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Abstract

Development and testing of single- and multi-species models for
fisheries management under climate change

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Abstract

Despite the large body of research suggesting that the population dynamics of fishes are affected by climate and species interactions, the majority of tactical fisheries management use single-species population dynamics models that assume individual populations are independent of one another and their environment. Multi-species management strategies that account for shifting productivity due to climate variability and species interactions have been proposed as an alternative to single-species approaches. However, research is needed to evaluate the performance of multi-species management strategies relative to single-species approaches while accounting for the feedback between management and fish populations through continued data collection and assessment. Here we expand on an existing climate-enhanced multi-species statistical catch-at-age modelling framework used in the Bering Sea Alaska, to add important features for application to four groundfish fisheries in the Gulf of Alaska. We further evaluate the performance of single- and multi-species management strategies using management strategy evaluation approaches. The first chapter develops the climate-linked multi-species statistical catch-at-age models for groundfish in the Gulf of Alaska. The second chapter uses the multi-species model as an operating model to assess the performance of single-species harvest control rules under predation scenarios. The third chapter compares the performance of single- and multi-species management strategies when the multi-species operating model is projected under alternative climate projections. Overall, we found single-species management strategies are robust to mis-specification in predator-prey and recruitment dynamics. Multi-species management strategies can outperform single-species strategies in terms of catch, trading off performance in catch variability and conservation performance metrics, when the multi-species estimation model is correctly specified. However, when multi-species estimation models are mis-specified, they may no longer outperform single-species approaches and care should be taken when selecting the multi-species harvest control rule. Our work addresses key questions regarding the performance of Ecosystem-Based Management compared to traditional single species management under climate change and the utility of management strategies that include ecosystem considerations such as multispecies interactions.

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Introduction

Variation in the productivity of exploited marine resources has long been understood to coincide with or be the result of variability in surrounding ecosystem conditions (Hjort, 1914). Changes in the productivity of marine resources can have multiple consequences for dependent human communities as ecosystem-driven shifts in the abundance, distribution, and size of exploited marine organisms can change the availability or value of marine organisms to communities (Pinsky and Fogarty, 2012; Smith et al., 2017). For example, fisheries can lag behind climate-driven distribution shifts of target species, and in some cases adaption to such spatial shifts is inhibited by regulatory burdens (Fisher et al., 2021; Liu et al., 2023; Pinsky and Fogarty, 2012). While the dynamics of marine organisms can be the result of multiple direct and indirect changes in marine ecosystems, shifts in productivity are often hypothesized to be in response to changing thermal conditions, predation, and harvest (Houde, 2008; Pinsky and Byler, 2015; Rose et al., 2024). The implications of such changes are concerning given the anticipated increases in temperature and restructuring of marine ecosystems due to anthropogenic climate change (IPCC, 2023, 2014; Pörtner et al., 2019). However, a challenge in marine resource management is understanding the specific mechanisms by which ecosystem change impacts marine populations and translating such knowledge into viable management actions and policies.

Currently, incorporation of ecosystem processes does not play a very large quantitative role in the majority of tactical management of exploited marine (or fisheries) resources despite copious calls for Ecosystem Based Fisheries Management (EBFM) (Dolan et al., 2016; Marshall et al., 2019; Skern-Mauritzen et al., 2015). EBFM is an adaptive approach that aims to account for the physical, biological, and social interactions among ecosystem components, accounting for uncertainty and multiple societal objectives (Dolan et al., 2016; Fogarty, 2014). For example, fluctuations in the biomass of prey species can impact the abundance of predators (Pikitch et al., 2014), and vice-versa (Jacobsen and Essington, 2018; Myers et al., 2007), and EBFM aims to explicitly incorporate such dynamics into the management process. EBFM also encompasses the incorporation of environmental covariates such as temperature into harvest control rules (e.g. Hill et al., 2016). However, continued research is needed to identify ecological processes that are not only relevant to an exploited resource, but how such processes can be effectively modelled and made relevant to management (Punt et al., 2014).

The continued development and testing of analytical tools that are purported to address EBFM needs is essential for guiding the management of fisheries resources in achieving and balancing multiple social, economic, and conservation objectives in the face of changing climate and ecological processes (Andersen et al., 2015; Deroba et al., 2015; Essington et al., 2018; Gaichas et al., 2017; Grüss et al., 2016; Punt et al., 2016). For example, the NOAA Fisheries guiding principles for EBFM include exploring and addressing trade-offs among fisheries, and incorporating ecosystem considerations into management advice (NMFS, 2016). Models of intermediate complexity for ecosystem assessments (MICE) are particularly valuable for providing tactical and strategic EBFM advice by accounting for trade-offs among multiple species targeted by several fisheries. MICE can be fit to data, provide estimates of parameter uncertainty, and can be parameterized to incorporate various ecological and ecosystem processes (Plagányi et al., 2014). Such models range in complexity from extended single-species population dynamics models, which relate static indices of predation (e.g. predator biomass) to the dynamics of a species of interest (Hollowed et al., 2000; Livingston and Methot, 1998; Spencer et al., 2016), to whole-

of-ecosystem models that evaluate energy pathways from biophysical drivers up to upper trophic levels and human systems (Fulton et al., 2011; Ortiz et al., 2016). Continued research and development of such models is needed to implement more effective EBFM across ecosystems, including the exploration of alternative parameterizations of ecological processes and uncertainty (Gaichas et al., 2017; Grüss et al., 2016; Trijoulet et al., 2019).

The goal of this dissertation is to extend and apply a climate-enhanced multispecies statistical catch-at-age analysis model originally developed for groundfish in the Bering Sea (CEATTLE [Climate-Enhanced, Age-based model with Temperature-specific Trophic Linkages and Energetics]; Holsman et al., 2016) and explore key questions regarding the multispecies “MICE”. Specifically, my dissertation will focus on the application and testing of CEATTLE fit to data for four groundfish in the Alaska: walleye pollock *Gadus chalcogrammus*, Pacific cod *Gadus macrocephalus*, arrowtooth flounder *Atheresthes stomias*, and Pacific halibut *Hippoglossus stenolepis*. These species were selected because management advice for them may differ depending how trophic interactions are modelled and because of their relative importance to commercial fisheries in the region.

The specific questions and associated chapters of my dissertation research focus on:

1. How do alternative assumptions regarding predation and halibut abundance impact the estimates of biomass of groundfish in the Gulf of Alaska?
2. Does ignoring time-varying predation mortality inhibit the ability of single-species management strategies to achieve management objectives?
3. Do multi-species management strategies better achieve management objectives in the face of predation and climate change?

The first chapter of this dissertation focuses on extending and applying CEATTLE to groundfish in the Gulf of Alaska using Template Model Builder (Kristensen et al., 2016). CEATTLE models comprise multiple age/sex-structured assessment models connected via a predation mortality component derived from MSVPA framework (Holsman et al., 2023, 2016). Predation mortality is modelled using a Type II functional response and is derived from temperature-dependent bioenergetics-based rations (i.e. annual consumption), static diet proportion-based suitability coefficients (i.e. predator selectivity), and predator abundance (Jurado-Molina et al., 2005). Models were fit to survey and fishery data for the Gulf of Alaska provided by the Alaska Fishery Science Center (AFSC) for Pacific cod, walleye pollock, and arrowtooth flounder (Livingston et al., 2017) and the International Pacific Halibut Commission (IPHC) for Pacific halibut (Stewart and Webster, 2022). Several models were developed to account for uncertainty in the distribution and abundance of Pacific halibut and a model averaging approach was used to estimate key quantities of interest.

The second chapter of this dissertation focuses on using the CEATTLE models developed for in Chapter 1 and for the Bering Sea as operating models and estimation methods for a management strategy evaluation designed to assess whether ignoring predation inhibits the performance of single-species management. Management currently accounts for technical interactions between each fishery, but assessment methods, biological reference points, and harvest control rules do not explicitly account for time-varying predation by assuming time-invariant (but perhaps age-specific) natural mortality. However, research has demonstrated that ignoring predation (time-varying mortality) can lead to a biased perception of underlying population dynamics and poor predictive performance of assessment models (Deroba and Schueller, 2013; Trijoulet et al., 2019).

The current management approach of using single-species assessment models linked to single-species harvest control rules was evaluated under alternative predation and fishing scenarios using a management strategy evaluation approach that accounts feedback control. The analysis used the models from the Gulf of Alaska and the eastern Bering Sea given the potential impact of differing trophic dynamics on management in the two systems.

In the Gulf of Alaska, climate change is likely to impact the recruitment and bioenergetics of groundfish, impacting species interactions via foraging rates, and predator-prey abundance (Barnes et al., 2018; Clark and Hare, 2002; Holsman et al., 2019; Holsman and Aydin, 2015). Such shifts in predator-prey interactions undermine the assumed equilibrium of reference points in single-species management, which highlights the need to evaluate the impact of climate-driven trophic dynamics on management performance. Harvest control rules and biological reference points that account for shifting productivity due to climate variability and species interactions have been proposed as an alternative to single species approaches (Moffitt et al., 2016; O’Leary et al., 2019). Therefore, building upon my work from chapter 2, the third chapter uses a management strategy evaluation approach to evaluate if multi-species harvest control rules better achieve management objectives in the face of predation and climate change. Data were simulated from multi-species operating models that incorporated different Coupled Model Intercomparison Project phase 6 (CMIP6) climate projections under different carbon scenarios (SSP1-2.6, SSP2-4.5, and SSP5-8.5) which were downscaled to the Gulf of Alaska using a high resolution ROMSNPZ model (Hermann et al. in prep). The scenarios represented a range of future emission scenarios resulting in 2 to 5 degrees of warming. The performance of single- and multi-species management strategies fit to the simulated data was then compared across scenarios.

The tools developed through this dissertation have had immediate and lasting significance for fisheries management in Alaska and can be used to advance EBFM in the Gulf of Alaska. Models developed in Chapter 1 have been directly used as a supplement to current tactical fisheries management in the GOA by producing multi-species biological reference points and informing future research needs for EBFM in the region. The code base and modelling framework have been applied to systems outside of Alaska. This work provides a quantitative basis to guide the use of single- and multi-species managements strategies and advances the operational use of multi-species stock assessments in Alaska. The management strategy evaluations developed in chapters 2 and 3 advance the testing of EBFM tools and represents an advancement in the use of multi-species models in full management strategy evaluations. The use of multiple management strategies, systems, and scenarios aims to increase the application of the results to fisheries systems outside of Alaska.

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Chapter 1: An ensemble approach to understand predation mortality for groundfish in the Gulf of Alaska

ABSTRACT

There is increasing consensus of the need for ecosystem-based fisheries management (EBFM), which accounts for trophic interactions and environmental conditions when managing exploited marine resources. Continued development and testing of analytical tools that are expected to address EBFM needs are essential for guiding the management of fisheries resources in achieving and balancing multiple social, economic, and conservation objectives. To address these needs, we present and compare alternative climate-informed multi-species statistical catch-at-age models to account for spatio-temporal differences in stock distributions, with application to four groundfish species (walleye pollock *Gadus chalcogrammus*, Pacific cod *Gadus macrocephalus*, arrowtooth flounder *Atheresthes stomias*, and Pacific halibut *Hippoglossus stenolepis*) in the Gulf of Alaska, USA. We integrate across multiple forms of uncertainty regarding the data and distribution of Pacific halibut using an ensemble modelling approach. Models developed here can be used to supplement current tactical fisheries management and inform on the trade-offs between harvesting across groundfish in the Gulf of Alaska. This approach may be applicable for other situations where spatial and temporal overlap is extensive among closely coupled species.

1.1 INTRODUCTION

Changes in the population dynamics of exploited marine resources have long been understood to coincide with, or be the result, of trophic interactions (Hjort, 1914; Volterra, 1926). Yet, for various reasons, incorporation of ecosystem covariates and processes directly in stock assessments and management advice is not commonplace, although it is increasing (Dolan et al., 2016; Marshall et al., 2019; Skern-Mauritzen et al., 2015). Ecosystem Based Fisheries Management (EBFM) tools provide frameworks for quantifying ecological and climate impacts on harvest recommendations, and are increasingly important in the context of climate change (e.g., Barbeaux et al., 2020). EBFM aims to manage fisheries resources by recognizing, in part, the trophic interactions among multiple fisheries (Dolan et al., 2016), for example, that fluctuations in the biomass of prey species can impact the abundance of predators (Pikitch et al., 2014) and vice-versa (Myers et al., 2007). EBFM approaches range from qualitative advice and inclusion of ecosystem information as context for near-term decision making to explicit incorporation of trophic and climate interactions into the management process (Fogarty and Rose, 2014; Howell et al., 2021; Levin et al., 2009; Marshall et al., 2018; Plagányi et al., 2022; Zador et al., 2017).

The continued development and testing of analytical tools that are expected to address EBFM needs is essential for guiding the management of fisheries resources in achieving and balancing multiple social, economic, and conservation objectives (Andersen et al., 2015; Deroba et al., 2015; Essington et al., 2018; Gaichas et al., 2017; Grüss et al., 2016; Punt et al., 2016). Multispecies and ecosystem models can directly account for trade-offs across objectives for multiple interdependent fisheries through explicit incorporation of trophic interactions (Fulton et al., 2019). Multispecies and ecosystem models range in complexity and application. At its most complex are well-known end-to-end ecosystem models such as Ecopath with Ecosim (Christensen and Walters, 2004) and Atlantis (Fulton et al., 2011) that model the energy pathways of entire food webs given parameter inputs. Such models are often used to support strategic, long-term management decision making

by focusing on predicting broad scale changes across fisheries because of inherent structural uncertainty and a lack of fitting to observed data. At the less complex end of the range, are models of intermediate complexity for ecosystem assessments (MICE) (Plagányi et al., 2014), which estimate the ecological and population dynamics of a small number of interacting species to address specific management concerns. MICE strike a balance between the single-species population dynamics models used to support tactical fisheries management decisions and end-to-end ecosystem models. MICE have particular utility in EBFM as they are statistically fit to data and provide estimates of parameter uncertainty, are designed to incorporate various ecological and ecosystem processes, and can be readily applied in an management strategy evaluation framework to quantify trade-offs among multiple species targeted by several fisheries (Plagányi et al., 2014).

Multispecies statistical catch-at-age analysis (MSCAA) is one type of MICE that has been developed to provide EBFM advice (Curti et al., 2013; Holsman et al., 2016; Jurado-Molina et al., 2005; Kinzey and Punt, 2009; Tsehaye et al., 2014; Van Kirk et al., 2010). Developed in part from the underpinnings of multispecies virtual population analysis (MSVPA; Jurado-Molina et al., 2005; Magnusson, 1995), MSCAA links single-species age-structured models through predation. The biological realism of these models comes at the cost of increased complexity, and possible increased uncertainty in estimated quantities (research on forecast performance is limited). Predation is conditioned on bioenergetics and diet information to parameterize consumption and the preference patterns of predators (Curti et al., 2013; Holsman et al., 2016; Kinzey and Punt, 2009). MSCAA can also estimate parameter uncertainty and account for process and observation error (Trijoulet et al., 2019). MSCAA can be parameterized similarly to single-species models used for tactical management and, therefore, are easily transitioned into current management frameworks. Similarly, MSCAA can also be used to derive fisheries reference points used for tactical management decision making (Gislason, 1999; Holsman et al., 2020; Moffitt et al., 2016).

MSCAA are particularly valuable for estimating time- and age-varying natural mortality and in some cases have been found to have improved predictive performance as compared to single species models that ignored predation (Trijoulet et al., 2020). However, MSCAA models may be particularly difficult to apply in situations where interacting populations do not share similar spatio-temporal distributions. For example, Pacific halibut *Hippoglossus stenolepis* are broadly distributed across the eastern Pacific Ocean and exhibit considerable interannual and seasonal movement (Carpi et al., 2021). However, food web analysis has indicated that Pacific halibut is highly connected to populations that inhabit much smaller ranges in the Gulf of Alaska (GOA), including: walleye pollock *Gadus chalcogrammus*, Pacific cod *Gadus macrocephalus*, and arrowtooth flounder *Atheresthes stomias* (Gaichas and Francis, 2008). The interannual and seasonal movement of Pacific halibut is hypothesized to have consequences for the dynamics of other groundfish species (Barnes et al., 2018). While there is interest in developing MSCAA in systems such as the GOA, misspecification of spatio-temporal distributions of populations can lead to bias in estimates of predation and biomass in MSCAA models (Kempf et al., 2010), limiting their utility for providing management advice. This highlights the need to develop models that account for variable spatio-temporal distributions among stocks to understand processes such as the historical and future impacts of Pacific halibut predation on groundfish stocks in the GOA.

Several approaches have been proposed to account for interdependent stocks that vary in their spatial overlap. Estimates of predator abundance have been multiplied by indices of predator-prey overlap to scale predation mortality (Kempf et al., 2010). This approach may be biased if the data used to derive overlap indices are limited by the spatio-temporal distribution of sampling. For example, due to seasonality in the timing of the interannual migration of Pacific halibut through

the GOA, actual overlap at shelf depths may differ between synoptic summer survey observations and cumulative annual patterns. Alternatively, predator biomass can be derived from survey data across the distribution of prey species and input into extended single-species models and MSCAA (e.g., Carroll et al., 2019; Spencer et al., 2016; van Kirk et al., 2012) or total predator abundance input into extended single-species models and scaled by an estimable proportionality constant (e.g., Hollowed et al., 2000). However, these approaches do not dynamically account for impacts of predator age- and size-structure on prey populations, or the influence of environmental conditions (e.g., temperature) on predation demand. While MSCAA are sufficiently flexible to incorporate different approaches for accounting for variable spatio-temporal overlap of predator and prey, each approach will likely lead to differing perceptions of the dynamics of prey populations and should be evaluated relative to the data available.

As an alternative to developing a single “best” model, we developed a suite of models that differ in structure and/or data extent. We used this suite as an ensemble to provide a better representation of uncertainty in predation mortality arising from differences in spatio-temporal distributions of predator and prey populations (Millar et al., 2015; Hoeting et al., 1999, Stewart and Hicks, 2018). The ensemble consists of alternative MSCAA that account for spatio-temporal differences in stock distributions, with application to groundfish in the GOA. The core model was based on a climate-enhanced MSCAA model originally developed for groundfish in the Bering Sea (CEATTLE; Holsman et al., 2016). We adopted it to the GOA ecosystem and included key groundfish stocks (walleye pollock, Pacific cod, Pacific halibut, and arrowtooth flounder). CEATTLE (Climate-Enhanced, Age-based model with Temperature-specific Trophic Linkages and Energetics) uses fishery and survey data to estimate trends in biomass, predation, and recruitment. It is linked to climate via temperature-specific, bioenergetics-based predation functions. We expand on the original model to allow for multiple fisheries, surveys, sexes, selectivity functions, and the inclusion of fixed predator abundances (e.g., predators-as-fleets or “extended MSCAA”) to account for the population dynamics of Pacific halibut. Additionally, sensitivity to how Pacific halibut predation is incorporated was explored by using an ensemble approach to average over, respectively, alternative parameterizations, data, and historical distributions.

1.2 METHODS

1.2.1 Study area

The GOA is a topographically diverse ecosystem that supports many commercial fisheries whose target species exhibit strong trophic interactions (Zador et al., 2019). Walleye pollock, Pacific cod, Pacific halibut, and arrowtooth flounder are some of the most intensively sampled fish species in the GOA (Gaichas and Francis, 2008; Livingston et al., 2017), and they support some of the largest fisheries in the region by volume (Fissel et al., 2020). For this study, we used the management areas for each species in the western and central GOA (Fig. 1.1). Pollock in the GOA is managed in National Marine Fisheries Service (NMFS) management areas 610, 620, 630, and 640 west of 140° W (Dorn et al., 2018). Pacific cod is managed in NMFS areas 610 to 659, with the majority (90%) of the biomass found west of 140° W (Barbeaux et al., 2018). Arrowtooth flounder is managed in NMFS areas 610 to 650, with the majority (85%) of the biomass found west of 140° W (Spies and Palsson, 2018). Pacific halibut is managed and assessed from California to the Bering Sea (Stewart and Hicks, 2019). However, given the majority of the biomass for the three other groundfish is found in the western and central GOA, we parametrized the model based on halibut from the IPHC Regulatory Areas 3A and 3B (grey region, Fig. 1.1).

1.2.2 Assessment data

The MSCAA developed here is only fitted to data for walleye pollock, Pacific cod and arrowtooth flounder; the model is not fitted to data for Pacific halibut - the numbers-at-age over time for Pacific halibut are instead pre-specified. This approach was used to simplify estimation because Pacific Halibut are primarily predators in the system (Gaichas et al., 2011) and predation on halibut was not a focus of this study. Additionally, Pacific halibut dynamics are driven by environmental- and density-related factors over a much wider geographic range than the GOA (Clark and Hare, 2002). The data included in the likelihood function are indices of relative abundance or biomass and age- or length-composition data from the National Oceanic and Atmospheric Administration, Alaska Fishery Science Center (NOAA, AFSC) and Alaska Department of Fish and Game (ADFG), time series of total catch (metric tonnes) and fishery age- or length-composition data for these species. Index and composition data used for parameter estimation are the same as those used in recent stock-assessments (Barbeaux et al., 2018; Dorn et al., 2018; Spies and Pálsson, 2018). Data input directly (i.e., not included in the likelihood function) include the mean weight-at-age, maturity-at-age, spawning month, ageing error, and age-length transition matrices, which were extracted from recent stock-assessments (Barbeaux et al., 2018; Dorn et al., 2018; Spies and Pálsson, 2018).

Estimated mid-year numbers-at-age for Pacific Halibut from the most recent stock assessment and relative abundance-at-age from the IPHC set-line survey were used as model inputs. The assessment of Pacific halibut consists of multi-model averaging across four equally weighted models fit using Stock Synthesis (Methot and Wetzel, 2013) to estimate trends between 1996 and 2018 (Stewart and Hicks, 2019): long-time (1917-2018) and short-time (1996-2018) series models with either a single-fleet (coast-wide) or four-fleet configuration (areas-as-fleets). The areas-as-fleets approach is used to account for potential differences in selectivity and catchability of fisheries and surveys among regions, allowing the model to better account for spatio-temporal trends in data collection and fishing patterns. This avoids issues of extrapolating data to the coastwide level. Each of the models also differ in terms of the scale of natural mortality. Numbers-at-age from the four IPHC models represent the Pacific halibut stock from California to the Bering Sea. To scale the annual numbers-at-age to the GOA, the annual proportion of the halibut stock age 5+ by mass in IPHC Regulatory Areas 3A and 3B between 1993 and 2019 was taken from the IPHC fishery-independent setline survey (Stewart and Webster, 2022; Supplementary Fig. S.1). The weight-at-age for halibut was also restricted to just IPHC Regulatory Areas 3A and 3B. Relative abundance-at-age estimates of halibut age 5+ from the IPHC fisheries independent set-line survey were used as a sensitivity analysis (see below). Very few Pacific halibut less than 5 years old are captured by the IPHC fisheries independent set-line survey and, therefore, therefore using age-5+ includes the broadest age range possible (Stewart and Webster, 2022).

1.2.3 Diet data

Data used to parameterize predation include temperature-specific predation ration from Holsman and Aydin (2015) and Holsman et al. (2019a), water temperature from the AFSC bottom trawl survey, and the average diet proportions by weight of predators-at-age for prey-at-age sampled from the AFSC bottom trawl survey (Livingston et al., 2017)(Table 1.1). The average diet proportion by weight of predators-at-age for prey-at-age ($\bar{U}_{pbjisa}$; Eq. 1.1 below) was estimated using stomach content data following an approach adapted from previous studies (Barnes et al., 2020; Stewart and Hamel, 2014; Supplementary material S1). $\bar{U}_{pbjisa}$ was assumed to pertain for all years to account for biennial sampling and a lack of standardized data prior to 1990 (Table 1.1;

Equation 1.2) and averaged across data starting in 1990, 1993, or 1996 to 2015 depending on model variant (see below). While stomach content data were sampled prior to 1990, sampling was opportunistic and the diet data for the years prior to 1990 were consequently excluded (i.e., averages from stomach data for 1990- 2015 were applied to these earlier years). The average diet proportion was estimated by averaging annual proportions of prey-at-age in the stomach of a predator-at-age across years relative to annual abundance-at-age:

$$\text{Eq. 1.1.} \quad \bar{U}_{pbjisa} = \frac{\sum_y \hat{U}_{pbjisay} \hat{I}_{py}}{\sum_y \hat{I}_{py}}$$

where $\bar{U}_{pbjisa}$ is the average proportion of prey i of sex s and age a in the stomach of predator p of sex b and age j , $\hat{U}_{pbjisay}$ is the annual proportion, and $\hat{I}_{py}$ relative abundance of predator p in year y estimated from the AFSC bottom trawl survey (see supplementary material S1 for derivation). MSCAA models require data on the proportion of prey-at-age, by weight, in the stomach of predator-at-age relative to all other prey/ages while diet proportion data were obtained as weights categorized into predators-at-length and prey-at-length. Moreover, the AFSC uses a length-based stratified random sampling design for bottom trawl surveys in the GOA. $\hat{U}_{pbjisay}$ was calculated from the annual length-based diet proportions (see supplementary material S1 for calculation) by utilizing age-transition matrices to account for variability in length-at-age:

$$\text{Eq. 1.2.} \quad \hat{U}_{pbjisay} = \frac{\sum_a \sum_k \hat{U}_{pkily} ALK_{isaly} ALK_{pbjky}}{\sum_a \sum_k ALK_{isaly} ALK_{pbjky}}$$

where $\hat{U}_{pkily}$ is the proportion of prey i of length l in the stomachs of predator p of length k in year y and ALK_{isaly} and ALK_{pbjky} are annual age-length transition matrices for prey species i and predator species p , respectively, used to account for interannual variability in length-at-age (see supplementary material for more information).

1.2.4 Population model

CEATTLE is an age-structured model that follows cohorts of individuals of a species, age, and sex through time (Table 1.2). Annual recruitment (Eq. S1.T1.1.) and the initial age-structure (Eq. S1.T1.2.) are estimated and are treated as random effects, with the variance in recruitment estimated. Walleye pollock and Pacific cod are treated as sex-combined while males and females are modelled separately for arrowtooth flounder and Pacific halibut to account for differential growth and sex-specific predation. The sex-ratio at birth is assumed to be 0.5 for arrowtooth flounder and Pacific halibut. Natural mortality (M) can be input, estimated, or partitioned into predation mortality ($M2$) and non-predation related mortality ($M1$) (Eq S1.T1.11 and S1.T1.13), the latter of which is either input or estimated, and accounts for mortality related to causes other than predation by the species included in the model.

1.2.5 Predation ($M2$)

Predation mortality is modelled following previous MSCAA models (Curti et al., 2013; Holsman et al., 2016; Tsehay et al., 2014). Predation mortality due to a predator-at-age is derived from empirically derived suitability coefficients, estimates of annual consumption, estimated or input biomass, and input biomass of other prey in the system (B_p^{other}) (Table 1.1). Suitability represents a predator's prey and size preference and factors such as spatial overlap in the distribution of predators and prey. Suitability is derived empirically from the ratio of mean proportion (by weight) of prey-at-age in the stomach of predators-at-age (Eq. 1.1; Table 1.1). Magnusson (1995) provides

details on the derivation of suitability coefficients. Bioenergetics-based, temperature- and age-dependent consumption rates (g/g/d) were based on previous studies (Holsman et al., 2019a; Holsman and Aydin, 2015). Estimated average biomass is used to derive predation mortality and because of the interdependence between predation and biomass, predation mortality and the underlying age-structured dynamics was iteratively estimated until convergence occurred. Preliminary analysis suggested that three iterations were sufficient for convergence. Models were insensitive to a range of B_p^{other} and therefore, we, utilized values from Holsman et al. (2016), which were derived from ecosystem-wide biomass estimates for the Eastern Bering Sea.

1.2.6 Observation model (walleye pollock, Pacific cod, arrowtooth flounder)

CEATTLE was fit to time series of fishery and survey biomass, sex-ratio, and length- or age-composition data. Log-fishery catch, log-survey biomass and sex-ratio were assumed to be normally distributed, while age- and length-composition data were fit assuming multinomial distributions (Table 1.3). Variance parameters for the lognormal distributions and initial input sample size for the multinomial distributions were assumed known. Separate selectivity and catchability functions were estimated for each survey or fishery (Table 1.4). For walleye pollock and arrowtooth flounder CEATTLE was parameterized almost exactly as in recent stock assessments (Dorn et al., 2018; Spies and Palsson, 2018). The implementation of CEATTLE for walleye pollock differed from the actual assessment in that lognormal recruitment deviates for all years rather than only the foremost and terminal years were penalized assuming a normal distribution and known or estimated variance. The implementation for arrowtooth flounder differed from the actual assessment in that non-parametric selectivity penalties for males were assumed to be the same as for females. The Pacific cod assessment was simplified to use marginal length-composition data rather than conditional age-at-length, and selectivity functions were selected to mimic the general form of selectivity in the Pacific cod assessment, while limiting the use of double normal time-varying selectivity (Table 1.4). Comparison of time-series of biomass and spawning stock biomass between single-species CEATTLE models and the actual stock assessments showed agreement when CEATTLE ignored predation (Supplementary Fig. S1.2).

1.2.7 Including halibut in the model

Rather than estimate the numbers-at-age for both sexes of Pacific halibut as part of the model fitting process, estimated numbers-at-age for both sexes were directly input into the model (Eq. S1. T1.3.). Numbers were either provided as absolute or relative numbers-at-age. In the former case, numbers-at-age were calculated as the numbers-at-age for both sexes at the mid-point of the year from the four IPHC sub-models multiplied by the annual proportion of the halibut stock age 5+ in management area 3 (d_{iy}) from IPHC fisheries independent set-line survey (Stewart and Webster, 2022). In the case of relative numbers-at-age, relative abundance-at-age for both sexes of halibut age 5+ in IPHC Regulatory Areas 3A and 3B from the IPHC fisheries independent set-line survey ($\hat{I}_{isay}$; Stewart and Webster, 2022) were multiplied by an estimable parameter ($\tilde{q}_i$) to scale the relative-numbers-at-age to numbers-at-age that may be relevant for predation. We assumed a linear relationship between relative-abundance-at-age and abundance-at-age following the Pacific halibut stock assessment. No data for Pacific halibut are included in the likelihood function so any estimate of $\tilde{q}_i$ is based on the fit to the data for the remaining species.

1.2.8 Model variants

Sixteen model variants were constructed to evaluate the impact of alternative ways to include predation by Pacific halibut in the assessment. Specifically, models were fit that excluded and included predation mortality and evaluated alternative assumptions regarding the distribution and abundance of Pacific halibut. To account for time differences in data availability (Table 1.5), eight long time-series models (models 1-8) were constructed that spanned 1977 to 2018; three medium time-series models (models 9-11) were constructed that spanned 1993 to 2018; and five short time-series models (models 12-16) were constructed that spanned 1996 to 2018. The long time-series models represent the longest time-series for which data were available for all species and utilizes diet proportion data averaged over 1990 and 2015 (Eq. 1.1). The medium time series models account for the period when relative abundance-at-age data are available for Pacific halibut and utilize diet proportion data averaged over 1993 and 2015. The short time-series models account for the period during which mid-year numbers-at-age of Pacific halibut were available from the short-term models in the multimodel assessment (estimates of mid-year numbers-at-age were unavailable for the start year of the model) and we averaged diet proportion data from 1996 through 2015. Models were constructed using estimates of the mid-year numbers-at-age from each of the four Pacific halibut models (long- and short time-series coastwide and areas-as-fleets models) to account for differences in the assumptions and data used in the Pacific halibut assessment (Stewart and Hicks, 2019). As mentioned above, numbers-at-age of Pacific halibut were scaled to the GOA using the relative proportion of age-5+ halibut (based on selectivity of the survey) in IPHC Regulatory Areas 3A and 3B between 1993 and 2018. Alternative assumptions regarding the distribution of halibut in the GOA prior to 1993 are described below and in Table 1.5.

The long time-series models for 1977 to 2018 were:

- Model 1: a model that did not include predation (i.e., a set of single-species models), representing a base model.
- Model 2: a model that did not include halibut predation to allow comparisons in which halibut does not impact the dynamics of groundfish in the GOA.
- Models 3-5: models that included pre-specified mid-year numbers-at-age of Pacific halibut from the coastwide long-time (1917-2018) series model developed by the IPHC. To account for a lack of information on halibut distribution prior to 1993, numbers-at-age prior to 1993 were multiplied by the 50th (model 3), 15th (model 4), and 85th (model 5) quantiles of the proportion of adult halibut in area 3 between 1993 and 2018 assuming no temporal variation prior to 1993 (Supplementary Fig. S1.1).
- Models 6-8: as for models 3-5 but using numbers-at-age of Pacific halibut from the areas-as-fleets long-time series model.

The three medium term models for 1993 to 2018 were:

- Model 9: a set of single-species models to represent a base single-species model.
- Model 10: a model that did not include halibut predation.
- Model 11: a model with relative abundance-at-age of Pacific halibut in area 3 multiplied by an estimated parameter to allow the model to estimate the relative contribution of Pacific halibut predation to describe the dynamics of pollock, Pacific cod, and arrowtooth flounder.

The five short term models for 1996 to 2018 were:

- Model 12: a set of single-species models to represent a base single-species model.
- Model 13: a model that did not include halibut predation.

- Model 14: a model with pre-specified mid-year numbers-at-age of Pacific halibut from the coastwide short-time series model.
- Model 15: as for model 14, but using numbers-at-age for Pacific halibut from the areas-as-fleets short-time series model
- Model 16: as for model 11, but using relative abundance-at-age of Pacific halibut multiplied by an estimated scaling parameter, but with the model starting in 1996.

1.2.9 Model comparison and model averaging

Individual models were fit using Template Model Builder (TMB; Kristensen et al., 2015) and were compared using the Akaike Information Criterion (AIC; Burnham and Anderson, 2004) and associated delta AIC (ΔAIC) and AIC weights (W_i) and by evaluating the fit to each data source. In age-structured stock assessments, AIC is sensitive to the relative contribution of each likelihood component and tuning weights can be used to reduce conflicts between different data sources (Francis, 2011). Therefore, we used the tuned sample sizes for arrowtooth flounder and walleye pollock and tuned the sample size of marginal age- and length- composition data of Pacific cod using the harmonic mean of the effective sample size from the McAllister and Ianelli method (McAllister and Ianelli, 1997; Punt, 2017). Composition weights were tuned using the single-species models and held at those values for all multispecies models. AIC was compared separately for the long (1977 to 2018), medium (1993 to 2018), and short time series models (1996 to 2018) given the differences in likelihood between those sets of models. Similarly, multispecies models are sensitive to the value of residual natural mortality (M_1), so we estimated age-invariant M_1 for each species and sex across all models that included predation. For models that excluded predation, age-variant total natural mortality (M) was fixed at the value input or estimated (in the case of Pacific cod) in recent assessments (Supplementary Table S1.3; Barbeaux et al., 2018; Dorn et al., 2018; Spies and Palsson, 2018).

We used an ensemble modelling approach to account for uncertainty arising from the time-series of data used, the distribution of Pacific halibut in the GOA, and in the numbers-at-age of Pacific halibut (arising from treatments of historical data and spatial dimension of the data used for the ensemble halibut model; Stewart and Hicks, 2019). Four ensemble models were developed assuming equal weights for numbers-at-age of Pacific halibut used in the individual model: Avg 1) a single-species ensemble model (Models 1, 9, and 12), Avg 2) a multi-species ensemble model assuming no halibut predation (Models 2, 10, and 13), Avg 3) a multi-species ensemble model including halibut predation derived in part from pre-specified mid-year numbers-at-age of each of the four halibut sub-models (Models 3-8 and 14-15), and Avg 4) a multi-species ensemble model including halibut predation derived in part from relative numbers-at-age (Models 11 and 16). For Avg 3, models 3-5 and 6-8 were collectively given the same weight as models 14-15. Confidence intervals for derived quantities from ensemble models were estimated via a simulation approach. Parameter sets were simulated from a multivariate normal distribution with a mean of the maximum likelihood estimated parameters and variance of the inverse of the estimated joint Hessian matrix. Estimates of derived quantities of interest (recruitment, biomass, spawning stock biomass) were then calculated for each parameter set. Confidence intervals were then calculated across sets of derived quantities across sub-models.

1.3 RESULTS

1.3.1 Fit to data

Three single-species and 13 multi-species age-structured models were fit to fishery and survey data for walleye pollock, arrowtooth flounder, Pacific cod, and Pacific halibut data in the GOA.

Models that included predation mortality, but excluded predation from Pacific halibut led to the lowest AIC for all time-series (Tables 5-6). For the long and medium time-series models (Models 1-8), single-species models provided the best fit overall to the composition data (Table 6). Alternatively, for the long and medium time-series models (Models 9-11), models that included predation provided the best fit to the index data (Table 6). For short-time series models (Models 12-16), the single-species model (Model 12) led to the best fit to the index data (model 12), while the model that included predation (Model 13) led to the best fit to the composition data and the two models had a comparable AIC.

1.3.2 Comparison of alternative time series length from individual models

The long-, medium-, and short-term multi-species models fit with different Pacific halibut numbers-at-age had similar trends in population quantities for some time periods (Supplementary Figs. S1.3-5). However, the long-term models differed slightly between short- and medium-term models. For example, recent estimates of biomass and spawning stock biomass of walleye pollock and arrowtooth flounder were estimated to be slightly greater in 1996 from long time-term multi-species models (Supplementary Figs. S1.3-4). While we estimated that arrowtooth flounder consumed the most biomass of walleye pollock in all multi-species models, the short-term models (Models 13-16) estimated that arrowtooth flounder consumed more biomass of walleye pollock than the long- and medium-term models (Supplementary Fig. S1.7). Cannibalism of arrowtooth flounder also differed among the long-, medium-, and short-term models (Supplementary Fig. S1.7) and total natural mortality ($M1 + M2$) was estimated to be lower in the long- versus short-term models for walleye pollock (Supplementary Fig. S1.9).

1.3.3 Comparison of alternative halibut distributions from individual models

For the long time-series models, estimates of biomass, spawning stock biomass, and recruitment varied little among assumptions regarding historical Pacific halibut distribution in the GOA pre-1993 (Supplementary Figs. S1.3-5). 15th, 50th, or 85th quantile of adult halibut in area 3 between 1993 and 2018 was assumed for pre-1993 abundance in area 3 led to little difference in derived quantities. Similarly, using the numbers-at-age from the Pacific halibut areas-as-fleets and coast-wide models led to very similar trends in derived quantities for all individual models.

1.3.4 Time series of derived quantities from ensemble models

Ensemble models were constructed by averaging individual model results across predation types ignoring AIC (no predation, no halibut predation, halibut predation vis absolute or relative numbers at age; Table 1.5). There were relatively large differences in estimates of biomass, spawning stock biomass, and recruitment of walleye pollock and arrowtooth flounder relative to the single-species ensemble model for ensemble models that included predation and estimated residual natural mortality (Figs. 1.2 and 1.3). For example, across all years, ensemble models that included predation estimated biomass of pollock to be on average 2.03 (Avg 2), 2.21 (Avg 3), and 2.07 (Avg 4) times larger than estimates from the single-species ensemble model. Similarly, spawning stock biomass of walleye pollock was estimated to be 1.70 (Avg 2), 1.84 (Avg 3), and 1.71 (Avg 4) times greater across all years when predation was included. These differences were also evident when comparing individual multi-species models to single-species models (Models 1-16; Supplementary Figs. S1.3-4). Estimates of arrowtooth flounder biomass and recruitment were larger in scale, but similar in trend, across models that included predation when compared to the single-species ensemble model. However, spawning stock biomass of arrowtooth flounder was

lower across models that included predation. Estimates of biomass and spawning stock biomass of Pacific cod from the ensemble models were less sensitive to the inclusion of predation, although estimates of recruitment of Pacific cod were greater in ensemble models that included predation (Figs. 1.2 and 1.3).

1.3.5 Biomass consumed

Biomass consumed as prey of each species included in the model differed across model variants. When predation from Pacific halibut was included in the multi-species ensemble models as absolute numbers-at-age (Avg 3), biomass consumed as prey was relatively higher for all species (Fig. 1.4), leading to slightly lower estimates of biomass, spawning stock biomass, and recruitment. Trends were similar between multi-species ensemble models that excluded Pacific halibut predation (Avg 2) and treated Pacific halibut as relative numbers-at-age (Avg 4). The ensemble multi-species model that excluded predation from Pacific halibut (Avg 2) estimated that on average 661,560 mt of pollock, 29,072 mt of arrowtooth flounder, and 6,249 mt of Pacific cod was consumed annually by predators included in the model (Fig. 1.4). However, the ensemble multi-species model that included predation from Pacific halibut as absolute numbers-at-age (Avg 3) estimated that on average 750,942 mt of pollock, 36,771 mt of arrowtooth flounder, and 7,082 mt of Pacific cod was consumed annually by predators included in the model (Fig. 1.4). When Pacific halibut was included as relative numbers-at-age (Avg 4), average consumed biomass was estimated at 726,737 mt of pollock, 26,749 mt of arrowtooth flounder, and 6,214 mt of Pacific cod, i.e. 110%, 92%, and 99% of that from Avg 2, respectively. Temporal trends in biomass consumed as prey were similar across ensemble models (Fig. 1.4).

Annual trends in biomass consumed as prey varied among species owing to trends in prey and predator abundance. Biomass of pollock consumed as prey peaked in 2014, coinciding with a peak in recruitment (Fig. 1.4). Similarly, peaks in biomass consumed as prey of arrowtooth flounder and Pacific cod coincided with elevated recruitment because younger individuals are more abundant and are more vulnerable to predation (Fig. 1.4). Depending on the model, consumption of arrowtooth flounder as prey peaked in 2000 or 2001 and of Pacific cod as prey peaked in 2006 or 2007 (Fig. 1.4). Across all model variants, arrowtooth flounder was the primary consumer of prey biomass in the model across all species, followed by Pacific halibut (Fig. 1.4). Predation mortality was the greatest for younger age-classes across all species, peaking between 2002 and 2006 owing to increased biomass of arrowtooth flounder. Despite their smaller size, predation mortality by arrowtooth flounder males (and total natural mortality) was greater for males than for females. For example, on average across all years, total natural mortality at age-1 was 1.4 yr^{-1} for pollock, 0.36 yr^{-1} for arrowtooth flounder females, 0.44 yr^{-1} for arrowtooth flounder males, and 0.95 yr^{-1} for Pacific cod in the ensemble model with absolute abundance-at-age of Pacific halibut (Avg 3; Fig. 1.4; Table S1.3). By age-5 total natural mortality of all species consisted mostly of M1, which was 0.45 yr^{-1} for pollock, 0.32 yr^{-1} for arrowtooth flounder females, 0.39 yr^{-1} for arrowtooth flounder males, and 0.47 yr^{-1} for Pacific cod as estimated from Avg 3 (Table S1.3).

1.3.6 Comparison of fixed vs relative halibut abundance

We developed models that used relative and absolute numbers-at-age for Pacific halibut to evaluate how pre-specifying predators in the model impacted the results. The scaling parameter when Pacific halibut was incorporated as relative numbers-at-age in IPHC Regulatory Areas 3A and 3B from the IPHC fishery-independent set-line survey was estimated with very high uncertainty to be 0.0021 (s.e. = 0.97) in Model 11 and 0.0025 (s.e. 1.44) in Model 16. The low estimate of this

scaling parameter for Model 11 and 16 indicates that low Pacific halibut predation provided a better fit to the data. Biomass, spawning stock biomass, and recruitment of all species were similar between multi-species ensemble models that excluded Pacific halibut predation (Avg 2) and the multi-species model that included relative halibut numbers-at-age (Avg 4; Figs. 2-4). Similarly, time series trends of predation mortality for walleye pollock, Pacific cod, and arrowtooth flounder from Avg 2 and Avg 4 were very similar (Fig. 1.5-1.7). However, for cod and arrowtooth flounder, predation mortality was estimated to be greater and residual natural mortality (M1) was estimated to be lower in Avg 2 when compared to Avg 4 (Fig. 1.7).

1.4 DISCUSSION

We found that perceptions of groundfish biomass in the GOA were sensitive to assumptions regarding predation. The GOA is a diverse and dynamic ecosystem that supports many commercial fisheries whose target species exhibit strong trophic interactions (Gaichas et al., 2015; Zador and Yasumiishi, 2016). Food web analysis has indicated that walleye pollock, Pacific cod, Pacific halibut, and arrowtooth flounder are highly ecologically connected and support some of the most valuable fisheries in the GOA (Barnes et al., 2020; Gaichas et al., 2015; Gaichas and Francis, 2008; Livingston et al., 2017; Thorson et al., 2019). While there is interest in developing models that can inform strategic and tactical EBFM of groundfish in the GOA, large scale spatial and temporal differences in the distribution of these species (primarily related to Pacific halibut) limits their utility to support the provision of management advice. We found that the MSCAA approach used here effectively integrates multiple forms of uncertainty regarding the distribution of Pacific halibut and the subsequent impacts of predation on groundfish in the GOA.

1.4.1 Extended MSCAA

The key forms of uncertainty we addressed related to the abundance and distribution of Pacific halibut in the GOA. However, rather than estimate the spatial distribution dynamics of Pacific halibut directly by fitting a habitat model to monitoring data, we input the absolute or relative numbers-at-age directly into the model. This builds upon previous approaches that have extended single- or multi-species models to account for predation from pre-specified total predator abundance (Hollowed et al., 2000; Spencer et al., 2016; van Kirk et al., 2012) by allowing for the impacts of predator age-structure on the dynamics of prey species. As recruited Pacific halibut are mainly considered predators in the system (Gaichas et al., 2010) and our study focused on “top-down” predator dynamics, the extended multi-species approach allows us to simplify parameter estimation rather than recreate the dynamics of multiple complex stock assessment models used for management (Stewart and Hicks, 2019) while also addressing uncertainty in the predator numbers-at-age following the ensemble approach currently used for Pacific halibut management (Stewart and Hicks, 2019). Such an approach would not be appropriate for “bottom-up” predator-prey dynamics, such as prey-dependent reproduction, survival, and growth (Tulloch et al., 2018). However, this approach could be extended to other systems where “top-down” predation mortality is hypothesized to be a primary driver of target species’ dynamics or where data limitations have historically precluded inclusion of predation in MICE models (e.g., marine mammals and fish). Additionally, the approach can be used to project the impact of future changes in “top-down” predation mortality given projected changes in predator-prey overlap or predator abundance.

1.4.2 Individual models

Currently, the Pacific halibut stock is assessed from California to Alaska using an ensemble of four equally weighted age-structured models (Stewart and Hicks, 2019) to account for uncertainty in the historical data available for Pacific halibut and the distribution of the fishery (Stewart and Martell, 2015). We developed multiple MSCAA models that included numbers-at-age from each IPHC model scaled by the proportion of the Pacific halibut stock in the GOA. Data on the proportion of the stock in the GOA are not available prior to 1993 and it is uncertain if recent decreases in the proportion of the Pacific halibut stock in the GOA reflect the historical distribution of Pacific halibut or the distribution in the absence of fishing (Stewart and Hicks, 2019). However, alternative assumptions regarding the historical distribution prior to 1993 relative to current trends of halibut in the GOA had little impact on the derived quantities. Similarly, derived quantities were relatively insensitive to which model was used to derive numbers-at-age of Pacific halibut. The insensitivity of the model results to parameterization of absolute numbers-at-age of Pacific halibut is likely due to the low relative contribution of halibut predation mortality compared to that of arrowtooth flounder. This is similar to results from Barnes et al. (2020), who found that arrowtooth flounder was the primary consumer of walleye pollock in the Gulf of Alaska. This is generally consistent with the relatively broad range of prey consumed by Pacific halibut (Barnes et al., 2018).

Using an index of relative abundance-at-age derived from the IPHC setline survey in the GOA multiplied by an estimable scaling coefficient allowed us to evaluate alternative estimates of Pacific halibut in the GOA. This is similar to previous single-species approaches that estimated a scaling constant for predator abundance (Hollowed et al., 2000). Some caveats to this approach are that using the IPHC setline survey ignores the impacts of selectivity and scaling (i.e., catchability). The scaling coefficients were also estimated with a very high degree of uncertainty. Future research that aims to use indices of relative abundance-at-age would benefit by utilizing a prior distribution for the scaling coefficient or including additional data in the model likelihood to improve estimation. While this approach was used to evaluate alternatives to directly inputting estimates of absolute abundance at age, the small values of the estimated scaling coefficients for Models 11 and 16 led to results similar to models that excluded Pacific halibut predation. However, the increased flexibility in model parameterization allowed for slightly different fits to the data relative to Models 10 and 13, respectively. This approach may be useful for systems where data are not available to develop age-structured assessments for predators and rather indices of relative abundance are available, or cases where the spatial dynamics of a predator do not align well with those of the focal species.

Comparing models that included and excluded predation is a classic example of the bias-variance trade-off (Collie et al., 2016). Evaluating short-term models with fixed and relative numbers-at-age of halibut confirmed that the latter, more flexible approach provided a better fit to the data by eliminating Pacific halibut predation. The small value of the estimable scaling coefficient for Pacific halibut relative numbers-at-age effectively “shrunk” Pacific halibut predation. Similarly, multi-species models that excluded predation from Pacific halibut provided a better fit to the data and provided lower estimates of among and within-model variance in derived quantities (as illustrated by the sensitivity of model outputs to time-series length and model averaged confidence intervals). Both examples are likely a consequence of overfitting the available data. Previous studies have demonstrated that models that do not include predation mortality may overfit data and perform poorly at predicting unobserved data (Trijoulet et al., 2019). Given that perceptions of recruitment and biomass are sensitive to model formation and the inclusion of predation, future research would benefit from evaluating the predictive performance of models

developed here (Carvalho et al., 2021). This will also better affirm the need to account for the impacts of time-varying predator-prey dynamics on target species' dynamics as clearly illustrated here, which suggests that increases in predator abundance leads to increased mortality of prey.

1.4.3 Ensembles

Rather than use a single “best” model for inference, an ensemble model approach was used to integrate across assumptions related to the abundance and distribution of Pacific halibut in the GOA. Ensemble modelling approaches are gaining traction in fisheries assessment because of their ability to incorporate uncertainty in the state-of-nature and data available (Ianelli et al., 2016; Stewart and Martell, 2015; Zerbini et al., 2019). Derived quantities from ensemble models can be sensitive to the weighting scheme used, and a variety of weighting schemes have been proposed: including information theoretic approaches (Symonds and Moussalli, 2011), Bayesian model averaging approaches (Zerbini et al., 2019), and approaches that rely on expert judgement (Stewart and Hicks, 2018). The data used for parameter estimation differed across individual models and, therefore, information theoretic and Bayesian model averaging approaches were not viable. To be consistent with the IPHC assessment we adopted a model averaging approach similar to theirs by giving equal weight to each model or input numbers-at-age (Stewart and Hicks, 2019). We did not average across predation dynamics because we were primarily interested in evaluating the impacts of predation and the inclusion of Pacific halibut in the assessment. However, future applications may benefit from integrating across states-of-nature in regard to predation.

1.4.4 Comparison to previous studies

Estimates of consumption from the GOA CEATTLE model differ slightly from those estimated from previous studies. Barnes et al. (2020) estimated that total consumption of walleye pollock by arrowtooth flounder, Pacific halibut, Pacific cod, and sablefish (*Anoplopoma fimbria*) to be 3.8 million metric tonnes in 1997 while Hollowed et al. (2000)(*sensu* Barnes et al., 2020) estimated that total consumption of walleye pollock by arrowtooth flounder, Pacific halibut, and stellar sea lions (*Eumetopias jubatus*) to be 3 million metric tonnes in 1997. We estimated consumption of walleye pollock to be 762,020 metric tonnes in 1997 by predators included in Avg 3. Apart from predators analyzed, differences in estimates of walleye pollock consumed may have resulted because Barnes et al. (2020) and Hollowed et al. (2000) used different methods to extrapolate predator and prey consumption rates to the population level, potentially leading to larger estimates of predation than reported here in both cases. For example, Barnes et al. (2020) and Hollowed et al. (2000) did not include differences in prey age preferences across predator ages. Additionally, our model accounts for cannibalism despite lower estimates of consumed biomass of pollock, unlike Hollowed et al. (2000). As expected, given that these models were developed using similar datasets, we estimated that arrowtooth flounder was the primary consumer of the species included in the model, corroborating previous work in the GOA (Barnes et al., 2020; Gaichas et al., 2015; Hollowed et al., 2000).

Stock assessments for Pacific cod and arrowtooth flounder currently assume that natural mortality is age-invariant (Barbeaux et al., 2018; Spies and Palsson, 2018). However, when accounting for predation, total natural mortality is elevated for younger age classes, decreasing with age. In the case of Pacific cod, estimates of total natural mortality for older age classes of 0.451-0.478 yr⁻¹ were slightly lower than the age-invariant M of 0.505 yr⁻¹ (Barbeaux et al., 2018). MSCAA can be particularly useful by providing estimates of mean total natural mortality to be input into single-species stock assessments used for management (Dorn et al., 2018; ICES, 2019;

Plagányi et al., 2022). Finally, because MSCAA models account for time- and age-varying natural mortality by explicitly modelling the time-varying dynamics of predator populations and age-specific predator suitability, outputs of time- and age-varying natural mortality can be used to identify how shifting predator-prey populations are impacting the dynamics of target species of interest.

1.4.5 Future

There are several assumptions utilized by the present modelling approach that may bias inference. First, the model assumes a Type II MSVPA functional response. Kinzey and Punt (2009) found that a predator pre-emption functional response best fit data from groundfish in the Aleutian Islands region. While comparing functional response models was beyond the scope of the present study, future research efforts would benefit by evaluating alternative functional response models given that model outputs are sensitive to the choice and parameterization of such models (Kinzey and Punt, 2009). Second, due to data limitations we used an estimate of average diet proportion to inform predation from multiple years and ignored variability (and uncertainty) in the diet data. Trijoulet et al. (2019) found that MSCAA were sensitive to the availability and quality of diet data. We used an average diet proportion estimate to account for biannual survey effort and data limitations prior to 1990. Comparing individual models that spanned different periods showed that they were relatively insensitive to the time-series of assessment and diet data used. However, future research using alternative methods to account for diet variability (e.g., using interpolation methods for years with missing data sensu Grüss et al. (2020)) would be useful. Alternatively, diet data could be included in the model likelihood and suitability coefficients estimated.

Models developed here can be used to inform current and alternative tactical management procedures by showing responses arising from multi-species interactions. They can be used in management strategy evaluation approaches to account for the impact of multi-species interactions when evaluating the performance of alternative management strategies (Kaplan et al., 2021; Pérez-Rodríguez et al., 2022; Chapters 2 and 3). It may also be plausible to design multi-species reference points from these models to better facilitate operationalizing EBFM (Holsman et al., 2020). Ecological reference points (e.g., Moffitt et al., 2016; Chagaris et al., 2020) and dynamic reference points (e.g., MacCall et al., 1985) can be derived from CEATTLE and provide alternative ways to guide fisheries management in a single-species context, accounting for predator-prey dynamics and variation in productivity, respectively. CEATTLE can also be used to inform reference point estimation under climate change (sensu Holsman et al., 2020). This is of particular importance given projected impacts of climate change and observed recent extreme events (e.g., the marine heatwave of 2014-2016; Barbeaux et al., 2020) and interactions with groundfish dynamics in the GOA (e.g., Cheung and Frölicher, 2020). Through the implementation of CEATTLE, trade-offs between harvesting of Pacific cod, pollock, arrowtooth flounder, and Pacific halibut under future climate conditions can be quantified. Such outputs, coupled with short- and long-term climate forecasts, can inform fisheries management advice that is robust to climate change and the apparent increases in environmental variability (Hollowed et al., 2020; Gaichas et al., 2017; Hazen et al., 2018; Kaplan et al., 2020; Holsman et al., 2019b; Karp et al., 2019).

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TABLES

Table 1.1. Predation mortality equations for predators of species p , sex b , age j , and prey of species i , sex s and age a . Modified from Holsman et al. 2016 Table 2. Input ration parameters include: observed bottom temperature (T_y °C), Thermal optima for consumption (T_p^{co} °C), thermal limit of consumption (T_p^{cm} °C), rate at which consumption increased over relatively low water temperatures (Q_p^c), weight specific intercept (α_p^δ) and slope (β_p^δ) of maximum consumption, and scalar for maximum to observed consumption (φ_{pbjy}). For all parameter definitions see Table S1.

Definition	Equation	
Predation mortality	$M2_{isay}$	T1.1.1
	$= \sum_{pbj} \left(\frac{\bar{N}_{pbjy} \delta_{pbjy} \hat{S}_{pbjisa}}{\sum_{isa} (\hat{S}_{pbjisa} \bar{B}_{isay}) + B_p^{other} (1 - \sum_{isa} (\hat{S}_{pbjisa}))} \right)$	
Predator-prey suitability	$\hat{S}_{pbjisa} = \frac{1}{n_y} \sum_y \left(\frac{\frac{\bar{U}_{psaisa}}{\bar{B}_{isay}}}{\sum_{isa} \left(\frac{\bar{U}_{pbjisa}}{\bar{B}_{isay}} \right) + \frac{1 - \sum_{isa} \bar{U}_{pbjisa}}{B_p^{other}}} \right)$	T1.1.2
Individual specific ration ($kg \ kg^{-1} \ yr^{-1}$)	$\delta_{pbjy} = \varphi_{pbjy} \alpha_p^\delta W_{pbjy}^{(1+\beta_p^\delta)} f(T_y)_p$	T1.1.3
Temperature scaling algorithm	$f(T_y)_p = V^X e^{(X(1-V))}$	T1.1.4
...	$V = (T_p^{cm} - T_y) / (T_p^{cm} - T_p^{co})$	T1.1.4a
...	$X = (Z^2 (1 + (1 + 40/Y)^{0.5})^2) / 400$	T1.1.4b
...	$Z = \ln(Q_p^c) (T_p^{cm} - T_p^{co})$	T1.1.4c
...	$Y = \ln(Q_p^c) (T_p^{cm} - T_p^{co} + 2)$	T1.1.4d

Table 1.2. General population dynamics equations for species i , sex s , age a , and length l in year y , and the observation and fishery model for survey or fishery f_i . For parameter definitions see Table S1.1.

Definition	Equation	
Recruitment	$N_{is1y} = R_{isy} = \bar{R}_i e^{\tau_{iy}} \rho_{i1}$	T1.2.1
Initial abundance	$N_{isa1} = \begin{cases} \bar{R}_i e^{(-\sum_{j=1}^{a-1} M_{1isj} + \tau_{ia})} \rho_{i1} & \text{if } j < A_i \\ \frac{\bar{R}_i e^{(-\sum_{j=1}^{a-1} M_{1isj} + \tau_{ia})} \rho_{i1}}{(1 - e^{(-M_{1isA_i})})} & \text{if } j = A_i \end{cases}$	T1.2.2
Numbers at age	$\begin{cases} N_{isa+1y+1} = N_{isay} e^{-Z_{isay}} \\ N_{isA_iy+1} = N_{isA_i-1y} e^{-Z_{isA_i-1y}} + N_{isA_iy} e^{-Z_{isA_iy}} & \text{if } i \neq \text{Halibut} \\ N_{isay} = d_{iy} * N_{Input, isay} & \text{if } i = \text{Halibut and model} \neq 11 \\ N_{isay} = \tilde{q}_i * \hat{I}_{isay} & \text{if } i = \text{Halibut and model} = 11 \end{cases}$	T1.2.3
Average numbers at age	$\bar{N}_{isay} = \frac{N_{isay} * (1 - e^{-Z_{isay}})}{Z_{isay}}$	T1.2.4
Survey biomass (kg)	$\hat{B}_{fiy} = \sum_s \sum_a N_{isay} e^{-Month_{fi} * Z_{isay}} W_{fi say} sel_{fi say} q_{fiy}$	T1.2.5
Survey abundance (numbers)	$\hat{I}_{fiy} = \sum_s \sum_a N_{isay} e^{-Month_{fi} * Z_{isay}} sel_{fi say} q_{fiy}$	T1.2.6
Catch-at-age	$C_{fi say} = \frac{F_{fi say}}{Z_{isay}} (1 - e^{-Z_{isay}}) N_{isay}$	T1.2.7
Total catch (kg)	$\hat{C}_{fiy}^* = \sum_s \sum_j \frac{F_{fi say}}{Z_{isay}} (1 - e^{-Z_{isay}}) N_{isay} W_{fi say}$	T1.2.8
Biomass at age (kg)	$B_{isay} = N_{isay} W_{B_i ay}$	T1.2.9
Spawning biomass at age (kg)	$SB_{iay} = \begin{cases} N_{iay} e^{-Month_{ssb_i}/12 * Z_{iay}} W_{ssb_i ay} \rho_{ia} \delta_{ia} & \text{if 1 sex model} \\ N_{i1ay} e^{-Month_{ssb_i}/12 * Z_{i1ay}} W_{ssb_i1ay} \delta_{ia} & \text{if 2 sex model} \end{cases}$	T1.2.10
Total mortality at age	$Z_{isay} = M_{1isa} + M_{2isay} + \sum_{f_i} F_{fi say}$	T1.2.11
Fishing mortality at age and fleet	$F_{fi say} = \bar{F}_{fi} e^{\epsilon_{fiy}} sel_{fi say}$	T1.2.12
Residual/natural mortality	$M_{1isj} = \begin{cases} M_{1isj} & \text{if single-species} \\ \bar{M}_{1is} & \text{if multi-species} \end{cases}$	T1.2.13
Predicted age composition	$\hat{O}_{fi say} = \frac{\sum_a C_{fi say} AE_{i\hat{a}a}}{\sum_s \sum_a \sum_a C_{fi say} AE_{i\hat{a}a}} \text{ if } f_i = \text{fishery}$	T1.2.14
	$\hat{O}_{fi say} = \frac{\sum_a N_{isay} e^{-Month_{fi} * Z_{isay}} sel_{fi say} AE_{i\hat{a}a}}{\sum_s \sum_a \sum_a N_{isay} e^{-Month_{fi} * Z_{isay}} sel_{fi say} AE_{i\hat{a}a}} \text{ if } f_i = \text{survey}$	
Predicted length composition	$\hat{O}_{fi sly} = \frac{\sum_a \sum_a C_{fi say} AE_{i\hat{a}a} ATM_{fi sal}}{\sum_s \sum_l \sum_a \sum_a C_{fi say} AE_{i\hat{a}a} ATM_{fi sal}} \text{ if } f_i = \text{fishery}$	T1.2.15
	$\hat{O}_{fi sly} = \frac{\sum_a \sum_a N_{isay} e^{-Month_{fi} * Z_{isay}} sel_{fi say} AE_{i\hat{a}a} ATM_{fi sal}}{\sum_s \sum_l \sum_a \sum_a N_{isay} e^{-Month_{fi} * Z_{isay}} sel_{fi say} AE_{i\hat{a}a} ATM_{fi sal}} \text{ if } f_i = \text{survey}$	

Table 1.3. Components of the likelihood function for species i , sex s , and age a during year y for survey s or fishery f . Modified from Holsman et al. (2016). For parameter definitions see Table S1.1.

Description	Equation	
Data components		
Survey biomass	$\ln(B_{fiy}) \sim N\left(\ln(\hat{B}_{fiy}) - \frac{\sigma_{fiy}^2}{2}, \sigma_{fiy}^2\right)$	T1.3.1
Total catch	$\ln(C_{fiy}^*) \sim N\left(\ln(\hat{C}_{fiy}^*) - \frac{\sigma_{fiy}^2}{2}, \sigma_{fiy}^2\right)$	T1.3.2
Age composition	$-\sum_i \sum_s n_{fisy} \sum_{\hat{a}} \sum_y (\hat{O}_{fisay} + 0.00001)$	T1.3.3
	$\quad \quad \quad * \ln(O_{fisay} + 0.00001)$	
Length composition	$-\sum_i \sum_s n_{fisy} \sum_{\hat{a}} \sum_y (\hat{O}_{fistly} + 0.00001)$	T1.3.4
	$\quad \quad \quad * \ln(O_{fistly} + 0.00001)$	
Sex ratio	$\frac{\sum_a N_{i1ay}}{\sum_s \sum_a N_{isay}} \sim N(\bar{\rho}_i, \sigma_{\rho_i}^2)$	T1.3.5
Penalties		
Non-parametric selectivity	$\sum_i \sum_s \sum_a^{A_i-1} \chi_{fi} \left[\ln\left(\frac{e^{\psi_{fisa}}}{e^{\psi_{fisa+1}}}\right) - \ln\left(\frac{e^{\psi_{fisa+1}}}{e^{\psi_{fisa+2}}}\right) \right]^2$ $\chi_{fi} = 0 \quad \text{if } e^{\psi_{fisa}} \leq e^{\psi_{fisa+1}}$	T1.3.6
Recruitment deviate	$\tau_{iy} \sim N\left(-\frac{\sigma_{Ri}^2}{2}, \sigma_{Ri}^2\right)$	T1.3.7
Fishing mortality deviate	$\epsilon_{fiy} \sim N\left(-\frac{\sigma_{fi}^2}{2}, \sigma_{fi}^2\right)$	T1.3.8
Annual selectivity deviate	$\psi_{fiy} \sim N\left(-\frac{\sigma_{\psi_{fi}}^2}{2}, \sigma_{\psi_{fi}}^2\right)$	T1.3.9
Mean catchability priors	$\bar{q}_{fi} \sim N\left(\bar{q}_{fi} - \frac{\sigma_{\bar{q}_{fi}}^2}{2}, \sigma_{\bar{q}_{fi}}^2\right)$	T1.3.10
Catchability deviates 1 (random deviates)	$\omega_{fiy} \sim N\left(-\frac{\sigma_{\omega_{fi}}^2}{2}, \sigma_{\omega_{fi}}^2\right)$	T1.3.11a
Catchability deviates 2 (random walk)	$\omega_{fiy+1} \sim N\left(\omega_{fiy} - \frac{\sigma_{\omega_{fi}}^2}{2}, \sigma_{\omega_{fi}}^2\right)$	T1.3.11b

Table 1.4. Overview of the parameterization of the survey and fishery fleets and the data sources used for GOA CEATTLE. For more detailed information on data refer to stock assessment reports (Barbeaux et al., 2018; Dorn et al., 2018; Spies and Palsson, 2018; Stewart and Hicks, 2019). Parentheses refer to specific equations in Table S1.2. Note: all surveys except the Shelikof Strait winter acoustic survey are conducted during the summer.

Fleet	Data type	Selectivity	Catchability
Pollock:			
Shelikof Strait acoustic survey	Age-1 relative abundance	Fixed: $sel_{fi1y}=1$	Time-invariant (ST2.9)
	Age-2 relative abundance	Fixed: $sel_{fi2y}=1$	Time-invariant (ST2.9)
	Age-3+ relative biomass	Descending logistic (ST2.7)	Time-varying random walk (ST2.10; T3.11b)
	Age composition		
NMFS bottom trawl survey	Relative biomass	Logistic (ST2.2)	Time-invariant (ST2.9)
	Age composition		Mean N(0.85, 0.1) prior (T3.10)
ADFG trawl survey	Relative biomass	Logistic (ST2.2)	Time-varying random walk (ST2.10; T3.11b)
	Age composition		
Summer acoustic survey	Relative biomass	Fixed: $sel_{fiay}=1$	Time-invariant (ST2.9)
	Age composition		
Pollock fishery	Total catch	Time-varying double logistic 2 (ST2.6)	
	Age composition		
Arrowtooth flounder:			
NMFS bottom trawl survey	Relative biomass	Logistic (ST2.2)	Fixed $q_{fi} = 1$
	Length composition		
	Age composition		
Fishery	Total catch	Non-parametric (ST2.21)	
	Length composition		
Pacific cod:			
NMFS bottom trawl survey	Relative abundance	Logistic (ST2.2)	Time-invariant (ST2.9)
	Age composition		
	Length composition		
NMFS sablefish longline survey	Relative abundance	Non-parametric (ST2.1)	Time-invariant (ST2.9)
	Length composition		
Trawl fishery	Total catch	Logistic (ST2.2)	
	Length composition		
Longline fishery	Total catch	Logistic (ST2.2)	
	Length composition		
Pot fishery	Total catch	Non-parametric (ST2.1)	
	Length composition		
Pacific halibut:			
IPHC longline survey	Relative abundance-at-age		

Table 1.5. Overview of the GOA CEATTLE model variants and ensemble model weights. ‘Mode’ refers to whether estimation included predation mortality (single- vs multi-species) and ‘halibut model’ refers to the assessment model from the multi-model ensemble used for the input numbers-at-age of Pacific halibut. ‘Historical distribution’ refers to the quantiles of percentage of pre-1993 adult halibut in the GOA relative to 1993 to 2018.

Model	Model Avg (weight)	Start year	Mode	Halibut model	Historical distribution	JNLL [†]	K [‡]	AIC	ΔAIC	Wi
1	1 (0.33)	1977	Single-	None		68,378	605	137,967	1	0.35
2	2 (0.33)	1977	Multi-	None		68,374	609	137,965	0	0.65
3	3 (0.83)	1977	Multi-	Coastwide long	50%	68,384	609	137,987	21	0.00
4	3 (0.83)	1977	Multi-	Coastwide long	15%	68,384	609	137,987	21	0.00
5	3 (0.83)	1977	Multi-	Coastwide long	95%	68,384	609	137,987	22	0.00
6	3 (0.83)	1977	Multi-	AAF* long	50%	68,384	609	137,985	20	0.00
7	3 (0.83)	1977	Multi-	AAF* long	15%	68,384	609	137,985	20	0.00
8	3 (0.83)	1977	Multi-	AAF* long	95%	68,384	609	137,986	20	0.00
9	1 (0.33)	1993	Single-	None		53,168	447	107,230	14	0.00
10	2 (0.33)	1993	Multi-	None		53,157	451	107,216	0	0.73
11	4 (0.5)	1993	Multi-	Relative abundance		53,157	452	107,218	2	0.27
12	1 (0.33)	1996	Single-	None		45,817	411	92,455	0	0.40
13	2 (0.33)	1996	Multi-	None		45,813	415	92,455	0	0.41
14	3 (0.25)	1996	Multi-	Coastwide short		45,816	415	92,461	6	0.02
15	3 (0.25)	1996	Multi-	AAF* short		45,816	415	92,463	8	0.01
16	4 (0.5)	1996	Multi-	Relative abundance		45,813	416	92,457	2	0.16

* AAF = areas-as-fleets; [†] JNLL = joint negative log-likelihood, [‡] K = Number of fixed and random effects parameters.

Table 1.6. Overview GOA CEATTLE model variants and negative log-likelihood components. ‘Mode’ refers to whether estimation included predation mortality (single- vs multi-species) and ‘halibut model’ refers to the assessment model from the multi-model ensemble used for the input numbers-at-age of Pacific halibut. ‘Historical distribution’ refers to the quantiles of percentage of pre-1993 adult halibut in the GOA relative to 1993 to 2018.

Model	Start year	Mode	Halibut model	Historical distribution	Index data	Total catch	Composition data	Rec devs	Sel pen	q pen	F dev
1	1977	Single-	None		158	-411	68,259	229	113	-149	167
2	1977	Multi-	None		143	-410	68,268	227	109	-147	156
3	1977	Multi-	Coastwide long	50%	143	-410	68,271	230	110	-147	157
4	1977	Multi-	Coastwide long	15%	143	-410	68,271	230	110	-147	157
5	1977	Multi-	Coastwide long	95%	143	-410	68,271	230	110	-147	157
6	1977	Multi-	AAF* long	50%	143	-410	68,271	230	110	-147	157
7	1977	Multi-	AAF* long	15%	143	-410	68,271	230	110	-147	157
8	1977	Multi-	AAF* long	95%	143	-410	68,271	230	110	-147	157
9	1993	Single-	None		144	-266	53,053	89	137	-83	48
10	1993	Multi-	None		143	-266	53,054	84	132	-82	45
11	1993	Multi-	Relative abundance		143	-266	53,054	84	132	-82	45
12	1996	Single-	None		139	-234	45,705	77	115	-72	36
13	1996	Multi-	None		147	-234	45,697	75	114	-70	37
14	1996	Multi-	Coastwide short		147	-234	45,697	75	115	-70	37
15	1996	Multi-	AAF* short		147	-234	45,698	75	115	-70	37
16	1996	Multi-	Relative abundance		147	-234	45,697	75	114	-70	37

* AAF = areas-as-fleets

FIGURES

Fig. 1.1. Study area and stock boundaries of the GOA CEATTLE model. Included are IPHC Regulatory Areas 3A and 3B and NMFS reporting areas 610 to 650.

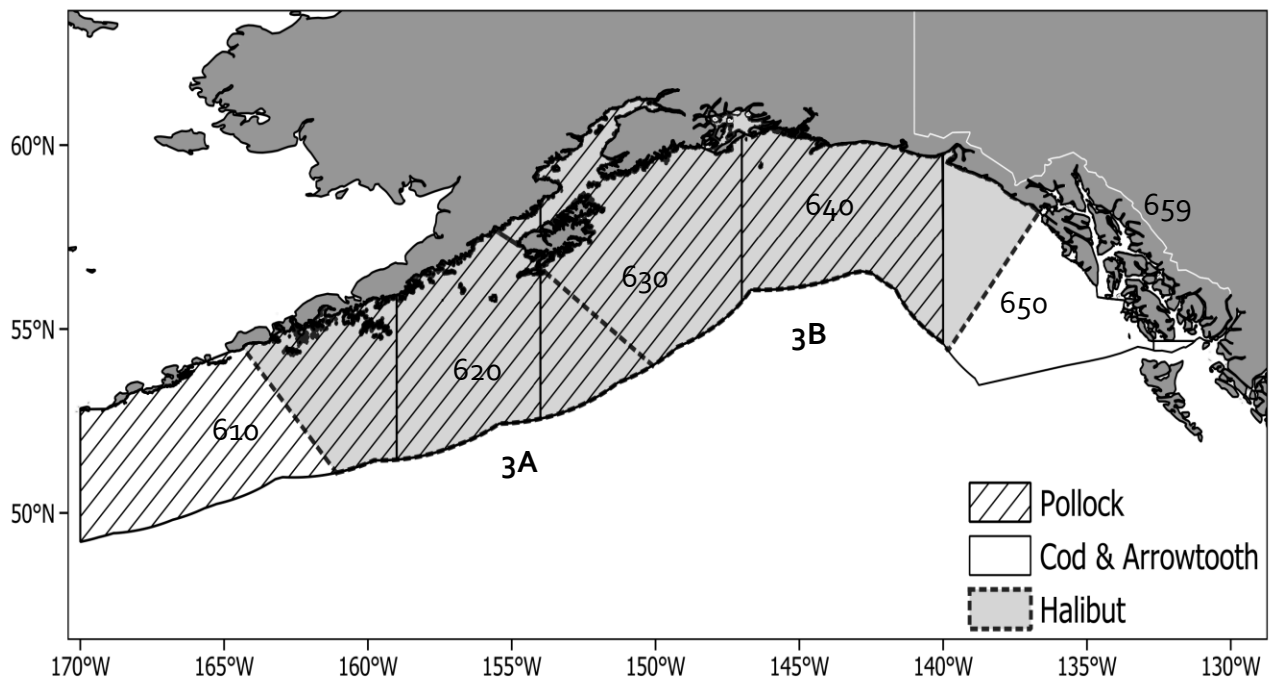


Fig. 1.2. Estimates of age-1+ total biomass (solid line) and 95% confidence interval (shaded region) from ensemble GOA CEATTLE Models. See Table 1.5 for model descriptions. Note: total biomass for Pacific halibut from Avg 4 is calculated from relative abundance-at-age for both sexes of halibut age 5+ in IPHC Regulatory Areas 3A and 3B from the IPHC fisheries independent set-line survey multiplied by an estimable scaling parameter (See Eq. T1.1.3, T1.1.9, and T1.1.10). Confidence intervals for Avg 4 are also excluded given unrealistically high uncertainty.

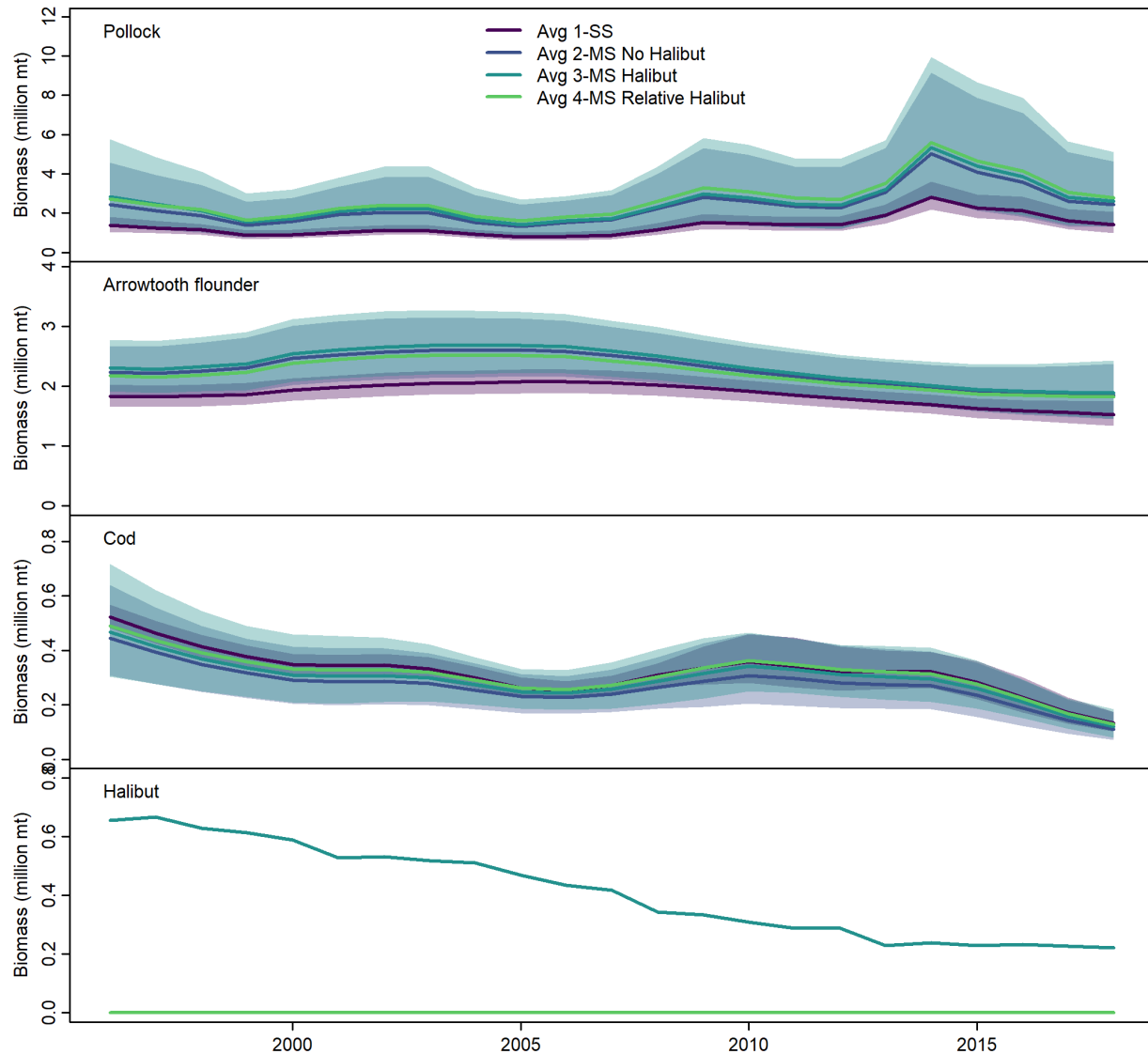


Fig. 1.3. Estimates of spawning stock biomass (left panel) and recruitment (right panel) and associated 95% confidence intervals (shaded region) from ensemble GOA CEATTLE models. See Table 1.5 for model descriptions. Note: estimates for Pacific halibut are excluded because they are not estimated/included in the model. Confidence intervals for Avg 4 are also excluded given high uncertainty.

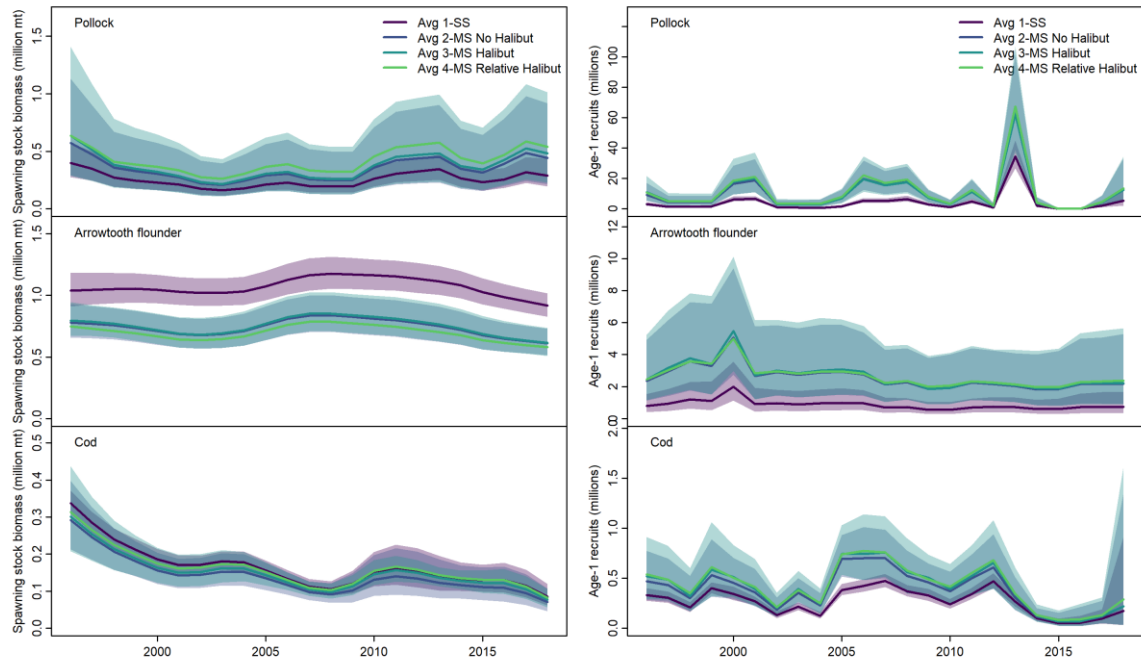


Fig. 1.4. Estimates of total biomass consumed as prey (left panel) and biomass consumed as prey by predator (right panel) from the ensemble GOA CEATTLE models. See Table 1.5 for model descriptions. For the right panel, solid lines indicate biomass consumed by pollock, dashed lines indicate biomass consumed by arrowtooth flounder, dotted lines indicate biomass consumed by cod, and dotted-dashed lines indicate biomass consumed by Pacific halibut.

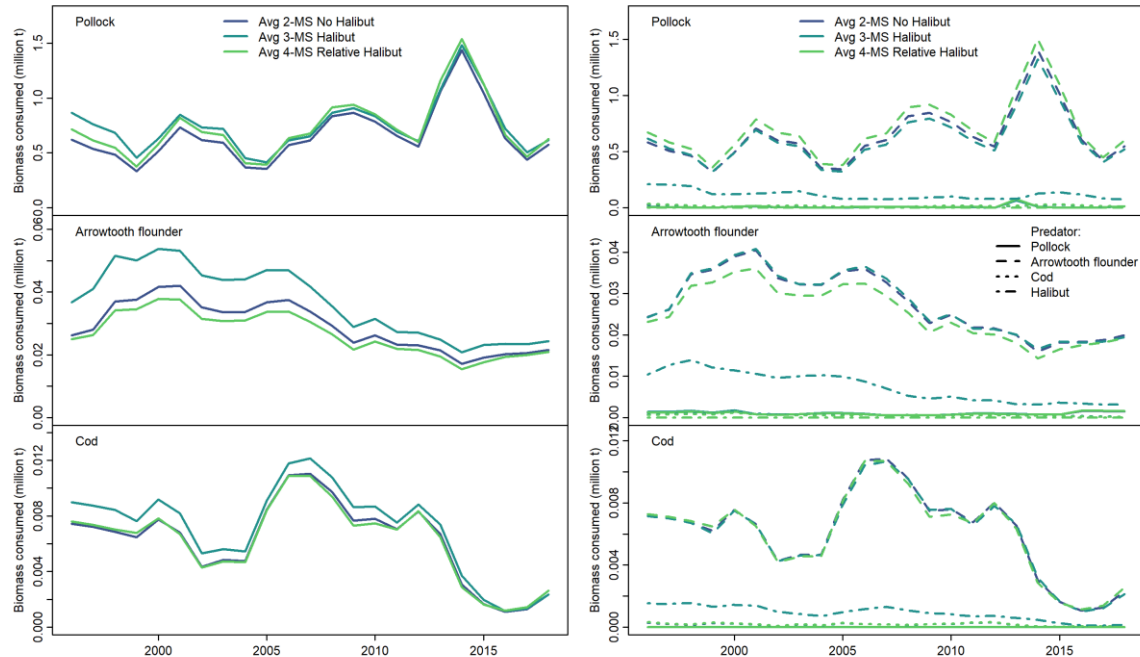


Fig. 1.5. Estimated total natural mortality ($M1 + M2$) for walleye pollock from ensemble models.

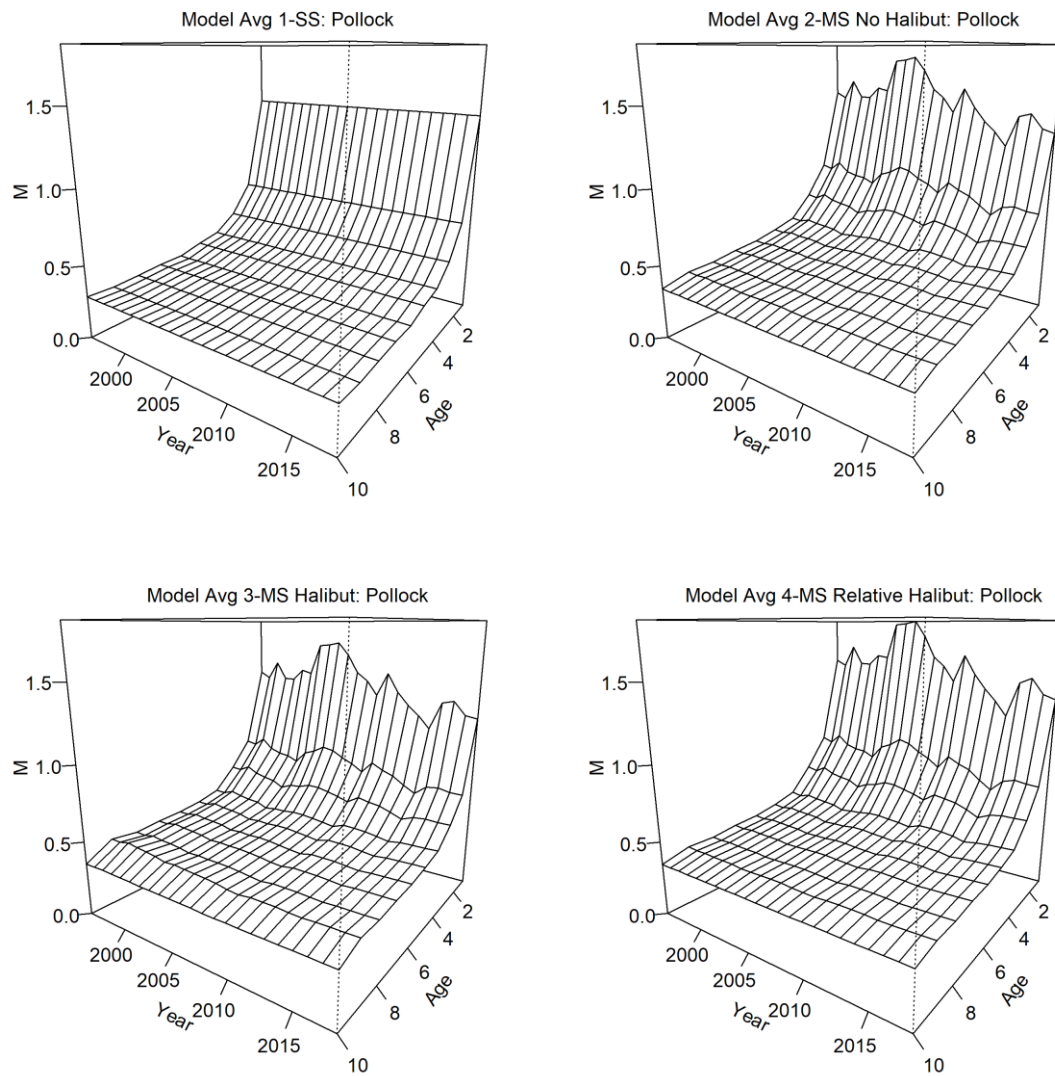


Fig. 1.6. Estimated residual mortality (M1) and predation mortality (M2) for Pacific cod from ensemble models that included predation. NOTE: For Model Avg 1 total natural mortality (M) is set to 0.504911 yr^{-1} .

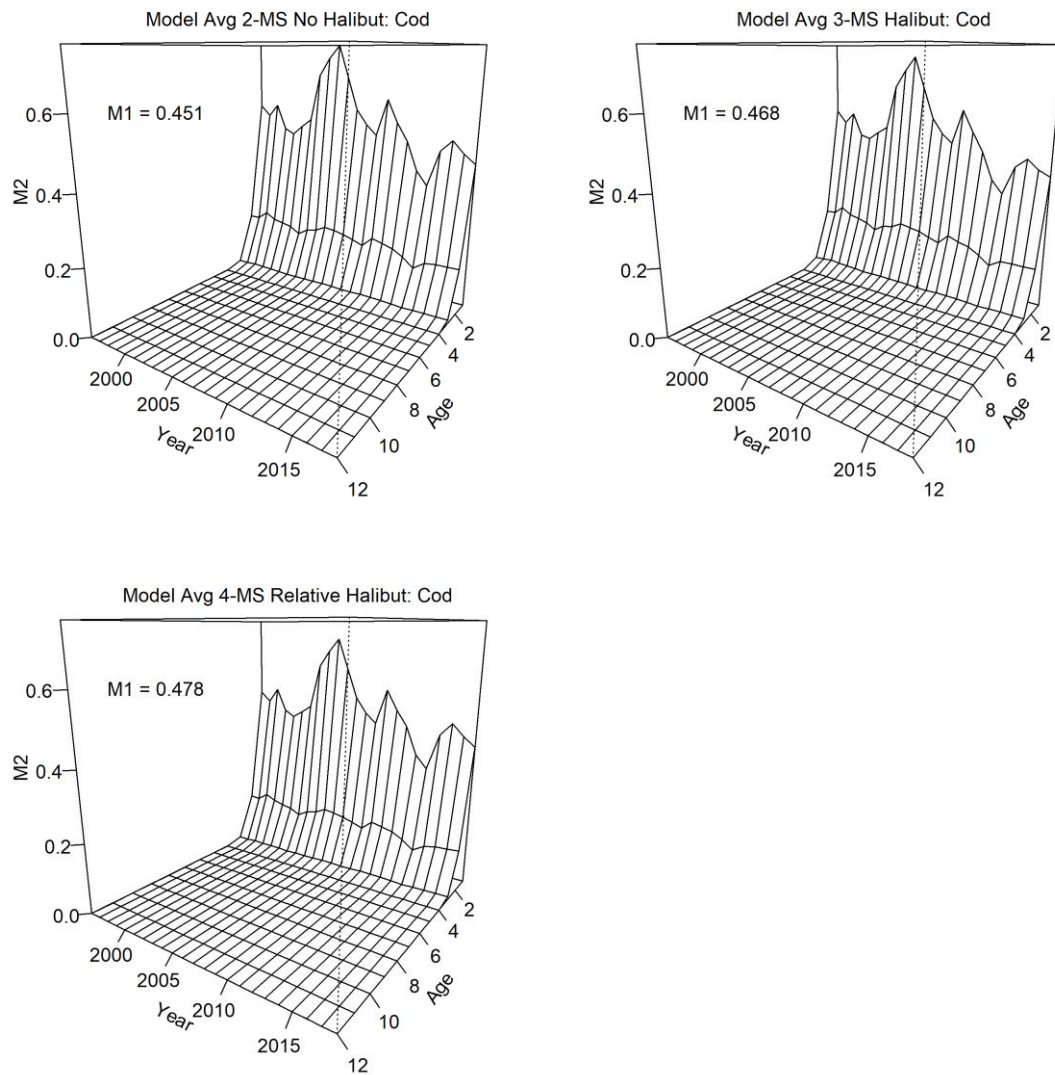
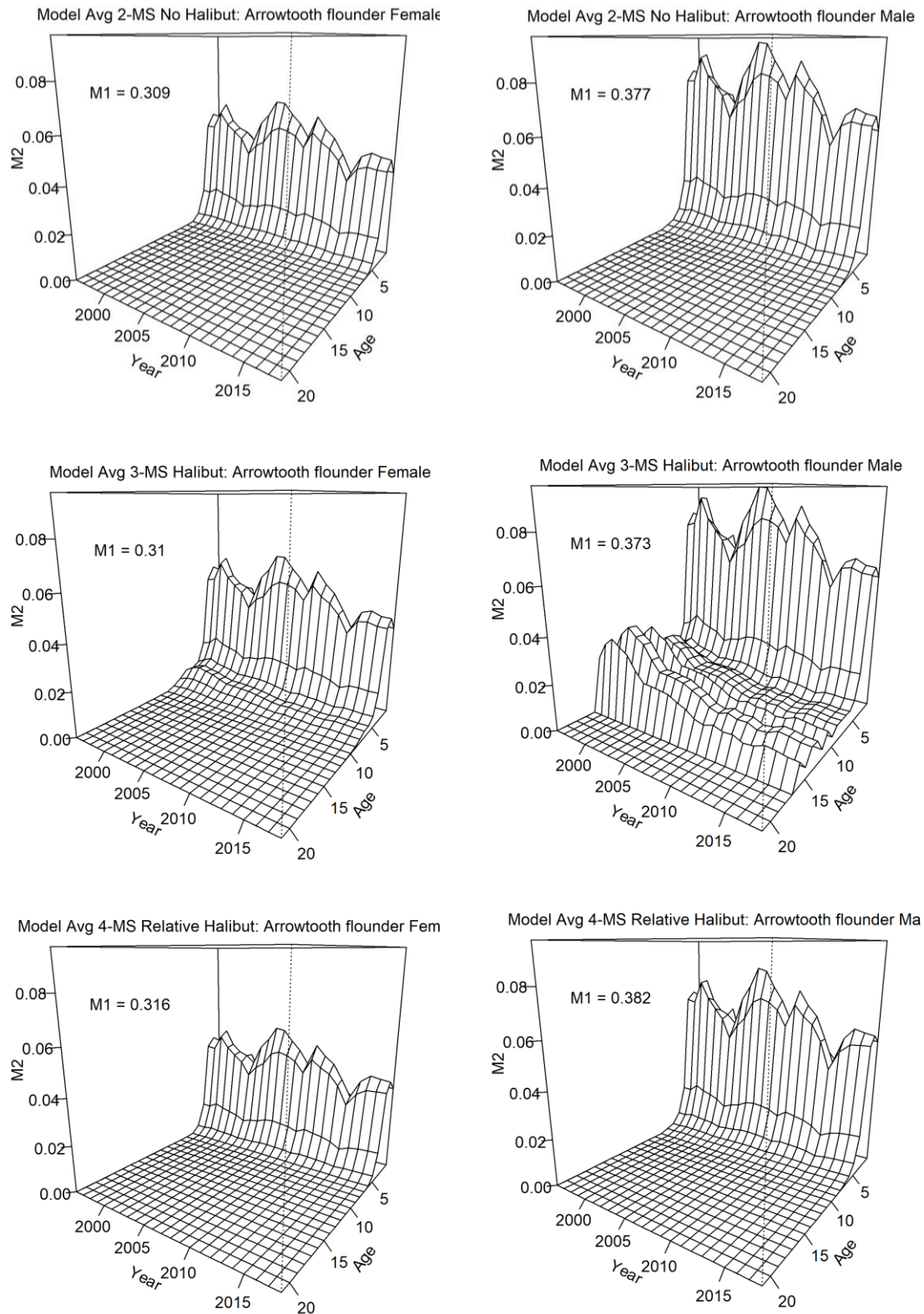


Fig. 1.7. Estimated residual mortality (M1) and predation mortality (M2) for Pacific cod from ensemble models that included predation. NOTE: For Model Avg 1 total natural mortality (M) is set to 0.2 yr^{-1} for females and 0.35 yr^{-1} for males.



Chapter 2: Implications of predator-prey dynamics for single species management

ABSTRACT

Despite the large body of research suggesting that the population dynamics of fishes are affected by their predators and prey, the majority of tactical fisheries management uses single-species population dynamics models that assume individual populations are independent of one another. For example, time-varying predation mortality is thought to represent a large proportion of mortality for groundfish in Alaska, but assessment models, biological reference points, and harvest control rules do not explicitly account for predation and assume time-invariant natural mortality (M). Research is needed to identify the relevance of predation mortality to single-species management performance while accounting for the feedback between management and fish populations through continued data collection and assessment. We conduct a management strategy evaluation (MSE) using two multi-species statistical catch-at-age models as operating models to assess whether ignoring predation can affect the performance of single-species management. We evaluate the ability of single-species management strategies to achieve single- and multi-species reference points, maximize catch, minimize catch variability, and reduce model bias. The incorporation of explicit predation mortality and full feedback control in our MSE framework allowed us to account for trophic dynamics in the evaluation of single-species management strategies. Our results demonstrate that single-species management strategies are robust to time-varying predation mortality across two systems with differing trophic dynamics, with the performance varying based on the amount of bias in natural mortality. The relative performance of specific harvest control rules varied across performance metrics and selection of an optimal management strategy will depend on trade-offs between management objectives.

2.1. INTRODUCTION

Tactical fisheries management mostly relies on the use of single-species population dynamics models that explicitly assume that the dynamics of individual populations are independent of one another (Marshall et al., 2019; Maunder and Punt, 2013a; Skern-Mauritzen et al., 2015). This practice dominates despite a large body of research demonstrating that the population dynamics of fishes are conditional on the dynamics of their predator (Hixon and Jones, 2005; Pikitch et al., 2014; Steele, 1997) and prey populations (Jacobsen and Essington, 2018; Myers et al., 2007). Time-variation in life history parameters can, to some extent, implicitly account for historical predator-prey dynamics in single-species models, when data are available (Fournier and Archibald, 1982; Jiao et al., 2012; Maunder and Punt, 2013b; Stock and Miller, 2021). Moreover, analysis of single-species models has demonstrated that assuming nonstationary life history parameters can reduce bias in estimates of biological reference points (BRPs) used for management (Deroba and Schueller, 2013; Stawitz et al., 2019; Szuwalski and Punt, 2013). However, many BRPs rely on assuming that life history parameters are time-invariant or at equilibrium, which is known to be inaccurate given interactions between predator and prey populations (Gislason, 1999). BRPs derived from single-species models can be biased (Essington, 2004) because trade-offs between the production of predator-prey species are ignored (Collie and Gislason, 2001; Gislason, 1999; Schiano et al., 2023; Tyrrell et al., 2011). Consequently, ignoring predator-prey dynamics can lead to a biased perception of stock status and poor predictive performance (Trijoulet et al., 2019; Tyrrell et al., 2011).

Multi-species population dynamics models are commonly proposed as a solution for non-equilibrium dynamics when predator-prey interactions are relevant to species of management interest (Collie et al., 2016; Plagányi et al., 2014), as they explicitly account for key predator-prey dynamics among multiple species. Management strategies based on single-species models are commonly cited as being at a high risk of not achieving management objectives, as evidenced by simulation, projection, and model comparison studies using single-species and multi-species models, such as size spectrum models (Andersen et al., 2015; Blanchard et al., 2014; Gaichas et al., 2017), multi-species surplus production models (Essington, 2004; Mueter and Megrey, 2006), and multi-species statistical catch-at-age analysis (MSCAA) or virtual population analysis (MSVPA). (Gislason, 1999; Schiano et al., 2023; Trijoulet et al., 2019). Trijoulet et al. (2019) found that models that did not include predation mortality overfit observed data and led to poor predictive performance of unobserved data. Bias in estimates of spawning stock biomass (SSB) and recruitment from models that ignored predation mortality varied between 23% and 229% (Trijoulet et al., 2019). Essington (2004) found that estimates of BRPs from single-species models were biased, with optimal fishing effort (fishing effort that maximizes total profit) on prey populations overestimated and optimal fishing effort on predators underestimated. Consequently, research on BRPs has long recommended that management strategies be conditioned on predator-prey relationships (Collie and Gislason, 2001; Tyrrell et al., 2011).

Previous efforts to evaluate the impacts of predator-prey dynamics on single-species management strategies have largely focused on projecting populations under alternative harvest and predation scenarios (e.g., Gislason, 1999; Essington, 2004) or fitting single-species models to data simulated from multi-species models (e.g. Trijoulet et al., 2019). These approaches evaluate bias in model outputs due to model misspecification, but are limited in their ability to assess management performance because they do not account for the feedback between management strategies and fish populations through continued data collection and analysis (Andersen et al., 2015; Gaichas et al., 2017; Gislason, 1999; Trijoulet et al., 2019). Including feedback from continued sampling and assessment of fish populations provides adaptive estimates of sustainable yields that could track the impacts of trophic interactions on population dynamics. Consequently, single-species management may result in appropriately conservative harvests (Melnichuk et al., 2013). While accounting for feedback control and multi-species dynamics, Fulton et al. (2019) found that single-species population dynamics models coupled with spatial management and gear and entry restrictions performed the best at achieving a variety of management objectives for one specific case study area in Australia. Therefore, evaluation of the impacts of predator-prey dynamics on single-species management strategies should ideally account for feedback control. Such an approach can also confirm whether predator-prey dynamics are sufficiently impactful to bias single-species management strategies and require the adoption of multi-species management strategies.

Management strategy evaluation (MSE) can assess the consequences of the uncertainty associated with achieving management objectives, given alternative hypotheses related to ecosystem functioning, while accounting for the feedback between management and fish dynamics (Punt et al., 2016a). MSE uses simulation to evaluate the performances of management strategies (i.e., data collection schemes, estimation methods [including single-species population dynamics models], and subsequent harvest control rules) relative to management objectives. A set of operating models (OMs) representing a range of uncertainties are selected to represent the “true” system dynamics (i.e., fishery and population). Management strategies are then applied across operating models: data are simulated from the operating models, estimation models (EMs; i.e.,

assessment methods) are fit to the simulated data, and the catch limits based on harvest control rules are input back into the operating model and the “true” population dynamics updated for the subsequent time step. While MSEs based on multi-species models have been utilized to evaluate the impacts of alternative prey management strategies on predators of commercial or conservation interest (e.g., A’mar et al., 2009; Punt et al., 2016; Deroba et al., 2019), their application to understanding the impacts of alternative predator management strategies on prey populations has been limited.

The Gulf of Alaska (GOA) and Eastern Bering Sea (EBS) are diverse ecosystems that support many commercial fisheries whose target species exhibit strong, but differing, trophic interactions (Gaichas et al., 2015). Walleye pollock (*Gadus chalcogrammus*, Gadidae) and Pacific cod (*G. macrocephalus*, Gadidae) support some of the largest and most valuable fisheries in the region and the United States (Fissel et al., 2020), and arrowtooth flounder (*Atheresthes stomias*, Pleuronectidae) is an important predator species of walleye pollock in both systems. The total catch of pollock regularly exceeds 1.5 million metric tonnes annually, with an ex-vessel value of over 400 million USD (Fissel et al., 2020). Network, diet, and foodweb analyses have indicated that pollock has high trophic connectivity with cod and arrowtooth flounder (Chapter 1; Barnes et al., 2020; Gaichas et al., 2015; Gaichas and Francis, 2008; Holsman et al., 2016; Livingston et al., 2017; Reum et al., 2019). For example, food web analyses have estimated that total mortality of walleye pollock in the Bering Sea is mainly driven by cannibalism (40% of total mortality) and fishing (15% of total mortality), while in the GOA, total mortality of walleye pollock is thought to be driven by predation from arrowtooth flounder (33% of total mortality) and cod (16% of total mortality; Gaichas et al., 2015). While time-varying predation mortality is thought to represent a large proportion of the mortality on pollock (Gaichas et al., 2011), assessment models, biological reference points, and harvest control rules do not explicitly account for time-varying predation and assume time-invariant (but perhaps age-specific) natural mortality (M). Specifically, management of each species is currently based on single-species age-structured population dynamics assessment models.

We conducted a MSE based on two multi-species population dynamics models developed for the GOA and EBS to assess whether ignoring time-varying M due to predation limits the performance of single-species management. The two multi-species population dynamics were selected to evaluate the performance of single-species management strategies across systems that differ in their predator-prey dynamics. Specifically, multi-species models were used as operating models to evaluate the ability of single-species management strategies to achieve single-species BRPs, maximize catch, minimize catch variability, and reduce bias in biomass estimates. The EBS and GOA models were used given the differences in the trophic linkages and fisheries between systems. Our study improves upon previous efforts to evaluate the performances of single-species management strategies by: a) accounting for feedback control (continued monitoring and assessment), b) including alternative hypotheses of stock dynamics, and c) accounting for feedback between species with trophic linkages in the operating model. This research furthers our understanding of the performance of single-species management given predator-prey dynamics by comparing single-species management strategies within two multi-species systems (using single-species operating models as a control),.

2.2 METHODS

2.2.1 Operating models

We utilized a multi-species age-structured population dynamics model developed for walleye pollock, Pacific cod, and arrowtooth flounder in the EBS (Holsman et al., 2016) and the GOA (Chapter 1) to develop the operating models. The age-structured model links species through age- and time-varying predation mortality derived from multi-species virtual population analysis and bioenergetics theories (Tables 2.1 and 2.2). Temperature-specific consumption and the prey preference of predators (Table 2.2) were parameterized using bioenergetics and diet information. Apart from time-varying predation mortality, the model is parameterized similarly to the single-species models used for tactical management advice, and can be run in single-species mode by “turning-off” time-varying predation mortality or in multi-species mode by “turning-on” time-varying predation mortality. We utilized the model as an operating model to evaluate the current management frameworks in the GOA and EBS with and without time-varying predation mortality (i.e., “multi-species mode” and “single-species mode”, respectively).

We developed a set of six operating models that varied in their parameterization of mortality and recruitment and applied the set to both the EBS and GOA (for a total of 12 operating models). Three operating models for M were developed to represent two single-species and one multi-species parameterization. The single-species parameterizations either specified time- and age-invariant M estimated from the conditioning data or time-invariant and (in some cases) age-varying M based on the pre-specified M values (Supplementary Table S2.1) utilized in stock assessments (Barbeaux et al., 2018; Dorn et al., 2018; Ianelli et al., 2017; Spies et al., 2018; Spies and Palsson, 2018; Thompson, 2017). The multi-species parameterization specified time- and age-varying M (multi-species model) where M was partitioned into predation mortality ($M2$) and an estimated age- and time-invariant residual mortality ($M1$) by fitting the operating model to the conditioning data. $M1$ represents mortality due to predation from other species not included in the model, disease, senescence, etc. (Table 2.1). $M2$ follows a Holling Type II functional response that is the standard form for MSVPA-based predation mortality and assumes that predation rate decreases asymptotically with prey abundance (Magnusson, 1995; Table 2.2).

For recruitment, we developed two parameterizations. The first followed the approach currently implemented by the single-species models used for management advice in this region, where expected recruitment for each species is treated as constant, and annual recruitment is generated as follows:

$$\text{Eq. 2.1:} \quad N_{is1y} = R_{isy} = \bar{R}_i e^{\tau_{iy}} \rho_{i1}$$

where R_{isy} is the age-1 recruitment for species i of sex s during year y , τ_{iy} are the normally distributed annual recruitment deviations, and ρ_{i1} is the proportion of females at age-1. The second approach was developed to evaluate the impacts of both predation and stock-dependence in recruitment, and followed a Ricker stock-recruit relationship:

$$\text{Eq. 2.2:} \quad R_{isy} = a_i S B_{iy-1} e^{-\beta_i S B_{iy-1}} e^{\tau_{iy}} \rho_{i1}$$

where a_i is related to density-independent mortality and β_i is related to both density-independent and -dependent mortality. The three mortality parameterizations were combined with the two recruitment parameterizations resulting in six operating models each for the EBS and GOA.

The parameters for the twelve operating models were specified to represent the historical biological and fishery conditions by fitting or “conditioning” the operating models to data from the EBS and GOA. The six operating models for the EBS were conditioned to historical fishery and survey data for arrowtooth flounder (1 sex), Pacific cod (1 sex), and walleye pollock (1 sex) from 1979 to 2017 (Holsman et al., 2016) while the six operating models for the GOA were

conditioned using data for arrowtooth flounder (2 sexes), Pacific cod (1 sex), and walleye pollock (1 sex) from 1977 to 2018 (Model 2 from Chapter 1). Annual recruitment deviates were treated as random effects and then were projected forward from 2017 (EBS) or 2018 (GOA) until 2060, 300 times, with future recruitment deviates sampled, with replacement, from those for the conditioning period (Chapter 1). The years for which there are data are henceforth referred to as the “conditioning period” or “historical period” (e.g., 1979 to 2017 for EBS) and the proceeding years are referred to as the “projection period” (e.g., 2018 to 2060 for EBS). We selected 2060 as the end of the projection period to allow at least two full generations of each species to be modelled. Projected selectivity, catchability, relative number of foraging days, maturity-at-age, length-at-age, ageing error, and weight-at-age were assumed to be time-invariant and set to the values for the last year with data. Projected bottom temperature was set to the mean across the entire time series. This allowed us to isolate the impacts of time-varying predation mortality from the impacts of time-varying life history, fishery/survey characteristics, or environmental conditions.

2.2.3 Data simulation

Data used for the estimation models for the conditioning period and the projection period mirrored the historical data collection in the EBS and GOA (Supplementary Table S.2). Rather than use the historical data to first fit the estimation models, we used a single set of data generated from the operating model without observation error from the historical period to isolate the impacts of model misspecification. For the projection period, survey and fishery data were simulated from the same sampling distributions and assumed that future sampling will be similar to recent sampling efforts. Indices of relative abundance were simulated from lognormal distributions assuming the annual standard deviation of the log was the same the average from the last two years of the conditioning period. Age- and length-composition data were simulated from multinomial distributions assuming the annual input multinomial sample sizes were the same as the averages from the last two years of the conditioning period. Catches from each fishery during the projection period were determined using a harvest control rule (see below) and assumed known exactly (i.e., no observation or implementation error). All operating models assumed there were three fleets that fished for Pacific cod in the GOA, while a single fishing fleet fished for the remaining stocks, with distinct fisheries for each region. Projected catches were apportioned across three fleets for GOA Pacific cod fishery based on the ratio of average fully-selected fishing mortalities from the last two years of the conditioning period.

2.2.4 Management strategies

Here we refer to a management strategy as the combination of an estimation model (e.g., assessment method) and harvest control rule. For each species we evaluated management strategies based on the combination of two estimation models and eight harvest control rules. Each species was assessed using one of two single-species age-structured estimation models that varied in their specification of M . The estimation models either estimated a time- and age-invariant M or used a pre-specified time-invariant, but age-varying for some species, M (as above) and were hence intentionally mis-specified compared to the multi-species operating models (Table 2.1). The estimation models were annually fit using penalized likelihood, with the variance in recruitment deviations pre-specified at the true value (Table 2.1). For all estimation models, we assumed constant expected recruitment following the approach used for management advice in this region (Eq. 2.1). Recruitment deviations were estimated for all years in the estimation models, including for the terminal year.

Catch was determined using target fishing mortality rate ($F_{Target} \text{ yr}^{-1}$) derived from a harvest control rule applied to the estimated spawning stock biomass (SSB) projected forward one year assuming mean annual recruitment and terminal selectivity, maturity, and weight-at-age (Table 2.1). Harvest control rules were used to define limit reference points to determine if a stock is perceived to be undergoing overfishing ($F > F_{Limit}$) or to be overfished ($B < B_{Limit}$). Biological reference points in the harvest control rules were either based on SSB-per-recruit ($F_{X\%}$ and $SB_{X\%}$) or depletion (F_X and SB_X), where X represents the proportion (Supplementary Table S2.3). For example, $F_{35\%}$ is the fishing mortality rate associated with an equilibrium SSB-per-recruit that is 35% of the SSB-per-recruit in the absence of fishing. $SB_{35\%}$ refers to the long-term average SSB that would be expected under stock-independent mean recruitment and $F = F_{35\%}$. Alternatively, F_{35} is the fishing mortality rate associated with an equilibrium SSB that is 35% (SB_{35}) of equilibrium unfished spawning biomass SB_0 . For estimation models that assume constant expected recruitment (i.e., all estimation models), $SB_{35\%}$ and SB_{35} and, consequently, $F_{35\%}$ and F_{35} are equivalent.

The following harvest control rules were evaluated for each estimation model (Fig. 2.1). These were selected based on their use across systems that have high value fisheries that target key prey species such as pollock.

1. The North Pacific Fishery Management Council (NPFMC) Tier 3 spawner-per-recruit-based harvest control rule (used in Alaska) that is currently used for all species in the analysis (NPFMC, 2019, 2017).
 - a. Tier 3: spawner-per-recruit-based reference points are estimated as follows:
 - i. Stock status: $SSB/SB_{40\%} \geq 1$
 - $F_{Limit} = F_{35\%}$
 - $F_{Target} = F_{40\%}$
 - ii. Stock status: $\alpha < SSB/SB_{40\%} < 1$
 - $F_{Limit} = F_{35\%} * (SSB/SB_{40\%} - \alpha) / (1 - \alpha)$
 - $F_{Target} = F_{40\%} * (SSB/SB_{40\%} - \alpha) / (1 - \alpha)$
 - iii. Stock status: $SSB/SB_{40\%} \leq \alpha$
 - $F_{Limit} = 0$
 - $F_{Target} = 0$
 - b. α is set to 0.05 for the EBS and GOA. B_{Limit} , determining if the stock is overfished is set to $0.5 * SB_{35\%}$ (see Table S2.2 for derivation).
 - c. Additionally, fishing mortality is set to 0 for pollock or Pacific cod if the biomass is projected to fall below 20% of equilibrium unfished spawning biomass SB_0 (SB_{20}) in the following year to maintain forage resources for marine mammals (NPFMC, 2019).
2. A harvest control rule based on the Pacific Fishery Management Council (PFMC) Category 1 harvest control rule (used in the US West Coast), which assumes that the estimated F_{Limit} is normally distributed with a standard deviation (sigma) = 0.5 and an uncertainty quantile buffer (P^*) of 0.45 (PFMC, 2022). Limit biological reference points are based on spawner-per-recruit-based proxies for maximum sustainable yield: $F_{Limit} = F_{45\%}$ and $B_{Limit} = 0.25 * SB_0$ for roundfish (pollock and Pacific cod); $F_{Limit} = F_{30\%}$ and $B_{Limit} = 0.125 * SB_0$ for flatfish (arrowtooth flounder).
 - a. Target biological reference points are calculated based on the normal cumulative distribution function ($\Phi(\text{quantile}, \text{mean}, \text{standard deviation})$) (Owen Hamel,

NOAA Northwest Fisheries Science Center, personal comm.), P^* , and sigma as follows:

- i. Stock status: $SSB > SB_{40}$
 - $F_{Target} = \Phi(0.45, F_{Limit}, 0.5)$
- ii. Stock status: $SB_{10} < SSB \leq SB_{40}$
 - $F_{Target} = \Phi(0.45, F_{Limit}, 0.5) \frac{4}{3} * \frac{SSB - SB_{10}}{SB}$
- iii. Stock status: $SSB < SB_{10}$
 - $F_{Target} = 0$
- b. For arrowtooth flounder SB_{40} and SB_{10} are replaced by SB_{25} and SB_5 , respectively.
3. The Australian Southern and Eastern Scalefish and Shark Fishery (SESSF) biomass-based Tier 1 harvest control rule where $F_{Limit} = F_{20}$, and $B_{Limit} = SB_{20}$ (AFMA, 2017).
 - a. F_{Target} reference points were calculated as follows:
 - i. Stock status: $SSB > SB_{35}$
 - $F_{Target} = F_{48}$
 - ii. Stock status: $SB_{35} > SSB > SB_{20}$
 - $F_{Target} = F_{48} * (SSB/SB_{20} - 1)$
 - iii. Stock status: $B < SB_{20}$
 - $F_{Target} = 0$
4. The New England Fishery Management Council (NEFMC) equilibrium (and constant) $F_{Target} = 0.75 * F_{40\%}$ is used for management for the northeast US multi-species fishery where $F_{Limit} = F_{40\%}$, $B_{Limit} = 0.5 * SB_{40\%}$. F_{Limit} and B_{Limit} were only used to define whether the stock is undergoing overfishing or overfished, respectively, rather than adjust the target fishing mortality.
5. Constant F, set to the average F from the last five years the estimation model was fitted to. We set $F_{Limit} = F_{35\%}$ and B_{Limit} is set to $0.5 * SB_{35\%}$ following the NPFMC Tier 3 harvest control rule to define overfishing and overfished within the estimation model.

The NPFMC Tier 3, PFMC Category 1, and SESSF Tier 1 harvest control rules were also evaluated using dynamic biomass reference points. Dynamic biomass reference points are generalized from dynamic SB_0 (MacCall et al., 1985), which calculates stock biomass in each year in the absence of fishing ($SB_{0,y}$). Dynamic biomass reference points calculate the biological reference points integrating all cohorts extant in the population at any given time, explicitly accounting for time-varying growth and recruitment (Table S2.2; Berger, 2019) and may account to some extent for non-stationarity in population parameters. Specifically, the static/equilibrium biomass reference point SB_0 in harvest control rules 1-3 was replaced by $SB_{0,y}$. Table 2.2 provides a summary of the full set of management strategies. Note that we did not account for rebuilding plans (Wetzel et al., 2018) for when a stock was assessed as overfished. Additionally, we assumed that all future catch would be fully utilized. Currently, quotas of pollock in the EBS and arrowtooth flounder in the EBS and GOA are not fully utilized due to ecosystem and economic considerations, respectively (Ianelli et al., 2017; Spies et al., 2018; Spies and Palsson, 2018).

2.2.5 Performance metrics

For single-species estimation models and operating models, reference points used to calculate performance metrics were defined as in section 2.2.4. For the multi-species operating models, biological reference points are conditional on the biomass of other species and temperature in the system (i.e., multi-species biological reference points). We therefore defined the “true” B_{Limit} for

multi-species operating models as $B_{Limit} = 0.25 * SB_0$ where SB_0 is defined by projecting all species forward allowing for species interactions under no fishing and mean recruitment and temperature until 2060, regardless of estimation model and harvest control rule. The “true” overfishing limit was then determined by the fishing mortality rates that led to $0.25 * SB_0$ for all species simultaneously. The 25% threshold is arbitrary but consistent with the limit reference points included in the harvest control rules evaluated. However, for all operating models with stock-dependent Ricker recruitment, equilibrium SB_0 was determined based on projecting the stock-recruitment curve forward with mean recruitment (no recruitment deviations). For all operating models the following performance metrics were evaluated:

1. Average annual catch across all projection years and simulations.
2. Average interannual variation in catch (IAV) across all projection years (n) and simulations:

$$• \quad IAV_{f_i} = \sqrt{\frac{\sum_y^{n-1} (\hat{C}_{iy+1}^* - \hat{C}_{f_{iy}}^*)^2}{n-1}} \bigg/ \frac{\sum_y \hat{C}_{iy}^*}{n}$$

3. Probability of the fishery being open across projection years and simulations (sim):

$$• \quad \frac{\sum_{sim} \sum_y 1[\hat{C}_{iy}^* > 0]}{\sum_{sim} \sum_y 1}$$

4. Average relative mean squared error for the estimates of spawning biomass in 2060 across simulations.

5. Probability that the population is perceived as undergoing overfishing in the terminal year of the estimation model as determined from the estimated $\hat{F}_{Limit}$ across projection years and simulations:

$$• \quad \frac{\sum_{sim} \sum_y 1[\hat{F}_{iy} > \hat{F}_{Limit_i}]}{\sum_{sim} \sum_y 1}$$

6. Probability that the population is perceived to be overfished in the terminal year of the estimation model as determined from estimated $\hat{B}_{Limit}$ across projection years and simulations:

$$• \quad \frac{\sum_{sim} \sum_y 1[\hat{S}B_{iy} < \hat{B}_{Limit_i}]}{\sum_{sim} \sum_y 1}$$

7. Probability that the population is undergoing overfishing as determined from the “true” F_{Limit} from the operating model across simulations:

$$• \quad \frac{\sum_{sim} \sum_y 1[F_{iy} > F_{Limit_i}]}{\sum_{sim} \sum_y 1}$$

8. Probability that the population is overfished as determined from the “true” B_{Limit} from the operating model across simulations:

$$• \quad \frac{\sum_{sim} \sum_y 1[SB_{iy} < B_{Limit_i}]}{\sum_{sim} \sum_y 1}$$

9. Average terminal (*i.e.*, 2060) spawning stock depletion relative to equilibrium SB_0 across all simulations.

10. Average terminal (*i.e.*, 2060) spawning stock depletion relative to dynamic $SB_{0,y}$ across all simulations.

where $\hat{C}_{iy}^*$ is the catch across fleets, F_{iy} is the fishing mortality (yr^{-1}), and SB_{iy} is SSB during year y for species i .

These performance metrics were selected based on management objectives to optimize yields (performance metric 1), promote management measures that avoid significant disruption to existing economic structures (performance metrics 2 & 3), and prevent overfishing and sustain the long-term health of the resource (performance metrics 5-8). Performance metrics based solely on the estimation model (5 & 6) were utilized to mimic single-species management strategies in practice, as scientists must ascertain whether a stock is overfished or undergoing overfishing based on a perception of the stock that may not accurately reflect the true stock dynamics.

Overall, six operating models, two estimation models, eight harvest control rules, and ten performance metrics were evaluated for each area. Factors considered in the management strategy evaluation are illustrated in Table 2.3. 300 simulations were used for each scenario (e.g., simulated data and sampled recruitment deviates). Dominant management strategies (i.e., strategies with the best overall performance) were determined based on average performance metrics equally weighted across all (1-10), economic (1-3), or conservation (5-8) performance metrics across all scenarios. The base case, representing the current management strategy includes estimation models that pre-specified or estimated M and utilize the NPFMC Tier 3 harvest control rule applied to single- and multi-species operating models with stock-independent recruitment (Table 2.3).

2.3 RESULTS

2.3.1 Operating models

The six operating models differed in their values for M across age and time and, therefore, SSB and recruitment. Specifically, the single-species operating model with estimated, age-invariant M and multi-species operating model with stock-dependent recruitment led to the highest values for SSB for pollock in the EBS (Fig. 2.2). However, estimated pollock recruitment was higher in both the stock-dependent and -independent multi-species operating models because of higher mortality on younger ages. For the GOA, the multi-species operating model led to the highest values for recruitment and SSB for pollock (Fig. 2.2). For cod and arrowtooth flounder the single-species operating model with pre-specified, age-varying M led to the highest values of SSB, due to differences in assumed and estimated values of M (Supplementary Table S2.1). Pollock was consumed by older pollock, arrowtooth flounder and cod in the EBS, while in the GOA pollock was primarily consumed by arrowtooth flounder (Fig. 2.2).

The estimation model and associated harvest control rule were able to achieve their target reference points when the estimation model had the same specification of M and recruitment as the operating model (i.e., no mis-specification). For example, terminal depletion for the NPFMC Tier 3 harvest control rule was close to the target of 40% when the estimation model matched the operating model in the EBS and GOA (Table 2.4). In the case of the single-species operating model with age-varying M , the estimation model that pre-specified the same age-varying M led to a depletion of 40% throughout the projection period under the NPFMC Tier 3 harvest control rule for all species and systems (Fig. 2.3 upper panel). Fishing mortality across the projection period was on average similar to the target fishing mortality rate in the operating model (Supplementary Fig. S2.1 upper panels). This was also the case for the single-species estimation model that estimated age-invariant M when applied to the operating model with age-invariant M under the NPFMC Tier 3 harvest control rule for all species and systems (Supplementary Table S2.5). However, there was variable performance in management strategies across species when there was mismatch in the specification of M between the estimation model and operating model.

2.3.2 Performance of the current harvest control rule across single-species operating models

Results for pollock are presented in-text with results for Pacific cod and arrowtooth flounder presented in Supplementary Figs S2.5-S2.6 and Supplementary Tables S2.6 & S2.7. Average catch and interannual catch variability varied with the perceived (estimation model) and true (operating model) scale of the population for the management strategies based on single-species estimation models that pre-specified or estimated M combined with the harvest control rule currently used in Alaska (NPFMC Tier 3). For the EBS, average catch and interannual catch variability for pollock was greater for the estimation model that estimated age-invariant M than for the estimation model that pre-specified age-varying M across single-species operating models (Table 2.4). However, in the GOA average catch and interannual catch variability were similar between estimation models when applied to single-species operating models. The specific difference in both performance metrics between estimation models depended on the difference in the pre-specified and estimated natural mortalities relative to the true natural mortality in the operating model. Similarly, average catch and interannual catch variability were similar across estimation models for cod in the EBS and lower for cod in the GOA for the estimation model that estimated M because of the estimated value of M was lower than the pre-specified value (Supplementary Table S2.6).

Both single-species estimation methods combined with the NPFMC Tier 3 harvest control rule achieved conservation goals based on the conservation performance metrics (5-8) and performance metrics 9-10 (terminal depletion) for pollock (Table 2.5) when the estimation model was correctly specified. The probability of being overfished was close to 0 for single-species operating models. Even when the estimation model was not correctly specified, there was a low probability of being overfished as determined from the estimation model (perception) or operating model (truth) across single-species operating models in the EBS. When M in the estimation model was not correctly specified in the GOA, there was a 12-19% probability of pollock being overfished in single-species operating models. This led to a terminal depletion of 30-36%. Similarly, the probability of experiencing overfishing for pollock was $\geq 67\%$ for all estimation models in the GOA when single-species estimation models and operating models differed in their treatment of M (Table 2.4). There was only a high probability of overfishing for pollock in the EBS when the estimation model estimated M and the operating model included age-varying M given the higher level of productivity the estimation model perceived (Table 2.4). However, despite overfishing occurring in the single-species operating models, there was a low or zero probability that the estimation models perceived the stock to be experiencing overfishing or to be overfished for all species. Terminal depletion relative to equilibrium SB_0 was always greater than 40% when the single-species operating model included stock-dependent Ricker recruitment. Terminal depletion relative to dynamic $SB_{0,y}$ was less sensitive to model mis-specification in the EBS than the GOA, where depletion was always less than 40% when M was mis-specified.

2.3.3 Performance of alternative harvest control rules across single-species operating models

Alternative harvest control rules had similar, or better, performance than the NPFMC Tier 3 harvest control rule across single-species operating models for the EBS and GOA. Across single-species operating models, the NPFMC Tier 3 harvest control rule led to the highest average catch and catch variability for pollock (Figs 2.4 & 2.5). In contrast, the NEFMC $F_{40\%}$ and average F strategies led to the lowest catch variability and lowest average catches. Strategies using dynamic $SB_{0,y}$ reference points generally had lower catch variability for pollock (Fig. 2.5). All management strategies led to a high probability of the fisheries being open (Supplementary Fig. S2.4). The estimation models that pre-specified M led to a low probability that single-species operating

models were subject to overfishing in the EBS (Fig. 2.6). In both the EBS and GOA, estimation models that estimated M combined with the NPFMC Tier 3 or PFMC Category 1 harvest control rules led to a >39% probability the single-species operating models with age-varying M was undergoing overfishing. Additionally, in the GOA, the NEFMC $F_{40\%}$ harvest control rule combined with the estimation model that estimated M led to overfishing when the operating model included age-varying M in the GOA. Alternatively, the NPFMC Tier 3 and PFMC Category 1 harvest control rules combined with a mis-specified estimation model that pre-specified M also led to a >70% probability of the pollock undergoing overfishing when the operating model specified age-invariant M estimated from the conditioning data. All single-species operating models had a low probability of being overfished for the EBS, (Fig. 2.7). For pollock in the GOA, both estimation models combined with the NPFMC Tier 3 or PFMC Category 1 harvest control rules using dynamic reference points had the highest probability of pollock being overfished, particularly when the operating model with age-varying M and had stock-dependent Ricker recruitment (Supplementary Table S2.5). Across single-species operating models, terminal depletion relative to equilibrium SB_0 for pollock was always above 36% in the EBS and 30% in the GOA (Fig. 2.8; Supplementary Table S2.5). However, terminal depletion relative to dynamic $SB_{0,y}$ for pollock was always above 35% in the EBS and 25% in the GOA. Harvest control rules using dynamic biomass reference points generally led to lower terminal depletion relative to equilibrium SB_0 and dynamic $SB_{0,y}$ than their equilibrium counterparts for both the GOA and EBS (Fig. 2.9; Supplementary Table S2.5).

2.3.4 Performance of single-species management strategies across multi-species operating models

When the operating model was multi-species, both estimation models using the NPFMC Tier 3 harvest control rule achieved conservation objectives for all species in the EBS and GOA. There was a low or zero probability of overfishing or being overfished, as determined by the estimation model and operating model (Table 2.4). However, the estimation model that estimated M combined with the NPFMC Tier 3 harvest control rule led to a 2% probability of the pollock fishery in the EBS being closed when the operating model included a stock-independent recruitment and a 5% probability of it being closed when the operating model included a stock-dependent recruitment. Despite this, terminal depletion was always above 57% relative to equilibrium SB_0 and 52% relative to dynamic $SB_{0,y}$ for pollock across systems when using single-species estimation models combined with NPFMC Tier 3 harvest control rules.

Harvest control rules other than the NPFMC Tier 3 performed similarly, or better across multi-species operating models in the EBS and GOA. Across management strategies that did not use the NPFMC Tier 3 harvest control rule, there was a < 1% probability of the pollock fishery being closed in both systems. The estimation model that estimated M combined with the PFMC category 1 harvest control rule had a 12-24% probability of perceiving pollock in the EBS to be experiencing overfishing and a 1-7% probability of perceiving pollock to be overfished across multi-species operating models (Supplementary Table S2.5; Supplementary Fig. S2.4). All other management strategies had a low (<4%) probability of perceiving pollock to be overfished or experiencing overfishing. There was a 0% probability of the multi-species operating models being subject to overfishing in the GOA and EBS (Fig. 2.6). In the EBS and GOA, most management strategies had a 0% probability of the operating model being overfished. However, estimation models that estimated M led to a 1% probability of multi-species operating models with a stock-dependent Ricker stock-recruitment relationship being overfished in the EBS and a 2-7% probability of multi-

species operating models with stock-independent recruitment being overfished in the GOA (Supplementary Table S2.5). However, across management strategies (excluding those using NPFMC Tier 3 harvest control rules) average terminal depletion was always above 82% relative to equilibrium SB_0 and 72% relative to dynamic $SB_{0,y}$ in the EBS and above 63% relative to equilibrium SB_0 and 58% relative to dynamic $SB_{0,y}$ in the GOA.

2.3.5 Dominant strategies

No one management strategy performed the best across all regions and species. Dominant strategies were determined by weighting all performance metrics equally and ranking management strategies based on the number of times a strategy performed the best on average across the 300 simulations (Supplementary Table S2.8). Generally, estimation models that pre-specified age-varying M outperformed estimation models that estimated M for pollock in the EBS and GOA because the pre-specified values were lower than the value in the single- and multi-species operating models that estimated M . The opposite was true for Pacific cod in the GOA, where the pre-specified value of M was higher than the value single- and multi-species operating models estimated from the conditioning data, resulting in better management performance for estimation models that estimated M .

Specifically, across estimation models and harvest control rules, the best performing (dominant) strategy for pollock across all operating models was the estimation model that pre-specified M combined with the NEFMC $F_{40\%}$ harvest control rule in the EBS and GOA. The NEFMC $F_{40\%}$ harvest control rule combined with the estimation model that pre-specified M performed the best for pollock in the EBS and GOA across economic performance metrics (1-3) (Supplementary Table S2.9). For arrowtooth flounder, the dominant strategy across all performance metrics was the estimation model that pre-specified M combined with the NEFMC $F_{40\%}$ harvest control rule (Supplementary Table S2.7). Regional differences in performance emerged in the conservation performance metrics (5-8) for pollock and in all performance metrics for Pacific cod. The estimation model that pre-specified M combined with the NEFMC $F_{40\%}$ harvest control or SESSF Tier 1 harvest control rule using dynamic biomass reference points performed the best for pollock in the EBS, while the estimation model that pre-specified M combined with the SESSF Tier 1 harvest control rule using dynamic biomass reference points performed the best in the GOA (Supplementary Table S2.10). For Pacific cod, the dominant strategy across all performance metrics was the NEFMC $F_{40\%}$ harvest control rule combined with the estimation model that pre-specified M in the EBS and the estimation model that estimated M combined with the SESSF Tier 1 harvest control rule using dynamic biomass reference points in the GOA (Supplementary Table S2.8).

2.4 DISCUSSION

We evaluated the impacts of predator-prey dynamics on the performance of single-species management strategies using an MSE approach that explicitly accounted for intraspecies predation, age-structure of predators, feedback between predator and prey species, stock-dependent recruitment, and feedback between management and fish dynamics. Overall, we found that single-species management strategies were robust at achieving management goals across two systems with differing predator-prey dynamics even when the predation and stock-recruitment dynamics were not explicitly incorporated. Across single-species management strategies, there was a high probability that the fishery remained open when the operating model was multi-species. Pollock stocks were rarely subject to overfishing and the probability of being overfished was

always less than 7%. Terminal depletion relative to dynamic $SB_{0,y}$ was never lower than 0.70 in the EBS and 0.52 in the GOA for pollock when the operating model was multi-species. Through continued sampling and assessment, single-species estimation models that estimated M were able to adapt to the scale of multi-species operating models. However, harvest control rules that utilized dynamic reference points did not improve management performance relative to conservation objectives.

Our results improve upon previous studies that evaluated the performance of single-species management under alternative predator-prey scenarios. A'mar et al. (2010) conducted an MSE to examine the efficacy of the current single-species management system for pollock in the GOA across multiple predation scenarios for arrowtooth flounder, Pacific cod, and Pacific halibut, using a multi-species biomass dynamics model to drive predation. The authors recommended moving to a multi-species age-structured model as an operating model to account for changes in the age-/size-structure of predators on the pollock population. We expanded upon their analysis by accounting for cannibalism, the age-structure of predators, and the feedback between predator and prey species. Similar to our results, they found that the single-species management strategy that assumed a time-invariant M achieved management goals of maintaining SSB above and fishing mortality below limit reference points. Contrary to our work, Pérez-Rodríguez et al., (2022) found that single-species management strategy goals were not achievable for three trophically linked species in the Flemish Cap ecosystem. However, their work did not include the full feedback control due to computational limitations.

Management strategies should ideally be selected based on the specific goals of the fishery and life history of the stock to account for the variable performance across estimation methods and harvest control rules highlighted in this work. Methods that estimated M were better able to approximate the underlying scale of the population and led to a lower probability of being overfished. This fits with previous work demonstrating that estimating age- and time-invariant M performs better than pre-specifying a mis-specified value when the true M is time- and/or age-varying (Johnson et al., 2015; Punt et al., 2021). For example, while pre-specifying M at a value lower than the true value led to less interannual catch variability, pre-specifying M at a higher value than the true value led to higher interannual catch variability and inability to achieve conservation objectives. Among harvest control rules, the NPFMC Tier 3 harvest control rule led to a higher probability that pollock was perceived or defined as subject to overfishing. This was less prevalent for arrowtooth flounder because of differences in life history (*i.e.* lower interannual recruitment variability and a longer life span). Dynamic reference points have been proposed as a solution to non-stationary population dynamics. However, utilizing dynamic reference points led to lower levels of terminal depletion relative to equilibrium SB_0 and dynamic $SB_{0,y}$, particularly when the operating model included a stock-dependent stock-recruit relationship, which is consistent with other MSEs exploring the performance of management strategies based on dynamic reference points (Bessell-Browne et al., 2024).

A challenge of this work was comparing the performances of management strategies across single- and multi-species operating models. Biological reference points are comparable across the single-species operating and estimation models but, in multi-species models, the biomass of one species is conditional on the biomass of the other species. Therefore, multi-species biological reference points are not directly comparable to those computed using single-species operating models. There are multiple methods for defining biological reference points for multi-species models (Holsman et al., 2016; Moffitt et al., 2016). Multi-species SB_{25} represents a larger stock size than the single-species SB_{20} used in most of the harvest control rules evaluated, providing a

conservative comparison. Similarly, terminal depletion was always at least twice multi-species SB_{25} on average across management strategies and stock-recruitment relationships. However, the biomass of prey species may be lower with no fishing than when fishing has reduced predation and a target biomass rather than target depletion may be a more desirable biological reference point for comparison across single- and multi-species operating models.

While the performances of single-species management strategies were generally robust to the predation and stock-recruit relationships evaluated, we did not evaluate the performances of multi-species management strategies. Multi-species management strategies can be designed to maximize yields across prey species while limiting undesired levels of depletion by altering fishing on predators (Moffitt et al., 2016; Pérez-Rodríguez et al., 2022). Multi-species management strategies have been demonstrated to outperform single-species management strategies at achieving goals for trophically linked fisheries. For example, Pérez-Rodríguez *et al.* (2022) found that a two-stage multi-species harvest control rule outperformed standard single-species management strategies by increasing fishing of key predators when they were at high biomass, maintaining yields and biomass of prey species. Similarly, more holistic ecosystem-based management has been shown to outperform purely single-species management strategies by Fulton et al. (2019), although the authors did not explicitly evaluate multi-species harvest control rules.

While our results suggest that single-species management strategies are relatively robust to predation dynamics for these three species, multi-species harvest control rules could be designed to better achieve management goals by explicitly accounting for predation dynamics. For example, while arrowtooth flounder is underutilized in both the EBS and GOA, for this work, we assumed that this species was fully fished. However, had we limited fishing on arrowtooth flounder, we may have had different outcomes because the predation intensity on pollock would have been greater. Within these systems, management strategies could be designed to promote fishing of arrowtooth flounder to maintain high yields of pollock and cod. Further research would be necessary to understand the impacts of reduced predator release via underutilization, given that our work demonstrates that pollock management goals were achievable when arrowtooth flounder is fully utilized.

The predator-prey dynamics that we evaluated were only “top-down” because the multi-species model only accounts for time-varying predation mortality. It would be useful for future work to evaluate the sensitivity of single-species management strategies to “bottom-up” predator-prey dynamics, such as prey-limited growth and survival (e.g., Fitzpatrick et al., 2022). Multiple fisheries are developing harvest control rules to maintain high biomass of prey species for the conservation of fisheries that target predators (Chagaris et al., 2020) or predators of conservation concern (Punt et al., 2016b). However, similar to work that has evaluated the impacts of predation on single-species management strategies, previous work on “bottom-up” impacts often has not accounted for feedback control in the management system. Multi-species models are also sensitive to the functional form of predation and numerical response (Kinzey and Punt, 2009). Here, we evaluated one functional form, but future work should evaluate whether single- and multi-species harvest control rules are robust to differing predator-prey relationships.

Given the scenarios evaluated, the performances of single-species management strategies were relatively robust to both multi-species dynamics and the stock-recruit relationship scenarios evaluated. Estimation models that estimated M were better able to approximate the underlying scale of the population in the operating model and led to better management performance. The relative performance of specific harvest control rules varied across performance metrics and selection of an optimal management strategy will depend on trade-offs between management

objectives. Explicitly incorporating predation mortality and full feedback control allows MSE frameworks to account for predator-prey dynamics when evaluating the performance of single-species management strategies.

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TABLES

Table 2.1. General population dynamics equations for the operating models and estimation models for species i , sex s , age a , and length l in year y , and the observation and fishery model for survey or fishery f_i . See Table S2.3 for parameter definitions.

Definition	Equation
Initial abundance	$N_{isa1} = \begin{cases} \bar{R}_{F_i} e^{(-\sum_{j=1}^{a-1} M_{1isj} + F_{0i} + \tau_{ia})} \rho_{i1} & \text{if } j < A_i \\ \frac{\bar{R}_{F_i} e^{(-\sum_{j=1}^{a-1} M_{1isj} + F_{0i} + \tau_{ia})} \rho_{i1}}{(1 - e^{(-M_{1isA_i} + F_{0i})})} & \text{if } j = A_i \end{cases}$
Numbers at age	$\begin{cases} N_{isa+1y+1} = N_{isay} e^{-Z_{isay}} \\ N_{isA_iy+1} = N_{isA_i-1y} e^{-Z_{isA_i-1y}} + N_{isA_iy} e^{-Z_{isA_iy}} \end{cases}$
Survey biomass (kg)	$\widehat{CPUE}: B_{f_iy} = \sum_s \sum_a N_{isay} e^{-Month_{f_i} * Z_{isay}} W_{f_iy} sel_{f_iy} q_{f_iy}$
Survey abundance (numbers)	$\widehat{CPUE}: I_{f_iy} = \sum_s \sum_a N_{isay} e^{-Month_{f_i} * Z_{isay}} sel_{f_iy} q_{f_iy}$
Catch-at-age	$C_{f_iy} = \frac{F_{f_iy}}{Z_{isay}} (1 - e^{-Z_{isay}}) N_{isay}$
Total catch (kg)	$\hat{C}_{f_iy}^* = \sum_s \sum_j \frac{F_{f_iy}}{Z_{isay}} (1 - e^{-Z_{isay}}) N_{isay} W_{f_iy}$
Age-1+ biomass (kg)	$B_{iy} = \sum_s \sum_{a>0} N_{isay} W_{B_{iay}}$
Spawning biomass at age (kg)	$SB_{iay} = \begin{cases} N_{iay} e^{-Month_{ssb_i}/12 * Z_{iay}} W_{ssb_iy} \rho_{ia} \delta_{ia} & \text{if 1 sex model} \\ N_{i1ay} e^{-Month_{ssb_i}/12 * Z_{i1ay}} W_{ssb_i1ay} \delta_{ia} & \text{if 2 sex model} \end{cases}$
Total mortality at age (single-species)	$Z_{isay} = M_{1isa} + \sum_{f_i} F_{f_iy}$
Total mortality at age (multi-species)	$Z_{isay} = M_{1isa} + M_{2isay} + \sum_{f_i} F_{f_iy}$
Fishing mortality at age and fleet	$F_{f_iy} = \bar{F}_{f_i} e^{\epsilon_{f_iy}} sel_{f_iy}$
Projected fishing mortality	$F_{f_iy} = F_{Target_i} sel_{f_iy} \psi_{f_i}$
Predicted age composition	$\hat{\theta}_{f_i\hat{s}ay} = \frac{\sum_a C_{f_iy} AE_{i\hat{a}a}}{\sum_s \sum_{\hat{a}} \sum_a C_{f_iy} AE_{i\hat{a}a}} \quad \text{if } f_i = \text{fishery}$ $\hat{\theta}_{f_i\hat{s}ay} = \frac{\sum_a N_{isay} e^{-Month_{f_i} * Z_{isjy}} sel_{f_iy} AE_{i\hat{a}a}}{\sum_s \sum_{\hat{a}} \sum_a N_{isay} e^{-Month_{f_i} * Z_{isjy}} sel_{f_iy} AE_{i\hat{a}a}} \quad \text{if } f_i = \text{survey}$
Predicted length composition	$\hat{\theta}_{f_i\hat{s}ly} = \frac{\sum_{\hat{a}} \sum_a C_{f_iy} AE_{i\hat{a}a} ATM_{isal}}{\sum_s \sum_l \sum_{\hat{a}} \sum_a C_{f_iy} AE_{i\hat{a}a} ATM_{isal}} \quad \text{if } f_i = \text{fishery}$ $\hat{\theta}_{f_i\hat{s}ly} = \frac{\sum_{\hat{a}} \sum_a N_{isay} e^{-Month_{f_i} * Z_{isay}} sel_{f_iy} AE_{i\hat{a}a} ATM_{isal}}{\sum_s \sum_l \sum_{\hat{a}} \sum_a N_{isay} e^{-Month_{f_i} * Z_{isjy}} sel_{f_iy} AE_{i\hat{a}a} ATM_{isal}} \quad \text{if } f_i = \text{survey}$

Table 2.2. Predation mortality equations for predators of species p , sex b , age j , and prey of species i , sex s and age a . For parameter definitions see Supplementary Table S2.3.

Definition	Equation
Predation mortality	$M2_{isay} = \sum_{pbj} \left(\frac{\bar{N}_{pbjy} \delta_{pbjy} \hat{S}_{pbjisa}}{\left(\sum_{isa} (\hat{S}_{pbjisa} \bar{B}_{isay}) + B_p^{other} (1 - \sum_{isa} (\hat{S}_{pbjisa})) \right)} \right)$
Predator-prey suitability	$\hat{S}_{pbjisa} = \frac{1}{n_y} \sum_y \left(\frac{\frac{\bar{U}_{psaisa}}{w_{isay} \bar{N}_{isay}^{H_i}}}{\sum_{isa} \left(\frac{\bar{U}_{pbjisa}}{w_{isay}} \right) + \frac{1 - \sum_{isa} \bar{U}_{pbjisa}}{B_p^{other}}} \right)$
Individual specific ration ($kg \ kg^{-1} \ yr^{-1}$)	$\delta_{pbjy} = \varphi_{pbjy} \alpha_p^\delta W_{pbjy}^{(1+\beta_p^\delta)} f(T_y)_p$
Temperature scaling algorithm	$f(T_y)_p = V^X e^{(X(1-V))}$
...	$V = (T_p^{cm} - T_y) / (T_p^{cm} - T_p^{co})$
...	$X = (Z^2 (1 + (1 + 40/Y)^{0.5})^2) / 400$
...	$Z = \ln(Q_p^c) (T_p^{cm} - T_p^{co})$
...	$Y = \ln(Q_p^c) (T_p^{cm} - T_p^{co} + 2)$

Table 2.3. Factors considered in the management strategy evaluation scenarios. The options indicated in bold-underline typeface represent the base-case analysis.

Factor	Options (bold is base-case)
System	GOA, EBS
OM	<u>-Species age-invariant M, single-species age-varying M, multi-species time- and age-varying M</u>
OM recruitment	<u>Stock-independent</u> , stock-dependent Ricker
EM	<u>Single-species pre-specified M (Fix M), Single-species estimated M (Est M)</u>
Harvest control rule	1. <u>NPFMC Tier 3 HCR</u> a. <u>Equilibrium</u> b. Dynamic 2. PFMC Category 1 40-10 HCR a. Equilibrium b. Dynamic 3. SESSF Tier 1 HCR a. Equilibrium b. Dynamic 4. NEFMC equilibrium $F_{40\%}$ 5. Average F

Table 2.4. Summary of the performance metrics for pollock in the in the EBS and GOA from estimation models (EMs) that pre-specified time-invariant but sometimes age-varying M (fix M) or estimated time- and age-invariant M (Est M) combined with HCR 1a (NPFMC Tier 3 harvest control rule) across operating models (OMs) with no stock-recruit relationship (SRR) or with a Ricker stock-recruit relationship. Note: catch is scaled to 1,000s mt. Grey shading indicates where the estimation model matched the operating model.

OM		Single-species fix M				Single-species est M				Multi-species			
OM SRR		No SRR		Ricker		No SRR		Ricker		No SRR		Ricker	
Performance metric/EM		Fix M	Est M	Fix M	Est M	Fix M	Est M	Fix M	Est M	Fix M	Est M	Fix M	Est M
EBS	1. Average catch	2,121	2,309	2,586	2,985	2,443	3,358	2,828	4,423	2,744	3,451	2,906	5,778
	2. Catch IAV	0.2	0.26	0.24	0.29	0.17	0.29	0.22	0.31	0.18	0.35	0.22	0.47
	3. P(Open)	1	1	1	0.99	1	1	1	0.99	1	0.98	1	0.95
	4. Average SB_{2060} RMSE	0	0.01	0	0.01	0.07	0	0.06	0	0	0.01	0.09	0
	5. EM: $P(F_y > F_{Limit})$	0	0	0	0	0	0	0	0	0	0.02	0	0.04
	6. EM: $P(SB_y < B_{Limit})$	0	0	0	0.01	0	0	0	0.01	0	0.01	0	0.02
	7. OM: $P(F_y > F_{Limit})$	0	0.39	0	0.47	0	0	0	0	0	0	0	0
	8. OM: $P(SB_y < B_{Limit})$	0	0.02	0	0.02	0	0.01	0	0.01	0	0	0	0.01
	9. OM: $Depletion_{2060}$	0.42	0.37	0.82	0.77	0.57	0.42	0.95	0.81	1.08	0.88	0.98	0.8
	10. OM: $Depletion_{2060}$ (dynamic B_0)	0.41	0.36	0.69	0.64	0.57	0.42	0.78	0.67	0.96	0.79	0.85	0.71
GOA	1. Average catch	151	181	320	318	136	119	291	278	298	511	563	999
	2. Catch IAV	0.34	0.41	0.35	0.39	0.32	0.29	0.33	0.3	0.28	0.39	0.33	0.43
	3. P(Open)	1	0.97	1	0.99	0.99	1	1	1	1	0.99	1	1
	4. Average SB_{2060} RMSE	0.01	0.05	0.01	0.05	0.13	0.01	0.12	0.01	0.01	0.11	0.01	0.14
	5. EM: $P(F_y > F_{Limit})$	0	0.04	0	0.04	0	0.01	0	0	0	0.01	0	0.02
	6. EM: $P(SB_y < B_{Limit})$	0	0.01	0	0	0	0	0	0	0	0	0	0
	7. OM: $P(F_y > F_{Limit})$	0.08	0.67	0.08	0.84	0.7	0.22	0.91	0.31	0	0	0	0
	8. OM: $P(SB_y < B_{Limit})$	0.03	0.19	0	0	0.12	0.02	0	0	0	0.06	0	0
	9. OM: $Depletion_{2060}$	0.42	0.32	1.97	1.26	0.33	0.41	1.3	1.71	1.02	0.58	5.44	3.28
	10. OM: $Depletion_{2060}$ (dynamic B_0)	0.42	0.32	0.46	0.3	0.33	0.41	0.36	0.48	0.95	0.54	1.11	0.64

FIGURES

Figure 2.1. Harvest control rules for the management strategies. The dashed line indicates where fishing mortality is set to 0 for pollock or Pacific cod if the biomass is projected to fall below 20% of equilibrium unfished spawning biomass SB_0 (SB_{20}) to maintain forage resources for marine mammals (NPFMC, 2019).

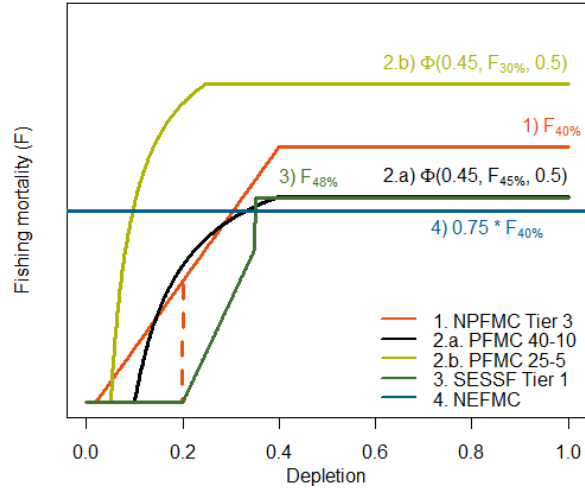


Figure 2.2. Historical (*i.e.* pre-management using the evaluated harvest strategies) time-series of recruitment (top panel), SSB, stock-recruit relationship, and biomass consumed as prey by each predator (bottom panel) as determined from the operating models in the Eastern Bering Sea (EBS) and Gulf of Alaska (GOA). OMs with a Ricker stock recruit relationship are indicated by the dashed lines in the top two panels. Note the different scales between panels.

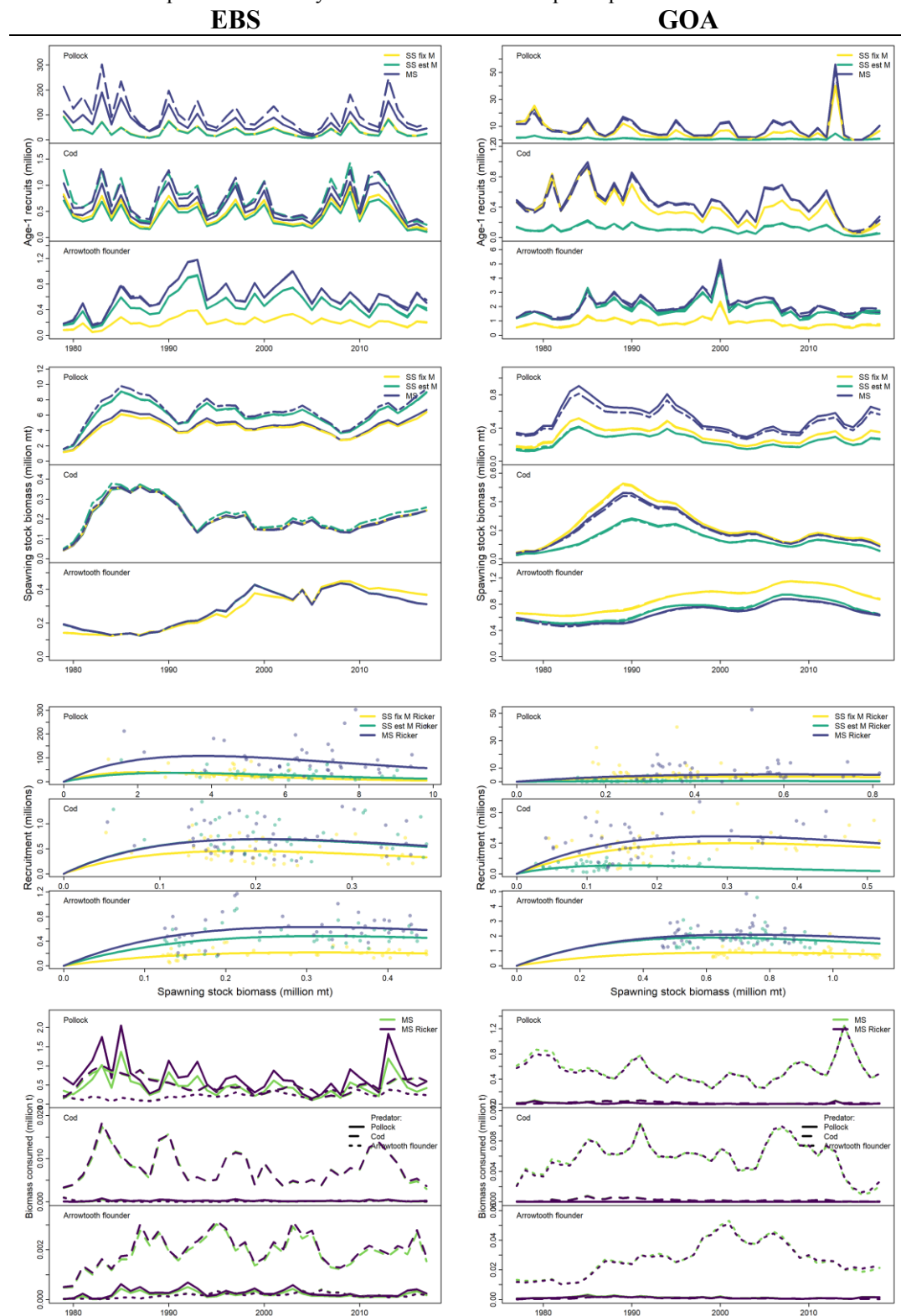


Figure 2.3a. Time-series of spawning stock depletion as determined from the models with no stock-recruit relationship (left) and terminal (i.e., 2060) estimation model (right: with no stock-recruit relationship) that pre-specified natural mortality combined with HCR 1a (NPFMC Tier 3 harvest control rule) in the EBS. The estimation model is applied annually until 2060 across 300 simulations. Depletion under mean recruitment for the operating model given no fishing is indicated by the black dashed line and target and limit depletion are indicated by the blue and red lines, respectively (both estimation model and operating model). See Fig. S2.2 for analogous figure from the operating model with a Ricker stock-recruit relationship.

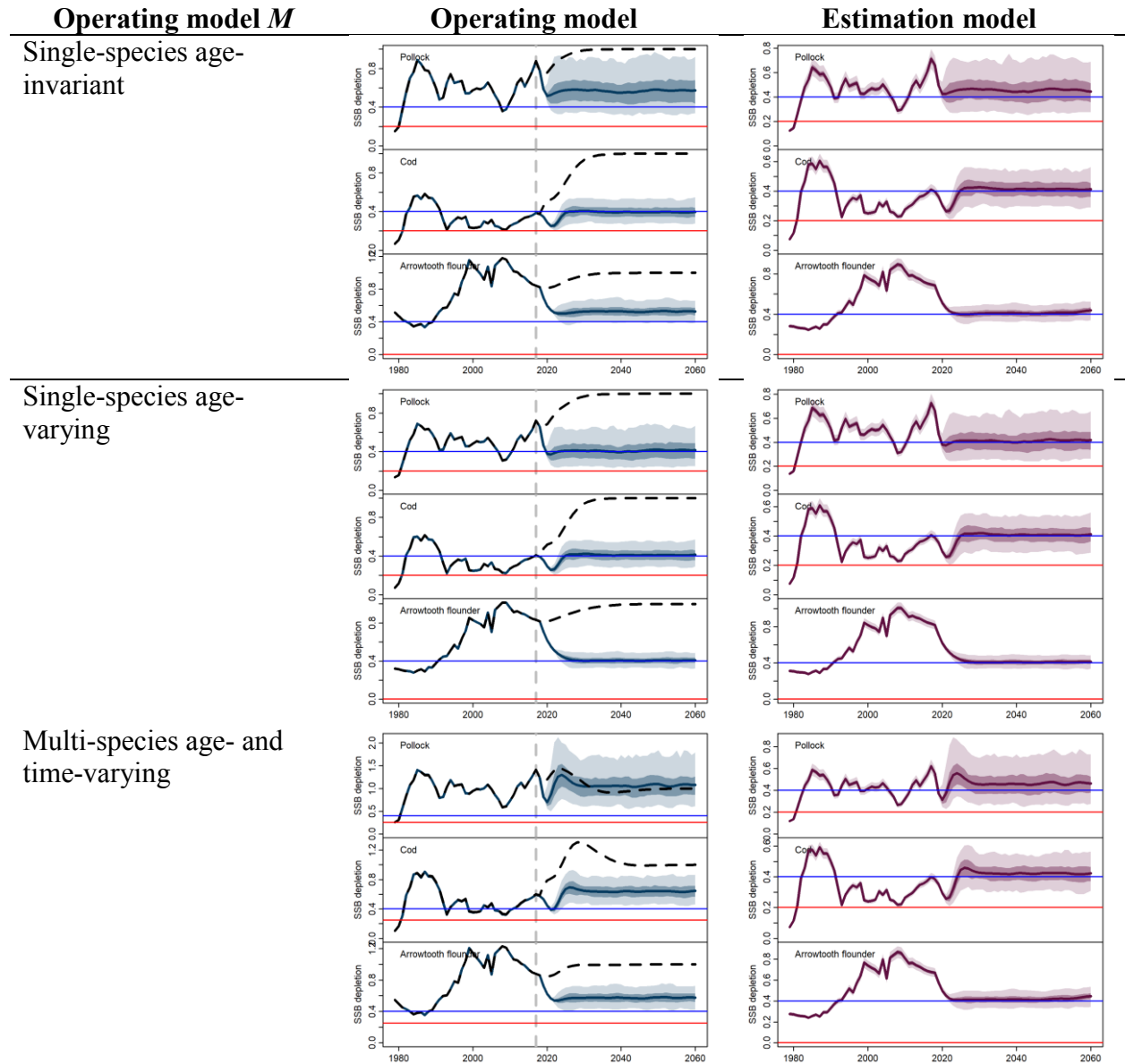


Figure 2.3b.

Time-series of spawning stock depletion as determined from the operating model with no stock-recruit relationship (left) and terminal (i.e., 2060) estimation model (right: with no stock- recruit relationship) that pre-specified natural mortality combined with HCR 1a (NPFMC Tier 3 harvest control rule) in the GOA. The estimation model is applied annually until 2060 across 300 simulations. Depletion under mean recruitment for the operating model given no fishing is indicated by the black dashed line and target and limit depletion are indicated by the blue and red lines, respectively (both estimation and operating model).

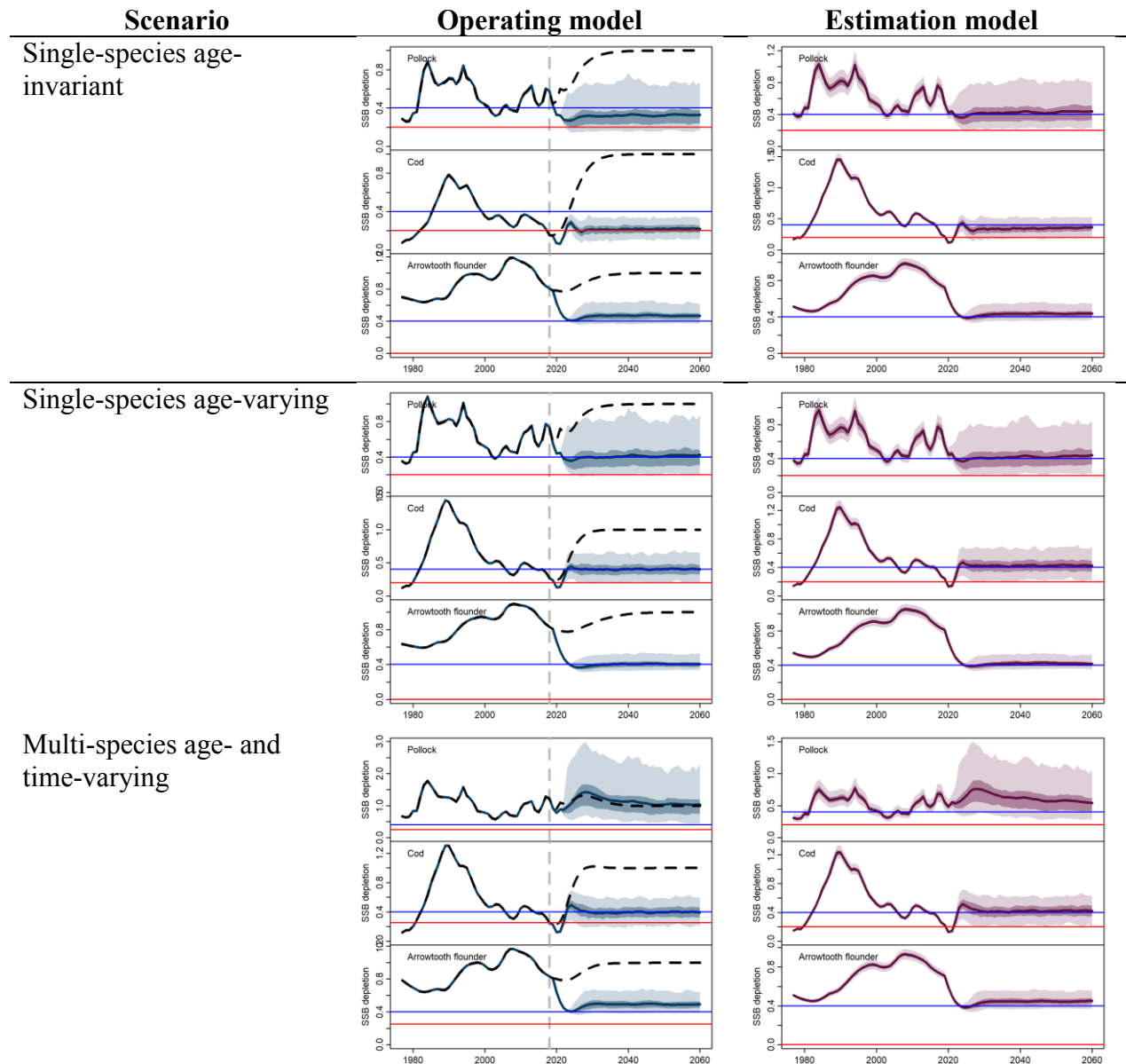


Figure 2.4. Summary of performance metric 1: average catch (mt) for pollock in the EBS and GOA (rows) across operating models (columns). Estimation models that estimated M are indicated by the grey shading and harvest control rules (HCR) using dynamic biomass reference points are indicated by the triangles.

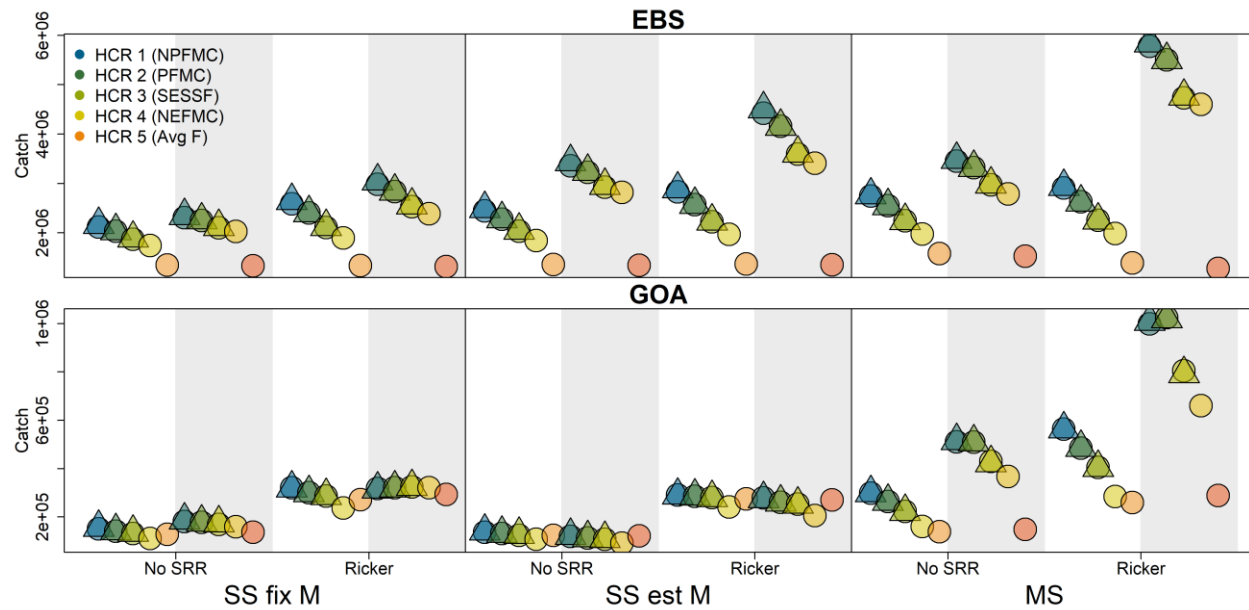


Figure 2.5. Summary of performance metric 2: average interannual catch variability (IAV) for pollock in the EBS and GOA across scenarios. Estimation models that estimated M are indicated by the grey shading and harvest control rules (HCR) using dynamic biomass reference points are indicated by the triangles.

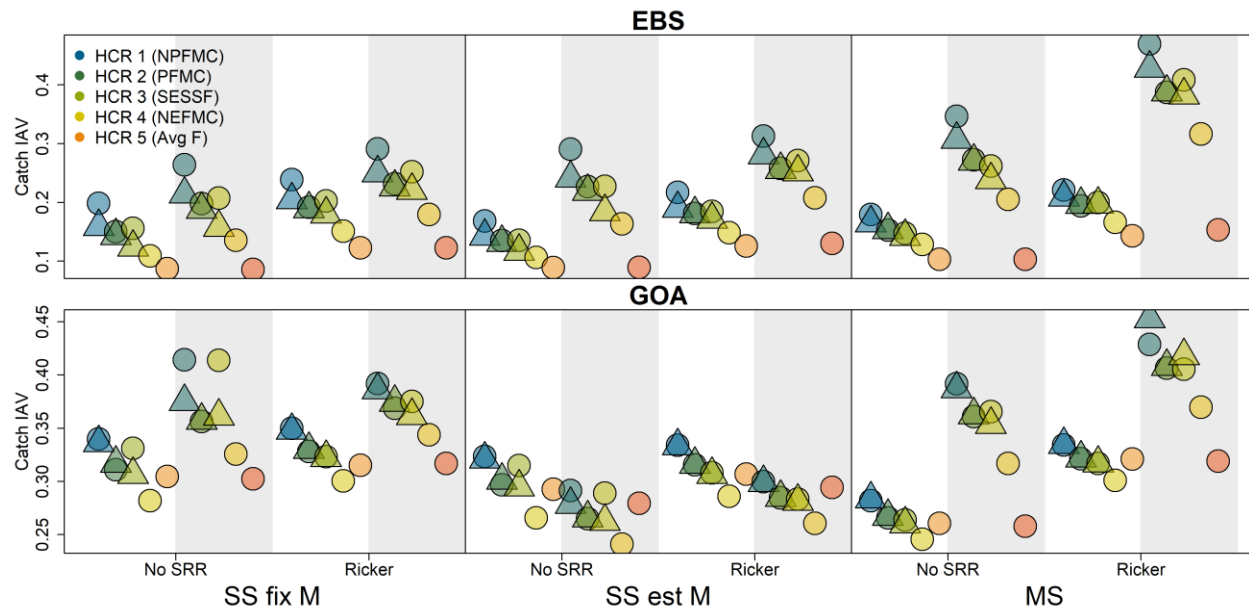


Figure 2.6. Summary of performance metric 7: probability that the population is undergoing overfishing as determined from the operating model for pollock in the EBS and GOA across scenarios. Estimation models that estimated M are indicated by the grey shading and harvest control rules (HCR) using dynamic biomass reference points are indicated by the triangles.

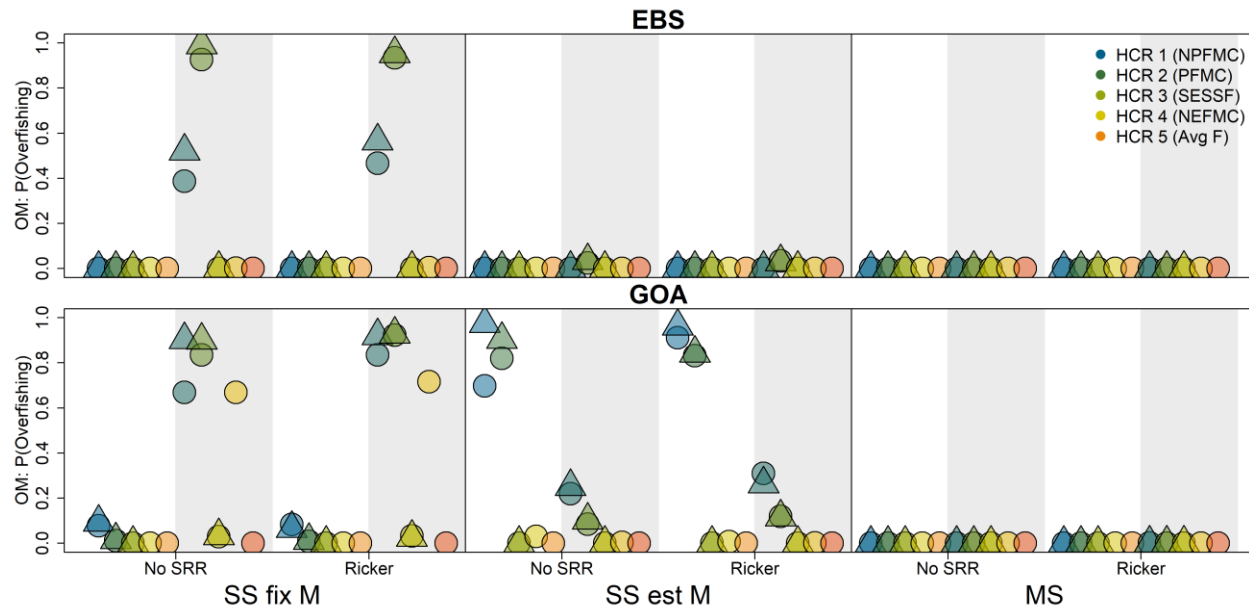


Figure 2.7. Summary of performance metric 8: probability that the population is not overfished as determined from the operating model for pollock in the EBS and GOA across scenarios. Estimation models that estimated M are indicated by the grey shading and harvest control rules (HCR) using dynamic biomass reference points are indicated by the triangles.

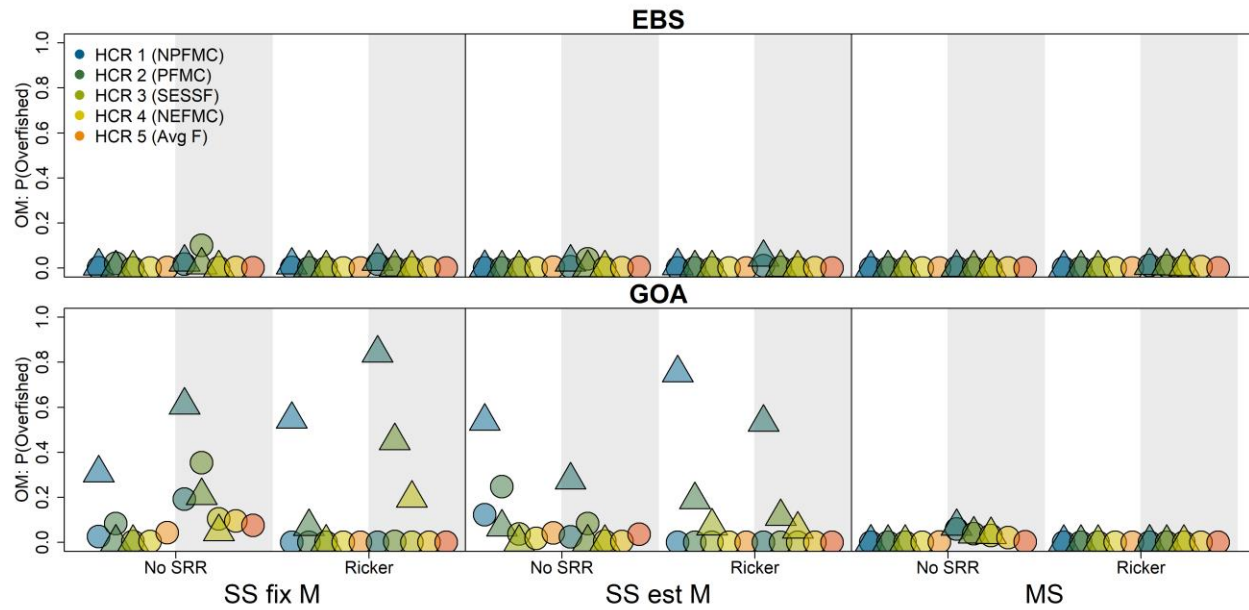


Figure 2.8. Summary of performance metric 9: spawning stock biomass depletion in 2060 relative to equilibrium SB_0 as determined from the operating model for pollock in the EBS and GOA across scenarios. Estimation models that estimated M are indicated by the grey shading and harvest control rules (HCR) using dynamic biomass reference points are indicated by the triangles. The blue dashed line indicates 40% depletion.

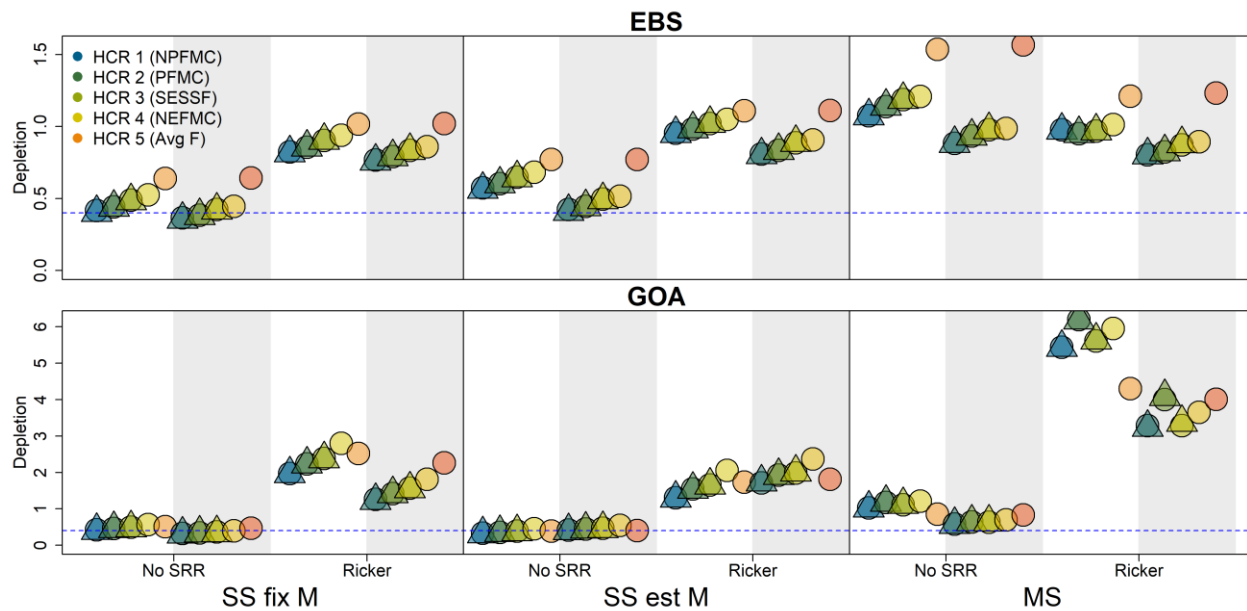
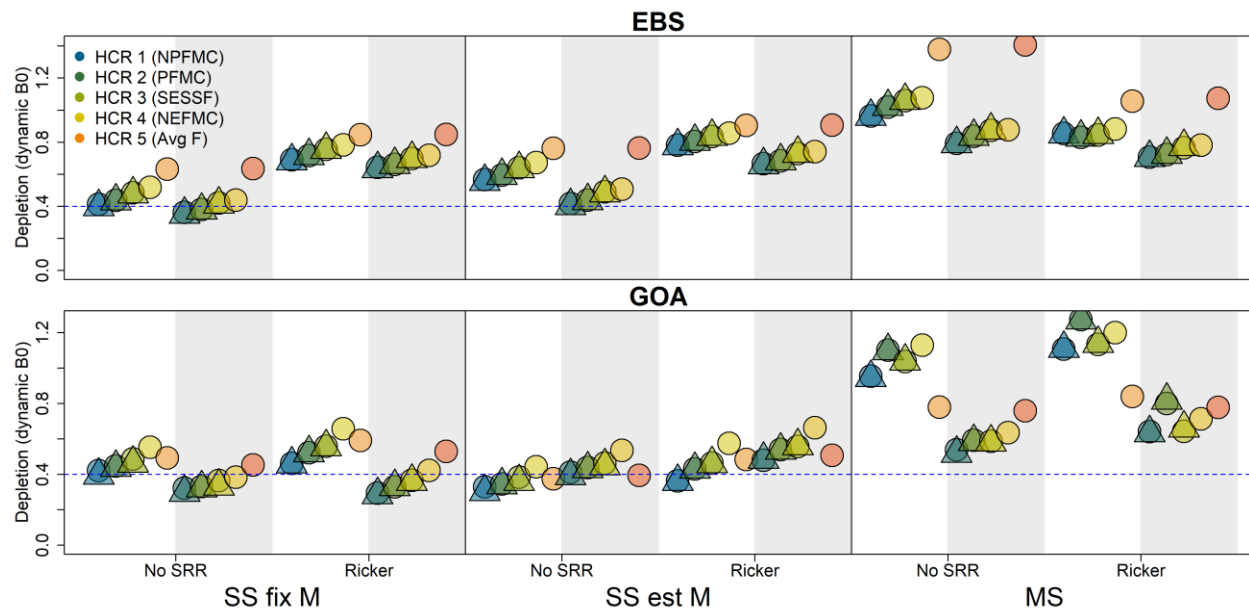


Figure 2.9. Summary of performance metric 10: spawning stock biomass depletion in 2060 relative to dynamic $SB_{0,y}$ as determined from the operating model for pollock in the EBS and GOA across scenarios. Estimation models that estimated M are indicated by the grey shading and harvest control rules (HCR) using dynamic biomass reference points are indicated by the triangles. The blue dashed line indicates 40% depletion.



Chapter 3: Performance of multi- and single-species management strategies in the face of predation and climate change

ABSTRACT

The majority of fisheries management jurisdictions use single-species population dynamics models that assume individual populations are independent of one another and their environment to support tactical decision making despite the large body of research suggesting that the population dynamics of fishes are affected by climate and species interactions. Multi-species harvest control rules that account for shifting productivity due to climate variability and species interactions have been proposed as an alternative to single-species approaches. However, research is needed to evaluate the performance of multi-species harvest control rules relative to single-species approaches while accounting for the feedback between management and fish populations through continued data collection and assessment prior to their widespread adoption. Here we conduct a management strategy evaluation using a climate-linked multi-species population dynamics model developed for the Gulf of Alaska as an operating model to assess the performance of single- and multi-species harvest control rules under climate change. We evaluate the ability of a range of single- and multi-species management strategies to maximize catch, minimize catch variability, and maintain spawning stock biomass. While multi-species management strategies lead to increases in average catch, they are associated with high levels of depletion and large catch variability, particularly when stock-dependent recruitment is not accounted for in stock assessments. This was consistent across the climate scenarios evaluated, although stocks were a lower abundance for the climate scenarios with larger increases in temperature over time. This work addresses key questions regarding the performance of Ecosystem Based Management compared to traditional single-species management under climate change and the utility of management strategies that include ecosystem considerations such as multispecies interactions.

3.1 INTRODUCTION

Identifying management strategies that account for trophic interactions and climate change is an ongoing challenge for fisheries management (Hollowed et al., 2020; Moffitt et al., 2016; Wildermuth et al., 2023). For most fishes, warming conditions are associated with increased metabolic costs and anabolic processes that require increased energetic demands, impacting growth, reproduction, survival, and, subsequently, trophic interactions among species (Rall et al., 2010; Rose et al., 2024; Suryan et al., 2021). For example, survival may decrease when increases in energetic demands from increased temperatures may not be matched by increases in prey available for consumption (Barbeaux et al., 2020). Climate change is therefore expected to alter the productivity and trophic interactions of exploited fishes (Brodeur et al., 2019; Cheung et al., 2016; Cooley et al., 2023; Griffith et al., 2018). Resulting changes in the productivity of marine resources can have multiple consequences for dependent human communities as shifts in the abundance, distribution, and size of exploited fishes can change their availability and/or value to communities (Pinsky and Fogarty, 2012; Smith et al., 2017). For example, unaccounted for shifts in productivity and trophic interactions can potentially lead to unsustainable harvests (Wiedenmann and Jensen, 2019). While the dynamics of marine populations can be the result of multiple direct and indirect changes in marine ecosystems, shifts in productivity are often hypothesized to be in response to changing thermal conditions, predation, and harvest (Houde,

2008; Pinsky and Byler, 2015). The implications of such changes are concerning given the anticipated increases in temperature and consequential restructuring of marine ecosystems due to anthropogenic climate change (IPCC, 2022; Pörtner et al., 2019)

Currently, trophic interactions and climate variability do not play much of a quantitative role in the management of exploited marine (or fisheries) resources despite copious calls for Ecosystem Based Fisheries Management (EBFM) (Dolan et al., 2016; Marshall et al., 2019; Skern-Mauritzen et al., 2015). Rather, tactical fisheries management is usually based on single-species population dynamics models that do not explicitly account for the impacts of environmental conditions and trophically linked species (although such impacts are increasingly being explored and stock assessments implicitly account for such impacts through estimates of time-varying recruitment and growth). Similarly, despite advances in single-species modelling to account for time-varying dynamics that may result from trophic and environmental interactions (Berg and Nielsen, 2016), trophic interactions and climate change can undermine the assumed equilibrium that single-species biological reference points (BRPs) are commonly based on.

EBFM is an adaptive approach that aims to account for the physical, biological, and social interactions among ecosystem components, accounting for uncertainty and multiple societal objectives (Fogarty, 2014). One of the key components of EBFM is to explicitly incorporate predator-prey and environmental processes into the management process given their impact on the productivity of exploited fishes (Hill et al., 2016; Jacobsen and Essington, 2018; Pikitch et al., 2014). However, while efforts have been made to explore the consequences of incorporating environmental processes into single-species-based management (e.g., Haltuch et al., 2011; Punt et al., 2014), the continued development and testing of frameworks that account for trophic interactions and environmental processes is essential for addressing EBFM needs (Andersen et al., 2015; Deroba et al., 2015; Essington et al., 2018; Gaichas et al., 2017; Punt et al., 2016).

Management strategies that account for shifting productivity due to climate variability or trophic interactions have been proposed as an alternative to “classical” single-species approaches (Moffitt et al., 2016; O’Leary et al., 2019; Pérez-Rodríguez et al., 2022). In particular, multi-species management strategies utilize multi-species biological reference points, which inherently balance trade-offs between harvests across trophically linked species because they are derived from multi-species population dynamics models that explicitly incorporate trophic interactions and, in some cases, climate-drivers (e.g., Andersen et al., 2015; Blanchard et al., 2014; Fulton et al., 2019; Gaichas et al., 2017; Holsman et al., 2016). Multi-species management strategies may lead to more socially acceptable trade-offs than single-species management strategies because they also quantify trade-offs among multiple fisheries (Fulton et al., 2019). Additionally, single-species management strategies based on multi-species models such as size spectrum models (Andersen et al., 2015; Blanchard et al., 2014; Gaichas et al., 2017), multi-species surplus production models (Essington, 2004; Mueter and Megrey, 2006), and multi-species age-structured models (Gislason, 1999; Trijoulet et al., 2019b) have been shown to have a high risk of not achieving management objectives. Management strategies derived from multi-species population dynamics models linked with climate forecasts also have the potential to inform the adaption and resilience of fisheries management and stakeholder outcomes to climate change (Fulton et al., 2014; Gaichas et al., 2017; Plagányi et al., 2014; Tommasi et al., 2017). However, despite their potential benefit and designation as core components of EBFM, evaluation is needed to determine if multi-species management strategies can actually better achieve management objectives than single-species strategies.

The performances of alternative management strategies can be evaluated using management strategy evaluation (MSE). MSE is a simulation technique for assessing the uncertainty associated with achieving management objectives given alternative hypotheses related to ecosystem functioning while accounting for the feedback between management and fish dynamics (Punt et al., 2016). A set of operating models (OMs) representing alternative hypotheses regarding the state of the system and climate are selected to simulate the application of alternative management strategies. The performance of each management strategy (estimation method and harvest control rule) is then evaluated relative to objectives for the stock and fishery (often including both conservation and economic goals). However, the use of MSE to determine the impact of predator-prey dynamics on fisheries management and the utility of multi-species management strategies is limited. A'mar et al. (2010) used MSE to assess the efficacy of single-species management when predation mortality was time-varying and found that the current management strategy of assuming constant natural mortality was effective at achieving conservation objectives at the cost of underutilizing the resource. However, their analyses did not account for cannibalism, time- and age-dependent predation mortality, nor the potential feedbacks from additional predator-prey and climate interactions.

Multi-species management strategies should be ideal for fisheries that exhibit strong trophic interactions and, in some cases, outperform management strategies based on single-species models (Essington, 2004; Pérez-Rodríguez et al., 2022). Additionally, fisheries where the incorporation of climate and trophic dynamics into population dynamics models may better explain variation in available data are reasons to evaluate multi-species management strategies. For example, the Gulf of Alaska (GOA) is a highly-productive area, with commercial fisheries whose target species exhibit strong trophic interactions (Zador et al., 2019) that are impacted by climate (Hare and Mantua, 2000; Litzow, 2006). Walleye pollock *Gadus chalcogrammus*, Pacific cod *Gadus macrocephalus*, and arrowtooth flounder *Atheresthes stomias* are highly ecologically connected fish species in the GOA (Gaichas and Francis, 2008; Livingston et al., 2017), and time-varying predation mortality represents a large proportion of mortality for walleye pollock, driven by consumption by Pacific cod, and arrowtooth flounder (Chapter 1; Gaichas et al., 2011). Management of GOA fisheries accounts for technical interactions between each fishery, but relies on single-species population dynamics models. Multi-species population dynamics models that explicitly account for time-varying predation have been developed for the system and demonstrate improved fit to available data compared to single-species counterparts (Chapter 1). Additionally, arrowtooth flounder can inhabit warmer waters than are currently present in the GOA and are likely to increase in abundance under future climate scenarios – their continued population growth since the 1977 regime shift is often partially attributed to climate warming (Clark and Hare, 2002; Spies and Palsson, 2017). Future temperature increases may therefore increase mortality for other commercially valuable groundfish such as Pacific cod and pollock, and their predation mortality can be greater than fishing mortality (Barbeaux et al., 2020; Gaichas et al., 2015). The strong trophic and climate dynamics and interest to better incorporate the impact of species interactions and climate on the management of these highly valuable fisheries makes the GOA an ideal system in which to evaluate the performances of multi-species management strategies

Here, we develop an MSE based on a multi-species assessment model developed for walleye pollock, Pacific cod, and arrowtooth flounder in the GOA (Chapter 1) to evaluate the performance of multi-species management strategies under climate change. Here we define multi-species management strategies as the combination of multi-species stock assessment models and multi-species harvest control rules. We evaluate if multi-species management strategies can better

achieve management objectives under multiple climate and predation scenarios than single-species management strategies. Using a multi-species operating model, the performance of single- and multi-species assessment models linked to single- and multi-species harvest control rules are compared under alternative hypotheses of stock dynamics (stock-dependent recruitment vs constant expected recruitment) and climate while accounting for observation error and feedback control. This research therefore addresses key questions regarding the performance of tactical EBFM compared to traditional single-species management strategies and the utility of management strategies that include ecosystem considerations such as multi-species interactions.

3.2 METHODS

The basis for the MSE is the climate-enhanced multi-species statistical catch-at-age analysis model developed for groundfish in the Bering Sea (CEATTLE [Climate-Enhanced, Age-based model with Temperature-specific Trophic Linkages and Energetics]; Holsman et al., 2016,2023) and expanded for groundfish in the GOA (Chapter 1). Developed in part from the underpinnings of multi-species statistical catch-at-age analysis (MSCAA, Jurado-Molina et al., 2005) and multi-species virtual population analysis (MSVPA; Magnusson, 1995), CEATTLE links single-species age-structured models through predator-prey interactions conditioned on the temperature-dependent bioenergetic demand and diet-based prey-selectivity patterns of predators (Table 3.1). Predation mortality assumes a Holling Type II functional response and parameters are either pre-specified or estimated by fitting to survey and fishery data (Table 3.2). For the GOA, CEATTLE spans 1977 to 2020 and is parameterized similarly to the single-species assessment models for walleye pollock, Pacific cod, and arrowtooth flounder used to provide management advice (Chapter 1; Barbeaux et al., 2018; Dorn et al., 2018; Spies and Palsen, 2018). CEATTLE can be run in single-species mode by “turning-off” time-varying predation mortality or in multi-species mode by “turning-on” time-varying predation mortality. The effects of changing climate are accounted for by conducting projections in which the temperature that determine feeding change over time.

3.2.1 Operating models with climate linkages

Operating models for the present study were constructed from multi-species CEATTLE models. All operating models were conditioned by fitting to historical survey and fishery data (Chapter 1) and hence included time- and age-varying M . Operating models were conditioned by treating the annual recruitment deviates as penalized parameters and then were projected forward from 2021 until 2100, with future recruitment deviates sampled, with replacement, from those for the conditioning period. Projected selectivity, catchability, relative number of foraging days, maturity-at-age, and ageing error were time-invariant and set to the values for the last year with data used to condition the operating model.

We utilized two recruitment parameterizations relating recruitment to environmental indices, which differed in their inclusion of stock-recruitment relationships. The first, where expected recruitment is independent of spawning biomass given a climate regime, the logarithm of recruitment for each species was related to environmental indices (described below) via a linear relationship:

$$\text{Eq. 3.1.} \quad R_{isy} = \bar{R}_i e^{\mathbf{X}\mathbf{B}_i\tau_{iy}} \rho_{i1}$$

where R_{isy} is the age-1 recruitment for species i and sex s during year y , $\bar{R}_i$ is the mean recruitment corresponding to the mean values for the environmental indices, $\mathbf{X}$ is the model matrix of scaled environmental indices, $\mathbf{B}$ is the vector of associated regression coefficients, τ_{iy} is the annual

recruitment deviate, assumed to be drawn from a lognormal distribution, and ρ_{i1} is the proportion of females at age-1 (assumed to be independent of time).

The second stock-recruitment relationship, was a stock-dependent Ricker stock-recruitment relationship that, under climate, the density-independent factor (α_i) was related to environmental indices via a linear relationship (Ianelli et al., 2011; Spencer et al., 2016):

$$\text{Eq. 3.2.} \quad R_{isy} = \alpha_i e^{XB_i SB_{iy-1}} e^{-\beta_i SB_{iy-1}} e^{\tau_{iy}} \rho_{i1}$$

where α_i is related to density-independent mortality corresponding to the mean values for the environmental indices, β_i is related to density-dependent mortality, and SB_{iy} is the spawning biomass for species i and year y .

For environmental indices, operating models were developed where bioenergetic demand and recruitment deviations were related to long-term climate model-derived environmental indices to understand trade-offs of alternative management strategies under climate change. For bioenergetics demand, the rate of maximum consumption was driven by projections of annual summer bottom temperature (Eq T1.3 of Table 3.1). For recruitment, studies using stock assessment output (Clark and Hare, 2002) and data from small mesh trawls (Anderson and Piatt, 1999) have indicated that the logarithm of recruitment of Pacific cod, pollock, and arrowtooth flounder is linearly related with interdecadal climate regimes that are associated with large scale spatio-temporal shifts in sea surface temperature across the GOA. In addition, large zooplankton biomass is associated with overwinter survival of Pacific cod and pollock (Hunt et al., 2011).

Projections of summer bottom temperature, winter sea surface temperature, and fall large zooplankton biomass were derived from a downscaled Intergovernmental Panel on Climate Change (IPCC) projection model from the coupled model intercomparison project phase 6 (CMIP; O'Neill et al., 2016): GFDL-ESM2M (sensu Hermann et al., 2019; Hollowed et al., 2020). The IPCC projection model was downscaled using a Regional Ocean Modeling System (ROMS) developed for the Gulf of Alaska, similar to models developed for the Bering Sea (Hermann et al., 2019; Kearney et al., 2020). ROMS simulations, referred to historical, hindcast, and projection simulations, were utilized representing model spinup (1970 to 2020), the final year of the spinup forced with observed oceanographic conditions to better represent observed conditions (1980 to 2020), and GFDL-ESM2M downscaled projection (2020 to 2100), respectively. For CMIP-6, climate projections were combined with integrated models of societal development and associated greenhouse gas emission rates and atmospheric carbon mitigation levels represent by different shared socioeconomic pathways (SSP). We included the high baseline (SSP5-8.5), medium pathway (SSP2-4.5), and high mitigation with a lower future increase in temperature (SSP1-2.6) scenarios. Time-series of summer bottom temperature (June-August), winter sea surface temperature (November-January), and fall large zooplankton biomass (August-October) were extracted from each ROMS simulation across the National Marine Fisheries Service (NMFS) management areas 610, 620, and 630 (Supplementary Fig. S3.1). The time-series from the projection simulation were bias-corrected as follows:

$$x_y^{proj'} = \bar{x}_T^{hind} + x_y^{proj} - \bar{x}_T^{hist}$$

where $x_y^{proj'}$ is the bias corrected projected time-series of variable x in year y , $\bar{x}_T^{hind}$ is the average value of the hindcast time-series during the reference period T (2000-2020), x_y^{proj} is the projection time-series, and $\bar{x}_T^{hist}$ is the average value of the historical time-series during the reference period. This represents a single realization from a projection model and does not account for uncertainty in future environmental conditions in order to reduce computational complexity.

Operating models were conditioned by fitting to the time-series of environmental indices from the ROMS “hindcast” simulation for the conditioning period (1980-2020) and projected forward using indices from each bias corrected projection. Recruitment was linked to scaled winter sea surface temperature, scaled winter sea surface temperature squared, and scaled fall large zooplankton biomass (Eqs. 3.1 & 3.2). Each environmental index linked to recruitment was scaled to mean and standard deviation of the conditioning period (1980-2020). Temperature linked bioenergetics demand was a function of summer bottom temperature (Table 3.1). Rather than use the “historical” ROMS time-series for 1977-1979, which may not represent observed conditions, we used the mean from the conditioning period.

3.2.2 Management strategies

3.2.2.1. Data collection

Simulated data for the conditioning (1977 to 2020) and projection (2021 to 2100) periods assumed the same sampling distributions and efforts as the historical data used to condition the OM (Table 3.3). Specifically, for the projection period, indices of relative abundance were simulated from lognormal distributions assuming the annual standard deviation to be equal to the average of the last two years of the conditioning period. Age- and length-composition data were simulated from multinomial distributions assuming the annual input multinomial sample sizes were the same as the averages from the last two years of the conditioning period. The average standard deviation or sample size from the last two years of the conditioning period was selected to reflect the assumption that future sampling effort will be similar to the most recent sampling effort. Catches from each fishery during the projection period were determined using a harvest control rule (see below) and assumed to be taken and recorded exactly.

3.2.2.2. Estimation methods

Each species was assessed using 1) a single-species age-structured assessment for which natural mortality was sex- and age-varying and pre-specified, 2) a single-species age-structured assessment that estimated a sex-varying, but time- and age-invariant natural mortality, or 3) a multi-species age-structured assessment (Table 3.1). These three assessment options were selected because they represent assessment methods currently used for tactical and strategic decision making in the region. The pre-specified M rates were extracted from stock assessments (Supplementary Table S3.1; Barbeaux et al., 2018; Dorn et al., 2018; Spies and Palsson, 2018). All estimation methods (EMs) were fit annually to the simulated historical and projected survey and fishery data assuming no stock-recruit relationship (Tables 3.1-3.2). Annual recruitment was parameterized assuming a mean recruitment with annual recruitment deviates estimated using penalized likelihood and no environmental covariates following the approach currently used for single- and multi-species assessments actually used for management. Penalized likelihood was used rather than treating the annual deviates as random effects to decrease computation time. The variance in recruitment for each estimation model was extracted from recent assessments (Barbeaux et al., 2018; Dorn et al., 2018; Spies and Palsson, 2018).

3.2.2.3. Harvest control rules

Catch was determined by applying a harvest control rule-derived target fishing mortality rate ($F_{Target} \text{ yr}^{-1}$) to each estimation method projected forward one year assuming mean annual recruitment and terminal selectivity, maturity, weight-at-age (Table 3.4). Harvest control rules were used to define limit reference points to determine if a stock is perceived to be undergoing

overfishing ($F > F_{Limit}$) or to be overfished ($B < B_{Limit}$). Biological reference points in the harvest control rules were either based on SSB-per-recruit ($F_{X\%}$ and $SB_{X\%}$) or depletion (F_X and SB_X), where X defines the proportion the reference point is of the unfished value (Table 3.4). For example, $F_{35\%}$ is the fishing mortality rate associated with an equilibrium SSB-per-recruit that is 35% of the spawning stock biomass-per-recruit in the absence of fishing. $SB_{35\%}$ refers to the long-term average (e.g., the average across the assessment period) SSB that would be expected under average recruitment and $F = F_{35\%}$. Alternatively, F_{35} is the fishing mortality rate associated with an equilibrium SSB that is 35% (SB_{35}) of equilibrium unfished spawning biomass SB_0 . When there is no stock-recruitment relationship (i.e., for all single-species estimation methods), $SB_{35\%}$ and SB_{35} and, consequently, $F_{35\%}$ and F_{35} are equivalent.

For single-species age-structured assessments, we use the North Pacific Fishery Management Council (NPFMC) Tier 3 spawner-per-recruit-based harvest control rule that is currently used to provide management advice for all species in this analysis (NPFMC, 2017), which are estimated as follows:

- i. Stock status: $SB/SB_{40\%} \geq 1$
 - $F_{Limit} = F_{35\%}$
 - $F_{Target} = F_{40\%}$
- ii. Stock status: $\alpha < SB/SB_{40\%} < 1$
 - $F_{Limit} = F_{35\%} * (SB/SB_{40\%} - \alpha)/(1 - \alpha)$
 - $F_{Target} = F_{40\%} * (SB/SB_{40\%} - \alpha)/(1 - \alpha)$
- iii. Stock status: $SB/SB_{40\%} \leq \alpha$
 - $F_{Limit} = 0$
 - $F_{Target} = 0$

where α is set to 0.05 and B_{Limit} is set to $0.5 * SB_{35\%}$. Additionally, fishing mortality is set to 0 for pollock or Pacific cod if the spawning biomass is below SB_{20} to maintain forage for stellar sea lions. The NPFMC Tier 3 harvest control rule was also evaluated using dynamic biomass reference points, which are generalized from dynamic SB_0 (MacCall et al., 1985). Dynamic biomass reference points calculate the stock biomass in each year in the absence of fishing ($SB_{0,y}$). The dynamic biomass reference points integrate across all cohorts in the population and account for time-varying growth and recruitment (Table 3.4). SB_0 is replaced by $SB_{0,y}$, and $SB_{X\%}$ by $SB_{X\%,y}$ in the NPFMC Tier 3 harvest control rule with dynamic biomass reference points.

For the multi-species age-structured assessment, the following harvest control rules were evaluated:

MS-B40-a: A multi-species strategy similar to that currently reported to fisheries managers for the Bering Sea but modified here to allow for stepwise evaluation in the MSE scenarios (Holsman et al., 2023). The target and limit biomass reference points are adapted from the NPFMC Tier 3 approach where $B_{Target} = SB_{40}$ and SB_0 is defined by projecting a species forward under no fishing and mean recruitment for 50 years. F_{Target} then defined as the fishing mortality rate that lead to $0.40 * SB_{0..}$. Rather than determine the reference points for all species simultaneously, reference points were determined for Pacific cod and arrowtooth flounder first, when there was no fishing for pollock. Then reference points were determined for pollock where fishing was set to F_{Target} for Pacific cod and arrowtooth flounder. This strategy elevates SB_0 for pollock, by reducing predation mortality from Pacific cod and arrowtooth flounder. Alternative

orders had little effect on SB_0 for Pacific cod and arrowtooth flounder and were not evaluated further.

MS-B40-b: A multi-species strategy adapted from the NPFMC Tier 3 approach as previously described, but with the reference points for all species determined simultaneously (i.e., SB_0 is defined by projecting all species forward in the multi-species estimation model under no fishing simultaneously and F_{Target} is determined simultaneously for all three species). SB_0 for pollock in this case is lower than the MS-B40-a definition due to increased predation by arrowtooth flounder and Pacific cod.

MS-MSY: A multi-species system-wide unconstrained strategy where the sum of catch across all species is maximized under mean recruitment (i.e., multi-species MSY), where F_{Target} for each species is the fishing mortality rate that maximizes catch across all species simultaneously (i.e., $MS-F_{MSY}$), $B_{Target} = MS-B_{MSY}$ (the biomass corresponding to $F = MS-F_{MSY}$), $B_{Limit} = 0.5 * MS-B_{MSY}$, and $F_{Limit} = 0.5 * MS-F_{MSY}$. SB_0 is defined by projecting all species forward in the multi-species estimation model under no fishing simultaneously.

MS-cMSY: A multi-species system-wide constrained strategy. As for MS-MSY, but target depletion is limited to $0.20 * SB_0$ (Moffitt et al., 2016).

The system-wide strategies (MS-MSY and MS-cMSY) represent an attempt to achieve system-wide MSY, with the system-wide constrained strategy (MS-cMSY) representing trade-offs between conservation and economic objectives. For fisheries that are underutilized, such as arrowtooth flounder, each scenario was also run where projected catch was limited to the historical maximum. There is one directed fishing fleet for each fishery except for Pacific cod. Therefore, observed catches were apportioned across the trawl, longline, and pot fishing fleets for Pacific cod based on the ratio of average fully-selected fishing mortalities during the last two years of the conditioning period.

Given the past underutilization of some stocks, each management strategy was also evaluated where the catch for each species was capped as the historical maximum catch. There was no implementation or observation error for catch. However, if the recommended catch from a management strategy exceeded the exploitable biomass in the operating model, catch was set to exploitable biomass.

3.2.3 Performance metrics

The performances of each management strategy under each scenario were evaluated relative to the following fishery and conservation objectives for each species:

11. Average annual catch across all projection years and simulations

12. Average interannual variation in catch (IAV) across all projection years (n)

$$\bullet \quad IAV_{fi} = \sqrt{\frac{\sum_y^{n-1} (\hat{c}_{i,y+1}^* - \hat{c}_{fi,y}^*)^2}{n-1}} \bigg/ \frac{\sum_y \hat{c}_{i,y}^*}{n}$$

13. Probability that the population is overfished as determined from the “true” B_{Limit} (20% $SB_{0,y}$) across simulations

$$\bullet \quad \frac{\sum_s \sum_y 1[SB_{iy} < 0.2 SB_{i,0,y}]}{\sum_s \sum_y 1}$$

14. Average operating model terminal (i.e., 2100) spawning stock biomass across all simulations.

15. Average operating model terminal (i.e., 2100) spawning stock depletion across all simulations relative to dynamic $SB_{i,0,y}$.

where $\hat{C}_{i,y}^*$ is the total catch across fleets and $SB_{i,y}$ is SSB in year y for species i . These performance metrics were selected based on economic (performance metrics 1-2) and conservation objectives (performance metrics 3-5) for the fisheries. The operating model is no longer under equilibrium when it is driven by climate so B_{Limit} and depletion are defined relative to the expected biomass under no fishing given the recruitment trend and recruitment variation (i.e., dynamic $SB_{0,y}$). The average operating model terminal (i.e., 2100) spawning stock biomass under no fishing $SB_{0,y}$ was also derived for each operating model.

3.2.4 Experimental design

Factors considered in the analysis are presented in Table 3.5. A full factorial design using 200 simulations for each scenario was conducted to assess the performances of single- and multi-species management strategies under climate change and predation. The no climate change scenarios were designed to compare the performances of single- and multi-species management strategies under stationary expected recruitment and represents the base case. The climate change scenarios were designed to evaluate the impact of low, medium, and high degree of warming, respectively. Environmental indices used to drive recruitment and bioenergetics were respectively derived from the high mitigation with a 2-degree future increase in temperature (SSP1-2.6) scenario, the medium pathway (SSP2-4.5) scenario, and the high baseline (SSP5-8.5) scenario.

3.3 RESULTS

3.3.1 Operating models under climate change

The eight operating models (four climate scenarios x two stock-recruitment options) differed in their projected spawning stock biomass and recruitment under no fishing. Temperature was projected to increase and large zooplankton biomass to decrease between SSP1-2.6 to SSP5-8.5 (Supplementary Fig. S3.1). Including the scaled environmental covariates improved the fit of the operating models to the conditioning data for the operating model with (negative log-likelihood [NLL] = 4,283 without environmental covariates vs NLL = 4,278 with environmental covariates) and without ([NLL] = 4,422 without environmental covariates vs NLL = 4,418 with environmental covariates) a stock-recruit relationship (Supplementary Fig. S3.2). The estimated effect size (**B**) from conditioning the operating models to the scaled environmental covariates was larger for pollock than Pacific cod and arrowtooth flounder (Table 3.6), resulting in steeper declines in recruitment for the medium and high baseline (SSP2-4.5 and SSP5-8.5) climate scenarios (Supplementary Fig. S3.3). Spawning stock biomass remained stable and near historical levels for Pacific cod and arrowtooth flounder under the no climate change and the high mitigation with a 2-degree future increase in temperature (SSP1-2.6) scenario (Supplementary Fig. S3.4). Pollock was projected to decrease under all climate scenarios, collapsing to near zero spawning stock biomass under the medium and high baseline (SSP2-4.5 and SSP5-8.5) climate scenarios.

3.3.2 Performance of single- vs. multi-species management strategies under no climate change

Single- and multi-species management strategies varied in their perception of spawning stock biomass and associated reference points when looking at their fit to the conditioning data (Fig. 3.1). The multi-species MSY based strategies recommended higher levels of catch (Supplementary Fig. S3.3), resulting in lower projected spawning stock biomass compared to the multi-species depletion-based strategies. Of all the multi-species strategies, the multi-species strategy based on

the approach similar to that currently used to guide strategic management (MS-B40-a), which elevates SB_0 for pollock by reducing predation mortality from Pacific cod and arrowtooth flounder was the most conservative. For example, when first fit to the conditioning data from 1977 to 2020, MS-B40-a defined SB_0 for pollock at 1,269,418 mt, while all other multi-species management strategies defined SB_0 for pollock at 624,323 mt.

Across simulations, multi-species management strategies led to higher average catch for pollock and arrowtooth flounder for the operating models with no climate change that did not include a stock-recruitment relationship (Fig. 3.2). This came at a cost of higher variability in annual catch for pollock and arrowtooth flounder for all strategies except MS-B40-a (Fig. 3.3). However, capping catch at the historical maxima reduced catch variability. Of all strategies, the multi-species strategies based on multi-species MSY (MS-MSY and MS-cMSY) had the highest catch levels for each species (Table 3.7), although this was achieved by depleting arrowtooth flounder to reduce predation mortality and maintain high catches for pollock (Supplementary Table S3.4; Supplementary Figs S3.4-9S3.). However, when the operating model included a stock-recruitment relationship, the high catches recommended from all multi-species management strategies except for MS-B40-a reduced spawning stock biomass (Figs 3.3-3.6), leading to lower average catches for multi-species-strategies than for single-species management strategies (Fig. 3.2). This occurred for pollock even when there was a cap on catch limits. Additionally, the unconstrained multi-species MSY (MS-MSY) strategy led to collapse of pollock when the operating models included a Ricker stock-recruitment relationship (Table 3.8). For cod, average catch was higher from single-species estimation methods that pre-specified M because the pre-specified values were generally greater than the value estimated within multi-species operating models.

In terms of conservation performance metrics, the high levels of catch recommended by the multi-species MSY based strategies also led to a high probability of all species being overfished (*i.e.* depletion dropping below 20% relative to dynamic $SB_{0,y}$) for the no climate change operating models (Fig. 3.4). Constraining depletion to be above 20% SB_0 in the MS-cMSY strategy reduced the probability of being overfished, but not substantially for pollock. The operating models without stock-recruit relationship had a lower probability of being overfished than operating models with Ricker stock-recruitment because the latter assumed lower levels of recruitment at low stock sizes. In the case of pollock, there was still a > 39% probability of being overfished when caps on catch were utilized for the Ricker operating model. Multi-species management strategies based on $B_{Target} = SB_{40}$ were more conservative than their MS-MSY based counterparts. For example, to achieve MSY in the operating model without stock-recruitment relationship, terminal depletion was < 37% for all species (Table 3.7). The multi-species strategy based on the strategy currently used to guide strategic management (MS-B40-a), which elevates SB_0 for pollock by reducing predation mortality from Pacific cod and arrowtooth flounder was the most conservative based on the higher biomass target reference point compared to the other multi-species strategies. Single-species management strategies using equilibrium reference points led to a < 1% probability of both no climate change operating models (stock-independent or –dependent) being overfished across species (Supplementary Tables S3.3-S3.5). Resultantly, all multi-species management strategies except for MS-B40-a led to lower spawning stock biomass (Fig. 3.5) and, subsequently, higher depletion (Fig. 3.6) in 2100 compared to the single-species management strategies for all species.

Basing reference points on dynamic SB_0 aims to account for changes over time in model parameters. Both single-species estimation methods utilizing dynamic reference points were able to achieve higher levels of catch with reduced catch variability for pollock across operating models

(Table 3.7; Supplementary Tables S3.3-S3.5). This came at a tradeoff for lower spawning stock biomass in 2100 compared to single-species management strategies using equilibrium reference points. However, there was a < 1% probability of single-species management strategies leading to overfished operating models.

3.3.4 Performance of single- vs. multi-species management strategies under climate change

The multi-species management strategies generally did not outperform single-species management strategies for the future climate change scenarios. Similar to the no climate change scenarios, the multi-species management strategies led to a higher average catch for pollock than the single-species management strategies when there was no stock-recruitment relationship in the operating model. Across species, average catch for each management strategy decreased with increasing warming from SSP1-2.6 to SSP5-8.5 (Fig. 3.2), and catch variability increased (Fig. 3.3). The latter is likely due to oscillations in expected recruitment due to the effects of the environmental drivers (Supplementary Fig. S3.1). However, when the operating model included stock-dependent recruitment, all management strategies led to similar levels of catch variability across climate scenarios (Supplementary Tables S3.3-S3.5). Applying a cap on catches was no longer as constraining for pollock for the three climate scenarios as productivity was projected to decrease.

There was no clear trend in the probability of species being overfished among climate scenarios (Fig. 3.4). Applying a cap on catches reduced the probability of pollock and arrowtooth flounder being overfished, regardless of the management strategy. However, increased warming reduced the effectiveness of the cap for pollock in the operating model without stock-dependent recruitment. Pollock was more likely to be overfished when catch limits were based on the multi-species management strategies for climate scenarios SSP2-4.5 and SSP5-8.5 than SSP1-2.6. Operating models with Ricker stock-recruitment relationships had a higher probability of being overfished when single-species management strategies used dynamic reference points for the climate scenario. However, the probability of being overfished from all single-species management strategies was still less than that from multi-species management strategies (except MS-B40-a) for pollock and arrowtooth flounder. For pollock and arrowtooth flounder, multi-species management strategies other than MS-B40-a led to the lowest terminal spawning stock biomass under climate change followed by single-species management strategies using dynamic reference points (Fig. 3.6). The multi-species strategy similar to that currently used to guide strategic management (MS-B40-a) has a similar performance to the single-species management strategies across climate scenarios.

3.4 DISCUSSION

We evaluated if multi-species management strategies that account for “top-down” predation mortality can outperform single-species management strategies under various no climate change and climate change scenarios using a management strategy evaluation approach. The multi-species estimation methods perceived the stocks to be more productive than single-species estimation methods and, therefore, recommended higher levels of catch. When the multi-species estimation models were correctly specified, the higher levels of catch were attainable. However, when multi-species estimation models were not correctly specified in terms of stock-dependent recruitment, single-species management strategies outperformed multi-species strategies across performance metrics. This is because the multi-species management strategies assumed that recruitment would remain constant even at the lower levels of spawning biomass. Single-species strategies led to higher average catches with lower interannual variability and lower risk of depletion for the climate

scenarios in contrast to multi-species management strategies that reduced spawning stock biomass to levels where the high catches were no longer attainable, or, in the case of pollock led to stock collapse. Even when multi-species estimation methods were correctly specified, strategies based on these methods performed poorly for conservation-based performance metrics. For example, multi-species MSY-based strategies resulted in large reductions in spawning stock biomass to maximize catch.

Multi-species management strategies based on depletion (e.g., F_{40}) were more conservative and outperformed MSY-based strategies on conservation-based performance metrics. This is most evident for the multi-species management strategy based on a strategy similar to that currently used to supplement management advice (MS-B40-a), which led to greater catch, similar catch variability, and greater spawning stock biomass for pollock than its single-species counterparts. All other multi-species management strategies led to a higher probability of stocks being overfished and higher catch variability for pollock for the than single-species strategies.

The performance of multi-species management strategies relative to their single-species counterparts did not change across the climate scenarios evaluated. Recruitment was projected to decrease under all climate scenarios, and, in the case of pollock, lead to near 0 spawning stock biomass even under no fishing for the high degree of warming (SSP5-8.5) scenario. While catches for all species decreased under climate change for both the single- and multi-species management strategies as recruitment decreased, catch variability of pollock increased to a greater extent under the more aggressive multi-species management strategies than single-species strategies. Multi-species strategies were more likely to lead to overfished stocks across all climate scenarios. Stocks were not overfished when single-species strategies using equilibrium reference points were applied as they sustained stocks above depletion targets.

3.4.1 Multi-species management strategies

Multi-species management strategies have been proposed as an alternative to single-species management strategies to account for shifting productivity due to predator-prey dynamics (Collie and Gislason, 2001; Moffitt et al., 2016; O’Leary et al., 2019; Schiano et al., 2023). Most previous research has evaluated the use of multi-species management strategies by projecting models under alternative harvest control rules or catch series (Essington, 2004; Holsman et al., 2016; Moffitt et al., 2016). However, the incorporation of feedback control (continued data collection and assessment) is valuable for evaluating the performance on management strategies because management strategies can adjust to future data inputs (Punt et al., 2016). In the case of multi-species management strategies, full feedback control is rarely included given the computational demands and the lack of standardized software. Contrary to previous research showing the benefit of management strategies based on multi-species models (e.g., Essington, 2004), we found that multi-species management strategies did not always outperform single-species management strategies across all performance metrics evaluated. While multi-species management strategies led to higher catch limits, these catches also sometimes led to increased catch variability and more depletion. Some management strategies may also be unrealistic given current fishery dynamics. For example, multi-species strategies based on multi-species MSY recommended high catches of arrowtooth flounder and pollock. It is uncertain that the current arrowtooth flounder fishery would increase their catches given a current lack of markets. The most conservative multi-species management strategy based on the approach currently used to supplement management advice (MS-B40-a), did not have this problem and led to greater catch, similar catch variability, and greater spawning stock biomass for pollock than single-species strategies. Caps on catch were

evaluated to, in part, account for a lack of attainment, but multi-species strategies still led to higher depletion and a higher risk of being overfished. Additionally, adding depletion constraints to the multi-species MSY strategy did not completely mitigate the negative consequences of aiming to achieve the multi-species MSY. The constrained multi-species MSY strategy led to similar levels of depletion, collapse, and interannual catch variability as the MS-MSY strategy, probably due to the low threshold biomass. Increasing the threshold would mitigate negative performance at a cost of reduced catch. However, a threshold above 40% would be needed because a 40% threshold would be equivalent to the depletion-based MS-B40-b strategy, which had similar performance issues when the estimation method was mis-specified.

Despite the poor performance of some multi-species management strategies evaluated, future work could optimize multi-species management strategies for specific system and fishery goals. For example, parameters such as residual mortality can be tuned so that harvest recommendations from multi-species can better match the historical scale of the fishery (Holsman et al., 2023, 2016). Using a "short-cut" management strategy evaluation Pérez-Rodríguez et al. (2022) optimized the targets and limits of a two-stage harvest control rule in a multi-species model. They found that the two-stage harvest control rule outperformed other control rules given the trophic dynamics of their model and recommend designing management strategies jointly between trophically linked species. Here we focused on evaluating management strategies based on approaches used to advise fisheries management and did not optimize the strategies for computational reasons. However, similar approaches could be applied here to evaluate what levels of targets and limits to use to optimize the performance of management strategies evaluated. For example, a higher depletion constraint on the constrained multi-species MSY strategy would likely lead to better conservation performance at the cost of lower average catch. There is a tradeoff between depletion, catch, and catch variability and specific selection of management strategy will depend on the specific fishery goals. Higher yields lead to greater depletion and catch variability, which may be undesirable for fisheries managers. The poor performance of some multi-species management strategies was due to depletion and overfished status. However, here we arbitrarily defined overfished at 20% $SB_{0,y}$ which is above the spawning stock biomass required for multi-species MSY when no stock recruitment function was used, which may be an inappropriate reference point. Given constant expected recruitment in the estimation method, the multi-species MSY strategy perceives it is able to achieve high levels of yield despite depleting the stocks. Exploration of alternative definitions of targets, limits, and MSY based strategies incorporating stock-recruitment relationships would be beneficial for further work.

3.4.2 Single-species approaches to ecosystem based fisheries management

Apart from multi-species harvest control rules, the use of dynamic reference points in single-species models has been proposed as an alternative to equilibrium based reference points under non-stationary dynamics (MacCall et al., 1985; O'Leary et al., 2019). Here we found that management strategies using dynamic reference points may perform worse in terms of conservation performance metrics than their equilibrium counterparts both when the estimation method did not include a stock-recruitment relationship and the operating model either included a stock-recruitment relationship or recruitment was non-stationary (i.e., under climate change). Catches were higher and interannual catch variability was generally lower for management strategies using dynamic reference points, but there was a higher probability of the stocks being overfished and lower terminal spawning stock biomass. This mirrors results found from recent

studies illustrating the performance of dynamic reference points in single-species settings (Bessell-Browne et al., 2024; Szuwalski et al., 2023).

Caps on catches have also been proposed as an ecosystem-based approach to reduce the negative impacts of climate change (Holsman et al., 2020) and, while currently not constraining, are implemented in the GOA. By placing caps on fishery catches, fishery management may forestall the eventual collapse of those fisheries. The operating models we used coupled with the IPCC environmental indices projected severe depletion of stocks under the medium and high emission scenarios. The caps we utilized helped reduce catch variability across climate scenarios and limit the probability of operating models becoming overfished (Figs 3.4-3.6). The caps also maintained higher levels of biomass in the terminal year of the projection for the high mitigation scenario (SSP1-2.6). Similar to Holsman et al. (2020), given the severe levels of depletion for SSP2-4.5 and SSP5-8.5 under no fishing, the caps did little to maintain biomass towards the end of the projection.

3.4.3 Additional caveats

One caveat of this work is the specification of the predator-prey dynamics in both the estimation and operating models. First, we assumed an Holling Type II functional response in the multi-species operating model. This functional response is the most common form currently used in multi-species age structured models (Begley and Howell, 2004; Curti et al., 2013; Fitzpatrick et al., 2022; Trijoulet et al., 2019b). However, another parameterizations of the functional response may better represent species interactions and provide improved fits to the data (Hunsicker et al., 2011; Kinzey and Punt, 2009; Plaganyi, 2013). Therefore, we recommend analyses to assess if single-species management strategies provide better performance than multi-species management strategies across different functional forms of predation. We also assumed that the multi-species estimation method was correctly specified in terms of the functional response of predation mortality and diet data. Uncertainty in diet sampling can impact time-series estimates (Curti et al., 2013; Trijoulet et al., 2019a; Van Kirk et al., 2015) and future work would benefit from incorporating diet sampling into multi-species estimation methods and the evaluation of multi-species management strategies. While the multi-species management strategies did not always perform well when stock-dependent recruitment was not correctly accounted for, future work may benefit from evaluating if misspecification of the functional response leads to similar poor performance. Other work has found that traditional single-species harvest control rules don't perform well under different predator-prey dynamics (Pérez-Rodríguez et al., 2022) and the multi-species reference points will vary in the presence of prey-dependent growth (Collie and Gislason, 2001; Fitzpatrick et al., 2022). It would be worth evaluating if the results we found are consistent when trophic dynamics are more complex (e.g., prey species eats larval predators) or also include “bottom-up” processes such as prey-dependent growth and survival. The multi-species MSY based strategies also assumed no stock-recruitment relationship, which is likely not realistic. We recommend incorporating a more realistic stock-recruitment relationship into the multi-species estimation methods. Finally, we projected mean recruitment to decrease across climate scenarios, but changes in the recruitment variability may also occur due to climate change and incorporating changes in recruitment variability may influence the results.

3.4.3 Conclusion

This comparison of single- and multi-species management strategies indicates that multi-species management strategies do not necessarily lead to improved management performance even when

the assessments on which they are based better reflect reality. This is in part due to the harvest control rules tested, which aim to achieve high yields by accounting for reduced predation mortality by reducing predator abundance. The most conservative multi-species management strategy (MS-B40-a) did not result in similar poor performance that occurred with the other multi-species management strategies because it was less aggressive in terms of achieving high yield, resulting in greater catch, similar catch variability, and greater spawning stock biomass for pollock than the single-species strategies evaluated. The results also further highlights the consequences of model mis-specification when applying management strategies, and that robustness to uncertainty (in this case the form of the stock-recruitment relationship) is essential when selecting management strategies. Similarly, allowing for dynamic reference points when applying single-species management could be expected to account to some extent for factors ignored in single-species assessments, but in common with one previous studies (Bessell-Browne et al., 2024), this outcome was not evident in the results. Climate-driven changes in expected recruitment were much more influential than the effects of trophic dynamics, although these are likely more difficult to parameterize using existing data – the single-species management strategies with dynamic reference points account for time-varying recruitment to some extent but were overall not able to mitigate the effects to any substantial extent. Overall, while multi-species management strategies and management strategies based on dynamic reference points hold promise to better achieve management goals, considerable uncertainty remains regarding their performance in (simulated) feedback situations.

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TABLES

Table 3.1. Predation mortality equations for predators of species p , sex b , age j , and prey of species i , sex s and age a as a function of summer bottom temperature (T_y). For parameter definitions see Table S3.2.

Definition	Equation	
Predation mortality	$M2_{isay}$	T1.1
	$= \sum_{pbj} \left(\frac{\bar{N}_{pbjy} \delta_{pbjy} \hat{S}_{pbjisa}}{(\sum_{isa} (\hat{S}_{pbjisa} \bar{B}_{isay}) + B_p^{other} (1 - \sum_{isa} (\hat{S}_{pbjisa})))} \right)$	
Predator-prey suitability	$\hat{S}_{pbjisa} = \frac{1}{n_y} \sum_y \left(\frac{\frac{\bar{U}_{psaisa}}{w_{isay} \bar{N}_{isay}^{H_i}}}{\sum_{isa} \left(\frac{\bar{U}_{pbjisa}}{w_{isay}} \right) + \frac{1 - \sum_{isa} \bar{U}_{pbjisa}}{B_p^{other}}} \right)$	T1.2
Individual specific ration ($kg\ kg^{-1}\ yr^{-1}$)	$\delta_{pbjy} = \varphi_{pbjy} \alpha_p^\delta W_{pbjy}^{(1+\beta_p^\delta)} f(T_y)_p$	T1.3
Temperature scaling algorithm	$f(T_y)_p = V^X e^{(X(1-V))}$	T1.4
...	$V = (T_p^{cm} - T_y) / (T_p^{cm} - T_p^{co})$	T1.5
...	$X = (Z^2 (1 + (1 + 40/Y)^{0.5})^2) / 400$	T1.6
...	$Z = \ln(Q_p^c) (T_p^{cm} - T_p^{co})$	T1.7
...	$Y = \ln(Q_p^c) (T_p^{cm} - T_p^{co} + 2)$	T1.8

Table 3.2. General population dynamics equations for the multi-species operating models (OMs) and the single-species estimation methods (EMs) for species i , sex s , age a , and length l in year y , and the observation and fishery model for survey or fishery f_i . See Table S3.S2 for parameter definitions.

Definition	Equation	
Recruitment	$N_{is1y} = R_{isy} = \bar{R}_i e^{\tau_{iy}} \rho_{i1}$ $N_{is1y} = R_{isy} = \frac{\alpha_i S B_{iy}}{\beta_i + S B_{iy} \gamma_i} e^{\tau_{iy}} \rho_{i1}$	T2.1
Initial abundance	$N_{isa1} = \begin{cases} \bar{R}_i e^{(-\sum_{j=1}^{a-1} M1_{isj} + \tau_{ia})} \rho_{i1} & \text{if } j < A_i \\ \frac{\bar{R}_i e^{(-\sum_{j=1}^{a-1} M1_{isj} + \tau_{ia})} \rho_{i1}}{(1 - e^{(-M1_{isa})})} & \text{if } j = A_i \end{cases}$	T2.2
Numbers at age	$\begin{cases} N_{isa+1y+1} = N_{isay} e^{-Z_{isay}} \\ N_{isA_iy+1} = N_{isA_i-1y} e^{-Z_{isA_i-1y}} + N_{isA_iy} e^{-Z_{isA_iy}} \end{cases}$	T2.3
Survey biomass (kg)	$CPUE: B_{fiy} = \sum_s \sum_a N_{isay} e^{-Month_{fi} * Z_{isay}} W_{fi say} sel_{fi say} q_{fiy}$	T2.4
Survey abundance (numbers)	$CPUE: I_{fiy} = \sum_s \sum_a N_{isay} e^{-Month_{fi} * Z_{isay}} sel_{fi say} q_{fiy}$	T2.5
Catch-at-age	$C_{fi say} = \frac{F_{fi say}}{Z_{isay}} (1 - e^{-Z_{isay}}) N_{isay}$	T2.6
Total catch (kg)	$\hat{C}_{fiy}^* = \sum_s \sum_j \frac{F_{fi say}}{Z_{isay}} (1 - e^{-Z_{isay}}) N_{isay} W_{fi say}$	T2.7
Age-1+ biomass (kg)	$B_{iy} = \sum_s \sum_{a>0} N_{isay} W_{B_i ay}$	T2.8
Spawning biomass at age (kg)	$SB_{iay} = \begin{cases} N_{iay} e^{-Month_{ssb_i}/12 * Z_{iay}} W_{ssb_i ay} \rho_{ia} \delta_{ia} & \text{if 1 sex model} \\ N_{i1ay} e^{-Month_{ssb_i}/12 * Z_{i1ay}} W_{ssb_i 1ay} \delta_{ia} & \text{if 2 sex model} \end{cases}$	T2.9
Total mortality at age (single-species)	$Z_{isay} = M1_{isa} + \sum_{f_i} F_{fi say}$	T2.10
Total mortality at age (multi-species)	$Z_{isay} = M1_{isa} + M2_{isay} + \sum_{f_i} F_{fi say}$	T2.11
Fishing mortality at age and fleet	$F_{fi say} = \bar{F}_{fi} e^{\epsilon_{fiy}} sel_{fi say}$	T2.12
Projected fishing mortality	$F_{fi say} = F_{Target_i} sel_{fi say} \psi_{fi}$	T2.13
Predicted age composition	$\hat{O}_{f_i say} = \frac{\sum_a C_{fi say} A E_{i \hat{a} a}}{\sum_s \sum_{\hat{a}} \sum_a C_{fi say} A E_{i \hat{a} a}} \quad \text{if } f_i = \text{fishery}$	T2.14

Predicted length
composition

$$\begin{aligned}
 \hat{O}_{f_i s \hat{a} y} &= \frac{\sum_a N_{i s a y} e^{-Month_{f_i} * Z_{i s j y} sel_{f_i s a y} A E_{i \hat{a} a}}}{\sum_s \sum_{\hat{a}} \sum_a N_{i s a y} e^{-Month_{f_i} * Z_{i s j y} sel_{f_i s a y} A E_{i \hat{a} a}}} \quad \text{if } f_i = \text{survey} \\
 \hat{O}_{f_i s l y} &= \frac{\sum_{\hat{a}} \sum_a C_{f_i s a y} A E_{i \hat{a} a} A T M_{i s a l}}{\sum_s \sum_l \sum_{\hat{a}} \sum_a C_{f_i s a y} A E_{i \hat{a} a} A T M_{i s a l}} \quad \text{if } f_i = \text{fishery} \\
 \hat{O}_{f_i s l y} &= \frac{\sum_{\hat{a}} \sum_a N_{i s a y} e^{-Month_{f_i} * Z_{i s a y} sel_{f_i s a y} A E_{i \hat{a} a} A T M_{i s a l}}}{\sum_s \sum_l \sum_{\hat{a}} \sum_a N_{i s a y} e^{-Month_{f_i} * Z_{i s j y} sel_{f_i s a y} A E_{i \hat{a} a} A T M_{i s a l}}} \quad \text{if } f_i = \text{survey}
 \end{aligned}
 \tag{T2.15}$$

Table 3.3. Overview of historical data collection from survey and fishery fleets for the GOA used for stock assessment. For more detailed information on data refer to stock assessment reports (Barbeaux et al., 2018; Dorn et al., 2018; Spies & Palsson, 2018; Holsman et al., 2016).

Species	Fleet	Data type	Data collection cycle
Pollock	Shelikof straight acoustic survey	Age-3+ relative biomass	Biennial
		Age-1 relative abundance	
		Age-2 relative abundance	
		Age composition	
	NMFS bottom trawl survey	Relative biomass	Biennial
		Age composition	
	ADFG trawl survey	Relative biomass	Annual
		Age composition	
	Summer acoustic survey	Relative biomass	Biennial
		Age composition	
Arrowtooth:	Fishery	Total catch	Annual
		Age composition	
		Length composition	
	NMFS bottom trawl survey	Absolute biomass	Biennial
		Length composition	
		Age composition	
Pacific cod:	Fishery	Total catch	Annual
		Length composition	
		Age composition	
	NMFS bottom trawl survey	Relative abundance	Biennial
		Length composition	
		Age composition	
	NMFS sablefish longline survey	Relative abundance	Biennial
		Length composition	
		Age composition	
	Trawl fishery	Total catch	Annual
		Length composition	
		Age composition	
	Longline fishery	Total catch	Annual
		Length composition	
	Pot fishery	Total catch	Annual
		Length composition	

Table 3.4. Equations for multi-species and single-species equilibrium and dynamic biological reference points for species i , sex s , age a , length l in year y , and fishery f_i . See Table S3.S2 for parameter definitions.

Definition	Equation	
<i>Equilibrium</i>		
Equilibrium projected F	$F_{f_i 1a} = F_{Target_i} sel_{f_i 1a} \rho_{f_i}$	T4.1
Unfished equilibrium spawning stock biomass-per-recruit	$SPR_{0,i} = \sum_{a=1}^{A_i-1} \bar{R}_i \rho_{i1} e^{-\sum_{j=1}^{a-1} (M_{1i1j}) - \frac{Month_{ssbi}}{12} * M_{1i1a}} W_{ssbi 1a} \delta_{ia}$ $+ \bar{R}_i \rho_{i1} \frac{e^{-\sum_{j=1}^{A_i-1} (M_{1i1j})}}{1 - e^{-M_{1i1A_i}}} e^{-\frac{Month_{ssbi}}{12} * 1_{i1A_i}} W_{ssbi 1A_i} \delta_{iA_i}$	T4.2
Fished equilibrium spawning stock biomass-per-recruit	$SPR_{X,i} = \sum_{a=1}^{A_i-1} \bar{R}_i \rho_{i1} e^{-\sum_{j=1}^{a-1} (M_{1i1j} + \sum_{f_i} F_{f_i 1j}) - \frac{Month_{ssbi}}{12} * (M_{1i1a} + \sum_{f_i} F_{f_i 1a})} W_{ssbi 1a} \delta_{ia}$ $+ \bar{R}_i \rho_{i1} \frac{e^{-\sum_{j=1}^{A_i-1} (M_{1i1j} + \sum_{f_i} F_{f_i 1j})}}{1 - e^{-M_{1i1A_i} + \sum_{f_i} F_{f_i 1A_i}}} e^{-\frac{Month_{ssbi}}{12} * (M_{1i1A_i} + \sum_{f_i} F_{f_i 1A_i})} W_{ssbi 1A_i} \delta_{iA_i}$	T4.3
F associated with $SPR_{X,i}$ that is X% of $SPR_{0,i}$	$F_{X\%,i} = F_{Target_i} \text{ where } \frac{SPR_{X,i}}{SPR_{0,i}} = X$	T4.4
X% of equilibrium spawning biomass	$SB_{X,i} = \frac{X}{100} SB_{0,i}$	T4.5
<i>Dynamic (recruitment, growth, and selectivity)</i>		
Projected fishing mortality	$F_{f_i say} = F_{Target_{iy}} sel_{f_i say} \rho_{f_i}$	T4.6
Unfished numbers-at-age	$N_{i1a+1y+1} = N_{i1ay} e^{-M_{isay}}$	T4.7
Unfished spawning stock biomass	$N_{i1A_i y+1} = N_{i1A_i-1y} e^{-M_{i1A_i-1y}} + N_{i1A_i y} e^{-M_{i1A_i y}}$ $SB_{0,iy} = \sum_{a=1}^{A_i} N_{i1ay} e^{-Month_{ssbi}/12 * M_{i1ay}} W_{ssbi 1ay} \rho_{ia} \delta_{ia}$	T4.8
Fished numbers-at-age	$N_{i1a+1y+1} = N_{i1ay} e^{-M_{isay} - \sum_{f_i} F_{f_i say}}$	T4.9
Fished spawning stock biomass	$N_{i1A_i y+1} = N_{i1A_i-1y} e^{-M_{i1A_i-1y} - \sum_{f_i} F_{f_i say} A_i - 1y} + N_{i1A_i y} e^{-M_{i1A_i y} - \sum_{f_i} F_{f_i say} A_i y}$ $SB_{X,iy} = \sum_{a=1}^{A_i} N_{i1ay} e^{-Month_{ssbi}/12 * (M_{i1ay} + \sum_{f_i} F_{f_i say})} W_{ssbi 1ay} \rho_{ia} \delta_{ia}$	T4.10
Fishing mortality rate associated with $SB_{X,iy}$ that is X% of $SB_{0,iy}$	$F_{X,iy} = F_{Target_{iy}} \text{ where } \frac{SB_{X,iy}}{SB_{0,iy}} = X$	T4.11

Table 3.5. Factors considered for the operating models and management strategies for the simulation experiments. The options indicated in bold-underline typeface represent the base-case analysis. A full factorial design was used.

Factor	Options (bold is base-case)
<i>Operating models</i>	
Base model	<u>Multi-species time- and age-varying M</u>
Climate scenario	<u>No climate change</u> , high mitigation with a 2-degree future increase in temperature (SSP1-2.6), medium pathway (SSP2-4.5), and high baseline (SSP5-8.5)
Recruitment scenario	<u>Constant expected relationship</u> , Ricker
<i>Management strategies</i>	
Estimation model	Single-species pre-specified M
• Harvest control rule	• NPFMC Tier 3 HCR • Dynamic NPFMC Tier 3 HCR
	Single-species EM estimate M
	• NPFMC Tier 3 HCR • Dynamic NPFMC Tier 3 HCR
	Multi-species estimation model
	• Individual stock strategy 1 (MS-B40-a) • Individual stock strategy 2 (MS-B40-b) • System-wide unconstrained MSY (MS-MSY) • System-wide constrained MSY (MS-cMSY)
Utilization	Stocks fully utilized, or catch is capped at historical maximum

Table 3.6. Estimated regression coefficients for scaled environmental indices related to recruitment in the multi-species operating models.

	No stock-recruit relationship			Ricker stock-recruit		
	<i>Winter SST</i>	<i>SST²</i>	<i>Fall zooplankton</i>	<i>Winter SST</i>	<i>SST²</i>	<i>Fall zooplankton</i>
Pollock	1.362	-2.033	0.048	1.154	-1.800	0.053
Cod	1.656	-1.706	-0.127	1.302	-1.327	-0.083
ATF	0.393	-0.461	0.014	0.234	-0.311	0.017

Table 3.7. Summary of the performance metrics from single- and multi-species management strategies across no climate change operating models with contrast expected recruitment. Note: catch and spawning stock biomass (SSB) are scaled to '000 mt. Grey shading indicates where the estimation method matched the operating model.

	EM	1. Single-spp fix M		2. Single-spp est M		3. Multi-species			
	PM/HCR	<i>Equilibrium</i>	<i>Dynamic</i>	<i>Equilibrium</i>	<i>Dynamic</i>	<i>MS-B40-a</i>	<i>MS-B40-b</i>	<i>MS-MSY</i>	<i>MS-cMSY</i>
Pollock	1. Average catch	574	582	424	444	618	916	1,197	1,149
	2. Catch IAV	0.29	0.29	0.25	0.24	0.29	0.4	0.64	0.54
	3. OM: $P(SB_y < B_{Limit})$	0	0	0	0	0	0.04	0.91	0.78
	4. OM: SSB_{2100}	702	691	875	853	904	380	79	140
	5. OM: $Depletion_{2100}$	0.69	0.68	0.87	0.84	0.89	0.37	0.08	0.14
Cod	1. Average catch	31	31	19	19	22	22	37	35
	2. Catch IAV	0.24	0.2	0.19	0.18	0.15	0.15	0.39	0.25
	3. OM: $P(SB_y < B_{Limit})$	0.01	0.01	0	0	0	0	0.27	0.12
	4. OM: SSB_{2100}	157	153	269	270	251	251	101	126
	5. OM: $Depletion_{2100}$	0.37	0.36	0.64	0.65	0.6	0.6	0.24	0.3
ATF	1. Average catch	98	99	111	111	122	123	133	133
	2. Catch IAV	0.14	0.14	0.22	0.21	0.26	0.26	0.33	0.33
	3. OM: $P(SB_y < B_{Limit})$	0	0	0	0	0	0	0	0
	4. OM: SSB_{2100}	368	366	330	327	293	298	264	264
	5. OM: $Depletion_{2100}$	0.52	0.52	0.47	0.46	0.42	0.42	0.37	0.37

Table 3.8. Summary of the performance metrics from single- and multi-species management strategies across no climate change operating models with Ricker stock-recruitment relationships. Note: catch and spawning stock biomass (SSB) is scaled to ‘000 mt. Grey shading indicates where the estimation method matched the operating model.

	EM	1. Single-spp fix M		2. Single-spp est M		3. Multi-species			
	PM/HCR	<i>Equilibrium</i>	<i>Dynamic</i>	<i>Equilibrium</i>	<i>Dynamic</i>	<i>MS-B40-a</i>	<i>MS-B40-b</i>	<i>MS-MSY</i>	<i>MS-cMSY</i>
Pollock	1. Average catch	573	558	602	634	844	240	103	114
	2. Catch IAV	0.29	0.29	0.26	0.26	0.29	0.84	3.02	2.3
	3. OM: $P(SB_y < B_{Limit})$	0	0	0	0	0	0.84	0.94	0.92
	4. OM: SSB_{2100}	715	644	1,066	1,071	1,385	41	0	0
	5. OM: $Depletion_{2100}$	0.74	0.64	1.16	1.14	1.51	0.04	0	0
Cod	1. Average catch	29	29	20	20	24	23	23	27
	2. Catch IAV	0.25	0.2	0.18	0.17	0.15	0.15	0.53	0.28
	3. OM: $P(SB_y < B_{Limit})$	0.01	0.01	0	0	0	0	0.78	0.39
	4. OM: SSB_{2100}	152	146	288	290	275	272	52	117
	5. OM: $Depletion_{2100}$	0.39	0.37	0.74	0.74	0.7	0.69	0.13	0.3
ATF	1. Average catch	89	89	90	90	88	89	87	87
	2. Catch IAV	0.15	0.15	0.27	0.27	0.37	0.37	0.49	0.5
	3. OM: $P(SB_y < B_{Limit})$	0	0	0	0	0.03	0.02	0.23	0.23
	4. OM: SSB_{2100}	319	314	262	246	182	186	143	142
	5. OM: $Depletion_{2100}$	0.45	0.44	0.37	0.35	0.26	0.26	0.2	0.2

FIGURES

Figure 3.1. Time-series of spawning stock biomass as determined from the estimation methods and associated harvest control rules fit to data from 1977 to 2020 and projected from 2021 until 2100 under mean recruitment. Spawning stock biomass under no fishing is indicated by the dashed lines (black for multi-species estimation method).

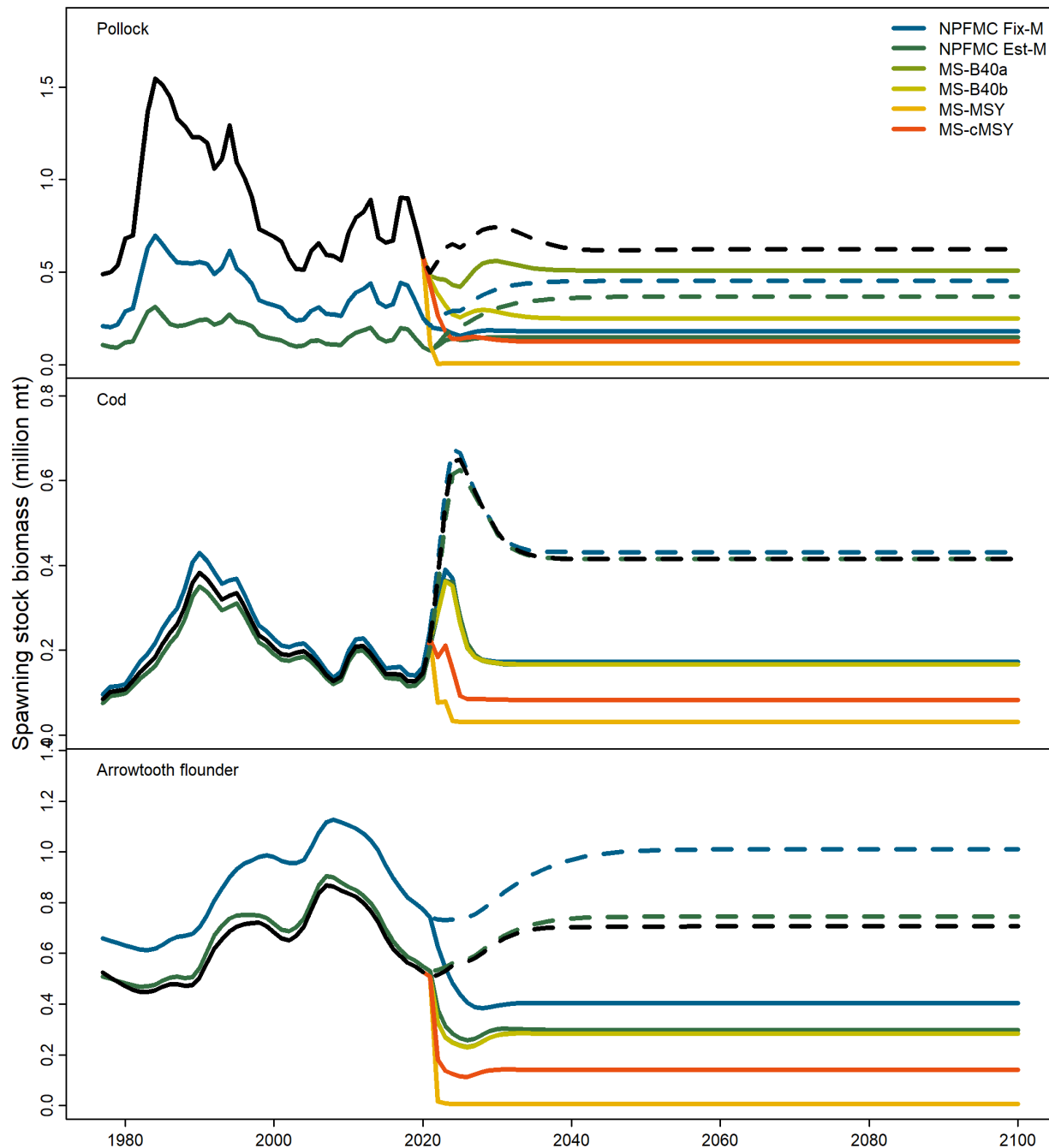


Figure 3.2. Summary of performance metric 1: average catch ('000 mt) across operating models (columns). Operating models with Ricker stock-recruitment relationships are indicated by the grey shading and harvest control rules (HCRs) using dynamic biomass reference points are indicated by the triangles. Note scale of y-axis differs between panels.

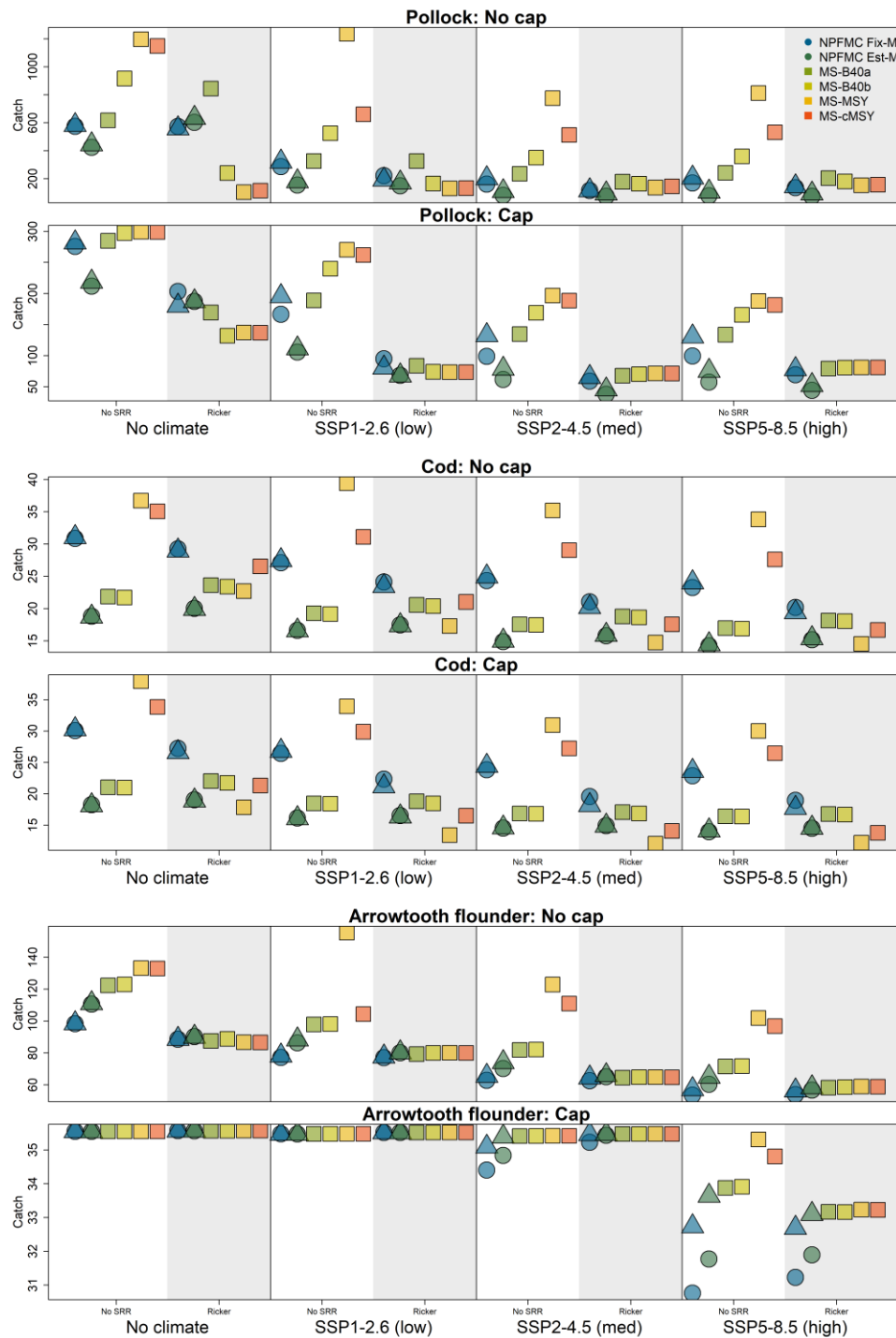


Figure 3.3. Summary of performance metric 2: average interannual catch variability (IAV) across operating models (columns). Operating models with Ricker stock-recruitment relationships are indicated by the grey shading and harvest control rules (HCRs) using dynamic biomass reference points are indicated by the triangles. Note scale of y-axis.

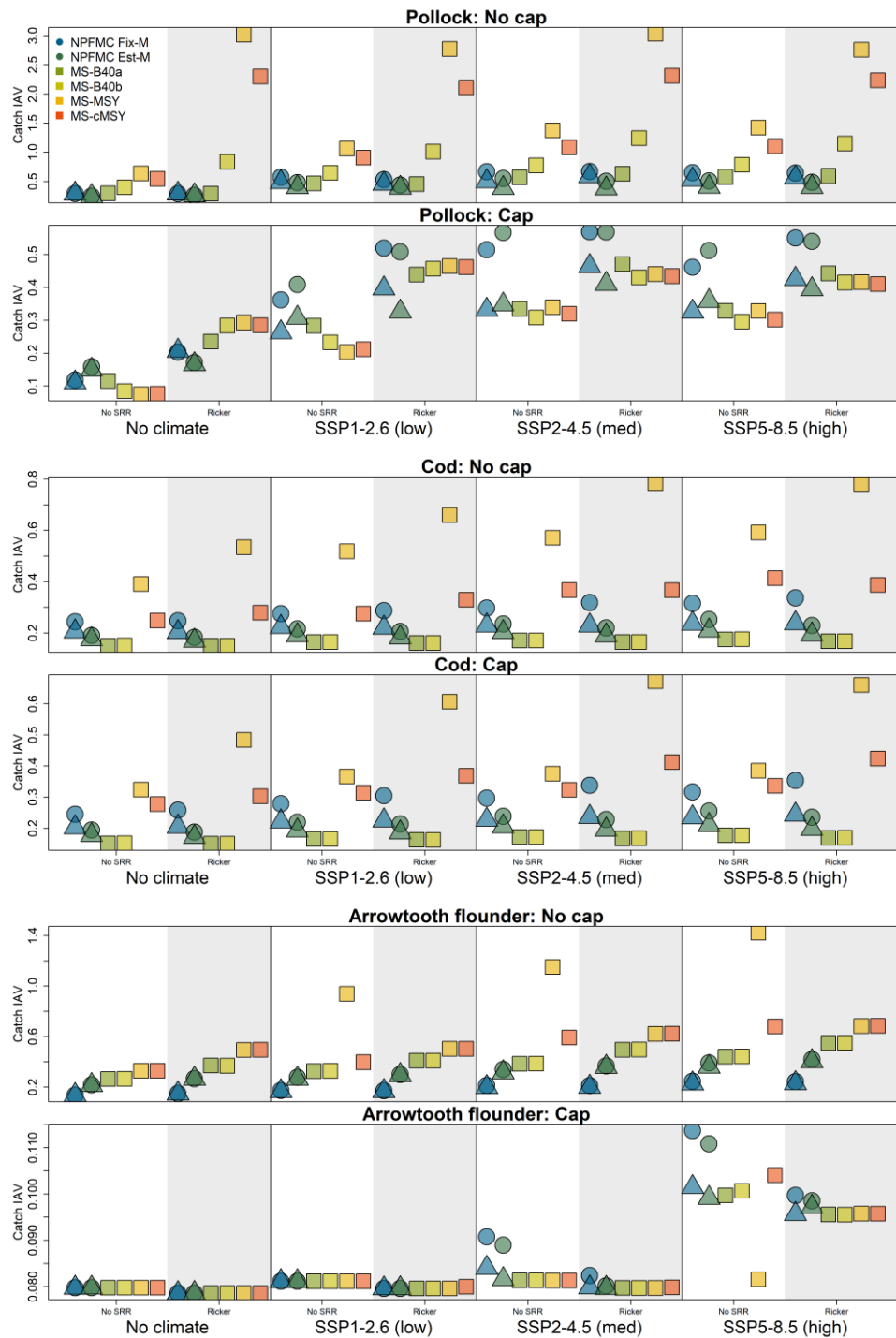


Figure 3.4. Summary of performance metric 3: probability that the population is overfished as determined from the operating model across operating models (columns). Operating models with Ricker stock-recruitment relationships are indicated by the grey shading and harvest control rules (HCRs) using dynamic biomass reference points are indicated by the triangles.

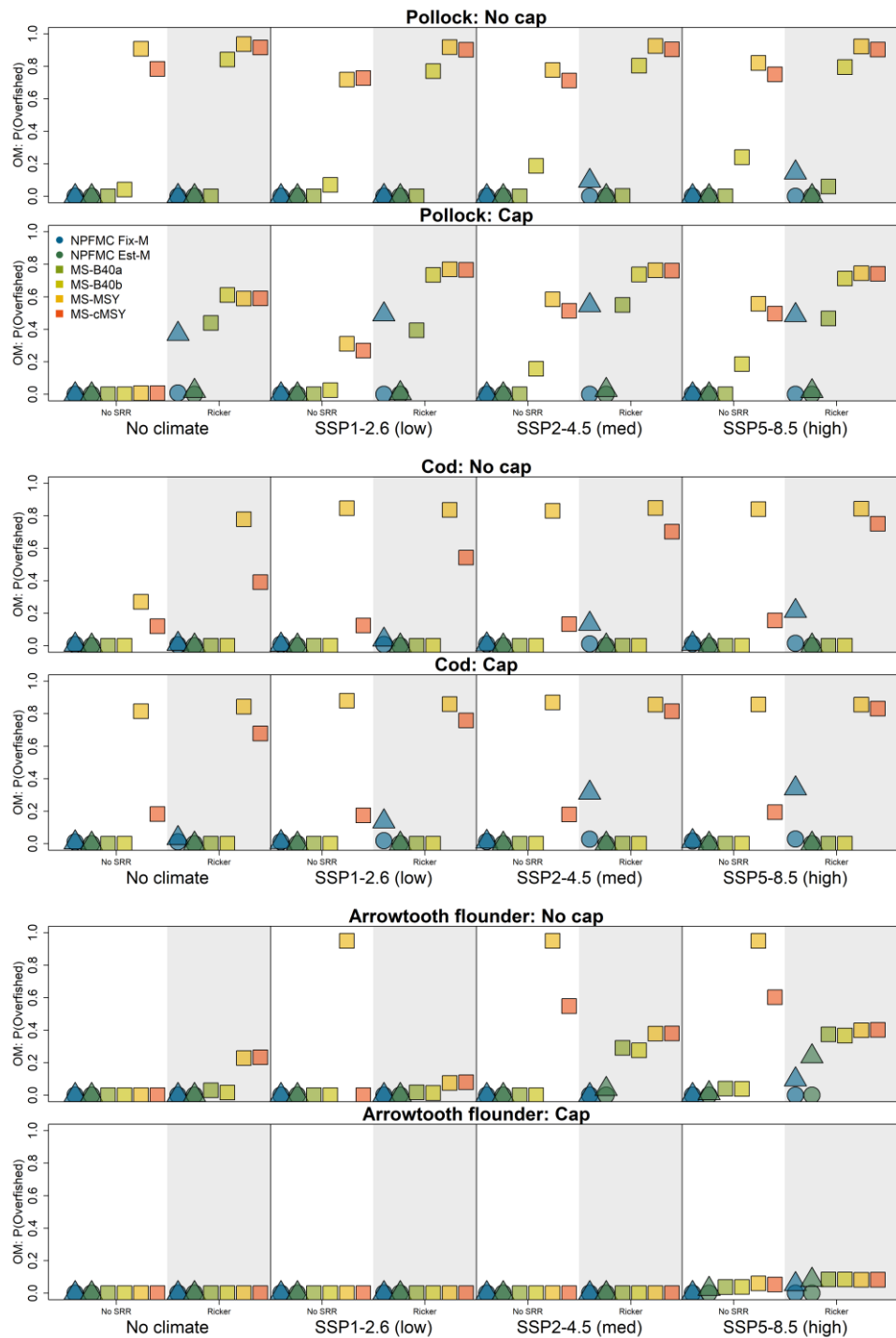


Figure 3.5. Summary of performance metric 4: average terminal (*i.e.*, 2100) spawning stock biomass (1,000 mt) across operating models (columns). Operating models with Ricker stock-recruitment relationships are indicated by the grey shading and harvest control rules (HCRs) using dynamic biomass reference points are indicated by the triangles. Note scale of y-axis differs on each panel.

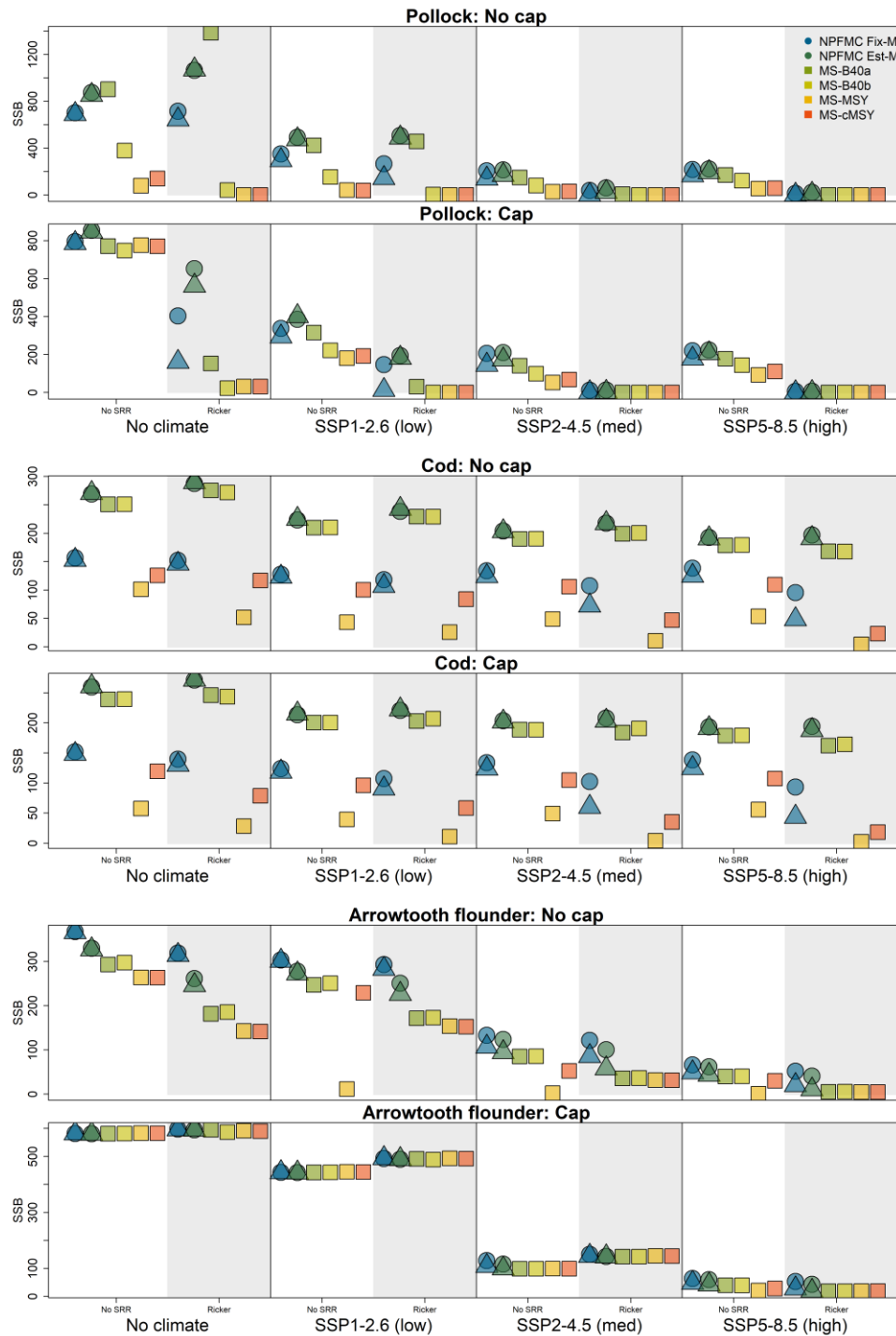
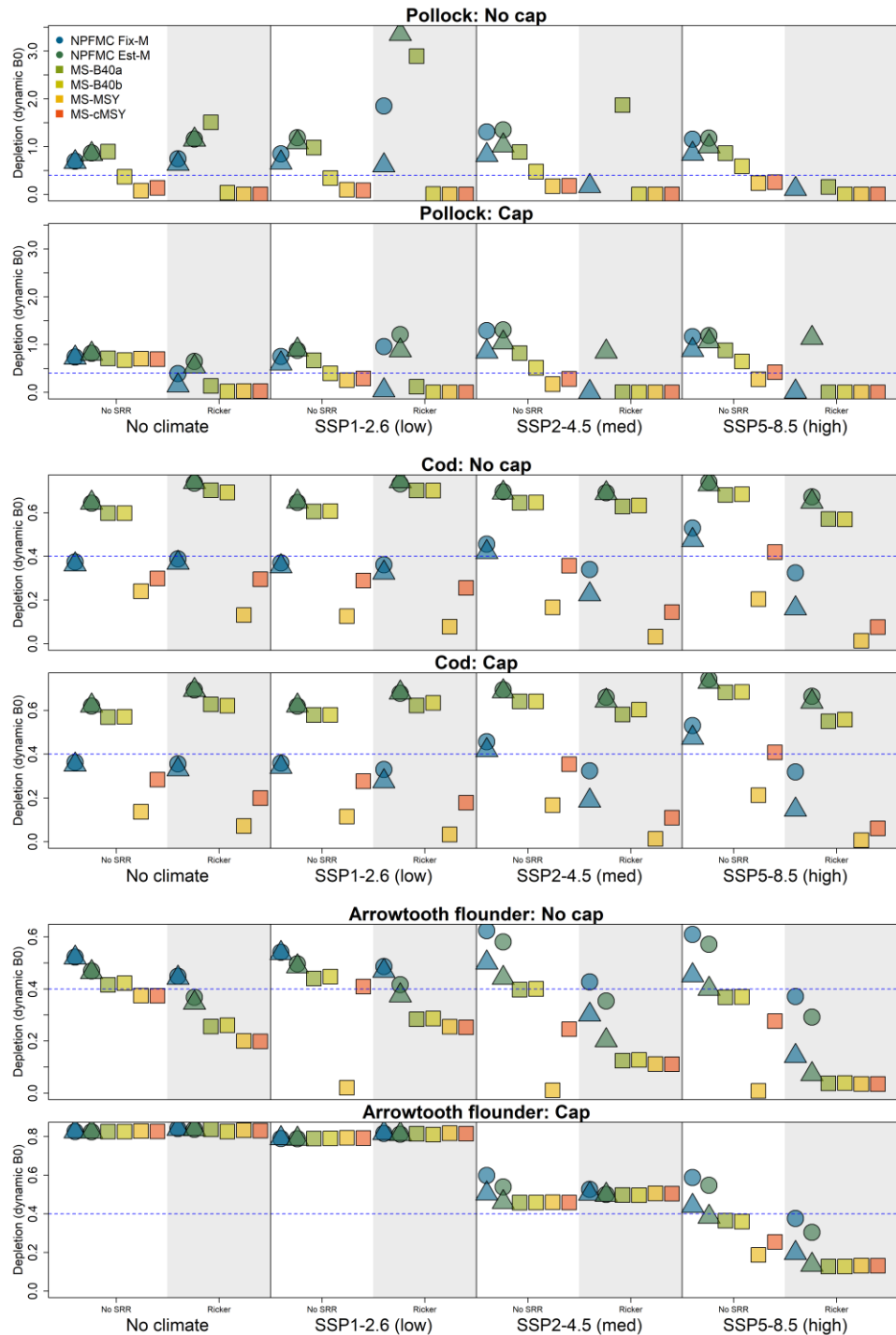


Figure 3.6. Summary of performance metric 6: average terminal (i.e., 2100) spawning stock biomass depletion relative to dynamic $SB_{0,y}$ across operating models (columns). Operating models with Ricker stock-recruitment relationships are indicated by the grey shading and harvest control rules (HCRs) using dynamic biomass reference points are indicated by the triangles. 40% $SB_{0,y}$ is indicated by the blue dashed line.



Discussion

There has long been interest in accounting for trophic interactions when managing fisheries because harvesting one species can have impacts for both predators and prey (Hilborn et al., 2017; Myers et al., 2007; Pikitch et al., 2014). However, the development of tools for incorporating trophic interactions into fisheries management is challenging because of the additional need for data to parameterize trophic interactions and uncertainty regarding the reference points to supply fisheries managers (Collie and Gislason, 2001; Curti et al., 2013; Moffitt et al., 2016). There is also limited testing of the performance of multi-species models given the bespoke nature of most such models and their longer development time. In contrast, the single-species models used for the majority of fisheries management are often simpler to parametrize, have well developed frameworks for estimation and model testing, and have a considerable amount of research aimed at understanding their management performance (Dichmont et al., 2016; Fournier and Archibald, 1982; Maunder and Punt, 2013; Punt, 2023). The research presented in this dissertation aimed to address those challenges by developing a framework for the fitting of multi-species models and by comparing the performance of management strategies derived from single- and multi-species models.

The first chapter developed a multi-species population dynamics model for the Gulf of Alaska. The model was fit to survey and fishery data for four groundfish species: walleye pollock *Gadus chalcogrammus*, Pacific cod *Gadus macrocephalus*, arrowtooth flounder *Atheresthes stomias*, and Pacific halibut *Hippoglossus stenolepis*. The chapter used an ensemble modelling approach to integrate across multiple forms of uncertainty regarding the data and distribution of Pacific halibut to estimate time- and age-varying predation mortality. The results showed that, of the four species, arrowtooth flounder was the primary predator of walleye pollock and the trophic dynamics tend to be more top down than the dynamics found in the Bering Sea, which has been shown to be more cannibalism driven (Holsman et al., 2016). While the model was heavily influenced by the multi-species model developed for the Bering Sea (Holsman et al., 2016), a key component of the work was the development of a flexible modelling package built using Template Model Builder (TMB; (Kristensen et al., 2016). TMB allows the estimation of normally distributed random effects and represents an advancement in the estimation of multi-species models compared to those previously developed using other frameworks (Begley and Howell, 2004; Fournier et al., 2012). The package was developed so that a variety of parameterizations could be used for the fishery, survey, and population models so that the development and testing of multi-species models could be easily facilitated in the future.

The second chapter expanded upon the first by using the models developed for the Gulf of Alaska and Bering Sea to evaluate if management-strategies based on single-species population dynamics perform poorly because they do not account for predation mortality. Chapter 2 utilized a full management strategy evaluation approach to account for feedback within the management system (continued data collection and assessment), which is then able to track changes in the abundance of species. Multi-species models for the Gulf of Alaska and Bering Sea were utilized as operating models given the different trophic dynamics in their systems to simulate data used for single-species management strategies. Management strategies utilized across a variety of fisheries systems with “strong” trophic interactions were then tested to evaluate how they perform. Overall, Chapter 2 found that the single-species management strategies perform well despite not accounting for predation mortality and stock-dependent recruitment. The management strategies evaluated

were able to maintain consistent yields and there was a low probability of the stocks in the operating model being overfished even when there were multispecies interactions that were ignored by the estimation methods. The best performing management strategy will depend on the specific goals for a fishery. However, management strategies that estimated natural mortality and utilized equilibrium reference points had less risk of depleting stocks. This work advances upon research aimed at the understanding the performance of single-species management strategies (e.g., A'mar et al., 2010; Essington, 2004; Trijoulet et al., 2019) by accounting for feedback control, the age-structure of predators, and the impacts of both predation and stock-dependence.

The third and final chapter advanced the first and second by incorporating downscaled climate projections into the multi-species model developed for the Gulf of Alaska and comparing the performance of single- and multi-species management strategies under climate change. Multi-species management strategies have been proposed as an approach that can outperform single-species management strategies by explicitly accounting for and/or exploiting the conditional relationships among species (Collie and Gislason, 2001; Fitzpatrick et al., 2022; Holsman et al., 2016; Moffitt et al., 2016; Tyrrell et al., 2011). However, to date, multi-species management strategies have not been fully tested using management strategy evaluation. Chapter 3 consequently conducted a management strategy evaluation comparing the performance of single-species management strategies currently used for tactical advice with multi-species management strategies used for strategic advice in the Gulf of Alaska and management strategies based on multi-species MSY and depletion. As operating models, Chapter 3 used the climate-linked multi-species models with and without stock-recruitment relationships. Overall, the multi-species management strategies were able to achieve higher levels of catch when the model on which the estimation method was based was correctly specified, at a cost of higher catch variability and lower stock size. However, when the multi-species estimation method did not correctly allow for stock-dependent recruitment, the more aggressive multi-species management strategies performed worse across all metrics than the single-species management strategies for the key prey species in the system. The most conservative multi-species management strategy (MS-B40-a), which is similar to approaches for supplemental management for the GOA did not result in similar poor performance because it was less aggressive in terms of achieving high yield, resulting in greater catch, similar catch variability, and greater spawning stock biomass for pollock than the single-species strategies evaluated.

Overall, the results of the dissertation show that single-species management strategies are robust to time- and age-varying predation mortality, may outperform multi-species management strategies when there is model mis-specification, and that a key component of multi-species management performance is the correct specification of the stock-recruitment relationship and associated harvest control rule. While there is evidence that management strategies based on multi-species models can provide improved management performance (Pérez-Rodríguez et al., 2022), we recommend additional testing and evaluation. Specifically, I recommend additional development of multi-species management strategies to account for stock-recruitment relationships and further testing of both single- and multi-species management strategies under additional functional forms of predation, diet uncertainty, and “bottom-up” processes using the framework and software presented here. For example, the multi-species MSY based strategies relied on estimation methods that assumed constant expected recruitment. This resulted in high levels of depletion to maximize yield. This scenario may not be realistic and efforts to estimate stock-recruitment relationships (Thorson et al., 2018) to better approximate MSY would be worthwhile. While MSY-based reference points are the dominant paradigm in contemporary

fisheries management, the trophic interactions modelled here could be used to derive reference points based on the desired level of biomass across species for various user groups (Chagaris et al., 2020).

The use of multi-species models for advancing EBFM is a valuable avenue of research. The trophic dynamics in the GOA CEATTLE model are rather simple and top-down, and multi-species management strategies may perform better when there are more constraints within the technical and trophic interactions among species. For example, when prey species eat juvenile predators there can be more dynamic trade-offs between harvesting species (Pérez-Rodríguez et al., 2022). Technical interactions and effort limits among fisheries may also constrain fishing among multiple species and can be incorporated in future work. Further incorporation of prey-dependent growth (Fitzpatrick et al., 2022), time-varying suitability (Trijoulet et al., 2019a), and shifts in predator-prey overlap (Barnes et al., 2018) may improve our ability to account for ecological constraints and variation in predator-prey dynamics.

Within the current single-species management paradigm, the estimates of time- and age-varying mortality estimated here can be incorporated into assessments in Alaska to derive more “realistic” reference points (Tyrrell et al., 2011). The stock assessments currently used to provide the advice on which management of pollock in the GOA is based uses an ensemble average mortality estimate, partially derived from a multi-species age-structured model (Dorn et al., 2018), which could be updated given the work presented here.

Chapters 2 & 3 showed the performance of management strategies under both climate and predator-prey dynamics. The effects of climate change was projected to have a larger impact on management outcomes than unaccounted predation dynamics, leading to decreases in catch, increased catch variability, and lower spawning stock biomass. However, the climate projections integrated into CEATTLE represent a single realization of IPCC models and do not account for the full range of uncertainty in future environmental conditions. It is likely that there will be more variability in environmental conditions in the North Pacific due to climate change, which will have negative impacts on fisheries (Cheung and Frölicher, 2020; Frölicher et al., 2018; Oliver et al., 2018). Finally, this research did not account for the range of uncertainty given the computational demands, but future work could simulate variability around a fitted trend line and incorporate that into the MSE framework. The framework and software developed in this dissertation allows further research development across systems to address these issues.

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Chapter 1 Supplementary Materials

SUPPLEMENTARY TEXT

Diet proportion

The diet proportion by weight of predators-at-age for prey-at-age was estimated following an approach adapted from previous studies (Barnes et al., 2020; Stewart and Hamel, 2014). The AFSC uses a stratified random sampling design for bottom trawl surveys in the GOA. From each haul, fish are identified to species and the total estimated weight of each species is recorded. A subsample of each species and haul are measured for length, age, and weight (depending on the species). Separately, stomach contents are subsampled from up to five fish per species, haul, and size class starting in 1990. While stomach content data were sampled prior to 1990, sampling techniques were not standardized and the data were not included in the analyses. Fish prey are identified to species or the lowest taxonomic group depending on digestion, and standard length measured either directly when feasible or back-calculated from otoliths (Livingston et al., 2017). Size classes used for diet sampling are <31 cm, 31 to 50 cm, 51 to 70 cm, and > 70 cm for arrowtooth flounder, Pacific cod, and Pacific halibut. For walleye pollock, size classes used for diet sampling are < 30 cm, 30 to 39 cm, 40 to 49 cm, and ≥ 50 cm. To account for subsampling of hauls for length measurements we calculated the predicted number of fish of predator species p caught in haul h ($\hat{N}_{ph}$)¹ as:

Eq. S1.1.
$$\hat{N}_{ph} = \frac{W_{ph}}{W_{ps}} * N_{ps}$$

where W_{ph} is the total weight of predator p in haul h , W_{ps} is the total weight of predator p subsampled for lengths from that haul, and N_{ps} is the number of predators in sample s . The proportion of predator-at-length within each haul P_{pkh} was calculated as:

Eq. S1.2.
$$P_{pkh} = \frac{N_{pkh}}{\sum_k N_{pkh}}$$

where N_{pkh} is the number of predators of species p in length bin k in haul h sampled for length. To account for subsampling of fish for stomach content analysis the proportion of predator-at-length sampled for stomach content analysis P_{pkh_f} was calculated as:

Eq. S1.3.
$$P_{pkh_f} = \frac{N_{pkh_f}}{\sum_k N_{pkh_f}}$$

where N_{pkh_f} is the number of predators of species p of length bin k sampled for food habits in haul h . Weights to account for length-based subsampling WF_{pkh} were calculated for each stomach content sample as follows:

Eq. S1.4.
$$WF_{pkh} = \frac{P_{pk,h}}{P_{pk,h_f}}$$

¹ Year y subscripts are ignored above for simplicity.

To account for differential sampling density among strata s in the GOA and spatial differences between survey effort and predator abundance a design-based estimator of relative density was derived:

$$\text{Eq. S1.5.} \quad \hat{I}_{pS} = A_S * \frac{\sum_h \hat{N}_{ph}/a_h}{H_S}$$

$$\text{Eq. S1.6.} \quad \hat{I}_p = \sum_S \hat{I}_{pS}$$

where $\hat{I}_{pS}$ is the relative density of predator p in stratum S , $\hat{I}_p$ is the relative density of predator p , H_S is the total number of hauls in stratum S , a_h is the area towed during haul h , and A_S is the total area of stratum S . Vertical area/volume habitat is assumed proportional to horizontal area between strata. Annual estimates of proportion, by weight, of a prey species i in the stomach of a predator-at-length $\hat{U}_{i|pk}$ in for each year were estimated as follows:

$$\text{Eq. S1.7.} \quad \hat{U}_{i|pk} = \frac{\sum_S \hat{I}_{pS} \sum_h \sum_q w_{i|pkq} * WF_{pkh}}{\sum_S \sum_h \sum_q \sum_i w_{i|pkq} * WF_{pkh} * \hat{I}_{pS}}$$

where $w_{i|pkq}$ is the mass of prey species i in stomach sample q (which is in haul h of stratum S) for predator p in size-class k , WF_{pkh} is the length-subsampling weight, and $\hat{I}_{pS}$ is the empirical estimator of relative abundance of predator p per strata.

Depending on digestion, all fish and crab prey are measured for standard length. However, given the small sample size of prey length in the stomach content data, length/biomass expansion was only conducted for the proportion of prey species by weight in a predator-at-length relative to all other species. The proportion by weight of a prey-at-length in a predator-at-length relative to all other lengths of prey species i was calculated separately and across data from all years. First, standard lengths (SL) of prey were converted to fork length (FL) following previously estimated conversions (Alaska Pacific University, Fisheries, Aquatic Science, and Technology Laboratory, Unpublished Data; Geoff Lang personal communication). Fork lengths FL of prey item u of species i were then converted to weights using power equation parameters from recent stock assessments:

$$\text{Eq. S1.8.} \quad W_{iu} = a_i * FL_{iu}^{b_i}$$

The proportion by weight of a prey-at-length in a predator-at-length relative to all other lengths of that prey species $\hat{U}_{i|ipk}$ was calculated as follows:

$$\text{Eq. S1.9.} \quad \hat{U}_{i|ipk} = \frac{\sum_l n_{pkil} W_{ilpku}}{\sum_l n_{pki} W_{ilpku}}$$

where n_{pkil} is the number of prey samples of species i in length bin l in the stomach of predator p of length bin k , n_{pki} is the number of samples of prey species i of any length in the predator length-bin, W_{ilpku} is the weight of prey sample u of species i of length-bin l in the stomach of predator p of length bin k .

An estimate of annual proportion of prey-at-length by weight in the stomach of predator-at-length relative to all species/length groups was then estimated as follows:

$$\text{Eq. S1.10.} \quad \hat{U}_{pkily} = \hat{U}_{i|pk} * \hat{U}_{i|ipk}$$

MSCAA models require the inputs of proportion of prey-at-age, by weight, in the stomach of predator-at-age relative to all other prey/ages. Diet proportion by weight of predators-at-length for

prey-at-length $\hat{U}_{pkily}$ were then converted to age based by multiplying age-transition matrices to account for variability in length-at-age:

$$\text{Eq. S1.11.} \quad \hat{U}_{pbjisay} = \frac{\sum_a \sum_k \hat{U}_{pkily} ALK_{isaly} ALK_{pbjky}}{\sum_a \sum_k ALK_{isaly} ALK_{pbjky}}$$

where $\hat{U}_{pbjisay}$ is the proportion of prey i of sex s and age a in the stomach of predator p of sex b and age j in year y and ALK_{isaly} and ALK_{pbjky} are annual age-transition matrices of prey species i and predator species p , respectively. Annual age-length keys using two cm length-bins for the above were empirically derived from AFSC length and age subsamples for walleye pollock, Pacific cod, and arrowtooth flounder. Sex specific age-length keys were created for arrowtooth flounder. Annual age-length keys using 1-cm size bins provided by the IPHC were used for Pacific halibut. However, samples used for stomach content analysis and for length/biomass samples may be different, leading to a predator-at-length being sampled for stomach contents, but not length/abundance information. This is particularly problematic when using the 1 cm length bins for Pacific halibut, which results in a 60% loss of diet information because length-subsampling weights are estimated to be zero. We therefore used 2-cm length bins and assumed each 1-cm bin within the 2-cm bin had the same diet proportion for Pacific halibut, resulting in only 3% loss of information halibut. Similarly, age-length keys for Pacific halibut only represented ages 2-15. We therefore assumed diet proportions were the same for age-1 and age-2 halibut and age-15 and age-15+ halibut (ages not accounted for represented a small proportion of the total samples).

References

- Barnes, C.L., Beaudreau, A.H., Dorn, M.W., Holsman, K.K., Mueter, F.J., 2020. Development of a predation index to assess trophic stability in the Gulf of Alaska. *Ecol. Appl.* 30, 1–17. doi:10.1002/eap.2141
- Stewart, I.J., Hamel, O.S., 2014. Bootstrapping of sample sizes for length- or age-composition data used in stock assessments. *Can. J. Fish. Aquat. Sci.* 71, 581–588. doi:10.1139/cjfas-2013-0289

SUPPLEMENTARY TABLES

Supplementary Table S1.1. Parameter definition for the GOA CEATTLE Models.

Category	Parameter	Definition	Estimated/Input
Index	i	Species	
	s	Sex	
	a	Age	
	$\hat{a}$	Observed age	
	A	Plus group	
	l	Length	
	y	Year	
	p	Predator species	
	b	Predator sex	
	j	Predator age	
	k	Predator length	
Population model	f_i	Fleet/survey	
	S	Strata	
	R_{isy}	Recruitment	Estimated
	$\bar{R}_i$	Mean recruitment	Estimated
	τ_{iy}	Annual recruitment deviate	Estimated
	ρ_{ia}	Sex-ratio	Estimated or input
	$M1_{isa}$	Residual mortality	Estimated
	$M2_{isay}$	Predation-mortality	Estimated
	F_{fisy}	Fleet-specific fishing mortality	Estimated
	F_{isay}	Total fishing mortality	Estimated
	Z_{isay}	Total mortality	Estimated
	$\bar{F}_{fi}$	Mean fishing mortality	Estimated
	ϵ_{fiy}	Annual fishing mortality deviate	Estimated
	N_{isay}	Numbers-at-age	Estimated or input
	$\bar{N}_{isay}$	Average numbers-at-age	Estimated or input
	SSB_{ijy}	Spawning-stock-biomass (kg)	Estimated or derived
	B_{isay}	Biomass (kg)	Estimated or derived
	$\bar{B}_{isay}$	Average biomass	Estimated or derived
	d_{iy}	Percent of population in GOA	Input
	$\hat{S}_{pbjisa}$	Predator-prey suitability	Estimated
	B_p^{other}	Biomass of “other prey”	Input
	T_y	Observed bottom temperature (°C)	Input
Predation model	T_p^{co}	Thermal optima for consumption (°C)	Input
	T_p^{cm}	Thermal limit of consumption (°C)	Input
	Q_p^c	Rate at which consumption increased over relatively low water temperatures	Input
	$\alpha_p^\delta, \beta_p^\delta$	Weight specific intercept and slope of maximum consumption	Input
	φ_{pbjy}	Scalar for maximum to observed consumption	Input
	$\bar{U}_{pbj,isa}$	Average proportion of prey-at-age in the stomach of a predator-at-age	Input
Observation model	$\tilde{q}_i$	Relative abundance-at-age scalar	Estimated
	$\hat{B}_{fiy}$	Survey/fishery relative biomass (kg)	Estimated
	$\hat{I}_{fiy}$	Survey/fishery relative abundance (numbers)	Estimated
	sel_{fisy}	Selectivity	Estimated
	q_{fiy}	Catchability	Estimated

ω_{fiy}	Annual catchability deviate	Estimated
W	Weight (kg)	Input
C_{fisy}	Catch-at-age	Input
$\hat{C}_{fiy}^*$	Predicted total catch (kg)	Estimated
$\hat{O}_{fisy}/\hat{O}_{fisy}$	Predicted age/length composition	Estimated
$AE_{i\hat{a}a}$	Ageing error matrix	Input
ATM_{fisal}	Age-transition matrix (growth trajectory)	Input
ALK_{isaly}	Age-length transition matrix	Input

Supplementary Table S1.2. Selectivity and catchability equations for species i , sex s , age a , and length l in year y , and the observation and fishery model for survey or fishery f_i .

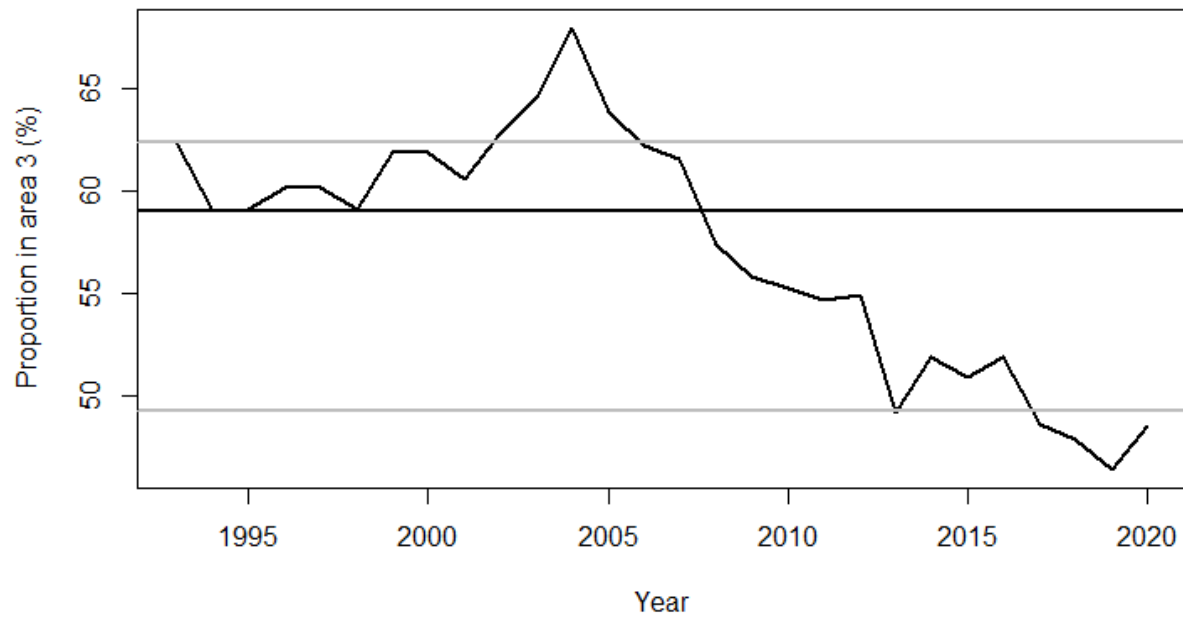
Definition	Equation	
Selectivity functions:		
Non-parametric	$sel_{f_i s a} = e^{\psi_{f_i s a}}$	S1.T2.1
Logistic	$sel_{f_i s a} = \frac{1}{1 + e^{-slp_{f_i}(a - lnf_{f_i})}}$	S1.T2.2
Time-varying logistic	$sel_{f_i s a y} = \frac{1}{1 + e^{-\left(slp_{f_i} + e^{\psi_{f_i s y}^{slp}}\right)\left(a - \left(lnf_{f_i} + \psi_{f_i s y}^{lnf}\right)\right)}}$	S1.T2.3
Double logistic	$sel_{f_i s a} = \left(\frac{1}{1 + e^{-slp1_{f_i}(a - lnf1_{f_i})}}\right)\left(1 - \frac{1}{1 + e^{-slp2_{f_i}(a - lnf2_{f_i})}}\right)$	S1.T2.4
Time-varying double logistic 1	$sel_{f_i s a y} = \left(\frac{1}{1 + e^{-\left(slp1_{f_i} + e^{\psi_{f_i s y}^{slp1}}\right)\left(a - \left(lnf1_{f_i} + \psi_{f_i s y}^{lnf1}\right)\right)}}$	S1.T2.5
Time-varying double logistic 2	$sel_{f_i s a y} = \left(\frac{1}{1 + e^{-slp_{f_i}(a - lnf_{f_i})}}\right)\left(1 - \frac{1}{1 + e^{-\left(slp2_{f_i} + e^{\psi_{f_i s y}^{slp2}}\right)\left(a - \left(lnf2_{f_i} + \psi_{f_i s y}^{lnf2}\right)\right)}}$	S1.T2.6
Descending logistic	$sel_{f_i s a} = 1 - \frac{1}{1 + e^{-slp2_{f_i}(a - lnf2_{f_i})}}$	S1.T2.7
Time-varying descending logistic	$1 - \frac{1}{1 + e^{-\left(slp2_{f_i} + e^{\psi_{f_i s y}^{slp2}}\right)\left(a - \left(lnf2_{f_i} + \psi_{f_i s y}^{lnf2}\right)\right)}}$	S1.T2.8
Catchability		
Time-invariant	$q_{f_i y} = e^{\bar{q}_{f_i}}$	S1.T2.9
Time-varying	$q_{f_i y} = e^{\bar{q}_{f_i} + \omega_{f_i y}}$	S1.T2.10

Supplementary Table S1.3. Model averaged estimates of average (across years) residual mortality (MI ; yr^{-1}) and age-specific total natural mortality (M ; yr^{-1}). M for Avg1 was input for all species.

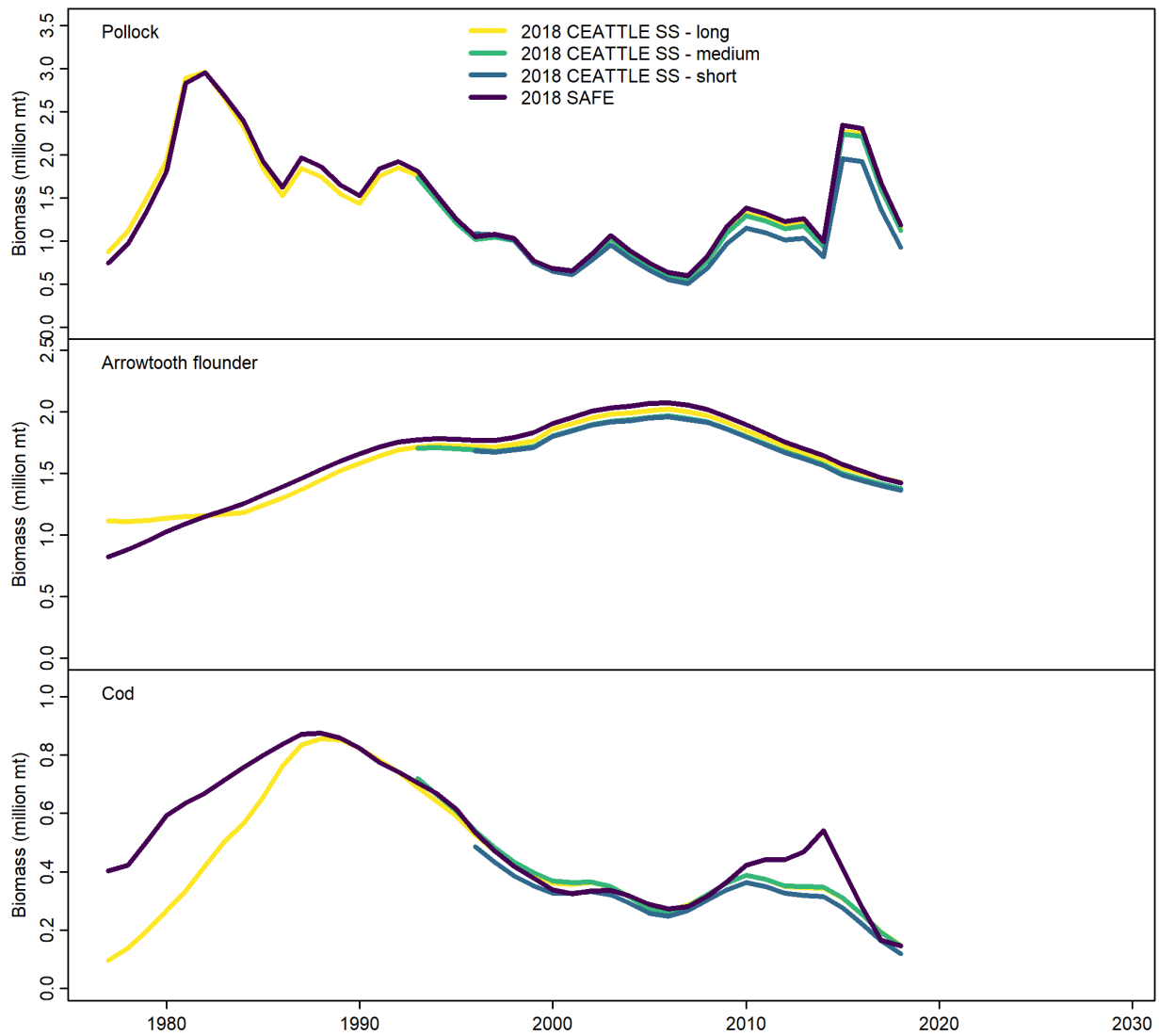
Age	Pollock				ATF Fem				ATF Male				Cod			
	Avg1	Avg2	Avg3	Avg4	Avg1	Avg2	Avg3	Avg4	Avg1	Avg2	Avg3	Avg4	Avg1	Avg2	Avg3	Avg4
M1	1.390	0.340	0.329	0.343	0.2	0.309	0.310	0.316	0.35	0.377	0.373	0.382	0.505	0.451	0.468	0.478
1	1.390	1.459	1.403	1.529	0.2	0.354	0.357	0.359	0.35	0.445	0.445	0.447	0.505	0.960	0.947	0.958
2	0.690	0.823	0.801	0.844	0.2	0.362	0.364	0.363	0.35	0.454	0.452	0.450	0.505	0.598	0.625	0.606
3	0.480	0.611	0.616	0.630	0.2	0.356	0.359	0.358	0.35	0.448	0.446	0.444	0.505	0.462	0.486	0.487
4	0.370	0.474	0.486	0.477	0.2	0.323	0.327	0.329	0.35	0.398	0.397	0.400	0.505	0.451	0.468	0.478
5	0.340	0.436	0.450	0.437	0.2	0.312	0.317	0.319	0.35	0.384	0.386	0.388	0.505	0.451	0.468	0.478
6	0.300	0.409	0.428	0.411	0.2	0.309	0.315	0.316	0.35	0.380	0.384	0.384	0.505	0.451	0.468	0.478
7	0.300	0.398	0.418	0.399	0.2	0.309	0.315	0.316	0.35	0.378	0.386	0.383	0.505	0.451	0.468	0.478
8	0.290	0.380	0.401	0.382	0.2	0.309	0.313	0.316	0.35	0.377	0.386	0.382	0.505	0.451	0.468	0.478
9	0.280	0.378	0.412	0.379	0.2	0.309	0.311	0.316	0.35	0.377	0.386	0.382	0.505	0.451	0.468	0.478
10	0.290	0.344	0.344	0.347	0.2	0.309	0.310	0.316	0.35	0.377	0.381	0.382	0.505	0.451	0.468	0.478
11					0.2	0.309	0.310	0.316	0.35	0.377	0.390	0.382	0.505	0.451	0.468	0.478
12					0.2	0.309	0.310	0.316	0.35	0.377	0.380	0.382	0.505	0.451	0.468	0.478
13					0.2	0.309	0.310	0.316	0.35	0.377	0.391	0.382				
14					0.2	0.309	0.310	0.316	0.35	0.377	0.391	0.382				
15					0.2	0.309	0.310	0.316	0.35	0.377	0.382	0.382				
16					0.2	0.309	0.310	0.316	0.35	0.377	0.390	0.382				
17					0.2	0.309	0.310	0.316	0.35	0.377	0.373	0.382				
18					0.2	0.309	0.310	0.316	0.35	0.377	0.373	0.382				
19					0.2	0.309	0.310	0.316	0.35	0.377	0.373	0.382				
20					0.2	0.309	0.310	0.316	0.35	0.377	0.373	0.382				
21					0.2	0.309	0.310	0.316	0.35	0.377	0.373	0.382				

SUPPLEMENTARY FIGURES

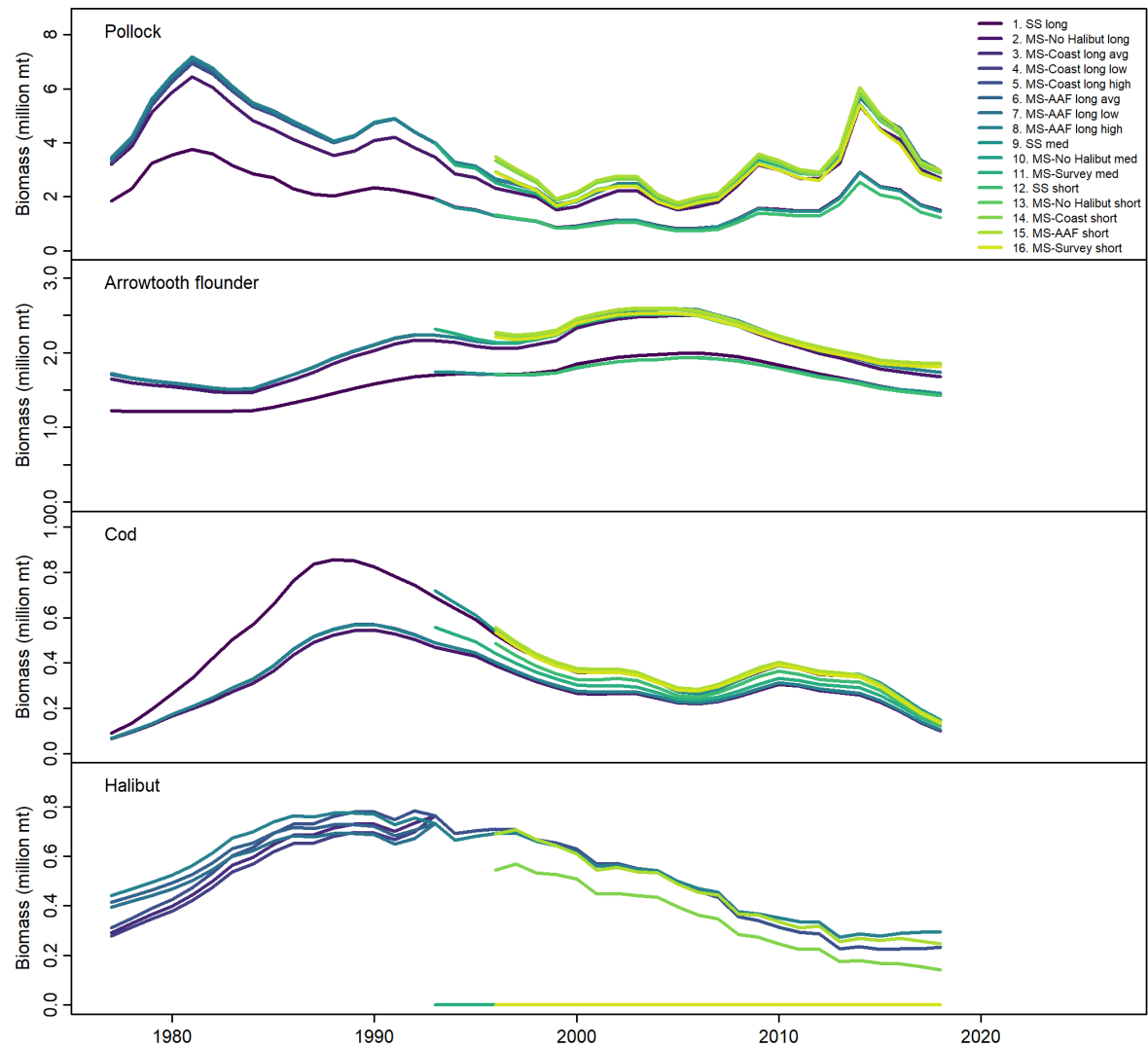
Supplementary Fig.S1. 1. Annual proportion of the halibut stock age 5+ by mass in IPHC Regulatory Areas 3A and 3B between 1993 and 2019 from the IPHC fishery-independent setline survey. Horizontal grey and black lines refer to the 15th, 50th and 85th quantiles.



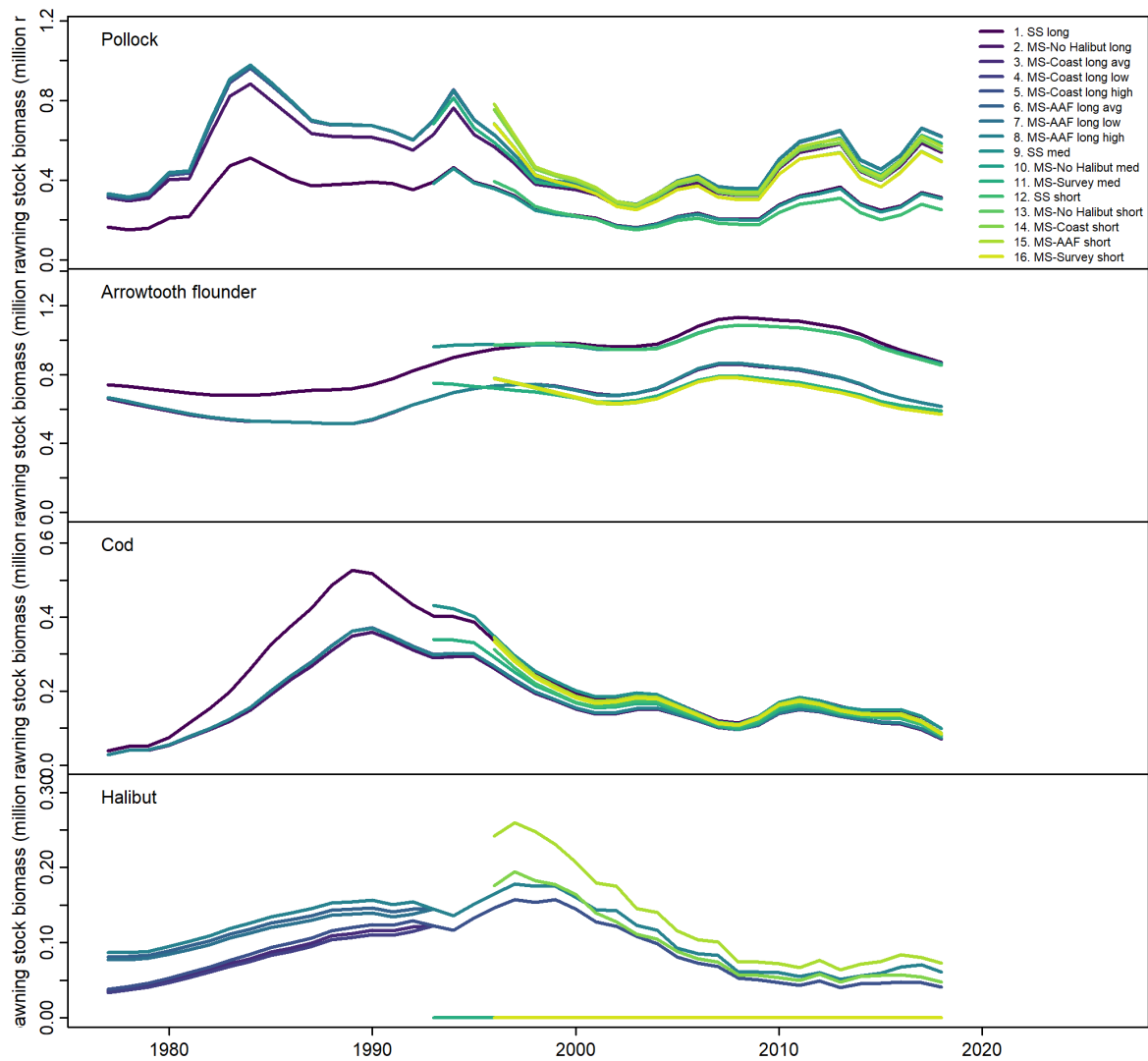
Supplementary Fig. S1.2. Estimates of total biomass from the GOA CEATTLE single-species long, medium, and short time-series models (SS long, SS med, SS short, respectively) and 2018 stock assessments (SAFE Models). See Table 1.5 for model descriptions.



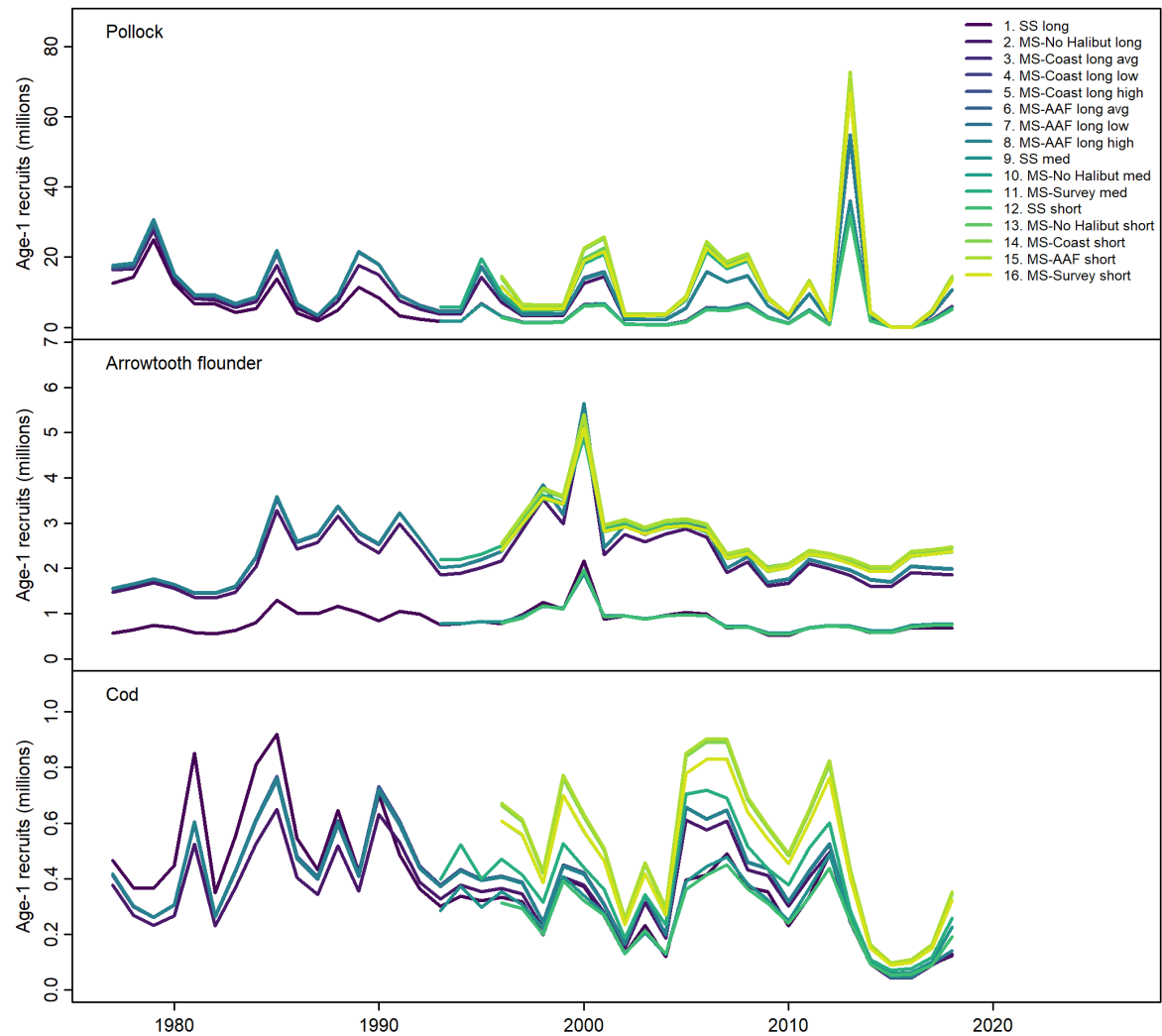
Supplementary Fig. S1.3. Estimates of total biomass from the GOA CEATTLE Models. See Table 1.5 for model descriptions.



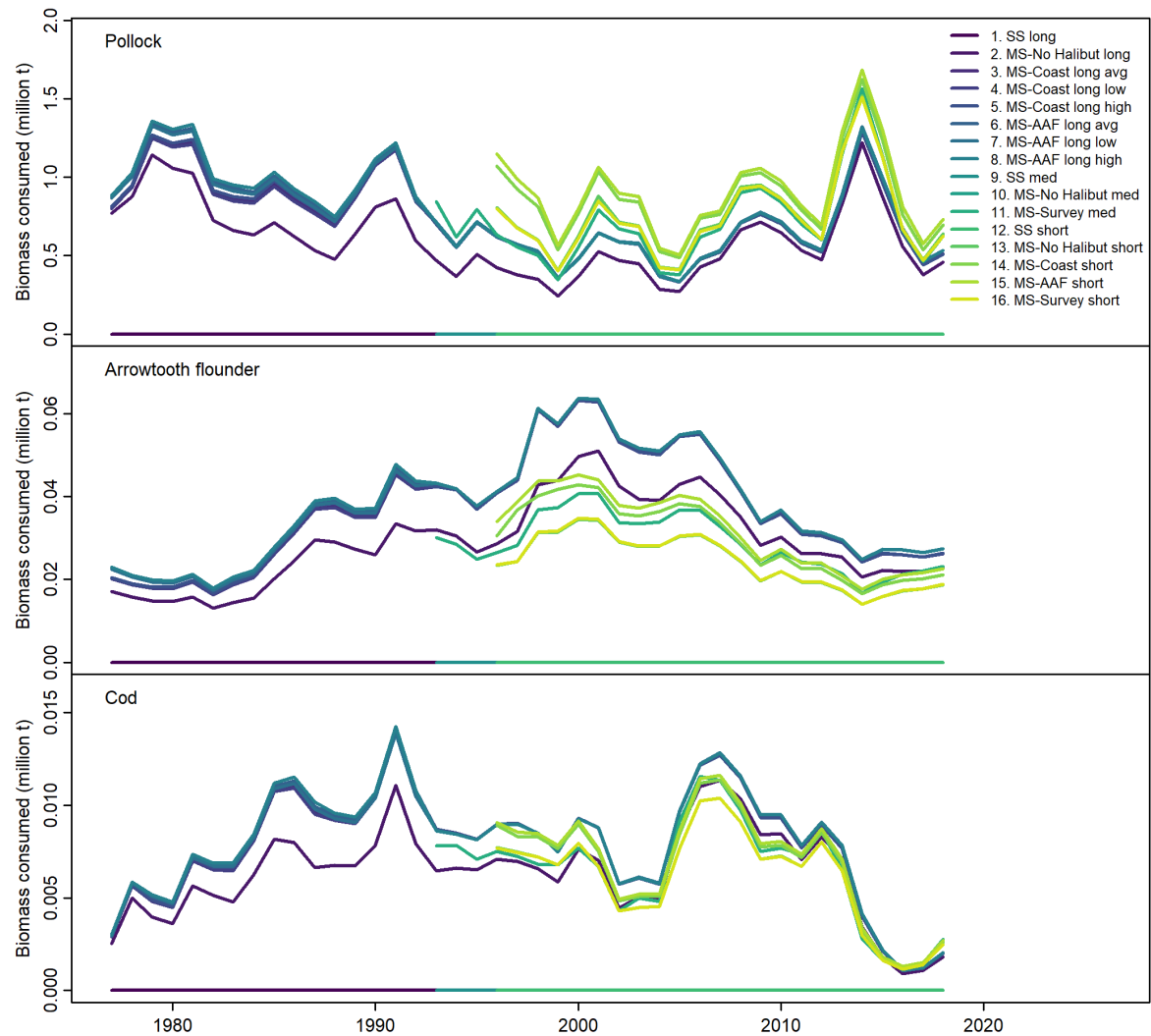
Supplementary Fig. S1.4. Estimates of spawning biomass from the GOA CEATTLE models. See Table 1.5 for model descriptions.



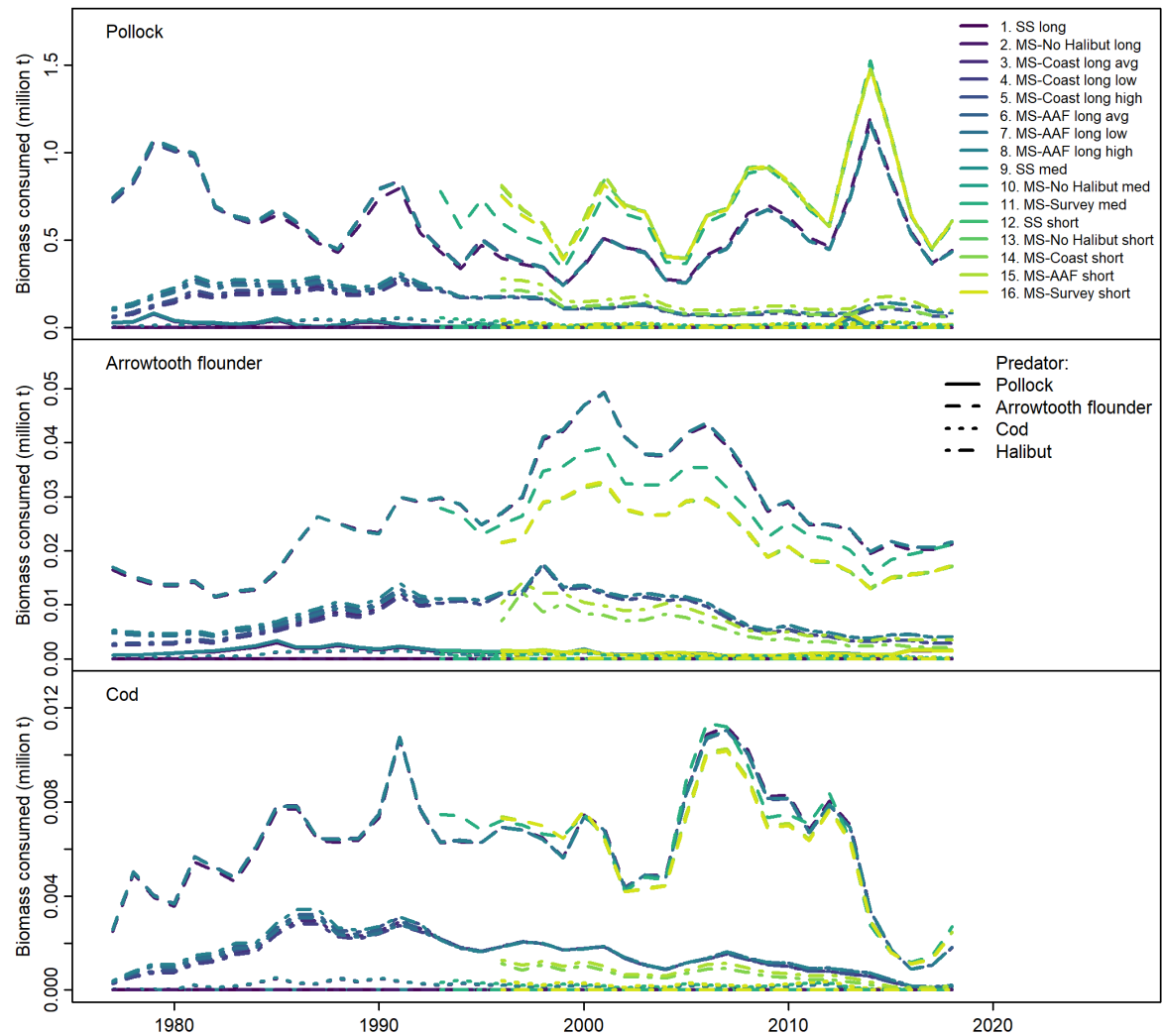
Supplementary Fig. S1.5. Estimates of recruitment from the GOA CEATTLE models. See Table 1.5 for model descriptions.



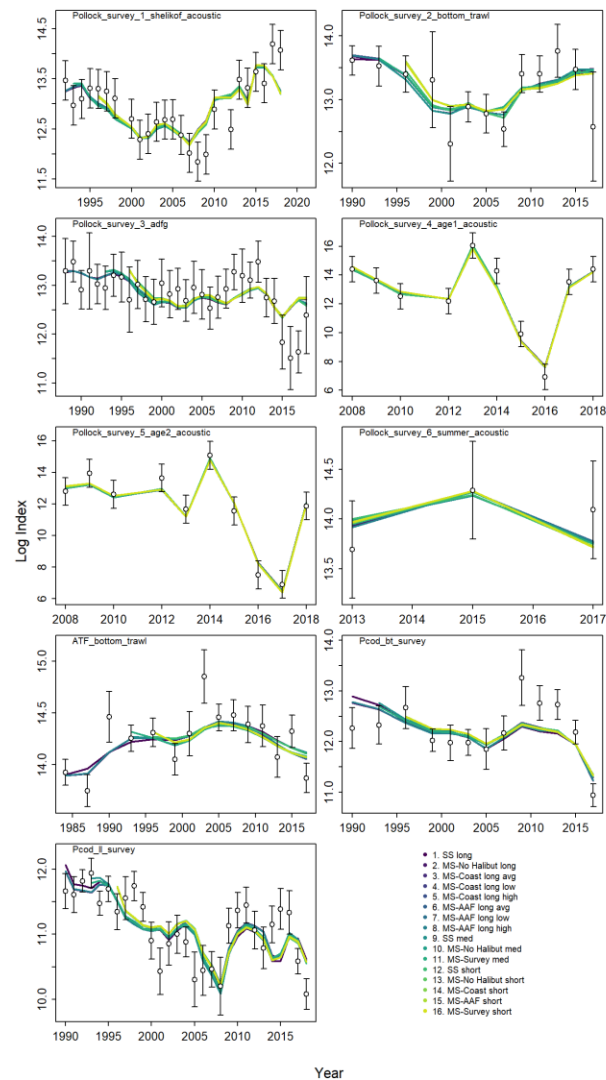
Supplementary Fig. S1.6. Estimates of biomass consumed as prey from the GOA CEATTLE models. See Table 1.5 for model descriptions.



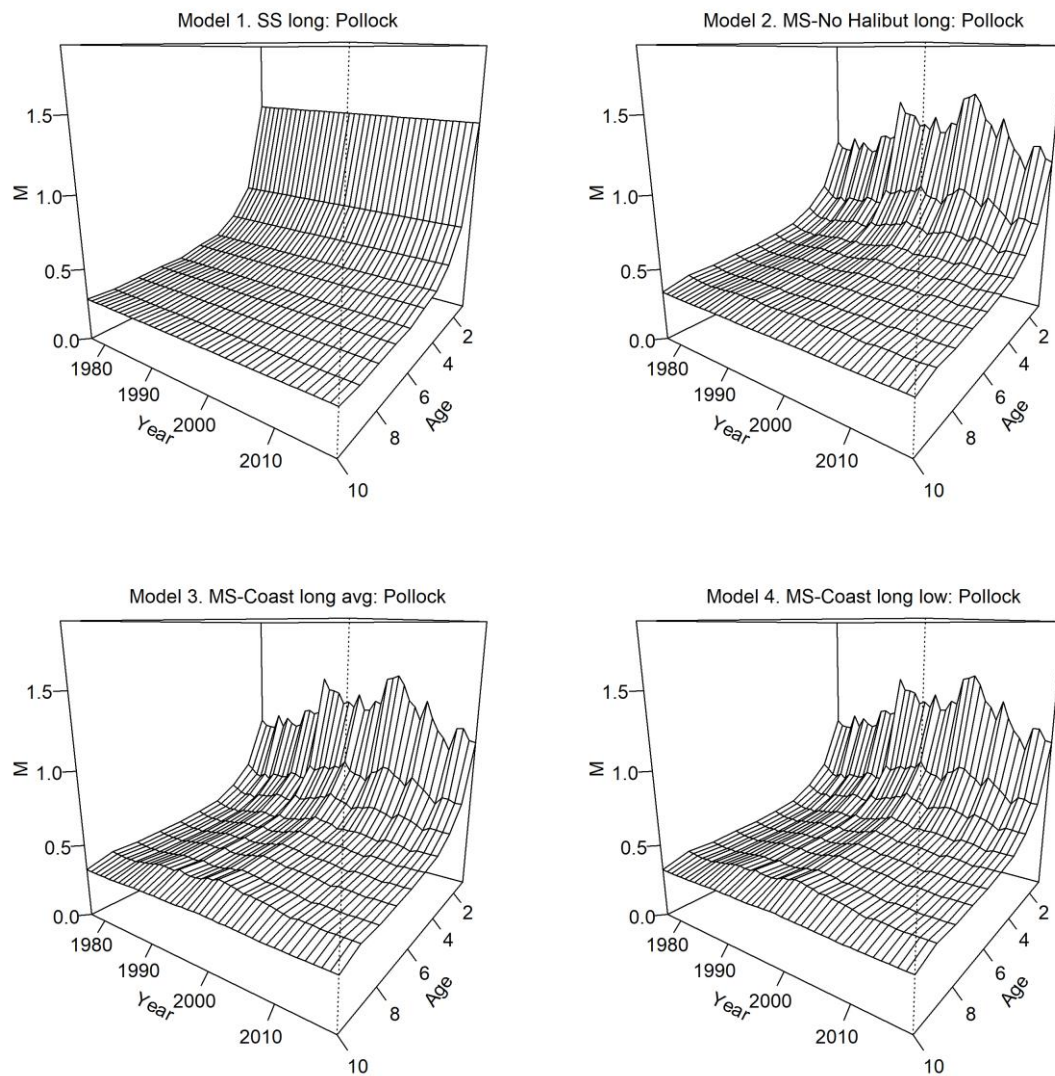
Supplementary Fig. S1.7. Estimates of biomass consumed as prey by predator from the GOA CEATTLE models. See Table 1.5 for model descriptions.

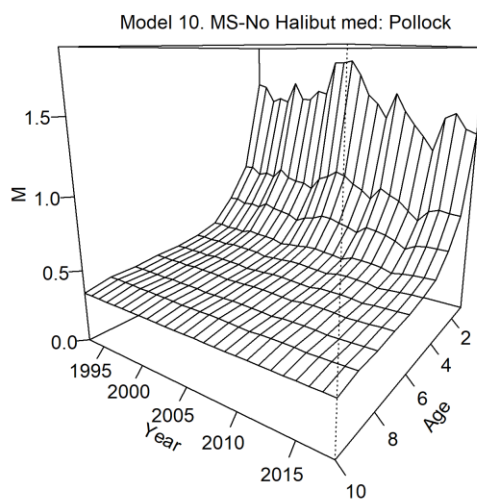
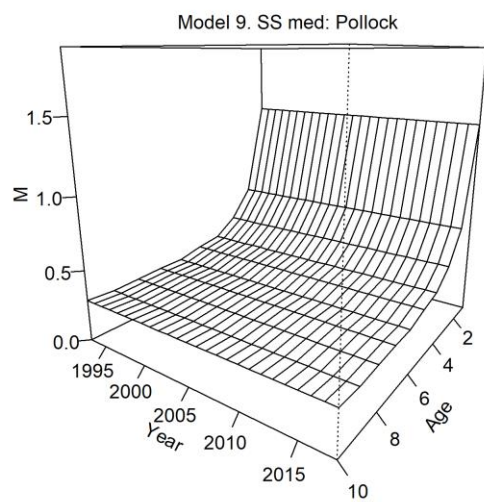
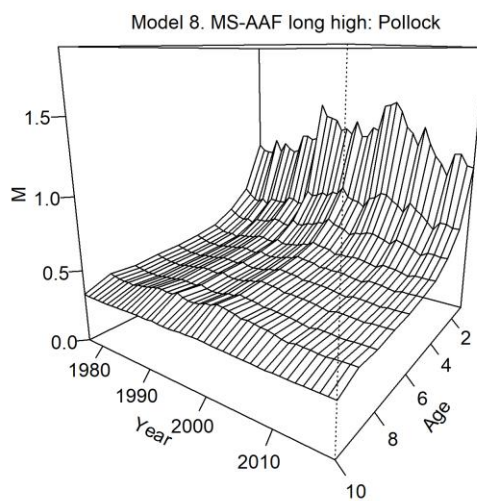
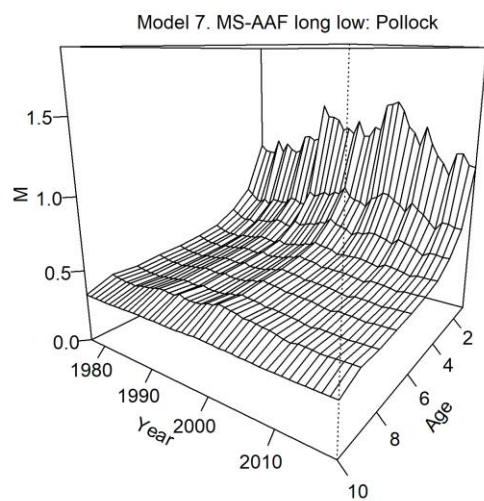
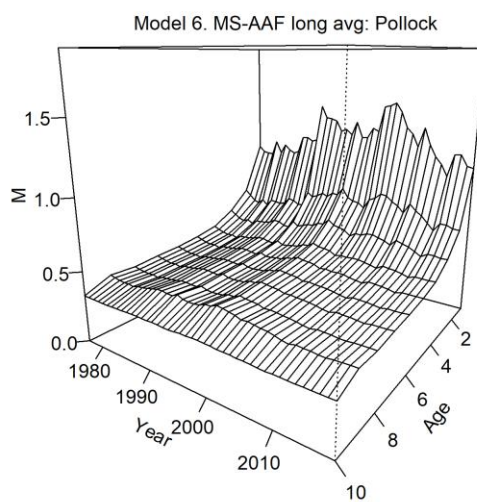
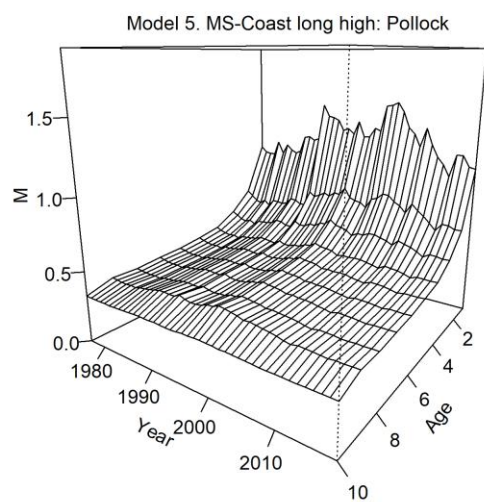


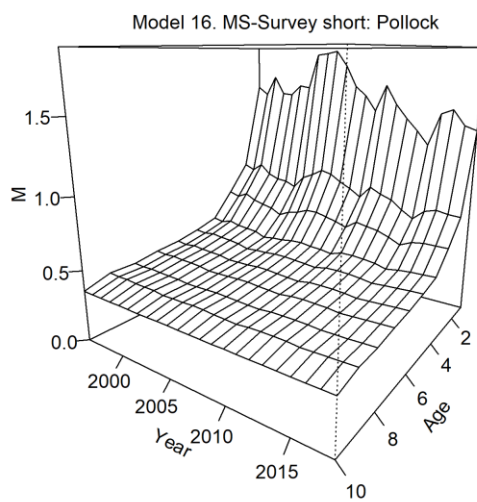
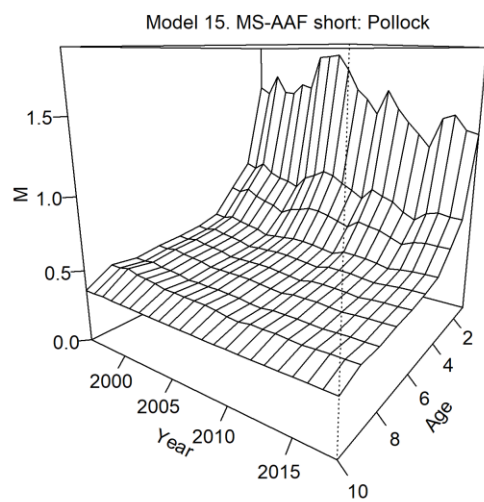
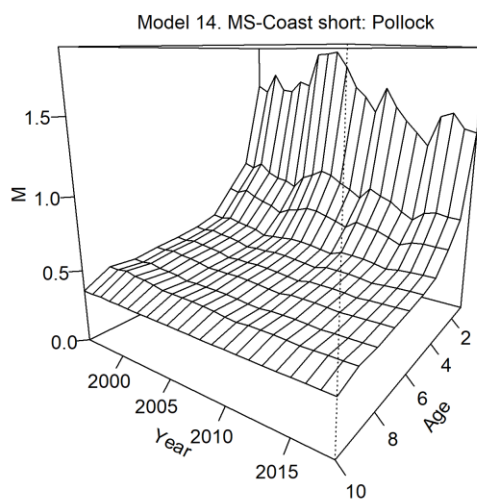
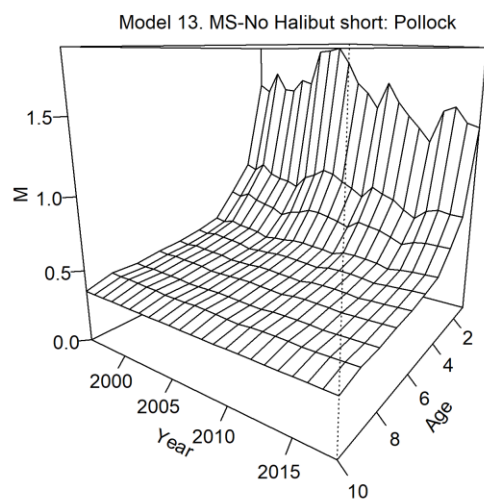
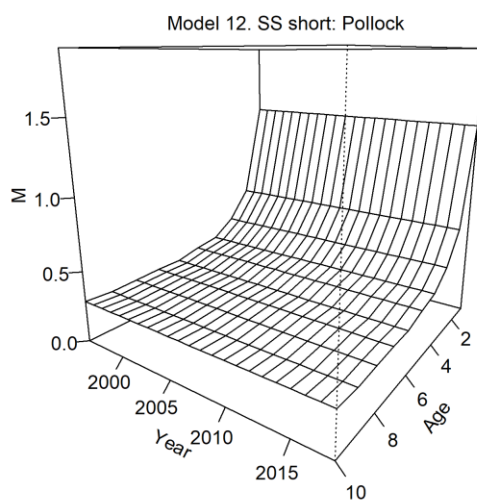
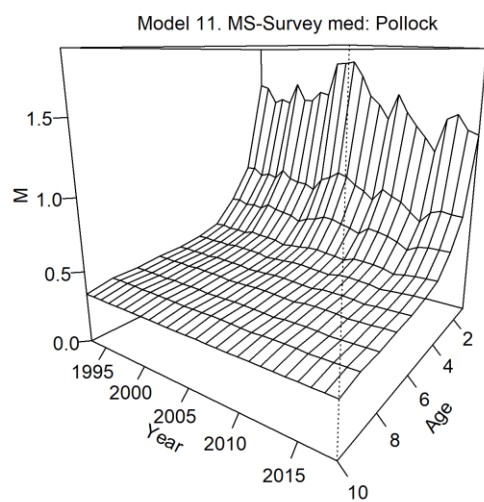
Supplementary Fig. S1.8. Estimated (lines) and observed (points) with 95% confidence intervals for the indices of relative abundance from the GOA CEATTLE models. See Table 1.5 for model descriptions.



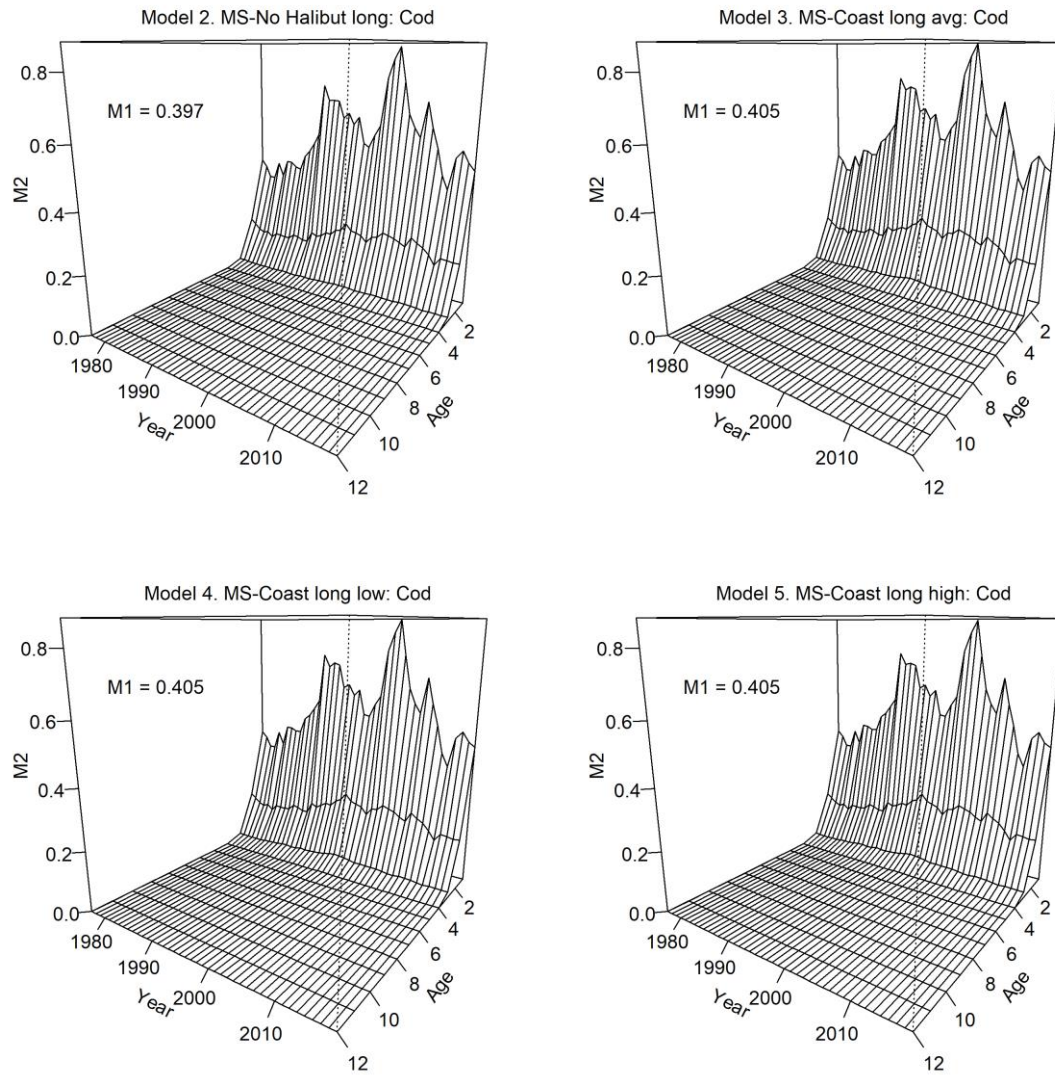
Supplementary Fig. S1.9. Estimated total natural mortality ($M1 + M2$) for walleye pollock. See Table 1.5 for model descriptions.

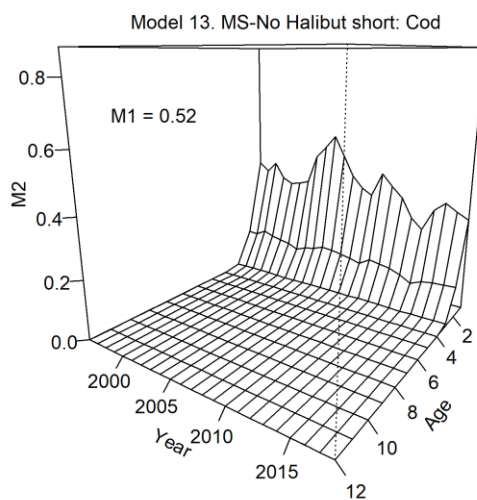
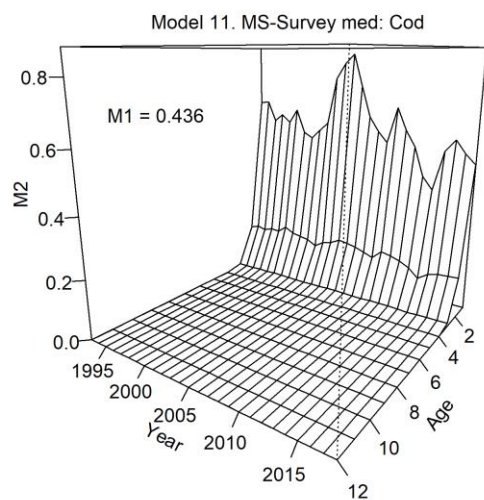
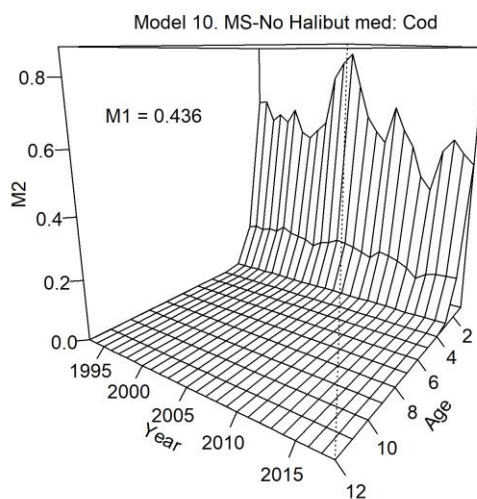
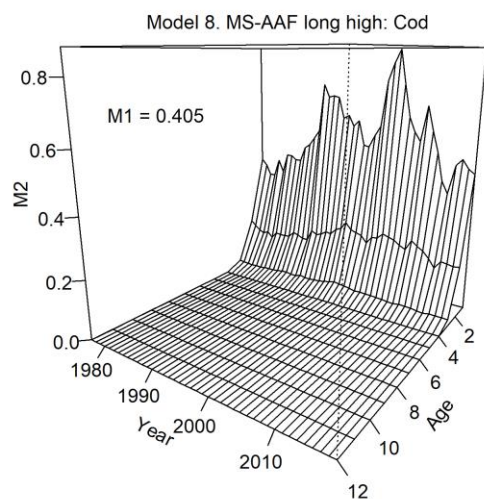
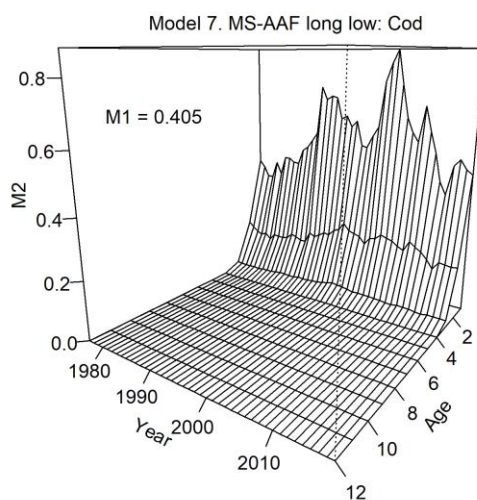
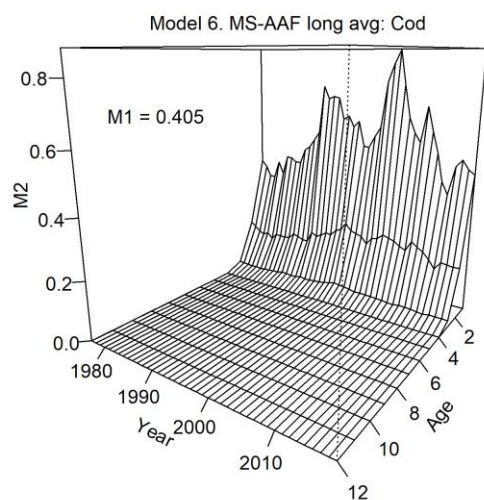


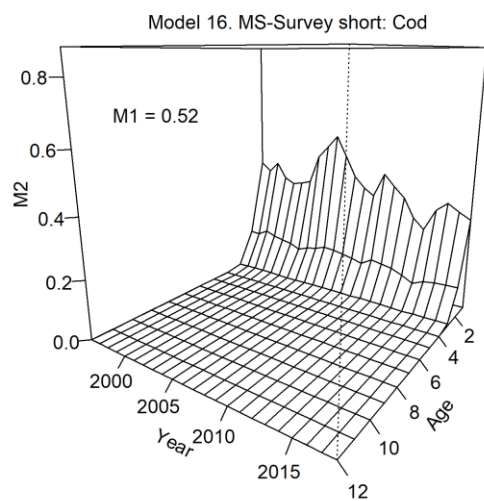
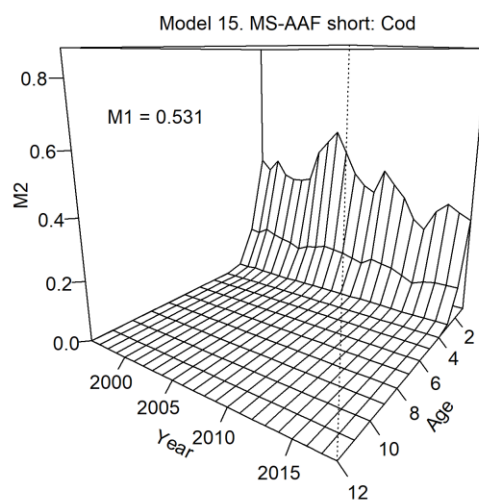
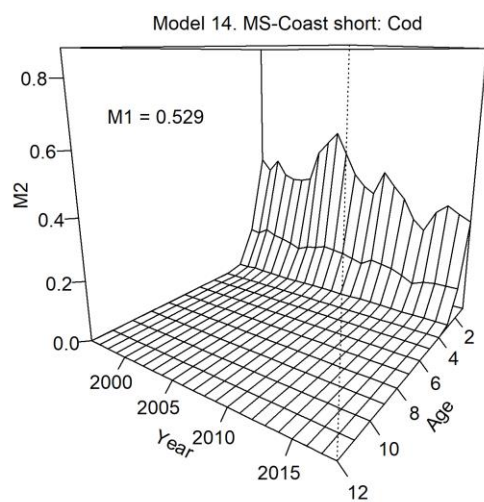




Supplementary Fig. S1.10. Estimated residual mortality (M1) and predation mortality (M2) for Pacific cod from models that included predation. NOTE: For single-species models (Models 1, 9, and 12) total natural mortality (M) is set to 0.504911. See Table 1.5 for model descriptions.







Supplementary Fig. S1.11. Estimated residual mortality (M1) and predation mortality (M2) for arrowtooth flounder from models that included predation. NOTE: For single-species models (Models 1, 9, and 12) total natural mortality (M) is set to 0.2 yr^{-1} for females and 0.35 yr^{-1} for males. See Table 1.5 for model descriptions.

Females

Males

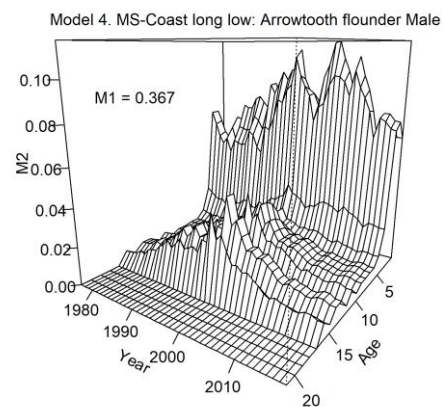
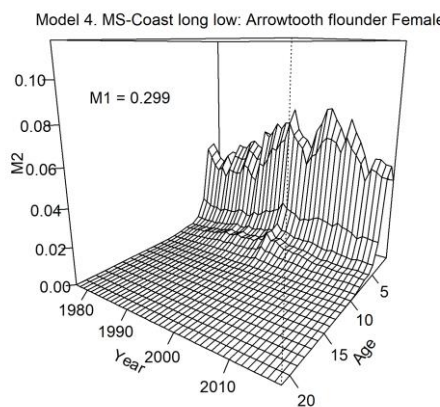
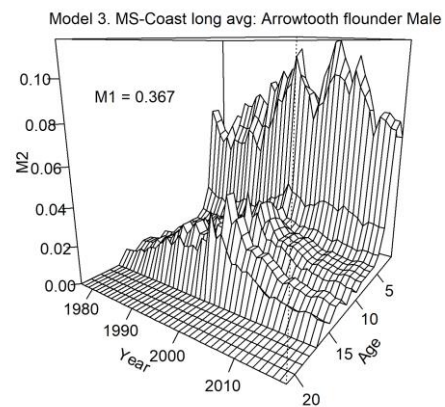
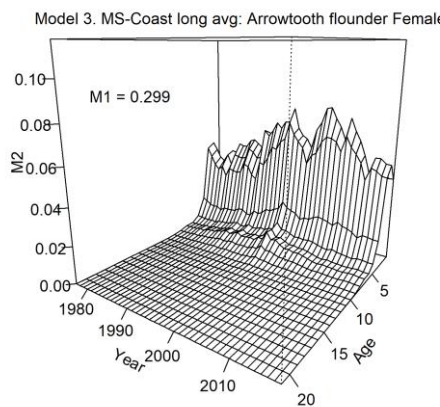
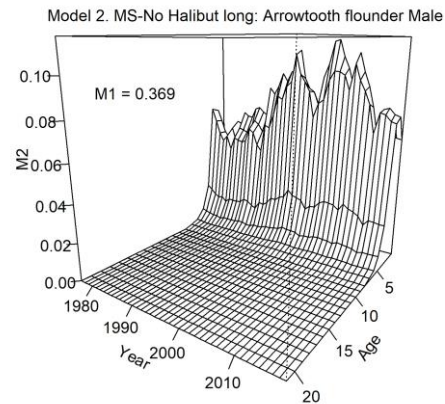
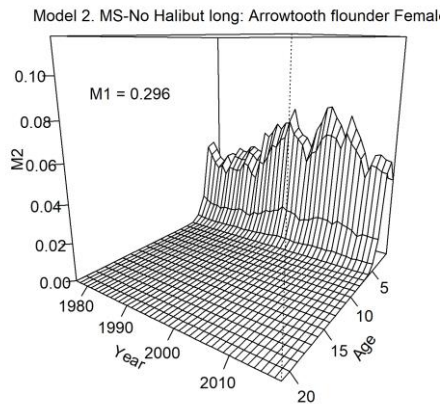


Fig. S1.11 cont.
Females

Males

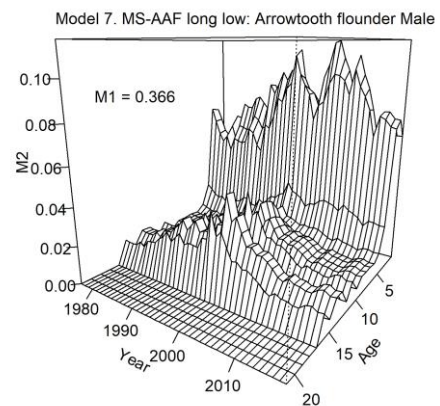
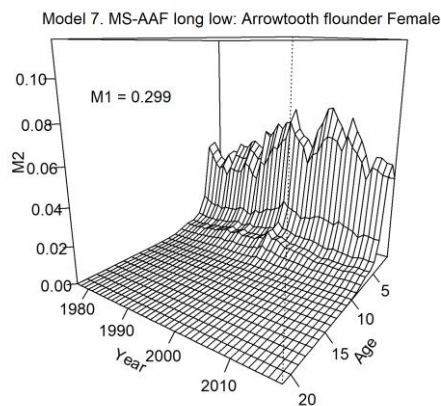
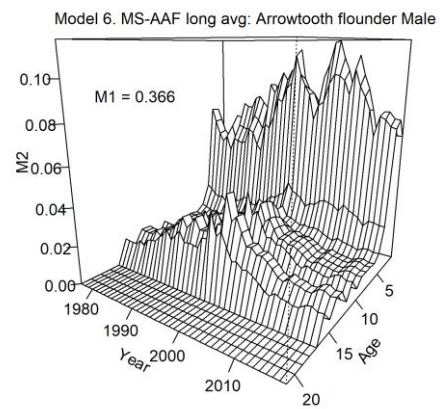
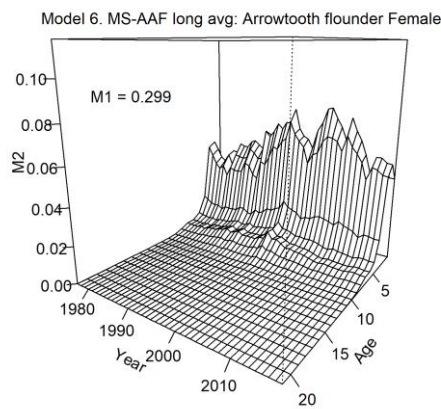
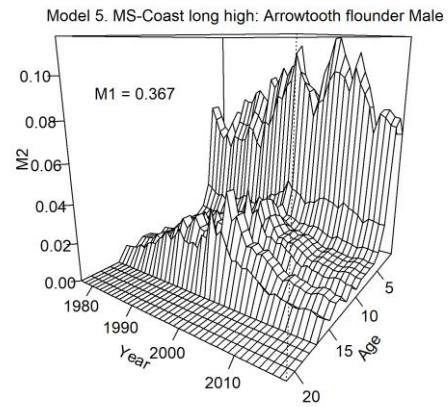
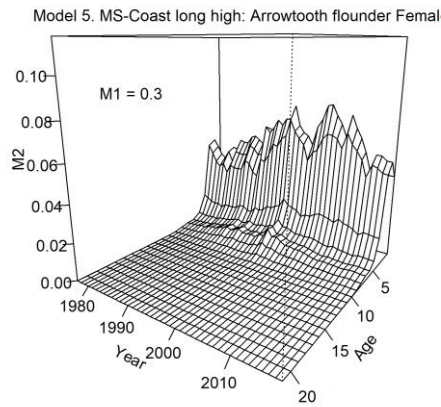


Fig. S1.11 cont.
Females

Males

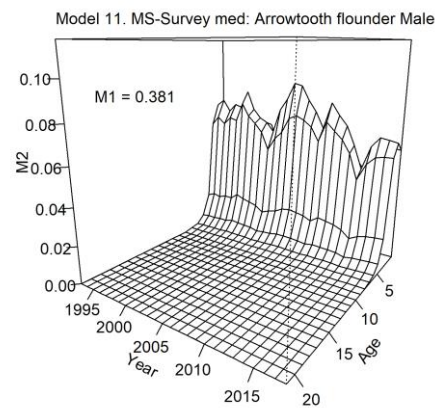
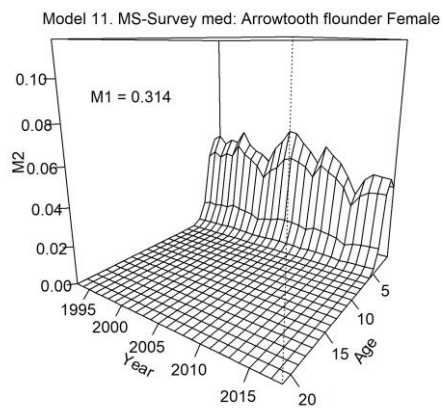
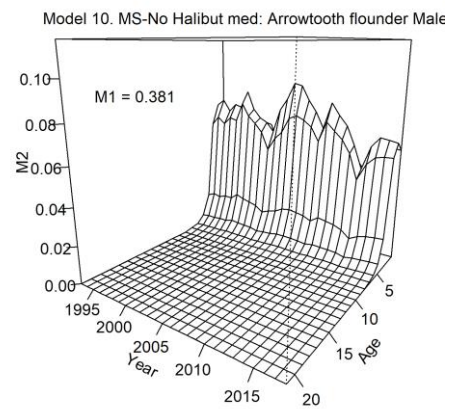
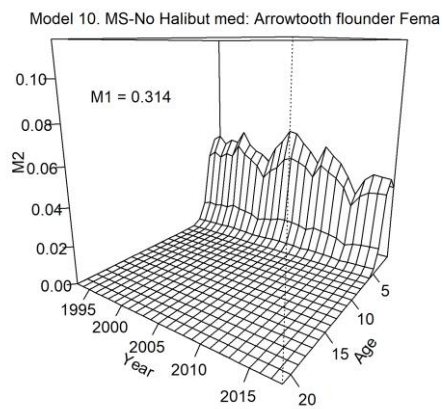
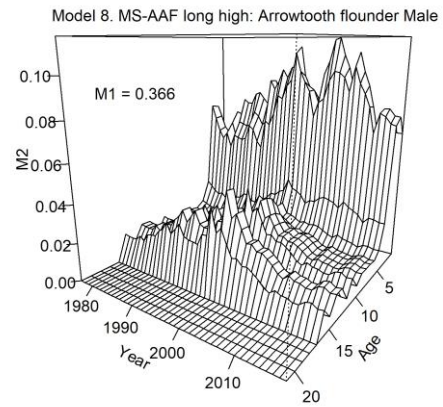
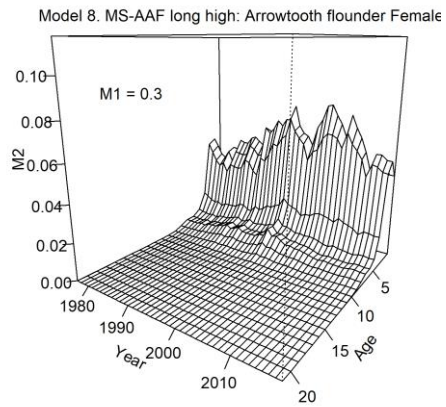


Fig. S1.11 cont.
Females

Males

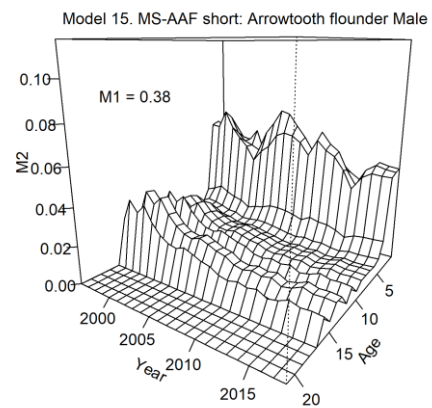
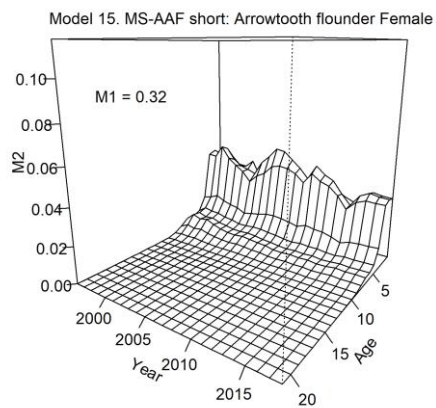
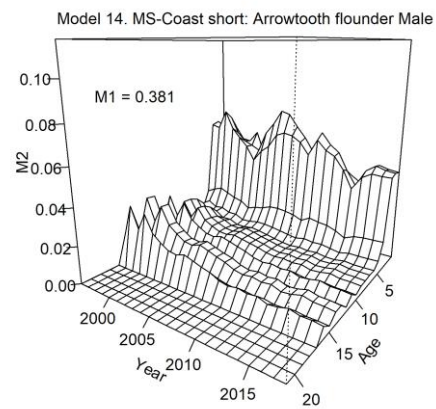
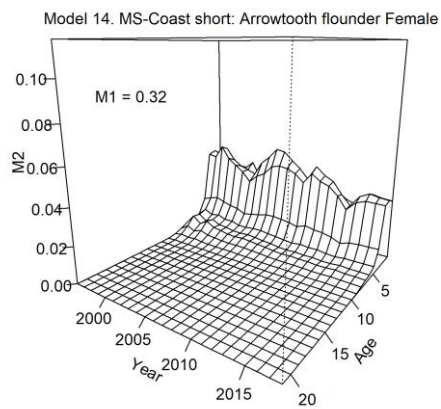
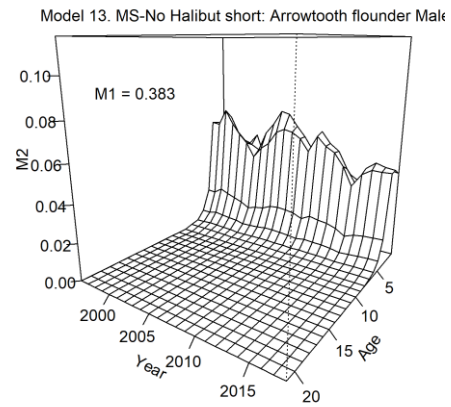
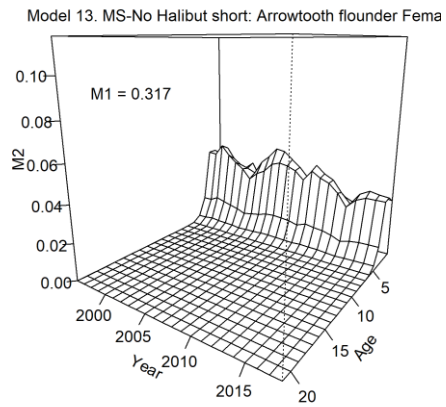
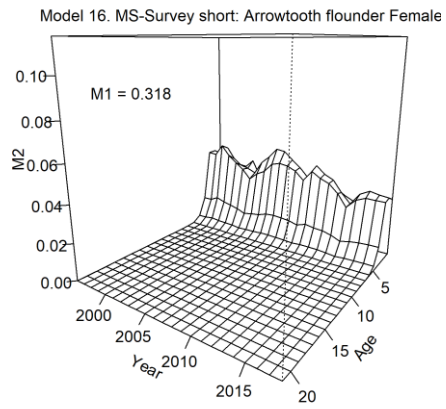
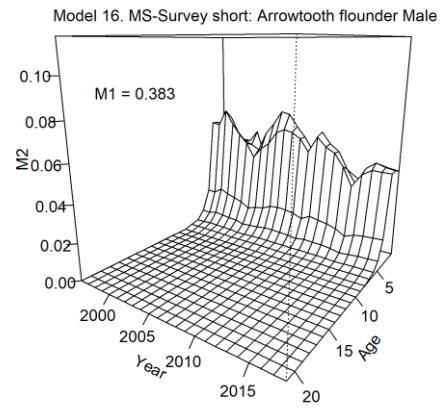


Fig. S1.11 cont.
Females



Males



Chapter 2 Supplementary Materials

SUPPLEMENTARY TABLES

Supplementary Table S2.1. Total natural mortality (M ; yr^{-1}) estimates used for single-species OMs in the EBS and GOA: 1) pre-specified (Fix) natural mortality, 2) estimated (Est) time- and age-invariant natural mortality with stock-independent recruitment, and 3) estimated time- and age-invariant natural mortality with stock-dependent Ricker recruitment (E-R). Pre-specified natural mortalities were extracted from recent stock assessments (Barbeaux et al., 2018; Dorn et al., 2018; Spies and Palsson, 2018, 2019; Ianelli et al., 2020; Thompson et al., 2020).

Age	Pollock						Cod						ATF			ATF Female			ATF Male		
	EBS			GOA			EBS			GOA			EBS			GOA			GOA		
	Fix	Est	E-R	Fix	Est	E-R	Fix	Est	E-R	Fix	Est	E-R	Fix	Est	E-R	Fix	Est	E-R	Fix	Est	E-R
1	0.90	0.39	0.39	1.39	0.26	0.26	0.38	0.36	0.45	0.50	0.33	0.32	0.27	0.34	0.34	0.20	0.29	0.29	0.35	0.37	0.37
2	0.45	0.39	0.39	0.69	0.26	0.26	0.38	0.36	0.45	0.50	0.33	0.32	0.26	0.34	0.34	0.20	0.29	0.29	0.35	0.37	0.37
3	0.30	0.39	0.39	0.48	0.26	0.26	0.38	0.36	0.45	0.50	0.33	0.32	0.26	0.34	0.34	0.20	0.29	0.29	0.35	0.37	0.37
4	0.30	0.39	0.39	0.37	0.26	0.26	0.38	0.36	0.45	0.50	0.33	0.32	0.25	0.34	0.34	0.20	0.29	0.29	0.35	0.37	0.37
5	0.30	0.39	0.39	0.34	0.26	0.26	0.38	0.36	0.45	0.50	0.33	0.32	0.25	0.34	0.34	0.20	0.29	0.29	0.35	0.37	0.37
6	0.30	0.39	0.39	0.30	0.26	0.26	0.38	0.36	0.45	0.50	0.33	0.32	0.24	0.34	0.34	0.20	0.29	0.29	0.35	0.37	0.37
7	0.30	0.39	0.39	0.30	0.26	0.26	0.38	0.36	0.45	0.50	0.33	0.32	0.24	0.34	0.34	0.20	0.29	0.29	0.35	0.37	0.37
8	0.30	0.39	0.39	0.29	0.26	0.26	0.38	0.36	0.45	0.50	0.33	0.32	0.23	0.34	0.34	0.20	0.29	0.29	0.35	0.37	0.37
9	0.30	0.39	0.39	0.28	0.26	0.26	0.38	0.36	0.45	0.50	0.33	0.32	0.23	0.34	0.34	0.20	0.29	0.29	0.35	0.37	0.37
10	0.30	0.39	0.39	0.29	0.26	0.26	0.38	0.36	0.45	0.50	0.33	0.32	0.23	0.34	0.34	0.20	0.29	0.29	0.35	0.37	0.37
11	0.30	0.39	0.39				0.38	0.36	0.45	0.50	0.33	0.32	0.22	0.34	0.34	0.20	0.29	0.29	0.35	0.37	0.37
12	0.30	0.39	0.39				0.38	0.36	0.45	0.50	0.33	0.32	0.22	0.34	0.34	0.20	0.29	0.29	0.35	0.37	0.37
13													0.22	0.34	0.34	0.20	0.29	0.29	0.35	0.37	0.37
14													0.22	0.34	0.34	0.20	0.29	0.29	0.35	0.37	0.37
15													0.21	0.34	0.34	0.20	0.29	0.29	0.35	0.37	0.37
16													0.21	0.34	0.34	0.20	0.29	0.29	0.35	0.37	0.37
17													0.21	0.34	0.34	0.20	0.29	0.29	0.35	0.37	0.37
18													0.21	0.34	0.34	0.20	0.29	0.29	0.35	0.37	0.37
19													0.21	0.34	0.34	0.20	0.29	0.29	0.35	0.37	0.37
20													0.21	0.34	0.34	0.20	0.29	0.29	0.35	0.37	0.37
21													0.21	0.34	0.34	0.20	0.29	0.29	0.35	0.37	0.37

Supplementary Table S2.2. Equations for multi-species and single-species equilibrium and dynamic biological reference points for species i , sex s , age a , length l in year y , and fishery f_i . See Table S2.3 for parameter definitions.

Definition	Equation
<i>Equilibrium</i>	
Equilibrium projected fishing mortality	$F_{f_i 1a} = F_{Target_i} sel_{f_i 1a} \rho_{f_i}$
Unfished equilibrium spawning stock biomass-per-recruit	$SPR_{0,i} = \sum_a^{A_i-1} \bar{R}_i \rho_{i1} e^{-\sum_{j=1}^{a-1} (M_{1i1j}) - \frac{Month_{ssb_i}}{12} * M_{1i1a}} W_{ssb_i 1a} \delta_{ia}$ $+ \bar{R}_i \rho_{i1} \frac{e^{-\sum_{j=1}^{A_i-1} (M_{1i1j})}}{1 - e^{-M_{1i1A_i}}} W_{ssb_i 1A_i} \delta_{iA_i} e^{-\frac{Month_{ssb_i}}{12} * M_{1i1A_i}}$
Unfished equilibrium spawning biomass	$SB_{0,i} = SPR_{0,i}$
(no stock-recruit curve)	
Fished equilibrium spawning stock biomass-per-recruit	$SPR_{X,i} = \sum_a^{A_i-1} \bar{R}_i \rho_{i1} e^{-\sum_{j=1}^{a-1} (M_{1i1j} + \sum_{f_i} F_{f_i 1j}) - \frac{Month_{ssb_i}}{12} * (M_{1i1a} + \sum_{f_i} F_{f_i 1a})} W_{ssb_i 1a} \delta_{ia}$ $+ \bar{R}_i \rho_{i1} \frac{e^{-\sum_{j=1}^{A_i-1} (M_{1i1j} + \sum_{f_i} F_{f_i 1j})}}{1 - e^{-M_{1i1A_i} + \sum_{f_i} F_{f_i 1A_i}}} W_{ssb_i 1A_i} \delta_{iA_i} e^{-\frac{Month_{ssb_i}}{12} * (M_{1i1A_i} + \sum_{f_i} F_{f_i 1A_i})}$
Fishing mortality rate associated with $SPR_{X,i}$ that is X% of $SPR_{0,i}$	$F_{X\%,i} = F_{Target_i} \text{ where } \frac{SPR_{X,i}}{SPR_{0,i}} = X$
Equilibrium spawning biomass at $F_{X\%,i}$	$SB_{X\%,i} = SPR_{X,i}$
(no stock-recruit curve)	
X% of equilibrium spawning biomass	$SB_{X,i} = \frac{X}{100} SB_{0,i}$
<i>Dynamic (recruitment, growth, and selectivity)</i>	
Dynamic projected fishing mortality	$F_{f_i say} = F_{Target_{iy}} sel_{f_i say} \rho_{f_i}$
Unfished numbers-at-age	$N_{is1y} = R_{isy} = \bar{R}_i e^{\tau_{iy}} \rho_{i1}$ $N_{i1a+1y+1} = N_{i1ay} e^{-M_{isay}}$
Unfished dynamic spawning stock biomass	$N_{i1A_i y+1} = N_{i1A_i-1y} e^{-M_{i1A_i-1y}} + N_{i1A_i y} e^{-M_{i1A_i y}}$ $SB_{0,iy} = \sum_a N_{i1ay} e^{-Month_{ssb_i}/12 * M_{i1ay}} W_{ssb_i 1ay} \rho_{ia} \delta_{ia}$
Unfished dynamic spawning stock biomass-per-recruit (no stock-recruit curve)	$SB_{0,iy} = SPR_{0,iy}$
Fished numbers-at-age	$N_{is1y} = R_{isy} = \bar{R}_i e^{\tau_{iy}} \rho_{i1}$ $N_{i1a+1y+1} = N_{i1ay} e^{-M_{isay} - \sum_{f_i} F_{f_i say}}$ $N_{i1A_i y+1} = N_{i1A_i-1y} e^{-M_{i1A_i-1y} - \sum_{f_i} F_{f_i say}} + N_{i1A_i y} e^{-M_{i1A_i y} - \sum_{f_i} F_{f_i say}}$

Fished dynamic spawning stock
biomass

$$SB_{X,iy} = \sum_a N_{i1ay} e^{-Month_{ssb_i}/12 * (M_{i1ay} + \sum_{f_i} F_{f_i}^{say})} W_{ssb_i1ay} \rho_{ia} \delta_{ia}$$

Fishing mortality rate
associated with $SB_{X,iy}$ that is

$$F_{X,iy} = F_{Target_{iy}} \text{ where } \frac{SB_{X,iy}}{SB_{0,iy}} = X$$

X% of $SB_{0,iy}$

Supplementary Table S2.3. Parameter definition for the CEATTLE Models.

Category	Parameter	Definition
Index	i	Species
	s	Sex
	a	Age
	$\hat{a}$	Observed age
	A	Plus group
	l	Length
	y	Year
	Y	Last year of estimation (not projection)
	p	Predator species
	b	Predator sex
	j	Predator age
	k	Predator length
	f_i	Fleet/survey
Population model	R_{isy}	Recruitment
	$\bar{R}_i$	Mean recruitment
	τ_{iy}	Annual recruitment deviate
	δ_{ia}	Maturity-at-age
	ρ_{ia}	Sex-ratio
	$M1_{isa}$	Residual mortality yr ⁻¹
	$M2_{isay}$	Predation-mortality yr ⁻¹
	$F_{f_i say}$	Fleet-specific fishing mortality yr ⁻¹
	F_{isay}	Total fishing mortality yr ⁻¹
	Z_{isay}	Total mortality yr ⁻¹
	$\bar{F}_{f_i}$	Mean fishing mortality yr ⁻¹
	$\epsilon_{f_i y}$	Annual fishing mortality deviate
	ψ_{f_i}	Fishing mortality apportionment per fleet
	N_{isay}	Numbers-at-age
	$\bar{N}_{isay}$	Average numbers-at-age
	SB_{ijy}	Spawning-stock-biomass (kg)
	B_{isay}	Biomass (kg)
	$\bar{B}_{isay}$	Average biomass (kg)
	$\hat{S}_{pbj isa}$	Predator-prey suitability
	H_i	Holling functional response parameter
	B_p^{other}	Biomass of “other prey” (kg)
	T_y	Observed bottom temperature (°C)
	T_p^{co}	Thermal optima for consumption (°C)
	T_p^{cm}	Thermal limit of consumption (°C)
Predation model	Q_p^c	Rate at which consumption increased over relatively low water temperatures
	$\alpha_p^\delta, \beta_p^\delta$	Weight specific intercept and slop of maximum consumption
	φ_{pbj}	Scalar for maximum to observed consumption
	$\bar{U}_{pbj, isa}$	Average proportion of prey-at-age in the stomach of a predator-at-age
	$\tilde{q}_i$	Relative abundance-at-age scalar
Observation model		

$\widehat{CPUE}: B_{f_i y}$	Survey/fishery relative biomass (kg)
$\widehat{CPUE}: I_{f_i y}$	Survey/fishery relative abundance (numbers)
$sel_{f_i say}$	Selectivity
$q_{f_i y}$	Catchability
W	Weight (kg)
$C_{f_i say}$	Catch-at-age
$\hat{C}_{f_i y}^*$	Total catch (kg)
$\hat{O}_{f_i say} / \hat{O}_{f_i sly}$	Predicted age/length composition
$AE_{i\hat{a}a}$	Ageing error matrix
ATM_{isal}	Age-transition matrix (growth trajectory)
$\hat{S}_{pbjisa}$	Predator-prey suitability

Supplementary Tables S2.4. Summary of performance metrics across OMs for pollock.

Supplementary Table S2.4.PM-1. Summary of performance metric 1 (average annual catch) across OMs for **Pollock**.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker
EBS	Fix M	HCR 1a (NPFMC)	2,121	2,586	2,443	2,828	2,744	2,906
		HCR 1b (Dynamic NPFMC)	2,166	2,650	2,489	2,887	2,766	2,939
		HCR 2a (PFMC)	2,033	2,401	2,278	2,571	2,549	2,630
		HCR 2b (Dynamic PFMC)	2,041	2,405	2,285	2,572	2,548	2,620
		HCR 3a (SESSF)	1,872	2,108	2,037	2,225	2,242	2,258
		HCR 3b (Dynamic SESSF)	1,891	2,126	2,052	2,236	2,246	2,258
		HCR 4 (NEFMC)	1,743	1,897	1,844	1,969	1,975	1,988
		HCR 5 (Avg F)	1,348	1,336	1,359	1,372	1,581	1,393
	Est M	HCR 1a (NPFMC)	2,309	2,985	3,358	4,423	3,451	5,778
		HCR 1b (Dynamic NPFMC)	2,349	3,047	3,436	4,506	3,485	5,844
		HCR 2a (PFMC)	2,248	2,838	3,226	4,156	3,320	5,504
		HCR 2b (Dynamic PFMC)	2,260	2,844	3,244	4,156	3,322	5,504
		HCR 3a (SESSF)	2,103	2,530	2,923	3,596	2,973	4,732
		HCR 3b (Dynamic SESSF)	2,127	2,560	2,960	3,611	2,983	4,764
		HCR 4 (NEFMC)	2,028	2,389	2,818	3,409	2,788	4,602
		HCR 5 (Avg F)	1,334	1,316	1,346	1,353	1,530	1,280
GOA	Fix M	HCR 1a (NPFMC)	151	320	136	291	298	563
		HCR 1b (Dynamic NPFMC)	156	319	141	289	299	564
		HCR 2a (PFMC)	141	300	131	285	263	484
		HCR 2b (Dynamic PFMC)	143	300	132	286	264	487
		HCR 3a (SESSF)	131	286	123	279	223	405
		HCR 3b (Dynamic SESSF)	136	287	127	280	222	404
		HCR 4 (NEFMC)	111	236	108	242	160	284
		HCR 5 (Avg F)	127	271	124	274	138	260
	Est M	HCR 1a (NPFMC)	181	318	119	278	511	999
		HCR 1b (Dynamic NPFMC)	186	315	123	275	515	1,008
		HCR 2a (PFMC)	177	320	113	261	509	1,024
		HCR 2b (Dynamic PFMC)	178	319	114	261	509	1,019
		HCR 3a (SESSF)	169	324	108	253	429	805
		HCR 3b (Dynamic SESSF)	174	325	110	252	424	792
		HCR 4 (NEFMC)	159	321	91	206	367	660
		HCR 5 (Avg F)	137	293	122	270	148	288

Supplementary Table S2.4.PMSupplementary Table S2.4.PM-2. Summary of performance metric 2 (average interannual variation in catch (IAV)) across OMs for **Pollock**.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker
EBS	Fix M	HCR 1a (NPFMC)	0.2	0.24	0.17	0.22	0.18	0.22
		HCR 1b (Dynamic NPFMC)	0.16	0.2	0.14	0.19	0.17	0.21
		HCR 2a (PFMC)	0.15	0.19	0.14	0.18	0.15	0.19
		HCR 2b (Dynamic PFMC)	0.14	0.19	0.13	0.18	0.15	0.2
		HCR 3a (SESSF)	0.16	0.2	0.14	0.18	0.15	0.2
		HCR 3b (Dynamic SESSF)	0.12	0.18	0.12	0.17	0.14	0.2
		HCR 4 (NEFMC)	0.11	0.15	0.11	0.15	0.13	0.17
		HCR 5 (Avg F)	0.09	0.12	0.09	0.13	0.1	0.14
	Est M	HCR 1a (NPFMC)	0.26	0.29	0.29	0.31	0.35	0.47
		HCR 1b (Dynamic NPFMC)	0.21	0.25	0.24	0.28	0.31	0.43
		HCR 2a (PFMC)	0.2	0.23	0.23	0.26	0.27	0.39
		HCR 2b (Dynamic PFMC)	0.19	0.23	0.22	0.26	0.27	0.39
		HCR 3a (SESSF)	0.21	0.25	0.23	0.27	0.26	0.41
		HCR 3b (Dynamic SESSF)	0.16	0.22	0.18	0.25	0.24	0.38
		HCR 4 (NEFMC)	0.14	0.18	0.16	0.21	0.21	0.32
		HCR 5 (Avg F)	0.09	0.12	0.09	0.13	0.1	0.15
GOA	Fix M	HCR 1a (NPFMC)	0.34	0.35	0.32	0.33	0.28	0.33
		HCR 1b (Dynamic NPFMC)	0.34	0.35	0.32	0.33	0.28	0.33
		HCR 2a (PFMC)	0.31	0.33	0.3	0.32	0.27	0.32
		HCR 2b (Dynamic PFMC)	0.32	0.33	0.3	0.32	0.27	0.32
		HCR 3a (SESSF)	0.33	0.32	0.31	0.31	0.26	0.32
		HCR 3b (Dynamic SESSF)	0.31	0.32	0.29	0.31	0.26	0.32
		HCR 4 (NEFMC)	0.28	0.3	0.27	0.29	0.25	0.3
		HCR 5 (Avg F)	0.3	0.32	0.29	0.31	0.26	0.32
	Est M	HCR 1a (NPFMC)	0.41	0.39	0.29	0.3	0.39	0.43
		HCR 1b (Dynamic NPFMC)	0.38	0.39	0.28	0.3	0.39	0.45
		HCR 2a (PFMC)	0.36	0.37	0.27	0.28	0.36	0.41
		HCR 2b (Dynamic PFMC)	0.36	0.37	0.27	0.28	0.36	0.41
		HCR 3a (SESSF)	0.41	0.38	0.29	0.28	0.37	0.41
		HCR 3b (Dynamic SESSF)	0.36	0.36	0.26	0.28	0.35	0.42
		HCR 4 (NEFMC)	0.33	0.34	0.24	0.26	0.32	0.37
		HCR 5 (Avg F)	0.3	0.32	0.28	0.29	0.26	0.32

Supplementary Table S2.4.PMSupplementary Table S2.4.PM-3. Summary of performance metric 3 (probability of the fishery being closed) across OM for **Pollock**.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker
EBS	Fix M	HCR 1a (NPFMC)	1	1	1	1	1	1
		HCR 1b (Dynamic NPFMC)	1	0.99	1	1	1	0.99
		HCR 2a (PFMC)	1	1	1	1	1	1
		HCR 2b (Dynamic PFMC)	1	1	1	1	1	1
		HCR 3a (SESSF)	1	1	1	1	1	1
		HCR 3b (Dynamic SESSF)	1	1	1	1	1	1
		HCR 4 (NEFMC)	1	1	1	1	1	1
		HCR 5 (Avg F)	1	1	1	1	1	1
	Est M	HCR 1a (NPFMC)	1	0.99	1	0.99	0.98	0.95
		HCR 1b (Dynamic NPFMC)	1	0.99	1	0.98	0.99	0.97
		HCR 2a (PFMC)	1	1	1	1	1	1
		HCR 2b (Dynamic PFMC)	1	1	1	1	1	1
		HCR 3a (SESSF)	1	1	1	1	1	0.99
		HCR 3b (Dynamic SESSF)	1	1	1	1	1	0.99
		HCR 4 (NEFMC)	1	1	1	1	1	1
		HCR 5 (Avg F)	1	1	1	1	1	1
GOA	Fix M	HCR 1a (NPFMC)	1	1	0.99	1	1	1
		HCR 1b (Dynamic NPFMC)	1	1	1	1	1	1
		HCR 2a (PFMC)	1	1	1	1	1	1
		HCR 2b (Dynamic PFMC)	1	1	1	1	1	1
		HCR 3a (SESSF)	1	1	1	1	1	1
		HCR 3b (Dynamic SESSF)	1	1	1	1	1	1
		HCR 4 (NEFMC)	1	1	1	1	1	1
		HCR 5 (Avg F)	1	1	1	1	1	1
	Est M	HCR 1a (NPFMC)	0.97	0.99	1	1	0.99	1
		HCR 1b (Dynamic NPFMC)	1	1	1	1	0.99	0.98
		HCR 2a (PFMC)	1	1	1	1	1	1
		HCR 2b (Dynamic PFMC)	1	1	1	1	1	1
		HCR 3a (SESSF)	0.99	1	1	1	1	1
		HCR 3b (Dynamic SESSF)	1	1	1	1	1	1
		HCR 4 (NEFMC)	1	1	1	1	1	1
		HCR 5 (Avg F)	1	1	1	1	1	1

Supplementary Table S2.4.PMSupplementary Table S2.4.PM-4. Summary of performance metric 4 (average relative mean squared error in estimate of spawning biomass in 2060) across OMs for **Pollock**.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker
EBS	Fix M	HCR 1a (NPFMC)	0	0	0.07	0.06	0	0.09
		HCR 1b (Dynamic NPFMC)	0	0	0.06	0.06	0	0.08
		HCR 2a (PFMC)	0	0	0.07	0.07	0.01	0.08
		HCR 2b (Dynamic PFMC)	0	0	0.07	0.07	0.01	0.08
		HCR 3a (SESSF)	0	0	0.07	0.07	0.01	0.08
		HCR 3b (Dynamic SESSF)	0	0	0.08	0.07	0.01	0.08
		HCR 4 (NEFMC)	0	0	0.08	0.08	0.01	0.09
		HCR 5 (Avg F)	0	0	0.09	0.08	0	0.1
	Est M	HCR 1a (NPFMC)	0.01	0.01	0	0	0.01	0
		HCR 1b (Dynamic NPFMC)	0.01	0.01	0	0	0.01	0
		HCR 2a (PFMC)	0.01	0.01	0	0	0.02	0.01
		HCR 2b (Dynamic PFMC)	0.01	0.01	0	0	0.02	0.01
		HCR 3a (SESSF)	0.02	0.02	0	0	0.03	0.01
		HCR 3b (Dynamic SESSF)	0.02	0.02	0	0	0.03	0.01
		HCR 4 (NEFMC)	0.02	0.02	0	0	0.03	0.01
		HCR 5 (Avg F)	0.02	0.02	0	0	0.06	0.09
GOA	Fix M	HCR 1a (NPFMC)	0.01	0.01	0.13	0.12	0.01	0.01
		HCR 1b (Dynamic NPFMC)	0.01	0.01	0.12	0.13	0.01	0.01
		HCR 2a (PFMC)	0.01	0.01	0.15	0.13	0.02	0.01
		HCR 2b (Dynamic PFMC)	0.01	0.01	0.14	0.14	0.02	0.01
		HCR 3a (SESSF)	0.01	0.01	0.16	0.15	0.03	0.01
		HCR 3b (Dynamic SESSF)	0.01	0.01	0.16	0.15	0.03	0.01
		HCR 4 (NEFMC)	0.01	0.01	0.19	0.17	0.06	0.03
		HCR 5 (Avg F)	0.01	0.01	0.18	0.15	0.07	0.04
	Est M	HCR 1a (NPFMC)	0.05	0.05	0.01	0.01	0.11	0.14
		HCR 1b (Dynamic NPFMC)	0.05	0.06	0.01	0.01	0.12	0.16
		HCR 2a (PFMC)	0.06	0.07	0.01	0.02	0.15	0.23
		HCR 2b (Dynamic PFMC)	0.06	0.07	0.01	0.02	0.16	0.23
		HCR 3a (SESSF)	0.09	0.09	0.02	0.02	0.15	0.18
		HCR 3b (Dynamic SESSF)	0.09	0.1	0.02	0.02	0.15	0.2
		HCR 4 (NEFMC)	0.15	0.19	0.02	0.02	0.2	0.22
		HCR 5 (Avg F)	0.45	0.54	0.01	0.02	0.15	0.36

Supplementary Table S2.4.PM-5. Summary of performance metric 5 (probability that the population is perceived as undergoing overfishing in the terminal year of the EM) across OMs for **Pollock**.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker
EBS	Fix M	HCR 1a (NPFMC)	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0	0
		HCR 2a (PFMC)	0.02	0.02	0.02	0.02	0.02	0.02
		HCR 2b (Dynamic PFMC)	0.02	0.02	0.02	0.02	0.02	0.02
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0
	Est M	HCR 1a (NPFMC)	0	0	0	0	0.02	0.04
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0.02	0.04
		HCR 2a (PFMC)	0.03	0.04	0.03	0.03	0.12	0.24
		HCR 2b (Dynamic PFMC)	0.04	0.04	0.03	0.03	0.12	0.2
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0
GOA	Fix M	HCR 1a (NPFMC)	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0	0
		HCR 2a (PFMC)	0.01	0.01	0	0	0	0
		HCR 2b (Dynamic PFMC)	0.01	0.01	0.01	0	0	0
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0
	Est M	HCR 1a (NPFMC)	0.04	0.04	0.01	0	0.01	0.02
		HCR 1b (Dynamic NPFMC)	0.03	0.03	0	0	0.01	0.01
		HCR 2a (PFMC)	0.03	0.04	0.01	0.01	0.01	0.03
		HCR 2b (Dynamic PFMC)	0.04	0.04	0.01	0.01	0.01	0.03
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0

Supplementary Table S2.4.PM-6. Summary of performance metric 6 (probability that the population is perceived to be overfished in the terminal year of the EM) across OM for **Pollock**.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker
<i>EBS</i>	<i>Fix M</i>	HCR 1a (NPFMC)	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0	0
		HCR 2a (PFMC)	0.01	0.01	0	0.01	0	0.01
		HCR 2b (Dynamic PFMC)	0	0.01	0	0.01	0	0.01
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0
	<i>Est M</i>	HCR 1a (NPFMC)	0	0.01	0	0.01	0.01	0.02
		HCR 1b (Dynamic NPFMC)	0	0	0	0.01	0	0.01
		HCR 2a (PFMC)	0.03	0.04	0.03	0.03	0.03	0.07
		HCR 2b (Dynamic PFMC)	0	0.02	0	0.03	0.01	0.05
		HCR 3a (SESSF)	0	0	0	0	0	0.01
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0.01
		HCR 4 (NEFMC)	0	0	0	0	0	0.01
		HCR 5 (Avg F)	0	0	0	0	0	0
<i>GOA</i>	<i>Fix M</i>	HCR 1a (NPFMC)	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0	0
		HCR 2a (PFMC)	0.03	0	0.03	0	0	0
		HCR 2b (Dynamic PFMC)	0	0	0	0	0	0
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0
	<i>Est M</i>	HCR 1a (NPFMC)	0.01	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0	0.01
		HCR 2a (PFMC)	0.09	0.03	0.02	0	0.02	0
		HCR 2b (Dynamic PFMC)	0.01	0.01	0	0	0.01	0.03
		HCR 3a (SESSF)	0.01	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0.01	0	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0

Supplementary Table S2.4.PM-7. Summary of performance metric 7 (probability that the population is undergoing overfishing as determined from the OM) across OMs for **Pollock**.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker
<i>EBS</i>	<i>Fix M</i>	HCR 1a (NPFMC)	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0	0
		HCR 2a (PFMC)	0	0	0	0	0	0
		HCR 2b (Dynamic PFMC)	0	0	0	0	0	0
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0
	<i>Est M</i>	HCR 1a (NPFMC)	0.39	0.47	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0.52	0.57	0	0	0	0
		HCR 2a (PFMC)	0.93	0.93	0.02	0.03	0	0
		HCR 2b (Dynamic PFMC)	0.99	0.95	0.03	0.03	0	0
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0
<i>GOA</i>	<i>Fix M</i>	HCR 1a (NPFMC)	0.08	0.08	0.7	0.91	0	0
		HCR 1b (Dynamic NPFMC)	0.09	0.06	0.97	0.96	0	0
		HCR 2a (PFMC)	0.01	0.01	0.82	0.83	0	0
		HCR 2b (Dynamic PFMC)	0.01	0.01	0.9	0.84	0	0
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0.03	0.01	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0
	<i>Est M</i>	HCR 1a (NPFMC)	0.67	0.84	0.22	0.31	0	0
		HCR 1b (Dynamic NPFMC)	0.9	0.92	0.25	0.26	0	0
		HCR 2a (PFMC)	0.84	0.92	0.08	0.12	0	0
		HCR 2b (Dynamic PFMC)	0.9	0.93	0.1	0.12	0	0
		HCR 3a (SESSF)	0.03	0.03	0	0	0	0
		HCR 3b (Dynamic SESSF)	0.03	0.03	0	0	0	0
		HCR 4 (NEFMC)	0.67	0.72	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0

Supplementary Table S2.4.PM-8. Summary of performance metric 8 (probability that the population is overfished as determined from the OM) across OMs for **Pollock**.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker
<i>EBS</i>	<i>Fix M</i>	HCR 1a (NPFMC)	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0.01	0.01	0	0.01	0	0
		HCR 2a (PFMC)	0.02	0	0	0	0	0
		HCR 2b (Dynamic PFMC)	0	0	0	0	0	0
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0
	<i>Est M</i>	HCR 1a (NPFMC)	0.02	0.02	0.01	0.01	0	0.01
		HCR 1b (Dynamic NPFMC)	0.03	0.03	0.03	0.05	0	0.01
		HCR 2a (PFMC)	0.1	0	0.04	0	0	0.01
		HCR 2b (Dynamic PFMC)	0.01	0	0	0	0	0.01
		HCR 3a (SESSF)	0	0	0	0	0	0.01
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0.01
		HCR 4 (NEFMC)	0	0	0	0	0	0.01
		HCR 5 (Avg F)	0	0	0	0	0	0
<i>GOA</i>	<i>Fix M</i>	HCR 1a (NPFMC)	0.03	0	0.12	0	0	0
		HCR 1b (Dynamic NPFMC)	0.31	0.55	0.54	0.75	0	0
		HCR 2a (PFMC)	0.08	0	0.25	0	0	0
		HCR 2b (Dynamic PFMC)	0	0.07	0.07	0.19	0	0
		HCR 3a (SESSF)	0	0	0.04	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0.07	0	0
		HCR 4 (NEFMC)	0	0	0.02	0	0	0
		HCR 5 (Avg F)	0.04	0	0.04	0	0	0
	<i>Est M</i>	HCR 1a (NPFMC)	0.19	0	0.02	0	0.06	0
		HCR 1b (Dynamic NPFMC)	0.61	0.84	0.28	0.53	0.07	0
		HCR 2a (PFMC)	0.35	0	0.08	0	0.04	0
		HCR 2b (Dynamic PFMC)	0.21	0.45	0	0.11	0.04	0
		HCR 3a (SESSF)	0.1	0	0	0	0.03	0
		HCR 3b (Dynamic SESSF)	0.05	0.2	0	0.06	0.03	0
		HCR 4 (NEFMC)	0.1	0	0	0	0.02	0
		HCR 5 (Avg F)	0.08	0	0.04	0	0	0

Supplementary Table S2.4.PM-9. Summary of performance metric 9 (terminal spawning stock biomass depletion relative to equilibrium SB0) across OMs for **Pollock**.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker
EBS	Fix M	HCR 1a (NPFMC)	0.42	0.82	0.57	0.95	1.08	0.98
		HCR 1b (Dynamic NPFMC)	0.4	0.82	0.56	0.95	1.07	0.97
		HCR 2a (PFMC)	0.44	0.86	0.6	0.98	1.14	0.95
		HCR 2b (Dynamic PFMC)	0.44	0.86	0.6	0.98	1.14	0.95
		HCR 3a (SESSF)	0.49	0.9	0.65	1.02	1.19	0.97
		HCR 3b (Dynamic SESSF)	0.48	0.9	0.64	1.02	1.19	0.97
		HCR 4 (NEFMC)	0.53	0.94	0.68	1.05	1.21	1.01
		HCR 5 (Avg F)	0.64	1.02	0.77	1.11	1.54	1.21
	Est M	HCR 1a (NPFMC)	0.37	0.77	0.42	0.81	0.88	0.8
		HCR 1b (Dynamic NPFMC)	0.36	0.76	0.41	0.8	0.88	0.8
		HCR 2a (PFMC)	0.38	0.79	0.44	0.83	0.93	0.82
		HCR 2b (Dynamic PFMC)	0.38	0.79	0.44	0.83	0.93	0.82
		HCR 3a (SESSF)	0.42	0.83	0.5	0.89	0.98	0.87
		HCR 3b (Dynamic SESSF)	0.42	0.83	0.49	0.89	0.98	0.88
		HCR 4 (NEFMC)	0.45	0.86	0.52	0.91	0.99	0.89
		HCR 5 (Avg F)	0.64	1.02	0.77	1.11	1.57	1.23
GOA	Fix M	HCR 1a (NPFMC)	0.42	1.97	0.33	1.31	1.02	5.44
		HCR 1b (Dynamic NPFMC)	0.41	1.96	0.31	1.29	1.02	5.44
		HCR 2a (PFMC)	0.46	2.23	0.35	1.55	1.18	6.19
		HCR 2b (Dynamic PFMC)	0.45	2.23	0.35	1.54	1.17	6.18
		HCR 3a (SESSF)	0.49	2.38	0.39	1.65	1.11	5.61
		HCR 3b (Dynamic SESSF)	0.48	2.37	0.37	1.65	1.12	5.63
		HCR 4 (NEFMC)	0.57	2.8	0.45	2.05	1.21	5.95
		HCR 5 (Avg F)	0.51	2.52	0.38	1.73	0.85	4.3
	Est M	HCR 1a (NPFMC)	0.32	1.26	0.41	1.71	0.58	3.28
		HCR 1b (Dynamic NPFMC)	0.3	1.23	0.4	1.73	0.57	3.24
		HCR 2a (PFMC)	0.34	1.41	0.44	1.93	0.64	4
		HCR 2b (Dynamic PFMC)	0.33	1.41	0.44	1.91	0.64	4.08
		HCR 3a (SESSF)	0.36	1.56	0.47	1.99	0.63	3.29
		HCR 3b (Dynamic SESSF)	0.34	1.54	0.46	2.01	0.63	3.37
		HCR 4 (NEFMC)	0.39	1.81	0.55	2.37	0.69	3.65
		HCR 5 (Avg F)	0.46	2.26	0.4	1.81	0.83	4.01

Supplementary Table S2.4.PM-10. Summary of performance metric 10 (terminal spawning stock biomass depletion relative to dynamic SB0) across OM's for **Pollock**.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker
EBS	Fix M	HCR 1a (NPFMC)	0.41	0.69	0.57	0.78	0.96	0.85
		HCR 1b (Dynamic NPFMC)	0.4	0.68	0.55	0.78	0.96	0.85
		HCR 2a (PFMC)	0.44	0.72	0.59	0.8	1.02	0.83
		HCR 2b (Dynamic PFMC)	0.43	0.72	0.59	0.8	1.02	0.83
		HCR 3a (SESSF)	0.48	0.76	0.64	0.83	1.06	0.85
		HCR 3b (Dynamic SESSF)	0.48	0.75	0.63	0.84	1.06	0.85
		HCR 4 (NEFMC)	0.52	0.78	0.67	0.86	1.08	0.88
		HCR 5 (Avg F)	0.63	0.85	0.76	0.91	1.38	1.06
	Est M	HCR 1a (NPFMC)	0.36	0.64	0.42	0.67	0.79	0.71
		HCR 1b (Dynamic NPFMC)	0.35	0.63	0.4	0.66	0.79	0.7
		HCR 2a (PFMC)	0.38	0.66	0.44	0.68	0.84	0.72
		HCR 2b (Dynamic PFMC)	0.38	0.66	0.44	0.68	0.84	0.72
		HCR 3a (SESSF)	0.42	0.7	0.49	0.73	0.87	0.77
		HCR 3b (Dynamic SESSF)	0.41	0.7	0.48	0.73	0.87	0.77
		HCR 4 (NEFMC)	0.44	0.72	0.51	0.74	0.88	0.78
		HCR 5 (Avg F)	0.64	0.85	0.76	0.91	1.41	1.07
GOA	Fix M	HCR 1a (NPFMC)	0.42	0.46	0.33	0.36	0.95	1.11
		HCR 1b (Dynamic NPFMC)	0.4	0.46	0.3	0.36	0.95	1.11
		HCR 2a (PFMC)	0.45	0.52	0.35	0.43	1.1	1.27
		HCR 2b (Dynamic PFMC)	0.44	0.52	0.34	0.43	1.1	1.27
		HCR 3a (SESSF)	0.49	0.56	0.38	0.46	1.04	1.13
		HCR 3b (Dynamic SESSF)	0.46	0.56	0.36	0.46	1.04	1.14
		HCR 4 (NEFMC)	0.55	0.66	0.44	0.58	1.13	1.2
		HCR 5 (Avg F)	0.49	0.59	0.38	0.48	0.78	0.84
	Est M	HCR 1a (NPFMC)	0.32	0.3	0.41	0.48	0.54	0.64
		HCR 1b (Dynamic NPFMC)	0.3	0.28	0.39	0.48	0.52	0.64
		HCR 2a (PFMC)	0.33	0.33	0.44	0.54	0.59	0.8
		HCR 2b (Dynamic PFMC)	0.32	0.33	0.43	0.54	0.58	0.82
		HCR 3a (SESSF)	0.36	0.37	0.46	0.56	0.59	0.64
		HCR 3b (Dynamic SESSF)	0.33	0.36	0.45	0.56	0.58	0.66
		HCR 4 (NEFMC)	0.38	0.42	0.54	0.66	0.64	0.71
		HCR 5 (Avg F)	0.45	0.53	0.39	0.51	0.76	0.78

Supplementary Tables 5. Summary of performance metrics across OMs for Pacific cod.

Supplementary Table S2.5.PM-1. Summary of performance metric 1 (average annual catch) across OMs for Cod.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker
EBS	Fix M	HCR 1a (NPFMC)	147	173	148	174	158	187
		HCR 1b (Dynamic NPFMC)	149	175	150	176	159	187
		HCR 2a (PFMC)	141	160	142	162	149	172
		HCR 2b (Dynamic PFMC)	141	161	142	162	149	172
		HCR 3a (SESSF)	131	146	133	147	136	157
		HCR 3b (Dynamic SESSF)	132	146	133	148	136	156
		HCR 4 (NEFMC)	118	126	119	127	120	134
		HCR 5 (Avg F)	172	212	172	212	179	226
	Est M	HCR 1a (NPFMC)	147	173	145	196	158	197
		HCR 1b (Dynamic NPFMC)	150	175	147	197	160	197
		HCR 2a (PFMC)	141	161	138	185	149	182
		HCR 2b (Dynamic PFMC)	141	161	138	185	149	182
		HCR 3a (SESSF)	131	146	129	167	137	165
		HCR 3b (Dynamic SESSF)	132	146	130	168	137	165
		HCR 4 (NEFMC)	118	126	116	150	120	143
		HCR 5 (Avg F)	171	209	171	205	178	220
GOA	Fix M	HCR 1a (NPFMC)	27	58	20	43	28	61
		HCR 1b (Dynamic NPFMC)	28	57	20	43	29	61
		HCR 2a (PFMC)	26	55	20	42	27	59
		HCR 2b (Dynamic PFMC)	26	54	20	42	28	58
		HCR 3a (SESSF)	23	48	18	40	24	51
		HCR 3b (Dynamic SESSF)	23	48	19	39	24	50
		HCR 4 (NEFMC)	23	47	19	39	24	48
		HCR 5 (Avg F)	23	48	19	39	23	47
	Est M	HCR 1a (NPFMC)	23	51	14	28	23	50
		HCR 1b (Dynamic NPFMC)	23	50	15	28	23	49
		HCR 2a (PFMC)	21	47	13	24	21	46
		HCR 2b (Dynamic PFMC)	21	47	13	24	21	45
		HCR 3a (SESSF)	20	44	12	21	20	41
		HCR 3b (Dynamic SESSF)	19	41	13	21	19	38
		HCR 4 (NEFMC)	18	37	11	17	17	33
		HCR 5 (Avg F)	23	48	19	39	22	46

Supplementary Table S2.5.PM-2. Summary of performance metric 2 (average interannual variation in catch (IAV)) across OM for **Cod**.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker
<i>EBS</i>	<i>Fix M</i>	HCR 1a (NPFMC)	0.15	0.14	0.14	0.15	0.15	0.15
		HCR 1b (Dynamic NPFMC)	0.1	0.11	0.1	0.12	0.11	0.13
		HCR 2a (PFMC)	0.11	0.12	0.11	0.12	0.12	0.13
		HCR 2b (Dynamic PFMC)	0.11	0.11	0.1	0.12	0.11	0.13
		HCR 3a (SESSF)	0.14	0.14	0.13	0.15	0.14	0.14
		HCR 3b (Dynamic SESSF)	0.1	0.1	0.09	0.11	0.1	0.12
		HCR 4 (NEFMC)	0.09	0.1	0.08	0.11	0.09	0.11
		HCR 5 (Avg F)	0.15	0.15	0.15	0.15	0.16	0.16
	<i>Est M</i>	HCR 1a (NPFMC)	0.15	0.14	0.14	0.16	0.14	0.15
		HCR 1b (Dynamic NPFMC)	0.1	0.11	0.1	0.13	0.11	0.13
		HCR 2a (PFMC)	0.11	0.12	0.11	0.13	0.11	0.13
		HCR 2b (Dynamic PFMC)	0.11	0.11	0.1	0.13	0.11	0.13
		HCR 3a (SESSF)	0.14	0.14	0.13	0.15	0.13	0.14
		HCR 3b (Dynamic SESSF)	0.1	0.1	0.1	0.13	0.1	0.13
		HCR 4 (NEFMC)	0.09	0.1	0.08	0.11	0.09	0.11
		HCR 5 (Avg F)	0.15	0.14	0.15	0.14	0.16	0.15
	<i>GOA</i>	<i>Fix M</i> HCR 1a (NPFMC)	0.37	0.31	0.48	0.35	0.35	0.29
		HCR 1b (Dynamic NPFMC)	0.3	0.3	0.36	0.33	0.28	0.28
		HCR 2a (PFMC)	0.29	0.28	0.35	0.29	0.28	0.26
		HCR 2b (Dynamic PFMC)	0.28	0.28	0.3	0.29	0.27	0.26
		HCR 3a (SESSF)	0.31	0.26	0.36	0.26	0.28	0.25
		HCR 3b (Dynamic SESSF)	0.26	0.26	0.26	0.26	0.24	0.25
		HCR 4 (NEFMC)	0.24	0.25	0.23	0.24	0.23	0.23
		HCR 5 (Avg F)	0.25	0.25	0.24	0.24	0.23	0.23
		<i>Est M</i> HCR 1a (NPFMC)	0.31	0.28	0.23	0.21	0.27	0.25
		HCR 1b (Dynamic NPFMC)	0.25	0.27	0.2	0.21	0.22	0.24
		HCR 2a (PFMC)	0.26	0.26	0.19	0.2	0.22	0.23
		HCR 2b (Dynamic PFMC)	0.25	0.26	0.17	0.2	0.22	0.23
		HCR 3a (SESSF)	0.28	0.26	0.22	0.21	0.24	0.23
		HCR 3b (Dynamic SESSF)	0.23	0.25	0.18	0.2	0.2	0.22
		HCR 4 (NEFMC)	0.21	0.23	0.16	0.18	0.19	0.21
		HCR 5 (Avg F)	0.25	0.26	0.24	0.25	0.23	0.24

Supplementary Table S2.5.PM-3. Summary of performance metric 3 (probability of the fishery being open) across OMs for **Cod**.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker
<i>EBS</i>	<i>Fix M</i>	HCR 1a (NPFMC)	1	1	1	1	1	1
		HCR 1b (Dynamic NPFMC)	1	1	1	1	1	1
		HCR 2a (PFMC)	1	1	1	1	1	1
		HCR 2b (Dynamic PFMC)	1	1	1	1	1	1
		HCR 3a (SESSF)	1	1	1	1	1	1
		HCR 3b (Dynamic SESSF)	1	1	1	1	1	1
		HCR 4 (NEFMC)	1	1	1	1	1	1
		HCR 5 (Avg F)	1	1	1	1	1	1
	<i>Est M</i>	HCR 1a (NPFMC)	1	1	1	1	1	1
		HCR 1b (Dynamic NPFMC)	1	1	1	1	1	1
		HCR 2a (PFMC)	1	1	1	1	1	1
		HCR 2b (Dynamic PFMC)	1	1	1	1	1	1
		HCR 3a (SESSF)	1	1	1	1	1	1
		HCR 3b (Dynamic SESSF)	1	1	1	1	1	1
		HCR 4 (NEFMC)	1	1	1	1	1	1
		HCR 5 (Avg F)	1	1	1	1	1	1
<i>GOA</i>	<i>Fix M</i>	HCR 1a (NPFMC)	0.94	0.95	0.91	0.95	0.94	0.96
		HCR 1b (Dynamic NPFMC)	1	1	0.95	0.97	1	1
		HCR 2a (PFMC)	1	1	0.98	1	1	1
		HCR 2b (Dynamic PFMC)	1	1	1	1	1	1
		HCR 3a (SESSF)	0.97	0.99	0.97	1	0.97	1
		HCR 3b (Dynamic SESSF)	1	1	1	1	1	1
		HCR 4 (NEFMC)	1	1	1	1	1	1
		HCR 5 (Avg F)	1	1	1	1	1	1
	<i>Est M</i>	HCR 1a (NPFMC)	0.95	0.96	0.92	0.93	0.95	0.96
		HCR 1b (Dynamic NPFMC)	1	1	0.95	0.95	1	1
		HCR 2a (PFMC)	1	1	1	1	1	1
		HCR 2b (Dynamic PFMC)	1	1	1	1	1	1
		HCR 3a (SESSF)	0.98	1	0.92	0.93	0.98	1
		HCR 3b (Dynamic SESSF)	1	1	0.95	0.95	1	1
		HCR 4 (NEFMC)	1	1	1	1	1	1
		HCR 5 (Avg F)	1	1	1	1	1	1

Supplementary Table S2.5.PM-4. Summary of performance metric 4 (average relative mean squared error in estimate of spawning biomass in 2060) across OMs for **Cod**.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker
<i>EBS</i>	<i>Fix M</i>	HCR 1a (NPFMC)	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0	0
		HCR 2a (PFMC)	0	0	0	0	0	0
		HCR 2b (Dynamic PFMC)	0	0	0	0	0	0
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0
	<i>Est M</i>	HCR 1a (NPFMC)	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0	0
		HCR 2a (PFMC)	0	0	0	0	0	0
		HCR 2b (Dynamic PFMC)	0	0	0	0	0	0
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0
<i>GOA</i>	<i>Fix M</i>	HCR 1a (NPFMC)	0	0	0.15	0.15	0.01	0.02
		HCR 1b (Dynamic NPFMC)	0	0	0.14	0.15	0.01	0.02
		HCR 2a (PFMC)	0	0	0.16	0.16	0.01	0.01
		HCR 2b (Dynamic PFMC)	0	0	0.15	0.16	0.01	0.01
		HCR 3a (SESSF)	0	0	0.2	0.19	0.01	0.02
		HCR 3b (Dynamic SESSF)	0	0	0.18	0.18	0.01	0.01
		HCR 4 (NEFMC)	0	0	0.18	0.19	0.01	0.01
		HCR 5 (Avg F)	0	0	0.17	0.18	0.01	0.01
	<i>Est M</i>	HCR 1a (NPFMC)	0.02	0.01	0	0.01	0.01	0.01
		HCR 1b (Dynamic NPFMC)	0.02	0.01	0.01	0.01	0.02	0.01
		HCR 2a (PFMC)	0.02	0.01	0.01	0.02	0.02	0.01
		HCR 2b (Dynamic PFMC)	0.02	0.01	0.01	0.02	0.02	0.01
		HCR 3a (SESSF)	0.01	0.01	0.01	0.02	0.01	0.01
		HCR 3b (Dynamic SESSF)	0.03	0.02	0.01	0.02	0.02	0.02
		HCR 4 (NEFMC)	0.04	0.03	0.02	0.03	0.03	0.03
		HCR 5 (Avg F)	0.02	0.01	0	0	0.01	0.01

Supplementary Table S2.5.PM-5. Summary of performance metric 5 (probability that the population is perceived as undergoing overfishing in the terminal year of the EM) across OMs for **Cod**.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker
EBS	Fix M	HCR 1a (NPFMC)	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0	0
		HCR 2a (PFMC)	0.02	0.02	0.02	0.02	0.02	0.02
		HCR 2b (Dynamic PFMC)	0.02	0.02	0.02	0.02	0.02	0.02
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0
	Est M	HCR 1a (NPFMC)	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0	0
		HCR 2a (PFMC)	0.02	0.02	0.02	0.02	0.02	0.02
		HCR 2b (Dynamic PFMC)	0.02	0.02	0.02	0.02	0.02	0.02
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0
GOA	Fix M	HCR 1a (NPFMC)	0.01	0.01	0.09	0.09	0.02	0.02
		HCR 1b (Dynamic NPFMC)	0.03	0.01	0.11	0.09	0.04	0.03
		HCR 2a (PFMC)	0.21	0.19	0.35	0.41	0.23	0.21
		HCR 2b (Dynamic PFMC)	0.24	0.2	0.42	0.39	0.24	0.21
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0.01	0	0	0
		HCR 5 (Avg F)	0.07	0.04	0.29	0.23	0.07	0.05
	Est M	HCR 1a (NPFMC)	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0.01	0	0	0	0	0
		HCR 2a (PFMC)	0.1	0.1	0.02	0.02	0.07	0.06
		HCR 2b (Dynamic PFMC)	0.13	0.11	0.02	0.01	0.07	0.05
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0.25	0.2	0.95	0.91	0.39	0.39

Supplementary Table S2.5.PM-6. Summary of performance metric 6 (probability that the population is perceived to be overfished in the terminal year of the EM) across OM for **Cod**.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker
EBS	Fix M	HCR 1a (NPFMC)	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0	0
		HCR 2a (PFMC)	0.01	0	0.01	0	0	0
		HCR 2b (Dynamic PFMC)	0	0	0	0	0	0
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0.04	0.01	0.04	0.01	0.03	0.01
	Est M	HCR 1a (NPFMC)	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0	0
		HCR 2a (PFMC)	0.01	0	0.01	0	0	0
		HCR 2b (Dynamic PFMC)	0	0	0	0	0	0
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0.04	0.01	0.06	0	0.04	0
GOA	Fix M	HCR 1a (NPFMC)	0.05	0.03	0.07	0.05	0.05	0.03
		HCR 1b (Dynamic NPFMC)	0	0	0.04	0.02	0	0
		HCR 2a (PFMC)	0.09	0.05	0.17	0.06	0.08	0.05
		HCR 2b (Dynamic PFMC)	0.01	0	0.06	0.03	0.01	0
		HCR 3a (SESSF)	0.03	0.01	0.03	0	0.03	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0.05	0.04	0.07	0.05	0.05	0.04
		HCR 5 (Avg F)	0.05	0.01	0.06	0.04	0.05	0.02
	Est M	HCR 1a (NPFMC)	0.05	0.02	0.04	0.02	0.04	0.01
		HCR 1b (Dynamic NPFMC)	0	0	0.02	0	0	0
		HCR 2a (PFMC)	0.1	0.06	0.11	0.09	0.09	0.07
		HCR 2b (Dynamic PFMC)	0.01	0	0.07	0.05	0.02	0
		HCR 3a (SESSF)	0.02	0	0.05	0.05	0.02	0
		HCR 3b (Dynamic SESSF)	0	0	0.02	0.02	0	0
		HCR 4 (NEFMC)	0.05	0.04	0.09	0.07	0.05	0.04
		HCR 5 (Avg F)	0.05	0.04	0.18	0.09	0.06	0.05

Supplementary Table S2.5.PM-7. Summary of performance metric 7 (probability that the population is undergoing overfishing as determined from the OM) across OMs for **Cod**.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker
<i>EBS</i>	<i>Fix M</i>	HCR 1a (NPFMC)	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0	0
		HCR 2a (PFMC)	0	0	0	0	0	0
		HCR 2b (Dynamic PFMC)	0	0	0	0	0	0
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0
	<i>Est M</i>	HCR 1a (NPFMC)	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0	0
		HCR 2a (PFMC)	0	0	0	0.01	0	0
		HCR 2b (Dynamic PFMC)	0	0	0	0.01	0	0
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0
<i>GOA</i>	<i>Fix M</i>	HCR 1a (NPFMC)	0.03	0.02	0.91	0.95	0	0
		HCR 1b (Dynamic NPFMC)	0.06	0.03	0.95	0.97	0	0
		HCR 2a (PFMC)	0.42	0.35	0.95	0.97	0	0
		HCR 2b (Dynamic PFMC)	0.48	0.37	1	1	0	0
		HCR 3a (SESSF)	0	0	0.01	0.02	0	0
		HCR 3b (Dynamic SESSF)	0	0	0.01	0.03	0	0
		HCR 4 (NEFMC)	0	0	1	1	0	0
		HCR 5 (Avg F)	0.19	0.12	0.99	0.98	0	0
	<i>Est M</i>	HCR 1a (NPFMC)	0	0	0.01	0.01	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0.01	0	0
		HCR 2a (PFMC)	0	0	0	0	0	0
		HCR 2b (Dynamic PFMC)	0	0	0.01	0	0	0
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0.12	0.1	0.95	0.93	0	0

Supplementary Table S2.5.PM-8. Summary of performance metric 8 (probability that the population is overfished as determined from the OM) across OMs for **Cod**.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker
EBS	Fix M	HCR 1a (NPFMC)	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0	0
		HCR 2a (PFMC)	0.01	0	0.02	0	0	0
		HCR 2b (Dynamic PFMC)	0	0	0	0	0	0
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0.01	0	0.01	0	0.03	0.01
	Est M	HCR 1a (NPFMC)	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0	0
		HCR 2a (PFMC)	0.01	0	0.01	0	0	0
		HCR 2b (Dynamic PFMC)	0	0	0	0	0	0
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0.01	0	0.01	0	0.03	0
GOA	Fix M	HCR 1a (NPFMC)	0.07	0	0.45	0.11	0.14	0.07
		HCR 1b (Dynamic NPFMC)	0	0.05	0.26	0.18	0.16	0.08
		HCR 2a (PFMC)	0.13	0.08	0.68	0.1	0.13	0.07
		HCR 2b (Dynamic PFMC)	0.01	0.09	0.67	0.21	0.13	0.08
		HCR 3a (SESSF)	0.04	0.02	0.2	0.05	0.09	0.07
		HCR 3b (Dynamic SESSF)	0	0.02	0.17	0.08	0.1	0.07
		HCR 4 (NEFMC)	0.06	0	0.25	0.1	0.11	0.07
		HCR 5 (Avg F)	0.1	0.05	0.09	0.05	0.12	0.08
	Est M	HCR 1a (NPFMC)	0.05	0	0.07	0.05	0.08	0.07
		HCR 1b (Dynamic NPFMC)	0	0.05	0.02	0.08	0.09	0.07
		HCR 2a (PFMC)	0.09	0.07	0.1	0.07	0.08	0.07
		HCR 2b (Dynamic PFMC)	0	0.07	0.07	0.05	0.08	0.07
		HCR 3a (SESSF)	0	0	0.07	0.02	0.06	0.05
		HCR 3b (Dynamic SESSF)	0	0	0.02	0.02	0.07	0.05
		HCR 4 (NEFMC)	0.05	0	0.09	0.07	0.08	0.07
		HCR 5 (Avg F)	0.1	0.05	0.08	0.05	0.11	0.07

Supplementary Table S2.5.PM-9. Summary of performance metric 9 (terminal spawning stock biomass depletion relative to equilibrium SB0) across OMs for **Cod**.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker
EBS	Fix M	HCR 1a (NPFMC)	0.41	0.72	0.4	0.76	0.64	0.72
		HCR 1b (Dynamic NPFMC)	0.4	0.71	0.39	0.75	0.63	0.72
		HCR 2a (PFMC)	0.44	0.76	0.43	0.79	0.69	0.77
		HCR 2b (Dynamic PFMC)	0.44	0.76	0.43	0.79	0.69	0.77
		HCR 3a (SESSF)	0.48	0.8	0.47	0.83	0.73	0.81
		HCR 3b (Dynamic SESSF)	0.48	0.8	0.47	0.83	0.73	0.81
		HCR 4 (NEFMC)	0.55	0.86	0.53	0.89	0.81	0.86
		HCR 5 (Avg F)	0.29	0.56	0.28	0.62	0.44	0.56
	Est M	HCR 1a (NPFMC)	0.41	0.72	0.41	0.69	0.68	0.7
		HCR 1b (Dynamic NPFMC)	0.4	0.71	0.4	0.68	0.67	0.7
		HCR 2a (PFMC)	0.44	0.76	0.45	0.72	0.74	0.75
		HCR 2b (Dynamic PFMC)	0.44	0.76	0.44	0.72	0.74	0.75
		HCR 3a (SESSF)	0.48	0.8	0.48	0.78	0.78	0.78
		HCR 3b (Dynamic SESSF)	0.48	0.8	0.48	0.77	0.78	0.78
		HCR 4 (NEFMC)	0.54	0.86	0.55	0.83	0.87	0.84
		HCR 5 (Avg F)	0.3	0.57	0.28	0.65	0.44	0.59
GOA	Fix M	HCR 1a (NPFMC)	0.4	0.89	0.22	0.6	0.39	0.87
		HCR 1b (Dynamic NPFMC)	0.39	0.89	0.21	0.6	0.39	0.87
		HCR 2a (PFMC)	0.42	0.95	0.23	0.64	0.42	0.94
		HCR 2b (Dynamic PFMC)	0.42	0.95	0.23	0.65	0.42	0.95
		HCR 3a (SESSF)	0.48	1.06	0.27	0.72	0.47	1
		HCR 3b (Dynamic SESSF)	0.48	1.06	0.27	0.74	0.47	1.01
		HCR 4 (NEFMC)	0.49	1.07	0.27	0.75	0.47	1.01
		HCR 5 (Avg F)	0.48	1.06	0.26	0.73	0.44	0.97
	Est M	HCR 1a (NPFMC)	0.48	0.98	0.43	0.98	0.52	1.08
		HCR 1b (Dynamic NPFMC)	0.48	0.99	0.43	1	0.53	1.11
		HCR 2a (PFMC)	0.51	1.05	0.49	1.09	0.57	1.19
		HCR 2b (Dynamic PFMC)	0.52	1.06	0.48	1.09	0.58	1.19
		HCR 3a (SESSF)	0.54	1.1	0.52	1.13	0.57	1.17
		HCR 3b (Dynamic SESSF)	0.56	1.15	0.52	1.14	0.6	1.21
		HCR 4 (NEFMC)	0.6	1.2	0.6	1.24	0.65	1.27
		HCR 5 (Avg F)	0.48	1.05	0.27	0.73	0.44	0.96

Supplementary Table S2.5.PM-10. Summary of performance metric 10 (terminal spawning stock biomass depletion relative to dynamic SB0) across OM's for **Cod**.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker
EBS	Fix M	HCR 1a (NPFMC)	0.41	0.67	0.4	0.68	0.61	0.63
		HCR 1b (Dynamic NPFMC)	0.4	0.66	0.38	0.67	0.6	0.63
		HCR 2a (PFMC)	0.44	0.7	0.43	0.71	0.65	0.67
		HCR 2b (Dynamic PFMC)	0.44	0.7	0.43	0.71	0.65	0.67
		HCR 3a (SESSF)	0.48	0.74	0.47	0.75	0.69	0.7
		HCR 3b (Dynamic SESSF)	0.48	0.74	0.46	0.74	0.69	0.7
		HCR 4 (NEFMC)	0.54	0.79	0.53	0.8	0.76	0.75
		HCR 5 (Avg F)	0.29	0.52	0.28	0.56	0.42	0.49
	Est M	HCR 1a (NPFMC)	0.41	0.67	0.41	0.62	0.65	0.61
		HCR 1b (Dynamic NPFMC)	0.4	0.65	0.4	0.61	0.64	0.61
		HCR 2a (PFMC)	0.44	0.7	0.44	0.65	0.7	0.65
		HCR 2b (Dynamic PFMC)	0.44	0.7	0.44	0.65	0.7	0.65
		HCR 3a (SESSF)	0.48	0.74	0.48	0.7	0.74	0.68
		HCR 3b (Dynamic SESSF)	0.48	0.74	0.48	0.69	0.74	0.68
		HCR 4 (NEFMC)	0.54	0.79	0.55	0.74	0.82	0.72
		HCR 5 (Avg F)	0.3	0.53	0.28	0.59	0.42	0.51
GOA	Fix M	HCR 1a (NPFMC)	0.4	0.53	0.22	0.38	0.39	0.51
		HCR 1b (Dynamic NPFMC)	0.39	0.52	0.21	0.38	0.38	0.51
		HCR 2a (PFMC)	0.42	0.56	0.23	0.41	0.42	0.55
		HCR 2b (Dynamic PFMC)	0.42	0.56	0.23	0.41	0.42	0.56
		HCR 3a (SESSF)	0.48	0.63	0.27	0.46	0.46	0.59
		HCR 3b (Dynamic SESSF)	0.47	0.63	0.26	0.47	0.46	0.59
		HCR 4 (NEFMC)	0.48	0.63	0.27	0.47	0.46	0.6
		HCR 5 (Avg F)	0.48	0.63	0.26	0.46	0.43	0.57
	Est M	HCR 1a (NPFMC)	0.48	0.58	0.43	0.62	0.51	0.64
		HCR 1b (Dynamic NPFMC)	0.48	0.59	0.42	0.63	0.53	0.65
		HCR 2a (PFMC)	0.51	0.62	0.48	0.69	0.56	0.7
		HCR 2b (Dynamic PFMC)	0.51	0.63	0.48	0.69	0.57	0.7
		HCR 3a (SESSF)	0.53	0.65	0.51	0.71	0.57	0.69
		HCR 3b (Dynamic SESSF)	0.56	0.68	0.51	0.72	0.59	0.71
		HCR 4 (NEFMC)	0.6	0.71	0.59	0.78	0.64	0.75
		HCR 5 (Avg F)	0.48	0.62	0.26	0.46	0.44	0.56

Supplementary Tables 6. Summary of performance metrics across OMs for arrowtooth flounder.

Supplementary Table S2.6.PM-1. Summary of performance metric 1 (average annual catch) across OMs for **Arrowtooth flounder**.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker
EBS	Fix M	HCR 1a (NPFMC)	33	47	38	57	40	59
		HCR 1b (Dynamic NPFMC)	34	47	38	57	40	59
		HCR 2a (PFMC)	34	48	40	59	41	61
		HCR 2b (Dynamic PFMC)	34	48	40	59	41	61
		HCR 3a (SESSF)	30	42	33	49	34	50
		HCR 3b (Dynamic SESSF)	30	42	33	49	34	50
		HCR 4 (NEFMC)	25	36	27	40	28	41
		HCR 5 (Avg F)	12	15	12	17	12	17
	Est M	HCR 1a (NPFMC)	34	48	47	67	50	73
		HCR 1b (Dynamic NPFMC)	34	48	48	67	50	73
		HCR 2a (PFMC)	35	49	50	68	52	74
		HCR 2b (Dynamic PFMC)	35	49	50	68	52	74
		HCR 3a (SESSF)	30	43	42	62	44	66
		HCR 3b (Dynamic SESSF)	30	43	42	62	44	66
		HCR 4 (NEFMC)	26	37	37	56	39	59
		HCR 5 (Avg F)	12	15	12	17	12	17
GOA	Fix M	HCR 1a (NPFMC)	86	123	99	136	101	134
		HCR 1b (Dynamic NPFMC)	87	123	100	136	101	134
		HCR 2a (PFMC)	89	126	103	140	104	137
		HCR 2b (Dynamic PFMC)	89	126	103	140	104	137
		HCR 3a (SESSF)	75	107	85	116	85	115
		HCR 3b (Dynamic SESSF)	75	107	85	116	85	115
		HCR 4 (NEFMC)	66	92	72	99	72	98
		HCR 5 (Avg F)	19	24	20	26	20	27
	Est M	HCR 1a (NPFMC)	85	121	110	148	109	143
		HCR 1b (Dynamic NPFMC)	85	121	111	148	109	143
		HCR 2a (PFMC)	87	123	117	152	115	147
		HCR 2b (Dynamic PFMC)	87	123	117	152	116	147
		HCR 3a (SESSF)	74	106	95	131	93	127
		HCR 3b (Dynamic SESSF)	74	106	95	131	93	127
		HCR 4 (NEFMC)	65	91	86	119	83	115
		HCR 5 (Avg F)	22	28	22	28	22	30

Supplementary Table S2.6.PM-2. Summary of performance metric 2 (average interannual variation in catch (IAV)) across OMs for **Arrowtooth flounder**.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker
EBS	Fix M	HCR 1a (NPFMC)	0.08	0.07	0.09	0.08	0.09	0.09
		HCR 1b (Dynamic NPFMC)	0.07	0.07	0.09	0.09	0.09	0.09
		HCR 2a (PFMC)	0.08	0.07	0.09	0.09	0.09	0.09
		HCR 2b (Dynamic PFMC)	0.08	0.07	0.09	0.09	0.09	0.09
		HCR 3a (SESSF)	0.06	0.06	0.08	0.08	0.08	0.08
		HCR 3b (Dynamic SESSF)	0.06	0.06	0.08	0.08	0.08	0.08
		HCR 4 (NEFMC)	0.05	0.05	0.07	0.07	0.07	0.07
		HCR 5 (Avg F)	0.04	0.04	0.06	0.06	0.06	0.06
	Est M	HCR 1a (NPFMC)	0.09	0.07	0.13	0.1	0.12	0.1
		HCR 1b (Dynamic NPFMC)	0.08	0.07	0.11	0.09	0.11	0.1
		HCR 2a (PFMC)	0.08	0.07	0.12	0.1	0.12	0.11
		HCR 2b (Dynamic PFMC)	0.08	0.07	0.12	0.1	0.12	0.11
		HCR 3a (SESSF)	0.06	0.06	0.09	0.08	0.09	0.08
		HCR 3b (Dynamic SESSF)	0.06	0.06	0.08	0.08	0.08	0.08
		HCR 4 (NEFMC)	0.05	0.05	0.07	0.07	0.07	0.07
		HCR 5 (Avg F)	0.04	0.04	0.04	0.05	0.04	0.06
GOA	Fix M	HCR 1a (NPFMC)	0.08	0.06	0.07	0.05	0.07	0.05
		HCR 1b (Dynamic NPFMC)	0.08	0.06	0.07	0.05	0.07	0.05
		HCR 2a (PFMC)	0.09	0.06	0.08	0.06	0.07	0.06
		HCR 2b (Dynamic PFMC)	0.09	0.06	0.08	0.06	0.07	0.06
		HCR 3a (SESSF)	0.06	0.04	0.05	0.04	0.05	0.04
		HCR 3b (Dynamic SESSF)	0.06	0.04	0.05	0.04	0.05	0.04
		HCR 4 (NEFMC)	0.05	0.04	0.04	0.04	0.04	0.04
		HCR 5 (Avg F)	0.02	0.03	0.02	0.03	0.02	0.03
	Est M	HCR 1a (NPFMC)	0.09	0.06	0.14	0.11	0.12	0.1
		HCR 1b (Dynamic NPFMC)	0.08	0.06	0.14	0.11	0.12	0.1
		HCR 2a (PFMC)	0.09	0.07	0.17	0.13	0.15	0.12
		HCR 2b (Dynamic PFMC)	0.09	0.07	0.17	0.13	0.15	0.12
		HCR 3a (SESSF)	0.06	0.04	0.1	0.07	0.09	0.07
		HCR 3b (Dynamic SESSF)	0.06	0.04	0.1	0.07	0.09	0.07
		HCR 4 (NEFMC)	0.05	0.04	0.08	0.06	0.07	0.06
		HCR 5 (Avg F)	0.02	0.03	0.02	0.03	0.02	0.03

Supplementary Table S2.6.PM-3. Summary of performance metric 3 (probability of the fishery being open) across OMs for **Arrowtooth flounder**.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker
EBS	Fix M	HCR 1a (NPFMC)	1	1	1	1	1	1
		HCR 1b (Dynamic NPFMC)	1	1	1	1	1	1
		HCR 2a (PFMC)	1	1	1	1	1	1
		HCR 2b (Dynamic PFMC)	1	1	1	1	1	1
		HCR 3a (SESSF)	1	1	1	1	1	1
		HCR 3b (Dynamic SESSF)	1	1	1	1	1	1
		HCR 4 (NEFMC)	1	1	1	1	1	1
		HCR 5 (Avg F)	1	1	1	1	1	1
	Est M	HCR 1a (NPFMC)	1	1	1	1	1	1
		HCR 1b (Dynamic NPFMC)	1	1	1	1	1	1
		HCR 2a (PFMC)	1	1	1	1	1	1
		HCR 2b (Dynamic PFMC)	1	1	1	1	1	1
		HCR 3a (SESSF)	1	1	1	1	1	1
		HCR 3b (Dynamic SESSF)	1	1	1	1	1	1
		HCR 4 (NEFMC)	1	1	1	1	1	1
		HCR 5 (Avg F)	1	1	1	1	1	1
GOA	Fix M	HCR 1a (NPFMC)	1	1	1	1	1	1
		HCR 1b (Dynamic NPFMC)	1	1	1	1	1	1
		HCR 2a (PFMC)	1	1	1	1	1	1
		HCR 2b (Dynamic PFMC)	1	1	1	1	1	1
		HCR 3a (SESSF)	1	1	1	1	1	1
		HCR 3b (Dynamic SESSF)	1	1	1	1	1	1
		HCR 4 (NEFMC)	1	1	1	1	1	1
		HCR 5 (Avg F)	1	1	1	1	1	1
	Est M	HCR 1a (NPFMC)	1	1	1	1	1	1
		HCR 1b (Dynamic NPFMC)	1	1	1	1	1	1
		HCR 2a (PFMC)	1	1	1	1	1	1
		HCR 2b (Dynamic PFMC)	1	1	1	1	1	1
		HCR 3a (SESSF)	1	1	1	1	1	1
		HCR 3b (Dynamic SESSF)	1	1	1	1	1	1
		HCR 4 (NEFMC)	1	1	1	1	1	1
		HCR 5 (Avg F)	1	1	1	1	1	1

Supplementary Table S2.6.PM-4. Summary of performance metric 4 (average relative mean squared error in estimate of spawning biomass in 2060) across OMs for **Arrowtooth flounder**.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker
EBS	Fix M	HCR 1a (NPFMC)	0	0	0.01	0.01	0.01	0.01
		HCR 1b (Dynamic NPFMC)	0	0	0.01	0.01	0.01	0.01
		HCR 2a (PFMC)	0	0	0.01	0.01	0.01	0.01
		HCR 2b (Dynamic PFMC)	0	0	0.01	0.01	0.01	0.01
		HCR 3a (SESSF)	0	0	0.01	0.01	0.01	0.01
		HCR 3b (Dynamic SESSF)	0	0	0.01	0.01	0.01	0.01
		HCR 4 (NEFMC)	0	0	0.01	0.01	0.02	0.01
		HCR 5 (Avg F)	0	0	0.03	0.03	0.03	0.03
	Est M	HCR 1a (NPFMC)	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0	0
		HCR 2a (PFMC)	0	0	0	0	0	0
		HCR 2b (Dynamic PFMC)	0	0	0	0	0	0
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0
GOA	Fix M	HCR 1a (NPFMC)	0	0	0.14	0.14	0.19	0.17
		HCR 1b (Dynamic NPFMC)	0	0	0.14	0.14	0.19	0.17
		HCR 2a (PFMC)	0	0	0.15	0.14	0.19	0.18
		HCR 2b (Dynamic PFMC)	0	0	0.15	0.14	0.19	0.18
		HCR 3a (SESSF)	0	0	0.14	0.13	0.17	0.16
		HCR 3b (Dynamic SESSF)	0	0	0.14	0.13	0.17	0.16
		HCR 4 (NEFMC)	0	0	0.13	0.12	0.16	0.15
		HCR 5 (Avg F)	0	0	0.11	0.1	0.12	0.11
	Est M	HCR 1a (NPFMC)	0	0	0.01	0.01	0.01	0.01
		HCR 1b (Dynamic NPFMC)	0	0	0.01	0.01	0.01	0.01
		HCR 2a (PFMC)	0	0	0.01	0.01	0.01	0.01
		HCR 2b (Dynamic PFMC)	0	0	0.01	0.01	0.01	0.01
		HCR 3a (SESSF)	0	0	0.01	0.01	0.01	0
		HCR 3b (Dynamic SESSF)	0	0	0.01	0.01	0.01	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0

Supplementary Table S2.6.PM-5. Summary of performance metric 5 (probability that the population is perceived as undergoing overfishing in the terminal year of the EM) across OMs for **Arrowtooth flounder**.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker
EBS	Fix M	HCR 1a (NPFMC)	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0	0
		HCR 2a (PFMC)	0	0	0	0	0	0
		HCR 2b (Dynamic PFMC)	0	0	0	0	0	0
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0
	Est M	HCR 1a (NPFMC)	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0	0
		HCR 2a (PFMC)	0	0	0	0	0	0
		HCR 2b (Dynamic PFMC)	0	0	0	0	0	0
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0
GOA	Fix M	HCR 1a (NPFMC)	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0	0
		HCR 2a (PFMC)	0	0	0	0	0	0
		HCR 2b (Dynamic PFMC)	0	0	0	0	0	0
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0
	Est M	HCR 1a (NPFMC)	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0	0
		HCR 2a (PFMC)	0	0	0	0	0	0
		HCR 2b (Dynamic PFMC)	0	0	0	0	0	0
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0

Supplementary Table S2.6.PM-6. Summary of performance metric 6 (probability that the population is perceived to be overfished in the terminal year of the EM) across OMs for **Arrowtooth flounder**.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker
EBS	Fix M	HCR 1a (NPFMC)	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0	0
		HCR 2a (PFMC)	0	0	0	0	0	0
		HCR 2b (Dynamic PFMC)	0	0	0	0	0	0
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0
	Est M	HCR 1a (NPFMC)	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0	0
		HCR 2a (PFMC)	0	0	0	0	0	0
		HCR 2b (Dynamic PFMC)	0	0	0	0	0	0
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0
GOA	Fix M	HCR 1a (NPFMC)	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0	0
		HCR 2a (PFMC)	0	0	0	0	0	0
		HCR 2b (Dynamic PFMC)	0	0	0	0	0	0
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0
	Est M	HCR 1a (NPFMC)	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0	0
		HCR 2a (PFMC)	0	0	0	0	0	0
		HCR 2b (Dynamic PFMC)	0	0	0	0	0	0
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0

Supplementary Table S2.6.PM-7. Summary of performance metric 7 (probability that the population is undergoing overfishing as determined from the OM) across OMs for **Arrowtooth flounder**.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker
EBS	Fix M	HCR 1a (NPFMC)	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0	0
		HCR 2a (PFMC)	0	0	0	0	0	0
		HCR 2b (Dynamic PFMC)	0	0	0	0	0	0
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0
	Est M	HCR 1a (NPFMC)	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0	0
		HCR 2a (PFMC)	0	0	0	0	0	0
		HCR 2b (Dynamic PFMC)	0	0	0	0	0	0
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0
GOA	Fix M	HCR 1a (NPFMC)	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0	0
		HCR 2a (PFMC)	0	0	0	0	0	0
		HCR 2b (Dynamic PFMC)	0	0	0	0	0	0
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0
	Est M	HCR 1a (NPFMC)	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0	0
		HCR 2a (PFMC)	0	0	0	0	0	0
		HCR 2b (Dynamic PFMC)	0	0	0	0	0	0
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0

Supplementary Table S2.6.PM-8. Summary of performance metric 8 (probability that the population is overfished as determined from the OM) across OMs for **Arrowtooth flounder**.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker
<i>EBS</i>	<i>Fix M</i>	HCR 1a (NPFMC)	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0	0
		HCR 2a (PFMC)	0	0	0	0	0	0
		HCR 2b (Dynamic PFMC)	0	0	0	0	0	0
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0
	<i>Est M</i>	HCR 1a (NPFMC)	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0	0
		HCR 2a (PFMC)	0	0	0	0	0.01	0
		HCR 2b (Dynamic PFMC)	0	0	0	0	0.01	0
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0
<i>GOA</i>	<i>Fix M</i>	HCR 1a (NPFMC)	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0	0
		HCR 2a (PFMC)	0	0	0	0	0	0
		HCR 2b (Dynamic PFMC)	0	0	0	0	0	0
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0
	<i>Est M</i>	HCR 1a (NPFMC)	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0	0
		HCR 2a (PFMC)	0	0	0	0	0	0
		HCR 2b (Dynamic PFMC)	0	0	0	0	0	0
		HCR 3a (SESSF)	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	0	0	0	0	0	0
		HCR 4 (NEFMC)	0	0	0	0	0	0
		HCR 5 (Avg F)	0	0	0	0	0	0

Supplementary Table S2.6.PM-9. Summary of performance metric 9 (terminal spawning stock biomass depletion relative to equilibrium SB0) across OMs for **Arrowtooth flounder**.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker
EBS	Fix M	HCR 1a (NPFMC)	0.41	0.63	0.53	0.83	0.57	0.85
		HCR 1b (Dynamic NPFMC)	0.4	0.63	0.53	0.84	0.58	0.86
		HCR 2a (PFMC)	0.38	0.6	0.51	0.8	0.55	0.82
		HCR 2b (Dynamic PFMC)	0.38	0.6	0.51	0.8	0.55	0.82
		HCR 3a (SESSF)	0.48	0.76	0.6	0.94	0.64	0.95
		HCR 3b (Dynamic SESSF)	0.48	0.76	0.6	0.94	0.64	0.95
		HCR 4 (NEFMC)	0.56	0.87	0.67	1.04	0.71	1.04
		HCR 5 (Avg F)	0.81	1.13	0.87	1.26	0.92	1.24
	Est M	HCR 1a (NPFMC)	0.4	0.61	0.41	0.6	0.44	0.64
		HCR 1b (Dynamic NPFMC)	0.39	0.61	0.4	0.6	0.44	0.64
		HCR 2a (PFMC)	0.37	0.58	0.37	0.53	0.4	0.58
		HCR 2b (Dynamic PFMC)	0.37	0.58	0.37	0.53	0.4	0.58
		HCR 3a (SESSF)	0.47	0.74	0.48	0.75	0.52	0.78
		HCR 3b (Dynamic SESSF)	0.47	0.74	0.48	0.75	0.52	0.78
		HCR 4 (NEFMC)	0.55	0.86	0.54	0.86	0.59	0.87
		HCR 5 (Avg F)	0.81	1.13	0.86	1.25	0.91	1.22
GOA	Fix M	HCR 1a (NPFMC)	0.4	0.67	0.47	0.72	0.49	0.72
		HCR 1b (Dynamic NPFMC)	0.4	0.67	0.47	0.72	0.49	0.72
		HCR 2a (PFMC)	0.38	0.64	0.45	0.69	0.47	0.69
		HCR 2b (Dynamic PFMC)	0.38	0.64	0.45	0.69	0.47	0.69
		HCR 3a (SESSF)	0.48	0.79	0.54	0.83	0.57	0.85
		HCR 3b (Dynamic SESSF)	0.48	0.79	0.54	0.83	0.57	0.85
		HCR 4 (NEFMC)	0.55	0.88	0.61	0.92	0.63	0.94
		HCR 5 (Avg F)	0.87	1.19	0.89	1.22	0.9	1.27
	Est M	HCR 1a (NPFMC)	0.42	0.69	0.42	0.61	0.46	0.65
		HCR 1b (Dynamic NPFMC)	0.42	0.69	0.42	0.61	0.46	0.65
		HCR 2a (PFMC)	0.41	0.67	0.39	0.56	0.43	0.59
		HCR 2b (Dynamic PFMC)	0.41	0.67	0.39	0.56	0.43	0.59
		HCR 3a (SESSF)	0.49	0.8	0.49	0.75	0.53	0.79
		HCR 3b (Dynamic SESSF)	0.49	0.8	0.49	0.75	0.53	0.79
		HCR 4 (NEFMC)	0.56	0.89	0.55	0.83	0.58	0.87
		HCR 5 (Avg F)	0.85	1.17	0.87	1.2	0.88	1.25

Supplementary Table S2.6.PM-10. Summary of performance metric 10 (terminal spawning stock biomass depletion relative to dynamic SB0) across OMs for **Arrowtooth flounder**.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker
EBS	Fix M	HCR 1a (NPFMC)	0.41	0.49	0.53	0.6	0.57	0.63
		HCR 1b (Dynamic NPFMC)	0.4	0.49	0.53	0.61	0.57	0.63
		HCR 2a (PFMC)	0.38	0.47	0.51	0.58	0.55	0.61
		HCR 2b (Dynamic PFMC)	0.38	0.47	0.51	0.58	0.55	0.61
		HCR 3a (SESSF)	0.48	0.59	0.6	0.68	0.64	0.7
		HCR 3b (Dynamic SESSF)	0.48	0.59	0.6	0.68	0.64	0.7
		HCR 4 (NEFMC)	0.56	0.68	0.67	0.75	0.71	0.77
		HCR 5 (Avg F)	0.81	0.88	0.87	0.91	0.92	0.91
	Est M	HCR 1a (NPFMC)	0.39	0.47	0.41	0.43	0.44	0.47
		HCR 1b (Dynamic NPFMC)	0.39	0.47	0.4	0.43	0.44	0.47
		HCR 2a (PFMC)	0.37	0.45	0.37	0.38	0.4	0.43
		HCR 2b (Dynamic PFMC)	0.37	0.45	0.37	0.38	0.4	0.43
		HCR 3a (SESSF)	0.47	0.57	0.48	0.54	0.52	0.58
		HCR 3b (Dynamic SESSF)	0.47	0.57	0.48	0.54	0.52	0.58
		HCR 4 (NEFMC)	0.55	0.67	0.54	0.62	0.58	0.65
		HCR 5 (Avg F)	0.81	0.88	0.86	0.9	0.9	0.9
GOA	Fix M	HCR 1a (NPFMC)	0.4	0.52	0.47	0.55	0.49	0.53
		HCR 1b (Dynamic NPFMC)	0.4	0.52	0.47	0.55	0.49	0.53
		HCR 2a (PFMC)	0.38	0.5	0.45	0.53	0.47	0.51
		HCR 2b (Dynamic PFMC)	0.38	0.5	0.45	0.53	0.47	0.51
		HCR 3a (SESSF)	0.48	0.61	0.55	0.64	0.57	0.63
		HCR 3b (Dynamic SESSF)	0.48	0.61	0.55	0.64	0.57	0.63
		HCR 4 (NEFMC)	0.55	0.68	0.61	0.7	0.63	0.7
		HCR 5 (Avg F)	0.87	0.92	0.89	0.93	0.9	0.94
	Est M	HCR 1a (NPFMC)	0.42	0.53	0.42	0.47	0.46	0.48
		HCR 1b (Dynamic NPFMC)	0.41	0.53	0.42	0.47	0.46	0.48
		HCR 2a (PFMC)	0.4	0.52	0.39	0.43	0.43	0.43
		HCR 2b (Dynamic PFMC)	0.4	0.52	0.39	0.43	0.43	0.43
		HCR 3a (SESSF)	0.49	0.62	0.5	0.57	0.53	0.58
		HCR 3b (Dynamic SESSF)	0.49	0.62	0.5	0.57	0.53	0.58
		HCR 4 (NEFMC)	0.56	0.69	0.55	0.63	0.58	0.64
		HCR 5 (Avg F)	0.85	0.91	0.87	0.92	0.88	0.92

Supplementary Tables 7. Number of times a management strategy performed the best for performance metrics across OMs.

Supplementary Table S2.7a. Number of times a management strategy performed the best for performance metrics across OMs for **Pollock**. Note, the maximum for each OM is 10 and across OMs is 60.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker	All OMs
EBS	Fix M	HCR 1a (NPFMC)	3	2	5	3	5	3	21
		HCR 1b (Dynamic NPFMC)	4	2	4	2	4	3	19
		HCR 2a (PFMC)	2	2	2	3	3	3	15
		HCR 2b (Dynamic PFMC)	3	3	4	3	3	3	19
		HCR 3a (SESSF)	5	3	5	5	5	3	26
		HCR 3b (Dynamic SESSF)	5	5	5	5	5	5	30
		HCR 4 (NEFMC)	8	8	9	9	8	9	51
	Est M	HCR 1a (NPFMC)	1	1	2	2	1	1	8
		HCR 1b (Dynamic NPFMC)	4	2	4	3	2	2	17
		HCR 2a (PFMC)	1	1	1	1	2	1	7
		HCR 2b (Dynamic PFMC)	1	1	1	1	2	1	7
		HCR 3a (SESSF)	2	3	2	3	3	2	15
		HCR 3b (Dynamic SESSF)	5	3	5	3	5	2	23
		HCR 4 (NEFMC)	4	3	3	3	5	2	20
GOA	Fix M	HCR 1a (NPFMC)	0	2	0	3	4	4	13
		HCR 1b (Dynamic NPFMC)	2	2	2	2	3	4	15
		HCR 2a (PFMC)	1	2	1	1	4	6	15
		HCR 2b (Dynamic PFMC)	2	2	2	2	4	4	16
		HCR 3a (SESSF)	2	5	2	5	5	5	24
		HCR 3b (Dynamic SESSF)	5	4	4	4	5	5	27
		HCR 4 (NEFMC)	6	8	3	5	8	6	36
	Est M	HCR 1a (NPFMC)	0	1	0	2	0	0	3
		HCR 1b (Dynamic NPFMC)	1	0	2	2	2	0	7
		HCR 2a (PFMC)	0	1	1	2	2	4	10
		HCR 2b (Dynamic PFMC)	1	0	2	2	2	1	8
		HCR 3a (SESSF)	1	1	2	5	2	3	14
		HCR 3b (Dynamic SESSF)	1	1	5	4	4	2	17
		HCR 4 (NEFMC)	2	3	5	7	4	2	23

Supplementary Table S2.7b. Number of times a management strategy performed the best for performance metrics across OMs for **Cod**. Note, the maximum for each OM is 10 and across OMs is 60.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker	All OMs
<i>EBS</i>	<i>Fix M</i>	HCR 1a (NPFMC)	3	5	4	5	4	5	26
		HCR 1b (Dynamic NPFMC)	6	5	6	6	5	6	34
		HCR 2a (PFMC)	2	3	2	3	3	3	16
		HCR 2b (Dynamic PFMC)	4	4	4	4	4	4	24
		HCR 3a (SESSF)	5	5	5	5	5	5	30
		HCR 3b (Dynamic SESSF)	5	5	5	5	5	5	30
		HCR 4 (NEFMC)	8	8	6	8	6	7	43
	<i>Est M</i>	HCR 1a (NPFMC)	3	5	4	5	5	5	27
		HCR 1b (Dynamic NPFMC)	6	7	5	6	6	6	36
		HCR 2a (PFMC)	2	3	2	2	3	3	15
		HCR 2b (Dynamic PFMC)	4	4	4	3	4	4	23
		HCR 3a (SESSF)	5	5	5	5	5	5	30
		HCR 3b (Dynamic SESSF)	5	5	5	5	5	5	30
		HCR 4 (NEFMC)	5	5	8	5	8	6	37
<i>GOA</i>	<i>Fix M</i>	HCR 1a (NPFMC)	0	2	0	1	1	2	6
		HCR 1b (Dynamic NPFMC)	2	0	1	0	1	1	5
		HCR 2a (PFMC)	1	1	0	0	2	2	6
		HCR 2b (Dynamic PFMC)	1	1	1	1	2	2	8
		HCR 3a (SESSF)	2	2	2	2	2	2	12
		HCR 3b (Dynamic SESSF)	5	4	2	3	4	4	22
		HCR 4 (NEFMC)	1	3	1	1	2	2	10
	<i>Est M</i>	HCR 1a (NPFMC)	1	1	0	0	1	1	4
		HCR 1b (Dynamic NPFMC)	2	1	0	1	2	1	7
		HCR 2a (PFMC)	1	1	1	1	2	2	8
		HCR 2b (Dynamic PFMC)	2	1	1	1	2	2	9
		HCR 3a (SESSF)	2	3	2	3	3	5	18
		HCR 3b (Dynamic SESSF)	5	5	3	3	4	4	24
		HCR 4 (NEFMC)	7	8	6	6	7	7	41

Supplementary Table S2.7c. Number of times a management strategy performed the best for performance metrics across OMs for **Arrowtooth flounder**. Note, the maximum for each OM is 10 and across OMs is 60.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker	All OMs
EBS	Fix M	HCR 1a (NPFMC)	5	5	5	5	5	5	30
		HCR 1b (Dynamic NPFMC)	5	5	5	5	5	5	30
		HCR 2a (PFMC)	5	5	5	5	5	5	30
		HCR 2b (Dynamic PFMC)	5	5	5	5	5	5	30
		HCR 3a (SESSF)	5	5	5	5	5	5	30
		HCR 3b (Dynamic SESSF)	5	5	5	5	5	5	30
		HCR 4 (NEFMC)	8	8	9	8	9	8	50
	Est M	HCR 1a (NPFMC)	5	5	5	5	4	5	29
		HCR 1b (Dynamic NPFMC)	5	5	5	4	4	5	28
		HCR 2a (PFMC)	5	6	5	6	4	5	31
		HCR 2b (Dynamic PFMC)	7	6	6	5	5	4	33
		HCR 3a (SESSF)	5	5	5	5	5	5	30
		HCR 3b (Dynamic SESSF)	5	5	5	5	5	5	30
		HCR 4 (NEFMC)	5	5	5	6	5	6	32
GOA	Fix M	HCR 1a (NPFMC)	5	5	5	5	5	5	30
		HCR 1b (Dynamic NPFMC)	5	5	5	5	5	5	30
		HCR 2a (PFMC)	6	5	5	6	5	6	33
		HCR 2b (Dynamic PFMC)	5	6	6	5	6	5	33
		HCR 3a (SESSF)	5	5	5	5	5	5	30
		HCR 3b (Dynamic SESSF)	5	5	5	5	5	5	30
		HCR 4 (NEFMC)	5	5	8	8	8	8	42
	Est M	HCR 1a (NPFMC)	5	5	5	5	5	5	30
		HCR 1b (Dynamic NPFMC)	5	5	5	5	5	5	30
		HCR 2a (PFMC)	6	6	4	5	5	6	32
		HCR 2b (Dynamic PFMC)	5	5	5	6	6	5	32
		HCR 3a (SESSF)	5	5	5	5	5	5	30
		HCR 3b (Dynamic SESSF)	5	5	5	5	5	5	30
		HCR 4 (NEFMC)	8	8	5	5	5	5	36

Supplementary Tables 8. Number of times a management strategy performed the best for economic performance metrics (1-3) across OMs.

Supplementary Table S2.8a. Number of times a management strategy performed the best for economic performance metrics (1-3) across OMs for **Pollock**. Note, the maximum for each OM is 3 and across OMs is 18.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker	All OMs
EBS	Fix M	HCR 1a (NPFMC)	0	0	1	0	1	0	2
		HCR 1b (Dynamic NPFMC)	1	0	1	0	0	0	2
		HCR 2a (PFMC)	1	1	1	1	1	1	6
		HCR 2b (Dynamic PFMC)	1	1	1	1	1	1	6
		HCR 3a (SESSF)	1	0	1	1	1	0	4
		HCR 3b (Dynamic SESSF)	1	1	1	1	1	1	6
		HCR 4 (NEFMC)	2	2	2	2	2	2	12
	Est M	HCR 1a (NPFMC)	0	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	2	1	1	1	1	1	7
		HCR 2a (PFMC)	1	1	1	1	1	0	5
		HCR 2b (Dynamic PFMC)	1	1	1	1	1	0	5
		HCR 3a (SESSF)	0	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	1	0	1	0	1	0	3
		HCR 4 (NEFMC)	1	1	1	1	1	1	6
GOA	Fix M	HCR 1a (NPFMC)	0	0	0	1	1	1	3
		HCR 1b (Dynamic NPFMC)	1	1	1	1	1	1	6
		HCR 2a (PFMC)	1	1	1	1	1	1	6
		HCR 2b (Dynamic PFMC)	1	1	1	1	1	1	6
		HCR 3a (SESSF)	0	1	0	1	1	1	4
		HCR 3b (Dynamic SESSF)	1	1	1	1	1	1	6
		HCR 4 (NEFMC)	2	2	1	1	2	2	10
	Est M	HCR 1a (NPFMC)	0	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	1	0	1	1	1	0	4
		HCR 2a (PFMC)	0	1	1	1	1	2	6
		HCR 2b (Dynamic PFMC)	1	0	1	1	1	0	4
		HCR 3a (SESSF)	0	0	0	1	0	0	1
		HCR 3b (Dynamic SESSF)	0	1	1	1	1	0	4
		HCR 4 (NEFMC)	1	1	2	2	1	1	8

Supplementary Table S2.8b. Number of times a management strategy performed the best for economic performance metrics (1-3) across OMs for **Cod**. Note, the maximum for each OM is 3 and across OMs is 18.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker	All OMs
EBS	Fix M	HCR 1a (NPFMC)	0	1	1	1	0	1	4
		HCR 1b (Dynamic NPFMC)	1	1	2	1	1	1	7
		HCR 2a (PFMC)	1	1	1	1	1	1	6
		HCR 2b (Dynamic PFMC)	1	1	1	1	1	1	6
		HCR 3a (SESSF)	1	1	1	1	1	1	6
		HCR 3b (Dynamic SESSF)	1	1	1	1	1	1	6
		HCR 4 (NEFMC)	2	2	1	2	1	1	9
	Est M	HCR 1a (NPFMC)	0	1	1	1	1	1	5
		HCR 1b (Dynamic NPFMC)	2	2	1	2	2	2	11
		HCR 2a (PFMC)	1	1	1	1	1	1	6
		HCR 2b (Dynamic PFMC)	1	1	1	1	1	1	6
		HCR 3a (SESSF)	1	1	1	1	1	1	6
		HCR 3b (Dynamic SESSF)	1	1	1	1	1	1	6
		HCR 4 (NEFMC)	1	1	2	1	2	2	9
GOA	Fix M	HCR 1a (NPFMC)	0	1	0	1	0	1	3
		HCR 1b (Dynamic NPFMC)	1	0	1	0	1	0	3
		HCR 2a (PFMC)	1	1	0	0	1	1	4
		HCR 2b (Dynamic PFMC)	1	1	1	1	1	1	6
		HCR 3a (SESSF)	0	0	0	0	0	0	0
		HCR 3b (Dynamic SESSF)	1	1	0	1	1	1	5
		HCR 4 (NEFMC)	1	1	1	1	1	1	6
	Est M	HCR 1a (NPFMC)	0	0	0	0	0	0	0
		HCR 1b (Dynamic NPFMC)	0	0	0	0	0	0	0
		HCR 2a (PFMC)	1	1	1	1	1	1	6
		HCR 2b (Dynamic PFMC)	1	1	1	1	1	1	6
		HCR 3a (SESSF)	0	0	0	0	0	1	1
		HCR 3b (Dynamic SESSF)	1	1	0	0	1	1	4
		HCR 4 (NEFMC)	2	2	2	2	2	2	12

Supplementary Table S2.8c. Number of times a management strategy performed the best for economic performance metrics (1-3) across OM for **Arrowtooth flounder**. Note, the maximum for each OM is 3 and across OM is 18.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker	All OMs
EBS	Fix M	HCR 1a (NPFMC)	1	1	1	1	1	1	6
		HCR 1b (Dynamic NPFMC)	1	1	1	1	1	1	6
		HCR 2a (PFMC)	1	1	1	1	1	1	6
		HCR 2b (Dynamic PFMC)	1	1	1	1	1	1	6
		HCR 3a (SESSF)	1	1	1	1	1	1	6
		HCR 3b (Dynamic SESSF)	1	1	1	1	1	1	6
		HCR 4 (NEFMC)	2	2	2	1	2	1	10
	Est M	HCR 1a (NPFMC)	1	1	1	1	1	1	6
		HCR 1b (Dynamic NPFMC)	1	1	1	1	1	1	6
		HCR 2a (PFMC)	1	1	1	2	1	2	8
		HCR 2b (Dynamic PFMC)	2	2	2	1	2	1	10
		HCR 3a (SESSF)	1	1	1	1	1	1	6
		HCR 3b (Dynamic SESSF)	1	1	1	1	1	1	6
		HCR 4 (NEFMC)	1	1	1	2	1	2	8
GOA	Fix M	HCR 1a (NPFMC)	1	1	1	1	1	1	6
		HCR 1b (Dynamic NPFMC)	1	1	1	1	1	1	6
		HCR 2a (PFMC)	2	1	1	1	1	1	7
		HCR 2b (Dynamic PFMC)	1	2	1	1	1	1	7
		HCR 3a (SESSF)	1	1	1	1	1	1	6
		HCR 3b (Dynamic SESSF)	1	1	1	1	1	1	6
		HCR 4 (NEFMC)	1	1	2	2	2	2	10
	Est M	HCR 1a (NPFMC)	1	1	1	1	1	1	6
		HCR 1b (Dynamic NPFMC)	1	1	1	1	1	1	6
		HCR 2a (PFMC)	1	1	1	1	1	2	7
		HCR 2b (Dynamic PFMC)	1	1	2	2	2	1	9
		HCR 3a (SESSF)	1	1	1	1	1	1	6
		HCR 3b (Dynamic SESSF)	1	1	1	1	1	1	6
		HCR 4 (NEFMC)	2	2	1	1	1	1	8

Supplementary Tables 9. Number of times a management strategy performed the best for conservation performance metrics (5-8) across OMs.

Supplementary Table S2.9a. Number of times a management strategy performed the best for conservation performance metrics (5-8) across OMs for **Pollock**. Note, the maximum for each OM is 4 and across OMs is 24.

System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker	All OMs
EBS	Fix M	HCR 1a (NPFMC)	3	2	4	3	4	3	19
		HCR 1b (Dynamic NPFMC)	3	2	3	2	4	3	17
		HCR 2a (PFMC)	1	1	1	2	2	2	9
		HCR 2b (Dynamic PFMC)	2	2	3	2	2	2	13
		HCR 3a (SESSF)	4	3	4	4	4	3	22
		HCR 3b (Dynamic SESSF)	4	4	4	4	4	4	24
		HCR 4 (NEFMC)	4	4	4	4	4	4	24
	Est M	HCR 1a (NPFMC)	1	1	2	2	1	1	8
		HCR 1b (Dynamic NPFMC)	2	1	3	2	1	1	10
		HCR 2a (PFMC)	0	0	0	0	1	1	2
		HCR 2b (Dynamic PFMC)	0	0	0	0	1	1	2
		HCR 3a (SESSF)	2	3	2	3	3	2	15
		HCR 3b (Dynamic SESSF)	4	3	4	3	4	2	20
		HCR 4 (NEFMC)	2	1	2	2	3	1	11
GOA	Fix M	HCR 1a (NPFMC)	0	2	0	2	3	3	10
		HCR 1b (Dynamic NPFMC)	1	1	1	1	2	3	9
		HCR 2a (PFMC)	0	1	0	0	3	3	7
		HCR 2b (Dynamic PFMC)	1	1	1	1	3	3	10
		HCR 3a (SESSF)	2	4	2	4	4	4	20
		HCR 3b (Dynamic SESSF)	4	3	3	3	4	4	21
		HCR 4 (NEFMC)	2	4	1	3	4	4	18
	Est M	HCR 1a (NPFMC)	0	1	0	2	0	0	3
		HCR 1b (Dynamic NPFMC)	0	0	1	1	1	0	3
		HCR 2a (PFMC)	0	0	0	1	1	1	3
		HCR 2b (Dynamic PFMC)	0	0	1	1	1	1	4
		HCR 3a (SESSF)	1	1	2	4	2	3	13
		HCR 3b (Dynamic SESSF)	1	0	4	3	3	2	13
		HCR 4 (NEFMC)	0	1	1	3	2	1	8

Supplementary Table S2.9b. Number of times a management strategy performed the best for conservation performance metrics (5-8) across OM_s for **Cod**. Note, the maximum for each OM is 4 and across OM_s is 24.

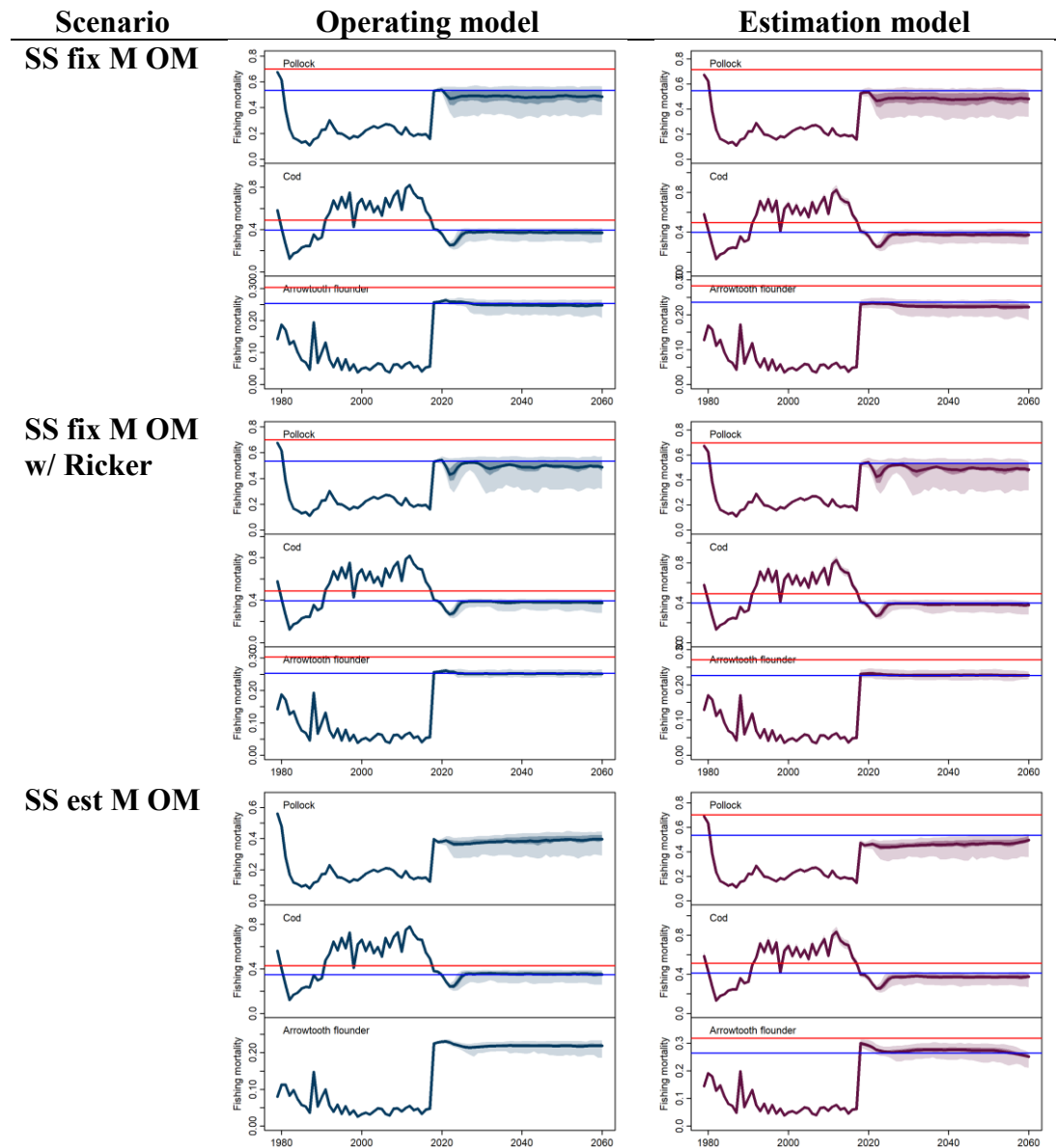
System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker	All OM _s
<i>EBS</i>	<i>Fix M</i>	HCR 1a (NPFMC)	3	4	3	4	4	4	22
		HCR 1b (Dynamic NPFMC)	4	4	4	4	4	4	24
		HCR 2a (PFMC)	1	2	1	2	2	2	10
		HCR 2b (Dynamic PFMC)	3	3	3	3	3	3	18
		HCR 3a (SESSF)	4	4	4	4	4	4	24
		HCR 3b (Dynamic SESSF)	4	4	4	4	4	4	24
		HCR 4 (NEFMC)	4	4	4	4	4	4	24
	<i>Est M</i>	HCR 1a (NPFMC)	3	4	3	4	4	4	22
		HCR 1b (Dynamic NPFMC)	4	4	4	4	4	4	24
		HCR 2a (PFMC)	1	2	1	1	2	2	9
		HCR 2b (Dynamic PFMC)	3	3	3	2	3	3	17
		HCR 3a (SESSF)	4	4	4	4	4	4	24
		HCR 3b (Dynamic SESSF)	4	4	4	4	4	4	24
		HCR 4 (NEFMC)	4	4	4	4	4	4	24
<i>GOA</i>	<i>Fix M</i>	HCR 1a (NPFMC)	0	1	0	0	1	1	3
		HCR 1b (Dynamic NPFMC)	1	0	0	0	0	1	2
		HCR 2a (PFMC)	0	0	0	0	1	1	2
		HCR 2b (Dynamic PFMC)	0	0	0	0	1	1	2
		HCR 3a (SESSF)	2	2	1	1	2	2	10
		HCR 3b (Dynamic SESSF)	4	3	2	2	3	3	17
		HCR 4 (NEFMC)	0	2	0	0	1	1	4
	<i>Est M</i>	HCR 1a (NPFMC)	1	1	0	0	1	1	4
		HCR 1b (Dynamic NPFMC)	2	1	0	1	2	1	7
		HCR 2a (PFMC)	0	0	0	0	1	1	2
		HCR 2b (Dynamic PFMC)	1	0	0	0	1	1	3
		HCR 3a (SESSF)	2	3	2	3	3	4	17
		HCR 3b (Dynamic SESSF)	4	4	3	3	3	3	20
		HCR 4 (NEFMC)	2	3	2	2	2	2	13

Supplementary Table S2.9c. Number of times a management strategy performed the best for conservation performance metrics (5-8) across OM_s for **Arrowtooth flounder**. Note, the maximum for each OM is 4 and across OM_s is 24.

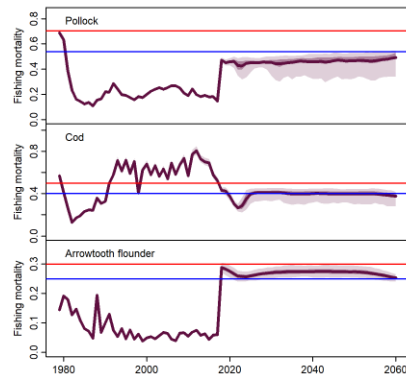
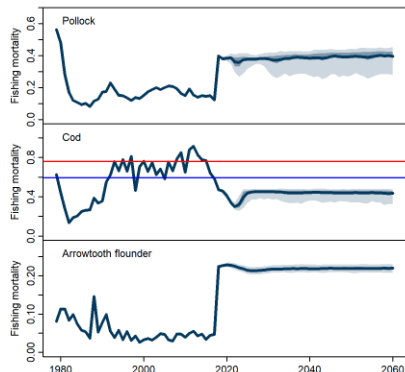
System	EM	HCR	1. SS fix M	2. w Ricker	3. SS est M	4. w Ricker	5. MS	6. w Ricker	All OM _s
EBS	Fix M	HCR 1a (NPFMC)	4	4	4	4	4	4	24
		HCR 1b (Dynamic NPFMC)	4	4	4	4	4	4	24
		HCR 2a (PFMC)	4	4	4	4	4	4	24
		HCR 2b (Dynamic PFMC)	4	4	4	4	4	4	24
		HCR 3a (SESSF)	4	4	4	4	4	4	24
		HCR 3b (Dynamic SESSF)	4	4	4	4	4	4	24
		HCR 4 (NEFMC)	4	4	4	4	4	4	24
	Est M	HCR 1a (NPFMC)	4	4	4	4	3	4	23
		HCR 1b (Dynamic NPFMC)	4	4	4	3	3	4	22
		HCR 2a (PFMC)	4	4	4	4	3	3	22
		HCR 2b (Dynamic PFMC)	4	4	4	4	3	3	22
		HCR 3a (SESSF)	4	4	4	4	4	4	24
		HCR 3b (Dynamic SESSF)	4	4	4	4	4	4	24
		HCR 4 (NEFMC)	4	4	4	4	4	4	24
GOA	Fix M	HCR 1a (NPFMC)	4	4	4	4	4	4	24
		HCR 1b (Dynamic NPFMC)	4	4	4	4	4	4	24
		HCR 2a (PFMC)	4	4	4	4	4	4	24
		HCR 2b (Dynamic PFMC)	4	4	4	4	4	4	24
		HCR 3a (SESSF)	4	4	4	4	4	4	24
		HCR 3b (Dynamic SESSF)	4	4	4	4	4	4	24
		HCR 4 (NEFMC)	4	4	4	4	4	4	24
	Est M	HCR 1a (NPFMC)	4	4	4	4	4	4	24
		HCR 1b (Dynamic NPFMC)	4	4	4	4	4	4	24
		HCR 2a (PFMC)	4	4	3	4	4	4	23
		HCR 2b (Dynamic PFMC)	4	4	3	4	4	4	23
		HCR 3a (SESSF)	4	4	4	4	4	4	24
		HCR 3b (Dynamic SESSF)	4	4	4	4	4	4	24
		HCR 4 (NEFMC)	4	4	4	4	4	4	24

SUPPLEMENTARY FIGURES

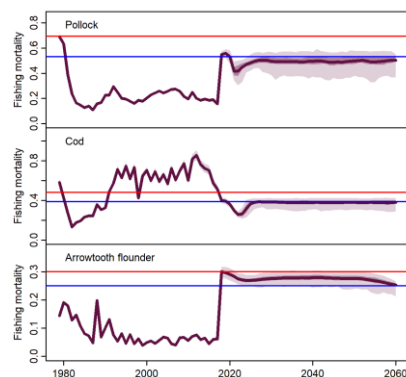
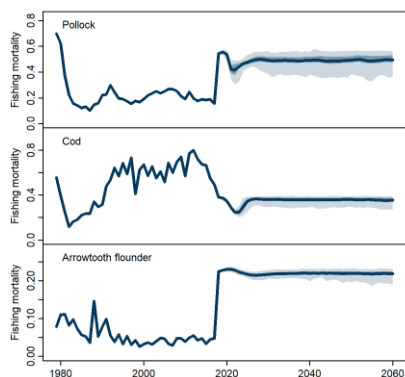
Supplementary Figure S2.1a. Time-series of fishing mortality as determined from OM and EM (OM; left) and terminal (i.e. 2060) estimation model (EM; right: with no stock-recruit relationship) that pre-specified natural mortality combined with HCR 1a (NPFMC Tier 3 harvest control rule) in the EBS. The EM is applied annually until 2060 across 300 simulations. Target and limit reference points are indicated by the blue and red lines, respectively. Note: for some OM, limit reference points are outside the axis.



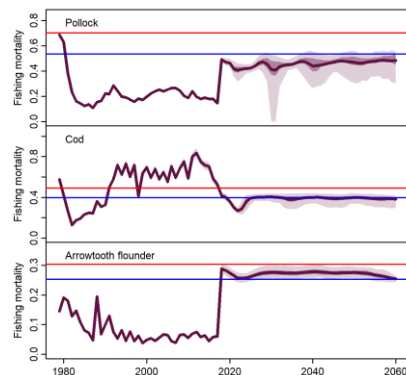
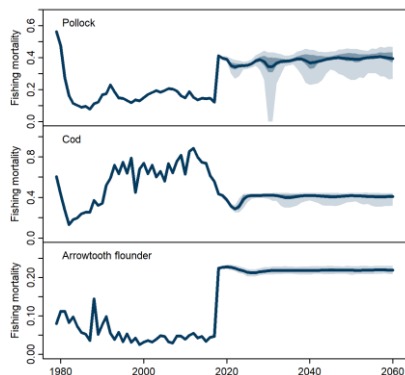
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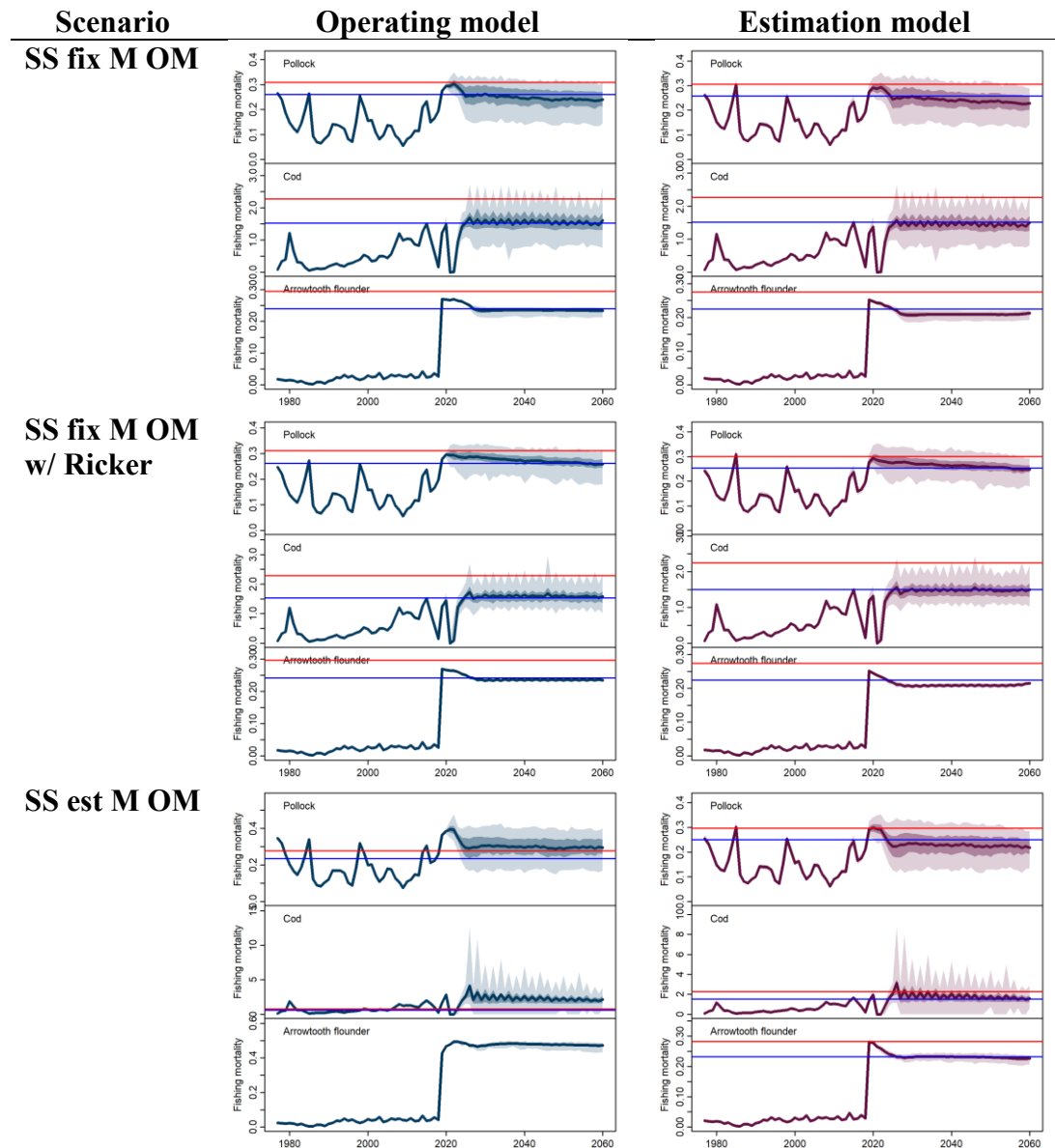
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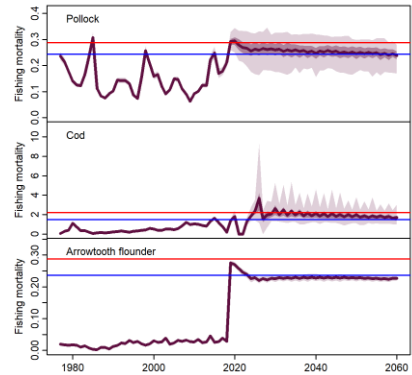
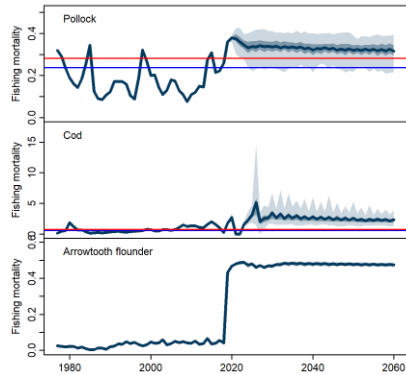
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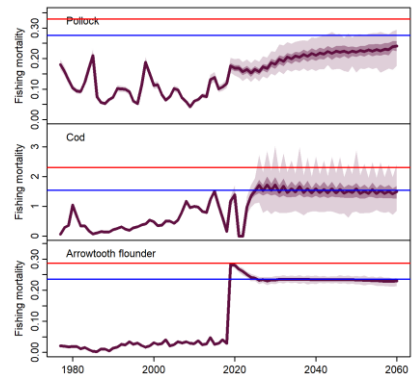
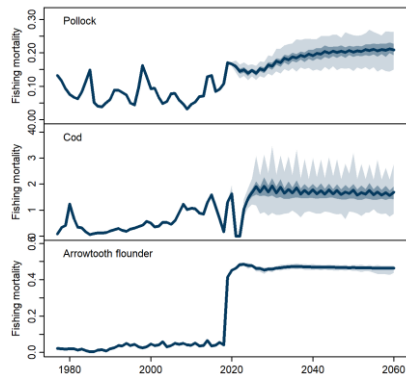
Supplementary Figure S2.1b. Time-series of fishing mortality as determined from OM and EM (OM; left) and terminal (i.e. 2060) estimation model (EM; right: with no stock-recruit relationship) that pre-specified natural mortality combined with HCR 1a (NPFMC Tier 3 harvest control rule) in the GOA. The EM is applied annually until 2060 across 300 simulations. Target and limit reference points are indicated by the blue and red lines, respectively. Note: for some OM, limit reference points are outside the axis.



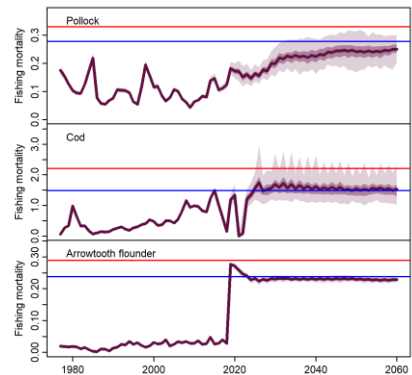
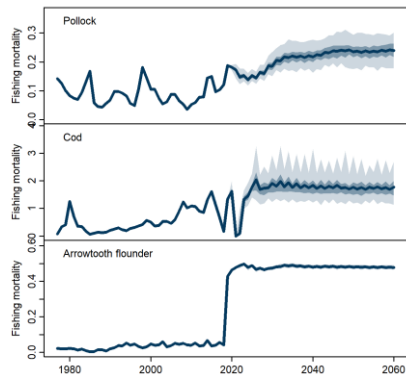
**SS est M OM
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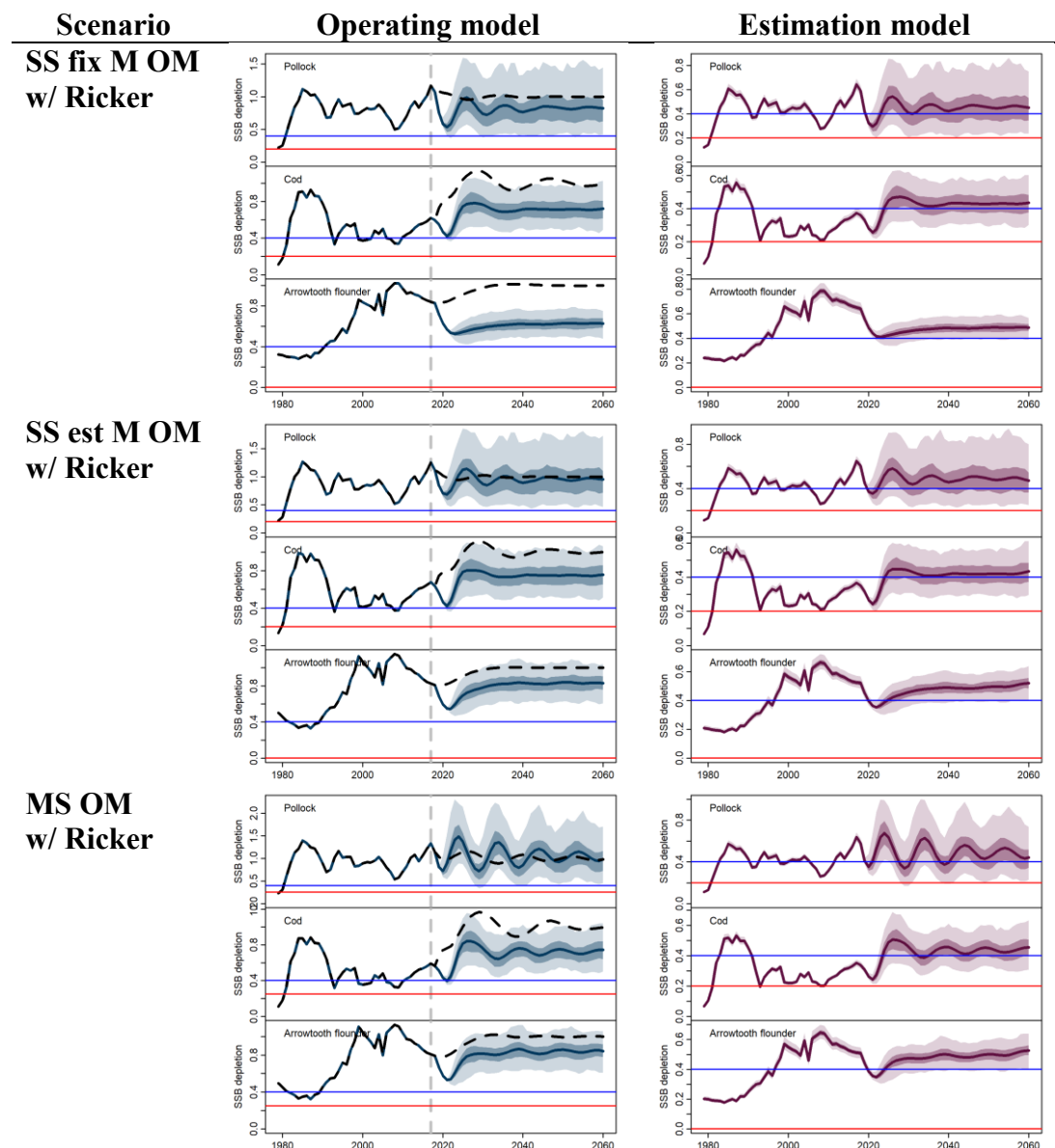
MS OM



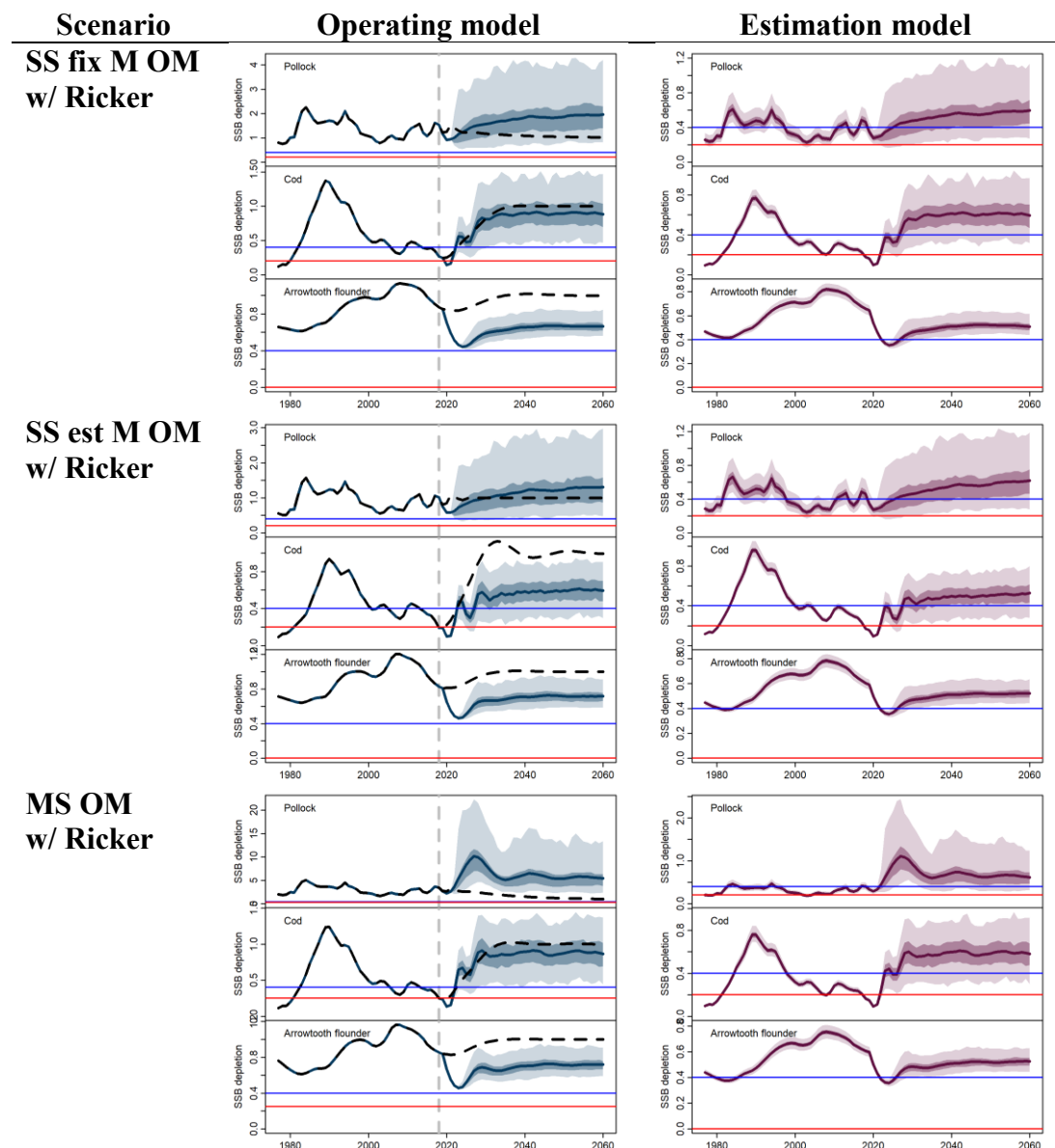
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w/ Ricker**



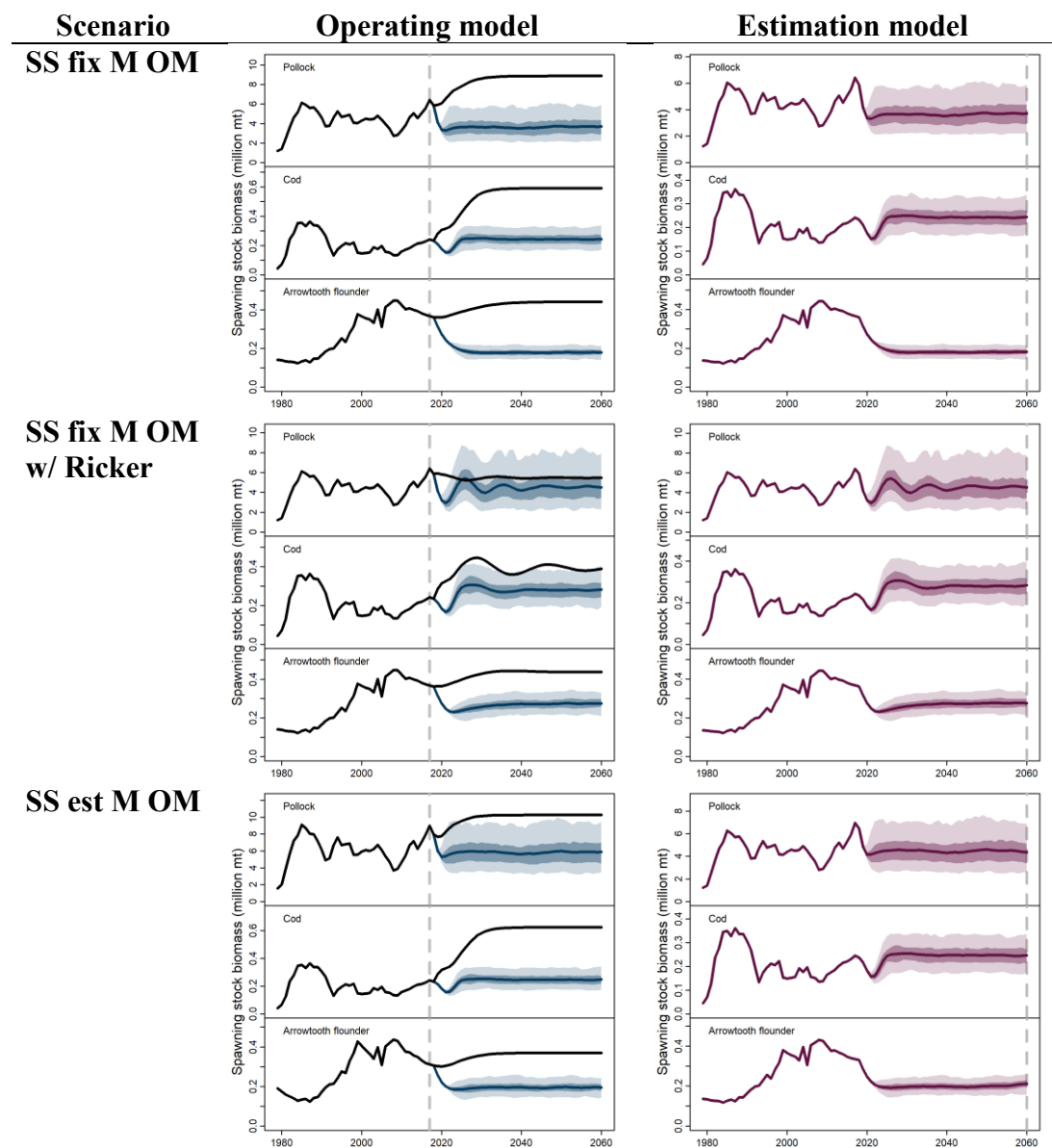
Supplementary Figure S2.2a. Time-series of spawning stock depletion as determined from the operating model with Ricker stock recruit relationship (OM; left) and terminal (i.e. 2060) estimation model (EM; right: with no stock recruit relationship) that pre-specified natural mortality combined with HCR 1a (NPFMC Tier 3 harvest control rule) in the EBS. The EM is applied annually until 2060 across 300 simulations. Depletion under for the OM given no fishing is indicated by the black dashed line and target and limit depletion are indicated by the blue and red lines, respectively (both EM and OM).



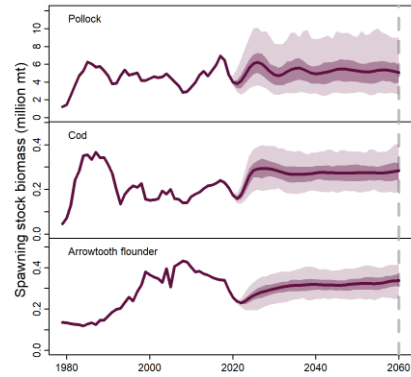
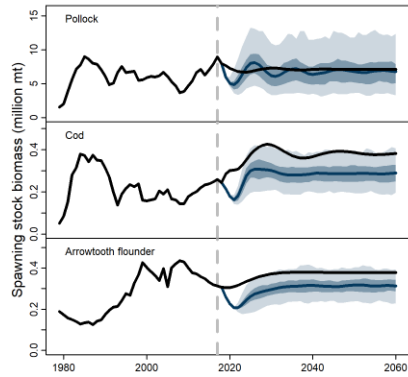
Supplementary Figure S2.2b. Time-series of spawning stock depletion as determined from the operating model with Ricker stock recruit relationship (OM; left) terminal (i.e. 2060) estimation model (EM; right: with no stock recruit relationship) that pre-specified natural mortality combined with HCR 1a (NPFMC Tier 3 harvest control rule) in the GOA. The EM is applied annually until 2060 across 300 simulations. Depletion under for the OM given no fishing is indicated by the black dashed line and target and limit depletion are indicated by the blue and red lines, respectively.



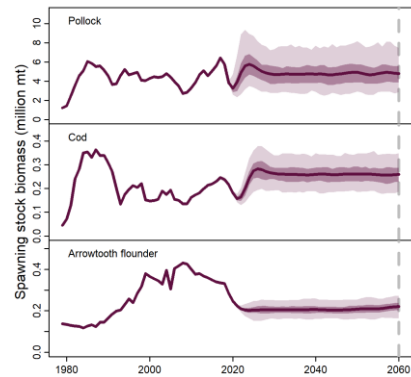
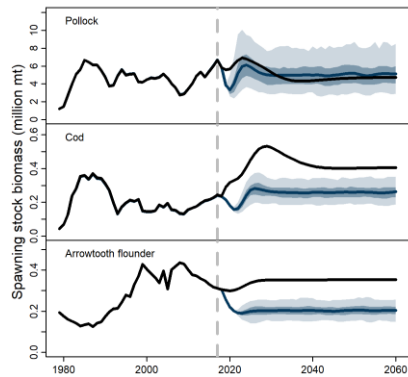
Supplementary Figure S2.3a. Time-series of spawning stock biomass as determined from OM and EM (OM; left) and terminal (i.e. 2060) estimation model (EM; right: with no stock recruit relationship) that pre-specified natural mortality combined with HCR 1a (NPFMC Tier 3 harvest control rule) in the EBS. The EM is applied annually until 2060 across 300 simulations.



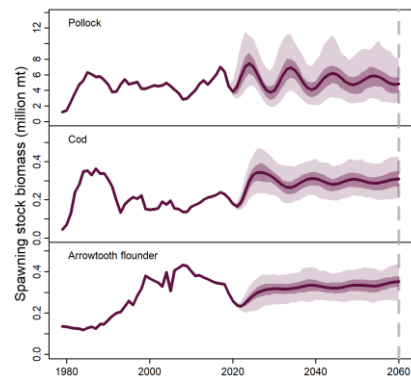
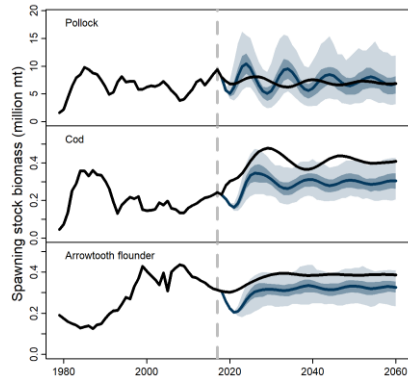
**SS est M OM
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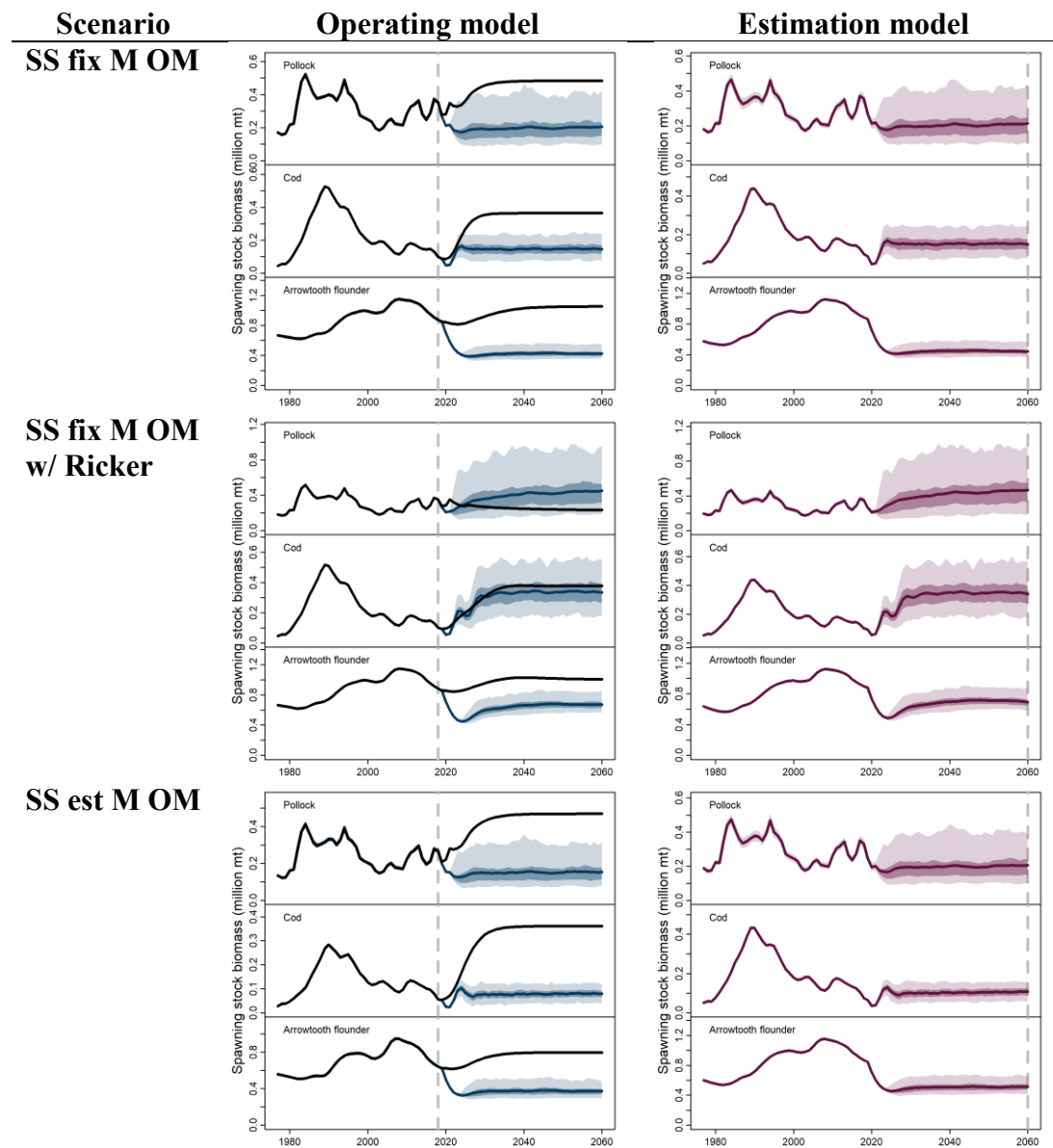
MS OM



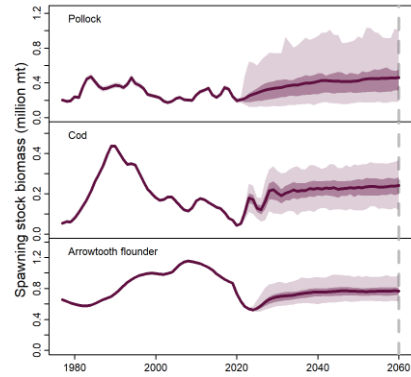
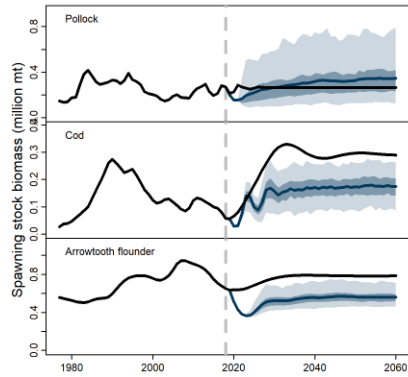
**MS OM
w/ Ricker**



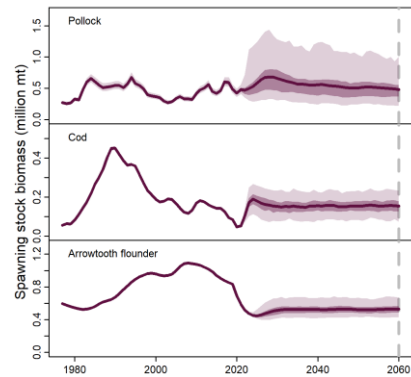
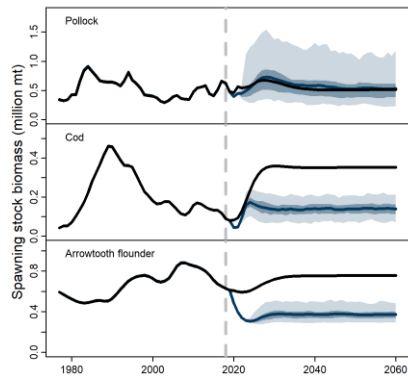
Supplementary Figure S2.3b. Time-series of spawning stock biomass as determined from OM and EM (OM; left) and terminal (i.e. 2060) estimation model (EM; right: with no stock recruit relationship) that pre-specified natural mortality combined with HCR 1a (NPFMC Tier 3 harvest control rule) in the GOA. The EM is applied annually until 2060 across 300 simulations.



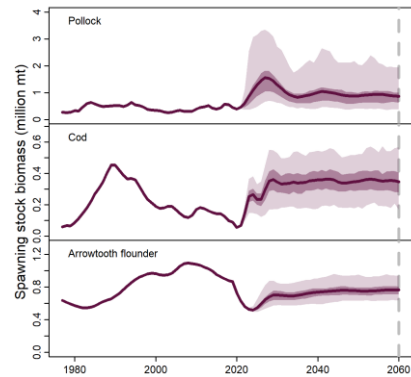
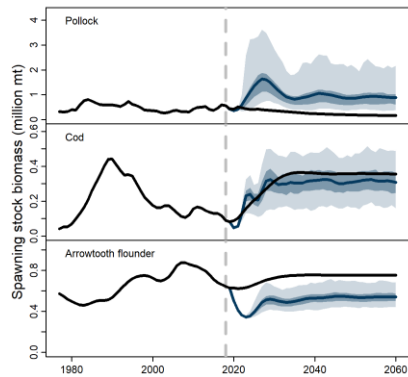
**SS est M OM
w/ Ricker**



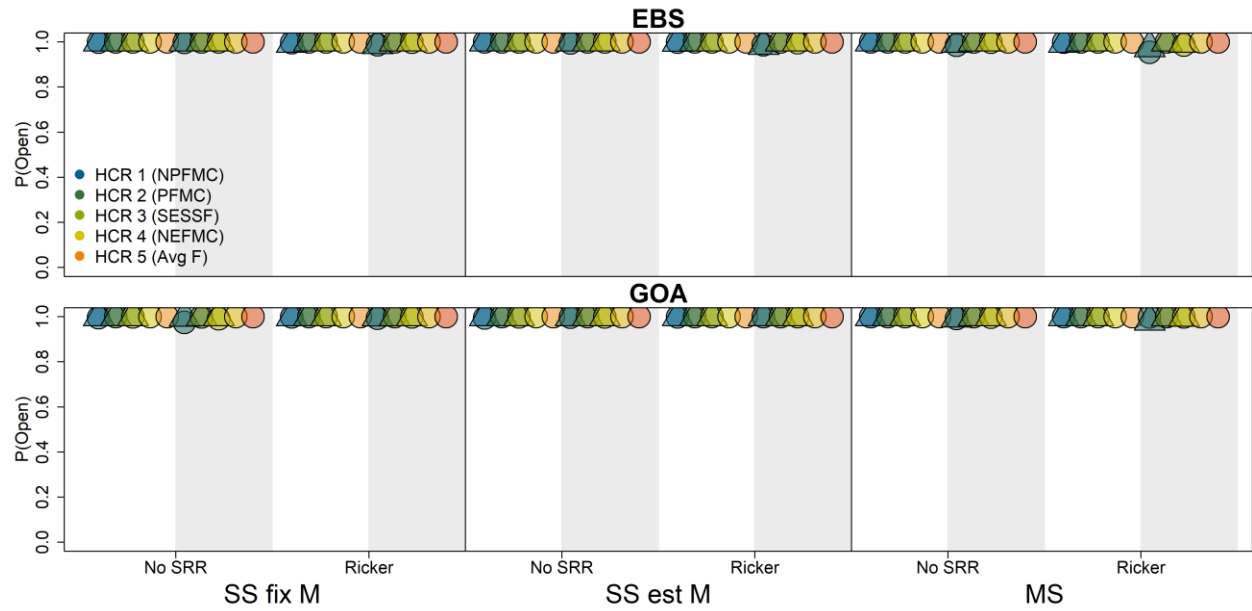
MS OM



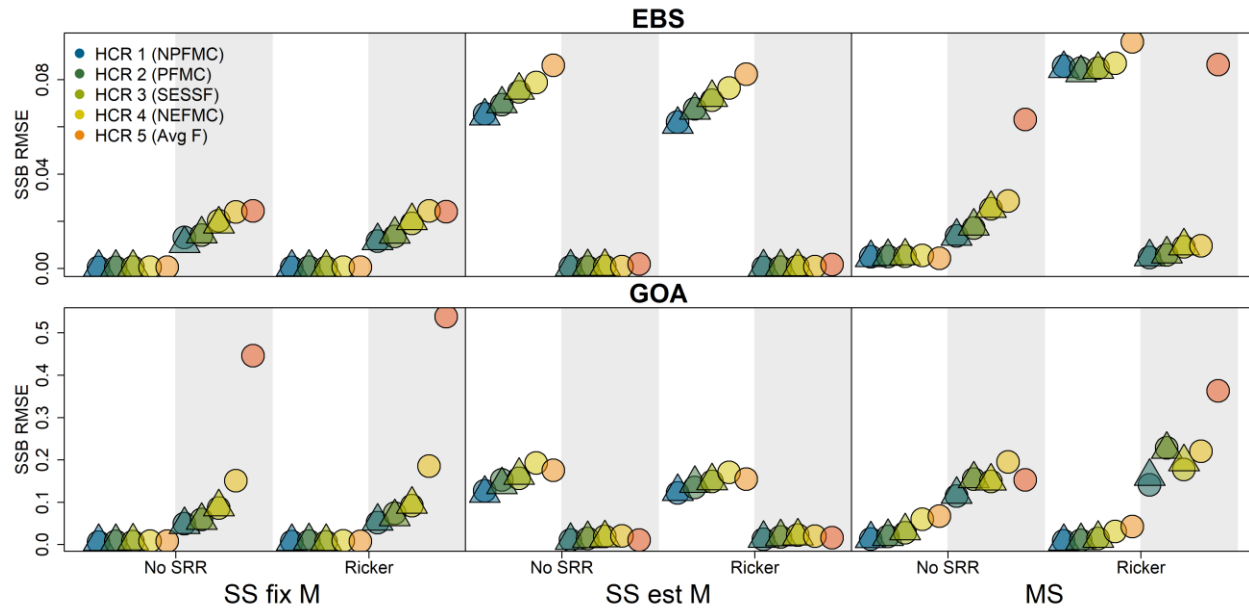
**MS OM
w/ Ricker**



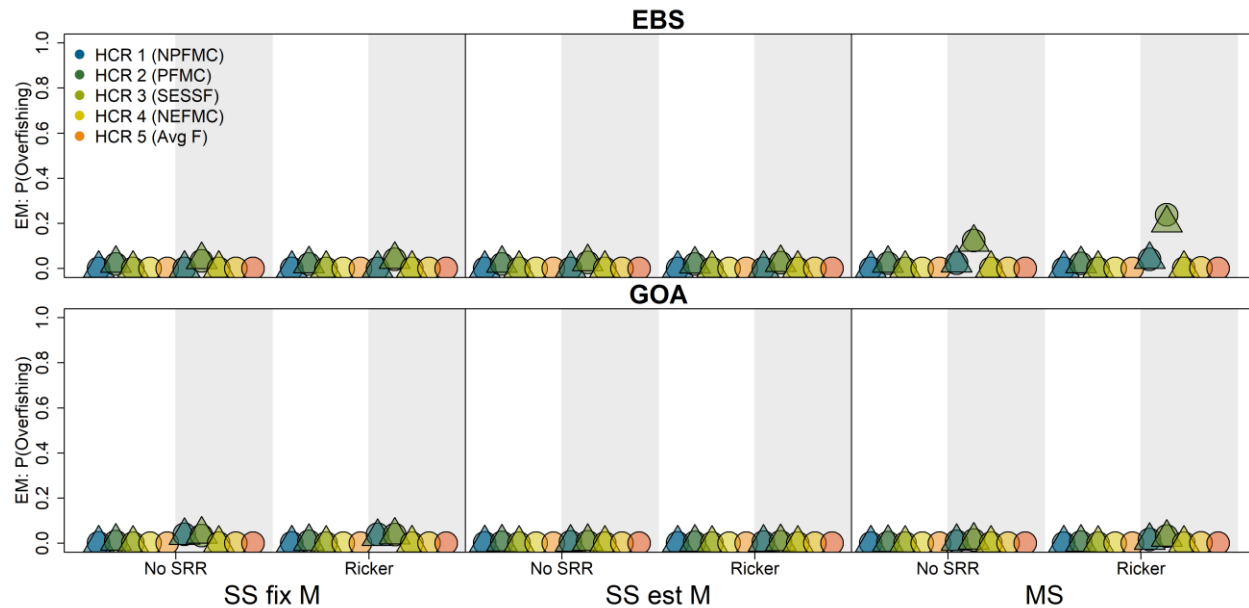
Supplementary Figure S2.4a. Summary of performance metric 3: probability of the fishery being open for pollock in the EBS and GOA across scenarios. Estimation models that estimated M are indicated by the grey shading and harvest control rules (HCR) using dynamic biomass reference points are indicated by the triangles.



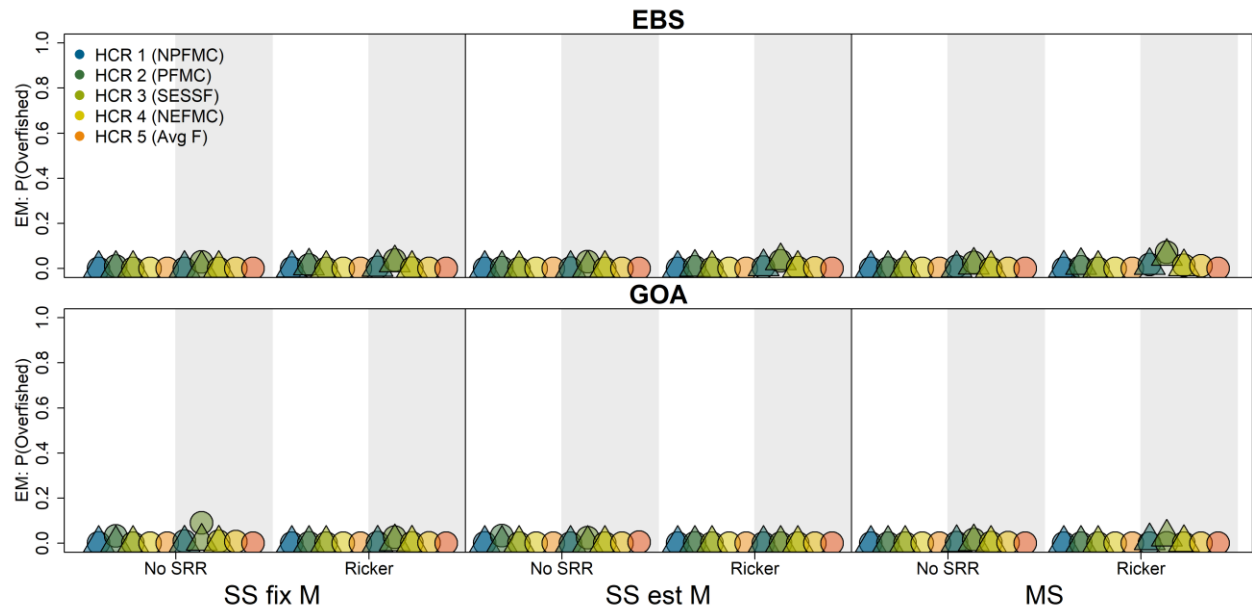
Supplementary Figure S2.4b. Summary of performance metric 4: average relative mean squared error in estimate of spawning biomass in 2060 for pollock in the EBS and GOA across scenarios. Estimation methods that estimated M are indicated by the grey shading and harvest control rules (HCR) using dynamic biomass reference points are indicated by the triangles.



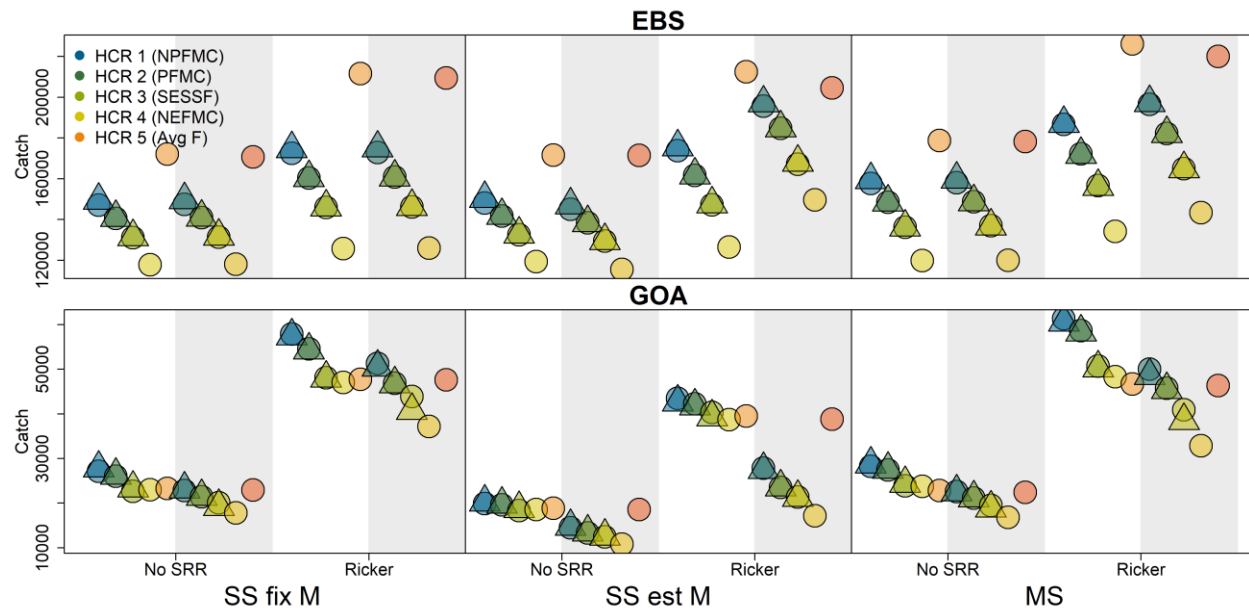
Supplementary Figure S2.4c. Summary of performance metric 5: probability that the population is perceived as undergoing overfishing as determined from the EM for pollock in the EBS and GOA across scenarios. Estimation models that estimated M are indicated by the grey shading and harvest control rules (HCR) using dynamic biomass reference points are indicated by the triangles.



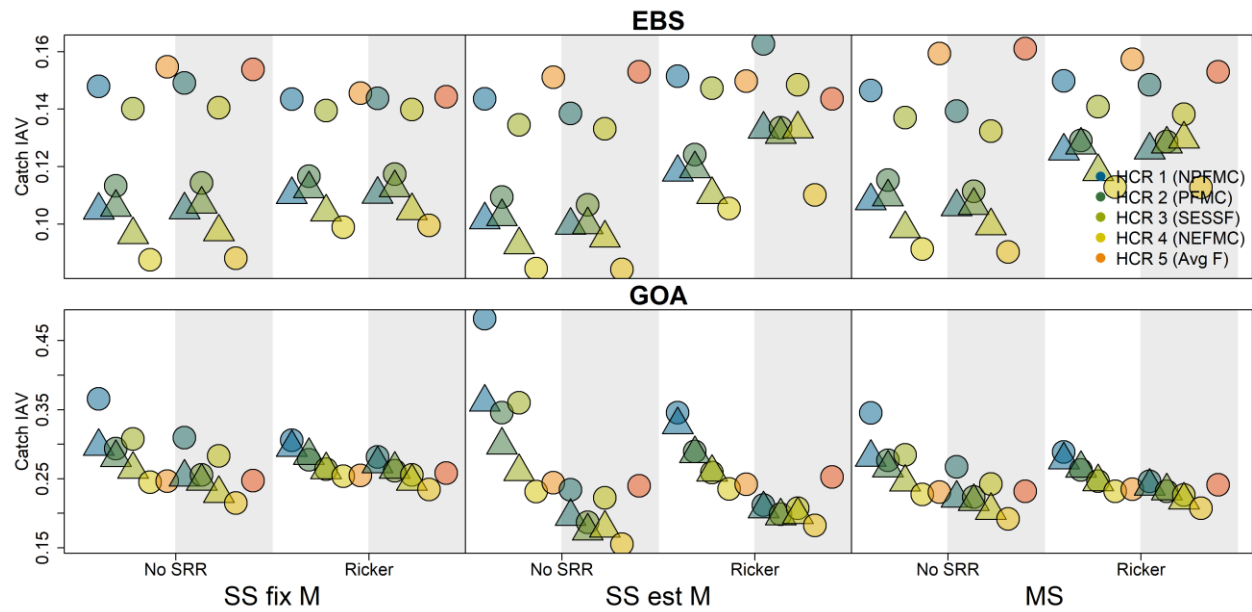
Supplementary Figure S2.4d. Summary of performance metric 6: probability that the population is perceived as overfished as determined from the EM for pollock in the EBS and GOA across scenarios. Estimation models that estimated M are indicated by the grey shading and harvest control rules (HCR) using dynamic biomass reference points are indicated by the triangles.



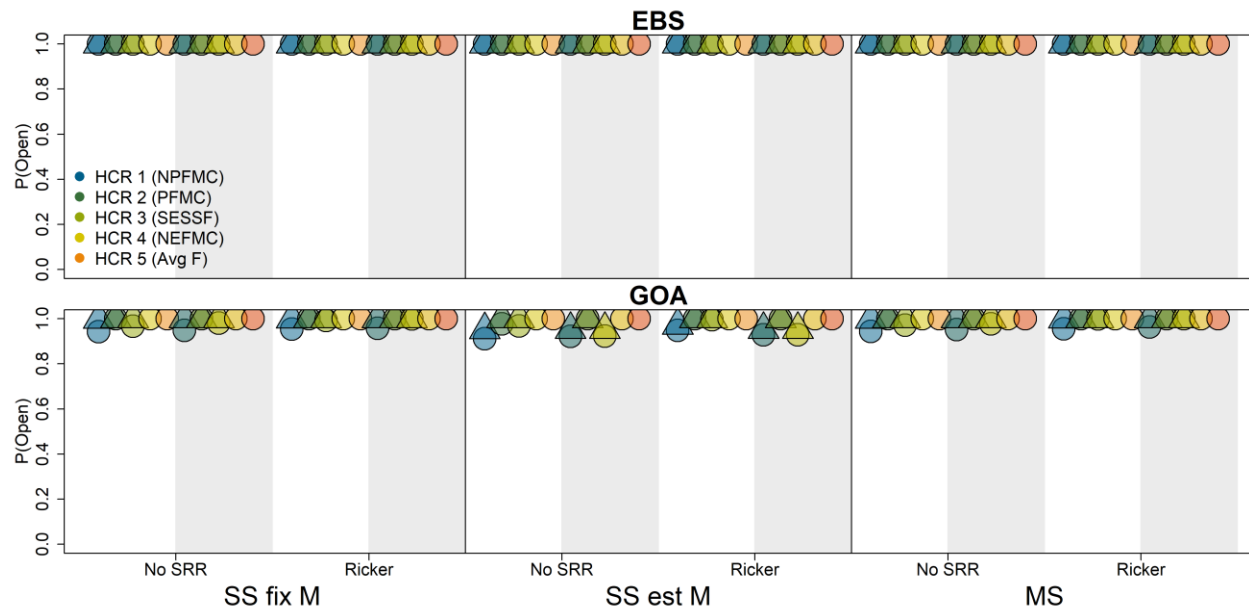
Supplementary Figure S2.5a. Summary of performance metric 1: average catch (mt) for Pacific cod in the EBS and GOA across scenarios. Estimation models that estimated M are indicated by the grey shading and harvest control rules (HCR) using dynamic biomass reference points are indicated by the triangles.



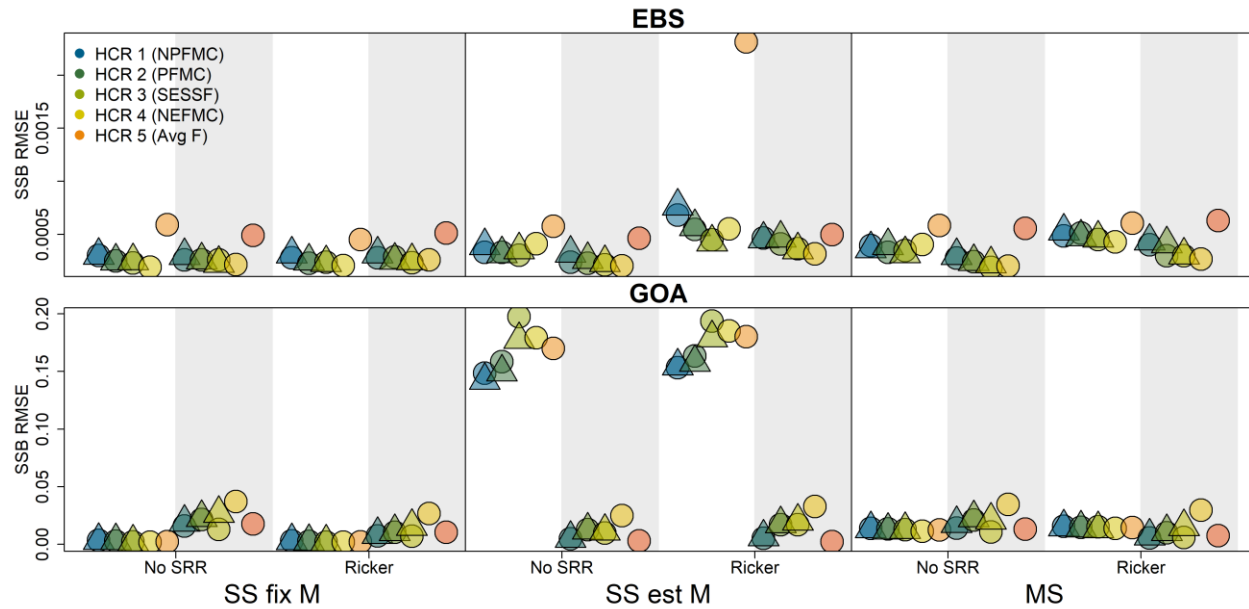
Supplementary Figure S2.5b. Summary of performance metric 2: average interannual catch variability (IAV) for Pacific cod in the EBS and GOA across scenarios. Estimation models that estimated M are indicated by the grey shading and harvest control rules (HCR) using dynamic biomass reference points are indicated by the triangles.



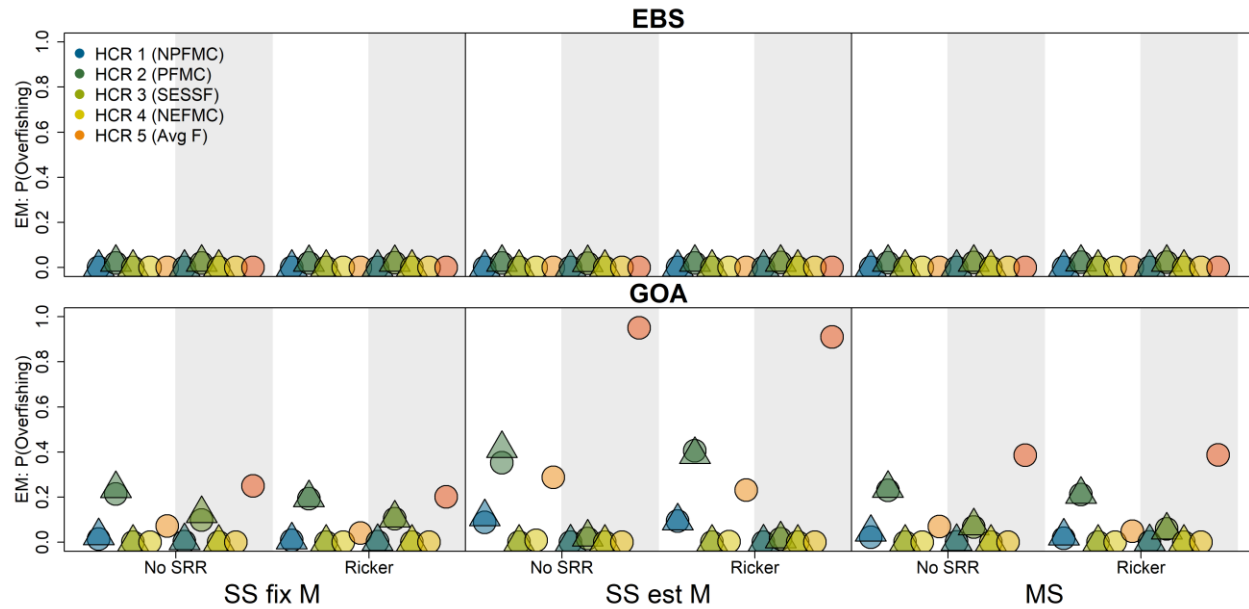
Supplementary Figure S2.5c. Summary of performance metric 3: probability of the fishery being open for Pacific cod in the EBS and GOA across scenarios. Estimation models that estimated M are indicated by the grey shading and harvest control rules (HCR) using dynamic biomass reference points are indicated by the triangles.



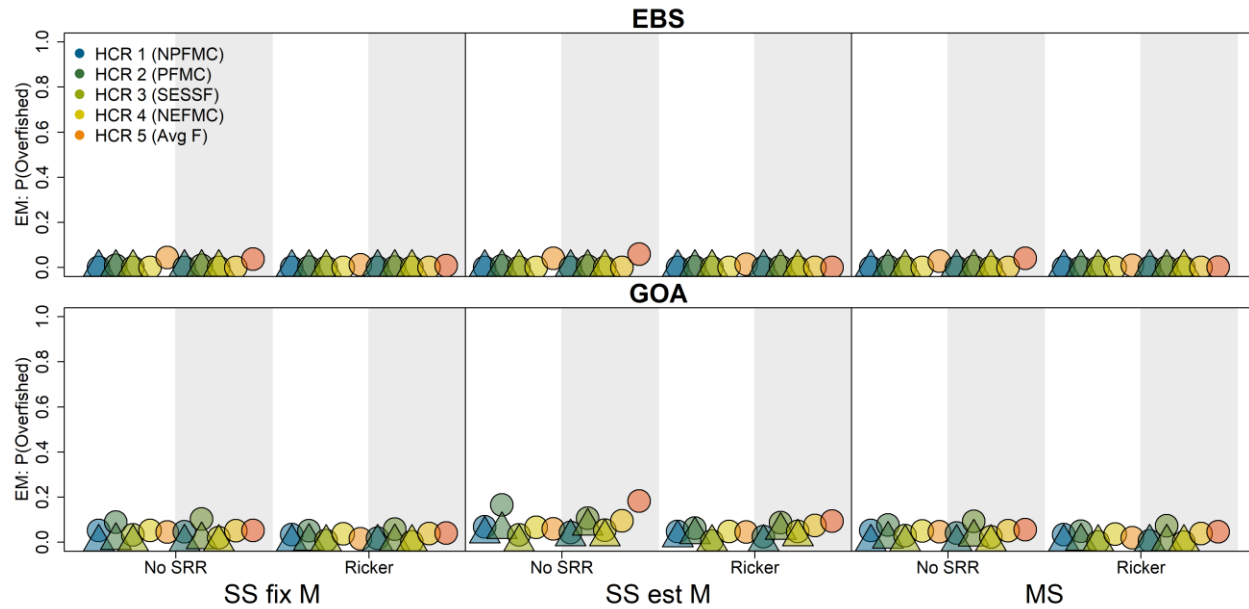
Supplementary Figure S2.5d. Summary of performance metric 4: average relative mean squared error in estimate of spawning biomass in 2060 for Pacific cod in the EBS and GOA across scenarios. Estimation models that estimated M are indicated by the grey shading and harvest control rules (HCR) using dynamic biomass reference points are indicated by the triangles.



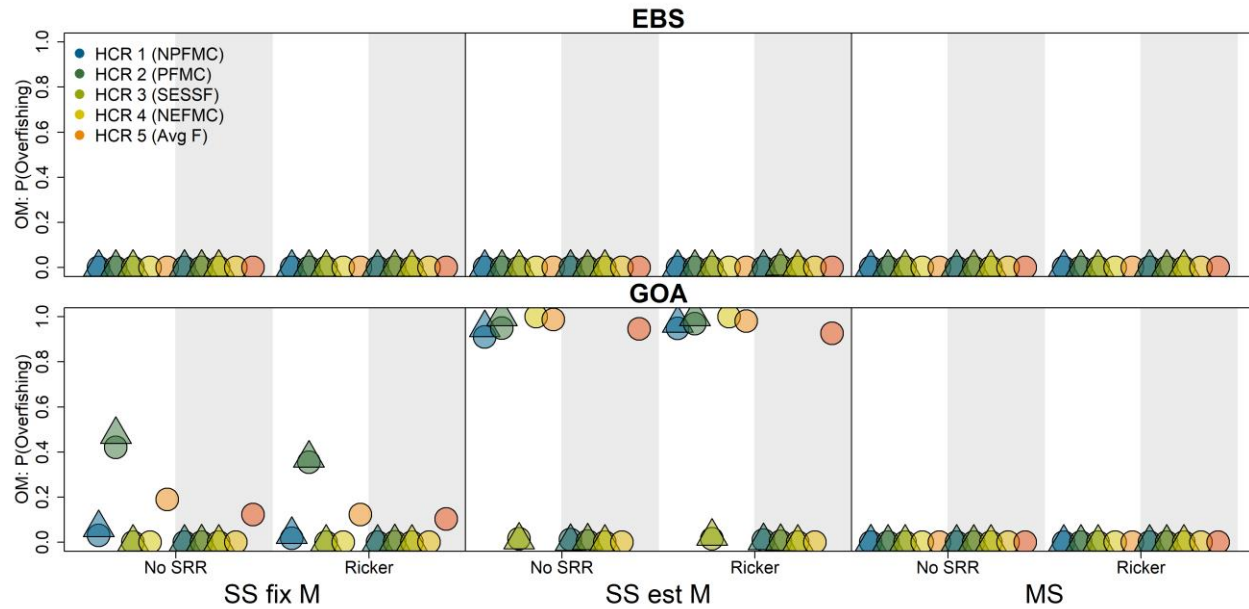
Supplementary Figure S2.5e. Summary of performance metric 5: probability that the population is perceived as undergoing overfishing as determined from the EM for Pacific cod in the EBS and GOA across scenarios. Estimation models that estimated M are indicated by the grey shading and harvest control rules (HCR) using dynamic biomass reference points are indicated by the triangles.



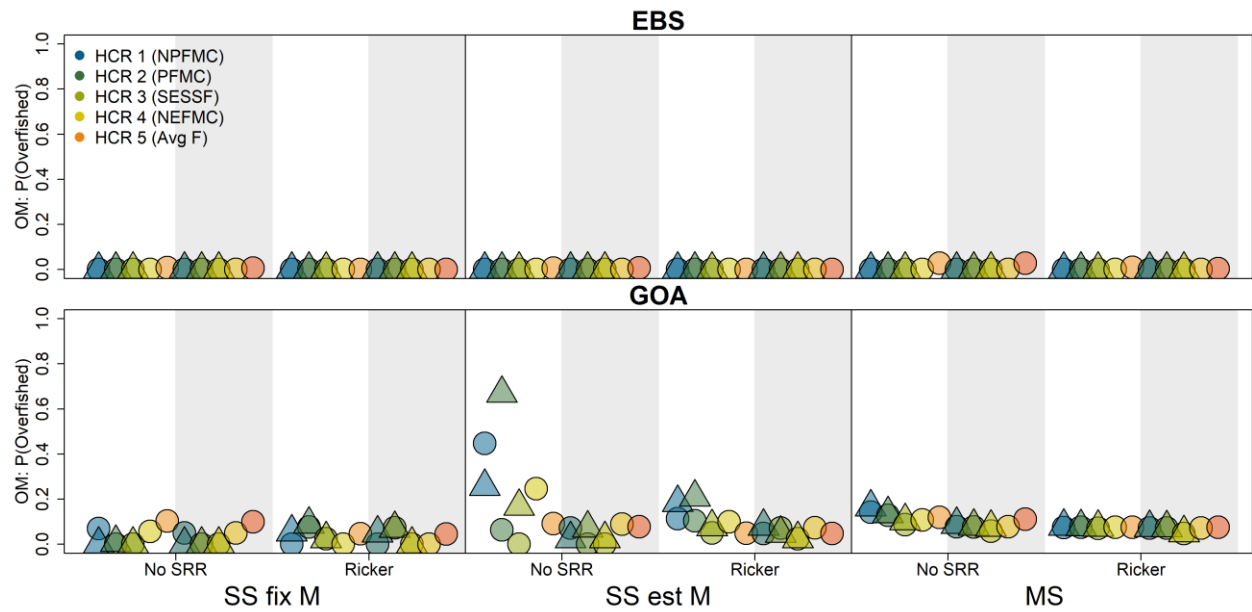
Supplementary Figure S2.5f. Summary of performance metric 6: probability that the population is perceived as overfished as determined from the EM for Pacific cod in the EBS and GOA across scenarios. Estimation models that estimated M are indicated by the grey shading and harvest control rules (HCR) using dynamic biomass reference points are indicated by the triangles.



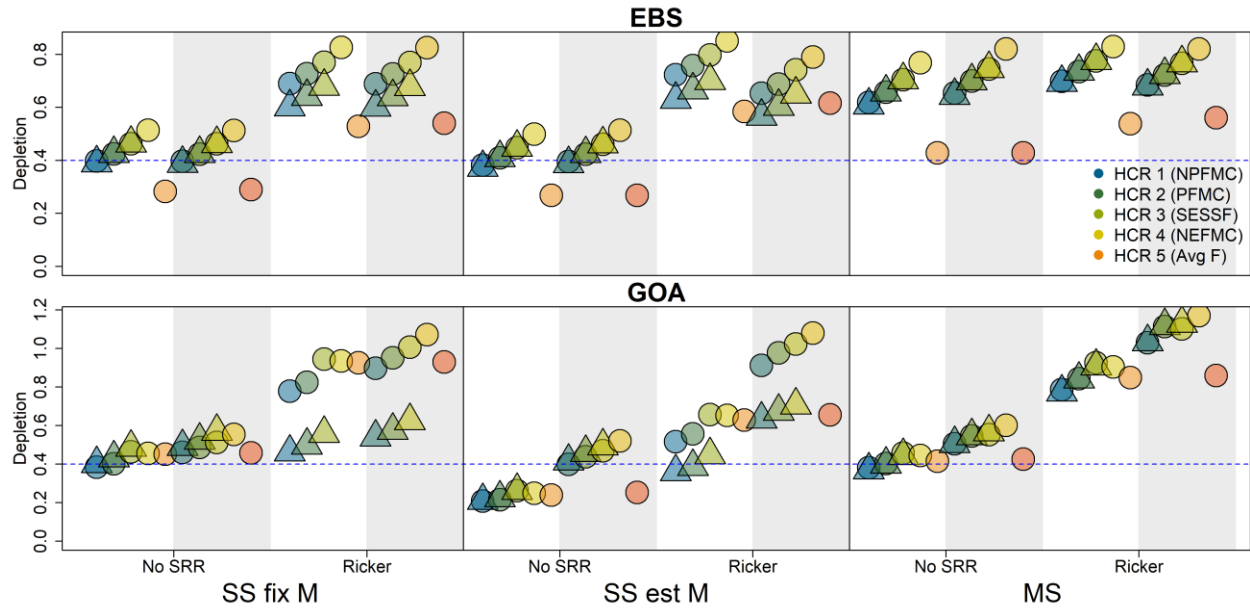
Supplementary Figure S2.5g. Summary of performance metric 7: probability that the population is undergoing overfishing as determined from the OM for Pacific cod in the EBS and GOA across scenarios. Estimation models that estimated M are indicated by the grey shading and harvest control rules (HCR) using dynamic biomass reference points are indicated by the triangles.



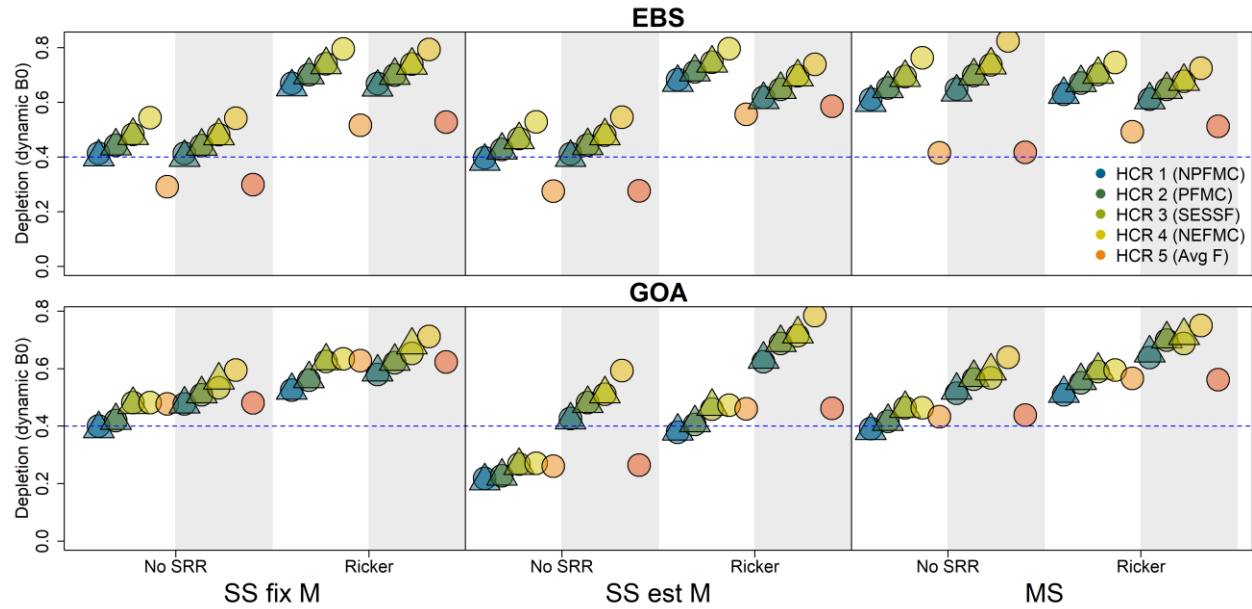
Supplementary Figure S2.5h. Summary of performance metric 8: probability that the population is overfished as determined from the OM for Pacific cod in the EBS and GOA across scenarios. Estimation models that estimated M are indicated by the grey shading and harvest control rules (HCR) using dynamic biomass reference points are indicated by the triangles.



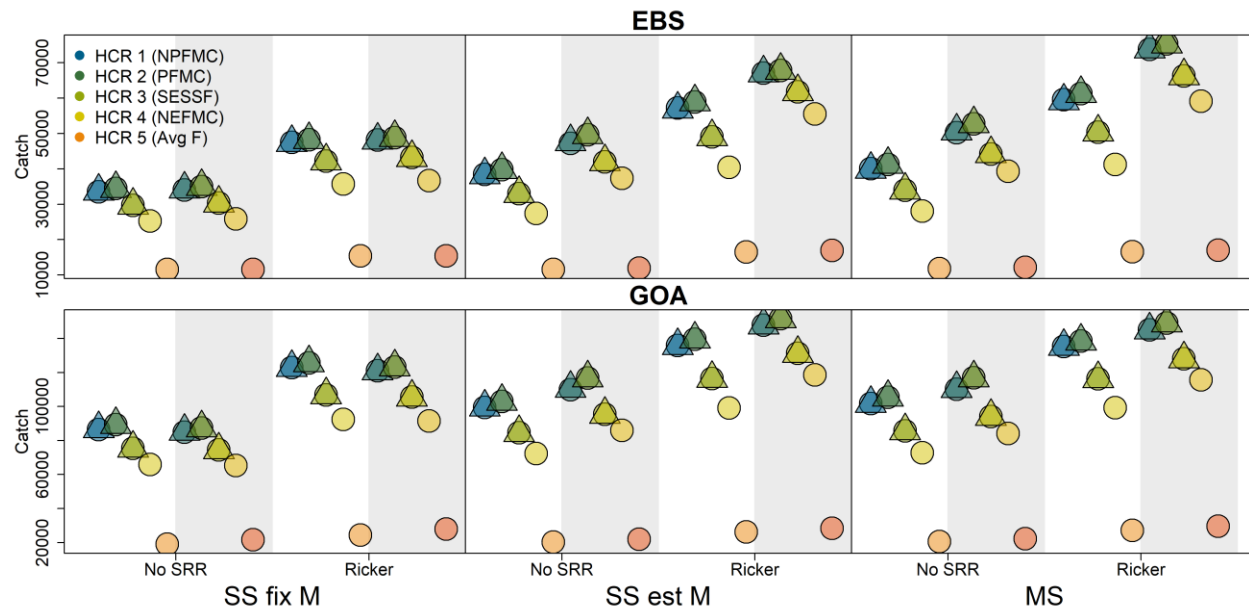
Supplementary Figure S2.5i. Summary of performance metric 9: spawning stock biomass depletion in 2060 relative to equilibrium SB_0 as determined from the OM for Pacific cod in the EBS and GOA across scenarios. Estimation models that estimated M are indicated by the grey shading and harvest control rules (HCR) using dynamic biomass reference points are indicated by the triangles. The blue dashed line indicates 40% depletion.



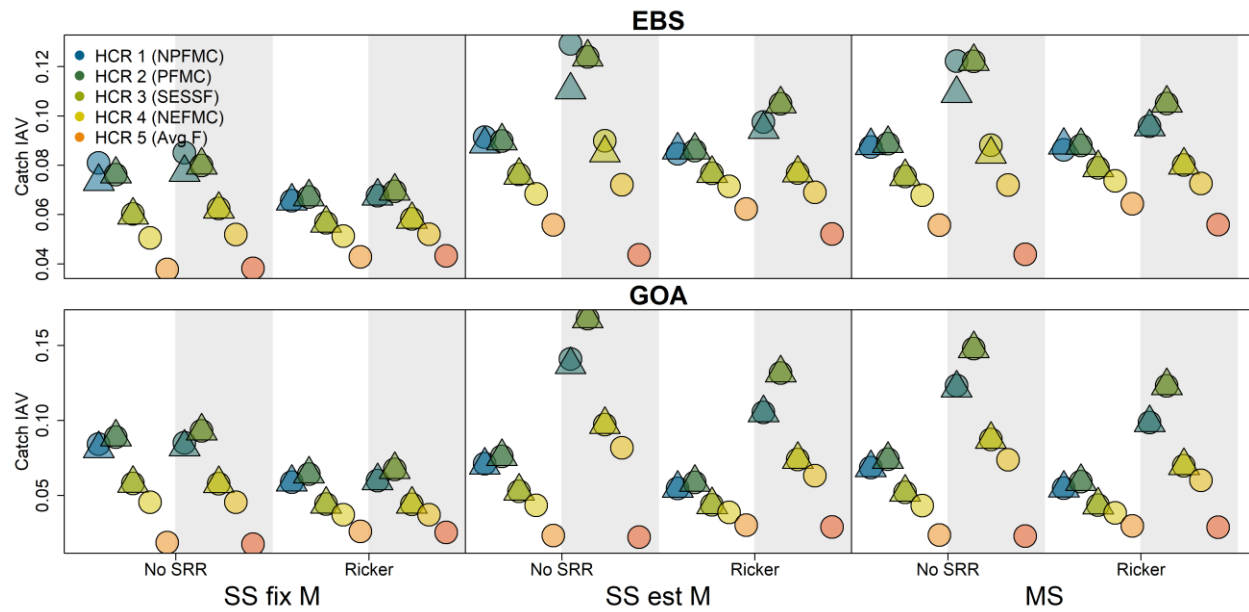
Supplementary Figure S2.5j. Summary of performance metric 10: spawning stock biomass depletion in 2060 relative to dynamic $SB_{0,y}$ as determined from the OM for Pacific cod in the EBS and GOA across scenarios. Estimation models that estimated M are indicated by the grey shading and harvest control rules (HCR) using dynamic biomass reference points are indicated by the triangles. The blue dashed line indicates 40% depletion.



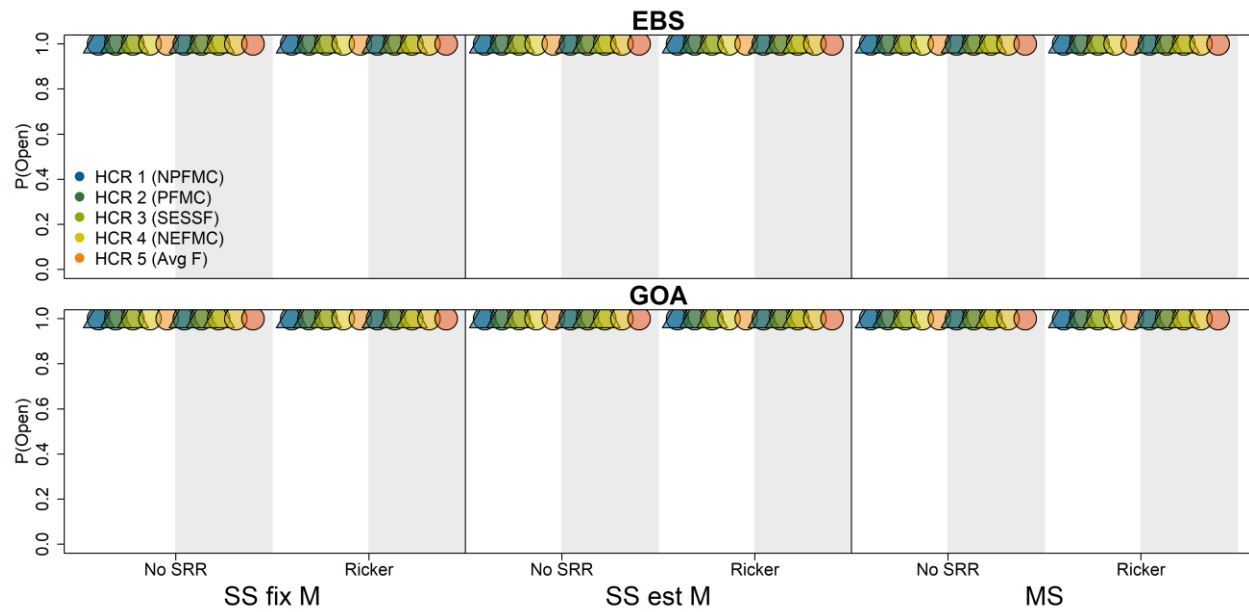
Supplementary Figure S2.6a. Summary of performance metric 1: average catch (mt) for arrowtooth flounder in the EBS and GOA across scenarios. Estimation models that estimated M are indicated by the grey shading and harvest control rules (HCR) using dynamic biomass reference points are indicated by the triangles.



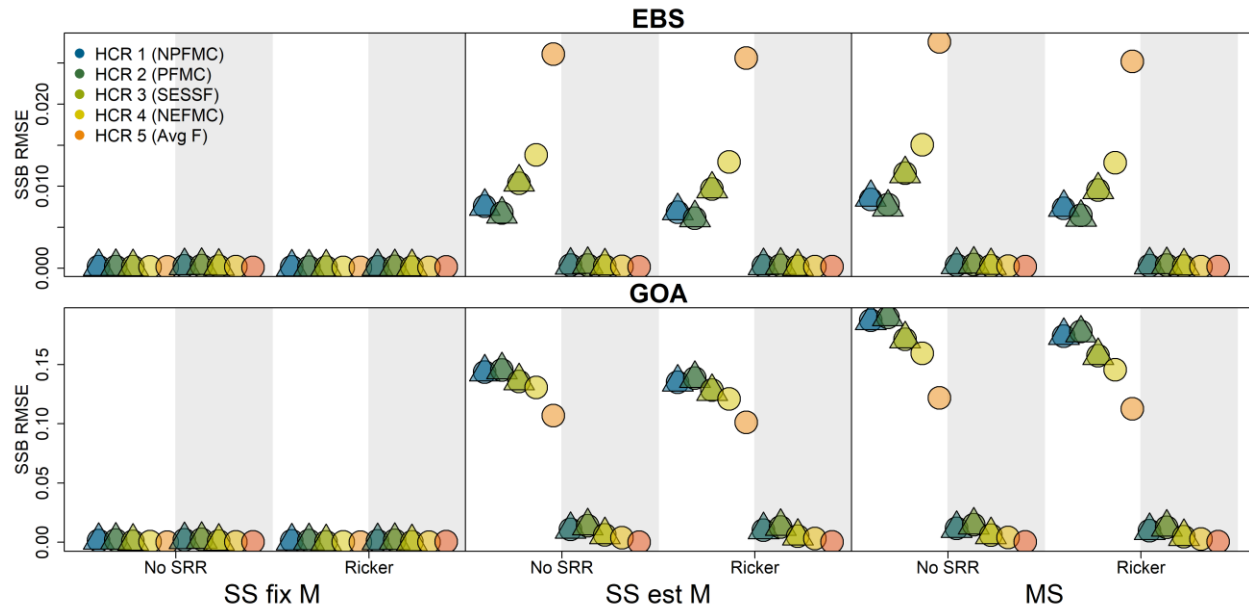
Supplementary Figure S2.6b. Summary of performance metric 2: average interannual catch variability (IAV) for Arrowtooth flounder in the EBS and GOA across scenarios. Estimation models that estimated M are indicated by the grey shading and harvest control rules (HCR) using dynamic biomass reference points are indicated by the triangles.



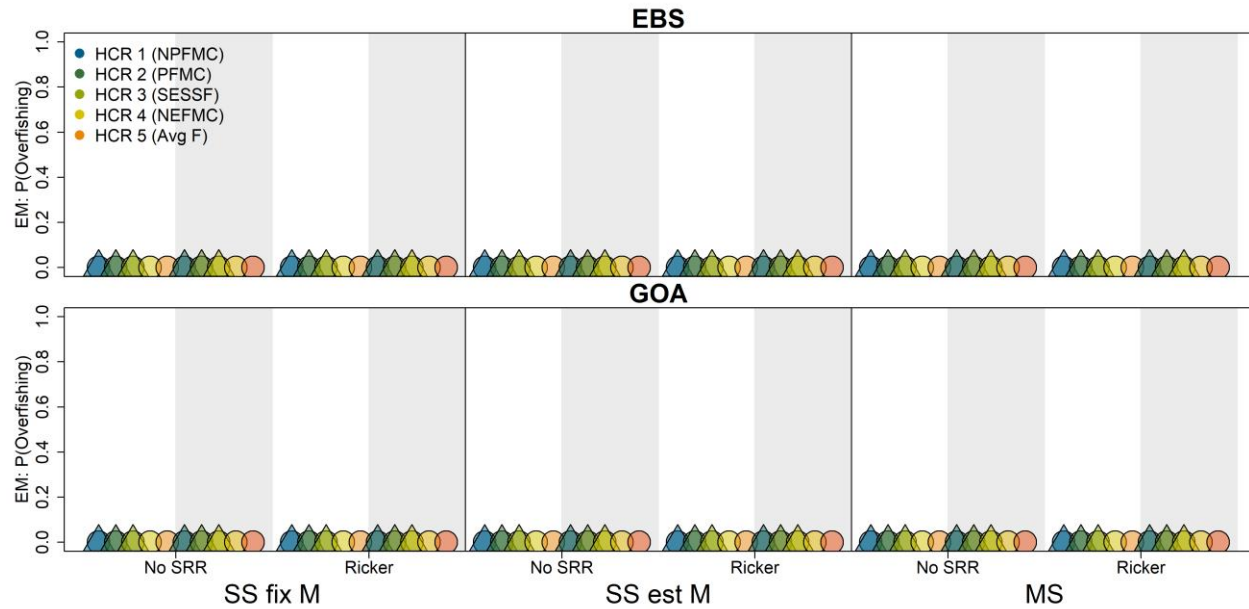
Supplementary Figure S2.6c. Summary of performance metric 3: probability of the fishery being open for Arrowtooth flounder in the EBS and GOA across scenarios. Estimation models that estimated M are indicated by the grey shading and harvest control rules (HCR) using dynamic biomass reference points are indicated by the triangles.



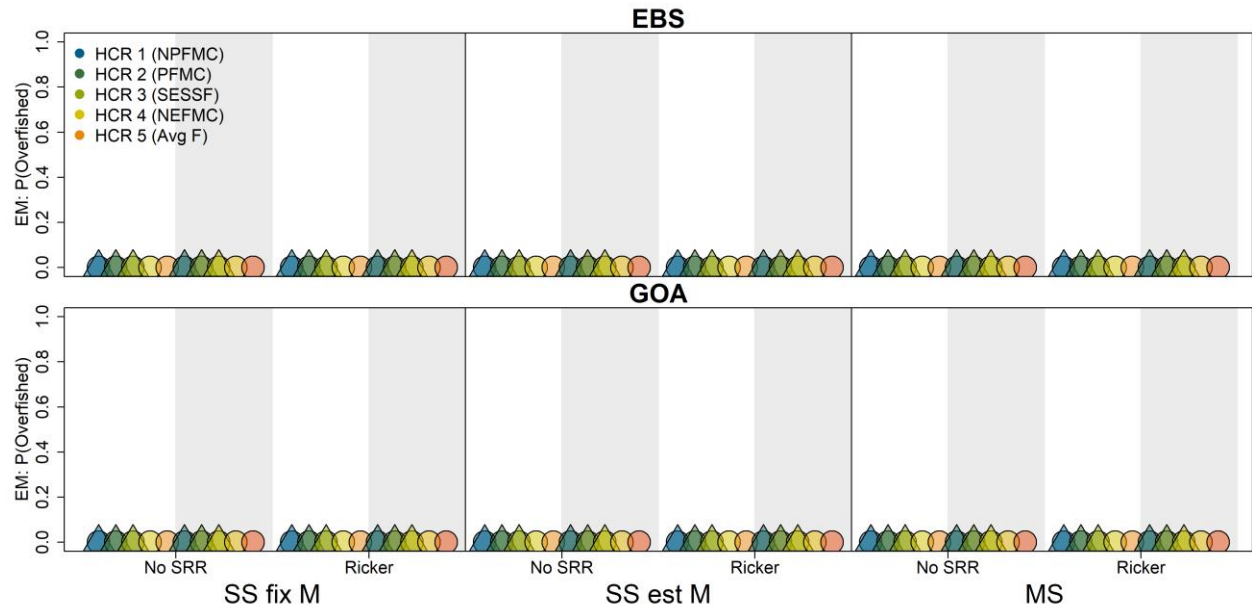
Supplementary Figure S2.6d. Summary of performance metric 4: average relative mean squared error in estimate of spawning biomass in 2060 for Arrowtooth flounder in the EBS and GOA across scenarios. Estimation models that estimated M are indicated by the grey shading and harvest control rules (HCR) using dynamic biomass reference points are indicated by the triangles.



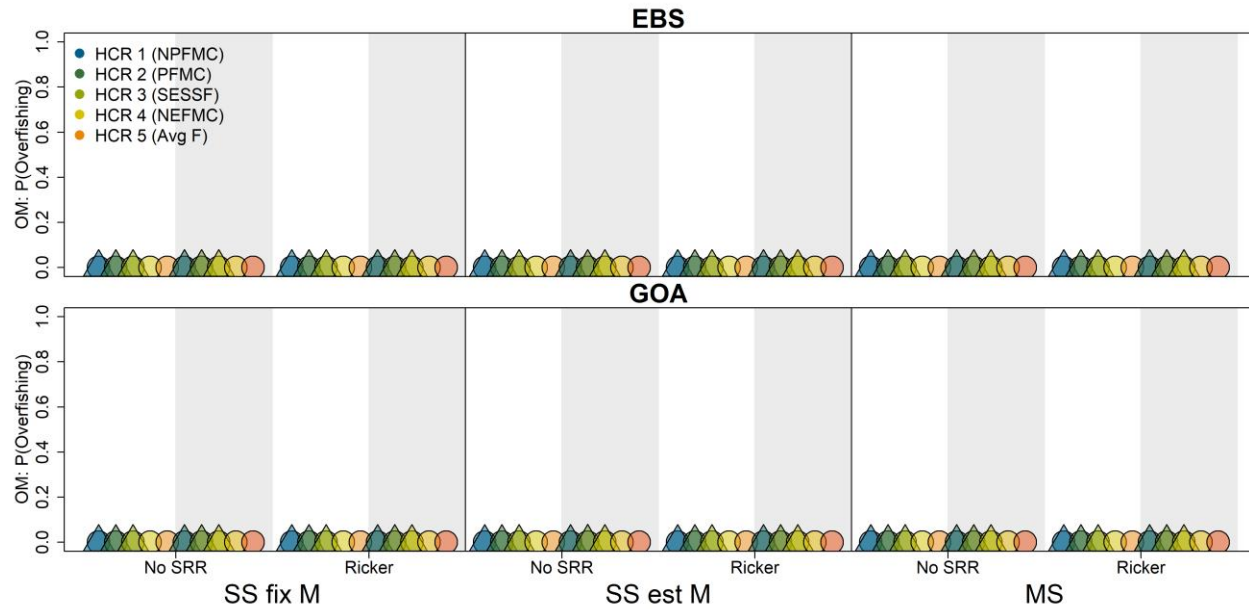
Supplementary Figure S2.6e. Summary of performance metric 5: probability that the population is perceived as undergoing overfishing as determined from the EM for Arrowtooth flounder in the EBS and GOA across scenarios. Estimation models that estimated M are indicated by the grey shading and harvest control rules (HCR) using dynamic biomass reference points are indicated by the triangles.



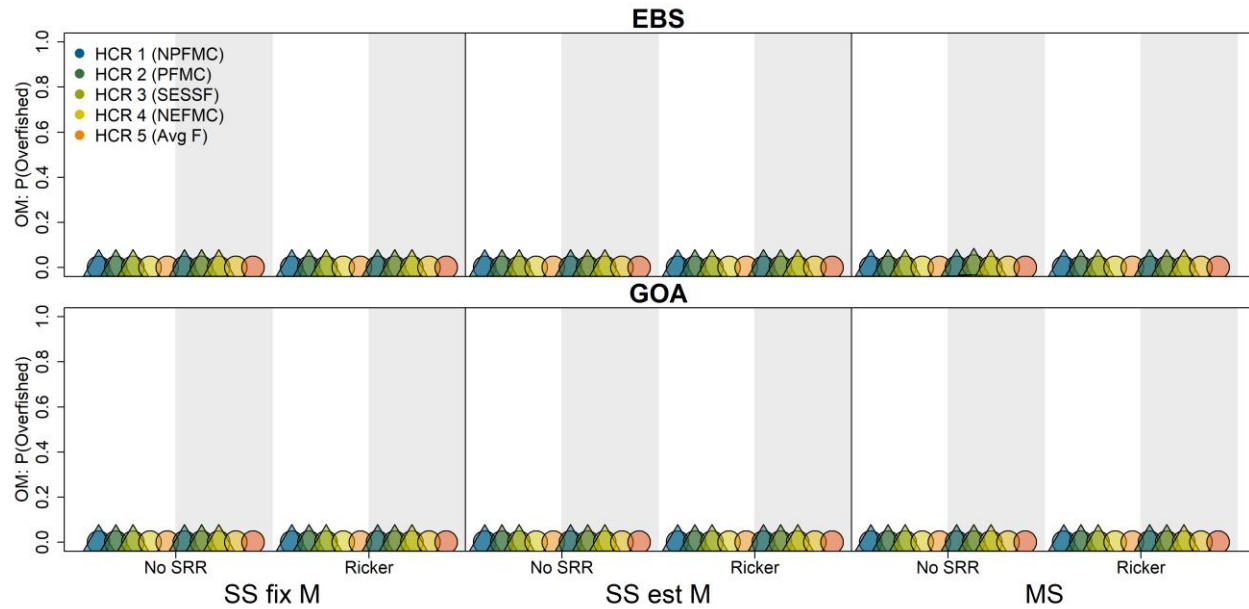
Supplementary Figure S2.6f. Summary of performance metric 6: probability that the population is perceived as overfished as determined from the EM for Arrowtooth flounder in the EBS and GOA across scenarios. Estimation models that estimated M are indicated by the grey shading and harvest control rules (HCR) using dynamic biomass reference points are indicated by the triangles.



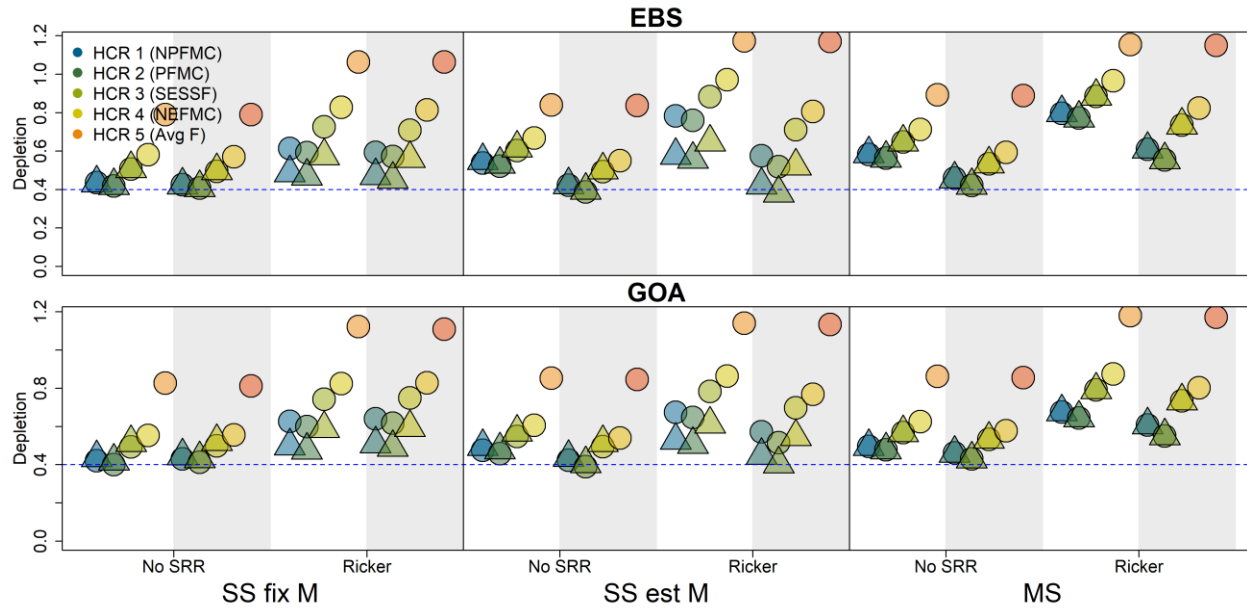
Supplementary Figure S2.6g. Summary of performance metric 7: probability that the population is undergoing overfishing as determined from the OM for Arrowtooth flounder in the EBS and GOA across scenarios. Estimation models that estimated M are indicated by the grey shading and harvest control rules (HCR) using dynamic biomass reference points are indicated by the triangles.



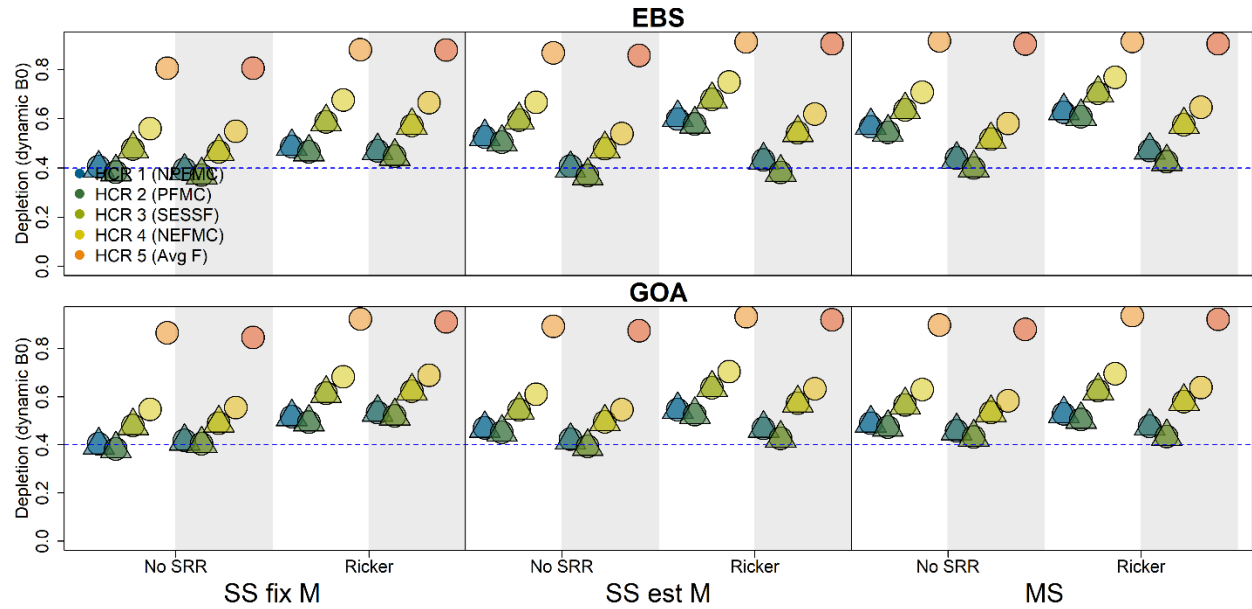
Supplementary Figure S2.6h. Summary of performance metric 8: probability that the population is overfished as determined from the OM for Arrowtooth flounder in the EBS and GOA across scenarios. Estimation models that estimated M are indicated by the grey shading and harvest control rules (HCR) using dynamic biomass reference points are indicated by the triangles.



Supplementary Figure S2.6i. Summary of performance metric 9: spawning stock biomass depletion in 2060 relative to equilibrium SB_0 as determined from the OM for Arrowtooth flounder in the EBS and GOA across scenarios. Estimation models that estimated M are indicated by the grey shading and harvest control rules (HCR) using dynamic biomass reference points are indicated by the triangles. The blue dashed line indicates 40% depletion.



Supplementary Figure S2.6j. Summary of performance metric 10: spawning stock biomass depletion in 2060 relative to dynamic $SB_{0,y}$ as determined from the OM for Arrowtooth flounder in the EBS and GOA across scenarios. Estimation models that estimated M are indicated by the grey shading and harvest control rules (HCR) using dynamic biomass reference points are indicated by the triangles. The blue dashed line indicates 40% depletion.



Chapter 3 Supplementary Materials

SUPPLEMENTARY TABLES

Supplementary Table S3.1. Total natural mortality (M ; yr^{-1}) estimates used for single-species estimation models that pre-specified (Fix) natural mortality with constant expected recruitment. Pre-specified natural mortalities were extracted from recent stock assessments ([Barbeaux *et al.*, 2018](#); [Dorn *et al.*, 2018](#); [Spies and Palsson, 2018](#)).

Age	Pollock	Cod	Arrowtooth females	Arrowtooth males
1	1.39	0.50	0.20	0.35
2	0.69	0.50	0.20	0.35
3	0.48	0.50	0.20	0.35
4	0.37	0.50	0.20	0.35
5	0.34	0.50	0.20	0.35
6	0.30	0.50	0.20	0.35
7	0.30	0.50	0.20	0.35
8	0.29	0.50	0.20	0.35
9	0.28	0.50	0.20	0.35
10	0.29	0.50	0.20	0.35
11		0.50	0.20	0.35
12		0.50	0.20	0.35
13			0.20	0.35
14			0.20	0.35
15			0.20	0.35
16			0.20	0.35
17			0.20	0.35
18			0.20	0.35
19			0.20	0.35
20			0.20	0.35
21			0.20	0.35

Supplementary Table S3.2. Parameter definitions for the CEATTLE Models

Category	Parameter	Definition
Index	i	Species
	s	Sex
	a	Age
	$\hat{a}$	Observed age
	A	Plus group
	l	Length
	y	Year
	Y	Last year of estimation (not projection)
	p	Predator species
	b	Predator sex
	j	Predator age
	k	Predator length
	f_i	Fleet/survey
Population model	R_{isy}	Recruitment
	$\bar{R}_i$	Mean recruitment
	τ_{iy}	Annual recruitment deviate
	δ_{ia}	Maturity-at-age
	ρ_{ia}	Sex-ratio
	$M1_{isa}$	Residual mortality yr ⁻¹
	$M2_{isay}$	Predation-mortality yr ⁻¹
	$F_{f_i say}$	Fleet-specific fishing mortality yr ⁻¹
	F_{isay}	Total fishing mortality yr ⁻¹
	Z_{isay}	Total mortality yr ⁻¹
	$\bar{F}_{f_i}$	Mean fishing mortality yr ⁻¹
	$\epsilon_{f_i y}$	Annual fishing mortality deviate
	ψ_{f_i}	Fishing mortality apportionment per fleet
	N_{isay}	Numbers-at-age
	$\bar{N}_{isay}$	Average numbers-at-age
	SB_{ijy}	Spawning-stock-biomass (kg)
	B_{isay}	Biomass (kg)
	$\bar{B}_{isay}$	Average biomass (kg)
Predation model	$\hat{S}_{pbj isa}$	Predator-prey suitability
	H_i	Holling functional response parameter
	B_p^{other}	Biomass of “other prey” (kg)
	T_y	Observed bottom temperature (°C)
	T_p^{co}	Thermal optima for consumption (°C)
	T_p^{cm}	Thermal limit of consumption (°C)
	Q_p^c	Rate at which consumption increased over relatively low water temperatures
	$\alpha_p^\delta, \beta_p^\delta$	Weight specific intercept and slop of maximum consumption
	ϕ_{pbj}	Scalar for maximum to observed consumption
	$\bar{U}_{pbj, isa}$	Average proportion of prey-at-age in the stomach of a predator-at-age

Observation model	$\tilde{q}_i$	Relative abundance-at-age scalar
	$\widehat{CPUE}: B_{f_i y}$	Survey/fishery relative biomass (kg)
	$\widehat{CPUE}: I_{f_i y}$	Survey/fishery relative abundance (numbers)
	$sel_{f_i say}$	Selectivity
	$q_{f_i y}$	Catchability
	W	Weight (kg)
	$C_{f_i say}$	Catch-at-age
	$\hat{C}_{f_i y}^*$	Total catch (kg)
	$\hat{\theta}_{f_i say} / \hat{\theta}_{f_i sly}$	Predicted age/length composition
	$AE_{i\hat{a}a}$	Ageing error matrix
	ATM_{isal}	Age-transition matrix (growth trajectory)
	$\hat{S}_{pbjisa}$	Predator-prey suitability

Supplementary Table S3.3.PM-1. Summary of performance metric 1 (average annual catch (1,000 mt)) across OMs for **Pollock**.

Cap	EM	1. No climate	2. w/ SRR	3. 1-2.6	4. w/ SRR	5. 2-4.5	6. w/ SRR	7. 5-8.5	8. w/ SRR
FALSE	<i>NPFMC Fix-M</i>	574	573	286	220	161	115	168	135
	<i>NPFMC Fix-M (Dynamic B0)</i>	582	558	321	193	201	116	206	144
	<i>NPFMC Est-M</i>	424	602	154	149	80	73	77	74
	<i>NPFMC Est-M (Dynamic B0)</i>	444	634	181	171	110	93	106	92
	<i>MS-B40 iter</i>	618	844	326	326	235	178	241	204
	<i>MS-B40 simul</i>	916	240	524	164	350	163	359	179
	<i>MS-MSY</i>	1,197	103	1,235	130	776	136	812	152
	<i>MS-cMSY</i>	1,386	114	788	132	512	144	531	157
TRUE	<i>NPFMC Fix-M</i>	276	203	167	95	99	59	100	69
	<i>NPFMC Fix-M (Dynamic B0)</i>	282	180	195	81	133	65	131	78
	<i>NPFMC Est-M</i>	212	187	106	68	62	38	58	44
	<i>NPFMC Est-M (Dynamic B0)</i>	219	187	111	68	79	45	75	52
	<i>MS-B40 iter</i>	285	169	189	84	135	68	134	79
	<i>MS-B40 simul</i>	297	132	240	74	169	70	166	81
	<i>MS-MSY</i>	299	137	270	73	197	71	188	81
	<i>MS-cMSY</i>	299	137	262	74	188	71	182	81

Supplementary Table S3.3.PM-2. Summary of performance metric 2 (average interannual variation in catch (IAV)) across OMs for **Pollock**.

Cap	EM	1. No climate	2. w/ SRR	3. 1-2.6	4. w/ SRR	5. 2-4.5	6. w/ SRR	7. 5-8.5	8. w/ SRR
FALSE	<i>NPFMC Fix-M</i>	0.29	0.29	0.57	0.53	0.67	0.67	0.65	0.64
	<i>NPFMC Fix-M (Dynamic B0)</i>	0.29	0.29	0.49	0.46	0.5	0.59	0.53	0.57
	<i>NPFMC Est-M</i>	0.25	0.26	0.48	0.44	0.55	0.5	0.51	0.49
	<i>NPFMC Est-M (Dynamic B0)</i>	0.24	0.26	0.4	0.39	0.39	0.38	0.4	0.4
	<i>MS-B40 iter</i>	0.29	0.29	0.47	0.45	0.57	0.63	0.58	0.59
	<i>MS-B40 simul</i>	0.4	0.84	0.65	1.01	0.77	1.24	0.78	1.15
	<i>MS-MSY</i>	0.64	3.02	1.06	2.77	1.37	3.03	1.42	2.76
	<i>MS-cMSY</i>	0.54	2.3	0.89	2.11	1.08	2.31	1.1	2.24
TRUE	<i>NPFMC Fix-M</i>	0.12	0.2	0.36	0.52	0.51	0.57	0.46	0.55
	<i>NPFMC Fix-M (Dynamic B0)</i>	0.11	0.21	0.26	0.4	0.33	0.46	0.33	0.43
	<i>NPFMC Est-M</i>	0.16	0.17	0.41	0.51	0.57	0.57	0.51	0.54
	<i>NPFMC Est-M (Dynamic B0)</i>	0.15	0.17	0.31	0.33	0.35	0.41	0.36	0.39
	<i>MS-B40 iter</i>	0.12	0.24	0.28	0.44	0.33	0.47	0.33	0.44
	<i>MS-B40 simul</i>	0.08	0.28	0.23	0.46	0.31	0.43	0.3	0.41
	<i>MS-MSY</i>	0.08	0.29	0.2	0.46	0.34	0.44	0.33	0.42
	<i>MS-cMSY</i>	0.08	0.29	0.21	0.46	0.32	0.43	0.3	0.41

Supplementary Table S3.3.PM-3. Summary of performance metric 3 (probability that the population is overfished as determined from the OM) across OMs for **Pollock**.

Cap	EM	1. No climate	2. w/ SRR	3. 1-2.6	4. w/ SRR	5. 2-4.5	6. w/ SRR	7. 5-8.5	8. w/ SRR
FALSE	<i>NPFMC Fix-M</i>	0	0	0	0	0	0	0	0
	<i>NPFMC Fix-M (Dynamic B0)</i>	0	0	0	0	0	0.09	0	0.15
	<i>NPFMC Est-M</i>	0	0	0	0	0	0	0	0
	<i>NPFMC Est-M (Dynamic B0)</i>	0	0	0	0	0	0	0	0
	<i>MS-B40 iter</i>	0	0	0	0	0	0	0	0.06
	<i>MS-B40 simul</i>	0.04	0.84	0.07	0.77	0.19	0.8	0.24	0.8
	<i>MS-MSY</i>	0.91	0.94	0.72	0.92	0.78	0.93	0.82	0.92
	<i>MS-cMSY</i>	0.67	0.92	0.66	0.9	0.71	0.9	0.75	0.9
TRUE	<i>NPFMC Fix-M</i>	0	0.01	0	0	0	0	0	0
	<i>NPFMC Fix-M (Dynamic B0)</i>	0	0.37	0	0.49	0	0.55	0	0.49
	<i>NPFMC Est-M</i>	0	0	0	0	0	0	0	0
	<i>NPFMC Est-M (Dynamic B0)</i>	0	0.02	0	0.01	0	0.03	0	0.02
	<i>MS-B40 iter</i>	0	0.44	0	0.39	0	0.55	0	0.47
	<i>MS-B40 simul</i>	0	0.61	0.03	0.74	0.16	0.74	0.19	0.71
	<i>MS-MSY</i>	0.01	0.59	0.31	0.77	0.58	0.76	0.56	0.75
	<i>MS-cMSY</i>	0.01	0.59	0.27	0.77	0.51	0.76	0.5	0.74

Supplementary Table S3.3.PM-4. Summary of performance metric 4 (terminal spawning stock biomass (1,000 mt)) across OM for **Pollock**.

Cap	EM	1. No climate	2. w/ SRR	3. 1-2.6	4. w/ SRR	5. 2-4.5	6. w/ SRR	7. 5-8.5	8. w/ SRR
FALSE	<i>NPFMC Fix-M</i>	702	715	351	266	206	38	217	13
	<i>NPFMC Fix-M (Dynamic B0)</i>	691	644	296	143	138	1	166	0
	<i>NPFMC Est-M</i>	875	1,066	493	507	215	61	222	22
	<i>NPFMC Est-M (Dynamic B0)</i>	853	1,071	475	489	170	24	195	9
	<i>MS-B40 iter</i>	904	1,385	424	458	149	7	171	0
	<i>MS-B40 simul</i>	380	41	154	3	81	0	121	0
	<i>MS-MSY</i>	79	0	42	0	27	0	54	0
	<i>MS-cMSY</i>	161	0	38	0	30	0	57	0
TRUE	<i>NPFMC Fix-M</i>	795	404	337	147	207	12	220	6
	<i>NPFMC Fix-M (Dynamic B0)</i>	786	161	294	13	145	0	177	0
	<i>NPFMC Est-M</i>	854	652	386	195	210	13	224	7
	<i>NPFMC Est-M (Dynamic B0)</i>	847	561	402	182	173	3	206	2
	<i>MS-B40 iter</i>	771	153	316	30	141	0	178	0
	<i>MS-B40 simul</i>	748	22	222	0	98	0	144	0
	<i>MS-MSY</i>	776	32	181	0	52	0	93	0
	<i>MS-cMSY</i>	770	31	192	0	69	0	111	0

Supplementary Table S3.3.PM-5. Summary of performance metric 5 (terminal spawning stock biomass depletion relative to dynamic SB0) across OM's for **Pollock**.

Cap	EM	1. No climate	2. w/ SRR	3. 1-2.6	4. w/ SRR	5. 2-4.5	6. w/ SRR	7. 5-8.5	8. w/ SRR
FALSE	<i>NPFMC Fix-M</i>	0.69	0.74	0.85	1.85	1.31	23.85	1.15	11.85
	<i>NPFMC Fix-M (Dynamic B0)</i>	0.68	0.64	0.66	0.61	0.82	0.18	0.85	0.11
	<i>NPFMC Est-M</i>	0.87	1.16	1.19	3.69	1.35	39.18	1.18	20.11
	<i>NPFMC Est-M (Dynamic B0)</i>	0.84	1.14	1.09	3.35	1.02	12.61	1	6.58
	<i>MS-B40 iter</i>	0.89	1.51	0.98	2.9	0.89	1.87	0.86	0.16
	<i>MS-B40 simul</i>	0.37	0.04	0.34	0.01	0.48	0	0.59	0
	<i>MS-MSY</i>	0.08	0	0.1	0	0.17	0	0.24	0
	<i>MS-cMSY</i>	0.16	0	0.09	0	0.18	0	0.25	0
TRUE	<i>NPFMC Fix-M</i>	0.74	0.39	0.75	0.96	1.29	5.06	1.17	4.44
	<i>NPFMC Fix-M (Dynamic B0)</i>	0.72	0.14	0.6	0.04	0.85	0.01	0.88	0.01
	<i>NPFMC Est-M</i>	0.82	0.65	0.88	1.21	1.31	5.57	1.19	5.5
	<i>NPFMC Est-M (Dynamic B0)</i>	0.81	0.54	0.89	0.88	1.04	0.85	1.07	1.14
	<i>MS-B40 iter</i>	0.71	0.14	0.67	0.12	0.82	0	0.88	0
	<i>MS-B40 simul</i>	0.68	0.02	0.4	0	0.51	0	0.65	0
	<i>MS-MSY</i>	0.7	0.03	0.26	0	0.17	0	0.28	0
	<i>MS-cMSY</i>	0.69	0.03	0.29	0	0.28	0	0.42	0

Supplementary Table S3.3.PM-6. Summary of performance metric 6 (terminal dynamic SB0 (1,000 mt)) across OMs for **Pollock**.

Cap	EM	1. No climate	2. w/ SRR	3. 1-2.6	4. w/ SRR	5. 2-4.5	6. w/ SRR	7. 5-8.5	8. w/ SRR
FALSE	<i>NPFMC Fix-M</i>	1,017	974	438	206	164	3	193	1
	<i>NPFMC Fix-M (Dynamic B0)</i>	1,017	974	438	206	164	3	193	1
	<i>NPFMC Est-M</i>	1,017	974	438	206	164	3	193	1
	<i>NPFMC Est-M (Dynamic B0)</i>	1,017	974	438	206	164	3	193	1
	<i>MS-B40 iter</i>	1,017	974	438	206	164	3	193	1
	<i>MS-B40 simul</i>	1,017	974	438	206	164	3	193	1
	<i>MS-MSY</i>	1,017	972	438	207	164	3	193	1
	<i>MS-cMSY</i>	1,014	974	439	206	165	3	191	1
TRUE	<i>NPFMC Fix-M</i>	1,017	974	438	206	164	3	193	1
	<i>NPFMC Fix-M (Dynamic B0)</i>	1,017	974	438	206	164	3	193	1
	<i>NPFMC Est-M</i>	1,017	974	438	206	164	3	193	1
	<i>NPFMC Est-M (Dynamic B0)</i>	1,017	974	438	206	164	3	193	1
	<i>MS-B40 iter</i>	1,017	974	438	206	164	3	193	1
	<i>MS-B40 simul</i>	1,017	974	438	206	164	3	193	1
	<i>MS-MSY</i>	1,017	974	438	206	164	3	189	1
	<i>MS-cMSY</i>	1,019	974	439	206	166	3	187	1

Supplementary Table S3.4.PM-1. Summary of performance metric 1 (average annual catch (1,000 mt)) across OM_s for **Cod**.

Cap	EM	1. No climate	2. w/ SRR	3. 1-2.6	4. w/ SRR	5. 2-4.5	6. w/ SRR	7. 5-8.5	8. w/ SRR
FALSE	<i>NPFMC Fix-M</i>	31	29	27	24	24	21	23	20
	<i>NPFMC Fix-M (Dynamic B0)</i>	31	29	27	23	25	20	24	19
	<i>NPFMC Est-M</i>	19	20	17	17	15	16	14	15
	<i>NPFMC Est-M (Dynamic B0)</i>	19	20	17	17	15	16	14	15
	<i>MS-B40 iter</i>	22	24	19	21	18	19	17	18
	<i>MS-B40 simul</i>	22	23	19	20	17	19	17	18
	<i>MS-MSY</i>	37	23	39	17	35	15	34	15
	<i>MS-cMSY</i>	35	27	32	21	29	18	28	17
TRUE	<i>NPFMC Fix-M</i>	30	27	26	22	24	20	23	19
	<i>NPFMC Fix-M (Dynamic B0)</i>	30	27	27	21	24	18	24	18
	<i>NPFMC Est-M</i>	18	19	16	17	15	15	14	14
	<i>NPFMC Est-M (Dynamic B0)</i>	18	19	16	16	15	15	14	15
	<i>MS-B40 iter</i>	21	22	18	19	17	17	16	17
	<i>MS-B40 simul</i>	21	22	18	18	17	17	16	17
	<i>MS-MSY</i>	38	18	34	13	31	12	30	12
	<i>MS-cMSY</i>	34	21	30	16	27	14	26	14

Supplementary Table S3.4.PM-2. Summary of performance metric 2 (average interannual variation in catch (IAV)) across OM_s for **Cod**.

Cap	EM	1. No climate	2. w/ SRR	3. 1-2.6	4. w/ SRR	5. 2-4.5	6. w/ SRR	7. 5-8.5	8. w/ SRR
FALSE	<i>NPFMC Fix-M</i>	0.24	0.25	0.28	0.29	0.3	0.32	0.32	0.34
	<i>NPFMC Fix-M (Dynamic B0)</i>	0.2	0.2	0.22	0.22	0.23	0.23	0.24	0.24
	<i>NPFMC Est-M</i>	0.19	0.18	0.22	0.21	0.24	0.22	0.25	0.23
	<i>NPFMC Est-M (Dynamic B0)</i>	0.18	0.17	0.19	0.18	0.2	0.19	0.21	0.19
	<i>MS-B40 iter</i>	0.15	0.15	0.16	0.16	0.17	0.16	0.17	0.17
	<i>MS-B40 simul</i>	0.15	0.15	0.16	0.16	0.17	0.16	0.18	0.17
	<i>MS-MSY</i>	0.39	0.53	0.52	0.66	0.57	0.78	0.59	0.78
	<i>MS-cMSY</i>	0.33	0.28	0.36	0.33	0.37	0.37	0.41	0.39
TRUE	<i>NPFMC Fix-M</i>	0.25	0.26	0.28	0.31	0.3	0.34	0.32	0.35
	<i>NPFMC Fix-M (Dynamic B0)</i>	0.2	0.21	0.22	0.23	0.23	0.24	0.24	0.24
	<i>NPFMC Est-M</i>	0.19	0.19	0.22	0.21	0.24	0.23	0.26	0.24
	<i>NPFMC Est-M (Dynamic B0)</i>	0.18	0.17	0.19	0.19	0.21	0.2	0.21	0.2
	<i>MS-B40 iter</i>	0.15	0.15	0.17	0.16	0.17	0.17	0.18	0.17
	<i>MS-B40 simul</i>	0.15	0.15	0.17	0.16	0.17	0.17	0.18	0.17
	<i>MS-MSY</i>	0.32	0.48	0.37	0.61	0.38	0.67	0.39	0.66
	<i>MS-cMSY</i>	0.28	0.3	0.31	0.37	0.32	0.41	0.34	0.42

Supplementary Table S3.4.PM-3. Summary of performance metric 3 (probability that the population is overfished as determined from the OM) across OMs for **Cod**.

Cap	EM	1. No climate	2. w/ SRR	3. 1-2.6	4. w/ SRR	5. 2-4.5	6. w/ SRR	7. 5-8.5	8. w/ SRR
FALSE	<i>NPFMC Fix-M</i>	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02
	<i>NPFMC Fix-M (Dynamic B0)</i>	0.01	0.01	0.01	0.04	0.01	0.13	0.01	0.21
	<i>NPFMC Est-M</i>	0	0	0	0	0	0	0	0
	<i>NPFMC Est-M (Dynamic B0)</i>	0	0	0	0	0	0	0	0
	<i>MS-B40 iter</i>	0	0	0	0	0	0	0	0
	<i>MS-B40 simul</i>	0	0	0	0	0	0	0	0
	<i>MS-MSY</i>	0.27	0.78	0.85	0.84	0.83	0.85	0.84	0.84
	<i>MS-cMSY</i>	0.12	0.39	0.13	0.54	0.13	0.7	0.16	0.75
TRUE	<i>NPFMC Fix-M</i>	0.01	0.01	0.01	0.02	0.01	0.03	0.02	0.03
	<i>NPFMC Fix-M (Dynamic B0)</i>	0.01	0.03	0.01	0.14	0.01	0.31	0.02	0.34
	<i>NPFMC Est-M</i>	0	0	0	0	0	0	0	0
	<i>NPFMC Est-M (Dynamic B0)</i>	0	0	0	0	0	0	0	0
	<i>MS-B40 iter</i>	0	0	0	0	0	0	0	0
	<i>MS-B40 simul</i>	0	0	0	0	0	0	0	0
	<i>MS-MSY</i>	0.82	0.84	0.88	0.86	0.87	0.86	0.86	0.86
	<i>MS-cMSY</i>	0.18	0.68	0.17	0.76	0.18	0.82	0.19	0.83

Supplementary Table S3.4.PM-4. Summary of performance metric 4 (terminal spawning stock biomass (1,000 mt)) across OM for **Cod**.

Cap	EM	1. No climate	2. w/ SRR	3. 1-2.6	4. w/ SRR	5. 2-4.5	6. w/ SRR	7. 5-8.5	8. w/ SRR
FALSE	<i>NPFMC Fix-M</i>	157	152	128	118	134	108	138	95
	<i>NPFMC Fix-M (Dynamic B0)</i>	153	146	123	107	124	72	125	48
	<i>NPFMC Est-M</i>	269	288	223	238	204	218	193	197
	<i>NPFMC Est-M (Dynamic B0)</i>	270	290	225	243	203	218	191	191
	<i>MS-B40 iter</i>	251	275	210	229	190	199	179	168
	<i>MS-B40 simul</i>	251	272	210	229	190	200	179	168
	<i>MS-MSY</i>	101	52	43	26	49	10	54	4
	<i>MS-cMSY</i>	136	117	106	84	106	47	109	23
TRUE	<i>NPFMC Fix-M</i>	152	140	124	107	134	102	139	93
	<i>NPFMC Fix-M (Dynamic B0)</i>	148	130	119	91	124	60	125	44
	<i>NPFMC Est-M</i>	260	271	214	221	204	208	193	194
	<i>NPFMC Est-M (Dynamic B0)</i>	261	272	215	222	202	203	191	188
	<i>MS-B40 iter</i>	239	246	200	203	189	184	179	162
	<i>MS-B40 simul</i>	240	244	200	207	189	191	179	164
	<i>MS-MSY</i>	58	28	40	11	49	4	56	2
	<i>MS-cMSY</i>	120	79	96	59	105	35	107	18

Supplementary Table S3.4.PM-5. Summary of performance metric 5 (terminal spawning stock biomass depletion relative to dynamic SB0) across OM for **Cod**.

Cap	EM	1. No climate	2. w/ SRR	3. 1-2.6	4. w/ SRR	5. 2-4.5	6. w/ SRR	7. 5-8.5	8. w/ SRR
FALSE	<i>NPFMC Fix-M</i>	0.37	0.39	0.37	0.36	0.46	0.34	0.53	0.32
	<i>NPFMC Fix-M (Dynamic B0)</i>	0.36	0.37	0.35	0.33	0.42	0.23	0.47	0.16
	<i>NPFMC Est-M</i>	0.64	0.74	0.65	0.73	0.7	0.69	0.74	0.67
	<i>NPFMC Est-M (Dynamic B0)</i>	0.65	0.74	0.65	0.74	0.69	0.69	0.73	0.65
	<i>MS-B40 iter</i>	0.6	0.7	0.61	0.7	0.65	0.63	0.68	0.57
	<i>MS-B40 simul</i>	0.6	0.69	0.61	0.7	0.65	0.63	0.68	0.57
	<i>MS-MSY</i>	0.24	0.13	0.13	0.08	0.17	0.03	0.2	0.01
	<i>MS-cMSY</i>	0.32	0.3	0.3	0.26	0.36	0.15	0.42	0.08
TRUE	<i>NPFMC Fix-M</i>	0.36	0.36	0.36	0.33	0.46	0.32	0.53	0.32
	<i>NPFMC Fix-M (Dynamic B0)</i>	0.35	0.33	0.34	0.28	0.42	0.19	0.47	0.15
	<i>NPFMC Est-M</i>	0.62	0.69	0.62	0.68	0.69	0.66	0.74	0.66
	<i>NPFMC Est-M (Dynamic B0)</i>	0.62	0.69	0.62	0.68	0.69	0.64	0.73	0.64
	<i>MS-B40 iter</i>	0.57	0.63	0.58	0.62	0.64	0.58	0.68	0.55
	<i>MS-B40 simul</i>	0.57	0.62	0.58	0.63	0.64	0.6	0.68	0.56
	<i>MS-MSY</i>	0.14	0.07	0.12	0.03	0.17	0.01	0.21	0.01
	<i>MS-cMSY</i>	0.28	0.2	0.28	0.18	0.35	0.11	0.41	0.06

Supplementary Table S3.4.PM-6. Summary of performance metric 6 (terminal dynamic SB0 (1,000 mt)) across OMs for **Cod**.

Cap	EM	1. No climate	2. w/ SRR	3. 1-2.6	4. w/ SRR	5. 2-4.5	6. w/ SRR	7. 5-8.5	8. w/ SRR
FALSE	<i>NPFMC Fix-M</i>	417	390	344	325	292	313	260	292
	<i>NPFMC Fix-M (Dynamic B0)</i>	417	390	344	325	292	313	260	292
	<i>NPFMC Est-M</i>	417	390	344	325	292	313	260	292
	<i>NPFMC Est-M (Dynamic B0)</i>	417	390	344	325	292	313	260	292
	<i>MS-B40 iter</i>	417	390	344	325	292	313	260	292
	<i>MS-B40 simul</i>	417	390	344	325	292	313	260	292
	<i>MS-MSY</i>	417	389	344	325	292	313	260	292
	<i>MS-cMSY</i>	416	390	344	325	292	313	259	292
TRUE	<i>NPFMC Fix-M</i>	417	390	344	325	292	313	260	292
	<i>NPFMC Fix-M (Dynamic B0)</i>	417	390	344	325	292	313	260	292
	<i>NPFMC Est-M</i>	417	390	344	325	292	313	260	292
	<i>NPFMC Est-M (Dynamic B0)</i>	417	390	344	325	292	313	260	292
	<i>MS-B40 iter</i>	417	390	344	325	292	313	260	292
	<i>MS-B40 simul</i>	417	390	344	325	292	313	260	292
	<i>MS-MSY</i>	417	390	344	325	292	313	260	292
	<i>MS-cMSY</i>	418	390	345	325	292	313	260	292

Supplementary Table S3.5.PM-1. Summary of performance metric 1 (average annual catch (1,000 mt)) across OMs for **Arrowtooth flounder**.

Cap	EM	1. No climate	2. w/ SRR	3. 1-2.6	4. w/ SRR	5. 2-4.5	6. w/ SRR	7. 5-8.5	8. w/ SRR
FALSE	<i>NPFMC Fix-M</i>	98	89	77	77	63	63	54	54
	<i>NPFMC Fix-M (Dynamic B0)</i>	99	89	78	78	66	65	57	56
	<i>NPFMC Est-M</i>	111	90	86	80	70	65	60	57
	<i>NPFMC Est-M (Dynamic B0)</i>	111	90	88	80	74	66	65	58
	<i>MS-B40 iter</i>	122	88	98	79	82	64	72	58
	<i>MS-B40 simul</i>	123	89	98	80	82	65	72	59
	<i>MS-MSY</i>	133	87	155	80	123	65	102	59
	<i>MS-cMSY</i>	168	87	134	80	111	65	97	59
TRUE	<i>NPFMC Fix-M</i>	36	36	35	36	34	35	31	31
	<i>NPFMC Fix-M (Dynamic B0)</i>	36	36	35	36	35	35	33	33
	<i>NPFMC Est-M</i>	36	36	35	36	35	35	32	32
	<i>NPFMC Est-M (Dynamic B0)</i>	36	36	35	36	35	35	34	33
	<i>MS-B40 iter</i>	36	36	35	36	35	35	34	33
	<i>MS-B40 simul</i>	36	36	35	36	35	35	34	33
	<i>MS-MSY</i>	36	36	35	36	35	35	35	33
	<i>MS-cMSY</i>	36	36	35	36	35	35	35	33

Supplementary Table S3.5.PM-2. Summary of performance metric 2 (average interannual variation in catch (IAV)) across OM s for **Arrowtooth flounder**.

Cap	EM	1. No climate	2. w/ SRR	3. 1-2.6	4. w/ SRR	5. 2-4.5	6. w/ SRR	7. 5-8.5	8. w/ SRR
FALSE	<i>NPFMC Fix-M</i>	0.14	0.15	0.17	0.17	0.21	0.21	0.25	0.24
	<i>NPFMC Fix-M (Dynamic B0)</i>	0.14	0.15	0.17	0.17	0.2	0.2	0.23	0.23
	<i>NPFMC Est-M</i>	0.22	0.27	0.28	0.3	0.34	0.37	0.39	0.42
	<i>NPFMC Est-M (Dynamic B0)</i>	0.21	0.27	0.27	0.29	0.32	0.36	0.36	0.4
	<i>MS-B40 iter</i>	0.26	0.37	0.33	0.41	0.38	0.5	0.44	0.55
	<i>MS-B40 simul</i>	0.26	0.37	0.33	0.41	0.39	0.5	0.44	0.55
	<i>MS-MSY</i>	0.33	0.49	0.94	0.5	1.15	0.62	1.42	0.68
	<i>MS-cMSY</i>	0.4	0.5	0.5	0.5	0.59	0.62	0.68	0.68
TRUE	<i>NPFMC Fix-M</i>	0.08	0.08	0.08	0.08	0.09	0.08	0.11	0.1
	<i>NPFMC Fix-M (Dynamic B0)</i>	0.08	0.08	0.08	0.08	0.08	0.08	0.1	0.1
	<i>NPFMC Est-M</i>	0.08	0.08	0.08	0.08	0.09	0.08	0.11	0.1
	<i>NPFMC Est-M (Dynamic B0)</i>	0.08	0.08	0.08	0.08	0.08	0.08	0.1	0.1
	<i>MS-B40 iter</i>	0.08	0.08	0.08	0.08	0.08	0.08	0.1	0.1
	<i>MS-B40 simul</i>	0.08	0.08	0.08	0.08	0.08	0.08	0.1	0.1
	<i>MS-MSY</i>	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.1
	<i>MS-cMSY</i>	0.08	0.08	0.08	0.08	0.08	0.08	0.1	0.1

Supplementary Table S3.5.PM-3. Summary of performance metric 3 (probability that the population is overfished as determined from the OM) across OMs for **Arrowtooth flounder**.

Cap	EM	1. No climate	2. w/ SRR	3. 1-2.6	4. w/ SRR	5. 2-4.5	6. w/ SRR	7. 5-8.5	8. w/ SRR
FALSE	<i>NPFMC Fix-M</i>	0	0	0	0	0	0	0	0
	<i>NPFMC Fix-M (Dynamic B0)</i>	0	0	0	0	0	0	0	0.1
	<i>NPFMC Est-M</i>	0	0	0	0	0	0	0	0
	<i>NPFMC Est-M (Dynamic B0)</i>	0	0	0	0	0	0.04	0.01	0.24
	<i>MS-B40 iter</i>	0	0.03	0	0.02	0	0.29	0.04	0.37
	<i>MS-B40 simul</i>	0	0.02	0	0.01	0	0.28	0.04	0.37
	<i>MS-MSY</i>	0	0.23	0.95	0.08	0.95	0.38	0.95	0.4
	<i>MS-cMSY</i>	0.38	0.23	0.4	0.08	0.55	0.38	0.6	0.4
TRUE	<i>NPFMC Fix-M</i>	0	0	0	0	0	0	0	0
	<i>NPFMC Fix-M (Dynamic B0)</i>	0	0	0	0	0	0	0	0.05
	<i>NPFMC Est-M</i>	0	0	0	0	0	0	0	0
	<i>NPFMC Est-M (Dynamic B0)</i>	0	0	0	0	0	0	0.03	0.08
	<i>MS-B40 iter</i>	0	0	0	0	0	0	0.04	0.08
	<i>MS-B40 simul</i>	0	0	0	0	0	0	0.04	0.08
	<i>MS-MSY</i>	0	0	0	0	0	0	0.06	0.08
	<i>MS-cMSY</i>	0	0	0	0	0	0	0.05	0.08

Supplementary Table S3.5.PM-4. Summary of performance metric 4 (terminal spawning stock biomass (1,000 mt)) across OM for **Arrowtooth flounder**.

Cap	EM	1. No climate	2. w/ SRR	3. 1-2.6	4. w/ SRR	5. 2-4.5	6. w/ SRR	7. 5-8.5	8. w/ SRR
FALSE	<i>NPFMC Fix-M</i>	368	319	303	293	133	122	66	52
	<i>NPFMC Fix-M (Dynamic B0)</i>	366	314	301	283	107	86	49	20
	<i>NPFMC Est-M</i>	330	262	278	251	124	101	62	41
	<i>NPFMC Est-M (Dynamic B0)</i>	327	246	273	226	95	58	44	10
	<i>MS-B40 iter</i>	293	182	247	172	85	36	40	5
	<i>MS-B40 simul</i>	298	186	251	173	86	36	40	6
	<i>MS-MSY</i>	264	143	12	154	2	32	1	5
	<i>MS-cMSY</i>	166	142	151	153	53	32	30	5
TRUE	<i>NPFMC Fix-M</i>	582	597	443	492	128	150	64	53
	<i>NPFMC Fix-M (Dynamic B0)</i>	582	597	443	493	108	144	48	28
	<i>NPFMC Est-M</i>	581	595	442	490	115	143	59	43
	<i>NPFMC Est-M (Dynamic B0)</i>	581	595	442	490	99	142	42	19
	<i>MS-B40 iter</i>	581	595	443	491	99	142	40	18
	<i>MS-B40 simul</i>	581	587	443	489	99	142	39	18
	<i>MS-MSY</i>	583	591	445	493	99	144	21	19
	<i>MS-cMSY</i>	583	590	444	492	99	144	28	19

Supplementary Table S3.5.PM-5. Summary of performance metric 5 (terminal spawning stock biomass depletion relative to dynamic SB0) across OMs for **Arrowtooth flounder**.

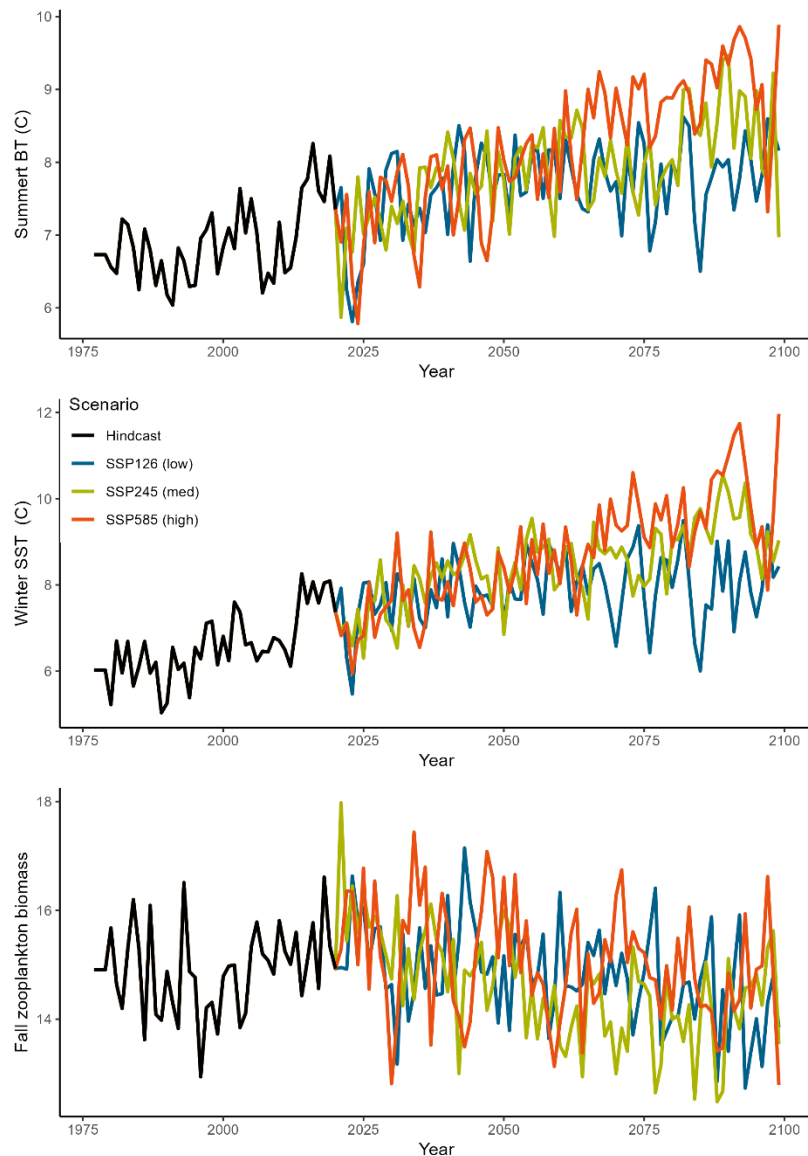
Cap	EM	1. No climate	2. w/ SRR	3. 1-2.6	4. w/ SRR	5. 2-4.5	6. w/ SRR	7. 5-8.5	8. w/ SRR
FALSE	<i>NPFMC Fix-M</i>	0.52	0.45	0.54	0.49	0.62	0.43	0.61	0.37
	<i>NPFMC Fix-M (Dynamic B0)</i>	0.52	0.44	0.54	0.47	0.5	0.3	0.45	0.14
	<i>NPFMC Est-M</i>	0.47	0.37	0.5	0.42	0.58	0.35	0.57	0.29
	<i>NPFMC Est-M (Dynamic B0)</i>	0.46	0.35	0.49	0.37	0.44	0.2	0.4	0.07
	<i>MS-B40 iter</i>	0.42	0.26	0.44	0.28	0.4	0.12	0.37	0.04
	<i>MS-B40 simul</i>	0.42	0.26	0.45	0.29	0.4	0.13	0.37	0.04
	<i>MS-MSY</i>	0.37	0.2	0.02	0.25	0.01	0.11	0.01	0.04
	<i>MS-cMSY</i>	0.24	0.2	0.27	0.25	0.25	0.11	0.28	0.03
TRUE	<i>NPFMC Fix-M</i>	0.83	0.84	0.79	0.82	0.6	0.53	0.59	0.38
	<i>NPFMC Fix-M (Dynamic B0)</i>	0.83	0.84	0.79	0.82	0.5	0.5	0.44	0.2
	<i>NPFMC Est-M</i>	0.82	0.84	0.79	0.81	0.54	0.5	0.55	0.3
	<i>NPFMC Est-M (Dynamic B0)</i>	0.82	0.84	0.79	0.81	0.46	0.5	0.38	0.14
	<i>MS-B40 iter</i>	0.82	0.84	0.79	0.81	0.46	0.5	0.36	0.13
	<i>MS-B40 simul</i>	0.83	0.83	0.79	0.81	0.46	0.5	0.36	0.13
	<i>MS-MSY</i>	0.83	0.83	0.79	0.82	0.46	0.51	0.19	0.13
	<i>MS-cMSY</i>	0.83	0.83	0.79	0.81	0.46	0.5	0.25	0.13

Supplementary Table S3.5.PM-6. Summary of performance metric 6 (terminal dynamic SB0 (1,000 mt)) across OMs for **Arrowtooth flounder**.

Cap	EM	1. No climate	2. w/ SRR	3. 1-2.6	4. w/ SRR	5. 2-4.5	6. w/ SRR	7. 5-8.5	8. w/ SRR
FALSE	<i>NPFMC Fix-M</i>	703	710	560	603	214	284	109	140
	<i>NPFMC Fix-M (Dynamic B0)</i>	703	710	560	603	214	284	109	140
	<i>NPFMC Est-M</i>	703	710	560	603	214	284	109	140
	<i>NPFMC Est-M (Dynamic B0)</i>	703	710	560	603	214	284	109	140
	<i>MS-B40 iter</i>	703	710	560	603	214	284	109	140
	<i>MS-B40 simul</i>	703	710	560	603	214	284	109	140
	<i>MS-MSY</i>	703	710	560	603	214	284	109	140
	<i>MS-cMSY</i>	703	710	560	603	214	284	109	140
TRUE	<i>NPFMC Fix-M</i>	703	710	560	603	214	284	109	140
	<i>NPFMC Fix-M (Dynamic B0)</i>	703	710	560	603	214	284	109	140
	<i>NPFMC Est-M</i>	703	710	560	603	214	284	109	140
	<i>NPFMC Est-M (Dynamic B0)</i>	703	710	560	603	214	284	109	140
	<i>MS-B40 iter</i>	703	710	560	603	214	284	109	140
	<i>MS-B40 simul</i>	703	710	560	603	214	284	109	140
	<i>MS-MSY</i>	703	710	560	603	214	284	109	140
	<i>MS-cMSY</i>	703	710	560	603	214	284	109	140

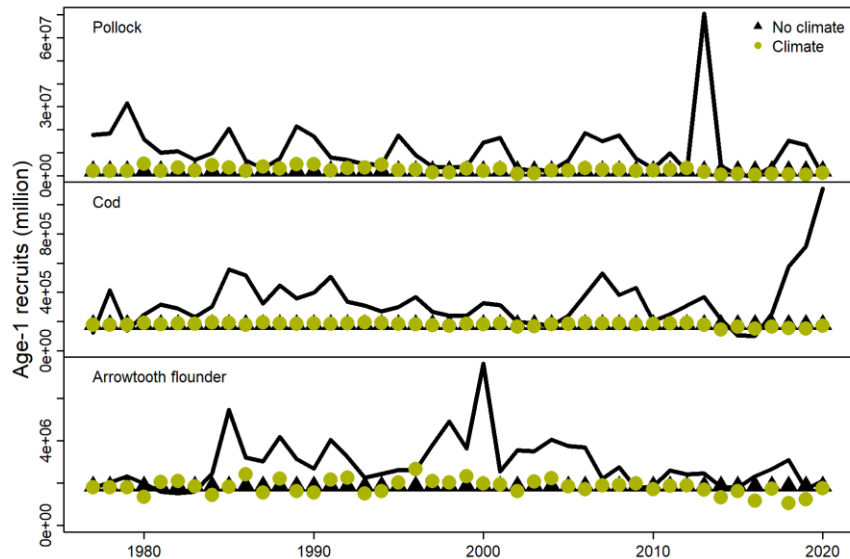
SUPPLEMENTARY FIGURES

Supplementary Figure S3.1. Time-series of summer bottom temperature (June-August), winter sea surface temperature (November-January), and fall large zooplankton biomass (August-October) extracted from each ROMS simulation across the National Marine Fisheries Service (NMFS) management areas 610, 620, and 630 from GFDL-ESM2M downscaled ROMS simulations for high baseline (SSP5-8.5; red), medium pathway (SSP2-4.5; green), and high mitigation with a 2-degree future increase in temperature (SSP1-2.6; blue) CMIP-6 scenarios.

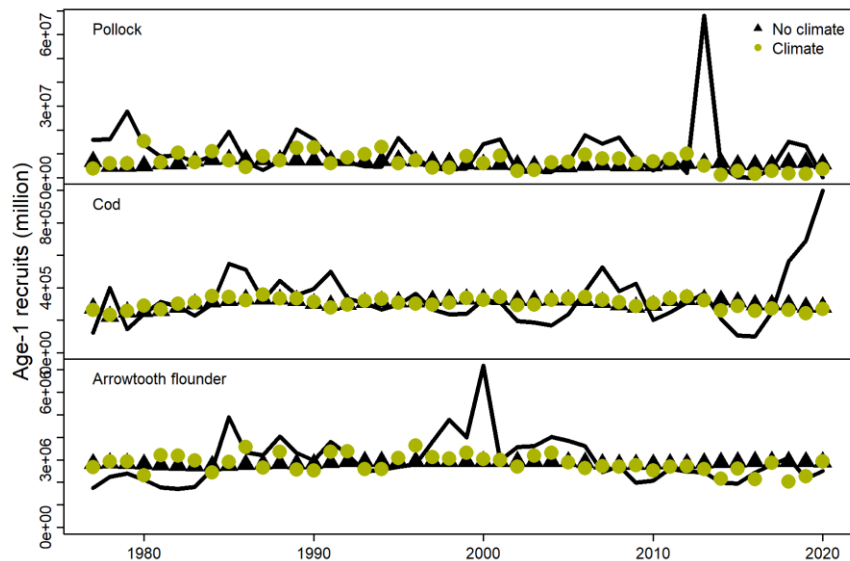


Supplementary Figure S3.2. Time-series of age-1 recruitment for operating models during the conditioning period (1977-2020) with no stock-recruitment relationship (upper) and Ricker recruitment (lower). The triangles indicate the expected recruitment (without recruitment deviates) without environmental covariates and the circles indicated the expected recruitment with environmental covariates.

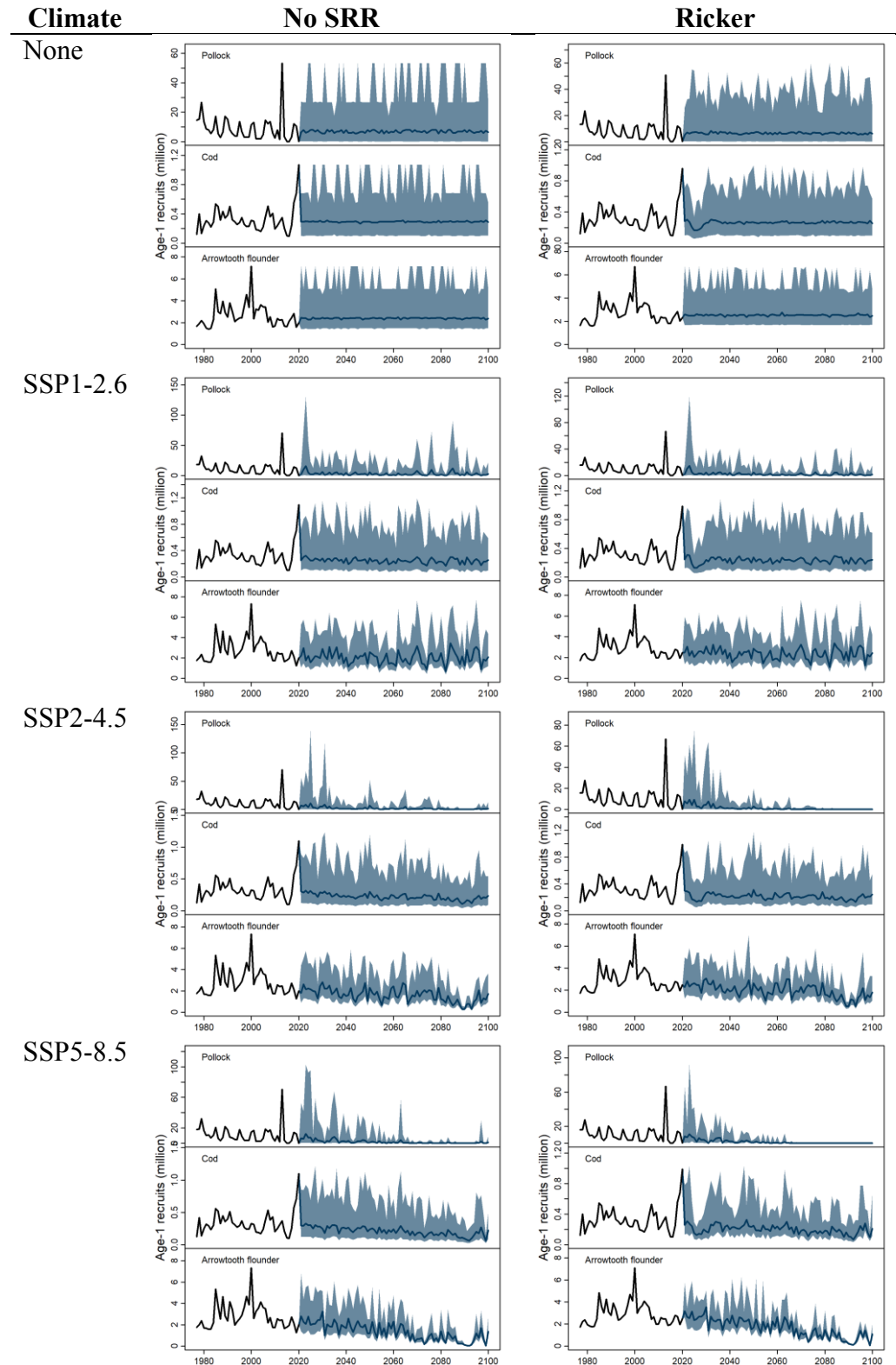
No stock-recruitment relationship



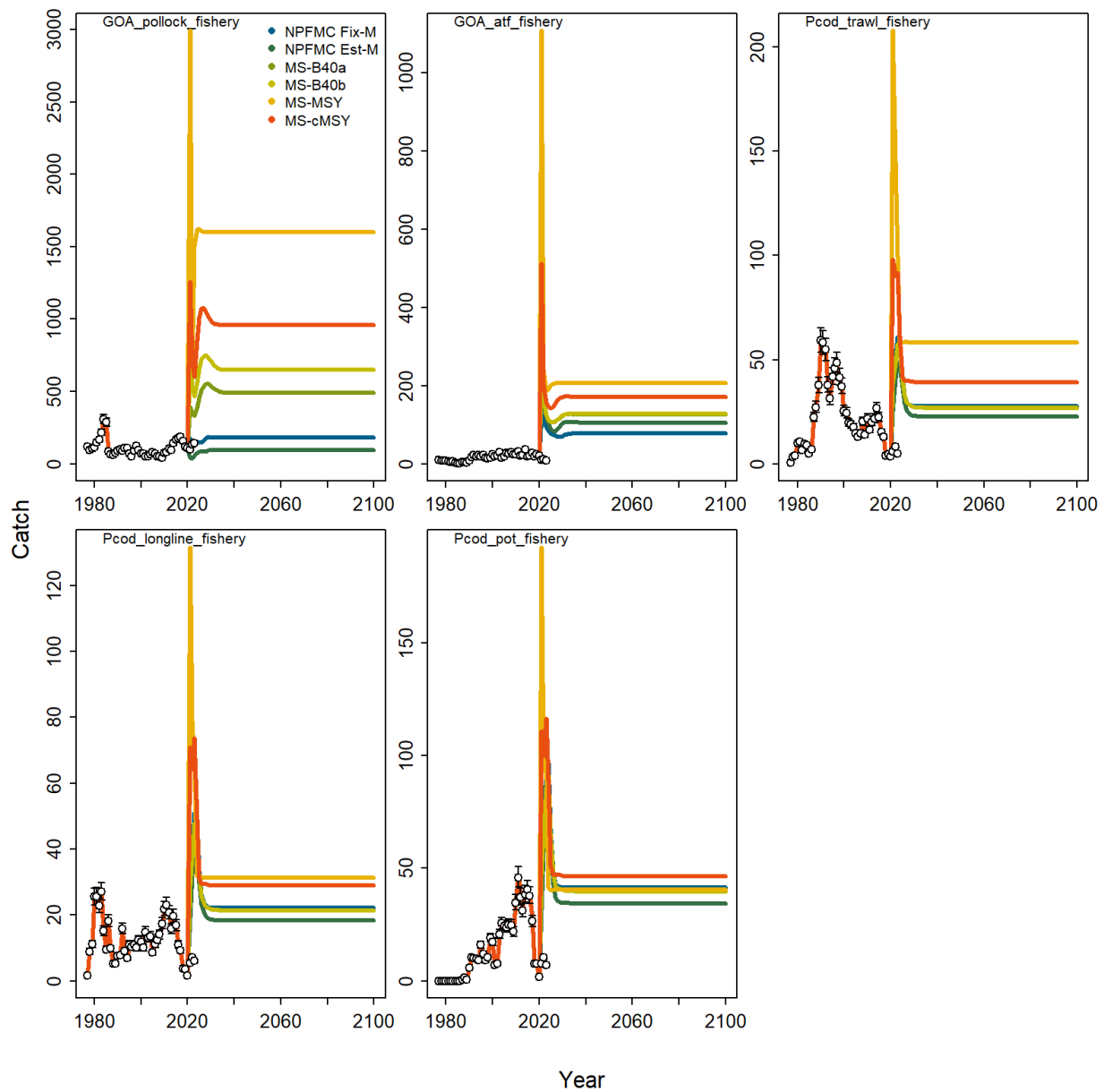
Ricker stock-recruitment relationship



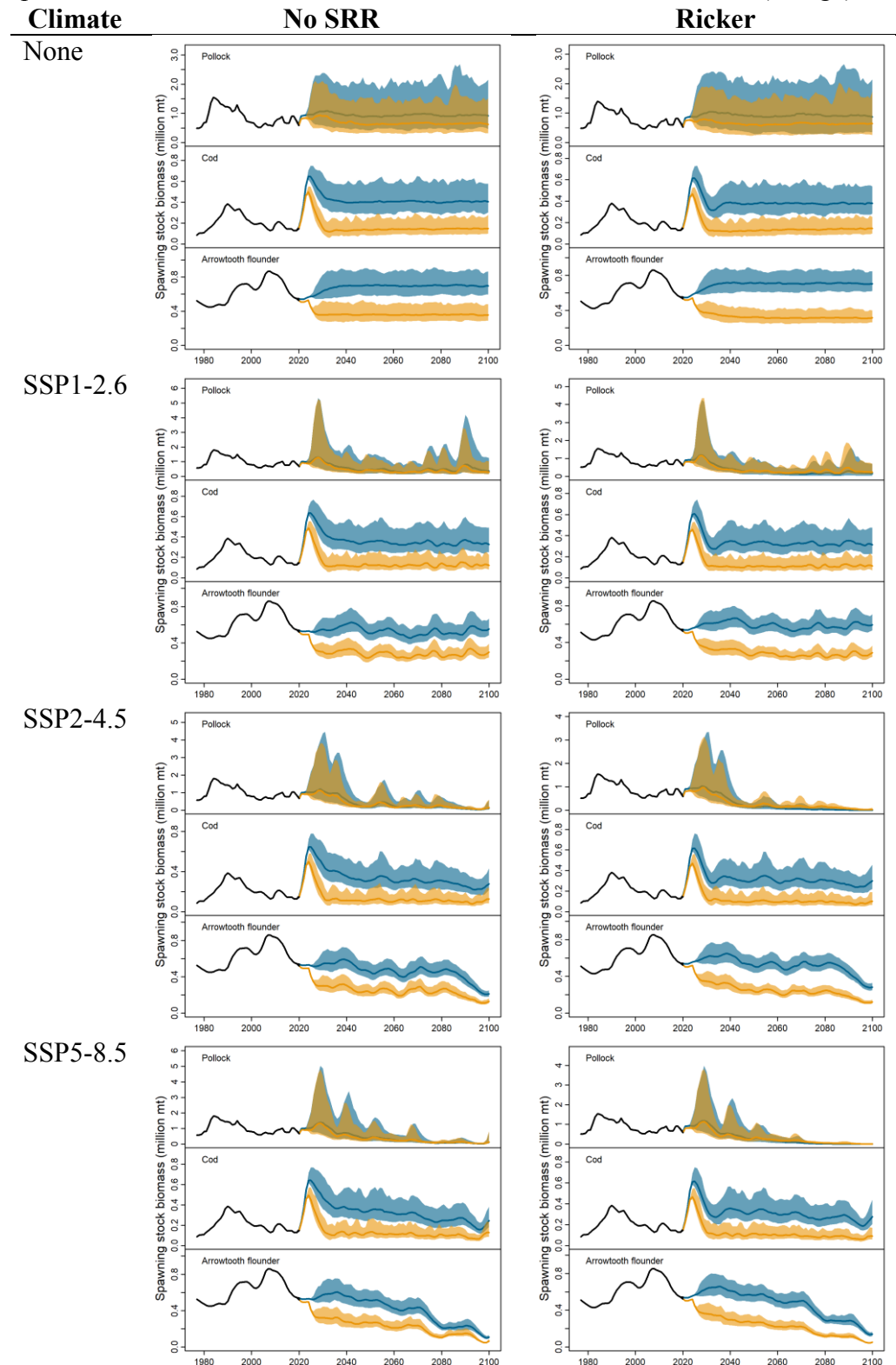
Supplementary Figure S3.3. 95% simulation intervals of age-1 recruitment for operating models with no stock-recruitment relationship (left; no SRR) and Ricker recruitment (right) under no fishing.



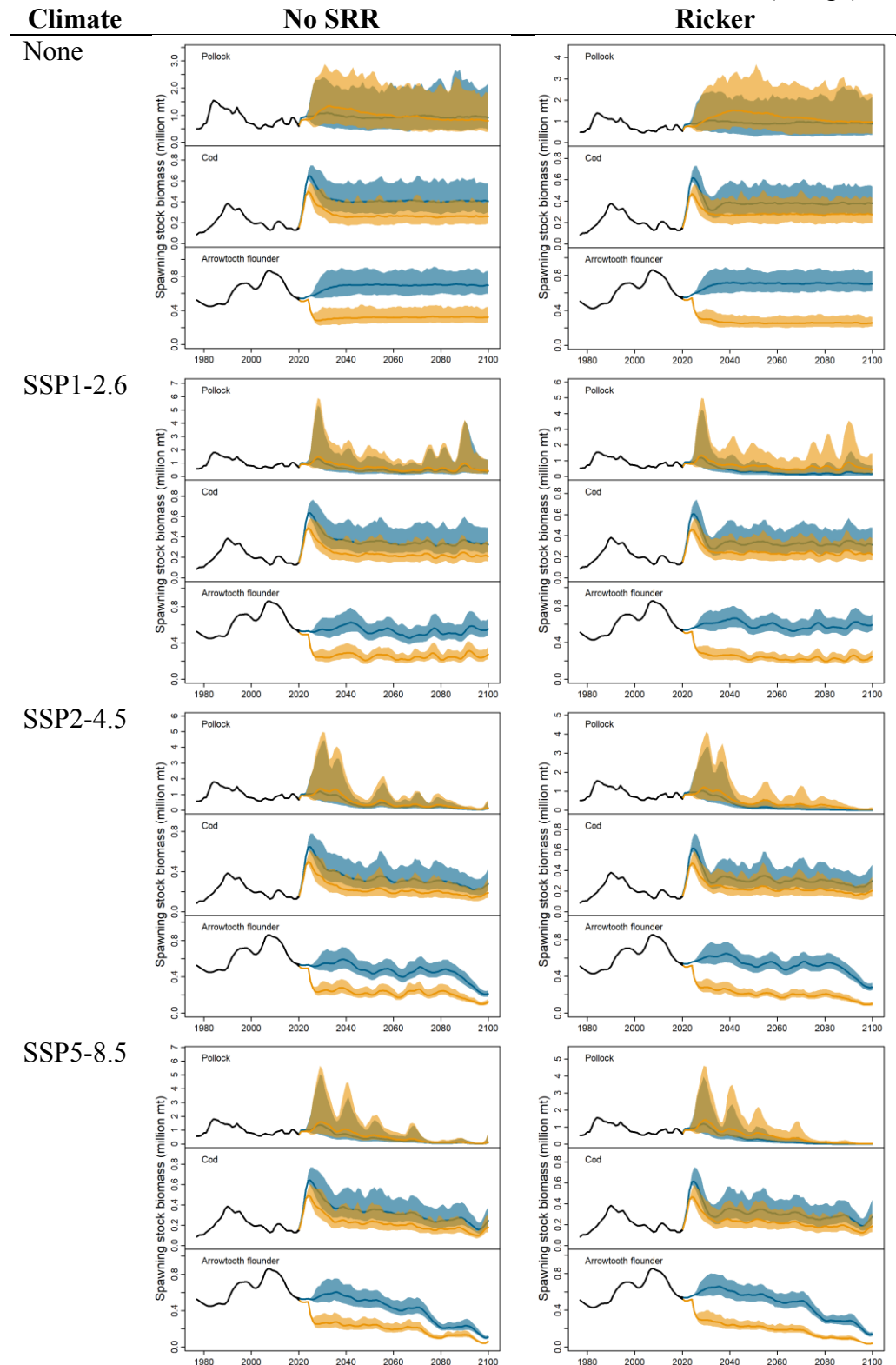
Supplementary Figure S3.4. Time-series of recommended catch ('000 mt) as determined from the estimation methods and associated harvest control rules fit to data from 1977 to 2020 and projected until 2100 under mean recruitment.



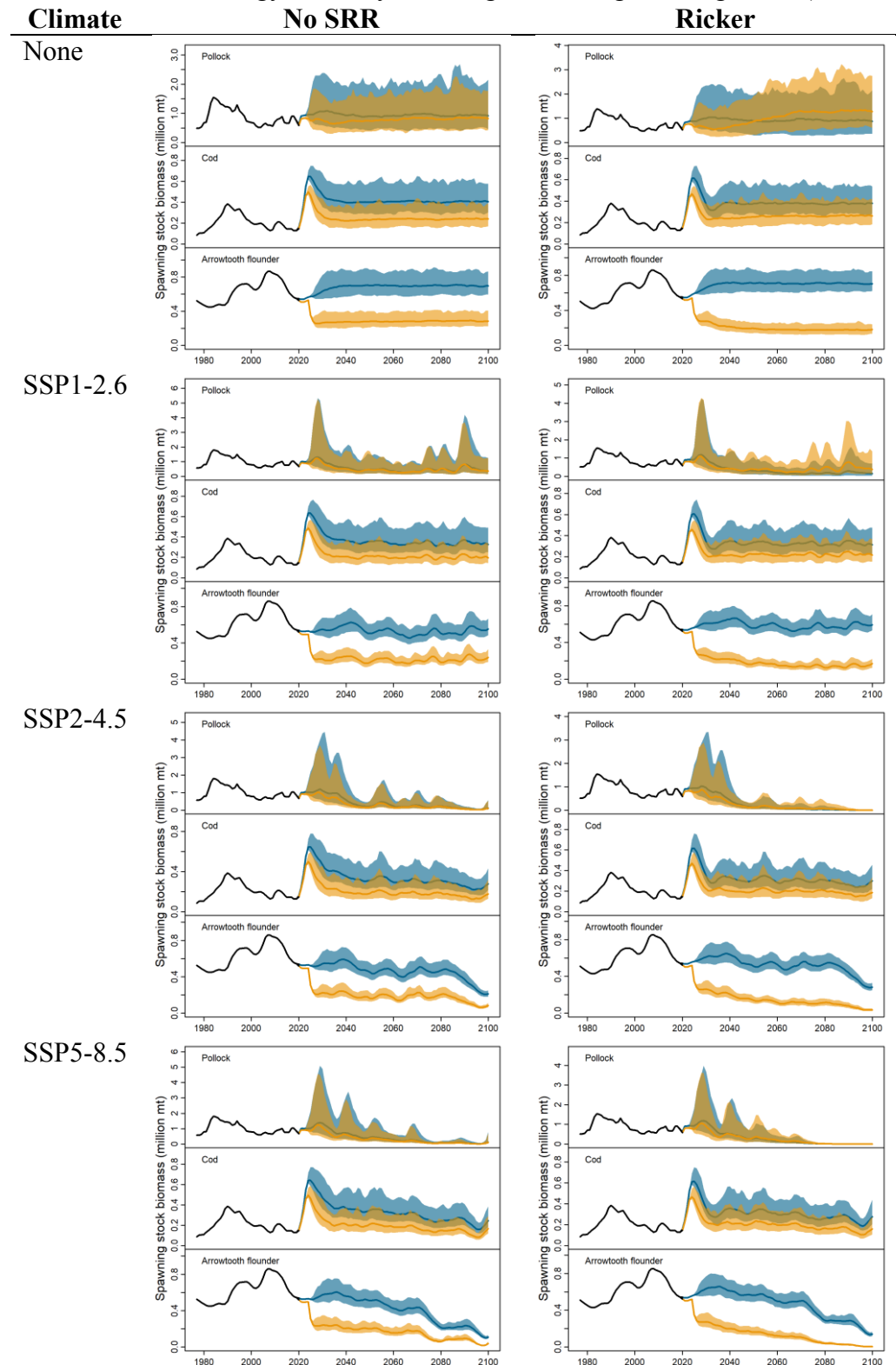
Supplementary Figure S3.5. 95% simulation intervals for spawning stock biomass for operating models with no stock-recruitment relationship (left; no SRR) and Ricker recruitment (right) when there is no fishing (blue) and catch is derived from the single-species estimation method that pre-specified M combined with the NPFMC Tier 3 harvest control rule (orange).



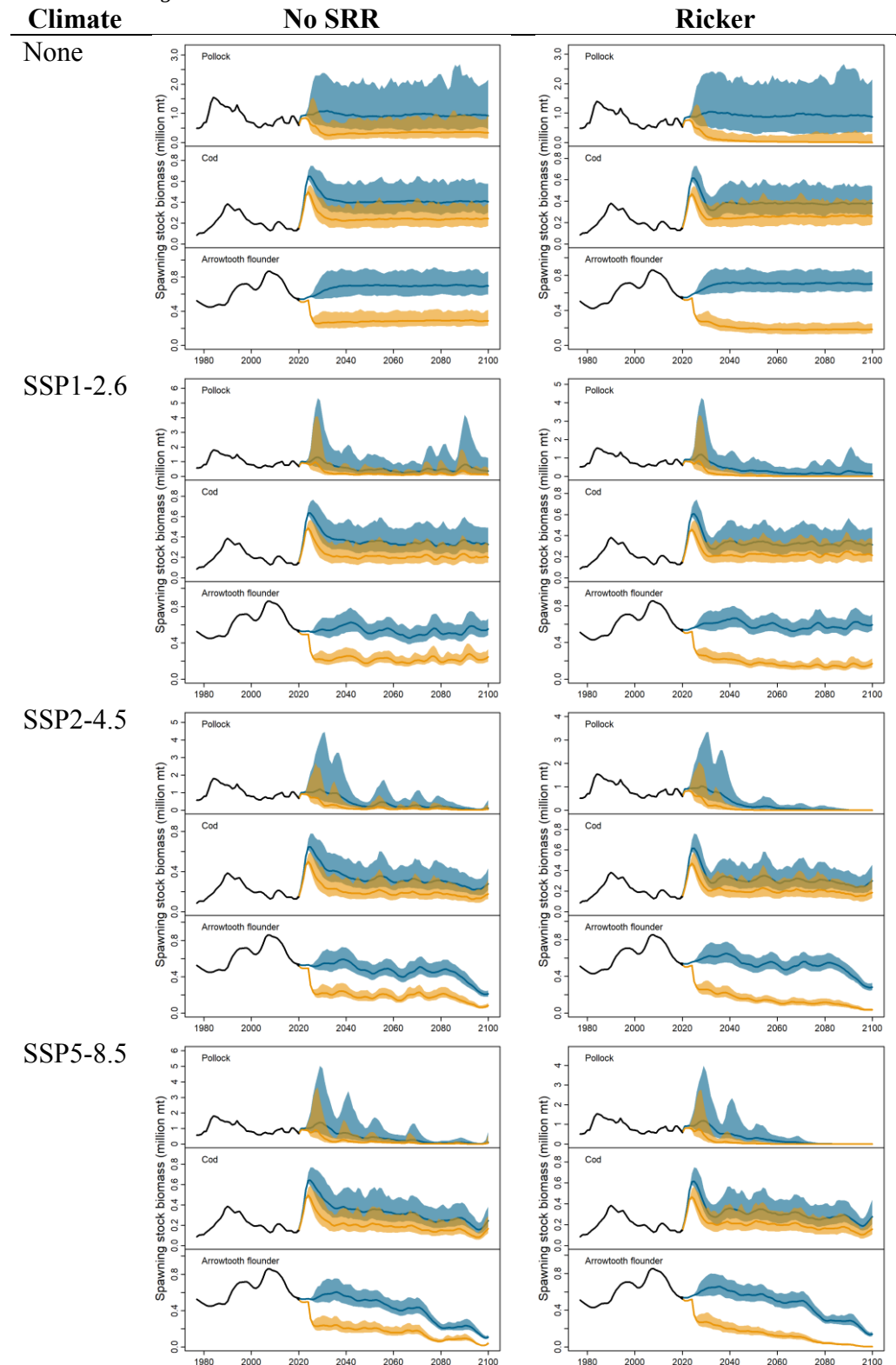
Supplementary Figure S3.6. 95% simulation intervals for spawning stock biomass for operating models with no stock-recruitment relationship (left; no SRR) and Ricker recruitment (right) when there is no fishing (blue) and catch is derived from the **single-species** estimation method that estimated M combined with the NPFMC Tier 3 harvest control rule (orange).



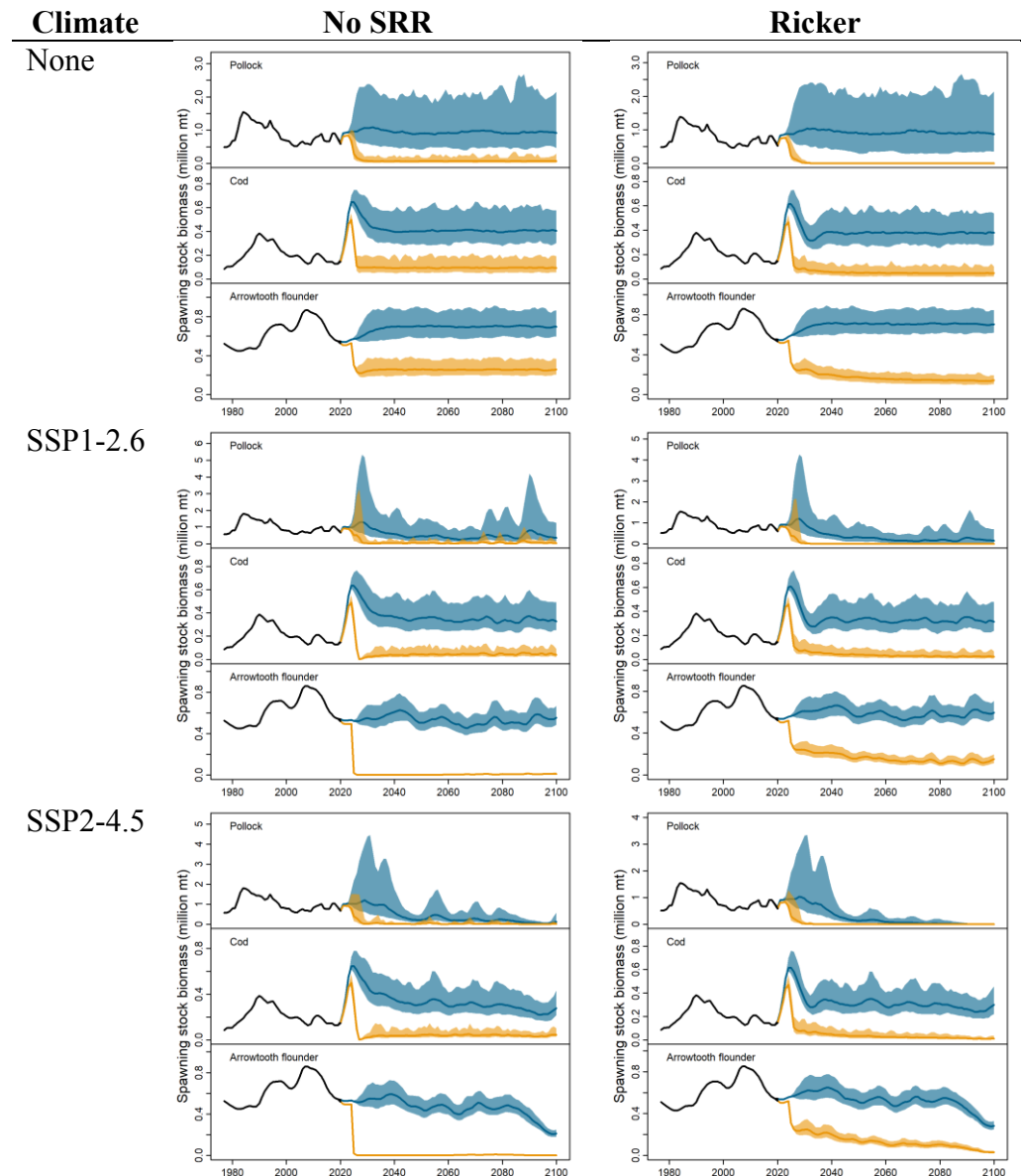
Supplementary Figure S3.7. 95% simulation intervals of spawning stock biomass for operating models with no stock-recruitment relationship (left; no SRR) and Ricker recruitment (right) when there is no fishing (blue) and catch from multi-species estimation model combined with the individual stock strategy currently used to guide strategic management (**MS-B40-a**) in orange.



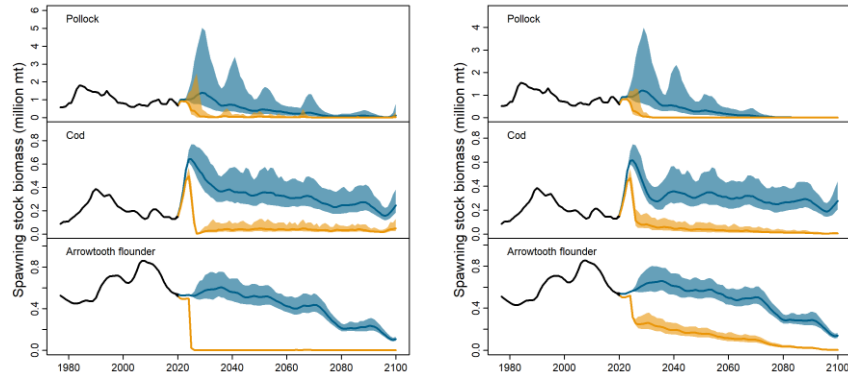
Supplementary Figure S3.8. 95% simulation intervals of spawning stock biomass for operating models with no stock-recruitment relationship (left; no SRR) and Ricker recruitment (right) when there is no fishing (blue) and catch is derived from the multi-species estimation model combined with the $B_{Target} = SB_{40}$ strategy determined simultaneously (**MS-B40-b**) in orange.



Supplementary Figure S3.9. 95% simulation intervals of spawning stock biomass for operating models with no stock-recruitment relationship (left; no SRR) and Ricker recruitment (right) when there is no fishing (blue) and catch is derived from the multi-species estimation model combined with the multi-species MSY strategy (**MS-MSY**) in orange.



SSP5-8.5



Supplementary Figure S3.10. 95% simulation intervals of spawning stock biomass for operating models with no stock-recruitment relationship (left; no SRR) and Ricker recruitment (right) when there is no fishing (blue) and catch is derived from the multi-species estimation model combined with the constrained multi-species MSY strategy (**MS-cMSY**) in orange.

