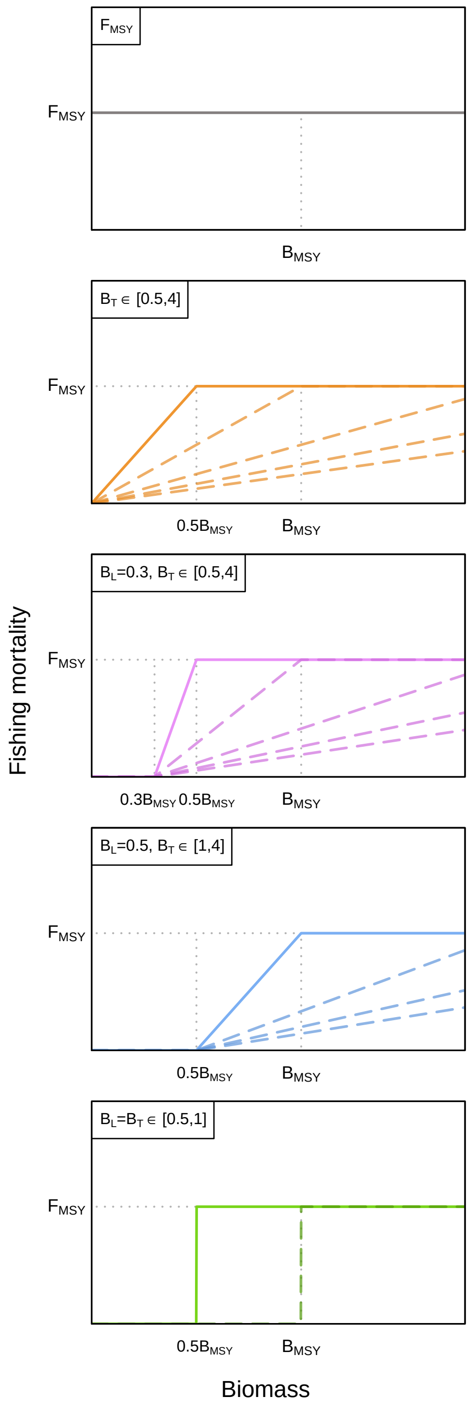

FIGURE 2

Relationship between fishing mortality (F) and biomass (B) for a range of harvest control rules considered in this study. Fishing at F_{MSY} can be independent of biomass (gray line) or dependent on biomass by using various biomass threshold (B_{T}) and limit B_{L} reference points (coloured lines). Numbers after biomass reference points refer to fractiles or multiples of B_{MSY}. Bold coloured lines correspond to an example of each HCR type, while faded lines show the alternative implementations of the respective HCR types.

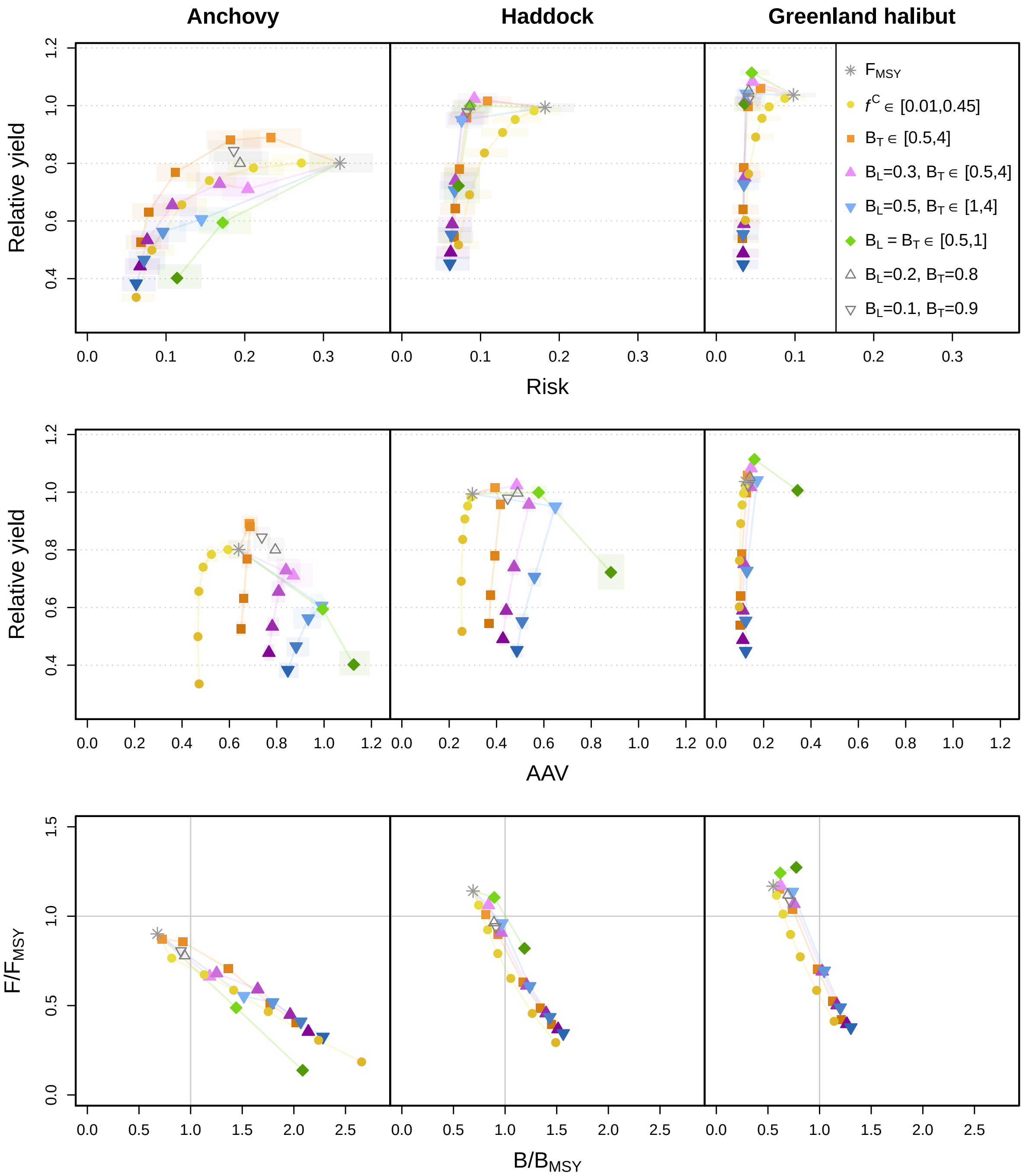

FIGURE 3

Trade-off graphs of risk and relative yield (upper row) and absolute interannual variability in yield (AAV) and relative yield (middle row) as well as Kobe plots (B/B_{MSY} vs F/F_{MSY}; lower row) for anchovy, haddock, and Greenland halibut (columns). Starting from the gray star symbol (fishing at F/F_{MSY}), the lines connect following HCRs with increasing uncertainty buffers (decreasing fractiles): $f^{\mathrm{C}} = \{0.45, 0.35, 0.25, 0.15, 0.05, 0.01\}$ (yellow circles); and following HCRs with increasing biomass thresholds (and limits): $B_{\mathrm{T}} = \{0.5, 1, 2, 3, 4\}$ (orange squares); $B_{\mathrm{L}} = 0.3, B_{\mathrm{T}} = \{0.5, 1, 2, 3, 4\}$ (purple triangles); $B_{\mathrm{L}} = 0.5, B_{\mathrm{T}} = \{1, 2, 3, 4\}$ (blue triangles); $B_{\mathrm{L}} = \{0.5, 1\}, B_{\mathrm{T}} = \{0.5, 1\}$ (green diamonds). The open gray triangles show the additional rules $B_{\mathrm{L}} = 0.2, B_{\mathrm{T}} = 0.8$ and $B_{\mathrm{L}} = 0.1, B_{\mathrm{T}} = 0.9$. The shaded areas around the symbols in the upper and middle row represent the 95% intervals of the respective metrics.

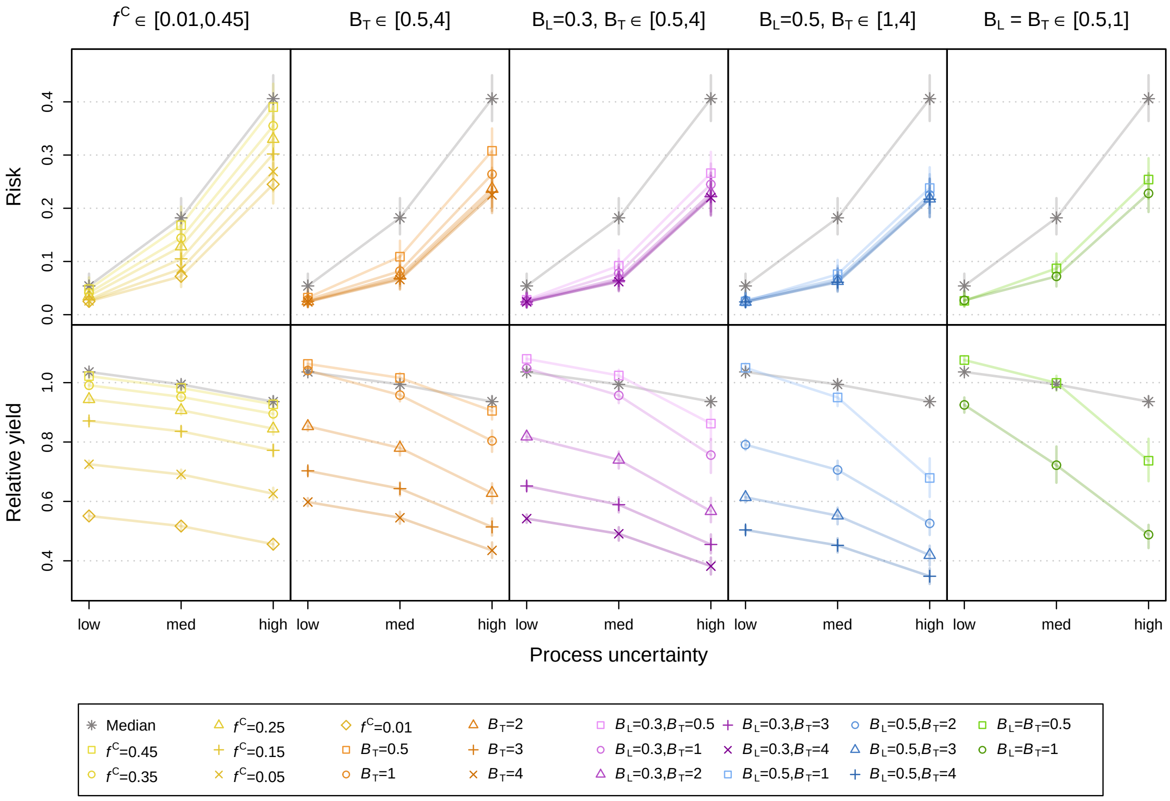

FIGURE 4

Risk (upper row) and relative yield (lower row) for three scenarios with three process uncertainty levels for haddock and various HCRs (colours) sorted by HCR type (columns). Low and high process noise levels assume a recruitment deviations of 50\respectively. Vertical lines represent the 95% confidence intervals.

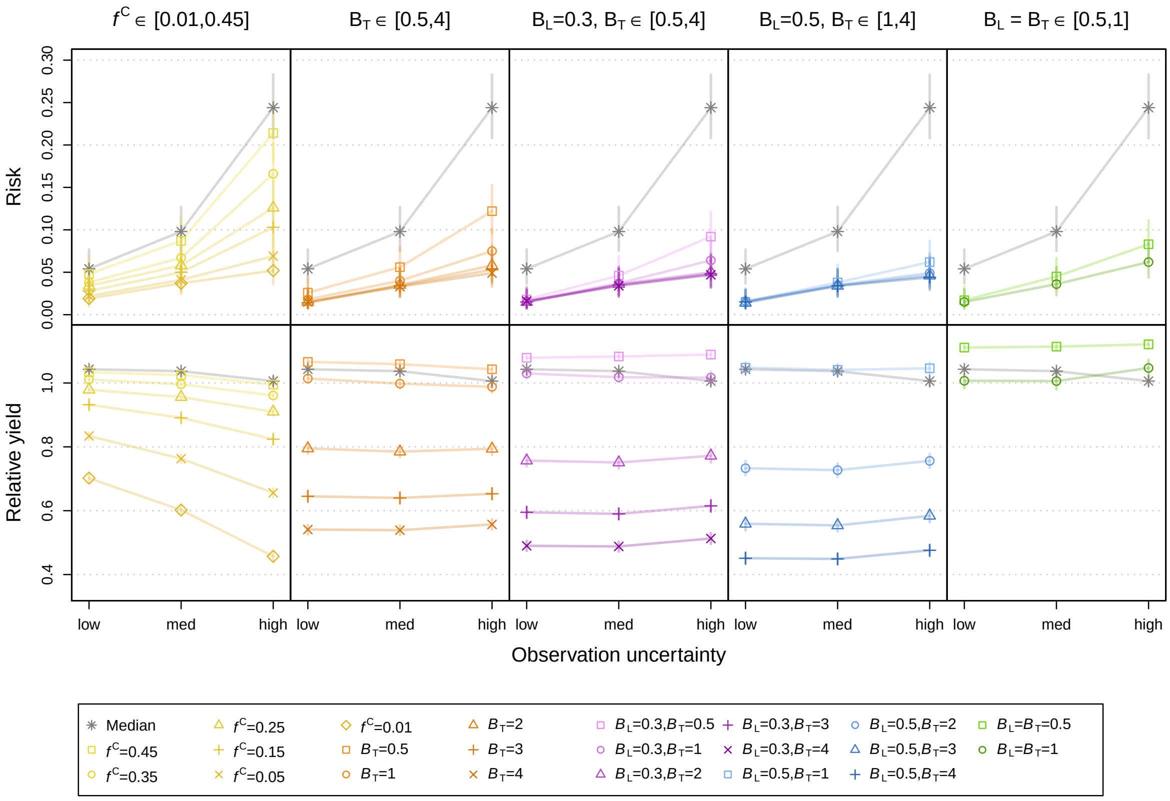

FIGURE 5

Risk (upper row) and relative yield (lower row) for three scenarios with three levels of observation uncertainty for Greenland halibut and various HCRs (colours) sorted by HCR type (columns). Low, med, and high observation noise levels assume SDs of $0.15, 0.3, 0.6$, respectively. Vertical lines represent the 95% confidence intervals.

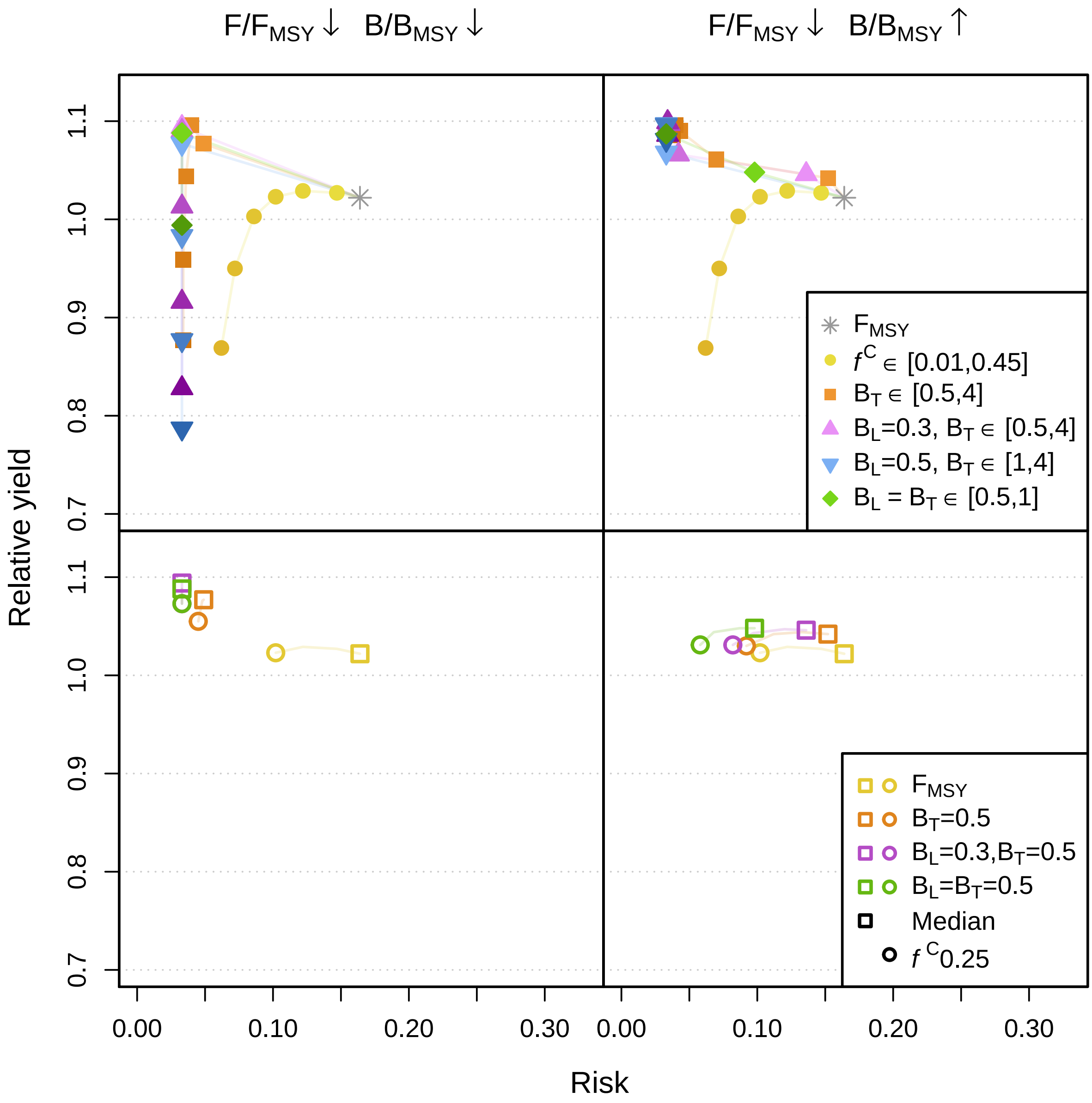

FIGURE 6

Trade-off between risk and relative yield for simulated assessments and underestimated F/F_{MSY} and B/B_{MSY} (left column) and underestimated F/F_{MSY} and overestimated B/B_{MSY} (right column) for anchovy. Upper row shows HCRs with biomass reference points and uncertainty buffers, lower row shows combined HCRs for the two scenarios.

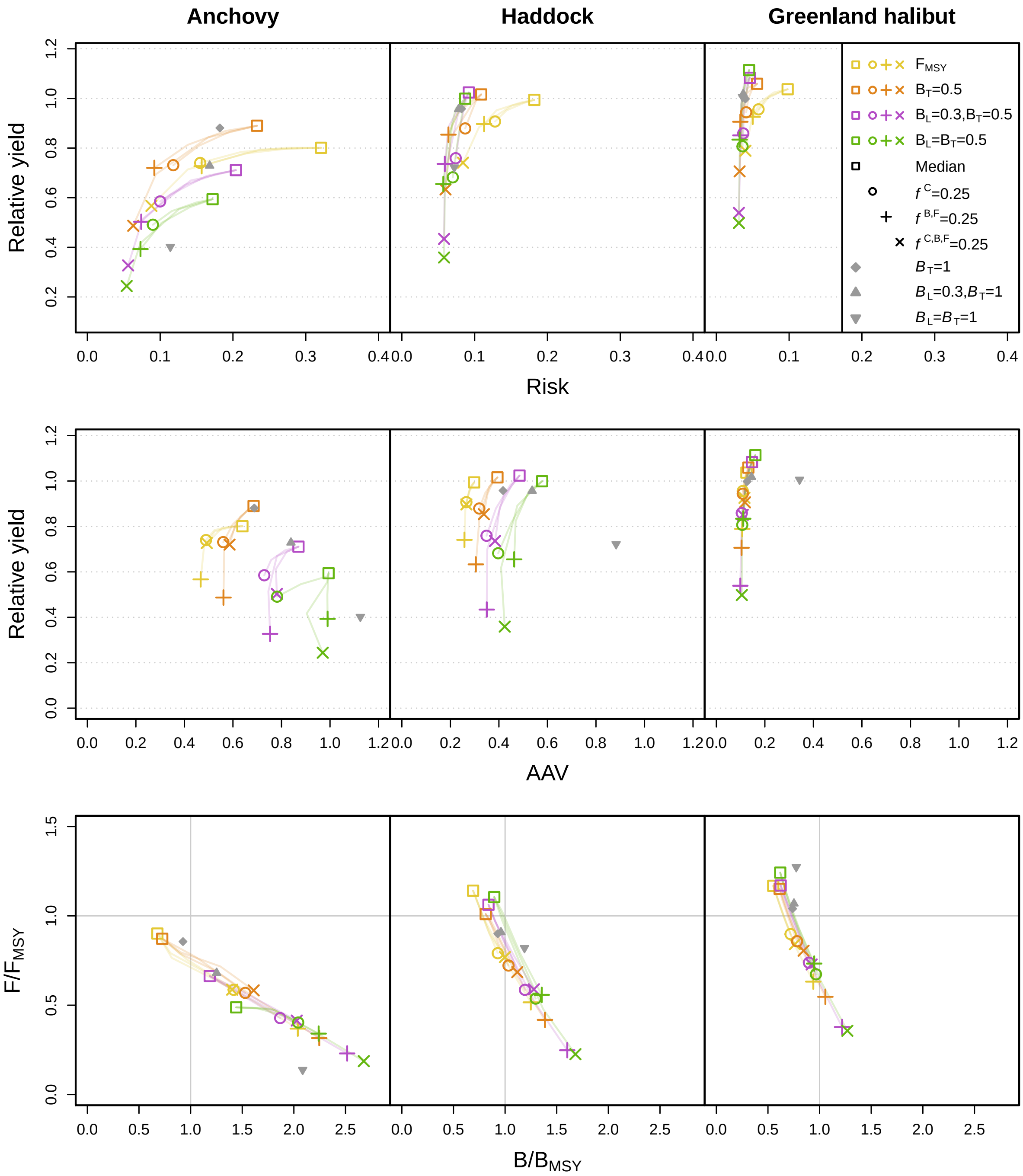

FIGURE 7

Trade-off between risk and relative yield (upper row) and absolute inter-annual variability in yield (AAV) and relative yield (middle row) as well as Kobe plots (B/B_{MSY} vs F/F_{MSY}; lower row) for anchovy, haddock, and Greenland halibut (columns). Colours represent included HCR types: F_{MSY}, $B_{\mathrm{T}} = 0.5$, $B_{\mathrm{L}} = 0.3, B_{\mathrm{T}} = 0.5$, $B_{\mathrm{L}} = B_{\mathrm{T}} = 0.5$. Symbols represent median (square) of each HCR type as well as in combination with three fractile types: $f^{\mathrm{C}} = 0.25$ (circles), $f^{\mathrm{B,F}} = 0.25$ (plus symbol), and $f^{\mathrm{C,B,F}} = 0.25$ (x symbol). Lines connect median, $0.45, 0.35,$ and 0.25 fractile for each HCR type.

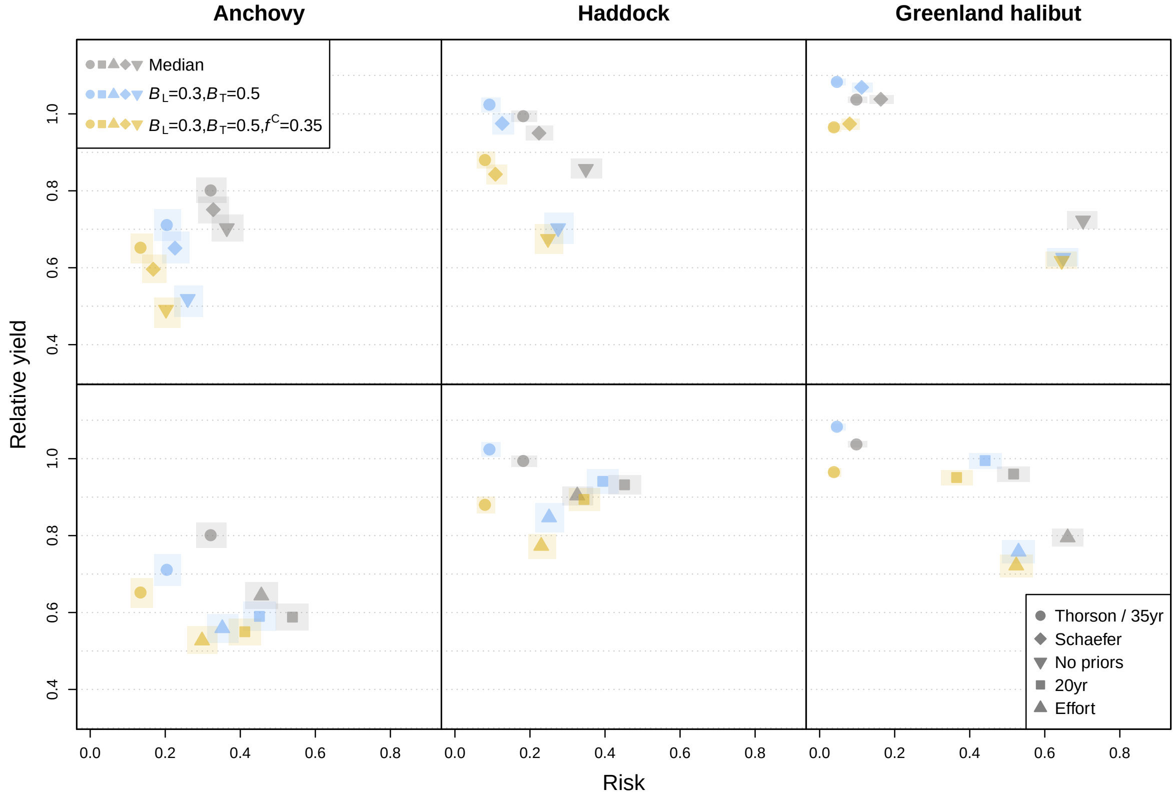

FIGURE 8

Trade-off between risk and relative yield for scenarios with various priors (upper row) and available data (bottom row) for the three stocks (columns). The colours represent three different HCRs, while the shape of the symbols refer to scenarios with various assumptions regarding priors and data availability: "Thorson/35yr" (circle) assumes prior for shape of production curve following Thorson et al. (2014) and 35 years of data, "Schaefer" (diamond) assumes wide prior for the production curve around 2, "No priors" (pyramid point down) does not use any priors, "20yr" (square) uses one abundance index of 20 years, and "Effort" (pyramid point-up) assumes 35 years of catch and effort data.