Dynamics and impacts of changing reference points with a focus on recruitment productivity

Paula Silvar Viladomiu

A thesis presented in fulfilment
of the requirements for the degree of
Doctor of Philosophy

Supervisors: Dr Cóilín Minto, Dr Deirdre Brophy, and
Dr David Reid

Atlantic Technological University
Marine and Freshwater Research Center
Galway City, Ireland

October, 2022

This PhD is part of the large-scale collaborative project Fisheries Knowledge for Optimal Sustainable Management (FishKOSM) led by the Marine Institute and is funded by the Department of Agriculture, Food and the Marine Competitive Research Funding Programmes (Reference 15/S774).

Declaration

I hereby declare that this material, which I now submit to the Atlantic Technological University in fulfilment of the requirements for the award of the degree of Doctor of Philosophy is entirely my own original work and has not been taken from the work of others, save to the extent that such work has been cited and acknowledged within the text of my work.

Signed:

Paula Silvar Viladomiu
ID No. G00364959
Dated: 26th October 2022

Table of Contents

List of Figures

List of Tables

List of Abbreviations Used

This list contains common abbreviations and their definitions.

Acronyms

AIC	Akaike Information Criterion
AR	Autoregressive
CFP	Common European Fisheries Policy
DFA	Dynamic Factor Analysis
DLM	Dynamic Linear Model
EBFM	Ecosystem Based Fisheries Management
EM	Expectation-maximization algorithm
F	Fishing mortality rate
FAO	Food and Agriculture Organization
HCR	Harvest Control Rule
HMM	Hidden Markov Model
ICES	International Council for the Exploration of the Sea
MAD	Median absolute deviation
MCMC	Markov Chain Monte Carlo
MSA	Magnuson–Stevens Fisheries Conservation and Management
MSE	Management Strategy Evaluation
MSY	Maximum Sustainable Yield
NOAA	National Oceanic and Atmospheric Administration
PA	Precautionary Approach
PPM	Peterman's Productivity Method
PROST	Projection Stochastic assessment model
RFMO	Regional Fisheries Management Organisations
SAM	State-space Assessment Model
SMS	Stochastic Multispecies Model
SPR	Spawner Biomass-per-Recruit
SR	Stock-Recruitment
SSB	Stock Spawning Biomass
TAF	Transparent Assessment Framework
TMB	Template Model Builder
UN	United Nations
WSSD	World Summit on Sustainable Development
YPR	Yield-per-Recruit

Reference points

B_0	Unfished biomass reference point
B_{lim}	Biomass limit reference point
B_{loss}	Lowest observed biomass level
B_{MSY}	Biomass at MSY reference point
B_{pa}	Biomass precautionary approach reference point
F_{eco}	Ecosystem rescaled fishing mortality target reference point
F_{lim}	Fishing mortality limit reference point
F_{MSY}	Fishing mortality at MSY reference point
F_{pa}	Fishing mortality precautionary approach reference point
$F_{p.05}$	Fishing mortality precautionary criterion reference point
MSY $B_{trigger}$	Biomass trigger at MSY reference point
MBAL	Minimum Biological Acceptable Level

ICES Study groups and workshops

SGPA	Study Group on the Precautionary Approach
SGPRP	Study Group on Precautionary Reference Points for Advice on Fisheries Management
WKFRAME	Workshop on Implementing the ICES F_{MSY} framework
WKGMSE3	Third Workshop on Management Strategy Evaluations
WKGMSEMAC	Workshop on Management Strategy Evaluations of Mackerel
WKIrish	Workshop on the Irish Sea
WKMSYREF	Workshop to consider reference points for all stocks
WKMSYREF2	Workshop to consider F_{MSY} ranges for stocks in ICES categories 1 and 2 in Western Waters
WKMSYREF3	Workshop to consider the basis for F_{MSY} ranges for all stocks
WKMSYREF4	Workshop to consider F_{MSY} ranges for stocks in ICES categories 1 and 2 in Wester Waters
WKNSMSE3	Workshop on North Sea stocks Management Strategy Evaluation in 2018
WKREF	Workshop on Limit and Target Reference Points
WKREBUILD	Workshop on Guidelines and Methods for the Evaluation of Rebuilding Plans
WKRPCHANGE	Workshop of Fisheries Management Reference Points in a Changing Environment

Dynamics and impacts of changing reference points with a focus on recruitment productivity

Paula Silvar-Viladomiu

Abstract

Managing fish stocks in the context of changing ecosystems and productivity is an ongoing challenge for fisheries science. Reference points are key tools for enabling effective management, defining management goals, guiding management actions and providing advice on sustainable catches. Measuring productivity is crucial for estimating reference points. For many fish stocks, there is evidence that productivity has changed over time in a non-stationary manner. While understanding why these changes have occurred is important, in the more immediate term, understanding how productivity is changing and accounting for those changes is crucial for tactical management.

The objectives of this thesis were to (i) explore reference point estimation and retrospective changes, (ii) highlight a method developed by Randall Peterman and colleagues (Peterman's Productivity Method) as a method to track temporal changes in recruitment productivity of fish stocks, and (iii) apply this method to the Celtic Seas ecoregion.

Chapter 1 provides context into the evolution of fisheries science historical background, overviews reference point evolution and paradigms, and emphasizes the importance of reference points for fisheries management. Challenges posed by ecosystem concerns in fisheries management and reference points in dynamic ecosystems are discussed. Implications of dynamic productivity of fish stocks are also considered.

Chapter 2 provides an empirical review of the reference points used by the International Council for the Exploration of the Sea (ICES) to base advice on fishing opportunities. The ICES reference point framework and its historical evolution are reviewed in detail. The extent to which reference point estimation is consistent with the ICES guidelines is evaluated. Chapter 3 studies retrospective changes in reference points and implications for fisheries sustainability in the ICES region. Changes in stock status are decomposed and quantified to distinguish the effect of monitoring from changes in reference points. Frequent changes in reference points

are found with significant impacts on sustainability status, and reasons for change in reference points are researched.

Chapter 4 explores the *status quo* of reference points and highlights a method to estimate dynamic reference points to adapt single-species reference points to changing ecosystem concerns. This chapter provides a comprehensive review of the estimation of reference points in both single-species and ecosystem contexts. Current reference points ignore persistent dynamic productivity change by assuming that the SR relationship is stationary and with constant recruitment parameters over selected time periods. The method presented, Peterman's Productivity Method (PPM), is capable of tracking temporal dynamics of recruitment productivity via time-varying stock-recruitment parameters. Adding the temporal dimension of changes in productivity when estimating reference points can broadly account for non-stationary ecosystem considerations in fisheries management advice. In Chapter 5, PPM is applied to analyze stochastic changes in recruitment productivity for Celtic Seas ecoregion stocks and common temporal productivity trends are synthesized. Many stocks in the Celtic Seas ecoregion display non-stationary recruitment productivity with diverse temporal trends.

Chapter 6 elaborates on the importance of research synthesis such as the ones conducted in this thesis. Details of current reference points used in the ICES framework are discussed along with implications and causes of reference point changes over time. Further elaboration on Peterman's Productivity Method as a link to non-stationary ecosystem concerns is provided. Dynamics in productivity of the Celtic Seas ecoregion stocks and implications for management advice are discussed. Recommendations for future research on dynamic recruitment productivity are given to keep developing the method and the science to reconcile reference points and ecosystem concerns.

This thesis provides a substantial contribution to current research on the adaptation of reference points and fisheries advice to changing ecosystems by reviewing and synthesising ICES reference point estimation, analysing retrospective changes to reference points, demonstrating how Peterman's Productivity Method can account for changes in productivity, and applying this approach to stocks in the Celtic Seas ecoregion.

Acknowledgements

I would like to thank the Department of Agriculture, Food and the Marine for funding the FishKOSM project which my research is part of, as well as the HEA support for Covid-19 related Research Costed Extensions for providing the funding for an extension. Thank you, former Galway-Mayo Institute of Technology and new Atlantic Technological University and the Marine and Freshwater Research Center for providing the facilities for this thesis to be conducted.

A huge thanks go to my supervisors, who have provided guidance and support throughout. I would like to thank my main PhD supervisor, Dr Cóilín Minto, for his stimulating meetings and his patience. His extensive knowledge of fisheries science, statistics, and modelling has been a tremendous help and has allowed me learn greatly. Thanks to Dr Deirdre for her concise and helpful comments, which help me improve the research and the drafts. I would also like to thank Dr David Reid for his valuable insights into ecosystem-based fisheries management and comprehensive knowledge of the Celtic Seas ecosystem.

I am very grateful to my co-authors for their help and their thoughtful comments in the manuscript drafts. Thank you Dr Luke Batts, Dr Ghassen Halouani, Dr Colm Lordan, Dr David Miller, Dr Jeremy Collie, and Dr Rich Bell for their share of their expertise. Thank you to Professor Randall Peterman and his group for the initial development of the method inspiring part of this work and subsequent discussions. Thanks also to Paul Dolder and Luke Batts for his help formatting the thesis.

Thank you to my friends and colleagues at the MFRC. It has been great having your company all this years for excursions, hotpots, diners, nights out, movies, and painting sessions. Special thanks to BFFs: Dr Elena Pagter, Dr Maria Perez Tadeo, Dr Christie O'Donnel, Dr Andrew Power, Dr James O'Connor, Dr Joaoinho Frias, Laura Vilches, Niall Keogh, and Ryan McKenna.

I'd also would like to say thanks all my friends from home for their love and support. From the Pueblo, Irene, Sara, Clara, Adri, and Dennis os quiero. EMBC girls, I love you. My dear SDC girls, Icia, Noe, Martas, and Ros. Particular thanks to Dr Maria Torres for her support and coaching in hard moments throughout this thesis.

Huge thanks to my family, for their company and reassurance during this

PhD. I could not have done this without them. Thanks to my mum, my dad, my sister, and Barni for their love and encouragement. Special thanks to my aunt Nuri for her support and her unconditional help. The painting calls have been so inspiring and refreshing. Thanks to my cousin Irene and my Grandma for their stories over the phone.

Chapter 1

General thesis introduction

1.1 Introduction

1.1.1 Historical background on the evolution of fisheries science

Fluctuations in the abundance of fish populations and their causes have been studied since the middle of the 1880s (Gulland 1988). In 1884 a controversy emerged on whether fish populations were inexhausted or whether they were affected and limited by harvesting (see Huxley 1884 speech). Towards the end of the 19^{th} century, scientists began finding evidence that fisheries were reduced and fished populations were declining, which prompted concerns about overfishing (Garstang 1900). The International Council of the Exploration of the Sea (ICES), was established in 1902 and formed an overfishing committee during its first meetings to study the decrease of fish and evidence of overfishing. As commercial fishing was developing, the study of fish population dynamics, status, and causes of change became critical; the need to manage fisheries and regulate fishing was realised. This induced the development of data collection and analysis methods for stock assessment (reviewed in Gulland 1988). In the 1910s, Fedor Baranov developed a theory for cohort progression where fishing and natural mortality acted continuously. The resulting catch equation showed how catch was a function of fishing and natural mortality. This theory considered that the reduction in fish abundance is related to catches (widely used in fisheries modelling).

ICES played a major role in establishing the scientific basis for fisheries models (Quinn 2003). ICES meetings encouraged important developments in data collection systems and scientific stock studies (reviewed in Gulland 1988; Quinn 2003). Hjort emphasized the importance of recruitment (early life history of fish populations) and recognized recruitment variability as being a prime factor in determining the size of fish populations (Hjort 1914). In 1931, Russel developed a simple general theory for assessing the status of fish populations (Russell 1931). Russel identified factors in absolute rates influencing populations weight changes: the increase due to the recruitment rate, the increase due to the growth of fish, the decrease because of natural mortality, and the decrease because of the catch rate.

Hjort (1933) formulated the theory that a fishery would have an optimum yield derived from the equilibrium conditions of a population model. Hjort showed that the equilibrium catch would be for levels of fishing effort and how this could be maximised. Later known as maximum sustainable yield (MSY). During the World Wars, it was demonstrated how important fishing was in depleting fish populations; with the cessation of fishing, it was observed that stock's abundance increased (Smith 1994). Quantitative fisheries models kept developing and advancing making it possible to estimate MSY, e.g. surplus production models (Schaefer 1954), yield-per-recruit theory (Beverton and Holt 1957), and the concept was consolidated. Cushing (1973) differentiated between "growth overfishing", which is catch that exceeds MSY at a given effort level, and "recruitment overfishing", which is the catch that would reduce recruitment.

The concept of MSY gained a lot of popularity around the 1950s and it was solidified. Subsequently, MSY was criticised from multiple angles (Larkin 1977). Larkin (1977) published the "epitaph" to MSY elaborating on his concerns about: species interactions, sub-populations, mixed fisheries, estimation problems, and the appropriateness of MSY as a management goal. However, as explained in the next section, a new interpretation of MSY made it the dominant fisheries management strategy (Mace 2001).

1.1.2 Reference point evolution and paradigms

Scientific fisheries management advice focuses on promoting sustainability and avoiding overfishing of fish stocks (Caddy and Mahone 1995). Reference points play a key role in this process. Caddy and Mahone (1995) reviewed the development and diversity of reference points and provided an overview of their formulation, technical basis, utility, and limitations. Reference points capture the management objectives of the fishery and depending on the interpretation of these objectives, appropriate technical basis are defined for the reference points. Some initial interpretations to prevent overfishing were to avoid recruitment overfishing (Mace 2001; Sissenwine and Shepherd 1987).

The development of the precautionary approach to fisheries management to ensure resource conservation was crucial in the evolution of reference points (reviewed in Restrepo et al. 1999). The precautionary approach is a way of thinking about fisheries and making management decisions that can help prevent overfishing and rebuild depleted stocks. Restrepo et al. (1999) defined that "In fisheries, the precautionary approach is about applying judicious and responsible fisheries management practices, based on sound scientific research and analysis proactively (to avoid or reverse overexploitation) rather than reactively (once all doubt has been removed and the resource is severely overexploited), to ensure the sustainability of fisheries resources and associated ecosystem for the benefit of future as well as current generations". Recognition of uncertainties in fisheries science and challenges in fisheries management also led to the stipulation that the precautionary approach should be applied to management (reviewed in Hilborn et al. 2001). The evolution of the precautionary approach and the awareness of the ecosystem effects of fishing, resulted in a new interpretation of MSY (reviewed in Mace 2001). This new interpretation consisted of a fundamental change of MSY from a target catch state towards a limit fishing mortality rate at MSY (Mace 2001).

In 1995, after a scientific and technical meeting in Rome, the Food and Agriculture Organization (FAO) of the United Nations published a code of conduct for responsible fisheries that set out principles and international standards of behaviour for responsible practices in view of ensuring the effective conservation, management and development of living aquatic resources, with due respect for the ecosystem and biodiversity (FAO 1995a). The code recognized that long-term sustainable use of fisheries resources is the overriding objective of conservation and management. It advocated for the adoption of appropriate management measures, based on the best scientific evidence available, designed to maintain or restore stocks at levels capable of producing maximum sustainable yield. The code recommended the application of the precautionary approach and stressed the need for research on the effect of climate or environmental change on fish stocks and ecosystems. The FAO published Technical Guidelines on the precautionary approach (FAO 1995b) focusing on definitions of overfishing incorporating target and limit reference points, decision rules to prevent overfishing and promote stock rebuilding and incorporation of uncertainty by using a risk-averse approach. The UN Fish Stock Agreement contains guidelines for implementing the precautionary approach including indications to specify precautionary reference points and management strategies (UN 1995).

In 2002, the Johannesburg Plan of Implementation of the World Summit on Sustainable Development provided the fundamental principles and the programme of action for achieving sustainable development. The plan called for an ecosystem approach and rebuilding of fisheries to MSY, promoting science-based decision-making and reaffirming the precautionary approach (UN 2002). In addition to international agreements, each region has fisheries policies that set the context for fisheries advice (e.g. EC 2013; MSA 2007).

Typically, the precautionary approach and MSY are common paradigms underlying the estimation of reference points globally (Mace 2001; Hilborn 2020; Marchal et al. 2016; Silvar-Viladomiu et al. 2022a).

In Europe, ICES evolved to have a major responsibility in the provision of scientific advice to various commissions such as the European Commission and the North-East Atlantic Fisheries Commission. Advice agencies, such as ICES, collaborate to provide stock assessments and estimate reference points in accordance with the policy of the region or the country (ICES 2019a). Despite general agreement regarding the conceptual bases behind reference points, the interpretation, technical definition, and use are complex and vary between regions (Hilborn 2020; Ricard et al. 2012). ICES began developing reference points for advice focusing on maintaining stocks within safe limits, avoiding reduction of average recruitment in relation to biomass (ICES 2003a). Implementation of MSY-based approaches began developing in 2007 during the ICES Workshop on Limit and Target Reference Points (ICES 2007). Consequently, general guidelines and tools were developed for reference point estimation (reviewed in Silvar-Viladomiu et al. 2022a). Currently, ICES gives advice based on MSY reference points integrating the precautionary approach (ICES 2021c; ICES 2021a).

1.1.3 Role and importance of reference points for fisheries management

Reference points have proven crucial for the implementation of effective management by enabling the establishment of a set of rules to control fishing pressure (Caddy and Mahone 1995). These reference points are key for tactical management because they represent targets and thresholds by which the biological state of the stock can be evaluated and the allowable catch can be advised (Gabriel and Mace 1999). Reference points are defined based on the conceptual criteria that embody the management objectives for the fishery (e.g. MSY and avoiding overfishing). A target reference point indicates the level of fishing or biomass which is considered to be desirable and at which the management action should aim (Caddy and Mahone 1995). A limit reference point indicates a state of a fishery or stock which is considered undesirable and which management action should avoid (Caddy and Mahone 1995). These reference points define levels of a stock specifying a predefined course of management actions depending on the status of the stock, i.e. Harvest

Control Rules (HCR; Kvamsdal et al. 2016; Getz and Haight 1989). HCRs are considered a key component of the precautionary approach to fisheries management (Restrepo et al. 1999; FAO 1995b). A HCR provides the scientific basis for the tactics employed in a fishery and depends on explicit or perceived management objectives on which to base scientific management (Punt 2010). There are different types but, in general, they control catch or fishing mortality to permit the achievement of management goals.

Although many stocks were overfished (Ludwig et al. 1993), the state of the world's fisheries has been improving with reductions in fishing mortality rate of many assessed stocks achieved through management (Worm et al. 2009; Fernandes and Cook 2013; Cardinale et al. 2013; Hilborn et al. 2020). Overfishing is a major threat to marine ecosystems because it can cause stock collapses, reduce biodiversity and alter ecosystem functions (Worm et al. 2006). Reduction in fishing mortality has been shown to help recover stock biomass (Cardinale et al. 2013; Fernandes and Cook 2013; Zimmermann and Werner 2019; Hilborn et al. 2020). Reference points can trigger management actions (by measuring the status of fish stocks, and defining management goals) contributing to the reduction of the overall fishing mortality rate, which helps to ensure the conservation of marine ecosystems (Mace 2001; Hilborn et al. 2020). Cardinale et al. (2013) showed that the exploitation status for many EU stocks had greatly improved during the last decade due to management (i.e. fishing mortality has been reduced) and was close to the fishing mortality rate that will deliver MSY. Fernandes and Cook (2013) demonstrated that these reductions in fishing mortality were associated with declines in fishing effort. Globally, Hilborn et al. (2020) showed that the recovery in abundance trends was correlated with changes in fishing pressure. Their study indicates that overall, in assessed areas, stock abundance was currently above the level that would produce MSY. Zimmermann and Werner (2019) also demonstrated the importance of the reproductive output for the stock's recovery and the positive correlation between recruitment and changes in spawning biomass.

1.1.4 Ecosystem concerns in fisheries management

A major criticism of MSY is that it does not take into account species and ecosystem interactions (Larkin 1977; Vert-pre et al. 2013; May et al. 1979). The need for Ecosystem-Based Fisheries Management (EBFM) has been long globally accepted and is included in most fisheries policies (FAO 2003; MSA

2007; EC 2013). In recent decades, fisheries science and management have been evolving towards EBFM. Taking an EBFM requires a holistic approach to fisheries management, which takes into account species interactions and environmental system-wide effects, considering humans as an integral part of the ecosystem (Fogarty 2014). The implementation and operationalization of the EBFM face several challenges (see Cowan et al. 2012; Dolan et al. 2016), for example, difficulty in providing operational guidelines for defining and attaining ecosystem-based objectives. Ecosystem approach methods can be very data-demanding and highly complex (Collie et al. 2016). Significant effort has gone into developing models and remarkable advances have been made (see Geary et al. 2020). These studies greatly improved our understanding of the effects of fisheries and other anthropogenic impacts on ecosystems, and emphasized the importance of ecosystem biological and environmental interactions in fish population dynamics (e.g. Collie and Gislason 2001; Trijoulet et al. 2020; Ottersen et al. 2001; Gaines et al. 2018). Important advances have been made towards the inclusion in decision-making frameworks of ecosystem models (e.g. Bentley et al. 2021; Chagaris et al. 2020; Lucey et al. 2021), multispecies models (e.g. Plagányi et al. 2014; Lewy and Vinther 2004), and links with environmental and ecological drivers (e.g. Crone et al. 2019). However, in terms of tactical management for fisheries advice, the use of these tools and the inclusion of explicit environmental and biological drivers affecting fish population dynamics is still relatively limited (Skern-Mauritzen et al. 2016).

To operationalize EBFM the use of single-species and optimum yield frameworks has been proposed (Pauly and Froese 2021; Patrick and Link 2015). Single-species frameworks are not incompatible with EBFM, therefore these approaches can be reconciled. Single-species stock assessment frameworks are more attainable than most ecosystem approach methods as they are less data-demanding (Pauly and Froese 2021). However, as suggested by Sissenwine et al. (2014), current frameworks for stock advice need more flexibility to include more scientific uncertainty and recognize the dynamics of the ecosystem (e.g. deal with technical and biological interactions in multispecies fisheries and ecosystems). In the EU, reference ranges have been developed to give flexibility around fishing mortality at MSY in mixed fisheries, where several stocks and fleets share the same space (i.e. technical interactions) (Rindorf et al. 2017a). In mixed fisheries contexts, major advances have been made in developing simulation frameworks to optimising yields (e.g. Garcia et al.

2020). Additionally, a method has been proposed that, using the outputs of an existing ecosystem model for the region, can scale fishing mortality within the reference ranges giving the ecosystem conditions Bentley et al. (2021). Nevertheless, challenges remain on how to align sustainable yield with including ecosystem considerations. Overall, for both single-species and EBFM, the levels of fishing must be aligned with the stock productivity (Mace 2001). Therefore, ensuring sustainability of the stock and the ecosystem requires consideration of the ecosystem impacts on fish productivity (King et al. 2015; Clausen et al. 2018).

1.1.5 Reference points and dynamic ecosystems

Initial deterministic static interpretations to estimate reference points have evolved to include variability of productivity around a long-term equilibrium (Rindorf et al. 2017b; Silvar-Viladomiu et al. 2022b). The estimation of MSY using historical data typically assumes that past conditions have a similar probability of occurring in the future (Caddy and Mahone 1995). In 1996, Caddy challenged the equilibrium paradigm arguing that steady state in fisheries is relatively rare (Caddy 1996). Despite this, fisheries advice is often based on an equilibrium paradigm in terms of productivity; most calculations relative to reference points are long-term equilibrium yields and stock sizes (Hilborn 2002). Recruitment productivity, which measures the renewal of a population with the relation between spawner abundance and subsequent recruitment (i.e. stock-recruitment relationship), is assumed stationary in the estimation of reference points, i.e. a time-independent relationship with constant parameters in time (Hilborn and Walters 1992).

Ecosystems are non-stationary; ecosystem changes are related to changes in environmental variability, food-web interactions, fishing pressure (especially overfishing), and climate change (reviewed in Fogarty and Collie 2020). The FAO fish stock assessment manual established that reference points must be regularly updated, taking into consideration possible changes in the biological parameters or exploitation patterns (FAO 2003). This point was reiterated by ICES (ICES 2021a) in light of the dynamic nature of marine ecosystems. However, a protocol for revising the reference points in response to changing ecosystem or fisheries conditions is generally missing (Sissenwine et al. 2014).

Regime shifts are abrupt changes in the environment or the ecosystem state which can cause changes in fish productivity (King et al. 2015; Vert-pre et al. 2013). In the revision and estimation of reference points, a common adaptation when regime shifts are detected is to reduce the data to the most recent productivity regime (Punt et al. 2014a). However, this approach has disadvantages such as losing information in the data (Silvar-Viladomiu et al. 2022b; Collie et al. 2021). In a review of management strategies that take into account climate and environmental variation Punt et al. (2014a) found that explicitly identifying and implementing mechanisms did not improve the performance of the management strategy. Of the case studies, where management has been adapted to productivity and regime shifts, reviewed by King et al. (2015), the operationalization of the relationship between environmental drivers and productivity was often unsuccessful mainly because of uncertainty in process understanding. In addition, accounting for regime shifts was shown challenging due to, for example, recruitment time series being shorter than the span of the regime shift and time series having high variability hindering the detection of the regime shift.

1.1.6 Dynamic productivity of fish stocks

Taking into account the influences of ecosystem changes in stock population dynamics and productivity in management advice is important because it could cause risk of failing to prevent overfishing (Lindegren et al. 2009; Pershing et al. 2015). Climate change will impact ecosystems and influence changes in productivity and reference points (Free et al. 2019; Gaines et al. 2018; Ianelli et al. 2011). At a global level, there has been evidence of changes in productivity in a non-stationary manner (Vert-pre et al. 2013; Britten et al. 2017). An increasing number of studies found evidence of temporal changes in recruitment productivity of many stocks (Dorner et al. 2008; Minto et al. 2014; Britten et al. 2017; Tableau et al. 2019). This evidence poses challenges for defining reference points for management. A key effort for implementing EBFM in dynamic ecosystems lies in the detection of changes in population productivity and their causes or drivers: how is fish productivity changing and why?

The quest to understand why productivity changes is important for management. Identifying the drivers and the explicit mechanisms of the processes that change the productivity of fish stocks is crucial to inform predictions. However, due to the existence of many direct and indirect processes (Lindmark et al. 2022), complex dynamics can arise (Sugihara et al. 2012). Finding strong links between drivers and productivity changes is challenging (Vert-pre et al. 2013; Tableau et al. 2019). One critical complication for the implementation of mechanistic links is that the relationships can change over time (Myers 1998; Ottersen et al. 2013; Litzow et al. 2020). These issues translate to the difficult implementation of these relationships in management.

It is now evident that the lack of consideration of the underlying ecosystem's effects on productivity in the estimation of reference points can cause bias in management (Zhang et al. 2021a; Holt and Michielsens 2020; Clausen et al. 2018). Understanding how population productivity varies with abundance has been considered crucial in traditional fisheries management (Quinn and Deriso 1999). This thesis posits that in the context of changing ecosystems it is also crucial to understand how productivity varies over time. And this time-varying productivity should be accounted for in the estimation of reference points for fisheries management.

Environmental and stock structure changes can cause productivity parameters to change (Walters 1987). Zeng et al. (1998) demonstrated that time-varying parameter techniques offer an advance for modelling population dynamics in changing environments because population dynamics processes may operate at different times and under different density ranges. Rose (2004) showed that overfishing, abundance and climate effects are complex and reflected in population parameters not being constant over time. Randall Peterman and his group developed a state-space modelling approach to estimate parameters of the stock-recruitment relationship that vary over time which enabled tracking temporal dynamics of recruitment productivity (Peterman et al. 2000; Peterman et al. 2003). This approach has great potential and flexibility for taking into account underlying ecosystem changes in the modelling of recruitment productivity and estimation of reference points (Minto et al. 2014; Silvar-Viladomiu et al. 2022b).

1.2 Overview and aims of the thesis

This thesis addresses a crucial gap for fisheries management advice in light of ecosystem dynamics by (i) reviewing reference points estimation and retrospective changes, (ii) highlighting Peterman's Productivity Method as a method to track temporal changes in recruitment productivity, and (iii) applying this method to the Celtic Seas ecoregion. Research presented in Chapters

2 and 3 throw light onto important concerns on reference point estimation and retrospective changes. Reference points include precautionary, stochastic and uncertainty elements, but stationarity is assumed. Reference points change over time and these retrospective changes have significant implications for sustainability status. Chapter 4 proposes a method developed by Peterman and colleagues to link single-species advice and ecosystem concerns. Peterman's Productivity Method can track temporal changes in recruitment productivity, and the application of this method and estimation of dynamic reference points would give flexibility to the advice framework needed to account for non-stationarity ecosystem concerns. Chapter 5 applies the method to model dynamic recruitment productivity of stocks in the Celtic seas ecoregion.

This thesis provides a substantial contribution to current research on the adaptation of reference points and fisheries advice to changing ecosystems, by reviewing and synthesising ICES reference point estimation, analysing retrospective changes to reference points, demonstrating how Peterman's Productivity Method can account for changes in productivity, and applying this approach to model dynamic recruitment productivity of stocks in the Celtic Seas ecoregion.

A brief overview of the chapter structure is provided here:

Chapter 1. General thesis introduction

Chapter 1 provides an overview of: historical background on the evolution of fisheries science, reference point evolution and paradigms, role and importance of reference points for fisheries management, ecosystem concerns in fisheries management, reference points and dynamic ecosystems and dynamic productivity of fish stocks.

Chapter 2. An empirical review of ICES reference points

Chapter 2 provides an empirical review and synthesis of the ICES reference point framework for current advice, describing how reference points are defined and estimated and how they have been developed. Based on the review of reference points estimation for all ICES category 1 stocks, recomendations are given for future advances.

This chapter is in press at the *ICES Journal of Marine Science*:

Silvar-Viladomiu, P., Batts, L., Minto, C., Miller, D., Lordan, C. (2022). An empirical review of ICES reference points, ICES Journal of Marine Science, 79, 10, 2563–2578. https://doi.org/10.1093/icesjms/fsac194

Chapter 3. Moving reference point goalposts and implications for fisheries sustainability

Chapter 3 focuses on understanding retrospective changes in reference points in the ICES region over the last decade by exploring whether reference points had changed, how this change impacts the status of commercial fish stocks, and what causes these changes.

This chapter has been published in *Fish and Fisheries*:

Silvar-Viladomiu, P., Minto, C., Halouani, G., Batts, L., Brophy, D., Lordan, C., and Reid, D. G. (2021). Moving reference point goalposts and implications for fisheries sustainability, Fish and Fisheries, 22, 1345—1358. https://doi.org/10.1111/faf.12591

Chapter 4. Peterman's productivity method for estimating dynamic reference points in changing ecosystems

Chapter 4 is a *quo vadimus* paper that describes the *status quo* and the future landscape of stock reference points in changing ecosystems. The chapter starts with a review of current single-species reference points and estimation, describes ecosystem concerns and methodological approaches, and finally highlights a method as a link between current reference points and changing ecosystems concerns: Peterman's Productivity Method. Randall Peterman and colleagues developed a method to estimate dynamic recruitment productivity via time-varying stock-recruitment parameters (Peterman et al. 2003). Challenges and future developments in this area are outlined.

This chapter has been published in the *ICES Journal of Marine Science*:

Silvar-Viladomiu, P., Minto, C., Brophy, D., and Reid, D. G. (2022). Peterman's productivity method for estimating dynamic reference points in changing ecosystems, ICES Journal of Marine Science, 79, 4, 1034–1047. https://doi.org/10.1093/icesjms/fsac035

Chapter 5. Stochastic modelling and synthesis of dynamic fish recruitment productivity in the Celtic Seas ecoregion

In Chapter 5, Peterman's Productivity Method (highlighted in Chapter 4) is applied to model and synthesise dynamic fish recruitment productivity of Celtic Seas ecoregion stocks. Time-invariant and time-varying versions of the Ricker model were evaluated, where parameters were allowed to vary over time according to a stochastic process. We evaluated recruitment productivity correlations across stocks and identify common productivity trends in the Celtic Seas ecoregion.

This chapter is in preparation for submission:

Silvar-Viladomiu, P., Minto, C., Lordan, C., Brophy, D., Bell, R., Collie, J., and Reid, D. G. Stochastic modelling and synthesis of dynamic fish recruitment productivity in the Celtic Seas ecoregion.

Chapter 6. General thesis discussion

Chapter 6 synthesises the findings of Chapters 2-5 and places the results in the context of the general introduction. I elaborate on the current ICES reference point framework and changes in reference points over time. This chapter also reflects on the application of Peterman's Productivity Method as a link to adapt single-species reference points to ecosystem concerns. Implications of time-varying stochastic recruitment productivity in Celtic Seas ecoregion and the relationship to dynamic reference points are provided. Finally, recommendations for future research on dynamic recruitment productivity are discussed.

Chapter 2

An empirical review of ICES reference points

This chapter is a verbatim copy of the accepted manuscript by the *ICES Journal of Marine Science*, which can be found in Appendix B.1:

Silvar-Viladomiu, P., Batts, L., Minto, C., Miller, D., Lordan, C. (2022). An empirical review of ICES reference points, ICES Journal of Marine Science, 79, 10, 2563–2578. https://doi.org/10.1093/icesjms/fsac194

Abstract

The International Council for the Exploration of the Sea (ICES) has provided scientific stock advice based on reference points to manage fisheries in the North Atlantic Ocean and adjacent seas for decades. ICES advice integrates the precautionary approach with the objective of achieving maximum sustainable yield. Here, we examine ICES reference point evolution over the last 25 yr and provide a comprehensive empirical review of current ICES reference points for data-rich stocks (Category 1; 79 stocks). The consistency of reference point estimation with the ICES guidelines is evaluated. We demonstrate: (1) how the framework has evolved over time in an intergovernmental setting, (2) that multiple precautionary components and sources of stochasticity are included, (3) that the relationship and historical context of stock size and recruitment are crucial for non-proxy reference points, (4) that reference points are reviewed, frequently taking into account fluctuations and multiple sources of variability, (5) that there are occasional inconsistencies with the guidelines, and (6) that more comprehensive and clearer documentation is needed. Simplifying the stock-recruit typology and developing quantitative criteria would assist with this critically important classification. We recommend a well-documented, transparent and reproducible framework, and periodic syntheses comparing applications across all stocks.

Keywords: precautionary approach; maximum sustainable yield; ICES region; synthesis; limit and target reference points; stock population dynamics

2.1 Introduction

Reference points are key to providing fisheries advice and enabling effective management of fish stocks (Sissenwine and Shepherd 1987; Hilborn et al. 2020). A crucial consideration in reviewing reference points is how they are currently used and interpreted in advice products. Target and limit reference points can be used to evaluate stock and fishery status and can also be used in, or for the evaluation of, Harvest Control Rules (HCRs) that apply harvest strategies to set allowable catch (Punt 2010). Internationally, most advice recipients use similar terminology around the need to establish limit reference points, such that "*Limit reference points set boundaries to constrain harvesting within safe biological limits so stocks can produce maximum sustainable yield*" and target reference points, where "*Fishery management strategies shall ensure* *that target reference points are not exceeded on average*" (UN 1995). The UN Fish Stocks Agreement in 1995 set out the principles for the conservation and management of fish stocks. Under this agreement management should be designed to maintain or restore stocks to levels capable of producing Maximum Sustainable Yield (MSY) and must be based on the Precautionary Approach (PA) and the best available scientific information. Many fishing jurisdictions agree to provide advice that integrates the PA with MSY and embraces the ecosystem approach, e.g. the Common Fisheries Policy (EC 2013), the UK Fisheries Act (Anon 2020), and the Magnuson-Stevens Fishery Conservation and Management Act (MSA 2007) in the United States. These are typical foundations for the basis of reference point estimation. Whilst there are common paradigms and similar terminology, there are many different approaches to setting and estimating reference points (Ricard et al. 2012), depending on the region, jurisdiction, and the HCR used to trigger management decisions.

Reference points are commonly expressed in terms of a stock's biomass or spawning stock biomass (SSB) state and fishing mortality rate (F). Reference points that would produce MSY can be derived from per-recruit analyses coupled with the stock-recruit (SR) relationship in a stochastic projection using, in addition, biological parameters and fishery patterns from the stock assessment (Hilborn and Walters 1992). Recruitment productivity is often based on the stock-recruitment (SR) relationship. Common functional forms to model the SR relationship are the Ricker (Ricker 1954), the Beverton-Holt (Beverton and Holt 1957), and segmented regression or hockey-stick (Mesnil and Rochet 2010). Despite its importance, estimating SR parameters is challenging because the relationship is not well understood for many stocks due to a lack of data or the relationship itself being weak because of recruitment variation (Shepherd and Cushing 1990; Myers 2001; Thorson et al. 2014). Other factors that limit our knowledge of SR relationships are process and observation errors; uncertainty in variables (recruitment or SSB estimates); and non-stationarity (Hilborn and Walters 1992; Dickey-Collas et al. 2015; Minto et al. 2014; Perälä et al. 2017). Proxy reference points based on percentages from per-recruit analysis can be used when MSY-based estimates cannot be obtained (Geromont and Butterworth 2015). However, these exclude the SR relationship and other stock information that can make them unreliable. In the northeast Atlantic, yield-per-recruit (YPR) proxies were commonly used proxies for F_{MSY} (ICES 2007) because they rely on few data but are still useful to provide management recommendations for some stocks. Some US regions set percentages of spawner-per-recruit (SPR) or unfished biomass (B_0) as MSY reference point proxies (Wetzel and Punt 2017). Preferred proxies and percentages used vary between regions. These are usually based on meta-analysis of data-rich stocks. Setting the appropriate proxy and level for a reference point depends on life history features, and all available information on the SR relationship should be used (Mace 1994; Cadrin 2012).

Biomass limit reference points have a key role in identifying safe biological limits. These reference points could be interpreted as the level of stock biomass at which recruitment is impaired, or where there is recruitment overfishing. Recruitment overfishing occurs when a population has been fished down to a point where spawning biomass is so low that recruitment decreases substantially (Sissenwine and Shepherd 1987; Cushing 1975). Estimation of biomass limit reference points varies a lot regionally, and the estimation method impacts the level and the associated uncertainty of the reference point (Deurs et al. 2021). Some regions define biomass reference points as a chosen percentage below B_{MSY}, e.g. 0.5 B_{MSY} or higher in the United States (Punt et al. 2014c). However, recent stock size trends and fluctuations might not be informative regarding B_{MSY}, in addition to the SR relationship possibly not being well understood. Also, a percentage of unfished biomass, B_0, can be used as the basis for a biomass limit reference point in parts of the United States (Wetzel and Punt 2017). Fishing mortality limit reference points, such as F_{lim}, also have an important role in safeguarding safe biological limits. Fishing mortality should always be below that which will drive the spawning stock to the B_{lim} threshold.

Fish stocks display marked variability in life history, recruitment, and historical exploitation (Caddy and Mahone 1995). To estimate reliable reference points, these important features need to be taken into account, i.e. natural patterns of fluctuation in the dynamics of biomass, recruitment, and changes in fishing pressure and selectivity over time. In particular, recruitment temporal dynamics are complex and are challenging to deal with in the estimation of reference points (Sharma et al. 2019). For instance, sporadic large recruitment can influence the estimates of SR parameters. Additionally, there must be sufficient contrast in the SSB data to accurately understand the underlying SR relationship and estimate reference points (Anon 1999). If the contrast is small, estimates could be determined mainly by process or measurement error and thus could be unreliable. In these cases, the choice of reference point should be more precautionary (Anon 1999). Additionally, uncertainty related to the modelling tools, management, and advice implementation has to be dealt with when setting reference points (Kell et al. 2005).

The International Council for the Exploration of the Sea (ICES) has been providing scientific stock advice to government and international regulatory bodies that manage fisheries in the North Atlantic Ocean and adjacent seas for decades. ICES advice is diverse and based on requests from a range of requestors, including governments, governmental agencies, RFMOs, commissions, etc. The current approach integrates the PA with the objective of achieving MSY in accordance with the international guidelines to manage fish stocks (ICES 2021a). The ICES interpretation of MSY is maximizing the average long-term yield from a given fish stock while maintaining the stock in productive condition. When providing fisheries advice for stocks with full analytical assessments, ICES refers to two types of reference points: PA reference points and MSY reference points.

Within ICES, several relevant discussions on reviewing reference points have occurred in recent workshops (ICES 2020a; ICES 2021e; ICES 2020c), which has led to the Workshop on ICES reference points (WKREF1 and WKREF2). The purpose of WKREF1 and WKREF2 was to review and re-evaluate ICES reference points and produce clear evidence-based recommendations to the Advisory Committee (ACOM), and produce a road map to implementation to develop user-friendly guidelines and tools for the future. Both target and limit reference points were considered in terms of how they can be used in the evaluation of stock status, the ICES MSY advice framework, and more generally in management strategy evaluations (MSEs) to define if HCRs are both precautionary and in accordance with the MSY approach.

In this article, we reviewed reference points used in ICES fisheries advice up to 2021. We start by examining the evolution of the ICES reference point framework over the past 25 yr, followed by a summary of the current approach. Then, we investigate (i) most recent updates in ICES reference points; (ii) the key role of ICES biomass limit reference point (B_{lim}) and its relationship with SR typologies in the guidelines; (iii) the estimation of MSY reference points and how uncertainty and variability are included; and (iv) interdependencies among reference points, particularly the impact of B_{lim} changes on other reference points. Finally, based on this comprehensive empirical review, we summarize six concluding points and give recommendations for the future.

2.2 Evolution of ICES-advised reference points

The ICES reference point framework has been strongly influenced by policy needs and drivers but also by the availability of tools to estimate reference points in a consistent way (Figure 2.1). The ICES Study Group on the Precautionary Approach (SGPA) in 1998 defined B_{lim} as the biomass "*below which recruitment becomes impaired or the dynamics of the stock are unknown*" (ICES 1998). The word 'impaired' is synonymous with the concept that, on average, recruitment becomes systematically reduced as biomass declines below a certain point. During the early 2000s, the various SGPA meetings developed understanding of precautionary reference points considerably (ICES 2001; ICES 2002; ICES 2003b). This culminated in the Study Group on Precautionary Reference Points for Advice on Fisheries Management (SGPRP) in 2003, which was the first systematic attempt to estimate PA reference points for most data-rich ICES stocks (i.e. Category 1, stocks for which a full analytical assessment could be conducted; ICES 2003a). ICES advised on the state of the stock relative to a limit reference point (B_{lim}) that should be avoided to ensure that stocks remain within safe biological limits, i.e. a high probability that SSB is above B_{lim} and that fishing mortality is below a value F_{lim} that will drive the SSB to B_{lim}. At that stage, ICES had already started to define SR types based on SR plot categorization, and use segmented regression to estimate breakpoints in the SR relationship. The definition of B_{lim} was "*the SSB below which is a substantial increase in the probability of obtaining reduced (or 'impaired') recruitment i.e. the estimate of B_{lim} should be risk-averse so that when the stock is at B_{lim} the probability that recruitment is substantially impaired is still small, but below B_{lim} that probability increases*".

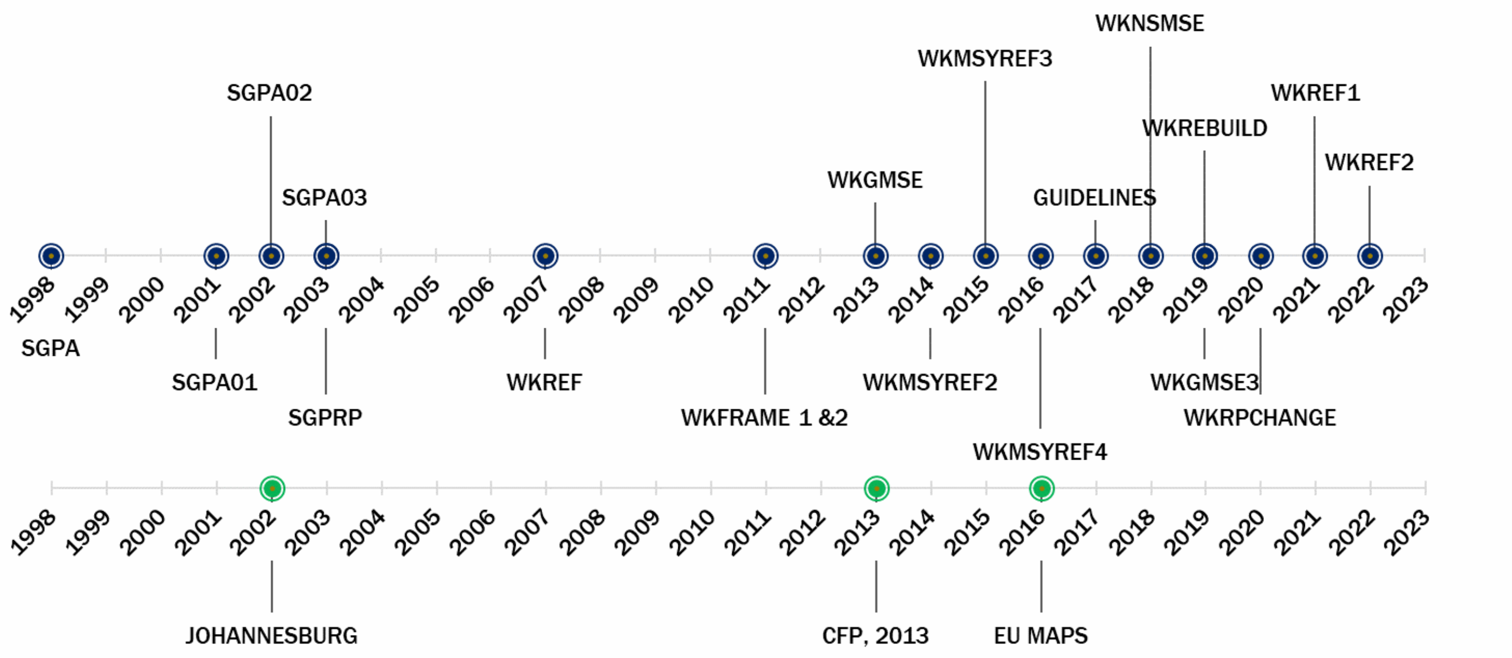

Figure 2.1: The working group timeline that produced key developments in the evolution of ICES Precautionary Approach and Maximum Sustainable Yield reference points. Acronyms used are: SGPA (Study Group on the Precautionary Approach), SGPRP (Study Group on Precautionary Reference points for Advice on Fisheries Management), WKREF (Workshop on Limit and Target Reference Points), WKFRAME (Workshop on Implementing the ICES F_{MSY} framework), WKGMSE (Workshop on guidelines for management strategy evaluations), WKMSYREF2 (Workshop to consider reference point for all stocks), WKMSYREF3 (Workshop to consider the basis for F_{MSY} ranges for all stocks), WKMSYREF4 (Workshop to consider F_{MSY} ranges for stocks in ICES categories 1 and 2 in Western Waters), WKNSMSE (Workshop on North Sea stocks Management Strategy Evaluation), WKREBUILD (Workshop on Guidelines and Methods for the Evaluation of Rebuilding Plans), WKRPCHANGE (Workshop of Fisheries Management Reference Points in a Changing Environment), WKREF (Workshop on guidelines for reference points), CFP (Common Fisheries Policy), and EU MAPS (European Union regional Multiannual Plans).

In 2002, the Johannesburg Declaration of the World Summit on Sustainable Development (WSSD; UN 2002) called for an ecosystem approach and rebuilding fisheries to Maximum Sustainable Yield (MSY). In 2007, the ICES Workshop on Limit and Target Reference Points (WKREF) was established with terms of reference that included review of reference points with respect to regime shifts and the science and implementation of MSY-based approaches (ICES 2007). Various problems with limits and targets were identified, and there was no consensus on a way forward. It was thought "*that distance between B_{pa} and B_{lim} could take into account the uncertainty due to different regimes*". From the review of the scientific and management literature, WKREF concluded that MSY is a difficult concept for management purposes because it is difficult to assess, unstable over time, and only applicable in a single species context. Single-species MSY and $\mathrm{B_{MSY}}$ will not work for predators and prey at the same time (May et al. 1979; Walters et al. 2005).

The Workshop on Implementing the ICES $\mathrm{F_{MSY}}$ framework (WKFRAME) in 2010 and 2011 was tasked with drafting technical guidelines to assist ICES expert groups in the implementation of the ICES MSY framework for advice (ICES 2011). A trigger biomass point, MSY $\mathrm{B_{trigger}}$, was defined as a low biomass that is encountered with a low probability if a stock is exploited at $\mathrm{F_{MSY}}$. This differs from $\mathrm{B_{MSY}}$, which is the expected average biomass if the stock is exploited at $\mathrm{F_{MSY}}$. These workshops discussed the role of MSY $\mathrm{B_{trigger}}$ and indicated "*it should be selected as a biomass that is encountered with low probability if F_{MSY} is implemented*" and that "*under MSY exploitation it should be a property of the expected distribution of SSB*". However, ensuring compatibility with the PA was also raised as an issue, including the need to avoid $\mathrm{B_{lim}}$ in the long term, taking model error into account. At this stage, generic tools that were easily and widely applicable started to develop. The methodology PlotMSY was developed in AD-Model Builder to perform deterministic equilibrium yield analysis coupled with stochastic simulation procedures (ICES 2010), using the assessment summary and sensitivity data. In PlotMSY, SR model uncertainty was taken into account by model averaging of three functions (Ricker, Beverton-Holt, and hockey-stick). The tool was used by the ICES community to provide robust estimation of MSY estimates (ICES 2017b), which was a major step forward to stochastically estimating reference points.

Various ICES advice recipients developed strong policies to implement an ecosystem and MSY approach in their fisheries management systems. Within the EU, legal obligations to implement MSY management and establish multiannual plans reflecting the specificities of different fisheries based on the best available science were set out in the reformed CFP (EC 2013). There were significant technical developments around Management Strategy Evaluations (MSEs; ICES 2013; Punt et al. 2014b), and work on developing a new ICES tool to estimate MSY reference points began (the stochastic equilibrium software EqSim). EqSim provides MSY reference points based on the equilibrium distribution of stochastic projections. In EqSim, parameters related to productivity (i.e. natural mortality, maturity, growth) are randomly re-sampled from a specified period of the assessment and recruitments are re-sampled from their predictive distribution (ICES 2017b). This methodology can take into account the uncertainty in the SR model by applying model averaging of different SR functional forms, as well as incorporate advice error. After limited progress at the Workshop to consider reference points for all stocks (WKMSYREF), there was significant development as EqSim was more widely tested at WKMSYREF2 (ICES 2017b). A joint ICES/MYFISH (`https://www.myfishproject.eu/`) "Workshop to consider the basis for F_{MSY} ranges for all stocks" (WKMSYREF3; ICES 2015b; ICES 2015a), systematically estimated MSY reference points and F_{MSY} ranges for the North Sea and Baltic stocks to address a special request from the EU for MSY ranges for their regional multiannual plans (MAPS; EC 2013). A year later, the "Workshop to consider F_{MSY} ranges for stocks in ICES categories 1 and 2 in Western Waters" (WKMSYREF4) developed the approach further and estimated MSY ranges for demersal stocks in western waters (ICES 2017b). The ICES technical guidelines to estimate "ICES fisheries management reference points for category 1 and 2 stocks" were published in 2017 (ICES 2017a).

Since 2017, several ICES expert groups have identified challenges and suggested developments in reference point estimation (Figure 2.1) – including the ICES Workshop on North Sea stocks Management Strategy Evaluation in 2018 (WKNSMSE), the ICES Workshop on Guidelines and Methods for the Evaluation of Rebuilding Plans in 2019 (WKREBUILD), the ICES third Workshop on Guidelines for Management Strategy Evaluations in 2019 (WKGMSE3), the ICES Workshop on Management Strategy Evaluations of Mackerel in 2020 (WKMSEMAC), and the ICES Workshop of Fisheries Management Reference Points in a Changing Environment in 2020 (WKRPCHANGE). Current guidelines (ICES 2021c) were criticized in various working groups as they were thought to be complex, convoluted, and not always well understood or followed by assessment practitioners. There is little documentation on EqSim to help those at benchmarks with implementation and interpretation. Other issues highlighted were that determination of B_{lim} requires a subjective classification of the SR pairs into types (ICES 2020c); discrepancies were found between reference points from the standard ICES approach and MSEs (ICES 2019c); major sources of uncertainty in reference points were related to changes over time in biological and SR parameters(ICES 2021a); and determining the time period used to derive reference points was considered challenging because estimation becomes unreliable as time are reduced (ICES 2021a). In recent years, ICES has been in the process of reviewing and modifying their reference point estimation guidelines through two workshops WKREF1 and WKREF2 (Figure 2.1). We argue that part of the reform must consider exactly how current procedures are implemented comparatively across stocks. Hereafter, as a part of the continual process to improve ICES reference point estimation, we provide an empirical review of how category 1 reference points are currently derived. Such synthesis enables cross-comparisons of stocks displaying consistencies, highlights inconsistencies, and points towards further improvements.

2.2.1 ICES current reference points approach

Recently, ICES published updated guidelines for estimating reference points (ICES 2021c). The emerging five-step procedure for estimating reference points was strongly linked to the advice framework and the need to ensure that the ICES MSY advice rule (AR) was also consistent with the ICES PA (ICES 2021c; Figure 2.2). The ICES MSY AR is a HCR that leads to catch advice corresponding to a fishing mortality of equal to F_{MSY} when SSB is at or above MSY $B_{trigger}$ but reduced relative to F_{MSY} when the stock is below MSY $B_{trigger}$ (ICES 2021e). The ICES approach aims to maximize long-term yield while safeguarding against low SSB. Thus, more caution is needed below B_{lim} (see dashed line below B_{lim} in Figure 2.2). The advised catch might be zero when the stock cannot be rebuilt above B_{lim} in the year after the advice with greater than 50% probability.

The current five steps to estimate reference points involve (i) identifying appropriate data (truncate time series or not), (ii) identifying SR type (six different types are described with different recommended actions; Table 2.1), (iii) estimating biomass limit reference points, (iv) deriving PA reference

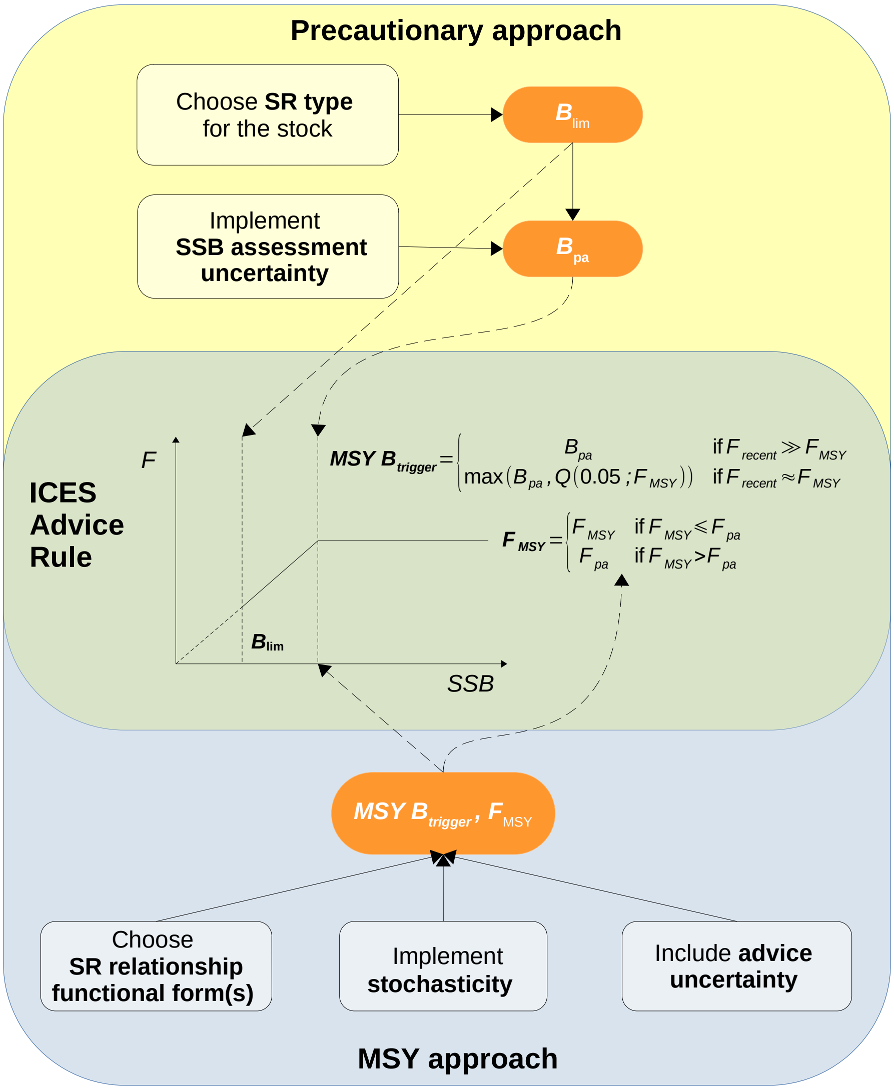

Figure 2.2: The ICES advice rule (Category 1 stocks) integrates the precautionary approach (yellow) with Maximum Sustainable Yield (blue). Where if F_{recent} has been in the vicinity of $\mathrm{F_{MSY}}$ for 5 or more years, then the fifth percentile of SSB, when fished at $F_{MSY}[Q(0.05; F_{MSY})]$ is used as the trigger point, otherwise $\mathrm{B_{pa}}$ is used. The precautionary criterion ($\mathrm{F_{pa}}$, also called $\mathrm{F_{p.05}}$) is a fishing mortality that results in $\geq 95\%$ annual probability that SSB remains at or above $\mathrm{B_{lim}}$ in long-term equilibrium and caps $\mathrm{F_{MSY}}$.

points from limit reference points, and (v) estimating MSY reference points without and later with the AR. First, the value of $\mathrm{F_{MSY}}$ is calculated, including stochasticity and advice error. Second, the MSY $\mathrm{B_{trigger}}$ is selected without advice error. For most stocks that lack data on fishing at $\mathrm{F_{MSY}}$, MSY $\mathrm{B_{trigger}}$

is set at B_{pa} (ICES 2021c). For stocks with evidence of fishing mortality being at or below F_{MSY}, MSY $B_{trigger}$ is selected to be the maximum value between the fifth percentile of the distribution of SSB when fishing at F_{MSY} (excluding advice error but including stochasticity in population and fishery) and B_{pa} (Figure 2.2). Then, the ICES MSY AR is evaluated via stochastic simulation with F_{MSY} and MSY $B_{trigger}$ and checked that the fishing mortality that results in a low long-term probability (≤ 0.05) of SSB to be below B_{lim} (called the precautionary criterion or F_{pa}) is lower than the initial F_{MSY}. If F_{MSY} is $\geq$ F_{pa}, then the advised F_{MSY} is capped to the value of F_{pa} (Figure 2.2).

Key steps for estimating ICES reference points are identifying SR stock type and deriving biomass limit reference points. These steps are related because the technical basis for B_{lim} is generally determined by the classification of stock characteristics into SR typologies (Table 2.1). In the ICES guidelines, historical fishing mortality is not considered when deciding the stock typology, but it is relevant for some SR types when setting B_{lim} (Table 2.1). To estimate MSY-based reference points, it is typically assumed that the associated parameters remain constant or vary around a historical long-term mean. ICES considers MSY reference points to be valid only in the short and medium-term (5-10 yr), as ecosystems and fisheries are dynamic over time. Therefore, reference points are subject to regular reviews (ICES 2021e).

Table 2.1: ICES Stock type classification for category 1 stocks and limit point estimation option (ICES 2021c).

SR type	Stock characteristics			B_{lim} settings options
	Recruitment	SSB	SR plot	
Type 1	Occasional large year classes	–	–	B_{lim} is based on the lowest SSB that produced large recruitment unless F has been low throughout the observed history, in which case $B_{loss} = B_{pa}$.
Type 2	–	Wide dynamic range	Impaired recruitment has been observed	B_{lim} = segmented regression change point.
Type 3	–	Wide dynamic range	Impaired recruitment has been observed, but no clear asymptote	B_{lim} may be close to the highest SSB observed. The estimate depends on an evaluation of the historical fishing mortality.
Type 4	–	Wide dynamic range	Recruitment increases as SSB decreases	No B_{lim} from this data, only the PA reference point. (B_{loss} would be a candidate for B_{pa}).
Type 5	–	–	No impaired recruitment has been observed, no clear relation	$B_{lim} = B_{loss}$.
Type 6	–	Narrow dynamic range	No impaired recruitment has been observed, no clear relation	No B_{lim} from this data, only the PA reference point (B_{loss} could be a candidate for B_{pa}, however, this depends on an evaluation of the historical fishing mortality).

2.3 Methods

2.3.1 ICES category 1 reference point database

Estimation of reference points is dependent on the definition or technical basis used, method settings, and data/output used. We assembled a database of reference point estimation data for 79 ICES category 1 stocks. All stock-specific available documentation was reviewed including benchmark and inter-benchmark reports, working group reports, special requests, expert group reports, and specific working documents (specific topic documents submitted during benchmarks that support the main assessment). Collated data relate to reference points and their estimation, including re-evaluation year, estimation framework, B_{lim} and F_{MSY} technical basis, SR type, SR settings, assessment error settings, time-period settings, references, EqSim settings, and hitting precautionary bounds (Table 2.2). We developed an R code to clean the information as collated from the documents (see Table 2.2 for cleaning details). This comprised grouping categories to summarize information expressed in different texts into homogenized terms. For stocks that used EqSim (*eqsim_run* from the R package msy; `https://github.com/ices-tools-prod/msy`), we also revised raw reported information to fill in default values, assuming: (a) if SR truncation was not stated, then the data were not truncated; (b) if autocorrelation, process error, recruitment, and catch trimming of extreme values were not stated, then we assume EqSim function default (i.e. autocorrelation: on, process error: on, recruitment trimming of extreme values: restrict the range of recruitment deviations to +/- three standard deviations on the log scale, catch trimming of extreme values: off). We did not assume default values on the assessment uncertainty parameters and period selection of biological and selectivity parameters because the function defaults differ from the guidelines. When an SR type was not stated in the report, it was inferred from SR plot characteristics by following ICES guidelines for SR type identification (ICES 2021c) and using expert knowledge among the authors.

2.3.2 Stock biomass and fishing mortality features

We estimated spawning stock biomass and fishing mortality metrics to assess the consistency with the SR typology guidelines (Table 2.1). We extracted stock assessment results (fishing mortality, spawning size biomass, and recruitment data) from the ICES Stock Assessment Graphs database via XML

Table 2.2: ICES category 1 reference point database. Description of data collated, whether they are EqSim specific and cleaning procedure for each data variable.

Data variable	**Description**	**EqSim specific**	**Cleaned**
Refpt_framework	Reference point framework	No	Homogenize terms
SR_type	SR stock type	No	No
SR_type_n	Inferred SR stock type, assigned to stocks with no stated typology in reports	No	No
Blim_tecbasis	B_{lim} technical basis	No	Homogenize terms
Blim	B_{lim} value	No	No
FMSY_tecbasis	F_{MSY} technical basis	No	Homogenize terms
FMSY	F_{MSY} value	No	No
SR_model	SR functional form model	No	Homogenize terms
SR_modelweights	SR models weights	Yes	No
Breakpoint.fixed.at	Breakpoint of the fixed segmented regression	Yes	Homogenize terms
SR_data_truncated	Whether data was truncated (Yes/No/Not stated)	No	Assumed No if not stated
AutocorrelationR	Whether autocorrelation parameter was used (TRUE/FALSE/Not stated)	Yes	Assumed TRUE if not stated
SR_period	Year period of SR pairs period used to derive reference point	No	No
process.error	Whether process error parameter was used (TRUE/FALSE/Not stated)	Yes	Assumed TRUE if not stated
recruitment.trim	Whether recruitment trimming was used (Yes/No/Not stated)	Yes	Assumed Yes c(-3,3) if not stated
FCV	Value set for the coefficient of variation of F (F_{CV})	Yes	No
FPHI	Value set for the autocorrelation of F (F_{ϕ})	Yes	No
SSBCV	Value set for the coefficient of variation ofSSB(SSB_{CV})	Yes	No
bio.years	Year period used for biological parameters	Yes	Calculation of number of years
Selectivity_pattern_period	Year period used for biological parameters	Yes	Calculation of number of years
bio.years	Year period used for biological parameters	Yes	Calculation of number of years
extreme.trim	Whether extreme catch values trimming was used (Yes/No/Not stated)	Yes	Assumed No if not stated
Hitting.precautionary. bounds.FMSY.Fpa	Whether the precautionary bounds were hit ($F_{MSY} > F_{pa}$ or $F_{MSY} < F_{pa}$ or not stated)	No	Homogenize
Report_reference	Reference from which the information was extracted	No	No

parsing (ICES 2021d). All the calculations were made using the most recent assessment for each stock. We calculated the coefficient of variation of the full time series of SSB assuming a log-normal distribution ($CV\ SSB$) as a stock-level summary of the stock biomass spread. To summarize the history of stock fishing mortality, of relevance to B_{lim} choice, we calculated the mean

F relative to F_{MSY} over the full time series.

$$F_{rel} = \frac{\frac{\sum_{t=1}^{n} F_t}{n}}{F_{MSY}} \tag{2.1}$$

, where t is the year and n is the number of years in the time series for a given stock.

2.3.3 Spasmodic stocks categorization

Spasmodic stocks (SR type 1; Table 2.1) are defined by ICES as "stocks with occasional large year classes" (ICES 2021c). To assist the identification of spasmodic stocks and determine the consistency of the spasmodic stock definition, we evaluated the variance of recruitment time series. First, we fitted a loess smother with a 0.3 span to the natural logarithmic transformed recruitment. A span of 0.3 (a trade-off between over-smoothing and over-fitting) would capture approximately decadal-scale long term changes, which we seek to remove in our assessment of spasmodic stocks. Such low-frequency variability could be caused by historic fishing patterns reducing SSB and thus reducing recruitment and does not reflect the high amplitude variation of spasmodic stocks (Spencer and Collie 1997). To characterize the high frequency variability, we calculated the empirical cumulative distribution function (CDF) of the detrended recruitment proportional to the maximum. We also calculated the CDF of the raw recruitment time series proportional to the maximum to compare results (detrended or not). The CDF is useful as it displays the fraction of the observed values less than a given value and thus informs on how infrequent specific recruitment events are. Intuitively, spasmodic recruitment would be typically low recruitment events with occasional large recruitment events, which translates into a steeply climbing CDF. To identify time series with high variance, we estimated the theoretical expected 80% interval for CDFs of time series with lognormal variance of 1. We used a variance value of 1 as this is the 90th quantile of detrended residuals from the Ram Legacy Stock Assessment Database (version 4.44) across all stocks in the database. The criteria used identify an extreme pattern for a given variance. To estimate the theoretical expected interval, we used 42 yr, which is the median length of the SR pairs across all the studied stocks (this could be tailored for individual stocks).

2.3.4 Changes in reference points database

For a total of 79 stocks, we also acquired retrospective data of past assessments from the year of the working group WKMSYREF4 to the most recent assessment year (2016-2021). We accounted for the change in 2017 of the codes that are used to identify each stock (stock label key). We obtained reference points data (F_{MSY}, MSY $B_{trigger}$, B_{lim}, and B_{pa}), and time-series data on stock size, fishing mortality, and recruitment. We retained only assessments that used "SSB" in the stock size description. Changes in reference points between sequential assessments were identified for analysis; we calculated the change in reference point (RP) as the proportional change relative to the preceding assessment $(RP^{y} - RP^{y-1})/RP^{y-1}$, where y is the assessment year, following the method in Silvar-Viladomiu et al. (2021). Simultaneous changes in F_{MSY} and B_{lim}, and MSY $B_{trigger}$ and B_{lim} were visualized.

2.4 Consistency of current ICES reference points

In this section, we present the results from evaluating the consistency of 2021 ICES reference points with the guidelines (ICES 2021c). We evaluated reference point updates, SR type classification in relation to B_{lim} technical basis and stock characteristics (SSB, fishing mortality, SR relationship, and recruitment variability), the framework to implement stochastic MSY, and simultaneous changes in reference points.

2.4.1 Evaluation and update of reference points

Currently, from the 79 stocks classified as ICES category 1, most reference points have been changed within the last 5 years (81.01% for F_{MSY} and 75.95% for B_{lim}), with two stocks with long-established reference points (northeast Arctic capelin in 2001 and cod in 2003; Figure 2.3). There are four stocks with recent estimates of F_{MSY} but older estimates of B_{lim}. This might reflect changes to the ICES reference points guidelines to cap from F_{MSY} to F_{pa} (the F that would lead to $SSB \geq B_{lim}$ with a 95% probability in the long term, previously known as $F_{p.05}$; Figure 2.3).

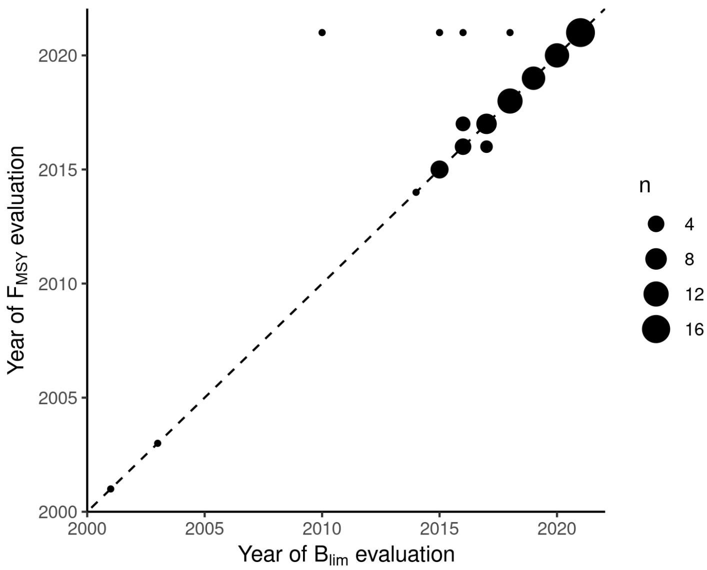

Figure 2.3: Year of the most recent evaluation for F_{MSY} and B_{lim} reference points for the current advice of ICES category 1 fish stocks.

2.4.2 Stock SR typology and biomass limit reference points

For many stocks, the SR type was not specified in the documentation reflecting difficulties to assign it (not stated SR type in the reports n = 40). The typologies were often consistent with the selection of B_{lim} recommended in the guidelines (Figure 2.4; Table 2.1). For type 1 stocks (spasmodic stocks), three B_{lim} technical bases were used, B_{lim} was B_{loss} (lowest observed SSB), a fraction of B_{pa}, or the lowest SSB where recruitment was good/high or not impaired. The basis recommended in the guidelines was the lowest SSB, where large recruitment is observed. Stocks categorized as type 2 (evidence that recruitment is or has been impaired) typically define B_{lim} as the breakpoint of the segmented regression. The lowest SSB where recruitment was good/high or not impaired was also used to define B_{lim} for several type 2 stocks (Figure 2.4). There is one case (herring in the northeast Atlantic and Arctic Oceans, her.27.1-24a514a) where the B_{lim} technical basis for a type 2 stock is MBAL, which refers to the old minimum biological acceptable level, commonly including a buffer. For SR type 3 stocks (wide dynamic range of SSB and evidence that recruitment is or has been impaired, with no clear asymptote in recruitment at high SSB), selection of B_{lim} was the lowest SSB where recruitment is good/high or not impaired. However, the recommended choice is the SSB close to the highest observed value, depending on an evaluation of the historical fishing mortality. There was no stock SR type 4 reported; however, we inferred that herring in Iceland grounds (her.27.5a) could fall under that category given that recruitment increases as SSB decreases. The B_{lim} basis for that stock was SSB with a high probability of impaired recruitment. For SR type 5 (no impaired recruitment or no clear relation between stock and recruitment), the most frequent technical basis for B_{lim} was B_{loss}. For stocks of type 6 (narrow dynamic range of SSB and showing no evidence of past or present impaired recruitment), B_{lim} cannot be directly derived and so it was used a fraction of B_{pa}. Other technical bases for B_{lim} based on spawner per-recruit or unfished biomass analysis, e.g. 35% SPR, 20% B_0, were occasionally used (Figure 2.4).

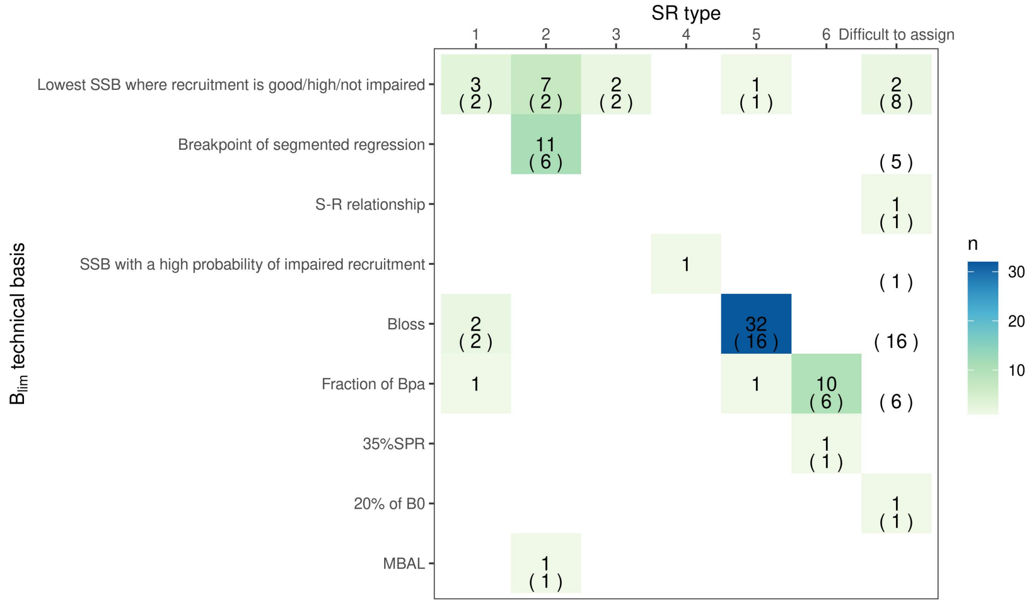

Figure 2.4: Crosstabulation of reported and inferred SR typology and B_{lim} technical basis. Showing the number of inferred SR type stocks above and the number of stated SR type stocks below in brackets.

2.4.3 Stock typology, SSB range, and historical fishing mortality

Some assigned typologies adhere well to their definitions (e.g. type 6 - narrow range of SSB), whereas there are examples of similar degrees of variation in SSB being categorized differently across stocks (e.g. narrow for one stock but wide for another; Figure 2.5). Most stocks that were categorized as SR types with wide SSB ranges (i.e. types 2, 3, and 4) had larger SSB variation, but there were some exceptions, e.g. herring in the northeast Atlantic and Arctic Ocean (her.27.1-24a514a), witch in the North Sea, Skagerrak, Kattegat, and eastern English Channel (wit.27.3a47d), and sole in the North Sea (sol.27.4), which were categorized as type 2 but showed relatively low SSB variation (Figure 2.5).

Historical fishing pressure showed an important relationship with the SR type. Predominantly type 2 stocks, which present evidence of impaired recruitment, showed high average historical fishing mortality, e.g. cod in the eastern Baltic Sea (cod.27.22-24) and sardine in the Cantabrian Sea and Atlantic Iberian waters (pil.27.8c9a) in Figure 2.5. Exceptions could be related to the perception of fishing pressure over time in long time series, e.g. stocks that have been fished over F_{MSY} only in recent years. Herring in the northeast Atlantic and Arctic Ocean (her.27.1-24a514a; Figure 2.5) was categorized as type 2 but showed low relative fishing mortality in the last three decades. Stock SR types 5 and 6, with no evidence that recruitment is or has been impaired (no clear relationship between stock and recruitment) showed different ranges of SSB variation but typically lower fishing pressure over time, e.g. herring in the Gulf of Bothnia (her.27.3031) and horse mackerel in Atlantic Iberian waters (hom.27.9a) in Figure 2.5. However, there were some stocks categorized as SR type 5 but with high relative fishing mortality, e.g. cod in the eastern English Channel and southern Celtic Seas (cod.27.7e-k) and haddock in Rockall (had.27.6b) in Figure 2.5. Also, stocks that have been historically fished over F_{MSY} but used truncated SR data to define the typology could result in selecting a SR type with no evidence of impaired recruitment, e.g. type 6 for the North Sea, eastern English Channel, and Skagerrak cod (cod.27.47d20; Figure 2.5).

2.4.4 Stock typology and recruitment variability

Recruitment dynamics impact the choice of SR typology, specifically, spasmodic stocks that are classified as SR type 1 according to the guidelines. Low frequency trends in recruitment, which absorbed the effect of historical fishing, showed multiple patterns across all stocks (Appendix A.1 Figure SM1). Three stocks classified as SR type 1 (spasmodic) were identified as having high detrended recruitment variability (Figure 2.6). These stocks were cod in East and South Greenland (cod.2127.1f14), haddock in the northeast Arctic (had.27.1-2), and haddock in the North Sea and West of Scotland (had.27.46a20), inferred in this study (Appendix A.1 Figure SM2). Recruitment time series for these stocks display a clear pattern of occasionally large

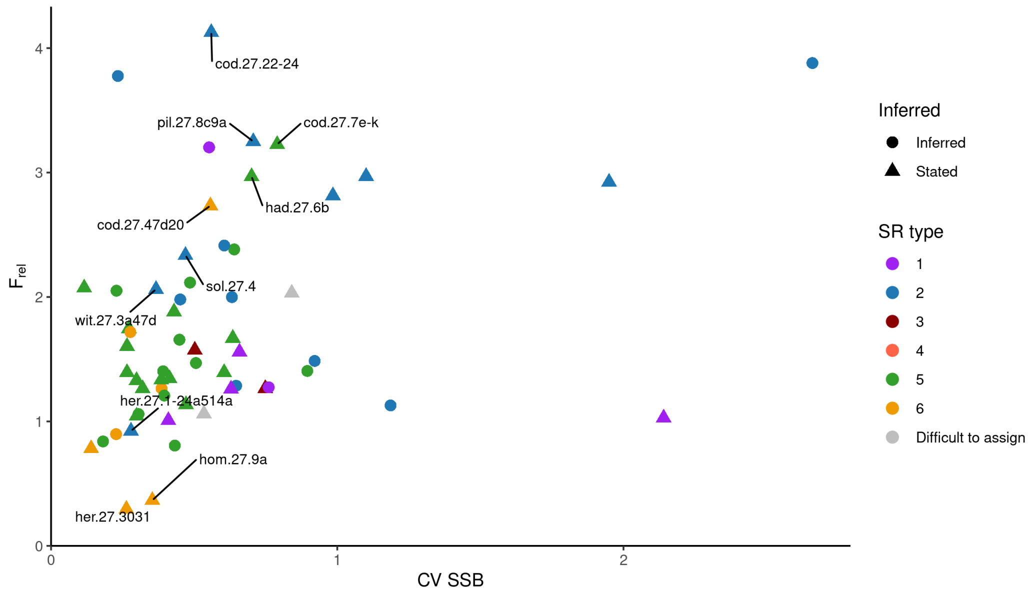

Figure 2.5: Relative fishing mortality and variability in SSB by inferred or stated SR type of the 79 ICES category 1 stocks that were analysed. F_{rel} is the average fishing mortality relative to F_{MSY} over the data period, and CV SSB is the coefficient of variation of SSB for log-normally distributed data on a proportion scale. The shape of data points represents if the SR type has been inferred in this study or stated in the reports.

year classes (Figure 2.7A). One SR type 1 stock showed comparatively lower variance for both recruitment and detrended recruitment. This was herring in the Irish Sea, Celtic Sea, and southwest of Ireland (her.27.nirs; Figure 2.7A and Appendix A.1 SM2). Two SR type 1 stocks, horse mackerel in the northeast Atlantic (hom.27.2a4a5b6a7a-ce-k8) and haddock in the southern Celtic Seas and English Channel (had.27.7b-k), showed high variability for recruitment but not for detrended recruitment (Appendix A.1 Figure SM2). This could result from occasional large recruitments occurring only early (or only once) in the time series with significant lower variability thereafter, e.g. horse mackerel in the northeast Atlantic (hom.27.2a4a5b6a7a-ce-k8; Figure 2.7B).

We also found stocks with high recruitment variability and possibly spasmodic but not classified as SR type 1. We identified high detrended recruitment variability for two stocks classified as SR type 2, cod in the western Baltic Sea (cod.27.22-24) and sole in the North Sea (sol.27.4). The recruitment time series for these stocks also showed infrequent strong recruitment (Figure 2.7B). Two stocks classified as difficult to assign showed high detrended recruitment variability (Figure 2.6), Greenland halibut in the northeast Arctic (ghl.27.1-2) and capelin in the northeast Arctic and Barents Seas (cap.27.1-2). One stock inferred as SR type 2 showed high detrended recruitment variability; this refers to cod in the northeast Arctic (cod.27.1-2). Golden redfish in Iceland and Faroes grounds, West of Scotland, North of the Azores, and East of Greenland (reg.27.561214), which was inferred as type 5, showed relatively high detrended recruitment variability (Figure 2.6), due to sporadic high recruitment year classes (Figure 2.7B). Several stocks showed high recruitment variability but not after removing the trend (Appendix A.1 Figure SM2), e.g. sprat in Skagerrak, Kattegat, and North Sea (spr.27.3a4), sardine in Cantabrian Sea and Atlantic Iberian waters (pil.27.8c9a), and haddock in Iceland grounds (had.27.5a), and in Faroes grounds (had.27.5b).

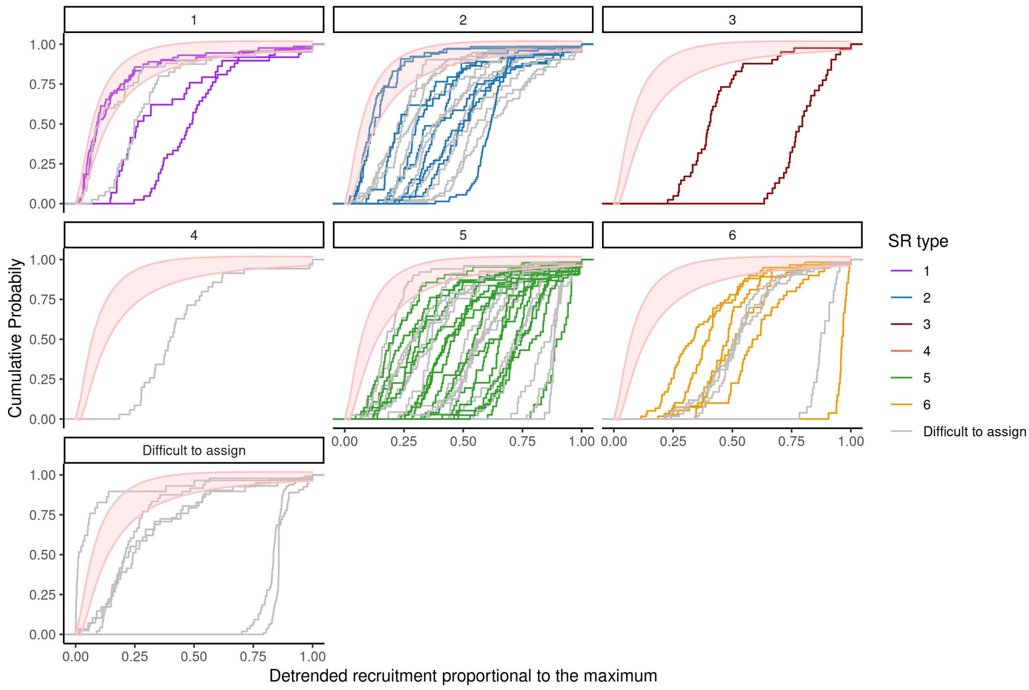

Figure 2.6: Empirical cumulative distribution function of recruitment relative to maximum recruitment by inferred SR type. Colour shows stated SR type. The pink area shows the theoretical expected 80% interval for CDFs of time series (length = 42) of lognormal variance = 1.

2.4.5 Stochastic frameworks to estimate MSY-based reference points

The modelling framework used for estimating ICES category 1 MSY-based reference points was substantially homogeneous (Figure 2.8A), with the majority of the stocks estimated with the generic tool for stochastic simulation

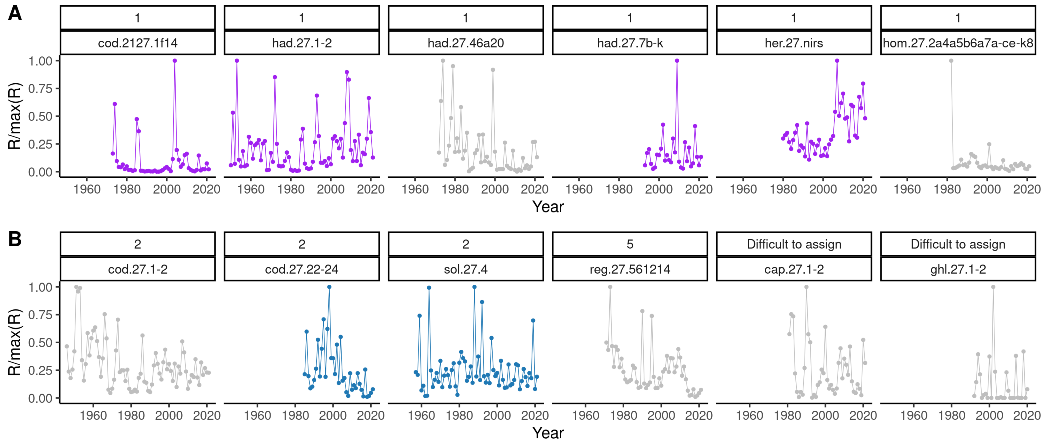

Figure 2.7: Recruitment time series proportioned to the maximum recruitment year class for a selection of category 1 stocks. The top panel (A) shows all stocks inferred as SR type 1 (spasmodic); the bottom panel (B) shows examples of high variability in recruitment time series for other SR types. Colour reflects stated SR type (purple: SR type 1, blue: SR type 2, grey: not stated).

framework EqSim (n = 54). For 11 stocks, mostly short-lived pelagic species, simulation frameworks developed specifically to conduct full feedback, MSEs were used applying the ICES guidelines. Reference points were estimated within the Gadget assessment model for four stocks. For spurdog in the northeast Atlantic, reference points were estimated within the age-length and sex-structured assessment model. Northeast Arctic haddock reference points were estimated with a framework called PROST – Projection Stochastic (Figure 2.8A).

Key recruitment considerations for the derivation of MSY-based reference points are the choice of SR functional form, accounting for variability and temporal dynamics, and determining and accounting for regime shifts. Accounting for temporal dynamics is achieved by including autocorrelation in recruitment, process error, and trimming of occasional extreme values. For stocks that used EqSim, autocorrelation and process error were mostly included as a default setting and thus typically accounted for in the estimation (Figure 2.8B left). Autocorrelation is included for the recruitment residuals of the SR model according to an AR(1) process. Process error is included with the stochastic predictive distribution of recruitment plus the simulated observation error. Removal of recruitment extreme values was often applied, and the option of trimming extreme catch values was occasionally used (Figure 2.8B left). The issue of regime shifts is linked to the classic dilemma between using

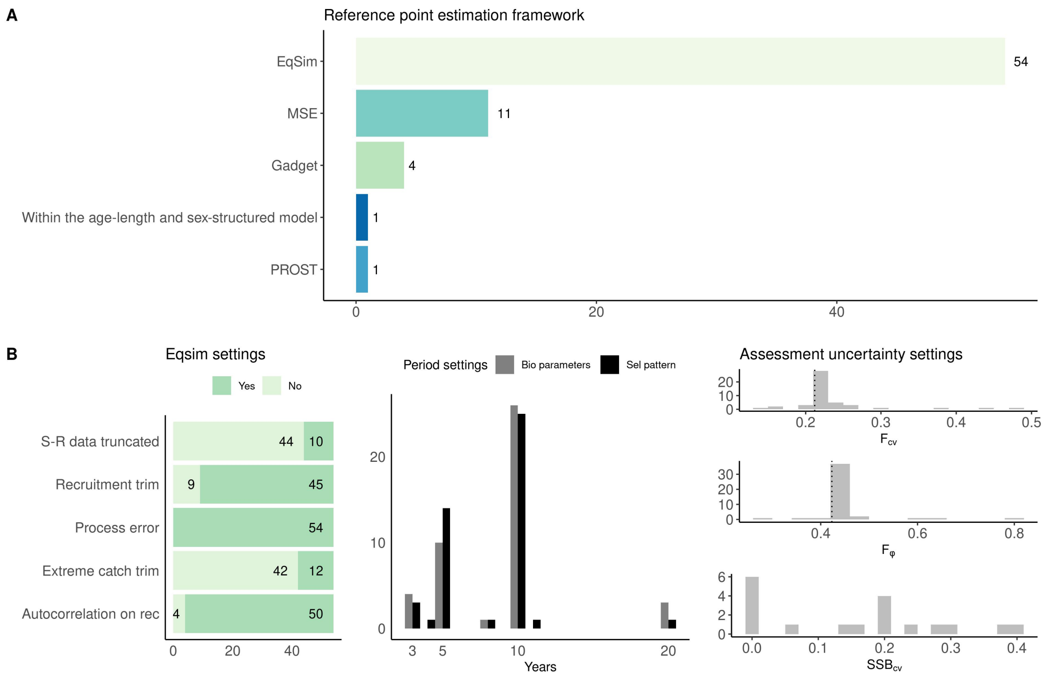

Figure 2.8: Summary plots of reference point estimation frameworks and settings used for ICES category 1 stocks as of November 2021. Top panel (A) count plot of used reference point estimation frameworks in assessments. Bottom panel (B) with data treatment in EqSim-based estimation of reference points (left), parameter period settings (middle), and assessment uncertainty settings (right).

full-time series or selecting a reduced-time series. Stock recruitment pairs were truncated for the estimation of reference points for 10 stocks (Figure 2.8B left). Time windows for biological productivity or selectivity parameters were 10 yr for the majority of stocks unless patterns were found in the data, in which case 5 or 3 yr were typically used (Figure 2.8B center). The uncertainty of the advice (F_{CV}, F_{ϕ}) within EqSim was often set with default values ($F_{CV}n = 27$, $F_{\phi}n = 33$, Figure 2.8B right). In WKMSYREF4, parameters for assessment error were evaluated and the following values were assigned as default values: assessment error in the advice year $(F_{CV}) = 0.212$; autocorrelation in assessment error $(F_{\phi}) = 0.423$. These values are the medians of the results for five stocks for which the evaluations were completed in WKMSYREF3.

2.4.6 Changes in reference points

Reference points have changed relatively frequently, with substantial changes between years (once or twice in the last 6 yr; Appendix A.1 Figure SM3). Given the reference point technical basis, changes in MSY $B_{trigger}$ are directly related to changes in B_{lim}, though changes in F_{MSY} are typically not related to changes in B_{lim}. The main impact of changes in B_{lim} was on changes in MSY $B_{trigger}$ (Figure 2.9A), as MSY $B_{trigger}$ is often defined as B_{pa}, which is often a multiple of B_{lim}. However, revisions of the technical basis of MSY $B_{trigger}$ and B_{pa} can cause changes in MSY $B_{trigger}$ not related to a B_{lim} change. For example, the technical basis for MSY $B_{trigger}$ for many stocks was set to B_{pa} because the criterion of being fished at or below F_{MSY} for around 5 yr was not met. As stocks are fished consistently with F_{MSY}, they may change to a MSY $B_{trigger}$ corresponding to the fifth percentile of SSB when fishing at F_{MSY}. The majority of changes in B_{lim} were not related to changes in F_{MSY} (Figure 2.9B). Nevertheless, changes in B_{lim} might have had an impact on F_{MSY} where the value of F_{MSY} is capped and set at F_{pa} due to a higher than 5% probability of SSB going below B_{lim}, where an increase in the value of B_{lim} is related to a decrease in the F_{MSY} value (Figure 2.9B).

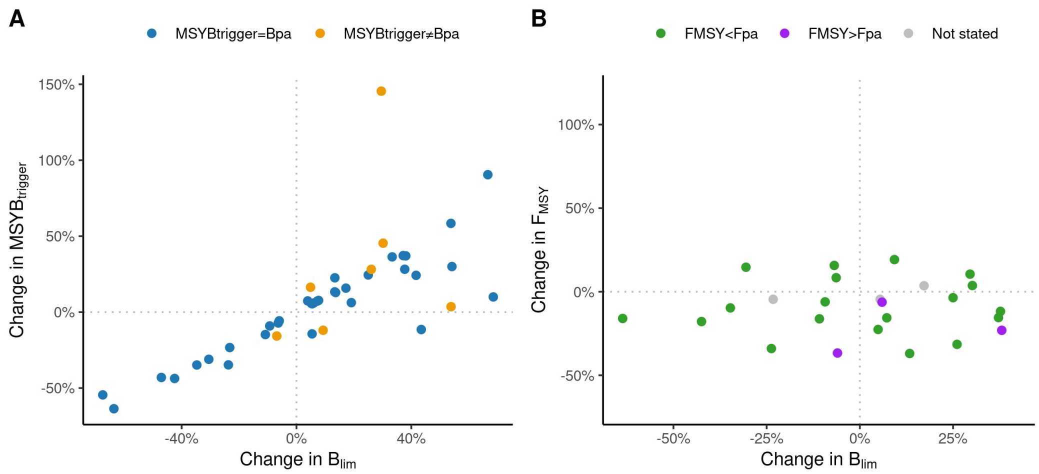

Figure 2.9: Simultaneous changes in reference points. Impact of changes in B_{lim} on the ICES biomass trigger point MSY $B_{trigger}$ (A); Impact of changes in B_{lim} on F_{MSY} for the most recent 5 years (B). Colour shows whether stocks are currently hitting precautionary bounds ($F_{MSY} > F_{pa}$) and therefore there is a capping on F_{MSY}.

2.5 Conclusions

In this paper, we have extensively reviewed the evolution of ICES reference points and the estimation procedure currently used for management advice within the ICES framework. The review has addressed historically important events related to the evolution of the ICES reference point framework and evaluated how guidelines link with current reference point estimation. We have also examined the settings and processes considered in the estimation of reference points. What conclusions do we have after the review?

1. **ICES reference point framework has evolved in an intergovernmental setting.** Reference points used in ICES advice have evolved and are influenced by policy and scientific development. As an intergovernmental agency, ICES advice recognizes several international agreements and responds to the policy and legal needs of ICES member countries that use the advice as to the scientific basis for management. Advice basis and therefore reference points have evolved with their requirements, starting with the PA and expanding to integrate the MSY approach. Additionally, the ICES framework also evolves along with new available research and tools (e.g. EqSim).

2. **ICES reference points incorporate multiple precautionary aspects and sources of stochasticity.** The objective of ICES AR is to maximize long-term average yield with a safeguard against low SSB and staying within the precautionary bounds. The current system incorporates many features of the precautionary approach, particularly as it pertains to recruitment overfishing.

   (a) ICES recognizes that fish stocks should be above B_{lim} and fish at a level that keeps fish stocks above B_{lim}. The biomass limit reference point is the central reference point to the precautionary approach. It is set by graphic rules based on SR data pairs. The choice of B_{lim} aims to ensure that the biomass below which recruitment is impaired is detected (ICES 2021c). The lowest level of biomass (B_{loss}) is typically used as a biomass limit reference point when there is no clear SR relationship. We note that the typologies of SR data pairs are not hypothesis-driven, which provides flexibility but also leaves the process open to subjective decisions across stocks.

   (b) The EqSim framework is the standard ICES software, which was used to estimate reference points for the majority of the ICES stocks studied. The framework enables the implementation of stochasticity in biological and fisheries processes and therefore is more precautionary. Including stochastic processes in the estimation of MSY has been demonstrated in surplus production models to lead to more conservative reference points (Bousquet et al. 2008; Bordet and Rivest 2014). Advice error can be applied on the target

F (F_{pa} and F_{ϕ}), usually using the default values. These values were the median evaluated values for five ICES stocks (her.27.3a47d, sol.27.7d, pok.27.3a46, sol.27.4, ple.27.420). This advice uncertainty is supposed to represent how uncertain our estimates of fishing mortality are in the advice year.

(c) Within the ICES process for estimating reference points, F_{MSY} and MSY $B_{trigger}$ are evaluated to check that they meet the precautionary criterion. The precautionary criterion reference point (F_{pa}) represents the fishing mortality corresponding to 5% probability of SSB being below B_{lim} in the long term, estimated by stochastic simulation (i.e. biological and fishery variability and advice error included). When the precautionary criterion is lower than the estimated F_{MSY}, then the F_{MSY} is capped to its value.

(d) The MSY-based biomass reference point should be below typical natural variation (here, the fifth percentile), and its selection safeguards against unexpected low SSB when fishing at F_{MSY}. Therefore, the technical basis adopted for the biomass reference point MSY $B_{trigger}$ depends on the fishing history relative to the F_{MSY}. The MSY $B_{trigger}$ is set to B_{pa}, a more precautionary value, when there are no more than 5 yr of fishing mortality equal to or lower than F_{MSY}.

3. **The relationship and historical context of stock size and recruitment are crucial for non-proxy reference points and are embedded in ICES guidelines.** On the one hand, ICES reference point estimation is typically external to the assessment process; therefore, the understanding of the SR relationship and the choice of SR functional form is key. The graphical characteristics of the SR relationship are what define the SR type classification and impact the consequent B_{lim} choice. For the estimation of MSY-based reference points, the choice of SR relationship functional form (e.g. the commonly used Beverton-Holt model, segmented regression model, and Ricker model) impacts the reference point value. The Eqsim software can fit a combination of SR models and implement a goodness-of-fit model weighting. Usually, as a first step, to account for SR functional form uncertainty, all three SR models are examined, and depending on the weighted results, the models that have significant contributions are chosen. The segmented regression

model can estimate the break-point or have it fixed at the biomass limit reference point as a way to restrict the breakpoint when there is no reliable data for its estimation. On the other hand, due to limit and MSY-based reference points only being entirely informed if the stock has been overexploited (Tsikliras and Froese 2019), regional historical evolution of the stock determines the data available to inform reference points. Historically, many fish stocks in the North Atlantic have been heavily exploited (Fernandes and Cook 2013). Although exploitation pressure has decreased during the last decades, there is evidence of historical overfishing in the data for many of the stocks. The historical exploitation patterns result in having a high contrast in SSB data and evidence of stocks where recruitment is impaired. Having a contrast in SSB may give evidence of how recruitment is impacted, which can inform the estimation of F_{MSY}. Whereas in other areas, where there is a lack of contrast, proxies are derived.

4. **Reference points are reviewed frequently, taking into account fluctuations and multiple sources of variability.** We found that reference points have changed frequently and substantially. These changes in reference points have been shown to have an important impact on stock status (Silvar-Viladomiu et al. 2021). The frequency of PA reference point evaluations can differ from the MSY reference point evaluations. Simultaneous changes in B_{lim} and MSY $B_{trigger}$ reference points are correlated because B_{lim} is typically used to estimate B_{pa}, and B_{pa} is commonly used as an MSY $B_{trigger}$. Reference points are revised in benchmarks to update productivity change concerns, along with assessment methodology and data updates. In the estimation of reference points, variation in processes related to productivity can be included in several ways. The SR variation pattern is assessed to detect regime changes. If strong evidence of a regime shift is found, the time series may be truncated, though there are reasons not to truncate: reduction to shorter time series might increase the uncertainty associated with the reference point (Deurs et al. 2021), and changes are often gradual, in which case choosing a time window might not be appropriate (Collie et al. 2021). EqSim settings enable accounting for variation and uncertainty, for example, process error in the SR relationship (stochastic uncertainty around the SR model), which is typically included in the estimation. Temporal dynamics can be accounted for by autocorrelation

in recruitment and trimming of occasional extreme values. Trimming of extreme values to account for high variability can be also applied to catch data. Selection for the data window of productivity parameters (i.e. natural mortality, weights-at-age, maturity, and fishery selection pattern) is shortened when persistent trends are found in the data.

5. **There are occasionally inconsistencies with the guidelines.** By reviewing all stocks, it becomes apparent that the current SR type and consequent choice of B_{lim} have some occasional inconsistencies with the guidelines. We identified that a high percentage of stocks were found difficult to classify by assessors, which might be a reflection of ambiguity in SR types in the current guidelines. The implementation of the classification framework depends on whether assessors can determine if there is a clear SR relationship, which may be challenging. Comparably across all stocks, SSB measures show inconsistencies with the description in the SR types for some stocks. For example, some SR type 2 stocks show no evidence of a wide dynamic range in SSB, e.g. her.27.1-24a514a. In some cases, even when stocks appear to have impaired recruitment (type 2), the segmented regression change point was not chosen as the B_{lim} value, e.g. the B_{lim} value for cod.27.22-24 is the lowest SSB where recruitment is good/high or not impaired. The current SR type classification definitions might have gaps, e.g. how to classify a stock with evidence of impaired recruitment but with a narrow dynamic range. For stocks with no clear SR relationship, the choice of B_{lim} was more consistently B_{loss} or a fraction of B_{pa} for stocks with a narrow SSB range. The classification of spasmodic stocks was shown to be difficult, as well as the consequent choice of an appropriate B_{lim} level for these stocks.

6. **More comprehensive and clearer documentation of reference point estimation is needed.** Documentation on assessors decisions made for reference point estimation (e.g. settings) lacked consistency across stocks and details were sometimes missing or difficult to find. The code used for the estimation was only occasionally attached to the reports. Although there are guidelines on general steps for the estimation of ICES fisheries management reference points (ICES 2021e), there is a lack of a detailed document of guidelines for the use of the EqSim framework.

2.6 Recommendations for the future

Advice based on reference points is requested by governments to manage their fisheries. For most data-rich stocks, fisheries managers in the northeast Atlantic require annual advice on fishing opportunities to be able to set advice on catch for the next year. Best practice involves validation, verification, transparency, and repeatability within very strict time constraints to produce yearly fishing advice. The current ICES framework can deliver at that level. Based on our review of the framework, we offer the following recommendations and research suggestions to improve the reference point framework for the near future.

The biomass limit reference point plays a key role in classifying the condition of the stock and determining if recruitment is likely to be impaired. The choice of B_{lim} is related to the classification of SR types, which was found to lead to ambiguous results in several cases. In WKREBUILD, it was highlighted that the determination of B_{lim} used a more or less subjective classification of the SR pairs into types (ICES 2020c). We found that a significant number of stocks were difficult to classify for assessors. A simplified and reduced framework of classification for the choice of SR types may help reduce ambiguity. In addition, the development of quantitative criteria and analytical tools that establish cut-offs to assist in the decision of SR type may be useful. For example, use measures of SSB range and SSB variation to define "narrow dynamic range" and "wide dynamic range". Also, developing criteria to define spasmodic stocks, such as CDFs intervals, would help the classification to be less subjective and more transparent. Additionally, developing generalized quantitative criteria to establish B_{lim}, e.g. give specific details on how to define the lowest SSB for good/high or not impaired recruitment.

Stocks with spasmodic recruitment are common for some fish species, and their management is particularly challenging (Licandeo et al. 2020). In ICES, spasmodic stocks (SR type 1) are defined as "stocks with occasional large year classes" (ICES 2021c). Spencer and Collie (1997) identified spasmodic stocks as those having the highest variation in their study, with low-frequency components without clear periodicities. Stocks with spasmodic recruitment may have long periods of weak recruitment with infrequent or irregular strong recruitment, which has complex links to stock productivity. More research is needed to define spasmodic criteria, as well as on simulation frameworks to evaluate how to define reference points and manage this type of stock (e.g.

Atlantic redfish in Licandeo et al. 2020).

In WKRPCHANGE, it has been suggested that addressing PA/MSY needs to take better account of changing productivity drivers, e.g. growth, reproduction, recruitment, density-dependence, and survival (ICES 2021a). Marine ecosystems are dynamic and might be affected by climate change impacting reference points. The productivity of fish stocks has been observed to vary globally in a non-stationary manner (Vert-pre et al. 2013; Minto et al. 2014; Britten et al. 2016; Perälä et al. 2017). In the ICES reference point framework, there are tools to account for temporal dynamics, and reference points are evaluated regularly at benchmarks to revisit their assumptions on future productivity. However, more research is needed on regime shifts and the consequences of, for instance, truncating data time series. Truncating the data can have significant impacts on the resulting parameter estimates. It has been observed that reducing the length of time series used to estimate reference points increases the uncertainty associated with them, particularly with biomass limit reference points (Deurs et al. 2021). It is still relatively unclear how to determine the period to use to estimate reference points. A better understanding of the nature of recruitment variability and the impact of changes will be key for estimating reference points. Research on how to detect when there has been a significant change in productivity (e.g. Peterman and Dorner 2012; Minto et al. 2014; Perälä et al. 2017; Tableau et al. 2019) could clarify recommendations to deal with productivity change. Furthermore, more research is needed to improve our understanding of ecosystem dynamics and their impact, and how to integrate these concerns into the framework for estimating reference points (Collie et al. 2021; Silvar-Viladomiu et al. 2022b).

As estimation of ICES reference points is typically made outside the assessment model, there is associated uncertainty in current abundance estimates, recruitment, and current fishing mortality regarding models and data used. Propagating the assessment uncertainty into the reference point estimate is important. We found that mainly default advice error values were used to account for advice uncertainty. These values were calculated as the median of five ICES stocks, and it would be an improvement to guide the estimation of more stock-specific values. While there is some guidance in the WKMSYREF3 report (ICES 2015b), more documentation is needed along with extending the research on estimation and the inclusion of advice uncertainty and dealing with short time series.

WKGMSE3 recommended the consideration of using more flexible MSE simulation frameworks for estimating reference points. MSEs have the potential to identify and account for more sources of uncertainties associated with reference points, e.g. density-dependent changes in underlying biological processes, SR pair time period error, and assessment/advice formulation error (ICES 2020a). Simulation models can also help develop management procedures and HCRs that are robust to perceived uncertainties, e.g. about recruitment. Further research is needed to develop guidelines for when and how reference points should be extracted from an MSE when one is conducted, using clear terminology and on how to deal with different outcomes with regard to precaution in reference point estimation and MSEs. Communication is extremely important because the decisions and assumptions taken to build MSEs are key to understanding the results. In general, WKGMSE3 recommended improving communication between scientists and managers (ICES 2020a).

Overall, moving forward, we recommend improving communication and transparency related to reference points in order to facilitate access to methods and data used. Extensive documentation consistent across stocks is needed for both general (cross-framework) and specific (EqSim) decisions and setting choices. In the same way, TAF (Transparent Assessment Framework; `https://taf.ices.dk/app/about`) was developed for assessments in order to achieve retrospective implementation of the full procedure. We should also be able to replicate reference point estimation at any historical time point by, for example, embedding reference point estimation within TAF.

In an environment like ICES, there is a significant variation in the ability, experience, and knowledge among experts conducting these analyses. For reference point estimation, it is difficult to find a balance between preserving some flexibility and having scientifically underpinned guidelines that are precise and detailed (rather than general steps and recommendations). Furthermore, those guidelines should be easily interpreted and understood by assessors. Given the differences between stocks, species, and surrounding ecosystems, some experienced scientists want flexibility to make the best scientific choices and apply their preferred analytical tools. In general, the priority for the framework should be to offer well-documented guidance with clearly stated assumptions but without being too prescriptive. In order to achieve this, the process might benefit from a more simplified methodology and terminology, which may reduce ambiguity. Additionally, as noted in WKRPCHANGE (ICES 2021e), the process of updating reference points in the context of

ICES advice would benefit from specific additional guidelines clarifying when reference points should be re-evaluated, how to test for non-stationarity or regime shifts, and when to reevaluate assumptions (i.e. changes in fishing patterns and productivity).

Finally, we recommend periodic syntheses such as these that take a detailed comparative look at what is being done across all stocks. These syntheses can then be compared and contribute to practices worldwide to continually strive to improve reference point estimation as a key step in the provision of scientific management advice.

2.7 Acknowledgements

We thank Martin Pastoors and one anonymous reviewer for providing constructive critiques on drafts of this manuscript. The authors are grateful to all scientist involved in ICES assessments and expert working groups upon whose work this study is based. This research was funded by the Marine Institute Ireland grant FEAS/ Ref Pts Desk Stud Fisheries Ecosystem Advisory Services – Reference points desktop study.

Chapter 3

Moving reference point goalposts and implications for fisheries sustainability

This chapter is a verbatim copy of a publish manuscript in *Fish and Fisheries*, which can be found in Appendix B.2:

Silvar-Viladomiu, P., Minto, C., Halouani, G., Batts, L., Brophy, D., Lordan, C., and Reid, D. G. (2021). Moving reference point goalposts and implications for fisheries sustainability. Fish and Fisheries, 22, 1345– 1358. `https://doi.org/10.1111/faf.12591`

Abstract

For many environmental indicators, the sustainable status can change because of changes in either the monitored state or the policy goal. Fisheries provide an intensively monitored setting to investigate the relative impacts of such change. Key fisheries sustainability indicators comprise the ratio between fishing pressure or biomass and their respective reference levels. We developed a retrospective database of population status, reference point changes, and reported reasons for changes for all data-rich stocks in the ICES region. We derived methods to distinguish the impacts of either source of change (monitored state or policy goal) on sustainable status. We found that reference points changed frequently (64% of populations had reference point changes) with varying magnitudes. Contrary to expectation, reference point changes were often not compensated by changes in the state thus significantly impacting inferred sustainability status and dependent scientific advice. Across a range of life histories and assessments, changes in reference points dominate retrospective revisions in status over the full time series. Overall, status before and after the change of reference point had no significant directional differences that would suggest reference point change effecting movement towards or away from sustainability. Although multiple factors have contributed to reference point changes, our results show that the reference point definition and the technical basis for estimation were the most important reasons for change. Recognizing that reference points are not constant in time but rather form reference series is paramount to quantifying present and historical sustainability. Properly documenting, justifying, and quantifying the impacts of such change is an ongoing challenge.

Keywords: Fisheries management; North Atlantic Ocean; population monitoring and assessment; sustainable targets and limits; UN sustainable development

3.1 Introduction

Within the United Nations 2030 Agenda, goal 14 for sustainable development relates to life below water and targets improved understanding of the status of commercial fish stocks (FAO 2020). Historically, overfishing has been widespread concern and the most decisive factor driving the collapse of marine ecosystems and losses of ecosystem biodiversity (Jackson 2001; Worm et al.

2006). The ability of fishery management systems to maintain fishing pressure at levels that can sustain productive fisheries depends on the availability of stock information and the capacity to adjust harvest in response to changes in stock abundance. Recent analyses demonstrate that on average assessed fisheries are improving with respect to management goals in regions where there are research, assessment, and management plans (Fernandes and Cook 2013; Hilborn et al. 2020; Ricard et al. 2012; Worm et al. 2009).

Fisheries science has made substantial progress in developing tools to assist in achieving policy goals. Management goals, commonly referred to as goalposts by fisheries managers, are expressed as reference points for a sustainable harvest. Quantitative measures of stock status relative to reference points are used to provide advice on sustainable catches, often in conjunction with harvest control rules (Kvamsdal et al. 2016). The status of a stock can be estimated in terms of both the fishing pressure level (typically fishing mortality rate, F) and abundance state level (typically biomass or spawning stock biomass, SSB) relative to their reference point, often at Maximum Sustainable Yield (MSY). The ratio of F to $\mathrm{F_{MSY}}$ (termed relative fishing mortality) indicates how far a stock is being fished from an optimally sustainable rate. Similarly, the ratio of SSB to the biomass reference point (termed relative biomass) shows if a stock is at a size that will provide MSY in the long term.

The concept of MSY is a common management goal underpinning reference points (Mace 2001). MSY can be defined as "the highest theoretical equilibrium yield that can be continuously taken on average from a stock under existing average environmental conditions without significantly affecting the reproduction process" (EC 2013). The precautionary approach (PA) plays an important role in fisheries management and is necessary, but a not exclusive condition for MSY. The International Council of the Exploration of the Sea (ICES) provides advice in accordance with MSY when data are available, that is consistent with the PA (ICES 2019a); populations need to be maintained within safe biological limits to make MSY possible. ICES advice is based on the fishing mortality reference point $\mathrm{F_{MSY}}$, and the biomass trigger point MSY $\mathrm{B_{trigger}}$ (see Table 3.1 with definitions of those and related reference points). For data-rich stocks, advice on sustainable catch focuses on attaining a fishing mortality rate of no more than $\mathrm{F_{MSY}}$ (fishing mortality status lower than 1) while maintaining the stock above full reproductive capacity. When SSB declines below MSY $\mathrm{B_{trigger}}$ (biomass status lower than 1), management must take action to reduce fishing mortality (ICES 2019a).

Table 3.1: The main reference points used in the ICES advice rule.

Reference point	Definition
MSY $B_{trigger}$	Maximum sustainable yield biomass trigger is defined as the 5th percentile of the distribution of *SSB* when fishing at F_{MSY}, but for most stocks that lack data on fishing at F_{MSY}, MSY $B_{trigger}$ is set at B_{pa}.
B_{pa}	Precautionary approach biomass reference point is a stock status reference point above which the stock is considered to have full reproductive capacity. Typically defined such that there is a 5% probability that the actual biomass is below B_{lim} taking account of assessment error.
B_{lim}	Biomass limit reference point is the key reference point, from which all other PA reference points are estimated. B_{lim} is the deterministic biomass limit below which a stock is considered to have reduced reproductive capacity.
F_{MSY}	Fishing mortality that provides maximum yield given the current assessment/advice error and biology and fisheries parameters.

The production of scientific fisheries management advice involves feedback loops of data and analysis, review, and decision-making (Privitera-Johnson and Punt 2020). The assessment type performed for each stock and the type of advice given depends mainly on available knowledge. In ICES, stocks are classified into six main data categories; for categories 1 to 4, there are guidelines to estimate reference points (ICES 2017a; ICES 2018a). ICES provides advice according to their MSY approach for category 1 and 2 stocks and PA advice for category 3 – 6 stocks. Through the ICES framework, most stocks undergo benchmarks every 3 – 5 years, where the methods and data used in given assessments are externally reviewed to determine assessment quality. Reference points used in ICES stock assessments are thought to be valid only in the short and medium term due to changes in marine ecosystems (ICES 2021e). As part of the benchmark process, reference points are reviewed to ensure that they reflect the current understanding of stock dynamics and are updated if necessary (ICES 2019a). Since reference points are estimated from assessment outcomes, they are impacted by revisions (to the underlying assumptions, data input and methods) made not only to the assessment but also to the process specific to their derivation.

Previous studies have investigated how fishing mortality and/or biomass estimates vary among assessments over time using several approaches to measure variation (Evans 1996; Ralston et al. 2011; Wiedenmann and Jensen 2018). While investigating changes in the numerator of a sustainability indicator (e.g. $F/\mathrm{F}_{\mathrm{MSY}}$) is important, we highlight the importance of changes in both the numerator and denominator (i.e. the defined sustainable target or limit). To our knowledge, no study has analysed the sources and the relative impact of changes in reference points on the inferred stock status, which is of critical concern to management. Changes to reference points may be seen as "moving the goalposts" in one direction or another. To improve understanding of changes in fisheries status it is necessary to discern how components that comprise status (i.e. numerator and denominator) change. Using an extended ICES assessments and denominator) change. Using an extended ICES assessments database, we disentangle changes in key stock status indicators such as relative fishing mortality ($F/\mathrm{F}_{\mathrm{MSY}}$) and relative biomass ($SSB$/MSY $\mathrm{B}_{\mathrm{trigger}}$). In addition, we present an analysis of reasons for changes among assessments to identify important sources of variation and uncertainty in reference points. Our key research questions thus comprise (i) how have reference points changed in the region?; (ii) how do changes in reference points impact sustainable stock status?; and (iii) what drives changes in reference points?

3.2 Materials and Methods

3.2.1 Time series and reference points dataset

International Council of the Exploration of the Sea (ICES) stock assessments provide detailed analyses of the dynamics and status of almost 200 stocks representing important commercial fisheries for the European Union and neighbouring countries. We obtained assessment output and reference points from ICES stock assessments accessed by XML query portal System (`http://standardgraphs.ices.dk/StandardGraphsWebServices.asmx/`) or from the relevant ICES report (`http://stockdatabase.ices.dk/Default.aspx`).

A total of 124 Stocks were subsetted to those that have reference point estimates. These were mainly category 1 stocks although six of the selected stocks were re-categorized during the timeframe of the study (either downgraded or upgraded in data/advice categories). In 2017, ICES changed the codes that are used to identify each stock (stock label key). These changes were incorporated into our analysis. For the stock label keys in our list, we acquired and integrated time series data on fishing mortality rate (F), spawning stock biomass (SSB) and MSY reference points ($\mathrm{F}_{\mathrm{MSY}}$ and MSY $\mathrm{B}_{\mathrm{trigger}}$). These data were downloaded on 17 April 2020. We excluded *Nephrops* stocks due to the comparatively short length of the time series and the predominant use of proxy yield-per-recruit reference points. Changes in reference points between sequential assessments were identified for analysis. Change in reference point (RP) was calculated as the proportional change relative to the preceding assessment $(RP_y - RP_{y-1})/RP_{y-1}$, where y is the assessment year. The cleaning of the database was supported by reference to the relevant published reports. We filtered changes due to rounding and to being relative reference points to the time series mean of fishing mortality or spawning stock biomass. Adjustments were made to stocks that had non-comparable reference point values (different measurement definitions used between assessments), see Appendix A.2 Table SI1. Status analysis was not performed for reference points with substituted values because, for example, the fishing mortality definition relative F in these assessments could not be compared to absolute values in the other assessments.

3.2.2 Status change decomposition

For a given assessment and year, status is calculated by dividing timeseries of estimated fishing mortality rate (F) or biomass state (SSB) by the relevant reference point. Sustainability status can change depending on changes to the numerator (F or SSB) or denominator ($\mathrm{F}_{\mathrm{MSY}}$ or $MSYB_{trigger}$). We derived expectations for the effect of changes in both numerator and denominator on sustainability status. To analyse changes in status between assessments, we first introduced the notation y to denote the assessment year and t the actual year of the time series, for example $F_{y=2020}^{t=2000}$, denotes the fishing mortality in year 2000 as estimated in the assessment of 2020. For each stock, year, and pair of consecutive assessments, we defined the inter-assessment change in status D_t as the proportional difference in status for a given time series year t:

$$D_t = \frac{\frac{X_t^y}{X_{MSY}^y} - \frac{X_t^{y-1}}{X_{MSY}^{y-1}}}{\frac{X_t^{y-1}}{X_{MSY}^{y-1}}} \tag{3.1}$$

where X is either fishing mortality rate or spawning stock biomass and X_{MSY} is the relevant reference point. Pairs of consecutive assessments were categorized according to whether or not a change in a reference point occurred. We visualized time series of inter-assessment differences (Equation 3.1) to understand how much status changes between consecutive assessments with reference point changes.

We estimated mean status before and after the change in reference point and an unequal variances t test was used to compare the values and evaluated if there were significant directional changes. We also compared the magnitude of the variability of the changes in F and SSB for the complete data set (containing all pairs of sequential assessments) to the variability of the subsetted data set containing only pairs when a change in reference point occurred. For that purpose, we measured the median absolute deviation (MAD) of the difference in mean rate F and state SSB.

For the status decomposition analysis, we used the subsetted data when a change in the reference point occurred. Change in status among sequential assessments was quantified by the change in average status between consecutive assessments over either the entire overlapping time series or the last 5 years of overlap (to infer recent status changes). The difference in average status can be decomposed into mean effects of the influence of changes in rate or state between consecutive assessments (i.e. the numerator) and changes in the reference point (i.e. the denominator). This decomposition comprises two parameters: δ, which encapsulates the proportional change in the reference point $X^y_{MSY} = \delta X^{y-1}_{MSY}$; and γ, which encapsulates the proportional change in average rate (F) or state(SSB) over time ($\sum_{t=1}^{n} X^u_t \ / \ n = \gamma \sum_{t=1}^{y} X^{y-1}_t / n$). We derive the expected difference in status using γ and δ:

$$E(\frac{X^y_t}{X^y_{MSY}} - \frac{X^{y-1}_t}{X^{y-1}_{MSY}}) = \frac{\gamma E(X^{y-1}_t)}{\delta X^{y-1}_{MSY}} - \frac{E(X^{y-1}_t)}{X^{y-1}_{MSY}}) \tag{3.2}$$

The mean proportional status change (w) is obtained by dividing the expected difference in status by the expected previous status:

$$w = \frac{E(\frac{X^y_t}{X^y_{MSY}} - \frac{X^{y-1}_t}{X^{y-1}_{MSY}})}{\frac{X^{y-1}_t}{X^{y-1}_{MSY}}} = \frac{\gamma}{\delta} - 1 \tag{3.3}$$

The impact of either change cannot be isolated (as the derivatives with respect to each naturally depend on the other). Nevertheless, we can empirically evaluate given changes to determine how much the relative status changes with respect to changes in either component. The mean change in status with respect to the proportional change in the reference point (δ) and with respect to the proportional change in estimate time series (γ) can be estimated with the following differential equations:

$$\frac{dw}{d\gamma} = \frac{1}{\delta}; \frac{dw}{d\delta} = \frac{-\gamma}{\delta^2} \tag{3.4}$$

We used a Pearson correlation test to evaluate the relationship between the two estimated parameters of proportional change.

3.2.3 Covariates of change dataset

We review relevant advice reports for assessment years y and $y-1$ to collect information on modifications that may have impacted the value of the reference points. Information on specific important revisions in assessment or benchmark meetings was typically presented in the advisory reports. Information regarding the technical basis for a reference point is presented at the reference point summary table. However, detailed information on settings for the estimation of the reference point was extracted from extensive reading of the referenced document, for example assessment reports or reference point estimation working group WKMSYREF (ICES 2014; ICES 2017b). These reports are available at the ICES library website (`http://www.ices.dk/publications/library/Pages/default.aspx`).

Every event of reference point change might have been associated with multiple modifications, typically within a benchmark assessment process. For example, the North Sea, eastern English Channel, Skagerrak cod (*Gadus morhua*, Gadidae) assessment was benchmarked in 2015, resulting in changes to the input data structure, maturity, natural mortality and model settings causing reference points to be re-estimated. Besides, the MSY fishing mortality reference point was updated from F_{max} to $\mathrm{F_{MSY}}$ from EqSim (stochastic equilibrium reference point software) analysis, and the rationale for $\mathrm{B_{lim}}$ was changed from $\mathrm{B_{loss}}$ to the SSB associated with the last above-average recruitment.

For every event of change in a reference point, the relevant information was collated into a new database and summarized as reference point covariates. We defined covariates based on the most frequent changes and modifications made. We aim to summarize revision generalized across all stock assessments. Covariates comprise categorical variables of occurrence and factor variables of a varying number of levels (Appendix A.2 Table SI2). "Assessment" covariates were used for the analysis of both fishing mortality and biomass reference points. These comprised modifications such as (1) modification of stock definition; (2) revisions of input data both fisheries-dependent; and (3) independent (e.g. inclusion or exclusion of fisheries-dependent and fisheries-independent data, e.g. discards, commercial index, survey index); (4) re-assessed maturity; (5) re-assessed natural mortality; and (6) a heterogeneous group encompassing other revisions and updates of assessment methodology, additionally (7) revision of the assessment type, which includes information of changes in the model selected to assess the stock, with categories representing levels by the combination of the previous and subsequent model.

For most ICES assessments, derivation of F_{MSY} is typically a separate process that uses assessment outputs for age-based models, and so we evaluated changes in F_{MSY} with "Assessment" covariates and covariates specific to its derivation ("RP" covariates). These comprise (8) modifications to the definition of F_{MSY},(9) change in the functional form of the stock-recruitment relationship, (10) revisions to the time frame of recruitment data input and (11) the time window of productivity parameters (growth, maturity, natural mortality, selectivity). The two former were included because ICES guidelines (ICES 2017a) recommend the use full time series of recruitment unless strong evidence exists of a regime shift; and the use of the last 10 years of biological parameters (weights, maturity, natural mortality) and fishery parameters (selectivity) unless there is evidence of persistent trends. Revision to the definition of F_{MSY} was categorized according to the information provided regarding the initial and subsequent choice of advised F_{MSY}, for example changes from the use of certain F_{MSY} proxies to the use of F_{MSY}.

Following the ICES MSY approach (Table 3.1, ICES 2017a), for MSY $B_{trigger}$ we included in the covariates the re-evaluation of the technical basis of MSY $B_{trigger}$ and related reference points (B_{pa} and B_{lim}). This framework includes transition rules, for example when a stock is fished at or below F_{MSY} for 5 or more years then the basis is MSY $B_{trigger}$ changes from B_{pa} to the 5th percentile of B_{MSY}. For ICES stock assessments, the biomass reference point B_{lim} is the main precautionary reference point, and B_{pa} is usually derived from it accounting for assessment uncertainty. Thus, to analyse changes in MSY $B_{trigger}$ we included covariates that are involved in setting MSY $B_{trigger}$ as (12) the revaluation of the technical basis of MSY $B_{trigger}$ and its related reference points (13) B_{lim} and (14) B_{pa}.

3.2.4 Reference point change analysis

We conducted an *a posteriori* regression analysis of sources of those historical changes collated from the published reports. The influence of covariates on reference points was analysed by a multiple linear regression taking the proportional change in the reference point (δ) as the response. All covariates relevant to the reference point were first included as main effects to explain proportional changes in reference points; all possible combinations of submodels were then fit and ranked by the Akaike information criterion (AIC), we used the R function *glmulti()* for the model selection (Calcagno and Mazancourt 2010). Finally, we conducted a two- sided F-test ANOVA to the best-supported multiple linear model and investigated the percentage of the variance explained by the selected covariates.

3.3 Results

3.3.1 Reference point changes

We identified that 50 stocks (21 species) have had changes in MSY-based reference points between 2011 and 2019 (Figure 3.1). This represents 64% of the stocks with estimates of absolute reference points. There were a total of 79 events of change in F_{MSY} and 51 in MSY $B_{trigger}$, of which 42 were simultaneous changes in both reference points. Of all stocks, North Sea, eastern English Channel and Skagerrak cod 2015 and West of Scotland cod 2019 had the highest increase in F_{MSY} (74%). Cantabrian Seas and Atlantic Iberian waters sardine (*Sardina pilchardus*, Clupeidae) 2019 had the greatest decrease (73%), which is considerably larger than the magnitude of any other decreases. The biomass reference point, MSY $B_{trigger}$, increased by 145% for North Sea, Skagerrak plaice (*Pleuronectes platessa*, Pleuronectidae) 2017, when MSY $B_{trigger}$ changed from B_{pa} to the 5th percentile of B_{MSY}. The largest decrease in MSY $B_{trigger}$ occurred in Rockall haddock (*Melanogrammus aeglefinus*, Gadidae) in 2019 (64%).

For some stocks, reference points continually declined or increased, for example Baltic Sea sprat (*Sprattus sprattus*, Clupeidae) F_{MSY} and seabass (*Dicentrarchus labrax*, Moronidae) MSY $B_{trigger}$, but importantly for many stocks with multiple reference point changes, these included a mixture of decreases and increases (Figure 3.1). This raises the question of whether those changes reflect short-term productivity fluctuations or difficulties estimating suitable reference points. We found that simultaneous changes in both reference points showed no relationship between increases or decreases in F_{MSY} and MSY $B_{trigger}$ (Appendix A.2 Figure SI1).

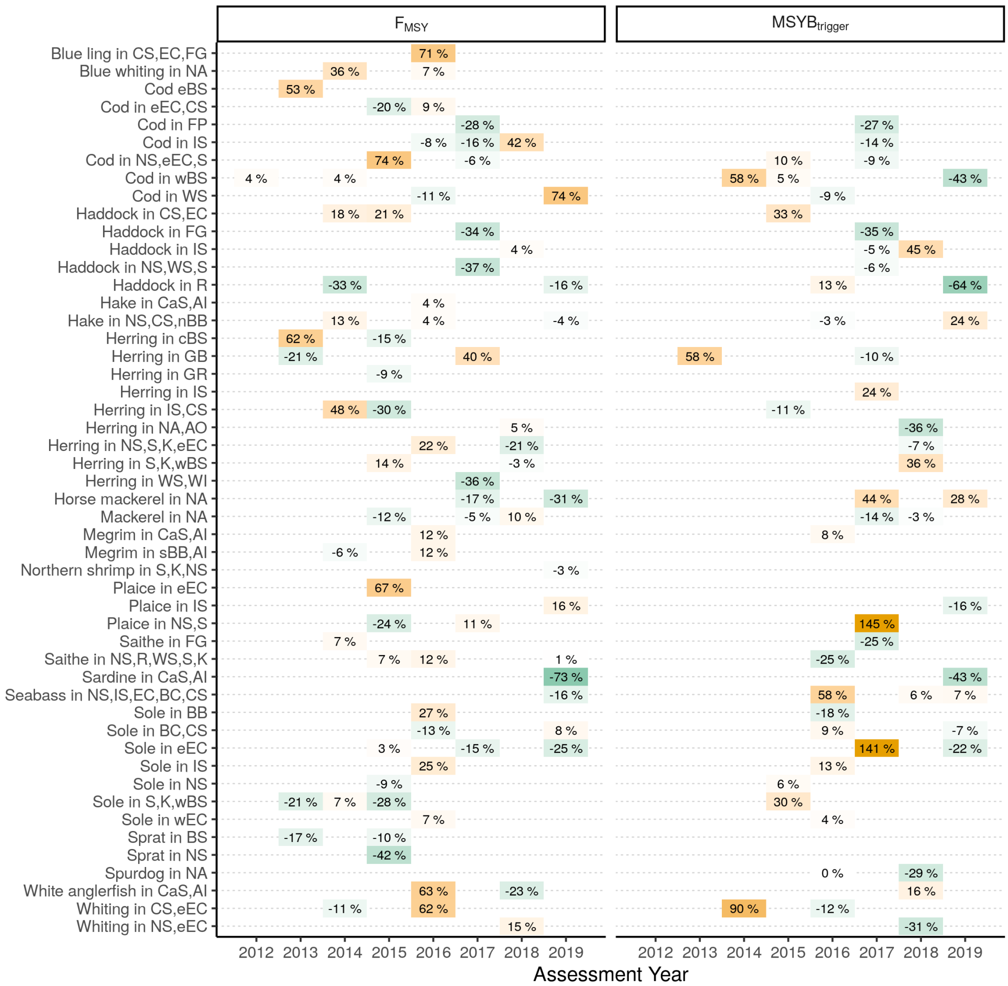

Figure 3.1: Changes in reference points for stock assessments for the period 2011–2019, measured in percentage change relative to the preceding assessment. Stocks are ordered by species. Acronyms used in stock description are: BB, Bay of Biscay; BC, Bristol Channel; CS, Celtic Sea; BS, Baltic sea; CaS, Cantabrian Sea; AI, Atlantic Iberian waters; EC, English Channel; FG, Faroes grounds; GR, Gulf of Riga; GB Gulf of Bothnia; FP, Faroes Plateau; IS, Irish Sea; NA North Atlantic; AO, Arctic Ocean; NS North Sea; S, Skagerrak; K, Kattegat; R, Rockall; WS West of Scotland; c, central; n, northern; e, eastern; w, western.

3.3.2 Sustainability status changes

Examining timelines of changes in status (F/F_{MSY} and $SSB/MSYB_{trigger}$) between assessments in which reference points changed (Appendix A.2 Figures

SI2 and SI3), we observed a variety of temporal patterns in the nature and magnitude of the changes (Appendix A.2 Figures SI4 and SI5). In some cases, the changes of reference point caused almost indiscernible changes in status (e.g. relative fishing mortality of Western Baltic Sea sole (*Solea solea*, Soleidae) 2014 in Figure 3.2),while elsewhere important status changes occurred when reference points changed (e.g. relative fishing mortality Cantabrian Seas and Atlantic Iberian waters sardine 2019). Occasionally, the sign of the change in status cross-over, meaning that the status trajectories between the assessments intersect, for example Skagerrak and Kattegat, western Baltic Sea sole 2015 in Figure 3.2. Status often varied markedly in the most recent years due to variability in fishing mortality rate (F) or biomass state (SSB) esti-mates, which are typically more variable in terminal years owing to a lack of convergence of the estimates (e.g. as caused by cohorts just entering the fishery and assessment). For example, in Cantabrian Seas and Atlantic Iberian waters sardine, a change to the 2019 assessment caused a relative increase in the F/F_{MSY} estimates that decreased in magnitude from 2010 to 2019 while a change to the 2015 assessment for Rockhall haddock caused a positive trend in the relative decrease of $SSB/MSYB_{trigger}$ from 2012 to 2015 (Figure 3.2). Several cases showed significant fluctuations in the magnitude of the relative change in status; some with a clear pattern (e.g. Rockhall haddock 2019) and others with a steady directional trend (e.g. Celtic Sea, Irish Sea herring (*Clupea harengus*, Clupeidae) deviation in 2013, Figure 3.2). To reflect these differences, we analysed status changes using both the complete time series and only the last 5 years to capture trends in changes in recent years.

Overall, while there are many examples of large changes in status for individual stock, there is no clear movement away from or towards sustainability (Figure 3.3 top panel). For the most recent five years, the changes in relative fishing mortality and relative biomass state showed greater spread than when all years were included. Changes in status were not directional based on unequal variances t test of the status before and after the assessment update (change in average relative fishing mortality recent: $t_{(159,46)} = -0.04$, $p = .965$; complete time series: $t_{(164,81)} = -0.06$, $p = .95$; change in average relative biomass recent: $t_{(101,23)} = -0.19$, $p = .849$; complete time series: $t_{(99,41)} = 0.05$, $p = .957$). The changes in average F or SSB, when a change in reference point occurred, had similar or greater variability than when all pairs of sequential assessments are considered (change in average relative fishing mortality recent: $MAD_{change} = 1.49$, $MAD_{allpairs} = 0.03$; complete time

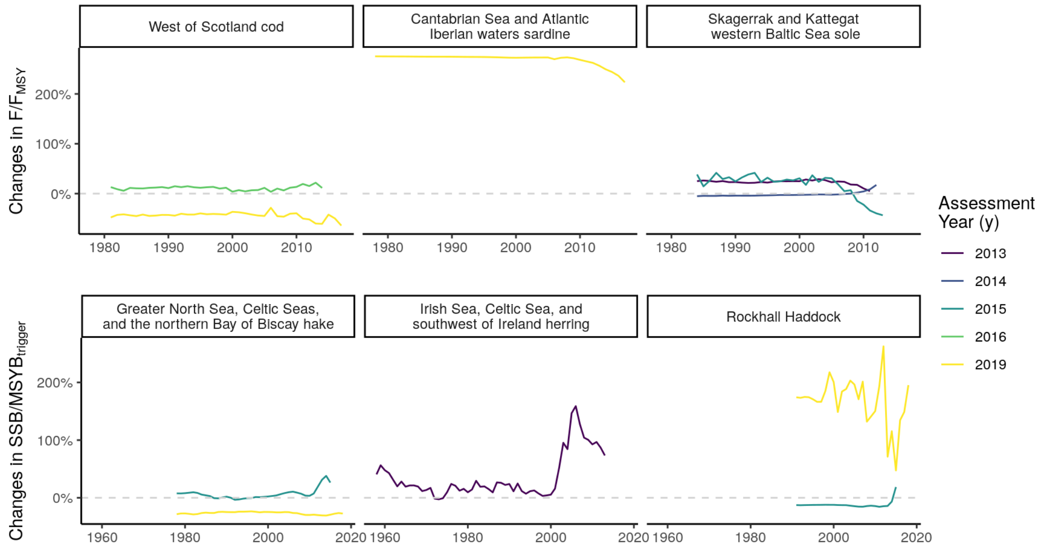

Figure 3.2: Example of changes in status timelines. Top-panel shows relative fishing mortality rate (F/F_{MSY}); and bottom panel shows relative biomass state ($SSB/MSYB_{trigger}$) proportional changes of assessment year (y) relative to the previous ($y-1$), for assessments in which changes in reference points were implemented.

series: $MAD_{change} = 1.48$, $MAD_{allpairs} = 0.009$; change in average relative biomass recent: $MAD_{change} = 4,807.33$, $MAD_{allpairs} =$ 5,187.62; complete time series: $MAD_{change} = 2,494.93$, $MAD_{allpairs} = 1,490.71$). Therefore, the changes in sequential estimates of F and SSB were more marked when a change in reference point occurred.

3.3.3 Effect of reference point changes on sustainability status

We define δ as the proportional change in the reference point and γ as the proportional change in average rate (F) or state (SSB) overtime. There was some evidence of a weak positive relationship between changes in rate or state and reference point (Figure 3.4),which was significant only for biomass over the recent part of the time series ($\rho = 0.33$, $p = .018$) and over the complete time series ($\rho = 0.53$, $p < .001$). Where the proportional changes in the numerator and denominator were equal, no change in status occurs (1:1 line in Figure 3.4). However, particularly looking at the data for the complete time series, average status changes were mainly due to changes in reference points (horizontal spread of points in Figure 3.4a2, 3.4b2). Some of the greatest changes in relative fishing mortality were associated with changes in F_{MSY}, for example

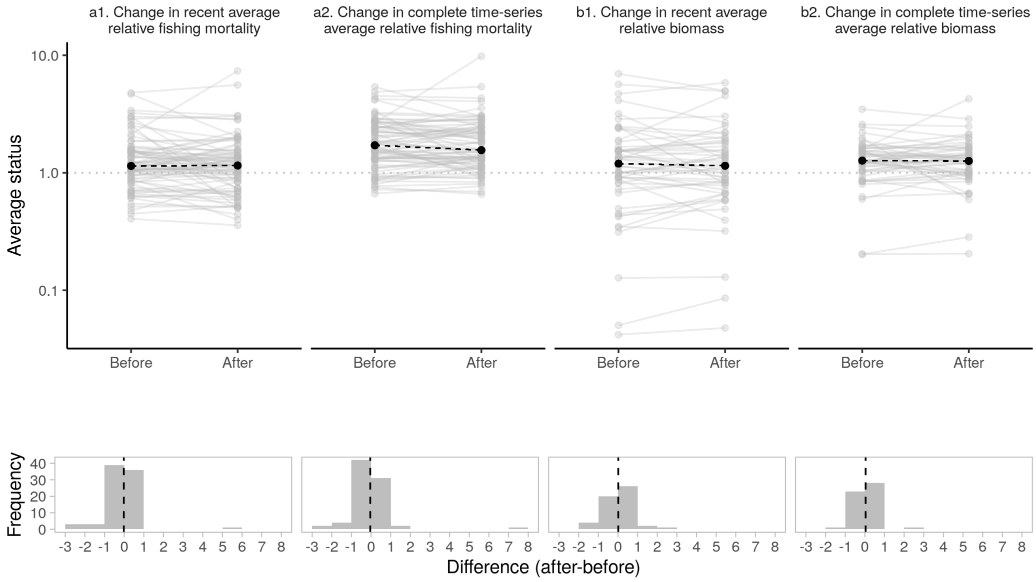

Figure 3.3: Mean status before and after at changes in reference points. Top-panel shows mean status on logarithmic scale in terms of relative fishing mortality (a) and relative biomass (b), over last five recent years (a1, b1) and complete time series (a2, b2). Bottom panel shows the distribution of the difference of status between before and after the reference point change. Black point and dashed line represents median values.

increase in relative fishing mortality for sardine in 2019 (Figure 3.4a point 61); and decrease in North Sea, eastern English Channel, Skagerrak cod in 2015 (Figure 3.4a point 11). Similarly for relative biomass, large changes were related mainly with changes in MSY $B_{trigger}$, for example Rockhall haddock in 2019 (Figure 3.4b point 28) and North Sea and kagerrak plaice in 2017 (Figure 3.4b point 63). Yet, eastern English Channel sole 2017 had important changes in both the biomass estimate and MSY $B_{trigger}$ (Figure 3.4b point 80). Only occasionally were the changes in rate or state compensated by changes in reference point over the most recent period such that no change in status occurred. This counters a common belief that changes in the estimated state will be compensated for by changes in the reference points, which are caused by new information on processes. There were examples of where this compensation occurred: relative fishing mortality of Gulf of Bothnia herring (Figure 3.4a point 39); and relative biomass of Northeast Atlantic horse mackerel (*Scomber scombrus*, Scombridae; in Figure 3.4b point 51), and North Sea and eastern English Channel whiting (*Merlangius merlangus*, Gadidae; in Figure 3.4b point 91).

The marginal relationship between mean status change (over the complete

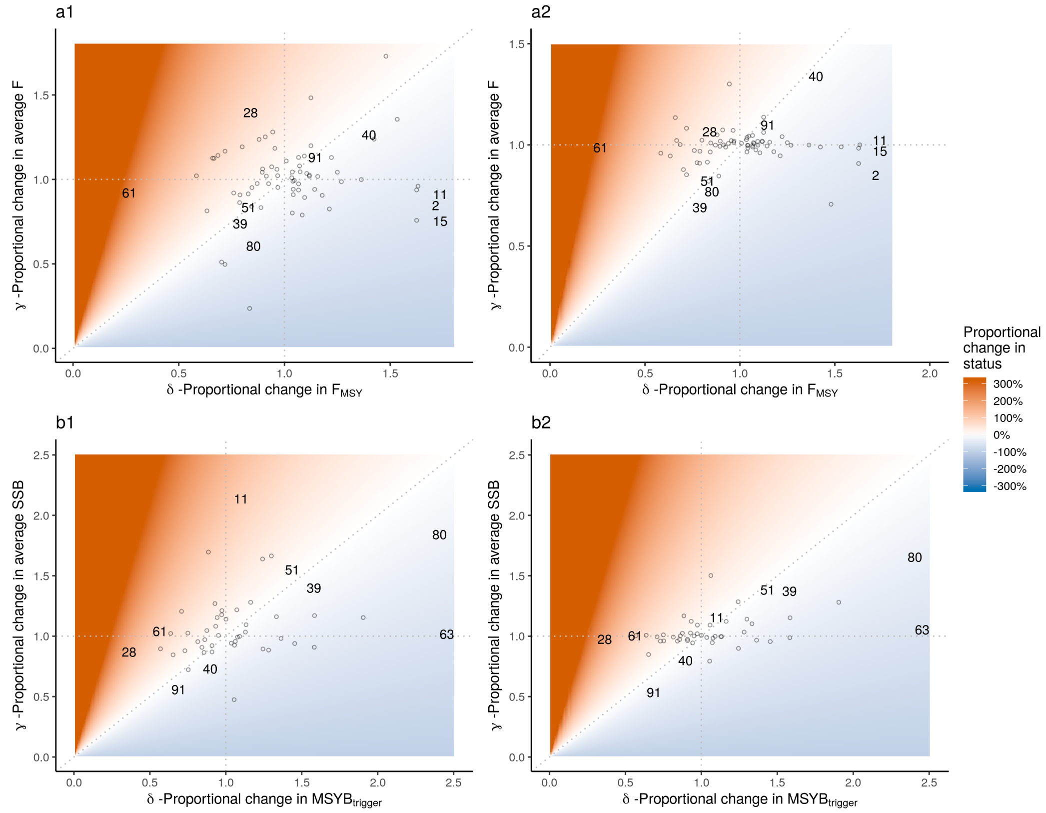

Figure 3.4: Change in sustainability status decomposition. Relationship between proportional change in average rate or state (γ) and proportional change in reference point ($\delta_a = F^{y}_{MSY} / F^{y-1}_{MSY}$; $\delta_b = MSYB^{y}_{trigger} / MSYB^{y-1}_{trigger}$), background colour represents impact in status change for relative fishing mortality rate, $F/\mathrm{F_{MSY}}$ (a) and relative biomass state, $SSB/\mathrm{MSY\ B_{trigger}}$ (b), over recent years (a1, b1) and the complete time series (a2, b2). The plot numbers correspond to the event numbers in Appendix A.2 Table SI1: (2) 2016 blue ling in Celtic Seas, English Channel and Faroes grounds; (11) 2015 cod in North sea, eastern English Channel, Skagerrak; (15) 2019 cod in West of Scotland; (28) 2019 haddock in Rockall; (39) 2013 herring in gulf of Bothnia; (40) 2017 herring in gulf of Bothnia; (51) 2017 horse mackerel in North Atlantic; (61) 2018 white anglerfish in Cantabrian Sea and Atlantic Iberian waters; (80) 2017 sole in eastern English Channel; (91) 2018 whiting in North Sea and eastern English Channel.

time series) and proportional change in reference point displayed a curvilinear inverse response adhering to the expected relationship (Figure 3.5 top panel). As the reference point is the denominator of status ($F/\mathrm{F_{MSY}}$ and $SSB/\mathrm{MSY\ B_{trigger}}$), if the numerator compensated for the change in the denominator one would expect a flat relationship in Figure 3.5. We found that reductions in reference points ($\delta < 1$) resulted in steeper increases in status, whereas increases in reference points ($\delta > 1$) resulted in more moderate reductions in status (e.g. from the theoretical proportional change in mean status $\frac{\gamma}{\delta} - 1$, a 10% reduction in the reference point would result in an approximate 11% increase in status whereas a 10% increase in the reference point would result in an approximate 9% increase in the status where $\gamma = 1$). This negative relationship between changes in status and the change in the reference point appears stronger (less variable) for relative fishing mortality than for the relative biomass (Figure 3.5 top panel). Occasionally, there were assessments where the reference point decreased but status also decreased, or where both increase. The observed marginal relationship with the proportional change in rate or state (γ) was diffuse compared to the theoretical relationship (Figure 3.5 bottom panel). Over recent years of overlap, the marginal relationship of changes showed in general more variability for the proportional change in reference point and less variability in the marginal relationship with the proportional change in rate or state estimates (Appendix A.2 Figure SI6).

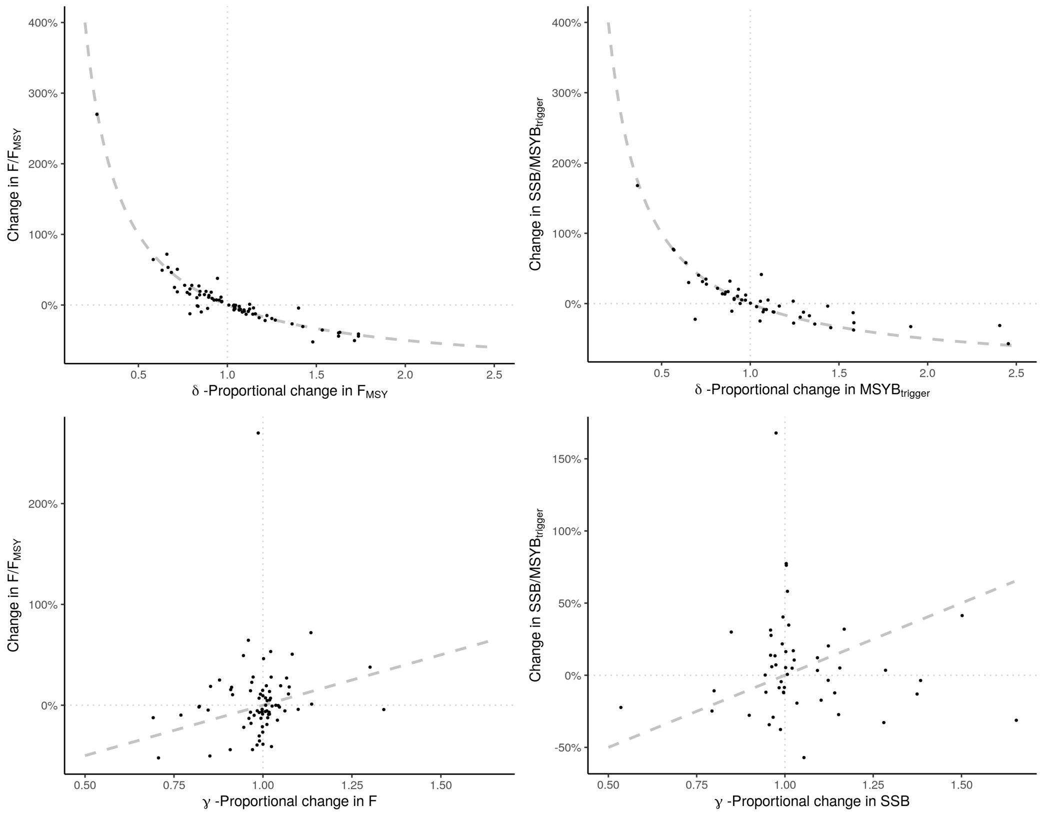

Figure 3.5: Marginal relationship between average change in status and δ, proportional change in reference point, at the top panel; and γ, proportional change in rate (left) or state (right), at the bottom panel considering the complete time series. Grey line shows the expected theoretical change with a change in δ (top) or γ (bottom).

3.3.4 Possible reasons for reference points change

Across all the covariates, the distribution of the magnitude of change in both reference points displayed heterogeneous patterns with wide ranges; no covariate showed a clear directional effect (Appendix A.2 Figures SI7 and SI8). Most changes in reference point occurred due to a combination of effects rather than a single cause; we found that covariates occurred simultaneously, they might be correlated and also interact (Appendix A.2 Figures SI9 and SI10).

Events of change in both F_{MSY} and MSY $B_{trigger}$ presented similar frequency of occurrence for "Assessment" covariates. Input fisheries-dependent and fisheries-independent data were revised for roughly 20% of the cases. The assessment model was modified in approximately 15% of the cases, the most frequent change being from XSA to SAM (n = 5). Re-assessment of natural mortality was found in 11% of the cases for F_{MSY} and 6% of the cases for MSY $B_{trigger}$. Changes in natural mortality estimates comprise revision of assumptions (e.g. using a new single species method, introducing multispecies estimates), or updates (e.g. time-varying mortality updated, multispecies estimates using a new multispecies model run). Less frequently encountered covariates (> 10% of the cases) were the revision of maturity estimates and the revision of the definition of the stock.

Although multiple factors have contributed to changes in reference points, our results showed that the evolution in the definition for fishing mortality reference point (F_{MSY}) and re-evaluation of the technical basis for limit biomass reference point (B_{lim}) were the most important (Table 3.2). Revision of fishing mortality reference point definition was the most frequent covariate identified (n = 30, 40% of the cases). This key covariate explained the largest part of the variance (39.8%) of the model ($F - statistic_{13} = 3.6$, $p = .0004$, Table 3.2). It presented the change of many previous definitions (e.g. proxy values) and diversity of stochasticity implementation methods, to a unified F_{MSY} estimation framework Eqsim (Figure 3.6a). We found that advised F_{MSY} based on analogies from other stocks (n = 2) or provisional from simulation frameworks (n = 8) were on average higher than subsequent F_{MSY}; however, per-recruit proxies were lower based on small sample sizes (F_{max} n = 8; $F_{0.1}$ n = 4). Only one observed change was related to a revision of the fishing mortality reference point from the calculated value (F_{MSY}) to F_{p05} established by stochastic simulations when the precautionary criterion is not met (Figure

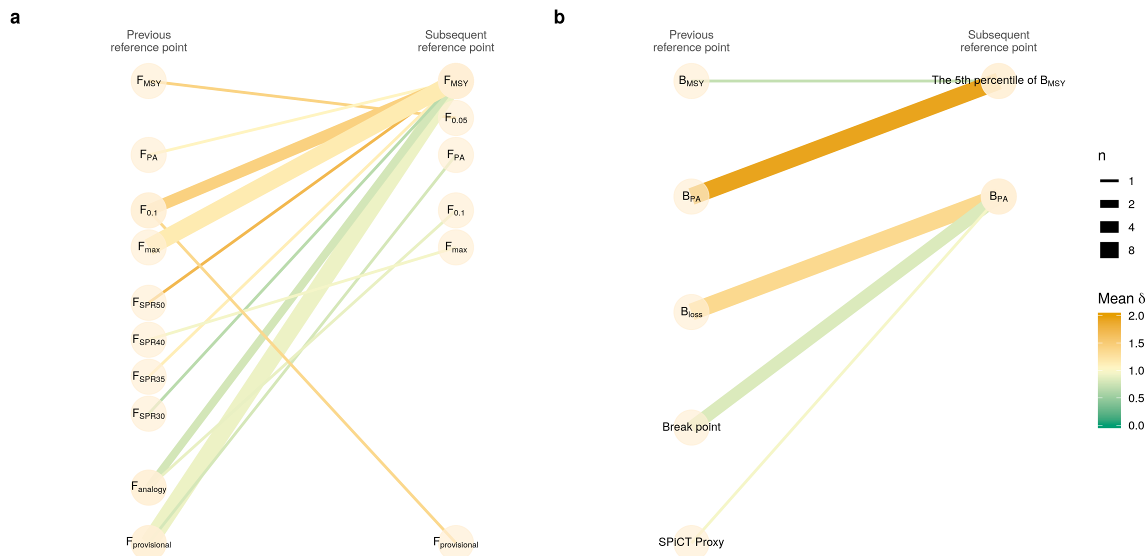

Figure 3.6: (a) Average change in advised reference point F_{MSY} with levels of revision in definition of fishing mortality reference point: F_{MSY} , yield-per-recruit proxies ($F_{0.1}$, F_{max}), spawner biomass per-recruit proxies (F_{SPR30} , F_{SPR35}, F_{SPR40}, F_{SPR50}), F_{pa}, reference point from analogy of other stocks and provisional reference point; and (b) average change in advised reference point MSY $B_{trigger}$ with levels of revision of the technical basis: B_{MSY} , B_{pa} , Break point, B_{loss} , proxy from Spict model. The width of the line shows the number of occurrence of that specific revision. Warm colours are mean increase and cool colours mean decrease of reference point advised value.

3.6a). For the biomass reference point, revision of B_{lim} technical basis explained 29.94% of the variance of the model ($F - statistic_{13} = 2.23$, $p = .04$, Table 3.2). B_{lim} technical basis was revised for 19% of the cases and MSY $B_{trigger}$ for 16%. From the re-evaluations of MSY $B_{trigger}$ (n = 13), for 23% of the cases the technical basis was changed from B_{pa} to the 5th percentile of B_{MSY} (Figure 3.6b). The most frequent revision found was re-evaluation of the technical basis of B_{pa} (23% of the cases), which involves modification of how the assessment uncertainty is accounted for. Both selected models to explain changes in reference points had large residual variability at 44.62% and 21.02% for F_{MSY} and MSY $B_{trigger}$, respectively (Table 3.2) likely reflecting the binary nature of the covariates without the magnitude of change.

The different nature of ICES fishing mortality target and biomass threshold reference point was reflected in the analysis. As F_{MSY} is a model estimate output, it is impacted by modifications to input data (e.g. selection pattern and biological parameter) and underlying assumptions (i.e. stock–recruitment relationship functional form). We found that to derive F_{MSY}, the assumption of the stock–recruitment relationship functional form was revised for 24% of the cases (n = 19). Modelling of the stock–recruitment relationship (a key density-dependent process) remains a challenge and this is known as the main source of variation (ICES 2015b; Simmonds et al. 2011). During workshops to consider the basis for F_{MSY} ranges for all stocks, WKMSYREF (ICES 2015b; ICES 2017b) several stock–recruitment models were investigated from functional form combinations to the use of segmented regression. In terms of data input to derive reference points, we found that the time series to estimate F_{MSY} was revised in 11% of the cases for recruitment and 7.5% for productivity parameters. Time series of recruitment and *SSB* to model the stock–recruitment relationship are re-evaluated to ensure the selection of the relevant period when there is a change in the perception of the productivity regime (i.e. shifts or trend). Both, revision of stock–recruitment functional form and selected time series of recruitment, were important variables in the model, which explained around 5% of the variance each ($p < .05$, Table 3.2). In contrast, MSY $B_{trigger}$ (when set to B_{pa}) is based on biomass assessment estimates, because is often derived from B_{lim} (typically set by stock–recruitment typology rules). Therefore, it is more sensitive to changes affecting the estimates of biomass, for example revision of assessment model type, fishery-dependent and fishery-independent data, methodological revisions and re-assessment of maturity (Table 3.2).

Table 3.2: Table displaying the results of selected model explained by the covariates.

Covariate	Model for changes in F_{MSY} ($R^2 = 0.55$, $R^2_{adj} = 0.37$, F-Statistic = 3.16 with p = 2.69e-4)	Percent of variance explained	Model for changes in MSY $B_{trigger}$ (R^2 = 0.79, $R^2_{adj} = 0.54$, F-Statistic = 3.2 with p = .003)	Percent of variance explained
(1) Revision_Assessment_Stock_definition	–	–	–	–
(2) Revision_Assessment_input_data_FisheriesDependent	–	–	$F - statistic_{(1)} = 6.74$; $p = .0161^{*}$	9.68%
(3) Revision_Assessment_input_data_FisheriesIndependent	–	–	$F - statistic_{(1)} = 1.77$; $p = .1958$	7.37%
(4) Revision_Assessment_maturity	$F - statistic_{(1)} = 3.93$; $p = .0522^{\cdot}$	3.14%	$F - statistic_{(1)} = 1.85$; $p = .187$	1.69%
(5) Revision_Assessment_M	–	–	–	–
(6) Revision_Assessment_methodology	–	–	$F - statistic_{(1)} = 8.17$; $p = .00889^{**}$	6.51%
(7) Revision_Assessment_type	$F - statistic_{(6)} = 1.57$; $p = .174$	15.34%	$F - statistic_{(4)} = 5.94$; $p = .00196^{**}$	14.42%
(8) Revision_RP_FMSY_definition	$F - statistic_{(13)} = 3.62$; $p = .0004^{***}$	39.75%	–	–
(9) Revision_RP_SR_functional_form	$F - statistic_{(1)} = 4.25$; $p = .0439^{*}$	5.64%	–	–
(10) Revision_RP_input_timeseriesRecruitment	$F - statistic_{(1)} = 3.94$; $p = .0320^{*}$	5.64%	–	–
(11) Revision_RP_input_parameterstimeseries	–	–	–	–
(12) Revision_RP_MSYBtrigger_tb	–	–	$F - statistic_{(5)} = 2.59$; $p = .0531^{\cdot}$	5.05%
(13) Revision_RP_Blim_tb	–	–	$F - statistic_{(13)} = 2.23$; $p = .0439^{*}$	29.94%
(14) Revision_RP_Bpa_tb	–	–	–	–
Residuals	–	44.62%	–	21.02%

Note: Signif. Codes: 0"***" 0.001"**" 0.01"*" 0.05"." 0.1"" 1.

3.4 Discussion

3.4.1 Evolution of sustainable targets and thresholds

Reference points play a key role in fisheries management by providing targets and thresholds to guide management actions (Mace 2001). Reference points may change, not only reflecting the non-stationary nature of the ecosystem but also our ability to capture those changes. The frequency at which reference points are updated varies globally, for example, tuna Regional Fisheries Management Organizations and North Pacific Fisheries Management council update reference points with each assessment (Kell et al. 2016). ICES stocks provide a unique opportunity in terms of breadth and frequency of change (Figure 3.1) to investigate the impact of changes in reference points. By using ICES stocks for this analysis, we gained a data-rich and detailed overview of the evolution of reference points and their key management use in measuring sustainability status. Stock status before and after a change in a reference point had no significant directional differences (Figure 3.3) that would suggest a retrospective movement towards or away from sustainability. But there have been important effects of reference point changes for specific stocks with implications for sustainable harvest advice and perceived conservation status. We showed that, across a range of life histories and assessments, changes in reference point dominate changes in status over the full time series (Figure 3.4). Analysis of recent years shows more variability due to terminal estimate variability and bias (known as retrospective pattern in assessment updates; ICES 2020b) but also highlights the importance of changes in reference points on status. For simultaneous changes in F_{MSY} and MSY $B_{trigger}$, we would expect an inverse relationship (i.e. a decrease in F_{MSY} would be associated with an increase in MSY $B_{trigger}$ and vice versa), assuming that the same method was used and only new information in processes was included. However, a substantial number of events deviated from the expected direction (Appendix A.2 Figure SI1), which might be indicative of changes in perceived productivity.

Reference point changes reflect simultaneously the evolution of management policy and scientific understanding and methodology. In 2009, ICES adopted the MSY framework on top of their precautionary framework and began adapting the advice provided (Lassen et al. 2014). The framework includes transition rules; for example, when a stock is fished at or below F_{MSY} for 5 or more years then the basis of MSY $B_{trigger}$ changes from B_{pa} to the 5th percentile of B_{MSY} (ICES 2017a). This is because productivity and B_{MSY} estimates may change as stocks increase when fishing mortality is reduced to more sustainable levels (i.e. F_{MSY}). Another occurrence was the re-estimation of F_{MSY} and precautionary reference points during the workshops WKMSYREF (2013–2015). This was stimulated by the request of the European Commission for advice on potential intervals above and below F_{MSY} for selected stocks. Evaluations of MSY were made using EqSim or similar methods to implement stochasticity (ICES 2014; ICES 2017b). Changes in software used to derive F_{MSY} are important because the underlying uncertainty assumptions and the way stochasticity is implemented may vary, which affects the estimates (ICES 2017b; ICES 2019c).

Across different regions, past studies of the variability among historical assessment and projection simulations have shown that there are numerous potential causes for changes in assessment estimates over time (Privitera-Johnson and Punt 2020; Punt et al. 2018; Ralston et al. 2011; Wiedenmann and Jensen 2018). Previous studies have shown sensitivity of MSY-based reference points to the functional form and parameters of the stock–recruitment relationship (Simmonds et al. 2011; Zhu et al. 2012). A recent study initiates there search on the uncertainty associated with biomass limit reference points (Deurs et al. 2021). They were found to be sensitive to the estimation method, time series length, and stock development trends. However, to our knowledge, no study has systematically quantified the impact and reasons for changes in reference points over time. We explored the effect of modifications to reference points that were stated in assessment reports. Were we to also re-run the assessment models and reference point estimation procedure it would be possible to investigate the deterministic impact of any given changes singularly or in combination. This mechanistic approach would be greatly facilitated through transparent frameworks for data and modelling and advice such as the recently developed ICES Transparent Assessment Framework (`https://taf.ices.dk/app/about` last accessed August 15th, 2020). Such an analysis is beyond the scope of this work but would be extremely useful and could be operationalized where changes are proposed. Our analysis sets the groundwork for future mechanistic investigation of the causes underlying changes in reference points and status on a stock-by-stock basis.

3.4.2 Implications for fisheries management

Time-varying reference points will become increasingly important for management given: (i) continual improvements in stock assessments (in terms of new and improved data and estimation) and continually improved knowledge of stock biology; (ii) the development of operational ecosystem approach and the increasing inclusion of ecosystem concerns in assessments (Marshall et al. 2019; Skern-Mauritzen et al. 2016); and (iii) growing evidence of dynamics, shifts in productivity, and the influence of climate change, which emphasizes the need to adapt reference points (Britten et al. 2017; Collie et al. 2012; Minto et al. 2014; Vert-pre et al. 2013; Szuwalski and Hollowed 2016; Tableau et al. 2019). These changes in reference points will require inclusion in future interpretations of stock status (Hilborn 2020).

We underscore the importance of keeping track of changes and modifications to understand their impact and allow comparisons across stock assessments that underpin fisheries management. Our results also highlight the continual importance of accounting for scientific uncertainty to distinguish it from real changes in the ecosystem or the fishery, which are fundamentally different. We emphasize them any examples in Figure 3.1 of where reference points decrease and then increase or vice versa and posit that these cases will offer useful insights into the general process lending towards further investigation of the stability and performance of management advice under true and perceived change. Given the challenges faced by estimation and the use of reliable reference points for management (Hilborn 2002), reference points are better seen as reference series. The relevant reference point in the reference series should also be time-dependent (possibly with lags) when inferring historical sustainability rather than assessing historical status relative to the most recent reference point. We recommend careful documentation of changes to assessment assumptions and data inputs (Punt et al. 2018), as well as the revision in estimation or selection of reference points and detection of shifts in productivity (Clausen et al. 2018). Communicating, explaining and justifying the changes is remarkably important to understand them and their relevance. Nowadays, this can be readily achieved using change logs that are common in other continual development processes such as software development.

Although this work is tailored for ICES reference points, the approach to decompose changes in status into components can be applied to other regions and globally (e.g. using the RAM Legacy Database). Methods developed here are applicable in settings where the ratio of a state to a changing goal is used to indicate status (e.g. Sustainable Development Goals: 6 Clean Water and Sanitation; 13 Climate Action; 15: Life On Land).

3.5 Acknowledgments

We are grateful to Kenneth Patterson for his valuable contribution and feedback in early stages of this manuscript. We thank European stock assessment scientists, data collectors, and ICES upon whose assessments our work is based. This analysis was funded by Irish Department Agriculture, Food and the Marine's Competitive Research Funding Programmes (DAFM) as part of the FishKOSM project (Ref 15/S/744).

Chapter 4

Peterman's productivity method for estimating dynamic reference points in changing ecosystems

This chapter is a verbatim copy of a publish manuscript in the *ICES Journal of Marine Science*, which can be found in Appendix B.3:

Silvar-Viladomiu, P., Minto, C., Brophy, D., and Reid, D. G. (2022). Peterman's productivity method for estimating dynamic reference points in changing ecosystems, ICES Journal of Marine Science, 79, 4, 1034–1047. `https://doi.org/10.1093/icesjms/fsac035`

Abstract

Target and limit reference points are fundamental management components used to define sustainable harvest strategies. Maximum Sustainable Yield (MSY) and the precautionary principle underpin many reference points. Non-proxy reference points based on MSY in age-based single-species assessments depend on the stock-recruitment (SR) relationship, which can display complex variability. Current reference points ignore persistent dynamic change by assuming that the SR relationship is stationary and with constant recruitment parameters over selected time periods. We highlight Peterman's productivity method (PPM), which is capable of tracking temporal dynamics of recruitment productivity via time-varying SR parameters. We show how temporal variability in SR parameters affects fishing mortality and biomass MSY-based reference points. Implementation of PPM allows for integrated dynamic ecosystem influences in tactical management while avoiding overwrought and sometimes ephemeral mechanistic hypotheses tested on small and variable SR datasets. While some of these arguments have been made in individual papers, in our opinion the method has not yet garnered the attention that is due to it.

Keywords: EBFM reference points; non-stationary productivity; scientific fisheries management advice; stochastic processes; stock-recruitment relationship; time-varying parameters

4.1 Introduction

Reference points play a key role in the provision of scientific advice for fisheries management (Garcia 1996). They provide the basis to define targets and limits that establish operational objectives, necessary for effective fisheries management (Sissenwine and Shepherd 1987; Schnute and Haigh 2006; Hilborn et al. 2020). Reference points provide benchmarks to promote the sustainability of the stocks and reliant fisheries (Mace 1994). By identifying limits that should not be exceeded and targets that should be achieved, they support harvest control rules (HCRs) that guide management decisions (Punt 2010; Kvamsdal et al. 2016). They have an essential role in current management frameworks, to provide recommendations for fishing strategies and to define tactical management measures, e.g. catch and effort limits, and the design of management plans.

Major paradigms used to define reference points internationally are Maximum Sustainable Yield (MSY) and the precautionary approach (FAO 1995a). The Food and Agriculture Organization (FAO) of the United Nations defines MSY as: "the highest theoretical equilibrium yield that can be continuously taken (on average) from a stock under existing (average) environmental conditions without affecting significantly the reproduction process". Managing fish stocks under the precautionary approach and MSY has been generally advocated by international agreements (FAO 1995a; UN 1995; UN 2002). The UN Fish Stock Agreement contains guidelines for applying a precautionary approach within an MSY framework. During the World Summit on Sustainable Development, organized by the UN in 2002, it was agreed in the Johannesburg Declaration to "maintain or restore stocks to levels that can produce the MSY with the aim of achieving these goals for depleted stocks on an urgent basis and where possible not later than 2015" (UN 2002). These concepts are embraced by intergovernmental organizations and are reflected in important fisheries policies, e.g. Common European Fisheries Policy (EC 2013) and Magnuson–Stevens Fisheries Conservation and Management (MSA 2007) in the United States.

While MSY has been criticized from multiple angles (Larkin 1977), a change in focus, away from MSY as a target catch state towards a target and limit fishing mortality rate at MSY (Mace 2001), has made it one of the main operational guides for sustainability in global fisheries management (Worm et al. 2009; Marchal et al. 2016). Indeed, given difficulties in establishing economic management objectives, MSY emerges as a default fall-back option (Beverton and Holt 2004), if not the appropriate economic objective in itself considering all components of the overall fishing sector (Christensen 2010).

One of the main criticisms of MSY is whether it is possible to take ecological aspects into account (Larkin 1977; May et al. 1979; Mace 2001). Studies highlight the challenge of achieving MSY simultaneously for cohabiting species (Mackinson et al. 2009). There is also indication that single-species MSY may need to be adapted when ecological interactions are present— i.e. predation, competition (May et al. 1979; Gislason 1999; Collie and Gislason 2001). Additionally, the growing evidence of regime shifts (Vert-pre et al. 2013; Perälä et al. 2017); and the effect of climate change in fish stocks (Free et al. 2019) emphasize the presence of non-stationary population processes, which mean that reference points will also vary.

The need to adopt a more holistic approach to fisheries management has been globally accepted (FAO 2003). Thus, the ecosystem approach is included in most fisheries' international agreements and policies. Ecosystem-based fisheries management (EBFM) requires comprehension of the broader picture (biophysical interactions, biodiversity, food-web structure, ecological processes, and ecosystem functioning). Therefore, the science for its operationalization and implementation is often considered challenging (Cowan et al. 2012; Dolan et al. 2016). It is crucial to develop reference points as operationally powerful as those currently used in single-species management advice yet in accordance with ecosystem concerns. There is still no agreement on how to evolve the MSY concept and what should be considered targets and limits within EBFM (Rindorf et al. 2017b). The MSY concept applied correctly might be more useful to EBFM than other data-demanding methods (Pauly and Froese 2021).

There is a "gap" between single-species methods that provide reference points for advice to trigger tactical management and ecosystem-based methods that often do not have clearly defined operative standards for tactical management (Fogarty 2014). This gap is difficult to bridge because more complex models present greater modelling challenges (Quinn 2003), making the outcomes less suitable for management. Both methods are needed to support: (a) tactical advice able to make management decisions in an immediate term and (b) strategic advice based on the understanding of the system and the study of ecosystem drivers and their effects. In this article, we focus on how to deal with changing ecosystems within tactical fisheries management. We present a possible bridge to align stock reference points with ecosystem concerns.

In our opinion, the keystone lies in the static assumptions to model recruitment productivity, made in most single-species reference point estimations, which do not reflect non-stationary behaviours shown in fish productivity (Peterman et al. 2000; Minto et al. 2014; Perälä et al. 2017). We briefly review reference point estimation in single-species contexts and highlight how time-varying approaches provide operational objectives for management reflective of a dynamic ecosystem. We believe that the framework for doing this is available, we provide due recognition to the originators — Professor Randall Peterman and his group — , and look to challenges and future developments. We conducted hypothetical numerical simulations to show the role of temporal variability in stock–recruitment (SR) relationship parameters and their impact on reference point estimates. For our example, we chose to explore the commonly applied Beverton–Holt SR model to complement previous research on non-stationary SR relationships, which used the linearized Ricker model.

Finally, we propose priority research areas in this field that will improve model development and application.

4.2 Status quo of single-species reference points

Globally, there is broad agreement regarding the concepts underlying reference points used to assess the status of fish stocks for management advice. Nevertheless, the interpretation and application of reference points have evolved and differed among regions (Ricard et al. 2012; Hilborn 2020). We give an overview of the status quo of single-species reference points, focusing on approaches used in areas with advanced fisheries management systems: e.g. the United States and Europe (ICES region). This background provides an entry point for our arguments regarding Peterman's productivity method (PPM).

4.2.1 MSY reference points

Understanding how population productivity varies with abundance is crucial in determining maximal surpluses and thus defining single-species reference points (Quinn and Deriso 1999). Reference points are usually expressed in terms of fishing mortality rate (F) and biomass, typically spawning stock biomass (SSB). The scientific concept of MSY was introduced with the aggregated Schaefer model (Schaefer 1954), which assumes that population growth is density-dependent with a linear decrease in per-capita rate of population growth with increasing abundance, resulting in a logistic population model that is decremented by given catches. The logistic model has production as a quadratic function of abundance. In Schaefer surplus production model (Schaefer 1954), MSY is obtained at half of the carrying capacity or equilibrium level. Subsequently, Pella and Tomlinson (1969) proposed an extension to allow for asymmetric production curves.

For surplus production models, MSY reference points (F_{MSY} and B_{MSY}) are internally estimated as functions of model parameters. These methods, also called biomass dynamic models, focus on population growth and mortality. The productivity of the stock is modelled with a limited set of parameters including the intrinsic growth rate and carrying capacity of the population. Surplus production models are often used for data-limited stocks because they are less data demanding, although Bouch et al. (2020) highlight estimation challenges associated with data availability with respect to the stock history.

Age- or length-structured methods allow the cohorts to be followed, and so they use data structured in age or length classes to analyze population changes. These methods provide a more complete analysis of the stock by following the dynamics of individual cohorts. Age- or length-structured methods contain three basic components: growth, mortality, and recruitment (Quinn and Deriso 1999). In addition to age and length information of the population, the required inputs (which may sometimes be estimated) are biological information including growth parameters, mortality, and maturity. Whereas the majority of contemporary data-rich stock assessments use age-structured models, the choice of model type is usually region-specific (Dichmont et al. 2016). Integrated assessments (Maunder and Punt 2013), that allow many data types in a single analysis, are becoming more popular, e.g. Stock Synthesis SS3 (Methot and Wetzel 2013) in the west coast of the United States; as are state–space models such as SAM (Nielsen and Berg 2014) in the ICES region.

In age-structured assessments, to estimate MSY, the productivity and hence yield from a population is modelled as a function of fishing mortality rate and pattern, and from this, the relationships of yield to biomass and fishing mortality are derived. The age-based MSY has arisen from fundamental population dynamics models based on per-recruit theory (Beverton and Holt 1957), and is derived from three relationships (see example Figure 4.1): (i) spawning stock biomass per-recruit (*SPR*) that models the spawning mass productivity for a given recruit as a function of fishing mortality *SPR(F)*; (ii) SR relationship that models the relationship between the number of recruits to the spawner biomass; and (iii) yield per-recruit that models the mass removed from the population per-recruit by fishing. The per-recruit analysis is related to biological variables (i.e. maturity or fecundity, growth/weight at age, and natural mortality), fishery parameters (i.e. selectivity), and rate of removals. In age-structured methods, MSY-based reference points were typically estimated externally to the assessment model. Although integrated assessment methods can estimate reference points internally as functions of model parameters, sometimes fixing parameters of the SR relationship.

The relationship between stock size and recruitment defines the reproductive productivity of the stock and is, therefore, key to the estimation of non-proxy reference points. Understanding the SR relationship is crucial for MSY-based reference point estimation (Shepherd 1982; Conn et al. 2010). The inverse of the equilibrium *SPR(F)* provides a slope that intersects with the SR function at the equilibrium level of recruitment (Figure 4.1). The most popular functions developed to understand the SR relationship are: Beverton–Holt model (Equation 4.1; Beverton and Holt 1957), Ricker model (Ricker 1954), and hockey-stick segmented regression (Barrowman and Myers 2000; Mesnil and Rochet 2010). These models determine the density-dependent form and hence the compensation of the stock before recruitment. The parameters of the SR model relate to the reproductive potential of the stock and the rate at which recruitment changes with increasing eggs or abundance. For example, in the commonly used Beverton–Holt equation,

$$R = \frac{\alpha SSB}{\beta + SSB} \tag{4.1}$$

, where recruitment increases towards an asymptote as spawning stock increases, α is the maximum number of recruits produced, and β is the spawning stock needed to produce (on average) recruitment equal to $\alpha/2$. The SR relationship is typically modelled as stationary (parameters are averages across time) and so assumed constant over time (Hilborn and Walters 1992).

Despite its importance, the SR relationship is challenging to model for many stocks because of insufficient contrast and a high degree of variability. For stocks where recruitment information is lacking or there is high recruitment variability, per-recruit analysis can offer proxies to use as reference points (Gabriel and Mace 1999). The validity of per recruit levels as proxies for MSY reference points is highly dependent on the life history characteristics of the stock (Mace 1994). It is recommended to support the choice of appropriate proxy with the SR information available (Cadrin 2012). Spawner per-recruit levels are commonly used as proxies for MSY-based reference points in the US (Maunder and Deriso 2014; Wetzel and Punt 2017), where they are developed for individual stocks and designed to work in a precautionary sense.

4.2.2 Biomass limit reference points

Limit reference points are critically important for defining HCRs. HCRs are a structured framework for providing scientific management advice (Punt 2010) and are considered a key component of the precautionary approach to fisheries management (FAO 1995b). In HCRs, biomass limit reference points are used to indicate the level of biomass below which reproductive potential is impacted to avoid recruitment overfishing; typically interpreted as the SSB

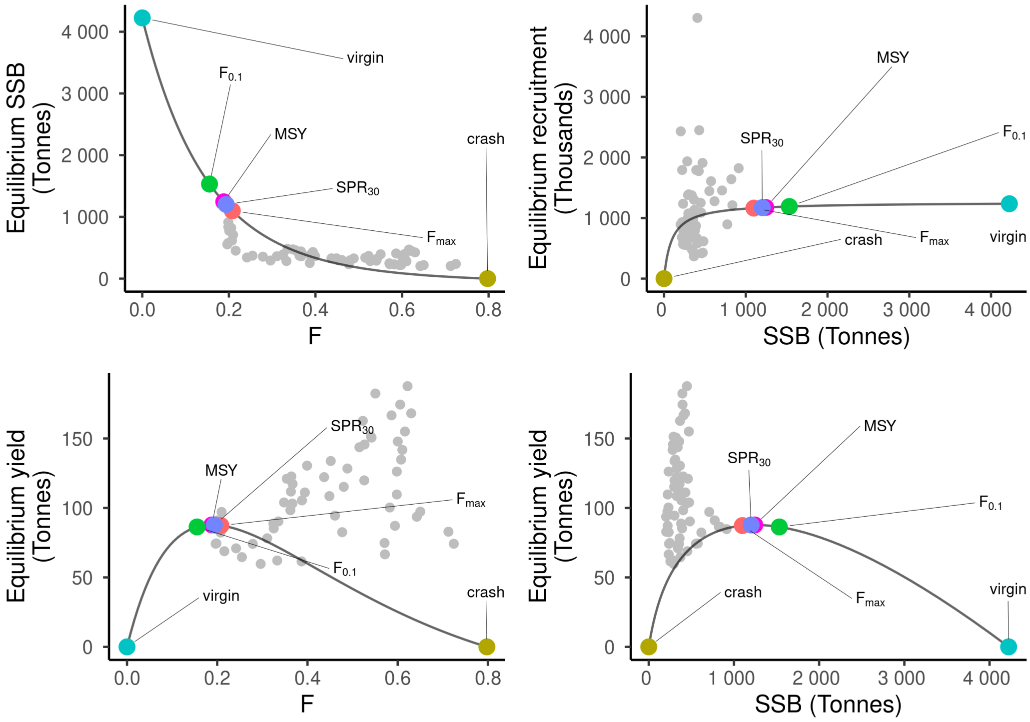

Figure 4.1: Reference points (virgin, crash, MSY and per-recruit proxies) and relationships between SSB and F, recruitment and SSB, yield and F and Yield and SSB at equilibrium with fitted Beverton-Holt functional form for North Sea Skagerrack plaice (plaice in IV); plots modified from output of FLRBRP analysis from FLR package in R (`https://flr-project.org/doc/Reference_points_for_fisheries_management_with_FLBRP.html`). Grey dots represent data observations for ICES stock plaice in IV division at the assessment in 2018 (ICES 2018b), being 2018 the terminal year and the dots observations in preceding years.

under which recruitment declines. There are several ways to set biomass limit reference points (Punt et al. 2014c) depending on the HCRs in which they are to be used. The approach chosen to estimate biomass limit reference points impacts both the level and the amount of uncertainty associated (Deurs et al. 2021). In the United States, a percentage of B_{MSY} is typically used to define limit biomass reference points. In situations when the SR relationship is not well understood, a fraction of the unfished biomass (B_0) can be used to define the biomass limit reference point and occasionally also as a proxy for MSY biomass reference point. In ICES, the key biomass reference point is B_{lim}, which is defined as the deterministic limit of biomass below which a stock is considered to have reduced reproductive capacity. This reference point is determined following SR typology rules that account for how stock biomass relates to recruitment at the window of data available (ICES 2017a).

A commonly used biomass limit reference point is the lowest observed biomass (B_{loss}) for stocks with no clear relation between stock and recruitment. The biomass limit reference point is the basis of all precautionary reference points in the ICES advice rule used to estimate other precautionary reference points.

4.2.3 Stochastic MSY

Initial static and deterministic interpretations of equilibrium MSY were thought to be inappropriate because they ignore the fact that fish populations fluctuate in abundance (Mace, 2001). Most current MSY interpretations aim to deal with those dynamics and account for sources of uncertainty. The processes for taking into account uncertainty in reference point vary; different methods to assess stocks deal with including variance and uncertainty differently (Patterson et al., 2001; Dichmont et al., 2016).

In assessments, biological information (growth, mortality, and maturity) vary by age structure and can vary over time (Methot and Wetzel 2013; Nielsen and Berg 2014; Dichmont et al. 2016). To derive reference points when biological variables vary over time, a typical approach is to estimate their average value and account for temporal variability with parametric bootstrap or random sampling methods. A temporal window of biological information time series might be used, e.g. ICES guidelines state to use a 10-year time window (ICES 2017a) unless temporal patterns are found, in which case the time-window is shortened.

Recruitment typically fluctuates considerably, reflecting that this is often the most variable component in assessments (Maunder and Thorson 2019). Complete time series of recruitment are typically used to derive reference points unless regime shifts are detected. The SR relationship is modelled as a stationary process with some variability (Figure 4.2). Fluctuations in recruitment are commonly treated as a random process (e.g. log-normal) around an assumed relationship between stock size and recruits. Reference points are based on the long-term mean SR relationship (fixed parameters of the functional form chosen), and independent or mean-reverting autocorrelated process errors. Commonly no process error in the parameters is incorporated (i.e. process uncertainty of the model structure reflecting the natural variability of the processes affecting the dynamics). The residuals of the fitting frequently have temporal patterns with autocorrelation of residuals sometimes being stronger than the SR relationship itself (e.g. North Sea and Skagerrak plaice, Figure 4.2). The stochastic equilibrium software for MSY modelling has been developed by ICES to implement stochasticity in reference point estimation (EqSim, `https://github.com/ices-tools-prod/msy`). EqSim performs random sampling of the biological and fishery variables and samples from the predictive recruitment distribution. Simulated autocorrelation in recruitment can be included if shown to be important. Eqsim can also deal with structural uncertainty of the SR functional form by applying the averaging of a combination of models (ICES 2017a).

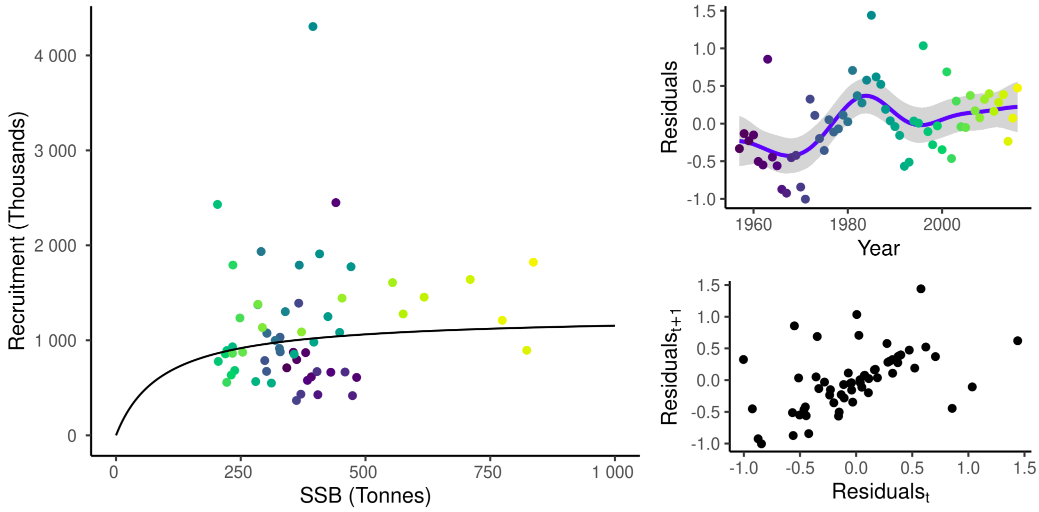

Figure 4.2: Stock-recruitment relationship of North Sea and Skagerrak plaice (plaice IV). Left panel shows the relationship between SSB and recruitment with fitted Beverton-Holt functional form; right panel shows the temporal evolution of residuals of the SR relationship (top), and the relationship between residuals at year *t* with residuals at year *t+1* (bottom). Dots represent data observations, colour scale represents the assessment year, and the blue line is a gam model of the residuals with a first-order penalty.

Simulations of the entire system in Management Strategy Evaluation frameworks (MSE; Punt et al. 2014b) play a key role in identifying sources of uncertainty and stochastic elements, and in testing the precautionary criteria (Kell et al. 2005). In an MSE, the whole management system is modelled in the operating model (reality system or true state) and the management procedure (perceived state). The MSEs have become crucial to evaluate reference points and the performance of HCRs relative to agreed management goals (De Oliveira et al. 2009). Development of MSEs is impacting the choice of reference points, which to be precautionary must consider uncertainty in both the science (stock assessment and reference point estimation) and the management process. A present focus of MSE is evaluating the ICES precautionary criteria, specifically, if advised reference points ensure the populations are maintained within safe biological limits under given uncertainties (ICES 2017a).

4.3 Reference points for changing ecosystems

Ecosystems are non-stationary, often presenting complex dynamical behaviour (Sugihara et al. 2012; Fogarty et al. 2016). Globally, the productivity of assessed fish stocks has been observed to fluctuate in a non-stationary manner (Vert-pre et al. 2013; Perälä et al. 2017; Britten et al. 2017). Changes in productivity constitute a challenge for defining management reference points. A major limitation of single-species management is that interactions with ecosystem drivers are usually not accounted for. An important element in transitioning to EBFM would be to include these ecosystem concerns in the estimation of single-species reference points. In this section, we address approaches to deal with changing ecosystems in the calculation of reference points.

4.3.1 Ecosystem concerns

Tools for EBFM comprise a heterogeneous group of models, used for multiple objectives (see Geary et al. 2020 for a complete overview on ecosystem models). Each marine ecosystem has its own features and functional responses with spatial and temporal scales that are still relatively unknown (Hunsicker et al. 2011). Modelling tools that include ecosystem considerations increase in complexity to incorporate ecological interactions, environmental drivers, and human impact (Collie et al. 2016). When complexity increases it also increases the knowledge needed to build the models, the parameters to estimate, and the uncertainty propagated (Hollowed et al. 2011). Therefore, complexity translates to an increase in data demand and a potential decrease in predictive ability (Geary et al. 2020). Despite this, ecosystem models have developed substantially in the last decades and have proved fundamental for strategic management advice (Nielsen et al. 2018), offering a key holistic view of the system (Benson and Stephenson 2017). Including ecosystem concerns, while balancing complexity, e.g. Models of Intermediate Complexity for Ecosystems (MICE models), helps improve understanding of the processes and disentangle important ecological components (Plagányi et al. 2014). Studies on empirical reference points from multispecies and ecosystem approaches, i.e. multispecies

MSY (Gislason 1999; Collie and Gislason 2001; Moffitt et al. 2016), aggregate biomass MSY (Gaichas et al. 2012), ecosystem global MSY (Trenkel 2018), have shown intriguing mismatches with single-species reference points. Although generally not used for tactical management, these studies emphasize that incorporating ecosystem effects does alter MSY-based reference points.

In the United States, a food web ecosystem model of intermediate complexity was used to estimate ecological reference points for Atlantic Menhaden (Chagaris et al. 2020). In this way, information on ecosystem drivers and predator–prey interactions were incorporated into the assessment and management. To our knowledge, this is the only case where an ecosystem model was used to set an alternative ecological reference point. Additionally, ecosystem model information was proposed as guidance within the ICES stock advice framework. In the EU, where several stocks and fleets share the same space, reference ranges—developed from the concept of Pretty Good Yield (Hilborn 2010)—are used to give flexibility around fishing mortality at MSY in mixed fishery contexts (Kempf et al. 2016; Rindorf et al. 2017a). The ICES working group WKIRISH (ICES 2020b) has suggested that indicators from an ecosystem model can be used to provide information on ecosystem conditions and make recommendations regarding where in the precautionary F ranges we should be setting fishing mortality from an ecosystem point of view, so called F_{eco} (Bentley et al. 2021; Howell et al. 2021). In these cases, the ecological drivers selected depend on the stock interaction with the ecosystem studied.

Incorporation of holistic ecosystem considerations can be done at the simulation level to evaluate alternative management strategies. If there is an ecosystem model developed for the region, MSE can incorporate that ecosystem model as the operating model (see Perryman et al. 2021 review). Higher complexity and descriptive properties of the ecosystem model as the operating model provides the capacity to evaluate the performance of an HCR taking into account ecosystem considerations (Lucey et al. 2021). For example, the end-to-end ecosystem model, Atlantis, has been used in an MSE for the Southeast Australian fisheries (Fulton et al. 2014).

4.3.2 Inclusion of mechanistic drivers

A huge array of factors (biological interactions, climatic forcing, maternal effects, climate change, and so on) can influence stock productivity. Inclusion of ecosystem drivers in an explicit mechanistic way requires a significant expansion of assessment frameworks to enable a more data and time-intensive assessment approach (Burgess et al. 2017). These ecosystem considerations are currently seldom included in stock assessment or at the HCR level. Skern-Mauritzen et al. (2016) found a diversity of ecosystem drivers and approaches based mainly on expert knowledge and specific to a certain fishery. Most cases were identified among US and ICES stocks. But in general, these were rarely included in operational management advice. Their inclusion is limited by the high level of understanding required, and the complexity of the interactions, relationships, and their stability, which can be ephemeral (Myers 1998; Sugihara et al. 2012).

1. *Inclusion of trophic interactions.* The most typical trophic interaction included in assessments is the predator–prey relationship, which can be incorporated in parameters of natural mortality and growth rate. Predation mortality rates can be estimated from stomach content analysis with multispecies models. Multispecies dynamic models are extensions of single-species assessment models that integrate trophic predator–prey interactions with the mortality caused by the predator derived from the predator diet data (Trijoulet et al. 2019). Addition of mechanistic trophic interactions has been observed to greatly impact reference points (Gislason 1999; Trijoulet et al. 2020). In some cases, parameter estimates from multispecies models are thought to be more realistic than estimates from single-species approaches (Hollowed 2000). Hence, natural mortality parameters from multispecies models are occasionally used in stock assessments. For example, several North Atlantic stocks assessed by ICES use the natural mortality estimates from a Stochastic Multi Species model (SMS; Lewy and Vinther 2004) in the single-species assessment to provide management advice (ICES, 2018a). Predation also impacts and can be incorporated into the SR relationship to help understand trophic interactions in recruitment dynamics (Swain and Sinclair 2000; Minto and Worm 2012; Collie et al. 2013).

2. *Inclusion of environmental and ecological variables.* Environmental and ecological variables have shown a strong impact on population dynamics. Examples of environmental drivers include temperature (e.g. sea surface temperature), hydrodynamics, precipitation, wind-mixing energy, North Atlantic Oscillation index, up-welling index, and river input. Other influential ecological drivers might be zooplankton, chl *a* (hence primary productivity), and eutrophication. The environment is

considered to primarily affect recruitment dynamics showing relatively rapid responses, especially for short-lived species (Clausen et al. 2018). Apart from stock responses to these variables being specific to species and systems, ecosystems are non-stationary, and therefore, different states may have different influential drivers (Skern-Mauritzen et al. 2016). Resulting in the inclusion of environmental drivers being challenging (see Crone et al. 2019 for good practices). Including environmental variables in the SR model has often failed, which might be due to non-stationary relationships or because multiple variables were tested without correcting for multiple tests (Myers 1998; King et al. 2015). Besides, the link between SR and environmental drivers might not be linear (Subbey et al. 2014). Several assessment models can include environmental drivers, but in practice, their inclusion results in little improvement with respect to management performance (Punt et al. 2014c; Haltuch et al. 2019). Therefore, environmental driver inclusion remains rare and most reference points and HCRs do not explicitly incorporate those relationships (Haltuch et al. 2019).

4.3.3 Re-estimation of reference points

Currently, reference points reflect average ecological and environmental conditions over the time period of the data. By definition, MSY-based reference points are estimated given prevailing average environmental conditions (MSA 2007; EC 2013). Average fishery and population dynamics of a stock along with environmental conditions are inherently included in their estimation (integrated in the average SR, growth, post-recruit mortality, and maturity parameters). The FAO Fish stock assessment manual establishes that reference points must be regularly updated, taking into consideration possible changes in the biological parameters or exploitation patterns (FAO 2003). If reference points are not changed once established, they will not reflect the dynamic nature of the ecosystem (Kell et al. 2016). Hence, reference points are usually reevaluated in the light of environmentally and stock density induced changes in stock productivity and changes in species interactions (ICES 2021e). In theory, the faster the dynamics evolve, the more often reference points would need to be updated (Burgess et al. 2017).

Typically, reference points are revised with varying regularity. ICES considers reference points to be valid only in the medium term (5–10 years), and therefore, they should be updated according to new population and fishery information, and process understanding (ICES, 2021b). During assessment benchmarks, data and parameters (biological, fishery, and SR relationship) are revised and observed changes are taken into account. In the ICES region, reference points have been observed to change frequently impacting the perception of sustainability status (Silvar-Viladomiu et al. 2021). The ICES working group WKRPCHANGE (ICES 2021a) identified several reference points that are allowed to vary according to prevailing conditions. In the United States, the National Standards guidelines state that because MSY is a long-term average, it does not need to be estimated annually, but should be re-estimated as required by changes in long-term environmental or ecological conditions, fishery technological characteristics, or new scientific information (NOAA Fisheries 2016). Even so, certain agencies update reference points with each assessment, e.g. North Pacific Fisheries Management Council (check SMART tool; NOAA Fisheries 2021).

In updating reference points, changes in productivity or regime shifts are generally taken into account by the revision of the time series used for their derivation. Regime shifts or trends present can be identified ad hoc or through regime detection algorithm (e.g. STARS; Rodionov 2004). Some approaches to deal with regime-shifts and changes in productivity are: (i) moving window, which includes modelling recruitment from a specified number of years (King et al. 2015); (ii) use of a detection algorithm to select the data with which to base reference points (Punt et al. 2014c); and (iii) tailoring or truncation of the data series to a temporal window after a shift has been detected (Szuwalski and Punt 2013). A common difficulty, however, is how to decide which time period to choose as representative of present dynamics. Estimation of reference points might become unreliable as the time series is reduced (Deurs et al. 2021). Particularly, where one parameter (e.g. density-dependent asymptotic recruitment) may not be updated at all given recent ranges of the stock but the slope at the origin might be. Truncating data in this case risks losing relevant partial information from earlier periods.

4.3.4 Dynamic proxy reference points

A reference point that takes into account shifts in the underlying productivity of the stock has been proposed for the virgin biomass. In the United States, where the virgin biomass reference point is extensively used for HCRs, a time-varying approach called dynamic virgin biomass was developed— dynamic B_0 (A'Mar et al. 2009; Field et al. 2010). Contrary to the static virgin biomass, which is an equilibrium-based measure, dynamic virgin biomass is a reference population state representing the biomass that would have resulted across time in the absence of fishing. The dynamic B_0 approach uses the values of the parameters estimated in the assessment to project the population over time with no fishing, obtaining a time series of B_0. The biomass varies in time because of the estimated recruitment deviations and time-varying growth and natural mortality. The population is simulated typically under the assumption of a stationary SR relationship or driven by a separable function of environmental drivers and stock size.

Dynamic B_0 is increasingly being used because it can track population productivity over time if fishing had not occurred (Punt et al. 2014c), but explicit mechanisms involved in the change in productivity do not need to be identified. A'Mar et al. (2009) evaluated a management strategy with dynamic virgin biomass and showed that management and estimation performance was improved by adjusting the exploitation rate based on recent recruitment. Dynamic B_0 performs better than static B_0 when stock productivity shifts directionally (Berger 2019). The Inter-American Tropical Tuna Commission (IATTC) recommends the use of dynamic virgin biomass when trends in productivity or regime shift are detected (Maunder and Punt 2013).

4.3.5 PPM: dynamic recruitment productivity

Methods capable of modelling dynamic processes and detecting process variation over time are increasingly used (Auger-Méthé et al. 2021). Dynamic state–space models to fit time-series data have been implemented both within age-based assessment models (Aeberhard et al. 2018) and for the estimation of population biomass dynamics and productivity (Walters 1986; Pella 1993; Schnute and Richards 1995; Millar and Meyer 2000). State–space models allow simultaneous estimation of variability in ecological dynamics and measurements (Thorson et al. 2015). Several estimation methods have been developed to fit state–space models: the Kalman filter and non-linear extensions, ADMB (Automatic Differentiation Model Builder) Laplace and higher-order quadrature approximations, TMB (Template model Builder) approximations, EM (Expectation-maximization algorithm), particle filters, and MCMC (Markov chain Monte Carlo methods). The well-known Kalman filter is an optimal linear Gaussian estimation and forecasting method designed to extract signals from noisy data.

Peterman et al. (2000) first introduced the use of the Kalman filter to identify temporal patterns in recruitment productivity parameters. This method was built on earlier applications of the Kalman filter in fisheries (Walters 1986; Sullivan 1992; Pella 1993; Gudmundsson 1994; Schnute 1994), though these were not explicitly implemented on SR parameters. The entry of new recruits into the population modelled by the SR relationship is a fundamental part of stock productivity. Recruitment productivity represents the most important and largest source of variation in population processes (Quinn and Collie 2005). Randall Peterman and colleagues modelled the SR relationship as a dynamic process by allowing process variation in the parameter governing recruitment productivity.

In this article, we assign the term Peterman's productivity method (PPM) to estimation, filtering and smoothing methods, based in the first instance on the Kalman filter, where SR parameters are part of the dynamic state process, and thus allowed to vary over time (Peterman et al. 2000). The method enables recruitment productivity to be modelled as a dynamic process with temporal dimension, by allowing the process signal to be absorbed by the time-varying parameters. These parameters track the variability of productivity dynamics and reconstruct estimates of stock productivity in the past, allowing us to better predict recovery times based on present productivity (Peterman et al. 2003).

Minto et al. (2014) extended the PPM to a multi-stock setting and studied the variation in the maximum reproductive rate parameter of the SR relationship for North Atlantic cod stocks. They showed that recruitment productivity of North Atlantic cod populations has varied markedly over time and that populations go through long periods of both high and low productivity. Multivariate developments on PPM enable the strength of the correlation between the populations to be estimated within the model. Thus, providing increased understanding of the similarity or dissimilarity of productivity dynamics inter- and intra-species within and across regions. Tableau et al. (2019) expanded the methodology exploring links with environmental variables and evaluating differences between species and areas in the Northwest Atlantic. The number of estimated parameters were reduced because they assumed a common signal to noise ratio among stocks. The multi-stock estimation allows us to disentangle and account for the different sources of uncertainty (i.e. measurement and process) and increases the robustness of the estimates even with limited length of the data time-series. Links with environmental drivers can be easily incorporated in the PPM. Nevertheless, prior work found relatively few relationships between productivity and the selected covariates (Tableau et al. 2019). Adjacent stocks of the same species exhibited similar productivity patterns with the strength of covariation declining over distance, which shows that the method is powerful for detecting coherent ecological signals rather than tracking noise.

The PPM enables us to model stochastic process on some or all parameters of the SR relationship, and in theory separate signal from noise in the recruitment productivity process. But, how sensitive are management reference points to changing recruitment productivity? Either the density-dependent or density-independent parameters, or both, can vary in time and impact biomass or fishing mortality reference points differently. To visualize the effects of changes in either parameter in MSY-based reference points, we ran a simulation example based on the North Sea and Skagerrak plaice stock. We projected the stock forward 50 years under a hypothetical random walk on either parameter with a process variation of 0.2 on the annual deviations and estimated the resulting dynamic reference points. We chose a random walk over an explicit mechanism for illustration. When, in a Beverton-Holt SR functional form (Equation 4.1), the α parameter varies in time we found that it has a strong impact on the biomass MSY reference point. Being the maximum recruitment, the α parameter affects mainly density-dependent regulation of the population (Figure 4.3A). Time-varying β parameter, which is mainly related to density-independent processes, caused strong impact on the fishing mortality reference point because it affects the slope at the origin of the SR relationship (Figure 4.3B). Note that in this common formulation of the Beverton–Holt density-independent and density-dependent processes are present in both parameters (Beverton and Holt 1957) but dominate as above. Dynamic reference points estimated with PPM, which incorporate the integrated signal on recruitment, are fundamentally different approach to dynamic B_0. In dynamic B_0, temporal changes in stock dynamics and underlying productivity are accounted for by implementing stochasticity through variability in recruitment deviations assuming a static SR relationship. Modelling time-varying SR parameters also differs from projecting a population forward under a mean-reverting autocorrelated process that assumes deviations return to the expected static form.

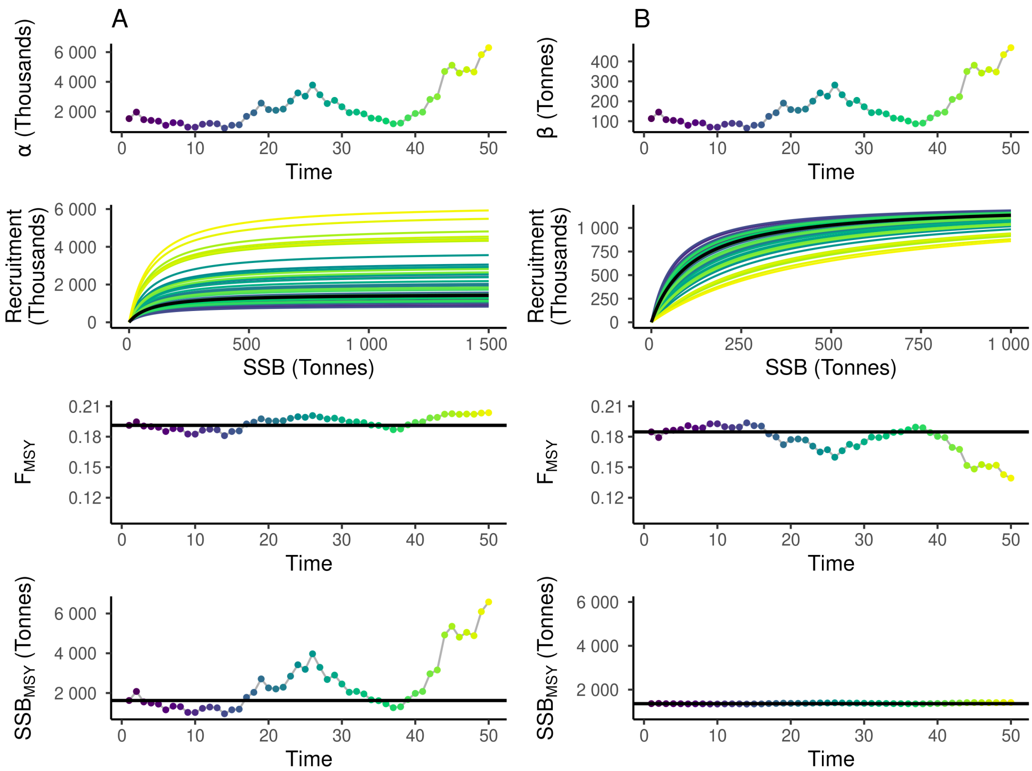

Figure 4.3: Impact on reference points of SR parameter temporal dynamics. Simulated projections of time-varying parameter α (A, left) and parameter β (B, right); and below the impact in estimated recruitment productivity, and fishing mortality and spawning biomass MSY-based reference points. Black line represents static reference points. Simulations are based on Plaice in IV data (ICES 2018b) with Beverton-Holt SR model, using for reference point calculation FLBRP from FLR R software (starting values: $\alpha_0 = 12633$ thousands, $\beta_0 = 93995$). Both parameters are allowed to vary according to a random walk on the log scale with deviations from a normal distribution with mean zero and a standard deviation of 0.2. Colour scale represents the assessment year.

We show that including time-varying productivity parameters can impact biomass and fishing mortality reference point estimates. Being able to track these changes in time can provide substantive improvements when biological or fisheries conditions are changing. In which case, estimated reference points using time-varying SR parameters are less biased (Holt and Michielsens 2020). The PPM not only allows us to estimate present productivity and historical trends but also to capture the underlying change in recruitment productivity. These dynamic reference points can be used in harvest policies based on dynamic productivity forecasts to provide catch advice; applications of dynamic HCRs result in higher catches and reduced risk (Collie et al. 2012) and are more robust to climate change impacts (Collie et al. 2021).

The PPM does not explicitly model measurement error in SSB (Peterman et al. 2003). Although recruitment and SSB are the best estimates currently available, there is inherent uncertainty associated with them (Brooks and Deroba 2015). This uncertainty from the previous model can potentially be propagated in the subsequent analysis. Uncertainty propagation could be implemented by drawing from the estimator of SR parameters either by assuming multivariate normality using the estimated Hessian matrix or by using MCMC to sample from the posterior distribution. It may also be possible to directly use the covariance matrix in the estimation likelihood in TMB as a known measurement error component (Thorson and Minto 2015).

4.4 Towards a dynamic future

Status quo reference points include stochasticity, yet assume that fluctuation in biological parameters (growth and mortality), the SR relationship, and the resulting stock productivity are centred on a stationary mean at a given harvest rate. Reference points are subject to updates but regime shifts are notably difficult to predict and defining time windows can be difficult. In stochastic implementations of MSY, random variability is usually added as an error around average expected recruitment; but this is unlikely to completely capture the dynamics of the process in time (Kell et al. 2016). Marine ecosystems are not stationary; long-term trends are present, including those induced by climate change (Szuwalski and Hollowed 2016). Population dynamics have multiple complex interactions with the ecosystem (top panel Figure 4), and dynamics thereof (Deyle et al. 2013). Beyond direct influence of environmental drivers and direct trophic effects, population dynamics are affected indirectly by changes in food-web structure, composition, and processes within the food-web, e.g. trophic cascades (Frank et al. 2005; Casini et al. 2008). The relationship between early life history (recruitment) and stock size, which has strong influence on population dynamics, has shown marked variation over time for many stocks (Minto et al. 2014; Britten et al. 2016; Perälä et al. 2017; Szuwalski et al. 2019; Tableau et al. 2019). The challenge is to manage fisheries to sustainability in light of scientific uncertainty, natural variability, and changing ecosystems. Current advice frameworks may not sufficiently address the dynamic nature of MSY and reference points (Sissenwine et al.

2014). So far, pretty good yield ranges have been proposed in the EU to allow flexibility around MSY fishing mortality reference points in mixed fisheries contexts (Rindorf et al. 2017a).

How can we bridge the gap between current MSY reference points and EBFM? On the one hand, current advice is based on the assumption that SR is stationary (left bottom panel Figure 4.4). On the other hand, the dynamics created by the ecosystem are complex and manifold and so it can be difficult to use direct ecosystem process information to inform management decisions. Mechanistic inclusion of drivers in the SR relationship (right bottom panel Figure 4.4) is risky because effects might be direct or indirect, linear or non-linear, and multiple ecological factors may interact and vary over time. We argue that modelling dynamic productivity using PPM might bridge the gap and ultimately reconcile the MSY concept and EBFM (centre bottom panel Figure 4.4). Dynamic parameter models have demonstrated potential to implicitly incorporate the response of the stock to ecosystem change without specifying the exact driver or functional mechanism involved (Minto et al. 2014; Nesslage and Wilberg 2019). Dynamic parameters applied to the SR relationship enable estimation of MSY-based reference points that take into account temporal changes in recruitment productivity. Several studies have shown that in the presence of temporal variability in stock productivity, dynamic processes should be accounted for to estimate reliable reference points (Berger 2019; Mildenberger et al. 2019; Zhang et al. 2021a). Given that productivity is non-stationary, rather than reference points based on past average productivity, PPM provides a more informative picture of the present productivity and its dynamics and therefore enables the estimation of reference points in tune with the current state of the ecosystem (Tableau et al. 2019; Britten et al. 2017).

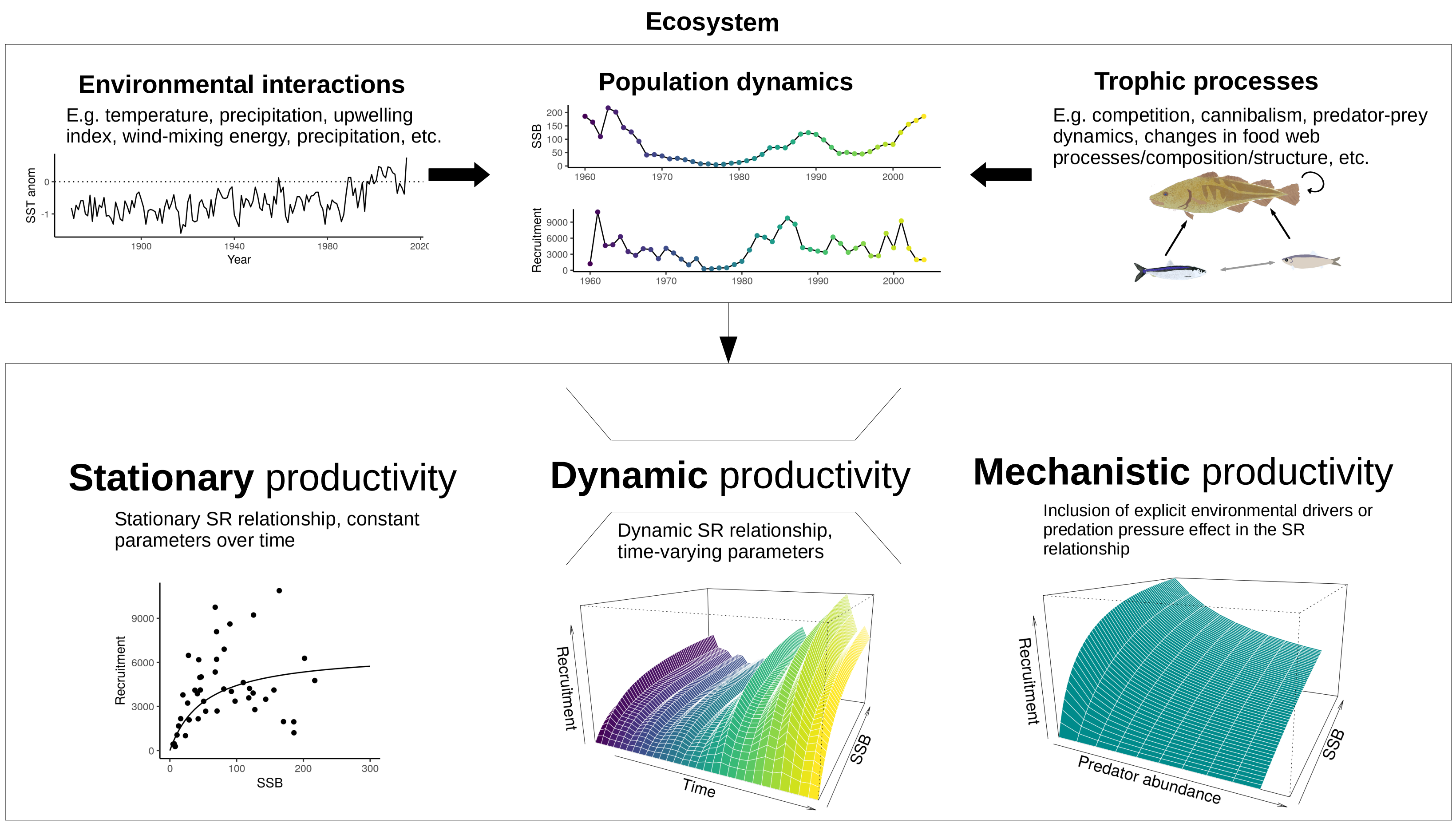

Figure 4.4: In reality, many ecosystem drivers influence population dynamics (top panel). We argue that time-varying parameters as available via Peterman's Productivity Method provide a bridge between stationary and mechanistic modelling of recruitment productivity.

While EBFM comprises broader concerns than recruitment productivity in fisheries management, we believe that using PPM has an important role to include the influence of changing ecosystems on current fish stock management. It would be very valuable for managers and assessment scientists to fully understand the ecosystem processes and ecological mechanisms causing these dynamics. That is not always possible, but this should not stop us considering the implications of these processes, even if they are not completely understood. The main advantage of this method for immediate application in management is that it can be applied without understanding the process that caused the change in stock productivity. Presently, time-varying productivity relationships may be where we have the greatest opportunity to empirically deliver on some of the requirements of EBFM in tactical fisheries management (Minto et al. 2014). Sustainable harvest depends critically on compensatory processes such as the SR relationship. Application of PPM in the SR relationship to estimate dynamic reference points might be a first step towards accounting for changing ecosystems in a MSY management goal. Previous studies have demonstrated the strengths of PPM in capturing complex dynamics in recruitment productivity, improving recruitment forecast, and enabling sustainable dynamic harvest practices (Peterman et al. 2000; Collie et al. 2012; Minto et al. 2014; Britten et al. 2016; Tableau et al. 2019; Holt and Michielsens 2020). Also, reference points from PPM within HCRs have recently been shown to provide resilience to climate-induced effects (Collie et al. 2021).

Incorporating ecosystem variability in reference points could make communication with stakeholders more challenging. Usually the more complicated the modelling approach the more difficult it becomes to communicate, particularly when those lead to a reduction in fishing opportunities. As we develop more complex models we also have to think harder about how we communicate these models so that social license is not lost. It is important to encourage engagement in participatory science for management, e.g. stakeholders should be aware of why it is important to include productivity dynamics. Social license is not only obtained with simple models, social license is also obtained by including elements that are relevant to include. For instance, by not accounting for ecosystem concerns in reference points social license might be removed. The work developed in WKIrish (ICES 2020b) is an example of where a more complex understanding of the system improved social license. In that project, fishers and stakeholders were recognized as knowledge experts of the system, and so their understanding of the system was included. By the end, fishers and stakeholders had a very good understanding of the complex analysis performed.

While PPM has much potential, important issues remain on how to manage stocks with dynamic reference points. As to Quo Vadimus—we propose the following four priority research areas to further PPM:

1. Estimability—can time-varying SR parameters be reliably estimated? Does PPM have the ability to detect change where there is change and reject it where there is no change? Estimated covariation from independent assessments (Minto et al. 2014; Tableau et al. 2019) suggests that real ecological changes are tracked. But state–space models are difficult to estimate (Auger-Méthé et al. 2016), time series length can be constraining, and some convergence issues were found when both parameters of the SR relationships were allowed to vary ovetime (Szuwalski et al. 2019).

2. Uncertainty propagation—we use estimated recruitment and SSB that have associated uncertainties and covariations (Dickey-Collas et al. 2015; Brooks and Deroba 2015). We disagree that these outputs should not be considered "data" (Brooks and Deroba 2015), however, as we consider "data" in a broad information context rather than restricted to raw observations. Many stock assessments use model-derived indices as "data" input. A main goal of stock assessments is to estimate abundance state and exploitation rate, often fitting and tracking independent survey-derived recruitment indices. We argue that in the context of much ecosystem uncertainty, estimated recruitment is some of the best information we have on productivity dynamics. We certainly need to propagate uncertainty correctly but the message that these data should only be used with extreme caution could hamper enormous potential for delivering on EBFM. With respect to the stock assessment model, comparisons of external and internally estimated signals would help guide practitioners. Stock-assessment free methods, such as (Perälä et al. 2017) also have great potential to inform the debate on what is signal and what is post-assessment artifact.

3. What are the consequences of poorly estimated time-varying reference points vs. well-estimated static relationships? Juxtaposing the relative risks of managing under the presumption of no change when there is

change and vice versa. So far, estimators of the model quality, e.g. AIC, have been used to compare time-varying models and static approaches. Statistical inference for these models is an active area of research such as prediction error variance. In addition, time-varying approaches can be evaluated with MSE or stochastic programming methods (Collie et al. 2021). Generally, evaluation within MSE is recommended before using these reference points to inform management decisions (Holt and Michielsens 2020).

4. Nature of change—the Kalman filter is restricted to linear Gaussian processes. Available integration methods for latent variables such as Laplace approximation (TMB) or MCMC enable a great variety of stochastic processes (including regimes, hidden Markov states, HMM filter, extended Kalman filter, unscented Kalman filter, Kim filter, and continuous processes in non-linear systems) to be considered and compared. These methods can be applied to time-varying parameters under different recruitment model structures (e.g. Beverton–Holt model). Of particular importance is where change happens more abruptly than the process expects it to and takes more time to adjust, essentially the Kalman filter smooths over an abrupt jump (Peterman et al. 2000). Perälä et al. (2017) addressed this with a Bayesian change point model with stationary processes within each regime. While the nature of the process and estimation method may change we believe that using the term "Peterman's productivity method", applies for all settings where the SR parameters evolve in time and recognizes the originator for a set of methods that will broaden from the original Kalman filter.

Finally, we note that by using PPM we may gain an understanding of how productivity has changed, but without knowledge of the mechanism, we cannot predict where it is going (in the medium to long term). While we may track productivity and manage accordingly, we must recognize the need for continual mechanistic insights at broader levels to inform strategic management. All the while, we rest on the feedback nature of HCRs to compensate for our ignorance (Collie et al. 2021).

4.5 Acknowledgements

The authors are grateful to Professor Randall Peterman and his group for the initial development of the method highlighted here and subsequent discussions. Comments from three anonymous reviewers helped improve the manuscript.

Chapter 5

Stochastic modelling and synthesis of dynamic fish recruitment productivity in the Celtic Seas ecoregion

This chapter is a verbatim copy of the manuscript in preparation for submission:

Silvar-Viladomiu, P., Minto, C., Lordan, C., Brophy, D., Bell, R., Collie, J., and Reid, D. G. Stochastic modelling and synthesis of dynamic fish recruitment productivity in the Celtic Seas ecoregion.

Abstract

The Celtic Seas ecoregion is undergoing major changes, which influence fish productivity. Environmental changes, historical fishing patterns, and climate change produce changes in the ecosystem and impact fish population dynamics. Globally, the productivity of many stocks has shown evidence of change over decadal timescales. Varying factors might drive these dynamics in the Celtic Seas ecoregion, but for many stocks, these mechanisms have not been fully understood to be included in management advice. We study dynamic productivity for 28 stocks in the Celtic Seas by tracking integrated stochastic signals in the relationship between stock size and recruitment using state-space modelling applying Peterman's Productivity Method. By allowing parameters to vary in time, this method enable us to capture temporal process variation in recruitment productivity. Our research objectives were to (1) fit Ricker stock-recruitment models with time-varying parameters to all age- or length-based assessed stocks in the Celtic Seas ecoregion, (2) evaluate which parameters vary in time, (3) examine temporal characteristics of historical recruitment productivity, (4) evaluate productivity correlation across stocks, and (5) identify common patterns in recruitment productivity in the ecoregion. For 25 out of 28 stocks, at least one of the three time-varying parameter models had a better fit than the time-invariant model. In the Celtic Seas ecoregion, fish productivity has diverse temporal patterns, with some stocks displaying relevant long-term decreasing productivity trends. Getting insight into temporal changes in productivity is very valuable and has important implications for sustainable fisheries.

Keywords: time-varying productivity parameters; Peterman's Productivity Method; dynamic reference points; non-stationarity; ecosystem approach

5.1 Introduction

The ICES Celtic Seas ecoregion covers a major part of the northwestern European continental shelf. This ecoregion also includes areas of the deeper eastern Atlantic Ocean as well as coastal waters that are heavily influenced by oceanic inputs (ICES 2021b). Previous studies in the area suggest that marine communities respond to the combined effect of fisheries and climate (Lynam et al. 2010). Environmental changes, such as changes in the North Atlantic Oscillation (NAO), can produce temporal changes in oceanographic conditions which, in turn, can cause ecological responses such as changes in the reproduction timing, abundance, growth, spatial distribution, mortality and inter-specific relationships (Ottersen et al. 2001). Climate change and extreme events could potentially cause important changes in the ecoregion (Richardson and Schoeman 2004; Drinkwater et al. 2010). While broad environmental variability and trends are evident, the mechanisms affecting the ecosystem and the populations are complex (Sugihara et al. 2012; Fogarty et al. 2016). Thus, although it is known that environmental drivers affect recruitment (e.g. Kristiansen et al. 2011), these relationships are not fully understood and tend to be not stable over time (Myers 1998; Stige et al. 2006; Ottersen et al. 2013).

Research has shown that main influences affecting fish abundance and their population dynamics are current and historical fishing pressure in the region (Hernvann and Gascuel 2020; Kempf et al. 2022). High levels of fishing pressure affect a stock's reproductive output by reducing the spawning stock biomass and the numbers of old and more fecund individuals (Wright and Gibb 2005; Ohlberger et al. 2022). At low population sizes, the variability in recruitment survival has been found to increase (Minto et al. 2008). In addition, recovery for overfished stocks at low abundance can be impaired (allee effect or depensation; Perälä et al. 2022). In the Celtic Seas, fishing pressure steadily increased from the mid-1980s and peaked in the late 1990s when abundance of exploited stocks reached its historical minimum level (Fernandes and Cook 2013; Hernvann and Gascuel 2020). However, spawner abundance and age-structure has partly recovered over the past decades, coinciding with a reduction in fishing mortality (Cardinale et al. 2013; Fernandes and Cook 2013; Hilborn 2020; Zimmermann and Werner 2019).

The effects of high fishing pressure make ecosystems and stocks more sensitive to additional stresses such as climate change (Brander 2007; Heath 2005). Climate change can complicate changes in ecosystems, by for example affecting community composition (Genner et al. 2004), shifting distribution ranges (Payne et al. 2022), and inducing changes in productivity (Gaines et al. 2018). Changes in ecosystems structure and functioning arising from environmental change and fishing pressure are expected to affect fisheries (Planque et al. 2010; Travis et al. 2014). Ecological changes can be gradual, causing impacts in the long-term, or sudden and abrupt (Reid et al. 2016). Sudden unexpected shifts between dynamic ecosystem states called regime shifts can occur driven by both external forcing and internal perturbation, which can result in system-wide trophic cascades (Daskalov et al. 2007; Casini et al. 2008; Möllmann and

Diekmann 2012). Changes in ecosystems (gradual or abrupt) pose challenges for fisheries management because they cause changes in productivity of fish stocks (Vert-pre et al. 2013; King et al. 2015; Clausen et al. 2018).

Recruitment productivity is vital for the renewal of the population. In stock assessments, the relationship between recruits and spawners is key for management of fisheries but notoriously variable and traditionally difficult to understand (Hilborn and Walters 1992; Myers 1994). The stock-recruitment relationships used to estimate reference points are typically modelled as a stationary process where the parameters are fixed based on historically constant estimates (Collie et al. 2012; Collie et al. 2021; Silvar-Viladomiu et al. 2022b). However, globally many stocks productivity is non-stationary, displaying evidence of temporal variation in parameters of the stock-recruitment relationship (Peterman et al. 2003; Dorner et al. 2008; Minto et al. 2014; Britten et al. 2016; Tableau et al. 2019). Temporal changes in productivity have important implications for reference points (Kell et al. 2016; Holt and Michielsens 2020; Zhang et al. 2021a; Silvar-Viladomiu et al. 2022b; Clausen et al. 2018), upon which fishing opportunities advice is based. Stock-recruitment models with time-varying parameters developed by Peterman and colleagues (Peterman's Productivity Method; Silvar-Viladomiu et al. 2022b) can track integrated underlying signals of change in productivity without needing an understanding of the mechanism behind it (Peterman et al. 2003). Allowing the parameters to vary over time permits the separation of process variation in the parameters from measurement error in survival (Minto et al. 2014). The PPM with Kalman Filter enables us to reconstruct changes in productivity and identify trends (Peterman et al. 2003).

For sustainable management, it is critically important that temporal trends in recruitment productivity of Celtic Seas ecoregion stocks are detected in a timely and reliable manner (Dorner et al. 2008). To better understand how rather than why recruitment productivity has varied over decadal timescales, we applied PPM and extracted filtered and smoothed time series patterns for multiple species and stocks in the Celtic Seas ecoregion. For 28 stocks, our objectives were to (1) fit stock-recruitment models with different time-varying parameters configurations, (2) evaluate which parameters vary in time, (3) examine temporal characteristics of historical recruitment productivity, (4) evaluate productivity correlation across stocks, and (5) identify common patterns in recruitment productivity of Celtic Seas ecoregion stocks.

5.2 Materials and Methods

5.2.1 Recruitment and Spawning Stock biomass estimates

We used the time series of spawning stock biomass and recruitment estimates from the most recent stock assessments issued by the International Council for the Exploration of the Sea (ICES). For stocks residing at least partially in the Celtic Seas ecoregion, we extracted the data via XML from the ICES Stock Assessment Graphs database (ICES 2022a). From that list, the stocks her.27.1-24a514a (Norwegian spring-spawning herring), and lin.27.5b (Faroe grounds ling) were excluded from the analysis because the stocks boundaries showed only a minor overlap with the Celtic Seas ecoregion. We filtered for assessments that estimated spawning stock biomass and used “SSB” in the stock size description. Twenty-nine stocks were selected, most of which were category 1 (i.e. stocks with quantitative assessments), except for cod.27.7a and her.27.6a7bc which at the time of data extraction were category 3 (i.e. stocks for which survey-based assessments or exploratory assessment indicate trends). However, we used data from the 2018 assessment when the stocks were considered as category 1, so a full analytical stock assessment was carried out. One stock with a short time series (less than 20 years) was excluded from the analysis (bli.27.5b67, blue ling in Celtic Seas and Faroes grounds). Assessment methodologies were typically age or length-structured (Table 5.1). Stocks were classified using metadata from the assessment by functional groups based on ICES fisheries guild classification (pelagic, demersal, benthic, and elasmobranch), and by region (northern, central, southern and wide area).

5.2.2 Model details

We applied Peterman's productivity method (PPM), which is a state-space dynamic model for estimating time-varying parameters of the stock-recruitment relationship. We focused on the univariate (single-population) PPM to study stock-recruitment relationship of Celtic Seas ecoregion stocks. We described the stock-recruitment relationship with the Ricker model (Ricker 1954), which depends on two parameters: a maximum-productivity and a density-dependent coefficient. We evaluated four different PPM models: (i) time-invariant Ricker model, (ii) time-variant maximum-productivity Ricker model, (iii) time-variant density-dependent mortality Ricker model, (iv) time-covariant

Table 5.1: Details of the Celtic Seas Ecoregion stocks investigated. Assessment types: SAM (State-space Assessment Model), XSAM (Statistical state-space Assessment Model), MYCC (Multi-Year Catch Curves), SS3 (Stock Synthesis 3), TSA (Time-series analysis age-based stock assessment methodology), XSA(Extended Survivors Analysis), ASAP (Age-Structured Assessment Programme).

Stock Key Label	**Description**	**Scientific name**	**Age-at-R**	**Assess-ment type**	**Series length**	**Functional Group**	**Region**
aru.27.5b6a	Greater silver smelt in divisions 5.b and 6.a (Faroes grounds and west of Scotland)	*Argentina silus*	5	Gadget	22	Pelagic	Northern
bli.27.5b67	Blue ling in subareas 6-7 and Division 5.b (Celtic Seas and Faroes grounds)	*Molva dypterygia*	9	MYCC	17	Demersal	Wide area
bss.27.4bc7ad-h	Seabass in Divisions 4.b-c, 7.a, and 7.d-h (central and southern North Sea, Irish Sea, English Channel, Bristol Channel, and Celtic Sea)	*Dicentrarchus labrax*	0	SS3	37	Demersal	Central
cod.27.6a	Cod in Division 6.a (West of Scotland)	*Gadus morhua*	1	SAM	40	Demersal	Northern
cod.27.7a	Cod in Division 7.a (Irish Sea)	*Gadus morhua*	0	ASAP	51	Demersal	Central
cod.27.7e-k	Cod in divisions 7.e-k (eastern English Channel and southern Celtic Seas)	*Gadus morhua*	1	SAM	41	Demersal	Southern
dgs.27.nea	Spurdog in Subareas 1-10, 12 and 14 (the northeast Atlantic and adjacent waters)	*Squalus acanthias*	0	*	116	Elasmobranch	Wide area
had.27.46a20	Haddock in Subarea 4, Division 6.a, and Subdivision 20 (North Sea, West of Scotland, Skagerrak)	*Melanogrammus aeglefinus*	0	TSA	50	Demersal	Northern
had.27.6b	Haddock in Division 6.b (Rockall)	*Melanogrammus aeglefinus*	1	XSA	30	Demersal	Northern
had.27.7a	Haddock in Division 7.a (Irish Sea)	*Melanogrammus aeglefinus*	0	ASAP	29	Demersal	Central
had.27.7b-k	Haddock in Divisions 7.b-k (southern Celtic Seas and English Channel)	*Melanogrammus aeglefinus*	0	SAM	29	Demersal	Southern
her.27.6a7bc	Herring in divisions 6.a and 7.b-c (West of Scotland, West of Ireland)	*Clupea harengus*	1	SAM	62	Pelagic	Northern
her.27.irls	Herring in divisions 7.a South of 52°30'N, 7.g-h, and 7.j-k (Irish Sea, Celtic Sea, and southwest of Ireland)	*Clupea harengus*	1	ASAP	63	Pelagic	Southern
her.27.nirs	Herring in Division 7.a North of 52°30'N (Irish Sea)	*Clupea harengus*	1	SAM	41	Pelagic	Central
hke.27.3a46-8abd	Hake in subareas 4, 6, and 7, and divisions 3.a, 8.a-b, and 8.d, Northern stock (Greater North Sea, Celtic Seas, and the northern Bay of Biscay)	*Merluccius merluccius*	0	SS3	44	Demersal	Wide area
hom.27.2a4a5b6a7a-ce-k8	Horse mackerel in Subarea 8 and divisions 2.a, 4.a, 5.b, 6.a, 7.a-c,e-k (the northeast Atlantic)	*Trachurus trachurus*	0	SS3	40	Pelagic	Northern
mac.27.nea	Mackerel in subareas 1-8 and 14 and division 9.a (the northeast Atlantic and adjacent waters)	*Scomber scombrus*	0	SAM	42	Pelagic	Wide area
meg.27.7b-k8abd	Megrim in divisions 7.b-k, 8.a-b, and 8.d (west and southwest of Ireland, Bay of Biscay)	*Lepidorhombus whiffiagonis*	1	**	37	Benthic	Southern
mon.27.78abd	White anglerfish in Subarea 7 and divisions 8.a-b and 8.d (Celtic Seas, Bay of Biscay)	*Lophius piscatorius*	0	a4a	36	Benthic	Southern
ple.27.7a	Plaice in Division 7.a (Irish Sea)	*Pleuronectes platessa*	1	SAM	40	Benthic	Central
pok.27.3a46	Saithe in Subareas 4, 6 and Division 3.a (North Sea, Rockall and West of Scotland, Skagerrak and Kattegat)	*Pollachius virens*	3	SAM	52	Demersal	Northern
reg.27.561214	Golden redfish in subareas 5, 6, 12, and 14 (Iceland and Faroes grounds, West of Scotland, North of Azores, East of Greenland)	*Sebastes norvegicus*	5	Gadget	46	Demersal	Northern
sol.27.7a	Sole in Division 7.a (Irish Sea)	*Solea solea*	2	XSA	50	Benthic	Central
sol.27.7e	Sole in Division 7.e (western English Channel)	*Solea solea*	2	XSA	51	Benthic	Southern
sol.27.7fg	Sole in divisions 7.f and 7.g (Bristol Channel, Celtic Sea)	*Solea solea*	1	SAM	50	Benthic	Southern
whb.27.1-91214	Blue whiting in subareas 1-9, 12, and 14 (the northeast Atlantic and adjacent waters)	*Micromesistius poutassou*	1	SAM	40	Pelagic	Wide area
whg.27.6a	Whiting in Division 6.a (West of Scotland)	*Merlangius merlangus*	0	SAM	41	Demersal	Northern
whg.27.7a	Whiting in Division 7.a (Irish Sea)	*Merlangius merlangus*	0	ASAP	42	Demersal	Central
whg.27.7b-ce-k	Whiting in divisions 7.b-c and 7.e-k (southern Celtic Seas and eastern English Channel)	*Merlangius merlangus*	0	SAM	22	Demersal	Southern

*Age and length-structured model with separate sexes, ** Bayesian statistical catch at age using catches in the model.

maximum-productivity and density-dependent mortality Ricker model. To estimate time-varying parameters, the Kalman Filter was implemented by maximization of the likelihood within the DLM package (Petris et al. 2009) in the statistical software R.

First, we estimated the time-invariant linearized Ricker model, using the natural logarithm of the survival ration R/S (also termed the "killing power", Myers 2001). This model is stationary in its parameters because it assumes that the parameters are constant across the entire time series of spawner and recruit data. The time-invariant linearized Ricker model follows the function below:

$$\begin{aligned} \ln\left(\frac{R_t}{S_{t-\tau}}\right) &= a_t + bS_{t-\tau} + \upsilon_t \\ \upsilon_t &\sim N(0, \sigma_\upsilon^2) \end{aligned} \tag{5.1}$$

where R_t is the recruitment in year t, $S_{t-\tau}$ is the spawning stock biomass in time t (lag by the age of recruitment τ), a is the maximum-productivity, b is the density-dependent mortality, and υ_t is an amalgam of process and observation errors. The maximum-productivity coefficient (a) is the natural logarithm of α in the traditional Ricker formulation, which is the maximum reproductive rate and represents the product of the fecundity and density-independent mortality integrated over time from spawning to recruitment (Ricker 1954). The density-dependent mortality gives the rate at which recruitment is reduced by density-dependent mortality.

For the second model, we estimated time-varying maximum-productivity. We allow the stochastic parameter variation via a random walk process:

$$\begin{aligned} a_t &= a_{t-1} + \omega_t \\ \omega_t &\sim N(0, \sigma_\omega^2) \end{aligned} \tag{5.2}$$

where ω_t is the process error. We assumed a random-walk process for the system equation because we had no a priori knowledge of temporal patterns in the parameter. Besides, a random-walk model performed well at tracking a wide variety of underlying temporal trends (Peterman et al. 2000; Dorner et al. 2008; Minto et al. 2014). The density-dependent parameter, b, in this model is time-invariant. We calculated the signal-to-nose ratio ($\sigma_\omega^2/\sigma_\upsilon^2$) for each stock to quantify the variance partitioned to the temporal trend compared with the high-frequency variation (observation noise and high inter-annual frequency process variation).

For the third model, we estimated time-varying density-dependent mortality, following stochastic variation with a random walk process:

$$\begin{aligned} b_t &= b_{t-1} + \omega_t \\ \omega_t &\sim N(0, \sigma_\omega^2) \end{aligned} \tag{5.3}$$

where ω_t is the process error. The maximum-productivity parameter, a, in this model is time-invariant.

For the fourth model, we estimate time-varying maximum-productivity and density-dependent mortality by allowing both parameters to covary following a correlated random walk:

$$\begin{bmatrix} a_t \\ b_t \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} a_{t-1} \\ b_{t-1} \end{bmatrix}, \begin{bmatrix} \sigma_a^2 & \rho\sigma_a\sigma_b \\ \rho\sigma_a\sigma_b & \sigma_b^2 \end{bmatrix} \right) \tag{5.4}$$

where ρ is the correlation between the process deviations of a and b.

Model comparison

To identify the best model for the given time series we used goodness-of-fit statistics. We evaluated the models based on the model selection criterion AICc (Akaike information criterion for small sample size; Burnham and Anderson 2004). The best-fitted model was judged by the difference (δ) between the AICc values of the models, including the number of variance parameters and the dimension of the state vector. The most parsimonious of the four model fits per stock was the model with the lowest AICc value. Models within 2 AICc units of the lowest were considered equally plausible models. Models with the lowest AICc with a difference of equal or more than 2 units were considered to have substantial support or evidence. Models with 4 or more units of difference have considerable more support than the models with higher AICc.

5.2.3 Celtic ecoregion stocks productivity trends

To understand temporal patterns in stock productivity we focus on the estimated a_t time series from the time-variant maximum-productivity models. Being the density-independent parameter, time-varying maximum productivity influences stock recruitment regardless of spawner abundance (Dorner et al. 2008) and integrates the direct environmental signal.

Correlation analysis between stock's productivity patterns

We estimated the Spearman rank pairwise correlation between stock-specific time-varying trends in productivity. The estimated time series of a_t values constituted our measure of productivity. We compared correlations across stocks to quantify the extent to which similar patterns in the a_t parameter are shared among stocks.

Dynamic factor analysis: Common productivity trends

We used dynamic factor analysis (DFA) to describe main common trends among maximum-productivity time series of Celtic Seas ecoregion stocks. This is a dimension-reduction technique specially designed for multivariate time series data recommended to be applied in fisheries science (Zuur et al. 2003). We used DFA to model shared temporal trends in maximum productivity time series for the overall Celtic Seas ecoregion over the time period 1970 to 2022, because many stocks had considerable missing data prior to 1970. The number of common trends was set to four to keep a reduced number of trends but still have a reasonable model fit. We fit the model in R using the package MARSS (Holmes et al. 2012). We use "dfa" configuration form with a diagonal and unequal covariance matrix where the variances were allowed to vary between stocks and covariances were assumed 0.

5.3 Results

Results are divided into two sections. First, we compared goodness-of-fit of a time-invariant and three time-variant stock-recruitment model. For the second part, we focused on correlations and common trends across the stocks in time-varying maximum productivity.

5.3.1 Time-varying parameter PPM model comparison

For 25 out of 28 stocks, at least one of the three time-varying parameter models had a better fit than the time-invariant model (based on the difference between two models' AICc values). We found strong evidence that 24 stocks had time-varying parameters because time-invariant models had considerably less support (with AICc $\delta > 4$; Table 5.2). Two stocks had considerable more support for the time-invariant model (had.27.7a, had.27.7b-k), and one stock had substantial more support (whg.27.7b-ce-k; Table 5.2).

Comparisons of model fits showed that the model with time-varying maximum-productivity had the strongest support for 20 stocks, and the model with time-varying density-dependent mortality had the strongest support for 4 stocks. However, for 9 stocks both time-varying parameters models were equally plausible because they had similar AIC support ($\delta \leq 2$; Table 5.2). For 14 stocks, the time-varying maximum-productivity had substantially more support relative to the time-varying density-dependent mortality ($\delta > 2$; Table 5.2), and for 2 stocks time-varying density-dependence mortality had substantially more support relative to the time-varying maximum productivity (ple.27.7a, pok.27.3a46; Table 5.2). Models with both parameters covarying in time never showed better AICc support because AICc penalized the use of an excessive number of parameters (Table 5.2).

For most stocks, results of the time-variant maximum-productivity model and the model with both parameters covarying showed similar trends for both a and b parameters (Appendix A.3 Figure SM1, SM2). Thus, for these models, density-dependent mortality was constant, with the exception of bss.27.4bc7ad-h, cod.27.6a, cod.27.7e-k, hke.27.3a46-8abd, ple.27.7a, pok.27.3a46, reg.27.561214 (Appendix A.3 Figure SM2). Occasionally, in the time-varying model the constant parameter had scaling differences with the time-invariant estimate (Appendix A.3 Figure SM1, SM2). For stocks in the Celtic Seas ecoregion, only had.27.7a had trends in time-varying density-dependent mortality but not in time-varying maximum-productivity (Appendix A.3 Figure SM1, SM2).

5.3.2 Celtic Seas ecoregion trends in stock productivity

For many of the stocks examined, temporal trends in the maximum-productivity parameter showed differences in current productivity levels compared with the time-invariant historical average productivity (dotted line in Figure 5.1). For

Table 5.2: Summary of model fits. Model AICc for the different models, lower AICc values signaled with an asterisk, and shades of gray highlight the best fitting model in a darker shade and same shade for stocks within 2 units, lighter shade for stocks $2 < \delta < 4$ of the best fiting model. Stock description are provided in Table 5.1.

	Time-invariant		**Time-varying a**			**Time-varing b**				**Time-covarying a and b**				
N of variance parameters	**1**		**2**			**2**				**4**				
State vector parameters	**2**		**2**			**2**				**2**				
Stock	**LogL**	**AICc**	**LogL**	**AICc**	δ_{a-a_t}	**LogL**	**AICc**	δ_{a-b_t}	δ_{at-bt}	**LogL**	**AICc**	δ_{a-cov}	δ_{a_t-cov}	δ_{b_t-cov}
aru.27.5b6a	27.36	-47.45	30.58	-50.93*	3.48	29.33	-48.45	1.00	-2.48	29.33	-9.45	-38.00	-41.48	-39.00
bss.27.4bc7ad-h	-51.64	110.01	-42.73	94.72*	15.29	-41.79	92.84	17.17	1.88	-41.79	98.39	11.62	-3.67	-5.55
cod.27.6a	-38.38	83.42	-31.35	71.85	11.57	-31.32	71.79*	11.63	0.06	-31.32	76.59	6.83	-4.74	-4.80
cod.27.7a	-63.90	134.31	-35.33	79.53*	54.78	-41.08	91.02	43.29	-11.49	-41.08	84.57	49.74	-5.04	6.45
cod.27.7e-k	-49.65	105.95	-36.90	82.9*	23.05	-37.83	84.77	21.18	-1.87	-37.83	87.71	18.24	-4.81	-2.94
dgs.27.nea	208.07	-409.93	327.20	-646.03*	236.10	281.38	-554.4	144.47	-91.63	281.38	-641.62	231.69	-4.41	87.22
had.27.46a20	-80.37	167.25	-50.53	109.94*	57.31	-68.99	116.99	50.26	-7.05	-54.06	114.78	52.47	-4.84	2.21
had.27.6b	-54.09	115.11	-44.64	98.89*	16.22	-49.55	108.7	6.41	-9.81	-49.55	104.94	10.17	-6.05	3.76
had.27.7a	-40.82	88.59*	-42.35	94.36	-5.77	-41.58	92.83	-4.24	1.53	-41.58	100.52	-11.93	-6.16	-7.69
had.27.7b-k	-33.82	74.6*	-37.06	83.79	-9.19	-37.07	83.81	-9.21	-0.02	-37.07	89.95	-15.35	-6.16	-6.14
her.27.6a7bc	-42.27	90.96	3.42	1.87*	89.09	-19.83	48.38	42.58	-46.51	-19.83	6.7	84.26	-4.83	41.68
her.27.irls	-58.15	122.71	-31.40	71.48*	51.23	-33.53	71.55	51.16	-0.07	-31.44	76.28	46.43	-4.80	-4.73
her.27.nirs	-26.78	60.19	-14.86	38.79*	21.40	-13.87	40.87	19.32	-2.08	-15.90	44.11	16.08	-5.32	-3.24
hke.27.3a46-8abd	-22.83	52.25	-13.63	36.26	15.99	-13.28	35.57*	16.68	0.69	-13.29	40.71	11.54	-4.45	-5.14
hom.27.2a4a5b6a7a-ce-k8	-45.96	98.59	-43.68	96.49	2.10	-43.68	96.49	2.10	0.00	-43.68	101.9	-3.31	-5.41	-5.41
mac.27.nea	7.25	-7.87	42.03	-74.98*	67.11	9.03	-8.97	1.10	-66.01	9.03	-69.66	61.79	-5.32	60.69
meg.27.7b-k8abd	9.70	-12.69	22.02	-34.83*	22.14	16.02	-27.83	15.14	-7.00	18.52	-29.34	16.65	-5.49	1.51
mon.27.78abd	-20.65	48.05	-14.18	37.65*	10.40	-14.39	38.07	9.98	-0.42	-14.39	43.26	4.79	-5.61	-5.19
ple.27.7a	2.02	2.62	12.23	-15.32	17.94	14.23	-19.32*	21.94	4.00	14.23	-13.92	16.54	-1.40	-5.40
pok.27.3a46	-44.91	96.3	-8.36	25.55	70.75	-7.80	21.32*	74.98	4.23	-6.24	26.3	70.00	-0.75	-4.98
reg.27.561214	-62.32	131.21	-36.25	81.46*	49.75	-37.19	81.7	49.51	-0.24	-36.37	86.18	45.03	-4.72	-4.48
sol.27.7a	-47.52	101.57	-25.73	60.34*	41.23	-29.97	68.83	32.74	-8.49	-29.97	65.41	36.16	-5.07	3.42
sol.27.7e	-8.02	22.54	10.00	-11.13*	33.67	10.07	-11.26	33.80	0.13	10.07	-6.22	28.76	-4.91	-5.04
sol.27.7fg	-12.92	32.36	7.27	-5.65*	38.01	5.39	-1.89	34.25	-3.76	5.39	-0.58	32.94	-5.07	-1.31
whb.27.1-91214	-42.64	91.95	-27.90	64.95*	27.00	-40.63	90.4	1.55	-25.45	-40.63	105.37	-13.42	-40.42	-14.97
whg.27.6a	-29.21	65.06	-17.61	44.33*	20.73	-19.76	48.63	16.43	-4.30	-19.76	49.69	15.37	-5.36	-1.06
whg.27.7a	-25.17	56.96	-11.17	31.43*	25.53	-12.96	35.01	21.95	-3.58	-12.96	36.74	20.22	-5.31	-1.73
whg.27.7b-ce-k	-15.88	39.02*	-16.20	42.63	-3.61	-17.34	44.9	-5.88	-2.27	-17.34	49.66	-10.64	-7.03	-4.76

some stocks, the current productivity level was substantially lower than at the beginning of the time series (e.g. West of Scotland whiting, whg.27.6a), but for other stocks current productivity was substantially higher (e.g. Irish Sea herring, her.27.nirs) than or similar to historical productivity. The amplitudes of the time-varying productivity (in logarithmic scale) vary from less than 1 (e.g. Faroes grounds and West of Scotland greater silver smelt, aru.27.5b6a) to around 5 (e.g. northeast Atlantic blue whiting, whb.27.1-91214). This variability corresponds to the recruit number per metric ton of the spawning stock biomass on a logarithmic scale. The longest series available was for the northeast Atlantic spurdog (1905-2020), in Figure 5.1, we included this time series truncated because for most species the time series were considerably shorter.

The fraction between the observation or measurement error and the process variability is the signal-to-noise ratio. There were some cases where the univariate method could not separate the observation noise from the process variation, and so one of them was insignificant. For stocks with a signal-to-noise ratio equal to 0, the process variation could not be estimated properly (e.g. had.27.7a, hom.27.2a4a5b6a7a-ce-k8; Appendix A.3 Table SM1). Irish Sea haddock (had.27.7a) and northeast Atlantic horse mackerel (hom.27.2a4a5b6a7a-ce-k8) displayed productivity nearly constant, at the same level as the time-invariant one with wide error intervals (Figure 5.1). For some stocks (e.g. aru.27.5b6a, mac.27.nea; Appendix A.3 Table SM1) the estimated observation noise was very small, resulting in a extremely high signal-to-noise ratio.

With regards to Northern Celtic Seas ecoregion stocks, maximum productivity has declined considerably for many stocks (Figure 5.1), e.g. West of Scotland cod (cod.26.6a), North Sea, Rockall and West of Scotland saithe (pok.27.3a46), West of Scotland whiting (whg.27.6a). West Scotland cod (cod.26.6a) and North Sea, Rockall and West of Scotland saithe (pok.27.3a46) stocks are currently at depressed productivity levels. North Sea and West Scotland haddock (had.27.46a20) also displayed declining productivity until 2012 with productivity increasing thereafter. West of Scotland whiting (whg.27.6a) showed a steep decrease until 2009 and a stabilization since. West of Scotland and West of Ireland herring (her.27.6a7bc) and West of Scotland saithe (pok.27.3a46) displayed fluctuations with an overall declining long-term trend. Productivity of Faroes grounds and West of Scotland greater silver smelt (aru.27.5b6a) and Rockall haddock (had.27.6b) fluctuated, with a lower productivity point around 2009 (Figure 5.1).

In the central Celtic Seas ecoregion, stocks showed a large diversity of patterns (Figure 5.1). Most stocks had higher time-varying productivity in the terminal year compared to the time-invariant one, except for Irish Sea plaice (ple.27.7a). Irish Sea sole (sol.27.7a) displayed decreasing productivity but with some increase in recent years. North Sea, Irish Sea, English Channel, Bristol Channel, and Celtic Sea seabass (bss.27.4bc7ad-h) displayed increased productivity with a peak in the early 2000s and a decrease since then. The average time-varying productivity was higher than the time-invariant productivity level (Figure 5.1). Irish Sea whiting (whg.27.7a) had a low productivity level in the early 1990s, productivity increased until the early 2000s and decreased since 2013 to levels similar to those at the beginning of the time series. A decreasing trend was observed for Irish Sea cod (cod.27.7a) for all the time series. Irish Sea herring (her.27.nirs) productivity was fairy stable at a low level for the start of the time series and in the late 1990s has a marked increase with a fairy stable period at a higher level since mid-2000s.

Southern Celtic Seas ecoregion stocks had higher levels of currently time-varying productivity than the time-invariant one, except for Celtic Seas cod which has a similar level (Figure 5.1). Celtic Seas cod (cod.27.7e-k) productivity increased with a peak in the mid-1990s and has been decreasing since to levels lower than those observed at the start of the series, with a short increase in the last year of the time series. Similarly, Celtic Seas whiting (whg.27.7b-ce-k) displayed an erratic decline in productivity since 1990. This productivity trend differed from those for other stocks in the Southern Celtic Seas ecoregion. Irish Sea, Celtic Sea and southwest of Ireland herring (her.27.irls) displayed fluctuations but did not display any long-term trends. Productivity of West and Southwest of Ireland and Bay of Biscay megrim (meg.27.7b-k8abd) and similarly Celtic Seas and Bay of Biscay white anglerfish (mon.27.78abd) fluctuated with a slow long-term increasing trend. Bristol Channel and Celtic Sea sole (sol.27.7fg) displayed erratic fluctuations in productivity with increase in the most recent years. Western English Channel sole (sol.27.7e) displayed a slow increase in productivity, similar to Celtic Seas and English Channel haddock (had.27.7b-k).

Widely distributed stocks in the Celtic Seas ecoregion typically displayed erratic fluctuations (Figure 5.1). Northern hake stock (hke.27.3a46-8abd) productivity increased with a peak around 2009 and has declined since then.

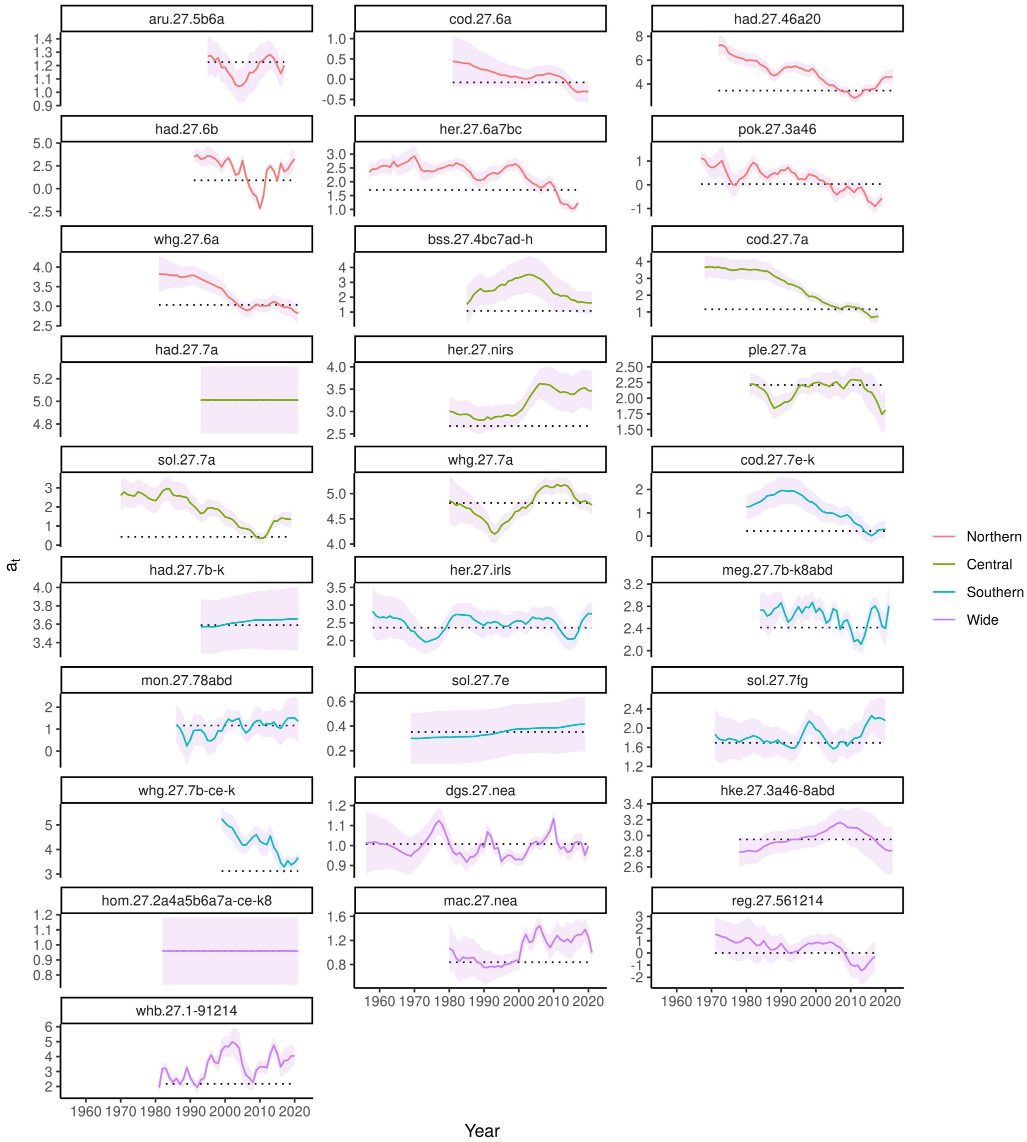

Figure 5.1: Estimated time series trends in maximum productivity (a_t) and 95% confidence intervals for stocks in the Celtic Seas ecoregion. The horizontal dashed line is the time-invariant maximum productivity parameter. Colour represent the region (red for northern stocks, green for central stocks, blue for southern stocks and purple for wide area stocks). Stock description are provided in Table 5.1.

Northeast Atlantic mackerel (mac.27.nea) displayed relatively constant productivity until 2000, and a subsequent marked increase, then fluctuated around a higher productivity level since. Northeast Atlantic spurdog displayed relatively constant productivity until the late 1950's and has subsequently fluctuated erratically with no long-term directional trend (Figure 5.1). Iceland and Faroes grounds, West of Scotland, North of Azores and East of Greendland golden redfish (reg.27.561214) displayed a long-term trend in productivity slowly decreasing. Northeast Atlantic blue whiting (whb.27.1-91214) displayed an erratic long-term trend in productivity slowly increasing.

Correlation analysis between stock's productivity patterns

The correlation of time-varying maximum productivity across stocks showed patterns in productivity within and among regions. Correlations within northern Celtic Seas ecoregion stocks were mostly positive (Figure 5.2), suggesting that regional-scale factors might be important drivers of changes in recruitment productivity. However, West Scotland cod and Faroes grounds and West of Scotland greater silver smelt showed negative or weak correlation with other northern stocks. Among central Celtic Seas ecoregion stocks, some correlations were strong, positive between Irish Sea whiting, haddock and herring, and negative with Irish Sea cod and sole. In southern Celtic Sea ecoregion, most stocks displayed weak correlations but there was a strong correlation between Celtic Sea whiting and cod and between Western English Channel sole and Celtic Seas and English Channel haddock. These stock pairs were negatively correlated with each other. Celtic Seas and Bay of Biscay sole displayed weak correlations with all the southern stocks. Widely distributed stocks typically display weak or negative correlations between each other.

Occasionally, productivity time series had strong positive correlations among stocks from different regions, e.g. West of Scotland and West of Ireland herring and West of Scotland saithe are strongly correlated with central and southern Northern Sea, Irish Sea, English Channel, Bristol Channel, and Celtic Sea seabass, Irish Sea cod, Celtic Seas cod, and Celtic Seas whiting (Figure 5.2). In other cases, productivity correlations with most stocks were weak, e.g for northeast Atlantic mackerel, Irish Sea plaice, Celtic Seas and Bay of Biscay white angler fish, and West and Southwest of Ireland and Bay of Biscay megrim, suggesting unique patterns in recruitment productivity for these stocks.

We found that correlations within species were strong and positive for some species but could be negative in other cases. All cod stocks in the ecoregion showed positive correlations in productivity patterns, and with some other stocks from other regions, e.g. herring, saithe, and seabass (Figure 5.2). Haddock stocks productivity time series are positively correlated for North Sea and West of Scotland stock and Rockall stock, and for Irish Sea and Celtic seas stocks, but these pairs of stocks were negatively correlated with each

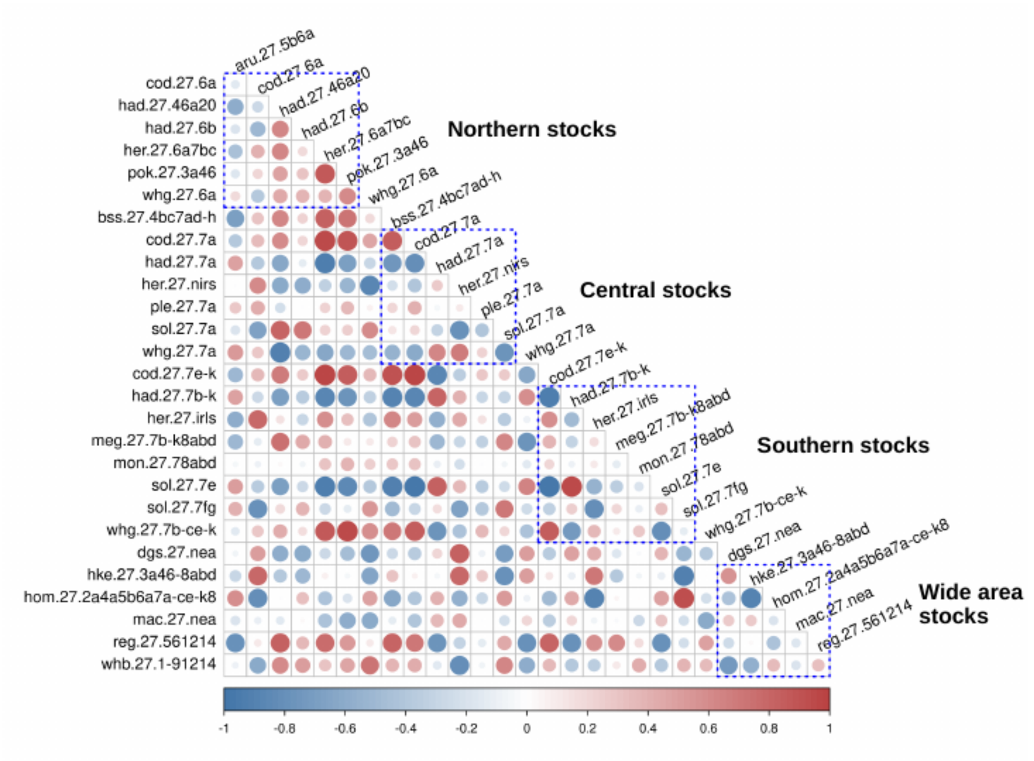

Figure 5.2: Estimated pairwise productivity correlation for stocks in the Celtic Seas ecoregion (significance level of 0.01). Red represents positive correlations and blue represents negative correlations. Stock description are provided in Table 5.1. Dashed blue line squares represent regions in the ecoregion.

other (Figure 5.2).

Celtic Seas ecoregion productivity patterns

In the Celtic Seas ecoregion, there was more than one underlying common pattern in productivity among stocks. Variability patterns of the productivity time series for Celtic Seas ecoregion stocks could not be reduced to only one main common pattern (Appendix A.3 Table SM2), thus a four-trend dynamic factor analysis was estimated. The four-trend model had 24 stocks that relate to the trends with a percentage of variance explained higher than 50% (Table 5.3). The first common productivity trend gradually decreased until the early 1980s and increased subsequently, with a decline from 2005 until the early 2010s followed by an increase until the end of the time series (Figure 5.3). Northern stocks positively related to this trend are haddock in North Sea, West of Scotland and Skagerrak, haddock in Rockall, and West of Scotland and West of Ireland herring (Table 5.3). In other regions, stocks related to this trend are North Sea, Irish Sea, English Channel, Bristol Channel, and

Celtic Sea seabass, West and Southwest of Ireland, and Bay of Biscay megrim, Celtic Seas and Bay of Biscay white anglerfish, Bristol channel and Celtic Seas sole, and northeast Atlantic blue whiting. All sole stocks in the ecoregion are related to the first common productivity trend, with low loadings.

Table 5.3: Results of the four-trend dynamic factor analysis. Factor loadings in bold are above the cutoff of 0.05 in absolute value. Stock description are provided in Table 5.1.

Region	**Stock**	**Factor loadings trend 1**	**Factor loadings trend 2**	**Factor loadings trend 3**	**Factor loadings trend 4**	**% Variability explained by the trends**
Northern region	cod.27.6a	**-0.18**	**0.08**	**0.06**	**0.09**	95.74
	had.27.46a20	**0.13**	**-0.09**	-0.01	**0.08**	93.47
	had.27.6b	**0.17**	**-0.1**	**0.07**	-0.02	71.14
	pok.27.3a46	0.01	0.02	**0.05**	**0.1**	82.34
	whg.27.6a	**-0.08**	-0.04	**0.12**	0.04	98.93
	aru.27.5b6a	**-0.58**	-0.03	**0.38**	**-0.07**	96.54
	her.27.6a7bc	**0.05**	**0.06**	0.03	**0.13**	80.18
Central region	ple.27.7a	**-0.09**	**0.16**	-0.02	0.04	50.75
	sol.27.7a	0.03	**-0.1**	0.02	**0.06**	92.65
	bss.27.4bc7ad-h	**0.2**	**0.15**	$1e10^{-3}$	0.04	93.4
	cod.27.7a	-0.01	-0.02	$6e10^{-4}$	**0.11**	100
	had.27.7a	**-0.26**	**0.05**	-0.01	-0.01	63.33
	whg.27.7a	**-0.14**	**0.08**	**-0.13**	-0.01	94.78
	her.27.nirs	-0.01	**0.05**	**-0.13**	-0.03	95.02
Southern region	meg.27.7b-k8abd	**0.17**	**-0.06**	0.04	0.02	46.05
	mon.27.78abd	**0.05**	$3e10^{-3}$	**-0.12**	-0.01	52.58
	sol.27.7e	0.01	0.02	0.01	**-0.11**	99.09
	sol.27.7fg	**0.08**	**-0.13**	$2e10^{-3}$	-0.1	59.31
	cod.27.7e-k	$6e10^{-4}$	0.03	**0.12**	**0.06**	96.42
	had.27.7b-k	-0.02	-0.02	**-0.18**	$1e10^{-3}$	99.75
	whg.27.7b-ce-k	**-0.07**	**0.1**	**0.23**	-0.03	85.07
	her.27.irls	**-0.12**	0.03	**0.09**	-0.03	32.88
Wide area	cod.27.7a	-0.01	-0.02	$6e10^{-4}$	**0.11**	100
	dgs.27.nea	-0.01	0.03	**-0.11**	0.03	29.53
	hke.27.3a46-8abd	**-0.06**	**0.18**	0.01	-0.02	93.59
	reg.27.561214	**0.13**	0.02	-0.03	**0.11**	68.44
	hom.27.2a4a5b6a7	-0.03	**-0.2**	0.03	-0.03	100
	mac.27.nea	$4e10^{-3}$	0.04	**-0.13**	-0.02	80.88
	whb.27.1-91214	**0.16**	-0.01	**-0.05**	-0.03	43.79

The second common trend displayed a gradual decrease until the early 1980s followed by an increase in productivity until late 2000s and a marked decline thereafter (Figure 5.3). Most central stocks in the ecoregion are related positively to this trend, except for cod and sole in the Irish Sea (Table 5.3). Additionally, West of Scotland cod, West of Scotland and West of Ireland herring, Celtic Seas whiting, and northern hake stock were strongly related to this trend.

The third common trend displayed a productivity peak around the mid-1990s followed by a marked decline until the late 2000s with stabilization until the end of the time series (Figure 5.3). Most northern stocks are positively related to this trend, except for North Sea, West of Scotland and Skagerrak haddock

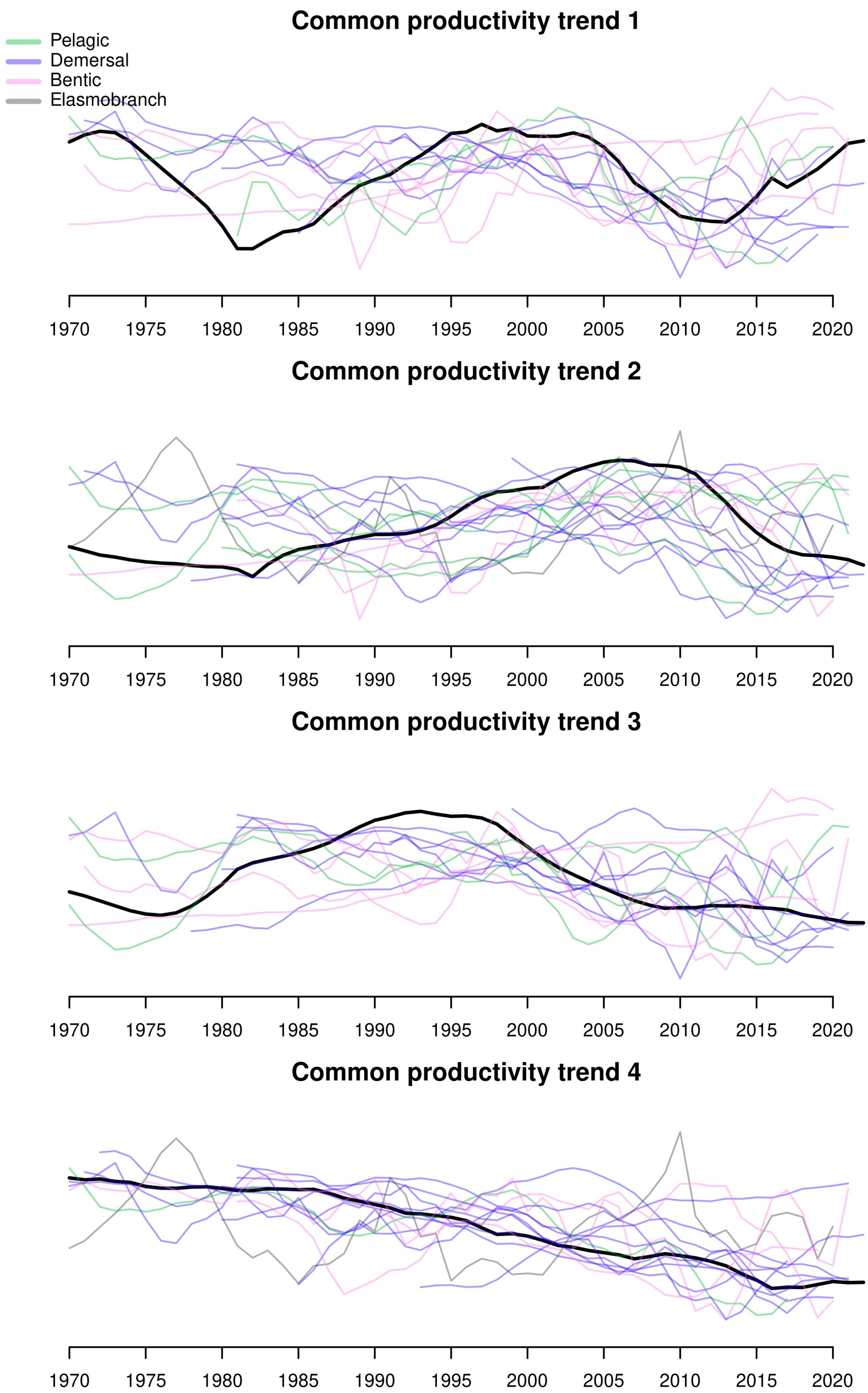

Figure 5.3: Four common productivity trends in the Celtic Seas ecoregion in black. Coloured lines are the productivity of stocks with positive loading for the trend. The colour represents the functional group.

(Table 5.3). Celtic Seas cod, whiting and herring are also positively related to this trend.

The fourth common trend displayed a consistent decrease in productivity with a slight stabilization in the most recent years (Figure 5.3). Many northern stocks are related to this trend, except for Rockall haddock and the greater silver smelt stock. All cod stocks in the ecoregion are highly positively related to this trend with important loadings (Table 5.3). Also, Irish Sea sole and golden redfish in Iceland, Faroes grounds, West of Scotland, North of Azores, and East of Greenland.

5.4 Discussion

We found evidence of non-stationary productivity for many stocks in the Celtic Seas ecoregion manifested as important changes in the temporal trends in recruitment productivity parameters. In this section, we consider the important biological insights of PPM models, examine productivity dynamics in the Celtic Seas ecoregion, explain data and method caveats, and remark implications for management.

5.4.1 Biological insight of PPM models

Peterman's productivity method enabled the identification of temporal patterns in the parameters of the stock-recruitment model. The PPM permits estimation of the integrated effects of underlying processes influencing recruitment while reducing the confounding from random sources of noise or variability independent of the trend (Holt and Peterman 2004; Peterman et al. 2003). This improves estimates of systematic underlying changes in productivity - revealing the underlying signal (Peterman et al. 2000; Dorner et al. 2008). We showed that parameters of the stock-recruitment relationship often vary over time which offers valuable insight into complex temporally variable regulation processes in changing ecosystems. In the Ricker model, the parameters have differentiated density-dependent effect of spawner abundance on productivity and density-independent effects. However, detecting which parameter varies in time, which is of great ecological interest, is difficult. For some stocks, goodness fit differences between the time-variant models (time-varying maximum-productivity and time-varying density-independent mortality) were small. Applying ensemble modelling (Jardim et al. 2021) could be useful in cases when the understanding of the dynamics is incomplete (i.e. averaging the weight of each time-variant model based on AIC).

Our analysis indicated that, for most stocks in the Celtic Seas ecoregion, time-varying maximum-productivity was the best fit for the data, although changes in density-dependence were also important for some stocks. The maximum-productivity is the mean productivity at low stock sizes and captures variations in recruitment separating environmental effects and maternal effects from the effects of density in adult biomass. Preliminary univariate implementations of PPM indicated that models with time-varying maximum productivity and constant density-dependent mortality fitted best (Peterman et al. 2003; Dorner et al. 2008). Additionally, multivariate implementations also show improved goodness of fit of the time-varying maximum-productivity (Minto et al. 2014). The Minto et al. (2014) results for density-dependence have shown it to be relatively stable in time. We found that when both parameters were allowed to covary in time, for many stocks, the density-dependent parameter remained constant in time.

5.4.2 Productivity dynamics in the Celtic Seas Ecoregion

For most stocks in the Celtic Seas ecoregion recruitment productivity has varied over time, which suggests that the productivity of many stocks is non-stationary, as found also by Minto et al. (2014) for Atlantic cod stocks and by Tableau et al. (2019) for New England stocks. The observed changes in productivity might be caused by internal changes and multiple drivers and mechanisms, which might depend on fish species or even stocks as life-history characteristics of populations might differ (Subbey et al. 2014). Additionally, the effect of these processes may change over time (Stige et al. 2006; Ottersen et al. 2013). Hence, changes and timing are very stock dependent. Applying PPM we can model how recruitment productivity change over time. We observed long-term trends, for example, the overall decline in productivity for stocks in the northern region of the Celtic Seas ecoregion with a considerable positive correlation. This suggests that regional factors might be important drivers of changes in productivity of the northern Celtic Seas ecoregion. For other regions, we found no clear spatial patterns; some stocks with consistent patterns but other stocks responded differently. This might reflect that fish populations are affected by more than one driver or react differently to the same drivers. Mechanistic understanding of why Celtic Seas stocks productivity has changed is beyond the scope of this study but it would be important to investigate in the future. In this section, we hypothesise some of the possible reasons of changes in productivity.

We found some consistent patterns within stocks of the same species but also inconsistent patterns. For example, patterns in productivity of haddock stocks were positively correlated for neighboring stocks, and negatively correlated between northern and central-southern stocks. The consistent patterns in productivity observed between some stocks indicates that common factors (e.g. environmental conditions) may influence those populations. However, effects of climate variability on fish productivity can vary between regions (Parsons and Lear 2001). Internal changes such as changes in age-structure also influence stock productivity (Stenseth et al. 1999; Wright and Gibb 2005; Ohlberger et al. 2022). These changes in stock structure can be caused by fishing or climate change, and the Celtic Seas ecoregion has had high levels of fishing pressure historically (Zimmermann and Werner 2019). For cod stocks, there is a general decline in productivity, which suggests common processes might be operating. The decline in productivity might have been caused by overexploitation (Myers et al. 1996). Additionally, cod survival during early life stages was found to decline with increasing temperatures in the northeastern USA (Fogarty et al. 2008). Brander (2007) found significant effect of environmental variability (NAO) when the spawning stock biomass was low. The consequences of environmental-related regime shifts on cod productivity were found to be accentuated when fishing mortality is high and populations are small (Perälä et al. 2020). While being different populations, a combination of these effects could be contributing to the downward productivity trend of cod stocks.

5.4.3 Data and method caveats

The Ricker stock-recruitment model, used for this study has overcompensation at higher spawner abundances, which does not happen for all species. Time-varying Ricker parameters have been widely used for salmon populations (Peterman et al. 2003; Holt and Peterman 2004; Peterman and Dorner 2012). The Ricker model has been considered to provide a reasonable model for estimating the slope at the origin of stocks (Myers et al. 1999). Minto et al. (2014) applied PPM with time-varying parameters in a Ricker model for cod populations, and Tableau et al. (2019) applied it to New England fish populations. The Ricker model has the advantage of its easy linearization, which allowed the use of the Kalman filter to estimate the time-varying parameters. Additionally, the parameter separation into density-independent and density-dependent components of the Ricker makes for a more straightforward interpretation. Both the parameter α in Ricker models, and the slope at the origin for the Beverton-Holt can be interpreted as the maximum annual reproductive rate directly or by standardization (Myers 2001). The main difference between these models would be caused by the different forms of density-dependent mortality assumed by the model. Nonetheless, more research and development is needed to be able to implement the PPM in other stock-recruitment models such as the Beverton-Holt.

Data used to estimate recruitment productivity, i.e. recruits and spawner abundance, are estimates from stock assessment models and have considerable uncertainty and correlations associated (Brooks and Deroba 2015). Nevertheless, estimated recruitment variability in data-rich stocks with recruitment indices is thought to be more robust to recruitment assumptions, and so the recruitment variability signal in the data is sufficiently strong (Dickey-Collas et al. 2015). The majority of the stocks in this study were category 1, i.e. stocks with analytical assessments. Additionally, many of the stocks studied were historically overexploited, which provided resolution and contrast on population dynamics at low population abundance. The method would be improved investigating the inclusion of assessment uncertainty and covariance of the recruitment and spawning stock biomass estimates.

The univariate PPM approach failed to separate the measurement error and the process variability for some of the stocks time series. This issue is related to a flat likelihood around its maximum in the estimation process (Petris et al. 2009; Tableau et al. 2019). Although, this might be resolved with longer time series, when longer time series are not available, estimating the time-varying parameters collectively using a multivariate model could be a solution (Minto et al. 2014). Moreover, estimating a common signal-to-noise ratio reduces the number of parameters to estimate and is thought to be more robust to shorter time series (Tableau et al. 2019). However, the univariate approach, used in this study, is useful for assessing a single stock and getting a population's view on recruitment productivity variability in time. Potentially, knowing the region's signal-to-noise ratio could be used to inform the model and might help in cases where the separation of observation error from process error is not robust. More generally, understanding how the signal to noise ratio varies across regions may provide insights on the nature of change more globally.

5.4.4 Implications for management

Currently, constant stock-recruitment parameters over the available time series are typically used to derive single-species reference points (stationary stock-recruitment relationship). Such an approach is thought to include average environmental and fishing conditions but is not robust if the ecosystem changes. The maximum-productivity parameter, studied here, is one of the most important parameter in population dynamics (Myers 2001), critical in many problems in fisheries management because it affects the estimation of reference points and sustainable harvest rates. We discovered long-term trends and mismatches between time-invariant and time-varying maximum-productivity. We showed temporal patterns in recruitment productivity of Celtic Seas ecoregion stocks, which is relevant for management advice, specially in the presence of long-term trends and depressed productivity levels. For example, stocks that have continuously decline in productivity, i.e. stocks related to common trend 4, would be immediate red flags of time-invariant reference points.

Advice frameworks typically consider stock productivity regime shifts. When regime shifts are detected a data window of spawner and recruit pairs are used or time series are truncated (ICES 2021c). Choosing recruitment windows to derive reference points can be problematic because shorter time series increases uncertainty in reference points (Deurs et al. 2021) and because productivity changes can be gradual (Collie et al. 2021). Incorporation of ecosystem and climate information into stock assessments and advice has shown to be necessary but challenging (Punt et al. 2014a; Bentley et al. 2021). We argue that in the context of ecosystem changes affecting productivity, tracking time-varying stock recruitment productivity, estimating dynamic reference points, and measuring current productivity levels is crucial for management (Collie et al. 2021; Silvar-Viladomiu et al. 2022b). Tableau et al. (2019) demonstrated that the short-term forecast power for time-varying productivity models generally outperformed time-invariant models. Beyond forecasting, time-varying productivity models can directly inform sustainable harvest practices (Collie et al. 2012; Collie et al. 2021). Stochastic dynamic programming studies have shown that the time-invariant harvest control rule based on average productivity performed similarly as the dynamic harvest control rule except at low productivity (Collie et al. 2021). This occurs because changes in maximum productivity at low productivity have a stronger effect on the optimal harvest rate than changes in the same parameter at high productivity. Consequently, special care is needed at low productivity levels.

Implementations of time-varying productivity frameworks have shown ability to improve on time-invariant management (Collie et al. 2012), with special importance for management in the context of climate change (Collie et al. 2021). Dynamic methods, such as the PPM, that are capable of tracking changes in stock productivity are outstanding because although a mechanistic understanding of the processes that affect productivity is important ultimately, is not needed for tactical decision making now (Minto et al. 2014; Collie et al. 2021; Silvar-Viladomiu et al. 2022b). In view of the evidence that Celtic Seas ecoregion fish recruitment productivity is changing over time, fisheries advice science should take it into account and management must respond to be robust to these productivity changes.

5.5 Acknowledgements

We thank the Celtic Seas ecoregion data collectors, stock assessors and ICES upon whose work the present synthesis depends. This analysis was funded by the Irish Department of Agriculture, Food and the Marine's Competitive Research Funding Programmes (DAFM) as part of the FishKOSM project (Ref 15/S/744).

Chapter 6

General thesis discussion

This thesis furthers understanding of reference points currently used for fisheries management and the dynamic stock-recruitment modelling approach (PPM) to account for productivity changes. Single-species reference points were examined and the importance of ecosystem dynamics and temporal productivity changes were revealed. The PPM, developed by Randall Peterman and colleagues, is highlighted for adapting single-species reference points to account for ecosystem change. In this general discussion, I go through the main findings and conclusions of this thesis and discuss the implications for scientific management advice and the potential for future research.

6.1 Research synthesis

Chapters 2 and 3 (Silvar-Viladomiu et al. 2021; Silvar-Viladomiu et al. 2022a) provide a comparative research synthesis of reference points estimation and retrospective reference point changes in the ICES region. Those synthetic efforts offer a unique overview that enables the identification of common patterns across a range of life histories and cross-comparisons between assessments and stocks. In Chapter 2, patterns and inconsistencies in the estimation of reference points were analysed across category 1 ICES stocks. Retrospective analyses in Chapter 3 offer a unique view of historical past changes in stock status providing comparative understanding of the relative impact of changes in reference points and identifying important reasons for change. Collectively, the results of Chapters 2 and 3 identify general patterns, highlight inconsistencies among stocks, and allow for the identification of areas for further development (discussed in section 6.8 bellow).

These syntheses make a substantial contribution to improving reference point estimation as a key step in the provision of scientific management advice. For the creation of these Chapters, substantial information from assessments, reports, working documents, etc. was collated and summarized. Two extensive datasets were produced, containing information on reference point changes and estimation details. The dataset with all ICES reference points estimation details for all data-rich stocks can offer the base for studies on current general practices across all stocks. In addition, the datasets can be used to make informed comparisons with practices in other regions. The dataset with quantitative measures of retrospective reference point changes, assessment estimates outputs, and possible reasons for change provides extensive data to further investigate these important changes and compare it to cases in other regions. Additionally, the method develop in Chapter 3 to decompose changes can be applied to other regions or other indicators. These two chapters revealed the value of synthesis and comparative studies and recommended increased use of this kind of study in the future. Next, I delve in further detail to discuss current ICES practices for the reference point estimation.

6.2 Reference points in the ICES framework

Reference point estimation is challenging and faces complications arising from poor assumptions in some models (e.g. static or stationary), and lack of contrast and reliability in the data (Mace 2001; Caddy 1996). The framework for reference points used for ICES advice has been carefully designed throughout the years taking these challenges into account to estimate appropriate reference points that are precautionary and aim for the sustainability of the stocks. Chapter 2 shows how the ICES framework has evolved in an intergovernmental setting influenced by policy and the legal needs of the countries that use the advice and scientific developments, starting with the precautionary approach and expanding to integrate the maximum sustainable yield approach. In ICES, there has been an increasing focus on the role of reference points and the processes used to estimate them, several ICES working groups have addressed and identified concerns related to reference points (e.g. ICES 2020c; ICES 2021e). As an international advisory agency, it is crucial to understand ICES reference points (interpretation and estimation) underlying their scientific advice. For this reason, the outcomes of Chapter 2 on reference point estimation are valuable. Chapter 2 shows how multiple precautionary components and sources of stochasticity and uncertainty are included into the current reference point ICES framework.

In the ICES framework, the biomass limit reference point (B_{lim}) is the key precautionary approach reference point and plays a pivotal role in classifying the condition of the stock and determining if recruitment is likely to be impaired. Chapter 2 revealed that the framework for selecting the method used to estimate B_{lim} needs to be simplified. This is crucial because the choice of the estimation method is the most influential factor in the value of B_{lim} (Deurs et al. 2021). This framework, currently, depends on the classification of stocks into stock-recruitment typologies based on stock graphical characteristics (recruitment, spawning stock biomass and stock-recruitment relationship). This critically important classification would benefit from simplification and the development of quantitative criteria to assess the characteristics of the stocks. Additionally, new scientific research should be included in the framework. A recent study on the allee effect (depensation at low population sizes) has important implications to define B_{lim}; Perälä et al. (2022) demonstrated for Newfoundland Atlantic cod that there is allee effect and identified the allee-effect threshold below which recovery is impaired. To be more precautionary, the allee effect should be analysed to define B_{lim} (Perälä et al. 2022).

The ICES working group WKREF1 has proposed to reduce the framework to 3 types to define B_{lim}: (1) with a clear stock-recruitment break point, (2) with no clear break point, and (3) spasmodic recruitment. They have also proposed to include the possibility to determine B_{lim} as a percentage of the unfished biomass (B_0) based on biological principles and life history of the stocks for stock with no clear break point (ICES 2022b). In other regions, such as the United States, the biomass limit reference point can be based on percentages of B_0, which is not presently included in the ICES guidelines. Current ICES guidelines recommend when no impaired recruitment has been observed and no clear relationship between recruitment and spawner biomass is present, that the B_{lim} should be set to the lowest biomass observed (B_{loss}). The lowest biomass observed has been considered to have no biological underpining (ICES 2022b). Percentages of B_0 proxy reference points are typically used in areas where spawner and recruitment data are not sufficiently informative for many stocks (i.e. productivity at low sizes is highly uncertain)(Preece et al. 2011). The level of B_0 in relation to B_{lim} depends on life history characteristics and therefore is stock specific (Mace 1994). For some stocks, appropriate levels of B_0 might be difficult to find within safe biological levels (ICES 2022c). During WKREF2 there was no consensus on whether the suggestions to simplify the framework made in WKREF1 should replace the current guidelines, and further work and tests on reference point candidates were recommended (ICES 2022c). For simplifying the method to select B_{lim}, a better understanding of these proxy is needed. It would be helpful to compare selected percentages of B_0 with current values of B_{lim} in a stock basis. Suggestions for improvements of the ICES framework based on this thesis research are discussed in the section 6.8 below.

A particularly challenging type of stock to manage is a stock with spasmodic recruitment, where single data points can be highly influential (Licandeo et al. 2020; Spencer and Collie 1997). For stocks with these characteristics, productivity is complex because they have sporadic year classes with very high recruitment but these are difficult to predict (Licandeo et al. 2020). Spasmodic stocks (stock type 1), in ICES, are characterized by having sporadic recruitment year classes considerably higher than the rest of year classes (ICES 2021c). Classifying a stock as spasmodic is not straightforward; in Chapter 2 a criterion is developed based on cumulative distribution functions which have the potential to help the classification of stocks. Using the cumulative distribution function, after removing low frequency variability, can be used to identify high variance and infrequent strong recruitment.

The empirical review of reference points in the ICES region, conducted in Chapter 2, highlights that the relationship and historical context of stock and recruitment is crucial for MSY-based and limit reference points. Understanding the stock-recruitment relationship is pivotal to reliably estimate non-proxy MSY reference points (Punt 2010; Shepherd 1982; Conn et al. 2010). Having contrast in spawning stock biomass and recruitment data is important to help understand this relationship. However, high variability in recruitment and non-stationarity can hinder the ability to understand this relationship (Minto et al. 2008; Perälä et al. 2017; Minto et al. 2014; Hilborn and Walters 1992; Myers 1994; Myers 2001; Thorson et al. 2014). The ICES tool EqSim to estimate stochastic reference points can model stock-recruitment relationship including several functional forms and implementing autocorrelation and stochastic predictive distribution of recruitment plus the simulated observation error (Chapter 2). This aims to account for stock-recruitment model structure uncertainty and recruitment interannual variability. High variability in recruitment and catches can be accounted for by the exclusion of extreme values (Chapter 2). Dealing with recruitment variation and variable stock-recruitment relationship is crucial and has important implications for the estimation of reference points (Sharma et al. 2019). Many of the points made further in this discussion relate to this issue.

Chapter 2 identifies that an improved framework would involve better documentation and extended guidelines for estimating and updating reference points. Reference points estimation need transparency (Hilborn 2002); a major recommendation in Chapter 2 is to provide a well documented, transparent and reproducible framework to estimate reference points such as the recently developed TAF (Transparent Assessment Framework; `https://taf.ices.dk/app/about`). The TAF is an online resource of ICES stock assessments for each assessment year, where the assessment (code, data input and output) can be openly found. This framework, extended to reference point estimation, would allow access to estimation details and enable the ability to re-run the estimation with new data or methods.

6.3 Changes in reference points over time

Typically reference points are estimated as long-term targets or limits (Rindorf et al. 2017b; Chapter3) but used on a short-term basis to set Total Allowable Catches. Many agencies report on the status of fish stocks relative to reference points and recent high-profile papers report on the status of assessed fisheries globally via aggregating status indicators and reporting on global trends relative to the reference point representing the sustainability goal (Fernandes and Cook 2013; Hilborn et al. 2020). However, in practice, reference points are considered to be valid in the medium term by most advice agencies, particularly MSY-based reference points (ICES 2019a). Reference points are commonly reviewed and re-estimated as required by changes in environmental and ecological conditions and new scientific information and understanding (ICES 2021a). In Chapter 3, we showed that reference points change over time, reflecting changing population and fishery dynamics and understanding thereof, which suggests that reference points are better described as reference series. Instead of assessing historical status of stocks relative to the most recent reference point (such as done in the previously mentioned studies), reference series should also be used when inferring historical sustainability and reporting on global trends.

Notably, changes in reference points are often not compensated by changes in the state or fishing rate of the stock, which has a significant impact on the stock sustainability status (Chapter 3). During the ICES review process in benchmark meetings, a blend of changes can occur: (i) changes in understanding and methodology, (ii) new data, (iii) updated parameters (e.g. natural mortality, maturity, weights-at-age), (iv) change in the reference point technical basis, and (v) regime shifts detection. In Chapter 3, important reasons for changes in reference points were changes to the definition and technical basis for their estimation. Separating and assessing fundamentally different reasons for change is valuable but difficult and can only be achieved if the framework is transparent and reproducible and there is extensive documentation (discussed in section 6.8 below).

Management advice on fishing opportunities is based on stock sustainability status indicators (Punt 2010; ICES 2021a). As demonstrated in Chapter 3, changes in reference points affect the perception of status and therefore fishing advice with important implications for management. The occurrence of these changes is unavoidable as policy can evolve, the science advances, our understanding improves, and new tools are developed. For example, during WKREF1 and WKREF2 (ICES 2022b; ICES 2022c), changes to the ICES reference point framework were proposed. Implementation of changes to the framework can risk social license and therefore should be extensively documented with clear terminology and rationale (ICES 2022c). Besides, changes in stock productivity (Vert-pre et al. 2013; Minto et al. 2014; Clausen et al. 2018) and climate change can impact reference points (Free et al. 2019). Not taking into account these important productivity changes in reference points could undermine social license (Silvar-Viladomiu et al. 2022b), but communication with managers and stakeholders is crucial in this process, otherwise they may view changes in reference points as reflecting poor knowledge or previous errors (Rindorf et al. 2017b).

6.4 Adaptations to changes in productivity

During the process of reviewing reference points, the presence of regime shifts influencing productivity was evaluated (Chapter 2; Chapter 3). In ICES, full spawning and recruitment time series are used unless there is very strong evidence of regime change, when the time series was truncated to estimate reference points (Chapter 2, Chapter 3). Most current approaches to deal with productivity changes in reference points estimation are mainly developed for changes of an abrupt nature that are persistent over time (i.e. one regime shift). Given an abrupt change, a shorter time series of recent data is thought to perform better at informing on the current population status (Zhang et al. 2021b). Common approaches to deal with regime shifts are defining a moving window or truncating the time series used (A'Mar et al. 2009; King et al. 2015). To truncate or shorten the time series, the main difficulty is the identification and selection of the data that represents the present regime (Punt et al. 2014c). Variability in recruitment can hinder the ability to detect regime changes in productivity (King et al. 2015). Selection of the data can be done by expert assessment or using algorithms. A widely used algorithm to identify regime shifts is the Sequential Test Algorithm of Regime Shifts (STARS; Rodionov 2004). Another method is the Bayesian online change-point detection (BOCPD) which demonstrated the ability to detect productivity regime shits in Atlantic cod stocks (Perälä and Kuparinen 2015). Using algorithms in the ICES framework could improve the selection of time series to derive reference points, although shortening the time series still has limitations.

Shortening time series data to estimate reference points risks losing relevant information from earlier periods and, therefore, creates errors in reference point estimates (ICES 2021e). Deurs et al. (2021) found that biomass limit reference points are sensitive to the length of the time series used being a major source of uncertainty. Truncating time series might translate into losing contrast over short time series and therefore unreliable referent point estimates. Short time series data reduce the ability to account for measurement error due to reduced sample size (Zhang et al. 2021b). Reducing time series can also lead to greater variance and greater risk when there are no such changes (Szuwalski and Punt 2013; Punt et al. 2014a). The uncertainty associated with incorrectly identifying changes in productivity may depend on the life history of the species (Berger 2019). Investigations on regime shift approaches in management strategy evaluations showed that truncating time series may lead to imprecise reference points when the regime was not captured exactly (e.g. when using relatively few data points creates noisy estimates, or when the system is non-regime based) (Szuwalski and Punt 2013).

Changes in productivity are important and difficult to both detect and take into account in the estimation of reference points (Collie et al. 2021; Peterman et al. 2003; King et al. 2015). Most current approaches are focused on regime shifts, nevertheless, changes in productivity can be of a different nature (e.g. gradual). The use of dynamic B_0 was proposed as a dynamic proxy reference point to account for changes in productivity (Berger 2019; King et al. 2015; Punt et al. 2014c). The use of $\mathrm{F}_{\mathrm{eco}}$ has been proposed to adapt fishing mortality to changes in productivity, using the outputs of an ecosystem model of the region (Bentley et al. 2021; ICES 2020b; Howell et al. 2021). In the next section, I elaborate on why the method highlighted in Chapter 4 can contribute to the evolution of MSY-based reference points in the context of changing ecosystems by tracking temporal changes in productivity.

6.5 Peterman's Productivity Method as a link to non-stationary ecosystem concerns

In Chapter 4 (Silvar-Viladomiu et al. 2022b), Peterman's productivity method (PPM) is highlighted as a possible link between stationary single-species reference point approaches and changing ecosystem concerns by using dynamic models for defining reference points for fisheries advice. Professor Randall Peterman and colleagues developed this method which includes time-varying parameters in the stock-recruitment model (Peterman et al. 2000). This is a state-space method that permits separating important temporal trends from less important inter-annual variation, which is one of the biggest challenges faced by fisheries scientists and managers when trying to detect changes in productivity (Peterman et al. 2003; Dorner et al. 2008; Minto et al. 2014; Holt and Peterman 2004).

The MSY is based on a long-term equilibrium paradigm, by definition, MSY is "the highest theoretical equilibrium yield that can be continuously taken (on average) from a stock under existing (average) environmental conditions without affecting significantly the reproduction process" (FAO 1995a). However, environmental conditions are not stable and the ecosystems which stocks inhabit are dynamic (Fogarty et al. 2016). Additionally, climate change will bring new challenges, as the productivity of individual stocks change affecting reference points (Free et al. 2019). Global analyses have shown that if reference points do not account for non-stationary changes in productivity, the underlying management theory, with respect to sustainable yield, is incorrect and time-invariant equilibrium-based reference points will be inefficient or risky (Vert-pre et al. 2013; Britten et al. 2017).

Initial static and deterministic interpretations of equilibrium reference points have evolved to account for variation and include stochastic elements (Chapter 2). In current time-invariant approaches, the stock-recruitment relationship is typically modelled as a stationary process with an error around constant parameters. The next step could be towards estimating dynamic reference points to define sustainability in changing ecosystems using PPM which is capable of accounting for temporal changes in the underlying productivity via time-varying parameters (Minto et al. 2014; Peterman et al. 2003). With this approach fishing, population and ecosystem processes affecting recruitment would be integrated into reference points to help inform management decisions.

Current stationary stock-recruitment models fail to explain the data and the temporal variation (Mueter et al. 2007; Dorner et al. 2018; Chapter4). This is clear evidence of the existence of temporal changes in recruitment productivity. Current approaches, like the ones used by ICES (Chapter 2), take into account autocorrelation for the recruitment residuals of the stock-recruitment model according to an AR(1) process, while the PPM takes into account shifts in productivity and captures the dynamics of the integrated signal on recruitment by including a process on the parameter describing variation in time (Peterman et al. 2003; Dorner et al. 2008; Minto et al. 2014):

$$\alpha_{t+1} = \alpha_t + \omega_t \tag{6.1}$$

This is fundamentally different from projecting the residuals of a static stock-recruitment relationship with an autocorrelated process because the latter assumes reversion to the mean. In a mean-reverting process, the parameter will revert to the long-term mean or averaged level of the data.

Overall, PPM has proved capable of capturing the underlying ecosystem signal in recruitment in several studies (e.g. Minto et al. 2014; Tableau et al. 2019). PPM provides a more holistic view of the ecosystem temporal dynamics reflected in time-varying parameters of recruitment productivity (Dorner et al. 2008; Minto et al. 2014) and allows for more flexibility in the estimation of time-varying reference points (Chapter 4). Thus, this approach may provide an excellent opportunity to deliver on some of the requirements of EBFM in tactical fisheries management (Minto et al. 2014; Chapter4).

The main advantages of the PPM approach are that it is not necessary to understand and project ecosystem changes nor to identify the current ecosystem regime and there is no need to shorten the time series. As discussed in Chapter 4, this method does not investigate mechanistic insights into the processes affecting productivity, but, how productivity is changing. Contrary to ecosystem models (e.g. Bentley et al. 2021) or multispecies models (e.g. Plagányi et al. 2014) that need extensive amounts of data (e.g. stomach content, environmental variables, ecological variables), this method is capable of increasing model complexity and inferring on the underlying signal without requiring additional data. An important advantage is its immediate application to management advice, as it can be applied without understanding the process that caused the change (Peterman et al. 2003; Minto et al. 2014; Chapter4). These advantages are critical in fisheries issues because time and data are important constraining factors, as advice on fishing opportunities for many stocks is given annually and often data is limited in stock assessments (ICES 2022c; Chapter 2).

Including PPM in the estimation of reference points capture productivity dynamics and offers a view of how productivity changes, providing a link between single-species models and non-stationarity ecosystem concerns (Chapter 4). PPM has been shown to improve short-term forecast power compared to time-invariant models (Tableau et al. 2019). Notably, the utility of PPM goes beyond forecasting because it can directly inform sustainable harvest practices, such as the research of Collie et al. (2012) and Collie et al. (2021). Using stochastic dynamic programming Collie et al. (2021) contrasted static, myopic (where the future productivity is unknown; Walters and Parma 1996) and optimal parameter harvest control rules over future horizons. They demonstrated the importance of updating reference points according to PPM adapting to changes in productivity, especially at low stock sizes.

Estimability problems can arise on state-space models (Auger-Méthé et al. 2016). Difficulties have been found when estimating parameters, particularly when the measurement or observation error is much larger than the process variation. Estimability problems, such as the ones found in Chapter 5 for the univariate model, might be resolved with longer time series or multivariate approaches (Minto et al. 2014; Tableau et al. 2019). Whilst further investigation into robust estimation methods is needed, attempting to separate low from high-frequency variability and interannual noise in recruitment productivity is more general than fixing the parameters or using static parameters that only allow for observation error around a constant recruitment function (Peterman et al. 2003; Holt and Peterman 2004; Dorner et al. 2008; Minto et al. 2014). Areas of improvement of PPM are discussed in section 6.8 below.

6.6 Stochastic recruitment productivity dynamics in Celtic Seas ecoregion

The ICES Celtic Seas ecoregion is an important region for commercial fishing for many countries in the European Union (ICES 2019b). The findings in Chapter 5 could have critical implications for management advice of Celtic Seas ecoregion stocks. Changes in productivity over time were identified for many stocks and intriguing differences were found between time-invariant and present time-varying productivity levels for some stocks.

Overall, in the Celtic Seas ecoregion, there was no evidence of one coherent trend in fish recruitment productivity. These trends may be describing the response of fish stock productivity to the underlying dynamics in the ecosystem. The analysis presented in Chapter 5 suggests that Celtic Seas stocks are responding to combined multiple effects (e.g. fisheries and climate). Free et al. (2019) found different responses in the direction and magnitude of population productivity to warming. Other studies of time-varying productivity have found coherent signals for nearby stocks of the same species (Minto et al. 2008; Tableau et al. 2019; Peterman and Dorner 2012). Minto et al. (2014) analyzed temporal productivity trends of Atlantic Cod and found that adjacent stocks exhibited similar productivity patterns with the strength of covariation declining over distance. In the Celtic Seas ecoregion, correlated productivity patterns were found for cod, but this did not hold for all stocks of the same species (Chapter 5).

Findings in Chapter 5 permit us to conclude that there are trends in productivity in the Celtic Seas ecoregion. Given our incomplete knowledge of the dynamic processes linking ecosystem change and stock productivity, tracking how productivity changes with PPM is crucial and can inform management decisions (Dorner et al. 2008; Minto et al. 2014). These should be accounted for in science, advice and management, with the exploration of dynamic productivity in management strategy evaluations for example. If there is an ecosystem trend driving a directional fish productivity trend, then the stationary assumptions of the single-species approach of historical long-term time-invariant productivity do not hold and there will be increasing bias as time passes. This is especially significant in the presence of long-term trends of declining productivity (e.g. cod stocks in the Celtic Seas ecoregion) for which there might be important bias in time-invariant reference points.

Reference ranges for management plans have been estimated for some stock in the Celtic Seas ecoregion (e.g. Rockal haddock, western English Channel and southern Celtic Seas cod, western english Channel sole, southern Celtic Seas and western English Channel whiting). These upper and lower levels of fishing mortality are consistent with ranges resulting in no more than 5% reduction in long-term yield compared with MSY (Rindorf et al. 2017a), which gives flexibility to the reference point. For salmon stocks in Ireland, river-specific reference points ranges have been estimated, incorporating natural variability

(White et al. 2016). Estimation of time-varying reference points applying PPM for the Celtic Seas ecoregion stocks would integrate temporal productivity variation into the reference point (Chapter 4). Including time-varying reference points into the evaluation of the stocks and investigating the trade-off of not responding to changing productivity would be valuable for the management of the stocks in the ecoregion (Chapter 5).

6.7 Time-varying recruitment productivity and management advice

An increasing number of studies are finding evidence of time-varying parameters in the stock-recruitment relationship (Dorner et al. 2008; Minto et al. 2014; Britten et al. 2016; Tableau et al. 2019; Malick and Cox 2016; Peterman and Dorner 2012; Szuwalski et al. 2019; Chapter 5). These studies show that temporal changes in productivity can be of different natures, e.g. abrupt, persistent, fluctuate, gradual increases or declines. These changes in recruitment productivity affect reference points (Holt and Michielsens 2020; Zhang et al. 2021a; Chapter4). As empirical evidence in fish populations accumulates, management advice is required to revisit the traditional assumptions of constant long-term MSY and reference points and emphasise the need for EBFM. As mentioned in the previous section, when applying PPM to estimate dynamic reference points, changes in productivity are tracked and the integrated underlying ecosystem signal on recruitment is incorporated. However, there are unresolved questions in terms of their application:

1. *What is the form of the change?* The form of the stochastic evolution can move from ARMA or random walks to other processes. Whatever their form is, trends in productivity have important implications for management (Walters 1987). Simulations showed that random walks performed well at tracking a wide variety of true underlying temporal trends (Peterman et al. 2000). Decadal random walks have been found to fit time-varying stock-recruitment parameters well across multiple studies with a wide range of stocks (e.g. Dorner et al. 2008; Minto et al. 2014; Holt and Peterman 2004; Tableau et al. 2019).

2. *Will the change in productivity persist?* In terms of management, it is imperative to consider the uncertainty about whether the change will last (Holt and Michielsens 2020). Ignoring persistent changes or long-term

directional trends in productivity, especially if productivity declines over time, results in unreliable time-invariant reference points. An important focus should be the analysis on detecting if there is a significant trend and taking it into account in management advice. If there is a regime shift from a higher productivity regime to a low-productivity regime the reference point will be biased and there will be an increased risk of overfishing (Vert-pre et al. 2013). Management advice should adapt to the change with caution in case the regime shifts back. When there is high uncertainty that the change in productivity will persist, changes in productivity in time-varying reference points can be used complementary to the time-invariant reference points to give insight to managers into stock productivity changes.

3. *How should management respond to changes in productivity to achieve management goals?* Implementing major changes in reference points and advised catch levels on an annual basis might be untenable (Tableau et al. 2019), therefore time-varying reference points need to be designed to account for changes in productivity in an optimal way for the overall management system. Management Strategy Evaluation (MSE) frameworks have a critical role in testing the tactical models and reference points (De Oliveira et al. 2009; Punt et al. 2014b). The question of how quickly and how much to respond to changes in estimated productivity parameters can be tested in simulation frameworks such as MSEs. These frameworks can be applied for testing tactical models and decisions made based on knowledge of productivity changes (King et al. 2015). Developing a full MSE applying PPM could be used to define how to optimally take into account variability in productivity for meeting management objectives (Randall Peterman *personal communication*). Studies with MSE could also be used to compare the effectiveness of different methods of dealing with non-stationarity (Randall Peterman *personal communication*). An MSE framework should be used before using time-varying reference points to inform management decisions. As suggested by Holt and Michielsens (2020), MSEs can be used to test time-varying productivity frameworks and determine whether time-varying productivity should be accounted for when estimating stock-recruitment parameters and deriving benchmark estimates. Simulation frameworks can evaluate the consequences of ignoring the changes in productivity when providing management advice. The choice of whether to adopt

PPM to estimate reference points to account for changes in productivity will depend on the choice of reference points and how they are used to inform management decisions and the underlying dynamics (Holt and Michielsens 2020). In simulations with dynamic B_0, Berger (2019) demonstrated that the performance of time-invariant and time-varying reference points is dependent upon combinations of stock productivity regime, fishing mortality regime, and species life history. Simulation of sustainable harvest strategies, similar to Zhang et al. (2021a), can test for case-specific time-varying parameters under different assumptions and their impacts on reference points.

6.8 Recommendations for future research

The reference point review in Chapter 2 conducted in the thesis pointed out several recommendations. Future research should focus on finding the best choices for B_{lim} definition due to its importance in the ICES reference point framework. Research is needed to develop quantitative criteria to define stock characteristics (i.e. spawning stock biomass, fishing mortality, and recruitment) and the choices of B_{lim}, to help the classification and to support reference point definition respectively. Findings in Chapter 3, on the importance of retrospective changes in reference points, revealed the value of identifying the reasons for change. Implementation of a transparent framework (similar to TAF) for estimating reference points would facilitate a reference point estimation process that could be replicated and allow for the separation of causes of change in reference points and estimate their relative impact.

Furthermore, the research conducted in Chapters 4 and 5 identified several areas for further development of PPM and the inclusion of ecosystem non-stationary concerns in fisheries advice for management. This section presents the main research fields identified:

Identifying the stock-recruitment parameter that varies in time is challenging (Chapter 5). Other studies have allowed both parameters to vary over time but independently (Britten et al. 2016; Szuwalski et al. 2019). More research is needed to refine statistical model selection criteria, and develop statistical tests to identify which parameters are varying. Simulation studies have shown that information criterion (AICc and BIC) while useful, tend to favour time-invariant models despite bias in parameter estimates (Holt and Michielsens

2020). Moreover, investigation is needed on application of ensemble models (Jardim et al. 2021) for different configurations of time-varying models.

While Peterman used the Kalman filter for the linearized Ricker model, PPM is not restricted to the use of the Kalman filter on the linearized Ricker. Most of the previous studies that apply PPM, implement the Ricker stock-recruitment model (e.g. Peterman et al. 2003; Dorner et al. 2008; Minto et al. 2014; Tableau et al. 2019). The Ricker parameter, α, is useful because it measures the maximum reproductive rate at low stock sizes (Ricker 1954). Although Ricker's model is convenient because of its easy linearization (Myers 2001), more research is needed to explore the estimation of time-varying parameters for other functional forms. In addition, other methods could be used to estimate time-varying parameters under different recruitment model structures (e.g. Laplace approximation in ADMB or TMB and MCMC). The Kalman filter has been widely used because it provides a powerful mechanism for estimating parameters and detecting various sources of noise (Zeng et al. 1998). More research is needed on how to implement these other estimation methods to expand the methodology.

Further work should evaluate the propagation of uncertainty from the stock assessment. In the reference point derivation, the parameters of the stock-recruitment relationship can be estimated inside or outside the stock assessment model (Sharma et al. 2019). In the areas advised by ICES, reference points are typically estimated outside the stock assessment model. On the one hand, a drawback of this approach is that both variables (stock size measured in spawning stock biomass and recruitment) are estimates of the assessment model and therefore have associated uncertainties and covariations (Brooks and Deroba 2015). Recruitment time series are sensitive to the assumptions of the model used to estimate them, which can impact the perception of variability (Dickey-Collas et al. 2015). Outside *post hoc* analyses have been considered to not adequately account for uncertainty and to overlook potential bias in assessment estimates and correlation between estimates (Brooks and Deroba 2015). On the other hand, the approach of estimating reference points inside the assessment model, typically used in integrated assessments (Punt et al. 2013), adds structure to the assessment model and can mitigate the error-in-variables problem. However, this is more susceptible to structure uncertainty if the model is misspecified (Carvalho et al. 2017). In addition, these approaches often fix stock-recruitment parameters. Overall, for both approaches, investigation is needed on accounting for uncertainty propagated from the assessment when applying PPM. There is a need to develop methods to incorporate uncertainty from the assessment model in recruitment and spawning stock biomass in the PPM analysis (e.g. MCMC samples from recruitment and spawning stock biomass estimation distribution).

The debate on whether stock assessment estimates can be used as data in subsequent analysis, has raised concerns about whether time series of stock dynamics were being determined by the models used to generate them rather than by the underlying ecological phenomena (Dickey-Collas et al. 2015). In real data applications, both assessment-based (Minto et al. 2014; Tableau et al. 2019) and survey-based (Perälä et al. 2017) dynamic recruitment productivity studies have found temporal changes in stock-recruitment parameters, but no studies have compared assessment-based and survey-based signals. Comparisons of external and internally estimated signals would help inform the debate on what is the integrated signal and what is the post-assessment artefact. To throw light on this issue it would be crucial for a study to compare results from survey-derived and assessment-derived PPM signals to assess the impact of the uncertainty carried from the previous model that estimates recruitment and spawning stock biomass. Some of this work is underway in the NOAA-funded Climate and Fisheries Adaptation funded project (Understanding Climate Impacts on Fish Stocks and Fisheries to Inform Sustainable Fisheries Management led by Jeremy Collie).

As discussed in the previous section, it is crucial to find appropriate management responses when productivity is changing. Simulation frameworks such as MSEs that offer a better understanding of management systems are key to evaluating the performance of using PPM and how to deal with productivity change (Holt and Michielsens 2020). Changes in productivity in simulation frameworks should be further explored to test non-stationary impacts, appropriate management responses, and outcome uncertainty. These can help analyse how to incorporate and propagate uncertainty and evaluate the consequences of violating the common assumptions and ensure outcomes are robust. More research is needed on how to optimally manage with time-varying reference points. Further work is needed comparing the performance of different management policies over future scenarios (such as Collie et al. 2021). FLBEIA is a bio-economic model that follows a MSE approach, which can evaluate different policies for multiple stocks and fleets (Garcia et al. 2017). Investigating dynamic recruitment productivity and time-varying reference points within FLBEIA and mixed fisheries contexts would be most relevant.

Lastly, in terms of EBFM, additional challenges remain. Further research is needed to have a holistic view of the system (especially in the context of climate change), for example, on ecosystem processes, geographic changes in spatial distribution (such as Payne et al. 2022), and impacts in non-target species. In particular, further research efforts should be made to identify environmental and biological drivers and improve understanding of the mechanism and process by which productivity change. This would improve predictability when forecasting future productivity to inform management decisions. Further research is needed to include biological and environmental drivers in state-space models. Tableau et al. (2019) applied PPM to model dynamic productivity of New England fish stocks and included sea surface temperature, the north Atlantic oscillation, the mid Atlantic cold pool, and the Gulf stream north wall index. However, no strong links were found. Knowledge of environmental drivers is relevant for understanding time variation in the productivity of fish stocks, therefore, further investigation would be very valuable to help understand those relationships.

Bibliography

A'Mar, T. Z., A. E. Punt and M. W. Dorn (2009). 'The evaluation of two management strategies for the gulf of Alaska walleye pollock fishery under climate change'. In: *ICES Journal of Marine Science*. DOI: 10.1093/icesjms/fsp044.

Aeberhard, W. H., J. M. Flemming and A. Nielsen (2018). 'Review of State-Space Models for Fisheries Science'. In: DOI: 10.1146/annurev-statistics-031017-100427.

Anon (1999). *Pacific salmon commission joint chinook technical committee report tcchinook*. Tech. rep. 99.

Anon (2020). *The UK Fisheries Act*. Tech. rep. URL: https://www.legislation.gov.uk/ukpga/2020/22/contents/enacted.

Auger-Méthé, M., C. Field, C. M. Albertsen, A. E. Derocher, M. A. Lewis, I. D. Jonsen and J. M. Flemming (2016). 'State-space models' dirty little secrets: Even simple linear Gaussian models can have estimation problems'. In: *Scientific Reports*. DOI: 10.1038/srep26677.

Auger-Méthé, M., K. Newman, D. Cole, F. Empacher, R. Gryba, A. A. King, V. Leos-Barajas, J. Mills Flemming, A. Nielsen, G. Petris and L. Thomas (2021). 'A guide to state–space modeling of ecological time series'. In: *Ecological Monographs* 91.4, ecm.1470. DOI: 10.1002/ecm.1470.

Barrowman, N. J. and R. A. Myers (2000). 'Still more spawner-recruitment curves: the hockey stick and its generalizations'. In: *Canadian Journal of Fisheries and Aquatic Sciences*. DOI: 10.1139/cjfas-57-4-665.

Benson, A. J. and R. L. Stephenson (2017). 'Options for integrating ecological, economic, and social objectives in evaluation and management of fisheries'. In: *Fish and Fisheries*. DOI: 10.1111/faf.12235.

Bentley, J. W., M. G. Lundy, D. Howell, S. E. Beggs, A. Bundy, F. de Castro, C. J. Fox, J. J. Heymans, C. P. Lynam, D. Pedreschi, P. Schuchert, N. Serpetti, J. Woodlock and D. G. Reid (2021). 'Refining Fisheries Advice With

Stock-Specific Ecosystem Information'. In: *Frontiers in Marine Science* 8. DOI: 10.3389/fmars.2021.602072.

Berger, A. M. (2019). 'Character of temporal variability in stock productivity influences the utility of dynamic reference points'. In: *Fisheries Research*. DOI: 10.1016/j.fishres.2018.11.028.

Beverton, R. J. H. and S. J. Holt (1957). *On the Dynamics of Exploited Fish Populations*. Vol. 4. 2, p. 540. DOI: 10.1007/BF00044132.

Beverton, R. J. H. and S. J. Holt (2004). *On the dynamics of exploited fish populations*. English. Caldwell (N.J.): Blackburn Press.

Bordet, C. and L. P. Rivest (2014). 'A stochastic Pella Tomlinson model and its maximum sustainable yield'. In: *Journal of Theoretical Biology* 360. DOI: 10.1016/j.jtbi.2014.06.012.

Bouch, P., C. Minto and D. G. Reid (2020). 'Comparative performance of data-poor CMSY and data-moderate SPiCT stock assessment methods when applied to data-rich, real-world stocks'. In: *ICES Journal of Marine Science*. Ed. by Shijie Zhou. DOI: 10.1093/icesjms/fsaa220.

Bousquet, N., T. Duchesne and L. P. Rivest (2008). 'Redefining the maximum sustainable yield for the Schaefer population model including multiplicative environmental noise'. In: *Journal of Theoretical Biology* 254.1. DOI: 10.1016/j.jtbi.2008.04.025.

Brander, K. M. (2007). *Global fish production and climate change*. DOI: 10.1073/pnas.0702059104.

Britten, G. L., M. Dowd, L. Kanary and B. Worm (2017). 'Extended fisheries recovery timelines in a changing environment'. In: *Nature Communications* 8.1, p. 15325. DOI: 10.1038/ncomms15325.

Britten, G. L., M. Dowd and B. Worm (2016). 'Changing recruitment capacity in global fish stocks'. In: *Proceedings of the National Academy of Sciences* 113.1, pp. 134–139. DOI: 10.1073/pnas.1504709112.

Brooks, E. N. and J. J. Deroba (2015). 'When "data" are not data: The pitfalls of post hoc analyses that use stock assessment model output'. In: *Canadian Journal of Fisheries and Aquatic Sciences*. DOI: 10.1139/cjfas-2014-0231.

Burgess, M. G., H. C. Giacomini, C. S. Szuwalski, C. Costello and S. D. Gaines (2017). 'Describing ecosystem contexts with single-species models: a theoretical synthesis for fisheries'. In: *Fish and Fisheries*. DOI: 10.1111/faf.12179.

Burnham, Kenneth P. and David R. Anderson (2004). *Multimodel inference: Understanding AIC and BIC in model selection*. DOI: 10.1177/0049124104268644.

Caddy, J F and R Mahone (1995). 'Reference points for fishery management'. In: *Fisheries Research* 347, p. 83. DOI: 10.1109/MRA.2005.1511869.

Caddy, J.F. (1996). 'Regime shifts and paradigm changes: is there still a place for equilibrium thinking?' In: *Fisheries Research* 25.3-4, pp. 219–230. DOI: 10.1016/0165-7836(95)00443-2.

Cadrin, S. X. (2012). 'Unintended Consequences of MSY Proxies for Defining Overfishing'. In: *ICES CM* L:23, p. 12.

Calcagno, V. and C. de Mazancourt (2010). 'glmulti : An R Package for Easy Automated Model Selection with (Generalized) Linear Models'. In: *Journal of Statistical Software* 34.12, p. 29. DOI: 10.18637/jss.v034.i12.

Cardinale, M., H. Dörner, A. Abella, J. L. Andersen, J. Casey, R. Döring, E. Kirkegaard, A. Motova, J. Anderson, E. J. Simmonds and C. Stransky (2013). 'Rebuilding EU fish stocks and fisheries, a process under way?' In: *Marine Policy* 39.1. DOI: 10.1016/j.marpol.2012.10.002.

Carvalho, F., A. E. Punt, Y. Chang, M. N. Maunder and K. R. Piner (2017). 'Can diagnostic tests help identify model misspecification in integrated stock assessments?' In: *Fisheries Research* 192, pp. 28–40. DOI: 10.1016/j.fishres.2016.09.018.

Casini, M., J. Lövgren, J. Hjelm, M. Cardinale, J. C. Molinero and G. Kornilovs (2008). 'Multi-level trophic cascades in a heavily exploited open marine ecosystem'. In: *Proceedings of the Royal Society B: Biological Sciences*. DOI: 10.1098/rspb.2007.1752.

Chagaris, D., K. Drew, A. Schueller, M. Cieri, J. Brito and A. Buchheister (2020). 'Ecological Reference Points for Atlantic Menhaden Established Using an Ecosystem Model of Intermediate Complexity'. In: *Frontiers in Marine Science*. DOI: 10.3389/fmars.2020.606417.

Christensen, V. (2010). 'MEY = MSY'. In: *Fish and Fisheries* 11.1, pp. 105–110. DOI: 10.1111/j.1467-2979.2009.00341.x.

Clausen, L. W., A. Rindorf, M. van Deurs, M. Dickey-Collas and N. T. Hintzen (2018). 'Shifts in North Sea forage fish productivity and potential fisheries yield'. In: *Journal of Applied Ecology* 55.3. Ed. by Robert Arlinghaus, pp. 1092–1101. DOI: 10.1111/1365-2664.13038.

Collie, J. S., R. J. Bell, S. B. Collie and C. Minto (2021). 'Harvest strategies for climate-resilient fisheries'. In: *ICES Journal of Marine Science*. DOI: 10.1093/icesjms/fsab152.

Collie, J. S., L. W. Botsford, A. Hastings, I. C. Kaplan, J. L. Largier, P. A. Livingston, E. Plagányi, K. A. Rose, B. K. Wells and F. E. Werner (2016). 'Ecosystem models for fisheries management: finding the sweet spot'. In: *Fish and Fisheries* 17.1, pp. 101–125. DOI: 10.1111/faf.12093.

Collie, J. S. and H. Gislason (2001). 'Biological reference points for fish stocks in a multispecies context'. In: *Canadian Journal of Fisheries and Aquatic Sciences* 58.11, pp. 2167–2176. DOI: 10.1139/cjfas-58-11-2167.

Collie, J. S., C. Minto, B. Worm and R. Bell (2013). 'Predation on prerecruits can delay rebuilding of depleted COD stocks'. In: *Bulletin of Marine Science*. DOI: 10.5343/bms.2011.1134.

Collie, J. S., R. M. Peterman and B. M. Zuehlke (2012). 'A fisheries risk-assessment framework to evaluate trade-offs among management options in the presence of time-varying productivity'. In: *Canadian Journal of Fisheries and Aquatic Sciences* 69.2. Ed. by Yong Chen, pp. 209–223. DOI: 10.1139/f2011-148.

Conn, P. B., E. H. Williams and K. W. Shertzer (2010). 'When can we reliably estimate the productivity of fish stocks?' In: *Canadian Journal of Fisheries and Aquatic Sciences*. DOI: 10.1139/f09-194.

Cowan, J. H., J. C. Rice, C. J. Walters, R. Hilborn, T. E. Essington, J. W. Day and K. M. Boswell (2012). 'Challenges for Implementing an Ecosystem Approach to Fisheries Management'. In: *Marine and Coastal Fisheries*. DOI: 10.1080/19425120.2012.690825.

Crone, P. R., M. N. Maunder, H. H. Lee and K. R. Piner (2019). 'Good practices for including environmental data to inform spawner-recruit dynamics in integrated stock assessments: Small pelagic species case study'. In: *Fisheries Research*. DOI: 10.1016/j.fishres.2018.12.026.

Cushing, D. H (1975). *Marine ecology and fisheries*. Cambridge University Press Cambridge ; New York, xiv, 278 p.

Cushing, D. H. (1973). 'Dependence of Recruitment on Parent Stock'. In: *Journal of the Fisheries Research Board of Canada* 30.12, pp. 1965–1976. DOI: 10.1139/f73-320.

Daskalov, G. M., A. N. Grishin, S. Rodionov and V. Mihneva (2007). 'Trophic cascades triggered by overfishing reveal possible mechanisms of ecosystem regime shifts'. In: *Proceedings of the National Academy of Sciences of the*

United States of America 104.25, pp. 10518–10523. DOI: 10.1073/pnas.0701100104.

De Oliveira, J. A. A., L. T. Kell, A. E. Punt, B. A. Roel and D. S. Butterworth (2009). 'Managing without best Predictions: The Management Strategy Evaluation Framework'. In: *Advances in Fisheries Science*. Oxford, UK: Blackwell Publishing Ltd., pp. 104–134. DOI: 10.1002/9781444302653.ch6.

Deurs, M., M. E. Brooks, M. Lindegren, O. Henriksen and A. Rindorf (2021). 'Biomass limit reference points are sensitive to estimation method, time-series length and stock development'. In: *Fish and Fisheries* 22.1, pp. 18–30. DOI: 10.1111/faf.12503.

Deyle, E. R., M. Fogarty, C. H. Hsieh, L. Kaufman, A. D. MacCall, S. B. Munch, C. T. Perretti, H. Ye and G. Sugihara (2013). 'Predicting climate effects on Pacific sardine'. In: *Proceedings of the National Academy of Sciences of the United States of America*. DOI: 10.1073/pnas.1215506110.

Dichmont, C. M., R. A. Deng, A. E. Punt, J. Brodziak, Y. Chang, J. M. Cope, J. N. Ianelli, C. M. Legault, R. D. Methot, C. E. Porch, M. H. Prager and K. W. Shertzer (2016). 'A review of stock assessment packages in the United States'. In: *Fisheries Research* 183, pp. 447–460. DOI: 10.1016/j.fishres.2016.07.001.

Dickey-Collas, M., N. T. Hintzen, R. D. M. Nash, P-J. Schön and M. R. Payne (2015). 'Quirky patterns in time-series of estimates of recruitment could be artefacts'. In: *ICES Journal of Marine Science* 72.1, pp. 111–116. DOI: 10.1093/icesjms/fsu022. URL: https://academic.oup.com/icesjms/article/72/1/111/821856.

Dolan, T. E., W. S. Patrick and J. S. Link (2016). 'Delineating the continuum of marine ecosystem-based management: a US fisheries reference point perspective'. In: *ICES Journal of Marine Science* 73.4, pp. 1042–1050. DOI: 10.1093/icesjms/fsv242.

Dorner, B., R. M. Peterman and S. L. Haeseker (2008). 'Historical trends in productivity of 120 Pacific pink, chum, and sockeye salmon stocks reconstructed by using a Kalman filter'. In: *Canadian Journal of Fisheries and Aquatic Sciences* 65.9. DOI: 10.1139/F08-094.

Dorner, Brigitte, Matthew J. Catalano and Randall M. Peterman (2018). 'Spatial and temporal patterns of covariation in productivity of Chinook salmon populations of the northeastern Pacific Ocean'. In: *Canadian*

Journal of Fisheries and Aquatic Sciences 75.7, pp. 1082–1095. DOI: 10.1139/cjfas-2017-0197.

Drinkwater, K. F., G. Beaugrand, M. Kaeriyama, S. Kim, G. Ottersen, R. I. Perry, H. O. Pörtner, J. J. Polovina and A. Takasuka (2010). 'On the processes linking climate to ecosystem changes'. In: *Journal of Marine Systems* 79.3-4. DOI: 10.1016/j.jmarsys.2008.12.014.

EC (2013). 'Common fisheries policy (CFP) Regulation No. 1380/2013 of the European Paliament and of the Council'. In: *Official Journal of the European Communities* 001, p. 354. DOI: 2004R0726-v.7of05.06.2013.

Evans, G. T. (1996). 'Using the elementary operations of sequential population analysis to display problems in catch or survey data'. In: *Canadian Journal of Fisheries and Aquatic Sciences* 53.2, pp. 239–243. DOI: 10.1139/f95-191.

FAO (1995a). 'Code of Conduct for Responsible Fisheries'. In: *Food and Agriculture Organization of the United Nations*. DOI: ISBN92-5-103834-5.

FAO (1995b). 'Precautionary approaches to fisheries. Part 1: Guidelines on the precautionary approach to capture fisheries and species introductions'. In: *FAO Fisheries Technical Paper*.

FAO (2003). *The Ecosystem Approach to Fisheries, FAO Technical Guidelines for Responsible Fisheries*. Tech. rep., p. 112. DOI: 10.1017/CBO9781107415324.004.

FAO (2020). *Proceedings of the International Symposium on Fisheries Sustainability: strengthening the science-policy nexus*. Vol. FAO Headqu. Rome. FAO, p. 116. DOI: 10.4060/ca9165en.

Fernandes, P. G. and R. M. Cook (2013). 'Reversal of Fish Stock Decline in the Northeast Atlantic'. In: *Current Biology* 23.15, pp. 1432–1437. DOI: 10.1016/j.cub.2013.06.016.

Field, J. C., A. D. MacCall, R. W. Bradley and W. J. Sydeman (2010). 'Estimating the impacts of fishing on dependent predators: a case study in the California Current'. In: *Ecological Applications* 20.8, pp. 2223–2236. DOI: 10.1890/09-0428.1.

Fogarty, M., L. Incze, K. Hayhoe, D. Mountain and J. Manning (2008). 'Potential climate change impacts on Atlantic cod (Gadus morhua) off the northeastern USA'. In: *Mitigation and Adaptation Strategies for Global Change* 13.5-6. DOI: 10.1007/s11027-007-9131-4.

Fogarty, M. J. (2014). 'The art of ecosystem-based fishery management'. In: *Canadian Journal of Fisheries and Aquatic Sciences* 71.3. Ed. by Kenneth Rose, pp. 479–490. DOI: 10.1139/cjfas-2013-0203.

Fogarty, M. J., R. Gamble and C. T. Perretti (2016). 'Dynamic Complexity in Exploited Marine Ecosystems'. In: *Frontiers in Ecology and Evolution* 4. DOI: 10.3389/fevo.2016.00068.

Fogarty, Michael J and Jeremy S Collie (2020). *Fishery Ecosystem Dynamics*. eng. Oxford: Oxford University Press, p. 336. DOI: 10.1093/oso/9780198768937.001.0001.

Frank, K. T., B. Petrie, J. S. Choi and W. C. Leggett (2005). 'Trophic Cascades in a Formerly Cod-Dominated Ecosystem'. In: *Science* 308.5728, pp. 1621–1623. DOI: 10.1126/science.1113075.

Free, C. M., J. T. Thorson, M. L. Pinsky, K. L. Oken, J. Wiedenmann and O. P. Jensen (2019). 'Impacts of historical warming on marine fisheries production'. In: *Science*. DOI: 10.1126/science.aau1758.

Fulton, E. A., A. D. M. Smith, D. C. Smith and P. Johnson (2014). 'An integrated approach is needed for ecosystem based fisheries management: Insights from ecosystem-level management strategy evaluation'. In: *PLoS ONE*. DOI: 10.1371/journal.pone.0084242.

Gabriel, W. L. and P. M. Mace (1999). 'A review of biological reference points in the context of the precautionary approach'. In: *Proceedings of the fifth national NMFS stock assessment workshop*.

Gaichas, S., R. Gamble, M. Fogarty, H. Benoît, T. Essington, C. Fu, M. Koen-Alonso and J. Link (2012). 'Assembly rules for aggregate-species production models: Simulations in support of management strategy evaluation'. In: *Marine Ecology Progress Series*. DOI: 10.3354/meps09650.

Gaines, S. D., C. Costello, B. Owashi, T. Mangin, J. Bone, J. G. Molinos, M. Burden, H. Dennis, B. S. Halpern, C. V. Kappel, K. M. Kleisner and D. Ovando (2018). 'Improved fisheries management could offset many negative effects of climate change'. In: *Science Advances* 4.8. DOI: 10.1126/sciadv.aao1378.

Garcia, D., P. Dolder, A. Iriondo, C. Moore and A. Urtizberea (2020). 'A multi-stock harvest control rule based on "pretty good yield" ranges to support mixed-fisheries management'. In: *ICES Journal of Marine Science* 77, pp. 119–135. DOI: 10.1093/icesjms/fsz181.

Garcia, D., S. Sánchez Maroño, R. Prellezo, A. Urtizberea and M. Andrés (2017). 'FLBEIA : A simulation model to conduct Bio-Economic evaluation of fisheries management strategies'. In: *SoftwareX* 6, pp. 141–147. DOI: 10.1016/j.softx.2017.06.001.

Garcia, S. M. (1996). 'The precautionary approach to fisheries and its implications for fishery research, technology and management: An updated review'. In: *Precautionary approach to fisheries. Part 2. FAO Fisheries Technical Paper*. 335.2.

Garstang, W. (1900). 'The Impoverishment of the Sea. A Critical Summary of the Experimental and Statistical Evidence bearing upon the Alleged Depletion of the Trawling Grounds'. In: *Journal of the Marine Biological Association of the United Kingdom* 6, pp. 1–69.

Geary, W. L., M. Bode, T. S. Doherty, E. A. Fulton, D. G. Nimmo, A. I. T. Tulloch, V. J. D. Tulloch and E. G. Ritchie (2020). 'A guide to ecosystem models and their environmental applications'. In: *Nature Ecology and Evolution*, pp. 1–13. DOI: 10.1038/s41559-020-01298-8.

Genner, M. J., D. W. Sims, V. J. Wearmouth, E. J. Southall, A. J. Southward, P. A. Henderson and S. J. Hawkins (2004). 'Regional climatic warming drives long-term community changes of British marine fish'. In: *Proceedings of the Royal Society B: Biological Sciences* 271.1539. DOI: 10.1098/rspb.2003.2651.

Geromont, H. F. and D. S. Butterworth (2015). *FAO Report : A review of assessment methods and the development of managemnet procedures for data-poor fisheries*. Tech. rep., p. 219.

Getz, W. and R. G. Haight (1989). *Population Harvesting: demographic models of fish, forest, and animal resources*. Princeton Univ Pr.

Gislason, H. (1999). 'Single and multispecies reference points for Baltic fish stocks'. In: *ICES Journal of Marine Science* 56.5, pp. 571–583. DOI: 10.1006/jmsc.1999.0492.

Gudmundsson, G. (1994). 'Time Series Analysis of Catch-At-Age Observations'. In: *Applied Statistics* 43.1, p. 117. DOI: 10.2307/2986116.

Gulland, J. A. (1988). *Fish Population Dynamics: The Implications for Management*. Jonh Wiley & Sons, p. 440.

Haltuch, M. A., E. N. Brooks, J. Brodziak, J. A. Devine, K. F. Johnson, N. Klibansky, R. D.M. Nash, M. R. Payne, K. W. Shertzer, S. Subbey and B. K. Wells (2019). 'Unraveling the recruitment problem: A review of environmentally-informed forecasting and management strategy evaluation'. In: *Fisheries Research*. DOI: 10.1016/j.fishres.2018.12.016.

Heath, M. R. (2005). 'Changes in the structure and function of the North Sea fish foodweb, 1973-2000, and the impacts of fishing and climate'. In: *ICES Journal of Marine Science* 62.5. DOI: 10.1016/j.icesjms.2005.01.023.

Hernvann, P. Y. and D. Gascuel (2020). 'Exploring the impacts of fishing and environment on the Celtic Sea ecosystem since 1950'. In: *Fisheries Research* 225. DOI: 10.1016/j.fishres.2019.105472.

Hilborn, R. (2010). 'Pretty Good Yield and exploited fishes'. In: *Marine Policy* 34.1, pp. 193–196. DOI: 10.1016/j.marpol.2009.04.013.

Hilborn, R. (2020). 'Measuring fisheries management performance'. In: *ICES Journal of Marine Science* 77.7-8. Ed. by Ernesto Jardim, pp. 2432–2438. DOI: 10.1093/icesjms/fsaa119.

Hilborn, R., R. O. Amoroso, C. M. Anderson, J. K. Baum, T. A. Branch, C. Costello, C. L. de Moor, A. Faraj, D. Hively, O. P. Jensen, H. Kurota, L. R. Little, P. M. Mace, T. McClanahan, M. C. Melnychuk, C. Minto, G. C. Osio, A. M. Parma, M. Pons, S. Segurado, C. S. Szuwalski, J. R. Wilson and Y. Ye (2020). 'Effective fisheries management instrumental in improving fish stock status'. In: *Proceedings of the National Academy of Sciences* 117.4, pp. 2218–2224. DOI: 10.1073/pnas.1909726116.

Hilborn, R., J. Maguire, A. M. Parma and A. A. Rosenberg (2001). 'The Precautionary Approach and risk management: can they increase the probability of successes in fishery management?' In: *Canadian Journal of Fisheries and Aquatic Sciences* 58.1, pp. 99–107. DOI: 10.1139/f00-225.

Hilborn, R. and C. J. Walters (1992). *Quantitative Fisheries Stock Assessment*. Boston, MA: Springer US, p. 570. DOI: 10.1007/978-1-4615-3598-0.

Hilborn, Ray (2002). 'The dark side of reference points'. In: *Bulletin of Marine Science* 70.2, pp. 403–08.

Hjort, J. (1914). 'Fluctuations in the great fisheries of Northern Europe viewed in the light of biological research'. In: *Rapports et Procès-Verbaux des Réunions* 20, pp. 1–228.

Hjort, J. (1933). 'The optimum catch'. In: *Hvalradets Skrifter* 7, pp. 92–127.

Hollowed, A. B. (2000). 'Are multispecies models an improvement on single-species models for measuring fishing impacts on marine ecosystems?' In: *ICES Journal of Marine Science* 57.3, pp. 707–719. DOI: 10.1006/jmsc.2000.0734.

Hollowed, A. B., K. Y. Aydin, T. E. Essington, J. N. Ianelli, B. A. Megrey, A. E. Punt and A. D. M. Smith (2011). 'Experience with quantitative ecosystem assessment tools in the northeast Pacific'. In: *Fish and Fisheries*. DOI: 10.1111/j.1467-2979.2011.00413.x.

Holmes, E. E., E. J. Ward and K. Wills (2012). 'MARSS: Multivariate autoregressive state-space models for analyzing time-series data'. In: *R Journal* 4.1. DOI: 10.32614/rj-2012-002.

Holt, C. A. and C. G. J. Michielsens (2020). 'Impact of time-varying productivity on estimated stock–recruitment parameters and biological reference points'. In: *Canadian Journal of Fisheries and Aquatic Sciences*. DOI: 10.1139/cjfas-2019-0104.

Holt, C. A. and R. M. Peterman (2004). 'Long-term trends in age-specific recruitment of sockeye salmon (Oncorhynchus nerka) in a changing environment'. In: *Canadian Journal of Fisheries and Aquatic Sciences* 61.12. DOI: 10.1139/f04-193.

Howell, D., A. M. Schueller, J. W. Bentley, A. Buchheister, D. Chagaris, M. Cieri, K. Drew, M. G. Lundy, D. Pedreschi, D. G. Reid and H. Townsend (2021). 'Combining Ecosystem and Single-Species Modeling to Provide Ecosystem-Based Fisheries Management Advice Within Current Management Systems'. In: *Frontiers in Marine Science* 7. DOI: 10.3389/fmars.2020.607831.

Hunsicker, M. E., L. Ciannelli, K. M. Bailey, J. A. Buckel, J. Wilson White, J. S. Link, Timothy E. Essington, S. Gaichas, T. W. Anderson, R. D. Brodeur, K. Chan, K. Chen, G. Englund, K. T. Frank, V. Freitas, M. A. Hixon, T. Hurst, D. W. Johnson, J. F. Kitchell, D. Reese, G. A. Rose, H. Sjodin, W. J. Sydeman, H. W. van der Veer, K. Vollset and S. Zador (2011). 'Functional responses and scaling in predator-prey interactions of marine fishes: contemporary issues and emerging concepts'. In: *Ecology Letters* 14.12, pp. 1288–1299. DOI: 10.1111/j.1461-0248.2011.01696.x.

Huxley, T. (1884). 'Inaugural address'. In: *Fisheries Exhibition Literature* 4, pp. 1–22.

Ianelli, J. N., A. B. Hollowed, A. C. Haynie, F. J. Mueter and N. A. Bond (2011). 'Evaluating management strategies for eastern Bering Sea walleye pollock (*Theragra chalcogramma*) in a changing environment'. In: *ICES Journal of Marine Science* 68.6. DOI: 10.1093/icesjms/fsr010.

ICES (1998). 'Report of the study group on the precautionary approach to fisheries management'. In: *ICES CM* ACFM:10, p. 43.

ICES (2001). 'The Study Group on the Further Development of the Precautionary Approach to Fishery Management (Copenhagen, 2-5 April 2001)'. In: *ICES CM* ACFM:11, p. 51.

ICES (2002). 'Study Group on the Further Development of the Precautionary Approach to Fisheries Management (Lisbon, 4-8 March 2002)'. In: *ICES CM* ACFM:10, p. 144.

ICES (2003a). 'Report of the Study Group on Precautionary Reference Points for Advice on Fishery Management (SGPRP), 24– 26 February 2003, ICES Headquarters, Copenhagen, Denmark'. In: *ICES CM* ACFM:15, p. 85.

ICES (2003b). 'Study Group on the Further Development of the Precautionary Approach to Fisheries Management (Lisbon, 4-8 March 2002)'. In: *ICES CM* ACFM:9, p. 144.

ICES (2007). 'Report of the Workshop on Limit and Target Reference Points (WKREF), 29 January – 2 February 2007, Gdynia, Poland'. In: *ICES CM 2007* ACOM: 54, p. 89.

ICES (2010). 'Report of the Workshop on Implementing the ICES F MSY framework (WKFRAME), 22- 26 March 2010, Copenhagen, Denmark'. In: *ICES CM 2010* ACOM: 54, p. 83.

ICES (2011). 'Report of the Workshop on Implementing the ICES Fmsy Framework (WKFRAME-2), 10-14 January 2011, ICES, Denmark'. In: *ICES CM* ACOM:33, p. 110.

ICES (2013). 'Report of the Workshop on Guidelines for Management Strategy Evaluations (WKGMSE), 21 - 23 January 2013, ICES HQ, Copenhagen, Denmark'. In: *ICES CM 2013* ACOM:39, p. 121. DOI: `ICESCM2013ACOM39`.

ICES (2014). 'Report of the Workshop to consider reference points for all stocks (WKMSYREF2)'. In: *ICES CM 2014* ACOM:47, p. 91.

ICES (2015a). *ICES Special Request Advice Greater North Sea and Baltic Sea Ecoregions Published.* Tech. rep., p. 11.

ICES (2015b). 'Report of the Joint ICES-MYFISH Workshop to consider the basis for FMSY ranges for all stocks (WKMSYREF3)'. In: *ICES CM 2015* 17–21 Nove, p. 156. DOI: `ICESCM2014/ACOM:64`.

ICES (2017a). 'ICES Advice Technical Guidelines. ICES fisheries management reference points for category 1 and 2 stocks'. In: *ICES Advice* Book 12.20 January, p. 19. DOI: `10.17895/ices.pub.3036`.

ICES (2017b). 'Report of the Workshop to consider FMSY ranges for stocks in ICES categories 1 and 2 in Western Waters (WKMSYREF4), 13–16

October 2015, Brest, France'. In: *ICES CM 2015* ACOM:58.58, p. 187. DOI: https://doi.org/10.17895/ices.pub.5348.

ICES (2018a). 'ICES Technical Guidelines. ICES reference points for stocks in categories 3 and 4'. In: *ICES Advice* 13 February, p. 50. DOI: https://doi.org/10.17895/ices.pub.3977.

ICES (2018b). 'Report of the Working Group on the Assessment of Demersal Stocks in the North Sea and Skagerrak (WGNSSK), 24 April-3 May, Oostende, Belgium'. In: *ICES CM* 2018/ACOM, p. 22.

ICES (2019a). *Advice basis.* DOI: https://doi.org/10.17895/ices.advice.5757.

ICES (2019b). 'Celtic Seas Ecoregion – Ecosystem overview'. In: *Report of the ICES Advisory Committee, 2019* Section 7.1. DOI: https://doi.org/10.17895/ices.advice.5749.

ICES (2019c). 'Workshop on North Sea Stocks Management Strategy Evaluation (WKNSMSE)'. In: *ICES Scientific Reports* 1.12, p. 378. DOI: 10.17895/ices.pub.5090.

ICES (2020a). 'The third Workshop on Guidelines for Management Strategy Evaluations (WKGMSE3)'. In: *ICES Scientific Reports* 2.116, p. 112. DOI: http://doi.org/10.17895/ices.pub.7627.

ICES (2020b). 'Workshop on an Ecosystem Based Approach to Fishery Management for the Irish Sea (WKIrish6; outputs from 2019 meeting)'. In: *ICES Scientific Reports* 2.3, p. 32. DOI: http://doi.org/10.17895/ices.pub.5551.

ICES (2020c). 'Workshop on guidelines and methods for the evaluation of rebuilding plans (WKREBUILD)'. In: *ICES Scientific Reports* 2.55, p. 79. DOI: http://doi.org/10.17895/ices.pub.6085.

ICES (2021a). 'Advice on fishing opportunities'. In: *ICES Technical Guidelines. In Report of the ICES Advisory Committee, 2021. ICES Advice 2021* section 1.1.1. DOI: https://doi.org/10.17895/ices.advice.7720.

ICES (2021b). 'Celtic Seas Ecoregion – Ecosystem overview'. In: *Report of the ICES Advisory Committee, 2021.* ICES Advice 2021, Section 7.1. DOI: https://doi.org/10.17895/ices.advice.7631.

ICES (2021c). 'ICES fisheries management reference points for category 1 and 2 stocks; Technical Guidelines.' In: *In Report of the ICES Advisory Committee* ICES Advic.March, pp. 1–19. DOI: https://doi.org/10.17895/ices.advice.7891.

ICES (2021d). *ICES Stock Assessment Graphs Database.*

ICES (2021e). ‘Workshop of Fisheries Management Reference Points in a Changing Environment (WKRPChange, outputs from 2020 meeting)’. In: *ICES Scientific Reports* 3.6, p. 39. DOI: `https://doi.org/10.17895/ices.pub.7660`.

ICES (2022a). *ICES Stock Assessment Graphs Database.*

ICES (2022b). ‘Workshop on ICES reference points (WKREF1)’. In: *ICES Scientific Reports* 4.2, p. 70. DOI: `http://doi.org/10.17895/ices.pub.9822`.

ICES (2022c). ‘Workshop on ICES reference points (WKREF2)’. In: *ICES Scientific Reports* 4.68, p. 96. DOI: `https://doi.org/10.17895/ices.pub.20557008.v1`.

Jackson, J. B. C. (2001). ‘Historical Overfishing and the Recent Collapse of Coastal Ecosystems’. In: *Science* 293.5530, pp. 629–637. DOI: `10.1126/science.1059199`.

Jardim, E., M. Azevedo, J. Brodziak, E. N. Brooks, K. F. Johnson, N. Klibansky, C. P. Millar, C. Minto, I. Mosqueira, R. D. M. Nash, P. Vasilakopoulos and B. K. Wells (2021). ‘Operationalizing ensemble models for scientific advice to fisheries management’. In: *ICES Journal of Marine Science* 78.4, pp. 1209–1216. DOI: `10.1093/icesjms/fsab010`.

Kell, L. T., R. D. M. Nash, M. Dickey-Collas, I. Mosqueira and C. Szuwalski (2016). ‘Is spawning stock biomass a robust proxy for reproductive potential?’ In: *Fish and Fisheries* 17.3, pp. 596–616. DOI: `10.1111/faf.12131`.

Kell, L. T., G. M. Pilling, G. P. Kirkwood, M. Pastoors, B. Mesnil, K. Korsbrekke, P. Abaunza, R. Aps, A. Biseau, P. Kunzlik, C. Needle, B.A . Roel and C. Ulrich-Rescan (2005). ‘An evaluation of the implicit management procedure used for some ICES roundfish stocks’. In: *ICES Journal of Marine Science* 62.4, pp. 750–759. DOI: `10.1016/j.icesjms.2005.01.001`.

Kempf, A., J. Mumford, P. Levontin, A. Leach, A. Hoff, K. G. Hamon, H. Bartelings, M. Vinther, M. Stäbler, J. J. Poos, S. Smout, H. Frost, S. van den Burg, C. Ulrich and A. Rindorf (2016). ‘The MSY concept in a multi-objective fisheries environment - Lessons from the North Sea’. In: *Marine Policy* 69, pp. 146–158. DOI: `10.1016/j.marpol.2016.04.012`.

Kempf, J., P. Breen, E. Rogan and D. G. Reid (2022). ‘Trends in the abundance of Celtic Sea demersal fish: Identifying the relative importance of fishing and environmental drivers’. In: *Frontiers in Marine Science* 9. DOI: `10.3389/fmars.2022.978654`.

King, J. R., G. A. McFarlane and A. E. Punt (2015). 'Shifts in fisheries management: adapting to regime shifts'. In: *Philosophical Transactions of the Royal Society B: Biological Sciences* 370.1659, p. 20130277. DOI: 10.1098/rstb.2013.0277.

Kristiansen, T., K. F. Drinkwater, R. G. Lough and S. Sundby (2011). 'Recruitment variability in North Atlantic cod and match-mismatch dynamics'. In: *PLoS ONE*. DOI: 10.1371/journal.pone.0017456.

Kvamsdal, S. F., A. Eide, N. Ekerhovd, K. Enberg, A. Gudmundsdottir, A. H. Hoel, K. E. Mills, F. J. Mueter, L. Ravn-Jonsen, L. K. Sandal, J. E. Stiansen and N. Vestergaard (2016). 'Harvest control rules in modern fisheries management'. In: *Elementa: Science of the Anthropocene* 4.000114. Ed. by Jody W. Deming and Rögnvaldur Hannesson, pp. 1–22. DOI: 10.12952/journal.elementa.000114.

Larkin, P. A. (1977). 'An Epitaph for the Concept of Maximum Sustained Yield'. In: *Transactions of the American Fisheries Society* 106.1, pp. 1–11. DOI: 10.1577/1548-8659(1977)106<1:AEFTCO>2.0.CO;2.

Lassen, H., C. Kelly and M. Sissenwine (2014). 'ICES advisory framework 1977–2012: from Fmax to precautionary approach and beyond'. In: *ICES Journal of Marine Science* 71.2, pp. 166–172. DOI: 10.1093/icesjms/fst146.

Lewy, P. and M. Vinther (2004). 'A stochastic age-length-structured multispecies model applied to North Sea stocks'. In: *ICES C.M.*, p. 33.

Licandeo, Roberto, Daniel E. Duplisea, Caroline Senay, Julie R. Marentette and Murdoch K. McAllister (2020). 'Management strategies for spasmodic stocks: A canadian atlantic redfish fishery case study'. In: *Canadian Journal of Fisheries and Aquatic Sciences*. DOI: 10.1139/cjfas-2019-0210.

Lindegren, M., C. Möllmann, A. Nielsen and N. C. Stenseth (2009). 'Preventing the collapse of the Baltic cod stock through an ecosystem-based management approach'. In: *Proceedings of the National Academy of Sciences of the United States of America* 106.34. DOI: 10.1073/pnas.0906620106.

Lindmark, M., A. Audzijonyte, J. L. Blanchard and A. Gårdmark (2022). 'Temperature impacts on fish physiology and resource abundance lead to faster growth but smaller fish sizes and yields under warming'. In: *Global Change Biology* October 2021, pp. 1–15. DOI: 10.1111/gcb.16341.

Litzow, Michael A., Mary E. Hunsicker, Nicholas A. Bond, Brian J. Burke, Curry J. Cunningham, Jennifer L. Gosselin, Emily L. Norton, Eric J. Ward and Stephani G. Zador (2020). 'The changing physical and ecological meanings of North Pacific Ocean climate indices'. In: *Proceedings of the National Academy of Sciences* 117.14, pp. 7665–7671. DOI: 10.1073/pnas.1921266117.

Lucey, S. M., K. Y. Aydin, S. K. Gaichas, S. X. Cadrin, G. Fay, M. J. Fogarty and A. E. Punt (2021). 'Evaluating fishery management strategies using an ecosystem model as an operating model'. In: *Fisheries Research* 234, p. 105780. DOI: 10.1016/j.fishres.2020.105780.

Ludwig, D., R. Hilborn and C. Walters (1993). 'Uncertainty, Resource Exploitation, and Conservation: Lessons from History'. In: *Science* 260.5104, pp. 17–36. DOI: 10.1126/science.260.5104.17.

Lynam, C. P., C. Cusack and D. Stokes (2010). 'A methodology for community-level hypothesis testing applied to detect trends in phytoplankton and fish communities in Irish waters'. In: *Estuarine, Coastal and Shelf Science* 87.3. DOI: 10.1016/j.ecss.2010.01.019.

Mace, P. M. (1994). 'Relationships between Common Biological Reference Points Used as Thresholds and Targets of Fisheries Management Strategies'. In: *Canadian Journal of Fisheries and Aquatic Sciences* 51.1, pp. 110–122. DOI: 10.1139/f94-013.

Mace, P. M. (2001). 'A new role for MSY in single-species and ecosystem approaches to fisheries stock assessment and management'. In: *Fish and Fisheries* 2.1, pp. 2–32. DOI: 10.1046/j.1467-2979.2001.00033.x.

Mackinson, S., B. Deas, D. Beveridge and J. Casey (2009). 'Mixed-fishery or ecosystem conundrum? Multispecies considerations inform thinking on long-term management of North Sea demersal stocks'. In: *Canadian Journal of Fisheries and Aquatic Sciences* 66.7. Ed. by Kenneth Rose, pp. 1107–1129. DOI: 10.1139/F09-057.

Malick, M. J. and S. P. Cox (2016). 'Regional-scale declines in productivity of pink and chum salmon stocks in western North America'. In: *PLoS ONE* 11.1. DOI: https://doi.org/10.1371/journal.pone.0146009.

Marchal, P., J. Levring Andersen, M. Aranda, M. Fitzpatrick, L. Goti, O. Guyader, G. Haraldsson, A. Hatcher, T. Jacob Hegland, P. Le Floc'h, C. Macher, L. Malvarosa, C. D. Maravelias, S. Mardle, A. Murillas, R. J. Nielsen, R. Sabatella, A. D. M. Smith, K. Stokes, T. Thoegersen and C. Ulrich (2016). 'A comparative review of fisheries management experiences in the European Union and in other countries worldwide: Iceland, Australia, and New Zealand'. In: *Fish and Fisheries* 17.3, pp. 803–824. DOI: 10.1111/faf.12147.

Marshall, K. N., L. E. Koehn, P. S. Levin, T. E. Essington and O. P. Jensen (2019). 'Inclusion of ecosystem information in US fish stock assessments suggests progress toward ecosystem-based fisheries management'. In: *ICES Journal of Marine Science* 76.1. Ed. by Marta Coll, pp. 1–9. DOI: 10.1093/icesjms/fsy152.

Maunder, M. and R. Deriso (2014). 'Proposal for biomass and fishing mortality limit reference points based on reduction in recruitment'. In: *IATTC Stock Assessment Report*. Vol. 15, pp. 193–206.

Maunder, M. N. and A. E. Punt (2013). 'A review of integrated analysis in fisheries stock assessment'. In: *Fisheries Research* 142, pp. 61–74. DOI: 10.1016/j.fishres.2012.07.025.

Maunder, M. N. and J. T. Thorson (2019). 'Modeling temporal variation in recruitment in fisheries stock assessment: A review of theory and practice'. In: *Fisheries Research* 217, pp. 71–86. DOI: 10.1016/j.fishres.2018.12.014.

May, R. M., J. R. Beddington, C. W. Clark, S. J. Holt and R. M. Laws (1979). 'Management of Multispecies Fisheries'. In: *Science* 205.4403, pp. 267–277. DOI: 10.1126/science.205.4403.267.

Mesnil, B. and M. Rochet (2010). 'A continuous hockey stick stock–recruit model for estimating MSY reference points'. In: *ICES Journal of Marine Science* 67.8, pp. 1780–1784. DOI: 10.1093/icesjms/fsq055.

Methot, R. D. and C. R. Wetzel (2013). 'Stock synthesis: A biological and statistical framework for fish stock assessment and fishery management'. In: *Fisheries Research* 142, pp. 86–99. DOI: 10.1016/j.fishres.2012.10.012.

Mildenberger, T. K., C. W. Berg, M. W. Pedersen, A. Kokkalis and J. R. Nielsen (2019). 'Time-variant productivity in biomass dynamic models on seasonal and long-term scales'. In: *ICES Journal of Marine Science*. Ed. by Shijie Zhou. DOI: 10.1093/icesjms/fsz154.

Millar, R. B. and R. Meyer (2000). 'Non-linear state space modelling of fisheries biomass dynamics by using Metropolis-Hastings within-Gibbs sampling'. In: *Journal of the Royal Statistical Society: Series C (Applied Statistics)* 49.3, pp. 327–342. DOI: 10.1111/1467-9876.00195.

Minto, C., J. Mills Flemming, G. Lee Britten and B. Worm (2014). 'Productivity dynamics of Atlantic cod'. In: *Canadian Journal of Fisheries and Aquatic Sciences* 71.2. Ed. by Kenneth Rose, pp. 203–216. DOI: 10.1139/cjfas-2013-0161.

Minto, C., R. A. Myers and W. Blanchard (2008). 'Survival variability and population density in fish populations'. In: *Nature* 452.7185, pp. 344–347. DOI: 10.1038/nature06605.

Minto, C. and B. Worm (2012). 'Interactions between small pelagic fish and young cod across the North Atlantic'. In: *Ecology* 93.10, pp. 2139–2154. DOI: 10.1890/10-2036.1.

Moffitt, E. A., A. E. Punt, K. Holsman, K. Y Aydin, J. N. Ianelli and I. Ortiz (2016). 'Moving towards ecosystem-based fisheries management: Options for parameterizing multi-species biological reference points'. In: *Deep Sea Research Part II: Topical Studies in Oceanography* 134, pp. 350–359. DOI: 10.1016/j.dsr2.2015.08.002.

Möllmann, C. and R. Diekmann (2012). 'Marine Ecosystem Regime Shifts Induced by Climate and Overfishing. A Review for the Northern Hemisphere'. In: *Advances in Ecological Research*. Vol. 47. DOI: 10.1016/B978-0-12-398315-2.00004-1.

MSA (2007). 'Magnuson-Stevens Fishery Conservation and Management Act'. In: *U.S. Government (2007) Public Law 94-265*, p. 170.

Mueter, Franz J., Jennifer L. Boldt, Bernard A. Megrey and Randall M. Peterman (2007). 'Recruitment and survival of Northeast Pacific Ocean fish stocks: temporal trends, covariation, and regime shifts'. In: *Canadian Journal of Fisheries and Aquatic Sciences* 64.6, pp. 911–927. DOI: 10.1139/f07-069.

Myers, R. (1994). 'In search of thresholds for recruitment overfishing'. In: *ICES Journal of Marine Science* 51.2, pp. 191–205. DOI: 10.1006/jmsc.1994.1020. URL: https://academic.oup.com/icesjms/article-lookup/doi/10.1006/jmsc.1994.1020.

Myers, R. A. (1998). 'When do environment-recruitment correlations work?' In: *Reviews in Fish Biology and Fisheries*, pp. 285–305. DOI: 10.1023/A:1008828730759.

Myers, R. A. (2001). 'Stock and recruitment: Generalizations about maximum reproductive rate, density dependence, and variability using meta-analytic approaches'. In: *ICES Journal of Marine Science* 58.5. DOI: 10.1006/jmsc.2001.1109.

Myers, R. A., K. G. Bowen and N. J. Barrowman (1999). 'Maximum reproductive rate of fish at low population sizes'. In: *Canadian Journal of Fisheries and Aquatic Sciences* 56.12. DOI: 10.1139/f99-201.

Myers, R. A., J. A. Hutchings and N. J. Barrowman (1996). *Hypotheses for the decline of cod in the North Atlantic.* DOI: 10.3354/meps138293.

Nesslage, G. M. and M. J. Wilberg (2019). 'A performance evaluation of surplus production models with time-varying intrinsic growth in dynamic ecosystems'. In: *Canadian Journal of Fisheries and Aquatic Sciences* 76.12, pp. 2245–2255. DOI: 10.1139/cjfas-2018-0292.

Nielsen, A. and C. W. Berg (2014). 'Estimation of time-varying selectivity in stock assessments using state-space models'. In: *Fisheries Research* 158, pp. 96–101. DOI: 10.1016/j.fishres.2014.01.014.

Nielsen, R. J., E. Thunberg, D. S. Holland, J. O. Schmidt, E. A. Fulton, F. Bastardie, A. E. Punt, I. Allen, H. Bartelings, M. Bertignac, E. Bethke, S. Bossier, R. Buckworth, G. Carpenter, A. Christensen, V. Christensen, J. M. Da-Rocha, R. Deng, C. Dichmont, R. Doering, A. Esteban, J. A. Fernandes, H. Frost, D. Garcia, L. Gasche, D. Gascuel, S. Gourguet, R. A. Groeneveld, J. Guillén, O. Guyader, K. G. Hamon, A. Hoff, J. Horbowy, T. Hutton, S. Lehuta, L. R. Little, J. Lleonart, C. Macher, S. Mackinson, S. Mahevas, P. Marchal, R. Mato-Amboage, B. Mapstone, F. Maynou, M. Merzéréaud, A. Palacz, S. Pascoe, A. Paulrud, E. Plaganyi, R. Prellezo, E. I. van Putten, M. Quaas, L. Ravn-Jonsen, S. Sanchez, S. Simons, O. Thébaud, M. T. Tomczak, C. Ulrich, D. van Dijk, Y. Vermard, R. Voss and S. Waldo (2018). 'Integrated ecological-economic fisheries models-Evaluation, review and challenges for implementation'. In: *Fish and Fisheries* 19.1, pp. 1–29. DOI: 10.1111/faf.12232.

NOAA Fisheries (2016). *National Standard 1- Optimum Yield.* (Visited on 08/12/2021).

NOAA Fisheries (2021). *Stock SMART data records.* (Visited on 08/12/2021).

Ohlberger, J., O. Langangen and L. C. Stige (2022). 'Age structure affects population productivity in an exploited fish species'. In: *Ecological Applications.* DOI: 10.1002/eap.2614.

Ottersen, G., B. Planque, A. Belgrano, E. Post, P. C. Reid and N. C. Stenseth (2001). *Ecological effects of the North Atlantic Oscillation.* DOI: 10.1007/s004420100655.

Ottersen, G., L. C. Stige, J. M. Durant, K. S. Chan, T. A. Rouyer, K. F. Drinkwater and N. C. Stenseth (2013). 'Temporal shifts in recruitment dynamics of North Atlantic fish stocks: Effects of spawning stock and temperature'. In: *Marine Ecology Progress Series* 480. DOI: 10.3354/meps10249.

Parsons, L. S. and W. H. Lear (2001). *Climate variability and marine ecosystem impacts: A north Atlantic perspective.* DOI: 10.1016/S0079-6611(01)00021-0.

Patrick, W. S. and J. S. Link (2015). 'Hidden in plain sight: Using optimum yield as a policy framework to operationalize ecosystem-based fisheries management'. In: *Marine Policy*. DOI: 10.1016/j.marpol.2015.08.014.

Pauly, D. and R. Froese (2021). 'MSY needs no epitaph—but it was abused'. In: *ICES Journal of Marine Science* 78.6. Ed. by Emory Anderson, pp. 2204–2210. DOI: 10.1093/icesjms/fsaa224.

Payne, M. R., G. Danabasoglu, N. Keenlyside, D. Matei, A. K. Miesner, S. Yang and S. G. Yeager (2022). 'Skilful decadal-scale prediction of fish habitat and distribution shifts'. In: *Nature Communications* 13.1, p. 2660. DOI: 10.1038/s41467-022-30280-0.

Pella, J. J. (1993). 'Utility of structural time series models and the Kalman Filter for predicting consequences of fishery actions'. In: *Proceedings of the International Symposium on Management Strategies for Exploited Fish Populations*, pp. 571–628.

Pella, J. J. and P. K. Tomlinson (1969). 'A generalized stock production model'. In: *Bulletin. Inter-American Tropical Tuna Commission* 13.3, pp. 421–458.

Perälä, T., J. A. Hutchings and A. Kuparinen (2022). 'Allee effects and the Allee-effect zone in northwest Atlantic cod'. In: *Biology Letters* 18.2. DOI: 10.1098/rsbl.2021.0439.

Perälä, T. and A. Kuparinen (2015). 'Detecting regime shifts in fish stock dynamics'. In: *Canadian Journal of Fisheries and Aquatic Sciences*. DOI: 10.1139/cjfas-2014-0406.

Perälä, T., E. M. Olsen and J. A. Hutchings (2020). 'Disentangling conditional effects of multiple regime shifts on Atlantic cod productivity'. In: *PLoS ONE*. DOI: 10.1371/journal.pone.0237414.

Perälä, T. A., D. P. Swain and A. Kuparinen (2017). 'Examining nonstationarity in the recruitment dynamics of fishes using Bayesian change point analysis'. In: *Canadian Journal of Fisheries and Aquatic Sciences* 74.5, pp. 751–765. DOI: 10.1139/cjfas-2016-0177.

Perryman, H. A., C. Hansen, D. Howell and E. Olsen (2021). 'A Review of Applications Evaluating Fisheries Management Scenarios through Marine Ecosystem Models'. In: *Reviews in Fisheries Science and Aquaculture* 29.4, pp. 800–835. DOI: 10.1080/23308249.2021.1884642.

Pershing, A. J., M. A. Alexander, C. M. Hernandez, L. A. Kerr, A. Le Bris, K. E. Mills, J. A. Nye, N. R. Record, H. A. Scannell, J. D. Scott, G. D. Sherwood and A. C. Thomas (2015). 'Slow adaptation in the face of rapid warming leads to collapse of the Gulf of Maine cod fishery'. In: *Science* 350.6262, pp. 809–812. DOI: 10.1126/science.aac9819.

Peterman, R. M. and B. Dorner (2012). 'A widespread decrease in productivity of sockeye salmon (Oncorhynchus nerka) populations in western North America'. In: *Canadian Journal of Fisheries and Aquatic Science* 69, pp. 1255–1260. DOI: 10.1139/F2012-063.

Peterman, R. M., B. J Pyper and B. W. MacGregor (2003). 'Use of the Kalman filter to reconstruct historical trends in productivity of Bristol Bay sockeye salmon (Oncorhynchus nerka)'. In: *Canadian Journal of Fisheries and Aquatic Sciences* 60.7, pp. 809–824. DOI: 10.1139/f03-069.

Peterman, R. M., B. J. Pyper and J. A. Grout (2000). 'Comparison of parameter estimation methods for detecting climate-induced changes in productivity of Pacific salmon (¡i¿Oncorhynchus¡/i¿ spp.)' In: *Canadian Journal of Fisheries and Aquatic Sciences* 57.1, pp. 181–191. DOI: 10.1139/cjfas-57-1-181.

Petris, G., S. Petrone and P. Campagnoli (2009). 'Dynamic Linear Models with R'. In: *Journal of Applied Statistics - J APPL STAT*. Vol. 38, pp. 31–84. DOI: 10.1007/b135794_2.

Plagányi, E., E. Punt, R. Hillary, E. B. Morello, O. Thébaud, T. Hutton, R. D. Pillans, J. T. Thorson, E. A. Fulton, A. D. M. Smith, F. Smith, P. Bayliss, M. Haywood, V. Lyne and P. C. Rothlisberg (2014). 'Multispecies fisheries management and conservation: tactical applications using models of intermediate complexity'. In: *Fish and Fisheries* 15.1, pp. 1–22. DOI: 10.1111/j.1467-2979.2012.00488.x.

Planque, B., J. M. Fromentin, P. Cury, K. F. Drinkwater, S. Jennings, R. I. Perry and S. Kifani (2010). *How does fishing alter marine populations and ecosystems sensitivity to climate?* DOI: 10.1016/j.jmarsys.2008.12.018.

Preece, A., R. Hillary and C. Davies (2011). *Identification of candidate limit reference points for the key target species in WCPFCWCPFC-SC7-2011/MI-WP-03*. Tech. rep.

Privitera-Johnson, K. M. and A. E. Punt (2020). 'Leveraging scientific uncertainty in fisheries management for estimating among-assessment variation in overfishing limits'. In: *ICES Journal of Marine Science* 77.2. Ed. by Shijie Zhou, pp. 515–526. DOI: 10.1093/icesjms/fsz237.

Punt, A. E. (2010). 'Harvest Control Rules and Fisheries Management'. In: *Handbook of marine fisheries conservation and management*. Oxford University Press, Inc., pp. 598–610.

Punt, A. E., T. A'mar, N. A. Bond, D. S. Butterworth, C. L. de Moor, J. A. A. De Oliveira, M. A. Haltuch, A. B. Hollowed and C. Szuwalski (2014a). 'Fisheries management under climate and environmental uncertainty: control rules and performance simulation'. In: *ICES Journal of Marine Science* 71.8, pp. 2208–2220. DOI: `10.1093/icesjms/fst057`.

Punt, A. E., D. S. Butterworth, C. L. de Moor, J. De Oliveira and M. Haddon (2014b). 'Management strategy evaluation: best practices'. In: *Fish and Fisheries* 17.2, pp. 303–334. DOI: `10.1111/faf.12104`.

Punt, A. E., J. Day, G. Fay, M. Haddon, N. Klaer, R. L. Little, K. Privitera-Johnson, A. D.M. Smith, D. C. Smith, M. Sporcic, R. Thomson, G. N. Tuck, J. Upston and S. Wayte (2018). 'Retrospective investigation of assessment uncertainty for fish stocks off southeast Australia'. In: *Fisheries Research* 198, pp. 117–128. DOI: `10.1016/j.fishres.2017.10.007`.

Punt, A. E., T. Huang and M. N. Maunder (2013). 'Review of integrated size-structured models for stock assessment of hard-to-age crustacean and mollusc species'. In: *ICES Journal of Marine Science* 70.1, pp. 16–33. DOI: `10.1093/icesjms/fss185`.

Punt, A. E., A. D. M. Smith, D. C. Smith, G. N. Tuck and N. L. Klaer (2014c). 'Selecting relative abundance proxies for BMSY and BMEY'. In: *ICES Journal of Marine Science* 71.3, pp. 469–483. DOI: `10.1093/icesjms/fst162`.

Quinn, T. J. (2003). 'Ruminations on the development and future of population dynamics models in fisheries'. In: *Natural Resource Modeling* 16.4, pp. 341–392. DOI: `10.1111/j.1939-7445.2003.tb00119.x`.

Quinn, T. J. and J. S. Collie (2005). 'Sustainability in single–species population models'. In: *Philosophical Transactions of the Royal Society B: Biological Sciences* 360.1453. Ed. by J. R. Beddington and G. P. Kirkwood, pp. 147–162. DOI: `10.1098/rstb.2004.1577`.

Quinn, T. J. and R. B. Deriso (1999). *Quantitative fish dynamics*. Oxford University Press, p. 560.

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

Reid, P. C., R. E. Hari, G. Beaugrand, D. M. Livingstone, C. Marty, D. Straile, J. Barichivich, E. Goberville, R. Adrian, Y. Aono, R. Brown, J. Foster, P. Groisman, P. Hélaouët, H. H. Hsu, R. Kirby, J. Knight, A. Kraberg, J. Li, T. T. Lo, R. B. Myneni, R. P. North, J. A. Pounds, T. Sparks, R. Stübi, Y. Tian, K. H. Wiltshire, D. Xiao and Z. Zhu (2016). 'Global impacts of the 1980s regime shift'. In: *Global Change Biology* 22.2. DOI: 10.1111/gcb.13106.

Restrepo, V. R., P. M. Mace and F. M. Serchuk (1999). 'The precautionary approach: a new paradigm or business as usual'. In: *Our living oceans. Report on the status of US living marine resources*, pp. 61–70.

Ricard, D., C. Minto, O. P. Jensen and J. K. Baum (2012). 'Examining the knowledge base and status of commercially exploited marine species with the RAM Legacy Stock Assessment Database'. In: *Fish and Fisheries* 13.4, pp. 380–398. DOI: 10.1111/j.1467-2979.2011.00435.x.

Richardson, A. J. and D. S. Schoeman (2004). 'Climate impact on plankton ecosystems in the Northeast Atlantic'. In: *Science* 305.5690. DOI: 10.1126/science.1100958.

Ricker, W. E. (1954). 'Stock and Recruitment'. In: *Journal of the Fisheries Research Board of Canada* 11.5, pp. 559–623. DOI: 10.1139/f54-039.

Rindorf, A., M. Cardinale, S. Shephard, J. A. A. De Oliveira, E. Hjorleifsson, A. Kempf, A. Luzenczyk, C. Millar, D. C. M. Miller, C. L. Needle, J. Simmonds and M. Vinther (2017a). 'Fishing for MSY: using "pretty good yield" ranges without impairing recruitment'. In: *ICES Journal of Marine Science* 74.2. Ed. by Emory Anderson, pp. 525–534. DOI: 10.1093/icesjms/fsw111.

Rindorf, A., C. M. Dichmont, J. Thorson, A. Charles, L. W. Clausen, P. Degnbol, D. Garcia, N. T. Hintzen, A. Kempf, P. Levin, P. M. Mace, C. Maravelias, C. Minto, J. Mumford, S. Pascoe, R. Prellezo, A. E. Punt, D. G. Reid, C. Röckmann, R. L. Stephenson, O. Thebaud, G. Tserpes and R. Voss (2017b). 'Inclusion of ecological, economic, social, and institutional considerations when setting targets and limits for multispecies fisheries'. In: *ICES Journal of Marine Science* 74.2, pp. 453–463. DOI: 10.1093/icesjms/fsw226.

Rodionov, S. N. (2004). 'A sequential algorithm for testing climate regime shifts'. In: *Geophysical Research Letters* 31.9, n/a–n/a. DOI: 10.1029/2004GL019448.

Rose, G. A. (2004). 'Reconciling overfishing and climate change with stock dynamics of Atlantic cod (Gadus morhua) over 500 years'. In: *Canadian*

Journal of Fisheries and Aquatic Sciences 61.9, pp. 1553–1557. DOI: 10.1139/f04-173.

Russell, E. S. (1931). 'Some theoretical Considerations on the "Overfishing" Problem'. In: *ICES Journal of Marine Science* 6.1, pp. 3–20. DOI: 10.1093/icesjms/6.1.3.

Schaefer, M. B. (1954). 'Some aspects of the dynamics of populations important to the management of the commercial Marine fisheries'. In: *Inter-American Tropical Tuna Commission* 1.2, pp. 23–56.

Schnute, J. T. (1994). 'A General Framework for Developing Sequential Fisheries Models'. In: *Canadian Journal of Fisheries and Aquatic Sciences* 51.8, pp. 1676–1688. DOI: 10.1139/f94-168.

Schnute, J. T. and R. Haigh (2006). 'Reference points and management strategies: lessons from quantum mechanics'. In: *ICES Journal of Marine Science* 63.1, pp. 4–11. DOI: 10.1016/j.icesjms.2005.07.011.

Schnute, J. T. and L. J. Richards (1995). 'The influence of error on population estimates from catch-age models'. In: *Canadian Journal of Fisheries and Aquatic Sciences* 52.10, pp. 2063–2077. DOI: 10.1139/f95-800.

Sharma, R., C. E. Porch, E. A. Babcock, M. N. Maunder and A. E. Punt (2019). 'Recruitment: Theory, estimation, and application in fishery stock assessment models'. In: *Fisheries Research* 217, pp. 1–4. DOI: 10.1016/j.fishres.2019.03.015.

Shepherd, J. G. (1982). 'A versatile new stock-recruitment relationship for fisheries, and the construction of sustainable yield curves'. In: *ICES Journal of Marine Science* 40.1, pp. 67–75. DOI: 10.1093/icesjms/40.1.67.

Shepherd, J. G. and D. H. Cushing (1990). 'Regulation in fish populations: myth or mirage?' In: *Philosophical Transactions - Royal Society of London, B* 330.1257. DOI: 10.1098/rstb.1990.0189.

Silvar-Viladomiu, P., L. Batts, C. Minto, D. Miller and C. Lordan (2022a). 'An empirical review of ICES reference points'. In: *ICES Journal of Marine Science* 79, pp. 2563–2578. DOI: https://doi.org/10.1093/icesjms/fsac194.

Silvar-Viladomiu, P., C. Minto, D. Brophy and D. G. Reid (2022b). 'Peterman's productivity method for estimating dynamic reference points in changing ecosystems'. In: *ICES Journal of Marine Science* 79. Ed. by Sam Subbey, pp. 1034–1047. DOI: 10.1093/icesjms/fsac035.

Silvar-Viladomiu, P., C. Minto, G. Halouani, L. Batts, D. Brophy, C. Lordan and D. G. Reid (2021). 'Moving reference point goalposts and implications for fisheries sustainability'. In: *Fish and Fisheries* 22.6, pp. 1345–1358. DOI: 10.1111/faf.12591.

Simmonds, E. J., A. Campbell, D. Skagen, B. A. Roel and C. Kelly (2011). 'Development of a stock–recruit model for simulating stock dynamics for uncertain situations: the example of Northeast Atlantic mackerel (Scomber scombrus)'. In: *ICES Journal of Marine Science* 68.5, pp. 848–859. DOI: 10.1093/icesjms/fsr014.

Sissenwine, M. M., P. M. Mace and H. J. Lassen (2014). 'Preventing overfishing: evolving approaches and emerging challenges'. In: *ICES Journal of Marine Science* 71.2, pp. 153–156. DOI: 10.1093/icesjms/fst236.

Sissenwine, M. M. and J. G. Shepherd (1987). 'An Alternative Perspective on Recruitment Overfishing and Biological Reference Points'. In: *Canadian Journal of Fisheries and Aquatic Sciences* 44.4, pp. 913–918. DOI: 10.1139/f87-110.

Skern-Mauritzen, M., G. Ottersen, N. O. Handegard, G. Huse, G. E. Dingsør, N. C. Stenseth and O. S. Kjesbu (2016). 'Ecosystem processes are rarely included in tactical fisheries management'. In: *Fish and Fisheries* 17.1, pp. 165–175. DOI: 10.1111/faf.12111.

Smith, Tim D. (1994). *Scaling Fisheries: The Science of Measuring the Effects of Fishing, 1855–1955*. Cambridge Studies in Applied Ecology and Resource Management. Cambridge University Press. DOI: 10.1017/CBO9780511470868.

Spencer, P. D. and J. S. Collie (1997). 'Patterns of population variability in marine fish stocks'. In: *Fisheries Oceanography* 6.3. DOI: 10.1046/j.1365-2419.1997.00039.x.

Stenseth, N. C., O. N. Bjørnstadf, W. Falck, J. M. Fromentin, J. Gjøsieter and J. S. Gray (1999). 'Dynamics of coastal cod populations: intra- and intercohort density dependence and stochastic processes'. In: *Proceedings of the Royal Society of London. Series B: Biological Sciences* 266.1429, pp. 1645–1654. DOI: 10.1098/rspb.1999.0827.

Stige, L. C., G. Ottersen, K. Brander, K. S. Chan and N. C. Stenseth (2006). *Cod and climate: Effect of the North Atlantic Oscillation on recruitment in the North Atlantic*. DOI: 10.3354/meps325227.

Subbey, S., J. A. Devine, U. Schaarschmidt and R. D.M. Nash (2014). 'Modelling and forecasting stock–recruitment: current and future perspectives'. In: *ICES Journal of Marine Science* 71.8, pp. 2307–2322. DOI: 10.1093/icesjms/fsu148.

Sugihara, G., R. May, H. Ye, C. Hsieh, E. Deyle, M. Fogarty and S. Munch (2012). 'Detecting Causality in Complex Ecosystems'. In: *Science* 338.6106, pp. 496–500. DOI: 10.1126/science.1227079.

Sullivan, P. J. (1992). 'A Kalman Filter Approach to Catch-at-Length Analysis'. In: *Biometrics* 48.1, p. 237. DOI: 10.2307/2532752.

Swain, D. P. and A. F. Sinclair (2000). 'Pelagic fishes and the cod recruitment dilemma in the Northwest Atlantic'. In: *Canadian Journal of Fisheries and Aquatic Sciences* 57.7, pp. 1321–1325. DOI: 10.1139/f00-104.

Szuwalski, C. S., G. L. Britten, R. Licandeo, R. O. Amoroso, R. Hilborn and C. Walters (2019). 'Global forage fish recruitment dynamics: A comparison of methods, time-variation, and reverse causality'. In: *Fisheries Research* 214, pp. 56–64. DOI: 10.1016/j.fishres.2019.01.007.

Szuwalski, C. S. and A. B. Hollowed (2016). 'Climate change and non-stationary population processes in fisheries management'. In: *ICES Journal of Marine Science* 73.5, pp. 1297–1305. DOI: 10.1093/icesjms/fsv229.

Szuwalski, C. S. and A. E. Punt (2013). 'Fisheries management for regime-based ecosystems: a management strategy evaluation for the snow crab fishery in the eastern Bering Sea'. In: *ICES Journal of Marine Science* 70.5, pp. 955–967. DOI: 10.1093/icesjms/fss182.

Tableau, A., J. S. Collie, R. J. Bell and C. Minto (2019). 'Decadal changes in the productivity of New England fish populations'. In: *Canadian Journal of Fisheries and Aquatic Sciences* 76.9, pp. 1528–1540. DOI: 10.1139/cjfas-2018-0255.

Thorson, J. T., O. P. Jensen and E. F. Zipkin (2014). 'How variable is recruitment for exploited marine fishes? A hierarchical model for testing life history theory'. In: *Canadian Journal of Fisheries and Aquatic Sciences* 71.7. DOI: 10.1139/cjfas-2013-0645.

Thorson, J. T. and C. Minto (2015). 'Mixed effects: a unifying framework for statistical modelling in fisheries biology'. In: *ICES Journal of Marine Science* 72.5, pp. 1245–1256. DOI: 10.1093/icesjms/fsu213.

Thorson, J. T., A. O. Shelton, E. J. Ward and H. J. Skaug (2015). 'Geostatistical delta-generalized linear mixed models improve precision for estimated abundance indices for West Coast groundfishes'. In: *ICES Journal of Marine Science* 72.5, pp. 1297–1310. DOI: 10.1093/icesjms/fsu243.

Travis, J., F. C. Coleman, P. J. Auster, P. M. Cury, J. A. Estes, J. Orensanz, C. H. Peterson, M. E. Power, R. S. Steneck and J. T. Wootton (2014). 'Integrating the invisible fabric of nature into fisheries management'. In:

Proceedings of the National Academy of Sciences 111.2, pp. 581–584. DOI: 10.1073/pnas.1305853111.

Trenkel, V. M. (2018). 'How to provide scientific advice for ecosystem-based management now'. In: *Fish and Fisheries* 19.2, pp. 390–398. DOI: 10.1111/faf.12263.

Trijoulet, V., G. Fay, K. L Curti, B. Smith and T. J. Miller (2019). 'Performance of multispecies assessment models: insights on the influence of diet data'. In: *ICES Journal of Marine Science* 76.6. Ed. by Christos Maravelias, pp. 1464–1476. DOI: 10.1093/icesjms/fsz053.

Trijoulet, V., G. Fay and T. J. Miller (2020). 'Performance of a state-space multispecies model: What are the consequences of ignoring predation and process errors in stock assessments?' In: *Journal of Applied Ecology* 57.1. Ed. by Melinda Coleman, pp. 121–135. DOI: 10.1111/1365-2664.13515.

Tsikliras, A. C. and R. Froese (2019). 'Maximum Sustainable Yield'. In: *Encyclopedia of Ecology*. 2nd ed. Elsevier, pp. 108–115. DOI: 10.1016/B978-0-12-409548-9.10601-3.

UN (1995). 'Agreement for the implementation of the provisions of the United Nations Conventionon the law of the sea of 10 December 1982 relating to the conservation and management of straddling fish stocks and highly migratory fish stocks'. In: *UN General Assembly Annex 3*. Vol. A/CONF.164, p. 40. DOI: 10.1016/B978-0-12-384719-5.00223-9. URL: https://www.un.org/Depts/los/convention_agreements/convention_overview_fish_stocks.htm.

UN (2002). *Johannesburg plan of implementation of the world summit on sustainable development. IV. Protecting and managing the natural resource base of economic and social development*. Tech. rep., pp. 14–30. URL: http://www.un.org/esa/sustdev/documents/WSSD_POI_PD/English/POIChapter4.htm.

Vert-pre, K. A., R. O. Amoroso, O. P. Jensen and R. Hilborn (2013). 'Frequency and intensity of productivity regime shifts in marine fish stocks'. In: *Proceedings of the National Academy of Sciences* 110.5, pp. 1779–1784. DOI: 10.1073/pnas.1214879110.

Walters, C J (1986). *Adaptive Management of Renewable Resources*. Basingstoke, p. 374.

Walters, C. and A. M. Parma (1996). 'Fixed exploitation rate strategies for coping with effects of climate change'. In: *Canadian Journal of Fisheries and Aquatic Sciences* 53.1, pp. 148–158. DOI: 10.1139/f95-151.

Walters, C. J., V. Christensen, S. J. Martell and J. F. Kitchell (2005). 'Possible ecosystem impacts of applying MSY policies from single-species assessment'. In: *ICES Journal of Marine Science*. Vol. 62. 3. DOI: 10.1016/j.icesjms.2004.12.005.

Walters, Carl J. (1987). 'Nonstationarity of Production Relationships in Exploited Populations'. In: *Canadian Journal of Fisheries and Aquatic Sciences* 44.S2, s156–s165. DOI: 10.1139/f87-319.

Wetzel, C. R. and A. E. Punt (2017). 'The performance and trade-offs of alternative harvest control rules to meet management goals for U.S. west coast flatfish stocks'. In: *Fisheries Research* 187, pp. 139–149. DOI: 10.1016/j.fishres.2016.11.019.

White, J., N. Ó Maoiléidigh, P. Gargan, E. de Eyto, G. Chaput, W. Roche, P. McGinnity, W. W. Crozier, P. Boylan, D. Doherty, K. O'Higgins, B. Kennedy, I. Lawler, D. Lyons and F. Marnell (2016). 'Incorporating natural variability in biological reference points and population dynamics into management of Atlantic salmon (Salmo salar L.) stocks returning to home waters'. In: *ICES Journal of Marine Science* 73.6, pp. 1513–1524. DOI: 10.1093/icesjms/fsw015.

Wiedenmann, J. and O. P. Jensen (2018). 'Uncertainty in stock assessment estimates for New England groundfish and its impact on achieving target harvest rates'. In: *Canadian Journal of Fisheries and Aquatic Sciences* 75.3, pp. 342–356. DOI: 10.1139/cjfas-2016-0484.

Worm, B., E. B. Barbier, N. Beaumont, J. E. Duffy, C. Folke, B. S. Halpern, J. B. C. Jackson, H. K. Lotze, F. Micheli, S. R. Palumbi, E. Sala, K. A. Selkoe, J. J. Stachowicz and R. Watson (2006). 'Impacts of Biodiversity Loss on Ocean Ecosystem Services'. In: *Science* 314.5800, pp. 787–790. DOI: 10.1126/science.1132294.

Worm, B., R. Hilborn, J. K. Baum, T. A. Branch, J. S. Collie, C. Costello, M. J. Fogarty, E. A. Fulton, J. A. Hutchings, S. Jennings, O. P. Jensen, H. K. Lotze, P. M. Mace, T. R. McClanahan, C. Minto, S. R. Palumbi, A. M. Parma, D. Ricard, A. A. Rosenberg, R. Watson and D. Zeller (2009). 'Rebuilding Global Fisheries'. In: *Science* 325.5940, pp. 578–585. DOI: 10.1126/science.1173146.

Wright, P. J. and F. M. Gibb (2005). 'Selection for birth date in North Sea haddock and its relation to maternal age'. In: *Journal of Animal Ecology* 74.2. DOI: 10.1111/j.1365-2656.2005.00924.x.

Zeng, Zheng, Robert M. Nowierski, Mark L. Taper, Brian Dennis and William P. Kemp (1998). 'Complex Population Dynamics in the Real World: Modeling the Influence of Time-Varying Parameters and Time Lags'. In: *Ecology* 79.6, p. 2193. DOI: 10.2307/176721.

Zhang, F., P. M. Regular, L. Wheeland, R. M. Rideout and J. M. Morgan (2021a). 'Accounting for non-stationary stock–recruitment relationships in the development of MSY-based reference points'. In: *ICES Journal of Marine Science* 78.6. Ed. by Emory Anderson, pp. 2233–2243. DOI: 10.1093/icesjms/fsaa176.

Zhang, F., K. B. Reid and T. D. Nudds (2021b). 'The longer the better? Trade-offs in fisheries stock assessment in dynamic ecosystems'. In: *Fish and Fisheries* 22.4. DOI: 10.1111/faf.12550.

Zhu, J., Y. Chen, X. Dai, S. J. Harley, S. D. Hoyle, M. N. Maunder and A. M. Aires-da-Silva (2012). 'Implications of uncertainty in the spawner–recruitment relationship for fisheries management: An illustration using bigeye tuna (Thunnus obesus) in the eastern Pacific Ocean'. In: *Fisheries Research* 119-120, pp. 89–93. DOI: 10.1016/j.fishres.2011.12.008.

Zimmermann, F. and K. M. Werner (2019). 'Improved management is the main driver behind recovery of Northeast Atlantic fish stocks'. In: *Frontiers in Ecology and the Environment* 17.2. DOI: 10.1002/fee.2002.

Appendix A

Supplementary Information

A.1 Supplementary Information for Chapter 2. An empirical review of current ICES reference point estimation

Supplementary material for

An empirical review of current ICES reference point estimation

Paula Silvar-Viladomiu[1], Luke Batts[1], Cóilín Minto[1], David Miller[2], Colm Lordan[3]

[1]Marine and Freshwater Research Centre, Galway-Mayo Institute of Technology, Dublin Road, Galway, Ireland

[2] International Council for the Exploration of the Sea

[3]Marine Institute, Rinville, Oranmore, Co. Galway, Ireland

*Paula Silvar-Viladomiu
Email: paula.silvarviladomiu@research.gmit.ie

This PDF file includes:

Figures SM1 to SM3

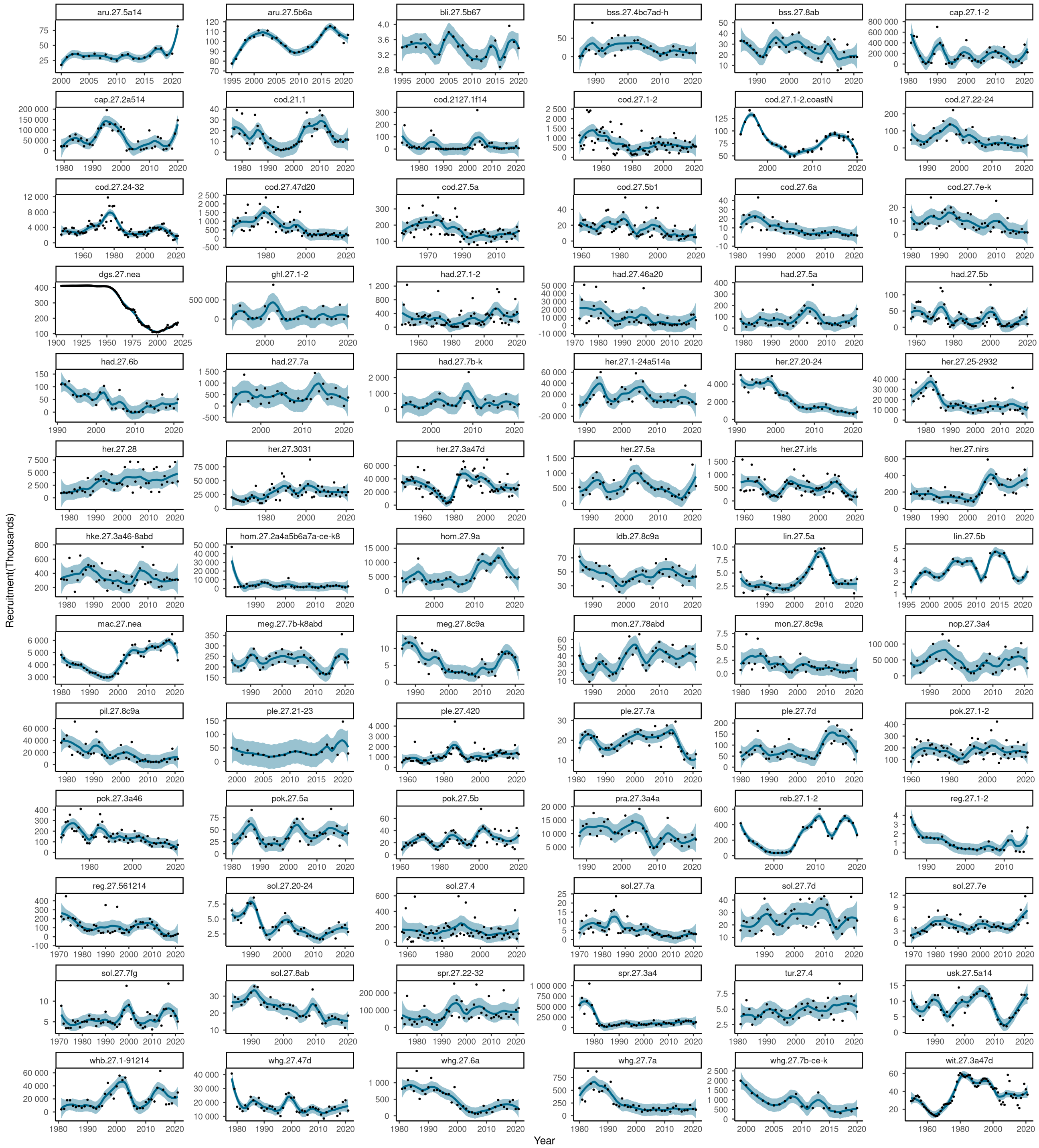

Figure SM1. Recruiment time series for stocks with time series over 20 years. Blue line represents a loess model (span = 0.3). The blue area represents the 95% CI.

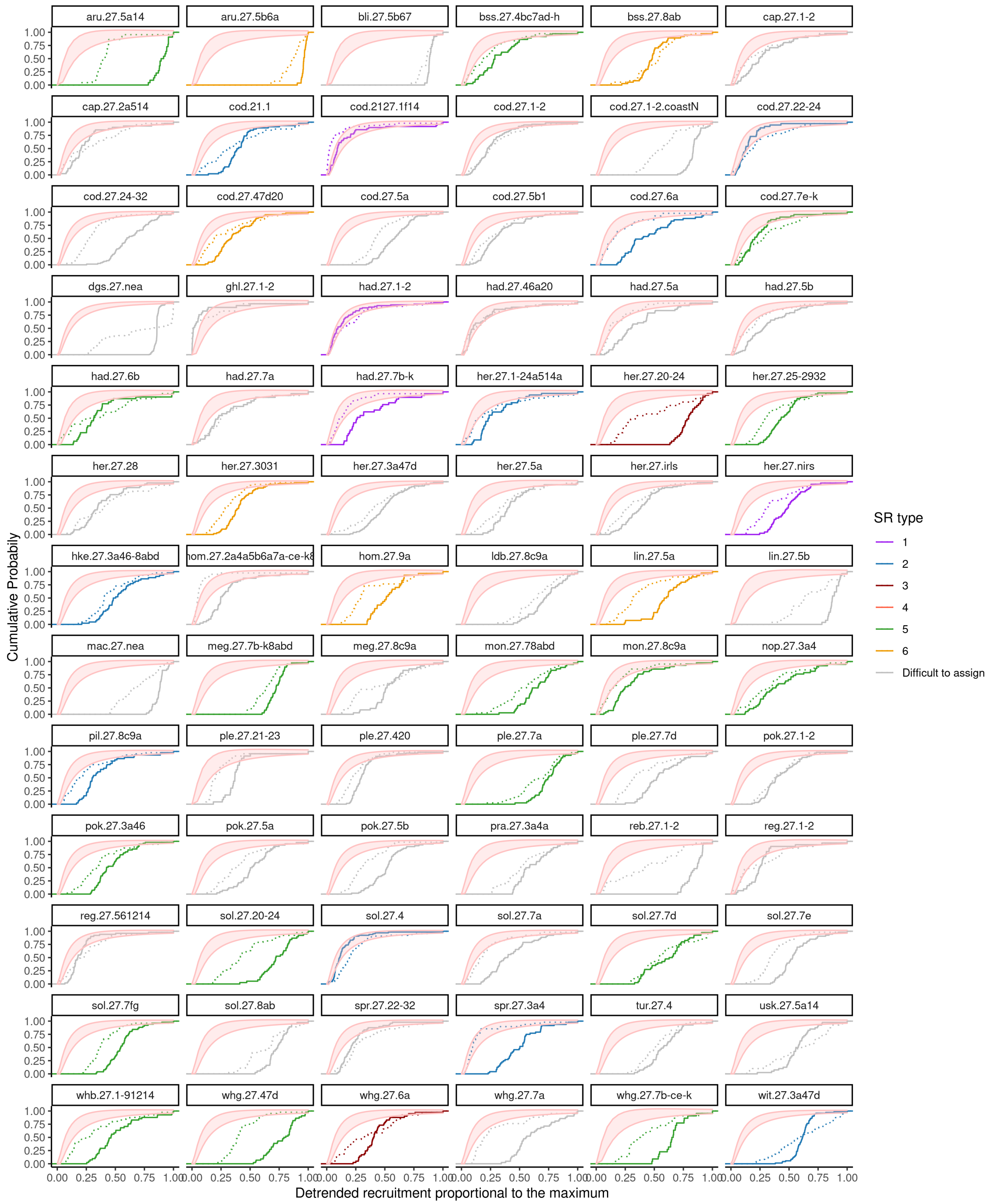

Figure SM2. Empirical cumulative distribution function of recruitment relative to maximum recruitment. Colour shows stated stock-recruit type and dashed lines represent the cumulative probability of the recruitment proportional to the maximum. Pink area shows the theoretical expected 80% interval for CDFs of time series of lognormal variance = 1.

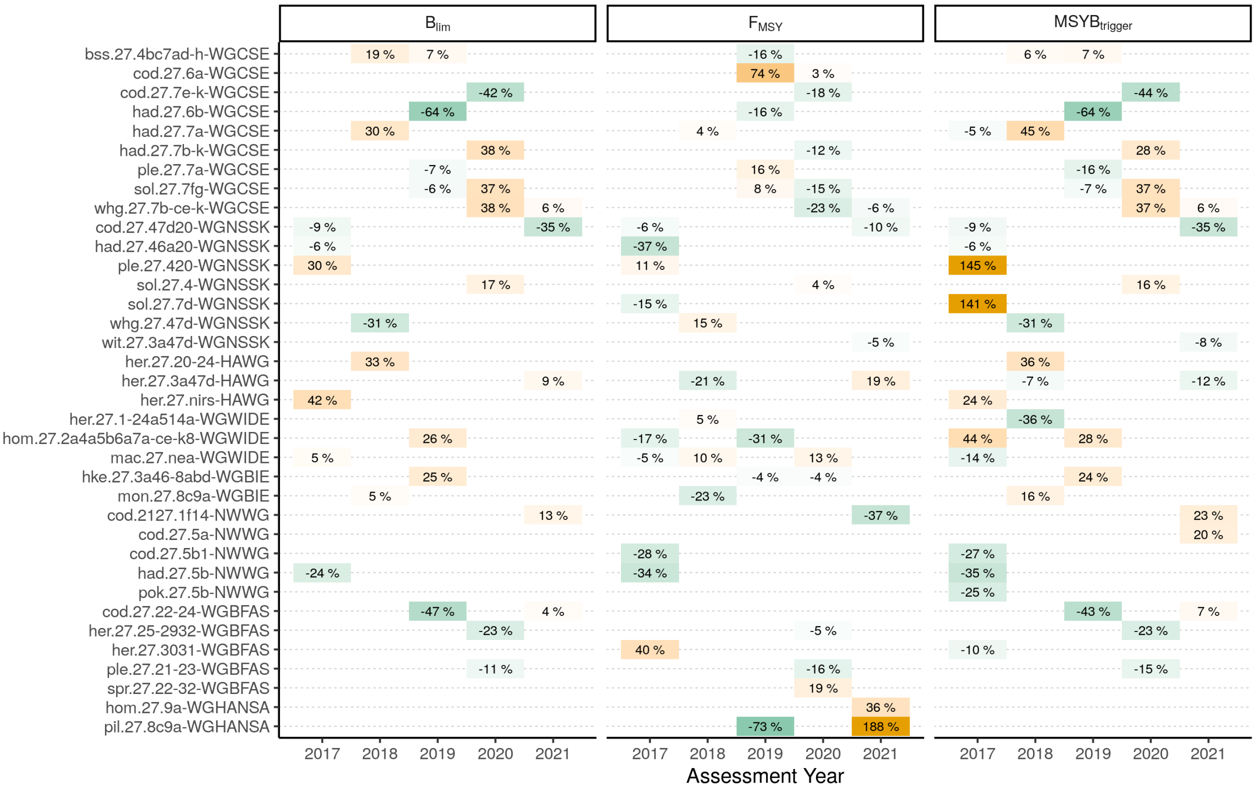

Figure SM3. Sequential changes in ICES category 1 stocks reference points (B_{lim}, F_{MSY} and MSY $B_{trigger}$) since WKMSYREF4.

A.2 Supplementary Information for Chapter 3. Moving reference point goalposts and implications for fisheries sustainability

Supplementary Information for

Moving reference point goalposts and implications for fisheries sustainability

Paula Silvar-Viladomiu[1], Cóilín Minto[1], Ghassen Halouani[1,2], Luke Batts[1], Deirdre Brophy[1], Colm Lordan[3], David G. Reid[3].

[1]Galway-Mayo Institute of Technology GMIT, Dublin road, Galway, Ireland.

[2]IFREMER, Unité halieutique Manche Mer du Nord Ifremer, HMMN, F62200 Boulogne sur mer, France.

[3]Marine Institute, Rinville, Oranmore, Co. Galway, Ireland.

*Paula Silvar-Viladomiu.
Email**:** paula.silvarviladomiu@research.gmit.ie

This PDF file includes:

Tables SI1 to SI2
Figures SI1 to SI10

Table SI1. Table with the list of events of change in reference points. The super-indexes represent: 1, stocks with no comparable reference points (i.e. use of a different definition of F); 2, stocks with substituted relative reference point for their absolute value; 3, duplicated stock. Asterisks for relative reference points or substituted values. The events 1 and 3 were removed from the analysis.

ID	event	F_{MSY} (y-1)	F_{MSY} (y)	$MSYB_{trigger}$ (y-1)	$MSYB_{trigger}$ (y)	Stock Key Description	Scientific name	Abbreviated name
1	ank.27.8c9a 2012[1]	0.43	1.00*	NA	NA	Black-bellied anglerfish in divisions 8.c and 9.a (Cantabrian Sea, Atlantic Iberian waters)	*Lophius budegassa*	Black-bellied anglerfish in CaS,AI
2	bli.27.5b67 2016	0.07	0.12	NA	NA	Blue ling in subareas 6-7 and Division 5.b (Celtic Seas, English Channel, and Faroes grounds)	*Molva dypterygia*	Blue ling in CS,EC,FG
3	bss.27.4bc7ad-h 2016	NA	NA	8000	12673	Seabass in Divisions 4.b-c, 7.a, and 7.d-h (central and southern North Sea, Irish Sea, English Channel, Bristol Channel, and Celtic Sea)	*Dicentrarchus labrax*	Seabass in NS,IS,EC,BC,CS
4	bss.27.4bc7ad-h 2018	NA	NA	12673	13465	Seabass in Divisions 4.b-c, 7.a, and 7.d-h (central and southern North Sea, Irish Sea, English Channel, Bristol Channel, and Celtic Sea)	*Dicentrarchus labrax*	Seabass in NS,IS,EC,BC,CS
5	bss.27.4bc7ad-h 2019	0.20	0.17	13465	14439	Seabass in Divisions 4.b-c, 7.a, and 7.d-h (central and southern North Sea, Irish Sea, English Channel, Bristol Channel, and Celtic Sea)	*Dicentrarchus labrax*	Seabass in NS,IS,EC,BC,CS
6	cod.27.22-24 2012	0.24	0.25	NA	NA	Cod in subdivisions 22-24, western Baltic stock (western Baltic Sea)	*Gadus morhua*	Cod in wBS
7	cod.27.22-24 2014	0.25	0.26	23000	36400	Cod in subdivisions 22-24, western Baltic stock (western Baltic Sea)	*Gadus morhua*	Cod in wBS
8	cod.27.22-24 2015	NA	NA	36400	38400	Cod in subdivisions 22-24, western Baltic stock (western Baltic Sea)	*Gadus morhua*	Cod in wBS
9	cod.27.22-24 2019	NA	NA	38400	21876	Cod in subdivisions 22-24, western Baltic stock (western Baltic Sea)	*Gadus morhua*	Cod in wBS
10	cod.27.24-32 2013	0.30	0.46	NA	NA	Cod in subdivisions 24-32, eastern Baltic stock (eastern Baltic Sea)	*Gadus morhua*	Cod in eBS
11	cod.27.47d20 2015	0.19	0.33	150000	165000	Cod in Subarea 4, Division 7.d, and Subdivision 20 (North Sea, eastern English Channel, Skagerrak)	*Gadus morhua*	Cod in NS,eEC,S
12	cod.27.47d20 2017	0.33	0.31	165000	150000	Cod in Subarea 4, Division 7.d, and Subdivision 20 (North Sea, eastern English Channel, Skagerrak)	*Gadus morhua*	Cod in NS,eEC,S
13	cod.27.5b1 2017	0.32	0.23	40000	29226	Codin Subdivision 5.b.1 (Faroe Plateau)	*Gadus morhua*	Cod in FP
14	cod.27.6a 2016	0.19	0.17	22000	20000	Cod in Division 6.a (West of Scotland)	*Gadus morhua*	Cod in WS
15	cod.27.6a 2019	0.17	0.29	NA	NA	Cod in Division 6.a (West of Scotland)	*Gadus morhua*	Cod in WS
16	cod.27.7a 2016	0.40	0.37	NA	NA	Cod in Division 7.a (Irish Sea)	*Gadus morhua*	Cod in IS
17	cod.27.7a 2017	0.37	0.31	10000	8616	Cod in Division 7.a (Irish Sea)	*Gadus morhua*	Cod in IS
18	cod.27.7a 2018	0.31	0.44	NA	NA	Cod in Division 7.a (Irish Sea)	*Gadus morhua*	Cod in IS
19	cod.27.7e-k 2015	0.40	0.32	NA	NA	Cod in divisions 7.e-k (eastern English Channel and southern Celtic Seas)	*Gadus morhua*	Cod in eEC,CS
20	cod.27.7e-k 2016	0.32	0.35	NA	NA	Cod in divisions 7.e-k (eastern English Channel and southern Celtic Seas)	*Gadus morhua*	Cod in eEC,CS
21	dgs.27.nea 2016	NA	NA	963700	964563	Spurdog in Subareas 1-10, 12 and 14 (the Northeast Atlantic and adjacent waters)	*Squalus acanthias*	Spurdog in NA
22	dgs.27.nea 2018	NA	NA	964563	683340	Spurdog in Subareas 1-10, 12 and 14 (the Northeast Atlantic and adjacent waters)	*Squalus acanthias*	Spurdog in NA
23	had.27.46a20 2017	0.30	0.19	NA	NA	Haddock in Subarea 4, Division 6.a, and Subdivision 20 (North Sea, West of Scotland, Skagerrak)	*Melanogrammus aeglefinus*	Haddock in NS,WS,S
24	had.27.6a 2017[3]	0.30	0.19	NA	NA	Haddock in Division 6.a	*Melanogrammus aeglefinus*	Haddock in NS
25	had.27.5b 2017	0.25	0.16	35000	22843	Haddock in Division 5.b (Faroes grounds)	*Melanogrammus aeglefinus*	Haddock in FG
26	had.27.6b 2014	0.30	0.20	NA	NA	Haddock in Division 6.b (Rockall)	*Melanogrammus aeglefinus*	Haddock in R
27	had.27.6b 2016	NA	NA	9000	10200	Haddock in Division 6.b (Rockall)	*Melanogrammus aeglefinus*	Haddock in R
28	had.27.6b 2019	0.20	0.17	10200	3712	Haddock in Division 6.b (Rockall)	*Melanogrammus aeglefinus*	Haddock in R
29	had.27.7a 2017	NA	NA	3093	2944	Haddock in Division 7.a (Irish Sea)	*Melanogrammus aeglefinus*	Haddock in IS
30	had.27.7a 2018	0.27	0.28	2944	4280	Haddock in Division 7.a (Irish Sea)	*Melanogrammus aeglefinus*	Haddock in IS
31	had.27.7b-k 2014	0.28	0.33	NA	NA	Haddock in Divisions 7.b-k (southern Celtic Seas and English Channel)	*Melanogrammus aeglefinus*	Haddock in CS,EC
32	had.27.7b-k 2015	0.33	0.40	7500	10000	Haddock in Divisions 7.b-k (southern Celtic Seas and English Channel)	*Melanogrammus aeglefinus*	Haddock in CS,EC
33	her.27.1-24a514a 2018	0.15	0.16	5000000	3184000	Herring in subareas 1, 2, 5 and divisions 4.a and 14.a,	*Clupea harengus*	Herring in NA,AO

						Norwegian spring-spawning herring (the Northeast Atlantic and Arctic Ocean)		
34	her.27.20-24 2015	0.28	0.32	NA	NA	Herring in subdivisions 20-24, spring spawners (Skagerrak, Kattegat, and western Baltic)	*Clupea harengus*	Herring in S,K,wBS
35	her.27.20-24 2018	0.32	0.31	110000	150000	Herring in subdivisions 20-24, spring spawners (Skagerrak, Kattegat, and western Baltic)	*Clupea harengus*	Herring in S,K,wBS
36	her.27.25-2932 2013	0.16	0.26	NA	NA	Herring in subdivisions 25-29 and 32, excluding the Gulf of Riga (central Baltic Sea)	*Clupea harengus*	Herring in cBS
37	her.27.25-2932 2015	0.26	0.22	NA	NA	Herring in subdivisions 25-29 and 32, excluding the Gulf of Riga (central Baltic Sea)	*Clupea harengus*	Herring in cBS
38	her.27.28 2015	0.35	0.32	NA	NA	Herring in Subdivision 28.1 (Gulf of Riga)	*Clupea harengus*	Herring in GR
39	her.27.3031 2013	0.19	0.15	200000	316000	Herring in Subdivisions 30 and 31 (Gulf of Bothnia)	*Clupea harengus*	Herring in GB
40	her.27.3031 2017	0.15	0.21	316000	283180	Herring in Subdivisions 30 and 31 (Gulf of Bothnia)	*Clupea harengus*	Herring in GB
41	her.27.3a47d 2016	0.27	0.33	NA	NA	Herring in Subarea 4 and divisions 3.a and 7.d, autumn spawners (North Sea, Skagerrak and Kattegat, eastern English Channel)	*Clupea harengus*	Herring in NS,S,K,eEC
42	her.27.3a47d 2018	0.33	0.26	1500000	1400000	Herring in Subarea 4 and divisions 3.a and 7.d, autumn spawners (North Sea, Skagerrak and Kattegat, eastern English Channel)	*Clupea harengus*	Herring in NS,S,K,eEC
43	her.27.6a7bc 2017[2]	0.25*	0.16	NA	NA	Herring in divisions 6.a and 7.b-c (West of Scotland, West of Ireland)	*Clupea harengus*	Herring in WS,WI
44	her.27.irls 2014	0.25	0.37	NA	NA	Herring in divisions 7.a South of 52°30'N, 7.g-h, and 7.j-k (Irish Sea, Celtic Sea, and southwest of Ireland)	*Clupea harengus*	Herring in IS,CS
45	her.27.irls 2015	0.37	0.26	61000	54000	Herring in divisions 7.a South of 52°30'N, 7.g-h, and 7.j-k (Irish Sea, Celtic Sea, and southwest of Ireland)	*Clupea harengus*	Herring in IS,CS
46	her.27.nirs 2017	NA	NA	9500	11800	Herring in Division 7.a North of 52°30'N (Irish Sea)	*Clupea harengus*	Herring in IS
47	hke.27.3a46-8abd 2014	0.24	0.27	NA	NA	Hake in subareas 4, 6, and 7, and divisions 3.a, 8.a-b, and 8.d, Northern stock (Greater North Sea, Celtic Seas, and the northern Bay of Biscay)	*Merluccius merluccius*	Hake in NS,CS,nBB
48	hke.27.3a46-8abd 2016	0.27	0.28	46200	45000	Hake in subareas 4, 6, and 7, and divisions 3.a, 8.a-b, and 8.d, Northern stock (Greater North Sea, Celtic Seas, and the northern Bay of Biscay)	*Merluccius merluccius*	Hake in NS,CS,nBB
49	hke.27.3a46-8abd 2019	0.28	0.27	45000	56000	Hake in subareas 4, 6, and 7, and divisions 3.a, 8.a-b, and 8.d, Northern stock (Greater North Sea, Celtic Seas, and the northern Bay of Biscay)	*Merluccius merluccius*	Hake in NS,CS,nBB
50	hke.27.8c9a 2016	0.24	0.25	NA	NA	Hake in divisions 8.c and 9.a, Southern stock (Cantabrian Sea and Atlantic Iberian waters)	*Merluccius merluccius*	Hake in CaS,AI
51	hom.27.2a4a5b6a7a-ce-k8 2017	0.13	0.11	634577	911588	Horse mackerel in Subarea 8 and divisions 2.a, 4.a, 5.b, 6.a, 7.a-c,e-k (the Northeast Atlantic)	*Trachurus trachurus*	Horse mackerel in NA
52	hom.27.2a4a5b6a7a-ce-k8 2019	0.11	0.07	911587	1168270	Horse mackerel in Subarea 8 and divisions 2.a, 4.a, 5.b, 6.a, 7.a-c,e-k (the Northeast Atlantic)	*Trachurus trachurus*	Horse mackerel in NA
53	ldb.27.8c9a 2014	0.18	0.17	NA	NA	Four-spot megrim in divisions 8.c and 9.a (southern Bay of Biscay and Atlantic Iberian waters East)	*Lepidorhombus boscii*	Megrim in sBB,AI
54	ldb.27.8c9a 2016	0.17	0.19	NA	NA	Four-spot megrim in divisions 8.c and 9.a (southern Bay of Biscay and Atlantic Iberian waters East)	*Lepidorhombus boscii*	Megrim in sBB,AI
55	mac.27.nea 2015	0.25	0.22	NA	NA	Mackerel in subareas 1-8 and 14 and division 9.a (the Northeast Atlantic and adjacent waters)	*Scomber scombrus*	Mackerel in NA
56	mac.27.nea 2017	0.22	0.21	3000000	2570000	Mackerel in subareas 1-8 and 14 and division 9.a (the Northeast Atlantic and adjacent waters)	*Scomber scombrus*	Mackerel in NA
57	mac.27.nea 2018	0.21	0.23	2570000	2500000	Mackerel in subareas 1-8 and 14 and division 9.a (the Northeast Atlantic and adjacent waters)	*Scomber scombrus*	Mackerel in NA
58	meg.27.8c9a 2016	0.17	0.19	910	980	Megrim in divisions 8.c and 9.a (Cantabrian Sea and Atlantic Iberian waters)	*Lepidorhombus whiffiagonis*	Megrim in CaS,AI
59	mon.27.8c9a 2016	0.19	0.31	NA	NA	White anglerfish in divisions 8.c and 9.a (Cantabrian Sea and Atlantic Iberian waters)	*Lophius piscatorius*	White anglerfish in CaS,AI
60	mon.27.8c9a 2018	0.31	0.24	5400	6283	White anglerfish in divisions 8.c and 9.a (Cantabrian Sea and Atlantic Iberian waters)	*Lophius piscatorius*	White anglerfish in CaS,AI
61	pil.27.8c9a 2019	0.12	0.03	446331	252523	Sardine in divisions 8.c and 9.a (Cantabrian Sea and Atlantic Iberian waters)	*Sardina pilchardus*	Sardine in CaS,AI
62	ple.27.420 2015	0.25	0.19	NA	NA	Plaice in Subarea 4 (North Sea) and Subdivision 20 (Skagerrak)	*Pleuronectes platessa*	Plaice in NS,S
63	ple.27.420 2017	0.19	0.21	230000	564599	Plaice in Subarea 4 (North Sea) and Subdivision 20 (Skagerrak)	*Pleuronectes platessa*	Plaice in NS,S
64	ple.27.7a 2019	0.17	0.20	10392	8757	Plaice in Division 7.a (Irish Sea)	*Pleuronectes platessa*	Plaice in IS
65	ple.27.7d 2015[2]	0.15*	0.25	NA	NA	Plaice in Division 7.d (eastern English Channel)	*Pleuronectes platessa*	Plaice in eEC
66	ple.27.7e 2015[1,2]	0.24	0.56*	1650	2400*	Plaice in Division 7.e (western English Channel)	*Pleuronectes platessa*	Plaice in wEC
67	pok.27.3a46 2015	0.30	0.32	NA	NA	Saithe in Subareas 4, 6 and Division 3.a (North Sea, Rockall and West of Scotland, Skagerrak and Kattegat)	*Pollachius virens*	Saithe in NS,R,WS,S,K
68	pok.27.3a46 2016	0.32	0.36	200000	150000	Saithe in Subareas 4, 6 and Division 3.a (North Sea, Rockall and West of Scotland, Skagerrak and Kattegat)	*Pollachius virens*	Saithe in NS,R,WS,S,K
69	pok.27.3a46 2019	0.36	0.36	NA	NA	Saithe in Subareas 4, 6 and Division 3.a (North Sea, Rockall and West of Scotland, Skagerrak and Kattegat)	*Pollachius virens*	Saithe in NS,R,WS,S,K
70	pok.27.5b 2014	0.28	0.30	NA	NA	Saithe in Division 5.b (Faroes grounds)	*Pollachius virens*	Saithe in FG

71	pok.27.5b 2017	NA	NA	55000	41400	Saithe in Division 5.b (Faroes grounds)	*Pollachius virens*	Saithe in FG
72	pra.27.3a4a 2015[1]	1.00	0.62	NA	NA	Northern shrimp in divisions 3.a and 4.a East (Skagerrak and Kattegat and northern North Sea in the Norwegian Deep)	*Pandalus borealis*	Northern shrimp in S,K,NS
73	pra.27.3a4a 2019	0.62	0.60	NA	NA	Northern shrimp in divisions 3.a and 4.a East (Skagerrak and Kattegat and northern North Sea in the Norwegian Deep)	*Pandalus borealis*	Northern shrimp in S,K,NS
74	sol.27.20-24 2013	0.38	0.30	NA	NA	Sole in subdivisions 20-24 (Skagerrak and Kattegat, western Baltic Sea)	*Solea solea*	Sole in S,K,wBS
75	sol.27.20-24 2014	0.30	0.32	NA	NA	Sole in subdivisions 20-24 (Skagerrak and Kattegat, western Baltic Sea)	*Solea solea*	Sole in S,K,wBS
76	sol.27.20-24 2015	0.32	0.23	2000	2600	Sole in subdivisions 20-24 (Skagerrak and Kattegat, western Baltic Sea)	*Solea solea*	Sole in S,K,wBS
77	sol.27.4 2015	0.22	0.20	35000	37000	Sole in Subarea 4 (North Sea)	*Solea solea*	Sole in NS
78	sol.27.7a 2016	0.16	0.20	3100	3500	Sole in Division 7.a (Irish Sea)	*Solea solea*	Sole in IS
79	sol.27.7d 2015	0.29	0.30	NA	NA	Sole in Division 7.d (eastern English Channel)	*Solea solea*	Sole in eEC
80	sol.27.7d 2017	0.30	0.26	8000	19251	Sole in Division 7.d (eastern English Channel)	*Solea solea*	Sole in eEC
81	sol.27.7d 2019[2]	0.26	0.19*	19251	1572*	Sole in Division 7.d (eastern English Channel)	*Solea solea*	Sole in eEC
82	sol.27.7e 2016	0.27	0.29	2800	2900	Sole in Division 7.e (western English Channel)	*Solea solea*	Sole in wEC
83	sol.27.7fg 2016	0.31	0.27	2200	2400	Sole in divisions 7.f and 7.g (Bristol Channel, Celtic Sea)	*Solea solea*	Sole in BC,CS
84	sol.27.7fg 2019	0.27	0.30	2400	2228	Sole in divisions 7.f and 7.g (Bristol Channel, Celtic Sea)	*Solea solea*	Sole in BC,CS
85	sol.27.8ab 2016	0.26	0.33	13000	10600	Sole in divisions 8.a-b (northern and central Bay of Biscay)	*Solea solea*	Sole in BB
86	spr.27.22-32 2013	0.35	0.29	NA	NA	Sprat in Subdivisions 22-32 (Baltic Sea)	*Sprattus sprattus*	Sprat in BS
87	spr.27.22-32 2015	0.29	0.26	NA	NA	Sprat in Subdivisions 22-32 (Baltic Sea)	*Sprattus sprattus*	Sprat in BS
88	spr.27.4 2015	1.20	0.70	NA	NA	Sprat in Subarea 4 (North Sea)	*Sprattus sprattus*	Sprat in NS
89	whb.27.1-91214 2014	0.22	0.30	NA	NA	Blue whiting in subareas 1-9, 12, and 14 (Northeast Atlantic and adjacent waters)	*Micromesistius poutassou*	Blue whiting in NA
90	whb.27.1-91214 2016	0.30	0.32	NA	NA	Blue whiting in subareas 1-9, 12, and 14 (Northeast Atlantic and adjacent waters)	*Micromesistius poutassou*	Blue whiting in NA
91	whg.27.47d 2018	0.15	0.17	241837	166708	Whiting in Subarea 4 and Division 7.d (North Sea and eastern English Channel)	*Merlangius merlangus*	Whiting in NS,eEC
92	whg.27.7b-ce-k 2014	0.36	0.32	21000	40000	Whiting in divisions 7.b-c and 7.e-k (southern Celtic Seas and eastern English Channel)	*Merlangius merlangus*	Whiting in CS,eEC
93	whg.27.7b-ce-k 2016	0.32	0.52	40000	35000	Whiting in divisions 7.b-c and 7.e-k (southern Celtic Seas and eastern English Channel)	*Merlangius merlangus*	Whiting in CS,eEC

Table SI2. Description of covariates.

	Covariate	Definition
Common	(1) Revision_Assessment_Stock_definition	Revision of the stock definition. Occurrence of a modification of stock definition, e.g. stocks merged, separated, added divisions.
	(2) Revision_Assessment_input_data_ FisheriesDependent	Revision of assessment data fisheries dependent. Occurrence, e.g. inclusion, exclusion or revision of discard and commercial index, revision of weights at age.
	(3) Revision_Assessment_input_data_ FisheriesIndependent	Revision of assessment data fisheries independent. Occurrence, e.g. inclusion, exclusion or revision of survey index.
	(4) Revision_Assessment_maturity	Revision of assessment maturity. Occurrence of revision of maturity, e.g. updates, revised assumptions, modify estimation method.
	(5) Revision_Assessment_M	Revision of assessment natural mortality (M). Occurrence of revision of natural mortality parameter, e.g. multispecies model update of M, modification of assumptions or method to estimate M.
	(6) Revision_Assessment_methodology	Revision of assessment methodology. Occurrence of heterogeneous group of revisions comprising, e.g. modify settings and assumptions of the model, estimation improvements and corrections of the models, methodological updates and revision of age range for F.
	(7) Revision_Assessment_type	Revision of assessment type model. Categories of revision of the selected assessment model by levels of previous post modification of assessment model. Assessment types: XSA -Extended Survivor Analysis SAM -State-space assessment model ADAPT -Age Structured Assessment Procedure AartsPoos - Aarts and Poos Model SS3 -Stock Synthesis 3
F_{MSY}	(8) Revision_RP_FMSY_definition	Revision of F_{MSY} definition of technical basis, categories specifying levels by previous post type of modifications. F_{MSY} definitions: • F_{MSY} • Proxies from per recruit analysis: F_{max}, F0.1, $F_{SPR50\%}$, $F_{SPR40\%}$, $F_{SPR30\%}$, $F_{SPR35\%}$ • F_{MSY} provisional derived from simulation frameworks • F_{MSY} analogy from other stocks • $F_{P.05}$ upper F limit that is considered precautionary for MSY rules • F_{PA} Precautionary approach fishing mortality
	(9) Revision_RP_SR_functional_form	Revision of stock recruitment functional form or combination of forms selected to model the stock recruitment relationship. Occurrence of revision of the functional from used to estimate stock-recruitment relationship
	(10) Revision_RP_input_timeseriesRecruitment	Revision of input recruitment time series to estimate the reference point. Occurrence of revision of the time-series of recruitment input for the estimation of F_{MSY}, e.g. shorter recruitment time series, longer recruitment window. ICES guidelines recommends full time series unless strong evidence exists that a consistent change has occurred.
	(11) Revision_RP_input_parameterstimeseries	Revision of input parameters time series related to the productivity of the stock. Occurrence of revisions of time window of biological parameters (weights, maturity, natural mortality) or fishery parameters (selectivity) imputed to estimate F_{MSY}, ICES guidelines recommend by default be derived from the last 10 years but it can be shortened (5 years) when persistent trends are present or longed, when there is no evidence of temporal trends.
$MSB_{trigger}$	(12) Revision_RP_MSYBtrigger_tb	Revision of $MSYB_{trigger}$ technical basis. Categories with levels of specific re-evaluations of $MSYB_{trigger}$ technical basis. For instance, some technical basis of $MSYB_{trigger}$ can be: • B_{pa} • $MSYB_{trigger}$ as the 5th percentile on the distribution of SSB when fishing at F_{MSY} • Other stock specific
	(13) Revision_RP_Blim_tb	Revision of B_{lim} technical basis. Categories with levels of specific re-evaluations of B_{lim} technical basis. The selection of Blim depends on the type of stock recruitment relationship. For instance, some technical basis of B_{lim} can be: • B_{loss} • Break point of the segmented regression • Other stock specific
	(14) Revision_RP_Bpa_tb	Occurrence revision of B_{pa} technical basis e.g. revision of technical basis or how uncertainty is taken into account.

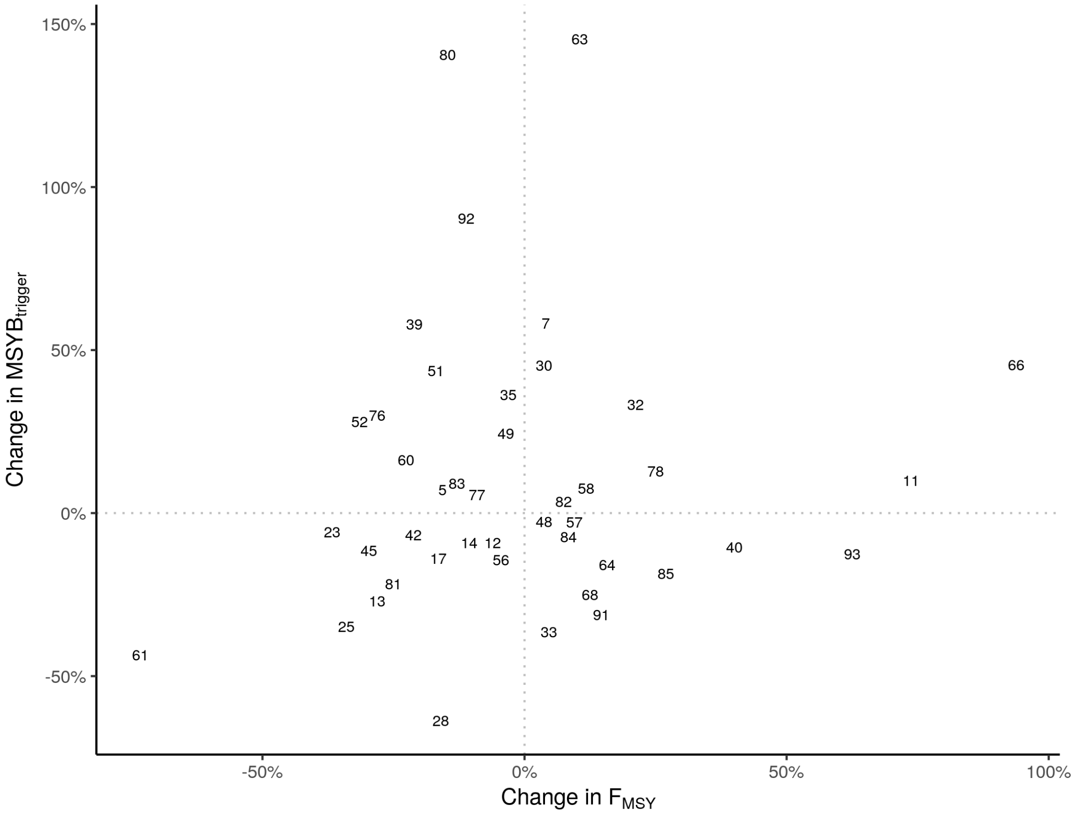

Fig. SI1 Relationship between simultaneous changes in F_{MSY} and $MSYB_{trigger}$, measured in percentage change relative to the preceding assessment. The plot numbers correspond to the event id in Table SI1.

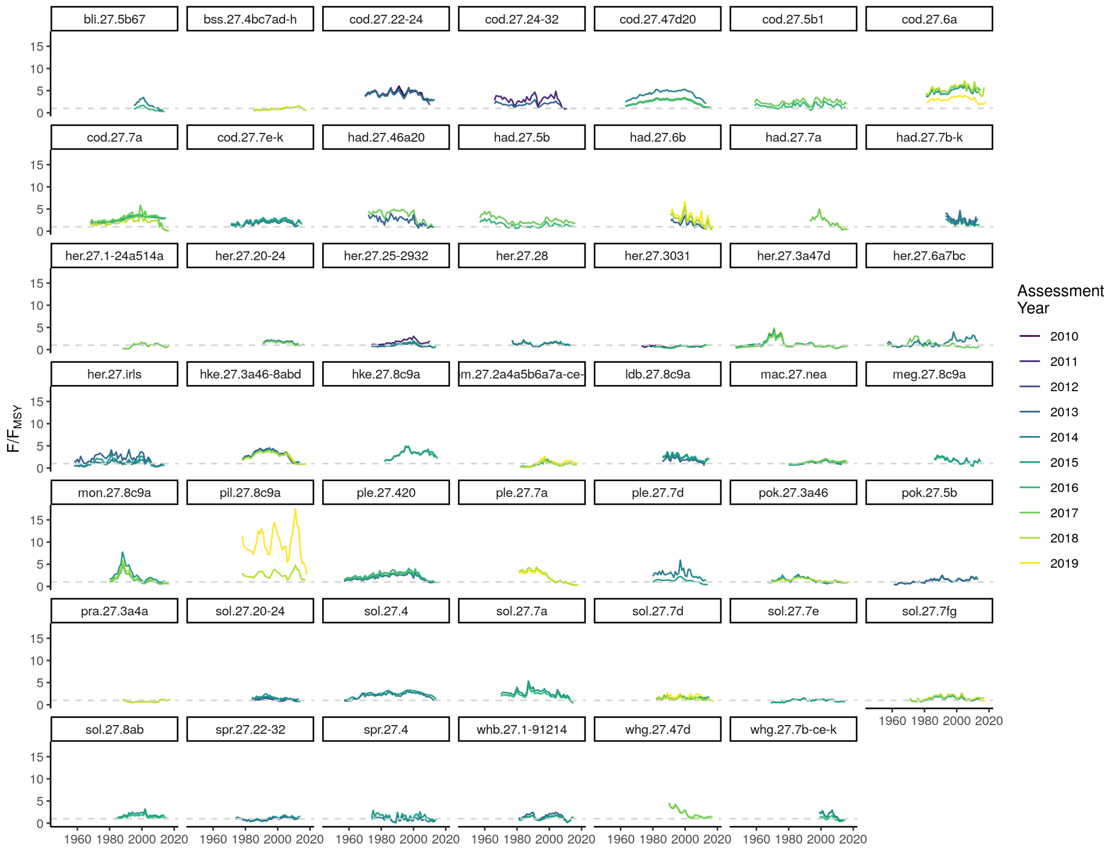

Fig. SI2. Relative fishing mortality rate (F/F_{MSY}) time series when a change in F_{MSY} was implemented. Colour shows the assessment year (y). The horizontal dotted line represents status = 1.

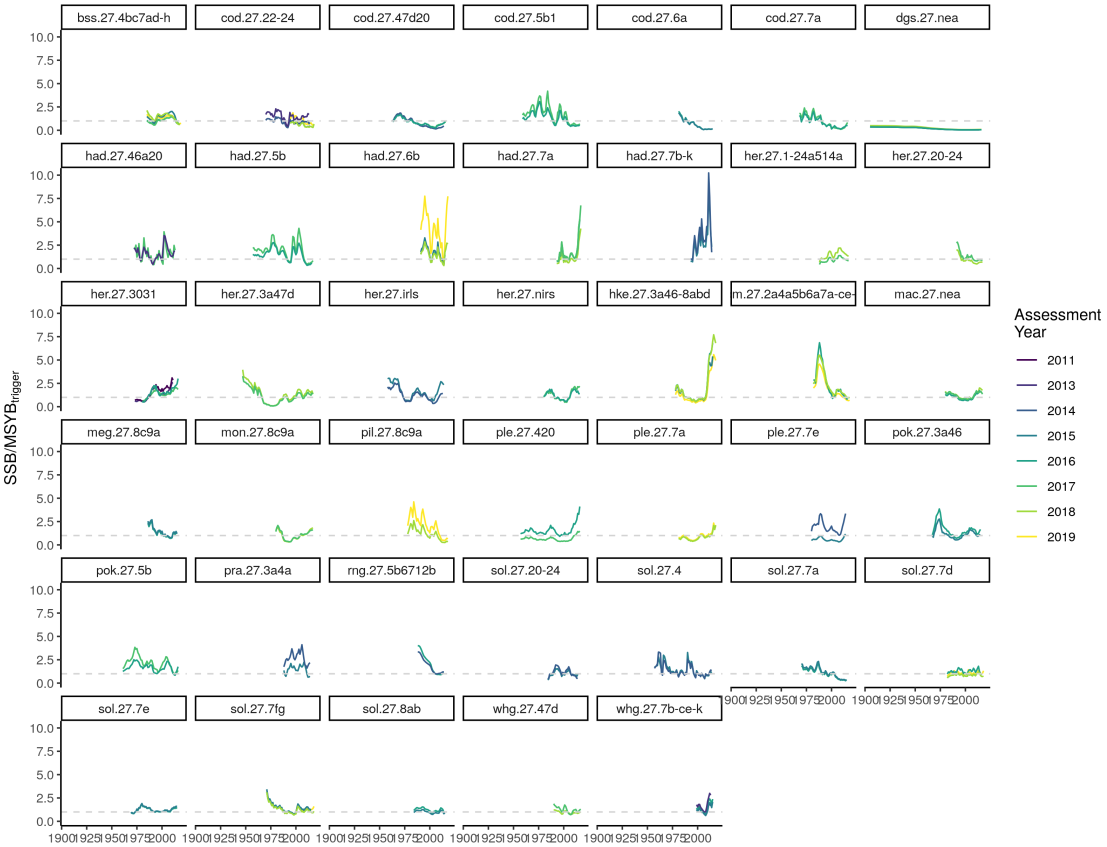

Fig. SI3. Relative biomass (SSB/MSYB$_{trigger}$) time series when a change in MSYB$_{trigger}$ was implemented. Colour shows the assessment year (y). The horizontal dotted line represents status = 1.

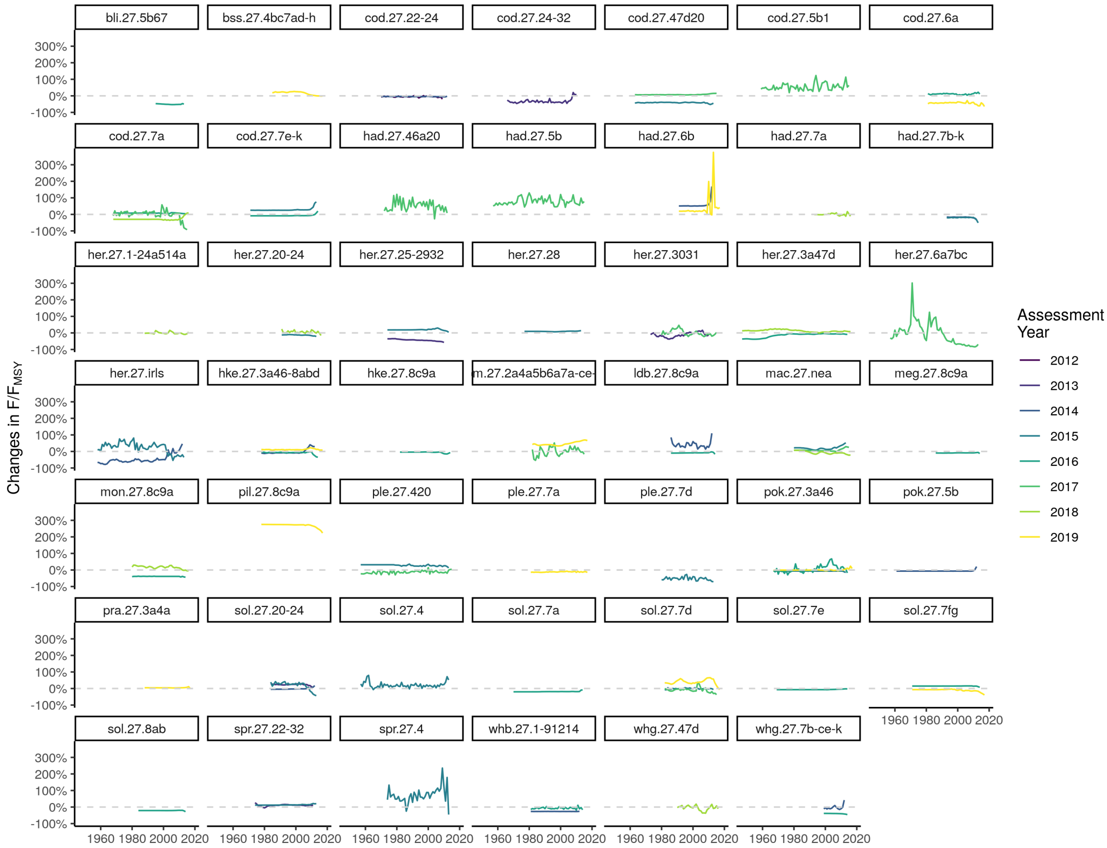

Fig. SI4. Timelines of relative fishing mortality rate (F/F_{MSY}) proportional changes of assessment year (y) relative to the previous (y-1), for assessments in which changes in F_{MSY} were implemented.

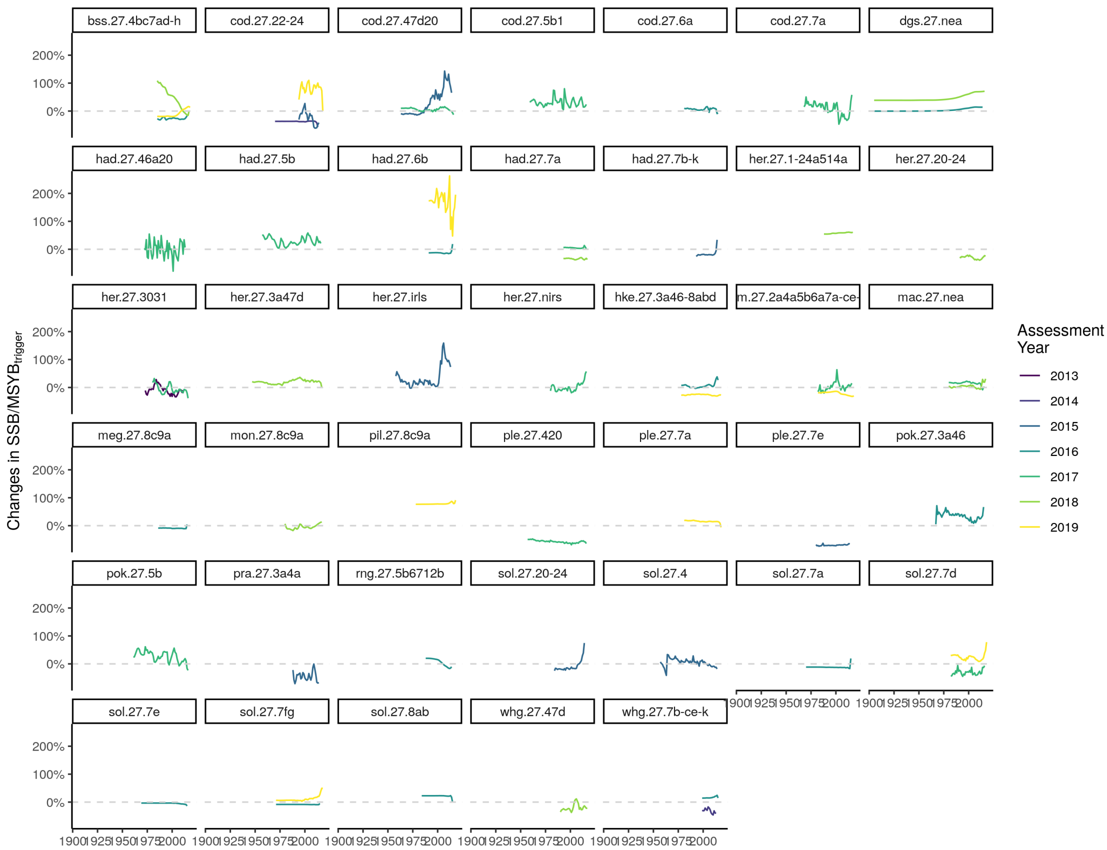

Fig. SI5. Timelines of relative fishing mortality rate (SSB/MSYB$_{trigger}$) proportional changes of assessment year (y) relative to the previous (y-1), for assessments in which changes in MSYB$_{trigger}$ were implemented.

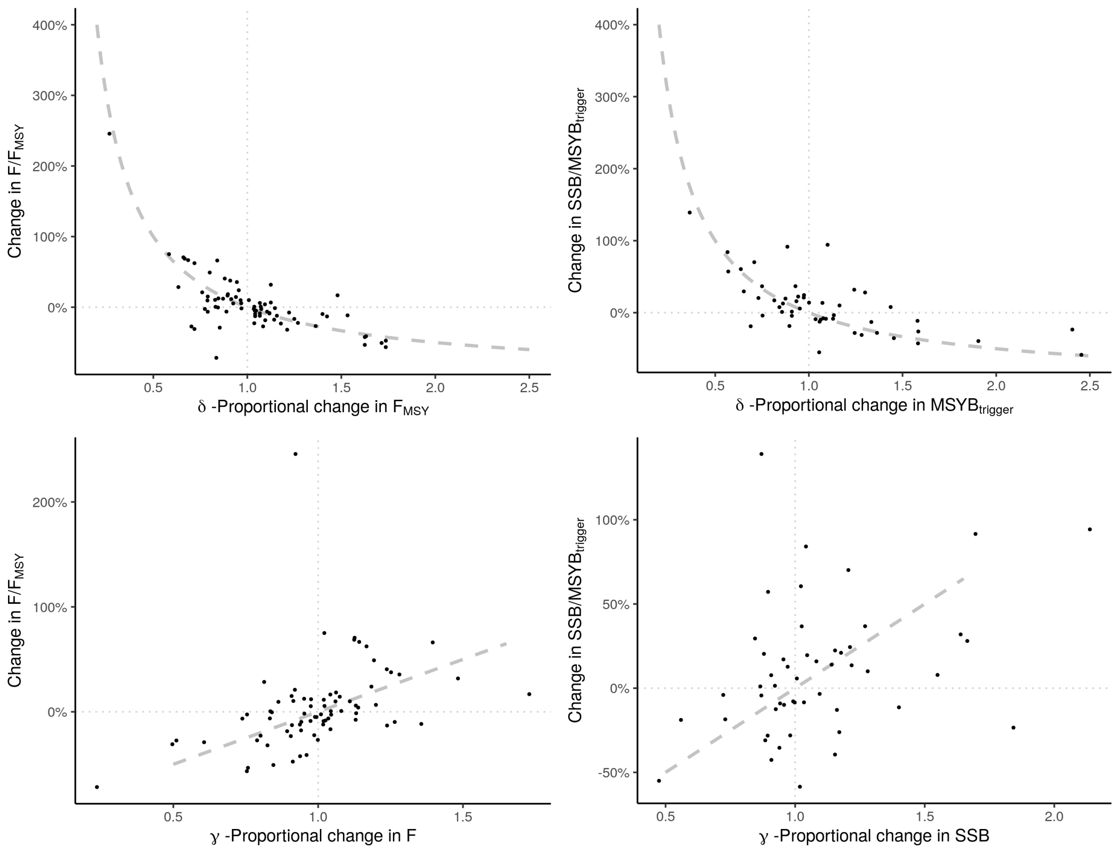

Fig. SI6. Marginal relationship between average change in status and δ, proportional change in reference point, at the top panel; and γ, proportional change in rate (left) or state (right), at the bottom panel considering the recent 5 years of overlap. Grey line shows the expected change with a change in δ or γ.

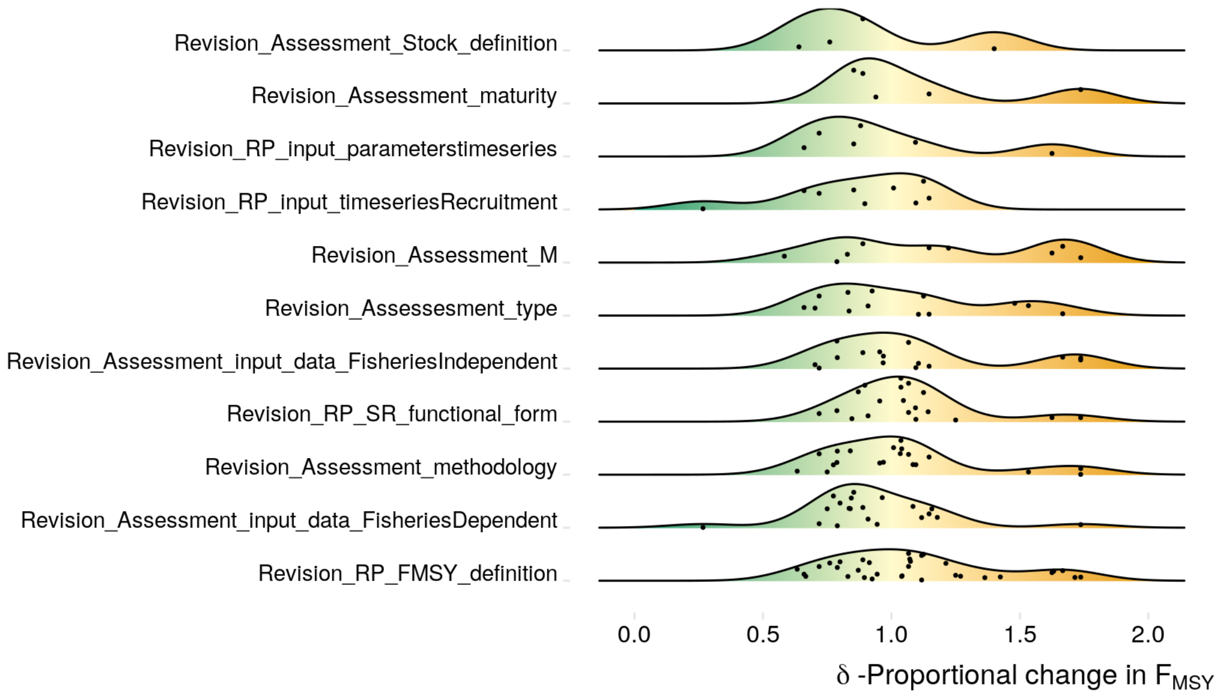

Fig. SI7. Distribution of changes in F_{MSY} segregated by covariate. Warm colours are increase and cool colours are decrease of F_{MSY} advised value. Covariates are ordered vertically based on frequency of observed changes, more frequent in lower panels.

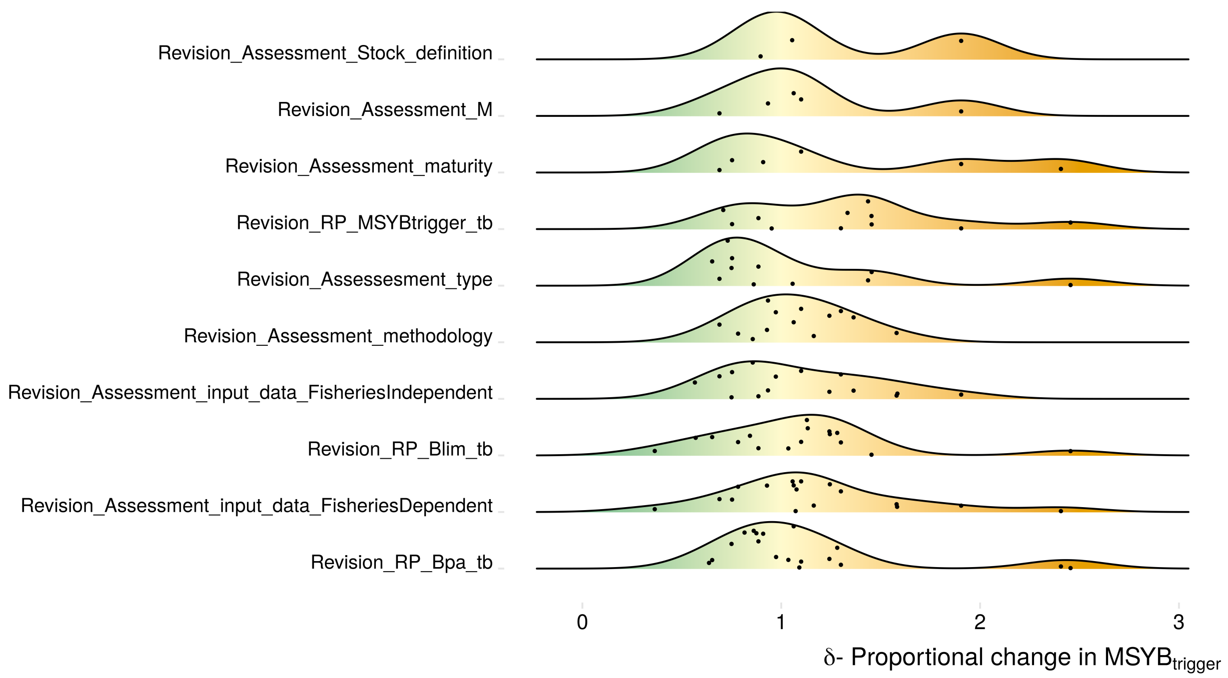

Fig. SI8. Distribution of changes in MSYB$_{trigger}$ segregated by covariate. Warm colours are percentage increase and cool colours are percentage of decrease of MSYB$_{trigger}$ advised value. Covariates are ordered vertically based on frequency of observed changes, more frequent in lower panels.

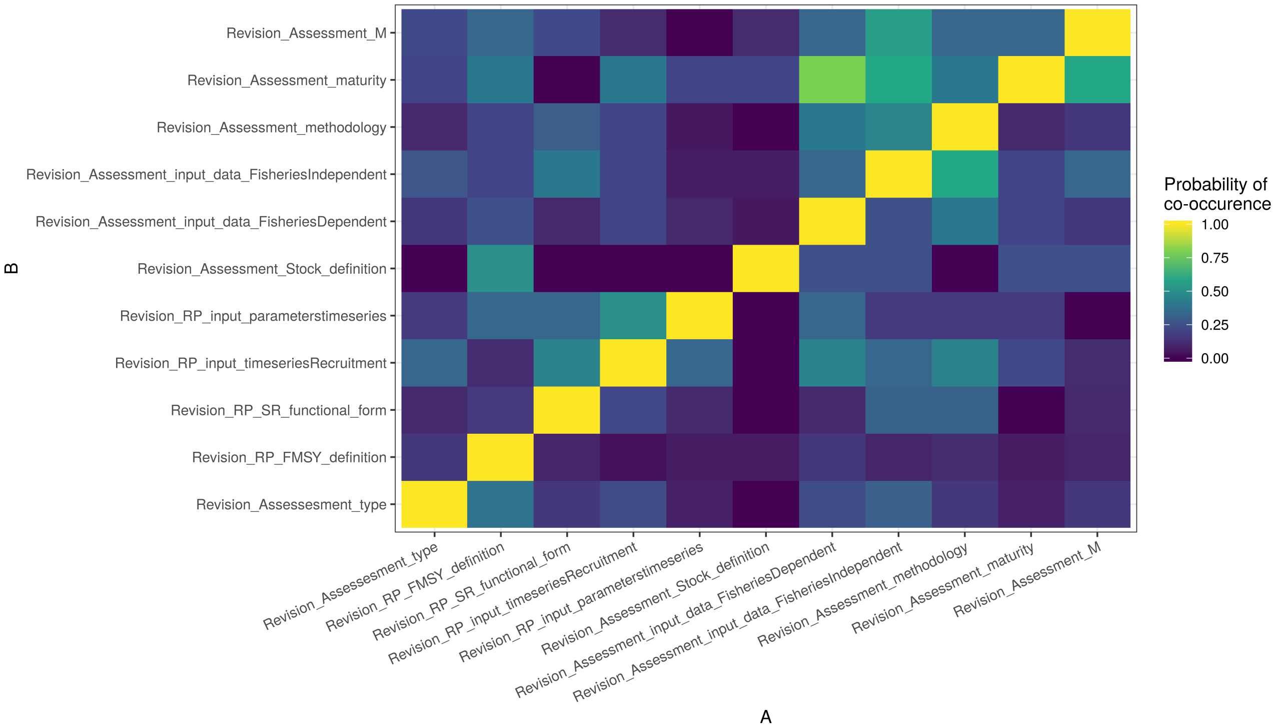

Fig. SI9. Probability of observing revision “A” when observing revision “B” for changes in F_{MSY}.

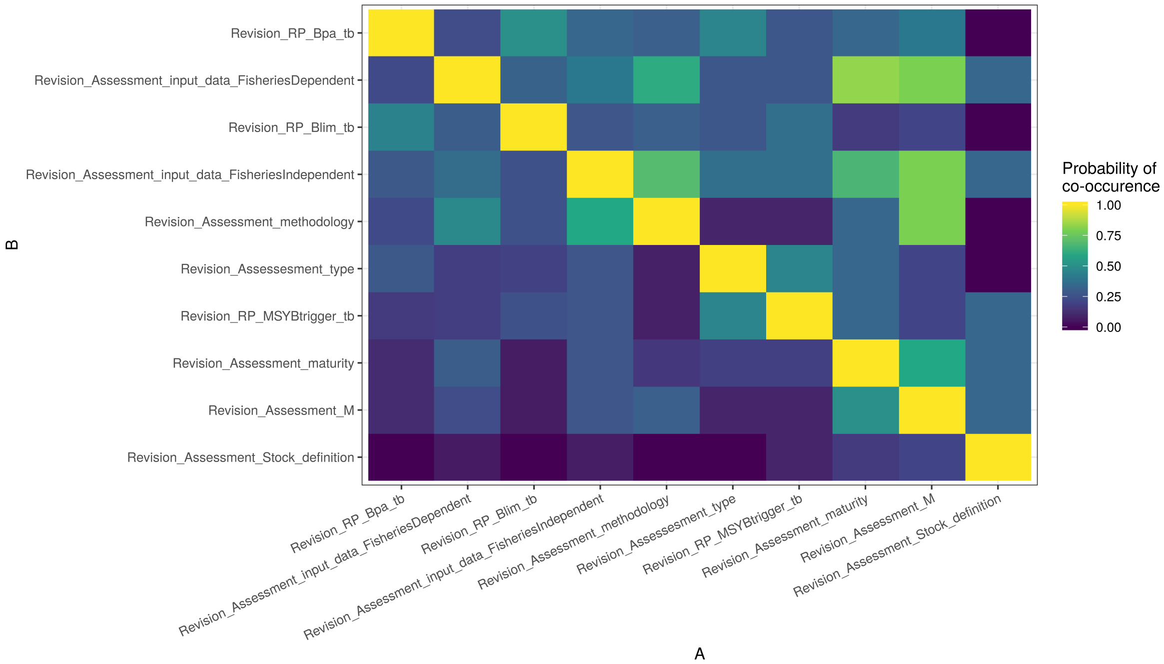

Fig. SI10. Probability of observing revision "A" when observing revision "B" for changes in $MSYB_{trigger}$.

A.3 Supplementary Information for Chapter 5. Stochastic modelling and synthesis of dynamic fish recruitment productivity in the Celtic Seas ecoregion

Supplementary Material for

Stochastic modelling and synthesis of dynamic fish recruitment productivity in the Celtic Seas ecoregion

Paula Silvar-Viladomiu, Cóilín Minto, Colm Lordan, Deirdre Brophy, Rich Bell, Jeremy Collie, and David Reid

*Paula Silvar-Viladomiu

Email: paula.silvarviladomiu@research.gmit.ie

This PDF file includes:

- Figures SM1 to SM3
- Tables SM1 to SM2

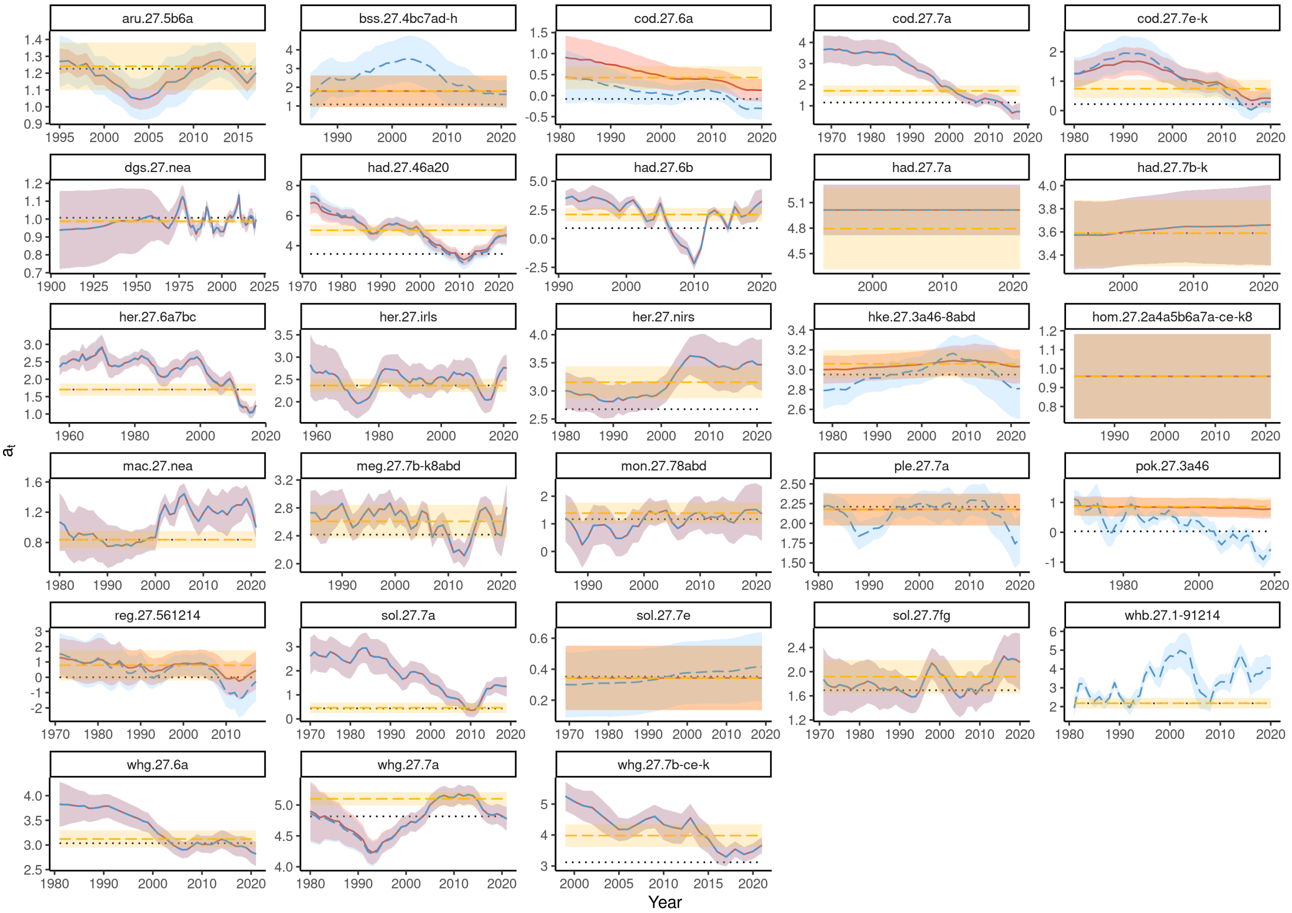

Figure SM1. Results of maximum-productivity parameter (a_t) and the 95%confidence intervals for the Celtic Seas ecoregion stocks; blue represent time-varying maximum-productivity model, yellow represents time-varying density-dependent mortality model, and red represents both parameters covarying model. Dashed black line represents time-invariant model.

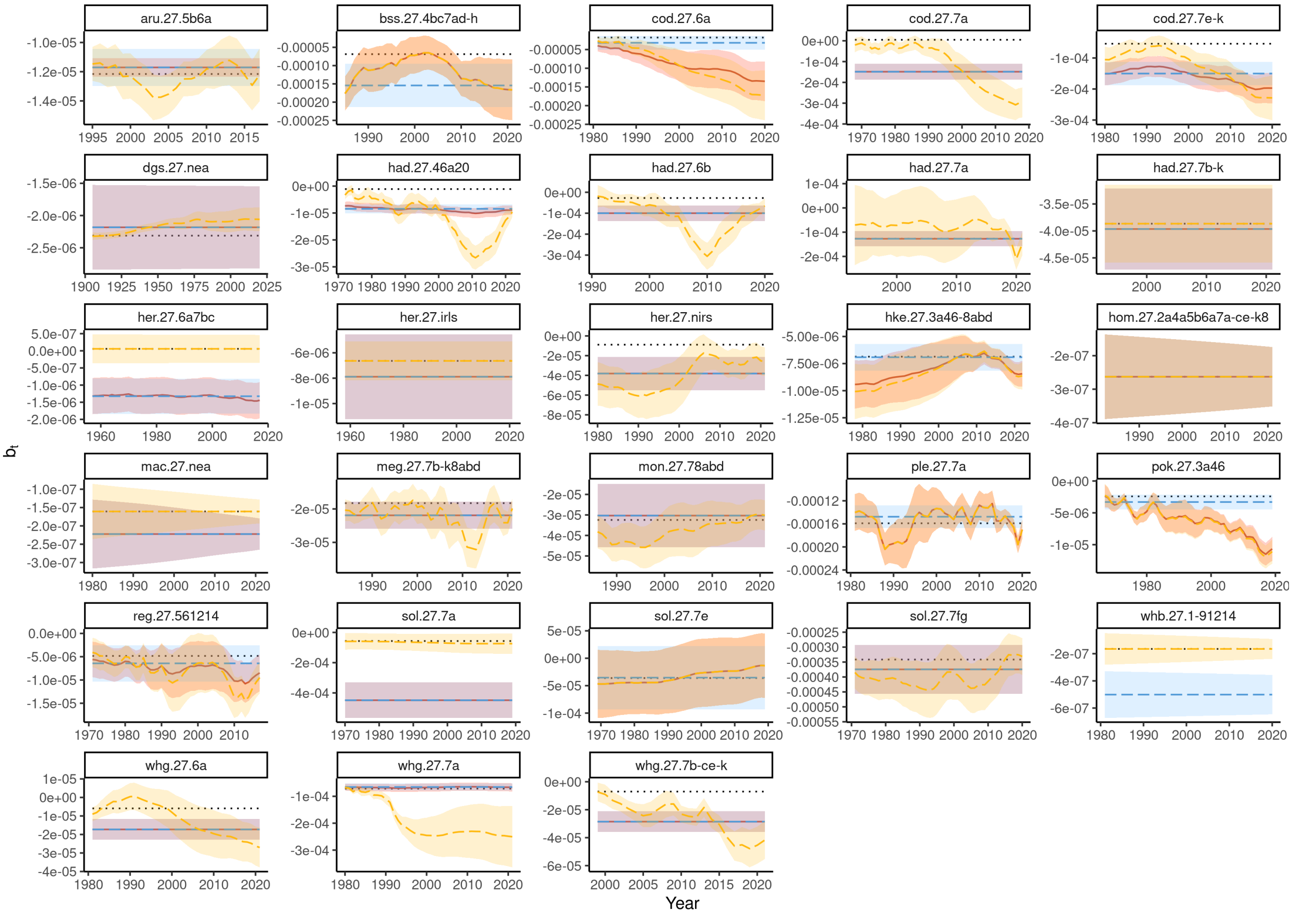

Figure SM2. Results of density-dependent mortality parameter (b_t) and the 95% confidence intervals for the Celtic Seas ecoregion stocks; blue represent time-varying maximum-productivity model, yellow represents time-varying density-dependent mortality model, and red represents both parameters covarying model. Dashed black line represents time-invariant model.

Table SM1. Time-varying maximum-productivity model summary.

Stock key	Year range	Signal-to-noise ratio ($\sigma^2_\omega/\sigma^2_v$)	Process error (σ^2_ω)	Observation error (σ^2_v)	Maximum-productivity a_t	Density-dependent mortality b
aru.27.5b6a	1995-2017	262.56E+03	1.61E-03	6.12E-09	1.18E+00	-11.71E-06
bss.27.4bc7ad-h	1985-2021	211.11E-03	127.49E-03	603.88E-03	2.51E+00	-154.35E-06
cod.27.6a	1981-2020	45.70E-03	16.93E-03	370.42E-03	95.09E-03	-32.02E-06
cod.27.7a	1968-2018	142.99E-03	52.23E-03	365.27E-03	2.45E+00	-148.80E-06
cod.27.7e-k	1980-2020	126.40E-03	55.85E-03	441.85E-03	1.14E+00	-150.15E-06
dgs.27.nea	1905-2020	12.86E+00	642.55E-06	49.96E-06	982.94E-03	-2.18E-06
had.27.46a20	1972-2022	355.26E-03	171.24E-03	482.01E-03	4.88E+00	-8.45E-06
had.27.6b	1991-2020	13.28E+00	1.18E+00	88.57E-03	2.07E+00	-99.91E-06
had.27.7a	1993-2021	20.69E-09	21.72E-09	1.05E+00	5.01E+00	-127.24E-06
had.27.7b-k	1993-2021	3.09E-03	1.98E-03	640.67E-03	3.62E+00	-39.65E-06
her.27.6a7bc	1957-2017	701.98E-03	37.24E-03	53.04E-03	2.26E+00	-1.32E-06
her.27.irls	1958-2021	159.75E-03	43.28E-03	270.93E-03	2.47E+00	-7.89E-06
her.27.nirs	1980-2021	127.48E-03	18.23E-03	142.98E-03	3.18E+00	-38.16E-06
hke.27.3a46-8abd	1978-2022	41.38E-03	5.96E-03	144.12E-03	2.96E+00	-6.91E-06
hom.27.2a4a5b6a7a-ce-k8	1982-2021	1.53E-06	940.87E-09	613.55E-03	959.20E-03	-262.82E-09
mac.27.nea	1980-2021	365.35E+39	9.62E-03	26.32E-45	1.04E+00	-222.36E-09
meg.27.7b-k8abd	1984-2021	93.13E+03	24.58E-03	263.91E-09	2.61E+00	-21.91E-06
mon.27.78abd	1986-2021	1.75E+00	90.76E-03	51.88E-03	1.08E+00	-30.33E-06
ple.27.7a	1981-2020	489.44E-03	12.38E-03	25.29E-03	2.12E+00	-147.67E-06
pok.27.3a46	1967-2019	1.13E+00	66.94E-03	59.29E-03	239.47E-03	-3.30E-06
reg.27.561214	1971-2017	705.61E-03	162.87E-03	230.82E-03	421.65E-03	-6.43E-06
sol.27.7a	1970-2019	418.19E-03	84.47E-03	201.98E-03	1.83E+00	-448.45E-06
sol.27.7e	1969-2019	5.08E-03	406.03E-06	79.92E-03	349.54E-03	-35.34E-06
sol.27.7fg	1971-2020	377.74E-03	20.16E-03	53.36E-03	1.82E+00	-374.53E-06
whb.27.1-91214	1981-2020	638.27E+03	308.01E-03	482.57E-09	3.36E+00	-501.06E-09
whg.27.6a	1981-2021	111.90E-03	17.48E-03	156.25E-03	3.34E+00	-17.27E-06
whg.27.7a	1980-2021	205.87E-03	22.17E-03	107.69E-03	4.77E+00	-65.34E-06
whg.27.7b-ce-k	1999-2021	2.84E+00	81.22E-03	28.59E-03	4.22E+00	-28.53E-06

Table SM2. Summary of dynamic factor analysis models.

Trend s	Log-Likelihood	AIC	AICc	BIC
1	-1122.12	2356.239	2362.048	2639.191
2	-915.3479	2356.239	2009.703	2416.072
3	-625.0607	1996.696	1491.047	2018.868
4	-450.8007	1468.121	1205.037	1846.666
5	-265.8199	1169.601	898.0349	1645.97
6	-106.1323	847.6397	641.9074	1488.807
7	-3.591069	574.2647	500.1821	1438.885
8	79.87587	288.2483	396.5189	1420.058
9	163.0088	161.9825	293.2229	1394.846
10	211.5845	102.8309	258.5081	1431.697
11	276.0768	9.846385	191.1782	1429.661

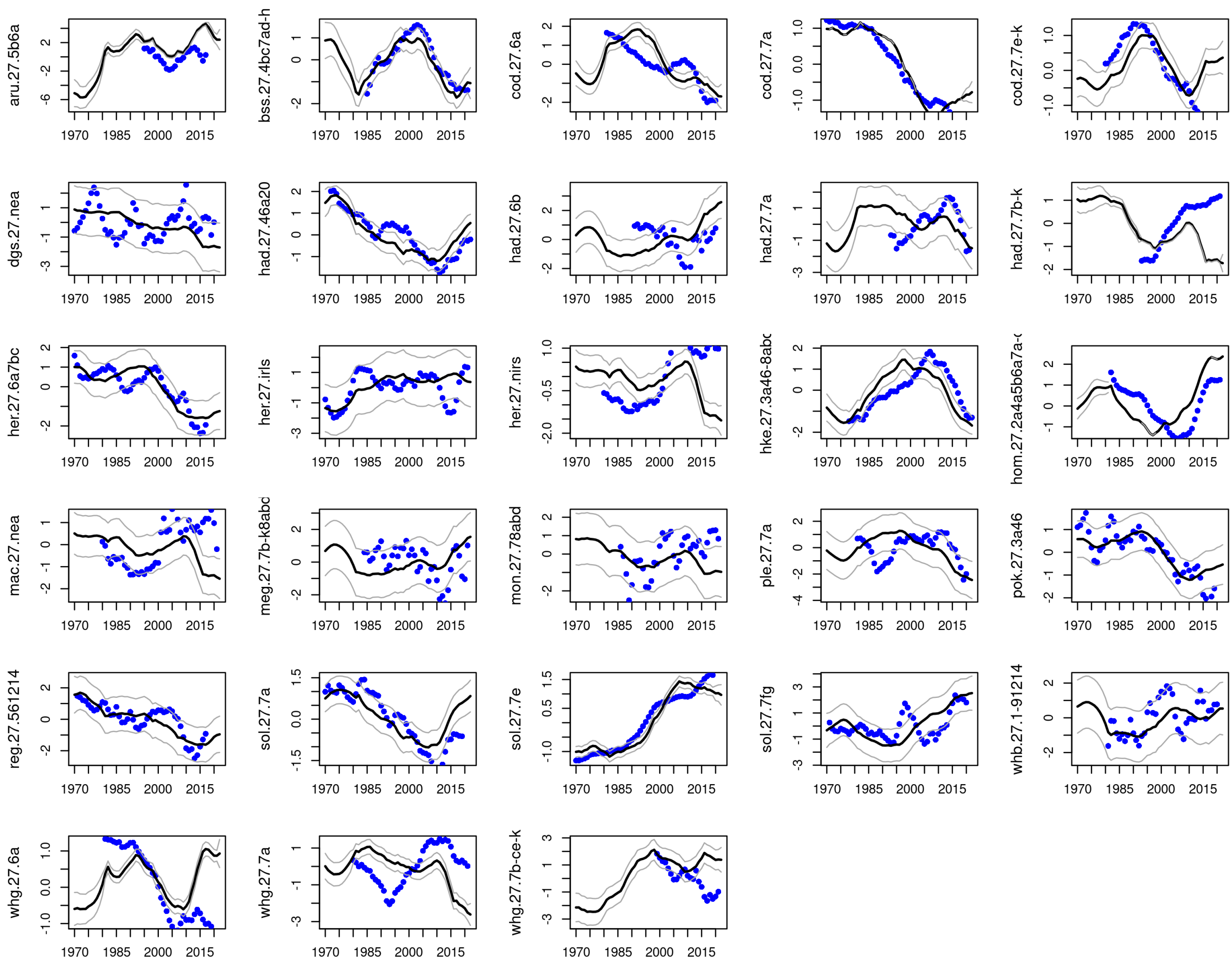

Figure SM3. Four trend DFA model fit and stock data.

Appendix B

Published manuscripts

B.1 Published Version of Chapter 2

Silvar-Viladomiu, P., Batts, L., Minto, C., Miller, D., Lordan, C. (2022). An empirical review of ICES reference points, ICES Journal of Marine Science, 79, 10, 2563–2578. https://doi.org/10.1093/icesjms/fsac194

ICES Journal of Marine Science, 2022, **79**, 2563–2578
DOI: 10.1093/icesjms/fsac194
Advance access publication date: 9 November 2022
Review Article

An empirical review of ICES reference points

Paula Silvar-Viladomiu [1,*], Luke Batts [1], Cóilín Minto [1], David Miller [2] and Colm Lordan [3]

[1]Atlantic Technological University, Dublin Road, Galway, Co. Galway H91 T8NW, Ireland
[2]International Council for the Exploration of the Sea (ICES), H. C. Andersens Boulevard 44–46, 1553 Copenhagen V, Denmark
[3]Marine Institute, Fisheries and Ecosystems Advisory, Rinville, Oranmore, Co. Galway H91 R673, Ireland

*Corresponding author: tel: +34648841990; e-mail: paula.silvarviladomiu@research.gmit.ie.

The International Council for the Exploration of the Sea (ICES) has provided scientific stock advice based on reference points to manage fisheries in the North Atlantic Ocean and adjacent seas for decades. ICES advice integrates the precautionary approach with the objective of achieving maximum sustainable yield. Here, we examine ICES reference point evolution over the last 25 yr and provide a comprehensive empirical review of current ICES reference points for data-rich stocks (Category 1; 79 stocks). The consistency of reference point estimation with the ICES guidelines is evaluated. We demonstrate: (1) how the framework has evolved over time in an intergovernmental setting, (2) that multiple precautionary components and sources of stochasticity are included, (3) that the relationship and historical context of stock size and recruitment are crucial for non-proxy reference points, (4) that reference points are reviewed frequently, taking into account fluctuations and multiple sources of variability, (5) that there are occasional inconsistencies with the guidelines, and (6) that more comprehensive and clearer documentation is needed. Simplifying the stock-recruit typology and developing quantitative criteria would assist with this critically important classification. We recommend a well-documented, transparent, and reproducible framework, and periodic syntheses comparing applications across all stocks.

Keywords: ICES region, limit and target reference points, maximum sustainable yield, precautionary approach, stock population dynamics, synthesis.

Introduction

Reference points are key to providing fisheries advice and enabling effective management of fish stocks (Sissenwine and Shepherd, 1987; Hilborn *et al.*, 2020). A crucial consideration in reviewing reference points is how they are currently used and interpreted in advice products. Target and limit reference points can be used to evaluate stock and fishery status and can also be used in, or for the evaluation of, Harvest Control Rules (HCRs) that apply harvest strategies to set allowable catch (Punt, 2010). Internationally, most advice recipients use similar terminology around the need to establish limit reference points, such that "*Limit reference points set boundaries to constrain harvesting within safe biological limits so stocks can produce maximum sustainable yield*" and target reference points, where "*Fishery management strategies shall ensure that target reference points are not exceeded on average*" (UN, 1995). The UN Fish Stocks Agreement in 1995 set out the principles for the conservation and management of fish stocks. Under this agreement, management should be designed to maintain or restore stocks to levels capable of producing Maximum Sustainable Yield (MSY) and must be based on the Precautionary Approach (PA) and the best available scientific information. Many fishing jurisdictions agree to provide advice that integrates the PA with MSY and embraces the ecosystem approach, e.g. the Common Fisheries Policy (EC, 2013), the UK Fisheries Act (Anon, 2020), and the Magnuson-Stevens Fishery Conservation and Management Act (MSA, 2007) in the United States. These are typical foundations for the basis of reference point estimation. Whilst there are common paradigms and similar terminology, there are many different approaches to setting and estimating reference points (Ricard *et al.*, 2012), depending on the region, jurisdiction, and the HCR used to trigger management decisions.

Reference points are commonly expressed in terms of a stock's biomass or spawning stock biomass (SSB) state and fishing mortality rate (F). Reference points that would produce MSY can be derived from per-recruit analyses coupled with the stock–recruit (SR) relationship in a stochastic projection using, in addition, biological parameters and fishery patterns from the stock assessment (Hilborn and Walters, 1992). Recruitment productivity is often based on the stock–recruitment (SR) relationship. Common functional forms to model the SR relationship are the Ricker (Ricker, 1954), the Beverton–Holt (Beverton and Holt, 1957), and segmented regression or hockey-stick (Mesnil and Rochet, 2010). Despite its importance, estimating SR parameters is challenging because the relationship is not well understood for many stocks due to a lack of data or the relationship itself being weak because of recruitment variation (Shepherd and Cushing, 1990; Myers, 2001; Thorson *et al.*, 2014). Other factors that limit our knowledge of SR relationships are process and observation errors; uncertainty in variables (recruitment or SSB estimates); and non-stationarity (Hilborn and Walters, 1992; Dickey-Collas *et al.*, 2014; Minto *et al.*, 2014; Perälä *et al.*, 2017). Proxy reference points based on percentages from per-recruit analysis can be used when MSY-based estimates cannot be obtained (Geromont and Butterworth, 2015). However, these exclude the SR relationship and other stock information that can make them unreliable. In the northeast Atlantic, yield-per-recruit (YPR) proxies were commonly used proxies for F_{MSY} (ICES, 2007) because they rely on few data but are still useful to provide management recommendations for some stocks. Some US regions set percentages of spawner-per-recruit (SPR) or unfished biomass (B_0) as MSY reference point proxies (Wetzel and Punt, 2017). Preferred proxies and percentages used vary between regions. These are usually based on meta-analysis of data-rich stocks. Setting the appropriate proxy and level for a

Received: April 29, 2022. **Revised:** September 30, 2022. **Accepted:** October 3, 2022

reference point depends on life history features, and all available information on the SR relationship should be used (Mace, 1994; Cadrin, 2012).

Biomass limit reference points have a key role in identifying safe biological limits. These reference points could be interpreted as the level of stock biomass at which recruitment is impaired, or where there is recruitment overfishing. Recruitment overfishing occurs when a population has been fished down to a point where spawning biomass is so low that recruitment decreases substantially (Cushing, 1975; Sissenwine and Shepherd, 1987). Estimation of biomass limit reference points varies a lot regionally, and the estimation method impacts the level and the associated uncertainty of the reference point (Deurs *et al.*, 2021). Some regions define biomass reference points as a chosen percentage below B_{MSY}, e.g. 0.5 B_{MSY} or higher in the United States (Punt *et al.*, 2014). However, recent stock size trends and fluctuations might not be informative regarding B_{MSY}, in addition to the SR relationship possibly not being well understood. Also, a percentage of unfished biomass, B_0, can be used as the basis for a biomass limit reference point in parts of the United States (Wetzel and Punt, 2017). Fishing mortality limit reference points, such as F_{lim}, also have an important role in safeguarding safe biological limits. Fishing mortality should always be below that which will drive the spawning stock to the B_{lim} threshold.

Fish stocks display marked variability in life history, recruitment, and historical exploitation (Caddy and Mahone, 1995). To estimate reliable reference points, these important features need to be taken into account, i.e. natural patterns of fluctuation in the dynamics of biomass, recruitment, and changes in fishing pressure and selectivity over time. In particular, recruitment temporal dynamics are complex and are challenging to deal with in the estimation of reference points (Sharma *et al.*, 2019). For instance, sporadic large recruitment can influence the estimates of SR parameters. Additionally, there must be sufficient contrast in the SSB data to accurately understand the underlying SR relationship and estimate reference points (Anon, 1999). If the contrast is small, estimates could be determined mainly by process or measurement error and thus could be unreliable. In these cases, the choice of reference point should be more precautionary (Anon, 1999). Additionally, uncertainty related to the modelling tools, management, and advice implementation has to be dealt with when setting reference points (Kell *et al.*, 2005).

The International Council for the Exploration of the Sea (ICES) has been providing scientific stock advice to government and international regulatory bodies that manage fisheries in the North Atlantic Ocean and adjacent seas for decades. ICES advice is diverse and based on requests from a range of requestors, including governments, governmental agencies, RFMOs, commissions, etc. The current approach integrates the PA with the objective of achieving MSY in accordance with the international guidelines to manage fish stocks (ICES, 2021a). The ICES interpretation of MSY is maximizing the average long-term yield from a given fish stock while maintaining the stock in productive condition. When providing fisheries advice for stocks with full analytical assessments, ICES refers to two types of reference points: PA reference points and MSY reference points.

Within ICES, several relevant discussions on reviewing reference points have occurred in recent workshops (ICES, 2020a, 2021b), which has led to the Workshop on ICES reference points (WKREF1 and WKREF2). The purpose of WKREF1 and WKREF2 was to review and re-evaluate ICES reference points and produce clear evidence-based recommendations to the Advisory Committee (ACOM), and produce a road map to implementation to develop user-friendly guidelines and tools for the future. Both target and limit reference points were considered in terms of how they can be used in the evaluation of stock status, the ICES MSY advice framework, and more generally in management strategy evaluations (MSEs) to define if HCRs are both precautionary and in accordance with the MSY approach.

In this article, we reviewed reference points used in ICES fisheries advice up to 2021. We start by examining the evolution of the ICES reference point framework over the past 25 yr, followed by a summary of the current approach. Then, we investigate (i) most recent updates in ICES reference points; (ii) the key role of ICES biomass limit reference point (B_{lim}) and its relationship with SR typologies in the guidelines; (iii) the estimation of MSY reference points and how uncertainty and variability are included; and (iv) interdependencies among reference points, particularly the impact of B_{lim} changes on other reference points. Finally, based on this comprehensive empirical review, we summarize six concluding points and give recommendations for the future.

Evolution of ICES-advised reference points

The ICES reference point framework has been strongly influenced by policy needs and drivers but also by the availability of tools to estimate reference points in a consistent way (Figure 1). The ICES Study Group on the Precautionary Approach (SGPA) in 1998 defined B_{lim} as the biomass "*below which recruitment becomes impaired or the dynamics of the stock are unknown*" (ICES, 1998). The word "impaired" is synonymous with the concept that, on average, recruitment becomes systematically reduced as biomass declines below a certain point. During the early 2000s, the various SGPA meetings developed understanding of precautionary reference points considerably (ICES, 2001, 2002, 2003a). This culminated in the Study Group on Precautionary Reference Points for Advice on Fisheries Management (SGPRP) in 2003, which was the first systematic attempt to estimate PA reference points for most data-rich ICES stocks (i.e. Category 1, stocks for which a full analytical assessment could be conducted; ICES, 2003b). ICES advised on the state of the stock relative to a limit reference point (B_{lim}) that should be avoided to ensure that stocks remain within safe biological limits, i.e. a high probability that SSB is above B_{lim} and that fishing mortality is below a value F_{lim} that will drive the SSB to B_{lim}. At that stage, ICES had already started to define SR types based on SR plot categorization, and use segmented regression to estimate breakpoints in the SR relationship. The definition of B_{lim} was "*the SSB below which is a substantial increase in the probability of obtaining reduced (or 'impaired') recruitment i.e. the estimate of B_{lim} should be risk-averse so that when the stock is at B_{lim} the probability that recruitment is substantially impaired is still small, but below B_{lim} that probability increases*".

In 2002, the Johannesburg Declaration of the World Summit on Sustainable Development (WSSD; UN, 2002) called for an ecosystem approach and rebuilding fisheries to maximum sustainable yield (MSY). In 2007, the ICES Workshop on Limit and Target Reference Points (WKREF) was established with terms of reference that included review of

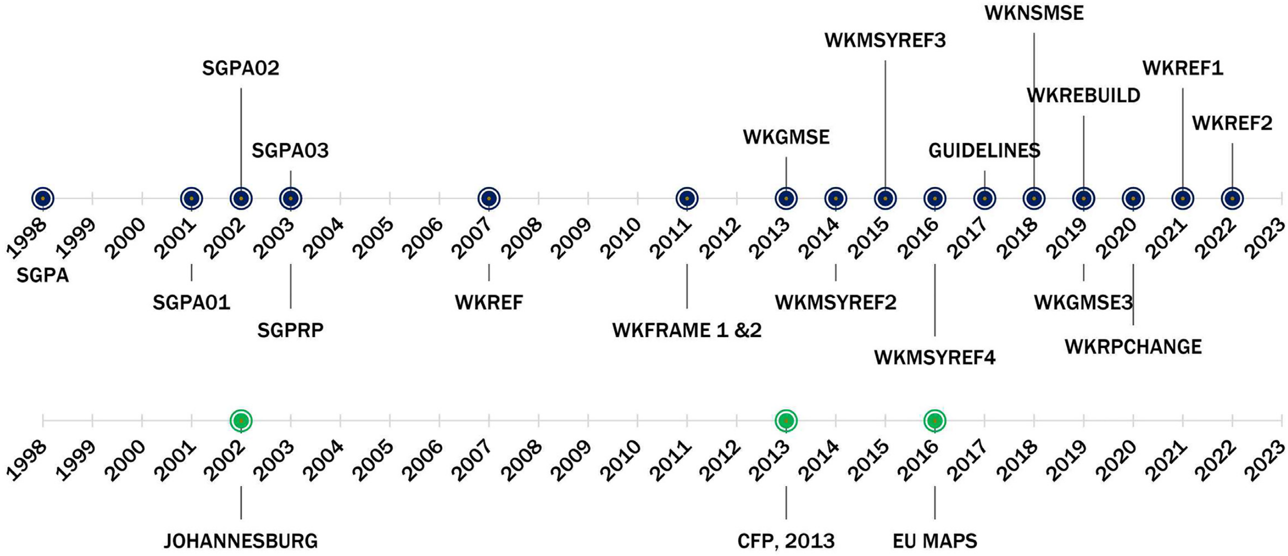

Figure 1. The working group timeline that produced key developments in the evolution of ICES Precautionary Approach and Maximum Sustainable Yield reference points. Acronyms used are: SGPA (Study Group on the Precautionary Approach), SGPRP (Study Group on Precautionary Reference points for Advice on Fisheries Management), WKREF (Workshop on Limit and Target Reference Points), WKFRAME (Workshop on Implementing the ICES F_{MSY} framework), WKGMSE (Workshop on guidelines for management strategy evaluations), WKMSYREF2 (Workshop to consider reference point for all stocks), WKMSYREF3 (Workshop to consider the basis for F_{MSY} ranges for all stocks), WKMSYREF4 (Workshop to consider F_{MSY} ranges for stocks in ICES categories 1 and 2 in Western Waters), WKNSMSE (Workshop on North Sea stocks Management Strategy Evaluation), WKREBUILD (Workshop on Guidelines and Methods for the Evaluation of Rebuilding Plans), WKRPCHANGE (Workshop of Fisheries Management Reference Points in a Changing Environment), WKREF (Workshop on guidelines for reference points), CFP (Common Fisheries Policy), and EU MAPS (European Union regional Multiannual Plans).

reference points with respect to regime shifts and the science and implementation of MSY-based approaches (ICES, 2007). Various problems with limits and targets were identified, and there was no consensus on a way forward. It was thought "*that distance between B_{pa} and B_{lim} could take into account the uncertainty due to different regimes*". From the review of the scientific and management literature, WKREF concluded that MSY is a difficult concept for management purposes because it is difficult to assess, unstable over time, and only applicable in a single species context. Single-species MSY and B_{MSY} will not work for predators and prey at the same time (May *et al.*, 1979; Walters *et al.*, 2005).

The Workshop on Implementing the ICES F_{MSY} framework (WKFRAME) in 2010 and 2011 was tasked with drafting technical guidelines to assist ICES expert groups in the implementation of the ICES MSY framework for advice (ICES, 2011). A trigger biomass point, MSY $B_{trigger}$, was defined as a low biomass that is encountered with a low probability if a stock is exploited at F_{MSY}. This differs from B_{MSY}, which is the expected average biomass if the stock is exploited at F_{MSY}. These workshops discussed the role of MSY $B_{trigger}$ and indicated "*it should be selected as a biomass that is encountered with low probability if F_{MSY} is implemented*" and that "*under MSY exploitation it should be a property of the expected distribution of SSB*". However, ensuring compatibility with the PA was also raised as an issue, including the need to avoid B_{lim} in the long term, taking model error into account. At this stage, generic tools that were easily and widely applicable started to develop. The methodology PlotMSY was developed in AD-Model Builder to perform deterministic equilibrium yield analysis coupled with stochastic simulation procedures (ICES, 2010), using the assessment summary and sensitivity data. In PlotMSY, SR model uncertainty was taken into account by model averaging of three functions (Ricker, Berverton–Holt, and smooth hockey-stick). The tool was used by the ICES community to provide robust estimation of MSY estimates (ICES, 2014), which was a major step forward to stochastically estimating reference points.

Various ICES advice recipients developed strong policies to implement an ecosystem and MSY approach in their fisheries management systems. Within the EU, legal obligations to implement MSY management and establish multiannual plans reflecting the specificities of different fisheries based on the best available science were set out in the reformed CFP (EC, 2013). There were significant technical developments around Management Strategy Evaluations (MSEs; ICES, 2013a; Punt *et al.*, 2016), and work on developing a new ICES tool to estimate MSY reference points began (the stochastic equilibrium software EqSim). EqSim provides MSY reference points based on the equilibrium distribution of stochastic projections. In EqSim, parameters related to productivity (i.e. natural mortality, maturity, growth) are randomly re-sampled from a specified period of the assessment and recruitments are resampled from their predictive distribution (ICES, 2014). This methodology can take into account the uncertainty in the SR model by applying model averaging of different SR functional forms, as well as incorporate advice error. After limited progress at the Workshop to consider reference points for all stocks (WKMSYREF), there was significant development as EqSim was more widely tested at WKMSYREF2 (ICES, 2014). A joint ICES/MYFISH (https://www.myfishproject.eu/) "Workshop to consider the basis for F_{MSY} ranges for all stocks" (WKMSYREF3; ICES, 2015a, b), systematically estimated MSY reference points and F_{MSY} ranges for the North Sea and Baltic stocks to address a special request from the EU for MSY ranges for their regional multiannual plans (MAPS;

EC, 2013). A year later, the "Workshop to consider F_{MSY} ranges for stocks in ICES categories 1 and 2 in Western Waters" (WKMSYREF4) developed the approach further and estimated MSY ranges for demersal stocks in western waters (ICES, 2017a). The ICES technical guidelines to estimate "ICES fisheries management reference points for category 1 and 2 stocks" were published in 2017 (ICES, 2017b).

Since 2017, several ICES expert groups have identified challenges and suggested developments in reference point estimation (Figure 1)—including the ICES Workshop on North Sea stocks Management Strategy Evaluation in 2018 (WKNSMSE), the ICES Workshop on Guidelines and Methods for the Evaluation of Rebuilding Plans in 2019 (WKREBUILD), the third ICES Workshop on Guidelines for Management Strategy Evaluations in 2019 (WKGMSE3), the ICES Workshop on Management Strategy Evaluations of Mackerel in 2020 (WKMSEMAC), and the ICES Workshop of Fisheries Management Reference Points in a Changing Environment in 2020 (WKRPCHANGE). Current guidelines (ICES, 2021c) were criticized in various working groups as they were thought to be complex, convoluted, and not always well understood or followed by assessment practitioners. There is little documentation on EqSim to help those at benchmarks with implementation and interpretation. Other issues highlighted were that determination of B_{lim} requires a subjective classification of the SR pairs into types (ICES, 2020a); discrepancies were found between reference points from the standard ICES approach and MSEs (ICES, 2019); major sources of uncertainty in reference points were related to changes over time in biological and SR parameters (ICES, 2021b); and determining the time period used to derive reference points was considered challenging because estimation becomes unreliable as time series are reduced (ICES, 2021b). In recent years, ICES has been in the process of reviewing and modifying their reference point estimation guidelines through two workshops WKREF1 and WKREF2 (Figure 1). We argue that part of the reform must consider exactly how current procedures are implemented comparatively across stocks. Hereafter, as a part of the continual process to improve ICES reference point estimation, we provide an empirical review of how category 1 reference points are currently derived. Such synthesis enables cross-comparisons of stocks displaying consistencies, highlights inconsistencies, and points towards further improvements.

ICES current reference points approach

Recently, ICES published updated guidelines for estimating reference points (ICES, 2021c). The emerging five-step procedure for estimating reference points was strongly linked to the advice framework and the need to ensure that the ICES MSY advice rule (AR) was also consistent with the ICES PA (ICES, 2021c; Figure 2). The ICES MSY AR is a HCR that leads to catch advice corresponding to a fishing mortality of equal to F_{MSY} when SSB is at or above MSY $B_{trigger}$ but reduced relative to F_{MSY} when the stock is below MSY $B_{trigger}$ (ICES, 2021a). The ICES approach aims to maximize long-term yield while safeguarding against low SSB. Thus, more caution is needed below B_{lim} (see dashed line below B_{lim} in Figure 2). The advised catch might be zero when there is not a high (95%) probability of SSB $\geq B_{lim}$; otherwise, it is capped by the catch that leads to a 95% probability of SSB $\geq B_{lim}$ after the advice year.

The current five steps to estimate reference points involve (i) identifying appropriate data (truncate time series or not), (ii) identifying SR type (six different types are described with different recommended actions; Table 1), (iii) estimating biomass limit reference points, (iv) deriving PA reference points from limit reference points, and (v) estimating MSY reference points without and later with the AR. First, the value of F_{MSY} is calculated, including stochasticity and advice error. Second, the MSY $B_{trigger}$ is selected without advice error. For most stocks that lack data on fishing at F_{MSY}, MSY $B_{trigger}$ is set at B_{pa} (ICES, 2021c). For stocks with evidence of fishing mortality being at or below F_{MSY}, MSY $B_{trigger}$ is selected to be the maximum value between the fifth percentile of the distribution of SSB when fishing at F_{MSY} (excluding advice error but including stochasticity in population and fishery) and B_{pa} (Figure 2). Then, the ICES MSY AR is evaluated via stochastic simulation with F_{MSY} and MSY $B_{trigger}$ and checked that the fishing mortality that results in a low long-term probability ($\leq$0.05) of SSB to be below B_{lim} (called the precautionary criterion or F_{pa}) is lower than the initial F_{MSY}. If $F_{MSY} > F_{pa}$, then the advised F_{MSY} is capped to the value of F_{pa} (Figure 2).

Key steps for estimating ICES reference points are identifying SR stock type and deriving biomass limit reference points. These steps are related because the technical basis for B_{lim} is generally determined by the classification of stock characteristics into SR typologies (Table 1). In the ICES guidelines, historical fishing mortality is not considered when deciding the stock typology, but it is relevant for some SR types when setting B_{lim} (Table 1). To estimate MSY-based reference points, it is typically assumed that the associated parameters remain constant or vary around a historical long-term mean. ICES considers MSY reference points to be valid only in the short and medium-term (5–10 yr) as ecosystems and fisheries are dynamic over time. Therefore, reference points are subject to regular reviews (ICES, 2021a).

Methods

ICES category 1 reference point database

Estimation of reference points is dependent on the definition or technical basis used, method settings, and data/output used. We assembled a database of reference point estimation data for 79 ICES category 1 stocks. All stock-specific available documentation was reviewed, including benchmark and inter-benchmark reports, working group reports, special requests, expert group reports, and specific working documents (specific topic documents submitted during benchmarks that support the main assessment). Collated data relate to reference points and their estimation, including re-evaluation year, estimation framework, B_{lim} and F_{MSY} technical basis, SR type, SR settings, assessment error settings, time-period settings, references, EqSim settings, and hitting precautionary bounds (Table 2). We developed an R code to clean the information as collated from the documents (see Table 2 for cleaning details). This comprised grouping categories to summarize information expressed in different texts into homogenized terms. For stocks that used EqSim (*eqsim_run* from the R package *msy*; https://github.com/ices-tools-prod/msy), we also revised raw reported information to fill in default values, assuming: (a) if SR truncation was not stated, then the data were not truncated; (b) if autocorrelation, process error, recruitment, and catch trimming of extreme values were not stated, then we assume EqSim function default (i.e. autocorrelation: on, process error: on, recruitment trimming of extreme values: restrict the

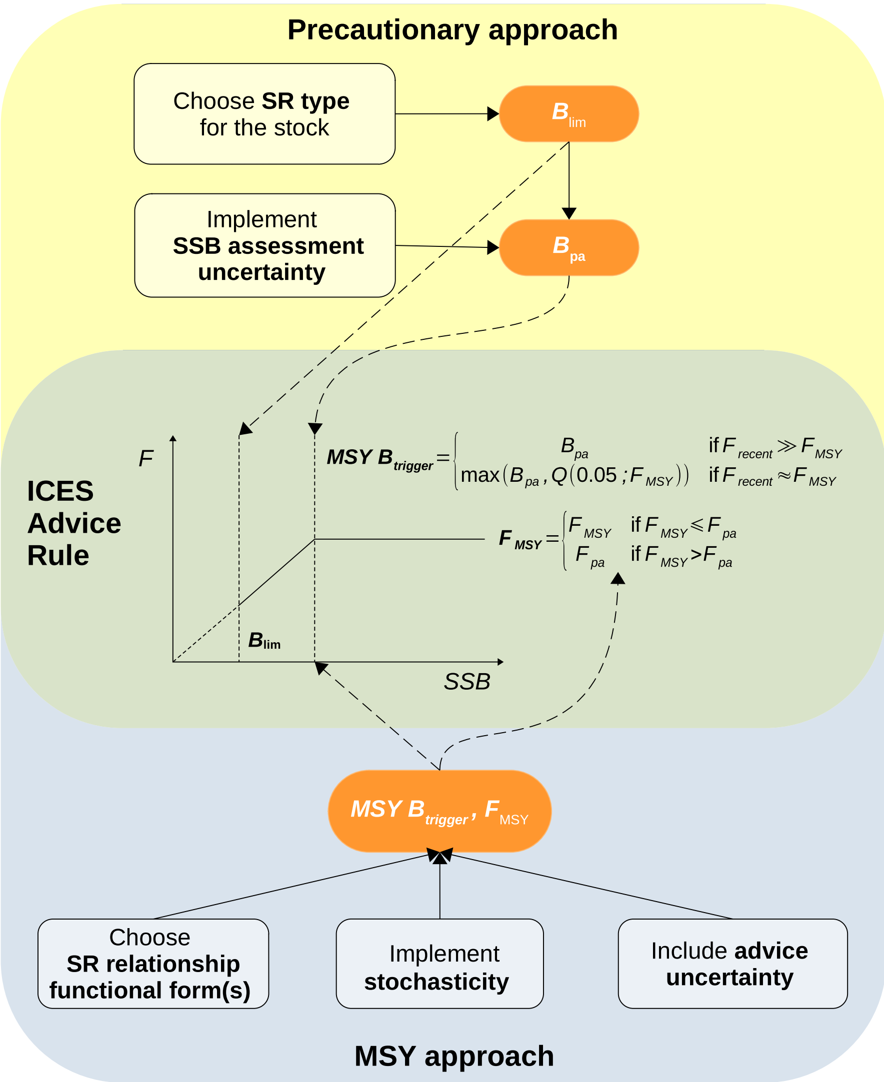

Figure 2. The ICES advice rule (Category 1 stocks) integrates the precautionary approach (yellow) with the Maximum Sustainable Yield (blue). If F_{recent} has been in the vicinity of F_{MSY} for 5 or more years, then the fifth percentile of SSB, when fished at F_{MSY} [Q(0.05; F_{MSY})] is used as the trigger point, otherwise B_{pa} is used. The precautionary criterion (F_{pa}, also called $F_{p.05}$) is a fishing mortality that results in >95% annual probability that SSB remains at or above B_{lim} in long-term equilibrium and caps F_{MSY}.

range of recruitment deviations to +/− three standard deviations on the log scale, catch trimming of extreme values: off). We did not assume default values on the assessment uncertainty parameters and period selection of biological and selectivity parameters because the function defaults differ from the guidelines. When an SR type was not stated in the report, it was inferred from SR plot characteristics by following ICES guidelines for SR type identification (ICES, 2021c) and using expert knowledge among the authors.

Stock biomass and fishing mortality features

We estimated spawning stock biomass and fishing mortality metrics to assess the consistency with the SR typology guidelines (Table 1). We extracted stock assessment results (fishing mortality, spawning size biomass, and recruitment data) from the ICES Stock Assessment Graphs database via XML parsing (ICES, 2021d). All the calculations were made using the most recent assessment for each stock. We calculated the coefficient of variation of the full time series of SSB assuming a log-normal distribution (*CV* SSB) as a stock-level summary of the stock biomass spread. To summarize the history of stock fishing mortality, of relevance to B_{lim} choice, we calculated the mean F relative to F_{MSY} over the full time series.

$$F_{rel} = \frac{\frac{\sum_{t=1}^{n} F_t}{n}}{F_{MSY}},$$

where t is the year and n is the number of years in the time series for a given stock.

Spasmodic stocks categorization

Spasmodic stocks (SR type 1; Table 1) are defined by ICES as “stocks with occasional large year classes” (ICES, 2021b). To assist the identification of spasmodic stocks and determine the consistency of the spasmodic stock definition, we

Table 1. ICES Stock type classification for category 1 stocks and limit point estimation option (ICES, 2021c).

SR type	Stock characteristics Recruitment	SSB	SR plot	B_{lim} settings options
Type 1 Spasmodic stocks	Occasional large year classes	-	-	B_{lim} is based on the lowest SSB that produced large recruitment unless F has been low throughout the observed history, in which case $B_{\mathrm{loss}} = B_{\mathrm{pa}}$.
Type 2	-	Wide dynamic range	Impaired recruitment has been observed	$B_{\mathrm{lim}} =$ segmented regression change point.
Type 3	-	Wide dynamic range	Impaired recruitment has been observed, but no clear asymptote	B_{lim} may be close to the highest SSB observed. The estimate depends on an evaluation of the historical fishing mortality.
Type 4	-	Wide dynamic range	Recruitment increases as SSB decreases	No B_{lim} from this data, only the PA reference point. (B_{loss} would be a candidate for B_{pa}).
Type 5	-	-	No impaired recruitment has been observed, no clear relation	$B_{\mathrm{lim}} = B_{\mathrm{loss}}$.
Type 6	-	Narrow dynamic range	No impaired recruitment has been observed, no clear relation	No B_{lim} from this data, only the PA reference point (B_{loss} could be a candidate for B_{pa}, however, this depends on an evaluation of the historical fishing mortality).

Table 2. ICES category 1 reference point database.

Data variable	Description	EqSim specific	Cleaned
Refpt_framework	Reference point framework	No	Homogenize terms
SR_type	*SR* stock type	No	No
SR_type_n	Inferred *SR* stock type, assigned to stocks with no stated typology in reports	No	No
B_{lim}*_tecbasis*	B_{lim} technical basis	No	Homogenize terms
B_{lim}	B_{lim} value	No	No
F_{MSY}*_tecbasis*	F_{MSY} technical basis	No	Homogenize terms
F_{MSY}	F_{MSY} value	No	No
SR_model	SR functional form model	No	Homogenize terms
SR_modelweights	SR models weights	Yes	No
Breakpoint.fixed.at	Breakpoint of the fixed segmented regression	Yes	Homogenize terms
SR_data_truncated	Whether data was truncated (Yes/No/Not stated)	No	Assumed No if not stated
AutocorrelationR	Whether autocorrelation parameter was used (TRUE/FALSE/Not stated)	Yes	Assumed TRUE if not stated
SR_period	Year period of SR pairs period used to derive reference point	No	No
process.error	Whether process error parameter was used (TRUE/FALSE/Not stated)	Yes	Assumed TRUE if not stated
recruitment.trim	Whether recruitment trimming was used (Yes/No/Not stated)	Yes	Assumed Yes c(−3,3) if not stated
F_{CV}	Value set for the coefficient of variation of F (F_{CV})	Yes	No
F_{PHI}	Value set for the autocorrelation of F (F_{φ})	Yes	No
SSB_{CV}	Value set for the coefficient of variation of SSB (SSB_{CV})	Yes	No
bio.years	Year period used for biological parameters	Yes	Calculation of number of years
Selectivity_pattern_period	Year period used for biological parameters	Yes	Calculation of number of years
extreme.trim	Whether extreme catch values trimming was used (Yes/No/Not stated)	Yes	Assumed No if not stated
Hitting.precautionary.bounds. F_{MSY}.Fpa	Whether the precautionary bounds were hit ($F_{\mathrm{MSY}} > F_{\mathrm{pa}}$ or $F_{\mathrm{MSY}} < F_{\mathrm{pa}}$ or not stated)	No	Homogenize
Report_reference	Reference from which the information was extracted	No	No

Description of data collated, whether they are an EqSim specific or cleaning procedure for each data variable.

evaluated the variance of recruitment time series. First, we fitted a loess smother with a 0.3 span to the natural logarithmic transformed recruitment. A span of 0.3 (a trade-off between over-smoothing and over-fitting) would capture approximately decadal-scale long-term changes, which we seek to remove in our assessment of spasmodic stocks. Such low-frequency variability could be caused by historic fishing patterns reducing SSB and thus reducing recruitment and does not reflect the high amplitude variation of spasmodic stocks (Spencer and Collie, 1997). To characterize the high frequency variability, we calculated the empirical cumulative distribution function (CDF) of the detrended recruitment proportional to the maximum. We also calculated the CDF of the raw recruitment time series proportional to the maximum to compare results (detrended or not). The CDF is useful as it displays the fraction of the observed values less than a given value and thus informs on how infrequent specific recruitment events are. Intuitively, spasmodic recruitment would be typically low recruitment events with occasional large recruitment events, which translates into a steeply climbing CDF. To identify time series with high variance, we estimated the theoretical expected 80% interval for CDFs of time series with lognormal variance of 1. We used a variance value of 1 as this is the 90th quantile of detrended residuals from the Ram Legacy Stock Assessment Database (version 4.44) across all stocks in the database. The criteria used identify an extreme pattern for a given variance. To estimate the theoretical expected interval, we used 42 yr, which is the median length of the SR pairs across all the studied stocks (this could be tailored for individual stocks).

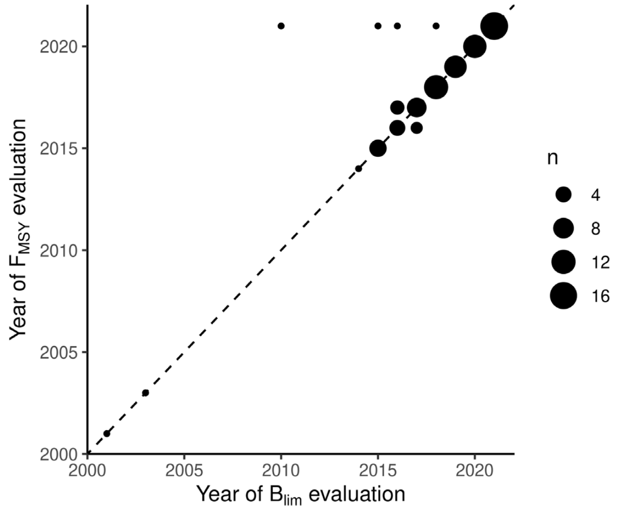

Figure 3. Year of the most recent evaluation for F_{MSY} and B_{lim} reference points for the current advice of ICES category 1 fish stocks.

Changes in reference points database

For a total of 79 stocks, we also acquired retrospective data of past assessments, from the year of the working group WKMSYREF4 to the most recent assessment year (2016–2021). We accounted for the change in 2017 of the codes that are used to identify each stock (stock label key). We obtained reference points data (F_{MSY}, MSY $B_{trigger}$, B_{lim}, and B_{pa}), and time-series data on stock size, fishing mortality, and recruitment. We retained only assessments that used "SSB" in the stock size description. Changes in reference points between sequential assessments were identified for analysis; we calculated the change in reference point (RP) as the proportional change relative to the preceding assessment $(RP^y–RP^{y-1})/RP^{y-1}$, where y is the assessment year, following the method in Silvar-Viladomiu *et al.* (2021). Simultaneous changes in F_{MSY} and B_{lim}, and MSY $B_{trigger}$ and B_{lim} were visualized.

Consistency of current ICES reference points

In this section, we present the results from evaluating the consistency of 2021 ICES reference points with the guidelines (ICES, 2021c). We evaluated reference point updates, SR type classification in relation to B_{lim} technical basis and stock characteristics (SSB, fishing mortality, SR relationship, and recruitment variability), the framework to implement stochastic MSY, and simultaneous changes in reference points.

Evaluation and update of reference points

Currently, from the 79 stocks classified as ICES category 1, most reference points have been changed within the last 5 yr (81.01% for F_{MSY} and 75.95% for B_{lim}), with two stocks with long-established reference points (northeast Arctic capelin in 2001 and cod in 2003; Figure 3). There are four stocks with recent estimates of F_{MSY} but older estimates of B_{lim}. This might reflect changes to the ICES reference points guidelines to cap from F_{MSY} to F_{pa} (the F that would lead to SSB $\geq B_{lim}$ with a 95% probability in the long term, previously known as $F_{p.05}$; Figure 3).

Stock SR typology and biomass limit reference points

For many stocks, the SR type was not specified in the documentation, reflecting difficulties to assign it (not stated SR type in the reports $n = 40$). The typologies were often consistent with the selection of B_{lim} recommended in the guidelines (Figure 4; Table 1). For type 1 stocks (spasmodic stocks), three B_{lim} technical bases were used, B_{lim} was B_{loss} (lowest observed SSB), a fraction of B_{pa}, or the lowest SSB where recruitment was good/high or not impaired. The basis recommended in the guidelines was the lowest SSB, where large recruitment is observed. Stocks categorized as type 2 (evidence that recruitment is or has been impaired) typically define B_{lim} as the breakpoint of the segmented regression. The lowest SSB where recruitment was good/high or not impaired was also used to define B_{lim} for several type 2 stocks (Figure 4). There is one case (herring in the northeast Atlantic and Arctic Oceans, her.27.1–24a514a) where the B_{lim} technical basis for a type 2 stock is MBAL, which refers to the old minimum biological acceptable level, commonly including a buffer. For SR type 3 stocks (wide dynamic range of SSB and evidence that recruitment is or has been impaired, with no clear asymptote in recruitment at high SSB), selection of B_{lim} was the lowest SSB where recruitment is good/high or not impaired. However, the recommended choice is the SSB close to the highest observed value, depending on an evaluation of the historical fishing mortality. There was no stock SR type 4 reported; however, we inferred that herring in Iceland grounds (her.27.5a) could fall under that category given that recruitment increases as SSB decreases. The B_{lim} basis for that stock was SSB with a high probability of impaired recruitment. For SR type 5 (no impaired recruitment or no clear relation between stock and recruitment), the most frequent technical basis for B_{lim} was B_{loss}. For stocks of type 6 (narrow dynamic range of SSB and showing no evidence of past or present impaired recruitment), B_{lim} cannot be directly derived and so it was used a fraction of B_{pa}. Other technical bases for B_{lim} based on spawner per-recruit or unfished biomass analysis, e.g. 35% SPR, 20% B_0, were occasionally used (Figure 4).

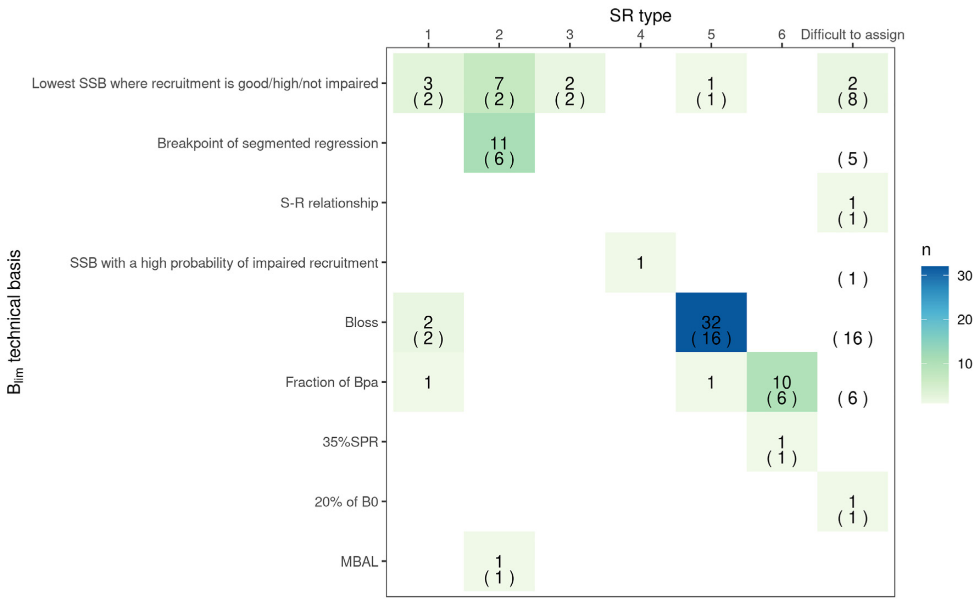

Figure 4. Crosstabulation of reported and inferred SR typology and B_{lim} technical basis. Showing the number of inferred SR type stocks above and the number of stated SR type stocks below in brackets.

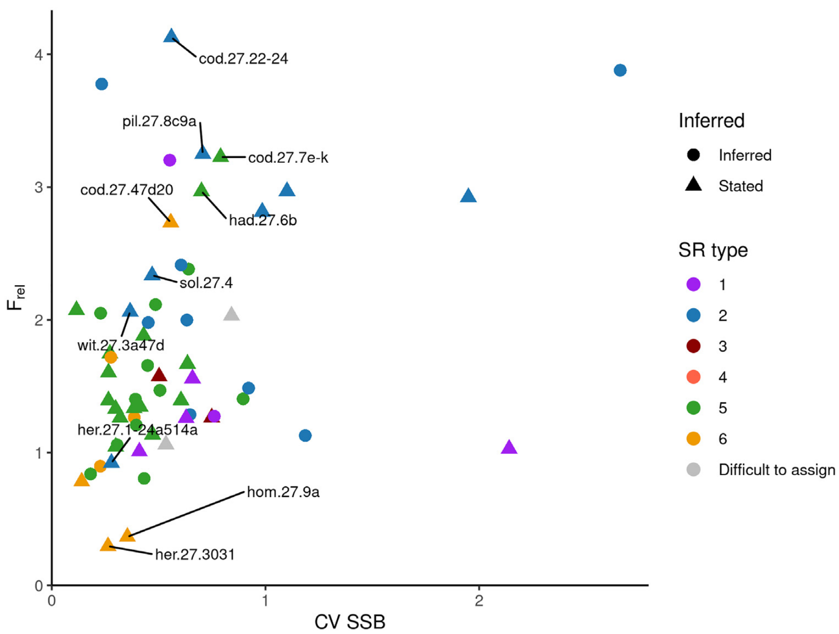

Figure 5. Relative fishing mortality and variability in SSB by inferred or stated SR type of the 79 ICES category 1 stocks that were analysed. F_{rel} is the average fishing mortality relative to F_{MSY} over the data period, and *CV* SSB is the coefficient of variation of SSB for log-normally distributed data on a proportion scale. The shape of data points represents if the SR type has been inferred in this study or stated in the reports.

Stock typology, SSB range, and historical fishing mortality

Some assigned typologies adhere well to their definitions (e.g. type 6—narrow range of SSB), whereas there are examples of similar degrees of variation in SSB being categorized differently across stocks (e.g. narrow for one stock but wide for another; Figure 5). Most stocks that were categorized as SR types with wide SSB ranges (i.e. types 2, 3, and 4) had larger SSB variation, but there were some exceptions, e.g. herring in the northeast Atlantic and Arctic Ocean (her.27.1–24a514a), witch in the North Sea, Skagerrak, Kattegat, and eastern English Channel (wit.27.3a47d), and sole in the North Sea (sol.27.4), which were categorized as type 2 but showed relatively low SSB variation (Figure 5).

Historical fishing pressure showed an important relationship with the SR type. Predominantly type 2 stocks, which present evidence of impaired recruitment, showed high average historical fishing mortality, e.g. cod in the eastern Baltic Sea (cod.27.22–24) and sardine in the Cantabrian Sea and Atlantic Iberian waters (pil.27.8c9a) in Figure 5. Exceptions could be related to the perception of fishing pressure over time in long time series, e.g. stocks that have been fished over

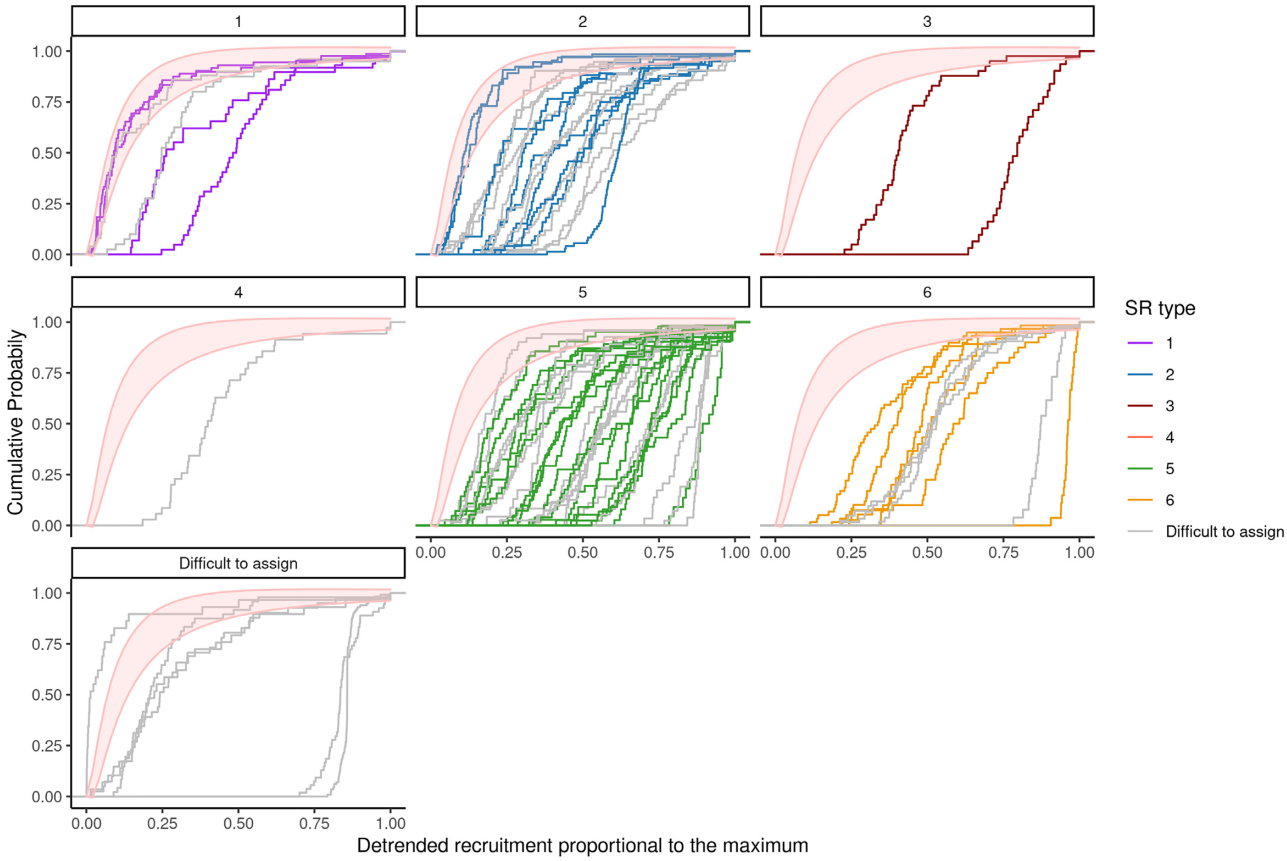

Figure 6. The empirical cumulative distribution function of recruitment relative to maximum recruitment by inferred SR type. Colour shows stated SR type. The pink area shows the theoretical expected 80% interval for CDFs of time series (length = 42) of lognormal variance = 1.

F_{MSY} only in recent years. Herring in the northeast Atlantic and Arctic Ocean (her.27.1–24a514a; Figure 5) was categorized as type 2 but showed low relative fishing mortality in the last three decades. Stock SR types 5 and 6, with no evidence that recruitment is or has been impaired (no clear relationship between stock and recruitment), showed different ranges of SSB variation but typically lower fishing pressure over time, e.g. herring in the Gulf of Bothnia (her.27.3031) and horse mackerel in Atlantic Iberian waters (hom.27.9a) in Figure 5. However, there were some stocks categorized as SR type 5 but with high relative fishing mortality, e.g. cod in the eastern English Channel and southern Celtic Seas (cod.27.7e-k) and haddock in Rockall (had.27.6b) in Figure 5. Also, stocks that have been historically fished over F_{MSY} but used truncated SR data to define the typology could result in selecting a SR type with no evidence of impaired recruitment, e.g. type 6 for the North Sea, eastern English Channel, and Skagerrak cod (cod.27.47d20; Figure 5).

Stock typology and recruitment variability

Recruitment dynamics impact the choice of SR typology, specifically, spasmodic stocks that are classified as SR type 1 according to the guidelines. Low frequency trends in recruitment, which absorbed the effect of historical fishing, showed multiple patterns across all stocks (Supplementary Figure S1). Three stocks classified as SR type 1 (spasmodic) were identified as having high detrended recruitment variability (Figure 6). These stocks were cod in East and South Greenland (cod.2127.1f14), haddock in the northeast Arctic (had.27.1–2), and haddock in the North Sea and West of Scotland (had.27.46a20), inferred in this study (Supplementary Figure S2). Recruitment time series for these stocks display a clear pattern of occasionally large year classes (Figure 7a). One SR type 1 stock showed comparatively lower variance for both recruitment and detrended recruitment. This was herring in the Irish Sea, Celtic Sea, and southwest of Ireland (her.27.nirs; Figure 7a and Supplementary Material S2). Two SR type 1 stocks, horse mackerel in the northeast Atlantic (hom.27.2a4a5b6a7a-ce-k8) and haddock in the southern Celtic Seas and English Channel (had.27.7b-k), showed high variability for recruitment but not for detrended recruitment (Supplementary Figure S2). This could result from occasional large recruitments occurring only early (or only once) in the time series with significant lower variability thereafter, e.g. horse mackerel in the northeast Atlantic (hom.27.2a4a5b6a7a-ce-k8; Figure 7b).

We also found stocks with high recruitment variability and possibly spasmodic but not classified as SR type 1. We identified high detrended recruitment variability for two stocks classified as SR type 2, cod in the western Baltic Sea (cod.27.22–24), and sole in the North Sea (sol.27.4). The recruitment time series for these stocks also showed infrequent strong recruitment (Figure 7b). Two stocks classified as difficult to assign showed high detrended recruitment variability (Figure 6), Greenland halibut in the northeast Arctic (ghl.27.1–2) and Capelin in the northeast Arctic and Barents Seas (cap.27.1–2). One stock inferred as SR type 2 showed high detrended recruitment variability; this refers to cod in the northeast Arctic

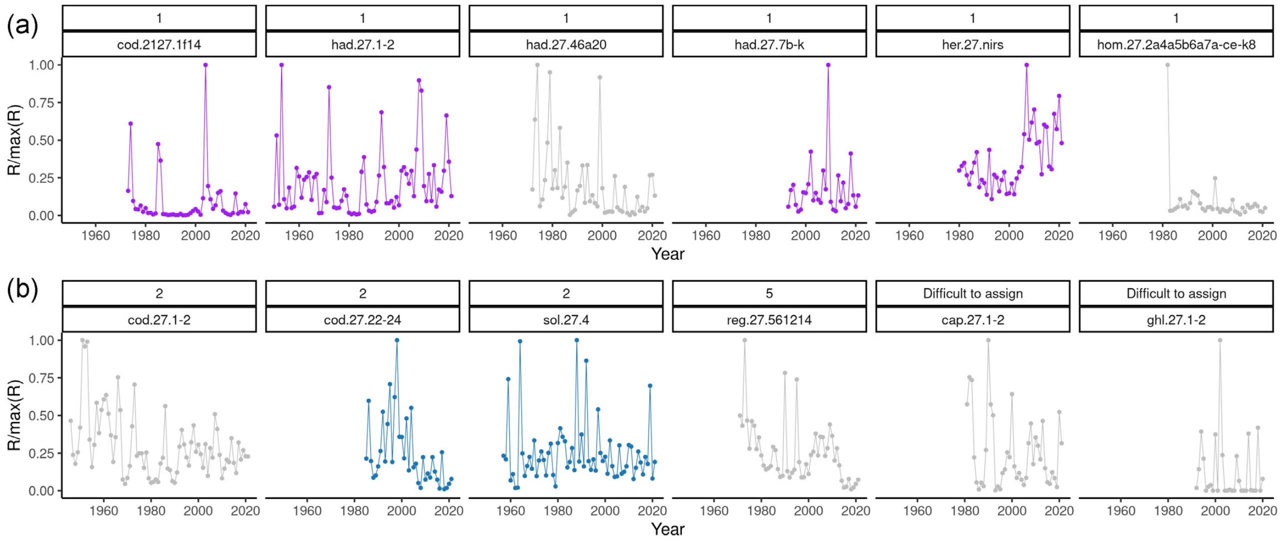

Figure 7. Recruitment time series proportioned to the maximum recruitment year class for a selection of category 1 stocks. The top panel (a) shows all stocks inferred as SR type 1 (spasmodic); the bottom panel (b) shows examples of high variability in recruitment time series for other SR types. Colour reflects stated SR type (purple: SR type 1, blue: SR type 2, grey: not stated).

(cod.27.1–2). Golden redfish in Iceland and Faroes grounds, West of Scotland, North of the Azores, and East of Greenland (reg.27.561214), which was inferred as type 5, showed relatively high detrended recruitment variability (Figure 6), due to sporadic high recruitment year classes (Figure 7b). Several stocks showed high recruitment variability but not after removing the trend (Supplementary Figure S2), e.g. sprat in Skagerrak, Kattegat, and North Sea (spr.27.3a4), sardine in Cantabrian Sea and Atlantic Iberian waters (pil.27.8c9a), and haddock in Iceland grounds (had.27.5a), and in Faroes grounds (had.27.5b).

Stochastic frameworks to estimate MSY-based reference points

The modelling framework used for estimating ICES category 1 MSY-based reference points was substantially homogeneous (Figure 8a), with the majority of the stocks estimated with the generic tool for stochastic simulation framework EqSim ($n = 54$). For 11 stocks, mostly short-lived pelagic species, simulation frameworks developed specifically to conduct full feedback MSEs were used applying the ICES guidelines. Reference points were estimated within the Gadget assessment model for four stocks. For spurdog in the northeast Atlantic, reference points were estimated within the age-length and sex-structured assessment model. Northeast Arctic haddock reference points were estimated with a framework called PROST—Projection Stochastic (Figure 8a).

Key recruitment considerations for the derivation of MSY-based reference points are the choice of SR functional form, accounting for variability and temporal dynamics, and determining and accounting for regime shifts. Accounting for temporal dynamics is achieved by including autocorrelation in recruitment, process error, and trimming of occasional extreme values. For stocks that used EqSim, autocorrelation and process error were mostly included as a default setting and thus typically accounted for in the estimation (Figure 8b left). Autocorrelation is included for the recruitment residuals of the SR model according to an AR(1) process. Process error is included with the stochastic predictive distribution of recruitment plus the simulated observation error. Removal of recruitment extreme values was often applied, and the option of trimming extreme catch values was occasionally used (Figure 8b left). The issue of regime shifts is linked to the classic dilemma between using full-time series or selecting a reduced-time series. Stock recruitment pairs were truncated for the estimation of reference points for 10 stocks (Figure 8b left). Time windows for biological productivity or selectivity parameters were 10 yr for the majority of stocks unless patterns were found in the data, in which case 5 or 3 yr were typically used (Figure 8b centre).

The uncertainty of the advice (F_{CV}, F_{φ}) within EqSim was often set with default values (F_{CV} n = 27, F_{φ} n = 33, Figure 8b right). In WKMSYREF4, parameters for assessment error were evaluated and the following values were assigned as default values: assessment error in the advice year (F_{CV}) = 0.212; autocorrelation in assessment error (F_{φ}) = 0.423. These values are the medians of the results for five stocks for which the evaluations were completed in WKMSYREF3.

Changes in reference points

Reference points have changed relatively frequently, with substantial changes between years (once or twice in the last 6 yr; Supplementary Material Figure 3). Given the reference point technical basis, changes in MSY B_{trigger} are directly related to changes in B_{lim}, though changes in F_{MSY} are typically not related to changes in B_{lim}. The main impact of changes in B_{lim} was on changes in MSY B_{trigger} (Figure 9a), as MSY B_{trigger} is often defined as B_{pa}, which is often a multiple of B_{lim}. However, revisions of the technical basis of MSY B_{trigger} and B_{pa} can cause changes in MSY B_{trigger} not related to a B_{lim} change. For example, the technical basis for MSY B_{trigger} for many stocks was set to B_{pa} because the criterion of being fished at or below F_{MSY} for around 5 yr was not met. As stocks are fished consistently with F_{MSY}, they may change to a MSY B_{trigger} corresponding to the fifth percentile of SSB when fishing at F_{MSY}. The majority of changes in B_{lim} were not related to changes

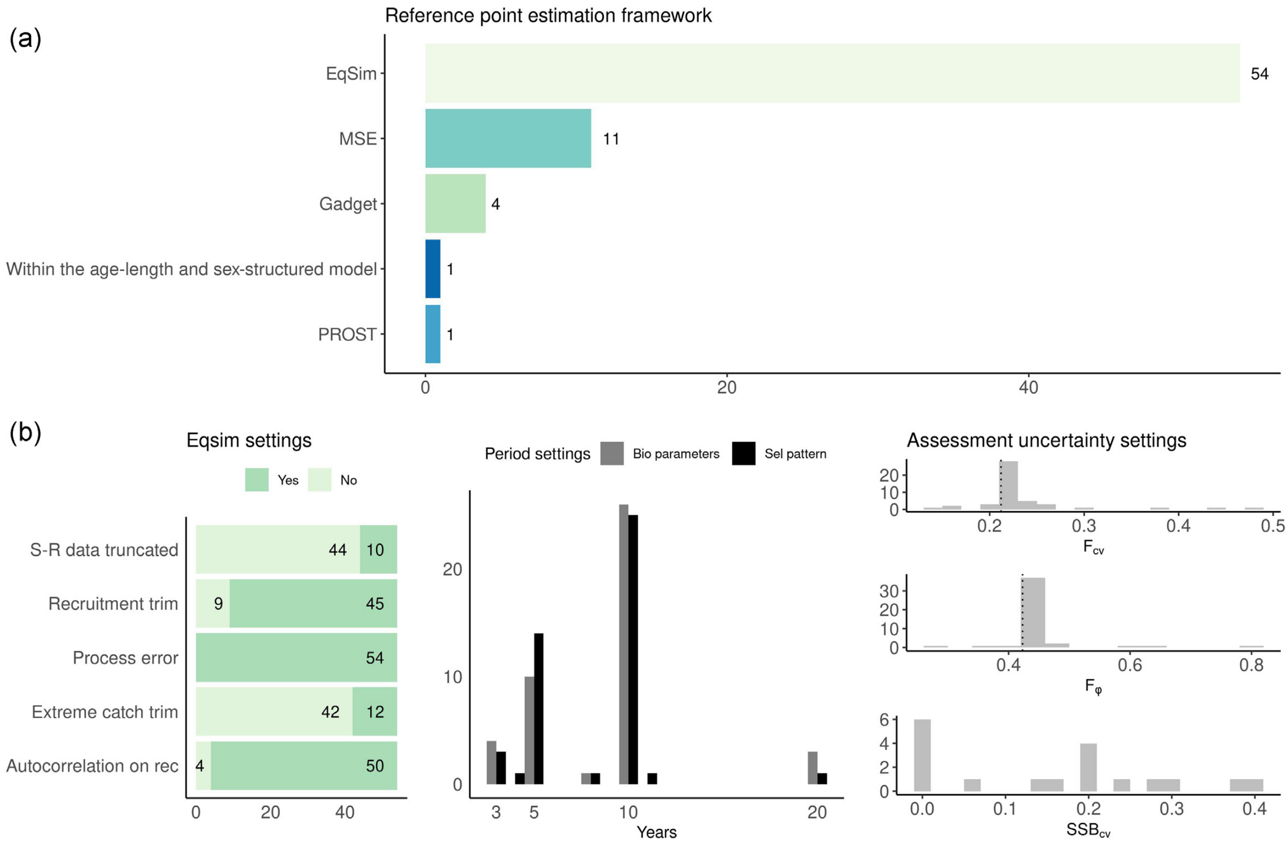

Figure 8. Summary plots of reference point estimation frameworks and settings used for ICES category 1 stocks as of November 2021. Top panel (a) count plot of used reference point estimation frameworks in assessments. Bottom panel (b) with data treatment in EqSim-based estimation of reference points (left), parameter period settings (middle), and assessment uncertainty settings (right).

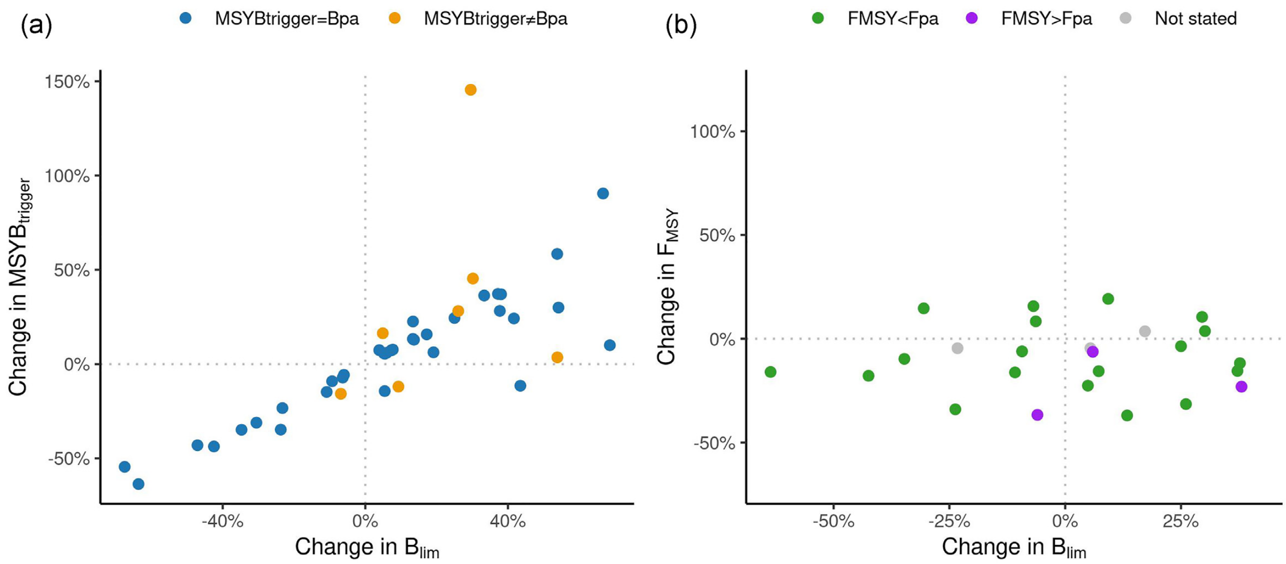

Figure 9. Simultaneous changes in reference points. Impact of changes in B_{lim} on the ICES biomass trigger point MSY $B_{trigger}$ (a); Impact of changes in B_{lim} on F_{MSY} for the most recent 5 years (b). Colour shows whether stocks are currently hitting precautionary bounds ($F_{MSY} > F_{pa}$) and therefore there is a capping on F_{MSY}.

in F_{MSY} (Figure 9b). Nevertheless, changes in B_{lim} might have had an impact on F_{MSY} where the value of F_{MSY} is capped and set at F_{pa} due to a higher than 5% probability of SSB going below B_{lim}, where an increase in the value of B_{lim} is related to a decrease in the F_{MSY} value (Figure 9b).

Conclusions

In this paper, we have extensively reviewed the evolution of ICES reference points and the estimation procedure currently used for management advice within the ICES framework. The review has addressed historically important events related to the evolution of the ICES reference point framework and evaluated how guidelines link with current reference point estimation. We have also examined the settings and processes considered in the estimation of reference points. What conclusions do we have after the review?

1. **ICES reference point framework has evolved in an intergovernmental setting.** Reference points used in ICES advice have evolved and are influenced by policy and scientific development. As an intergovernmental agency, ICES advice recognizes several international agreements and responds to the policy and legal needs of ICES member countries that use the advice as to the scientific basis for management. Advice basis and therefore reference points have evolved with their requirements, starting with the PA and expanding to integrate the MSY approach. Additionally, the ICES framework also evolves along with new available research and tools (e.g. EqSim).
2. **ICES reference points incorporate multiple precautionary aspects and sources of stochasticity**. The objective of ICES AR is to maximize long-term average yield with a safeguard against low SSB and staying within the precautionary bounds. The current system incorporates many features of the precautionary approach, particularly as it pertains to recruitment overfishing.

(i) ICES recognizes that fish stocks should be above B_{lim} and fish at a level that keeps fish stocks above B_{lim}. The biomass limit reference point is the central reference point to the precautionary approach. It is set by graphic rules based on SR data pairs. The choice of B_{lim} aims to ensure that the biomass below which recruitment is impaired is detected (ICES, 2021c). The lowest level of biomass (B_{loss}) is typically used as a biomass limit reference point when there is no clear SR relationship. We note that the typologies of SR data pairs are not hypothesis-driven, which provides flexibility but also leaves the process open to subjective decisions across stocks.

(ii) The EqSim framework is the standard ICES software, which was used to estimate reference points for the majority of the ICES stocks studied. The framework enables the implementation of stochasticity in biological and fisheries processes and therefore is more precautionary. Including stochastic processes in the estimation of MSY has been demonstrated in surplus production models to lead to more conservative reference points (Bousquet *et al.*, 2008; Bordet and Rivest, 2014). Advice error can be applied on the target F (F_{CV} and F_{φ}), usually using the default values. These values were the median evaluated values for five ICES stocks (her.27.3a47d, sol.27.7d, pok.27.3a46, sol.27.4, ple.27.420). This advice uncertainty is supposed to represent how uncertain estimates of fishing mortality are in the advice year.

(iii) Within the ICES process for estimating reference points, F_{MSY} and MSY B_{trigger} are evaluated to check that they meet the precautionary criterion. The precautionary criterion reference point (F_{pa}) represents the fishing mortality corresponding to 5% probability of SSB being below B_{lim} in the long term, estimated by stochastic simulation (i.e. biological and fishery variability and advice error included). When the precautionary criterion is lower than the estimated F_{MSY}, then the F_{MSY} is capped to its value.

(iv) The MSY-based biomass reference point should be below typical natural variation (here, the fifth percentile), and its selection safeguards against unexpected low SSB when fishing at F_{MSY}. Therefore, the technical basis adopted for the biomass reference point MSY B_{trigger} depends on the fishing history relative to the F_{MSY}. The MSY B_{trigger} is set to B_{pa}, a more precautionary value, when there are no more than 5 yr of fishing mortality equal to or lower than F_{MSY}.

3. **The relationship and historical context of stock size and recruitment are crucial for non-proxy reference points and are embedded in ICES guidelines**. On the one hand, ICES reference point estimation is typically external to the assessment process; therefore, the understanding of the SR relationship and the choice of SR functional form is key. The graphical characteristics of the SR relationship are what define the SR type classification and impact the consequent B_{lim} choice. For the estimation of MSY-based reference points, the choice of SR relationship functional form (e.g. the commonly used Beverton–Holt model, segmented regression model, and Ricker model) impacts the reference point value. The EqSim software can fit a combination of SR models and implement a goodness-of-fit model weighting. Usually, as a first step, to account for SR functional form uncertainty, all three SR models are examined, and depending on the weighted results, the models that have significant contributions are chosen. The segmented regression model can estimate the break-point or have it fixed at the biomass limit reference point as a way to restrict the breakpoint when there is no reliable data for its estimation. On the other hand, due to limit and MSY-based reference points only being entirely informed if the stock has been overexploited (Tsikliras and Froese, 2019), regional historical evolution of the stock determines the data available to inform reference points. Historically, many fish stocks in the North Atlantic have been heavily exploited (Fernandes and Cook, 2013). Although exploitation pressure has decreased during the last decades, there is evidence of historical overfishing in the data for many of the stocks. The historical exploitation patterns result in having a high contrast in SSB data and evidence of stocks where recruitment is impaired. Having a contrast in SSB may give evidence of how recruitment is impacted, which can inform the estimation of F_{MSY}. Whereas in other areas, where there is a lack of contrast, proxies are derived.
4. **Reference points are reviewed frequently, taking into account fluctuations and multiple sources of variability.** We found that reference points have changed frequently and substantially. These changes in reference points have been shown to have an important impact on stock status (Silvar-Viladomiu *et al.*, 2021). The frequency of PA reference point evaluations can differ from the MSY reference point evaluations. Simultaneous changes in B_{lim} and MSY B_{trigger} reference points are correlated because B_{lim} is typically used to estimate B_{pa}, and B_{pa} is commonly used as an MSY B_{trigger}. Reference points are revised in benchmarks to update productivity

change concerns, along with assessment methodology and data updates. In the estimation of reference points, variation in processes related to productivity can be included in several ways. The SR variation pattern is assessed to detect regime changes. If strong evidence of a regime shift is found, the time series may be truncated, though there are reasons not to truncate: reduction to shorter time series might increase the uncertainty associated with the reference point (Deurs *et al.*, 2021), and changes are often gradual, in which case choosing a time window might not be appropriate (Collie *et al.*, 2021). EqSim settings enable accounting for variation and uncertainty, for example, process error in the SR relationship (stochastic uncertainty around the SR model), which is typically included in the estimation. Temporal dynamics can be accounted for by autocorrelation in recruitment and trimming of occasional extreme values. Trimming of extreme values to account for high variability can be also applied to catch data. Selection for the data window of productivity parameters (i.e. natural mortality, weights-at-age, maturity, and fishery selection pattern) is shortened when persistent trends are found in the data.

5. **There are occasionally inconsistencies with the guidelines.** By reviewing all stocks, it becomes apparent that the current SR type and consequent choice of B_{lim} have some occasional inconsistencies with the guidelines. We identified that a high percentage of stocks were found difficult to classify by assessors, which might be a reflection of ambiguity in SR types in the current guidelines. The implementation of the classification framework depends on whether assessors can determine if there is a clear SR relationship, which may be challenging. Comparably across all stocks, SSB measures show inconsistencies with the description in the SR types for some stocks. For example, some SR type 2 stocks show no evidence of a wide dynamic range in SSB, e.g. her.27.1–24a514a. In some cases, even when stocks appear to have impaired recruitment (type 2), the segmented regression change point was not chosen as the B_{lim} value, e.g. the B_{lim} value for cod.27.22–24 is the lowest SSB where recruitment is good/high or not impaired. The current SR type classification definitions might have gaps, e.g. how to classify a stock with evidence of impaired recruitment but with a narrow dynamic range. For stocks with no clear SR relationship, the choice of B_{lim} was more consistently B_{loss} or a fraction of B_{pa} for stocks with a narrow SSB range. The classification of spasmodic stocks was shown to be difficult, as well as the consequent choice of an appropriate B_{lim} level for these stocks.
6. **More comprehensive and clearer documentation of reference point estimation is needed.** Documentation on assessors' decisions made for reference point estimation (e.g. settings) lacked consistency across stocks and details were sometimes missing or difficult to find. The code used for the estimation was only occasionally attached to the reports. Although there are guidelines on general steps for the estimation of ICES fisheries management reference points (ICES, 2021c), there is a lack of a detailed document of guidelines for the use of the EqSim framework.

Recommendations for the future

Advice based on reference points is requested by governments to manage their fisheries. For most data-rich stocks, fisheries managers in the northeast Atlantic require annual advice on fishing opportunities to be able to set advice on catch for the next year. Best practice involves validation, verification, transparency, and repeatability within very strict time constraints to produce yearly fishing advice. The current ICES framework can deliver at that level. Based on our review of the framework, we offer the following recommendations and research suggestions to improve the reference point framework for the near future.

The biomass limit reference point plays a key role in classifying the condition of the stock and determining if recruitment is likely to be impaired. The choice of B_{lim} is related to the classification of SR types, which was found to lead to ambiguous results in several cases. In WKREBUILD, it was highlighted that the determination of B_{lim} used a more or less subjective classification of the SR pairs into types (ICES, 2020a). We found that a significant number of stocks were difficult to classify for assessors. A simplified and reduced framework of classification for the choice of SR types may help reduce ambiguity. In addition, the development of quantitative criteria and analytical tools that establish cut-offs to assist in the decision of SR type may be useful. For example, use measures of SSB range and SSB variation to define "narrow dynamic range" and "wide dynamic range". Also, developing criteria to define spasmodic stocks, such as CDFs intervals, would help the classification to be less subjective and more transparent. Additionally, developing generalized quantitative criteria to establish B_{lim}, e.g. give specific details on how to define the lowest SSB for good/high or not impaired recruitment.

Stocks with spasmodic recruitment are common for some fish species, and their management is particularly challenging (Licandeo *et al.*, 2020). In ICES, spasmodic stocks (SR type 1) are defined as "stocks with occasional large year classes" (ICES, 2021c). Spencer and Collie (1997) identified spasmodic stocks as those having the highest variation in their study, with low-frequency components without clear periodicities. Stocks with spasmodic recruitment may have long periods of weak recruitment with infrequent or irregular strong recruitment, which has complex links to stock productivity. More research is needed to define spasmodic criteria, as well as on simulation frameworks to evaluate how to define reference points and manage this type of stock (e.g. Atlantic redfish in Licandeo *et al.*, 2020).

In WKRPCHANGE, it has been suggested that addressing PA/MSY needs to take better account of changing productivity drivers, e.g. growth, reproduction, recruitment, density-dependence, and survival (ICES, 2021b). Marine ecosystems are dynamic and might be affected by climate change impacting reference points. The productivity of fish stocks has been observed to vary globally in a non-stationary manner (Vert-pre *et al.*, 2013; Minto *et al.*, 2014; Britten *et al.*, 2016; Perälä *et al.*, 2017). In the ICES reference point framework, there are tools to account for temporal dynamics, and reference points are evaluated regularly at benchmarks to revisit their assumptions on future productivity. However, more research is needed on regime shifts and the consequences of, for instance, truncating data time series. Truncating the data can have significant impacts on the resulting parameter estimates. It has been observed that reducing the length of time series used to estimate reference points increases the uncertainty associated with them, particularly with biomass limit reference points (Deurs *et al.*, 2021). It is still relatively unclear how to determine the period to use to estimate reference points. A better understanding of the nature of recruitment variability and the impact of changes will be key for estimating reference points. Research on how to detect when there has been a significant change in productivity (e.g. Peterman and Dorner, 2012; Minto *et al.*, 2014; Perälä *et al.*, 2017; Tableau *et al.*, 2019) could clarify recommendations to deal with productivity change. Furthermore, more research is needed to improve our understanding of ecosystem dynamics and their impact, and how to integrate these concerns into the framework for estimating reference points (Collie *et al.*, 2021; Silvar-Viladomiu *et al.*, 2022).

As estimation of ICES reference points is typically made outside the assessment model, there is associated uncertainty in current abundance estimates, recruitment, and current fishing mortality regarding models and data used. Propagating the assessment uncertainty into the reference point estimate is important. We found that mainly default advice error values were used to account for advice uncertainty. These values were calculated as the median of five ICES stocks, and it would be an improvement to guide the estimation of more stock-specific values. While there is some guidance in the WKMSYREF3 report (ICES, 2015a), more documentation is needed along with extending the research on estimation and the inclusion of advice uncertainty and dealing with short time series.

WKGMSE3 recommended the consideration of using more flexible MSE simulation frameworks for estimating reference points. MSEs have the potential to identify and account for more sources of uncertainties associated with reference points, e.g. density-dependent changes in underlying biological processes, SR pair time period error, and assessment/advice formulation error (ICES, 2020b). Simulation models can also help develop management procedures and HCRs that are robust to perceived uncertainties, e.g. about recruitment. Further research is needed to develop guidelines for when and how reference points should be extracted from an MSE when one is conducted, using clear terminology and on how to deal with different outcomes with regard to precaution in reference point estimation and MSEs. Communication is extremely important because the decisions and assumptions taken to build MSEs are key to understanding the results. In general, WKGMSE3 recommended improving communication between scientists and managers (ICES, 2020b).

Overall, moving forward, we recommend improving communication and transparency related to reference points in order to facilitate access to methods and data used. Extensive documentation consistent across stocks is needed for both general (cross-framework) and specific (EqSim) decisions and setting choices. In the same way, TAF (Transparent Assessment Framework; https://taf.ices.dk/app/about) was developed for assessments in order to achieve retrospective implementation of the full procedure. We should also be able to replicate reference point estimation at any historical time point by, for example, embedding reference point estimation within TAF.

In an environment like ICES, there is a significant variation in the ability, experience, and knowledge among experts conducting these analyses. For reference point estimation, it is difficult to find a balance between preserving some flexibility and having scientifically underpinned guidelines that are precise and detailed (rather than general steps and recommendations). Furthermore, those guidelines should be easily interpreted and understood by assessors. Given the differences between stocks, species, and surrounding ecosystems, some experienced scientists want flexibility to make the best scientific choices and apply their preferred analytical tools. In general, the priority for the framework should be to offer well-documented guidance with clearly stated assumptions but without being too prescriptive. In order to achieve this, the process might benefit from a more simplified methodology and terminology, which may reduce ambiguity. Additionally, as noted in WKRPCHANGE (ICES, 2021b), the process of updating reference points in the context of ICES advice would benefit from specific additional guidelines clarifying when reference points should be re-evaluated, how to test for non-stationarity or regime shifts, and when to re-evaluate assumptions (i.e. changes in fishing patterns and productivity).

Finally, we recommend periodic syntheses such as these that take a detailed comparative look at what is being done across all stocks. These syntheses can then be compared and contribute to practices worldwide to continually strive to improve reference point estimation as a key step in the provision of scientific management advice.

Acknowledgements

We thank Martin Pastoors and one anonymous reviewer for providing constructive critiques on drafts of this manuscript. The authors are grateful to all scientist involved in ICES assessments and expert working groups upon whose work this study is based.

Supplementary data

The supplementary material is available at ICESJMS online version of the manuscript.

Conflict of interest

Authors declare no competing interests.

Author contributions

All authors contributed to the conceptualization, design, draft, revision of the manuscript, and creation of the diagrams. LB and PSV collected the data. PSV, CM, and LB performed the analysis and created the figures.

Funding

This work was supported by the Marine Institute Ireland grant FEAS/Ref Pts Desk Stud (Fisheries Ecosystem Advisory Services—Reference points desktop study).

Data availability statement

Data available on request.

References

Anon. 1999. Pacific salmon commission joint chinook technical committee report tcchinook (99)-3. https://www.psc.org/publications/technical-reports/technical-committee-reports/chinook/ (last accessed 21 October 2022).

Anon. 2020. The UK fisheries act. https://www.legislation.gov.uk/ukpga/2020/22/contents/enacted (last accessed 21 October 2022).
Beverton, R. J. H., and Holt, S. J., 1957. On the dynamics of exploited fish populations. U.K. Ministry of Agriculture and Fisheries, London. Fisheries Investigations Series 2, 19, 533 pp.
Bordet, C., and Rivest, L. P. 2014. A stochastic pella tomlinson model and its maximum sustainable yield. Journal of Theoretical Biology, 360: 46–53.
Bousquet, N., Duchesne, T., and Rivest, L. P. 2008. Redefining the maximum sustainable yield for the Schaefer population model including multiplicative environmental noise. Journal of Theoretical Biology, 254: 65–75.
Britten, G. L., Dowd, M., and Worm, B. 2016. Changing recruitment capacity in global fish stocks. Proceedings of the National Academy of Sciences, 113: 134–139.
Caddy, J. F., and Mahone, R. 1995. Reference points for fishery management. FAO Fisheries Technical Paper. 347: 83pp. Rome, FAO.
Cadrin, S. X. 2012. Unintended consequences of MSY proxies for defining overfishing. ICES Document CM 2012/L:23, 12pp.
Collie, J. S., Bell, R. J., Collie, S. B., and Minto, C. 2021. Harvest strategies for climate-resilient fisheries. ICES Journal of Marine Science, 78: 2774–2783.
Cushing, D. H. 1975. Marine Ecology and Fisheries. Cambridge University Press, New York, NY.
Deurs, M., Brooks, M. E., Lindegren, M., Henriksen, O., and Rindorf, A. 2021. Biomass limit reference points are sensitive to estimation method, time-series length and stock development. Fish and Fisheries, 22: 18–30.
Dickey-Collas, M., Hintzen, N. T., Nash, R. D. M., Schön, P.-J., and Payne, M. R. 2014. Quirky patterns in time-series of estimates of recruitment could be artefacts. ICES Journal of Marine Science, 72(1): 111–116.
EC. 2013. Common fisheries policy (CFP) regulation no. 1380/2013 of the European parliament and of the council. Official Journal of the European Communities, 001: 354.
Fernandes, P. G., and Cook, R. M. 2013. Reversal of fish stock decline in the northeast Atlantic. Current Biology, 23: 1432–1437.
Geromont, H. F., and Butterworth, D. S. 2015. A review of assessment methods and the development of managemnet procedures for data-poor fisheries. FAO report. University of Cape Town. 219pp. https://doi.org/10.25375/uct.19168118.v1 (last accessed 21 October 2022).
Hilborn, R., Amoroso, R. O., Anderson, C. M., Baum, J. K., Branch, T. A., Costello, C., de Moor, C. L. *et al.*. 2020. Effective fisheries management instrumental in improving fish stock status. Proceedings of the National Academy of Sciences, 117: 2218–2224.
Hilborn, R., and Walters, C. J. 1992. Quantitative Fisheries Stock Assessment. Springer US, Boston, MA.
ICES. 1998. Report of the study group on the precautionary approach to fisheries management. ICES Document CM 1998/ACFM:10, 43pp.
ICES. 2001. The study group on the further development of the precautionary approach to fishery management (Copenhagen, 2–5 April 2001). ICES Document CM 2001/ACFM:11, 51pp.
ICES. 2002. Study group on the further development of the precautionary approach to fisheries management (Lisbon, 4–8 March 2002). ICES Document CM 2003/ACFM:10, 157pp.
ICES. 2003a. Study group on the further development of the precautionary approach to fisheries management (Lisbon, 4–8 March 2002). ICES Document CM 2003/ACFM:9, 144pp.
ICES. 2003b. Report of the Study Group on Precautionary Reference Points for Advice on Fishery Management (SGPRP), 24–26 February 2003, ICES Headquarters, Copenhagen, Denmark. ICES Document CM 2003b/ACFM:15, 85pp.
ICES. 2007. Report of the workshop on limit and target reference points (WKREF), 29 January–2 February 2007, Gdynia, Poland. ICES Document CM 2007/ACFM:05, 89pp.
ICES. 2010. Report of the workshop on implementing the ICES F_{MSY} framework (WKFRAME), 22–26 March 2010, Copenhagen, Denmark. ICES Document CM 2010/ACOM:54, 83pp.
ICES. 2011. Report of the workshop on implementing the ICES F_{MSY} framework (WKFRAME-2), 10–14 January 2011, ICES, Denmark. ICES Document CM 2011/ACOM:33, 110pp.
ICES. 2013. Report of the workshop on guidelines for management strategy evaluations (WKGMSE), 21–23 January 2013, ICES HQ, Copenhagen, Denmark. ICES Document CM 2013/ACOM:39, 121pp.
ICES. 2014. Report of the workshop to consider reference points for all stocks (WKMSYREF2), 8–10 January 2014, ICES headquarters, Copenhagen, Denmark. ICES CM 2014/ACOM:47, 91pp.
ICES. 2015a. Report of the joint ICES-MYFISH workshop to consider the basis for F_{MSY} ranges for all stocks (WKMSYREF3). ICES 17–21 November, ICES Document CM 2015a/ACOM:64, 156pp.
ICES. 2015b. ICES special request advice greater North Sea and Baltic Sea Ecoregions. ICES Advisory Committee 2015. ICES Advice, Book 6, Section 6.2.3.1, 11pp.
ICES. 2017a. Report of the workshop to consider F_{MSY} ranges for stocks in ICES categories 1 and 2 in western waters (WKMSYREF4), 13–16 October 2015, Brest, France. ICES Document CM 2017a/ACOM, 58: 187.
ICES. 2017b. ICES advice technical guidelines. ICES fisheries management reference points for category 1 and 2 stocks. ICES Advice Book, 12: 19.
ICES. 2019. Workshop on North Sea stocks management strategy evaluation (WKNSMSE). ICES Scientific Reports, 1: 378.
ICES. 2020a. Workshop on guidelines and methods for the evaluation of rebuilding plans (WKREBUILD). ICES Scientific Reports, 2: 79.
ICES. 2020b. The third workshop on guidelines for management strategy evaluations (WKGMSE3). ICES Scientific Reports, 2: 112.
ICES. 2021a. Advice on fishing opportunities. ICES Technical Guidelines. In Report of the ICES Advisory Committee, 2021. ICES Advice 2021, section 1.1.1. 9pp.
ICES. 2021b. Workshop of fisheries management reference points in a changing environment (WKRP change, outputs from 2020 meeting). ICES Scientific Reports, 3: 39.
ICES. 2021c. ICES fisheries management reference points for category 1 and 2 stocks; technical guidelines. Rep ICES Advice Committee, 2021, 1–19pp.
ICES. 2021d. ICES Stock Assessment Graphs Database. November/2021. ICES, Copenhagen.
Kell, L. T., Pastoors, M. A., Scott, R. D., Smith, M. T., Van Beek, F. A., O'Brien, C. M., and Pilling, G. M. 2005. Evaluation of multiple management objectives for northeast Atlantic flatfish stocks: sustainability vs. stability of yield. ICES Journal of Marine Science, 62: 1104–1117.
Licandeo, R., Duplisea, D. E., Senay, C., Marentette, J. R., and McAllister, M. K. 2020. Management strategies for spasmodic stocks: a Canadian Atlantic redfish fishery case study. Canadian Journal of Fisheries and Aquatic Sciences, 77: 684–702.
Mace, P. M. 1994. Relationships between common biological reference points used as thresholds and targets of fisheries management strategies. Canadian Journal of Fisheries and Aquatic Sciences, 51: 110–122.
May, R. M., Beddington, J. R., Clark, C. W., Holt, S. J., and Laws, R. M. 1979. Management of multispecies fisheries. Science, 205: 267–277.
Mesnil, B., and Rochet, M.-J. 2010. A continuous hockey stick stock–recruit model for estimating MSY reference points. ICES Journal of Marine Science, 67: 1780–1784.
Minto, C., Mills Flemming, J., Britten, G. L., and Worm, B. 2014. Productivity dynamics of Atlantic cod. Canadian Journal of Fisheries and Aquatic Sciences, 71: 203–216.
MSA. 2007. Magnuson-Stevens fishery conservation and management act. *In* U.S. Government (2007) Public Law 94–265. 170pp. https://media.fisheries.noaa.gov/dam-migration/msa-amended-2007.pdf. (last accessed 21 Oct 2022).

Myers, R. 2001. Stock and recruitment: generalizations about maximum reproductive rate, density dependence, and variability using meta-analytic approaches. ICES Journal of Marine Science, 58: 937–951.

Perälä, T. A., Swain, D. P., and Kuparinen, A. 2017. Examining nonstationarity in the recruitment dynamics of fishes using bayesian change point analysis. Canadian Journal of Fisheries and Aquatic Sciences, 74: 751–765.

Peterman, R. M., and Dorner, B. 2012. A widespread decrease in productivity of sockeye salmon (*Oncorhynchus nerka*) populations in western North America. Canadian Journal of Fisheries and Aquatic Sciences, 69: 1255–1260.

Punt, A. E. 2010. Harvest control rules and fisheries management. *In* Handbook of Marine Fisheries Conservation and Management. Oxford University Press, Inc., Oxford. pp. 598–610.

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

Punt, A. E., Smith, A. D. M., Smith, D. C., Tuck, G. N., and Klaer, N. L. 2014. Selecting relative abundance proxies for BMSY and BMEY. ICES Journal of Marine Science, 71: 469–483.

Ricard, D., Minto, C., Jensen, O. P., and Baum, J. K. 2012. Examining the knowledge base and status of commercially exploited marine species with the RAM legacy stock assessment database. Fish and Fisheries, 13: 380–398.

Ricker, W. E. 1954. Stock and recruitment. Journal of the Fisheries Research Board of Canada, 11: 559–623.

Sharma, R., Porch, C. E., Babcock, E. A., Maunder, M. N., and Punt, A. E. 2019. Recruitment: theory, estimation, and application in fishery stock assessment models. Fisheries Research, 217: 1–4.

Shepherd, J. G., and Cushing, D. H. 1990. Regulation in fish populations: myth or mirage? Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences, 330: 151–164.

Silvar-Viladomiu, P., Minto, C., Brophy, D., and Reid, D. G. 2022. Peterman's productivity method for estimating dynamic reference points in changing ecosystems. ICES Journal of Marine Science, 79: 1034–1047.

Silvar-Viladomiu, P., Minto, C., Halouani, G., Batts, L., Brophy, D., Lordan, C., and Reid, D. G. 2021. Moving reference point goalposts and implications for fisheries sustainability. Fish and Fisheries, 22: 1345–1358.

Sissenwine, M. P., and Shepherd, J. G. 1987. An alternative perspective on recruitment overfishing and biological reference points. Canadian Journal of Fisheries and Aquatic Sciences, 44: 913–918.

Spencer, P. D., and Collie, J. S. 1997. Patterns of population variability in marine fish stocks. Fisheries Oceanography, 6: 188–204.

Tableau, A., Collie, J. S., Bell, R. J., and Minto, C. 2019. Decadal changes in the productivity of New England fish populations. Canadian Journal of Fisheries and Aquatic Sciences, 76: 1528–1540.

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

Tsikliras, A. C., and Froese, R. 2019. Maximum sustainable yield. *In* Encyclopedia of Ecology, 2nd edn. Elsevier, Amsterdam. pp 108–115.

UN. 1995. Agreement for the implementation of the provisions of the United Nations conventionon the law of the sea of 10 December 1982 relating to the conservation and management of straddling fish stocks and highly migratory fish stocks. *In* UN General Assembly Annex 3. 40pp. https://www.un.org/Depts/los/convention_agreements/texts/fish_stocks_agreement/CONF164_37.htm. (last accessed 21 Oct 2021).

UN. 2002. Johannesburg plan of implementation of the world summit on sustainable development. IV. Protecting and managing the natural resource base of economic and social development. https://www.un.org/esa/sustdev/documents/WSSD_POI_PD/English/POIChapter4.htm. (last accessed 21 October 2022).

Vert-pre, K. A., Amoroso, R. O., Jensen, O. P., and Hilborn, R. 2013. Frequency and intensity of productivity regime shifts in marine fish stocks. Proceedings of the National Academy of Sciences, 110: 1779–1784.

Walters, C. J., Christensen, V., Martell, S. J., and Kitchell, J. F. 2005. Possible ecosystem impacts of applying MSY policies from single-species assessment. ICES Journal of Marine Science, 62: 558–568.

Wetzel, C. R., and Punt, A. 2017. The performance and trade-offs of alternative harvest control rules to meet management goals for U.S. west coast flatfish stocks. Fisheries Research, 187: 139–149.

Handling Editor: Jan Jaap Poos

B.2 Published Version of Chapter 3

Silvar-Viladomiu, P., Minto, C., Halouani, G., Batts, L., Brophy, D., Lordan, C., and Reid, D. G. (2021). Moving reference point goalposts and implications for fisheries sustainability, Fish and Fisheries, 22, 1345– 1358. https://doi.org/10.1111/faf.12591

Received: 4 March 2021 | Revised: 5 June 2021 | Accepted: 15 June 2021

DOI: 10.1111/faf.12591

ORIGINAL ARTICLE

FISH and FISHERIES WILEY

Moving reference point goalposts and implications for fisheries sustainability

Paula Silvar-Viladomiu[1] | Cóilín Minto[1] | Ghassen Halouani[1,2] | Luke Batts[1] | Deirdre Brophy[1] | Colm Lordan[3] | David G. Reid[3]

[1]Marine and Freshwater Research Centre, Galway-Mayo Institute of Technology, Galway, Ireland

[2]IFREMER, Unité halieutique Manche Mer du Nord Ifremer, HMMN, Boulogne sur mer, France

[3]Marine Institute, Oranmore, Galway, Ireland

Correspondence
Paula Silvar-Viladomiu, Galway-Mayo Institute of Technology GMIT, Dublin road, Galway, Ireland.
Email: paula.silvarviladomiu@research.gmit.ie

Funding information
Department of Agriculture, Food and the Marine, Ireland, Grant/Award Number: Ref 15/S/744

Abstract

For many environmental indicators, the sustainable status can change because of changes in either the monitored state or the policy goal. Fisheries provide an intensively monitored setting to investigate the relative impacts of such change. Key fisheries sustainability indicators comprise the ratio between fishing pressure or biomass and their respective reference levels. We developed a retrospective database of population status, reference point changes and reported reasons for changes for all data-rich stocks in the ICES region. We derived methods to distinguish the impacts of either source of change (monitored state or policy goal) on sustainable status. We found that reference points changed frequently (64% of populations had reference point changes) with varying magnitudes. Contrary to expectation, reference point changes were often not compensated by changes in the state thus significantly impacting inferred sustainability status and dependent scientific advice. Across a range of life histories and assessments, changes in reference points dominate retrospective revisions in status over the full time series. Overall, status before and after the change of reference point had no significant directional differences that would suggest reference point change effecting movement towards or away from sustainability. Although multiple factors have contributed to reference point changes, our results show that the reference point definition and the technical basis for estimation were the most important reasons for change. Recognizing that reference points are not constant in time but rather form reference series is paramount to quantifying present and historical sustainability. Properly documenting, justifying and quantifying the impacts of such change is an ongoing challenge.

KEYWORDS

Fisheries management, North Atlantic Ocean, population monitoring and assessment, sustainable targets and limits, UN sustainable development

1 | INTRODUCTION

Within the United Nations 2030 Agenda, goal 14 for sustainable development relates to life below water and targets improved understanding of the status of commercial fish stocks (FAO, 2020). Historically, overfishing has been widespread concern and the most decisive factor driving the collapse of marine ecosystems and losses of ecosystem biodiversity (Jackson, 2001; Worm et al., 2006). The ability of fishery management systems to maintain fishing pressure at levels that can sustain productive fisheries depends on the availability of stock information and the capacity to adjust harvest in response to changes in stock abundance. Recent analyses demonstrate that on average assessed fisheries are improving with respect to management goals in regions where there are research, assessment, and management plans (Fernandes & Cook, 2013; Hilborn et al., 2020; Ricard et al., 2012; Worm et al., 2009).

Fisheries science has made substantial progress in developing tools to assist in achieving policy goals. Management goals, commonly referred to as goalposts by fisheries managers, are expressed as reference points for a sustainable harvest. Quantitative measures of stock status relative to reference points are used to provide advice on sustainable catches, often in conjunction with harvest control rules (Kvamsdal et al., 2016). The status of a stock can be estimated in terms of both the fishing pressure level (typically fishing mortality rate, *F*) and abundance state level (typically biomass or spawning stock biomass, *SSB*) relative to their reference point, often at Maximum Sustainable Yield (MSY). The ratio of *F* to F_{MSY} (termed relative fishing mortality) indicates how far a stock is being fished from an optimally sustainable rate. Similarly, the ratio of *SSB* to the biomass reference point (termed relative biomass) shows if a stock is at a size that will provide MSY in the long term.

The concept of MSY is a common management goal underpinning reference points (Mace, 2001). MSY can be defined as "the highest theoretical equilibrium yield that can be continuously taken on average from a stock under existing average environmental conditions without significantly affecting the reproduction process" (EC, 2013). The precautionary approach (PA) plays an important role in fisheries management and is necessary, but a not exclusive condition for MSY. The International Council of the Exploration of the Sea (ICES) provides advice in accordance with MSY when data are available, that is consistent with the PA (ICES, 2019a); populations need to be maintained within safe biological limits to make MSY possible. ICES advice is based on the fishing mortality reference point F_{MSY}, and the biomass trigger point $MSYB_{trigger}$ (see Table 1 with definitions of those and related reference points). For data-rich stocks, advice on sustainable catch focuses on attaining a fishing mortality rate of no more than F_{MSY} (fishing mortality status lower than 1) while maintaining the stock above full reproductive capacity. When *SSB* declines below $MSYB_{trigger}$ (biomass status lower than 1), management must take action to reduce fishing mortality (ICES, 2019a).

The production of scientific fisheries management advice involves feedback loops of data and analysis, review, and decision-making (Privitera-Johnson & Punt, 2020). The assessment type performed for each stock and the type of advice given depends mainly on available knowledge. In ICES, stocks are classified into six main data categories; for categories 1 to 4, there are guidelines to estimate reference points (ICES, 2017a, 2018). ICES provides advice according to their MSY approach for category 1 and 2 stocks and PA advice for category 3–6 stocks. Through the ICES framework, most stocks undergo benchmarks every 3–5 years, where the methods and data used in given assessments are externally reviewed to determine assessment quality. Reference points used in ICES stock assessments are thought to be valid only in the short and medium term due to changes in marine ecosystems (ICES, 2021). As part of the benchmark process, reference points are reviewed to ensure that they reflect the current understanding of stock dynamics and are updated if necessary (ICES, 2019a). Since reference points are estimated from assessment outcomes, they are impacted by revisions (to the underlying assumptions, data input and methods) made not only to the assessment but also to the process specific to their derivation.

Previous studies have investigated how fishing mortality and/or biomass estimates vary among assessments over time using several approaches to measure variation (Evans, 1996; Ralston et al., 2011; Wiedenmann & Jensen, 2018). While investigating changes in the numerator of a sustainability indicator (e.g. F/F_{MSY}) is important, we highlight the importance of changes in both the numerator and denominator (i.e. the defined sustainable target or limit). To our knowledge, no study has analysed the sources and the relative impact of changes in reference points on the inferred stock status, which is of critical concern to management. Changes to reference points may be seen as "moving the goalposts" in one direction or another. To

TABLE 1 The main reference points used in the ICES advice rule

Reference point	Definition
$MSYB_{trigger}$	Maximum sustainable yield biomass trigger is defined as the 5th percentile of the distribution of *SSB* when fishing at F_{MSY}, but for most stocks that lack data on fishing at F_{MSY}, $MSYB_{trigger}$ is set at B_{PA}
B_{PA}	Precautionary approach biomass reference point is a stock status reference point above which the stock is considered to have full reproductive capacity. Typically defined such that there is a 5% probability that the actual biomass is below B_{lim} taking account of assessment error.
B_{lim}	Biomass limit reference point is the key reference point, from which all other PA reference points are estimated. B_{lim} is the deterministic biomass limit below which a stock is considered to have reduced reproductive capacity
F_{MSY}	Fishing mortality that provides maximum yield given the current assessment/advice error and biology and fisheries parameters.

improve understanding of changes in fisheries status it is necessary to discern how components that comprise status (i.e. numerator and denominator) change. Using an extended ICES assessments database, we disentangle changes in key stock status indicators such as relative fishing mortality (F/F_{MSY}) and relative biomass ($SSB/MSYB_{trigger}$). In addition, we present an analysis of reasons for changes among assessments to identify important sources of variation and uncertainty in reference points. Our key research questions thus comprise (i) how have reference points changed in the region?; (ii) how do changes in reference points impact sustainable stock status?; and (iii) what drives changes in reference points?

2 | METHODS

2.1 | Time series and reference points datasets

International Council of the Exploration of the Sea (ICES) stock assessments provide detailed analyses of the dynamics and status of almost 200 stocks representing important commercial fisheries for the European Union and neighbouring countries. We obtained assessment output and reference points from ICES stock assessments accessed by XML query portal System (http://standardgraphs.ices.dk/StandardGraphsWebServices.asmx/) or from the relevant ICES reports (http://stockdatabase.ices.dk/Default.aspx).

A total of 124 Stocks were subsetted to those that have reference point estimates. These were mainly category 1 stocks although six of the selected stocks were re-categorized during the timeframe of the study (either downgraded or upgraded in data/advice categories). In 2017, ICES changed the codes that are used to identify each stock (stock label key). These changes were incorporated into our analysis. For the stock label keys in our list, we acquired and integrated time series data on fishing mortality rate (*F*), spawning stock biomass (*SSB*) and MSY reference points (F_{MSY} and $MSYB_{trigger}$). These data were downloaded on 17 April 2020. We excluded *Nephrops* stocks due to the comparatively short length of the time series and the predominant use of proxy yield-per-recruit reference points. Changes in reference points between sequential assessments were identified for analysis. Change in reference point (*RP*) was calculated as the proportional change relative to the preceding assessment $(RP^{y}-RP^{y-1})/RP^{y-1}$, where *y* is the assessment year. The cleaning of the database was supported by reference to the relevant published reports. We filtered changes due to rounding and to being relative reference points to the time series mean of fishing mortality or spawning stock biomass. Adjustments were made to stocks that had non-comparable reference point values (different measurement definitions used between assessments), see Table S1. Status analysis was not performed for reference points with substituted values because, for example, the fishing mortality definition relative *F* in these assessments could not be compared to absolute values in the other assessments.

2.2 | Status change decomposition

For a given assessment and year, status is calculated by dividing time series of estimated fishing mortality rate (*F*) or biomass state (*SSB*) by the relevant reference point. Sustainability status can change depending on changes to the numerator (*F* or *SSB*) or denominator (F_{MSY} or $MSYB_{trigger}$). We derived expectations for the effect of changes in both numerator and denominator on sustainability status. To analyse changes in status between assessments, we first introduced the notation *y* to denote the assessment year and *t* the actual year of the time series, for example $F_{t=2000}^{y=2020}$, denotes the fishing mortality in year 2000 as estimated in the assessment of 2020. For each stock, year, and pair of consecutive assessments, we defined the inter-assessment change in status D_t as the proportional difference in status for a given time series year *t*:

$$D_t = \frac{\frac{X_t^y}{X_{MSY}^y} - \frac{X_t^{y-1}}{X_{MSY}^{y-1}}}{\frac{X_t^{y-1}}{X_{MSY}^{y-1}}} \tag{1}$$

where *X* is either fishing mortality rate or spawning stock biomass and X_{MSY} is the relevant reference point. Pairs of consecutive assessments were categorized according to whether or not a change in a reference point occurred. We visualized time series of inter-assessment differences (Equation 1) to understand how much status changes between consecutive assessments with reference point changes.

We estimated mean status before and after the change in reference point and an unequal variances *t* test was used to compare the values and evaluated if there were significant directional changes. We also compared the magnitude of the variability of the changes in *F* and *SSB* for the complete data set (containing all pairs of sequential assessments) to the variability of the subsetted data set containing only pairs when a change in reference point occurred. For that purpose, we measured the median absolute deviation (MAD) of the difference in mean rate *F* and state *SSB*.

For the status decomposition analysis, we used the subsetted data when a change in the reference point occurred. Change in status among sequential assessments was quantified by the change in average status between consecutive assessments over either the entire overlapping time series or the last 5 years of overlap (to infer recent status changes). The difference in average status can be decomposed into mean effects of the influence of changes in rate or state between consecutive assessments (i.e. the numerator) and changes in the reference point (i.e. the denominator). This decomposition comprises two parameters: δ, which encapsulates the proportional change in the reference point $X^{y}_{MSY} = \delta X^{y-1}_{MSY}$; and γ, which encapsulates the proportional change in average rate (*F*) or state (*SSB*) over time ($\sum_{t=1}^{n} X_t{}^{y}/n = \gamma \sum_{t=1}^{n} X_t{}^{y-1}/n$). We derive the expected difference in status using γ and δ:

$$E\left(\frac{X^{y}}{X^{y}_{MSY}} - \frac{X^{y-1}}{X^{y-1}_{MSY}}\right) = \frac{\gamma E(X^{y-1})}{\delta X^{y-1}_{MSY}} - \frac{E(X^{y-1})}{X^{y-1}_{MSY}} \tag{2}$$

The mean proportional status change (*w*) is obtained by dividing the expected difference in status by the expected previous status:

$$w = \frac{E\left(\frac{X^{y}}{X^{y}_{MSY}} - \frac{X^{y-1}}{X^{y-1}_{MSY}}\right)}{E\left(\frac{X^{y-1}}{X^{y-1}_{MSY}}\right)} = \frac{\gamma}{\delta} - 1$$

The impact of either change cannot be isolated (as the derivatives with respect to each naturally depend on the other). Nevertheless, we can empirically evaluate given changes to determine how much the relative status changes with respect to changes in either component. The mean change in status with respect to the proportional change in the reference point (δ) and with respect to the proportional change in estimate time series (γ) can be estimated with the following differential equations:

$$\frac{dw}{d\gamma} = \frac{1}{\delta}; \frac{dw}{d\delta} = \frac{-\gamma}{\delta^2}$$

We used a Pearson correlation test to evaluate the relationship between the two estimated parameters of proportional change.

2.3 | Covariates of change dataset

We review relevant advice reports for assessment years *y* and *y-1* to collect information on modifications that may have impacted the value of the reference points. Information on specific important revisions in assessment or benchmark meetings was typically presented in the advisory reports. Information regarding the technical basis for a reference point is presented at the reference point summary table. However, detailed information on settings for the estimation of the reference point was extracted from extensive reading of the referenced document, for example assessment reports or reference point estimation working group WKMSYREF (ICES, 2013; 2017b) . These reports are available at the ICES library website (http://www.ices.dk/publications/library/Pages/default.aspx).

Every event of reference point change might have been associated with multiple modifications, typically within a benchmark assessment process. For example, the North Sea, eastern English Channel, Skagerrak cod (*Gadus morhua*, Gadidae) assessment was benchmarked in 2015, resulting in changes to the input data structure, maturity, natural mortality and model settings causing reference points to be re-estimated. Besides, the MSY fishing mortality reference point was updated from F_{max} to F_{MSY} from *Eqsim* (stochastic equilibrium reference point software) analysis, and the rationale for B_{lim} was changed from B_{loss} to the *SSB* associated with the last above-average recruitment.

For every event of change in a reference point, the relevant information was collated into a new database and summarized as reference point covariates. We defined covariates based on the most frequent changes and modifications made. We aim to summarize revision generalized across all stock assessments. Covariates comprise categorical variables of occurrence and factor variables of a varying number of levels (Table S2). “Assessment” covariates were used for the analysis of both fishing mortality and biomass reference points. These comprised modifications such as (1) modification of stock definition; (2) revisions of input data both fisheries-dependent; and (3) independent (e.g. inclusion or exclusion of fisheries-dependent and fisheries-independent data, e.g. discards, commercial index, survey index); (4) re-assessed maturity; (5) re-assessed natural mortality; and (6) a heterogeneous group encompassing other revisions and updates of assessment methodology, additionally (7) revision of the assessment type, which includes information of changes in the model selected to assess the stock, with categories representing levels by the combination of the previous and subsequent model.

For most ICES assessments, derivation of F_{MSY} is typically a separate process that uses assessment outputs for age-based models, and so we evaluated changes in F_{MSY} with “Assessment” covariates and covariates specific to its derivation (“RP” covariates). These comprise (8) modifications to the definition of F_{MSY}, (9) change in the functional form of the stock–recruitment relationship, (10) revisions to the time frame of recruitment data input and (11) the time window of productivity parameters (growth, maturity, natural mortality, selectivity). The two former were included because ICES guidelines (ICES, 2017a) recommend the use full time series of recruitment unless strong evidence exists of a regime shift; and the use of the last 10 years of biological parameters (weights, maturity, natural mortality) and fishery parameters (selectivity) unless there is evidence of persistent trends. Revision to the definition of F_{MSY} was categorized according to the information provided regarding the initial and subsequent choice of advised F_{MSY}, for example changes from the use of certain F_{MSY} proxies to the use of F_{MSY}.

Following the ICES MSY approach (Table 1, ICES, 2017a), for $MSYB_{trigger}$ we included in the covariates the re-evaluation of the technical basis of $MSYB_{trigger}$ and related reference points (B_{PA} and B_{lim}). This framework includes transition rules, for example when a stock is fished at or below F_{MSY} for 5 or more years then the basis is $MSYB_{trigger}$ changes from B_{PA} to the 5th percentile of B_{MSY}. For ICES stock assessments, the biomass reference point B_{lim} is the main precautionary reference point, and B_{PA} is usually derived from it accounting for assessment uncertainty. Thus, to analyse changes in $MSYB_{trigger}$ we included covariates that are involved in setting $MSYB_{trigger}$ as (12) the revaluation of the technical basis of $MSYB_{trigger}$ and its related reference points (13) B_{lim} and (14) B_{PA}.

2.4 | Reference point change analysis

We conducted an a posteriori regression analysis of sources of those historical changes collated from the published reports. The influence of covariates on reference points was analysed by a multiple linear regression taking the proportional change in the reference point (δ) as the response. All covariates relevant to the reference point were first included as main effects to explain proportional changes in reference points; all possible combinations of sub-models were then fit and ranked by the Akaike information criterion (AIC), we used the R function glmulti() for the model selection (Calcagno & Mazancourt, 2010). Finally, we conducted a two-sided *F*-test ANOVA to the best-supported multiple linear model and investigated the percentage of the variance explained by the selected covariates.

3 | RESULTS

3.1 | Reference point changes

We identified that 50 stocks (21 species) have had changes in MSY-based reference points between 2011 and 2019 (Figure 1). This represents 64% of the stocks with estimates of absolute reference points. There were a total of 79 events of change in F_{MSY} and 51 in $MSYB_{trigger,}$ of which 42 were simultaneous changes in both reference points. Of all stocks, North Sea, eastern English Channel and Skagerrak cod 2015 and West of Scotland cod 2019 had the highest increase in F_{MSY} (74%). Cantabrian Seas and Atlantic Iberian waters sardine (*Sardina pilchardus*, Clupeidae) 2019 had the greatest decrease (73%), which is considerably larger than the magnitude of any other decreases. The biomass reference point, $MSYB_{trigger}$, increased by 145% for North Sea, Skagerrak plaice (*Pleuronectes platessa*, Pleuronectidae) 2017, when $MSYB_{trigger}$ changed from B_{PA} to the 5th percentile of B_{MSY}. The largest decrease in $MSYB_{trigger}$ occurred in Rockall haddock (*Melanogrammus aeglefinus*, Gadidae) in 2019 (64%).

For some stocks, reference points continually declined or increased, for example Baltic Sea sprat (*Sprattus sprattus*, Clupeidae) F_{MSY} and seabass (*Dicentrarchus labrax*, Moronidae) $MSYB_{trigger}$, but importantly for many stocks with multiple reference point changes, these included a mixture of decreases and increases (Figure 1). This raises the question of whether those changes reflect short-term productivity fluctuations or difficulties estimating suitable reference points. We found that simultaneous changes in both reference points showed no relationship between increases or decreases in F_{MSY} and $MSYB_{trigger}$ (Figure S1).

3.2 | Sustainability status changes

Examining timelines of changes in status (F/F_{MSY} and $SSB/MSYB_{trigger}$) between assessments in which reference points changed (Figures S2 and S3), we observed a variety of temporal patterns in the nature and magnitude of the changes (Figures S4 and S5). In some cases, the changes of reference point caused almost indiscernible changes in status (e.g. relative fishing mortality of Western Baltic Sea sole (*Solea solea*, Soleidae) 2014 in Figure 2), while elsewhere important status changes occurred when reference points changed (e.g. relative fishing mortality Cantabrian Seas and Atlantic Iberian waters sardine 2019). Occasionally, the sign of the change in status cross-over, meaning that the status trajectories between the assessments intersect, for example Skagerrak and Kattegat, western Baltic Sea sole 2015 in Figure 2. Status often varied markedly in the most recent years due to variability in fishing mortality rate (*F*) or biomass state (*SSB*) estimates, which are typically more variable in terminal years owing to a lack of convergence of the estimates (e.g. as caused by cohorts just entering the fishery and assessment). For example, in Cantabrian Seas and Atlantic Iberian waters sardine, a change to the 2019 assessment caused a relative increase in the F/F_{MSY} estimates that decreased in magnitude from 2010 to 2019 while a change to the 2015 assessment for Rockhall haddock caused a positive trend in the relative decrease of $SSB/MSYB_{trigger}$ from 2012 to 2015 (Figure 2). Several cases showed significant fluctuations in the magnitude of the relative change in status; some with a clear pattern (e.g. Rockhall haddock 2019) and others with a steady directional trend (e.g. Celtic Sea, Irish Sea herring (*Clupea harengus*, Clupeidae) deviation in 2013, Figure 2). To reflect these differences, we analysed status changes using both the complete time series and only the last 5 years to capture trends in changes in recent years.

Overall, while there are many examples of large changes in status for individual stock, there is no clear movement away from or towards sustainability (Figure 3 top panel). For the most recent five years, the

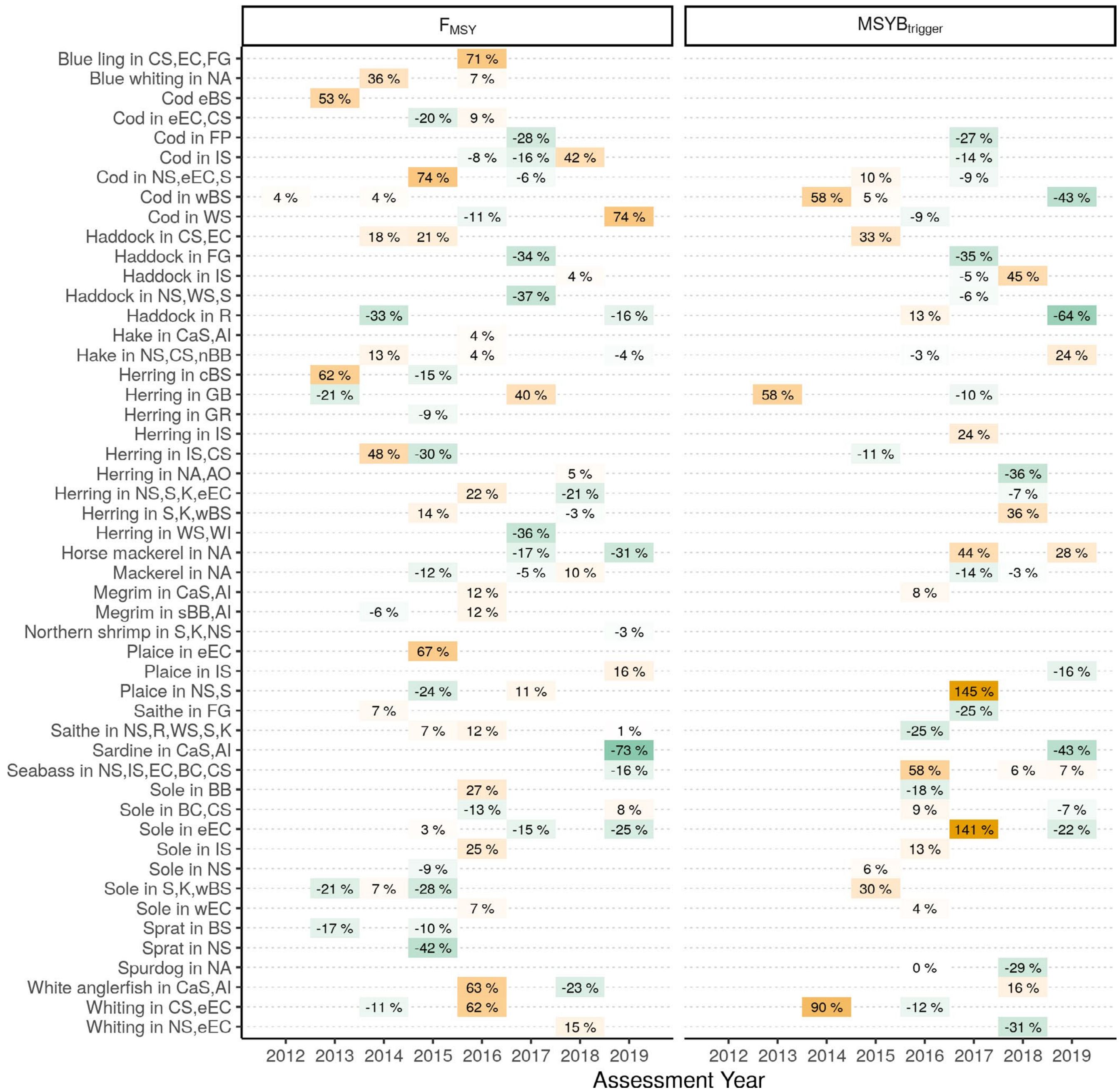

FIGURE 1 Changes in reference points for stocks assessments for the period 2011–2019, measured in percentage change relative to the preceding assessment. Stocks are ordered by species. Acronyms used in stock description are: BB, Bay of Biscay; BC, Bristol Channel; CS, Celtic Sea; BS, Baltic sea; CaS, Cantabrian Sea; AI, Atlantic Iberian waters; EC, English Channel; FG, Faroes grounds; GR, Gulf of Riga; GB Gulf of Bothnia; FP, Faroes Plateau; IS, Irish Sea; NA North Atlantic; AO, Arctic Ocean; NS North Sea; S, Skagerrak; K, Kattegat; R, Rockall; WS West of Scotland; c, central; n, northern; e, eastern; w, western

changes in relative fishing mortality and relative biomass state showed greater spread than when all years were included. Changes in status were not directional based on unequal variances *t* test of the status before and after the assessment update (change in average relative fishing mortality recent: $t_{(159,46)} = -0.04$, $p = .965$; complete time series: $t_{(164,81)} = -0.06$, $p = .95$; change in average relative biomass recent: $t_{(101,23)} = -0.19$, $p = .849$; complete time series: $t_{(99,41)} = 0.05$, $p = .957$). The changes in average F or SSB, when a change in reference point occurred, had similar or greater variability than when all pairs of sequential assessments are considered (change in average relative fishing mortality recent: $MAD_{change} = 1.49$, $MAD_{all\ pairs} = 0.03$; complete time series: $MAD_{change} = 1.48$, $MAD_{all\ pairs} = 0.009$; change in average relative biomass recent: $MAD_{change} = 4{,}807.33$, $MAD_{all\ pairs} = 5{,}187.62$; complete time series: $MAD_{change} = 2{,}494.93$, $MAD_{all\ pairs} = 1{,}490.71$). Therefore, the changes in sequential estimates of *F* and *SSB* were more marked when a change in reference point occurred.

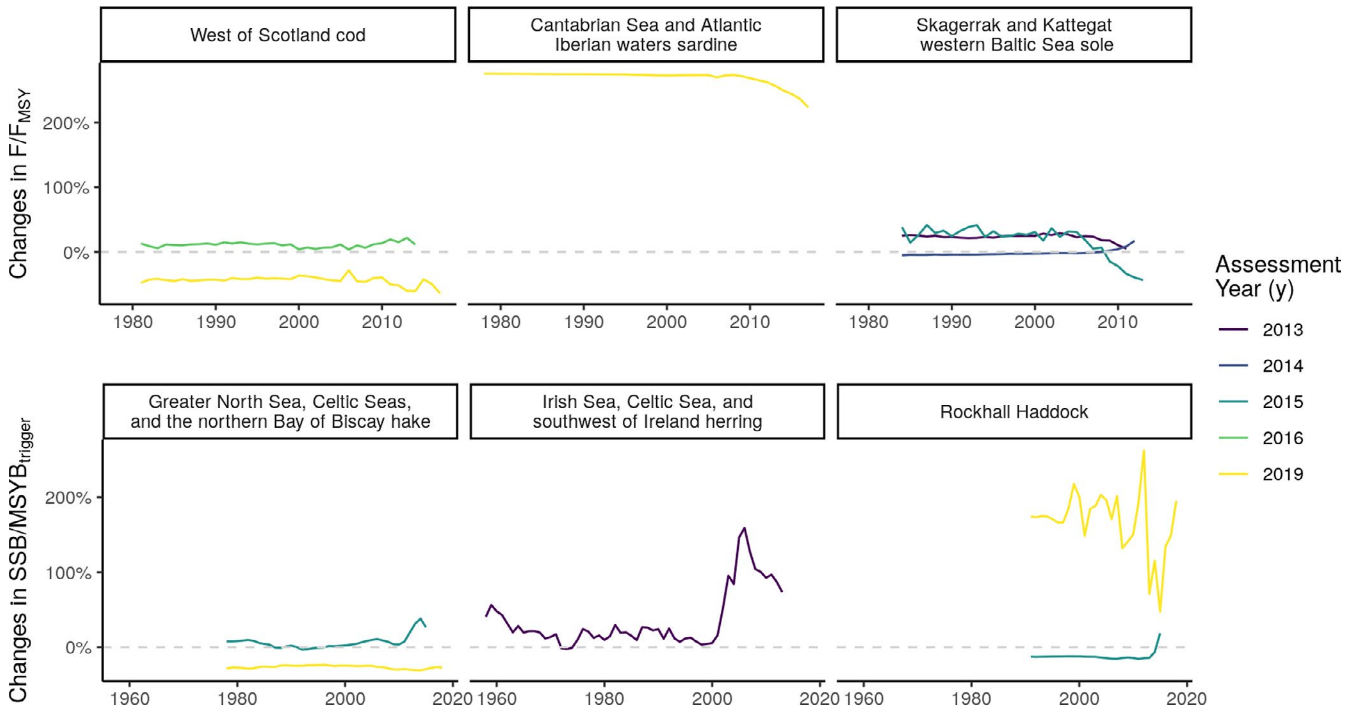

FIGURE 2 Example of changes in status timelines. Top-panel shows relative fishing mortality rate (F/F_{MSY}); and bottom panel shows relative biomass state ($SSB/MSYB_{trigger}$) proportional changes of assessment year (y) relative to the previous (y-1), for assessments in which changes in reference points were implemented

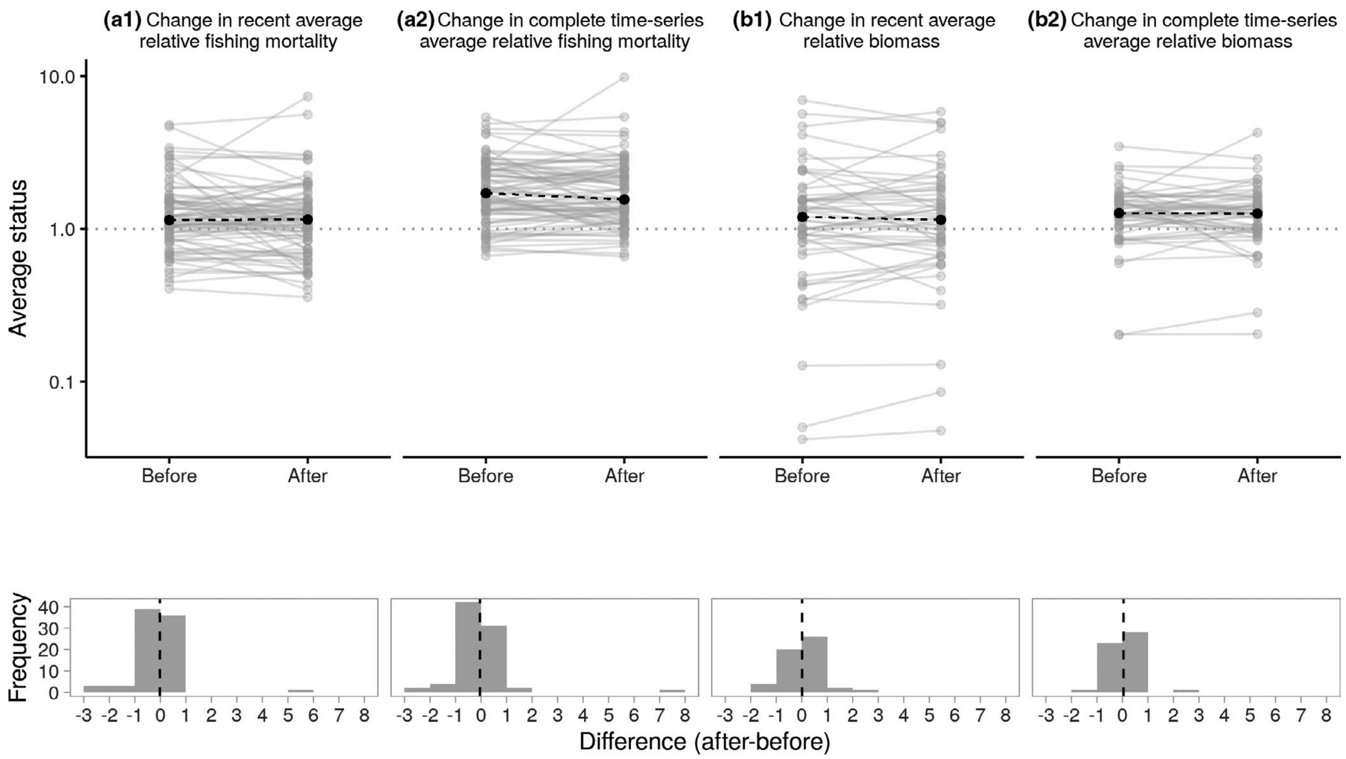

FIGURE 3 Mean status before and after at changes in reference points. Top-panel shows mean status on logarithmic scale in terms of relative fishing mortality (a) and relative biomass (b), over last five recent years (a1, b1) and complete time series (a2, b2). Bottom panel shows the distribution of the difference of status between before and after the reference point change. Black point and dashed line represents median values

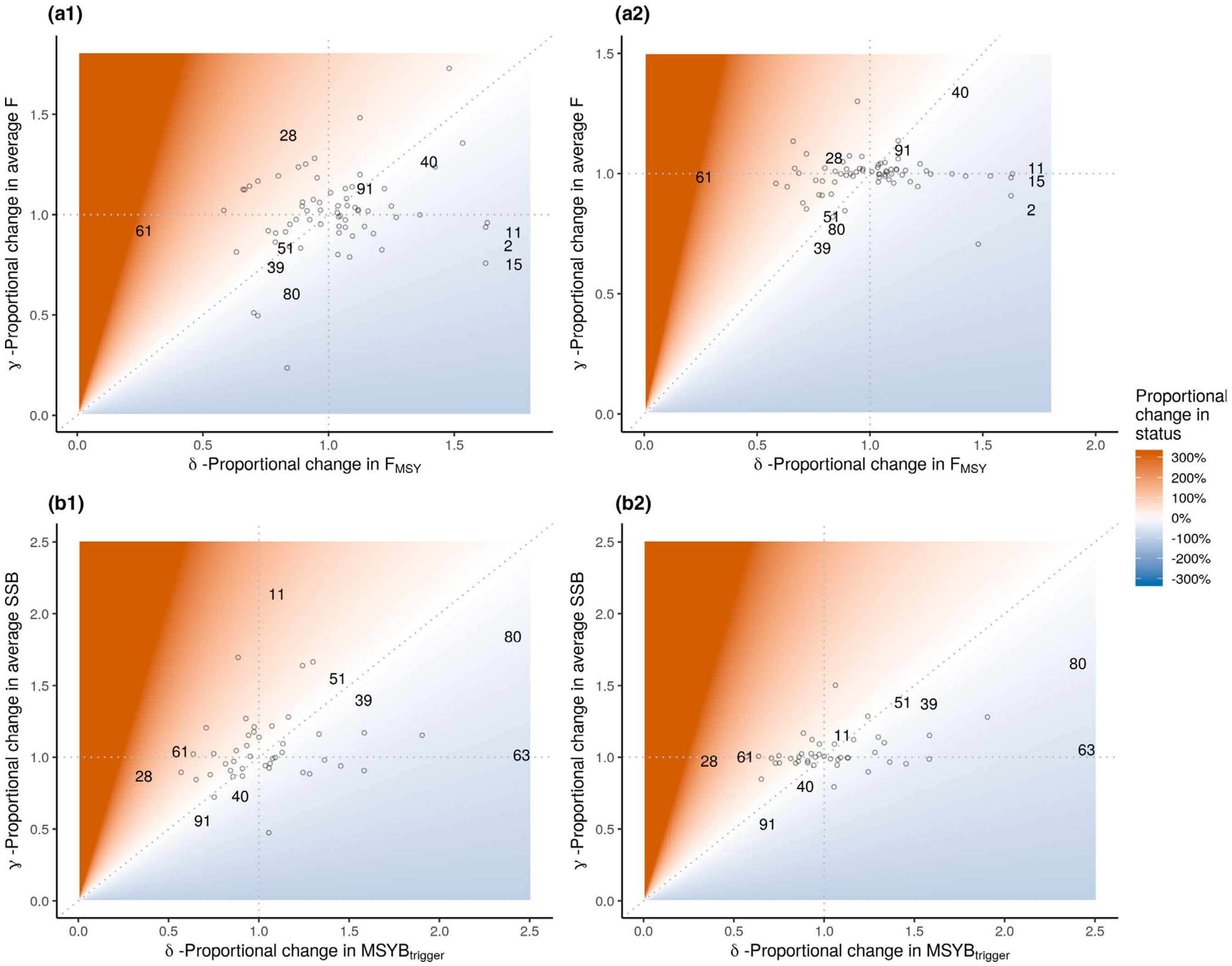

FIGURE 4 Change in sustainability status decomposition. Relationship between proportional change in average rate or state (γ) and proportional change in reference point ($\delta_a = F_{MSY}{}^{y}/F_{MSY}{}^{y-1}$; $\delta_b = MSYB_{trigger}{}^{y}/MSYB_{trigger}{}^{y-1}$), background colour represents impact in status change for relative fishing mortality rate, F/F_{MSY} (a) and relative biomass state, $SSB/MSYB_{trigger}$ (b), over recent years (a1, b1) and the complete time series (a2, b2). The plot numbers correspond to the event numbers in Table S1: (2) 2016 blue ling in Celtic Seas, English Channel and Faroes grounds; (11) 2015 cod in North sea, eastern English Channel, Skagerrak; (15) 2019 cod in West of Scotland; (28) 2019 haddock in Rockall; (39) 2013 herring in gulf of Bothnia; (40) 2017 herring in gulf of Bothnia; (51) 2017 horse mackerel in North Atlantic; (61) 2018 white anglerfish in Cantabrian Sea and Atlantic Iberian waters; (80) 2017 sole in eastern English Channel; (91) 2018 whiting in North Sea and eastern English Channel

3.3 | Effect of reference point changes on sustainability status

We define δ as the proportional change in the reference point and γ as the proportional change in average rate (*F*) or state (*SSB*) over time. There was some evidence of a weak positive relationship between changes in rate or state and reference point (Figure 4), which was significant only for biomass over the recent part of the time series (rho = 0.33, p = .018) and over the complete time series (rho = 0.53, p < .001). Where the proportional changes in the numerator and denominator were equal, no change in status occurs (1:1 line in Figure 4). However, particularly looking at the data for the complete time series, average status changes were mainly due to changes in reference points (horizontal spread of points in Figure 4a2, 4b2). Some of the greatest changes in relative fishing mortality were associated with changes in F_{MSY}, for example increase in relative fishing mortality for sardine in 2019 (Figure 4a point 61); and decrease in North Sea, eastern English Channel, Skagerrak cod in 2015 (Figure 4a point 11). Similarly for relative biomass, large changes were related mainly with changes in $MSYB_{trigger}$, for example Rockhall haddock in 2019 (Figure 4b point 28) and North Sea and Skagerrak plaice in 2017 (Figure 4b point 63). Yet, eastern English Channel sole 2017 had important changes in both the biomass estimate and $MSYB_{trigger}$ (Figure 4b point 80). Only occasionally were the changes in rate or state compensated by changes in reference point over the most recent period such that no change in status occurred. This counters a common belief that changes in the estimated state will be compensated for by changes in the reference points, which

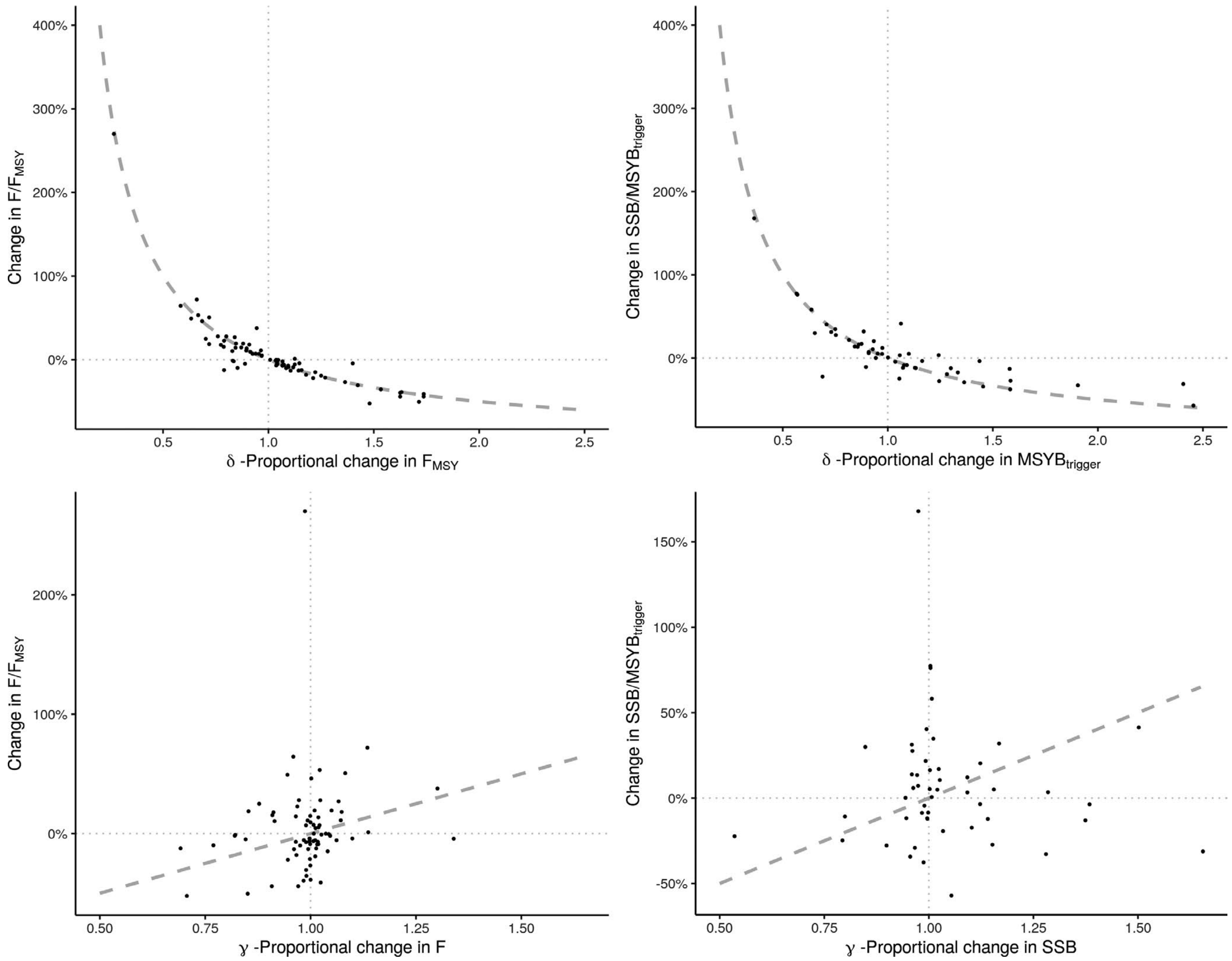

FIGURE 5 Marginal relationship between average change in status and δ, proportional change in reference point, at the top panel; and γ, proportional change in rate (left) or state (right), at the bottom panel considering the complete time series. Grey line shows the expected theoretical change with a change in δ (top) or γ (bottom)

are caused by new information on processes. There were examples of where this compensation occurred: relative fishing mortality of Gulf of Bothnia herring (Figure 4a point 39); and relative biomass of Northeast Atlantic horse mackerel (*Scomber scombrus*, Scombridae; in Figure 4b point 51), and North Sea and eastern English Channel whiting (*Merlangius merlangus*, Gadidae; in Figure 4b point 91).

The marginal relationship between mean status change (over the complete time series) and proportional change in reference point displayed a curvilinear inverse response adhering to the expected relationship (Figure 5 top panel). As the reference point is the denominator of status (F/F_{MSY} and $SSB/MSYB_{trigger}$), if the numerator compensated for the change in the denominator one would expect a flat relationship in Figure 5. We found that reductions in reference points ($\delta < 1$) resulted in steeper increases in status, whereas increases in reference points ($\delta > 1$) resulted in more moderate reductions in status (e.g. from the theoretical proportional change in mean status $\frac{\gamma}{\delta} - 1$, a 10% reduction in the reference point would result in an approximate 11% increase in status whereas a 10% increase in the reference point would result in an approximate 9% increase in the status where $\gamma = 1$). This negative relationship between changes in status and the change in the reference point appears stronger (less variable) for relative fishing mortality than for the relative biomass (Figure 5 top panel). Occasionally, there were assessments where the reference point decreased but status also decreased, or where both increase. The observed marginal relationship with the proportional change in rate or state (γ) was diffuse compared to the theoretical relationship (Figure 5 bottom panel). Over recent years of overlap, the marginal relationship of changes showed in general more variability for the proportional change in reference point and less variability in the marginal relationship with the proportional change in rate or state estimates (Figure S6).

3.4 | Possible reasons for reference points change

Across all the covariates, the distribution of the magnitude of change in both reference points displayed heterogeneous patterns with wide ranges; no covariate showed a clear directional effect (Figures S7 and S8). Most changes in reference point occurred due to a combination of effects rather than a single cause; we found that covariates occurred simultaneously, they might be correlated and also interact (Figures S9 and S10).

Events of change in both F_{MSY} and $MSYB_{trigger}$ presented similar frequency of occurrence for "Assessment" covariates. Input fisheries-dependent and fisheries-independent data were revised for roughly 20% of the cases. The assessment model was modified in approximately 15% of the cases, the most frequent change being from XSA to SAM ($n = 5$). Re-assessment of natural mortality was found in 11% of the cases for F_{MSY} and 6% of the cases for $MSYB_{trigger}$. Changes in natural mortality estimates comprise revision of assumptions (e.g. using a new single species method, introducing multispecies estimates), or updates (e.g. time-varying mortality updated, multispecies estimates using a new multispecies model run). Less frequently encountered covariates (>10% of the cases) were the revision of maturity estimates and the revision of the definition of the stock.

Although multiple factors have contributed to changes in reference points, our results showed that the evolution in the definition for fishing mortality reference point (F_{MSY}) and re-evaluation of the technical basis for limit biomass reference point (B_{lim}) were the most important (Table 2). Revision of fishing mortality reference point definition was the most frequent covariate identified ($n = 30$, 40% of the cases). This key covariate explained the largest part of the variance (39.8%) of the model (F-statistic$_{(13)} = 3.6$, $p = .0004$, Table 2). It presented the change of many previous definitions (e.g. proxy values) and diversity of stochasticity implementation methods, to a unified F_{MSY} estimation framework *Eqsim* (Figure 6a). We found that advised F_{MSY} based on analogies from other stocks ($n = 2$) or provisional from simulation frameworks ($n = 8$) were on average higher than subsequent F_{MSY}; however, per-recruit proxies were lower based on small sample sizes (F_{max} $n = 8$; $F_{0.1}$ $n = 4$). Only one observed change was related to a revision of the fishing mortality reference point from the calculated value (F_{MSY}) to $F_{p0.5}$ established by stochastic simulations when the precautionary criterion is not met (Figure 6a). For the biomass reference point, revision of B_{lim} technical basis explained 29.94% of the variance of the model (F-statistic$_{(13)} = 2.23$, $p = .04$, Table 2). B_{lim} technical basis was revised for 19% of the cases and $MSYB_{trigger}$ for 16%. From the re-evaluations of $MSYB_{trigger}$ ($n = 13$), for 23% of the cases the technical basis was changed from B_{PA} to the 5th percentile of B_{MSY} (Figure 6b). The most frequent revision found was re-evaluation of the technical basis of B_{PA} (23% of the cases), which involves modification of how the assessment uncertainty is accounted for. Both selected models to explain changes in reference points had large residual variability at 44.62% and 21.02% for F_{MSY} and $MSYB_{trigger,}$ respectively (Table 2) likely reflecting the binary nature of the covariates without the magnitude of change.

The different nature of ICES fishing mortality target and biomass threshold reference point was reflected in the analysis. As F_{MSY} is a model estimate output, it is impacted by modifications to input data (e.g. selection pattern and biological parameter) and underlying assumptions (i.e. stock–recruitment relationship functional form). We found that to derive F_{MSY}, the assumption of the stock–recruitment relationship functional form was revised for 24% of the cases ($n = 19$). Modelling of the stock–recruitment relationship (a key density-dependent process) remains a challenge and this is known as the main source of variation (ICES, 2015; Simmonds et al., 2011). During workshops to consider the basis for F_{MSY} ranges for all stocks, WKMSYREF (ICES, 2015; 2017b) several stock–recruitment models were investigated from functional form combinations to the use of segmented regression. In terms of data input to derive reference points, we found that the time series to estimate F_{MSY} was revised in 11% of the cases for recruitment and 7.5% for productivity parameters. Time series of recruitment and *SSB* to model the stock–recruitment relationship are re-evaluated to ensure the selection of the relevant period when there is a change in the perception of the productivity regime (i.e. shifts or trend). Both, revision of stock–recruitment functional form and selected time series of recruitment, were important variables in the model, which explained around 5% of the variance each ($p < .05$, Table 2). In contrast, $MSYB_{trigger}$ (when set to B_{PA}) is based on biomass assessment estimates, because is often derived from B_{lim} (typically set by stock–recruitment typology rules). Therefore, it is more sensitive to changes affecting the estimates of biomass, for example revision of assessment model type, fishery-dependent and fishery-independent data, methodological revisions and re-assessment of maturity (Table 2).

4 | DISCUSSION

4.1 | Evolution of sustainable targets and thresholds

Reference points play a key role in fisheries management by providing targets and thresholds to guide management actions (Mace, 2001). Reference points may change, not only reflecting the non-stationary nature of the ecosystem but also our ability to capture those changes. The frequency at which reference points are updated varies globally, for example, tuna Regional Fisheries Management Organizations and North Pacific Fisheries Management council update reference points with each assessment (Kell et al., 2016). ICES stocks provide a unique opportunity in terms of breadth and frequency of change (Figure 1) to investigate the impact of changes in reference points. By using ICES stocks for this analysis, we gained a data-rich and detailed overview of the evolution of reference points and their key management use in measuring sustainability status. Stock status before and after a change in a reference point had no significant directional differences (Figure 3) that would suggest a retrospective movement towards or away from sustainability. But there have been important effects of reference point changes for specific stocks with implications for sustainable harvest advice and perceived conservation status. We showed that, across a range of life histories and assessments, changes in reference point dominate changes in status over the full time series (Figure 4). Analysis of recent years shows more variability due to terminal estimate variability and bias (known as retrospective pattern in assessment updates (ICES, 2020)) but

TABLE 2 Table displaying the results of selected model explained by the covariates

Covariate	Model for changes in F_{MSY} ($R^2 = 0.55$, $R^2_{adj} = 0.37$, F-Statistic = 3.16 with $p = 2.69e{-4}$)	Percentage of the variance explained	Model for changes in $MSYB_{trigger}$ ($R^2 = 0.79$, $R^2_{adj} = 0.54$, F-Statistic = 3.2 with $p = .003$)	Percentage of the variance explained
(1) Revision_Assessment_Stock_definition	–	–	–	–
(2) Revision_Assessment_input_data_FisheriesDependent	–	–	F-statistic$_{(1)} = 6.74$; $p = .0161$*	9.68%
(3) Revision_Assessment_input_data_FisheriesIndependent	–	–	F-statistic$_{(1)} = 1.77$; $p = .1958$	7.37%
(4) Revision_Assessment_maturity	F-statistic$_{(1)} = 3.93$; $p = .0522$·	3.14%	F-statistic$_{(1)} = 1.85$; $p = .187$	1.69%
(5) Revision_Assessment_M	–	–	–	–
(6) Revision_Assessment_methodology	–	–	F-statistic$_{(1)} = 8.17$; $p = .00889$**	6.51%
(7) Revision_Assessment_type	F-statistic$_{(6)} = 1.57$; $p = .174$	15.34%	F-statistic$_{(4)} = 5.94$; $p = .00196$**	14.42%
(8) Revision_RP_FMSY_definition	F-statistic$_{(13)} = 3.62$; $p = .0004$***	39.75%	–	–
(9) Revision_RP_SR_functional_form	F-statistic$_{(1)} = 4.25$; $p = .0439$*	5.64%	–	–
(10) Revision_RP_input_timeseriesRecruitment	F-statistic$_{(1)} = 3.94$; $p = .0320$*	5.64%	–	–
(11) Revision_RP_input_parameterstimeseries	–	–		–
(12) Revision_RP_MSYBtrigger_tb	–	–	F-statistic$_{(5)} = 2.59$; $p = .0531$·	5.05%
(13) Revision_RP_Blim_tb	–	–	F-statistic$_{(13)} = 2.23$; $p = .0439$*	29.94%
(14) Revision_RP_Bpa_tb	–	–	–	–
Residuals	–	44.62%	–	21.02%

Note: Signif. Codes: 0 "***" 0.001 "**" 0.01 "*" 0.05 "·" 0.1 " " 1.

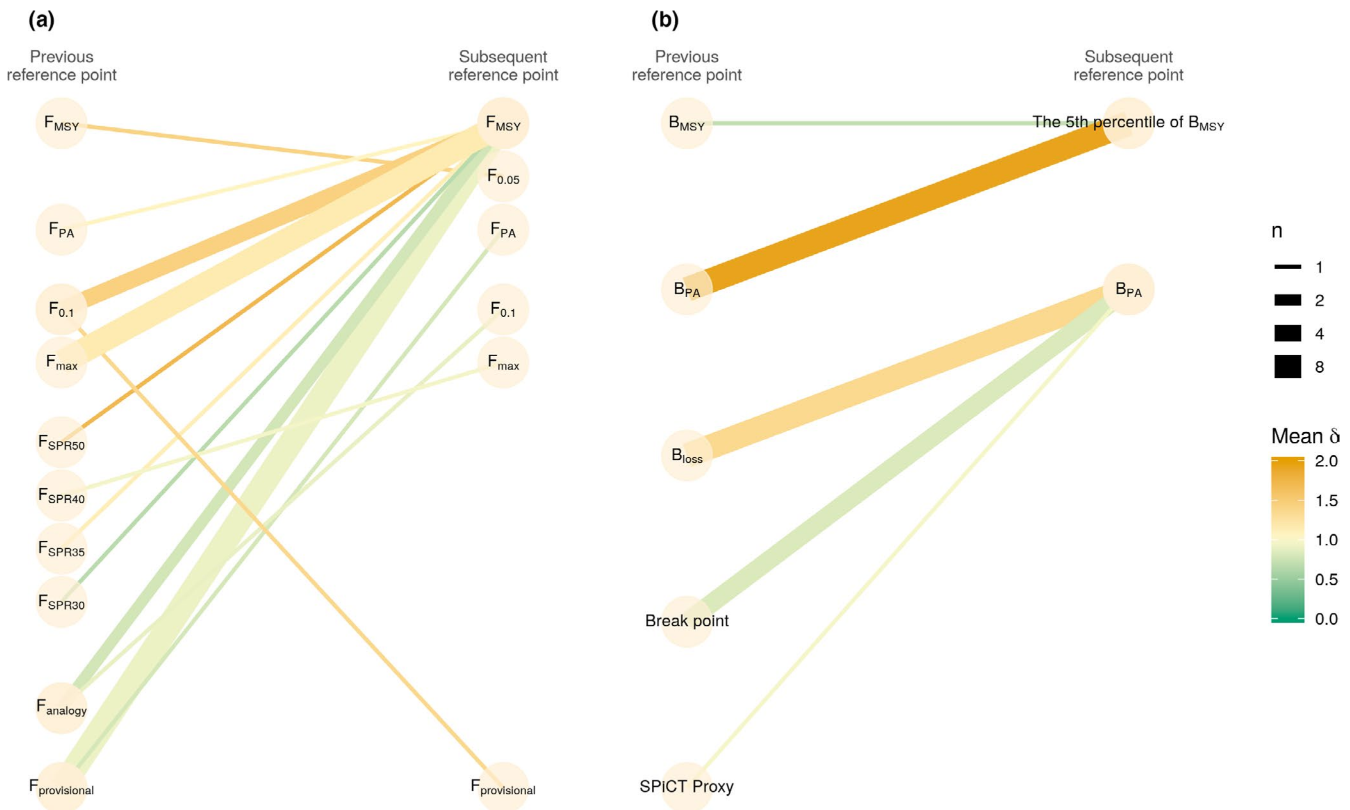

FIGURE 6 (a) Average change in adviced reference point F_{MSY} with levels of revision in definition of fishing mortality reference point: F_{MSY}, yield-per-recruit proxies ($F_{0.1}$, F_{max}), spawner biomass per-recruit proxies (F_{SPR30}, F_{SPR35}, F_{SPR40}, F_{SPR50}), F_{PA}, reference point from analogy of other stocks and provisional reference point; and (b) average change in adviced reference point $MSYB_{trigger}$ with levels of revision of the technical basis: B_{MSY}, B_{PA}, Break point, B_{loss}, proxy from Spict model. The width of the line shows the number of occurrence of that specific revision. Warm colours are mean increase and cool colours mean decrease of reference point advised value

also highlights the importance of changes in reference points on status. For simultaneous changes in F_{MSY} and $MSYB_{trigger}$, we would expect an inverse relationship (i.e. a decrease in F_{MSY} would be associated with an increase in $MSYB_{trigger}$ and vice versa), assuming that the same method was used and only new information in processes was included. However, a substantial number of events deviated from the expected direction (Figure S1), which might be indicative of changes in perceived productivity.

Reference point changes reflect simultaneously the evolution of management policy and scientific understanding and methodology. In 2009 ICES adopted the MSY framework on top of their precautionary framework and began adapting the advice provided (Lassen et al., 2014). The framework includes transition rules; for example, when a stock is fished at or below F_{MSY} for 5 or more years then the basis if $MSYB_{trigger}$ changes from B_{PA} to the 5th percentile of B_{MSY} (ICES, 2017a). This is because productivity and B_{MSY} estimates may change as stocks increase when fishing mortality is reduced to more sustainable levels (i.e. F_{MSY}). Another occurrence was the re-estimation of F_{MSY} and precautionary reference points during the workshops WKMSYREF (2013–2015). This was stimulated by the request of the European Commission for advice on potential intervals above and below F_{MSY} for selected stocks. Evaluations of MSY were made using *Eqsim* or similar methods to implement stochasticity (ICES, 2013; 2017b). Changes in software used to derive F_{MSY} are important because the underlying uncertainty assumptions and the way stochasticity is implemented may vary, which affects the estimates (ICES, 2017b; 2019b).

Across different regions, past studies of the variability among historical assessment and projection simulations have shown that there are numerous potential causes for changes in assessment estimates over time (Privitera-Johnson & Punt, 2020; Punt et al., 2018; Ralston et al., 2011; Wiedenmann & Jensen, 2018). Previous studies have shown sensitivity of MSY-based reference points to the functional form and parameters of the stock–recruitment relationship (Simmonds et al., 2011; Zhu et al., 2012). A recent study initiates the research on the uncertainty associated with biomass limit reference points (Deurs et al., 2021). They were found to be sensitive to the estimation method, time series length, and stock development trends. However, to our knowledge, no study has systematically quantified the impact and reasons for changes in reference points over time. We explored the effect of modifications to reference points that were stated in assessment reports. Were we to also re-run the assessment models and reference point estimation procedure it would be possible to investigate the deterministic impact of any given changes singularly or in combination. This mechanistic approach would be greatly facilitated through transparent frameworks for data and modelling and advice such as the recently developed ICES Transparent

Assessment Framework (https://taf.ices.dk/app/about last accessed August 15th, 2020). Such an analysis is beyond the scope of this work but would be extremely useful and could be operationalized where changes are proposed. Our analysis sets the groundwork for future mechanistic investigation of the causes underlying changes in reference points and status on a stock-by-stock basis.

4.2 | Implications for fisheries management

Time-varying reference points will become increasingly important for management given: (i) continual improvements in stock assessments (in terms of new and improved data and estimation) and continually improved knowledge of stock biology; (ii) the development of operational ecosystem approach and the increasing inclusion of ecosystem concerns in assessments (Marshall et al., 2019; Skern-Mauritzen et al., 2016); and (iii) growing evidence of dynamics, shifts in productivity, and the influence of climate change, which emphasizes the need to adapt reference points (Britten et al., 2017; Collie et al., 2012; Minto et al., 2014; Szuwalski & Hollowed, 2016; Table au et al., 2019; Vert-pre et al., 2013). These changes in reference points will require inclusion in future interpretations of stock status (Hilborn, 2020).

We underscore the importance of keeping track of changes and modifications to understand their impact and allow comparisons across stock assessments that underpin fisheries management. Our results also highlight the continual importance of accounting for scientific uncertainty to distinguish it from real changes in the ecosystem or the fishery, which are fundamentally different. We emphasize the many examples in Figure 1 of where reference points decrease and then increase or vice versa and posit that these cases will offer useful insights into the general process lending towards further investigation of the stability and performance of management advice under true and perceived change. Given the challenges faced by estimation and the use of reliable reference points for management (Hilborn, 2002), reference points are better seen as reference series. The relevant reference point in the reference series should also be time-dependent (possibly with lags) when inferring historical sustainability rather than assessing historical status relative to the most recent reference point. We recommend careful documentation of changes to assessment assumptions and data inputs (Punt et al., 2018), as well as the revision in estimation or selection of reference points and detection of shifts in productivity (Clausen et al., 2018). Communicating, explaining and justifying the changes is remarkably important to understand them and their relevance. Nowadays, this can be readily achieved using changelogs that are common in other continual development processes such as software development.

Although this work is tailored for ICES reference points, the approach to decompose changes in status into components can be applied to other regions and globally (e.g. using the RAM Legacy Database). Methods developed here are applicable in settings where the ratio of a state to a changing goal is used to indicate status (e.g. Sustainable Development Goals: 6 Clean Water and Sanitation; 13 Climate Action; 15: Life On Land).

ACKNOWLEDGEMENTS

We are grateful to Kenneth Patterson for his valuable contributions and feedback in early stages of this manuscript. We thank European stock assessment scientists, data collectors, and ICES upon whose assessments our work is based. This analysis was funded by the Irish Department of Agriculture, Food and the Marine's Competitive Research Funding Programmes (DAFM) as part of the FishKOSM project (Ref 15/S/744).

CONFLICT OF INTEREST

Authors declare no competing interests.

DATA AVAILABILITY STATEMENT

All data and code we used for analyses are available on our GitHub repository: https://github.com/paulasv/IMGP_2020. All raw assessment data is available for download at ICES webpage.

ORCID

Paula Silvar-Viladomiu https://orcid.org/0000-0002-9983-3744

REFERENCES

Britten, G. L., Dowd, M., Kanary, L., & Worm, B. (2017). Extended fisheries recovery timelines in a changing environment. *Nature Communications*, *8*(1), 15325. https://doi.org/10.1038/ncomms15325

Calcagno, V., & de Mazancourt, C. (2010). glmulti: An R package for easy automated model selection with (Generalized) linear models. *Journal of Statistical Software*, *34*(12), 29. https://doi.org/10.18637/jss.v034.i12

Clausen, L. W., Rindorf, A., van Deurs, M., Dickey-Collas, M., & Hintzen, N. T. (2018). Shifts in North Sea forage fish productivity and potential fisheries yield. *Journal of Applied Ecology*, *55*(3), 1092–1101. https://doi.org/10.1111/1365-2664.13038

Collie, J. S., Peterman, R. M., & Zuehlke, B. M. (2012). A fisheries risk-assessment framework to evaluate trade-offs among management options in the presence of time-varying productivity. *Canadian Journal of Fisheries and Aquatic Sciences*, *69*(2), 209–223. https://doi.org/10.1139/f2011-148

Deurs, M., Brooks, M. E., Lindegren, M., Henriksen, O., & Rindorf, A. (2021). Biomass limit reference points are sensitive to estimation method, time-series length and stock development. *Fish and Fisheries*, *22*(1), 18–30. https://doi.org/10.1111/faf.12503

EC. (2013). Common fisheries policy (CFP) Regulation No. 1380/2013 of the European Paliament and of the Council. *Official Journal of the European Communities*, *001*, 354. http://data.europa.eu/eli/reg/2013/1380/oj

Evans, G. T. (1996). Using the elementary operations of sequential population analysis to display problems in catch or survey data. *Canadian Journal of Fisheries and Aquatic Sciences*, *53*(2), 239–243. https://doi.org/10.1139/f95-191

FAO. (2020). *Proceedings of the international symposium on fisheries sustainability: Strengthening the science-policy nexus. FAO fisheries and aquaculture proceedings* No. 65 (Vol. FAO Headqu). FAO. https://doi.org/10.4060/ca9165en

Fernandes, P. G., & Cook, R. M. (2013). Reversal of fish stock decline in the Northeast Atlantic. *Current Biology*, *23*(15), 1432–1437. https://doi.org/10.1016/j.cub.2013.06.016

Hilborn, R. (2002). The dark side of reference points. *Bulletin of Marine Science*, *70*(2), 403–408.

Hilborn, R. (2020). Measuring fisheries management performance. *ICES Journal of Marine Science*, *77*(7–8), 2432–2438. https://doi.org/10.1093/icesjms/fsaa119

Hilborn, R., Amoroso, R. O., Anderson, C. M., Baum, J. K., Branch, T. A., Costello, C., de Moor, C. L., Faraj, A., Hively, D., Jensen, O. P., Kurota, H., Little, L. R., Mace, P., McClanahan, T., Melnychuk, M. C., Minto, C., Osio, G. C., Parma, A. M., Pons, M., … Ye, Y. (2020). Effective fisheries management instrumental in improving fish stock status. *Proceedings of the National Academy of Sciences*, *117*(4), 2218–2224. https://doi.org/10.1073/pnas.1909726116

ICES. (2013). Report of the Workshop to consider reference points for all stocks (WKMSYREF2), *8–10 Janua*(ICES CM 2014/ACOM:47), 91 pp.

ICES. (2015). Report of the Joint ICES-MYFISH Workshop to consider the basis for FMSY ranges for all stocks (WKMSYREF3). *ICES*, *17–21 Nove*(ICES CM 2014/ACOM:64), 156 pp. https://doi.org/ICES CM 2014/ACOM:64. https://doi.org/10.17895/ices.pub.5661

ICES (2017a). ICES advice technical guidelines. ICES fisheries management reference points for category 1 and 2 stocks. *ICES Advice*, Book 12(20 January), 19. https://doi.org/10.17895/ices.pub.3036

ICES. (2017b). Report of the Workshop to consider FMSY ranges for stocks in ICES categories 1 and 2 in Western Waters (WKMSYREF4). *13–16 October 2015*, *Brest*, *France*, (ICES CM 2015/ACOM:58), 187 pp.

ICES (2018). ICES Technical Guidelines. ICES reference points for stocks in categories 3 and 4. *ICES Advice*, (13 February), 50. https://doi.org/10.17895/ices.pub.3977

ICES. (2019a). Advice basis. *In Report of the ICES Advisory Committee*, *2019*. https://doi.org/10.17895/ices.advice.5757

ICES (2019b). Workshop on North Sea Stocks Management Strategy Evaluation (WKNSMSE). *ICES Scientific Reports*, *1*(12), 378. https://doi.org/10.17895/ices.pub.5090

ICES. (2020). Workshop on Catch Forecast from Biased Assessments (WKFORBIAS; outputs from 2019 meeting). *ICES Scientific Reports*, (2:28), 38. https://doi.org/10.17895/ices.pub.5997

ICES (2021). Workshop of Fisheries Management Reference Points in a Changing Environment (WKRPChange, outputs from 2020 meeting). *ICES Scientific Reports*, *3*(6), 39. https://doi.org/10.17895/ices.pub.7660

Jackson, J. B. C. (2001). Historical overfishing and the recent collapse of coastal ecosystems. *Science*, *293*(5530), 629–637. https://doi.org/10.1126/science.1059199

Kell, L. T., Nash, R. D. M., Dickey-Collas, M., Mosqueira, I., & Szuwalski, C. (2016). Is spawning stock biomass a robust proxy for reproductive potential? *Fish and Fisheries*, *17*(3), 596–616. https://doi.org/10.1111/faf.12131

Kvamsdal, S. F., Eide, A., Ekerhovd, N.-A., Enberg, K., Gudmundsdottir, A., Hoel, A. H., & Vestergaard, N. (2016). Harvest control rules in modern fisheries management. *Elementa: Science of the Anthropocene*, *4*(000114), 1–22. https://doi.org/10.12952/journal.elementa.000114

Lassen, H., Kelly, C., & Sissenwine, M. (2014). ICES advisory framework 1977–2012: From Fmax to precautionary approach and beyond. *ICES Journal of Marine Science*, *71*(2), 166–172. https://doi.org/10.1093/icesjms/fst146

Mace. (2001). A new role for MSY in single-species and ecosystem approaches to fisheries stock assessment and management. *Fish and Fisheries*, *2*(1), 2–32. https://doi.org/10.1046/j.1467-2979.2001.00033.x

Marshall, K. N., Koehn, L. E., Levin, P. S., Essington, T. E., & Jensen, O. P. (2019). Inclusion of ecosystem information in US fish stock assessments suggests progress toward ecosystem-based fisheries management. *ICES Journal of Marine Science*, *76*(1), 1–9. https://doi.org/10.1093/icesjms/fsy152

Minto, C., Mills Flemming, J., Britten, G. L., & Worm, B. (2014). Productivity dynamics of Atlantic cod. *Canadian Journal of Fisheries and Aquatic Sciences*, *71*(2), 203–216. https://doi.org/10.1139/cjfas-2013-0161

Privitera-Johnson, K. M., & Punt, A. E. (2020). Leveraging scientific uncertainty in fisheries management for estimating among-assessment variation in overfishing limits. *ICES Journal of Marine Science*, *77*(2), 515–526. https://doi.org/10.1093/icesjms/fsz237

Punt, A. E., Day, J., Fay, G., Haddon, M., Klaer, N., Little, L. R., & Wayte, S. (2018). Retrospective investigation of assessment uncertainty for fish stocks off southeast Australia. *Fisheries Research*, *198*, 117–128. https://doi.org/10.1016/j.fishres.2017.10.007

Ralston, S., Punt, A. E., Hamel, O. S., Devore, J. D., & Conser, R. J. (2011). A meta-analytic approach to quantifying scientific uncertainty in stock assessments. *Fishery Bulletin*, *109*(2), 217–231.

Ricard, D., Minto, C., Jensen, O. P., & Baum, J. K. (2012). Examining the knowledge base and status of commercially exploited marine species with the RAM legacy stock assessment database. *Fish and Fisheries*, *13*(4), 380–398. https://doi.org/10.1111/j.1467-2979.2011.00435.x

Simmonds, E. J., Campbell, A., Skagen, D., Roel, B. A., & Kelly, C. (2011). Development of a stock–recruit model for simulating stock dynamics for uncertain situations: The example of Northeast Atlantic mackerel (Scomber scombrus). *ICES Journal of Marine Science*, *68*(5), 848–859. https://doi.org/10.1093/icesjms/fsr014

Skern-Mauritzen, M., Ottersen, G., Handegard, N. O., Huse, G., Dingsør, G. E., Stenseth, N. C., & Kjesbu, O. S. (2016). Ecosystem processes are rarely included in tactical fisheries management. *Fish and Fisheries*, *17*(1), 165–175. https://doi.org/10.1111/faf.12111

Szuwalski, C. S., & Hollowed, A. B. (2016). Climate change and non-stationary population processes in fisheries management. *ICES Journal of Marine Science*, *73*(5), 1297–1305. https://doi.org/10.1093/icesjms/fsv229

Tableau, A., Collie, J. S., Bell, R. J., & Minto, C. (2019). Decadal changes in the productivity of New England fish populations. *Canadian Journal of Fisheries and Aquatic Sciences*, *76*(9), 1528–1540. https://doi.org/10.1139/cjfas-2018-0255

Vert-pre, K. A., Amoroso, R. O., Jensen, O. P., & Hilborn, R. (2013). Frequency and intensity of productivity regime shifts in marine fish stocks. *Proceedings of the National Academy of Sciences*, *110*(5), 1779–1784. https://doi.org/10.1073/pnas.1214879110

Wiedenmann, J., & Jensen, O. P. (2018). Uncertainty in stock assessment estimates for New England groundfish and its impact on achieving target harvest rates. *Canadian Journal of Fisheries and Aquatic Sciences*, *75*(3), 342–356. https://doi.org/10.1139/cjfas-2016-0484

Worm, B., Barbier, E. B., Beaumont, N., Duffy, J. E., Folke, C., Halpern, B. S., & Watson, R. (2006). Impacts of biodiversity loss on ocean ecosystem services. *Science*, *314*(5800), 787–790. https://doi.org/10.1126/science.1132294

Worm, B., Hilborn, R., Baum, J. K., Branch, T. A., Collie, J. S., Costello, C., & Zeller, D. (2009). Rebuilding global fisheries. *Science*, *325*(5940), 578–585. https://doi.org/10.1126/science.1173146

Zhu, J., Chen, Y., Dai, X., Harley, S. J., Hoyle, S. D., Maunder, M. N., & Aires-da-Silva, A. M. (2012). Implications of uncertainty in the spawner–recruitment relationship for fisheries management: An illustration using bigeye tuna (Thunnus obesus) in the eastern Pacific Ocean. *Fisheries Research*, *119–120*, 89–93. https://doi.org/10.1016/j.fishres.2011.12.008

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section.

How to cite this article: Silvar-Viladomiu, P., Minto, C., Halouani, G., Batts, L., Brophy, D., Lordan, C., & Reid, D. G. (2021). Moving reference point goalposts and implications for fisheries sustainability. *Fish and Fisheries*, 22, 1345–1358. https://doi.org/10.1111/faf.12591

B.3 Published Version of Chapter 4

Silvar-Viladomiu, P., Minto, C., Brophy, D., and Reid, D. G. (2022). Peterman's productivity method for estimating dynamic reference points in changing ecosystems, ICES Journal of Marine Science, 79, 4, 1034–1047. https://doi.org/10.1093/icesjms/fsac035

ICES Journal of Marine Science, 2022, **0**, 1–14
DOI: 10.1093/icesjms/fsac035
Quo Vadimus

Peterman's productivity method for estimating dynamic reference points in changing ecosystems

Paula Silvar-Viladomiu [1,*], Cóilín Minto [1], Deirdre Brophy [1] and David G. Reid [2]

[1]Marine and Freshwater Research Centre, Galway-Mayo Institute of Technology, GMIT postal code is H91 T8NW Dublin Road, Galway, Ireland
[2]Marine Institute, H91 R673 Rinville, Oranmore, Co., Galway, Ireland

*Corresponding author: tel: +34648841990; e-mail: paula.silvarviladomiu@research.gmit.ie.

Target and limit reference points are fundamental management components used to define sustainable harvest strategies. Maximum Sustainable Yield (MSY) and the precautionary principle underpin many reference points. Non-proxy reference points based on MSY in age-based single-species assessments depend on the stock–recruitment (SR) relationship, which can display complex variability. Current reference points ignore persistent dynamic change by assuming that the SR relationship is stationary and with constant recruitment parameters over selected time periods. We highlight Peterman's productivity method (PPM), which is capable of tracking temporal dynamics of recruitment productivity *via* time-varying SR parameters. We show how temporal variability in SR parameters affects fishing mortality and biomass MSY-based reference points. Implementation of PPM allows for integrated dynamic ecosystem influences in tactical management while avoiding overwrought and sometimes ephemeral mechanistic hypotheses tested on small and variable SR datasets. While some of these arguments have been made in individual papers, in our opinion the method has not yet garnered the attention that is due to it.

Keywords: EBFM reference points, non-stationary productivity, scientific fisheries management advice, stochastic processes, stock–recruitment relationship, time-varying parameters.

Introduction

Reference points play a key role in the provision of scientific advice for fisheries management (Garcia, 1996). They provide the basis to define targets and limits that establish operational objectives, necessary for effective fisheries management (Sissenwine and Shepherd, 1987; Schnute and Haigh, 2006; Hilborn *et al.*, 2020). Reference points provide benchmarks to promote the sustainability of the stocks and reliant fisheries (Mace, 1994). By identifying limits that should not be exceeded and targets that should be achieved, they support harvest control rules (HCRs) that guide management decisions (Punt, 2010; Kvamsdal *et al.*, 2016). They have an essential role in current management frameworks, to provide recommendations for fishing strategies and to define tactical management measures, e.g. catch and effort limits, and the design of management plans.

Major paradigms used to define reference points internationally are Maximum Sustainable Yield (MSY) and the precautionary approach (FAO, 1995a). The Food and Agriculture Organization (FAO) of the United Nations defines MSY as: "the highest theoretical equilibrium yield that can be continuously taken (on average) from a stock under existing (average) environmental conditions without affecting significantly the reproduction process". Managing fish stocks under the precautionary approach and MSY has been generally advocated by international agreements (FAO, 1995a; UN, 1995, 2002). The UN Fish Stock Agreement contains guidelines for applying a precautionary approach within an MSY framework. During the World Summit on Sustainable Development, organized by the UN in 2002, it was agreed in the Johannesburg Declaration to, "maintain or restore stocks to levels that can produce the MSY with the aim of achieving these goals for depleted stocks on an urgent basis and where possible not later than 2015" (UN, 2002). These concepts are embraced by intergovernmental organizations and are reflected in important fisheries policies, e.g. Common European Fisheries Policy (EC, 2013) and Magnuson–Stevens Fisheries Conservation and Management (MSA, 2007) in the United States.

While MSY has been criticized from multiple angles (Larkin, 1977), a change in focus, away from MSY as a target catch state towards a target and limit fishing mortality rate at MSY (Mace, 2001), has made it one of the main operational guides for sustainability in global fisheries management (Worm *et al.*, 2009; Marchal *et al.*, 2016). Indeed, given difficulties in establishing economic management objectives, MSY emerges as a default fall-back option (Beverton and Holt, 1993), if not the appropriate economic objective in itself considering all components of the overall fishing sector (Christensen, 2010).

One of the main criticisms of MSY is whether it is possible to take ecological aspects into account (Larkin, 1977; May *et al.*, 1979; Mace, 2001). Studies highlight the challenge of achieving MSY simultaneously for cohabiting species (Mackinson *et al.*, 2009). There is also indication that single-species MSY may need to be adapted when ecological interactions are present—i.e. predation, competition—(May *et al.*, 1979; Gislason, 1999; Collie and Gislason, 2001). Additionally, the growing evidence of regime shifts (Vert-pre *et al.*, 2013; Perälä *et al.*, 2017); and the effect of climate change in fish stocks (Free *et al.*, 2019) emphasize the presence of non-stationary population processes, which mean that reference points will also vary.

The need to adopt a more holistic approach to fisheries management has been globally accepted (FAO, 2003). Thus,

Received: August 9, 2021. **Revised:** February 9, 2022. **Accepted:** February 16, 2022

the ecosystem approach is included in most fisheries' international agreements and policies. Ecosystem-based fisheries management (EBFM) requires comprehension of the broader picture (biophysical interactions, biodiversity, food-web structure, ecological processes, and ecosystem functioning). Therefore, the science for its operationalization and implementation is often considered challenging (Cowan *et al.*, 2012; Dolan *et al.*, 2016). It is crucial to develop reference points as operationally powerful as those currently used in single-species management advice yet in accordance with ecosystem concerns. There is still no agreement on how to evolve the MSY concept and what should be considered targets and limits within EBFM (Rindorf *et al.*, 2017b). The MSY concept applied correctly might be more useful to EBFM than other data-demanding methods (Pauly and Froese, 2021).

There is a "gap" between single-species methods that provide reference points for advice to trigger tactical management and ecosystem-based methods that often do not have clearly defined operative standards for tactical management (Fogarty, 2014). This gap is difficult to bridge because more complex models present greater modelling challenges (Quinn, 2008), making the outcomes less suitable for management. Both methods are needed to support: (a) tactical advice able to make management decisions in an immediate term and (b) strategic advice based on the understanding of the system and the study of ecosystem drivers and their effects. In this article, we focus on how to deal with changing ecosystems within tactical fisheries management. We present a possible bridge to align stock reference points with ecosystem concerns.

In our opinion, the keystone lies in the static assumptions to model recruitment productivity, made in most single-species reference point estimations, which do not reflect non-stationary behaviours shown in fish productivity (Peterman *et al.*, 2000; Minto *et al.*, 2014; Perälä *et al.*, 2017). We briefly review reference point estimation in single-species contexts and highlight how time-varying approaches provide operational objectives for management reflective of a dynamic ecosystem. We believe that the framework for doing this is available, we provide due recognition to the originators—Professor Randall Peterman and his group—, and look to challenges and future developments. We conducted hypothetical numerical simulations to show the role of temporal variability in stock–recruitment (SR) relationship parameters and their impact on reference point estimates. For our example, we chose to explore the commonly applied Beverton–Holt SR model to complement previous research on non-stationary SR relationships, which used the linearized Ricker model. Finally, we propose priority research areas in this field that will improve model development and application.

Status quo of single-species reference points

Globally, there is broad agreement regarding the concepts underlying reference points used to assess the status of fish stocks for management advice. Nevertheless, the interpretation and application of reference points have evolved and differed among regions (Ricard *et al.*, 2012; Hilborn, 2020). We give an overview of the status quo of single-species reference points, focusing on approaches used in areas with advanced fisheries management systems: e.g. the United States and Europe (ICES region). This background provides an entry point for our arguments regarding Peterman's productivity method (PPM).

MSY reference points

Understanding how population productivity varies with abundance is crucial in determining maximal surpluses and thus defining single-species reference points (Quinn and Deriso, 1999). Reference points are usually expressed in terms of fishing mortality rate (*F*) and biomass, typically spawning stock biomass (*SSB*). The scientific concept of MSY was introduced with the aggregated Schaefer model (Schaefer, 1954), which assumes that population growth is density-dependent with a linear decrease in per-capita rate of population growth with increasing abundance, resulting in a logistic population model that is decremented by given catches. The logistic model has production as a quadratic function of abundance. In Schaefer surplus production model (Schaefer, 1954), MSY is obtained at half of the carrying capacity or equilibrium level. Subsequently, (Pella and Tomlinson, 1969) proposed an extension to allow for asymmetric production curves.

For surplus production models, MSY reference points (F_{MSY} and B_{MSY}) are internally estimated as functions of model parameters. These methods, also called biomass dynamic models, focus on population growth and mortality. The productivity of the stock is modelled with a limited set of parameters including the intrinsic growth rate and carrying capacity of the population. Surplus production models are often used for data-limited stocks because they are less data demanding, although Bouch *et al.* (2020) highlight estimation challenges associated with data availability with respect to the stock history.

Age- or length-structured methods allow the cohorts to be followed, and so they use data structured in age or length classes to analyze population changes. These methods provide a more complete analysis of the stock by following the dynamics of individual cohorts. Age- or length-structured methods contain three basic components: growth, mortality, and recruitment (Quinn and Deriso, 1999). In addition to age and length information of the population, the required inputs (which may sometimes be estimated) are biological information including growth parameters, mortality, and maturity. Whereas the majority of contemporary data-rich stock assessments use age-structured models, the choice of model type is usually region-specific (Dichmont *et al.*, 2016). Integrated assessments (Maunder and Punt, 2013), that allow many data types in a single analysis, are becoming more popular, e.g. Stock Synthesis SS3 (Methot and Wetzel, 2013) in the west coast of the United States; as are state–space models such as SAM (Nielsen and Berg, 2014) in the ICES region.

In age-structured assessments, to estimate MSY, the productivity and hence yield from a population is modelled as a function of fishing mortality rate and pattern, and from this, the relationships of yield to biomass and fishing mortality are derived. The age-based MSY has arisen from fundamental population dynamics models based on per-recruit theory (Beverton and Holt, 1957), and is derived from three relationships (see example Figure 1): (i) spawning stock biomass per-recruit (*SPR*) that models the spawning mass productivity for a given recruit as a function of fishing mortality *SPR(F)*; (ii) SR relationship that models the relationship between the number of recruits to the spawner biomass; and (iii) yield per-recruit that models the mass removed from the population per-recruit by fishing. The per-recruit analysis is related to biological variables (i.e. maturity or fecundity, growth/weight at age, and natural mortality), fishery parameters (i.e. selectivity), and rate of removals. In age-structured methods, MSY-based reference

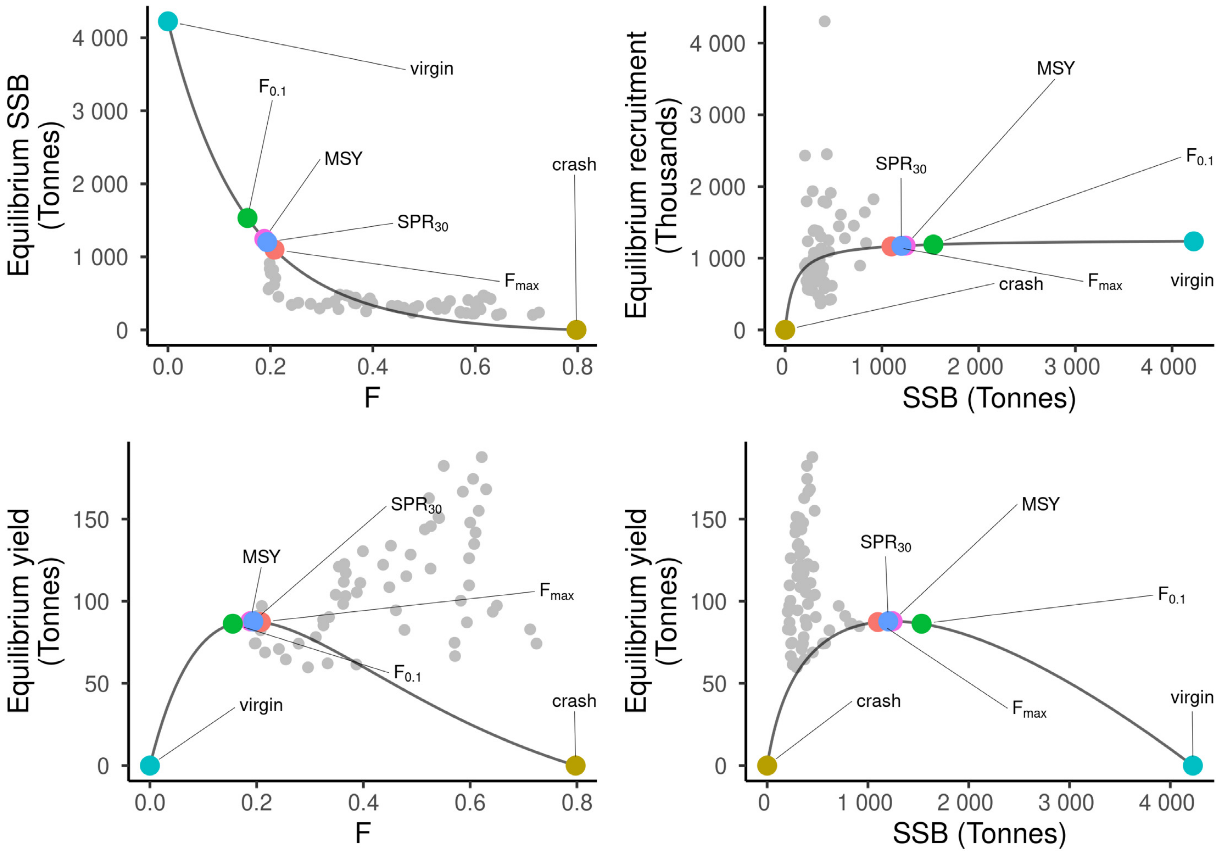

Figure 1. Reference points (virgin, crash, MSY, and per-recruit proxies) and relationships between SSB and F, recruitment and SSB, yield and F, and Yield and SSB at equilibrium with fitted Beverton–Holt functional form for North Sea Skagerrak plaice (Plaice in IV); plots modified from output of FLBRP analysis from FLR package in R (https://flr-project.org/doc/Reference_points_for_fisheries_management_with_FLBRP.html). Grey dots represent data observations for ICES stock Plaice in IV division at the assessment in 2018 (ICES, 2018b), being 2018 the terminal year and the dots observations in preceding years.

points were typically estimated externally to the assessment model. Although integrated assessment methods can estimate reference points internally as functions of model parameters, sometimes fixing parameters of the SR relationship.

The relationship between stock size and recruitment defines the reproductive productivity of the stock and is, therefore, key to the estimation of non-proxy reference points. Understanding the SR relationship is crucial for MSY-based reference point estimation (Shepherd, 1982; Conn *et al.*, 2010). The inverse of the equilibrium *SPR(F)* provides a slope that intersects with the SR function at the equilibrium level of recruitment (Figure 1). The most popular functions developed to understand the SR relationship are: Beverton–Holt model (Equation (1); Beverton and Holt, 1957), Ricker model (Ricker, 1954), and hockey-stick segmented regression (Barrowman and Myers, 2000; Mesnil and Rochet, 2010). These models determine the density-dependent form and hence the compensation of the stock before recruitment. The parameters of the SR model relate to the reproductive potential of the stock and the rate at which recruitment changes with increasing eggs or abundance. For example, in the commonly used Beverton–Holt equation,

$$R = \frac{\alpha SSB}{\beta + SSB}, \tag{1}$$

where recruitment increases towards an asymptote as spawning stock increases, α is the maximum number of recruits produced, and β is the spawning stock needed to produce (on average) recruitment equal to $\alpha/2$. The SR relationship is typically modelled as stationary (parameters are averages across time) and so assumed constant over time (Hilborn and Walters, 1992).

Despite its importance, the SR relationship is challenging to model for many stocks because of insufficient contrast and a high degree of variability. For stocks where recruitment information is lacking or there is high recruitment variability, per-recruit analysis can offer proxies to use as reference points (Gabriel and Mace, 1999). The validity of per recruit levels as proxies for MSY reference points is highly dependent on the life history characteristics of the stock (Mace, 1994). It is recommended to support the choice of appropriate proxy with the SR information available (Cadrin 2012). Spawner per-recruit levels are commonly used as proxies for MSY-based reference points in the US (Maunder and Deriso, 2014; Wetzel and Punt, 2017), where they are developed for individual stocks and designed to work in a precautionary sense.

Biomass limit reference points

Limit reference points are critically important for defining HCRs. HCRs are a structured framework for providing scientific management advice (Punt, 2010) and are considered a key component of the precautionary approach to fisheries management (FAO, 1995b). In HCRs, biomass limit reference points are used to indicate the level of biomass below which

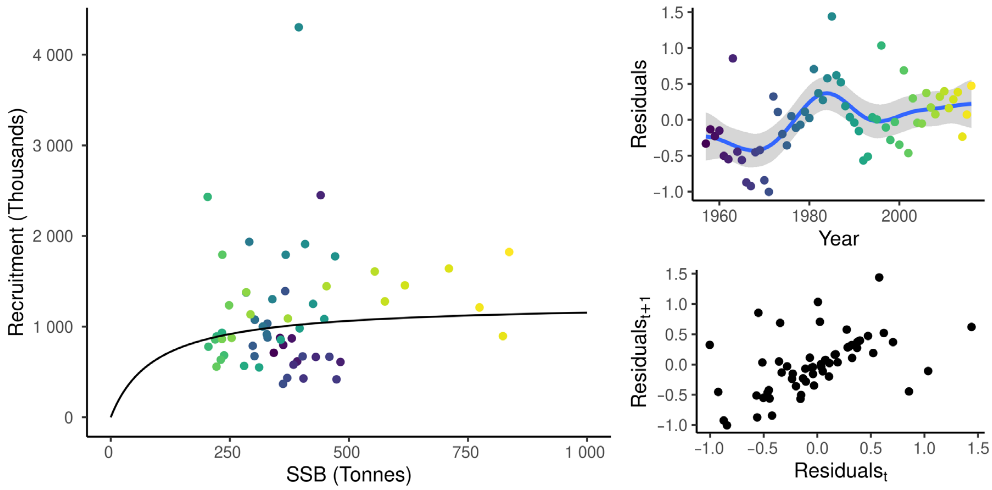

Figure 2. SR relationship of the North Sea and Skagerrak plaice. Left panel shows the relationship between SSB and recruitment with fitted Beverton–Holt functional form; right panel shows the temporal evolution of residuals of the SR relationship (top), and the relationship between residuals at year *t* with residuals at year *t+1* (bottom). Dots represent data observations, colour scale represents the assessment year, and the blue line is a gam model of the residuals with a first-order penalty.

reproductive potential is impacted to avoid recruitment overfishing; typically interpreted as the SSB under which recruitment declines. There are several ways to set biomass limit reference points (Punt *et al.*, 2014b) depending on the HCRs in which they are to be used. The approach chosen to estimate biomass limit reference points impacts both the level and the amount of uncertainty associated (Deurs *et al.*, 2021). In the United States, a percentage of B_{MSY} is typically used to define limit biomass reference points. In situations when the SR relationship is not well understood, a fraction of the unfished biomass (B_0) can be used to define the biomass limit reference point and occasionally also as a proxy for MSY biomass reference point. In ICES, the key biomass reference point is B_{lim}, which is defined as the deterministic limit of biomass below which a stock is considered to have reduced reproductive capacity. This reference point is determined following SR typology rules that account for how stock biomass relates to recruitment at the window of data available (ICES, 2017a). A commonly used biomass limit reference point is the lowest observed biomass (B_{loss}) for stocks with no clear relation between stock and recruitment. The biomass limit reference point is the basis of all precautionary reference points in the ICES advice rule used to estimate other precautionary reference points.

Stochastic MSY

Initial static and deterministic interpretations of equilibrium MSY were thought to be inappropriate because they ignore the fact that fish populations fluctuate in abundance (Mace, 2001). Most current MSY interpretations aim to deal with those dynamics and account for sources of uncertainty. The processes for taking into account uncertainty in reference point vary; different methods to assess stocks deal with including variance and uncertainty differently (Patterson *et al.*, 2001; Dichmont *et al.*, 2016).

In assessments, biological information (growth, mortality, and maturity) vary by age structure and can vary over time (Methot and Wetzel, 2013; Nielsen and Berg, 2014; Dichmont *et al.*, 2016). To derive reference points when biological variables vary over time, a typical approach is to estimate their average value and account for temporal variability with parametric bootstrap or random sampling methods. A temporal window of biological information time series might be used, e.g. ICES guidelines state to use a 10-year time window (ICES, 2017a) unless temporal patterns are found, in which case the time-window is shortened.

Recruitment typically fluctuates considerably, reflecting that this is often the most variable component in assessments (Maunder and Thorson, 2019). Complete time series of recruitment are typically used to derive reference points unless regime shifts are detected. The SR relationship is modelled as a stationary process with some variability (Figure 2). Fluctuations in recruitment are commonly treated as a random process (e.g. log-normal) around an assumed relationship between stock size and recruits. Reference points are based on the long-term mean SR relationship (fixed parameters of the functional form chosen), and independent or mean-reverting autocorrelated process errors. Commonly no process error in the parameters is incorporated (i.e. process uncertainty of the model structure reflecting the natural variability of the processes affecting the dynamics). The residuals of the fitting frequently have temporal patterns with autocorrelation of residuals sometimes being stronger than the SR relationship itself (e.g. North Sea and Skagerrak plaice, Figure 2). The stochastic equilibrium software for MSY modelling has been developed by ICES to implement stochasticity in reference point estimation (Eqsim, https://github.com/ices-tools-prod/msy). Eqsim performs random sampling of the biological and fishery variables and samples from the predictive recruitment distribution. Simulated autocorrelation in recruitment can be included if shown to be important. Eqsim can also deal with structural uncertainty of the SR functional form by applying the averaging of a combination of models (ICES, 2017b).

Simulations of the entire system in Management Strategy Evaluation frameworks (MSE; Punt *et al.*, 2016) play a key role in identifying sources of uncertainty and stochastic elements, and in testing the precautionary criteria (Kell *et al.*, 2005). In an MSE, the whole management system is modelled in the operating model (reality system or true state) and the management procedure (perceived state). The MSEs have become crucial to evaluate reference points and the performance of HCRs relative to agreed management goals (De Oliveira *et al.*, 2009). Development of MSEs is impacting the choice of reference points, which to be precautionary must consider uncertainty in both the science (stock assessment and reference point estimation) and the management process. A present focus of MSE is evaluating the ICES precautionary criteria, specifically, if advised reference points ensure the populations are maintained within safe biological limits under given uncertainties (ICES, 2017a).

Reference points for changing ecosystems

Ecosystems are non-stationary, often presenting complex dynamical behaviour (Sugihara *et al.*, 2012; Fogarty *et al.*, 2016). Globally, the productivity of assessed fish stocks has been observed to fluctuate in a non-stationary manner (Vert-pre *et al.*, 2013; Perälä *et al.*, 2017; Britten *et al.*, 2017). Changes in productivity constitute a challenge for defining management reference points. A major limitation of single-species management is that interactions with ecosystem drivers are usually not accounted for. An important element in transitioning to EBFM would be to include these ecosystem concerns in the estimation of single-species reference points. In this section, we address approaches to deal with changing ecosystems in the calculation of reference points.

Ecosystem concerns

Tools for EBFM comprise a heterogeneous group of models, used for multiple objectives (see Geary *et al.*, 2020 for a complete overview on ecosystem models). Each marine ecosystem has its own features and functional responses with spatial and temporal scales that are still relatively unknown (Hunsicker *et al.*, 2011). Modelling tools that include ecosystem considerations increase in complexity to incorporate ecological interactions, environmental drivers, and human impact (Collie *et al.*, 2016). When complexity increases it also increases the knowledge needed to build the models, the parameters to estimate, and the uncertainty propagated (Hollowed *et al.*, 2011). Therefore, complexity translates to an increase in data demand and a potential decrease in predictive ability (Geary *et al.*, 2020). Despite this, ecosystem models have developed substantially in the last decades and have proved fundamental for strategic management advice (Nielsen *et al.*, 2018), offering a key holistic view of the system (Benson and Stephenson, 2017). Including ecosystem concerns, while balancing complexity, e.g. Models of Intermediate Complexity for Ecosystems (MICE models), helps improve understanding of the processes and disentangle important ecological components (Plagányi *et al.*, 2014). Studies on empirical reference points from multispecies and ecosystem approaches, i.e. multispecies MSY (Gislason, 1999; Collie and Gislason, 2001; Moffitt *et al.*, 2016), aggregate biomass MSY (Gaichas *et al.*, 2012), ecosystem global MSY (Trenkel, 2018), have shown intriguing mismatches with single-species reference points. Although generally not used for tactical management, these studies emphasize that incorporating ecosystem effects does alter MSY-based reference points.

In the United States, a food web ecosystem model of intermediate complexity was used to estimate ecological reference points for Atlantic Menhaden (Chagaris *et al.*, 2020). In this way, information on ecosystem drivers and predator–prey interactions were incorporated into the assessment and management. To our knowledge, this is the only case where an ecosystem model was used to set an alternative ecological reference point. Additionally, ecosystem model information was proposed as guidance within the ICES stock advice framework. In the EU, where several stocks and fleets share the same space, reference ranges—developed from the concept of Pretty Good Yield (Hilborn, 2010)—are used to give flexibility around fishing mortality at MSY in mixed fishery contexts (Kempf *et al.*, 2016; Rindorf *et al.*, 2017a). The ICES working group WKIRISH (ICES, 2020) has suggested that indicators from an ecosystem model can be used to provide information on ecosystem conditions and make recommendations regarding where in the precautionary F ranges we should be setting fishing mortality from an ecosystem point of view, so called F_{eco} (Bentley *et al.*, 2021; Howell *et al.*, 2021). In these cases, the ecological drivers selected depend on the stock interaction with the ecosystem studied.

Incorporation of holistic ecosystem considerations can be done at the simulation level to evaluate alternative management strategies. If there is an ecosystem model developed for the region, MSE can incorporate that ecosystem model as the operating model (see Perryman *et al.*, 2021 review). Higher complexity and descriptive properties of the ecosystem model as the operating model provides the capacity to evaluate the performance of an HCR taking into account ecosystem considerations (Lucey *et al.*, 2021). For example, the end-to-end ecosystem model, Atlantis, has been used in an MSE for the Southeast Australian fisheries (Fulton *et al.*, 2014).

Inclusion of mechanistic drivers

A huge array of factors (biological interactions, climatic forcing, maternal effects, climate change, and so on) can influence stock productivity. Inclusion of ecosystem drivers in an explicit mechanistic way requires a significant expansion of assessment frameworks to enable a more data and time-intensive assessment approach (Burgess *et al.*, 2017). These ecosystem considerations are currently seldom included in stock assessment or at the HCR level. Skern-Mauritzen *et al.* (2016) found a diversity of ecosystem drivers and approaches based mainly on expert knowledge and specific to a certain fishery. Most cases were identified among US and ICES stocks. But in general, these were rarely included in operational management advice. Their inclusion is limited by the high level of understanding required, and the complexity of the interactions, relationships, and their stability, which can be ephemeral (Myers, 1998; Sugihara *et al.*, 2012).

1. *Inclusion of trophic interactions.* The most typical trophic interaction included in assessments is the predator–prey relationship, which can be incorporated in parameters of natural mortality and growth rate. Predation mortality rates can be estimated from stomach-content analysis with multispecies models. Multispecies dynamic models are extensions of single-species assessment models that integrate trophic predator–prey interactions with the mortality caused by the predator derived from the predator diet data (Trijoulet *et al.*, 2019). Addition of mechanistic trophic interactions has been observed to greatly impact reference points (Gislason, 1999; Trijoulet *et al.*, 2020). In some cases, parameter estimates from multispecies models are thought to be more realistic than estimates from single-species approaches

(Hollowed, 2000). Hence, natural mortality parameters from multispecies models are occasionally used in stock assessments. For example, several North Atlantic stocks assessed by ICES use the natural mortality estimates from a Stochastic Multi Species model (SMS; Lewy and Vinther, 2004) in the single-species assessment to provide management advice (ICES, 2018a). Predation also impacts and can be incorporated into the SR relationship to help understand trophic interactions in recruitment dynamics (Swain and Sinclair, 2000; Minto and Worm, 2012; Collie *et al.,* 2013).

2. *Inclusion of environmental and ecological variables.* Environmental and ecological variables have shown a strong impact on population dynamics. Examples of environmental drivers include temperature (e.g. sea surface temperature), hydrodynamics, precipitation, wind-mixing energy, North Atlantic Oscillation index, upwelling index, and river input. Other influential ecological drivers might be zooplankton, chl *a* (hence primary productivity), and eutrophication. The environment is considered to primarily affect recruitment dynamics showing relatively rapid responses, especially for short-lived species (Clausen *et al.,* 2018). Apart from stock responses to these variables being specific to species and systems, ecosystems are non-stationary, and therefore, different states may have different influential drivers (Skern-Mauritzen *et al.,* 2016). Resulting in the inclusion of environmental drivers being challenging (see Crone *et al.,* 2019 for good practices). Including environmental variables in the SR model has often failed, which might be due to non-stationary relationships or because multiple variables were tested without correcting for multiple tests (Myers, 1998; King *et al.,* 2015). Besides, the link between SR and environmental drivers might not be linear (Subbey *et al.,* 2014). Several assessment models can include environmental drivers, but in practice, their inclusion results in little improvement with respect to management performance (Punt *et al.,* 2014a; Haltuch *et al.,* 2019). Therefore, environmental driver inclusion remains rare and most reference points and HCRs do not explicitly incorporate those relationships (Haltuch *et al.,* 2019).

Re-estimation of reference points

Currently, reference points reflect average ecological and environmental conditions over the time period of the data. By definition, MSY-based reference points are estimated given prevailing average environmental conditions (MSA, 2007; EC, 2013). Average fishery and population dynamics of a stock along with environmental conditions are inherently included in their estimation (integrated in the average SR, growth, post-recruit mortality, and maturity parameters). The FAO Fish stock assessment manual establishes that reference points must be regularly updated, taking into consideration possible changes in the biological parameters or exploitation patterns (FAO, 2003). If reference points are not changed once established, they will not reflect the dynamic nature of the ecosystem (Kell *et al.,* 2016). Hence, reference points are usually re-evaluated in the light of environmentally and stock density induced changes in stock productivity and changes in species interactions (ICES, 2021a). In theory, the faster the dynamics evolve, the more often reference points would need to be updated (Burgess *et al.,* 2017).

Typically, reference points are revised with varying regularity. ICES considers reference points to be valid only in the medium term (5–10 years), and therefore, they should be updated according to new population and fishery information, and process understanding (ICES, 2021b). During assessment benchmarks, data and parameters (biological, fishery, and SR relationship) are revised and observed changes are taken into account. In the ICES region, reference points have been observed to change frequently impacting the perception of sustainability status (Silvar-Viladomiu *et al.,* 2021). The ICES working group WKRPCHANGE (ICES, 2021a) identified several reference points that are allowed to vary according to prevailing conditions. In the United States, the National Standards guidelines state that because MSY is a long-term average, it does not need to be estimated annually, but should be re-estimated as required by changes in long-term environmental or ecological conditions, fishery technological characteristics, or new scientific information (NOAA Fisheries, 2016). Even so, certain agencies update reference points with each assessment, e.g. North Pacific Fisheries Management Council (check SMART tool; NOAA Fisheries, 2021).

In updating reference points, changes in productivity or regime shifts are generally taken into account by the revision of the time series used for their derivation. Regime shifts or trends present can be identified *ad hoc* or through regime detection algorithm (e.g. STARS; Rodionov, 2004). Some approaches to deal with regime-shifts and changes in productivity are: (i) moving window, which includes modelling recruitment from a specified number of years (King *et al.,* 2015); (ii) use of a detection algorithm to select the data with which to base reference points (Punt *et al.,* 2014a); and (iii) tailoring or truncation of the data series to a temporal window after a shift has been detected (Szuwalski and Punt, 2013). A common difficulty, however, is how to decide which time period to choose as representative of present dynamics. Estimation of reference points might become unreliable as the time series is reduced (Deurs *et al.,* 2021). Particularly, where one parameter (e.g. density-dependent asymptotic recruitment) may not be updated at all given recent ranges of the stock but the slope at the origin might be. Truncating data in this case risks losing relevant partial information from earlier periods.

Dynamic proxy reference points

A reference point that takes into account shifts in the underlying productivity of the stock has been proposed for the virgin biomass. In the United States, where the virgin biomass reference point is extensively used for HCRs, a time-varying approach called dynamic virgin biomass was developed—dynamic B_0 (A'Mar *et al.,* 2009; Field *et al.,* 2010). Contrary to the static virgin biomass, which is an equilibrium-based measure, dynamic virgin biomass is a reference population state representing the biomass that would have resulted across time in the absence of fishing. The dynamic B_0 approach uses the values of the parameters estimated in the assessment to project the population over time with no fishing, obtaining a time series of B_0. The biomass varies in time because of the estimated recruitment deviations and time-varying growth and natural mortality. The population is simulated typically under the assumption of a stationary SR relationship or driven by a separable function of environmental drivers and stock size.

Dynamic B_0 is increasingly being used because it can track population productivity over time if fishing had not occurred (Punt *et al.*, 2014a), but explicit mechanisms involved in the change in productivity do not need to be identified. A'Mar *et al.* (2009) evaluated a management strategy with dynamic virgin biomass and showed that management and estimation performance was improved by adjusting the exploitation rate based on recent recruitment. Dynamic B_0 performs better than static B_0 when stock productivity shifts directionally (Berger, 2019). The Inter-American Tropical Tuna Commission (IATTC) recommends the use of dynamic virgin biomass when trends in productivity or regime shifts are detected (Maunder and Deriso, 2014).

PPM: dynamic recruitment productivity

Methods capable of modelling dynamic processes and detecting process variation over time are increasingly used (Auger-Méthé *et al.*, 2021). Dynamic state–space models to fit time-series data have been implemented both within age-based assessment models (Aeberhard *et al.*, 2018) and for the estimation of population biomass dynamics and productivity (Walters, 1986; Pella, 1993; Schnute and Richards, 1995; Millar and Meyer, 2000). State–space models allow simultaneous estimation of variability in ecological dynamics and measurements (Thorson and Minto 2015). Several estimation methods have been developed to fit state–space models: the Kalman filter and non-linear extensions, ADMB (Automatic Differentiation Model Builder) Laplace and higher-order quadrature approximations, TMB (Template model Builder) approximations, EM (Expectation-maximization algorithm), particle filters, and MCMC (Markov chain Monte Carlo methods). The well-known Kalman filter is an optimal linear Gaussian estimation and forecasting method designed to extract signals from noisy data.

Peterman *et al.* (2000) first introduced the use of the Kalman filter to identify temporal patterns in recruitment productivity parameters. This method was built on earlier applications of the Kalman filter in fisheries (Walters, 1986; Sullivan, 1992; Pella, 1993; Gudmundsson, 1994; Schnute, 1994), though these were not explicitly implemented on SR parameters. The entry of new recruits into the population modelled by the SR relationship is a fundamental part of stock productivity. Recruitment productivity represents the most important and largest source of variation in population processes (Quinn and Collie, 2005). Randall Peterman and colleagues modelled the SR relationship as a dynamic process by allowing process variation in the parameter governing recruitment productivity.

In this article, we assign the term *Peterman's productivity method* (PPM) to estimation, filtering and smoothing methods, based in the first instance on the Kalman filter, where SR parameters are part of the dynamic state process, and thus allowed to vary over time (Peterman *et al.*, 2000). The method enables recruitment productivity to be modelled as a dynamic process with temporal dimension, by allowing the process signal to be absorbed by the time-varying parameters. These parameters track the variability of productivity dynamics and reconstruct estimates of stock productivity in the past, allowing us to better predict recovery times based on present productivity (Peterman *et al.*, 2003).

Minto *et al.* (2014) extended the PPM to a multi-stock setting and studied the variation in the maximum reproductive rate parameter of the SR relationship for North Atlantic cod stocks. They showed that recruitment productivity of North Atlantic cod populations has varied markedly over time and that populations go through long periods of both high and low productivity. Multivariate developments on PPM enable the strength of the correlation between the populations to be estimated within the model. Thus, providing increased understanding of the similarity or dissimilarity of productivity dynamics inter- and intra-species within and across regions. Tableau *et al.* (2019) expanded the methodology exploring links with environmental variables and evaluating differences between species and areas in the Northwest Atlantic. The number of estimated parameters were reduced because they assumed a common signal to noise ratio among stocks. The multi-stock estimation allows us to disentangle and account for the different sources of uncertainty (i.e. measurement and process) and increases the robustness of the estimates even with limited length of the data time-series. Links with environmental drivers can be easily incorporated in the PPM. Nevertheless, prior work found relatively few relationships between productivity and the selected covariates (Tableau *et al.*, 2019). Adjacent stocks of the same species exhibited similar productivity patterns with the strength of covariation declining over distance, which shows that the method is powerful for detecting coherent ecological signals rather than tracking noise.

The PPM enables us to model a stochastic process on some or all parameters of the SR relationship, and in theory separate signal from noise in the recruitment productivity process. But, how sensitive are management reference points to changing recruitment productivity? Either the density-dependent or density-independent parameters, or both, can vary in time and impact biomass or fishing mortality reference points differently. To visualize the effects of changes in either parameter in MSY-based reference points, we ran a simulation example based on the North Sea and Skagerrak plaice stock. We projected the stock forward 50 years under a hypothetical random walk on either parameter with a process variation of 0.2 on the annual deviations and estimated the resulting dynamic reference points. We chose a random walk over an explicit mechanism for illustration. When, in a Beverton–Holt SR functional form [Equation (1)], the α parameter varies in time we found that it has a strong impact on the biomass MSY reference point. Being the maximum recruitment, the α parameter affects mainly density-dependent regulation of the population (Figure 3a). Time-varying β parameter, which is mainly related to density-independent processes, caused strong impact on the fishing mortality reference point because it affects the slope at the origin of the SR relationship (Figure 3b). Note that in this common formulation of the Beverton–Holt density-independent and density-dependent processes are present in both parameters (Beverton and Holt 1957) but dominate as above. Dynamic reference points estimated with PPM, which incorporate the integrated signal on recruitment, are fundamentally different approach to dynamic B_0. In dynamic B_0, temporal changes in stock dynamics and underlying productivity are accounted for by implementing stochasticity through variability in recruitment deviations assuming a static SR relationship. Modelling time-varying SR parameters also differs from projecting a population forward under a mean-reverting autocorrelated process that assumes deviations return to the expected static form.

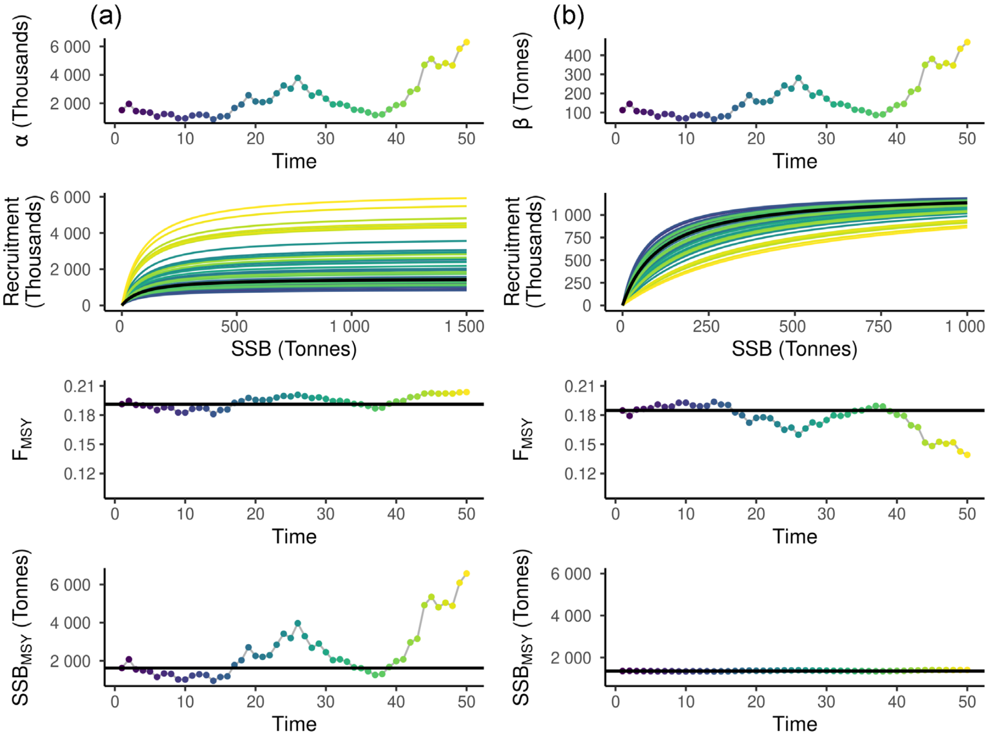

Figure 3. Impact on reference points of SR parameter temporal dynamics. Simulated projections of time-varying parameter α (a, left) and parameter β (b, right); and below the impact in estimated recruitment productivity, and fishing mortality and spawning biomass MSY-based reference points. Black line represents static reference points. Simulations are based on Plaice in IV data (ICES, 2018b) (ICES, 2018b) with Beverton–Holt SR model, using for reference point calculation FLBRP from FLR R software (starting values: $\alpha_0 = 12\,633$ thousands, $\beta_0 = 93\,995$). Both parameters are allowed to vary according to a random walk on the log scale with deviations from a normal distribution with mean zero and a standard deviation of 0.2. Colour scale represents the assessment year.

We show that including time-varying productivity parameters can impact biomass and fishing mortality reference point estimates. Being able to track these changes in time can provide substantive improvements when biological or fisheries conditions are changing. In which case, estimated reference points using time-varying SR parameters are less biased (Holt and Michielsens, 2020). The PPM not only allows us to estimate present productivity and historical trends but also to capture the underlying change in recruitment productivity. These dynamic reference points can be used in harvest policies based on dynamic productivity forecasts to provide catch advice; applications of dynamic HCRs result in higher catches and reduced risk (Collie *et al.*, 2012) and are more robust to climate change impacts (Collie *et al.*, 2021).

The PPM does not explicitly model measurement error in *SSB* (Peterman *et al.*, 2003). Although recruitment and SSB are the best estimates currently available, there is inherent uncertainty associated with them (Brooks and Deroba 2015). This uncertainty from the previous model can potentially be propagated in the subsequent analysis. Uncertainty propagation could be implemented by drawing from the estimator of SR parameters either by assuming multivariate normality using the estimated Hessian matrix or by using MCMC to sample from the posterior distribution. It may also be possible to directly use the covariance matrix in the estimation likelihood in TMB as a known measurement error component (Thorson *et al.*, 2015).

Towards a dynamic future

Status quo reference points include stochasticity, yet assume that fluctuation in biological parameters (growth and mortality), the SR relationship, and the resulting stock productivity are centred on a stationary mean at a given harvest rate. Reference points are subject to updates but regime shifts are notably difficult to predict and defining time windows can be difficult. In stochastic implementations of MSY, random variability is usually added as an error around average expected recruitment; but this is unlikely to completely capture the dynamics of the process in time (Kell *et al.*, 2016). Marine ecosystems are not stationary; long-term trends are present, including those induced by climate change (Szuwalski and Hollowed, 2016). Population dynamics have multiple complex interactions with the ecosystem (top panel Figure 4), and dynamics thereof (Deyle *et al.*, 2013). Beyond direct influence of environmental drivers and direct trophic effects, population dynamics are affected indirectly by changes in food-web structure, composition, and processes within the food-web, e.g. trophic cascades (Frank *et al.*, 2005; Casini *et al.*, 2008). The relationship between early life history (recruitment) and stock size, which has strong influence on population dynamics, has shown marked variation over time for many stocks (Minto *et al.*, 2014; Britten *et al.*, 2016; Perälä *et al.*, 2017; Szuwalski *et al.*, 2019; Tableau *et al.*, 2019). The challenge is to manage fisheries to sustainability in light of scientific uncertainty, natural variability, and changing ecosystems. Current advice

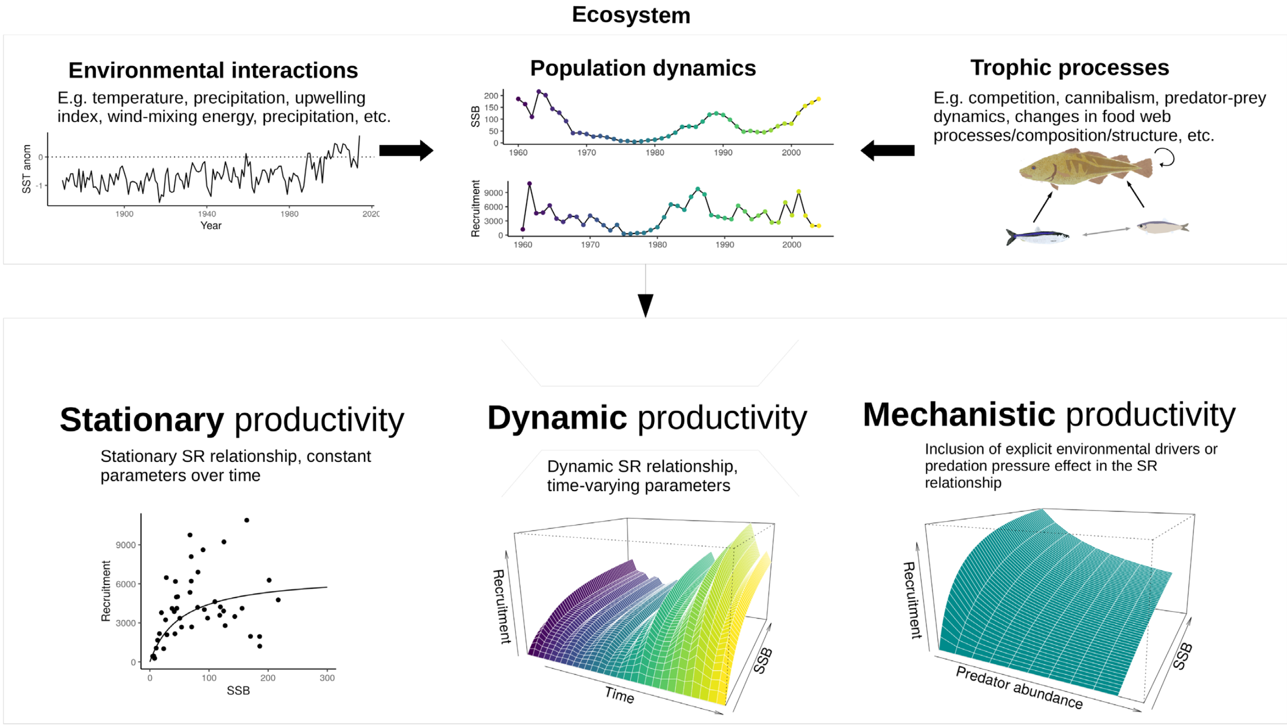

Figure 4. In reality, many ecosystem drivers influence population dynamics (top panel). We argue that time-varying parameters as available *via* PPM provide a bridge between stationary and mechanistic modelling of recruitment productivity.

frameworks may not sufficiently address the dynamic nature of MSY and reference points (Sissenwine *et al.*, 2014). So far, pretty good yield ranges have been proposed in the EU to allow flexibility around MSY fishing mortality reference points in mixed fisheries contexts (Rindorf *et al.*, 2017a).

How can we bridge the gap between current MSY reference points and EBFM? On the one hand, current advice is based on the assumption that SR is stationary (left bottom panel Figure 4). On the other hand, the dynamics created by the ecosystem are complex and manifold and so it can be difficult to use direct ecosystem process information to inform management decisions. Mechanistic inclusion of drivers in the SR relationship (right bottom panel Figure 4) is risky because effects might be direct or indirect, linear or non-linear, and multiple ecological factors may interact and vary over time. We argue that modelling dynamic productivity using PPM might bridge the gap and ultimately reconcile the MSY concept and EBFM (centre bottom panel Figure 4). Dynamic parameter models have demonstrated potential to implicitly incorporate the response of the stock to ecosystem change without specifying the exact driver or functional mechanism involved (Minto *et al.*, 2014; Nesslage and Wilberg, 2019). Dynamic parameters applied to the SR relationship enable estimation of MSY-based reference points that take into account temporal changes in recruitment productivity. Several studies have shown that in the presence of temporal variability in stock productivity, dynamic processes should be accounted for to estimate reliable reference points (Berger, 2019; Mildenberger *et al.*, 2019; Zhang *et al.*, 2021). Given that productivity is non-stationary, rather than reference points based on past average productivity, PPM provides a more informative picture of the present productivity and its dynamics and therefore enables the estimation of reference points in tune with the current state of the ecosystem (Britten *et al.*, 2017; Tableau *et al.*, 2019).

While EBFM comprises broader concerns than recruitment productivity in fisheries management, we believe that using PPM has an important role to include the influence of changing ecosystems on current fish stock management. It would be very valuable for managers and assessment scientists to fully understand the ecosystem processes and ecological mechanisms causing these dynamics. That is not always possible, but this should not stop us considering the implications of these processes, even if they are not completely understood. The main advantage of this method for immediate application in management is that it can be applied without understanding the process that caused the change in stock productivity. Presently, time-varying productivity relationships may be where we have the greatest opportunity to empirically deliver on some of the requirements of EBFM in tactical fisheries management (Minto *et al.*, 2014). Sustainable harvest depends critically on compensatory processes such as the SR relationship. Application of PPM in the SR relationship to estimate dynamic reference points might be a first step towards accounting for changing ecosystems in a MSY management goal. Previous studies have demonstrated the strengths of PPM in capturing complex dynamics in recruitment productivity, improving recruitment forecast, and enabling sustainable dynamic harvest practices (Peterman *et al.*, 2000; Collie *et al.*, 2012; Minto *et al.*, 2014; Britten *et al.*, 2016; Tableau *et al.*, 2019; Holt and Michielsens, 2020). Also, reference points from PPM within HCRs have recently been shown to provide resilience to climate-induced effects (Collie *et al.*, 2021).

Incorporating ecosystem variability in reference points could make communication with stakeholders more challenging. Usually the more complicated the modelling approach the more difficult it becomes to communicate, particularly when those lead to a reduction in fishing opportunities. As we develop more complex models we also have to think harder about how we communicate these models so that social license is not lost. It is important to encourage engagement in participatory science for management, e.g. stakeholders should be aware of why it is important to include productivity dynamics. Social license is not only obtained with simple models, social license is also obtained by including elements that are relevant to include. For instance, by not accounting for ecosystem concerns in reference points social license might be removed. The work developed in WKIrish (ICES, 2020) is an example of where a more complex understanding of the system improved social license. In that project, fishers and stakeholders were recognized as knowledge experts of the system, and so their understanding of the system was included. By the end, fishers and stakeholders had a very good understanding of the complex analysis performed.

While PPM has much potential, important issues remain on how to manage stocks with dynamic reference points. As to *Quo Vadimus*—we propose the following four priority research areas to further PPM:

1. Estimability—can time-varying SR parameters be reliably estimated? Does PPM have the ability to detect change where there is change and reject it where there is no change? Estimated covariation from independent assessments (Minto *et al.*, 2014; Tableau *et al.*, 2019) suggests that real ecological changes are tracked. But state–space models are difficult to estimate (Auger-Méthé *et al.*, 2016), time series length can be constraining, and some convergence issues were found when both parameters of the SR relationships were allowed to vary over time (Szuwalski *et al.*, 2019).
2. Uncertainty propagation—we use estimated recruitment and SSB that have associated uncertainties and covariations (Dickey-Collas *et al.*, 2014; Brooks and Deroba, 2015). We disagree that these outputs should not be considered "data" (Brooks and Deroba, 2015), however, as we consider "data" in a broad information context rather than restricted to raw observations. Many stock assessments use model-derived indices as "data" input. A main goal of stock assessments is to estimate abundance state and exploitation rate, often fitting and tracking independent survey-derived recruitment indices. We argue that in the context of much ecosystem uncertainty, estimated recruitment is some of the best information we have on productivity dynamics. We certainly need to propagate uncertainty correctly but the message that these data should only be used with extreme caution could hamper enormous potential for delivering on EBFM. With respect to the stock assessment model, comparisons of external and internally estimated signals would help guide practitioners. Stock-assessment free methods, such as (Perälä *et al.*, 2017) also have great potential to inform the debate on what is signal and what is post-assessment artifact.
3. What are the consequences of poorly estimated time-varying reference points vs. well-estimated static relationships? Juxtaposing the relative risks of managing under the presumption of no change when there is change and *vice versa*. So far, estimators of the model quality, e.g. AIC, have been used to compare time-varying models and static approaches. Statistical inference for these models is an active area of research such as prediction error variance. In addition, time-varying approaches can be evaluated with MSE or stochastic programming methods (Collie *et al.*, 2021). Generally, evaluation within MSE is recommended before using these reference points to inform management decisions (Holt and Michielsens, 2020).
4. Nature of change—the Kalman filter is restricted to linear Gaussian processes. Available integration methods for latent variables such as Laplace approximation (TMB) or MCMC enable a great variety of stochastic processes (including regimes, hidden Markov states, HMM filter, extended Kalman filter, unscented Kalman filter, Kim filter, and continuous processes in non-linear systems) to be considered and compared. These methods can be applied to time-varying parameters under different recruitment model structures (e.g. Beverton–Holt model). Of particular importance is where change happens more abruptly than the process expects it to and takes more time to adjust, essentially the Kalman filter smooths over an abrupt jump (Peterman *et al.*, 2000). Perälä *et al.* (2017) addressed this with a Bayesian change point model with stationary processes within each regime. While the nature of the process and estimation method may change we believe that using the term "Peterman's productivity method", applies for all settings where the SR parameters evolve in time and recognizes the originator for a set of methods that will broaden from the original Kalman filter.

Finally, we note that by using PPM we may gain an understanding of how productivity has changed, but without knowledge of the mechanism, we cannot predict where it is going (in the medium to long term). While we may track productivity and manage accordingly, we must recognize the need for continual mechanistic insights at broader levels to inform strategic management. All the while, we rest on the feedback nature of HCRs to compensate for our ignorance (Collie *et al.*, 2021).

Funding

This analysis was funded by the Irish Department of Agriculture, Food and the Marine's Competitive Research Funding Programmes (DAFM) as part of the FishKOSM project (Ref15/S/744).

Data availability

No new data were generated or analyzed in support of this research.

Authors' contribution

All authors contributed to the conceptualization, design, draft, and revision of the manuscript. PSV and CM performed the simulation and created the figures.

Competing interest

Authors declare no competing interests.

Acknowledgements

The authors are grateful to Professor Randall Peterman and his group for the initial development of the method highlighted here and subsequent discussions. Comments from three anonymous reviewers helped improve the manuscript.

References

A'Mar, ZT, Punt, AE, and Dorn, MW (2009) The evaluation of two management strategies for the gulf of Alaska walleye pollock fishery under climate change. ICES Journal of Marine Science.66, 1614–1632. doi: 10.1093/icesjms/fsp044.

Aeberhard, WH, Flemming, JM, and Nielsen, A (2018) Review of state-space models for fisheries science. Annual Review of Statistics and Its Application, 5: 215–235.

Auger-Méthé, M, Field, C, Albertsen, CM *et al.* (2016) State-space models' dirty little secrets: even simple linear Gaussian models can have estimation problems. Scientific Reports.6, 26677. doi: 10.1038/srep26677

Auger-Méthé, M, Newman, K, Cole, D *et al.* (2021) A guide to state–space modeling of ecological time series. Ecological Monographs. 91, e01470, https://doi.org/10.1002/ecm.1470.

Barrowman, NJ, and Myers, RA (2000) Still more spawner-recruitment curves: the hockey stick and its generalizations. Canadian Journal of Fisheries and Aquatic Sciences. 57, 665–676. doi: 10.1139/cjfas-57-4-665

Benson, AJ, and Stephenson, RL (2018) Options for integrating ecological, economic, and social objectives in evaluation and management of fisheries. Fish and Fisheries. 19, 40–56. doi: 10.1111/faf.12235.

Bentley, JW, Lundy, MG, Howell, D *et al.* (2021) Refining fisheries advice with stock-specific ecosystem information. Frontiers in Marine Science. 8. ISSN 2296-7745. doi: 10.3389/fmars.2021.602072.

Berger, AM (2019) Character of temporal variability in stock productivity influences the utility of dynamic reference points. Fisheries Research.217, 185–197. doi: 10.1016/j.fishres.2018.11.028.

Beverton, RJH, and Holt, SJ (1993)On the dynamics of exploited fish populations, VI, 538. Springer, Dordrecht. doi: 10.1007/978-94-011-2106-4.

Beverton, RJH, and Holt, SJ (1957) On the Dynamics of Exploited Fish Populations. Springer, Netherlands.

Bouch, P, Minto, C, and Reid, DG (2021) Comparative performance of data-poor CMSY and data-moderate SPiCT stock assessment methods when applied to data-rich, real-world stocks. ICES Journal of Marine Science. 78, 264–276. doi: 10.1093/icesjms/fsaa220.

Britten, GL, Dowd, M, Kanary, L, and Worm, B (2017) Extended fisheries recovery timelines in a changing environment. Nature Communications 8:15325. doi: 10.1038/ncomms15325.

Britten, GL, Dowd, M, and Worm, B (2016) Changing recruitment capacity in global fish stocks. Proceedings of the National Academy of Sciences 113:134–139. doi: 10.1073/pnas.1504709112.

Brooks, EN, and Deroba, JJ (2015) When "data" are not data: the pitfalls of post hoc analyses that use stock assessment model output. Canadian Journal of Fisheries and Aquatic Sciences.72, 634–641. doi: 10.1139/cjfas-2014-0231.

Burgess, MG, Giacomini, HC, Szuwalski, CS *et al.* (2017) Describing ecosystem contexts with single-species models: a theoretical synthesis for fisheries. Fish and Fisheries.18, 264–284. doi: 10.1111/faf.12179.

Cadrin, SX (2012) Unintended consequences of MSY proxies for defining overfishing. *In* Proceedings of the American Fisheries Society 140th Annual Meeting. 23. pp. 12. University of Massachusetts Dartmouth.

Casini, M, Lövgren, J, Hjelm, J *et al.* (2008) Multi-level trophic cascades in a heavily exploited open marine ecosystem. Proceedings of the Royal Society B: Biological Sciences. 275, 1793–1801. doi: 10.1098/rspb.2007.1752.

Chagaris, D, Drew, K, Schueller, A *et al.* (2020) Ecological reference points for Atlantic menhaden established using an ecosystem model of intermediate complexity. Frontiers in Marine Science.7: 227172435. doi: 10.3389/fmars.2020.606417.

Christensen, V (2010) MEY = MSY. Fish and Fisheries 11:105–110. doi: 10.1111/j.1467-2979.2009.00341.x.

Clausen, LW, Rindorf, A, van Deurs, M *et al.* (2018) Shifts in North Sea forage fish productivity and potential fisheries yield. Journal of Applied Ecology 55:1092–1101. doi: 10.1111/1365-2664.13038.

Collie, J, Minto, C, Worm, B, and Bell, R (2013) Predation on prerecruits can delay rebuilding of depleted COD stocks. Bulletin of Marine Science.89, 107–122. doi: 10.5343/bms.2011.1134.

Collie, JS, Bell, RJ, Collie, SB, and Minto, C (2021) Harvest strategies for climate-resilient fisheries. ICES Journal of Marine Science.78, 2774–2783. doi: 10.1093/icesjms/fsab152.

Collie, JS, Botsford, LW, Hastings, A *et al.* (2016) Ecosystem models for fisheries management: finding the sweet spot. Fish and Fisheries 17:101–125. doi: 10.1111/faf.12093.

Collie, JS, and Gislason, H (2001) Biological reference points for fish stocks in a multispecies context. Canadian Journal of Fisheries and Aquatic Sciences 58:2167–2176. doi: 10.1139/cjfas-58-11-2167.

Collie, JS, Peterman, RM, and Zuehlke, BM (2012) A fisheries risk-assessment framework to evaluate trade-offs among management options in the presence of time-varying productivity. Canadian Journal of Fisheries and Aquatic Sciences 69:209–223. doi: 10.1139/f2011-148.

Conn, PB, Williams, EH, and Shertzer, KW (2010) When can we reliably estimate the productivity of fish stocks? Canadian Journal of Fisheries and Aquatic Sciences.67, 511–523. doi: 10.1139/f09-194.

Cowan, JH, Rice, JC, Walters, CJ *et al.* (2012) Challenges for implementing an ecosystem approach to fisheries management. Marine and Coastal Fisheries.4, 496–510. doi: 10.1080/19425120.2012.690825.

Crone, PR, Maunder, MN, Lee, HH, and Piner, KR (2019) Good practices for including environmental data to inform spawner-recruit dynamics in integrated stock assessments: small pelagic species case study. Fisheries Research. 217, 122–132. doi: .

De Oliveira, JAA, Kell, LT, Punt, AE *et al.* (2009) Managing without best predictions: the management strategy evaluation framework. *In* Advances in Fisheries Science. Blackwell Publishing Ltd., Oxford, pp. 104–134.

Deurs, M, Brooks, ME, Lindegren, M *et al.* (2021) Biomass limit reference points are sensitive to estimation method, time-series length and stock development. Fish and Fisheries 22:18–30. doi: 10.1111/faf.12503.

Deyle, ER, Fogarty, M, Hsieh, CH *et al.* (2013) Predicting climate effects on Pacific sardine. Proceedings of the National Academy of Sciences.110, 6430–6435. doi: 10.1073/pnas.1215506110.

Dichmont, CM, Deng, RA, Punt, AE *et al.* (2016) A review of stock assessment packages in the United States. Fisheries Research 183:447–460. doi: 10.1016/j.fishres.2016.07.001.

Dickey-Collas, M, Hintzen, NT, Nash, RDM *et al.* (2014) Quirky patterns in time-series of estimates of recruitment could be artefacts. ICES Journal of Marine Science, 72:111–116.

Dolan, TE, Patrick, WS, and Link, JS (2016) Delineating the continuum of marine ecosystem-based management: a US fisheries reference point perspective. ICES Journal of Marine Science 73:1042–1050. doi: 10.1093/icesjms/fsv242.

EC(2013) Common fisheries policy (CFP) regulation no. 1380/2013 of the European Parliament and of the Council. Official Journal of the European Communities 001:354.

FAO(1995a) Code of conduct for responsible fisheries. Food Agric Organ United Nations.

FAO (1995b) Precautionary approaches to fisheries. Part 1: guidelines on the precautionary approach to capture fisheries and species introductions. FAO Fisheries Technical Paper.

FAO(2003) The ecosystem approach to fisheries, FAO technical guidelines for responsible fisheries.

Field, JC, MacCall, AD, Bradley, RW, and Sydeman, WJ (2010) Estimating the impacts of fishing on dependent predators: a case study in the California Current. Ecological Applications 20:2223–2236. doi: 10.1890/09-0428.1.

Fogarty, MJ (2014) The art of ecosystem-based fishery management. Canadian Journal of Fisheries and Aquatic Sciences 71:479–490. doi: 10.1139/cjfas-2013-0203.

Fogarty, MJ, Gamble, R, and Perretti, CT (2016) Dynamic complexity in exploited marine ecosystems. Frontiers in Ecology and Evolution 4. 68. doi: 10.3389/fevo.2016.00068.

Frank, KT, Petrie, B, Choi, JS, and Leggett, WC (2005) Trophic cascades in a formerly cod-dominated ecosystem. Science 308:1621–1623. doi: 10.1126/science.1113075.

Free, CM, Thorson, JT, Pinsky, ML *et al.* (2019) Impacts of historical warming on marine fisheries production. Science,363: 979–983. doi: 10.1126/science.aau1758.

Fulton, EA, Smith, ADM, Smith, DC, and Johnson, P (2014) An integrated approach is needed for ecosystem based fisheries management: Insights from ecosystem-level management strategy evaluation. Plos ONE.9, e84242. doi: 10.1371/journal.pone.0084242.

Gabriel, WL, and Mace, PM (1999) A review of biological reference points in the context of the precautionary approach. *In* Proceedings of the Fifth National NMFS Stock Assess Workshop. Northeast Fisheries Science Center.

Gaichas, S, Gamble, R, Fogarty, M *et al.* (2012) Assembly rules for aggregate-species production models: simulations in support of management strategy evaluation. Marine Ecology Progress Series.459, 275–292. doi: 10.3354/meps09650.

Garcia, SM (1996) The precautionary approach to fisheries and its implications for fishery research, technology and management: an updated review. *In* Precautionary Approach to Fisheries. Part 2. FAO Fisheries Technical Paper. FAO, Rome.

Geary, WL, Bode, M, Doherty, TS *et al.* (2020) A guide to ecosystem models and their environmental applications. Nature Ecology and Evolution.4, 1459–1471. doi: 10.1038/s41559-020-01298-8.

Gislason, H (1999) Single and multispecies reference points for Baltic fish stocks. ICES Journal of Marine Science 56:571–583. doi: 10.1006/jmsc.1999.0492.

Gudmundsson, G (1994) Time series analysis of catch-at-age observations. Applied Statistics.43, 117. doi: 10.2307/2986116.

Haltuch, MA, Brooks, EN, Brodziak, J *et al.* (2019) Unraveling the recruitment problem: a review of environmentally-informed forecasting and management strategy evaluation. Fisheries Research.217, 198–216. doi: 10.1016/j.fishres.2018.12.016.

Hilborn, R (2010) Pretty good yield and exploited fishes. Marine Policy 34:193–196. doi: 10.1016/j.marpol.2009.04.013.

Hilborn, R (2020) Measuring fisheries management performance. ICES Journal of Marine Science 77:2432–2438. doi: 10.1093/icesjms/fsaa119.

Hilborn, R, Amoroso, RO, Anderson, CM *et al.* (2020) Effective fisheries management instrumental in improving fish stock status. Proceedings of the National Academy of Sciences 117:2218–2224. doi: 10.1073/pnas.1909726116.

Hilborn, R, and Walters, CJ (1992) Quantitative Fisheries Stock Assessment. Springer, Boston, MA.

Hollowed, A (2000) Are multispecies models an improvement on single-species models for measuring fishing impacts on marine ecosystems? ICES Journal of Marine Science 57:707–719. doi: 10.1006/jmsc.2000.0734.

Hollowed, AB, Aydin, KY, Essington, TE *et al.* (2011) Experience with quantitative ecosystem assessment tools in the northeast Pacific. Fish and Fisheries.12, 189–208. doi: 10.1111/j.1467-2979.2011.00413.x.

Holt, CA, and Michielsens, CGJ (2020) Impact of time-varying productivity on estimated stock–recruitment parameters and biological reference points. Canadian Journal of Fisheries and Aquatic Sciences.77, 836–847. doi: 10.1139/cjfas-2019-0104.

Howell, D, Schueller, AM, Bentley, JW *et al.* (2021) Combining ecosystem and single-species modeling to provide ecosystem-based fisheries management advice within current management systems. Frontiers in Marine Science, 7: 607831. doi: 10.3389/fmars.2020.607831.

Hunsicker, ME, Ciannelli, L, Bailey, KM *et al.* (2011) Functional responses and scaling in predator-prey interactions of marine fishes: contemporary issues and emerging concepts. Ecology Letters 14:1288–1299. doi: 10.1111/j.1461-0248.2011.01696.x.

ICES(2017a) ICES Fisheries Management Reference Points for Category 1 and 2 Stocks. ICES Advice. 12, 19. pp. doi: 10.17895/ices.pub.3036.

ICES(2017b) Report of the Workshop to consider FMSY Ranges for Stocks in ICES Categories 1 and 2 in Western Waters (WKMSYREF4), 13–16 October 2015, ICES C 2015/ACOM, Brest, France. ICES: 187. pp. doi: 10.17895/ices.pub.5348.

ICES(2018a) Report of the Working Group on Multispecies Assessment Methods (WGSAM). ICES C 2018/HAPIS. 89pp.

ICES(2018b) Report of the Working Group on the Assessment of Demersal Stocks in the North Sea and Skagerrak (WGNSSK), 24 April-3 May, ICES C 2018/ACOM, Oostende, Belgium. 22pp.

ICES (2020) Workshop on an Ecosystem Based Approach to Fishery Management for the Irish Sea (WKIrish6; outputs from 2019 meeting). ICES Scientific Reports. 2. 32 pp. doi: 10.17895/ices.pub.5551.

ICES(2021a) Workshop of Fisheries Management Reference Points in a Changing Environment (WKRPChange, outputs from 2020 meeting). ICES Scientific Reports. 3. 39pp. 10.17895/ices.pub.7660.

ICES(2021b) Advice on Fishing Opportunities. doi: Report of the ICES Advisory Committee. 10.17895/ices.advice.7720.

Kell, LT, Nash, RDM, Dickey-Collas, M *et al.* (2016) Is spawning stock biomass a robust proxy for reproductive potential? Fish and Fisheries 17:596–616. doi: 10.1111/faf.12131.

Kell, LT, Pilling, GM, Kirkwood, GP *et al.* (2005) An evaluation of the implicit management procedure used for some ICES roundfish stocks. ICES Journal of Marine Science 62:750–759. doi: 10.1016/j.icesjms.2005.01.001.

Kempf, A, Mumford, J, Levontin, P *et al.* (2016) The MSY concept in a multi-objective fisheries environment - lessons from the North Sea. Marine Policy 69:146–158. doi: 10.1016/j.marpol.2016.04.012.

King, JR, McFarlane, GA, and Punt, AE (2015) Shifts in fisheries management: adapting to regime shifts. Philosophical Transactions of the Royal Society B: Biological Sciences 370:20130277. doi: .

Kvamsdal, SF, Eide, A, Ekerhovd, N-A *et al.* (2016) Harvest control rules in modern fisheries management. Elementa: Science of the Anthropocene 4:1–22. doi: 10.12952/journal.elementa.000114.

Larkin, PA (1977) An epitaph for the concept of maximum sustained yield. Transactions of the American Fisheries Society 106:1–11. doi: 10.1577/1548-8659(1977)106⟨1:AEFTCO⟩2.0.CO;2

Lewy, P, and Vinther, M (2004) A stochastic age-length-structured multispecies model applied to North Sea stocks. ICES CM 2004/ FF:20. 33pp.

Lucey, SM, Aydin, KY, Gaichas, SK *et al.* (2021) Evaluating fishery management strategies using an ecosystem model as an operating model. Fisheries Research 234:105780. doi: 10.1016/j.fishres.2020.105780.

Mace, PM (1994) Relationships between common biological reference points used as thresholds and targets of fisheries management strategies. Canadian Journal of Fisheries and Aquatic Sciences 51:110–122. doi: 10.1139/f94-013.

Mace, PM (2001) A new role for MSY in single-species and ecosystem approaches to fisheries stock assessment and management. Fish and Fisheries 2:2–32. doi: 10.1046/j.1467-2979.2001.00033.x.

Mackinson, S, Deas, B, Beveridge, D, and Casey, J (2009) Mixed-fishery or ecosystem conundrum? Multispecies considerations inform thinking on long-term management of North Sea demersal stocks. Canadian Journal of Fisheries and Aquatic Sciences 66:1107–1129. doi: 10.1139/F09-057.

Marchal, P, Andersen, JL, Aranda, M *et al.* (2016) A comparative review of fisheries management experiences in the European Union and in

other countries worldwide: Iceland, Australia, and New Zealand. Fish and Fisheries 17:803–824. doi: 10.1111/faf.12147.
Maunder, M, and Deriso, R (2014) Proposal for biomass and fishing mortality limit reference points based on reduction in recruitment. *In* Proceedings of the SAC-05-14 Fifth Meeting of the Inter-American Tropical Tuna Commission Scientific Advisory Committe. La Jolla, CA. 193–206
Maunder, MN, and Punt, AE (2013) A review of integrated analysis in fisheries stock assessment. Fisheries Research 142:61–74. doi: 10.1016/j.fishres.2012.07.025.
Maunder, MN, and Thorson, JT (2019) Modeling temporal variation in recruitment in fisheries stock assessment: a review of theory and practice. Fisheries Research 217:71–86. doi: 10.1016/j.fishres.2018.12.014.
May, RM, Beddington, JR, Clark, CW *et al.* (1979) Management of multispecies fisheries. Science 205:267–277. doi: 10.1126/science.205.4403.267.
Mesnil, B, and Rochet, M-J (2010) A continuous hockey stick stock–recruit model for estimating MSY reference points. ICES Journal of Marine Science 67:1780–1784. doi: 10.1093/icesjms/fsq055.
Methot, RD, and Wetzel, CR (2013) Stock synthesis: a biological and statistical framework for fish stock assessment and fishery management. Fisheries Research 142:86–99. doi: 10.1016/j.fishres.2012.10.012.
Mildenberger, TK, Berg, CW, Pedersen, MW *et al.* (2019) Time-variant productivity in biomass dynamic models on seasonal and long-term scales. ICES Journal of Marine Science. 77: 174–187. doi: 10.1093/icesjms/fsz154.
Millar, RB, and Meyer, R (2000) Non-linear state space modelling of fisheries biomass dynamics by using Metropolis-Hastings within-Gibbs sampling. Journal of the Royal Statistical Society: Series C (Applied Statistics) 49:327–342. doi: 10.1111/1467-9876.00195.
Minto, C, Mills Flemming, J, Britten, GL, and Worm, B (2014) Productivity dynamics of Atlantic cod. Canadian Journal of Fisheries and Aquatic Sciences 71:203–216. doi: 10.1139/cjfas-2013-0161.
Minto, C, and Worm, B (2012) Interactions between small pelagic fish and young cod across the North Atlantic. Ecology 93:2139–2154. doi: 10.1890/10-2036.1.
Moffitt, EA, Punt, AE, Holsman, K *et al.* (2016) Moving towards ecosystem-based fisheries management: options for parameterizing multi-species biological reference points. Deep Sea Research Part II: Topical Studies in Oceanography 134:350–359. doi: 10.1016/j.dsr2.2015.08.002.
MSA(2007) Magnuson-Stevens Fishery Conservation and Management Act. U.S. Government Public Law 94-265. 170pp.
Myers, RA (1998) When do environment-recruitment correlations work? Reviews in Fish Biology and Fisheries 8, 285–305. doi: 10.1023/A:1008828730759.
Nesslage, GM, and Wilberg, MJ (2019) A performance evaluation of surplus production models with time-varying intrinsic growth in dynamic ecosystems. Canadian Journal of Fisheries and Aquatic Sciences 76:2245–2255. doi: 10.1139/cjfas-2018-0292.
Nielsen, A, and Berg, CW (2014) Estimation of time-varying selectivity in stock assessments using state-space models. Fisheries Research 158:96–101. doi: 10.1016/j.fishres.2014.01.014.
Nielsen, JR, Thunberg, E, Holland, DS *et al.* (2018) Integrated ecological-economic fisheries models-evaluation, review and challenges for implementation. Fish and Fisheries 19:1–29. doi: 10.1111/faf.12232.
NOAA Fisheries(2016) National Standard 1- Optimum Yield. *In* Code of Federal Regulations. https://www.ecfr.gov/current/title-50/chapter-VI/part-600/subpart-D/section-600.310(last accessed 8 Dec 2021).
NOAA Fisheries(2021) Stock SMART data records. https://www.st.nmfs.noaa.gov/stocksmart?app=download-data(last accessed 8 Dec 2021).
Patterson, K, Cook, R, Darby, C *et al.* (2001) Estimating uncertainty in fish stock assessment and forecasting. Fish and Fisheries 2:125–157. doi: 10.1046/j.1467-2960.2001.00042.x.
Pauly, D, and Froese, R (2021) MSY needs no epitaph—but it was abused. ICES Journal of Marine Science 78:2204–2210. doi: 10.1093/icesjms/fsaa224.
Pella, JJ (1993) Utility of structural time series models and the Kalman Filter for predicting consequences of fishery actions. *In* Proceedings of the International Symposium on Management Strategies for Exploited Fish Populations. Alaska Sea Grant College Program, University of Alaska. 571–628.
Pella, JJ, and Tomlinson, PK (1969) A generalized stock production model. Bulletin Inter-American Tropical Tuna Commission 13:421–458
Perälä, TA, Swain, DP, and Kuparinen, A (2017) Examining nonstationarity in the recruitment dynamics of fishes using Bayesian change point analysis. Canadian Journal of Fisheries and Aquatic Sciences 74:751–765. doi: 10.1139/cjfas-2016-0177.
Perryman, HA, Hansen, C, Howell, D, and Olsen, E (2021) A review of applications evaluating fisheries management scenarios through marine ecosystem models. Reviews in Fisheries Science and Aquaculture 29:800–835. doi: 10.1080/23308249.2021.1884642.
Peterman, RM, Pyper, BJ, and Grout, JA (2000) Comparison of parameter estimation methods for detecting climate-induced changes in productivity of Pacific salmon (*Oncorhynchus* spp.). Canadian Journal of Fisheries and Aquatic Sciences 57:181–191. doi: 10.1139/cjfas-57-1-181.
Peterman, RM, Pyper, BJ, and MacGregor, BW (2003) Use of the Kalman filter to reconstruct historical trends in productivity of Bristol Bay sockeye salmon (*Oncorhynchus nerka*). Canadian Journal of Fisheries and Aquatic Sciences 60:809–824. doi: 10.1139/f03-069.
Plagányi, ÉE, Punt, AE, Hillary, R *et al.* (2014) Multispecies fisheries management and conservation: tactical applications using models of intermediate complexity. Fish and Fisheries 15:1–22. doi: 10.1111/j.1467-2979.2012.00488.x.
Punt, AE (2010) Harvest control rules and fisheries management. *In* Handbook of Marine Fisheries Conservation and Management. pp. 598–610. Oxford University Press, Oxford.
Punt, AE, A'mar, T, Bond, NA *et al.* (2014) Fisheries management under climate and environmental uncertainty: control rules and performance simulation. ICES Journal of Marine Science 71:2208–2220. doi: 10.1093/icesjms/fst057.
Punt, AE, Butterworth, DS, de Moor, CL *et al.* (2016) Management strategy evaluation: best practices. Fish and Fisheries 17:303–334. doi: 10.1111/faf.12104.
Punt, AE, Smith, ADM, Smith, DC *et al.* (2014) Selecting relative abundance proxies for BMSY and BMEY. ICES Journal of Marine Science 71:469–483. doi: 10.1093/icesjms/fst162.
Quinn, TJ (2008) Ruminations on the development and future of population dynamics models in fisheries. Natural Resource Modeling 16:341–392. doi: 10.1111/j.1939-7445.2003.tb00119.x.
Quinn, TJ, and Collie, JS (2005) Sustainability in single–species population models. Philosophical Transactions of the Royal Society B: Biological Sciences 360:147–162. doi: 10.1098/rstb.2004.1577.
Quinn, TJ, and Deriso, RB (1999) Quantitative Fish Dynamics. Oxford University Press, Oxford.
Ricard, D, Minto, C, Jensen, OP, and Baum, JK (2012) Examining the knowledge base and status of commercially exploited marine species with the RAM Legacy Stock Assessment Database. Fish and Fisheries 13:380–398. doi: 10.1111/j.1467-2979.2011.00435.x.
Ricker, WE (1954) Stock and recruitment. Journal of the Fisheries Research Board of Canada 11:559–623. doi: 10.1139/f54-039.
Rindorf, A, Cardinale, M, Shephard, S *et al.* (2017a) Fishing for MSY: using "pretty good yield" ranges without impairing recruitment. ICES Journal of Marine Science 74:525–534. doi: 10.1093/icesjms/fsw111.
Rindorf, A, Mumford, J, Baranowski, P *et al.* (2017b) Moving beyond the MSY concept to reflect multidimensional fisheries management

objectives. Marine Policy 85:33–41. doi: 10.1016/j.marpol.2017.08.012.
Rodionov, SN (2004) A sequential algorithm for testing climate regime shifts. Geophysical Research Letters 31. Schaefer MB (1954) Some asp. L09204, SN 0094-8276. doi: 10.1029/2004GL019448.
Schaefer, MB (1954) Some aspects of the dynamics of populations important to the management of the commercial marine fisheries. Inter-American Trop Tuna Comm 1:23–56.
Schnute, JT (1994) A general framework for developing sequential fisheries models. Canadian Journal of Fisheries and Aquatic Sciences 51:1676–1688. doi: 10.1139/f94-168.
Schnute, JT, and Haigh, R (2006) Reference points and management strategies: lessons from quantum mechanics. ICES Journal of Marine Science 63:4–11. doi: 10.1016/j.icesjms.2005.07.011.
Schnute, JT, and Richards, LJ (1995) The influence of error on population estimates from catch-age models. Canadian Journal of Fisheries and Aquatic Sciences 52:2063–2077. doi: 10.1139/f95-800.
Shepherd, JG (1982) A versatile new stock-recruitment relationship for fisheries, and the construction of sustainable yield curves. ICES Journal of Marine Science 40:67–75. doi: 10.1093/icesjms/40.1.67.
Silvar-Viladomiu, P, Minto, C, Halouani, G *et al.* (2021) Moving reference point goalposts and implications for fisheries sustainability. Fish and Fisheries 22:1345–1358. doi: 10.1111/faf.12591.
Sissenwine, MM, Mace, PM, and Lassen, HJ (2014) Preventing overfishing: evolving approaches and emerging challenges. ICES Journal of Marine Science 71:153–156. doi: 10.1093/icesjms/fst236.
Sissenwine, MP, and Shepherd, JG (1987) An alternative perspective on recruitment overfishing and biological reference points. Canadian Journal of Fisheries and Aquatic Sciences 44:913–918. doi: 10.1139/f87-110.
Skern-Mauritzen, M, Ottersen, G, Handegard, N.O., Huse, G., Dingsør, G.E., Stenseth, N.C., Kjesbu, O.S. *et al.* (2016) Ecosystem processes are rarely included in tactical fisheries management. Fish and Fisheries 17: 165–175. doi: 10.1111/faf.12111.
Subbey, S, Devine, JA, Schaarschmidt, U, and Nash, RDM (2014) Modelling and forecasting stock–recruitment: current and future perspectives. ICES Journal of Marine Science 71:2307–2322. doi: 10.1093/icesjms/fsu148.
Sugihara, G, May, R, Ye, H *et al.* (2012) Detecting causality in complex ecosystems. Science 338:496–500. doi: 10.1126/science.1227079.
Sullivan, PJ (1992) A Kalman filter approach to catch-at-length analysis. Biometrics 48:237. doi: 10.2307/2532752.
Swain, DP, and Sinclair, AF (2000) Pelagic fishes and the cod recruitment dilemma in the Northwest Atlantic. Canadian Journal of Fisheries and Aquatic Sciences 57:1321–1325. doi: 10.1139/f00-104.
Szuwalski, CS, Britten, GL, Licandeo, R *et al.* (2019) Global forage fish recruitment dynamics: a comparison of methods, time-variation, and reverse causality. Fisheries Research 214:56–64. doi: 10.1016/j.fishres.2019.01.007.
Szuwalski, CS, and Hollowed, AB (2016) Climate change and non-stationary population processes in fisheries management. ICES Journal of Marine Science 73:1297–1305. doi: 10.1093/icesjms/fsv229.
Szuwalski, CS, and Punt, AE (2013) Fisheries management for regime-based ecosystems: a management strategy evaluation for the snow crab fishery in the eastern Bering Sea. ICES Journal of Marine Science 70:955–967. doi: 10.1093/icesjms/fss182.
Tableau, A, Collie, JS, Bell, RJ, and Minto, C (2019) Decadal changes in the productivity of New England fish populations. Canadian Journal of Fisheries and Aquatic Sciences 76:1528–1540. doi: 10.1139/cjfas-2018-0255.
Thorson, JT, and Minto, C (2015) Mixed effects: a unifying framework for statistical modelling in fisheries biology. ICES Journal of Marine Science 72:1245–1256. doi: 10.1093/icesjms/fsu213.
Thorson, JT, Shelton, AO, Ward, EJ, and Skaug, HJ (2015) Geostatistical delta-generalized linear mixed models improve precision for estimated abundance indices for West Coast groundfishes. ICES Journal of Marine Science 72:1297–1310. doi: 10.1093/icesjms/fsu243.
Trenkel, VM (2018) How to provide scientific advice for ecosystem-based management now. Fish and Fisheries 19:390–398. doi: 10.1111/faf.12263.
Trijoulet, V, Fay, G, Curti, KL *et al.* (2019) Performance of multispecies assessment models: insights on the influence of diet data. ICES Journal of Marine Science 76:1464–1476. doi: 10.1093/icesjms/fsz053.
Trijoulet, V, Fay, G, and Miller, TJ (2020) Performance of a state-space multispecies model: what are the consequences of ignoring predation and process errors in stock assessments? Journal of Applied Ecology 57:121–135. doi: 10.1111/1365-2664.13515.
UN(1995) Agreement for the implementation of the provisions of the United Nations Conventionon the law of the sea of 10 December 1982 relating to the conservation and management of straddling fish stocks and highly migratory fish stocks. UN General Assembly Annex. 3. 40pp.
UN(2002) Johannesburg plan of implementation of the world summit on sustainable development. IV. Protecting and managing the natural resource base of economic and social development.
Vert-pre, KA, Amoroso, RO, Jensen, OP, and Hilborn, R (2013) Frequency and intensity of productivity regime shifts in marine fish stocks. Proceedings of the National Academy of Sciences 110:1779–1784. doi: 10.1073/pnas.1214879110.
Walters, CJ (1986) Adaptive Management of Renewable Resources. The Blackburn Press, Basingstoke.
Wetzel, CR, and Punt, A (2017) The performance and trade-offs of alternative harvest control rules to meet management goals for U.S. west coast flatfish stocks. Fisheries Research 187:139–149. doi: 10.1016/j.fishres.2016.11.019.
Worm, B, Hilborn, R, Baum, JK *et al.* (2009) Rebuilding global fisheries.Science 325:578–585. doi: 10.1126/science.1173146.
Zhang, F, Regular, PM, Wheeland, L *et al.* (2021) Accounting for non-stationary stock–recruitment relationships in the development of MSY-based reference points. ICES Journal of Marine Science 78:2233–2243. doi: 10.1093/icesjms/fsaa176.

Handling Editor: Sam Subbey