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Developing empirical management procedures to meet management objectives for data-limited fisheries

A thesis submitted for the degree of Doctor of Philosophy (PhD)

by

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Statement of Originality

This thesis version is submitted for fulfilling the requirements of obtaining a PhD degree at Imperial College London and I expect to be examined on this version.

I declare that the work of this thesis is my own and all else is appropriately referenced. This thesis was supervised by

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Copyright Declaration

Abstract

Most of the world's fish stocks are considered data-limited and there are insufficient data for complex stock assessment models; nevertheless, scientifically sound management advice is required. Empirical management procedures rely on empirical data and can guide management decisions. The main goals of this project were to develop and test empirical management procedures to improve data-limited fisheries management. Candidate management procedures can be evaluated using management strategy evaluation, which simulates the managed system and management in a feedback loop. Here, many generic operating models were generated covering a wide range of life histories. First, a trend-based empirical management procedure was explored. Simulations revealed that the management performance depended on the individual growth rate of the species, and the method delivered poor performance with high risk of stock depletion for faster-growing species. However, management performance could be improved by applying a genetic algorithm and optimisation towards specified management objectives such as long-term sustainable exploitation and risk limits demanded by stakeholders. An alternative empirical method (harvest rates) was found to be applicable to faster-growing species. Optimised parameterisations of the empirical methods from generic simulations were confirmed for several case study stocks with more available data. These analyses suggested that the generic methods lead to precautionary management, but management performance can be improved through case-specific optimisation. The outcomes of this project showed that the current management practices of data-limited fisheries resources applied by the International Council for the Exploration of the Sea in Europe are insufficient and do not ensure sustainable and precautionary exploitation, even though this is required through international treaties. However, the management procedures evaluated in this study show a way to overcome current management deficiencies and indicate that simple empirical management procedures are a scientifically sound alternative to expensive model-based management approaches.

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List of abbreviations

Abbreviation	Meaning
a4a	assessment for all initiative
ALK	age-length key
Cefas	Centre for Environment, Fisheries and Aquaculture Science
CPU	central processing unit
CPUE	catch per unit effort
CV	coefficient of variation
DCAC	depletion corrected average catch
Defra	UK Department for Environment, Food & Rural Affairs
EU	European Union
F	fishing mortality
FAO	Food and Agriculture Organization
FLR	Fisheries Library in R
HCR	harvest control rule
HPC	high-performance computing
ICCAT	International Commission for the Conservation of Atlantic Tunas
ICES	International Council for the Exploration of the Sea
ICV	Inter-annual catch variability
IWC	International Whaling Commission
CCAMLR	Commission for the Conservation of Antarctic Marine Living Resources
M	natural mortality
MP	management procedure
MPI	message passing interface
MSC	Marine Stewardship Council
MSE	management strategy evaluation
MSY	maximum sustainable yield
OM	operating model

PA	precautionary approach
PID	proportional, integral, derivative
PSA	productivity and susceptibility analysis
R	recruitment
SAM	state-space assessment model
SD	standard deviation
SPiCT	surplus production in continuous time model
SSB	spawning stock biomass
TAC	total allowable catch
TSB	total stock biomass
VPA	virtual population analysis
WKLIFE	Workshop on the Development of Assessments based on LIFE history traits and Exploitation Characteristics

Chapter 1

Introduction

1.1 Background

The consumption of marine fish as food and a source of protein by humans has a long history. In the early periods of large-scale fishing activities by humans, fish populations were seen by many as inexhaustible natural resources. However, with technological advancements and more intensive fishing, large fish populations started to decline, and the impact of human activities on fish populations started to dawn. One of the early scientists to express this was Russell (1931), who mentioned that the size of a fish stock (a self-contained part of a population of a specific species in an area that is subject to fishing) depends on processes increasing the stock size (recruitment and growth) and decreasing it (deaths due to natural causes, i.e. natural mortality, and fishing). Consequently, when total deaths exceed production, the stock size will decline, and to counter this trend, catches need to be reduced.

Fish stocks themselves cannot be managed, but the fishery harvesting those stocks can be. This is where fisheries management comes in, which is meant to ensure sustainable exploitation of harvested fish stocks (Hilborn & Walters, 1992). There are several possible interpretations of what constitutes sustainability. For example, the Food and Agricultural Organization (FAO) offers a broad definition: "Sustainable development is the management and conservation of the natural resource base, and the orientation of technological and institutional change in such a manner as to ensure the attainment and continued satisfaction of human needs for present and future generations. Such development conserves land, water, plant genetic resources, is environmentally non-degrading, technologically appropriate, economically viable and socially acceptable." (Garcia, 1996).

For fisheries management to be successful, management objectives need to be defined, setting out the general aims of fisheries management. Fisheries management objectives often include sustainability considerations or specific interpretations of sustainability, such as keeping a fish stock at a healthy stock size. Such objectives are often operationalised by defining reference points in a management framework. This approach allows taking corrective action, such as reducing catch, when the stock size of a fish stock falls below a trigger reference point. Management reference points always refer to observed or modelled stock estimates in a management framework because the underlying reality (the fish stock) is unknown and can only be inferred from observations.

Two common management paradigms are the precautionary approach (PA) and the maximum sustainable yield (MSY). The precautionary approach (Garcia, 1996) is aimed at avoiding a low stock size, below which recruitment is thought to be impaired, by considering uncertainty (the condition of being uncertain about states or processes because of a lack of knowledge), error (a mistake caused by making wrong assumptions), and risk (the potential of negative consequences of a decision). The precautionary approach is operationalised through the definition of biological limit reference points, and fisheries management should ensure that management measures keep the risk of falling below this limit reference point low. On the other hand, the MSY principle defines the stock condition where a stock is most productive and can produce the highest long-term catch. The MSY approach is often used as a management objective target (e.g. ICES, 2019a).

Fisheries management is always based on incomplete knowledge. For commercially and politically important fish populations, extensive data sampling programmes might exist that cover both fisheries-dependent and fisheries-independent sources. For example, such data exist for many fish stocks in the Northeast Atlantic and international data collection is coordinated by the International Council for the Exploration of the Sea (ICES). Such a data-rich situation allows the application of complex mathematical stock assessment algorithms to estimate stock development over time and current stock status. However, even in such a case, the perception of the fish stock is based on a model, which is, by definition, a simplification of reality (Burnham, 2004) that does not include the full complexity of the modelled system. Furthermore, all models are wrong to some degree, but some can nevertheless be useful (Box, 1976).

For the majority of fish stocks in the world, data availability is insufficient and quantitative stock assessment models cannot be applied successfully (Rosenberg et al., 2014). The reasons for the lack of data can be manifold and include little commercial or political interest (e.g. for bycatch species), or capacity limitations (e.g. insufficient scientific funding, expertise, and resources) that do not allow the set up of data collection programmes for all stocks. Such fish stocks and their fisheries, for which no quantitative stock assessments exist, are generally classified as “data-limited” (Rosenberg et al., 2014).

Definitions of what constitutes data-limited can vary depending on the fisheries management body. In this thesis, the classification of ICES is used, which defines categories depending on the data availability and the applicability of stock assessment methods (ICES, 2019a). In this ICES context, the term data-limited refers to fish stocks for which quantitative stock assessments do not exist, or if they exist, are considered too uncertain to provide estimates of absolute stock metrics and are merely used to inform on stock trends such as the development of relative stock size over time. This separates data-limited fish stocks from the data-rich stocks and also from data-poor stocks, for which almost no data and knowledge are available. The data categorisation and the extent of data limitations are described and discussed in detail in Chapter 4.

The current best practice for evaluating management strategies is by conducting simulations using management strategy evaluation (MSE; Smith, 1994; Punt et al., 2016), which dates back to the 1980s at the International Whaling Commission (Butterworth, 2007). MSE aims to simulate the entire managed system as well as the management system within a feedback loop to evaluate the management performance of candidate management strategies. Within an MSE, an operating model represents the biological stock and the fishery harvesting this stock. Observations from this operating model are passed on to a management strategy, which uses these data and deploys a decision rule to derive a management decision, such as setting a catch limit. The management decision is then fed back into the operating model. This feedback loop is then simulated through time and the management performance evaluated. Management strategies that have been formally defined (including all data and how data is processed) and evaluated through MSE, are generally called management procedures (tRFMO, 2018). The MSE approach, its origins, its role in the development of operational management strategies, and how it became the current paradigm in fisheries science are discussed in Chapter 2.

The MSE approach encourages participation from stakeholders such as fishers, policymakers, and environmentalists who might have substantially different views on fisheries management objectives. MSE can help to illustrate trade-offs between management objectives and develop management procedures that balance potentially conflicting objectives. In addition, stakeholder participation can increase trust in the process of developing management procedures because different stakeholder groups can express their views and are involved in the decision process.

A crucial factor when using modelling approaches to guide management decisions is the characterisation of uncertainty to ensure the robustness of the modelling approach as well as management decisions to uncertainty. This is particularly important in data-limited situations where uncertainty is usually larger and a more comprehensive range of uncertainty needs to be included. Important factors of uncertainty to consider are natural variation and epistemic uncertainty. Natural variation can occur in many biological processes, such as individual growth or recruitment success. Epistemic uncertainty describes the uncertainty caused by incomplete knowledge of the processes in the studied system, such as how biological processes are linked. In modelling approaches, epistemic uncertainty can, in theory, be reduced by collecting more data and conducting additional studies, whereas natural variation cannot be reduced and needs to be modelled. Chapter 2 provides a more detailed explanation of how uncertainty is handled in MSE.

Management procedures can broadly be grouped into model-based and empirical management procedures (Rademeyer et al., 2007). Model-based management procedures make use of a population model to set management decisions. Alternatively, empirical management procedures are model-free, require only empirical data, and can be more suitable in situations with limited data because these do not rely on capacity (data and people) intensive modelling approaches. A review of empirical management procedures in a data-limited context is provided in Chapter 3.

For the Northeast Atlantic, ICES is the main international body to provide scientific advice on fishing opportunities, which is then applied into legislation by EU member states and in negotiations with independent coastal states (ICES, 2019e). ICES advice on fishing opportunities includes advice for data-limited fish stocks. Within ICES, the main avenue for developing methodology applicable to data-limited fish stocks is through the ICES "Workshop on the Development of Quantitative Assessment Methodologies based on LIFE-history traits, exploitation characteristics, and other relevant parameters for data-limited stocks" (ICES, 2012d, WKLIFE). This workshop attracts experts on data-limited stocks both from within the ICES community as well as from around the world. The first meeting of WKLIFE took place in 2012 (ICES, 2012d), and initiated the development of the data-limited advisory method framework currently in place. Usually, ICES workshops happen once or a limited number of times in consecutive years. However, due to its importance for the ICES advisory process, the workshop series has been running continuously, and the tenth WKLIFE meeting was held in 2020 (ICES, 2020a).

The general aim of this PhD project is to improve the management of data-limited fisheries resources, mainly within the ICES system, by developing and testing data-limited empirical management procedures. The project is ideally placed to satisfy this aim because of its unique collaboration between academia (Imperial College London) and the responsible UK government agency (Centre for Environment, Fisheries and Aquaculture Science, Cefas), and the collaboration with ICES. The work conducted in this PhD project is closely aligned with the objectives of ICES WKLIFE and is an integral part of the workshop. This cooperation with ICES offers an opportunity for the direct uptake of the outcomes of the PhD project into an advisory framework, with potential application to dozens of fish stocks.

1.2 Problem statement

There are two main problems fisheries management must address;

(i) Conservation: management decisions need to ensure precautionary exploitation to avoid overfishing (unsustainable high fishing pressure) as well as recovering overfished stocks (reduced stock size because of overfishing), and

(ii) Exploitation: maximising yield (e.g. with the MSY approach) to provide a food source and sustained income for fishers.

These two elements are both important and need to be considered in combination. Focusing purely on conservation with precautionary fisheries management could easily be achieved by restricting any fishing activities; however, this comes at a high economic and food security cost. The two management objectives are often a legal requirement of national or international regulations and treaties. Examples are the Common Fisheries Policy of the European Union (EU, 2013) and the United Kingdom's Fisheries Act 2020 (HM Government, 2020). The UK's Fisheries Act, for instance, mandates fisheries management to follow precautionary and MSY principles, and this applies to all exploited fish stocks, irrespective of their status.

The majority of the world's fish stocks are data-limited (Rosenberg et al., 2014) but nevertheless require appropriate fisheries management. The lack of knowledge and data makes the exploration and development of candidate management strategies particularly challenging because of high uncertainty and a lack of clearly defined management objectives. On the other hand, data-limited fisheries management can be more interesting because management needs to be robust to a plethora of uncertainties, and requires thinking outside the box of traditional fisheries management, calling for the adoption of novel approaches.

ICES classifies fish stocks into categories depending on data availability and developed methods to provide advice for each of them (ICES, 2012b). This PhD project focuses on ICES category 3 data-limited stocks, for which catch data and a reliable abundance index exist. In the absence of reliable quantitative stock assessments, stock size and fishing pressure are unknown for these stocks. Since 2012, an index-adjusted status quo catch rule has been used for advice purposes. This catch rule scales the recent catch advice depending on the stock trend inferred from an abundance index, in combination with an uncertainty cap limiting the change in advice from year to year, and a precautionary buffer reducing the advice when the stock is thought not to be in a good state (ICES, 2018b). The management advice based on this framework has major deficiencies (e.g. can increase risk over time or induce large long-term oscillations; Fischer et al., 2021b) and was only meant as an interim solution. Furthermore, despite being labelled the ICES precautionary approach, the index-adjusted status-quo catch rule was never shown to follow precautionary principles, and due to the lack of any management target, it is not MSY-compliant.

The research problem addressed within this PhD project is further elaborated and narrowed down in the following three review chapters (Chapters 2, 3, and 4), which provide a more detailed context of the MSE paradigm, including how MSE aims to create a modelled system of reality, a description of the current ICES advice system and why it fails to deliver what is promised, and a review of possible alternative management procedures.

1.3 Objectives and approach

The general idea of this PhD project is to advance and improve data-limited fisheries management by developing and testing management procedures using MSE. The PhD project provides evidence that the currently-applied data-limited ICES methods are inadequate for fisheries management. Furthermore, it provides a scientific justification for revising the current ICES system by proposing alternative methods. The focus will be on empirical control rules, and these will be subjected to rigorous simulation testing to ensure they are fit for purpose and comply with legal frameworks setting out management objectives.

Because the main study focuses on data-limited fish stocks, initial simulations will be conducted generically, i.e. generic operating models will be created from life-history parameters and many different life histories included. This approach will allow the screening of candidate management procedures, and inferences to be made about management performance for different life histories.

Subsequently, the empirical methods will be modified to improve management performance. This analysis will include exploring fisheries management objectives, such as risks and catch and their trade-offs. Once management objectives have been defined, the management procedures can be tuned to satisfy these with optimisation methods, such as genetic algorithms (Holland, 1992). Such optimisations are very computationally demanding and will therefore require high-performance computing systems.

The ideal outcomes of the simulation testing are establishing generic methods providing a suitable management measure for data-limited stocks in the absence of further knowledge or data, and providing guidelines on how to apply these methods depending on factors such as life history and historical exploitation.

Model validation is notoriously difficult for simulations in fisheries science because the studied system (a fish stock) is never known in its entirety, and only inferences from observations are possible. One approach for validating generic simulation results for data-limited stocks is using data-rich fish stocks for which fully quantitative assessments exist and stock parameters are known with more confidence. This approach will be used for several case studies and allows the conditioning of potentially more realistic operating models against which the data-limited methods previously developed with generic simulations can be benchmarked.

An important consideration for developing management procedures in this PhD project is their robustness to various uncertainties. In the initial generic simulations, robustness is considered by simulating many different life histories and conducting sensitivity analyses. This is meant to ensure that outcomes are robust to potentially arbitrary decisions such as the model structure or the level of uncertainty. The subsequent simulations for case study stocks follow a structured approach by conducting robustness trials with a range of alternative operating models representing different assumptions about model structure and parameters. This structured approach allows an evaluation of the robustness of the previously developed generic management procedures.

1.4 Publications

At the time of writing (July 2022), the following four articles have already been published in peer-reviewed journals:

- Chapter 6

  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*(5), 1914–1926. https://doi.org/10.1093/icesjms/fsaa054

- Chapter 7

Fischer, S. H., De Oliveira, J. A. A., Mumford, J. D. & Kell, L. T. (2021a). Using a genetic algorithm to optimize a data-limited catch rule. *ICES Journal of Marine Science*, *78*(4), 1311–1323. https://doi.org/10.1093/icesjms/fsab018

- Chapter 8

  Fischer, S. H., De Oliveira, J. A. A., Mumford, J. D. & Kell, L. T. (2021b). Application of explicit precautionary principles in data-limited fisheries management. *ICES Journal of Marine Science*, *78*(8), 2931–2942. https://doi.org/10.1093/icesjms/fsab169

- Chapter 9

  Fischer, S. H., De Oliveira, J. A. A., Mumford, J. D. & Kell, L. T. (2022). Exploring a relative harvest rate strategy for moderately data-limited fisheries management. *ICES Journal of Marine Science*, 12 pp. https://doi.org/10.1093/icesjms/fsac103

One chapter is based on a submitted manuscript:

- Chapter 11

  Fischer, S. H., De Oliveira, J. A. A., Mumford, J. D. & Kell, L. T. (n.d.). Risk equivalence in data-limited and data-rich fisheries management: an example based on the ICES advice framework (manuscript submitted to *Fish and Fisheries*)

I am the first author for all published or draft publications mentioned here. The contributions of co-authors were limited to discussions of the ideas and analysis, critical revision, and final approval. Where material from the published articles was reused in this thesis, this is explicitly stated at the beginning of the respective chapters.

1.5 Structure of this thesis

The thesis is structured as follows:

- Chapter 1 (this chapter) introduces the work of this thesis, articulates the main problem addressed, and sets the objectives of this project.

- Chapters 2, 3, and 4 comprise the literature review. Chapter 2 introduces the MSE approach, Chapter 3 reviews and categorises empirical management procedures, and Chapter 4 introduces the advisory framework used by ICES.

- Chapter 5 describes the creation of the generic operating models from life-history parameters used in subsequent chapters and includes an elasticity analysis of the operating models.
- Chapter 6 describes the early simulation testing of an empirical management procedure (the “rfb rule’) and how the management performance of this rule could be linked to life history of the simulated stocks.
- Chapter 7 shows how a genetic algorithm can be used to improve the management performance of the rfb rule towards achieving long-term sustainability objectives.
- Chapter 8 builds on Chapter 7 and adds the consideration of explicit risk limits in the optimisation of the rfb rule to ensure compliance with the precautionary approach.
- Chapter 9 analyses an alternative management procedure based on the concept of harvest rates.
- Chapter 10 explores very fast-growing species, how they could be simulated, and the implications for management.
- Chapter 11 uses case-specific simulations to compare the empirical data-limited methods of this thesis to the data-rich ICES methods used for managing fisheries.
- Chapter 12 is a conclusion of the findings and discusses the impact of the work to date.

The complete thesis is relatively long. To improve the readability of the thesis, all chapters, excluding the introduction and conclusion, short abstracts are included at the beginning of each chapter. Furthermore, the main original research chapters (Chapters 6-11) are essentially self-contained and can be read independently. Nevertheless, these chapters build upon each other with many back-references, and later chapters address gaps identified earlier.

Chapter 2

An introduction to management strategy evaluation

2.1 Abstract

The term management strategy evaluation (MSE) describes a simulation technique in which the performance of management procedures is tested against management objectives. An MSE comprises two main parts: an operating model and a management procedure, connected through a feedback loop. The operating model contains the biological stock and the fishery exploiting it. From this operating model, observations are passed on to the management procedure, in which a decision rule takes this information and generates a management measure, such as a catch quota. This management decision is then returned to the operating model. Operating models are often based on the outcomes of complex stock assessment models, or in more data-limited situations, can be generated based on life-history considerations. For an MSE to be successful, it is essential that realistic uncertainty considerations are included and that quantifiable management objectives exist. MSEs have been used in fisheries science for several decades and are considered the state-of-the-art methodology for evaluating the robustness of candidate management procedures.

2.2 Background

The traditional approach in fisheries science to manage fisheries is to follow the "best assessment paradigm" (Stewart & Martell, 2015). In this approach, the best scientific knowledge is used in a stock assessment model and the results of the model are used to guide management decisions, for example, with a harvest control rule that sets a management measure such as a catch limit. Alternative models might be considered and a "best assessment" is selected based on criteria such as the goodness of fit to observed data. The approach can include a short-term forecast, in which the stock as perceived by the assessment model is projected into the future and a specific management target, such as the fishing mortality corresponding to the maximum sustainable yield (F_{MSY}), is converted into a catch value (ICES, 2019a).

An issue with this best assessment approach is that while an assessment might be the best available scientific knowledge about a fish stock, the perception might still be biased. Furthermore, specific management objectives might be defined and formalised in a harvest control rule; however, statements about the ability of the management approach to meet these objectives are limited because the feedback of the fisheries management on the stock is unknown. To address these issues, the management strategy evaluation (MSE) approach was developed (Smith, 1994;

Punt et al., 2016). In an MSE, the impact of management on the managed system is simulated in a closed-loop simulation. MSE allows the development and evaluation of the management approaches to ensure that management objectives are met. Butterworth (2007) described MSE as the modern alternative to the traditional best assessment approach.

2.3 The management strategy evaluation framework

MSE is a framework to test management procedures with simulations (De Oliveira et al., 2009; Punt et al., 2016). The simulation consists of a feedback control loop that includes the managed system and the influence of management on this system, and is represented by two main building blocks, the operating model and the management procedure (Figure 2.1).

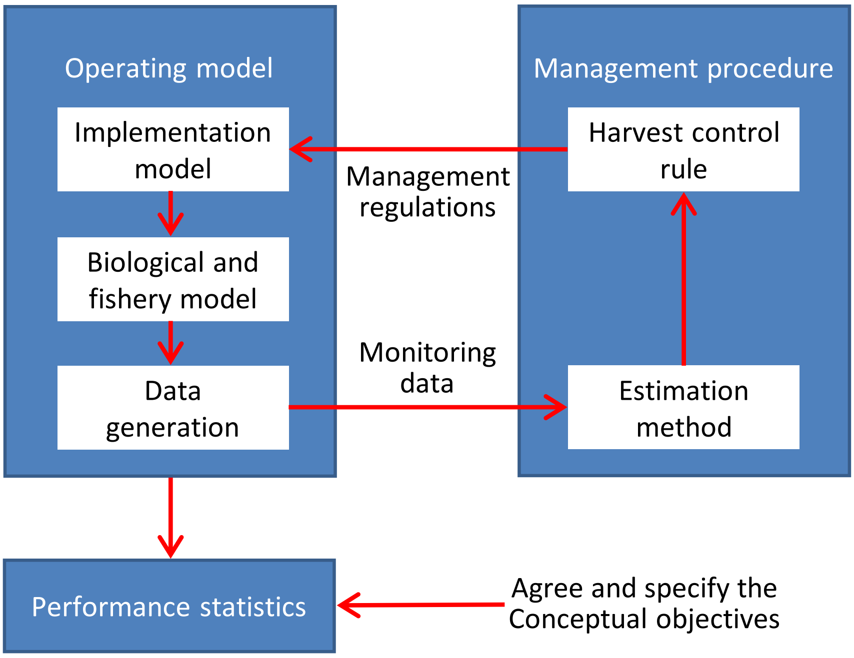

Figure 2.1: Conceptual overview of the management strategy evaluation modelling process. Figure adapted from Figure 1 of Punt et al. (2016). © 2014 John Wiley & Sons Ltd.

The operating model represents the true dynamics of the managed system (De Oliveira et al., 2009) and comprises the biological system (one or more fish stocks) and the fishery operating on it. Within the operating model, data such as catches and survey indices are generated and fed into the management procedure. The exact data depend on the requirements of the management procedure, and observation noise is often added to the data to mimic sampling uncertainty. The management procedure assesses the status of the stock(s) based on the data obtained from the operating model and sets management options subject to the perceived stock status. The management procedure can be based on a fully quantitative stock assessment as an estimation model (a model-based management procedure), in which case a harvest control rule can be applied to the results of a short-term forecast from the estimation model. Alternatively, in more data-limited situations, an empirical (model-free) management procedure can be applied, which uses simple empirical indicators from the operating model directly in a harvest control rule to set management measures. The following chapter (Chapter 3) introduces the concept of empirical management procedures. The management procedure's output is a management measure such as total allowable catch or effort, which is returned to the operating model and subsequently implemented, thereby closing the feedback loop. This management cycle is then simulated over a time horizon of several years.

The performance of the management procedure can then be summarised through performance statistics, such as average stock status (spawning stock biomass, SSB), exploitation (fishing mortality, F) or catch, catch variability, and biological risks (e.g. risk of the stock falling below limit reference points). Such statistics allow the comparison of alternative management procedures (or variations thereof), and it is possible to check if the tested management procedures meet predefined criteria, e.g. compliance with the precautionary approach.

Punt et al. (2016) describe seven sequential steps required to conduct an MSE: (1) identify management objectives, (2) identify uncertainties, (3) develop operating models, (4) select operating model parameters and uncertainty, (5) identify candidate management procedures, (6) simulate, and (7) summarise and interpret performance.

MSE is not a strict protocol but rather a flexible framework that encourages stakeholder participation and includes simulation testing. The actual design of simulation exercises can be adapted to specific needs.

2.4 History of management strategy evaluation

The history of MSE in the management of marine living resources dates back to the second half of the 20th century. Early attempts to simulate fisheries management can be found in Southward (1968), who simulation tested management scenarios for Pacific halibut, and Hilborn (1979), who simulated generic fish stocks (slow and fast-growing). Although not called MSE at the time, these two examples followed the same principles and included feedback control. The MSE approach was then fully introduced into fisheries science in the 1980s by the International

Whaling Commission (IWC; Butterworth, 2007; Punt & Donovan, 2007), which is often attributed to be the pioneer for MSE (De Oliveira et al., 2009). Previously, the IWC had based its management advice on the “new management procedure” that failed because it did not achieve the intended objectives of facilitating scientific agreement, and because of continued arguments within the IWC’s community about appropriately accounting for uncertainty (Butterworth, 2007). Subsequently, the “revised management procedure” was defined and during the process of its development, the MSE approach, called the management procedure approach within the IWC, evolved. This approach includes the simulation testing of alternative or variants of decision rules to come up with an optimal solution (Butterworth, 2007). The IWC has formally adopted the revised management procedure; however, they have never formally implemented it to set catch limits because of a commercial whaling moratorium (Punt & Donovan, 2007), although individual nations may have used the revised management procedure (with case-specific tuning) to set catch limits for their whaling activities. Nevertheless, the process leading to this approach can be considered a success because it paved the way for the MSE approach.

After the development of MSE in the IWC, this simulation-based approach found its way into other management systems concerning renewable living resources, particularly into fisheries science. Smith (1994) is one of the first to use the term MSE in a fisheries science context and praises this approach as “the light on the hill” (Smith, 1994, p. 249) for testing and developing management strategies. Furthermore, Smith formulates the critical argument that an MSE “focuses on the needs of the decision-maker by providing a basis for choosing between alternative decisions or strategies, rather than seeking to identify an ‘optimal’ decision” (Smith, 1994, p. 252). This statement is crucial for this approach because scientists could theoretically simulation test a vast range of possible scenarios, which is of limited value, and the decision-makers should, therefore, “be explicit about management objectives and targets” (Smith, 1994, p. 252) before an evaluation is carried out.

Butterworth and Punt (1999) mention several studies in which MSEs were carried out during the 1990s. The authors mainly list studies from the southern hemisphere, and the list includes fish stocks such as South African Cape hake, anchovy, sardine and rock lobster, Namibian orange roughy, New Zealand rock lobster, Australian gemfish and Southern bluefin tuna. Furthermore, North Sea cod (Pelletier & Laurec, 1992) is mentioned, which might well be the first (published) MSE in Europe.

The terms management procedure approach and MSE are largely synonymous in describing the simulation testing of management procedures to derive sound management advice (Butterworth, 2007) and either is favoured in different scientific and political communities around the world. The tuna regional fisheries management organisation's glossary on MSE (tRFMO, 2018) describes a management procedure as a management strategy in which all elements have been formally defined and their combination has been evaluated with simulations. The term management procedure approach is commonly used within the IWC (e.g. Punt & Donovan, 2007) and in South Africa (e.g. Geromont et al., 1999), whereas the term MSE is used in many other organisations and parts of the world, such as within the International Council for the Exploration of the Sea (ICES) and Europe, North America, and Australia (e.g. Smith et al., 1999; Kell et al., 2005; Wetzel & Punt, 2011). In some contexts, the term MSE can indicate a larger process with explicit stakeholder participation (e.g. commonly adopted by tuna regional fishery management organisations; Sharma et al., 2020), and the simulation of candidate management procedures (i.e. management procedure evaluation) is only a part of this process. In this thesis, the term management strategy evaluation (MSE) is used in the sense of a closed-loop simulation of management procedures.

2.5 Operating models

Operating models represent the true dynamics of the simulated system and should, therefore, be as realistic as possible and account for uncertainty (De Oliveira et al., 2009). Operating models need to be set up and conditioned to represent biological stocks, their intrinsic stock dynamics, and the fishery exploiting the stocks.

The usual approach to developing an operating model is to condition it on stock assessment results, which can be considered the best available science on stock perception. However, this approach can only be used for stocks for which stock assessments are available, i.e. usually for data-rich stocks only.

The benefit of having a stock assessment is that many of the parameters required to simulate a stock have already been explored as part of the process of setting up a stock assessment. This exploration includes considerations of stock structure, biological parameters such as natural mortality and maturity, and data from the fishery. The results of a stock assessment provide essential details such as the age structure of the population (if an age-structured assessment is available) and the current condition of the stock in terms of stock size and fishing mortality. Furthermore, modern stochastic stock assessments provide estimates of uncertainty of various variables and parameters, depending on the model formulation, and can include uncertainty quantification of stock numbers and fishing mortality at age, catch and survey data (Nielsen & Berg, 2014). The availability of stock assessment results also provides a historical time series of recruitment estimates and allows for the definition of an appropriate stock-recruitment model, a crucial component during a simulation that defines stock productivity.

The operating models for North Sea stocks (cod, haddock, whiting, saithe and herring, ICES, 2019h) developed for the evaluation of long-term management plans could be considered a state-of-the-art implementation of a stochastic single-species operating model. These operating models were based on the results of an age-structured stochastic stock assessment model with time-varying selectivity (SAM, Nielsen & Berg, 2014). SAM is defined as a state-space model in which processes (stock numbers and fishing mortality), as well as observations (catches and surveys), are modelled as stochastic processes. This formulation allows the estimation of uncertainty in processes and observations, which, when implemented into the operating model of an MSE, improves realism. The recruitment model was generated by fitting it to the estimates of recruitment and SSB and converting model residuals into a continuous distribution with a kernel density smoother, which allowed recruitment residuals to be sampled for the forward projection in the MSE.

The generation and evaluation of data-limited stocks and management procedures are challenging due to the data limitations. There are two main approaches to handle this situation: (i) borrow operating models from data-rich stocks and (ii) generate operating models based on life-history considerations.

2.5.1 Borrowing from data-rich stocks

In many examples of testing data-limited management procedures, the operating models were conditioned on stock assessments of data-rich stocks, e.g. Klaer et al. (2012) conditioned operating models on Australian stocks (tiger flathead, jackass morwong, school whiting) or Geromont and Butterworth (2015b) on North Sea plaice and sole, and New England witch flounder and plaice. In these cases, the operating models mimic the stock and fishery as perceived by the stock assessment model, and the operating model structure follows the model structure of the stock assessment model. MSEs conducted with such operating models can only be indicative of the performance of potential management procedures because they have not been tested on the stocks for which these management procedures are intended. Furthermore, the development of data-rich operating models can be a time-consuming process. Therefore, evaluations are often limited to few stocks, and conclusions on management performance depending on life history are limited. In order to improve the scope of the outcomes of such MSEs, data-rich operating models are sometimes used as the basis and then subjected to artificial fishing histories. Examples are the operating models of Klaer et al. (2012) that are conditioned on data-rich stocks but are then projected forward to derive distinct depletion levels (35% and 60% of unfished biomass).

An exception to the use of data-rich operating models is the analysis of Plagányi et al. (2018), which evaluated a data-limited management procedure for a tropical rock lobster. For this stock, a (data-limited) stock assessment model exists, and the aim for developing this model was that it could then be used in an MSE. Such cases are rare because the development of quantitative stock assessments, including the necessary data collection, is expensive and can usually only be afforded for economically important stocks. Sometimes, only specific parameters are borrowed (i.e. copied) from other data-rich stocks, e.g. in the swordfish model of Campbell and Dowling (2005), natural mortality is borrowed from the data-rich stock assessment of southern bluefin tuna.

2.5.2 Using life-history information

The alternative to borrowing data-rich operating models is to generate operating models from life-history information. This approach is based on the idea that biological parameters are correlated, and is founded on early work of Beverton and Holt (1959), which has been used several times (e.g. Prince et al., 2015). The correlations can be expressed as mathematical relationships between parameters derived from empirical data, and this can be used to approximate missing parameters.

An example of a biological parameter that is notoriously difficult to estimate, even for data-rich stocks, is natural morality (Quinn & Deriso, 1999). Natural mortality is a crucial parameter in analytical stock assessments, as well as in simulations. There are a range of options to calculate natural mortality, such as through analyses of catch curves or length-frequencies, mark-recapture experiments, collection of dead organisms, multi-species models, or inferences from life-history (Quinn & Deriso, 1999). Analytical approaches require substantial amounts of data, and are therefore expensive and not applicable to data-limited stocks. However, empirical relationships exist; for example Lorenzen (1996) or Gislason et al. (2010) provide formulations for estimating natural mortality at length from simple growth parameters.

An example where operating models were created from life-history parameters is the study of Carruthers et al. (2014), where six fish stocks were simulated (mackerel, butterfish, snapper, porgy, sole, rockfish) and the same approach was subsequently used for three additional stocks (Atlantic bluefin tuna, Pacific herring and canary rockfish, Carruthers et al., 2016). Included were parameters about individual growth (von Bertalanffy growth parameters), the length-weight relationship, natural mortality, maturity, selectivity, and the stock-recruitment model. Despite basing the operating models on life-history parameters, the parameters themselves were extracted from data-rich stock assessments.

Geromont and Butterworth (2015a) deployed a similar approach but did not create stock-specific operating models, but instead a single operating model as a conglomerate of several species by defining ranges of life-history parameters. This approach allows the evaluation of management procedures with a generic stock but without being able to make statements about life-history dependent performance.

Jardim et al. (2015) generated operating models for 50 different stocks, which covered a wide range of life-history traits. Nevertheless, the parameters for these stocks were species averages and did not correspond to particular stock units. Hence, not all these simulated stocks are necessarily realistic because sets of life-history parameters are correlated, and averaging them can create unrealistic combinations.

Wetzel and Punt (2011) created two generic operating models, flatfish and rockfish, based on life-history parameters, and essentially used the algorithms of an integrated stock assessment model (stock synthesis, Methot & Wetzel, 2013) for the operating model conditioning. However, it should be noted that this operating model was used to test catch-only methods in a simulation, but without the usual feedback loop of an MSE.

Simulating operating models from life-history parameters has the benefit that many stocks can be created covering a wide range of life-history traits. Furthermore, because the stocks are simulated, any fishing history can be applied to them. This process allows the generation of operating models with different starting conditions, and therefore the sensitivity of management procedures to the stock condition can be analysed.

2.6 Management objectives

Defining explicit management objectives is important for fisheries management in general, as well as for the successful evaluation of management procedures. Punt et al. (2016) state the identification of management objectives as the first step of an MSE. A common principle adopted by international agreements is the precautionary approach (Garcia, 1996). In general, the precautionary approach aims to reduce the risk of damaging the exploited resource and to account for uncertainty (see Chapter 8 for a detailed description of the precautionary approach and how it can be implemented into fisheries management). In addition, there are other management principles such as the maximum sustainable yield (MSY, i.e. aiming to move fish stocks to a level where they are most productive in the long term) that can be adopted alongside the precautionary approach. As an example, within ICES, the aim is to maximise the long-term yield (i.e. follow the MSY approach); however, this is secondary to the overarching requirement of following the precautionary approach (ICES, 2019h, 2019a, see Chapter 11 for an example how these two principles can be combined). Management objectives are usually defined broadly in national or international fisheries policies and are not always expressed precisely. Such general objectives are challenging to interpret for the purpose of MSE where conceptual objectives need to be converted into operational objectives in order to quantify these in terms of performance statistics (De Oliveira et al., 2009; Punt et al., 2016).

Furthermore, the management objectives of stakeholders can differ, where, for example, fishers aim for high yields and catch stability, whereas others might consider the reduction of the risk of low stock status more important. Consequently, trade-offs of conflicting objectives need to be balanced.

Management objectives are even more difficult in data-limited situations, where certainty about the stock condition is lacking. Therefore, in simulations of data-limited management procedures, it is often only feasible to compare alternative management procedures without the possibility of providing specific risk levels.

2.7 Uncertainty

De Oliveira et al. (2009) and Kell et al. (2006) state the following elements of an MSE where uncertainty can be implemented:

- process error (uncertainty in the dynamics of the modelled system, i.e. natural variability)

- observation error (uncertainty about observed data used in the management procedure)
- estimation error (uncertainty in the estimation of parameters in the operating model and management procedure)
- model error (uncertainty in the operating model and management procedure model structure, i.e. epistemic uncertainty)
- implementation error (uncertainty in the implementation of the management measures of the management procedure)

The quantification of uncertainty is a crucial part of setting up an MSE because it can influence the outcome. For MSEs based on quantitative stock assessments, the stock assessment model often allows measuring uncertainty. In more data-limited situations, setting appropriate uncertainty levels is more challenging due to the lack of empirical data. Therefore, it is even more important to conduct robustness tests to evaluate the impact of the sources and magnitude of uncertainty. In some cases, the uncertainty level can be rather arbitrary, as pointed out by Carruthers et al. (2014) who based the probability distributions in their MSE on "expert judgement".

2.8 Criticism

Despite many benefits, the MSE approach has been drawing some criticism over time and still has some opponents in the scientific community. A prominent example is a controversial article published by Rochet and Rice (2009) that criticised MSE and already included the authors' opinion in the title, asking whether MSE is "ignorance disguised as mathematics" and suggested that the "use of complex mathematics and statistical tools risks giving users a false sense of rigour" (Rochet & Rice, 2009, p. 55). However, less than a year later, a high-profile response from MSE experts around the world (Butterworth et al., 2010) appeared to defend MSE and clarify misunderstandings of the MSE principle by the former authors.

In stochastic MSEs, deterministic variables are replaced with probability distributions from which values are drawn, e.g. through Monte Carlo simulations. Due to uncertainty in many processes of the underlying dynamics, it is common practice to produce several model formulations, e.g. in the form of alternative operating models or scenarios. Rochet and Rice (2009) argue that using probabilistic approaches is paradoxical because this implies having more knowledge than for deterministic approaches. Additionally, typical risk evaluations are based on rare events at the tails of probability distributions and therefore less reliable, e.g. the precautionary approach is often formalised in a way that the probability of a stock falling below a limit reference point should not exceed a specific risk threshold, such as 5%, whereas central tendencies are more reliable. As an alternative to MSE, Rochet and Rice (2009) recommend alternative approaches such as qualitative modelling with simple models, learning from post hoc analyses where management strategies have been implemented in reality, and checking their internal consistency and how they would be implemented.

In their response, Butterworth et al. (2010) point out that the criticism of MSE is mostly based on specific technical details that usually only appear when an MSE is poorly implemented by ignoring best practices and misunderstandings of the scope of MSE. MSE can rather be regarded as a holistic approach that encourages stakeholder participation. Using inappropriate parameterisation and model formulation undoubtedly hampers the outcomes of an MSE. The quantification of uncertainty in an MSE is challenging and should be considered carefully in order to define realistic levels. It is good practice to describe and document the assumption of an MSE (including uncertainty) and to justify those assumptions. The suggestion of Rochet and Rice (2009) to use deterministic values instead of a probability distribution in case of uncertainty is refuted by Butterworth et al. (2010). Butterworth et al. (2010) point out that deterministic values are derived from empirical data (obtained through some sampling approach that also entails uncertainty), and it would be wrong to assume a point estimate with absolute certainty; therefore, including some uncertainty should be justified. One of the primary purposes of MSE is to compare different management procedures, including potential trade-offs, and should always include robustness tests of key assumptions.

There are no comprehensive alternatives to MSE available for testing and comparing management procedures. Some methods can complement MSE, but are usually already included in the process. The only way to explore the impact of feedback between a management procedure and the managed system is to conduct a feedback simulation loop. Post hoc analyses can provide some ideas about the performance of management procedures; however, being able to draw useful conclusions is rare. The performance of the implementation of management procedures in reality depends on various factors such as stock characteristics (life history, fishing history, etc.), implementation, or enforcement of management measures, and it is nearly impossible to attribute good or poor performance of a management procedure to any such factor.

Good management procedures are robust to uncertainty and provide default management options. The results of MSE should be periodically re-evaluated to make use of new information, particularly if a stock moves out of the range of plausible conditions tested within an MSE.

Kraak et al. (2010) discuss scientists' discomfort when asked to report concrete risk values derived from MSE evaluations. Most MSEs are conducted as a response to requests from management bodies or stakeholders. These requests usually ask that management procedures meet explicit risk thresholds, which can pressure scientists to report risk metrics with a precision that cannot be sufficiently supported by considerations of various uncertainties. In contrast to such MSE requests, purely academical MSEs in the peer-reviewed literature are commonly comparative, and different management procedures or management procedures subject to different scenarios are compared. The suggestion of Kraak et al. (2010) to discredit MSEs in general and management procedures derived from MSE exercises due to possibly poorly understood uncertainties is likely irrational and poorly justified, in particular, because no viable alternatives are presented. Furthermore, Kraak et al. (2010) recommend using simpler empirical management procedures, but fail to acknowledge that the performance of empirical management procedures cannot be predicted or evaluated without conducting feedback simulations.

In general, the criticism of MSE based on considerations of the risk of rare events (stock collapse) can hardly be blamed on the MSE approach and is rather a criticism of how management bodies formulate requests to evaluate management procedures. For example, imposing the restriction that a risk metric cannot exceed 5% is arbitrary in the same way that a specific level of uncertainty is implemented. Such decisions might be considered a social choice based on tolerances for risk and the expectation of reward.

It is highly questionable if the application of simpler modelling approaches provides more certainty because, for the development of simpler models, even more assumptions and simplifications have to be made, which are less likely to be able to model the dynamics observed in reality.

For an MSE to be successful, it is good practice to learn from previous examples and follow guidelines (e.g. ICES, 2013b, 2019g, 2020b) and best practices (Punt et al., 2016).

2.9 Software

There are various software options for conducting MSEs, including software suites designed explicitly for conducting MSEs as well as bespoke implementations. In the past, MSEs were often coded in various programming or scripting languages for specific MSE exercises or reused for similar MSEs. The main disadvantage of custom software is that only a very limited number of people are working on the code and can easily read it. This can mean that systematic or coding errors can be hidden in the code without being noticed and hindering peer review. Using open-source MSE frameworks avoids such issues.

On an anecdotal note, MSE simulations were historically conducted with programming languages such as Fortran, considered to be suitable for heavy computational tasks in many scientific fields at the time (Decyk et al., 2007; Mendez et al., 2014). Roel and De Oliveira (2007) used a simulation framework in Fortran to evaluate harvest control rules for the European widely distributed Western horse mackerel stock.

Some analytical stock assessment models allow their internal routines to be used as operating models or even to run full MSEs, and a notable example is the integrated stock assessment method Stock Synthesis (Methot & Wetzel, 2013).

Within the last 20 years or so, in fisheries science as well as in many other scientific fields, there has been a tendency to move towards the R language (R Core Team, 2020). A popular open-source software suite for modelling population dynamics in fisheries science is the Fisheries Library in R (FLR, Kell et al., 2007). FLR is a product of several national and international projects, most notably of the European Commission of the European Union. First developed as an Excel spreadsheet-based tool at the Centre for Environment, Fisheries and Aquaculture Science (Cefas, United Kingdom) in Lowestoft (J. De Oliveira and L. Kell, personal communication), FLR was then moved to the R programming language (R Core Team, 2020). The basis of FLR is the "FLCore" R package which defines most data classes and generic methods and follows a modular approach with a plethora of additional R packages for specific analyses, e.g. "FLash" for the projection of a fish stock forward in time. FLR is particularly popular within the ICES community, where it is used for stock assessments as well as MSEs.

Traditionally, MSEs with FLR were based on custom scripts for specific projects. Recently, and driven by the assessment for all initiative (a4a), a standardised MSE framework for FLR has been developed (Jardim et al., 2017). This framework is based on the FLR packages and comprises a modular design with separate modules for observations, stock estimation, application of a decision rule, implementation error, and projection. Following a standardised and modular approach facilitates peer review and collaborations. A notable example where this FLR MSE framework has been used is the evaluation of long-term management plans for several North Sea gadoids (ICES, 2019h).

Although traditionally used for data-rich analyses, FLR has also been used for data-limited analyses, and this PhD project is promoting its use further. An early attempt to simulate data-limited operating models based purely on life-history parameters (primarily on the life-history relationships of Gislason et al., 2008; Gislason et al., 2010) was part of a project of the Food and Agriculture Organization (FAO) to evaluate data-poor methods (Rosenberg et al., 2014). The same procedure was later used for testing a super ensemble of catch-only methods in a control rule (Anderson et al., 2017; Walsh et al., 2018). Jardim et al. (2015) adapted this approach and tested empirical data-limited (model-free) management procedures for a wide range of life histories.

Recently, during the course of this PhD project, the procedure for generating operating models based on life-history parameters was further developed and formalised in the FLR package "FLife". The analyses described in Chapter 6 and published in Fischer et al. (2020) are possibly the first peer-reviewed publication that used FLife to create operating models for an MSE. This work was initially based on custom MSE subroutines, but due to the standardisation approach of the FLR MSE framework, the MSE framework was modified to handle data-limited MSEs, and the work was moved into the framework.

The main advantage of FLR over alternatives is that it provides a comprehensive software ecosystem. The modular approach allows a high degree of flexibility, external methods (e.g. stock assessment methods) can be incorporated, and FLR has an R interface familiar to many fisheries scientists. Punt et al. (2016) in their MSE best practices paper recommend the use of already tested generic software and specifically highlight FLR as a tool developed for MSE.

An emerging alternative to FLR is the data-limited toolkit (DLMtool; Carruthers & Hordyk, 2018) and its data-rich version, MSEtool (Huynh et al., 2020). Both tools follow many of FLR's pioneering principles of an MSE software suite, e.g. are written in R, use object-oriented programming and define generic classes and methods. DLMtool is designed as a standalone R package meant to facilitate running MSEs. Because it is a relatively new R package, it does not have a community of active users as big as FLR's. Furthermore, some of the functions for creating operating models and running MSE include default parameters and parameter ranges. Such features allow inexperienced scientists to set up and run MSEs reasonably quickly. However, this comes with the caveat that potential users might not fully understand the structure and dynamics of the simulation, which in turn can provide a false sense of security in outcomes, ignoring potentially arbitrary defaults. Due to its design as a single R package, the flexibility is more restricted compared to FLR and, e.g. adding alternative management procedures or statistics might require interventions from the original developers.

2.10 Alternatives

Finding viable alternatives to MSE is challenging because MSE is rather a framework to simulate management procedures and simulation specifications can be tailored to the needs of the MSE exercise. Furthermore, MSE is already the alternative to the best assessment paradigm.

A possible intermediate approach between the best assessment approach and MSE might be to use model ensembles. In an ensemble approach, several assessment models are combined and collectively used for management decisions. Model ensembles are, for example, used in climate or weather modelling or by the International Pacific Halibut Commission (Stewart & Martell, 2015). Some scientists advocate model ensembles to improve fisheries management advice (Jardim et al., 2021) because more than one plausible hypothesis can be considered. However, ensemble approaches require potentially subjective decisions for the selection of models as well as how individual models are weighted.

On the other hand, following best practices for MSE (Punt et al., 2016) already includes considerations of alternative hypotheses for generating operating models. Although ensemble models are a step toward MSE, management advice based on ensembles is difficult to evaluate in simulations because assessment model ensembles can have a much higher computational complexity and therefore impair thorough simulation testing. Furthermore, ensemble approaches rely on modelling approaches which might not be feasible for data-limited fisheries resources, although examples of data-limited ensemble approaches exist (e.g. Rudd et al., 2019). Furthermore, instead of reducing the complexity of management decisions, the ensemble increases complexity, potentially impairing communication with stakeholders. The focus of this thesis was on relatively simple empirical approaches to guide management decisions for data-limited fisheries resources and consequently, stock assessment ensembles are not considered.

MSEs can be complex and sometimes simplifications or shortcuts are favoured. For example, this became evident at a recent ICES workshop on MSE guidelines (ICES, 2020b). In a data-rich MSE with a management procedure based on a stock assessment model, a "full MSE" usually includes the stock assessment model in the feedback loop of the simulation. In a shortcut MSE, the assessment model is replaced by an assessment emulator, which takes the observations from the operating model and adds uncertainty to these estimates. This approach can substantially reduce the computational complexity of an MSE simulation. A further simplification would be to remove the specification of the management procedure (with specified observations and assessment model) altogether and only test a generic principle, e.g. a harvest control rule aiming at a target such as F_{MSY}. This approach was labelled "harvest control rule evaluation" by ICES (2020b). While potentially useful for exploring generic strategies, these shortcuts do not allow a thorough evaluation and definition of a management procedure and it might be argued that these are not MSEs. Furthermore, such simplifications only make sense if stock assessment models are used, which means that these shortcuts do not apply to empirical management procedures.

The only alternative to simulations to receive feedback on a management procedure would be applying a management procedure to a real fish stock. However, experimental application of a management procedure to a real fish stock is infeasible because of the possible damage to the stock and the fishery, scientific standards for experiments cannot be upheld (controls, replicates, and alternative trials are impossible once a management procedure has been implemented), and such experiments would be ridiculously expensive to monitor (De Oliveira et al., 2009). Furthermore, it would be nearly impossible to evaluate the performance of the management procedure because the actual state of the stock is unknown and can only be estimated through assessing the stock and because environmental factors might also cause changes to a stock.

2.11 Conclusion

The MSE approach is the state-of-the-art approach in fisheries science for developing and testing candidate management procedures to ensure that these meet management objectives. Consequently, MSE will be deployed as the primary method in this PhD project to develop empirical management procedures for data-limited fisheries resources. Best practices will be followed to avoid criticism and help acceptance of the work. Furthermore, extensive robustness tests will be conducted. Due to limited data and models for such resources, initial simulation testing will be based on generically developed operating models covering a range of life histories. However, later on, case-specific simulations will be conducted for selected case study stocks to verify the outcomes of the generic simulations.

Chapter 3

A review of empirical data-limited management procedures

3.1 Abstract

Management procedures (MPs) in fisheries management can broadly be grouped into model-based MPs that deploy modelling approaches to set management measures and empirical MPs that only rely on empirical data. A review of empirical MPs is presented. The most simple form of an empirical MP is a constant catch MP. On the other hand, indicator adjusted MPs adapt catch advice based on the information from an indicator, such as an index of abundance or the mean catch length. Indicator adjusted MPs can be further categorised into four main types; (i) stepwise adjustment, (ii) indicator trend, (iii) indicator target, and (iv) harvest control rule type. Additional elements of empirical MPs can include options to restrict catch variability or multipliers for additional precaution. Empirical MPs are usually tested by means of management strategy evaluations, and their performance often depends on simulation characteristics. In general, constant catch MPs yield less satisfactory performance compared to adaptive MPs. Adaptive empirical MPs, when tuned to case-specific conditions, can exhibit good management performance and match, or even exceed, much more complex model-based MPs.

3.2 Introduction

According to Rademeyer et al. (2007), management procedures (MPs) can be grouped into model-based MPs and empirical MPs. In model-based MPs, population models are used to assess fish stocks by gathering information about stock metrics such as stock size or fishing pressure and stock status relative to predefined reference points such as maximum sustainable yield (MSY) or unfished biomass. Depending on the model, such MPs require a substantial amount of informative data, which are commonly unavailable for data-limited stocks. On the other hand, empirical or model-free MPs do not rely on population models and are simply based on available data, usually in the form of indicators such as an abundance index. It should be noted that empirical MPs might not always use raw data but sometimes apply simple models, for example, to smooth the output of an indicator (e.g. Hillary et al., 2016).

This chapter provides a systematic review of empirical MPs used in data-limited fisheries management. The review was conducted systematically, and a record of the methodology for searching and selecting literature is available in Appendix A.

3.3 Empirical management procedures

The review presented here focuses on empirical MPs in data-limited situations, that is in situations where there might be fishery-independent indicators such as an abundance or biomass index, or fishery-dependent indicators considered representative of a fish stock, such as CPUE (catch per unit effort) indices or the mean catch length. The available data in these data-limited situations might be enough for simple stock assessments, for example, biomass dynamic or simple integrated assessment models. However, such models can be controversial due to their formulation or underlying assumptions. Furthermore, their applicability might be impaired by short time series, lack of contrast in data, model convergence issues, violations of model assumptions, or because model fits do not meet minimum acceptance criteria. Therefore, using these models might provide a dangerously false sense of certainty about stock dynamics. Consequently, this chapter only considers empirical MPs that do not use results of population models because empirical MPs have wider applicability in data-limited situations.

Dowling et al. (2015a) conducted a review of empirical MPs for data-poor situations in which there are even fewer data available and these are not part of this review. Dowling et al. (2015a) also noted that there are numerous approaches worldwide; however, most of them are case-specific without the development of generic guidance. Such data-poor empirical MPs use indicators, and when multiple indicators are included, their combined information can either be used sequentially, collectively, or with hierarchical approaches. Subsequent to analysing such indicators, the information needs to feed into the creation of decision rules for management purposes. For data-poor situations Dowling et al. (2015a) mention that this can be done by (i) expert judgement, (ii) collection of more data, (iii) definition of overriding exemptions, and (iv) the formulation of specific decision rules to adjust manageable quantities such as catch or effort. Although empirical approaches are traditionally applied in data-limited situations, they could also be considered for less data-limited stocks and might provide a simpler and cheaper approach to fisheries management, as advocated for by Kelly and Codling (2006).

Generically, most empirical MPs can be written in the form

$$C_{\text{new}} = C_{\text{ref}}\ \alpha \tag{3.1}$$

where C_{new} is the new management measure, e.g. catch advice, C_{ref} is a reference level, e.g. the previous catch, and α is a multiplier scaling the reference level and is usually a function of one or more empirical indicators (see e.g. Geromont & Butterworth, 2015a; Jardim et al., 2015).

Various proposed, tested and implemented empirical MPs exist, and this chapter is a proposal to categorise them following a study of the literature and the considerations of Geromont (2014). A useful overview of various control rule formulations, including empirical approaches, can be found in Breen et al. (2003). Model-based data-limited MPs have already been extensively reviewed, e.g. in Carruthers et al. (2014), Carruthers et al. (2016) or Wetzel and Punt (2011). Furthermore, Dowling et al. (2015a, 2015b) provide a comprehensive review and guidelines for data-poor MPs. However, their review lacks the inclusion of less data-poor, i.e. data-limited cases, and does not detail available formulations of MPs and the guidelines are rather vague in terms of application to real data.

3.4 Constant catch

The most simplistic empirical MP is to set a constant catch without any feedback. In Equation (3.1), C_{ref} then corresponds to a reference catch level. For example, this could be the average of the catches in the five years prior to the implementation of the constant catch and the multiplier α can be a scalar for scaling the reference catch level (Geromont & Butterworth, 2015a). Such a constant catch can either be kept for the foreseeable future or, alternatively, reviewed periodically and adjusted based on newly available catch values in recent years (Carruthers et al., 2014).

3.5 Indicator adjusted catch

Usually, in data-limited situations, some indicator representing the fish stock or the fishery is available and can be used to adjust the catch advice. Such indicator adjusted catch MPs usually follow the principle of Equation (3.1), where the reference catch C_{ref} is set to the previous catch value C_{prev}:

$$C_{\text{new}} = C_{\text{prev}}\ \alpha. \tag{3.2}$$

3.5.1 Stepwise adjustment

Possibly the most rudimentary version of an indicator adjusted catch MP is the stepwise constant catch MP, where the catch advice is “stepped” up or down depending on whether an indicator exceeds certain thresholds. Jardim et al. (2015) and Geromont and Butterworth (2015a) nearly simultaneously proposed empirical MPs that follow this logic; however, Jardim et al. (2015) refer to this MP as based on survey confidence intervals, whereas Geromont and Butterworth (2015a) call it a stepwise constant catch MP. The two MPs do not necessarily look similar on first consideration, but they follow the same principle and are reformulated here to show the similarities between them.

Jardim et al. (2015) designed the empirical MP following Equation (3.2), where α is defined depending on the recent indicator value I and conditional on upper (I_u) and lower (I_l) reference values:

$$\alpha = \begin{cases} 1+\delta_u, & \text{if } I > I_u \\ 1, & \text{if } I_l \leq I \leq I_u \\ 1-\delta_l, & \text{if } I < I_l \end{cases} \tag{3.3}$$

with δ_u and δ_l defining the increase and decrease in the catch advice, which can be asymmetric. Jardim et al. (2015) applied this to an abundance index and defined I_u and I_l based on the confidence intervals of the index so that a change in catch was advised when the index exceeds a specific percentile of an assumed distribution of the time series of index values.

Geromont and Butterworth (2015a) formulated their MP as

$$C_{\text{new}} = \begin{cases} C_{\text{prev}} + \delta C_{\text{ref}}, & \text{if } I > I_u \\ C_{\text{prev}}, & \text{if } I_l \leq I \leq I_u \\ C_{\text{prev}} - \delta C_{\text{ref}}, & \text{if } I < I_l \end{cases}, \tag{3.4}$$

where the catch advice is increased from the previous catch C_{prev} by a proportion δ of a reference catch level C_{ref} if the indicator I exceeds an upper threshold I_u and decreased vice versa if the indicator falls below a lower threshold I_l. Note that the new catch advice is always based on the previous catch advice. Therefore, in the first year of the implementation, the catch needs to be defined manually, e.g. with Equation (3.1) as described in the constant catch MP above. Geromont and Butterworth (2015a) proposed this constant catch MP with the mean catch length as an indicator. The rule is intended to react only to stronger signals in the indicator (here, the mean catch length, but it could also be applied to an abundance index) and therefore does not react to small changes due to random noise.

3.5.2 Indicator trend

Instead of adjusting the catch advice only in case an indicator exceeds a threshold, the trend of an indicator can be used directly to adjust the catch advice. This MP follows Equation (3.2) where α can be defined as

$$\alpha = 1 + \lambda s \tag{3.5}$$

with the slope s from a linear or log-linear regression of an indicator for several recent years and λ being an additional control parameter for the translation of the magnitude of change in the indicator into the catch advice (Butterworth & Geromont, 2001; Campbell & Dowling, 2005; Geromont & Butterworth, 2015a). The indicator used in the regression is usually an abundance index (Cox & Kronlund, 2008; Doonan et al., 2015; Geromont & Butterworth, 2015a, 2015b; Plagányi et al., 2018; Plagányi et al., 2019). Kurota (2005) and Kurota et al. (2010) describe an MP where this indicator trend regression is used on an abundance index but as part of a more complex MP and Campbell and Dowling (2005) describe another version where it is applied to the effort (number of hooks in a swordfish fishery) instead of catch. Cox and Kronlund (2008) devised an indicator trend rule that includes parameters weighting the influence of the previous catch and the indicator trend.

The element reflecting the indicator trend (α in Equations 3.2 and 3.5) is not restricted to a single index, but can also include several indices (S), each with a specific weighting (w), as in Plagányi et al. (2018):

$$\alpha = \sum_{i \in S} w_i \left(1 + \lambda s_i\right) \tag{3.6}$$

The MP used by the Commission for the Conservation of Southern Bluefin Tuna (Hillary et al., 2016) includes a version of the indicator trend following Equation (3.2) and replacing Equation (3.5) with:

$$\alpha = \begin{cases} 1 - \lambda_1 \; |s|^{\gamma}, & \text{if } s < 0 \\ 1 + \lambda_2 \; s, & \text{if } s \geq 0 \end{cases}, \tag{3.7}$$

where the control parameters λ_1 and λ_2 cause an asymmetric response depending on whether the indicator is increasing or decreasing and γ is an additional asymmetry parameter. The MP of Equation (3.7) is conceptually an empirical MP. However, a simple model is used to combine two independent indices into a single indicator (Hillary et al., 2016).

Alternatively, the trend in the indicator can be derived with a ratio by dividing an average of recent values by the average of previous values. The International Council for the Exploration of the Sea (ICES), for example, has been applying a "2 over 3" rule for ICES category 3 data-limited stocks (stocks for which survey indices provide reliable indications of trends in stock metrics):

$$\alpha = \frac{\sum_{i=y-2}^{y-1} I_i/2}{\sum_{i=y-5}^{y-3} I_i/3}, \tag{3.8}$$

where I is a biomass index and y the assessment year (ICES, 2012b). This rule was later revisited by Jardim et al. (2015).

Instead of averaging index values over several years as in Equation 3.8, Apostolaki and Hillary (2009) suggested using the average of several year-to-year changes:

$$\alpha = \sum_{i=y-N+1}^{y} w_i \left(I_i/I_{i-1}\right), \tag{3.9}$$

where N is the number of years to use and w a weighting factor, e.g. based on index variability.

3.5.3 Indicator target

The values from an indicator can also be used to modify the catch advice in order to move the stock towards a target reference value of the indicator. This can simply be done by defining α from Equation (3.2) as:

$$\alpha = I_{\text{recent}}/I_{\text{target}}, \tag{3.10}$$

where I_{recent} is the recent value of the indicator I and I_{target} a target or reference value. If I_{recent} is above I_{target}, the catch advice is increased and if I_{recent} is below, the catch advice is decreased.

Jardim et al. (2015) used the mean length in the catch as an indicator and defined the reference length based on simple life-history considerations.

Geromont and Butterworth (2015a) suggested a more complex formulation:

$$C_{\text{new}} = \begin{cases} 0.5C_{\text{ref}}\left[1 + \frac{I_{\text{recent}} - I_0}{I_{\text{target}} - I_0}\right], & \text{if } I_{\text{recent}} \geq I_0 \\ 0.5C_{\text{ref}}\left[\frac{I_{\text{recent}}}{I_0}\right]^2, & \text{if } I_{\text{recent}} < I_0 \end{cases}, \tag{3.11}$$

where C_{ref} is a predefined reference catch level and I_0 another tuning parameter. Hoshino et al. (2020) adapted this rule by adding additional parameters and applied it to effort instead of catch. This formulation can be used with either mean catch length or an abundance index as an indicator.

3.5.4 Harvest control rule type

For many data-rich fish stocks, harvest control rules (HCRs) are used for fisheries management and often follow the form shown in Figure 3.1a.

In such HCRs, the fishing mortality (F_{HCR}) is set depending on the size of an indicator, usually spawning stock biomass (SSB). If the indicator is at or below a limit reference point (I_{lim}), F_{HCR} is set to 0 and if the indicator is at or above a trigger reference point (I_{trigger}), F_{HCR} is set to F_{target}, which could be F_{MSY}. Between I_{lim} and I_{trigger}, the fishing mortality is linearly interpolated.

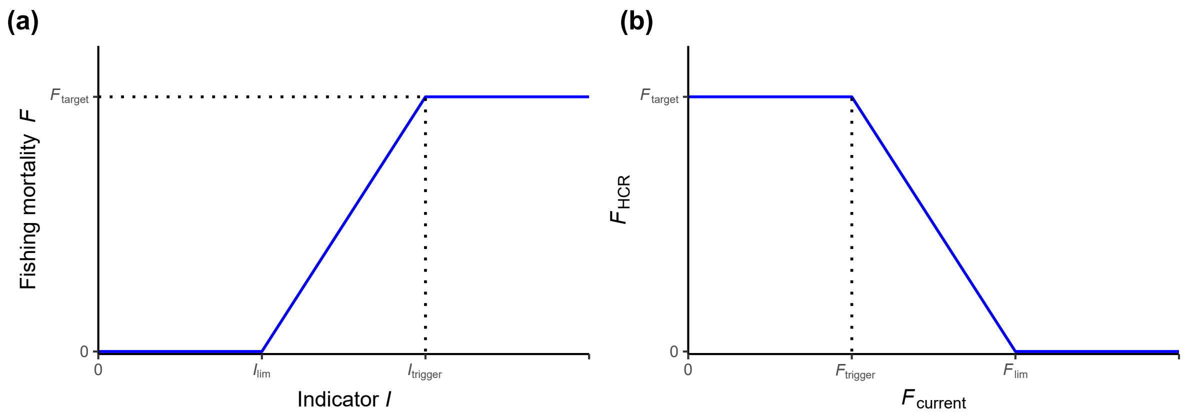

Figure 3.1: Conceptual harvest control rule (a), and application of this principle in Klaer et al. (2012) in (b).

Management procedures in data-limited cases can follow a similar principle. Figure 3.1b illustrates the HCR of Klaer et al. (2012). The fishing mortality used in the HCR (F_{HCR}) is derived from a perception of the current fishing mortality (F_{current}):

$$F_{\text{HCR}} = \begin{cases} F_{\text{target}}, & \text{if } F_{\text{current}} \leq F_{\text{trigger}} \\ F_{\text{target}} \frac{F_{\text{current}} - F_{\text{lim}}}{I_{\text{trigger}} - F_{\text{lim}}}, & \text{if } F_{\text{trigger}} < F_{\text{current}} < F_{\text{lim}} \\ 0, & \text{if } F_{\text{current}} \geq F_{\text{lim}} \end{cases} \tag{3.12}$$

The actual fishing mortality is unknown; however, the mean catch length acts as a proxy for it. A yield-per-recruit analysis is used to create a table that links mean catch length to fishing mortality. The x-axis of Figure 3.1b is inverted compared to Figure 3.1a because a higher fishing pressure correlates to a smaller mean catch length. Klaer et al. (2012) defined the reference points based on assumed fishing mortalities that reduce the stock size to a proportion of unfished biomass (20% for F_{lim}, 40% for F_{trigger}, and 48% for F_{target}). The new catch advice is then set following the logic of Equation (3.1), where C_{ref} is calculated as the moving average of the catch over several years and the multiplier α defined as:

$$\alpha = \frac{1 - e^{-F_{\text{HCR}}}}{1 - e^{-F_{\text{current}}}}. \tag{3.13}$$

3.6 Other empirical management procedures

Apart from the generic MPs mentioned so far, there are other MPs using empirical indicators. Most of them are, however, increasingly designed for specific fisheries and situations. Examples are the decision rules for rock lobster that set catch limits based on recent CPUE, either with discrete values from a lookup table or interpolations between specified values. Such rules are, for example, used for rock lobster in South Australia (Punt et al., 2012) and New Zealand (Breen et al., 2009).

3.7 Additional MP elements

The previously mentioned MPs set the catch advice based on information from indicators. Additional elements to stabilise the change in catch advice or for further precaution can be implemented. Catch constraints limit the variability of the catch advice and usually define that the change in the new catch advice cannot exceed a certain percentage, such as 20%, compared to the previous value (e.g. Geromont & Butterworth, 2015b).

The precaution of empirical MPs can be increased by including a multiplier < 1, which reduces the catch advice. Within ICES, the current framework for providing catch advice for data-limited stocks includes a precautionary buffer that reduces the catch advice by 20% (i.e. a multiplier of 0.8) if the stock status is estimated to be poor based on MSY proxy methods, or if there is no knowledge about the stock status (ICES, 2019a). Once this buffer has been applied, it can only be considered again after three years. The Australian tier system includes considerations of precautionary multipliers to reduce catch advice, and the reductions should be larger the more data-limited the stocks are (Department of Agriculture and Water Resources, 2018).

3.8 Discussion of empirical management procedures

The various types of empirical MPs have different properties and are designed to react to specific changes in a fish stock in order to provide management advice. The usual approach to evaluating MPs is to conduct an MSE and compare the performance of the MPs by means of performance metrics over a projected period, such as stock status in relation to reference points, risk of the stock falling below limit reference values, catch and catch variability (Carruthers et al., 2016). A direct comparison of MPs is usually only possible when they are compared within the same study because studies differ in their set-up of operating models (stocks and their parameterisations, fishing histories, adoption of process and observation noise), implementation details (projection periods, the frequency of setting management measures) and how the performance of MPs is measured. Therefore, the discussion of empirical MPs here mainly compares their performance within simulation studies; however, general conclusions are indicated as well. The discussion focuses on scientific studies on MPs and a comparison of different approaches. These studies are often generic and not always for direct application in specific regions. The process of MSE development and interactions with stakeholders is not part of this discussion.

The use of the terms management procedure and control rule is sometimes stretched beyond their original definition in the literature. An example is Sun et al. (2018) who evaluated "harvest control rules" that purely limit the minimum or maximum length of individuals caught in the fishery. While it is perfectly valid and sensible to use such technical measures, they might rather be considered conservation measures because they do not provide management advice considering recent stock developments. The other extreme are highly complex MPs, such as the one described by Licandeo et al. (2020). Their MP uses an indicator trend control principle, but combines several of them, uses various data sources, and includes several additional components such as a penalty, cap, split into different species, and a small fish protocol. This led to such a complex formulation (which required case-specific tuning for its parameters) that even for an expert audience, comprehension might be impaired. Furthermore, the usual benefit that empirical MPs can be communicated easily to various stakeholders might be lost.

3.8.1 Constant catch

The simplest data-limited MP is to set a constant catch and possibly review the catch level periodically. One unique advantage of constant catch MPs is that the inter-annual catch variability is zero and this MP, therefore, provides stability for fishers. However, this can easily change when a stock is declining, effort limitations reduce the catch that can be taken due to fisheries regulations, or because effort increases are not cost-effective.

Occasionally, constant catch MPs have been included in simulations comparing different data-limited MPs (Carruthers et al., 2014; Geromont & Butterworth, 2015a). The general verdict of these simulations is that constant catch MPs deliver only poor performance and are outperformed by MPs that dynamically adjust catch to account for changes in the stock. Nevertheless, specific parameterisations of constant catch MPs can perform surprisingly well if the stocks are in a good condition prior to the implementation of the MP and the catch level is appropriate. In a simulation, different constant catch values can be tested, and an appropriate catch level (e.g. MSY) can be determined. For depleted stocks, it might be possible to identify a constant catch that allows the stock to recover; however, such a catch is likely to be low.

Consequently, the constant catch MP approach is impractical for application to real fish stocks because the condition of data-limited stocks and appropriate catch levels are unknown.

Despite their limitations, versions of the constant catch MP (third highest or median of landings in the past ten years) have been applied in the US (SAFMC, 2011; Carruthers et al., 2014).

3.8.2 Indicator adjusted catch

Geromont and Butterworth (2015a) tested a range of empirical MPs, comprising constant catch, indicator trend, and indicator target adjusted rules, using length and CPUE indices. In their simulations, MPs that dynamically adjusted the catch performed better with higher yield and lower risk of stock depletion than a constant catch MP. This outcome is not unexpected because a constant catch MP has no mechanism to adapt to changes in the population. It might work reasonably well if the stock is in a good state prior to the first implementation of the MP and the catch level is appropriate. Constant catch MPs have the lowest possible catch variability (i.e. 0), but other performance metrics depend on the stock status and exploitation and reducing catch variability is seldom the only priority in fisheries management. Regarding the rules that adjust the catch based on indicators, Geromont and Butterworth (2015a) found that MPs that include only catch data (inclusive of mean catch length) are outperformed by less data-limited MPs that can make use of an abundance index.

In general, Geromont and Butterworth (2015a) stated that even their more data-limited MPs performed surprisingly well. However, this conclusion comes with several caveats due to the specification of the simulations. For example, the operating models for this simulation were not necessarily realistic and did not represent specific stocks or species. Instead, each operating model represented a range of life histories, depletion states and productivity levels. Additionally, the parameterisations of the MPs are almost impossible to implement in reality. The MPs were tuned to achieve specific targets, which were defined as reaching $1.2B_{\mathrm{MSY}}$ after a projection period of 10 years and maximising yield while considering a risk trade-off. The tuning was mainly done by selecting a reference catch level in the first year of the implementation of the MP. This reference level is dependent on the previous stock status and exploitation and can, therefore, easily be derived in a simulation. However, in reality, the condition of data-limited stocks is unknown and, consequently, the reference catch cannot be set in the same way as for a simulation. Additionally, Geromont and Butterworth (2015a) focused on meeting performance criteria after 10 years and such a short projection cannot necessarily guarantee long-term sustainable management.

Geromont and Butterworth (2015b) revisited some of their MPs (MPs with an abundance index as an indicator) and tested them with a hindcast for several real stocks, based on the results of analytical stock assessments, and found them to perform comparably to data-rich MPs.

Cox and Kronlund (2008) found that their indicator trend adjusted MP performed reasonably well and close to model-based MPs for sablefish, but only if the parameters of the rule were set appropriately. Furthermore, they note the danger of hyperstability in fishery-dependent indices.

Jardim et al. (2015) compared the performance of three empirical indicator MPs; (1) an indicator trend MP based on a biomass index, (2) a stepwise adjustment MP based on the confidence intervals of a biomass index, and (3) an indicator target MP using the mean catch length and a length-based proxy for F_{MSY}. These MPs were tested in an MSE for 50 generic fish stocks and two fishing histories (developing fishery and overexploited). Jardim et al. (2015) found that the indicator trend rule could not recover depleted stocks, kept them around their original depletion level and caused high biological risks. The other two MPs showed better performance, with the length-based indicator target MP recovering many stocks (although some collapsed) and the stepwise adjustment MP successfully recovering all stocks.

The general conclusion of Jardim et al. (2015) would be to assume that the stepwise adjustment MP outperformed the other two. However, for the stepwise adjustment MP to be able to recover stocks, it had to be modified so that it included asymmetric confidence intervals and asymmetric gain/loss terms (i.e. the catch was reduced more when the MP indicated a decline in the stock compared to an increase of the same magnitude). The specific reference values for the confidence intervals and the gain/loss terms were a result of tuning the MP and are specific to the simulated conditions, including the set-up of the operating models, depletion and fishing history, levels of process and observations noise, etc. Therefore, it would be premature to put the stepwise adjustment MP forward and neglect the other two MPs without further investigation. The indicator trend and target rules might not have performed equally well in this specific simulation; however, they are much more generic and simpler to apply without the requirement of case-specific tuning exercises.

Carruthers et al. (2016) carried out an extensive MSE evaluation of data-limited MPs, including many of the empirical indicator MPs previously tested in Geromont and Butterworth (2015a, constant catch, stepwise adjustment, indicator trend and target MPs) and compared their performance with less data-limited MPs using derivatives of surplus production or analytical stock assessments. As previously noted (Geromont & Butterworth, 2015a), the performance of empirical indicator MPs depends on their specific parameterisation, and MPs that dynamically adjust catch perform better than those that do not. However, many of the indicator trend and target MPs were able to recover initially depleted stocks (SSB $< B_{\mathrm{MSY}}/2$) and produced results similar to more complex model-based MPs, but were often conservative and delivered a low yield.

Another finding of Carruthers et al. (2016) was that the empirical indicator MPs often outperform simple model-based approaches such as DCAC (Depletion Corrected Average Catch; MacCall, 2009), particularly at low stock sizes, and are less susceptible to observation bias. Although comprehensive, the simulation exercise of Carruthers et al. (2016) offers limited guidance for the application of data-limited empirical indicator based MPs because the results, as shown previously and discussed above, do not favour specific MPs. It is pointed out again that the suitability of an MP is dependent on the life history and condition of a stock, and, importantly, on the specific parameterisation of the MP, which is difficult to obtain in data-limited situations.

Much of the analysis of Carruthers et al. (2016) was repeated for Caribbean stocks (Sagarese et al., 2018) and stocks in the Gulf of Mexico (Sagarese et al., 2019), by testing the same empirical MPs with the same simulation framework. Outcomes were similar and indicated that adaptive MPs outperform constant catch scenarios, and could be considered for application.

A direct comparison of indicator trend and target rules is challenging because outcomes depend on simulation conditions and performance metrics. Hoshino et al. (2020) compared trend and target type rules for tropical tunas (skipjack and yellowfin tuna) and expressed a slight preference for target-based rules when considering biomass related objectives, but noted that the difficulty of setting target reference values in data-limited situations reduced their applicability.

Prince et al. (2011) developed a full framework as a decision tree around an indicator (CPUE) adjusted catch for the Australian longline fishery. The initial catch advice is set by adapting the previous catch advice and moving the current CPUE towards a target CPUE. Additional steps in the decision tree consider specific components of the monitored stocks (recruits, prime, old) and can modify the initial catch advice. Although the application of the framework relies only on simple empirical data, it does not entirely follow the empirical MP principles because reference levels and qualitative stock evaluations make use of the spawning potential ratio, which essentially requires a simple stock assessment model. Nevertheless, simulating testing of this framework showed that it led to precautionary management, and was subsequently implemented for the Australian eastern tuna and billfish fishery.

The framework of Prince et al. (2011) makes use of possibly divergent trends in different demographic parts of a population by a post hoc modification of an initial catch advice. An alternative is to include different elements directly into a control rule, such as the explicit inclusion of a recruitment index in Plagányi et al. (2018) and Plagányi et al. (2019) to account for recruitment variability.

3.8.3 Harvest control rule type

The definition of the HCR type MP of Klaer et al. (2012) is stretching the definition of an empirical MP. Although the application of the MP requires only empirical data (mean catch length), prior to its first implementation, a yield-per-recruit model needs to be run to link mean catch length and fishing mortality. For this model, various life-history parameters, such as von Bertalanffy growth parameters, natural mortality, maximum age, and assumptions about selectivity are necessary, which are more data than usually available for many data-limited stocks. Klaer et al. (2012) tested this MP in an MSE with three data-rich stocks and found that its performance was acceptable, although dependent on the depletion of the stocks prior to the application, and susceptible to misspecifications of model parameters (e.g. natural mortality) and uncertainty. Uncertainty for the catch length was implemented with a low coefficient of variation of around 0.1 and a robustness test (halving and doubling) of the uncertainty led to substantial changes of the MP's performance. Another issue this MP has in common with many other data-limited MPs is that the new catch advice is based on a reference catch. Klaer et al. (2012) calculated this reference catch based on several years depending on the longevity of species (maximum age minus age at 50% selectivity), with more years for longer-lived stocks. For one stock, jackass morwong, an average of more than 20 years is used, which will likely remove any shorter-term trends. Although it might be beneficial to link the reference catch to life-history traits, using averages over too many years could be considered excessive.

The use of limit, trigger, and target reference levels is an advantage; however, their definition as a constant proportion of unfished biomass irrespective of the stock is somewhat arbitrary. Klaer et al. (2012) based the reference levels on the Australian Commonwealth fisheries harvest strategy policy (Department of Agriculture and Water Resources, 2018), which specifies the target stock level as 48% of unfished biomass as a generic proxy for maximum economic yield. Using species-specific reference values, such as MSY, might improve the performance of the framework.

Mean catch length can be used as an indicator for the exploitation of a fish stock; however, its use as the sole indicator is likely not to work in all cases sufficiently. The translation of changes in fishing mortality into mean catch length can have a substantial time lag.

3.8.4 Additional elements

Empirical MPs provide recommendations for setting catch advice based on specific rules and parameterisations, and when unfiltered, this can lead to large fluctuations in catch advice. This is particularly pronounced if the underlying data are noisy or uncertain. Therefore, additional elements to increase stability and precaution can be required.

Catch constraints limit the variability in catch advice and, thereby, avoid large changes. Limiting catch changes can provide stability for the fishing industry and allow forward planning. However, such constraints can also negatively impact fish stocks because steep declines in stock biomass or unnoticed stock collapses are not translated directly into the fishery, possibly deteriorating the stock condition even further. The ICES advice framework does not generally include catch constraints for data-rich stocks (unless they are defined in management plans for specific stocks); however, for data-limited stocks, there is an "uncertainty cap", limiting the change in catch advice to no more than 20% (ICES, 2019a).

To increase the precaution of empirical MPs, multipliers < 1 can be added. The 2012 ICES framework for category 3 data-limited stocks (ICES, 2012b) deploys an indicator trend MP (the "2 over 3" rule in Equation 3.8) with a precautionary buffer defined as a multiplier of $m = 0.8$ (ICES, 2019a). This framework is described in detail in Chapter 4. The continuous application of such a multiplier to an empirical MP can lead to a continuous reduction of catch advice unless the indicator trend indicates an increase in the catch advice of at least $1/0.8 = 1.25$. ICES ameliorates this downward spiral by restricting its use to only once every three years and by making the application conditional on perceived stock status.

The situation is slightly different if the MP includes a target such as the rule defined in Equations (3.2) and (3.10):

$$C_{\text{new}} = C_{\text{prev}} \frac{I_{\text{recent}}}{I_{\text{target}}} m, \tag{3.14}$$

where conceptually the multiplier can be included in the target value as

$$I'_{\text{target}} = \frac{I_{\text{target}}}{m}, \tag{3.15}$$

which then leads to

$$C_{\text{new}} = C_{\text{prev}} \, \frac{I_{\text{recent}}}{I'_{\text{target}}}. \tag{3.16}$$

From this formulation, it is clear that the multiplier simply increases the target value, i.e. makes it more precautionary, and avoids the perception of a downward spiral of catch reductions.

3.8.5 Other empirical management procedures

The study of Pomarede et al. (2010) includes an empirical MP based on a fisheries-independent biomass index. However, this MP is rather suitable for data-rich situations because it was designed to be used on absolute biomass estimates (from an acoustic survey or a population model) and was therefore not directly relevant for the review of data-limited empirical MPs in this chapter. Nevertheless, the MP is potentially interesting because the design differs substantially from the other empirical MPs mentioned so far. Pomarede et al. (2010) used the signal from a biomass index but defined a control rule based on the principle of a PID (proportional, integral, derivative) controller, i.e. the catch was adjusted depending on different properties of the index time series. PID controllers are frequently used to control systems in industrial settings. Applying the PID principle to fisheries management required case-specific optimisation and did not lead to generic control rule configurations. Although Pomarede et al. (2010) managed to increase the catch compared to alternative management approaches, this came at the cost of increasing the risk of stock collapses.

3.8.6 Application of empirical management procedures

So far, most of the discussion dealt with the concept of empirical MPs and their performance in simulation testing via MSE. Nonetheless, empirical MPs have been and are still being deployed in various fisheries around the world, and a few notable examples are mentioned here.

An indicator trend MP based on a CPUE index following Equations (3.2) and (3.5) has been applied to Namibian hake (Butterworth & Geromont, 2001). As described above and detailed in Chapter 4, ICES applies an indicator trend MP based on a biomass index to category 3 data-limited stocks (ICES, 2019a).

In Australia, a four-tier system has been implemented since 2005 (Smith et al., 2008), where tier 4 applies to data-limited stocks for which usually only fishery dependent data exist. The tier 4 harvest control rule was originally an indicator trend rule (following Equations 3.2 and

3.5) using fishery dependent CPUE as the index. This rule was later changed to an indicator target rule, where the implicit target is the maximum economic yield (defined as 48% of unfished biomass, CSIRO, 2009). Because these tier 4 stocks are data-limited and, therefore, current and unfished biomass are unknown, the indicator target is only a simple approximation and does not necessarily reflect maximum economic yield. For additional precaution, a multiplier < 1 is applied to derive a recommended biological catch, where the multiplier is set depending on the data limitations with smaller values for more data-limited tiers. CSIRO (2009) recommended a multiplier of 0.75 for tier 4 in the absence of better information. Some deviations to these rules are possible and, for example, O'Neill et al. (2010) proposed a control rule that combines stepwise adjustment and indicator trend principles for Australian spanner crab.

3.9 Conclusion

There is a plethora of possible empirical MPs and parameterisations. Some of them have been extensively tested and compared in simulations. However, the outcomes of simulations and comparisons can largely only be considered within the same study due to specific simulated conditions. So far, no clear winner has emerged, and this is unlikely to happen. In real-life situations, there is often not much choice between alternative MPs due to data limitations.

Indicator target type MPs might be considered as the most desirable solutions to manage fisheries for data-limited stocks. Their applicability and performance are, however, dependent on the existence of an appropriate target metric. For data-limited stocks, the definition of target levels is notoriously difficult, if not impossible, and often only possible by making assumptions and crude approximations. Furthermore, they entail the risk of misspecification of target levels, which can have a severely detrimental impact on the stocks they are meant to sustain. Indicator trend type MPs do not need the definition of a reference target level. Nonetheless, their application is not always straightforward, because changes in the indicator do not necessarily warrant a direct translation into catch advice, e.g. because of the life history of the stock or because the indicator trend could be driven by noise rather than a signal from stock dynamics. The definition of empirical MPs, as described so far, usually comprises one major component, which is responsible for the setting or changing of the catch advice. This component is sometimes complemented with additional elements for extra stability or precaution.

The first empirical MP explored in this thesis is the “rfb rule”, which includes both a trend (from a biomass index) and a target (for mean catch length) element (Chapters 6, 7, and 8). The rfb rule was chosen because it takes the current ICES approach for category 3 stocks and improves on it by considering additional elements. The second empirical MP uses a target, but is based on the principle of a harvest rate (Chapter 9). The harvest rate rule was chosen as an alternative approach to the rfb rule because it does not rely on adjusting the previous advice value but instead sets catch independently based on a target harvest rate. These two empirical MPs were first developed with generic operating models, and then the generic MPs were also evaluated with case-specific simulations for three case study stocks (Chapter 11).

Chapter 4

Data-limited fisheries management and the International Council for the Exploration of the Sea

4.1 Abstract

The International Council for the Exploration of the Sea (ICES) provides scientific advice on fishing opportunities for many fish stocks in the Northeast Atlantic. ICES classifies fish stocks into six categories depending on data availability. Category 1 is the most data-rich and allows the application of potentially complex stock assessments, and short-term forecasts can be used to provide catch advice following maximum sustainable yield principles. The subsequent categories encompass increasingly data-limited fish stocks, and alternative methods are used to provide catch advice. Category 3 data-limited stocks are stocks for which an indicator of stock size exists and are the main focus of this PhD project. This category was chosen because it includes the majority of ICES data-limited stocks. ICES has used a data-limited advice framework since 2012, and for most category 3 stocks, catch advice is based on a simple status quo catch rule following the perceived stock trend, the "2 over 3" rule. Additional elements are meant to reduce the catch advice when the stock is considered to be in an unfavourable condition (the precautionary buffer) and limit changes in the catch advice (the uncertainty cap). However, this rule does not include any target and can, at best, aim to keep a stock at its status quo. Consequently, precautionary exploitation is not guaranteed.

4.2 Introduction

In European waters, the management of fishing resources is mainly governed by the Common Fisheries Policy of the European Union (EU; EU, 2013) and other national legislation for non-EU countries. The International Council for the Exploration of the Sea (ICES) provides the scientific basis for the advice on fishing opportunities (ICES, 2019a) for many fish stocks in the Northeast Atlantic. The process within ICES involves expert groups for drafting the advice, which is then passed on to an advice drafting group and finalised by the ICES Advisory Committee. The result of this process is a series of advice sheets for specific stocks which give one or more catch options, and which are then used, for example, by the European Union's Agriculture and Fisheries Council to set binding catch limits, expressed as Total Allowable Catches (TACs), the primary means of fisheries management in the EU. For some stocks that extend into non-EU member states' territorial waters, such as Norway, Iceland, or the United Kingdom, bilateral or multilateral consultations and agreements are in place. Importantly, ICES scientific recommendations are decoupled from international borders and advice on fishing opportunities is based on biological fish stock units.

4.3 The historical approach for data-limited fish stocks in ICES

The following sections give a short overview of how data-limited fish stocks were treated within ICES for advice purposes. Here, only the period after around 2000 is considered because going further back in time makes the differentiation between data-limited and non-data-limited stocks increasingly difficult. Methods deployed decades ago, might at that time have been considered as state-of-the-art quantitative models but could nowadays instead qualify as data-limited approaches.

Historically, there was no specific definition of what comprised data-limited stocks within ICES, and ICES mainly provided advice for fish stocks for which a quantitative assessment was available, i.e. for data-rich stocks. However, there were a few stocks without quantitative assessments, but for which ICES was nevertheless asked to provide advice, and these would later be considered data-limited. Back then, the ICES advice for these stocks was mainly based on precautionary principles with limit and threshold reference points, when these were available (ICES, 2009).

In the years 2010-2012, prior to the implementation of the data-limited framework, ICES advice for stocks without analytical assessment was based on the following simple table (ICES, 2010, p. 8):

	No Overfishing	Overfishing or Unknown Exploitation Status
Decreasing stock trend	Reduce catch from recent level at rate of stock decrease	Reduce catch from recent level at rate greater than the rate of stock decrease
Stable stock trend	Maintain catch at recent level	Reduce catch from recent level
Increasing stock trend	Increase catch from recent level at rate of stock increase	Maintain catch at recent level

This table provided only incomplete guidance depending on a stock trend and overfishing status. Subsequently, in 2011, the table was appended, and the recommendation for stocks for which no stock trend was available and exploitation status was unknown was to maintain status quo, which meant that catches should not be allowed to increase (ICES, 2011a). Again, the table provided only vague guidance about how to give catch advice based on the stock trend and overfishing status without defining exactly how to determine these stock characteristics. Because the options in this table take only discrete representations of the stock characteristics, they are discontinuous, and the outcome of applying this table is potentially subjective.

4.4 The current data-limited approach in ICES

Since 2012, ICES fish stocks have been classified into six categories depending on data availability and assessment methodology (ICES, 2012b, pp. 4-5):

> **Category 1; data-rich stocks (quantitative assessments)**
>
> These are the stocks that are not considered data-limited and this category includes stocks with full analytical assessments and forecasts as well as stocks with quantitative assessments based on production models.
>
> **Category 2; stocks with analytical assessments and forecasts that are only treated qualitatively**
>
> This category includes stocks with quantitative assessments and forecasts which for a variety of reasons are merely indicative of trends in fishing mortality, recruitment, and biomass.
>
> **Category 3; stocks for which survey-based assessments indicate trends**
>
> This category includes stocks for which survey indices (or other indicators of stock size such as reliable fishery-dependent indices; e.g. lpue, cpue, and mean length in the catch) are available that provide reliable indications of trends in stock metrics such as mortality, recruitment, and biomass.
>
> **Category 4; stocks for which reliable catch data are available**
>
> This category includes stocks for which a time-series of catch can be used to approximate MSY.
>
> **Category 5; data-poor stocks**
>
> This category includes stocks for which only landings data are available.
>
> **Category 6; negligible landings stocks and stocks caught in minor amounts as bycatch**

> This category includes stocks where landings are negligible compared with discards. It also includes stocks that are part of stock complexes and are primarily caught as bycatch species in other targeted fisheries. The development of indicators may be most appropriate to such stocks.

The larger the number of the category, the more data-limited the stocks are, ranging from data-rich, i.e. not data-limited, for stocks in category 1 to data-poor stocks in category 6. In general, the stocks in categories 3-6 can be described as data-limited, although there are cases where category 1 stocks have been temporarily downgraded to category 3 while assessment or data problems are resolved. Depending on the stock category, ICES applies different methodologies to provide advice on fishing opportunities. This categorisation was initially developed in 2012 at the first Workshop on the Development of Assessments based on LIFE history traits and Exploitation Characteristics (WKLIFE) with a total of seven categories, but subsequently, after review, narrowed down to the six categories presented above (ICES, 2012d). Previously, there was no specific categorisation and most stocks for which ICES provided advice were data-rich stocks with analytical assessments and forecast, with all other stocks considered data-poor. However, for some of these "data-poor" stocks, there were more data available than for others, and the idea behind the new categorisation was that it allowed the development and application of methods for data-limited stocks to provide sound scientific advice.

According to WKLIFE (ICES, 2012d), of more than 160 stocks for which ICES provided advice in 2012, 122 were data-limited, i.e. category 3-6.

If there are sufficient data and knowledge available (i.e. for stocks in categories 1 and 2), ICES gives advice based on the Maximum Sustainable Yield (MSY) approach, including precautionary considerations, or alternatively, if a management plan exists, has been agreed on and evaluated, the advice is based on such a plan (ICES, 2019a). For stocks in categories 3-6, data availability is generally too scarce for fully analytical assessment, and the ICES advice is based on a precautionary approach (ICES, 2019a).

In 2012, after developing the stock categorisation, ICES published a guidelines document which set out the methods to be applied depending on the stock categories (ICES, 2012b). These guidelines have been used since then, but several additions and clarifications have been added over the years. The following section provides a short overview of the available methodologies.

For stocks in **category 1**, the MSY approach is applied. This is achieved by targeting a fishing mortality (F), which gives the maximised long-term sustainable yield. For these stocks, fully analytical assessments are conducted which estimate F and spawning stock biomass (SSB) and, subsequently, a short-term forecast is performed to convert the target F into a catch value. The models applied are usually age-structured stock assessment models or age-aggregated surplus production models, making use of fishery-dependent (e.g. catch) and independent (survey indices) data. The MSY approach requires the definition of reference points. The target fishing mortality is F_{MSY}, if the stock size is at or above the biomass reference point MSYB_{trigger}. If the stock is estimated to be below this point, the target fishing mortality is reduced by SSB/MSYB_{trigger}, i.e. by multiplying F_{MSY} with the current stock size divided by MSYB_{trigger}. Should the stock not be able to recover above a biomass limit reference point below which there is a high risk of recruitment impairment, B_{lim}, in the short-term forecast, further reductions or even zero catch can be advised.

Category 2 is intended for stocks that have quantitative assessments but essentially due to model or data issues, the assessment results are only trusted in terms of relative values. For these stocks, the same methods as in category 1 are deployed, and the MSY approach is followed; however, more conservative reference points such as $F_{0.1}$ instead of F_{MSY} can be used. This category has hardly been used. In 2012, 5 out of 248 stocks for which ICES provided advice were in this category (ICES, 2013c) and in more recent years, the number has even decreased further. In the years 2017-2019, out of the released advice for stocks, only one stock was in category 2 respectively, sardine in the Bay of Biscay in 2017 and 2018, and the beaked redfish stock in Iceland and Faroe grounds, North of Azores, and East of Greenland in 2019 (ICES, 2019b).

Category 3 might be considered the most important category of the data-limited framework in terms of the number of stocks allocated. According to the ICES stock assessment database (ICES, 2022a), ICES provided advice for 179 stocks in 2021, of which 80 were considered data-limited, and the majority of these (55) were in category 3. The total number of ICES category 3 stocks is likely higher because, for some of these stocks, advice is provided for more than one year (usually two years) until new advice is released. For this category, an age-aggregated abundance index time series, preferably a biomass index, and the previous catch or advice values are required. Several methods are available for this category. The most common is the survey-adjusted status quo catch rule which has the form:

$$A_{y+1} = A_{\text{current}}\ \alpha, \tag{4.1}$$

where the new catch advice A_{y+1} is calculated based on the recent advice value (or catch) A_{current} and the multiplier:

$$\alpha = \frac{\sum_{i=y-x}^{y-1} I_i/x}{\sum_{i=y-z}^{y-x-1} I_i/(z-x)}. \tag{4.2}$$

Here, I is the survey index and y the year. The parameters x and z define the years used to compute averages of the survey index. The default values are $x = 2$, and $z = 5$, i.e. α is calculated from the survey index as the average of the last two years, divided by the average of the preceding three years. Within ICES, this rule is commonly called the "2 over 3" rule, referring to the number of years used in the numerator and denominator.

The "2 over 3 rule" is the commonly used method for category 3 stocks. There are extensions and alternative methods, which rely on additional information. These methods have been defined in the original guidelines (ICES, 2012b) but have been rarely or never implemented. If more information is available, such as estimates or proxies of SSB and F and the reference points MSYB_{trigger} and F_{MSY}, the rule can be extended to:

$$A_{y+1} = A_{\text{current}}\ \alpha\ \beta, \tag{4.3}$$

with α from Equation (4.2) and

$$\beta = \left(\frac{F_{\text{target}}}{F_{\text{SQ}}}\right), \tag{4.4}$$

where F_{target} is the target fishing mortality, usually a proxy for F_{MSY} (e.g. $F_{0.1}$) or a transition towards it, and F_{SQ} the current estimate of fishing mortality. If SSB and F are estimated to be above reference points, α is set to 1, if SSB is above but F at or below reference points, β is set to 1, and lastly, if SSB is below the reference point, the target fishing mortality (F_{y+1}) is reduced in the same way as for category 1 stocks (with appropriate proxies for SSB and MSY B_{trigger}, based on the index used; see above).

A third alternative for category 3 stocks sets a reference catch rate from a historical reference period (one during which the survey index has been generally stable or increasing) as the catch C divided by the survey index I from this period:

$$F_{\text{proxy}} = \frac{C_{\text{ref}}}{I_{\text{ref}}}. \tag{4.5}$$

The catch advice is then based on this catch rate by using the recent survey index value:

$$A_{y+1} = I_{\text{recent}} F_{\text{proxy}}. \tag{4.6}$$

This method has hardly been used and in 2019 was only applied to two stocks; blue ling and greater silver smelt in East Greenland and Icelandic grounds (ICES, 2019b).

For stocks in **category 4**, the primary method used is the Depletion Corrected Average Catch (DCAC, MacCall, 2009). DCAC is a catch-only method, which returns a catch value as an approximation of MSY yield. The advice for category 4 stocks is this DCAC catch value or a stepwise approach towards it. An alternative is to use a catch curve analysis, if more data are available (e.g. age- or length-disaggregated catch numbers) to estimate current F and a proxy for F_{MSY}. The advice would then be calculated as $A_{y+1} = A_{\text{current}}\beta$, with β as defined in Equation (4.4) for category 3. Under category 4, sedentary species (e.g. Norway lobster) have their own approach where data (e.g. density, mean weights, discard rates) from neighbouring areas can be borrowed.

The remaining two categories, **category 5** and **category 6**, share common methods due to severe data limitations. For these stocks, stock levels, F and reference points are commonly entirely unknown, and the catch advice is simply set to a previous advice value leading to a constant catch advice. Another option is to perform a risk assessment with a productivity and susceptibility analysis (PSA) with the aim of promoting biodiversity, although this approach has never been applied for advice purposes (ICES, 2019b).

There are two additional elements for the methods described above. For stocks in categories 2-6, an uncertainty cap of 20% applies. This uncertainty cap is a catch constraint, limiting the interannual change in the advice so that the new advice cannot be more than 20% above or less than 20% below the previous advice. The uncertainty cap is meant to protect against large changes in the advice caused by noise in the data. Furthermore, a precautionary buffer (PA buffer) can be applied, reducing the advice value by 20%, if the stock is estimated or thought to be in an unfavourable state, i.e. low biomass or high fishing mortality. However, there were originally no concrete specifications on how to assess stocks status, exemption criteria, or how frequently and long the buffer should be applied. Later simulation work at the ICES WKLIFE workshops led to refinements of the application of the PA buffer (ICES, 2017d). If the stocks are thought to be very low, recovery plans or zero catch advice can be issued (ICES, 2012b).

The original idea behind this framework (ICES, 2012b) with different methods is that it should define a precautionary approach and that for more data-limited stocks, more conservative reference points in combination with a further margin of precaution are used. However, in reality, ICES (2012b) is more a method catalogue which does not ensure more precaution in case of more data limitations.

The ICES data-limited framework suggests assessment methods and how to derive catch advice. However, some flexibility is allowed, and other methods can be used if considered appropriate by experts in ICES working groups.

The framework is not entirely static, and stocks can move between categories, e.g. if more data become available, or if more existing data are used, a stock can move to a higher (less data-limited) category. Conversely, stocks can move to a lower (more data-limited) category due to arising data or assessment issues.

The framework also has some unusual applications, illustrated here for the plaice stock in the Western English Channel (ICES, 2019f, 2019d). This stock was assessed as category 1 data-rich stock with a fully analytical age-structured stock assessment and the MSY framework was used to derive catch advice until 2015. Then, after a benchmark workshop, the stock was downgraded to category 3 due to issues with the assessment model fit and underlying data. Since then, the advice has been based on the "2 over 3" rule. However, this rule is not applied to a biomass index, but instead, the full analytical assessment is still performed, and the assessment results are used as input for the data-limited method. Essentially, this means that the empirical 2 over 3 rule is applied to modelled population estimates.

The ICES advice for stocks contains an evaluation of the current stock status relative to reference points, and, if available, reference points according to the ICES MSY approach (F_{MSY} and MSYB_{trigger}) are used (ICES, 2019a). Since the categorisation of stocks into categories in 2012 for advice purposes (ICES, 2012a), the stock status evaluation relative to the MSY approach reference points is possible due to the availability of quantitative assessments and reference points. For stocks in categories 3 and 4, however, such an evaluation has not always been possible because of missing MSY evaluations or quantitative assessments in general, and had to fall back to precautionary or qualitative evaluations (such as increasing or decreasing stock trend). In recent years, efforts have been made within ICES workshops (ICES, 2015a, 2016) to develop and apply methods that can be used to determine stock status relative to MSY reference points for data-limited stocks.

There is an accepted set of methods available in ICES guidelines which can be used for determining stock status (ICES, 2018b). These include a state-space biomass-dynamic model, the Surplus Production in Continuous Time (SPiCT, Pedersen & Berg, 2017) model and three methods that use catch length frequencies to inform on stocks status or exploitation: the length-based spawner per recruit model (LB-SPR, Hordyk et al., 2015), mean length Z (MLZ, Gedamke & Hoenig, 2006) and length-based indicators (ICES, 2014, 2015a, 2018b). The results from these methods are generally treated as proxies for MSY reference points and the biomass reference point MSYB_{trigger} defined as $1/2B_{\mathrm{MSY}}$ (ICES, 2018b). Additionally, the stock status evaluation is also used to decide on the application of the precautionary buffer to the catch advice, if either fishing mortality is above or SSB below the proxy reference point, or both, then the catch advice should be reduced once in accordance with the precautionary buffer, i.e. reduced by 20%, and the application reconsidered after three years (ICES, 2019a). For stocks in categories 5 and 6, evaluation of stock status is generally not possible due to data limitations and only qualitative evaluations (e.g. increasing or decreasing trend), if at all, are possible.

4.5 The history of the "2 over 3" catch rule

The history of the "2 over 3" rule (see Equations 4.1 and 4.2 above) within ICES is somewhat opaque. The following section is aimed at shedding some light into how this rule emerged and why it was chosen.

The 2009 communication from the European Commission on consultations on fishing opportunities for 2010 (European Commission, 2009) states the intention of the European Commission to develop a management strategy for fish stocks for which ICES has not been able to provide catch advice based on a quantitative assessment and forecast. Therefore, a request from the European Commission to ICES was formulated with a simple rule, and ICES was asked to evaluate and, if necessary, modify this rule (European Commission, 2009). This request was renewed in 2010 (Annex IV of European Commission, 2010) because ICES did not return a full response in 2009. The request asked for the new rule to be evaluated with respect to the precautionary and MSY approach.

The request specified a rule for data-limited stocks, excluding short-lived stocks, which comprised several elements. The main component of this rule was the aim to reach F_{MSY}, by increasing or decreasing TACs (European Commission, 2010, Annex IV, components 1 and 2) and this aim was overriding subsequent components. However, there were no specifications on how to evaluate or achieve this, and for most data-limited stocks, there were no estimates or proxies available for fishing mortality. Subsequent components of this new rule were dealing with considerations about stock abundance information; the first being that the TAC should be kept constant in the absence of reliable abundance information or no trend therein (component 4). The last element of the new rule (component 5) might well be considered as the first mentioning of a catch rule that would eventually lead to the formulation of the "2 over 3" rule (European Commission, 2010, Annex IV, Rule 5, p. 19):

> 5. Where ICES considers that representative stock abundance information exists, the following rule applies:
>
> a. If the average estimated abundance in the last two years exceeds the average estimated abundance in the three preceding years by 20% or more, a 15% increase in TAC applies.
>
> b. If the average estimated abundance in the last two years is 20% or more lower than the average estimated abundance in the three preceding years, a 15% decrease in TAC applies.

This early definition already used the average of the abundance in the last two years divided by the average in the three preceding years to inform on the stock trend. However, instead of using this ratio directly, it implied a step function to be applied on the newly advised catch with three distinct values; reduce TAC by 15%, increase TAC by 15% or keep the previous TAC, depending on whether the stock trend indicates a decline of 20% or more, an increase of 20% or more, or a change below the 20% thresholds.

Following this request from the European Commission, this rule (European Commission, 2010, Annex IV, components 4 and 5) was evaluated with a management strategy evaluation within the ICES community (De Oliveira et al., 2010) and presented at ICES workshops such as WKFRAME (ICES, 2011b) and WKLIFE (ICES, 2012d). The initial evaluation of the rule only included a limited set of operating models (cod-like and herring-like) and few scenarios. However, the evaluation concluded that the rule performed unsatisfactorily because it was not sufficiently reactive due to the 20% threshold required in the abundance trend for the catch to be changed (De Oliveira et al., 2010). Furthermore, the performance of the rule could be improved by replacing the step function with a linear transition when the abundance trend was below the 20% threshold. This early work already cautioned that the rule is rather designed to keep a stock stable but does not ensure an appropriate stock condition.

During a review of the first WKLIFE workshop in early 2012 (ICES, 2012d), the current formulation of the “2 over 3” rule was mentioned for the first time as a method to derive advice for category 3 data-limited stocks in a framework for data-limited stocks. This framework later evolved into the ICES data-limited stock guidance document (ICES, 2012b) as described above.

The reason for recommending this method was based on the concept of Russell (1931) that if a stock is overfished, the stock size will decrease and to counteract this decline, catches should be reduced (ICES, 2012b). Early simulations showed that the rule could stabilise a stock (ICES, 2012d). Alternatives were proposed but required more data which are commonly not available for category 3 stocks.

The catch rule entails some issues which are evident even without simulations but simply by looking at its formulation. The change in the catch advice is governed by values from an index that might not necessarily be representative for the stock. Furthermore, the rule uses only historical data that are further smoothed by using averages over two or three years. There is always a time lag between the index data and the year for which the advice is given. This smoothing might be a desirable feature if the stock is starting to increase because it will require some time until this change will be reflected in increasing catches. However, if the stock decreases or even collapses, it can take up to several years until the method advises a catch reduction. Additionally, the catch rule does not contain a target and only alters the catch advice depending on the stock trend as perceived from an index, therefore not safeguarding sustainable and precautionary exploitation. If the fishery is the driving component of the exhibited stock dynamics, such a rule can lead to dangerous oscillatory behaviour because the catch advice always follows the stock trend but with a delay.

4.6 History of the length-based rfb rule

During the process of developing the methods in ICES that are currently used for advice purposes, other catch rules were proposed but were not adopted. Here, the history of the length-based catch rule (called the rfb rule in this thesis), which is one of the main topics in this PhD project, is traced back to its origins.

At the beginning of 2012, before the development and adoption of the “2 over 3 rule”, at the third ICES workshop on implementing the F_{MSY} framework (WKFRAME 3, ICES, 2012c), a new empirical catch rule was conceptualised with the intention of being applied to stocks without full analytical assessments and forecasts, i.e. for non-data-rich stocks. The idea of the concept was to assess the pressure and state of the stock relative to proxy reference points, to include a quality of information element and to have a target component in order to move the stock towards a target. The conceptual rule was formulated as:

$$A_{y+1} = A_{\text{current}} \; r \; f \; b, \tag{4.7}$$

where the new catch advice A_{y+1} was calculated from the current catch (or advice value) A_{current} and multiplied by three components, representing the stock response rate (r), a proxy for the ratio of a proxy F_{MSY} divided by the current fishing pressure (f), and a biomass safeguard component (b) as the current stock size divided by the biomass reference value MSYB_{trigger} and used when the stock drops below MSY B_{trigger}.

The initial consideration was that not all three components would be available, and in the light of a precautionary principle, missing components should be replaced by the value 1 (i.e. removed) and an additional penalty factor ($\theta < 1$) added. In case of more than one missing element, the penalty factor should be smaller to ensure greater precaution.

The component r was thought to represent the trend in the stock size and should, therefore, consider the reproductive population, i.e. SSB or a suitable proxy thereof. In order to represent a trend, r would have to be calculated as a ratio of the values of any two years or a ratio of averages over several years, to be selected based on longevity and productivity of the stock. Regarding the number of years to be used, the WKFRAME report states that “as an arbitrary default, we suggest n=5” (ICES, 2012c, p. 15) and the trend could be derived either by the slope of the logarithms or by using the average of the last two years’ values divided by the average of the preceding three years’ values. No suggestions were made about how to calculate component f. Components r and f were initially thought to be used only where they could be quantified and if the signal in the data was different from 1 and beyond a threshold, so that weak signals would not influence the catch rule. The suggestion to use the average over several years was intentional so that stock variability caused by internal factors such as recruitment is not picked up, and only signals caused by exploitation have an impact on the rule. In general, the concept of the rule was to design a rule compliant with the precautionary approach but with integrated MSY objectives.

The early description of this rule can be seen as a concept, because no specific guidance was provided on how to calculate the components or what data to use. This rule was initially not implemented; however, when removing components f and b, the rule becomes the basis of the "2 over 3" rule, which was included as an option for category 3 data-limited stocks, and was applied in 2012 for the first time in the advice given for 2013.

This catch rule concept was neglected after the implementation of the data-limited framework (ICES, 2012b) for several years, but is an integral part of this PhD project and explored in Chapters 6, 7, 8, and 11.

A second empirical management procedure will be explored in later chapters of this thesis. This management procedure is based on the principle of a harvest rate, similar to the rule described in Equation (4.6) above. This empirical harvest rate rule and its history in ICES will be introduced in Chapter 9.

4.7 Conclusion

ICES classifies fish stocks into six categories depending on the availability of data and the applicability of methods. While such as structured approach is desirable to ensure fisheries management advice is appropriate for different stocks, the ICES implementation could be considered insufficient because the methods for data-limited stocks do not ensure compliance with precautionary and sustainability principles. However, this situation offers scope for improvement and this PhD project aims to improve the scientific basis on which ICES advice for category 3 data-limited stocks is based.

Chapter 5

Generating operating models from life-history parameters

5.1 Foreword

This chapter describes the generation of the generic operating models for 29 fish stocks, which were used in subsequent chapters in the context of simulations following the management strategy evaluation approach. A summary of this chapter's operating model description was included in the Supplementary Material of Fischer et al. (2020):

> 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*(5), 1914–1926. https://doi.org/10.1093/icesjms/fsaa054

Additionally, this chapter includes an elasticity analysis of the operating models. A preliminary version of this elasticity analysis was presented at the tenth International Council for the Exploration of the Sea (ICES) Workshop on the Development of Quantitative Assessment Methodologies based on LIFE-history traits, exploitation characteristics, and other relevant parameters for data-limited stocks (WKLIFE X) and was included in the workshop report (section 3.5 of ICES, 2020a):

> ICES. (2020a). Tenth Workshop on the Development of Quantitative Assessment Methodologies based on LIFE-history traits, exploitation characteristics, and other relevant parameters for data-limited stocks (WKLIFE X). *ICES Scientific reports*, *2*(98), 72 pp. https://doi.org/10.17895/ices.pub.5985

The following sections in this chapter are an adaptation of these publications.

5.2 Abstract

The application of the management strategy evaluation approach requires the creation of operating models. However, many fish stocks are data-limited, and there are insufficient data for analytical stocks assessments on which operating models could be based. The alternative is to consider life-history information. A total of 29 data-limited fish stocks were simulated based on a set of available life-history parameters and these stocks covered a wide range of life-history traits, including slow- and fast-growing, short- and long-lived, demersal and pelagic species, round and flatfish, elasmobranchs and shellfish. The primary input parameters comprised von Bertalanffy growth parameters, allometric length-weight conversion factors, and age at 50% maturity. Established functional relationships were deployed to estimate remaining biological parameters,

such as natural mortality, as well as for characterising the fishery. An elasticity analysis was conducted to determine the influence of the primary input parameters on the operating models. The elasticity analysis revealed that the individual von Bertalanffy growth rate k, and to a lesser extent, the recruitment steepness h, were most influential.

5.3 Introduction

The application of the management strategy evaluation (MSE) approach requires the creation of operating models. For data-limited stocks, analytical stock assessments usually do not exist on which operating models could be conditioned. An alternative is to simulate fish stocks considering life-history information.

One of the earliest attempts to create operating models relying on life-history parameters and life-history relationships (Gislason et al., 2008; Gislason et al., 2010) using the Fisheries Library in R (FLR, Kell et al., 2007) was for a project for the Food and Agriculture Organization (FAO; Rosenberg et al., 2014) in which data-poor methods were evaluated. The same procedure was later used for testing a super ensemble of catch-only methods in a control rule (Anderson et al., 2017; Walsh et al., 2018). Jardim et al. (2015) further adapted the approach and tested data-limited empirical management procedures for a wide range of life histories. The procedure to generate operating models based on life-history parameters was recently further developed and formalised into the FLR package FLife (https://github.com/flr/FLife/). FLife allows the generation of complex age-structured operating models and requires only some life-history parameters. The package follows a modular approach and missing parameters can be inferred through established life-history invariants or functional relationships.

The operating models in this chapter were generated based on life-history parameters and making use of FLife. The decision to use this approach was based on the consideration that data-limited stocks mostly lack analytical stock assessments and are often poorly studied. Nevertheless, life-history information is often available. Furthermore, it is possible to quickly simulate many fish stocks without the need to develop resource-intensive stock assessment models. The approach allows to include a wide range of life-history traits, such as slow-growing long-lived species (e.g. elasmobranchs), fast-growing short-lived species (e.g. small pelagics), and demersal round- and flatfish.

Fish species can occur in several areas around the world, some population substructures might exist, and there are different approaches on sampling species and estimating life-history parameters. Therefore, there is a considerable spread for the values of parameters. Jardim et al. (2015) retrieved life-history parameters from Fishbase (www.fishbase.org), an online database of fish species, for their operating models and averaged life-history parameters for 50 species. Consequently, the resulting operating models are rather reflective of species averages instead of considering specific fish stocks. At least some of these operating models might therefore be biologically implausible.

The operating models generated for this PhD project are based on life-history parameters from real fish stock units in the North-East Atlantic (North Sea region, Celtic Sea region, Bay of Biscay, and widely distributed stocks) and are consequently more realistic. The parameters were sourced from peer-reviewed literature, reports of scientific institutes and ICES. The sets of life-history parameters for a specific species are internally consistent and refer to the same fish stock as far as possible. A total of 29 stocks were simulated and covered stocks which were considered data-limited but for which enough information was available to condition operating models. The operating models were based on a few primary input parameters. These life-history parameters are usually available for data-limited stocks and can sufficiently define a fish stock to generate an age-structured operating model, capturing its intrinsic dynamics and behaviour towards extrinsic forces such as fishing. This approach led to operating models that exhibit life-history characteristics of specific species but their stock condition and fishing history do not match actual fish stock units. Therefore, these operating models are referred to as "generic operating models" in this thesis. This approach raises the question of which parameters are most influential and how robust the model is to parameter value changes.

The influence of parameters in a model can be evaluated with an elasticity analysis. In an elasticity analysis, the influence of input parameters of a model is evaluated, e.g. by calculating the first-order derivatives of one or more important model output parameters with respect to model input parameters, which can be represented with a Jacobian matrix.

The generation of operating models is a complex process and requires the inclusion of assumptions, e.g. about life-history invariants (Beverton & Holt, 1959; Beverton, 1992; Prince et al., 2015). Furthermore, this process includes numerical optimisations, e.g. for the calculation of equilibrium dynamics. Therefore, operating model parameters cannot be purely algebraically linked to the primary input parameters. Consequently, the gradients of the elasticity analysis have to be approximated numerically.

5.4 Operating model description

This section describes the generic operating models used for simulation testing of the empirical data-limited management procedures (the rfb rule in Chapters 6, 7, and 8; and the hr rule in Chapter 9). The age-structured operating models for the 29 simulated stocks were created using the Fisheries Library in R (FLR, Kell et al., 2007) package FLife (https://github.com/flr/FLife). If not specified otherwise, the default configurations of FLife version 2.1.1 (https://git.io/JLSYZ) were deployed. The full input parameters and source code for the creation of the operating models is available on GitHub at https://git.io/JIidn.

Input parameters used were the allometric length-weight parameters (a, b), von Bertalanffy growth parameters L_∞, k and t_0, and the length or age at 50% maturity (L_{50}, t_{50}). These input values are given in Table 5.1. Table 5.2 gives further parameters characterising the operating models of the 29 simulated stocks.

5.4.1 Growth

To model individual growth, the von Bertalanffy growth model (von Bertalanffy, 1938) and as reformulated by Beverton (1954) was used:

$$L_t = L_\infty(1 - e^{-k(t-t_0)}) \tag{5.1}$$

where L_t is the individual length at age t, L_∞ the theoretical asymptotic length, k the individual growth rate and t_0 the hypothetical age at which the length of the individual is zero. FLife defines a default $t_0 = -0.1$ years in the absence of empirical data. Ages were modelled from age 1 onward up to a maximum age $t_{\max}$, which was set as a plusgroup. $t_{\max}$ was defined as the age, rounded up, where growth reaches 95% of L_∞. This is calculated by solving the von Bertalanffy equation for t and setting $L = 0.95L_\infty$:

$$t_{\max} = t_0 - \frac{\ln(0.05)}{k}. \tag{5.2}$$

Table 5.1: Life-history parameters of the 29 simulated stocks, including their scientific and common names, ICES ecoregion where the life-history parameters are sourced from, a unique stock ID, sex (male M, female F, combined C) and the life-history parameters used as input for the operating models; von Bertalanffy growth equation parameters (k, L_∞, t_0), length-weight parameters (a, b), and length and age at 50% maturity (L_{50}, t_{50}).

Scientific name	**Common name**	**ICES ecoregion**	**ID**	**sex**	k [year^{-1}]	L_∞ [cm]	t_0 [years]	**a**	**b**	L_{50} [cm]	t_{50} [years]
Lophius budegassa	blackbellied angler	Celtic Sea	ang3	F	0.08	110.1	0.39	0.0259	2.858	54.8	9
Raja clavata	thornback ray	Celtic Sea	rjc2	F	0.09	139.5	-1.84	0.0024	3.2653	71.8	6.13
Sebastes norvegicus	golden redfish	Northern	smn	C	0.11	50.2	0.08	0.0178	2.972	40.3	14.84**
Anarhichas lupus	Atlantic wolffish	North Sea	wlf	F	0.11	115.1	-0.39	0.0046	3.185	21.5	3.8
Lepidorhombus whiffiagonis	megrim	North Sea	meg	C	0.12	54	-0.1*	0.0022	3.3433	23	3
Molva molva	ling	Widely	lin	C	0.14	119	-0.1*	0.0036	3.108	74	7.2
Raja clavata	thornback ray	North Sea	rjc	F	0.14	118	-0.88	0.0045	3.0686	77.1	6.69**
Scyliorhinus canicula	lesser spotted dogfish	Celtic Sea	syc	F	0.15	75.14	-0.96	0.0019	3.1541	57	7.9
Mustelus asterias	starry smooth-hound	Widely	sdv	F	0.15	123.5	-0.1*	0.001	3.27	81.9	7.15**
Lophius piscatorius	angler	Celtic Sea	ang	C	0.18	105.555	-0.38	0.0198	2.895	73	6.16**
Lophius piscatorius	angler	North Sea	ang2	C	0.18	106	-0.1*	0.0297	2.841	61	4.66*
Pollachius pollachius	pollack	North Sea	pol	C	0.19	85.6	-0.1*	0.0076	3.069	47.1	4.11**
Melanogrammus aeglefinus	haddock	Celtic Sea	had	C	0.20	79.9	-0.36	0.0113	2.96		2
Nephrops	Norway lobster	Biscay-Iberia	nep	M	0.20	70	-0.1*	0.00028	3.229	28.4	2.50**
Mullus surmuletus	striped red mullet	Celtic Sea	mut	F	0.21	47.5	-0.1*	0.0057	3.243	16.9	1.99**
Spondyliosoma cantharus	black seabream	Celtic Sea	sbb	F	0.22	41.25	-1.16	0.0148	3.004	22	2.30**
Pleuronectes platessa	European plaice	Celtic Sea	ple	F	0.23	48	-0.1*	0.011	2.958	22.9	2.72**
Scyliorhinus canicula	lesser spotted dogfish	Biscay-Iberia	syc2	F	0.23	66.2	-0.71	0.0022	3.119	59.1	9.00**
Argentina silus	greater argentine	Widely	arg	C	0.23	44	-0.1*	0.005	3.075	38	8.2
Scopthalmus maximus	turbot	North Sea	tur	F	0.32	66.7	0.29	0.0149	3.079	34.2	2.2
Chelidonichtys lucerna	tub gurnard	Celtic Sea	gut	F	0.32	66.8	-0.46	0.0043	3.21	40.1	2.41**
Merlangius merlangus	whiting	Celtic Sea	whg	F	0.38	38	-1.01	0.0103	2.395	28	2.50**
Scophthalmus rhombus	brill	North Sea	bll	F	0.38	58	-0.27	0.014	3.01	31.3	1.6
Microstomus kitt	lemon sole	North Sea	lem	C	0.42	37	-0.1*	0.0123	2.971	27	3.02**
Engraulis encrasicolus	anchovy	Biscay-Iberia	ane	C	0.44	23	-0.1*	0.005	3.107	16.8	2.88**
Zeus faber	John Dory	Celtic Sea	jnd	F	0.47	50.8	-1.47	0.0399	2.754	34.5	0.95**
Sardina pilchardus	European pilchard	Celtic Sea	sar	C	0.60	22	-0.1*	0.0053	3.162	14.3	1.65**
Clupea harengus	herring	Celtic Sea	her	F	0.61	33	-0.1*	0.0048	3.198	23	1.87**
Ammodytes spp.	sandeels	North Sea	san	C	1.00	24	-0.1*	0.0049	2.783	12	0.59**

* Denotes where default values for t_0 have been used.

** These t_{50} values were calculated with the von Bertalanffy growth equation parameters and L_{50}.

Table 5.2: Further operating model values for the 29 simulated stocks. The stock ID corresponds to the ID in Table 5.1. Shown are the maximum age (plus-group $t_{\max}$), age range for mean fishing mortality (minfbar, maxfbar), Beverton-Holt stock-recruitment parameters (α, β), spawners per recruit at $F = 0$ (SPR_0), MSY reference points (F_{MSY}, MSY, B_{MSY}, mean length at MSY: L_{opt}), growth rate (instantaneous growth rate at the limit of zero stock size r, and conditional growth rate at MSY r_c, both derived from a Leslie matrix model), mean natural mortality of the mature proportion of the stock (M), and the ratios M/k (von Bertalanffy k), F_{MSY}/M and $B_{\mathrm{MSY}}/\mathrm{B}_0$ (unfished spawning stock biomass, 1000 for all stocks).

ID	t_{max}	**minfbar**	**maxfbar**	α	β	$\mathbf{SPR_0}$	$F_{\mathbf{MSY}}$	**MSY**	$B_{\mathbf{MSY}}$	$L_{\mathbf{opt}}$	r	r_c	M	M/k	$F_{\mathbf{MSY}}/M$	$B_{\mathbf{MSY}}/\mathbf{B}_0$
ang3	38	4	20	14.22	90.91	76.71	0.06	22.08	275.28	109.00	0.13	0.05	0.09	1.15	0.65	0.28
rjc	32	2	15	0.07	90.91	14697.76	0.06	21.94	287.85	102.81	0.16	0.05	0.10	1.09	0.61	0.29
smn	28	9	23	52.76	90.91	20.68	0.11	51.59	227.85	49.70	0.12	0.06	0.12	1.07	0.91	0.23
wlf	27	1	10	0.44	90.91	2489.95	0.07	27.75	282.61	82.22	0.25	0.09	0.15	1.36	0.49	0.28
meg	25	1	5	17.51	90.91	62.30	0.08	25.43	323.66	35.88	0.25	0.07	0.18	1.54	0.42	0.32
lin	22	2	15	1.03	90.91	1061.06	0.09	40.86	263.18	85.71	0.19	0.08	0.14	1.01	0.67	0.26
rjc	21	2	13	0.31	90.91	3515.48	0.10	45.76	250.00	83.96	0.22	0.09	0.14	1.02	0.70	0.25
syc	20	3	13	2.74	90.91	398.58	0.12	60.23	234.23	52.37	0.22	0.10	0.16	1.04	0.74	0.23
sdv	20	2	11	1.39	90.91	782.43	0.09	42.97	265.69	91.96	0.19	0.08	0.15	0.99	0.59	0.27
ang	17	1	9	0.35	90.91	3084.69	0.10	58.02	251.17	72.08	0.24	0.10	0.18	0.99	0.59	0.25
ang2	17	1	8	0.41	90.91	2677.30	0.12	58.29	249.22	70.65	0.32	0.13	0.20	1.10	0.61	0.25
pol	16	1	6	1.18	90.91	927.67	0.12	48.29	284.13	58.74	0.30	0.11	0.21	1.12	0.54	0.28
had	15	1	5	0.83	90.91	1312.47	0.15	43.96	310.45	52.55	0.42	0.13	0.26	1.30	0.58	0.31
nep	15	1	4	29.81	90.91	36.60	0.15	53.51	278.87	49.33	0.47	0.17	0.28	1.38	0.54	0.28
mut	15	1	5	5.78	90.91	188.70	0.20	83.72	231.43	31.22	1.04	0.40	0.35	1.66	0.59	0.23
sbb	13	1	5	2.14	90.91	509.71	0.22	74.92	256.33	24.73	0.55	0.21	0.28	1.29	0.77	0.26
ple	13	1	5	7.57	90.91	144.02	0.21	90.74	234.03	29.31	0.64	0.27	0.32	1.40	0.65	0.23
syc2	13	4	11	6.96	90.91	156.77	0.15	122.34	212.04	43.79	0.24	0.13	0.22	0.96	0.69	0.21
arg	13	3	11	36.11	90.91	30.21	0.16	116.74	220.42	26.86	0.23	0.11	0.24	1.04	0.65	0.22
tur	10	1	3	1.68	90.91	651.13	0.23	75.03	293.59	66.03	0.59	0.21	0.40	1.25	0.57	0.29
gut	9	1	5	0.96	90.91	1130.63	0.26	100.71	256.06	44.72	0.65	0.26	0.37	1.15	0.71	0.26
whg	7	1	4	32.98	90.91	33.08	0.39	209.17	211.60	20.30	0.85	0.41	0.44	1.15	0.90	0.21
bll	8	1	4	1.07	90.91	1021.82	0.40	143.51	235.34	41.26	1.23	0.51	0.48	1.27	0.84	0.24
lem	8	1	4	11.49	90.91	94.91	0.30	143.99	249.78	21.68	0.55	0.23	0.46	1.10	0.65	0.25
ane	7	1	4	95.92	90.91	11.37	0.40	331.09	195.77	13.87	1.11	0.61	0.57	1.30	0.69	0.20
jnd	5	1	3	0.59	90.91	1853.54	0.60	243.49	216.83	34.89	1.99	0.97	0.52	1.11	1.15	0.22
sar	5	1	3	51.17	90.91	21.32	0.76	372.20	202.48	15.76	2.04	1.08	0.81	1.35	0.94	0.20
her	5	1	3	12.99	90.91	83.98	0.64	402.75	198.70	23.76	2.16	1.20	0.76	1.25	0.84	0.20
san	3	1	2	83.89	90.91	13.00	1.47	588.43	211.17	16.01	2.85	1.70	1.21	1.21	1.21	0.21

Lengths (L_t) could be converted into weights (W_t) with an allometric length-weight relationship

$$W_t = aL_t^b, \tag{5.3}$$

where a and b are empirical length-weight parameters. Figure 5.1 shows the modelled length and weight for two examples stocks (pollack and herring). The biological parameters were kept constant over time.

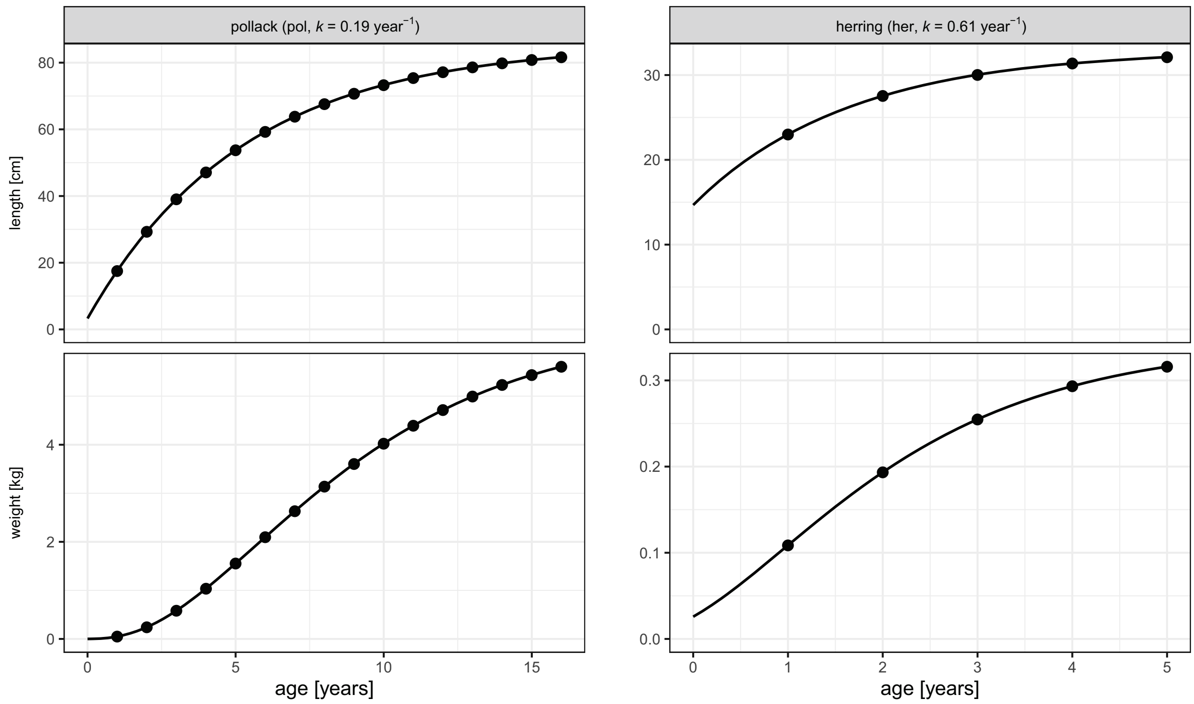

Figure 5.1: Modelled length and weight at age for two example stocks. The points indicate the values corresponding to the ages used in the operating models.

After this initial modelling of growth as length, the operating model was built with an age structure, and only the lengths corresponding to the ages of the operating model were used subsequently.

Missing input parameters can be estimated by FLife using empirical relationships; namely

$$k = 3.15L_\infty^{-0.64} \tag{5.4}$$

(Gislason et al., 2008) and

$$L_{50} = 0.72L_\infty^{0.93} \tag{5.5}$$

(Gislason et al., 2008). However, the application of either Equation (5.4 and 5.5) was not required for any of the 29 modelled stocks because empirical estimates were available for both parameters for each simulated stock.

5.4.2 Natural mortality

Natural mortality M was modelled as length dependent according to Equation 2 in Gislason et al. (2010):

$$\ln(M_L) = 0.55 - 1.61\ln(L) + 1.44\ln(L_\infty) + \ln(k) \tag{5.6}$$

To derive natural mortality at age (M_t), the von Bertalanffy growth Equation (5.1) is substituted into Equation (5.6). Figure 5.2 illustrates natural mortality.

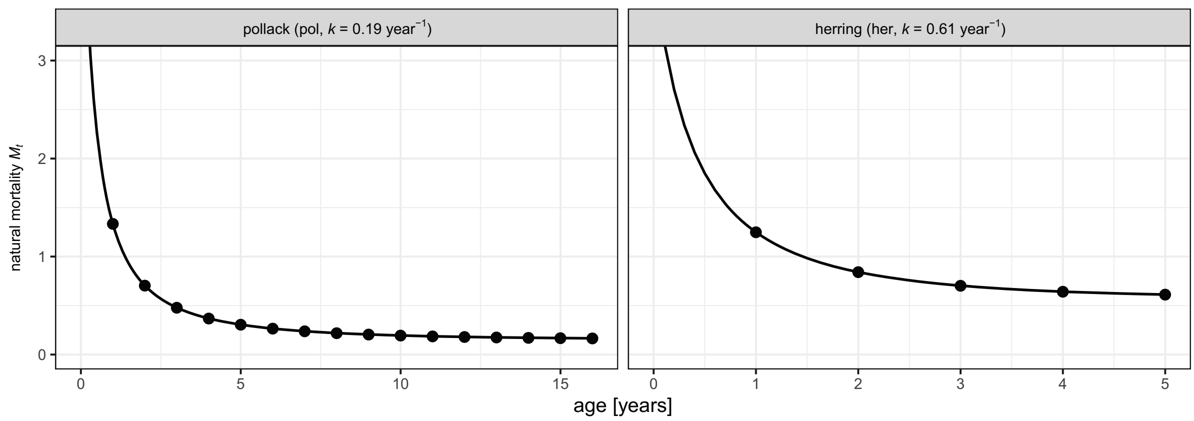

Figure 5.2: Modelled natural mortality at age for two example stocks. The points indicate the values corresponding to the ages used in the operating models, which start at age 1.

5.4.3 Maturity

Maturity at age m_t is modelled with a logistic function:

$$m_t = \begin{cases} m_{\min}, & \text{if } t < (t_{50} - 5) \\ \frac{m_{\max}}{1+19^{(t_{50}-t)/t_{\mathrm{to95}}}}, & \text{if } (t_{50} - 5) \le t \le (t_{50} + 5) \\ m_{\max}, & \text{if } t > (t_{50} + 5) \end{cases} \tag{5.7}$$

where $m_{\min}$ and $m_{\max}$ are the minimum and maximum value of the maturity, t_{50} the age at 50% maturity and t_{to95} defines the steepness of the curve (the offset between t_{50} and the age at 95% maturity). This functional form follows the modelling of maturity in the integrated stock assessment model CASAL (Bull et al., 2012). For the 29 stocks simulated here, the default parameterisation of FLife was kept ($m_{\text{min}} = 0$, $m_{\text{max}} = 1$, $t_{\text{to95}} = 1$) which resulted in an asymptotic maturity curve (Figure 5.3).

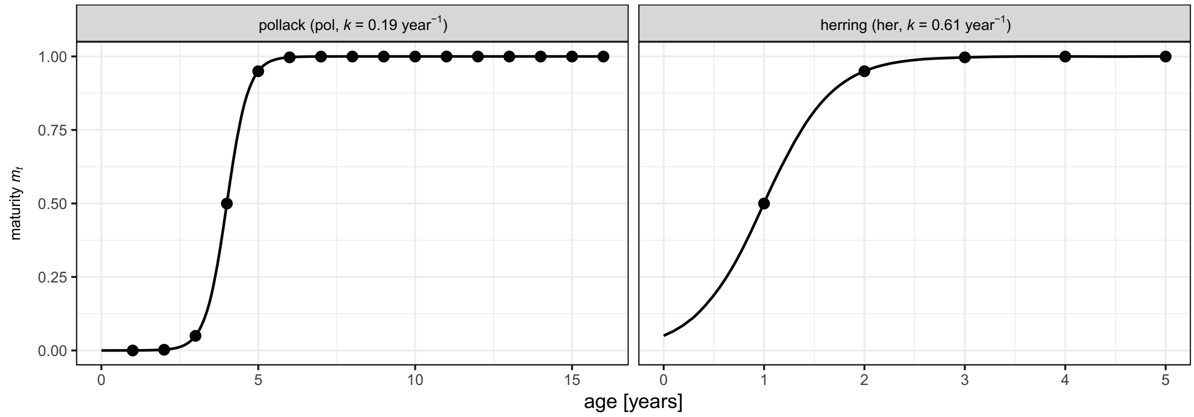

Figure 5.3: Modelled maturity ogive at age for two example stocks.

5.4.4 Fishery

The fishery was modelled as a single fleet with one gear per stock and fishing occurred throughout the year. The catches from the fishery were modelled as total catches without separating them into landings and discards. The fishery was defined by the fisheries selectivity at age (s_t) and modelled with a flexible double normal function:

$$s_t = \begin{cases} 2^{-\left(\frac{t-t_1}{s_L}\right)^2}, & \text{if } t < t_1 \\ 2^{-\left(\frac{t-t_1}{s_R}\right)^2}, & \text{if } t \geq t_1 \end{cases} \tag{5.8}$$

with the three parameters t_1, s_L and s_R. This function allows various functional forms of the selectivity curve, including asymptotic and dome-shaped selectivity. t_1 defines the age with the maximum selectivity ($s_{t=t_1} = 1$) and s_L and s_R define the shape of the left and right and arm of the curve. This double normal selectivity curve is commonly applied in integrated stock assessment models, such as CASAL (Bull et al., 2012) or Stock Synthesis (Methot & Wetzel, 2013; Methot et al., 2020). For the 29 stocks simulated here, the default parameterisation of FLife was kept ($t_1 = t_{50}$, $s_L = 1$, $s_R = 5000$) which resulted in an asymptotic selectivity curve where the first age with full selectivity corresponded to t_{50} (Figure 5.4).

For simplicity and better comparability, only one functional form (asymptotic) was considered for fishery selectivity in the generic operating models of all simulated stocks. In reality,

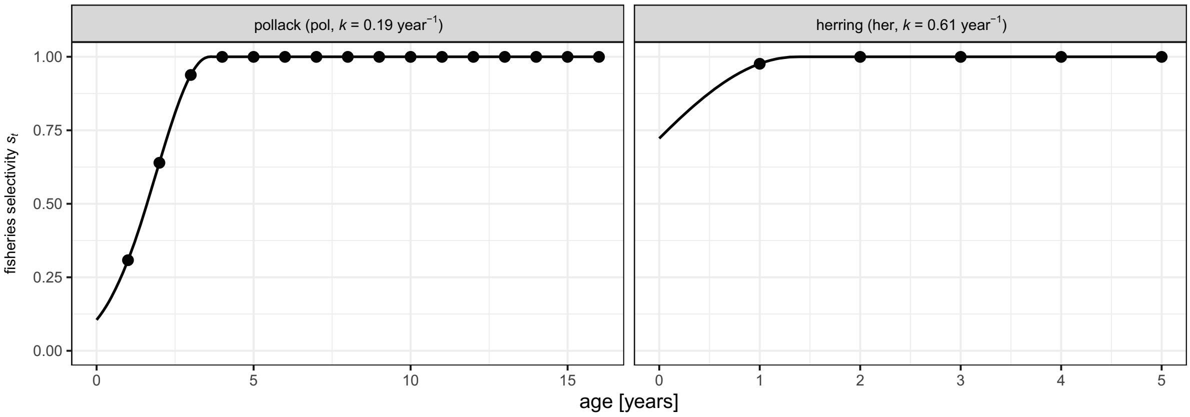

Figure 5.4: Modelled fisheries selectivity at age for two example stocks.

various functional forms are common, depending on the specific fishery, including options where fish are only selected after maturity or dome-shaped selectivity where older fish are not fully selected. Alternative selectivities can substantially affect the operating models and change operating model characteristics such as fishing reference points, possibly impairing direct comparability. In the case-specific simulations in Chapter 11, fishery selectivity is based on the perception from stock assessment models. For two of the three case study stocks (plaice and herring), fishery selectivity was estimated to be largely asymptotic in recent years with maximum selectivity at the oldest modelled age. For the third case study stock (cod), fishery selectivity was dome-shaped in recent years but only because the oldest modelled age had a lower selectivity.

5.4.5 Recruitment

Recruitment (R) was modelled with the Beverton-Holt stock-recruitment model. Beverton and Holt (1957) originally defined recruitment as a function of the number of eggs; however, the model is mainly used as a function of spawning stock biomass (SSB) nowadays. Various formulations and reparameterisations of the Beverton-Holt stock-recruitment model exist, for example:

$$R = \frac{\alpha \text{ SSB}}{\beta + \text{SSB}} \tag{5.9}$$

This model has two parameters, α and β, which can be reformulated in terms of recruitment steepness h (defined as the proportion of expected recruitment produced at 20% of unfished SSB, B_0, relative to unfished recruitment, R_0). This gives

$$\alpha = \frac{4hR_0}{5h - 1} \tag{5.10}$$

and

$$\beta = \frac{B_0(1-h)}{5h-1}. \tag{5.11}$$

Equations (5.10) and (5.11) can be substituted into Equation (5.9):

$$R = \frac{0.8R_0h\text{SSB}}{0.2B_0(1-h)+(h-0.2)\text{SSB}} \tag{5.12}$$

The steepness was set for all stocks to $h = 0.75$ and B_0 arbitrarily to 1000. The form of the Beverton-Holt stock recruitment model is shown in Figure 5.5

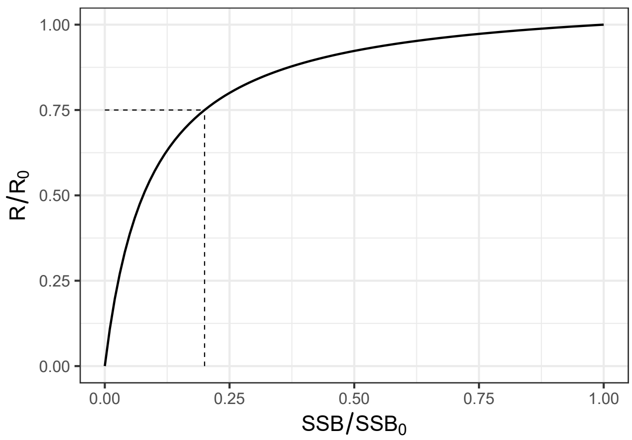

Figure 5.5: Beverton-Holt stock recruitment model. The dashed lines indicate the steepness of $h = 0.75$. Both recruitment (R) and spawning stock biomass (SSB) are shown relative to their unfished values (R_0, SSB_0).

5.4.6 Population dynamics

Population dynamics followed the usual exponential decay equations:

$$N_{t,y} = \begin{cases} R_y \; e^{\varepsilon_y^R} & t = 1 \\ N_{t-1,y-1} \; e^{-F_{t-1,y-1}-M_{t-1,y-1}} & 1 < t < T \\ N_{t-1,y-1} \; e^{-F_{t-1,y-1}-M_{t-1,y-1}} + N_{t,y-1} \; e^{-F_{t,y-1}-M_{t,y-1}} & t = T \end{cases} \tag{5.13}$$

where the first age class ($t = 1$) is the recruitment age (following Equation 5.12) and T is the maximum age ($t_{\max}$, set as a plusgroup). A log-normal recruitment process error is included with e^{ε^R} where $\varepsilon^R \sim N(0, \sigma^2)$ and defaults to $\sigma = 0.6$ in subsequent chapters.

The log-normal recruitment error was applied without bias correction, as is common practice in many models in fisheries science. The consequence was that the median of the modelled recruitment values in the simulations matched the recruitment from the recruitment model, i.e. that, on average, the same number of simulation replicates had values above and below, but the mean recruitment was $\sigma^2/2$ higher than the median. However, in the following chapters, most metrics from the simulations are presented as medians and not means and are therefore less affected by this potential bias.

Catch numbers were calculated following the Baranov catch equation (Sharov, 2021):

$$C_{t,y} = \frac{F_{t,y}}{F_{t,y} + M_{t,y}} \; N_{t,y} \; \left(1 - e^{-F_{t,y} - M_{t,y}}\right) \tag{5.14}$$

5.4.7 Equilibrium dynamics and reference points

The definitions of stock and fishery characteristics from the previous sections allowed setting up the biological stock and fishery of the operating model. This was done with FLR's FLife package (https://github.com/flr/FLife), which uses the routines from another FLR package called FLBRP (https://github.com/flr/FLBRP). Essentially, the process consists of determining the equilibrium conditions of the operating models. The first step is to find the recruitment model parameters which lead to the selected stock size under no fishing. For the generic operating models, this state was defined with an unfished SSB of 1000. Subsequently, alternative equilibrium states that include fishing can be found, for example, the state with the highest long-term sustainable catch. The unfished state was the starting condition for hypothetical fishing histories and could then be used to evaluate candidate management procedures.

Several reference points were used to indicate the stock status and exploitation level and also as a measure to quantify the performance of management procedures tested with MSE simulations. These reference points were derived from equilibrium conditions of the operating models without uncertainty around parameters, i.e. they are deterministic reference points.

The following reference points were used:

- **$B_{\mathbf{MSY}}$, $F_{\mathbf{MSY}}$, MSY**

  The equilibrium reference points for SSB, F and catch corresponding to the state of the stock when it is at its highest long-term yield (maximum sustainable yield, MSY).

- **$B_{\mathbf{lim}}$**

B_{lim} is an SSB limit reference point below which a stock is thought to be at increased risk of impaired recruitment and management should ensure that stocks do not fall below this level. B_{lim} is commonly used in ICES to ensure compatibility with the precautionary approach (ICES, 2017b). The operating models used a Beverton-Holt stock-recruitment model with a smooth recruitment curve, and therefore, no obvious point exists for defining impaired recruitment. For the stocks simulated here, the suggestion of ICES (2017f) was adopted, which defines B_{lim} as the SSB where recruitment is impaired by 30% (i.e. $R = 0.7R_0$). By default, all stock used the same recruitment model, unfished SSB ($B_0 = 1000$) and recruitment steepness ($h = 0.75$, see Figure 5.5), which meant that B_{lim} was identical for all stocks: $B_{\text{lim}} = 0.163B_0 = 163$.

- $B_{\textbf{collapse}}$

  The level below which a stock was thought to be collapsed (B_{collapse}) was set to 0.1% of B_0.

- $F_{\textbf{crash}}$

  F_{crash} was the lowest fishing mortality which caused the stocks to collapse in equilibrium conditions. This reference point was useful for the generation of fishing histories because once this fishing mortality was reached, stocks would crash.

5.4.8 Observations

Biomass index

A biomass index was created from the biological stock in the operating model as a measure to represent the trend in the biomass of the stock. This biomass index was aggregated over all ages:

$$I_y = \left(\sum_{t=1}^{t_{max}} N_{t,y} s_{\text{idx},t} W_t \right) e^{\varepsilon_y}, \tag{5.15}$$

where $N_{t,y}$ is the number of individuals in the stock at age t in year y, s_{idx} the index selectivity, and W_t the weight of the individuals at age t. Observation uncertainty was introduced through the log-normal error term e^{ε_y} with $\varepsilon_y \sim N(0, \sigma^2_{\text{idx}})$. The error was implemented to the age-aggregated biomass index; however, this is mathematically identical to including the same error to all ages, e.g. to the numbers or weights at age.

The default observation uncertainty was set to $\sigma_{\text{idx}} = 0.2$, which is a common value (see e.g. Jardim et al., 2015) and appropriate for many ICES stocks (see Appendix B for details), although sensitivity analyses on the impact of uncertainty levels on simulation results have been conducted (see Chapter 6).

The default index used in Chapters 6, 7, and 8 resembled a scientific survey and the index selectivity $s_{\text{idx},t}$ based on a logistic function:

$$s_{\text{idx},t} = \frac{s_{\text{idx,max}}}{1 + e^{-s_{\text{idx,steepness}}(t - s_{\text{idx,50}})}} \tag{5.16}$$

with $s_{\text{idx,max}} = 1$ (maximum selectivity), $s_{\text{idx,steepness}} = 1$ (steepness of selectivity curve) and $s_{\text{idx,50}} = 0.1t_{50}$ (age where 50% of individuals are selected by the index, i.e. the inflection point of the selectivity curve, Figure 5.6).

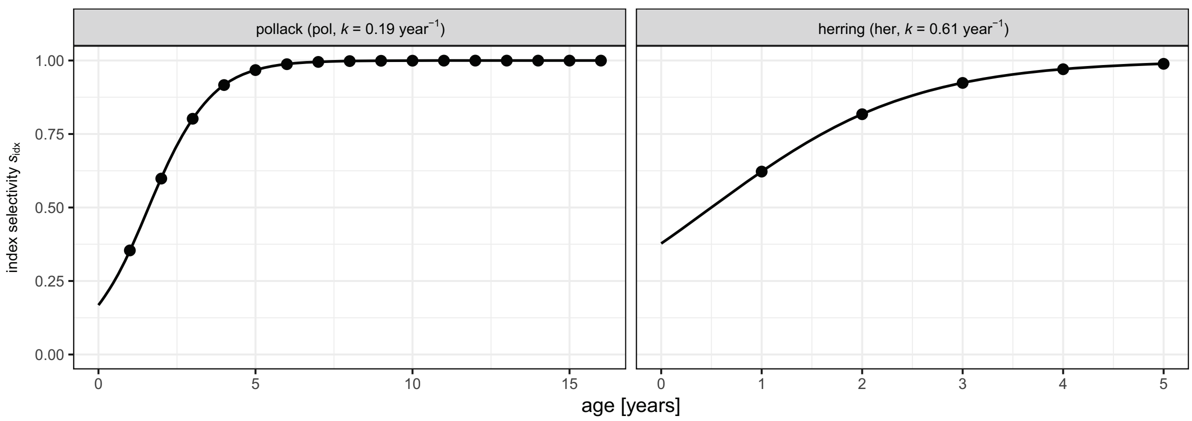

Figure 5.6: Index selectivity for two example stocks.

Catch

Realised catches from the fishery were thought to be known perfectly and passed without error to the management procedure, if not explicitly indicated otherwise.

Mean catch length

Some of the empirical management procedures relied on the mean catch length (the mean of the length of fish caught by the fishery). However, the operating model and the catch numbers were age-structured. Consequently, generating an index of the mean length of individuals in the catch required the simulation of length frequencies. Two approaches were adopted, (i) where full length frequencies were simulated and (ii) a shortcut approach:

(i) **Full length frequencies**

This approach was used for the initial simulation testing in Chapter 6. The catch length distribution was derived from the catch at age distribution from the operating model by applying an inverse age-length key. The inverse age-length key was based on the von Bertalanffy growth curve and uncertainty around the length at age was added by applying a normal distribution on the expected length at age.

To do this, length at age (L_t) was first calculated based on the catch weight at age (W_t) from the operating model with the length-weight relationship parameters (a, b) and the allometric length-weight relationship (Equation 5.3), solved for L_t:

$$L_t = \left(\frac{W_t}{a}\right)^{1/b} \tag{5.17}$$

This approach using Equation (5.17) led to lengths that were mathematically identical to the lengths from the von Bertalanffy growth model (Equations 5.1) because weights at age in the operating model were calculated with the same von Bertalanffy growth model and parameters and then converting length to weight with the allometric length-weight parameters.

The simulated stocks are data-limited and there are no generic length-at-age distributions easily available to model length distributions. Therefore, in order to simulate a probabilistic inverse age-length key, the (deterministic) lengths at age were spread with a normal distribution and a discrete length distribution generated for each age:

$$L'_t = N(\mu, \sigma^2), \tag{5.18}$$

with $\mu = L_t$ and $\sigma^2 = 1$. Each L'_t contained lengths rounded to the nearest centimetre and was cut off:

$$(\mu - 2\sigma) \leq L'_t \leq (\mu + 2\sigma) \tag{5.19}$$

and

$$0 \leq L'_t \leq L_\infty. \tag{5.20}$$

The result of this approach was a probabilistic inverse age-length key with length probabilities for each age of the operating model. The possible length probabilities at age from this key were standardised subsequently. This inverse length-key was then applied to the catch at age distribution to derive the length distribution of the catch.

Sampling from the length distribution (for the management procedure) was approximated by including a log-normal error term with a distribution (in log-space) of $N(\mu, \sigma^2)$ with $\mu = C_L$ and $\sigma = 0.2$, where C_L is the catch at length, in 1cm length bins.

The final mean catch length was then generated with

$$\bar{L}_y = \frac{\sum_{k \epsilon K} C_k L_k}{\sum_{k \epsilon K} C_k}, \tag{5.21}$$

where K was the set of length bins above the length of first capture L_c, L_k the length of the length bin, and C_k the aggregated number of individuals in the catch in L_k (after including the uncertainty described above). L_c was defined following ICES (2012e) as the first length bin where the catch is at or above half the mode of the distribution of catch numbers.

This approach of approximating length sampling was considered appropriate because the management procedure used only the mean length in the catch and a comparison of mean lengths derived from the approximation and sampling of the catch length frequencies resulted in very similar lengths (both in terms of median as well as uncertainty, see Appendix B). Furthermore, this approach substantially reduced the runtime and computational requirements of the simulation, compared to including a full sampling protocol.

(ii) **Shortcut**

Despite approximating sampling, the approach described above had still a high computational complexity. For every simulation year and replicate, a full catch length distribution was generated, with length bins for every length up to L_∞. This resulted in large objects which had to be stored in memory. Such computations were acceptable if only few scenarios and options were run (see Chapter 6). However, in subsequent chapters (Chapters 7, 8, and 9), many tens of thousands of simulations were required, and, therefore, the generation of the mean catch length index was simplified. Following Jardim et al. (2015), ages were converted deterministically into lengths and the index computed as the mean of these lengths weighted by the catch numbers:

$$\bar{L}_y = \frac{\sum_{t \epsilon T} C_t L_t}{\sum_{t \epsilon T} C_t} e^{\varepsilon_y}, \tag{5.22}$$

where L_t was the deterministic length at age t derived from Equation (5.17), T the set of ages t where $L_t \geq L_c$, and C_t are the catch numbers. Uncertainty was added to the aggregated length with a log-normal error term (e^{ε_y}, with $\varepsilon \sim N(0, \sigma^2)$) with a default of $\sigma = 0.2$ (Jardim et al., 2015).

5.5 Elasticity analysis

5.5.1 Methods

From the total list of 29 stocks, two example stocks were selected for the elasticity analysis. These stocks comprised the large demersal medium-fast growing stock pollack (*Pollachius pollachius*) and the pelagic fast-growing stock herring (*Clupea harengus*). The primary input parameters to generate these stocks were the same as defined in Table 5.2.

These input parameters were then used to create operating models with the FLR (Kell et al., 2007) package FLife. An elasticity analysis of the influence of these primary input parameters on important output parameters describing the characteristics of the operating models was conducted. The output parameters considered were

- α, β (the Beverton-Holt stock-recruitment parameters),
- F_{MSY}, B_{MSY}, TSB_{MSY}, R_{MSY}, MSY (the MSY reference points for fishing mortality, SSB, total stock biomass, recruitment and catch),
- TSB_0, R_0 (unfished reference points for total stock biomass and recruitment),
- r, r_c (instantaneous growth rate at the limit of zero stock size and conditional growth rate at MSY),
- SPR_0, SPR_{MSY} (spawning potential ratio at zero stock size and at MSY),
- M (adult natural mortality, calculated as the average of natural mortality at age, weighted by maturity at age), and
- F_{MSY}/M and M/k (ratios of parameters).

The elasticity analysis was conducted by numerically approximating the gradient of the output parameters relative to the primary input parameters at the value of the primary input parameters, i.e. their first-order derivatives.

5.5.2 Results

Table 5.3 shows the results of the elasticity analysis in the form of the Jacobian matrices for the two stocks, pollack and herring.

The comparison of absolute values of the different derived operating model parameters is meaningless due to different units and only a comparison to the default value is interpretable. In general, the primary input parameter k (von Bertalanffy growth parameter) appeared most influential on most operating model characteristics such as MSY reference points (F_{MSY}, B_{MSY}) and growth rate (r) for both stocks. The second most influential parameters was recruitment steepness h. The effects of k on the operating models are visualised in Figure 5.7 for pollack and Figure 5.8 for herring. Figures 5.7c and 5.8c show the impact of k on the output parameters included in the elasticity analysis. The slopes of the curves at the default value of k correspond to the values from the Jacobian matrices from Table 5.3.

5.6 Discussion

When data-limited fish stocks are simulated, it is necessary to make assumptions because of the lack of knowledge and data about such stocks. The implementation of specific assumptions and functional relationships between biological parameters might be, at least partially, considered arbitrary. Assumptions and functional relationships required for the generation of the operating models for the 29 simulated stocks, were based on established empirical analyses (e.g. Gislason et al., 2010), which are also commonly used in other data-limited fisheries simulations. Nevertheless, model uncertainties and their implications need to be considered when the operating models are deployed.

The elasticity analysis provided insights into which primary input parameters were important for the definition of operating models. The analysis revealed that the von Bertalanffy growth parameter k and recruitment steepness h were most influential for the majority of operating model parameters. For some operating model parameters, additional input parameters appeared important, e.g. for the Beverton-Holt recruitment model parameter α, the allometric length-

Table 5.3: Jacobian matrices for the elasticity analysis of pollack and herring. Columns correspond to the input parameters used in the creation of the operating models and rows show the generated operating model parameters. The row and column labelled “default” represent the default values for the input and output parameters for comparison.

	default	L_∞	k	t_0	a	b	t_{50}	h
pollack								
default		85.6	0.19	-0.1	0.0076	3.069	4.1	0.75
α	1.2	−0.1	−7.5	2.3	−154.7	−5.0	0.1	−0.6
β	90.9	0.0	0.0	0.0	0.0	0.0	0.0	−5289
$F_{\mathbf{MSY}}$	0.1	0.0	0.6	0.0	0.0	0.0	0.0	0.2
$B_{\mathbf{MSY}}$	284.1	0.2	−291.4	20.3	−0.2	39.4	−70.9	−3536
$\mathbf{TSB}_{\mathbf{MSY}}$	454.4	−0.7	1067.3	−23.7	−0.2	−88.3	−9.2	−2892
$R_{\mathbf{MSY}}$	0.9	0.0	−5.9	1.8	−117.2	−3.8	0.0	0.6
MSY	48.3	−0.1	285.4	−6.4	0.0	−13.5	24.0	59.0
$\mathbf{TSB}_0$	1232.0	−1.2	2031.0	−64.3	0.0	−180.4	107.5	0.0
R_0	1.1	0.0	−6.8	2.1	−141.8	−4.6	0.1	0.0
r	0.3	0.0	0.8	0.0	0.0	0.0	0.1	0.8
r_c	0.1	0.0	0.4	0.0	0.0	0.0	0.1	0.2
$\mathbf{SPR}_0$	927.7	41.2	5882.5	−1828.0	122 061.6	3937.2	−67.4	0.0
$\mathbf{SPR}_{\mathbf{MSY}}$	318.9	14.3	1774.5	−611.2	41 963.0	1387.0	−83.5	−5959
M	0.2	0.0	0.5	0.0	0.0	0.0	0.0	0.0
$F_{\mathbf{MSY}}/M$	0.5	0.0	1.4	−0.1	0.0	−0.1	0.0	1.2
M/k	1.1	0.0	−3.5	0.1	0.0	0.0	0.0	0.0
herring								
default		33	0.606	-0.1	0.0048	3.198	1.9	0.75
α	13.0	−1.4	−5.4	16.9	−2706.2	−43.3	6.3	−6.3
β	90.9	0.0	0.0	0.0	0.0	0.0	0.0	−5289
$F_{\mathbf{MSY}}$	0.6	0.0	0.9	0.0	0.0	−0.1	−0.3	1.9
$B_{\mathbf{MSY}}$	198.7	0.3	−42.2	−12.9	0.8	9.0	−35.6	−5110
$\mathbf{TSB}_{\mathbf{MSY}}$	296.9	−0.1	91.4	−31.1	1.1	−2.1	−67.2	−6249
$R_{\mathbf{MSY}}$	8.9	−1.0	−4.3	11.4	−1856.7	−29.6	3.8	4.8
MSY	402.7	−4.1	950.0	50.9	0.0	−68.4	353.0	787.5
$\mathbf{TSB}_0$	1234.6	−1.7	504.6	−42.1	0.0	−43.5	17.2	0.0
R_0	11.9	−1.3	−4.9	15.5	−2480.7	−39.7	5.8	0.0
r	2.2	0.0	2.0	0.4	0.0	−0.2	1.1	4.8
r_c	1.2	0.0	1.6	0.3	0.0	−0.1	1.0	2.4
$\mathbf{SPR}_0$	84.0	9.2	34.7	−109.1	17 496.2	280.0	−40.6	0.0
$\mathbf{SPR}_{\mathbf{MSY}}$	22.3	2.5	6.0	−29.9	4644.9	75.0	−13.5	−69.3
M	0.8	0.0	0.6	0.2	0.0	0.0	0.0	0.0
$F_{\mathbf{MSY}}/M$	0.8	0.0	0.5	−0.2	0.0	−0.1	−0.4	2.5
M/k	1.3	0.0	−1.1	0.3	0.0	0.0	0.0	0.0

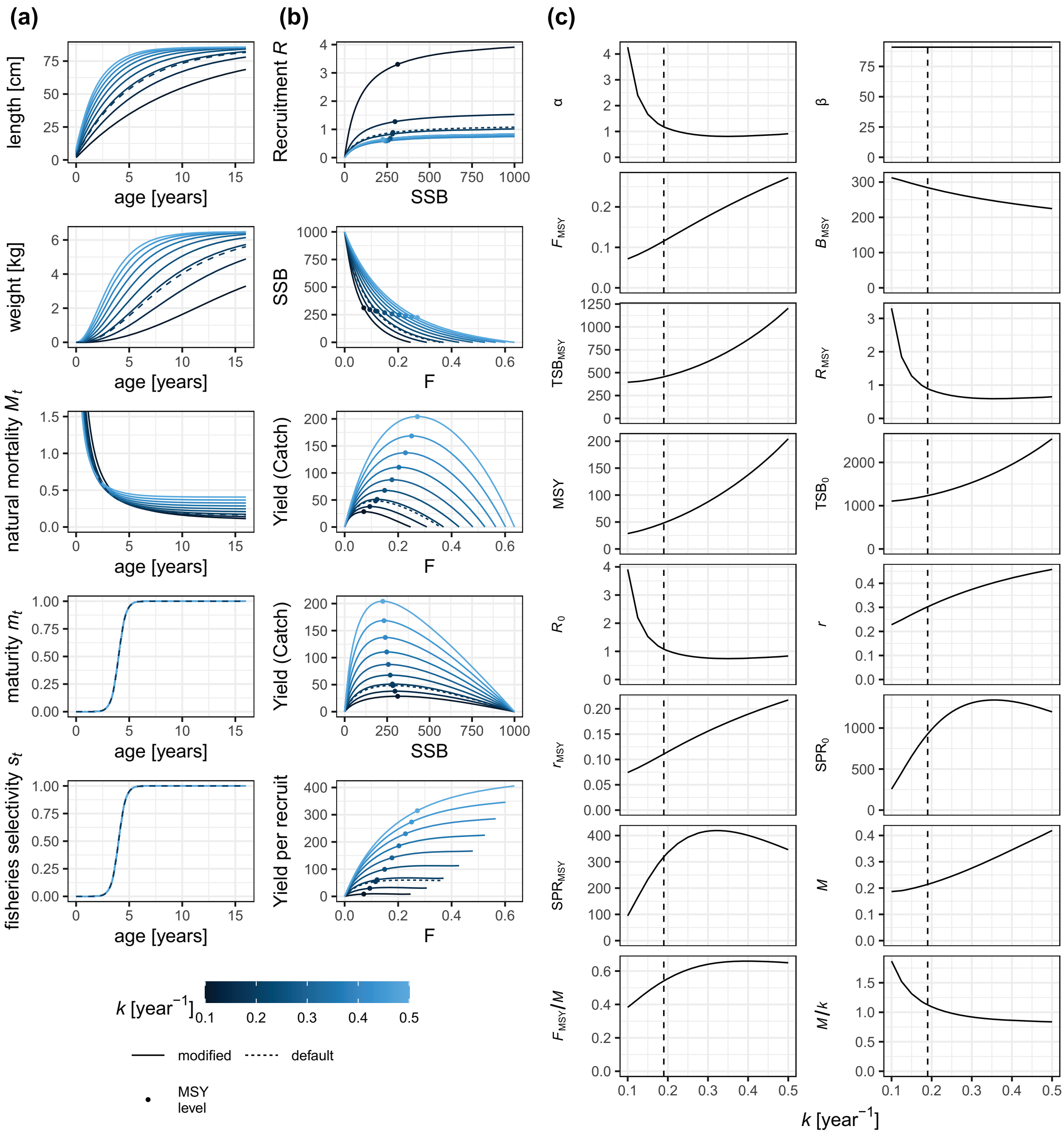

Figure 5.7: Effect of the von Bertalanffy growth parameter k on the pollack operating model. (a) shows the basic age-dependent relationships, (b) the equilibrium dynamics with the MSY levels indicated by the points, and (c) the operating model parameters as a function of k, where the default value of k is indicated by the dashed vertical line.

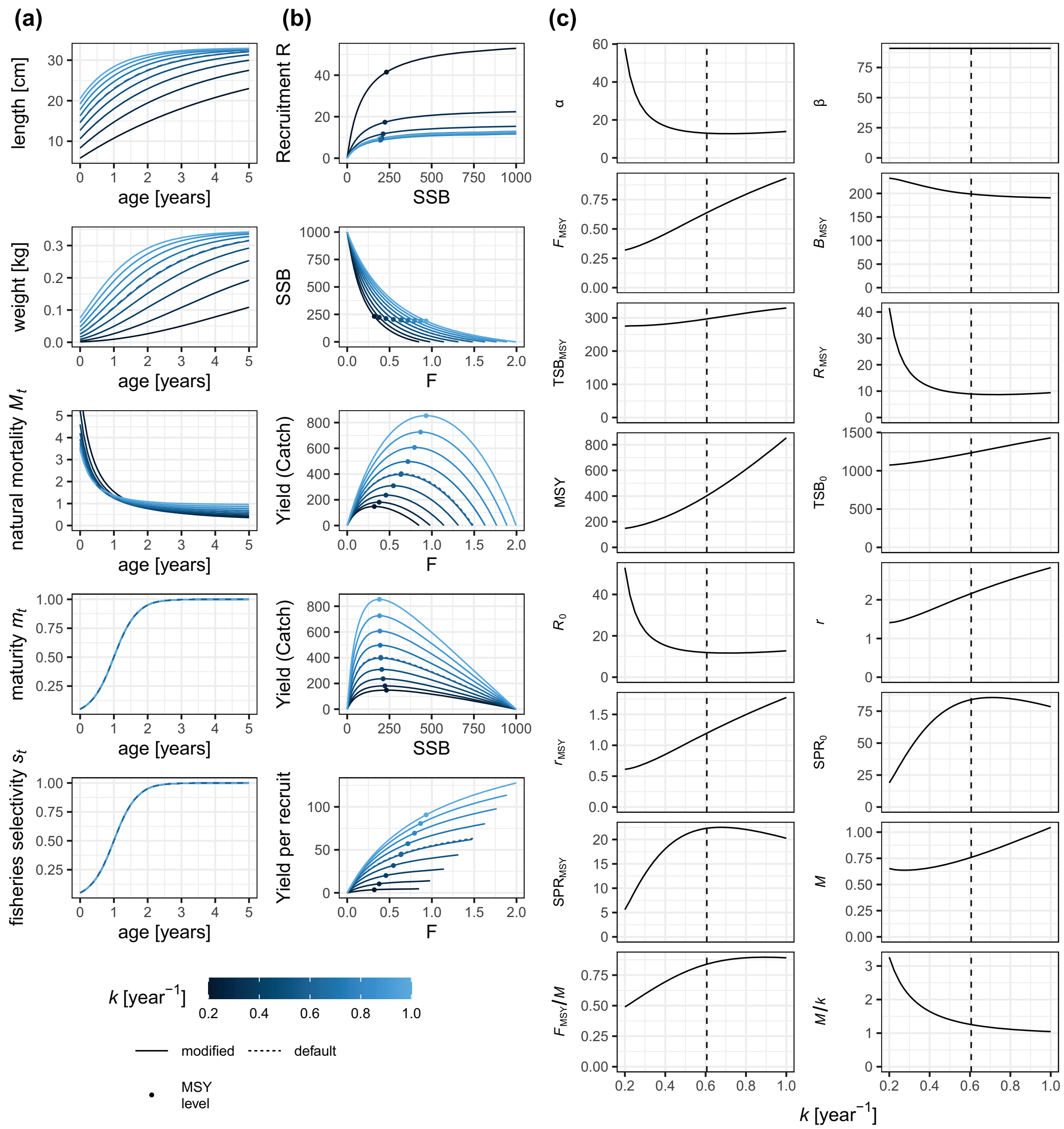

Figure 5.8: Effect of the von Bertalanffy growth parameter k on the herring operating model. See Figure 5.7 for details.

weight parameter a is highly influential. However, this can be explained with the fact that the allometric a works like a scaling factor, linking the weight-at-age and length. Therefore, a scaling of the allometric a also caused a scaling of the biomass of the stock, which in turn modifies the recruitment parameter without changing the operating model characteristics apart from the absolute scale of biomass.

The steepness of the stock-recruitment model was unsurprisingly one of the most influential parameters. Changes in the steepness cause direct changes in the productivity of a stock, e.g. a higher steepness will inevitably lead to higher productivity at lower stock sizes and, therefore, MSY reference points change.

Regarding the von Bertalanffy growth parameters, k was more important than L_∞. It was more important how fast an individual approaches its asymptotic size L_∞, as expressed by k, than the absolute value of L_∞. The parameter t_0 is used to shift the entire growth curve along the age-axis. For many of the simulated stocks, this value is poorly estimated or not available and a default of $t_0 = -0.1$ years was implemented instead. The elasticity analysis provides reassurance about the appropriateness of using a default value, because t_0 had only a minor effect on the operating models.

Subsequent analyses, where the performance of empirical management procedures was linked to the primary operating model parameters (see Chapter 6), found that the control rule's performance was dependent on the value of k of the operating models. The elasticity analysis conducted here supports this finding and yields further evidence that k is a crucial factor suitable for describing the characteristics of a fish stock. k is important to distinguish between species but also the specific value of k for a stock is important and the estimation procedure of k from empirical data should be scientifically sound to ensure realism in simulations. Values for k can be obtained even for data-limited stocks. The practical implication of the outcome of the elasticity analysis was that k can be used to help characterise a stock.

5.7 Conclusion

In the absence of extensive data sets and stock assessment models for data-limited stocks, generic operating models can be created from a limited set of life-history parameters. This chapter provided a description of the generation of the generic operating models, which were used in a management strategy evaluation in subsequent chapters. A total of 29 fish stocks were simulated and these stocks covered a wide range of life-history traits. This approach of simulating many life histories allowed a robust evaluation of management procedures.

The set-up of generic operating models can rely on potentially arbitrary decisions regarding the functional form of biological processes, parameter values, or the level of uncertainty. An elasticity analysis of primary operating model input parameters revealed that the individual growth rate (the von Bertalanffy parameter k) was the most influential for the definition of the operating model. This meant that the value of k was important for a specific operating model but also that k could be used to distinguish between different operating models with different k values. Consequently, in subsequent chapters, the generic operating models are sometimes grouped in terms of k. In the following chapters, where empirical management procedures are developed and tested, the influence of the operating model characteristics is explored. This is done in the form of sensitivity analyses, for example, for observation uncertainty, in order to ensure that the outcomes of simulations are robust and not an artefact of the specific set-up of the generic operating models.

Chapter 6

Linking the performance of a data-limited empirical catch rule to life-history traits[1]

[1]This chapter is an adaptation of Fischer et al. (2020). Contains public sector information licensed under the Open Government Licence v3.0 (http://www.nationalarchives.gov.uk/doc/open-government-licence/version/3/)

6.1 Foreword

The work presented in this chapter summarises the results of the first simulations of a data-limited empirical catch rule (the rfb rule). These initial simulations provided insights into the performance of this catch rule and paved the way for optimisations of the catch rule towards specific management objectives, which are explored in the following chapters. Preliminary results were presented at the eighth International Council for the Exploration of the Sea (ICES) Workshop on the Development of Quantitative Assessment Methodologies based on LIFE-history traits, exploitation characteristics, and other relevant parameters for data-limited stocks (ICES WKLIFE VIII; ICES, 2018c). Subsequently, additional analyses were undertaken and the work was peer-reviewed and published in Fischer et al. (2020):

> 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*(5), 1914–1926. https://doi.org/10.1093/icesjms/fsaa054

The following sections in this chapter are an adaptation of this publication.

6.2 Abstract

Worldwide, the majority of fish stocks are data-limited and lack fully quantitative stock assessments. Within ICES, such data-limited stocks are currently managed by setting total allowable catch without the use of target reference points. To ensure that such advice is precautionary, a management strategy evaluation was used to evaluate an empirical rule that bases catch advice on recent catches, information from a biomass survey index, catch length frequencies, and MSY reference point proxies (the rfb rule). Twenty-nine fish stocks were simulated covering a wide range of life histories. The performance of the rule varied substantially between stocks, and the risk of breaching limit reference points was inversely correlated to the von Bertalanffy growth parameter k. Faster-growing stocks with $k > 0.32$ year^{-1} had a high probability of stock collapse. A time series cluster analysis revealed four types of dynamics, i.e. groups with similar terminal spawning stock biomass (collapsed, B_{MSY}, $2B_{\mathrm{MSY}}$, $3B_{\mathrm{MSY}}$). It was shown that a single generic catch rule cannot be applied across all life histories, and management should instead be linked to life-history traits.

6.3 Introduction

When managing fisheries, decisions must be made with incomplete knowledge, which is why international agreements request the adoption and implementation of the precautionary approach (Garcia, 1996). In addition, fish retailers and consumers are increasingly looking for assurances that the food they buy is sustainably produced. Therefore, many regional fisheries management organisations have implemented management frameworks based on target and limit reference points to prevent overfishing and ensure targets are achieved. Despite this, most fisheries and commercially exploited stocks still lack reliable estimates of stock status and effective management due to poor data, limited knowledge, and insufficient resources (Jardim et al., 2015; Fitzgerald et al., 2018).

Since 2012, ICES has applied a framework to provide catch advice for the European data-limited stocks (ICES, 2012b, 2013a). The increasingly sophisticated methods developed for stock assessment are not always suited to data-poor fisheries (Bentley, 2015). Therefore, recently, many data-limited approaches have emerged and re-emerged to meet the increasing demand for science-based fisheries management for data-limited stocks (Wetzel & Punt, 2011; Costello et al., 2012; Dowling et al., 2015a; Dowling et al., 2016; Chrysafi & Kuparinen, 2016; Rosenberg et al., 2018). However, in a review of data-limited methods, Dowling et al. (2019) noted the dangers in the indiscriminate use of generic methods and recommended obtaining better data, using care in acknowledging and interpreting uncertainties, developing harvest strategies that are robust to the higher levels of uncertainty, and tailoring them to the specific species' and fisheries' data and context.

One way to do this is to evaluate candidate data-limited management frameworks using management strategy evaluation (MSE; Smith, 1994; Punt et al., 2016). MSE uses an operating model (OM) to represent a fish stock and the fisheries operating on it. The OM is used to simulate resource dynamics in simulation trials and to generate pseudo data to evaluate the performance of a management procedure. The management procedure is the combination of pre-defined data, together with an algorithm to which such data are input to set a management measure, such as a total allowable catch (TAC). This in turn is converted into a catch that is removed from the OM in a feedback loop (Punt et al., 2016).

The application of MSEs has been mainly focused on data-rich situations, where enough data are available to condition the OM using stock assessment models. A management procedure may be either model-based, where a stock assessment is used to estimate stock status and set management measures (e.g. Kell et al., 2005), or empirical where a trend in an indicator is used to set the catch (Hillary et al., 2016). MSEs for data-limited purposes are somewhat rarer, although there are notable studies. For example, Carruthers et al. (2012) evaluated methods based on catch data alone and found that catch-based methods were, on average, more negatively biased than stock assessment methods that explicitly model population dynamics and use additional fishing effort data. In a subsequent study, Carruthers et al. (2014) found that methods that rely only on historical catches performed worse than maintaining current fishing levels and that only methods that dynamically accounted for changes in abundance or depletion performed well at low stock sizes. Geromont and Butterworth (2015a) tested a range of simple catch rules based on historical catches, length data, or survey index data and found that such simple rules perform well and could be used in practice. Punt et al. (2001) explored a range of empirical indicators and noted that length- or weight-based indicators outperform catch rate indicators; however, caution needs to be exercised about reference levels. A review of data-poor empirical harvest strategies can be found in Dowling et al. (2015a).

Within ICES, simple catch rules have been developed for data-limited stocks (ICES, 2012b). For example, the "2 over 3" rule aims to keep stocks at their current level by multiplying recent catches by the trend in a biomass index:

$$A_{y+1} = A_{y-1} \frac{\sum_{i=y-2}^{y-1} I_i/2}{\sum_{i=y-5}^{y-3} I_i/3}, \tag{6.1}$$

where A_{y+1} is the newly advised catch for year $y+1$, A_{y-1} is the previously advised catch [note: this could be observed catch, C_{y-1} e.g. when the advice is first produced, or when the advised catch is no longer appropriate because a stock has undergone a benchmark; for the purposes of this study, C_{y-1} was used following the original definition in ICES (2012b)] and I is a biomass index. This rule, in combination with a catch constraint (called uncertainty cap in ICES, limits change in catch advice to no more than 20%) and precautionary buffer (which reduces the catch advice by 20% if the stock is judged to be outside safe biological levels), is currently (as of 2021) applied to give catch advice within ICES for category 3 data-limited stocks (ICES, 2018a).

The ICES "2 over 3" rule lacks a management target, can induce oscillatory behaviour resulting in increased biological risk over time, and includes a time lag in the translation of changes in the biological stock into advice (ICES, 2013c, 2017e). An alternative catch rule, making use of more data sources, has therefore been proposed (ICES, 2012c):

$$A_{y+1} = C_{y-1}\ r\ f\ b, \tag{6.2}$$

where the advised catch A_{y+1} is based on the previous observed catch C_{y-1}, multiplied by three components r, f and b, each representing a stock characteristic. Component r corresponds to the trend in a biomass index (I), component f is a proxy for the ratio F_{MSY} (the fishing mortality corresponding to the maximum sustainable yield, MSY) divided by the current exploitation based on length data from the catch, and component b is a biomass safeguard that protects the stock once the biomass index drops below a threshold. This rule is subsequently called the rfb rule, referring to its three components. Initially, the rfb rule was merely a concept without specifying what data should be used and how the components could be derived from them (ICES, 2012c). Recently, the rule has been revisited by ICES (2017f) and suggestions made for simulation testing and application to actual stocks. Several options for the three components have been proposed, and initial simulation testing narrowed it down to only one option per component (ICES, 2017e). This rfb rule is the focus of the present study, which aims to (i) establish procedures to simulate data-limited fish stocks based on life-history parameters, (ii) simulation-test the aforementioned catch rule, (iii) associate the performance of the catch rule to life-history parameters, and (iv) provide guidance on the application of the catch rule and thereby advancing the management of data-limited fisheries.

Jardim et al. (2015) tested a simplified version of the rule where components r and f were tested one-at-a-time and component b excluded and concluded that the rule based on r [Equation (6.2)] performed the poorest, and while the rule based on f was able to reverse decreasing trends in biomass, it resulted in catch levels below MSY and could not prevent some stocks declining when subject to over-exploitation.

As the purpose of this study is to test catch rules for data-limited stocks, assumptions and approximations must be made. A similar approach to Jardim et al. (2015) was used where stocks are simulated based on a set of life-history parameters and where fishing scenarios are developed. The simulations were conducted in the Fisheries Library in R (FLR; Kell et al., 2007) software suite, within an MSE framework originally developed by Jardim et al. (2017) for data-rich stocks but adapted and extended to accommodate data-limited stocks.

The study stocks are given in Table 6.1; there are 29 data-limited stocks from European waters (North Sea region, Celtic Sea region, Bay of Biscay, and widely distributed stocks) and they encompass a wide range of life histories, including roundfish, flatfish, elasmobranchs, shellfish, and demersal as well as pelagic species. Jardim et al. (2015) used averaged life-history parameters for species to simulate stocks; in contrast, in the present study, stock-specific parameters were chosen, so that simulated stocks resemble real stocks in terms of biology (growth, productivity, etc.). As this is a data-limited simulation approach, however, artificial fishing histories had to be developed.

Table 6.1: The 29 stocks on which the operating models are based.

Scientific name	**Common name**	**ID**	k **(year^{-1})**
Lophius budegassa	Blackbellied angler	ang3	0.08
Raja clavata	Thornback ray	rjc2	0.09
Sebastes norvegicus	Golden redfish	smn	0.11
Anarhichas lupus	Atlantic wolffish	wlf	0.11
Lepidorhombus whiffiagonis	Megrim	meg	0.12
Molva molva	Ling	lin	0.14
Raja clavata	Thornback ray	rjc	0.14
Scyliorhinus canicula	Lesser spotted dogfish	syc	0.15
Mustelus asterias	Starry smooth-hound	sdv	0.15
Lophius piscatorius	Angler	ang	0.18
Lophius piscatorius	Angler	ang2	0.18
Pollachius pollachius	Pollack	pol	0.19
Melanogrammus aeglefinus	Haddock	had	0.20
Nephrops norvegicus	Norway lobster	nep	0.20
Mullus surmuletus	Striped red mullet	mut	0.21
Spondyliosoma cantharus	Black seabream	sbb	0.22
Pleuronectes platessa	European plaice	ple	0.23
Scyliorhinus canicula	Lesser spotted dogfish	syc2	0.23
Argentina silus	Greater argentine	arg	0.23
Scopthalmus maximus	Turbot	tur	0.32
Chelidonichtys lucerna	Tub gurnard	gut	0.32
Merlangius merlangus	Whiting	whg	0.38
Scophthalmus rhombus	Brill	bll	0.38
Microstomus kitt	Lemon sole	lem	0.42
Engraulis encrasicolus	Anchovy	ane	0.44
Zeus faber	John Dory	jnd	0.47
Sardina pilchardus	European pilchard	sar	0.60
Clupea harengus	Herring	her	0.61
Ammodytes spp.	Sandeels	san	1.00

Given are the scientific and common names, a unique stock ID and the von Bertalanffy growth parameter k.

There are a plethora of approaches on how to analyse the results of an MSE, and this study focuses on the time series of stock metrics such as spawning stock biomass (SSB) and on summary statistics derived from stock metrics over the course of the projection period. To determine which of the OM parameters could explain the performance of the rfb rule for a specific stock, a penalised regression model (glmnet; Friedman et al., 2010) was deployed, because such a model allowed the inclusion of correlated parameters (a particular feature of the OMs) by imposing a penalty on them. In addition, penalised regression allows fitting the entire elastic-net regularisation path from lasso to ridge regression (Hoerl & Kennard, 1988; Tibshirani, 1996; Zou & Hastie, 2005), where a lasso regression rejects non-crucial parameters and a ridge regression retains all parameters but reduces their influence by penalising them, if necessary. Another approach used is to find patterns in resultant time series. Simple groupings might become apparent on visual inspection. A time series cluster analysis was employed because it provides an objective statistical approach to grouping the results into clusters with similar trajectories when no prior information about the clusters exists.

6.4 Methods

OMs were conditioned for 29 stocks, simulated based on a limited set of life-history parameters: allometric parameters for length-weight conversion, a and b, von Bertalanffy growth model parameters L_∞, k, and t_0 (von Bertalanffy, 1950), and age at 50% maturity a_{50}. Based on these data, using the FLR (Kell et al., 2007) package FLife, and closely following the approach of Jardim et al. (2015), age-structured OMs were created. Growth was modelled with the von Bertalanffy growth equation, recruitment by a Beverton-Holt stock recruit function with steepness $h = 0.75$ (for the default scenario), virgin SSB set to 1000 (units) for all stocks, the maximum age $a_{\max}$ and plus-group set as the age (rounded up) where the stock reached 95% of L_∞, maturity modelled with a sigmoid function centred on a_{50}, and fisheries selectivity modelled with a sigmoid function where the first age at full selectivity equalled a_{50}. Natural mortality M was length-dependent, following Gislason et al. (2010), but converted to age using the von Bertalanffy growth equation. Survey selectivity was modelled with a sigmoid function and the inflection point set to $0.1a_{\max}$, and the biomass index was derived by summing the survey catch biomass over all ages. Catch length frequencies were generated by applying a simulated inverse age-length key to the catch at age distribution. Full specifications, including equations, are described in Chapter 5.

Two fishing histories were created for all simulated stocks. Initially, the stocks were fished at $0.5F_{\mathrm{MSY}}$ for 75 years, and subsequently for another 25 years in a roller-coaster or a one-way fishing scenario (Figure 6.1). In the one-way scenario, the fishing mortality was increased exponentially from $0.5F_{\mathrm{MSY}}$ to $0.8F_{\mathrm{crash}}$ over 25 years, with F_{crash} defined as the lowest fishing mortality that causes the stock to collapse in equilibrium. In the roller-coaster scenario, the fishing mortality was increased from $0.5F_{\mathrm{MSY}}$ to 0.75_{crash}, kept at $0.75F_{\mathrm{crash}}$ for 5 years, and then reduced to F_{MSY} by the end of the 25 years. After both fishing histories, the stocks were severely depleted; however, in the one-way history, the stocks were at their lowest levels and declining, whereas in the roller-coaster history the stocks had started to recover. This exploitation state was then used as starting point for the MSE simulation.

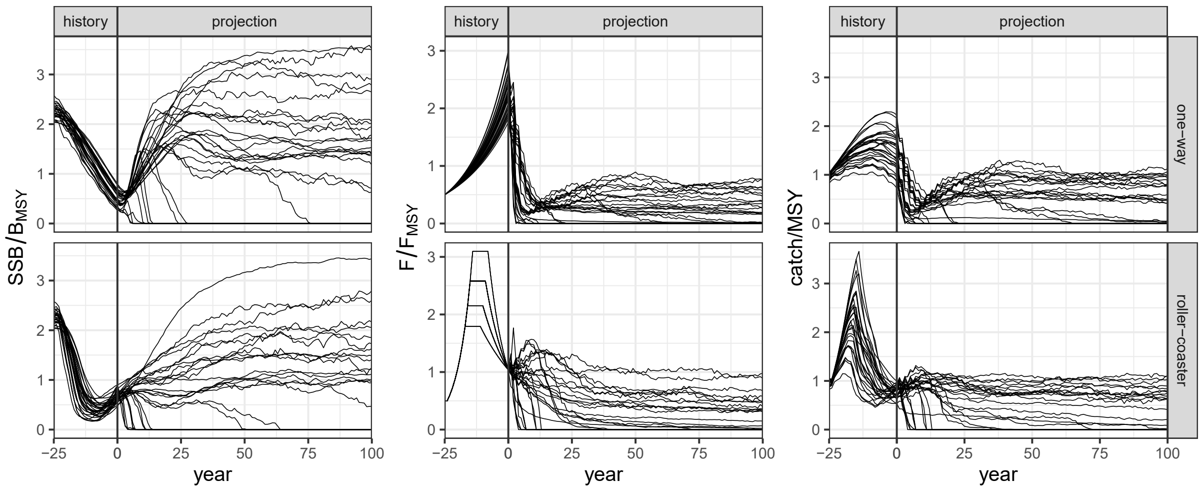

Figure 6.1: Median trajectories for SSB, mean fishing mortality, and catch relative to MSY reference points for the 29 simulated stocks when managed with the rfb rule. Shown are the historical fishing period ("history", years -25 to 0) and the results of subsequently applying the rfb rule (years 1 to 100). The top row shows the one-way fishing history and the bottom row the roller-coaster fishing history.

6.4.1 Catch rule

The main catch rule tested is the rfb rule which sets catch advice by multiplying recent catch with three factors corresponding to perceptions of stock characteristics based on catch and survey data [Equation (6.2)]. Component r corresponds to the trend in a biomass index and is based on the "2 over 3" rule [Equation (6.1)]:

$$r = \frac{\sum_{i=y-2}^{y-1} I_i/2}{\sum_{i=y-5}^{y-3} I_i/3}, \tag{6.3}$$

where I is the biomass index. Component f is a proxy for the ratio F_{MSY} divided by the current exploitation based on length data from the catch:

$$f = \frac{\bar{L}_{y-1}}{L_{F=M}}, \tag{6.4}$$

where $\bar{L}_{y-1}$ is the mean length in the catch above the length of first capture (L_c), weighted by catch numbers at length, with L_c defined as the first length class having at least 50% of the mode in the observed catch length frequency. The reference length $L_{F=M}$ is a proxy for the length at MSY proposed by Beverton and Holt (1957), under the assumption that $F = M$. Using the simplification that $M/k = 1.5$ the reference length can be calculated as (Jardim et al., 2015):

$$L_{F=M} = 0.75L_c + 0.25L_\infty. \tag{6.5}$$

Finally, component b of the rfb rule is a biomass safeguard protecting the stock when the biomass index drops below a threshold:

$$b = \min\left\{1, \frac{I_{y-1}}{I_{\mathrm{trigger}}}\right\}. \tag{6.6}$$

I_{trigger} was based on the lowest historical biomass index value I_{loss} and defined as $I_{\mathrm{trigger}} = 1.4I_{\mathrm{loss}}$.

6.4.2 Projection

The OM was projected forward for a period of 100 years. Errors were implemented with a log-normal distribution and included for the biomass index ($SD = 0.2$), recruitment ($SD = 0.6$), life-history parameter L_∞ ($SD = 0.1$), which is used both in the calculation of catch length frequencies and in the calculation of the length reference point $L_{F=M}$, catch numbers at length ($SD = 0.2$), and implementation of the advice into catch ($SD = 0.1$). Note that no additional uncertainty is included for L_c, which is already calculated from simulated observed data. The error distributions were set prior to running the simulation, and random number deviates were identical for all stocks. Based on these uncertainties, 500 replicates were created for each stock.

6.4.3 Modifications to the catch rule

Various modifications of the rfb rule were explored and are detailed in Table 6.2. One option tested was the addition of a multiplier x to the rfb rule:

$$A_{y+1} = C_{y-1}\ r\ f\ b\ x. \tag{6.7}$$

The components of the rfb rule are multiplied to calculate the advised catch. This means, conceptually, the multiplier x can be thought of as being part of component f, i.e. the multiplier adjusts the reference length:

$$f' = f\ x = \frac{\bar{L}_{y-1}}{L_{F=M}}\ x = \frac{\bar{L}_{y-1}}{L_{F=M}/x} = \frac{\bar{L}_{y-1}}{L'_{F=M}} \tag{6.8}$$

where f' is the component f adjusted by x and $L'_{F=M}$ is the reference length adjusted by x. The value of the x can be below or above 1; $x < 1$ increases the reference length and makes the rfb rule more precautionary, $x > 1$ decreases the reference length and makes the rule less precautionary. Ultimately this means that a multiplier $x < 1$ does not lead to a continuous decline in the advised catch over time but changes the target of the rfb rule.

In addition, the impact of including catch constraints was examined by including upper constraints (maximum allowed increase in catch advice compared to previous advice), lower constraints (maximum allowed decrease) and their combinations of upper and lower constraints.

By default, the management simulated here followed the ICES assessment cycle for data-limited stocks (ICES, 2012b, 2018a). This meant that the rfb rule was applied in an intermediate (assessment) year y based on data up to the previous year ($y-1$) and the TAC was set biennially for the following 2 years $y+1$ and $y+2$. The data used in the rfb rule were from the years up to the year before the intermediate year; i.e. $y-1$ for the catch data for components C_{y-1} and f, $y-1$ for the index for b, and years $y-5...y-1$ for r. The effect of time lags on management was explored by including more recent data and also setting the TAC annually (Table 6.2).

6.4.4 Sensitivity to operating model assumptions

A sensitivity analysis of the performance of the rfb rule to OM assumptions was conducted. This included investigations into steepness, recruitment variability, and observation uncertainties (see Table 6.2). Full details and results of this analysis are provided in Appendix B.

Table 6.2: Explored modifications of the catch rule and sensitivity analysis of operating model parameterisation on the performance of the catch rule.

Modification	Default value	Alternative values
Catch rule modifications		
Catch rule multiplier	1	0.5, 0.6, 0.7, 0.8, 0.85, 0.9, 0.95
Catch constraints (including combinations)		
Upper	∞	1.1, 1.15, 1.2, 1.25, 1.3, 1.5
Lower	0	0.5, 0.6, 0.7, 0.75, 0.8, 0.85, 0.9
Timing (relative to intermediate year y, including combinations)		
Biomass index	$y-1$	y, $y+1$
Recent catch	$y-1$	y
TAC interval (years)	2 (biennial)	1 (annual)
Parameter	**Default value**	**Alternative parameterisations**
Sensitivity analysis (explored in Appendix B)		
Steepness h		
Fixed	0.75	0.6, 0.9
Functional relationships	Constant	Linked to k, linked to L_{50}/L_{∞} (Wiff et al., 2018)
Borrowed values	0.75	Species specific h from Myers et al. (1999)
Uncertainty and variability		
Recruitment variability (SD)	0.6	0.3, 0.9
Biomass index uncertainty (SD)	0.2	0.4, 0.6
Length-frequency uncertainty (SD)	0.2	0.4, 0.6

6.4.5 Perfect information scenario

Finally, to check whether the rfb rule worked when all the information available to it was available without error, an additional scenario was run for all the simulated stocks and fishing histories. For these scenarios, only recruitment variability was implemented. The survey index was replaced with the SSB from the OM to remove the impact of survey selectivity, I_{trigger} was set to B_{trigger} which, in agreement with ICES data-limited guidelines (ICES, 2018b), was set to $0.5B_{\text{MSY}}$. This modification meant that the biomass threshold was set irrespective of the historical exploitation and was comparable for all stocks. The reference length for the f component of the rfb rule was defined as the equilibrium length obtained in the OM when fishing at F_{MSY}.

6.4.6 Performance of the catch rule

The performance of the rfb rule was assessed based on six performance statistics, computed over the entire 100-year projection period and 500 replicates:

i. catch/MSY: the median of the distribution of catch/MSY,

ii. collapse risk: risk of stock collapse, i.e. the proportion of the projected stock where the stock is $< 0.1\%$ of virgin SSB,

iii. B_{lim} risk: risk of the stock falling below B_{lim} [proportion of the projected stock where the stock is below B_{lim}, defined as the stock level where recruitment is at 70% of the recruitment achieved at virgin SSB, i.e. 16.3% of virgin SSB for all stocks, because they had the same value of steepness (h) for the Beverton-Holt stock recruitment relationship],

iv. ICV: the median of the distribution of inter-annual variability in catch, calculated as $|(C_y - C_{y-v})/C_{y-v}|$, where C_y is the catch for the year y in which a TAC has been set and v is the TAC period, e.g. $v = 2$ for a biennial TAC, and

v. SSB/B_{MSY} and F/F_{MSY} the median of the distribution of stock status (SSB and F relative to MSY reference points B_{MSY} and F_{MSY}, respectively).

Initial analyses revealed that, for some stocks and scenarios, the stocks collapsed, and catches were reduced to zero as a result. Depending on the stock productivity, some stocks subsequently recovered towards virgin biomass due to the zero catch. This behaviour was deemed inappropriate for further exploration of the performance as it implied a reduced risk. Consequently, when running the simulations, once a replicate of a scenario had collapsed, the stock level and catch in subsequent simulation years were both set to zero.

6.4.7 Penalised regression

Many of the life-history parameters (both primary parameters used to create stocks and parameters derived from the simulated stocks) are highly correlated. For example, natural mortality M, von Bertalanffy growth model parameter k, F_{MSY}, MSY, population growth rate g (at the limit of zero stock size), and conditional growth rate g_c (growth rate at MSY) had positive Pearson correlation coefficients $\rho \geq 0.92$ between each other, and k and L_∞ correlated negatively with $\rho = -0.70$.

Therefore, to determine which of the stock characteristics influenced the performance of the rfb rule, a penalised regression model was applied (glmnet; Friedman et al., 2010). A multi-response Gaussian model (Simon et al., 2013) was applied that selected the predictor variables that could explain all six performance statistics (catch/MSY, collapse risk, B_{lim} risk, ICV, SSB/B_{MSY} and F/F_{MSY}). First, only the primary input parameters were used as predictor variables: a, b (length-weight relationship), L_∞, k , t_0 (von Bertalanffy growth model parameters), and a_{50} (age at 50% maturity). Second, the analysis was repeated with additional derived parameters: α, β (Beverton-Holt stock recruitment model parameters), $spr0$ (spawning potential ratio), L_{opt} (mean length when the stock is at MSY level), g, g_c (population growth rates), M (natural mortality), M/k, F_{MSY}/M, and B_{MSY}/B_0 (B_{MSY} relative to virgin biomass, i.e. location of peak in production curve).

6.4.8 Clustering

A cluster analysis of the relative stock status SSB/B_{MSY} time series was conducted using the dynamic time warping technique (Berndt & Clifford, 1994; Aghabozorgi et al., 2015) as distance measure. Several clustering algorithms (partitional, fuzzy, hierarchical) were trialled. Partitional and fuzzy clustering imply stochasticity, because the results depend on the random location of where the algorithm starts. This proved unreliable for the cluster analysis presented here, because the results were unstable, and even iterating the analysis did not lead to stable clusters. Hierarchical clustering, on the other hand, does not rely on stochasticity for the formation of the clusters. In addition, once a hierarchical cluster analysis is conducted, the output can be visualised in a dendrogram and any arbitrary number of clusters can be pursued without having to rely on potentially biased cluster validity indices to select the optimum number of clusters.

6.4.9 Data and software

The simulations were conducted in R, a free software environment for statistical computing and graphics (R Core Team, 2020) and the MSE framework was based on the Fisheries Library in R (FLR; Kell et al., 2007) software suite and several of its R packages. The OMs were created from life-history parameters with FLR's FLife package (https://github.com/flr/FLife). The structure of the simulation framework followed the assessment for all (a4a) initiative on a standardised MSE framework jointly developed by Jardim et al. (2017). Initially, this chapter's work was coded in stand-alone scripts. Concurrently to the work of this study, the a4a MSE framework was formalised into an R package (Mosqueira & Jardim, 2020, https://github.com/flr/mse). This R package was then adapted during this PhD project in order to handle the data-limited situation of this chapter (https://github.com/shfischer/mse). The original scripts for the simulations were subsequently adapted for running in this R package without compromising reproducibility.

The full source code, input data and instructions on creating the OMs and running the MSE presented in this study are available from GitHub (https://git.io/JIidn).

6.5 Results

Figure 6.1 shows the median trajectories for the 29 simulated stocks when the rfb rule was implemented for the two fishing histories. In the one-way fishing history, 10 (anchovy, black seabream, brill, herring, John Dory, lemon sole, sandeels, European pilchard, tub gurnard, and whiting) out of the 29 stocks collapsed by the end of the 100-year simulation period. In the roller-coaster fishing history, two additional stocks (angler and pollack) collapsed. The remaining stocks survived and displayed stock-specific long-term oscillations. One stock, megrim, approached virgin SSB and the other stocks reached terminal biomass values between 12 and 74% of virgin SSB.

In general, the rfb rule was influenced most by component r representing the trend from the biomass index [Equation (6.3)]. Figure 6.2 shows the time series of the individual components for two example stocks (pollack and herring). This behaviour is likely because changes in the

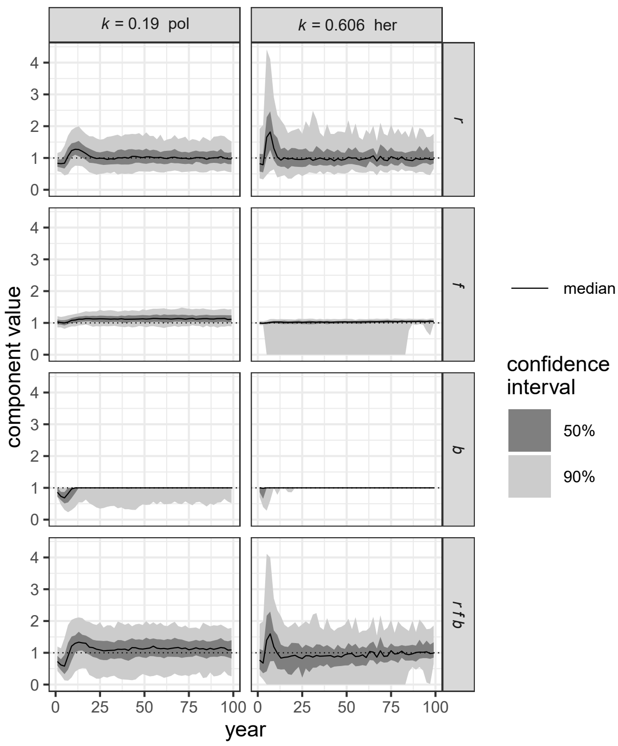

Figure 6.2: Components of the rfb rule (r, f, and b) and their product ($r\ f\ b$, which scales the recent catch) for two example stocks: herring (her) and pollack (pol). The higher the deviation of a component from one (up or down), the higher is its contribution in the rfb rule. Please note that for herring, the stock collapsed in most simulated replicates (the median SSB collapsed after 6 years) and in the distributions shown for the components, these collapsed replicates were excluded because they did not provide any stock status information.

stock size can be observed directly in the biomass index and have a relatively high magnitude. Changes in the mean catch length are commonly smaller and the time it can require until changes in the fishing pressure translate into the mean catch length can be longer. In the beginning, after the implementation of the rfb rule, component b [Equation (6.6)] acted and reduced the catch; however, this effect lasted only for a few years. Component f [Equations (6.4) and (6.5)] gave some information throughout the entire simulation period, but at a markedly lower magnitude compared to r. Figure 6.3 presents the SSB and the catch for the two stocks, including individual simulation replicates.

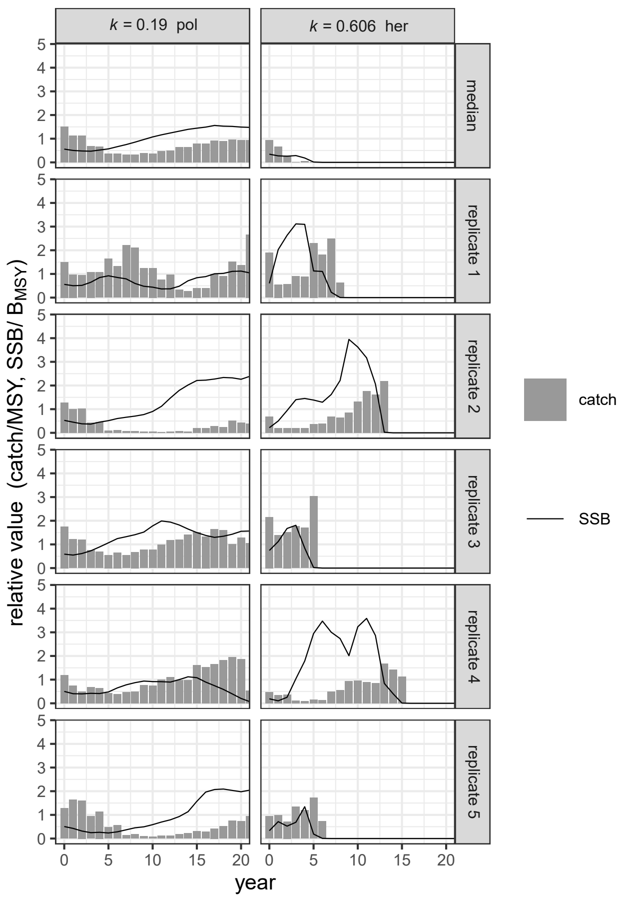

Figure 6.3: Catch and SSB for two stocks, pollack (pol) and herring (her), when managed with the rfb rule for the first 20 years of the projection period. Shown are the median of the 500 simulation replicates (first row) and 5 example replicates (subsequent rows).

6.5.1 Penalised regression

Performing a lasso regression with the primary input and the full parameter set (including derived parameters) both resulted in a model fit that selected solely the von Bertalanffy growth parameter k to explain the six performance statistics for the one-way fishing scenario (Figure

6.4). Allowing elastic-net regularisation in the penalised regression model led to minor improvements in the model fit (the mean squared error was reduced from 0.85 to 0.73) but came at the cost of adding complexity to the model by returning non-zero coefficients for all supplied input parameters. Consequently, k was selected as the single most important factor for the performance of the rfb rule for the simulated stocks. Higher values of k were linked to higher risks (both collapse risk and B_{lim} risk) and catch variability and lower or zero long-term catch, F/F_{MSY} and $\mathrm{SSB}/B_{\mathrm{MSY}}$. The results were similar for the roller-coaster scenario.

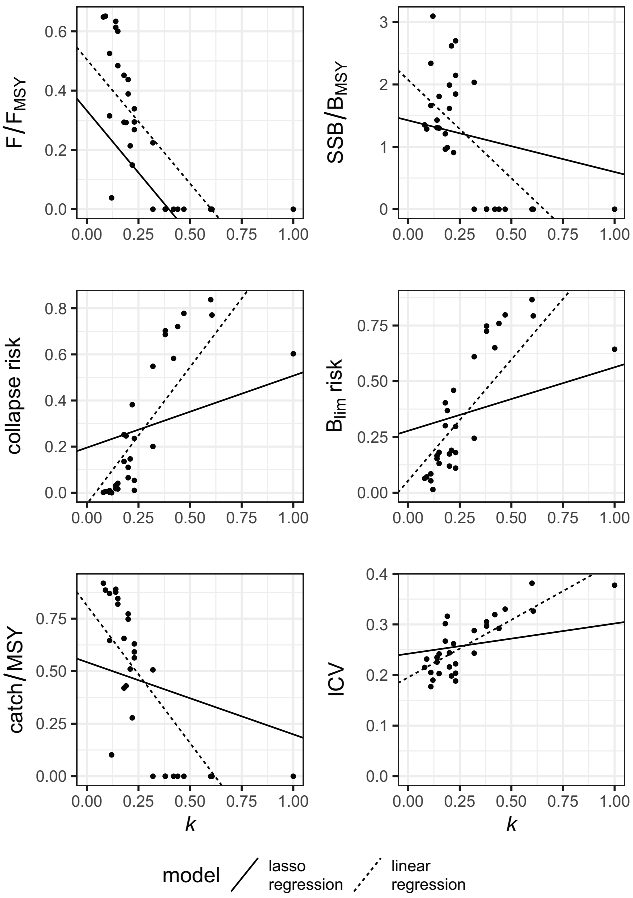

Figure 6.4: Six performance statistics vs. the von Bertalanffy growth model parameter k for the tested rfb rule and the one-way fishing history for all 29 stocks. The solid lines show the fit from the lasso regression model, and the dotted lines show a linear regression for each individual performance statistic.

6.5.2 Clustering

Clustering was performed on the time series of the annual medians of $\mathrm{SSB}/B_{\mathrm{MSY}}$ of the entire 100-year projection period for the 29 simulated stocks. Figure 6.5 shows the results from the hierarchical clustering for up to four clusters for the one-way fishing history. Hierarchical clustering does not compute centroids for the clusters; for plotting purposes (Figure 6.5b), centroids for the clusters were calculated post hoc as the annual average of the SSB/B_{MSY} values of all stocks within a cluster. If all stocks were kept in a single cluster, the centroid SSB/B_{MSY} trend showed a recovery after the start of the MSE simulation and equilibrated at a level slightly > 1. The first separation in the hierarchical cluster distinguished between two distinct patterns (second row in Figure 6.5b); the first cluster was composed of stocks that experienced early peaks and collapsed within ∼25 years, whereas the stocks in the second cluster survived (apart from one exception; black seabream). This split corresponds well to the von Bertalanffy k values for these stocks (Figure 6.5c). The first cluster (collapsed) is comprised of stocks with $k \geq 0.32$ year^{-1}. On the other hand, the stocks with lower k ($k \leq 0.32$ year^{-1}) survived. There is an overlap for the $k = 0.32$ year^{-1} stocks: one survived (turbot) and one collapsed (tub gurnard).

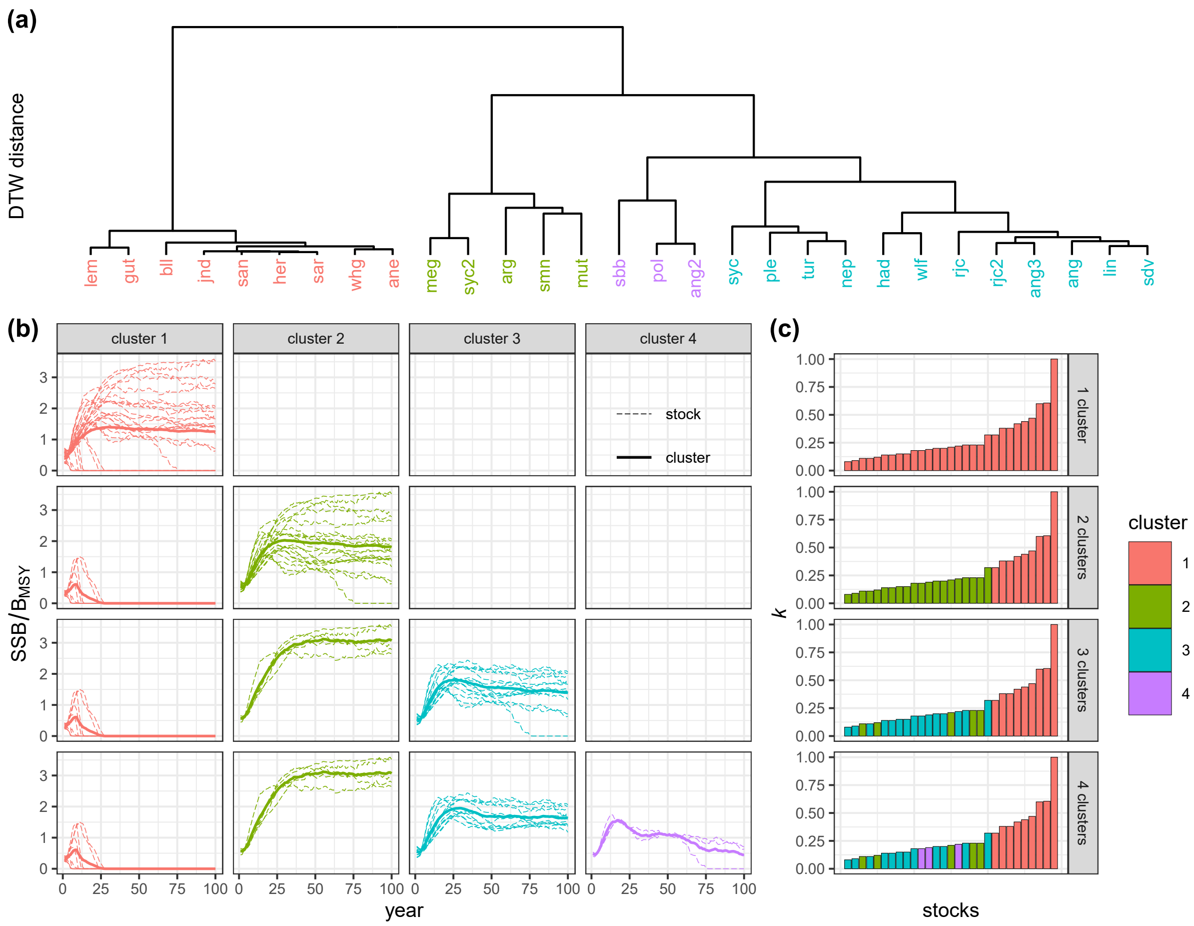

Figure 6.5: Results of the hierarchical clustering analysis of relative SSB for the one-way fishing history. (a) A dendrogram of the time series for the 29 simulated stocks, the names correspond to the stock IDs defined in Table 6.1. The y-axis corresponds to the dynamic type warping distance between the time series. (b) The median SSB/B_{MSY} times series for all stocks (dashed lines) and the centroids (solid bold line). Rows represent the number of clusters, and each column is one cluster. (c) von Bertalanffy growth model parameter k for all stocks, sorted in ascending order and colour-coded for the clusters shown in (b).

Following the dendrogram further, the next two splits occurred within the cluster of surviving stocks. First, there is a separation of stocks that stay $\sim 1.5B_{\mathrm{MSY}}$ in the long term and the ones that end up $\sim 3B_{\mathrm{MSY}}$ (third row of Figure 6.5b). Second, the stocks reaching levels $1.5B_{\mathrm{MSY}}$ are divided further into one cluster where the SSB converged at $\sim 2B_{\mathrm{MSY}}$ and one cluster where the SSB stays $\sim B_{\mathrm{MSY}}$ (fourth row of Figure 6.5b). In terms of k, these stocks overlap when there are four clusters and no clear distinction is evident. Moving further along the dendrogram, these clusters are divided further; however, clusters increasingly represent individual stocks instead of general trends, because stocks are singled out as the number of clusters grows. The clusters in Figure 6.5 are colour-coded, and this colour code is maintained throughout the study. Results in this figure are for the one-way trip fishing history, but results for the roller-coaster fishing history are almost identical when considering four clusters.

6.5.3 Modifications to the catch rule

Adding a multiplier [x in Equation (6.7)] of less than one to the rfb rule reduced the risk (both collapse risk and B_{lim} risk) for all stocks and for both fishing histories (Figure 6.6). This risk reduction was a result of higher terminal SSB values: the smaller the multiplier, the higher the SSB values, capped at the top at the virgin biomass level. For the stocks where the median SSB collapsed during the simulation period (cluster 1), adding the multiplier delayed this collapse, and by reducing the multiplier further, the collapse was avoided altogether. This behaviour of the SSB trajectory was stock specific. For example, in the default rfb rule, the median SSB of anchovy in the one-way fishing scenario reached zero 12 years after the start of the simulation and adding a multiplier of only 0.9 avoided this collapse. On the other hand, pilchard and John Dory collapsed in the roller-coaster fishing history after 5 years and this collapse could only be averted by implementing a multiplier ≤ 0.7.

The performance of the rfb rule for these cluster 1 stocks was highly sensitive to small changes in the multiplier. Once a threshold multiplier was reached, the long-term stock levels increased rapidly and overshot B_{MSY}, thereby foregoing catch. Stocks in cluster 2 were kept $\sim B_{\mathrm{MSY}}$ in the long term when the rfb rule was applied without a multiplier. Introducing the multiplier for these stocks reduced their risks but moved them above B_{MSY}. Stock levels for stocks from clusters 3 and 4 were shifted further above B_{MSY} when the multiplier was added. In the one-way fishing history, for 13 of the 29 stocks tested, adding the multiplier reduced the catch; this was also the case for 8 stocks in the roller-coaster fishing history. The maximum

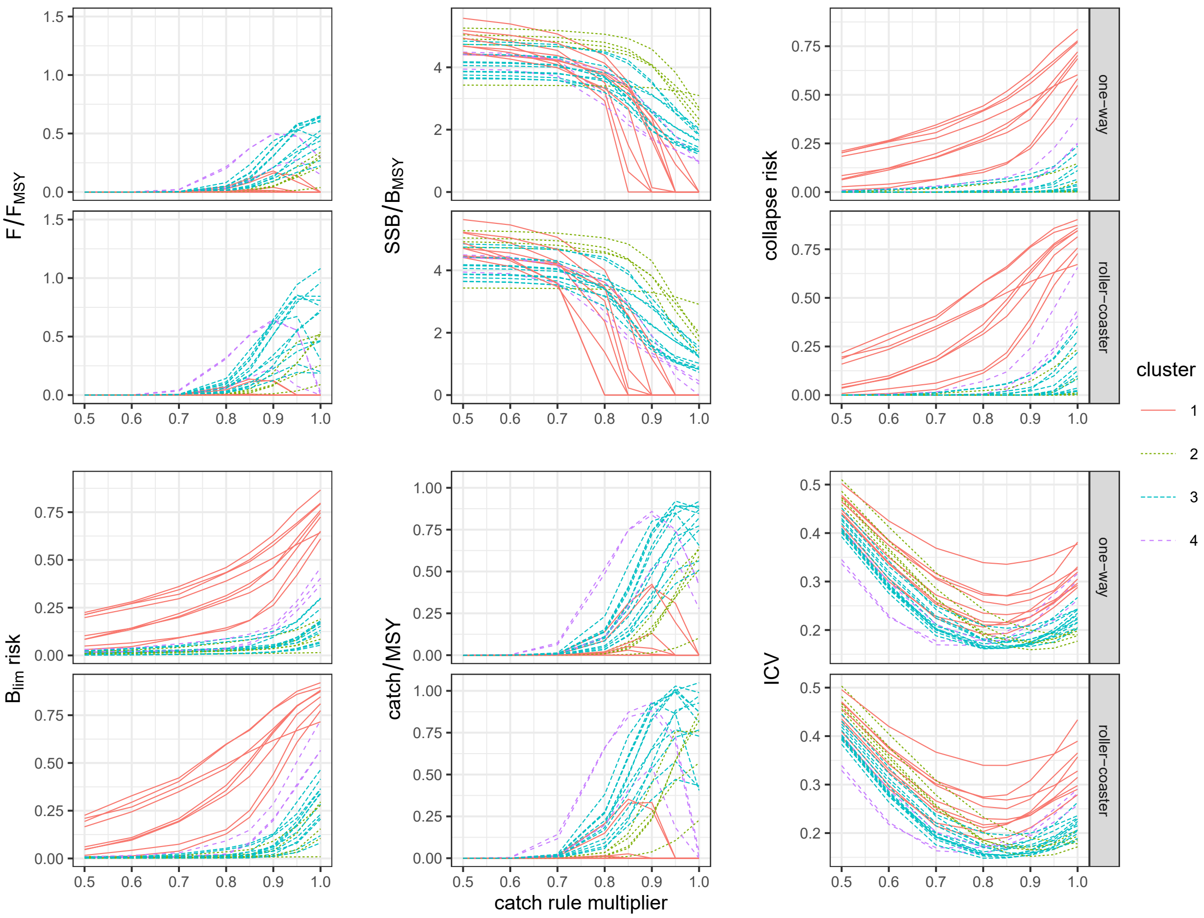

Figure 6.6: Effect of implementing a multiplier to the rfb rule on the six performance statistics for the 29 simulated stocks and both fishing histories. The clusters correspond to the ones defined in Figure 6.5.

catch for cluster 1 (collapsed) stocks occurred at multiplier levels between 0.7 and 0.9, but the peak was substantially below MSY. For the remaining stocks, the catch peaked at multipliers ≥ 0.9. When considering all stocks together, there does not seem to be a single multiplier that increases risk performance for all stocks without jeopardising catch for some.

Implementing an upper catch constraint reduced the risks for all stocks, and more restrictive constraints led to lower risks (Figure 6.7a). The upper constraint leading to the maximum catch was stock specific and occurred at constraints between 1.1 and no constraint. However, for most stocks, the catch is relatively stable for constraints ≥ 1.2 and this value seems to be a reasonable compromise between risk reduction and maximising catch. Including a lower constraint on the catch increased the risk of stock collapse and resulted in a subsequent reduction in catch. If the lower constraint was implemented in combination with an upper constraint, for some stocks, a small peak in catch was observed at lower constraint levels > 0 and < 1. Figure 6.7b shows the effect of including lower catch constraints on the performance of the rfb

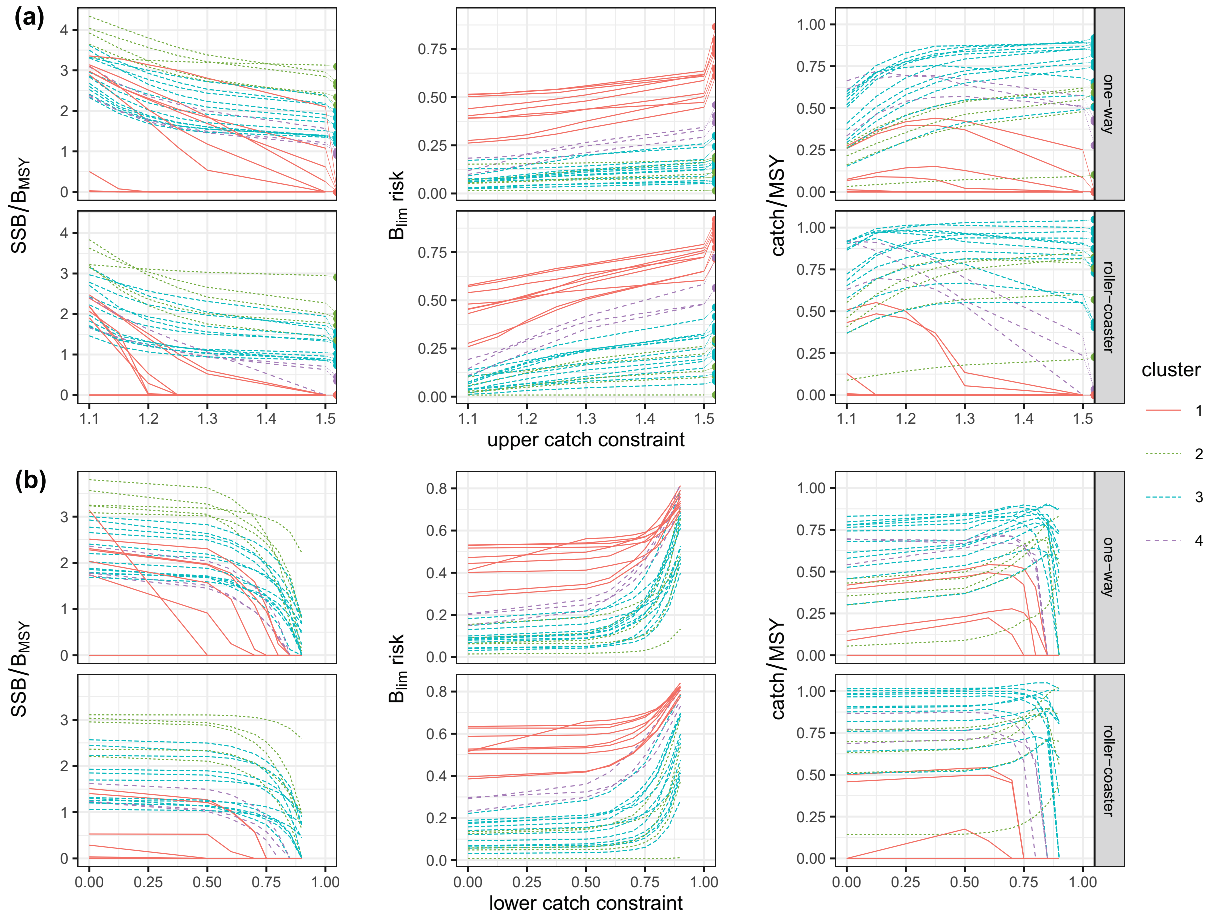

Figure 6.7: Effect of catch constraints on three performance statistics. (a) The effect of upper catch constraints without a lower constraint. The points above an upper catch constraint of 1.5, connected with thin lines, indicate the performance when no upper catch constraint was implemented. (b) The effect of lower catch constraints in combination with an upper catch constraint of 1.2. The clusters correspond to the ones defined in Figure 6.5.

rule in combination with an upper constraint of 1.2. More restrictive lower constraints (i.e. restricting catch reductions) caused a large increase in risks and a large decrease in catch, with this behaviour being particularly pronounced at constraint levels > 0.7. Below 0.7, the risks and catches were relatively stable.

For the stocks surviving the default implementation of the rfb rule ($k \leq 0.32$ year^{-1}), using more recent data and setting the TAC more frequently improved performance by reducing oscillations and reaching final biomass values earlier (Figure 6.8). The lowest fluctuations were observed when the TAC was set annually, the catch data provided up to the intermediate year, and the survey data up to the beginning of the advice year. The terminal biomass values were similar irrespective of the timing. One exception is black seabream (not shown), which collapsed when the rfb rule was implemented with default parameters, but all tested combinations resulted in stock levels just above B_{MSY}. Some of the high-k stocks (cluster 1) could be saved; however,

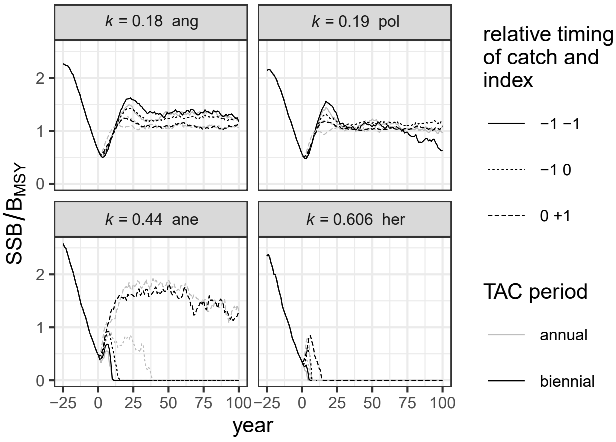

Figure 6.8: Effect of time lags for the data used in the rfb rule and periodicity of TAC setting (annual vs. biennial) for four example stocks (sorted by von Bertalanffy k) in the one-way fishing history. The timing is relative to the intermediate year (0); -1 refers to the year before the intermediate year and $+1$ refers to the year after the intermediate year. Relative timing is distinguished by line type, and TAC period by line shading.

three stocks (John Dory, pilchard, and herring) still collapsed even if the TAC was set annually and the most recent data were used.

6.5.4 Perfect information scenario

When the rfb rule was implemented with perfect information and knowledge (i.e. the SSB from the OM was used as the index and I_{trigger} set to $0.5B_{\text{MSY}}$ from the OM), the performance of the rfb rule was substantially improved for the low-to-medium-k stocks ($k \leq 0.32$ year^{-1}) and most converged towards B_{MSY}, indicating that the rfb rule did work under these unrealistically perfect conditions (Figure 6.9). Performance was not improved for the higher-k stocks from cluster 1. These stocks still collapsed early and only the highest-k stock, sandeel, showed a recovery to very high biomass levels, but this behaviour could be attributed to the stock being close to collapse, with catches reduced to very low levels, and consequently, the stock could recover with almost no fishing activity.

6.6 Discussion

This study simulation tested a simple catch rule (the rfb rule), making use of proxy MSY reference points for a range of data-limited fish stocks. The main result was that the performance of the rfb rule was stock specific and could broadly be linked to life-history characteristics, with

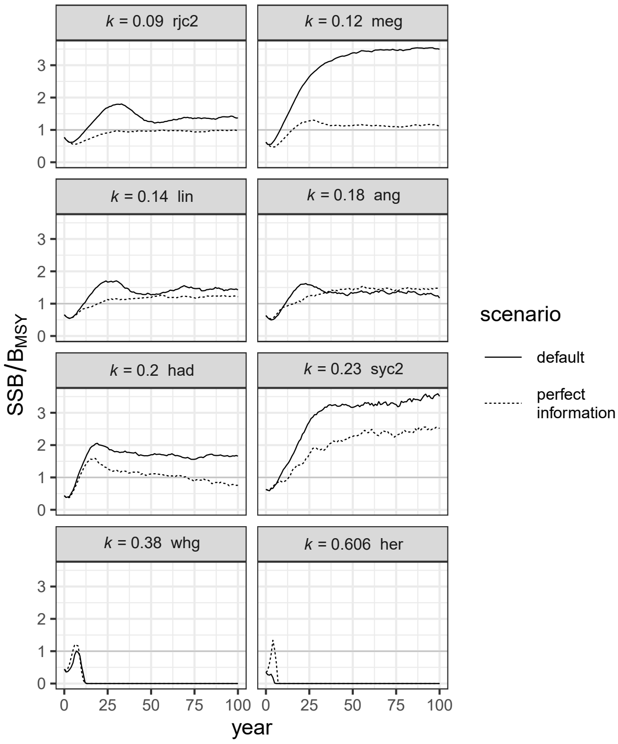

Figure 6.9: Application of the rfb rule with and without perfect information for eight example stocks (as defined in Table 6.1) for the one-way fishing history. In the perfect information scenario, no uncertainty, apart from recruitment variability, has been implemented; the survey is an exact representation of the SSB and $I_{\mathrm{trigger}} = 0.5B_{\mathrm{MSY}}$.

the von Bertalanffy growth parameter k emerging as the most important one from a penalised regression model.

It was clear from a visual inspection of the results that the response of stocks to the application of the rfb rule could be organised into different groups and, therefore, a time series clustering approach using dynamic time warping was adopted. The relative stock status SSB/B_{MSY} was selected as a time series index because it provided the overall best indicator of the performance of the rfb rule over time. Biomass was used in relative terms because the rfb rule's long-term target is MSY, and consequently, both undershooting (overfishing) and overshooting (losing yield through fishing below MSY) of B_{MSY} could be identified and was comparable across all simulated stocks. Both the clustering analysis and the penalised regression approach indicated that there is a clear relationship between the life histories of the simulated stocks and the performance of the rfb rule. The most important finding is the separation of the simulation trajectories into two groups based on the results of the cluster analysis: one where the stocks collapsed during the simulation and the other where the stocks survived and ended up at or above B_{MSY}. The split corresponded well to the von Bertalanffy growth parameter k and the rfb rule seemed to perform reasonably for stocks with $k < 0.32$ year^{-1} (species with slower individual growth), but very poorly for stocks with $k > 0.32$ year^{-1} (species with faster individual growth). The $k < 0.32$ year^{-1} stocks reached levels of between B_{MSY} and $3B_{\mathrm{MSY}}$, i.e. stock collapses were avoided in all but one case, but frequently there was a loss in yield compared to the yield achieved when fishing at F_{MSY}.

The result that the rfb rule performed worse for the more productive stocks (with higher k) compared to the less productive stocks (with lower k) might at first glance appear counter-intuitive. The performance of the rfb rule as measured by the summary statistics, however, is an emergent property of the interaction between the OM and the catch rule. The advised catch was mainly influenced by the r component of the rule (the trend in the relative index of abundance; Figure 6.2), and stocks with higher k are inherently more variable, which in turn leads to higher fluctuations in catch. When subjected to the rfb rule, the higher-k stocks collapsed early during the simulation. This behaviour can be attributed to an initial rapid recovery, which resulted in an increase in catch (Figure 6.3). Once the stocks started to decline again, however, the catch was not reduced quickly enough to avoid stock collapse. This undesirable feature is caused by the design of the rfb rule, which bases the newly advised catch on the previous catch and observed data with a time lag. Since the less productive stocks (those with low k) were also less variable, the rfb rule was sufficiently reactive to avoid stock collapse.

The threshold of $k = 0.32$ year^{-1} can likely be explained by the biology of the species. Species with lower individual growth ($k < 0.32$ year^{-1}) are long-lived, populations consist of many age classes, and are characterised by relatively low natural mortality. Examples of such species are elasmobranchs (e.g. thornback ray), deep sea species (e.g. redfish) and demersal flatfish (e.g. European plaice). Stocks with $k > 0.32$ year^{-1} exhibit faster individual growth (i.e. reach adult size faster), populations consist of fewer age classes, and are characterised by higher natural mortality. This means that the population dynamics of such species are more dynamic compared to slower-growing species and they are more impacted by changes in recruitment, e.g. through environmental influences. Examples are faster-growing flatfishes (e.g. brill), larger pelagic species (e.g. John Dory) and small pelagics (e.g. anchovy).

Previous studies have tested simple empirical data-limited catch rules with various simulated stocks (e.g. Jardim et al., 2015), or based OMs on knowledge from fully analytical stock assessments (e.g. Geromont & Butterworth, 2015a; Carruthers et al., 2016). In the simulation exercise of Carruthers et al. (2016), various data-limited methods were tested, but only three stocks (Pacific herring, Atlantic bluefin tuna, and Pacific canary rockfish) were simulated and, therefore, possible inferences from life histories were limited. Jardim et al. (2015) tested a simplified version of the rfb rule tested here, including only a single component at a time (either r using survey data or f using length-frequency data). The results from their simulation study are in agreement with the current work, showing a wide range of stock trajectories and yields often below MSY. The basis for the simulation of the stocks in Jardim et al. (2015) was averaged life-history parameters to generate a variety of life-history traits. The work presented here went one step further and used life-history parameters from real stock units; by doing so, it was possible to link the performance of the rfb rule back to the original life-history parameters.

Modifications to the rfb rule (multipliers, catch constraints, using more recent data) were able to improve its performance. However, the improvement was stock specific and a trade-off between yield and risk was evident. Although the application of the multiplier always reduced the risk, the stocks frequently ended up above B_{MSY} and the rfb rule was overly reactive to minor changes in the multiplier for higher-k stocks, not a good feature in a situation of high uncertainty. For stocks for which the rfb rule kept the stock at or above B_{MSY} in the long term, the multiplier moved the stock level further away from B_{MSY} and reduced yield. Stocks that collapsed when the default rfb rule was applied (the higher-k stocks) could be saved, but only at the cost of moving the stocks far above B_{MSY} and losing yield.

Regarding the catch constraint, an upper limit of 1.2 was deemed appropriate because the long-term yield hardly changed for most stocks if less restrictive constraints were implemented; furthermore, this value provides an important reduction in risk compared to the application of the rfb rule without any constraints. For this level of upper constraint, a lower constraint of 0.7 seemed to be a suitable choice because implementing more restrictive lower constraints would cause a large increase in risk and a drop in yield. Less restrictive lower constraints did not have much impact on either yield or risk.

As could be expected, more recent data did improve the performance of the rfb rule, mainly by reducing oscillations, but this approach did not prove successful for all high-k stocks.

Challenges remain for the catch rule tested here. For example, the components of the rfb rule make use of different commercial and scientific data and are designed to account for stock dynamics. However, if just one of the components of the rfb rules fails or produces very low (close to zero) or high values, it will inevitably overrule the other components and dominate the final catch advice; in such circumstances, the use of the catch constraints becomes important.

The analysis into the components of the catch rule showed that the rfb rule is mainly dominated by the trend in the index, frequently masking information from the other components. The biomass safeguard is important to recover the stock above a threshold, but depending on how this level is set, it may not be effective enough (e.g. if the threshold is set too low). The problem of dominant components of the rfb rule can be dealt with through variable weighting of the different components and is explored in subsequent chapters.

If there is perfect information available (catch data, survey index, mean length in the catch) and reference points were set correctly according to MSY, then the rfb rule performed well and approached the desired MSY target for low-to-medium-k stocks. The results from these perfect information scenarios showed the importance of setting reference points appropriately, because, for example, setting the index trigger value dependent on the fishing history based on the lowest ever observed value governed where the biomass ended up. The lower-k stocks were less depleted relative to B_{MSY} and, therefore, the trigger point in the b component of the rfb rule was higher, which in turn resulted in a higher terminal biomass when the stocks were subjected to the rfb rule. In a real-life application of the rfb rule to data-limited stocks, reference values are uncertain, possibly impeding the performance of the rule. The following two chapters (Chapters 7 and 8) explore more flexible formulations of the rfb rule, including changing the period used to derive the stock trend and weightings of the individual components of the rfb rule. Chapter 11 considers the application of the rfb rule to three case study stocks for which more data are available.

During this work, concerns were raised about the appropriateness of the OM assumptions. This study simulated data-limited stocks, and assumptions were needed due to a lack of information. However, extensive sensitivity tests of the results to OM assumptions have been conducted (Table 6.2) and are described in Appendix B. One assumption was to use a constant recruitment steepness of 0.75 in the recruitment model for all stocks. Steepness is notoriously difficult to estimate, particularly for data-limited stocks for which no analytical assessments exist. This issue was addressed by conducting additional sensitivity runs with different steepness levels (lower and higher), borrowing values from previous studies, and imposing relationships between steepness and life-history parameters. The results were generally insensitive to the steepness assumptions. The additional sensitivity tests on variability and uncertainty showed that the results of this study are largely robust and the conclusions valid irrespective of these model assumptions (see Appendix B).

The starting point for the simulations in this study represented highly depleted stocks and might be considered as a worst-case. This condition was used to examine whether the rfb rule was able to correctly identify the depletion and recover stocks. In addition, due to the long simulation period (100 years), all stocks moved away from their initial state during the simulation and this provided insight into whether a long-term equilibrium was reached. In the following chapters, the rfb rule is modified to explore if specific pre-defined management targets can be achieved. For this purpose, alternative fishing histories (e.g. starting from a less-depleted state) and the length of the projection are considered.

In nature, individual growth varies between individuals in the same population. The Rosa Lee phenomenon describes the effect that observed individual growth of fish can appear truncated because faster-growing individuals in a population are removed from the population at a younger age due to size-selective fishing (Lee, 1912; Kraak et al., 2019). In contrast, slower-growing individuals in the same population survive longer. This phenomenon can cause changes in the observed individual lengths of fish over time, e.g. when fishing pressure or selectivity changes. The stock dynamics in the present simulations are unaffected by this phenomenon because the operating models were age-structured and length data was only generated as auxiliary information for informing management procedures. Furthermore, growth was modelled deterministically, i.e. did not vary between individuals and fishery selectivity did not change over time. Future studies could consider the possible influence of the Rosa Lee phenomenon on management procedures such as the rfb rule as a robustness test, given that length data and length-based reference values are used. However, the impact might be minor because changes in growth could be detected in observations and lead to a periodic revision of length reference values to account for these changes. Kraak et al. (2019) recommend that the Rosa Lee phenomenon should be considered in simulations when fishery selectivity changes, which was not the case in the present study.

6.7 Conclusion

This chapter presented the first simulations of the rfb rule, an empirical management procedure suitable for data-limited fisheries management. These simulations were conducted using MSE and the generic OMs developed in the previous chapter. The results revealed that the management performance of the rfb rule depended on the life history characteristics of the fished species. There was a clear split between species with slower individual growth, for which the rfb rule delivered a reasonable management performance, whereas the performance was poor with high risks of stock depletion and collapse for species with faster individual growth. This is an indication that a one-size-fits-all approach is unlikely to work. The management performance could be improved by modifying the rfb rule; however, the results were stocks-specific. The following chapter will explore options to formalise measuring management performance and apply an optimisation procedure based on a genetic algorithm to improve fisheries management.

Chapter 7

Using a genetic algorithm to optimise a data-limited catch rule[1]

[1]This chapter is an adaptation of Fischer et al. (2021a). Contains public sector information licensed under the Open Government Licence v3.0 (http://www.nationalarchives.gov.uk/doc/open-government-licence/version/3/).

7.1 Foreword

The work presented in this chapter builds on the initial simulations testing of the empirical management procedure (the "rfb rule") in the previous chapter and aims to improve the management performance of the rule by developing an optimisation procedure. Preliminary results were presented at the ninth and tenth International Council for the Exploration of the Sea (ICES) Workshop on the Development of Quantitative Assessment Methodologies based on LIFE-history traits, exploitation characteristics, and other relevant parameters for data-limited stocks (ICES WKLIFE IX and X; ICES, 2019c, 2020a). Subsequently, additional analyses were undertaken, and the work was peer-reviewed and published in Fischer et al. (2021a):

> Fischer, S. H., De Oliveira, J. A. A., Mumford, J. D. & Kell, L. T. (2021a). Using a genetic algorithm to optimize a data-limited catch rule. *ICES Journal of Marine Science*, *78*(4), 1311–1323. https://doi.org/10.1093/icesjms/fsab018

The following sections in this chapter are an adaptation of this publication.

7.2 Abstract

Many data-limited fish stocks worldwide require management advice. Simple empirical management procedures have been used to manage data-limited fisheries but do not necessarily ensure compliance with maximum sustainable yield objectives and precautionary principles. Genetic algorithms are efficient optimisation procedures for which the objectives are formalised as a fitness function. This optimisation can be included when testing management procedures in a management strategy evaluation. This chapter explored the application of a genetic algorithm to an empirical catch rule (the "rfb rule") and found that this approach could substantially improve the performance of the catch rule. The optimised parameterisation and the magnitude of the improvement were dependent on the specific stock, stock status and definition of the fitness function. The genetic algorithm proved to be an efficient and automated method for tuning the catch rule and removed the need for manual intervention during the optimisation process. The approach could also be applied to other management procedures, case-specific tuning, and even data-rich stocks. Finally, a recommendation is made about the phasing out of the current generic ICES "2 over 3" advice rule in favour of case-specific catch rules of the form tested here, although neither work well for fast-growing stocks.

7.3 Introduction

The majority of the world's fish stocks are data-limited, and analytical stock assessments do not exist (Rosenberg et al., 2014). Nevertheless, fisheries scientists and managers are often requested by stakeholders to advise on fishing opportunities in order to ensure the sustainability of fisheries activities.

ICES provides advice on fishing opportunities for many fish stocks in the Northeast Atlantic. For this purpose, fish stocks are classified into six categories, depending on the availability of data and the applicability of assessment methods (ICES, 2012b, 2019a). Data-rich stocks fall into the highest category (category 1). For these stocks, analytical stock assessments offer quantitative information about stock metrics, and ICES provides advice based on a framework that includes considerations of the precautionary approach (Garcia, 1996) for biological risk and target fishing levels that are defined by reference points following the maximum sustainable yield (MSY) principle (ICES, 2019a). The lowest category is category 6 and includes data-poor bycatch stocks with negligible landings. In between are data-limited stocks, and for these, ICES bases its advice on a precautionary approach (ICES, 2012b).

ICES category 3 data-limited stocks are stocks for which survey-based assessments indicate trends in stock dynamics (ICES, 2012b). Even though some survey indices exist for these stocks, it is not always possible to apply simple stock assessment methods, such as biomass dynamic models or simplified integrated models (e.g. extended simple stock synthesis; Cope et al., 2015). This might be because of short time-series, conflicting signals from the catch, catch per unit effort, survey and length data, lack of contrast in these data, or model convergence issues. Management procedures based on empirical rules are an alternative and can sometimes perform at least as well as those based on analytical methods (Carruthers et al., 2014; Geromont & Butterworth, 2015b). For category 3 stocks, ICES typically applies a "2 over 3" rule to an index of abundance (the average of the last two values divided by the average of the three values preceding those) and has introduced MSY principles for stock status evaluations based on MSY proxy methods (ICES, 2018b). However, this approach considers solely the application of a precautionary buffer to reduce the catch advice based on the "2 over 3" rule in case of a non-favourable stock status and does not include any MSY targets. It is therefore not explicitly aligned towards MSY.

Fischer et al. (2020, see Chapter 6) deployed a management strategy evaluation (MSE; Smith, 1994; Punt et al., 2016) approach to simulation test an alternative catch rule that includes an MSY target, which is based on an empirical rule of the form:

$$A_{y+1} = C_{y-1}\ r\ f\ b. \tag{7.1}$$

This harvest control rule (the rfb rule) sets the catch advice for the following year (A_{y+1}) on the recently observed catch (C_{y-1}) multiplied by three components; a biomass trend r, an exploitation proxy f, and a biomass safeguard b. Component r represents the recent stock trend derived from a biomass index, f is calculated by comparing the recent mean length in the catch to a length-based proxy for F_{MSY}, and b reduces the catch when the biomass index falls below a threshold.

The rfb rule is currently being considered by ICES (ICES, 2017e, 2018c, 2019c) as a potential successor for assessing category 3 data-limited stocks. The simulations of Fischer et al. (2020, described in Chapter 6) showed that its performance is crucially dependent on the life history of the stock, and in particular on the von Bertalanffy growth parameter k. The rfb rule performed reasonably well for stocks with $k \leq 0.32$ year^{-1} (slower-growing species) by keeping these stocks at or above B_{MSY}, but very poorly for stocks with higher k (fast-growing and small pelagic stocks), resulting in increased risks of stock collapses in these cases.

In an MSE context, the term tuning describes the process of adjusting the control parameters of a management procedure to improve performance statistics for the purpose of meeting specific management objectives in a simulation (tRFMO, 2018). This concept has also been considered at the International Whaling Commission to adapt management procedures to balance management objectives such as risk, stock status, and aboriginal subsistence whaling needs (Givens et al., 1999). In the previous chapter, some attempts were made to improve the performance of the rfb rule by manually tuning the rule by the addition of multipliers (to change the target level) and catch constraints (to limit catch variability). The results showed that the rfb rule was mainly dominated by the stock trend (component r), whereas the remaining components had less influence on the newly advised catches. The logical course of action is to apply weights to the three components in order to reduce or increase their influence. The application of weights should not just be a process of adding arbitrary correction factors but implemented with consistent and logical rules. Trying to manually modify a single component of the rfb rule or a limited combination of components to improve performance might be feasible with a grid search; however, such a manual optimisation task is an onerous activity and decisions are potentially arbitrary. Givens et al. (1999) note that depending on the way optimisations and approximations are specified, outcomes might give preference to different approaches, e.g. by focusing only on specific management goals. If the components are going to be tuned on a case-specific basis and their interactions considered in a multi-dimensional search, then there are an almost infinite number of scenarios and potentially confounding results between parameters, which means traditional approaches are impractical.

In the absence of predefined and clearly articulated management objectives, the results of such a tuning exercise must be carefully examined, and this can easily lead to a time-consuming activity. For example, trade-offs between opposing objectives need to be considered, such as maximising catch and biomass or reducing depletion risk and catch variability. Moreover, trust is a crucial element and stakeholders will need to agree to the procedure and accept outputs and revisions in the light of new developments. Therefore, the application of an automated or semi-automated optimisation procedure without the need for manual intervention is desirable. For this approach, the objectives of the optimisation process must be precisely defined and be formalised as an objective function.

In this study, the use of a genetic algorithm as an optimisation method is explored. Genetic algorithms belong to the more general class of evolutionary algorithms which are inspired by the principles of biological evolution (Darwin, 1859) and can be used as an optimisation procedure. In a genetic algorithm, the functional behaviour of genetic operators is mimicked in order to create variability in a population, which is then subjected to selection in a competitive environment (Holland, 1992).

The genetic algorithm approach was already well developed in the 1970s but did not gain much attraction in the scientific community initially (Holland, 1992). However, with the development of faster and more advanced computers, its application became more feasible. To date, genetic algorithms have been applied to optimisation problems in various scientific fields, including the design of integrated circuits, communication networks, and stock market portfolios (Holland, 1992). In fisheries science, genetic algorithms have, for example, been applied to the optimisation of bioeconomic models (Mardle et al., 2000), or fitting stock-recruitment models (Chen et al., 2000) and growth functions (Taylor & Mildenberger, 2017).

Numerous other optimisation methods exist; however, not all of them are equally applicable to specific optimisation problems. The genetic algorithm approach was chosen because it is a flexible optimisation approach, allows the inclusion of computing-intensive fitness functions, and has been shown to perform well for various optimisations. It is also able to consider many possible solutions simultaneously within one generation, and it is, therefore, less prone to converging on local optima (Chen et al., 2000).

The genetic algorithm can be applied to the optimisation of management procedures that include harvest control rules such as the rfb rule. For a control rule to be optimised, there is a need for it to be adaptable. This adaptability can be achieved by making the existing components of the rule more flexible (e.g. by changing the definition of a component) or through the inclusion of additional parameters (e.g. weighting components or a multiplier) that can be used for tuning. An individual of the population in the genetic algorithm is defined by its genetic material (the genotype). In the context of a control rule, parameters could be considered as genes. All parameters together form the genotype of an individual. Such a genotype must be translated in order to obtain observable traits (the phenotype). This translation corresponds to running an MSE projection with the parameters of the control rule, and summary statistics could then characterise its phenotype.

Figure 7.1 illustrates the principles of a genetic algorithm. The initial population (the first generation) in the genetic algorithm consists of many individuals, each with a different set of parameters. This population would include the default parameterisation of the rule, as well as randomly chosen parameterisations. For the population to evolve, the fitness of each individual must be evaluated with a fitness function, e.g. by comparing summary statistics for predefined targets or thresholds. Prior to creating the second generation, natural selection is applied to the initial generation, and only the fittest individuals survive and form a reproductive population. This reproductive population is the basis for the next generation and their genes (control rule parameters) are passed on to the next generation; however, natural variability is introduced through two genetic operators: crossover and mutation. The individuals in the new generation are generated by combining the parameters of two parent-individuals (crossover), as well as introducing random changes to the parameters (mutation). Furthermore, an elitist strategy allows the survival of some of the individuals with the highest fitness values. Elitism is useful to ensure that the best performing parameterisations do not disappear, and that there is no deterioration in the performance over the generations. This process is then repeated for every subsequent generation until convergence criteria are reached, and the optimisation terminates.

In the present study, the application of the genetic algorithm to the optimisation problem of the data-limited catch rule from Equation (7.1) is explored. By doing so, the aim is to improve the performance of the generic catch rule, and, more generally, evaluate whether the approach can be used for faster-growing (higher-k) stocks for which the default catch rule parameterisation showed poor performance (Fischer et al., 2020, Chapter 6). Also, the results of this catch rule are compared to both its default and optimised settings, and to the current ICES "2 over 3" advice rule for ICES category 3 data-limited stocks.

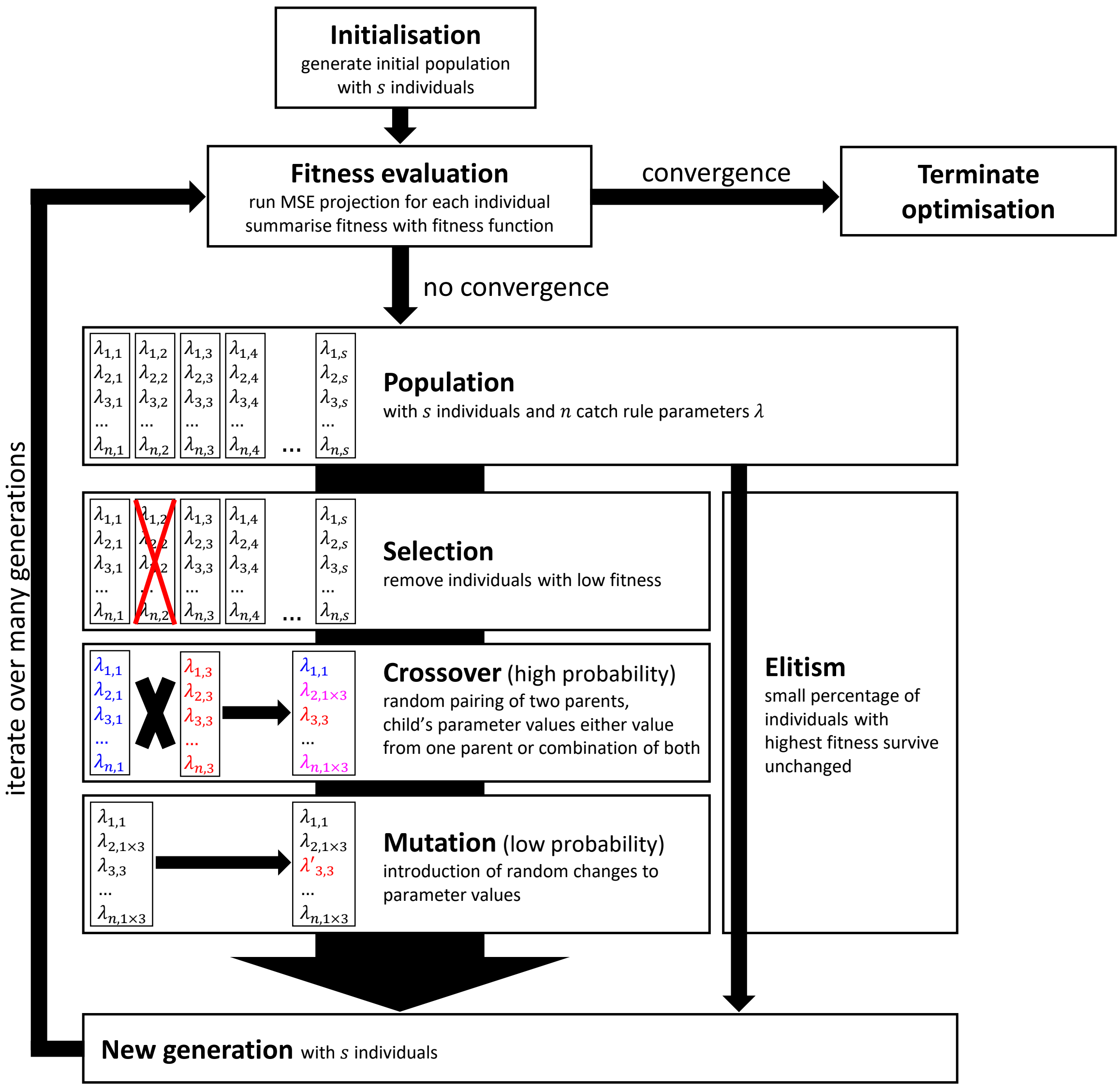

Figure 7.1: Conceptual representation of the genetic algorithm as an optimisation procedure for a management procedure.

7.4 Methods

7.4.1 Operating models

The 29 stocks defined in Chapter 5 (see Table 5.1) were used for the operating models and these covered a wide range of life-history traits. Age-structured operating models were created using the FLR (Kell et al., 2007) package FLife and were conditioned using life-history parameters. Most biological parameters (e.g. natural mortality) were linked to individual growth using life-history relations (e.g. Gislason et al., 2010). Full details of the operating model generation, assumptions, and structure are described in Chapter 5.

Two fishing histories were created starting from an unfished state for a period of 100 years ($y = -99, ..., 0$, enough for slower-growing stocks to respond to changes in exploitation) and with 500 simulation replicates (Figure 7.2). The approach of using alternative fishing histories

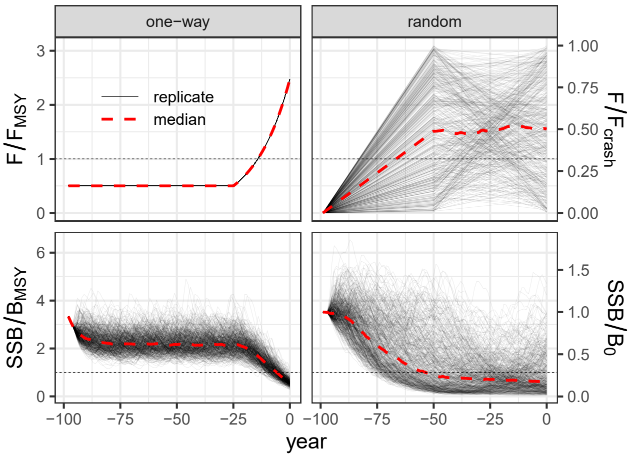

Figure 7.2: Comparison of the two fishing histories in the operating models, shown here for pollack. The black curves represent the 500 simulation replicates and the dashed horizontal lines indicate F_{MSY} and B_{MSY}.

was chosen to cover different possible exploitation patterns, including a pattern of overexploitation against which the default rfb rule was already tested, and as a way to compare the catch rule performance depending on the exploitation history. The baseline was the "one-way" fishing history from Chapter 6, in which stocks were fished for 75 years at $0.5F_{\text{MSY}}$, and then the fishing mortality was increased exponentially to $0.8F_{\text{crash}}$ over the following 25 years, where F_{crash} is defined as the lowest fishing mortality that causes the stock to collapse in equilibrium. This fishing history meant that the stocks were highly depleted and declining at the end of the fishing history. An alternative fishing history ("random") was generated with random fishing trajectories. This was achieved by defining the fishing mortality at three points in time; starting from an unfished state ($F_{y=-99} = 0$), setting fishing mortality after 50 and 100 years by drawing from independent uniform distributions [$F_{y=-50} \sim U(0, F_{\text{crash}})$ and $F_{y=0} \sim U(0, F_{\text{crash}})$], and using a simulation replicate-specific linear interpolation for the intermediate years. This random fishing history covered a wide range of fishing patterns, including increasing, stable, and decreasing fishing mortality, and combinations thereof (see Figure 7.2).

7.4.2 Management procedure

After the 100-year fishing history, a management procedure based on a modified version of the rfb rule defined in Equation (7.1) was implemented for 50 years (years 1 to 50). In order to make the rule more flexible, additional elements were introduced:

$$A_{y+1} = C_{y-1}\ r^{e_r}\ f^{e_f}\ b^{e_b}\ x. \tag{7.2}$$

The newly introduced exponents e_r, e_f, and e_b allowed the weighting of the three components r (biomass trend), f (exploitation proxy), and b (biomass safeguard). The multiplier x worked by modifying the advised catch, e.g. by increasing the catch (less precaution) or decreasing it (more precaution). The components of the rfb rule are multiplicative; consequently, the multiplier can be considered as working on the total catch advice or any individual component (e.g. by changing the target of the f-component). Setting $e_r = e_f = e_b = 1$ corresponds to the default rfb rule parameterisation without weighting, $e_j < 1$ reduces the influence of any component j (r, f or b) and makes it less reactive to the underlying data, with $e_j = 0$ removing it altogether, and $e_j > 1$ giving component j more weight by making it more reactive.

The inclusion of additional parameters such as the exponents was not considered in the previous Chapter 6 because the tuning of the rfb rule in Chapter 6 was conducted manually. Including many tuning parameters in manual tuning, e.g. with a factorial design, would have led to an unmanageable number of parameter combinations. In the present chapter, the tuning was conducted semi-automatically with a genetic algorithm, which allowed considering a much larger parameter space.

The r component reflects the trend in a biomass index time series and defaults to the average of the last two years' values divided by the average of the three preceding years' values, which corresponds to the current implementation of the "2 over 3" rule within ICES (ICES, 2012b). Component r was adapted so that it corresponded to an average of n_1 years divided by n_2 years of the biomass index (I) and the most recent year was defined as an offset n_0 to the intermediate (assessment) year y:

$$r = \frac{\sum_{i=y-n_0-n_1+1}^{y-n_0}(I_i/n_1)}{\sum_{i=y-n_0-n_1-n_2+1}^{y-n_0-n_1}(I_i/n_2)} \tag{7.3}$$

Components f and b were kept unchanged:

$$f = \frac{\bar{L}_{y-1}}{L_{F=M}}, \tag{7.4}$$

where $\bar{L}_{y-1}$ is the mean catch length above the length of first capture and $L_{F=M}$ a theoretical MSY reference length assuming $M/k = 1.5$ and $F = M$ based on Beverton and Holt (1957) and proposed by Jardim et al. (2015); and

$$b = \min\left\{1, \frac{I_{y-n_0}}{I_{\text{trigger}}}\right\}, \tag{7.5}$$

with $I_{\text{trigger}} = 1.4I_{\text{loss}}$, where I_{loss} is the lowest observed biomass index value in the historical fishing period. This relationship is an analogy to the rationale for ICES data-rich stocks, where, in the absence of better knowledge, a trigger biomass level (used as the breakpoint of a hockey-stick harvest control rule) can be set relative to a biomass limit reference point, which corresponds to the lowest observed biomass (ICES, 2017b, 2017f).

The final parameter of this flexible rfb rule was the frequency of advice (v), which defines the number of years the catch advice is kept constant before applying the rule again. The default was $v = 2$ years, i.e. biennial advice as is standard for category 3 data-limited stocks within ICES (ICES, 2012b, 2018a).

Errors were assumed to be log-normal, and observation uncertainty was applied on top of the age-aggregated biomass and length indices with $SD = 0.2$. Variability was implemented for recruitment, assuming a Beverton-Holt stock-recruitment model with $\sigma_R = 0.6$, a typical value within the range of values considered in other studies (e.g. Carruthers et al., 2014). The generation of the operating models and the formulation and quantification of uncertainty were explored in detail previously, and considered appropriate (see Chapter 5 and Appendix B). Recruitment variability and random observation errors were compiled prior to running the MSE and were identical for all stocks and runs; therefore, the results of a projection with a specific catch rule parameterisation were fully reproducible and comparable.

7.4.3 Summary statistics

Five summary statistics were selected to evaluate the performance of the rfb rule, which were computed over the entire 50-year projection period and all 500 simulation replicates. These were the medians of SSB/B_{MSY}, F/F_{MSY}, Catch/MSY and ICV (inter-annual catch variability, defined as $|(C_y - C_{y-v})/C_{y-v}|$, where C_y is the catch for the year y and v the frequency of advice, e.g. $v = 2$ for a biennial advice) and the B_{lim} risk (defined as the number of times SSB is below B_{lim} over all years and replicates, expressed as a proportion, with B_{lim} defined as the SSB where recruitment is impaired by 30%; see Fischer et al. (2020, Chapter 6) for detailed descriptions of these metrics).

7.4.4 Optimisation procedure

The rfb rule was optimised by altering parameters of the rfb rule with a genetic algorithm as an optimisation procedure towards meeting management objectives defined with a fitness function (described below). The eight parameters of the rfb rule (n_0, n_1, n_2, e_r, e_f, e_b, v, x) described above were included in the optimisation procedure, and a specific set of these eight parameters was seen as one individual in one generation of the algorithm. The population size was set to 100, i.e. in every generation, 100 parameter sets were simulated. The first generation contained rfb rule parameter suggestions, which included (i) the default rfb rule, (ii) the default rfb rule with an annual catch advice (i.e. $v = 1$), (iii) using the most recent data without lags (i.e. $n_0 = 0$), (iv) constant catch, and (v) combinations where one or more of the rfb rule components were turned off (i.e. $e_j = 0$ for one or more components, j), and comprised a total of 35 suggestions (see Table C.1 in Appendix C). The remaining 65 individuals of the first generation were created randomly.

The simulation for each individual included running a full-feedback MSE projection over the 50-year projection period and 500 replicates. Subsequently, the fitness of the 100 individuals was evaluated against a predefined fitness function. The fitness function, ϕ, summarises the output of one MSE projection and assigns a numerical value to its fitness. The summary statistics defined above were used as the basis for the fitness function definition. The rfb rule investigated here is designed to provide management in compliance with MSY. Therefore, the deviation of SSB, F, and catch from their MSY reference point can be used:

$$\phi_{\text{SSB}} = -\left|\frac{\text{SSB}}{B_{\text{MSY}}} - 1\right|, \tag{7.6}$$

$$\phi_{F} = -\left|\frac{F}{F_{\text{MSY}}} - 1\right| \text{ and} \tag{7.7}$$

$$\phi_{\text{Catch}} = -\left|\frac{\text{Catch}}{\text{MSY}} - 1\right|. \tag{7.8}$$

Absolute values are used here because both an under and overshooting of the MSY reference points is considered unfavourable. The remaining two summary statistics can be used similarly because both risk and ICV should be reduced:

$$\phi_{\text{risk}} = -\ P_{B_{\text{lim}}},\ \text{and} \tag{7.9}$$

$$\phi_{\text{ICV}} = -\ \text{ICV}. \tag{7.10}$$

SSB/B_{MSY}, F/F_{MSY}, Catch/MSY, and ICV in Equations (7.6), (7.7), (7.8), and (7.10) are, as defined above, the medians over the 50 years and 500 replicates per simulation, i.e. one value per simulation. B_{lim} risk $P_{B_{\text{lim}}}$ in Equation (7.9) is a single value per simulation.

The genetic algorithm worked by evaluating the fitness function, and the optimisation procedure progressed by maximising the value of this fitness function. In this case, the summary statistics used in the fitness function indicated better performance when their absolute values were smaller, i.e. a smaller deviation from their target. To account for this, their absolute values were made negative so that the maximisation deployed in the optimisation procedure aimed at increasing values for the fitness evaluations.

The final fitness function could then be any one of the Equations (7.6-7.10) or the sum of an arbitrary combination thereof. Several fitness functions were explored, and the default fitness function used was:

$$\phi_{\text{SSB+Catch+risk+ICV}} = \phi_{\text{SSB}} + \phi_{\text{Catch}} + \phi_{\text{risk}} + \phi_{\text{ICV}}. \tag{7.11}$$

In this fitness function, ϕ_{SSB} penalises deviations up and down from B_{MSY} equally but overshooting of B_{MSY} might be considered less unfavourable than undershooting it. However,

B_{lim} risk risk increases with lower SSB, and therefore, ϕ_{risk} penalises lower SSB. Furthermore, both overshooting and undershooting B_{MSY} will likely reduce catch below MSY because the stock becomes less productive, which is then picked up by ϕ_{Catch}.

After running the 100 MSE projections (each one corresponding to an individual) in one generation of the genetic algorithm and calculating the fitness of each individual, natural selection was applied to generate the reproductive population (Figure 7.1). The probability of selecting an individual was proportional to its fitness. In the creation of the next generation, natural variability was applied to the parameters. Individuals were randomly grouped into reproductive pairs. In these pairs, crossover occurred with a probability of $p = 0.8$ and meant that an offspring individual with eight parameters was generated as a combination of the parameters of two parent individuals. Mutation introduced random changes to the parameters by drawing from a uniform distribution and had a probability of $p = 0.1$. Elitism was set to 5%, i.e. within each generation, the individuals were ranked by fitness and the top 5% were passed into the next generation without changes. This process was repeated over many generations. A termination occurred if either (i) a maximum of 100 generations was reached or (ii) due to stationarity if no improvement in the fitness was observed within 10 consecutive generations. The genetic algorithm was run with the R package GA (Scrucca, 2013).

7.4.5 Current ICES management

The generic advice rule for category 3 data-limited stocks, as currently applied by ICES (2012b, 2019a), was simulated. This served as a benchmark against which the new rfb rule (and its optimised parameterisations) could be compared, and also offered insights into the performance of the current rule. The catch advice is biennial and based on the "2 over 3" rule (ICES, 2012b), which is essentially Equation (7.2) where C_{y-1} is set to the previously advised catch A_{y-1}, r is the default of Equation (7.3) with $n_0 = 1$, $n_1 = 2$, and $n_2 = 3$, the weights are set as follows: $e_r = 1$, $e_f = 0$, $e_b = 0$, the multiplier set to $x = 1$, and a precautionary buffer (b_{PA}) is introduced, i.e.

$$A_{y+1} = A_{y-1} \, \frac{\sum_{i=y-2}^{y-1}(I_i/2)}{\sum_{i=y-5}^{y-3}(I_i/3)} \, b_{\mathrm{PA}}. \tag{7.12}$$

In addition to that, an uncertainty cap limits the change in the catch advice to no more than 20%. The precautionary buffer reduces the catch advice if the stock is estimated to be in an unfavourable condition based on a comparison with proxy reference points estimated, e.g. by the surplus production model in continuous time (SPiCT; Pedersen & Berg, 2017) or length-based analyses. In the current ICES system, if such an assessment exists, the results are either used solely for informing on the stock status, or the "2 over 3" rule is applied on the biomass estimates from this assessment. Stock status is evaluated as positive if both $F \leq F_{\mathrm{MSY}}$ and $SSB \geq 0.5B_{\mathrm{MSY}}$, and negative if either or both conditions are not met (ICES, 2019a). If the status is negative, the catch advice is reduced by 20%; however, once the buffer is applied, it can only be considered again three years later. This parameterisation of the precautionary buffer is based on an MSE evaluation conducted by ICES (2017d) in which various sizes and intervals for the application of the precautionary buffer were tested depending on the stock status evaluated by the SPiCT assessments. This evaluation was conducted for 12 fish stocks and three initial exploitation levels ($0.5F_{\mathrm{MSY}}$, F_{MSY}, $2F_{\mathrm{MSY}}$), and a total of 36 million SPiCT assessments were run.

In the present study, the stock status evaluation was approximated based on the pooled sensitivity of these SPiCT assessments run by ICES (2017d). This yielded a true positive rate of 0.99 (detection of a positive stock status, as defined above, by the model when the true state in the operating model was positive) and a true negative rate of 0.42 (detection of a negative stock status by the model when the true state in the operating model was negative). The stock status approximation was implemented here by extracting the stock status from the operating model and adding uncertainty to this evaluation by drawing from a binomial distribution $B(1,\ p)$, where p is the success rate (0.99 for positive and 0.42 for negative stock status), independently for each simulation replicate and year. This approach was a simple approximation appropriate for the analyses here; however, it has the caveat that the identification of correct stock status by SPiCT was assumed to be a random process defined by the success rate, irrespective of other possible factors influencing performance. More complex model approximations could be considered in future analyses.

7.4.6 Scenarios

The scenarios explored were:

1. **Fitness function explorations**. Pollack (pol, *Pollachius pollachius*) was chosen as a typical example stock ($k = 0.19$ year^{-1}, a medium value within the range for which the rfb rule performed reasonably; Fischer et al., 2020, Chapter 6) to test the influence of different formulations of the fitness function and fishing histories.

2. **Catch advice interval**. The impact of the interval for which the catch advice is set was explored for the example pollack stock.

3. **Stock-specific optimisation**. The genetic algorithm was applied independently to all 29 stocks using the fitness function formulation selected in the first step in order to test the approach for different life histories.

4. **Stock groups**. The stocks were split into three groups using their von Bertalanffy k value (low: $0.08 \leq k \leq 0.19$; medium: $0.20 \leq k \leq 0.32$; high: $0.32 \leq k \leq 1$; unit for k: year^{-1}), based on the results of ICES (2018c) and Fischer et al. (2020, Chapter 6). Here, the stocks within a group were combined, and identical catch rule parameters applied and projected forward simultaneously. The fitness function was defined as the sum of the fitness values per stock. This scenario was used to explore the behaviour of the optimisation procedure when applied to a group of life histories, e.g. fast-growing compared to long-lived species, and to test whether a generic catch rule parameterisation could be applied. [Note: there was an overlap at $k = 0.32\ \text{year}^{-1}$ between the medium and high groups because turbot (tur, *Scophthalmus maximus*) belonged to the group for which the rfb rule worked, whereas it did not work for tub gurnard (gut, *Chelidonichthys lucerna*).]

5. **Current ICES rule**. The performance of the rfb rule and its optimised parameterisations were compared to the ICES "2 over 3" advice rule for category 3 data-limited stocks as a direct comparison of the new rule with the currently applied advice rule.

7.4.7 Data and software

The MSE framework was based on the Fisheries Library in R (FLR; Kell et al., 2007) software suite and several of its R packages. The MSE framework was based on FLR's mse package, as adapted for data-limited situations in the previous chapter. The MSE modules were based on the methods developed for the previous chapter but adapted to allow more flexible control rules, and streamlined for high-performance computing. The results of this study are fully reproducible and input data, software code, and summarised results as presented in this chapter were made open source and are available from GitHub at https://git.io/JkllU.

7.5 Results

7.5.1 Fitness function explorations

For the fitness function explorations with pollack, the genetic algorithm terminated after 16 to 27 generations (well before the 100-generation cut-off), depending on the fitness function definition and fishing history. The optimised rfb rule parameters depended on the specific fitness function (Table 7.1). For five of the six runs, the "2 over 3" ratio of the biomass index was kept, whereas the offset between the last biomass index year and the intermediate year was always removed ($n_0 = 0$). In general, the weighting of component r of the rfb rule did not change substantially; however, components f and b were down-weighted, and the advice interval v and the multiplier x remained at or around their default values.

Table 7.1: Default and optimised catch rule parameters of the rfb rule. Shown are the results for the fitness function explorations with the pollack stock, the stock-specific optimisation for all 29 stocks, and the optimisation where stocks are split into three groups based on k. See Equations (7.2) and (7.3) for definitions of the parameters.

operating model			**genetic algorithm**			**catch rule parameters**							
fishing history	**stock**	k [year^{-1}]	**fitness function** ϕ	**generations**	**fitness improvement[%]**	n_0	n_1	n_2	e_r	e_f	e_b	v	x
default parameters													
one-way						1	2	3	1	1	1	2	1
random						1	2	3	1	1	1	2	1
fitness function explorations													
one-way	pol	0.19	ϕ_{SSB}	27	100	0	2	3	1.2	0.7	0.8	3	1.06
one-way	pol	0.19	ϕ_{Catch}	19	100	0	2	3	1.0	0.4	0.4	2	1.00
one-way	pol	0.19	$\phi_{\text{SSB+risk+ICV}}$	16	48	0	2	3	1.0	0.5	0.5	2	1.03
one-way	pol	0.19	$\phi_{\text{SSB+Catch+risk+ICV}}$	18	64	0	2	3	0.9	0.4	0.5	2	1.03
one-way	pol	0.19	$\phi_{\text{SSB+F+Catch+risk+ICV}}$	26	72	0	2	2	1.1	0.4	0.3	2	1.01
random	pol	0.19	$\phi_{\text{SSB+Catch+risk+ICV}}$	26	57	0	2	3	0.7	0.3	0.4	2	1.02
stock specific optimisation													
one-way	ang3	0.08	$\phi_{\text{SSB+Catch+risk+ICV}}$	25	70	0	3	3	1.3	0.4	0.7	3	1.06
one-way	rjc2	0.09	$\phi_{\text{SSB+Catch+risk+ICV}}$	23	66	0	3	4	1.2	0.7	0.6	3	1.02
one-way	smn	0.11	$\phi_{\text{SSB+Catch+risk+ICV}}$	21	71	0	2	3	0.8	0.2	0.3	2	1.02
one-way	wlf	0.11	$\phi_{\text{SSB+Catch+risk+ICV}}$	23	83	0	2	3	1.0	0.5	0.3	2	1.07
one-way	meg	0.12	$\phi_{\text{SSB+Catch+risk+ICV}}$	24	89	0	2	3	1.0	0.4	0.7	2	1.24
one-way	lin	0.14	$\phi_{\text{SSB+Catch+risk+ICV}}$	23	60	0	3	3	1.2	0.6	0.5	3	1.01
one-way	rjc	0.14	$\phi_{\text{SSB+Catch+risk+ICV}}$	35	60	0	2	3	1.1	0.6	0.4	2	1.00
one-way	syc	0.15	$\phi_{\text{SSB+Catch+risk+ICV}}$	34	65	0	3	3	0.9	0.3	0.3	2	1.01
one-way	sdv	0.15	$\phi_{\text{SSB+Catch+risk+ICV}}$	14	62	1	2	3	1.0	0.1	0.1	2	0.98
one-way	ang	0.18	$\phi_{\text{SSB+Catch+risk+ICV}}$	19	57	0	2	3	0.9	0.3	0.3	2	0.99
one-way	ang2	0.18	$\phi_{\text{SSB+Catch+risk+ICV}}$	24	57	0	2	3	0.9	0.5	0.6	2	1.02
one-way	pol	0.19	$\phi_{\text{SSB+Catch+risk+ICV}}$	18	64	0	2	3	0.9	0.4	0.5	2	1.03
one-way	had	0.20	$\phi_{\text{SSB+Catch+risk+ICV}}$	35	77	0	2	3	0.9	0.3	0.8	2	1.08
one-way	nep	0.20	$\phi_{\text{SSB+Catch+risk+ICV}}$	11	76	1	2	3	1.0	0.0	0.3	1	1.00
one-way	mut	0.21	$\phi_{\text{SSB+Catch+risk+ICV}}$	20	75	0	2	3	0.8	0.4	0.6	2	1.10
one-way	sbb	0.22	$\phi_{\text{SSB+Catch+risk+ICV}}$	21	59	0	2	2	0.9	0.5	0.7	2	1.06
one-way	ple	0.23	$\phi_{\text{SSB+Catch+risk+ICV}}$	28	75	0	2	2	0.9	0.4	0.4	2	1.07
one-way	syc2	0.23	$\phi_{\text{SSB+Catch+risk+ICV}}$	30	68	1	2	3	1.0	0.2	0.2	2	1.01
one-way	arg	0.23	$\phi_{\text{SSB+Catch+risk+ICV}}$	14	64	0	2	3	0.9	0.2	0.2	2	1.00
one-way	tur	0.32	$\phi_{\text{SSB+Catch+risk+ICV}}$	32	75	0	2	2	0.9	0.4	0.4	2	1.09
one-way	gut	0.32	$\phi_{\text{SSB+Catch+risk+ICV}}$	22	51	0	2	2	0.8	0.3	0.6	2	1.02
one-way	whg	0.38	$\phi_{\text{SSB+Catch+risk+ICV}}$	27	58	0	2	3	0.6	0.6	0.7	2	1.00
one-way	bll	0.38	$\phi_{\text{SSB+Catch+risk+ICV}}$	28	52	0	2	3	0.7	0.4	0.9	3	1.00
one-way	lem	0.42	$\phi_{\text{SSB+Catch+risk+ICV}}$	28	50	0	3	3	0.6	0.3	0.8	3	1.03
one-way	ane	0.44	$\phi_{\text{SSB+Catch+risk+ICV}}$	14	42	0	2	3	0.8	0.8	0.7	2	1.01
one-way	jnd	0.47	$\phi_{\text{SSB+Catch+risk+ICV}}$	25	55	0	3	3	0.3	0.4	1.4	3	0.94
one-way	sar	0.60	$\phi_{\text{SSB+Catch+risk+ICV}}$	25	48	0	2	3	0.6	0.8	1.3	3	0.96
one-way	her	0.61	$\phi_{\text{SSB+Catch+risk+ICV}}$	24	51	0	2	3	0.4	0.5	1.1	2	0.96
one-way	san	1.00	$\phi_{\text{SSB+Catch+risk+ICV}}$	25	45	0	2	2	0.3	0.5	1.1	2	1.00
stock groups optimisation													
one-way	low-k	0.08-0.19	$\phi_{\text{SSB+Catch+risk+ICV}}$	15	68	1	2	3	1.0	0.0	0.2	2	1.00
one-way	medium-k	0.20-0.32	$\phi_{\text{SSB+Catch+risk+ICV}}$	19	67	0	2	3	0.8	0.2	0.8	2	1.07
one-way	high-k	0.32-1.00	$\phi_{\text{SSB+Catch+risk+ICV}}$	34	28	0	3	3	0.6	0.4	1.0	3	1.00

In the one-way fishing history, the median of the SSB increased after the implementation of the default rfb rule from its depleted state, but overshot B_{MSY}, peaked at just below $2B_{\text{MSY}}$, and then equilibrated at around $1.5B_{\mathrm{MSY}}$ at the end of the 50-year projection period (Figure 7.3a). All tested fitness functions resulted in median SSB trajectories without the initial SSB peak and terminated closer to B_{MSY}. Despite exhibiting similar SSB trajectories, trade-offs between the summary statistics were evident (Figure 7.3c). The fitness functions with only a single component (ϕ_{Catch}, ϕ_{SSB}) led to parameter combinations which resulted in values of the corresponding summary statistic being close to their targets; however, the remaining summary statistics did not always improve for ϕ_{SSB} (although it did for ϕ_{Catch}). Adding additional components to the fitness function alleviated this and improved the respective summary statistics.

The progress of the optimisation process with a genetic algorithm is visualised in Figure 7.3b for the one-way fishing history with the fitness function including SSB, catch, risk, and ICV. The best fitness values in each generation (with a population size of 100) converged quickly, and the algorithm terminated after 18 generations due to stationarity, because no further improvement within 10 consecutive generations was made.

For the alternative historical fishing history (random), only the $\phi_{\mathrm{SSB+Catch+risk+ICV}}$ fitness function was explored, and improved the performance of the rfb rule, as seen for the stock trajectories and all summary statistics (Figure 7.3a and c). The SSB, F, and catch moved closer to the MSY reference points and reached this state earlier, and risk and ICV were reduced. This fitness formulation ($\phi_{\mathrm{SSB+Catch+risk+ICV}}$) was selected for further analysis because it offered a balance between achieving MSY (for both SSB and catch), reducing risk and minimising inter-annual variations in the catch. Ideally, a decision on which components to include in the fitness formulation would be closely aligned to management objectives.

7.5.2 Catch advice interval

The impact of the frequency of setting the catch advice was explored for pollack in the one-way fishing history by fixing the interval and then optimising the rfb rule for the remaining parameters with the genetic algorithm and using $\phi_{\mathrm{SSB+Catch+risk+ICV}}$. The maximum fitness was obtained with a biennial catch advice. When setting an annual or triennial catch advice, the fitness deteriorated by 20 and 12% respectively when compared to biennial catch advice (results not shown).

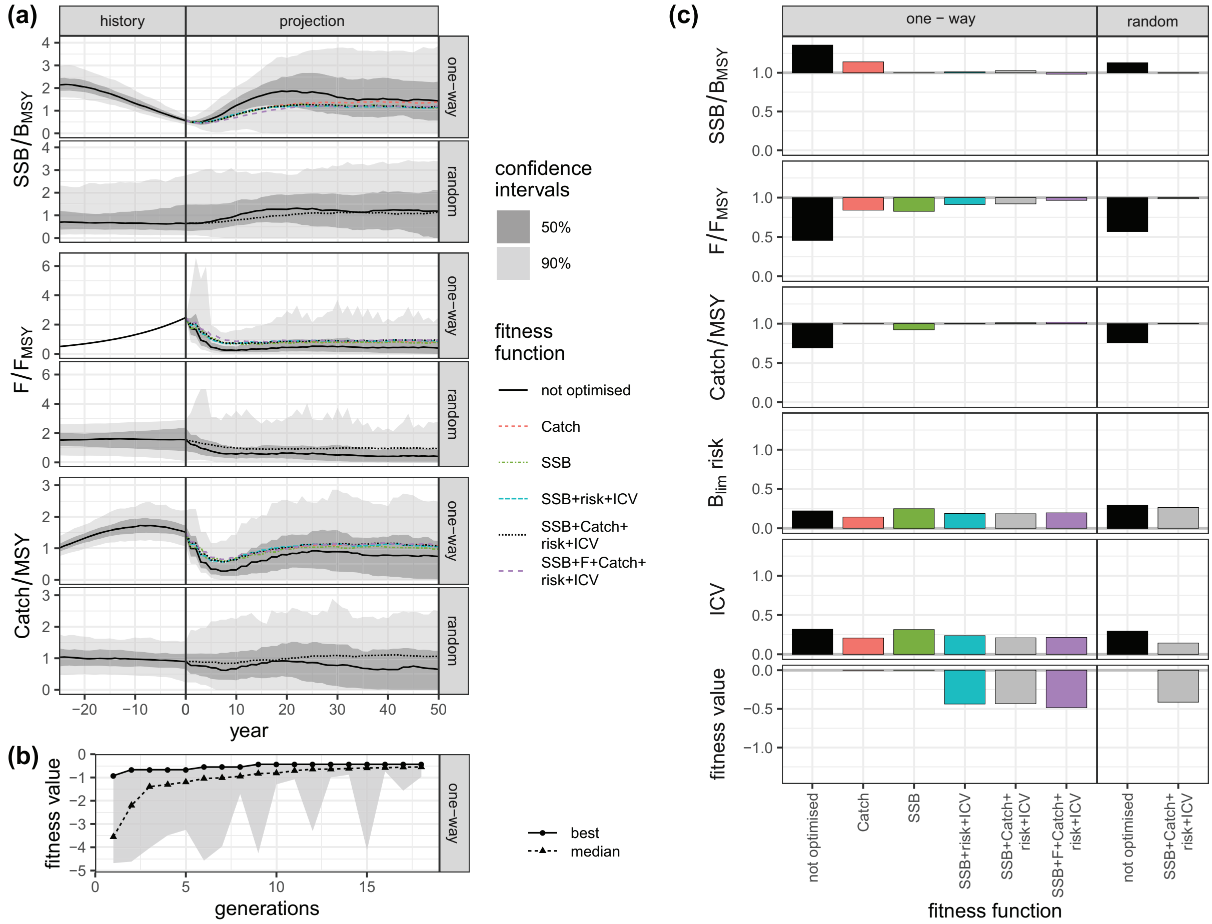

Figure 7.3: Results of the exploration of fitness functions for pollack. (a) shows the trajectories of the default rfb rule (labelled "not optimised", including confidence intervals) and median trajectories for the optimised rfb rule of several fitness functions. Shown are the historical fishing period ("history") and the subsequent application of the rfb rule ("projection"), for the "one-way" and the "random" fishing history. (b) visualises the progress of the search procedure of the genetic algorithm for the $\phi_{\text{SSB+Catch+risk+ICV}}$ fitness function. The shaded area indicates the total range of observed fitness values. (c) displays the summary statistics for the default rfb rule parameterisation in comparison with the optimised solutions, both for the one-way and random fishing history. The height of the bars indicates the deviation (up or down) from the target of the optimisation (MSY reference points for SSB, F, and catch; 0 for B_{lim} risk and ICV). No fitness value is shown for the non-optimised rule.

7.5.3 Stock specific optimisation

The stock-specific optimisation of the rfb rule led to stock-specific catch rule parameters and substantially improved the fitness of the rule for all stocks (Table 7.1). The components of the fitness function are summarised in Figure 7.4a. For the low- to medium-k stocks ($k \leq$

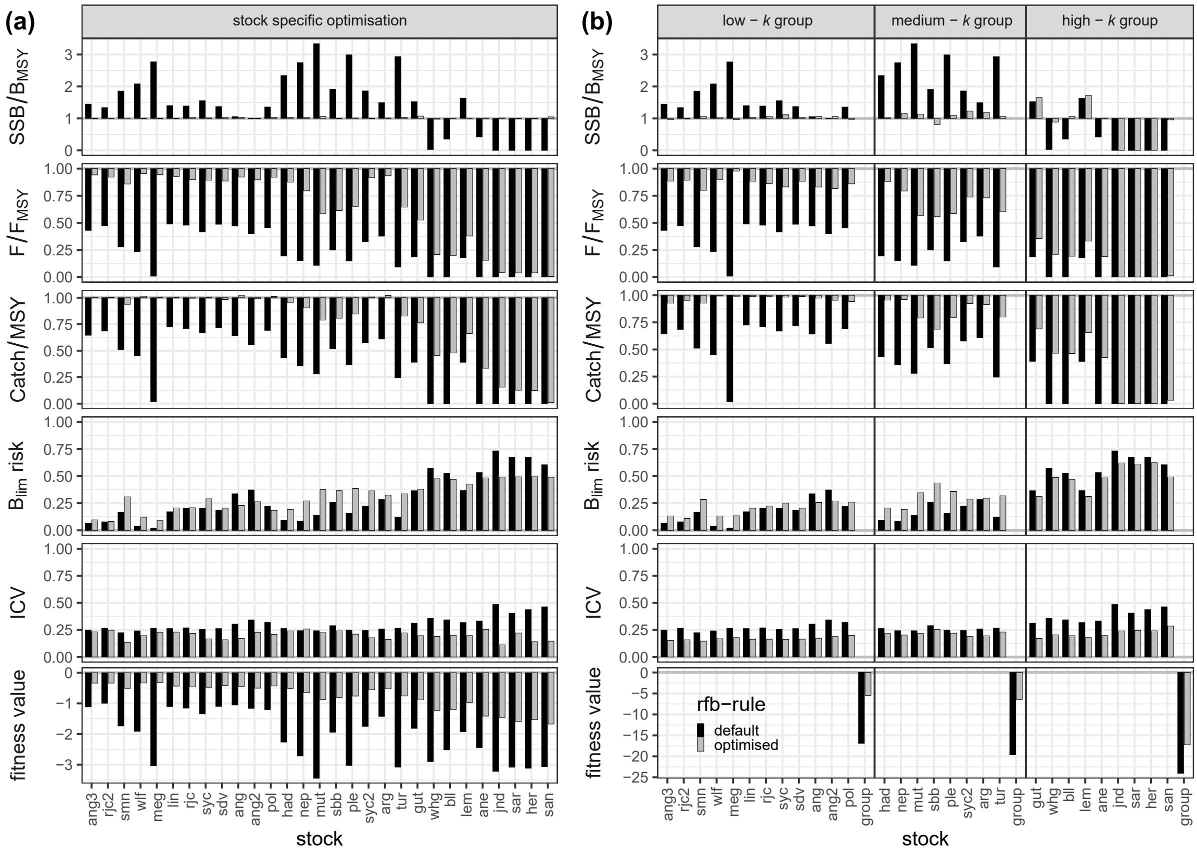

Figure 7.4: Summary statistics for all 29 stocks of the MSE, for the default and optimised rfb rule parameterisation, and the one-way fishing history. The fitness function corresponds to "SSB+Catch+risk+ICV" in Figure 7.3. The stocks are sorted by the von Bertalanffy growth parameter k in ascending order from left to right. (a) shows the results of stock-specific optimisations in which the genetic algorithm was run independently for all stocks and in (b) the optimisation was conducted for three stock groups based on k. For the groups in (b), only one fitness value exists per group, which is the sum of the values for the stocks in the group. The stock abbreviations are defined in Table 5.1 in Chapter 5.

0.32 year^{-1}), SSB, F and catch summary statistics were moved close to their MSY reference points. This meant a reduction in SSB for many stocks compared to the default rfb rule, which is reflected in a slight increase in risk and decrease in catch variability. For most high-k stocks ($k \geq 0.32$ year^{-1}), some improvement of the performance was achieved; however, the catch was still low and fitness value improvements were less pronounced than for stocks with lower k.

7.5.4 Stock groups

The optimisation for the stock groups based on k (low, $0.08 \leq k \leq 0.19$; medium, $0.20 \leq k \leq 0.32$; high, $0.32 \leq k \leq 1$; unit for k: year^{-1}) was able to improve the performance of the rfb rule compared to its default parameterisation (Table 7.1, Figure 7.4b). When the fitness values from the stock-specific optimisation are summed up by stock group and compared to the fitness of the stock group optimisation, then the total improvement was always better for the stock-specific optimisation. The overall improvement for the low and medium-k groups was close to the stock-specific optimisation. For the high-k group, the improvement was less pronounced and the rfb rule showed poor performance.

7.5.5 Current ICES rule

The current ICES "2 over 3" advice rule for category 3 stocks (with uncertainty cap and precautionary buffer) was compared to the rfb rule (Figure 7.5). The performance of the "2 over 3"

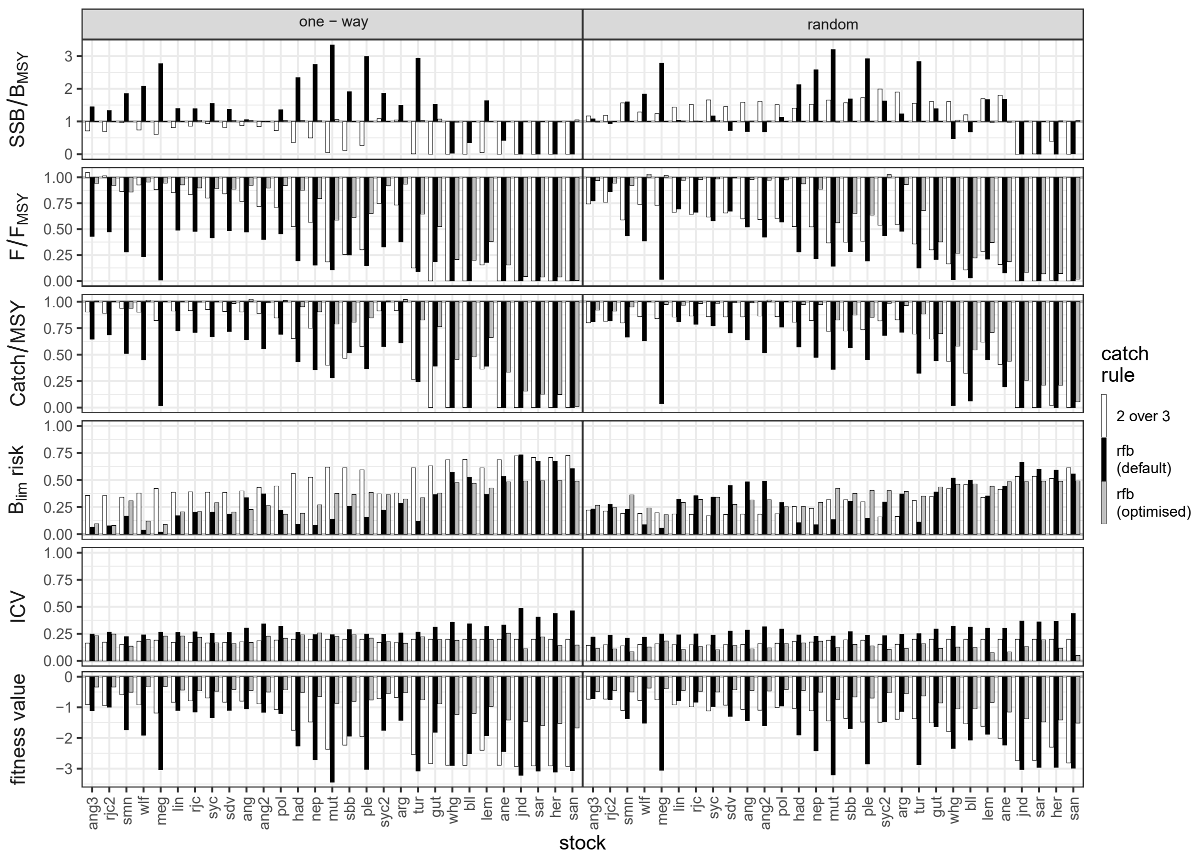

Figure 7.5: Comparison of the summary statistics of the current ICES management procedure and the default and optimised rfb rule for two fishing histories. The fitness function corresponds to "SSB+Catch+risk+ICV" in Figure 7.3. The stocks are sorted by the von Bertalanffy growth parameter k in ascending order from left to right.

rule was dependent on the stock and fishing history. At first glance, the performance of the "2 over 3" rule appeared better compared to the default rfb rule when considering fitness, except for some high-k stocks. However, the optimised rfb rule consistently performed better than both of them throughout. In the one-way fishing history, the "2 over 3" rule resulted in SSB values at or below B_{MSY}, with low SSBs for some medium k stocks, and generally high B_{lim} risks.

The performance of the default rfb rule by stock was similar for SSB, F, catch, and ICV when comparing fishing histories (one-way vs. random). In contrast, the performance of the "2 over 3" rule was highly influenced by the fishing history prior to its implementation, with low SSB values for some of the medium-k stocks, and generally high levels of B_{lim} risk under the one-way fishing history.

For better comparability, the uncertainty cap of the "2 over 3" rule (limiting catch advice variability to no more than 20%) was added to the default parameterisation of the rfb rule (see Figure C.1 in Appendix C). For most stocks, this moved the performance of the rfb rule closer to the "2 over 3" rule. Some stocks exhibited an increased B_{lim} risk, whereas the risk was reduced for others.

7.6 Discussion

The main aim of this study was to explore the application of a genetic algorithm to the optimisation of the performance of a data-limited catch rule (the rfb rule), first tested in the previous chapter. The results presented provide evidence that the rfb rule's performance can be substantially improved. The improvement was dependent on the simulated stock (i.e. defined by life history), generally better for species with slow to medium individual growth than those with faster individual growth, and dependent on which management objectives were included in the fitness function.

The optimisation of the rfb rule was performed for 29 stocks, which were generated based on life-history parameters and relationships to develop age-structured operating models, and provides a theoretical basis for developing hypotheses about population dynamics. The reason for this approach was that these stocks are considered data-limited, and therefore analytical stock assessments do not exist. Extensive sensitivity analyses have been conducted previously (see Chapter 5, Chapter 6, and Appendix B) on the assumptions and parameterisations of the operating models such as steepness, recruitment variability, and observation uncertainty.

Even though the operating models are based on real stock units, they might not necessarily exactly represent the stocks (e.g. fishing histories were simulated to represent certain conditions); nevertheless, they cover a wide range of life histories. The purpose of this study was, therefore, only to a lesser extent to provide stock-specific tuning parameters for the rfb rule. If stock-specific tuning of the rule is required, it is recommended that additional data be gathered to fine-tune the operating models and apply the optimisation procedure set out here.

For most stocks, the optimised rfb rule parameterisation included a biennial catch advice interval. Therefore, not unexpectedly, when this interval was fixed to a different value in the optimisation procedure for pollack, the performance of the rule deteriorated. This result is an indication that updating the advice more frequently does not necessarily result in better management, particularly when ICV is considered an important component of the fitness function. ICES usually provides biennial catch advice for category 3 data-limited stocks, which reduces the operational effort for conducting stock assessments for the many data-limited stocks compared to an annual cycle. Nevertheless, for most stocks, the usual 1-year time lag for the survey data was removed in the optimised rfb rule parameterisation. Essentially, this means that data up to the intermediate year are used to provide the catch advice for the following advice year. This situation is feasible in an ICES setting where, for many stocks, scientific catch recommendations for the advice year are released in the middle of the intermediate year. Consequently, survey data from the beginning of the intermediate year are available and can be included in the analyses. In the present simulations, surveys were timed to occur at the start of the year.

Previous work on the rfb rule (see Chapter 6, and Fischer et al., 2020) revealed that the rule performs poorly for stocks with higher von Bertalanffy growth parameter k values ($k \geq 0.32$ year^{-1}). Despite making the rfb rule much more flexible by allowing the reduction of the time lag and introducing weighting of the catch rule components, the rule still did not perform markedly better for these stocks, and caused low yields and a high risk of dropping below biomass reference points. For the remaining low- to medium-k stocks ($k \leq 0.32$ year^{-1}), the performance improvements through the genetic algorithm were substantial, both for stock-specific as well as the broader k-group optimisation. Therefore, it appears that, for higher-k stocks, the rfb rule cannot provide reliable management options which are compliant with precautionary and MSY principles, and alternatives need to be found.

Higher-k stocks are inherently more dynamic, i.e. exhibit more inter-annual variability and have high population growth rates. Therefore, they respond more quickly to changes in fishing behaviour, environmental forcing, and errors in the feedback control rule. Alternative management procedures, such as simple constant harvest rate-based rules using an index of relative abundance (e.g. an acoustic survey), might provide better management without the need to enforce MSY reference levels. In addition, the f-component of the rfb rule based on mean catch length and an F_{MSY} proxy may not be optimal for these species, and alternative length-based indicators that track incoming year-classes and identify future abundance may potentially perform better. Lessons can also be learned from the management of fisheries targeting fast-growing and pelagic stocks in other parts of the world, such as for Pacific sardine (PFMC, 2019) or the South African pelagic fishery (Cochrane et al., 1998; De Oliveira & Butterworth, 2004).

The first step in addressing the optimisation of procedures for managing marine living resources, like any other optimisation problem, requires the specification of management objectives. Different stakeholders may have vastly different preferences for utility functions (Fishburn & Kochenberger, 1979), and fisheries management, like many other real-world problems, must consider multiple objectives due to the potentially conflicting interests of different asset and stakeholder groups (Rindorf et al., 2017), e.g. fishers, policymakers, environmentalists, wholesalers, retailers, consumers, and scientists. In an ideal set-up of an MSE exercise, all stakeholders are involved from the beginning and have their say in the selection of management objectives as well as inevitable trade-offs. In reality, it can be challenging to receive any interaction from stakeholders; for example, even though methods workshops in ICES are open to the public, feedback about management objectives sometimes has to be explicitly requested, or such management objectives assumed by analysts (ICES, 2020b).

Alternative tuning algorithms to the optimisation deployed here exist (e.g. Givens et al., 1999). Optimisation towards achieving some minimum performance (e.g. conservation considerations) is possible but is likely to reduce the overall performance by forfeiting yield. The implications of including specific risk thresholds are a subject of future work.

Several fitness functions were explored and resulted in different catch rule parameters and performance metrics. When only a single component, e.g. SSB, was included, the SSB metric reached levels very close to its optimum (B_{MSY}); however, other important metrics such as B_{lim} risk and ICV were neglected. The fitness function selected here can be considered partially arbitrary, although based on careful consideration; it appears to balance the objective of achieving MSY (for both SSB and catch) while reducing risk and minimising inter-annual catch variability. The weighting of the fitness function elements can be a point of discussion, and specific stakeholders might favour alternative parameterisations. Furthermore, equal weighting was applied to the deviation of performance metrics from their MSY level (up or down). In terms of SSB, dropping below B_{MSY} should be reduced when considering conservation, whereas the opposite is less critical. Nevertheless, the fitness function included B_{lim} risk, and therefore, low stock levels triggered a different response in the optimisation.

Any improvement can only be as good as the definition of the fitness function, and the optimisation is purely based on evaluating this fitness function, ignoring any other feature. Therefore, fitness functions must be carefully designed, and it should be recognised that there might not be a single fitness function covering all aspects. The type of fitness function used in this study could be tailored for stock-specific case studies, as it included all metrics important for the objective of a specific management system to account for trade-offs. The development of case-specific control rules is an improvement over the current approach of one rule for all.

Another important concept that could be explored is the monetisation of the outcome of applying a specific management procedure, e.g. by quantifying the monetary value of exploiting a fish stock with the price of premiums for an insurance against economic risks of the fishery (Mumford et al., 2009). Such an evaluation would allow the comparison of the application of new catch rules compared to traditional management rules, or even the benefit of optimising management procedures, and should be considered in future studies.

The types of simulations, as run here with the genetic algorithm included in a full-feedback MSE framework, are highly computationally demanding. The simulations, in particular for the runs combining several stocks, had central processing unit (CPU) runtimes of up to several thousand hours. Therefore, it is implausible to attempt to run these simulations on personal computers, and instead a high-performance computing (HPC) cluster with massive parallelisation techniques was utilised (the high-performance computing system of the Imperial College Research Computing Service, www.doi.org/10.14469/hpc/2232). The computations were spread simultaneously over numerous computing nodes and hundreds of CPU cores to reduce the runtime to mere hours. Specifically, a hybrid parallelisation approach was adopted where the individual projections of the MSE (catch rule parameterisations) were parallelised by executing them on different computing nodes with the message passing interface (MPI; Walker, 1992), and the MSE projections themselves were parallelised within computing nodes.

For the purpose of this study, the MSE simulations were based on FLR's standardised MSE framework (Jardim et al., 2017) and this was linked to a genetic algorithm optimisation approach, adapted for massive parallelisation. The outcomes presented here provide evidence that it is possible to link the two and that management procedures can be improved successfully with this approach. The FLR MSE framework has recently been gaining popularity for conducting MSEs within the ICES community, and has, for example, been used to evaluate long-term management plans of North Sea gadoid stocks (cod, haddock, whiting, and saithe, ICES, 2019h) based on an EU-Norway request to ICES. This evaluation included running an MSE for data-rich stocks and a fully analytical stock assessment (SAM, Nielsen & Berg, 2014) in the feedback loop, which caused substantial computational complexity. In order to optimise a management procedure (maximise yield while maintaining precautionary risk considerations), an exhaustive grid search with manual interventions was conducted over two harvest control rule parameters (F_{target} and B_{trigger}). With a framework which includes machine intelligence for the optimisation, like the one developed for the data-limited rfb rule here, the computational effort could likely be greatly reduced, thereby reducing computational expenses and also shortening the runtime required for obtaining results. Therefore, the optimisation procedure explored here in a data-limited context could also be applied to data-rich situations and this is explored in Chapter 11.

The application of a genetic algorithm as an optimisation procedure piloted here was specific to an empirical management procedure considered by ICES. Nevertheless, the use of this approach is not limited to ICES or Europe and can be applied in any management system. The optimisation is aimed at satisfying concrete management objectives, formalised in a fitness function. Therefore, any management objective (be it for data-rich, data-limited, or data-poor situations) can be included, as long as it is possible to characterise the objectives mathematically.

The settings for the genetic algorithm (maximum number of generations, convergence criteria, population size, mutation, and crossover probabilities, etc.) might be, at least partially, considered arbitrary, and were a compromise between reducing computational complexity (computing time, memory demand, etc.) and at the same time providing a reliable optimisation. The optimisation process is entirely reproducible, but it is based on a stochastic process and therefore dependent on random numbers. The set-up of the search itself can be considered an optimisation problem (hyperparameter optimisation). Due to the nature of the optimisation procedure, it cannot be guaranteed that the optimised solution is indeed the global optimum of the multi-dimensional parameter space (Holland, 1992). Nonetheless, the solutions presented here are a substantial improvement to the base case (the default catch rule parameters) and can be quantified with the fitness values and its components. An optimisation with a genetic algorithm has the benefit that the progress can be observed directly, and the path leading to the final solution can be traced back. Other machine learning methods, such as neural networks, might also be used; however, they might be regarded as black boxes which provide results, but it is not always possible to describe them in a way humans can understand.

Finally, the performance of the rfb rule analysed in this study was compared to the current ICES advice rule for category 3 data-limited fish stocks (i.e. the "2 over 3" rule with an uncertainty cap and a precautionary buffer; ICES, 2012b, 2019a). At first glance, the performance of the "2 over 3" rule might appear better than the default rfb rule, particularly when considering the random fishing history. However, the behaviour of the rule is highly influenced by the stock and its status prior to the implementation, as shown previously (Jardim et al., 2015; ICES, 2017d; Fischer et al., 2020) and again here for the two fishing histories. The "2 over 3" rule is aimed at maintaining a status quo and does not include any target.

7.7 Conclusion

The outcome of this chapter is a recommendation to phase out the use of the "2 over 3" rule within ICES and the rfb rule tested in this study is proposed as an improved successor. The reasoning in favour of the new catch rule is that (i) it includes an MSY based target in addition to the index trend, (ii) it underwent extensive MSE testing prior to its implementation, (iii) it yields more stable outcomes irrespective of the stock status, and (iv) its flexibility allows case-specific optimisation. Nonetheless, the rfb rule cannot be recommended for higher-k (fast-growing) stocks due to its poor performance, even when optimised. For such stocks, alternative management procedures, such as constant harvest rates, need to be considered and are explored in subsequent chapters.

The work presented in this chapter can be seen as an optimisation towards general management objectives, including MSY and some risk considerations. However, for the application to stocks within ICES, the ICES precautionary approach requests that the risk of falling below the limit reference points (B_{lim}) does not exceed 5% (ICES, 2019a). The following chapter explores the feasibility of including such an explicit risk limit in an optimisation procedure and its implications on management decisions.

Chapter 8

Application of explicit precautionary principles in data-limited fisheries management[1]

[1] This chapter is an adaptation of Fischer et al. (2021b). Contains public sector information licensed under the Open Government Licence v3.0 (http://www.nationalarchives.gov.uk/doc/open-government-licence/version/3/).

8.1 Foreword

This chapter is an extension of the optimisation of the empirical management procedure (the "rfb rule") explored in the previous two chapters. This chapter includes considerations of explicit risk limits in the management objectives and the use of flexible catch constraints. Preliminary results were presented at the tenth International Council for the Exploration of the Sea (ICES) Workshop on the Development of Quantitative Assessment Methodologies based on LIFE-history traits, exploitation characteristics, and other relevant parameters for data-limited stocks (ICES WKLIFE X; ICES, 2020a). Subsequently, additional analyses were undertaken, and the work was peer-reviewed and published in Fischer et al. (2021b):

> Fischer, S. H., De Oliveira, J. A. A., Mumford, J. D. & Kell, L. T. (2021b). Application of explicit precautionary principles in data-limited fisheries management. *ICES Journal of Marine Science*, *78*(8), 2931–2942. https://doi.org/10.1093/icesjms/fsab169

The following sections in this chapter are an adaptation of this publication.

8.2 Abstract

Many management bodies require applying the precautionary approach when managing marine fisheries resources to achieve sustainability and avoid exceeding limits. For data-limited stocks, however, defining and achieving management objectives can be difficult. Management procedures can be optimised towards specific management objectives with genetic algorithms. This chapter explored the feasibility of including an objective that limited the risk of a stock falling below various limit reference points in the optimisation routine for an empirical data-limited control rule which uses a biomass index, mean catch length and includes constraints (the "rfb rule"). This was tested through management strategy evaluation on several fish stocks representing various life-history traits. Risk objectives could be met, but more restrictive risk limits can lead to a potential loss of yield. Outcomes were sensitive to simulation conditions such as observation uncertainty, which can be highly uncertain in data-limited situations. The rfb rule outperforms the method currently applied by ICES, particularly when risk limitation objectives are considered. The work in this chapter concludes that the application of explicit precautionary levels is useful to avoid overfishing. However, caution must be taken against the indiscriminate use of arbitrary risk limits without scientific evaluation to analyse their impact on stock yields and sustainability.

8.3 Introduction

One of the main objectives of fisheries management is to ensure the long-term sustainability of the resources being exploited. An imperative for the successful management of fish stocks is the existence of clearly defined management objectives and robust ways to achieve them. However, for many of the world's fish stocks, there are insufficient data and knowledge to conduct reliable quantitative stock assessments (Rosenberg et al., 2014). The limitations do not solely impact data and knowledge of managed resources but can extend to the management objectives themselves. Management goals for data-limited fish stocks are frequently vague and might only be formulated to ensure precautionary exploitation without specific performance metrics or guidelines.

Management measures for many fish stocks in the Northeast Atlantic are based upon scientific recommendations from ICES. ICES applies an advice framework for data-rich stocks that considers both maximum sustainable yield (MSY) and precautionary principles (ICES, 2019a). Within this framework, catch advice is derived from short-term forecasts, typically with a target fishing mortality at the level that would achieve MSY (F_{MSY}). Precautionary considerations require that limit reference points are also defined to ensure that low stock size and unsustainable fishing mortality are avoided with a high probability.

The precautionary approach was first introduced in ICES in the late 1990s and is based on the principle that a fish stock should not fall below a point where recruitment or productivity is impaired (Lassen et al., 2014). For data-rich stocks, this point is typically defined as a spawning stock biomass (SSB) limit reference point (B_{lim}). ICES technical guidelines state that management must ensure that the probability of SSB falling below B_{lim} must not exceed 5% (ICES, 2017b, 2019a). The precautionary principle is implicitly implemented in ICES advice by defining threshold reference points (such as B_{pa}) that ensure that the limit reference points are avoided with a high probability (Hauge et al., 2007). The ICES MSY advice rule itself (fish at F_{MSY} unless SSB < MSY B_{trigger}, in which case reduce F linearly to zero by the extent that SSB < MSY B_{trigger}) is designed to ensure that stocks are capable of producing MSY, but the constraint that MSY $B_{\text{trigger}} \geq B_{\text{pa}}$ ensures this rule is consistent with the precautionary principle. Alternatives to the ICES MSY advice rule are possible but need to demonstrate that they comply with the precautionary 5% risk limit. To do this, evaluations are preferably conducted using management strategy evaluation (MSE), and recent examples of this procedure are the evaluations of long-term management strategies for North Sea stocks (cod, haddock, saithe, whiting, and herring; ICES, 2019h) or Northeast Atlantic mackerel (ICES, 2020c).

In data-limited cases, quantitative assessment models are often unavailable and knowledge about stock development and status does not exist. Consequently, stock size or fishing mortality cannot be judged relative to target or limit reference points, impairing risk considerations. For such cases, ICES applies a precautionary framework aimed at ensuring sustainable catch advice by using all available information (ICES, 2019a). Despite this overarching precautionary principle, there are no specific definitions or guidelines about what constitutes precaution or how this could be measured. Instead, ICES classifies fish stocks into six categories depending on the extent of data limitations and provides a set of possible methods to derive catch advice and evaluate stock status relative to MSY proxy reference levels, if possible (ICES, 2012b, 2018b).

Stocks for which there is no quantitative assessment, but for which an index of relative abundance exists, are defined as category 3 stocks. For these stocks, ICES catch advice is currently (as of 2021) derived in most cases from a simple “2 over 3” rule, which sets the catch advice by multiplying the most recent advised catch by the average of the last two index values divided by the average of the three preceding index values (ICES, 2012b, 2018b, 2019a). This approach is complemented by an uncertainty cap limiting the change between advised catches to no more than 20%. Additionally, a precautionary buffer reduces the catch advice by 20% when the stock is judged to be in an unfavourable condition (if either biomass is thought to be below a possible biomass limit, usually 50% of a B_{MSY} proxy value, or fishing mortality is thought to be above an F_{MSY} proxy value) or unknown, but can only be applied once in a three-year period. At best, this rule can maintain the current stock status because it lacks a target.

Since the first implementation of the 2 over 3 rule in 2012, it was only meant as an interim solution until better options could be developed. Despite some early simulation testing (De Oliveira et al., 2010; ICES, 2012d), it was never shown that the 2 over 3 rule provided precautionary advice or was, in fact, compliant with the principles of the ICES precautionary approach. Currently, alternative management approaches are being considered for implementation into the ICES advice framework. The prime forum for developing and testing alternative data-limited approaches in ICES is the WKLIFE workshop (ICES, 2012d), which has been running since 2012, with the tenth meeting in the series held in 2020 (ICES, 2020a).

Two main strains of methods for category 3 stocks are currently being considered; model-based and model-free. The model-based strain considers control rules based on a surplus production model (SPiCT; Pedersen & Berg, 2017), including short-term forecasting. To account for uncertainty and provide precautionary advice, percentiles different from 50% of model estimates are deployed (Mildenberger et al., 2022). However, it is common that stock assessment models cannot be used for data-limited stocks, e.g. because of convergence issues or insufficient data. Simpler models relying on fewer data, such as catch only methods, exist, but are only considered for stocks with more severe data limitations (categories 4–6). The alternative is a model-free empirical rule, and ICES considers the rfb rule for these cases. The rfb rule includes additional elements for providing catch advice: in addition to the 2 over 3 component (r), there is an exploitation proxy target derived from the mean length in the catch (f), and a biomass safeguard reducing the catch advice once the stock falls below a threshold (b). New guidelines with these rules have been drafted (Annex 3 of ICES, 2020a) and are intended to replace current methods. Simple empirical management procedures are a viable possibility for managing fisheries, are easier to implement, cheaper because they rely on fewer data, and their management performance can match more complex stock assessment frameworks (Geromont & Butterworth, 2015a, 2015b; Carruthers et al., 2016). Another benefit is that they are less susceptible to environmental changes, such as those induced by climate change, because management follows trends in the stock instead of chasing the expensive "best assessment" approach.

Early simulation testing of the rfb rule (Fischer et al., 2020, Chapter 6) showed that its performance depended on the individual growth rate of the managed stock and the performance was poor, with high risks of stock collapses, for fast-growing stocks (von Bertalanffy $k \geq 0.32$ year^{-1}). For slow- to medium-growing stocks, the rfb rule performed reasonably but often led to stock levels above B_{MSY} and therefore forfeited yield. However, the performance could be improved by optimising the rule towards MSY (Fischer et al., 2021a, Chapter 7).

In the previous chapter (Chapter 7), a procedure to optimise the rfb rule to meet specific management objectives by applying a genetic algorithm (Holland, 1992) was established, and the principle is visualised in Figure 8.1. For the optimisation, the objectives need to be defined mathematically in the form of a fitness function. Fischer et al. (2021a, Chapter 7) deployed a generic fitness function to achieve MSY while also reducing the risk of stocks falling below limit biomass reference levels and catch variability. Furthermore, Fischer et al. (2021a, Chapter 7) evaluated the performance of the 2 over 3 rule and compared it to the rfb rule. The results showed that the 2 over 3 rule's performance crucially depends on the stock status before its implementation; it merely maintains that level and does not provide precautionary management

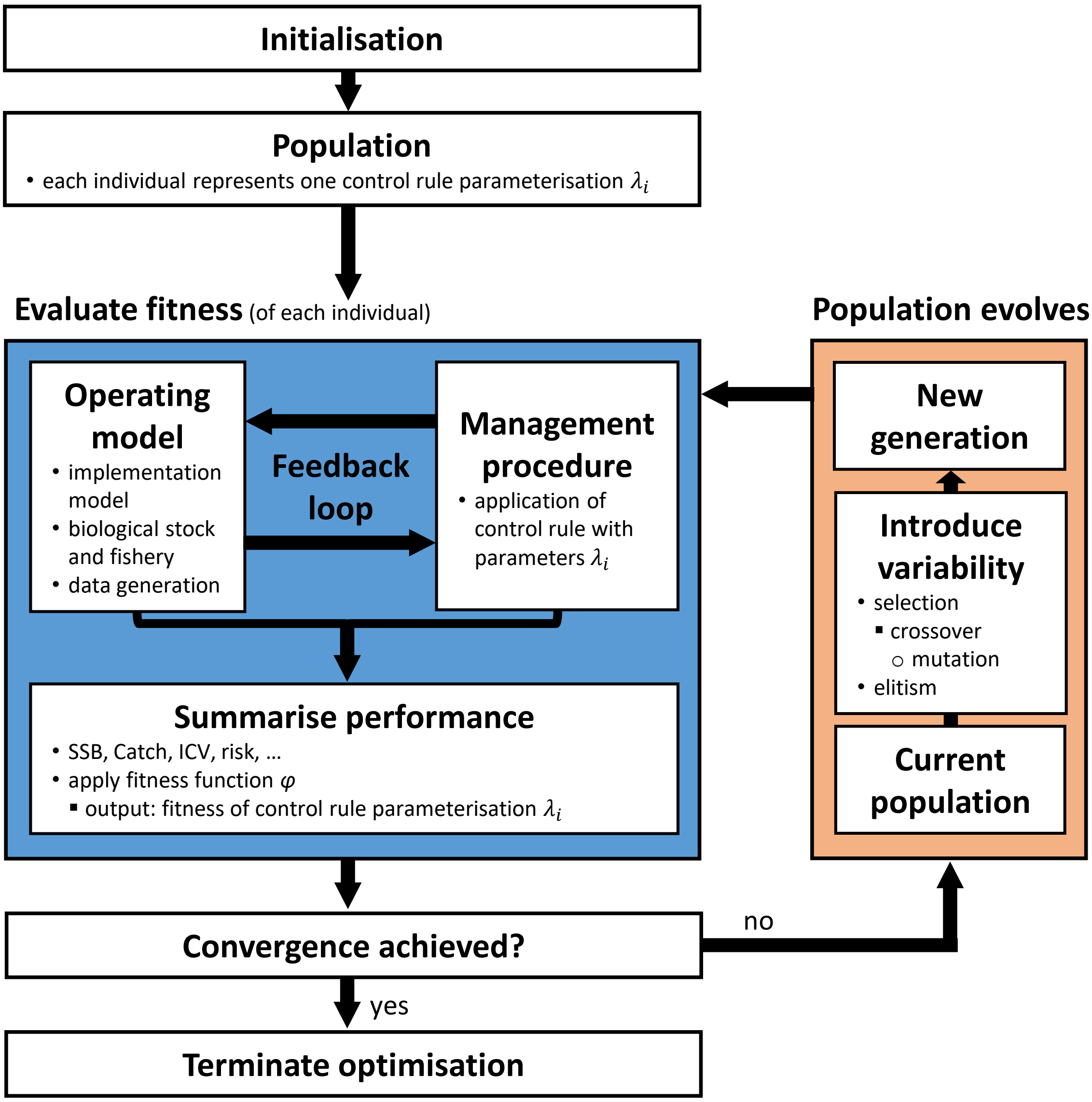

Figure 8.1: Principle of using a genetic algorithm to optimise a management procedure in a management strategy evaluation.

advice. In the simulations, the rfb rule outperformed the 2 over 3 rule, in particular when optimised for a specific stock, for all simulated life histories and fishing histories (Chapter 7).

This chapter explored including explicit precautionary elements in data-limited fisheries management with the example of the empirical rfb rule. This included considerations of the definition of risk levels and how MSE simulation conditions, such as historical fishing patterns, the length of the simulation, or the levels of uncertainty and variability, can affect the selection of management options. Finally, an exploration of how the rfb rule can be optimised to meet specific precautionary considerations was conducted and their trade-offs are discussed.

8.4 Methods

8.4.1 Management strategy evaluation

The age-structured operating models developed in Chapter 6 in FLR (Kell et al., 2007), and as parameterised in Chapter 7 (Fischer et al., 2021a), were redeployed. These comprised 29 stocks generated from life-history parameters covering a wide range of life-history traits (see Table 5.1). There were two distinct 100-year fishing histories; a *one-way* fishing history (fished at $0.5F_{\mathrm{MSY}}$ for 75 years, then increase fishing mortality exponentially to $0.8F_{\mathrm{crash}}$ over 25 years, where F_{crash} is defined as the lowest fishing mortality that causes the stock to collapse in equilibrium), and a *random* fishing history with arbitrary fishing mortality trajectories ($F_{y=-99} = 0$, and two points in time where fishing mortality is drawn from independent uniform distributions: $F_{y=-50} \sim U(0, F_{\mathrm{crash}})$ and $F_{y=0} \sim U(0, F_{\mathrm{crash}})$, with linear interpolations in-between). These two fishing histories offered insights into situations with a strong initial depletion (one-way) and an alternative with a wide range of depletion (random). Errors were assumed to be log-normal, and each stock consisted of 500 independent simulation replicates. Recruitment was simulated by a Beverton-Holt model with steepness $h = 0.75$ and recruitment variability $\sigma_R = 0.6$. Subsequent to the fishing history, a management procedure was implemented for 50 years. Observation errors were implemented to the aggregated biomass index and mean catch length index with $\sigma_{\mathrm{obs}} = 0.2$. Full specifications of the operating models and simulation conditions are available in Chapters 5, 6 and 7.

8.4.2 Management procedure

The management procedure was based on the rfb rule (see Chapter 6; ICES, 2017f; Fischer et al., 2020):

$$A_{y+1} = C_{y-1}\ r\ f\ b, \tag{8.1}$$

where the newly advised catch A_{y+1} in year $y + 1$ is based on the previously realised catch C_{y-1}, multiplied by three components corresponding to the stock trend (r) from a biomass index, an exploitation proxy (f) derived from the mean catch length and a biomass safeguard (b) protecting the stock when the biomass index falls below a critical threshold. Fischer et al.

(2021a, Chapter 7) expanded the rfb rule for optimisation purposes:

$$A_{y+1} = C_{y-1} \left(\frac{\sum_{i=y-n_0-n_1+1}^{y-n_0} (I_i/n_1)}{\sum_{i=y-n_0-n_1-n_2+1}^{y-n_0-n_1} (I_i/n_2)} \right)^{e_r} \left(\frac{\bar{L}_{y-1}}{L_{F=M}} \right)^{e_f} \left(\min\left\{1, \frac{I_{y-n_0}}{I_{\text{trigger}}}\right\} \right)^{e_b} x \tag{8.2}$$

The parameters of this rule are defined in Table 8.1. Seven of the parameters in Equation (8.2) were tuneable (n_0, n_1, n_2, e_r, e_f, e_b, x), i.e. could be changed during the optimisation process. Additionally, the catch advice interval v defines the number of years for which the advice is kept constant before the rfb rule is applied again. Finally, an uncertainty cap can limit the allowed increase (u_u) and decrease (u_l) in the catch advice A_{y+1} relative to the previously realised catch C_{y-1}. The inclusion of these additional parameters resulted in 10 tuneable parameters that could be used in the optimisation.

Table 8.1: Parameters of the flexible rfb rule (as shown in Equation (8.2) and described in subsequent text).

Parameter	Definition	Default
Generic parameters		
y	assessment year	
A	catch advice	
C	realised catch	
I	biomass index	
$\bar{L}$	mean catch length above the length of first capture (L_c)	
$L_{F=M}$	theoretical proxy MSY reference length assuming $F = M$ and $M/k = 1.5$	
I_{trigger}	biomass safeguard reference value, set to 1.4 I_{loss}, where I_{loss} is the lowest observed historical value	
Tuneable parameters		
n_0	offset between last biomass index year and assessment year	1
n_1, n_2	number of biomass index years in the numerator and denominator of component r	$n_1 = 2, n_2 = 3$
e_r, e_f, e_b	exponents for weighting of components r, f and b	1
x	multiplier, scaling the catch advice	1
v	catch advice interval, number of years for which the catch advice is kept constant	2 (biennial)
u_u, u_l	catch constraint (upper and lower limit), restricting the allowed change in the catch advice A_{y+1} relative to the previously realised catch C_{y-1}	$u_u = \infty$, $u_l = 0$

8.4.3 Genetic algorithm

The genetic algorithm as applied and parameterised in the previous chapter (Chapter 7; Fischer et al., 2021a) was used to optimise the rfb rule. The population size of the algorithm was set to 100 individuals. Each of these individuals was characterised by a specific parameterisation of the 10 tuneable parameters of the rfb rule described above. This projection was summarised in a single value using a fitness function. Those individuals with the highest fitness were selected and formed the reproductive population. The next generation was generated by including natural variability through genetic operators (crossover with a probability of $p = 0.8$ and mutation with $p = 0.1$) working on the 10 tuneable parameters of the rfb rule. Additionally, an elitist strategy allowed the survival of those 5% of individuals with the highest fitness. This iterative process was repeated for every subsequent generation until either (i) a limit of 100 generations was reached or (ii) due to stationarity of the best fitness value in a generation for 10 consecutive generations.

8.4.4 Precautionary considerations

The previous chapter (Chapter 7; Fischer et al., 2021a) defined a fitness function which included four components:

$$\phi_{\text{MSY}} = \phi_{\text{SSB}} + \phi_{\text{Catch}} + \phi_{\text{risk}} + \phi_{\text{ICV}}, \tag{8.3}$$

where the individual components were

$$\phi_{\text{SSB}} = -\left|\frac{\text{SSB}}{B_{\text{MSY}}} - 1\right|, \tag{8.4}$$

$$\phi_{\text{Catch}} = -\left|\frac{\text{Catch}}{\text{MSY}} - 1\right|, \tag{8.5}$$

$$\phi_{\text{risk}} = -\ P_{B_{\text{lim}}},\ \text{and} \tag{8.6}$$

$$\phi_{\text{ICV}} = -\ \text{ICV}. \tag{8.7}$$

The summary statistics used in these fitness elements were calculated over the 50-year projection and 500 simulation replicates. SSB/B_{MSY} and Catch/MSY were the medians of their respective distributions and $P_{B_{\text{lim}}}$ (the B_{lim} risk) the proportion of the SSB values falling below the biomass limit reference point B_{lim} (defined as the SSB corresponding to a recruitment impairment of 30%). The inter-annual catch variability (ICV) was the median of $|(C_y - C_{y-v})/C_{y-v}|$ (exclusive of undefined values due to division by zero) calculated every v years, where C_y is the catch for the year y and v the frequency of advice, e.g. $v = 2$ for a biennial advice. Effectively, this fitness function was aimed at reaching MSY reference levels for SSB and catch, while at the same time reducing risk and ICV.

The elements of ϕ_{MSY} are unitless, can have values between 0 and 1, and are summed up to derive the total fitness value. This design is a mathematical formulation of generic fisheries management objectives, including MSY (ϕ_{SSB}, ϕ_{Catch}), catch stability (ϕ_{ICV}) and a precautionary element reducing stock depletion (ϕ_{risk}). However, these elements consider different elements of the biological stock and the fishery, and a change in one element can cause trade-offs in others. For example, an increase in the catch will cause a decrease in the SSB, and a decrease in the SSB increases B_{lim} risk. This means that the elements of the fitness function are not fully substitutable and are a compromise of potentially conflicting management objectives, added together without weighting. Weighting the elements of the fitness function is possible, but exploring many different potential weightings would massively increase the computational complexity and is beyond the scope of this chapter.

The ICES precautionary criterion generally states that the probability of SSB falling below B_{lim} should not exceed 5% (ICES, 2019a). Therefore, ϕ_{MSY} is not entirely aligned towards the ICES precautionary approach, and ϕ_{risk} will need to be changed. Compliance with the precautionary approach can be achieved by including a penalty in the fitness when the risk exceeds 5%, which was implemented by replacing ϕ_{risk} with a fitness function component for which the fitness value was linked to the B_{lim} risk ($P_{B_{\text{lim}}}$) via a penalty function Ω:

$$\phi_{\text{risk-PA}} = -\,\Omega\left(P_{B_{\text{lim}}}\right)\ , \tag{8.8}$$

and

$$\Omega\left(P_{B_{\text{lim}}}\right) = \frac{\tau_m}{1 + e^{-\left(P_{B_{\text{lim}}} - \tau_i\right)\tau_s}}\ . \tag{8.9}$$

This function has a sigmoid shape (Figure 8.2) and is characterised by three parameters; τ_m defines the maximum penalty, τ_i the inflection point and τ_s the steepness of the curve. The three parameters' values were based on considerations for one example stock (pollack, *Pollachius pollachius*). When pollack was projected forward with zero catch, the sum of $\phi_{\text{SSB}}+\phi_{\text{Catch}}+\phi_{\text{ICV}}$ [Equations (8.4), (8.5), and (8.7)] had an absolute value of just below 5. Therefore, the maximum penalty τ_m was set to 5. This parameterisation had the effect that the rfb rule parameterisation leading to zero-catch always had higher fitness than the rfb rule parameterisations where B_{lim} risk exceeded 5%. The penalty curve inflection point was set to $\tau_i = 0.06$ so that the risk could slightly exceed 5% without immediately incurring the maximum penalty. The penalty steepness was set to $\tau_s = 500$ so that the penalty quickly reached its maximum value but avoided a knife-edge which might cause problems during the optimisation.

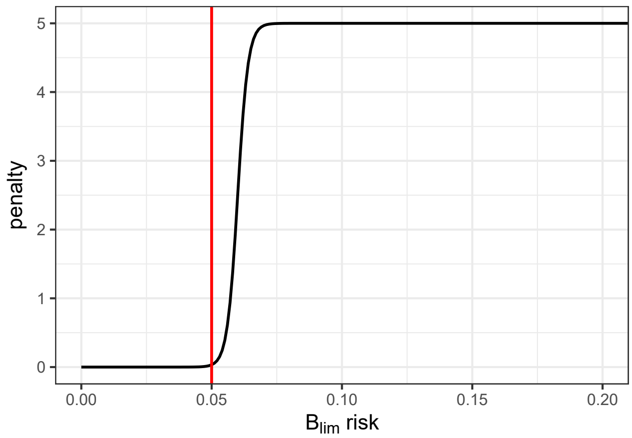

Figure 8.2: Fitness penalty (Ω) as a function of B_{lim} risk ($P_{B_{\text{lim}}}$), as defined in Equation (8.9). The vertical red line represents the B_{lim} risk limit of 5%.

The final fitness function, which included MSY objectives for catch and SSB and included precautionary considerations for the risk, was defined as:

$$\phi_{\text{MSY-PA}} = \phi_{\text{SSB}} + \phi_{\text{Catch}} + \phi_{\text{risk-PA}} + \phi_{\text{ICV}}. \tag{8.10}$$

Each of the elements in $\phi_{\text{MSY-PA}}$ is negative because the genetic algorithm maximised the fitness. The fitness value of $\phi_{\text{MSY-PA}}$ quantifies the management performance of the simulation results (see e.g. Figures 8.5 and 8.7, described in the Results section). Fitness values closer to 0 (less negative) indicate better performance. The aim of the optimisation procedure was to provide precautionary management solutions, and options where risk exceeds 5% are clearly indicated by red shading.

8.4.5 Scenarios

The scenarios explored were:

1. **Sensitivity**. Pollack was chosen as a typical example stock ($k = 0.19$ year^{-1}, a medium value within the range for which the rfb rule performed reasonably; Fischer et al., 2020, Chapter 6). As a baseline, the rfb rule was tuned solely with the multiplier [x in Equation (8.2)] and all remaining parameters set to their default values (see Table 8.1) so that the B_{lim} risk was 5%. Subsequently, the sensitivity of the B_{lim} risk to the following

simulation conditions was explored: the definition of B_{lim}, the starting condition of the stock before the implementation of the rfb rule, the length of the implementation period, the observation uncertainty (for biomass index and mean catch length, σ_{obs}), recruitment variability (σ_R) and recruitment steepness (h). For the runs considering the B_{lim} definition and the stock status ($\text{SSB}_{y=0}/B_{\text{MSY}}$), the number of simulation replicates was increased from 500 to 10,000 so that they could be split into groups (with steps of $0.1B_{\text{MSY}}$), and sufficient replicates in each group were available to calculate B_{lim} risk (> 200 replicates for all groups with $\text{SSB}_{y=0}/B_{\text{MSY}} \leq 1.5$).

2. **Short- vs long-term optimisation**. The standard implementation period for the rfb rule was 50 years and the optimisation considered the performance over the full period. The impact of this implementation period on B_{lim} risk and catch was explored by considering three time horizons; the first 10 years (years 1-10), the last 10 years (years 41-50), and all years (years 1-50).

3. **rfb rule parameters**. The impact of using all or a subset of the 10 tuneable parameters of the rfb rule on achieving the precautionary management objectives (SSB, catch, B_{lim} risk and ICV, summarised by $\phi_{\text{MSY-PA}}$) was explored for the example stock (pollack).

4. **Risk limit**. The sensitivity of the optimisation (SSB, catch, B_{lim} risk and ICV) to the 5% B_{lim} risk limit was explored for all 29 stocks. For this purpose, the rfb rule was tuned with the multiplier (x), and the remaining parameters were set to their default values. A comparison was made between the default 5% risk limit, doubling the risk limit to 10%, and an additive 5% point risk limit increase, defined as the stock-specific B_{lim} risk under no fishing and adding 5% points on top of that.

5. **Stock-specific optimisation**. The genetic algorithm was applied to optimise the full rfb rule using $\phi_{\text{MSY-PA}}$ for all 29 stocks and the management performance was summarised with the value of $\phi_{\text{MSY-PA}}$.

6. **Comparison to MSY and ICES rule**. The results of the optimisation process from the previous step (including all rfb rule parameters) were compared to the results from the previous chapter (Chapter 7; Fischer et al., 2021a), which applied the ϕ_{MSY} fitness function and also tested the current ICES 2 over 3 advice rule for category 3 data-limited stocks. The 2 over 3 rule is essentially a simplification of the rfb rule (with $n_0 = 1$, $n_1 = 2$, $n_2 = 3$,

$e_r = 1$, $e_f = 0$, $e_b = 0$, $v = 2$, $x = 1$, $u_u = 1.2$ and $u_l = 0.8$) but includes a precautionary buffer. This buffer reduces the catch advice by 20% if either fishing mortality is above its MSY reference level, or biomass below half its MSY reference level, based on MSY proxy reference evaluations, such as with the surplus production in continuous time model (SPiCT; Pedersen & Berg, 2017), and can be applied once every three years (see Fischer et al., 2021a, and Chapter 7 for details on the implementation).

7. **Uncertainty cap** The optimisations of the rfb rule in the previous points either did not include the uncertainty cap, or the values of the uncertainty cap were part of the optimisation procedure. Fisheries managers might insist on the inclusion of an uncertainty cap to avoid large catch variability. Therefore, a final set of simulations was conducted where the uncertainty cap in the optimisation was fixed to the values (+20%, -30%, i.e. $u_u = 1.2$ and $u_l = 0.7$) suggested by Fischer et al. (2020, Chapter 6).

8.4.6 Data and software

The MSE framework was the same as developed in the previous chapter (see Chapter 7) and based on FLR (Kell et al., 2007). The results of this study are fully reproducible and input data, software code, and summarised results as presented in this chapter were made open source and are available from GitHub at https://git.io/JCEbw.

8.5 Results

8.5.1 Sensitivity

Figure 8.3 summarises the influence of the simulation specifications on B_{lim} risk for pollack in the random fishing history. A B_{lim} risk of 5% was achieved when setting the multiplier to $x = 0.75$ (Figure 8.3a), and this parameterisation was used as the baseline for the sensitivity analyses. B_{lim} risk was sensitive to the definition of B_{lim} (larger reference points reduced the risk), the initial stock status before the implementation of the rfb rule (stronger initial depletion caused higher risks), the length of the implementation (risk declined over time), observation uncertainty for the biomass index and mean catch length (higher uncertainty increased the risk) and recruitment steepness (higher steepness reduced the risk, Figure 8.3b-e,g). The B_{lim} risk was insensitive to recruitment variability for $x = 0.75$; however, with larger multipliers (e.g. $x = 1$), the risk increased with increasing recruitment variability (Figure 8.3f).

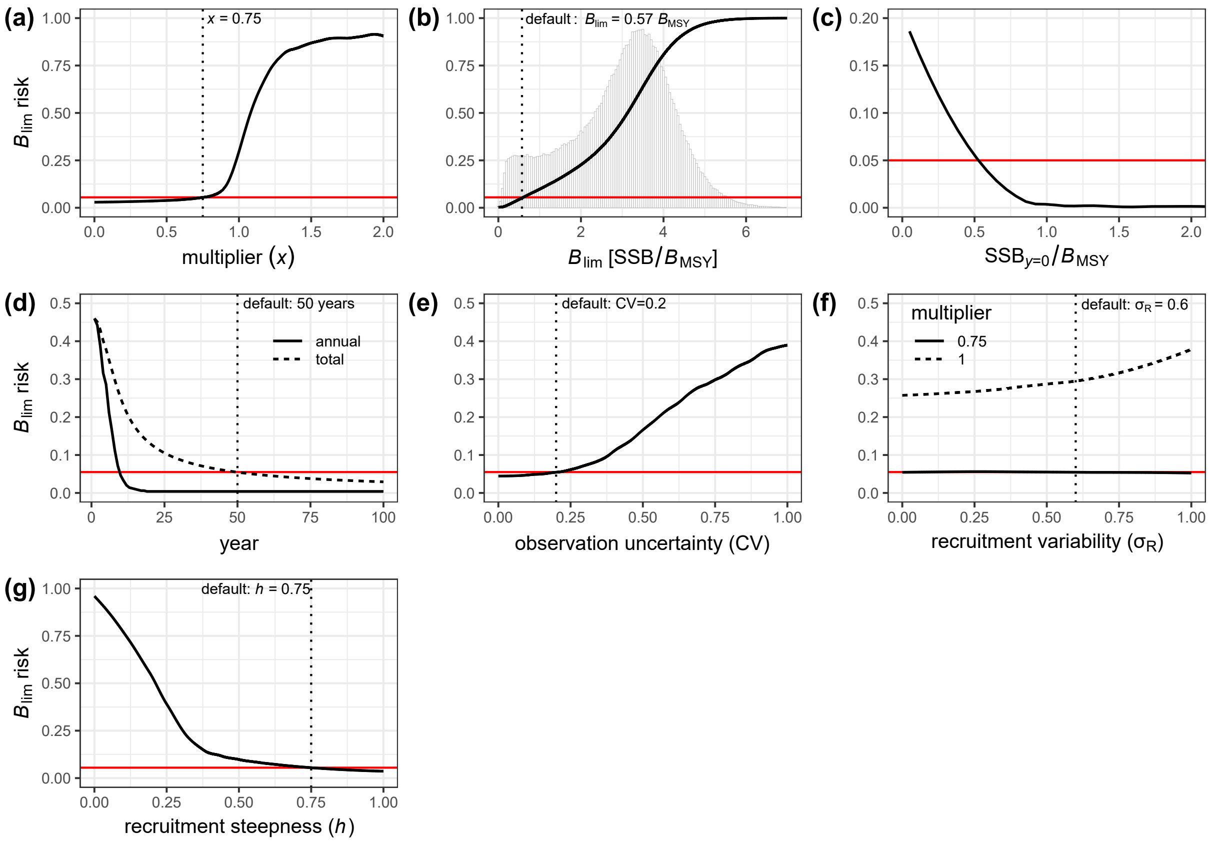

Figure 8.3: Summary of the sensitivity analyses of B_{lim} risk to simulation conditions for pollack under the random fishing history. B_{lim} risk reaches 5% for a multiplier of $x = 0.75$ of the rfb rule (a), which is used for the remaining sensitivity analyses. Shown is the B_{lim} risk depending on the definition of B_{lim}, including a histogram of the distribution of SSB values (b), the initial stocks status before the implementation of the rfb rule (c), the implementation period (d), the level of observation uncertainty for both the biomass index and mean catch length (e), recruitment variability (f) and recruitment steepness (g). The solid red horizontal line indicates the 5% risk limit, and the dotted vertical line the default parameterisations. In (d), shown are both the "annual" risk and the "total" risk from the start of the projection to the current year. The risk curve for recruitment variability (f) is flat for $x = 0.75$, and therefore sensitivity is also illustrated for $x = 1$.

8.5.2 Short- vs long-term optimisation

The selection of the time period over which the summary statistics are calculated influenced the selection of an rfb rule parameterisation so that the 5% B_{lim} risk limit was met. This is shown for two stocks in Figure 8.4. For pollack, in the one-way fishing history, $x = 0.76$ met the risk requirement when the full 50-year projection is considered. When only the last 10 years of the projection were taken into account, the multiplier could increase to $x = 0.92$. However, for the first 10 years of the simulation, no multiplier led to B_{lim} risk $\leq 5\%$. Short-term (first 10 years) risk for none of the faster-growing species ($k \geq 0.32\mathrm{year}^{-1}$) could be reduced to 5%.

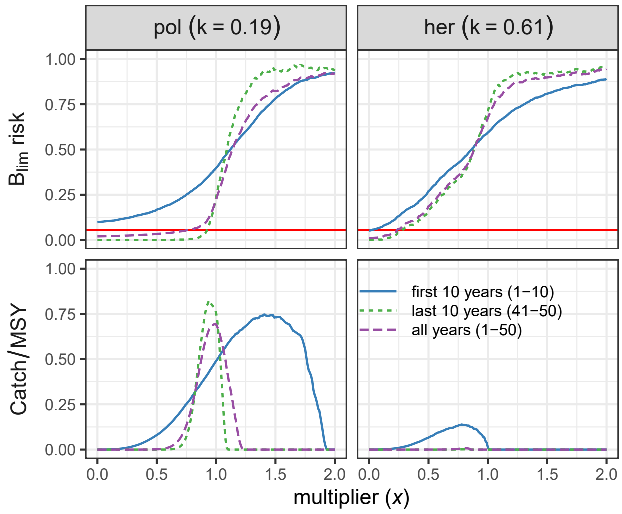

Figure 8.4: Impact of the time period used for calculating summary statistics. Results are shown for two stocks; pollack (pol) and herring (her) in the one-way fishing history. The red horizontal line indicates the 5% risk limit. Results for the remaining stocks are included in Figure D.1 in Appendix D.

The short-term risk was more influenced by the starting condition of the simulation (i.e. fishing history), compared to calculating risk over a longer time.

8.5.3 rfb rule parameters

The outcome of including different elements of the rfb rule in optimising the rule for pollack is shown in Figure 8.5, and the optimised parameterisations are listed in Table D.1 in Appendix D. The results were similar for both fishing histories. Including only the multiplier [x, see Equation (8.2) and Table 8.1] was sufficient to reduce the B_{lim} risk to 5% with the $\phi_{\text{MSY-PA}}$ fitness function of the genetic algorithm. However, this risk reduction led to a substantial loss of catch and high SSB compared to the default (i.e. not optimised) rfb rule parameterisation. The performance could be substantially improved (higher yield while staying within the 5% risk limit) when more elements of the rule were introduced (n_0, n_1, n_2, e_r, e_f, e_b, and v). The uncertainty cap (restricting the difference of the catch advice compared to the previously realised catch; u_u and u_l) on its own could not reduce the risk to 5%. Including the uncertainty cap in combination with other rfb rule parameters (either with the multiplier or with all parameters) did not affect the optimisation and the optimised parameterisation kept the default uncertainty cap (i.e. no cap).

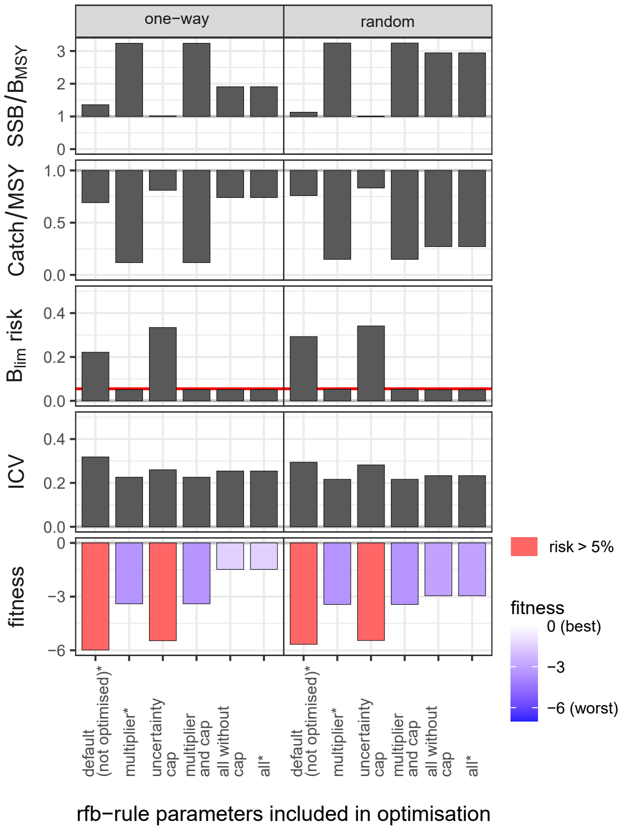

Figure 8.5: Results of using different elements of the rfb rule in the optimisation procedure (with $\phi_{\text{MSY-PA}}$) for pollack for two fishing histories (one-way and random). All optimisations apart from the default use the genetic algorithm. The red horizontal line in the third row of plots highlights the 5% B_{lim} risk limit. Fitness values (last row) where the risk exceeds 5% are highlighted in red. Results marked with * are shown again in Figure 8.7 (c, f, g) for comparison.

8.5.4 Risk limit

The selection of the B_{lim} risk limit had a substantial impact on the optimised rfb rule parameterisation. An analysis of the risk limits related to the selection of the rule's multiplier x is shown in Figure 8.6 for four example stocks (the remaining stocks are presented in Figure D.2 in Appendix D). It was possible for all 29 stocks (and both fishing histories) to set a multiplier that reduced the risk to $\leq 5\%$. An explicit 5% risk limit was the most restrictive for all stocks and resulted in the lowest long-term catch, followed by the additive 5% point and the 10% limits.

8.5.5 Stock-specific optimisation

Figure 8.7 shows the management performance of the rfb rule for the various optimisations, a comparison with the results of Fischer et al. (2021a, optimisation without the risk limit, and the 2 over 3 rule, see Chapter 7) and a zero fishing option. The performance is expressed through the fitness [$\phi_{\text{MSY-PA}}$, Equation (8.10)] and non-precautionary parameterisations (B_{lim} risk $> 5\%$)

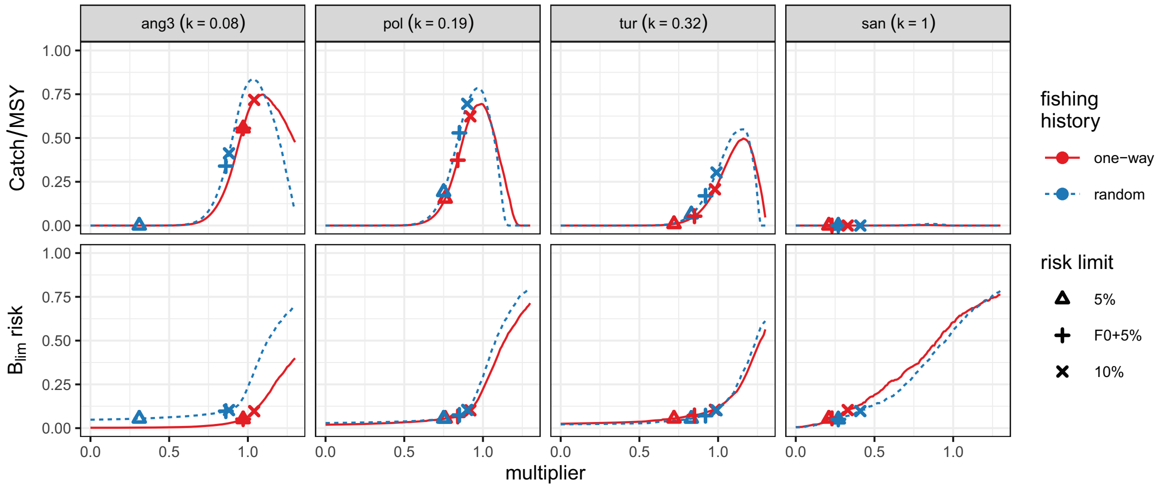

Figure 8.6: Impact of different precautionary B_{lim} risk limits on summary statistics in optimising the rfb rule with a multiplier (the remaining parameters are set to their default values of Table 8.1). Results are shown for four example stocks; blackbellied angler (ang3), pollack (pol), turbot (tur) and sandeel (san). The optimised solutions are highlighted with symbols. F0+5% indicates the additive 5% point risk limit increase compared to no fishing. The "5%" risk limit optimisation results (triangles) for pollack correspond to the "multiplier" optimisation in Figure 8.5.

are clearly highlighted in red. The fitness split into its elements (SSB, catch, ICV, risk penalty) is available from Figure D.3 in Appendix D.

For all 29 stocks and both fishing histories, the B_{lim} risk could be reduced to 5%, both when using only the multiplier (f in Figure 8.7) or all rfb rule parameters in the optimisation (g in Figure 8.7) with the genetic algorithm. When using only the multiplier, the catches were often low and SSB well above B_{MSY}. Including all rfb rule parameters in the optimisation improved performance for most stocks, with higher catches while keeping B_{lim} risk within the 5% limit. The performance of the rule for the higher-k stocks ($k \geq 0.32$ year^{-1}) was poor (high B_{lim} risk, low catch/MSY), and meeting the 5% risk limit was only possible by reducing catches to zero or near-zero. The optimised rfb rule parameterisations were specific to the stock and fishing history and are summarised in Table D.1 in Appendix D.

8.5.6 Comparison to MSY and ICES rule

Figure 8.7 includes a comparison of the performance of the $\phi_{\text{MSY-PA}}$-optimised rfb rule (f, g) to the optimisation with ϕ_{MSY} (d, e) of Fischer et al. (2021a, Chapter 7) and the ICES 2 over 3 rule (b). The ICES 2 over 3 rule often led to high B_{lim} risks and risk was always > 5%. There were clear trade-offs between the ϕ_{MSY}-optimised and the $\phi_{\text{MSY-PA}}$-optimised rfb rule, where the

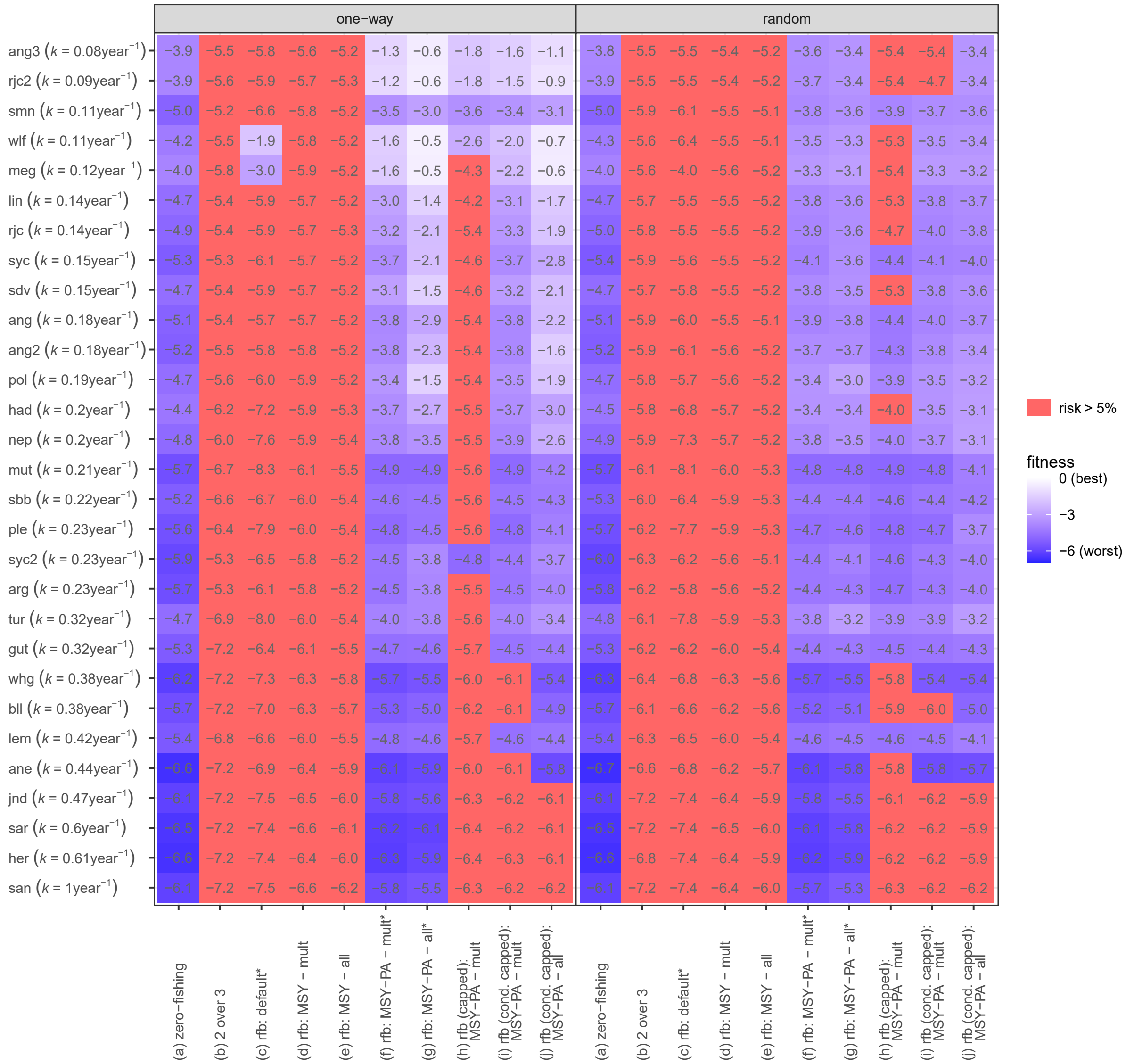

Figure 8.7: Fitness ($\phi_{\text{MSY-PA}}$) as a measure of management performance of the rfb rule, achieved through optimisation with the genetic algorithm, and comparison to a "zero-fishing" option (a) and the 2 over 3 rule (b, from Fischer et al., 2021a, Chapter 7). Non-precautionary management (B_{lim} risk exceeds 5%) is highlighted in red. "rfb: default" denotes the non-optimised parameterisation (c), "rfb: MSY" are the parameterisations optimised without the risk limit (d, e, from Fischer et al., 2021a, Chapter 7), "rfb: MSY-PA" include the 5% risk limit (f-j), "rfb (capped)" indicates that the uncertainty cap is fixed (+20%, -30%, h) and for "rfb (cond. capped)" the cap is conditional and only implemented when $I \geq I_{\text{trigger}}$ in Equation (8.2) (i, j). The "mult" indicates optimisations with only the multiplier of the rfb rule (d, f, h, i) and "all" with all parameters (e, g, j). The labels highlighted by * (c, f, g) refer to the same optimisations shown in Figure 8.5 for pollack.

first delivered highest yields close to B_{MSY} but B_{lim} risks above 5%, whereas the latter resulted in B_{lim} risks within the 5% limit, but with markedly lower yields.

8.5.7 Uncertainty cap

For all but two stocks (lesser spotted dogfish, syc2 and golden redfish, smn), fixing the uncertainty cap (limiting catch advice increase to +20% and the decrease to −30%) meant that the optimisation of the rfb rule with $\phi_{\text{MSY-PA}}$ and the multiplier was impaired and the risk could not be reduced to 5% in at least one of the fishing histories (h in Figure 8.7). To overcome this problem, the rfb rule was tested with a conditional uncertainty cap, where the cap is only applied when the biomass index is above its threshold level [$I \geq I_{\mathrm{trigger}}$ in Equation (8.2)]. The results of these optimisations (i and j in Figure 8.7) show that the 5% risk limit could be met for most stocks, at least when the optimisation was conducted with all parameters. Exceptions are the four fastest-growing species (John Dory, jnd, European pilchard, sar, herring, her, and sandeel, san), where the inclusion of the conditional uncertainty cap did not allow the risk to meet the 5% limit. In some cases (see, e.g. plaice, ple, and turbot, tur, in Figure 8.7), the introduction of the conditional cap resulted in a better fitness when the optimisation included all parameters (j), compared to the free selection of the (unconditional) cap (g).

8.6 Discussion

The outcomes of this study were manifold, and the main results are summarised in Figure 8.7. The key message is that explicit precautionary consideration (such as the 5% risk limit) could be incorporated into data-limited fisheries management, shown here with the example of the rfb rule and through the application of a genetic algorithm. This approach allowed the specification of management objectives and the exploration of trade-offs. The level of complexity of a decision rule can impact the overall management performance and more complex case-specific adaptions delivered higher yield while remaining precautionary.

Results of any simulation study depend on the simulation specifications, and models are simplifications of reality (Burnham, 2004). The present study is no exception, and the sensitivity analysis reiterated this by showing that the presumed precautionary management performance of the rfb rule (quantified through the B_{lim} risk) was influenced by simulated conditions such as the initial stock status. The MSE concept inherently relies on simulations and associated assumptions, which can lead to criticism (Rochet & Rice, 2009, 2010; Kraak et al., 2010), but following best practices (e.g. Punt et al., 2016) and including a wide range of uncertainties can restore confidence in the conclusions (Butterworth et al., 2010).

For data-rich stocks, operating models can be conditioned on analytical stock assessments, which provide crucial knowledge about stock status relative to reference points, intrinsic population dynamics, mechanistic relationships between biological parameters (e.g. stock-recruitment models) and uncertainty associated with model estimates and observations. The consideration of uncertainty is a fundamental step when conducting MSE evaluations, usually implemented by conditioning a range of operating models on available data. The lack of such data in data-limited situations implies adopting a potentially arbitrary set of simulation assumptions. It is therefore important to include a range of sensitivity analyses to ensure the robustness of any conclusions drawn.

Uncertainty is exacerbated for simulations of the rfb rule because the rule is meant to be applied in data-limited situations. For example, the biomass limit reference point (B_{lim}) was defined in terms of recruitment impairment (Fischer et al., 2020, Chapters 6 and 7) and is therefore dependent on recruitment steepness, which is difficult to estimate even for data-rich stocks. However, the value of B_{lim} relative to unfished biomass, $0.16B_0$, closely resembles the generic value of $0.2B_0$ adopted by other management bodies such as the International Whaling Commission (IWC), the Commission for the Conservation of Antarctic Marine Living Resources (CCAMLR), and Australia and New Zealand (Preece et al., 2012).

A 5% limit is commonly used in many scientific fields to describe rare events or to safeguard against their occurrence, e.g. by defining that statistical analyses are significant for $p \leq 0.05$. However, this limit itself is controversial in the scientific community (Wasserstein & Lazar, 2016; Amrhein et al., 2019). The origin of the 5% limit used in the ICES interpretation of the precautionary approach is somewhat opaque. The approach was initially introduced into the ICES fisheries advice framework without specific risk limits, and stated that limit reference points should be avoided with a high probability (ICES, 1997), with reference to a United Nations agreement on the implementation of the precautionary approach. Subsequently, referring to the considerations of Butterworth and Bergh (1993) on precautionary decision rules, ICES (1998, p. 25) note that an "example of a precautionary criterion for management might be [defined as a] probability of less than 5% of reducing the resource below B within 10 years", without specifying or giving justifications for the 5%, the reference point B or the 10-year period. Such risk levels were originally meant as interim solutions until more appropriate risk levels had been agreed among stakeholders. However, this value has not changed since then and is currently enshrined into the ICES advice framework (ICES, 2019a) and also recommended for MSE testing of data-limited management procedures (ICES, 2017f). ICES (2020b) note that the appropriateness of the 5% risk limit was queried again with advice recipients in 2020 and recipients expressed their satisfaction about using this value without suggesting alternatives.

In other parts of the world, risk considerations similar to the ICES precautionary approach are applicable. For example, the harvest strategy standard for New Zealand fisheries (Ministry of Fisheries, 2008) includes a clause stipulating that management procedures need to ensure that breaching a soft limit does not exceed 5%. The justification of using specific risk limits is always challenging and can easily draw criticism. The benefit of using a modelling approach is that different risk limits can be tested and their implications on management performance can be illustrated, which in turn allows an informed judgement about the acceptability of a particular risk limit.

The choice of probability can also have an economic impact since a fishery might secure a price premium if it can gain an ecolabel certificate. For example, the Marine Stewardship Council (MSC) fisheries standard (MSC, 2018) requires that it must be highly likely ($\geq 80^{\text{th}}$ percentile) or there is a high degree of certainty ($\geq 95^{\text{th}}$ percentile) that the stock is above the point at which recruitment is impaired.

Specific risk values crucially influence management rules and decisions. As shown here for the rfb rule, doubling the allowed risk to 10% had a large impact on the optimised rule's performance and resulted in much higher long-term catches while being precautionary at a 10% risk level. A more restrictive risk limit such as 1% would be impossible to meet for some stocks because the risk without fishing exceeds 1% for some stocks and fishing histories. For those stocks for which this risk limit could be met, this would lead to a strong reduction catch or is only possible by setting the catch to zero.

Relative risk metrics might be considered a plausible alternative to absolute risk. Relative risk can be defined as the risk relative to some baseline risk, such as the risk without any fishing activity. The benefit of this approach is that natural variability is explicitly considered, e.g. when a fish stock naturally exhibits high fluctuations and, therefore, the risk of falling below a limit reference point is high, even without any fishing activity. One example explored here for the rfb rule was an additive risk of 5% points, added on top of the risk without fishing.

On the other hand, defining the risk increase of 5% points is arbitrary in the same way as defining an absolute risk limit. Another alternative to quantify risk is the approach used for South African short-lived pelagic species where the shift of the biomass distribution of a stock is compared to the distribution under no fishing (de Moor et al., 2011), but generally only possible if such information is available. The definition and usefulness of risk criteria in fisheries management should be explored further, in particular, whether the same approach should be applied irrespective of life history or other stock characteristics. Tools such as genetic algorithms can be useful because they allow the exploration of management solutions and illustrate trade-offs.

Fischer et al. (2020, Chapter 6) developed the operating models for the 29 stocks used in the simulations, and provided extensive sensitivity analyses on their assumptions and parameterisations, including the appropriateness of levels of uncertainty. The simulation approach used here can be considered generic, but conditioned on life-history traits. Generic simulations need to account for additional uncertainty, which was implemented here by considering two alternative fishing histories, one where the starting condition implied a high stock depletion, and the other provided a large spread of different depletion levels. For optimum performance of any decision rule, more data should be collected to enable case-specific testing and optimisation. Such case-specific simulations are explored in Chapter 11.

For all 29 stocks and both fishing histories simulated in this study, projecting forward with zero fishing led to B_{lim} risks below 5%, which meant that there was scope for fishing activities while remaining within the 5% risk limit. The 2 over 3 rule generally resulted in high B_{lim} risks (16-73%), and its performance was strongly dependent on the initial stock status. Therefore, the current management of ICES category 3 data-limited stocks based on the 2 over 3 rule with uncertainty cap and precautionary buffer cannot be considered precautionary. Except for two slow-growing stocks (Atlantic wolffish and megrim in the one-way fishing history), applying the default rfb rule parameterisation led to risks above 5%.

However, when the rfb rule was optimised with the genetic algorithm, and the fitness function included the 5% risk limit, an optimised parameterisation of the rfb rule was found, which complied with the risk limit, both when only modifying the rule's multiplier or the complete set of parameters. However, clear trade-offs between the two solutions were evident. The parameterisation based on the multiplier achieved risk compliance by reducing the catch advice and forfeiting much of the long-term catch. On the other hand, the solution with all of the rfb rule's parameters tuned resulted in better performance with higher catches. The comparison of the optimised rfb rule with (this chapter) and without the 5% risk limit (Fischer et al., 2021a, Chapter 7) revealed that the inclusion of the limit was restrictive and led to lower catches. The decision on which approach should be implemented in reality is essentially up to managers. Including risk limits can be restrictive; however, this might be considered necessary to ensure precautionary management. An interesting observation was made about the implementation of the uncertainty cap. For pollack, the inclusion of the cap did not improve management performance, and the optimisation procedure selected the parameterisation, which turned off the cap. When a fixed cap (+20%, -30%) was enforced, for most stocks, this meant that the 5% risk limit could not be met. To avoid this, the implementation of a conditional uncertainty cap (+20%, -30%) is suggested, which is only activated when the biomass index is at or above its trigger value.

Previous work showed that the rfb rule resulted in poor performance with high risks of stock collapses and low yields for faster-growing stocks (with von Bertalanffy growth parameter $k \geq 0.32$ year^{-1}; Fischer et al., 2020, Chapter 6), and even optimising the rule towards MSY objectives did not markedly improve the outcome (Fischer et al., 2021a, Chapter 7). The general conclusion was that the rfb rule should not be implemented for such fast-growing stocks because of their highly variable populations dynamics and dependence on recruitment success (see, e.g. Cury et al., 2014). The present work supports this recommendation. The rfb rule could be optimised to meet a specific precautionary criterion (constraining the risk of the stock falling below B_{lim} to a specific limit). Nevertheless, meeting this criterion was only possible by accepting an extreme trade-off for the yield, i.e. advising very low precautionary catch levels. Alternative management procedures, e.g. based on harvest rates or escapement strategies (ICES, 2020a), appear more suitable and are explored in Chapters 9 and 10.

The main recommendation from this chapter is to replace the 2 over 3 rule with the rfb rule for ICES category 3 data-limited stocks with slow to medium individual growth ($k \leq 0.32$ year^{-1}). If case-specific simulations are not possible, the rfb rule can be applied with generic multipliers meant to ensure precautionary management. Based on the results of this work, ICES guidelines have been drafted (ICES, 2020a). The justification for selecting specific multipliers is illustrated in Figure 8.8. The generic multipliers were set based on where the B_{lim} average risk met 5% (median over individual stocks and combining both fishing histories). This led to a generic multiplier of $x = 0.95$ for low-k stocks ($k < 0.2$ year^{-1}) and $x = 0.9$ for medium-k stocks (0.2 year$^{-1} \leq k \leq 0.32$ year^{-1}).

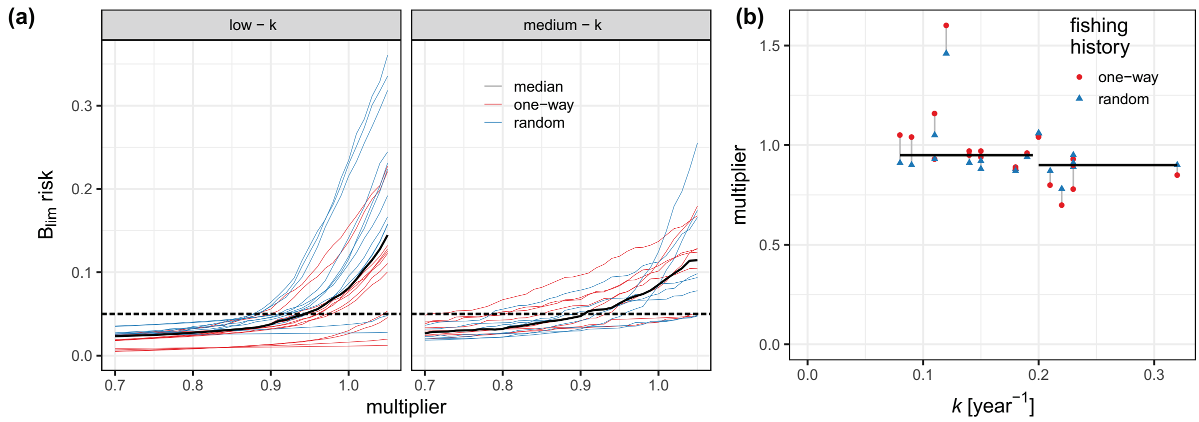

Figure 8.8: Justification of generic multipliers for the rfb rule. Results are shown for 100-year simulations and stocks are split into low-k ($k < 0.20$ year^{-1}) and medium-k (0.20 year$^{-1} \leq k \leq$ 0.32 year^{-1}) groups. (a) illustrates where the median B_{lim} risk meets 5% and (b) the stock specific optimal multipliers in relation to the generic multipliers (horizontal black lines).

The rfb rule was already applied this way to the first two stocks in the 2021 ICES advice, plaice in the Celtic Sea south and southwest of Ireland (ICES divisions 7.h-k; ICES, 2021m) and sole in the Cantabrian Sea and Atlantic Iberian water (ICES divisions 8.c and 9.a; ICES, 2021l). A further rollout is anticipated for 2022. Ideally, case-specific simulations are conducted and should consider stock characteristics, such as adapting the simulation period to life history, using more specific uncertainty estimates (e.g. correlation structure of residuals), and alternative operating models. An example for such a situation is the western English Channel plaice stock, where ICES advice is currently based on the 2 over 3 rule (ICES, 2021k), but this stock is relatively data-rich, facilitating case-specific simulations and will be used as a case study in Chapter 11. Case-specific analyses are likely to lead to better overall management performance while maintaining precautionary principles.

8.7 Conclusion

This chapter was the third chapter of this PhD thesis exploring the empirical rfb rule. The initial exploration of the rfb rule in Chapter 6 revealed that the rule's management performance depends on the individual growth rate of the species, and better performance was observed for slower-growing species. In Chapter 7, an optimisation procedure based on a genetic algorithm was implemented and found suitable to improve the rule's performance towards specific management objectives. The present chapter went further and included explicit risk limits to ensure compliance with the precautionary approach and found that such limits can be considered. This study concludes the generic analyses of the rfb rule and the following chapter (Chapter 9) explores an alternative approach based on a relative harvest rate approach. This harvest rate approach is particularly aimed at closing the gap left by the rfb rule, i.e. for faster-growing species for which the rfb rule should not be applied.

Chapter 9

Exploring a relative harvest rate strategy for moderately data-limited fisheries management[1]

[1]This chapter is an adaptation of Fischer et al. (2022).

9.1 Foreword

The previous three chapters were on the empirical trend-based rfb rule. This chapter explores an alternative empirical control rule based on a harvest rate. Preliminary results were presented at the tenth International Council for the Exploration of the Sea (ICES) Workshop on the Development of Quantitative Assessment Methodologies based on LIFE-history traits, exploitation characteristics, and other relevant parameters for data-limited stocks (ICES WKLIFE X; ICES, 2020a). Subsequently, additional analyses were undertaken, and the work was peer-reviewed and published in Fischer et al. (2022):

> Fischer, S. H., De Oliveira, J. A. A., Mumford, J. D. & Kell, L. T. (2022). Exploring a relative harvest rate strategy for moderately data-limited fisheries management. *ICES Journal of Marine Science*, 12 pp. https://doi.org/10.1093/icesjms/fsac103

The following sections in this chapter are an adaptation of this publication.

9.2 Abstract

Moderately data-limited fisheries can be managed with simple empirical management procedures without analytical stock assessments. Often, control rules adjust advised catches by the trend of an abundance index. This chapter explores an alternative approach where a relative harvest rate, defined by the catch relative to a biomass index, is used and the target level derived from analysing historical catch length data. This harvest rate rule was tested generically with management strategy evaluation. A genetic algorithm was deployed as an optimisation procedure to tune the parameters of the control rule to meet maximum sustainable yield and precautionary management objectives. Results indicated that this method could outperform trend-based strategies, particularly when optimised, achieving higher long-term yields while remaining precautionary. However, optimum harvest rate levels can be narrow and challenging to find because they depend on historical exploitation and life history characteristics. Misspecification of target levels can have a detrimental impact on management. Nevertheless, harvest rates appear to be a suitable management option for moderately data-limited resources, and their application has modest data requirements. Harvest rate strategies are especially suitable for stocks for which case-specific analyses can be conducted.

9.3 Introduction

Fisheries management should ensure the sustainable exploitation of harvested fish stocks (Hilborn & Walters, 1992). Management principles such as maximum sustainable yield (MSY, i.e. keeping the stock at or above a level where it is most productive) or the precautionary approach (i.e. reduce the risk of stock depletion; Garcia, 1996) are often mandated through national or international legislation, such as the European Union's common fisheries policy (EU, 2013). However, most of the world's fish stocks are considered data-limited and complex stock assessments or forecasts do not exist (Rosenberg et al., 2014). For such stocks, simpler stock assessment models can sometimes be used to help comply with these management principles. Alternatively, model-free management procedures relying only on empirical data have been shown to be viable management options (Geromont & Butterworth, 2015a; Carruthers et al., 2016).

ICES is the provider of scientific advice on fishing opportunities for many fish stocks in the Northeast Atlantic (ICES, 2021a) and classifies stocks into six categories (Table 9.1). According to their stock assessment database (ICES, 2021i), ICES provided advice for 175 fish stocks in 2020, of which around 50% were considered data-limited (ICES categories 3-6). Of these data-limited stocks, 55% were classified as category 3. For category 3 stocks, catches, including catch length data, as well as a stock index (often from a scientific survey), exist (ICES, 2021a). While the data might be enough to apply surplus production or integrated assessment models, these models are not used because of insufficiently long time series, lack of contrast in the data to inform models, violations of model assumptions, model convergence issues, unacceptably high uncertainty estimates, or because models fail acceptance criteria (Punt et al., 2020). This chapter (and the entire thesis) follow the ICES interpretation of the term "data-limited", which might be considered as "data-moderate" or even "data-rich" elsewhere.

There are two main approaches to how empirical management procedures generate catch advice: (1) indicator-adjusted catch rules which adjust the previous catch by a multiplier derived from an indicator, such as the trend from a stock index, and (2) by defining a harvest rate and applying this to a biomass estimate. ICES is currently in the process of revising its data-limited management framework from 2012 (ICES, 2012b) and is replacing methods for category 3 stocks (ICES, 2020a, 2022b). One of the replacement methods is the rfb rule (Fischer et al., 2020; Fischer et al., 2021a, 2021b, see Chapters 6, 7, and 8), an indicator-adjusted catch rule in which the catch advice is adjusted by the trend in a relative biomass index and the signal from length data. However, indicator-adjusted catch rules can be problematic because the new advice is directly linked to the previous value, which can induce oscillatory behaviour, restrict flexibility, or react slowly to changes in the stock if the index trend is estimated over several historical years.

Table 9.1: Overview of the ICES data categories. Data and advice method columns describe typical scenarios but deviations from these exist. Revisions for category 2 and 3 suggested by ICES (2020a, 2022b) are included.

Category	**Description (ICES, 2021a)**	**Typical data**	**Typical advice method**
1	*Stocks with quantitative assessments*	Catch and survey data (mostly age-structured)	Stock assessment & short-term forecast
2	*Stocks with analytical assessments and forecasts that are only treated qualitatively*	Catch and survey data (mostly age-aggregated)	Stock assessment & short-term forecast
3	*Stocks for which survey-based assessments or exploratory assessments indicate trends*	Catch (with length data) and stock index (survey/commercial) without age structure, life-history information	Empirical (model-free) methods
4	*Nephrops stocks where information on possible abundance can be inferred*	Catch, recent survey index value, biological data (can be borrowed)	Precautionary MSY harvest rate applied to index
5	*Stocks for which either only data on landings or a short time-series of catch are available*	Landings	Recent advice kept or reduced (if previous reduction was more than 3 years ago)
6	*Stocks for which there are negligible landings and stocks caught in minor amounts as bycatch*	Unreliable catch	Recent advice kept or reduced (if previous reduction was more than 3 years ago)

The use of harvest rates can overcome some of the shortcomings of indicator-adjusted catch rules. In its simplest form, a harvest rate is the catch divided by the abundance of an exploited stock, e.g. derived from a stock index. This allows the definition of a target harvest rate, implemented by multiplying it with the current index value to calculate a new catch limit. A potential benefit of such an approach is that a new catch advice can be set independently of the previous catch. A main challenge for harvest rate-based management in a data-limited situation is the definition of the target level. Here, the situation where the target harvest rate is derived empirically (as opposed to using a model in data-rich situations) is considered.

The use of harvest rates for data-limited fisheries management is not new. The 2012 ICES framework for data-limited stocks includes an F_{proxy} rule (method 3.3 of ICES, 2012b). This rule can be considered a variant of a harvest rate rule, where a target is set based on historical F_{proxy} values (catch divided by stock index) and used to derive catch advice for the next year, with an uncertainty cap (limiting changes in catch advice to 20%) and a precautionary buffer (reducing the catch advice by 20%). This rule has occasionally been used in ICES (ICES, 2021i), e.g. for East and South Greenland cod (*Gadus morhua*, 2016-2017; ICES, 2017a), East Greenland and Iceland grounds greater silver smelt *Argentina silus*, 2012-2019; ICES, 2021e and blue ling (*Molva dypterygia*, 2012-2018; ICES, 2021c). In these cases, the management target was largely based on expert judgement. This included selecting a time period of several years based on considerations such as whether F_{proxy} values appeared stable or a stock index indicated a generally stable or increasing trend for stock biomass. The target harvest rate was then defined as the average F_{proxy} for these years.

Harvest rates are commonly used for data-rich fisheries management and this is often associated with running stock assessment models to estimate the stock size. The ICES advisory framework for data-rich stocks goes one step further by conducting short-term forecasts and setting catch limits based on a hierarchy of advice rules (ICES, 2019a, 2021a). Previous data-limited simulation studies considered the applicability of control rules by comparing stock index values relative to a target value, but either used the comparison to adjust a previous catch (Geromont & Butterworth, 2015a; Carruthers et al., 2016) or to move the current catch towards a target level (Geromont & Butterworth, 2015b). The direct application of harvest rates based on a stock index has not been considered for data-limited fisheries management recently in the peer-reviewed scientific literature.

This chapter explores the applicability of a relative harvest rate rule for moderately data-limited fisheries management, in particular how it could complement the current set of rules, especially where current approaches are inadequate and do not follow required management principles. To accomplish this, management strategy evaluation (MSE; Punt et al., 2016), in the sense of a closed-loop simulation for evaluating management procedures but without extensive stakeholder engagement is used.

MSE (Smith, 1994; Punt et al., 2016) is widely considered the state-of-the-art for exploring management strategies. It is crucial that candidate management procedures are simulation tested before implementation to ensure their robustness to a range of uncertainties. Many MSEs are conducted on a case-specific basis for well monitored and commercially important species, e.g. international tuna stocks (Sharma et al., 2020). The simulation of stocks with limited data can be more challenging due to the lack of data and knowledge. Nevertheless, notable studies screened various data-limited methods (Geromont & Butterworth, 2015a; Jardim et al., 2015; Carruthers et al., 2016).

To conduct the MSE, the generic operating models described in Chapter 5 were used because these cover a wide range of life-history traits. Furthermore, Fischer et al. (2021a, see Chapter 7) showed that the performance of control rules could be substantially improved through tuning with a genetic algorithm. A genetic algorithm is a computationally efficient method for solving multi-dimensional optimisation problems, and works by mimicking principles of biological evolution by introducing variability into the tuneable parameters and subjecting parameterisations to a competitive environment where selection favours individuals with higher fitness (Holland, 1992). In the context of a fisheries management procedure, the elements of a control rule are the tuneable parameters, and the fitness can be measured as the management performance relative to agreed management objectives, such as long-term sustainable exploitation. This can include explicit precautionary considerations (Fischer et al., 2021b, see Chapter 8), such as the 5% risk limit that is part of the ICES precautionary approach (ICES, 2019a, 2021h).

Specifically, this chapter explores an approach in which a target harvest rate is linked to empirical data (mean catch length as a proxy for fishing pressure). The resultant management procedure is simulation tested using MSE, and then optimised considering the ICES precautionary approach and MSY. Finally, the relative harvest rate rule is compared with other more traditional ICES data-limited fisheries management approaches.

9.4 Methods

9.4.1 Operating Models

The age-structured operating models developed in Chapter 5 in the Fisheries Library in R (FLR; Kell et al., 2007), and as parameterised in Chapter 7 (Fischer et al., 2021a), were used. These operating models were generated from life-history parameters and considerations of life-history relationships, and comprised 29 generic stocks, covering a wide range of life-history traits (see Table 5.1 in Chapter 5). All operating models were subjected to three 100-year fishing histories (Figure 9.1; Fischer et al., 2020; Fischer et al., 2021a). In the *one-way* fishing history, fishing mortality (F) was increased exponentially, in the *roller-coaster* history, F was first increased but then decreased again, and in the *random* history, random F trajectories occurred, leading to a range of depletion levels at the beginning of the MSE. The operating models were stochastic and uncertainty was included in 500 simulation replicates through a log-normal process (recruitment error $\sigma_R = 0.6$, added to the Beverton-Holt stock-recruitment model) and observation errors ($\sigma_{\text{obs}} = 0.2$, added to the aggregated total biomass and mean catch length indices). These are the same assumptions as used in the previous two chapters on the rfb rule (Chapters 7 and 8). Details of the operating models are described in Appendix E.

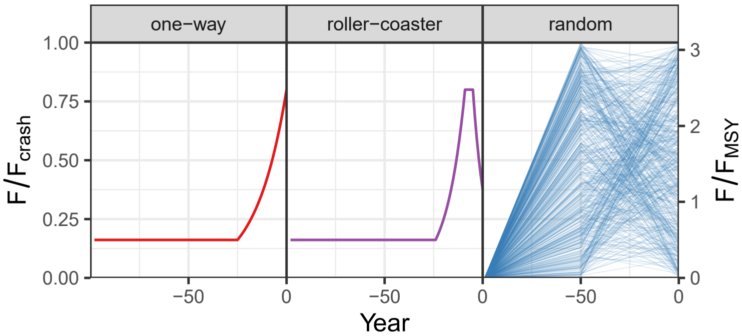

Figure 9.1: The three fishing histories of the operating models.

9.4.2 Relative harvest rate management procedure

A relative harvest rate H can be defined as the ratio of the catch C divided by a stock size indicator I, e.g. a biomass index:

$$H_y = C_y / I_y, \tag{9.1}$$

for year y. I can be a relative index and does not need to represent the total stock biomass because it is only used relative to the catch. For simplicity, I was assumed to be a total biomass index in the simulations. Figure 9.2 explains how a target harvest rate can be derived purely from empirical data. The procedure consists of determining reference years where historical mean catch length is above a reference length, calculating the relative harvest rates for these years, and taking their average to define a target harvest rate H_{target}. The MSY proxy reference length defined by Jardim et al. (2015) is used:

$$L_{F=M} = 0.75 L_c + 0.25 L_\infty, \tag{9.2}$$

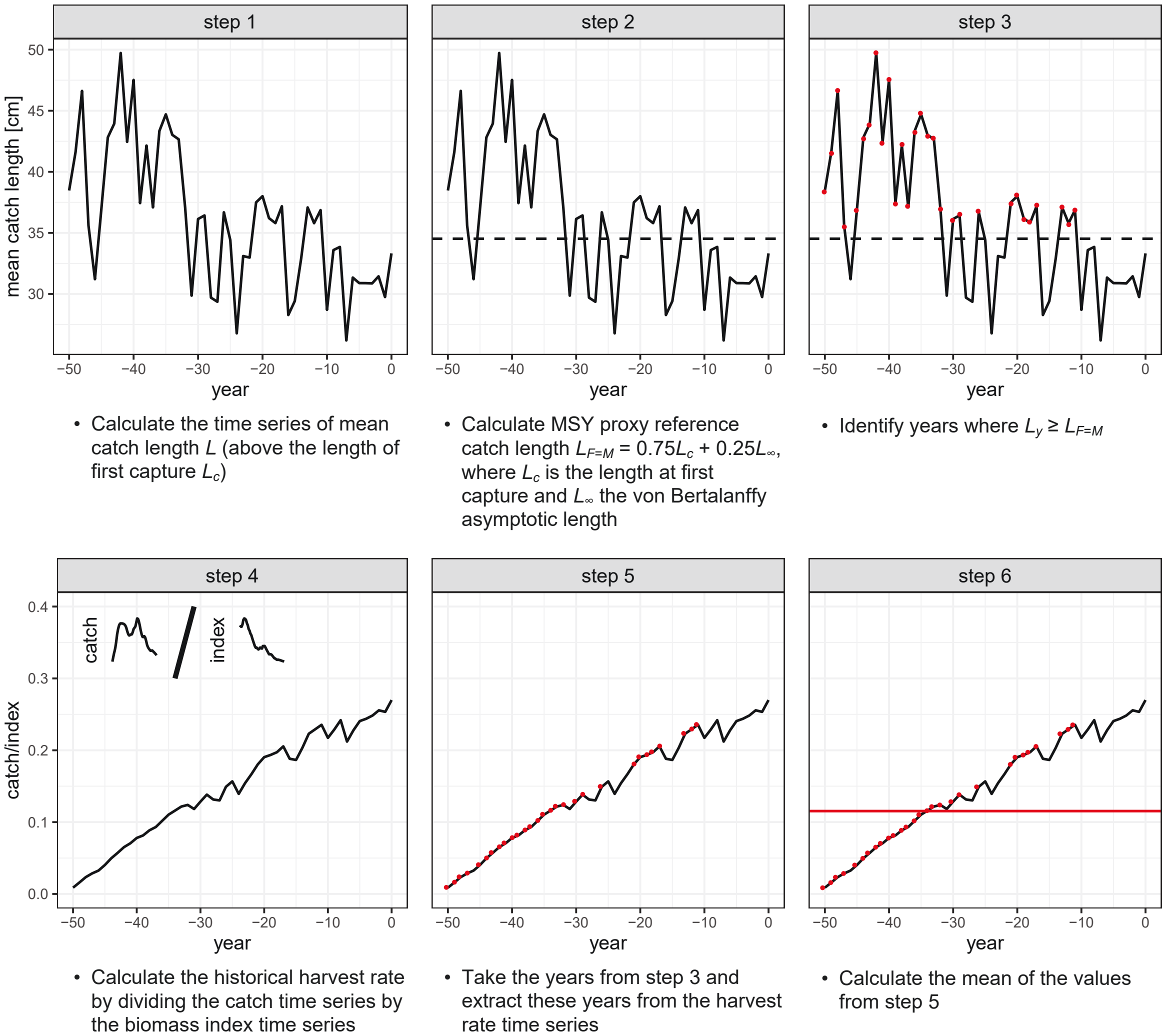

Figure 9.2: Derivation of a target harvest rate from empirical data. Shown is one example simulation replicate for pollack. Please note that the index can be a relative index.

where L_c is the length at first capture and L_∞ the von Bertalanffy asymptotic length. This reference length assumes $M/k = 1.5$ (where k is the von Bertalanffy growth parameter) and fishing at the natural mortality rate $F = M$ as a proxy for F_{MSY}, and follows the concepts of Beverton and Holt (1957). This reference length is the same as used for the rfb rule (see Chapters 6, 7, and 8). The length data are only required for setting a target harvest rate (H_{target}) and not used later in the implementation of the management procedure.

This target harvest rate H_{target} can then be used to determine the advised catch for the next year A_{y+1}:

$$A_{y+1} = I\ H_{\mathrm{target}}, \tag{9.3}$$

where I is the recent index value. Additional precaution can be introduced with a biomass safeguard b, which reduces the targeted harvest rate when the index falls below an index trigger value, I_{trigger} (see Table 9.2). The biomass safeguard b essentially imposes a hockey-stick functional form on the control rule (Figure 9.3), similar to the ICES MSY advice rule used for category 1 data-rich stocks (ICES, 2019a).

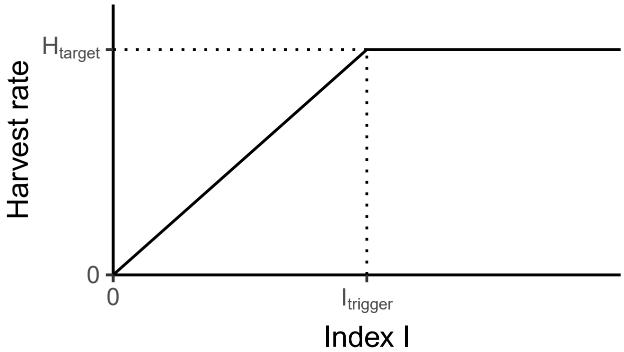

Figure 9.3: Hockey-stick principle of the harvest rate control rule. The harvest rate shown is the $H_{\text{target}}\ b$ component of Equation (9.4) and the shape of the curve is determined by the biomass safeguard b.

I_{trigger} can be linked to the lowest observed index value I_{loss} through a multiplicative buffer w (see Table 9.2), often set to $w = 1.4$ in the absence of better knowledge (ICES, 2017f, 2021h). This biomass safeguard is the same as used for the rfb rule (see Chapters 6, 7, and 8).

In order for the harvest rate control rule to be optimised, the components of the rule can be made more flexible by adding additional parameters. This allows the components to be calibrated for best performance:

$$A_{y+1} = \sum_{i=y-n_0-n_1+1}^{y-n_0} \left(\frac{I_i}{n_1}\right)\ H_{\text{target}}\ b\ x. \tag{9.4}$$

The relative harvest rate management procedure of Equation (9.4) is referred to as "harvest rate rule". See Table 9.2 for details and descriptions of all parameters. The multiplier x is applied to the entire control rule. However, because the elements of the control rule are multiplicative, it can also be thought of as being part of the harvest rate ($H'_{\text{target}} = x\ H_{\text{target}}$), i.e. changing the target level of the rule.

Finally, the catch advice can be set constant for an interval of v years before the control rule is applied again, and catch constraints (called uncertainty caps in ICES) limit the allowed increase (u_u) and decrease (u_l) of the catch advice. This leads to a total of seven tuneable parameters (x, n_0, n_1, w, v, u_u, u_l).

Table 9.2: Parameters of the flexible harvest rate rule (as shown in Equation (9.4) and described in the subsequent text).

Parameter	Description	Definition	Default
Components of the harvest rate rule			
A	Catch advice	See Equation (9.4)	
I_y	Index value	Index value in year y	
H_{target}	Harvest rate target	$C_{\text{y}}/I_{\text{y}}$ for reference years y	
b	Biomass safeguard	$b = min(1, I_{y-n_0}/I_{\text{trigger}})$	
x	Multiplier		$x = 1$
Generic parameters			
y	Year	Year relative to assessment year	
n_0	Time lag	Offset between last biomass index year and assessment year	$n_0 = 1$
n_1	Index range	Number of index years	$n_1 = 1$
I_{trigger}	Index trigger	Value below which the biomass safeguard reduces catch advice $I_{\text{trigger}} = wI_{\text{loss}}$	
I_{loss}		Lowest observed index value	
w	Index trigger buffer	Connects I_{loss} to I_{trigger}	$w = 1.4$
Additional parameters			
v	Interval	Number of years for which the catch advice is kept constant	$v = 1$
u_u, u_l	Upper and lower uncertainty cap	Catch constraint (upper and lower limit), restricting the allowed change in the catch advice A_{y+1} relative to last advice A_y, implemented after deriving A_{y+1} from Equation (9.4): $\min\left\{\max\left(u_l A_y, A_{y+1}\right), u_u A_y\right\}$	$u_u = \infty$, $u_l = 0$

9.4.3 Optimisation

Fischer et al. (2021a, 2021b, see Chapter 7) showed that a genetic algorithm effectively optimises empirical management procedures towards specific management objectives and defined two fitness functions:

$$\phi_{\text{MSY}} = -\left|\overline{B}/B_{\text{MSY}} - 1\right| - \left|\overline{C}/\text{MSY} - 1\right| - \overline{\text{ICV}} - P_{B_{\text{lim}}} \tag{9.5}$$

and

$$\phi_{\text{MSY-PA}} = -\left|\overline{B}/B_{\text{MSY}} - 1\right| - \left|\overline{C}/\text{MSY} - 1\right| - \overline{\text{ICV}} - \Omega\left(P_{B_{\text{lim}}}\right), \tag{9.6}$$

where $\overline{B}$, $\overline{C}$, and $\overline{\text{ICV}}$ are the medians of spawning stock biomass (SSB), catch, and inter-annual catch variability (calculated over a 50-year projection and 500 simulation replicates), B_{MSY} and MSY the MSY reference values, B_{lim} risk ($P_{B_{\text{lim}}}$) the risk of the SSB falling below the biomass limit reference point (defined as the SSB where recruitment is impaired by 30%, i.e. $B_{\text{lim}} = B_{R=0.7R_0}$), and Ω a penalty function reducing ϕ when B_{lim} risk exceeds 5% (i.e. formalised the ICES precautionary criterion, $\Omega\left(P_{B_{\text{lim}}}\right) = 5/\left(1 + e^{-500(P_{B_{\text{lim}}}-0.06)}\right)$). ICV was defined as $|(C_y - C_{y-v})/C_{y-v}|$ for years y in which a new advice was set and the advice interval v. The fitness function ϕ_{MSY} measured MSY management performance by including all four summary statistics, i.e. its aim was to move SSB to B_{MSY}, catch to MSY, and reduce ICV and risk. In $\phi_{\text{MSY-PA}}$, a penalty was applied when risk exceeded 5%. Elements of ϕ are negative because ϕ was maximised with the genetic algorithm and a maximum fitness of zero implies SSB is at B_{MSY}, catch at MSY, and ICV is zero, and furthermore, that risk is zero (for ϕ_{MSY}) or well below 5% (for $\phi_{\text{MSY-PA}}$).

9.4.4 Scenarios

The scenarios explored were:

1. **Pure harvest rate**

   First, the pure harvest rate from Equation (9.3) was explored. For this purpose, the harvest rate was implemented for 100 years and simulations were based on the random fishing history. The index was a total biomass index at the beginning of the year for which the catch advice was given ($I = I_{y+1}$) and without any observation uncertainty.

   The target harvest rate was defined with a uniform distribution $H \sim U(0, 1)$. This allowed an analysis of the performance of the pure harvest rate, depending on initial stock depletion and the level of the harvest rate. The number of simulation replicates was increased to 10,000 to ensure enough replicates for subsets of harvest rates and depletion levels. These initial simulations served as a baseline to explore the scope of the harvest rate principle.

2. **Sensitivity analysis**

   The sensitivity of the harvest rate rule to the assumed conditions was analysed for the three main summary statistics (SSB, catch, B_{lim} risk). The baseline was the default harvest rate rule [Equation (9.4), Table 9.2], calculating the target harvest rate according to Figure 9.2, applied for 50 years and with 500 simulation replicates, and for the three fishing histories (one-way, roller-coaster, random). Pollack (pol, *Pollachius pollachius*), a medium-fast growing species ($k = 0.19$ year^{-1}), was chosen as an example stock. This was the same example stock used in the previous chapter (Chapter 8), which allowed comparability of the outcomes of the sensitivity analysis between different management procedures.

The sensitivity analysis considered recruitment variability ($0 \leq \sigma_R \leq 1$, default $\sigma_R = 0.6$), recruitment steepness ($0.2 \leq h \leq 1$, default $h = 0.75$ year^{-1}), recruitment auto-correlation ($0 \leq \rho_R < 1$, default $\rho_R = 0$), observation uncertainty (length and biomass index, $0 \leq \sigma_{\text{obs}} \leq 1$, default $\sigma_{\text{obs}} = 0.2$), observation auto-correlation ($0 \leq \rho_{\text{obs}} < 1$, default $\rho_{\text{obs}} = 0$), and the duration of the implementation (1-100 years, default 50 years).

Additionally, the sensitivity to stock status prior to implementing the rule ($\text{SSB}_{y=0}/B_{\text{MSY}}$) was evaluated. For this purpose, the random fishing history was used and the number of simulation replicates increased from 500 to 10,000. Subsequently, the simulation replicates were sorted by $\text{SSB}_{y=0}/B_{\text{MSY}}$ and split into groups corresponding to different stock status levels ($0 - 1.7B_{\text{MSY}}$ in groups of $0.1B_{\text{MSY}}$). This way, each group contained > 200 replicates, sufficient to calculate summary statistics.

Lastly, the sensitivity of the harvest rate rule to the index selectivity was evaluated. The performance of the harvest rate rule with the default index (a total biomass index) was compared to scenarios where the index selectivity matched maturity (SSB index), fishery selectivity (commercial index), and for an index with dome-shaped selectivity (Figure E.4 in Appendix E).

3. **Harvest rate level**

   The impact of the level of the target harvest rate on the performance of the harvest rate rule was explored by implementing the rule with multipliers $0 \leq x \leq 2$ in steps of 0.01 [but otherwise default parameters of Equation (9.4)] and with default simulation dimensions (50 years, 500 replicates) for all stocks.

4. **Parameters of the harvest rate rule**

   The impact of the various parameters of the harvest rule on the optimisation procedure with the genetic algorithm was explored for pollack. The optimisation was performed individually for each parameter (x, n_0, n_1, w, v, u_u, or u_l), combining both uncertainty caps (u_l and u_u), all parameters without the uncertainty cap (x, n_0, n_1, w, and v), and all parameters (x, n_0, n_1, w, v, u_u, and u_l).

Following the conclusion of Fischer et al. (2021b, see Chapter 8) that uncertainty caps can impair the recovery of depleted stocks and make it impossible to meet risk thresholds, additional optimisations with conditional uncertainty caps (fixed at $u_l = 0.7$, $u_u = 1.2$), only implemented when $I \geq I_{\text{trigger}}$, were conducted for the multiplier and all parameters. The optimisation was performed for the fitness function aiming at MSY [ϕ_{MSY}, Equation (9.5)] and the fitness function including the precautionary risk limit [$\phi_{\text{MSY-PA}}$, Equation (9.6)].

5. **Optimisation for all stocks**

   The optimisation procedure with the genetic algorithm is computationally complex; therefore, the full optimisation for all stocks was limited to the $\phi_{\text{MSY-PA}}$ fitness function. Finally, the harvest rate rule was compared to two indicator-adjusted catch rules; the 2 over 3 rule as simulated by Fischer et al. (2021a, see Chapter 7) and the rfb rule from Fischer et al. (2021b, see Chapter 8). The 2 over 3 rule was the standard ICES method for category 3 stocks until 2021 and adjusts the catch based on the trend from a biomass index. The rfb rule is intended to replace the 2 over 3 rule and, in addition to the biomass index trend, also uses catch length data to inform on fishing pressure. Full details of these two catch rules are available in Chapters 6, 7, and 8 and are summarised in Appendix E.

9.4.5 Data and software

The MSE framework was the same as used in the previous chapters (see Chapters 7 and 8) and based on FLR (Kell et al., 2007). The results of this study are fully reproducible and input data, software code, and summarised results as presented in this chapter were made open source and are available from GitHub at https://git.io/JMFJd.

9.5 Results

9.5.1 Pure harvest rate

When the pure harvest rate was implemented for only 10 years (first row of Figure 9.4), the realised catch over this period was affected by the initial stock status, with lower catches in cases of higher depletion but this effect disappeared when the rule was implemented for more years. Short-term catches could be substantially above MSY, but could not be sustained in the longer term.

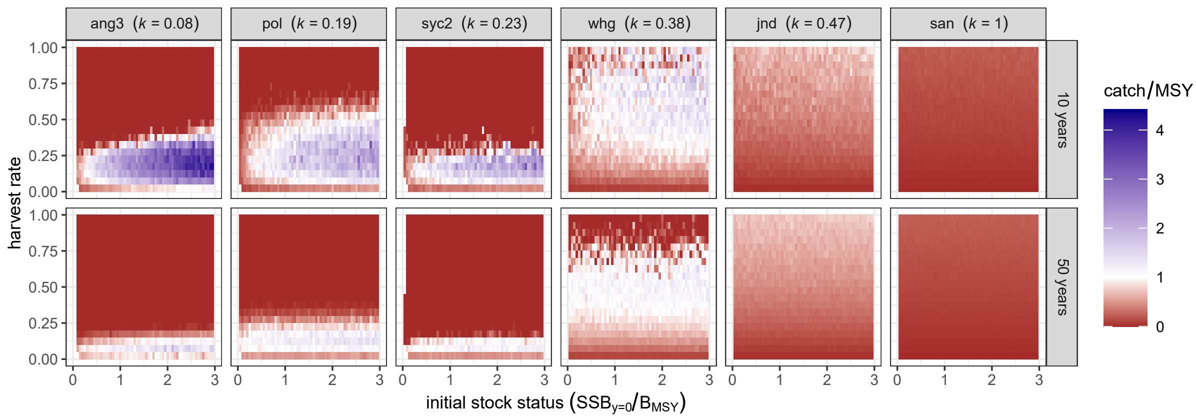

Figure 9.4: Realised catch for a pure harvest rate management procedure, depending on the level of the harvest rate, the stock status prior to implementing the rule, and the implementation period. In this management procedure, the index corresponded to the total biomass at the beginning of the advice year and no biomass safeguard was used. Shown is the catch relative to MSY, averaged over two implementation periods (10 and 50 years), and for six example stocks: blackbellied anglerfish (ang3), pollack (pol), lesserspotted dogfish (syc2), whiting (whg), John Dory (jnd), and sandeel (san), sorted by von Bertalanffy growth rate k (unit: year^{-1}). The results for the remaining stocks are included in Figure E.2 in Appendix E.

There was a harvest rate that returned the highest catches; however, the level and spread of this harvest rate were stock-specific. In general, this high-catch area was at lower harvest rates for slower-growing stocks and at higher harvest rates for faster-growing stocks. For example, the harvest rate for blackbellied angler (ang3) resulting in catches > 0.9MSY in the longer term was in a narrow range with $H < 0.15$, but for whiting (whg) $0.2 \leq H \leq 0.6$. For the fastest-growing stock (sandeel; san), the catch was always low and < 0.3MSY.

There are some exceptions to the general trend, e.g. a lower harvest rate for the very late maturing lesserspotted dogfish (syc2 in Figure 9.4) or a higher harvest rate for the early maturing Atlantic wolffish (wlf in Figure E.2 in Appendix E). This behaviour can be explained by the fact that fishery selectivity was linked to maturity and the harvest rate was proportional to the total (not exploitable) biomass index. This meant, for example, that for the lesserspotted dogfish, it was not possible to fish a larger proportion of the stock because younger ages were not available to the fishery but contributed to the stock biomass (see Figure E.3 in Appendix E). In contrast, for Atlantic wolffish, more age classes could be fished and this allowed taking a higher proportion of the stock.

9.5.2 Sensitivity analysis

The results of the sensitivity analysis for pollack are summarised in Figure 9.5. Higher recruitment variability (i.e. larger recruitment events due to log-normal distributed residuals) or steepness (i.e. higher productivity at lower stock size) led to higher SSB and catch, and lower risk. However, for the one-way fishing history, the risk was low (0.03) and unaffected by recruitment variability, only increasing substantially when the steepness was very low ($h < 0.5$, default $h = 0.75$). Increasing observation uncertainty (i.e. representing a more data-limited situation) caused a lower SSB and catch, and higher risk. Including temporal auto-correlation for recruitment or observation residuals had negligible effects.

The initial stock status prior to implementing the harvest rate rule correlated positively and almost linearly with the averaged SSB after implementing the rule and negatively with risk, meaning that a depleted stock stayed depleted during the application of the rule with default settings. Regarding the implementation period, the summary statistics showed little variability and stabilised after around 10 years in the random fishing history. Conversely, for the one-way and roller-coaster fishing history, SSB and catch were initially low ($\text{SSB}/B_{\text{MSY}} = 0.5$ and $\text{catch}/\text{MSY} = 0.5$), increased after the implementation of the harvest rate rule and stabilised subsequently, leading to a reduction of the initially high risk.

The harvest rate rule was relatively robust to alternative index selectivities because using a different survey in the projection also meant that the target harvest rate, derived from historical observations, was changed accordingly. The influence on the long-term performance was negligible, but slight differences in behaviour in the first few years after implementing the harvest rate rule occurred (Figure 9.6 and Figure E.5 in Appendix E). For example, an SSB index detected the depletion of the one-way fishing history earlier, resulting in stronger initial catch reductions and faster stock recovery than the total biomass index.

9.5.3 Harvest rate level

The inclusion of a multiplier had a substantial effect on the performance of the full harvest rate control rule. A catch maximum was observed for each stock, but the location (i.e. the multiplier leading to the catch maximum) and catch value depended on the stock and fishing history (Figure 9.7a).

The general pattern was the same as for the pure harvest rate, and for slower-growing species, the optimum harvest rate (expressed through the multiplier) and the realised catch were higher

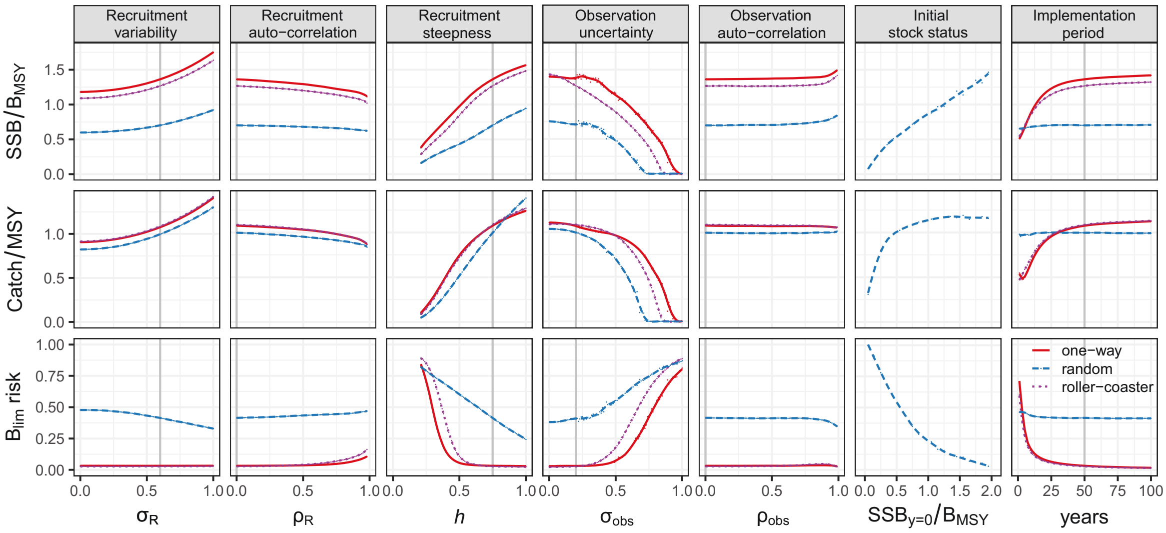

Figure 9.5: Summary of the sensitivity analysis for pollack. Shown are summary statistics (SSB, catch and B_{lim} risk) as a result of applying the default harvest rate rule and depending on simulated conditions (recruitment variability, steepness, observation uncertainty, initial stock status, and implementation period). Dots are simulation outcomes and the lines are the result of applying a smoother. Vertical lines indicate default values. For the initial stock status, simulation replicates were increased from 500 to 10,000 and results are only shown for the random fishing history. B_{lim} risk for the implementation period is the risk up to the respective year.

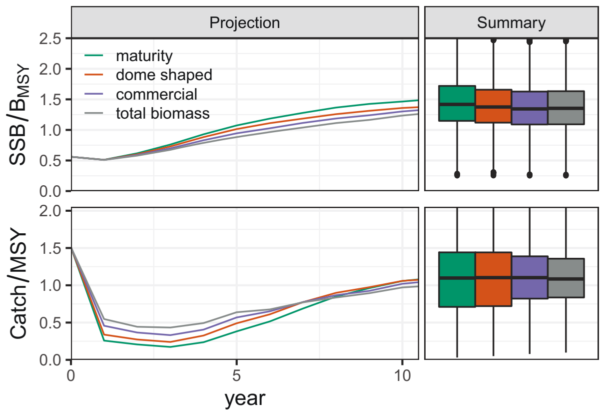

Figure 9.6: Impact of the index selectivity on the harvest rate rule for pollack for the one-way fishing history. The projections (left) show the first 10 years, the summary boxplots (right) the full 50-year projections.

than for faster-growing species. This relationship can be illustrated with the von Bertalanffy k parameter of the stocks (Figure 9.7b). Pearson correlation coefficients indicated a negative correlation between the multipliers where the catch was maximised ($\rho \leq -0.89$, $p \leq 7.5 \times 10^{-11}$) and between the maximum catch and k ($\rho \leq -0.86$, $p \leq 3.5 \times 10^{-9}$).

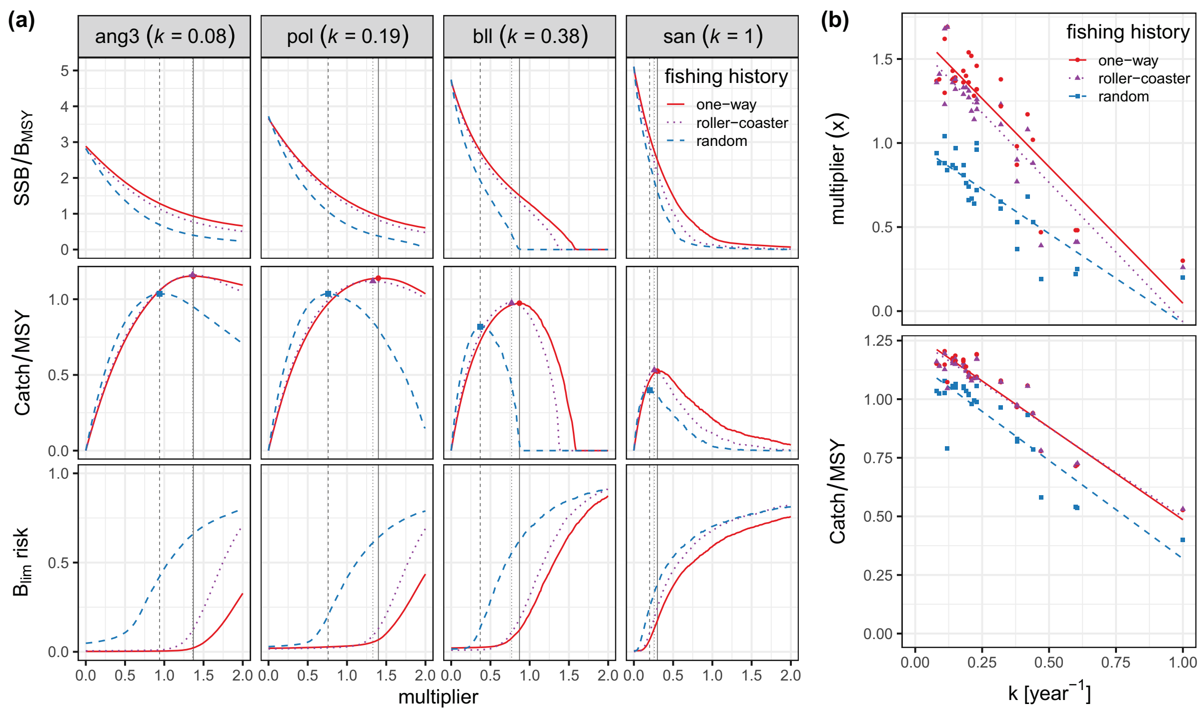

Figure 9.7: Impact of a harvest rate multiplier on the performance of the harvest rate rule. (a) shows the summary statistics for four example stocks; anglerfish (ang3), pollack (pol), brill (bll) and sandeel (san). The location of the maximum catch (second row) is indicated by small points and vertical lines corresponding to the multiplier. (b) shows the correlation between the location of the maximum catch in terms of the multiplier in (a) and the von Bertalanffy k, and between the maximum catch level of (a) and k, for all 29 simulated stocks for three fishing histories.

The results for the one-way and roller-coaster fishing histories were very similar, which was also the case for the previous sensitivity analysis. Therefore, the following sections only consider the one-way and random fishing histories.

9.5.4 Parameters of the harvest rate rule

When considering the impact of the individual parameters of the harvest rate rule for pollack, the time lag (n_0) and interval (v) had negligible influence, while the index trigger buffer (w) and index range (n_1) led to small improvements (Figure 9.8). Although the uncertainty caps (u_l, u_u) had little or no influence on their own when considering a risk limit in the fitness function ($\phi_{\text{MSY-PA}}$; Figure 9.8b), they had a stronger impact (either individually or together) when a risk limit was not included (ϕ_{MSY}; Figure 9.8a). The use of a multiplier (x) had a strong impact on its own in all cases, apart from the one-way fishing history when a risk limit was not included.

The improvement was generally better when the optimisation was conducted for several parameters. The addition of uncertainty caps led to no or minor performance improvement compared to the optimisation with all parameters excluding the uncertainty caps and the op-

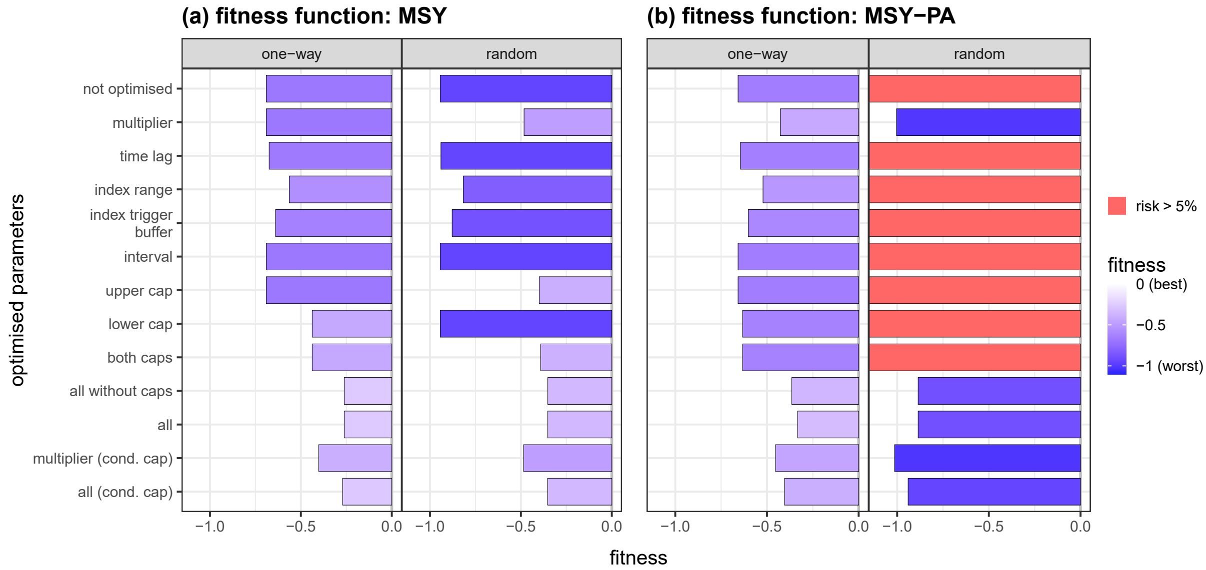

Figure 9.8: Fitness values as a proxy for management performance for the harvest rate rule when including single or combinations of the rule's parameters into the optimisation with the genetic algorithm for pollack. Shown are optimisation for the fitness function without a risk limit (a) and with a risk limit (b). The following parameter combinations were tested: multiplier (x), time lag (n_0), index range (n_1), index trigger buffer (w), interval (v), upper cap (u_u), lower cap (u_l), both caps (u_u, u_l), all parameters without the caps (x, n_0, n_1, w, v), all parameters (x, n_0, n_1, w, v, u_u, u_l), multiplier with conditional caps (x, $u_u = 1.2$, $u_l = 0.7$), and all parameters with conditional caps (x, n_0, n_1, w, v, $u_u = 1.2$, $u_l = 0.7$). Shorter bars indicate better performance. In (b), optimisations where risk exceeds 5% are coloured in red, and bars are cut off on the left because fitness values are < -5 due to the risk penalty. The split of the fitness function into its elements is illustrated in Figure E.6 in Appendix E.

timisation selected either no or very wide caps (Table E.1 in Appendix E). This is an important result for the industry, which prizes more stable catch advice (compare "all" and "all (cond. cap)" to "all without caps"). The default harvest rate resulted in a risk above 5% for the random fishing history. In the optimisation scenarios where the fitness function included the risk limit ($\phi_{\text{MSY-PA}}$; Figure 9.8b), this risk could only be reduced sufficiently when the multiplier was included, either on its own, or in combination with other parameters.

9.5.5 Optimisation for all stocks

The magnitude of the fitness improvement was stock-specific. Figure 9.9 shows the optimisation results for all stocks (including the conditional uncertainty cap) and a comparison to the results of Fischer et al. (2021a, 2021b, see Chapters 7 and 8). The inclusion of all parameters in the optimisation of the harvest rate rule resulted only in marginal improvements compared to the optimisation with the multiplier.

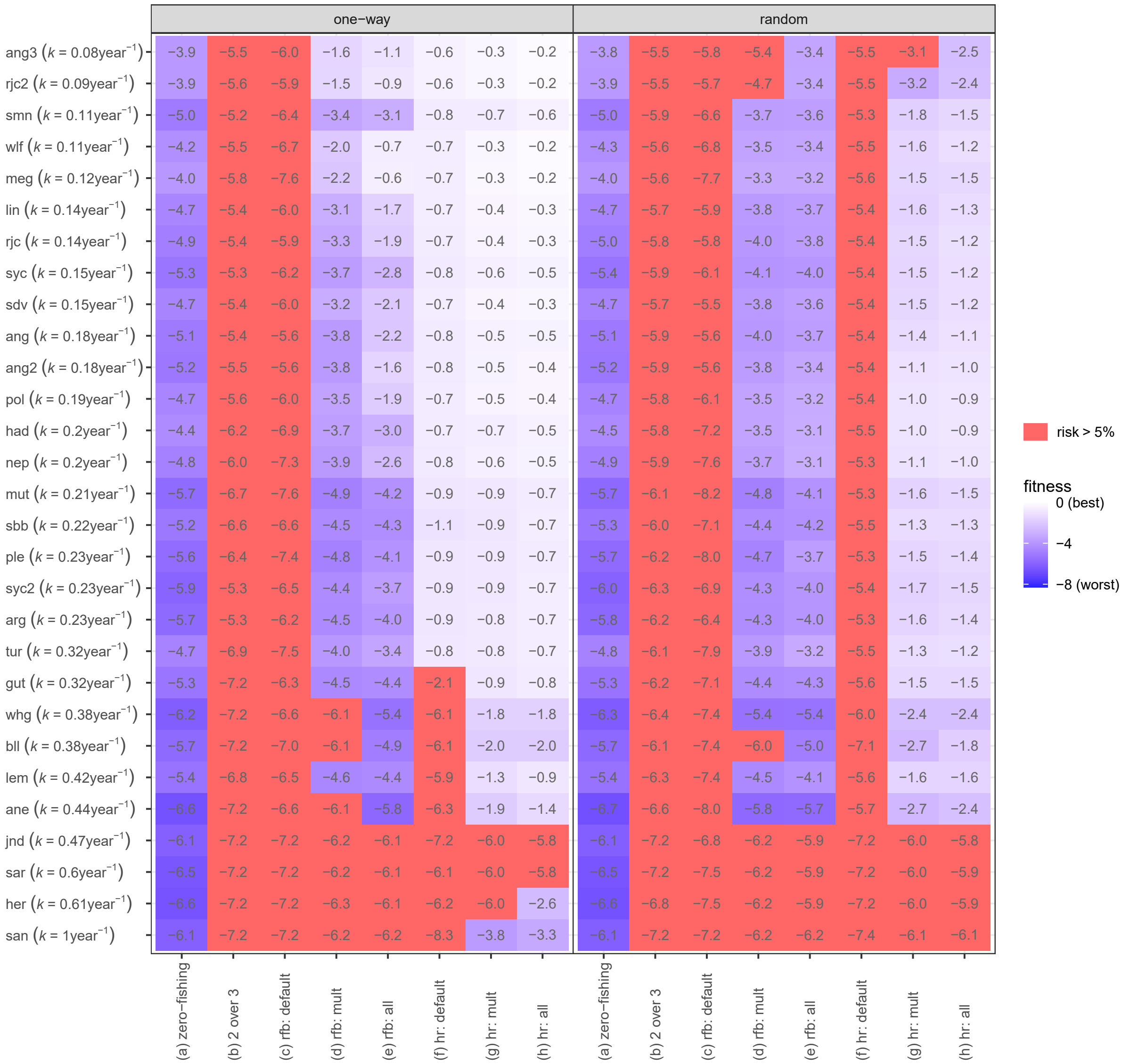

Figure 9.9: Fitness ($\phi_{\text{MSY-PA}}$) as a measure of management performance of the harvest rate rule, achieved through optimisation with the genetic algorithm and a comparison with other management options. Non-precautionary management (risk exceeds 5%) is highlighted in red. Shown are a "zero-fishing" option (a), the 2 over 3 rule (b, from Fischer et al., 2021a, Chapter 7), the rfb rule (c-e, from Fischer et al., 2021b, Chapter 8) and the harvest rate rule (f-h). For the rfb and harvest rate rules, three options are shown; the default rules (c, f, not optimised), optimisation with a multiplier (d, g), and optimisations where all parameters are included (e, h). For c-h a conditional uncertainty cap (+20%, -30%) is included. Optimised parameterisations of the harvest rate rule are available from Table E.1 in Appendix E.

Fitness values were highest for the one-way fishing history (stronger but narrow initial depletion) compared to the random fishing history (large spread of initial depletion). In the one-way history, fitness appeared to be correlated to individual growth with the best management performance for the slowest-growing species. In the random history, management performance seemed best for species in the middle of the range tested, with a clear deterioration (i.e. poorer management performance and increased risk) for the faster-growing species, but also the slowest-growing species. For example, for the slowest growing stock (blackbellied angler, ang3), when the optimisation was performed only with a multiplier in the random fishing history, no multiplier could reduce risk to 5% and the optimised solution was not precautionary (Figure 9.9). However, this was caused by the restriction of the conditional uncertainty cap, and if the cap was removed, a precautionary solution is possible (see Figure E.7 in Appendix E). Figure 9.10 visualises the optimised multipliers (option "(g) hr: mult" in Figure 9.9).

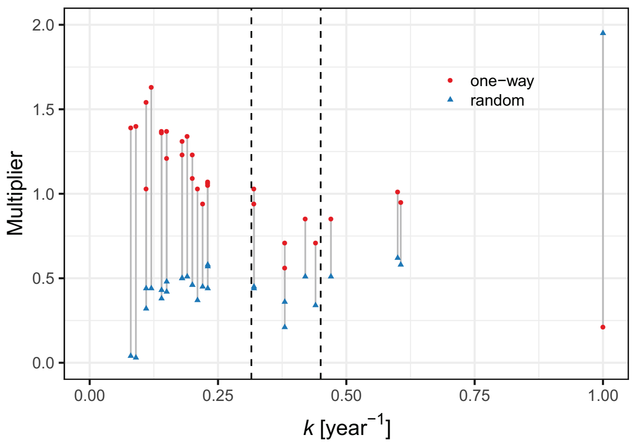

Figure 9.10: Optimised multiplier values of the harvest rate for all 29 stocks. The values shown correspond to option "(g) hr: mult" in Figure 9.9 and are sorted by von Bertalanffy k. Multipliers for the same stocks are connected with vertical grey lines. The dashed vertical lines indicate the area 0.32 year^{-1} $\leq k <$ 0.45 year^{-1}, which is the area for which ICES suggests considering a harvest rate approach (ICES, 2020a, 2022b).

The harvest rate rule always outperformed the corresponding rfb rule (apart from sandeel for the default configuration), although it could not always provide precautionary management for the fastest-growing species for the fully optimised configuration in both fishing histories (Figure 9.9).

9.6 Discussion

The key message from this chapter is that the application of harvest rates through a biomass index is a suitable method for the management of moderately data-limited fisheries. However, this requires first finding a harvest rate level corresponding to the desired management objectives, for example, with empirical data. Simple modifications of a harvest rate rule, such as including a multiplier, can be sufficient to meet these objectives.

In the present work, uncertainty was addressed by simulating many species, conducting a sensitivity analysis, and including alternative historical fishing histories. In the one-way fishing history, the initial stock status was narrow but strongly depleted. This condition allowed the exploration of a recovery phase. The alternative random fishing history offered a wide spread of depletion levels. This alternative history might be regarded as a more favourable starting state; however, it proved rather challenging because both MSY and precautionary principles were needed, i.e. a management procedure needed to limit risk (avoid low stock size) and deliver good long-term yields. The results indicated that the desired harvest rate parameterisation can differ substantially between fishing histories, even when implemented over a long time. Consequently, caution is recommended when applying a harvest rate rule generically and considering exploitation information and conducting stock-specific analyses is encouraged.

The quantities explored in the sensitivity analyses cover essentially different elements of the simulation, and the impact of specific quantities has different management implications. For example, recruitment variability is a proxy for process error which is given by the underlying population dynamics—this is something we have to live with. On the other hand, observation uncertainty is an observation error and could be reduced through better sampling, while uncertainty about steepness can be dealt with by building rules robust to it, or conducting further research to reduce uncertainty. Larger observation uncertainty degraded management performance (reduced stock size, higher risk of falling below the biomass limit, and reduced catch) and could correspond to a more severely data-limited situation. Consequently, a more conservative harvest rate would need to be used to avoid exceeding risk limits in such a situation.

The harvest rate principle is straightforward and, crucially, does not rely on knowledge about the absolute size of a fish stock, such as through the use of a stock assessment or an estimate of the index catchability, and can instead be used on a relative basis. The challenge is setting a harvest rate target corresponding to the desired management objectives. The proposal of using empirical data (mean catch length) appeared to work well to inform on historical exploitation. Nevertheless, this is just one option, and other methods can be considered, e.g. simple biomass models. For some stocks, acoustic surveys might exist, providing an estimate of absolute biomass, making the application of a harvest rate strategy simpler because absolute management thresholds could be set.

If a target level is set too low, this will lead to lighter exploitation than expected, but conversely, if the target harvest rate is too high, this quickly leads to overfishing. Therefore, setting target harvest rates should be considered with utmost care. This is particularly important for cases when the target is set based on historical observations. For example, if overfishing has occurred during the entire historical period for which data are available, an appropriate reference that does not lead to overfishing is unlikely to be found. On the other hand, if a stock has only been lightly exploited, selecting a target value does not cause issues for stock conservation but some yield might be forfeited.

A crucial assumption in implementing a relative harvest rate strategy is that the biomass index is an adequate measure of the stock biomass and captures trends. The absolute scale of the index is not important because the harvest rate is defined relative to the index. This means that a systematic bias in either catch or index will not affect management as long as the bias does not change over time. When exploring different index selectivities, this had negligible long-term impacts on the management performance of the harvest rate rule. This outcome was not surprising because the target harvest rate (defined by reference years and not index values) was scaled accordingly when an alternative index was used. However, this requires a standardised index (e.g. from a scientific survey or a standardised index of commercial catch per unit effort). Any temporal changes to the index (or fishery) selectivity or survey design are likely to negatively impact fisheries management because translating the relative target harvest rate with the index into a catch value does not return the correct absolute scale. Consequently, the proposed harvest rate rule is only applicable in cases where a standardised index exists and continues into the future.

The application and optimisation of the harvest rate rule in the generic context was not successful for the few fastest-growing species. Such species mainly include short-lived species, small pelagics, or fish with otherwise very high individual growth rates. Modelling such populations can be complex, but it is feasible given sufficient considerations (Siple et al., 2021). The fast dynamics (boom and bust; de Moor et al., 2011) might warrant alternative modelling approaches where sub-annual dynamics are explicitly considered. Consequently, more case-specific models and alternative management procedures, such as escapement strategies, might be useful to consider. Consequently, the following chapter (Chapter 10) explores an alternative modelling approach where seasonal dynamics and their impact on fisheries management are explicitly considered.

The new guidelines of the ICES data-limited methods framework (ICES, 2022b) recommend the empirical rfb rule, for which new catch advice is derived by adjusting the previous advice by the trend of a biomass index, the mean of length of fish in the catch and a biomass safeguard. This rule is restricted to species with slow to medium individual growth (von Bertalanffy $k < 0.32\ \text{year}^{-1}$) based on the outcomes of the studies presented in Chapters 6, 7, and 8. The rfb rule appears to struggle with the rapid population dynamics of faster-growing species and cannot provide long-term sustainable management unless the catch is reduced to very low levels. ICES (2022b) already suggested a harvest rate rule for faster-growing species ($0.32\ \text{year}^{-1} \leq k < 0.45\ \text{year}^{-1}$) with a generic precautionary multiplier of $x = 0.5$ based on preliminary analyses on a few faster-growing stocks as part of the study leading to the present chapter.

Furthermore, the comparison of the harvest rate rule to the rfb rule (Figure 9.9) showed that, when optimised, the harvest rate rule appears to outperform the rfb rule, with higher catches while offering the same level of precaution. The biggest improvement in the harvest rate rule's performance was by introducing a multiplier. In most cases, introducing more parameters led to only minor further improvements, but came at the cost of making the rule much more complex. Nevertheless, the challenge of setting a multiplier value remained, as illustrated in Figure 9.10, where the multiplier levels for the same stocks depend on the fishing history, although a generic precautionary multiplier of $x = 0.5$ appears precautionary for all stocks with $k < 0.45\ \text{year}^{-1}$. This precautionary value might forfeit some of the yields for slower-growing species, but this could be ameliorated with case-specific simulations. Such case-specific analyses could also explore management trade-offs in more detail, ideally with stakeholder engagement.

9.7 Conclusion

In conclusion, it is recommended that harvest-rate-based management be considered for moderately data-limited fisheries management. Developing a generic one-size-fits-all parameterisation for a relative harvest rate rule is challenging; therefore, case-specific simulations may be needed.

A key benefit is that applying a harvest rate strategy, once set up, requires few data apart from an index, and is, therefore, suitable for many moderately data-limited stocks. Nevertheless, continued monitoring of stock status and exploitation is suggested to ensure the harvest rate rule performs as expected.

Chapter 10

Exploration of seasonal modelling for fast-growing fish stocks

10.1 Abstract

Previous simulation testing of empirical (model-free) control rules for managing data-limited fisheries showed that such rules did not work well for very fast-growing species, resulting in low catches and high risks of stock depletion. This chapter was aimed at exploring possible reasons for this outcome and options for creating more appropriate models for very fast-growing species. Sandeel was used as a case study, and a seasonal operating model created based on life-history parameters to analyse the impact of sub-annual dynamics. This operating model could then be used to evaluate management principles in a management strategy evaluation. Simulation results indicated that sandeel exhibits strong sub-annual dynamics and operating model characteristics depend on the time step of the simulation. Both harvest rate and escapement strategies appeared to be suitable management strategies. However, the timing of management measures was crucial and setting a catch advice more frequently led to higher long-term sustainable catches. This study was exploratory; nevertheless, the outcomes are useful for managing fast-growing species and future studies. Such species can be challenging to model appropriately, are likely less suitable for using generically developed management strategies than slower-growing species, and benefit from case-specific analyses.

10.2 Introduction

Previous simulation testing of empirical (model-free) control rules for the management of data-limited fisheries showed that the performance of such control rules was linked to life history, particularly to the individual growth of exploited species (Chapters 6, 7, 8, and 9). This individual growth could be defined through the von Bertalanffy growth parameter k, which determines how fast an individual reaches its asymptotic size.

The trend-based rfb rule (Chapters 6, 7, and 8) showed a distinct turning point, where the rule provided satisfactory management performance for species with slow to medium individual growth ($k \leq 0.32 \text{ year}^{-1}$). However, performance was very poor for faster-growing species ($k > 0.32 \text{ year}^{-1}$), resulting in high depletion risks and low long-term catches. The depletion risk could only be reduced to levels acceptable within a precautionary approach by reducing catches to very low levels or even to zero. The application of a harvest rate rule led to improvements for moderately fast-growing species ($k \leq 0.45 \text{ year}^{-1}$), such as lemon sole, brill, or whiting, compared to the rfb rule (Chapter 9), but still showed poor performance for the very fast-growing species ($k > 0.45$ year^{-1}).

This outcome leaves faster-growing fish species, for which neither of the empirical control rules from the generic simulation testing appeared appropriate. Such species included common, very fast-growing, short-lived small pelagics, such as sprat, pilchard or anchovy, and larger species, such as John Dory.

Considering the results of previous simulations where neither of the empirical control rules provided satisfactory management performance, two reasons for this outcome might be considered. Either

(i) the control rules do not work for such species, for example, because of their fast stock dynamics or because indicators such as length-based indices might not work well for fast-growing species, as suggested by Kell et al. (2022), or

(ii) the operating models for these stocks, based on an annual time step, do not fully capture their rapid stock dynamics.

Figure 10.1 shows the individual growth of one example fast-growing species (sandeel). This figure illustrates that, initially, the length increases rapidly, and the asymptotic size is reached after only a few years. This means that there are substantial changes in length from year to year. Many biological parameters can be linked to size, such as individual weight, maturity or natural mortality (Gislason et al., 2010), and large changes in size can lead to large changes in these parameters. Additionally, the selectivity of fishing gears is usually size-dependent, which means that the selection for a fish of the same age class can change substantially within a year. In the previous modelling approaches, stocks were modelled with an annual time step starting from age 1. This approach is appropriate for slower-growing species because of relatively small changes from age to age. However, for fast-growing species, modelling sub-annual steps is likely to be more appropriate.

Additionally, fast-growing species often have a different role in an ecosystem compared to slower-growing species (Siple et al., 2021). For example, fast-growing species occupy a lower trophic level, are often prey for other marine predators, are fished for purposes other than human consumption (e.g. aquaculture feed) and might exhibit schooling behaviour. Fast-growing species often have a high natural mortality, particularly at young ages, which means that many individuals die young, making the species short-lived. Furthermore, such stocks can have con-

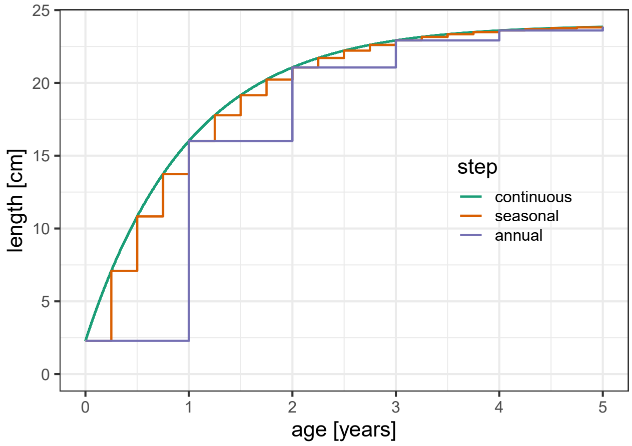

Figure 10.1: Individual growth (von Bertalanffy growth model) for sandeel.

siderable recruitment variability. Therefore, the stocks exhibit large fluctuations caused by recruitment events because recruits comprise a considerable part of the population. This also means that such stocks are more susceptible to environmental conditions and changes. These boom and bust dynamics can be challenging for fisheries management (de Moor et al., 2011) and it is difficult to distinguish signals from noise in observations.

This chapter explored how fast-growing species could be modelled more appropriately with sub-annual time steps and their implications for management. For this purpose, the stock with the highest individual growth (sandeel) was used as a case study to create a generic operating model. Subsequently, harvest rate-based management was considered along with an alternative based on an escapement strategy. This work does not aim to provide a definitive generic management solution for fast-growing species, but is intended to illustrate challenges when modelling such species and possible ways forward for the future.

10.3 Methods

10.3.1 Operating model

The fastest-growing species (sandeel) from the 29 stocks considered previously (Chapter 5) was selected as a case study. Operating models were created based on its life-history parameters (Table 10.1) following the life-history relationships of the FLR (Kell et al., 2007) package FLife. The resulting von Bertalanffy growth curve is shown in Figure 10.1. Age 0 was included in the operating models to ensure capturing the seasonal dynamics of young fish.

Table 10.1: Life-history parameters for the sandeel operating model. Shown are von Bertalanffy growth parameters (L_∞, k, t_0), length at 50% maturity (L_{50}), length-weight parameters (a, b), and recruitment steepness (h). Values highlighted with * are previously defined default values (Chapter 5) in the absence of stock-specific information.

L_∞ **[cm]**	k **[year^{-1}]**	t_0 **[years]**	L_{50} **[cm]**	a	b	h
24	1.00	-0.1*	12	0.0049	2.783	0.75*

Two operating models with different time steps were created: (i) the annual operating model used a single time step per year, as before, and (ii) the seasonal (quarterly) operating model used four time steps per year. In the seasonal operating model, all biological and fishery parameters were based on the length in the corresponding season, but the functional forms were kept the same as previously described for the annual models (see Chapter 5 for descriptions, including equations). This applied to natural mortality (following Gislason et al., 2010), maturity (logistic), weights at age (following the length-weight relationship), and fisheries selectivity (double normal). Spawning was assumed as a single event at the beginning of the year. This meant that fish were growing during the year, and consequently, natural mortality decreased while maturity, weight and selectivity increased. Recruitment was modelled with a Beverton-Holt stock-recruitment function.

Previous projections (Chapters 6, 7, 8, and 9) used FLR's FLash package (https://github.com/flr/FLash), which has limited seasonal modelling capabilities. Therefore, seasonal projections were conducted with the newer FLR package FLasher (https://github.com/flr/FLasher).

10.3.2 MSY estimation

The first step was determining maximum sustainable yield (MSY). FLR packages do not yet offer internal routines for the estimation of MSY reference points for fully seasonal models. Therefore, deterministic MSY reference points were estimated by projecting the two operating models forward for 100 years with a constant fishing mortality (F) and finding the F with the highest long-term (last 10 years) catches.

10.3.3 Exploration of empirical management procedures

Two empirical management procedures were tested with the seasonal operating model:

- A harvest rate strategy, fishing a proportion of the stock:

$$C_{y,q} = H\ B_{y,q}, \tag{10.1}$$

where $C_{y,q}$ is the catch in year y and season q, H the harvest rate ($0 \leq H \leq 1$), and $B_{y,q}$ the total biomass at the beginning of y and q.

- An escapement strategy, where an escapement biomass $B_{\text{escapement}}$ is defined, and the biomass above this value is fished:

$$C_{y,q} = \max(B_{y,q} - B_{\text{escapement}}, 0). \tag{10.2}$$

The work of this chapter is only exploratory and assumes that an unbiased estimate of total biomass, $B_{y,q}$ (or at least an estimate of known bias), is available, e.g. as would be obtained from a hydroacoustic survey.

Deterministic evaluation

Firstly, both control rules were tested deterministically (without process or observation error) with the seasonal operating model. This evaluation was done similarly to the MSY estimation above with 100-year projections, and the harvest rate and escapement biomass maximising long-term catch were determined. Optimum values were determined for quarterly, biannual and annual catches, i.e. the catch target was set once and then kept constant for one, two or four seasons before the control rules were applied again.

Stochastic simulations

Secondly, the optimised values of H or $B_{\text{escapement}}$ from the deterministic evaluation were used in a stochastic simulation with the seasonal operating model. For simplicity, these exploratory simulations only considered stochasticity for the recruitment process with recruitment variability $\sigma_R = 0.6$, the same value used for the generic simulations in previous chapters. Simulations were only conducted for the optimised values of H or $B_{\text{escapement}}$ from the deterministic evaluation where catches were set annually. In the stochastic simulations, the catch was then also only set once at the beginning of each year and equally distributed to the four seasons.

The two control rules rely on an estimate of the stock biomass. Therefore, the impact of time lags was evaluated for time lags of $0, 1, ..., 8$ seasons, where one season corresponds to a quarter of a year. A time lag of 0 meant that the biomass estimate was from the beginning of the year for which the catch was set, a time lag of 1 season meant that the estimate was from the beginning of the fourth season of the previous year, and a time lag of 8 corresponded to the biomass from two years ago.

10.3.4 Data availability

Input data and software code for this study are available open access from GitHub at https://git.io/JDID1.

10.4 Results

10.4.1 MSY estimation

The estimation of MSY reference levels for the annual and seasonal sandeel operating models is shown in Figure 10.2. The difference in recruitment levels is due to the high M values in the first two quarters of the seasonal operating model (linked to length) compared to the annual value used in the annual operating model. Figure 10.3 illustrates projections of the operating models. Expectedly, the seasonal operating model shows intra-annual fluctuations of the biomass caused by seasonal growth.

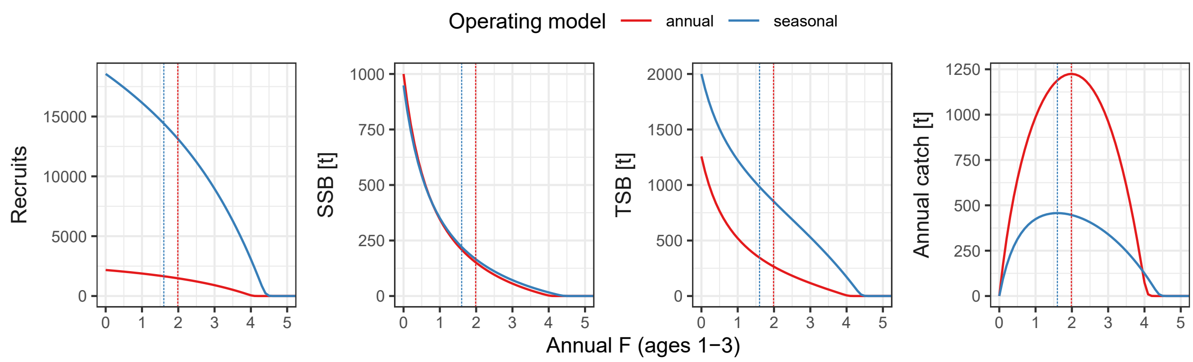

Figure 10.2: Estimation of MSY for seasonal and annual sandeel operating models. Shown are recruits, spawning stock biomass (SSB, i.e. mature proportion of the stock), total stock biomass (TSB) and catch. Values correspond to long-term averages (median of last 10 years of a 100-year constant F projection).

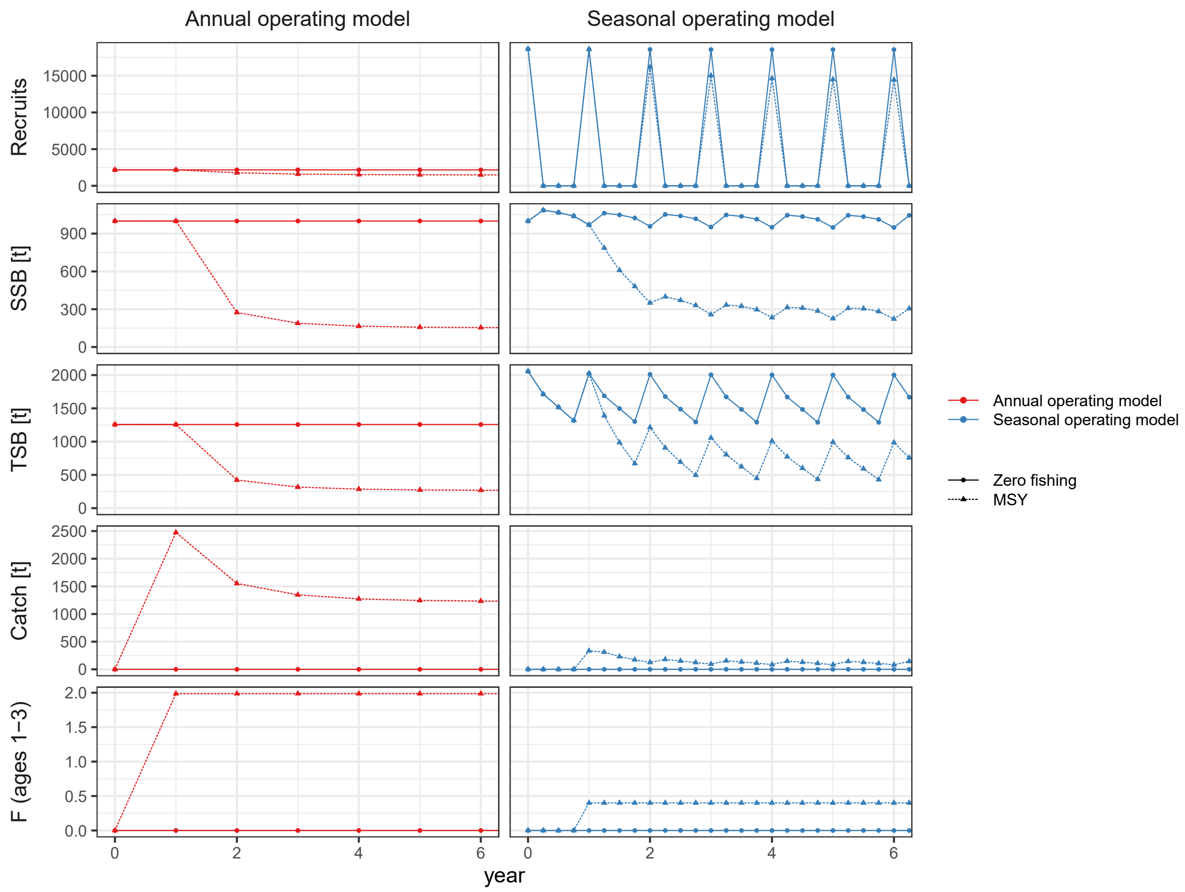

Figure 10.3: Comparison of annual and seasonal projections for sandeel. Zero-fishing and fishing at F_{MSY} options are shown, starting from an unfished condition. Please note that in the seasonal operating model (on the right), there are four (seasonal) catch and F values per year; therefore, they appear higher in the annual operating model (on the left), where there is only one value per year.

10.4.2 Exploration of empirical management procedures

Deterministic evaluation

The exploration of the long-term deterministic harvest rates with the seasonal sandeel operating model is displayed in Figure 10.4. Updating the advice more frequently (quarterly > biannual > annual) led to higher long-term catches at the optimum harvest rate, and the optimum was at a higher harvest rate.

Figure 10.5 illustrates the analysis for the escapement strategy. Similar to the harvest rates, updating the advice more frequently resulted in higher long-term catch for the optimum escapement biomass. However, the optimum escapement biomass for the annual and biannual catch interval was nearly identical but higher for the seasonal catch interval.

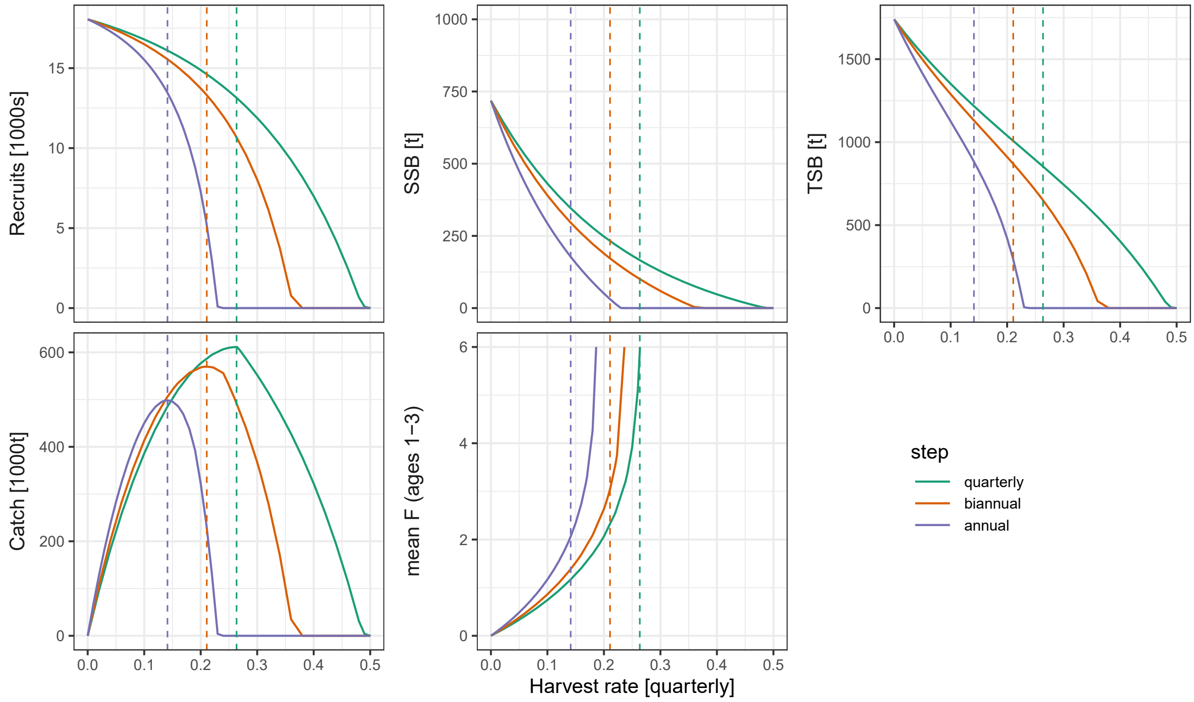

Figure 10.4: Deterministic exploration of harvest rates for the seasonal sandeel operating model. The results shown are long-term averages. Vertical dashed lines indicate the harvest rate with the highest long-term catch.

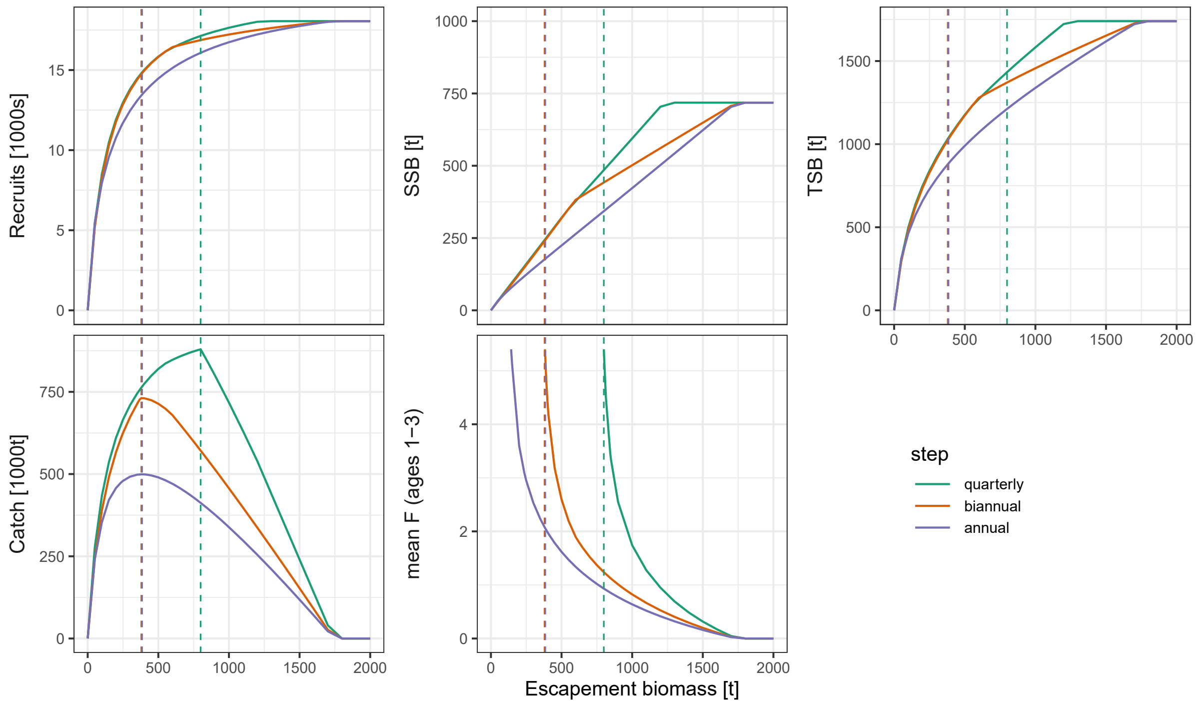

Figure 10.5: Deterministic exploration of the escapement strategy for the seasonal sandeel model. The results shown are long-term averages. Vertical dashed lines indicate the escapement biomass with the highest long-term catch.

The deterministic equilibrium values of the optimised harvest rates and escapement strategy (i.e. where the solid lines intersect with their corresponding dashed vertical lines in Figure 10.4 and Figure 10.5) are shown by quarter in Figure 10.6.

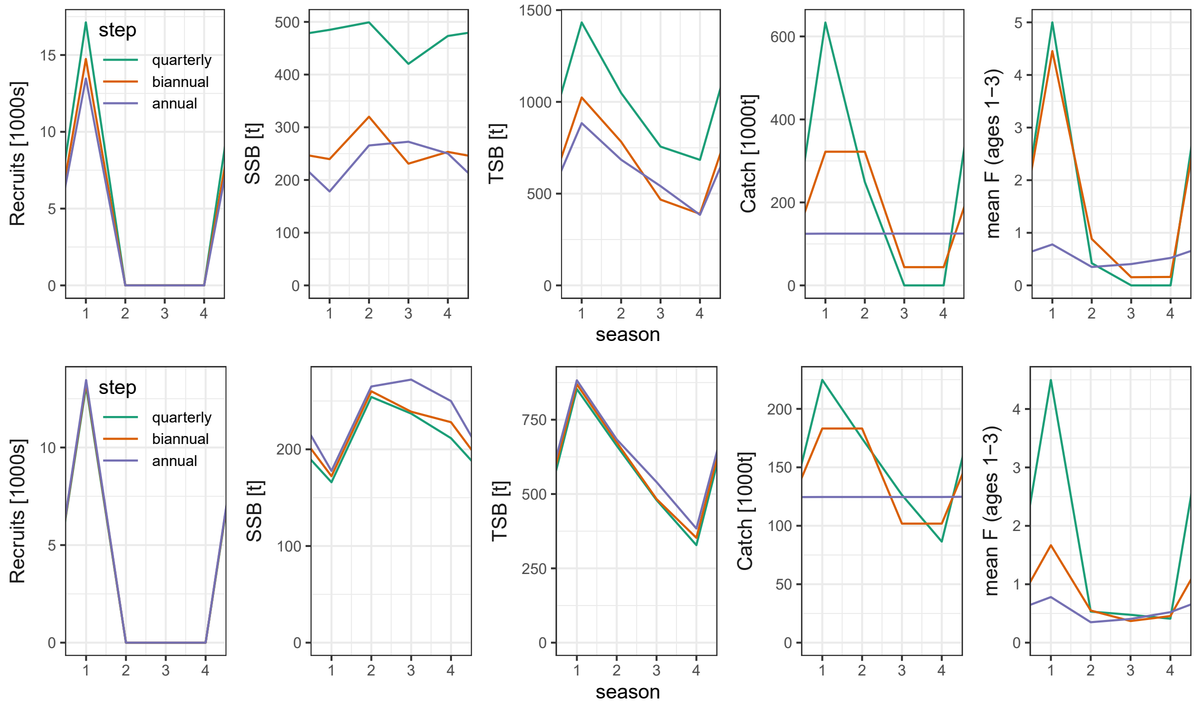

Figure 10.6: Equilibrium values of the deterministic optimum harvest rate (top) and escapement strategy (bottom) for sandeel. Shown is the equilibrium seasonal cycle over one year.

Stochastic simulations

The stochastic simulations of the optimum harvest rate and escapement strategy for annual catches (as opposed to quarterly or biannual) are summarised in Figure 10.7. The optimum escapement biomass led to a narrow range of SSB values just below B_{MSY}, whereas the range was larger for the optimum harvest rate. The timing of the biomass estimate had a strong impact on the performance of the empirical control rules. A time lag of one season (0.25 years) resulted in a lower catch and a higher stock size. However, a time lag of exactly one year caused a near-collapse of the stock and led to very low stock size and catch.

10.5 Discussion

This chapter aimed to investigate options for conducting seasonal MSEs through exploratory simulations. Although not exhaustive, the conclusions from this work can help steer future efforts for exploring management options for fast-growing fish stocks.

There have been recent developments in the FLR package framework, and the projection module FLasher now facilitates seasonal projections with any arbitrary number of time steps per

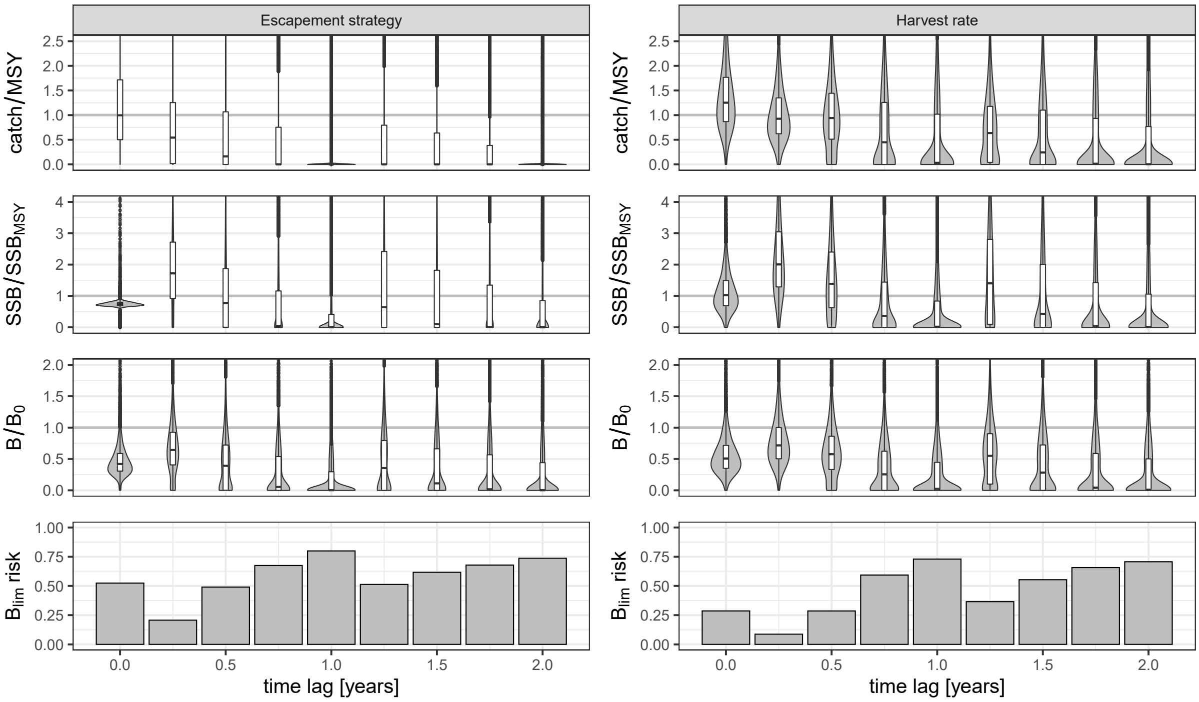

Figure 10.7: Summary of stochastic simulations for the optimum escapement biomass (left) and harvest rate (right) for annual catches (as opposed to quarterly or biannual) for sandeel. The summary statistics show the distribution of the performance metrics (catch relative to MSY, SSB relative to $\mathrm{B_{MSY}}$, total biomass relative to unfished biomass) and the average B_{lim} risk for a 25-year projection. The time lag (x-axis) refers to the time lag between the calculation of the annual catch and the timing of the biomass estimate on which it is based.

year. However, seasonal simulations are considerably slower because several steps are required per year, which increases computational complexity and makes analyses more time-consuming.

The seasonal operating model developed for sandeel was new, and therefore a comparison to the previous annual modelling approach would be warranted. In the seasonal operating model, all biological and fisheries parameters accounted for seasonal growth, and consequently differed between seasons, whereas these were constant for the annual operating model. These changes caused differences in the dynamics of the stock and how it responded to fishing, as can be seen from Figure 10.2 and Figure 10.3. The change in SSB as a function of F is relatively similar because both operating models were conditioned to have an unfished (virgin) SSB of around the same absolute value. On the other hand, virgin recruitment differs substantially between models despite having the same recruitment steepness. This is due to factors such as the natural mortality of recruits, which is higher in the seasonal operating model. Furthermore, selection in the fishery differs. In the annual operating model, fish of a certain age are subject to the same selectivity throughout the year. In contrast, in the seasonal operating model, fish of the same age class are increasingly more likely to be selected as the year progresses due to individual growth.

Two alternative empirical management procedures were explored; a harvest rate and an escapement strategy. Both approaches might be considered demanding regarding their data requirements because they rely on a recent biomass estimate. The International Council for the Exploration of the Sea (ICES) recommends using an escapement strategy for data-rich short-lived species (ICES, 2019a). However, this relies on the existence of an analytical stock assessment. The recommended catch is then based on a short-term forecast in which a catch is determined so that the risk of the stock falling below the limit reference point B_{lim} does not exceed 5% after fishing. For the exploration of the harvest rate and escapement strategy for sandeel in this study, the control rules were applied empirically without running any stock assessment or forecast and are therefore more suitable for data-limited stocks.

An escapement strategy could be considered compelling because the role of fast-growing species in the ecosystem can be considered, for example, leaving enough prey to its natural predators, which means it is a step towards ecosystem-based fisheries management (e.g. Bentley et al., 2021).

One of the main conclusions is that the timing for the management of fast-growing species is crucial, which applies both to the interval for which a catch is set as well as the time lag on which management decisions are based. Setting the catch advice more frequently seemed to improve management performance, and, ideally, the advice is updated more than once per year. Doing this allows the extraction of higher long-term yields for such productive fisheries resources. Furthermore, the timing of observations is very important because of seasonal growth patterns influencing stock dynamics. For example, simulation results indicated that setting an annual catch advice based on a biomass estimate from a suboptimal time of the year might be detrimental to the stock and fishery. However, it would be possible to tune a control rule to account for seasonal growth if there is a gap between the timing of the biomass estimate and the application of the control rule. In addition, simulations showed that even fishing at the optimal (MSY) harvest rate but with a time lag of just one year resulted in very poor performance, leading to low stock size and consequently low long-term catch. This is because the stock was strongly impacted by recruitment. The biomass estimate might be high in one year because of a strong recruitment event, but after just one year, many recruits may have disappeared (due to high natural mortality for recruits, and fishing in the previous year) and are not available anymore for the fishery.

The stochastic simulations in this chapter were exploratory and only included recruitment variability, which means that considerations of uncertainty in these simulations were limited. Including additional sources of uncertainty or a broader interpretation of uncertainty could have led to different implications.

It appears difficult to define generic recommendations for sustainable management procedures or harvest levels of fast-growing species, apart from advising a very low, highly precautionary catch. The best way forward for managing such fisheries resources is likely to conduct case-specific simulations. The present exploratory analyses proved that seasonal MSE simulations are feasible. Such simulation models should be conditioned on a specific stock with as much information as possible, such as growth patterns, time of spawning, and the fishery. Additionally, this would allow the inclusion of suitable uncertainty estimates where relevant. This approach is likely to determine appropriate management options leading to better management performance with higher yields, while ensuring compliance with precautionary principles.

10.6 Conclusion

While exploratory, the seasonal simulations for sandeel allow drawing conclusions for the future development of management procedures appropriate for data-limited fast-growing fish stocks. Firstly, it is helpful to develop seasonal operating models for fast-growing species to account for their seasonal dynamics and potentially seasonal fishery, which is not feasible with annual operating models. Both candidate management procedures (harvest rates and escapement strategy) appeared promising, but this was conditional on their parameterisation and ensuring appropriate timing. In conclusion, it is recommended to conduct case-specific simulations and tune candidate management procedures to fulfil the required management objectives.

Chapter 11

Risk equivalence in data-limited and data-rich fisheries management: an example based on the ICES advice framework[1]

[1]This chapter is based on a manuscript submitted to the journal Fish and Fisheries.

11.1 Foreword

This is the last chapter before the conclusions. In the previous chapters, generic empirical management procedures were developed. In this chapter, these management procedures are tested for several case study stocks with case-specific simulations. The content of this chapter is based on a manuscript submitted to the journal Fish and Fisheries:

> Fischer, S. H., De Oliveira, J. A. A., Mumford, J. D. & Kell, L. T. (n.d.). Risk equivalence in data-limited and data-rich fisheries management: an example based on the ICES advice framework (manuscript submitted to *Fish and Fisheries*)

11.2 Abstract

Fisheries management needs to ensure that resources are exploited sustainably and the risk of depletion is at an acceptable level. However, often uncertainty about resource dynamics exists and data availability may differ substantially between fish stocks. This situation can be addressed through tiered systems, where tiers represent different data limitations, and tier-specific stock assessment methods are defined, aiming for risk equivalence across tiers. As case studies, three stocks of European plaice, Atlantic cod, and Atlantic herring were selected, where advice is provided by the International Council for the Exploration of the Sea (ICES). A management strategy evaluation was conducted to compare risk equivalence between the data-rich ICES MSY rule, based on a quantitative stock assessment, and the revised data-limited empirical management procedures of the ICES advice framework. The simulations indicated that the data-limited methods were precautionary and did not lead to a higher risk of depletion than the data-rich methods. Although the catch based on generic data-limited methods was lower, stock-specific optimisation improved management performance with catch levels comparable to the data-rich method. Furthermore, the simulation indicated potential issues with the ICES MSY rule's management performance when setting management reference points suboptimally, resulting in increased risk. It is concluded that the recent revisions of the ICES system explicitly account for risk equivalence for data-limited fisheries management and are a major step forward. Finally, further consideration of simple empirical management procedures is supported, irrespective of data limitations due to their ability to meet fisheries management objectives with greater simplicity.

11.3 Introduction

Assessing possible impacts of anthropogenic influences on ecosystems is important, and this is often formalised with risk assessments, widely used in many fields of environmental management (Burgman, 2005). The exploitation of marine living resources is no exception and has spawned the management strategy evaluation approach (MSE; Smith, 1994), which is considered best practice for the evaluation of the impact of management strategies (Punt et al., 2016). MSE aims to simulate the resource dynamics (biological fish stocks) and the fishery exploiting it in an operating model (OM), and the management system as a management procedure (MP) in a feedback loop. Uncertainty about resource dynamics can be included by considering alternative hypotheses in the form of alternative OMs because the underlying reality is unknown and can only be inferred from observations (Kell et al., 2021). Candidate MPs are then simulation tested and a selection can be made based on which MP best meets management objectives while considering uncertainty.

Assessing risks requires a definition of what constitutes risk. Roux et al. (2022) define risk as the probability of exceeding reference levels leading to potential adverse consequences (biological, ecological, social, or economic). In fisheries management, risk is often defined as the probability of the exploited resource being overfished (Dichmont et al., 2016) and failing to meet targets, i.e. management objectives. Uncertainty in the understanding of processes is explicitly considered in the precautionary approach to fisheries management (Garcia, 1996), which aims to reduce the risk of adverse consequences. MSE can be used as a tool to identify where a reduction of scientific uncertainty could improve fisheries management (Fromentin et al., 2014).

The availability of data and knowledge can differ substantially between fish stocks, requiring the application of different methods to derive scientific management advice. Tiered systems, which classify fish stocks into tiers or categories depending on the available data, have been developed to account for this discrepancy. Such tiered systems are, for example, used in Australia (Department of Agriculture and Water Resources, 2018), the United States of America (PFMC, 2014), and Europe (ICES, 2012b). The general aim of such frameworks is to provide more precautionary advice when there are fewer data (i.e. more uncertainty), e.g. through the inclusion of buffers depending on the stock category (Dichmont et al., 2016). This implies that there is a benefit of improving data collection and knowledge because more data could increase the yield.

Ideally, tiered fisheries management frameworks ensure risk equivalence between categories, i.e. in a situation with poor or limited data and consequently higher uncertainty, management should not permit higher risks. Dichmont et al. (2016) reviewed the tier approaches of Australia's Southern and Eastern Scalefish and Shark Fishery, the US west coast groundfishery, the US Alaskan crab fishery, and the European Union fisheries. They found that none of the systems achieved complete risk equivalency, and only the Australian system explicitly aimed towards it. Dichmont et al. (2017) then subjected the Australian system with its tiers to an MSE with a full ecosystem model and found that risk equivalence was not achieved. However, Fulton et al. (2016) noted that introducing buffers similar to the one applied on the US west coast could move the Australian system closer to full risk equivalence between the tiers. Other studies comparing methods among tiers exist, but these compared generic methods rather than specific management frameworks (e.g. Carruthers et al., 2014; Geromont & Butterworth, 2015a)

The International Council for the Exploration of the Sea (ICES) provides catch advice for fish stocks in the Northeast Atlantic (ICES, 2021a). Since 2012, ICES classified fish stocks into six categories depending on available data and applicable methods (ICES, 2012b), from category 1 (most data-rich) to the most data-limited category 6.

Stocks in category 1 are usually assessed with age-structured stock assessments, and the catch advice is based on a short-term forecast. In most cases, this advice is based on the ICES MSY rule (ICES, 2021a), which is a harvest control rule aiming at the fishing mortality corresponding to the maximum sustainable yield (MSY), F_{MSY}, but with F reduced when the spawning stock biomass (SSB) is estimated to be below a trigger value (MSYB_{trigger}). Guidelines specify how these management reference points should be derived (ICES, 2021h), and this usually involves a stochastic long-term simulation assuming stationarity ("EqSim" software; Simmonds et al., 2022). EqSim is conditioned on the point estimates from a stock assessment and only includes limited uncertainty considerations.

The 2012 ICES data-limited stock assessment framework (ICES, 2012b) is a collection of methods for stocks in categories 2-6, i.e. for those without absolute estimates of biomass and fishing mortality. Category 2 was originally meant for stocks with quantitative assessments, which were considered to provide only relative estimates due to large uncertainty. For stocks in categories 3–6, there is typically no stock assessment due to data limitations or because assessment models do not meet acceptance criteria. For category 3 stocks, a survey or catch per unit effort index exists and can indicate stock trends. The standard method for this category is a status quo catch rule, which adjusts the recently advised catch by the trend in a stock index, typically a “2 over 3” rule, where the trend is defined as the average of the two most recent index values divided by the average of the three preceding values. The remaining stocks are classified as category 4 (stock with reliable catch data only), 5 (stocks with landings data only), and 6 (negligible bycatch stocks). According to the ICES stock assessment database (ICES, 2022a), ICES provided advice for 179 stocks in 2021, of which 99, 6, 55, 1, 13, and 5 were in categories 1–6, respectively.

Although the 2012 ICES data-limited framework aimed to provide advice following a precautionary approach, this was actually never shown to be the case. Recently, there have been developments to revise the ICES data-limited framework and draft guidelines were proposed in 2020 to overhaul the system for category 3 stocks (ICES, 2020a). Figure 11.1 illustrates the revised framework. The first step is to check whether a surplus production model (e.g. SPiCT; Pedersen & Berg, 2017) can be fit. If such a model fit meets acceptance criteria, the stock can be upgraded to category 2 and a short-term forecast with a fractile rule (Mildenberger et al., 2022), aiming at a fishing mortality below F_{MSY}, is used to provide catch advice.

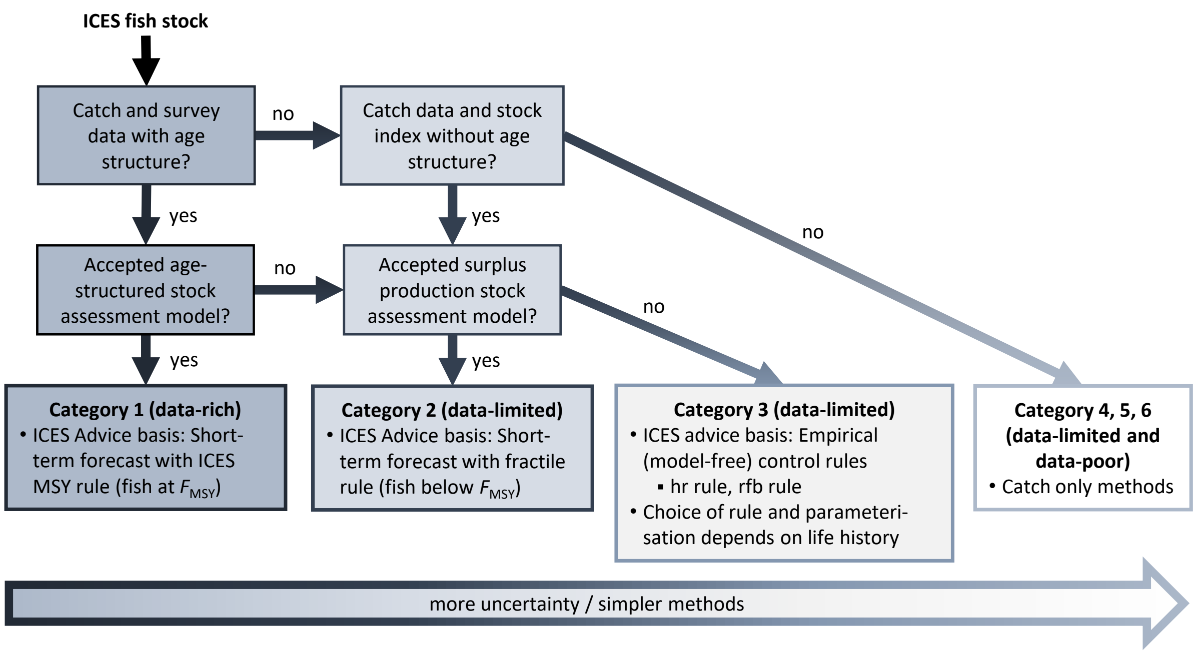

Figure 11.1: Simplified illustration of the revised ICES advice framework following the revisions for categories 2 and 3 proposed by ICES (2020a). The figure shows typical situations but deviations exist, e.g. for short-lived species.

In the absence of quantitative stock assessments, empirical (model-free) MPs were developed through testing with a generic MSE and tuning to achieve precautionary criteria for a wide range of life histories and uncertainties. One of the new empirical MPs is the "rfb rule" (developed in Chapters 6, 7, and 8; see also Fischer et al., 2020; Fischer et al., 2021a, 2021b) which derives advice by adjusting the previous catch advice by the trend from a biomass index, the catch length data as a proxy for fishing pressure, and a biomass safeguard protecting against low stock size. Another suggested MP is a harvest rate rule which sets catch advice by targeting a relative harvest rate (catch divided by a biomass index, developed in Chapter 9). The rfb rule was already applied to two stocks in 2021 (ICES, 2021m, 2021l), and a further rollout is anticipated for 2022.

The aim of the study in this chapter was to compare the risks of data-limited category 3 methods with data-rich category 1 methods. Statements on the comparison of risk or other management performance metrics for a specific stock are only useful if methods are compared under equivalent conditions. Consequently, a simulation framework was developed that allows MSE to be conducted for data-limited and data-rich MPs. Evaluations should include several life histories, initial stock conditions, and sources of uncertainty. Consequently, three ICES stocks were selected as case studies for which OMs could be generated.

The first case study stock was European plaice (*Pleuronectes platessa*, Pleuronectidae) in the western English Channel (ICES, 2021k), a slow-growing flatfish. This stock was historically treated as a category 1 stock, and the advice was based on the age-structured extended survivors analysis (XSA; Shepherd, 1999), a computationally efficient version of a virtual population analysis (VPA) with survey tuning. However, in 2015, this stock was downgraded to category 3 due to high assessment uncertainty (ICES, 2015b). Nevertheless, the assessment was retained, and its SSB estimates were used as the index for the 2 over 3 rule. Since then, the data situation of the stock has improved substantially, sampling levels are at or above levels seen for other data-rich stocks, and this stock offers an opportunity to condition a case-specific MSE to a data-limited stock.

The other two case studies were commercially important and well-researched category 1 stocks; Atlantic cod (*Gadus morhua*, Gadidae) in the North Sea, eastern English Channel, and Skagerrak (ICES, 2021d), a demersal roundfish with medium individual growth, and finally, autumn spawning Atlantic herring (*Clupea harengus*, Clupeidae) in the North Sea, Skagerrak, Kattegat, and eastern English Channel (ICES, 2021f), a medium-sized fast-growing pelagic species.

The objectives of this study were to (i) conduct an MSE for three case study stocks and evaluate both the new ICES data-limited approach (the generic empirical MPs developed in previous chapters) and the traditional ICES data-rich approach (the ICES MSY rule), (ii) compare management performance of these approaches, particularly considering meeting management objectives and risk equivalence, and (iii) explore the benefit of case-specific tuning of the generic empirical MPs.

11.4 Methods

An MSE framework using the Fisheries Library in R (FLR; Kell et al., 2007) was developed to evaluate data-rich and data-limited MPs.

11.4.1 Operating models

Age-structured stochastic operating models (OMs) were conditioned for three contrasting fish stocks from the Northeast Atlantic (plaice, cod, herring, Table 11.1). OMs were based on the model fits of the state-space stock assessment model (SAM; Nielsen & Berg, 2014), which estimates processes (stock numbers at age, recruitment, fishing mortality), observations (catch numbers, survey indices), as well as uncertainties and uncertainty structures of estimated parameters. Uncertainty was introduced into the OMs by sampling from the variance-covariance matrix of the SAM model fit, whose structure was defined by the specific model configuration, and generating 1,000 different (but internally consistent) simulation replicates, each representing one possible outcome. This approach of using SAM model fits was developed by an ICES MSE workshop on North Sea stocks and full details of this approach are available from the workshop report (WKNSMSE; ICES, 2019h). For cod and herring, OMs were based on the latest stock assessments conducted by ICES working groups and accepted by ICES for advice purposes in 2021 (ICES, 2021d, 2021f). For plaice, the OM was based on an exploratory assessment from ICES (2021k), with full catch data including discards. Although the OMs are conditioned on real stock units, they might not exactly represent the ICES benchmarked assessments for these due to small changes (Table 11.1), but the OMs are very similar to the accepted ICES assessments (Figure 11.2).

Recruitment was modelled by fitting stock-recruitment models to historical SSB-recruitment pairs. The choice and parameterisation of recruitment models followed the suggestions of ICES

Table 11.1: The three baseline operating models.

	Plaice	Cod	Herring
• Species	European plaice *Pleuronectes platessa*	Atlantic cod *Gadus morhua*	Atlantic herring *Clupea harengus*
• Stock unit	western English Channel	North Sea, eastern English Channel, and Skagerrak	North Sea, Skagerrak, Kattegat, and eastern English Channel
• Stock ID	ple.27.7e	cod.27.47d20	her.27.3a47d
• Last stock assessment	2021 (ICES, 2021k)	2021 (ICES, 2021d)	2021 (ICES, 2021f)
Operating model specifications			
• Time series	full (1980-2020)	full (1963-2021)	full (1947-2021)
• Ages	2-10	1-6	0-8
• Stock recruitment model	Beverton-Holt, fitted to full time series, with residual auto-correlation $\rho = 0.6$	hockey-stick, fitted to 1998-2021 (following ICES, 2019h, 2021b, 2021p)	hockey-stick, fitted to 2002-2021 and breakpoint fixed to B_{lim} (following ICES, 2021g)
• Survey indices	2: UK-FSP Q3 (beam trawl) ages 2-8; UK-Q1SWBeam (beam trawl) ages 2-9	3: IBTS Q1 (bottom trawl) ages 1-5; IBTS Q3 (bottom trawl) ages 1-4; IBTS Q3 (bottom trawl) age 0	4: IBTS Q1 (bottom trawl) age 1; IBTS Q1 (herring larva index) age 0; IBTS Q3 (bottom trawl) ages 0-5; HERAS (acoustic) ages 1-8
• Biomass index	UK-FSP Q3	IBTS Q3	HERAS
• Length data source	Commercial catch sampling and Q1SWBeam	IBTS Q1 and Q3	HERAS
• Resampling period used in projection	last 5 years	last 5 years (ICES, 2019h, 2021b)	last 10 years (ICES, 2019h, 2021g)
• Deviation from stock assessment	used exploratory assessment from ICES (2021o)	removed maturity estimation from model and provided as input (faster model, negligible difference); removed survey age correlation (computational complexity reduced, negligible difference)	removed LAI SSB index (faster model, negligible difference) following ICES (2019h)

expert groups which ICES uses to calculate ICES management reference points (see Table 11.1 for details). In the present study, variability in future recruitment values (process error) was

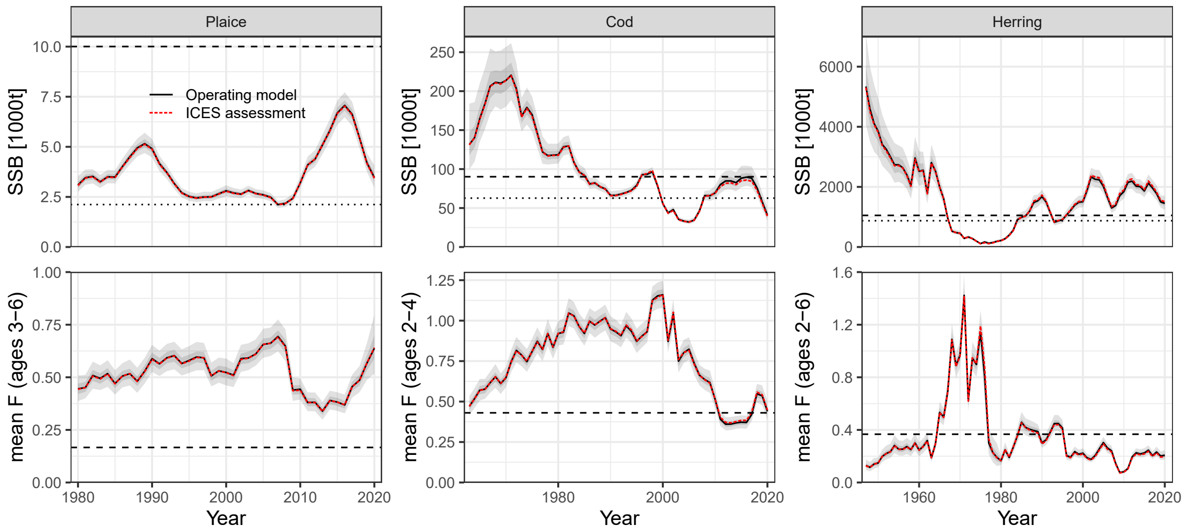

Figure 11.2: Comparison of spawning stock biomass (SSB) and fishing mortality (F) of baseline operating models (OMs) to ICES assessments. Shaded areas are 50% and 90% confidence intervals of the OMs. Horizontal dashed lines indicate OM B_{MSY} and horizontal dotted lines B_{lim}.

introduced by taking model log-residuals, fitting a kernel density smoother to residuals, and sampling from this distribution (Figure 11.3). This process allowed a wider range of residuals to be generated compared to bootstrapping residuals. Auto-correlation of future residuals was included if auto-correlation was significant in historical residuals. The model fitting and sampling were done independently for each simulation replicate.

OMs were prepared for a projection of 20 years for all stocks. Variability in biological parameters (weights at age, natural mortality, maturity, etc.) and fishery selectivity was modelled by resampling from the historical period for each replicate (see Table 11.1). Process error was included for recruitment (through recruitment residuals) and for older age classes with survival and other process error structure estimated by SAM.

Observations were generated for all survey indices used in the conditioning of the OMs (Table 11.1). Biomass indices were created by multiplying survey index numbers at age with survey weights and aggregating these. Uncertainty for index and catch observations was modelled based on the SAM estimates of observation error and observation error structure (see ICES, 2019h, for details). Catch length frequencies were derived by applying stochastic age-length keys to the observed catch numbers at age.

OM MSY reference points were estimated using the MSE simulation framework (including process error) and projecting forward for 100 years with constant Fs. MSY was derived by

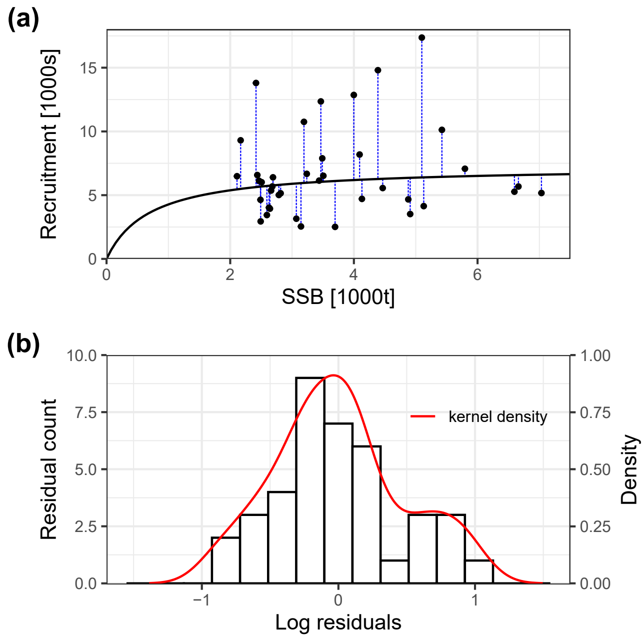

Figure 11.3: Visualisation of recruitment modelling for plaice. Shown are the Beverton-Holt recruitment model fit (solid black curve in a; points are stock-recruit pairs) and the distribution of log residuals (bars in b). Residuals for the MSE projection are sampled from the kernel density distribution (red curve in b).

maximising the long-term catch (median of the last 10 years). The biomass limit reference point (B_{lim}) is meant to represent the SSB below which recruitment is impaired (ICES, 2021h). Consequently, B_{lim} was set to the breakpoint of the hockey-stick model for cod and herring. This approach was not applicable for the Beverton-Holt model used for plaice. As an alternative, the principle used by ICES for determining management reference points (ICES, 2021h) was followed, and the lowest observed SSB was selected. This value was then linked to the recruitment model and corresponded to 77% of the unfished recruitment, similar to the 70% used for the generic operating models in previous chapters (Chapters 5–9). The MSY estimates derived from the baseline OMs through stochastic projections are summarised in Table 11.2.

Table 11.2: Reference points of the baseline operating models and comparison to ICES reference points.

stock	**Operating model reference points**					**ICES reference points**		
	B_0 **[t]**	F_{MSY}	**MSY [t]**	B_{MSY} **[t]**	B_{lim} **[t]**	F_{MSY}	**MSY** B_{trigger} **[t]**	B_{lim} **[t]**
Plaice	38,340	0.167	1,703	10,005	2,119	0.24	2,443	2,110
Cod	415,979	0.430	55,391	90,187	62,734	0.28	97,777	69,841
Herring	3,621,774	0.367	403,512	1,052,763	874,198	0.31	1,232,828	874,198

Using the stochastic OM projections to estimate reference points led to reference points matching the structure and dynamics of these OMs. However, details adopted for projections may not exactly match those adopted by the ICES expert groups when calculating ICES management reference points. Therefore, there are differences between the baseline OM reference points and ICES-derived management reference points (Table 11.2), as already shown by ICES (2019h). For example, F_{MSY} estimates for cod and herring were higher than their corresponding ICES estimates.

A range of alternative OMs was created to cover different assumptions made in the condition of the baseline OM so that the robustness of MPs could be evaluated (Table 11.3). These OMs were conditioned individually following the processes described above and covered considerations such as recruitment (failure, higher recruitment), natural mortality, or discards. Reference points were estimated for each alternative OM.

Table 11.3: Alternative operating models.

	Plaice	**Cod**	**Herring**
Recruitment	• *R: failure*: recruitment failure (2021-2025) • *R: no AC*: without recruitment residual auto-correlation	• *R: failure*: recruitment failure (2021-2025) • *R: higher*: higher recruitment (model fitted to 1988-2021)	• *R: failure*: recruitment failure (2021-2025) • *R: higher*: higher recruitment (model fitted to 1947-2021)
Natural mortality (M)	• *M: high*: $M + 50\%$ • *M: low*: $M - 50\%$ • *M: Gislason*: age-dependent M (Gislason et al., 2010)	• *M: dens. dep.*: density dependent M through cannibalism (ICES, 2017c, 2019h) • *M: no migr.*: removed inflated M for ages 3+ accounting for migration	
Catch	• *Catch: no disc.*: assume 100% discard survival		

11.4.2 Management procedures

The tested MPs are detailed in Table 11.4, and included the data-rich (ICES category 1) MSY rule (ICES, 2021h), the data-limited (ICES category 3) empirical 2 over 3 rule (ICES, 2012b), the rfb rule (Fischer et al., 2020; Fischer et al., 2021a, 2021b, described in Chapters 6, 7, and 8), and the hr rule (ICES, 2020a, described in Chapter 9). The ICES MSY rule MP mimicked the process conducted by ICES working groups, including a SAM assessment and a short-term forecast. The ICES management reference points (Table 11.2) were used for this process and not the OM-specific values. A slight deviation was done for herring because the ICES advice is based on a deterministic multifleet short-term forecast following a single fleet SAM model. For the MSE conducted here, this was simplified to a single fleet forecast because the aim was to evaluate the performance of the MP for a fast-growing pelagic species and not to consider individual fleet behaviour. The rfb and hr rules were tested for all stocks. The 2 over 3 rule was only tested for plaice because this is the method currently used for producing ICES advice for this stock (ICES, 2021k).

The inclusion of the ICES category 2 fractile rule (Mildenberger et al., 2022) into the study was considered. However, this MP requires a surplus production model and the suggested SPiCT model (Pedersen & Berg, 2017) has been repeatedly shown to fail to model the dynamics of the plaice stock (ICES, 2021o). Furthermore, attempts to fit it to cod resulted in unacceptably high uncertainty and for both cod and herring acceptance criteria were not met (see Appendix F for details).

Table 11.4: Evaluated management procedures (MPs).

MP	Equation and description	Reference
data-rich MPs		
ICES MSY rule	$F_{y+1} = F_{target} \min(1, B_{y+1}/B_{\text{trigger}})$ where F_{y+1} is the fishing mortality targeted in the advice year, F_{target} and B_{trigger} the management target (F_{MSY}) and trigger ($\text{MSY}B_{\text{trigger}}$), respectively, defined by ICES, B_{y+1} the SSB at the beginning of the advice year.	ICES (2021a)
data-limited MPs		

Table 11.4: (continued)

MP	Equation and description	Reference
2 over 3 rule	$A_{y+1} = A_y \ r \ b_{\text{PA}}$ with the new catch advice A_{y+1}, previous catch advice A_y, biomass index trend r, and precautionary buffer b_{PA}: $r = \frac{\sum_{i=y-2}^{y-1}(I_i/2)}{\sum_{i=y-5}^{y-3}(I_i/3)}$ $b_{\text{PA}} = \begin{cases} 1, & \text{if both } F \leq F_{\text{MSY}} \text{ \& } B \geq 0.5B_{\text{MSY}}\text{, OR} \\ & \text{if } b_{\text{PA}} = 0.8 \text{ within last two years} \\ 0.8 & \text{otherwise} \end{cases}$ where I is the biomass index, and F and B are estimated with a proxy MSY method, such as length-based indicators or a surplus production model. The rule is applied every second year ($v = 2$). The change in catch advice is limited to 20% through an uncertainty cap ($u_u = 1.2$, $u_l = 0.8$).	ICES (2012b)
2 over 3 rule with XSA	Same as 2 over 3 rule above, except: the SSB estimates from XSA are used as biomass index, the F and B evaluation is done with SSB estimates relative to ICES management reference points (F_{MSY} and MSYB_{trigger}), and the rule is applied every year.	ICES (2021o)
rfb rule	$A_{y+1} = A_y \ r \ f \ b$ with the new catch advice A_{y+1}, previous catch advice A_y, biomass index trend r, fishing proxy f, and biomass safeguard b: $r = \left(\frac{\sum_{i=y-n_0-n_1+1}^{y-n_0}(I_i/n_1)}{\sum_{i=y-n_0-n_1-n_2+1}^{y-n_0-n_1}(I_i/n_2)} \right)^{e_r}$ $f = \left(\frac{\bar{L}_{y-1}}{L_{F=M}} \right)^{e_f} x$ $b = \left(\min \left\{ 1, \frac{I_{y-n_0}}{I_{\text{trigger}}} \right\} \right)^{e_b}$ where I is the biomass index, $\bar{L}$ the mean catch length above length of first capture L_c, $L_{F=M}$ an MSY proxy reference length, I_{trigger} an index trigger value calculated from the lowest observed index value I_{loss} via an index trigger buffer w ($I_{\text{trigger}} = wI_{\text{loss}}$, default $w = 1.4$), n_0 the offset between last biomass index year and assessment year (default $n_0 = 1$), n_1 and n_2 the number of biomass index years in the numerator and denominator of r (default $n_1 = 2$, $n_2 = 3$), x a multiplier for scaling the advice (default $x = 0.95$ for stocks with von Bertalanffy $k < 0.2$ year^{-1}, $x = 0.9$ for stocks with $0.2 \leq k < 0.32$ year^{-1}), and e_r, e_f, e_b exponents for weighting r, f and b (default $e_r = e_f = e_b = 1$). The default advice interval is biennial ($v = 2$) and changes in catch advice are limited with an uncertainty cap to an increase of +20% ($u_u = 1.2$) and decrease of −30% ($u_l = 0.7$) but the application of the cap is conditional on $I_{y-n_0} \geq I_{\text{trigger}}$.	Fischer et al. (2020) and Fischer et al. (2021a, 2021b), ICES (2020a)

Table 11.4: (continued)

MP	Equation and description	Reference
hr rule	$A_{y+1} = I\ H\ b$ with new catch advice A_{y+1}, biomass index value I, target harvest rate H, and biomass safeguard b: $I = \sum_{i=y-n_0-n_1+1}^{y-n_0} (I_i/n_1)$ $H = C_{\text{ref}}/I_{\text{ref}}\ x$ $b = \min\left(1, \frac{I_{y-n_0}}{I_{\text{trigger}}}\right)$ where I is the biomass index, n_0 the offset between last biomass index year and assessment year (default $n_0 = 1$), n_1 the number of biomass index years used in I, C the realised catch, $C_{\text{ref}}/I_{\text{ref}}$ the harvest rate from a reference period, x a multiplier for scaling H (default $x = 0.5$), and I_{trigger} an index trigger value calculated from the lowest observed index value I_{loss} via an index trigger buffer w ($I_{\text{trigger}} = wI_{\text{loss}}$, default $w = 1.4$). The default advice interval is annual ($v = 1$) and changes in catch advice are limited with an uncertainty cap to an increase of +20% ($u_u = 1.2$) and decrease of −30% ($u_l = 0.7$) but the application of the cap is conditional on $I_{y-n_0} \geq I_{\text{trigger}}$.	ICES (2020a)

11.4.3 Performance statistics

Management performance of the MPs was evaluated through three main metrics: stock size (SSB relative to B_{MSY}), catch (relative to MSY), and depletion risk (called B_{lim} risk, $P_{B_{\text{lim}}}$, proportion of simulation replicates for which the stock is below the biomass limit reference point B_{lim}). These metrics were calculated for the long term (the last 10 years of the 20-year projection).

11.4.4 Optimisation

The rfb and hr rules were optimised with a genetic algorithm following the approach developed by Fischer et al. (2021a, 2021b, see Chapters 7, 8, and 9). This approach essentially mimics evolution, and individuals (MP parameterisations) are subjected to natural variability in a selective environment, favouring individuals with higher fitness (better management performance). In the generic simulations of Fischer et al. (2021b) (Chapter 8), the fitness was defined with a fitness function aiming to move the stock towards MSY while keeping $P_{B_{\text{lim}}}$ low. The ICES precautionary approach requires an MP to deliver management that ensures $P_{B_{\text{lim}}} \leq 5\%$ (ICES, 2021a), otherwise management is considered non-precautionary. In the present analysis for plaice, cod, and herring, the fitness function aimed to maximise long-term catch relative to

MSY (C_{lt}), but with a penalty if $P_{B_{\text{lim}}}$ exceeded 5%, following the concept adopted by ICES for case-specific MSEs (e.g. ICES, 2019h, 2020c):

$$\phi = C_{\text{lt}} - \frac{1}{1 + e^{-\left(P_{B_{\text{lim}}} - 0.06\right)500}} \tag{11.1}$$

The genetic algorithm was set up with a population size of 1,000 individuals. Variability was introduced through two genetic operators, crossover with $p = 0.8$ and mutation with $p = 0.1$, as well as elitism with $p = 0.05$ (Fischer et al., 2021a). Convergence of the optimisation was achieved when either a maximum of 100 generations was reached or no further improvement within 10 generations.

This optimisation was conducted first with the multiplier x (Table 11.4) and then with all MP parameters (n_0, n_1, n_2, e_r, e_f, e_b, x, v for the rfb rule, n_0, n_1, w, x, v for the hr rule) for all three stocks and the baseline OMs. The conditional uncertainty caps restricting changes in catch advice were kept fixed at +20% and −30% following the considerations of Fischer et al. (2020), Fischer et al. (2021b, Chapters 6 and 8) and ICES (2020a) because this is often requested by the fishing industry and can restrict large changes due to noisy data.

The optimisation was conducted with the baseline OMs for the three stocks (plaice, cod, and herring). The optimised parameterisations were then subjected to the alternative OMs.

11.4.5 Data and software

The results of this study are fully reproducible and input data, software code, and summarised results as presented in this chapter were made open source and are available from GitHub at https://github.com/shfischer/MSE_risk_comparison.

11.5 Results

11.5.1 Management procedures in the baseline operating model

Figure 11.4 shows a comparison of the management performance of all tested MPs. The corresponding stock summary projections are shown in Figure 11.5.

The ICES MSY rule induced non-precautionary long-term management for all three stocks, but catch and SSB were close to their MSY reference values for cod and herring. For plaice, using the ICES MSY rule led to a long-term $P_{B_{\text{lim}}}$ of 39.8%, and the SSB remained well below B_{MSY}. For plaice, this outcome was because the ICES management reference point target F_{MSY}

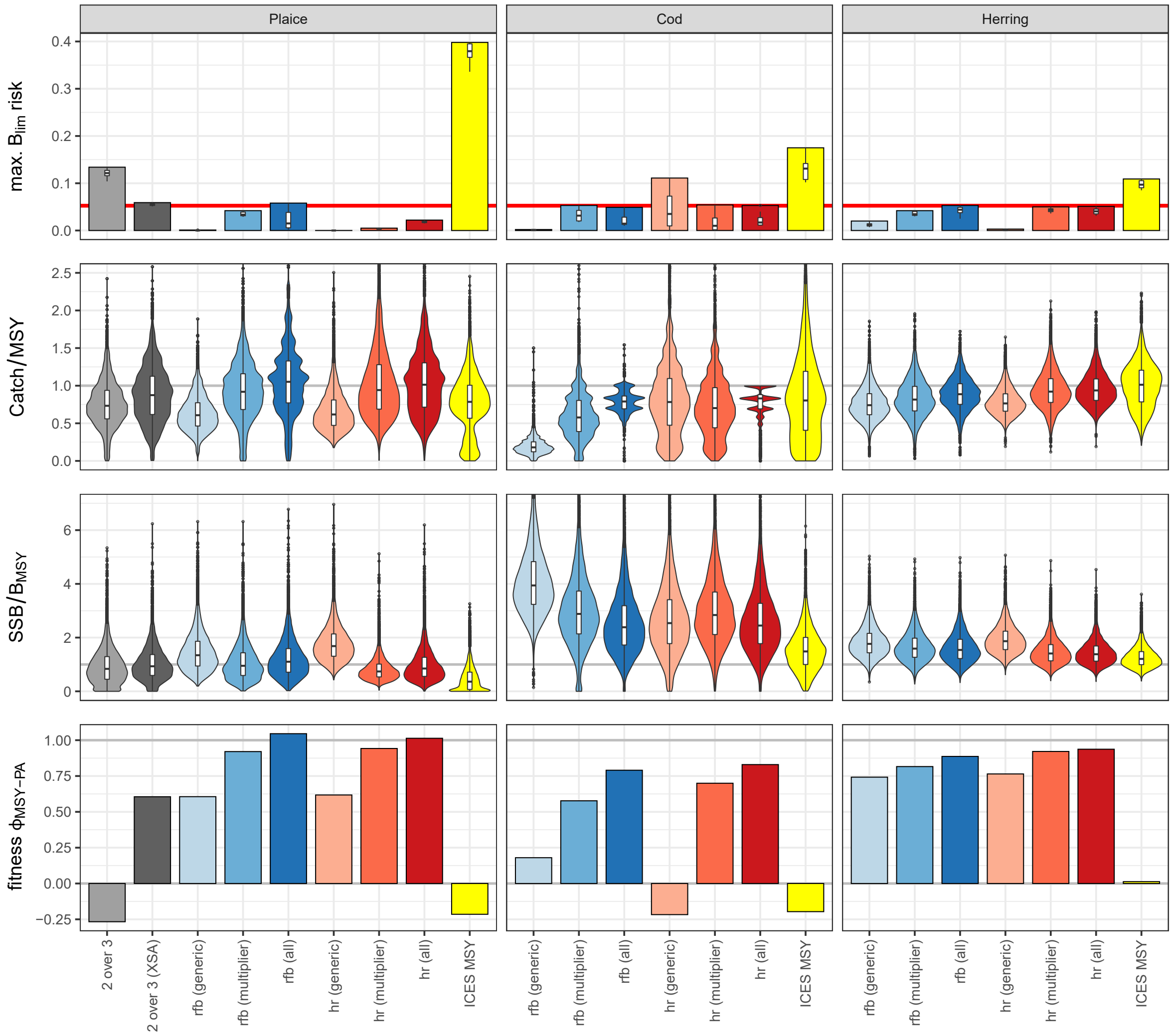

Figure 11.4: Summary statistics of all tested management procedures for all three stocks under their respective baseline operating models. Management procedures are colour-coded (2 over 3 rule in grey, rfb rule in blue, hr rule in red, and ICES MSY rule in yellow). For the rfb and hr rule, three options are shown: the generic parameterisations ("generic", light shading), the parameterisation obtained by optimising with a multiplier ("multiplier", medium shading), and the optimised parameterisation with all parameters ("all", dark shading). The risk is the maximum annual risk over the last 10 years, with the distribution of annual values shown inside the bars, catch and SSB show the distribution of the long-term (last 10 years), and the fitness is a single value defined by Equation (11.1), where larger (more positive) values indicate better management performance.

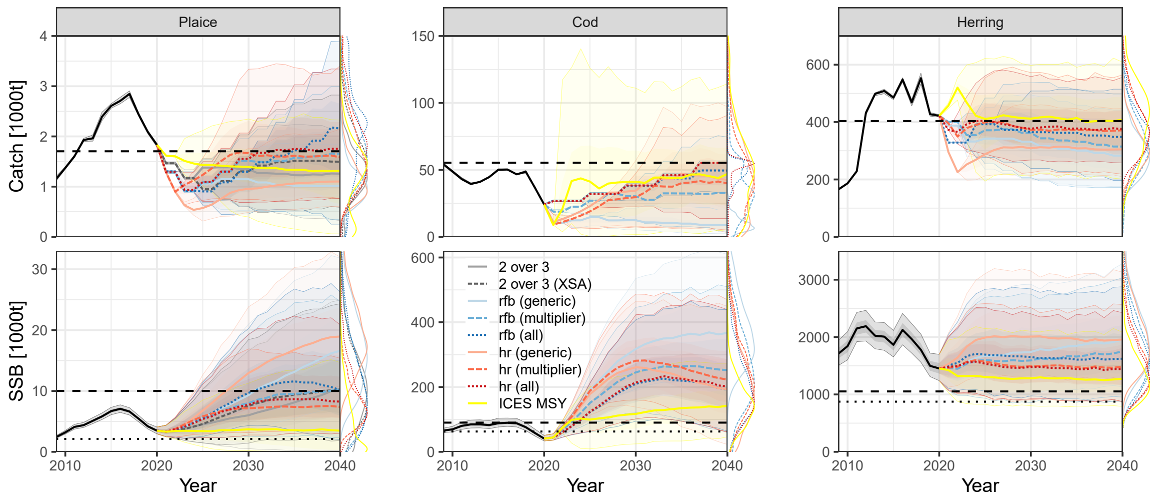

Figure 11.5: Projections corresponding to the management procedures shown in Figure 11.4 for the baseline operating models. The curves represent medians, surrounded by 50% and 90% confidence intervals (shaded areas). The dashed horizontal lines indicate MSY reference values (MSY, B_{MSY}) and the dotted lines the biomass limit reference value (B_{lim}). The lines on the right of the panels show the distribution in the last simulation year (2040).

was higher than the OM F_{MSY} (Table 11.2), leading to overfishing, and worse performance (lower catch, higher $P_{B_{\text{lim}}}$) than the optimised rfb and hr rules. For cod and herring, the management target was lower than the OM F_{MSY} (Table 11.2) and the ICES MSY rule did not cause overfishing, on average. Nevertheless, the rule did not lead to precautionary management because despite the SSB being above B_{MSY}, the uncertainty in the simulation was large enough to result in $P_{B_{\text{lim}}} > 5\%$. It should be noted that the ICES MSY rule applied here used non-tuned ICES management reference points, as is standard practice in ICES. If the ICES MSY rule had been tuned, as was done for the empirical MPs, this might have improved management performance.

For plaice, the 2 over 3 rule used with a biomass index led to a maximum $P_{B_{\text{lim}}}$ of 13.4%, and despite an increase in the median SSB over time, $P_{B_{\text{lim}}}$ increased continuously due to increasing uncertainty (Figure 11.5). When used in combination with the XSA assessment, the $P_{B_{\text{lim}}}$ was 5.9%, with slightly higher catches and stock size.

The generic (non-optimised) rfb rule resulted in precautionary management with $P_{B_{\text{lim}}} < 5\%$ for all stocks, but with relatively low catch and SSB generally above B_{MSY}. The optimisation of the rule purely with a multiplier substantially improved performance, with higher catches and SSB trajectories closer to B_{MSY}, and this improvement was larger when all control rule parameters were included.

Similar to the rfb rule, the generic hr rule provided precautionary management for plaice and herring with SSB overshooting B_{MSY}, with the optimisation using the multiplier increasing the catch, and with a further slight increase when including all control rule parameters. The generic hr rule was not precautionary for cod with a $P_{B_{\mathrm{lim}}}$ of 11% because once the SSB started to recover, catches increased quickly, reverting the trend and reducing SSB again. However, the optimisation made the hr rule precautionary by reducing the harvest rate target in the optimisation with the multiplier, or reducing the time lag for the optimisation with all parameters (Table 11.5), while retaining a similar long-term catch level (Figure 11.4).

Table 11.5: Default and optimised parameterisations for the rfb and hr rule. "-" indicates the default parameterisation, "mult" the optimisation with the multiplier and "all" the optimisation with all parameters. "Generations" is the number of generations in the optimisation until converge was achieved. "Improvement" is the improvement in the fitness relative to the default parameterisation. For a definition of the control rule parameters, see Table 11.4. Italicised values indicate values included in the optimisation.

Stock	**Optimisation**	**Generations**	**Improvement[%]**	**Control rule parameters**									
rfb rule				n_0	n_1	n_2	e_r	e_f	e_b	v	x	u_u	u_l
Plaice	-	-	-	1	2	3	1	1	1	2	0.95	1.2	0.7
	mult	1	52	1	2	3	1	1	1	2	*1.16*	1.2	0.7
	all	11	73	*0*	*5*	*4*	*1.7*	*1.7*	*1.9*	*2*	*1.65*	1.2	0.7
Cod	-	-	-	1	2	3	1	1	1	2	0.95	1.2	0.7
	mult	1	221	1	2	3	1	1	1	2	*1.73*	1.2	0.7
	all	13	339	*0*	*4*	*3*	*0.1*	*1.3*	*0.4*	*4*	*1.06*	1.2	0.7
Herring	-	-	-	1	2	3	1	1	1	2	0.90	1.2	0.7
	mult	1	10	1	2	3	1	1	1	2	*0.93*	1.2	0.7
	all	18	20	*0*	*2*	*3*	*1.2*	*1.5*	*1.4*	*3*	*0.94*	1.2	0.7
hr rule				n_0	n_1				w	v	x	u_u	u_l
Plaice	-	-	-	1	1				1.4	1	0.50	1.2	0.7
	mult	1	53	1	1				1.4	1	*1.23*	1.2	0.7
	all	22	64	*1*	*2*				*0.8*	*2*	*1.28*	1.2	0.7
Cod	-	-	-	1	1				1.4	1	0.50	1.2	0.7
	mult	1	422	1	1				1.4	1	*0.42*	1.2	0.7
	all	11	482	*0*	*1*				*1.0*	*4*	*0.84*	1.2	0.7
Herring	-	-	-	1	1				1.4	1	0.50	1.2	0.7
	mult	1	21	1	1				1.4	1	*0.78*	1.2	0.7
	all	14	23	*0*	*2*				*1.0*	*1*	*0.78*	1.2	0.7

11.5.2 Robustness to alternative operating models

The robustness of the MPs to the alternative OMs is illustrated in Figure 11.6. The relative performance of the MPs was similar between the OMs.

Different M assumptions for the plaice OM resulted mainly in shifts of all summary statistics, with lower catch, SSB and risk in case of lower M, and vice versa in case of higher or age-dependent M. Assuming discard survival had a minor influence on the empirical MPs

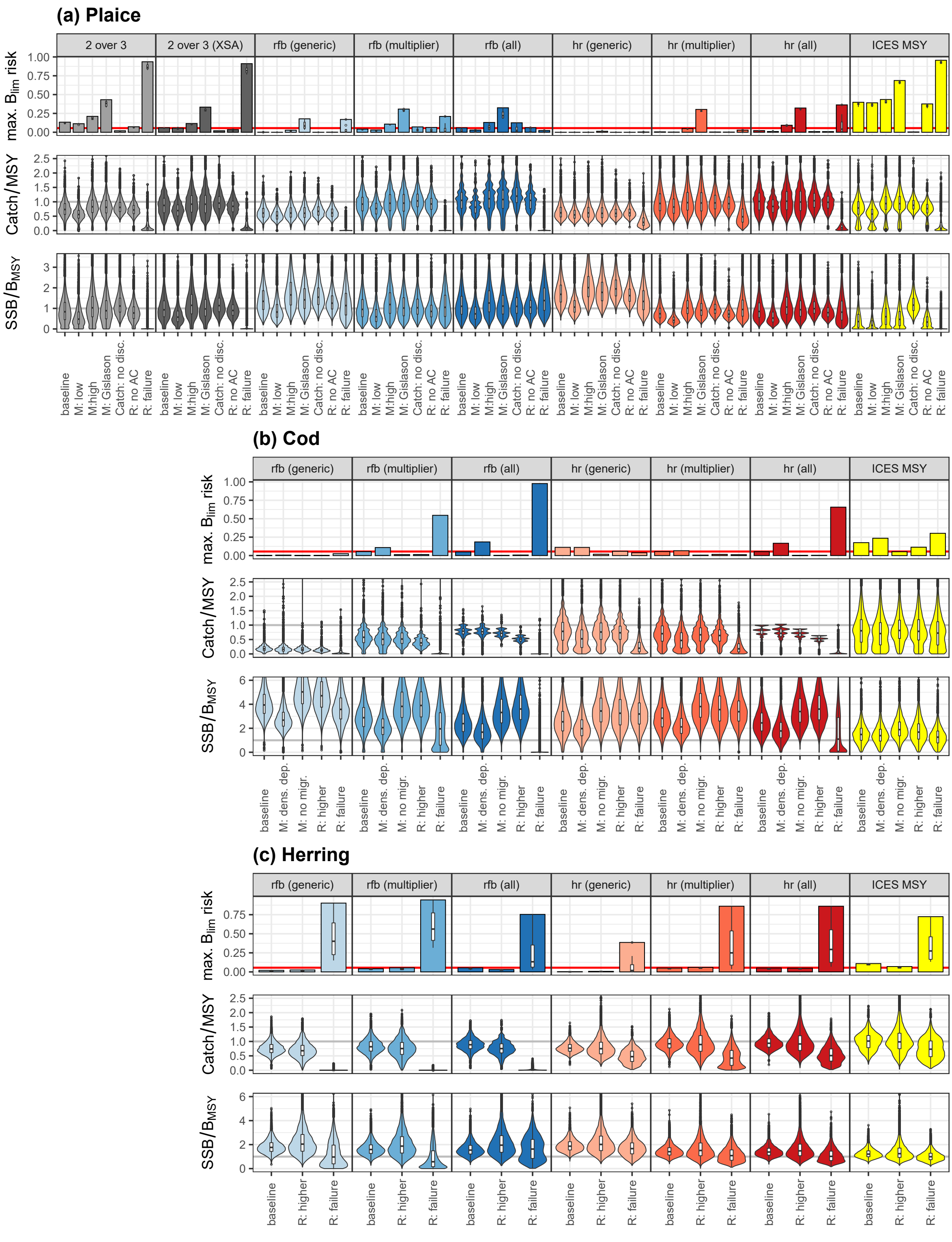

Figure 11.6: Summary statistics of all tested management procedures for all stocks and all alternative operating models. See Figure 11.4 for details on the presentation and Table 11.3 for operating model definitions.

but avoided the poor performance of the ICES MSY rule. Turning off the recruitment autocorrelation led to negligible differences.

For cod, assuming density-dependent M due to cannibalism led to a higher $P_{B_{\text{lim}}}$ for all MPs. On the other hand, removing the migration adjusted M of older fish meant that the $P_{B_{\text{lim}}}$ for all MPs dropped below 5% because this meant that fewer older fish had died. Which in turn means that fishing at the same F led to a higher SSB, representing a more productive stock scenario (see Figure F.4 and Table F.1 in Appendix F). Similarly, assuming a higher recruitment regime resulted in a lower $P_{B_{\text{lim}}}$ and larger SSB for cod and herring.

Reduced recruitment at the beginning of the projection resulted in lower stock sizes and reduced catches. The impact of this recruitment failure scenario on the stock is illustrated for cod in Figure 11.7. The reduced recruitment impaired initial stock recovery, and the SSB started

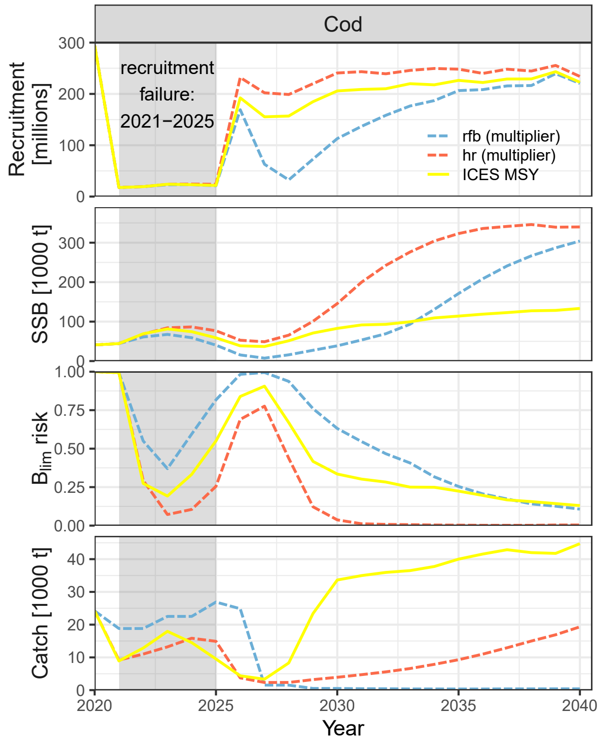

Figure 11.7: Impact of the recruitment failure alternative operating model on the management procedures, illustrated for cod.

to decline after 2-3 years. The rfb rule appeared to struggle under these conditions, and the catch advice was only reduced at the end of the recruitment failure period after the SSB reached a very low level. Once the catch advice had been reduced to very low levels, the SSB started to recover; however, the catch advice had already reached very low levels and stayed there until the end of the projection. The hr rule coped better than the rfb rule and after the stock started to recover, the catch increased again, but it took until the end of the projection until previously seen catch levels were reached. The ICES MSY rule recovered catches the fastest but this reduced stock recovery and kept the risk high.

11.6 Discussion

The main aim of this study was to test data-limited empirical MPs (developed in previous chapters) and compare their performance to data-rich methods to evaluate risk equivalence. This study was conducted with three case study stocks. The key outcome was that while the data-rich and data-limited approaches have the same theoretical management objectives (maximise yield while restricting risk following the precautionary approach), in the simulation, the precautionary element was only met for the data-limited empirical MPs. However, when applied generically, the data-rich methods resulted in higher catches, although case-specific tuning of the data-limited MPs could increase yield to a similar level.

The testing of MPs with MSE can be broadly divided into generic method testing and case-specific evaluations. In generic method testing, MPs are tested and possibly refined across a range of OMs (e.g. Wetzel & Punt, 2011; Geromont & Butterworth, 2015a; Jardim et al., 2015; Carruthers et al., 2016; Mildenberger et al., 2022). While generic testing is useful for screening methods and tuning generically to specific life histories, evaluations of management performance for specific stocks and conditions are limited. This requires case-specific analyses with OMs conditioned to the stock (e.g. Bergh & Butterworth, 1987; De Oliveira & Butterworth, 2004; Kell et al., 2005; Sharma et al., 2020). This study adopted a case-specific approach and simulation tested generic methods developed in previous chapters to evaluate if the outcomes from the generic testing are valid.

The state-space SAM model (Nielsen & Berg, 2014) allowed the rapid conditioning of OMs for several stocks. SAM is increasingly used in Europe and could facilitate MSE development for many stocks, and has already been used by ICES (2019h, 2020c) and Goto et al. (2022). In many scientific disciplines, model validation is common (e.g. Jin et al., 2008; Balmaseda et al., 1995; Weigel et al., 2008). In fisheries science, model validation of state-space models can be difficult because validation requires that the system is observable and measurable (Hodges & Dewar, 1992).

The ICES MSY rule is the main harvest control rule used for most data-rich stocks in the Northeast Atlantic (ICES, 2021a). The principle of targeting F_{MSY} and reducing this when a stock moves below a biomass trigger value has been widely adopted. Nevertheless, the ICES MSY rule led to non-precautionary management for all three stocks tested in this study, and the same was found previously for North Sea whiting and herring by ICES (2019h). This outcome appears to be caused less by the formulation of the ICES MSY rule and more by how it is operationalised.

The management reference points such as F_{MSY} are estimated with stochastic long-term projections (ICES, 2021h), and uncertainties, even when available from a stochastic stock assessment, are largely ignored. Furthermore, there can be spurious assumptions in the estimation of ICES management reference points. For example, natural mortality in the current North Sea cod stock assessment is inflated ("corrected") for ages 3+ to account for an assumed migration of older fish out of the stock area, and might be better considered as a case of "retrospective pattern hacking" so that the assessment passes acceptance criteria (ICES, 2021b). However, while this correction is considered for the recent historical period, it is ignored in the MSY estimation by ICES, leading to a considerable step change in the inputs used for the MSY calculations compared to the recent historical period.

It should be noted that the ICES MSY rule's parameters used in the MSE were not tuned through MSE simulations and, instead, the values recommended by ICES were adopted. If these parameters had been tuned, the management performance of the ICES MSY rule might have been better than presented here. Future studies might consider a situation where both data-rich and data-limited MPs are tuned.

The OMs were conditioned on SAM, which implies that SAM describes nature almost perfectly. This could be considered an unfair advantage for the MP based on SAM. Nevertheless, the performance of this MP was only moderate, and it resulted in high risks. Potentially, this could mean that the performance might be further impaired when reality was not as simple as implied by SAM and when more realistic representations of uncertainty were to be considered (Kell et al., 2006).

The outcomes of MSE exercises can be lost quickly in ICES. For example, North Sea cod, saithe, and herring were included in an MSE evaluation in ICES (2019h), including recommendations on management reference points. However, since then, management reference points for these stocks have been revised with the standard ICES short-cut approach after the stock assessments were updated in benchmark workshops. Furthermore, the data-rich ICES MSY rule might not always be such a good choice for providing management advice, especially if the rule has not been simulation tested.

Three data-limited MPs were tested, the 2 over 3 rule, the rfb rule, and the hr rule. The 2 over 3 rule performed worst for plaice, was not precautionary, and had the undesirable feature of increasing risk over time. This outcome is not surprising because the 2 over 3 rule aims to adjust the catch based on the stock trend but lacks a target. Currently, this rule is used for plaice, but in combination with an XSA assessment. This MP performed slightly better but exceeded the 5% risk limit of the ICES precautionary approach. Furthermore, both versions of the 2 over 3 rule were highly susceptible to the recruitment failure scenario, with $P_{B_{\mathrm{lim}}}$ above 90%. Consequently, this study provides further reassurance to phase out the 2 over 3 rule because it is not fit for purpose.

Generic (not tuned) parameterisations of the rfb and the hr rule resulted in long-term precautionary management, except for the hr rule for cod. However, this precaution was achieved by reducing catch and stocks moving to high levels. Such a management approach might be perceived as overly cautious, but is necessary in case of data limitations to ensure compliance with the precautionary approach and follows the principle of a risk-equivalent framework where better knowledge can reduce uncertainty and increase yield. In general, while the hr rule might achieve higher yields and is less susceptible to adverse events such as recruitment failures, it is crucially dependent on defining a target harvest rate appropriate for the stock. Here, the historical mean catch length was used to define a reference for the target harvest rate (see Chapter 9), which might not be successful for every stock. Therefore, the hr rule may require more in-depth analyses to ensure future management is precautionary.

In their generic evaluation of the rfb rule, Fischer et al. (2021b) concluded that the management performance of the rfb rule could be substantially improved through tuning, but this would require case-specific analyses. This was done here for the rfb and the hr rule and three case study stocks (plaice, cod, herring) using a genetic algorithm as an optimisation procedure. Including only a multiplier improved the rules markedly and increased catches. Optimising over more control rule parameters led to further improvements but came at the cost of much higher complexity and made the management often more susceptible to different assumptions, as tested with the alternative OMs. This is because the optimisation was only performed with the baseline OM and alternative OMs were only considered for exploring the robustness of generic and optimised MPs. For additional precaution, a reference set, i.e. an ensemble of OMs to reflect a broader range of uncertainties, could be defined and deployed in the optimisation. However, the process of deciding which OMs to include in a reference set can be time-consuming and is likely infeasible to carry out for the dozens of fish stocks for which ICES provides advice. Additionally, optimising over a large ensemble of OMs further increases computational complexity.

The definition of the objective function (or fitness function in the genetic algorithm) needs to be carefully considered. Here, the objective was long-term sustainability, i.e. the initial simulation period only indirectly influenced the optimisation objectives through stock dynamics, and was not included in the objective function. This approach decoupled the initial conditions from the optimisation, and this was, for example, useful for cod, which started below B_{lim}, and could therefore not possibly meet precautionary criteria. Furthermore, the optimisation considered the long-term average catch (last 10 years of a 20-year projection), without considering trends or variability. This meant, for example, that in the rfb rule's optimisation with all parameters for plaice, the catch was still increasing at the end of the simulation because this solution provided the highest precautionary average catch. The incorporation of such performance statistics is common practice in MSE. For example, the International Commission for the Conservation of Atlantic Tunas (ICCAT, 2021) includes the depletion at the end of a 30-year projection as a tuning target for candidate MPs.

When comparing the rfb and hr rule, the generic rfb rule appears to offer a more reliable precautionary management option than the hr rule, but this comes at the cost of potentially low catch for the sake of precaution. On the other hand, the hr rule, particularly if optimised, can deliver higher yields but requires more considerations when choosing the target harvest rate, and the generic parameterisation might not always provide a precautionary management solution, as shown for cod. However, if more data are available and case-specific analyses can be conducted, as was the case for the plaice stock, then the hr rule appears to provide excellent management advice and has the potential to outperform much more complex options such as the ICES MSY rule.

Current draft ICES guidelines recommend the generic application of the rfb rule for stocks with slow to medium individual growth (von Bertalanffy growth parameter $k < 0.32\ \mathrm{year}^{-1}$), and the hr rule for stocks with faster individual growth ($k < 0.45\ \mathrm{year}^{-1}$) but excluding very fast-growing and short-lived species (ICES, 2020a). The study in this chapter supports this recommendation, but goes beyond that by suggesting that both rules might be applied beyond their generic limits, as shown here for herring, a fast-growing, but relatively long-lived pelagic species, for which both rules appeared suitable. However, applying the rules beyond their generic limits should be accompanied by case-specific testing.

Risk equivalence can be considered a cornerstone of fisheries management frameworks and ensures that different management approaches provide the same risk appetite. This means that less certainty, for example, due to limited knowledge about a fish stock, should not lead to riskier management decisions. Any statement of risk equivalence requires the definition of risk and an acceptable risk limit. The precautionary approach to fisheries management (Garcia, 1996) aims at reducing the risk of adverse consequences. The ICES interpretation of the precautionary approach is to limit the risk of a stock falling below the biomass limit reference point to 5% (ICES, 2021a). This explicit definition of risk facilitates the evaluation of risk equivalence.

Simulating different MPs in a common simulation framework allows a direct comparison and statements about risk equivalence. While this was tested for management frameworks in regions such as Australia (Fulton et al., 2016; Dichmont et al., 2017), it had not been done before for ICES, apart from Geromont and Butterworth (2015b), who conducted a hindcast analysis and concluded that simple but theoretical empirical rules can achieve similar performance to complex assessments.

The ICES data-limited system has been subject to only limited development over the past 10 years, despite attempts to improve it, e.g. through a dedicated workshop series on data-limited methods (ICES, 2012d). However, a revision of the ICES system has now started, and the changes are substantial (ICES, 2020a). The new generic data-limited methods were designed to meet the same precautionary criteria as used in data-rich considerations, which means they explicitly consider risk equivalence, and this was confirmed with case-specific testing. This approach follows the recommendations of Dichmont et al. (2016) that risk-equivalent frameworks should be tested with MSE, ideally with case-specific analyses, but in their absence, generic simulations can be used.

11.7 Conclusions and recommendations

1. The new empirical ICES methods for moderately data-limited fish stocks (ICES category 3) have undergone extensive simulation testing and review as part of this PhD project. The methods' ability to meet management objectives is further strengthened with the case studies of this chapter. Consequently, the further rollout of the generic empirical rules

in ICES scheduled for 2022 is endorsed. Furthermore, for stocks for which case-specific analyses are possible, such as the plaice stock, this can be done to improve realised catch without jeopardising precaution. The inclusion of risk equivalence in the ICES system is a major step forward and moves the ICES data-limited framework on par with other parts of the world, where this is already included.

2. More generally, it is recommended that risk equivalence be considered in any changes to an advice framework to ensure that alternative management approaches or higher uncertainty due to, for example, data limitations, do not compromise conservation. Additionally, accounting for risk equivalence mandates the definition of an acceptable risk limit. Once such a limit is set, a benefit is that alternative management strategies can be selected based on, for example, socio-economic criteria, as long as they are risk-equivalent. The approach of, firstly, conducting generic MP testing to identify and tune suitable methods and, secondly, conducting case-specific simulations to confirm the performance of the generic methods, appeared to work well. Therefore, this approach could be adopted more widely, both for revisions of data-rich and data-limited fisheries management.

3. Finally, this study promotes using simple empirical strategies for managing fisheries resources, independently of their data limitations, as pursuing the best assessment approach will not always be necessary. Complex procedures, including analytical stock assessments and projections, might appear tempting but can easily lead to issues (e.g. non-precautionary management) when implemented suboptimally, or target and reference levels are set incorrectly. Such issues could be avoided by conducting full MSEs, including robustness tests. On the other hand, empirical methods have major benefits such as being simpler to test and optimise in simulation studies, easier to apply to data, potentially cheaper due to reduced frequency of data requirements, can reach equivalent catch levels, and are more straightforward to communicate to stakeholders and managers than much more complex approaches. This does not mean that stock assessments should be dropped entirely because they are still required for assessing stock status and conditioning OMs for simulations, but there might be a reduced need to do this annually.

Chapter 12

Conclusions

12.1 Introduction

This chapter concludes the study by summarising the outcomes concerning the objectives set out in the introduction chapter, discussing the output and impact of the work, and indicating potential gaps and how they could be addressed in future research.

12.2 Overview

The flowchart in Figure 12.1 summarises the academic journey of this PhD project. The project started with the broad aim to improve fisheries management for data-limited fish stocks and settled on using management strategy evaluation (MSE) as a means to develop and test empirical management procedures (MPs). Simulations of the currently applied method by the International Council for the Exploration of the Sea (ICES) to moderately data-limited stocks revealed insufficiencies, and the method neither follows principles of the precautionary approach nor offers long-term sustainability. Therefore, an alternative MP (the rfb rule) was developed and offered better management performance for fish stocks with slow to medium individual growth. Furthermore, the rule's management performance could be improved by tuning it towards specific management objectives, including limiting the risk of stock depletion. The rfb rule appeared inappropriate for faster-growing species due to unacceptably high depletion risks. However, an alternative (the hr rule) was found to perform better for faster-growing species, apart from the fastest-growing short-lived species. Such short-lived species are a challenge for fisheries management, particularly in data-limited situations, and will likely require case-specific studies. The development of the rfb and hr rules was based on generic simulations for a wide range of life-history traits. Nevertheless, the conclusions were confirmed by more specific simulations for a few case studies. These simulations revealed that the generically developed empirical methods are risk equivalent to more data-rich management approaches.

12.3 Generic simulations and case studies

The general strategy for developing the empirical MPs (the rfb and hr rules) was to conduct generic simulations covering a wide range of life-history traits. Such generic simulations might attract criticism about the selection of scenarios and their realism. However, when data are too

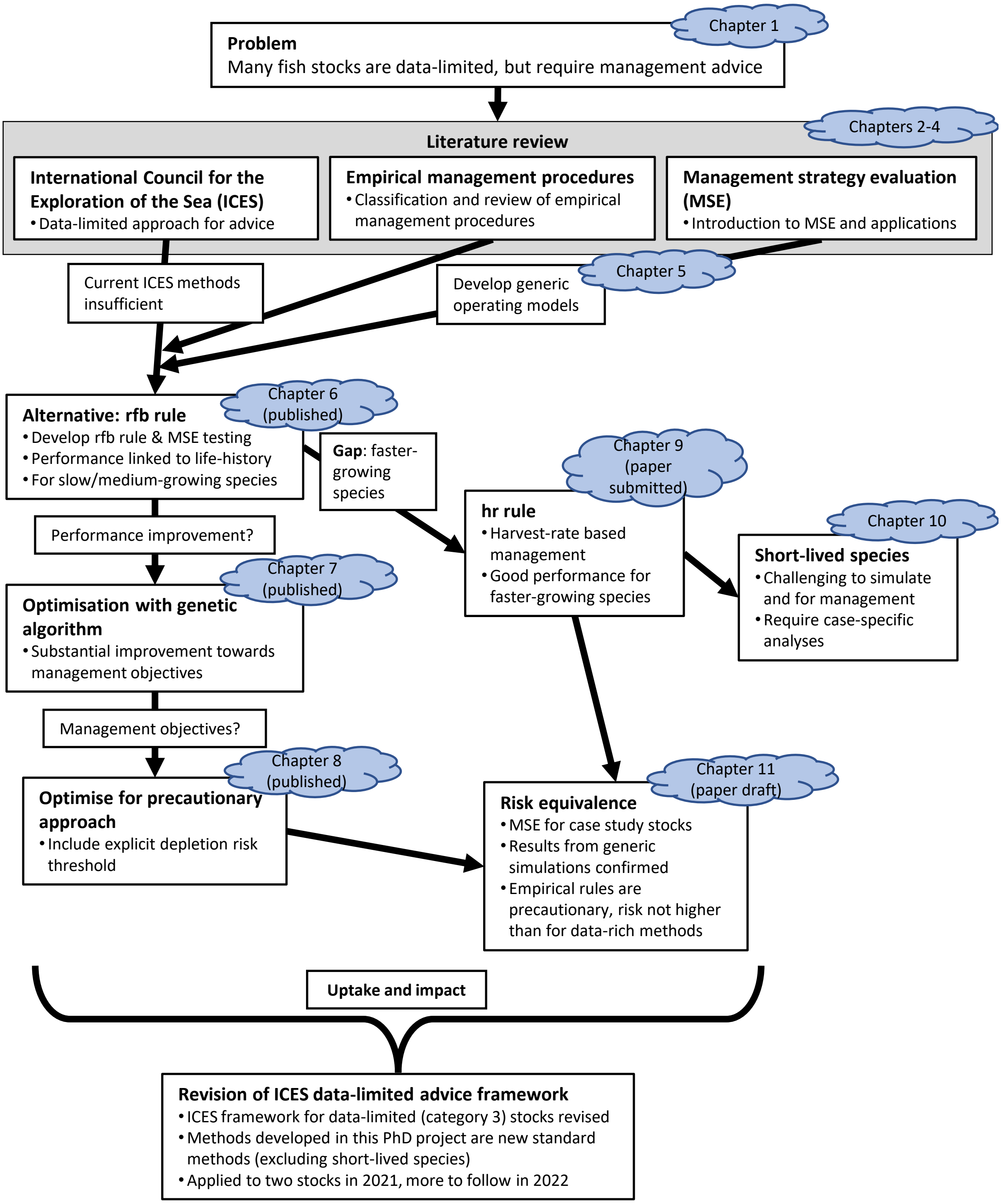

Figure 12.1: Summary of the PhD project in a flowchart. Blue coloured clouds represent the main academic outputs and publications.

limited to conduct case-specific analyses, this can be the only feasible approach to develop and quickly screen candidate MPs.

Nevertheless, the methods developed with generic simulations were later subjected to case-specific simulations for three case study stocks, for which more realistic operating models could be conditioned on complex stochastic stock assessment models. These analyses confirmed the results of the generic simulations, i.e. that the empirical methods provide a precautionary management option and are risk-equivalent to more complex data-rich approaches.

While model validation is notoriously difficult in fisheries science, the case-specific simulations at least partially addressed this by confirming conclusions from generic analyses. However, the case-specific models were conditioned on complex state-space stock assessment, and these assessments themselves cannot be fully validated against reality. Consequently, these case-specific simulations could be regarded as only a verification of the generic conclusions with a different simulation model.

12.4 Management objectives

The evaluation of the management performance of MPs relies on the definition of management objectives. Such management objectives are often mandated by national and international legislation. ICES requires management advice to follow a precautionary approach (i.e. reduce the risk of stock depletion to levels where productivity is impaired) and, if possible, also to aim towards maximum sustainable yield (MSY; ICES, 2019a). The existence of concrete objectives allows the evaluation of MPs, the development of generic MPs, as well as their optimisation through optimisation routines, such as the genetic algorithm deployed here. One of the main conclusions of this project is that relatively simple empirical MPs can achieve these management objectives.

12.5 Uptake and impact

An important issue for any scientific analysis is the impact on policy and considerations for implementation. The work conducted for this PhD project was not purely academic but has already directly impacted the management of data-limited fisheries in Europe through ICES. The main forum in ICES for the development and advancement of data-limited methods is the WKLIFE workshop series (ICES, 2012d), where the work was presented and discussed (ICES, 2017e, 2018c, 2019c, 2020a), and was a major contributor to the success of these workshops. Furthermore, credibility for the approaches and conclusions was achieved through review within WKLIFE and the independent peer-review associated with publications in scientific journals (Fischer et al., 2020; Fischer et al., 2021a, 2021b).

WKLIFE drafted guidelines for a data-limited advice framework for category 3 stocks (Annex 3 of ICES, 2020a), intended to replace the previous framework from 2012 (ICES, 2012b). This framework is illustrated in Figure 12.2. Essentially, the approach is first to explore if a surplus production model can be used to model stock dynamics. If such a model is successful, the stock will be upgraded to the less data-limited category 2. However, in many cases, using an assessment model will not be possible due to issues such as model convergence, lack of contrast in data, violation of model assumptions, or insufficient data, and stocks will remain in category 3. For these stocks, with the exception of short-lived species, the empirical methods developed during this PhD project will be applied (Figure 12.2).

The draft framework was already applied in 2021 to category 3 stocks which underwent a benchmark (a process where data and assessment methods are reviewed and updated). This included two stocks to which the rfb rule was applied (Figure 12.3) and meant that for these two stocks, the official ICES recommendations on catches given to clients (the European Union and the United Kingdom) were based on the rfb rule:

- European plaice (*Pleuronectes platessa*) in the southern Celtic Sea and southwest of Ireland (ICES division 27.7hjk; ICES, 2021m):

  ICES advises that when the MSY approach is applied, catches in 2022 should be no more than 114 tonnes.

- Common sole (*Solea solea*) in the Cantabrian Sea and Atlantic Iberian waters (ICES divisions 27.8c and 27.9a; ICES, 2021l):

  ICES advises that when MSY approach is applied, catches should be no more than 284 tonnes for each of the years 2022 and 2023.

The exploitation of the plaice stock is shared between the United Kingdom and the European Union's member states. The total allowable catch (TAC) was set according to the ICES recommendation (114t for 2022) after bilateral negotiations (European Commission, 2022b). For sole, the TAC area does not match the stock unit for which ICES gives advice, and the TAC was set

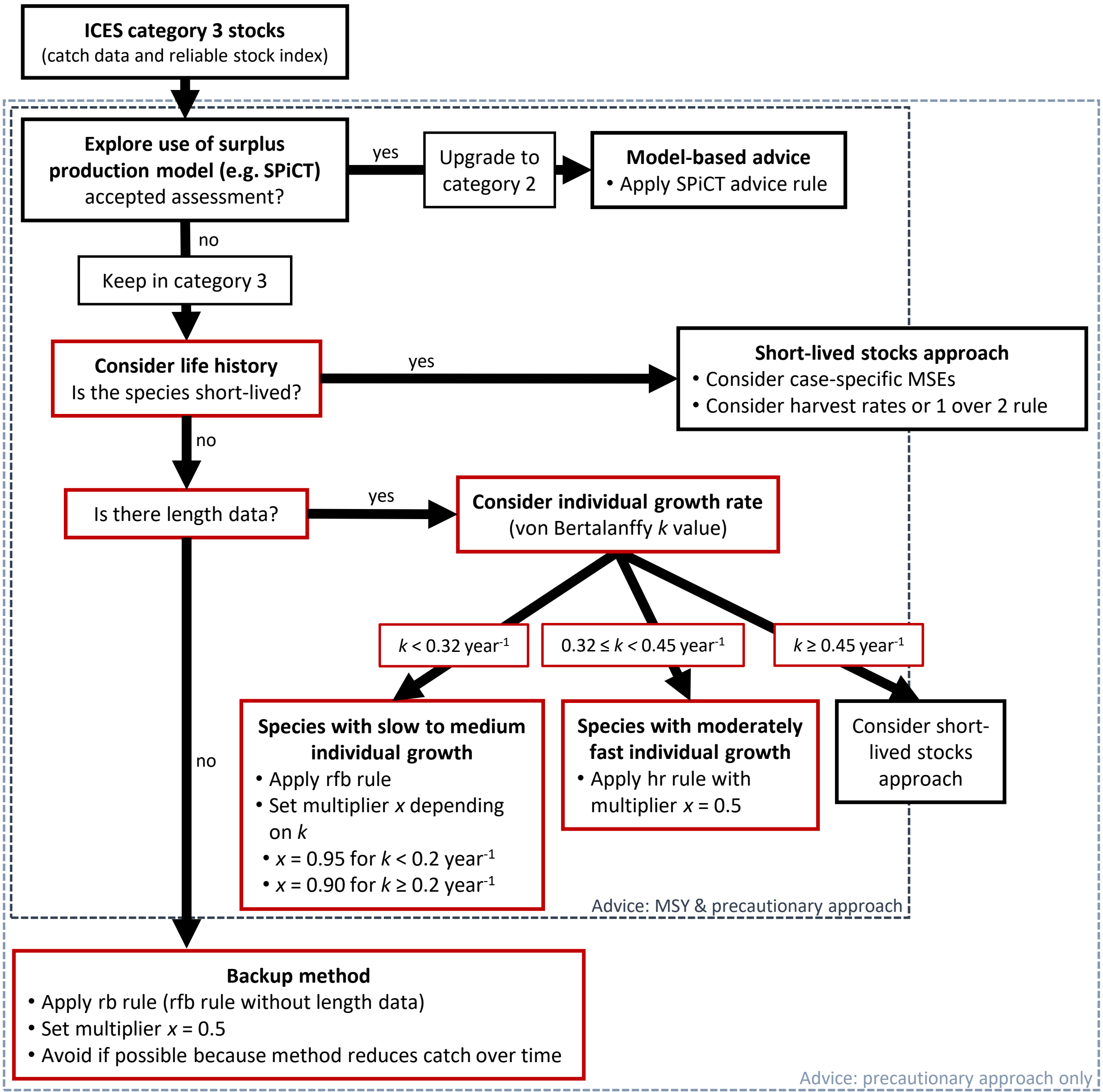

Figure 12.2: Illustration of the revised ICES advice framework for category 3 data-limited stocks proposed by ICES (2020a). Decisions and methods influenced by this PhD project are indicated by red boxes. The advice following the precautionary approach (outer dashed box) concerns reducing depletion risk. The MSY advice (inner dashed box) is based on rules that include an MSY target and aim to maximise catch within the restrictions of the precautionary approach. The short-lived stocks approach is between the two advice approaches because some but not all methods consider MSY. SPiCT is the surplus production in continuous time model (Pedersen & Berg, 2017).

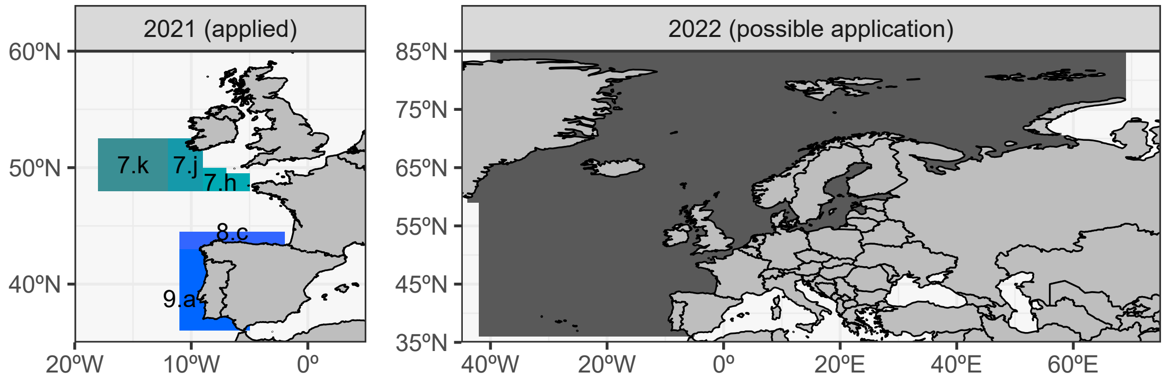

Figure 12.3: Map of where the empirical methods were applied (left) or are considered (right).

slightly higher than the ICES recommendation (320t instead of 284t; European Commission, 2022a). This means the rfb rule not only led to scientific advice but also directly impacted policy.

Late in 2021, the ICES advisory committee decided to continue the rollout of the new framework and that this should be applied to all category 3 data-limited stocks for which new advice is scheduled in 2022. Consequently, the empirical methods developed as part of this PhD project are likely to become the standard methods in ICES to provide scientific catch recommendations for category 3 stocks apart from short-lived species.

Due to disruptions in early 2022, ICES adopts a flexible approach where the application of the new methods is encouraged. However, some stocks might require additional analyses or benchmarks and the application of the methods can be delayed if necessary. Coinciding with the submission of this PhD thesis, the annual meetings of ICES assessment working groups have started, and there are positive signs of the new methods being used. Furthermore, due to possible time constraints in 2022, the deployment of the empirical methods (developed as part of this PhD project) is being prioritised over ambitions to upgrade stocks to less data-limited categories that include the use of model-based approaches, because empirical methods are easier and quicker to implement compared to time and resource-intensive modelling approaches. This means that the empirical methods could be applied for up to 45 candidate stocks in 2022 (personal communication with ICES professional officers), including some widely distributed stocks, and these cover the entire Northeast Atlantic (FAO fishing area 27, Figure 12.3).

For short-lived species that were not directly suitable for management using the rules developed in this PhD project, there is still some influence from the research reported here. For example, the advice for English Channel sprat in 2021 was based on a harvest rate rule (ICES division 27.7de; ICES, 2021n), and the target harvest rate was estimated with a case-specific MSE (ICES, 2021j) based on the MSE framework developed for the rfb and hr rules.

In conclusion, the overarching goal of this PhD project to revise the data-limited framework used by ICES has been achieved, and the implementation of the new methods has started. The new methods are not perfect but can be considered a major step towards providing fisheries advice that explicitly follows required management objectives, such as the precautionary approach, with the option to move towards MSY if data permit.

12.6 Importance and scientific novelty

The work of this PhD project addresses the important issue of delivering and improving scientifically sound management advice for data-limited fisheries resources. National and international requirements demand that fisheries management follows predefined management objectives, but current management practices do not always ensure this. In the Northeast Atlantic alone, there are several dozen fish stocks that ICES classifies as data-limited category 3 and the fisheries management for these stocks can benefit from the methods developed in this PhD project. Furthermore, the implementation of these methods has already begun in 2021 and will expand in 2022. The approach adopted by this PhD project is novel by (1) the systematic articulation of management objectives in quantitative models, (2) explicitly addressing risk, (3) the application of genetic algorithms for the optimisation of fisheries management approaches, (4) developing a generic approach to develop management procedures applicable to many fish stocks, and (5) demonstrating a feasible validation procedure using better-known stocks.

12.7 Gaps and future directions

While comprehensive, the work of this project is far from complete. A plethora of challenges remain for data-limited fisheries management. The work was focused on moderately data-limited fish stocks (ICES category 3). However, some stocks are more severely data-limited, and the simple empirical control rules developed here cannot be applied. Future research should address this gap and extend method development for cases in which, for example, no reliable stock index exists. In the ICES system, this would be category 4 and below.

The simulations were based on single-stock single-fleet models without systematic external influences. However, many fish species are caught in mixed fisheries and interact with each other and their environment. In more data-rich situations, complex simulation models covering larger parts of the ecosystem and anthropogenic influences are sometimes used but this can prove challenging in data-limited situations. Nevertheless, future studies into data-limited fisheries management could consider more holistic simulation approaches, including considerations of multiple fleets, mixed fisheries, multispecies interactions, or even full ecosystem models. Furthermore, the impacts of climate change on marine ecosystems, such as observed through regime shifts or changes in species distributions due to global warming, should not be neglected.

This project focused on the management of fisheries resources. However, the principles applied here, such as testing management options prior to implementation or their optimisation to meet specific management objectives, apply to other areas of natural resource management as well as to other scientific domains.

12.8 Closing remarks

If the past is any indication, methods guiding scientific advice are continuously changing and advancing, often for the better, and this will not stop after the completion of this PhD project. The methods developed in this thesis are far from perfect but at least are a step in the right direction towards applying approaches that have been thoroughly simulation tested before their implementation in reality. I hope the results of this PhD project helped to advance the field of data-limited fisheries management towards ensuring long-term sustainable exploitation of marine resources. Lastly, seeing the hard scientific work of several years being applied to guide management decisions is hugely rewarding.

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Appendix A

Appendix to Chapter 3

A.1 Record of the literature search for the systematic review of empirical management procedures

The literature search was conducted using the Web of Science citation database (https://webofknowledge.com). All databases available on Web of Science (Web of Science Core Collection, BIOSIS Citation Index, CABI: CAB Abstracts, KCI-Korean Journal Database, MEDLINE, Russian Science Citation Index, SciELO Citation Index) were included and the search spanned all available years (1950-2021).

The search was defined so that it included a wide range of synonyms for “empirical management procedure” in the context of fisheries management:

```
(((((empirical) OR (empiric)) AND
       (("catch rule") OR ("catch rules") OR
        ("control rule") OR ("control rules") OR
        ("management procedure") OR
        ("management procedures") OR
        ("harvest control rule") OR
        ("harvest control rules") OR
        ("management strategy") OR
        ("management strategies") OR
        ("harvest strategy") OR
        ("harvest strategies")
       ) AND
       ((fisheries management) OR
        (fishery management)))))
```

The last update of this search was executed on 02/02/2021 and led to a total of 135 results.

The search term was defined broadly to include as many results as possible, which included empirical management procedures. Consequently, the results included papers from other scientific fields and results where the term "empirical" was not related to "management procedures". The list was subsequently filtered by going through the results manually, first by reading the abstract, and if no decision could be made, by going through the full document. This procedure resulted in a list of 20 papers for inclusion in the review:

1. Fischer et al. (2020)
2. Hoshino et al. (2020)
3. Licandeo et al. (2020)
4. Sagarese et al. (2019)
5. Plagányi et al. (2019)
6. Sun et al. (2018)
7. Plagányi et al. (2018)
8. Sagarese et al. (2018)
9. Jardim et al. (2015)
10. Dowling et al. (2015a)
11. Doonan et al. (2015)
12. Geromont and Butterworth (2015a)
13. Geromont and Butterworth (2015b)
14. Punt et al. (2012)
15. Prince et al. (2011)
16. Kurota et al. (2010)
17. Cox and Kronlund (2008)
18. Rademeyer et al. (2007)
19. Kelly and Codling (2006)
20. Campbell and Dowling (2005)

Fischer et al. (2020) was excluded because it is my own work and included in a later chapter. One further paper was included because it was mentioned in the MSE best practice paper by Punt et al. (2016)

21. Pomarede et al. (2010)

The references cited in each of these papers were subjected to the same selection criteria defined above, and this process repeated recursively, if necessary. This led to 13 additional papers:

22. Butterworth and Geromont (2001)
23. Kurota (2005)
24. ICES (2012b)
25. Klaer et al. (2012)
26. Carruthers et al. (2014)
27. Carruthers et al. (2016)
28. Dowling et al. (2015b)
29. Hillary et al. (2016)
30. O'Neill et al. (2010)
31. Smith et al. (2008)
32. Breen et al. (2009)
33. Apostolaki and Hillary (2009)
34. Breen et al. (2003)

The remaining references were either referenced in previously included papers and relevant to the review but were not specifically about empirical MPs

35. MacCall (2009)
36. Wetzel and Punt (2011)

a synthesis of already included references

37. Geromont (2014)

or updates of previously mentioned management frameworks

38. Department of Agriculture and Water Resources (2018)
39. SAFMC (2011)
40. CSIRO (2009)
41. ICES (2019a)

Appendix B

Appendix to Chapter 6

The following is an Appendix to Chapter 6 and adapted from the supplementary material published in Fischer et al. (2020):

> 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*(5), 1914–1926. https://doi.org/10.1093/icesjms/fsaa054

B.1 Sensitivity analysis of operating model assumptions

B.1.1 Background

This part of the Appendix describes additional sensitivity analyses of the assumptions used to create the operating models and observations.

The recruitment in the operating model for all stocks was modelled with a Beverton-Holt stock-recruitment model (see Chapter 5 and Equations 5.9 to 5.12). The steepness of the recruitment model was set to a fixed value of $h = 0.75$. Recruitment variability was implemented with a log-normal noise term with $sd = 0.6$ (in log-space). During the work, concerns were raised about whether it is appropriate to use a constant value for recruitment steepness and how this might affect results. Additional work was carried out to explore the impact of the recruitment assumptions, and also the influence of uncertainty in the indices for biomass and length-frequencies.

The default value for steepness of $h = 0.75$ used in this study was adopted from a previous study by Jardim et al. (2015) who based their decision on Myers et al. (1999). This value (0.75) is a medium value from the range of estimates in Myers et al. (1999) and, therefore, is suitable for generic simulations. Myers et al. (1999) estimated e.g. averages of $h = 0.71$ for Clupeidae, $h = 0.79$ for Gadidae and $h = 0.80$ for Pleuronectidae.

In empirical data, relationships between steepness and life-history parameters are scarce and notoriously difficult to estimate, and this is particularly the case for data-limited stocks for which usually no data or assessment exist on which to base estimates of steepness. The stocks simulated in the present study are based on life-history parameters from real stock units and are not simply averages for species. These stocks are data-limited and therefore no analytical assessments exist on which to base steepness, i.e. the steepness for these stocks is entirely unknown. Consequently, a generic medium value was adopted. Myers et al. (1999) estimated h for 57 species. Median von Bertalanffy growth parameter k values for 53 of these species (Figure B.1) were extracted from Fishbase (Froese & Pauly, 2019). There did not appear to be any correlation between these two parameters.

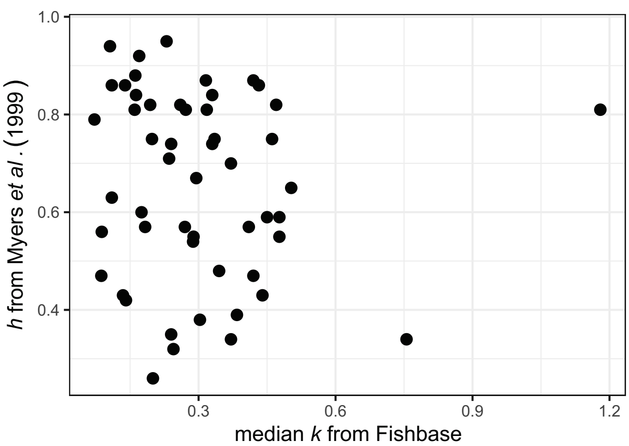

Figure B.1: Steepness (h) as estimated by Myers et al. (1999) for 53 fish species versus von Bertalanffy growth parameter k, queried from Fishbase (Froese & Pauly, 2019).

Wiff et al. (2018) screened fish stocks for a link between h and life-history parameters, and found a logit-link relationship between h and the ratio L_{50}/L_{∞}, but with high uncertainty and limited predictive power (see Figure 1 in Wiff et al., 2018).

B.1.2 Sensitivity runs

In order to test the sensitivity of the simulations to the imposed recruitment assumptions, additional sets of operating models (OM) with different assumptions about recruitment were created and the MSE simulation was repeated with them.

Recruitment steepness

1. Steepness levels: low ($h = 0.6$), medium ($h = 0.75$; default for this study) and high ($h = 0.9$). In a Beverton-Holt recruitment model, steepness cannot go above $h = 1$, and $h = 0.9$ was selected as the high value in order to avoid the absolute maximum. This high steepness value means that recruitment is only impaired at low SSB and is therefore largely decoupled from SSB. This corresponds to a 20% increase in steepness, and vice versa, the low value was selected as a reduction of 20% (i.e. $h = 0.6$).

2. Linking steepness to life-history. Despite the lack of a clear relationship between steepness and the life-history parameter k (Figure B.1), two additional sets of OMs were created where a link between steepness and life-history parameters was imposed. Please note that these scenarios are purely exploratory and without a sound empirical evidence basis, and the authors do not believe they are necessarily realistic. For the first set of OMs, steepness was arbitrarily linked to the von Bertalanffy growth parameters k in a way that the stock with the lowest k had a steepness of $h = 0.5$, and the stock with the highest k in the study a steepness of $h = 0.9$:

$$h = 0.4652 + 0.4348k$$

   For the second alternative set of OMs, h was linked to the ratio L_{50}/L_∞ according to Wiff et al. (2018) with a logit link function:

$$h = \frac{0.2 + e^{2.706 - 3.698 L_{50}/L_\infty}}{1 + e^{2.706 - 3.698 L_{50}/L_\infty}}$$

   The resulting steepness values are shown in Table B.1.

3. An attempt was made to use realistic values for the simulated stocks. Myers et al. (1999) estimated steepness for 57 species, and for 13 out of the 29 simulated stocks, a steepness value could be borrowed from that study. For seven stocks, the match was based on the exact species, and the remaining six were matched based on the family. These steepness values are shown in Table B.1. It should be noted that these steepness values are not necessarily appropriate: the stocks were simulated based on life-history parameters from real stock units; in contrast, the borrowed steepness values are species-specific, based on entirely different stock units, and from a different time period, and therefore might not match the simulated stocks.

4. The default recruitment variability in the Beverton-Holt recruitment model was defined with $sd = 0.6$ (of the lognormal noise term). Lower variability was tested with $sd = 0.3$ and higher variability with $sd = 0.9$.

Observation uncertainty

The implementation of uncertainty for the indices used in the catch rule was explored.

5. The uncertainty in the biomass index (used in the r component of the catch rule) was increased from $sd = 0.2$ to $sd = 0.4$ and $sd = 0.6$. The same was done for the length-frequencies used in the f component for the calculation of mean length in the catch (increase from $sd = 0.2$ to $sd = 0.4$ and $sd = 0.6$). Finally, the implemented uncertainty for the biomass index and catch length frequencies was increased simultaneously and both set to $sd = 0.4$.

Two additional analyses were carried out regarding the value and implementation of observation uncertainty (without running the MSE).

6. The default uncertainty of the biomass index was defined by an error term with $sd = 0.2$. A quick review was conducted for survey indices used within ICES for data-rich stocks for which age-structured and fully quantitative stock assessments provide estimates of stock size, which allow the quantification of index uncertainty (see Table B.2). Biomass indices were derived for these stocks with a sum-product of the numbers at age in the index and the stock weights at age. This biomass index and the biomass estimated from the stock assessment were then standardised and the coefficient of variation (CV) of the ratio of the two biomasses, index/assessment calculated.

7. The length distribution of the catch was calculated with an inverse age-length key (see Chapter 5), and the mean length in the catch derived from the length distribution after adding observation noise. A sampling process was not simulated in order to reduce the computational time. However, the approach used in the MSE simulation was compared with one where no uncertainty is implemented and one approach where mean length in the catch is derived by sampling from the catch length distribution.

Table B.1: Steepness scenarios for the 29 simulated stocks.

Species	**Name**	**ID**	**default** h **(medium)**	**low** h	**high** h	$h \sim k$	$h \sim L_{50}/L_\infty$	h **from Myers et al. (1999)**	**source**
Lophius budegassa	Blackbellied angler	ang3	0.75	0.6	0.9	0.50	0.76	0.63	species
Raja clavata	thornback ray	rjc2	0.75	0.6	0.9	0.50	0.75		
Sebastes norvegicus	golden redfish	smn	0.75	0.6	0.9	0.51	0.55	0.39	family (genus)
Anarchias lupus	Atlantic wolffish	wlf	0.75	0.6	0.9	0.51	0.91		
Lepidorhombus whiffiagonis	megrim	meg	0.75	0.6	0.9	0.52	0.80		
Molva molva	ling	lin	0.75	0.6	0.9	0.53	0.68		
Raja clavata	thornback ray	rjc	0.75	0.6	0.9	0.53	0.66		
Scyliorhinus canicula	lesser spotted dogfish	syc	0.75	0.6	0.9	0.53	0.58		
Mustelus asterias	starry smooth-hound	sdv	0.75	0.6	0.9	0.53	0.65		
Lophius piscatorius	angler	ang	0.75	0.6	0.9	0.54	0.63	0.64	family
Lophius piscatorius	angler	ang2	0.75	0.6	0.9	0.54	0.71	0.64	family
Pollachius pollachius	pollack	pol	0.75	0.6	0.9	0.55	0.73	0.79	family
Melanogrammus aeglefinus	haddock	had	0.75	0.6	0.9	0.55	0.83	0.74	species
Nephrops	Norway lobster	nep	0.75	0.6	0.9	0.55	0.82		
Mullus surmuletus	Striped red mullet	mut	0.75	0.6	0.9	0.56	0.84		
Spondyliosoma cantharus	black sea-bream	sbb	0.75	0.6	0.9	0.56	0.74	0.95	family
Pleuronectes platessa	European plaice	ple	0.75	0.6	0.9	0.57	0.78	0.86	species
Scyliorhinus canicula	lesser spotted dogfish	syc2	0.75	0.6	0.9	0.57	0.48		
Argentina silus	greater argentine	arg	0.75	0.6	0.9	0.57	0.50		
Scopthalmus maximus	turbot	tur	0.75	0.6	0.9	0.60	0.75		
Chelidonichtys lucerna	tub gurnard	gut	0.75	0.6	0.9	0.60	0.70		
Merlangius merlangus	whiting	whg	0.75	0.6	0.9	0.63	0.60	0.81	species
Scophthalmus rhombus	brill	bll	0.75	0.6	0.9	0.63	0.74		
Microstomus kitt	lemon sole	lem	0.75	0.6	0.9	0.65	0.60	0.8	family
Engraulis encrasicolus	anchovy	ane	0.75	0.6	0.9	0.66	0.60	0.47	species
Zeus faber	John Dory	jnd	0.75	0.6	0.9	0.67	0.64		
Sardina pilchardus	European pilchard	sar	0.75	0.6	0.9	0.73	0.66	0.34	species
Clupea harengus	herring	her	0.75	0.6	0.9	0.73	0.63	0.74	species
Ammodytes spp.	sandeels	san	0.75	0.6	0.9	0.90	0.76		

Table B.2: Survey index CVs for some example data-rich stocks within ICES. Shown are only the main surveys covering several age classes. The analysis is based on recent ICES stock assessments which were used to provide advice (ICES, 2018d, 2019e).

Species	**Stock area**	**Assessment year**	**Survey index**	**Survey year range**	**Survey ages**	**CV***
Cod	North Sea	2019	IBTS Q1	1983-2018	1-5	0.23
			IBTS Q3	1992-2018	1-4	0.21
Plaice	Irish Sea	2018	UK BT	1993-2018	1-7	0.25
Herring	North Sea	2018	HERAS	1989-2018	1-8	0.20
			IBTS Q3	1998-2018	0-5	0.31
Whiting	North Sea	2018	IBTS Q1	1983-2018	1-5	0.41
			IBTS Q3	1991-2017	0-5	0.25
Haddock	North Sea	2018	IBTS Q1	1983-2018	1-5	0.38
			IBTS Q3	1991-2017	0-5	0.19
Sole	western English Channel	2019	Q1SWBeam	2006-2018	2-11	0.20
			FSP UK	2004-2018	2-11	0.19

* The CVs are derived by converting the age-structured survey abundance indices into survey biomass indices; assessment biomass estimates were extracted from the stock assessment; biomass indices and assessment biomass estimates were then standardised over their corresponding year range and the CV calculated of the ratio index/assessment.

B.1.3 Results of sensitivity runs

The SSB trends from the sensitivity runs are shown in Figures B.2-B.8 and a comparison of the summary statistics in Figures B.9-B.10.

Recruitment

When simulating the stocks with different steepness levels (0.6, 0.75, 0.9), the SSB trajectories for the stocks were similar and no major deviations were apparent (Figure B.2). As discussed in Chapter 6, with default steepness of $h = 0.75$, there was a clear split between stocks with $k \leq 0.32$ year^{-1} which survived during the simulation period, whereas stocks with higher k collapsed. Assuming a higher steepness (0.9) did not change this general separation of the stock survival based on k. There was an exception for two lower-k stocks (angler, ang2 with $k = 0.18$ year^{-1} and pollack, pol with $k = 0.19$ year^{-1}), which collapsed with the higher steepness. The higher-k stocks still collapsed, some of them even earlier, except for sandeel (san, $k = 1$ year^{-1}), which recovered to very high levels, but this can be attributed to a failure of the catch rule, which reduced the catch heavily early in the projection and kept it low afterwards (because it was close to zero), moving the stock towards virgin biomass. Using a lower steepness (0.6) did not change the general pattern for the simulated stocks apart from black seabream (sbb, $k = 0.22$ year^{-1}), which collapsed under the default steepness assumption, but did not collapse with the lower steepness.

Figure B.3 shows the SSB trajectories for the two scenarios where a relationship between life-history parameters and steepness is imposed, and the results are very similar to the default assumption of constant steepness, regardless of life-history.

Figure B.4 shows the results for the 13 stocks for which species-specific steepness values could be borrowed from Myers et al. (1999). The results are similar and the outcome (collapsed or not collapsed) remains unchanged.

The alternative steepness scenarios did not cause major deviations or biases in the summary statistics (Figure B.9a-e).

The results were relatively insensitive to recruitment variability (Figure B.5, Figure B.9f-g). For the lower-k stocks, increasing recruitment variability led to higher terminal SSBs without changing the general trends; for stocks with $k \geq 0.32$ year^{-1}, this increasing recruitment variability led to earlier collapses. Lower recruitment variability had the opposite effect. One exception is black seabream ($k = 0.22$ year^{-1}), which avoided the stock collapse when simulated with lower recruitment variability.

Observation uncertainty

Increasing the uncertainty in the biomass index had a minor impact on SSB trajectories for the higher-k stocks (Figure B.6). However, for the lower-k stocks, increasing index uncertainty had an effect on some stocks. For two stocks (angler, ang $k = 0.18$ year^{-1} and pollack, pol $k = 0.19$ year^{-1}), this caused a declining trend in SSB and a collapse after more than 60 years. For three additional stocks, tripling the index uncertainty caused stock collapses (ling, lin $k = 0.14$ year^{-1}, starry smooth-hound, sdv $k = 0.15$ year^{-1}, angler, ang $k = 0.18$ year^{-1} and plaice, ple $k = 0.23$ year^{-1}). Increasing the uncertainty of the catch length-frequencies had a minor effect (Figure B.7). Analogously, increasing uncertainty simultaneously for the biomass index and catch length-frequencies led to results very similar to when only uncertainty for the biomass index was modified (Figure B.8). The index uncertainty increases had some effects on the summary statistics (Figure B.10), reflecting stock collapses, in particular when implementing high index uncertainty.

Table B.2 presents the CVs of the deviation for some data-rich ICES stocks.

Figure B.11 shows a comparison of approaches to estimate mean length in the catch.

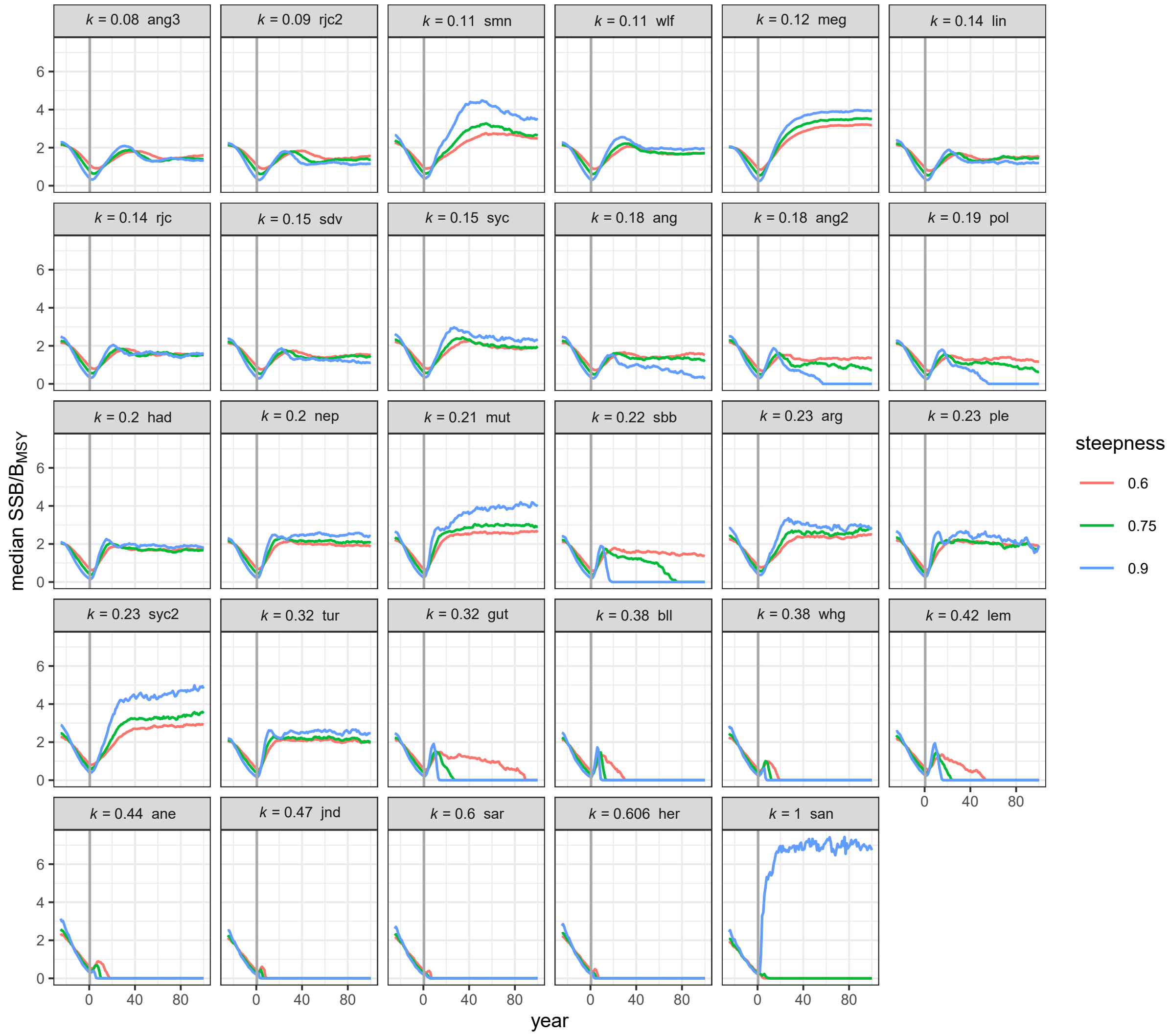

Figure B.2: Comparison of the SSB trajectories depending on the three tested steepness values. Shown are median trajectories for SSB/B_{MSY} for the 29 simulated stocks, sorted by von Bertalanffy growth parameter k (unit: year^{-1}) and for the one-way fishing history. The vertical grey line indicates the start of the implementation of the catch rule.

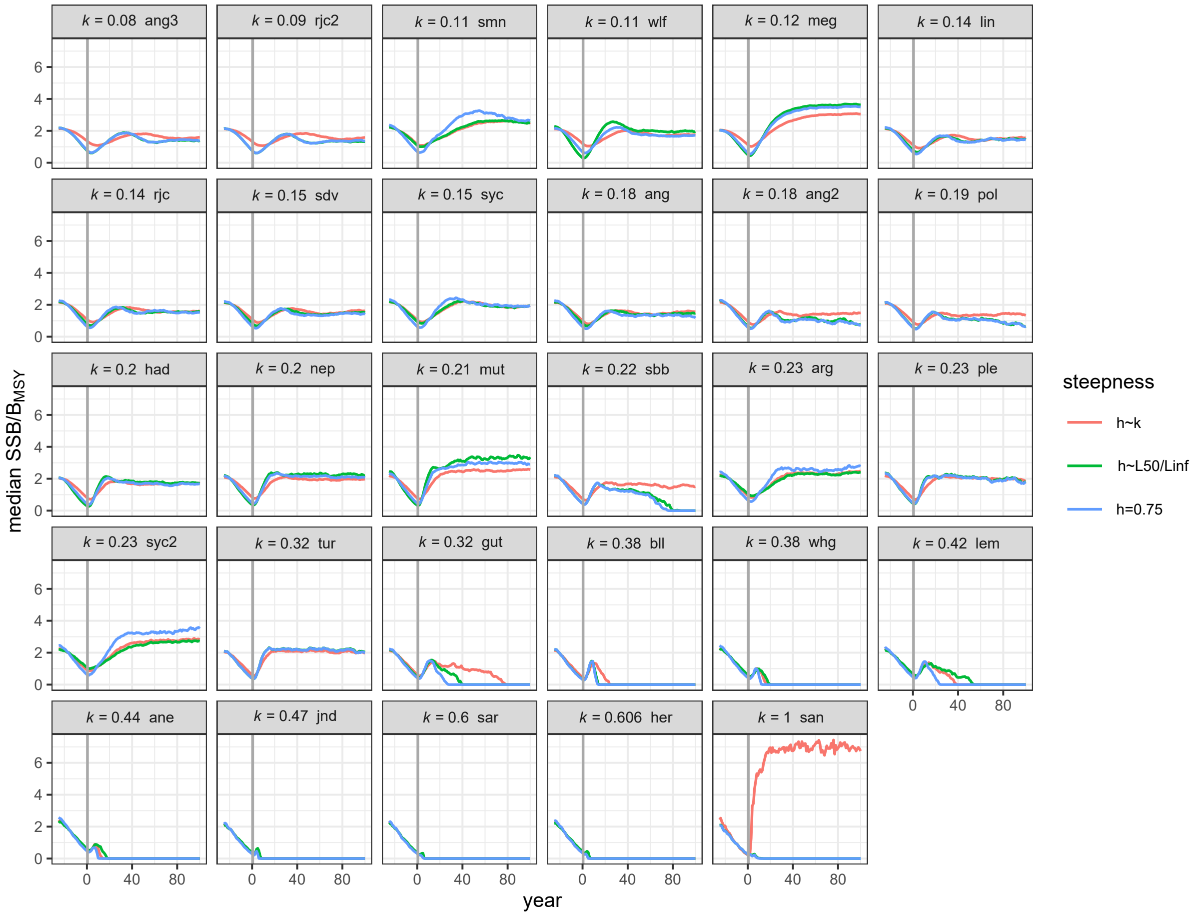

Figure B.3: Comparison of the SSB trajectories for default steepness and scenarios imposing a link with life-history parameters. "h∼k" denotes the scenario where steepness is linked to k and "h∼50/Linf" uses the relationship from Wiff et al. (2018), see text above for more details. See Figure B.2 for more details.

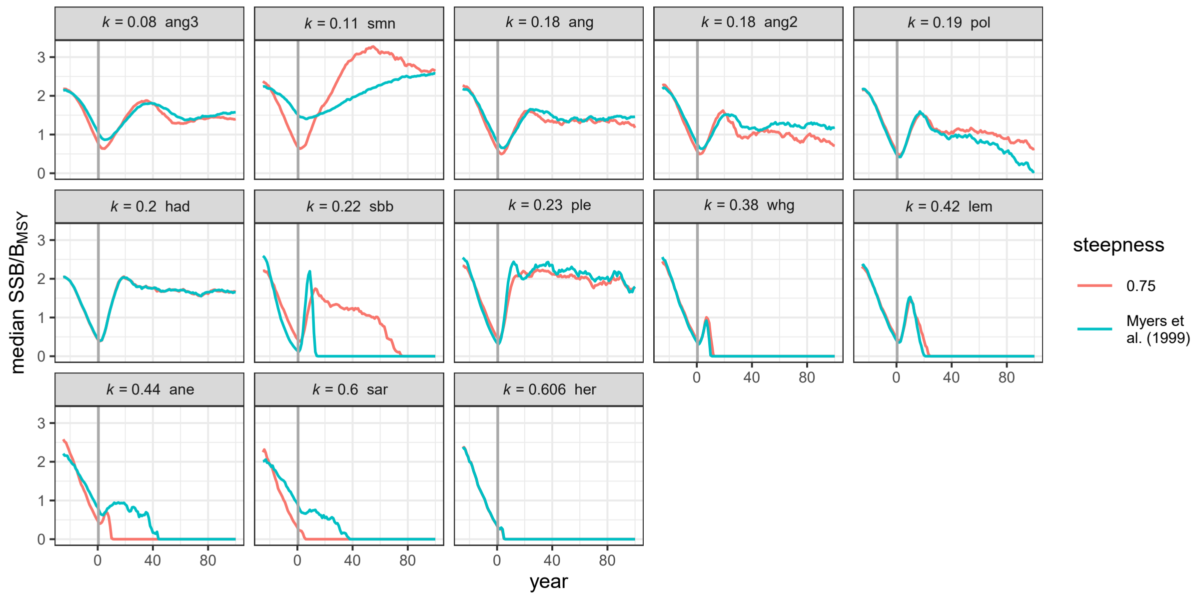

Figure B.4: Comparison of the SSB trajectories for default steepness and the OMs where steepness values were borrowed from Myers et al. (1999). Shown are only the stocks for which steepness could be borrowed. See Figure B.2 for more details.

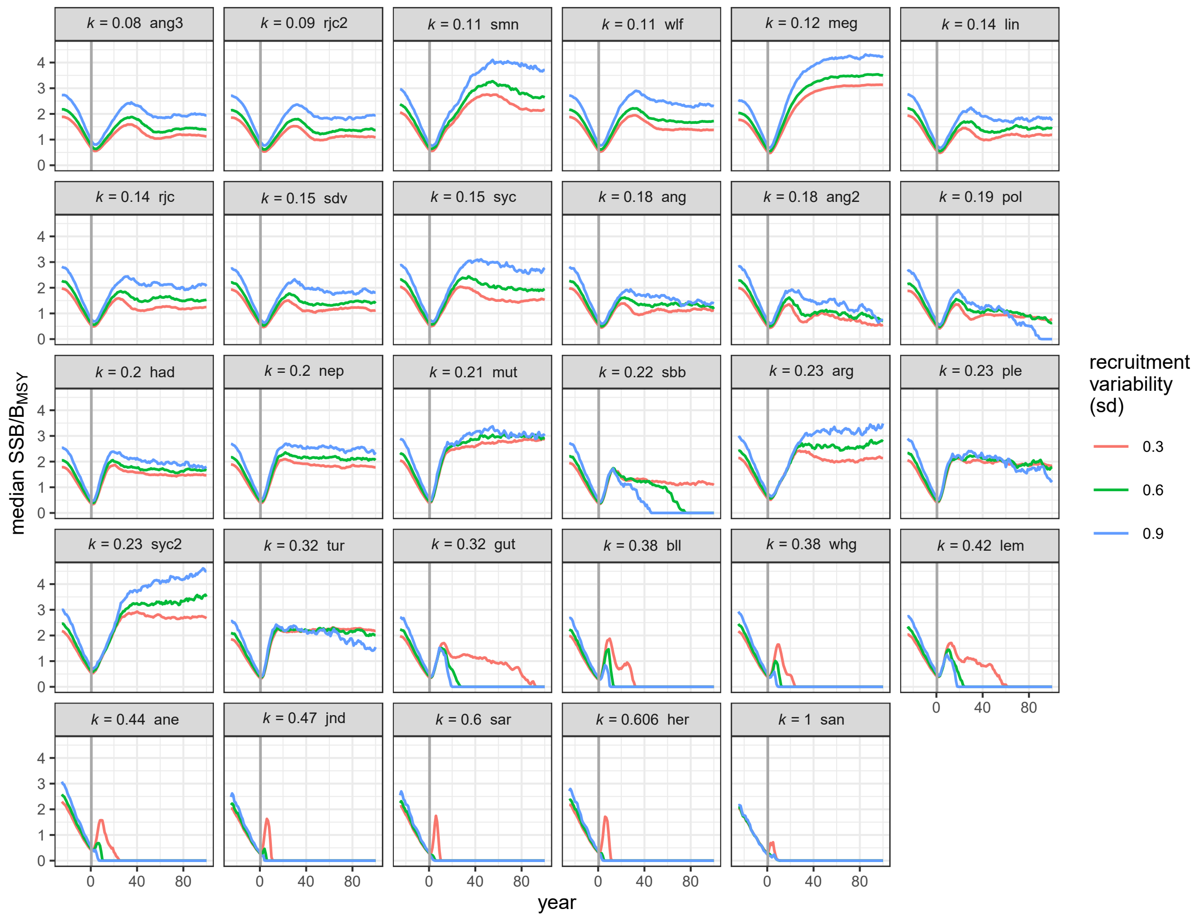

Figure B.5: Impact of recruitment variability on SSB trajectories; $sd = 0.6$ is the default scenario. See Figure B.2 for more details.

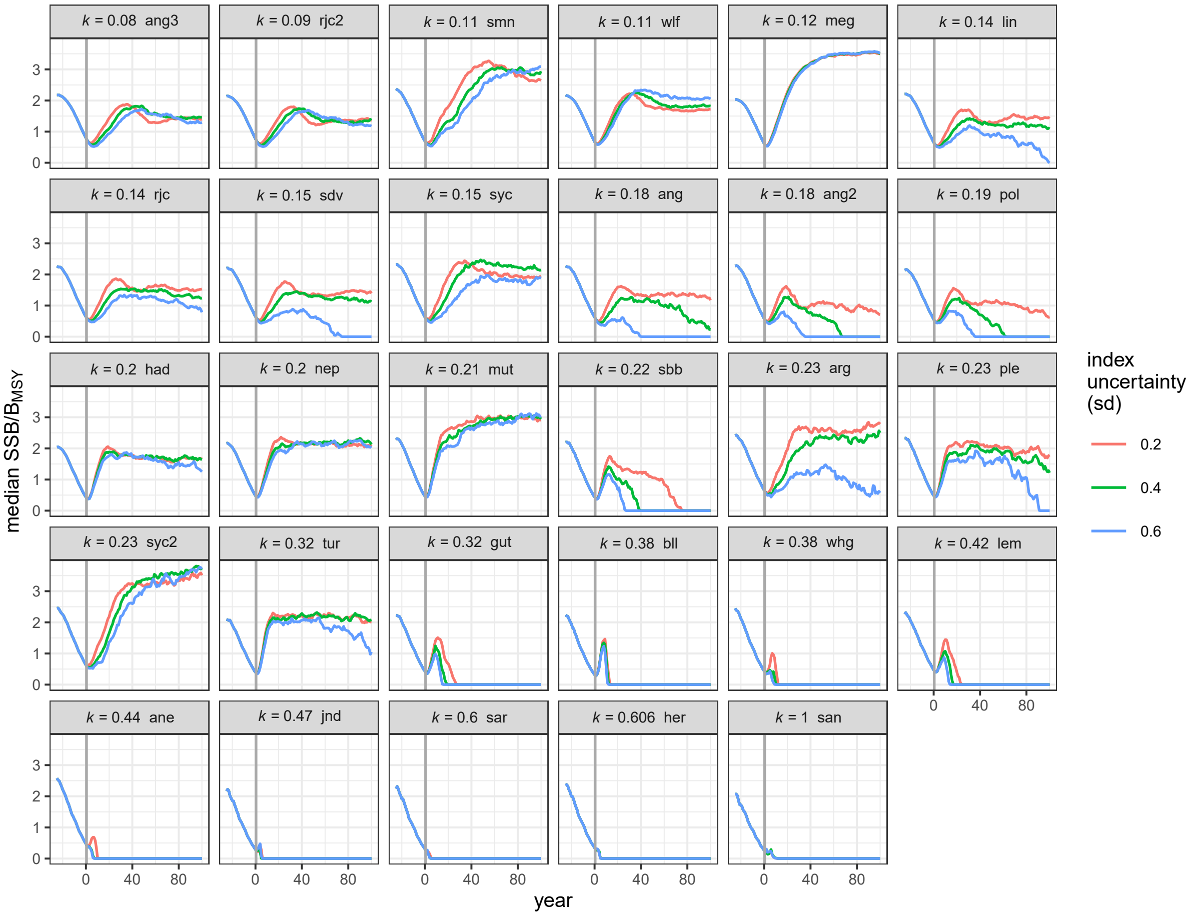

Figure B.6: Impact of biomass index uncertainty on SSB trajectories; $sd = 0.2$ is the default scenario. See Figure B.2 for more details.

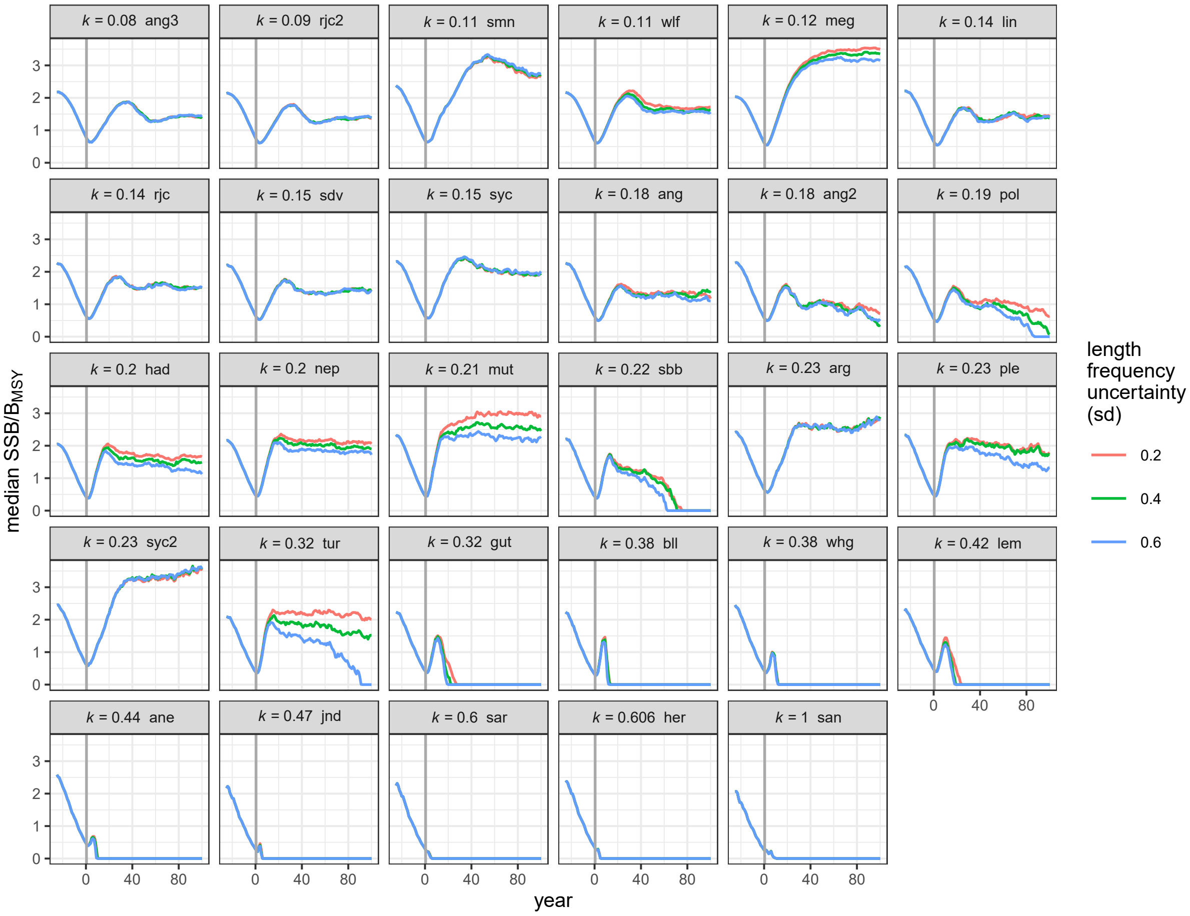

Figure B.7: Impact of length-frequency uncertainty on SSB trajectories; $sd = 0.2$ is the default scenario. See Figure B.2 for more details.

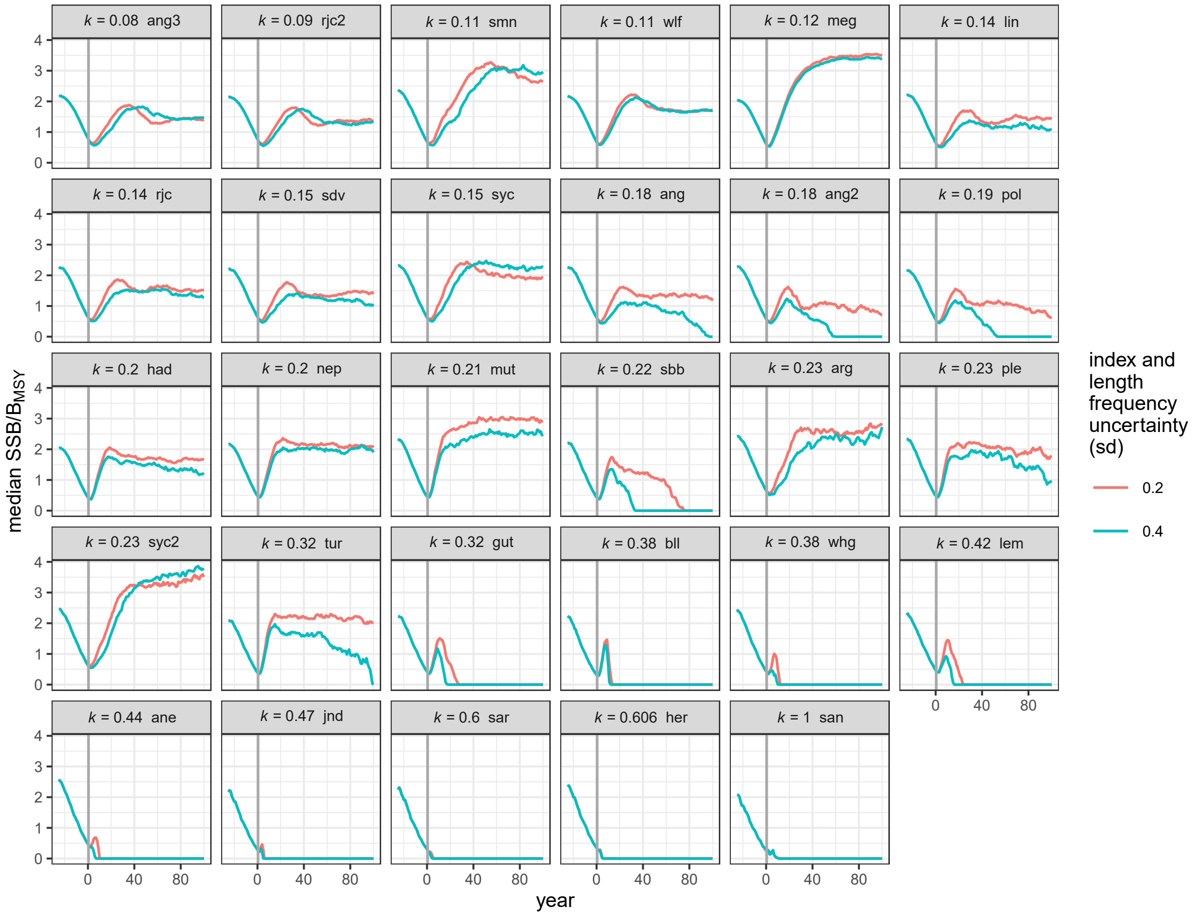

Figure B.8: SSB trajectories for the default scenario and a scenario were the biomass index and length-frequency uncertainties were increased. See Figure B.2 for more details.

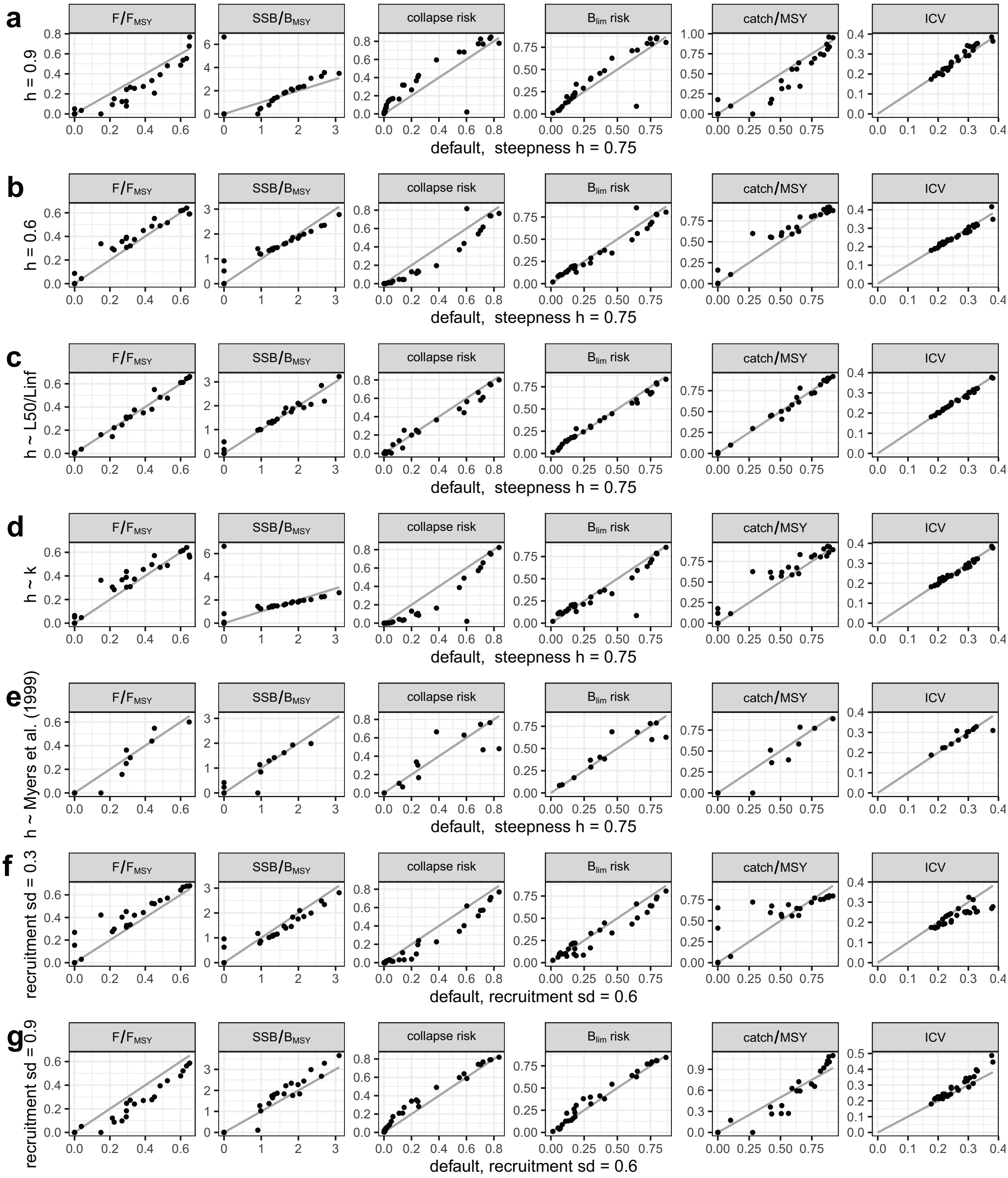

Figure B.9: Comparison of summary statistics from the default scenario (on x-axis, columns represent different summary statistics) versus sensitivity runs with different recruitment assumptions (on y-axis, rows represent different scenarios). Each point in the plots corresponds to one of the 29 simulated stocks in the one-way fishing history. Row "e" contains fewer stocks and only the ones for which steepness values were available. The grey diagonal line is y=x.

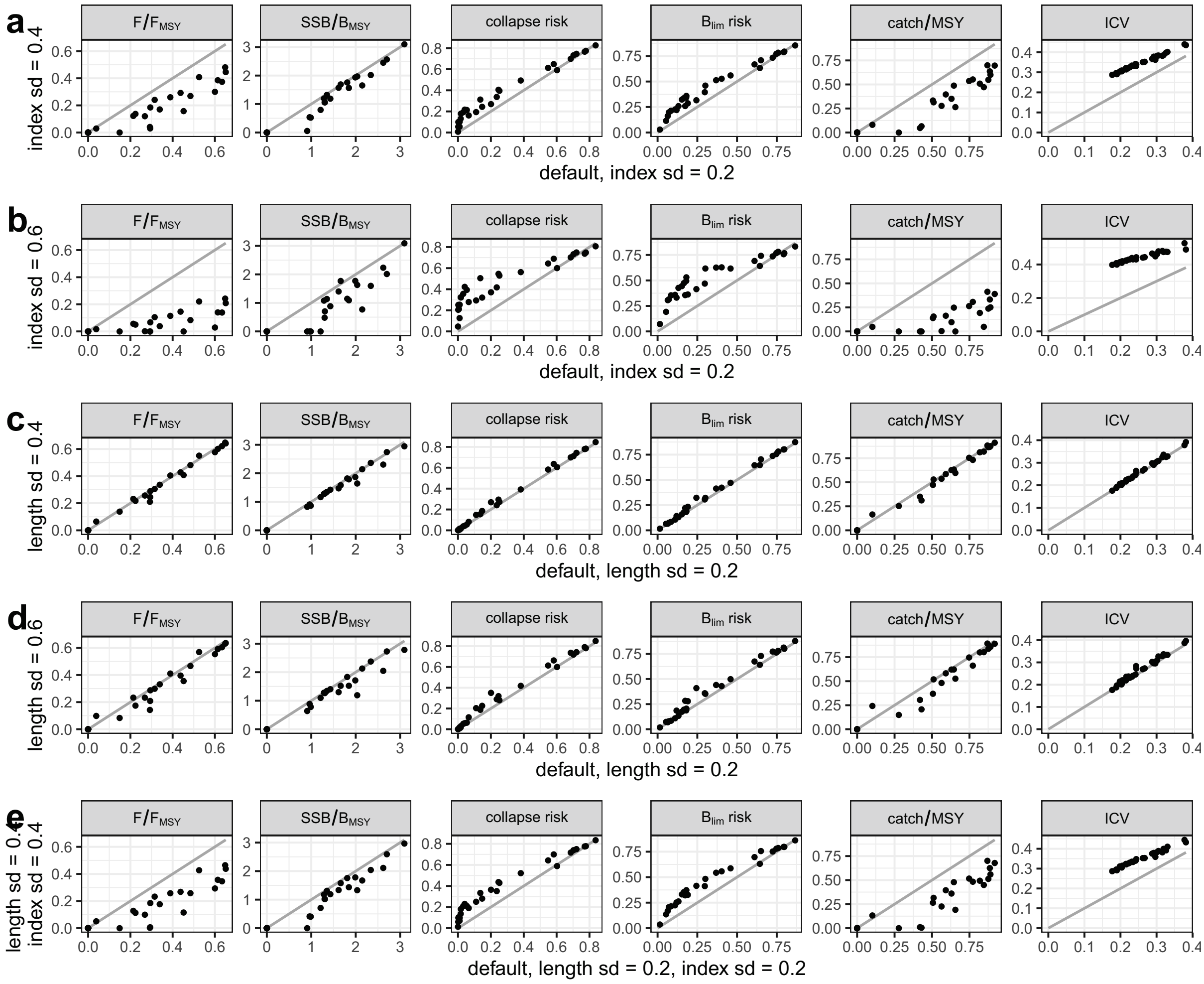

Figure B.10: Comparison of summary statistics from the default scenario (on x-axis, columns represent different summary statistics) versus scenarios with higher index uncertainties (on y-axis, rows represent different scenarios). See Figure B.9 for more details.

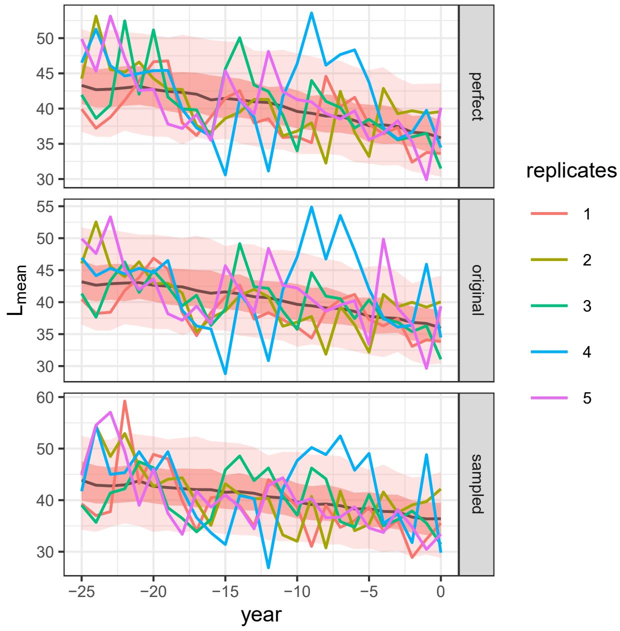

Figure B.11: A comparison of mean lengths for one example stock, pollack, during the historical fishing period. Shown are the lengths from the inverse age-length key without observation error (top row), the approach where uncertainty is added to the numbers at length by applying an error term with $sd = 0.2$ in log-space (middle row, the default method used in the MSE simulation), and an approach where mean length is calculated from sampling (for each year and replicate, 50 samples were randomly drawn and the mean length calculated from these samples, bottom row). The solid black line is the median, surrounded by 50 and 90% confidence intervals. The coloured curves are the first 5 (of 500) replicates.

B.1.4 Discussion

The sensitivity runs detailed here support the conclusions from Chapter 6.

Recruitment

The results of the MSE simulations are relatively insensitive to assumptions about recruitment steepness, and the division between surviving stocks with lower k and collapsing stocks with higher k remains.

The scenarios linking steepness to life-history parameters should be considered as purely exploratory and are not necessarily realistic. The attempt to use realistic steepness parameters for some stocks, borrowing values from Myers et al. (1999), should also be treated with caution. Despite using species-specific steepness, they might not ultimately match the stocks simulated in this study. Some of the higher-k stocks had low steepness values according to Myers et al. (1999), and these might be questionable for such dynamic pelagic species.

Recruitment steepness is difficult to estimate, and steepness estimates depend on the methodology deployed and stock assessment results on which the estimation procedure is based. This is even more difficult for data-limited stocks, the subject of the present study, for which quantitative stock assessments do not exist, rendering steepness estimation procedures infeasible. The situation is exacerbated by a lack of scientifically sound relationships between steepness and life-history traits. Some studies have found links, such as Wiff et al. (2018), but these links entail a high uncertainty, therefore limiting their usefulness for simulation testing. Implementing the steepness link from Wiff et al. (2018) merely led to noise for stock trajectories and summary statistics in the simulation results. Consequently, using a single generic medium steepness value was appropriate, and the sensitivity to this steepness has been evaluated by including lower and higher levels of steepness.

The simulations were shown to be largely insensitive to different levels of recruitment variability. Despite using somewhat arbitrary levels of recruitment variability, the chosen approach was appropriate and did not generally affect the conclusions.

Observation uncertainty

Index uncertainty did have an effect on some stocks and caused poorer performance. However, most stocks were unaffected, and the general outcome (split between lower- and higher-k stocks) is still valid.

The uncertainty implemented for the catch length-frequency had a minor effect, because, as discussed in Chapter 6, component f had only a minor contribution to the advised catch, whereas component r (biomass index trend) dominated.

The quantification of the level of observation error, i.e. the difference between the observed index and the actual stock, might be considered arbitrary in the case for the data-limited stocks, because the actual stock size is unknown, and as a result, the CV for observation error cannot be estimated. A quick review of survey indices used within ICES for data-rich stocks (see Table B.2) was conducted. For these stocks, quantitative assessment results exist, and it is possible to quantify the deviation between survey biomass and assessment estimate. Several of these indices have CVs around 0.2. Even though these surveys are primarily targeting data-rich stocks, the same surveys also catch individuals from data-limited stocks, and are used in their assessments.

The mean length in the catch was simulated without sampling; however, a comparison of this approach with mean length derived from sampling revealed that the approximation led to very similar results, both in terms of median as well as in the spread (see Figure B.11), and the approach is therefore appropriate. The main reason the sampling approach was not followed was because it added a substantial overhead to computational time.

Fisheries selectivity

The fisheries selectivity in the operating models used Equation 5.16 (see Chapter 5) and occurred before maturity for all stocks. This was applied to all stocks and allowed easy comparison between stocks. Alternative selectivity scenarios and sensitivity runs were considered; however, results were not included here for the following reasons:

1. Consistency

   Selectivity cannot be changed during the simulation and before the first implementation of the catch rule without impairing temporal consistency, because the catch rule bases the new catch advice on the previous catch, and some of the components of the catch rule also use data from previous catches.

2. Operating models

   It is not possible to solely look at the effect of a different selectivity because a change in the selectivity does not only impact the catch, but results in a different operating model with different characteristics (depending on the form of the alternative selectivity) and reference points.

   Alternative parameterisations for selectivity modify the historical fishing pattern because the historical fishing scenarios were based on fishing mortality and the reference point F_{crash} (e.g. in the one-way fishing scenario, the fishing mortality is increased from $0.5F_{\text{MSY}}$ to $0.8F_{\text{crash}}$ within 25 years). F_{crash} changes with selectivity, and the starting point of the MSE, when the catch rule is implemented the first time, is different, both in terms of absolute biomass as well as relative to B_{MSY}. This would impair direct comparability between selectivity scenarios.

3. Catch rule components

   The catch rule produces catch advice that is the result of complex interactions among the catch rule components, which use different sources of information (previous catches, catch length frequencies, and survey biomass index). Selectivity affects the components differently, and variations in selectivity could potentially lead to a mismatch of derived information. The biomass index has a selectivity different from fisheries selectivity and covers younger fish; it is therefore only indirectly influenced by changes in fisheries selectivity. However, component f of the catch rule (derived from catch length frequency) is directly influenced: an alternative selectivity will lead to a different age and length distribution of the catch, and also change the length reference point $L_{F=M}$. Increasingly later-occurring selectivity will lead to older fish in the catch, and the length distribution is therefore likely to be less informative due to the length growth of individuals. In an extreme case where selectivity occurs well after maturity, components r and f of the catch rule will use information from different parts of the stock with potentially conflicting signals.

Alternative selectivity scenarios have been trialled, but the results for some stocks were not trivial due to the reasons mentioned above.

Conclusion

In conclusion, the exploration into the recruitment assumptions showed that the results and conclusions from this study are largely robust to the values of steepness h and recruitment variability. In reality, steepness is notoriously difficult to estimate, and correlations with life-history information are scarce to find in empirical data, and not part of this study.

Appendix C

Appendix to Chapter 7

The following is an Appendix to Chapter 7 and adapted from the supplementary material published in Fischer et al. (2021a):

> Fischer, S. H., De Oliveira, J. A. A., Mumford, J. D. & Kell, L. T. (2021a). Using a genetic algorithm to optimize a data-limited catch rule. *ICES Journal of Marine Science*, *78*(4), 1311–1323. https://doi.org/10.1093/icesjms/fsab018

C.1 Tables

Table C.1: The rfb rule parameters of the first generation used in the genetic algorithm. Shown are both the 35 parameter suggestions and the remaining 65 random parameters. The parameters are defined in Equations 7.2 and 7.3 in Chapter 7. # is the sequential ID of the 100 individuals.

#	n_0	n_1	n_2	e_r	e_f	e_b	v	x
Default value								
	1	2	3	1	1	1	2	1
Allowed range								
	{0, 1}	{1, 2, 3, 4, 5}	{1, 2, 3, 4, 5}	{0, 0.1, 0.2, ... 2}	{0, 0.1, 0.2, ... 2}	{0, 0.1, 0.2, ... 2}	{1, 2, 3, 4, 5}	{0, 0.01, 0.02, ... 2}
Parameter suggestions								
1	0	1	1	1	1	1	1	1
2	0	1	1	1	1	1	2	1
3	0	1	1	0	0	0	2	1
4	1	2	3	0	0	0	1	0
5	1	2	3	1	0	0	1	0
6	1	2	3	0	1	0	1	0
7	1	2	3	1	1	0	1	0
8	1	2	3	0	0	1	1	0
9	1	2	3	1	0	1	1	0
10	1	2	3	0	1	1	1	0
11	1	2	3	1	1	1	1	0

Table C.1 (continued).

#	n_0	n_1	n_2	e_r	e_f	e_b	v	x
12	1	2	3	0	0	0	2	0
13	1	2	3	1	0	0	2	0
14	1	2	3	0	1	0	2	0
15	1	2	3	1	1	0	2	0
16	1	2	3	0	0	1	2	0
17	1	2	3	1	0	1	2	0
18	1	2	3	0	1	1	2	0
19	1	2	3	1	1	1	2	0
20	1	2	3	0	0	0	1	1
21	1	2	3	1	0	0	1	1
22	1	2	3	0	1	0	1	1
23	1	2	3	1	1	0	1	1
24	1	2	3	0	0	1	1	1
25	1	2	3	1	0	1	1	1
26	1	2	3	0	1	1	1	1
27	1	2	3	1	1	1	1	1
28	1	2	3	0	0	0	2	1
29	1	2	3	1	0	0	2	1
30	1	2	3	0	1	0	2	1
31	1	2	3	1	1	0	2	1
32	1	2	3	0	0	1	2	1
33	1	2	3	1	0	1	2	1
34	1	2	3	0	1	1	2	1
35	1	2	3	1	1	1	2	1
Random parameters								
36	1	5	2	1.3	0.9	1.7	4	0.01
37	0	3	2	0.6	1.0	1.4	2	1.21
38	1	3	2	0.8	1.3	0.7	3	1.81
39	0	2	3	2.0	0.3	0.3	2	1.41
40	0	4	5	1.7	0.7	0.8	2	0.53
41	0	3	3	1.9	0.8	1.9	3	1.70
42	0	3	2	1.6	0.2	1.6	2	0.67
43	0	2	1	1.6	1.9	1.5	4	1.16
44	1	2	3	0.5	1.7	1.9	3	0.87
45	0	3	4	1.5	1.8	2.0	5	0.10
46	0	3	2	2.0	1.9	1.2	4	1.46
47	1	1	2	0.6	0.1	0.1	2	1.10
48	0	1	2	0.8	0.8	0.7	2	1.50
49	0	4	4	1.6	1.1	0.6	4	0.10
50	1	5	3	0.2	0.2	0.2	3	1.43
51	1	3	4	0.7	1.6	0.1	2	0.60
52	1	3	4	0.9	1.5	0.7	1	0.57
53	0	3	3	0.3	0.1	0.7	1	1.66
54	1	5	3	1.2	1.0	0.3	4	0.17
55	0	3	3	1.9	1.8	1.2	4	0.09
56	1	4	2	2.0	0.1	0.8	5	0.70
57	1	3	3	0.4	0.6	1.9	2	1.08
58	1	2	5	1.1	1.0	1.3	5	1.22
59	1	2	2	0.8	1.2	0.7	2	0.54

Table C.1 (continued).

#	n_0	n_1	n_2	e_r	e_f	e_b	v	x
60	1	4	3	1.4	0.5	0.4	4	0.41
61	1	3	2	0.5	0.8	0.2	2	0.76
62	0	2	3	0.9	0.7	2.0	1	0.95
63	0	4	2	0.3	1.9	0.8	4	1.67
64	1	1	3	0.7	0.2	1.1	4	0.24
65	1	4	5	1.5	0.1	1.5	5	1.35
66	0	3	4	1.0	1.9	1.7	4	0.99
67	1	3	5	0.1	0.9	1.1	4	1.80
68	0	2	3	1.6	0.7	0.0	2	1.10
69	0	3	3	0.8	0.3	1.8	3	0.26
70	0	3	3	2.0	0.1	1.5	3	0.88
71	0	2	1	0.6	1.3	0.8	1	0.38
72	0	3	2	1.7	1.2	0.2	2	0.87
73	1	1	3	0.2	2.0	0.1	3	0.45
74	1	2	2	1.8	1.2	1.6	4	1.92
75	0	2	5	0.9	0.1	1.7	4	0.90
76	1	2	3	0.2	0.3	1.3	2	1.55
77	0	5	2	0.7	1.0	0.3	4	0.32
78	0	3	2	1.7	0.0	0.7	1	1.73
79	0	4	4	0.6	0.9	1.5	3	0.41
80	1	5	4	1.2	0.5	1.8	2	0.36
81	0	3	2	1.7	1.9	1.4	3	0.33
82	0	1	1	0.1	1.4	0.5	5	1.13
83	1	2	4	1.4	0.3	1.3	2	1.45
84	0	4	3	1.4	1.0	0.6	2	1.75
85	1	2	2	0.9	1.4	1.9	4	1.42
86	0	4	1	0.9	0.9	0.3	4	0.95
87	1	4	1	1.1	1.9	0.8	3	1.64
88	0	4	3	1.9	1.4	0.5	4	0.03
89	0	3	2	0.5	0.8	0.2	3	1.99
90	0	3	2	0.4	0.2	1.7	3	1.27
91	1	5	2	0.8	0.5	1.1	3	0.86
92	1	4	2	0.7	1.7	1.3	2	0.06
93	0	4	2	1.7	0.9	0.8	1	1.51
94	1	3	3	0.4	1.0	1.7	2	0.42
95	1	5	4	1.0	1.4	1.5	2	2.00
96	0	2	1	0.9	1.5	0.7	4	1.81
97	1	2	3	1.1	0.3	1.9	4	1.42
98	0	5	5	1.3	1.7	1.3	2	1.46
99	0	3	2	2.0	1.9	0.1	3	0.94
100	1	5	1	0.5	1.2	1.2	3	1.73

C.2 Figures

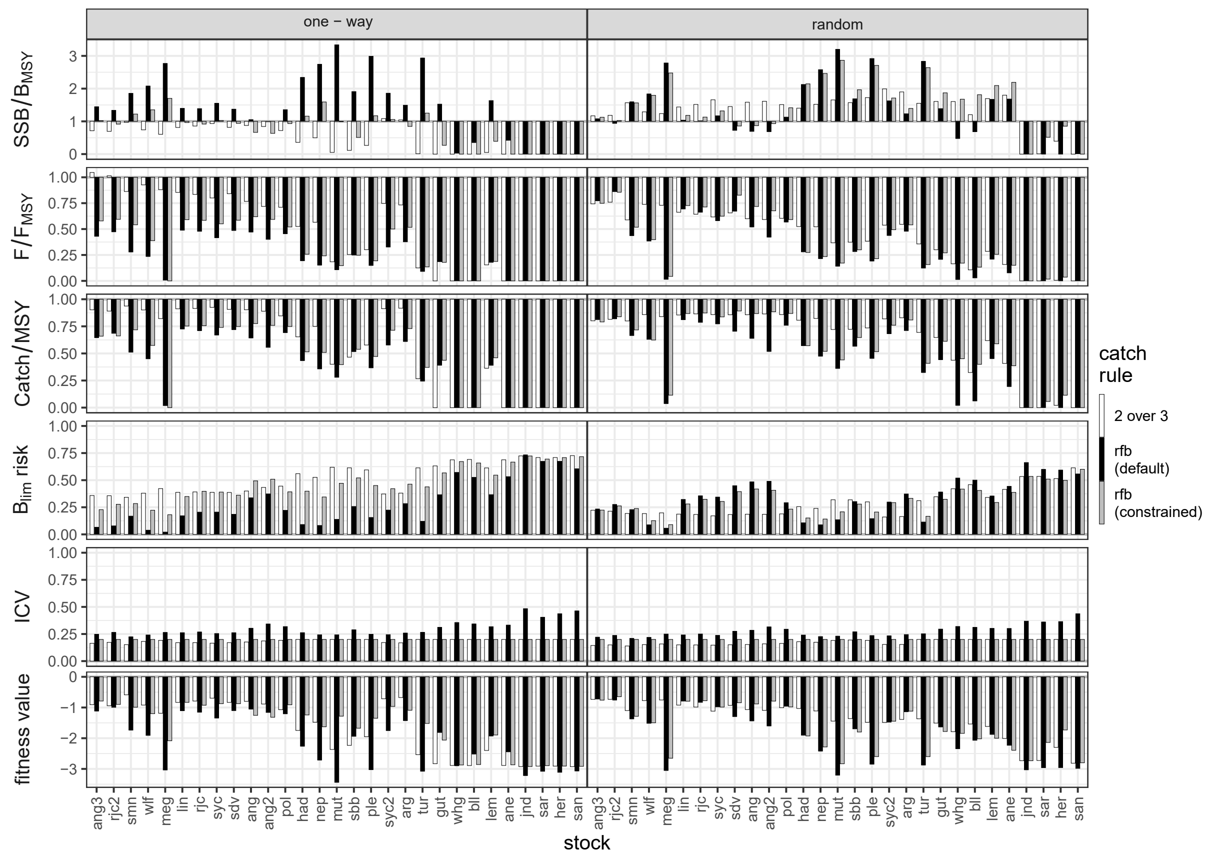

Figure C.1: Comparison of the summary statistics of the current ICES management procedure with the rfb rule excluding (default) and including a 20% uncertainty cap for two fishing histories. The fitness function corresponds to "SSB+Catch+risk+ICV" of Chapter 7. The stocks are sorted by the von Bertalanffy growth parameter k in ascending order from left to right.

Appendix D

Appendix to Chapter 8

The following is an Appendix to Chapter 8 and adapted from the supplementary material published for Fischer et al. (2021b):

> Fischer, S. H., De Oliveira, J. A. A., Mumford, J. D. & Kell, L. T. (2021b). Application of explicit precautionary principles in data-limited fisheries management. *ICES Journal of Marine Science*, *78*(8), 2931–2942. https://doi.org/10.1093/icesjms/fsab169

D.1 Tables

Table D.1: Default and optimised rfb rule parameters. See Equation (8.2) and Table 8.1 in Chapter 8 for definitions of the parameters. Shown are only the parameters included in the optimisation and fixed parameters (in italics). "generations" is the number of generations required in the genetic algorithm to obtain convergence. "fitness improvement" is the improvement relative to the fitness of the default rfb rule parameterisation. (Table continued on next page)

Fishing history	**Stock**	**Generations**	n_0	n_1	n_2	e_r	e_f	e_b	v	x	u_u	u_l	**Fitness improvement [%]**
Default rfb rule parameters													
			1	**2**	**3**	**1.0**	**1.0**	**1.0**	**2**	**1.00**	∞	**0**	
Parameter exploration for pollack (see Figure 8.5 in Chapter 8)													
one-way	pol	1								0.74			43
one-way	pol	19									1.32	0.74	9
one-way	pol	10								0.74	∞	0	43
one-way	pol	22	0	2	3	1.3	0.6	1.7	2	0.94			75
one-way	pol	10	0	2	3	1.3	0.6	1.7	2	0.94	∞	0	75
random	pol	1								0.73			39
random	pol	15									1.53	0.68	4
random	pol	10								0.73	∞	0	39
random	pol	59	0	3	4	1.2	1	1.5	2	0.73			48
random	pol	10	0	3	4	1.2	1	1.5	2	0.73	∞	0	48
Optimisation with multiplier for all stocks ["(f) rfb: MSY-PA - mult" in Figure 8.7 in Chapter 8]													
one-way	ang3	1								0.97			77

Table D.1: (continued).

Fishing history	Stock	Generations	n_0	n_1	n_2	e_r	e_f	e_b	v	x	u_u	u_l	Fitness improvement [%]
one-way	rjc2	1								0.96			79
one-way	smn	1								0.79			46
one-way	wlf	1								1.04			16
one-way	meg	1								1.40			45
one-way	lin	1								0.81			50
one-way	rjc	1								0.80			46
one-way	syc	1								0.78			39
one-way	sdv	1								0.80			48
one-way	ang	1								0.69			33
one-way	ang2	1								0.70			35
one-way	pol	1								0.74			43
one-way	had	1								0.64			49
one-way	nep	1								0.80			50
one-way	mut	1								0.66			41
one-way	sbb	1								0.54			32
one-way	ple	1								0.66			39
one-way	syc2	1								0.79			32
one-way	arg	1								0.73			27
one-way	tur	1								0.67			49
one-way	gut	1								0.51			28
one-way	whg	1								0.38			22
one-way	bll	1								0.33			24
one-way	lem	1								0.48			27
one-way	ane	1								0.40			11
one-way	jnd	1								0.21			22
one-way	sar	1								0.21			17
one-way	her	1								0.23			16
one-way	san	1								0.20			23
random	ang3	1								0.23			34
random	rjc2	1								0.24			33
random	smn	1								0.76			38
random	wlf	1								0.66			46
random	meg	1								0.86			17
random	lin	1								0.62			30
random	rjc	1								0.67			28
random	syc	1								0.74			28
random	sdv	1								0.62			36
random	ang	1								0.67			34
random	ang2	1								0.70			39
random	pol	1								0.73			39
random	had	1								0.77			49
random	nep	1								0.82			49
random	mut	1								0.74			40
random	sbb	1								0.65			31
random	ple	1								0.75			39
random	syc2	1								0.82			29
random	arg	1								0.77			24
random	tur	1								0.79			51
random	gut	1								0.65			29
random	whg	1								0.47			17
random	bll	1								0.41			20
random	lem	1								0.60			29
random	ane	1								0.47			11

Table D.1: (continued).

Fishing history	Stock	Generations	n_0	n_1	n_2	e_r	e_f	e_b	v	x	u_u	u_l	Fitness improvement [%]
random	jnd	1								0.28			22
random	sar	1								0.27			17
random	her	1								0.29			16
random	san	1								0.27			23
Optimisation with all parameters for all stocks [“(g) rfb: MSY-PA - all” in Figure 8.7 in Chapter 8]													
one-way	ang3	18	0	4	3	1.5	0.6	1.2	3	1.00	∞	0.50	89
one-way	rjc2	30	0	3	3	1.4	0.7	0.5	2	0.97	∞	0.24	91
one-way	smn	30	1	3	5	1.6	0.3	0.8	3	0.79	∞	0.25	54
one-way	wlf	50	0	2	3	1.4	0.3	1.0	2	1.07	∞	0.26	75
one-way	meg	36	0	2	3	1.5	0.0	1.0	2	1.00	∞	0.37	83
one-way	lin	30	0	3	5	1.2	0.8	1.6	1	0.92	∞	0.35	76
one-way	rjc	33	0	3	4	1.5	1.2	1.0	2	0.82	∞	0.08	65
one-way	syc	88	0	3	5	1.8	0.6	1.1	3	0.85	∞	0.33	66
one-way	sdv	70	0	3	5	1.5	0.9	1.3	3	0.88	∞	0.18	75
one-way	ang	22	0	3	3	1.9	0.9	0.9	2	0.72	∞	0.34	50
one-way	ang2	74	0	4	3	1.3	0.7	0.9	2	0.80	2.08	0.28	59
one-way	pol	10	0	2	3	1.3	0.6	1.7	2	0.94	∞	0.00	75
one-way	had	100	0	3	5	1.6	0.6	1.0	3	0.74	∞	0.25	63
one-way	nep	12	0	3	3	1.3	0.9	1.6	2	0.82	∞	0.25	54
one-way	mut	10	1	2	3	1.0	1.0	1.0	2	0.66	∞	0.00	41
one-way	sbb	30	0	3	5	1.0	0.8	0.8	2	0.57	∞	0.25	33
one-way	ple	73	0	3	5	1.3	0.6	0.6	2	0.70	∞	0.13	43
one-way	syc2	35	0	3	3	1.7	0.3	1.1	3	0.80	∞	0.17	42
one-way	arg	30	0	3	5	1.9	0.5	0.8	4	0.66	∞	0.36	37
one-way	tur	36	0	3	3	1.4	0.9	0.9	2	0.74	∞	0.11	52
one-way	gut	10	0	2	1	0.6	1.3	0.8	1	0.38	1.14	0.26	29
one-way	whg	10	0	2	1	0.6	1.3	0.8	1	0.38	1.14	0.26	25
one-way	bll	10	0	2	1	0.6	1.3	0.8	1	0.38	1.14	0.26	28
one-way	lem	36	0	3	3	0.5	0.4	0.9	1	0.41	∞	0.55	29
one-way	ane	53	1	3	3	0.8	0.8	0.7	1	0.17	∞	0.64	15
one-way	jnd	27	1	4	3	0.9	0.6	1.1	2	0.09	∞	0.38	25
one-way	sar	10	0	4	4	1.6	1.1	0.6	4	0.10	4.11	0.27	18
one-way	her	10	0	2	1	0.6	1.3	0.8	1	0.38	1.14	0.26	20
one-way	san	16	1	2	3	0.8	1.3	1.0	1	0.22	1.53	0.09	26
random	ang3	38	1	2	5	0.7	0.5	0.8	1	0.19	∞	0.18	38
random	rjc2	16	1	2	3	0.9	1.1	0.7	1	0.19	1.53	0.04	37
random	smn	30	1	4	5	1.2	0.7	0.9	3	0.72	∞	0.22	42
random	wlf	44	1	4	4	1.6	1.0	1.0	2	0.64	∞	0.15	49
random	meg	82	1	4	5	1.5	1.1	1.1	2	0.85	∞	0.10	22
random	lin	30	1	3	5	1.5	1.0	1.0	2	0.63	∞	0.17	34
random	rjc	41	0	4	4	1.4	1.0	1.1	2	0.65	∞	0.18	34
random	syc	41	0	4	5	1.8	0.7	1.2	4	0.65	∞	0.31	36
random	sdv	30	1	3	5	1.5	0.9	0.9	2	0.62	∞	0.08	39
random	ang	36	1	3	5	1.0	1.0	1.0	2	0.66	∞	0.07	36
random	ang2	10	1	2	3	1.0	1.0	1.0	2	0.70	∞	0.00	39
random	pol	10	0	3	4	1.2	1.0	1.5	2	0.73	∞	0.00	48
random	had	10	1	2	3	1.0	1.0	1.0	2	0.77	∞	0.00	49
random	nep	29	1	3	3	1.0	0.8	1.0	3	0.80	∞	0.19	52
random	mut	10	1	2	3	1.0	1.0	1.0	2	0.74	∞	0.00	40
random	sbb	10	1	2	3	1.0	1.0	1.0	2	0.65	∞	0.00	31
random	ple	19	0	4	2	0.9	1.0	0.6	3	0.71	∞	0.05	41
random	syc2	47	1	3	5	1.2	0.9	1.3	3	0.78	3.82	0.19	34

Table D.1: (continued).

Fishing history	**Stock**	**Generations**	n_0	n_1	n_2	e_r	e_f	e_b	v	x	u_u	u_l	**Fitness improvement [%]**
random	arg	14	1	3	4	1.0	0.8	0.9	3	0.72	∞	0.17	25
random	tur	37	0	2	2	0.9	0.9	0.9	1	0.96	∞	0.47	59
random	gut	14	0	2	3	1.0	1.0	1.1	2	0.67	∞	0.00	30
random	whg	29	0	2	3	0.7	0.8	0.7	2	0.58	∞	0.29	19
random	bll	30	1	3	3	0.1	0.9	1.5	2	0.57	∞	0.08	23
random	lem	11	1	2	3	0.3	0.0	0.3	1	0.68	∞	0.00	32
random	ane	13	1	2	3	0.4	1.0	0.7	1	0.33	∞	0.75	15
random	jnd	10	0	2	1	0.6	1.3	0.8	1	0.38	1.14	0.26	26
random	sar	10	0	2	1	0.6	1.3	0.8	1	0.38	1.14	0.26	21
random	her	19	1	2	3	0.6	0.8	0.6	1	0.26	∞	0.56	19
random	san	10	0	2	1	0.6	1.3	0.8	1	0.38	1.14	0.26	28
Optimisation with multiplier and fixed uncertainty cap for all stocks [“(h) rfb (capped): MSY-PA - mult” in Figure 8.7 in Chapter 8]													
one-way	ang3	1								0.83	*1.2*	*0.7*	69
one-way	rjc2	1								0.81	*1.2*	*0.7*	69
one-way	smn	1								0.63	*1.2*	*0.7*	46
one-way	wlf	1								0.74	*1.2*	*0.7*	-41
one-way	meg	1								0.51	*1.2*	*0.7*	-42
one-way	lin	1								0.38	*1.2*	*0.7*	29
one-way	rjc	1								1.09	*1.2*	*0.7*	8
one-way	syc	1								0.34	*1.2*	*0.7*	25
one-way	sdv	1								0.38	*1.2*	*0.7*	22
one-way	ang	1								1.03	*1.2*	*0.7*	5
one-way	ang2	1								1.03	*1.2*	*0.7*	6
one-way	pol	1								1.11	*1.2*	*0.7*	9
one-way	had	1								1.28	*1.2*	*0.7*	23
one-way	nep	1								1.28	*1.2*	*0.7*	28
one-way	mut	1								1.24	*1.2*	*0.7*	32
one-way	sbb	1								1.12	*1.2*	*0.7*	16
one-way	ple	1								1.21	*1.2*	*0.7*	29
one-way	syc2	1								0.50	*1.2*	*0.7*	27
one-way	arg	1								1.08	*1.2*	*0.7*	10
one-way	tur	1								1.31	*1.2*	*0.7*	29
one-way	gut	1								1.07	*1.2*	*0.7*	11
one-way	whg	1								0.92	*1.2*	*0.7*	18
one-way	bll	1								0.84	*1.2*	*0.7*	11
one-way	lem	1								1.08	*1.2*	*0.7*	13
one-way	ane	1								0.95	*1.2*	*0.7*	13
one-way	jnd	1								0.61	*1.2*	*0.7*	15
one-way	sar	1								0.59	*1.2*	*0.7*	13
one-way	her	1								0.64	*1.2*	*0.7*	15
one-way	san	1								0.49	*1.2*	*0.7*	15
random	ang3	1								1.08	*1.2*	*0.7*	2
random	rjc2	1								1.05	*1.2*	*0.7*	2
random	smn	1								0.62	*1.2*	*0.7*	36
random	wlf	1								1.24	*1.2*	*0.7*	17
random	meg	1								1.73	*1.2*	*0.7*	-36
random	lin	1								1.08	*1.2*	*0.7*	2
random	rjc	1								0.36	*1.2*	*0.7*	15
random	syc	1								0.48	*1.2*	*0.7*	22
random	sdv	1								0.35	*1.2*	*0.7*	9
random	ang	1								0.34	*1.2*	*0.7*	27
random	ang2	1								0.46	*1.2*	*0.7*	30

Table D.1: (continued).

Fishing history	Stock	Generations	n_0	n_1	n_2	e_r	e_f	e_b	v	x	u_u	u_l	Fitness improvement [%]
random	pol	1								0.41	*1.2*	*0.7*	30
random	had	1								0.38	*1.2*	*0.7*	41
random	nep	1								0.50	*1.2*	*0.7*	46
random	mut	1								0.30	*1.2*	*0.7*	39
random	sbb	1								0.29	*1.2*	*0.7*	28
random	ple	1								0.42	*1.2*	*0.7*	37
random	syc2	1								0.73	*1.2*	*0.7*	25
random	arg	1								0.65	*1.2*	*0.7*	18
random	tur	1								0.42	*1.2*	*0.7*	49
random	gut	1								0.31	*1.2*	*0.7*	28
random	whg	1								1.13	*1.2*	*0.7*	15
random	bll	1								1.15	*1.2*	*0.7*	11
random	lem	1								0.27	*1.2*	*0.7*	30
random	ane	1								1.17	*1.2*	*0.7*	14
random	jnd	1								1.05	*1.2*	*0.7*	17
random	sar	1								1.10	*1.2*	*0.7*	16
random	her	1								1.10	*1.2*	*0.7*	16
random	san	1								0.93	*1.2*	*0.7*	16
Optimisation with multiplier and fixed conditional uncertainty cap for all stocks ["(i) rfb (cond. capped): MSY-PA - mult" in Figure 8.7 in Chapter 8]													
one-way	ang3	1								1.00	*1.2*	*0.7*	73
one-way	rjc2	1								0.99	*1.2*	*0.7*	74
one-way	smn	1								0.80	*1.2*	*0.7*	48
one-way	wlf	1								1.08	*1.2*	*0.7*	-8
one-way	meg	1								1.43	*1.2*	*0.7*	28
one-way	lin	1								0.80	*1.2*	*0.7*	48
one-way	rjc	1								0.79	*1.2*	*0.7*	44
one-way	syc	1								0.78	*1.2*	*0.7*	39
one-way	sdv	1								0.79	*1.2*	*0.7*	47
one-way	ang	1								0.67	*1.2*	*0.7*	33
one-way	ang2	1								0.69	*1.2*	*0.7*	34
one-way	pol	1								0.73	*1.2*	*0.7*	42
one-way	had	1								0.30	*1.2*	*0.7*	49
one-way	nep	1								0.75	*1.2*	*0.7*	49
one-way	mut	1								0.59	*1.2*	*0.7*	42
one-way	sbb	1								0.35	*1.2*	*0.7*	33
one-way	ple	1								0.53	*1.2*	*0.7*	39
one-way	syc2	1								0.79	*1.2*	*0.7*	33
one-way	arg	1								0.72	*1.2*	*0.7*	28
one-way	tur	1								0.49	*1.2*	*0.7*	50
one-way	gut	1								0.36	*1.2*	*0.7*	30
one-way	whg	1								1.11	*1.2*	*0.7*	17
one-way	bll	1								1.16	*1.2*	*0.7*	13
one-way	lem	1								0.19	*1.2*	*0.7*	30
one-way	ane	1								1.11	*1.2*	*0.7*	12
one-way	jnd	1								0.96	*1.2*	*0.7*	17
one-way	sar	1								1.04	*1.2*	*0.7*	16
one-way	her	1								1.03	*1.2*	*0.7*	16
one-way	san	1								1.10	*1.2*	*0.7*	17
random	ang3	1								1.11	*1.2*	*0.7*	2
random	rjc2	1								0.00	*1.2*	*0.7*	14
random	smn	1								0.76	*1.2*	*0.7*	40
random	wlf	1								0.24	*1.2*	*0.7*	46

Table D.1: (continued).

Fishing history	**Stock**	**Generations**	n_0	n_1	n_2	e_r	e_f	e_b	v	x	u_u	u_l	**Fitness improvement [%]**
random	meg	1								0.01	*1.2*	*0.7*	18
random	lin	1								0.49	*1.2*	*0.7*	30
random	rjc	1								0.64	*1.2*	*0.7*	28
random	syc	1								0.71	*1.2*	*0.7*	28
random	sdv	1								0.54	*1.2*	*0.7*	34
random	ang	1								0.65	*1.2*	*0.7*	33
random	ang2	1								0.70	*1.2*	*0.7*	38
random	pol	1								0.71	*1.2*	*0.7*	39
random	had	1								0.72	*1.2*	*0.7*	49
random	nep	1								0.83	*1.2*	*0.7*	50
random	mut	1								0.57	*1.2*	*0.7*	40
random	sbb	1								0.51	*1.2*	*0.7*	31
random	ple	1								0.70	*1.2*	*0.7*	39
random	syc2	1								0.83	*1.2*	*0.7*	31
random	arg	1								0.77	*1.2*	*0.7*	25
random	tur	1								0.65	*1.2*	*0.7*	50
random	gut	1								0.53	*1.2*	*0.7*	29
random	whg	1								0.16	*1.2*	*0.7*	21
random	bll	1								1.20	*1.2*	*0.7*	9
random	lem	1								0.52	*1.2*	*0.7*	31
random	ane	1								0.30	*1.2*	*0.7*	15
random	jnd	1								1.10	*1.2*	*0.7*	16
random	sar	1								1.14	*1.2*	*0.7*	15
random	her	1								1.14	*1.2*	*0.7*	16
random	san	1								1.17	*1.2*	*0.7*	16
Optimisation with all parameters and fixed conditional uncertainty cap for all stocks [“(j) rfb (cond. capped): MSY-PA - all” in Figure 8.7 in Chapter 8]													
one-way	ang3	16	1	3	3	1.1	0.3	0.6	1	0.99	*1.2*	*0.7*	81
one-way	rjc2	21	0	3	3	1.3	1.0	0.6	2	0.99	*1.2*	*0.7*	85
one-way	smn	37	0	3	3	1.0	0.9	1.1	5	0.65	*1.2*	*0.7*	53
one-way	wlf	47	0	4	3	1.0	0.4	0.9	1	1.07	*1.2*	*0.7*	65
one-way	meg	16	0	3	3	1.5	0.8	1.1	1	1.52	*1.2*	*0.7*	80
one-way	lin	20	0	3	3	1.7	1.0	1.5	1	0.96	*1.2*	*0.7*	71
one-way	rjc	19	0	3	3	1.1	0.7	1.6	1	0.97	*1.2*	*0.7*	69
one-way	syc	26	0	3	3	1.7	0.6	1.5	3	0.87	*1.2*	*0.7*	55
one-way	sdv	14	0	3	3	1.0	0.7	1.0	1	0.92	*1.2*	*0.7*	65
one-way	ang	20	0	3	4	1.3	0.7	1.6	1	0.90	*1.2*	*0.7*	62
one-way	ang2	51	0	3	4	1.3	0.8	1.5	1	0.93	*1.2*	*0.7*	72
one-way	pol	18	0	3	3	1.4	0.7	1.6	1	0.94	*1.2*	*0.7*	68
one-way	had	10	0	2	3	0.9	0.7	2.0	1	0.95	*1.2*	*0.7*	58
one-way	nep	15	0	3	3	1.4	0.6	1.3	1	0.97	*1.2*	*0.7*	66
one-way	mut	10	0	2	3	0.9	0.7	2.0	1	0.95	*1.2*	*0.7*	50
one-way	sbb	12	0	3	3	1.2	0.3	1.1	1	0.56	*1.2*	*0.7*	36
one-way	ple	10	0	2	3	0.9	0.7	2.0	1	0.95	*1.2*	*0.7*	48
one-way	syc2	25	0	3	3	2.0	0.4	1.2	3	0.82	*1.2*	*0.7*	43
one-way	arg	23	0	3	3	1.5	0.8	1.3	4	0.66	*1.2*	*0.7*	35
one-way	tur	10	0	2	3	0.9	0.7	2.0	1	0.95	*1.2*	*0.7*	57
one-way	gut	20	1	4	3	1.3	0.9	1.2	1	0.55	*1.2*	*0.7*	32
one-way	whg	16	1	3	3	0.8	0.6	0.8	1	0.39	*1.2*	*0.7*	26
one-way	bll	17	0	2	3	0.7	0.7	0.4	1	0.17	*1.2*	*0.7*	29
one-way	lem	15	0	4	3	0.9	0.7	1.1	1	0.57	*1.2*	*0.7*	32
one-way	ane	14	0	2	3	0.9	0.6	0.8	1	0.40	*1.2*	*0.7*	16
one-way	jnd	18	1	3	2	0.8	0.4	1.1	3	0.88	*1.2*	*0.7*	18

Table D.1: (continued).

Fishing history	**Stock**	**Gener-ations**	n_0	n_1	n_2	e_r	e_f	e_b	v	x	u_u	u_l	**Fitness im-provement [%]**
one-way	sar	28	1	3	3	1.1	1.0	0.9	3	1.01	*1.2*	*0.7*	17
one-way	her	33	1	3	3	1.0	1.0	1.0	3	0.98	*1.2*	*0.7*	17
one-way	san	14	1	2	3	0.5	1.0	0.8	1	1.05	*1.2*	*0.7*	17
random	ang3	10	1	2	4	1.5	1.0	0.9	1	0.00	*1.2*	*0.7*	38
random	rjc2	13	0	2	3	0.8	0.3	0.3	1	0.00	*1.2*	*0.7*	38
random	smn	13	1	3	3	1.2	0.2	1.3	3	0.74	*1.2*	*0.7*	41
random	wlf	10	1	3	4	0.9	1.5	0.7	1	0.57	*1.2*	*0.7*	47
random	meg	12	0	4	3	0.2	0.7	0.4	2	0.01	*1.2*	*0.7*	18
random	lin	14	1	3	4	1.2	1.5	0.9	1	0.56	*1.2*	*0.7*	32
random	rjc	47	0	4	4	1.9	1.5	1.0	4	0.42	*1.2*	*0.7*	31
random	syc	20	1	3	3	1.0	0.9	1.2	2	0.74	*1.2*	*0.7*	29
random	sdv	15	0	4	5	1.7	0.8	0.9	2	0.54	*1.2*	*0.7*	38
random	ang	24	0	4	4	1.1	0.8	1.1	1	0.68	*1.2*	*0.7*	37
random	ang2	17	0	3	4	1.6	1.5	1.3	2	0.67	*1.2*	*0.7*	45
random	pol	20	0	3	3	1.6	0.8	1.7	1	0.72	*1.2*	*0.7*	44
random	had	26	0	3	3	1.1	0.8	1.3	1	0.82	*1.2*	*0.7*	54
random	nep	10	0	2	3	0.9	0.7	2.0	1	0.95	*1.2*	*0.7*	58
random	mut	15	0	2	3	0.9	0.7	1.8	1	0.90	*1.2*	*0.7*	49
random	sbb	61	1	3	4	1.2	1.3	0.6	3	0.50	*1.2*	*0.7*	34
random	ple	10	0	2	3	0.9	0.7	2.0	1	0.95	*1.2*	*0.7*	52
random	syc2	40	1	3	5	1.2	0.7	1.4	3	0.80	*1.2*	*0.7*	35
random	arg	30	0	3	3	1.5	0.8	1.7	4	0.68	*1.2*	*0.7*	30
random	tur	10	0	2	3	0.9	0.7	2.0	1	0.95	*1.2*	*0.7*	59
random	gut	12	1	2	3	1.2	1.2	1.1	1	0.63	*1.2*	*0.7*	31
random	whg	11	0	3	2	0.3	1.1	0.9	1	0.53	*1.2*	*0.7*	21
random	bll	12	0	1	3	0.4	0.7	0.9	1	0.37	*1.2*	*0.7*	25
random	lem	14	0	3	3	1.0	1.5	1.1	1	0.74	*1.2*	*0.7*	36
random	ane	11	0	2	3	1.0	0.7	1.2	1	0.58	*1.2*	*0.7*	16
random	jnd	17	1	2	3	0.1	0.0	0.8	2	1.00	*1.2*	*0.7*	20
random	sar	15	1	2	3	0.0	0.0	0.7	2	1.00	*1.2*	*0.7*	20
random	her	13	1	2	3	0.1	0.2	0.6	2	1.01	*1.2*	*0.7*	20
random	san	13	1	2	3	0.3	0.4	1.0	2	1.00	*1.2*	*0.7*	17

D.2 Figures

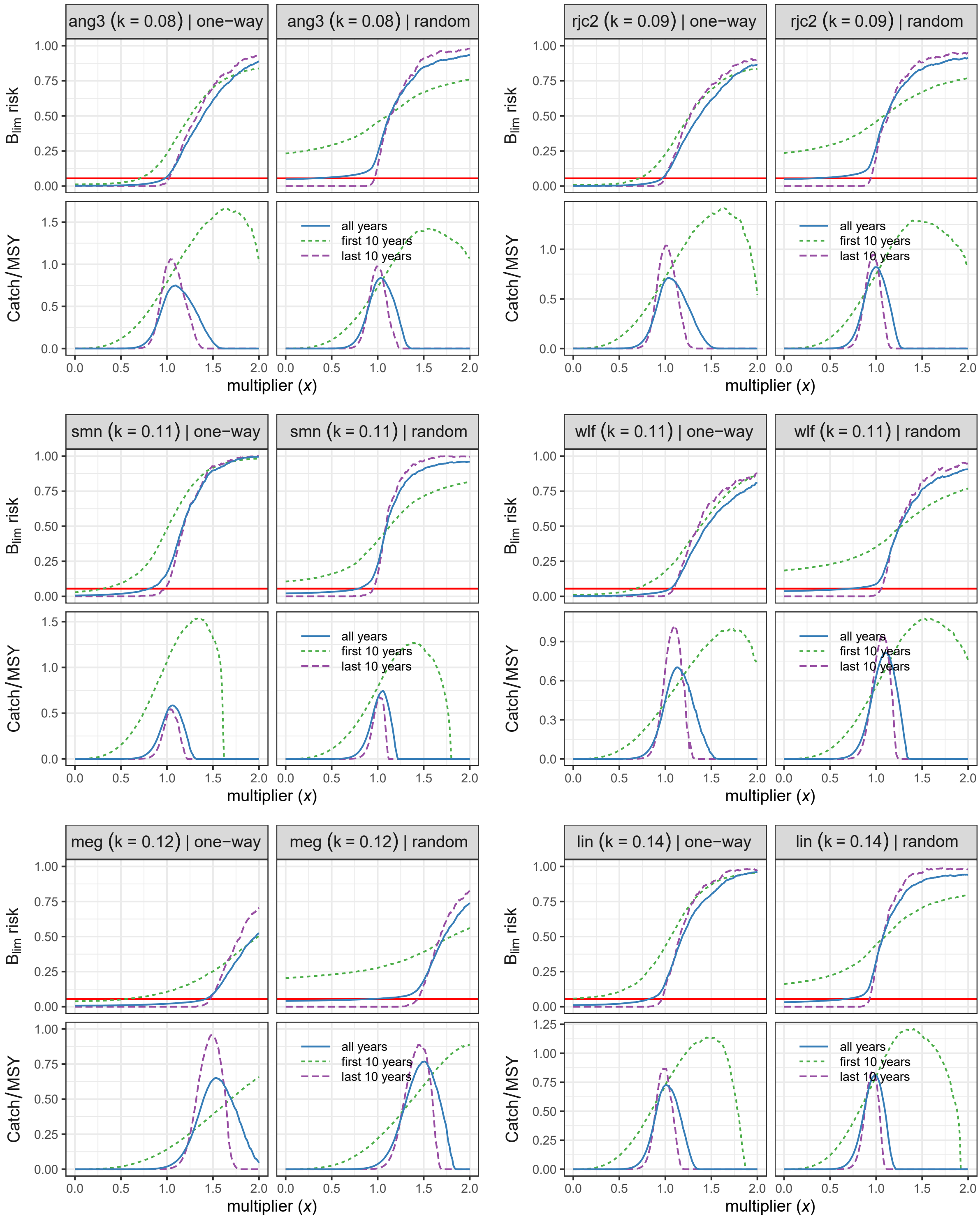

Figure D.1: Impact of the time period used for calculating summary statistics. The red horizontal line indicates the 5% risk limit. (Figure continued on next page)

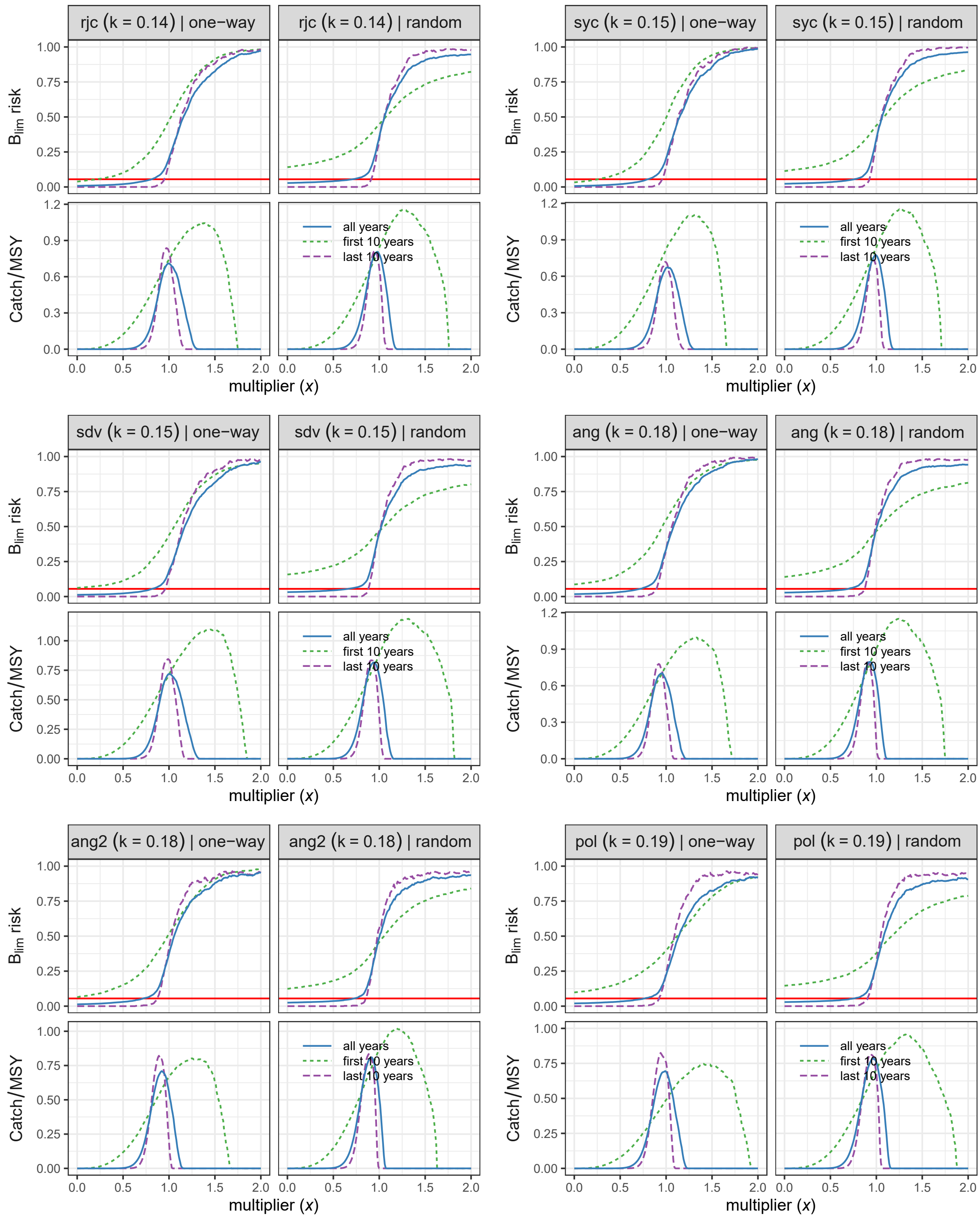

Figure D.1: (continued).

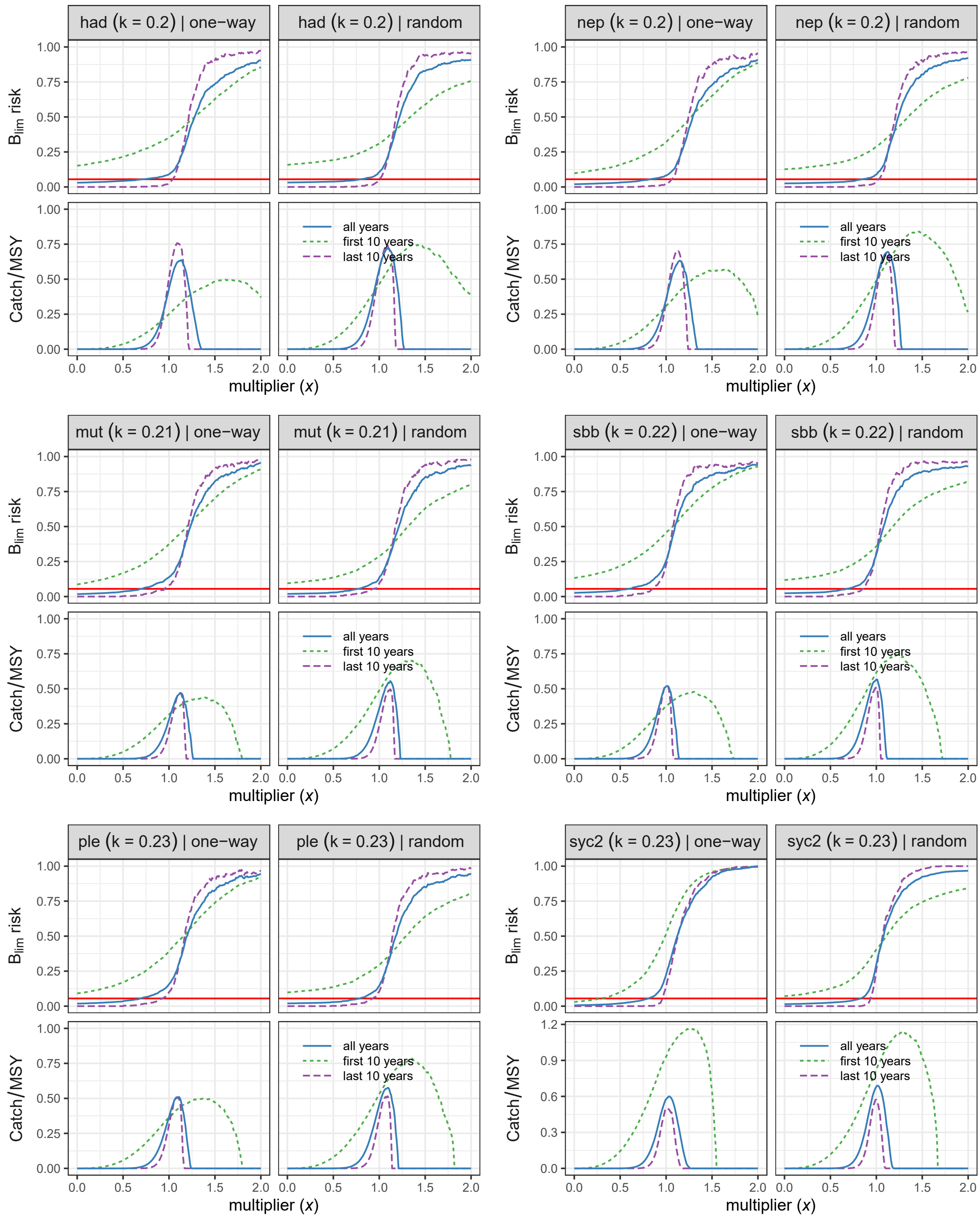

Figure D.1: (continued).

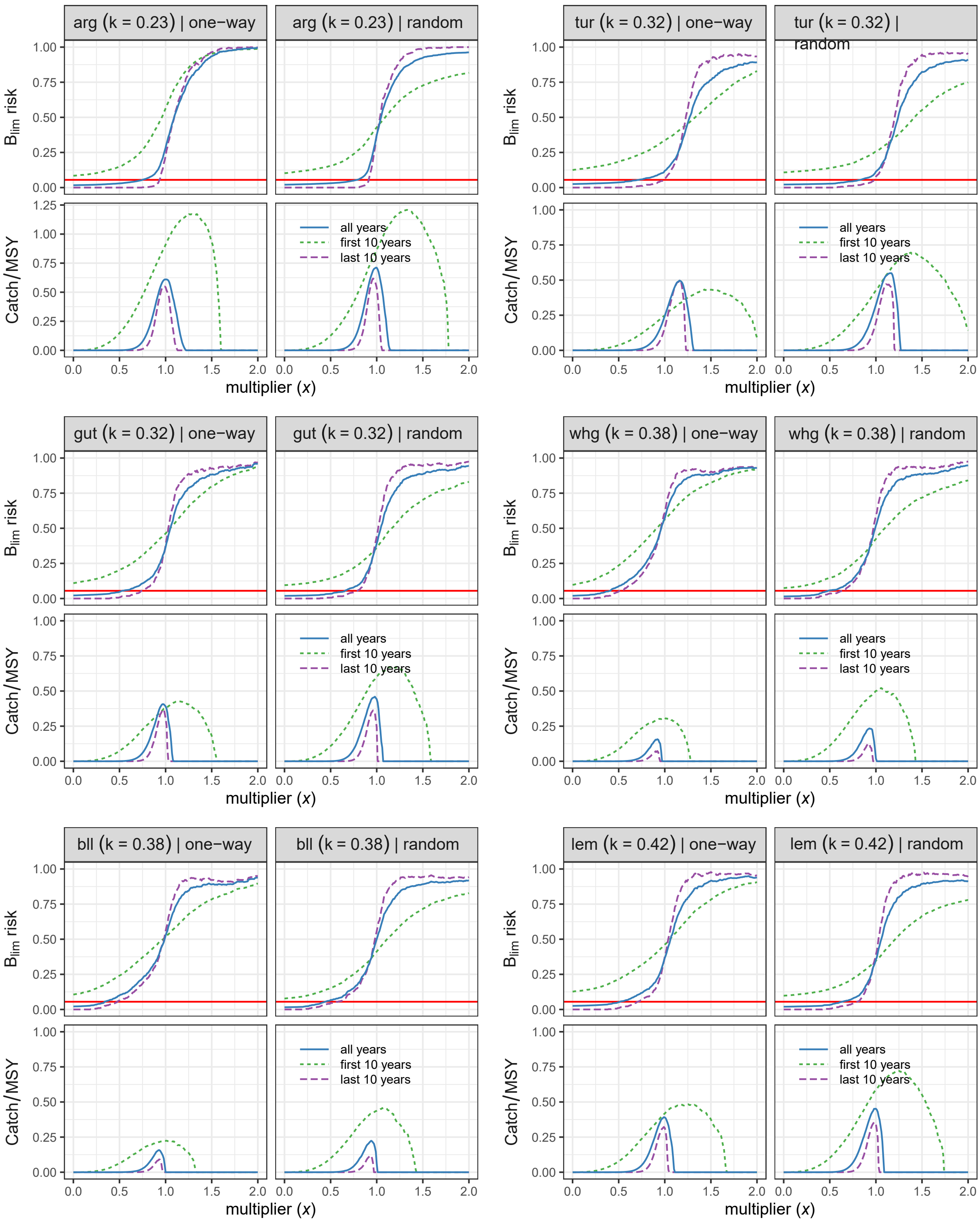

Figure D.1: (continued).

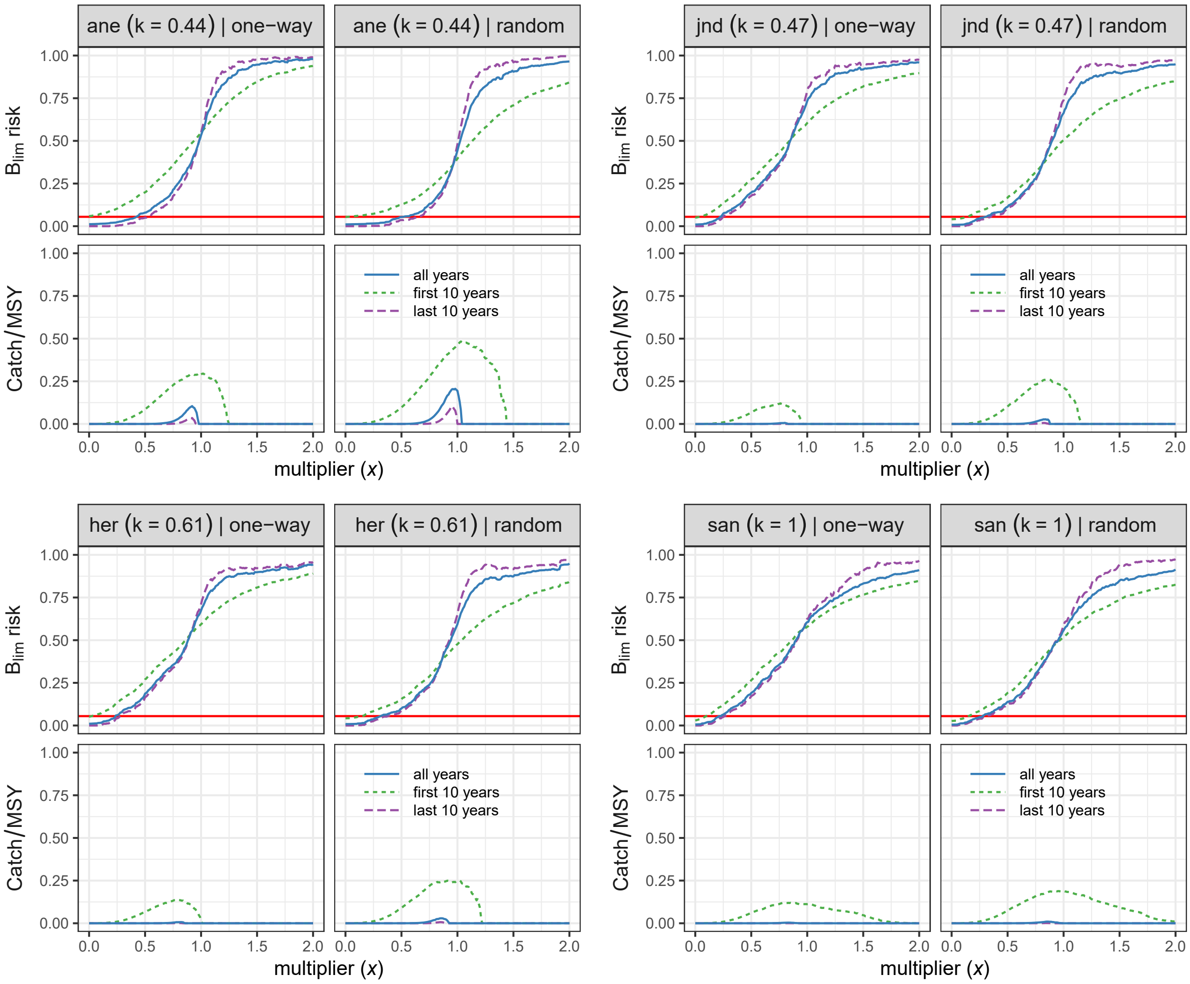

Figure D.1: (continued).

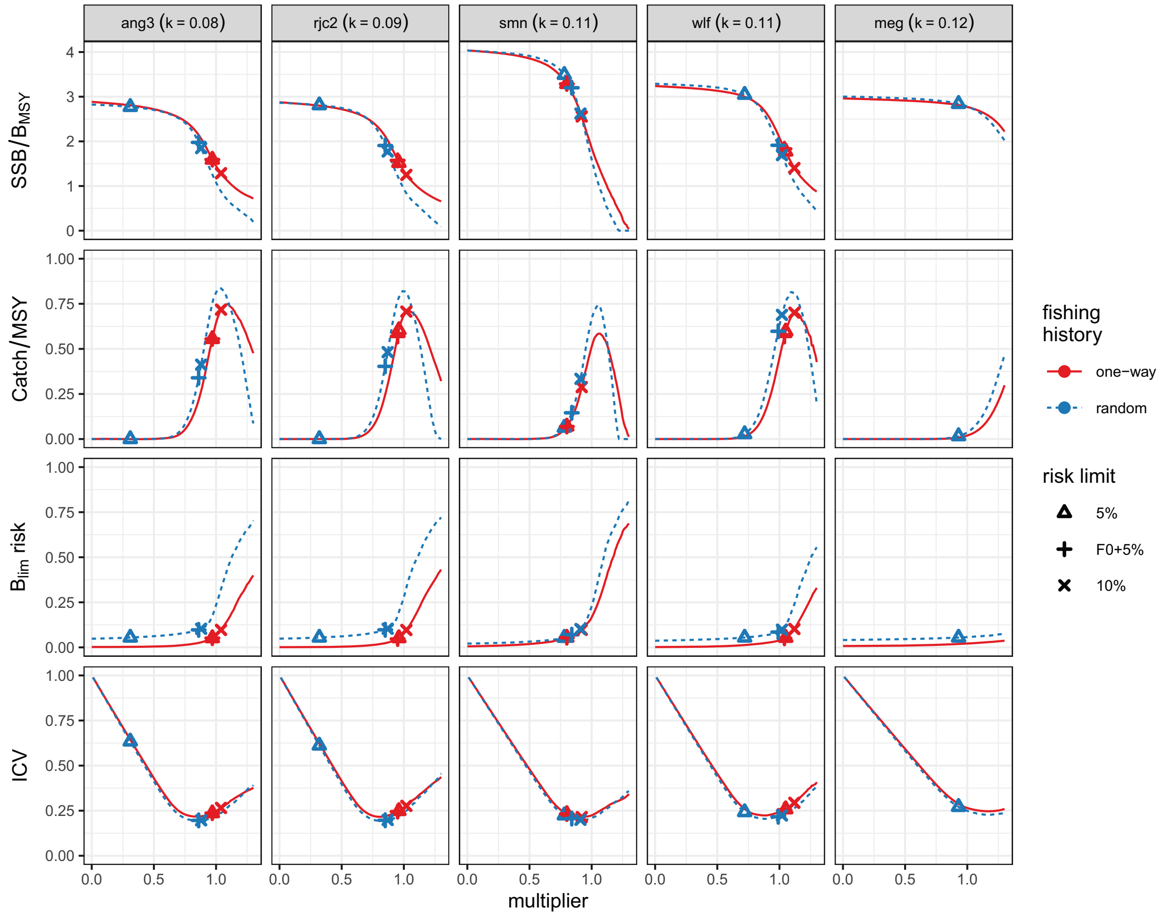

Figure D.2: Impact of different precautionary B_{lim} risk limits on summary statistics in optimising the rfb rule with a multiplier (the remaining parameters are set to their default values of Table 8.1 in Chapter 8). F0+5% indicates the additive 5% point risk limit increase compared to no fishing. The stock IDs correspond to the ones defined in Table 5.1 in Chapter 5. (Figure continued on next page)

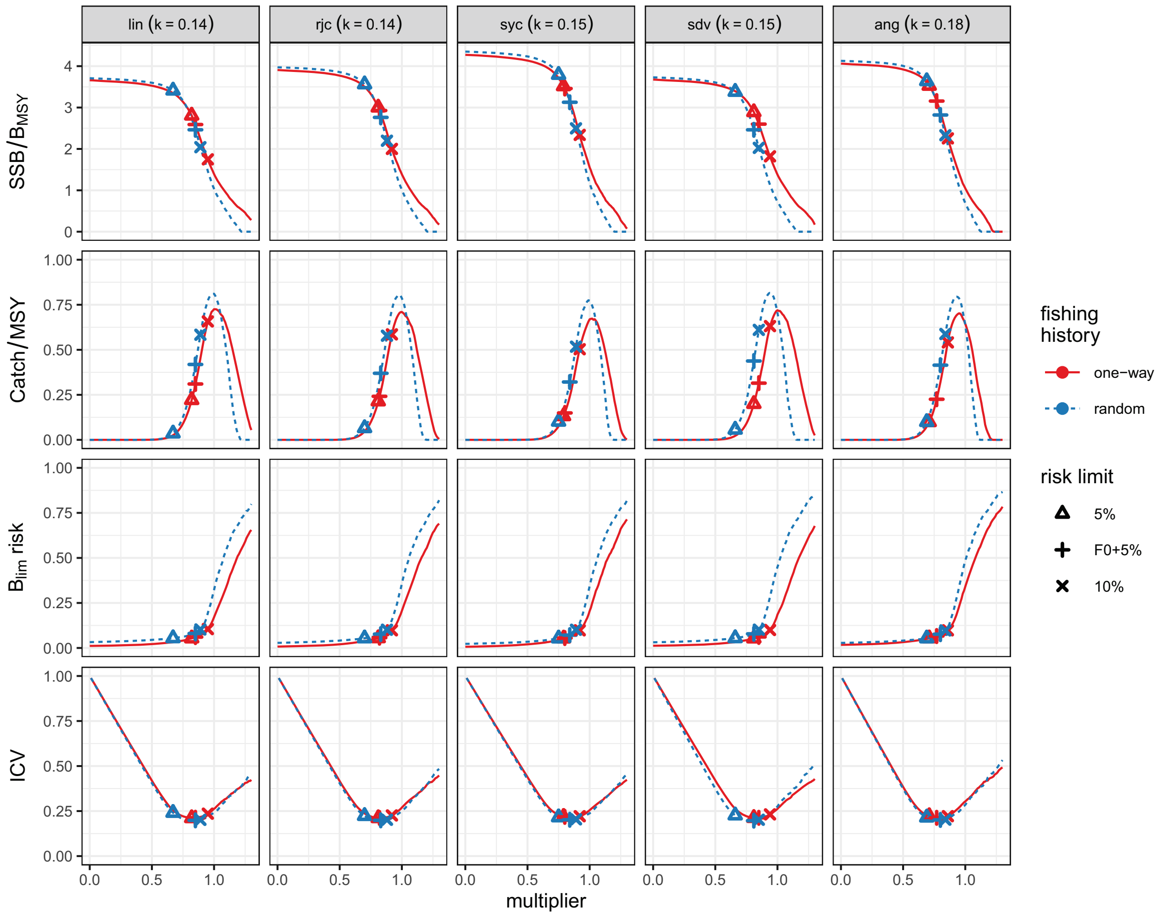

Figure D.2: (continued).

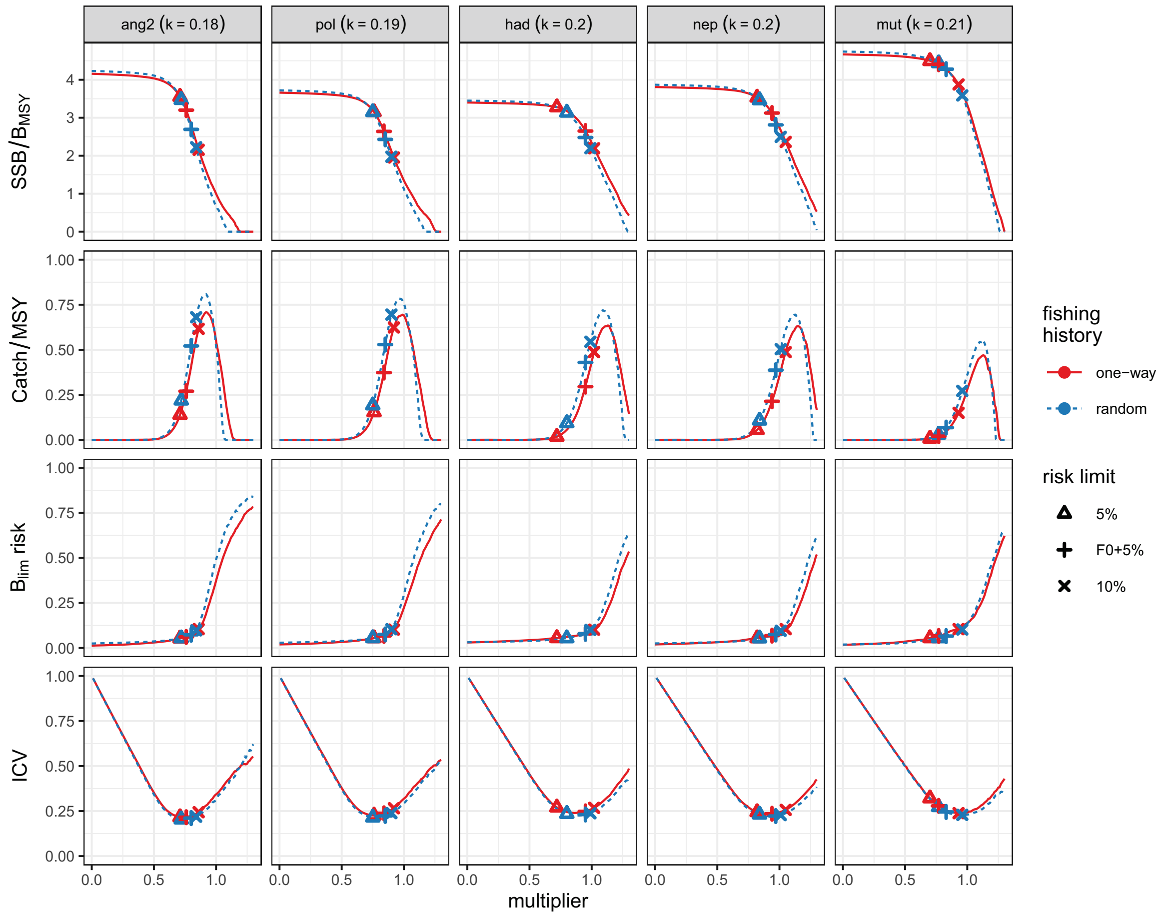

Figure D.2: (continued).

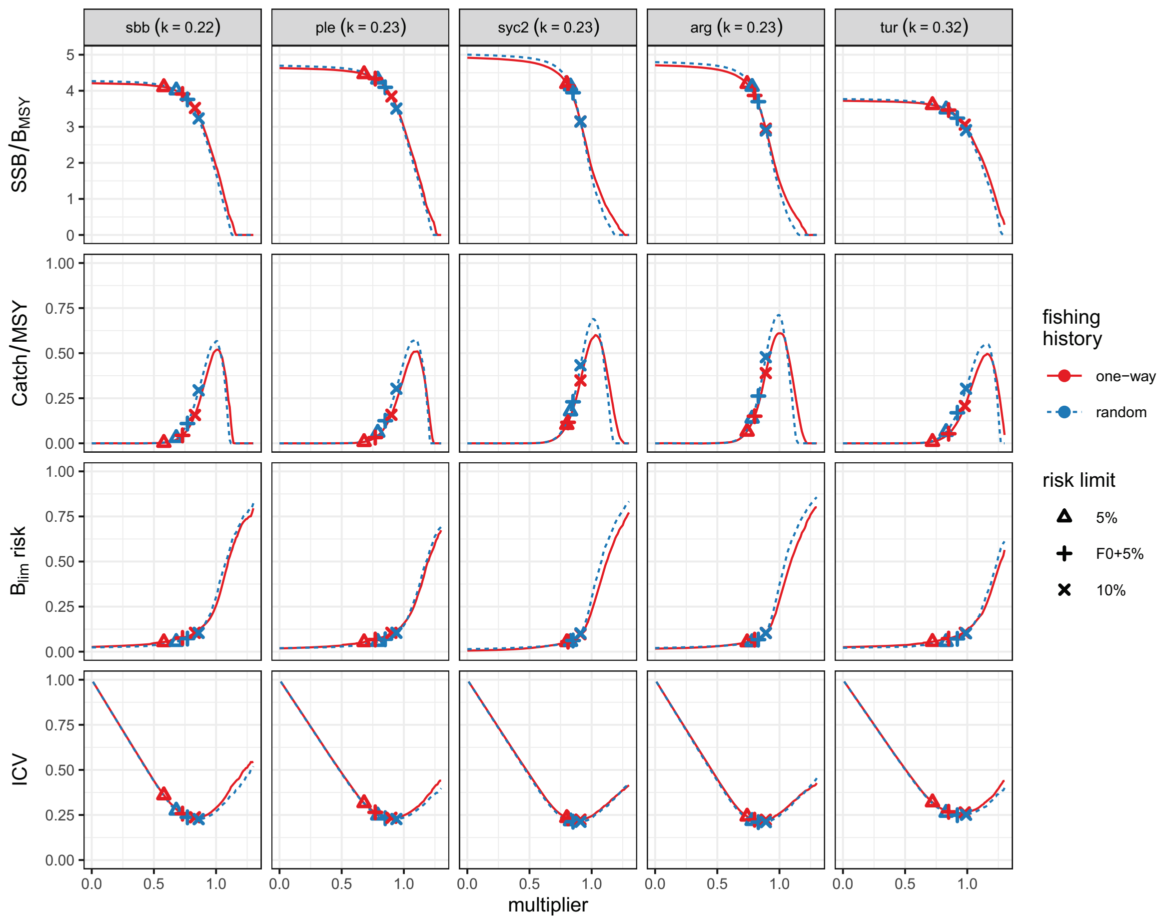

Figure D.2: (continued).

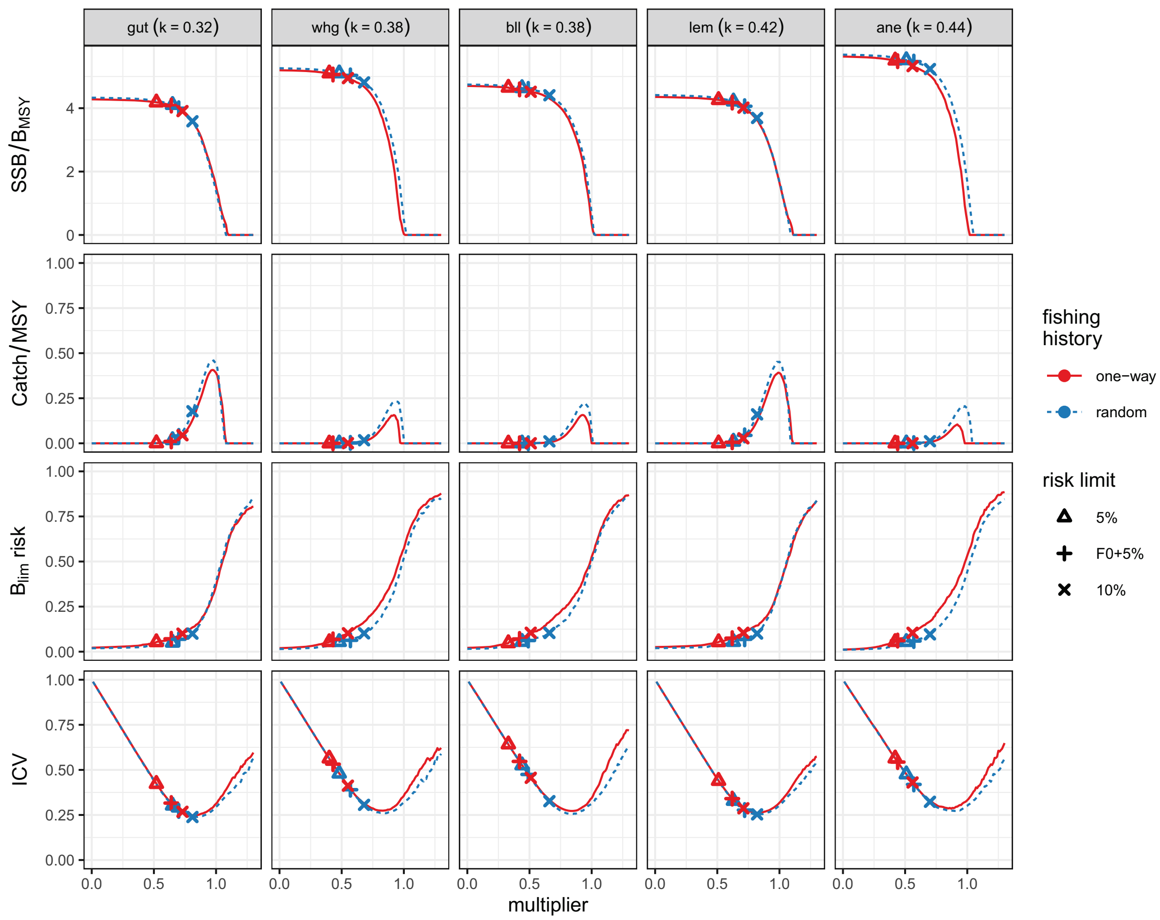

Figure D.2: (continued).

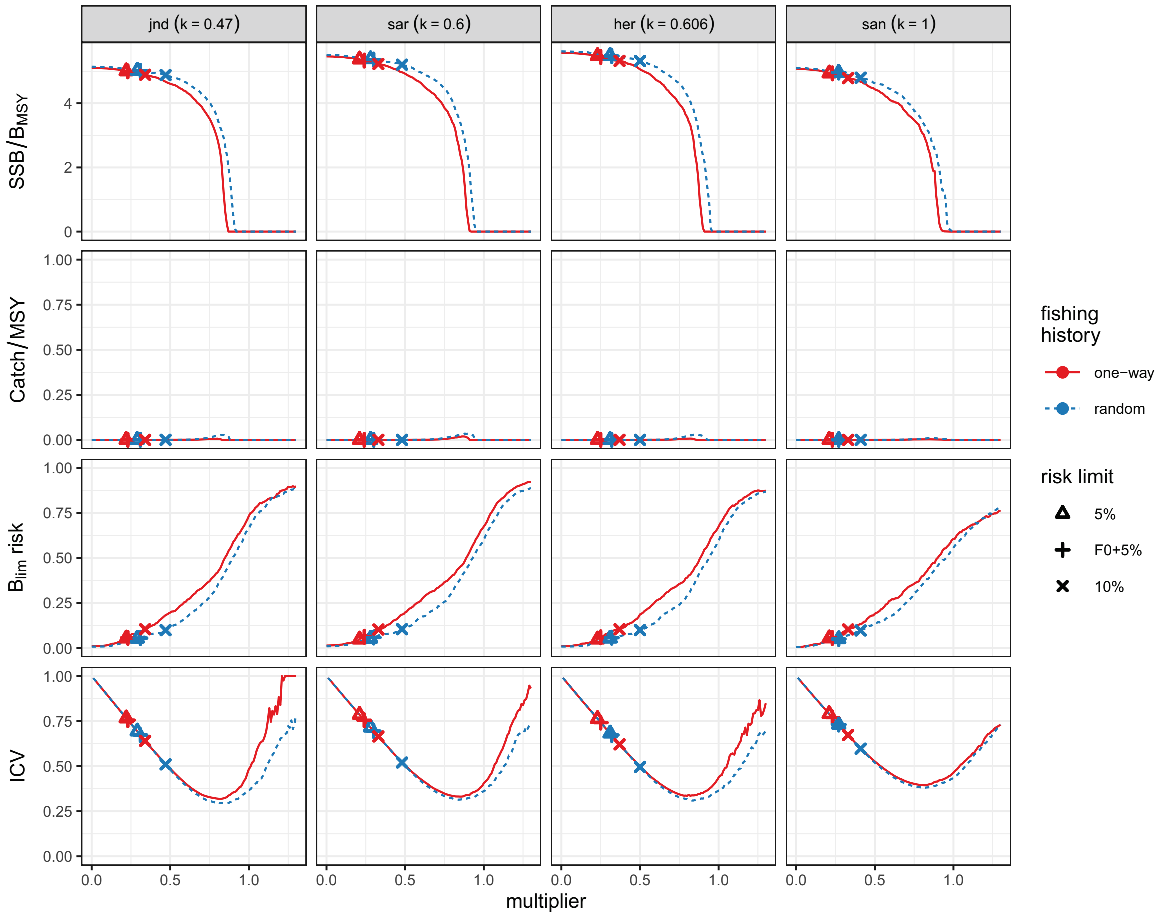

Figure D.2: (continued).

Figure D.3: Performance improvement of the rfb rule for all stocks, achieved through optimisation with the genetic algorithm, and comparison to a "zero-fishing" option and the 2 over 3 rule (from Fischer et al., 2020). For details of options (a)-(j), see Figure 8.7 in Chapter 8. For illustrative purposes, the risk penalty is shown for "rfb: MSY" (d, e) even though this was not included in the optimisation. Shorter bars (less negative fitness) indicate better performance. SSB and catch can be above or below the optimisation target (see Figure 8.5 in Chapter 8), indicated by "+" and "-". The parameterisation where the risk is above 5% are easily identifiable as the bars with large risk-PA elements (in red). The stock IDs correspond to the ones defined in Table 5.1 in Chapter 5. (Figure continued on next page)

Figure D.3: (continued).

Figure D.3: (continued).

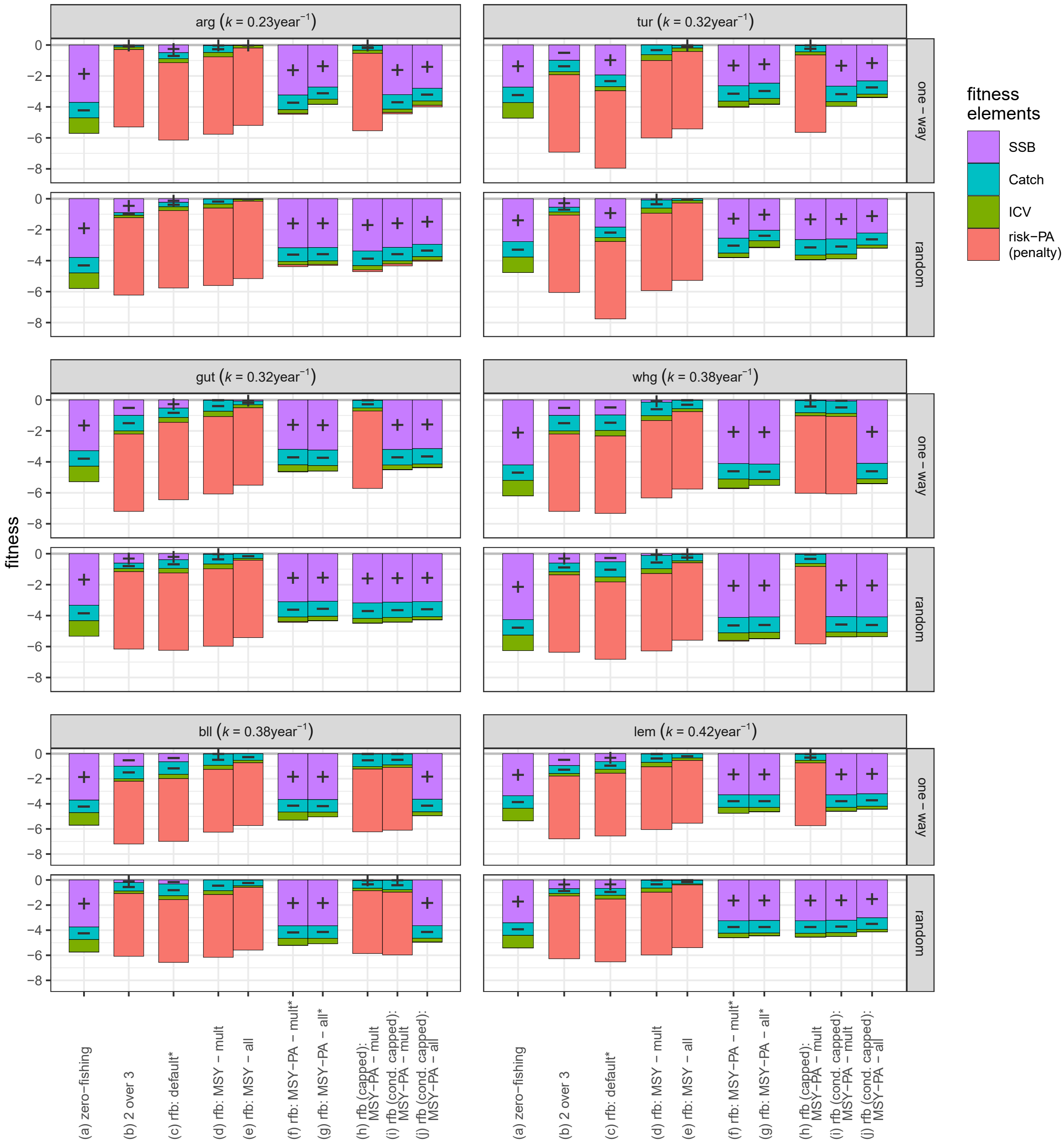

Figure D.3: (continued).

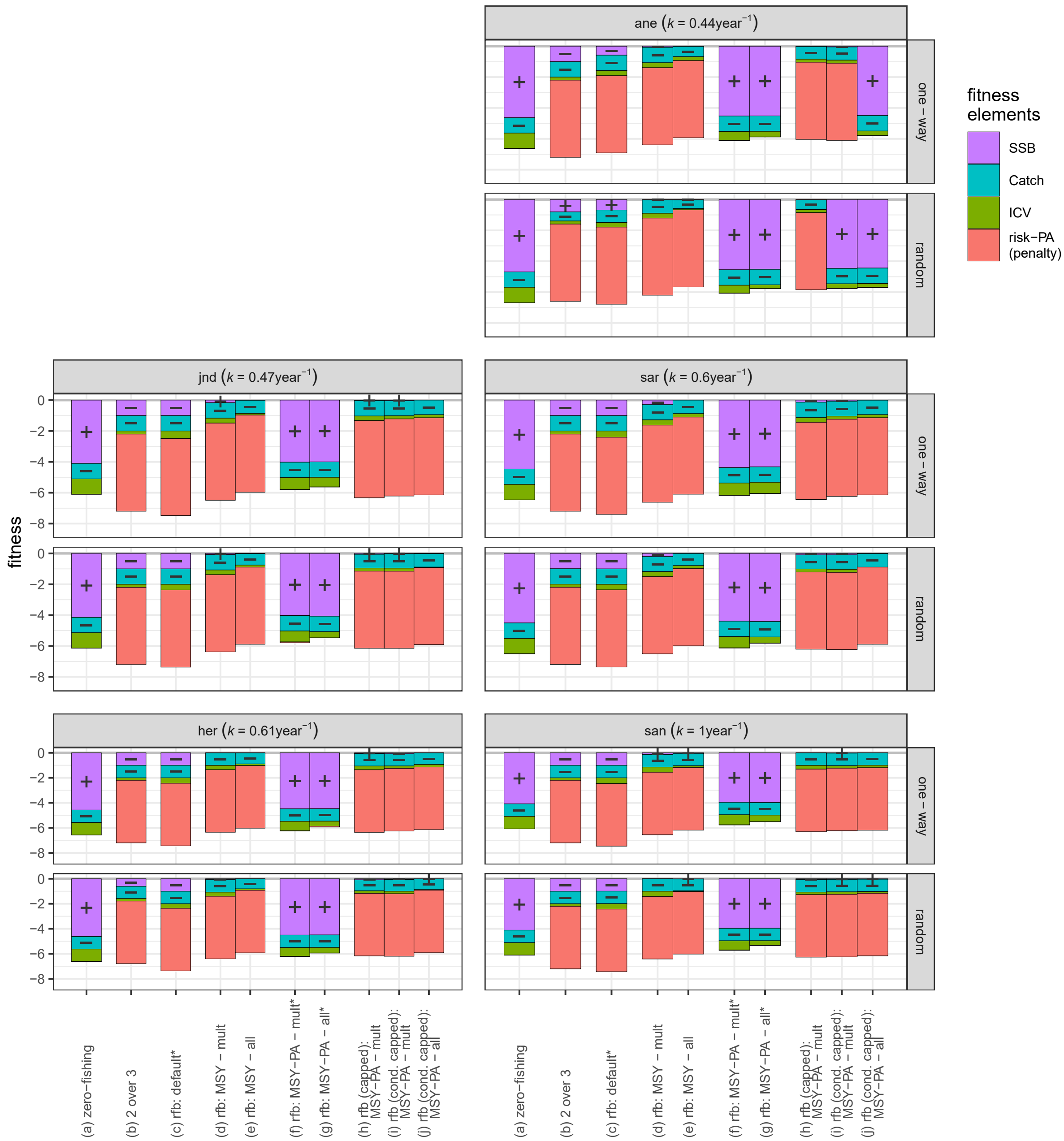

Figure D.3: (continued).

Appendix E

Appendix to Chapter 9

The following is an Appendix to Chapter 9 and based on the supplementary material prepared for Fischer et al. (2022):

> Fischer, S. H., De Oliveira, J. A. A., Mumford, J. D. & Kell, L. T. (2022). Exploring a relative harvest rate strategy for moderately data-limited fisheries management. *ICES Journal of Marine Science*, 12 pp. https://doi.org/10.1093/icesjms/fsac103

E.1 Operating models

The 29 generic operating models are those described in Chapter 5 (Table 5.1). These were generated from life-history information and did not correspond to actual ICES stocks. See Fischer et al. (2020, and Chapters 5 and 6) for details on how the stocks were generated and the equations used in the management strategy evaluation. Where deviations from Fischer et al. (2020) occurred, these are described in the following sections.

E.1.1 Fishing histories

The starting position for all stocks was an unfished condition where spawning stock biomass (SSB) was at the unfished biomass (B_0) in year $y = -100$. Subsequently, all stocks were subjected to three 100-year (years $y = -99$ to $y = 0$) fishing histories (*one-way*, *roller-coaster*, and *random*), see Figure E.1. Fishing histories were defined by the fishing mortality F, relative to F_{MSY} and F_{crash} (the lowest F that caused the stock to collapse in equilibrium). In the *one-way* fishing history, stocks were first fished at $F = 0.5F_{\mathrm{MSY}}$ for 75 years, and subsequently, F was increased exponentially to $0.8F_{\mathrm{crash}}$ over 25 years. In the *roller-coaster* fishing history,

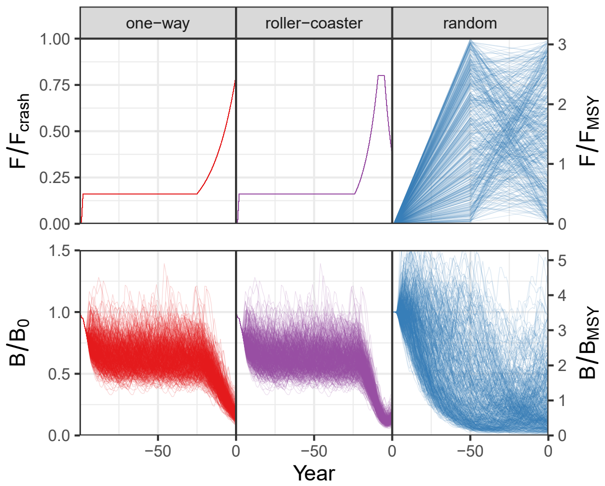

Figure E.1: The three fishing histories of the operating models. Each curve represents one simulation replicate. The SSB (second row) is illustrated for pollack. The starting point in this figure is the unfished stock in year $y = -100$. The fishing history starts in year $y = -99$.

stocks were fished at $F = 0.5F_{\mathrm{MSY}}$ for 75 years, F was increased exponentially to $0.8F_{\mathrm{crash}}$ over 15 years, kept at $0.8F_{\mathrm{crash}}$ for five years, and then reduced to F_{MSY} over the last five years. The *random* fishing history started with zero fishing $F_{y=-99} = 0$ and was then defined by two points in time, where F was drawn independently from a uniform distribution, $F_{y=-50} \sim U(0, F_{\mathrm{crash}})$ and $F_{y=0} \sim U(0, F_{\mathrm{crash}})$, with linear interpolation between these years. This was done independently for each simulation replicate.

E.1.2 Observations

Biomass index

The biomass index I was calculated as

$$I_y = \left(\sum_a N_{a,y} \; s_a \; W_a \right) \; e^{\varepsilon_y}, \tag{E.1}$$

where y is the year, a the age, N the stock numbers from the operating model, s the index selectivity and W the individual weight. A log-normal observation error was added to the aggregated index with e^{ε_y}, where $\varepsilon_y \sim N(0, \sigma_y^2)$ with standard deviation σ (default: $\sigma = 0.2$). The default index was a total biomass index, i.e. selectivity $s_a = 1$.

Catch

Catches were assumed to be known without error.

Catch length data

Catch length distributions were generated by converting ages into lengths with the von Bertalanffy equation:

$$L_a = L_\infty \left(1 - e^{-k(a-a_0)}\right), \tag{E.2}$$

where L_∞, k, and a_0 are the stock-specific von Bertalanffy parameters. The observed mean length $\overline{L}$ in the catch was then calculated as:

$$\overline{L_y} = \frac{\sum_{L>L_c} L\ C_{L,y}}{\sum_{L>L_c} C_{L,y}}\ e^{\varepsilon_y}, \tag{E.3}$$

where L_c is the length at first capture, L are the length classes, and C_L the catch numbers at length. A log-normal observation error was added to the aggregated mean length with e^{ε_y}, where $\varepsilon_y \sim N(0, \sigma_y^2)$ with standard deviation σ (default: $\sigma = 0.2$).

E.2 Alternative management procedures

The harvest rate rule was compared to two alternative management procedures, the 2 over 3 rule simulated by Fischer et al. (2021a, see Chapter 7) and the rfb rule simulated by Fischer et al. (2021b, see Chapter 8).

E.2.1 The 2 over 3 rule

The 2 over 3 rule has the following form:

$$A_{y+1} = A_y\ r\ b_{\mathrm{PA}}, \tag{E.4}$$

where A_{y+1} is the advised catch for year $y + 1$, A_y the previous catch advice, r the trend from a biomass index, and b_{PA} a precautionary buffer. r is defined as

$$r = \frac{\sum_{i=y-2}^{y-1}(I_i/2)}{\sum_{i=y-5}^{y-3}(I_i/3)}, \tag{E.5}$$

where I is the biomass index. The precautionary buffer reduces the catch advice, usually based on the results of running a surplus production model, and is defined as

$$b_{\mathrm{PA}} = \begin{cases} 1, & \text{if both } F \leq F_{\mathrm{MSY}} \text{ \& } B \geq 0.5B_{\mathrm{MSY}}\text{, OR} \\ & \text{if } b_{\mathrm{PA}} = 0.8 \text{ within last two years} \\ 0.8 & \text{otherwise} \end{cases} \tag{E.6}$$

The 2 over 3 rule is usually applied with a biennial advice interval ($v = 2$).

E.2.2 The rfb rule

The rfb rule has the following form:

$$A_{y+1} = A_y \; r \; f \; b \; x, \tag{E.7}$$

where r is the trend from a biomass index, f a fishing proxy, b a biomass safeguard, and x a multiplier. The elements are defined as:

$$r = \left(\frac{\sum_{i=y-n_0-n_1+1}^{y-n_0} (I_i/n_1)}{\sum_{i=y-n_0-n_1-n_2+1}^{y-n_0-n_1} (I_i/n_2)} \right)^{e_r} \tag{E.8}$$

$$f = \left(\frac{\bar{L}_{y-1}}{L_{F=M}} \right)^{e_f} \tag{E.9}$$

$$b = \left(\min \left\{ 1, \frac{I_{y-n_0}}{I_{\mathrm{trigger}}} \right\} \right)^{e_b} \tag{E.10}$$

where I is the biomass index, $\bar{L}$ the mean catch length above the length of first capture L_c, $L_{F=M}$ a MSY proxy reference length, I_{trigger} the index trigger value calculated from the lowest observed index value I_{loss} ($I_{\mathrm{trigger}} = 1.4 I_{\mathrm{loss}}$), n_0 the offset between last biomass index year and assessment year, n_1 and n_2 the number of biomass index years in the numerator and denominator of r, and e_r, e_f, and e_b exponents for weighting r, f and b. The default values are $n_0 = 1$, $n_1 = 2$, $n_2 = 3$, $e_r = e_f = e_b = 1$. The default advice interval is biennial $v = 2$. The rfb rule is used with an uncertainty cap (u_l, u_u) restricting changes in the catch advice, which, by default, is conditional on $I_{y-n_0} \geq I_{\mathrm{trigger}}$ and set to $u_l = 0.7$ and $u_u = 1.2$.

E.3 Additional results

E.3.1 Tables

Table E.1: Default and optimised harvest rate rule parameters. See Table 9.2 in Chapter 9 for definitions of the parameters. Empty cells for parameters take on the default values and are not included in the optimisation. "Generations" is the number of generations required in the genetic algorithm to obtain convergence. "SSB" and "Catch" are relative to their MSY values, "ICV" is the inter-annual catch variability and "risk" the B_{lim} risk. Uncertainty cap values marked with * indicate a fixed conditional uncertainty cap. "Fitness improvement" is the improvement relative to the fitness of the default parameterisation corresponding to the same fishing history and uncertainty cap configuration [no uncertainty cap ($u_u = \infty$, $u_l = 0$) or a fixed conditional uncertainty cap ($u_u = 1.20$, $u_l = 0.70$) if fixed in the optimisation]. (Table continued on next page)

Fitness function	**Fishing history**	**Stock**	**Generations**	x	n_0	n_1	w	v	u_u	u_l	**SSB**	**Catch**	**ICV**	**Risk**	**Fitness improvement [%]**
Default parameters															
				1.00	**1**	**1.4**	**1**	**1.00**	∞	**0**					
Parameter exploration for pollack with MSY fitness function (without risk limit, see Figure 9.8 in Chapter 9)															
MSY	one-way	pol	1	1.00							1.36	1.08	0.22	0.032	0
MSY	one-way	pol	1		0						1.35	1.08	0.22	0.030	2
MSY	one-way	pol	1			5					1.37	1.09	0.06	0.045	18
MSY	one-way	pol	1				0				1.34	1.06	0.20	0.037	7
MSY	one-way	pol	1					1			1.36	1.08	0.22	0.032	0
MSY	one-way	pol	1						∞		1.36	1.08	0.22	0.032	0
MSY	one-way	pol	1							0.90	1.06	1.03	0.10	0.248	37
MSY	one-way	pol	10						∞	0.90	1.06	1.03	0.10	0.248	37
MSY	one-way	pol	42	1.27	0	5	0.5	1			1.00	1.12	0.05	0.088	62
MSY	one-way	pol	10	1.27	0	5	0.5	1	∞	0	1.00	1.12	0.05	0.088	62
MSY	one-way	pol	1	1.46					1.20*	0.70*	1.00	1.13	0.20	0.066	48
MSY	one-way	pol	29	1.27	0	4	0.7	1	1.20*	0.70*	1.00	1.12	0.07	0.087	65
MSY	random	pol	1	0.79							1.01	1.03	0.21	0.234	49
MSY	random	pol	1		0						0.70	1.00	0.23	0.412	0
MSY	random	pol	1			4					0.70	0.99	0.08	0.428	13
MSY	random	pol	1				2.0				0.77	1.01	0.27	0.370	7
MSY	random	pol	1					1			0.70	1.00	0.23	0.415	0
MSY	random	pol	1						1.12		1.00	1.03	0.12	0.252	58

Table E.1: (continued).

Fitness function	Fishing history	Stock	Generations	x	n_0	n_1	w	v	u_u	u_l	SSB	Catch	ICV	Risk	Fitness improvement [%]
MSY	random	pol	1							0.18	0.70	1.00	0.23	0.415	0
MSY	random	pol	13						1.11	0.50	1.01	1.02	0.11	0.249	59
MSY	random	pol	45	0.79	0	5	0.6	1			1.01	1.05	0.05	0.243	63
MSY	random	pol	10	0.79	0	5	0.6	1	∞	0	1.01	1.05	0.05	0.243	63
MSY	random	pol	1	0.86					1.20*	0.70*	1.00	1.04	0.20	0.243	35
MSY	random	pol	18	0.80	1	4	1.0	1	1.20*	0.70*	1.00	1.03	0.07	0.256	53
Parameter exploration for pollack with MSY-PA fitness function (with risk limit, see Figure 9.8 in Chapter 9)															
MSY-PA	one-way	pol	1	1.29							1.04	1.13	0.24	0.049	35
MSY-PA	one-way	pol	1		0						1.35	1.08	0.22	0.030	2
MSY-PA	one-way	pol	1			5					1.37	1.09	0.06	0.045	21
MSY-PA	one-way	pol	1				0				1.34	1.06	0.20	0.037	8
MSY-PA	one-way	pol	1					1			1.36	1.08	0.22	0.032	0
MSY-PA	one-way	pol	1						∞		1.36	1.08	0.22	0.032	0
MSY-PA	one-way	pol	1							0.63	1.34	1.07	0.22	0.046	4
MSY-PA	one-way	pol	10						∞	0.63	1.34	1.07	0.22	0.046	4
MSY-PA	one-way	pol	28	1.23	1	2	1.4	1			1.09	1.13	0.12	0.048	45
MSY-PA	one-way	pol	13	1.22	0	2	1.3	1	∞	0.07	1.08	1.13	0.12	0.042	49
MSY-PA	one-way	pol	1	1.34					1.20*	0.70*	1.10	1.13	0.20	0.049	38
MSY-PA	one-way	pol	15	1.21	1	3	1.6	1	1.20*	0.70*	1.15	1.14	0.10	0.047	45
MSY-PA	random	pol	1	0.48							1.69	0.94	0.20	0.051	82
MSY-PA	random	pol	1		0						0.70	1.00	0.23	0.412	0
MSY-PA	random	pol	1			4					0.70	0.99	0.08	0.428	3
MSY-PA	random	pol	1				2				0.77	1.01	0.27	0.370	0
MSY-PA	random	pol	1					1			0.70	1.00	0.23	0.415	0
MSY-PA	random	pol	1						1.12		1.00	1.03	0.12	0.252	7
MSY-PA	random	pol	1							0.18	0.70	1.00	0.23	0.415	0
MSY-PA	random	pol	23						1.12	0.34	1.00	1.03	0.12	0.253	7
MSY-PA	random	pol	43	0.46	0	5	0.8	1			1.76	0.94	0.05	0.048	84
MSY-PA	random	pol	10	0.46	0	5	0.1	1	∞	0	1.76	0.94	0.05	0.048	84
MSY-PA	random	pol	1	0.51					1.20*	0.70*	1.70	0.95	0.20	0.051	81
MSY-PA	random	pol	26	0.46	1	3	1.5	1	1.20*	0.70*	1.77	0.93	0.08	0.048	83
Optimisation with multiplier ((m) in Figure E.7)															

Table E.1: (continued).

Fitness function	Fishing history	Stock	Generations	x	n_0	n_1	w	v	u_u	u_l	SSB	Catch	ICV	Risk	Fitness improvement [%]
MSY-PA	one-way	ang3	1	1.26							1.00	1.15	0.29	0.010	22
MSY-PA	one-way	rjc2	1	1.28							1.00	1.14	0.28	0.005	23
MSY-PA	one-way	smn	1	0.95							1.40	1.11	0.25	0.046	81
MSY-PA	one-way	wlf	1	1.40							1.00	1.14	0.25	0.013	35
MSY-PA	one-way	meg	1	1.52							1.00	1.07	0.24	0.043	52
MSY-PA	one-way	lin	1	1.29							1.00	1.16	0.26	0.047	33
MSY-PA	one-way	rjc	1	1.26							1.03	1.16	0.25	0.048	30
MSY-PA	one-way	syc	1	1.12							1.20	1.15	0.24	0.048	15
MSY-PA	one-way	sdv	1	1.29							1.00	1.16	0.26	0.046	34
MSY-PA	one-way	ang	1	1.17							1.14	1.15	0.24	0.048	22
MSY-PA	one-way	ang2	1	1.23							1.10	1.14	0.24	0.047	29
MSY-PA	one-way	pol	1	1.29							1.04	1.13	0.24	0.049	35
MSY-PA	one-way	had	1	1.11							1.26	1.08	0.22	0.050	10
MSY-PA	one-way	nep	1	1.21							1.20	1.10	0.22	0.048	25
MSY-PA	one-way	mut	1	1.01							1.50	1.05	0.23	0.048	1
MSY-PA	one-way	sbb	1	0.96							1.45	1.05	0.23	0.049	26
MSY-PA	one-way	ple	1	1.03							1.47	1.06	0.23	0.049	2
MSY-PA	one-way	syc2	1	0.95							1.54	1.09	0.23	0.048	84
MSY-PA	one-way	arg	1	0.99							1.48	1.10	0.24	0.048	1
MSY-PA	one-way	tur	1	1.05							1.41	1.05	0.23	0.048	5
MSY-PA	one-way	gut	1	0.95							1.49	1.04	0.24	0.049	60
MSY-PA	one-way	whg	1	0.73							1.97	0.91	0.29	0.050	76
MSY-PA	one-way	bll	1	0.68							1.89	0.94	0.27	0.048	78
MSY-PA	one-way	lem	1	0.87							1.70	0.99	0.24	0.049	83
MSY-PA	one-way	ane	1	0.71							2.08	0.88	0.30	0.049	74
MSY-PA	one-way	jnd	1	0.40							2.44	0.76	0.34	0.050	73
MSY-PA	one-way	sar	1	0.37							2.81	0.68	0.36	0.051	67
MSY-PA	one-way	her	1	0.38							2.80	0.68	0.35	0.047	67
MSY-PA	one-way	san	1	0.18							3.33	0.44	0.48	0.049	54
MSY-PA	random	ang3	1	0.11							2.43	0.26	0.20	0.054	54
MSY-PA	random	rjc2	1	0.12							2.38	0.33	0.20	0.054	56
MSY-PA	random	smn	1	0.41							2.27	0.68	0.20	0.051	67
MSY-PA	random	wlf	1	0.30							1.89	0.74	0.20	0.053	73

Table E.1: (continued).

Fitness function	Fishing history	Stock	Generations	x	n_0	n_1	w	v	u_u	u_l	SSB	Catch	ICV	Risk	Fitness improvement [%]
MSY-PA	random	meg	1	0.41							1.94	0.59	0.13	0.051	72
MSY-PA	random	lin	1	0.38							2.04	0.78	0.20	0.052	72
MSY-PA	random	rjc	1	0.40							2.04	0.82	0.20	0.051	73
MSY-PA	random	syc	1	0.46							2.08	0.84	0.20	0.052	72
MSY-PA	random	sdv	1	0.41							1.95	0.82	0.20	0.053	74
MSY-PA	random	ang	1	0.47							1.97	0.87	0.20	0.051	75
MSY-PA	random	ang2	1	0.47							1.82	0.93	0.20	0.051	79
MSY-PA	random	pol	1	0.48							1.69	0.94	0.20	0.051	82
MSY-PA	random	had	1	0.44							1.63	0.94	0.21	0.050	84
MSY-PA	random	nep	1	0.44							1.73	0.94	0.21	0.050	81
MSY-PA	random	mut	1	0.36							2.09	0.88	0.21	0.051	73
MSY-PA	random	sbb	1	0.44							1.84	0.93	0.22	0.051	80
MSY-PA	random	ple	1	0.42							2.06	0.89	0.22	0.049	75
MSY-PA	random	syc2	1	0.52							2.34	0.83	0.20	0.051	67
MSY-PA	random	arg	1	0.54							2.24	0.84	0.20	0.052	69
MSY-PA	random	tur	1	0.45							1.81	0.90	0.21	0.048	80
MSY-PA	random	gut	1	0.43							1.94	0.90	0.22	0.048	78
MSY-PA	random	whg	1	0.37							2.51	0.76	0.26	0.049	70
MSY-PA	random	bll	1	0.27							2.40	0.77	0.25	0.046	74
MSY-PA	random	lem	1	0.50							2.05	0.87	0.23	0.050	76
MSY-PA	random	ane	1	0.34							2.77	0.70	0.27	0.048	64
MSY-PA	random	jnd	1	0.14							3.22	0.53	0.29	0.044	60
MSY-PA	random	sar	1	0.15							3.46	0.49	0.32	0.052	56
MSY-PA	random	her	1	0.15							3.55	0.48	0.31	0.044	55
MSY-PA	random	san	1	0.07							3.88	0.29	0.42	0.036	48
Optimisation with all parameters ((n) in Figure E.7)															
MSY-PA	one-way	ang3	33	1.08	0	4	0.6	2	∞	0.74	1.00	1.10	0.09	0.033	66
MSY-PA	one-way	rjc2	13	1.18	1	5	0.4	2	4.54	0.33	0.99	1.11	0.07	0.015	64
MSY-PA	one-way	smn	11	0.91	1	4	0.3	1	1.65	0.66	1.37	1.09	0.05	0.048	87
MSY-PA	one-way	wlf	28	1.30	0	4	0.9	1	∞	0.41	1.02	1.12	0.06	0.021	67
MSY-PA	one-way	meg	20	1.40	0	2	1.1	1	∞	0.33	1.02	1.05	0.11	0.046	70
MSY-PA	one-way	lin	28	1.10	0	5	0.8	1	∞	0.32	1.13	1.12	0.05	0.042	54
MSY-PA	one-way	rjc	28	1.16	0	3	1.2	1	∞	0.13	1.09	1.15	0.08	0.044	52

Table E.1: (continued).

Fitness function	Fishing history	Stock	Generations	x	n_0	n_1	w	v	u_u	u_l	SSB	Catch	ICV	Risk	Fitness improvement [%]
MSY-PA	one-way	syc	24	1.02	0	3	0.5	1	∞	0.21	1.28	1.11	0.07	0.044	34
MSY-PA	one-way	sdv	28	1.15	0	3	0.5	1	∞	0.21	1.07	1.13	0.07	0.046	58
MSY-PA	one-way	ang	13	1.15	0	3	1.4	1	∞	0.39	1.15	1.15	0.09	0.048	41
MSY-PA	one-way	ang2	39	1.12	0	3	1.1	1	∞	0.31	1.20	1.13	0.08	0.046	41
MSY-PA	one-way	pol	13	1.22	0	2	1.3	1	∞	0.07	1.08	1.13	0.12	0.042	49
MSY-PA	one-way	had	17	1.07	0	2	1.3	1	∞	0.06	1.29	1.09	0.12	0.047	24
MSY-PA	one-way	nep	10	1.21	1	1	1.4	1	∞	0.00	1.20	1.10	0.22	0.048	25
MSY-PA	one-way	mut	11	1.00	0	2	1.3	1	∞	0.00	1.51	1.07	0.13	0.045	10
MSY-PA	one-way	sbb	18	0.95	0	2	1.4	1	∞	0.16	1.47	1.07	0.13	0.046	34
MSY-PA	one-way	ple	18	1.04	0	2	1.3	1	∞	0.07	1.45	1.08	0.13	0.048	14
MSY-PA	one-way	syc2	13	0.93	1	3	0.2	1	∞	0.02	1.52	1.08	0.08	0.048	87
MSY-PA	one-way	arg	28	0.94	1	3	1.0	1	∞	0.26	1.52	1.07	0.08	0.048	19
MSY-PA	one-way	tur	30	1.02	0	2	0.8	1	∞	0.10	1.44	1.06	0.13	0.046	14
MSY-PA	one-way	gut	20	1.01	0	2	1.6	1	∞	0.20	1.40	1.09	0.15	0.046	67
MSY-PA	one-way	whg	14	0.87	0	1	1.3	1	∞	0.00	1.69	0.99	0.30	0.049	82
MSY-PA	one-way	bll	24	0.83	0	1	1.1	1	∞	0.16	1.62	1.01	0.28	0.048	84
MSY-PA	one-way	lem	15	0.98	0	2	1.7	1	∞	0.25	1.51	1.07	0.16	0.050	87
MSY-PA	one-way	ane	28	0.88	0	1	1.3	1	∞	0.13	1.74	0.98	0.33	0.048	81
MSY-PA	one-way	jnd	43	0.49	0	2	0.8	1	∞	0.19	2.16	0.86	0.24	0.047	80
MSY-PA	one-way	sar	36	0.40	0	2	0.7	1	∞	0.32	2.69	0.74	0.24	0.044	71
MSY-PA	one-way	her	28	0.55	0	1	0.6	1	∞	0.25	2.24	0.83	0.39	0.035	76
MSY-PA	one-way	san	24	0.28	0	1	0.6	1	∞	0.15	2.75	0.58	0.54	0.045	63
MSY-PA	random	ang3	21	0.11	1	4	1.6	1	∞	0.08	2.45	0.26	0.06	0.053	57
MSY-PA	random	rjc2	29	0.12	1	3	1.9	1	∞	0.05	2.40	0.33	0.07	0.053	60
MSY-PA	random	smn	19	0.44	1	5	1.6	3	2.58	0.34	2.22	0.73	0.10	0.049	71
MSY-PA	random	wlf	37	0.32	1	4	1.6	3	∞	0.14	1.88	0.79	0.13	0.051	77
MSY-PA	random	meg	37	0.40	0	3	1.6	1	∞	0.19	1.95	0.60	0.06	0.050	74
MSY-PA	random	lin	20	0.37	1	4	1.4	1	∞	0.32	2.10	0.78	0.06	0.050	75
MSY-PA	random	rjc	51	0.41	1	4	1.6	1	∞	0.25	2.03	0.85	0.06	0.048	77
MSY-PA	random	syc	27	0.48	1	4	1.8	2	∞	0.37	2.05	0.88	0.10	0.047	77
MSY-PA	random	sdv	33	0.41	1	4	1.8	2	∞	0.25	1.99	0.84	0.09	0.047	77
MSY-PA	random	ang	14	0.48	1	4	1.4	1	∞	0.25	1.96	0.90	0.06	0.050	79
MSY-PA	random	ang2	59	0.47	1	4	1.9	1	∞	0.22	1.85	0.95	0.06	0.047	82

Table E.1: (continued).

Fitness function	Fishing history	Stock	Generations	x	n_0	n_1	w	v	u_u	u_l	SSB	Catch	ICV	Risk	Fitness improvement [%]
MSY-PA	random	pol	10	0.46	0	5	0.1	1	∞	0.00	1.76	0.94	0.05	0.048	84
MSY-PA	random	had	15	0.42	0	2	0.7	1	∞	0.23	1.67	0.94	0.11	0.047	85
MSY-PA	random	nep	33	0.42	0	2	0.9	1	∞	0.16	1.77	0.94	0.11	0.047	83
MSY-PA	random	mut	33	0.35	0	3	0.7	1	∞	0.17	2.13	0.89	0.09	0.047	76
MSY-PA	random	sbb	14	0.45	0	2	1.0	1	∞	0.07	1.80	0.95	0.12	0.051	82
MSY-PA	random	ple	24	0.41	0	3	0.8	1	∞	0.25	2.09	0.90	0.09	0.046	77
MSY-PA	random	syc2	28	0.53	1	4	0.6	1	∞	0.24	2.32	0.85	0.06	0.048	71
MSY-PA	random	arg	26	0.55	1	4	1.3	1	∞	0.25	2.22	0.87	0.06	0.050	73
MSY-PA	random	tur	15	0.45	0	2	1.2	1	∞	0.23	1.81	0.92	0.12	0.045	82
MSY-PA	random	gut	18	0.42	0	2	1.1	1	∞	0.58	1.96	0.91	0.13	0.043	80
MSY-PA	random	whg	19	0.40	0	2	0.9	1	∞	0.23	2.37	0.82	0.17	0.047	74
MSY-PA	random	bll	38	0.33	0	1	0.8	1	∞	0.17	2.10	0.86	0.26	0.046	79
MSY-PA	random	lem	28	0.50	0	3	0.6	1	∞	0.20	2.05	0.89	0.10	0.050	78
MSY-PA	random	ane	21	0.38	0	2	0.9	1	∞	0.20	2.57	0.77	0.17	0.047	69
MSY-PA	random	jnd	24	0.22	0	1	0.5	1	∞	0.21	2.61	0.70	0.33	0.046	70
MSY-PA	random	sar	20	0.22	0	1	1.3	1	∞	0.03	2.89	0.64	0.35	0.037	66
MSY-PA	random	her	20	0.25	0	1	0.8	1	∞	0.13	2.78	0.66	0.35	0.048	67
MSY-PA	random	san	19	0.11	0	1	0.7	1	∞	0.08	3.39	0.40	0.46	0.033	56
Optimisation with multiplier with fixed conditional uncertainty caps ((g) in Figure E.7 and Figure 9.9 in Chapter 9)															
MSY-PA	one-way	ang3	1	1.39					1.20*	0.70*	1.00	1.15	0.20	0.013	38
MSY-PA	one-way	rjc2	1	1.40					1.20*	0.70*	1.00	1.13	0.20	0.007	40
MSY-PA	one-way	smn	1	1.03					1.20*	0.70*	1.43	1.10	0.20	0.047	3
MSY-PA	one-way	wlf	1	1.54					1.20*	0.70*	1.00	1.15	0.20	0.016	47
MSY-PA	one-way	meg	1	1.63					1.20*	0.70*	1.02	1.08	0.20	0.047	56
MSY-PA	one-way	lin	1	1.37					1.20*	0.70*	1.03	1.15	0.20	0.047	43
MSY-PA	one-way	rjc	1	1.36					1.20*	0.70*	1.05	1.16	0.20	0.049	41
MSY-PA	one-way	syc	1	1.21					1.20*	0.70*	1.22	1.15	0.20	0.048	26
MSY-PA	one-way	sdv	1	1.37					1.20*	0.70*	1.04	1.15	0.20	0.047	43
MSY-PA	one-way	ang	1	1.23					1.20*	0.70*	1.20	1.14	0.20	0.048	29
MSY-PA	one-way	ang2	1	1.31					1.20*	0.70*	1.14	1.14	0.20	0.048	36
MSY-PA	one-way	pol	1	1.34					1.20*	0.70*	1.10	1.13	0.20	0.049	38
MSY-PA	one-way	had	1	1.09					1.20*	0.70*	1.38	1.08	0.20	0.051	5

Table E.1: (continued).

Fitness function	**Fishing history**	**Stock**	**Generations**	x	n_0	n_1	w	v	u_u	u_l	**SSB**	**Catch**	**ICV**	**Risk**	**Fitness improvement [%]**
MSY-PA	one-way	nep	1	1.23					1.20*	0.70*	1.28	1.10	0.20	0.048	24
MSY-PA	one-way	mut	1	1.03					1.20*	0.70*	1.63	1.04	0.20	0.048	2
MSY-PA	one-way	sbb	1	0.94					1.20*	0.70*	1.63	1.04	0.20	0.049	17
MSY-PA	one-way	ple	1	1.06					1.20*	0.70*	1.58	1.05	0.20	0.050	4
MSY-PA	one-way	syc2	1	1.05					1.20*	0.70*	1.53	1.10	0.20	0.048	6
MSY-PA	one-way	arg	1	1.07					1.20*	0.70*	1.51	1.10	0.20	0.049	9
MSY-PA	one-way	tur	1	1.03					1.20*	0.70*	1.58	1.03	0.20	0.049	1
MSY-PA	one-way	gut	1	0.94					1.20*	0.70*	1.68	1.01	0.20	0.050	57
MSY-PA	one-way	whg	1	0.71					1.20*	0.70*	2.37	0.85	0.20	0.050	71
MSY-PA	one-way	bll	1	0.56					1.20*	0.70*	2.49	0.80	0.20	0.052	68
MSY-PA	one-way	lem	1	0.85					1.20*	0.70*	1.94	0.94	0.20	0.051	79
MSY-PA	one-way	ane	1	0.71					1.20*	0.70*	2.49	0.82	0.20	0.050	70
MSY-PA	one-way	jnd	1	0.85					1.20*	0.70*	1.01	0.21	0.20	0.470	16
MSY-PA	one-way	sar	1	1.01					1.20*	0.70*	1.02	0.20	0.20	0.476	1
MSY-PA	one-way	her	1	0.95					1.20*	0.70*	1.04	0.24	0.20	0.473	4
MSY-PA	one-way	san	1	0.21					1.20*	0.70*	3.89	0.35	0.20	0.050	54
MSY-PA	random	ang3	1	0.04					1.20*	0.70*	2.65	0.10	0.20	0.055	43
MSY-PA	random	rjc2	1	0.03					1.20*	0.70*	2.70	0.09	0.20	0.055	43
MSY-PA	random	smn	1	0.44					1.20*	0.70*	2.26	0.70	0.20	0.051	66
MSY-PA	random	wlf	1	0.32					1.20*	0.70*	1.89	0.76	0.20	0.054	72
MSY-PA	random	meg	1	0.44					1.20*	0.70*	1.93	0.60	0.13	0.052	72
MSY-PA	random	lin	1	0.38					1.20*	0.70*	2.11	0.76	0.20	0.052	70
MSY-PA	random	rjc	1	0.43					1.20*	0.70*	2.01	0.84	0.20	0.053	72
MSY-PA	random	syc	1	0.48					1.20*	0.70*	2.10	0.85	0.20	0.052	71
MSY-PA	random	sdv	1	0.42					1.20*	0.70*	1.99	0.82	0.20	0.053	72
MSY-PA	random	ang	1	0.50					1.20*	0.70*	1.97	0.88	0.20	0.052	75
MSY-PA	random	ang2	1	0.50					1.20*	0.70*	1.82	0.94	0.20	0.050	79
MSY-PA	random	pol	1	0.51					1.20*	0.70*	1.70	0.95	0.20	0.051	81
MSY-PA	random	had	1	0.46					1.20*	0.70*	1.69	0.94	0.20	0.051	82
MSY-PA	random	nep	1	0.46					1.20*	0.70*	1.78	0.94	0.20	0.051	79
MSY-PA	random	mut	1	0.37					1.20*	0.70*	2.24	0.85	0.20	0.051	69
MSY-PA	random	sbb	1	0.45					1.20*	0.70*	1.97	0.91	0.20	0.050	76
MSY-PA	random	ple	1	0.44					1.20*	0.70*	2.15	0.88	0.20	0.051	71

Table E.1: (continued).

Fitness function	Fishing history	Stock	Generations	x	n_0	n_1	w	v	u_u	u_l	SSB	Catch	ICV	Risk	Fitness improvement [%]
MSY-PA	random	syc2	1	0.57					1.20*	0.70*	2.29	0.86	0.20	0.051	68
MSY-PA	random	arg	1	0.58					1.20*	0.70*	2.23	0.86	0.20	0.051	70
MSY-PA	random	tur	1	0.45					1.20*	0.70*	1.96	0.87	0.20	0.050	76
MSY-PA	random	gut	1	0.44					1.20*	0.70*	2.09	0.87	0.20	0.050	74
MSY-PA	random	whg	1	0.36					1.20*	0.70*	2.86	0.70	0.20	0.051	60
MSY-PA	random	bll	1	0.21					1.20*	0.70*	2.97	0.62	0.20	0.052	63
MSY-PA	random	lem	1	0.51					1.20*	0.70*	2.22	0.84	0.20	0.050	71
MSY-PA	random	ane	1	0.34					1.20*	0.70*	3.12	0.65	0.20	0.050	53
MSY-PA	random	jnd	1	0.51					1.20*	0.70*	1.02	0.24	0.20	0.478	17
MSY-PA	random	sar	1	0.62					1.20*	0.70*	1.00	0.18	0.20	0.485	16
MSY-PA	random	her	1	0.58					1.20*	0.70*	1.00	0.24	0.20	0.486	17
MSY-PA	random	san	1	1.95					1.20*	0.70*	1.01	0.09	0.20	0.483	17
Optimisation with all parameters with fixed conditional uncertainty caps ((h) in Figure E.7 and Figure 9.9 in Chapter 9)															
MSY-PA	one-way	ang3	42	1.09	0	5	0.7	1	1.20*	0.70*	1.03	1.11	0.04	0.016	67
MSY-PA	one-way	rjc2	24	1.14	0	4	0.6	1	1.20*	0.70*	1.01	1.11	0.05	0.011	69
MSY-PA	one-way	smn	24	0.90	0	4	1.2	1	1.20*	0.70*	1.40	1.09	0.06	0.047	27
MSY-PA	one-way	wlf	24	1.32	1	4	0.5	1	1.20*	0.70*	1.00	1.12	0.06	0.04	73
MSY-PA	one-way	meg	22	1.53	0	4	1.5	1	1.20*	0.70*	1.01	1.09	0.07	0.046	74
MSY-PA	one-way	lin	22	1.17	0	3	1.2	1	1.20*	0.70*	1.07	1.14	0.08	0.046	58
MSY-PA	one-way	rjc	19	1.15	0	3	1.2	1	1.20*	0.70*	1.10	1.14	0.08	0.048	54
MSY-PA	one-way	syc	25	1.05	0	3	1.3	1	1.20*	0.70*	1.26	1.13	0.08	0.044	39
MSY-PA	one-way	sdv	34	1.11	0	3	1.1	1	1.20*	0.70*	1.12	1.12	0.08	0.045	53
MSY-PA	one-way	ang	24	1.05	0	3	1.3	1	1.20*	0.70*	1.28	1.12	0.09	0.044	37
MSY-PA	one-way	ang2	18	1.19	0	3	1.4	1	1.20*	0.70*	1.14	1.15	0.10	0.046	49
MSY-PA	one-way	pol	15	1.21	1	3	1.6	1	1.20*	0.70*	1.15	1.14	0.10	0.047	45
MSY-PA	one-way	had	28	1.13	0	2	1.4	1	1.20*	0.70*	1.27	1.10	0.14	0.05	27
MSY-PA	one-way	nep	24	1.14	0	4	1.5	1	1.20*	0.70*	1.28	1.11	0.08	0.048	39
MSY-PA	one-way	mut	31	1.02	0	3	1.6	1	1.20*	0.70*	1.53	1.07	0.12	0.048	18
MSY-PA	one-way	sbb	18	0.97	0	3	1.7	1	1.20*	0.70*	1.49	1.08	0.12	0.048	35
MSY-PA	one-way	ple	30	1.02	0	3	1.5	1	1.20*	0.70*	1.51	1.07	0.12	0.049	19
MSY-PA	one-way	syc2	24	0.96	1	4	1.4	1	1.20*	0.70*	1.51	1.10	0.07	0.048	24
MSY-PA	one-way	arg	21	0.96	0	4	1.4	1	1.20*	0.70*	1.52	1.09	0.07	0.047	23

Table E.1: (continued).

Fitness function	**Fishing history**	**Stock**	**Generations**	x	n_0	n_1	w	v	u_u	u_l	**SSB**	**Catch**	**ICV**	**Risk**	**Fitness improvement [%]**
MSY-PA	one-way	tur	13	1.08	0	2	1.4	1	1.20*	0.70*	1.44	1.07	0.17	0.048	18
MSY-PA	one-way	gut	21	1.09	0	1	1.5	1	1.20*	0.70*	1.48	1.07	0.20	0.046	65
MSY-PA	one-way	whg	10	0.71	1	1	1.4	1	1.20*	0.70*	2.37	0.85	0.20	0.05	71
MSY-PA	one-way	bll	10	0.56	1	1	1.4	1	1.20*	0.70*	2.49	0.80	0.20	0.052	68
MSY-PA	one-way	lem	10	1.00	0	1	1.4	1	1.20*	0.70*	1.67	1.02	0.20	0.049	84
MSY-PA	one-way	ane	17	0.88	0	1	1.4	1	1.20*	0.70*	2.11	0.92	0.20	0.048	78
MSY-PA	one-way	jnd	14	0.45	0	3	0.4	3	1.20*	0.70*	1.01	0.40	0.20	0.481	19
MSY-PA	one-way	sar	29	0.46	0	3	0.5	3	1.20*	0.70*	0.99	0.37	0.20	0.487	3
MSY-PA	one-way	her	20	0.46	0	1	1.0	1	1.20*	0.70*	3.00	0.68	0.20	0.05	59
MSY-PA	one-way	san	24	0.28	0	1	1.0	1	1.20*	0.70*	3.52	0.46	0.20	0.05	60
MSY-PA	random	ang3	18	0.10	1	4	1.9	1	1.20*	0.70*	2.48	0.24	0.06	0.053	55
MSY-PA	random	rjc2	24	0.11	1	4	1.9	1	1.20*	0.70*	2.43	0.31	0.06	0.053	57
MSY-PA	random	smn	24	0.47	1	4	1.9	2	1.20*	0.70*	2.16	0.76	0.10	0.048	72
MSY-PA	random	wlf	20	0.37	1	4	1.8	2	1.20*	0.70*	1.78	0.84	0.12	0.053	77
MSY-PA	random	meg	48	0.40	0	3	1.5	1	1.20*	0.70*	1.96	0.60	0.06	0.051	74
MSY-PA	random	lin	26	0.41	1	3	1.7	1	1.20*	0.70*	1.97	0.83	0.08	0.052	76
MSY-PA	random	rjc	24	0.44	1	4	1.8	1	1.20*	0.70*	1.94	0.88	0.06	0.05	79
MSY-PA	random	syc	24	0.52	1	4	1.7	2	1.20*	0.70*	1.95	0.91	0.11	0.052	77
MSY-PA	random	sdv	18	0.41	1	4	1.7	1	1.20*	0.70*	1.98	0.84	0.06	0.05	77
MSY-PA	random	ang	29	0.50	1	3	1.7	1	1.20*	0.70*	1.91	0.92	0.08	0.051	79
MSY-PA	random	ang2	24	0.47	1	3	1.6	1	1.20*	0.70*	1.84	0.94	0.08	0.049	81
MSY-PA	random	pol	26	0.46	1	3	1.5	1	1.20*	0.70*	1.77	0.93	0.08	0.048	83
MSY-PA	random	had	24	0.41	0	4	1.4	1	1.20*	0.70*	1.74	0.93	0.07	0.049	84
MSY-PA	random	nep	14	0.42	0	4	1.4	1	1.20*	0.70*	1.81	0.94	0.07	0.049	82
MSY-PA	random	mut	46	0.34	0	3	0.8	1	1.20*	0.70*	2.20	0.87	0.10	0.05	72
MSY-PA	random	sbb	10	0.45	1	1	1.4	1	1.20*	0.70*	1.97	0.91	0.20	0.05	76
MSY-PA	random	ple	26	0.42	0	2	1.1	1	1.20*	0.70*	2.11	0.89	0.15	0.048	74
MSY-PA	random	syc2	18	0.54	1	4	1.5	1	1.20*	0.70*	2.28	0.86	0.06	0.049	72
MSY-PA	random	arg	15	0.56	1	4	1.6	1	1.20*	0.70*	2.19	0.88	0.06	0.05	74
MSY-PA	random	tur	48	0.41	0	3	1.1	1	1.20*	0.70*	1.97	0.88	0.11	0.044	78
MSY-PA	random	gut	10	0.44	1	1	1.4	1	1.20*	0.70*	2.09	0.87	0.20	0.05	74
MSY-PA	random	whg	10	0.36	1	1	1.4	1	1.20*	0.70*	2.86	0.70	0.20	0.051	60
MSY-PA	random	bll	18	0.33	0	1	1.3	1	1.20*	0.70*	2.40	0.81	0.20	0.049	75

Table E.1: (continued).

Fitness function	**Fishing history**	**Stock**	**Generations**	x	n_0	n_1	w	v	u_u	u_l	**SSB**	**Catch**	**ICV**	**Risk**	**Fitness improvement [%]**
MSY-PA	random	lem	10	0.51	1	1	1.4	1	1.20*	0.70*	2.22	0.84	0.20	0.05	71
MSY-PA	random	ane	22	0.37	0	2	0.9	1	1.20*	0.70*	2.80	0.73	0.20	0.052	59
MSY-PA	random	jnd	27	0.52	0	2	0.7	1	1.20*	0.70*	1.02	0.41	0.20	0.47	19
MSY-PA	random	sar	18	0.49	0	3	0.7	3	1.20*	0.70*	1.00	0.29	0.20	0.486	18
MSY-PA	random	her	18	0.58	0	2	0.6	2	1.20*	0.70*	1.00	0.32	0.20	0.485	18
MSY-PA	random	san	10	1.95	1	1	1.4	1	1.20*	0.70*	1.01	0.09	0.20	0.483	17

E.3.2 Figures

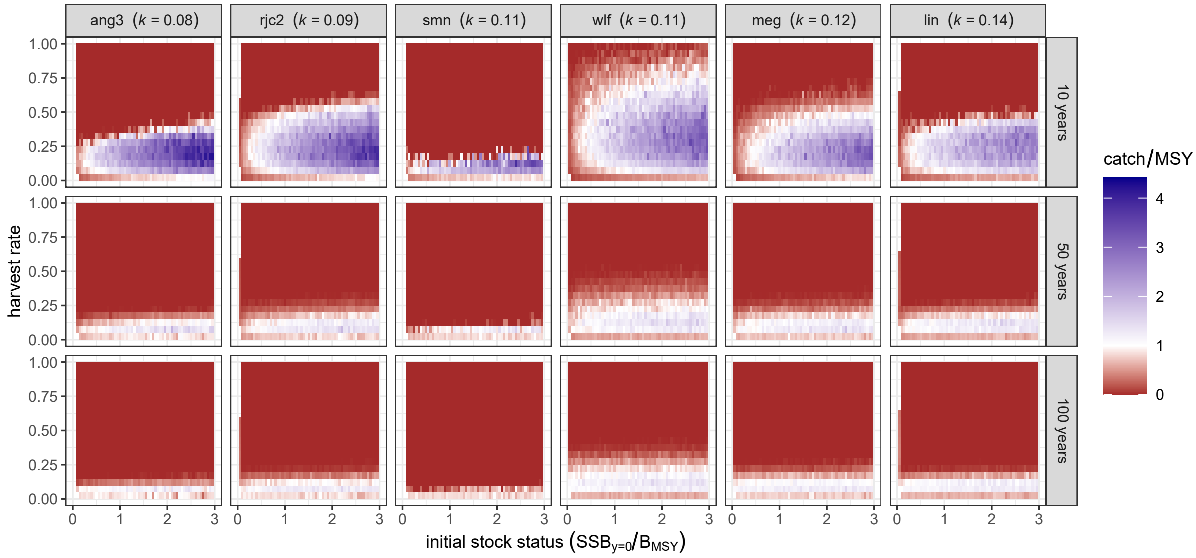

Figure E.2: Realised catch of a pure harvest rate management procedure. Shown is the catch relative to MSY, averaged over three implementation periods (10, 50, and 100 years). The stock IDs correspond to the ones defined in Table 5.1 in Chapter 5. Stocks are sorted by von Bertalanffy individual growth rate k (unit: $year^{-1}$). The colour scale is standardised for these and the following plots in this Figure. (Figure continued)

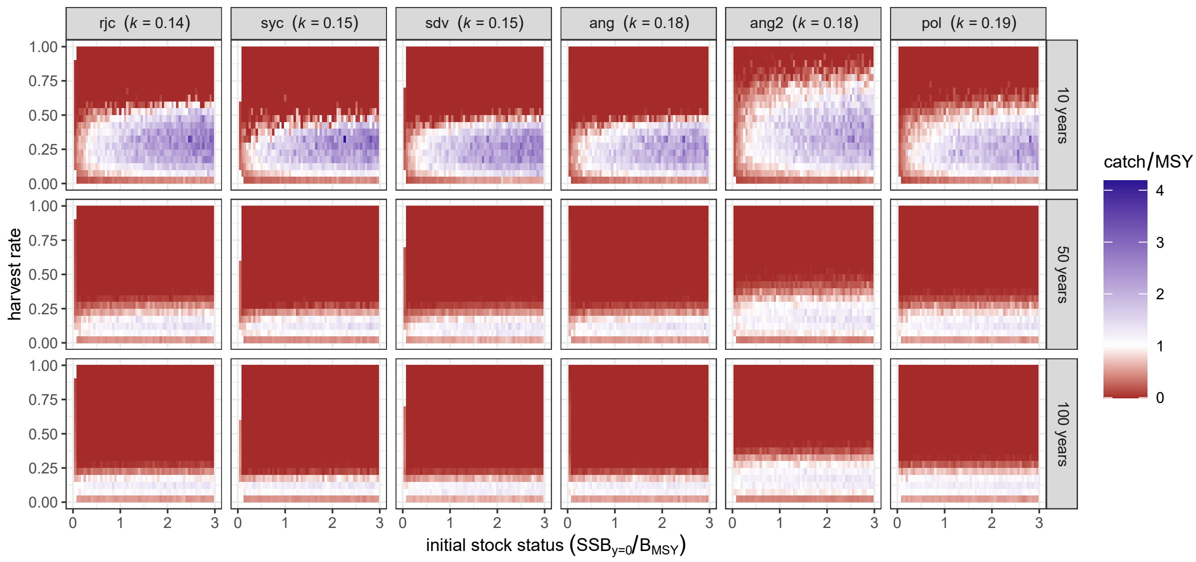

Figure E.2: (continued).

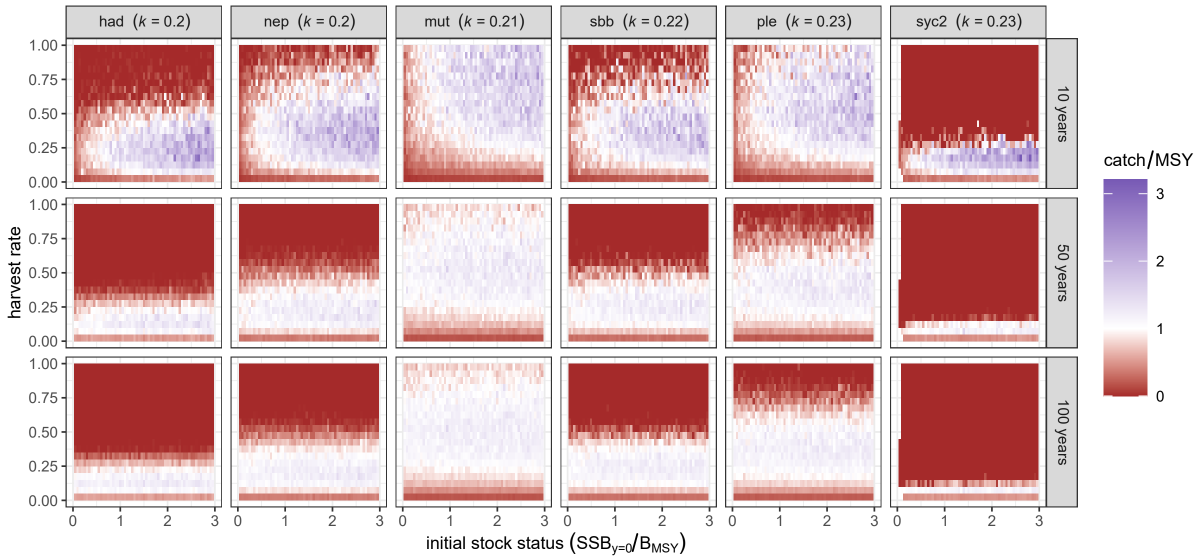

Figure E.2: (continued).

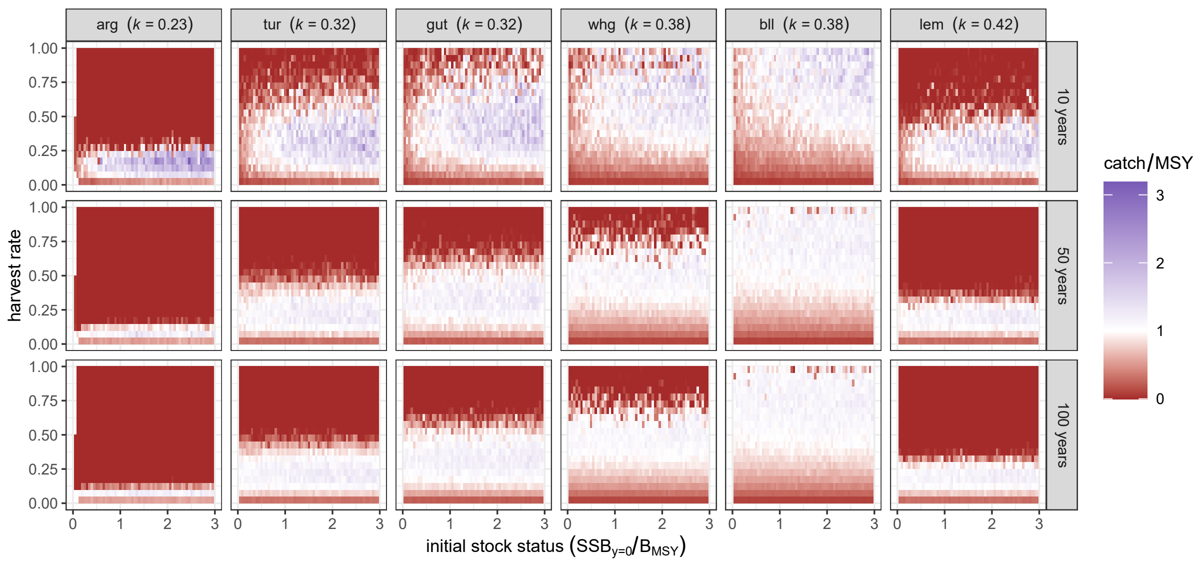

Figure E.2: (continued).

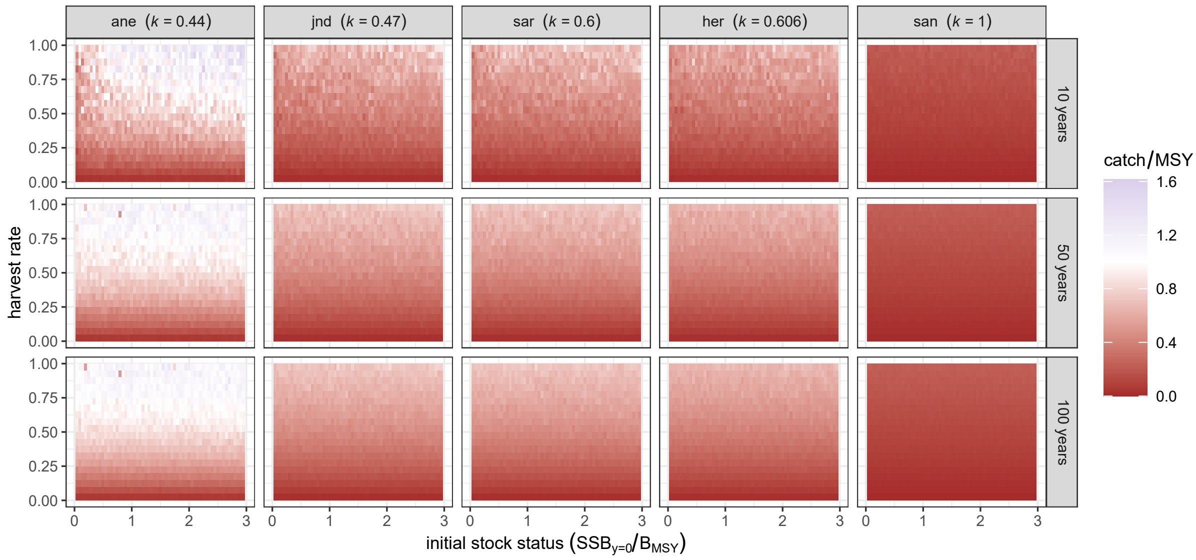

Figure E.2: (continued).

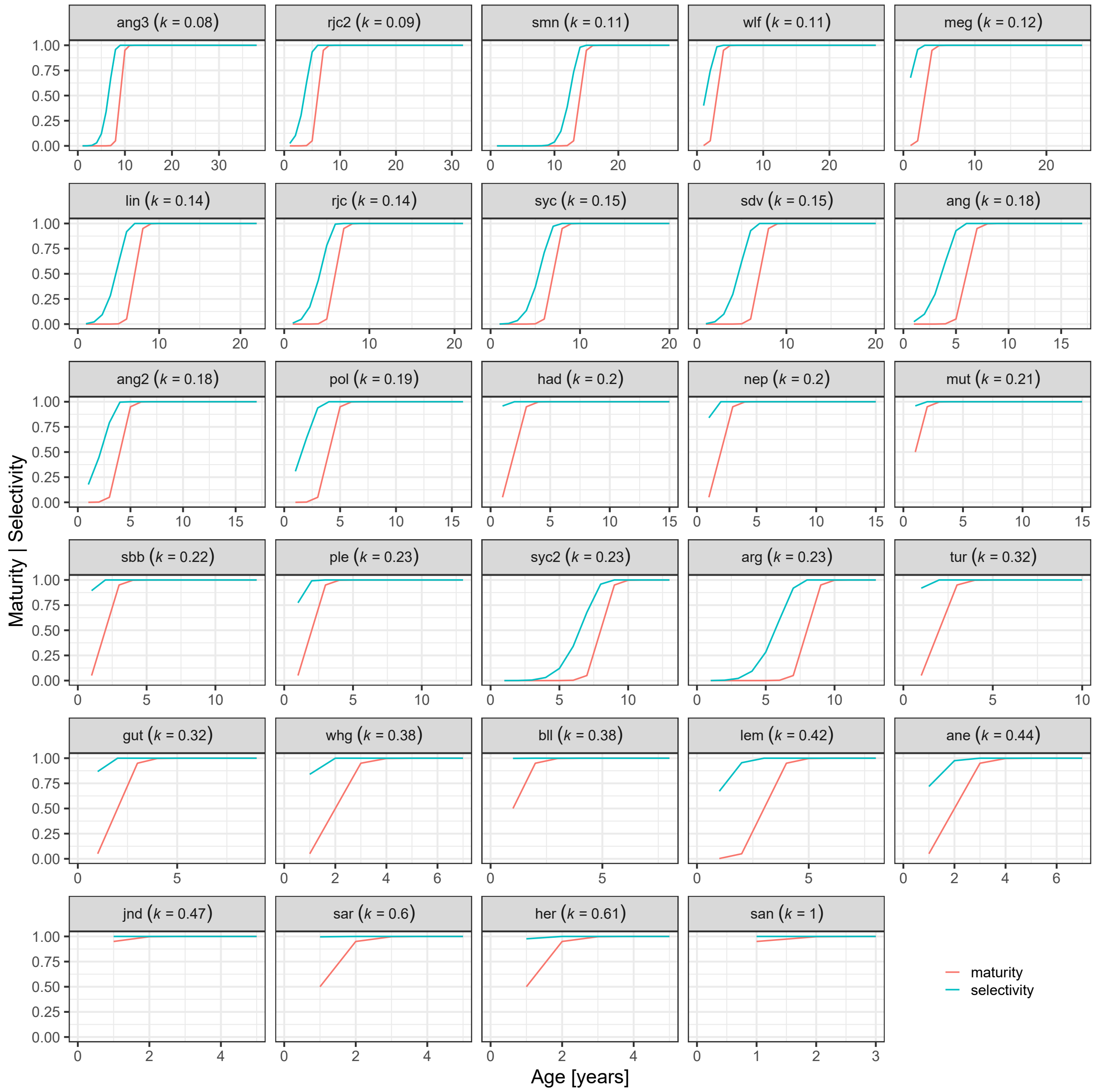

Figure E.3: Fishery selectivity and maturity for the simulated stocks. The stock IDs correspond to the ones defined in Table 5.1 in Chapter 5. Stocks are sorted by von Bertalanffy individual growth rate k (unit: $year^{-1}$).

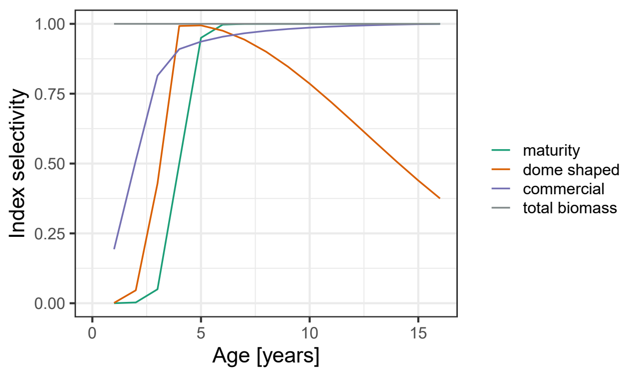

Figure E.4: Index selectivities for pollack.

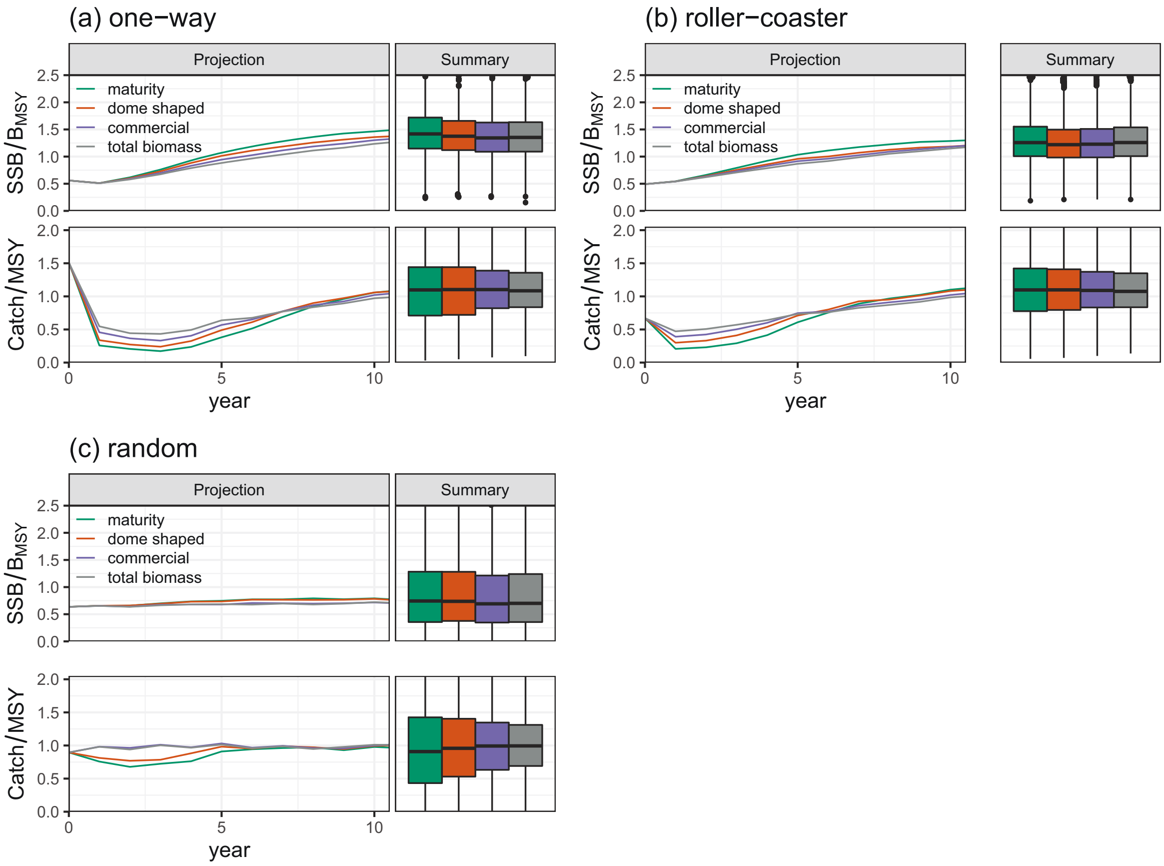

Figure E.5: Impact of the index selectivity on the harvest rate rule for pollack and the three fishing histories (a-c). The projections (left) show the first 10 years, the summary boxplots (right) the full 50-year projections.

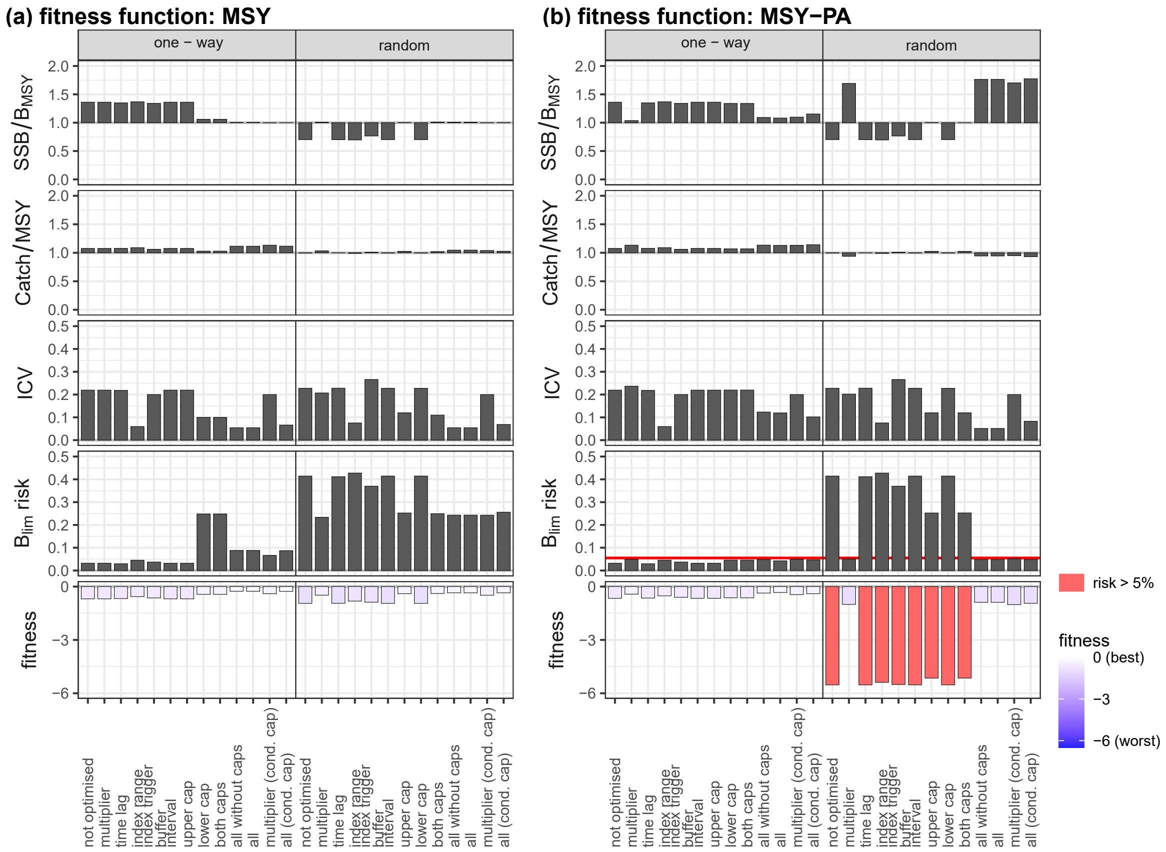

Figure E.6: Performance of the harvest rate rule when including single or combinations of the rule's parameters into the optimisation for pollack. Shown are optimisation for the summary statistics without a risk limit (a) and with a risk limit (b). The following parameter combinations were tested: multiplier (x), time lag (n_0), index range (n_1), index trigger buffer (w), interval (v), upper cap (u_u), lower cap (u_l), both caps (u_u, u_l), all parameters without the caps (x, n_0, n_1, w, v), all parameters (x, n_0, n_1, w, v, u_u, u_l), multiplier with conditional caps (x, $u_u = 1.2$, $u_l = 0.7$), and all parameters with conditional caps (x, n_0, n_1, w, v, $u_u = 1.2$, $u_l = 0.7$).

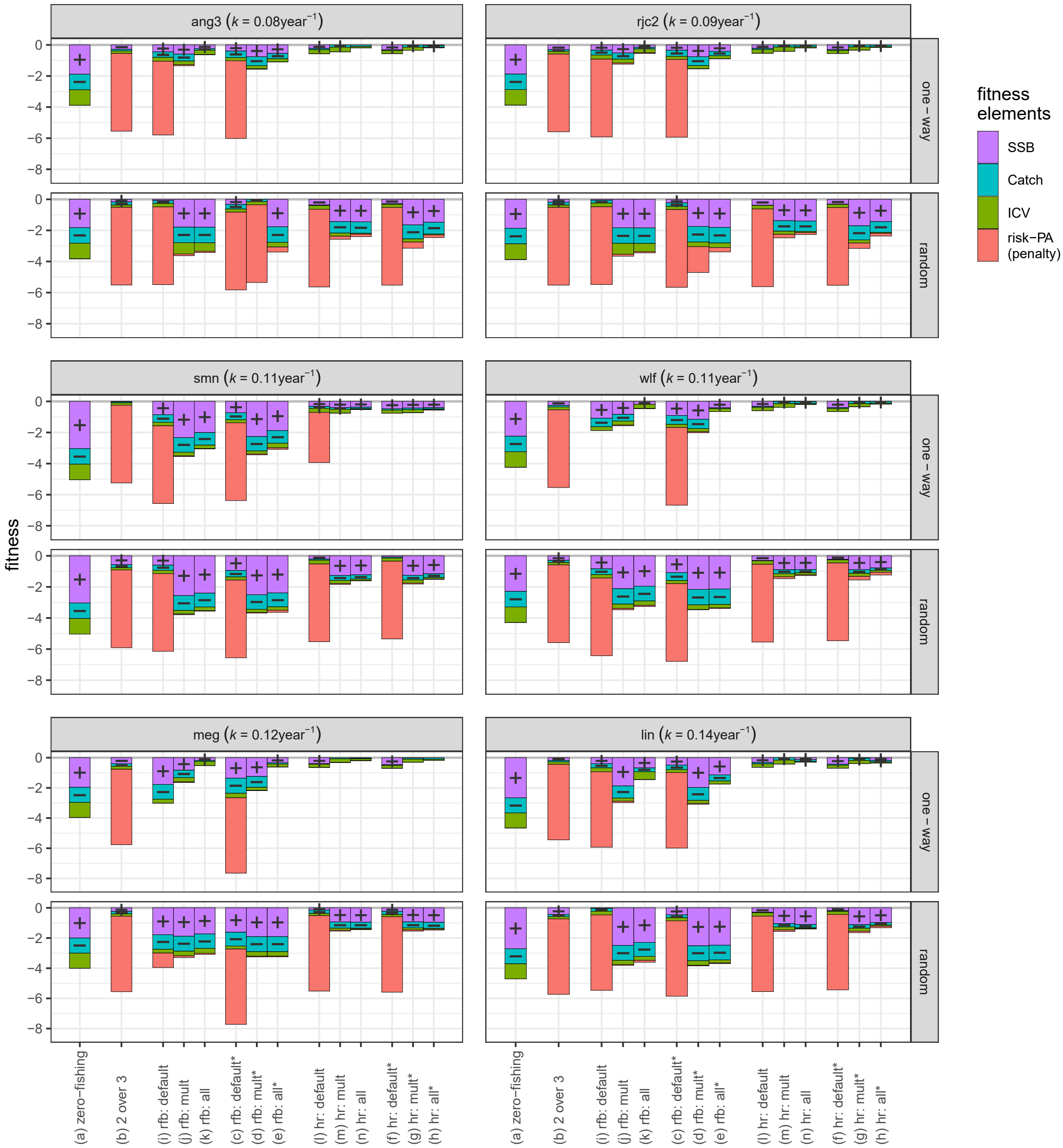

Figure E.7: Performance improvement of the harvest rate rule for all stocks, achieved through optimisation with the genetic algorithm (based on ($\phi_{\text{MSY-PA}}$)) and a comparison with other management options. Shown are a "zero-fishing" option (a), the 2 over 3 rule (b, from Fischer et al., 2021a, see Chapter 7), the rfb rule (c-e, i-k, from Fischer et al., 2021b, see Chapter 8) and the harvest rate rule (f-h, l-n). The options a-h are the same as those of Figure 9.9 in Chapter 9. For the rfb and harvest rate rules, three options are shown; the default rules (c, i, f, l, not optimised), optimisation with a multiplier (d, j, g, m), and optimisations where all parameters are included (e, k, h, n). Options marked with * included the conditional uncertainty cap (+20%, −30%, c-e, f-h). Shorter bars (less negative fitness) indicate better performance. SSB and catch can be above or below the optimisation target (see Figure E.6), indicated by "+" and "−". The parameterisation where the risk is above 5% are easily identifiable as the bars with large risk-PA elements (in red). The stock IDs correspond to the ones defined in Table 5.1 in Chapter 5. (Figure continued on next page)

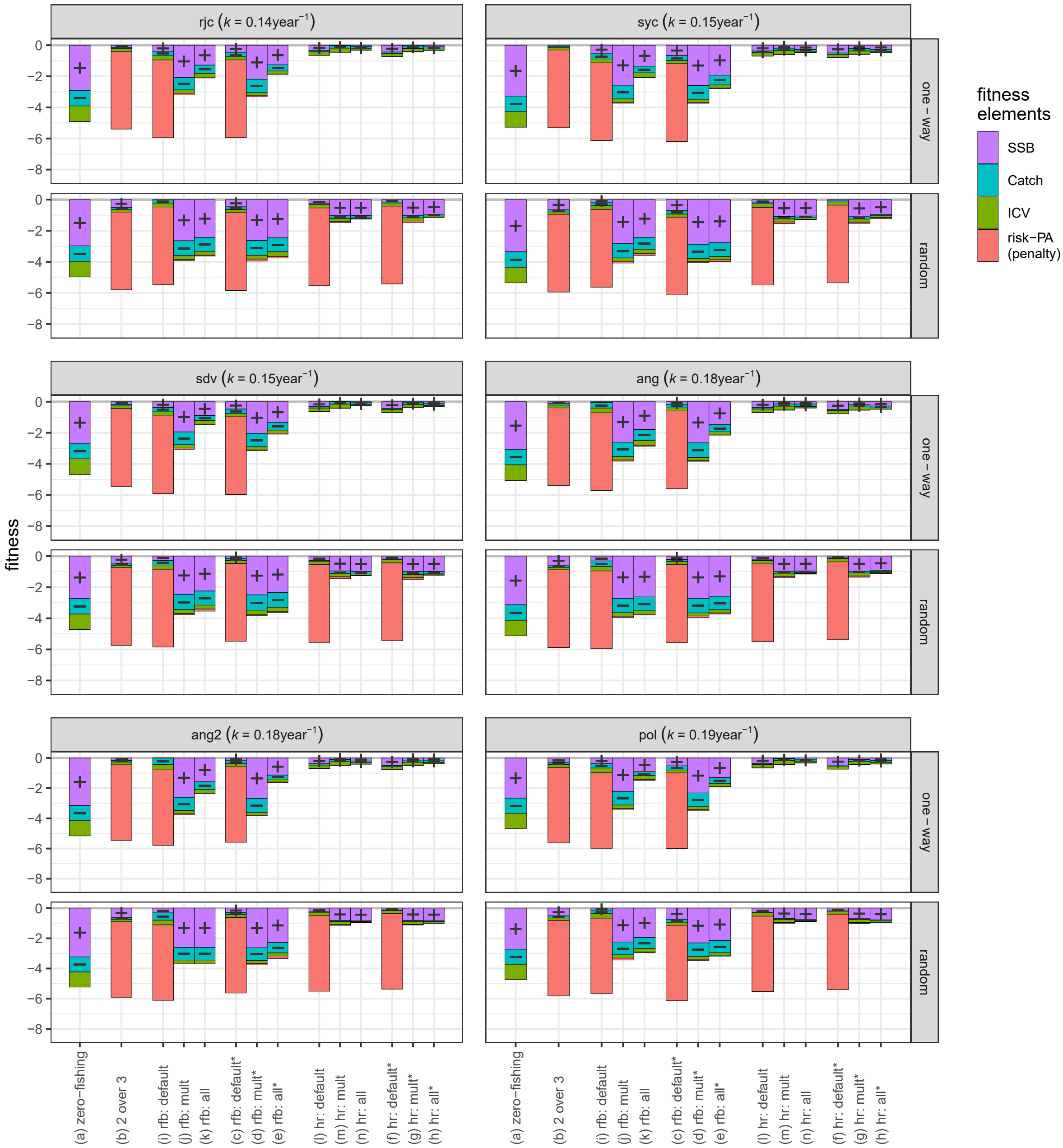

Figure E.7: (continued).

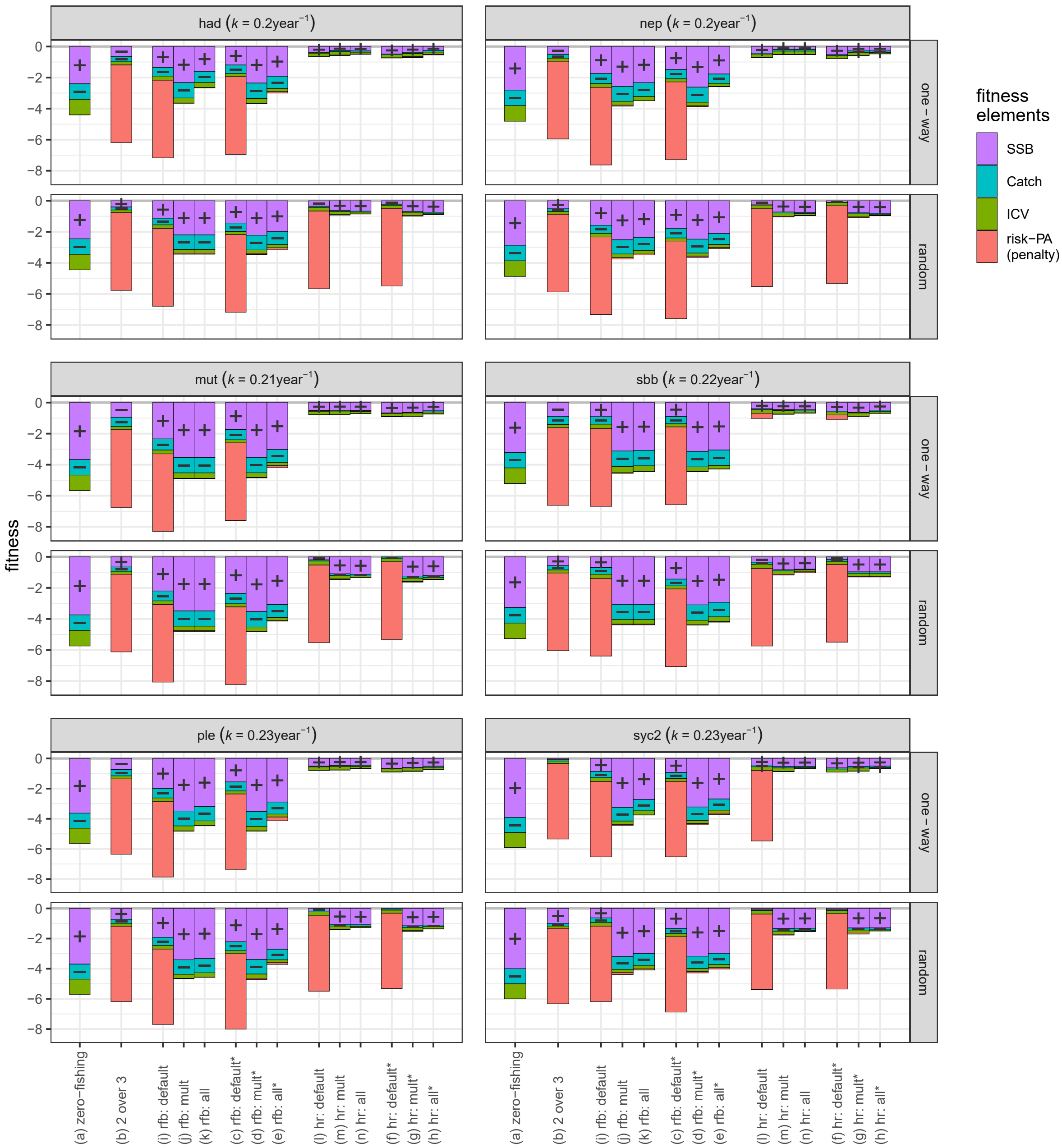

Figure E.7: (continued).

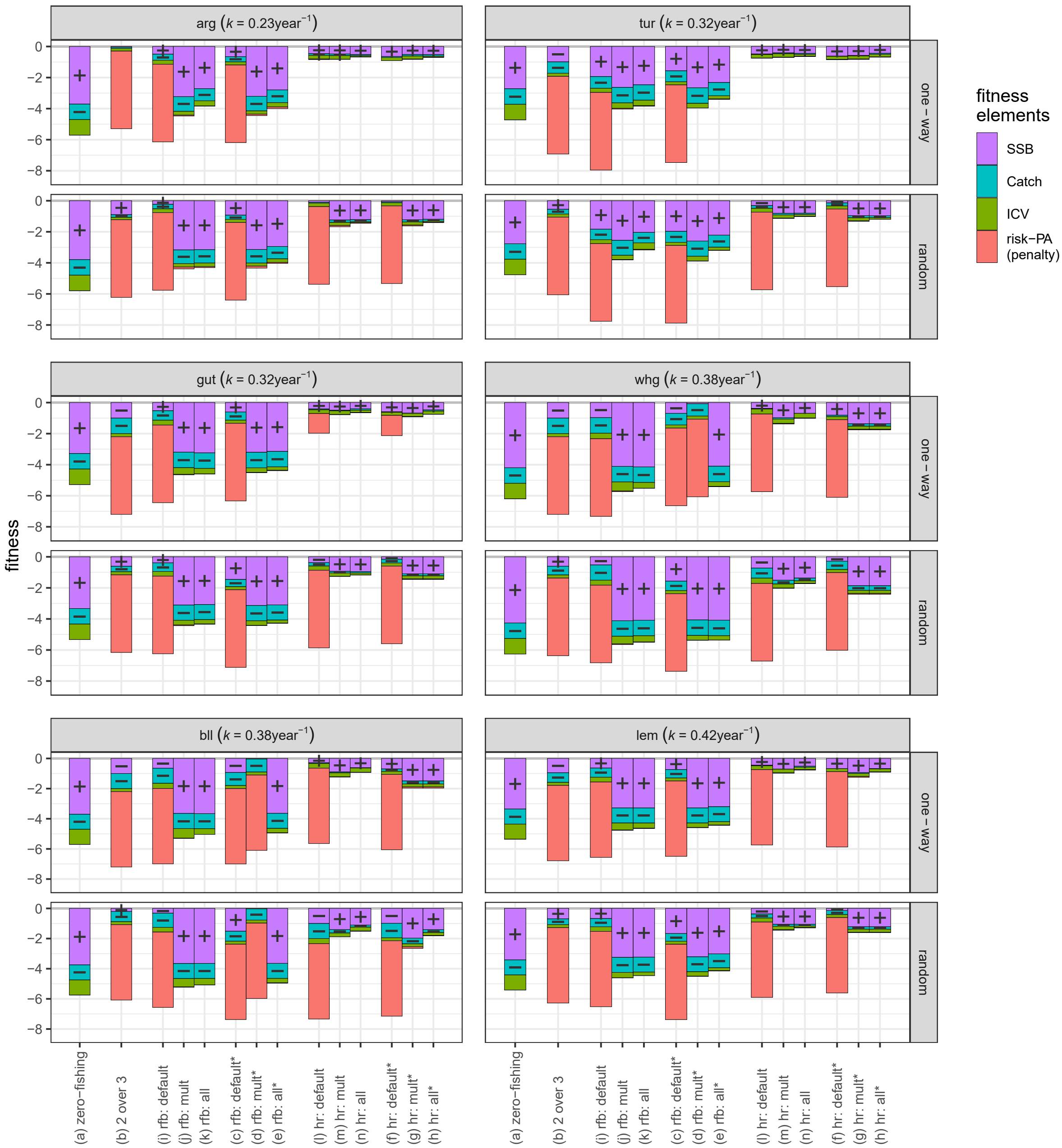

Figure E.7: (continued).

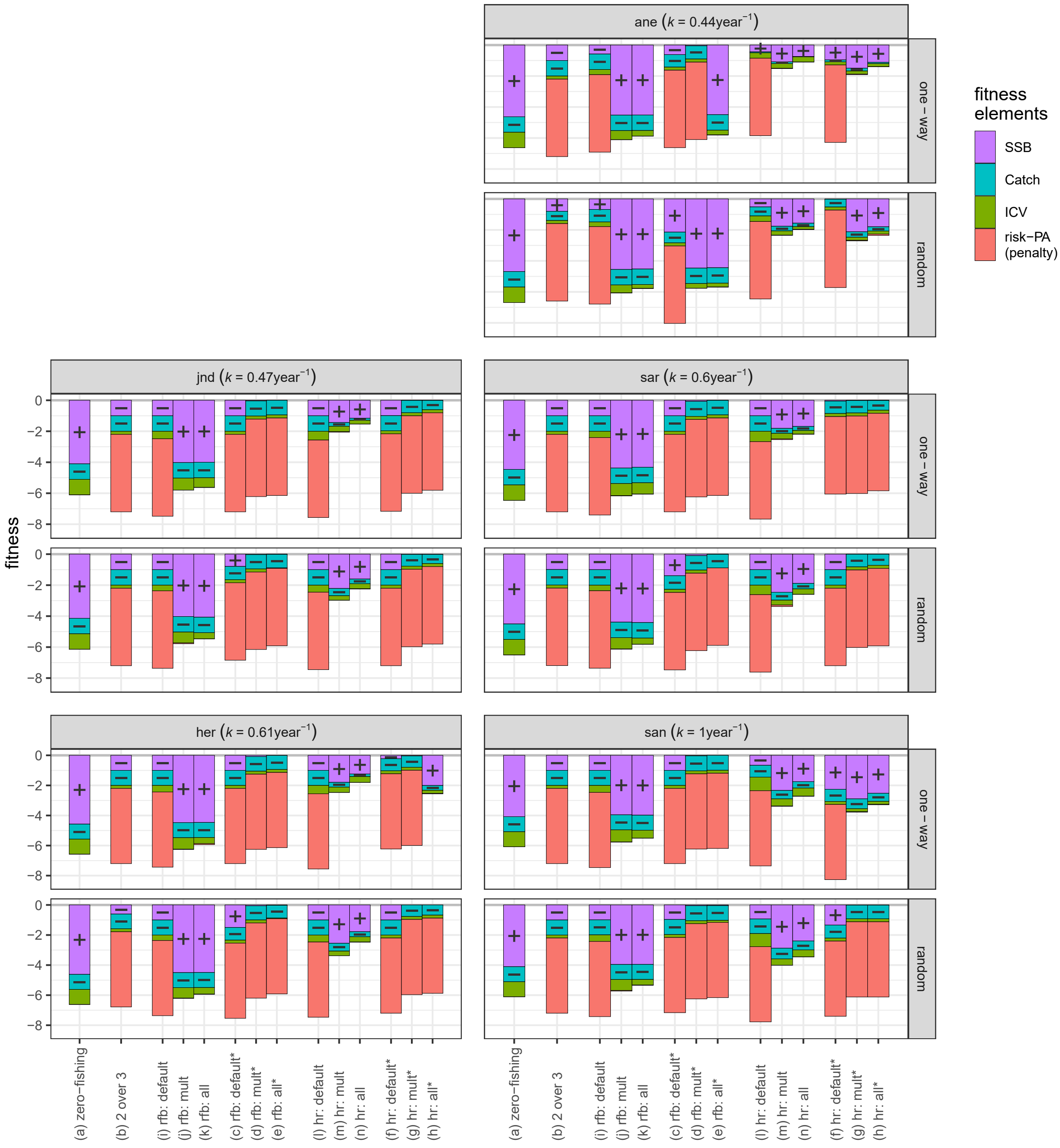

Figure E.7: (continued).

Appendix F

Appendix to Chapter 11

The following is an Appendix to Chapter 11 and based on the supplementary material prepared for Fischer et al. (n.d.):

> Fischer, S. H., De Oliveira, J. A. A., Mumford, J. D. & Kell, L. T. (n.d.). Risk equivalence in data-limited and data-rich fisheries management: an example based on the ICES advice framework (manuscript submitted to *Fish and Fisheries*)

F.1 Operating model

F.1.1 Operating model conditioning

The conditioning of the operating models (OMs) for all three stocks (plaice, cod, and herring) followed the approach set out by ICES (2019h). This means that the OMs were based on the model fits of the state-space assessment model SAM (Nielsen & Berg, 2014) to data and included SAM estimates of uncertainty (parameter uncertainty, process error, observation error). The uncertainty was implemented into the OM by generating 1,000 self-consistent simulation replicates. Each of these replicates represented one parameter set derived by the sampling from the variance-covariance matrix of the SAM model fit (ICES, 2019h). The baseline OMs were based on model fits similar to the stock assessments used by ICES (see Table 11.1 in Chapter 11). In the alternative OMs, representing alternative assumptions (e.g. natural mortality, recruitment, etc.), the SAM model was fit again and the process described above was repeated independently.

F.1.2 Population dynamics

Population dynamics were simulated with age-structured OMs. Population dynamics mimicked the internal dynamics of the state-space SAM model (Nielsen & Berg, 2014). Stock numbers were calculated as

$$N_{a,y,i} = \begin{cases} R_{y,i} & a = 1 \\ N_{a-1,y-1,i}\ e^{-F_{a-1,y-1,i}-M_{a-1,y-1,i}}\ e^{\varepsilon_{a,y,i}} & 1 < a < A \\ \left(N_{a-1,y-1,i}\ e^{-F_{a-1,y-1,i}-M_{a-1,y-1,i}} + N_{a,y-1,i}\ e^{-F_{a,y-1,i}-M_{a,y-1,i}}\right)\ e^{\varepsilon_{a,y,i}} & a = A \end{cases} \tag{F.1}$$

where $N_{a,y,i}$ are stock numbers for age a, year y and simulation replicate i, with $a = 1$ being the first age class, A the last age class (plusgroup), R are recruits, F is the fishing mortality, M the natural mortality, and ε the multivariate normal survival process error ($\varepsilon \sim N(0, \Sigma)$, where Σ is estimated by SAM).

The recruitment models for the three stocks are illustrated in Figure F.1.

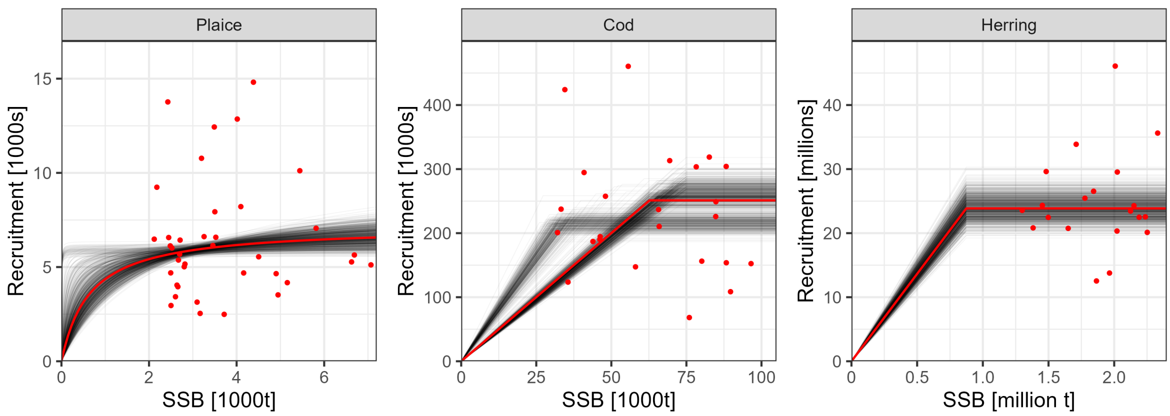

Figure F.1: Recruitment models of the baseline operating models for the three stocks. Red points indicate the medians of the SSB-recruitment pairs on which the stock-recruitment models were conditioned. The thin black curves represent the recruitment models for the 1000 simulation replicates and the red curve represents a recruitment model based on the medians of the model parameters.

Recruitment R was modelled with a Beverton-Holt model for plaice:

$$R_{y,i} = \frac{\alpha\ \mathrm{SSB}_{y,i}}{\beta + \mathrm{SSB}_{y,i}}\ e^{\gamma_{y,i}}, \tag{F.2}$$

where γ is the recruitment process error (recruitment residuals). Recruitment residuals are derived by sampling from the historical residuals (smoothed with kernel density smoother) and can include auto-correlation if significant for the historical residuals (see Chapter 11 for details and illustration). For cod and herring, recruitment was modelled with a segmented regression (hockey-stick) model:

$$R_{y,i} = \begin{cases} \alpha \ \mathrm{SSB}_{y,i} \ e^{\gamma_{y,i}} & \mathrm{SSB}_{y,i} \leq \beta \\ \alpha \ \beta \ e^{\gamma_{y,i}} & \mathrm{SSB}_{y,i} > \beta, \end{cases} \tag{F.3}$$

with γ as above for Equation (F.2).

Catch numbers were calculated following the Baranov catch equation (Sharov, 2021):

$$C_{a,y,i} = \frac{F_{a,y,i}}{F_{a,y,i} + M_{a,y,i}} \ N_{a,y,i} \ \left(1 - e^{-F_{a,y,i} - M_{a,y,i}}\right) \tag{F.4}$$

F.1.3 Biological data and fisheries selectivity

Biological data (weights at age for the stock and catch, natural mortality, and maturity) of the OM for the historical period (for which real data existed and are used in the ICES stock assessments) were identical to those used in the stock assessment and the same for each simulation replicate. Time-varying fishery selectivity (assuming a single fleet) is estimated by SAM. Consequently, the selectivity differed by simulation replicate in the historical period.

For the projected period (20 years) in the MSE, variability was introduced for biological parameters and fishery selectivity by resampling from the historical period. Values were resampled from the last five historical years for plaice and cod (ICES, 2015b, 2021b) and from the last 10 years for herring (ICES, 2021g), following decisions by ICES expert groups.

The resampling process was implemented by randomly selecting a year from the pool of years (last 5 or 10 historical years), and taking all biological parameters for all ages in this year, so that possible correlations between ages or different biological parameters were maintained. This process was repeated for fishery selectivity, independently for each simulation replicate and separate from the biological resampling.

F.1.4 Observations

Observations were generated from the OMs and passed to the management procedure (MP). The data generated by OMs for the historical period were identical to the data observed in reality.

For the projection years, the error structure from SAM was used to model the observations, and these observations were added to the historical observations. All OM uncertainty estimates (residuals) were generated before the simulations, so that they were identical in all simulations of the same OM to facilitate comparisons between different MPs.

Catch observations

Catch observations were based on the operating model catch numbers of Equation (F.4) and included an observation error term:

$$C^{\text{obs}}_{a,y,i} = C_{a,y,i}\ e^{\varepsilon_{a,y,i}}, \tag{F.5}$$

with $\varepsilon_{a,y,i} \sim N(0, \sigma^2_{a,i})$ and σ being the observation standard deviation estimated by SAM.

The total catch C^T was derived by multiplying catch numbers with the individual weight (W^C) and aggregating over all OM age classes:

$$C^T_{y,i,s} = \sum_{a=1}^{A} C^{\text{obs}}_{a,y,i}\ W^C_{a,y,i,s}. \tag{F.6}$$

Indices

Survey index observations J were generated from the OM with

$$J_{a,y,i,s} = q_{a,y,i,s}\ N_{a,y,i}\ e^{-t_s(F_{a,y,i}+M_{a,y,i})}\ e^{\varepsilon_{a,y,i,s}}, \tag{F.7}$$

where s is the index, q the catchability, t the timing of the survey in the year, and $\varepsilon_{a,y,i,s} \sim N(0, \sigma^2_{a,y,s})$ the observation error with standard deviation σ estimated by SAM.

Biomass indices I were generated from the surveys with

$$I_{y,i,s} = \sum_{a=a_{\text{min},s}}^{a_{\text{max},s}} J_{a,y,i,s}\ W^{\text{I}}_{a,y,i,s}, \tag{F.8}$$

where a_{min} and a_{min} are the minimum and maximum ages for survey s, J the observed index values from Equation (F.7), and W^I the weights at age in the index.

Length data

The OMs were age-structured and did not use lengths internally. However, the data-limited management procedures (MPs) required length data from the catch. Therefore, the age frequencies of the catch were converted into length frequencies with stock-specific age-length keys (ALKs). The ALKs describe the distribution of lengths for each age class of the OM. These ALKs were applied to the catch at age data and the catch numbers aggregated by length class to generate the catch at length distribution. For historical years for which yearly ALKs were available, these were used. For the remaining historical years, the available ALKs were combined into a pooled ALK. For the projected years in the MSE, length distributions were derived by randomly choosing from the available ALKs, separately for each simulation year and replicate.

The observed length distributions were generated by sampling from the OM length distribution (described in the previous paragraph). In each year, 2,000 length samples were drawn, which is a typical sampling level for plaice in previous years (ICES, 2021o).

Subsequently, the mean length of the catch $\bar{L}$ was calculated as the average of the length classes (L) above the length of first capture (L_c, see section F.2.1), weighted by the number of fish in these length classes (C_L):

$$\overline{L_y} = \frac{\sum_{L>L_c} L \; C_{L,y}}{\sum_{L>L_c} C_{L,y}}. \tag{F.9}$$

Biological data

Biological data (weights at age, M, maturity, etc.) was passed from the OM to the MP. For the historical period (prior to implementing the MPs), the biological data passed to the MP was identical to those observed in reality. For the projection period, the biological data were the average of the values of those years from which the OM biological values were sampled (last 5 historical years for plaice and cod, last 10 historical years for herring).

For the alternative OMs, the MP received biological data from the baseline OM.

F.1.5 Alternative operating models

A range of alternative OMs was created to cover different assumptions made in the conditioning of the baseline OM (see Table 11.3 in Chapter 11).

- Recruitment

In the alternative recruitment OMs, the only difference from the baseline OM was the definition of the recruitment model.

- Recruitment failure (ID: *R: failure*) - plaice, cod & herring

  Reduced recruitment in the first five years of projection (2021-2025) by 90%.

- Higher recruitment (ID: *R: higher*) - cod & herring

  Recruitment model fitted to a longer historical period covering larger recruitment values (1988-2021 instead of 1998-2021 for cod, 1947-2021 instead of 2002-2021 for herring).

- No auto-correlation of recruitment (ID: *R: no AC*) - plaice

  The default plaice recruitment model included lag-1 auto-correlated recruitment residuals ($\rho = 0.6$). In this alternative OM, the auto-correlation was turned off.

• Natural mortality (M)

In these OMs, M in the stock assessment input data was changed, the SAM model fit to these data, and the OM conditioned on this alternative model.

- Higher and lower M (ID: *M: high*; *M: low*) - plaice

  In the baseline OM for plaice, M was identical for all ages ($M = 0.12$). In *M: high*, M was increased by 50% to $M = 0.18$, and in *M: low* reduced by 50% to $M = 0.06$.

- Age-dependent M (ID: *M: Gislason*) - plaice

  The age-invariant $M = 0.12$ for plaice was replaced by age-specific values. This was achieved by following Equation 2 of Gislason et al. (2010):

$$\ln(M_L) = 0.55 - 1.61 \ln(L) + 1.44 \ln(L_\infty) + \ln(k), \tag{F.10}$$

  which defines M by length (L) with the von Bertalanffy growth parameters L_∞ and k. Substituting the von Bertalanffy growth equation

$$L_a = L_\infty \left(1 - e^{-k(a-a_0)}\right), \tag{F.11}$$

  into Equation (F.10) allows the determination of M by age. Stock-specific von Bertalanffy growth parameters were used (see Table F.2).

- Density-dependent M (ID: *M: dens. dep.*) - cod

  M can be split into two elements, the residual mortality ($M1$) and the predation mortality ($M2$). M for cod is regularly updated based on multispecies analyses, which also include a cannibalism component in $M2$. Cannibalism can impact M of young cod. This OM adapted M for cod ages 1-3 based on the size of the stock, following the multispecies analysis of ICES (2017c), and as parameterised by ICES (2019h). See ICES (2019h) for details.

- Remove migration correction of M (ID: *M: no migr.*) - cod

  In the current ICES cod assessment, M for ages 3-6 is inflated to account for an assumed migration of older fish out of the stock area (ICES, 2021b, 2021p). In this OM, this migration correction was removed, both for the stock assessment on which the OM is conditioned, and for the projection in the MSE.

- Catch

  The OMs were based on the total catch (landings and discards) and MPs adjusted total catch.

  - Assume 100% discard survival (ID: *Catch: no disc.*) - plaice

    This OM assumed that discarding occurs but all discarded fish survived. This meant that the OM stock was conditioned on a stock assessment which included only landings and no discards. However, the data passed to the MPs included discards and the catch advice is set for total catch.

The alternative assumptions only affected the processes in the OMs but were not passed to the MPs. This meant there was a mismatch between the OMs and MPs, which could be used to test the robustness of the MPs to misspecifications.

A comparison of the alternative OMs is illustrated in Figure F.2 and Figure F.3 shows the corresponding recruitment models.

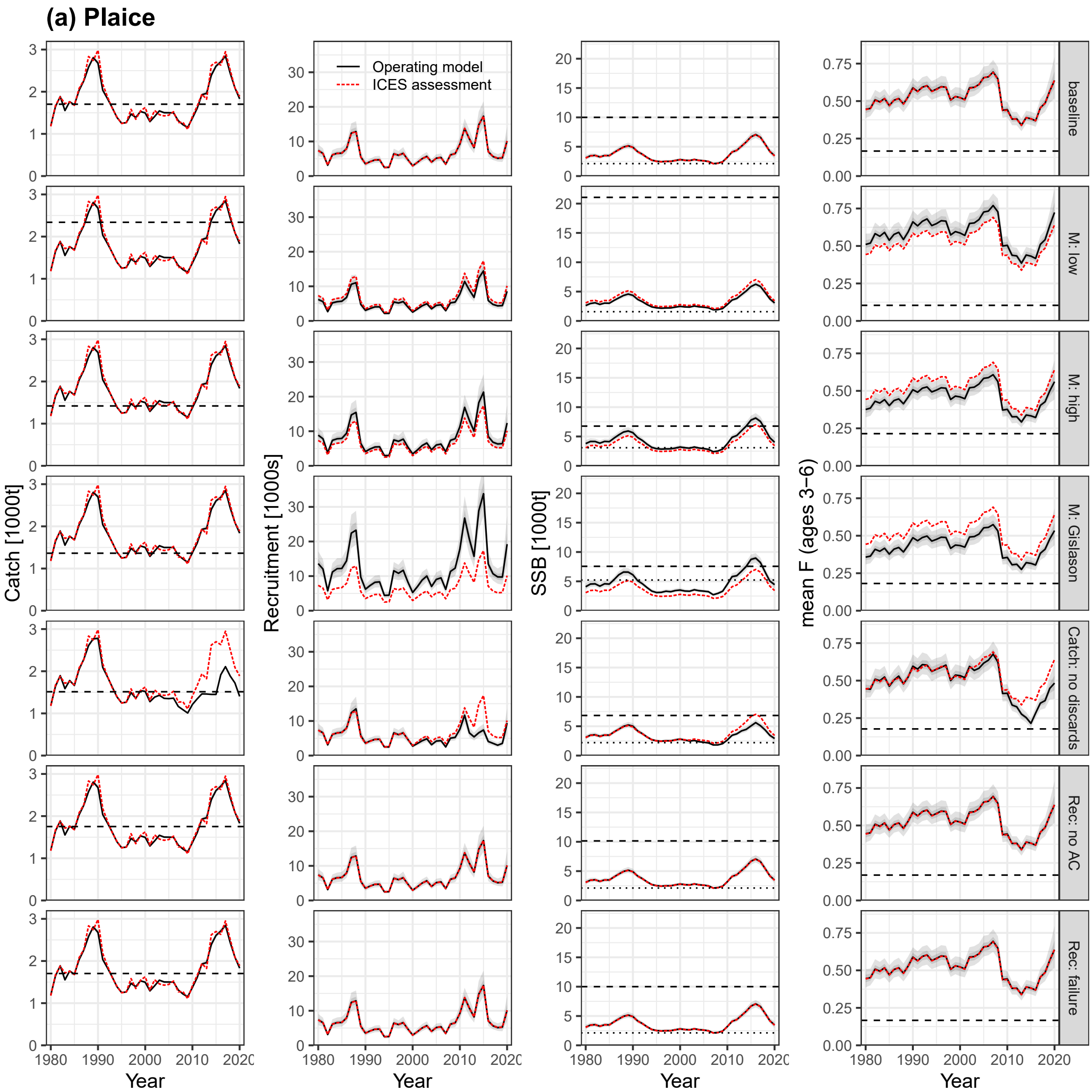

Figure F.2: Comparison of the alternative operating models and comparison to ICES assessments. The catch of the ICES assessment (red dashed curve) is the model input. Shaded areas are 50% and 90% confidence intervals of the OMs. Horizontal dashed lines indicate MSY reference values and horizontal dotted lines B_{lim}. (Figure continued)

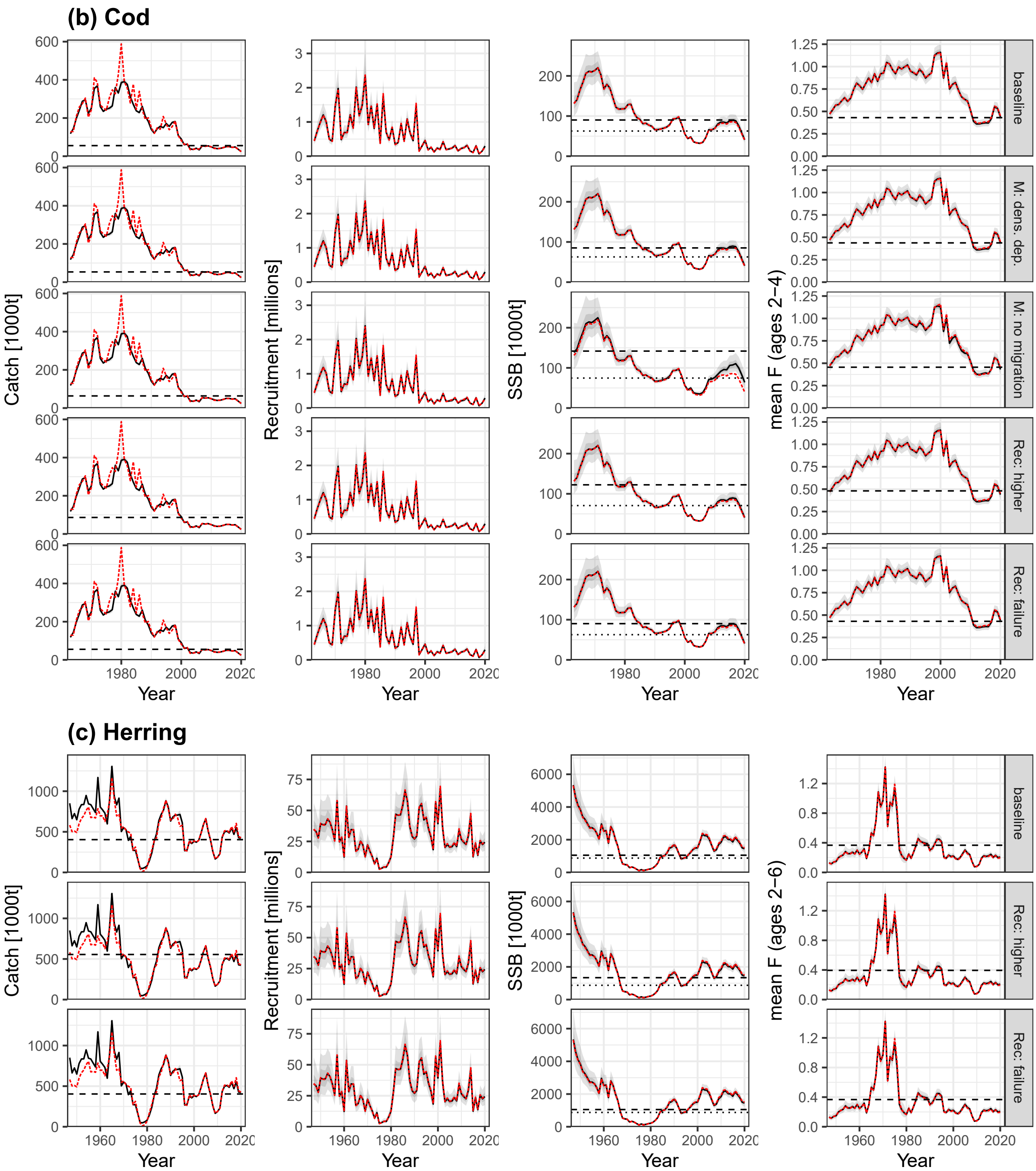

Figure F.2: (continued).

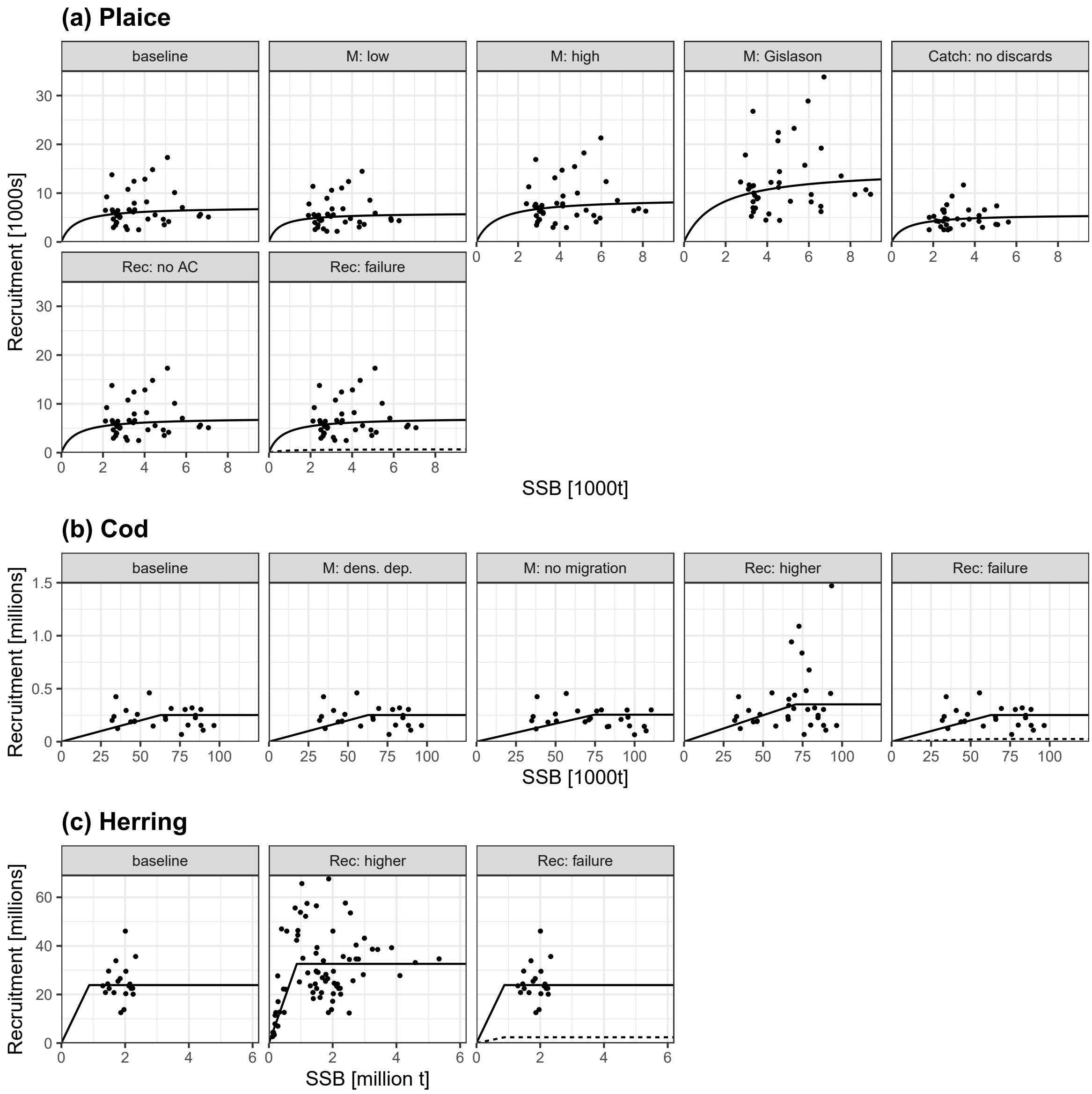

Figure F.3: Recruitment models of the alternative operating models for the three stocks. Shown are the median SSB-recruitment pairs (points) and the median recruitment models (curves). For the recruitment failure scenario, the dashed curves indicate the recruitment model during the years of recruitment failure and the solid curves the recruitment model for the remaining years.

F.1.6 Operating model reference points

The estimation of maximum sustainable yield (MSY) reference points for all OMs is illustrated in Figure F.4 and the results are listed in Table F.1. MSY estimates were achieved by a 100-year projection with constant F and maximising the long-term catch (median of last 10 years).

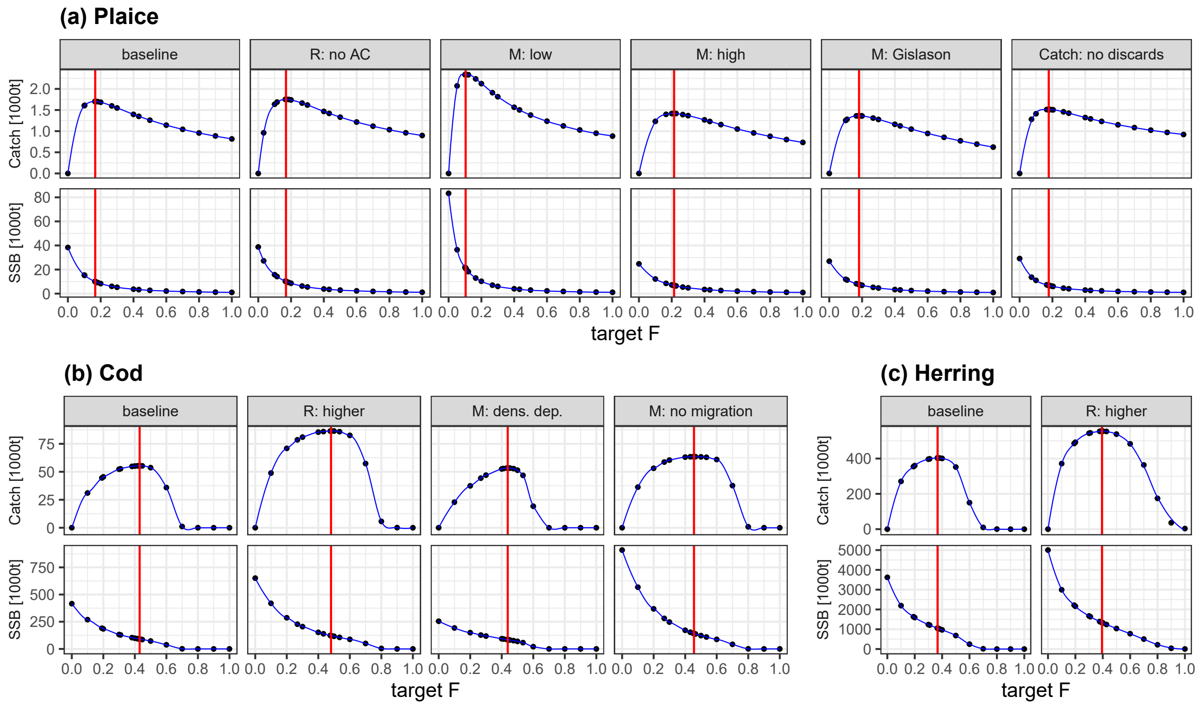

Figure F.4: Visualisation of the MSY estimation for all stocks and operating models. The points are the long-term averages (median of the last 10 years of a 100-year stochastic projection), the blue curves are a loess smoother fitted to these values. MSY estimates are highlighted with the red vertical lines.

Table F.1: Reference points for all operating models. B_0 and R_0 are virgin (unfished) spawning stock biomass (SSB) and recruitment; F_{MSY}, MSY B_{MSY}, and R_{MSY} are fishing mortality, catch, SSB, and recruitment at MSY; and B_{lim} is the biomass (SSB) limit reference point.

stock	**Operating model**	B_0 **[t]**	R_0 **[1000]**	$F_{\mathbf{MSY}}$	**MSY [t]**	$B_{\mathbf{MSY}}$ **[t]**	$R_{\mathbf{MSY}}$ **[1000]**	$B_{\mathbf{lim}}$ **[t]**
Plaice	baseline	38,340	6,887	0.167	1,703	10,005	6,570	2,119
Plaice	R: failure	38,340	6,887	0.167	1,703	10,005	6,570	2,119
Plaice	R: no AC	38,756	6,847	0.169	1,752	10,150	6,535	2,119
Plaice	M: low	83,294	5,797	0.104	2,339	21,063	5,700	1,572
Plaice	M: high	24,727	8,344	0.214	1,419	6,768	7,561	3,082
Plaice	M: Gislason	26,915	13,919	0.182	1,363	7,565	12,106	5,229
Plaice	Catch: no disc.	29,141	5,526	0.178	1,514	6,834	5,139	2,199
Cod	baseline	415,979	249,285	0.430	55,391	90,187	247,224	62,734
Cod	R: failure	415,979	249,285	0.430	55,391	90,187	247,224	62,734
Cod	R: higher	650,837	340,640	0.481	86,413	122,305	338,698	70,629
Cod	M: dens. dep.	254,704	249,285	0.438	53,401	85,125	242,638	62,734
Cod	M: no migr.	908,879	241,923	0.456	63,510	141,781	241,923	74,640
Herring	baseline	3,621,774	23,908,255	0.367	403,512	1,052,763	23,273,644	874,198
Herring	R: failure	3,621,774	23,908,255	0.367	403,512	1,052,763	23,273,644	874,198
Herring	R: higher	4,999,762	32,076,803	0.394	555,244	1,338,623	31,107,313	874,198

F.2 Application of empirical management procedures

F.2.1 Life-history parameters and length reference points

Length-based reference points are listed in Table F.2.

The length at first capture L_c was calculated following ICES (2012e) as the first length class where the abundance is at or above half of the abundance of the length class with the highest abundance (mode).

The MSY proxy length $L_{F=M}$ was calculated following Beverton and Holt (1957) and as derived by Jardim et al. (2015):

$$L_{F=M} = 0.75L_c + 0.25L_\infty. \tag{F.12}$$

This equation assumes a ratio of natural mortality (M) to the von Bertalanffy growth parameter (k) $M/k = 1.5$ and that fishing at $F = M$ is a proxy for MSY.

Table F.2: Life-history parameters for the three stocks.

Parameter	Plaice	Cod	Herring
von Bertalanffy growth parameters			
k [year^{-1}]	0.10	0.197	0.49
L_∞ [cm]	66	117	31
t_0 [years]	−2.0	−0.3	−0.7
Source	ICES (2021o)	growth model fit to 2016-2020 age-length keys from IBTS Q1 & Q3	growth model fit to 2016-2020 age-length keys from HERAS
Length at first capture L_c			
L_c [cm]	26	20	25
Source	ICES (2021o)	estimated from length distribution	estimated from length distribution
MSY proxy length $L_{F=M}$			
$L_{F=M}$ [cm]	36	44.25	26.5

This section describes how the default (generic) parameterisations of the rfb and hr rules were derived for the three stocks.

F.2.2 The biomass index

All three data-limited management procedures (the 2 over 3 rule, the rfb rule, and the hr rule) required a biomass index. For plaice, the UK-FSP Q3 survey (beam trawl survey and part of a fisheries-science partnership) was chosen because this survey has the best coverage of the stock and was most influential in previous stock assessment models (ICES, 2021o). Furthermore, this survey occurs in the third quarter of the year, and, therefore, the time lag between the survey timing and the catch advice is shorter compared to a survey at the beginning of the year. For cod, the IBTS Q3 survey (international bottom trawl survey) was selected due to its timing. For herring, the HERAS survey (herring acoustic survey) was chosen because this survey provides a long time series, has a good stock coverage, and includes the most ages for herring. Biomass indices were generated for these surveys by multiplying the survey numbers at age with the weight at age, and aggregating over the survey ages.

The three surveys are shown in Figure F.5. The biomass safeguard b of the rfb and hr rule required the definition of a trigger index value I_{trigger}. This value was derived from the lowest observed biomass index value I_{loss} as $I_{\text{trigger}} = w\ I_{\text{loss}}$ with $w = 1.4$ (see Figure F.5).

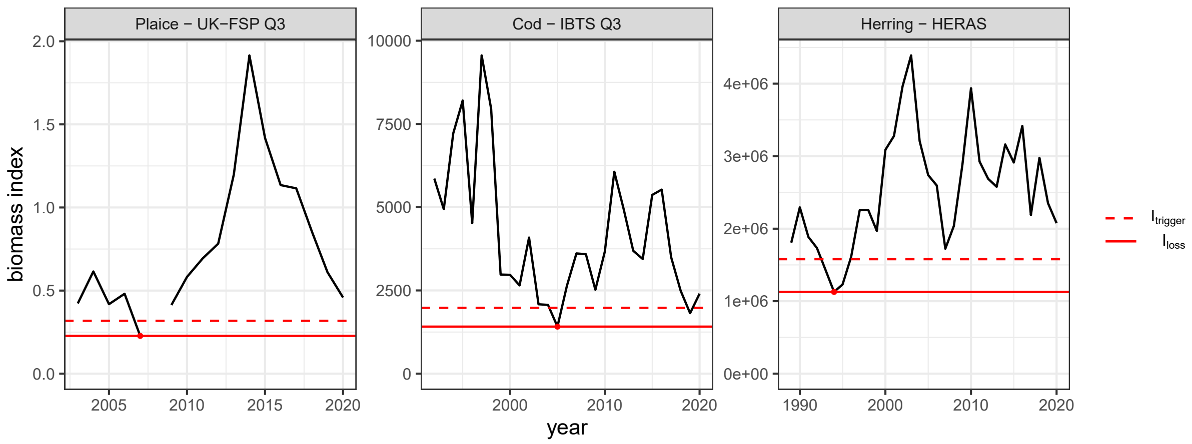

Figure F.5: The biomass indices used for the three stocks.

F.2.3 The rfb rule: multiplier

The f component of the rfb rule compares the mean length in the catch to an MSY reference length. The mean length in the catch is the mean length of fish above the length of first capture L_c (see definition above). The multiplier x of the rule is set depending on the von Bertalanffy growth parameter k (ICES, 2020a):

$$x = \begin{cases} 0.95, & \text{if} \quad k < 0.20\ \text{year}^{-1} \\ 0.90, & \text{if} \quad 0.20\ \text{year}^{-1} \leq k \leq 0.32\ \text{year}^{-1} \end{cases} \tag{F.13}$$

Therefore, the following values for x were chosen:

Table F.3: Selection of the multiplier x for the rfb rule depending on the von Bertalanffy growth parameter k.

	Plaice	**Cod**	**Herring**
k	0.10	0.197	0.49
x	0.95	0.95	0.9

For herring, k was above the recommended maximum $k = 0.32$ year^{-1}, so the more precautionary $x = 0.9$ was selected.

F.2.4 The hr rule: target harvest rate

The ICES guidelines for the application of the hr rule (ICES, 2020a) recommend that the target harvest rate H is derived (1) by estimating the mean length in the catch $\bar{L}$ above the length at first capture L_c, (2) determining the years in which $\bar{L} \geq L_{F=M}$, (3) calculating the historical harvest rate (catch C divided by biomass index I), and (4) selecting the harvest rates for the years determined in step 2 and taking their average.

This procedure is illustrated in Figure F.6 for the three stocks. For plaice, the mean catch length was taken from the ICES assessment (ICES, 2021o). For cod and herring, international length distributions are not available and length data were generated by applying age-length keys to the age-structured catch observations. Historical harvest rates were calculated by dividing the total catch by the values from the biomass indices. For plaice, none of the lengths were above the reference length $L_{F=M}$ and, consequently, the lowest observed harvest rate in 2014 was selected as target for the hr rule (Figure F.6). For cod, the mean length was above $L_{F=M}$ in 2008-2013 and 2015-2019 and for herring for the entire time series (Figure F.6).

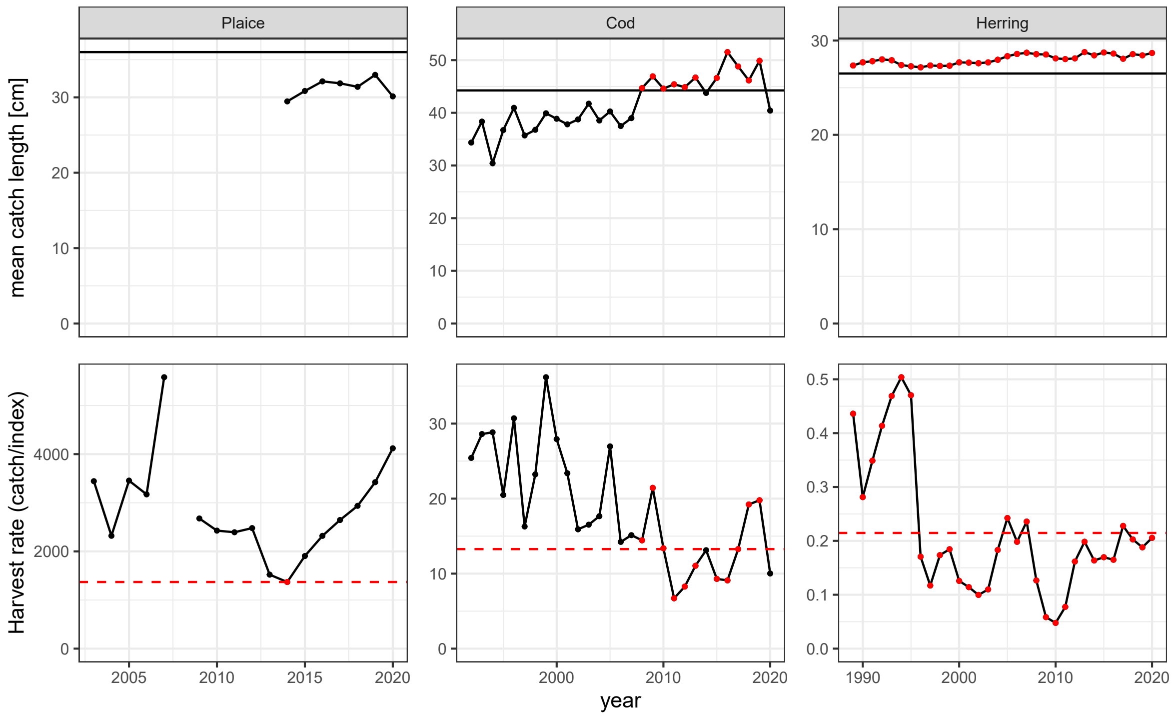

Figure F.6: Illustration of the derivation of the harvest rate target for the hr rule. The top row shows the mean catch length above the length of first capture L_c. The horizontal black line is the reference length $L_{F=M}$ and catch lengths above are highlighted in red. The bottom row shows the harvest rate (catch divided by the biomass index). Selected harvest rate values are highlighted in red and the horizontal red dashed lines indicate the average of these values.

F.3 Worm plots for all management procedures

Table F.4: Hyperlinks to worm plots for all stocks and MPs. For the rfb and hr rule, three options are available, the default non-optimised rule, the optimisation with a multiplier, and the optimisation with all parameters.

Stock	**Operating model**	**2 over 3 rule**		**rfb rule**			**hr rule**			**ICES MSY rule**
Plaice	baseline	default	XSA	default	multiplier	all	default	multiplier	all	default
Plaice	R: failure	default	XSA	default	multiplier	all	default	multiplier	all	default
Plaice	R: no AC	default	XSA	default	multiplier	all	default	multiplier	all	default
Plaice	M: low	default	XSA	default	multiplier	all	default	multiplier	all	default
Plaice	M: high	default	XSA	default	multiplier	all	default	multiplier	all	default
Plaice	M: Gislason	default	XSA	default	multiplier	all	default	multiplier	all	default
Plaice	Catch: no disc.	default	XSA	default	multiplier	all	default	multiplier	all	default
Cod	baseline			default	multiplier	all	default	multiplier	all	default
Cod	R: failure			default	multiplier	all	default	multiplier	all	default
Cod	R: higher			default	multiplier	all	default	multiplier	all	default
Cod	M: dens. dep.			default	multiplier	all	default	multiplier	all	default
Cod	M: no migr.			default	multiplier	all	default	multiplier	all	default
Herring	baseline			default	multiplier	all	default	multiplier	all	default
Herring	R: failure			default	multiplier	all	default	multiplier	all	default
Herring	R: higher			default	multiplier	all	default	multiplier	all	default

F.4 Exploration of surplus production models (ICES category 2 approach)

The revised ICES data-limited guidelines (ICES, 2020a) recommend using surplus production models for ICES category 2. The standard model is the surplus production in continuous time (SPiCT; Pedersen & Berg, 2017) model, a state-space implementation of a Pella-Tomlinson model. The advice for this category is then based on a stochastic short-term forecast with a fractile rule (Mildenberger et al., 2022). The fishing target for the advice year is F_{MSY}. However, the advised catch is not the point estimate (median) of the stochastic forecast catch but a percentile below the median. The default is to use the 35th percentile (ICES, 2020a). In this approach, the assessment uncertainty is propagated into the short-term forecast and higher assessment uncertainty decreases the advised catch, essentially advising a catch value corresponding to a fishing mortality below F_{MSY}.

This category 2 approach can only be used if SPiCT (or an alternative surplus production model) can be fitted and the model meets acceptance criteria (https://raw.githubusercontent.com/DTUAqua/spict/master/spict/inst/doc/spict_guidelines.pdf).

F.4.1 Plaice

SPiCT has been trialled several times in recent years as part of the ICES stock assessment working group (ICES, 2021o), but the model performance was always too poor to be considered for advice purposes. Various different model configurations, setting priors and fixing parameters were explored but did not lead to model runs meeting the SPiCT acceptance criteria. The assessment uncertainty was very high, and the model was highly sensitive to the last data year (strong retrospective patterns) as well as the selection of the first data year. Consequently, SPiCT was rejected by ICES (2021o) for the plaice stock and appeared unable to model the stock dynamics appropriately.

Figure F.7 shows a model fit that includes both (biomass) survey indices.

F.4.2 Cod

The SPiCT model was also explored for the cod stock. For this purpose, the two IBTS surveys (Q1 and Q3) were converted into biomass indices. Figure F.8 illustrates the SPiCT model fit for cod. The model exhibited unacceptably high uncertainty, estimated an unrealistic low fishing

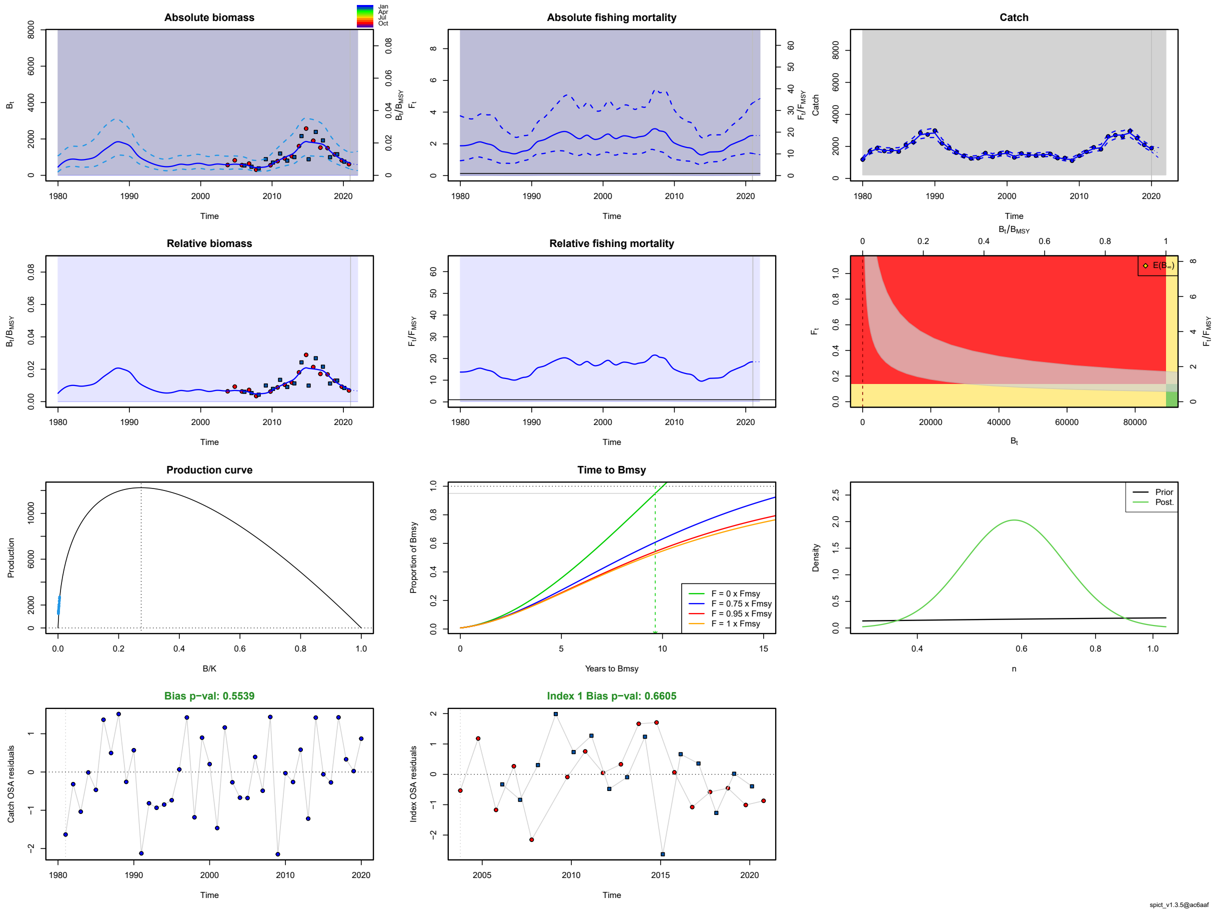

Figure F.7: Summary of the SPiCT assessment for plaice. Shown are the estimates of biomass and fishing mortality (absolute and relative to MSY), catch, a Kobe plot, the production curve, the time required to reach B_{MSY} from a forecast under different fishing scenarios, the shape parameter defining the shape of the production curve, and one-step-ahead residuals of catch and indices. Model estimates (solid curves) are surrounded by 95% confidence intervals. For biomass, fishing mortality, and catch, solid blue curves are the model estimates, dashed blue curves the confidence intervals of absolute estimates, blue shaded areas the confidence intervals of relative estimates, horizontal black lines the MSY level, and grey shaded areas the confidence intervals of the MSY level. In the biomass panel, the points are the scaled biomass index values and the in the catch panel the points are observed catches.

mortality, and failed to meet SPiCT acceptance criteria. Consequently, SPiCT could not be used for cod. Extensive explorations of model configurations and data might lead to a SPiCT assessment for cod that meets the SPiCT acceptance criteria; however, this was outside the scope of this study.

F.4.3 Herring

Lastly, SPiCT was also explored for the herring stock. Only the HERAS survey was included because this was the only survey for which weights at age were available to convert the index to a biomass index. Figure F.9 illustrates the SPiCT model fit for herring. Although the

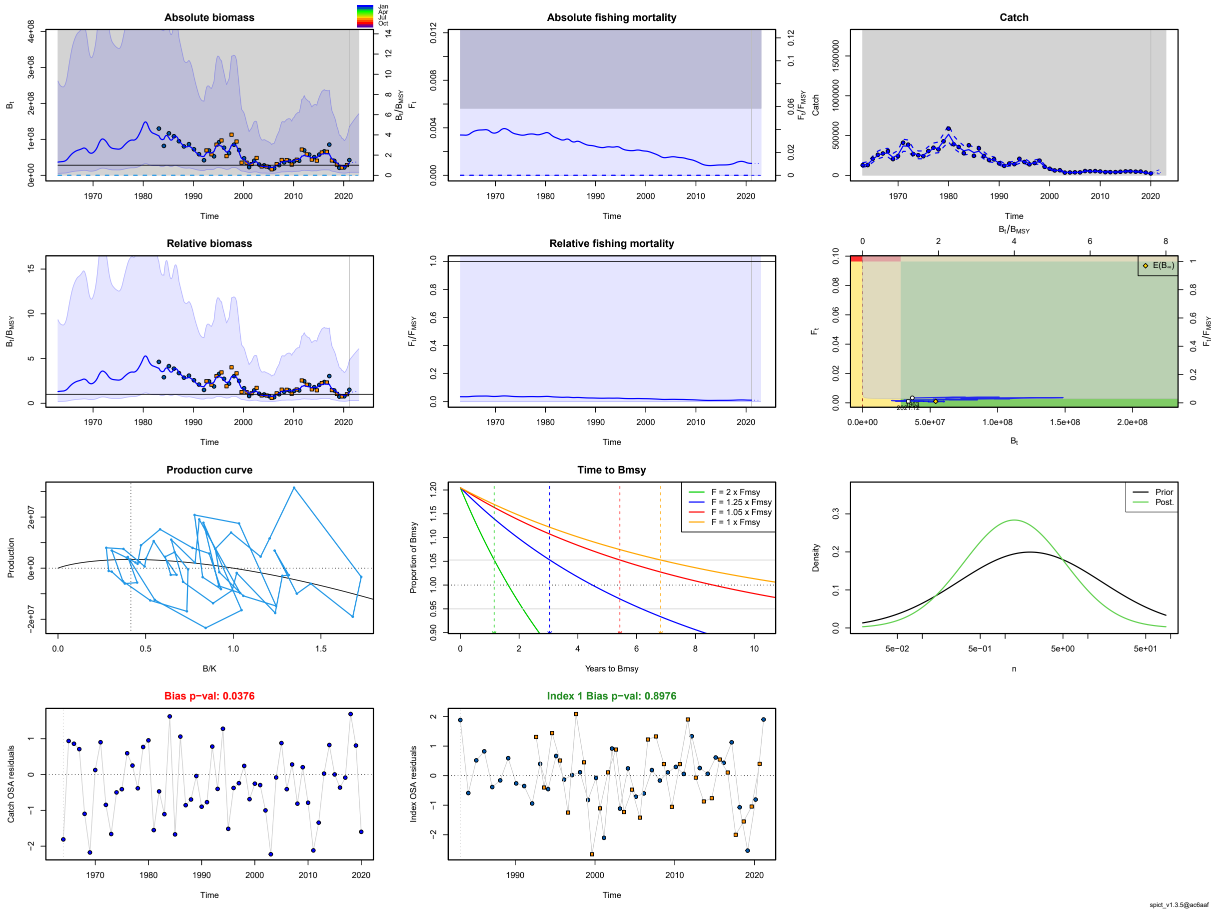

Figure F.8: Summary of the SPiCT assessment for cod. See Figure F.7 for details on the illustration.

model fit appears reasonable, not all acceptance criteria for SPiCT were met. In particular, the one-step-ahead catch residuals were not normally distributed, and the model was sensitive to the initial parameter values used in the model fitting process (5/10 runs with different initial parameters resulted in non-convergence and other initial parameters led to a doubling of the unfished biomass estimate). Extensive explorations of model configurations and data might lead to a SPiCT assessment for herring that meets the SPiCT acceptance criteria; however, this was outside the scope of this study. Therefore, SPiCT was rejected for herring. Furthermore, even with only one survey index, SPiCT took relatively long to converge and more than three times longer than the age-structured SAM model, which would increase the computational effort for an MSE simulation.

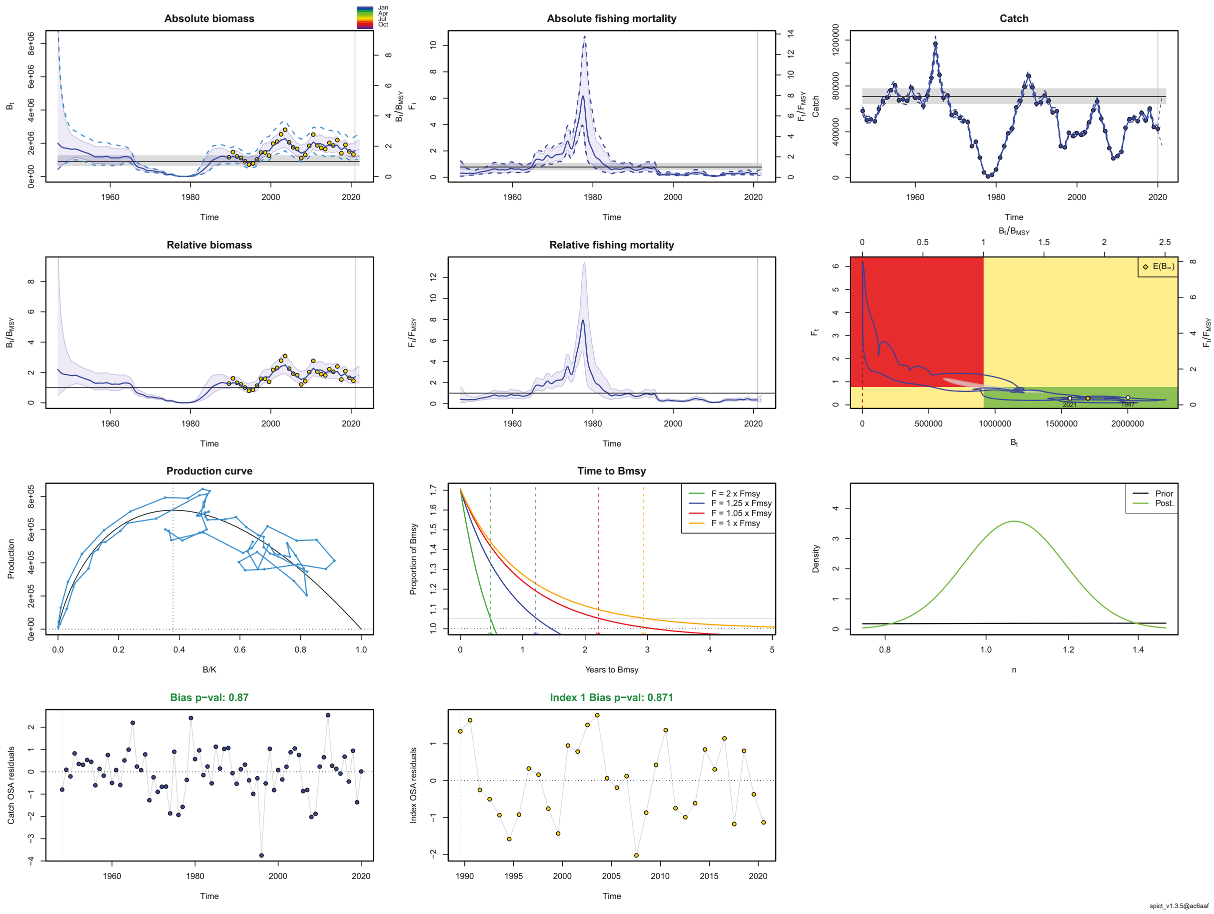

Figure F.9: Summary of the SPiCT assessment for herring. See Figure F.7 for details on the illustration.