Received: 28 July 2017 | Revised: 22 July 2018 | Accepted: 27 July 2018

DOI: 10.1111/faf.12316

ORIGINAL ARTICLE

WILEY FISH and FISHERIES

Trade-offs for data-limited fisheries when using harvest strategies based on catch-only models

Jessica C. Walsh[1] | Cóilín Minto[2] | Ernesto Jardim[3] | Sean C. Anderson[4,5] | Olaf P. Jensen[6] | Jamie Afflerbach[7] | Mark Dickey-Collas[8,9] | Kristin M. Kleisner[10] | Catherine Longo[11] | Giacomo Chato Osio[3] | Elizabeth R. Selig[12,13] | James T. Thorson[14] | Merrill B. Rudd[4] | Katherine J. Papacostas[12,15,16] | John N. Kittinger[17,18] | Andrew A. Rosenberg[19] | Andrew B. Cooper[1,20]

[1]School of Resource and Environmental Management, Simon Fraser University, Burnaby, British Columbia, Canada

[2]Marine and Freshwater Research Centre, Galway-Mayo Institute of Technology, Galway, Ireland

[3]Sustainable Resources Directorate, Water and Marine Resources Unit, European Commission Joint Research Centre (JRC), Ispra, Italy

[4]School of Aquatic and Fishery Sciences, University of Washington, Seattle, Washington

[5]Pacific Biological Station, Fisheries and Oceans Canada, Nanaimo, British Columbia, Canada

[6]Department of Marine & Coastal Sciences, Rutgers University, New Brunswick, New Jersey

[7]National Center for Ecological Analysis and Synthesis, University of California Santa Barbara, Santa Barbara, California

[8]International Council for the Exploration of the Sea, Copenhagen V, Denmark

[9]DTU Aqua National Institute of Aquatic Resources, Technical University of Denmark (DTU), Lyngby, Denmark

[10]Environmental Defense Fund, Boston, Massachusetts

[11]Marine Stewardship Council, London, UK

[12]Conservation International, Gordon and Better Moore Center for Science, Arlington, Virginia

[13]Norwegian Institute for Water Research, Oslo, Norway

[14]Fisheries Resource Analysis and Monitoring Division (FRAM), Northwest Fisheries Science Center, National Marine Fisheries Service, National Oceanic and Atmospheric Administration, Seattle, Washington

[15]ECS Federal, LLC, Fairfax, Virginia

[16]National Marine Fisheries Service, National Oceanic and Atmospheric Administration, Silver Spring, Maryland

[17]Conservation International, Center for Oceans, Honolulu, Hawaii

[18]Center for Biodiversity Outcomes, Life Sciences Center, Julie Ann Wrigley Global Institute of Sustainability, Arizona State University, Tempe, Arizona

[19]Union of Concerned Scientists, Cambridge, Massachusetts

[20]Seattle Children's Hospital, Seattle, Washington

Correspondence
Jessica C. Walsh, School of Biological Sciences, Simon Fraser University, Burnaby, British Columbia, Canada.
Email: jessica_walsh@sfu.ca

Funding information
Gordon and Betty Moore Foundation

Abstract

Many of the world's fisheries are unassessed, with little information about population status or risk of overfishing. Unassessed fisheries are particularly predominant in developing countries and in small-scale fisheries, where they are important for food security. Several catch-only methods based on time series of fishery catch and commonly available life-history traits have been developed to estimate stock status (defined as biomass relative to biomass at maximum sustainable yield: B/B_{MSY}). While their stock status performance has been extensively studied, performance of catch-only models as a management tool is unknown. We evaluated the extent to which a superensemble of three prominent catch-only models can provide a reliable basis for fisheries management and how performance compares across management strategies that control catch or fishing effort. We used a management strategy evaluation framework to determine whether a superensemble of catch-only models can reliably inform harvest control rules (HCRs). Across five simulated fish life histories and two harvest-dynamic types, catch-only models and HCR combinations reduced the risk of overfishing and increased the proportion of stocks above B_{MSY} compared to business as usual, though often resulted in poor yields. Precautionary HCRs based on fishing effort were robust and insensitive to error in catch-only models, while catch-based HCRs caused high probabilities of overfishing and more overfished populations. Catch-only methods tended to overestimate B/B_{MSY} for our simulated data sets. The catch-only superensemble combined with precautionary effort-based HCRs could be part of a stepping stone approach for managing some data-limited stocks while working towards more data-moderate assessment methods.

KEYWORDS

catch-only model, data-limited, data-poor, harvest control rule, management strategy evaluation, superensemble

1 | INTRODUCTION

Determining population status is a key step in managing fish stocks effectively. Approximately 53% of global reported catch is accounted for in the RAM Legacy Stock Assessment Database (Costello et al., 2016; RAM Legacy Stock Assessment Database 2017; Ricard, Minto, Jensen, & Baum, 2012). A quarter of the remaining global reported catch has undergone some form of data-limited stock assessment (FAO 2016), while 22% remains unassessed, with little information about population status or risk of overfishing. This is a conservative estimate, not accounting for unreported stocks. These data-limited stocks make up an increasing proportion of global reported catch over time, from 20% to 47% in the last 60 years (Vasconcellos & Cochrane, 2005), contributing to a significant proportion of food production, particularly in developing countries. However, management of data-limited stocks also poses a problem in developed regions of the world. In the United States, 70% of stocks are managed using “data-limited methods” (Newman, Berkson, & Suatoni, 2015), and in the European context, 165 of 262 stocks for which the International Council for the Exploration of the Sea (ICES) provides advice are considered data-limited, precluding absolute estimates of stock status in their existing MSY framework (ICES Advisory Committee 2017). Furthermore, legislative requirements in the United States, Australia and the European Union require catch limits or other harvest strategies to be set for many of these data-limited stocks, which has spurred the development of assessment methods and harvest control rules (HCRs) to meet this mandate (Chrysafi & Kuparinen, 2015; ICES Advisory Committee 2012; Newman et al., 2015). While a typical “data-rich” stock assessment includes life-history information, catch time series, abundance indices, and age or size composition, data-limited assessment and HCR approaches vary in their data requirements and are typically based on only one or two of these data streams (e.g., see Carruthers et al., 2014; Geromont & Butterworth, 2015). Here we focus on the application of catch-based approaches. Data-limited, catch-based methods for assessment and management differ in terms of their data requirements, assumptions, and outputs (Table 1).

Many data-limited stocks are managed with "empirical" harvest strategies, which use indicators to inform managers of whether and how they should adjust catch or effort, without ever directly estimating stock status. Static versions of empirical HCRs do not consider population processes estimated from stock assessment models or auxiliary data types but scale the catch (or effort) limit based on empirical observations and prespecified scalar adjustments (Carruthers et al., 2014).

Some "empirical" catch-based approaches rely directly on catch histories and may include auxiliary data types such as expert judgment, life-history information or fishery-dependent indicators such as changes in effort, size composition, species composition or distribution (Dowling et al., 2015; Newman et al., 2015). In the United States, 52% of managed stocks used only catch data to calculate the legislated allowable catch limits (Berkson & Thorson, 2014), such as setting a catch limit based on the median catch over the past 10 years of fishing. However, these static catch-based HCRs can result in high probabilities of overfishing, and subsequent low B/B_{MSY} or low yield across most simulated life-history traits (Carruthers et al., 2014).

Empirical catch-only HCRs can be extended to combine the catch time series with expert knowledge on categorical stock status to inform catch limits, including the Only Reliable Catch Series (ORCS; Berkson, Barbieri, Cadrin, & Trianni, 2011), the Restrepo method (Restrepo et al., 1998) and the depletion-adjusted catch scalar method (DACS; Berkson et al., 2011; Carruthers et al., 2014) (Table 1). These methods can be considered dynamic if they scale the catch limits according to rules based on a categorical estimate of biomass status (overexploited, fully exploited or underexploited) from expert knowledge or survey questions, and can be updated as new information is collected. In past simulated management strategy evaluations (MSEs), DACS had an intermediate level of performance, but was not able to avoid overfishing (Carruthers et al., 2014), while the ORCS and Restrepo methods were conservative, but had high probabilities of overfishing if the stock was incorrectly classified due to overly optimistic status estimates (Wiedenmann, Wilberg, & Miller, 2013). A revised version of the ORCS method shows improved status estimation accuracy using boosted classification trees and the historical catch statistics and scalars that performed best when compared to data-rich assessments (Free, Jensen, Wiedenmann, & Deroba, 2017), but the method has not yet been evaluated through an MSE.

Other methods for assessment and setting catch limits, including depletion-based stock reduction analysis (DB-SRA; Dick & MacCall, 2011) and depletion-corrected average catch (DCAC; MacCall, 2009), appear to provide more reliable estimates of sustainable catch and result in more effective management than the latter empirical HCRs (Carruthers et al., 2014). These depletion-based methods estimate sustainable catch using underlying population models (e.g., production models, stock reduction analysis) that require information on fishing mortality at maximum sustainable yield (F_{MSY}) and estimates of current depletion, making their data requirements prohibitive for many stocks. While estimates of current depletion may come from expert elicitation (Chrysafi, Cope, & Kuparinen, 2017), if this information is unavailable, unreliable or too uncertain to be meaningful, the ORCS and Restrepo methods have been recommended for use (Berkson et al., 2011; Wiedenmann et al., 2013). However, despite dynamic adjustments, these empirical catch-based HCRs can result in high probability of overfishing, low biomass or low yields (Carruthers et al., 2014). In short, it is difficult to provide robust and reliable management advice for data-limited stocks, despite a diverse array of catch-only methods to choose from (Table 1).

A group of data-limited methods, referred to here as "catch-only models," are model-based dynamic methods that assess stock status based primarily on catch data (Table 1). These catch-only models produce estimates of stock status, for example, total population biomass relative to biomass at maximum sustainable yield, B/B_{MSY} and some relevant biological and fishing reference points for management (e.g., MSY). Catch-only models require a time series of catch data (i.e., landings plus discards) and basic life-history parameters and can be applied when estimates of current depletion, fishing effort, biological survey data or length or age composition of the catch are not available. Rosenberg et al. (2014) tested the performance of four catch-only models on a simulated stock data set including: (a) "Catch MSY" (CMSY) developed by Martell and Froese (2013) and slightly modified in Rosenberg et al. (2014), (b) a catch-only model using sampling importance resampling (COMSIR: Vasconcellos & Cochrane, 2005), (c) a modified panel regression model fit to the RAM Legacy stock assessment database (mPRM: Costello et al., 2012), and (d) a state-space catch-only model (SSCOM: Thorson et al., 2013). The authors found that the models often provided biased and conflicting estimates of stock status, and none of the individual methods consistently performed best across all simulation scenarios tested (Rosenberg et al., 2014).

Ensembles and superensembles can account for the uncertainties and, in part, the biases associated with each individual model (Anderson et al., 2017). Ensemble models calculate the mean of individual model estimates. Superensembles, however, use the status estimates from individual catch-only models as data in an additional statistical model (e.g., a linear model or a machine-learning model) fitted to an independent data set (Anderson et al., 2017; Krishnamurti, 1999). Using a training data set of stocks with known population status, the superensemble "learns" when the underlying models perform well and incorporates this information when estimating status of an unassessed stock of interest. Anderson et al. (2017) combined the output (B/B_{MSY} estimates) from the four catch-only methods in four superensemble models and found that the random forest superensemble led to the greatest increase in accuracy of stock status

TABLE 1 Summary of data-limited catch-only methods for setting catch or effort limits, adapted from Table 1, Carruthers et al. (2014) and Table 3, Wiedenmann et al. (2013)

Method category	Examples	Description	Status assessment method	Catch data input	Other data input	Reference
Catch-only "data-limited" approaches						
Static catch-only empirical methods	• Summary catch statistics • Constant catch	Catch limits determined directly by mean or median of recent catch history, or a catch scalar, for example, 50% or 75% mean catch	No model: empirical HCR based on catch data	Recent catch time series	None	Wiedenmann et al. (2013); Carruthers et al. (2014); Geromont and Butterworth (2015)
Dynamic catch-only empirical methods scaled by categorical stock status	• Only Reliable Catch Series (ORCS) • Restrepo method • Depletion-adjusted catch scalar (DACS)	Scaled catch limits according to estimated stock status categories (under, fully or overexploited)	No model: expert opinion or survey questions used to determine categorical, subjective estimates of stock status	Recent catch time series	Expert knowledge of fishery, sometimes basic life-history information	Restrepo et al. (1998); Berkson et al. (2011); Wiedenmann et al. (2013); Carruthers et al. (2014)
Dynamic catch-only models	• CMSY, COMSIR, mPRM and SSCOM • Catch-only models (COM) superensemble, combined with dynamic HCRs	Dynamic catch- or effort-based HCRs informed by biomass status (B/B_{MSY}), estimated from catch-only models	Model-based: for example, regression, surplus production model or ensemble methods to estimate B/B_{MSY}	Catch time series (complete series is desirable)	Basic information on resilience and life-history traits to set priors in models	This study; Rosenberg et al. (2014); Anderson et al. (2017)
Catch-plus approaches						
Depletion-based approaches	• Depletion-based stock reduction analysis (DB-SRA) • Depletion-corrected average catch (DCAC)	Static or dynamic methods used to estimate overfishing level (OFL) based on estimates of depletion relative to unfished levels	Model-based: for example, production model, stock reduction analysis to estimate sustainable yield	Complete catch time series	Detailed life-history and stock abundance information, for example, F_{MSY}, natural mortality and current depletion	MacCall (2009); Dick and MacCall (2011); Carruthers et al. (2014)

estimates (Anderson et al., 2017). The use of multiple data-limited models to inform fishery management is not unusual; for example, catch limits for black sea bass in the mid-Atlantic region of the United States were set based on an average of estimates obtained through the DLMtool (Carruthers & Hordyk, 2017; McNamee, Fay, & Cadrin, 2016). However, superensembles can perform better than a simple model average (Anderson et al., 2017), making them a potentially useful new tool for managing data-limited stocks.

While the performance of this suite of catch-only models and their superensembles for estimating stock status has been extensively evaluated (Anderson et al., 2017; Rosenberg et al., 2014, 2017), these studies did not test whether these individual methods or the superensemble were suitable for guiding management. This study aims to advance understanding of the utility of catch-only models by examining the ability of a superensemble of catch-only methods to effectively inform HCRs and provide the basis for management advice. Specifically, we use the B/B_{MSY} status estimates from a random forest superensemble of three catch-only models (CMSY, COMSIR and mPRM) to inform a set of HCRs (Gabriel & Mace, 1999) that control either (a) input (i.e., fishing effort) or (b) output (i.e., catches) of the fishery. We evaluate how well these model-based catch-only management strategies maintain or recover stocks towards target biomass levels (B_{MSY}) and avoid severe population declines or overfishing while sustaining high yields. In doing so, we seek to identify whether and when they are reliable, or whether they should be avoided in practice.

2 | METHODS

Our analysis follows the simulation component of an MSE framework (Kell et al., 2007; Punt, Butterworth, de Moor, De Oliveira, & Haddon, 2014) consisting of five steps (Figure 1): (a) develop a simulated operating model representing the population dynamics of five fish stocks, (b) use a superensemble of catch-only models to assess population status and estimate fishery reference points of these simulated stocks, (c) apply catch or effort limits for management using four HCRs and a business as usual scenario, based on the superensemble status estimates, (d) project the effect of HCRs on the simulated stocks for 5- and for 20-year scenarios and (e) evaluate the performance of the catch-only models under different HCRs, based on biologically sustainable fishery objectives.

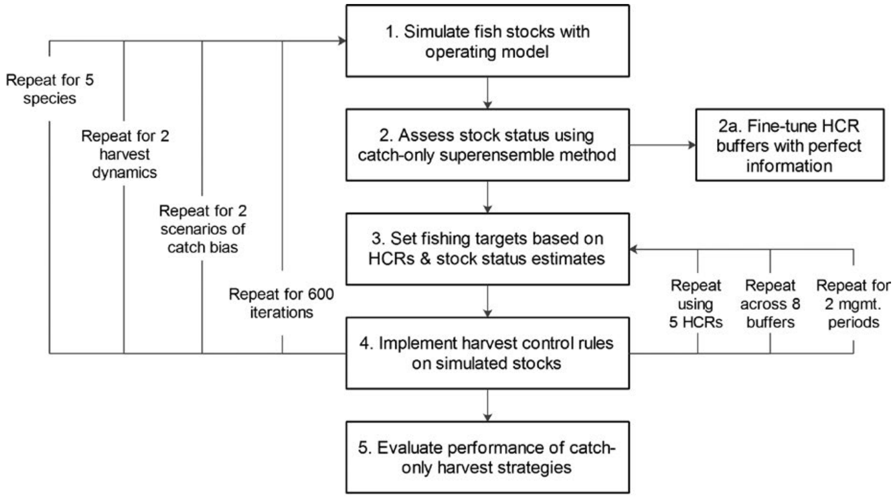
2.1 | Step 1: Develop operating models to simulate stocks

We simulated stocks based on life-history characteristics of five marine fish species from two different geographical regions of the east Pacific Ocean (Supporting Information Table S1). We modelled three species occurring on the west coast of the United States and Canada: bocaccio rockfish (*Sebastes paucispinis*, Sebastidae), Pacific sardine (*Sardinops sagax caerulea*, Clupeidae) and petrale sole (*Eopsetta jordani*, Pleuronectidae); and two species occurring in the Eastern Tropical Pacific Seascape (ETPS; the exclusive economic zones of Panama, Costa Rica, Colombia and Ecuador): corvina reina (*Cynoscion albus*, Sciaenidae) and skipjack tuna (*Katsuwonus pelamis*, Scombrinae). These species were selected because they are of economic importance in their respective regions and represent a variety of life-history traits with which to test the catch-only superensemble methods.

Fishing mortality was simulated using two scenarios of effort dynamics in the operating model (Figure 1), for example, the "one-way trip" and "bioeconomic coupling." In the one-way trip (OW) scenario, the harvest rate continually increased over time, so that it would reach 80% of F_{crash} (i.e., the lowest fishing mortality rate that drives spawning stock biomass to 0 in an equilibrium model) at the end of the 80-year simulation period (i.e., 60 years preassessment and 20 years of postassessment management). The effort dynamics with bioeconomic coupling (ED03) scenario represented an open-access single-species fishery, where the fishing mortality was determined by the biomass and effort in the previous year (Rosenberg et al., 2014; Thorson et al., 2013). We used the following equation for effort: $E_{t+1} = E_t\left(\frac{B_t}{a B_{MSY}}\right)^x$, where E_t is the fishing mortality (harvest rate) at time t, B is total stock biomass, a is the proportion of B_{MSY} at which bioeconomic equilibrium occurs (set at $a = 0.5$), and x is an exponent that determines the strength of coupling between effort and changes in biomass (set at $x = 0.3$). We use both OW and ED03 scenarios because effort dynamics have been documented in only 41% of assessed stocks in the RAM Legacy database (Szuwalski & Thorson, 2017), yet can strongly influence the performance of the catch-only models (Rosenberg et al., 2014: Mosqueira I. et al. unpublished data). Here, we assumed harvest rate is proportional to fishing effort, given fixed catchability and instantaneous fishing.

Each of the 10 simulated scenarios (across five species and two effort dynamics) had a fishing history of 60 years and was replicated 600 times (Figure 1). Variation across iterations within a scenario was generated by simulating annual recruitment variability, as well as variation in fishing mortality and implementation error. Additional description of these methods is included in the Supporting Information.

We extracted the catch data required for the catch-only models (described in the following step) by adding observation error to the simulated time series of catch. We assumed only the last 20 years of fishing had been recorded, even though fishing had occurred for 40 years prior to data collection. This was to mimic a realistic catch time series and length of fishing history currently available for several unassessed stocks (although this may be optimistic for many fisheries in developing countries). Different levels of observation error were added to the catch data to reflect possible differences in resources and capacity available for recording landings and estimating discards in each geographic region: US/Canadian fisheries had log-normal errors where $\sigma_C = 0.2$, and ETPS fisheries had log-normal errors where $\sigma_C = 0.5$ (Agnew et al., 2009). We also tested a scenario that included bias in the catch data to account for illegal, unreported and unregulated fishing (IUU). In the underreporting scenario (UR),



Parameters tested	Scenarios	Abbreviation
Harvest dynamics in operating model	One-way trip - constant increase in harvest rate	OW
	Bio-economic effort dynamics model	ED03
Under-reporting bias in catch data	No bias	UR0
	Negative bias in catch data (USA species: 20%, ETPS species: 50%)	UR20 or UR50
Harvest control rule (HCR)	Business as usual	BAU
	Effort-based 40-10 HCR	Effort 40-10
	Effort-based step HCR	Effort step
	Catch-based 40-10 HCR	Catch 40-10
	Catch-based step HCR	Catch step
Length of management	5 years	5 yr
	20 years	20 yr

FIGURE 1 Flow diagram of the management strategy evaluation framework used to evaluate the performance of catch-only harvest strategies and description of simulated and management scenarios tested

US/Canadian stocks had 20% negative bias in the catch data consistent across all years (i.e., 80% of true catch), and ETPS stocks had 50% negative bias, constantly applied across all years.

2.2 | Step 2: Stock assessment using a catch-only superensemble

We estimated the status (B/B_{MSY}) for each simulation replicate (600 iterations for each of 10 scenarios) using a superensemble model of three catch-only methods, previously selected and tested in Rosenberg et al. (2014)—Catch MSY (CMSY; Martell & Froese, 2013), the catch-only model using sampling importance resampling (COMSIR; Vasconcellos & Cochrane, 2005) and a modified panel regression model (mPRM; Costello et al., 2012). Descriptions of each model are provided in Rosenberg et al. (2014, 2017) and Anderson et al. (2017). A state-space catch-only model (SSCOM: Thorson et al., 2013) is another candidate catch-only method that estimates B/B_{MSY} that was included in Rosenberg et al. (2014), but its relatively long computational run-time prohibited its inclusion in this analysis. The inputs into the individual catch-only models were the 20-year catch time series (extracted from the operating model with observation error, with or without bias) and basic life-history traits, such as resilience of the species (Musick, 1999) and broad species categories (e.g., tuna, sardine). The priors used for CMSY and COMSIR are described in the Supporting Information. The CMSY and COMSIR catch-only models produce posterior distributions, and we used the medians of these posterior distributions as "estimates of status" in the ensemble model. The default model settings were used for all priors, parameters and sample sizes, described in Rosenberg et al. (2014) and implemented using the "datalimited" package (https://github.com/datalimited/datalimited) in R (R Development Core Team 2005).

The estimates of B/B_{MSY} status from each catch-only model were then used as inputs to a random forest superensemble model. Although there are a variety of methods that can be used to develop a superensemble, we chose the random forest machine-learning model because it was one of the top performing superensembles (lowest bias and highest accuracy) among the options tested against a simulated data set and a global compilation of stock assessments in the RAM Legacy database (Anderson et al., 2017). The superensemble model contained five covariates: the average stock status of the last 5 years $\left(t \in \{56, \ldots, 60\}\right)$ estimated from each of the three individual catch-only models and two variables that characterized the spectral densities of the catch time series at 5- and 20-year cycles (i.e., frequencies of 0.20 and 0.05). Superensembles require a training data set with known (or true) values of status. In this case, we trained the superensemble with the full factorial data set (i.e., with all combinations of different life-history, data-quality and harvest-dynamic characteristics considered in the simulation set-up) that was simulated independently (Anderson et al., 2017; Rosenberg et al., 2014) and is not otherwise used in this study. We applied the random forest models using the "randomForest" R package, with 1000 trees per run (Breiman, 2001).

2.3 | Step 3: Fine-tune and apply harvest control rules

We used status estimates from the catch-only superensemble and five HCR scenarios (Figure 2) to set future catch or effort limits. These catch or effort limits were determined using the estimated stock status (B/B_{MSY}) averaged over the last five years before the assessment from the superensemble. The first two HCRs were designed to achieve a target fishing mortality (F_{MSY}) by controlling fishing effort, using either (a) a modified 40-10 rule or (b) a step rule (description below, Figure 2, Supporting Information Tables S2 and S3). Two other HCRs were designed to achieve a target catch (MSY) by controlling for catches, using either (a) a modified 40-10 rule or (b) a step rule. We compared these four HCRs with a "business as usual" (BAU) scenario, which simulated a situation where no new management would take place after the assessment, following the underlying effort dynamics of the operating model (either a one-way trip or a system with bioeconomic coupling). In practice, catch-based HCRs are often implemented through quotas, for example, while controls on fishing effort can be implemented through approaches such as limiting the number of boats or days-at-sea (often referred to as managed access or input control) or required changes in fishing mortality can be converted to advised catches. We added a precautionary buffer to all HCR maximum target values, determined by scenarios using perfect (true) information from the operating model, described in the sections below.

2.3.1 | Effort-based 40-10 HCR

The effort-based 40-10 rule specifies that (a) when B/B_{MSY} is at or above a threshold point (40% unfished biomass (B_0) or carrying capacity (K)), the target is set to the instantaneous fishing mortality rate at maximum sustainable yield with an appropriate buffer (F_{MSY} × buffer), and (b) when stock biomass is below 10% carrying capacity, fishing stops. For stocks with biomass between 10 and 40% of unfished biomass, their target fishing mortality (F) is set based on the linear trajectory drawn between 10% B_0, 0 and 40% B_0, F_{MSY} × buffer (Figure 2, Supporting Information Table S2, Appendix S1). The target fishing mortality rate was then made relative to the current fishing harvest ratio (discrete fishing mortality) (Supporting Information Appendix S1, Table S3). This relative effort-based HCR was designed to reflect a data-limited situation, where stocks are managed by changing the effort fishing (F) relative to current effort, as it is more difficult to control and monitor for a specific fishing mortality. The 40-10 HCRs were inspired by similar management strategies and buffer zones currently used to set catch and fishing limits in several US regions (Punt & Ralston, 2007).

2.3.2 | Effort-based step HCR

The effort-based step HCR followed a step function that reduced the fishing mortality rates as biomass declined. The biomass threshold (trigger) and limit points were set at 110% and 60% B_{MSY}, respectively (Figure 2, Supporting Information Table S2). Above 110% B_{MSY}, fishing was set at F_{MSY} × an appropriate buffer. Between 60% and 110% B_{MSY}, the target fishing mortality was ½ F_{MSY} × buffer, and below 60%, B_{MSY} no fishing was allowed. This target fishing mortality rate was then made relative to the current fishing harvest ratio, as in the effort 40-10 rule. This rule was designed to be more

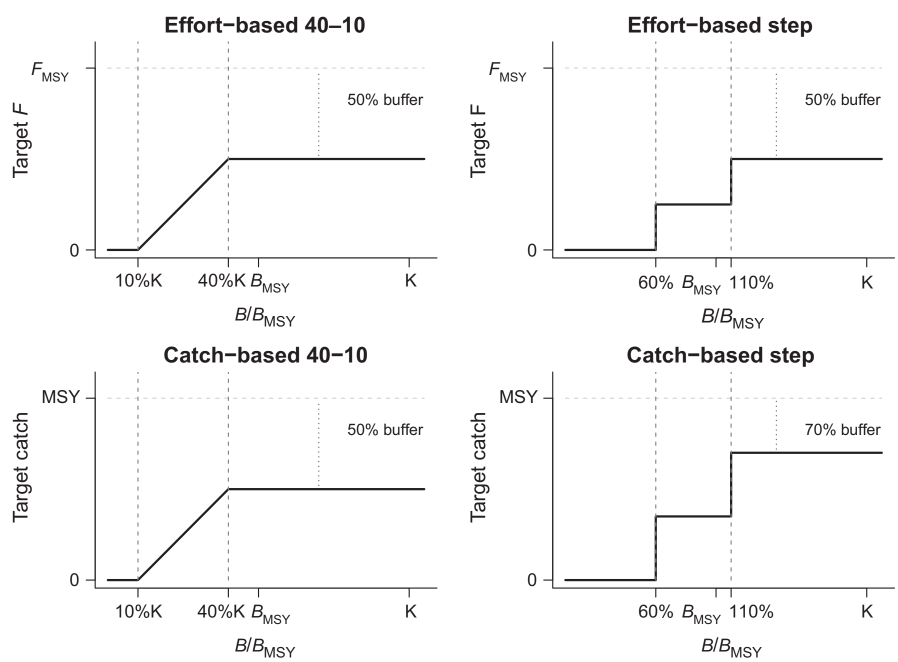


FIGURE 2 Schematics of the 40-10 and step harvest control rules (HCRs) controlling for fishing effort (top panels) or catch (bottom panels). The vertical dashed lines show the trigger and limit points for the 40-10 HCRs (40% and 10% of unfished biomass or carrying capacity, K), and for the step HCRs (110% and 60% of B_{MSY}). The vertical dotted line shows the buffers used for each HCR; for example, for the effort-based 40-10 rule, the buffer was 50% F_{MSY}

precautionary than the 40-10 rule to account for the uncertainty and possible inaccuracy in the catch-only superensemble assessments. The threshold and limit points are arbitrary, and future studies or management could be set based on known bias of the assessment model or sensitivity analyses to maximize objectives, as we do here.

2.3.3 | Catch-based 40-10 and step HCRs

The catch-based 40-10 rule and catch-based step rule follow the same threshold and limit points as the effort-based rules, but set a target yield based on MSY, rather than fishing mortality (i.e., MSY × buffer rather than F_{MSY} × buffer, Figure 2). Many jurisdictions, including the European Union and the United States, set catch-based total allowable catches (TACs) with F-based HCRs and a short-term forecast. While using MSY on the *y*-axis of the HCR is not typical, this approach is potentially suited to data-limited methods that produce catch advice, and its performance is therefore worth testing.

2.3.4 | Setting precautionary buffers for HCRs

To determine the buffer size required for each HCR, we projected the simulated stocks based on the HCRs set using perfect knowledge of B/B_{MSY}, MSY and F_{MSY}, with eight buffers ranging from 30% to 100% in 10% increments. These "true" values were taken directly from the operating model, rather than using the estimates from the catch-only superensemble (skipping Step 2: the stock status assessment; Figure 1). We selected the appropriate buffer for each HCR that maximized total catch over the management period, while ensuring the lower 10th percentile of B/B_{MSY} estimates over the final three years of a 20-year management period was above 0.25 (averaged across iterations and harvest dynamics per species). The buffers that satisfied these criteria for all species were as follows: 50% of F_{MSY} for the effort-based 40-10 and step rules, 50% of MSY for catch-based 40-10 rule and 70% of MSY for catch-based step rule. These HCR–buffer combinations will be referred to throughout this study as the calibrated HCRs. Standardizing the relative risk and yield for the HCRs using these fine-tuned buffers based on perfect information allowed us to articulate the effect that estimates of status and reference points from the catch-only models had on the performance of the HCRs.

2.4 | Step 4: Simulate the implementation of harvest control rules

We applied the HCRs to the simulated stocks and projected the populations forward for 5- and 20-year management periods for each scenario under the effort or catch limits generated by each HCR (e.g., Figure 3). All projections were set to reach the target values of the catch or fishing mortality on the first year of management and then held constant across the full management period, without further reassessment, simulating a simple best-case scenario for comparative purposes. We recognize that a more realistic approach would be to gradually build up to the target fishing levels. However, we leave this for consideration in future MSEs for specific stocks. Unlike other closed loop simulations, where stock assessments are conducted every few years to adjust the target fishing values, we removed the feedback control between the management and operating models. This is because once catch or fisheries effort has been regulated, the catch time series provides little new information to these catch-only models, that tend to be used once prior to management; indeed, an open system (lack of management) is an assumption of some of these methods (Vasconcellos & Cochrane, 2005). We acknowledge that the removal of reassessment feedback is problematic as it assumes management at constant levels of catch or effort, which could lead to under- or overfishing in the face of changes in biomass due to external factors (e.g., environmental conditions). In reality, if there was a source of information separate from the catch data (e.g., length frequencies or fishery-independent survey data), these could be used to reassess and tune the HCRs. In the current MSE without feedback control, the initial tuning of the HCRs to perfect information is a critical step that allows for the evaluation of the performance of the HCR over a short time horizon (e.g., 5 years) that is sensible. The 20-year management projections were a theoretical exercise to observe longer-term effects, and we would not recommend continuing management based on initial HCR targets for 20 years without frequent reassessment and feedback control via other external inputs as noted above.

To simulate the annual variability in implementation success and enforcement of the HCRs, we added log-normal errors ($\sigma_i = 0.1$) to the target catch levels and fishing mortality rates with bias correction on the mean: $\varepsilon_t = N(0-0.1^2/2, 0.1^2)$, corresponding to a coefficient of variation (CV) of approximately 10%. Stocks under the "business as usual" (BAU) scenario were projected forward with the same harvest dynamics used in the simulations (also with implementation error of $\sigma_i = 0.1$), either an increasing harvest rate (OW) or a bioeconomic coupled model (ED03). The code for the MSE is available here: https://github.com/datalimited/DLM-MSE.

We also ran the scenarios with the catch-based superensemble across the range of buffers (30%–100% in 10% increments) to determine the level of buffers with the less accurate stock status estimates that would be required to satisfy the risk and yield targets, for example, 10% percentile of B/B_{MSY} after 20 years of management >25% B_{MSY}, while maximizing yield across the management period.

2.5 | Step 5: Evaluate performance

We tested the performance of the five HCRs across 40 different management scenarios: five species, two underlying harvest dynamics, and two management periods, with and without bias in the catch data, each with 600 iterations (Figure 1). This was to determine whether a superensemble of catch-only models would allow managers to implement a harvest strategy reliably given the uncertainties in the estimates of B/B_{MSY} status.

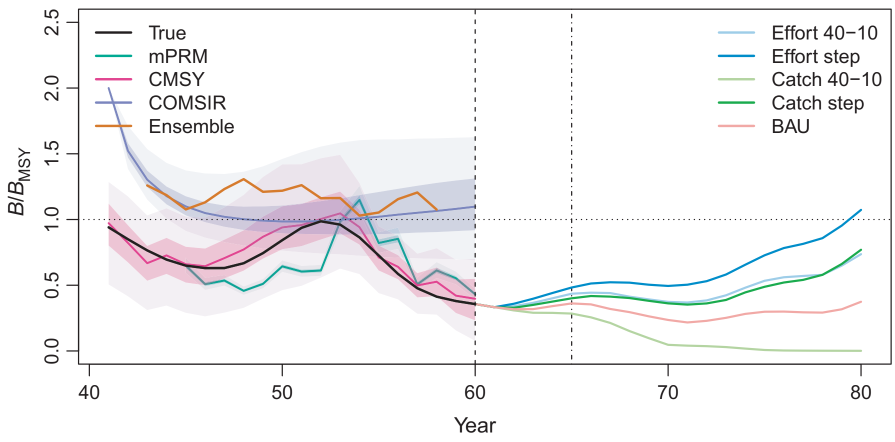


FIGURE 3 An example time series of population status (B/B_{MSY}) of corvina reina before and after the catch-only assessment (dotted line: t_{60}). This example is from the scenario that was simulated with one-way trip effort dynamics (black line). The catch-only assessment was conducted in year 60, assuming only 20 years of catch data were available, using three catch-only models (dark shading = 25th and 75th percentiles, light shading = 2.5th and 97.5th percentiles) and a random forest superensemble to estimate B/B_{MSY}. In this case, the superensemble and COMSIR overestimated stock status, while CMSY and mPRM were more accurate. Projections based on the catch-only assessment show the predicted outcomes from each harvest control rule (HCR) over a 5-year (dash-dot line, t_{65}) and 20-year management period: effort-based 40-10 HCR, an effort-based HCR set using a step function, a catch-based 40-10 HCR, a catch-based step HCR, and a business as usual scenario (BAU). In this case, the effort-based step HCR was the only strategy that recovered the stock after 20 years

We used the following objectives to evaluate performance of different HCRs:

1. Maintain sustainable stock biomass at or above B_{MSY} (proportion of stocks at the end of management period at or above B/B_{MSY} and lower 10th percentile of B/B_{MSY} at the end of the management period),
2. Avoid heavily overfished stocks or fishery collapse (proportion of years during management that had B > 25% $B_{MSY,}$ averaged across stocks),
3. Reach and maintain sustainable fishing mortality rates at or below F_{MSY}, (median F/F_{MSY} over the final three years of the management period),
4. Avoid overfishing during management (proportion of years where overfishing was not occurring (F < F_{MSY}) median across stocks),
5. Maximize yield during management period (mean annual catch over the management period relative to yield if fished at F_{MSY}), and
6. Reduce variability in annual catch (median standard deviation of catches over management period).

We identified trade-offs between management objectives across the different HCRs for each scenario, using radar plots. To understand the behaviour of the catch-only harvest strategies, we calculated the proportional error of the HCR target values based on the catch-only superensemble model compared to the HCR target values based on true values of B/B_{MSY} generated from the operating model, assuming perfect knowledge. The proportional error is calculated as the difference between the estimated and true values, divided by the true value. We also calculated the proportional errors produced by the superensemble for estimates of B/B_{MSY}, MSY, F_{MSY} and harvest ratio prior to management.

3 | RESULTS

3.1 | Reaching maximum sustainable yield and avoiding overfished stocks

Before applying the catch-only harvest strategies, the majority of simulated stocks were overfished (median B/B_{MSY} = 0.57) with 16.9% of stocks above B_{MSY} (Supporting Information Figure S1a). The catch-only superensemble generally overestimated stock status (median proportional error in OW scenario: 0.44; in ED03 scenario: 0.97, Supporting Information Figure S1b,c).

After 5 years of management, the HCRs based on the catch-only superensemble with calibrated buffers resulted in a higher probability of stocks being above B_{MSY} than BAU (objective 1, Table 2). Even so, most stocks remained overfished (stock status < B_{MSY}) after 5 years of management, across all species, underlying effort dynamics, and HCRs (Figure 4). The lower 10th percentiles of B/B_{MSY}, which is a measure of biological risk, were above 25% B_{MSY} for all HCRs under the one-way trip harvest dynamics after 5 years (Table 2). In the bioeconomic coupled harvest-dynamic scenario, only the stocks with effort-based HCRs were above this limit reference point after 5 years (Table 2). The short-lived species (sardine and skipjack tuna) responded more quickly to the management strategies, but also had higher uncertainty in their stock status after 5 years (Figure 4). Over the 5-year management period, the median proportion of years that biomass fell below 0.25 B_{MSY} (objective 2) was low across all HCRs, species and effort dynamics, although the catch-based HCRs had a higher probability of stocks at risk of collapse over time than BAU (Table 2).

After 20 years of management without reassessment, the catch-based 40-10 and step HCRs performed consistently worse

TABLE 2 Summary results of performance metrics for the harvest control rules (HCRs) with the precautionary buffers (in parentheses) across two harvest dynamics and two management periods, showing the average lower 10th percentile of B/B_{MSY} (averaged over the last 3 years of management), the proportion of iterations above B_{MSY} at the end of management period (B/B_{MSY} averaged over last 3 years greater or equal to 1), average proportion of years during management period within an iteration that were not heavily overfished and at risk of collapse (B/B_{MSY} > 0.25), average proportion of years during the management period within an iteration where overfishing was not occurring (F/F_{MSY} < 1), and the mean catch per year in management period, relative to fishing at F_{MSY}. All results are averaged across species and iterations. Shaded results show when the HCRs perform better than business as usual (BAU) for that scenario

Scenario	HCR (buffer)	10th percentile B/B_{MSY}	Prop. iterations above B_{MSY}	Prop. years not heavily overfished	Prop. years not overfishing	Mean catch relative to F_{MSY}
ED03 5yr	Effort 40-10 (0.5)	0.27	0.26	0.86	1	0.68
ED03 5yr	Effort step (0.5)	0.31	0.32	0.87	1	0.43
ED03 5yr	Catch 40-10 (0.5)	0.12	0.28	0.77	0.6	0.92
ED03 5yr	Catch step (0.7)	0.15	0.3	0.79	1	0.58
ED03 5yr	BAU	0.2	0.15	0.81	0.48	0.95
ED03 20yr	Effort 40-10 (0.5)	0.36	0.53	0.91	1	0.8
ED03 20yr	Effort step (0.5)	0.49	0.66	0.93	1	0.57
ED03 20yr	Catch 40-10 (0.5)	0.06	0.52	0.73	0.81	0.64
ED03 20yr	Catch step (0.7)	0.07	0.62	0.78	0.99	0.48
ED03 20yr	BAU	0.25	0.22	0.85	0.49	0.9
OW 5yr	Effort 40-10 (0.5)	0.38	0.25	0.96	0.64	0.95
OW 5yr	Effort step (0.5)	0.44	0.33	0.97	1	0.69
OW 5yr	Catch 40-10 (0.5)	0.27	0.28	0.92	0.56	0.95
OW 5yr	Catch step (0.7)	0.27	0.31	0.92	0.88	0.8
OW 5yr	BAU	0.31	0.13	0.93	0	1.26
OW 20yr	Effort 40-10 (0.5)	0.39	0.4	0.96	0.66	0.97
OW 20yr	Effort step (0.5)	0.51	0.59	0.98	1	0.81
OW 20yr	Catch 40-10 (0.5)	0.06	0.51	0.81	0.75	0.72
OW 20yr	Catch step (0.7)	0.07	0.56	0.82	0.92	0.61
OW 20yr	BAU	0.22	0.07	0.88	0	1.02

than BAU, with a high risk of collapse (10th percentiles of B/B_{MSY} were below 10% of B_{MSY}; Figure 4, Table 2). In contrast, the effort-based 40-10 and step HCRs resulted in lower probabilities of collapse, for example, 10th percentiles >25% B_{MSY} (Figure 4, Table 2). All HCRs resulted in much higher proportions of stocks above B_{MSY} than BAU (Table 2), but also had higher variation of final B/B_{MSY} values (across iterations per species) than BAU (Figure 4).

3.2 | Avoiding overfishing and maximizing yield

The third and fourth management objectives we tested were to reduce the likelihood of overfishing (defined as F/F_{MSY} > 1) after 5 or 20 years and over the course of management. The effort-based HCRs achieved higher proportions of stocks with fishing mortality at or below F_{MSY} at the end of the management period compared to catch-based HCRs and BAU (Supporting Information Figure S2). This was the case across all species, underlying effort dynamics and management periods, except the effort-based 40-10 HCR under the one-way trip scenario for rockfish, sole and tuna (Supporting Information Figure S2). In particular, the effort-based step HCR performed best, with 80.9% of stocks having a final fishing mortality lower than F_{MSY}, pooled across species, effort dynamics and management period (compared to effort-based 40-10: 65.9%, catch-based 40-10: 59.5%, catch-based step: 67.6%, BAU: 23.1%). The effort-based step HCR also had the lowest frequency of overfishing that occurred during the management period (Table 2).

The catch-based HCRs resulted in extreme and highly variable fishing mortalities (Supporting Information Figure S2). This outcome was consistent for both the step and 40-10 HCRs, both harvest dynamics (one-way trip and bioeconomic coupling), and 5- and 20-year

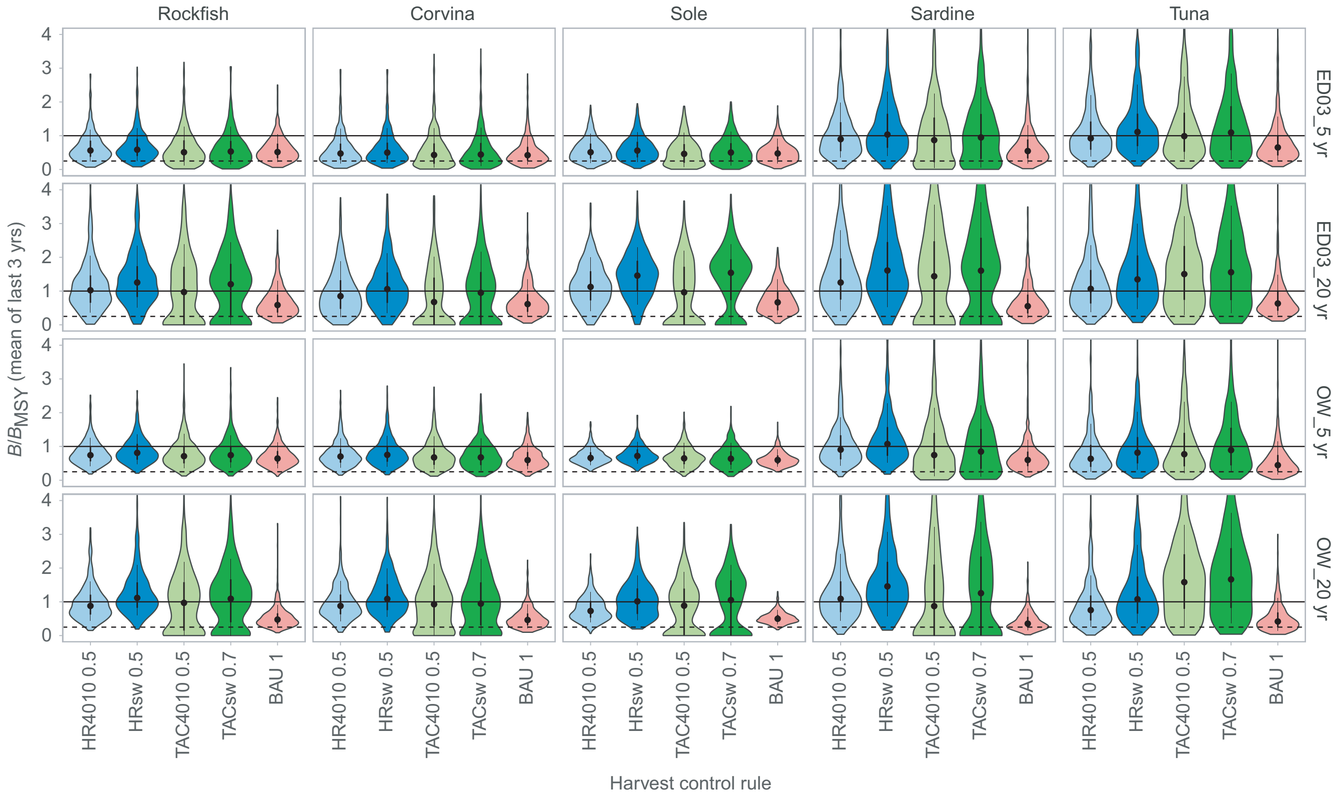


FIGURE 4 Bean plots of fisheries status (B/B_{MSY}) after 5 and 20 years of management using each harvest control rule for the one-way trip (OW) and bioeconomic coupling (ED) effort dynamic scenarios (600 iterations per species). Solid line shows B_{MSY} and stocks below the dotted line are heavily overfished (B/B_{MSY} <0.25)

management periods (Supporting Information Figure S2). The high and variable F/F_{MSY} values attributed to the catch-based HCRs were because the annual catch target remained constant even if total stock biomass declined over time. Catch-based HCR target values also had greater proportional error than the estimated effort-based HCR target values (Supporting Information Figure S3). CMSY and COMSIR often overestimated MSY (Supporting Information Figure S4a), leading to subsequently higher catch-based HCR quotas. In contrast, the effort-based HCRs are driven by F_{MSY} (derived from population growth rate (*r*) values from the catch-only models), which are much more accurate than the MSY estimates (Supporting Information Figure S4b).

The HCRs with calibrated buffers produced mean annual yields lower than BAU in most scenarios and were consistently below the potential yield if stocks were fished at F_{MSY} (objective 5, Supporting Information Figure S5). The mean annual yields produced across iterations within a scenario were highly variable during the first 5 years of management, particularly for long-lived stocks in the one-way trip scenario, but this variation stabilized over 20 years (Supporting Information Figure S5). Another measure of yield is the variation (standard deviation) across years within an iteration (objective 6). All HCRs had, on average, lower interannual variation in yield than BAU consistently across all scenarios (i.e., better performance), although the effort-based HCRs did result in high variation in some iterations for sardine and tuna (Supporting Information Figure S6).

3.3 | Trade-offs between objectives

No HCR performed the best across all management objectives, resulting in trade-offs between yield, sustainable harvest rates and biological status. The performance of HCRs was very similar across species except skipjack tuna, so we present trade-off plots for bocaccio rockfish as representative for all species (Figure 5) and tuna separately (Figure 6). For most species, the effort-based step HCR performed best at reducing the risk of being overfished (with higher values of 10th percentile B_{MSY}), while maintaining the highest proportion of stocks above B_{MSY} at the end of both management periods (Figure 5). However, the effort-based step HCR resulted in the lowest yields across all scenarios (Figure 5). The effort-based 40-10 rule had slightly lower performance than the effort-based step rule for overfished and overfishing metrics but yielded higher catches (Figure 5), although in the one-way trip scenarios, it resulted in slightly higher levels of overfishing. After 20 years, the catch-based HCRs caused at least 10% of stocks of all species except tuna to collapse to zero (Figure 5). In contrast, the catch-based HCRs did not cause tuna stocks to collapse after 20 years (Figure 6). Across all species, the effort-based HCRs were generally more risk averse and performed better than the BAU scenario for the biological status metrics, though as a consequence resulted in poor yields (Figure 5).

3.4 | Performance compared to management assuming perfect information

The five-year management projections based on true B/B_{MSY} and true biological references (i.e., the perfect information scenarios) demonstrated that most HCRs (except the effort-based 40-10 HCR) can recover short-lived species after 5 years and long-lived species after 20 years of management (i.e., median status equal to or greater than B_{MSY}, Supporting Information Figure S7). After 20 years, when the calibrated HCRs were implemented using perfect information, the catch-based step HCR performed better than any other HCR consistently across species and most management objectives except yield, but lack of reassessment during this period caused high variation in stock status (Supporting Information Figure S8). This is in contrast to the scenarios when management was based on estimates from the catch-only superensemble, where the effort-based step HCRs performed best across most objectives (Figure 5).

The overall performance of the HCRs using the catch-only superensemble was very poor in comparison with management projections based on perfect information across most metrics, except yield (Supporting Information Table S4). Over 5 years of management, the catch-only superensemble resulted in 10th percentiles of B/B_{MSY} that were 7% to 94% lower than when perfect information was used (Supporting Information Table S4). Catch-based HCRs based on catch-only superensembles performed particularly poorly in comparison with perfect information in the percentile of biomass and the proportion above B_{MSY} metrics (Supporting Information Table S4).

How large should the buffers be to maximize catch while ensuring the lower 10th percentile of B/B_{MSY} at the end of management is >25% B_{MSY}? Compared to the calibrated buffers that were fine-tuned based on perfect information (i.e., 50%–70% of MSY or F_{MSY}), the catch-only superensemble HCRs required more precautionary buffers to achieve this yield-risk objective (Supporting Information Table S5). This was to account for large errors in the estimates of B/B_{MSY} (Supporting Information Figure S1) and other parameters (Supporting Information Figure S4). The effort-based HCRs required 60 or 80% buffers, while the catch-based HCRs would only achieve the biomass objective with 30 and 40% buffers, when pooled across species (Supporting Information Table S5).

Over a 5-year management period, shifting the HCR buffers from 1 through to 0.3 resulted in a large reduction in yield with minimal improvement in the 10th percentile of B/B_{MSY}, particularly for long-lived species (Supporting Information Figure S9). After 20 years, the yield-risk relationship across the size of buffers was shallower for effort-based HCRs, as more precautionary buffers achieved similar yields, with lower risk of stock collapse. In contrast, for catch-based HCRs, lower buffers had no effect on the risk of collapse, until a definite threshold was reached at either 0.3 or 0.4 (except for tuna, Supporting Information Figure S9, Table S5).

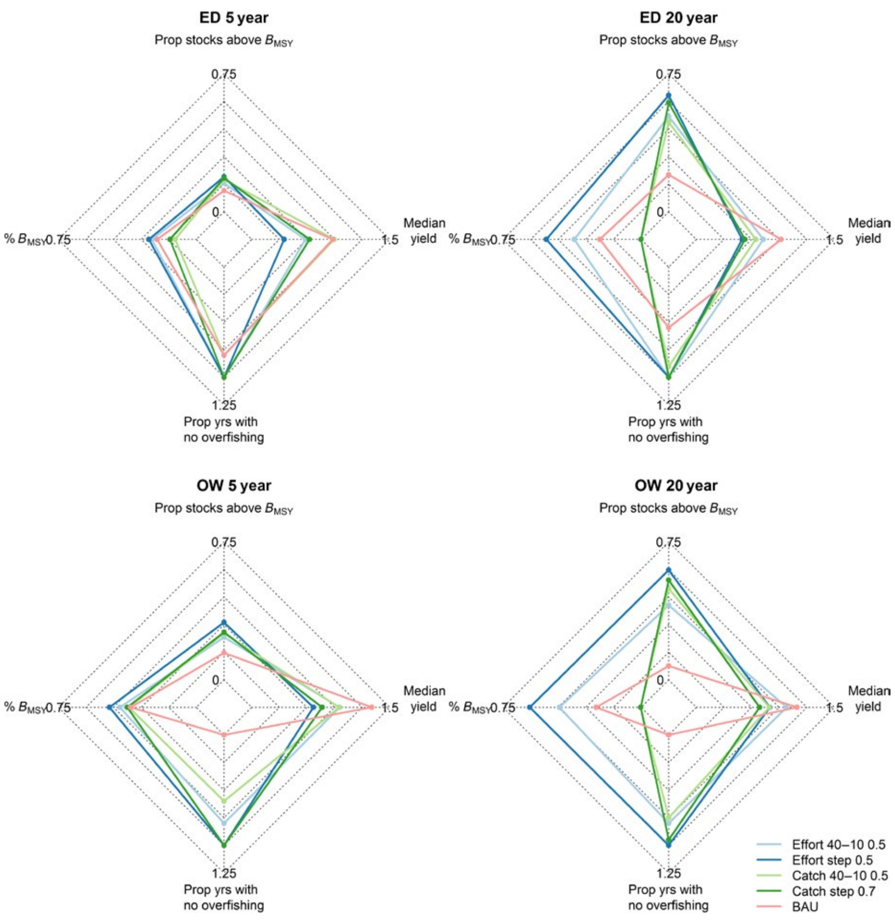


FIGURE 5 Performance of each harvest control rule based on the catch-only superensemble model and calibrated buffers for bocaccio rockfish representing the trade-off between four objectives, clockwise from left corner: (i) lower 10th percentile of B/B_{MSY} status (across iterations, averaged over the last three years of management), (ii) proportion of stocks that were above B/B_{MSY} at end of management period ($B/B_{MSY} > 1$), (iii) annual median yield over management period across iterations relative to yield if fished at F_{MSY} and (iv) median proportion of years where overfishing was not occurring across the management period ($F/F_{MSY} < 1$). Each plot shows a different scenario of harvest dynamics and management period, and the results from rockfish are representative of all other species, except tuna shown in Figure 6. All axes have centre values = 0. Each axis along the radar plot displays a different objective, where data points further from the centre of the graph indicate better performance

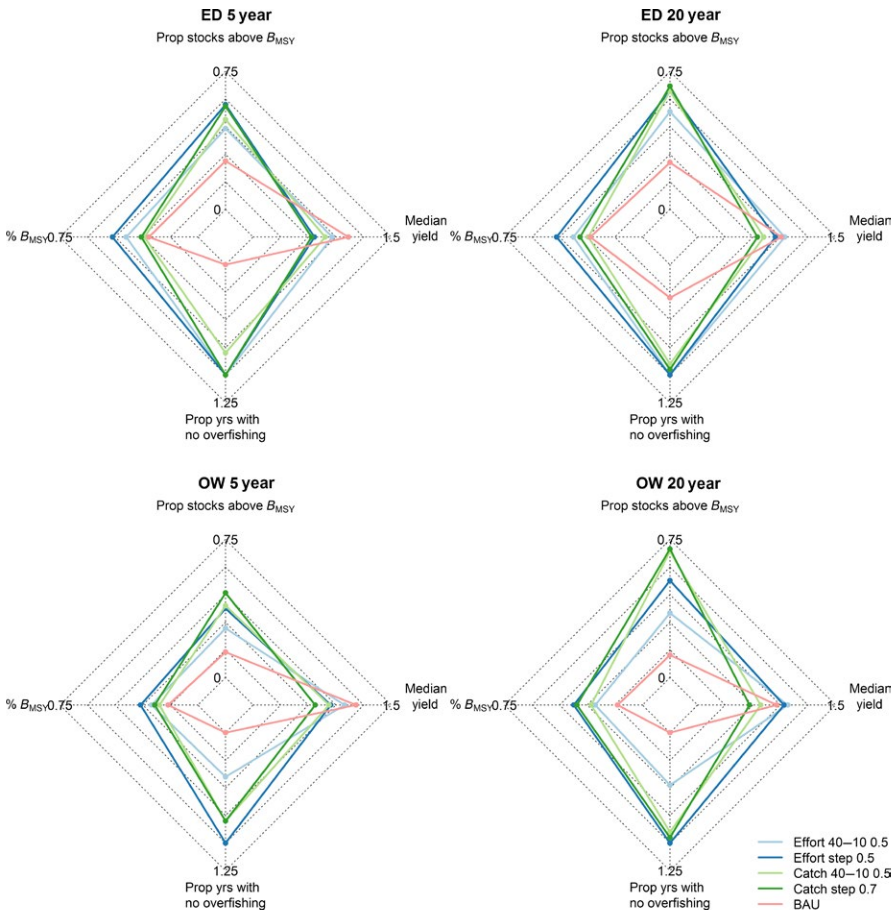


FIGURE 6 Performance of each harvest control rule for skipjack tuna across scenarios, based on the catch-only superensemble model and calibrated buffers representing the trade-off between four objectives clockwise from left corner: (i) lower 10th percentile of B/B_{MSY} status (across iterations, averaged over the last 3 years of management), (ii) proportion of stocks that were above B/B_{MSY} at end of management period ($B/B_{MSY} > 1$), (iii) annual median yield over management period across iterations relative to yield if fished at F_{MSY} and (iv) median proportion of years where overfishing was not occurring across the management period ($F/F_{MSY} < 1$)

3.5 | Sensitivity analysis with underreported catch

When catches were underreported (with negative bias), catch-only superensemble effort-based HCRs had similar or slightly worse performance across all metrics to management runs without bias in the catch (Supporting Information Table S6). However, the catch-based HCRs performed significantly better in the biomass metrics with underreporting than without (Supporting Information Table S6), especially for species with higher underreporting (corvina and tuna, UR = 50%, results not shown). This is because the proportional error of MSY with underreported catch was much lower (median: −0.22, min: −0.10, max: 15.7), compared with unbiased catch data (median: 0.14, min: −0.10, max: 27.5). Instead, the effort-based rules are derived from F_{MSY}, which had similar proportional error with or without catch biases (underreporting: median = −0.09, min = −0.83, max = 1.63, no underreporting: median = −0.09, min = −0.83, max = 1.62). The median proportional error of B/B_{MSY} with underreported catch was slightly higher (median proportional error: 0.73, min: −0.68, max: 28.3), compared with the proportional error from unbiased data (median: 0.65, min: −0.95, max: 21.94), although the effect on performance metrics was minimal. With underreporting bias in the catch data, the buffers required to reach a 10th percentile $B/B_{MSY} > 0.25$ for the effort-based HCRs were equal to or more precautionary than if the catch data were unbiased, while catch-based HCRs required less conservative buffers (Supporting Information Table S5).

4 | DISCUSSION

Our study builds on previous MSEs that test the performance of other data-limited methods and HCRs (Carruthers et al., 2014, 2015; Dichmont et al., 2017; Punt et al., 2014; Wetzel & Punt, 2011; Wiedenmann et al., 2013). However, these past studies have been largely restricted to empirical harvest strategies that bypass the need for estimating population status (Dowling et al., 2015). The recent development and testing of catch-only models and superensembles that estimate population status (B/B_{MSY}) has established several new management options to set catch limits for data-limited stocks, particularly the use of dynamic harvest control rules that rely on quantitative biomass status estimates. We demonstrate that, for the wide range of stocks and management scenarios we have simulated, catch-only models coupled with effort-based HCRs and precautionary buffers can improve the stock status and reduce the likelihood of overfishing though with considerable variability across runs.

4.1 | Performance of catch-only harvest strategies

In practice, fishing quotas and catch limits can reduce the risk of overfishing and effectively achieve a biomass that can sustain maximum sustainable yields (Edward & Dankel, 2016). None of the harvest strategies tested in our analysis performed best across all performance metrics and scenarios. However, the HCRs had better performance than BAU across most scenarios, except yield (Figures 5 and 6). Another specific exception was when BAU performed better than the catch-based HCRs for biological risk (10th percentile B/B_{MSY}) for the rockfish, corvina, sole and sardine (Figure 5). The effort-based HCRs were generally better at avoiding fishery collapse (10th percentile B/B_{MSY} > 0.25) and overfishing levels, and were able to recover the population status of most stocks to at or above B_{MSY} after 20 years. The effort-based HCR using a step function with a buffer of fishing at 50% F_{MSY} only above 110% of B_{MSY} (as calibrated based on perfect information) was the most effective management strategy at reducing the risk of overfishing and being heavily overfished. However, it did not maintain reasonable yields across most simulated scenarios of species and underlying effort dynamics, given the high precautionary buffer.

Catch-only models produced falsely high and often unsustainable recommendations for fishing catch targets (Supporting Information Figure S3) and catch-based HCRs resulted in severe overfishing (Supporting Information Figure S2) and overfished stocks (Figures 4 and 5). This was due to positive biases in MSY (Supporting Information Figure S4). These concerning levels of overfishing reduced the overall effectiveness of the catch-based HCRs for the five species in our simulated management setting. In contrast, effort-based HCRs had lower proportional errors (due to more accurate estimates of F_{MSY} values, Supporting Information Figure S4). This result is consistent with previous work showing that fishing-mortality-based management targets are more responsive to changes in biomass than fisheries management targets for total harvest (Squires et al., 2017).

The positively biased estimates of B/B_{MSY} from the catch-only superensemble (Supporting Information Figure S1) and the inaccuracy of the reference point estimates (MSY and F_{MSY}, Supporting Information Figure S4) required very precautionary buffers to consistently ensure the population biomass was above 0.25 B_{MSY} (Supporting Information Table S5). This in turn resulted in very low yields, which may not be acceptable to some fishery managers. This overestimation of B/B_{MSY} is interesting, given past research showed that the random forest catch-only superensemble had low bias when tested with cross-validation using a full factorial simulated data set, and on stocks from the RAM Legacy Database (Anderson et al., 2017). While the exact reason for the bias found in this study is unclear, we suspect it is because the superensemble was fit to simulated data from four effort dynamic options, while we only used two of these effort dynamics here.

The MSE also revealed that the management outcomes of the catch-only harvest strategies were sensitive to life-history traits. The choice of HCR and suitable buffer was more important for short-lived, fast-growing stocks (e.g., sardine or tuna) when relying on these catch-only harvest strategies, given the quick response time of these populations. Choosing an ineffective harvest control rule, such as a catch-based 40-10 rule or HCRs with less precautionary buffers, could have much more dramatic and negative outcomes for short-lived species. Alternative management strategies such as escapement rules may be more effective for short-lived species (Cochrane, Butterworth, De Oliveira, & Roel, 1998).

4.2 | Using catch-only methods within a stepping stone approach

We demonstrated that information on catch and simple life-history characteristics of targeted species can be used to develop estimates of stock status, which, when coupled with precautionary, model-based HCRs, could be a possible alternative in the toolbox to manage data-limited fisheries. This is a useful advance for stock assessment modelling, given that model-based HCRs would have previously been reserved for data-moderate or data-rich stocks. Rather than relying on past trends of catches such as the DACS, ORCS and Restrepo methods, the catch-only superensemble method informs HCRs with an estimate of biomass status. As new data-limited assessment models become available in future, they can be easily added to an ensemble or superensemble, making this approach flexible, cost-effective and relatively easy to implement. The downside to these methods is that precautionary buffers are required, leading to reduced yields. In addition to conservative buffers, as tested here, it would be important to consider a broader suite of decision rules and conservation measures, such as protected areas, seasonal closures and gear restrictions. As with all HCRs, we recommend conducting thorough simulation testing on a case-specific fishery, including an assessment of the influence of priors and potential error sources, before applying the superensemble catch-only methods to management of real stocks.

While the superensemble of catch-only models presented here tended to produce positively biased status estimates, the HCRs using these estimates and precautionary buffers did outperform the BAU scenarios, resulting in lower risks of severely overfished populations and effective stock recovery after 20 years. This suggested that there is value in using the limited available data in the early stages of a longer-term management plan. It may be possible to use the catch-only models as a preliminary assessment tool while preparing to transition to data-moderate assessment methods that include more data types. However, the catch-only methods are not intended to be a long-term solution for data-limited stocks. We envision that they could be used alongside monitoring programmes to collect additional data, which would eventually allow stocks under catch-only HCRs to transition to data-rich assessments methods in future. This way, they can act as a stepping stone in the right direction towards the implementation of methods integrating more information to inform estimates of stock status.

It is generally accepted that, in truly data-limited fisheries, more information could improve stock assessment, thus lowering the risk of overfishing (e.g., Dichmont et al., 2017), and potentially reducing the need for precautionary buffers. An example of an intermediate step between the catch-only approaches evaluated here and full stock assessment could be the collection of catch-at-age or effort data, which can be used to improve estimates of population status and fishing mortality rate within models such as the catch curve stock reduction analysis (Thorson & Cope, 2015). Investigating the potential benefits of incorporating additional information into catch-only models, such as the age or size composition of the catch or trends in fishing effort, will be an important focus for future research. Such an analysis would be able to answer questions about trade-offs between allocating time to implement an interim HCR or focusing efforts on collecting more data to conduct a more accurate assessment in a few years. Ultimately, data-limited fisheries are a result of limited resources being spent on their exploitation, management and monitoring. The need for more information creates a need for more resources, which is a governance challenge.

4.3 | Limitations of catch-only harvest strategies for implementation

There are several technical caveats and limitations that should be considered before using catch-only models to inform management strategies.

1. Quality of catch data: For many data-limited species, particularly in developing countries, even the modest data requirements of catch-only models are difficult to meet. Annual catch data, when it is available, may consist of extrapolated estimates from short intermittent data collection periods, only include a proportion of fishing vessels, or only account for landings from specific sectors (i.e., commercial), excluding discards or landings from small-scale or subsistence fisheries (Pauly & Zeller, 2016). We accounted for different observation error between developed and developing regions in the analyses, but any effects in the management performance were overridden by different life histories. This suggests that the HCRs are robust to modest to high levels of observation error. Additionally, catch-only models should be applied to catch data that have "contrast" through time, meaning that the stock has been at both high and low abundance levels. It has been noted that CMSY, in particular, should not be applied to very lightly exploited fish stocks as the time series will not contain sufficient information about productivity (Froese, Demirel, Coro, Kleisner, & Winker, 2017). Finally, it will be difficult to define the upper bound on carrying capacity in a developing fishery or a fishery that displays a continuous increase in catch as the maximum potential has yet to be realized.
2. Biases in catch data: The improved performance of catch-based HCRs when applied to biased catch data was counterintuitive (Supporting Information Tables S5 and S6) but occurred because an input of lower catch into the catch-only models produced a lower MSY estimate. The lower estimated MSY in turn resulted in lower catch or effort targets and thus higher biomass status. This created a negative feedback loop. The biological and economic consequences of this finding are important to consider: It is possible that overreporting catch (positive bias) could lead to an opposite result, with higher MSY estimates, higher catch and effort quotas and thus lower biomass.
3. Time series of catch data: The performance of these catch-only models has been simulation tested with a minimum of 20 years of data (of a 60-year fishing history) with minimal-to-moderate biases in observation error (this study, Rosenberg et al., 2014). An incomplete catch history already violates the assumption of the catch-only models that a complete catch history is required. Their performance with a shorter time series is unknown and is likely to decrease the precision and accuracy of the B/B_{MSY} estimates. For stocks where 20 years of catch data are not available, harvest strategies that involve gear restrictions, spatial closures or "move on" decision rules may be more appropriate (Dowling et al., 2015). This, indeed, may restrict the use of the catch-only superensemble in regions that have only recently started collecting the information (or recently improved the quality of data collection programmes).
4. Management history: The catch-only models are designed for stocks that have not been previously managed, because they rely on annual variation in total catch to estimate biomass status (see above point 1 regarding contrast in the data). Management that fixes catch at a certain level, such as a total allowable catch, stalls any useful information input into the model or can otherwise affect the interpretation of catch time-series data (Thorson et al., 2013). For this reason, they may be better suited as an initial guide, when starting to improve management of unassessed stocks, within a stepping stone approach before other data are collected.
5. Management capacity: Many data-limited fisheries are also limited in their management capacity, which often may preclude their ability to effectively control catch or effort. In this analysis, we assumed that there was capacity for management to be introduced and enforced for intended fisheries and that the catch or effort could be controlled with moderate (20%) to high (50%) levels of implementation error.
6. Assumptions used to set fishing targets: The superensemble of catch-only models used here was designed to only estimate B/B_{MSY}. It does not produce estimates of other information required to set the HCRs, such as F_{MSY} or MSY (although such a superensemble could potentially be built). Instead, to set the catch-based and effort-based HCRs, we relied on output from two of the underlying catch-only models and assumptions from

theoretical fisheries dynamics to estimate these biological reference points, for example, MSY = *rK*/4 (Supporting Information Table S3). While these assumptions are not ideal, they allowed us to implement more sophisticated, dynamic harvest rules that have previously not been possible for data-limited stocks. Biases and uncertainty in these estimated biological reference points propagated through the setting of harvest rates, which reduced the performance of each management strategy, but still provided better management outcomes than business as usual.

If these limitations are carefully considered, the catch-only superensemble may provide an alternative method of stock status estimation for some data-limited stocks—a transition step between catch-based empirical static or dynamic methods, and data-moderate methods. This could be an approach for data-limited fisheries where initial investments into collecting catch data can inform the implementation of more effective management systems that are data-driven and evidence-based. This set of conditions might occur more frequently for small-scale fisheries in developed countries.

5 | CONCLUSION

There is potential value in using catch-only superensemble models coupled with large precautionary buffers to inform short-term management, in addition to the current empirical methods derived from catch. Catch-only methods and HCR combinations did not recover most populations to B_{MSY} after 5 years, but they reduced the risk of overfishing and stock collapse. We found that the effort-based HCRs were more robust and less sensitive to error in catch-only models than catch-based HCRs. The positive biases and inaccuracies of the biological status and reference points estimated from the catch-only models strongly affected the long-term performance of the catch-based HCRs in terms of their risk of overfishing. In some circumstances when suitable catch data are available (e.g., small-scale fisheries in developed countries), these data-limited approaches could provide a "stop gap" to reduce overfishing and the probability of being overfished, at the expense of low yields. However, due to restrictive data requirements, technical caveats and large yield-risk trade-offs, catch-only superensembles are not likely to provide reliable or practical management advice for all data-limited fisheries (including those in developing regions limited in management and research capacity).

ACKNOWLEDGEMENTS

This work was funded by a grant from the Gordon and Betty Moore Foundation to Conservation International (CI). We thank the CI Eastern Tropical Pacific Seascape programme staff and partners who helped identify some of the target species included in our analysis. The authors have no conflict of interests.

ORCID

Jessica C. Walsh http://orcid.org/0000-0002-5284-4323
Cóilín Minto http://orcid.org/0000-0003-0630-6775
Sean C. Anderson http://orcid.org/0000-0001-9563-1937
Jamie Afflerbach http://orcid.org/0000-0002-5215-9342
Kristin M. Kleisner http://orcid.org/0000-0002-6918-1546
James T. Thorson http://orcid.org/0000-0001-7415-1010
John N. Kittinger http://orcid.org/0000-0001-8799-7373

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SUPPORTING INFORMATION

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How to cite this article: Walsh JC, Minto C, Jardim E, et al. Trade-offs for data-limited fisheries when using harvest strategies based on catch-only models. *Fish Fish*. 2018;00:1–17. https://doi.org/10.1111/faf.12316