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Final Report for

Evaluation of Acceptable Biological Catch Harvest Control Rules and Factors Affecting Their Performance

To

The Mid-Atlantic Fishery Management Council

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Report Description

This final report is provided as an executive summary followed by four manuscripts that we are preparing for submission to scientific journals. The executive summary provides the overview of the methods and results, and the details are in each manuscript.

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Executive Summary

Introduction

In the revised National Standard 1 Guidelines for the Magnuson-Stevens Fishery Conservation and Management Reauthorization Act (MSFCMRA 2006), the Statistical and Scientific Committee (SSC) of each of the eight regional management Councils has been tasked with recommending Acceptable Biological Catch (ABC) levels. Importantly, the ABCs will constrain the annual catch limit that must be set by the Council as the Councils cannot set a catch level above the ABC recommended by its SSC. Moreover, National Standard 1 requires that scientific uncertainty be used to guide the selection of an ABC by achieving a specific, acceptable risk of overfishing. These dual directives are being implemented by establishing control rules that govern decision making for fishery management. Many control rules have been developed and tested to manage fisheries (reviewed in Deroba and Bence 2008), yet few of these satisfy the requirements of the National Standard 1 Guidelines. In particular, achieving a specified level of risk of exceeding a fishing mortality threshold has generally not been an explicit criterion for control rules.

Many sources of scientific uncertainty affect our understanding of past population dynamics of a stock, its current status, and how it will respond to fishing in the future. Most stock assessments will not include all important sources of uncertainty. The relevant uncertainties can be usefully separated into four categories: data quality, model uncertainty, stock status and reference point uncertainty, and forecasting uncertainty. Each plays an important role in determining an ABC for a given stock.

When all important sources of uncertainty can be included in the stock assessment and estimation of biological reference points (BRPs), then the calculation of catch levels that achieve a desired level of risk is relatively straightforward. For this situation, Shertzer et al. (2008) proposed an approach that estimates the catch at the maximum fishing mortality threshold (MFMT) or overfishing limit (OFL) reference point, its uncertainty (distribution), and uncertainty in future population size (distribution) and then uses the joint distribution and a pre-specified level of tolerance (probability), P*, for exceeding the reference point to determine the ABC. Implementation of the algorithm involves estimating the distribution of the both the MFMT and of forecasted population size. From these, the level of catch that will achieve a certain probability of avoiding the OFL can be chosen. For this method to work all important sources of uncertainty in the joint distribution of the OFL reference point and forecasted population size must be known and that level of acceptable risk must be specified.

In situations where population status and reference points can be estimated (i.e. data rich situations), but their associated uncertainties are incompletely described, most Councils have adopted a P* approach, with each Council setting different target P* values, as well as assuming different amounts of uncertainty in the OFL distribution. For example, the MAFMC has adopted a threshold P* approach where the target P* is reduced as abundance falls below the biomass that supports maximum sustainable yield (B_{MSY}), and the CV of the distribution for OFL is increased with increasing uncertainty in assessment results based on meta-analysis and stock-specific factors.

Although many control rules have been adopted to comply with the revised Act, the relative performance among the methods and the level of risk associated with each have not been formally evaluated. Management strategy evaluations (MSE) can provide an estimate of the performance of these control rules (e.g., Punt 2003). MSEs involve simulation of an exploited population and its associated management regime so that the performance of different control rules can be evaluated by quantifying how frequently different management objectives are achieved. MSE is increasingly being adopted as a framework to evaluate alternative strategies for fisheries management (Kirkwood 1997; Butterworth and Punt 1999; Smith et al. 1999; Plagányi et al. 2007). Simulation testing generally requires an "operating model" that attempts to simulate the population dynamics of the stock, dynamics of fishery effort, sampling of the population and catch, assessment, and management (Butterworth and Punt 1999; Rademeyer et al. 2007; Butterworth 2008). The operating model represents a reference system in which the underlying "true" dynamics of the system are known, and is used to create "data sets" to which the management strategy is applied and the response of the reference system determined.

In addition to the control rule being used, other aspects of the management structure can affect performance of the fishery management system. Two of the challenges of using stock assessments in management decisions are data availability and the allocation of resources to conduct stock assessments in a frequent and timely manner. The use of the most recent data should be critical to stock assessment model performance because estimates from the most recent years are often used to provide management advice. However, extended timelines between the most recent data included in the stock assessments and management decision are common. Data-management lag (DML), the time between data collection and implementation of management measures, is commonly two to three years and can extend longer some cases. While DML and assessment timelines can strongly affect model predictions, few studies have examined their effects (Shertzer and Prager 2007; Brown et al. 2012; Li et al. in review) or tested approaches for improvements.

Objectives

Our objectives were to use an MSE framework to 1) characterize the performance of several ABC control rules under a range of life histories and fishing histories, 2) compare performance of management systems with different levels of assessment frequency and data-management lag, 3) determine the effectiveness of methods for reducing DML, and 4) estimate the degree of autocorrelation of stock assessment estimates for use in MSEs.

Methods

We conducted an MSE of fishery management performance over a range of scenarios encompassing different life histories, exploitation histories, and levels of assessment quality. The simulation model is a closed-loop MSE (Butterworth and Punt 1999; Milner-Gulland et al. 2010), implying that the important factors that affect the fishery management system are included in the simulation. The MSE has three main components and was developed in AD Model Builder (Fournier et al. 2012). The foundation of the MSE simulation is the operating model, which determines the population dynamics of the stock and how data are generated. Data generated in the operating model represent the true state of the population with some specified amount of observation error. The operating model generated data on fishery harvests, as well as a fishery-independent index of abundance. Mimicking the fishery management process, these data derived from the operating model were then used in the assessment model to estimate stock status and biological reference points. The assessment model was a statistical catch-at-age (SCAA) model (Fournier and Archibald 1982), and output from the assessment was used in the management model to determine the catch limit using a particular ABC control rule. A catch equivalent to the catch limit estimated in the management model was removed from the population in the operating model, without implementation error. This simulation loop continues for a set number of years. We did not include implementation error because our goal was to test performance of ABC control rules rather than to understand the performance of management for specific fisheries. Each multiyear simulation was repeated multiple times (usually 1000-2000) for each scenario (e.g. life history, data quality, recruitment variability) to capture the variability in the population dynamics, data generation, and assessment estimation. At the end of each run, the true and estimated values summarizing the population and fishery dynamics were stored and used to evaluate the ability of a control rule to meet multiple management objectives, and to quantify the amount of autocorrelation in the stock assessment error.

Objective 1: Performance of ABC control rules

Under the revised MSFCMA, ABCs must be set that limit overfishing, but limiting overfishing is not the only objective of fisheries management. Managers must try to limit overfishing while meeting additional objectives such as maintaining high biomass and high and stable yields. Thus, an ideal control rule would be one that satisfies most or all of these conditions. We explored the performance of eight ABC control rules. A control rule of ABC=OFL was used as a baseline to test the effect of using no buffer. The other seven control rules applied different buffer sizes. Six control rules were variations of the P* approach (Shertzer and Prager 2010), in which the distribution for the OFL was assumed to follow a lognormal distribution with different coefficients of variation (CVs). We explored three variations of the P* approach with a fixed target P* (i.e., P* was independent of biomass) of 0.4 for CVs of 0.38, 0.7, and 1.0, and three variations with the same CVs but with the target P* declining as biomass falls below its B_{MSY} proxy. The final control use evaluated was to set the target F at 75% of MFMT.

We ran the model over a range of scenarios to identify factors affecting the performance of the eight ABC control rules. For the baseline scenarios we explored three life histories, three exploitation histories, two levels of data (assessment) quality, and four levels of recruitment variability and recruitment autocorrelation. The different life histories explored were ‘slow’, ‘medium’ and ‘fast’ in which the life history speed reflects age at recruitment to the fishery, age at maturity, and natural mortality. Life histories were tailored to approximate Atlantic butterfish (*Peprilus triacanthus*), summer flounder (*Paralichthys dentatus*) for the medium life history, and spiny dogfish (*Squalus acanthias*) for the slow life history. For the data quality scenarios, we modeled a “good” and “bad” case, whereby several factors were adjusted to affect assessment performance. For each case we varied the CV of the observation error in the survey (lower for the good scenario), the number of samples collected to generate age structured data (higher for the good case), and the amount of autocorrelation in the time-varying parameters (lower in the good scenario). The primary performance measures we used to assess control rule performance were population size, fishery yield, variability in fishery yields, and probability of overfishing (P_{OF}). The latter measure is the central objective that the ABC control rule is seeking to achieve. For most measures, we used the mean over a portion of the management period, such as the first or last 5 years of the management period, or over the entire management period. The probability of overfishing was calculated as the proportion of years during the management period (when the ABC control rule is used) that F exceeded $F_{35\%}$, which was used as the MFMT. We summarized year-to-year variability in fishery yield by calculating the average of the absolute value (AAV; Punt 2003) of difference in yield from one year to the next across the management period.

We ran a range of sensitivity analyses to determine if control rule performance depended on particular assumptions in the model. The first set of sensitivity runs were nearly identical to the base scenarios, but with a gradual decline in steepness over the management period. For these runs, steepness was constant, at the value for each life history during the initial period, and declined linearly starting in year 31 to 50% of the initial value by the final year of the run. The next set of sensitivity runs used alternative limit fishing mortality rates. Based on our life history parameterization, the SPR at F_{MSY} was 0.344, 0.39, and 0.46 for the fast, medium and slow life histories. Because the greatest difference between the SPR at F_{MSY} and the assumed $F_{35\%}$ occurred for the slow history, we ran the model for this life history with $F_{lim} = F_{46\%}$. The final set of sensitivity analyses were restricted to the medium life history and explored several methods for specifying year-specific ABCs. The ABC could be constant over the assessment interval, year-specific based on using projections, or "phased in" gradually.

Objective 2: Assessment frequency and data-management lag

Combinations of data management lag (DML) and assessment interval were tested under a factorial design of scenarios that considered alternative assumptions about data quality, stock-recruitment variability, exploitation history, and life history. Alternative management models were described by combinations of stock assessment interval (assessments every one, two, three, five, seven and ten years) and DML (of one, two and three years). Each management combination was tested under a range of scenarios of good and poor data quality, fast and slow life history, and high and low variable recruitment variability to represent a broad range of potential fisheries. We modeled good and poor data quality scenarios that differed in difference combinations of observation error variance and level of process error in the operating model. Parameters of the operating model were chosen to represent species with a fast and a slow life history. Life histories were tailored to approximate summer flounder for the fast life history and spiny dogfish for the slow life history. The fast life history of the summer flounder included early recruitment into the fishery and early maturation, while the slow life history of the spiny dogfish represented lower natural mortality and late recruitment and maturation. Exploitation scenarios were implemented by including a fishing mortality multiplier (F = 0.5, 1.0, 2.5 x F_{MSY} for the light, moderate, or heavy exploitation) in the pre-management portion to affect the abundance at the beginning of the management period. Preliminary model testing showed little difference between exploitation histories; therefore, the 1000 simulations were summarized across exploitation history with the first 333 runs representing an underfished stock, the second

333 runs representing a fully fished stock, and the final 334 runs representing an overfished fished stock.

Objective 3: Methods for reducing data-management lag

We modified the model used for Objective 2 to test three methods of reducing DML relative to two controls. The specific approaches examined were: 1) a control with one year of DML, 2) using age-composition data for the terminal year of the survey, but no age-composition for the catch with one year of DML, 3) survey age-composition data, but reduced quality age-composition data for the fishery in the terminal year with one year of DML, 4) reduced quality data for both the survey and catch age-compositions in the terminal year of the assessment with one year of DML, and 5) a control with two years of DML. The reduced quality age-composition approaches represented cases in which size-at-age of the stock is variable such that using prior years' data would inject additional error into the age composition data. For these approaches, length data are available for the most recent year and size-age data from previous years would be used to convert length composition to age-composition. If size-at-age of the stock does not vary over time, then use of previous years' data should not result in lower quality age composition information. The two controls used full age-composition data for both the survey and the catch with one and two year DMLs. Each data lag reduction method was tested under scenarios with good and poor quality data, fast and slow life histories, and high and low recruitment variability to represent a broader range of fisheries, similar to those for Objective 2.

Objective 4: Assessment Error Autocorrelation

We ran the MSE model over a range of scenarios to identify factors affecting the level of autocorrelation in the estimation error from the assessment model. We explored three life histories, three exploitation histories, two management scenarios, and two levels of data quality and recruitment variability. Exploitation scenarios included light, moderate, or heavy exploitation in the pre-management portion to determine the abundance at the beginning of the management period. We included the same life histories as were modeled in Objective 1. For the data quality scenarios, we modeled a "good" and "poor" case, whereby several factors were adjusted to affect assessment performance. For each case we varied the CV of the observation error in the survey (lower for the good scenario), the number of samples collected to generate age structured data (higher for the good case), and the amount of autocorrelation in the time-varying parameters (lower in the good scenario). In addition, we explored two levels of recruitment variability. We ran 1000 iterations for each scenario. At the end of each run, the terminal estimate of biomass and recruitment from each assessment was stored along with the true values, and we calculated the amount of lag-1 autocorrelation in the error of biomass and recruitment estimates using a maximum likelihood approach.

Results

Objective 1: Performance of ABC control rules

We evaluated alternative ABC harvest control rules over a range of scenarios to determine their effectiveness at achieving a suite of management objectives. Across the scenarios explored, the control rules that used a buffer when setting the ABC (< OFL) were able to limit the frequency of overfishing, with each achieving a probability of overfishing (P_{OF}) below the 0.5 threshold required for federal U.S. management. On average, the more conservative control rules (larger buffers) resulted in a lower P_{OF} overall (often < 0.3 yr^{-1}), high long-term biomass, similar or slightly higher long-term yield, and more stable yield compared to the less conservative control rules. Thus, the more conservative control rules we explored appear well-suited to meet a range of long-term fisheries management objectives.

We explored eight control rules in our work, seven of which utilized a buffer when setting the ABC. The control rules that achieved the lowest probabilities of overfishing explored in this analysis utilized the biomass-dependent target P* with the high CVs for the OFL distribution, although the fixed P* control rules with a CV of 0.7 and 1.0, and 75% of MFMT also generally achieved P_{OF} at or below 0.3 for many of the scenarios. This work is in agreement with other work with regard to the effectiveness of threshold-based control rules (Punt et al. 2008; Irwin et al. 2008). Using a fixed P* of 0.4 with CVs ≥ 0.38 or the approach using 75% of F_{lim} as the target F were also effective control rules for limiting overfishing, but often resulted in slightly lower long-term average yield than the biomass-based control rules.

ABCs must be set for a number of years in the future, depending on the length of the interval between stock assessments. Setting a fixed ABC in the future or using projections had little effect on the probability of overfishing, population biomass, and fishery yield for both the two and five year assessment intervals. AAV of the catch was influenced by whether or not projections were done, and was lower when the ABC was fixed over the assessment interval. Using a weighted average of successive ABCs also resulted in a lower catch AAV than the other methods, but for longer intervals with high recruitment variability this approach resulted in a higher frequency of overfishing (P_{OF} > 0.5). If having more stable catches is an important goal for a fishery, then fixing the ABC over the assessment interval may be more effective than using projections to set year-specific ABCs.

Objective 2: Assessment frequency and data-management lag

We found substantial differences in management performance as a result of assessment frequency and DML across a range of scenarios. Specifically, increases in DML and assessment interval resulted in decreases in both the median catch and biomass (1-8% yr^{-1}) and increases in P_{OF}. Increases in DML caused larger changes than increases in assessment intervals, on average, for all performance metrics except probability of overfishing. The effect of DML and assessment interval was larger in the poor data scenarios, and the effects of DML and assessment interval varied among the life history and data quality scenarios. For example, there was about a twofold increase in the effects of DML and assessment interval between the good to poor data scenarios. Larger changes in performance metrics were evident with the fast life history compared to slow life history scenarios, but effects varied across performance metrics.

Objective 3: Methods for reducing data management lag

Lag reduction methods can be successful in reducing the effects of DML and meeting management goals. Overall, data lag reduction methods had the largest effects when the data quality was relatively poor and the smallest effects when data quality was high. Data lag reduction methods that used age-composition information from the survey, but no or reduced information from the catch in the terminal year of the stock assessment, achieved performance that was similar to using full data in the terminal year. Life history, data quality, and assessment interval all played important roles in the effects of DMLs and effectiveness of data lag reduction methods. Data lag reduction methods provided benefits over the status quo in almost all cases. However, the difference in performance was smallest in the good data quality scenarios. Additionally, the benefits of using data lag reduction methods were greatest with longer assessment intervals.

Objective 4: Assessment error autocorrelation

We estimated the amount of temporal autocorrelation in errors of estimated biomass and recruitment from SCAA stock assessment models over a series of scenarios spanning life histories, exploitation levels, recruitment variability, and data quality. Autocorrelation in the error in biomass estimates (ϕ_S) was positive and relatively high, with median estimates ranging between 0.6 and 0.9. Estimates were highest for the slow life history and lowest for the fast life history. Exploitation level also affected the amount of autocorrelation, with higher values for lightly exploited populations. On average, however, estimates of ϕ_S did not change over time as more data were included in the assessment, and were independent of whether or not a harvest policy was applied. In contrast, recruitment variability and data quality had relatively minor effects on autocorrelation of errors.

Conclusions and Recommendations

Identifying robust harvest control rules is essential for effective fisheries management in the face of uncertainty. This work showed that using even modest buffers when setting the ABC are generally effective at limiting overfishing, in the sense that the limit fishing mortality rate is not frequently exceeded, but that more conservative control rules may result in higher average biomass and yield long term. In addition, the more conservative options provide similar long-term benefits to the fishery while having a low risk of overfishing, and allow more rapid recovery of depleted populations. The results of this work may be used as a guide for managers in the selection of an appropriate ABC for their stock, and the flexible MSE framework developed here may be used to explore a wider range of control rules under different conditions or for particular case studies.

We found substantial differences in management performance as a result of assessment frequency and DML across a range of scenarios. Specifically, increases in DML and assessment interval resulted in decreases in both the median catch and biomass. Increases in DML caused larger changes relative to increases in assessment intervals, on average, for all performance metrics except the probability of overfishing and were especially noticeable in the poor data scenarios. The effects of DML and assessment interval on the performance metrics varied among the life history and data quality scenarios. For example, for average catch the effects of DML and assessment interval were relatively low for the fast life history and good data scenarios, with average catches decreased by 2% and 1%, respectively, but were magnified in the poor data scenario to a 4% and 3% decrease in catch with an additional year of DML or assessment interval, respectively. Larger changes in performance metrics were evident with the fast life history compared to slow life history scenarios, but effects varied across performance metrics. Methods for reducing DML by including years with partial data in the stock assessment performed reasonably well in improving management performance. One research priority is, therefore, continued development and testing of techniques to reduce DML.

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Chapter 1. An Evaluation of Acceptable Biological Catch (ABC) Harvest Control Rules for Data-Rich Fisheries

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Abstract

In the U.S., recent changes in fisheries legislation have altered how fisheries management actions are developed. Under the revised Magnuson-Stevens Fishery Conservation and Management Reauthorization Act of 2006 (MSFCMRA), acceptable biological catch limits (ABC) must be set to limit overfishing, using scientific uncertainty as a guide in the process. In this paper we developed a simulation model to evaluate a range ABC control rules to determine their relative performance at limiting overfishing and achieving other common fishery management objectives. We explored a range of scenarios to determine robustness of a control rule to different situations, including a range of life histories, exploitation histories, and data and stock assessment quality. Across the scenarios explored, the control rules that used a buffer when setting the ABC were able to limit the frequency of overfishing, with a probability of overfishing below the 0.5 threshold required for federal U.S. management. Using even modest buffers when setting the ABC are generally effective at limiting overfishing, in the sense that the limit fishing mortality rate is not frequently exceeded, but that more conservative control rules may result in higher average biomass and yield long term. In addition, the more conservative options provide similar long-term benefits to the fishery while having a low risk of overfishing, and allow more rapid recovery of depleted populations.

Keywords: Acceptable biological catch, harvest control rules, management strategy evaluation

Introduction

In the U.S., recent changes in fisheries legislation have altered how fisheries management actions are developed. The Magnuson-Stevens Fishery Conservation and Management Reauthorization Act of 2006 (MSFCMRA) aims to maintain healthy U.S. fisheries by, among other things, limiting overfishing. In the revised National Standard 1 under the, MSFCMRA the Scientific and Statistical Committees (SSC) of each of the eight regional management Councils have been tasked with recommending acceptable biological catch (ABC) levels. National Standard 1 suggests that scientific uncertainty be used to guide the selection of an ABC by achieving a specific, acceptable probability of overfishing (Federal Register, 2009). Importantly, the ABCs will constrain the annual catch limit (ACL) that must be set by the Council as they cannot recommend a catch level above the ABC recommended by its SSC. Many control rules to manage fisheries have been developed and tested (reviewed in Deroba and Bence 2008), yet few of these satisfy the desired properties of the revised MSFCMRA. In particular, achieving a specified probability of overfishing has generally not been an explicit criterion for control rules.

For stocks where stock assessments are possible (i.e., data-rich), the overfishing limit (OFL; the catch at F_{lim} that defines overfishing) is estimated using estimates from the terminal year of the model, and often for a number of years in the future using stochastic projections, producing a distribution for possible OFL values over time. It is difficult to capture all of the possible sources of uncertainty inherent in the estimation and projection processes, such that the uncertainty in the OFL is likely underestimated. For example, Ralston et al. (2011) found that the uncertainty in population biomass estimated within an assessment is often less than the uncertainty in biomass estimated among repeated assessments for the same stock.

One approach to account for this underestimation of uncertainty is to estimate the uncertainty in the OFL distribution outside the stock assessment. In several regions of the U.S., the point estimate of the OFL in a given year is treated as the median of a lognormal distribution, with a coefficient of variation (CV) that is specified by the SSC (PFMC 2010, MAFMC 2011). Given a distribution for the OFL, the next step is to select a target probability of overfishing, or P* (Shertzer et al. 2008). For example, with a P* of 0.4, the 40^{th} percentile of the OFL distribution would be selected as the ABC. Using this process, the buffer size between the ABC and the OFL increases as the target P* decreases and as the assumed CV of the OFL distribution increases (Figure 1).

The P* approach outlined above may be applied differently for different stocks, depending on the circumstances. For example, larger CVs may be selected for stocks with greater uncertainty in the assessment, such as a strong retrospective pattern (Mohn 1999). Alternatively, the target P* might be fixed for a stock, or it could be varied in response to the changes in the estimated biomass, with a lower P* for a more depleted stock (Figure 1). Alternative approaches for implementing the P* approach have been adopted across the U.S., but their relative performance has not been tested.

In this paper we developed a simulation model to evaluate a range ABC control rules to determine their relative performance for achieving common fishery management objectives. We explored a range of scenarios to determine robustness of a control rule to different situations, including a range of life histories, exploitation histories, and data and stock assessment quality.

For each control rule we measured performance in variety of ways. One of the primary goals of the MSFCMA is to avoid overfishing, and how well a control rule achieves this objective is an essential measure of its utility. ABC control rules must also balance the trade-offs between risk and reward because minimizing the probability of overfishing also minimizes yield. Thus, control rule performance was evaluated with respect to its impact on other fishery metrics in addition to probability of overfishing (Wilberg et al. 2011).

Methods

To test the performance of alternative ABC control rules, we conducted a management strategy evaluation (MSE) over a range of scenarios encompassing different life histories, exploitation histories, and levels of assessment quality. The simulation model is a closed-loop management strategy evaluation (Butterworth and Punt 1999; Butterworth et al. 2010; Milner-Gulland et al. 2010) with three main components, and was developed in AD Model Builder (Fournier et al. 2012). The foundation of the MSE simulation is the operating model, which determines the population dynamics of the stock and how data are generated. Data generated in the operating model are based on the true state of the population with some specified amount of observation error. The operating model generated data on fishery harvests, as well as a fishery-independent index of abundance. These data were then used in the assessment model to estimate stock status and biological reference points. The assessment model was an SCAA model (Fournier and Archibald 1982), and output from the assessment was used in the management model to determine the catch limit using a particular ABC control rule. The catch limit estimated in the management model was removed from the population, without implementation error, and the simulation loop continues for a set number of years. We did not include implementation error because our goal was to test performance of ABC control rules rather than to understand the performance of management for specific fisheries. This process was repeated 1000 times for each scenario (e.g. life history, data quality, recruitment variability) to account for the variability in the population dynamics, data generation, and assessment estimation. At the end of each run, the true and estimated values summarizing the population and fishery dynamics were stored and used to evaluate the ability of a control rule to meet multiple management objectives.

Operating, Assessment, and Management Models

The population dynamics in the operating model followed an age-structured model (Quinn and Deriso 1999) with the equations governing these dynamics in Table 1 and definitions of the equation state variables in Table 2. Equations used in the model are referenced by their number in Table 1, such that the formula for calculating numerical abundance-at-age is referred to as Eq. T1.1. The population began at unfished equilibrium abundance at age in year 1 of the simulation. Annual abundance of recruited ages was determined from the abundance of that cohort the previous year, decreased by continuous natural and fishing mortality (Eq. T1.1). Fishing mortality at age was the product of fishing intensity of full selected ages and selectivity at age, and natural mortality was independent of age, but a varied over time following an autocorrelated process on the log scale. Total mortality at age was the sum of fishing and natural mortality.

Recruitment followed the Beverton-Holt stock-recruit relationship, with bias-corrected lognormal and autocorrelated deviations (Eq. T1.2). Parameters controlling the degree of autocorrelation and variability in recruitment (Table 3) were based on the recruitment meta-analysis of Thorson et al. (2014). Total spawning biomass in a given year was calculated by summing the product of the proportion mature, weight at age and abundance at age over all recruited age classes (Eq. T1.3). Weight at age was an allometric function of length at age, which followed a von Bertalanffy growth function (Eqs. T1.5 and T1.6). The proportion mature at age was calculated using a logistic function (Eq. T1.7). Length, weight, and maturity at age were fixed for a given species life history.

The model contained a single fishery with a logistic selectivity function (Eq. T1.8). The selectivity ogive varied over time as the parameter that determines the age at 50% selectivity varies annually in an autocorrelated manner (Eq. T1.8), as selectivity in a fishery can vary in response to changing regulations, fishing practices, or changes in growth, although the source for the changes was not modeled explicitly. Because both natural (M) and fishing mortality (F) occurred continuously throughout the year, catch was calculated using the Baranov catch equation (Quinn and Deriso 1999; Eq. T1.9).

Each model run was divided into two periods, the initial and management periods. The initial period included the first 30 years for the simulation, while the management period was the remaining 35-45 years, depending on the life history of the stock. The population started in an unfished state. A single fishery developed during the first 30 years following a fixed pattern of total fishing mortality . F increased linearly until year 15, and was constant at its peak value for the remainder of the initial period. The peak fishing intensity (F = 0.5, 1.0, 2.5 × F_{MSY} for the light, moderate, or heavy exploitation scenarios) and realized patterns of recruitment, fishery selectivity, and natural mortality during this period determined the abundance and age structure of the population at the start of the management period.

At the start of management period (year 31) the population was first assessed using data generated during the initial period, starting in year 10, and with a 1-year lag between the last year of the data collected and when the assessment is done. The data used in the assessment were the fishery catch (both total and proportions-at-age) and a fishery-independent index of abundance (both total and proportions-at-age). These data sets were generated by applying observation error to the true values using lognormal errors for the total index and catch and multinomial distributions for the age compositions (Eqs. T1.10 - T1.14). The amount of observation error in the generation of the data varied to explore the interactions between data quality and the autocorrelation in assessment estimates.

The time series of catch and survey data were input into the SCAA model to estimate the abundance at age, fishing mortality rates in each year, and reference points for management. The estimated parameters were the abundance at age in the first year of the SCAA, recruitments and fishing mortality rates (across years), fishery selectivity parameters, survey selectivity parameters, and survey catchability. The SCAA used a maximum likelihood approach to estimate the parameters. Time-varying parameters that are estimated (survey catchability and age at 50% selectivity in the fishery) are assumed constant over time in the assessment model. Natural mortality was assumed to be constant over age and time at the mean value for the given life history (Table 3). All other required SCAA inputs (i.e., maturity- and weight-at-age) are set to the true values specified in the operating model. The SCAA model also estimated the spawning potential ratio (SPR) – based reference points to determine stock status and target catch (NEFSC 2002). The limit fishing mortality rate was specified at $F_{35\%}$ for all life histories because this is a commonly used limit fishing mortality rate in the U.S. $F_{35\%}$ did not exactly correspond to the fishing mortality rate that achieved maximum sustainable yield for any of the life histories. The spawning biomass reference point was calculated by multiplying the spawning stock biomass-per-recruit by the mean estimate of recruitment over the time series (NEFSC 2002; Haltuch et al. 2008). Because maturity and weight at age were fixed at the true values, the SPR-based reference points varied across assessments based on the estimated fishery selectivity and the estimated mean recruitment. Assessments occurred every two years starting in year 31.

For the baseline scenarios $F_{35\%}$ was the assumed to be the limit fishing mortality rate across life histories. Punt et al. (2008) showed that the target SPR% is tightly correlated with the steepness of the stock-recruitment relationship, such that selecting a particular SPR% for a stock implies a certain level of steepness. For an SPR of 35%, the corresponding steepness is approximately 0.89 which differs from the assumed steepness for some of the life histories we explored (Table 3). However, because an SPR of 35% is widely used as a proxy for many species with likely a range of steepness values, we felt this was a reasonable assumption. Additionally, managers never know the true steepness for a stock, which is one of the reasons for using SPR-based reference points. However, we also explored the effects of using a different SPR targets as a sensitivity analysis (described further in the *Sensitivity Runs* section below).

In the management model, a harvest control rule was applied using the abundance at age projected one year past the terminal year and the $F_{35\%}$ from the assessment model to determine the ABC using the specified control rule. The projected abundance at age was calculated using the terminal abundance, the assumed *M* and estimated *F* at age in the terminal year, with recruitment assumed equal to the mean level over the previous 10 years. Under the baseline model runs the ABC was constant for the interval between assessments (2 years), but we also explored the effects of using projections to set year-specific ABCs for the two-year interval and over a longer interval of five years. When projections were used, the same deterministic approach was used to calculate abundance at age in the projected year, assuming $F = F_{35\%}$ in all years after the terminal year. Note that this approach ignores the changes in abundance that might occur by setting the ABC < OFL, which would result in $F < F_{35\%}$ with accurate estimates of abundance. As a result, the deterministic projections provided more conservative estimates of the OFL. The estimated ABC is then removed from the population the following year, and the resulting F is calculated using the Baranov catch equation (Quinn and Deriso 1999).

Control rules

We explored the performance of eight ABC control rules (Table 4). One control rule was used as a baseline to test the effect of using no buffer when setting the ABC (ABC = OFL). The other seven control rules applied different buffer sizes when, with one doing so by setting the target F at 75% of F_{lim}. The remaining six control rules were variations of the P* approach (Shertzer and Prager 2008), in which the distribution for the OFL was assumed to follow a lognormal distribution with different CVs. We explored three variations of the P* approach with a fixed target P* (i.e., P* was independent of biomass) of 0.4 for CVs of 0.38, 0.7, and 1.0, and three variations with the same CVs but with the target P* declining as biomass falls below $S_{35\%}$, (i.e., varying P* control rules; Figure 1).

Parameterization and Model Runs

We ran the model over a range of scenarios to identify factors affecting the performance of ABC control rules. For the baseline scenarios we explored three life histories, three exploitation histories, two levels of data (assessment) quality, and four levels of recruitment variability and recruitment autocorrelation (Table 5). The different life histories explored were 'slow', 'medium' and 'fast' (Table 3). The slow life history had relatively slow growth, late maturation, and low steepness. In contrast, the fast life history had rapid growth, early maturation, and high steepness. The medium life history is between the slow and fast life histories. We used different aggregate age gins for the maximum age for each life history (7, 12, and 20 years for the fast, medium and slow life histories, respectively). Additionally, the mean natural mortality rate and steepness of the stock-recruitment function differed with life history. All other life history parameters were either fixed across life histories (L_∞ and the length-weight parameters b and c) or determined from the other parameters. The mean natural mortality rate was used to determine the growth rate, $k = M/1.5$, and age at 50% maturity, $m_{50\%} = M / 1.4$ (Charnov and Berrigan 1991; Charnov et al. 1993; Frisk et al. 2001), which then determined the initial age at 50% selectivity in the fishery ($s_{f,50\%}(t{=}1) = m_{50\%}$). For the survey, age at 50% selectivity was lower than that of the fishery, $s_{s,50\%} = 0.75\ s_{f,50\%}(t{=}1)$, and was rounded down to the nearest integer to determine the age at recruitment to the population, $a_R = \lfloor s_{s,50\%} \rfloor$.

For the data quality scenarios, we modeled a "good" and "bad" case, whereby several factors were adjusted to affect assessment performance (Table 5). For each case we varied the CV of the observation error in the survey (lower for the good scenario), the number of samples collected to generate age structured data (higher for the good case), and the amount of autocorrelation in the time-varying parameters (lower in the good scenario). In addition, we explored two levels of recruitment variability and two levels autocorrelation, resulting in four total runs. The levels of variability and autocorrelation based on the meta-analysis of Thorson et al. (2014).

Performance Measures

We ran 1000 iterations for each scenario. At the end of each run, a range of performance measures were calculated to summarize the ability of each control rule to meet a suite of management objectives (Table 6). The primary performance measures we used to assess control rule performance were population size, fishery yield, variability in fishery yields, and frequency of overfishing. For most measures, we used the mean over a portion of the management period, such as the first or last 5 years of the management period, or over the entire management period. The probability of overfishing was calculated as the proportion of years during the management period that F exceeded $F_{35\%}$. We summarized year-to-year variability in fishery yield by calculating the average of the absolute value (AAV; Punt 2003) of difference in yield from one year to the next across the management period.

Sensitivity Analyses

We ran a range of sensitivity analyses to determine if control rule performance depended on particular assumptions in the model. For the baseline model runs we explored two levels of assessment uncertainty (low / high), two levels of σ_R and two levels of ϕ_R for each life history and exploitation history (runs 1-8 in Table 5). For the baseline runs, steepness was fixed over time at the values for each life history, the ABC was constant during a 2-year interval between assessments, and the limit fishing mortality rate (F_{lim}) was $F_{35\%}$.

The first set of sensitivity runs were nearly identical to the base scenarios, but with a gradual decline in steepness over the management period (runs 9-16 in Table 5). For these runs, steepness was constant, at the value for each life history (Table 3) during the initial period, and declined linearly starting in year 31 to 50% of the initial value by the final year of the run.

The next set of sensitivity runs used alternative limit fishing mortality rates. Based on our life history parameterization (Table 3), the SPR at F_{MSY} was 0.344, 0.39, and 0.46 for the fast, medium and slow life histories. Because the greatest difference between the SPR at F_{MSY} and the assumed $F_{35\%}$ occurred for the slow history, we ran the model for this life history with $F_{lim} = F_{46\%}$ (runs 17-20 in Table 5).

The final set of sensitivity analyses (runs 21-52 in Table 5) were restricted to the medium life history and explored several methods for specifying year-specific ABCs. The ABC could be constant over the assessment interval, year-specific based on using projections, or "phased in" gradually. Under the phasing in approach, the ABC for a given year was a weighted average of the current estimate ($ABC_{cur}(t)$) and the estimated ABC from the final year of the previous assessment period (ABC_{prev}). For example, when setting multi-year ABCs in years t, t+1, etc., ABC_{prev} is the ABC that was set in year t-1. We assumed equal weight when averaging the ABC, such that $ABC(t) = 0.5 * ABC_{cur}(t) + 0.5 * ABC_{prev}$.

Results

Because of the large number of scenarios explored and the range of performance measures calculated for each run, a detailed description of the model results for each run is not feasible. We provide a summary of the general patterns observed across runs here, and results of all of the full model runs are presented in Appendix A.

Baseline Model Runs

Across the baseline scenarios (runs 1-8 in Table 5), control rules that applied a buffer between the ABC and the OFL resulted in a probability of overfishing (P_{OF}) below the 0.5 threshold for most model runs (Figure 2). Although each control rule was able to limit overfishing ($P_{OF} < 0.5$), the frequency of overfishing varied widely across control rules. For the light and moderate exploitation histories, the population biomass remained close to the S_{MSY} levels on average for many of runs, such that the control rules with a varying P* (Figure 1) were not triggered that often, and the target P* remained at or close to 0.4. As a result, the probability of overfishing (P_{OF}) for the different P* approaches resulted more from the assumed CV and less on whether or not P* was fixed or varied in response to biomass. For the scenarios with good data quality, the interquartile range (IQR) of estimates of P_{OF} were below 0.5 for the P* approaches using the larger CVs (0.7 and 1.0). For the CV of 0.38, some of the IQRs extended above 0.5 threshold for P_{OF}, particularly when P* was fixed at 0.4. For the heavy exploitation scenario, the varying P* control rules resulted in a P_{OF} consistently below 0.4, and in some cases below 0.2 for the larger assumed CVs. In addition for the heavy exploitation scenario, the P_{OF} decreased going from the fast to the slow life history for the threshold P* control rules because the fast life history rebuilt more rapidly to a biomass level above the threshold where P* is reduced. Across life histories and exploitation scenarios, the control rule that used a target F of 75% of F_{lim} performed similar to the P* approaches using the fixed target P* with CVs of 0.7 and 1.0 (Figure 2, top).

Decreasing the quality of data used in the stock assessment resulted in an expansion of the range of P_{OF} estimate across scenarios (Figure 2, bottom). In some cases, this resulted in the IQR extending above the 0.5 threshold, particularly for the fixed P* approaches with CVs of 0.38 and 0.7. While the majority of P_{OF} estimates remained well below 0.5 across the life history and exploitation histories explored, only the threshold P* approach (for all CVs) had IQR consistently below 0.5 (Figure 2, bottom).

The control rules generally resulted in long-term biomass (calculated as the mean of the final five years) close to S_{MSY} across life histories and exploitation histories (Figure 3). Biomass estimates were 20-40% higher for the most conservative control rules compared to the least conservative control rule explored (ABC = OFL). Populations that were overfished were generally able to rebuild over the management period, although population recovery was considerably slower for the slow life history. Within 5 and 15 years the fast and medium life histories were able to rebuild to near the biomass reference point (i.e., approximately double in size), but doubling time for the slow life history took considerably longer (25+ years) across control rules (Table A1). Rebuilding was fastest for the varying P* control rules and was also faster for the fixed control rules that imposed larger buffers between the ABC and OFL.

The average long-term yield (the average in the final 5 years) was fairly similar across control rules for a given life history and exploitation history (Figure 4). However, average yield during the first five years, varied across control rules depending on the exploitation scenario. The short-term yield was positively related to P_{OF} across control rules. In contrast, long-term yield was similar across all P_{OF} for the fast life history and was negatively related to P_{OF} for the medium and slow life histories (Figure 5). The average fishing intensity (F / F_{lim}) and the AAV; of yield for each control rule increased linearly for the increasing P_{OF} across scenarios, although the increase was less pronounced for the catch AAV (Figure 6).

For the baseline scenarios the relative performance of each control rule at limiting overfishing was similar across the different levels of stock assessment uncertainty, σ_R and ϕ_R explored, but other performance measures were affected by these parameters, most notably the average catch (Table A1). Average catch decreased as assessment uncertainty, σ_R and ϕ_R increased, with the lowest catches occurring for the high assessment uncertainty run with $\sigma_R = 1.25$ and $\phi_R = 0.44$ (Figure 7). While the specific parameterization had a large impact on some of the performance measures, the relative performance of each control rule was consistent across scenarios (Figure 7; Table A1).

Sensitivity Runs

For each life history and exploitation history we evaluated the sensitivity of control rule performance for different model parameterizations (Table 5). For the light and moderate exploitation scenarios, a gradual decline in steepness had little impact on the relative performance of the control rules, as the population biomass for each life history started at high levels when the decline started. For the heavy exploitation scenario, both the fast and medium life histories recovered rapidly enough that again the change in steepness had a small effect on the performance measures. For the heavily exploited slow life history, however, there was a decline in overall biomass and yield at the end of the management period, but the control rules that used buffers when setting the ABC were still able to keep the probability of overfishing below the 0.5 threshold for the majority of runs (Table A1).

An additional sensitivity run explored a different limit SPR% for the slow life history. For this run we used the SPR% that corresponded to the deterministic estimate of F_{MSY}, which was $F_{46\%}$ in this case (Table 3). Changing the value for F_{lim} did not alter the relative control rule performance with respect to overfishing frequency, but the lower target F did result in higher biomass on average, and slightly reduced yield. Using a different limit SPR% did impact the relative performance of the control rules with respect to long-term yield. For a limit SPR of 35%, the more conservative control rules resulted in higher long-term yield, on average (Figure 4). In contrast, long-term yield was similar across control rules using a limit SPR of 46% (Figure 8).

For the base line model runs the ABC calculated from a control was fixed for a 2-year interval between stock assessments. We evaluated different approaches for setting the ABC over this interval, and also how the length of the interval impacted control rule performance. For these runs a subset of control rules were selected: ABC = OFL, ABC set using the threshold P* approach with an assumed CV for the OFL distribution of 0.7, and a fixed P* of 0.4 with an assumed CV for the OFL of 0.38. For all the projection scenarios explored, P_{OF} varied more across control rules being tested than across the different projections methods used to calculate the catch for a given control rule. In general, P_{OF} was similar across projection scenarios, but the exception to this pattern occurred when the ABC was phased in with a 5 year assessment interval when recruitment variability was high (Figure 9). ABC averaging tended to result in somewhat higher P_{OF} than the other approaches, particularly when combined with a five year assessment interval. Although the P_{OF} was relatively insensitive across the projection scenarios, the AAV of the catch was sensitive to the different approaches. Overall, catch variability was lower when projections were not used. Catch variability also decreased with increasing length between assessments and when ABC averaging was used (Figure 10).

Discussion

We evaluated alternative ABC harvest control rules over a range of scenarios to determine their effectiveness at achieving a suite of management objectives. Under the revised MSFCMA, ABCs must be set that limit overfishing, but limiting overfishing is not the only objective of fisheries management. Managers must try to limit overfishing while meeting additional objectives such as maintaining high biomass and high and stable yields. Thus, an ideal control rule would be one that satisfies most or all of these conditions. Across the scenarios explored, the control rules that used a buffer when setting the ABC (< OFL) were able to limit the frequency of overfishing, with a probability of overfishing P_{OF} below the 0.5 threshold required for federal U.S. management. The more conservative control rules (larger buffers) resulted in a lower P_{OF} overall (often < 0.3), high long-term biomass, similar or slightly higher long-term yield, and more stable yield compared to the less conservative control rules, on average. Thus, the more conservative control rules we explored appear well-suited to meet a range of long-term fisheries management objectives.

We explored eight control rules in this analysis, seven of which utilized a buffer when setting the ABC. The control rules that achieved the lowest probabilities of overfishing explored in this analysis utilized the biomass-dependent target P* with the high CVs for the OFL distribution, although the fixed P* control rules with a CV of 0.7 and 1.0, and 75% of F_{lim} generally achieved P_{OF} at or below 0.3 for many of the scenarios. This work is in agreement with other work with regard to the effectiveness of threshold-based control rules (Punt et al. 2008; Irwin et al. 2008). Using a fixed P* of 0.4 with CVs ≥ 0.38 or the approach using 75% of F_{lim} as the target F were also effective control rules for limiting overfishing, but often resulted in slightly lower long-term average yield than the biomass-based control rules.

Although the long-term average yield of the more conservative control rules was similar to the less conservative control rules, the short-term effects on yield depended on the life history and exploitation history. Yield during the first few years of control rule implementation was lower for the more conservative options, resulting in a lower yield over the entire time period the control rule was applied. However, in our medium and slow life history scenarios, the more conservative control rules achieved higher long-term average yield than the other control rules. Beyond yield, there may be additional benefits to the more conservative options (i.e., more rapid growth for depleted populations), but managers must balance short-term and long-term trade-offs for a given fishery.

A second caveat associated with the long-term yield predictions for the conservative control rules is that this result might not hold for all situations. For the life histories modeled in this study, the peaks of the stochastic yield curves were relatively flat for range of F values around F_{MSY} (Figure 11). Control rules that that used larger buffers resulted in lower F values that were still within the range of peak yield on the stochastic yield curve. For species with less flat yield curves, the long-term yield may be lower for more conservative control rules. In addition, the target SPR% can impact the relative performance of a control rule with respect to long-term yield (Figure 4 compared to Figure 8). For example, using a target SPR% that is below the true SPR% at MSY with conservative control rule could result in a reduction in average long-term yield (i.e., being in the ascending portion of the yield curve). Managers therefore would benefit from the consideration of the interactions between the shape of the stochastic yield curve and the management targets (i.e., SPR%) for a given stock when deciding on how conservative the control rule should be for that species. The control rules we explored here could also have an effect on the shape of the yield curve (Irwin et al. 2008), and future work will explore the yield curve shape across control rules.

ABCs must be set for a number of years in the future, depending on the length of the interval between stock assessments. Setting a fixed ABC in the future or using projections had little effect on the probability of overfishing, population biomass, and fishery yield for both the two and five year assessment intervals. AAV of the catch was influenced by whether or not projections were done, and was lower when the ABC was fixed over the assessment interval. Using a weighted average of successive ABCs also resulted in a lower catch AAV than the other methods, but for longer intervals with high recruitment variability this approach resulted in a higher frequency of overfishing ($P_{OF} > 0.5$). If having more stable catches is an important goal for a fishery, then fixing the ABC over the assessment interval may be more effective than using projections to set year-specific ABCs.

The relative performance of the control rules was generally robust across the range of sensitivity runs explored in this work, but there may be circumstance where their relative performance breaks down. Our goal in this work was to obtain a general understanding of control rule performance, but an expansion of the sensitivity runs was beyond the scope of this work given the large number of runs (Table 5). However, there are a number of ways that the operating, assessment, and management models may be modified to test a particular scenario, and future work using this model test a wider range of scenarios to identify when these control rules begin to perform poorly. For example, the performance of the all of the control rules likely depends on assessment accuracy. We included two scenarios of data quality that differed in the amount of observation and process error that generated the data sets. Assessment accuracy can degrade substantially if process errors have trends over time (e.g., Wilberg et al. 2006) or if the data are relatively uninformative about the population state (e.g., Bence et al. 1993).

An additional source of error that we did not include in our simulations was implementation error, such that the specified ABC was removed from the population. We excluded implementation error from our models because our goal was to characterize ABC control rule performance rather than the performance of management for a given stock. For many fisheries, particularly those with large recreational sectors (e.g., Terceiro 2011), greatly exceeding the ABC may be a frequent occurrence. In such cases the control rules we explored would likely have resulted in greater P_{OF}, although it would depend on the pattern of implementation error. In federal U.S. fisheries management, implementation error should be considered by managers when setting annual catch limits (ACL), with larger buffers between the ACL and ABC when the error is large (Federal Register, 2009). Because we were focused on the performance of ABC control rules, we did not consider implementation error in our model. Consideration of both factors in a broader analysis might reveal interesting patterns with respect to control rule performance, particularly if the goal is to test a management system for a specific fishery.

Additional sensitivity runs of the model exploring a wider of ecosystem effects on a population are warranted. We explored the impacts a gradual decline in steepness of the stock-recruitment relationship, mimicking a long-term shift in stock productivity. An alternative option not explored in this work might be a dramatic change in steepness associated with a regime shift (Hare and Mantua 2000). MSE studies for species undergoing regime shifts have been conducted, although these studies generally focus on the development of specific control rules that include the effects of environmental covariates on recruitment and reference points (A'Mar et al. 2009; Punt and Szuwalski 2013). In general, attempts to account for changing environmental conditions in a harvest control rule result in greater variability in control rule performance, particularly when the projected changes do not occur (Punt et al. 2013). The control rules explored in this study do not attempt to account for changing environmental conditions, and future exploration of their robustness to a range of environmental changes is warranted.

Identifying robust harvest control rules is essential for effective fisheries management in the face of uncertainty. This work showed that using even modest buffers when setting the ABC are generally effective at limiting overfishing, in the sense that the limit fishing mortality rate is not frequently exceeded, but that more conservative control rules may result in higher average biomass and yield long term. In addition, the more conservative options provide similar long-term benefits to the fishery while having a low risk of overfishing, and allow more rapid recovery of depleted populations. The results of this work may be used as a guide for managers in the selection of an appropriate ABC for their stock, and the flexible MSE framework developed here may be used to explore a wider range of control rules under different conditions or for particular case studies.

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Table 1. Equations governing the population and data-generating dynamics in the operating model.

	Equation	Description
	Population dynamics	
1	$N(a,t) = \begin{cases} R(t) & a = a_R \\ N(a-1,t-1)e^{-Z(a-1,t-1)} & a_R < a < a_{max} \\ N(a-1,t-1)e^{-Z(a-1,t-1)} + & a = a_{max} \\ N(a,t-1)e^{-Z(a,t-1)} & \end{cases}$	Numerical abundance at age
2	$R(t) = \dfrac{S(t-a_R)}{\alpha + \beta S(t-a_R)} e^{\varepsilon_R - 0.5\sigma_R^2}$ $\alpha = \dfrac{S_0(1-h)}{4hR_0} \qquad \beta = \dfrac{5h-1}{4hR_0}$ $\varepsilon_R(t) = \rho_R \varepsilon_R(t-1) + \sqrt{1-\rho_R^2}\varphi_R(t)$ $\varphi_R(t) \sim N(0,\sigma_R^2)$	Stock-recruit relationship
3	$S(t) = \sum_a m(a)w(a)N(a,t)$	Spawning biomass
4	$Z(a,t) = M(t) + s(a,t)F(t)$ $M(t) = \bar{M}e^{\varepsilon_M(t) - 0.5\sigma_M^2}$ $\varepsilon_M(t) = \rho_M \varepsilon_M(t-1) + \sqrt{1-\rho_M^2}\varphi_M(t)$ $\varphi_M(t) \sim N(0,\sigma_M^2)$	Total mortality with time-varying natural mortality
	Life history	
5	$L(a) = L_\infty\left(1 - e^{-k(a-a_0}\right)$	Length at age
6	$w(a) = bL(a)^c$	Weight at length
7	$m(a) = \dfrac{1}{1 + e^{-\frac{a-m_{50}}{m_{slope}}}}$	Maturity at age
	Fishing dynamics	

8

$$s(a,t) = \frac{1}{1+e^{-\frac{a-s_{50}(t)}{s_{slope}}}}$$

$$s_{50\%}(t) = \bar{s}_{50\%}e^{\varepsilon_s(t)-0.5\sigma_s^2}$$
$$\varepsilon_s(t) = \rho_s\varepsilon_s(t-1)1) + \sqrt{1-\rho^2}\varphi(t))$$
$$\varphi(t) \sim N(0,\sigma_s^2)$$

Selectivity at age in fishery or survey, with time varying selectivity (only in the fishery)

9

$$C(a,t) = \frac{s(a,t)F(t)}{Z(a,t)}w(a)N(a,t)\left(1-e^{-Z(a,t)}\right)$$

$$C(t) = \sum_a C(a,t)$$

Total catch

Data-generating dynamics

10

$$C_{obs}(t) = C(t)^{\varepsilon_C(t)-0.5\sigma_C^2}$$

$$\varepsilon_C(t) \sim N(0,\sigma_C^2)$$

Observed catch

11

$$I(a,t) = q(t)s_s(a)N(a,t)$$

$$I(t) = \sum_a I(a,t)$$

$$q(t) = qe^{\varepsilon_q(t)-0.5\sigma_q^2}$$
$$\varepsilon(t) \sim N(0,\sigma_q^2)$$

True index of abundance

12

$$I_{obs}(t) = I(t)^{\varepsilon_I(t)-0.5\sigma_I^2}$$

$$\varepsilon_I(t) \sim N(0,\sigma_I^2)$$

Observed index of abundance

13

$$\mathbf{p}_{obs}(t) = \frac{1}{n}\mathbf{\Theta}(t)$$

$$\mathbf{\Theta}(t) \sim Multinomial(n,\mathbf{p}(t))$$

Observed vector of proportion-at-age in fishery *f*

$$\mathbf{p}(t) = \frac{1}{I(t)}\left(I(a_R, t), \dots, I(a_{max}, t)\right)$$

Table 2. Description of the index and state variables used in equations in the model (presented in Table 1). Parameter descriptions and values used are presented in Table 3.

Symbol	Description
Index variables	
t	Year
a	Age
State variables	
N	Numerical abundance
S	Spawning biomass (kg)
L	Length (cm)
W	Weight (kg)
m	Maturity (proportion)
s_s	Survey selectivity (proportion)
s_f	Fishery selectivity (proportion)
F	Fishing mortality rate (year-1)
Z	Total mortality rate (year-1)
C	Total fishery catch (kg)
C_{obs}	Observed fishery ctach (kg)
p_C	Proportions at age in catch
$p_{C,obs}$	Observed proportion at age in catch
I	Survey numerical index of abundance
I_{obs}	Observed survey numerical index of abundance
p_I	Proportions at age in survey
$p_{I,obs}$	Observed proportion at age in survey

Table 3. Parameters values used in the model. Life history – invariant parameters are presented at the top, with multiple values explored for the "good" and "bad" assessment cases.

Parameter	Description	Value		
σ_R	standard deviation of stock-recruit relationship	0.77, 1.25		
ϕ_R	autocorrelation in recruitment	0, 0.44		
σ_M	standard deviation of time-varying M	0.15		
ϕ_M	autocorrelation in M	0.3, 0.9		
σ_s	standard deviation of age at 50% selectivity	0.1		
ϕ_s	autocorrelation in selectivity	0.3, 0.9		
σ_C	standard deviation of catch estimates	0.15		
σ_I	standard deviation of survey estimates	0.29, 0.63		
n_C	effective sample size of the catch	200, 500		
n_I	effective sample size of the survey	200,500		
q	survey catchability	0.00005		
σ_q	standard deviation of survey catchability	0.01, 0.05		
		Slow	Medium	Fast
a_R	Age at recruitment (to population)	5	3	1
a_{max}	Maximum age	20	12	7
M	Mean natural mortality rate	0.1	0.2	0.4
R_0	Virgin recruitment	$1\text{x}10^6$	$1\text{x}10^6$	$1\text{x}10^6$
h	Steepness	0.6	0.75	0.9
a_0	Age at length=0	0	0	0
L_∞	Maximum length	90	90	90
k	Growth rate	0.07	0.13	0.27
b_1	L-W scalar	3.0×10^{-6}	3.0×10^{-6}	3.0×10^{-6}
b_2	L-W exponent	3	3	3
m_{50}	Age at 50% maturity	7	3.5	1.75
s_{50}	mean age at 50% selectivity in fishery	7	3.5	1.75
s_{50}	mean age at 50% selectivity in fishery	5.3	2.6	1.3
m_{slope}	Slope of maturity function	1	1	1
s_{slope}	Slope of selectivity function	1	1	1
S_0	Unfished spawning biomass	9,073,360	4,486,140	2,270,360
SPR target	Target spawning potential ratio	0.35	0.35	0.35
F_{SPR}	F at the target SPR	0.101	0.192	0.394
SPR at MSY	SPR corresponding to F_{MSY}	0.46	0.39	0.344
F_{MSY}	FMSY	0.068	0.167	0.4
S_{MSY}	Spawning biomass that produces MSY	3,324,186	1,502,760	738,941
MSY	Maximum sustainable yield	203,196	211,429	210,533
F_{max}	F that maximizes yield per recruit	0.146	0.252	0.46

Table 4. Acceptable biological catch (ABC) control rules explored in this analysis. P* refers to a target probability of overfishing. The overfishing limit (OFL) is the catch achieved by fishing at the limit fishing mortality reference point (F_{lim}) given the projected abundance at age in the assessment model. Many of the control rules differed in the coefficient of variation (CV) assumed for a lognormal distribution about the OFL. The control rules that varied P* did so using a biomass-based rule (Figure 1).

Control rule name code	Target F	Target P*	Assumed CV of OFL distribtuion	Buffer (ABC < OFL)?
OFL	F_{lim}	-	-	no
75% of F_{lim}	$0.75F_{lim}$	-	-	yes
P* var (0.38)	-	varies	0.38	yes
P* var (0.70)	-	varies	0.7	yes
P* var (1.0)	-	varies	1	yes
P* fix (0.38)	-	0.4	0.38	yes
P* fix (0.70)	-	0.4	0.7	yes
P* fix (1.0)	-	0.4	1	yes

Table 5. List of model runs explored in the model across life histories (F,M,S) and exploitation level in the analysis.

Model run	Life histories	Effective sample size (E)	Survey error (σ_I)	ϕ_M	ϕ_f	Recruitment variability (σ_R)	ϕ_R	SPR target	h	SA interval	ABC calc.
1	F,M,S	200	0.29	0.3	0.3	0.77	0.44	0.35	fixed	2	fixed
2	F,M,S	50	0.63	0.9	0.9	0.77	0.44	0.35	fixed	2	fixed
3	F,M,S	200	0.29	0.3	0.3	1.25	0.44	0.35	fixed	2	fixed
4	F,M,S	50	0.63	0.9	0.9	1.25	0.44	0.35	fixed	2	fixed
5	F,M,S	200	0.29	0.3	0.3	0.77	0	0.35	fixed	2	fixed
6	F,M,S	50	0.63	0.9	0.9	0.77	0	0.35	fixed	2	fixed
7	F,M,S	200	0.29	0.3	0.3	1.25	0	0.35	fixed	2	fixed
8	F,M,S	50	0.63	0.9	0.9	1.25	0	0.35	fixed	2	fixed
9	F,M,S	200	0.29	0.3	0.3	0.77	0.44	0.35	declining	2	fixed
10	F,M,S	50	0.63	0.9	0.9	0.77	0.44	0.35	declining	2	fixed
11	F,M,S	200	0.29	0.3	0.3	1.25	0.44	0.35	declining	2	fixed
12	F,M,S	50	0.63	0.9	0.9	1.25	0.44	0.35	declining	2	fixed
13	F,M,S	200	0.29	0.3	0.3	0.77	0	0.35	declining	2	fixed
14	F,M,S	50	0.63	0.9	0.9	0.77	0	0.35	declining	2	fixed
15	F,M,S	200	0.29	0.3	0.3	1.25	0	0.35	declining	2	fixed
16	F,M,S	50	0.63	0.9	0.9	1.25	0	0.35	declining	2	fixed
17	S	200	0.29	0.3	0.3	0.77	0.44	0.46	fixed	2	fixed
18	S	50	0.63	0.9	0.9	0.77	0.44	0.46	fixed	2	fixed
19	S	200	0.29	0.3	0.3	1.25	0.44	0.46	fixed	2	fixed
20	S	50	0.63	0.9	0.9	1.25	0.44	0.46	fixed	2	fixed
21	M	200	0.29	0.3	0.3	0.77	0.44	0.35	fixed	2	proj.
22	M	50	0.63	0.9	0.9	0.77	0.44	0.35	fixed	2	proj.
23	M	200	0.29	0.3	0.3	1.25	0.44	0.35	fixed	2	proj.
24	M	50	0.63	0.9	0.9	1.25	0.44	0.35	fixed	2	proj.
25	M	200	0.29	0.3	0.3	0.77	0.44	0.35	fixed	5	proj.
26	M	50	0.63	0.9	0.9	0.77	0.44	0.35	fixed	5	proj.
27	M	200	0.29	0.3	0.3	1.25	0.44	0.35	fixed	5	proj.
28	M	50	0.63	0.9	0.9	1.25	0.44	0.35	fixed	5	proj.
29	M	200	0.29	0.3	0.3	0.77	0.44	0.35	fixed	2	avg.
30	M	50	0.63	0.9	0.9	0.77	0.44	0.35	fixed	2	avg.
31	M	200	0.29	0.3	0.3	1.25	0.44	0.35	fixed	2	avg.
32	M	50	0.63	0.9	0.9	1.25	0.44	0.35	fixed	2	avg.
33	M	200	0.29	0.3	0.3	0.77	0.44	0.35	fixed	5	avg.
34	M	50	0.63	0.9	0.9	0.77	0.44	0.35	fixed	5	avg.
35	M	200	0.29	0.3	0.3	1.25	0.44	0.35	fixed	5	avg.
36	M	50	0.63	0.9	0.9	1.25	0.44	0.35	fixed	5	avg.
37	M	200	0.29	0.3	0.3	0.77	0.44	0.35	declining	2	proj.
38	M	50	0.63	0.9	0.9	0.77	0.44	0.35	declining	2	proj.
39	M	200	0.29	0.3	0.3	1.25	0.44	0.35	declining	2	proj.
40	M	50	0.63	0.9	0.9	1.25	0.44	0.35	declining	2	proj.
41	M	200	0.29	0.3	0.3	0.77	0.44	0.35	declining	5	proj.
42	M	50	0.63	0.9	0.9	0.77	0.44	0.35	declining	5	proj.
43	M	200	0.29	0.3	0.3	1.25	0.44	0.35	declining	5	proj.
44	M	50	0.63	0.9	0.9	1.25	0.44	0.35	declining	5	proj.
45	M	200	0.29	0.3	0.3	0.77	0.44	0.35	declining	2	avg.
46	M	50	0.63	0.9	0.9	0.77	0.44	0.35	declining	2	avg.
47	M	200	0.29	0.3	0.3	1.25	0.44	0.35	declining	2	avg.
48	M	50	0.63	0.9	0.9	1.25	0.44	0.35	declining	2	avg.
49	M	200	0.29	0.3	0.3	0.77	0.44	0.35	declining	5	avg.
50	M	50	0.63	0.9	0.9	0.77	0.44	0.35	declining	5	avg.
51	M	200	0.29	0.3	0.3	1.25	0.44	0.35	declining	5	avg.
52	M	50	0.63	0.9	0.9	1.25	0.44	0.35	declining	5	avg.

Table 6. Performance measures calculated for different time periods at the end of each model run. The AAV of the catch is calculated following Punt (2003) as $AAV = \sum_{t>1} |C(t) - C(t-1)| / \sum_t C(t)$

Performance Measure	Time Period(s)
Mean spawning biomass	all years / final 5 years
Relative change in biomass	first 5 years / first 15 years
Probability of being overfished	all years
Mean Catch	all years / final 5 years
Relative interannual variation (AAV) in catch	all years / final 5 years
Mean fishing mortality rate	all years
Overfishing probability (true)	all years
Overfishing probability (estimated)	all years
Probability of exceeding F_{MAX}	all years

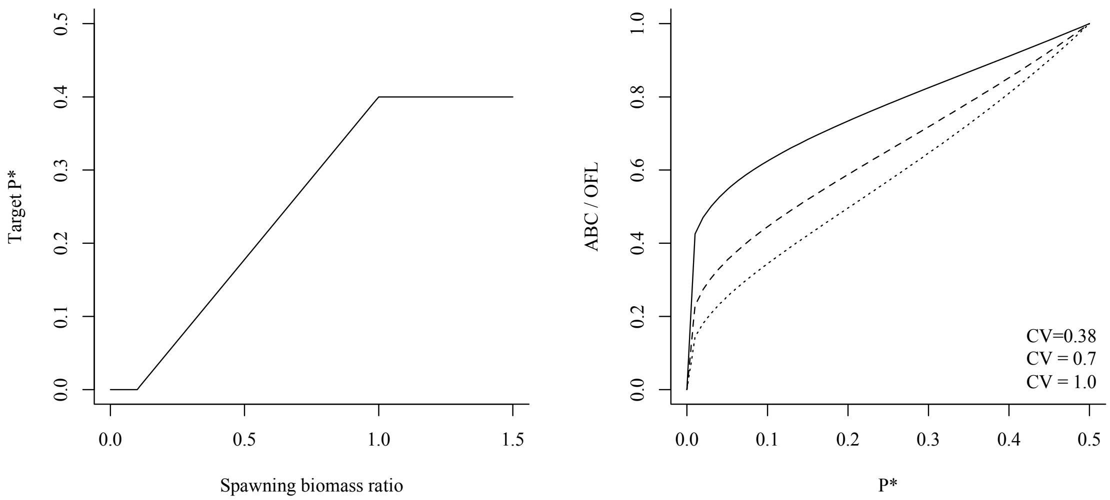
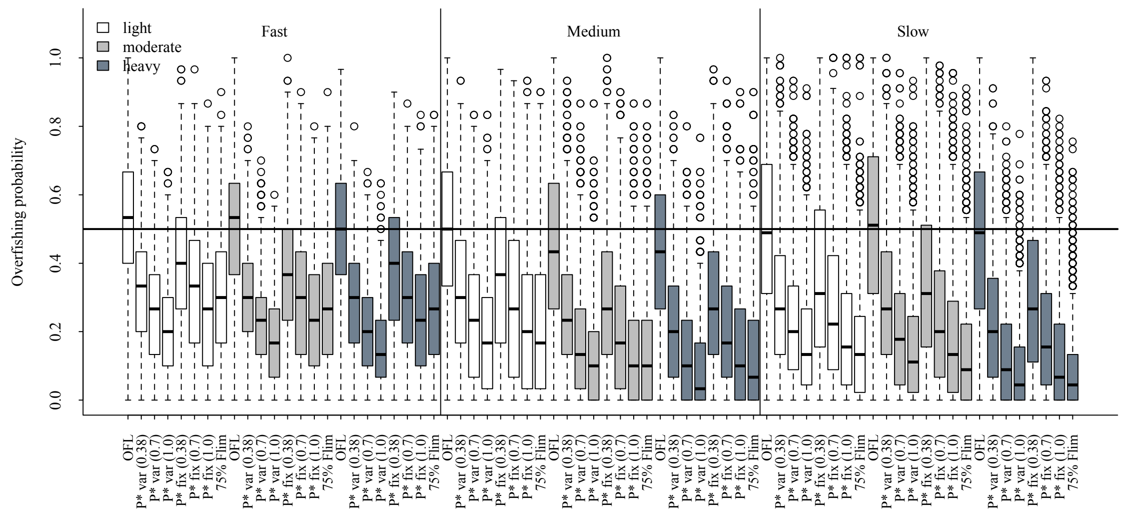


Figure 1. Left : Threshold-based P* control rule, where the target P* declines linearly as the estimated spawning biomass falls below the S_{MSY} level. Right: Buffer size (ABC / OFL) as a function of the target P* and the assumed CV of the distribution for the OFL.



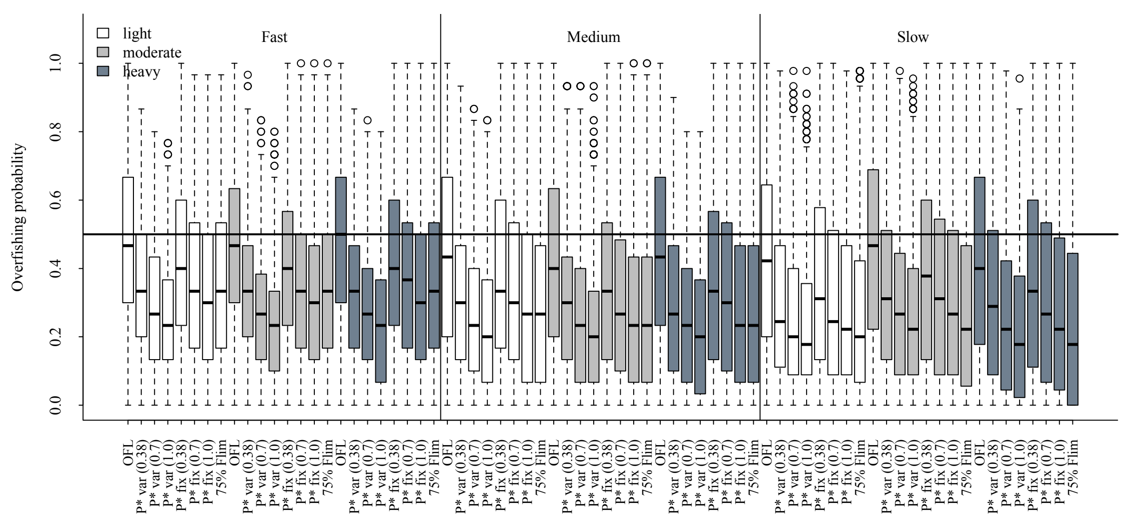


Figure 2. Probability of overfishing across control rules for the base model runs with low (top) and high (bottom) stock assessment uncertainty. The colors represent the different exploitation histories and are separated by life history (fast, medium, and slow).

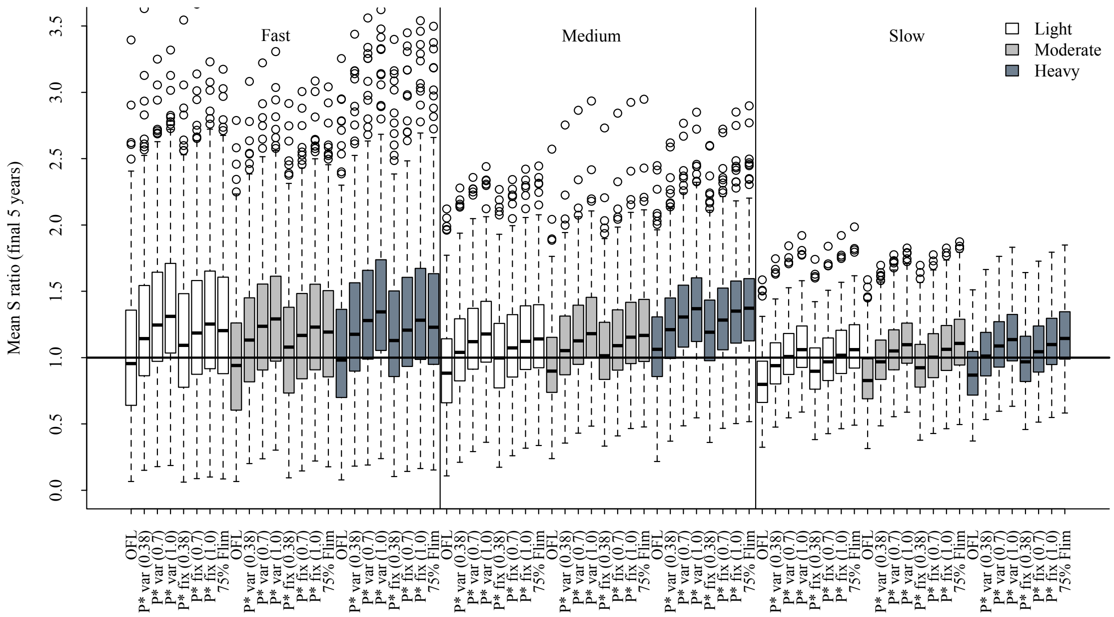


Figure 3. Mean spawning biomass ratio (S / S_{MSY}) in the final 5 years for the base model run with low assessment uncertainty. The colors represent the different exploitation histories and are separated by life history (fast, medium, and slow).

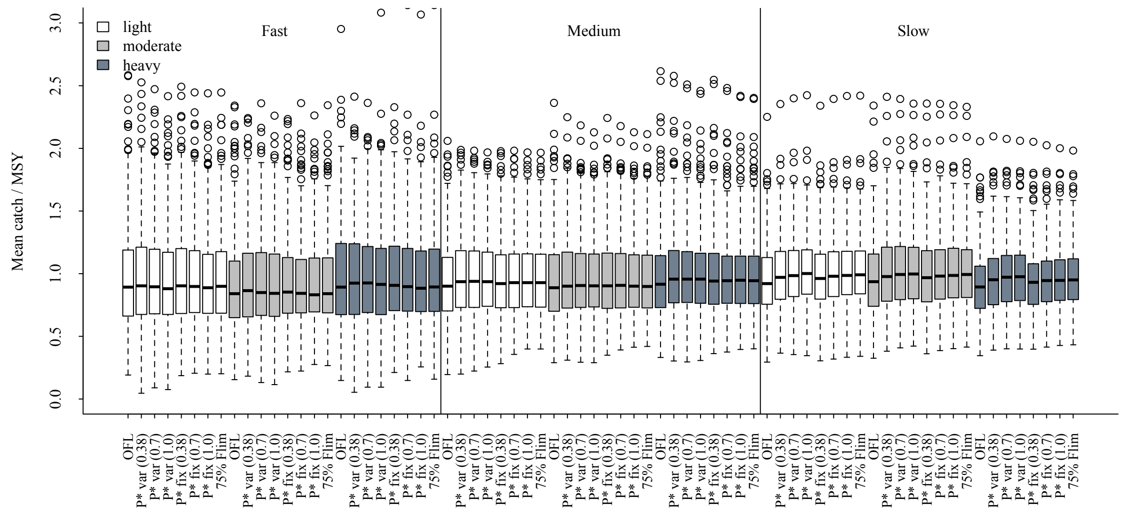


Figure 4. Average yield (relative to deterministic maximum sustainable yield) in the final five years for each control rule for runs for the high data quality scenarios with low recruitment variability with no autocorrelation.

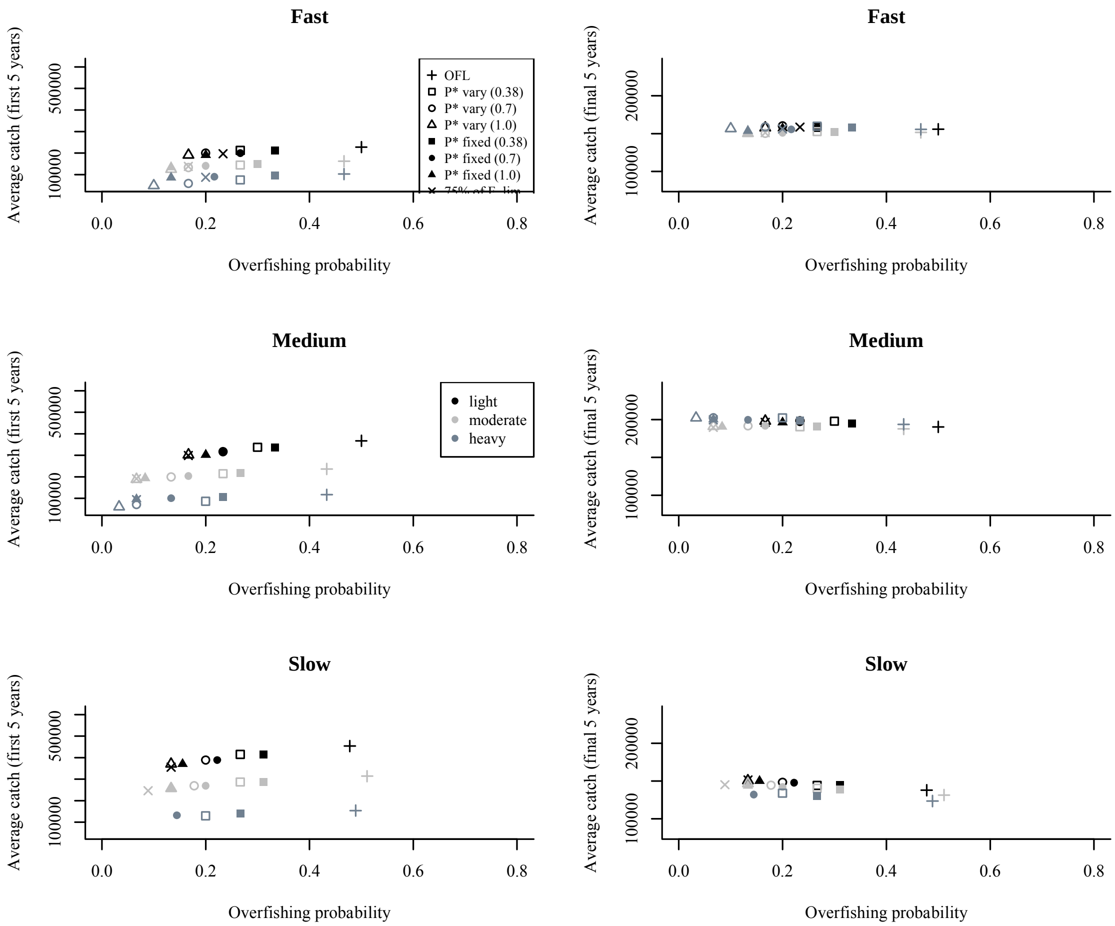


Figure 5. Tradeoffs between the probability of overfishing and short- (left) and long-term yield for the base model run with low assessment uncertainty. The symbols represent the control rules, and the colors represent the exploitation history. Note the different scales for the y-axis.

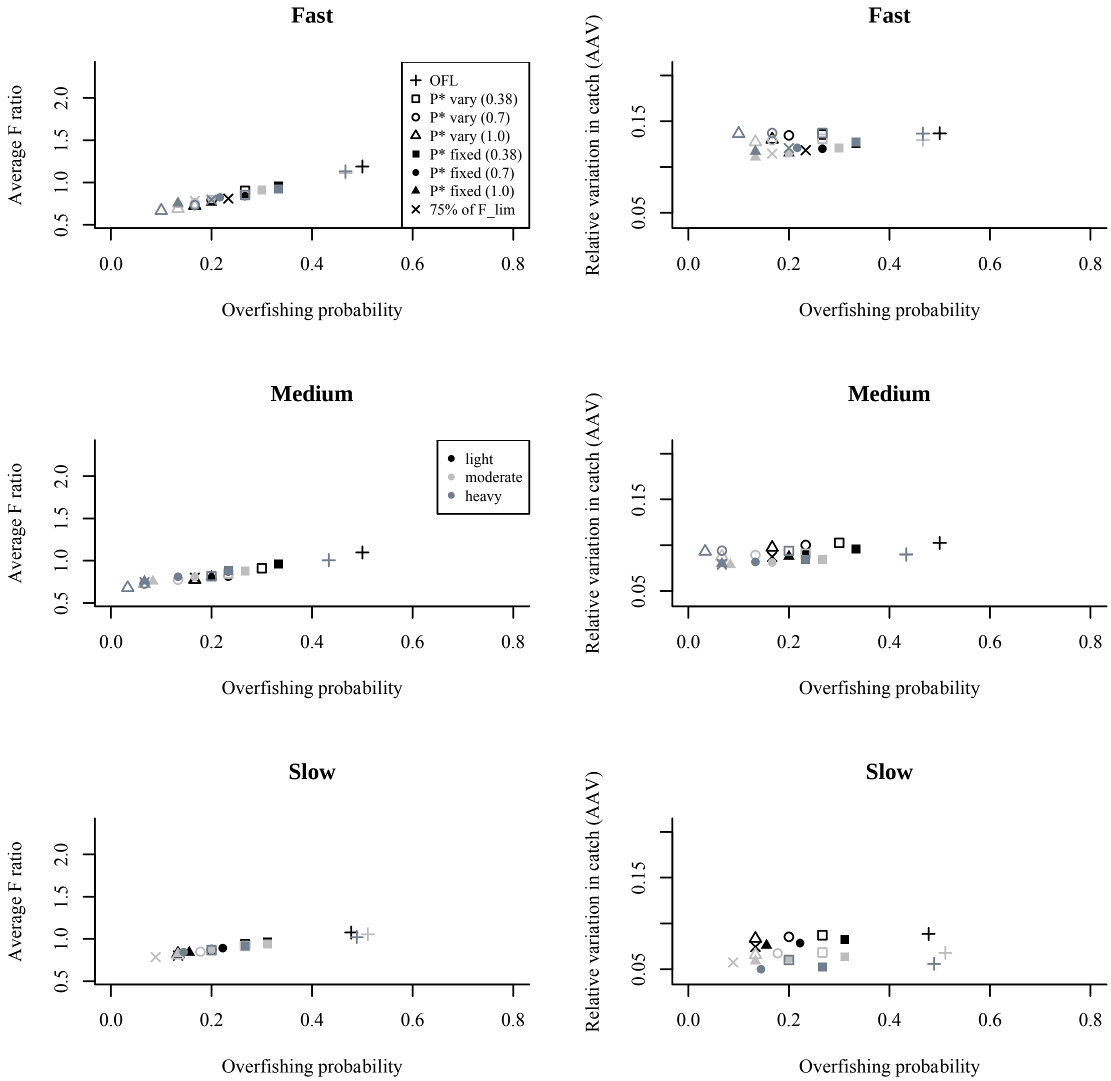


Figure 6. Relationship between the probability of overfishing and the mean F / F_{lim} (left) and the interannual variability in the catch (right) for the base model run with low assessment uncertainty. The symbols represent the control rules, and the colors represent the exploitation history.

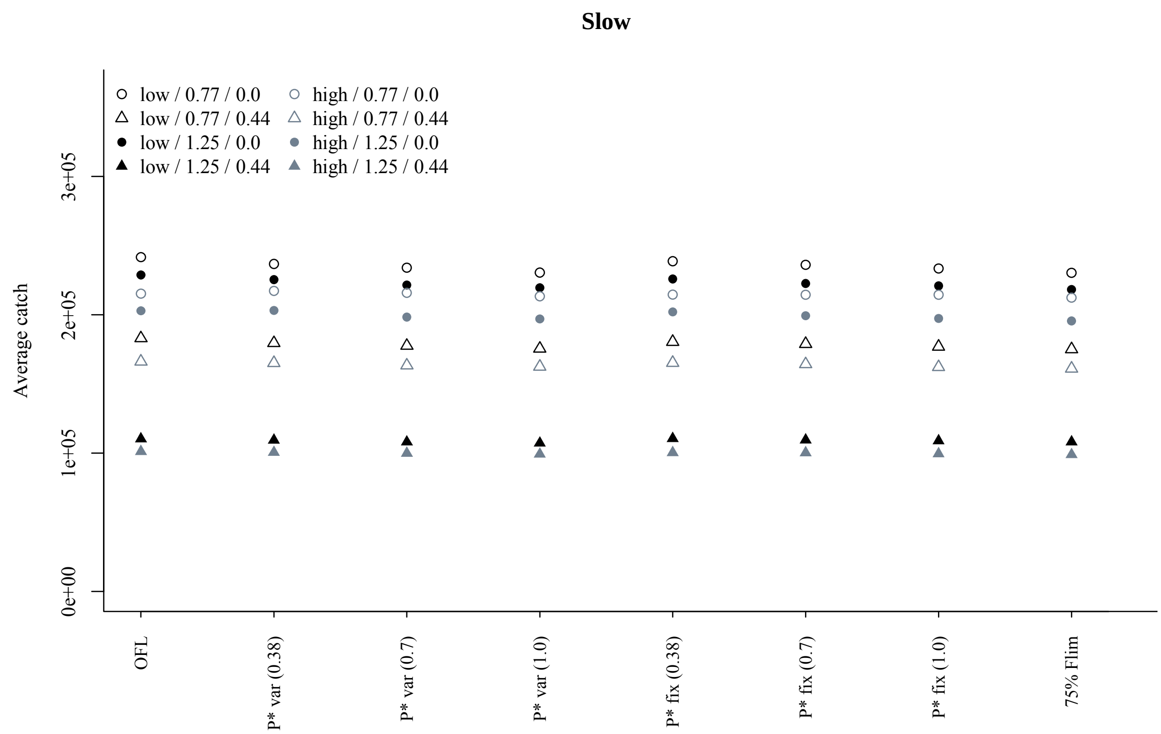


Figure 7. Average catch for the final 5 years across control rules for the slow life history across model runs of different assessment uncertainties (low / high), levels of recruitment variability (σ_R = 0.77 / 1.25), and recruitment autocorrelation (ϕ_R = 0, 0.44)

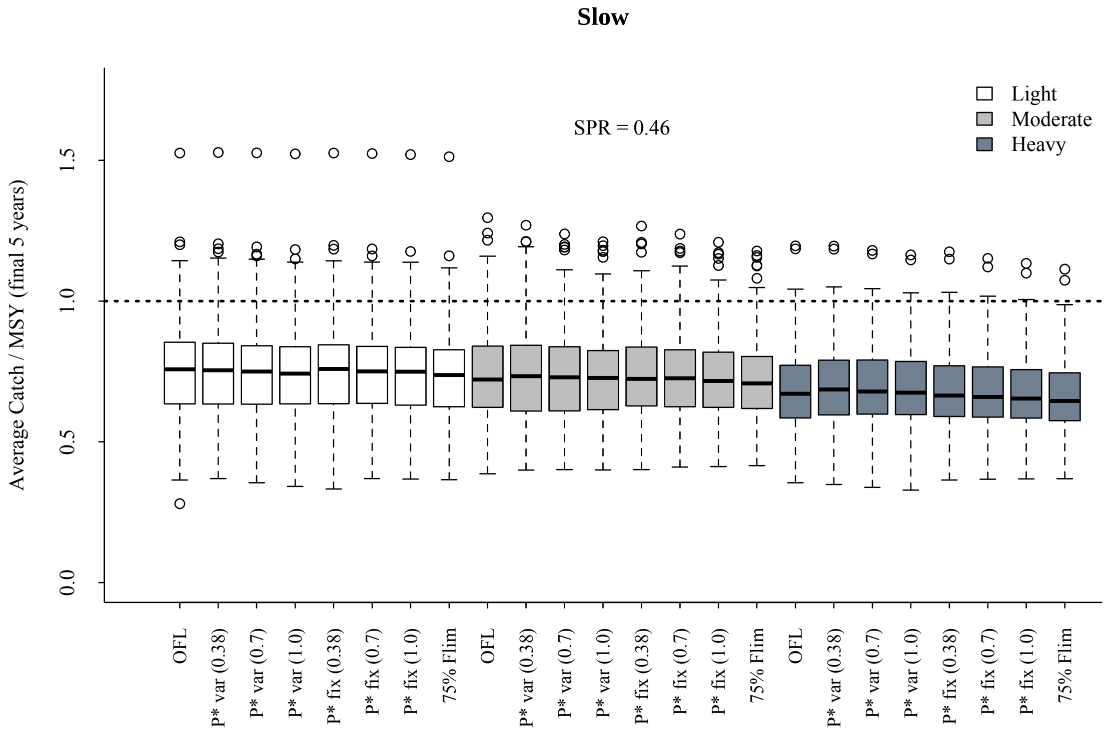
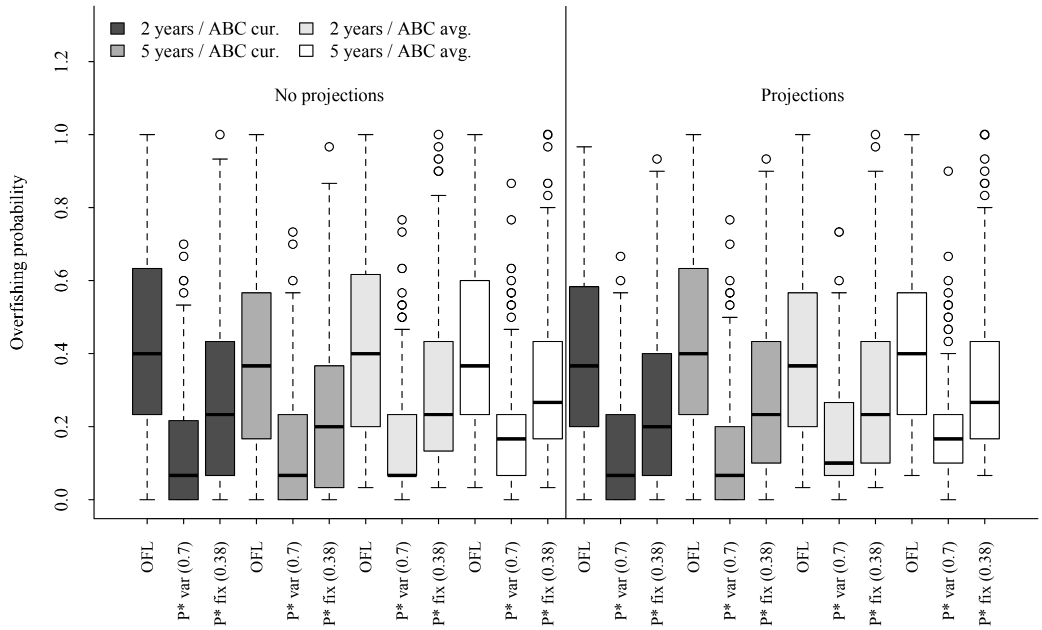


Figure 8. . Average yield (relative to deterministic maximum sustainable yield) in the final five years for each control rule for runs for the high data quality scenario with low recruitment variability and no autocorrelation in recruitment.



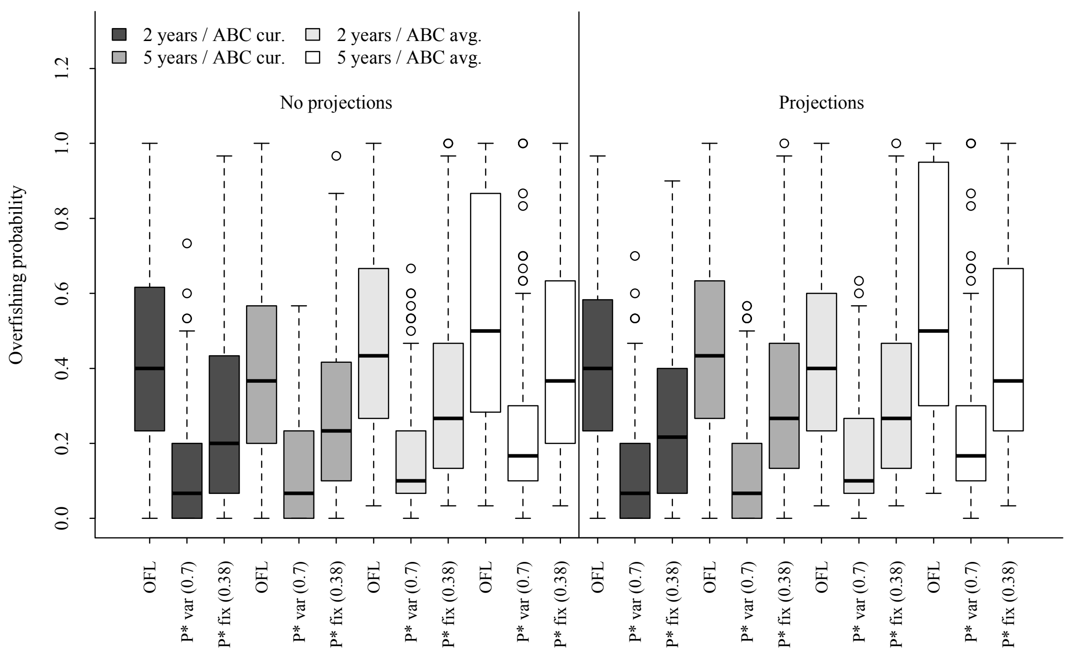


Figure 9. Probability of overfishing for 3 control rules used the set the ABC using projections, different intervals between assessments, and weighted averaging of the ABC. Results are shown for the heavy exploitation scenario for the medium life history, with low (top) and high recruitment variability (bottom).

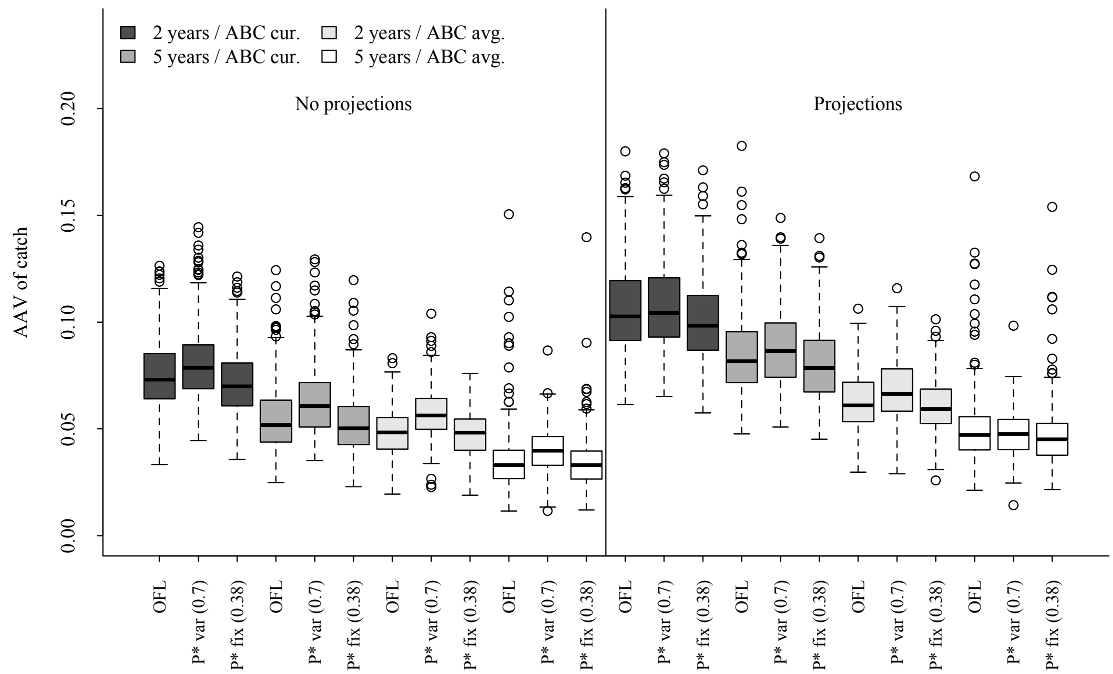


Figure 10. AAV of the catch for 3 control rules used the set the ABC using projections, different intervals between assessments, and weighted averaging of the ABC. Results are shown for the heavy exploitation scenario for the medium life history, with low recruitment variability.

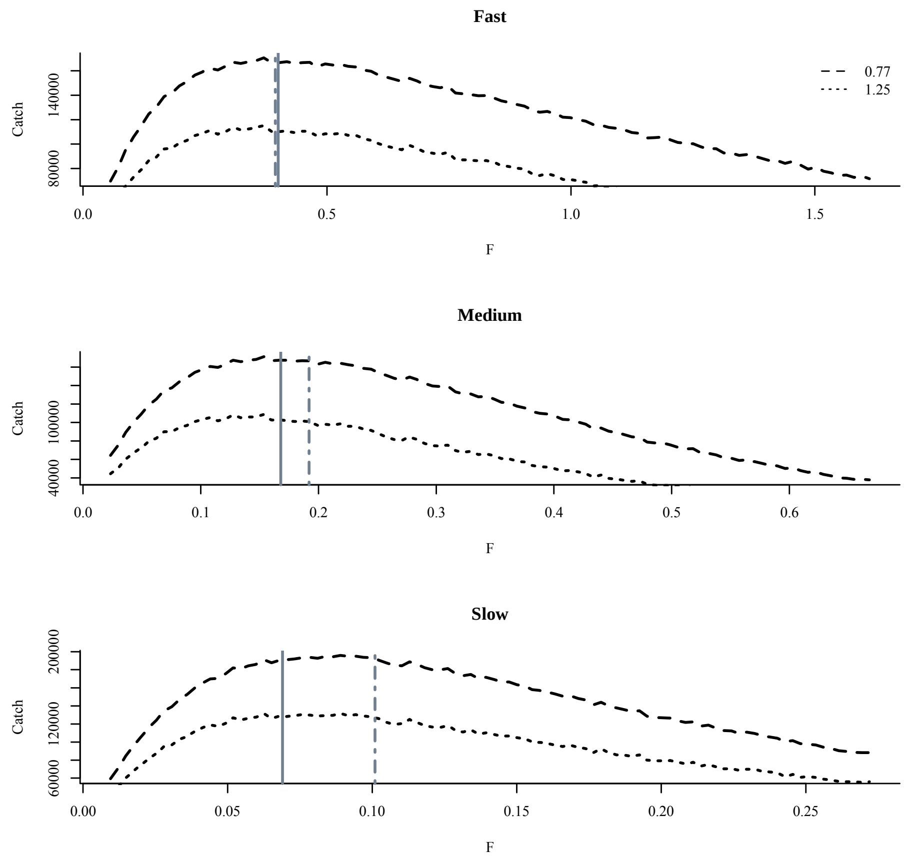


Figure 11 . Stochastic yield curves across life histories for two levels of recruitment variability (σ_R = 0.77 and 1.25). The solid and dashed vertical gray lines represent the deterministic estimates of F_{MSY} and $F_{35\%}$, respectively.

Chapter 2. Effects of assessment interval and data-management lag on Mid-Atlantic harvest control rule performance

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Abstract

The use of stock assessments to inform management and decision making has increased worldwide. Two of the challenges of using stock assessments in management decisions are data availability and the allocation of resources to conduct stock assessments in a frequent and timely manner. While data-management lag and assessment timelines can strongly affect model predictions, few studies have looked into their effects. We conducted a simulation evaluation that included the population dynamics, stock assessment, and management to determine effects of assessment interval and data-management lag on the probability of overfishing, average catch, average biomass, and the variation in catch. Assessment intervals ranged from annual assessments to assessments every ten years, and data-management lag (time between the last year of data in the assessment and when new regulations are implemented) ranged between one and three years. Further, we tested the management options under two life histories (fast and slow) and two data scenarios (good and poor) to identify interactions between these parameters and control rule performance. Increasing assessment interval and data-management lag caused a decrease in average catch and biomass across scenarios, with data-management lag having a larger effect compared to assessment interval. The probability of overfishing was generally higher when assessment intervals were longer and the variability in catch decreased with decreasing assessment intervals. Across all performance metrics the effects of poorer data resulted in magnified effects of assessment interval and data-management lag. Our results provide guidance to management by identifying the tradeoffs for management between frequency of assessment and data-management lags.

Introduction

The use of stock assessments to inform management and decision making has increased worldwide. Two of the challenges of using stock assessments in management decisions are data availability and the allocation of resources to conduct stock assessments in a frequent and timely manner. The use of the most recent data should be critical to stock assessment model performance because estimates from the most recent years are often used to provide management advice. However, the timeline between the most recent data included in the stock assessments and management decision (herein called data-management lag (DML)) can extend four years or longer in some places. While DML and assessment timelines can strongly affect accuracy of model predictions, few studies have looked into its effects (Shertzer and Prager 2007; Brown et al. 2012; Li et al. in review).

Assessment intervals vary widely among management bodies, and the intervals between stock assessments can have an important effect on management outcomes (Mace et al. 2001, ICES 2012; Li et al., in review). For example, the Northeast Atlantic uses annual assessments for the majority of their stocks (NRC 1998), most west coast U.S. assessment intervals range from annual to every three years, and the majority of east coast U.S. fisheries assessments are on an order of every three to five years. However, some stocks have assessments intervals of ten years or greater, such as Illex squid (*Illex argentinus*).

Frequent assessment is important in determining whether or not a stock is overfished because identifying early trends in biomass can avoid overfishing in the future (Mace 2001). Less productive stocks can be sensitive to assessment frequency, with potentially large decreases in SSB with long periods between assessments (Li et al., in review). Furthermore, if stock size is declining, moving from annual to multiannual assessments could lead to an increase in the risk of spawning stock biomass (SSB) falling below the threshold value and catch limits being held at too high of a level (ICES 2012). Additional factors affecting results of extended assessment intervals were dependent on the approach used to set target harvest, i.e. more successful candidates for longer assessment intervals being those regulated by more conservative control rules (Li et al., in review).

DML is caused by a variety of interacting factors, but can have detrimental consequences on management success the longer management is delayed (Shertzer and Prager 2007). The management process can result in a delay of up to three years between data collection and implementation of regulations in most U.S. regions. Shertzer and Prager (2007), discussed the delays of haddock (*Melanogrammus aeglefinus*), cod (*Gadus morhua*), and yellowtail founder (*Pleuronectes Ferrugineus*), whose fishery management plans were approved only after populations dropped to their lowest recorded levels. Delays can extend five to seven years in some species such as Orange roughy (*Hoplostethus atlanticus*) in South-East Australia (Bax et al. 2003) and up to 12 years in some whale species (Punt and Donovan 2007). The DML begins after data is collected for a particular stock or set of stocks. After collection, the data must be processed, which includes entering the data, verifying accuracy, aging samples, and any preliminary analyses needed to get information into the appropriate form for the stock assessment. The stock assessment itself can be completed in weeks to months if it is an update of a previously used model, or substantially longer if a new assessment methodology is being developed. If the stock assessment undergoes peer review before it is used in management, it often adds two to three months to the process. Lastly, developing and implementing management actions can take up to a year or more depending on the region and species. Management processes can extend even longer if management is then delayed due to issues such as scientific uncertainty or to reduce short-term losses in profit for fishers (Brown et al. 2012).

While DML is present in any management system, its effect has received relatively little scrutiny. A delay of one year causes slight increases in SSB and yield and a small negative bias in estimated SSB when comparing a scenario with no lag to an annual lag (Li et al., in review). Delays in management decisions when a fish stock is declining can require more conservative management, thus larger catch reductions to rebuild a stock (Shertzer and Prager 2007). Brown et al. (2012), considered the consequences of delayed management in response to ecosystem and climate change. They similarly found that delays reduced harvest and caused lower and more variable harvest. However, unlike Shertzer and Prager (2007), they found that even with precautionary approaches in management, failing to act on the most recent management advice resulted in significant increases in the risk of collapse.

In the U.S., recent modifications of legislation to guide fisheries management (Restrepo et al. 1998; NMFS 2006) has caused fisheries managers and scientists to consider how often assessments are conducted and how to design procedures that can quickly feed data into the management system. In the Mid-Atlantic region of the U.S., assessment intervals can range from annual to decadal, and DML can extend up to three years. Assessment interval timelines depend strongly on the fishery and ecosystem importance, stock status, and stock biology (NOAA 2014), while the DML is a result of the data collection and management processes. Similar to other regions of the U.S., after data collection the Mid-Atlantic has a lengthy Council process for setting regulations. The Mid-Atlantic Fishery Management Council (MAFMC) procedure begins with review and recommendation of an acceptable biological catch (ABC) limit by the MAFMC's scientific statistical committee (SSC). The ABC recommendation is then given to a committee who drafts recommendations for annual catch limits and regulations to achieve those catch limits; recommendations are then provided to the MAFMC. The MAFMC develops recommendations for regulations that go through a drafting process to identify and outline any changes. An environmental impact statement is completed which identifies environmental effects of the proposed action and submits alternative actions. Scoping meetings, which are public hearings organized to gather input on the range of issues to be considered are also conducted. A public hearing period is conducted, which is followed by a final MAFMC recommendation. The recommendations are then sent to NOAA's National Marine Fishery Service where similar steps are followed prior to implementation by the U.S. Secretary of Commerce.

Our objective was to use a management strategy evaluation (MSE) to test the effects of stock assessment interval and DML on Mid-Atlantic harvest control rule performance. The MSE used a simulation approach, which included the population dynamics and management processes. The management models varied by length of assessment intervals, ranging from annual to decadal, and DMLs, ranging from a one to three year lag. We examined a range of performance measures to represent objectives of fishery management including average catch, average biomass, and probability of overfishing. Additionally, we evaluated how life-history, data quality and stock-recruitment dynamics interacted with DML and assessment interval to affect management performance.

Methods

We conducted an MSE to estimate the effects of DML and assessment interval on Mid-Atlantic harvest control rule performance over a range of data quality, recruitment, and life history scenarios. The MSE included operating and stock assessment models (Figure 1). The operating model represented the true dynamics of the stock using an age-structured population model and implemented the management portion of the simulation by removing the ABC from the stock. The stock assessment model was called at regular intervals to estimate stock biomass and reference points for management using a statistical catch-at-age model. Target catch was then calculated using the MAFMC's harvest control rule, which includes a projection to the year the catch limit will be implemented and uses a probabilistic approach (Shertzer et al. 2010; MAFMC 2011). Alternative management models were described by combinations of stock assessment interval (assessments every one, two, three, five, seven and ten years) and DML (of one, two and three years). Each management combination was tested under a range of scenarios of good and poor data quality, fast and slow life history, and high and low variable recruitment variability in order to represent a broad range of potential fisheries. The model was run for a total of 80 years; in the first 30 years the fishery developed with unregulated fishing of varying intensities. During the remaining 50 years the management strategy was in effect. At the end of each simulation, performance of the control rule was summarized over the 50-year management period. All models were developed in ADMB (Fournier et al. 2012). Variable definitions and equations are provided in Tables 1 and 2.

Operating Model

The operating model simulated the population dynamics with an age-structured model. The model included 12 age classes for the fast life history, and 20 age classes for the slow life history, where 12+, and 20+ were aggregate age classes of fish ages 12 or 20 and older. Abundance at age in the first year was assumed to be in its unfished equilibrium state. We used a Beverton-Holt stock-recruitment relationship with a lognormally distributed random error to determine recruitment each year (Eq. T1.1). We implemented autocorrelated random errors in the stock-recruitment relationship with a correlation of 0.44 and a standard deviation of 0.77, which were the averages from a meta- analysis by Thorson et al. (2014), as well as a standard deviation of 1.25, which represented a higher level of variability. Abundance at age was calculated using an exponential mortality model with additive natural and fishing mortality (Eq. T1.2). The weight at age was calculated using length at age from a von Bertalanffy growth model (Eq. T1.4) and an allometric function of length at age (Eq. T1.3). Maturity at age followed a logistic function (Eq. T1.5). The spawning stock biomass (SSB) was the product of maturity-at-age, weight-at-age and abundance-at-age summed over ages for a given year (Eq. T1. 6).

The operating model included a single fishery, and selectivity followed a logistic function. Fishery selectivity and natural mortality were allowed to vary over time so that the assessment models would not follow exactly the same dynamics as the operating model. Fishery selectivity varied over time by applying an autocorrelated, lognormally distributed error with a standard deviation of 0.1 and autocorrelation of 0.3 or 0.9 to the sf50% parameter (Eq. T1.7 and T1.8).

Natural mortality also followed an autocorrelated lognormal random process over time with a log-scale standard deviation of 0.15 and an autocorrelation of 0.3 or 0.9 (Eq. T1.9). Fishing mortality was set to 0.05 yr^{-1} in the first year, after which it increased linearly until it plateaued in year 18 and remained constant until the management period began in year 30. The value of fishing mortality at the plateau depended on the exploitation history. Exploitation scenarios were light, moderate and heavy and used a fishing mortality multiplier (F = 0.5, 1.0, 2.5 x F_{MSY}, respectively) in the plateau year. Total mortality was the sum of the natural mortality and fishing mortality; fishing mortality at age was the product of the selectivity at age of the fishery and the overall fishing mortality rate for a year. Fishery catch-at-age was calculated using the Baranov catch equation (Eq. T1.10). The observed fishery catch was calculated by multiplying total fishery catch by a multiplicative lognormal error with a log-scale standard deviation set at 0.15 (Eq. T1.11).

The operating model also generated catch-at-age in a survey as the product of abundance, survey selectivity and survey catchability (Eq. T1. 12). Survey catchability varied according to a random walk on the log scale with normally distributed errors (with a standard deviation of 0.01 or 0.05 depending on the data quality scenario) to allow gradual variation in the catchability over time (Eq. T1.13). The observed index of abundance included observation error with a log-scale standard deviation of 0.3 or 0.7 depending on the data quality scenario (Eq. T1.14). The observed proportions at age in the fishery and survey were generated by sampling from a multinomial distribution using the true proportions at age (Eq. T1.15) and effective samples sizes of 50 or 200 depending on the data quality scenario. The data sets were provided to a statistical catch at age stock assessment model that estimated, among other things, the overfishing limit (OFL) and relative biomass, which were provided to the operating model in order to apply the management control rule. The OFL is the catch that should be achieved by fishing at the limit fishing mortality rate and was calculated by applying the estimated $F_{35\%}$ from the assessment to the projected estimate of abundance. An $F_{35\%}$ mortality rate was chosen to serve as a proxy for F_{MSY} because it is commonly used as a limit fishing mortality reference point for Mid-Atlantic stocks.

After each assessment the operating model implemented the Mid-Atlantic P* control rule to find an ABC from the OFL estimated in the assessment (MAFMC 2011). The P* approach adopted by MAFMC assumes that the OFL is lognormally distributed with a CV of 100% and a median from a stock assessment projection to the time the new catch limit would be implemented. The ABC was estimated as the catch that achieves the 40th percentile of the OFL distribution if estimated B/ $B_{35\%}$ (derived from the SPR model in the assessment) exceeded 1.0. If the estimated $B/B_{35\%}$ fell below 1.0 then the P* used to calculate ABC decreased linearly to zero until $B/B_{35\%}$ = 0.10; below this value the ABC was set to zero and the fishery was closed (MAFMC 2011; Figure 2). Once the ABC was determined, the operating model numerically calculated the fishing mortality associated with the ABC to apply to the stock without implementation error. The ABC remained constant for the duration of the period between assessments. Large assessment error can result in the calculated ABC exceeding the exploitable biomass of the population in some years. In such rare cases the actual catch was set to 50% of the exploitable biomass.

Assessment model

The assessment model used the data generated by the operating model with the first year of data collection beginning in year ten and the last year of data being the stock assessment year minus the DML to estimate the OFL. The assessment model was a statistical catch-at-age (SCAA) model that estimated the abundance, fishing mortality, biomass and fishing mortality reference points, and the OFL. The structure of the SCAA model followed the same equations as the operating model, except that survey catchability, fishery selectivity and natural mortality did not vary over time in the estimation model. The natural mortality in the assessment model was set to the true mean natural mortality of 0.2 for the fast life history and 0.1 for the slow life history. The negative log likelihood function included lognormal distributions for the fishery and survey catch and multinomial distributions for the age composition of the catch (Eq. T.1.16 and T.1.17).

The SCAA required data on the fishery catch-at-age and the survey index of abundance at age. Parameters estimated by the SCAA included recruitment for each year, fishery and survey selectivity parameters, abundance at age in the first year, fully selected fishing mortality for each year and survey catchability. The SCAA model also used the true biological inputs from the operating model such as the maturity at age and weight at age as well as the estimated selectivity at age to estimate the $F_{35\%}$ reference point. Abundance in the final year of the assessment model was projected forward past the DML years with recruitment and fishing mortality assumed constant in the projection years to estimate the OFL for the appropriate management year by finding the catch that would achieve $F_{35\%}$ given the projected abundance at age. $B_{35\%}$ was calculated by multiplying the spawning stock biomass per recruit from fishing at $F_{35\%}$ by the mean estimated recruitment over the time series. The OFL and biological reference points were then returned to the operating model in order to apply the control rule and find the ABC.

Scenarios

Combinations of DML and assessment interval were tested under a factorial design of scenarios that considered alternative assumptions about data quality, stock-recruitment variability, exploitation history, and life history. We modeled good and poor data quality scenarios. The good data scenario used a coefficient of variation of 0.3 and 0.15 for the total survey and fishery catch, respectively, and an effective sample size of 200 for the proportions at age in the survey and fishery catch. Alternatively, for the poor data scenario a coefficient of variation of 0.7 and 0.15 for the survey and catch, respectively, and an effective sample size of 50 for both the survey index of abundance and fishery catch. Survey catchability also varied by data quality scenarios by random walk using log scale normally distributed errors with a standard deviation of 0.01 for the good data scenario and 0.05 for the poor data scenario. Fishery selectivity varied over data quality scenario by applying an autocorrelated, lognormally distributed error with a standard deviation of 0.1 and autocorrelation of 0.3 or 0.9 to the sf50% parameter for the good and poor data scenario respectively. Natural mortality varied by an autocorrelated lognormal random process with a log-scale standard deviation of 0.15 and an autocorrelation of 0.3 for the good data scenario and 0.9 for the poor data scenario. The log-scale standard deviation of the recruitment error was 0.77, the mean recruitment variability from a meta-analysis study by Thorson et al. (2014); additional runs with higher recruitment variability used a log-scale standard deviation for recruitment variability of 1.25. Parameters of the operating model were chosen to represent species with a fast and a slow life history. Life histories were tailored to approximate summer flounder (*Paralichthys dentatus*) for the fast life history and spiny dogfish (*Squalus acanthias*) for the slow life history (parameters in Table 2). The fast life history of the summer flounder included early recruitment into the fishery and early maturation, while the slow life history of the spiny dogfish represented lower natural mortality and late recruitment and maturation. Exploitation scenarios were implemented by including a fishing mortality multiplier (F = 0.5, 1.0, 2.5 x F_{MSY} for the light, moderate, or heavy exploitation) in the pre-management portion in order to determine the abundance at the beginning of the management period. Preliminary model testing showed little difference between exploitation histories; therefore, the 1000 simulations were summarized across exploitation history with the first 333 runs representing an underfished stock, the second 333 runs representing a fully fished stock, and the final 334 runs representing an overfished fished stock.

Performance metrics

The model tracked a range of performance metrics including the true catch, true biomass, probability of overfishing and average annual variability (AAV) of the catch. The catch and biomass performance metrics took the average catch and biomass over the 50 year management period. The probability of overfishing metric was calculated as the proportion of years in which the true fishing mortality exceeded $F_{35\%}$ during the 50 year management period. The AAV in catch was the average of the absolute value of the difference of catch from year to year across the 50 year management period.

Results

Across all life history and data quality scenarios, increasing DML and assessment interval decreased the average catch, with DML having a larger effect on catch than assessment interval (Figure 3). The effects on catch were relatively low for the fast life history and good data scenario, with average catches decreased by 2% for each additional year of DML and 1% with each additional year between assessments. However, effects on catch were magnified in the poor data scenario to a 4% and 3% decrease in catch with an additional year of DML or assessment interval, respectively. Overall, the median average catch decreased by around 20% between good quality and poor quality data for both life history scenarios. Similarly, for both of the life histories with a good data scenario, an annual assessment with three years of DML achieved a similar level of average catch as an assessment every five years with one year of DML. In the poor data scenarios, an annual assessment with three years of DML had similar median average catch to an assessment every seven years with one year of DML. The slow life history scenario displayed less of an effect of assessment interval and DML on average catch in the good data scenario compared to the fast life history. However, the effects of DML were similar to those from the fast life history in the poor data scenario. On average the slow life history saw a 1% decrease in the median average catch with each additional year of DML for the good data scenario, which was magnified to a 5% decrease in the median average catch in the poor data scenario. Furthermore, with each additional year between assessments for the slow life history scenario the median average catch decreased by 2% for the good data scenario and 3% for the poor data scenario. The amount of recruitment variability had relatively little effect on management performance (3% increase in median for biomass and catch and 7% increase in the probability of overfishing) as well as larger variability across all performance metrics (Table 3).

The effect of DML and assessment frequency on average biomass differed with life history and data quality (Figure 4). For the fast life history and good data scenario, each additional year of

DML and time between assessments caused about a 1% decrease in average biomass. The median average biomass decreased about 3% with each additional year of DML and 2% with each additional year between assessments in the fast life history and poor data scenario. The poor data quality scenarios resulted in about 5% lower average biomass for the fast life history relative to the good data scenario, while the slow life history saw an 11% difference. The slow life history and good data scenario saw a larger effect of assessment interval than DML with a 1% decrease in biomass with each additional year of DML compared to a 2% decrease in biomass with each additional year between assessments. Effects were reversed in the slow life history with poor data scenario with each year of DML causing a 6% decrease in the median biomass compared to a 5% decrease with each additional year between assessments.

The probability of overfishing was affected by both data quality and assessment interval, but showed little response to DML, except when combined with higher assessment intervals (assessments every seven and ten years) across all scenarios (Figure 5). Median probabilities of overfishing ranged from 0.25 up to 0.4 across all scenarios with relatively small changes in the probability of overfishing with assessment intervals less than seven years (0.25-0.3). The effect of DML was negligible for the fast life history and poor data scenario, while the probability of overfishing increased 7% with each additional year between assessments. The effect of assessment interval was reduced for the good data scenario with a 4% increase in the probability of overfishing for each additional year between assessments. The effect of DML, conversely, was larger (2% increase in the probability of overfishing with each additional year of DML) relative to the poor data quality scenario. For fast life history scenarios the mean probability of overfishing was around 10% higher when conducting an assessment with poor data compared to an assessment with good data. In contrast, the difference between the two data quality scenarios was only about 2% for the slow life history. Each additional year between assessments caused a 6% increase in the probability of overfishing, and each additional year of DML resulted in a 4% increase in the probability of overfishing in the scenarios with good data. In the poor data scenario assessment interval and DML caused a 2% increase in the probability of overfishing.

Catch AAV generally decreased as DML and assessment interval increased (Figure 6). All life history and data quality scenarios followed a consistent downward trend with each additional year between assessments for assessment intervals up to five years. The catch AAV increased for the seven and ten year assessment intervals for some of the scenarios. For the fast life history scenarios, assessment interval caused a larger response in AAV than the DML. The catch AAV decreased about 7% with each additional year of DML for both the good and poor data scenarios compared to an 11% decrease with each additional year between assessments. The catch AAV was substantially higher in the poor data scenario for both life histories, showing the large inter-annual variation in catch that can occur as a result of low data quality. DML had a small effect on catch AAV for the slow life history in both poor data quality scenarios.

Discussion

We found substantial differences in management performance as a result of assessment frequency and DML across a range of scenarios. Specifically, increases in DML and assessment interval resulted in decreases in both the median catch and biomass. Increases in DML caused larger changes relative to increases in assessment intervals, on average, for all performance metrics except the probability of overfishing and were especially noticeable in the poor data scenarios. The effects of DML and assessment interval on the performance metrics varied among the life history and data quality scenarios. For example, for average catch the effects of DML and assessment interval were relatively low for the fast life history and good data scenarios, with average catches decreased by 2% and 1%, respectively, but were magnified in the poor data scenario to a 4% and 3% decrease in catch with an additional year of DML or assessment interval, respectively. Larger changes in performance metrics were evident with the fast life history compared to slow life history scenarios, but effects varied across performance metrics.

The effect of DML in our study was similar to that described in other studies (Shertzer and Prager 2007; De Leeuw et. al. 2008; Brown et al. 2012) in that delaying the management process can result in increased probability of collapse and variability in harvest. All studies agreed that lengthy DML has negative effects on achieving long-term management goals, and can result in unsatisfactory management outcomes. Our study examined shorter DML periods than previous studies (Shertzer and Prager 2007; Brown et al. 2012). However, both previous work and ours found that increases in DML can cause an increase in the frequency of overfishing, resulting in reduced catch and biomass. Our results for DML were similar to those from Li et al. (in review), with small effects (<2%) when moving from a DML of one year to two years for shorter assessment intervals (annual, two year and three year intervals). However, Li et al. (in review), recommended there was no reason to rush the data collection and management process because their changes in performance metrics were small. They did, however, warn against extrapolating results beyond the frequencies tested in their study. Assessment intervals and DMLs of at least two years are common in many fisheries, and, therefore, reducing DMLs and assessment intervals may improve management performance.

Our estimates of the effects of assessment interval on management performance were similar to previous findings (Mace et al. 2001; Li et al. in review), but we evaluated a wider range of assessment intervals (up to 10 years). Previous studies used a maximum interval of assessments every five years. Increases in assessment intervals caused decreases in average catch and biomass, increases in the probability of overfishing and increases in the catch AAV similar to Mace et al. (2001) and Li et al. (in review). One interesting finding from our study involved an increase in the effects of DML when assessment intervals increased past five years. For example, although the probability of overfishing saw little change with increasing DML in the shorter assessment intervals (around a 2% increase with each additional year of data lag), changes in the probability of overfishing with each additional year of DML increased 6% for the seven and ten year intervals. The interaction of DML and assessment interval was noticeable across both life history and data quality scenarios and highlights a breakdown in management performance when prolonged assessment intervals are paired with extended DMLs. Overall Li et al., (in review), saw slightly smaller effects than we did across all assessment interval scenarios. Results from their lower productive populations were closer to our results with lower SSB and yield for assessment interval. We may have seen stronger effects of assessment intervals because we used a different control rule as well as increased uncertainty in our stock assessments due to the fishery selectivity, natural mortality and survey catchability varying overtime in the operating model, but assumed constant in the assessment model.

For the seven and ten year assessment intervals greater changes in the catch AAV were seen compared to the shorter intervals in some scenarios. Average variation in catch should decrease as assessment intervals increase because catch was constant at the ABC between assessments. The seven and ten year assessment intervals resulted in an increase in catch variation in the fast life history, most likely due to the large changes in catch after each assessment. In some cases ABCs changed by more than 250% when moving from an inter-assessment year to the next assessment year in the seven and ten year intervals. Large fluctuations in catch can cause social and economic problems (Holland 2010), and are, therefore, undesirable. Our findings add to the growing literature supporting that assessment intervals of five years or longer may be ineffective in meeting management objectives because they often result in decreased catch, decreased biomass, higher probability of overfishing and extreme fluctuations in the overall catch rates (ICES 2012, Li et al., in review).

Data quality can affect management performance (McGoodwinn et. al. 2007; Smith et. al. 2011), and we observed substantial degradation of performance in our poor data quality scenarios. The large decreases in the median biomass and catch and increases in the probability of overfishing seen in the poor data scenarios of our study are likely due to poor assessment model performance. The poor data scenario included the larger variances for total fishery and survey catch as well as smaller effective sample sizes for the catch and survey age compositions. Additionally, the poor data scenarios included larger changes in survey catchability, natural mortality, and fishery selectivity, which were not included in the SCAA model, thereby increasing model misspecification. These factors caused estimates of biomass in the last year and reference point estimates to be relatively less accurate than the good data scenario. Because our management model used a short-term projection to determine the catch limit, uncertainty in the abundance at age in the last year would likely be magnified. Even with improved population projections, we would still expect to see poorer management results in scenarios with lower quality data (De Leeuw et. al. 2008).

The effects of life history on management performance were similar to results from previous studies (Mace et. al. 2001; Shertzer and Prager 2007; De Leeuw et. al. 2008; Brown et. al. 2012, ICES 2012, Li et. al., in review). DML and assessment interval had smaller effects in the slow life history scenarios than the fast life histories. These reduced effects of DML and assessment interval may be explained by smaller fishing mortality limit reference point (F_{lim}) for the slow life history than the fast life history; 0.07 and 0.19 respectively. Lower fishing and total mortality rates may cause reduced population responses due to more stability in the stock and less fluctuations in fishing effort year to year (Patterson and Résimont 2007).

Recruitment variability and autocorrelation can decrease the success of extended assessment intervals, but the results of our high variability scenarios were similar to the average variability scenarios. Under our high recruitment variability scenario, average catch and biomass were decreased on average 3% for each additional year of DML and 2% with each additional year between assessments. We also saw, on average, a 7% increase in the probability of overfishing with each additional year between assessments for the fast life history, poor data scenario when moving from a recruitment error standard deviation of 0.77 to 1.25. Higher recruitment variability resulted in larger declines in biomass because initial catch was held at too high of a level between assessments (ICES 2012).

The effects of assessment intervals and DML should be considered when developing fishery management plans. A system that allows up to three years of lag between collection of data and implementation of regulations, sacrifices considerable amounts of biomass and catch. Additionally, when extended DML is paired with longer assessment intervals, suboptimal outcomes are even more likely. Some potential approaches to reduce DML include a shorter management process and faster data processing. For example, the North Pacific Fishery Management Council (NPFMC) has been successful in achieving a one year DML in the majority of its fisheries (AFSC 2014). First, the NPFMC utilizes real-time in-season reporting of catches. In addition to active reporting, the NPFMC uses projections to set catch limits two years in the future, which goes through the public comment process the year prior to regulations being set, effectively removing the time lag for public comment in that year. Finally, the NPFMC has reduced the assessment timeline by using partial ageing data for the most recent year within the stock assessment for some species (AFSC 2014); in these cases, only the survey data is aged. Reducing DML requires a quicker turnover of data and a faster management process that may require increased resources to achieve the reduction. Decreasing the amount of data within stock assessments (e.g., partial age composition data in the final year) may also degrade model performance (Ono et al. 2014). The consequences of using only immediately available data (less data within assessments) to decrease data lag in comparison to data lag effects is an important matter to explore further. While the use of many of the techniques to decrease DML may not be immediately achievable in some regions, it identifies potential possibilities that should be considered in the future.

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Table 1. Equations governing the population and data-generating dynamics in the operating model.

	Equation	Description
1	$R_t = \frac{S_{t-a_R}}{1-\left(\frac{5h-1}{4h}\right)+\left(1-\frac{S_{t-a_R}}{S_{eq}}\right)} e^{\theta_R - 0.5^{\sigma_R^2}}$	Stock-recruit relationship
2	$N_{t,a} = \begin{cases} R_t & a = a_R \\ N_{t-1,a-1} e^{[-M - s_{a-1} F_{t-1}]} & a_R < a \leq a_{\max} \end{cases}$	Abundance at age
3	$L_a = L_\infty (1 - e^{-k(a-a_0)})$	Length at age
4	$w_a = b L_a{}^c$	Weight at length
5	$m_a = \frac{1}{1 + e^{-\left(\frac{a - m_{50\%}}{m_{slope}}\right)}}$	Maturity at age
6	$S_t = \sum_{a=a_R}^{a_{\max}} m_a w_a N_{t,a}$	Spawning biomass
7	$S_{t,a} = \frac{1}{1 + e^{-\left(\frac{a - S_{50\%,t}}{S_{slope}}\right)}}$	Selectivity at age in the fishery
8	$s_{50\%_t} = \bar{s}_{50\%} e^{\varepsilon_{s_t} - 0.5_s^2}$ $\varepsilon_{st} = \rho_s \varepsilon_{s_{t-1}} + \sqrt{1 - \rho_s^2 \phi_t}$ $\phi_t \sim N(0, \sigma_s^2)$	Time-varying and autocorrelated selectivity

9	$M_t = M e^{\varepsilon_{M_t} - 0.5\sigma_M^2}$	Time-varying and autocorrelated natural mortality
	$\varepsilon_{M,t} = \rho_M \varepsilon_{M_{t-1}} + \sqrt{1-\rho_M^2}\phi_{M,t}$	
	$\phi_{M,t} \sim N(0,\sigma_M^2)$	
10	$C_{t,a} = \frac{F_{t,a}}{Z_{t,a}}(1-e^{-Z_{t,a}})N_{t,a}W_{t,a}$	Baranov-catch Eq.
11	$C_{obs,t} = C_t e^{\varepsilon_{C_t} - 0.5\sigma_C^2}$	Observed catch
	$\varepsilon_{C_t} \sim N(0,\sigma_C^2)$	
12	$I_{t,a} = q_t s_{s,a} N_{t,a}$	True index of abundance
13	$q_t = q_{t-1} e^{\varepsilon_{qt}}$	Catchability
	$\varepsilon_{q_t} \sim N(0,\sigma_q^2)$	
14	$I_{obs_t} = e^{\varepsilon_{I_t} - 0.5\sigma_I^2} \sum_a I_{a,t}$	Observed index of abundance
	$\varepsilon_{I_t} \sim N(0,\sigma_I^2)$	
15	$P_{obs_t} = \frac{1}{n}\boldsymbol{\Theta_t}$	Proportion of catch-at-age
	$\boldsymbol{\Theta_t} \sim Multinomial(n, \mathbf{p_t})$	
	$\mathbf{p_t} = \frac{1}{I_t}\left(I_{a_r,t}, \dots, I_{a_{max},t}\right)$	
16	$\ell_t = 0.5n\log(\sigma_C^2) + \sum_t \left(\log\left(C_{obs_t}\right) - \log\left(C_{est_t}\right)\right)^2$	Lognormal likelihood components for the catch and

	$\ell_t = 0.5n\log(\sigma_I^2) + \sum_t \left(\log\left(I_{obs_t}\right) - \log(I_{est_t})\right)^2$	index of abundance
17	$\ell_t = -E_C \sum_t \sum_a p_{obs,C_{t,a}} \log(p_{est,C_{t,a}})$	Multinomial likelihood components for the proportion of the catch and index
	$\ell_t = -E_I \sum_t \sum_a p_{obs,I_{t,a}} \log(p_{est,I_{t,a}})$	

Table 2. Symbols used in the operating and assessment models and values for specified life history and time-varying parameters.

Parameter	Description	Life history Slow	Life history Fast
a_R	Age at recruitment	5	3
a_{max}	Maximum age	20	12
M	Natural mortality rate	0.1	0.2
R_0	Unfished equilibrium recruitment	$1x10^6$	$1x10^6$
h	Steepness	0.6	0.75
a_0	Age at length = 0	0	0
L_∞	Asymptotic maximum length	90	90
k	Growth rate	0.07	0.13
b	Length-weight relationship scalar	3.5×10^{-6}	3.5×10^{-6}
c	Length-weight relationship exponent	3.15	3.15
m_{50}	Age at 50% maturity	7	3.5
m_{slope}	Slope of maturity function	1	1
s_{f50}	Mean age at 50% selectivity in the fishery	1.75	3.5
s_{s50}	Mean age at 50% selectivity in the survey	1.3	2.6
s_{fslope}	Slope of fishery selectivity function	1	1
s_{sslope}	Slope of survey selectivity function	1	1
	Time Varying parameters		
σ_R	Standard deviation of stock-recruit relationship	0.77, 1.25	
Φ_R	Autocorrelation in recruitment	0.44	
σ_M	Standard deviation of time-varying M	0.15	

Φ_M	Autocorrelation in M	0.3, 0.9
σ_f	Standard deviation of age at 50% selectivity in fishery	0.1
Φ_f	Autocorrelation in fishery selectivity	0.3, 0.9
σ_C	Standard deviation of catch estimates	0.15
σ_I	Standard deviation of survey estimates	0.29, 0.63

	Additional model variables	
a	Age	
t	Year	
R	Recruitment	
S	Spawning biomass	
s_f	Fishery selectivity	
s_s	Survey selectivity	
N	Abundance	
m	maturity	
C	Catch	
I	Index of abundance	
q	Catchability	
Z	Total mortality	
W	Weight-at-age	
m	Maturity-at-age	
F	Fishing mortality	
E	Effective sample size of the catch/ index	
n	Number of observations	

p_{obs}	Observed proportion at age
p_{est}	Estimated proportions at age
$\boldsymbol{\Theta_t}$	Multinomial function
ℓ_t	Likelihood function
ε_{s_t}	Error for selectivity
ε_{q_t}	Error for catchability
ε_M	Error for natural mortality
ε_{I_t}	Error for index of abundance
ε_{C_t}	Error for catch
σ_q	Standard deviation for catchability
ρ_M	Correlation coefficient of natural mortality
ρ_s	Correlation coefficient of selectivity

Table 3. Median values for recruitment variability scenarios across performance metrics. SA refers to stock assessment intervals and DLM refers to data-management lag combinations.

	Fast life history, Good data quality				Fast life history, Poor data quality			
Combination	Catch	Biomass	Probability of overfishing	AAV in catch	Catch	Biomass	Probability of overfishing	AAV in catch
SA1, DML1	88859	651337	0.2353	0.1247	73307	628711	0.2941	0.2151
SA1, DML2	87139	650904	0.2549	0.1221	69198	606077	0.2745	0.2072
SA1, DML3	84271	640642	0.2745	0.1163	63615	560657	0.2941	0.1983
SA2, DML1	87890	642709	0.2549	0.1049	70350	621079	0.2941	0.1721
SA2, DML2	86188	643914	0.2549	0.1020	65976	587776	0.2941	0.1658
SA2, DML3	83207	625885	0.2745	0.0961	61499	544146	0.3137	0.1579
SA3, DML1	86520	635407	0.2745	0.0970	68639	597018	0.2941	0.1550
SA3, DML2	84847	631522	0.2745	0.0924	64303	568067	0.2941	0.1489
SA3, DML3	80621	620267	0.2941	0.0870	59494	495378	0.3137	0.1428
SA5, DML1	84505	618817	0.2941	0.0869	66753	581235	0.2941	0.1339
SA5, DML2	80690	606080	0.3137	0.0791	60410	533683	0.3137	0.1254
SA5, DML3	76276	583778	0.3137	0.0743	56966	471217	0.3137	0.1190
SA7, DML1	80947	596829	0.3137	0.0893	62676	538751	0.3137	0.1350
SA7, DML2	75743	580578	0.3137	0.0807	56582	507100	0.2941	0.1245
SA7, DML3	71639	545995	0.3333	0.0746	51674	439601	0.3137	0.1202
SA10, DML1	76685	571242	0.3333	0.0816	56603	483412	0.3333	0.1176
SA10, DML2	72555	547913	0.3529	0.0712	53129	468120	0.3529	0.1084
SA10, DML3	64033	471077	0.3725	0.0651	50361	395472	0.3725	0.1051

	Slow life history, Good data quality				Slow life history, Poor data quality			
Combination	Catch	Biomass	Probability of overfishing	AAV in catch	Catch	Biomass	Probability of overfishing	AAV in catch
SA1, DML1	85482	1079880	0.2157	0.1051	68201	1016910	0.2745	0.1990
SA1, DML2	83196	1062605	0.2353	0.1049	65055	951658	0.2843	0.1979
SA1, DML3	81141	1038235	0.2745	0.1048	61910	899883	0.2941	0.2003
SA2, DML1	82647	1060110	0.2549	0.0858	66414	993154	0.2745	0.1546
SA2, DML2	81006	1040820	0.2549	0.0853	62546	937609	0.2745	0.1528
SA2, DML3	78731	1011020	0.2745	0.0845	59798	843206	0.3137	0.1561
SA3, DML1	80755	1035620	0.2549	0.0773	64538	953185	0.2941	0.1336
SA3, DML2	78848	1021600	0.2745	0.0760	61237	891199	0.2941	0.1337
SA3, DML3	76764	984408	0.2941	0.0755	57085	808425	0.2941	0.1355
SA5, DML1	81999	984698	0.2941	0.0665	65172	901107	0.2941	0.1133
SA5, DML2	79941	955132	0.2941	0.0652	60961	837497	0.2941	0.1127
SA5, DML3	77818	919578	0.3333	0.0650	57844	738857	0.3137	0.1147
SA7, DML1	74253	936258	0.2941	0.0662	58127	796522	0.2941	0.1081
SA7, DML2	73115	893060	0.3333	0.0646	53187	730797	0.2941	0.1065
SA7, DML3	70882	852989	0.3529	0.0645	52080	652936	0.2941	0.1083
SA10, DML1	68483	863284	0.3333	0.0601	52925	698217	0.2941	0.0974
SA10, DML2	67151	813269	0.3725	0.0571	49740	627219	0.3333	0.0969
SA10, DML3	63916	731213	0.3922	0.0562	44723	539343	0.3725	0.0973

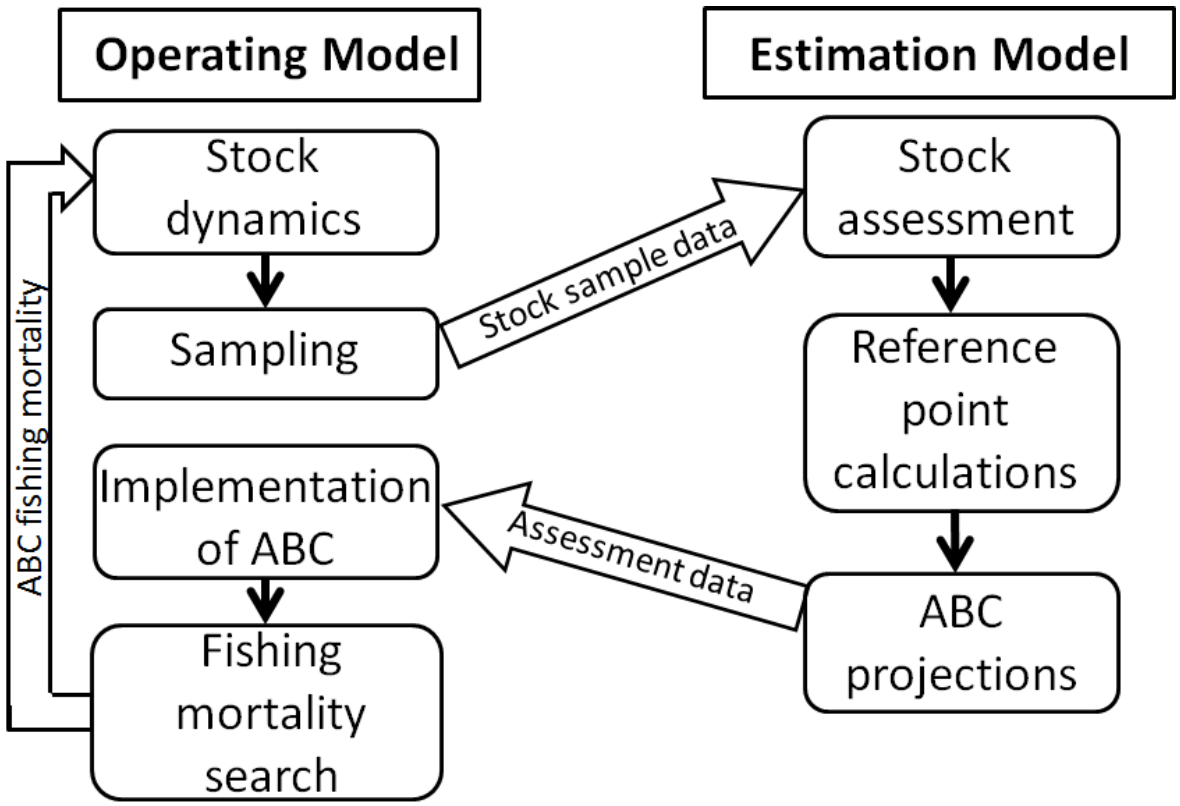

Fig. 1. Flow diagram of management strategy evaluation model with both operating and estimation models.

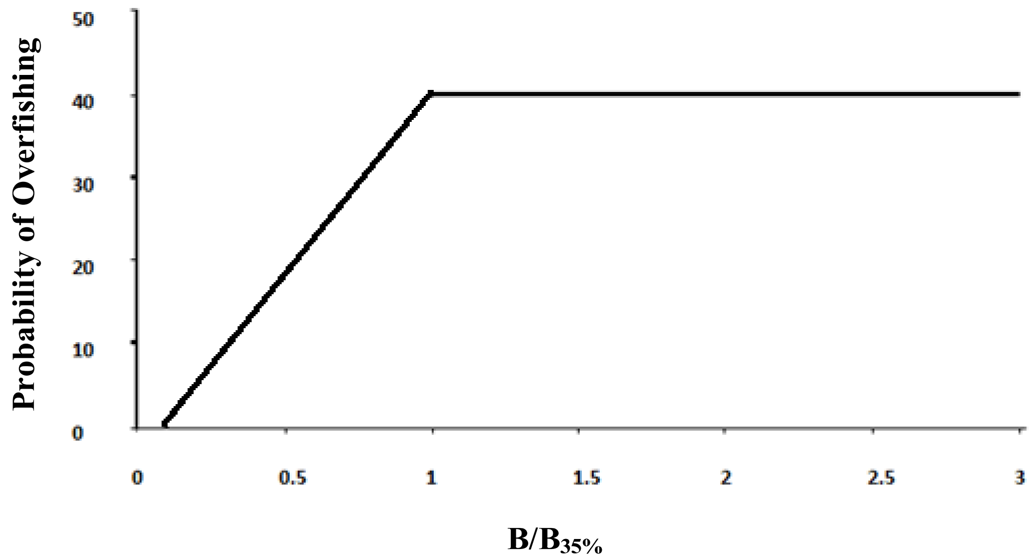

Fig. 2. Mid-Atlantic P* approach showing decreasing probability of overfishing with a declining $B/B_{35\%}$ ratio

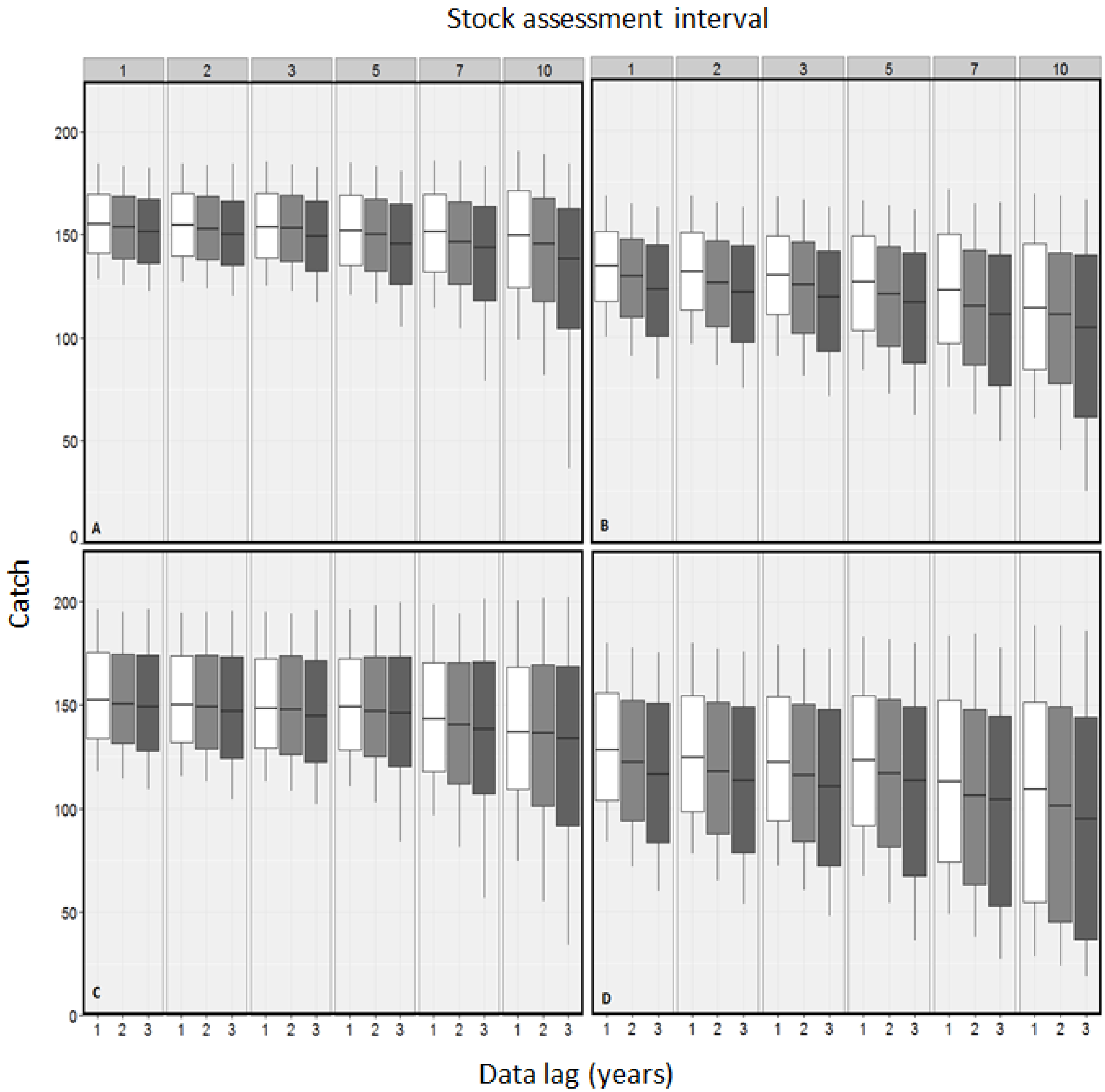

Fig. 3. Box plots of the catch for each life history and data scenario with a log-scale recruitment standard deviation of 0.77: A) fast life history with good data, B) fast life history with poor data, C) slow life history with good data, and D) slow life history with poor data. The horizontal lines of the box plot show the median catch, the box shows the interquartile range, and the whiskers represent the 10^{th} and 90^{th} percentiles.

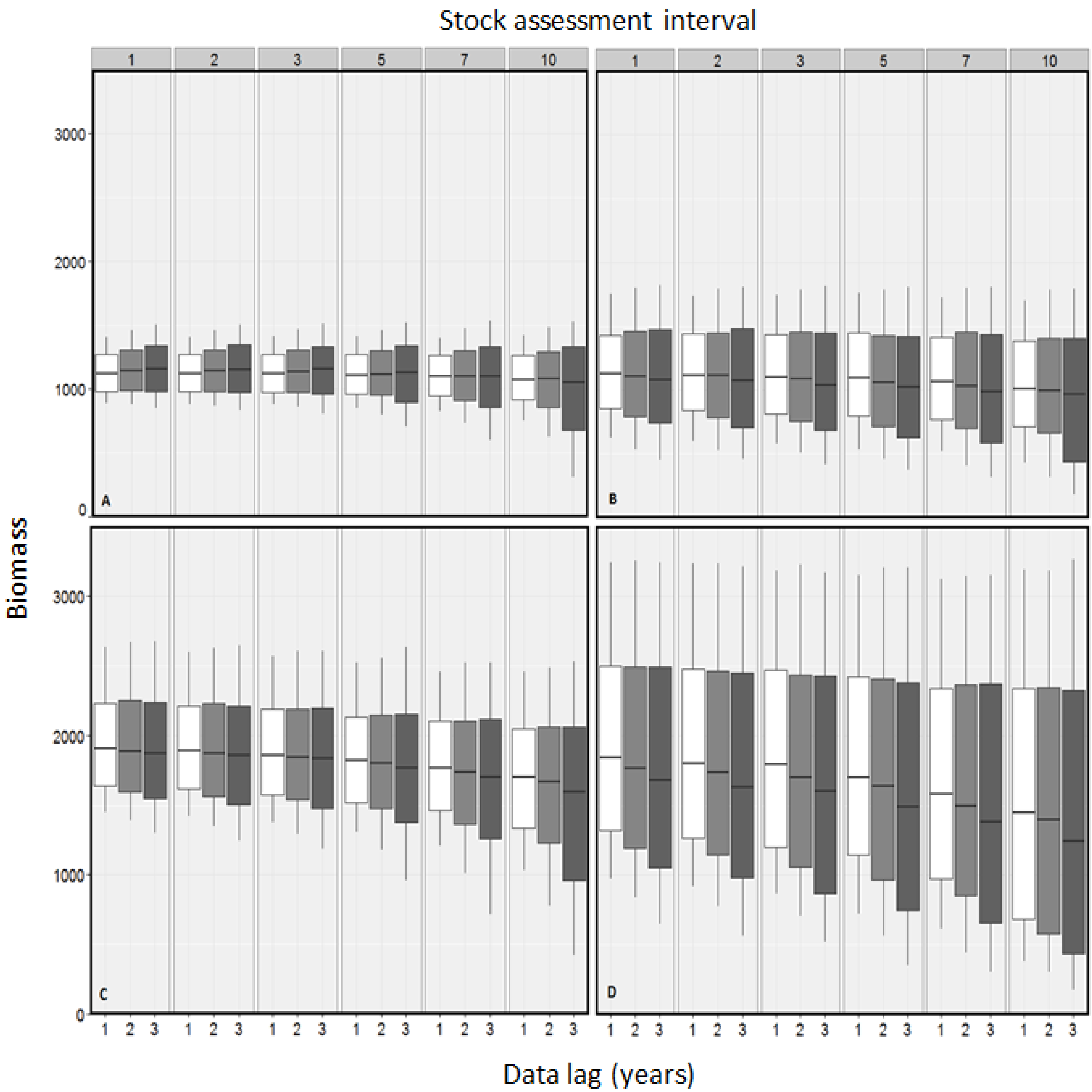

Fig. 4. Box plots of the biomass for each life history and data scenario with a log-scale recruitment standard deviation of 0.77: A) fast life history with good data, B) fast life history with poor data, C) slow life history with good data, and D) slow life history with poor data. The horizontal lines of the box plot show the median catch, the box shows the interquartile range, and the whiskers represent the 10^{th} and 90^{th} percentiles.

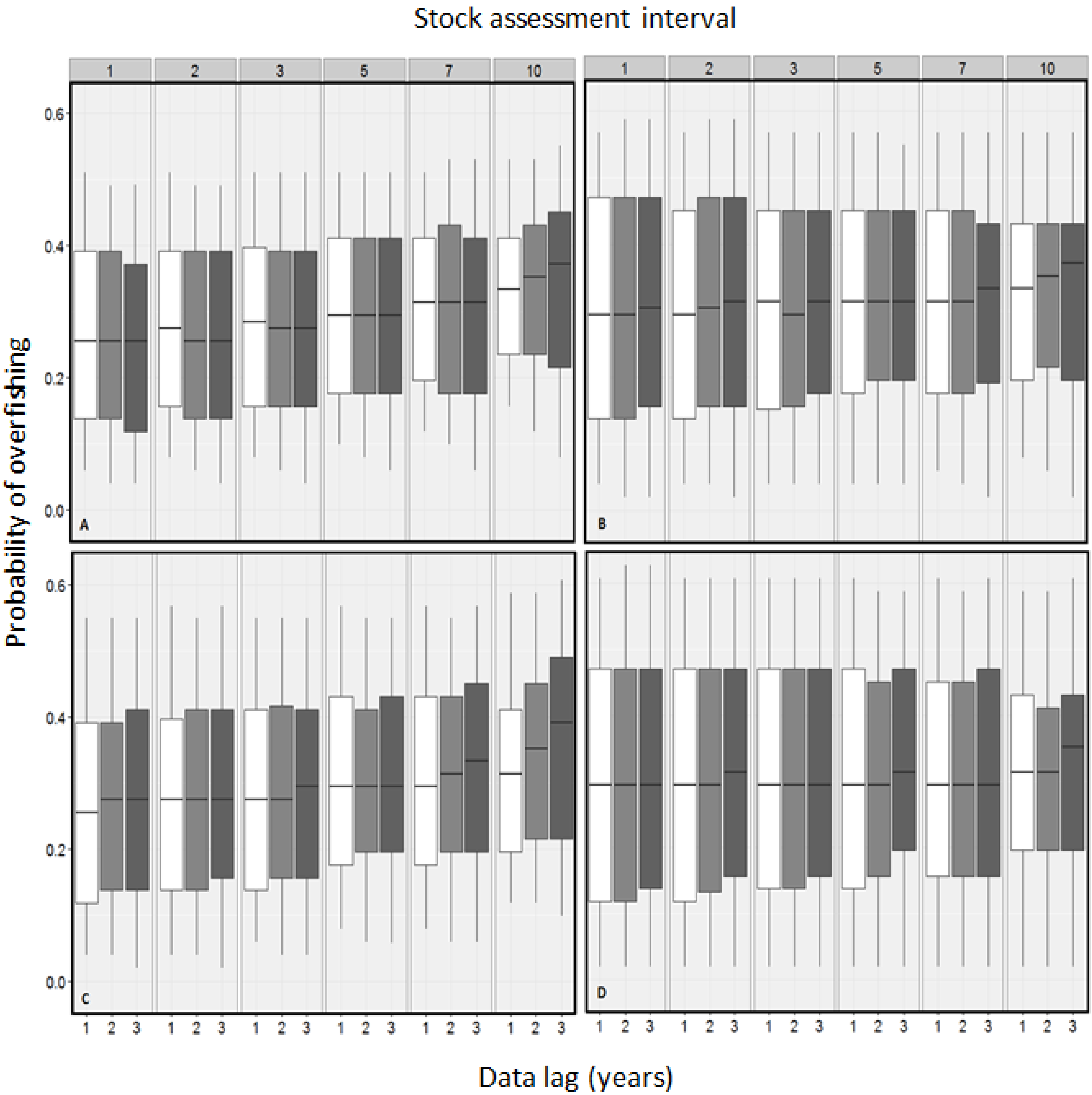

Fig. 5. Box plots of the probability for each life history and data scenario with a log-scale recruitment standard deviation of 0.77: A) fast life history with good data, B) fast life history with poor data, C) slow life history with good data, and D) slow life history with poor data. The horizontal lines of the box plot show the median catch, the box shows the interquartile range, and the whiskers represent the 10th and 90th percentiles.

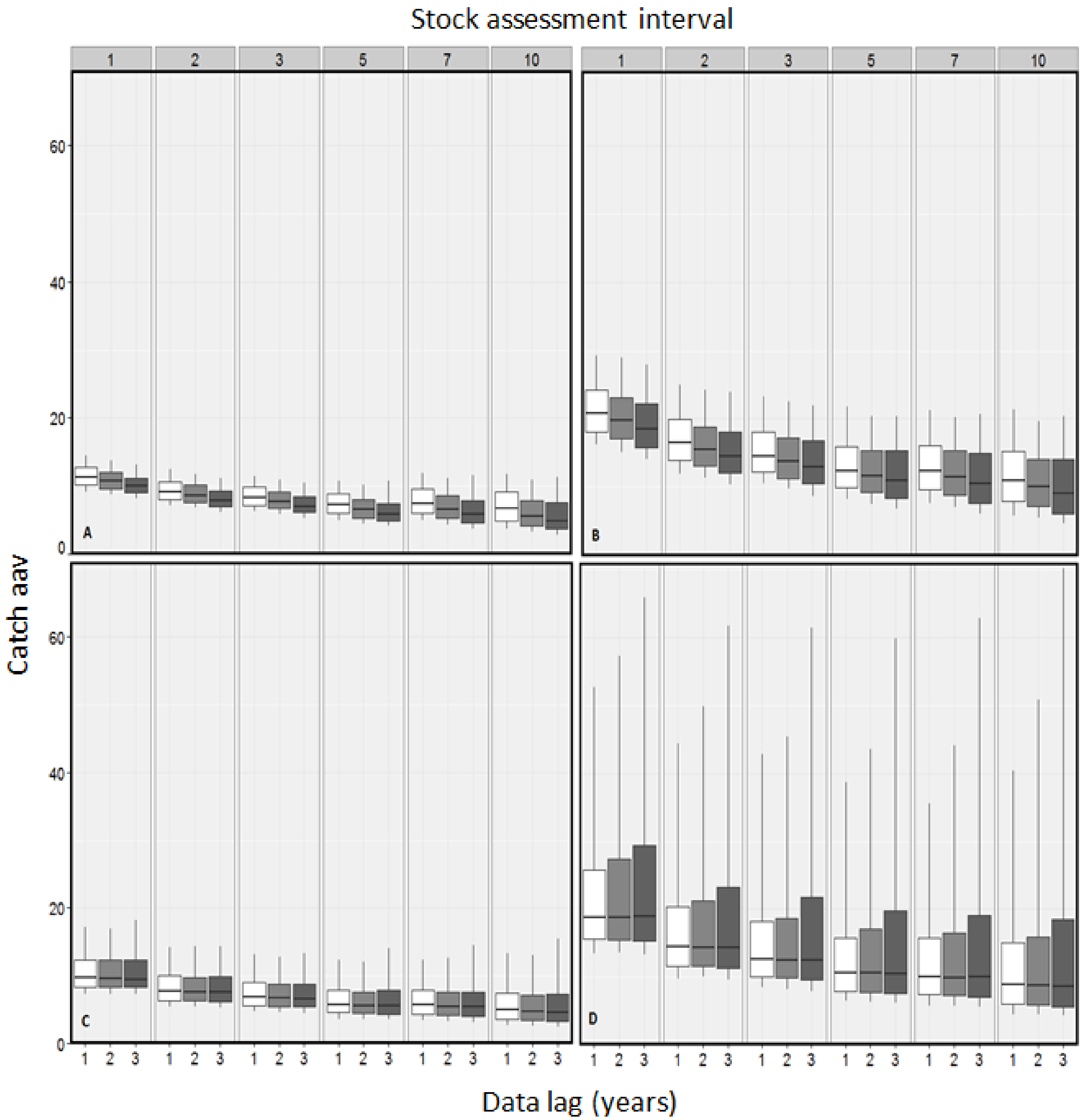

Fig. 6. Box plots of the catch average annual variation (aav) for each life history and data scenario with a log-scale recruitment standard deviation of 0.77: A) fast life history with good data, B) fast life history with poor data, C) slow life history with good data, and D) slow life history with poor data. The horizontal lines of the box plot show the median catch, the box shows the interquartile range, and the whiskers represent the 10th and 90th percentiles.

Chapter 3. Performance of lag reduction methods for the Mid-Atlantic harvest control rule

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Abstract

The use of the newest available data in stock assessments can be crucial to meeting management goals. Even so, many stock assessments throughout the world have data-management lags (the time between data collection and management implementation) that can extend more than three years. Prior research has suggested that management performance is improved by decreasing the length of the decision making process and using data that is available instead of waiting for all of the data from a year to be ready. We used a management strategy evaluation to test three methods to reduce data lag by using partial data in the last year of the assessment: 1) age-composition data for the terminal year of the survey, but no age-composition for the fishery catch, 2) full survey age-composition with reduced quality age-composition data for the catch in the terminal year of the stock assessment (to represent using prior years' age and length data to age the catch), and 3) reduced data for the age-compositions of the survey and catch in the terminal year of the assessment (to represent using prior years' data to age the catch and indices). These methods were tested against controls with one year of data and two years of data lag. Lag reduction methods that included some information about the age-composition of the catch and survey performed about as well as not having lag for both fast and slow life histories, but they sometimes resulted in higher probabilities of low biomass. Data-management lag and lag reduction methods should be considered when designing fishery management plans.

Introduction

Fisheries management has seen vast improvements recently with more sophisticated assessments and improved identification of uncertainty (Caddy and Cochrane 2001). Yet, even with enhanced techniques, there are still many practical problems in fisheries management throughout the world (Honey et al. 2010, Chen et al. 2002). One example of such a management issue is the inclusion of timely data within the stock assessment and lengthy regulation processes that delay implementation of catch limits. Previous studies have noted the importance of using the newest available data in assessments and the decrease in management performance when lengthy data-management lag (the time between data collection and management implementation using that data) is present (Shertzer and Prager 2007; Brown et al. 2012; Li et al., in review; Sylvia Chapter 2). However, we were unable to find any studies that tested methods to decrease data-management lag (DML).

DML is caused by a combination of data preparation, stock assessment, management processes and management delays (Shertzer and Prager 2007; Sylvia Chapter 2). For stocks that use age-structured assessments to provide management advice, the process begins with fishery catch and survey data being collected and processed, usually from multiple sources. Fishery catch can sometimes be challenging to collect, especially for fisheries with a recreational sector or commercial fisheries that operate in multiple jurisdictions. After the data are collected, it is then processed by verifying and checking the data as well as aging samples. One of the lengthiest portions of data collection and processing is the aging. Because aging otoliths can be an intricate and laborious process, it alone can add up to a year to the DML. Preliminary analyses are completed to modify information into the appropriate form for the stock assessment. The stock assessment period can then range from a month for updates of an existing model to much longer if new assessment methodology is developed. External peer reviews of stock assessments, done in many parts of the U.S., can add two to three months to the process. The management portion of DML which includes development and implementation of regulations can take up to a year depending on the region. The final element of DML can occur if management is then delayed. Management delay is common in many parts of the world due to issues such as scientific uncertainty, waiting for more data or to reduce unfavorable outcomes (Shertzer and Prager 2007; Brown et al. 2012). With all parts of DML adding to the timeline, the management process can see delays up to four years in some U.S. regions. Management delays can extend up to five years in Australian commonwealth fisheries (Smith et al. 2008) and can be even longer (e.g., delays of up to 15-25 years in Lake Ijsselmeer in the Netherlands; de Leeuw et al. 2008).

Few studies have been conducted on the effects of DML (Shertzer and Prager 2007; Brown et al. 2012; Li et al., in review; Sylvia Chapter 2). Each year of DML caused around a 5% decrease in biomass and catch for poor data quality scenarios while causing up to a 6% increase in the probability of overfishing when paired with longer assessment intervals (Sylvia Chapter 2). The largest effects of DML were seen with the longer assessment intervals and lower quality data. A study that tested the effect of DML for Great Lakes yellow perch (*Perca flavescens*) management found relatively small (<1%) decreases in spawning stock biomass (SSB) and yield when DMLs were increased from one to two years (Li et al., in review). However, increasing DML by delaying management actions can allow continued overexploitation, leading to rigid rebuilding plans and increased probability of stock collapse (Brown et al. 2012; Shertzer and Prager 2007). Waiting for more data may actually be harmful if it delays management even longer (Shertzer and Prager 2007). Slow, stepwise effort reductions in the management of Lake Ijsselmeer in the Netherlands resulted in meeting short term-interests, but failed in recovery of fish stocks and led to stock collapse (de Leeuw et al. 2008).

Strategies to reduce the effects of DML have been developed. Reducing harvest is a potential solution to mitigate the effects of delays, but does little to solve the extended DML problem within the management system (Brown et al. 2012). Making best use of the available data may help to avoid further stock decline or poor management outcomes. Some regions have adopted methods that allow them to use partial or missing age-composition data for the most recent year of stock assessments. Converting length composition to age-composition often times causes delays due to the aging process, but length composition data is typically available relatively quickly. Predicting ages of fish in the most recent year can often be accomplished by using length composition data in that year and length and age-composition data in previous years to make an inverse age-length key for the most recent year (Quinn and Deriso, 1999). Utilizing past data to estimate age-composition in the most recent year can significantly decrease the data lag that occurs as a result of the aging process. The North Pacific Fishery Management Council (NPFMC) has been successful in achieving a one year DML in majority of its fisheries by using some of the previously mentioned techniques (AFSC 2014). In addition to decreasing the management process by setting catch limits two years in advance, NPFMC has cut down the data lag by using real time in season reporting for catch data and by using assessment models that do not require catch-at-age data in the last year of the stock assessment for some species (AFSC 2014). To accomplish this reduction in DML, NPFMC ages only the survey data, and an inverse age-length key is used to estimate the terminal age-composition of the catch.

Our study builds upon previous study recommendations, specifically Shertzer and Prager (2007), by testing methods that use available data to fill in gaps that would otherwise be present in the most recent year. We used a management strategy evaluation (MSE) of the U.S. Mid-Atlantic fisheries management system to test the effect of several methods for reducing data lag in the management process. We compared several methods of reducing DML by using partial data in the last year of the stock assessment. The MSE simulated the population dynamics, the stock assessment and management process, based on data availability for stocks managed by the Mid-Atlantic Fishery Management Council (MAFMC). We evaluated effectiveness using a range of performance measures, which represent how well fishery management objectives were achieved. We tested the approaches under a range of data quality, life history, and stock-recruitment scenarios.

Methods

We conducted an MSE to test the performance of several methods of reducing DML for MAFMC stocks. We tested three lag reduction (LR) methods and two controls (C): C1) a control with one year, LR1) using age-composition data for the terminal year of the survey, but no age-composition for the catch, LR2) full survey age-composition data, but reduced quality age-composition data for the catch in the terminal year, LR3) reduced quality data for both the survey and catch age-compositions in the terminal year of the assessment, and C2) a control with two years of data lag . The reduced quality age-composition approaches represented cases in which size-at age of the stock is variable such that using prior years' data would inject additional error into the age composition data. For these approaches, length data is available for the most recent year and size-at-age data from previous years would be used to convert length composition to age-composition. If size-at-age of the stock does not vary over time, then use of previous years' data should not result in lower quality age composition information. The two controls used full age-composition data for both the survey and the catch with one and two year DMLs (see Table 1). Each lag reduction method was tested under scenarios with good and poor quality data, fast and slow life histories, and high and low recruitment variability in order to represent a broader range of fisheries.

The MSE included operating and assessment models (Figure 1). The operating model represented the true dynamics of the stock with an age-structured population model. Data representing catch and surveys were "sampled" from the operating model to represent the information typically used in the assessment process and varied based on the lag reduction method chosen. Subsequently, a statistical catch-at-age (SCAA) model was called at regular stock assessment intervals, varying from annual assessments to assessments every three years, to estimate biomass and age structure in the last year and fishing mortality and biomass reference points. The management portion of the model used the results of the stock assessment to determine target catch using the MAFMC harvest control rule, which includes a short-term projection to the year the catch limit will be implemented and uses a probabilistic approach (Shertzer et al. 2008; MAFMC 2011). We used four DML scenarios with differing data in the last year. Each simulation was run for a total of 80 years. In the first 30 years the fishery developed with unregulated fishing. During the remaining 50 years the management strategy was in effect. At the end of each simulation, performance of the control rule was summarized over the 50-year management period. All models were developed in ADMB (Fournier et al. 2012). Variable definitions and equations are provided in Tables 2 and 3.

Operating Model

The operating model simulated the population dynamics with an age-structured model. The model included 12 age classes for the fast life history, and 20 age classes for the slow life history, where 12+ and 20+ were aggregate age classes of fish ages 12 or 20 and older. Abundance-at-age in the first year was assumed to be in its unfished equilibrium state. We used a Beverton-Holt stock-recruitment relationship with an autocorrelated, lognormally distributed random error to determine recruitment each year (Eq. T2.1). The errors in the stock-recruitment relationship had a correlation of 0.44 and a log-scale standard deviation of 0.77 (the average from a meta- analysis by Thorson et al. (2014)) or 1.25, which represented a higher level of variability. Abundance-at-age was calculated using an exponential mortality model with additive natural and fishing mortality (Eq. T2.2). The weight-at-age was calculated using length-at-age from a von Bertalanffy growth model (Eq. T2.3) and an allometric function of length-at-age (Eq. T2.4). Maturity-at-age followed a logistic function of age (Eq. T2.5). The spawning stock biomass (SSB) was the product of maturity-at-age, weight-at-age and abundance-at-age summed over ages for a given year (Eq. T2. 6).

The operating model included a single fishery, and selectivity followed a logistic function of age. Selectivity of the fishery and natural mortality were allowed to vary over time so that the assessment models would not exactly match the dynamics of the operating model. Fishery selectivity varied over time by applying an autocorrelated, lognormally distributed error with a standard deviation of 0.1 and autocorrelation of 0.3 or 0.9 to the sf50% parameter (Eq. T2.7 and

T2.8), and natural mortality also followed an autocorrelated lognormal random process over time with a log-scale standard deviation of 0.15 and an autocorrelation of 0.3 (Eq. T2.9). Fishing mortality was set to 0.05 in the first year, after which it increased linearly until it plateaued in year 18 and remained constant until the management period began in year 30. The value of fishing mortality at the plateau depended on the exploitation history. Exploitation scenarios were light, moderate and heavy and used a fishing mortality multiplier (F = 0.5, 1.0, 2.5 x $F_{MSY,}$ respectively) in the plateau year. Total mortality was the sum of the natural mortality and fishing mortality; fishing mortality at age was the product of the selectivity at age of the fishery and the overall fishing mortality rate for a year. Fishery catch-at-age was calculated using the Baranov catch equation (Eq. T2.10).

The operating model also generated catch-at-age in a survey as the product of abundance, survey selectivity, and survey catchability (Eq. T2.11). Survey catchability varied according to a random walk on the log scale with normally distributed errors (with a standard deviation of 0.01 or 0.05 depending on the data quality scenario) to allow gradual variation in the catchability over time (Eq. T2.12). The observed catch was calculated by multiplying total fishery catch by a lognormal error with a log-scale standard deviation set at 0.15 (Eq. T2.13). The observed index of abundance was calculated similarly, where the log-scale standard deviation of the random error was set to 0.3 or 0.7 depending on the data quality scenario (Eq. T2.14). The observed proportions at age for the fishery and survey were generated by sampling from a multinomial distribution using the true proportions at age (Eq. T2.15) and effective samples sizes (ESSs) of 50 or 200 depending on the data quality scenario for all years prior to the terminal year of the stock assessment. The ESSs in the terminal year depended on the lag reduction methods.

Age-structured stock assessment models require two sources of data, the fishery catch at age and an additional source of auxiliary data, such as a survey index of abundance (Fournier and Archibald 1982; Quinn and Deriso, 1999). The observations of age-composition from fishery dependent and survey data are often modeled using a multinomial distribution (Quinn and Deriso, 1999). With increased sample sizes the observation error in the proportions would decrease. Likewise, the accuracy of the method used to age the sample affects the effective sample size. If resources are not available to complete the aging of samples in the most recent year, other methods are needed to obtain the age composition. One such method is to use size-age data from previous years to generate an inverse age-length key, which is then used to estimate age composition in the most recent year using the length data. If growth patterns are changing over time, using size-age data from prior years to estimate the most recent year's age composition will increase the amount of observation error. We approximated this process by using a lower effective sample size to generate age composition data in the most recent year using three approaches. Our study utilizes this idea by using a smaller effective sample size in order to simulate the error associated with using prior years' age-length data to age the samples in the most recent year. In practice this would be done using an inverse age-length key (Quinn and Deriso 1999) because the estimation of age composition using traditional age-length keys from prior years can introduce sampling error and bias into fishery assessments (Coggins, 2013).

Differences in quality of the age-composition data in the last year of the assessment were included by modifying the ESS of the survey and catch age-composition for that year. Reduced ESSs were chosen to represent the error associated with the use of an inverse-age-length key in order to estimate age-composition from the length composition and data from previous years.

For the two controls, the terminal year had the same ESS as the earlier years, 50 or 200 depending on the data quality scenario. LR1 included the same ESS for the terminal year as for previous years for the survey age-composition, but did not include any age-composition data for the fishery catch in the terminal year. LR2 used an ESS of 50 or 200 for the survey proportions at age and an ESS of 12 or 50 depending on data quality (poor and good respectively) for fishery proportions at age to represent the use of previous age and length data to infer ages for terminal year catch. LR3 used an ESS of 12 or 50 for both the survey and fishery proportions at age in the terminal year of the stock assessment to represent the use of previous age and length data to infer ages in the terminal year of the stock assessment. Sample sizes of the original ESS, one half the original ESS and one fourth the original ESS showed slight differences (<2%) in performance metrics for both data quality scenarios. An ESS of one fourth the original size should represent a case with substantial sampling variability because the estimation of age-composition using inverse age-length keys should not degrade in performance if growth does not change over time.

After each assessment the operating model implemented the MAFMC's P* control rule to estimate a target catch from the overfishing limit (OFL; MAFMC 2011). The OFL was estimated by applying the estimated $F_{35\%}$ from the assessment to the terminal estimate of abundance. $F_{35\%}$ is commonly used as a limit fishing mortality reference point (Clark 2002). The MAFMC P* approach assumes that the OFL is lognormally distributed with a median value from the stock assessment projections and a CV of 100%. The target catch was calculated as the catch that achieves the 40th percentile of the OFL distribution if estimated $B/B_{35\%}$ (derived from the SPR model in the assessment) exceeded 1.0. If estimated $B/B_{35\%}$ fell below 1.0 then the P* used to calculate ABC decreased linearly to zero until $B/B_{35\%} = 0.10$; below this value the target catch was set to 0 (MAFMC 2011; Figure 2). Once the target catch was determined, the operating model used a golden section search to find the fishing mortality resulting from achieving that catch. The target catch remained constant for the duration of the period between assessments.

Assessment model

We included two assessment models, which differed in whether age-composition data was available for the fishery in the terminal year. The assessment models used the data generated by the operating model with the first year of data collection beginning in year ten and the last year of data being the stock assessment year minus the DML. The assessment models were SCAA models that estimated the abundance, fishing mortality, fishing mortality and biomass reference points, and the OFL. The structure of the SCAA models followed the same equations as the operating model, except that survey catchability, fishery selectivity, and natural mortality did not vary over time. The natural mortality in the assessment model was set to the mean true natural mortality of 0.2 for the fast life history and 0.1 for the slow life history. The negative log likelihood functions included lognormal distributions for the fishery and survey catch and multinomial distributions for the age-composition of the catch (Eq. T.2.16 and T.2.17). Each SCAA required the two data sets that were created in the operating model: the fishery catch-at-age and the survey index of abundance-at-age. The individual assessment models differed based on how they handled the survey and fishery age-composition and are described below. While LR2 and LR3 as well as C1 and C2 used a likelihood function that included all years for all data sources, LR1 did not include the age-composition of the catch in the last year. All of the models were provided the effective sample sizes that were used to generate the age-composition data for each year.

Parameters estimated by the SCAAs included recruitment parameters, fishery and survey selectivity parameters, abundance-at-age in the first year, fully selected fishing mortality for each year, and survey catchability. The SCAA models also used the true biological inputs from the operating model such as the maturity at age and size at age as well as the estimated selectivity at age to estimate the $F_{35\%}$ and $B_{35\%}$ reference points. Abundance in the final year of the assessment model was projected forward past the DML years in order to estimate the OFL for the year in which the catch limit would be implemented by finding the catch that would achieve $F_{35\%}$ given the projected abundance-at-age. $B_{35\%}$ was calculated by multiplying the SPR from fishing at $F_{35\%}$ by the mean recruitment over the time series (Haltuch et al. 2008). The OFL and biological reference points were then returned to the operating model in order to apply the control rule and find the target catch.

Scenarios

Each lag reduction method was tested under annual, two year, and three year stock assessment intervals with a DML of one year and compared to the controls with a DML of one and two years. These combinations were tested under a factorial design of scenarios that considered alternative assumptions about data quality, stock-recruitment variability, exploitation history and life history. The simulations included two data quality types that differed in the amount of observation error in the survey index, the ESSs of the age-composition of the catch and survey, and the amount of variability in fishery selectivity, natural mortality, and survey catchability. The good data scenario used a coefficient of variation of 0.3 and 0.15 for the total survey and fishery catch, respectively, and an ESS of 200 for the proportions at age in the survey and fishery catch. For the poor data scenario a coefficient of variation of 0.7 and 0.15 for the survey and catch respectively and an effective sample size of 50 for both the survey index of abundance and fishery catch. Parameters of the operating model were chosen to represent species with a fast and a slow life history. Life histories were tailored to approximate summer flounder (*Paralichthys dentatus*) for the fast life history and spiny dogfish (*Squalus acanthias*) for the slow life history (parameters in Table 2). The fast life history of the summer flounder included early recruitment into the fishery and early maturation, while the slow life history of the spiny dogfish represented low natural mortality and late recruitment and maturation. Due to preliminary model testing showing little difference between exploitation histories, the 2000 simulations were summarized across exploitation history with the first 667 runs representing an underfished stock, the second 667 runs representing a fully fished stock, and the final 666 runs representing an overfished fished stock. Exploitation scenarios were implemented by including a fishing mortality multiplier (F = 0.5, 1.0, 2.5 x F_{MSY} for the light, moderate, or heavy exploitation) in the pre-management years.

Performance metrics

The model tracked a range of performance metrics including the true catch, true biomass, probability of overfishing, average annual variability (AAV) of the catch, fishery closures and overfishing. The catch and biomass performance metrics took the average catch and biomass from the 50 year management period. The probability of overfishing metric was calculated as the proportion of years in which the true fishing mortality exceeded the fishing mortality limit during the 50 year management period. The AAV in catch was the average of the absolute value of the difference of catch from year to year across the 50 year management period. Fishery closures were calculated by taking the number of times fishing mortality in the model was set to zero for the fishing year and divided by the number of runs. Similarly the probability of fishery closure is considered when stock size (biomass) is ½ of the B/B_{proxy} and was calculated by summing the number of times the B/B_{proxy} ratio was below 0.5 and divided by the number of runs. Means, maximums, minimums, standard deviations and percent change from one year to the next and between lag reduction methods were taken to compare scenario outcomes. We estimated 95% confidence intervals for the medians of each performance metric and included a Bonferonni correction to account for multiple comparisons between controls and lag reduction methods. A traditional method to calculate confidence intervals around the median was used because the median follows a normal distribution independent of the sample distribution (Samuels et al. 2012).

Results

Management that used approaches to reduce data lag by using partial data in the last year generally performed better than the approach that increased DML by using the most recent full year of data. Increases in assessment intervals increased the effects of DML with larger changes occurring between assessment intervals of one and two years and smaller changes between assessment intervals of two and three years across all performance metrics. LR1 and LR2 differed on average <2% from the results of C1 across all performance metrics and were effective in reducing the impacts of the two year DML. Life history also altered the effectiveness of lag reduction methods as the differences between the methods were smaller for the slow life history than the fast life history.

Catch for each lag reduction method was higher compared to C2 for all life history, data quality and assessment interval scenarios (Figure 3). The effects of the lag reduction methods were relatively small for the good data scenarios. Differences in median average catch were larger in the poor data scenario. Median average catch was 7% higher in C1 than C2. When compared to C2, the lag reduction methods achieved about a 7% increase in the median catch respectively for the scenario with fast life history and poor data. Increasing assessment intervals also increased the differences in average catch among controls and lag reduction method comparisons slightly. For the data poor scenario with the slow life history, C1, LR1, LR2, and LR3 produced a median average catch that was about 4% higher than C2.

The average biomass achieved by each of the lag reduction methods was similar to the results for catch (Figure 4). Overall, the lag reduction methods seemed to perform similar to C1. The effect of reducing DML on average biomass was greater for the fast life history and poor data scenario with a 9% decrease in the median biomass between C1 and C2. Lag reduction methods resulted in 6-8.3% higher median biomass than the control with a two-year DML. However, in the slow life history scenarios with poor data quality median average biomass was 6% lower in C1 than C2. Differences between C1 and LR1, LR2, and LR3 were less than 2% for the good data scenarios. Similarly, the lag reduction methods had performance that was similar to C1, 5-6% higher median average biomass compared to C2. Assessment interval effects for biomass were largest for the poor data scenarios with an average 3% increase with each additional year between assessments and saw the largest differences between C2 and the lag reduction methods for 3 year assessment intervals across all scenarios. The probability of fishery closure, when stock size (biomass) is ½ of the B/B_{proxy}, was much higher for both the data poor and slow life history scenarios, ranging from overfishing 2% of the time for the good data fast life history to 46% of the time for the poor data slow life history. All of the lag reduction methods had similar performance, <1% difference between their probabilities of fishery closure. However, two year data lag scenarios had a higher probability of fishery closure compared to C1 and the lag reduction methods.

Median probabilities of overfishing ranged from 29% to 43% across all methods and scenarios (Figure 5). The lag reduction methods generally resulted in a lower probability of overfishing than C2, except in the scenario with a fast life history and good data, which had very little difference among the methods.   Results of the slow life history good data scenario were very similar to those for the fast life history. The mean probability of overfishing was about 18% higher for C1 than C2 for the poor data quality scenarios and 2% higher for the good data quality scenarios. Changes between C1 and LR1 and LR2 for the both the good and poor data quality scenarios were virtually zero, while LR3 decreased the probability of overfishing by around 4% when compared C1. The effectiveness of lag reduction methods were largest with the 3 year assessment intervals across all scenarios with the largest effects seen in the poor data quality scenarios.

Confidence intervals around the median catch AAVs indicated no significant differences in performance among the approaches for all of the scenarios (Figure 6). The main differences in catch AAV were that it was lower in the good data quality scenarios than the poor data quality scenarios and that catch AAV generally decreased with increasing assessment interval.

Fishery closures occurred rarely (2%) for the good data quality scenarios and increased to an average 4% for the poor data quality scenarios for C1, LR1, and LR2 (Figure 7). LR3 had the highest probability of fishery closures, 6%, in the poor data quality scenario. Thus, LR3 achieved similar probability of overfishing as the other lag reduction methods by closing the fishery during more years. LR3 caused more frequent fishing closures due to low estimates of abundance in some years. The increases in biomass, decreases in probability of overfishing and increases in catch AAV seen in the above performance metrics are all results of these periods that no fishing was permitted in the model.

Discussion

Lag reduction methods can be successful in reducing the effects of DML to better achieve management goals. Overall, lag reduction methods had the largest effects when the data quality was relatively poor, and effects were small when data quality was high. Lag reduction methods that used age-composition information from the survey, but no or reduced information from the catch in the terminal year of the stock assessment achieved performance that was similar to C1 with full data in the terminal year. Life history, data quality, and assessment interval all played important roles in the effects of DML and effectiveness of lag reduction methods, but lag reduction methods provided benefits over waiting in almost all cases. However, the difference in performance was smallest in the good data quality scenarios. Additionally, the benefits of using lag reduction methods were greatest with longer assessment intervals.

The effects of DML in our study were similar to previous findings (Brown et al. 2012, Li et al. in review, Shertzer and Prager 2007, Sylvia Chapter 2) that delaying management can cause overfishing, decreased biomass, and decreased catches. Our results that there was very little effect of DML under the good data quality scenario agreed with those from Li et al. (in review). Potential costs of not using lag reduction methods especially in data poor scenarios are decreases in catch and higher chances of overfishing. The only negative effects of using lag reduction methods only occurred with method LR3 where there was an increase in the probability of fishery closures. Methods LR1 and LR2 saw very similar performance to having full data for the last year of the assessment.

Data quality can affect the ability of fisheries management to achieve its objectives (McGoodwinn et. al. 2007; Smith et. al. 2011). In the poor data quality scenarios lag reduction methods provided significantly better performance over waiting in terms of increased catch and biomass and decreased probability of overfishing. Management delays can cause an increase in the probability of stock collapse and decreases in catch when there is more uncertainty in assessments (Brown et al. 2010, Shertzer and Prager 2007). However, truly knowing whether or not a stock is in a data poor scenario may be difficult. While many fisheries management bodies label data poor or data limited stocks as having insufficient information to estimate appropriate reference points and stock status (Pilling et al. 2008), our poor quality scenarios were described by larger observation error and larger process error that was not included in the SCAA models. Because simulation models usually portray a greatly simplified view of true systems, most U.S. stock assessments likely resemble our poor data quality scenarios more so than the good data quality scenarios.

The effects of life history on fishery management performance from our study were similar to those found in previous studies (Shertzer and Prager 2007; De Leeuw et. al. 2008; Brown et. al. 2012; Li et. al. in press; Sylvia Chapter 2). Species with a slower life history had smaller effects of DML across all performance metrics than species with faster life histories. While effects of DML were relatively small in the slow life history scenarios, they were still significant for the poor data scenario. The smaller effect of DML with a slow life history may be due to lower fishing mortality rates (F_{lim} of 0.07 for the slow life history compared to 0.19 for the fast life history) resulting in smaller population changes and greater stock stability (Patterson and Résimont 2007). Although slow life history species may have a smaller response to DML in the short term, longer lived species may also take much longer to recover once affected by damaging consequences of delay (Shertzer and Prager 2007).

The effects of stock assessment interval on the management performance were similar to those from other studies (Mace et al. 2001; ICES 2012; Li et al., in review; Sylvia Chapter 2). Longer assessment intervals can mean larger decreases in average catch and biomass, increases in the probability of overfishing and increases in the catch AAV (Mace et al. 2001 and Li et al. in review). Longer assessment intervals can degrade management performance, but the effects are usually less than the effects of DML (Sylvia Chapter 2). Interactions between assessment intervals and DML however can be much worse than any single effect. Comparing stocks managed with annual assessments to ones with assessments every two years caused up to a 4% increase in the effects of DML across performance metrics.

LR1 performed relatively well at meeting management goals and required the least amount of data. Even with missing age-composition of the catch in the terminal year of the assessment, performance metrics showed less than a 2% difference between a C1 and LR1. Ono et al. (2014) similarly did not see strong differences with the addition of fishery age composition data to stock assessment. While our study used SCAA models, this technique may also be successfully applied to other stock assessment models. Seasonal separable VPA models, which estimated age-compositions for years in which catch-at-age data is missing, provided similar estimates to conventional stock assessments for Norway pout (*Trisopterus esmarkii*) and sandeel (*Ammodytes tobianus*) (Cook and Reeves 1993).

LR2 seemed to be the most successful at meeting management goals of the three lag reduction methods. LR2 differed, on average, <1% from the results of the annual DML (C1) across all performance metrics and was effective in offsetting the impacts of the two year DMLs. This method is currently used successfully with some stocks managed by the North Pacific Fishery Management Council in order to reach a one year data lag goal (AFSC 2014). LR2 was most successful because it had the best age composition data. Having a reduced effective sample size in the last year should not have a large effect on estimation model performance if information from the history of the fishery is available (Ono et al. 2014). Method LR2 was, however, the most data heavy of the three methods. While length-at-age data should be relatively fast to collect, additional data in the model may result in longer data collection preparation time and may still result in longer lags with comparatively small gains compared to LR1. While method LR3 produced similar average catch, biomass, and probability of overfishing with the other lag reduction methods, it also resulted in higher probabilities of fishery closure. Sampled catch-at-age data may fail at mimicking the population age-structure well (Pope 1988) and may explain why a lack of age composition of the index may cause degrading model performance.

Practical implementation of our results relies on the ability to collect informative age and length composition data, especially in years prior to the terminal year. C1 was used to represent an idealized case in which DML can be reduced to one year by either aging all the samples for that year or having a situation where growth does not change over time. Changes in fish growth overtime have been observed for many fish stocks (Thorson and Minte-Vera, 2014), however growth has remained relatively constant in many others (Hilborn and Minte-Vera, 2008; Thorson and Minte-Vera, 2014). Our C2 approach is represents how age composition data are used in many U.S. fisheries management systems, where years with missing data are excluded from the stock assessment, thus adding to DML. LR1 and LR2 represents fisheries with differing amounts of error between the data used in prior years and those used in the terminal year of the catch composition. Results of LR1 and LR2 emphasize that even if temporal trends in growth are not substantial, assessments that use previous years' age-length data may still perform well as long as there is some good age composition data is available. Our reductions in effective sample size in the last year are probably larger than would be expected if inverse age-length keys were used to generate age compositions for the most recent year. In fact, if growth has not changed over time, using all the age-length data to estimate expected size at age would likely outperform using individual year's data because the sampling error would be reduced. Our LR3 approach, however, demonstrated that there are limits to how little information can be included in the most recent year of the stock assessment and still obtain satisfactory management results. When the age compositions for the fishery and the survey in the most recent year had very low effective sample sizes, the fishery performed poorly with more frequent closures. Additionally, another lag reduction method we tested that used no catch or survey age-composition data in the terminal year of the assessment was rarely able to estimate recruitment in the last year and was excluded from the study.

While LR1 and LR2 had similar performance to C1, there are still additional potential cases where lag reduction methods may not succeed. Complications with missing age-composition data in the assessment such as failing to notice changing trends in recruitment and failure to forecast future conditions can be a likely result of these techniques (Mace et al. 2001). One strong assumption of the lag reduction methods is that there were no trends in growth over time. We would expect a breakdown in success of these methods if growth changed over time as growth rates must be explicitly estimated in age-structured population models (Quinn and Deriso, 1999). Ono et al. (2014) tested the quality and quantity of length and age-composition data in three species and found that the usefulness of age-composition data decreased as the variation of the relationship between length and age increased. Species or data sets with high variation in length-at-age may be less successful in the use of lag reduction methods. Stocks which rely only on catch data are not likely candidates for lag reduction methods.

Our research supports the conclusions of (Sylvia Chapter 2) that DML and assessment intervals can have a relatively large effect on fisheries management outcomes. The most effective way to decrease DML effects may be to decrease the fisheries management timeline (Shertzer and Prager 2007; Brown et al. 2010). We agree that shortening the management process would be an effective means to mitigate problems associate with DML without decreasing the amount of data used in stock assessments (Sylvia, chapter 2). Because changing the management system can be a lengthy process, we recommend adopting assessment procedures that attempt to fully use the most recent available data instead of waiting on more data (Shertzer and Prager 2007). Having no catch age-composition, or using length data to infer age-composition in the terminal year of the assessment are both successful techniques in reducing DML and should be considered as such in future fisheries management plans.

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Table 1. Design and details of lag reduction methods. Lag reduction method 1 is a control with annual data lag. Lag reduction method 2 is a control with two year data lag.

Lag reduction method	Full age-composition in terminal year	ESS_{survey}(terminal year)	ESS_{catch}(terminal year)	Data lag
C1	Yes	200, 50*	200, 50*	1
LR1	No	200, 50*	0	1
LR2	No	200, 50*	50, 12*	1
LR3	No	50, 12*	50, 12*	1
C2	Yes	200, 50*	200, 50*	2

Table 2. Equations governing the population and data-generating dynamics in the operating model

	Equation	Description
1	$R_t = \dfrac{S_{t-a_R}}{1-\left(\dfrac{5h-1}{4h}\right)+\left(1-\dfrac{S_{t-a_R}}{S_{eq}}\right)} e^{\theta_R - 0.5\sigma_R^2}$	Stock-recruit relationship
2	$N_{t,a} = \begin{cases} R_t & a = a_R \\ N_{t-1,a-1} e^{[-M - s_{a-1}F_{t-1}]} & a_R < a \le a_{\max} \end{cases}$	Abundance-at-age
3	$L_a = L_\infty(1-e^{-k(a-a_0)})$	Length-at-age
4	$w_a = bL_a{}^c$	Weight-at-length
5	$m_a = \dfrac{1}{1+e^{-\left(\frac{a-m_{50\%}}{m_{slope}}\right)}}$	Maturity-at-age
6	$S_t = \sum_{a=a_R}^{a_{\max}} m_a w_a N_{t,a}$	Spawning biomass
7	$S_{t,a} = \dfrac{1}{1+e^{-\left(\frac{a-S_{50\%,t}}{S_{slope}}\right)}}$	Selectivity-at-age in the fishery
8	$s_{50\%_t} = \bar{s}_{50\%} e^{\varepsilon_{s_t} - 0.5_s^2}$ $\varepsilon_{st} = \rho_s \varepsilon_{s_{t-1}} + \sqrt{1-\rho_s^2 \phi_t}$ $\phi_t \sim N(0, \sigma_s^2)$	Time-varying and autocorrelated selectivity
9	$M_t = Me^{\varepsilon_{M_t} - 0.5\sigma_M^2}$	Time-varying and autocorrelated natural mortality

$$\varepsilon_{M,t} = \rho_M \varepsilon_{M_{t-1}} + \sqrt{1-\rho_M^2 \phi_{M,t}}$$

$$\phi_{M,t} \sim N(0, \sigma_M^2)$$

10 $$C_{t,a} = \frac{F_{t,a}}{Z_{t,a}}(1-e^{-Z_{t,a}})N_{t,a}W_{t,a}$$ Baranov-catch Eq.

11 $$I_{t,a} = q_t s_{s,a} N_{t,a}$$ True index of abundance

12 $$q_t = q_{t-1} e^{\varepsilon_{qt}}$$ Catchability

$$\varepsilon_{q_t} \sim N(0, \sigma_q^2)$$

13 $$C_{obs,t} = C_t e^{\varepsilon_{C_t} - 0.5\sigma_C^2}$$ Observed catch

$$\varepsilon_{C_t} \sim N(0, \sigma_C^2)$$

14 $$I_{obs_t} = e^{\varepsilon_{I_t} - 0.5\sigma_I^2} \sum_a I_{a,t}$$ Observed index of abundance

$$\varepsilon_{I_t} \sim N(0, \sigma_I^2)$$

15 $$P_{obs_t} = \frac{1}{n} \mathbf{\Theta}_t$$ Proportion of catch-at-age

$$\mathbf{\Theta}_t \sim Multinomial(n, \mathbf{p}_t)$$

$$\mathbf{p}_t = \frac{1}{I_t}\left(I_{a_r,t}, \dots, I_{a_{max},t}\right)$$

16 $$\ell_1 = 0.5n\log(\sigma_C^2) + \sum_t \left(\log\left(C_{obs_t}\right) - \log\left(C_{est_t}\right)\right)^2$$ Lognormal likelihood components for the catch and index of abundance

$$\ell_t = 0.5n\log(\sigma_I^2) + \sum_t \left(\log\left(I_{obs_t}\right) - \log\left(I_{est_t}\right)\right)^2$$

17 $$\ell_3 = -E_C \sum_t \sum_a p_{obs,C_{t,a}} \log(p_{est,C_{t,a}})$$

Multinomial likelihood components for the proportion of the catch and index

$$\ell_4 = -E_I \sum_t \sum_a p_{obs,I_{t,a}} \log(p_{est,I_{t,a}})$$

Table 3. Symbols, specified life history and time-varying parameters of model.

		Life history	
Parameter	**Description**	**Slow**	**Fast**
a_R	Age at recruitment	5	3
a_{max}	Maximum age	20	12
M	Natural mortality rate	0.1	0.2
R_0	Unfished equilibrium recruitment	$1\text{x}10^6$	$1\text{x}10^6$
h	Steepness	0.6	0.75
a_0	Age at length = 0	0	0
L_∞	Asymptotic maximum length	90	90
k	Growth rate	0.07	0.13
b	Length-weight relationship scalar	$3.5 \text{ x } 10^{-6}$	$3.5 \text{ x } 10^{-6}$
c	Length-weight relationship exponent	3.15	3.15
m_{50}	Age at 50% maturity	7	3.5

m_{slope}	Slope of maturity function	1	1
s_{f50}	Mean age at 50% selectivity in the fishery	1.75	3.5
s_{s50}	Mean age at 50% selectivity in the survey	1.3	2.6
s_{fslope}	Slope of fishery selectivity function	1	1
s_{sslope}	Slope of survey selectivity function	1	1

Time Varying parameters

σ_R	Standard deviation of stock-recruit relationship	0.77, 1.25
Φ_R	Autocorrelation in recruitment	0.44
σ_M	Standard deviation of time-varying M	0.15
Φ_M	Autocorrelation in M	0.3, 0.9
σ_f	Standard deviation of age at 50% selectivity in fishery	0.1
Φ_f	Autocorrelation in fishery selectivity	0.3, 0.9
σ_C	Standard deviation of catch estimates	0.15
σ_I	Standard deviation of survey estimates	0.29, 0.63

Additional model variables

a	Age
t	Year
R	Recruitment
S	Spawning biomass
s_f	Fishery selectivity
s_s	Survey selectivity
N	Abundance
m	maturity
C	Catch

I	Index of abundance
q	Catchability
Z	Total mortality
W	Weight-at-age
m	Maturity-at-age
F	Fishing mortality
E	Effective sample size of the catch/ index
n	Number of observations
p_{obs}	Observed proportion at age
p_{est}	Estimated proportions at age
$\boldsymbol{\Theta_t}$	Multinomial function
ℓ_t	Likelihood function
ε_{s_t}	Error for selectivity
ε_{q_t}	Error for catchability
ε_M	Error for natural mortality
ε_{I_t}	Error for index of abundance
ε_{C_t}	Error for catch
σ_q	Standard deviation for catchability
ρ_M	Correlation coefficient of natural mortality
ρ_s	Correlation coefficient of selectivity

Table 4. 95 % confidence intervals for each life history and data scenarios, combinations are paired by stock assessment interval and lag reduction methods. C1 represents control 1 of the lag reduction methods with an annual data lag, LRM1 is lag reduction method 1, LR2 is lag reduction method 2 and LRM3 is lag reduction method 3. C2 is control 2 of the lag reduction method with a 2 year data lag. Confidence intervals were calculated around the median with a Bonferonni correction to account for multiple comparisons.

	Fast life history, Good data quality			
Combination	Catch	Biomass	Probability of overfishing	AAV in catch
1, C1	149872.4, 152671.6	1057152.8, 1086097.2	0.301, 0.326	0.102, 0.105
1, LRM1	149382.1, 152191.9	1056443.8, 1085771.2	0.301, 0.326	0.104, 0.106
1, LRM2	150113.5, 152911.5	1059006.2, 1088053.8	0.282, 0.307	0.103, 0.105
1, LRM3	150001.2, 152805.8	1059458.3, 1088606.7	0.292, 0.316	0.103, 0.105
1, C2	147139.1, 150415.9	1054232.0, 1089738.0	0.300, 0.327	0.098, 0.101
2, C1	148788.2, 151683.8	1051867.6, 1081402.4	0.302, 0.326	0.082, 0.085
2, LRM1	148474.3, 151409.7	1050691.8, 1080748.2	0.301, 0.326	0.083, 0.086
2, LRM2	148846.4, 151744.6	1066017.0, 1095678.0	0.302, 0.326	0.084, 0.087
2, LRM3	148618.9, 151524.1	1067035.1, 1097099.9	0.282, 0.306	0.087, 0.090
2, C2	145745.1, 149426.9	1046385.7, 1084399.3	0.300, 0.328	0.079, 0.082
3, C1	148292.1, 151297.9	1045451.6, 1075808.4	0.321, 0.345	0.075, 0.077
3, LRM1	148503.9, 151563.1	1042991.5, 1074173.5	0.321, 0.345	0.075, 0.078
3, LRM2	148748.1, 151809.9	1050940.4, 1081709.6	0.302, 0.326	0.076, 0.079
3, LRM3	148236.1, 151318.9	1057048.5, 1088516.5	0.302, 0.326	0.078, 0.081
3, C2	145218.0, 149685.0	1030411.4, 1073458.6	0.319, 0.348	0.070, 0.074

	Fast life history, Poor data quality			
Combination	Catch	Biomass	Probability of overfishing	AAV in catch
1, C1	127568.3, 131423.7	1029996.8, 1090433.2	0.3184, 0.3483	0.1888, 0.1973
1, LRM1	126889.6, 130973.4	1017022.0, 1080643.0	0.3181, 0.3486	0.1923, 0.2010
1, LRM2	127760.9, 131642.1	1036910.3, 1099054.7	0.3183, 0.3483	0.1887, 0.1971
1, LRM3	127514.0, 131390.0	1036611.5, 1098783.5	0.3183, 0.3483	0.1892, 0.1977
1, C2	118399.0, 124359.0	957009.2, 1034658.3	0.3532, 0.3919	0.1790, 0.1928
2, C1	125743.1, 129983.9	1007044.0, 1070811.0	0.3183, 0.3484	0.1458, 0.1547
2, LRM1	123538.9, 127984.1	1003869.6, 1069285.4	0.3179, 0.3487	0.1483, 0.1575
2, LRM2	124930.8, 129039.2	1035461.3, 1098968.7	0.3188, 0.3478	0.1534, 0.1621
2, LRM3	124453.9, 128671.1	1044723.6, 1109476.4	0.2997, 0.3277	0.1616, 0.1704
2, C2	114623.7, 120969.3	930327.9, 1010505.6	0.3821, 0.4218	0.1399, 0.1545
3, C1	996838.9, 1062011.1	121976.0, 126405.0	0.3380, 0.3679	0.1303, 0.1392
3, LRM1	979703.8, 1046956.2	121563.0, 126278.0	0.3375, 0.3683	0.1320, 0.1414
3, LRM2	1009667.6, 1074987.4	122951.7, 127428.3	0.3383, 0.3675	0.1343, 0.1435
3, LRM3	1019362.5, 1085092.5	122410.3, 126863.7	0.3191, 0.3476	0.1385, 0.1474
3, C2	907267.6, 990009.4	110857.7, 117578.3	0.4108, 0.4520	0.1210, 0.1368

	Slow life history, Good data quality			
Combination	Catch	Biomass	Probability of overfishing	AAV in catch
1, C1	1787503.8, 1849926.2	151451.6, 155410.4	0.299, 0.328	0.082, 0.092
1, LRM1	1785591.4, 1848433.6	151242.5, 155228.5	0.299, 0.328	0.083, 0.093
1, LRM2	1792442.5, 1854772.5	151183.4, 155131.6	0.299, 0.328	0.083, 0.093
1, LRM3	1790125.7, 1852504.3	151262.7, 155214.3	0.299, 0.328	0.083, 0.093
1, C2	1756096.4, 1824853.6	148449.9, 152670.1	0.318, 0.348	0.082, 0.094
2, C1	1753202.3, 1816382.7	148569.9, 152674.1	0.319, 0.348	0.064, 0.074
2, LRM1	1752144.7, 1815985.3	148388.6, 152526.4	0.319, 0.348	0.064, 0.074
2, LRM2	1768102.5, 1832042.5	148610.6, 152723.4	0.299, 0.328	0.065, 0.075
2, LRM3	1757832.5, 1822072.5	148205.8, 152300.2	0.300, 0.328	0.067, 0.077
2, C2	1727088.5, 1797711.5	146169.1, 150612.9	0.318, 0.348	0.064, 0.075
3, C1	1723293.4, 1787656.6	145426.1, 149629.9	0.319, 0.348	0.057, 0.066
3, LRM1	1720562.8, 1785702.2	145299.7, 149547.3	0.319, 0.348	0.056, 0.066
3, LRM2	1725256.5, 1790033.5	145614.5, 149820.5	0.319, 0.348	0.058, 0.068
3, LRM3	1739827.4, 1806607.6	147303.6, 151593.4	0.319, 0.348	0.060, 0.070
3, C2	1679967.0, 1753858.0	143856.0, 148615.0	0.338, 0.368	0.055, 0.067

	Slow life history, Poor data quality			
Combination	Catch	Biomass	Probability of overfishing	AAV in catch
1, C1	124306.2, 129342.8	1678362.7, 1798767.3	0.317, 0.350	0.161, 0.185
1, LRM1	123328.6, 128477.4	1658306.2, 1780558.8	0.317, 0.350	0.160, 0.185
1, LRM2	124430.7, 129475.3	1674319.1, 1795330.9	0.317, 0.350	0.160, 0.184
1, LRM3	124762.2, 129820.8	1662994.7, 1784370.3	0.317, 0.350	0.161, 0.185
1, C2	118757.0, 124507.0	1581803.3, 1714426.7	0.335, 0.371	0.160, 0.187
2, C1	121704.7, 127077.3	1610497.3, 1732942.7	0.336, 0.369	0.120, 0.144
2, LRM1	120930.1, 126427.9	1591832.5, 1716037.5	0.336, 0.370	0.119, 0.144
2, LRM2	121339.1, 126771.9	1618910.7, 1742684.3	0.317, 0.350	0.123, 0.148
2, LRM3	121159.6, 126586.4	1641798.8, 1766686.2	0.317, 0.349	0.128, 0.153
2, C2	115690.5, 121751.5	1533127.3, 1668607.7	0.354, 0.391	0.120, 0.148
3, C1	119846.8, 125470.2	1596476.3, 1721388.7	0.337, 0.369	0.103, 0.128
3, LRM1	119868.5, 125653.5	1579166.8, 1706223.2	0.336, 0.370	0.103, 0.129
3, LRM2	119310.0, 124991.0	1581327.2, 1707877.8	0.337, 0.369	0.105, 0.131
3, LRM3	119296.7, 125003.3	1587388.9, 1714706.1	0.337, 0.369	0.109, 0.134
3, C2	113999.3, 120494.7	1452285.9, 1591834.1	0.374, 0.411	0.100, 0.129

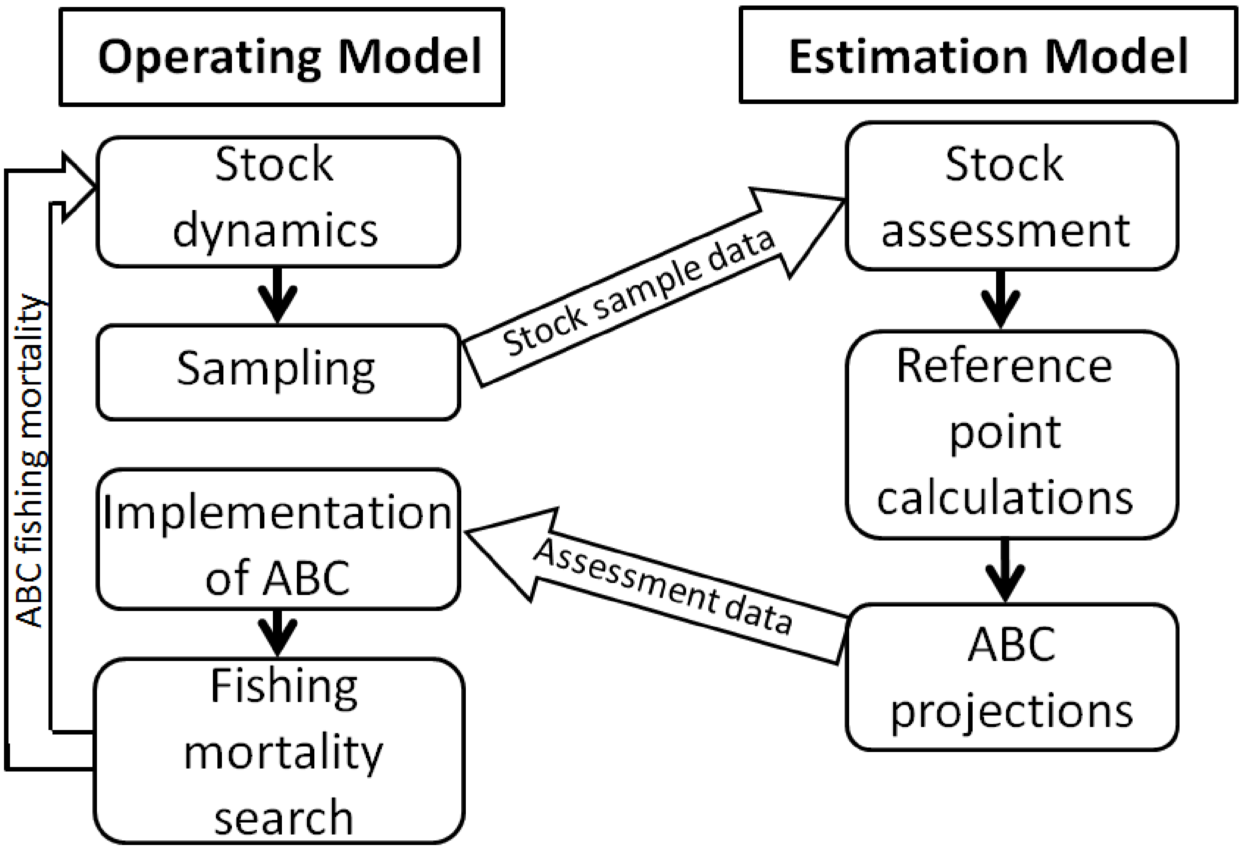

Fig. 1. Flow diagram of management strategy evaluation model with both operating and estimation models.

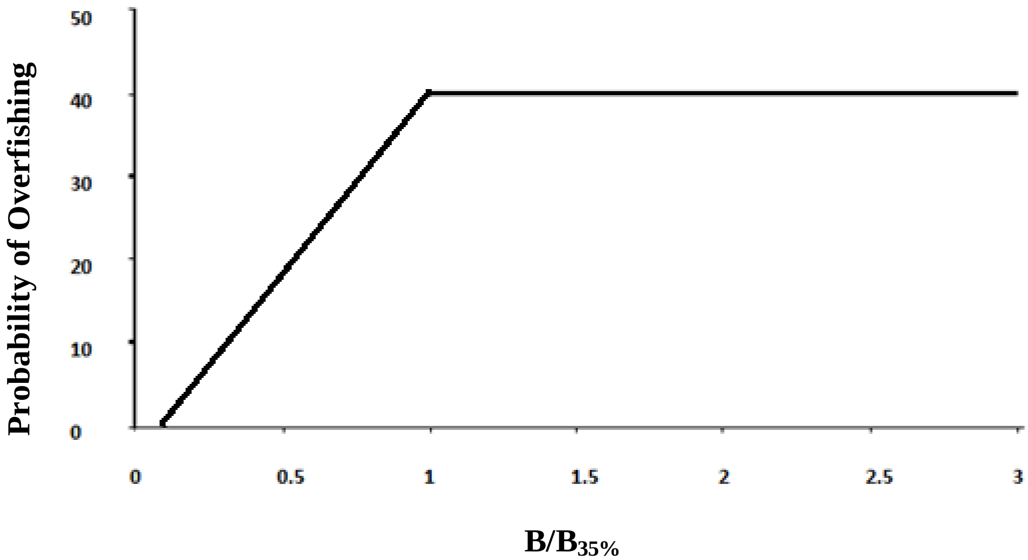

Fig. 2. Mid-Atlantic P* approach showing decreasing probability of overfishing with a declining $B/B_{35\%}$ ratio

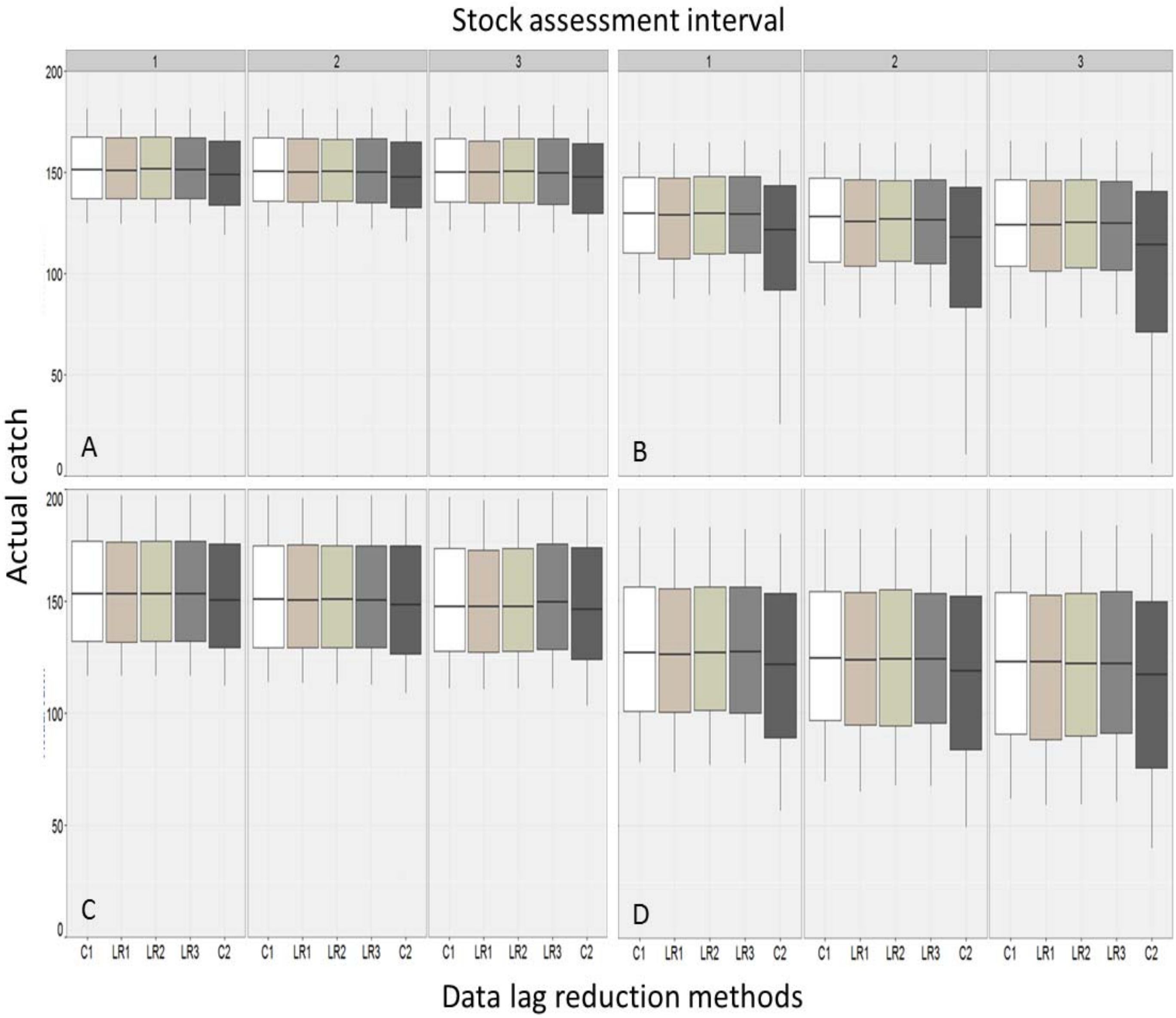

Fig. 3. Box plots of the catch for each life history and data scenarios. Scenario A is the fast life history with good data, scenario B is the fast life history with poor data. Scenario C is the slow life history with good data, and scenario D is the slow life history with poor data. C1 represents control 1 of the lag reduction methods with an annual data lag, LRM1 is lag reduction method 1, LR2 is lag reduction method 2 and LRM3 is lag reduction method 3. C2 is control 2 of the lag reduction method with a 2 year data lag. The horizontal lines of the box plot show the median biomass and the whiskers represent the 10^{th} and 90^{th} percentiles.

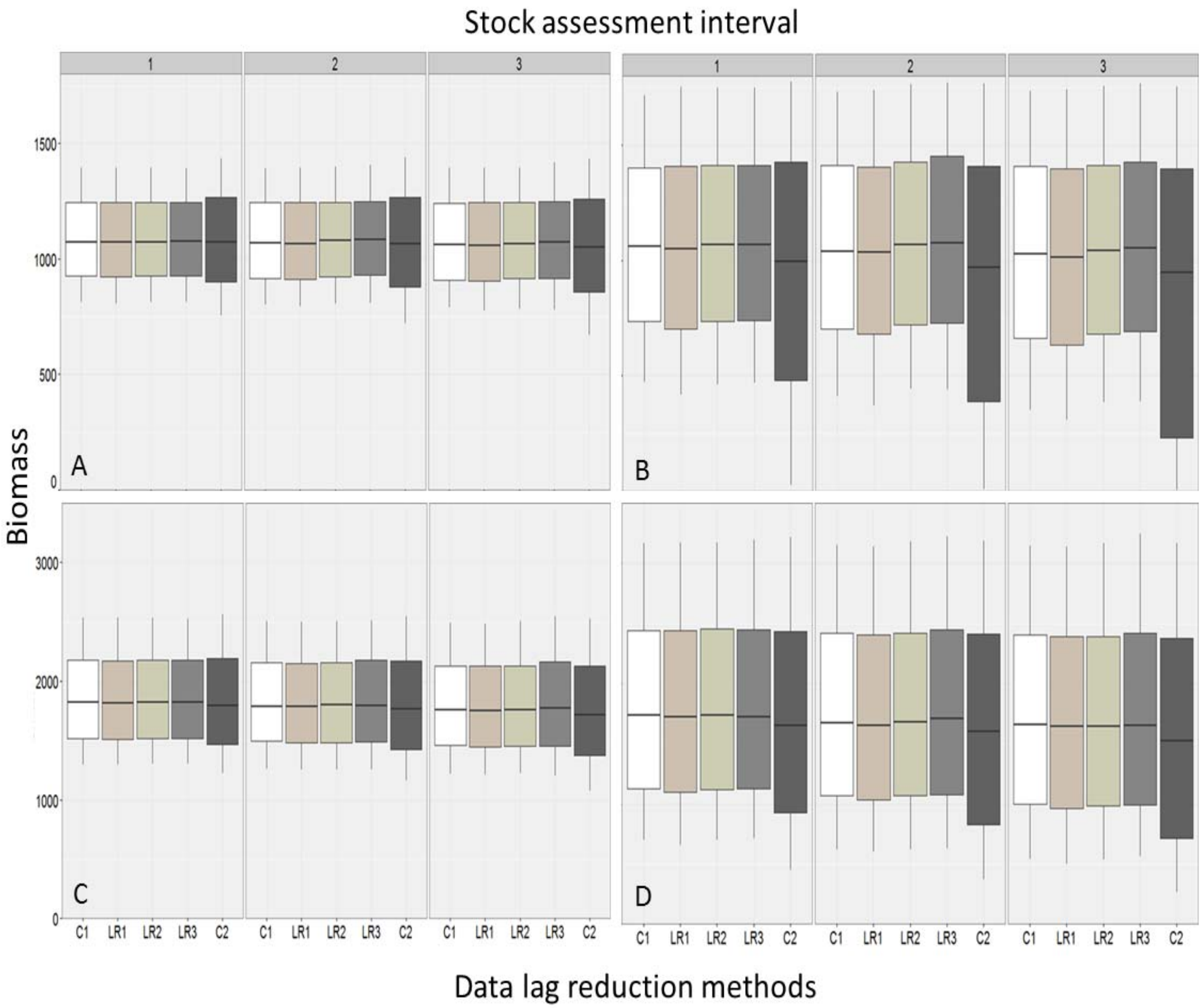

Fig. 4. Box plots of the biomass for each life history and data scenarios. Scenario A is the fast life history with good data, scenario B is the fast life history with poor data. Scenario C is the slow life history with good data, and scenario D is the slow life history with poor data. C1 represents control 1 of the lag reduction methods with an annual data lag, LRM1 is lag reduction method 1, LR2 is lag reduction method 2 and LRM3 is lag reduction method 3. C2 is control 2 of the lag reduction method with a 2 year data lag. The horizontal lines of the box plot show the median biomass and the whiskers represent the 10^{th} and 90^{th} percentiles.

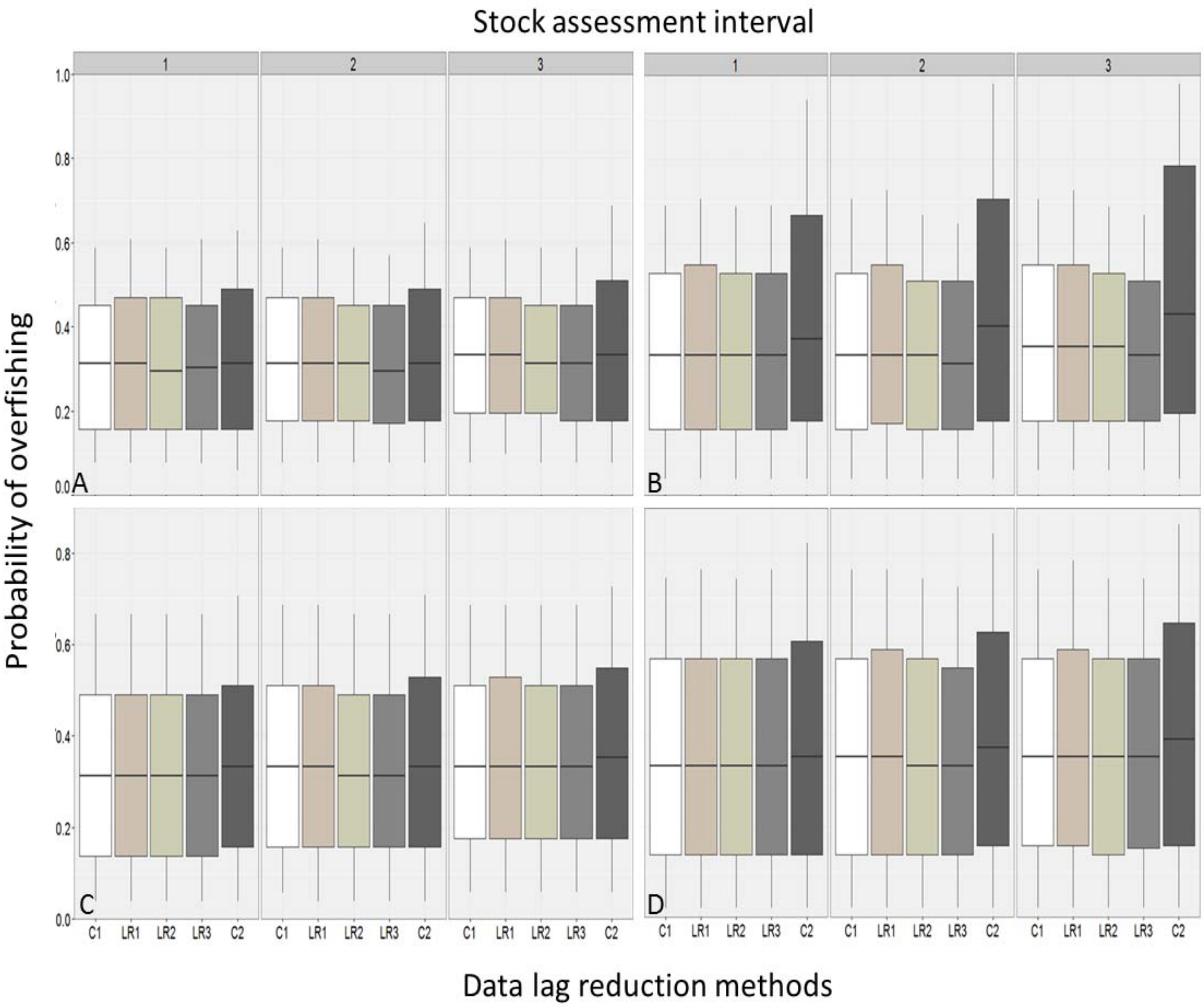

Fig. 5. Box plots of the probability of overfishing for each life history and data scenarios. Scenario A is the fast life history with good data, scenario B is the fast life history with poor data. Scenario C is the slow life history with good data, and scenario D is the slow life history with poor data. C1 represents control 1 of the lag reduction methods with an annual data lag, LR1 is lag reduction method 1, LR2 is lag reduction method 2 and LR3 is lag reduction method 3. C2 is control 2 of the lag reduction method with a 2 year data lag. The horizontal lines of the box plot show the median biomass and the whiskers represent the 10^{th} and 90^{th} percentiles.

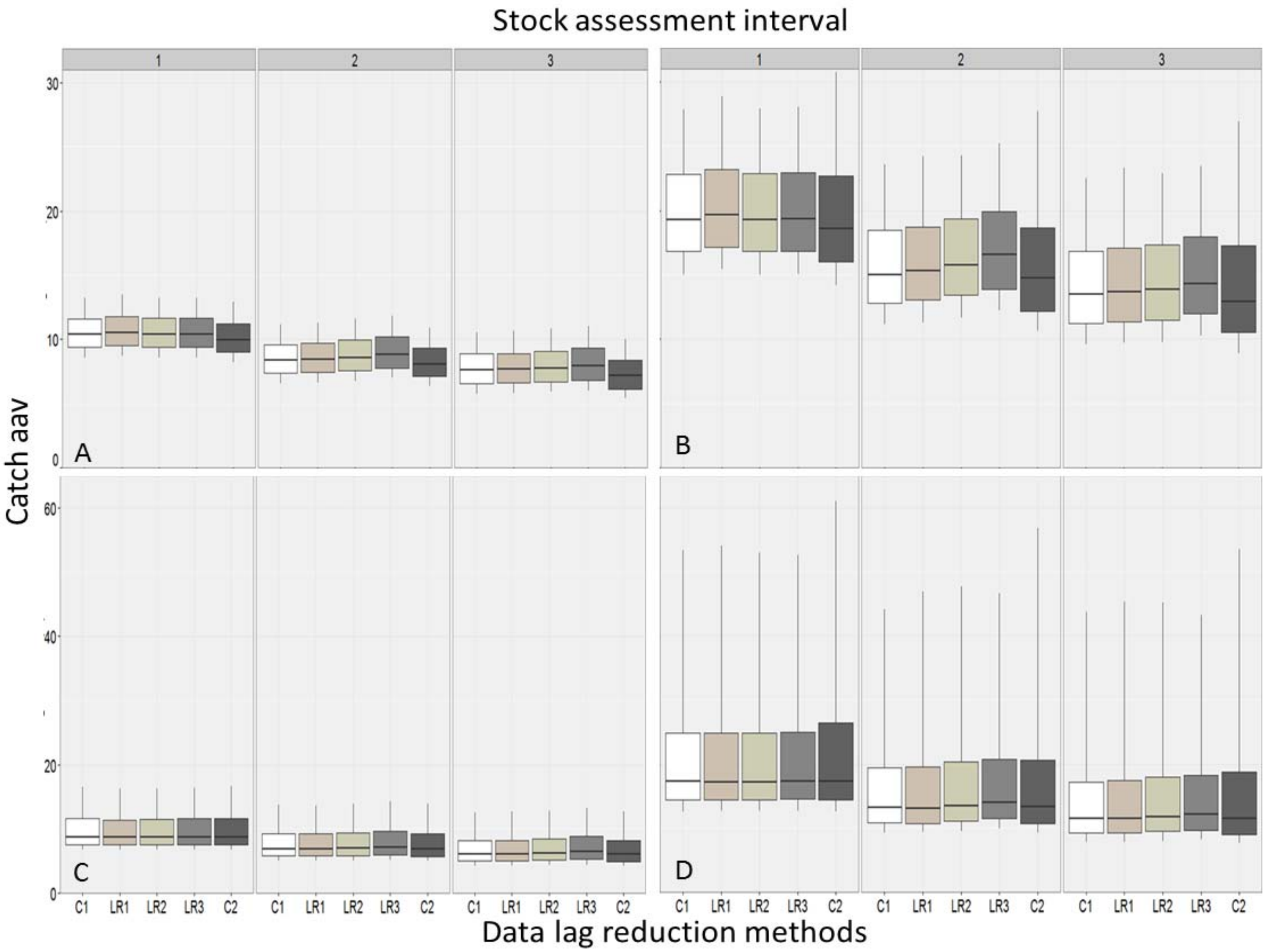

Fig. 6. Box plots of the AAV of catch for each life history and data scenarios. Scenario A is the fast life history with good data, scenario B is the fast life history with poor data. Scenario C is the slow life history with good data, and scenario D is the slow life history with poor data. C1 represents control 1 of the lag reduction methods with an annual data lag, LR1 is lag reduction method 1, LR2 is lag reduction method 2 and LR3 is lag reduction method 3. C2 is control 2 of the lag reduction method with a 2 year data lag. The horizontal lines of the box plot show the median biomass and the whiskers represent the 10^{th} and 90^{th} percentiles.

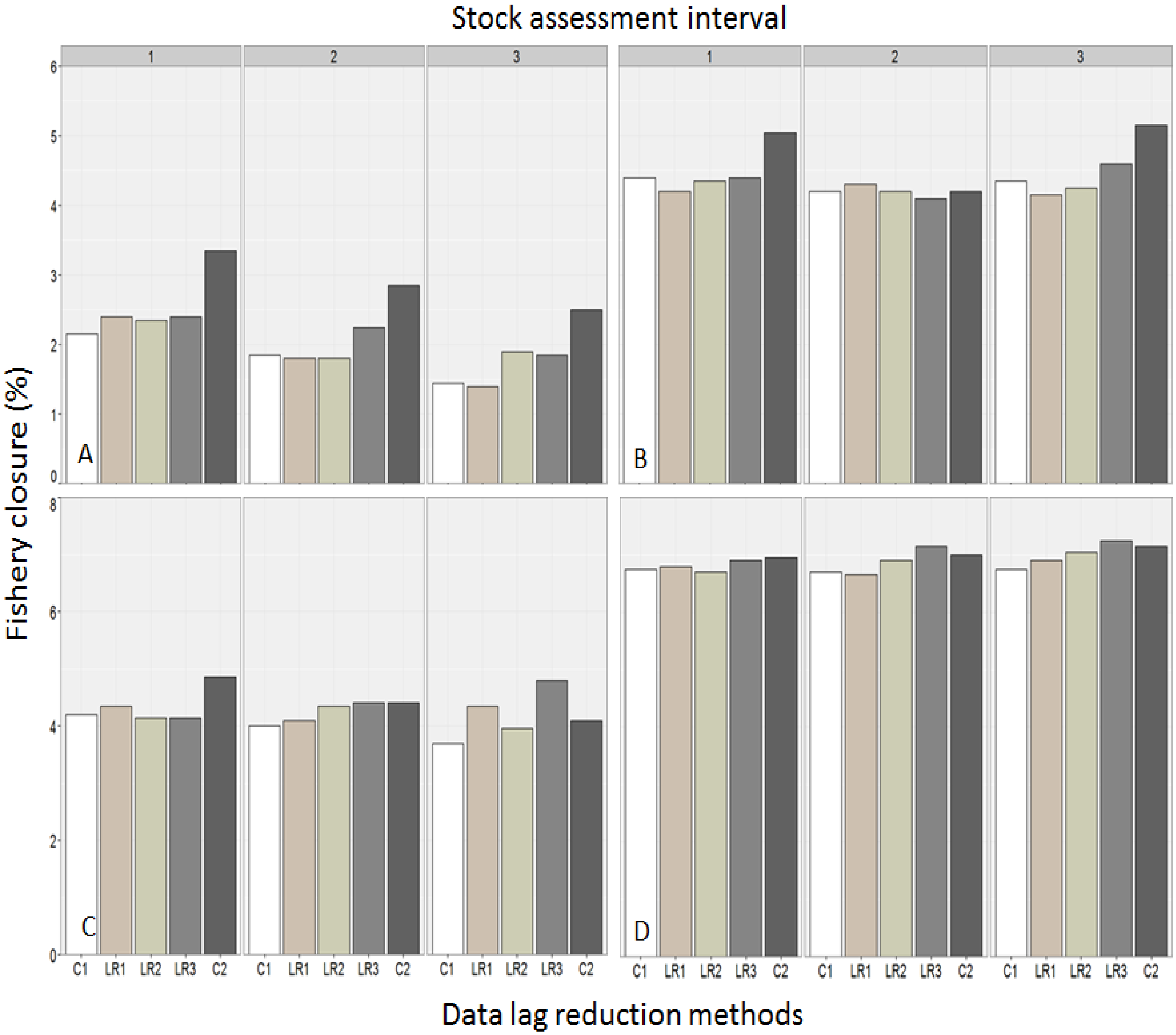

Fig. 7. Fishery closure percentage for each life history and data scenarios. Scenario A is the fast life history with good data, scenario B is the fast life history with poor data. Scenario C is the slow life history with good data, and scenario D is the slow life history with poor data. C1 represents control 1 of the lag reduction methods with an annual data lag, LR1 is lag reduction method 1, LR2 is lag reduction method 2 and LR3 is lag reduction method 3. C2 is control 2 of the lag reduction method with a 2 year data lag.

Chapter 4. Autocorrelated error in stock assessment estimates: Implications for management strategy evaluation

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Abstract

Management strategy evaluation (MSE) modeling is often used in fisheries science to evaluate the effects of different management. MSE models typically include a stock assessment component to estimate population size and management reference points based on data generated within the model, but including a full assessment within the model can be computationally intensive. A commonly used alternative to the full assessment approach is to simulate the error from the stock assessment as a stochastic process with an assumed level of autocorrelated estimation error. There is little guidance, however, on what might be a reasonable assumed amount of autocorrelation, and what factors might influence this amount. In this paper we estimated the amount of temporal autocorrelation in errors of estimated biomass and recruitment from statistical catch at age (SCAA) stock assessment models over a series of scenarios spanning life histories, exploitation levels, recruitment variability, and data quality. Autocorrelation in the error in biomass estimates (ϕ_S) was positive and relatively high, with median estimates ranging between 0.6 and 0.9. Estimates were highest for the slow life history and lowest for the fast life history. Exploitation level also affected the amount of autocorrelation, with higher values for lightly exploited populations. On average, however, estimates of ϕ_S did not change over time as more data were included in the assessment, and were independent of whether or not a harvest policy was applied. Recruitment variability and data quality had relatively minor effects on autocorrelation of errors.

Keywords: Management strategy evaluation, stock assessment error; lag-1 autocorrelation

Introduction

Simulation modeling is often used in fisheries science to evaluate the effects management decisions have on a resource (e.g. a population, assemblage, or community) and on stakeholders (Milner-Gulland et al. 2010). This class of simulation models is referred to as management strategy evaluation (MSE) or the management procedure (MP) approach (Butterworth et al. 2010). The MSE approach in fisheries has become a widely used tool to aid fisheries managers in variety of areas. For example, MSE has been used to identify robust harvest control rules in both data-rich (Punt et al. 2008; A'Mar et al. 2009) and data-poor situations (Wiedenmann et al. 2013; Carruthers et al. 2014), as well as for selecting effective regulations for controlling recreational harvests (Miller et al. 2010).

An MSE model typically has three components, an operating model, an assessment model, and a management model, and these components are designed to mimic the resource dynamics and scientific assessment process, and how these interact with the management options being tested. In the operating model the population(s) of interest is projected through time, and the true status is known. Data are generated in the operating model based on the true state and an observation process, usually with some level of observation error. These data are then used in the assessment model to estimate population status. The estimated status in the model informs the management model and is used in conjunction with a harvest strategy to determine the total allowable catch and possibly the regulations to achieve that catch. The catch is then removed from the population in the following time step, and this loop is repeated for a number of years and model iterations to account for uncertainty in the population, assessment and management dynamics.

For the stock assessment model of the MSE loop, two approaches are typically used, termed the "full" or "stochastic process" approaches (ICES 2013). The full approach implements a complete stock assessment model, such as statistical catch at age model (SCAA) that estimates a suite of parameters and produces estimates over the entire time series of data availability (A'Mar et al. 2009; Punt et al. 2002). Depending upon the assessment model being used and the data being generated, a large number of parameters may be estimated (100+), which can cause run times for the MSE to be quite lengthy. For example, most SCAA models require numerical solutions and search over the parameter space to find the best parameter estimates, requiring hundreds or thousands of iterations. This can cause run times to be 100-1000 times longer than an MSE without an integrated assessment model.

A commonly used alternative to the full approach is to simulate the error from the stock assessment as a stochastic process. The stochastic process approach greatly reduces the computation time of the MSE, which allows for a greater exploration of management options and uncertainty scenarios. One example of the stochastic process approach, the time series of estimated biomass (S_{est}) is modeled as a lag-1 autocorrelated error process around the true biomass (S)

$$
\begin{aligned}
&S_{est}(t) = S e^{\varepsilon_S(t) - 0.5\sigma_S^2} \\
&\varepsilon_S(t) = \phi_S \varepsilon_S(t-1) + \sqrt{1-\phi_S^2}\,\varphi_S(t) \qquad (1) \\
&\varphi_S(t) \sim N(0, \sigma_S^2)
\end{aligned}
$$

where ϕ_S determines the degree of autocorrelation in the estimates (Punt et al. 2008). Similar approaches have used a first order auto regressive process (Irwin et al. 2008; Wilberg et al. 2008). In the stochastic process approach all the error dynamics are controlled by specifying different levels of σ_S^2 and ϕ_S. Drawbacks of the stochastic process stock assessment approach are that it does not produce the full range of output of an assessment and it may not capture complex feedbacks between the state of the system and the variance, bias, and correlation of errors. If additional assessment output is needed in the MSE loop (e.g. fishery selectivity, recruitment time series), then additional assumptions must be made by the analyst. For example, Irwin et al. (2008) generated estimates of abundance at age using the same error structure used to estimate biomass, such that an overestimate of biomass of 10% was the result of an overestimate of abundance of 10% in all age classes. The stochastic process approach also requires specifying the variance and autocorrelation (e.g., ϕ_S). Simulation studies will often use a single value for ϕ_S (e.g. Irwin et al. 2008) or a range of values (e.g. Punt et al. 2008), but in general, the assumed values are high ($\rho_S > 0.7$). While the assumption of high positive autocorrelation of assessment errors seems reasonable based on the multi-year effects that are produced in age-structured models (e.g., Mohn 1999), there does not appear to be a foundation to assist researchers in choosing the appropriate values.

Given the increasing importance of MSE models in fisheries management (Butterworth et al. 2009; Milner-Gulland et al. 2010), and the potential impact the assumed value of ϕ_S can have on the results when using the stochastic process assessment approach, it would be valuable to have a more formal basis for for implementing the stochastic approach in MSEs. In this study we used a simulation model to estimate the degree of temporal autocorrelation in biomass estimates from a full SCAA assessment model. The simulation model was run over a range of species life histories and exploitation intensities to identify potential factors controlling the amount of autocorrelation.

Methods

To understand the temporal autocorrelation of errors in stock assessment estimates, the estimated values from a stock assessment model must be compared to the true values. Because the true dynamics (e.g. biomass, recruitment) are unknown for real world systems, we conducted a simulation study in which we simulated the true population dynamics and applied a stock assessment model over a range of scenarios encompassing different life histories, exploitation histories, and levels of data quality. The simulation model was developed in AD Model Builder (Fournier et al., 2012), and contains three main components. The foundation of the simulation is the operating model, which determines the population dynamics of the stock and how data are generated. Data generated in the operating model are based on the true dynamics within the model with some specified amount of observation error. The operating model generates data on fishery harvests, as well as a fishery-independent index of abundance. These data are then used in the assessment model to estimate stock status and biological reference points. The assessment model was an SCAA model (Fournier and Archibald 1982), and output from the assessment is used in the management model to determine the catch limit using a harvest policy. The catch limit estimated in the management model is removed from the population, without implementation error, and the simulation loop continued for a set number of years. This process is repeated many times for each model specification (e.g. life history) to account for the variability in the population dynamics, data generation, and assessment estimation. At the end of each run, the true and estimated values of biomass and recruitment are stored and used to calculate the amount of autocorrelation in the error in these estimates. Our simulation model evaluated the effects of two management models to determine how management may affect the quality of assessment estimates.

Operating, Assessment, and Management Models

The population dynamics followed an age-structured model (Quinn and Deriso 1999) with the equations governing the dynamics in Table 1. Equations used in the model are referenced by their number in Table 1, such that the numerical abundance-at-age is referred to as equation T1.1. The population began at unfished equilibrium abundance at age in year 1 of the simulation. Annual abundance of recruited ages was determined from the abundance of that cohort the previous year, decreased by continuous natural and fishing mortality (equation T1.1). Recruitment to the population followed the Beverton-Holt stock-recruit relationship, with bias-corrected lognormal stochasticity and autocorrelated deviations (equation T1.2). Parameters controlling the degree of autocorrelation and variability in recruitment (Table 2) were based on the recruitment meta-analysis of Thorson et al. (2014). Parameters for the Beverton-Holt model were derived from the unfished spawning biomass, unfished recruitment, and the steepness parameter (equation T1.3), where steepness represents the fraction of unfished recruitment that results when the spawning biomass is reduced to 20% of the unfished level. Total spawning biomass in a given year was calculated by summing the product of the maturity at age, weight at age and abundance at age over all recruited age classes (equation T1.4). Weight at age was an allometric function of length at age, which followed a von Bertalanffy growth function (equations T1.5 and T1.6). The proportion mature at age was calculated using a logistic function (equation T1.7). Length, weight, and maturity at age were fixed for a given species life history.

The model contained a single fishery, with a logistic selectivity function (equation T1.8). The selectivity ogive varied over time as the parameter that determines the age at 50% selectivity varies annually in an autocorrelated manner (equation T1.8), although the source for the changes was not modeled explicitly. Because both natural (M) and fishing mortality (F) occurred continuously throughout the year, catch was calculated using the Baranov catch equation (Quinn and Deriso 1999; equation T1.9).

Each model run was divided into two periods. The initial period covers 30 years, while the management period covers 25 years. The population started the initial period in the unfished state. A single fishery developed during the initial period, which was described by a linear increase in fishing mortality (F) until year 15, followed by a constant at the peak fishing mortality for the remainder of the initial period. The intensity of fishing (F = 0.5, 1.0, 2.5 × F_{MSY} for the light, moderate, or heavy exploitation scenarios) at the plateau during this period along with the pattern of recruitment determined the population abundance at the start of the management period.

At the start of management period (year 31) the population was first assessed using data generated during the initial period, starting in year 10, and with a 1-year lag between the last year of the data collected and when the assessment is done. Thus, the estimation model did not include the full fishing history for the stock. Fishery catch data (both total and proportions-at-age) and a fishery-independent survey-derived index of abundance (both total and proportions-at-age) were generated annually. These data were generated by applying observation error to the true values (equations T1.10 - T1.14) using lognormal distributions for the total catch and index of abundance and multinomial distributions for the proportions at age. We included two scenarios of coefficient of variation for the total catch and index data and effective sample sizes for the proportions at age to explore the interactions between data quality and the autocorrelation in assessment estimates (Table 2).

The time series of catch and survey data were input into the SCAA model to estimate the abundance at age and fishing mortality rates in each year. The parameters estimated in the SCAA were the initial abundance (associated with the first year of data), recruitments and fishing mortality rates (across years), fishery selectivity parameters, and the survey catchability. Parameters were estimated using a maximum likelihood approach with lognormal likelihood functions for the total catch and total index of abundance and multinomial likelihood functions for the proportions at age in the catch and index of abundance (Table 3). The selectivity and survey catchability parameters that varied over time in the operating model were assumed to be constant over time in the SCAA, and natural mortality was assumed to be constant at the true mean value. All other required SCAA inputs (i.e., maturity- and weight-at-age) were set to the true values specified in the operating model. The SCAA model also estimated the spawning potential ratio (SPR) based reference points to calculate a target catch (NEFSC 2002). The target fishing mortality rate was specified at $F_{35\%}$ for all life histories. The spawning biomass reference point and catch limit were calculated by multiplying the SPR and yield-per-recruit (YPR) from fishing at $F_{35\%}$, respectively, by the mean estimate of recruitment over the time series (NEFSC 2002; Haltuch et al. 2008). Because the weight at age and maturity at age were fixed at the true values, the SPR-based reference points varied across assessments based on the estimated fishery selectivity and the estimated mean recruitment. Assessments were conducted annually during years 31 – 55.

We explored a constant fishing mortality rate scenario and one in which the target fishing mortality rate was $F_{35\%}$. In the first management scenario, no harvest policy is used and the F throughout the management period is fixed at the plateau value from the initial period (0.5, 1.0 or 2.0 x F_{MSY}). In this case, the population experienced constant fishing mortality rates during the assessment period years 31 – 55. In the second management scenario, a harvest policy was applied whereby the target catch was estimated using the abundance in the terminal year and the $F_{35\%}$ from the assessment model; this level of catch is removed from the population the following year by calculating the resulting F using the Baranov catch equation (Quinn and Deriso 1999). Fishing at $F_{35\%}$ is reasonably close to the determinsistic F_{MSY} for all exploitation scenarios.

Parameterization and Model Runs

We ran the model over a range of scenarios to identify factors affecting the level of autocorrelation in the estimation error from the assessment model. We explored three life histories, three exploitation histories, two management scenarios, and two levels of data quality and recruitment variability (Table 4). The different life histories explored were ‘slow’, ‘medium’ and ‘fast’. The slow life history had slow growth, late maturation, and low productivity. In contrast, the fast life history had rapid growth, early maturation, and high productivity. The medium life history was between the slow and fast life histories. For each life history, we set the maximum age (7, 12, and 20 years for the fast, medium and slow life histories, respectively), mean natural mortality rate (0.4, 0.2, and 0.1), and steepness of the stock-recruitment function (0.9, 0.75, and 0.6). The maximum age was an aggregate age class. All other life history parameters were either fixed across life histories (L_∞ and the length-weight parameters b and c) or determined from the other parameters. The mean natural mortality, M, was used to determine growth rate, $k = M/1.5$, and age at 50% maturity, $m_{50\%} = M / 1.4$ (Charnov and Berrigan 1991; Charnov et al. 1993; Frisk et al. 2001), which then determined the initial age at 50% selectivity in the fishery ($s_{f,50\%}(t=1) = m_{50\%}$). Both M and $s_{f,50\%}$ varied through time in an autocorrelated manner; Eqn T1.8). For the survey, age at 50% selectivity was lower than that of the fishery, $s_{s,50\%} = 0.75\ s_{f,50\%}(t=1)$, and was rounded down to the nearest integer to determine the age at recruitment to the population, $a_R = \lfloor s_{s,50\%} \rfloor$.

For the data quality scenarios, we modeled a "good" and "poor" case, whereby several factors were adjusted to affect assessment performance (Table 4). For each case we varied the CV of the observation error in the survey (lower for the good scenario), the number of samples collected to generate age structured data (higher for the good case), and the amount of autocorrelation in the time-varying parameters (lower in the good scenario). In addition, we explored two levels of recruitment variability, with the levels of variability based on the meta-analysis of Thorson et al. (2014).

For each scenario, 1000 iterations were run. At the end of each run, the terminal estimate of biomass and recruitment from each assessment was stored along with the true values, and we calculated the amount of lag-1 autocorrelation in the error of biomass and recruitment estimates using a maximum likelihood approach (Table 3).

Results

For the model runs with a constant fishing mortality rate during the assessment period (runs 1-4 in Table 4), estimates of the lag-1 autocorrelation (ϕ_S) in biomass errors were always positive, with the majority of values between 0.5 and 1.0. Life history and exploitation history had clear effects on ϕ_S (Figure 2). Across life histories, ϕ_S was highest for the slow life history and lowest for the fast life history, with the medium one in between. Median estimates of ϕ_S ranged between 0.62 and 0.87 for fast life history, between 0.74 and 0.92 for the medium life history, and between 0.86 and 0.94 for the slow life history. For a particular life history, estimates of ϕ_S increased as the fishing mortality rate decreased. However, the magnitude of the differences across exploitation scenarios varied with the species life history. The largest differences in ϕ_S across fishing mortality rates exhibited with the fast life history, and the smallest were for the slow life history (Figure 2). Results from the scenario with higher recruitment variability were about that same as those from the scenario with lower recruitment variability. Poorer data quality usually resulted in slightly higher values of ϕ_S across life history, exploitation, and recruitment variability levels.

When a harvest policy was applied that used the stock assessment to estimate the target catch (model runs 5-8 in Table 4) the effect was a reduction in the range of potential estimates for ϕ_S. Median estimates of ϕ_S ranged between 0.64 and 0.69 for fast life history, between 0.71 and 0.81 for the medium life history, and between 0.85 and 0.87 for the slow life history (Table 5). Compared to the runs where no harvest policy was applied, the medians of ϕ_S when a harvest policy was applied were similar to the moderate fishing mortality rate runs. Across life histories, applying the harvest policy resulted in the largest change (generally a decline) in estimates of ϕ_S for the fast life history , and the smallest change for the slow life history (largest declines observed were 0.2 and 0.07, respectively; Table 5). Within a particular life history, the impact of the harvest policy had the greatest effect on estimates of ϕ_S for the light exploitation scenario (Table 5).

To determine if ϕ_S changed over the time as more data were included in the assessment, we split the time series in half and calculated ϕ_S for each half, then determined the difference between the estimates (late ϕ_S– early ϕ_S). The median difference was centered around 0 for all model runs, but the variability depended upon exploitation history and whether or not a harvest policy was applied. Using a harvest policy increased the range of ϕ_S for the light exploitation scenario and decreased the range for the heavy exploitation scenario (Figure 3).

The impact of exploitation history on estimates of ϕ_S was explored by relating the estimates of ϕ_S with the mean fishing mortality rate (relative to the true $F_{35\%}$) over the entire estimation period. There was a significant negative relationship between the mean $F / F_{35\%}$ and the estimated ϕ_S, such that increasing fishing pressure resulted in lower estimates of ϕ_S (Figure 4), although this relationship only explained 22% of the variability in ϕ_S.

For each time series of stock assessment estimates we also calculated the autocorrelation in the recruitment error, ϕ_R, across model runs (Figure 2 and Table 5). The pattern of ϕ_R across life histories followed the opposite trend compared to ϕ_S, with generally higher estimates of ϕ_R for the fast life history and the lowest estimates for the slow life history. Estimated ϕ_R was positively correlated with ϕ_S, but ϕ_R was usually less than ϕ_S (Figure 5). For the fast life history, estimates of ϕ_R and ϕ_S were scattered around the 1:1 line, although the slope of a linear regression through the data is significantly different from 1 (95% CI: 0.694 – 0.726**).** For both the medium and slow life histories, the majority of estimates are well below the 1:1 line, also with slopes different from unity (95% CI: 0.694 – 0.736 for the medium life history and 0.47 – 0.61 for the slow life history).

Discussion

In this paper we estimated the amount of temporal autocorrelation in errors of estimated biomass and recruitment from SCAA stock assessment models over a series of scenarios spanning life histories, exploitation levels, recruitment variability, and data quality. Autocorrelation in the error in biomass estimates (ϕ_S) was positive and relatively high, with median estimates ranging between 0.6 and 0.9. Estimates were highest for the slow life history and lowest for the fast life history. Exploitation level also affected the amount of autocorrelation, with higher values for lightly exploited populations. On average, however, estimates of ϕ_S did not change over time as more data were included in the assessment, and were independent of whether or not a harvest policy was applied. In contrast, recruitment variability and data quality had relatively minor effects on autocorrelation of errors.

In general, higher autocorrelation in the error in biomass estimates indicates poorer estimation by the stock assessment model, as estimates are more consistently above or below the true value. Therefore it is not surprising that estimation was poorer for the scenarios with light exploitation, as there was reduced contrast in the data to help with the estimation. It is well known that increased contrast in data such as a time series of relative abundance is more informative and improves parameter estimation in a range of assessment models (e.g., Hilborn and Mangel 1997; Magnusson and Hilborn 2007). For SCAA models, Magnusson and Hilborn (2006) showed that data with the additional contrast of a return trip provide no additional information to the model, and do not result in and increased ability to estimate parameters. Additionally, our results agree with other simulation studies that found SCAA models have substantially lower accuracy in low fishing mortality rate scenarios than high fishing mortality rate scenarios (Bence et al. 1993; Wilberg and Bence 2006). Although higher levels of fishing mortality improved estimation (Figure 5), a return trip, which occurred for the heavy exploitation scenarios with a harvest policy applied, resulted in comparable or slightly higher estimates of ϕ_S (Δ_ϕ between -0.05 and 0; Table 5).

Life history also had an important effect on ϕ_S. Estimates of ϕ_S increased with increasing longevity. A key difference across life history scenarios is the relative contribution of recruits to the total population biomass. For the fast life history with fewer age classes, higher growth rates and higher productivity at low population sizes, recruits comprise a greater proportion of the population biomass compared to the medium and slow life histories. Recruitment estimates generally had lower autocorrelation than biomass estimates (Figure 5), so it follows that for cases where recruits comprise a sizeable proportion of the biomass (the fast life history and the heavy exploitation scenario) that $\phi_S$would be lower. Additionally, the fishing mortality rates were lower, on average, for the slow life history than for the medium or fast life histories.

Our results have a number of implications for fisheries management simulations and development of MSE models. First, for MSE studies relying on the stochastic process method of simulating assessments, including autocorrelation of assessment errors is necessary to replicate the outcomes of actual assessment model. Our results provide a range of estimates that can inform choices of the crucial ϕ_S parameter. In studies using the stochastic process approach, higher values have typically been assumed. For example, Irwin et al. (2008) and Wilberg et al. (2008) fixed ϕ_S = 0.7 in their study of harvest policies for yellow perch (*Perca flavescens*) in Lake Michigan. Punt et al. (2008) explored a range of values ϕ_S = 0, 0.71, and 0.87 in their study of threshold control rules for groundfish along the western U.S., and they found that the level of ϕ_S had an effect on the interannual variability in catches resulting from a particular management policy, an important factor for consideration when selecting a harvest option. While the estimates of autocorrelation used in these studies are within the range of values identified in our simulations, a broader range of values, both below 0.7 and above 0.9 may be warranted under some conditions. The selection of a particular value should be tied to the life history and exploitation level of the species being modeled, with lower values of ϕ_S and ϕ_R in scenarios with high exploitation rates and fast life histories (Figure 2; Table 5).

Another important implication for MSE modeling is that the error in biomass and recruitment estimates does not show the same level of autocorrelation. Our study found that recruitment error autocorrelation, ϕ_R, was generally lower than biomass ϕ_S, particularly for the medium and slow life histories (Figure 5). When using the stochastic process MSE assessment approach, one way to estimate recruitments is to use the true age structure and the biomass estimated using Eqn. 1 (e.g. Irwin et a. 2008), but this method assumes the same level of autocorrelation in biomass and recruitment estimates. Our analyses show that an alternative approach to estimating recruitment may be more appropriate when using the stochastic process assessment method. One possibility is to draw recruitment and biomass errors from a multivariate distribution with a positive correlation between the errors depending upon the life history of the species being modeled (Table 5).

Ideally, parameters of a stochastic process could be chosen such that the full stock assessment and stochastic process approaches would result in the same general predictions for a given case study. The results of studies that have compared full and shortcut assessment approaches in MSE models indicate that the different assessment approaches can lead to differing predictions for what the optimal harvest policy may be under certain conditions (ICES 2013). This result does not necessarily invalidate the use of the stochastic process assessment approach in MSE models. Rather, it emphasizes the importance of carefully choosing the parameters for the stochastic process approach. For example, a full age-structured assessment will provide estimates (with error) of recruitments, selectivities, and possibly biological reference points. If the management system being modeled requires short term projections, then these estimates can be used in the projections, and error will propagate through time, potentially influencing the performance of a particular harvest policy. In contrast, the stochastic process approach does not produce these estimates, so assumptions must be made if projections are to be done. For example, selectivity at age may be fixed at the true value, and recruitments may be generated using the estimated biomass and the true proportions at age (Irwin et al. 2008). If a stochastic process approach is going to be used in an MSE, investigators should conduct some simulation studies to identify levels of autocorrelation in errors that allow the stochastic process to closely match the pattern of errors from full assessments.

Managing fish stocks in the face of uncertainty is a key challenge for fisheries managers, and MSE models are an essential tool to help identify robust management practices across a range of uncertain outcomes. However, MSE models that include a full stock assessment are limited in the number of scenarios that can be explored due to the sometimes lengthy computation time. Using the stochastic process approach within an MSE is a useful alternative, particularly when a large number of scenarios must be explored, and the results of this paper can be used as a guide in the selection of appropriate levels of autocorrelation in error in biomass and recruitment estimates. Future work, however, is needed to identify if either the full stock assessment or stochastic process approach is more robust in identifying optimal management policies because both approaches rely on substantial simplifications of complex processes.

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Table 1. Equations governing the population and data-generating dynamics in the operating model.

	Equation	Description
	Population dynamics	
1	$N(a,t)=\begin{cases} R(t) & a=a_R \\ N(a-1,t-1)e^{-Z(a-1,t-1)} & a_R<a<a_{max} \\ N(a-1,t-1)e^{-Z(a-1,t-1)}+ & a=a_{max} \\ N(a,t-1)e^{-Z(a,t-1)} & \end{cases}$	Numerical abundance at age
2	$R(t)=\dfrac{S(t-a_R)}{\alpha+\beta S(t-a_R)}e^{\varepsilon_R-0.5\sigma_R^2}$	Stock-recruit relationship
	$\alpha=\dfrac{S_0(1-h)}{4hR_0}$ $\quad\beta=\dfrac{5h-1}{4hR_0}$	
	$\varepsilon_R(t)=\rho_R\varepsilon_R(t-1)+\sqrt{1-\rho_R^2}\varphi_R(t)$	
	$\varphi_R(t)\sim N(0,\sigma_R^2)$	
3	$S(t)=\sum_a m(a)w(a)N(a,t)$	Spawning biomass
4	$Z(a,t)=M(t)+s(a,t)F(t)$	Total mortality with time-varying natural mortality
	$M(t)=\bar{M}e^{\varepsilon_M(t)-0.5\sigma_M^2}$	
	$\varepsilon_M(t)=\rho_M\varepsilon_M(t-1)+\sqrt{1-\rho_M^2}\varphi_M(t)$	
	$\varphi_M(t)\sim N(0,\sigma_M^2)$	

Life history

5 $L(a) = L_\infty\left(1 - e^{-k(a-a_0}\right)$ Length at age

6 $w(a) = bL(a)^c$ Weight at length

7 $m(a) = \frac{1}{1 + e^{-\frac{a-m_{50}}{m_{slope}}}}$ Maturity at age

Fishing dynamics

8 $s(a,t) = \frac{1}{1+e^{-\frac{a-s_{50}(t)}{s_{slope}}}}$ Selectivity at age in fishery or survey, with time varying selectivity (only in the fishery)

$s_{50\%}(t) = \bar{s}_{50\%}e^{\varepsilon_s(t)-0.5\sigma_s^2}$

$\varepsilon_s(t) = \rho_s\varepsilon_s(t-1)1) + \sqrt{1-\rho^2}\varphi(t))$

$\varphi(t)\sim N(0,\sigma_s^2)$

9 $C(a,t) = \frac{s(a,t)F(t)}{Z(a,t)}w(a)N(a,t)\left(1 - e^{-Z(a,t)}\right)$ Total catch

$C(t) = \sum_a C(a,t)$

Data-generating dynamics

10	$C_{obs}(t) = C(t)^{\varepsilon_C(t) - 0.5\sigma_C^2}$ $\varepsilon_C(t) \sim N(0, \sigma_C^2)$	Observed catch
11	$I(a,t) = q(t)s_s(a)N(a,t)$ $I(t) = \sum_a I(a,t)$ $q(t) = qe^{\varepsilon_q(t) - 0.5\sigma_q^2}$ $\varepsilon(t) \sim N(0, \sigma_q^2)$	True index of abundance
12	$I_{obs}(t) = I(t)^{\varepsilon_I(t) - 0.5\sigma_I^2}$ $\varepsilon_I(t) \sim N(0, \sigma_I^2)$	Observed index of abundance
13	$\mathbf{p}_{obs}(t) = \frac{1}{n}\mathbf{\Theta}(t)$ $\mathbf{\Theta}(t) \sim Multinomial(n, \mathbf{p}(t))$ $\mathbf{p}(t) = \frac{1}{I(t)}(I(a_R, t), \dots, I(a_{max}, t))$	Observed vector of propotion-at-age in fishery *f*

Table 2. Parameters values used in the model. Life history – invariant parameters are presented at the top, with multiple values explored for the "good" and "bad" assessment cases.

Parameter	Description	Value		
σ_R	standard deviation of stock-recruit relationship	0.77, 1.25		
ϕ_R	autocorrelation in recruitment	0.44		
σ_M	standard deviation of time-varying M	0.15		
ϕ_M	autocorrelation in M	0.3, 0.9		
σ_f	standard deviation of age at 50% selectivity in fishery	0.1		
ϕ_f	autocorrelation in fishery selectivity	0.3, 0.9		
σ_C	standard deviation of catch estimates	0.15		
σ_I	standard deviation of survey estimates	0.29, 0.63		
E_C	effective sample size of the catch	200, 50		
E_I	effective sample size of the survey	200, 50		
		Slow	Medium	Fast
a_R	Age at recruitment (to population)	5	3	1
a_{max}	Maximum age	20	12	7
M	Mean natural mortality rate	0.1	0.2	0.4
R_0	Virgin recruitment	1×10^6	1×10^6	1×10^6
h	Steepness	0.6	0.75	0.9
a_0	Age at length=0	0	0	0
L_∞	Maximum length	90	90	90
k	Growth rate	0.07	0.13	0.27
b_1	L-W scalar	3.0×10^{-6}	3.0×10^{-6}	3.0×10^{-6}
b_2	L-W exponent	3	3	3
m_{50}	Age at 50% maturity	7	3.5	1.75
s_{50}	mean age at 50% selectivity in fishery	7	3.5	1.75
s_{50}	mean age at 50% selectivity in fishery	5.3	2.6	1.3
m_{slope}	Slope of maturity function	1	1	1
s_{slope}	Slope of selectivity function	1	1	1

Table 3. Likelihood functions used in the statistical catch at age (SCAA) stock assessment model, and used to estimate the amount of lag-1 autcorrelation in the error of the stock assessment estimates.

Equation	**Description**
$\mathcal{L}_{SCAA} = \sum_i \ell(i)$	Full likelihood for SCAA model
$\ell(1) = 0.5n\log(\sigma_C^2) + \sum_t \left(\log\left(C_{obs}(t)\right) - \log(C_{est}(t))\right)^2$	Likelihood component for annual catches
$\ell(2) = 0.5n\log(\sigma_I^2) + \sum_t \left(\log\left(I_{obs}(t)\right) - \log(I_{est}(t))\right)^2$	Likelihood component for annual index of abundance
$\ell(3) = -E_C \sum_t \sum_a p_{obs,C}(a,t)\log(p_{est,C}(a,t))$	Likelihood component for annual proportion-at-age in the catch
$\ell(4) = -E_I \sum_t \sum_a p_{obs,I}(a,t)\log(p_{est,I}(a,t))$	Likelihood component for annual proportion-at-age in the index
$\mathcal{L}_\phi = -\frac{n}{2}\log(2\pi) - n\log(\sigma) - \sum_t S(t) + 0.5\log(1-\phi^2) - \frac{1}{2\sigma^2}\sum_{t>1}(\log(S(t) - \phi\log\left(S(t-1) - \log\left(S_{est}(t)\right) + \phi\log\left(S_{est}(t)\right)\right))^2 - \frac{1-\phi^2}{2\sigma^2}(\log(S(1) - \log(S_{est}(1)))^2$	Likelihood for estimating the lag-1 autocorrelation in the estimation error in biomass (or recruitment)

Table 4. List of model runs explored in the model for each life history and exploitation level.

Model run	Effective sample size (E)	Survey error (σ_I)	ϕ_M	ϕ_f	Recruitment variability (σ_R)	Harvest policy?
1	200	0.29	0.3	0.3	0.77	no
2	50	0.63	0.9	0.9	0.77	no
3	200	0.29	0.3	0.3	1.25	no
4	50	0.63	0.9	0.9	1.25	no
5	200	0.29	0.3	0.3	0.77	yes
6	50	0.63	0.9	0.9	0.77	yes
7	200	0.29	0.3	0.3	1.25	yes
8	50	0.63	0.9	0.9	1.25	yes

Table 5. Comparison of the median estimates of the autocorrelation in biomass assessment error (ϕ_S) across model runs when an assessment-based harvest policy was or was not used, and the difference between these estimates ($\Delta_\phi = \phi_S$(no policy) – ϕ_S(policy)).

Model Run	Exploitation history	Life history	ϕ_S (harvest policy)	ϕ_S (no policy)	$\Delta\phi_S$	ϕ_R (harvest policy)	ϕ_R (no policy)	$\Delta\phi_R$
Low assessment error and low recruitment variability	light	fast	0.69	0.87	0.17	0.63	0.65	0.02
		medium	0.82	0.90	0.09	0.53	0.49	-0.04
		slow	0.85	0.93	0.07	0.47	0.46	-0.02
	moderate	fast	0.69	0.75	0.06	0.62	0.62	0.00
		medium	0.82	0.85	0.04	0.50	0.48	-0.02
		slow	0.87	0.90	0.03	0.37	0.35	-0.02
	heavy	fast	0.67	0.61	-0.05	0.62	0.58	-0.04
		medium	0.80	0.76	-0.04	0.53	0.51	-0.01
		slow	0.87	0.85	-0.01	0.36	0.37	0.01
High assessment error and low recruitment variability	light	fast	0.71	0.87	0.16	0.65	0.70	0.05
		medium	0.81	0.92	0.11	0.59	0.56	-0.03
		slow	0.86	0.94	0.07	0.19	0.12	-0.07
	moderate	fast	0.67	0.75	0.08	0.61	0.65	0.04
		medium	0.79	0.85	0.06	0.53	0.49	-0.04
		slow	0.86	0.91	0.05	0.23	0.13	-0.10
	heavy	fast	0.66	0.63	-0.03	0.60	0.58	-0.02
		medium	0.78	0.79	0.00	0.50	0.51	0.02
		slow	0.87	0.87	0.00	0.17	0.18	0.01
Low assessment error and high recruitment variability	light	fast	0.67	0.86	0.20	0.61	0.63	0.01
		medium	0.82	0.90	0.09	0.50	0.44	-0.06
		slow	0.85	0.92	0.07	0.37	0.36	-0.01
	moderate	fast	0.67	0.74	0.07	0.59	0.59	0.00
		medium	0.81	0.85	0.04	0.45	0.43	-0.03
		slow	0.87	0.91	0.04	0.30	0.27	-0.03
	heavy	fast	0.66	0.62	-0.04	0.60	0.57	-0.02
		medium	0.80	0.76	-0.04	0.48	0.47	0.00
		slow	0.87	0.86	-0.01	0.31	0.29	-0.02
High assessment error and high recruitment variability	light	fast	0.69	0.87	0.18	0.62	0.67	0.05
		medium	0.81	0.92	0.11	0.48	0.36	-0.12
		slow	0.87	0.94	0.06	0.12	0.13	0.01
	moderate	fast	0.66	0.75	0.09	0.60	0.62	0.03
		medium	0.79	0.86	0.07	0.45	0.42	-0.02
		slow	0.86	0.91	0.05	0.08	0.05	-0.02
	heavy	fast	0.64	0.64	0.00	0.58	0.58	0.00
		medium	0.78	0.77	-0.02	0.45	0.46	0.01
		slow	0.87	0.87	0.00	0.07	0.06	-0.01

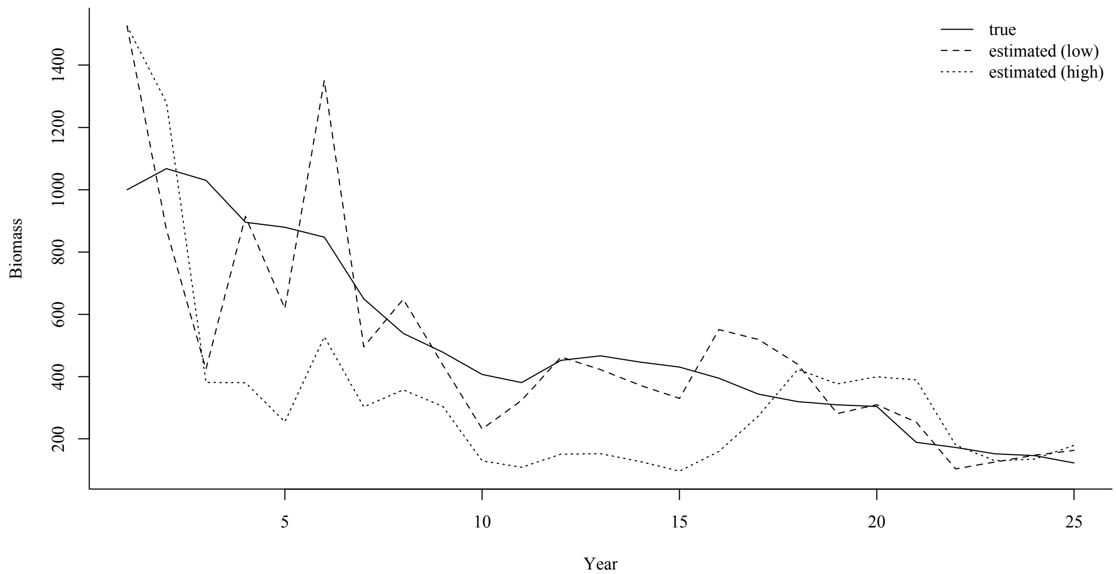
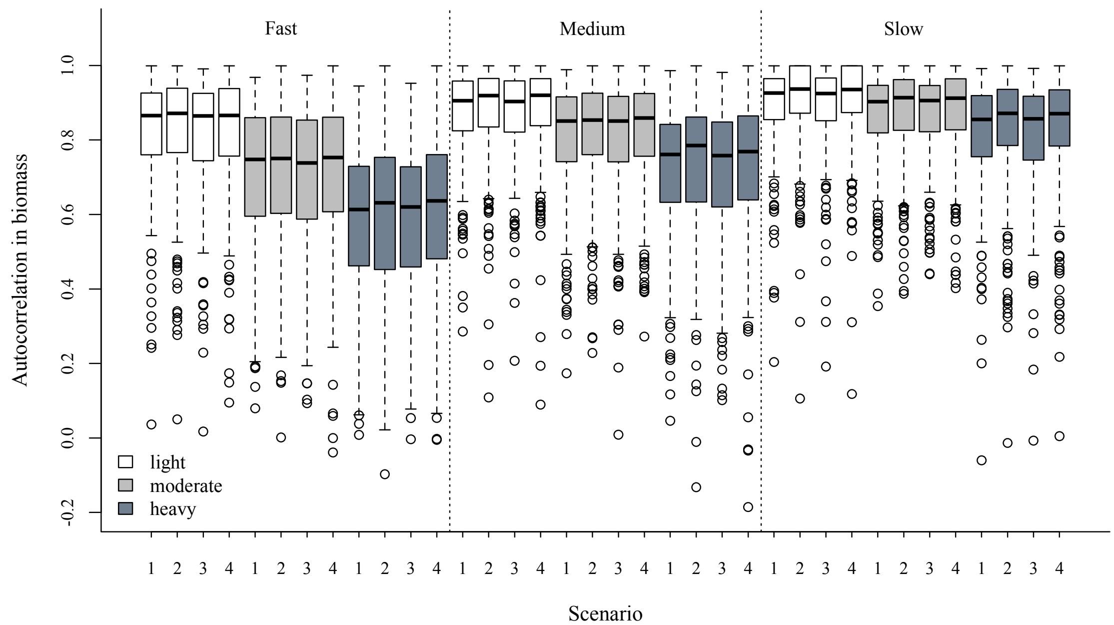


Figure 1. A simulated “true” biomass trajectory and estimated values using the stochastic process assessment approach (Eqn 1) and the same random errors but different levels of lag-1 autocorrelation in the estimates (low: ϕ_S= 0; high: ϕ_S = 0.9).



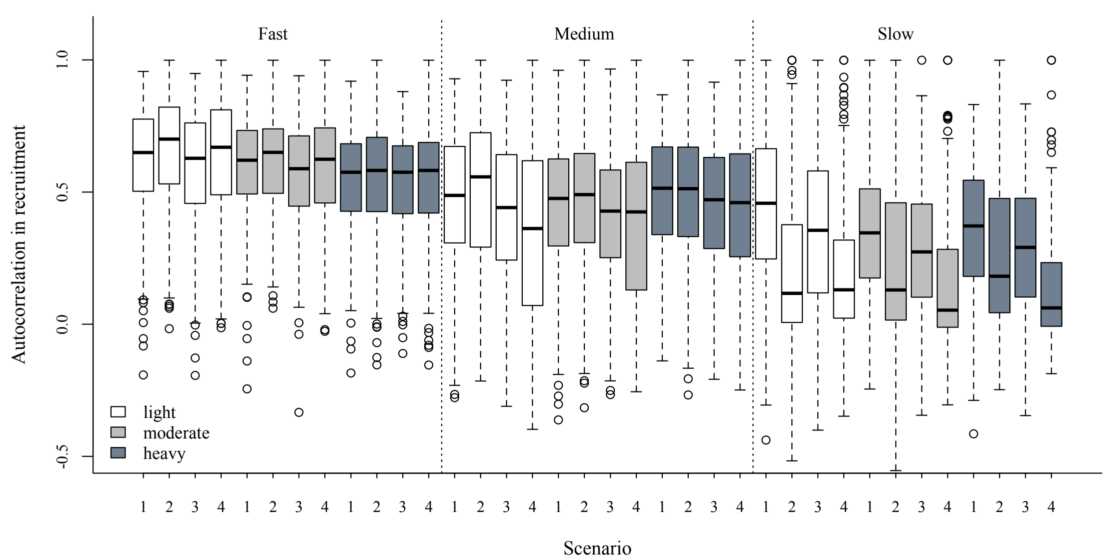


Figure 2. Estimated lag-1 autocorrelation in biomass (ϕ_S; top panel) and recruitment (ϕ_R; bottom panel) estimates across model scenarios 1-4 (see Table 4 for scenario details) for the different life histories and exploitation histories explored.

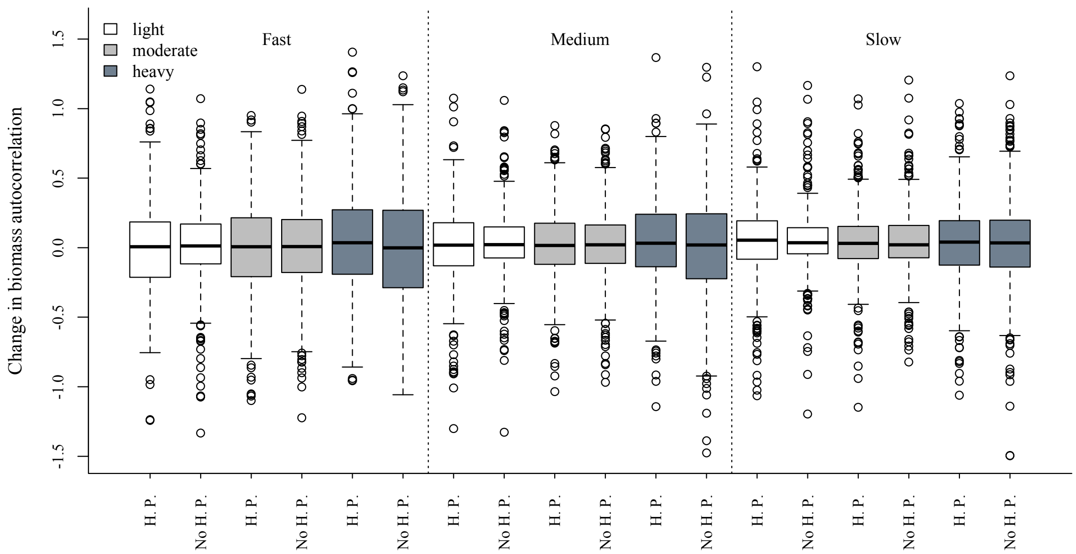


Figure 3. Change in the estimated autocorrelation in biomass error (ϕ_s) over time. Estimates of ϕ_s were calculated for the first and second halves of the time period, and change was calculated as the difference between these estimates. Results are shown across life histories, exploitation histories, and whether or not a harvest policy was used (denoted H.P. and No H.P.). Results for the No H.P. runs are aggregates of estimates from model runs 1-4 (Table 4), and for the H.P. runs are aggregates from model runs 5-8.

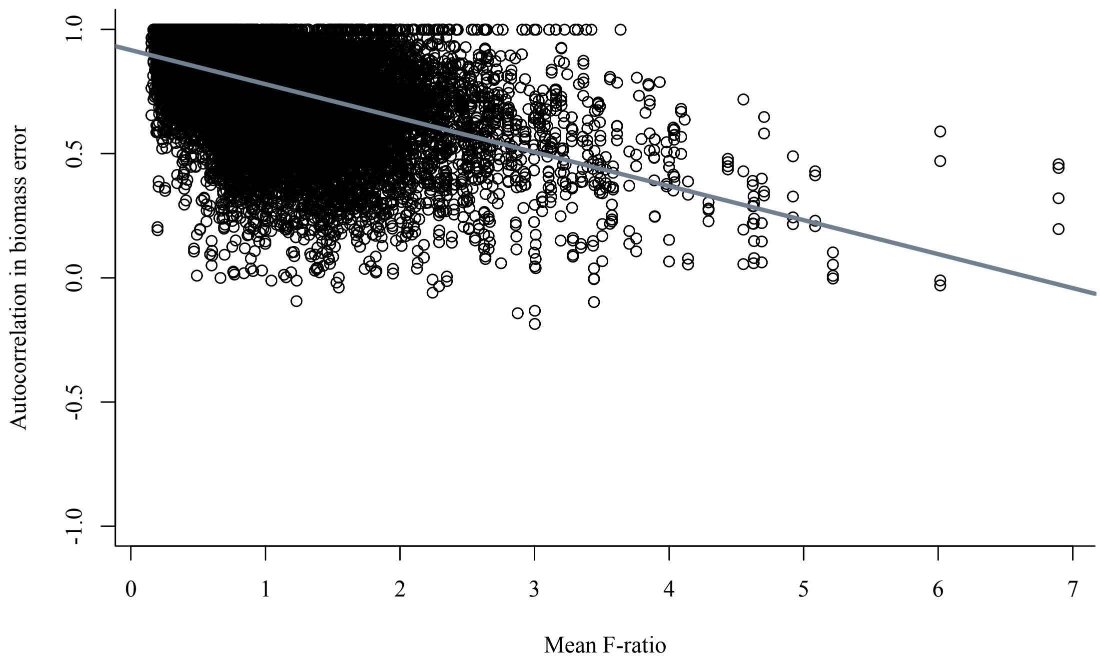


Figure 4. Estimated lag-1 autocorrelation (ϕ_s; Table 3) in biomass estimates across all model runs as a function of the mean fishing mortality ratio ($F_{\text{ratio}} = F / F_{\text{target}}$) over the entire time period. The gray line represents the best fit linear regression to the data: $\phi_s = 0.91 - 0.137\ F_{\text{ratio}}$; $R^2 = 0.22$; $p < 0.0001$.

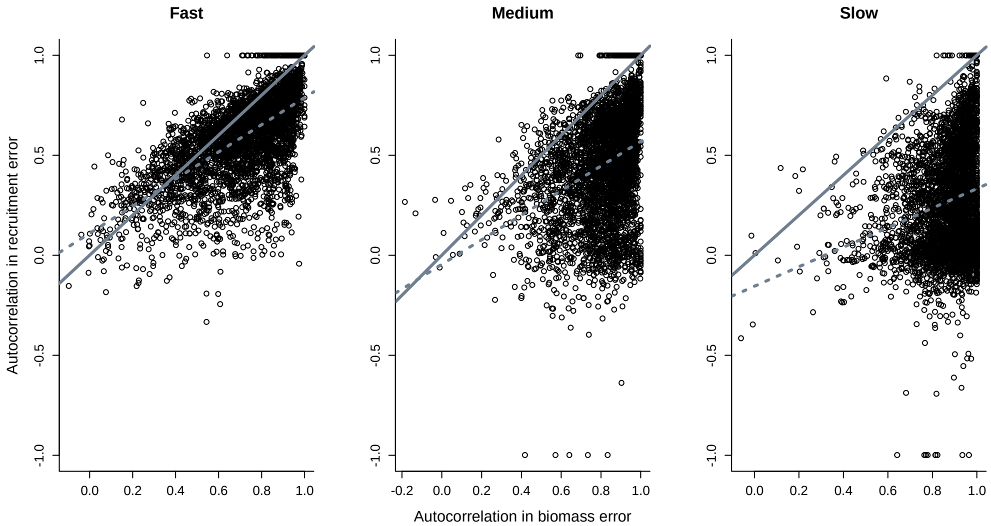


Figure 5. Estimated lag-1 autocorrelation in recruitment estimates across model scenarios compared to the estimated autocorrelation in biomass estimates across life histories. The solid gray line it the 1:1 line, while the dotted gray line represents the best fitting line to the data. Fast life history: $\phi_R = 0.1 + 0.71\ \phi_S$; $p < 0.0001$; $R^2 = 0.47$. Medium life history: $\phi_R = -0.11 + 0.73\ \phi_S$; $p < 0.0001$; $R^2 = 0.17$. Slow life history: $\phi_R = -0.18 + 0.54\ \phi_S$; $p < 0.0001$; $R^2 = 0.06$.

Appendix A. Expanded results of Acceptable Biological Catch control rule simulations. Numbers for performance measures indicate the median and the number in parentheses is the coefficient of variation (CV).

Life history	Assessment uncertainty	σ_R	ϕ_R	h	SPR target	SA years	Projections?	ABC avg.?	Exploitation history		S / S_{MSY}	Overfished probability	ΔS_5	ΔS_{15}	F / F_{MSY}	P_{OF} (true)	Initial C / MSY	Final C / MSY	Catch AAV
Fast	Low	0.77	0.00	fixed	0.35	2	no	no	Light	OFL	0.95 (0.54)	0.2 (0.77)	-0.47 (1.96)	-0.44 (1.67)	1.25 (0.33)	0.5 (0.42)	1.33 (0.39)	0.89 (0.44)	0.17 (0.27)
Fast	Low	1.25	0.00	fixed	0.35	2	no	no	Light	OFL	0.78 (0.94)	0.37 (0.45)	-0.47 (17.03)	-0.61 (9.28)	1.69 (0.26)	0.57 (0.27)	1.11 (0.62)	0.68 (0.89)	0.26 (0.28)
Fast	Low	0.77	0.44	fixed	0.35	2	no	no	Light	OFL	0.97 (0.45)	0.13 (0.97)	-0.41 (1.17)	-0.41 (1.07)	1.19 (0.33)	0.5 (0.47)	1.08 (0.32)	0.74 (0.33)	0.14 (0.27)
Fast	Low	1.25	0.44	fixed	0.35	2	no	no	Light	OFL	0.93 (0.71)	0.3 (0.62)	-0.45 (2.28)	-0.54 (1.72)	1.55 (0.32)	0.53 (0.34)	0.7 (0.42)	0.41 (0.58)	0.18 (0.27)
Fast	Low	0.77	0.00	fixed	0.35	2	no	no	Moderate	OFL	0.94 (0.51)	0.17 (0.86)	0 (6.24)	-0.02 (5.09)	1.19 (0.3)	0.47 (0.42)	0.94 (0.41)	0.84 (0.44)	0.17 (0.26)
Fast	Low	1.25	0.00	fixed	0.35	2	no	no	Moderate	OFL	0.75 (0.91)	0.37 (0.47)	-0.13 (4.7)	-0.24 (4.39)	1.56 (0.26)	0.57 (0.24)	0.78 (0.71)	0.61 (0.81)	0.26 (0.29)
Fast	Low	0.77	0.44	fixed	0.35	2	no	no	Moderate	OFL	0.97 (0.42)	0.1 (1.11)	0.03 (9.93)	0.02 (7.13)	1.11 (0.29)	0.47 (0.47)	0.77 (0.3)	0.72 (0.34)	0.13 (0.25)
Fast	Low	1.25	0.44	fixed	0.35	2	no	no	Moderate	OFL	0.81 (0.69)	0.27 (0.7)	-0.02 (7.11)	-0.11 (7.03)	1.38 (0.31)	0.53 (0.33)	0.49 (0.43)	0.42 (0.59)	0.17 (0.28)
Fast	Low	0.77	0.00	fixed	0.35	2	no	no	Heavy	OFL	0.98 (0.52)	0.17 (0.74)	0.7 (1.35)	0.98 (1.33)	1.19 (0.29)	0.5 (0.4)	0.6 (0.42)	0.89 (0.49)	0.17 (0.26)
Fast	Low	1.25	0.00	fixed	0.35	2	no	no	Heavy	OFL	0.92 (0.91)	0.38 (0.46)	0.52 (1.99)	0.67 (2.08)	1.57 (0.28)	0.55 (0.26)	0.46 (0.73)	0.74 (0.95)	0.26 (0.27)
Fast	Low	0.77	0.44	fixed	0.35	2	no	no	Heavy	OFL	1.04 (0.42)	0.13 (0.85)	0.82 (1.04)	1.15 (1.04)	1.13 (0.29)	0.47 (0.44)	0.49 (0.33)	0.74 (0.34)	0.14 (0.24)
Fast	Low	1.25	0.44	fixed	0.35	2	no	no	Heavy	OFL	1.08 (0.64)	0.27 (0.62)	0.75 (1.48)	1.13 (1.49)	1.33 (0.31)	0.53 (0.35)	0.27 (0.48)	0.47 (0.55)	0.18 (0.25)
Fast	Low	0.77	0.00	fixed	0.35	2	no	no	Light	P* var (0.38)	1.14 (0.45)	0.1 (1.01)	-0.37 (2.82)	-0.29 (3.44)	0.92 (0.29)	0.3 (0.55)	1.23 (0.4)	0.9 (0.43)	0.16 (0.26)
Fast	Low	1.25	0.00	fixed	0.35	2	no	no	Light	P* var (0.38)	1.05 (0.78)	0.27 (0.53)	-0.39 (532.28)	-0.36 (21.55)	1.13 (0.26)	0.37 (0.37)	1.02 (0.63)	0.72 (0.84)	0.26 (0.26)
Fast	Low	0.77	0.44	fixed	0.35	2	no	no	Light	P* var (0.38)	1.18 (0.37)	0 (1.29)	-0.33 (1.55)	-0.27 (1.84)	0.9 (0.29)	0.27 (0.6)	1.01 (0.33)	0.75 (0.32)	0.14 (0.28)
Fast	Low	1.25	0.44	fixed	0.35	2	no	no	Light	P* var (0.38)	1.14 (0.56)	0.17 (0.77)	-0.37 (3.4)	-0.33 (4.22)	1.01 (0.27)	0.33 (0.45)	0.65 (0.43)	0.48 (0.51)	0.18 (0.26)
Fast	Low	0.77	0.00	fixed	0.35	2	no	no	Moderate	P* var (0.38)	1.13 (0.42)	0.07 (1.13)	0.14 (2.62)	0.16 (2.31)	0.89 (0.24)	0.27 (0.59)	0.83 (0.46)	0.86 (0.41)	0.16 (0.25)
Fast	Low	1.25	0.00	fixed	0.35	2	no	no	Moderate	P* var (0.38)	0.99 (0.73)	0.23 (0.56)	0.06 (3.15)	0.09 (2.85)	1.06 (0.24)	0.33 (0.34)	0.7 (0.77)	0.66 (0.74)	0.26 (0.28)
Fast	Low	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* var (0.38)	1.16 (0.35)	0 (1.57)	0.17 (2.49)	0.2 (2.1)	0.86 (0.24)	0.27 (0.63)	0.68 (0.34)	0.72 (0.32)	0.13 (0.26)
Fast	Low	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* var (0.38)	1.07 (0.52)	0.13 (0.89)	0.16 (2.89)	0.23 (2.4)	0.95 (0.25)	0.3 (0.45)	0.44 (0.47)	0.45 (0.52)	0.18 (0.26)
Fast	Low	0.77	0.00	fixed	0.35	2	no	no	Heavy	P* var (0.38)	1.18 (0.44)	0.1 (0.87)	1.35 (0.91)	1.39 (1.1)	0.86 (0.25)	0.27 (0.56)	0.45 (0.52)	0.92 (0.48)	0.17 (0.26)
Fast	Low	1.25	0.00	fixed	0.35	2	no	no	Heavy	P* var (0.38)	1.14 (0.8)	0.25 (0.56)	1.29 (1.51)	1.33 (1.73)	1.04 (0.26)	0.33 (0.36)	0.35 (0.88)	0.77 (1.07)	0.26 (0.26)
Fast	Low	0.77	0.44	fixed	0.35	2	no	no	Heavy	P* var (0.38)	1.22 (0.35)	0.03 (1.02)	1.49 (0.66)	1.53 (0.84)	0.85 (0.25)	0.27 (0.65)	0.36 (0.42)	0.76 (0.32)	0.14 (0.24)
Fast	Low	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* var (0.38)	1.28 (0.52)	0.13 (0.76)	1.5 (0.99)	1.84 (1.17)	0.89 (0.25)	0.3 (0.48)	0.2 (0.61)	0.49 (0.51)	0.18 (0.24)
Fast	Low	0.77	0.00	fixed	0.35	2	no	no	Light	P* varied (0.7)	1.25 (0.43)	0.03 (1.22)	-0.31 (3.94)	-0.2 (6.36)	0.78 (0.29)	0.23 (0.67)	1.16 (0.41)	0.9 (0.43)	0.16 (0.26)
Fast	Low	1.25	0.00	fixed	0.35	2	no	no	Light	P* varied (0.7)	1.15 (0.74)	0.2 (0.61)	-0.32 (24.57)	-0.27 (9.17)	0.96 (0.28)	0.3 (0.44)	0.95 (0.64)	0.72 (0.83)	0.25 (0.25)
Fast	Low	0.77	0.44	fixed	0.35	2	no	no	Light	P* varied (0.7)	1.28 (0.34)	0 (1.59)	-0.28 (1.97)	-0.2 (2.73)	0.79 (0.28)	0.2 (0.73)	0.95 (0.34)	0.76 (0.31)	0.13 (0.28)
Fast	Low	1.25	0.44	fixed	0.35	2	no	no	Light	P* varied (0.7)	1.24 (0.52)	0.1 (0.94)	-0.31 (4.98)	-0.22 (9.91)	0.85 (0.27)	0.27 (0.53)	0.61 (0.44)	0.48 (0.5)	0.18 (0.25)
Fast	Low	0.77	0.00	fixed	0.35	2	no	no	Moderate	P* varied (0.7)	1.24 (0.39)	0 (1.41)	0.26 (1.96)	0.27 (1.87)	0.76 (0.23)	0.2 (0.71)	0.75 (0.49)	0.85 (0.41)	0.16 (0.26)
Fast	Low	1.25	0.00	fixed	0.35	2	no	no	Moderate	P* varied (0.7)	1.11 (0.69)	0.2 (0.65)	0.16 (2.65)	0.21 (2.54)	0.9 (0.26)	0.27 (0.42)	0.64 (0.81)	0.67 (0.73)	0.26 (0.27)
Fast	Low	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* varied (0.7)	1.25 (0.32)	0 (1.93)	0.26 (1.73)	0.33 (1.58)	0.75 (0.22)	0.17 (0.79)	0.63 (0.36)	0.71 (0.32)	0.13 (0.26)
Fast	Low	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* varied (0.7)	1.17 (0.48)	0.07 (1.06)	0.26 (2.17)	0.38 (1.91)	0.8 (0.24)	0.23 (0.56)	0.4 (0.5)	0.45 (0.5)	0.17 (0.26)
Fast	Low	0.77	0.00	fixed	0.35	2	no	no	Heavy	P* varied (0.7)	1.28 (0.41)	0.07 (0.97)	1.7 (0.8)	1.61 (1.03)	0.74 (0.25)	0.17 (0.71)	0.36 (0.6)	0.92 (0.47)	0.17 (0.25)
Fast	Low	1.25	0.00	fixed	0.35	2	no	no	Heavy	P* varied (0.7)	1.26 (0.76)	0.2 (0.61)	1.61 (1.33)	1.68 (1.65)	0.87 (0.26)	0.23 (0.48)	0.28 (0.99)	0.78 (1.09)	0.26 (0.25)
Fast	Low	0.77	0.44	fixed	0.35	2	no	no	Heavy	P* varied (0.7)	1.32 (0.32)	0.03 (1.05)	1.82 (0.57)	1.75 (0.77)	0.73 (0.24)	0.17 (0.83)	0.28 (0.49)	0.75 (0.31)	0.14 (0.24)
Fast	Low	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* varied (0.7)	1.4 (0.49)	0.1 (0.83)	1.9 (0.86)	2.08 (1.1)	0.75 (0.24)	0.2 (0.6)	0.16 (0.72)	0.48 (0.5)	0.18 (0.23)
Fast	Low	0.77	0.00	fixed	0.35	2	no	no	Light	P* varied (1.0)	1.31 (0.41)	0 (1.42)	-0.26 (5.43)	-0.16 (12.56)	0.72 (0.29)	0.17 (0.79)	1.11 (0.41)	0.88 (0.43)	0.16 (0.27)
Fast	Low	1.25	0.00	fixed	0.35	2	no	no	Light	P* varied (1.0)	1.2 (0.71)	0.17 (0.67)	-0.26 (14.83)	-0.2 (6.71)	0.87 (0.29)	0.27 (0.51)	0.91 (0.65)	0.72 (0.82)	0.25 (0.25)
Fast	Low	0.77	0.44	fixed	0.35	2	no	no	Light	P* varied (1.0)	1.35 (0.33)	0 (1.91)	-0.24 (2.46)	-0.16 (3.93)	0.73 (0.28)	0.17 (0.84)	0.91 (0.34)	0.75 (0.31)	0.13 (0.28)
Fast	Low	1.25	0.44	fixed	0.35	2	no	no	Light	P* varied (1.0)	1.3 (0.5)	0.07 (1.05)	-0.27 (7.4)	-0.18 (41.48)	0.75 (0.27)	0.2 (0.62)	0.58 (0.45)	0.47 (0.5)	0.17 (0.25)
Fast	Low	0.77	0.00	fixed	0.35	2	no	no	Moderate	P* varied (1.0)	1.29 (0.37)	0 (1.7)	0.33 (1.7)	0.33 (1.66)	0.69 (0.22)	0.13 (0.84)	0.7 (0.51)	0.84 (0.4)	0.16 (0.25)
Fast	Low	1.25	0.00	fixed	0.35	2	no	no	Moderate	P* varied (1.0)	1.18 (0.66)	0.17 (0.74)	0.23 (2.39)	0.29 (2.36)	0.79 (0.27)	0.23 (0.51)	0.58 (0.84)	0.67 (0.71)	0.25 (0.26)
Fast	Low	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* varied (1.0)	1.3 (0.3)	0 (2.34)	0.33 (1.45)	0.4 (1.35)	0.69 (0.21)	0.13 (0.93)	0.59 (0.38)	0.71 (0.31)	0.13 (0.26)
Fast	Low	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* varied (1.0)	1.25 (0.46)	0.03 (1.19)	0.35 (1.87)	0.44 (1.7)	0.72 (0.23)	0.17 (0.66)	0.37 (0.53)	0.45 (0.49)	0.17 (0.26)
Fast	Low	0.77	0.00	fixed	0.35	2	no	no	Heavy	P* varied (1.0)	1.34 (0.4)	0.03 (1.03)	1.93 (0.74)	1.73 (0.98)	0.67 (0.24)	0.13 (0.85)	0.31 (0.66)	0.91 (0.46)	0.17 (0.25)
Fast	Low	1.25	0.00	fixed	0.35	2	no	no	Heavy	P* varied (1.0)	1.34 (0.73)	0.17 (0.67)	1.84 (1.24)	1.89 (1.6)	0.75 (0.27)	0.2 (0.56)	0.23 (1.08)	0.78 (1.09)	0.25 (0.25)
Fast	Low	0.77	0.44	fixed	0.35	2	no	no	Heavy	P* varied (1.0)	1.38 (0.31)	0.03 (1.05)	2.01 (0.53)	1.88 (0.73)	0.67 (0.23)	0.1 (0.99)	0.23 (0.54)	0.74 (0.31)	0.14 (0.24)
Fast	Low	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* varied (1.0)	1.47 (0.47)	0.07 (0.88)	2.09 (0.8)	2.31 (1.05)	0.68 (0.24)	0.15 (0.72)	0.13 (0.81)	0.48 (0.48)	0.18 (0.23)
Fast	Low	0.77	0.00	fixed	0.35	2	no	no	Light	P* fixed (0.38)	1.09 (0.49)	0.1 (0.98)	-0.37 (2.7)	-0.35 (2.49)	1.01 (0.34)	0.37 (0.56)	1.23 (0.4)	0.9 (0.41)	0.15 (0.26)
Fast	Low	1.25	0.00	fixed	0.35	2	no	no	Light	P* fixed (0.38)	0.91 (0.87)	0.33 (0.54)	-0.39 (81.82)	-0.51 (36.45)	1.42 (0.3)	0.5 (0.35)	1.03 (0.62)	0.69 (0.84)	0.24 (0.27)
Fast	Low	0.77	0.44	fixed	0.35	2	no	no	Light	P* fixed (0.38)	1.1 (0.4)	0.03 (1.29)	-0.33 (1.52)	-0.33 (1.49)	0.96 (0.33)	0.33 (0.62)	1.01 (0.33)	0.75 (0.3)	0.13 (0.26)
Fast	Low	1.25	0.44	fixed	0.35	2	no	no	Light	P* fixed (0.38)	1.06 (0.63)	0.2 (0.79)	-0.37 (3.2)	-0.42 (2.65)	1.21 (0.34)	0.43 (0.44)	0.65 (0.43)	0.44 (0.51)	0.17 (0.27)
Fast	Low	0.77	0.00	fixed	0.35	2	no	no	Moderate	P* fixed (0.38)	1.08 (0.45)	0.07 (1.1)	0.1 (3.26)	0.13 (2.83)	0.96 (0.29)	0.33 (0.58)	0.86 (0.43)	0.85 (0.4)	0.15 (0.25)
Fast	Low	1.25	0.00	fixed	0.35	2	no	no	Moderate	P* fixed (0.38)	0.84 (0.84)	0.3 (0.56)	-0.02 (3.75)	-0.07 (3.43)	1.32 (0.3)	0.47 (0.33)	0.73 (0.72)	0.62 (0.76)	0.24 (0.29)
Fast	Low	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (0.38)	1.1 (0.37)	0 (1.56)	0.13 (3.1)	0.17 (2.6)	0.91 (0.28)	0.3 (0.64)	0.71 (0.31)	0.72 (0.31)	0.12 (0.25)
Fast	Low	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (0.38)	0.97 (0.61)	0.2 (0.87)	0.11 (3.75)	0.09 (3.26)	1.09 (0.34)	0.4 (0.45)	0.46 (0.43)	0.44 (0.54)	0.16 (0.27)
Fast	Low	0.77	0.00	fixed	0.35	2	no	no	Heavy	P* fixed (0.38)	1.13 (0.47)	0.13 (0.85)	0.9 (1.15)	1.28 (1.16)	0.97 (0.29)	0.37 (0.52)	0.57 (0.42)	0.91 (0.46)	0.16 (0.25)
Fast	Low	1.25	0.00	fixed	0.35	2	no	no	Heavy	P* fixed (0.38)	1.08 (0.86)	0.33 (0.55)	0.69 (1.82)	0.98 (1.89)	1.35 (0.31)	0.47 (0.34)	0.44 (0.74)	0.76 (0.94)	0.24 (0.27)
Fast	Low	0.77	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (0.38)	1.19 (0.37)	0.07 (1.04)	1 (0.85)	1.51 (0.87)	0.93 (0.28)	0.33 (0.6)	0.45 (0.33)	0.75 (0.31)	0.13 (0.23)
Fast	Low	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (0.38)	1.22 (0.58)	0.2 (0.77)	0.97 (1.29)	1.64 (1.28)	1.04 (0.34)	0.4 (0.45)	0.25 (0.49)	0.48 (0.51)	0.17 (0.24)
Fast	Low	0.77	0.00	fixed	0.35	2	no	no	Light	P* fixed (0.7)	1.19 (0.46)	0.07 (1.18)	-0.32 (3.62)	-0.28 (3.66)	0.86 (0.34)	0.27 (0.68)	1.16 (0.4)	0.9 (0.4)	0.15 (0.26)
Fast	Low	1.25	0.00	fixed	0.35	2	no	no	Light	P* fixed (0.7)	1 (0.84)	0.27 (0.6)	-0.34 (50.14)	-0.44 (37.32)	1.25 (0.33)	0.43 (0.41)	0.97 (0.62)	0.7 (0.81)	0.23 (0.27)
Fast	Low	0.77	0.44	fixed	0.35	2	no	no	Light	P* fixed (0.7)	1.2 (0.37)	0 (1.6)	-0.28 (1.92)	-0.26 (2.01)	0.84 (0.33)	0.27 (0.75)	0.95 (0.33)	0.75 (0.29)	0.12 (0.26)
Fast	Low	1.25	0.44	fixed	0.35	2	no	no	Light	P* fixed (0.7)	1.15 (0.58)	0.15 (0.92)	-0.31 (4.41)	-0.32 (4.09)	1 (0.35)	0.37 (0.53)	0.61 (0.43)	0.46 (0.48)	0.16 (0.27)
Fast	Low	0.77	0.00	fixed	0.35	2	no	no	Moderate	P* fixed (0.7)	1.17 (0.42)	0.03 (1.37)	0.16 (2.47)	0.22 (2.15)	0.84 (0.29)	0.23 (0.72)	0.81 (0.43)	0.84 (0.38)	0.15 (0.25)
Fast	Low	1.25	0.00	fixed	0.35	2	no	no	Moderate	P* fixed (0.7)	0.95 (0.79)	0.27 (0.64)	0.06 (3.3)	0.04 (3)	1.16 (0.34)	0.4 (0.42)	0.7 (0.72)	0.64 (0.73)	0.23 (0.28)
Fast	Low	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (0.7)	1.18 (0.34)	0 (1.97)	0.19 (2.12)	0.27 (1.84)	0.81 (0.26)	0.2 (0.81)	0.67 (0.31)	0.72 (0.29)	0.11 (0.24)
Fast	Low	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (0.7)	1.08 (0.56)	0.1 (1.04)	0.18 (2.85)	0.26 (2.4)	0.92 (0.34)	0.3 (0.56)	0.43 (0.43)	0.44 (0.5)	0.15 (0.26)
Fast	Low	0.77	0.00	fixed	0.35	2	no	no	Heavy	P* fixed (0.7)	1.21 (0.44)	0.1 (0.94)	1.05 (1.04)	1.5 (1.07)	0.85 (0.28)	0.23 (0.65)	0.54 (0.43)	0.9 (0.45)	0.15 (0.25)
Fast	Low	1.25	0.00	fixed	0.35	2	no	no	Heavy	P* fixed (0.7)	1.18 (0.82)	0.3 (0.6)	0.82 (1.71)	1.24 (1.78)	1.17 (0.33)	0.4 (0.42)	0.42 (0.74)	0.78 (1)	0.23 (0.27)
Fast	Low	0.77	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (0.7)	1.28 (0.34)	0.07 (1.08)	1.16 (0.76)	1.74 (0.79)	0.83 (0.27)	0.22 (0.74)	0.43 (0.34)	0.74 (0.29)	0.12 (0.22)
Fast	Low	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (0.7)	1.34 (0.55)	0.13 (0.85)	1.1 (1.19)	1.98 (1.17)	0.91 (0.35)	0.3 (0.55)	0.24 (0.49)	0.48 (0.48)	0.16 (0.23)
Fast	Low	0.77	0.00	fixed	0.35	2	no	no	Light	P* fixed (1.0)	1.25 (0.44)	0 (1.38)	-0.27 (4.79)	-0.23 (5.31)	0.78 (0.33)	0.23 (0.8)	1.11 (0.4)	0.89 (0.39)	0.14 (0.26)
Fast	Low	1.25	0.00	fixed	0.35	2	no	no	Light	P* fixed (1.0)	1.08 (0.8)	0.23 (0.66)	-0.3 (23.17)	-0.35 (14.51)	1.1 (0.35)	0.37 (0.47)	0.92 (0.62)	0.71 (0.79)	0.23 (0.27)
Fast	Low	0.77	0.44	fixed	0.35	2	no	no	Light	P* fixed (1.0)	1.28 (0.35)	0 (1.91)	-0.24 (2.36)	-0.21 (2.68)	0.77 (0.33)	0.2 (0.88)	0.91 (0.34)	0.75 (0.28)	0.12 (0.25)
Fast	Low	1.25	0.44	fixed	0.35	2	no	no	Light	P* fixed (1.0)	1.21 (0.56)	0.1 (1.03)	-0.28 (6.08)	-0.27 (6.5)	0.88 (0.36)	0.3 (0.61)	0.58 (0.43)	0.46 (0.46)	0.15 (0.26)
Fast	Low	0.77	0.00	fixed	0.35	2	no	no	Moderate	P* fixed (1.0)	1.23 (0.4)	0 (1.64)	0.21 (2.1)	0.31 (1.86)	0.76 (0.27)	0.17 (0.85)	0.78 (0.43)	0.83 (0.37)	0.14 (0.25)
Fast	Low	1.25	0.00	fixed	0.35	2	no	no	Moderate	P* fixed (1.0)	1.03 (0.76)	0.23 (0.7)	0.11 (3.03)	0.15 (2.74)	1.03 (0.35)	0.33 (0.48)	0.67 (0.72)	0.64 (0.71)	0.23 (0.28)
Fast	Low	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (1.0)	1.25 (0.32)	0 (2.4)	0.23 (1.72)	0.34 (1.53)	0.74 (0.25)	0.13 (0.94)	0.64 (0.31)	0.71 (0.28)	0.11 (0.24)
Fast	Low	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (1.0)	1.15 (0.53)	0.07 (1.16)	0.24 (2.43)	0.35 (2.03)	0.82 (0.34)	0.23 (0.65)	0.41 (0.43)	0.45 (0.47)	0.15 (0.26)
Fast	Low	0.77	0.00	fixed	0.35	2	no	no	Heavy	P* fixed (1.0)	1.28 (0.43)	0.07 (0.98)	1.14 (0.97)	1.66 (1)	0.78 (0.27)	0.2 (0.75)	0.52 (0.43)	0.88 (0.44)	0.15 (0.25)
Fast	Low	1.25	0.00	fixed	0.35	2	no	no	Heavy	P* fixed (1.0)	1.27 (0.79)	0.23 (0.64)	0.95 (1.65)	1.47 (1.71)	1.06 (0.35)	0.33 (0.48)	0.4 (0.74)	0.77 (1.03)	0.23 (0.27)
Fast	Low	0.77	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (1.0)	1.35 (0.33)	0.03 (1.07)	1.25 (0.71)	1.87 (0.74)	0.76 (0.26)	0.13 (0.87)	0.41 (0.34)	0.73 (0.28)	0.12 (0.22)
Fast	Low	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (1.0)	1.42 (0.52)	0.1 (0.9)	1.19 (1.12)	2.22 (1.11)	0.82 (0.34)	0.23 (0.64)	0.23 (0.5)	0.48 (0.46)	0.15 (0.23)
Fast	Low	0.77	0.00	fixed	0.35	2	no	no	Light	75% of F_lim	1.2 (0.45)	0.03 (1.25)	-0.3 (3.93)	-0.26 (4.15)	0.83 (0.33)	0.27 (0.72)	1.15 (0.4)	0.9 (0.4)	0.15 (0.26)
Fast	Low	1.25	0.00	fixed	0.35	2	no	no	Light	75% of F_lim	1.04 (0.82)	0.27 (0.62)	-0.33 (36.6)	-0.42 (23.95)	1.18 (0.33)	0.4 (0.43)	0.96 (0.62)	0.7 (0.81)	0.23 (0.27)
Fast	Low	0.77	0.44	fixed	0.35	2	no	no	Light	75% of F_lim	1.24 (0.36)	0 (1.7)	-0.27 (2.04)	-0.24 (2.22)	0.81 (0.32)	0.23 (0.78)	0.94 (0.34)	0.75 (0.29)	0.12 (0.26)
Fast	Low	1.25	0.44	fixed	0.35	2	no	no	Light	75% of F_lim	1.18 (0.57)	0.13 (0.96)	-0.3 (4.81)	-0.3 (4.74)	0.95 (0.35)	0.33 (0.55)	0.6 (0.43)	0.46 (0.47)	0.16 (0.26)
Fast	Low	0.77	0.00	fixed	0.35	2	no	no	Moderate	75% of F_lim	1.19 (0.41)	0 (1.46)	0.18 (2.31)	0.24 (2.04)	0.8 (0.28)	0.23 (0.75)	0.8 (0.43)	0.84 (0.38)	0.15 (0.25)
Fast	Low	1.25	0.00	fixed	0.35	2	no	no	Moderate	75% of F_lim	0.99 (0.78)	0.27 (0.66)	0.08 (3.17)	0.08 (2.9)	1.12 (0.34)	0.37 (0.43)	0.69 (0.72)	0.64 (0.72)	0.23 (0.29)
Fast	Low	0.77	0.44	fixed	0.35	2	no	no	Moderate	75% of F_lim	1.22 (0.33)	0 (2.11)	0.21 (1.94)	0.29 (1.72)	0.78 (0.26)	0.17 (0.85)	0.66 (0.31)	0.72 (0.29)	0.11 (0.24)
Fast	Low	1.25	0.44	fixed	0.35	2	no	no	Moderate	75% of F_lim	1.1 (0.55)	0.1 (1.06)	0.21 (2.66)	0.29 (2.24)	0.88 (0.33)	0.27 (0.59)	0.42 (0.43)	0.44 (0.49)	0.15 (0.26)
Fast	Low	0.77	0.00	fixed	0.35	2	no	no	Heavy	75% of F_lim	1.23 (0.44)	0.07 (0.96)	1.1 (1)	1.56 (1.04)	0.82 (0.28)	0.23 (0.68)	0.53 (0.43)	0.89 (0.44)	0.15 (0.25)
Fast	Low	1.25	0.00	fixed	0.35	2	no	no	Heavy	75% of F_lim	1.21 (0.81)	0.27 (0.61)	0.92 (1.67)	1.36 (1.75)	1.11 (0.34)	0.37 (0.43)	0.41 (0.74)	0.78 (1.03)	0.23 (0.27)
Fast	Low	0.77	0.44	fixed	0.35	2	no	no	Heavy	75% of F_lim	1.31 (0.34)	0.03 (1.06)	1.22 (0.73)	1.79 (0.77)	0.8 (0.26)	0.2 (0.79)	0.42 (0.34)	0.74 (0.29)	0.12 (0.22)
Fast	Low	1.25	0.44	fixed	0.35	2	no	no	Heavy	75% of F_lim	1.36 (0.53)	0.13 (0.87)	1.15 (1.14)	2.06 (1.15)	0.87 (0.33)	0.27 (0.57)	0.24 (0.5)	0.48 (0.48)	0.16 (0.23)
Fast	Low	0.77	0.00	fixed	0.35	2	no	no	Light	75% of F_lim	0.61 (0.67)	0.42 (0.43)	-0.66 (1.13)	-0.67 (0.85)	2 (0.25)	0.77 (0.22)	1.55 (0.37)	0.82 (0.52)	0.21 (0.26)
Fast	Low	1.25	0.00	fixed	0.35	2	no	no	Light	75% of F_lim	0.53 (1.06)	0.53 (0.28)	-0.7 (5.79)	-0.78 (3.22)	2.21 (0.18)	0.73 (0.16)	1.29 (0.6)	0.59 (0.98)	0.31 (0.28)
Fast	Low	0.77	0.44	fixed	0.35	2	no	no	Light	75% of F_lim	0.66 (0.58)	0.4 (0.49)	-0.64 (0.71)	-0.68 (0.58)	1.96 (0.26)	0.8 (0.23)	1.24 (0.29)	0.68 (0.41)	0.17 (0.27)
Fast	Low	1.25	0.44	fixed	0.35	2	no	no	Light	75% of F_lim	0.61 (0.85)	0.5 (0.35)	-0.67 (1.28)	-0.82 (0.82)	2.22 (0.21)	0.77 (0.18)	0.82 (0.4)	0.34 (0.69)	0.21 (0.26)

Life history	Assessment uncertainty	σ_R	ϕ_R	h	SPR target	SA years	Proj-tions?	ABC avg.?	Exploitation history		S / S_{MSY}	Overfished probability	ΔS_5	ΔS_{15}	F / F_{MSY}	P_{OF} (true)	Initial C / MSY	Final C / MSY	Catch AAV
Fast	Low	0.77	0.00	fixed	0.35	2	no	no	Moderate	75% of F_lim	0.62 (0.64)	0.4 (0.46)	-0.32 (3.94)	-0.4 (3.68)	1.91 (0.24)	0.77 (0.18)	1.09 (0.39)	0.75 (0.53)	0.2 (0.26)
Fast	Low	1.25	0.00	fixed	0.35	2	no	no	Moderate	75% of F_lim	0.47 (1.07)	0.5 (0.31)	-0.43 (14.52)	-0.58 (13.78)	2.16 (0.18)	0.73 (0.14)	0.88 (0.72)	0.49 (0.92)	0.3 (0.29)
Fast	Low	0.77	0.44	fixed	0.35	2	no	no	Moderate	75% of F_lim	0.61 (0.57)	0.33 (0.56)	-0.27 (2.01)	-0.37 (1.86)	1.83 (0.26)	0.8 (0.21)	0.91 (0.28)	0.64 (0.43)	0.16 (0.25)
Fast	Low	1.25	0.44	fixed	0.35	2	no	no	Moderate	75% of F_lim	0.48 (0.89)	0.5 (0.39)	-0.34 (4.91)	-0.61 (2.86)	2.16 (0.22)	0.77 (0.16)	0.57 (0.42)	0.33 (0.72)	0.21 (0.27)
Fast	Low	0.77	0.00	fixed	0.35	2	no	no	Heavy	75% of F_lim	0.66 (0.65)	0.43 (0.43)	0.21 (2.42)	0.21 (2.36)	1.93 (0.23)	0.77 (0.18)	0.69 (0.41)	0.81 (0.53)	0.21 (0.26)
Fast	Low	1.25	0.00	fixed	0.35	2	no	no	Heavy	75% of F_lim	0.6 (1.03)	0.5 (0.31)	0.08 (2.64)	-0.12 (2.72)	2.12 (0.19)	0.73 (0.16)	0.53 (0.75)	0.63 (1.01)	0.31 (0.27)
Fast	Low	0.77	0.44	fixed	0.35	2	no	no	Heavy	75% of F_lim	0.71 (0.52)	0.37 (0.5)	0.28 (2.21)	0.3 (2.07)	1.87 (0.24)	0.8 (0.18)	0.56 (0.31)	0.69 (0.38)	0.17 (0.24)
Fast	Low	1.25	0.44	fixed	0.35	2	no	no	Heavy	75% of F_lim	0.66 (0.79)	0.47 (0.38)	0.28 (2.35)	0.16 (2.56)	2.03 (0.22)	0.73 (0.16)	0.31 (0.48)	0.39 (0.65)	0.21 (0.25)
Fast	High	0.77	0	fixed	0.35	2	no	no	Light	OFL	1.04 (0.63)	0.23 (0.77)	-0.43 (2.32)	-0.46 (2.33)	1.34 (0.46)	0.43 (0.55)	1.28 (0.47)	0.78 (0.49)	0.24 (0.32)
Fast	High	1.25	0	fixed	0.35	2	no	no	Light	OFL	0.78 (0.94)	0.37 (0.53)	-0.46 (20.48)	-0.58 (17.03)	1.58 (0.38)	0.53 (0.42)	1.08 (0.65)	0.62 (0.88)	0.31 (0.35)
Fast	High	0.77	0.44	fixed	0.35	2	no	no	Light	OFL	1.03 (0.59)	0.2 (0.85)	-0.42 (1.47)	-0.42 (1.54)	1.27 (0.47)	0.43 (0.57)	1.05 (0.41)	0.64 (0.42)	0.22 (0.3)
Fast	High	1.25	0.44	fixed	0.35	2	no	no	Light	OFL	0.96 (0.75)	0.33 (0.67)	-0.46 (2.51)	-0.56 (2.29)	1.48 (0.42)	0.5 (0.48)	0.67 (0.5)	0.38 (0.61)	0.24 (0.32)
Fast	High	0.77	0	fixed	0.35	2	no	no	Moderate	OFL	1.02 (0.62)	0.23 (0.81)	-0.04 (9.7)	-0.05 (4.89)	1.32 (0.45)	0.47 (0.54)	0.92 (0.48)	0.75 (0.55)	0.24 (0.3)
Fast	High	1.25	0	fixed	0.35	2	no	no	Moderate	OFL	0.76 (0.92)	0.37 (0.55)	-0.17 (4.86)	-0.24 (4.09)	1.6 (0.38)	0.53 (0.41)	0.76 (0.8)	0.57 (0.83)	0.31 (0.34)
Fast	High	0.77	0.44	fixed	0.35	2	no	no	Moderate	OFL	0.99 (0.58)	0.2 (0.89)	0 (50.5)	-0.04 (8.01)	1.32 (0.47)	0.43 (0.57)	0.78 (0.39)	0.62 (0.46)	0.21 (0.28)
Fast	High	1.25	0.44	fixed	0.35	2	no	no	Moderate	OFL	0.84 (0.75)	0.3 (0.7)	-0.08 (9.13)	-0.14 (6.48)	1.48 (0.42)	0.5 (0.47)	0.48 (0.51)	0.38 (0.65)	0.23 (0.31)
Fast	High	0.77	0	fixed	0.35	2	no	no	Heavy	OFL	0.99 (0.62)	0.27 (0.68)	0.65 (1.62)	0.85 (1.58)	1.42 (0.44)	0.47 (0.53)	0.6 (0.5)	0.79 (0.55)	0.26 (0.29)
Fast	High	1.25	0	fixed	0.35	2	no	no	Heavy	OFL	0.93 (0.92)	0.4 (0.51)	0.43 (2.01)	0.69 (2.18)	1.6 (0.37)	0.53 (0.41)	0.44 (0.79)	0.66 (1)	0.31 (0.34)
Fast	High	0.77	0.44	fixed	0.35	2	no	no	Heavy	OFL	1.05 (0.57)	0.23 (0.75)	0.63 (1.42)	1.01 (1.3)	1.39 (0.44)	0.47 (0.54)	0.48 (0.41)	0.64 (0.43)	0.23 (0.26)
Fast	High	1.25	0.44	fixed	0.35	2	no	no	Heavy	OFL	1.02 (0.71)	0.3 (0.63)	0.59 (1.66)	1.08 (1.64)	1.48 (0.42)	0.5 (0.47)	0.26 (0.54)	0.41 (0.6)	0.23 (0.27)
Fast	High	0.77	0	fixed	0.35	2	no	no	Light	P* var (0.38)	1.22 (0.57)	0.17 (0.9)	-0.36 (3.17)	-0.29 (5.14)	1.04 (0.47)	0.3 (0.64)	1.2 (0.5)	0.78 (0.51)	0.25 (0.32)
Fast	High	1.25	0	fixed	0.35	2	no	no	Light	P* var (0.38)	1.03 (0.81)	0.27 (0.6)	0.38 (104.53)	-0.39 (14.97)	1.15 (0.41)	0.33 (0.53)	1 (0.68)	0.65 (0.86)	0.31 (0.33)
Fast	High	0.77	0.44	fixed	0.35	2	no	no	Light	P* var (0.38)	1.24 (0.51)	0.13 (0.94)	-0.33 (1.86)	-0.26 (2.8)	1.03 (0.47)	0.3 (0.65)	0.97 (0.44)	0.64 (0.44)	0.23 (0.31)
Fast	High	1.25	0.44	fixed	0.35	2	no	no	Light	P* var (0.38)	1.15 (0.62)	0.2 (0.81)	-0.39 (3.55)	-0.32 (5.68)	1.05 (0.43)	0.33 (0.59)	0.62 (0.53)	0.41 (0.58)	0.24 (0.3)
Fast	High	0.77	0	fixed	0.35	2	no	no	Moderate	P* var (0.38)	1.2 (0.54)	0.17 (0.94)	0.12 (3.64)	0.15 (2.52)	1.01 (0.46)	0.3 (0.64)	0.82 (0.55)	0.76 (0.56)	0.24 (0.3)
Fast	High	1.25	0	fixed	0.35	2	no	no	Moderate	P* var (0.38)	1.04 (0.76)	0.27 (0.62)	0.05 (3.32)	0.14 (2.86)	1.1 (0.39)	0.33 (0.53)	0.68 (0.87)	0.62 (0.8)	0.31 (0.33)
Fast	High	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* var (0.38)	1.22 (0.5)	0.1 (1.06)	0.14 (4.21)	0.2 (2.58)	1.01 (0.46)	0.33 (0.66)	0.71 (0.46)	0.65 (0.46)	0.21 (0.28)
Fast	High	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* var (0.38)	1.17 (0.6)	0.17 (0.83)	0.14 (3.44)	0.19 (2.52)	1.04 (0.41)	0.33 (0.6)	0.43 (0.58)	0.41 (0.61)	0.23 (0.3)
Fast	High	0.77	0	fixed	0.35	2	no	no	Heavy	P* var (0.38)	1.22 (0.54)	0.17 (0.78)	1.21 (1.18)	1.36 (1.31)	1.06 (0.46)	0.33 (0.63)	0.48 (0.61)	0.79 (0.56)	0.26 (0.3)
Fast	High	1.25	0	fixed	0.35	2	no	no	Heavy	P* var (0.38)	1.15 (0.81)	0.27 (0.58)	1.04 (1.57)	1.43 (1.88)	1.08 (0.41)	0.33 (0.53)	0.34 (0.93)	0.71 (1.02)	0.32 (0.32)
Fast	High	0.77	0.44	fixed	0.35	2	no	no	Heavy	P* var (0.38)	1.24 (0.49)	0.17 (0.83)	1.28 (0.98)	1.44 (1.04)	1.04 (0.46)	0.33 (0.66)	0.37 (0.54)	0.67 (0.43)	0.23 (0.27)
Fast	High	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* var (0.38)	1.29 (0.59)	0.2 (0.72)	1.2 (1.18)	1.79 (1.31)	1.04 (0.42)	0.3 (0.61)	0.2 (0.68)	0.44 (0.58)	0.24 (0.26)
Fast	High	0.77	0	fixed	0.35	2	no	no	Light	P* varied (0.7)	1.31 (0.54)	0.13 (0.98)	-0.32 (4.14)	-0.23 (11.26)	0.92 (0.49)	0.27 (0.7)	1.14 (0.52)	0.77 (0.52)	0.24 (0.31)
Fast	High	1.25	0	fixed	0.35	2	no	no	Light	P* varied (0.7)	1.13 (0.77)	0.23 (0.65)	-0.32 (33.15)	-0.28 (7.69)	0.99 (0.43)	0.3 (0.57)	0.95 (0.71)	0.67 (0.86)	0.3 (0.31)
Fast	High	0.77	0.44	fixed	0.35	2	no	no	Light	P* varied (0.7)	1.3 (0.48)	0.1 (1.03)	-0.28 (2.27)	-0.19 (4.22)	0.9 (0.48)	0.27 (0.7)	0.92 (0.46)	0.65 (0.44)	0.22 (0.31)
Fast	High	1.25	0.44	fixed	0.35	2	no	no	Light	P* varied (0.7)	1.26 (0.59)	0.17 (0.87)	-0.33 (4.85)	-0.24 (15.69)	0.94 (0.45)	0.27 (0.64)	0.59 (0.55)	0.41 (0.59)	0.24 (0.29)
Fast	High	0.77	0	fixed	0.35	2	no	no	Moderate	P* varied (0.7)	1.28 (0.5)	0.1 (1.03)	0.23 (2.66)	0.27 (2.07)	0.88 (0.47)	0.27 (0.72)	0.76 (0.6)	0.75 (0.55)	0.23 (0.29)
Fast	High	1.25	0	fixed	0.35	2	no	no	Moderate	P* varied (0.7)	1.18 (0.71)	0.2 (0.69)	0.18 (2.81)	0.28 (2.59)	0.95 (0.42)	0.27 (0.59)	0.62 (0.94)	0.62 (0.79)	0.3 (0.33)
Fast	High	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* varied (0.7)	1.31 (0.46)	0.1 (1.1)	0.26 (2.8)	0.31 (1.9)	0.87 (0.47)	0.27 (0.73)	0.64 (0.51)	0.64 (0.46)	0.21 (0.28)
Fast	High	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* varied (0.7)	1.26 (0.56)	0.13 (0.93)	0.27 (2.53)	0.3 (2.07)	0.9 (0.43)	0.27 (0.67)	0.39 (0.62)	0.41 (0.59)	0.23 (0.29)
Fast	High	0.77	0	fixed	0.35	2	no	no	Heavy	P* varied (0.7)	1.32 (0.51)	0.13 (0.83)	1.46 (1.02)	1.52 (1.21)	0.93 (0.47)	0.27 (0.71)	0.39 (0.69)	0.79 (0.57)	0.25 (0.3)
Fast	High	1.25	0	fixed	0.35	2	no	no	Heavy	P* varied (0.7)	1.25 (0.77)	0.23 (0.64)	1.37 (1.41)	1.57 (1.79)	0.95 (0.43)	0.27 (0.6)	0.27 (1.04)	0.72 (1.06)	0.31 (0.32)
Fast	High	0.77	0.44	fixed	0.35	2	no	no	Heavy	P* varied (0.7)	1.37 (0.47)	0.1 (0.91)	1.62 (0.83)	1.6 (0.96)	0.91 (0.48)	0.27 (0.74)	0.3 (0.64)	0.66 (0.45)	0.23 (0.27)
Fast	High	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* varied (0.7)	1.39 (0.56)	0.15 (0.77)	1.57 (1.02)	1.99 (1.24)	0.89 (0.44)	0.23 (0.69)	0.17 (0.78)	0.43 (0.59)	0.24 (0.26)
Fast	High	0.77	0	fixed	0.35	2	no	no	Light	P* varied (1.0)	1.37 (0.51)	0.1 (1.03)	-0.27 (5.21)	-0.18 (40.97)	0.83 (0.49)	0.23 (0.75)	1.09 (0.54)	0.77 (0.52)	0.24 (0.3)
Fast	High	1.25	0	fixed	0.35	2	no	no	Light	P* varied (1.0)	1.18 (0.74)	0.2 (0.69)	-0.27 (18.84)	-0.24 (6.07)	0.92 (0.45)	0.23 (0.62)	0.9 (0.73)	0.66 (0.86)	0.3 (0.31)
Fast	High	0.77	0.44	fixed	0.35	2	no	no	Light	P* varied (1.0)	1.35 (0.46)	0.07 (1.11)	-0.25 (2.66)	-0.14 (6.76)	0.84 (0.49)	0.23 (0.76)	0.88 (0.48)	0.63 (0.44)	0.22 (0.3)
Fast	High	1.25	0.44	fixed	0.35	2	no	no	Light	P* varied (1.0)	1.31 (0.57)	0.13 (0.93)	-0.29 (6.42)	-0.18 (101.85)	0.87 (0.46)	0.23 (0.7)	0.57 (0.57)	0.4 (0.59)	0.24 (0.29)
Fast	High	0.77	0	fixed	0.35	2	no	no	Moderate	P* varied (1.0)	1.34 (0.49)	0.07 (1.12)	0.29 (2.27)	0.32 (1.87)	0.8 (0.49)	0.2 (0.78)	0.71 (0.63)	0.74 (0.56)	0.23 (0.29)
Fast	High	1.25	0	fixed	0.35	2	no	no	Moderate	P* varied (1.0)	1.21 (0.69)	0.2 (0.75)	0.24 (2.56)	0.36 (2.43)	0.86 (0.44)	0.23 (0.66)	0.58 (0.98)	0.62 (0.79)	0.3 (0.32)
Fast	High	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* varied (1.0)	1.39 (0.44)	0.07 (1.17)	0.32 (2.26)	0.38 (1.67)	0.79 (0.48)	0.2 (0.8)	0.59 (0.54)	0.63 (0.46)	0.21 (0.28)
Fast	High	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* varied (1.0)	1.31 (0.54)	0.1 (1.02)	0.34 (2.16)	0.41 (1.86)	0.82 (0.44)	0.22 (0.74)	0.36 (0.65)	0.4 (0.59)	0.23 (0.28)
Fast	High	0.77	0	fixed	0.35	2	no	no	Heavy	P* varied (1.0)	1.39 (0.49)	0.1 (0.83)	1.64 (0.94)	1.66 (1.15)	0.84 (0.47)	0.23 (0.78)	0.33 (0.77)	0.78 (0.56)	0.25 (0.29)
Fast	High	1.25	0	fixed	0.35	2	no	no	Heavy	P* varied (1.0)	1.32 (0.75)	0.2 (0.66)	1.65 (1.33)	1.67 (1.75)	0.86 (0.44)	0.23 (0.64)	0.24 (1.11)	0.71 (1.08)	0.31 (0.31)
Fast	High	0.77	0.44	fixed	0.35	2	no	no	Heavy	P* varied (1.0)	1.44 (0.45)	0.1 (0.93)	1.81 (0.75)	1.76 (0.91)	0.83 (0.48)	0.2 (0.78)	0.26 (0.71)	0.66 (0.45)	0.22 (0.27)
Fast	High	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* varied (1.0)	1.5 (0.53)	0.13 (0.8)	1.81 (0.94)	2.17 (1.18)	0.8 (0.45)	0.2 (0.74)	0.14 (0.86)	0.44 (0.58)	0.24 (0.25)
Fast	High	0.77	0	fixed	0.35	2	no	no	Light	P* fixed (0.38)	1.14 (0.61)	0.2 (0.88)	-0.36 (2.95)	-0.39 (3.29)	1.15 (0.5)	0.37 (0.64)	1.2 (0.49)	0.77 (0.49)	0.24 (0.32)
Fast	High	1.25	0	fixed	0.35	2	no	no	Light	P* fixed (0.38)	0.87 (0.9)	0.33 (0.59)	-0.4 (64.16)	-0.5 (230.79)	1.4 (0.41)	0.47 (0.49)	1 (0.67)	0.63 (0.85)	0.29 (0.34)
Fast	High	0.77	0.44	fixed	0.35	2	no	no	Light	P* fixed (0.38)	1.17 (0.54)	0.17 (0.94)	-0.34 (1.79)	-0.34 (2.1)	1.15 (0.49)	0.37 (0.66)	0.98 (0.44)	0.63 (0.41)	0.2 (0.32)
Fast	High	1.25	0.44	fixed	0.35	2	no	no	Light	P* fixed (0.38)	1.06 (0.7)	0.23 (0.8)	-0.39 (3.25)	-0.43 (3.28)	1.24 (0.47)	0.4 (0.58)	0.63 (0.52)	0.4 (0.58)	0.22 (0.31)
Fast	High	0.77	0	fixed	0.35	2	no	no	Moderate	P* fixed (0.38)	1.13 (0.59)	0.17 (0.93)	0.06 (4.82)	0.05 (3.24)	1.13 (0.5)	0.37 (0.64)	0.86 (0.51)	0.75 (0.54)	0.22 (0.31)
Fast	High	1.25	0	fixed	0.35	2	no	no	Moderate	P* fixed (0.38)	0.88 (0.86)	0.33 (0.62)	-0.05 (3.91)	-0.07 (3.41)	1.43 (0.41)	0.47 (0.49)	0.72 (0.81)	0.58 (0.79)	0.29 (0.35)
Fast	High	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (0.38)	1.12 (0.54)	0.13 (1.06)	0.1 (6.1)	0.08 (3.61)	1.13 (0.5)	0.37 (0.66)	0.72 (0.42)	0.63 (0.44)	0.2 (0.29)
Fast	High	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (0.38)	1.04 (0.69)	0.23 (0.82)	0.04 (4.58)	0.02 (3.51)	1.23 (0.46)	0.4 (0.58)	0.45 (0.53)	0.39 (0.6)	0.22 (0.32)
Fast	High	0.77	0	fixed	0.35	2	no	no	Heavy	P* fixed (0.38)	1.14 (0.59)	0.23 (0.76)	0.8 (1.45)	1.1 (1.42)	1.24 (0.47)	0.4 (0.6)	0.56 (0.5)	0.77 (0.55)	0.24 (0.31)
Fast	High	1.25	0	fixed	0.35	2	no	no	Heavy	P* fixed (0.38)	1.04 (0.88)	0.33 (0.56)	0.61 (1.86)	0.98 (2.04)	1.4 (0.41)	0.47 (0.48)	0.42 (0.79)	0.67 (1.03)	0.3 (0.35)
Fast	High	0.77	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (0.38)	1.19 (0.53)	0.2 (0.81)	0.8 (1.23)	1.31 (1.15)	1.18 (0.47)	0.4 (0.63)	0.44 (0.43)	0.64 (0.43)	0.21 (0.27)
Fast	High	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (0.38)	1.18 (0.66)	0.27 (0.71)	0.76 (1.48)	1.39 (1.47)	1.26 (0.45)	0.43 (0.56)	0.25 (0.55)	0.41 (0.58)	0.22 (0.28)
Fast	High	0.77	0	fixed	0.35	2	no	no	Light	P* fixed (0.7)	1.23 (0.58)	0.17 (0.97)	-0.32 (3.64)	-0.33 (4.67)	1.05 (0.52)	0.3 (0.71)	1.15 (0.51)	0.77 (0.48)	0.22 (0.33)
Fast	High	1.25	0	fixed	0.35	2	no	no	Light	P* fixed (0.7)	0.95 (0.86)	0.3 (0.64)	-0.34 (117.18)	-0.44 (20.49)	1.26 (0.45)	0.4 (0.54)	0.95 (0.68)	0.64 (0.84)	0.28 (0.35)
Fast	High	0.77	0.44	fixed	0.35	2	no	no	Light	P* fixed (0.7)	1.25 (0.52)	0.13 (1.04)	-0.29 (2.11)	-0.28 (2.7)	1 (0.52)	0.3 (0.72)	0.93 (0.45)	0.64 (0.41)	0.2 (0.32)
Fast	High	1.25	0.44	fixed	0.35	2	no	no	Light	P* fixed (0.7)	1.15 (0.66)	0.2 (0.89)	-0.33 (4.12)	-0.34 (4.61)	1.09 (0.5)	0.33 (0.64)	0.59 (0.53)	0.41 (0.57)	0.21 (0.31)
Fast	High	0.77	0	fixed	0.35	2	no	no	Moderate	P* fixed (0.7)	1.21 (0.56)	0.13 (1.04)	0.14 (3.52)	0.15 (2.65)	1.02 (0.52)	0.3 (0.72)	0.81 (0.52)	0.75 (0.52)	0.21 (0.31)
Fast	High	1.25	0	fixed	0.35	2	no	no	Moderate	P* fixed (0.7)	1 (0.82)	0.27 (0.67)	0.03 (3.48)	0.05 (3.04)	1.26 (0.44)	0.4 (0.55)	0.69 (0.83)	0.58 (0.76)	0.28 (0.34)
Fast	High	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (0.7)	1.23 (0.52)	0.1 (1.16)	0.17 (3.88)	0.19 (2.54)	0.97 (0.52)	0.3 (0.76)	0.68 (0.44)	0.63 (0.44)	0.19 (0.29)
Fast	High	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (0.7)	1.09 (0.66)	0.17 (0.92)	0.12 (3.43)	0.15 (2.77)	1.09 (0.49)	0.33 (0.66)	0.42 (0.54)	0.4 (0.59)	0.21 (0.31)
Fast	High	0.77	0	fixed	0.35	2	no	no	Heavy	P* fixed (0.7)	1.24 (0.56)	0.18 (0.82)	0.88 (1.33)	1.31 (1.31)	1.1 (0.49)	0.33 (0.67)	0.54 (0.51)	0.77 (0.54)	0.23 (0.31)
Fast	High	1.25	0	fixed	0.35	2	no	no	Heavy	P* fixed (0.7)	1.15 (0.84)	0.3 (0.6)	0.74 (1.77)	1.27 (1.96)	1.27 (0.44)	0.4 (0.53)	0.41 (0.79)	0.67 (1.03)	0.28 (0.34)
Fast	High	0.77	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (0.7)	1.31 (0.51)	0.15 (0.87)	0.97 (1.12)	1.52 (1.06)	1.04 (0.49)	0.33 (0.7)	0.42 (0.44)	0.64 (0.42)	0.21 (0.26)
Fast	High	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (0.7)	1.25 (0.63)	0.23 (0.77)	0.92 (1.37)	1.78 (1.35)	1.09 (0.48)	0.33 (0.62)	0.24 (0.55)	0.41 (0.57)	0.22 (0.28)
Fast	High	0.77	0	fixed	0.35	2	no	no	Light	P* fixed (1.0)	1.27 (0.57)	0.13 (1.05)	-0.27 (4.36)	-0.28 (6.86)	0.96 (0.54)	0.27 (0.77)	1.09 (0.52)	0.75 (0.47)	0.22 (0.33)
Fast	High	1.25	0	fixed	0.35	2	no	no	Light	P* fixed (1.0)	1.01 (0.83)	0.27 (0.68)	-0.3 (35.34)	-0.43 (12.85)	1.16 (0.47)	0.33 (0.59)	0.91 (0.69)	0.64 (0.82)	0.27 (0.34)
Fast	High	0.77	0.44	fixed	0.35	2	no	no	Light	P* fixed (1.0)	1.3 (0.5)	0.1 (1.13)	-0.25 (2.43)	-0.23 (3.37)	0.92 (0.54)	0.27 (0.78)	0.89 (0.46)	0.62 (0.41)	0.19 (0.32)
Fast	High	1.25	0.44	fixed	0.35	2	no	no	Light	P* fixed (1.0)	1.22 (0.64)	0.17 (0.95)	-0.29 (5.08)	-0.31 (6.59)	1.01 (0.51)	0.3 (0.71)	0.57 (0.54)	0.4 (0.57)	0.21 (0.31)
Fast	High	0.77	0	fixed	0.35	2	no	no	Moderate	P* fixed (1.0)	1.26 (0.54)	0.1 (1.13)	0.2 (2.96)	0.23 (2.28)	0.92 (0.53)	0.27 (0.79)	0.78 (0.53)	0.74 (0.52)	0.21 (0.31)
Fast	High	1.25	0	fixed	0.35	2	no	no	Moderate	P* fixed (1.0)	1.06 (0.79)	0.27 (0.72)	0.09 (3.23)	0.11 (2.83)	1.18 (0.46)	0.37 (0.6)	0.67 (0.84)	0.59 (0.74)	0.27 (0.34)
Fast	High	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (1.0)	1.3 (0.49)	0.07 (1.24)	0.23 (3)	0.26 (2.1)	0.88 (0.54)	0.27 (0.82)	0.65 (0.45)	0.61 (0.43)	0.18 (0.29)
Fast	High	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (1.0)	1.19 (0.63)	0.13 (1.01)	0.15 (2.91)	0.26 (2.42)	0.99 (0.5)	0.3 (0.72)	0.41 (0.54)	0.39 (0.57)	0.2 (0.31)
Fast	High	0.77	0	fixed	0.35	2	no	no	Heavy	P* fixed (1.0)	1.32 (0.55)	0.17 (0.85)	0.96 (1.26)	1.43 (1.24)	1.03 (0.5)	0.3 (0.72)	0.52 (0.51)	0.76 (0.53)	0.22 (0.3)
Fast	High	1.25	0	fixed	0.35	2	no	no	Heavy	P* fixed (1.0)	1.18 (0.82)	0.3 (0.64)	0.78 (1.71)	1.38 (1.9)	1.16 (0.45)	0.33 (0.58)	0.4 (0.8)	0.69 (1.05)	0.28 (0.34)
Fast	High	0.77	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (1.0)	1.37 (0.49)	0.13 (0.9)	1.09 (1.04)	1.62 (0.99)	0.97 (0.5)	0.3 (0.74)	0.42 (0.45)	0.64 (0.42)	0.2 (0.27)
Fast	High	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (1.0)	1.34 (0.61)	0.2 (0.8)	0.99 (1.3)	1.99 (1.28)	0.99 (0.49)	0.3 (0.69)	0.23 (0.56)	0.4 (0.56)	0.21 (0.27)
Fast	High	0.77	0	fixed	0.35	2	no	no	Light	75% of F_lim	1.24 (0.58)	0.13 (0.98)	-0.31 (3.82)	-0.33 (5.3)	1.01 (0.52)	0.3 (0.72)	1.13 (0.51)	0.76 (0.48)	0.22 (0.32)
Fast	High	1.25	0	fixed	0.35	2	no	no	Light	75% of F_lim	0.98 (0.84)	0.3 (0.65)	-0.33 (67.09)	-0.42 (16.86)	1.22 (0.46)	0.37 (0.56)	0.94 (0.68)	0.64 (0.83)	0.28 (0.34)
Fast	High	0.77	0.44	fixed	0.35	2	no	no	Light	75% of F_lim	1.25 (0.51)	0.1 (1.07)	-0.28 (2.2)	-0.26 (2.93)	0.99 (0.53)	0.3 (0.73)	0.91 (0.45)	0.64 (0.41)	0.2 (0.31)
Fast	High	1.25	0.44	fixed	0.35	2	no	no	Light	75% of F_lim	1.17 (0.65)	0.2 (0.9)	-0.32 (4.37)	-0.32 (5.27)	1.06 (0.5)	0.33 (0.66)	0.58 (0.53)	0.4 (0.57)	0.21 (0.31)
Fast	High	0.77	0	fixed	0.35	2	no	no	Moderate	75% of F_lim	1.23 (0.55)	0.13 (1.06)	0.16 (3.27)	0.18 (2.49)	0.98 (0.52)	0.3 (0.75)	0.8 (0.53)	0.75 (0.52)	0.21 (0.31)
Fast	High	1.25	0	fixed	0.35	2	no	no	Moderate	75% of F_lim	1.05 (0.8)	0.27 (0.68)	0.05 (3.38)	0.06 (2.95)	1.21 (0.45)	0.38 (0.56)	0.68 (0.83)	0.58 (0.76)	0.27 (0.34)
Fast	High	0.77	0.44	fixed	0.35	2	no	no	Moderate	75% of F_lim	1.25 (0.51)	0.1 (1.17)	0.18 (3.45)	0.21 (2.35)	0.94 (0.52)	0.3 (0.78)	0.67 (0.44)	0.62 (0.43)	0.19 (0.29)
Fast	High	1.25	0.44	fixed	0.35	2	no	no	Moderate	75% of F_lim	1.15 (0.64)	0.17 (0.95)	0.14 (3.2)	0.19 (2.62)	1.04 (0.49)	0.33 (0.67)	0.42 (0.54)	0.39 (0.58)	0.21 (0.31)

Life history	Assessment uncertainty	σ_R	ϕ_R	h	SPR target	SA years	Proj-tions?	ABC avg.?	Exploitation history		S / S_{MSY}	Overfished probability	ΔS_5	ΔS_{15}	F / F_{MSY}	P_{OF} (true)	Initial C / MSY	Final C / MSY	Catch AAV
Fast	High	0.77	0	fixed	0.35	2	no	no	Heavy	75% of F_lim	1.25 (0.56)	0.17 (0.83)	0.93 (1.29)	1.39 (1.29)	1.07 (0.49)	0.3 (0.69)	0.52 (0.51)	0.77 (0.54)	0.23 (0.31)
Fast	High	1.25	0	fixed	0.35	2	no	no	Heavy	75% of F_lim	1.15 (0.83)	0.3 (0.62)	0.77 (1.74)	1.29 (1.94)	1.22 (0.44)	0.37 (0.55)	0.4 (0.8)	0.68 (1.04)	0.28 (0.33)
Fast	High	0.77	0.44	fixed	0.35	2	no	no	Heavy	75% of F_lim	1.33 (0.5)	0.13 (0.89)	1.05 (1.08)	1.57 (1.03)	0.99 (0.5)	0.3 (0.71)	0.42 (0.45)	0.64 (0.42)	0.21 (0.27)
Fast	High	1.25	0.44	fixed	0.35	2	no	no	Heavy	75% of F_lim	1.28 (0.62)	0.2 (0.78)	0.95 (1.33)	1.85 (1.33)	1.04 (0.48)	0.33 (0.65)	0.23 (0.56)	0.41 (0.57)	0.22 (0.28)
Fast	High	0.77	0	fixed	0.35	2	no	no	Light	75% of F_lim	0.66 (0.76)	0.4 (0.55)	-0.61 (1.51)	-0.64 (1.26)	1.87 (0.37)	0.63 (0.39)	1.47 (0.42)	0.76 (0.52)	0.28 (0.29)
Fast	High	1.25	0	fixed	0.35	2	no	no	Light	75% of F_lim	0.53 (1.06)	0.5 (0.38)	-0.66 (7.4)	-0.75 (4.45)	2.08 (0.28)	0.67 (0.28)	1.24 (0.61)	0.57 (0.95)	0.34 (0.35)
Fast	High	0.77	0.44	fixed	0.35	2	no	no	Light	75% of F_lim	0.68 (0.68)	0.38 (0.6)	-0.63 (0.99)	-0.64 (0.91)	1.85 (0.37)	0.63 (0.4)	1.22 (0.36)	0.62 (0.45)	0.25 (0.28)
Fast	High	1.25	0.44	fixed	0.35	2	no	no	Light	75% of F_lim	0.61 (0.9)	0.5 (0.47)	-0.66 (1.57)	-0.78 (1.22)	2.02 (0.32)	0.67 (0.32)	0.78 (0.46)	0.33 (0.68)	0.28 (0.3)
Fast	High	0.77	0	fixed	0.35	2	no	no	Moderate	75% of F_lim	0.65 (0.73)	0.37 (0.55)	-0.32 (6.05)	-0.37 (10.28)	1.9 (0.35)	0.67 (0.36)	1.04 (0.44)	0.71 (0.59)	0.28 (0.28)
Fast	High	1.25	0	fixed	0.35	2	no	no	Moderate	75% of F_lim	0.51 (1.07)	0.5 (0.38)	-0.4 (11.5)	-0.51 (7.72)	2.1 (0.27)	0.67 (0.26)	0.85 (0.77)	0.5 (0.92)	0.36 (0.33)
Fast	High	0.77	0.44	fixed	0.35	2	no	no	Moderate	75% of F_lim	0.7 (0.68)	0.4 (0.62)	-0.31 (2.83)	-0.35 (3.77)	1.86 (0.37)	0.63 (0.37)	0.86 (0.34)	0.57 (0.5)	0.25 (0.26)
Fast	High	1.25	0.44	fixed	0.35	2	no	no	Moderate	75% of F_lim	0.52 (0.88)	0.47 (0.48)	-0.35 (6.77)	-0.54 (6.01)	2.08 (0.31)	0.7 (0.3)	0.54 (0.48)	0.29 (0.74)	0.27 (0.29)
Fast	High	0.77	0	fixed	0.35	2	no	no	Heavy	75% of F_lim	0.71 (0.72)	0.43 (0.51)	0.16 (2.4)	0.35 (2.2)	1.93 (0.35)	0.67 (0.35)	0.66 (0.48)	0.76 (0.57)	0.29 (0.31)
Fast	High	1.25	0	fixed	0.35	2	no	no	Heavy	75% of F_lim	0.66 (1.03)	0.5 (0.39)	0.06 (2.48)	0.02 (2.71)	2.1 (0.28)	0.7 (0.28)	0.5 (0.79)	0.58 (1.03)	0.35 (0.34)
Fast	High	0.77	0.44	fixed	0.35	2	no	no	Heavy	75% of F_lim	0.72 (0.67)	0.43 (0.55)	0.18 (2.24)	0.41 (1.98)	1.9 (0.36)	0.67 (0.37)	0.53 (0.38)	0.6 (0.46)	0.26 (0.25)
Fast	High	1.25	0.44	fixed	0.35	2	no	no	Heavy	75% of F_lim	0.67 (0.83)	0.47 (0.45)	0.18 (2.25)	0.22 (2.41)	2.03 (0.31)	0.67 (0.32)	0.3 (0.52)	0.36 (0.67)	0.27 (0.25)

Life history	Assessment uncertainty	σ_R	ϕ_R	h	SPR target	SA years	Projec-tions?	ABC avg.?	Exploitation history	Control rule	S / S_{MSY}	Overfished probability	ΔS_5	ΔS_{15}	F / F_{MSY}	P_{OF} (true)	Initial C / MSY	Final C / MSY	Catch AAV
Medium	Low	0.77	0.00	fixed	0.35	2	no	no	Light	OFL	0.88 (0.37)	0 (1.61)	-0.34 (0.84)	-0.55 (0.69)	1.1 (0.3)	0.5 (0.53)	1.74 (0.41)	0.9 (0.35)	0.1 (0.3)
Medium	Low	1.25	0.00	fixed	0.35	2	no	no	Light	OFL	0.78 (0.6)	0.17 (1.02)	-0.38 (1.52)	-0.59 (1.69)	1.11 (0.36)	0.5 (0.47)	1.58 (0.58)	0.73 (0.68)	0.14 (0.27)
Medium	Low	0.77	0.44	fixed	0.35	2	no	no	Light	OFL	0.88 (0.37)	0 (1.61)	-0.34 (0.84)	-0.55 (0.69)	1.1 (0.3)	0.5 (0.53)	1.74 (0.41)	0.9 (0.35)	0.1 (0.3)
Medium	Low	1.25	0.44	fixed	0.35	2	no	no	Light	OFL	0.78 (0.6)	0.17 (1.02)	-0.38 (1.52)	-0.59 (1.69)	1.11 (0.36)	0.5 (0.47)	1.58 (0.58)	0.73 (0.68)	0.14 (0.27)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Light	OFL	0.91 (0.28)	0 (2.25)	-0.29 (0.8)	-0.47 (0.61)	1.08 (0.29)	0.5 (0.56)	1.24 (0.38)	0.71 (0.26)	0.09 (0.3)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Light	OFL	0.8 (0.39)	0 (1.59)	-0.32 (0.94)	-0.53 (0.83)	1.08 (0.3)	0.5 (0.55)	0.81 (0.45)	0.41 (0.41)	0.1 (0.3)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Light	OFL	0.9 (0.33)	0 (1.56)	-0.31 (0.81)	-0.52 (0.62)	1.13 (0.41)	0.5 (0.48)	1.31 (0.39)	0.68 (0.37)	0.06 (0.46)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Light	OFL	0.74 (0.52)	0.13 (1.14)	-0.34 (0.97)	-0.59 (0.81)	1.2 (0.52)	0.53 (0.45)	0.89 (0.45)	0.35 (0.59)	0.08 (0.45)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Light	OFL	0.91 (0.27)	0 (2.07)	-0.31 (0.77)	-0.47 (0.6)	1.1 (0.27)	0.5 (0.5)	1.29 (0.38)	0.71 (0.26)	0.12 (0.27)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Light	OFL	0.8 (0.38)	0 (1.49)	-0.34 (0.91)	-0.54 (0.81)	1.11 (0.28)	0.5 (0.49)	0.84 (0.45)	0.4 (0.41)	0.15 (0.26)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Light	OFL	0.85 (0.52)	0 (1.57)	-0.26 (0.92)	-0.51 (0.66)	1.14 (0.84)	0.53 (0.53)	1.19 (0.4)	0.64 (0.51)	0.1 (0.43)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Light	OFL	0.67 (0.69)	0.1 (1.17)	-0.29 (1.11)	-0.59 (0.85)	1.21 (0.91)	0.57 (0.5)	0.79 (0.46)	0.34 (0.7)	0.12 (0.38)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Light	OFL	0.85 (0.48)	0 (1.7)	-0.2 (0.98)	-0.53 (0.65)	1.13 (0.9)	0.53 (0.55)	1.06 (0.33)	0.67 (0.45)	0.06 (0.52)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Light	OFL	0.66 (0.67)	0.1 (1.19)	-0.23 (1.28)	-0.6 (0.86)	1.18 (0.91)	0.57 (0.51)	0.69 (0.4)	0.35 (0.66)	0.07 (0.49)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Light	OFL	0.62 (0.81)	0.02 (1.21)	-0.17 (1.15)	-0.53 (0.73)	1.28 (0.81)	0.67 (0.5)	1.01 (0.31)	0.61 (0.67)	0.04 (0.66)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Light	OFL	0.25 (1.16)	0.32 (0.88)	-0.2 (1.55)	-0.6 (1)	1.91 (0.7)	0.72 (0.45)	0.66 (0.39)	0.26 (0.97)	0.05 (0.59)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Light	OFL	0.87 (0.46)	0 (1.57)	-0.22 (0.93)	-0.56 (0.62)	1.16 (0.81)	0.53 (0.48)	1.09 (0.33)	0.66 (0.46)	0.07 (0.48)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Light	OFL	0.65 (0.72)	0.13 (1.1)	-0.25 (1.21)	-0.63 (0.81)	1.23 (0.88)	0.6 (0.45)	0.73 (0.4)	0.33 (0.72)	0.09 (0.42)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Light	OFL	0.5 (0.91)	0.17 (1.05)	-0.15 (1.31)	-0.54 (0.73)	1.42 (0.75)	0.68 (0.46)	0.94 (0.3)	0.57 (0.74)	0.05 (0.56)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Light	OFL	0.06 (1.29)	0.35 (0.82)	-0.17 (1.8)	-0.62 (1)	2.88 (0.65)	0.73 (0.41)	0.63 (0.38)	0.16 (1.07)	0.08 (0.49)
Medium	Low	0.77	0.00	fixed	0.35	2	no	no	Moderate	OFL	0.9 (0.34)	0 (2.32)	-0.09 (4.05)	-0.14 (4.39)	1.01 (0.2)	0.43 (0.56)	1.12 (0.37)	0.89 (0.36)	0.09 (0.24)
Medium	Low	1.25	0.00	fixed	0.35	2	no	no	Moderate	OFL	0.82 (0.56)	0.1 (1.15)	-0.15 (69.52)	-0.18 (29.62)	1.03 (0.27)	0.47 (0.49)	0.98 (0.62)	0.73 (0.65)	0.13 (0.26)
Medium	Low	0.77	0.44	fixed	0.35	2	no	no	Moderate	OFL	0.9 (0.34)	0 (2.32)	-0.09 (4.05)	-0.14 (4.39)	1.01 (0.2)	0.43 (0.56)	1.12 (0.37)	0.89 (0.36)	0.09 (0.24)
Medium	Low	1.25	0.44	fixed	0.35	2	no	no	Moderate	OFL	0.82 (0.56)	0.1 (1.15)	-0.15 (69.52)	-0.18 (29.62)	1.03 (0.27)	0.47 (0.49)	0.98 (0.62)	0.73 (0.65)	0.13 (0.26)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Moderate	OFL	0.95 (0.27)	0 (3.36)	-0.04 (6.01)	-0.06 (14.49)	1 (0.2)	0.43 (0.56)	0.8 (0.29)	0.72 (0.27)	0.07 (0.24)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Moderate	OFL	0.85 (0.39)	0 (1.93)	-0.08 (6.31)	-0.1 (12.17)	1.02 (0.2)	0.47 (0.55)	0.49 (0.4)	0.4 (0.42)	0.08 (0.25)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Moderate	OFL	0.94 (0.32)	0 (2.07)	-0.05 (5.67)	-0.06 (8.29)	1.04 (0.29)	0.45 (0.54)	0.81 (0.33)	0.72 (0.36)	0.05 (0.36)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Moderate	OFL	0.8 (0.49)	0 (1.44)	-0.08 (6.05)	-0.13 (7.76)	1.08 (0.42)	0.47 (0.49)	0.5 (0.44)	0.37 (0.56)	0.07 (0.38)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Moderate	OFL	0.96 (0.27)	0 (3.19)	-0.04 (5.87)	-0.06 (15.4)	1 (0.18)	0.43 (0.53)	0.81 (0.29)	0.72 (0.28)	0.1 (0.22)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Moderate	OFL	0.86 (0.39)	0 (1.83)	-0.09 (6.12)	-0.11 (12.32)	1.02 (0.19)	0.47 (0.5)	0.5 (0.4)	0.41 (0.43)	0.12 (0.24)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Moderate	OFL	0.92 (0.36)	0 (2.07)	-0.04 (6)	-0.08 (6.9)	1.04 (0.48)	0.47 (0.56)	0.79 (0.32)	0.71 (0.37)	0.07 (0.34)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Moderate	OFL	0.79 (0.56)	0.02 (1.42)	-0.08 (6.55)	-0.13 (6.86)	1.09 (0.73)	0.47 (0.53)	0.49 (0.43)	0.36 (0.58)	0.09 (0.33)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Moderate	OFL	0.93 (0.34)	0 (2.39)	-0.05 (5.63)	-0.1 (8.33)	1.05 (0.34)	0.5 (0.55)	0.81 (0.24)	0.7 (0.3)	0.05 (0.3)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Moderate	OFL	0.81 (0.53)	0 (1.47)	-0.09 (6.14)	-0.15 (8.02)	1.07 (0.68)	0.5 (0.51)	0.51 (0.36)	0.38 (0.51)	0.06 (0.33)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Moderate	OFL	0.84 (0.59)	0 (1.67)	-0.05 (5.45)	-0.12 (4.91)	1.14 (0.83)	0.57 (0.56)	0.82 (0.24)	0.68 (0.47)	0.03 (0.55)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Moderate	OFL	0.6 (0.92)	0.13 (1.1)	-0.11 (6.02)	-0.2 (5.31)	1.35 (0.8)	0.67 (0.5)	0.51 (0.36)	0.31 (0.79)	0.04 (0.58)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Moderate	OFL	0.93 (0.33)	0 (2.37)	-0.05 (5.5)	-0.1 (8.46)	1.05 (0.29)	0.5 (0.51)	0.82 (0.24)	0.71 (0.31)	0.06 (0.29)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Moderate	OFL	0.81 (0.54)	0.03 (1.41)	-0.1 (5.95)	-0.15 (7.77)	1.1 (0.65)	0.53 (0.47)	0.51 (0.36)	0.39 (0.53)	0.07 (0.31)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Moderate	OFL	0.83 (0.61)	0 (1.62)	-0.04 (5.63)	-0.13 (4.65)	1.16 (0.83)	0.57 (0.55)	0.81 (0.24)	0.66 (0.49)	0.03 (0.5)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Moderate	OFL	0.53 (0.96)	0.17 (1.07)	-0.1 (6.26)	-0.21 (5.1)	1.42 (0.78)	0.7 (0.5)	0.51 (0.36)	0.32 (0.82)	0.05 (0.5)
Medium	Low	0.77	0.00	fixed	0.35	2	no	no	Heavy	OFL	1.06 (0.33)	0.03 (1.35)	0.36 (1.14)	0.73 (1.03)	1.01 (0.21)	0.43 (0.56)	0.55 (0.4)	0.92 (0.38)	0.09 (0.23)
Medium	Low	1.25	0.00	fixed	0.35	2	no	no	Heavy	OFL	1.07 (0.56)	0.17 (0.89)	0.28 (1.84)	0.63 (1.59)	1.02 (0.24)	0.47 (0.49)	0.45 (0.76)	0.78 (0.91)	0.13 (0.24)
Medium	Low	0.77	0.44	fixed	0.35	2	no	no	Heavy	OFL	1.06 (0.33)	0.03 (1.35)	0.36 (1.14)	0.73 (1.03)	1.01 (0.21)	0.43 (0.56)	0.55 (0.4)	0.92 (0.38)	0.09 (0.23)
Medium	Low	1.25	0.44	fixed	0.35	2	no	no	Heavy	OFL	1.07 (0.56)	0.17 (0.89)	0.28 (1.84)	0.63 (1.59)	1.02 (0.24)	0.47 (0.49)	0.45 (0.76)	0.78 (0.91)	0.13 (0.24)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Heavy	OFL	1.07 (0.26)	0.05 (1.15)	0.44 (0.7)	1.04 (0.67)	0.97 (0.18)	0.4 (0.63)	0.38 (0.32)	0.71 (0.26)	0.07 (0.22)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Heavy	OFL	1.02 (0.38)	0.12 (1.07)	0.35 (1.11)	0.93 (1.02)	0.98 (0.19)	0.4 (0.61)	0.2 (0.5)	0.37 (0.43)	0.08 (0.23)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Heavy	OFL	1.07 (0.29)	0.07 (1.2)	0.47 (0.77)	1.15 (0.67)	0.96 (0.23)	0.37 (0.64)	0.36 (0.36)	0.73 (0.31)	0.05 (0.3)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Heavy	OFL	1.01 (0.43)	0.13 (1.02)	0.36 (1.23)	1.04 (1.06)	0.97 (0.28)	0.37 (0.59)	0.19 (0.53)	0.39 (0.48)	0.06 (0.32)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Heavy	OFL	1.08 (0.26)	0.03 (1.15)	0.49 (0.65)	1.08 (0.66)	0.95 (0.17)	0.37 (0.62)	0.36 (0.32)	0.72 (0.26)	0.1 (0.2)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Heavy	OFL	1.02 (0.38)	0.1 (1.05)	0.4 (1.03)	0.98 (1)	0.96 (0.18)	0.4 (0.59)	0.19 (0.5)	0.38 (0.43)	0.12 (0.22)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Heavy	OFL	1.08 (0.31)	0.1 (1.17)	0.31 (1.11)	1.1 (0.73)	1 (0.33)	0.4 (0.57)	0.43 (0.33)	0.72 (0.31)	0.08 (0.23)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Heavy	OFL	1 (0.47)	0.17 (0.95)	0.2 (1.86)	0.87 (1.2)	1.02 (0.62)	0.43 (0.54)	0.23 (0.5)	0.37 (0.51)	0.1 (0.28)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Heavy	OFL	1.11 (0.29)	0.1 (1.09)	0.25 (1.17)	1.06 (0.72)	1 (0.21)	0.4 (0.59)	0.46 (0.26)	0.74 (0.26)	0.05 (0.24)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Heavy	OFL	1.02 (0.44)	0.17 (0.91)	0.16 (2.14)	0.89 (1.21)	1.03 (0.52)	0.43 (0.55)	0.25 (0.44)	0.38 (0.46)	0.06 (0.33)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Heavy	OFL	1.2 (0.36)	0.1 (1.17)	0.19 (1.6)	0.99 (0.93)	0.99 (0.77)	0.37 (0.6)	0.49 (0.26)	0.72 (0.33)	0.03 (0.43)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Heavy	OFL	1.01 (0.7)	0.27 (0.84)	0.09 (3.23)	0.63 (1.82)	1.1 (0.99)	0.5 (0.57)	0.27 (0.43)	0.32 (0.7)	0.04 (0.65)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Heavy	OFL	1.11 (0.29)	0.1 (1.04)	0.28 (1.05)	1.16 (0.67)	0.98 (0.19)	0.37 (0.57)	0.44 (0.26)	0.75 (0.26)	0.06 (0.22)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Heavy	OFL	1.03 (0.44)	0.17 (0.91)	0.19 (1.9)	0.95 (1.13)	1 (0.52)	0.4 (0.54)	0.24 (0.44)	0.39 (0.46)	0.08 (0.28)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Heavy	OFL	1.23 (0.37)	0.13 (1.1)	0.1 (2.49)	0.92 (1.04)	1.01 (0.83)	0.4 (0.57)	0.53 (0.25)	0.71 (0.35)	0.05 (0.35)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Heavy	OFL	0.99 (0.74)	0.27 (0.8)	0.01 (6.3)	0.53 (2.1)	1.14 (0.98)	0.5 (0.56)	0.29 (0.43)	0.31 (0.74)	0.06 (0.52)
Medium	Low	0.77	0.00	fixed	0.35	2	no	no	Light	P* var (0.38)	1.04 (0.31)	0 (2.11)	-0.3 (0.97)	-0.44 (0.89)	0.91 (0.26)	0.3 (0.67)	1.6 (0.42)	0.94 (0.34)	0.1 (0.29)
Medium	Low	1.25	0.00	fixed	0.35	2	no	no	Light	P* var (0.38)	0.97 (0.5)	0.03 (1.27)	-0.34 (1.85)	-0.49 (2.55)	0.9 (0.28)	0.3 (0.61)	1.45 (0.59)	0.79 (0.64)	0.14 (0.26)
Medium	Low	0.77	0.44	fixed	0.35	2	no	no	Light	P* var (0.38)	1.04 (0.31)	0 (2.11)	-0.3 (0.97)	-0.44 (0.89)	0.91 (0.26)	0.3 (0.67)	1.6 (0.42)	0.94 (0.34)	0.1 (0.29)
Medium	Low	1.25	0.44	fixed	0.35	2	no	no	Light	P* var (0.38)	0.97 (0.5)	0.03 (1.27)	-0.34 (1.85)	-0.49 (2.55)	0.9 (0.28)	0.3 (0.61)	1.45 (0.59)	0.79 (0.64)	0.14 (0.26)
Medium	Low	0.77	0.00	fixed	0.35	2	no	no	Moderate	P* var (0.38)	1.05 (0.3)	0 (3.45)	-0.02 (53.81)	0.01 (9.88)	0.85 (0.18)	0.23 (0.78)	1.02 (0.38)	0.9 (0.35)	0.09 (0.24)
Medium	Low	1.25	0.00	fixed	0.35	2	no	no	Moderate	P* var (0.38)	0.97 (0.48)	0 (1.57)	-0.07 (9.55)	-0.01 (4.46)	0.84 (0.19)	0.23 (0.7)	0.87 (0.64)	0.75 (0.63)	0.13 (0.26)
Medium	Low	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* var (0.38)	1.05 (0.3)	0 (3.45)	-0.02 (53.81)	0.01 (9.88)	0.85 (0.18)	0.23 (0.78)	1.02 (0.38)	0.9 (0.35)	0.09 (0.24)
Medium	Low	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* var (0.38)	0.97 (0.48)	0 (1.57)	-0.07 (9.55)	-0.01 (4.46)	0.84 (0.19)	0.23 (0.7)	0.87 (0.64)	0.75 (0.63)	0.13 (0.26)
Medium	Low	0.77	0.00	fixed	0.35	2	no	no	Heavy	P* var (0.38)	1.21 (0.29)	0.03 (1.36)	0.59 (0.76)	1.08 (0.82)	0.82 (0.19)	0.2 (0.85)	0.41 (0.47)	0.96 (0.37)	0.09 (0.24)
Medium	Low	1.25	0.00	fixed	0.35	2	no	no	Heavy	P* var (0.38)	1.24 (0.49)	0.1 (1.05)	0.54 (1.27)	1.1 (1.3)	0.8 (0.21)	0.2 (0.77)	0.33 (0.89)	0.82 (0.94)	0.13 (0.24)
Medium	Low	0.77	0.44	fixed	0.35	2	no	no	Heavy	P* var (0.38)	1.21 (0.29)	0.03 (1.36)	0.59 (0.76)	1.08 (0.82)	0.82 (0.19)	0.2 (0.85)	0.41 (0.47)	0.96 (0.37)	0.09 (0.24)
Medium	Low	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* var (0.38)	1.24 (0.49)	0.1 (1.05)	0.54 (1.27)	1.1 (1.3)	0.8 (0.21)	0.2 (0.77)	0.33 (0.89)	0.82 (0.94)	0.13 (0.24)
Medium	Low	0.77	0.00	fixed	0.35	2	no	no	Light	P* varied (0.7)	1.12 (0.29)	0 (2.65)	-0.26 (1.09)	-0.39 (1.06)	0.82 (0.25)	0.23 (0.81)	1.5 (0.42)	0.94 (0.34)	0.1 (0.29)
Medium	Low	1.25	0.00	fixed	0.35	2	no	no	Light	P* varied (0.7)	1.06 (0.47)	0 (1.49)	-0.3 (2.17)	-0.43 (3.45)	0.8 (0.27)	0.23 (0.74)	1.36 (0.59)	0.8 (0.63)	0.14 (0.25)
Medium	Low	0.77	0.44	fixed	0.35	2	no	no	Light	P* varied (0.7)	1.12 (0.29)	0 (2.65)	-0.26 (1.09)	-0.39 (1.06)	0.82 (0.25)	0.23 (0.81)	1.5 (0.42)	0.94 (0.34)	0.1 (0.29)
Medium	Low	1.25	0.44	fixed	0.35	2	no	no	Light	P* varied (0.7)	1.06 (0.47)	0 (1.49)	-0.3 (2.17)	-0.43 (3.45)	0.8 (0.27)	0.23 (0.74)	1.36 (0.59)	0.8 (0.63)	0.14 (0.25)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Light	P* varied (0.7)	1.12 (0.22)	0 (3.7)	-0.22 (1.02)	-0.33 (0.91)	0.83 (0.23)	0.22 (0.84)	1.07 (0.39)	0.72 (0.26)	0.09 (0.3)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Light	P* varied (0.7)	1.05 (0.3)	0 (2.86)	-0.24 (1.27)	-0.37 (1.34)	0.81 (0.24)	0.2 (0.82)	0.7 (0.45)	0.43 (0.38)	0.1 (0.28)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Light	P* varied (0.7)	1.13 (0.24)	0 (2.37)	-0.22 (1.06)	-0.37 (0.92)	0.86 (0.31)	0.27 (0.72)	1.11 (0.41)	0.74 (0.31)	0.06 (0.44)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Light	P* varied (0.7)	1.05 (0.33)	0 (1.86)	-0.25 (1.3)	-0.44 (1.31)	0.86 (0.34)	0.27 (0.65)	0.76 (0.47)	0.41 (0.47)	0.07 (0.41)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Light	P* varied (0.7)	1.1 (0.22)	0 (3.45)	-0.23 (0.97)	-0.34 (0.87)	0.85 (0.22)	0.23 (0.75)	1.11 (0.39)	0.72 (0.26)	0.12 (0.24)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Light	P* varied (0.7)	1.04 (0.3)	0 (2.63)	-0.26 (1.2)	-0.38 (1.28)	0.84 (0.23)	0.23 (0.73)	0.72 (0.45)	0.43 (0.39)	0.15 (0.23)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Light	P* varied (0.7)	1.15 (0.24)	0 (2.57)	-0.18 (1.24)	-0.36 (0.99)	0.83 (0.34)	0.23 (0.74)	1.01 (0.41)	0.73 (0.31)	0.1 (0.31)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Light	P* varied (0.7)	1.07 (0.34)	0 (2)	-0.21 (1.55)	-0.41 (1.4)	0.83 (0.38)	0.23 (0.69)	0.68 (0.46)	0.42 (0.48)	0.12 (0.29)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Light	P* varied (0.7)	1.12 (0.25)	0 (3.02)	-0.16 (1.29)	-0.39 (0.93)	0.85 (0.4)	0.27 (0.83)	0.94 (0.32)	0.71 (0.31)	0.05 (0.41)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Light	P* varied (0.7)	1 (0.4)	0 (2.14)	-0.19 (1.74)	-0.44 (1.33)	0.84 (0.69)	0.27 (0.78)	0.62 (0.39)	0.41 (0.48)	0.06 (0.38)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Light	P* varied (0.7)	0.99 (0.51)	0 (1.98)	-0.13 (1.51)	-0.4 (1.03)	0.9 (0.99)	0.33 (0.83)	0.91 (0.31)	0.64 (0.48)	0.03 (0.63)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Light	P* varied (0.7)	0.81 (0.73)	0 (1.39)	-0.16 (2.09)	-0.45 (1.47)	0.98 (0.96)	0.4 (0.73)	0.6 (0.38)	0.35 (0.7)	0.04 (0.61)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Light	P* varied (0.7)	1.11 (0.26)	0 (2.87)	-0.17 (1.2)	-0.42 (0.86)	0.88 (0.43)	0.3 (0.71)	0.97 (0.32)	0.72 (0.33)	0.07 (0.37)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Light	P* varied (0.7)	0.99 (0.42)	0 (1.88)	-0.2 (1.61)	-0.47 (1.22)	0.9 (0.81)	0.33 (0.68)	0.65 (0.4)	0.4 (0.51)	0.09 (0.34)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Light	P* varied (0.7)	0.93 (0.56)	0 (1.76)	-0.11 (1.8)	-0.39 (1.03)	0.93 (0.97)	0.4 (0.77)	0.86 (0.29)	0.62 (0.52)	0.05 (0.48)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Light	P* varied (0.7)	0.75 (0.8)	0 (1.29)	-0.14 (2.52)	-0.44 (1.47)	1.02 (0.91)	0.43 (0.68)	0.57 (0.37)	0.34 (0.75)	0.06 (0.47)
Medium	Low	0.77	0.00	fixed	0.35	2	no	no	Moderate	P* varied (0.7)	1.13 (0.28)	0 (4.78)	0.02 (8.02)	0.09 (3.67)	0.77 (0.17)	0.13 (0.98)	0.94 (0.39)	0.91 (0.35)	0.09 (0.25)
Medium	Low	1.25	0.00	fixed	0.35	2	no	no	Moderate	P* varied (0.7)	1.06 (0.45)	0 (1.85)	-0.02 (5.62)	0.08 (3.16)	0.75 (0.19)	0.17 (0.88)	0.8 (0.65)	0.76 (0.62)	0.13 (0.26)
Medium	Low	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* varied (0.7)	1.13 (0.28)	0 (4.78)	0.02 (8.02)	0.09 (3.67)	0.77 (0.17)	0.13 (0.98)	0.94 (0.39)	0.91 (0.35)	0.09 (0.25)
Medium	Low	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* varied (0.7)	1.06 (0.45)	0 (1.85)	-0.02 (5.62)	0.08 (3.16)	0.75 (0.19)	0.17 (0.88)	0.8 (0.65)	0.76 (0.62)	0.13 (0.26)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Moderate	P* varied (0.7)	1.16 (0.23)	0 (8.35)	0.07 (3.02)	0.13 (1.95)	0.79 (0.18)	0.13 (0.98)	0.67 (0.33)	0.72 (0.27)	0.08 (0.25)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Moderate	P* varied (0.7)	1.1 (0.32)	0 (3.65)	0.04 (4.17)	0.12 (2.64)	0.76 (0.18)	0.13 (1)	0.4 (0.45)	0.43 (0.41)	0.09 (0.25)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Moderate	P* varied (0.7)	1.15 (0.26)	0 (5)	0.05 (3.62)	0.15 (2.05)	0.79 (0.2)	0.17 (0.86)	0.67 (0.38)	0.73 (0.34)	0.06 (0.34)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Moderate	P* varied (0.7)	1.1 (0.37)	0 (2.18)	0.03 (5.16)	0.15 (2.82)	0.78 (0.22)	0.2 (0.8)	0.4 (0.49)	0.41 (0.51)	0.07 (0.35)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Moderate	P* varied (0.7)	1.14 (0.23)	0 (7.65)	0.07 (3.19)	0.13 (2.06)	0.8 (0.17)	0.17 (0.88)	0.67 (0.33)	0.73 (0.28)	0.1 (0.22)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Moderate	P* varied (0.7)	1.1 (0.32)	0 (3.21)	0.04 (4.49)	0.13 (2.81)	0.78 (0.18)	0.13 (0.88)	0.4 (0.45)	0.42 (0.42)	0.13 (0.23)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Moderate	P* varied (0.7)	1.18 (0.26)	0 (5.5)	0.06 (3.24)	0.18 (1.91)	0.77 (0.21)	0.17 (0.9)	0.66 (0.36)	0.72 (0.33)	0.08 (0.26)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Moderate	P* varied (0.7)	1.11 (0.36)	0 (2.32)	0.04 (4.55)	0.18 (2.59)	0.77 (0.23)	0.17 (0.84)	0.4 (0.48)	0.41 (0.49)	0.09 (0.27)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Moderate	P* varied (0.7)	1.14 (0.26)	0 (5.49)	0.02 (6.15)	0.14 (2.12)	0.81 (0.19)	0.2 (0.92)	0.72 (0.26)	0.72 (0.27)	0.05 (0.29)

Life history	Assessment uncertainty	σ_R	ϕ_R	h	SPR target	SA years	Projec-tions?	ABC avg.?	Exploitation history	Control rule	S / S_{MSY}	Overfished probability	ΔS_5	ΔS_{15}	F / F_{MSY}	P_{OF} (true)	Initial C / MSY	Final C / MSY	Catch AAV
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Moderate	P* varied (0.7)	1.09 (0.37)	0 (2.39)	-0.01 (10.89)	0.14 (2.97)	0.8 (0.2)	0.2 (0.86)	0.45 (0.38)	0.41 (0.43)	0.06 (0.3)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Moderate	P* varied (0.7)	1.16 (0.33)	0 (3.17)	0 (12.09)	0.1 (3.35)	0.84 (0.5)	0.23 (0.88)	0.75 (0.25)	0.71 (0.3)	0.03 (0.36)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Moderate	P* varied (0.7)	1.03 (0.56)	0 (1.84)	-0.04 (35.14)	0.05 (5.46)	0.88 (0.94)	0.32 (0.84)	0.46 (0.38)	0.38 (0.54)	0.04 (0.45)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Moderate	P* varied (0.7)	1.12 (0.26)	0 (4.49)	0.03 (6.61)	0.13 (2.25)	0.83 (0.18)	0.2 (0.84)	0.73 (0.26)	0.73 (0.28)	0.06 (0.27)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Moderate	P* varied (0.7)	1.07 (0.39)	0 (2.17)	-0.01 (12.26)	0.12 (3.24)	0.83 (0.22)	0.23 (0.77)	0.45 (0.38)	0.42 (0.45)	0.08 (0.28)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Moderate	P* varied (0.7)	1.15 (0.34)	0 (3.01)	0 (10.45)	0.12 (3.33)	0.85 (0.5)	0.25 (0.87)	0.74 (0.25)	0.71 (0.31)	0.04 (0.3)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Moderate	P* varied (0.7)	1.03 (0.57)	0 (1.81)	-0.03 (25.74)	0.05 (5.42)	0.89 (0.94)	0.3 (0.83)	0.46 (0.38)	0.39 (0.54)	0.05 (0.39)
Medium	Low	0.77	0.00	fixed	0.35	2	no	no	Heavy	P* varied (0.7)	1.31 (0.28)	0 (1.38)	0.72 (0.65)	1.27 (0.76)	0.73 (0.19)	0.07 (1.12)	0.34 (0.53)	0.96 (0.36)	0.09 (0.24)
Medium	Low	1.25	0.00	fixed	0.35	2	no	no	Heavy	P* varied (0.7)	1.34 (0.47)	0.07 (1.16)	0.66 (1.1)	1.26 (1.21)	0.7 (0.21)	0.1 (1.01)	0.27 (0.99)	0.85 (0.93)	0.13 (0.24)
Medium	Low	0.77	0.44	fixed	0.35	2	no	no	Heavy	P* varied (0.7)	1.31 (0.28)	0 (1.38)	0.72 (0.65)	1.27 (0.76)	0.73 (0.19)	0.07 (1.12)	0.34 (0.53)	0.96 (0.36)	0.09 (0.24)
Medium	Low	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* varied (0.7)	1.34 (0.47)	0.07 (1.16)	0.66 (1.1)	1.26 (1.21)	0.7 (0.21)	0.1 (1.01)	0.27 (0.99)	0.85 (0.93)	0.13 (0.24)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Heavy	P* varied (0.7)	1.27 (0.22)	0.03 (0.95)	0.79 (0.41)	1.6 (0.51)	0.71 (0.18)	0.07 (1.21)	0.21 (0.42)	0.72 (0.24)	0.08 (0.22)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Heavy	P* varied (0.7)	1.24 (0.31)	0.07 (1.02)	0.72 (0.63)	1.7 (0.72)	0.69 (0.19)	0.07 (1.25)	0.1 (0.66)	0.41 (0.39)	0.09 (0.23)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Heavy	P* varied (0.7)	1.26 (0.24)	0.03 (0.99)	0.84 (0.43)	1.78 (0.5)	0.69 (0.21)	0.07 (1.21)	0.2 (0.46)	0.74 (0.29)	0.06 (0.26)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Heavy	P* varied (0.7)	1.26 (0.34)	0.07 (0.98)	0.75 (0.66)	1.86 (0.73)	0.66 (0.23)	0.07 (1.16)	0.1 (0.67)	0.43 (0.44)	0.07 (0.28)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Heavy	P* varied (0.7)	1.25 (0.22)	0.03 (0.94)	0.81 (0.4)	1.61 (0.51)	0.71 (0.18)	0.07 (1.14)	0.2 (0.42)	0.73 (0.24)	0.1 (0.2)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Heavy	P* varied (0.7)	1.23 (0.32)	0.07 (1.01)	0.74 (0.62)	1.68 (0.74)	0.69 (0.18)	0.07 (1.15)	0.1 (0.66)	0.41 (0.39)	0.13 (0.23)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Heavy	P* varied (0.7)	1.28 (0.25)	0.03 (1.04)	0.76 (0.47)	1.85 (0.48)	0.68 (0.22)	0.07 (1.25)	0.23 (0.43)	0.74 (0.28)	0.09 (0.22)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Heavy	P* varied (0.7)	1.29 (0.34)	0.07 (0.99)	0.67 (0.71)	1.95 (0.71)	0.65 (0.25)	0.07 (1.19)	0.11 (0.65)	0.43 (0.43)	0.1 (0.25)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Heavy	P* varied (0.7)	1.29 (0.24)	0.07 (0.97)	0.47 (0.65)	1.74 (0.49)	0.73 (0.18)	0.07 (0.94)	0.36 (0.28)	0.75 (0.24)	0.06 (0.21)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Heavy	P* varied (0.7)	1.29 (0.34)	0.1 (0.9)	0.39 (1.07)	1.75 (0.75)	0.71 (0.2)	0.1 (0.88)	0.19 (0.48)	0.44 (0.39)	0.07 (0.22)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Heavy	P* varied (0.7)	1.46 (0.25)	0.07 (1.1)	0.37 (0.85)	1.74 (0.55)	0.71 (0.21)	0.17 (0.79)	0.41 (0.27)	0.76 (0.23)	0.04 (0.26)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Heavy	P* varied (0.7)	1.44 (0.39)	0.13 (1)	0.3 (1.45)	1.53 (0.92)	0.71 (0.78)	0.17 (0.85)	0.22 (0.46)	0.41 (0.42)	0.05 (0.34)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Heavy	P* varied (0.7)	1.27 (0.25)	0.07 (0.96)	0.49 (0.63)	1.77 (0.5)	0.74 (0.18)	0.1 (0.89)	0.35 (0.28)	0.76 (0.25)	0.07 (0.21)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Heavy	P* varied (0.7)	1.27 (0.36)	0.1 (0.9)	0.4 (1.05)	1.76 (0.75)	0.73 (0.2)	0.1 (0.84)	0.19 (0.47)	0.44 (0.4)	0.08 (0.22)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Heavy	P* varied (0.7)	1.48 (0.25)	0.07 (1.11)	0.33 (0.94)	1.76 (0.55)	0.71 (0.26)	0.17 (0.68)	0.43 (0.27)	0.77 (0.23)	0.05 (0.22)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Heavy	P* varied (0.7)	1.48 (0.39)	0.13 (1)	0.25 (1.62)	1.52 (0.93)	0.71 (0.85)	0.17 (0.79)	0.23 (0.46)	0.41 (0.43)	0.06 (0.3)
Medium	Low	0.77	0.00	fixed	0.35	2	no	no	Light	P* varied (1.0)	1.18 (0.28)	0 (3.07)	-0.24 (1.19)	-0.36 (1.23)	0.78 (0.24)	0.17 (0.92)	1.43 (0.42)	0.94 (0.34)	0.1 (0.3)
Medium	Low	1.25	0.00	fixed	0.35	2	no	no	Light	P* varied (1.0)	1.12 (0.45)	0 (1.8)	-0.28 (2.47)	-0.4 (4.47)	0.75 (0.27)	0.17 (0.84)	1.3 (0.59)	0.81 (0.62)	0.13 (0.25)
Medium	Low	0.77	0.44	fixed	0.35	2	no	no	Light	P* varied (1.0)	1.18 (0.28)	0 (3.07)	-0.24 (1.19)	-0.36 (1.23)	0.78 (0.24)	0.17 (0.92)	1.43 (0.42)	0.94 (0.34)	0.1 (0.3)
Medium	Low	1.25	0.44	fixed	0.35	2	no	no	Light	P* varied (1.0)	1.12 (0.45)	0 (1.8)	-0.28 (2.47)	-0.4 (4.47)	0.75 (0.27)	0.17 (0.84)	1.3 (0.59)	0.81 (0.62)	0.13 (0.25)
Medium	Low	0.77	0.00	fixed	0.35	2	no	no	Moderate	P* varied (1.0)	1.18 (0.28)	0 (5.75)	0.04 (4.46)	0.14 (2.62)	0.73 (0.17)	0.07 (1.14)	0.89 (0.4)	0.9 (0.34)	0.09 (0.26)
Medium	Low	1.25	0.00	fixed	0.35	2	no	no	Moderate	P* varied (1.0)	1.11 (0.44)	0 (2.1)	0.01 (4.38)	0.14 (2.69)	0.7 (0.19)	0.1 (1.04)	0.76 (0.66)	0.76 (0.61)	0.13 (0.26)
Medium	Low	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* varied (1.0)	1.18 (0.28)	0 (5.75)	0.04 (4.46)	0.14 (2.62)	0.73 (0.17)	0.07 (1.14)	0.89 (0.4)	0.9 (0.34)	0.09 (0.26)
Medium	Low	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* varied (1.0)	1.11 (0.44)	0 (2.1)	0.01 (4.38)	0.14 (2.69)	0.7 (0.19)	0.1 (1.04)	0.76 (0.66)	0.76 (0.61)	0.13 (0.26)
Medium	Low	0.77	0.00	fixed	0.35	2	no	no	Heavy	P* varied (1.0)	1.37 (0.27)	0 (1.38)	0.81 (0.6)	1.38 (0.72)	0.68 (0.19)	0.03 (1.36)	0.29 (0.57)	0.96 (0.36)	0.09 (0.24)
Medium	Low	1.25	0.00	fixed	0.35	2	no	no	Heavy	P* varied (1.0)	1.43 (0.46)	0.07 (1.21)	0.75 (1.02)	1.4 (1.16)	0.65 (0.21)	0.07 (1.22)	0.22 (1.08)	0.84 (0.92)	0.13 (0.24)
Medium	Low	0.77	0.44	fixed	0.35	2	no	no	Heavy	P* varied (1.0)	1.37 (0.27)	0 (1.38)	0.81 (0.6)	1.38 (0.72)	0.68 (0.19)	0.03 (1.36)	0.29 (0.57)	0.96 (0.36)	0.09 (0.24)
Medium	Low	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* varied (1.0)	1.43 (0.46)	0.07 (1.21)	0.75 (1.02)	1.4 (1.16)	0.65 (0.21)	0.07 (1.22)	0.22 (1.08)	0.84 (0.92)	0.13 (0.24)
Medium	Low	0.77	0.00	fixed	0.35	2	no	no	Light	P* fixed (0.38)	1 (0.34)	0 (2.02)	-0.3 (0.97)	-0.47 (0.85)	0.96 (0.29)	0.33 (0.69)	1.6 (0.42)	0.92 (0.33)	0.1 (0.29)
Medium	Low	1.25	0.00	fixed	0.35	2	no	no	Light	P* fixed (0.38)	0.9 (0.55)	0.07 (1.23)	-0.34 (1.84)	-0.51 (2.29)	0.96 (0.33)	0.37 (0.61)	1.45 (0.59)	0.77 (0.63)	0.13 (0.26)
Medium	Low	0.77	0.44	fixed	0.35	2	no	no	Light	P* fixed (0.38)	1 (0.34)	0 (2.02)	-0.3 (0.97)	-0.47 (0.85)	0.96 (0.29)	0.33 (0.69)	1.6 (0.42)	0.92 (0.33)	0.1 (0.29)
Medium	Low	1.25	0.44	fixed	0.35	2	no	no	Light	P* fixed (0.38)	0.9 (0.55)	0.07 (1.23)	-0.34 (1.84)	-0.51 (2.29)	0.96 (0.33)	0.37 (0.61)	1.45 (0.59)	0.77 (0.63)	0.13 (0.26)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Light	P* fixed (0.38)	1 (0.25)	0 (2.85)	-0.25 (0.91)	-0.41 (0.75)	0.95 (0.27)	0.33 (0.73)	1.14 (0.38)	0.71 (0.25)	0.08 (0.29)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Light	P* fixed (0.38)	0.91 (0.35)	0 (2.06)	-0.27 (1.1)	-0.46 (1.03)	0.96 (0.28)	0.33 (0.7)	0.75 (0.45)	0.42 (0.38)	0.09 (0.29)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Light	P* fixed (0.38)	1 (0.28)	0 (1.98)	-0.26 (0.94)	-0.45 (0.76)	0.99 (0.38)	0.37 (0.62)	1.19 (0.4)	0.7 (0.32)	0.06 (0.46)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Light	P* fixed (0.38)	0.85 (0.45)	0 (1.49)	-0.29 (1.14)	-0.52 (1.01)	1.02 (0.49)	0.4 (0.57)	0.81 (0.46)	0.39 (0.52)	0.07 (0.44)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Light	P* fixed (0.38)	1 (0.25)	0 (2.74)	-0.27 (0.87)	-0.42 (0.72)	0.97 (0.26)	0.35 (0.65)	1.19 (0.38)	0.72 (0.25)	0.12 (0.25)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Light	P* fixed (0.38)	0.9 (0.35)	0 (1.88)	-0.29 (1.05)	-0.47 (1)	0.98 (0.26)	0.37 (0.63)	0.77 (0.45)	0.43 (0.38)	0.14 (0.24)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Light	P* fixed (0.38)	0.98 (0.39)	0 (2.04)	-0.21 (1.08)	-0.43 (0.82)	0.97 (0.76)	0.37 (0.68)	1.08 (0.4)	0.68 (0.41)	0.1 (0.38)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Light	P* fixed (0.38)	0.84 (0.57)	0 (1.55)	-0.24 (1.33)	-0.49 (1.08)	1.01 (0.93)	0.4 (0.65)	0.72 (0.46)	0.39 (0.6)	0.12 (0.35)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Light	P* fixed (0.38)	0.96 (0.37)	0 (2.32)	-0.17 (1.14)	-0.45 (0.79)	0.99 (0.82)	0.4 (0.71)	0.99 (0.32)	0.69 (0.36)	0.05 (0.47)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Light	P* fixed (0.38)	0.81 (0.56)	0 (1.47)	-0.2 (1.51)	-0.52 (1.07)	1.02 (0.95)	0.43 (0.67)	0.65 (0.4)	0.38 (0.55)	0.06 (0.46)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Light	P* fixed (0.38)	0.8 (0.65)	0 (1.5)	-0.15 (1.34)	-0.45 (0.89)	1.06 (0.91)	0.5 (0.67)	0.95 (0.31)	0.64 (0.54)	0.03 (0.66)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Light	P* fixed (0.38)	0.58 (0.95)	0.13 (1.11)	-0.17 (1.83)	-0.51 (1.22)	1.25 (0.81)	0.57 (0.58)	0.63 (0.38)	0.33 (0.8)	0.04 (0.63)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Light	P* fixed (0.38)	0.96 (0.38)	0 (2.13)	-0.19 (1.07)	-0.48 (0.74)	1.01 (0.71)	0.42 (0.61)	1.02 (0.33)	0.68 (0.39)	0.07 (0.44)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Light	P* fixed (0.38)	0.79 (0.57)	0.02 (1.34)	-0.22 (1.41)	-0.55 (0.99)	1.06 (0.91)	0.47 (0.57)	0.68 (0.4)	0.36 (0.59)	0.08 (0.4)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Light	P* fixed (0.38)	0.75 (0.73)	0 (1.36)	-0.12 (1.56)	-0.46 (0.88)	1.11 (0.87)	0.53 (0.62)	0.89 (0.3)	0.62 (0.6)	0.05 (0.54)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Light	P* fixed (0.38)	0.46 (1.03)	0.17 (1.02)	-0.15 (2.17)	-0.53 (1.22)	1.37 (0.77)	0.6 (0.55)	0.59 (0.37)	0.31 (0.86)	0.06 (0.5)
Medium	Low	0.77	0.00	fixed	0.35	2	no	no	Moderate	P* fixed (0.38)	1.01 (0.32)	0 (3.09)	-0.03 (17.94)	-0.04 (41.91)	0.88 (0.19)	0.27 (0.78)	1.03 (0.37)	0.9 (0.34)	0.08 (0.24)
Medium	Low	1.25	0.00	fixed	0.35	2	no	no	Moderate	P* fixed (0.38)	0.91 (0.52)	0 (1.44)	-0.09 (13.64)	-0.06 (5.98)	0.9 (0.22)	0.3 (0.67)	0.9 (0.62)	0.75 (0.61)	0.12 (0.26)
Medium	Low	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (0.38)	1.01 (0.32)	0 (3.09)	-0.03 (17.94)	-0.04 (41.91)	0.88 (0.19)	0.27 (0.78)	1.03 (0.37)	0.9 (0.34)	0.08 (0.24)
Medium	Low	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (0.38)	0.91 (0.52)	0 (1.44)	-0.09 (13.64)	-0.06 (5.98)	0.9 (0.22)	0.3 (0.67)	0.9 (0.62)	0.75 (0.61)	0.12 (0.26)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Moderate	P* fixed (0.38)	1.05 (0.25)	0 (5.5)	0.01 (13.03)	0.03 (4.54)	0.89 (0.19)	0.27 (0.77)	0.73 (0.29)	0.72 (0.26)	0.07 (0.24)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Moderate	P* fixed (0.38)	0.96 (0.36)	0 (2.35)	-0.03 (53.74)	0 (7.63)	0.9 (0.19)	0.27 (0.76)	0.45 (0.4)	0.41 (0.4)	0.08 (0.25)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Moderate	P* fixed (0.38)	1.05 (0.29)	0 (2.99)	0.01 (21.66)	0.04 (5.68)	0.9 (0.24)	0.3 (0.73)	0.73 (0.33)	0.72 (0.33)	0.05 (0.34)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Moderate	P* fixed (0.38)	0.94 (0.43)	0 (1.81)	-0.03 (416.58)	-0.02 (11.19)	0.93 (0.3)	0.33 (0.67)	0.46 (0.44)	0.39 (0.51)	0.06 (0.36)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Moderate	P* fixed (0.38)	1.04 (0.25)	0 (5.05)	0.02 (15.44)	0.02 (4.84)	0.9 (0.18)	0.27 (0.72)	0.74 (0.29)	0.73 (0.26)	0.09 (0.21)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Moderate	P* fixed (0.38)	0.96 (0.37)	0 (2.21)	-0.03 (135.72)	0 (8.51)	0.91 (0.19)	0.3 (0.68)	0.46 (0.4)	0.42 (0.41)	0.11 (0.23)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Moderate	P* fixed (0.38)	1.05 (0.3)	0 (3.11)	0.01 (14.69)	0.05 (5.42)	0.9 (0.29)	0.3 (0.77)	0.72 (0.32)	0.72 (0.32)	0.07 (0.28)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Moderate	P* fixed (0.38)	0.94 (0.45)	0 (1.86)	-0.03 (60.32)	0 (10.16)	0.92 (0.5)	0.33 (0.71)	0.45 (0.43)	0.39 (0.5)	0.08 (0.29)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Moderate	P* fixed (0.38)	1.04 (0.3)	0 (3.64)	-0.02 (74.32)	0 (6.03)	0.92 (0.26)	0.33 (0.76)	0.77 (0.24)	0.71 (0.27)	0.04 (0.28)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Moderate	P* fixed (0.38)	0.93 (0.45)	0 (1.85)	-0.06 (19.54)	-0.03 (12.76)	0.94 (0.43)	0.37 (0.69)	0.48 (0.36)	0.4 (0.45)	0.05 (0.31)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Moderate	P* fixed (0.38)	0.99 (0.46)	0 (2.22)	-0.03 (18.37)	-0.01 (32.94)	0.98 (0.79)	0.42 (0.74)	0.78 (0.24)	0.7 (0.37)	0.03 (0.45)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Moderate	P* fixed (0.38)	0.8 (0.74)	0.03 (1.31)	-0.09 (12.56)	-0.09 (38.08)	1.09 (0.89)	0.5 (0.64)	0.49 (0.36)	0.36 (0.65)	0.04 (0.56)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Moderate	P* fixed (0.38)	1.01 (0.3)	0 (3.49)	-0.01 (46.81)	0 (6.65)	0.93 (0.25)	0.33 (0.68)	0.77 (0.24)	0.71 (0.28)	0.05 (0.27)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Moderate	P* fixed (0.38)	0.92 (0.47)	0 (1.73)	-0.06 (16.99)	-0.04 (15.99)	0.96 (0.51)	0.37 (0.61)	0.48 (0.35)	0.4 (0.47)	0.07 (0.3)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Moderate	P* fixed (0.38)	0.98 (0.48)	0 (2.14)	-0.02 (22.01)	-0.01 (41.44)	0.99 (0.82)	0.4 (0.74)	0.78 (0.24)	0.69 (0.38)	0.03 (0.42)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Moderate	P* fixed (0.38)	0.77 (0.79)	0.03 (1.29)	-0.07 (13.95)	-0.09 (32.32)	1.12 (0.88)	0.5 (0.65)	0.49 (0.36)	0.36 (0.67)	0.05 (0.48)
Medium	Low	0.77	0.00	fixed	0.35	2	no	no	Heavy	P* fixed (0.38)	1.19 (0.31)	0.03 (1.39)	0.44 (0.95)	0.93 (0.88)	0.89 (0.2)	0.23 (0.78)	0.51 (0.4)	0.94 (0.37)	0.08 (0.22)
Medium	Low	1.25	0.00	fixed	0.35	2	no	no	Heavy	P* fixed (0.38)	1.2 (0.52)	0.13 (1.02)	0.35 (1.59)	0.85 (1.41)	0.9 (0.22)	0.3 (0.69)	0.41 (0.76)	0.81 (0.91)	0.12 (0.24)
Medium	Low	0.77	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (0.38)	1.19 (0.31)	0.03 (1.39)	0.44 (0.95)	0.93 (0.88)	0.89 (0.2)	0.23 (0.78)	0.51 (0.4)	0.94 (0.37)	0.08 (0.22)
Medium	Low	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (0.38)	1.2 (0.52)	0.13 (1.02)	0.35 (1.59)	0.85 (1.41)	0.9 (0.22)	0.3 (0.69)	0.41 (0.76)	0.81 (0.91)	0.12 (0.24)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Heavy	P* fixed (0.38)	1.18 (0.24)	0.03 (1.17)	0.51 (0.6)	1.26 (0.59)	0.87 (0.18)	0.23 (0.87)	0.35 (0.32)	0.71 (0.24)	0.07 (0.22)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Heavy	P* fixed (0.38)	1.13 (0.35)	0.1 (1.13)	0.41 (0.95)	1.15 (0.89)	0.87 (0.18)	0.2 (0.85)	0.19 (0.5)	0.38 (0.41)	0.08 (0.23)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Heavy	P* fixed (0.38)	1.17 (0.26)	0.03 (1.16)	0.54 (0.66)	1.35 (0.59)	0.85 (0.2)	0.2 (0.91)	0.33 (0.36)	0.73 (0.29)	0.05 (0.28)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Heavy	P* fixed (0.38)	1.13 (0.38)	0.1 (1.1)	0.44 (1.04)	1.28 (0.92)	0.85 (0.24)	0.23 (0.82)	0.17 (0.53)	0.4 (0.45)	0.06 (0.31)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Heavy	P* fixed (0.38)	1.17 (0.24)	0.03 (1.13)	0.55 (0.57)	1.28 (0.59)	0.86 (0.17)	0.2 (0.85)	0.34 (0.32)	0.72 (0.24)	0.1 (0.2)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Heavy	P* fixed (0.38)	1.12 (0.35)	0.1 (1.09)	0.46 (0.91)	1.18 (0.89)	0.86 (0.18)	0.22 (0.82)	0.17 (0.5)	0.39 (0.41)	0.12 (0.22)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Heavy	P* fixed (0.38)	1.21 (0.27)	0.07 (1.13)	0.4 (0.85)	1.31 (0.6)	0.87 (0.22)	0.23 (0.77)	0.39 (0.33)	0.73 (0.28)	0.08 (0.21)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Heavy	P* fixed (0.38)	1.15 (0.4)	0.13 (1.06)	0.28 (1.4)	1.12 (0.98)	0.87 (0.5)	0.27 (0.72)	0.21 (0.51)	0.39 (0.45)	0.09 (0.26)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Heavy	P* fixed (0.38)	1.21 (0.26)	0.07 (1.06)	0.29 (1)	1.25 (0.62)	0.89 (0.19)	0.23 (0.73)	0.44 (0.26)	0.74 (0.24)	0.05 (0.23)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Heavy	P* fixed (0.38)	1.15 (0.4)	0.13 (0.97)	0.2 (1.79)	1.06 (1.04)	0.91 (0.55)	0.27 (0.68)	0.24 (0.44)	0.39 (0.43)	0.06 (0.31)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Heavy	P* fixed (0.38)	1.31 (0.3)	0.1 (1.21)	0.22 (1.36)	1.16 (0.79)	0.89 (0.62)	0.27 (0.67)	0.48 (0.26)	0.72 (0.28)	0.03 (0.35)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Heavy	P* fixed (0.38)	1.15 (0.59)	0.2 (0.92)	0.12 (2.61)	0.82 (1.51)	0.97 (1.07)	0.37 (0.68)	0.26 (0.43)	0.34 (0.62)	0.04 (0.61)
Medium	Low	0.77	0.44	fixed	0.35	2	yes	yes	Heavy	P* fixed (0.38)	1.21 (0.26)	0.07 (1.02)	0.33 (0.92)	1.33 (0.6)	0.88 (0.18)	0.23 (0.73)	0.42 (0.26)	0.75 (0.25)	0.06 (0.21)
Medium	Low	1.25	0.44	fixed	0.35	2	yes	yes	Heavy	P* fixed (0.38)	1.15 (0.4)	0.13 (0.96)	0.23 (1.64)	1.15 (1)	0.9 (0.36)	0.27 (0.66)	0.23 (0.43)	0.4 (0.43)	0.07 (0.27)
Medium	Low	0.77	0.44	fixed	0.35	5	yes	yes	Heavy	P* fixed (0.38)	1.35 (0.32)	0.1 (1.15)	0.15 (1.86)	1.1 (0.85)	0.89 (0.82)	0.27 (0.63)	0.51 (0.25)	0.71 (0.31)	0.05 (0.32)
Medium	Low	1.25	0.44	fixed	0.35	5	yes	yes	Heavy	P* fixed (0.38)	1.16 (0.64)	0.23 (0.88)	0.07 (4.04)	0.75 (1.68)	0.99 (1.08)	0.37 (0.66)	0.28 (0.43)	0.33 (0.66)	0.05 (0.49)
Medium	Low	0.77	0.00	fixed	0.35	2	no	no	Light	P* fixed (0.7)	1.07 (0.32)	0 (2.52)	-0.26 (1.08)	-0.42 (1)	0.87 (0.28)	0.23 (0.83)	1.5 (0.42)	0.93 (0.32)	0.09 (0.28)
Medium	Low	1.25	0.00	fixed	0.35	2	no	no	Light	P* fixed (0.7)	0.98 (0.52)	0 (1.37)	-0.31 (2.14)	-0.47 (2.9)	0.87 (0.31)	0.28 (0.73)	1.36 (0.59)	0.79 (0.61)	0.13 (0.26)
Medium	Low	0.77	0.44	fixed	0.35	2	no	no	Light	P* fixed (0.7)	1.07 (0.32)	0 (2.52)	-0.26 (1.08)	-0.42 (1)	0.87 (0.28)	0.23 (0.83)	1.5 (0.42)	0.93 (0.32)	0.09 (0.28)
Medium	Low	1.25	0.44	fixed	0.35	2	no	no	Light	P* fixed (0.7)	0.98 (0.52)	0 (1.37)	-0.31 (2.14)	-0.47 (2.9)	0.87 (0.31)	0.28 (0.73)	1.36 (0.59)	0.79 (0.61)	0.13 (0.26)
Medium	Low	0.77	0.00	fixed	0.35	2	no	no	Moderate	P* fixed (0.7)	1.09 (0.3)	0 (4.26)	0 (13.64)	0.04 (5.42)	0.81 (0.19)	0.17 (0.97)	0.96 (0.37)	0.91 (0.33)	0.08 (0.24)
Medium	Low	1.25	0.00	fixed	0.35	2	no	no	Moderate	P* fixed (0.7)	0.98 (0.5)	0 (1.65)	-0.05 (7.59)	0 (4.01)	0.82 (0.2)	0.2 (0.84)	0.85 (0.62)	0.76 (0.6)	0.12 (0.26)

Life history	Assessment uncertainty	σ_R	ϕ_R	h	SPR target	SA years	Projections?	ABC avg.?	Exploitation history	Control rule	S / S_{MSY}	Overfished probability	ΔS_5	ΔS_{15}	F / F_{MSY}	P_{OF}(true)	Initial C / MSY	Final C / MSY	Catch AAV
Medium	Low	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (0.7)	1.09 (0.3)	0 (4.26)	0 (13.64)	0.04 (5.42)	0.81 (0.19)	0.17 (0.97)	0.96 (0.37)	0.91 (0.33)	0.08 (0.24)
Medium	Low	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (0.7)	0.98 (0.5)	0 (1.65)	-0.05 (7.59)	0 (4.01)	0.82 (0.2)	0.2 (0.84)	0.85 (0.62)	0.76 (0.6)	0.12 (0.26)
Medium	Low	0.77	0.00	fixed	0.35	2	no	no	Heavy	P* fixed (0.7)	1.28 (0.3)	0.03 (1.43)	0.48 (0.85)	1.09 (0.81)	0.81 (0.19)	0.13 (0.98)	0.48 (0.4)	0.94 (0.36)	0.08 (0.22)
Medium	Low	1.25	0.00	fixed	0.35	2	no	no	Heavy	P* fixed (0.7)	1.3 (0.5)	0.1 (1.1)	0.41 (1.45)	1 (1.31)	0.82 (0.2)	0.17 (0.85)	0.39 (0.76)	0.82 (0.9)	0.12 (0.24)
Medium	Low	0.77	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (0.7)	1.28 (0.3)	0.03 (1.43)	0.48 (0.85)	1.09 (0.81)	0.81 (0.19)	0.13 (0.98)	0.48 (0.4)	0.94 (0.36)	0.08 (0.22)
Medium	Low	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (0.7)	1.3 (0.5)	0.1 (1.1)	0.41 (1.45)	1 (1.31)	0.82 (0.2)	0.17 (0.85)	0.39 (0.76)	0.82 (0.9)	0.12 (0.24)
Medium	Low	0.77	0.00	fixed	0.35	2	no	no	Light	P* fixed (1.0)	1.12 (0.3)	0 (3.02)	-0.24 (1.19)	-0.39 (1.15)	0.82 (0.27)	0.2 (0.95)	1.43 (0.42)	0.93 (0.31)	0.09 (0.27)
Medium	Low	1.25	0.00	fixed	0.35	2	no	no	Light	P* fixed (1.0)	1.03 (0.5)	0 (1.58)	-0.28 (2.43)	-0.43 (3.6)	0.81 (0.31)	0.2 (0.84)	1.3 (0.59)	0.81 (0.6)	0.12 (0.25)
Medium	Low	0.77	0.44	fixed	0.35	2	no	no	Light	P* fixed (1.0)	1.12 (0.3)	0 (3.02)	-0.24 (1.19)	-0.39 (1.15)	0.82 (0.27)	0.2 (0.95)	1.43 (0.42)	0.93 (0.31)	0.09 (0.27)
Medium	Low	1.25	0.44	fixed	0.35	2	no	no	Light	P* fixed (1.0)	1.03 (0.5)	0 (1.58)	-0.28 (2.43)	-0.43 (3.6)	0.81 (0.31)	0.2 (0.84)	1.3 (0.59)	0.81 (0.6)	0.12 (0.25)
Medium	Low	0.77	0.00	fixed	0.35	2	no	no	Moderate	P* fixed (1.0)	1.15 (0.29)	0 (5.21)	0.03 (6)	0.09 (3.37)	0.76 (0.18)	0.08 (1.14)	0.92 (0.37)	0.9 (0.32)	0.08 (0.23)
Medium	Low	1.25	0.00	fixed	0.35	2	no	no	Moderate	P* fixed (1.0)	1.04 (0.48)	0 (1.83)	-0.02 (5.76)	0.06 (3.28)	0.76 (0.19)	0.13 (1.01)	0.81 (0.62)	0.76 (0.59)	0.11 (0.26)
Medium	Low	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (1.0)	1.15 (0.29)	0 (5.21)	0.03 (6)	0.09 (3.37)	0.76 (0.18)	0.08 (1.14)	0.92 (0.37)	0.9 (0.32)	0.08 (0.23)
Medium	Low	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (1.0)	1.04 (0.48)	0 (1.83)	-0.02 (5.76)	0.06 (3.28)	0.76 (0.19)	0.13 (1.01)	0.81 (0.62)	0.76 (0.59)	0.11 (0.26)
Medium	Low	0.77	0.00	fixed	0.35	2	no	no	Heavy	P* fixed (1.0)	1.35 (0.29)	0.02 (1.44)	0.52 (0.8)	1.2 (0.77)	0.76 (0.18)	0.07 (1.16)	0.45 (0.4)	0.95 (0.35)	0.08 (0.22)
Medium	Low	1.25	0.00	fixed	0.35	2	no	no	Heavy	P* fixed (1.0)	1.36 (0.49)	0.1 (1.14)	0.45 (1.37)	1.13 (1.26)	0.77 (0.2)	0.13 (1.01)	0.37 (0.76)	0.81 (0.89)	0.12 (0.24)
Medium	Low	0.77	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (1.0)	1.35 (0.29)	0.02 (1.44)	0.52 (0.8)	1.2 (0.77)	0.76 (0.18)	0.07 (1.16)	0.45 (0.4)	0.95 (0.35)	0.08 (0.22)
Medium	Low	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (1.0)	1.36 (0.49)	0.1 (1.14)	0.45 (1.37)	1.13 (1.26)	0.77 (0.2)	0.13 (1.01)	0.37 (0.76)	0.81 (0.89)	0.12 (0.24)
Medium	Low	0.77	0.00	fixed	0.35	2	no	no	Light	75% of F_lim	1.14 (0.3)	0 (3.18)	-0.23 (1.22)	-0.38 (1.2)	0.8 (0.27)	0.17 (1)	1.42 (0.42)	0.93 (0.31)	0.09 (0.27)
Medium	Low	1.25	0.00	fixed	0.35	2	no	no	Light	75% of F_lim	1.05 (0.49)	0 (1.65)	-0.27 (2.52)	-0.42 (3.86)	0.8 (0.3)	0.2 (0.88)	1.29 (0.59)	0.81 (0.59)	0.12 (0.25)
Medium	Low	0.77	0.44	fixed	0.35	2	no	no	Light	75% of F_lim	1.14 (0.3)	0 (3.18)	-0.23 (1.22)	-0.38 (1.2)	0.8 (0.27)	0.17 (1)	1.42 (0.42)	0.93 (0.31)	0.09 (0.27)
Medium	Low	1.25	0.44	fixed	0.35	2	no	no	Light	75% of F_lim	1.05 (0.49)	0 (1.65)	-0.27 (2.52)	-0.42 (3.86)	0.8 (0.3)	0.2 (0.88)	1.29 (0.59)	0.81 (0.59)	0.12 (0.25)
Medium	Low	0.77	0.00	fixed	0.35	2	no	no	Moderate	75% of F_lim	1.17 (0.29)	0 (5.41)	0.04 (5.18)	0.11 (3.05)	0.74 (0.18)	0.07 (1.19)	0.91 (0.37)	0.9 (0.32)	0.08 (0.24)
Medium	Low	1.25	0.00	fixed	0.35	2	no	no	Moderate	75% of F_lim	1.06 (0.48)	0 (1.89)	-0.01 (5.4)	0.07 (3.13)	0.75 (0.19)	0.13 (1.04)	0.79 (0.62)	0.76 (0.58)	0.11 (0.26)
Medium	Low	0.77	0.44	fixed	0.35	2	no	no	Moderate	75% of F_lim	1.17 (0.29)	0 (5.41)	0.04 (5.18)	0.11 (3.05)	0.74 (0.18)	0.07 (1.19)	0.91 (0.37)	0.9 (0.32)	0.08 (0.24)
Medium	Low	1.25	0.44	fixed	0.35	2	no	no	Moderate	75% of F_lim	1.06 (0.48)	0 (1.89)	-0.01 (5.4)	0.07 (3.13)	0.75 (0.19)	0.13 (1.04)	0.79 (0.62)	0.76 (0.58)	0.11 (0.26)
Medium	Low	0.77	0.00	fixed	0.35	2	no	no	Heavy	75% of F_lim	1.37 (0.28)	0 (1.44)	0.53 (0.78)	1.23 (0.76)	0.74 (0.18)	0.07 (1.23)	0.45 (0.4)	0.94 (0.35)	0.08 (0.22)
Medium	Low	1.25	0.00	fixed	0.35	2	no	no	Heavy	75% of F_lim	1.39 (0.49)	0.1 (1.13)	0.46 (1.34)	1.16 (1.24)	0.75 (0.19)	0.1 (1.05)	0.37 (0.76)	0.82 (0.89)	0.11 (0.24)
Medium	Low	0.77	0.44	fixed	0.35	2	no	no	Heavy	75% of F_lim	1.37 (0.28)	0 (1.44)	0.53 (0.78)	1.23 (0.76)	0.74 (0.18)	0.07 (1.23)	0.45 (0.4)	0.94 (0.35)	0.08 (0.22)
Medium	Low	1.25	0.44	fixed	0.35	2	no	no	Heavy	75% of F_lim	1.39 (0.49)	0.1 (1.13)	0.46 (1.34)	1.16 (1.24)	0.75 (0.19)	0.1 (1.05)	0.37 (0.76)	0.82 (0.89)	0.11 (0.24)
Medium	High	0.77	0.00	fixed	0.35	2	no	no	Light	OFL	0.96 (0.61)	0.17 (1.08)	-0.36 (1.04)	-0.58 (0.88)	1.27 (0.6)	0.43 (0.64)	1.78 (0.55)	0.78 (0.54)	0.18 (0.45)
Medium	High	1.25	0.00	fixed	0.35	2	no	no	Light	OFL	0.78 (0.8)	0.27 (0.92)	-0.39 (1.56)	-0.63 (1.83)	1.34 (0.67)	0.45 (0.62)	1.61 (0.69)	0.61 (0.87)	0.2 (0.45)
Medium	High	0.77	0.44	fixed	0.35	2	no	no	Light	OFL	0.96 (0.61)	0.17 (1.08)	-0.36 (1.04)	-0.58 (0.88)	1.27 (0.6)	0.43 (0.64)	1.78 (0.55)	0.78 (0.54)	0.18 (0.45)
Medium	High	1.25	0.44	fixed	0.35	2	no	no	Light	OFL	0.78 (0.8)	0.27 (0.92)	-0.39 (1.56)	-0.63 (1.83)	1.34 (0.67)	0.45 (0.62)	1.61 (0.69)	0.61 (0.87)	0.2 (0.45)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Light	OFL	0.97 (0.51)	0.08 (1.26)	-0.29 (1.08)	-0.49 (0.89)	1.18 (0.64)	0.4 (0.68)	1.25 (0.58)	0.65 (0.48)	0.16 (0.45)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Light	OFL	0.82 (0.63)	0.17 (1.1)	-0.32 (1.15)	-0.56 (1.06)	1.22 (0.68)	0.4 (0.68)	0.83 (0.64)	0.33 (0.65)	0.17 (0.48)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Light	OFL	0.89 (0.58)	0.23 (1.03)	-0.3 (1.09)	-0.55 (0.87)	1.5 (0.66)	0.47 (0.64)	1.29 (0.58)	0.53 (0.63)	0.12 (0.65)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Light	OFL	0.68 (0.76)	0.3 (0.95)	-0.33 (1.16)	-0.65 (1.03)	1.55 (0.73)	0.5 (0.63)	0.84 (0.63)	0.26 (0.85)	0.13 (0.68)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Light	OFL	0.96 (0.49)	0.1 (1.25)	-0.3 (1.04)	-0.5 (0.86)	1.21 (0.59)	0.37 (0.65)	1.33 (0.56)	0.64 (0.46)	0.2 (0.37)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Light	OFL	0.81 (0.61)	0.18 (1.06)	-0.34 (1.11)	-0.57 (1.03)	1.26 (0.62)	0.4 (0.63)	0.86 (0.62)	0.34 (0.63)	0.22 (0.37)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Light	OFL	0.76 (0.81)	0.23 (1.04)	-0.25 (1.19)	-0.55 (0.9)	1.53 (0.82)	0.55 (0.65)	1.17 (0.6)	0.46 (0.85)	0.16 (0.55)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Light	OFL	0.55 (0.99)	0.33 (0.94)	-0.29 (1.28)	-0.65 (1.06)	1.64 (0.86)	0.57 (0.65)	0.78 (0.65)	0.22 (1.04)	0.17 (0.54)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Light	OFL	0.67 (0.91)	0.13 (1.1)	-0.2 (1.23)	-0.57 (0.87)	1.36 (0.9)	0.57 (0.68)	1.06 (0.57)	0.48 (0.88)	0.1 (0.8)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Light	OFL	0.43 (1.05)	0.3 (0.95)	-0.25 (1.36)	-0.65 (1.03)	1.51 (0.86)	0.6 (0.66)	0.7 (0.63)	0.21 (1.04)	0.11 (0.79)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Light	OFL	0.26 (1.11)	0.33 (0.99)	-0.18 (1.36)	-0.57 (0.91)	1.98 (0.8)	0.7 (0.66)	0.99 (0.56)	0.4 (0.96)	0.07 (0.99)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Light	OFL	0.03 (1.34)	0.45 (0.85)	-0.22 (1.52)	-0.72 (1.14)	3.72 (0.73)	0.75 (0.62)	0.67 (0.61)	0.06 (1.23)	0.08 (0.95)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Light	OFL	0.66 (0.88)	0.2 (1.06)	-0.22 (1.18)	-0.6 (0.82)	1.42 (0.87)	0.57 (0.64)	1.1 (0.56)	0.46 (0.87)	0.11 (0.74)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Light	OFL	0.41 (1.06)	0.37 (0.9)	-0.27 (1.3)	-0.71 (0.97)	1.67 (0.84)	0.63 (0.62)	0.73 (0.62)	0.2 (1.07)	0.12 (0.71)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Light	OFL	0.1 (1.18)	0.37 (0.94)	-0.16 (1.49)	-0.59 (0.91)	2.6 (0.76)	0.73 (0.64)	0.94 (0.57)	0.32 (1.01)	0.08 (0.87)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Light	OFL	0.02 (1.41)	0.47 (0.83)	-0.19 (1.67)	-0.71 (1.14)	3.98 (0.69)	0.77 (0.6)	0.64 (0.61)	0.04 (1.29)	0.1 (0.81)
Medium	High	0.77	0.00	fixed	0.35	2	no	no	Moderate	OFL	0.94 (0.56)	0.07 (1.32)	-0.11 (3.54)	-0.23 (4.92)	1.11 (0.58)	0.4 (0.66)	1.1 (0.54)	0.77 (0.55)	0.16 (0.33)
Medium	High	1.25	0.00	fixed	0.35	2	no	no	Moderate	OFL	0.78 (0.73)	0.17 (1.01)	-0.16 (12.46)	-0.27 (2766.64	1.16 (0.67)	0.43 (0.65)	0.95 (0.78)	0.59 (0.84)	0.18 (0.36)
Medium	High	0.77	0.44	fixed	0.35	2	no	no	Moderate	OFL	0.94 (0.56)	0.07 (1.32)	-0.11 (3.54)	-0.23 (4.92)	1.11 (0.58)	0.4 (0.66)	1.1 (0.54)	0.77 (0.55)	0.16 (0.33)
Medium	High	1.25	0.44	fixed	0.35	2	no	no	Moderate	OFL	0.78 (0.73)	0.17 (1.01)	-0.16 (12.46)	-0.27 (2766.67	1.16 (0.67)	0.43 (0.65)	0.95 (0.78)	0.59 (0.84)	0.18 (0.36)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Moderate	OFL	0.9 (0.52)	0 (1.4)	-0.07 (3.47)	-0.14 (5.33)	1.15 (0.59)	0.47 (0.62)	0.82 (0.49)	0.62 (0.5)	0.14 (0.35)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Moderate	OFL	0.75 (0.65)	0.1 (1.19)	-0.11 (3.55)	-0.27 (5.09)	1.16 (0.61)	0.47 (0.61)	0.51 (0.57)	0.32 (0.68)	0.15 (0.37)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Moderate	OFL	0.86 (0.59)	0.1 (1.16)	-0.09 (3.91)	-0.23 (4.09)	1.31 (0.64)	0.5 (0.6)	0.81 (0.54)	0.56 (0.63)	0.11 (0.49)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Moderate	OFL	0.66 (0.77)	0.2 (1.02)	-0.13 (4.05)	-0.36 (4.26)	1.42 (0.7)	0.5 (0.6)	0.5 (0.61)	0.26 (0.86)	0.12 (0.51)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Moderate	OFL	0.92 (0.49)	0 (1.41)	-0.07 (3.48)	-0.16 (5.72)	1.13 (0.55)	0.43 (0.6)	0.82 (0.49)	0.62 (0.49)	0.17 (0.33)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Moderate	OFL	0.78 (0.62)	0.1 (1.19)	-0.11 (3.56)	-0.27 (5.39)	1.15 (0.56)	0.43 (0.58)	0.51 (0.57)	0.32 (0.66)	0.18 (0.33)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Moderate	OFL	0.79 (0.77)	0.1 (1.15)	-0.1 (3.83)	-0.24 (3.53)	1.36 (0.85)	0.5 (0.62)	0.81 (0.52)	0.5 (0.76)	0.12 (0.46)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Moderate	OFL	0.57 (0.95)	0.23 (1)	-0.13 (3.99)	-0.33 (3.89)	1.44 (0.86)	0.53 (0.61)	0.5 (0.61)	0.23 (1)	0.14 (0.46)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Moderate	OFL	0.74 (0.79)	0.03 (1.28)	-0.08 (3.35)	-0.2 (3.57)	1.22 (0.91)	0.53 (0.64)	0.82 (0.39)	0.54 (0.72)	0.08 (0.53)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Moderate	OFL	0.55 (0.95)	0.18 (1.04)	-0.13 (3.57)	-0.3 (3.85)	1.29 (0.89)	0.6 (0.61)	0.53 (0.48)	0.25 (0.91)	0.1 (0.52)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Moderate	OFL	0.58 (0.97)	0.12 (1.14)	-0.09 (3.53)	-0.23 (3.26)	1.38 (0.84)	0.67 (0.61)	0.81 (0.38)	0.5 (0.84)	0.06 (0.69)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Moderate	OFL	0.18 (1.23)	0.33 (0.9)	-0.12 (3.84)	-0.31 (3.89)	2.19 (0.75)	0.77 (0.56)	0.52 (0.47)	0.2 (1.09)	0.07 (0.63)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Moderate	OFL	0.78 (0.73)	0.03 (1.29)	-0.09 (3.37)	-0.2 (3.65)	1.21 (0.88)	0.53 (0.62)	0.81 (0.39)	0.55 (0.69)	0.09 (0.51)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Moderate	OFL	0.58 (0.93)	0.2 (1.03)	-0.11 (3.58)	-0.33 (3.9)	1.31 (0.88)	0.58 (0.59)	0.52 (0.47)	0.25 (0.92)	0.11 (0.48)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Moderate	OFL	0.54 (1)	0.13 (1.11)	-0.09 (3.51)	-0.23 (3.24)	1.4 (0.82)	0.67 (0.6)	0.82 (0.37)	0.5 (0.86)	0.06 (0.64)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Moderate	OFL	0.14 (1.26)	0.33 (0.89)	-0.12 (3.86)	-0.32 (3.88)	2.48 (0.74)	0.77 (0.55)	0.52 (0.46)	0.19 (1.1)	0.08 (0.57)
Medium	High	0.77	0.00	fixed	0.35	2	no	no	Heavy	OFL	1.04 (0.58)	0.17 (1.03)	0.23 (2)	0.63 (1.53)	1.12 (0.55)	0.43 (0.62)	0.59 (0.53)	0.74 (0.59)	0.16 (0.29)
Medium	High	1.25	0.00	fixed	0.35	2	no	no	Heavy	OFL	0.96 (0.77)	0.27 (0.79)	0.18 (2.42)	0.43 (2)	1.15 (0.65)	0.43 (0.62)	0.47 (0.79)	0.62 (1.07)	0.18 (0.32)
Medium	High	0.77	0.44	fixed	0.35	2	no	no	Heavy	OFL	1.04 (0.58)	0.17 (1.03)	0.23 (2)	0.63 (1.53)	1.12 (0.55)	0.43 (0.62)	0.59 (0.53)	0.74 (0.59)	0.16 (0.29)
Medium	High	1.25	0.44	fixed	0.35	2	no	no	Heavy	OFL	0.96 (0.77)	0.27 (0.79)	0.18 (2.42)	0.43 (2)	1.15 (0.65)	0.43 (0.62)	0.47 (0.79)	0.62 (1.07)	0.18 (0.32)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Heavy	OFL	1.08 (0.51)	0.13 (1.07)	0.42 (1.19)	0.96 (1.04)	1.03 (0.58)	0.38 (0.7)	0.38 (0.48)	0.61 (0.45)	0.13 (0.29)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Heavy	OFL	0.98 (0.63)	0.17 (0.95)	0.36 (1.64)	0.81 (1.37)	1.04 (0.6)	0.4 (0.69)	0.21 (0.61)	0.33 (0.63)	0.14 (0.3)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Heavy	OFL	1.06 (0.56)	0.13 (1.03)	0.46 (1.34)	1.02 (1.07)	1.06 (0.64)	0.4 (0.68)	0.37 (0.55)	0.61 (0.55)	0.09 (0.43)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Heavy	OFL	0.94 (0.7)	0.23 (0.89)	0.33 (1.82)	0.76 (1.45)	1.1 (0.69)	0.4 (0.68)	0.2 (0.66)	0.3 (0.72)	0.1 (0.46)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Heavy	OFL	1.08 (0.49)	0.1 (1.08)	0.48 (1.06)	1.02 (0.97)	1 (0.55)	0.37 (0.7)	0.36 (0.49)	0.62 (0.44)	0.16 (0.28)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Heavy	OFL	1 (0.61)	0.17 (0.96)	0.38 (1.48)	0.85 (1.3)	1 (0.57)	0.37 (0.68)	0.19 (0.62)	0.33 (0.61)	0.18 (0.27)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Heavy	OFL	1.04 (0.64)	0.17 (0.96)	0.29 (2.04)	0.85 (1.28)	1.16 (0.85)	0.45 (0.64)	0.44 (0.48)	0.56 (0.61)	0.12 (0.41)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Heavy	OFL	0.93 (0.79)	0.27 (0.83)	0.18 (2.93)	0.63 (1.74)	1.18 (0.94)	0.47 (0.65)	0.23 (0.6)	0.29 (0.8)	0.13 (0.41)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Heavy	OFL	1.04 (0.62)	0.17 (1.04)	0.25 (1.74)	0.96 (1.14)	1.06 (0.92)	0.43 (0.65)	0.48 (0.33)	0.63 (0.54)	0.08 (0.43)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Heavy	OFL	0.95 (0.78)	0.27 (0.83)	0.12 (2.99)	0.67 (1.66)	1.1 (0.96)	0.47 (0.66)	0.26 (0.48)	0.32 (0.75)	0.09 (0.41)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Heavy	OFL	1.12 (0.67)	0.17 (1)	0.15 (2.36)	0.8 (1.38)	1.05 (0.98)	0.43 (0.63)	0.5 (0.31)	0.6 (0.61)	0.05 (0.59)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Heavy	OFL	0.93 (0.9)	0.33 (0.75)	0.05 (4.71)	0.45 (2.28)	1.25 (0.92)	0.53 (0.59)	0.27 (0.46)	0.27 (0.87)	0.06 (0.59)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Heavy	OFL	1.09 (0.59)	0.13 (1.03)	0.27 (1.51)	1.04 (1.03)	1.03 (0.85)	0.4 (0.67)	0.46 (0.33)	0.65 (0.51)	0.09 (0.38)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Heavy	OFL	0.98 (0.73)	0.23 (0.85)	0.15 (2.55)	0.78 (1.49)	1.06 (0.94)	0.43 (0.66)	0.25 (0.48)	0.33 (0.71)	0.1 (0.36)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Heavy	OFL	1.16 (0.69)	0.2 (0.95)	0.07 (4.24)	0.72 (1.53)	1.09 (0.98)	0.45 (0.61)	0.54 (0.3)	0.59 (0.64)	0.06 (0.51)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Heavy	OFL	0.81 (0.93)	0.4 (0.72)	-0.03 (13.66)	0.31 (2.67)	1.31 (0.9)	0.57 (0.57)	0.29 (0.46)	0.25 (0.92)	0.07 (0.53)
Medium	High	0.77	0.00	fixed	0.35	2	no	no	Light	P* var (0.38)	1.13 (0.5)	0.07 (1.24)	-0.31 (1.17)	-0.47 (1.12)	1.02 (0.54)	0.27 (0.71)	1.64 (0.58)	0.83 (0.51)	0.18 (0.42)
Medium	High	1.25	0.00	fixed	0.35	2	no	no	Light	P* var (0.38)	1.04 (0.62)	0.17 (1.05)	-0.34 (1.8)	-0.5 (2.7)	1.02 (0.53)	0.3 (0.68)	1.49 (0.72)	0.69 (0.77)	0.2 (0.4)
Medium	High	0.77	0.44	fixed	0.35	2	no	no	Light	P* var (0.38)	1.13 (0.5)	0.07 (1.24)	-0.31 (1.17)	-0.47 (1.12)	1.02 (0.54)	0.27 (0.71)	1.64 (0.58)	0.83 (0.51)	0.18 (0.42)
Medium	High	1.25	0.44	fixed	0.35	2	no	no	Light	P* var (0.38)	1.04 (0.62)	0.17 (1.05)	-0.34 (1.8)	-0.5 (2.7)	1.02 (0.53)	0.3 (0.68)	1.49 (0.72)	0.69 (0.77)	0.2 (0.4)
Medium	High	0.77	0.00	fixed	0.35	2	no	no	Moderate	P* var (0.38)	1.12 (0.48)	0 (1.51)	-0.05 (8.66)	-0.08 (17.16)	0.91 (0.53)	0.3 (0.74)	0.98 (0.58)	0.83 (0.51)	0.16 (0.31)
Medium	High	1.25	0.00	fixed	0.35	2	no	no	Moderate	P* var (0.38)	1 (0.59)	0.1 (1.19)	-0.09 (35.11)	-0.07 (5.78)	0.89 (0.53)	0.3 (0.72)	0.84 (0.82)	0.66 (0.76)	0.18 (0.33)
Medium	High	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* var (0.38)	1.12 (0.48)	0 (1.51)	-0.05 (8.66)	-0.08 (17.16)	0.91 (0.53)	0.3 (0.74)	0.98 (0.58)	0.83 (0.51)	0.16 (0.31)
Medium	High	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* var (0.38)	1 (0.59)	0.1 (1.19)	-0.09 (35.11)	-0.07 (5.78)	0.89 (0.53)	0.3 (0.72)	0.84 (0.82)	0.66 (0.76)	0.18 (0.33)
Medium	High	0.77	0.00	fixed	0.35	2	no	no	Heavy	P* var (0.38)	1.21 (0.49)	0.1 (1.1)	0.49 (1.17)	0.96 (1.11)	0.89 (0.52)	0.27 (0.75)	0.46 (0.64)	0.8 (0.53)	0.16 (0.29)
Medium	High	1.25	0.00	fixed	0.35	2	no	no	Heavy	P* var (0.38)	1.18 (0.63)	0.17 (0.92)	0.42 (1.56)	0.81 (1.52)	0.87 (0.52)	0.27 (0.73)	0.35 (0.91)	0.69 (0.96)	0.19 (0.28)
Medium	High	0.77	0.44	fixed	0.35	2	no	no	Heavy	P* var (0.38)	1.21 (0.49)	0.1 (1.1)	0.49 (1.17)	0.96 (1.11)	0.89 (0.52)	0.27 (0.75)	0.46 (0.64)	0.8 (0.53)	0.16 (0.29)
Medium	High	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* var (0.38)	1.18 (0.63)	0.17 (0.92)	0.42 (1.56)	0.81 (1.52)	0.87 (0.52)	0.27 (0.73)	0.35 (0.91)	0.69 (0.96)	0.19 (0.28)
Medium	High	0.77	0.00	fixed	0.35	2	no	no	Light	P* varied (0.7)	1.23 (0.46)	0.03 (1.29)	-0.28 (1.28)	-0.41 (1.32)	0.92 (0.55)	0.25 (0.77)	1.53 (0.61)	0.82 (0.51)	0.18 (0.41)
Medium	High	1.25	0.00	fixed	0.35	2	no	no	Light	P* varied (0.7)	1.15 (0.59)	0.1 (1.16)	-0.31 (2.01)	-0.45 (3.56)	0.88 (0.55)	0.23 (0.74)	1.39 (0.74)	0.71 (0.76)	0.2 (0.39)
Medium	High	0.77	0.44	fixed	0.35	2	no	no	Light	P* varied (0.7)	1.23 (0.46)	0.03 (1.29)	-0.28 (1.28)	-0.41 (1.32)	0.92 (0.55)	0.25 (0.77)	1.53 (0.61)	0.82 (0.51)	0.18 (0.41)

Life history	Assessment uncertainty	σ_R	ϕ_R	h	SPR target	SA years	Projec-tions?	ABC avg.?	Exploitation history	Control rule	S / S_{MSY}	Overfished probability	ΔS_5	ΔS_{15}	F / F_{MSY}	P_{OF} (true)	Initial C / MSY	Final C / MSY	Catch AAV
Medium	High	1.25	0.44	fixed	0.35	2	no	no	Light	P* varied (0.7)	1.15 (0.59)	0.1 (1.16)	-0.31 (2.01)	-0.45 (3.56)	0.88 (0.55)	0.23 (0.74)	1.39 (0.74)	0.71 (0.76)	0.2 (0.39)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Light	P* varied (0.7)	1.2 (0.39)	0 (1.45)	-0.22 (1.33)	-0.35 (1.32)	0.89 (0.56)	0.27 (0.81)	1.07 (0.64)	0.64 (0.45)	0.16 (0.41)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Light	P* varied (0.7)	1.11 (0.45)	0 (1.41)	-0.25 (1.44)	-0.41 (1.63)	0.89 (0.56)	0.27 (0.8)	0.71 (0.69)	0.38 (0.56)	0.17 (0.41)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Light	P* varied (0.7)	1.21 (0.41)	0.03 (1.23)	-0.22 (1.34)	-0.38 (1.25)	0.98 (0.59)	0.3 (0.75)	1.1 (0.64)	0.61 (0.54)	0.12 (0.59)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Light	P* varied (0.7)	1.1 (0.49)	0.1 (1.16)	-0.25 (1.45)	-0.5 (1.53)	1.01 (0.59)	0.27 (0.73)	0.71 (0.69)	0.35 (0.67)	0.12 (0.6)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Light	P* varied (0.7)	1.19 (0.39)	0 (1.44)	-0.24 (1.27)	-0.36 (1.26)	0.92 (0.55)	0.27 (0.78)	1.14 (0.62)	0.66 (0.45)	0.2 (0.33)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Light	P* varied (0.7)	1.09 (0.45)	0.03 (1.37)	-0.26 (1.38)	-0.43 (1.57)	0.92 (0.54)	0.23 (0.76)	0.74 (0.68)	0.38 (0.55)	0.22 (0.33)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Light	P* varied (0.7)	1.22 (0.41)	0 (1.27)	-0.17 (1.5)	-0.37 (1.32)	0.96 (0.62)	0.3 (0.76)	0.99 (0.66)	0.61 (0.53)	0.15 (0.43)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Light	P* varied (0.7)	1.08 (0.5)	0.07 (1.18)	-0.23 (1.63)	-0.48 (1.61)	0.94 (0.61)	0.3 (0.73)	0.66 (0.71)	0.33 (0.69)	0.17 (0.43)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Light	P* varied (0.7)	1.07 (0.64)	0 (1.41)	-0.16 (1.49)	-0.4 (1.18)	0.95 (0.95)	0.37 (0.82)	0.95 (0.6)	0.54 (0.73)	0.09 (0.81)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Light	P* varied (0.7)	0.89 (0.81)	0 (1.28)	-0.21 (1.66)	-0.48 (1.45)	0.96 (1.04)	0.37 (0.85)	0.62 (0.66)	0.28 (0.89)	0.1 (0.78)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Light	P* varied (0.7)	0.89 (0.86)	0 (1.31)	-0.14 (1.64)	-0.43 (1.21)	1.05 (0.99)	0.5 (0.84)	0.89 (0.58)	0.47 (0.81)	0.06 (1.07)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Light	P* varied (0.7)	0.54 (1.03)	0.17 (1.09)	-0.18 (1.85)	-0.53 (1.53)	1.18 (0.92)	0.52 (0.8)	0.61 (0.63)	0.24 (1)	0.06 (1.02)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Light	P* varied (0.7)	1.02 (0.66)	0 (1.36)	-0.17 (1.42)	-0.44 (1.1)	0.99 (0.92)	0.37 (0.78)	0.98 (0.59)	0.53 (0.76)	0.11 (0.73)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Light	P* varied (0.7)	0.84 (0.83)	0.07 (1.21)	-0.22 (1.58)	-0.53 (1.35)	1.01 (1.01)	0.4 (0.81)	0.65 (0.65)	0.28 (0.92)	0.12 (0.68)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Light	P* varied (0.7)	0.81 (0.9)	0 (1.24)	-0.12 (1.82)	-0.44 (1.21)	1.08 (0.96)	0.5 (0.83)	0.85 (0.59)	0.45 (0.83)	0.07 (0.88)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Light	P* varied (0.7)	0.45 (1.07)	0.2 (1.05)	-0.15 (2.06)	-0.55 (1.54)	1.31 (0.89)	0.53 (0.78)	0.58 (0.64)	0.23 (1.03)	0.08 (0.85)
Medium	High	0.77	0.00	fixed	0.35	2	no	no	Moderate	P* varied (0.7)	1.23 (0.45)	0 (1.66)	0.01 (128.75)	0.03 (5.02)	0.81 (0.52)	0.23 (0.82)	0.91 (0.61)	0.85 (0.5)	0.16 (0.3)
Medium	High	1.25	0.00	fixed	0.35	2	no	no	Moderate	P* varied (0.7)	1.12 (0.56)	0.03 (1.35)	-0.04 (10.23)	0.05 (3.78)	0.78 (0.54)	0.23 (0.81)	0.78 (0.84)	0.67 (0.74)	0.18 (0.32)
Medium	High	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* varied (0.7)	1.23 (0.45)	0 (1.66)	0.01 (128.75)	0.03 (5.02)	0.81 (0.52)	0.23 (0.82)	0.91 (0.61)	0.85 (0.5)	0.16 (0.3)
Medium	High	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* varied (0.7)	1.12 (0.56)	0.03 (1.35)	-0.04 (10.23)	0.05 (3.78)	0.78 (0.54)	0.23 (0.81)	0.78 (0.84)	0.67 (0.74)	0.18 (0.32)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Moderate	P* varied (0.7)	1.18 (0.4)	0 (1.77)	0.04 (29.22)	0.08 (3.9)	0.84 (0.54)	0.27 (0.79)	0.68 (0.57)	0.66 (0.46)	0.15 (0.31)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Moderate	P* varied (0.7)	1.1 (0.48)	0 (1.63)	0 (49.63)	0 (4.77)	0.82 (0.54)	0.27 (0.8)	0.42 (0.66)	0.36 (0.59)	0.16 (0.31)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Moderate	P* varied (0.7)	1.14 (0.43)	0 (1.48)	0.03 (29.98)	0.05 (5.39)	0.9 (0.58)	0.33 (0.76)	0.67 (0.64)	0.64 (0.57)	0.1 (0.42)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Moderate	P* varied (0.7)	1.02 (0.53)	0 (1.34)	0 (45.52)	-0.04 (6.44)	0.91 (0.58)	0.3 (0.75)	0.4 (0.72)	0.34 (0.72)	0.11 (0.43)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Moderate	P* varied (0.7)	1.16 (0.4)	0 (1.75)	0.04 (35.71)	0.07 (4)	0.85 (0.53)	0.27 (0.76)	0.68 (0.57)	0.68 (0.46)	0.17 (0.27)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Moderate	P* varied (0.7)	1.08 (0.48)	0 (1.62)	0.01 (63.84)	-0.01 (4.96)	0.84 (0.52)	0.27 (0.77)	0.42 (0.65)	0.37 (0.59)	0.19 (0.26)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Moderate	P* varied (0.7)	1.14 (0.44)	0 (1.5)	0.03 (21.29)	0.08 (5.06)	0.87 (0.61)	0.3 (0.76)	0.66 (0.63)	0.63 (0.57)	0.12 (0.36)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Moderate	P* varied (0.7)	1.03 (0.54)	0 (1.37)	-0.01 (27.39)	0 (5.96)	0.89 (0.61)	0.3 (0.76)	0.4 (0.71)	0.33 (0.71)	0.14 (0.35)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Moderate	P* varied (0.7)	1.09 (0.52)	0 (1.81)	-0.01 (26.27)	0.05 (7.48)	0.88 (0.86)	0.33 (0.81)	0.73 (0.42)	0.59 (0.58)	0.09 (0.45)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Moderate	P* varied (0.7)	1.01 (0.64)	0 (1.54)	-0.03 (18.69)	-0.02 (8.62)	0.87 (1.04)	0.33 (0.85)	0.46 (0.5)	0.32 (0.73)	0.1 (0.43)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Moderate	P* varied (0.7)	1.02 (0.7)	0 (1.59)	-0.02 (14.08)	0.02 (21.48)	0.93 (1.06)	0.37 (0.86)	0.74 (0.4)	0.56 (0.66)	0.05 (0.64)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Moderate	P* varied (0.7)	0.79 (0.88)	0.07 (1.28)	-0.06 (12.03)	-0.03 (30.86)	1.01 (1)	0.4 (0.8)	0.46 (0.48)	0.28 (0.87)	0.06 (0.6)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Moderate	P* varied (0.7)	1.1 (0.51)	0 (1.82)	-0.01 (23.48)	0.03 (8.21)	0.9 (0.83)	0.33 (0.77)	0.73 (0.42)	0.6 (0.58)	0.1 (0.42)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Moderate	P* varied (0.7)	0.99 (0.65)	0 (1.51)	-0.03 (16.74)	-0.03 (9.87)	0.89 (1.01)	0.33 (0.79)	0.46 (0.5)	0.33 (0.74)	0.11 (0.4)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Moderate	P* varied (0.7)	1.01 (0.71)	0 (1.58)	-0.02 (16.86)	0.04 (18.51)	0.94 (1.05)	0.37 (0.85)	0.74 (0.38)	0.57 (0.67)	0.06 (0.61)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Moderate	P* varied (0.7)	0.78 (0.89)	0.07 (1.27)	-0.06 (13.71)	-0.02 (25.25)	1.02 (0.99)	0.4 (0.8)	0.46 (0.47)	0.29 (0.86)	0.07 (0.56)
Medium	High	0.77	0.00	fixed	0.35	2	no	no	Heavy	P* varied (0.7)	1.29 (0.46)	0.07 (1.18)	0.62 (0.95)	1.11 (0.99)	0.79 (0.53)	0.23 (0.82)	0.37 (0.72)	0.81 (0.52)	0.16 (0.28)
Medium	High	1.25	0.00	fixed	0.35	2	no	no	Heavy	P* varied (0.7)	1.29 (0.6)	0.13 (0.97)	0.54 (1.32)	1.05 (1.39)	0.76 (0.53)	0.2 (0.82)	0.28 (1.01)	0.71 (0.94)	0.18 (0.28)
Medium	High	0.77	0.44	fixed	0.35	2	no	no	Heavy	P* varied (0.7)	1.29 (0.46)	0.07 (1.18)	0.62 (0.95)	1.11 (0.99)	0.79 (0.53)	0.23 (0.82)	0.37 (0.72)	0.81 (0.52)	0.16 (0.28)
Medium	High	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* varied (0.7)	1.29 (0.6)	0.13 (0.97)	0.54 (1.32)	1.05 (1.39)	0.76 (0.53)	0.2 (0.82)	0.28 (1.01)	0.71 (0.94)	0.18 (0.28)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Heavy	P* varied (0.7)	1.28 (0.41)	0.07 (1.13)	0.81 (0.61)	1.5 (0.71)	0.72 (0.54)	0.2 (0.95)	0.21 (0.67)	0.64 (0.42)	0.14 (0.27)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Heavy	P* varied (0.7)	1.25 (0.48)	0.1 (1.02)	0.72 (0.81)	1.51 (0.88)	0.7 (0.56)	0.17 (0.97)	0.11 (0.82)	0.36 (0.54)	0.15 (0.27)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Heavy	P* varied (0.7)	1.26 (0.44)	0.07 (1.18)	0.81 (0.65)	1.66 (0.7)	0.72 (0.62)	0.17 (0.94)	0.2 (0.77)	0.65 (0.52)	0.09 (0.39)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Heavy	P* varied (0.7)	1.23 (0.51)	0.1 (1.01)	0.74 (0.86)	1.73 (0.88)	0.69 (0.62)	0.17 (0.95)	0.1 (0.9)	0.37 (0.62)	0.1 (0.39)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Heavy	P* varied (0.7)	1.27 (0.4)	0.07 (1.14)	0.83 (0.59)	1.47 (0.71)	0.73 (0.53)	0.2 (0.92)	0.2 (0.67)	0.65 (0.41)	0.16 (0.23)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Heavy	P* varied (0.7)	1.25 (0.48)	0.1 (1.03)	0.73 (0.79)	1.54 (0.89)	0.71 (0.54)	0.17 (0.94)	0.1 (0.83)	0.36 (0.54)	0.18 (0.23)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Heavy	P* varied (0.7)	1.3 (0.44)	0.07 (1.14)	0.72 (0.73)	1.7 (0.69)	0.72 (0.64)	0.17 (0.96)	0.23 (0.7)	0.65 (0.5)	0.12 (0.32)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Heavy	P* varied (0.7)	1.27 (0.51)	0.13 (0.99)	0.67 (0.94)	1.74 (0.86)	0.68 (0.64)	0.17 (0.97)	0.12 (0.84)	0.36 (0.61)	0.13 (0.34)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Heavy	P* varied (0.7)	1.31 (0.46)	0.1 (1.13)	0.45 (0.86)	1.57 (0.69)	0.75 (0.71)	0.2 (0.89)	0.37 (0.36)	0.64 (0.45)	0.08 (0.32)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Heavy	P* varied (0.7)	1.28 (0.55)	0.17 (0.93)	0.35 (1.3)	1.49 (0.91)	0.72 (0.89)	0.17 (0.91)	0.2 (0.52)	0.37 (0.58)	0.09 (0.31)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Heavy	P* varied (0.7)	1.43 (0.46)	0.1 (1.21)	0.34 (1.08)	1.53 (0.73)	0.74 (1.03)	0.17 (0.91)	0.42 (0.33)	0.65 (0.45)	0.06 (0.41)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Heavy	P* varied (0.7)	1.37 (0.58)	0.17 (0.98)	0.24 (1.75)	1.46 (1.1)	0.75 (1.2)	0.2 (0.9)	0.23 (0.49)	0.35 (0.63)	0.06 (0.45)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Heavy	P* varied (0.7)	1.29 (0.46)	0.1 (1.11)	0.47 (0.82)	1.57 (0.67)	0.76 (0.7)	0.2 (0.87)	0.36 (0.36)	0.65 (0.45)	0.09 (0.29)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Heavy	P* varied (0.7)	1.24 (0.55)	0.17 (0.92)	0.36 (1.25)	1.56 (0.9)	0.74 (0.87)	0.2 (0.89)	0.19 (0.52)	0.37 (0.57)	0.11 (0.29)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Heavy	P* varied (0.7)	1.45 (0.45)	0.1 (1.18)	0.31 (1.22)	1.54 (0.73)	0.73 (1.07)	0.2 (0.88)	0.43 (0.32)	0.66 (0.45)	0.06 (0.39)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Heavy	P* varied (0.7)	1.39 (0.58)	0.2 (0.96)	0.2 (1.98)	1.46 (1.11)	0.74 (1.21)	0.22 (0.87)	0.23 (0.49)	0.35 (0.63)	0.07 (0.42)
Medium	High	0.77	0.00	fixed	0.35	2	no	no	Light	P* varied (1.0)	1.28 (0.44)	0 (1.36)	-0.26 (1.37)	-0.38 (1.49)	0.85 (0.56)	0.2 (0.82)	1.46 (0.63)	0.82 (0.51)	0.17 (0.41)
Medium	High	1.25	0.00	fixed	0.35	2	no	no	Light	P* varied (1.0)	1.21 (0.57)	0.07 (1.22)	-0.29 (2.19)	-0.43 (4.38)	0.82 (0.57)	0.2 (0.8)	1.33 (0.76)	0.71 (0.75)	0.2 (0.38)
Medium	High	0.77	0.44	fixed	0.35	2	no	no	Light	P* varied (1.0)	1.28 (0.44)	0 (1.36)	-0.26 (1.37)	-0.38 (1.49)	0.85 (0.56)	0.2 (0.82)	1.46 (0.63)	0.82 (0.51)	0.17 (0.41)
Medium	High	1.25	0.44	fixed	0.35	2	no	no	Light	P* varied (1.0)	1.21 (0.57)	0.07 (1.22)	-0.29 (2.19)	-0.43 (4.38)	0.82 (0.57)	0.2 (0.8)	1.33 (0.76)	0.71 (0.75)	0.2 (0.38)
Medium	High	0.77	0.00	fixed	0.35	2	no	no	Moderate	P* varied (1.0)	1.26 (0.43)	0 (1.8)	0.03 (14.43)	0.08 (3.43)	0.76 (0.53)	0.2 (0.9)	0.86 (0.63)	0.85 (0.49)	0.15 (0.3)
Medium	High	1.25	0.00	fixed	0.35	2	no	no	Moderate	P* varied (1.0)	1.18 (0.54)	0 (1.48)	-0.02 (6.86)	0.13 (3.08)	0.73 (0.55)	0.2 (0.88)	0.72 (0.86)	0.67 (0.74)	0.18 (0.31)
Medium	High	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* varied (1.0)	1.26 (0.43)	0 (1.8)	0.03 (14.43)	0.08 (3.43)	0.76 (0.53)	0.2 (0.9)	0.86 (0.63)	0.85 (0.49)	0.15 (0.3)
Medium	High	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* varied (1.0)	1.18 (0.54)	0 (1.48)	-0.02 (6.86)	0.13 (3.08)	0.73 (0.55)	0.2 (0.88)	0.72 (0.86)	0.67 (0.74)	0.18 (0.31)
Medium	High	0.77	0.00	fixed	0.35	2	no	no	Heavy	P* varied (1.0)	1.34 (0.44)	0.03 (1.25)	0.7 (0.84)	1.25 (0.92)	0.72 (0.53)	0.2 (0.9)	0.32 (0.78)	0.81 (0.51)	0.16 (0.28)
Medium	High	1.25	0.00	fixed	0.35	2	no	no	Heavy	P* varied (1.0)	1.37 (0.58)	0.1 (1)	0.62 (1.2)	1.2 (1.32)	0.7 (0.55)	0.2 (0.89)	0.24 (1.09)	0.72 (0.93)	0.19 (0.27)
Medium	High	0.77	0.44	fixed	0.35	2	no	no	Heavy	P* varied (1.0)	1.34 (0.44)	0.03 (1.25)	0.7 (0.84)	1.25 (0.92)	0.72 (0.53)	0.2 (0.9)	0.32 (0.78)	0.81 (0.51)	0.16 (0.28)
Medium	High	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* varied (1.0)	1.37 (0.58)	0.1 (1)	0.62 (1.2)	1.2 (1.32)	0.7 (0.55)	0.2 (0.89)	0.24 (1.09)	0.72 (0.93)	0.19 (0.27)
Medium	High	0.77	0.00	fixed	0.35	2	no	no	Light	P* fixed (0.38)	1.05 (0.56)	0.1 (1.23)	-0.31 (1.16)	-0.5 (1.04)	1.09 (0.62)	0.33 (0.73)	1.64 (0.58)	0.8 (0.52)	0.17 (0.45)
Medium	High	1.25	0.00	fixed	0.35	2	no	no	Light	P* fixed (0.38)	0.89 (0.74)	0.2 (1.04)	-0.34 (1.78)	-0.56 (2.33)	1.13 (0.7)	0.37 (0.71)	1.49 (0.72)	0.64 (0.82)	0.19 (0.45)
Medium	High	0.77	0.44	fixed	0.35	2	no	no	Light	P* fixed (0.38)	1.05 (0.56)	0.1 (1.23)	-0.31 (1.16)	-0.5 (1.04)	1.09 (0.62)	0.33 (0.73)	1.64 (0.58)	0.8 (0.52)	0.17 (0.45)
Medium	High	1.25	0.44	fixed	0.35	2	no	no	Light	P* fixed (0.38)	0.89 (0.74)	0.2 (1.04)	-0.34 (1.78)	-0.56 (2.33)	1.13 (0.7)	0.37 (0.71)	1.49 (0.72)	0.64 (0.82)	0.19 (0.45)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Light	P* fixed (0.38)	1.06 (0.47)	0 (1.41)	-0.25 (1.21)	-0.42 (1.05)	1.05 (0.65)	0.33 (0.76)	1.14 (0.61)	0.64 (0.46)	0.15 (0.45)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Light	P* fixed (0.38)	0.92 (0.58)	0.1 (1.26)	-0.29 (1.29)	-0.49 (1.26)	1.07 (0.71)	0.33 (0.77)	0.76 (0.67)	0.34 (0.61)	0.16 (0.48)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Light	P* fixed (0.38)	1 (0.53)	0.1 (1.18)	-0.25 (1.22)	-0.48 (1.02)	1.21 (0.69)	0.37 (0.71)	1.18 (0.61)	0.56 (0.59)	0.11 (0.65)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Light	P* fixed (0.38)	0.81 (0.68)	0.18 (1.06)	-0.29 (1.31)	-0.58 (1.21)	1.28 (0.76)	0.4 (0.7)	0.76 (0.66)	0.28 (0.77)	0.12 (0.68)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Light	P* fixed (0.38)	1.06 (0.45)	0 (1.4)	-0.27 (1.16)	-0.43 (1.01)	1.05 (0.61)	0.33 (0.73)	1.21 (0.6)	0.65 (0.45)	0.19 (0.37)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Light	P* fixed (0.38)	0.92 (0.56)	0.1 (1.22)	-0.3 (1.24)	-0.51 (1.22)	1.08 (0.64)	0.33 (0.73)	0.79 (0.65)	0.35 (0.59)	0.21 (0.37)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Light	P* fixed (0.38)	0.88 (0.7)	0.07 (1.19)	-0.2 (1.35)	-0.47 (1.07)	1.19 (0.89)	0.43 (0.74)	1.06 (0.63)	0.5 (0.74)	0.14 (0.54)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Light	P* fixed (0.38)	0.7 (0.89)	0.2 (1.07)	-0.25 (1.45)	-0.58 (1.26)	1.32 (0.93)	0.45 (0.74)	0.71 (0.68)	0.25 (0.95)	0.16 (0.53)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Light	P* fixed (0.38)	0.82 (0.83)	0 (1.25)	-0.18 (1.37)	-0.49 (1.01)	1.12 (0.98)	0.47 (0.78)	0.99 (0.59)	0.53 (0.81)	0.09 (0.83)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Light	P* fixed (0.38)	0.64 (0.97)	0.2 (1.08)	-0.23 (1.51)	-0.58 (1.21)	1.17 (0.94)	0.5 (0.75)	0.65 (0.65)	0.26 (0.96)	0.1 (0.81)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Light	P* fixed (0.38)	0.53 (0.97)	0.13 (1.13)	-0.16 (1.51)	-0.49 (1.05)	1.36 (0.9)	0.62 (0.76)	0.94 (0.57)	0.48 (0.85)	0.05 (1.06)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Light	P* fixed (0.38)	0.21 (1.17)	0.33 (0.95)	-0.2 (1.69)	-0.61 (1.32)	1.98 (0.82)	0.67 (0.7)	0.63 (0.62)	0.21 (1.07)	0.07 (0.99)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Light	P* fixed (0.38)	0.79 (0.81)	0.03 (1.21)	-0.19 (1.3)	-0.52 (0.94)	1.17 (0.94)	0.47 (0.73)	1.03 (0.58)	0.51 (0.81)	0.1 (0.75)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Light	P* fixed (0.38)	0.59 (0.98)	0.22 (1.02)	-0.24 (1.44)	-0.63 (1.13)	1.29 (0.92)	0.5 (0.71)	0.68 (0.64)	0.25 (0.98)	0.11 (0.71)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Light	P* fixed (0.38)	0.43 (1.04)	0.17 (1.08)	-0.13 (1.66)	-0.51 (1.06)	1.49 (0.85)	0.62 (0.73)	0.88 (0.58)	0.46 (0.89)	0.07 (0.89)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Light	P* fixed (0.38)	0.07 (1.25)	0.37 (0.92)	-0.17 (1.87)	-0.62 (1.32)	2.75 (0.78)	0.67 (0.69)	0.61 (0.63)	0.16 (1.13)	0.08 (0.86)
Medium	High	0.77	0.00	fixed	0.35	2	no	no	Moderate	P* fixed (0.38)	1.04 (0.52)	0 (1.5)	-0.06 (6.48)	-0.13 (24.83)	0.96 (0.59)	0.33 (0.76)	1.01 (0.56)	0.78 (0.52)	0.15 (0.33)
Medium	High	1.25	0.00	fixed	0.35	2	no	no	Moderate	P* fixed (0.38)	0.93 (0.67)	0.13 (1.16)	-0.11 (448.65)	-0.15 (9.93)	0.98 (0.69)	0.33 (0.74)	0.88 (0.79)	0.62 (0.79)	0.17 (0.35)
Medium	High	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (0.38)	1.04 (0.52)	0 (1.5)	-0.06 (6.48)	-0.13 (24.83)	0.96 (0.59)	0.33 (0.76)	1.01 (0.56)	0.78 (0.52)	0.15 (0.33)
Medium	High	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (0.38)	0.93 (0.67)	0.13 (1.16)	-0.11 (448.65)	-0.15 (9.93)	0.98 (0.69)	0.33 (0.74)	0.88 (0.79)	0.62 (0.79)	0.17 (0.35)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Moderate	P* fixed (0.38)	1.02 (0.47)	0 (1.62)	-0.01 (6.92)	-0.05 (258.64)	0.99 (0.59)	0.37 (0.72)	0.75 (0.51)	0.64 (0.47)	0.13 (0.34)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Moderate	P* fixed (0.38)	0.87 (0.59)	0 (1.39)	-0.06 (6.45)	-0.14 (27.78)	1 (0.61)	0.37 (0.72)	0.46 (0.59)	0.34 (0.63)	0.14 (0.36)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Moderate	P* fixed (0.38)	0.95 (0.54)	0 (1.37)	-0.03 (7.99)	-0.09 (15.91)	1.09 (0.66)	0.37 (0.69)	0.73 (0.56)	0.59 (0.59)	0.1 (0.48)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Moderate	P* fixed (0.38)	0.79 (0.68)	0.1 (1.17)	-0.08 (7.6)	-0.19 (13.45)	1.18 (0.7)	0.4 (0.69)	0.45 (0.63)	0.3 (0.77)	0.11 (0.49)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Moderate	P* fixed (0.38)	1.03 (0.46)	0 (1.63)	-0.02 (6.88)	-0.06 (169.46)	1 (0.55)	0.37 (0.69)	0.75 (0.5)	0.65 (0.46)	0.16 (0.32)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Moderate	P* fixed (0.38)	0.89 (0.57)	0 (1.4)	-0.06 (6.38)	-0.16 (30.88)	0.99 (0.57)	0.37 (0.69)	0.47 (0.58)	0.34 (0.62)	0.17 (0.31)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Moderate	P* fixed (0.38)	0.93 (0.66)	0 (1.36)	-0.03 (8.14)	-0.08 (11.93)	1.09 (0.91)	0.4 (0.73)	0.74 (0.55)	0.56 (0.66)	0.11 (0.45)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Moderate	P* fixed (0.38)	0.77 (0.8)	0.1 (1.19)	-0.09 (7.82)	-0.17 (11.47)	1.14 (0.94)	0.43 (0.72)	0.46 (0.62)	0.29 (0.86)	0.13 (0.43)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Moderate	P* fixed (0.38)	0.91 (0.67)	0 (1.49)	-0.04 (5.53)	-0.08 (10.35)	1.04 (1)	0.4 (0.74)	0.77 (0.39)	0.58 (0.63)	0.08 (0.52)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Moderate	P* fixed (0.38)	0.75 (0.83)	0.1 (1.23)	-0.08 (5.47)	-0.18 (9.48)	1.1 (0.98)	0.47 (0.72)	0.5 (0.47)	0.29 (0.82)	0.09 (0.5)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Moderate	P* fixed (0.38)	0.79 (0.82)	0 (1.35)	-0.05 (5.34)	-0.1 (6.75)	1.14 (0.94)	0.5 (0.72)	0.78 (0.38)	0.55 (0.73)	0.05 (0.7)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Moderate	P* fixed (0.38)	0.47 (1.06)	0.2 (1.05)	-0.09 (5.44)	-0.17 (7.53)	1.4 (0.86)	0.6 (0.65)	0.5 (0.46)	0.27 (0.96)	0.06 (0.64)

Life history	Assessment uncertainty	σ_R	ϕ_R	h	SPR target	SA years	Projec-tions?	ABC avg.?	Exploitation history	Control rule	S / S_{MSY}	Overfished probability	ΔS_5	ΔS_{15}	F / F_{MSY}	P_{OF} (true)	Initial C / MSY	Final C / MSY	Catch AAV
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Moderate	P* fixed (0.38)	0.92 (0.64)	0 (1.5)	-0.05 (5.49)	-0.1 (10.33)	1.06 (0.94)	0.43 (0.71)	0.77 (0.39)	0.59 (0.62)	0.09 (0.49)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Moderate	P* fixed (0.38)	0.75 (0.81)	0.13 (1.2)	-0.07 (5.39)	-0.19 (9.5)	1.12 (0.97)	0.45 (0.68)	0.5 (0.47)	0.29 (0.81)	0.1 (0.47)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Moderate	P* fixed (0.38)	0.77 (0.84)	0 (1.33)	-0.06 (5.46)	-0.09 (6.8)	1.15 (0.93)	0.5 (0.71)	0.78 (0.36)	0.54 (0.74)	0.05 (0.64)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Moderate	P* fixed (0.38)	0.45 (1.08)	0.2 (1.04)	-0.09 (5.6)	-0.17 (7.6)	1.43 (0.84)	0.6 (0.64)	0.49 (0.45)	0.26 (0.96)	0.07 (0.58)
Medium	High	0.77	0.00	fixed	0.35	2	no	no	Heavy	P* fixed (0.38)	1.16 (0.53)	0.1 (1.12)	0.3 (1.53)	0.79 (1.27)	0.98 (0.56)	0.33 (0.73)	0.54 (0.54)	0.77 (0.54)	0.15 (0.29)
Medium	High	1.25	0.00	fixed	0.35	2	no	no	Heavy	P* fixed (0.38)	1.09 (0.71)	0.23 (0.89)	0.26 (2)	0.68 (1.73)	0.99 (0.61)	0.35 (0.71)	0.43 (0.79)	0.63 (1.01)	0.17 (0.29)
Medium	High	0.77	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (0.38)	1.16 (0.53)	0.1 (1.12)	0.3 (1.53)	0.79 (1.27)	0.98 (0.56)	0.33 (0.73)	0.54 (0.54)	0.77 (0.54)	0.15 (0.29)
Medium	High	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (0.38)	1.09 (0.71)	0.23 (0.89)	0.26 (2)	0.68 (1.73)	0.99 (0.61)	0.35 (0.71)	0.43 (0.79)	0.63 (1.01)	0.17 (0.29)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Heavy	P* fixed (0.38)	1.18 (0.47)	0.1 (1.13)	0.51 (0.98)	1.18 (0.88)	0.91 (0.58)	0.33 (0.8)	0.35 (0.49)	0.63 (0.42)	0.13 (0.28)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Heavy	P* fixed (0.38)	1.1 (0.57)	0.13 (1.01)	0.41 (1.34)	1.01 (1.16)	0.9 (0.61)	0.3 (0.8)	0.19 (0.62)	0.34 (0.58)	0.13 (0.28)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Heavy	P* fixed (0.38)	1.16 (0.51)	0.1 (1.11)	0.52 (1.08)	1.25 (0.89)	0.92 (0.66)	0.33 (0.79)	0.33 (0.56)	0.63 (0.51)	0.08 (0.44)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Heavy	P* fixed (0.38)	1.09 (0.62)	0.17 (0.96)	0.4 (1.48)	1.01 (1.21)	0.97 (0.7)	0.33 (0.78)	0.18 (0.67)	0.33 (0.66)	0.09 (0.44)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Heavy	P* fixed (0.38)	1.17 (0.46)	0.07 (1.16)	0.55 (0.89)	1.21 (0.84)	0.9 (0.55)	0.3 (0.79)	0.33 (0.49)	0.64 (0.41)	0.15 (0.26)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Heavy	P* fixed (0.38)	1.1 (0.56)	0.13 (1.02)	0.44 (1.24)	1.06 (1.13)	0.88 (0.57)	0.3 (0.79)	0.18 (0.62)	0.35 (0.57)	0.17 (0.26)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Heavy	P* fixed (0.38)	1.19 (0.55)	0.13 (1.08)	0.38 (1.47)	1.17 (0.99)	0.95 (0.88)	0.33 (0.75)	0.4 (0.49)	0.59 (0.54)	0.11 (0.39)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Heavy	P* fixed (0.38)	1.07 (0.67)	0.2 (0.93)	0.26 (2.07)	0.92 (1.36)	0.98 (0.99)	0.37 (0.74)	0.21 (0.61)	0.3 (0.71)	0.12 (0.39)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Heavy	P* fixed (0.38)	1.19 (0.55)	0.13 (1.07)	0.28 (1.41)	1.14 (0.95)	0.94 (0.93)	0.35 (0.75)	0.46 (0.33)	0.62 (0.49)	0.08 (0.4)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Heavy	P* fixed (0.38)	1.09 (0.67)	0.2 (0.91)	0.16 (2.34)	0.9 (1.36)	0.97 (1.02)	0.35 (0.74)	0.25 (0.48)	0.33 (0.68)	0.08 (0.39)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Heavy	P* fixed (0.38)	1.25 (0.58)	0.13 (1.11)	0.19 (1.86)	1 (1.13)	0.93 (1.04)	0.33 (0.72)	0.48 (0.31)	0.6 (0.54)	0.05 (0.54)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Heavy	P* fixed (0.38)	1.09 (0.8)	0.3 (0.81)	0.08 (3.52)	0.69 (1.83)	1.07 (1.01)	0.43 (0.67)	0.27 (0.46)	0.29 (0.8)	0.06 (0.59)
Medium	High	0.77	0.44	fixed	0.35	2	yes	yes	Heavy	P* fixed (0.38)	1.19 (0.52)	0.13 (1.08)	0.31 (1.26)	1.19 (0.87)	0.92 (0.86)	0.33 (0.75)	0.44 (0.33)	0.65 (0.47)	0.09 (0.35)
Medium	High	1.25	0.44	fixed	0.35	2	yes	yes	Heavy	P* fixed (0.38)	1.1 (0.65)	0.2 (0.92)	0.19 (2.09)	0.96 (1.27)	0.94 (1)	0.37 (0.74)	0.24 (0.47)	0.34 (0.65)	0.1 (0.35)
Medium	High	0.77	0.44	fixed	0.35	5	yes	yes	Heavy	P* fixed (0.38)	1.28 (0.59)	0.17 (1.06)	0.12 (2.74)	0.92 (1.21)	0.95 (1.06)	0.37 (0.69)	0.52 (0.3)	0.6 (0.56)	0.06 (0.5)
Medium	High	1.25	0.44	fixed	0.35	5	yes	yes	Heavy	P* fixed (0.38)	1.09 (0.82)	0.32 (0.79)	0.01 (6.31)	0.55 (2.04)	1.1 (1)	0.43 (0.65)	0.28 (0.45)	0.28 (0.84)	0.07 (0.53)
Medium	High	0.77	0.00	fixed	0.35	2	no	no	Light	P* fixed (0.7)	1.12 (0.54)	0.03 (1.34)	-0.28 (1.27)	-0.46 (1.19)	0.97 (0.64)	0.27 (0.8)	1.53 (0.6)	0.8 (0.52)	0.16 (0.45)
Medium	High	1.25	0.00	fixed	0.35	2	no	no	Light	P* fixed (0.7)	0.98 (0.7)	0.13 (1.13)	-0.32 (1.97)	-0.53 (2.83)	0.97 (0.68)	0.3 (0.77)	1.4 (0.74)	0.64 (0.8)	0.18 (0.44)
Medium	High	0.77	0.44	fixed	0.35	2	no	no	Light	P* fixed (0.7)	1.12 (0.54)	0.03 (1.34)	-0.28 (1.27)	-0.46 (1.19)	0.97 (0.64)	0.27 (0.8)	1.53 (0.6)	0.8 (0.52)	0.16 (0.45)
Medium	High	1.25	0.44	fixed	0.35	2	no	no	Light	P* fixed (0.7)	0.98 (0.7)	0.13 (1.13)	-0.32 (1.97)	-0.53 (2.83)	0.97 (0.68)	0.3 (0.77)	1.4 (0.74)	0.64 (0.8)	0.18 (0.44)
Medium	High	0.77	0.00	fixed	0.35	2	no	no	Moderate	P* fixed (0.7)	1.13 (0.49)	0 (1.67)	-0.01 (15.73)	-0.06 (12.8)	0.87 (0.59)	0.27 (0.84)	0.95 (0.57)	0.81 (0.49)	0.14 (0.32)
Medium	High	1.25	0.00	fixed	0.35	2	no	no	Moderate	P* fixed (0.7)	1.01 (0.64)	0.07 (1.29)	-0.07 (19.08)	-0.07 (5.63)	0.86 (0.67)	0.27 (0.81)	0.82 (0.8)	0.64 (0.77)	0.16 (0.34)
Medium	High	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (0.7)	1.13 (0.49)	0 (1.67)	-0.01 (15.73)	-0.06 (12.8)	0.87 (0.59)	0.27 (0.84)	0.95 (0.57)	0.81 (0.49)	0.14 (0.32)
Medium	High	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (0.7)	1.01 (0.64)	0.07 (1.29)	-0.07 (19.08)	-0.07 (5.63)	0.86 (0.67)	0.27 (0.81)	0.82 (0.8)	0.64 (0.77)	0.16 (0.34)
Medium	High	0.77	0.00	fixed	0.35	2	no	no	Heavy	P* fixed (0.7)	1.23 (0.51)	0.1 (1.18)	0.38 (1.32)	0.94 (1.13)	0.9 (0.57)	0.3 (0.81)	0.51 (0.55)	0.79 (0.51)	0.14 (0.28)
Medium	High	1.25	0.00	fixed	0.35	2	no	no	Heavy	P* fixed (0.7)	1.2 (0.68)	0.2 (0.96)	0.31 (1.78)	0.91 (1.59)	0.89 (0.63)	0.3 (0.77)	0.4 (0.8)	0.64 (0.96)	0.17 (0.28)
Medium	High	0.77	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (0.7)	1.23 (0.51)	0.1 (1.18)	0.38 (1.32)	0.94 (1.13)	0.9 (0.57)	0.3 (0.81)	0.51 (0.55)	0.79 (0.51)	0.14 (0.28)
Medium	High	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (0.7)	1.2 (0.68)	0.2 (0.96)	0.31 (1.78)	0.91 (1.59)	0.89 (0.63)	0.3 (0.77)	0.4 (0.8)	0.64 (0.96)	0.17 (0.28)
Medium	High	0.77	0.00	fixed	0.35	2	no	no	Light	P* fixed (1.0)	1.17 (0.51)	0 (1.42)	-0.26 (1.35)	-0.43 (1.31)	0.91 (0.65)	0.27 (0.86)	1.46 (0.62)	0.8 (0.5)	0.16 (0.44)
Medium	High	1.25	0.00	fixed	0.35	2	no	no	Light	P* fixed (1.0)	1.03 (0.67)	0.1 (1.2)	-0.29 (2.13)	-0.49 (3.28)	0.92 (0.69)	0.27 (0.83)	1.33 (0.75)	0.65 (0.78)	0.18 (0.44)
Medium	High	0.77	0.44	fixed	0.35	2	no	no	Light	P* fixed (1.0)	1.17 (0.51)	0 (1.42)	-0.26 (1.35)	-0.43 (1.31)	0.91 (0.65)	0.27 (0.86)	1.46 (0.62)	0.8 (0.5)	0.16 (0.44)
Medium	High	1.25	0.44	fixed	0.35	2	no	no	Light	P* fixed (1.0)	1.03 (0.67)	0.1 (1.2)	-0.29 (2.13)	-0.49 (3.28)	0.92 (0.69)	0.27 (0.83)	1.33 (0.75)	0.65 (0.78)	0.18 (0.44)
Medium	High	0.77	0.00	fixed	0.35	2	no	no	Moderate	P* fixed (1.0)	1.19 (0.47)	0 (1.81)	0.01 (198.41)	0.01 (6.2)	0.81 (0.59)	0.23 (0.91)	0.91 (0.57)	0.81 (0.48)	0.14 (0.31)
Medium	High	1.25	0.00	fixed	0.35	2	no	no	Moderate	P* fixed (1.0)	1.1 (0.61)	0.07 (1.4)	-0.05 (10.85)	0 (4.32)	0.8 (0.64)	0.23 (0.89)	0.79 (0.8)	0.65 (0.74)	0.16 (0.33)
Medium	High	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (1.0)	1.19 (0.47)	0 (1.81)	0.01 (198.41)	0.01 (6.2)	0.81 (0.59)	0.23 (0.91)	0.91 (0.57)	0.81 (0.48)	0.14 (0.31)
Medium	High	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (1.0)	1.1 (0.61)	0.07 (1.4)	-0.05 (10.85)	0 (4.32)	0.8 (0.64)	0.23 (0.89)	0.79 (0.8)	0.65 (0.74)	0.16 (0.33)
Medium	High	0.77	0.00	fixed	0.35	2	no	no	Heavy	P* fixed (1.0)	1.28 (0.49)	0.07 (1.24)	0.43 (1.19)	1.01 (1.05)	0.84 (0.57)	0.23 (0.86)	0.49 (0.55)	0.79 (0.5)	0.14 (0.28)
Medium	High	1.25	0.00	fixed	0.35	2	no	no	Heavy	P* fixed (1.0)	1.27 (0.65)	0.17 (1)	0.36 (1.66)	1.01 (1.5)	0.82 (0.64)	0.27 (0.83)	0.39 (0.81)	0.65 (0.94)	0.16 (0.28)
Medium	High	0.77	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (1.0)	1.28 (0.49)	0.07 (1.24)	0.43 (1.19)	1.01 (1.05)	0.84 (0.57)	0.23 (0.86)	0.49 (0.55)	0.79 (0.5)	0.14 (0.28)
Medium	High	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (1.0)	1.27 (0.65)	0.17 (1)	0.36 (1.66)	1.01 (1.5)	0.82 (0.64)	0.27 (0.83)	0.39 (0.81)	0.65 (0.94)	0.16 (0.28)
Medium	High	0.77	0.00	fixed	0.35	2	no	no	Light	75% of F_lim	1.19 (0.5)	0 (1.43)	-0.25 (1.38)	-0.42 (1.35)	0.89 (0.65)	0.27 (0.87)	1.44 (0.63)	0.8 (0.5)	0.16 (0.45)
Medium	High	1.25	0.00	fixed	0.35	2	no	no	Light	75% of F_lim	1.07 (0.66)	0.1 (1.21)	-0.29 (2.18)	-0.47 (3.46)	0.9 (0.69)	0.27 (0.84)	1.32 (0.75)	0.66 (0.77)	0.18 (0.44)
Medium	High	0.77	0.44	fixed	0.35	2	no	no	Light	75% of F_lim	1.19 (0.5)	0 (1.43)	-0.25 (1.38)	-0.42 (1.35)	0.89 (0.65)	0.27 (0.87)	1.44 (0.63)	0.8 (0.5)	0.16 (0.45)
Medium	High	1.25	0.44	fixed	0.35	2	no	no	Light	75% of F_lim	1.07 (0.66)	0.1 (1.21)	-0.29 (2.18)	-0.47 (3.46)	0.9 (0.69)	0.27 (0.84)	1.32 (0.75)	0.66 (0.77)	0.18 (0.44)
Medium	High	0.77	0.00	fixed	0.35	2	no	no	Moderate	75% of F_lim	1.22 (0.46)	0 (1.87)	0.02 (39.67)	0.03 (5.34)	0.79 (0.59)	0.23 (0.94)	0.89 (0.58)	0.81 (0.48)	0.14 (0.31)
Medium	High	1.25	0.00	fixed	0.35	2	no	no	Moderate	75% of F_lim	1.11 (0.6)	0.03 (1.44)	-0.04 (9.74)	0.01 (4.07)	0.79 (0.64)	0.22 (0.91)	0.78 (0.8)	0.65 (0.74)	0.16 (0.33)
Medium	High	0.77	0.44	fixed	0.35	2	no	no	Moderate	75% of F_lim	1.22 (0.46)	0 (1.87)	0.02 (39.67)	0.03 (5.34)	0.79 (0.59)	0.23 (0.94)	0.89 (0.58)	0.81 (0.48)	0.14 (0.31)
Medium	High	1.25	0.44	fixed	0.35	2	no	no	Moderate	75% of F_lim	1.11 (0.6)	0.03 (1.44)	-0.04 (9.74)	0.01 (4.07)	0.79 (0.64)	0.22 (0.91)	0.78 (0.8)	0.65 (0.74)	0.16 (0.33)
Medium	High	0.77	0.00	fixed	0.35	2	no	no	Heavy	75% of F_lim	1.29 (0.48)	0.07 (1.26)	0.44 (1.15)	1.05 (1.03)	0.83 (0.57)	0.2 (0.88)	0.48 (0.55)	0.79 (0.5)	0.14 (0.28)
Medium	High	1.25	0.00	fixed	0.35	2	no	no	Heavy	75% of F_lim	1.29 (0.64)	0.17 (1.01)	0.38 (1.62)	1.04 (1.47)	0.81 (0.64)	0.23 (0.85)	0.38 (0.81)	0.65 (0.94)	0.16 (0.28)
Medium	High	0.77	0.44	fixed	0.35	2	no	no	Heavy	75% of F_lim	1.29 (0.48)	0.07 (1.26)	0.44 (1.15)	1.05 (1.03)	0.83 (0.57)	0.2 (0.88)	0.48 (0.55)	0.79 (0.5)	0.14 (0.28)
Medium	High	1.25	0.44	fixed	0.35	2	no	no	Heavy	75% of F_lim	1.29 (0.64)	0.17 (1.01)	0.38 (1.62)	1.04 (1.47)	0.81 (0.64)	0.23 (0.85)	0.38 (0.81)	0.65 (0.94)	0.16 (0.28)

Life history	Assessment uncertainty	σ_R	ϕ_R	h	SPR target	SA years	Projec-tions?	ABC avg.?	Exploitation history	Control rule	S / S_{MSY}	Overfished probability	ΔS_5	ΔS_{15}	F / F_{MSY}	P_{OF} (true)	Initial C / MSY	Final C / MSY	Catch AAV
Slow	Low	0.77	0.00	fixed	0.35	2	no	no	Light	OFL	0.8 (0.27)	0 (2.7)	-0.26 (0.76)	-0.56 (0.4)	1.07 (0.28)	0.47 (0.51)	2.76 (0.61)	0.92 (0.3)	0.09 (0.66)
Slow	Low	1.25	0.00	fixed	0.35	2	no	no	Light	OFL	0.74 (0.41)	0 (1.68)	-0.28 (0.86)	-0.58 (0.65)	1.08 (0.29)	0.49 (0.49)	2.59 (0.75)	0.8 (0.54)	0.1 (0.64)
Slow	Low	0.77	0.44	fixed	0.35	2	no	no	Light	OFL	0.74 (0.24)	0 (2.94)	-0.27 (0.69)	-0.58 (0.31)	1.08 (0.28)	0.48 (0.51)	2.23 (0.58)	0.68 (0.26)	0.09 (0.67)
Slow	Low	1.25	0.44	fixed	0.35	2	no	no	Light	OFL	0.59 (0.34)	0 (1.64)	-0.3 (0.64)	-0.64 (0.3)	1.09 (0.28)	0.51 (0.49)	1.63 (0.6)	0.34 (0.4)	0.1 (0.69)
Slow	Low	0.77	0.44	fixed	0.46	2	no	no	Light	OFL	0.85 (0.18)	0 (4.47)	-0.17 (0.9)	-0.42 (0.45)	1.07 (0.32)	0.49 (0.55)	1.6 (0.68)	0.76 (0.22)	0.07 (0.77)
Slow	Low	1.25	0.44	fixed	0.46	2	no	no	Light	OFL	0.74 (0.26)	0 (3.3)	-0.21 (0.81)	-0.49 (0.43)	1.09 (0.31)	0.51 (0.54)	1.17 (0.7)	0.41 (0.34)	0.08 (0.78)
Slow	Low	0.77	0.00	fixed	0.35	2	no	no	Moderate	OFL	0.83 (0.27)	0 (3.19)	-0.19 (0.87)	-0.39 (0.58)	1.04 (0.19)	0.51 (0.51)	1.84 (0.4)	0.94 (0.32)	0.07 (0.25)
Slow	Low	1.25	0.00	fixed	0.35	2	no	no	Moderate	OFL	0.77 (0.46)	0 (1.81)	-0.2 (1.34)	-0.43 (1.09)	1.05 (0.2)	0.5 (0.48)	1.71 (0.52)	0.82 (0.73)	0.08 (0.25)
Slow	Low	0.77	0.44	fixed	0.35	2	no	no	Moderate	OFL	0.77 (0.24)	0 (3.23)	-0.2 (0.69)	-0.43 (0.39)	1.06 (0.18)	0.51 (0.49)	1.54 (0.38)	0.65 (0.26)	0.07 (0.27)
Slow	Low	1.25	0.44	fixed	0.35	2	no	no	Moderate	OFL	0.62 (0.35)	0 (1.62)	-0.25 (0.63)	-0.52 (0.36)	1.07 (0.19)	0.53 (0.46)	1.11 (0.41)	0.31 (0.42)	0.08 (0.28)
Slow	Low	0.77	0.44	fixed	0.46	2	no	no	Moderate	OFL	0.89 (0.18)	0 (7.89)	-0.09 (1.18)	-0.22 (0.84)	1.03 (0.18)	0.51 (0.55)	1.07 (0.39)	0.72 (0.21)	0.05 (0.23)
Slow	Low	1.25	0.44	fixed	0.46	2	no	no	Moderate	OFL	0.76 (0.26)	0 (3.04)	-0.13 (0.98)	-0.32 (0.69)	1.04 (0.18)	0.52 (0.53)	0.77 (0.42)	0.39 (0.35)	0.06 (0.25)
Slow	Low	0.77	0.00	fixed	0.35	2	no	no	Heavy	OFL	0.87 (0.27)	0 (3.48)	0.01 (12.82)	-0.01 (31.93)	1.01 (0.14)	0.47 (0.54)	0.99 (0.34)	0.89 (0.29)	0.06 (0.18)
Slow	Low	1.25	0.00	fixed	0.35	2	no	no	Heavy	OFL	0.8 (0.42)	0 (1.56)	-0.04 (10.57)	-0.04 (14.47)	1.02 (0.14)	0.49 (0.51)	0.91 (0.56)	0.76 (0.54)	0.07 (0.2)
Slow	Low	0.77	0.44	fixed	0.35	2	no	no	Heavy	OFL	0.81 (0.25)	0 (4.09)	-0.01 (13.82)	-0.07 (3.06)	1.02 (0.15)	0.49 (0.55)	0.76 (0.28)	0.61 (0.25)	0.06 (0.18)
Slow	Low	1.25	0.44	fixed	0.35	2	no	no	Heavy	OFL	0.63 (0.36)	0 (1.63)	-0.07 (2.67)	-0.23 (1.19)	1.03 (0.15)	0.51 (0.53)	0.5 (0.36)	0.26 (0.42)	0.06 (0.19)
Slow	Low	0.77	0.44	fixed	0.46	2	no	no	Heavy	OFL	0.92 (0.18)	0 (17.32)	0.09 (1.12)	0.2 (1.13)	1.01 (0.14)	0.49 (0.58)	0.56 (0.29)	0.67 (0.2)	0.04 (0.17)
Slow	Low	1.25	0.44	fixed	0.46	2	no	no	Heavy	OFL	0.76 (0.27)	0 (3.13)	0.03 (3.13)	0.01 (6.31)	1.02 (0.14)	0.5 (0.56)	0.38 (0.36)	0.33 (0.33)	0.05 (0.18)
Slow	Low	0.77	0.00	fixed	0.35	2	no	no	Light	P* var (0.38)	0.94 (0.22)	0 (3.52)	-0.23 (0.82)	-0.51 (0.44)	0.93 (0.26)	0.27 (0.67)	2.52 (0.64)	0.97 (0.29)	0.09 (0.63)
Slow	Low	1.25	0.00	fixed	0.35	2	no	no	Light	P* var (0.38)	0.89 (0.35)	0 (2.52)	-0.25 (0.94)	-0.53 (0.76)	0.92 (0.28)	0.27 (0.67)	2.37 (0.78)	0.83 (0.54)	0.1 (0.62)
Slow	Low	0.77	0.44	fixed	0.35	2	no	no	Light	P* var (0.38)	0.9 (0.19)	0 (3.59)	-0.24 (0.74)	-0.52 (0.33)	0.94 (0.25)	0.27 (0.67)	2.04 (0.6)	0.71 (0.24)	0.09 (0.66)
Slow	Low	1.25	0.44	fixed	0.35	2	no	no	Light	P* var (0.38)	0.77 (0.26)	0 (3.17)	-0.27 (0.68)	-0.59 (0.33)	0.92 (0.25)	0.27 (0.67)	1.49 (0.62)	0.37 (0.38)	0.1 (0.7)
Slow	Low	0.77	0.44	fixed	0.46	2	no	no	Light	P* var (0.38)	0.95 (0.16)	0 (5.12)	-0.15 (0.97)	-0.37 (0.5)	0.95 (0.3)	0.27 (0.74)	1.46 (0.7)	0.75 (0.22)	0.07 (0.74)
Slow	Low	1.25	0.44	fixed	0.46	2	no	no	Light	P* var (0.38)	0.85 (0.22)	0 (4.48)	-0.19 (0.86)	-0.45 (0.47)	0.94 (0.32)	0.27 (0.73)	1.07 (0.73)	0.41 (0.34)	0.08 (0.76)
Slow	Low	0.77	0.00	fixed	0.35	2	no	no	Moderate	P* var (0.38)	0.97 (0.23)	0 (6.4)	-0.16 (1.01)	-0.33 (0.71)	0.91 (0.18)	0.27 (0.69)	1.68 (0.41)	0.98 (0.32)	0.07 (0.25)
Slow	Low	1.25	0.00	fixed	0.35	2	no	no	Moderate	P* var (0.38)	0.92 (0.4)	0 (3.06)	-0.17 (1.63)	-0.37 (1.45)	0.9 (0.19)	0.27 (0.7)	1.56 (0.53)	0.86 (0.71)	0.08 (0.24)
Slow	Low	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* var (0.38)	0.93 (0.2)	0 (7.7)	-0.17 (0.76)	-0.37 (0.46)	0.92 (0.16)	0.27 (0.67)	1.41 (0.38)	0.69 (0.25)	0.07 (0.26)
Slow	Low	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* var (0.38)	0.79 (0.27)	0 (2.87)	-0.22 (0.7)	-0.46 (0.42)	0.9 (0.17)	0.27 (0.65)	1.02 (0.42)	0.34 (0.41)	0.08 (0.27)
Slow	Low	0.77	0.44	fixed	0.46	2	no	no	Moderate	P* var (0.38)	0.98 (0.16)	0 (11.58)	-0.07 (1.49)	-0.16 (1.15)	0.91 (0.17)	0.27 (0.78)	0.98 (0.39)	0.73 (0.22)	0.06 (0.23)
Slow	Low	1.25	0.44	fixed	0.46	2	no	no	Moderate	P* var (0.38)	0.88 (0.23)	0 (8.23)	-0.11 (1.16)	-0.28 (0.86)	0.91 (0.17)	0.24 (0.78)	0.7 (0.42)	0.39 (0.35)	0.06 (0.24)
Slow	Low	0.77	0.00	fixed	0.35	2	no	no	Heavy	P* var (0.38)	1.01 (0.23)	0 (6.47)	0.07 (2.26)	0.12 (2.21)	0.87 (0.14)	0.22 (0.78)	0.82 (0.38)	0.95 (0.29)	0.06 (0.19)
Slow	Low	1.25	0.00	fixed	0.35	2	no	no	Heavy	P* var (0.38)	0.97 (0.36)	0 (2.82)	0.03 (3.31)	0.11 (3.02)	0.85 (0.14)	0.2 (0.79)	0.77 (0.6)	0.81 (0.52)	0.08 (0.2)
Slow	Low	0.77	0.44	fixed	0.35	2	no	no	Heavy	P* var (0.38)	0.97 (0.21)	0 (12.25)	0.05 (2.54)	0.05 (4.17)	0.87 (0.14)	0.2 (0.79)	0.64 (0.33)	0.66 (0.24)	0.06 (0.18)
Slow	Low	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* var (0.38)	0.82 (0.28)	0 (4.14)	-0.01 (86.5)	-0.11 (3)	0.84 (0.14)	0.2 (0.81)	0.43 (0.39)	0.3 (0.39)	0.07 (0.19)
Slow	Low	0.77	0.44	fixed	0.46	2	no	no	Heavy	P* var (0.38)	1.02 (0.16)	0 (17.32)	0.16 (0.66)	0.35 (0.69)	0.86 (0.14)	0.18 (0.93)	0.42 (0.33)	0.69 (0.2)	0.05 (0.17)
Slow	Low	1.25	0.44	fixed	0.46	2	no	no	Heavy	P* var (0.38)	0.9 (0.23)	0 (7.33)	0.09 (1.36)	0.15 (1.67)	0.84 (0.14)	0.16 (0.98)	0.29 (0.41)	0.35 (0.33)	0.05 (0.18)
Slow	Low	0.77	0.00	fixed	0.35	2	no	no	Light	P* varied (0.7)	1.01 (0.21)	0 (3.95)	-0.2 (0.87)	-0.47 (0.47)	0.86 (0.25)	0.19 (0.79)	2.37 (0.66)	0.98 (0.29)	0.08 (0.65)
Slow	Low	1.25	0.00	fixed	0.35	2	no	no	Light	P* varied (0.7)	0.97 (0.33)	0 (2.93)	-0.23 (1)	-0.5 (0.86)	0.84 (0.27)	0.2 (0.78)	2.22 (0.8)	0.85 (0.54)	0.1 (0.62)
Slow	Low	0.77	0.44	fixed	0.35	2	no	no	Light	P* varied (0.7)	0.97 (0.18)	0 (3.87)	-0.22 (0.77)	-0.49 (0.36)	0.87 (0.25)	0.2 (0.79)	1.91 (0.62)	0.73 (0.24)	0.09 (0.66)
Slow	Low	1.25	0.44	fixed	0.35	2	no	no	Light	P* varied (0.7)	0.86 (0.23)	0 (3.84)	-0.26 (0.71)	-0.56 (0.35)	0.85 (0.25)	0.18 (0.77)	1.4 (0.64)	0.38 (0.38)	0.09 (0.69)
Slow	Low	0.77	0.44	fixed	0.46	2	no	no	Light	P* varied (0.7)	1.01 (0.15)	0 (4.99)	-0.14 (1.02)	-0.34 (0.53)	0.88 (0.3)	0.21 (0.85)	1.36 (0.72)	0.75 (0.22)	0.07 (0.73)
Slow	Low	1.25	0.44	fixed	0.46	2	no	no	Light	P* varied (0.7)	0.91 (0.21)	0 (5.35)	-0.18 (0.9)	-0.43 (0.5)	0.87 (0.31)	0.2 (0.83)	1 (0.74)	0.41 (0.35)	0.08 (0.74)
Slow	Low	0.77	0.00	fixed	0.35	2	no	no	Moderate	P* varied (0.7)	1.05 (0.22)	0 (7.96)	-0.13 (1.13)	-0.28 (0.84)	0.84 (0.17)	0.18 (0.88)	1.58 (0.41)	0.99 (0.31)	0.07 (0.25)
Slow	Low	1.25	0.00	fixed	0.35	2	no	no	Moderate	P* varied (0.7)	0.99 (0.38)	0 (3.97)	-0.15 (1.91)	-0.33 (1.81)	0.82 (0.18)	0.18 (0.85)	1.46 (0.53)	0.88 (0.7)	0.08 (0.24)
Slow	Low	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* varied (0.7)	1 (0.19)	0 (9.06)	-0.15 (0.83)	-0.33 (0.51)	0.85 (0.15)	0.18 (0.84)	1.32 (0.38)	0.71 (0.25)	0.07 (0.26)
Slow	Low	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* varied (0.7)	0.88 (0.25)	0 (6.05)	-0.19 (0.75)	-0.42 (0.47)	0.83 (0.16)	0.18 (0.82)	0.96 (0.42)	0.36 (0.4)	0.08 (0.26)
Slow	Low	0.77	0.44	fixed	0.46	2	no	no	Moderate	P* varied (0.7)	1.03 (0.15)	0 (11.2)	-0.05 (1.84)	-0.13 (1.51)	0.85 (0.17)	0.18 (0.98)	0.92 (0.4)	0.73 (0.22)	0.06 (0.24)
Slow	Low	1.25	0.44	fixed	0.46	2	no	no	Moderate	P* varied (0.7)	0.94 (0.21)	0 (12.38)	-0.1 (1.32)	-0.24 (1.01)	0.84 (0.17)	0.16 (0.97)	0.65 (0.42)	0.4 (0.36)	0.06 (0.24)
Slow	Low	0.77	0.00	fixed	0.35	2	no	no	Heavy	P* varied (0.7)	1.09 (0.22)	0 (14.27)	0.11 (1.52)	0.19 (1.48)	0.8 (0.14)	0.11 (0.99)	0.72 (0.41)	0.97 (0.28)	0.06 (0.19)
Slow	Low	1.25	0.00	fixed	0.35	2	no	no	Heavy	P* varied (0.7)	1.05 (0.34)	0 (3.91)	0.06 (2.36)	0.19 (2.14)	0.77 (0.15)	0.11 (1)	0.67 (0.64)	0.84 (0.51)	0.08 (0.2)
Slow	Low	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* varied (0.7)	0.91 (0.26)	0 (6.91)	0.03 (4.9)	-0.04 (14.07)	0.77 (0.15)	0.11 (1.01)	0.38 (0.42)	0.32 (0.39)	0.07 (0.19)
Slow	Low	0.77	0.00	fixed	0.35	2	no	no	Light	P* varied (1.0)	1.06 (0.21)	0 (4.12)	-0.19 (0.91)	-0.45 (0.51)	0.81 (0.25)	0.13 (0.89)	2.25 (0.68)	1 (0.29)	0.08 (0.66)
Slow	Low	1.25	0.00	fixed	0.35	2	no	no	Light	P* varied (1.0)	1.02 (0.32)	0 (3.21)	-0.22 (1.05)	-0.48 (0.93)	0.79 (0.26)	0.16 (0.85)	2.12 (0.82)	0.87 (0.54)	0.1 (0.64)
Slow	Low	0.77	0.44	fixed	0.35	2	no	no	Light	P* varied (1.0)	1.02 (0.18)	0 (4.22)	-0.21 (0.8)	-0.47 (0.38)	0.82 (0.25)	0.13 (0.9)	1.82 (0.63)	0.74 (0.24)	0.08 (0.69)
Slow	Low	1.25	0.44	fixed	0.35	2	no	no	Light	P* varied (1.0)	0.91 (0.22)	0 (4.04)	-0.24 (0.73)	-0.54 (0.37)	0.8 (0.25)	0.13 (0.85)	1.33 (0.65)	0.39 (0.37)	0.09 (0.7)
Slow	Low	0.77	0.44	fixed	0.46	2	no	no	Light	P* varied (1.0)	1.04 (0.15)	0 (5.22)	-0.13 (1.07)	-0.32 (0.56)	0.84 (0.3)	0.13 (0.95)	1.3 (0.73)	0.74 (0.22)	0.07 (0.74)
Slow	Low	1.25	0.44	fixed	0.46	2	no	no	Light	P* varied (1.0)	0.95 (0.2)	0 (5.4)	-0.17 (0.93)	-0.41 (0.52)	0.82 (0.3)	0.16 (0.93)	0.95 (0.76)	0.41 (0.35)	0.08 (0.74)
Slow	Low	0.77	0.00	fixed	0.35	2	no	no	Moderate	P* varied (1.0)	1.1 (0.22)	0 (8.76)	-0.12 (1.25)	-0.26 (0.96)	0.8 (0.17)	0.13 (1.01)	1.5 (0.41)	1 (0.31)	0.07 (0.25)
Slow	Low	1.25	0.00	fixed	0.35	2	no	no	Moderate	P* varied (1.0)	1.05 (0.37)	0 (4.87)	-0.14 (2.18)	-0.3 (2.17)	0.78 (0.18)	0.12 (0.99)	1.39 (0.53)	0.89 (0.7)	0.08 (0.24)
Slow	Low	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* varied (1.0)	1.05 (0.18)	0 (8.34)	-0.13 (0.88)	-0.3 (0.57)	0.81 (0.15)	0.13 (0.97)	1.26 (0.38)	0.72 (0.24)	0.07 (0.26)
Slow	Low	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* varied (1.0)	0.93 (0.24)	0 (7.57)	-0.18 (0.79)	-0.4 (0.51)	0.78 (0.15)	0.13 (0.97)	0.91 (0.42)	0.37 (0.4)	0.07 (0.26)
Slow	Low	0.77	0.44	fixed	0.46	2	no	no	Moderate	P* varied (1.0)	1.07 (0.15)	0 (17.32)	-0.04 (2.25)	-0.1 (1.95)	0.8 (0.17)	0.11 (1.14)	0.87 (0.4)	0.73 (0.22)	0.05 (0.24)
Slow	Low	1.25	0.44	fixed	0.46	2	no	no	Moderate	P* varied (1.0)	0.98 (0.21)	0 (13.81)	-0.09 (1.48)	-0.22 (1.16)	0.79 (0.17)	0.09 (1.11)	0.62 (0.42)	0.4 (0.36)	0.06 (0.24)
Slow	Low	0.77	0.00	fixed	0.35	2	no	no	Heavy	P* varied (1.0)	1.14 (0.22)	0 (12.89)	0.14 (1.25)	0.24 (1.23)	0.75 (0.14)	0.04 (1.19)	0.65 (0.44)	0.98 (0.28)	0.06 (0.2)
Slow	Low	1.25	0.00	fixed	0.35	2	no	no	Heavy	P* varied (1.0)	1.1 (0.33)	0 (4.81)	0.09 (1.99)	0.24 (1.81)	0.72 (0.15)	0.07 (1.17)	0.61 (0.66)	0.85 (0.5)	0.08 (0.21)
Slow	Low	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* varied (1.0)	0.96 (0.25)	0 (10.91)	0.05 (2.86)	0.01 (10.79)	0.72 (0.15)	0.07 (1.18)	0.35 (0.45)	0.33 (0.38)	0.07 (0.19)
Slow	Low	0.77	0.00	fixed	0.35	2	no	no	Light	P* fixed (0.38)	0.9 (0.25)	0 (3.43)	-0.23 (0.82)	-0.51 (0.44)	0.96 (0.29)	0.31 (0.68)	2.52 (0.64)	0.96 (0.29)	0.08 (0.67)
Slow	Low	1.25	0.00	fixed	0.35	2	no	no	Light	P* fixed (0.38)	0.84 (0.39)	0 (2.28)	-0.25 (0.94)	-0.54 (0.75)	0.97 (0.31)	0.33 (0.65)	2.37 (0.78)	0.84 (0.53)	0.1 (0.66)
Slow	Low	0.77	0.44	fixed	0.35	2	no	no	Light	P* fixed (0.38)	0.84 (0.22)	0 (3.84)	-0.24 (0.74)	-0.53 (0.35)	0.96 (0.28)	0.31 (0.67)	2.04 (0.6)	0.71 (0.24)	0.08 (0.69)
Slow	Low	1.25	0.44	fixed	0.35	2	no	no	Light	P* fixed (0.38)	0.7 (0.32)	0 (2.34)	-0.27 (0.68)	-0.6 (0.33)	0.98 (0.29)	0.33 (0.65)	1.49 (0.62)	0.36 (0.38)	0.09 (0.73)
Slow	Low	0.77	0.44	fixed	0.46	2	no	no	Light	P* fixed (0.38)	0.93 (0.17)	0 (5.27)	-0.15 (0.97)	-0.38 (0.51)	0.96 (0.33)	0.31 (0.73)	1.46 (0.7)	0.76 (0.21)	0.07 (0.76)
Slow	Low	1.25	0.44	fixed	0.46	2	no	no	Light	P* fixed (0.38)	0.81 (0.25)	0 (3.98)	-0.19 (0.86)	-0.46 (0.47)	0.98 (0.35)	0.32 (0.71)	1.07 (0.73)	0.42 (0.33)	0.07 (0.79)
Slow	Low	0.77	0.00	fixed	0.35	2	no	no	Moderate	P* fixed (0.38)	0.92 (0.25)	0 (4.88)	-0.16 (1)	-0.33 (0.71)	0.94 (0.2)	0.3 (0.71)	1.68 (0.41)	0.97 (0.31)	0.07 (0.25)
Slow	Low	1.25	0.00	fixed	0.35	2	no	no	Moderate	P* fixed (0.38)	0.86 (0.43)	0 (2.54)	-0.17 (1.61)	-0.38 (1.39)	0.94 (0.21)	0.31 (0.68)	1.56 (0.53)	0.85 (0.7)	0.08 (0.24)
Slow	Low	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (0.38)	0.88 (0.23)	0 (6.14)	-0.17 (0.76)	-0.38 (0.46)	0.94 (0.18)	0.31 (0.69)	1.41 (0.38)	0.68 (0.24)	0.06 (0.26)
Slow	Low	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (0.38)	0.72 (0.32)	0 (2.33)	-0.22 (0.7)	-0.47 (0.42)	0.95 (0.19)	0.33 (0.66)	1.02 (0.42)	0.33 (0.4)	0.07 (0.28)
Slow	Low	0.77	0.44	fixed	0.46	2	no	no	Moderate	P* fixed (0.38)	0.96 (0.17)	0 (11.61)	-0.07 (1.46)	-0.17 (1.1)	0.93 (0.18)	0.29 (0.78)	0.98 (0.39)	0.72 (0.2)	0.05 (0.23)
Slow	Low	1.25	0.44	fixed	0.46	2	no	no	Moderate	P* fixed (0.38)	0.84 (0.25)	0 (5.23)	-0.11 (1.14)	-0.28 (0.83)	0.94 (0.18)	0.31 (0.76)	0.7 (0.42)	0.39 (0.33)	0.06 (0.24)
Slow	Low	0.77	0.00	fixed	0.35	2	no	no	Heavy	P* fixed (0.38)	0.97 (0.25)	0 (4.95)	0.04 (3.39)	0.07 (3.31)	0.91 (0.14)	0.27 (0.75)	0.9 (0.34)	0.93 (0.28)	0.05 (0.18)
Slow	Low	1.25	0.00	fixed	0.35	2	no	no	Heavy	P* fixed (0.38)	0.91 (0.4)	0 (2.14)	0 (4.65)	0.03 (4.34)	0.92 (0.14)	0.29 (0.71)	0.84 (0.56)	0.79 (0.51)	0.07 (0.2)
Slow	Low	0.77	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (0.38)	0.92 (0.23)	0 (6.23)	0.02 (4.86)	0.01 (31.55)	0.91 (0.15)	0.27 (0.76)	0.69 (0.28)	0.64 (0.23)	0.05 (0.18)
Slow	Low	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (0.38)	0.72 (0.33)	0 (2.52)	-0.03 (6.1)	-0.16 (1.87)	0.92 (0.15)	0.29 (0.74)	0.46 (0.36)	0.29 (0.39)	0.06 (0.19)
Slow	Low	0.77	0.44	fixed	0.46	2	no	no	Heavy	P* fixed (0.38)	0.99 (0.17)	0 (17.32)	0.12 (0.87)	0.27 (0.86)	0.91 (0.14)	0.24 (0.85)	0.51 (0.29)	0.66 (0.2)	0.04 (0.17)
Slow	Low	1.25	0.44	fixed	0.46	2	no	no	Heavy	P* fixed (0.38)	0.84 (0.25)	0 (4.27)	0.05 (2.02)	0.08 (2.75)	0.92 (0.14)	0.26 (0.82)	0.34 (0.36)	0.34 (0.32)	0.05 (0.18)
Slow	Low	0.77	0.00	fixed	0.35	2	no	no	Light	P* fixed (0.7)	0.97 (0.24)	0 (3.9)	-0.2 (0.87)	-0.48 (0.48)	0.89 (0.29)	0.22 (0.8)	2.37 (0.66)	0.98 (0.28)	0.08 (0.69)
Slow	Low	1.25	0.00	fixed	0.35	2	no	no	Light	P* fixed (0.7)	0.9 (0.38)	0 (2.65)	-0.23 (1)	-0.51 (0.84)	0.89 (0.3)	0.22 (0.77)	2.22 (0.8)	0.86 (0.52)	0.09 (0.67)
Slow	Low	0.77	0.44	fixed	0.35	2	no	no	Light	P* fixed (0.7)	0.91 (0.21)	0 (4.37)	-0.22 (0.77)	-0.5 (0.37)	0.89 (0.29)	0.22 (0.81)	1.91 (0.62)	0.73 (0.23)	0.08 (0.7)
Slow	Low	1.25	0.44	fixed	0.35	2	no	no	Light	P* fixed (0.7)	0.77 (0.3)	0 (3.16)	-0.26 (0.71)	-0.57 (0.36)	0.91 (0.29)	0.23 (0.79)	1.4 (0.64)	0.38 (0.36)	0.09 (0.74)
Slow	Low	0.77	0.44	fixed	0.46	2	no	no	Light	P* fixed (0.7)	0.98 (0.16)	0 (5.45)	-0.14 (1.02)	-0.35 (0.55)	0.9 (0.34)	0.22 (0.86)	1.36 (0.72)	0.75 (0.21)	0.06 (0.76)
Slow	Low	1.25	0.44	fixed	0.46	2	no	no	Light	P* fixed (0.7)	0.86 (0.24)	0 (4.52)	-0.18 (0.9)	-0.43 (0.51)	0.91 (0.35)	0.22 (0.84)	1 (0.74)	0.42 (0.32)	0.07 (0.78)
Slow	Low	0.77	0.00	fixed	0.35	2	no	no	Moderate	P* fixed (0.7)	1 (0.24)	0 (6.49)	-0.13 (1.13)	-0.29 (0.83)	0.87 (0.19)	0.18 (0.91)	1.58 (0.41)	0.98 (0.3)	0.06 (0.23)
Slow	Low	1.25	0.00	fixed	0.35	2	no	no	Moderate	P* fixed (0.7)	0.94 (0.42)	0 (3.09)	-0.15 (1.87)	-0.34 (1.68)	0.86 (0.2)	0.2 (0.87)	1.46 (0.53)	0.87 (0.68)	0.07 (0.24)
Slow	Low	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (0.7)	0.96 (0.21)	0 (8.19)	-0.15 (0.83)	-0.33 (0.52)	0.87 (0.18)	0.2 (0.88)	1.32 (0.38)	0.7 (0.23)	0.06 (0.25)
Slow	Low	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (0.7)	0.79 (0.31)	0 (2.94)	-0.19 (0.75)	-0.43 (0.47)	0.88 (0.19)	0.22 (0.84)	0.96 (0.42)	0.35 (0.38)	0.07 (0.27)
Slow	Low	0.77	0.44	fixed	0.46	2	no	no	Moderate	P* fixed (0.7)	1.02 (0.16)	0 (14.39)	-0.05 (1.77)	-0.13 (1.41)	0.87 (0.18)	0.18 (1)	0.92 (0.39)	0.73 (0.2)	0.05 (0.23)
Slow	Low	1.25	0.44	fixed	0.46	2	no	no	Moderate	P* fixed (0.7)	0.89 (0.24)	0 (7.84)	-0.1 (1.3)	-0.25 (0.97)	0.87 (0.18)	0.18 (0.98)	0.66 (0.42)	0.39 (0.33)	0.05 (0.24)
Slow	Low	0.77	0.00	fixed	0.35	2	no	no	Heavy	P* fixed (0.7)	1.04 (0.24)	0 (7.05)	0.06 (2.24)	0.13 (2.08)	0.84 (0.14)	0.16 (0.94)	0.85 (0.34)	0.94 (0.27)	0.05 (0.18)
Slow	Low	1.25	0.00	fixed	0.35	2	no	no	Heavy	P* fixed (0.7)	0.99 (0.38)	0 (2.62)	0.02 (3.37)	0.09 (2.99)	0.85 (0.14)	0.16 (0.9)	0.78 (0.56)	0.81 (0.5)	0.07 (0.2)
Slow	Low	0.77	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (0.7)	1 (0.21)	0 (18.71)	0.05 (2.47)	0.06 (3.65)	0.84 (0.15)	0.14 (0.98)	0.65 (0.28)	0.65 (0.22)	0.05 (0.18)
Slow	Low	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (0.7)	0.8 (0.31)	0 (3.48)	-0.01 (59.66)	-0.11 (3.01)	0.85 (0.15)	0.17 (0.95)	0.43 (0.36)	0.3 (0.37)	0.06 (0.19)
Slow	Low	1.25	0.44	fixed	0.46	2	no	no	Heavy	P* fixed (0.7)	0.9 (0.25)	0 (5.73)	0.07 (1.63)	0.13 (2)	0.85 (0.14)	0.13 (1.03)	0.32 (0.36)	0.34 (0.31)	0.05 (0.18)
Slow	Low	0.77	0.00	fixed	0.35	2	no	no	Light	P* fixed (1.0)	1.02 (0.23)	0 (4.32)	-0.19 (0.91)	-0.45 (0.52)	0.84 (0.29)	0.16 (0.91)	2.25 (0.68)	0.99 (0.27)	0.08 (0.71)
Slow	Low	1.25	0.00	fixed	0.35	2	no	no	Light	P* fixed (1.0)	0.96 (0.37)	0 (2.91)	-0.22 (1.05)	-0.48 (0.91)	0.85 (0.3)	0.18 (0.86)	2.12 (0.82)	0.87 (0.51)	0.09 (0.69)
Slow	Low	0.77	0.44	fixed	0.35	2	no	no	Light	P* fixed (1.0)	0.97 (0.2)	0 (5.14)	-0.21 (0.8)	-0.48 (0.39)	0.84 (0.29)	0.16 (0.92)	1.82 (0.63)	0.74 (0.23)	0.08 (0.73)
Slow	Low	1.25	0.44	fixed	0.35	2	no	no	Light	P* fixed (1.0)	0.82 (0.29)	0 (3.82)	-0.24 (0.73)	-0.55 (0.38)	0.86 (0.29)	0.18 (0.89)	1.33 (0.65)	0.39 (0.35)	0.08 (0.75)
Slow	Low	0.77	0.44	fixed	0.46	2	no	no	Light	P* fixed (1.0)	1.02 (0.16)	0 (5.62)	-0.13 (1.07)	-0.32 (0.58)	0.85 (0.33)	0.16 (0.97)	1.3 (0.73)	0.75 (0.21)	0.06 (0.76)
Slow	Low	1.25	0.44	fixed	0.46	2	no	no	Light	P* fixed (1.0)	0.9 (0.23)	0 (5.03)	-0.17 (0.93)	-0.41 (0.53)	0.86 (0.34)	0.18 (0.95)	0.95 (0.76)	0.42 (0.32)	0.07 (0.78)
Slow	Low	0.77	0.00	fixed	0.35	2	no	no	Moderate	P* fixed (1.0)	1.06 (0.24)	0 (7.94)	-0.12 (1.24)	-0.26 (0.95)	0.82 (0.18)	0.13 (1.05)	1.5 (0.41)	0.99 (0.29)	0.06 (0.23)

Life history	Assessment uncertainty	σ_R	ϕ_R	h	SPR target	SA years	Projec-tions?	ABC avg.?	Exploitation history	Control rule	S / S_{MSY}	Overfished probability	ΔS_5	ΔS_{15}	F / F_{MSY}	P_{OF} (true)	Initial C / MSY	Final C / MSY	Catch AAV
Slow	Low	1.25	0.00	fixed	0.35	2	no	no	Moderate	P* fixed (1.0)	0.99 (0.4)	0 (3.43)	-0.14 (2.12)	-0.32 (1.99)	0.82 (0.19)	0.13 (1.02)	1.39 (0.53)	0.88 (0.67)	0.07 (0.23)
Slow	Low	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (1.0)	1.02 (0.21)	0 (9.64)	-0.13 (0.88)	-0.3 (0.57)	0.82 (0.17)	0.13 (1.03)	1.26 (0.38)	0.71 (0.23)	0.06 (0.24)
Slow	Low	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (1.0)	0.84 (0.3)	0 (3.55)	-0.18 (0.79)	-0.4 (0.51)	0.83 (0.18)	0.13 (0.99)	0.91 (0.42)	0.36 (0.37)	0.07 (0.26)
Slow	Low	0.77	0.44	fixed	0.46	2	no	no	Moderate	P* fixed (1.0)	1.05 (0.16)	0 (15.18)	-0.04 (2.13)	-0.11 (1.77)	0.82 (0.18)	0.11 (1.15)	0.88 (0.39)	0.72 (0.2)	0.05 (0.22)
Slow	Low	1.25	0.44	fixed	0.46	2	no	no	Moderate	P* fixed (1.0)	0.93 (0.23)	0 (9.52)	-0.09 (1.44)	-0.23 (1.1)	0.83 (0.18)	0.11 (1.12)	0.63 (0.42)	0.39 (0.32)	0.05 (0.24)
Slow	Low	0.77	0.00	fixed	0.35	2	no	no	Heavy	P* fixed (1.0)	1.1 (0.23)	0 (10.12)	0.08 (1.8)	0.17 (1.64)	0.8 (0.14)	0.09 (1.14)	0.81 (0.34)	0.95 (0.27)	0.05 (0.18)
Slow	Low	1.25	0.00	fixed	0.35	2	no	no	Heavy	P* fixed (1.0)	1.04 (0.37)	0 (3.04)	0.03 (2.82)	0.13 (2.45)	0.8 (0.14)	0.09 (1.07)	0.75 (0.56)	0.83 (0.49)	0.07 (0.2)
Slow	Low	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (1.0)	0.85 (0.3)	0 (4.29)	0 (10.84)	-0.08 (5.31)	0.8 (0.15)	0.09 (1.12)	0.41 (0.36)	0.31 (0.36)	0.06 (0.18)
Slow	Low	0.77	0.00	fixed	0.35	2	no	no	Light	75% of F_lim	1.06 (0.22)	0 (4.75)	-0.18 (0.94)	-0.43 (0.55)	0.8 (0.3)	0.13 (0.97)	2.16 (0.69)	0.99 (0.27)	0.08 (0.71)
Slow	Low	1.25	0.00	fixed	0.35	2	no	no	Light	75% of F_lim	1.01 (0.36)	0 (3.16)	-0.21 (1.09)	-0.46 (0.97)	0.81 (0.31)	0.13 (0.94)	2.04 (0.83)	0.88 (0.5)	0.09 (0.7)
Slow	Low	0.77	0.44	fixed	0.35	2	no	no	Light	75% of F_lim	1.01 (0.19)	0 (5.42)	-0.2 (0.83)	-0.46 (0.41)	0.8 (0.3)	0.13 (1)	1.75 (0.64)	0.75 (0.22)	0.07 (0.74)
Slow	Low	1.25	0.44	fixed	0.35	2	no	no	Light	75% of F_lim	0.87 (0.28)	0 (4.42)	-0.23 (0.75)	-0.53 (0.39)	0.82 (0.31)	0.13 (0.97)	1.28 (0.66)	0.39 (0.35)	0.08 (0.75)
Slow	Low	0.77	0.44	fixed	0.46	2	no	no	Light	75% of F_lim	1.06 (0.16)	0 (5.95)	-0.12 (1.11)	-0.3 (0.62)	0.8 (0.34)	0.13 (1.07)	1.23 (0.75)	0.74 (0.21)	0.06 (0.77)
Slow	Low	1.25	0.44	fixed	0.46	2	no	no	Light	75% of F_lim	0.94 (0.22)	0 (5.52)	-0.16 (0.96)	-0.39 (0.56)	0.81 (0.34)	0.13 (1.04)	0.9 (0.77)	0.41 (0.31)	0.07 (0.77)
Slow	Low	0.77	0.00	fixed	0.35	2	no	no	Moderate	75% of F_lim	1.11 (0.23)	0 (8.71)	-0.1 (1.36)	-0.24 (1.07)	0.78 (0.18)	0.09 (1.16)	1.44 (0.41)	0.99 (0.29)	0.06 (0.23)
Slow	Low	1.25	0.00	fixed	0.35	2	no	no	Moderate	75% of F_lim	1.03 (0.4)	0 (3.88)	-0.13 (2.38)	-0.29 (2.32)	0.78 (0.18)	0.09 (1.12)	1.34 (0.53)	0.89 (0.66)	0.07 (0.23)
Slow	Low	0.77	0.44	fixed	0.35	2	no	no	Moderate	75% of F_lim	1.06 (0.2)	0 (10.8)	-0.12 (0.94)	-0.28 (0.63)	0.79 (0.17)	0.09 (1.14)	1.21 (0.38)	0.71 (0.22)	0.06 (0.24)
Slow	Low	1.25	0.44	fixed	0.35	2	no	no	Moderate	75% of F_lim	0.89 (0.29)	0 (4.7)	-0.17 (0.83)	-0.38 (0.54)	0.79 (0.17)	0.09 (1.1)	0.88 (0.42)	0.37 (0.36)	0.06 (0.25)
Slow	Low	0.77	0.44	fixed	0.46	2	no	no	Moderate	75% of F_lim	1.09 (0.16)	0 (17.32)	-0.03 (2.71)	-0.08 (2.41)	0.77 (0.18)	0.04 (1.34)	0.83 (0.39)	0.71 (0.2)	0.05 (0.22)
Slow	Low	1.25	0.44	fixed	0.46	2	no	no	Moderate	75% of F_lim	0.97 (0.23)	0 (12.24)	-0.08 (1.63)	-0.2 (1.27)	0.78 (0.18)	0.07 (1.31)	0.6 (0.42)	0.39 (0.32)	0.05 (0.23)
Slow	Low	0.77	0.00	fixed	0.35	2	no	no	Heavy	75% of F_lim	1.14 (0.23)	0 (14.27)	0.09 (1.55)	0.21 (1.41)	0.76 (0.14)	0.04 (1.33)	0.77 (0.34)	0.95 (0.26)	0.05 (0.18)
Slow	Low	1.25	0.00	fixed	0.35	2	no	no	Heavy	75% of F_lim	1.09 (0.36)	0 (3.53)	0.05 (2.49)	0.16 (2.15)	0.76 (0.14)	0.04 (1.26)	0.72 (0.56)	0.84 (0.48)	0.06 (0.2)
Slow	Low	1.25	0.44	fixed	0.35	2	no	no	Heavy	75% of F_lim	0.9 (0.29)	0 (5.07)	0.02 (5.56)	-0.05 (13.19)	0.77 (0.15)	0.04 (1.34)	0.4 (0.36)	0.32 (0.35)	0.05 (0.18)
Slow	High	0.77	0.00	fixed	0.35	2	no	no	Light	OFL	0.79 (0.54)	0.09 (1.23)	-0.27 (0.94)	-0.62 (0.61)	1.36 (0.54)	0.4 (0.64)	2.82 (0.78)	0.77 (0.54)	0.18 (0.61)
Slow	High	1.25	0.00	fixed	0.35	2	no	no	Light	OFL	0.73 (0.64)	0.13 (1.13)	-0.29 (1.02)	-0.64 (0.86)	1.32 (0.56)	0.42 (0.63)	2.52 (0.88)	0.67 (0.73)	0.19 (0.62)
Slow	High	0.77	0.44	fixed	0.35	2	no	no	Light	OFL	0.76 (0.57)	0.12 (1.21)	-0.3 (0.87)	-0.64 (0.53)	1.38 (0.54)	0.42 (0.64)	2.38 (0.75)	0.54 (0.55)	0.19 (0.62)
Slow	High	1.25	0.44	fixed	0.35	2	no	no	Light	OFL	0.53 (0.7)	0.16 (1.08)	-0.32 (0.81)	-0.7 (0.47)	1.41 (0.55)	0.42 (0.64)	1.69 (0.77)	0.25 (0.72)	0.2 (0.65)
Slow	High	0.77	0.44	fixed	0.46	2	no	no	Light	OFL	0.88 (0.41)	0 (1.45)	-0.19 (1.07)	-0.46 (0.69)	1.26 (0.59)	0.4 (0.69)	1.7 (0.89)	0.61 (0.46)	0.15 (0.7)
Slow	High	1.25	0.44	fixed	0.46	2	no	no	Light	OFL	0.72 (0.5)	0.06 (1.33)	-0.23 (0.98)	-0.55 (0.6)	1.26 (0.6)	0.4 (0.68)	1.2 (0.9)	0.33 (0.59)	0.16 (0.74)
Slow	High	0.77	0.00	fixed	0.35	2	no	no	Moderate	OFL	0.81 (0.56)	0.03 (1.33)	-0.2 (1.14)	-0.46 (0.85)	1.2 (0.55)	0.46 (0.62)	2.04 (0.67)	0.8 (0.54)	0.14 (0.51)
Slow	High	1.25	0.00	fixed	0.35	2	no	no	Moderate	OFL	0.75 (0.69)	0.11 (1.18)	-0.22 (1.32)	-0.49 (1.19)	1.22 (0.58)	0.47 (0.62)	1.95 (0.76)	0.69 (0.88)	0.15 (0.51)
Slow	High	0.77	0.44	fixed	0.35	2	no	no	Moderate	OFL	0.72 (0.56)	0.07 (1.3)	-0.22 (1)	-0.5 (0.64)	1.21 (0.53)	0.47 (0.6)	1.72 (0.65)	0.52 (0.52)	0.14 (0.55)
Slow	High	1.25	0.44	fixed	0.35	2	no	no	Moderate	OFL	0.54 (0.69)	0.18 (1.09)	-0.26 (0.9)	-0.58 (0.54)	1.24 (0.53)	0.47 (0.59)	1.26 (0.68)	0.23 (0.73)	0.15 (0.6)
Slow	High	0.77	0.44	fixed	0.46	2	no	no	Moderate	OFL	0.84 (0.42)	0 (1.67)	-0.11 (1.48)	-0.29 (1.15)	1.16 (0.57)	0.49 (0.66)	1.17 (0.78)	0.63 (0.4)	0.11 (0.59)
Slow	High	1.25	0.44	fixed	0.46	2	no	no	Moderate	OFL	0.71 (0.51)	0 (1.42)	-0.16 (1.25)	-0.39 (0.87)	1.16 (0.57)	0.49 (0.65)	0.82 (0.8)	0.32 (0.55)	0.12 (0.64)
Slow	High	0.77	0.00	fixed	0.35	2	no	no	Heavy	OFL	0.86 (0.53)	0 (1.41)	0.01 (6.81)	-0.02 (15.25)	1.07 (0.49)	0.41 (0.66)	0.99 (0.63)	0.75 (0.48)	0.11 (0.27)
Slow	High	1.25	0.00	fixed	0.35	2	no	no	Heavy	OFL	0.81 (0.64)	0.11 (1.2)	-0.03 (14.16)	-0.13 (91.55)	1.08 (0.51)	0.41 (0.66)	0.95 (0.83)	0.65 (0.68)	0.12 (0.27)
Slow	High	0.77	0.44	fixed	0.35	2	no	no	Heavy	OFL	0.85 (0.54)	0 (1.53)	0 (5.14)	-0.09 (4.17)	1.04 (0.52)	0.4 (0.68)	0.74 (0.6)	0.52 (0.49)	0.11 (0.31)
Slow	High	1.25	0.44	fixed	0.35	2	no	no	Heavy	OFL	0.64 (0.65)	0.07 (1.27)	-0.07 (2.89)	-0.23 (1.7)	1.06 (0.54)	0.4 (0.68)	0.49 (0.65)	0.23 (0.63)	0.12 (0.33)
Slow	High	0.77	0.44	fixed	0.46	2	no	no	Heavy	OFL	0.93 (0.4)	0 (1.91)	0.09 (3.76)	0.18 (2.23)	1.04 (0.51)	0.42 (0.71)	0.55 (0.6)	0.59 (0.39)	0.09 (0.24)
Slow	High	1.25	0.44	fixed	0.46	2	no	no	Heavy	OFL	0.76 (0.48)	0 (1.52)	0.03 (31.8)	0.01 (41.46)	1.05 (0.52)	0.42 (0.7)	0.38 (0.66)	0.27 (0.5)	0.09 (0.26)
Slow	High	0.77	0.00	fixed	0.35	2	no	no	Light	P* var (0.38)	1 (0.44)	0.03 (1.38)	-0.23 (0.99)	-0.57 (0.66)	1.12 (0.49)	0.24 (0.75)	2.58 (0.81)	0.85 (0.48)	0.18 (0.61)
Slow	High	1.25	0.00	fixed	0.35	2	no	no	Light	P* var (0.38)	0.93 (0.52)	0.09 (1.29)	-0.27 (1.08)	-0.57 (0.96)	1.11 (0.5)	0.24 (0.74)	2.31 (0.91)	0.72 (0.67)	0.19 (0.61)
Slow	High	0.77	0.44	fixed	0.35	2	no	no	Light	P* var (0.38)	0.93 (0.45)	0.07 (1.38)	-0.27 (0.92)	-0.59 (0.56)	1.15 (0.49)	0.24 (0.75)	2.18 (0.78)	0.62 (0.48)	0.18 (0.62)
Slow	High	1.25	0.44	fixed	0.35	2	no	no	Light	P* var (0.38)	0.78 (0.52)	0.09 (1.29)	-0.3 (0.85)	-0.64 (0.5)	1.15 (0.49)	0.24 (0.75)	1.54 (0.8)	0.3 (0.61)	0.19 (0.65)
Slow	High	0.77	0.44	fixed	0.46	2	no	no	Light	P* var (0.38)	0.99 (0.34)	0 (1.59)	-0.17 (1.13)	-0.41 (0.74)	1.08 (0.57)	0.23 (0.82)	1.55 (0.92)	0.62 (0.45)	0.16 (0.7)
Slow	High	1.25	0.44	fixed	0.46	2	no	no	Light	P* var (0.38)	0.88 (0.4)	0 (1.55)	-0.21 (1.03)	-0.5 (0.64)	1.08 (0.56)	0.24 (0.82)	1.09 (0.94)	0.33 (0.56)	0.16 (0.73)
Slow	High	0.77	0.00	fixed	0.35	2	no	no	Moderate	P* var (0.38)	0.98 (0.47)	0 (1.58)	-0.17 (1.26)	-0.37 (1.02)	1.02 (0.5)	0.31 (0.72)	1.87 (0.7)	0.87 (0.49)	0.14 (0.5)
Slow	High	1.25	0.00	fixed	0.35	2	no	no	Moderate	P* var (0.38)	0.93 (0.58)	0 (1.41)	-0.19 (1.48)	-0.42 (1.5)	1 (0.51)	0.31 (0.72)	1.79 (0.79)	0.76 (0.84)	0.15 (0.5)
Slow	High	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* var (0.38)	0.92 (0.44)	0 (1.65)	-0.19 (1.1)	-0.43 (0.73)	1.02 (0.47)	0.31 (0.7)	1.58 (0.69)	0.59 (0.46)	0.14 (0.52)
Slow	High	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* var (0.38)	0.77 (0.52)	0.02 (1.42)	-0.23 (0.97)	-0.52 (0.6)	1 (0.47)	0.29 (0.7)	1.15 (0.71)	0.28 (0.63)	0.15 (0.56)
Slow	High	0.77	0.44	fixed	0.46	2	no	no	Moderate	P* var (0.38)	0.98 (0.36)	0 (2)	-0.09 (1.69)	-0.22 (1.46)	1.01 (0.56)	0.31 (0.77)	1.07 (0.83)	0.62 (0.4)	0.12 (0.59)
Slow	High	1.25	0.44	fixed	0.46	2	no	no	Moderate	P* var (0.38)	0.86 (0.42)	0 (1.83)	-0.13 (1.39)	-0.32 (1.03)	0.99 (0.56)	0.31 (0.78)	0.75 (0.85)	0.33 (0.53)	0.12 (0.62)
Slow	High	0.77	0.00	fixed	0.35	2	no	no	Heavy	P* var (0.38)	1.05 (0.45)	0 (1.6)	0.07 (15.94)	0.1 (4.16)	0.9 (0.47)	0.31 (0.76)	0.82 (0.7)	0.79 (0.46)	0.12 (0.24)
Slow	High	1.25	0.00	fixed	0.35	2	no	no	Heavy	P* var (0.38)	1.02 (0.54)	0.02 (1.35)	0.04 (10.71)	0.03 (4.51)	0.88 (0.49)	0.29 (0.76)	0.8 (0.9)	0.72 (0.64)	0.13 (0.25)
Slow	High	0.77	0.44	fixed	0.35	2	no	no	Heavy	P* var (0.38)	1.03 (0.44)	0 (1.81)	0.05 (39.82)	0.06 (10.14)	0.86 (0.47)	0.28 (0.78)	0.62 (0.68)	0.56 (0.45)	0.12 (0.27)
Slow	High	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* var (0.38)	0.87 (0.51)	0 (1.68)	-0.01 (6.86)	-0.1 (3.87)	0.85 (0.48)	0.27 (0.77)	0.42 (0.73)	0.26 (0.58)	0.12 (0.28)
Slow	High	0.77	0.44	fixed	0.46	2	no	no	Heavy	P* var (0.38)	1.05 (0.35)	0 (2.31)	0.15 (1.69)	0.31 (1.21)	0.86 (0.51)	0.29 (0.84)	0.42 (0.7)	0.6 (0.4)	0.09 (0.23)
Slow	High	1.25	0.44	fixed	0.46	2	no	no	Heavy	P* var (0.38)	0.9 (0.4)	0 (1.95)	0.09 (3.4)	0.15 (2.82)	0.84 (0.52)	0.27 (0.85)	0.29 (0.76)	0.3 (0.49)	0.1 (0.24)
Slow	High	0.77	0.00	fixed	0.35	2	no	no	Light	P* varied (0.7)	1.09 (0.4)	0 (1.45)	-0.21 (1.03)	-0.53 (0.7)	1.01 (0.49)	0.2 (0.79)	2.42 (0.84)	0.87 (0.47)	0.18 (0.62)
Slow	High	1.25	0.00	fixed	0.35	2	no	no	Light	P* varied (0.7)	1.02 (0.48)	0.04 (1.38)	-0.25 (1.12)	-0.53 (1.04)	1 (0.5)	0.2 (0.79)	2.16 (0.94)	0.75 (0.66)	0.19 (0.62)
Slow	High	0.77	0.44	fixed	0.35	2	no	no	Light	P* varied (0.7)	1.03 (0.42)	0.01 (1.37)	-0.25 (0.96)	-0.55 (0.59)	1.04 (0.5)	0.2 (0.79)	2.05 (0.81)	0.63 (0.46)	0.18 (0.64)
Slow	High	1.25	0.44	fixed	0.35	2	no	no	Light	P* varied (0.7)	0.89 (0.47)	0.07 (1.4)	-0.28 (0.88)	-0.61 (0.52)	1.03 (0.49)	0.2 (0.8)	1.44 (0.83)	0.32 (0.59)	0.19 (0.66)
Slow	High	0.77	0.44	fixed	0.46	2	no	no	Light	P* varied (0.7)	1.06 (0.32)	0 (1.54)	-0.15 (1.17)	-0.38 (0.78)	0.98 (0.58)	0.2 (0.87)	1.45 (0.95)	0.62 (0.45)	0.16 (0.71)
Slow	High	1.25	0.44	fixed	0.46	2	no	no	Light	P* varied (0.7)	0.96 (0.37)	0 (1.64)	-0.19 (1.06)	-0.47 (0.67)	0.98 (0.58)	0.18 (0.88)	1.03 (0.97)	0.34 (0.57)	0.16 (0.74)
Slow	High	0.77	0.00	fixed	0.35	2	no	no	Moderate	P* varied (0.7)	1.07 (0.44)	0 (1.76)	-0.15 (1.36)	-0.35 (1.16)	0.92 (0.5)	0.27 (0.79)	1.75 (0.73)	0.88 (0.48)	0.14 (0.49)
Slow	High	1.25	0.00	fixed	0.35	2	no	no	Moderate	P* varied (0.7)	1.02 (0.54)	0 (1.53)	-0.18 (1.62)	-0.38 (1.78)	0.91 (0.52)	0.27 (0.79)	1.68 (0.81)	0.78 (0.83)	0.15 (0.51)
Slow	High	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* varied (0.7)	1.02 (0.41)	0 (1.77)	-0.17 (1.18)	-0.38 (0.81)	0.93 (0.47)	0.26 (0.76)	1.48 (0.71)	0.62 (0.44)	0.14 (0.52)
Slow	High	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* varied (0.7)	0.87 (0.48)	0 (1.63)	-0.21 (1.03)	-0.48 (0.65)	0.91 (0.47)	0.24 (0.76)	1.08 (0.74)	0.29 (0.6)	0.14 (0.56)
Slow	High	0.77	0.44	fixed	0.46	2	no	no	Moderate	P* varied (0.7)	1.05 (0.34)	0 (2.13)	-0.07 (1.87)	-0.17 (1.75)	0.93 (0.57)	0.27 (0.84)	1 (0.87)	0.63 (0.4)	0.12 (0.6)
Slow	High	1.25	0.44	fixed	0.46	2	no	no	Moderate	P* varied (0.7)	0.93 (0.39)	0 (2.03)	-0.12 (1.51)	-0.29 (1.17)	0.91 (0.56)	0.27 (0.84)	0.7 (0.88)	0.33 (0.53)	0.12 (0.62)
Slow	High	0.77	0.00	fixed	0.35	2	no	no	Heavy	P* varied (0.7)	1.14 (0.42)	0 (1.8)	0.11 (5.08)	0.18 (2.44)	0.81 (0.48)	0.23 (0.84)	0.72 (0.74)	0.83 (0.45)	0.12 (0.24)
Slow	High	1.25	0.00	fixed	0.35	2	no	no	Heavy	P* varied (0.7)	1.11 (0.51)	0 (1.47)	0.07 (5.18)	0.12 (2.9)	0.78 (0.49)	0.22 (0.84)	0.69 (0.96)	0.75 (0.63)	0.13 (0.24)
Slow	High	0.77	0.44	fixed	0.35	2	no	no	Heavy	P* varied (0.7)	1.13 (0.41)	0 (2.03)	0.09 (6.04)	0.13 (3.49)	0.78 (0.48)	0.22 (0.86)	0.55 (0.73)	0.58 (0.44)	0.12 (0.26)
Slow	High	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* varied (0.7)	0.97 (0.47)	0 (1.84)	0.02 (50.18)	-0.03 (12.66)	0.76 (0.49)	0.2 (0.86)	0.38 (0.77)	0.28 (0.57)	0.12 (0.27)
Slow	High	0.77	0.44	fixed	0.46	2	no	no	Heavy	P* varied (0.7)	1.12 (0.33)	0 (2.76)	0.19 (1.25)	0.39 (0.97)	0.77 (0.51)	0.22 (0.93)	0.34 (0.77)	0.61 (0.4)	0.1 (0.23)
Slow	High	1.25	0.44	fixed	0.46	2	no	no	Heavy	P* varied (0.7)	0.98 (0.38)	0 (2.19)	0.12 (2.19)	0.22 (1.88)	0.75 (0.51)	0.22 (0.95)	0.24 (0.83)	0.3 (0.5)	0.1 (0.23)
Slow	High	0.77	0.00	fixed	0.35	2	no	no	Light	P* varied (1.0)	1.15 (0.39)	0 (1.45)	-0.2 (1.07)	-0.5 (0.74)	0.95 (0.5)	0.18 (0.83)	2.31 (0.85)	0.88 (0.47)	0.17 (0.64)
Slow	High	1.25	0.00	fixed	0.35	2	no	no	Light	P* varied (1.0)	1.08 (0.46)	0 (1.49)	-0.23 (1.16)	-0.52 (1.1)	0.93 (0.51)	0.18 (0.83)	2.06 (0.96)	0.75 (0.66)	0.18 (0.62)
Slow	High	0.77	0.44	fixed	0.35	2	no	no	Light	P* varied (1.0)	1.09 (0.4)	0 (1.37)	-0.23 (0.99)	-0.52 (0.61)	0.97 (0.5)	0.18 (0.83)	1.95 (0.83)	0.64 (0.46)	0.18 (0.65)
Slow	High	1.25	0.44	fixed	0.35	2	no	no	Light	P* varied (1.0)	0.94 (0.44)	0.02 (1.48)	-0.27 (0.91)	-0.58 (0.54)	0.97 (0.5)	0.18 (0.82)	1.37 (0.85)	0.33 (0.58)	0.19 (0.67)
Slow	High	0.77	0.44	fixed	0.46	2	no	no	Light	P* varied (1.0)	1.1 (0.31)	0 (1.55)	-0.14 (1.2)	-0.35 (0.82)	0.92 (0.6)	0.18 (0.91)	1.38 (0.97)	0.62 (0.46)	0.15 (0.73)
Slow	High	1.25	0.44	fixed	0.46	2	no	no	Light	P* varied (1.0)	1 (0.35)	0 (1.71)	-0.18 (1.09)	-0.46 (0.7)	0.92 (0.59)	0.16 (0.91)	0.97 (0.99)	0.34 (0.58)	0.16 (0.75)
Slow	High	0.77	0.00	fixed	0.35	2	no	no	Moderate	P* varied (1.0)	1.12 (0.42)	0 (1.8)	-0.13 (1.45)	-0.31 (1.3)	0.87 (0.5)	0.22 (0.83)	1.67 (0.74)	0.88 (0.47)	0.14 (0.49)
Slow	High	1.25	0.00	fixed	0.35	2	no	no	Moderate	P* varied (1.0)	1.08 (0.52)	0 (1.63)	-0.17 (1.74)	-0.35 (2.04)	0.85 (0.52)	0.22 (0.84)	1.59 (0.83)	0.79 (0.82)	0.14 (0.51)
Slow	High	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* varied (1.0)	1.07 (0.39)	0 (1.85)	-0.16 (1.24)	-0.36 (0.88)	0.88 (0.47)	0.22 (0.81)	1.41 (0.73)	0.62 (0.43)	0.13 (0.52)
Slow	High	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* varied (1.0)	0.94 (0.45)	0 (1.74)	-0.2 (1.08)	-0.45 (0.7)	0.86 (0.47)	0.22 (0.79)	1.03 (0.75)	0.3 (0.59)	0.14 (0.56)
Slow	High	0.77	0.44	fixed	0.46	2	no	no	Moderate	P* varied (1.0)	1.09 (0.33)	0 (2.2)	-0.06 (2.03)	-0.14 (2.05)	0.88 (0.58)	0.22 (0.89)	0.95 (0.89)	0.63 (0.41)	0.12 (0.6)
Slow	High	1.25	0.44	fixed	0.46	2	no	no	Moderate	P* varied (1.0)	0.97 (0.38)	0 (2.12)	-0.1 (1.61)	-0.26 (1.29)	0.86 (0.57)	0.22 (0.89)	0.67 (0.91)	0.32 (0.53)	0.12 (0.62)
Slow	High	0.77	0.00	fixed	0.35	2	no	no	Heavy	P* varied (1.0)	1.21 (0.41)	0 (1.94)	0.14 (3.43)	0.23 (1.91)	0.75 (0.48)	0.2 (0.91)	0.65 (0.78)	0.83 (0.45)	0.11 (0.24)
Slow	High	1.25	0.00	fixed	0.35	2	no	no	Heavy	P* varied (1.0)	1.15 (0.49)	0 (1.56)	0.1 (3.82)	0.18 (2.35)	0.72 (0.5)	0.18 (0.9)	0.62 (1)	0.76 (0.62)	0.13 (0.24)
Slow	High	0.77	0.44	fixed	0.35	2	no	no	Heavy	P* varied (1.0)	1.19 (0.4)	0 (2.21)	0.12 (3.78)	0.18 (2.42)	0.73 (0.49)	0.18 (0.93)	0.5 (0.77)	0.59 (0.44)	0.11 (0.26)
Slow	High	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* varied (1.0)	1.04 (0.45)	0 (1.98)	0.05 (14.67)	0.01 (27.05)	0.7 (0.5)	0.18 (0.92)	0.34 (0.81)	0.28 (0.56)	0.12 (0.26)
Slow	High	0.77	0.44	fixed	0.46	2	no	no	Heavy	P* varied (1.0)	1.16 (0.32)	0 (3.06)	0.22 (1.05)	0.44 (0.86)	0.72 (0.49)	0.18 (1)	0.29 (0.83)	0.61 (0.41)	0.1 (0.23)
Slow	High	1.25	0.44	fixed	0.46	2	no	no	Heavy	P* varied (1.0)	1.02 (0.36)	0 (2.53)	0.15 (1.76)	0.26 (1.56)	0.7 (0.5)	0.16 (1.02)	0.21 (0.89)	0.31 (0.5)	0.1 (0.23)
Slow	High	0.77	0.00	fixed	0.35	2	no	no	Light	P* fixed (0.38)	0.89 (0.49)	0.06 (1.36)	-0.23 (0.99)	-0.57 (0.67)	1.15 (0.55)	0.31 (0.74)	2.58 (0.81)	0.8 (0.51)	0.17 (0.64)
Slow	High	1.25	0.00	fixed	0.35	2	no	no	Light	P* fixed (0.38)	0.83 (0.59)	0.11 (1.26)	-0.27 (1.08)	-0.6 (0.94)	1.18 (0.57)	0.33 (0.72)	2.31 (0.91)	0.69 (0.7)	0.18 (0.63)
Slow	High	0.77	0.44	fixed	0.35	2	no	no	Light	P* fixed (0.38)	0.85 (0.52)	0.08 (1.34)	-0.27 (0.92)	-0.6 (0.57)	1.21 (0.54)	0.31 (0.75)	2.18 (0.78)	0.59 (0.52)	0.18 (0.64)
Slow	High	1.25	0.44	fixed	0.35	2	no	no	Light	P* fixed (0.38)	0.63 (0.64)	0.11 (1.2)	-0.3 (0.85)	-0.65 (0.51)	1.23 (0.56)	0.33 (0.73)	1.54 (0.8)	0.28 (0.67)	0.18 (0.68)
Slow	High	0.77	0.44	fixed	0.46	2	no	no	Light	P* fixed (0.38)	0.95 (0.38)	0 (1.58)	-0.17 (1.12)	-0.42 (0.74)	1.13 (0.61)	0.29 (0.79)	1.55 (0.92)	0.59 (0.45)	0.15 (0.72)
Slow	High	1.25	0.44	fixed	0.46	2	no	no	Light	P* fixed (0.38)	0.8 (0.47)	0 (1.45)	-0.21 (1.03)	-0.51 (0.64)	1.14 (0.62)	0.29 (0.78)	1.09 (0.94)	0.33 (0.57)	0.15 (0.75)
Slow	High	0.77	0.00	fixed	0.35	2	no	no	Moderate	P* fixed (0.38)	0.93 (0.52)	0 (1.49)	-0.17 (1.26)	-0.4 (0.99)	1.07 (0.56)	0.37 (0.71)	1.87 (0.7)	0.83 (0.5)	0.13 (0.54)
Slow	High	1.25	0.00	fixed	0.35	2	no	no	Moderate	P* fixed (0.38)	0.86 (0.64)	0.04 (1.33)	-0.2 (1.47)	-0.44 (1.4)	1.07 (0.57)	0.37 (0.71)	1.79 (0.78)	0.74 (0.85)	0.14 (0.54)
Slow	High	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (0.38)	0.82 (0.51)	0 (1.51)	-0.19 (1.1)	-0.44 (0.73)	1.07 (0.53)	0.37 (0.69)	1.58 (0.69)	0.56 (0.48)	0.13 (0.56)
Slow	High	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (0.38)	0.65 (0.63)	0.07 (1.27)	-0.23 (0.97)	-0.53 (0.6)	1.09 (0.54)	0.39 (0.69)	1.15 (0.71)	0.27 (0.67)	0.14 (0.61)
Slow	High	0.77	0.44	fixed	0.46	2	no	no	Moderate	P* fixed (0.38)	0.92 (0.39)	0 (1.92)	-0.09 (1.66)	-0.23 (1.36)	1.04 (0.58)	0.38 (0.76)	1.07 (0.82)	0.63 (0.39)	0.11 (0.63)
Slow	High	1.25	0.44	fixed	0.46	2	no	no	Moderate	P* fixed (0.38)	0.79 (0.47)	0 (1.65)	-0.13 (1.37)	-0.34 (0.99)	1.05 (0.58)	0.38 (0.75)	0.75 (0.84)	0.32 (0.52)	0.11 (0.67)
Slow	High	0.77	0.00	fixed	0.35	2	no	no	Heavy	P* fixed (0.38)	0.97 (0.49)	0 (1.55)	0.04 (48.38)	0.04 (8.85)	0.95 (0.5)	0.34 (0.75)	0.91 (0.64)	0.77 (0.46)	0.11 (0.25)

Life history	Assessment uncertainty	σ_R	ϕ_R	h	SPR target	SA years	Projec-tions?	ABC avg.?	Exploitation history	Control rule	S / S_{MSY}	Overfished probability	ΔS_5	ΔS_{15}	F / F_{MSY}	P_{OF} (true)	Initial C / MSY	Final C / MSY	Catch AAV
Slow	High	1.25	0.00	fixed	0.35	2	no	no	Heavy	P* fixed (0.38)	0.92 (0.6)	0.04 (1.34)	0 (36.51)	-0.02 (8.12)	0.95 (0.51)	0.36 (0.75)	0.87 (0.84)	0.68 (0.65)	0.12 (0.26)
Slow	High	0.77	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (0.38)	0.97 (0.49)	0 (1.75)	0.03 (15.16)	-0.01 (20.21)	0.93 (0.52)	0.31 (0.78)	0.68 (0.61)	0.54 (0.46)	0.1 (0.3)
Slow	High	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (0.38)	0.75 (0.6)	0 (1.5)	-0.04 (4.29)	-0.15 (2.44)	0.93 (0.54)	0.31 (0.77)	0.45 (0.67)	0.25 (0.59)	0.11 (0.32)
Slow	High	0.77	0.44	fixed	0.46	2	no	no	Heavy	P* fixed (0.38)	1.01 (0.37)	0 (2.17)	0.12 (2.33)	0.24 (1.56)	0.94 (0.5)	0.34 (0.8)	0.51 (0.6)	0.59 (0.38)	0.08 (0.23)
Slow	High	1.25	0.44	fixed	0.46	2	no	no	Heavy	P* fixed (0.38)	0.83 (0.44)	0 (1.79)	0.05 (6.29)	0.06 (5.53)	0.94 (0.52)	0.36 (0.8)	0.34 (0.66)	0.29 (0.48)	0.09 (0.25)
Slow	High	0.77	0.00	fixed	0.35	2	no	no	Light	P* fixed (0.7)	0.97 (0.47)	0 (1.46)	-0.21 (1.03)	-0.54 (0.71)	1.06 (0.56)	0.24 (0.8)	2.42 (0.84)	0.82 (0.49)	0.17 (0.65)
Slow	High	1.25	0.00	fixed	0.35	2	no	no	Light	P* fixed (0.7)	0.91 (0.56)	0.07 (1.35)	-0.25 (1.12)	-0.57 (1.01)	1.07 (0.59)	0.27 (0.78)	2.16 (0.94)	0.71 (0.68)	0.17 (0.65)
Slow	High	0.77	0.44	fixed	0.35	2	no	no	Light	P* fixed (0.7)	0.93 (0.49)	0.02 (1.43)	-0.25 (0.96)	-0.56 (0.6)	1.11 (0.55)	0.24 (0.81)	2.05 (0.81)	0.59 (0.5)	0.17 (0.67)
Slow	High	1.25	0.44	fixed	0.35	2	no	no	Light	P* fixed (0.7)	0.71 (0.6)	0.09 (1.29)	-0.28 (0.88)	-0.63 (0.53)	1.11 (0.57)	0.27 (0.8)	1.44 (0.83)	0.3 (0.64)	0.18 (0.69)
Slow	High	0.77	0.44	fixed	0.46	2	no	no	Light	P* fixed (0.7)	1 (0.36)	0 (1.66)	-0.15 (1.17)	-0.39 (0.79)	1.04 (0.62)	0.24 (0.85)	1.45 (0.95)	0.6 (0.45)	0.14 (0.74)
Slow	High	1.25	0.44	fixed	0.46	2	no	no	Light	P* fixed (0.7)	0.85 (0.44)	0 (1.57)	-0.19 (1.06)	-0.49 (0.67)	1.05 (0.63)	0.24 (0.85)	1.03 (0.97)	0.34 (0.56)	0.15 (0.77)
Slow	High	0.77	0.00	fixed	0.35	2	no	no	Moderate	P* fixed (0.7)	1.01 (0.49)	0 (1.65)	-0.15 (1.35)	-0.36 (1.1)	0.98 (0.56)	0.31 (0.79)	1.75 (0.72)	0.86 (0.48)	0.13 (0.54)
Slow	High	1.25	0.00	fixed	0.35	2	no	no	Moderate	P* fixed (0.7)	0.93 (0.61)	0 (1.44)	-0.18 (1.59)	-0.41 (1.6)	0.99 (0.58)	0.31 (0.79)	1.68 (0.81)	0.75 (0.84)	0.13 (0.56)
Slow	High	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (0.7)	0.89 (0.48)	0 (1.68)	-0.17 (1.17)	-0.39 (0.8)	0.99 (0.54)	0.31 (0.77)	1.48 (0.71)	0.58 (0.45)	0.13 (0.57)
Slow	High	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (0.7)	0.74 (0.59)	0 (1.42)	-0.21 (1.03)	-0.5 (0.65)	0.99 (0.55)	0.31 (0.76)	1.08 (0.73)	0.28 (0.63)	0.13 (0.62)
Slow	High	0.77	0.44	fixed	0.46	2	no	no	Moderate	P* fixed (0.7)	0.98 (0.37)	0 (2.1)	-0.07 (1.81)	-0.2 (1.57)	0.96 (0.6)	0.3 (0.83)	1 (0.85)	0.63 (0.38)	0.1 (0.66)
Slow	High	1.25	0.44	fixed	0.46	2	no	no	Moderate	P* fixed (0.7)	0.84 (0.45)	0 (1.85)	-0.12 (1.47)	-0.3 (1.09)	0.97 (0.59)	0.31 (0.82)	0.7 (0.87)	0.33 (0.5)	0.11 (0.68)
Slow	High	0.77	0.00	fixed	0.35	2	no	no	Heavy	P* fixed (0.7)	1.05 (0.47)	0 (1.74)	0.06 (13.61)	0.1 (4.16)	0.88 (0.51)	0.28 (0.83)	0.85 (0.64)	0.78 (0.44)	0.1 (0.25)
Slow	High	1.25	0.00	fixed	0.35	2	no	no	Heavy	P* fixed (0.7)	1 (0.57)	0 (1.43)	0.02 (10.37)	0.03 (4.66)	0.88 (0.54)	0.29 (0.82)	0.82 (0.85)	0.7 (0.62)	0.11 (0.25)
Slow	High	0.77	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (0.7)	1.05 (0.46)	0 (1.96)	0.04 (33.43)	0.05 (11.6)	0.85 (0.52)	0.24 (0.86)	0.64 (0.62)	0.55 (0.44)	0.1 (0.29)
Slow	High	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (0.7)	0.84 (0.56)	0 (1.65)	-0.02 (6.66)	-0.1 (3.5)	0.85 (0.55)	0.24 (0.85)	0.42 (0.67)	0.26 (0.57)	0.1 (0.31)
Slow	High	0.77	0.44	fixed	0.46	2	no	no	Heavy	P* fixed (0.7)	1.06 (0.35)	0 (2.59)	0.13 (1.81)	0.29 (1.29)	0.87 (0.52)	0.27 (0.89)	0.48 (0.6)	0.59 (0.38)	0.08 (0.24)
Slow	High	1.25	0.44	fixed	0.46	2	no	no	Heavy	P* fixed (0.7)	0.89 (0.42)	0 (2.01)	0.07 (3.97)	0.11 (3.46)	0.87 (0.5)	0.27 (0.88)	0.32 (0.66)	0.29 (0.47)	0.09 (0.25)
Slow	High	0.77	0.00	fixed	0.35	2	no	no	Light	P* fixed (1.0)	1.03 (0.45)	0 (1.53)	-0.2 (1.06)	-0.52 (0.74)	1 (0.56)	0.22 (0.85)	2.31 (0.85)	0.83 (0.48)	0.16 (0.67)
Slow	High	1.25	0.00	fixed	0.35	2	no	no	Light	P* fixed (1.0)	0.96 (0.54)	0 (1.42)	-0.23 (1.16)	-0.55 (1.07)	0.99 (0.59)	0.22 (0.83)	2.06 (0.95)	0.72 (0.67)	0.17 (0.66)
Slow	High	0.77	0.44	fixed	0.35	2	no	no	Light	P* fixed (1.0)	0.99 (0.47)	0 (1.51)	-0.23 (0.99)	-0.54 (0.62)	1.04 (0.56)	0.22 (0.86)	1.95 (0.83)	0.59 (0.48)	0.17 (0.68)
Slow	High	1.25	0.44	fixed	0.35	2	no	no	Light	P* fixed (1.0)	0.77 (0.58)	0.04 (1.36)	-0.27 (0.91)	-0.61 (0.55)	1.04 (0.57)	0.22 (0.85)	1.37 (0.85)	0.32 (0.62)	0.17 (0.7)
Slow	High	0.77	0.44	fixed	0.46	2	no	no	Light	P* fixed (1.0)	1.04 (0.34)	0 (1.73)	-0.14 (1.2)	-0.37 (0.82)	0.97 (0.64)	0.22 (0.91)	1.38 (0.97)	0.59 (0.46)	0.14 (0.76)
Slow	High	1.25	0.44	fixed	0.46	2	no	no	Light	P* fixed (1.0)	0.89 (0.43)	0 (1.66)	-0.18 (1.09)	-0.47 (0.7)	0.99 (0.64)	0.22 (0.89)	0.97 (0.99)	0.34 (0.56)	0.15 (0.78)
Slow	High	0.77	0.00	fixed	0.35	2	no	no	Moderate	P* fixed (1.0)	1.07 (0.47)	0 (1.74)	-0.13 (1.43)	-0.33 (1.21)	0.93 (0.56)	0.27 (0.85)	1.67 (0.74)	0.85 (0.47)	0.12 (0.54)
Slow	High	1.25	0.00	fixed	0.35	2	no	no	Moderate	P* fixed (1.0)	0.98 (0.59)	0 (1.53)	-0.17 (1.7)	-0.38 (1.79)	0.93 (0.58)	0.27 (0.84)	1.61 (0.82)	0.76 (0.82)	0.13 (0.57)
Slow	High	0.77	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (1.0)	0.96 (0.46)	0 (1.79)	-0.16 (1.23)	-0.37 (0.86)	0.93 (0.54)	0.24 (0.83)	1.41 (0.73)	0.59 (0.44)	0.12 (0.57)
Slow	High	1.25	0.44	fixed	0.35	2	no	no	Moderate	P* fixed (1.0)	0.8 (0.56)	0 (1.53)	-0.2 (1.07)	-0.48 (0.69)	0.94 (0.55)	0.27 (0.82)	1.03 (0.75)	0.29 (0.6)	0.13 (0.62)
Slow	High	0.77	0.44	fixed	0.46	2	no	no	Moderate	P* fixed (1.0)	1.02 (0.35)	0 (2.23)	-0.06 (1.94)	-0.17 (1.77)	0.91 (0.61)	0.24 (0.89)	0.95 (0.87)	0.62 (0.38)	0.1 (0.66)
Slow	High	1.25	0.44	fixed	0.46	2	no	no	Moderate	P* fixed (1.0)	0.87 (0.43)	0 (2)	-0.11 (1.56)	-0.28 (1.18)	0.91 (0.61)	0.27 (0.88)	0.67 (0.89)	0.33 (0.49)	0.11 (0.69)
Slow	High	0.77	0.00	fixed	0.35	2	no	no	Heavy	P* fixed (1.0)	1.11 (0.45)	0 (1.93)	0.08 (6.83)	0.13 (2.96)	0.83 (0.51)	0.22 (0.89)	0.81 (0.64)	0.8 (0.43)	0.1 (0.24)
Slow	High	1.25	0.00	fixed	0.35	2	no	no	Heavy	P* fixed (1.0)	1.06 (0.55)	0 (1.49)	0.03 (6.74)	0.08 (3.57)	0.82 (0.53)	0.22 (0.89)	0.78 (0.86)	0.72 (0.61)	0.11 (0.25)
Slow	High	0.77	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (1.0)	1.11 (0.44)	0 (2.19)	0.06 (9.59)	0.1 (5.26)	0.8 (0.53)	0.22 (0.93)	0.61 (0.63)	0.56 (0.42)	0.1 (0.28)
Slow	High	1.25	0.44	fixed	0.35	2	no	no	Heavy	P* fixed (1.0)	0.9 (0.54)	0 (1.79)	0 (11.57)	-0.07 (5.16)	0.8 (0.54)	0.22 (0.92)	0.4 (0.67)	0.27 (0.55)	0.1 (0.3)
Slow	High	0.77	0.44	fixed	0.46	2	no	no	Heavy	P* fixed (1.0)	1.1 (0.34)	0 (2.91)	0.14 (1.55)	0.33 (1.14)	0.82 (0.49)	0.22 (0.96)	0.45 (0.6)	0.59 (0.38)	0.08 (0.23)
Slow	High	1.25	0.44	fixed	0.46	2	no	no	Heavy	P* fixed (1.0)	0.93 (0.4)	0 (2.19)	0.08 (3.09)	0.14 (2.72)	0.82 (0.5)	0.22 (0.96)	0.31 (0.66)	0.29 (0.47)	0.08 (0.24)
Slow	High	0.77	0.00	fixed	0.35	2	no	no	Light	75% of F_lim	1.08 (0.43)	0 (1.58)	-0.19 (1.09)	-0.49 (0.77)	0.95 (0.57)	0.2 (0.89)	2.22 (0.87)	0.83 (0.48)	0.16 (0.68)
Slow	High	1.25	0.00	fixed	0.35	2	no	no	Light	75% of F_lim	1.01 (0.53)	0 (1.48)	-0.22 (1.19)	-0.54 (1.12)	0.95 (0.59)	0.2 (0.87)	1.98 (0.97)	0.72 (0.66)	0.17 (0.67)
Slow	High	0.77	0.44	fixed	0.35	2	no	no	Light	75% of F_lim	1.03 (0.45)	0 (1.57)	-0.22 (1.01)	-0.51 (0.64)	0.98 (0.57)	0.19 (0.9)	1.87 (0.85)	0.6 (0.48)	0.16 (0.68)
Slow	High	1.25	0.44	fixed	0.35	2	no	no	Light	75% of F_lim	0.81 (0.55)	0.01 (1.43)	-0.26 (0.93)	-0.59 (0.57)	0.98 (0.58)	0.22 (0.88)	1.33 (0.86)	0.32 (0.61)	0.17 (0.71)
Slow	High	0.77	0.44	fixed	0.46	2	no	no	Light	75% of F_lim	1.07 (0.33)	0 (1.81)	-0.13 (1.24)	-0.34 (0.86)	0.92 (0.65)	0.18 (0.95)	1.31 (0.99)	0.59 (0.46)	0.14 (0.77)
Slow	High	1.25	0.44	fixed	0.46	2	no	no	Light	75% of F_lim	0.93 (0.41)	0 (1.72)	-0.17 (1.12)	-0.46 (0.73)	0.93 (0.66)	0.2 (0.94)	0.93 (1.01)	0.34 (0.56)	0.15 (0.8)
Slow	High	0.77	0.00	fixed	0.35	2	no	no	Moderate	75% of F_lim	1.11 (0.46)	0 (1.85)	-0.12 (1.51)	-0.29 (1.31)	0.88 (0.56)	0.24 (0.89)	1.61 (0.76)	0.86 (0.46)	0.12 (0.54)
Slow	High	1.25	0.00	fixed	0.35	2	no	no	Moderate	75% of F_lim	1.03 (0.57)	0 (1.63)	-0.16 (1.79)	-0.36 (1.98)	0.88 (0.58)	0.22 (0.88)	1.55 (0.84)	0.76 (0.81)	0.13 (0.57)
Slow	High	0.77	0.44	fixed	0.35	2	no	no	Moderate	75% of F_lim	1.02 (0.44)	0 (1.89)	-0.14 (1.28)	-0.34 (0.92)	0.89 (0.54)	0.23 (0.87)	1.36 (0.74)	0.6 (0.43)	0.12 (0.58)
Slow	High	1.25	0.44	fixed	0.35	2	no	no	Moderate	75% of F_lim	0.83 (0.54)	0 (1.62)	-0.18 (1.11)	-0.45 (0.72)	0.89 (0.55)	0.24 (0.86)	0.99 (0.76)	0.3 (0.59)	0.12 (0.62)
Slow	High	0.77	0.44	fixed	0.46	2	no	no	Moderate	75% of F_lim	1.06 (0.34)	0 (2.33)	-0.05 (2.1)	-0.14 (2.03)	0.86 (0.62)	0.21 (0.95)	0.91 (0.89)	0.62 (0.38)	0.1 (0.66)
Slow	High	1.25	0.44	fixed	0.46	2	no	no	Moderate	75% of F_lim	0.92 (0.41)	0 (2.16)	-0.1 (1.65)	-0.26 (1.29)	0.86 (0.61)	0.22 (0.94)	0.64 (0.92)	0.33 (0.48)	0.1 (0.7)
Slow	High	0.77	0.00	fixed	0.35	2	no	no	Heavy	75% of F_lim	1.16 (0.43)	0 (2.14)	0.09 (4.87)	0.17 (2.43)	0.78 (0.51)	0.2 (0.94)	0.78 (0.65)	0.81 (0.42)	0.1 (0.25)
Slow	High	1.25	0.00	fixed	0.35	2	no	no	Heavy	75% of F_lim	1.1 (0.53)	0 (1.58)	0.05 (5.27)	0.11 (3.01)	0.78 (0.51)	0.2 (0.94)	0.75 (0.86)	0.73 (0.59)	0.11 (0.25)
Slow	High	0.77	0.44	fixed	0.35	2	no	no	Heavy	75% of F_lim	1.16 (0.43)	0 (2.34)	0.07 (5.99)	0.13 (3.65)	0.76 (0.53)	0.18 (0.98)	0.58 (0.63)	0.57 (0.41)	0.09 (0.28)
Slow	High	1.25	0.44	fixed	0.35	2	no	no	Heavy	75% of F_lim	0.95 (0.52)	0 (1.92)	0.01 (29.35)	-0.04 (8.29)	0.76 (0.54)	0.18 (0.98)	0.39 (0.68)	0.27 (0.54)	0.1 (0.3)
Slow	High	0.77	0.44	fixed	0.46	2	no	no	Heavy	75% of F_lim	1.13 (0.32)	0 (3.27)	0.15 (1.34)	0.36 (1.01)	0.77 (0.46)	0.18 (1.03)	0.43 (0.6)	0.58 (0.38)	0.08 (0.22)
Slow	High	1.25	0.44	fixed	0.46	2	no	no	Heavy	75% of F_lim	0.97 (0.39)	0 (2.45)	0.09 (2.51)	0.17 (2.23)	0.77 (0.48)	0.18 (1.03)	0.29 (0.66)	0.29 (0.46)	0.08 (0.24)