Operational Harvest Control Rules and their Application to a Recovering Forage Fish Stock

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Abstract

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Since the 1990s, international fisheries management has strived towards implementing precautionary management practices to reduce the risk of overfishing and subsequent stock collapse, and to promote rebuilding stocks from low levels. To achieve this, many fisheries have adopted pre-agreed upon catch setting algorithms known as harvest control rules (HCRs), which compute allowable catch as a function of stock status. Such HCRs can take many functional forms ranging from simple constant catch rules to complex empirical rules based on biomass levels, tagging data, and genetic mark recapture information. Here I examine the application of HCRs to Pacific herring (*Clupea pallasii*) in Prince William Sound (PWS), Alaska. The population experienced a major population crash in the early 1990s, following the Exxon Valdez oil spill, and has failed to recover in the 30 years since, despite the current HCR recommending no directed fishing take place since 1999. The collapse has therefore cost Alaska communities hundreds of millions of dollars in lost economic activity. Recent increases in biomass have pushed the stock near the lower biomass limit required for reopening the fishery, presenting an opportunity to reassess and evaluate HCRs for the fishery prior to its reopening.

I review existing operational examples of HCRs from multiple countries and regions across the world before applying them in a simulation framework to the PWS herring stock. In Chapter 1, I characterize patterns in operational HCR implementation across region, species type, and data

availability. There is substantial heterogeneity in HCR design across different regions, and little obvious patterns in HCR type by species. There is, however, a consistent trend of more complex model-based rules being reserved for stocks with the most available data and empirical and catch-based rules being used for data-poor stocks. I present a set of recommendations regarding HCR implementation based on the existing fisheries management literature and patterns in the operational adoption of such rules.

In Chapter 2, I develop a Management Strategy Evaluation (MSE) for the Pacific herring stock in PWS, with the specific goal of assessing the ability of using various HCRs to manage the stock over the next thirty years. Ten HCRs were assessed, ranging from simple threshold rules to novel rules that account for population age structure, weight distribution, and recent biomass changes. Simulation results demonstrate that threshold rules, including the existing rule, are able to adequately manage the stock, notably including a rule that allows for fishing at lower biomasses than other rules. Rules that account for age-structure and recent biomass changes also performed well and could be considered reasonable alternatives to the more common threshold rules, despite their lack of adoption in other fisheries. These results, while specific to the unique characteristics of the PWS herring population, demonstrate that careful integration of additional population information (e.g. age structure, trends, etc.) into the functional form of the HCR could be useful for managing stocks for which more typical HCR forms are not adequate, particularly for populations undergoing long periods of population recovery.

Table of Contents

LIST OF FIGURES **9**

LIST OF TABLES **10**

ACKNOWLEDGEMENTS **11**

INTRODUCTION **13**

CHAPTER 1: PATTERNS IN OPERATIONAL HARVEST CONTROL RULE IMPLEMENTATION **17**

ABSTRACT 17
INTRODUCTION 17
REGIONAL TRENDS IN HCRS 20
United States *20*
Canada *22*
Europe *23*
Australia *25*
Japan *27*
South Africa *27*
Highly Migratory and Transboundary Stocks *28*
PREFERENCES IN HCRS 29
RECOMMENDATIONS 32
Replace constant F rules with threshold F rules *32*
Use empirical rules where survey indices are available *33*
Use a tier-based approach *34*
Evaluate HCRs using MSE *35*
THE FUTURE OF HARVEST CONTROL RULES 36
CONCLUSION 38
TABLES AND FIGURES 40

CHAPTER 2: MANAGEMENT STRATEGY EVALUATION OF A DIVERSE ARRAY OF HARVEST CONTROL RULES FOR PRINCE WILLIAM SOUND PACIFIC HERRING **49**

ABSTRACT 49
INTRODUCTION 49
METHODS 53
Operating Model (OM) *53*
Estimation Method (EM) *56*
Harvest Control Rules (HCRs) *58*
Performance Metrics *60*
RESULTS 61
Biomass and Catch Trajectories *61*
Control Rule Performance *62*
Management Objective Tradeoffs *63*
DISCUSSION 64
Harvest Control Rules *64*
Model Complexity *68*

Extensions and Future Work *69*
CONCLUSION 71
TABLES AND FIGURES 72
APPENDIX A 102
GEOGRAPHIC REGIONS 102
HARVEST CONTROL RULE FORMS 103
ASSESSMENT MODEL TIERS 103
SPECIES GROUPS 104
APPENDIX B 105
REDUCED BAYESIAN SAMPLING ROUTINE 105
HISTORICAL AGE-STRUCTURE EVENNESS FOR PRINCE WILLIAM SOUND PACIFIC HERRING ... 107

List of Figures

Figure Number Page

1.1	Harvest control rule functional forms.	43
1.2	Patterns in HCR implementation by region.	44
1.3	Patterns in HCR implementation by species and region.	45
1.4	Patterns in HCR implementation by aggregated species types	46
1.5	Patterns in HCR implementation by ICES data tier.	47
1.6	Patterns in HCR implementation by model type.	48
2.1	Schematic of the management strategy evaluation simulation loop.	77
2.2	Example of a simulated recruitment timeseries from the OM.	78
2.3	Weight distribution of Pacific herring in PWS by age and the percent of each age class weighing more than the 110g cutoff weight used in the HCR.	79
2.4	Functional forms of the HCRs evaluated by MSE.	80
2.5	30-year biomass trajectories of the PWS herring population under each of the 10 tested HCRs.	81
2.6	Biomass and catch projections of the PWS herring stock under each of the 10 tested HCRs.	82
2.7	Performance metric summaries of the 10 tested HCRs.	83
2.8	Performance tradeoffs and total utility of the 10 tested HCRs.	84
B.1	Historical age-structure evenness of the PWS Pacific herring stock.	108

List of Tables

Table Number Page

1.1 Harvest control rule functional form descriptions and equations. 40

1.2 Count of HCRs of each functional form across geographic regions. 41

1.3 Count of species across species type and data tier 42

2.1 Symbols and parameters used throughout structural model equations. 72

2.2 Equations governing behavior of the operating model. 72

2.3 Natural mortality, survival, average proportion mature, average weight, average fecundity, and proportion of fish weighing > 110 g of each age class 73

2.4 Sampling distributions and parameterizations of simulated surveys. 73

2.5 Harvest control rule parameterizations. 74

2.6 Performance metric definitions and equations. 75

2.7 Threshold values used for each performance metric when calculating utility. 76

2.8 Total and relative utility values for each HCR. 76

B.1 Estimated biomass, model convergence diagnostics, and expected runtime under Bayesian sampling schemes using different numbers of model chains and total samples. 106

B.2 Historical population evenness of the PWS Pacific herring stock. 107

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Introduction

In the spring of 1989, the Exxon Valdez oil supertanker ran aground in Prince William Sound (PWS), Alaska, spilling 10.8 million gallons of crude oil into the surrounding ocean. The subsequent environmental impacts in and around PWS were wide-ranging and numerous. As a result, an estimated 30,000 sea birds, 1,000 sea otters, 100 bald eagles, and an entire pod of 22 killer whales died in the following months, as well as an untold number of Pacific herring (*Clupea pallasii*), salmon, and other fish species (Maki, 1991). Many of the affected populations rebounded to their pre-spill levels within a decade (Esler et al., 2018), with the critical exception of Pacific herring. Instead, the population of Pacific herring in PWS rapidly declined from over 80,000 mt of biomass prior to the spill to less than 20,000 mt by 1994, resulting in the complete closure of the herring fishery (Muradian et al., 2017), though there remains debate over the precise cause of the decline. In the nearly three decades since the initial population collapse, the PWS Pacific herring population has been subject to almost no fishing pressure (the fishery was briefly reopened in 1997 and 1998 but closed again due to low biomass in 1999) but has failed to rebound to pre-spill levels. Instead, it has rarely even reached the biomass threshold needed to permit the opening of the fishery (Muradian et al., 2017), costing surrounding Alaskan communities more than $250 million USD (Kopchak, 2013) since the late-1990s. This lack of population rebound is anomalous among PWS populations and for herring populations globally (Trochta et al., 2020).

Since its collapse in the early 1990s, PWS herring has been subject to substantial monitoring, including near-annual stock assessments. The population is presently assessed using the Bayesian Age Structured Assessment (BASA) model (Muradian et al., 2017), which estimates biomass, age composition, and recruitment on an annual basis. Recently, advancements to BASA has allowed for integrated environmental covariates for recruitment and natural mortality (Trochta

& Branch, 2021), as well as seroprevalence data as an index of disease (Trochta et al., 2022). However, there is still no clear understanding as to the precise cause of the initial population collapse or the lack of a natural population rebound during the last two decades. Model estimates of recruitment indicate recruitment has been lower during the past two decades than it was in the 1980s, leading to longer rebuilding times, but there remains no compelling evidence explaining the mechanism behind the recent low recruitment (Trochta & Branch, 2021). Hypotheses regarding changes in natural mortality and maturity have been explored but have not yielded any strong support. One leading hypothesis is that an outbreak of viral hemorrhagic septicemia virus (VHSV) led to the initial population crash in 1993 and has since inhibited the population from recovering to pre-crash levels (Marty et al., 2003; Marty et al., 2010; Ward et al., 2017).

One of the most common methods used by fisheries managers to regulate harvest is the development and application of a harvest control rule (HCR). HCRs are pre-specified rules that relate the amount of future allowable catch to some indicator of population size or recent catch. They are used worldwide and, in the U.S.A., are specifically called for under the Magnusson-Stevens Fisheries Management and Conservation Act of 1976 (H.R.200-94th Congress, 1976). They are also considered an integral part of the "precautionary approach to fisheries management" (Richards & Maguire, 1998; Hilborn et al., 2001), which serves as the basis for much of international fisheries management. There are a variety of functional forms that a HCR can take. Deroba and Bence (2008) broadly classify HCRs into four classes: constant catch, constant fishing mortality, constant escapement, and threshold rules; though Free et al. (2023) more recently expanded this classification to include "catch-based" rules and differentiated between "stepped" rules and more typical "threshold" rules. Threshold rules, which specify a biomass level below which the allowable fishing rate is decreased, are often considered to be among the best possible forms of HCR for managing populations that are heavily exploited (Quinn et al., 1990). Threshold rules are particularly useful for forage fish such as herring (Pikitch et al., 2012), as they are designed to promote and maintain higher levels of biomass and thus reduce the chances of overexploitation as compared to other forms of control rules (Getz & Haight, 1989). While constant-catch and constant fishing mortality strategies ensure minimal catch variability in the long term, and in many cases, high catch levels, they increase the risk of reducing the population below a critical biological threshold (Beddington & May, 1977). Threshold rules have been developed for hundreds of species around the world, including herring population (Enberg, 2005) and are used extensively for fisheries management in the United States, Canada, Europe, and Australia.

The current HCR in place for Pacific herring in PWS takes a threshold form that prohibits any fishing when biomass falls below 19,958 mt and allows for a linear increase in fishing mortality up to a biomass of 38,875 mt, after which fishing mortality is capped at 20% of total biomass (Morstad et al., 1996; Botz et al., 2010). However, it is not a requirement to reopen the fishery when the lower biomass limit has been exceeded. While stock biomass has increased beyond the level required by the existing management policy to open the fishery several times, the Alaska Department of Fish and Game (ADF&G) have opted to take a risk-averse approach to harvesting the PWS herring population to decrease the likelihood of future population crashes. Given the lack of natural recovery, and the extended time over which management has chosen to not allow fishing, analysis of new candidate HCRs for the population might identify pathways to reopen the fishery while still being risk averse after almost twenty-five years of closures.

Candidate HCRs are frequently evaluated using the development of a management strategy evaluation (MSE) framework. MSE is a simulation framework for assessing the relative performances of potential management strategies and has been employed in fisheries around the world (Butterworth, 2007; Rademeyer et al., 2007; Punt et al., 2016). The framework consists of two interacting models, an "operating model" (OM) that simulates the true state of the fishery (with process error) and an "estimation method" (EM) that assesses the state of the fishery based on its true state with observation error and provides the information need to compute an allowable catch (or level of effort) for the following year(s) using a HCR. The OM, EM, and HCR operate in a closed loop for many years (15–40 years is common), comprising a single simulation run. This process is then repeated many times (often 1,000 or more) to account for uncertainty in population dynamics, monitoring data, EM framework, and implementation error of the management policies. Performance metrics based on defined management objectives are computed across the simulation runs and used to compare the various candidate HCRs.

Here, I develop an MSE for Pacific herring in PWS to evaluate the efficacy of the established HCR against possible alternatives. Chapter 1 reviews operational HCRs across the world and characterizes trends in their functional form across species, data availability, and geography and serves to contextualize the choice of candidate HCRs for the PWS herring population. Chapter 2 covers the development of an MSE framework for PWS herring and the evaluation of ten HCRs ranging from variations of the current threshold rule to rules that account for population age structure, recent changes in biomass, and mean body weight. Overall, this thesis shows that species life history should not be used to determine the form of control rule used for management, while also expanding the range of possible HCR forms that can be used to manage forage fish stocks that are characterized by wide swings in population size. Finally, it serves as an important, early example of using Bayesian estimation methods within a complex simulation framework.

Chapter 1: Patterns in Operational Harvest Control Rule Implementation

Abstract

Harvest control rules (HCRs) are pre-specified algorithms that allow for making recommendations related to allowable levels of catch or effort based on management objectives. They provide a technical and scientific basis for managers to regulate fisheries and have consequently seen wide adoption. Here, we review trends in the functional form of HCRs in six major marine regions across the world, with a specific focus on trends by region, species type (life history), and data availability. Managers of data-rich fisheries prefer threshold control rules, in which the allowable fishing rate declines with decreasing stock size, while managers of data-limited fisheries show a preference for catch-based rules, where the following season's catch limit is a function of the previous year's catch. Recommendations for developing HCRs include adoption of threshold fishing mortality rules over constant fishing mortality rules, adoption of empirical HCRs that scale catch based on trends in empirical indicators for data-limited stocks, use of a tier system that guides HCR choice based on data availability and/or scientific uncertainty, and simulation testing of HCRs and their associated estimation methods using management strategy evaluation.

Introduction

The precautionary approach to fisheries management has been included in multiple international agreements since the 1990s (FAO, 1995; United Nations, 1995) and now forms the basis for much of international fisheries management, having been enshrined into the national fisheries policy of many nations, including the United States, Canada, and Australia, as well as the European Union (EU). Where fisheries management was once largely concerned with obtaining the maximum sustainable yield (MSY) from a fishery, the precautionary approach, among other policy instruments, directly emphasizes quantifying and accounting for uncertainty in population size, defining reference points, and developing harvest control rules (HCRs) to manage stocks (Richards & Maguire, 1998; Hilborn et al., 2001; Punt, 2006).

An HCR is a pre-agreed-upon algorithm for making recommendations related to allowable levels of catch or effort based on specific management objectives (often biological or fishery-based reference points). HCRs provide a technical and scientific basis for the methods managers use to regulate fisheries (Punt, 2010) and have, consequently, seen wide adoption throughout the world. Most HCRs provide output-based controls that seek to control the number of individuals, or the total biomass, removed from the population (e.g., through total allowable catch levels (TACs) or quotas) in each fishing season. However, HCRs can also control the total allowable fishing effort (TAE) that can be exerted on the population (AFMA, 2022; WCPFC, 2023), often using combinations of spatial, temporal, gear, or vessel limitations to regulate effort.

HCRs can take many functional forms but are often broadly classified as constant catch, catch-based, constant fishing mortality ("constant F"), constant escapement, or threshold rules (Table 1, Figure 1; Deroba & Bence, 2008; Free et al., 2023). Catch-based rules can be further broken down into non-empirical rules that derive future catch limits based on properties of the historical catch timeseries, and empirical catch-based rules that derive catch limit recommendations from monitoring data such as survey indices of abundance. Free et al. (2023) additionally differentiate between various forms of threshold F rules but we do not.

It is often desirable to use rules that relate catch levels to estimates of absolute biomass, as such rules can be designed to protect populations as they decline. For such data-rich situations, constant escapement rules seek to hold populations at target level while maximizing long term yield, at the cost of high annual catch variability; constant F rules limit variability and are responsive to fluctuations in stock size, but do not offer additional protections for populations at very low sizes; threshold rules, meanwhile, actively protect populations as they decline and hasten rebuilding times. Unfortunately, such model-based rules are not always feasible in data-limited situations, where population models cannot be developed to reliably estimate stock biomass. HCRs are still necessary in many data-limited situations, with some jurisdictions possessing a legal imperative to developed HCRs for all stocks regardless of data limitations. For such instances, constant catch and catch-based rules that do not rely on stock size estimates exist. Constant catch rules can result in high, relatively stable, catch levels, but do not offer any precautions against population decline, while catch-based rule offer limited protections by changing catch levels in response to empirical indicators believed to be indicative of population size.

HCRs may also be modified to account for fishing impacts, predator needs / ecosystem interactions, environmental conditions, or socioeconomic considerations. For example, HCRs can directly account for recent changes in biomass or survey indices, or account for age structure via controlling the shape of the age-based selectivity curve (e.g., Enberg, 2005). Additionally, HCRs can place caps on how rapidly catches are allowed to increase or decrease in successive years. These stability constraints are designed to keep catches relatively stable over the short term, which is often a desirable metric of fishery performance. Inclusion of environmental covariates is also possible (e.g. Pacific sardine, Sardinops sagax; PFMC, 2021) but is very rare in practice. With such a wide variety of rules and possibilities, management strategy evaluation (MSE) can be used to evaluate the ability of a given HCR to meet specific management objectives within a fishery (Butterworth, 2007; Rademeyer et al., 2007; Punt et al., 2016).

Here, we provide an overview of HCRs that are currently used for management, with a specific focus on trends in functional form by region, species type, and data availability. Stock-level information about HCRs – including functional form, the presence of stability constraints, the integration of environmental covariates, ecosystem interactions, or spatial considerations, and whether the rule was tested via MSE -- was collected and analyzed for fish stocks in the United States, Canada, Europe (via the International Council for Exploration of the Sea; ICES), Australia, and a selection of international and transboundary stocks managed by the tuna Regional Fisheries Management Organizations (RFMOs) and other international commissions, though the analyses should not be considered comprehensive of all HCRs for such regions. A discussion of global trends in HCR form, recommendations regarding HCR design and development, and the future of HCRs follows.

Regional Trends in HCRs

United States

Fisheries management in the U.S.A. is governed by the Magnuson-Stevens Fishery and Conservation Act (MSA), approved first in 1976 (H.R.200-94th Congress, 1976) and most recently reauthorized in 2006 (H.R.5946-109th Congress, 2007). The 2006 reauthorization of the MSA provides the legal framework for implementing the precautionary approach and requires annual catch limits for most federally managed stocks, that catch limits restrict the probability of overfishing to less than 50%, and that the probability of overfishing is further reduced in the face of increased scientific uncertainty. The MSA calls for using MSY as a catch target and defines overfishing as “the level of […] fishing mortality that jeopardizes the capacity of a fishery to produce maximum sustainable yield,” but does not provide additional details, instead leaving implementation to eight Regional Fishery Management Councils (RFMCs). These RFMCs have substantial flexibility in the development of HCRs, so long as rules meet the minimum requirements of the MSA (Free et al., 2023).

The allowed flexibility in HCR implementation has resulted in substantial regional differences in utilized HCRs throughout the U.S.A. (Free et al., 2023). Of the 507 stocks with operational HCRs in the U.S.A., 124 (24.5%) are managed using threshold rules, 152 (30.0%) using constant F rules, and 123 (24.3%) using catch-based rules (Table 1.2). However, threshold rules are implemented by just four of the eight RFMCs, with the South Atlantic, Gulf of Mexico, Caribbean, and Western Pacific RFMCs not managing any of the 111 stocks under their jurisdiction with such HCRs (Free et al., 2023). Similarly, the Mid-Atlantic and Western Pacific RFMCs do not use constant F HCRs to manage any of the 22 stocks under their jurisdiction, and almost all instances of constant catch rules are in the Caribbean Fisheries Management Council (Free et al., 2023). Meanwhile, empirical catch-based rules are used to manage only one species under U.S. jurisdiction (Barndoor skate, *Dipturus laevis*, New England Fisheries Management Council; Table 1.2).

Many of the RFMCs use some form of tier system to classify stocks based on data availability, model type, or confidence in reference-point estimates and apply pre-specified HCRs to each tier. However, the exact definitions of those tiers and HCRs differ among regions. Of the 256 stocks that could be assigned a specific data tier (stocks managed by the Caribbean Fisheries Management Council and New England Fisheries Management Council, as well as salmon stocks managed by the Pacific Fisheries Management Council and highly migratory species managed by the West Coast Fisheries Management Council, are not assigned to tiers) there is a clear tendency for management advice for stocks with lower-quality data to be based on simpler assessment methods and simpler HCR forms (e.g., catch-based) and for stocks with higher quality data and more complex assessment methods to be based on more complex HCR forms (e.g., threshold-based; Appendix A). Such trends are difficult to compare across regions due to substantial regional differences in the definition of the tiers and their levels. Analysis of HCR form across species types did not display any clear patterns (Figure 1.3).

HCRs in the U.S. rarely account for environmental covariates or consider more complex stock dynamics such as spatial patterns or multi-species interactions. Only 1 of 503 federally managed stocks (0.2%; Pacific sardine, PFMC, 2021) account for environmental linkages , while none directly account for spatial patterns or ecosystem interactions. RFMCs do however incorporate ecosystem and environmental considerations through adjustments to the allowable biological catch using risk tables (Dorn & Zador, 2020; Howell et al., 2021). No U.S. HCRs include stability constraints, though implementation of HCRs with stability constraints in the U.S. were outlined in a revision to the National Standard 1 guidelines in 2016 (Holland et al., 2020). Only the following two stocks are managed using HCRs that have been simulation tested using MSE: Pacific sardine (Hurtado-Ferro & Punt, 2014) and Atlantic herring (Deroba et al., 2018).

Canada

In 2009, Fisheries and Ocean Canada (DFO) established the Sustainable Fisheries Framework (SFF) to guide management of Canada's national fisheries resources (Fisheries and Oceans Canada, 2009b; Archibald et al., 2021). The SFF is intended to protect stock and ecosystem health through adoption of the precautionary approach, while also considering socio-economic concerns. The establishment of three stock status zones, based on the following biomass reference points "critical", "cautious", and "healthy" (Fisheries and Oceans Canada, 2009a) was among the first policies under the SFF. Harvest strategies were also required to establish pre-agreed management approaches for stocks within each zone. While there remains some discretion regarding the exact HCR implemented for each stock within Canadian waters, the SFF also outlines a provisional HCR for use when an alternative HCR is not available. This provisional HCR is a threshold-like rule where the allowable fishing rate is linearly decreased to 0.0 as stock biomass decreases from 80% of B_{MSY} to 40% of B_{MSY} (Fisheries and Oceans Canada, 2009a).

Of the 109 federally managed stocks in Canadian waters, 57 (52.3%) are managed using threshold-like rules and only 6 (5.5%) using constant-catch or catch-based rules. A substantial number of HCRs (19; 17.9%) are classified as "Unknown", indicating that the HCR could not be identified from the available management documents (Table 1.2). There were some trends in HCR form at the species and species-group level. All forage fish stocks with HCRs are managed using threshold rules, as are many groundfish and rockfish stocks and nearly half of all invertebrate stocks examined here (Figure 1.3). Some Canadian fisheries (15; 14.4%) are managed with a stability constraint and there is wide adoption of MSE-tested management strategies (14; 13.2%). While Canada does not, at present, implement a tiered system for fisheries management advice, a Regional Peer Review meeting held in 2016 discussed the development and implementation of a tier-based approach for managing Pacific groundfish stocks (DFO, 2016), citing the U.S.A. and Europe as examples of successful tiered systems.

Europe

European fisheries are managed using a complex network of inter-country agreements because most commercial stocks frequently cross international borders. The European Union's (EU's) Multiannual Plan is one such agreement amongst EU nations. However, the management of stocks that cross borders between EU and non-EU nations (e.g., stocks within the North Sea) complicates fisheries management in Europe. As such, ICES is frequently requested to provide catch advice for European fish stocks. Their advice, while not legally binding, is often used as a basis for European nations to negotiate TACs for shared stocks. Where available, ICES provides catch advice based on pre-agreed, precautionary management plans (de Oliveira, J.A.A., *pers. comm.*) but otherwise uses a tiered system of HCRs designed to hold stocks at MSY levels (ICES, 2022a).

Of the 240 stocks for which ICES has provided recent advice, management advice for 88 (36.7%) of them was based on a threshold rule, while 51 (21.3%) were managed using an empirical catch-based rule and 33 (13.8%) using a non-empirical catch-based rule. Eight (3.3%) stocks are managed using a constant F rule and eight additional stocks are managed using a constant escapement rule (Figure 1.1). Additionally, the retention of 28 (11.7%) stocks is prohibited. (Figure 1.1).

ICES sets catch advice using HCRs based on a six-tier system of data availability and quality (Figure 1.5; ICES, 2022a). Stocks for which the highest quality data are regularly available are considered Tier-1, while stocks for which little information is available are considered Tier-6. Of the 98 stocks that are considered Tier-1 or Tier-2, 85 (86.7%) are managed using threshold rules, while 51 of 75 (68%) Tier-3 and Tier 4 stocks are managed using empirical catch-based rules. Non-empirical catch-based rules are used to manage 24 of 29 (82.3%) Tier-5 stocks, and no catch is recommended for 18 of 32 (56.3%) of Tier-6 stocks. Tier-2 stocks are unique from those in the other tiers in that their catch advice is set using a probabilistic control rule, whereby catches are based on the 35th-percentile of the expected catch distribution under the corresponding Tier-1 HCR (ICES, 2022a), similar to the P* (p-star) approach used on the U.S. West Coast within the Pacific Fisheries Management Council (Prager et al., 2003; Shertzer et al., 2010).

Few HCRs in Europe account for spatial structure or environmental covariates. Stability constraints are much more common in Europe than elsewhere, with 71 stocks (29.5%) possessing explicit stability constraints, though such constraints are only in effect when stock biomass is greater than a stock-specific trigger reference point (ICES, 2022b). MSEs are also more commonly used for European fisheries than elsewhere in the world, with 21 (8.8%) stocks being managed by an HCR that has been simulation tested using a stock-specific MSE. HCRs used by ICES are all simulation tested to verify their consistency with the precautionary approach and their ability to achieve MSY (de Oliveira, J.A.A., *pers. comm.*) but stock specific MSEs are only undertaken under special circumstances.

Australia

The Australian Department of Agriculture, Fisheries and Forestry (DAFF) approved the Commonwealth Fisheries Harvest Strategy Policy and Guidelines (CHSP) in 2007 (DAFF, 2007), establishing an official harvest strategy for federally managed commercial fisheries in Australian waters. The CHSP calls for reductions in fishing mortality as stock indicators fall below established target reference points and a cessation of fishing activity if indicators fall below a limit reference point (DAFF, 2007), similar to the approach defined in Canada's SFF. However, the CHSP does not formally establish specific control rules for Australian fisheries, instead leaving implementation details up to the managers of each fishery so there remains substantial variability in the actual HCRs that are implemented, as in the U.S.A. Unlike HCRs in other regions, which often seek to hold stock biomass near the level that results in MSY, the CHSP explicitly calls for using the biomass corresponding to maximum economic yield (B_{MEY}) as the target biomass (DAFF, 2007). MEY is only estimated (via bio-economic modeling approaches) for a few fisheries (e.g.

the Northern Prawn Fishery, Dichmont et al., 2010), while other fisheries use a slightly larger biomass than B_{MEY} as the target reference point.

A 2013 review of the CHSP, found that 72 stocks managed by the Australian Commonwealth government, spanning 12/13 fisheries had harvest strategies in place (DAFF, 2013). Here, we have identified 89 stocks with harvest strategies (Figure 1.2). Threshold HCRs are applied to just 23 stocks (25.8%), despite the implicit call for their utilization in the CHSP. Twenty-eight stocks (31.5%) are instead managed using catch triggers that, when breached, result in pre-specified actions that may not include reductions in catch levels. These rules are classified here as constant catch rules (Table 1.2), as there is no pre-specified means of modifying catch levels in response to biomass or other indicators (either catch-per-unit-effort or survey indices). Constant F and catch-based rules are used sparingly (Table 1.2).

While the vast majority of Australian federal harvest strategies use output controls (85 stocks; 95.5%) to implement TACs based on Recommended Biological Catches, a small number (4 stocks; 4.5%) use input controls to restrict TAE, such as the redleg banana prawn (*Penaeus indicus*) and tiger prawn (*Penaeus monodon*) fisheries (AFMA, 2022). These TAE-style rules are sometimes implemented through spatial or temporal management practices, such as rotating closures (Plagányi et al., 2015), with 50 stocks (36.4%) being managed with some form of spatial management technique. MSE tested HCRs are also more common in Australia than in the U.S.A. or Canada (e.g. Punt et al., 2005; Dichmont et al., 2006; Dowling, 2011; Haddon, 2011). The Australian Southern and Eastern Scalefish and Shark Fishery use a tiered system based on data availability (Smith et al., 2008; Punt, 2010), with threshold rules being applied to stocks in higher tiers and catch triggers and catch-based rules being applied to stocks in lower tiers.

Japan

A TAC system was introduced by the Fishery Agency of Japan in 1997, following Japan's ratification of the United Nations Convention of the Law of the Sea (Ohshimo & Yamakawa, 2018), to attempt to conform to international standards for fisheries management. TAC management has been formally implemented for eight species as of 2018, including Pacific saury (*Cololabis saira*), walleye pollock (*Gadus chalcogrammus*), sardine (*Sardinops melanostictus*), common squid (*Todarodes pacificus*), and snow crab (*Chionoecetes opilio*), though Acceptable Biological Catch (ABC) levels have been defined for an additional 44 species, and 75 stocks (Ichinokawa et al., 2017; Ohshimo & Yamakawa, 2018), though information for only 68 such stocks could be procured (Table 1.2). There are an additional 21 stocks that are not managed by TACs or ABCs but instead continue with the traditional form of Japanese fisheries management which include combinations of input and technical controls, such as gear limitations (Ichinokawa et al., 2017). Where TACs and ABCs are defined, they tend to take one of two functional forms: threshold F or empirical catch-based. Threshold F rules are applied to 34 stocks (50%) while empirical catch-based rules are applied to an additional 30 stocks (44%). Four additional stocks are managed using HCRs but the functional form could not be identified (Figure 1.2).

South Africa

South Africa is perhaps best known for its adoption and implementation of operational management procedures (OMPs; now known as MSEs) for their marine fishery resources (de Moor et al., 2022). Since the mid-1990s, HCRs have been developed for eight different marine species, nearly all through the MSE process. Of those eight stocks, seven are currently managed using empirical catch-based rules, while a single stock of West Coast Rock Lobster

(*Jasus lalandii*) is managed using a constant catch rule (Table 1.2; Figure 1.2). Stability constraints feature in all seven of the empirical catch-based rules.

Highly Migratory and Transboundary Stocks

Tunas and other highly migratory pelagic species spend much of their lives in waters outside of the jurisdiction of any single country's authority and, consequently, are managed via tuna RFMOs. In the past decade, tuna RFMOs, including the International Commission for the Conservation of Atlantic Tunas (ICCAT), the Western and Central Pacific Fisheries Commission (WCPFC), the Indian Ocean Tuna Commission (IOTC), and the Commission for the Conservation of Southern Bluefin Tuna (CCSBT), have developed and formally adopted seven HCRs for pelagic species across three oceans. Four of these rules (for Atlantic albacore tuna*, Thunnus alalunga;* Indian and Pacific Ocean skipjack tuna, *Katsuwonus pelamis;* and Indian Ocean bigeye tuna, *Thunnus obesus*) are typical model-based threshold rules (IOTC, 2016; ICCAT, 2021; IOTC, 2022; WCPFC, 2023). Meanwhile, the HCR for Pacific skipjack tuna, approved by the WCPFC, which is an effort-based control rule that uses a non-linear, multi-threshold scaling function to set allowable fishing effort (WCPFC, 2023). ICCAT has also approved an empirical catch-based HCR for Atlantic bluefin tuna (*Thunnus thynnus*) based on survey abundance indices (ICCAT, 2022). Most interestingly, CCSBT has implemented a complex empirical HCR, known as "The Cape Town Procedure", for southern bluefin tuna that accounts for recent changes in a CPUE index, genetic tagging information, and close-kin mark recapture data (CCSBT, 2019). Nearly all these HCRs went through MSE testing prior to official adoption, and HCRs for several other tuna stocks are awaiting approval pending the completion of their respective MSEs.

Other major transboundary stocks that have not otherwise been covered include Pacific hake (*Merluccius productus*) off the west coast of North America (jointly managed by the U.S. Pacific Fisheries Management Council and DFO Canada), Pacific halibut (*Hippoglossus stenolepis*) off the North American west coast (managed by the International Pacific Halibut Commission), several stocks—including Atlantic cod (*Gadus morhua*), Atlantic haddock (*Melanogrammus aeglefinus*), and yellowtail flounder (*Limanda ferruginea*)—in and around the Gulf of Maine in the Northwest Atlantic, and Peruvian anchoveta (*Engraulis ringens)* jointly managed by Peru and Chile. Pacific hake is a data-rich stock managed using an MSE-tested threshold HCR (Jacobsen et al., 2021). Similarly, Pacific halibut is a data-rich stock managed using a threshold HCR (Stewart & Hicks, 2022). An MSE is currently in development by the IPHC. The Gulf of Maine stocks of Atlantic cod, Atlantic haddock, and yellowtail flounder straddle the international boundary between the U.S. and Canada and no formal agreement is in place for their joint management, although the Canada-U.S. Transboundary Resources Steering Committee suggests each country use precautionary catch limits. The U.S.A. and Canada then separately apply their own respective HCRs to set the nation-specific TACs for each species. The nation-specific HCRs for these species are included in the earlier, region-specific analyses. The Peruvian anchoveta stock, jointly managed by Peru and Chile, is managed using an empirical catch-based HCR (Canales & Cubillos, 2021).

Preferences in HCRs

Across the regions that were analyzed, there is a preference for threshold HCRs in an operational setting. Such rules are implicitly called for by the CHSP in Australia and the SFF in Canada and constitute 24.5%, 59.3%, 37.1%, 25.8%, and 50.0% of the HCRs in the U.S.A., Canada, Europe, Australia, and Japan respectively (Figure 1.2). This preference in functional form comes as little surprise, as threshold rules have long been considered amongst the best possible rules for managing exploited populations (Quinn et al., 1990). Catch-based rules are a second choice to threshold rules, constituting 24.5%, 3.1%, 35.4%, 16.1%, and 47.3% of HCRs in the U.S.A., Canada, Europe, Australia, and Japan respectively, while also being applied to some transboundary species. Meanwhile, the use of constant F and constant catch HCRs is uncommon outside of the U.S.A. (Table 1.2; Figure 1.2).

Catch-based rules were found to consist of two, mostly distinct, types: non-empirical rules that derive allowable catch purely from properties of the historical catch time series (e.g., median long-term catch over some time period) and empirical rules that derive allowable catch by scaling previous catch levels and often account for empirical indicators (e.g., abundance indices, average length, etc.). Non-empirical catch-based rules are used throughout the U.S.A. where they make up 123/124 (99.1%) of all catch-based rules, and are also applied to Tier-5 and Tier-6 stocks by ICES (ICES, 2022a). Empirical catch-based rules are used by ICES for almost all Tier-3 and Tier-4 stocks (ICES, 2022a).

There was also a preference towards tailoring HCRs to the types and amounts of available data. In almost all cases, threshold rules are only used for stocks with the most amount of information (e.g., data-rich stocks), as they require estimation of multiple reference points. Meanwhile catch-based rules are used only for stocks with lower levels of data availability (e.g., data-limited stocks), where often only a single reference point, or target level, and some performance indicator, or less, are available (Figure 1.5).

Species type and life history were found to be only weakly associated with control rule type, with many species types being managed by a plurality of the different HCR forms (Figure

1.4). Where patterns do exist, data availability is likely to be the underlying driver. For example, the high rate of use of Threshold F rules to manage gadoid and flatfish stocks likely descends from the fact that such stocks are, in many regions, data rich (Table 1.3) and thus Threshold F rules would be appropriate given the global trends in HCR type by data availability. Species types for which a greater proportion of assessed stocks are considered data-limited also possess a more diverse range of HCR types (Table 1.3)

Interestingly, there are very few instances in which operational HCRs include functional forms more complex than single-step threshold rules. Enberg (2005) demonstrated in a simulation study that accounting for age-structure has a positive impact on fishery performance but there are no known examples of such a rule being used operationally, despite many age-structured assessments that provide annual estimates of population age structure. Similarly, there is only a single known operational example of an HCR that directly accounts for environmental conditions. Such data, while often available to management bodies, are often only tentatively related to the underlying dynamics of the population. As such, there is substantial hesitation regarding the spurious integration of environmental covariates in population models used for management due to the potential negative consequences of mis-specifying the relationship between the population dynamics and the environmental covariates (De Oliveira & Butterworth, 2005). Similarly, only a small number of HCRs that use advanced data source such as tagging or genetic mark recapture to inform their catch setting algorithms (CCSBT, 2019; Brandao & Butterworth, 2023), though such data sources are rarely available, often due to the associated costs of running such programs.

HCRs are also utilized by countries and management bodies around the world that are not summarized in this document. For example, Chile has also begun adoption of HCRs for some of its national fisheries following international standards, such as the precautionary approach.

Indonesia has also begun development of HCRs for some of its pelagic fisheries in and around the Bali Strait (Harlyan et al., 2022). Meanwhile, New Zealand commonly uses a catch projections system to set TACs for its national fisheries although formal HCRs have been adopted for its rock lobster stocks. It is likely that countries in other regions of the world, including Central and South America, Africa, and Asia, also use HCRs to manage their domestic fisheries, though we did not collect data from those regions as part of this analysis.

Recommendations

Based on the found preferences in operational HCRs, we make the following recommendations for future development of HCRs, both in an operational and research setting:

Replace constant F rules with threshold F rules

Threshold HCRs are considered to be among the best control rule forms for managing exploited populations because they are designed to promote and maintain higher levels of biomass and thus reduce the chances of overexploitation, as compared to constant F and constant catch rules (Getz & Haight, 1989). They are also, implicitly, appropriate for implementing the precautionary approach, which explicitly calls for fisheries management to use limit and target reference points. Consequently, it comes as little surprise that they are commonly applied to data-rich stocks across the world (Figure 1.6). However, there remain a substantial number of stocks worldwide that are managed using constant F rules, particularly in the U.S.A. (Figure 1.2), even though threshold rules have been demonstrated to reduce the risk of overfishing with little cost to long-term catch (Wiedenmann et al., 2017; Mildenberger et al., 2022). A committee of the National Academy of Sciences advocated for wider adoption of threshold F rules within U.S. fisheries management, finding them to be more robust to many critical uncertainties than other HCR forms (National Research Council, 2014). Nearly the same recommendation was made as a means to enhance the resilience of U.S. fisheries management to climate change (Free et al., 2023), with the important caveat that constant F rules may be preferable for short-lived species whose populations undergo large, spasmodic, fluctuations in size (Mildenberger et al., 2022). Establishing default precautionary values for the breakpoints in threshold control rules will be a necessary step in more widely adopting threshold rules, though discussion on establishing threshold values is beyond the scope of this study.

Use empirical rules where survey indices are available

Some regions, particularly the U.S.A. and Australia, apply non-empirical catch-based HCRs to manage many data-limited stocks (Figure 1.2, Figure 1.6). These rules, while useful in very data-limited situations, must be highly precautionary to achieve desired management objectives, and thus often result in foregone catch (Wiedenmann et al., 2013; Carruthers et al., 2014). While not applicable to all data-limited situations, empirical rules make better use of available data in many cases, and can often allow for increased catch levels without substantially increasing the risk of overfishing (Free et al., 2023), thus they should be applied where data allow. For example, many rockfish and flatfish stocks on the U.S. West Coast appear regularly in fisheries independent surveys. This survey data could be used to develop indices of abundances for many of these species which could then be used to augment the catch-based rules that are used for management. These rules could be of particular use in regions that are still developing robust fisheries management plans or where there is limited ability to develop complex stock assessment models that are often needed to apply for threshold F and constant F rules. Additionally, empirical rules could be used to further adjust catches in response to more frequent survey indicators in the interim between stock assessments (Geromont & Butterworth, 2014). This could be of particular use in the U.S.A, where there are often many years between successive assessments of the same stock.

Use a tier-based approach

There are obvious trends in HCR form by data availability, notably a tendency to apply threshold rules to stocks for which there are ample data and a robust assessment model and apply catch-based rules to stocks with limited data or that use simpler assessment methods (Figure 1.6). In principle, the tendency to apply more complex HCRs to situations with more data is unsurprising, as such HCR forms rely on model-based biomass estimates as well as the estimation of multiple reference points that may be difficult to obtain using simpler methods or less data. There are many ways to approach the development of fisheries tier systems however, and this flexibility often makes cross-regional comparisons difficult. For example, ICES (ICES, 2022a) and the Australian Southern and Eastern Scalefish and Shark Fishery (Smith et al., 2008) use the type and quantity of available data to categorize stocks, while the U.S. North Pacific Fisheries Management Council uses the estimability of specific, model-derived quantities (such as F_{MSY}) for this purpose. These different notions about how to define tiers are largely incompatible with each other, as many "Tier 1" stocks from the Southern and Eastern Scalefish and Shark Fishery would be considered "Tier 4" or lower under the North Pacific Fisheries Management Councils system (Punt, A.E., *pers. comm.*). Regardless of the design of the system itself, a data- and model-based tier system has the clear benefit of tailoring catch advice to the best available scientific information and provides clear fallbacks if the models or data underpinning the management of higher tier stocks fall through (Punt et al., 2020). As such, future HCRs should be developed using a tier-based approach that accounts for the level of available information, as opposed to following regional and species-level trends. As there is no standard international tier-system at this time, we recommend use of the current ICES tiers (ICES, 2022b, 2022a) for management authorities interested in adopting a tier-based approach for HCRs. The ICES tiers have been thoroughly simulation tested (ICES, 2022d, 2022c) and found to be widely precautionary for many different stocks, demonstrating many different life-history characteristics and level of data availability.

Evaluate HCRs using MSE

There is no single HCR form that will work optimally for all stocks, as the "best" HCR will vary, often substantially, based on life history, scientific uncertainty, and management objectives (Deroba & Bence, 2008; Punt, 2010). Furthermore, even if tiered HCR systems are adopted, there may be stocks whose unique characteristics make the recommended HCR unsuitable for actual management. MSE, however, offers a robust means of testing the effectiveness of an HCR, coupled with other aspects of the management regime, under uncertainty, making it particularly useful for evaluating how well HCRs meet specific objectives. This is of great use when assessing how well HCRs may perform under future climate change scenarios (Haltuch, Melissa A et al., 2019; Jacobsen et al., 2021) and for complex ecosystems (Kaplan et al., 2020; Kaplan et al., 2021; Surma et al., 2021). Many U.S. RFMCs have recently commissioned MSEs to evaluate and update HCRs, including those for Atlantic herring (Deroba et al., 2018; Feeney et al., 2019) and New England groundfish (Mazur et al., 2021), and many tuna RFMOS are working on MSEs for large pelagic species. While development of MSEs has been restricted due to computational limitations until relatively recently, development and expansion of resources regarding computational limitations, limitations to using MSE to test future HCRs should be less than in the past, especially given the recent development of wrapper tools such as *SSmse* (Doering & Vaughan, 2023), *openMSE* (Carruthers et al., 2023), and *DLMtool* (Carruthers & Hordyk, 2018) that facilitate rapid, reproducible testing of bespoke models in an MSE framework.

The Future of Harvest Control Rules

Globally, fisheries management has trended toward the adoption of relatively simple threshold and catch-based HCRs that utilize model-based estimates of biomass or abundance indices to set future allowable catches. Recent reductions in the rate of overfishing and the number of overfished stocks globally imply that the use of these HCRs has had a generally positive impact on the state of marine fisheries (Hilborn et al., 2020; Melnychuk et al., 2021), though such conclusions are restricted to fisheries for which trends in stock status are available. However, further advances in HCRs may be necessary to adequately manage marine populations as fisheries management continues to transition towards an ecosystem-based approach and as climate change continues to impact marine populations.

Ecosystem-based fisheries management emphasizes the need to manage populations not as individual, non-interacting species but as components of wider marine ecosystems and to consider the role individual species play in their ecosystems when establishing management practices (Pikitch et al., 2004). It has been largely infeasible to simulation test HCRs in an ecosystem-based context but recent advances in ecosystem modeling now provide an opportunity to identify HCRs that are robust to both the needs of human fisheries and marine ecosystems (Fulton et al., 2014; Fulton et al., 2019; Surma et al., 2021). Analogous to the single-species case, multi-species and ecosystem-based HCRs would need to be parameterized using multi-species biological reference points (MBRPs), though there are many possible such reference points, and it remains unclear which, if any, should be used for ecosystem level management (Moffitt et al., 2016; Howell et al., 2021).

Climate change will substantially modify both the distribution and overall productivity of marine fisheries over the course of the next century (Free et al., 2020), necessitating reforms in fisheries management if both catches and marine populations are to be sustained. While the suggestions of Free et al. (2023) attempt to handle inevitable declines in stock productivity, there is also the problem of spatial changes in stock distribution. Changes in spatial distribution or habitat usage by species in response to climate change are likely to bias survey indices of abundance, which are frequently used to inform catches via HCRs in regions such as the U.S.A., Canada, and the EU (O'Leary et al., 2021; Bryan & Thorson, 2023). Spatial changes in habitat utilization of distribution also may simply move fish across jurisdictional borders, likely degrading the effectiveness of spatial management approaches (e.g., closed areas), which can experience substantial lags between the occurrence of a change in spatial utilization by a species and management implementation (Karp et al., 2019). More frequent stock assessments, and/or the development of spatially explicit stock assessment models may be needed to ensure that operational HCRs continue to manage their respective stocks effectively, where resources allow for them. Where resources cannot be allocated to additional full assessments, as is the case in many regions, regular analysis of spatial patterns in fishery activity or survey catches could be used to determine whether substantial shifts in distribution have occurred since the most recent full assessment and be used for prioritizing future assessments.

Recently, there has been growing interest in “probabilistic” control rules that account directly for scientific uncertainty in estimated population size. Such HCRs have been found to substantially decrease the risk of overfishing while having minimal impact on yield (Dankel et al., 2016; Wiedenmann et al., 2017; Mildenberger et al., 2020). These types of rules have seen limited adoption in European fisheries management (where they are used for Tier 2 stocks; ICES, 2022b), while stocks on the U.S. West Coast (as well as some Alaska groundfish and crab stocks) use the P* approach to loosely account for scientific uncertainty in management (Prager et al., 2003; Shertzer et al., 2010; Privitera-Johnson & Punt, 2019). These probabilistic rules can be designed to be inherently precautionary in their catch recommendations, making them particularly useful for managing stocks under uncertain climate futures and where ecosystem effects are uncertain or poorly understood. Combining aspects of "probabilistic" HCRs with uncertainty buffers (such as P*) has been found to produce the most favorable tradeoff with respect to yield and conservation while also being least sensitive to uncertainty in estimates of stock depletion (Mildenberger et al., 2022), a useful feature when applying management policies under highly uncertain conditions.

Conclusion

Fisheries management organizations worldwide have tended towards the adoption of threshold-based HCRs to manage data-rich, single-species fishery systems, while adopting catch-based HCRs for more data-limited systems. While such HCRs have been shown to be useful for managing many species, further adoption of threshold rules in place of once popular constant F rules and wider adoption of empirical catch-based rules that make use of available monitoring data could improve the management of many marine species in the short-term. These relatively simple changes would make many HCRs more precautionary than they currently are, while forgoing little, if any, catch. In many cases, the resources are already in place to make these improvements. For example, five of the U.S. RFMCs already possess robust, data-rich stock assessment programs that would allow for estimation of the types of reference points necessary to transition from constant F rules to threshold F rules (Free et al., 2023). The U.S.A. also has relatively robust fisheries survey programs that could augment some, if not many, of their catch-based and constant catch rules.

Over longer timescales, additional advances in HCR design will need to be made to account for the threat of climate change and the movement towards ecosystem-based fisheries management. These changes include further work on multi-species and ecosystem-based reference points to parameterize HCRs that are robust to the needs of marine ecosystems, adoption of “probabilistic” control rules to further account for scientific uncertainty in stock size, and dynamic ocean management to monitor spatial changes in species distribution and habitat usage. Advances in assessment methods and improvements in monitoring and survey data, will also be critical, and may lead to wider adoption or development of simpler, empirical, HCRs that are not as reliant on complex population models. Such rules may be more readily implementable for developing fisheries management authorities and regions with limited model development and monitoring capacity. Regardless, coming shifts in environmental conditions, fisheries management objectives, and model and data capacity will necessitate shifts in the way in which HCRs are designed and applied to marine fisheries.

Tables and Figures

Table 1.1: Descriptions and functional forms of the major classes of HCRs. C_y is catch during year y, B_y is stock biomass during year y, I is a general scalar that could take one many different functional forms, and h is harvest rate. B_{esc} is a biomass escapement threshold, B_{lim} and B_{tar} are biomass limit and target thresholds, respectively.

Name	Description	General Functional Form
Constant Catch	Catch is the same every year (c) regardless of stock size	$C_y = c$
Catch-Based	Catch is derived from the previous year's catch, modified by recent trends in catch relative to a target catch level $(\bar{C})$	$C_y = C_{y-1} \cdot I(\bar{C})$
Empirical Catch-Based	Catch is derived from the previous year's catch, modified by recent trends in abundance or fishing pressure relative to a target level or trend (x)	$C_y = C_{y-1} \cdot I(x)$
Constant Escapement	A minimum of B_{esc} fish remain after the end of the fishing season	$C_y = \begin{cases} 0 & B_y < B_{esc} \\ I \cdot B_y & B_y \geq B_{esc} \end{cases}$
Constant F	Catch is set to the same fixed proportion (h) of the current stock size every year	$C_y = hB_y$
Threshold F	Catch is reduced when stock size falls below a threshold, B_{tar}	$C_y = B_y \cdot \begin{cases} h_1 & B_y < B_{lim} \\ \frac{B_y - B_{lim}}{B_{tar} - B_{lim}}\left(h_2 - h_1\right) + h_1 & B_{lim} \leq B_y \leq B_{tar} \\ h_2 & B_y > B_{tar} \end{cases}$
Catch Prohibited	Catch is not allowed	$C_y = 0.0$

Table 1.2: Count of HCRs by functional form across Canada, Europe, the U.S.A., Australia, and Japan, South Africa, and the internal tuna RFMOs. Final row is the total count of rules in each region.

	Canada	**Europe**	**U.S.A.**	**Australia**	**Japan**	**South Africa**	**Trans-boundary**	**Total**
Threshold F	57	88	124	23	30	0	5	327
Constant F	9	8	152	12	0	0	0	181
Constant Escapement	11	8	4	0	0	0	0	23
Empirical Catch-Based	3	51	1	5	34	7	1	102
Catch-Based	0	33	123	17	0	0	1	174
Constant Catch	3	0	50	28	0	0	0	81
Catch Prohibited	2	28	17	0	0	0	0	47
Other	19	21	36	51	4	0	1	132
Total	104	237	507	136	68	7	9	1068

Table 1.3: Count of stocks of each species types that are “Data Rich”, “Data Moderate, or “Data-Limited”. Data category was assigned based on the type of assessment model used for management and follows the general categorization of the NOAA NGSA model tiers (Lynch et al. 2018).

Species Type	Data-Limited	Data Moderate	Data Rich	Total
Gadoid	15	26	58	99
Flatfish	25	33	45	103
Forage Fish	16	9	54	79
Rockfish	72	21	77	170
Elasmobranch	49	39	13	101
Salmonid	25	15	59	99
Invertebrate	56	54	18	128
Pelagic	22	9	28	59
Other	147	27	54	228
Total	427	233	406	1066

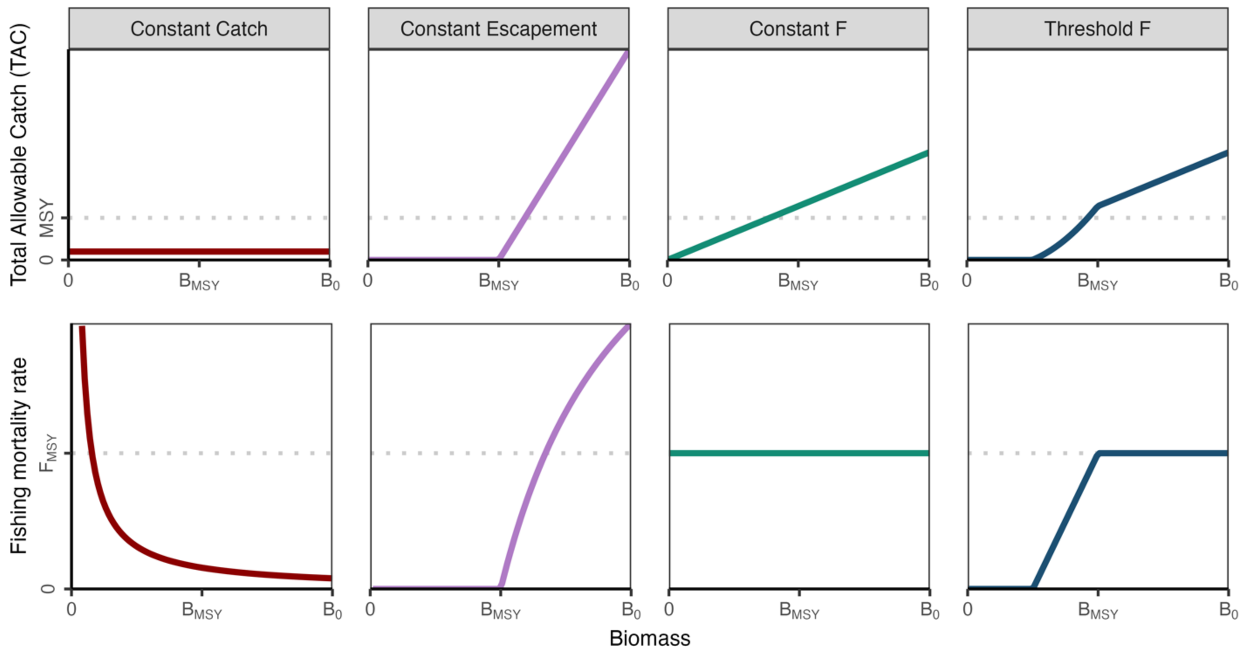

Figure 1.1: Functional diagrams of four of the six harvest control rule (HCR; column) typologies referred to in this study relating biomass at maximum sustainable yield (B_{MSY}) and equilibrium (B_0) to fishing mortality (F; bottom row) and total allowable catch (TAC; top row). Catch-based rules (including empirical catch-based rules) are not included as the shapes of such rules, being based on trends in indicator variables, are highly variable and stock specific. Catch-prohibited rules are akin to a Constant Catch or Constant F rule where the allowable catch or F is 0.0. Figure is adapted from Free et al. (2023). Colors are reused throughout to indicate the HCR functional form.

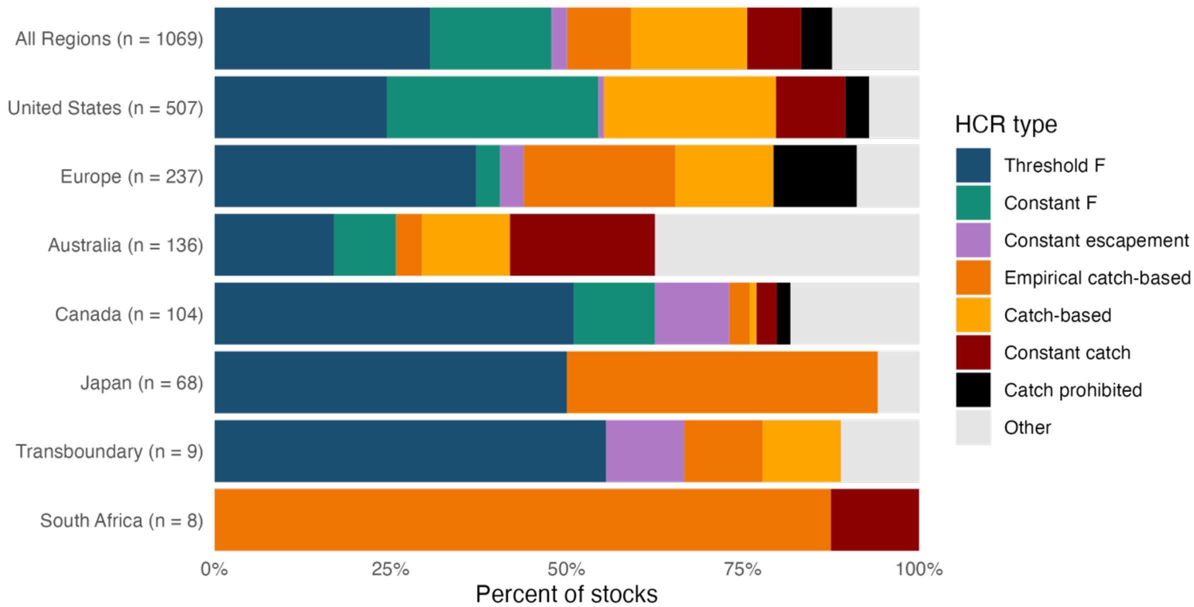

Figure 1.2: Percent of regional stocks for which management is developed using each type of HCR. The "Other" HCR types is for stocks that either do not possess an HCR, are legally exempt from being managed using an HCR under the corresponding fishery policies, or whose HCR form could not be positively identified.

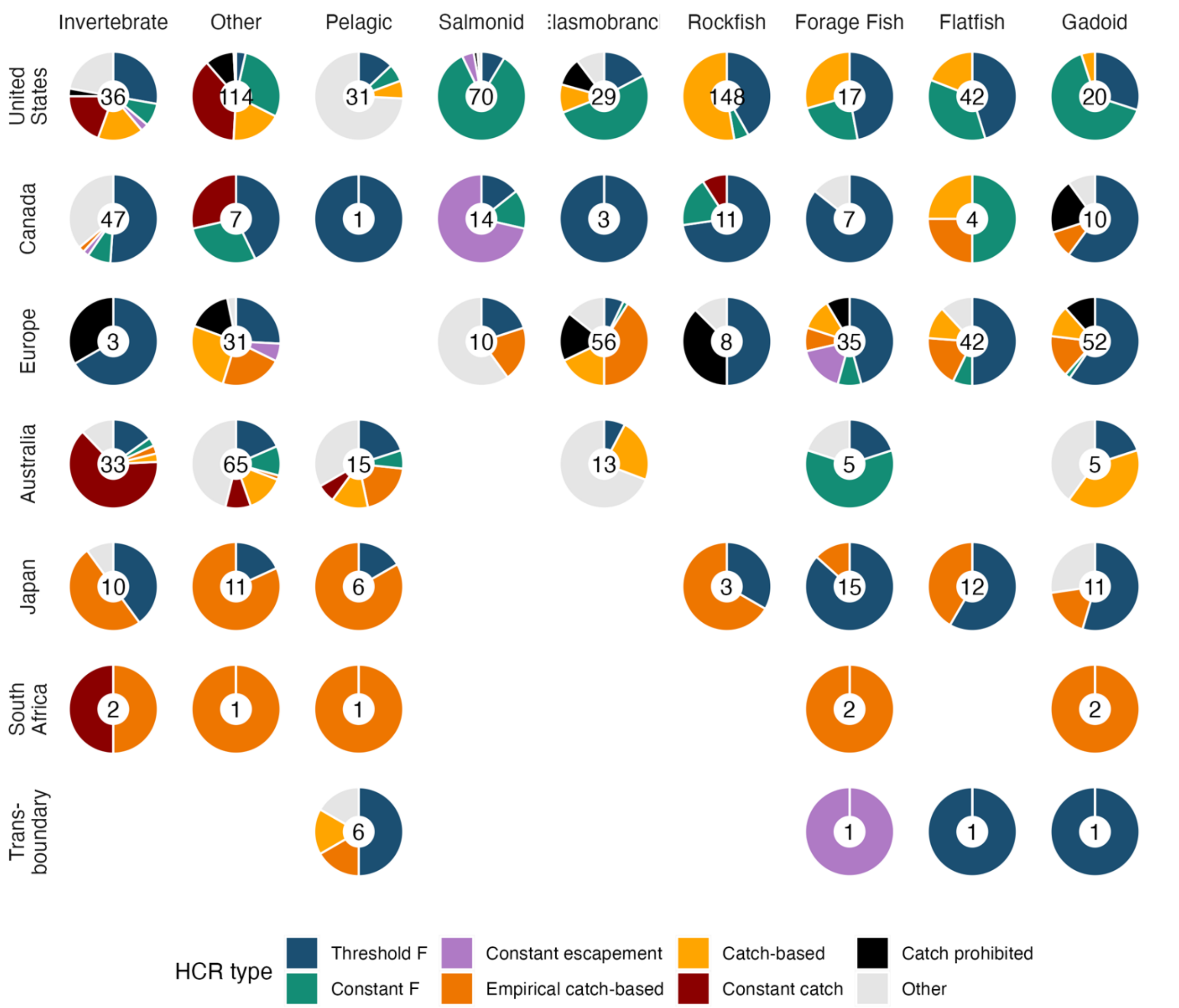

Figure 1.3: Percent of stocks of each species type in each region for which management is developed using each HCR type. Missing subplots indicate species types that are not managed by any HCR for a given region (e.g., Australia has no HCRs for salmonid or flatfish species). "Other" species category is reserved for species of reef fish and deep-sea fish.

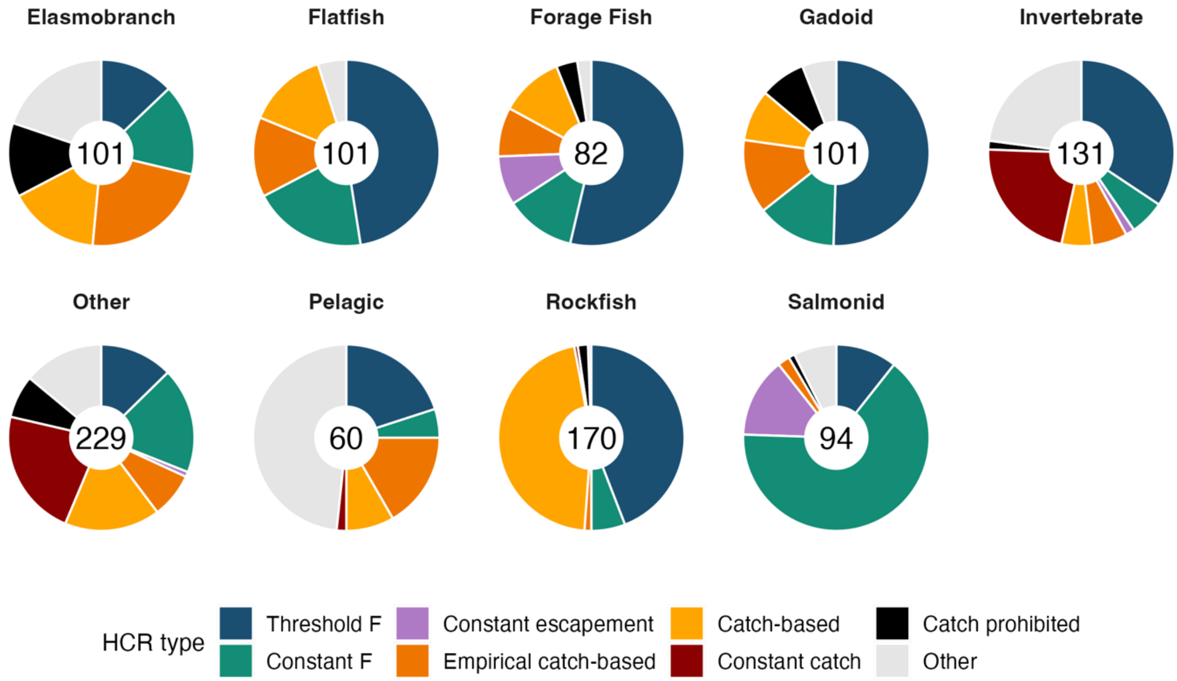

Figure 1.4: Proportion of stocks in each species group managed using each harvest control rule type. "Other" species group reserved for reef fish, deep sea fish, and species whose life history do not otherwise fit into the other groupings.

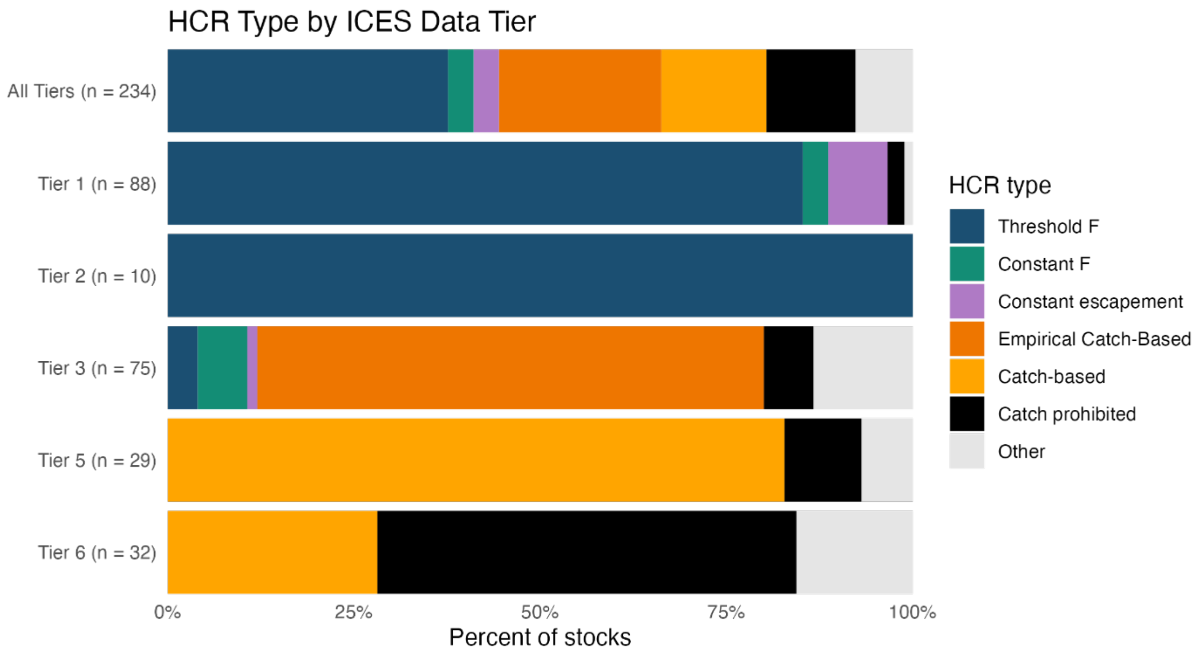

Figure 1.5: Percent of stocks in each ICES tier for which management is developed using each HCR type. Tiers 1–2 are considered data-rich, while Tiers 3–6 are considered data-limited, and Tiers 5–6 are often applied to bycatch species. “Other” is applied to stocks for which ICES has not been recently requested to provide catch advice on.

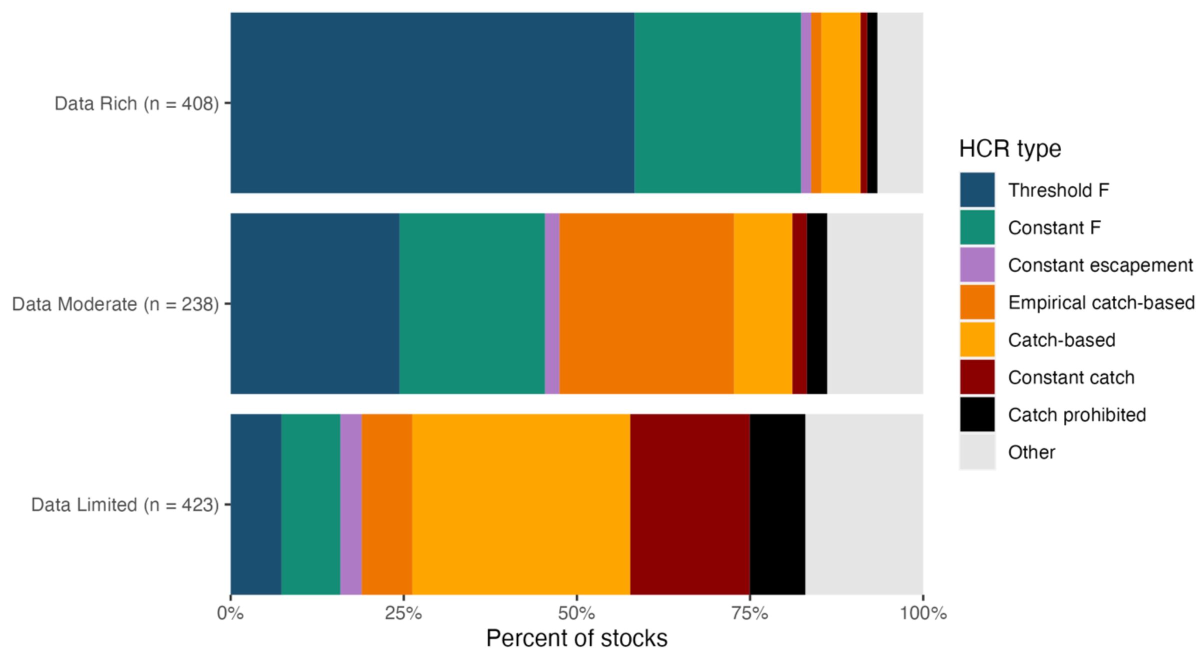

Figure 1.6: Percent of stocks managed in qualitative data tiers for which management is developed using each HCR type across Australia, Canada, Europe, Japan, and the U.S.A. Tier classifications are based on the U.S. Next-Generation Stock Assessment (NGSA) Model Category framework (Lynch et al., 2018), with NGSA categories 4-6 (age-structured assessments, length-structured assessments, and virtual population analysis) being considered "Data rich", categories 2-3 (aggregate biomass dynamics models and index-based methods) being considered "Data moderate", and category 1 being considered "Data limited" (see Appendix 1).

Chapter 2: Management strategy evaluation of a diverse array of harvest control rules for Prince William Sound Pacific Herring

Abstract

Management strategy evaluation (MSE) provides a mechanism to test the relative performances of alternative management strategies on a fishery. No directed fishery has occurred for Pacific Herring in Prince William Sound, Alaska in over 30 years, providing an opportunity to evaluate potential management strategies before fishing recommences. Here, we evaluate and compare ten harvest control rules (HCRs) ranging from simple threshold rules to rules accounting for population age structure, biomass trends, and weight distribution using an MSE integrated with a fully Bayesian stock assessment estimation method. We developed a utility function that shows simple threshold HCRs outperform more complex HCRs, especially in terms of catch stability. According to this utility function, the best rule had a lower limit threshold than the current default rule, while the worst rule had a higher limit threshold. Our simulations demonstrate that sufficient computing power exists for MSEs to test management strategies based on Bayesian estimation methods, thus opening a pathway for MSEs to simulation test probabilistic control rules, which provide a buffer against scientific uncertainty and should reduce the risk of overfishing.

Introduction

Fisheries management, at its core, involves deciding which of several management decisions will result in the most desirable outcome for the participants of a fishery (Hilborn & Walters, 1992). This process often occurs in two distinct phases: 1) for each possible management action, potential outcomes and their respective probabilities are identified; and 2) given the potential outcomes, a "best" management action is chosen and implemented. Hilborn and Walters (1992) propose that most of a fisheries manager's time is spent in phase one, and a great many tools have been developed over the years for managers to use during this first phase. For the most data-rich fisheries, this first phase of management often takes the form of a full stock assessment, in which data are collected about the current state of the population, a computational model of the biological dynamics of the population is built, and a statistical estimation framework is used to estimate the state of the fishery from the available data. However, once the stock assessment has estimated the population status, fisheries managers must still choose the best management action, for which there are far fewer tools available. The most prominent of these tools is management strategy evaluation (MSE).

MSE is a simulation framework for assessing the relative performances of potential management strategies that has been used in fisheries around the world (Rademeyer et al., 2007; Punt et al., 2016). The framework consists of two interacting components, an "operating model" (OM) that simulates the true state of the fishery (including stochasticity) and generates data (with observation error) mimicking the data currently available and potentially available in the future for the fishery and a "management strategy" that assesses the state of the fishery based on the generated data via an "estimation method" (EM) and calculates an allowable catch for the following year (Figure 2.1). The two models operate in a closed loop for many years (15–40 years is common), comprising a single simulation run. This process is then repeated, often 100–1,000 times, to account for uncertainty in population dynamics, monitoring data, and management implementation (Punt et al., 2016). Performance metrics are computed across the simulation runs and used to compare the various candidate management strategies based on how well they meet specific performance goals.

The MSE framework was first developed by the International Whaling Commission (IWC) in the 1980s to identify a catch limit algorithm for the harvest of baleen whale species that would be robust to scientific uncertainty (Punt & Donovan, 2007). The framework was subsequently applied in the 1990s in South Africa to identify robust harvest policies for multiple fish and invertebrate species (de Moor et al., 2022). In more recent years, the framework has expanded to many countries and regions (De Oliveira et al., 2008; Holland, 2010) including Australia (Punt & Smith, 1999; Dichmont et al., 2006), New Zealand (Bentley et al., 2003), Europe (Kell et al., 2005), Canada (Cox & Kronlund, 2008), and the United States (Hicks et al., 2013) and has been utilized by multiple Tuna Regional Fisheries Management Organizations for managing highly-migratory pelagic species (Polacheck et al., 1999; Kurota et al., 2010). The majority of operational MSEs across the world were developed specifically to evaluate potential harvest control rules (HCRs) or management procedures (MPs). However, the framework has found additional uses in a research context, where it has been used to conduct value of information studies (Carruthers & Kell, 2016; Xia et al., 2021) and test the robustness of existing management strategies and estimation methods to environmental change (A'mar et al., 2009; Punt et al., 2013), spatial complexity (Jacobsen et al., 2021), and ecosystem interactions (Fulton et al., 2014; Surma et al., 2021).

Adoption of MSE has been limited by computing power until relatively recently because MSEs run thousands of computationally costly estimation routines (Goethel et al., 2019), and even then has been largely restricted to frameworks using maximum-likelihood estimation. Few, if any, MSEs include a fully Bayesian estimation method. Recent integration of advanced Markov-chain Monte Carlo (MCMC) sampling methods into major fisheries stock assessment frameworks, notably the No U-Turn Sampler (NUTS) algorithm (Monnahan et al., 2017; Monnahan &

Kristensen, 2018; Monnahan et al., 2019), has markedly reduced the computational requirements of Bayesian estimation methods, allowing for their use within an MSE. This MSE represents one of the first to use a fully Bayesian estimation method, though several other operational and research MSEs have implemented OMs conditioned on Bayesian parameter estimates (e.g. Jacobsen et al., 2021). The use of Bayesian assessment methods has the benefit of allowing for the development of probability-based HCRs, where the allowable catch or harvest rate is a function of some percentile of the biomass distribution rather than the median or mean (Dankel et al., 2016).

We develop and apply an MSE framework with Bayesian estimation to Pacific herring (*Clupea pallasii*) in Prince William Sound (PWS), Alaska, taking advantage of the NUTS algorithm to allow for convergence of the estimation method in a matter of minutes instead of many hours. This population sustained annual catches averaging over 5,000 mt during the 1970s and 1980s but suffered from a severe population crash in 1992 that resulted in biomass declining by over 50% in less than a year and the closure of the directed fishery (Muradian et al., 2017). In the thirty years since the crash, the population has failed to rebound to pre-crash levels, despite continued fishery closures since 1999. However, the population has increased towards the lower regulatory threshold needed to reopen the fishery in recent years. The HCR that is presently in place for the population was agreed to in 1994 (Morstad et al., 1996; Botz et al., 2010), after the initial population crash, but has never been used for setting non-zero harvest rates. We therefore have a unique opportunity to develop and evaluate a new HCR before the fishery is reopened. Here we use MSE to evaluate ten harvest control rules in combination with a Bayesian estimation method for PWS herring that range from threshold rules (including the current rule), to those accounting for evenness in population age structure, recent trends in biomass, and average individual weight.

Methods

Operating Model (OM)

The OM utilized here is based on the population dynamics equations developed and discussed in Muradian et al. (2017) and updated by Trochta and Branch (2021). Broadly, the OM consists of a model for fishery removals with four fisheries; an age-structured population dynamics model with 10 age classes, constant natural mortality, and log-normally distributed recruitment; and an observation model that emulates the four scientific surveys currently used to monitor the PWS herring population.

Fisheries: Four historical fisheries have been present in PWS, purse-seine, gillnet, food-bait, and pound spawn-on-kelp fishery. Harvest allocations to each fishery were based on the most recent PWS herring management plan (Botz et al., 2010):

- Purse-Seine Fishery: 63.1%
- Gillnet Fishery: 3.7%
- Food-Bait Fishery: 17.7%
- Pound Spawn-on-Kelp Fishery: 15.7%

A fifth fishery (wild spawn-on-kelp fishery) is excluded from the OM as it does not remove spawning fish from the population. Historically, it was allocated 8.0% of the allowable harvest. The allocations above of the remaining four fisheries have been adjusted proportionately to reflect the four fisheries simulated here. The four fisheries are assumed to have the same age-3, knifeedged selectivity curve and could thus be thought of as a single fishery for the purposes of simulating removals from the OM but are retained separately in the OM to allow for more flexibility in future MSE applications. Removals for the purse-seine, gillnet, and food-bait fishery are distributed proportionally across all selected age classes and occur prior to spawning, as they remove reproductively active adult fish. Removals for the pound spawn-on-kelp fishery are similarly distributed across the population but occur after reproduction, as it removes spawned eggs. Adult mortality in the pound spawn-on-kelp fishery is assumed to be 100% and the removal of spawned eggs does not modify recruitment. Catches for all simulated fisheries are assumed to be known without error.

Biological Model: The OM includes an age-structured population dynamics model that closely mirrors the population dynamics model used in the current PWS herring stock assessment model (Muradian et al., 2017; Trochta & Branch, 2021). This model includes ages 0–8 and a plus-group at age 9 (Equations 2.8-2.10).

Survival by year and age class ($S_{y,a}$) is modeled as a function of natural mortality (M) split into two half years to account for natural and fishery mortality acting on the population in different seasons. Natural mortality includes disease, predation, competition, and other ecological factors. It is assumed to be fixed for age classes 0–8 at $M_{a_{0-8}} = 0.25\ yr^{-1}$, as this is considered the lowest reasonable value for background M (Quinn et al., 2001; Muradian et al., 2017). Meanwhile, M for the plus group is $M_{a_{9+}} = 0.87\ yr^{-1}$, as was estimated by the most recent herring stock assessment (Zahner & Branch, 2023). Age- and year-specific survival rates are calculated using Equation 2.7. Maturity, weight, and fecundity at age are all time-invariant and based on estimated mean values derived from historical surveys (Table 2.3).

Recruitment (R_y) is assumed to be log-normally distributed about the long-term average recruitment level ($\bar{R}$) of ~127 million annual recruits (Equation 2.8). The historical recruitment timeseries for this population (Figure 2.2) shows evidence of two recruitment regimes (Dias et al. 2022), a "high" regime during 1980–1992 and a "low" regime during 1993–2021. Means and standard deviations of the estimated recruitment deviations (δ_y) for each regime period were used to parameterize regime-specific normal distributions from which future recruitment deviations were drawn (High: $\delta_y \sim N(\mu = 0.345,\ \sigma = 1.140)$; Low: $\delta_y \sim N(\mu = -1.289,\ \sigma = 0.961)$). Recruitment deviations are not required to sum to zero over the simulation period and were converted into numbers of individuals using Equation 2.8. Forecasted recruitment assumed alternating 15-year regimes, the approximate length of the previous high recruitment regime, starting with the "high" regime in the first simulation year (Figure 2.2). The OM begins with a "high" regime to ensure that the population rebounds to a level where fishing is consistently occurring for all HCRs.

Observation Model: Three scientific survey indices were generated, aerial mile-days-of-milt survey, age-composition (ASL) survey, and age-1 aerial schools survey (see Table 2.4 for the parameterizations). Other data sources have been available in the past for use in monitoring the population including an egg-deposition survey (which is assumed to measure absolute abundance), two hydroacoustic surveys, and age-composition information derived from purse-seine fisheries catch. None of these data sources are simulated into the future as there is no guarantee that such data sources will be available in the future, and age-composition information is already available from the age-composition survey. Seroprevalence data is also annually available and have been shown to be useful in estimating disease mortality and population abundance (Trochta et al., 2022) but these data are not included in the estimation method or simulated in future years.

The mile-days-of-milt survey estimate is assumed to be log-normally distributed about the total post-fishery spawning biomass and proportional to true biomass as in the stock assessment (Muradian et al., 2017; Zahner & Branch, 2023). Age-composition data from the survey is assumed to follow a multinomial distribution with a sample size of 1,500 fish. Finally, the age-1 aerial school survey (Pegau, 2022) is assumed to follow a negative-binomial distribution with an overdispersion parameter set to the value of $k = 2.147$, as reported in the most recent stock assessment (Zahner & Branch, 2023). In this parametrization a smaller value of k represents less overdispersion Annual weight-at-age and fecundity-at-age are taken to be the average weight-at-age and fecundity-at-age in years they were collected since 1980 and are assumed to be known without error. The sex ratio of the population is assumed to follow a normal distribution with the mean and standard deviation of historical sex-ratio data collected during the ASL survey.

Estimation Method (EM)

The EM is the Bayesian Age Structured Assessment (BASA) model for PWS Pacific herring. The model fits to historical catch data, historical egg-deposition data, and more recent milt, hydroacoustic biomass, age-1 aerial, and age-composition survey data. The EM estimates recruitment separately for each year and does not assume that there are low and high recruitment regimes. The EM runs in AD Model Builder (ADMB) version 13.1 (Fournier et al., 2012), and MCMC sampling is performed using the NUTS algorithm through the ‘adnuts’ R package (Monnahan et al., 2019).

The EM used here requires approximately two minutes to obtain 2,000 MCMC samples across four MCMC chains using the NUTS algorithm for 42 years of data (Zahner & Branch, 2023). The addition of 30 years of simulated data from the MSE (a total of 72 years of data by the end of the simulations) would bring the average runtime of the model to approximately nine minutes (again for 2,000 MCMC samples and four chains). While this runtime is quite low compared to other Bayesian assessments (Monnahan et al., 2019) it would have required >50 days on the available computational resources to finish the 1,500 MSE simulations reported here.

Instead, we ran these simulations using a single MCMC chain for 1,000 iterations. The small number of iterations and single chain is often considered insufficient to guarantee model convergence or an accurate characterization of the posterior distributions of the parameters or derived quantities (Gelman et al., 2014). While neither ideal, nor best practice in Bayesian modeling, this MCMC sampling protocol was chosen to minimize total runtime, while still ensuring accurate calculations of the median estimated biomass, the derived quantity used to set the following years harvest rate by the HCRs. Analysis of the behavior of the BASA model under a variable number of MCMC chains and variable MCMC chain length (available in Appendix B) showed that the model converged (as defined by the single-chain Gelman-Rubin diagnostic) and accurately estimated population biomass (to within 1% of the biomass reported by the official 2022 stock assessment), while reducing runtime eightfold. Under this MCMC sampling protocol, total runtime of all simulations in this paper decreased to 7 days.

Each run of the EM was considered converged if the proportion of divergent transitions was <0.001 and Gelman-Rubin diagnostic $(\hat{R})$ based on a single chain was < 1.05 (Vehtari et al., 2021). Only simulations in which the EM converged for all 30 years and for all tested control rules were used for computing performance metrics.

Harvest Control Rules (HCRs)

Ten HCRs were evaluated (Table 2.5, Figure 2.4). Seven of these rules are threshold-based rules, described in this paragraph, and the remaining three (the Evenness rule, Gradient rule, and Big Fish rule) are discussed thereafter. The Default rule is the HCR that is currently used to support management of the PWS herring population (Morstad et al., 1996; Botz et al., 2010). It linearly scales the harvest rate from 0.0 to 0.2 when biomass is between 19,958 mt and 38,555 mt, with a harvest rate of 0.0 (h_{min}) below the lower threshold and 0.2 (h_{max}) above the upper threshold (Equation 2.13). The Low Harvest (Figure 2.4A.2) and High Harvest rules follow the same shape as the Default rule but with lower ($h_{max} = 0.10$) and higher ($h_{max} = 0.40$) maximum allowable harvest rates respectively. Similarly, the Low Threshold (Figure 2.4A.4) and High Threshold (Figure 2.4A.5) rules have lower ($l = 10{,}000$ mt) and higher ($l = 30{,}000$ mt) limit thresholds than the Default rule respectively. The Three-Step Threshold rule that follows the same shape and parameterization as the Default rule but with an added step at 60,000 mt, beyond which the allowable harvest rate is 0.6 (Figure 2.4A.6). The No Fishing (Figure 2.4A.8) rule has $h = 0.0$.

Equation 2.13: $h = \begin{cases} h_{min} & B < l \\ \dfrac{B - l}{u - l} \cdot h_{max} & l \leq B < u \\ h_{max} & B \geq u \end{cases}$

The Evenness rule (Figure 2.4B) reduces the allowable harvest rate when the population biomass is dominated by a single cohort. This HCR is implemented by reducing the harvest rate from the Default rule using the Shannon-Wiener evenness index (Equation 2.14) (Shannon &

Weaver, 1949), where p_a is the proportion of the population biomass in each age class a. Specifically, harvest rates from the Default rule are rescaled by a multiplier between 0.5 and 1.0 when the evenness index (J') is between 0.4 and 0.8 (i.e., when J'<0.4, harvest rates are multiplied by 0.5, when J'>0.8 harvest rates are multiplied by 1.0, and when $0.4 \leq J' \leq 0.8$ harvest rates are scaled proportionally from 0.5–1.0). These evenness threshold values were chosen from empirical estimates of age structure evenness, which ranged from 0.32 to 0.95 during 1980–2021 (Appendix B).

Equation 2.14:

$$h_{evenness} = h_{default} \cdot J$$

$$J = \begin{cases} 0.5 & J' < 0.4 \\ \dfrac{J' - 0.4}{0.8 - 0.4} \cdot 0.5 + 0.5 & 0.4 \leq J' \leq 0.8 \\ 1.0 & J' > 0.8 \end{cases}$$

$$J' = \frac{-\sum_{a=3}^{10} p_a \ln(p_a)}{7}$$

The Gradient rule (Figure 2.4C) rescales the harvest rate from the Default rule by the relative change in biomass in the most recent three-year period (Equation 2.15). The net effect is that allowable harvest rates increase when biomass is increasing and decline when biomass is declining. Fishing is not allowed when biomass is below the limit threshold of 19,958 mt, though there is no specific maximum harvest rate above the target threshold because the gradient component of the control rule acts as a multiplicative scalar on the default rule. This new "gradient-based" harvest rate (h') is averaged together with the harvest rate recommended by the "default" rule to reduce the annual variation in allowable harvest rate, (Equation 2.15).

$$h' = h_{default} \cdot \left(\frac{B_y}{B_{y-3}} \right)$$

Equation 2.15: $$h_{gradient} = \frac{h_{default} + h'}{2}$$

Finally, the Big Fish (Figure 2.4A.7) rule has the same shape and parameterization as the Default rule but sets the allowable harvest rate based on the biomass of fish weighing >110 g rather than total population biomass, as for other threshold rules. This accounts for fishery preferences for large fish, which are more valuable per unit weight than small fish. The weight of 110 g was selected because approximately 40% of sampled fish from 1980–2021 were larger than this threshold. Weights are not tracked for individual fish, thus the proportion of biomass of fish weighing >110 g in each age class is estimated from age-specific weight distributions (Figure 2.3), based on age-sex-length data for the fishery (Morella, 2022). For this rule, the harvest rate is set based on biomass of fish weighing greater than 110 g but applied to all fish above the age at selectivity.

Performance Metrics

The harvest control rules were assessed using eight metrics related to catch level, catch stability, and biomass level (Table 2.6). Biomass-related performance metrics are reported as relative to the biomass in each year that would have resulted in the absence of fishing ("dynamic" unfished biomass) to control for random variation in population dynamics. Performance metrics are computed over a 30-year period and presented as the median and 80% confidence interval across 150 simulations.

HCRs were evaluated using a utility function based on one performance metric from each of the three key axes of performance, average annual catch, average annual catch variation, and final year relative depletion. The utility function is based on Bentley et al. (2003) and defines two thresholds for each performance metric, a minimum acceptable value (*m)*, below which utility is 0 and a maximum utility value (*k),* above which utility is 1, with linear scaling between these thresholds (Table 2.7; Equation 2.16). The choice of values for *m* and *k* are subjective but are loosely derived from historical fishery performance and existing management objectives. The total utility of each HCR was computed by taking the geometric mean of the utility function value $U_{i,j}$ for average annual catch, average annual catch variation, and average relative biomass. This utility function has the benefit of ensuring that good performance in a single performance metric does not mask undesirable performance in another.

Equation 2.16: $$U_{i,j} = \begin{cases} 0 & I < m \\ \dfrac{I-m}{k-m} & m \le I \le k \\ 1 & I > k \end{cases}$$

Results

Biomass and Catch Trajectories

Pre-fishery biomass levels rebound to, or exceed, the target biomass level of 40,000 mt within the initial 15-year high-recruitment regime regardless of the harvest control rule that was applied (Figure 2.5A). Biomass declined toward the current limit biomass level of 19,958 mt with the start of the low-recruitment regime in year 16 of the simulation, before stabilizing for all control rules. By the end of each 30-year simulation, biomass under each control rule was very similar, with a

10% difference between the control rule resulting in the highest biomass level (No Fishing) and the control rule resulting in the lowest biomass level (Low Threshold) (Figure 2.5B). The median biomass at the end of the 30-year simulation under the No Fishing control rule was 17,385 mt.

Peak biomass was largely a function of the maximum harvest rate. Control rules with lower maximum harvest rates (the No Fishing and Low Harvest rules) yielded larger maximum biomass levels. Population biomass also spent more time above the management target threshold when maximum harvest rates were low (Figure 2.5A). In addition, lower maximum harvest rates resulted in more variable biomass trajectories, and less variable catch trajectories than HCRS with higher maximum harvest rates (Figure 2.6). The lower limit threshold had little effect on the biomass trajectory, though there were substantial differences in the resulting catch timeseries between control rules with different limit thresholds. The limit threshold position did not have any obvious effect on biomass variation (Figure 2.6).

Control Rule Performance

There were substantial differences in average annual catch (2,173–6,629 mt*;* excluding the No Fishing and Big Fish rules for which median annual catch was 0 mt; Figure 2.7A), average annual catch variation (0.375–0.858*;* excluding the No Fishing and Big Fish rules; Figure 2.7B) and the proportion of years of fishery closure (0–0.6*;* Figure 2.7H) across the control rules, while there were minimal differences in final year relative biomass (0.894–0.997; 2.7D). Control rules with lower maximum harvest rates and larger biomass levels over which fishing was allowed (the Low Harvest and Low Threshold rules) tended to have lower annual catch variation than control rules with the opposite properties.

The objective function identifies the Low Threshold, Evenness, and Default HCRs as having the highest total utility (Table 2.8). These three control rules all possess similar levels of annual catch, low annual catch variation (compared to the other HCRs), and similar levels of final year biomass. This indicates that the objective function is optimizing for low variation in annual catches, perhaps not surprising given the lack of contrast in rules between annual catches and final year biomass. In the remaining seven control rules, the objective function also assigns the highest utilities to the rules with the lowest annual catch variation (Table 2.8).

Management Objective Tradeoffs

There is an inherent tradeoff between annual catch, catch variation, and biomass. As annual catch increases relative biomass declines (Figure 2.8D) and annual catch variation increases (Figure 2.8G), while as biomass increases annual catch variation declines (Figure 2.8H). The three rules that the objective function identified as having the highest utility (the Low Threshold, Evenness, and Default rules) performed better than expected given the expected tradeoffs between performance metrics (Figure 2.8).

How these tradeoff relationships are transformed by the objective function into a utility value demonstrates which tradeoffs are most important for improving the utility of a control rule. For the catch-biomass tradeoff, all ten control rules occur in a narrow band of similar utility (Figure 2.8B). A similar pattern was present for the catch-catch variation tradeoff (Figure 2.8C). The biomass-catch variation tradeoff, however, occurred in a band that spans a wide range of utilities (Figure 2.8F), indicating that, by moving along this tradeoff, significant gains in utility can be achieved. The three control rules with the highest calculated utility all occur near the upper end of this tradeoff plot, highlighting that the biomass-catch variation tradeoff is the most important tradeoff to manipulate to improve overall HCR utility.

Discussion

Harvest Control Rules

Threshold-based harvest control rules, such as those investigated here, are generally considered to be among the best for managing heavily exploited populations in general (Quinn et al., 1990), and forage fish in particular (Pikitch et al., 2012), and have been implemented for dozens of fisheries in the United States alone (Free et al., 2023). Our results support simple threshold HCRs, as the four top-performing control rules all follow a simple threshold functional form. The more complex rules (Gradient and Big Fish), in attempting to account for more complicated dynamics, yield little increase in catch or biomass in return for much higher variation in annual catches. These two HCRs try to account for short-term trends in biomass or weight distribution, making them more susceptible to greatly changing harvest rates in response to survey variability or other short-term productivity declines that the less sensitive threshold rules may ignore. The Evenness and Three-Step Threshold rules, while not following the typical threshold functional form, have higher utility than the other complex rules for the inverse reason, their catch setting algorithms are not as susceptible to short term variation.

HCRs that account for gradients in either biomass estimates, survey indices, or other data have been developed for many other fisheries (e.g. Polacheck et al., 1999; Dichmont et al., 2006; Roel & De Oliveira, 2007; Plaganyi et al., 2018; CCSBT, 2019) but rarely take the form of the Gradient rule developed here. More often, these gradient-based rules compute the following year's catch as a function of the current year's catch, multiplied by the recent gradient in biomass or survey index and are applied to data-poor fisheries, particularly throughout Europe (ICES, 2022a). The functional form of the Gradient rule used in this study was developed to make full use of the available data for the population, while also considering recent changes in biomass. While gradient-based rules have seen substantial use throughout the world's fisheries, it is acknowledged that they carry greater risk of overfishing and subsequent biomass decline than constant F style rules (Polacheck et al., 1999; Roel & De Oliveira, 2007). The results of our simulations using the Gradient HCR were not substantially worse than many of the threshold HCRs, though this could be because of its inherent reliance on a threshold HCR to set the base catch level that is subsequently rescaled by the biomass gradient. A rule more similar to the data-poor rules used by ICES for Tier-3 stocks in Europe (ICES, 2022a), may show results more in line with those of other studies. Alternatively, this discrepancy between the results of our simulations and those performed by Polacheck et al. (1999) and Roel and De Oliveira (2007) could be due to substantial differences in the life histories of the species being examined (herring vs tuna and mackerel respectively). It is possible that the "boom-bust" dynamics of herring populations make including recent biomass gradients useful by allowing the fishery to take advantage of recent large year classes, but at the expense of higher annual catch variation.

To our knowledge no HCRs have previously been developed to account directly for population age-structure, like the Evenness rule presented here, even though age structure is considered important for sustaining long-term healthy fish populations (Berkeley et al., 2004). By explicitly accounting for cohort dominance, the Evenness HCR should be more resilient when much of the population consists of a single age class, as predicted by the portfolio effect (Schindler et al., 2010). Our results demonstrate that the Evenness rule outperforms most of the pure threshold rules with respect to average biomass levels and average annual catch variation, indicating that additional rules of this form could be worth exploring in other fisheries. It is likely that such HCRs would only be of particular use when applied to species and populations that are reliant on few large year-classes to sustain and grow the population (as is the case for most forage fish species) but further research into the appropriate form of the evenness scaling function (e.g. Equation 2.14) is needed to determine the conditions under which their use is appropriate. The Evenness rule developed here changes the allowable harvest rate based on age structure but alternative control rules could also manipulate the selectivity curve of a fishery as is recommended by Brunel and Piet (2013) (though this would be difficult for a purse-seine fishery, such as the one that predominately operates on PWS herring), or use slot limits to target particular ages (Barnett et al., 2017), a strategy that was found to positively impact catch, biomass, and catch variability in Norwegian spring spawning herring (*Clupea harengus)* (Enberg, 2005). Neither slot limits nor modifications to the fishery selectivity curve were used for the Evenness HCR due to difficulties posed by annual modification to fishing gear that would be required for implementation.

The Big Fish rule tested here is one of the first HCRs to set catch levels directly based on preferred weight of the individuals in the population, although weight distribution has been previously used as a performance metric for evaluating the performance of HCRs (e.g., Campbell & Dowling, 2003) and has even been shown to be a better indicator of biomass decline than catches or catch-per-unit-effort indices (Punt et al., 2001). While the Big Fish control rule did not perform particularly well when compared to the other threshold rules in this study, such a class of HCRs could be seen as analogous to length- or size-based control rules. In addition, if the performance metrics were weighted by economic value, the Big Fish rule may be ranked higher because catches of big fish are worth more to the fishing industry.

Utility functions are frequently used in the field of economics to identify optimal actions (Tversky & Kahneman, 1981) though there use in fisheries management, particularly in MSE, is limited. Where they are used in fisheries management, utility functions are often reduced to simple linear combinations of relevant management metrics (Keeney, 1977; Lane & Stephenson, 1998). This technique, however, makes specification of reasonable tradeoffs between competing metrics difficult to define for stakeholders (Bentley et al., 2003). We use the utility function described by Bentley et al. (2003) instead, because it allows for simple specification of minimum and maximum levels of utility for each metric, which is often easier for stakeholders to define. This type of utility function also has the benefit of quickly identifying HCRs that fail to meet pre-defined management objectives.

The utility function used here was constrained by the steep tradeoff between average biomass and average annual catch, and thus, generally, selected for HCRs with low annual catch variation (Figure 2.7, Figure 2.8). The catch-biomass tradeoff is common to many fisheries and is particularly steep here due to the population's reliance on large recruitment events to grow. With the catch-biomass tradeoff well defined, the top performing rules were those that performed well along the catch-catch variation tradeoff (Figure 2.8). Thus, HCRs that can simultaneously limit catch variation and maximize average biomass should perform best for this fishery, so long as they meet the minimum annual catch level (3,000 mt; Table 1.6). This could mean that constant fishing mortality rules, which limit annual catch variations could be viable, so long as the fishing mortality rate is sufficiently precautionary. Alternatively, placing annual limits on the amount that catches are allowed change (called "stability constraints") could improve some of the rules tested here (such as the gradient rule), which performed well with respect to catch and biomass, but suffered from high annual catch variation.

Model Complexity

One of the strengths of the MSE framework is its ability to evaluate how well HCRs perform when the underlying assumptions of the EM are incorrect by changing the OM. This study does not investigate the performance of its HCRs under different OMs and instead used an OM that nearly exactly matched the EM, except for mean recruitment. The OM used here is a relatively simple age-structured population dynamics model that includes a single spatial area, no time varying vital rates, no multispecies or ecosystem interactions, and integrates no environmental drivers. Siple et al. (2021) recommend that MSEs performed on small pelagic fishes, including most forage fish species, should account for one or more of these things to be compliant with Ecosystem Based Fisheries Management practices. However, including many of the recommendations made by Siple et al. (2021) was infeasible given the available data and current understanding of the biology, ecology, and dynamics of the PWS herring population. Furthermore, the objectives of this MSE were to specifically evaluate the efficacy of HCRs for managing the herring population. Future work plans to extend these results to test their robustness to model misspecification or added model complexity.

The one place in the OM where additional complexity was integrated was recruitment, which was modeled as a series of regimes (distinct from the EM which assumed recruitment deviates from a single long-term average level). Forage fish recruitment is characterized by "boom-bust" dynamics and, thus, the functional form of recruitment is exceptionally difficult to estimate (Subbey et al., 2014). Environmental drivers are frequently considered to be the cause of such variability, and can lead to distinct high and low recruitment regimes (Szuwalski et al., 2019) as was assumed by the OM. There is substantial literature regarding how to incorporate environmental drivers into MSEs (Brunel et al., 2010; Punt et al., 2013; Haltuch, M. A. et al., 2019), and there are multiple examples of MSEs using environmentally informed recruitment (e.g. Hurtado-Ferro et al., 2010; Tommasi et al., 2017). Much work has gone into trying to characterize drivers of recruitment for PWS herring, though no conclusive linkages have been discovered (Trochta & Branch, 2021), and there remains concern about using environmental indices directly for recruitment predictions where no relationships truly exist (De Oliveira & Butterworth, 2005). While environmental drivers were not directly included in the OM, modeling recruitment as occurring in distinct regimes is a first step towards accounting for environmental factors within the PWS ecosystem.

Extensions and Future Work

When maximum likelihood methods are used, catch advice usually relies on the mean of median of the estimated biomass distribution, or else assumes that biomass is normally distributed about the mean, which may not always be the case. The use of a fully Bayesian estimation method within this MSE alleviated this constraint, and opens the way for further use of probabilistic HCRs. Dankel et al. (2016) suggested that using such probabilistic control rules (then referred to as CI-HCRs) makes propagation of uncertainty more transparent and easier to understand for decision makers. The International Council for the Exploration of the Sea, uses a variation on this technique for its tier-2, data-rich stocks, where catch recommendations are set as a percentile of the catch distribution under an F_{MSY} harvest policy (ICES, 2022b). Similarly, on the U.S. West Coast, the National Marine Fisheries Service (NMFS) uses the P* (p-star) approach, whereby the allowable catch is reduced based on the uncertainty in biomass estimates for many stocks (Prager et al., 2003; Shertzer et al., 2010; Privitera-Johnson & Punt, 2019). Mildenberger et al. (2020) demonstrated that such probability-based HCRs lead to less variable fishing mortality rates and, ultimately, larger median population biomass, than their deterministic counterparts. While beyond the scope of this study, probabilistic control rules represent a potentially novel management technique that could now be computationally feasible to thoroughly study and test with MSE.

Another HCR form that was considered but ultimately discarded for this study would be rules that inherently account for regimes. Szuwalski and Punt (2012) developed and tested regime-based HCRs for snow crab in Alaska and found that their use can be risky unless the dynamics of the population are "truly regime-like". In contrast, Mohn and Chouinard (2007) found that populations displaying significant changes in productivity should be managed using HCRs that account for those changes in productivity. Among others, one of the major concerns regarding regime-based HCRs is how they detect a change in regime and how quickly they react to such a change. The Sequential T-test Analysis of Regime Shifts (STARS) algorithm (Rodionov, 2004) has been shown to be able to reliably detect changes in regimes, and has even been used within an MSE (Szuwalski & Punt, 2012) but it is an open question how managers should react to a detected change in regime. One option would be to select a distinct HCR to apply when each regime is active, although this could lead to overfishing if a shift from a high-productivity to a low-productivity regime occurs and is not promptly detected. Such situations could be common depending on how different the regimes are and how much uncertainty is present in the data being used to identify the regimes. A more advanced approach would be to have distinct regime-specific HCRs, as well as some linear combination of HCRs to apply when the ecosystem is moving between regimes, or when the regime cannot be positively identified. Either of these options could be useful in fisheries displaying long-running regimes, where shifts are infrequent but would likely lead to high annual catch variations if regimes switch frequently.

Future work on the PWS herring population should seek to better integrate the recommendations of Siple et al. (2021) or test the robustness of a subset of the HCRs evaluated here to additional complexity in the OM. For instance, Pacific herring are a key prey species for many marine predators in PWS (Pearson et al., 2012; Trochta & Branch, 2021), and, thus, a Model of Intermediate Complexity for Ecosystem (MICE) assessment (Plagányi et al., 2014) could be a valuable way to evaluate which control rules are robust to wider ecosystem needs. Additionally, integration of additional spatial complexity could be important for evaluating future survey design, as McGowan et al. (2021) found clear evidence of range contraction and expansion for PWS herring as the total population size fluctuated, which could bias future survey data if the entire range of the population is not surveyed.

Conclusion

With this MSE developed and validated, future work can begin to use it to investigate many other questions related to PWS herring. A value-of-information study would be useful for determining economically optimal survey coverage in future years, especially if the fishery was re-opened. There are also outstanding questions related to spatial stock structure and ecosystem interactions that could be investigated through the development of more complex OMs. Evaluating the robustness of the BASA model to model misspecification would also lend valuable insight into how best to manage this recovering population in coming years.

Tables and Figures

Table 2.1: Symbols and parameters used throughout the model equations.

Parameter Name	Symbol
Allowable harvest rate	h
Selectivity-at-age	v_a
Natural mortality at age	M_a
Long-term average log-recruitment (millions of individuals)	$\bar{R}$
Log-recruitment deviation from average in year, *y*	δ_y
Recruitment variability in year, *y*	σ_y^2

Table 2.2: Operating model (OM) equations (adapted from Muradian et al. (2017).

Equation Number	Description	Equation
2.1	Total allowable catch	$TAC = h \cdot B_y$
2.2	Purse-seine catch	$C_{1,y} = TAC \cdot 0.631$
2.3	Gillnet catch-at-age	$C_{2,y,a} = h \cdot 0.03 \cdot N_{y,a} \cdot v_a$
2.4	Pound catch-at-age	$C_{3,y,a} = h \cdot 0.177 \cdot N_{y,a} \cdot v_a$
2.5	Food-bait catch-at-age	$C_{4,y,a} = h \cdot 0.157 \cdot N_{y,a} \cdot v_a$
2.6	Spring catch (millions of fish), total number of fish caught by purse-seine, gillnet, and pound fishery	$C_{S,y,a} = \hat{\theta}_{y,a} C_{1,y} + C_{2,y,a} + C_{3,y,a}$
2.7	Half-year survival	$S_{y,a} = exp\left(-0.5M_a\right)$
2.8	Pre-fishery total abundance, age 0	$N_{y+1,\,0} = exp\left(\bar{R} + \delta_{y+1} - 0.5\sigma^2_{y+1}\right)$
2.9	Pre-fishery total abundance, ages 1-8	$N_{y+1,\,a+1} = \left[\left(N_{y,\,a} - C_{S,\,y,\,a}\right)S_{y,\,a} - C_{4,\,y,\,a}\right]S_{y,\,a}$
2.10	Pre-fishery total abundance, age 9+	$N_{y+1,\,9_+} = \left[\left(N_{y,\,8} - C_{S,\,y,\,8}\right)S_{y,\,8} - C_{4,\,y,\,8}\right]S_{y,\,8} + \left[\left(N_{y,\,9_+} - C_{S,\,y,\,9_+}\right)S_{y,\,9_+} - C_{4,\,y,\,9_+}\right]S_{y,\,9_+}$
2.11	Pre-fishery age composition	$\hat{\theta}_{y,a} = \dfrac{N_{y,a}}{\sum_a N_{y,a}}$
2.12	Pre-fishery total biomass	$B_y = \sum_{a=3}^{9+} N_{y,a} \cdot W_{y,a}$

Table 2.3: Natural mortality (*M*), survival (*S*), maturity, weight, fecundity, and proportion of the age class weighing >110 g for each of the 10 age classes used in the operating model and estimation model. Age classes for which biological information is unavailable due to data constraints are indicated by –.

Age	Natural Mortality (M)	Survival (S)	Proportion Mature	Average Weight (g)	Average Fecundity (eggs)	Proportion >110 g
0	0.25	0.778	0.00	–	–	–
1	0.25	0.778	0.00	–	–	–
2	0.25	0.778	0.00	–	–	–
3	0.25	0.778	0.60	70.34	10,289	0.01
4	0.25	0.778	0.96	90.24	14,084	0.28
5	0.25	0.778	1.00	116.16	17,308	0.65
6	0.25	0.778	1.00	131.81	20,284	0.85
7	0.25	0.778	1.00	146.67	22,775	0.94
8	0.25	0.778	1.00	161.97	25,397	0.99
9+	0.87	0.418	1.00	181.85	28,188	0.99

Table 2.4: Survey model sampling distributions and parameterizations. Standard deviations for the mile-days-of-milt survey follows from Muradian et al. (2019). $N_{y,a}$ represents the vector of number of individuals in each age class age three and greater during year y, s is the sample size of the multinomial distribution, p is the proportion of the population in each age class, q_j represents the catchability of the aerial school survey, and k is the overdispersion parameter for the negative binomial distribution.

Survey Name	Sampling Distribution	Parameters
Mile-days-of-Milt	Log normal: $\sim LN(\mu, \sigma)$	$\mu = 0$ $\sigma = 0.32$
Spawner Age-Composition	Multinomial: $\sim MN(s, p)$	$s = 1500$ $p = N_{y,a}/\sum N_{y,a}$
Age-1 Aerial Juvenile	Negative binomial $\sim NB(k, \mu)$	$\mu = N_{y,2}e^{q_j}$ $q_j = 71.16$ $k = 2.17$

Table 2.5: Harvest control rule parameterizations based on annual harvest rates (h). Limit and Target indicate the limit biomass threshold (below which h_{min} is applied) and target biomass threshold (above which h_{max} is applied).

HCR	Name	Type	h_{min}	h_{max}	Limit (mt)	Target (mt)	Notes
1	Default	Threshold	0.0	0.2	19,958	38,555	
2	Low Harvest	Threshold	0.0	0.1	19,958	38,555	
3	High Harvest	Threshold	0.0	0.4	19,958	38,555	
4	Low Threshold	Threshold	0.0	0.2	10,000	38,555	
5	High Threshold	Threshold	0.0	0.2	30,000	38,555	
6	Three-Step Threshold	Threshold	0.0	0.6	19,958	38,555	Default rule with additional step to h=0.6 occurring at a biomass of 60,000 mt
7	Evenness	Threshold	0.0	0.2	19,958	38,555	Default rule scaled by age structure evenness (Equation 2.14)
8	Biomass Gradient	Gradient	0.0	1.0	19,958	n/a	Default rule scaled by 3-year biomass change (Equation 2.15)
9	Big Fish	Threshold	0.0	0.2	19,958	38,555	Uses biomass of fish > 110 g instead of total biomass
10	No Fishing	Constant F	0.0	0.0	0	0.0	--

Table 2.6: Performance metrics used to compare and evaluate the relative performance of harvest control rules. Metrics were computed for each simulation and are reported as the median and 80% CI across simulations. B_y is the biomass in year *y* and C_y is the catch in year *y*.

Metric Name	**Symbol**	**Definition**	**Equation**
Annual Catch	C_{ann}	Average annual fishery catch (mt)	$C_{ann} = \frac{\sum_{i=1}^{30} C_y}{30}$
Average Annual Catch Variation	AAV	Average variation in catch between successive years	$AAV = \frac{1}{29}\sum_{y=2}^{30} \frac{\lvert C_y - C_{y-1} \rvert}{\overline{C}}$
Final Year Biomass Relative to Unfished Conditions	B_{fin}	Biomass in the final simulation year relative to unfished biomass	$B_{fin} = median\left(\frac{B_{30}}{B_{30}^{unfished}}\right)$
Average Biomass Relative to Unfished Conditions	B_{ann}	Average biomass across the simulation relative to unfished biomass	$B_{ann} = \frac{\sum_{y=1}^{30}\left(\frac{B_y}{B_y^{unfished}}\right)}{30}$
Lowest Biomass Relative to Unfished Conditions	B_{min}	Lowest single-year biomass relative to unfished biomass	$B_{min} = min\left(\frac{B_y}{B_y^{unfished}}\right)$
Proportion of Years Below Threshold	P_B	Proportion of simulation years median biomass (B_y) is less than 19,958 mt	$P_B = \frac{\sum_{y=1}^{30}\begin{cases} 0 & B_y \geq 19,958 \\ 1 & B_y < 19,958 \end{cases}}{30}$
Proportion of Years with an Open Fishery	P_O	Proportion of years that median biomass (B_y) is below the HCR specific limit threshold	$P_O = \frac{\sum_{y=1}^{30}\begin{cases} 0 & B_y \geq B_{lim} \\ 1 & B_y < B_{lim} \end{cases}}{30}$
Average Realized Harvest Rate	H_R	Median harvest rate across all simulation years	$H_R = \frac{median\left(\frac{C_y}{B_y}\right)}{30}$

Table 2.7: Threshold values for each performance metric used for calculation of total utility.

Performance Metric	**Minimum Acceptable Utility (m)**	**Maximum Utility Value (k)**
Annual Catch	3,000 mt	20,000 mt
Average Annual Catch Variation	1.0	0.0
Average Relative Biomass	0.5	1.0

Table 2.8: Total and relative utility values for each harvest control rule (HCR) as computed by Equation 2.16. Relative utilities are expressed relative to the HCR with the highest median total utility. The "Failed Metric" indicates which of the included metrics (annual catch, average annual catch variation, and average relative biomass) failed to meet the required minimum utility threshold (m).

Control Rule	Median Total Utility	Relative Utility	Failed Metric
Low Threshold	**0.336**	**1.000**	**–**
Default	0.309	0.921	–
Evenness	0.294	0.875	–
Gradient	0.227	0.675	–
Three-Step Threshold	0.212	0.631	–
High Harvest	0.206	0.613	–
Low Harvest	0.192	0.571	–
Big Fish Only	0.000	0.000	Annual Catch
High Threshold	0.000	0.000	Annual Catch
No Fishing	0.000	0.000	Annual Catch

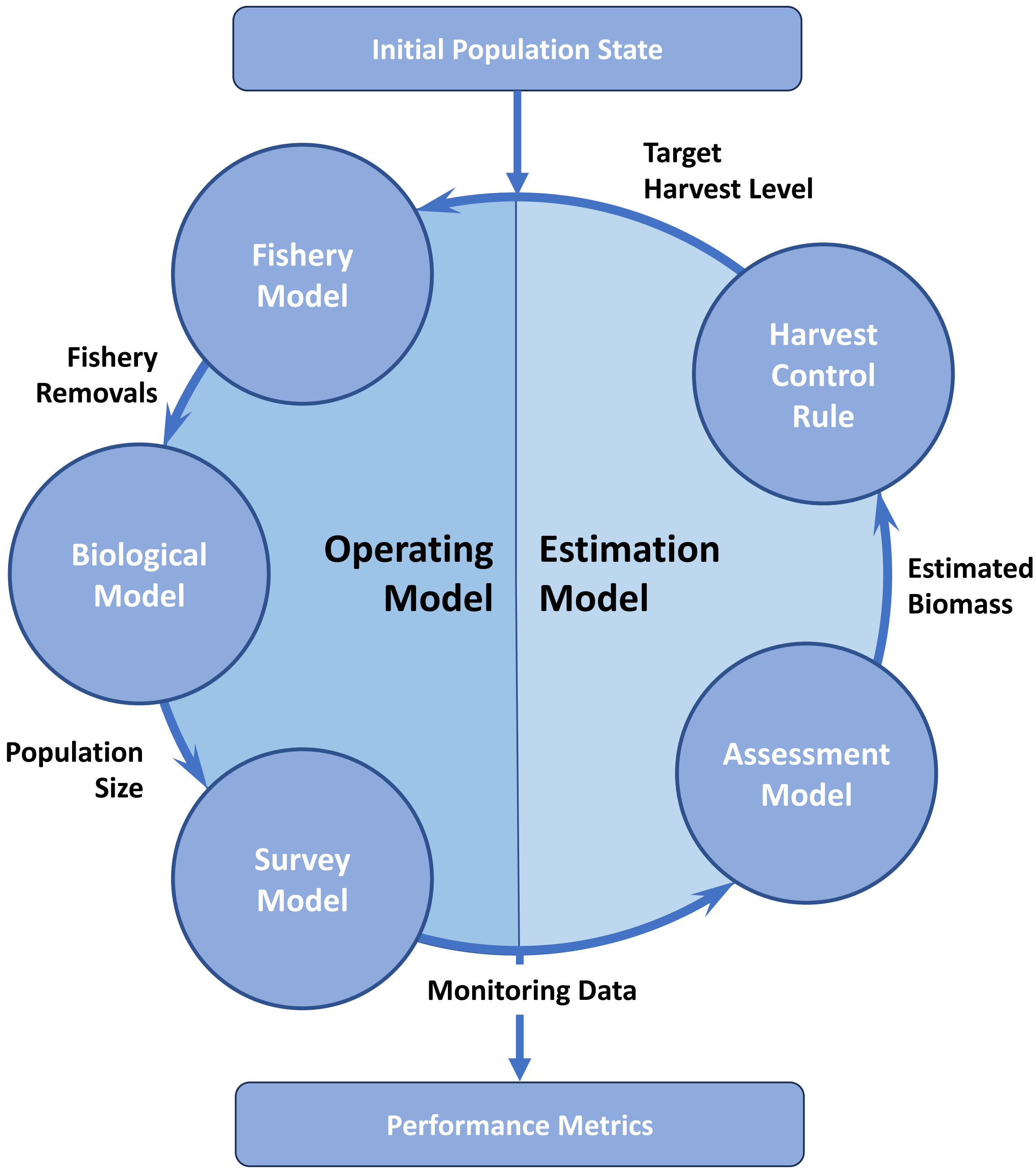

Figure 2.1: The MSE simulation framework (adapted from Punt et al. 2016).

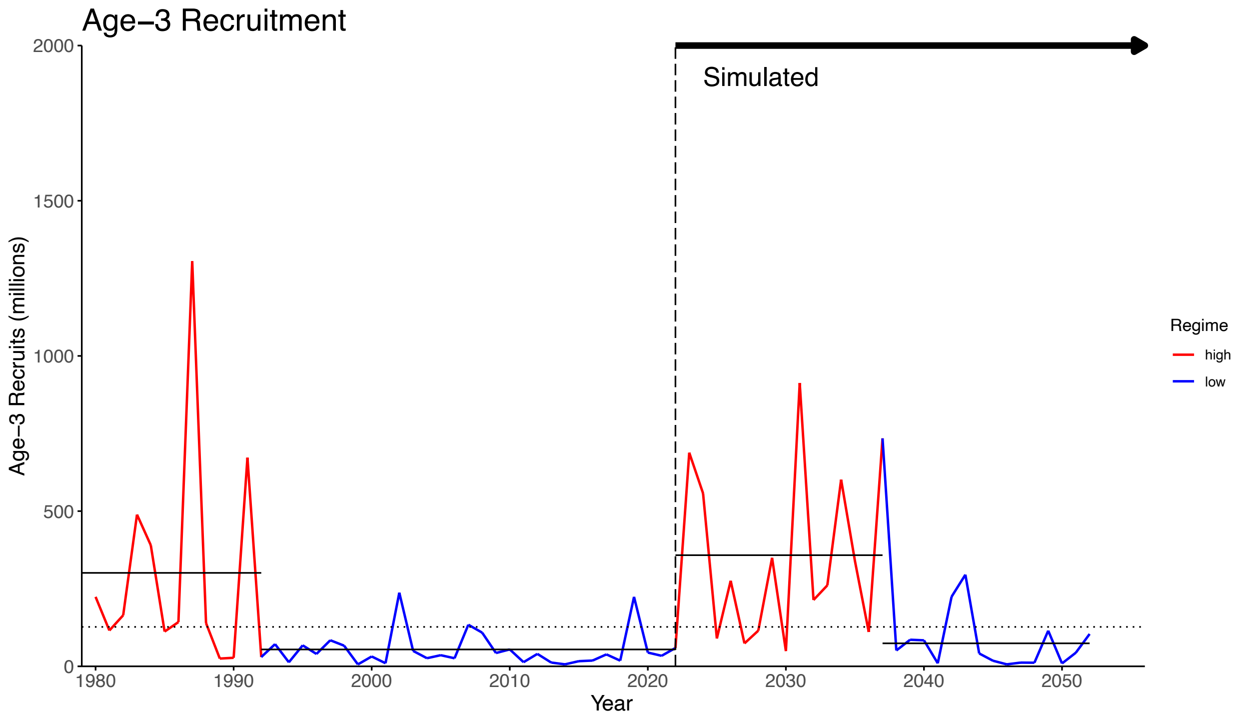

Figure 2.2: One randomly chosen future recruitment timeseries. The historical recruitment timeseries (1980–2021) shows evidence of two distinct regimes, a “high” regime (red) and a “low” regime (blue). Future recruitment is simulated from the high regime for 15 years and then from the low regime for 15 years. Solid horizontal lines indicate the mean recruitment level for each regime, and the horizontal dotted line indicates the average recruitment level ($\bar{R}$) from 1980–2022.

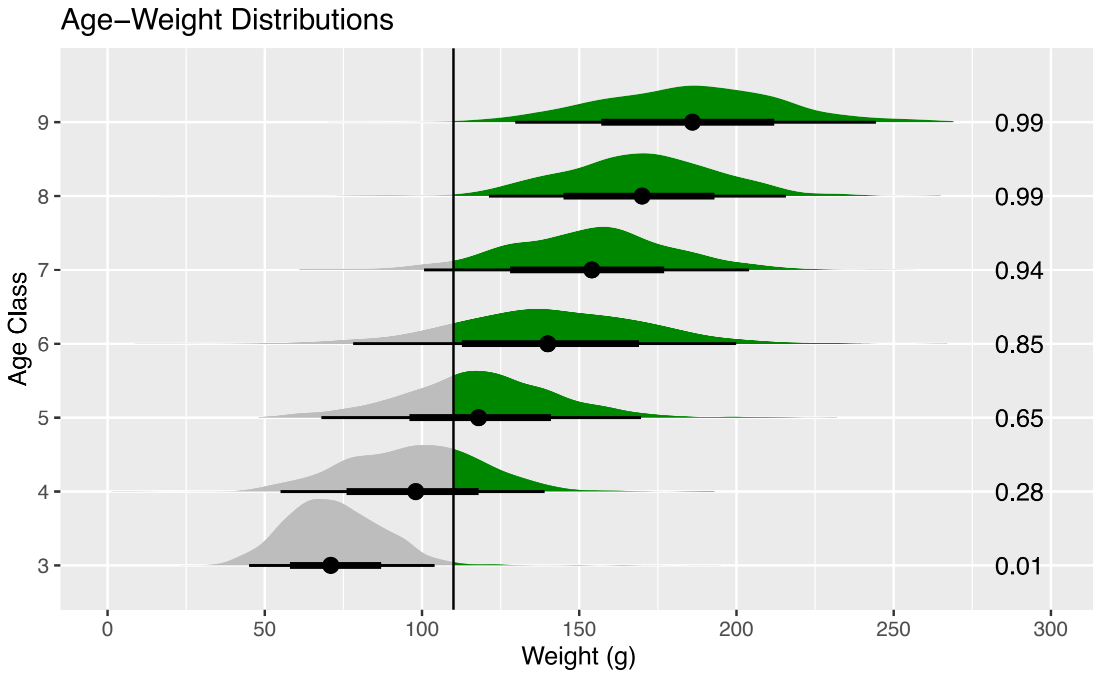

Figure 2.3: Weight distribution for age 3+ based on data from 1980–2021 provided by the Alaska Department of Fish & Game. The vertical line denotes the 110 g threshold used for the Big Fish rule, with the proportion above this line listed on the right for each age class. Points and lines show the median, 50% CI and 95% CI.

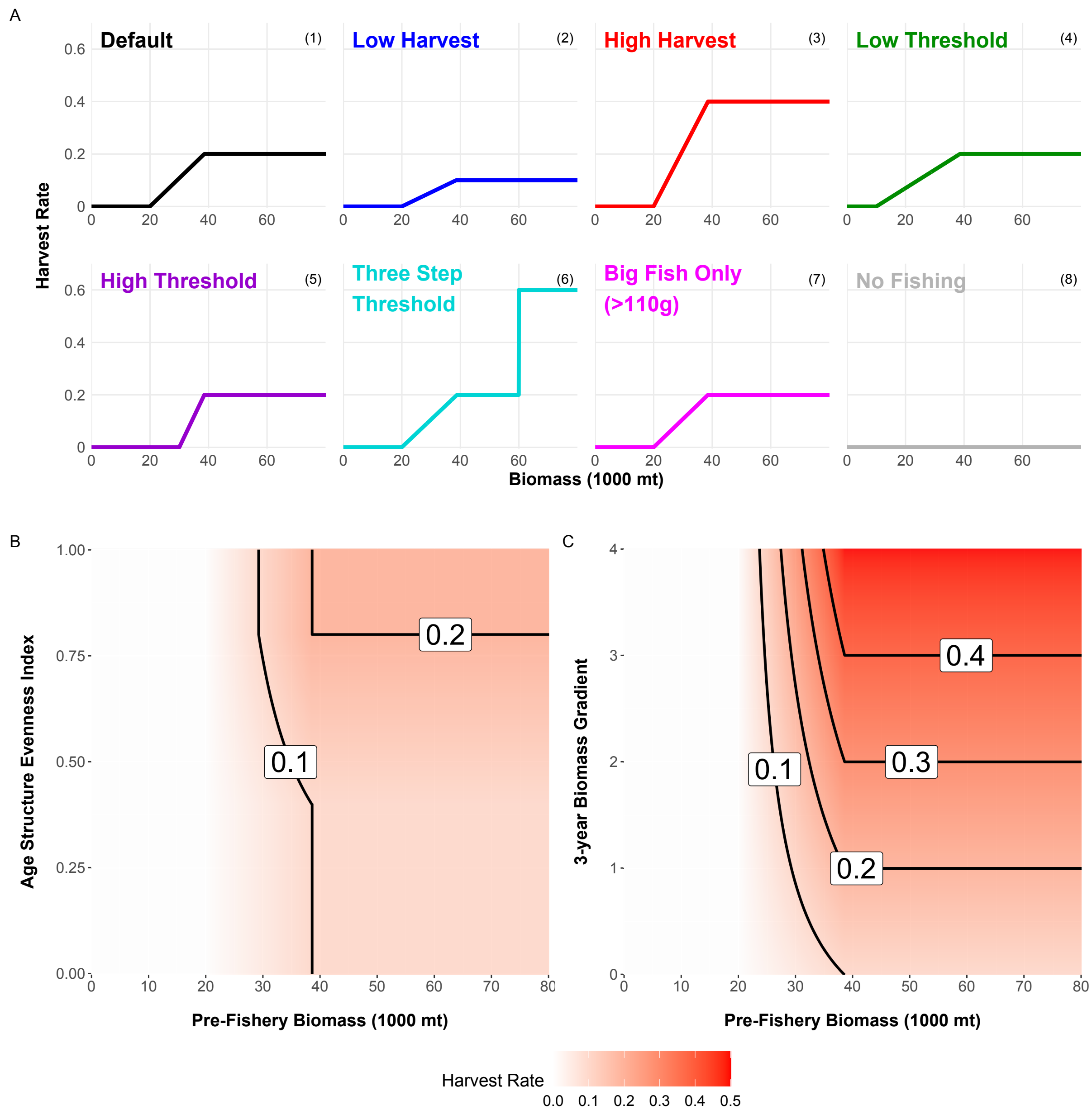

Figure 2.4: Relation between biomass and harvest rate for the ten harvest control rules (HCRs). The harvest rate for the Evenness and Gradient rules is indicated by the red shading and contour lines in the last two plots. [I advise relabelling the ten rules here 2.4A to 2.4J rather than 2.4.A1-2.4A7 and 2.4B and 2.4C]

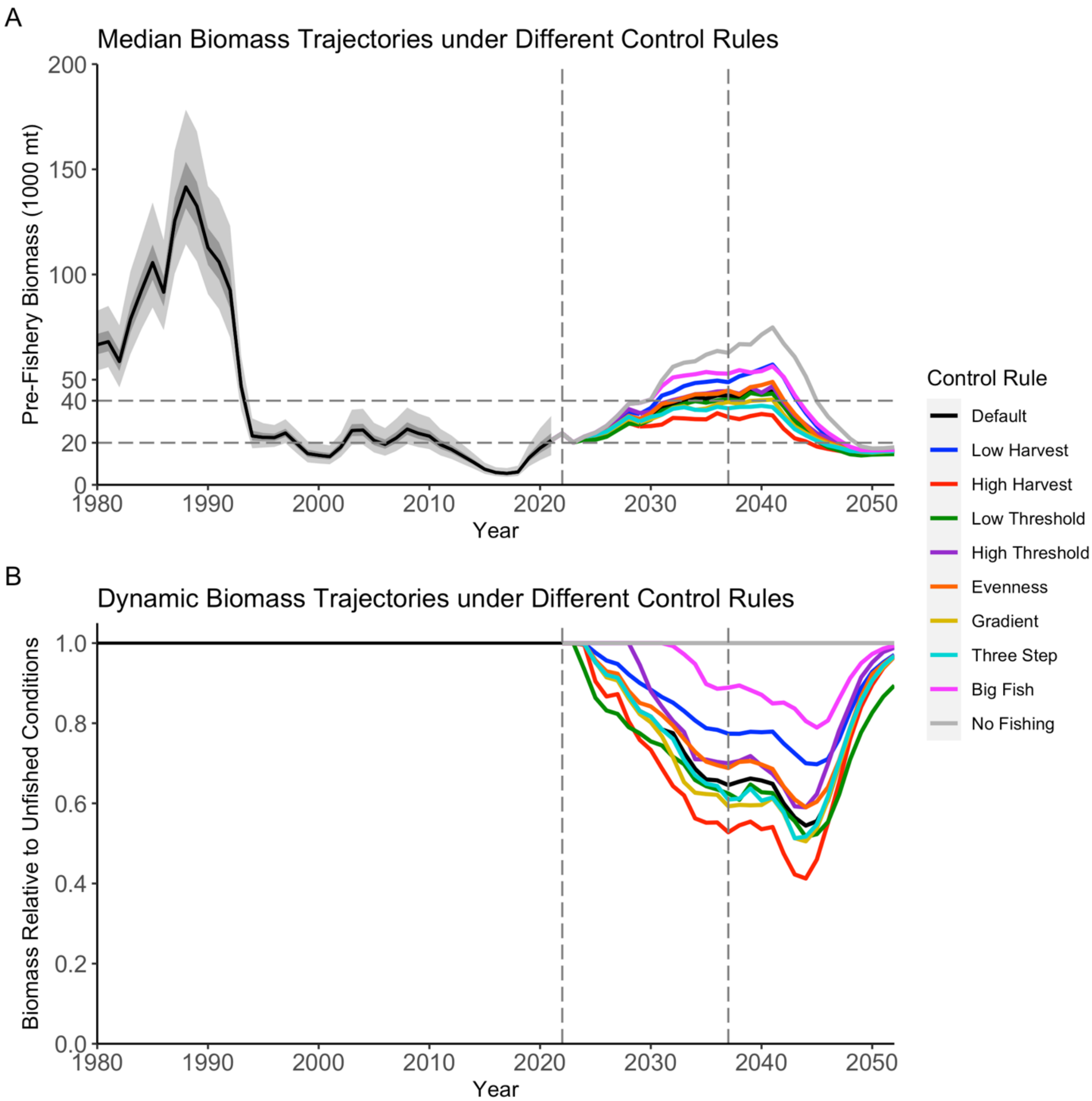

Figure 2.5: Biomass trajectories under the different HCRs. (a) The unscaled biomass trajectories in thousands of metric tons. (b) Biomass trajectories scaled relative to dynamic unfished biomass. Vertical dashed lines indicate the start of new recruitment regimes.

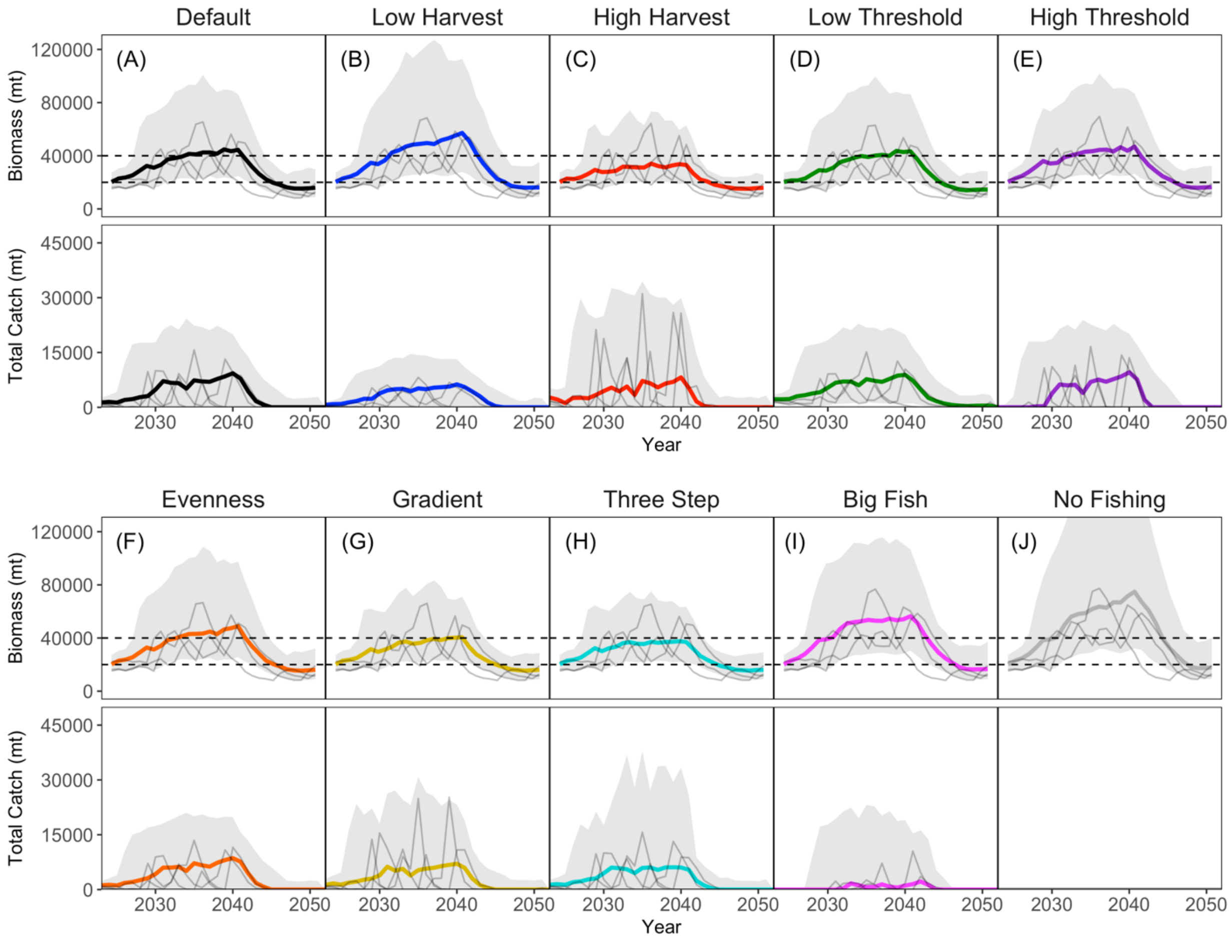

Figure 2.6: Biomass and annual catch trajectories over the 30-year simulation period. Thick colored lines are the median biomass and catch across 150 simulations, while thinner grey lines are five randomly selected biomass and catch trajectories. The grey shaded regions indicate the inner-80th percentiles.

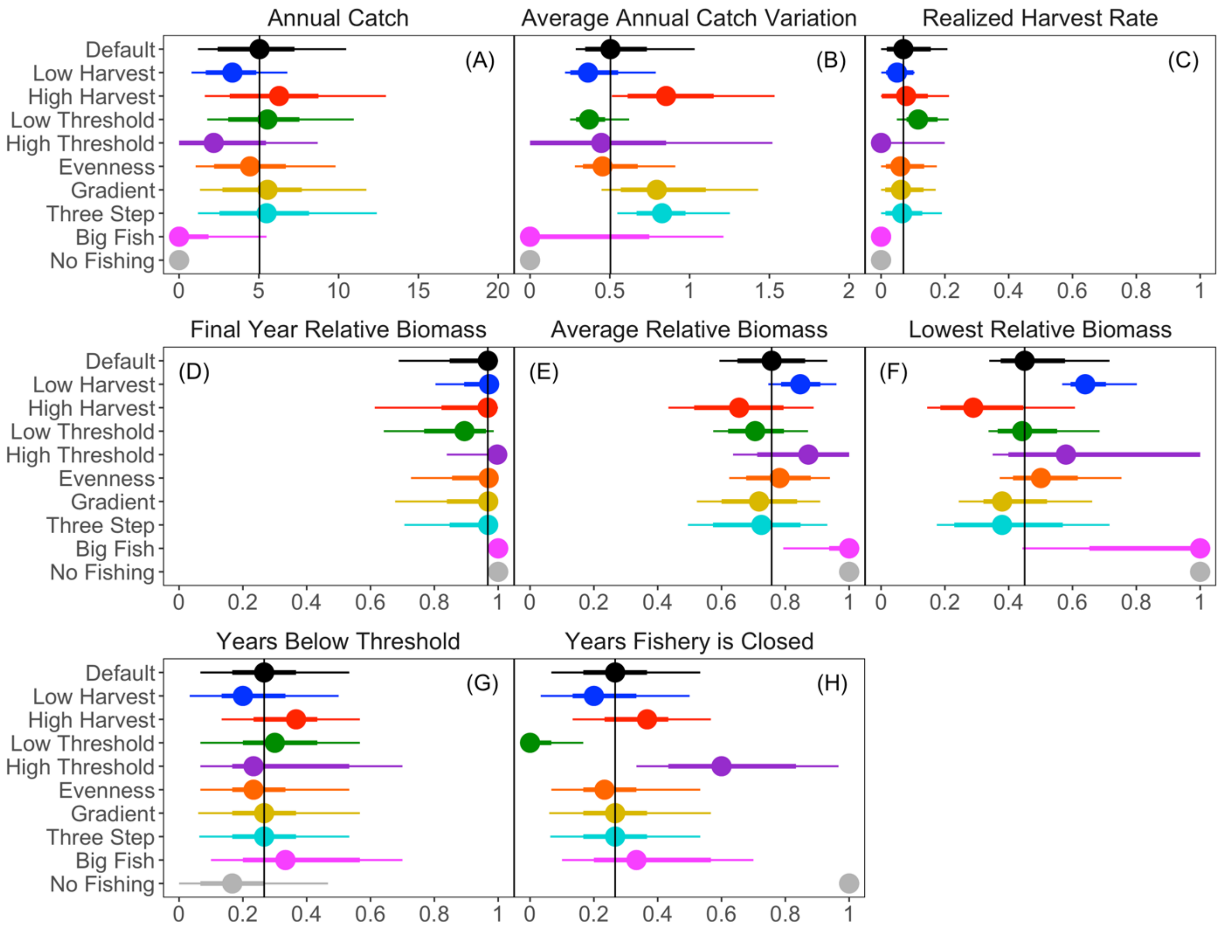

Figure 2.7: Performance metric summaries of tested harvest control rules. Large points indicate the median value of each performance metric across 150 simulations. Thick inner bars indicate the inner-50th percentile while the thin outer bars indicate the inner-80th percentile. Table 6 provides descriptions of the performance metrics.

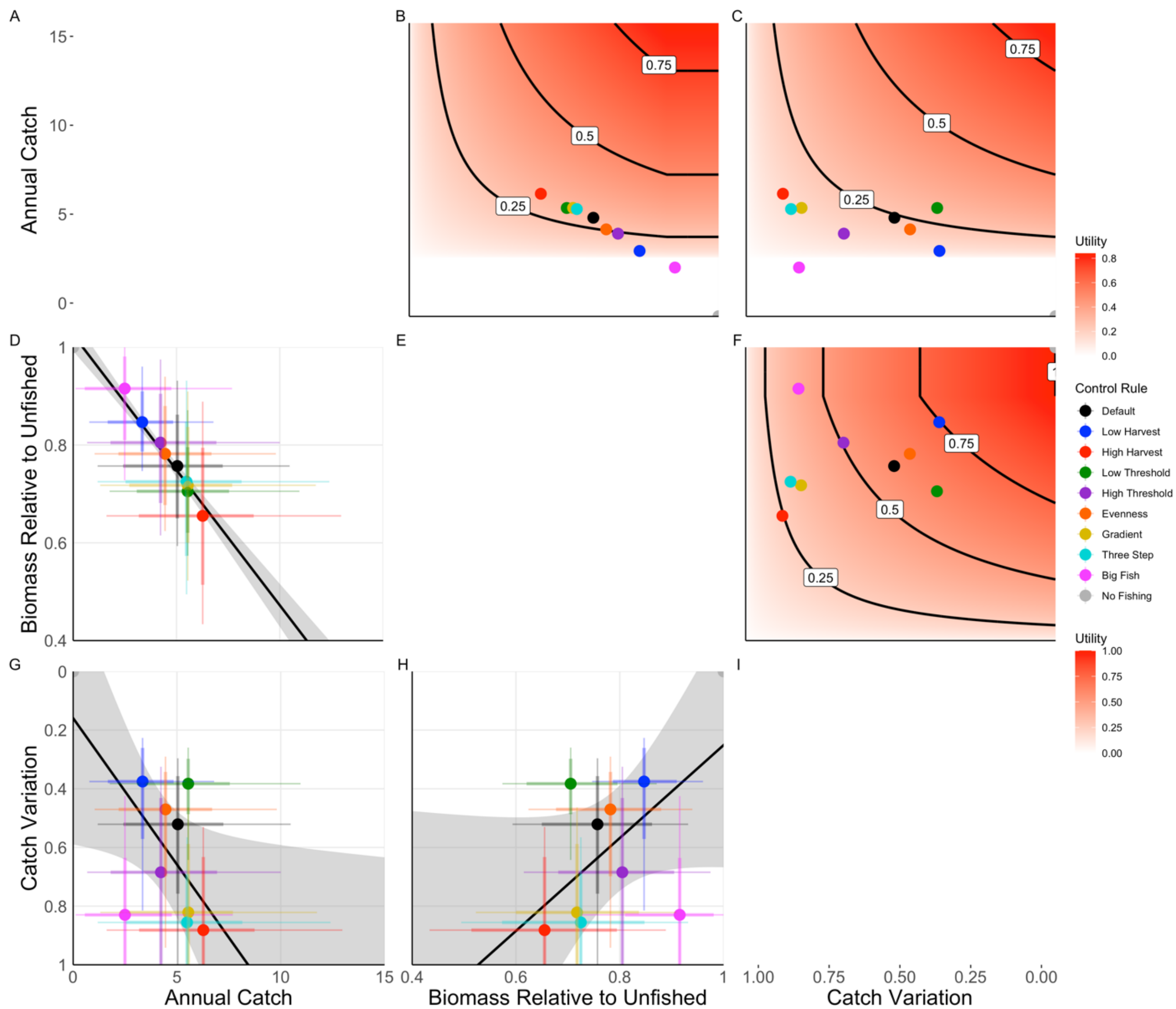

Figure 2.8: Performance tradeoff and total utility of harvest control rules. Colored points indicate the median metric value of each harvest control rule, while bars indicate the inner-50th and 80th percentiles. Solid black lines on lower three plots show the expected tradeoff between the two metrics. Background color on the upper three plots show the combined utility (Equations 2.16) for each combination of two of the three performance metrics.

Conclusion

Harvest control rules (HCRs) are among the most common forms of fisheries management in use at present, efficiently, and transparently, translating estimates of stock size and fishing mortality into allowable catch levels. They represent a critical tool for balancing trade-offs between the priorities of the fishing industry and subsistence fishers, who rely on consistent inter-annual catches, and conservation organizations, who seek to preserve fish populations. Historically, HCRs have been widely grouped as either constant catch, constant fishing mortality, constant escapement, or threshold rules (Deroba & Bence, 2008), though there remain an abundance of operational HCRs that take other forms. This wide range of functional forms, and their associated tradeoffs, has led to significant heterogeneity in the degree of their operational implementation (Free et al., 2023). Here, I explored trends in HCR form for fisheries around the world and performed a management strategy evaluation (MSE) to assess the efficacy of different HCR forms for the stock of Pacific herring in Prince William Sound, Alaska (PWS).

The adoption of HCRs across the world should come as no surprise, given their relationship with the precautionary approach to fisheries management and their inclusion in multiple major international agreements (FAO, 1995; United Nations, 1995). However, regardless of their near ubiquitous use in major fishing nations, Chapter 1 demonstrates wide-scale differences in the types of HCRs used to manage fish stocks across geographic regions. Some disparities are to be expected, given that many nations have their own unique fisheries management policy, and thus their own unique management objectives, but the degree of difference between regions is curious considering international agreement to implement the PA. For example, the U.S.A. makes liberal use of constant-F style rules, applying them to 152 stocks, where each of the other major regions only constant-F rules sparingly (29 stocks total). Similarly, Australia and the U.S.A. consistently apply constant catch rules to many data-limited stocks (78 stocks), where such rules are effectively non-existent in Canada and Europe (3 stocks). Constant F and constant catch control rules, while once widely accepted, are now considered to be largely non-precautionary due to their inability to react quickly to declines in stock size, whether induced by fishing or changes in environmental conditions. They have, thus, been restricted to use with more data-limited stocks, for which biomass and fishing mortality thresholds cannot be adequately defined. Meanwhile, European fisheries, following the advice of ICES, make substantial use of empirical catch-based rules (51 stocks) to manage data-moderate and data-limited stocks. Australia, Canada, and the U.S.A make only limited use of such techniques (9 stocks), despite their ability to increase catches without an associated rise in the risk of overfishing as compared to non-empirical catch-based or constant catch rules (Free et al., 2023).

One of the few aspects of HCRs that was agreed upon across regions and fisheries is the utilization of a "tiered approach to fisheries management", whereby different HCRs are applied based on the type of data or the reliability of the model outputs available for each stock. Such systems based on data availability are used throughout portions of the U.S.A, Europe, and Australia, and are in development for some fisheries in Canada. There are clear advantages to instituting and using a tiered approached for applying HCRs, including being able to flexibly tailor management approaches to available data streams and increased transparency regarding catch setting algorithms for stakeholders. However, there remains some discrepancy in the amount and types of data and assessment models required for a stock to be placed within a given tier. Of the four major regions analyzed in Chapter 1, members of the Europe Union, through ICES, possesses the most rigorous tier system, having been widely agreed upon by member nations of the EU and been thoroughly simulation tested to ensure compliance with the PA (see ICES, 2022a). This would make the ICES tier system a good starting point for standardizing fisheries management tiers and their associated HCRs globally. Certain aspects of management from other regions, such as the P* (p-star) approach from the U.S.A (Prager et al., 2003; Shertzer et al., 2010), and the use of maximum economic yield (MEY) as opposed to MSY from Australia (DAFF, 2007), could be further integrated to improve performance.

Wide scale acceptance of such a tier system, and corresponding HCRs, would likely require demonstrating not only that the tier system is compliant with multiple pre-existing national management policies—including the Magnusson-Stevens Fisheries Conservation and Management Act in the U.S.A., the Sustainable Fisheries Framework in Canada, the EU Mulitannual Plans in Europe, and the Commonwealth Fisheries Harvest Policy in Australia—but also that its implementation would result in improved, or, minimally, not degraded, performance for a vast majority of global fish stocks. Further use of the MSE framework, including the ability to rapidly develop and test species-specific operating models and management procedures, will be paramount for wide-scale acceptance of such a global tier system, and for ensuring that such tiers and HCRs are compliant not only with ideas of optimal single-species fisheries performance but also with the rapidly growing concept of ecosystem-based fisheries management (EBFM).

While a global tier-system of HCRs may be useful to strive towards at the international level, there will always be fisheries whose unique ecological or economic conditions necessitate a break from the outlined system. Pacific herring in PWS, represent one possible such case. The PWS herring population, which collapsed to less than 25% of its former population size in 1994, while technically managed using a threshold HCR (as would be recommended based on the amount of data available), has failed to rebound to pre-crash levels, despite almost 30 years of minimal fishing pressure. This lack of rebound is highly anomalous (Trochta et al., 2020) and calls into question whether the existing threshold HCR is appropriate to use in this circumstance. Chapter 2 develops an MSE for the PWS herring population to answer exactly this question.

Results from the herring MSE indicate that threshold HCRs remain a viable mechanism by which to manage the PWS herring stock, despite their seeming inability to return the stock to its former population size in recent years. Of the HCRs that were tested, this herring fishery performed best—when considering both fishery and conservation indicators—under a threshold rule that permitted fishing over a wider range of low stock biomasses. Such a rule was found to improve annual catches, decrease the probability of a complete fishery closure, and have limited impact on stock biomass. A novel HCR that integrates information regarding the current estimated age structure of the population was also found to result in slightly improved performance over the existing HCR, even though such an HCR form has never been previously used in an operational setting.

While the PWS MSE found threshold rules to be a viable management strategy for herring, their performance may be contingent on the presence, strength, and duration of favorable recruitment conditions within Prince William Sound. Many forage fish species experience spasmodic recruitment events even under ideal environmental conditions (Subbey et al., 2014), and PWS herring are no exception. High catch levels spanning 1930–1980 imply favorable recruitment conditions over much of that time period, while recent monitoring data and assessment estimates demonstrate substantially lower recruitment in more recent years (Muradian et al., 2017). The MSE simulations run in Chapter 2 are conditioned such that the population experiences 15 years of favorable recruitment conditions, like those in the 1980s, beginning in 2023. This decision was made to ensure that the fishery was open for a long duration under most of the tested HCRs, but it remains unclear whether the relative performance of the HCRs is contingent on the recruitment time series.

Future research could investigate the development of HCRs specifically meant to manage stocks that experience distinct productivity regimes. The duration of regimes, difference in average productivity levels, and timing of assessments or surveys would likely all play an important role in defining HCRs for regime-like stocks. Additionally, important interactions with other ecosystem components – notably humpback whales, seabirds, and some predatory fish species – were not considered in the design of the MSE or the HCRs that were tested, despite the recommendations of Siple et al. (2021) and Pikitch et al. (2012). A Model of Intermediate Complexity for Ecosystem assessment (Plagányi et al., 2014) could be a valuable future tool for evaluating if the current HCR, or the newly identified low threshold HCR, remain robust to ecosystem considerations within PWS. Analysis of the continued efficacy of the current monitoring approaches would also be a valuable extension to this work, particularly if the stock continues to rebound towards pre-crash levels and experiences an expansion in spawning area, as was found to have occurred during the biomass peak in the 1980s (McGowan et al., 2021).

In summary, this work reviews trends in the operational application of HCRs to over a thousand marine fisheries around the world before evaluating the efficacy of applying ten distinct rules to the PWS herring fishery that has been closed for since 2000. Operationally, HCR form was frequently found to align with the amount and type of data available, as well as the complexity of the implemented assessment method. Under a tiered approach to assigning HRCs, complex, model-based HCRs are reserved for the most data-rich stocks, while simpler, sometimes empirical HCRs, are applied in more data-poor situations. In the case of PWS herring, simulation results demonstrate that threshold rules are an appropriate management policy, while also indicating that accounting for additional stock information, such as annual age structure or recent biomass changes, may also be reasonable policies. The performance of these policies is, however, governed by highly variable, likely environmentally driven, patterns in recruitment that remain unpredictable. Regardless, this work demonstrates several possible ways forward for the PWS herring fishery, while also outlining where future research could be directed to improve management of this regional population.

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Appendix A

Geographic Regions

Stock level Harvest Control Rule (HCR) information – including the functional form of the catch setting algorithm, the presence of stability constraints, the inclusion of environmental covariates in the catch setting algorithm, the type of assessment model used, and the existence of a species-specific management strategy evaluation (MSE) – were collected from the following five regions: Australia, Canada, Japan, Western Europe, and the United States. A similar level of data was also collected for stocks managed by international tuna RFMOs and other international comissions.

Data for stocks in Australia were collated from the relevant harvest strategy documents published by the Australian Fisheries Management Authority (AFMA) for the 11 Australian Commonwealth fisheries. Data for stocks from Canada were collated from the associated Integrated Fisheries Management Plan documents published by Fisheries and Oceans Canada (DFO). Data for stocks in Japan was reused from Ohshimo and Yamakawa (2018). Data for European stocks was collated from the most recent ICES advice sheets, published and maintained by ICES. Data for stocks from the United States came from the associated Fisheries Management Plans published and maintained by the National Marine Fisheries Service (NMFS). U.S. data had already been collated by Free et al. (2023), and the generated HCR dataset was reused and augmented for this study. Data for highly migratory stocks under the jurisdiction of tuna RFMOs were collected from individual harvest plan documents published by the various RFMOs. Where possible, data were reviewed by scientists and managers familiar with the given management system to ensure accuracy. A complete list of stocks analyzed, as well as the associated HCR information is available as a supplement (Table A.S1).

Harvest Control Rule Forms

The shape of the HCR was classified into one of the following eight possible forms: *threshold F* rules that reduce allowable fishing mortality below a certain biomass level, *constant F* rules that apply the same level of fishing mortality across stock size, *constant escapement* rules that ensure a given level of escapement is achieved, *empirical catch-based* rules that update previous catch levels by empirical trends in survey indices, *catch-based* rules that update previous catch levels based on historical catch levels, *constant catch rules* that use the same catch level across all stock sizes, *catch prohibited* rules that do not allow fishing at any stock size, and *other* rules (Table 1.1; Figure 1.1). Other was used for HCRs where a functional form could not be identified or for stocks that were identified to not possess any HCR or were otherwise legally exempt from being managed by an HCR by their relevant management authority (e.g., tuna species in the U.S.A.). The classification system is directly descended from that used by Free et al. (2023) to classify U.S. stocks, but specifically differentiates between empirical and non-empirical catch-based rules and does not differentiate between "stepped F" and other "threshold F" rules.

Assessment Model Tiers

Where possible, the type of assessment method used for providing management advice for a particular stock was used to classify stocks into distinct "assessment tiers" (henceforth referred to as "tiers"). Many of the regions already possessed their own tier systems based on input data type and quality (ICES), assessment complexity, or parameter estimability (U.S. North Pacific Fisheries Management Council), although these tiers were rarely compatible among regions. All stocks were re-classified using the stock assessment model categories published as part of NOAA's Next Generation Stock Assessment [NSGA] plan (Lynch et al., 2018) to compare trends in HCRs among region and tier. These categories range from 1-6 in order of increasing assessment complexity: (1) data-limited, (2) index-based, (3) aggregate biomass dynamics, (4) virtual population analysis, (5) statistical catch-at-length, and (6) statistical catch-at-age. All regions were reclassified from their current tier systems to the new NGSA model categories based on the type of assessment used (Table A1). To better investigate aggregate trends, categories 4-6 were collapsed and considered "Data-Rich", categories 2-3 were collapsed and considered "Data-Moderate", and category 1 was considered "Data-Limited". Stocks that could not be assigned an NGSA model tier due to a lack of an identifiable assessment type were assigned a tier of 0, and subsequently considered "Unknown".

Species Groups

Species were categorized loosely into aggregated "species groups" based on life-history traits. These groups include *gadoids* (cods, haddocks, hakes), *flatfish* (e.g., flounders, sole, halibuts), *rockfish* (e.g., genus *Sebastes* and *Sebatolobus*), *forage fish* (e.g., herrings, anchovies, sardines), *elasmobranchs* (e.g., sharks, skates, dogfish), *salmonids* (e.g., salmons), *pelagics* (e.g., tunas, marlins, mackerels), *invertebrates* (e.g., crabs, lobsters, squids, shrimps), and *other* (e.g., reef fish, deep-sea fish). Some species that could not otherwise by confidently categorized were also included as "*other*". The species group assigned to each stock is available in Supplement A.S1.

Appendix B

Reduced Bayesian Sampling Routine

Best practices in Bayesian modeling often call for running multiple concurrent model chains for many thousands of samples, with additional checks for autocorrelation between samples within each model chain. These practices, if followed, result in high computational overhead in the form of model runtime. This high runtime often makes running large numbers of Bayesian models infeasible. This study ultimately ran 45,000 Bayesian models, and, thus, required models to run quickly, while still yielding accurate estimates of important derived quantities.

An external analysis performed using the Bayesian Age Structured Assessment (BASA) model for PWS herring with data through 2022 found that the median value of the critical derived quantity (pre-fishery spawning biomass) to be consistently estimated for models run using a variable number of model chains and chain lengths (Table B.1). Model convergence was also not substantially different across different numbers of chains or chain lengths. As such, we chose to run the Bayesian estimation model with 1 chain and 1,000 samples, allowing for all model runs to be completed in seven days, and accepting that the median estimate of pre-fishery biomass may be slightly imprecise (Table B.1). We believe that variability in the OM and across OM simulations ultimately swamps slight imprecision in the model parameter estimates caused by using a reduced number of chains and samples, and that, thus, the results presented in this study are robust to the exact Bayesian sampling scheme used.

Table B.1: Final year biomass, MCMC diagnostics, and total MSE runtime for different numbers of MCMC chains and different chain lengths. Total time is the expected total duration of the MSE for 10 control rules each simulated 150 times for 30 years (for a total of 45,000 assessments) parallelized across 20 compute cores. The total time is an underestimate due to sampling time increasing as additional years of data are added. The bolded row indicates the sampling routine used in this study.

N Chains	N Samples	Final Year Biomass	Proportion of divergences	Min ESS	Max Rhat	Time (s)	Total Time (dy)
1	**1,000**	**20,386.25**	**0**	**196**	**1.0239**	**53.60**	**1.395**
1	2,000	20,100.95	0	549	1.0111	102.70	2.674
1	5,000	20,125.95	0	253	1.0039	242.89	6.325
1	10,000	20,170.90	0	1988	1.0012	461.24	12.011
2	1,000	20,178.85	0	703	1.0075	62.20	3.239
2	2,000	20,143.50	0	1215	1.0043	112.80	5.875
2	5,000	20,070.20	0	1470	1.0022	263.39	13.718
2	10,000	20,153.40	0	4142	1.0008	514.72	26.808
4	1,000	20,161.00	0	1071	1.0057	67.48	7.029
4	2,000	20,172.50	0	2284	1.0037	122.92	12.804
4	5,000	20,145.35	0.0001	5913	1.0010	291.56	30.371
4	10,000	20,145.35	0.0001	5562	1.0007	571.43	59.524

Historical Age-Structure Evenness for Prince William Sound Pacific Herring

In common with many forage fish populations, the population of Pacific herring in PWS is characterized by unpredictable large recruitment events. This leads to the population age structure frequently being dominated by individuals from a single age class due to the relatively short life span of the species. The Evenness HCR attempts to take this directly into account by rescaling the allowable harvest rate based on the Shannon-Weiner definition of population evenness, applied to annual age structure. Historically, the age-structure of PWS Pacific herring has ranged widely, with many years being largely dominated by fish of a single age and some years with nearly equal proportions of fish in each age class. The Shannon-Weiner evenness metric (J) has consequently ranged from J=0.35 (2019) to J=0.95 (2013) (Table B.2, Figure B.1). The distribution of evenness values shows that the population tends towards more even age structures (large values of J), with over 30% of all years exhibiting an evenness value in the range of 0.80-0.90, and just two years (<5%) exhibiting evenness values <0.40.

Table B.2: Evenness values (J) computed using the Shannon-Weiner evenness formula for the PWS Pacific herring population since 1980. The age-composition from the ASL survey was used as the age-structure used for the calculation of J in each year (Zahner & Branch, 2023).

Year	J	Year	J	Year	J
1980		1994	0.65	2008	0.85
1981		1995	0.74	2009	0.75
1982	0.77	1996	0.84	2010	0.81
1983	0.83	1997	0.86	2011	0.79
1984	0.75	1998	0.79	2012	0.92
1985	0.86	1999	0.82	2013	0.95
1986	0.85	2000	0.88	2014	0.90
1987	0.85	2001	0.87	2015	0.88
1988	0.44	2002	0.58	2016	0.84
1989	0.41	2003	0.42	2017	0.67
1990	0.52	2004	0.48	2018	0.69
1991	0.67	2005	0.78	2019	0.32
1992	0.53	2006	0.75	2020	0.40
1993	0.65	2007	0.80	2021	0.53

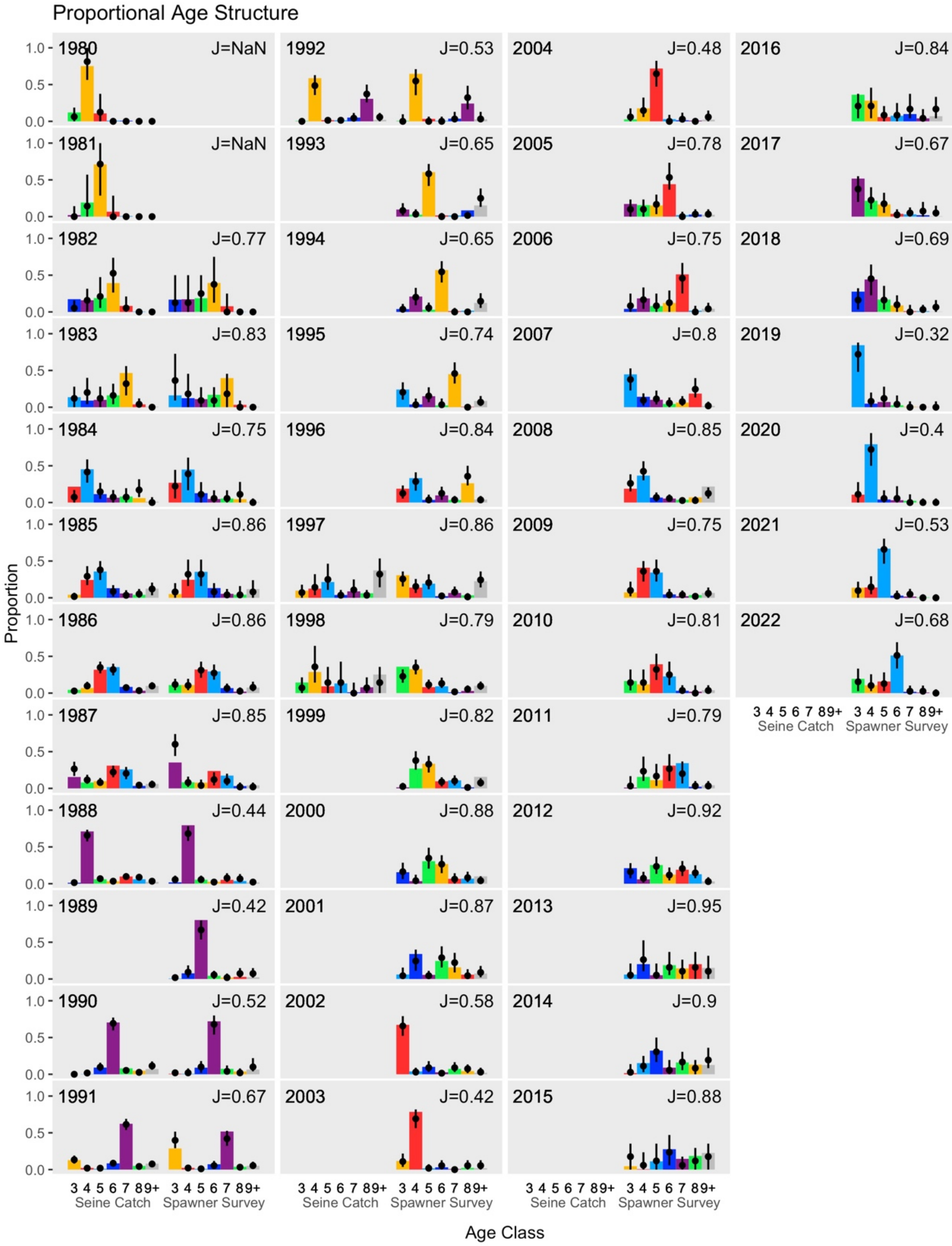

Figure B.1: Historical age compositions and corresponding evenness (J) values for each year. Evenness values calculated from the age composition from the ASL survey for each year. Each color bar follows a single cohort through the fishery.