Evaluating the utility of a Novel Harvest Control Rule in the management of long-lived sporadically recruiting species through Management Strategy Evaluation

Master of Science in Fisheries Biology and Management

By Cian Kelly

Department of Biology

University of Bergen,

Norway

August 2019

Abstract

Fish species that exhibit sporadic recruitment, late maturity and that are long-lived, can be difficult to manage. The issue arises from the high variability in stock dynamics. Where there are significant interannual fluctuations in biomass, it is difficult to harvest the population in a sustainable manner, avoiding stock collapse while maintaining high yields and catch stability. The aim of this project was to inform the management of species with the above stock characteristics through computer simulation of two Harvest Control Rules (HCRs) using Management Strategy Evaluation (MSE).

MSE is a method used to simulate the performance of different management strategies under different criteria. HCRs are the flexible management rules which convert biological information into catch advice. Both management tools have become increasingly common in fisheries management. Escapement HCRs are most commonly used for the conservation of the spawning population in short-lived species such as Atlantic salmon (*Salmo salar*). In this study, the utility of a Novel HCR, which reflected an Escapement HCR, was tested on a stock whose dynamics was informed by Greenland halibut (*Reinhardtius hippoglossoides*). The Novel HCR was formulated to conserve the biomass from spikes in recruitment of a long-lived species, by exclusively targeting the fraction of biomass above a threshold biomass level. The performance of this Novel HCR was compared to a traditional ‘hockey-stick’ ICES HCR through MSE using the FLBEIA model in R software.

The model results indicated that there were trade-offs between the two HCRs. The Novel HCR provided relatively high yields with low risk of stock collapse, but came at the cost of a high fraction of moratoria and high interannual variability in catches. Depending on the management objectives, the Novel HCR can be successfully used in the sustainable exploitation of long-lived species with sporadic recruitment. The results of this paper will help to inform the management of Greenland halibut in the Barents Sea.

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Key terms and definitions

Term	Definition
Management Strategy Evaluation MSE	Tool used to find the most appropriate management strategy according to management objectives (Punt et al. 2014).
Harvest Control Rule HCR	Rule that converts stock information into management information (Eikeset et al. 2013).
Recruitment	Number of individuals entering the exploitable stock each year (ICES Advice 2012).
SSB Spawning stock biomass	The absolute weight of all sexually mature individuals in the stock (ICES Advice 2012).
F Fishing mortality	Instantaneous rate of fishing mortality (ICES Advice 2012).
$\mathbf{B_{pa}}$	An SSB precautionary reference point that provides a buffer zone above B_{lim} and triggers management action (ICES 2007).
$\mathbf{B_{lim}}$	Limit reference point for SSB, below which recruitment is impaired/ stock dynamics are uncertain and therefore management action is triggered (ICES 2007)
$\mathbf{B_{trigger}}$	An SSB trigger level that prompts a management action (ICES Advice 2012).
$\mathbf{F_{target}}$	Fishing mortality target that gives high yield with low risk (ICES 2007).

1. Introduction

1.1. Brief history of and current trends in fisheries management

In addition to the natural fluctuations in fish populations, stocks respond significantly to commercial harvesting. Numbers at age, total numbers and total biomass are impacted by fishing pressure (Haddon 2011). As a result, stock collapses and recruitment failures have been features, rather than bugs, of modern industrialised fisheries. Furthermore, commercial fisheries impact weight at age, recruitment, and age of maturation which manifest in fisheries induced effects such as growth overfishing, recruitment overfishing and ecosystem overfishing (Diekert 2012; Gullestad et al. 2013). Thus, it is critical to the management of fisheries to quantify these changes through mathematical and statistical descriptions, in order to more clearly understand the human impact on natural populations.

Thomas Huxley once speculated that humankind can never seriously alter the number of fish in the sea, influencing the views of many generations. The “inexhaustibility paradigm” falsely predicted that stocks were never in any danger of depletion. In the past, perhaps this was the case (Haddon 2011). However, since Huxley’s days, technological advancements in steam engines, hydraulic winches, trawl nets, otter boards, more selective gear, acoustics etc. have cast humans in the role of a “superpredator”, where anthropogenic impacts can have ecosystem-scale alterations on marine species (Coll et al. 2008).

With no limit to the unrestrained industrialisation of the fisheries sector, stock collapses have become commonplace since the 1970’s, such as in the case of Canadian populations of Atlantic cod, North Sea herring, Norwegian spring-spawning herring and Irish Sea cod (Myers et al. 1997; Dickey-Collas et al. 2010; Gullestad et al. 2013; Kelly et al. 2006). However, there is evidence of positive trends. Developments in fisheries management in more recent times have been implicated in the subsequent recovery of stocks such as Atlantic halibut, North Sea herring and Norwegian spring-spawning herring (Trzkinski and Bowen 2016; Dickey Collas et al. 2010; Tjelmeland and Røttingen 2009). The cumulative increase in Spawning Stock Biomass (SSB) of commercial species is one indicator of the positive response of stocks to sustainable management (Figure 1).

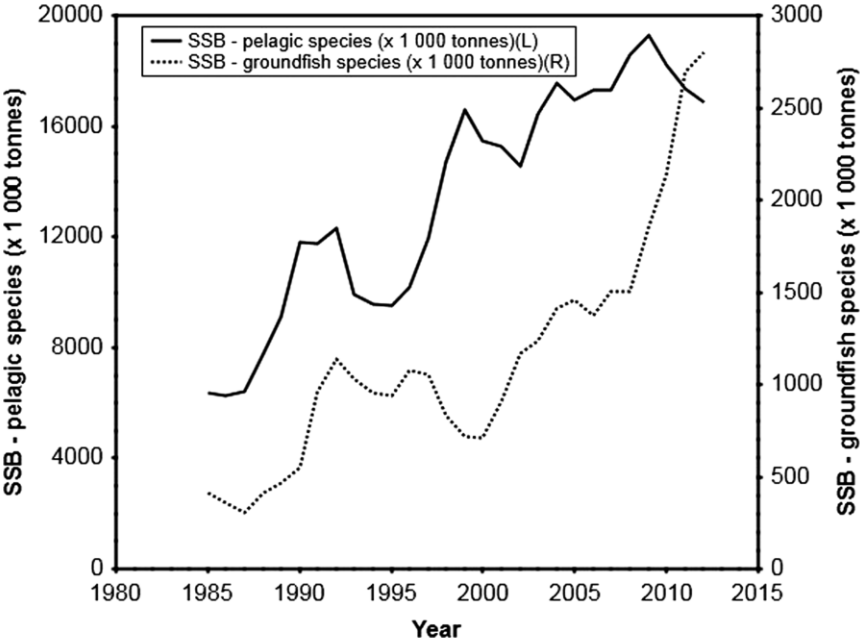


Figure 1. *Total spawning stocks of key Norwegian pelagic and groundfish species from 1985-2012 (Gullestad et al. 2013).*

The effort to manage Norwegian fisheries with a focus on long-term sustainability was spurred on by the collapse of Norwegian spring-spawning herring in the late 1960s (Gullestad et al. 2013). Instruments such as Total Allowable Catch (TAC), reduction in subsidies and access restrictions have been the most common tools used to procure sustainable yields (Årland and Bjørndal 2002). As a result, Norwegian fisheries management has attained the highest compliance score with regards the UN Code of Conduct for Responsible Fisheries (FAO, 1995). Sustainable management objectives have been central in modern Norwegian fisheries management (Gullestad et al. 2013).

Management objectives are management performance criteria that express the aims of management strategies, e.g. resource conservation (Mardle et al. 2002). They are often biomass and catch-based criteria, for example biomass limits that protect recruitment, or fishing mortality limits that keeps biomass above a threshold level (Kell et al. 2005). In order to achieve effective management practices, compromises between unaligned, and often incompatible objectives are a common feature of fisheries management (Vinther and Eero, 2013; Mardle et al. 2002). Management Strategy Evaluation (MSE) and Harvest Control Rules (HCRs) are common tools used to both achieve management objectives and evaluate trade-offs between objectives (Punt et al. 2014).

1.2. Achieving management objectives using MSE and HCRs

MSE is used to compare the effectiveness of data collection methodology and analysis among different models and to find the most appropriate management strategy given predefined objectives (Punt et al. 2016). MSE was developed to address flaws in the traditional methods of managing stocks (Butterworth et al. 2010). It differs from 'best assessment' practices where confidence intervals and sensitivity analyses are used to provide management advice based on some HCR. MSE, in contrast, deals with the full range of uncertainty and the plethora of trade-offs involved in choosing a management action (Punt et al. 2016).

Decision makers have been increasingly heeding advice from quantitative methods which use MSE to evaluate trade-offs in management strategies (Punt 2017). MSE is designed so that decision makers must clarify their objectives (Punt et al. 2016). The International Whaling Committee (IWC) spearheaded the use of MSE to limit catches on whales since the 1980s (Punt and Donovan 2007). MSE can also be used to select strategies for rebuilding stocks, such as in the case of Southern bluefin tuna (*Thunnus maccoyii*) (Polacheck et al. 1999). Frequently, management decisions must compromise between a set of unaligned management objectives with vastly different outcomes (Sainsbury et al. 2000). As mentioned previously, the criteria for success of management strategies are the management objectives. This means that MSE is operating at the interface of science and implementation of policy, informing managers of the possible trade-offs in managing a fishery (Punt et al. 2016).

There are a number of steps in MSE. Firstly, the management objectives are identified, followed by environmental and management uncertainties, on which operating models of the population are based. The parameters of the model are then chosen, and candidate management strategies are introduced. Each of these candidate strategies is implemented for each model. The performance statistics are then interpreted and refined relevant to the competing management goals achievable (Butterworth et al. 2010; Punt et al. 2016). Though HCRs can be set independent of any framework, MSE can be used to inform HCR choice using simulation. The latter was the case in this project.

The most widespread approach to reducing exploitation is reducing TAC, which has a varying impact on the recovery of the stock (Trzcinski and Bowen 2016). The TAC can be determined through many quantitative methods, including reference points and HCRs. Harvest strategies aim to produce management actions in line with management objectives.

They use reference points to inform decisions via a process of stakeholder engagement. Flexible rules (HCRs) are nested within these strategies (Dowling et al. 2008).

HCRs can be considered algorithms that convert biological information on stock status into management action (Eikeset et al. 2013). They have been formerly referred to as harvest strategies, where there is a strategy that informs catch output corresponding to the stock status at that time (Hilborn and Walters 1992). HCRs have been important in modulating fishing pressure in Norwegian fisheries. They have notably been used for cod and capelin in the Barents Sea and Norwegian spring-spawning herring (Howell and Filin 2013; Tjelmeland and Røttingen 2009).

Reference points, which can be biomass, catch or fishing mortality based, are alone not enough to make management actions, which is where HCRs create the structure to provide that scientific basis (Punt and Donovan 2007). Limit reference points express the risk of overfishing in terms of fishing mortality and biomass associated changes that impact long-term sustainability (Dichmont 2017). Reference points are usually determined from stock assessment, indicating when the stock has crossed a threshold of risk. B_{lim} generally indicates the biomass when there is a high risk of impaired recruitment, whilst B_{pa} and $B_{trigger}$ are reference points defined based on corresponding limit reference points, that act as buffers in HCRs and implicate a reduction in fishing mortality (Eikeset et al. 2013). These points are usually formulated *ad hoc* where stock-specific management strategies are needed. HCRs are setup to best achieve yields, informed by reference points.

A shortlist of candidate HCRs can provide an alternative creation of the most sustainable yields from the fishery (Thorpe and De Oliveira 2019). Constant escapement, fishing mortality and catch along with adaptive versions of these, are the most common HCRs utilised (Deroba and Bence 2008). These HCRs have stock-specific reference points. For example, the historic HCR for Norwegian spring-spawning herring stipulated a maximum F_{target} of 0.125 and a minimum acceptable SSB of 2.5 million tonnes (Figure 2) (Tjelmeland and Røttingen 2009). These conditional rules are developed relative to the species' life history.

Constant escapement is a HCR commonly used for short-lived species. In the case of Atlantic salmon, $B_{escapement}$ is used as a target, as the amount of biomass left to spawn, below which recruitment is deemed impaired (ICES 2017). NASCO plays a large role in the regulation of these fisheries and advises that the precautionary principle is followed (Windsor and Hutchinson 1994). In this case, that means lowering the risk that SSB falls below $B_{escapement}$.

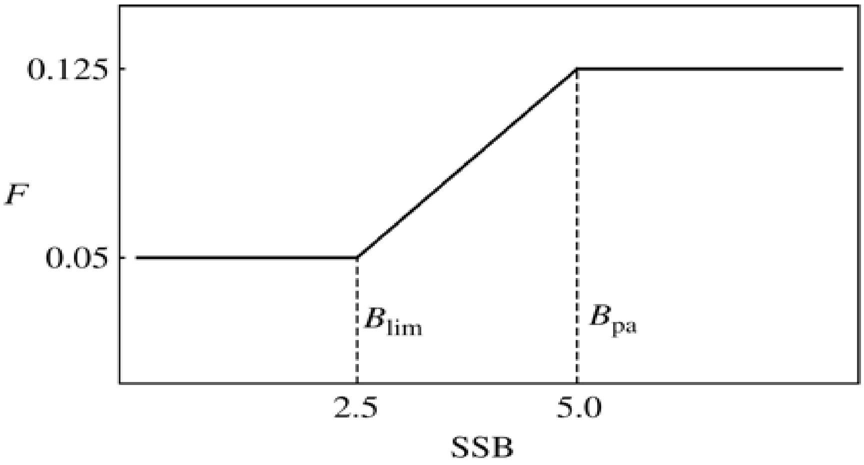


Figure 2. *Schematic representation of HCR used in the recovery of Norwegian spring-spawning herring (Tjelmeland and Røttingen 2009).*

Developing generic HCRs is an alternative to stock-specific strategies. Froese et al. (2010) presents an overview of overexploitation in European fisheries. The HCR in the paper was developed in response to the lack of adherence of international agreements in European fisheries management. It explores generic HCRs for stocks in Europe and generates one size fits all biomass-based HCR. Applied to North Sea herring, with Maximum Sustainable Yield (MSY) as the target, it is suggested that the 1970s stock collapse may have been avoidable. Froese et al. (2010) proposes the HCR under the premise that the precautionary principle has not been considered.

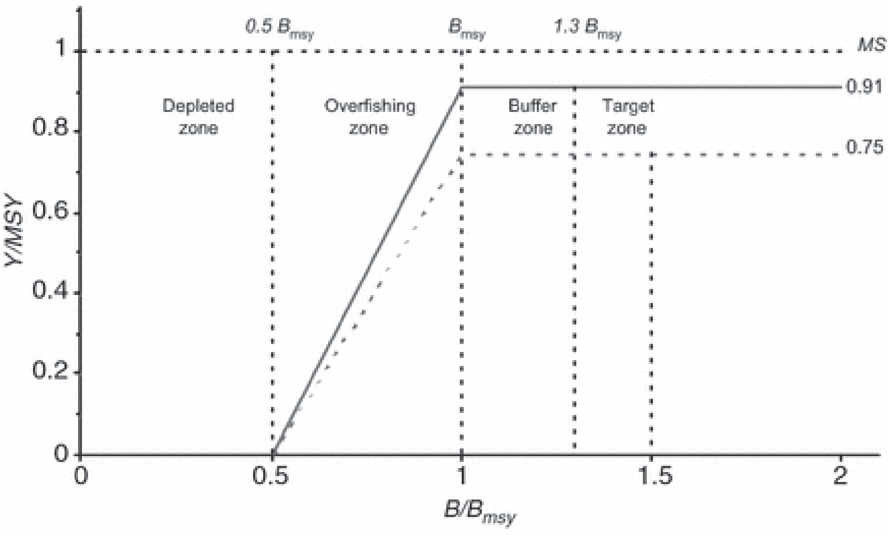


Figure 3. *Generic HCR proposed for European fisheries reference points in accordance with MSY targets (Froese et al. 2010).*

Given that the stock is providing both socioeconomic and ecosystem services, it is important to develop management objectives as a framework for decision making. The management objectives of fisheries management are similar across states, for example the Common Fisheries Policy in the EU—'rational exploitation on a sustainable basis'—and the Magnuson–Stevens Fishery Conservation and Management Act in the US, 'Ensure a safe and sustainable supply of seafood', share common goals in relation to policy (Mardle et al. 2002).

There are many biological criteria of MSE performance. Year to year fluctuations in catch, total catch and risk of dropping below a biomass threshold are common indicators of performance of HCRs (Punt 2017). Simulation modelling of alternative HCRs using the MSE approach is therefore an effective method of evaluating the performance of management strategies.

1.3. Simulation modelling in fisheries management

In response to the threat of human overexploitation, fisheries and ecosystem models have been developed to approximate the dynamics of real populations. The first models described increases and decreases in a population according to recruitment, growth, mortality and migration of fish (Russell 1931). Density dependence was introduced into quantitative models of population growth and stock recruitment relationships by Beverton and Holt (1957). Further contributions to biological dynamics and strong considerations of uncertainty in modelling those dynamics followed (Ricker 1958). Since then, increased computational power has vastly improved quantitative methods for simulating stock dynamics in response to fleet dynamics (Agnew 1982; ICES 2013). The emergence of new, more advanced models has been slow. This is because modelling complex fisheries systems is fraught with inextricably sophisticated interactions that force trade-offs in realism versus simplicity when considering the choice of model (Sharp et al. 1983). Decisions in fisheries management rely on reliable models of the stock status.

Reliable simulation models of stocks require many input parameters. These come from various sources. For example, in the case of natural mortality, most work in the field has been done on single species modelling where predator interactions are compressed into a natural mortality parameter (Haddon 2011). Otherwise, the natural mortality parameter is often specified given life history parameters or assumed to be 0.2 (Powers 2014).

Simulations of stock biomass into the future require age-structured data. Age-structured models are employed where information on recruitment and growth of cohorts are available to temporally differentiate biomass (Subbey et al. 2014). Age-structured population growth gives more accurate estimations of temporal changes in population (Haddon 2011). The development of age structured models both facilitated the management of fisheries using reference points and the projection of biomass into the future (Needle 2011). Corollary, this facilitated the development and implementation of HCRs.

MSE was developed to simulate scenarios with robustness to uncertainties in stock dynamics (De Moor et al.2011). Many species have high uncertainties in their life history dynamics. Deep sea-species such as Greenland halibut (*Reinhardtius hippoglossoides*) are typified by their longevity, late maturity, sporadic recruitment and slow growth (Jorgensen et al. 2014). Many commercial deep-sea species (>500m) display this specific life history. This is of concern when considered that they are heavily exploited, and many are classified as endangered by the IUCN (Koslow et al. 2000; Devine et al. 2006; World Conservation Union 2001). Thus, there is an imperative to develop HCRs that reduce the risk of overexploitation of these stocks.

Long-lived species have complex life history dynamics and the results of management actions are therefore very uncertain. MSE critically examines the performance of these management actions through computer intensive simulation (Sainsbury et al. 2000). MSE of HCRs is thus an important tool for the sustainable exploitation of stocks with highly irregular life histories.

1.4. Aims of this project

This project attempts to address the utility of a Novel HCR in the management of species that have long lifespans and exhibit spasmodic recruitment. Ultimately, the Novel HCR was designed to inform the future design of a HCR for Greenland halibut management, which currently doesn’t specify any **(**ICES 2019a**)**. The aim was to develop a Novel HCR that would only harvest the fraction of biomass above the $B_{trigger}$ reference point. This HCR was developed to resemble the Escapement HCR used for short-lived species such as Atlantic salmon (ICES 2017). While it is used for conservation of the spawning population in salmon management, it was considered as a method of conserving the sporadic spikes in recruitment in this study. Through MSE, the Novel HCR was compared to a more traditional ICES HCR using key performance criteria. The model setup, development of the two HCRs and the choice of performance criteria are all discussed in the next section.

2. Materials and Methods

2.1. Introduction to the model

A simulation model called FLBEIA was used to evaluate the success of a novel HCR over a more traditional HCR of stock biomass. The model was used to compare the performance of the HCRs when harvesting a generic, long-lived species with irregular recruitment. Performance was judged based on the output from the FLBEIA model used. FLBEIA is a package in R programming software (R Core Team 2014) which uses FLR libraries to simulate real fisheries dynamics. FLBEIA is built to simulate the performance of HCRs using MSE and is composed of two interacting blocks: An Operating Model and a Management Procedure. The operating model simulates the real system dynamics. It has arguments for fleet, biological and covariable components. The fleet and biological components interact through catch and effort. The Management Procedure simulates the management of the fishery with arguments for data collection, the assessment model and management advice (Garcia et al. 2017). The performance and evaluation of the HCR depends on all three components. This characteristic of MSE distinguishes it from traditional assessment of management objectives (Punt 2014). As the fishery system tested in this project was fictional, no stakeholder engagement was acquired. Instead, generic outcomes were chosen as performance criteria. For example, a HCR was not considered if it led to stock collapse in an unacceptable number of model simulations, failing to adhere to the precautionary approach. The choice of criteria was informed by ICES guidelines and applied MSE procedures (ICES 2013; ICES 2019b). In the next section, the design of the model to reflect the hypothetical stock dynamics is outlined.

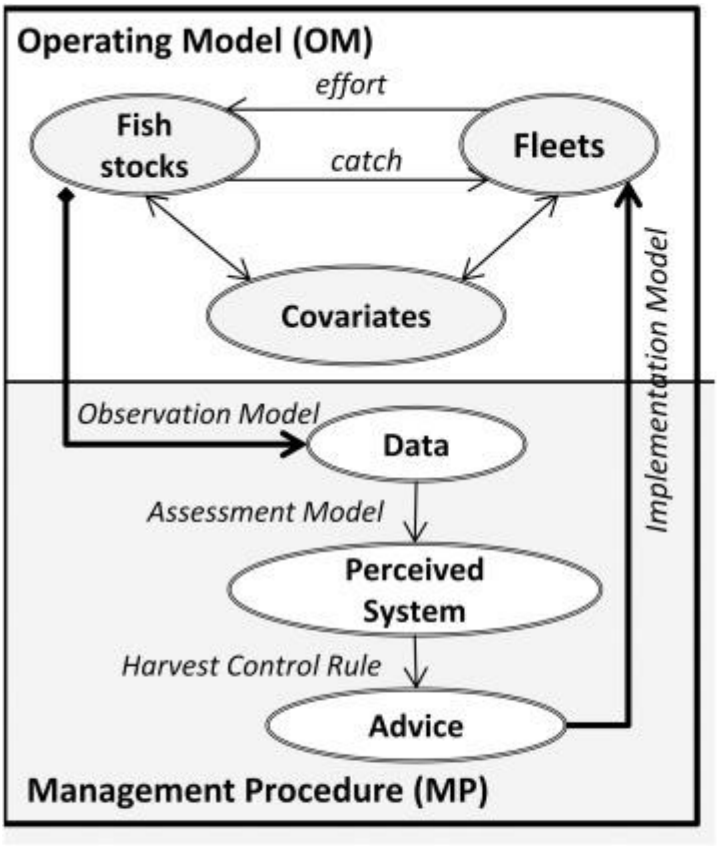


Figure 4. *Architecture of the FLBEIA model, displaying the interactions between the Operating Model, Management Procedure and the components of their blocks. Note: 'Fish stocks' will be referred to as the 'Biological' component (Garcia et al.2017).*

2.2. Designing the Operating model

The Operating model was designed using input data for biological and fleet components. No covariates were included in the model. Long-lived species require longer time series for estimation of age structured biomass to encompass the growth of older cohorts (Ono et al. 2014). Therefore, the model was created to reflect a time span of 100 years to facilitate the stabilisation of stock parameters and the projection of two generations of stock biomass. The first year of the model was composed of historical data which served as input for the biological and fleet parameters. The historical data was gathered from various sources to reflect the life history parameters of the hypothetical stock. The second year of the model was the beginning of the projection. All projections were set to take place in one season to eliminate variability due to seasonality. Fishing mortality began to be applied in the first year of the projection. The model is organised with a hierarchy of functions. FLBEIA is the first level function that calls the second level functions for each individual component of the model as arguments. For example, the stock recruitment argument, which had inputs for SSB and recruitment per projection year, was stored in one object which was called by the FLBEIA function (Garcia et al. 2017).

2.2.1. Biological component of the Operating Model

For the first year of the of the model (the historic period), biological parameters were designed to resemble a spasmodic, long lived species. There was a single stock active in the model. The stock was age structured, with an ASPG (Age Structured Population Growth) model chosen to simulate population dynamics. The ASPG function projected age structured populations one season ahead using the stochastic recruitment model and an exponential survival model for the age classes already in the model. All the individuals moved from an age class to the successive one on the 1st of January disregarding the season in which they were born. ASPG all occurred in one season to simplify the life history parameters of the hypothetical species. The population dynamics are written mathematically as:

If $s = 1$,

$$N_{a,y,} = \begin{cases} \left(\phi RI_{y=y-a_0}\right) & , a = a_0 \\ \left(N_{i_a}.e^{-\frac{M_{i_a}}{2}} - C_{i_a}\right).e^{-\frac{M_{i_a}}{2}} & , a_0 < a < A \\ \left(N_{i_{A-1}}.e^{-\frac{M_{i_{A-1}}}{2}} - C_{i_{A-1}}\right).e^{-\frac{M_{i_{A-1}}}{2}} + & \\ \left(N_{i_A}.e^{-\frac{M_{i_A}}{2}} - C_{i_A}\right).e^{-\frac{M_{i_A}}{2}} & , a = A \end{cases}$$

where ϕ is the recruitment function, *RI* the reproductive index, *N* the number of individuals, *M* the natural mortality, *C* the catch, a_0 the age at recruitment, and *a*, *y* are the subscripts for age and year, where $i_a = (a\text{-}1, y\text{-}1)$, $i_{A\text{-}1} = (A\text{-}1, y\text{-}1)$ and $i_A = (A, y\text{-}1)$.
The reproductive index *RI* is given by:

$$RI_{y-a_0} = \sum_a (N\,.\,wt\,.\,mat\,.\,fec\,.\exp - (M\,.\;M_{spwn} + F\,.\;F_{spwn}))_{a,y-a_0}$$

where *wt* is the mean weight, *mat* is the percentage of mature individuals, *fec* is the fecundity parameter, M_{spwn} and F_{spwn} are the proportion of natural and fishing mortality, respectively, occurring before spawning (Garcia et al. 2012).

To initiate the model, one year of historic input of numbers at age were needed. Input for the number of individuals at age one were selected to reflect figures for Greenland halibut from the report of the Arctic Fisheries Working Group (AFWG) (ICES 2007a). The successive age classes were calculated where numbers at age two were 90 percent of the numbers of individuals at age one. The 10 percent drop off carried on until the maximum age of 40. All individuals in the year class matured at age 10, at which point fishing pressure was applied. There was no sex specific maturity. Weight at age for the historic year was calculated using the Von Bertalanffy Growth Function (VBGF) with input parameters from FishBase (Froese and Pauly 2019). The VBGF was used to calculate weight-at-age using L_∞, K and t_0 as inputs (Sparre and Venema 1998):

$$W_t = c \,.\, {L_\infty}^3 .\ [1 - e^{(-K\,.\,(a-a_0))}]^3$$

gives the weight as a function of age where c is the condition factor, L_∞ is the asymptotic length, K is the curvature parameter and a_0 is the age at which the fish has zero length. The weight at age for the historic year was equal to the weight of the individual of the corresponding age for each year of the projection.

The recruitment function used to simulate entrance to the population, was the Beverton and Holt model. The function is written mathematically as:

$$R = \frac{\alpha \,.\, SSB}{\beta + SSB}$$

where α was the maximum asymptotic recruitment value and β was the SSB that provided half the maximum recruitment ($\alpha/2$) (Garcia et al. 2012) (Figure 5). The recruitment input values were chosen to reflect numbers similar to Greenland halibut (ICES 2017a).

There were three recruitment scenarios tested:

1. Deterministic recruitment.
2. Sporadic recruitment (SR).
3. Erratic recruitment (ER).

In the case of the deterministic projection model, α and β were constant for every year of the projection period, where recruitment varied only according to SSB. The deterministic model was used as to ensure stability of the stock dynamics when the HCR was applied to the biomass. The SR scenario was the one meant to most closely resemble the sporadic recruitment of the long-lived generic species. Finally, the ER scenario was used to test MSE on a species with erratic dynamics. This is done in real world MSE to view the robustness of HCRs in cases where there are high levels of uncertainty (ICES 2019b). In the case of SR and the ER a multiplier was used on α using a uniform probability distribution, where in each 10 year projection period there was a 10 percent chance of a spike in recruitment. In the SR scenario,

$$if\ u > 9, \quad \alpha' = \alpha\ .\ 5.5$$

$$if\ u < 9, \quad \alpha' = \alpha\ .\ 0.5$$

In the ER scenario:

$$if\ u > 9, \quad \alpha' = \alpha\ .\ 9.1$$

$$if\ u < 9, \quad \alpha' = \alpha\ .\ 0.1$$

where u is a random number between 0 and 10 in a uniform probability distribution, α' is the recalculated asymptotic recruitment value used in the Beverton and Holt stock recruitment model. In both recruitment scenarios, the expected average value of α' was equal to α.

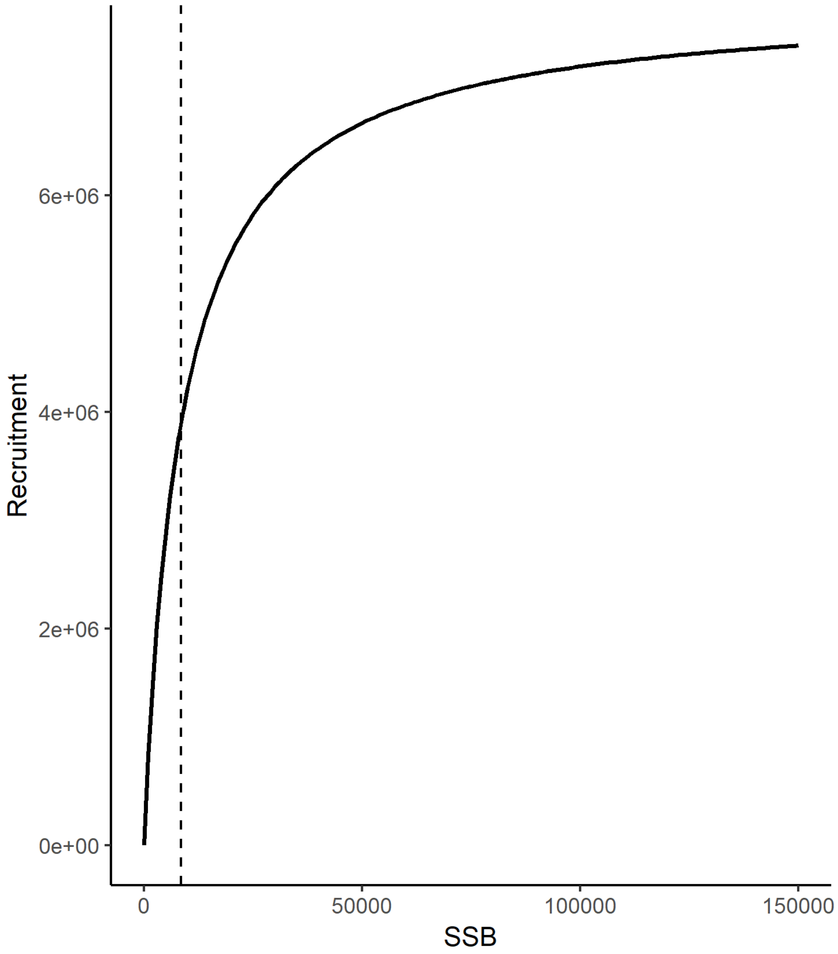


Figure 5. *Graphical representation of the Beverton and Holt stock recruitment relationship in response to SSB levels in the deterministic recruitment scenario. The dotted line shows the value of* β.

2.2.2. Fleet component of the Operating Model

The Operating Model was composed of a single fleet operating in a single season. The effort model used was a Simple Mixed Fisheries Behaviour (SMFB) model, which simulated the behaviour of the fleets. The function is season dependent and uses effort, catchability and catch threshold parameters as input. The catch production model calculated catch according to the SMFB and the F_{target} set in the HCR. There was a feedback between catch and effort, where catch is a product of effort and effort depends on the catch production model. The catch production model used was CobbDouglasAge where catch was calculated as:

$$C = \sum_{a} q \ .(E.\gamma) \ .SSB_a$$

where C is the catch, q is the catchability of the fleet, a is the subscript for age, E is the effort exerted by fleet f, γ is the proportion of effort exerted by fleet and B is the biomass (Garcia et al. 2012). A catch threshold (γ) of 0.9 was applied to prevent the whole population being caught in any one year of the projection. Parameters q and E were constant for each a and year. The value of E depended on the F_{target} applied in the iteration.

2.3. Management Procedure

2.3.1. The Observation Model

The Management Procedure was run once per year, consisting of the observation model, the assessment procedure and management advice. Catch, biological data and abundance indices were used in the observation model. The PerfectObs function was specified to draw the data from the Operating Model without any error sources. With perfect knowledge, it returns an observation of the population without uncertainty (Garcia et al. 2012).

2.3.2. The Management Advice

Advice was based on perfect knowledge of stock dynamics from the observation model. The management advice model specifies the HCR to be used on the single stock. The different HCRs used reflected both traditional and novel rules. All HCRs that were introduced to the model were catch based methods, where the effort model in the fleets Operating Model aligned with the management advice i.e. effort was restricted by the catch quota using the

SMFB effort model. The ICES HCR was a default HCR in FLBEIA. The reference points that are defined in the ICES HCR: $B_{trigger}$ initiates a level of F lower than SSB, B_{lim} is the SSB level that corresponds with impaired recruitment and F_{target} was fishing mortality that leads to MSY. The ICES HCR aims to keep fishing at the F_{target} level defined in the function where TAC advice is aligned with the fishing mortality (Garcia et al. 2012). B_{lim} is most commonly set based on stock assessment. In this case, it reflected the biomass that produced ~90 percent of the maximum recruitment. The ICES HCR was written mathematically as:

$$F_{target} = \begin{cases} 0 & ,if\ SSB < B_{lim} \\ F_{target} . \dfrac{SSB}{B_{trigger}} & ,if\ SSB < B_{trigger} \\ F_{target} & ,if\ SSB \geq B_{trigger} \end{cases}$$

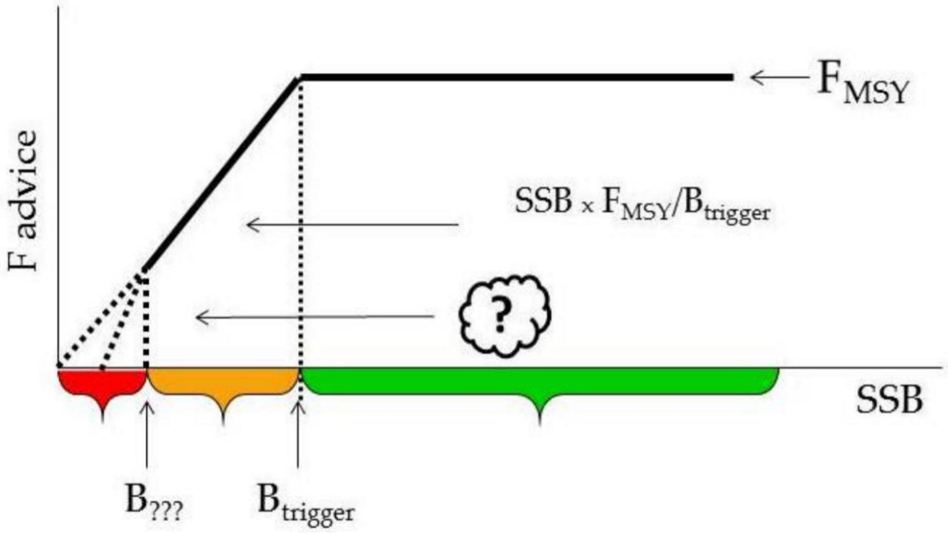


Figure 6. Graphical representation of the ICES HCR and reference points, where $B_{???}$ was zero SSB in the model and F_{msy} was F_{target} (Garcia et al. 2012).

2.4. Diagnostics

Diagnostic output and plots were produced to assess the input parameter values. Input values for the ASPG, SMFB and other models in the Operating Model were examined to scrutinise the initiation of FLBEIA. Age structured data for weight, numbers, spawning time, mortality, landings retention, landings and maturity were accepted when they reflected the life history desired in the hypothetical species. The inputs that were used for the projection period were examined to ensure they were consistent with the time specified functions described in the Operating Model. The initial number of individuals at each age reflected the total numbers alive given a constant natural mortality of 0.1 applied to each cohort. Weight at age in tonnes followed the standard VBGF curve. Maturity of cohorts didn’t occur until age 10 when they joined the SSB and were subject to fishing mortality. Finally, the landings retention curve confirmed that there were no landings of individuals below the age of 10 (Figure 7).

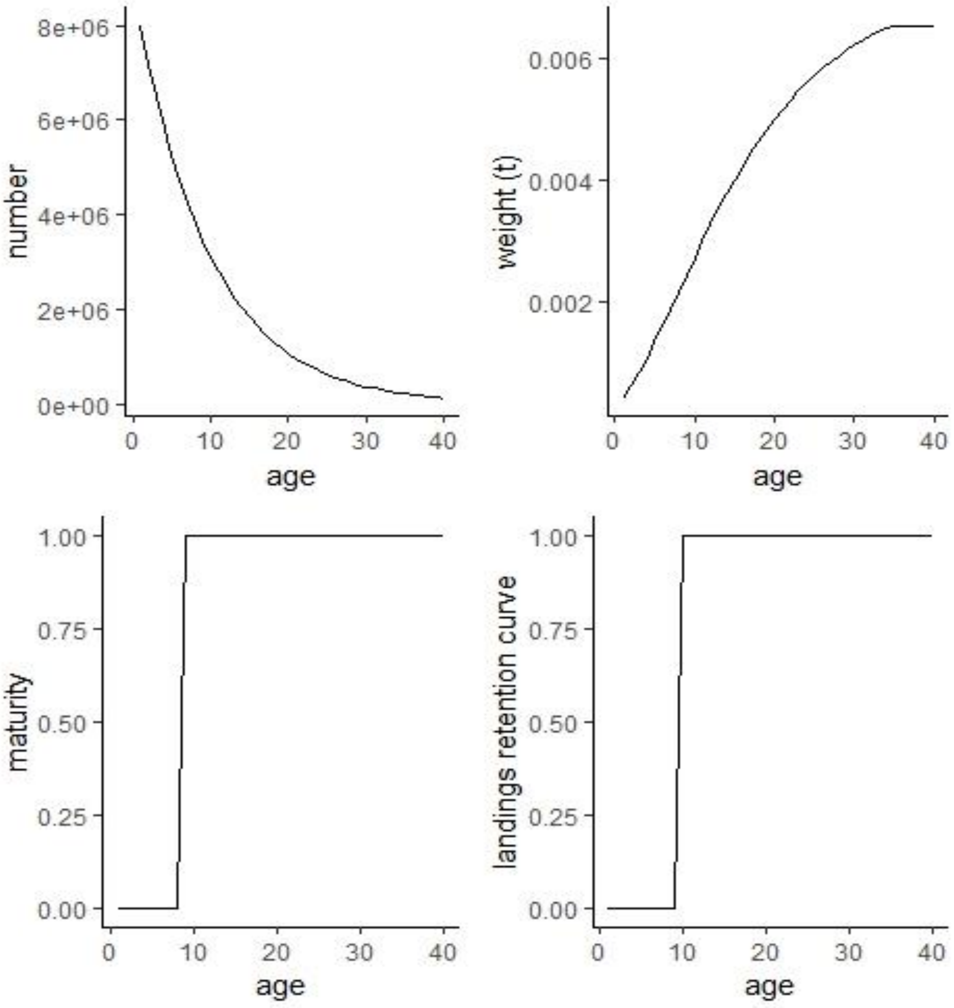


Figure 7. *Sample diagnostic plots for input parameters in the biological and fleet Operating Model.*

2.5. Tuning

The model was tuned by varying input parameters and scrutinising the corresponding output response. Catch and effort were altered in order to predict the interactions between fleets and biological components of the Operating Model. TAC, effort and landings were scaled up/down by a specified fraction and the responses in SSB and catch were examined. Taking recruitment as an example, the fishing mortality was doubled and the projection was run. Output from catch and SSB were examined to inspect the fluctuations across time. Errors in the Operating Model were debugged using the above method, in order to tune the hypothetical data to FLBEIA.

2.6.HCR setup

2.6.1. ICES HCR setup

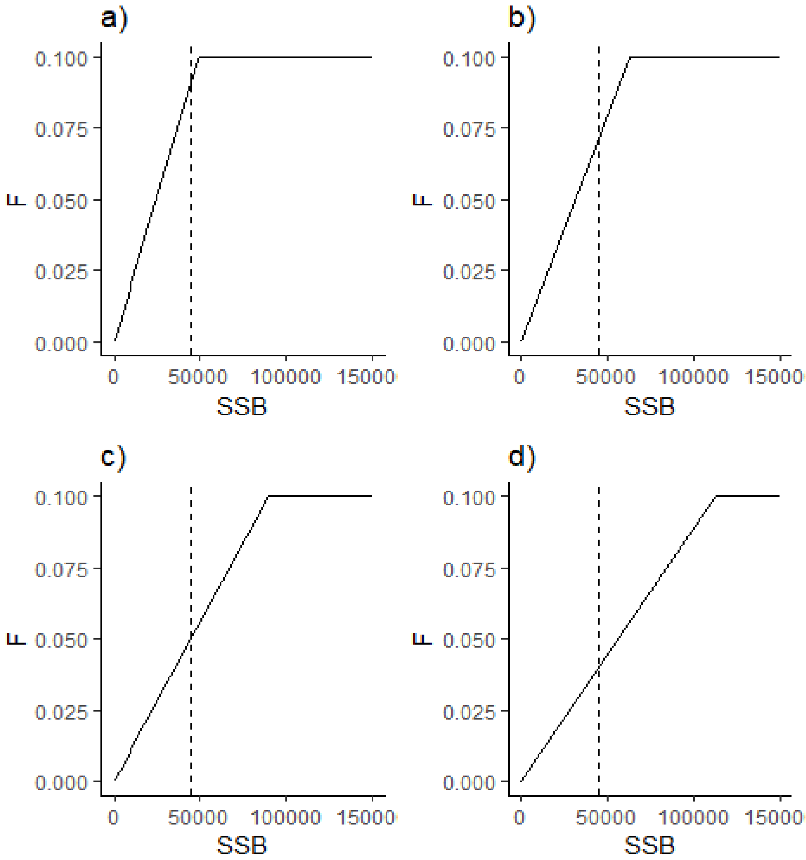


Figure 8. *Graphical representation of the ICES HCR applied with* $B_{trigger}$ *values of 1.1**B_{lim} *(a), 1.4**B_{lim} *(b), 2**B_{lim}*, (c), 2.5**B_{lim} *(d), where the dashed line is* B_{lim} *of 45000 tonnes.* F_{target} *in the above case was 0.1 for SSB >* $B_{trigger}$*.*

The ICES HCR used was the default function in FLBEIA (Figure 6). The ICES HCR is a "hockey-stick" model where there is a straight line from the origin to the F_{target}, followed by a horizontal line after $B_{trigger}$. Below the $B_{trigger}$ threshold, there is a reduction of linear reduction in F_{target} (Figure 8). It was formulated according to the default function in the FLBEIA manual and described above (Garcia et al. 2012). The ICES HCR was applied with F_{target} values of 0.01, 0.025, 0.05, 0.075, 0.1, 0.2, 0.3, 0.4 for the ER scenario. In the case of SR, additional values of 0.15, 0.25 and 0.35 were included. Each recruitment, F_{target} and $B_{trigger}$ combination was iterated 100 times and output was stored in summary objects. The mean catch, Realized F, risk of collapse, fraction of years with moratoria and catch variability were calculated from each summary object.

2.6.2. Novel HCR setup

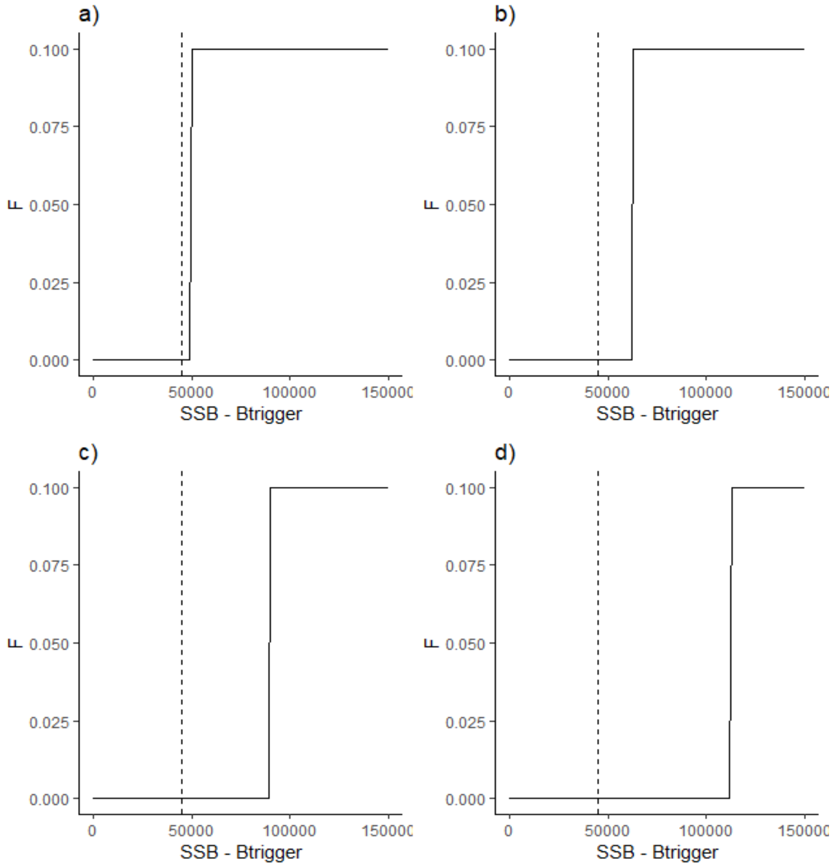


Figure 9. *Graphical representation of the novel HCR applied with* $B_{trigger}$ *values of 1.1**B_{lim} *(a), 1.4**B_{lim} *(b), 2**B_{lim} *(c), 2.5**B_{lim} *(d), where the dashed line is* B_{lim} *of 45000 tonnes.* F_{target} *in the above case was 0.1 for SSB >* $B_{trigger}$*.*

The Novel HCR was a modification of the default ICES HCR function in the FLBEIA model. The source code was changed so that F_{target} was only applied to the fraction of biomass above a precautionary level of biomass ($B_{trigger}$). This resembles a constant escapement strategy, where some proportion of the biomass is protected from harvesting altogether (Figure 9). Thus, F_{target} was only applied to SSB > $B_{trigger}$. The Novel HCR written mathematically is:

$$F_{target} = \begin{cases} 0 & , if\ SSB < Btrigger \\ F_{target} & , if\ SSB \geq Btrigger \end{cases}$$

The Novel HCR was applied with F_{target} values identical to the ICES HCR. Each recruitment, F_{target} and $B_{trigger}$ combination was iterated 100 times and output was stored in summary objects (Table 1). The mean catch, Realized F, risk of collapse, fraction of years with moratoria and catch variability were calculated from each summary object.

Table 1. *The F_{target} and $B_{trigger}$ combinations simulated and the number of iterations of each cell for both HCRs. Blue cells indicate scenarios that were iterated for SR but not ER.*

	$B_{trigger}$			
F_{target}	**49500 (1.1*Blim)**	**63000 (1.4*Blim)**	**90000 (2*Blim)**	**112500 (2.5*Blim)**
0.01	100	100	100	100
0.025	100	100	100	100
0.05	100	100	100	100
0.075	100	100	100	100
0.1	100	100	100	100
0.15	100	100	100	100
0.2	100	100	100	100
0.25	100	100	100	100
0.3	100	100	100	100
0.35	100	100	100	100
0.4	100	100	100	100

2.7. Performance indicators and post-processing

The summary files created from the FLBEIA model were stored and saved in objects that were downloaded and processed. FLBEIA summary output was then scrutinised so risk of SSB falling below B_{lim}, mean total catch, catch stability and mean realized fishing mortality could be compared. The first predictor to be scrutinised was the risk of stock collapse, qualified as SSB falling below B_{lim}. Risk is an indicator of the probability that SSB is below B_{lim} in any given year. If SSB was below B_{lim} for one or more of the final 10 years of the projection, it was qualified as a collapse for that iteration. If the risk was above 5% (>5/100 iterations), the scenario was not viable for comparison across other criteria. This method of calculating risk is aligned with precautionary criterion for MSE (ICES 2019b). The risk was recalculated for the erratically recruiting stock based on the F_{target} = 0 scenario. The risk threshold was doubled according to the chance of the stock falling below B_{lim} in the absence of fishing pressure, as per standard procedure for erratically recruiting stocks (ICES 2019b).

Fraction of moratoria was calculated to assess the frequency of fishery closures. It was only used to assess the performance of the Novel HCR. The overall fraction of years that experienced closures was calculated as a percentage across all iterations. That is, the fraction of years where SSB was below $B_{trigger}$. No threshold was predefined given that the criteria was only examined for the Novel HCR. Regardless, there was utility in examining this as it was indicator of how often the fishery was closed.

The average catch was calculated according to the mean in the final 10 years of the projection and median across the 100 iterations. The average Realized F was calculated in the same way. Average catch gave an indication of how successful the HCR was in maximising catch along the time series. Average Realized F was an indicator of the fraction of time that fishing was occurring above and below the $B_{trigger}$ threshold.

Interannual Catch Variability (ICV) was used as another indicator of the stability of the hypothetical fishery. In real world commercial fisheries catch stability is often valued above high catch when income stability depends upon it. ICV was calculated as:

$$\frac{|C_{y+1} - C_{y-1}|}{C_{y-1}}$$

where *C* is catch and *y* is the year. The average ICV was calculated as the mean of the final 10 years and the median over all iterations.

3. Results

3.1. Introduction

Results of the simulations of all scenarios are presented in tables below. All results were taken from the last ten years of each iteration. Firstly, F_{target} and $B_{trigger}$ combinations were screened for their risk of stock collapse. Mean catch, ICV and Realized F were then calculated for each scenario. These two steps were carried out for both the SR and ER scenarios. Corollary, the same performance criteria were used for the Novel HCR, with the addition of moratoria. The performance results that had an acceptable risk (<5%) were then scrutinised along all indicators to observe trade-offs between the two HCRs. This comparison was then used to gain insight on the utility of the Novel HCR and implications were subsequently discussed based on the relevant management objectives.

Risk was qualified differently for the ER condition, as discussed in the methods (Section 2.7). This was due to the inability of the stock to maintain biomass above B_{lim} for <5% of iterations where a moratorium was put on fishing ($F_{target} = 0$). The average risk of collapse was calculated as 22%. This figure was doubled and used as the new acceptable risk of 44%. This is a standard procedure in MSE when dealing with stocks of species with unstable dynamics (ICES 2019b).

3.2. Sporadic Recruitment

3.2.1. ICES HCR

Presented below are the performance results for the ICES HCR under the SR scenario.

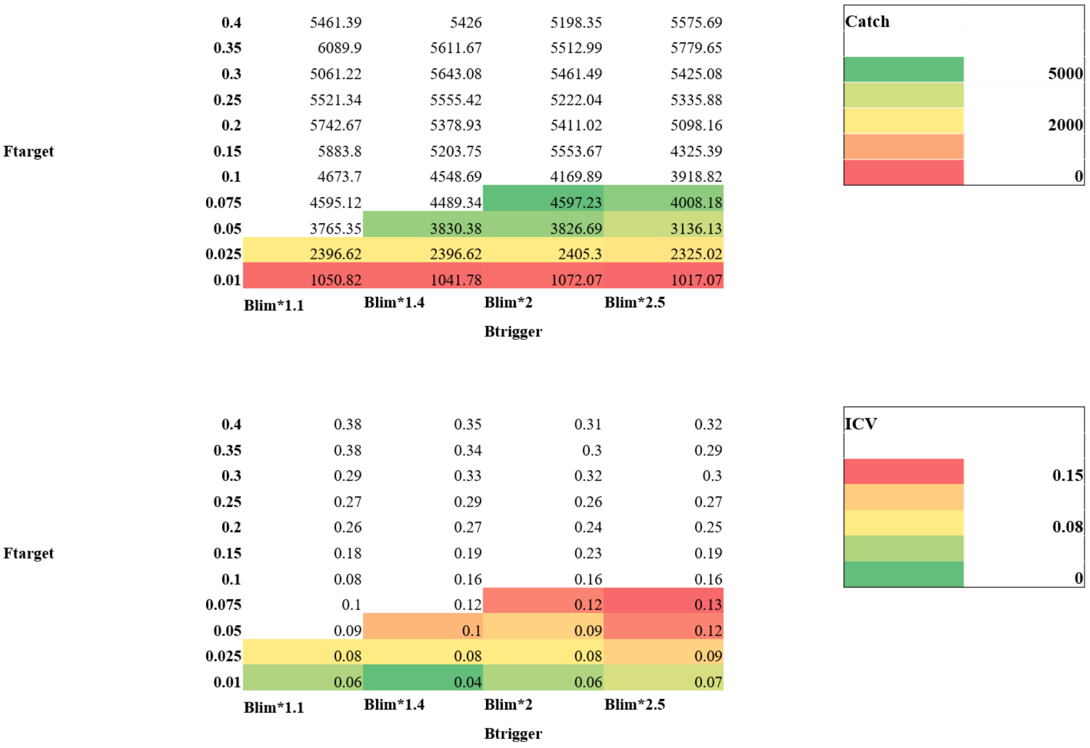
Table 2. *Risk, Catch, ICV and Realized F for lower F_{target} values and SR for the ICES HCR. Green cells indicate risk below 5%, while red cells indicate risk above 5%.*

F_{target}	$B_{trigger}$	Risk	Catch	ICV	Realized F
0.01	$1.1*B_{lim}$	0	1050.82	0.06	0.01
0.01	$1.4*B_{lim}$	0	1041.78	0.04	0.01
0.01	$2*B_{lim}$	0	1072.07	0.06	0.01
0.01	$2.5*B_{lim}$	0	1017.07	0.07	0.01
0.025	$1.1*B_{lim}$	0	2396.62	0.08	0.025
0.025	$1.4*B_{lim}$	0	2396.62	0.08	0.025
0.025	$2*B_{lim}$	0	2405.3	0.08	0.025
0.025	$2.5*B_{lim}$	0	2325.02	0.09	0.024
0.05	$1.1*B_{lim}$	19	3765.35	0.09	0.05
0.05	$1.4*B_{lim}$	0	3830.38	0.1	0.05
0.05	$2*B_{lim}$	0	3826.69	0.09	0.05
0.05	$2.5*B_{lim}$	0	3136.13	0.12	0.04
0.075	$1.1*B_{lim}$	28	4595.12	0.1	0.075
0.075	$1.4*B_{lim}$	26	4489.34	0.12	0.072
0.075	$2*B_{lim}$	0	4597.23	0.12	0.066
0.075	$2.5*B_{lim}$	0	4008.18	0.13	0.056

Table 3. *Risk, Catch, ICV and Realized F for higher F_{target} values and SR for the ICES HCR. Green cells indicate risk below 5%, while red cells indicate risk above 5%.*

F_{target}	$B_{trigger}$	Risk	Catch	ICV	Realized F
0.1	1.1*B_{lim}	70	4673.7	0.08	0.1
0.1	1.4*B_{lim}	62	4548.69	0.16	0.09
0.1	2*B_{lim}	38	4169.89	0.16	0.08
0.1	2.5*B_{lim}	7	3918.82	0.16	0.06
0.15	1.1*B_{lim}	84	5883.8	0.18	0.15
0.15	1.4*B_{lim}	84	5203.75	0.19	0.13
0.15	2*B_{lim}	68	5553.67	0.23	0.11
0.15	2.5*B_{lim}	49	4325.39	0.19	0.09
0.2	1.1*B_{lim}	99	5742.67	0.26	0.18
0.2	1.4*B_{lim}	95	5378.93	0.27	0.16
0.2	2*B_{lim}	90	5411.02	0.24	0.13
0.2	2.5*B_{lim}	89	5098.16	0.25	0.1
0.25	1.1*B_{lim}	99	5521.34	0.27	0.21
0.25	1.4*B_{lim}	100	5555.42	0.29	0.19
0.25	2*B_{lim}	100	5222.04	0.26	0.14
0.25	2.5*B_{lim}	93	5335.88	0.27	0.13
0.3	1.1*B_{lim}	98	5061.22	0.29	0.23
0.3	1.4*B_{lim}	99	5643.08	0.33	0.22
0.3	2*B_{lim}	98	5461.49	0.32	0.17
0.3	2.5*B_{lim}	100	5425.08	0.3	0.15
0.35	1.1*B_{lim}	100	6089.9	0.38	0.3
0.35	1.4*B_{lim}	100	5611.67	0.34	0.24
0.35	2*B_{lim}	100	5512.99	0.3	0.19
0.35	2.5*B_{lim}	99	5779.65	0.29	0.16
0.4	1.1*B_{lim}	100	5461.39	0.38	0.32
0.4	1.4*B_{lim}	100	5426	0.35	0.27
0.4	2*B_{lim}	100	5198.35	0.31	0.2

0.4	2.5*B_{lim}	100	5575.69	0.32	0.18



	0.4	5461.39	5426	5198.35	5575.69
	0.35	6089.9	5611.67	5512.99	5779.65
	0.3	5061.22	5643.08	5461.49	5425.08
	0.25	5521.34	5555.42	5222.04	5335.88
	0.2	5742.67	5378.93	5411.02	5098.16
Ftarget	**0.15**	5883.8	5203.75	5553.67	4325.39
	0.1	4673.7	4548.69	4169.89	3918.82
	0.075	4595.12	4489.34	4597.23	4008.18
	0.05	3765.35	3830.38	3826.69	3136.13
	0.025	2396.62	2396.62	2405.3	2325.02
	0.01	1050.82	1041.78	1072.07	1017.07
		Blim*1.1	**Blim*1.4**	**Blim*2**	**Blim*2.5**
				Btrigger	

Catch	
🟩	**5000**
🟩	
🟨	**2000**
🟧	
🟥	**0**

	0.4	0.38	0.35	0.31	0.32
	0.35	0.38	0.34	0.3	0.29
	0.3	0.29	0.33	0.32	0.3
	0.25	0.27	0.29	0.26	0.27
	0.2	0.26	0.27	0.24	0.25
Ftarget	**0.15**	0.18	0.19	0.23	0.19
	0.1	0.08	0.16	0.16	0.16
	0.075	0.1	0.12	0.12	0.13
	0.05	0.09	0.1	0.09	0.12
	0.025	0.08	0.08	0.08	0.09
	0.01	0.06	0.04	0.06	0.07
		Blim*1.1	**Blim*1.4**	**Blim*2**	**Blim*2.5**
				Btrigger	

ICV	
🟥	**0.15**
🟧	
🟨	**0.08**
🟩	
🟩	**0**

Figure 10. *Matrix of colour-coded results for* F_{target} *and* $B_{trigger}$ *combinations with catch and ICV using the ICES HCR under SR. White cells indicate results that had risk >5%.*

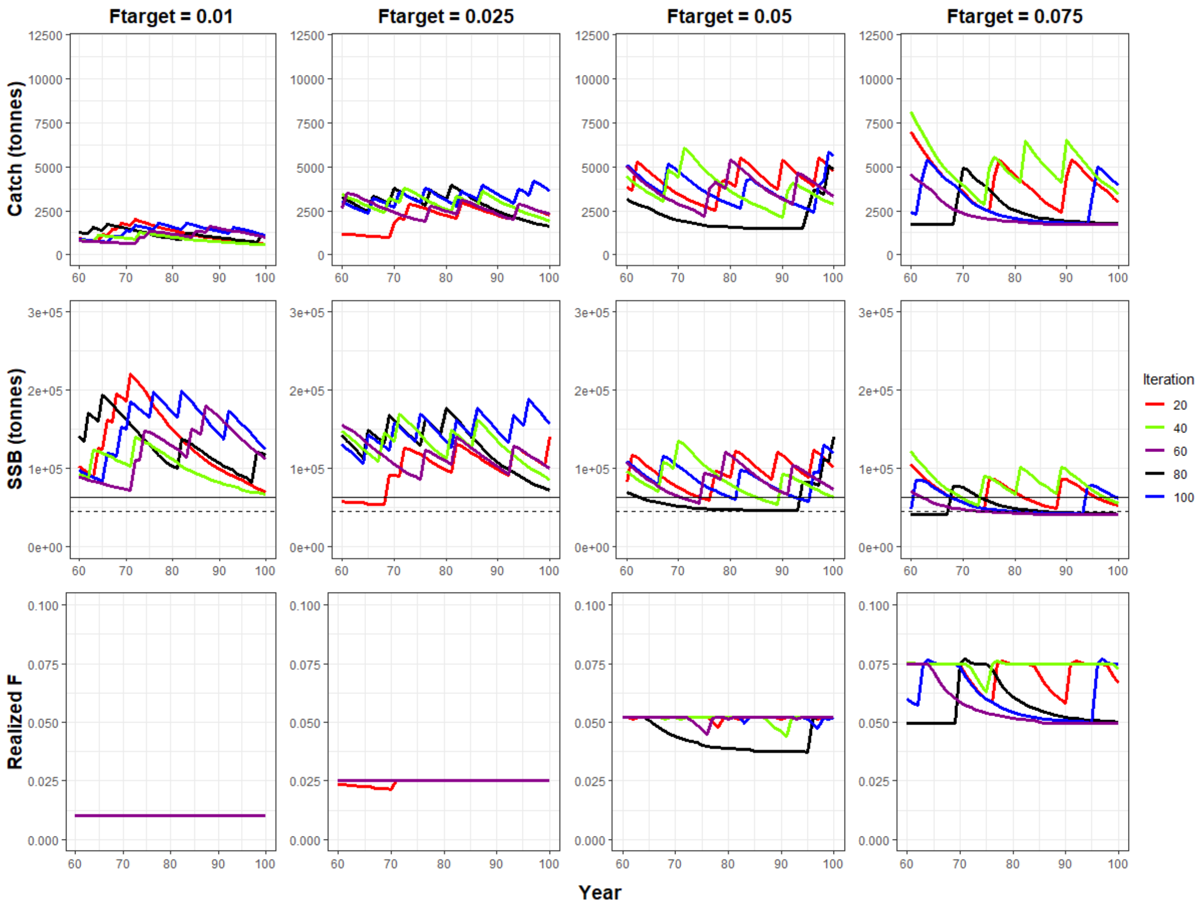


Figure 11. *ICES HCR projection graphs with examples of 5 iterations for each scenario. The results of catch (tonnes), SSB (tonnes) and Realized F are for the final 40 years of the projection under the SR scenario,* $B_{trigger}$ *of 1.4 ** B_{lim} *and low* F_{target} *values of 0.01, 0.025, 0.05 and 0.075. The figure portrays a time series equal to the maximum age of the stock and shows the final 10 years from where performance indicators were taken. The thick horizontal line indicates the* $B_{trigger}$ *level of 63000 (1.4 ** B_{lim}*) and the dashed line shows the* B_{lim} *of 45000.*

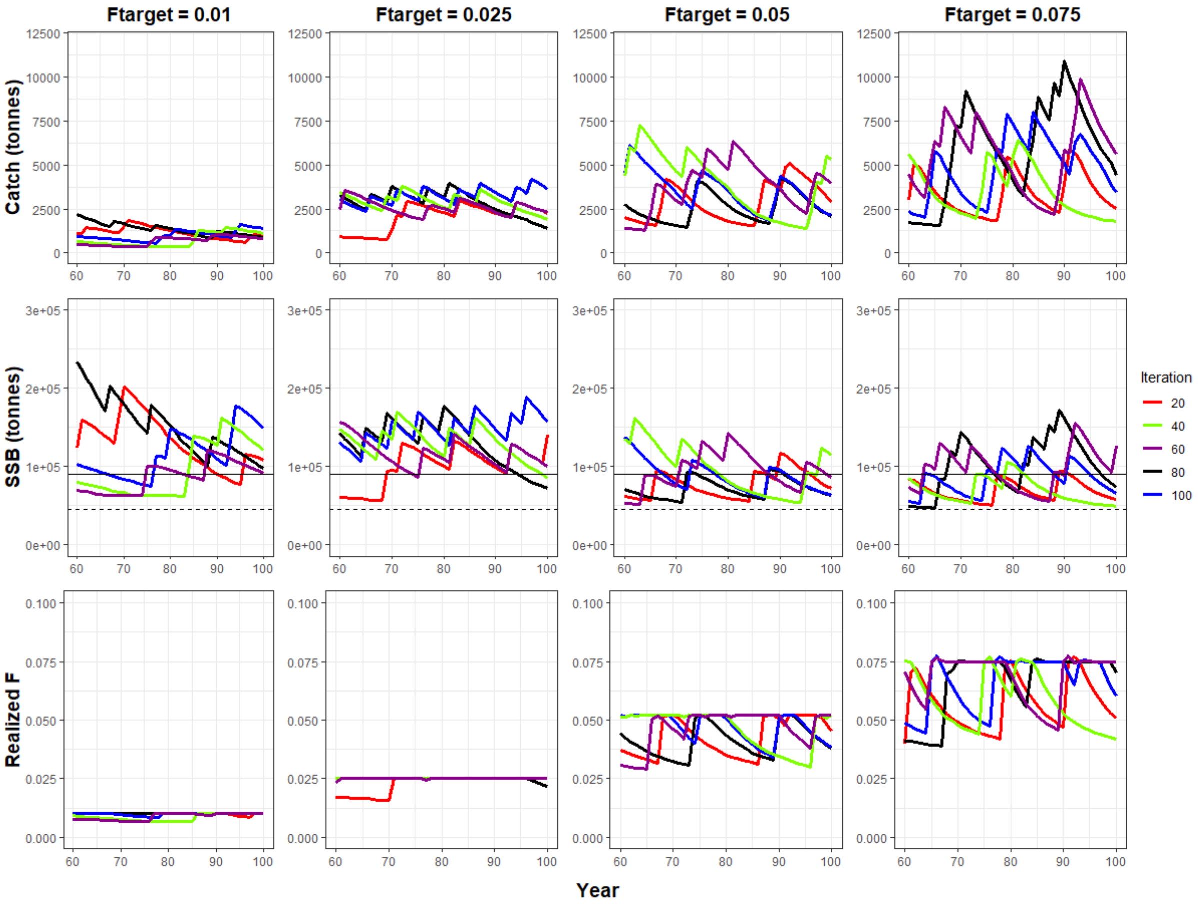


Figure 12. *ICES HCR projection graphs with examples of 5 iterations for each scenario. The results of catch (tonnes), SSB (tonnes) and Realized F are for the final 40 years of the projection under the SR scenario,* $B_{trigger}$ *of* $2 * B_{lim}$ *and low* F_{target} *values of 0.01, 0.025, 0.05 and 0.075. The figure portrays a time series equal to the maximum age of the stock and shows the final 10 years from where performance indicators were taken. The thick horizontal line indicates the* $B_{trigger}$ *level of 90000 (*$2 * B_{lim}$*) and the dashed line shows the* B_{lim} *of 45000.*

3.2.2. Novel HCR

Presented below are the performance results for the Novel HCR under the SR scenario.

Table 4. *Risk, Catch, ICV, Realized F and Moratoria for lower* F_{target} *values and SR for the Novel HCR. Green cells indicate risk below 5%, while red cells indicate risk above 5%.*

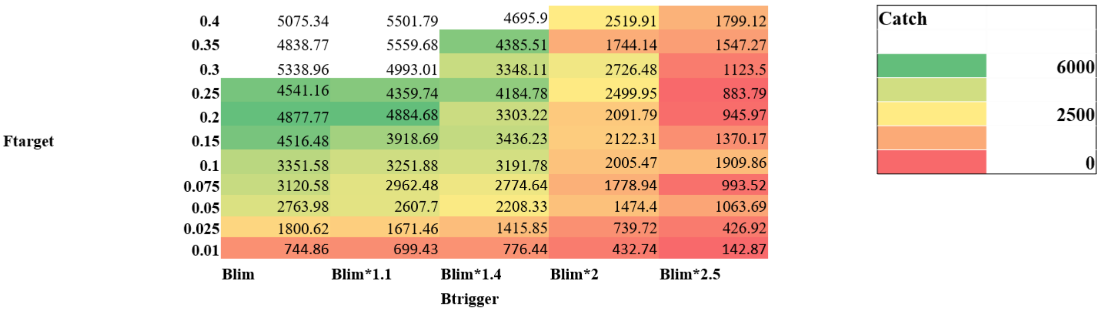
F_{target}	$B_{trigger}$	Risk	Catch	ICV	Realized F	Moratoria
0.01	B_{lim}	0	744.86	0.09	0.01	0
0.01	$1.1*B_{lim}$	0	699.43	0.09	0.01	0
0.01	$1.4*B_{lim}$	0	776.44	0.11	0.01	0

0.01	2*B_{lim}	0	432.74	0.19	0.01	12.5
0.01	2.5*B_{lim}	0	142.87	0.28	0.01	34.7
0.025	B_{lim}	0	1800.62	0.09	0.025	0
0.025	1.1*B_{lim}	0	1671.46	0.09	0.025	0
0.025	1.4*B_{lim}	0	1415.85	0.12	0.025	0
0.025	2*B_{lim}	0	739.72	0.24	0.025	17.5
0.025	2.5*B_{lim}	0	426.92	0.29	0.025	35.2
0.05	B_{lim}	0	2763.98	0.13	0.05	0
0.05	1.1*B_{lim}	0	2607.7	0.14	0.05	0
0.05	1.4*B_{lim}	0	2208.33	0.16	0.05	0
0.05	2*B_{lim}	0	1474.4	0.24	0.05	21.1
0.05	2.5*B_{lim}	0	1063.69	0.35	0.05	29.4
0.075	B_{lim}	0	3120.58	0.16	0.075	0
0.075	1.1*B_{lim}	0	2962.48	0.16	0.075	0
0.075	1.4*B_{lim}	0	2774.64	0.2	0.075	0
0.075	2*B_{lim}	0	1778.94	0.36	0.075	23.9
0.075	2.5*B_{lim}	0	993.52	0.39	0.075	41.1

Table 5. *Risk, Catch, ICV, Realized F and Moratoria for higher F_{target} values and SR for the Novel HCR. Green cells indicate risk below 5%, while red cells indicate risk above 5%.*

F_{target}	$B_{trigger}$	Risk	Catch	ICV	Realized F	Moratoria
0.1	B_{lim}	0	3351.58	0.19	0.1	0
0.1	1.1*B_{lim}	0	3251.88	0.18	0.1	0
0.1	1.4*B_{lim}	0	3191.78	0.24	0.1	1.1
0.1	2*B_{lim}	0	2005.47	0.33	0.09	31.5
0.1	2.5*B_{lim}	0	1909.86	0.4	0.05	56.6
0.15	B_{lim}	0	4516.48	0.29	0.15	0
0.15	1.1*B_{lim}	0	3918.69	0.26	0.15	0
0.15	1.4*B_{lim}	0	3436.23	0.29	0.15	0
0.15	2*B_{lim}	0	2122.31	0.41	0.11	38.3
0.15	2.5*B_{lim}	0	1370.17	0.45	0.08	51.8

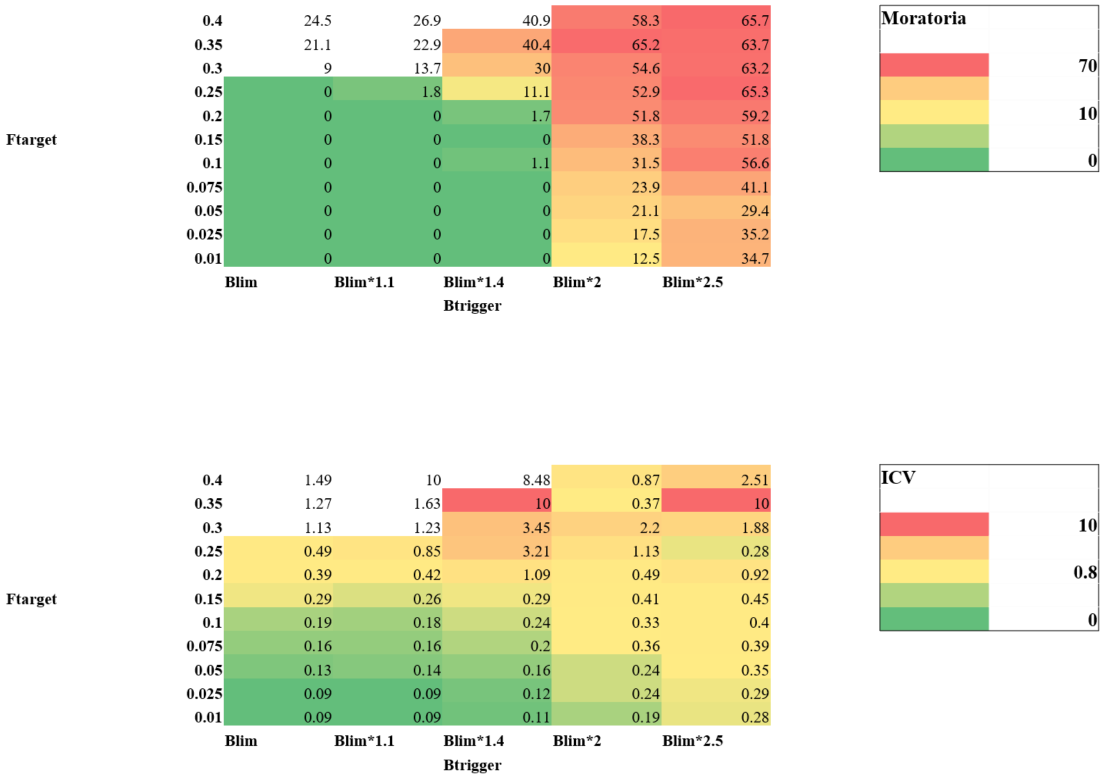
0.2	B_{lim}	0	4877.77	0.39	0.2	0
0.2	$1.1*B_{lim}$	0	4884.68	0.42	0.2	0
0.2	$1.4*B_{lim}$	0	3303.22	1.09	0.2	1.7
0.2	$2*B_{lim}$	0	2091.79	0.49	0.11	51.8
0.2	$2.5*B_{lim}$	0	945.97	0.92	0.08	59.2
0.25	B_{lim}	2	4541.16	0.49	0.25	0
0.25	$1.1*B_{lim}$	0	4359.74	0.85	0.25	1.8
0.25	$1.4*B_{lim}$	0	4184.78	3.21	0.25	11.1
0.25	$2*B_{lim}$	0	2499.95	1.13	0.13	52.9
0.25	$2.5*B_{lim}$	0	883.79	0.28	0.08	65.3
0.3	B_{lim}	42	5338.96	1.13	0.3	9
0.3	$1.1*B_{lim}$	22	4993.01	1.23	0.27	13.7
0.3	$1.4*B_{lim}$	0	3348.11	3.45	0.21	30
0.3	$2*B_{lim}$	0	2726.48	2.2	0.15	54.6
0.3	$2.5*B_{lim}$	0	1123.5	1.88	0.12	63.2
0.35	B_{lim}	62	4838.77	1.27	0.28	21.1
0.35	$1.1*B_{lim}$	41	5559.68	1.63	0.28	22.9
0.35	$1.4*B_{lim}$	1	4385.51	47.05	0.21	40.4
0.35	$2*B_{lim}$	0	1744.14	0.37	0.105	65.2
0.35	$2.5*B_{lim}$	0	1547.27	1142.96	0.14	63.7
0.4	B_{lim}	79	5075.34	1.49	0.4	24.5
0.4	$1.1*B_{lim}$	58	5501.79	118.02	0.32	26.9
0.4	$1.4*B_{lim}$	10	4695.9	8.48	0.24	40.9
0.4	$2*B_{lim}$	0	2519.91	0.87	0.2	58.3
0.4	$2.5*B_{lim}$	0	1799.12	2.51	0.16	65.7



Ftarget	Blim	Blim*1.1	Blim*1.4	Blim*2	Blim*2.5
0.4	5075.34	5501.79	4695.9	2519.91	1799.12
0.35	4838.77	5559.68	4385.51	1744.14	1547.27
0.3	5338.96	4993.01	3348.11	2726.48	1123.5
0.25	4541.16	4359.74	4184.78	2499.95	883.79
0.2	4877.77	4884.68	3303.22	2091.79	945.97
0.15	4516.48	3918.69	3436.23	2122.31	1370.17
0.1	3351.58	3251.88	3191.78	2005.47	1909.86
0.075	3120.58	2962.48	2774.64	1778.94	993.52
0.05	2763.98	2607.7	2208.33	1474.4	1063.69
0.025	1800.62	1671.46	1415.85	739.72	426.92
0.01	744.86	699.43	776.44	432.74	142.87

Btrigger

Catch	
🟩	6000
🟩	
🟨	2500
🟧	
🟥	0



			Btrigger		
Ftarget	Blim	Blim*1.1	Blim*1.4	Blim*2	Blim*2.5
0.4	24.5	26.9	40.9	58.3	65.7
0.35	21.1	22.9	40.4	65.2	63.7
0.3	9	13.7	30	54.6	63.2
0.25	0	1.8	11.1	52.9	65.3
0.2	0	0	1.7	51.8	59.2
0.15	0	0	0	38.3	51.8
0.1	0	0	1.1	31.5	56.6
0.075	0	0	0	23.9	41.1
0.05	0	0	0	21.1	29.4
0.025	0	0	0	17.5	35.2
0.01	0	0	0	12.5	34.7

			Btrigger		
Ftarget	Blim	Blim*1.1	Blim*1.4	Blim*2	Blim*2.5
0.4	1.49	10	8.48	0.87	2.51
0.35	1.27	1.63	10	0.37	10
0.3	1.13	1.23	3.45	2.2	1.88
0.25	0.49	0.85	3.21	1.13	0.28
0.2	0.39	0.42	1.09	0.49	0.92
0.15	0.29	0.26	0.29	0.41	0.45
0.1	0.19	0.18	0.24	0.33	0.4
0.075	0.16	0.16	0.2	0.36	0.39
0.05	0.13	0.14	0.16	0.24	0.35
0.025	0.09	0.09	0.12	0.24	0.29
0.01	0.09	0.09	0.11	0.19	0.28

Figure 13. *Matrix of colour-coded results for Ftarget and Btrigger combinations with catch, moratoria and ICV using the Novel HCR under SR. White cells indicate results that had risk >5%. Any ICV number >10 was collapsed to 10 in order to make the colour-coding visually useful.*

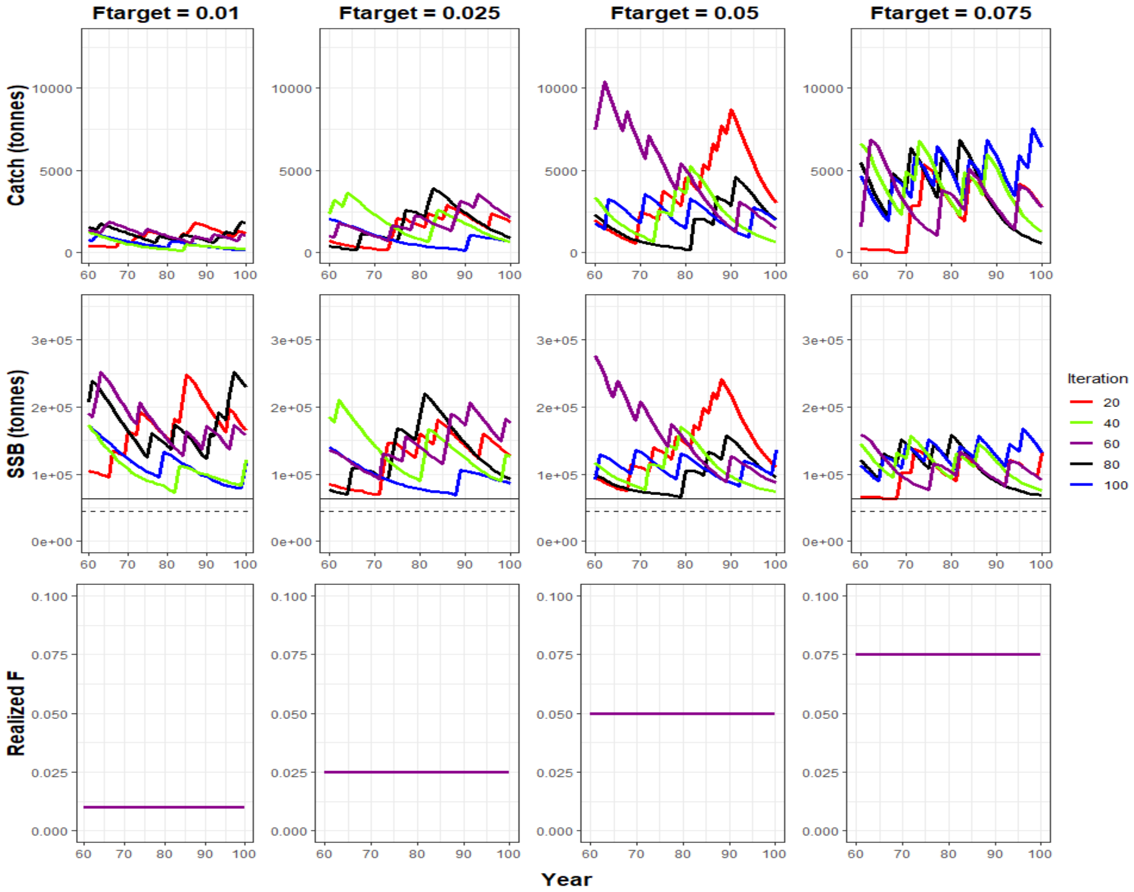


Figure 14. *Novel HCR projection graphs with examples of 5 iterations for each scenario. The results of catch (tonnes), SSB (tonnes) and Realized F are for the final 40 years of the projection under the SR scenario,* $B_{trigger}$ *of 1.4 ** B_{lim} *and low* F_{target} *values of 0.01, 0.025, 0.05 and 0.075. The figure portrays a time series equal to the maximum age of the stock and shows the final 10 years from where performance indicators were taken. The thick horizontal line indicates the* $B_{trigger}$ *level of 63000 (1.4 ** B_{lim}*) and the dashed line shows the* B_{lim} *of 45000.*

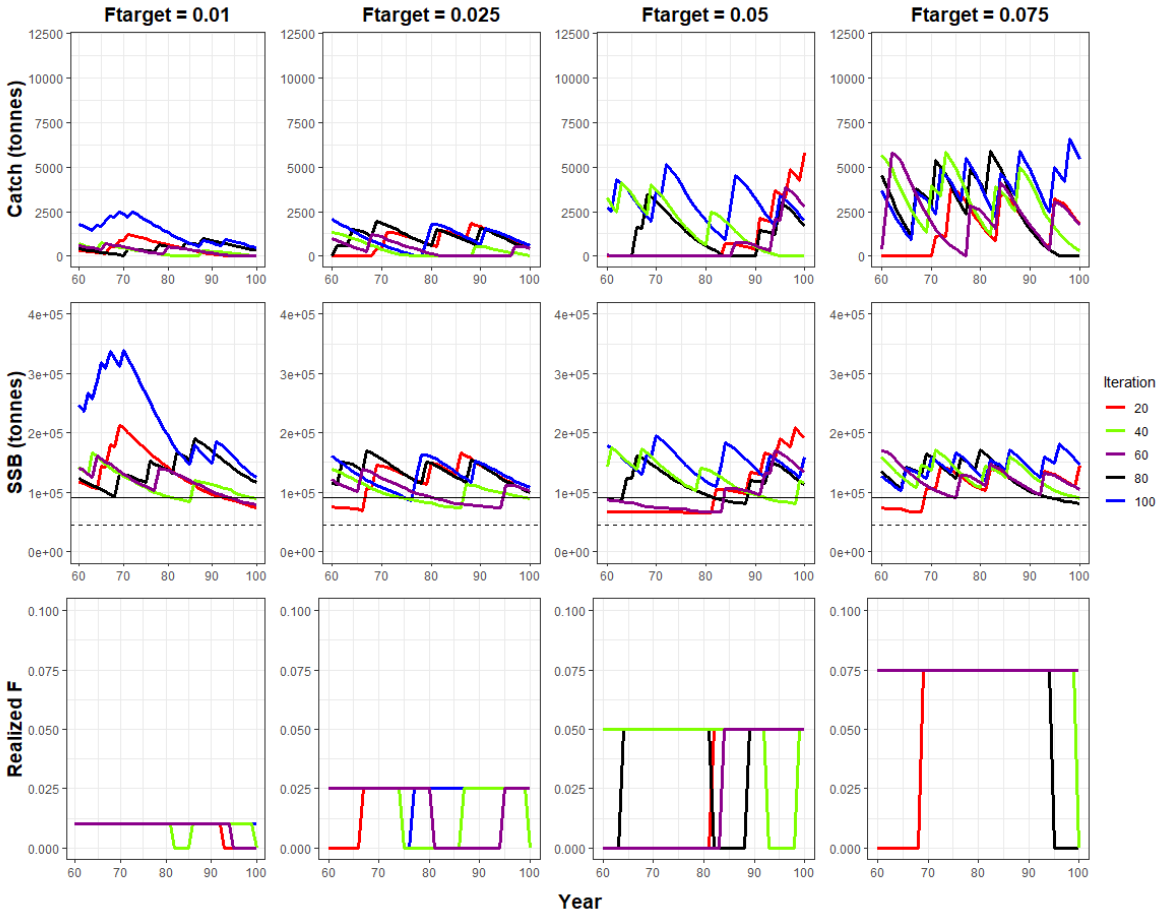


Figure 15. *Novel HCR projection graphs with examples of 5 iterations for each scenario. The results of catch (tonnes), SSB (tonnes) and Realized F are for the final 40 years of the projection under the SR scenario,* $B_{trigger}$ *of 2 ** B_{lim} *and low* F_{target} *values of 0.01, 0.025, 0.05 and 0.075. The figure portrays a time series equal to the maximum age of the stock and shows the final 10 years from where performance indicators were taken. The thick horizontal line indicates the* $B_{trigger}$ *level of 90000 (2 ** B_{lim}*) and the dashed line shows the* B_{lim} *of 45000.*

3.3. Erratic recruitment

3.3.1. ICES HCR

Presented below are the performance results for the ICES HCR under the ER scenario.

Table 6. *Risk, Catch, ICV and Realized F for lower* F_{target} *values and ER for the ICES HCR. Green cells indicate risk below 44%, while red cells indicate risk above 44%.*

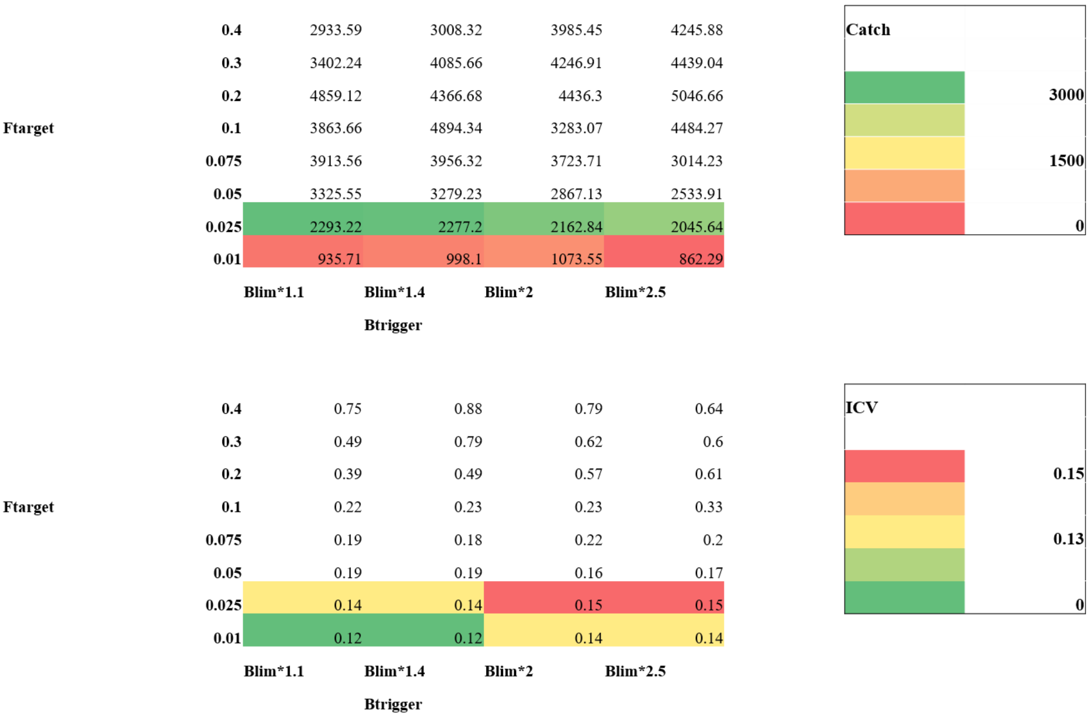
F_{target}	$B_{trigger}$	Risk	Catch	ICV	Realized F
0	NA	22	0	0	0
0.01	1.1*B_{lim}	30	935.71	0.12	0.01

0.01	1.4*B_{lim}	21	998.1	0.12	0.01
0.01	2*B_{lim}	24	1073.55	0.14	0.01
0.01	2.5*B_{lim}	27	862.29	0.14	0.01
0.025	1.1*B_{lim}	36	2293.22	0.14	0.025
0.025	1.4*B_{lim}	36	2277.2	0.14	0.025
0.025	2*B_{lim}	32	2162.84	0.15	0.023
0.025	2.5*B_{lim}	32	2045.64	0.15	0.021
0.05	1.1*B_{lim}	50	3325.55	0.19	0.05
0.05	1.4*B_{lim}	49	3279.23	0.19	0.05
0.05	2*B_{lim}	53	2867.13	0.16	0.04
0.05	2.5*B_{lim}	47	2533.91	0.17	0.04
0.075	1.1*B_{lim}	64	3913.56	0.19	0.071
0.075	1.4*B_{lim}	72	3956.32	0.18	0.063
0.075	2*B_{lim}	62	3723.71	0.22	0.057
0.075	2.5*B_{lim}	59	3014.23	0.2	0.047

Table 7. *Risk, Catch, ICV and Realized F for higher F_{target} values and ER for the ICES HCR. Green cells indicate risk below 44%, while red cells indicate risk above 44%.*

F_{target}	$B_{trigger}$	Risk	Catch	ICV	Realized F
0	NA	22	0	0	0
0.1	1.1*B_{lim}	85	3863.66	0.22	0.09
0.1	1.4*B_{lim}	68	4894.34	0.23	0.09
0.1	2*B_{lim}	74	3283.07	0.23	0.07
0.1	2.5*B_{lim}	61	4484.27	0.33	0.07
0.2	1.1*B_{lim}	96	4859.12	0.39	0.16
0.2	1.4*B_{lim}	96	4366.68	0.49	0.12
0.2	2*B_{lim}	96	4436.3	0.57	0.12
0.2	2.5*B_{lim}	88	5046.66	0.61	0.1
0.3	1.1*B_{lim}	100	3402.24	0.49	0.18
0.3	1.4*B_{lim}	100	4085.66	0.79	0.18
0.3	2*B_{lim}	100	4246.91	0.62	0.13

0.3	2.5*B_{lim}	99	4439.04	0.6	0.11
0.4	1.1*B_{lim}	100	2933.59	0.75	0.2
0.4	1.4*B_{lim}	100	3008.32	0.88	0.16
0.4	2*B_{lim}	100	3985.45	0.79	0.17
0.4	2.5*B_{lim}	99	4245.88	0.64	0.15



	0.4	2933.59	3008.32	3985.45	4245.88
	0.3	3402.24	4085.66	4246.91	4439.04
	0.2	4859.12	4366.68	4436.3	5046.66
Ftarget	**0.1**	3863.66	4894.34	3283.07	4484.27
	0.075	3913.56	3956.32	3723.71	3014.23
	0.05	3325.55	3279.23	2867.13	2533.91
	0.025	2293.22	2277.2	2162.84	2045.64
	0.01	935.71	998.1	1073.55	862.29
		Blim*1.1	**Blim*1.4**	**Blim*2**	**Blim*2.5**
			Btrigger		

Catch	
🟩	**3000**
🟩	
🟨	**1500**
🟧	
🟥	**0**

	0.4	0.75	0.88	0.79	0.64
	0.3	0.49	0.79	0.62	0.6
	0.2	0.39	0.49	0.57	0.61
Ftarget	**0.1**	0.22	0.23	0.23	0.33
	0.075	0.19	0.18	0.22	0.2
	0.05	0.19	0.19	0.16	0.17
	0.025	0.14	0.14	0.15	0.15
	0.01	0.12	0.12	0.14	0.14
		Blim*1.1	**Blim*1.4**	**Blim*2**	**Blim*2.5**
			Btrigger		

ICV	
🟥	**0.15**
🟧	
🟨	**0.13**
🟩	
🟩	**0**

Figure 16. *Matrix of colour-coded results for* F_{target} *and* $B_{trigger}$ *combinations with catch and ICV using the ICES HCR under ER. White cells indicate results that had risk >5%.*

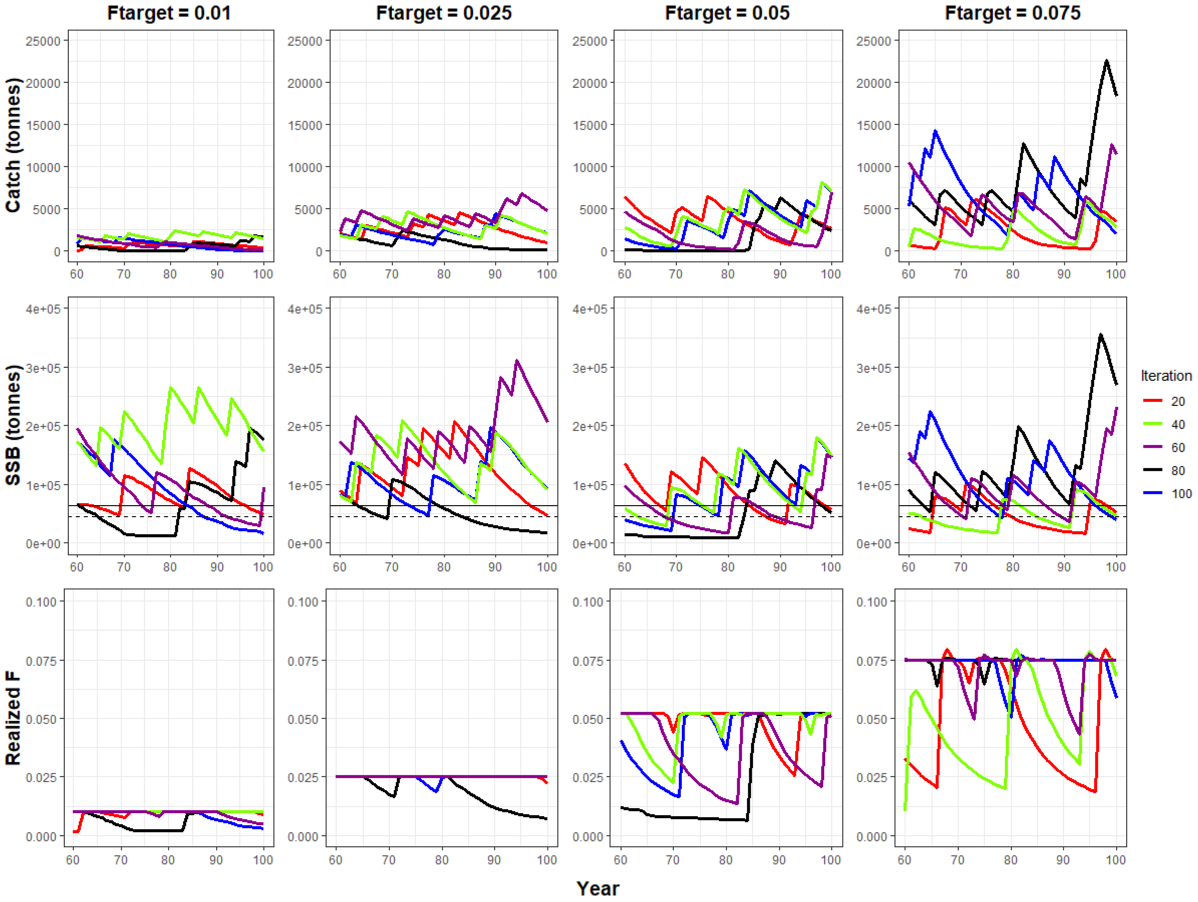


Figure 17. *ICES HCR projection graphs with examples of 5 iterations for each scenario. The results of catch (tonnes), SSB (tonnes) and Realized F are for the final 40 years of the projection under the ER scenario,* $B_{trigger}$ *of 1.4 ** B_{lim} *and low* F_{target} *values of 0.01, 0.025, 0.05 and 0.075. The figure portrays a time series equal to the maximum age of the stock and shows the final 10 years from where performance indicators were taken. The thick horizontal line indicates the* $B_{trigger}$ *level of 63000 (1.4 ** B_{lim}*) and the dashed line shows the* B_{lim} *of 45000.*

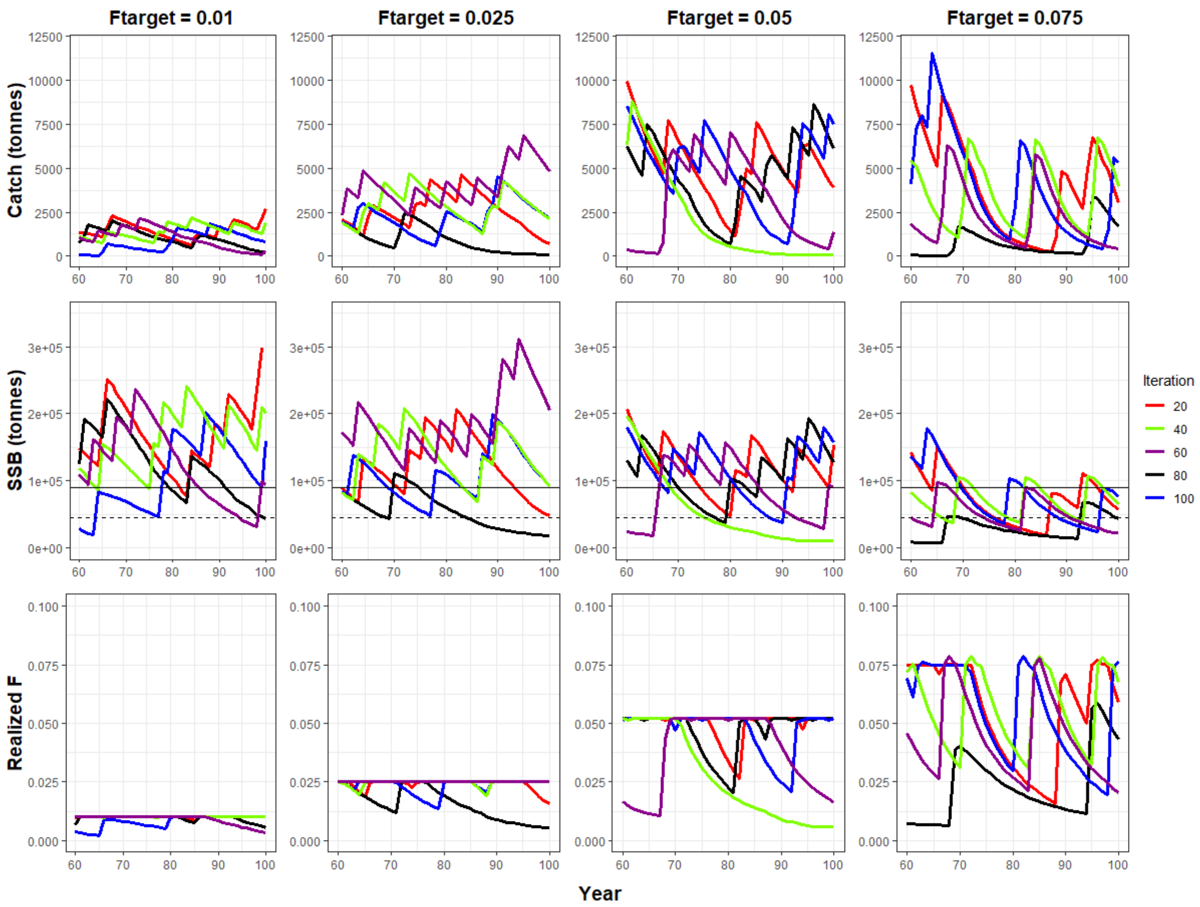


Figure 18. *ICES HCR projection graphs with examples of 5 iterations for each scenario. The results of catch (tonnes), SSB (tonnes) and Realized F are for the final 40 years of the projection under the ER scenario,* $B_{trigger}$ *of 2 ** B_{lim} *and low* F_{target} *values of 0.01, 0.025, 0.05 and 0.075. The figure portrays a time series equal to the maximum age of the stock and shows the final 10 years from where performance indicators were taken. The thick horizontal line indicates the* $B_{trigger}$ *level of 90000 (2 ** B_{lim}*) and the dashed line shows the* B_{lim} *of 45000.*

3.3.2. Novel HCR

Presented below are the performance results for the Novel HCR under the ER scenario.

Table 8. *Risk, Catch, ICV, Realized F and Moratoria for lower* F_{target} *values and ER for the Novel HCR. Green cells indicate risk below 44%, while red cells indicate risk above 44%.*

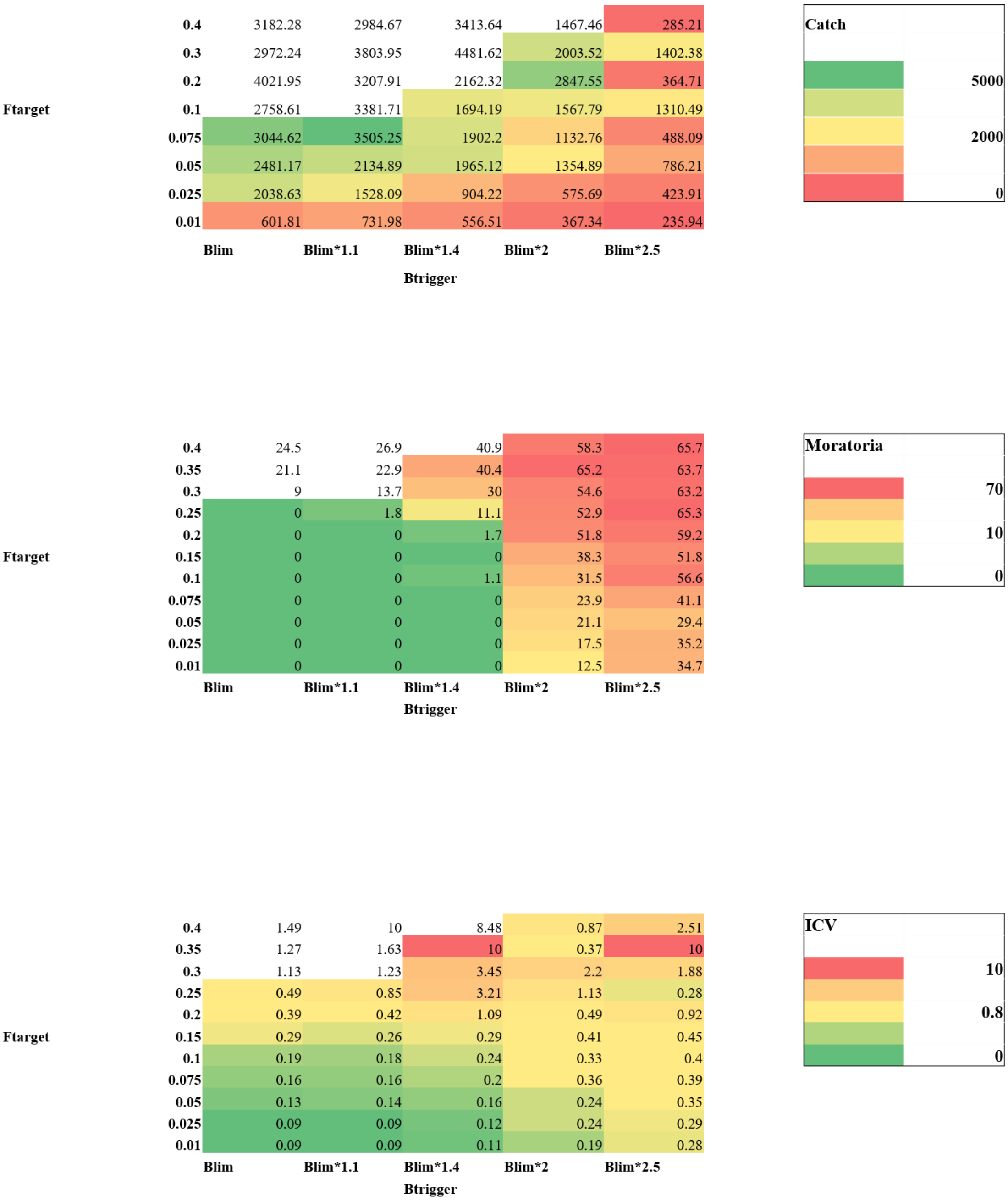
F_{target}	$B_{trigger}$	Risk	Catch	ICV	Realized F	Moratoria
0	NA	22	0	0	0	100
0.01	B_{lim}	28	601.81	0.17	0.01	16.7
0.01	$1.1*B_{lim}$	22	731.98	0.17	0.01	16.5

0.01	1.4*B_{lim}	20	556.51	0.24	0.01	18.6
0.01	2*B_{lim}	14	367.34	0.3	0.009	30
0.01	2.5*B_{lim}	24	235.94	0.3	0.007	43.2
0.025	B_{lim}	23	2038.63	0.19	0.025	12.2
0.025	1.1*B_{lim}	21	1528.09	0.25	0.025	12
0.025	1.4*B_{lim}	27	904.22	0.26	0.025	25.5
0.025	2*B_{lim}	24	575.69	0.3	0.02	40.2
0.025	2.5*B_{lim}	24	423.91	0.39	0.015	43
0.05	B_{lim}	37	2481.17	0.27	0.05	20.8
0.05	1.1*B_{lim}	38	2134.89	0.32	0.05	24.3
0.05	1.4*B_{lim}	30	1965.12	0.36	0.045	27.8
0.05	2*B_{lim}	19	1354.89	0.36	0.04	35.5
0.05	2.5*B_{lim}	24	786.21	0.39	0.03	45
0.075	B_{lim}	41	3044.62	0.34	0.075	23.3
0.075	1.1*B_{lim}	36	3505.25	0.35	0.075	24.1
0.075	1.4*B_{lim}	35	1902.2	0.37	0.06	31.6
0.075	2*B_{lim}	27	1132.76	0.36	0.045	44.8
0.075	2.5*B_{lim}	25	488.09	0.34	0.03	57.9

Table 9. *Risk, Catch, ICV, Realized F and Moratoria for higher F_{target} values and ER for the Novel HCR. Green cells indicate risk below 44%, while red cells indicate risk above 44%.*

F_{target}	$B_{trigger}$	Risk	Catch	ICV	Realized F	Moratoria
0	NA	22	0	0	0	100
0.1	B_{lim}	60	2758.61	0.41	0.08	30.1
0.1	1.1*B_{lim}	46	3381.71	0.41	0.09	30.3
0.1	1.4*B_{lim}	42	1694.19	0.41	0.07	39.7
0.1	2*B_{lim}	31	1567.79	0.44	0.055	48.2
0.1	2.5*B_{lim}	26	1310.49	0.39	0.05	54.8
0.2	B_{lim}	83	4021.95	0.42	0.12	47.3
0.2	1.1*B_{lim}	82	3207.91	1.4	0.12	46.6
0.2	1.4*B_{lim}	61	2162.32	0.89	0.1	52.8

0.2	2*B_{lim}	42	2847.55	0.57	0.1	53.9
0.2	2.5*B_{lim}	29	364.71	0.26	0.02	70.8
0.3	B_{lim}	99	2972.24	0.48	0.12	62.2
0.3	1.1*B_{lim}	95	3803.95	4053.58	0.15	54.3
0.3	1.4*B_{lim}	79	4481.62	1.51	0.15	55.4
0.3	2*B_{lim}	40	2003.52	0.55	0.12	66
0.3	2.5*B_{lim}	34	1402.38	0.26	0.09	71.6
0.4	B_{lim}	97	3182.28	6967.54	0.16	61.7
0.4	1.1*B_{lim}	98	2984.67	0.51	0.16	64.9
0.4	1.4*B_{lim}	90	3413.64	3.29	0.14	61.5
0.4	2*B_{lim}	47	1467.46	1.23	0.12	70.5
0.4	2.5*B_{lim}	41	285.21	0.21	0.08	74.1



Ftarget					
0.4	3182.28	2984.67	3413.64	1467.46	285.21
0.3	2972.24	3803.95	4481.62	2003.52	1402.38
0.2	4021.95	3207.91	2162.32	2847.55	364.71
0.1	2758.61	3381.71	1694.19	1567.79	1310.49
0.075	3044.62	3505.25	1902.2	1132.76	488.09
0.05	2481.17	2134.89	1965.12	1354.89	786.21
0.025	2038.63	1528.09	904.22	575.69	423.91
0.01	601.81	731.98	556.51	367.34	235.94
	Blim	Blim*1.1	Blim*1.4	Blim*2	Blim*2.5
			Btrigger		

Catch	
🟩	5000
🟩	
🟨	2000
🟧	
🟥	0

Ftarget					
0.4	24.5	26.9	40.9	58.3	65.7
0.35	21.1	22.9	40.4	65.2	63.7
0.3	9	13.7	30	54.6	63.2
0.25	0	1.8	11.1	52.9	65.3
0.2	0	0	1.7	51.8	59.2
0.15	0	0	0	38.3	51.8
0.1	0	0	1.1	31.5	56.6
0.075	0	0	0	23.9	41.1
0.05	0	0	0	21.1	29.4
0.025	0	0	0	17.5	35.2
0.01	0	0	0	12.5	34.7
	Blim	Blim*1.1	Blim*1.4	Blim*2	Blim*2.5
			Btrigger		

Moratoria	
🟥	70
🟧	
🟨	10
🟩	
🟩	0

Ftarget					
0.4	1.49	10	8.48	0.87	2.51
0.35	1.27	1.63	10	0.37	10
0.3	1.13	1.23	3.45	2.2	1.88
0.25	0.49	0.85	3.21	1.13	0.28
0.2	0.39	0.42	1.09	0.49	0.92
0.15	0.29	0.26	0.29	0.41	0.45
0.1	0.19	0.18	0.24	0.33	0.4
0.075	0.16	0.16	0.2	0.36	0.39
0.05	0.13	0.14	0.16	0.24	0.35
0.025	0.09	0.09	0.12	0.24	0.29
0.01	0.09	0.09	0.11	0.19	0.28
	Blim	Blim*1.1	Blim*1.4	Blim*2	Blim*2.5
			Btrigger		

ICV	
🟥	10
🟧	
🟨	0.8
🟩	
🟩	0

Figure 19. *Matrix of colour-coded results for* F_{target} *and* $B_{trigger}$ *combinations with catch, moratoria and ICV using the Novel HCR under ER. White cells indicate results that had risk >5%. Any ICV number >10 was collapsed to 10 in order to make the colour-coding visually useful.*

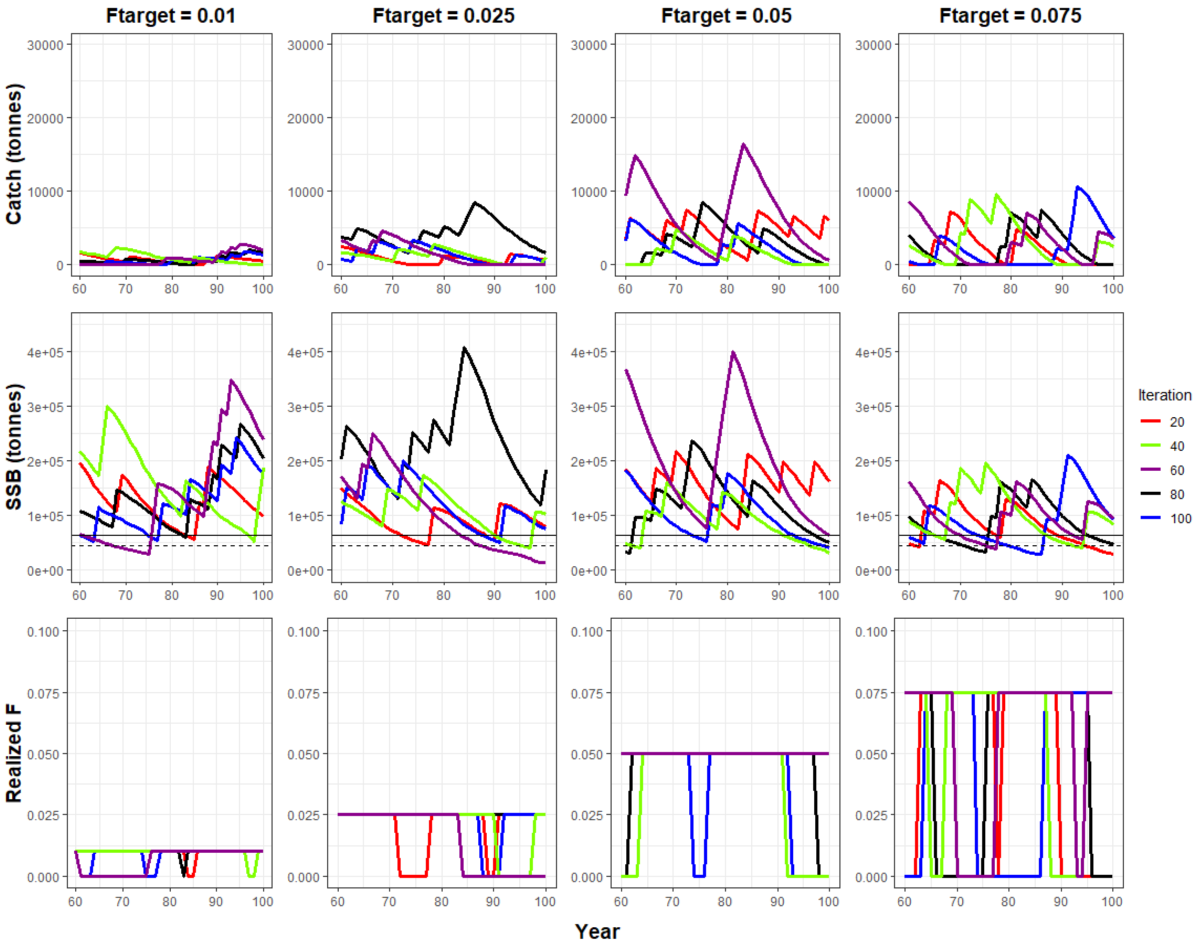


Figure 20. *Novel HCR projection graphs with examples of 5 iterations for each scenario. The results of catch (tonnes), SSB (tonnes) and Realized F are for the final 40 years of the projection under the ER scenario,* $B_{trigger}$ *of 2 ** B_{lim} *and low* F_{target} *values of 0.01, 0.025, 0.05 and 0.075. The figure portrays a time series equal to the maximum age of the stock and shows the final 10 years from where performance indicators were taken. The thick horizontal line indicates the* $B_{trigger}$ *level of 90000 (2 ** B_{lim}*) and the dashed line shows the* B_{lim} *of 45000.*

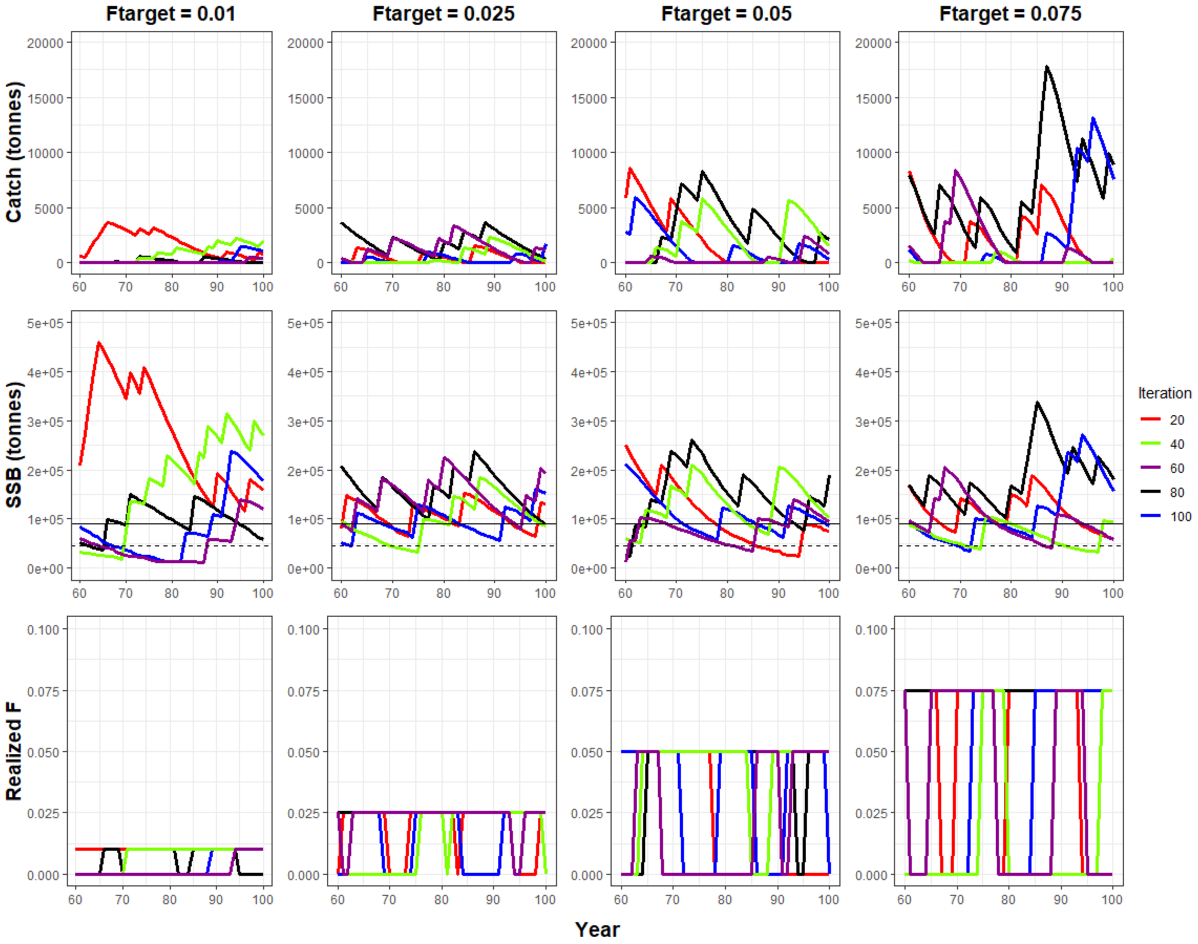


Figure 21. *Novel HCR projection graphs with examples of 5 iterations for each scenario. The results of catch (tonnes), SSB (tonnes) and Realized F are for the final 40 years of the projection under the ER scenario,* $B_{trigger}$ *of 2 ** B_{lim} *and low* F_{target} *values of 0.01, 0.025, 0.05 and 0.075. The figure portrays a time series equal to the maximum age of the stock and shows the final 10 years from where performance indicators were taken. The thick horizontal line indicates the* $B_{trigger}$ *level of 90000 (2 ** B_{lim}*) and the dashed line shows the* B_{lim} *of 45000.*

4. Discussion

4.1. Introduction

MSE is a method used to test multiple HCRs against certain performance criteria to determine the most effective one according to the objectives of the fishery. The final choice of HCR is made by the fisheries managers, the role of scientists to make the performance and trade-offs of the various rules explicit. This manuscript provides details of the trade-offs implied in the use of two competing HCRs: an ICES HCR and a Novel HCR. They were compared in two recruitment scenarios: SR (somewhat erratic recruitment) and ER (highly erratic recruitment, with the unfished stock naturally falling below B_{lim}). The results of these criteria and their trade-offs are presented and interpreted below. These trade-offs are provided as a reference for the further use of the model Novel HCR developed. The management implications of using each HCR are also explored.

4.2. Comments on results

4.2.1. Moratoria

An additional column was added to the Novel HCR results to reflect the number of moratoria on fishing. Similar to, but more severe than ICV, moratoria are generally an undesirable consequence for commercial fisheries. However, in some cases they may be necessary for rapid stock rebuilding and increased yield. Temporary moratoria on North Sea herring and Norwegian spring-spawning herring together with HCRs facilitated the rebuilding of these stocks (Sparholt et al. 2007). However, a high fraction of moratoria is generally suboptimal. This was of particular importance when examining the Novel HCR, where the reduction of biomass below the $B_{trigger}$ point prompted a moratorium by design. In contrast, the $B_{trigger}$ point in the ICES HCR triggered a continuous reduction in F_{target}, until SSB declined to zero and thus avoids fishery closures. For the Novel HCR there was a positive relationship between the level of $B_{trigger}$ and fraction of moratoria that was accentuated at high F_{target} values. There were many scenarios that had good yield, acceptable risk and relatively low ICV, but had a high fraction of moratoria (Table 4). At lower $B_{trigger}$ points, the Novel HCR leads to a smaller fraction of closures. It’s not until F_{target} is increased to 0.25 where there is a stark increase in the fraction of moratoria (Table 5). They also increase substantially at a $B_{trigger}$ of $1.4*B_{lim}$. It appears that there is a trade-off here between a lower risk of stock collapse ($SSB < B_{lim}$) and higher fraction of moratoria ($SSB < B_{trigger}$) in the choice of the Novel HCR over the ICES HCR. It’s important to re-emphasise here that these observations were made with an FLBEIA model running with perfect knowledge. The addition of noise is likely to add an extra stress on reference points and provide a more accurate measure of HCR robustness to moratoria.

4.2.2. Reference points and risk

The most important reference point in this study was $B_{trigger}$. $B_{trigger}$ in this study was triggering the reduction of F_{target} at two very different rates in the two competing HCRs. The $B_{trigger}$ point in the ICES HCR initiated a linear reduction in F_{target}. If there was SSB available to harvest, there was catch output as a result. The Novel HCR has a constant F_{target} and was applied to the difference between SSB and $B_{trigger}$. Below $B_{trigger}$, fishing was halted. $B_{trigger}$ is equivalent to a precautionary biomass reference point (B_{pa}), where the precautionary point is conservative and aiming to reduce risk (ICES 2012). This is how it is used in escapement strategies (e.g. conserving salmon spawners via escapement), as was discussed earlier (ICES 2017b). The $B_{trigger}$ point is a parallel of the $B_{escapement}$ reference point for Atlantic salmon, conserving the biomass above and reducing the risk of falling below the $B_{trigger}$ threshold.

The $B_{trigger}$ reference points were chosen to examine a wide range of scenarios. The lower the $B_{trigger}$ break point, the higher the fluctuations in average catch, ICV and risk were among F_{target} values. This non-linearity is a known feature in MSE arising from break points in HCRs (ICES 2019b). The 1.1*B_{lim} reference point was very low but was an interesting point to explore in reference to the robustness of the novel HCR. B_{lim} was also included as a trigger point in the Novel HCR (Table 4). Although this is not standard procedure, it provided useful information on the performance of the Novel HCR when a large fraction of SSB was available. However, if error was added to the stock dynamics, perhaps B_{lim} would not be a robust point in the control rule. This error can come in the form of process error on stock inputs or observation noise from a full assessment for the hypothetical species (ICES 2019b).

SSB remained above $B_{trigger}$ for most of the projection period using the Novel HCR in most scenarios with SR (Table 4; Table 5). It only fell below B_{lim} in scenarios where $B_{trigger}$ was low and F_{target} was high (Table 9). The ICES HCR in comparison spent most of the time in the buffer zone between $B_{trigger}$ and B_{lim}, unless $B_{trigger}$ was very low (Figure 11).

The higher $B_{trigger}$ points provided a low fraction of SSB available for use in the Novel HCR. This was reflected in the low results for average ratch (Table 4). There were low catches in both HCRs at higher $B_{trigger}$ points, but it was more pronounced in the Novel HCR where catches were considerably lower. Where recruitment was erratic, the Novel HCR appeared much more responsive to the $B_{trigger}$ point, reflected in the decrease in risk with higher $B_{trigger}$ values (Table 9). This was not observed to the same extent with the ICES HCR (Table 7). In both HCRs the higher $B_{trigger}$ points reduced the percentage risk of falling below B_{lim}. Thus, the $B_{trigger}$ point offered a trade-off between risk and total yield. There was a difference between both HCRs with regards risk also.

The Risk of the SSB falling below B_{lim} was related to both the recruitment scenario and HCR used. In the case of the ICES HCR, risk was high for F_{target} values above 0.1 for SR (Table 3). For ER, acceptable risk was only found at the low end of the F_{target} range (Table 5). The Novel HCR F_{target} can be pushed much higher before risk becomes unacceptable (Figure 13). For higher $B_{trigger}$ values, the Novel HCR has a relatively low risk, even in the case of ER.

4.2.3. Catch and Realized F

Catch was generally higher for the ICES HCR in the SR scenario, but the Novel HCR gave higher catch on the erratically recruiting stock (ER). Catch had a gradual decline in the Novel HCR until it reached $B_{trigger}$, below which fishing was halted. As only the fraction above $B_{trigger}$ was targeted, the Novel HCR was less influenced by the sporadic recruitment patterns, following the magnitude of SSB more closely (Figure. In comparison, the ICES HCR catch was much more reactive to recruitment spikes (Figure 12). catch is the primary marker of the performance of the fishery. Given acceptable risk, high yields are one of the most desirable consequences when employing a HCR.

Realized F was the fishing mortality output from the model for every year of the projection. The output from any year was a function of the F_{target}, $B_{trigger}$ and biomass, and was calculated according to the relevant HCR. Realized F is important only as an indicator of the time spent fishing above and below the $B_{trigger}$ point. At the higher F_{target} values, Realized F was averaging at much lower values for all scenarios. There were generally lower Realized F values for the ICES HCR at higher $B_{trigger}$ levels (Table 3). At higher F_{target} levels this was especially pronounced where there was a much smaller Realized F value than the F_{target} used in the HCR.

In contrast, the Realized F for the Novel HCR was generally approximately equal to the F_{target} specified in the code (Table 4). Only at higher $B_{trigger}$ levels the Realized F dropped. Above $B_{trigger}$, the Realized F was always equal to the F_{target} input (Table 5).

4.2.4. ICV

The ICV was much higher for the Novel HCR. The ICV increased with higher F_{target} values (Table 5). ICV was much lower for the ICES HCR, reflecting the relative stability in Catch over time, as a result of the gentle reduction in fishing pressure at low stock sizes (Table 3). The difference in ICV can be explained by the behaviour of the two HCRs in relation to the SSB. The ICES HCR was designed to return Catch at any SSB level. The Novel HCR was purposely omitting a fraction of SSB from harvesting and so the Catch fluctuated from zero below $B_{trigger}$ to much higher numbers above $B_{trigger}$ (Figure 15).

4.3. MSY and trade-offs

The Maximum Sustainable Yield (MSY) for all scenarios is defined as the highest yield obtained when risk was acceptable as defined for the two recruitment scenarios. The Novel HCR had the highest MSY for both recruitment scenarios, but also a much higher ICV level in both cases.

For SR, the Novel HCR MSY was 4884.68 tonnes with an ICV of 0.42 (Figure 13). The second highest level of Catch was 4516.48 tonnes with an ICV of 0.29, which sacrifices 7.54% Catch for 30.95% less catch variability. The MSY for the ICES under SR was 4597.23 tonnes with an ICV of 0.12 (Figure 10). The next option is catch of 3826.69 tonnes with an ICV of 0.09. This offers a trade-off of a loss of 16.76% catch, with 25% lower catch variability.

The ICES HCR MSY for ER was 2293.22 tonnes with an ICV of 0.14. This was the best performing option across all criteria (Figure 16). The Novel HCR with ER had an MSY of 3505.25 tonnes with an ICV of 0.35 (Figure 19). The alternative highest catch was 2481.17 tonnes with an ICV of 0.27, where 29.22% of catch can be sacrificed for a reduction in ICV of 22.86%. In each scenario above a high catch stability can be obtained at the cost of lowering yield and vice versa.

The performance of the HCRs are presented in this study without reference to any specific management objectives. The stock and fleets simulated were hypothetical. The decision to use a HCR is dependent on the fishery objectives, stakeholders, trade-offs etc. It is a political decision that can be informed through the simulation results. Given the acceptable risk of collapse, managers may favour stability in yields over maximum overall yield. In “Olympicfisheries" with open access and little regulation, there is an incentive to fish for higher yields at the expense of stability (Petursdottir et al. 2001). In the case of some species moratoria are acceptable if yields are high enough when the fishery is open. In other cases, catch stability may be valued over high catches.

Management advice is dependent on stakeholders, management objectives and real-world stock dynamics, which were all beyond the scope of a masters project. The purpose of this project is to present the options and trade-offs involved to managers and stakeholders of the relevant fishery. Although this is an academic exercise, the results here will help inform choices in the forthcoming Greenland halibut MSE.

4.4. Experimental design

The FLBEIA model was user friendly with regards the development of the Operating Model and the simulation of the projection. However, due to the structure of the FLBEIA-specific arguments, it proved difficult to alter the source code for the Novel HCR. As the model was designed to incorporate multiple fleets and economic metrics, there was much work involved in understanding how to design the hypothetical stock to be compatible with FLBEIA.

The ER was included as an extreme test case where there were extreme fluctuations between low recruitment and peak recruitment years. ICES has two standards for evaluating risk: one for stocks that don't collapse more than 5% of the time and another for those that do (ICES 2019b). We designed and ran simulations covering both of these scenarios. This served as an interesting scenario for the robustness of the HCRs to high stochasticity in biomass. In these scenarios the Risk of collapse was high among all the F_{target} and $B_{trigger}$ scenarios in the case of both HCRs. Even in the case of $F_{target} = 0$ the risk was above the ICES accepted threshold of 5%. This reflected the highly spasmodic recruitment programmed into the generic stock. To account for this pattern, risk was recalculated as discussed in the methodology (ICES 2019b). The recalculation of risk made available many scenarios for both HCRs for comparison under the performance criteria.

The grid of simulation cells was designed prior to any simulations being run. It is common in MSE design to formulate the scenarios prior to the computer work. This was the case in North Sea MSE, where some unnecessary scenarios were included (ICES 2019b). However, with hindsight it would have been better to begin with the lower F_{target} values and work up to avoid spending time computing many simulations with unacceptable risk levels.

The new generation of MSE modelling tools, such as FLBEIA, are flexible and powerful. They are more computer intensive than the previous generation of MSE tools due to both their complexity and the use of the R programming language. These factors were important in the ease of designing and implementing the scenarios presented above (ICES 2013). The major limitation that this imposed was that these scenarios were all run assuming perfect knowledge in implementation of the HCRs. This was due to time restrictions for the running of all scenarios. Given more computer time, the runs would have been extended to include process error and observation noise as per standard procedure (ICES 2019b).

The major caveat of this study is the use of hypothetical species dynamics. The growth, recruitment and mortality were all generated to reflect a stock with spasmodic recruitment and high longevity. However, the recruitment was entirely random, not correlated with any interacting variable. Real stocks must have some causal factor for spikes in recruitment, even if unknown to researchers. It is certain that at some level recruitment must be reduced and the simulations allow for the stock to recover from very low stock sizes. Real stocks have shown this ability to recover e.g. Norwegian Spring Spawning Herring and thus modelling at low SSB is difficult. For this theoretical study we have avoided this level of complexity. The desirable HCRs avoid reducing the stock to low SSB levels, and the ability to model the recovery from here is of secondary importance (Tjelemend and Røttingen 2009). So long as the HCR can avoid driving the stock to low stock sizes and the projection begins well above Bl_{im}, then detailed modelling of the low stock state is not required (ICES 2018).

Despite the limitations, this project provides insight into the performance of HCRs in achieving conflicting goals. Performance on risk, MSY, ICV and moratoria are in conflict, and the prioritisation of MSY come at the cost of stability (ICV). Likewise, maximising catch (MSY) may lead to more closures over time. This project explores the exact trade-offs inherent in the choice between HCRs.

The recruitment variability (even when mean recruitment remained the same) changed both how the given HCR performed and the relative difference between HCRs. For example, the risk of collapse for ER was much higher than in the SR scenario for both HCRs, but also between these HCRs, the Novel HCR had lower risk values than the ICES HCR. This is why variability is so important to model, and why we use MSE simulations rather than mean levels in the choice of HCRs to meet key objectives.

This project has tested out the flexibility of one of the new generation of MSE tools, validating that it is flexible enough to set up unusual stock structures and HCRs, and is therefore a viable basis which the Institute of Marine Research in Bergen can use to run future real-world MSEs. It has provided a framework which can be expanded upon when ICES run a real MSE for a species with similar characteristics to the one modelled here (which is currently scheduled for prior to the 2023 AFWG stock assessment).

4.5. Further research

As discussed before, the FLBEIA simulation was run assuming perfect knowledge of the fishery. There was no addition of noise to the data. This was a practical limitation given constraints on development time and computer power for this masters thesis. Ideally, the stock dynamics would have been iterated with the addition of error in the Operating Model. This is a standard procedure that would provide an even more realistic response of the hypothetical stock to the two HCRs. The aim would be to identify how their performance degrades under increasing levels of noise. Such an addition would be required before the results here could be translated into actual management. However, the work conducted here does give insight into the how the different HCRs behave under different recruitment variability.

Alternative formulations of the Novel HCR may be another avenue of inquiry which could be of interest. Above $B_{trigger}$, explorations of multiple patterns of F_{target} application were considered. Expert opinion from MSE specialists was taken onboard in one meeting at the Institute of Marine Research, Bergen. Again, unfortunately this is a matter for future concern due to time constraints regards formulation of the Novel HCR and computer power. Grid re-design would allow a more in-depth look at scenarios of interest also.

There are practical uses for the MSE performed in this study. The stock dynamics mirrored the Greenland halibut’s longevity and spasmodic recruitment and so, the performance of the candidate HCRs on the hypothetical stock is likely to be applicable. As Greenland halibut does not currently have a HCR, the results of this project will inform the process of developing a HCR in two ways (ICES 2019a). Firstly, it presents a candidate HCR for full MSE following ICES guidelines (ICES 2019b). Secondly, it will provide a framework within FLBEIA for building a robust model for this MSE. This MSE work is currently scheduled for 2022/2023 for use in 2023 advice.

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Acknowledgements:

I thank Mikko Heino, my supervisor at UiB for feedback on written material and Daniel Howell, my supervisor at IMR for helping me develop the model and giving constant feedback. I would also like to thank Dorleta Garcia (of AZTI in Spain), Goto Daisuke and Ibrahim Umar (both at IMR) who all provided help when needed.

I would also like to dedicate this project to my father, who passed away during the duration of my work.