Evaluating the Sustainability of a Cisco Fishery in Thunder Bay, Ontario under Alternative Harvest Policies

Nicholas C. Fisch[1*], James R. Bence[1], Jared T. Myers[2], Eric K. Berglund[3], and Daniel L. Yule[4].

1. Quantitative Fisheries Center, Department of Fisheries and Wildlife, Michigan State University, East Lansing, MI 48824-1101

2. U.S Fish and Wildlife Service, Ashland Fish and Wildlife Conservation Office, 2800 Lake Shore Dr. East, Ashland, WI 54806

3. Ontario Ministry of Natural Resources and Forestry, Upper Great Lakes Management Unit, 435 James Street South, Suite 221e, Thunder Bay, ON P7E 6S8, Canada

4. U.S. Geological Survey, Lake Superior Biological Station, 2800 Lake Shore Dr. East, Ashland, WI 54806

*Corresponding author: nfisch@ufl.edu

Abstract

Sustainable management of fish stocks is promoted through the application of Management Strategy Evaluations, providing information to managers on the relative performance of alternative management approaches (strategies) while accounting for uncertainty. In this study, we developed a simplified management strategy evaluation of a stock of cisco, *Coregonus artedi*, in Thunder Bay, Ontario, to determine both the sustainability of the current harvest control rule (i.e., a constant exploitation rate of 10%) and the performance of alternative harvest control rules in meeting fishery objectives. Success in meeting fishery objectives was evaluated through attained yields, inter-annual variation in yields, magnitude of spawning biomass, and the risk of reaching low spawning biomass – performance metrics established based on consultation with an advisory group to Lake Superior fishery managers. Our simulations explicitly accounted for uncertainty in the frequency of strong year classes being produced by cisco, the stock-recruit relationship, stock abundance, and the sex-specific nature of roe harvest. Assuming future productivity is similar to that observed over a period from 1985-2015, results suggest the current exploitation rate of 10% is sustainable in terms of maintaining spawning biomass above 20% of the unfished level. Variants of constant exploitation rate control rules that included thresholds defining when exploitation rate is to decrease as a function of spawning biomass increased yield, decreased risk, and increased the magnitude of spawning biomass at the end of the simulation period. However, these advantages came at the expense of greater inter-annual variation in yield. Constant catch control rules greatly underperformed constant exploitation rate control rules in terms of magnitude in yield, however they did reduce

inter-annual variation in yield compared to constant exploitation rate control rules. Furthermore, conditional versions of constant catch control rules (i.e., threshold stock sizes below which catch limit was reduced) mitigated risks of staying at low stock size.

[A] Introduction

Informed management of fish stocks to promote sustainable and economically viable yields requires clearly defined objectives and quantitative analyses on the effect of alternative harvest policies in achieving said objectives. This can be facilitated through a process known as Management Strategy Evaluation (MSE), or the evaluation of management strategies using simulation (Punt et al. 2008). A central tenet of these simulations is the attempt to account for uncertainty in key processes, such as the stock assessment, the stock-recruit relationship, or the implementation of a harvest control rule, as accounting for these uncertainties has been shown to affect the outcome of evaluations (Deroba and Bence, 2008). This can be done by including several possible scenarios within an operating model that encompass the realistic range of key uncertainties underlying the true dynamics of the fishery (Deroba and Bence, 2012). MSEs can allow for tailoring specific harvest control rules to meet given fishery objectives. Alternatively, due to limited information or analytical capacity, many fisheries are managed through the calculation of biological reference points (Goodyear 1993) used in defining targets or limits (Caddy and Mahon 1995; Quinn and Deriso 1999). These are based on generalizable rules that have been proposed and applied across fisheries with different life histories and harvest dynamics (i.e., fishing mortality should be lower than $F_{0.1}$, $SPR_{40\%}$). Time and data permitting, MSEs are preferred for fisheries management.

Loosely defined, harvest policies are guidelines on how harvest levels should be set in each season, whereas (harvest) control rules refer to the formulae used to specify a target or limit amount of harvest. Harvest control rules set target or limit harvest based on the state of the system (e.g., stock biomass) and are operationalized via policy parameters (e.g., the fishing mortality rate when stock size is high). When a control rule is implemented as part of a harvest policy, regulations can be set to roughly target a harvest (e.g., number of licenses or bag limits), and regulations can be supplemented by hard closures when the control rule specifies a limit (i.e., total allowable catch (TAC)). Harvest control rules can be part of a harvest policy, and the focus herein is on control rules that aim to set catch limits. These control rules generally fall into three separate categories; constant exploitation rate, constant catch, and constant escapement rules, in addition to variants of each aimed to correct perceived weaknesses (Deroba and Bence 2008). Constant exploitation rate rules aim to set catch limits to a constant proportion of stock size (Walters and Martell 2004). This builds in an inherent feedback system; as the stock declines, the harvests tend to also decrease, and vice versa. Constant catch rules set a limit of catch at some constant level regardless of stock size, valuing the stability in allowable catch. Constant escapement rules set catch limits at all biomass over some predetermined level, which is generally chosen to ensure sufficient levels of spawning stock remain in the population to provide for adequate replacement. Variants of these control rules can include the addition of thresholds, either biomass-based or exploitation rate-based, that aim to decrease exploitation rate or harvest at low stock sizes. Tuning or policy parameters refer to the specific exploitation rate, constant catch limit, or escapement level used to define a given harvest control rule and dictate the limit of harvest given the estimated state of the system. Policy parameters can also include biomass or exploitation rate thresholds that define variants of the three types of harvest control rules. Previous work has not led to general conclusions regarding what harvest control rule is best for given objectives and fishery dynamics (Deroba and Bence, 2008), so it is important to consider a suite of different harvest control rules and policy specific parameters of interest to stakeholders within the MSE.

Cisco, *Coregonus artedi*, currently support a roe fishery in Thunder Bay, Ontario, and are managed via a constant exploitation rate control rule, where the TAC is set to 10% of the estimated spawning stock biomass. The full harvest policy includes estimation of the spawning biomass through hydroacoustic surveys, and allocation of the TAC among a fixed set of license holders. While constant exploitation rate control rules can sometimes effectively achieve objectives (Walters and Martell 2004, Deroba and Bence 2008), the specific exploitation rate of 10% put into place in Thunder Bay has not been evaluated using MSE. Rather, it was chosen based on a recommendation for Lake Superior stocks based on exploitation rates seen as sustainable for long-lived Lake Superior fish stocks such as Lake Trout, *Salvelinus namaycush*, Lake Whitefish, *Coregonus clupeaformis*, and Lake Sturgeon, *Acipenser fulvescens* (Ebener et al. 2008, Stockwell et al. 2009). Whereas precautionary approaches to management are an important first step, such as setting conservative exploitation rates based on longer-lived species, the use of a harvest control rule tailored to cisco, obtained through a MSE that explicitly accounts for uncertainties related to cisco recruitment and assessment, could allow Lake Superior fisheries managers to better achieve objectives. No MSEs have previously been conducted for Cisco in the Laurentian Great Lakes. In addition, Cisco dynamics are characterized by extreme boom or bust recruitment, and development followed by use of a stock-recruitment relationship capturing this within a MSE was an important and somewhat novel aspect of this study.

We conducted a simplified MSE of the Thunder Bay cisco stock, projecting the stock into the future under a variety of different harvest control rules using a stochastic simulation model. Our objectives for this analysis were twofold: 1) determine whether the current exploitation rate of 10% promotes sustainability of Thunder Bay cisco, and 2) evaluate the performance of alternative harvest control rules at meeting cisco fishery objectives. Here we present results from a stochastic simulation model that attempts to account for uncertainty in the recruitment process, the assessment process, and the sex-specific nature of cisco harvest while evaluating alternative harvest control rules and tuning parameters. Success of different policies in achieving objectives was based on performance metrics, which were developed in consultation with agency personnel involved in advising agencies on fishery management. Such involvement of those engaged in the management process is often advised but less often practiced (Punt et al., 2016).

[A] Methods

[C] *Harvest Control Rules and Policy Parameters*

In preparation for this study, we presented our proposal and solicited input at the Lake Superior Technical Committee (LSTC) meeting in Sault Ste. Marie, Ontario, in July 2016. The LSTC consists of fishery biologists from agencies around Lake Superior, their purpose being to advise upper-level managers on the status of stocks and the means by which to achieve fishery objectives. Specifically, at this meeting we inquired which type of harvest control rules the LSTC would like us to consider and also which performance metrics were most important (i.e., "what are the objectives for the fishery?"). Based on input from the committee, we considered two main types of harvest control rules; constant exploitation rate and constant catch rules. We explicitly considered two variants of each control rule in addition to their standard formulation (Figure 1). For constant exploitation rate, we considered the following:

1) Constant U (CU), a simple constant exploitation rate control rule where the catch limit is proportional to spawning stock biomass (Figure 1A).

2) Constant U Threshold 1 (CUT1), defined as a constant exploitation rate until a threshold spawning stock biomass (SB_T) is reached, at which point the exploitation rate linearly declines as a function of spawning stock biomass until both are zero (Figure 1B).

3) Constant U Threshold 2 (CUT2), defined as a constant exploitation rate until an upper threshold spawning stock biomass (SB_{UT}) is reached, at which point exploitation rate linearly declines as a function of spawning stock biomass and becomes zero at some lower threshold of spawning stock biomass (SB_{LT}; Figure 1C).

For constant catch control rules, we considered:

1) Constant Catch (CC), where the catch limit is constant regardless of spawning stock size (Figure 1D).

2) Conditional Constant Catch 1 (CCC1), defined as constant catch until some threshold exploitation rate (U_T) is reached, a point at which the control rule

reverts to a constant exploitation rate at the predetermined threshold (Figure 1E; Clark and Hare 2004, Deroba and Bence 2008).

3) Conditional Constant Catch 2 (CCC2), defined as constant catch until a threshold spawning stock biomass (SB_T) is reached, at which point the catch limit is reduced to a new lower limit of constant catch (C_L, Figure 1F).

The variants of the CU rule aim to produce a compensatory response by gradually decreasing fishing mortality below a threshold. Meanwhile, variants of the CC rule aim to keep catch relatively stable while attempting to avoid high fishing mortality rates at low spawning stock sizes.

We considered spawning stock biomass thresholds (SB_T, SB_{UT}) of 20, 30, 40, and 50% of unfished spawning stock biomass, and lower spawning stock biomass thresholds for CUT2 (SB_{LT}) of 20 and 30% of unfished spawning stock biomass. We decided not to go lower than 20% of unfished spawning stock biomass as a threshold for CUT1 and CUT2, in accord with a general recommendation to cease fishing stocks that fall below that biomass (Thompson, 1993). This is also in agreement with numerous studies that have suggested that spawning biomass should be maintained between 20-50% of unfished spawning biomass (Clark, 1991; Fujioka et al., 1997; Quinn et al., 1990). We considered exploitation rates for CU, CUT1, and CUT2 of 0.05, 0.10, 0.15, 0.20, and 0.25, and constant catch limits (C) of 100,000 kg, 150,000 kg, 200,000 kg, 250,000 kg, and 300,000 kg. We chose exploitation rates and catch limits based on their proximity to the current constant exploitation rate (0.10) and to mean harvest levels over the past 17 years (163,015 kg, SD=26,548), respectively. Low catch limits may not be economically viable for fishers, and very high catch limits may exceed the current fishery capacity, as might high exploitation rates. We considered threshold exploitation rates at which CCC1 would revert to CU (U_T) of 0.15, 0.20, and 0.25. For CCC2 the lower catch limits (C_L) put in place when spawning stock biomass is estimated to be below the SB_{LT} thresholds were half of the catch limits (e.g., if the constant catch limit above the threshold was 100,000 kg a year, C_L would be 50,000 kg). In total, we simulated 51 different harvest control rule combinations (Table 1).

[C] *Performance Metrics*

Performance metrics the LSTC wanted us to consider included the magnitude of stock size, the probability of stock collapse, the magnitude of yield, and the variability in yield. The committee also noted that they were primarily interested in the performance of these metrics over a 50yr time span. For this reason, performance metrics included 1) the median spawning biomass in the final 5 years (Final SB; as a % of unfished level), 2) the percent of years the spawning biomass was below 20% of unfished spawning biomass (hereafter termed "risk" for brevity), 3) the average harvest (per year), and 4) the absolute annual variation in yield (AAV). AAV was calculated as in Punt et al. (2008):

$$AAV = \frac{\sum_{y>1} \left| H_y - H_{y-1} \right|}{\sum_{y>1} H_y}$$

Where H_y denotes harvest in a given year. These metrics were summarized in terms of the medians, 25th and 75th percentiles of their distributions over simulations.

Many of the harvest control rules and performance metrics are defined in terms of spawning stock biomass (SB):

$$SB_y = \sum_s \sum_a N_{y,a,s} P(Fish_a > 250mm) \overline{w}_{a,s}$$

where $\overline{w}_{a,s}$ is sex-specific average weight at age of a cisco estimated using a von-Bertalanffy function and a weight-length regression, and $P(Fish_a > 250mm)$ is defined as the probability that a cisco of a given age is greater than 250 mm; each of which was derived in Fisch et al. (2019). We assume that fish greater than 250 mm in length are mature, as cisco of this size caught in Thunder Bay generally are (Yule et al., 2008). We chose this definition of spawning biomass to align with how the current control rule allocates TAC of cisco in Thunder Bay (biomass of cisco > 250 mm).

We defined the estimated unfished spawning stock biomass, used in many control rules, as the median over simulations of the median spawning biomass over the final 950 years after running the simulation model for 1000 years with no harvest. For our performance metrics, some of which are defined in terms of unfished spawning biomass (risk and Final SB), we utilized a "true" unfished spawning biomass value specific to each individual simulation (each of 1000 run above). Simulations of harvest control rules then contained the same random number seed as simulations of the unfished scenario, so as to match individual simulations with their respective "true" unfished level for calculation of performance metrics. The single estimate of unfished spawning stock size (given a distribution for the frequency of boom recruitment years – see Recruitment section) used in the control rules was derived conditioned on the historical dynamics and data. Given that each individual simulation used different stock-recruitment and other demographic parameters (see Model section), each had different "true" unfished stock sizes (used in performance metrics), which differed from the estimated unfished stock size used in the control rules. Thus, our approach accounts for uncertainty in the estimate of the unfished biomass used in the control rule. This said, the estimate is in the center of the distribution of the "true" spawning biomasses used in the simulations. Our sensitivity analyses explore the consequences of changes that shift the distribution of unfished spawning biomasses, without shifting the estimate used in the control rule.

[C] *Model*

We developed a stochastic projection model (SPM) based on an integrated Statistical Catch-at-Age Assessment (SCAA) model developed in Fisch et al. (2019). For each control rule, 1000 simulations of the SPM were run to obtain distributions of performance metrics. The SPM is age- and sex-structured, beginning at age 2 and forming a plus group at 15. The SCAA model ends in 2015 and thus the SPM spans from 2016-2056 (50yr time horizon):

$$N_{y+1,a,s} = \begin{cases} 0.5R_{y+1} & \text{if } a = 2 \\ N_{y,a-1,s}e^{-(M_s+F_{y,a-1,s})} & \text{if } 3 \leq a < 15+ \\ N_{y,14,s}e^{-(M_s+F_{y,14,s})} + N_{y,15+,s}e^{-(M_s+F_{y,15+,s})} & \text{if } a = 15+ \end{cases}$$

where $N_{y,a,s}$ is the number of cisco age a of sex s in year y, R_y is recruitment in year y, M_s is the natural mortality for sex s (drawn from the SCAA posterior distribution for each simulation), and $F_{y,a,s}$ refers to fishing mortality for a given year, age, and sex combination. We began each simulation by drawing from the posterior distribution of sex-specific abundance at age in 2015 from the SCAA. A list of parameters in the SPM can be found in Table 2.

[C] *Recruitment*

Recruitment of cisco, at least over the past several decades in Lake Superior, has been characterized by a highly variable, boom-or-bust pattern where a large year class is produced, followed by successive years of little or no recruitment (Stockwell et. al, 2009; Fisch et al., 2019 - Figure 3). In the SPM, we modeled this process by drawing from a Bernoulli distribution each year that determined whether a given year would be boom or bust. The parameter for this Bernoulli distribution was drawn for each simulation from a uniform distribution with bounds l and u : $U[l,u]$. If a given year within a simulation was characterized as a boom year, a stock-recruit (SR) function was applied; if characterized as bust, the model drew a recruitment value from a lognormal distribution derived using recruitment estimates for bust years that were drawn from the posterior distribution of the SCAA for each simulation. For boom years, we derived the SR function based on the Ricker functional form (Ricker, 1975) using point estimates (medians) of the posterior distribution of recruitment and stock size estimates in the SCAA as data. Projected recruitment is then:

$$R_y = \alpha S_{y-2} e^{-\beta S_{y-2}} e^{\varepsilon_y}$$

$$\varepsilon_y \sim N(0, \sigma_r^2)$$

Where α and β are parameters of the SR model, which we drew at random for each simulation of the SPM from the posterior distribution, and ε_y are multiplicative deviations invoking stochastic recruitment over time within a simulation. We fixed σ_r at a value of 0.683 based on a meta-analysis of recruitment deviation from Thorson et al. (2014) for the order Salmoniformes. This was done due to the large value of estimated σ_r within the SR function (because of sparse data), which had the effect of producing many unrealistically high projected recruitments when initially used in the SPM. In an attempt to avoid using assessment output as data, we initially tried to estimate a SR function within the SCAA however found that the model would not converge on a solution. The derivation of the SR function can be found in the appendix. Our stock-recruitment equation contains no bias adjustment, because parameters were estimated based on analysis of log scale data.

Given uncertainty in what level of recruitment constitutes a boom or a bust year, and because the SR function and bounds of the uniform distribution are defined by this, we specifically explored two different recruitment scenarios. These scenarios are hereafter termed 7yr and 4yr (Figure 2), characterized by how we define what constitutes a boom year. The 7yr scenario treats years in the SCAA that had a median recruitment (age-2 abundance) over 200,000 as boom years (7/17 years in the SCAA fit this criteria), while the 4yr scenario treats years that had a median recruitment (age-2 abundance) over 1 million as boom years (4/17 years in the SCAA fit this criteria). We based the bounds of the uniform distribution for each recruitment scenario on the perceived frequency of boom year classes over a period from 1985-2015 using observations from both the SCAA (Fisch et al., 2019) and Figure 15 in Yule et al., (2006). These bounds were defined as U(0.25,0.40) for the 7yr scenario, based on evidence 0f ~9-11 boom year classes over the 30 year period, and U(0.15,0.25) for the 4yr scenario, based on evidence of ~6 boom year classes over the 30 year period. For each simulation we placed recruitment values in the SCAA that were not characterized as boom recruitment years in the bust category and used them to derive a lognormal distribution of bust recruitments.

[C] *Fishing Mortality*

Our approach to setting fishing mortality rates for each year of the simulation was to set fishing rates so the resulting harvest matched a value obtained by applying the control rule to the assessed spawning biomass (see Assessment Error below). Some complexity is added because we are modeling dynamics as sex specific and although cisco harvest is dominated by female fish (mean from 1999-2015 = 81%), there is inter-annual variation (SD = 5%). Our approach was to stochastically simulate the sex ratio of the fishing intensities (fully selected fishing mortality) each year, and then solve for the fishing intensity of females (and given the ratio, the fishing intensity of males) that produced the desired harvest. The sex ratio of fishing intensities is defined as:

$$f_y^r = \frac{f_{y,m}}{f_{y,m} + f_{y,f}}$$

Where f_y^r denotes the fishing intensity ratio in a given year, $f_{y,m}$ is male fishing intensity, and $f_{y,f}$ is female fishing intensity. We drew fishing intensity ratios for all 17 years of the SCAA for each simulation in the SPM and used them to define a beta distribution. We defined each beta distribution by two shape parameters, $p = \mu\left(\frac{\mu(1-\mu)}{\sigma^2} - 1\right)$ and $q = (1-\mu)\left(\frac{\mu(1-\mu)}{\sigma^2} - 1\right)$, where μ and σ^2 are the mean and variance of the ratio of fishing intensities pulled from the posterior distribution of the

SCAA for each simulation. We used the corresponding beta distribution for each simulation to draw fishing intensity ratios for each year within the SPM. We solved for fishing intensity for a given sex/year combination in each simulation using Newton-Raphson iterations given a desired harvest for that year and simulation:

$$\sum_s \sum_a \left[\frac{F_{a,y,s}}{M_s + F_{a,y,s}} N_{a,y-1,s} \left(1 - e^{-(M_s + F_{a,y,s})}\right) W_{a,s} \right] - H_y$$

$$F_{y,a,s} = s_a f_{y,s}$$

where s_a refers to age-specific cisco fishery selectivity (parameters that define selectivity function were drawn from the SCAA posterior distribution), $W_{a,s}$ refers to sex-specific average weight-at-age of commercially caught cisco, and H_y denotes harvest in a given year and is defined based on a control rule. We solved for female fishing intensity in a given year and calculated male fishing intensity using the fishing intensity ratio and female fishing intensity:

$$f_{y,m} = \frac{f_y^r * f_{y,f}}{1 - f_y^r}$$

We set a maximum fishing mortality rate of 3 to limit unrealistic scenarios that could have fishers catching nearly every fish in a given year.

[C] *Assessment Error*

We assume within the SPM that a stock assessment will be performed every year to estimate spawning stock biomass (which defines catch limits, as opposed to using hydroacoustic surveys). We simulated assessment estimation error within the SPM through an autoregressive process

$$\hat{S}B_y = SB_y e^{\varepsilon_y - \frac{\sigma_e^2}{2}} \qquad \varepsilon_y = \begin{cases} \delta_y & \text{for y} = 1 \\ \rho\varepsilon_{y-1} + \sqrt{1-\rho^2}\,\delta_y & \text{for y} > 1 \end{cases} \qquad \delta_y \sim N(0, \sigma_e^2)$$

Where $\hat{S}B_y$ denotes the assessed spawning biomass and SB_y is the true spawning biomass. We specified ρ and σ_e as 0.7 and 0.22, assuming a lognormal assessment error with a CV of about 0.22. We based this on the CV of spawning biomass in the final year of the SCAA (~0.22). We explored alternate values of rho and sigma $(\rho = 0.9, \sigma_e = 0.4)$ to assess the sensitivity of results to levels of assessment error. Similar procedures have been done in previous harvest policy projections (Irwin et al. 2008; Punt et al. 2008; Deroba and Bence 2012). We did not model implementation error within the SPM, given license holders rarely, if ever, go over their individual quotas. Thus, assuming fishers meet their quotas (unless the fishing mortality rate limit of 3.0 is reached) is likely a conservative assumption.

[C] *Sensitivity Analyses*

We examined sensitivity to the bounds of the uniform distribution for the probability of a boom year class by shifting the distribution ± 0.05 for each recruitment scenario. Several of the control rules we considered use estimated unfished spawning stock biomass, and this value (determined based on running the SPM for 1000 years with no harvest) depends on the distribution for the probability of boom years. Therefore, we explored two alternate scenarios for estimating unfished spawning biomass when shifting the distribution for boom years. First, we re-calculated the estimate of unfished spawning biomass used in the control rule based on the shifted uniform distributions, and second we set the estimate of unfished spawning biomass used in the control rule at the value calculated using the baseline uniform distribution bounds. The first scenario represents a case where the change in estimated unfished spawning biomass was accounted for in the control rule. The second scenario explores the situation where managers erroneously specify the unfished spawning biomass when the frequency of boom years was shifted, i.e., the shifts represent a situation where system productivity was both different and miss-specified in the control rule. For the first scenario, where unfished spawning biomass used in the control rules is recalculated according to the shift, we compare results with the baseline model, evaluating how a change in the frequency of boom recruitments (that is accounted for in terms of the change in estimated unfished spawning biomass) influenced outcomes. For the second scenario, we make two comparisons. First, by comparing with the first scenario (where the recruitment distribution was also shifted but estimated unfished spawning biomass was recalculated to account for this), we isolate the effect of miss-specifying unfished spawning biomass in the control rule. Second, by comparing with the baseline model we evaluated how a mistaken characterization of recruitment productivity influences our view on the performance of different harvest policies. Sensitivity runs related to different levels of assessment error, productivity, and estimated unfished spawning biomass solely included the 4yr recruitment scenario.

[A] Results

Estimated unfished spawning biomass for the 4yr and 7yr recruitment scenarios were 4,453,000 kg and 4,420,000, respectively. Results in text and Table 1 are presented as medians of distributions over simulations.

[B] *Recruitment Scenario*

Rankings for performance metrics among harvest control rules were largely robust to recruitment scenarios. However, absolute values did differ, with results reflecting the increased productivity for the 7yr scenario (i.e., higher yield, lower risk, higher Final SB, and lower AAV). For this reason, hereafter in text we present the results solely for the 4yr recruitment scenario, with results for the 7yr recruitment scenario in Table 1 and supplemental figures 4-7.

[B] *Average Yield*

Constant exploitation rate and its variants (CU, CUT1, CUT2) outperformed constant catch rules in terms of the maximum (over policy parameters) average yield over the 50yr simulation period (Figure 3). Within CU control rules, as we would expect, average yield was lowest for the 0.05 rate. As exploitation rate increased from 0.05 to 0.10-0.25 however, an asymptote was reached at about 250,000 kg of yield per year (Table 1, Figure 3). While the median (over simulations) average yield for CU reached an asymptote, the spread of the 25-75 quantile range slightly increased as exploitation rate increased from 0.05-0.25. Variants of the CU rule (CUT1 and CUT2) had higher average yields than their CU counterparts with similar exploitation rates (Figure 3). The largest average yield across all control rule scenarios (331,208 kg per year) resulted from the CUT2 rule with an exploitation rate of 0.20 that declined linearly to zero between 50% and 30% of unfished spawning stock biomass (Policy 1.3.10, Table 1, Figure 3). The constant catch control rules, even at their highest catch limits (300,000 kg per year), were only able to produce average yields of around 185,000 kg per year. In fact, when we increased catch limits above 300,000 kg (up to 850,000 kg) within CC, an asymptote in average yield was reached at around 230,000 kg per year. When thresholds were included in constant catch control rules (CCC1 and CCC2), yield did not increase compared to CC rules with similar catch limits and in fact slightly decreased in almost all cases (exception is policy 2.1.3 vs 2.2.3; Table 1, Figure 3).

[B] *Risk (% of years SB < 20% unfished level)*

Where CU rules did not show much difference in yield at 0.10-0.25 exploitation rates, they exhibited large differences in risk. As exploitation rate increased within the CU control rule from 0.05-0.25, the amount of risk more than tripled from 18% of years having a SB below 20% of the unfished level at an exploitation rate of 0.05 to 66% of years under an exploitation rate of 0.25 (Table 1, Supplemental Figure 2). For reference, under the unfished scenario (where SPM was run with no harvest), risk was 10%. The inclusion of thresholds in constant exploitation rate control rules greatly decreased risk within a given exploitation rate. For CUT1 rules, risk decreased both compared to the respective CU rule with the same exploitation rate and within the CUT1 rule as the threshold was increased from 20-50% of unfished SB. Risk was further decreased with the inclusion of a lower threshold SB within the CUT2 rules. That is, for exploitation rates of 0.10 and 0.20, risk was lower for the CUT2 rule than for its CUT1 and CU counterparts. For an exploitation rate of o.10, risk was 33% for CU, 24% at its lowest in CUT1, and 20% at its lowest in CUT2 (Policies 1.1.2, 1.2.8, and 1.3.5; Table 1). A similar result occurred for exploitation rates of 0.20, where under CU risk was 58%, 42% at its lowest under CUT1, and 34% at its lowest under CUT2 (Policies 1.1.4, 1.2.16, and 1.3.10; Table 1).

Within CC rules, risk increased from 22% at a catch limit of 100,000 kg a year to 53% at a catch limit of 300,000 kg a year. Risk decreased with the inclusion of exploitation rate thresholds for CCC1 policies. Within CCC1, risk increased as the threshold exploitation rate increased. For each limit of catch, the use of biomass thresholds under the CCC2 rule decreased risk compared to CC control rules. In addition, within CCC2 risk generally decreased as threshold SB levels increased. For example, under a catch limit of 200,000 kg a year (CC risk=41%), including a biomass threshold at 20% of unfished SB decreased risk to 34% and including a biomass threshold at 30% of unfished SB decreased risk to 31%. The lowest risk level over all control rules was therefore under a CCC2 rule with the lowest catch limit, 100,000 kg, and a threshold of 30% of the unfished spawning biomass at which point the catch limit would be cut in half (Policy 2.3.2, risk=18%).

[B] *Absolute Annual Variation in Yield (AAV)*

AAV was considerably smaller for the constant catch control rules compared to constant exploitation rate rules (Table 1, Supplemental Figure 3). For example, a CC rule with a catch limit of 200,000 kg a year (Policy 2.1.3) had an AAV of 0.06 while a CU rule with an exploitation rate of 0.15 (Policy 1.1.3) had an AAV of 0.33. Also, the inclusion of a threshold within any rule (CUT1 & CUT2 as compared to CU and CCC1 & CCC2 as compared to CC) increased AAV for all policies. Within constant exploitation rate control rules, AAV increased as exploitation rate increased. Within CUT1, AAV increased as threshold biomass levels increased over all exploitation rates. The inclusion of a lower threshold biomass at which exploitation rate would become zero (for CUT2) increased AAV further compared to CUT1 and CU control rules, and AAV increased as both upper and lower SB thresholds increased.

For constant catch control rules, AAV increased as catch limit increased, from 0 at 100,000 kg a year (Policy 2.1.1) to 0.11 at 300,000 kg a year (Policy 2.1.5). The inclusion of threshold exploitation rates for CCC1 increased AAV compared to CC policies with similar catch limits. For example, a CC rule with a catch limit of 250,000 kg a year (Policy 2.1.4) had an AAV of 0.09 while a CCC1 rule with a catch limit of 250,000 kg per year and a threshold exploitation rate of 0.15 (Policy 2.2.4) had an AAV of 0.14. Within CCC1, AAV generally decreased as the threshold exploitation rate increased for a given catch limit. The inclusion of biomass thresholds for CCC2 policies also increased AAV compared to CC policies with similar catch limits. Within CCC2, AAV generally increased as biomass thresholds increased.

[B] *Spawning Biomass at the end of the simulation period (Final SB)*

Spawning biomass at the end of the simulation period, defined as the median spawning biomass for the final 5 years of each simulation (Final SB, presented as a percentage of unfished SB), was similar among base harvest control rules (CU & CC, Figure 4). However, the spread of the Final SB for constant catch control rules was much greater than that of the constant exploitation rate control rules.

Within CU rules, Final SB decreased as exploitation rate increased, from 69% of the unfished level at an exploitation rate of 0.05 (Policy 1.1.1) to 7% at an exploitation rate of 0.25 (Policy 1.1.5). For any given exploitation rate, adding a SB threshold within CUT1 increased Final SB, and CUT2 rules involving an additional lower threshold further increased Final SB. For example, a CU rule with an exploitation rate of 0.10 produced a Final SB 37% of the unfished level (Policy 1.1.2) while a CUT2 rule with an exploitation rate of 0.10, an upper SB threshold of 50% of unfished SB, and a lower SB threshold of 30% of unfished SB produced a Final SB of 54% of the unfished level (Policy 1.3.5, Table 1). Within CUT1 rules of a given exploitation rate, Final SB generally increased as threshold biomass increased. Similarly, within CUT2 rules given a level of exploitation rate, Final SB generally increased as both upper and lower SB thresholds increased.

Within the CC control rule, Final SB declined as catch limits increased, from 66% of the unfished level at 100,000 kg a year (Policy 2.1.1), to 14% at 300,000 kg a year (Policy 2.1.5). The inclusion of threshold exploitation rates for CCC1 increased Final SB, and within CCC1 Final SB decreased as threshold exploitation rate increased. For all catch limits, the inclusion of SB thresholds within CCC2 rules increased Final SB levels compared to CC rules with similar catch limits. Final SB also increased as SB threshold increased within CCC2 rules.

[B] *Sensitivity*

Results were largely robust to higher levels of assessment error $(\sigma_e = 0.4)$ in addition to increased levels of autocorrelation $(\rho = 0.9)$, as the ranking of performance metrics among harvest control rules changed little when these parameters were changed compared to the baseline model results (Supplemental figures 8-15). For AAV, absolute values were higher among all constant exploitation rate control rules for $\sigma_e = 0.4$, and lower for $\rho = 0.9$, compared to the baseline model (Supplemental figures 10 & 14).

Under scenarios where bounds of the uniform distribution defining the probability of a boom year class are shifted up or down by 0.05, estimates of unfished spawning biomass for use in the control rules were 6,209,000 and 2,795,000 kg, respectively (for the 4yr scenario). For these scenarios, where a new estimate of unfished spawning biomass calculated according to the shift in the frequency of boom recruitments was used in the control rules, the shift had little influence on how the different control rules ranked with regard to the performance metrics (compared to the baseline; Supplemental figures 16-23). However, absolute values of the performance metrics did change substantially from the baseline model, as might be expected given we are comparing scenarios with different actual distributions of productivity. Specifically, when the uniform distribution for boom years was shifted downward by 0.05, yield and Final SB decreased for almost all control rules compared to the baseline model. In addition, AAV and risk increased for constant catch rules compared to the baseline model (Supplemental Figures 17-18). For the more productive counterpart (bounds of the uniform increased by 0.05), the opposite occurred in that Final SB and yield increased, and risk and AAV decreased compared to the baseline model, however this time over all control rules (not just constant catch, Supplemental Figures 20-23).

When we shifted the bounds of the uniform distribution defining the probability of a boom year class up or down 0.05 and the estimate of unfished spawning biomass used in the control rule came from the baseline model (this estimate was toward the low end or high end of the distribution of “true” unfished spawning biomass values, respectively, rather than being at the center of the distribution), the failure to adjust the estimate of the unfished biomass had little influence on the relative ranking of performance metrics among control rules, and absolute changes were relatively modest, in contrast to when we compared scenarios for which actual frequencies of boom year classes had changed. Here we are comparing scenarios with the same assumptions about actual boom year classes, but with this either being accounted for not accounted for in the estimate of unfished spawning biomass used in the control rule (Supplemental Figures 24-31). When the probability of a boom year class was shifted down by 0.05, but the estimate of unfished spawning biomass used in the control rule was based on the baseline model, changes to when the shift was accounted for in the estimation of unfished spawning biomass were increased AAV, decreased risk, and increased Final SB for control rules with biomass-based thresholds (Supplemental figures 25-27). When the probability of a boom year class was shifted upward by 0.05 and the estimate of unfished spawning biomass was based on the baseline model, the opposite occurred. There was an increase in risk, a decrease in AAV, and a decrease in Final SB for control rules with biomass based thresholds (Supplemental Figures 29-31), in comparison with when the shift was accounted for in the estimate of spawning biomass used in the control rule.

When the absolute values for these scenarios were compared instead to the baseline results (i.e., evaluating the combined effect of the shift and failure to account for it by changing the estimate of unfished spawning biomass), the scenario where the uniform distribution is shifted upward by 0.05 exhibited greater average harvest, lower risk, lower AAV, and greater Final SB (Supplemental Figures 32-35). The opposite occurred for the scenario where the uniform distribution was shifted downward by 0.05 (i.e., lower harvest, greater AAV, and lower Final SB compared to baseline;

Supplemental Figures 36-39), with the exception that risk was lower many CUT1 and CUT2 rules (Supplemental Figure 37).

[A] Discussion

To address the first objective—to determine whether the current 10% exploitation rate promotes sustainability of the Thunder Bay cisco fishery—we must specify what constitutes "sustainability" of cisco in Thunder Bay. One simple way to look at sustainability is to observe the distribution of SB each year over the time series and determine whether it is stable near the end, i.e., does the population distribution crash or is it on a downward trajectory? In this case the 10% rate is "sustainable", as the trajectory over the 50yr time period for the 4yr recruitment scenario is seemingly stable at a median estimate of around 1.5 million kg of SB (Figure 5).

A more robust way to explore the sustainability question may be to examine it in terms of maintaining SB above a threshold to ensure sufficient replenishment. Many studies have presented arguments for maintaining SB above certain thresholds in fish populations, often arguing for maintenance of >20% of unfished spawning stock size (Beddington and Cooke, 1983; Quinn et al., 1990; Clark 1991; Francis 1993; Goodyear, 1993; Hollowed and Megrey, 1993; Leaman, 1993; Thompson, 1993; Caddy and Mahon, 1995; Fujioka et al., 1997). If we utilize this criterion, the current 10% exploitation rate is usually "sustainable", as the SPM projects a median Final SB of 37% and 64% of the unfished level for the 4yr and 7yr scenarios respectively. This "sustainability" designation is largely insensitive to reduced productivity in terms of the probability of a boom year class. For example, when the SPM is re-run with bounds of the uniform distribution defining the probability of a boom year class shifted down by 0.05, Final SB is 29% of the unfished level (estimated using new bounds) under the 4yr recruitment scenario.

In terms of our second objective, determining whether the 10% CU control rule can be improved upon to both promote sustainability and meet fishery objectives, the answer is more complicated. Within the framework of the CU control rule and levels of exploitation we considered, the answer is no, as the current 10% rate effectively maximizes yield, maximizes Final SB, and minimizes both risk and AAV compared to higher exploitation rates. However, the adoption of a CUT1 or CUT2 rule will slightly increase yield, greatly decrease risk, and increase Final SB. It is also possible that slight improvements could be obtained by more fine evaluation of exploitation rates between 0.05 and 0.15. These results are similar to those found by Deroba and Bence (2012) for Lake Whitefish, *Coregonus clupeaformis*, in 1836 treaty waters of the Laurentian Great Lakes. The tradeoff lies in the AAV, where adoption of a CUT2 rule will increase year-to-year variation in yield most, followed by CUT1 rules compared to the current CU control rule. This is due to the compensatory mechanism within these control rules that aims to change exploitation rate below biomass thresholds. This difference averages around a ~0.04 increase in AAV from CU to CUT1 and a ~0.08 increase from CU to CUT2 under an exploitation rate of 0.10. If stakeholders are indifferent to this increase in AAV, and rather more interested in magnitude of yield, decrease in risk, and increase in the Final SB, a CUT2 rule is likely most appropriate for cisco in Thunder Bay. Conversely, if stakeholders are more interested in low variation in yield as a performance metric, a constant catch rule may be more appropriate. Constant catch rules greatly outperformed in terms of this metric, however at large costs in terms of increased risk and decreased

Final SB when achieving the same yield as exploitation rate-based rules. Out of the constant catch rules, CCC2 was most effective in decreasing risk, increasing Final SB, while not costing much in yield and AAV compared to CC rules with similar catch limits. If constancy in yield is held in high regard, as it may allow for more optimal planning of each fishing season (hiring of deck hands or processors, appropriate number of nets and plant processing capacity, etc.), then adoption of a constant catch control rule with a threshold of the CCC2 type will most appropriately meet fishery objectives.

Other than AAV, results were largely insensitive to changes in the level and correlation of assessment error. Not surprisingly, when the magnitude of assessment error was higher, AAV increased. This suggests that when low inter-annual variation in yield is valued highly, greater investment in assessment would be justified. The insensitivity of other performance metrics to assessment error has been noted in similar studies (Irwin et al., 2008; Punt et al., 2008; Deroba and Bence, 2012), where in others it has proved consequential (Katsukawa 2004), largely in the direction of increased assessment error decreasing the performance of control rules involving biomass thresholds. It may be that the levels of assessment error we simulated (σ_e =0.4) are not high enough to decrease the improvement of threshold-based control rules over those without thresholds. One could imagine that as assessment error increases to infinity, control rules based on changing exploitation or catch as a function of the assessed value would diminish in performance. Our approach to simulating assessment error via distributions instead of performing a full stock assessment simulation every year in the SPM was primarily driven by time constraints for analysis. The lack of sensitivity of metrics other than AAV to assessment error suggests that results are likely robust to this simplifying assumption. In future work, more detailed treatment of assessment error could prove beneficial. For example, our simulations assumed a stock assessment would be performed every year for the stock. Additional simulations contrasting when the control rule is applied to hydroacoustic estimates of abundance or based on past estimates when the survey could not be done (how TAC is currently set), versus when it is applied to model-based assessments would inform on the value of model-based assessments.

Although relative comparison of the harvest control rules was largely unchanged under different recruitment hypotheses/scenarios, the specific policy parameters that produce the "best" results (defined in terms of the various performance metrics) did change among these scenarios. For example, one could obtain the same levels of risk with higher exploitation rates or catch limits under the 7yr scenario, likely due to the increased frequency of "boom" year classes in the 7yr scenario. Given the uncertainty regarding recruitment, we suggest basing specific harvest policy decisions on the 4yr scenario, given that the policies and specific policy parameters for that scenario would produce reasonable performance for more productive scenarios. This subject is relevant once again when discussing sensitivity to changed productivity in terms of the probability of a boom year class. These sensitivity runs, which involved shifting the uniform distribution defining the probability of a boom year class up or down by 0.05 largely resulted in the same relative performance across all harvest control rules. Although not surprisingly, absolute values differed when the frequency of boom year classes changed, potentially resulting in different conclusions as to which specific control rule meets sustainability criteria. Nevertheless, under reduced productivity, for example due to less frequent boom year classes, a CUT2 rule at an exploitation rate of 0.10 can still achieve a final SB > 20% of the unfished level.

Importantly, the distributions of performance metrics that were achieved were generally robust to using an estimate of unfished spawning that was based on incorrect assumptions, provided the comparison was between scenarios with the same actual probabilities of boom year classes. Thus, at least based on our study, the issue with getting the estimate of unfished stock size incorrect has more to do with this being connected to incorrectly assessing the productivity of the stock and thus the sustainable exploitation, rather than sensitivity of stock dynamics and fishery outcomes to the estimated unfished spawning biomass used in the control rule. Similar to the results reported here, Irwin et al. (2008) also found for a policy like CUT2, the precise biomass at which exploitation began to be reduced was not critical to gaining the benefits of making exploitation rate dependent on stock size.

The reliability of estimated unfished biomass levels has been discussed in previous studies, where life history characteristics of a species and temporal autocorrelation in recruitment have been shown to alter estimation performance (Haltuch et al., 2008, 2009). Haltuch et al., (2008) found that for all methods of estimating unfished biomass examined, performance was generally poorer in the presence of high recruitment variability, which cisco clearly exhibit. If the specification of a specific unfished biomass based on the SPM is of concern to managers, an alternative is to set it based on some low objective value, e.g., no harvest below 500,000 kg of spawning biomass. Given the lack of sensitivity of results we saw to the threshold used, this could retain some desirable characteristics of threshold policies (decreased risk, increased Final SB) while not having to rely on correctly estimating the unfished level of the stock.

Our study is not without caveats and assumptions. A critical assumption we made was that the probability of a boom year class is static through time. The dominant theory in the literature as it pertains to what is driving these sporadic boom recruitment years for cisco is one of match-mismatch, where abiotic and biotic factors are hypothesized to line up once every few years to allow for large cisco recruitment events (Myers et al., 2015). Further simulations are necessary that take into account the potential effects of changing environmental conditions (e.g., climate change) on cisco recruitment in assessing the relative performance of harvest control rules.

In addition, our stock-recruitment function was quite uncertain. The input data came from stock assessment results (potential issues discussed in Maunder and Punt, 2013; Thorson et al., 2013; Brooks and Deroba, 2015) and provided only 4-7 years of data on recruitment and stock size for boom years. Given the scarcity of data and particularly data near the origin, we relied on published priors for recruits per unit spawning stock near the origin (Myers, 1999) and variation in recruitment given stock size (Thorson et al., 2014). While these priors are based on the same taxonomic family and order as cisco, respectively, most stocks used in constructing the priors were anadromous salmon, which exhibit very different life histories and reproductive strategies compared to cisco. Other uncertain aspects of the SR function such as the assumption of no depensation could also not be addressed with the available data.

It is important to note that the current control rule in Thunder Bay is defined as a function of the biomass of fish > 250mm. In Minnesota waters, the control rule is defined in terms of the biomass of fish > 305mm. For this study we followed the Thunder Bay convention in defining spawning biomass as cisco > 250mm given these individuals are generally mature (Yule et al., 2006; Yule et al., 2008). If the results of this comparison are to be used in determining harvest policies and control rules in other cisco harvesting regions, the implication of different definitions for spawning biomass should be considered.

In summary, we have shown in this study that the current exploitation rate of 0.10 on Thunder Bay cisco is sustainable (given certain criteria). We have also simulated the effects of a variety of alternate harvest control rules for managing cisco and found that, compared to the current control rule, the inclusion of biomass thresholds within CUT1 or CUT2 control rules can greatly decrease risk and increase yield and spawning biomass at the end of the time series, at a cost of increased year-to-year variation in yield. Finally, if constancy in year-to-year yield is held in the highest regard, we have shown that constant catch control rules greatly outperform constant exploitation rate control rules in terms of this performance metric for cisco in Thunder Bay, and the inclusion of biomass thresholds within CCC2 rules decreases risk and increases Final SB at little cost to yield and AAV.

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[A] Appendix

The SR function used to project recruitment in the case of a boom year was derived using spawning biomass (mature female kg) and recruitment data from median point estimates of the posterior distribution of the SCAA (Fisch et al., 2019). Given spawning biomass and recruitment are on a 2 year lag (i.e. SCAA has recruitment in 1999 and 2000) we calculated spawning biomass in 1997 and 1998 by hindcasting from the estimated 1999 stock abundance using natural mortality and harvest in 1997-1998. Due to the scarcity of stock-recruitment data (either seven or four data points for each recruitment scenario), we placed an informative prior on the log alpha parameter based on the family Salmonidae in Myers et al. (1999): $\log(\tilde{\alpha}) \sim N(1.43, 0.05^2)$. The recruitment estimates then had to be standardized

$$\tilde{R}_y = R_y SSBR_{F=0}(1 - e^{-M})$$

Where $\tilde{R}_y$ are the standardized recruitments, R_y are the recruitment medians from the SCAA, $SSBR_{F=0}$ is spawning biomass (mature female kg) produced per recruit in the unfished condition, and M is the female natural mortality point estimate from the SCAA (median). The Ricker model is then fit as

$$\log\left(\frac{\tilde{R}_y}{SB_{y-2}}\right) = \log(\tilde{\alpha}) - \beta * SB_{y-2} + \varepsilon_y$$

Where SB denotes spawning biomass, calculated as the weight of mature females. This model was run for 10 million iterations saving every 500th and burning in 2500 of the final iterations. When used in the SPM we must back transform $\tilde{\alpha}$

$$\alpha = \frac{e^{\tilde{\alpha}}}{SSBR_{F=0}(1-e^{-M})}$$

The recruitments for boom years are then projected by:

$$R_y = \alpha * SB_{y-2} * e^{-\beta * SB_{y-2}} * e^{\varepsilon_y}$$

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Tables

Table 1. Performance metrics for the 4yr and 7yr recruitment scenarios (4yr | 7yr). Values are presented as medians over simulations. Yield (kg) denotes mean yield over the 50 year time span. Risk is calculated as the percentage of years SB is below 20% of the unfished level. AAV measures inter-annual variation in yield as defined in methods. Final spawning biomass is the median SB of the last 5 years in a simulation (as a percentage of unfished). Catch limits in the policy parameters column for constant catch control rules are presented in 100,000 kg (i.e. 100k=100,000 kg). Each policy has a specific code identifier (e.g., 1.1.1).

Harvest Policy	Policy Parameters	Yield (kg)	Risk (%)	AAV	Final SB (%)
Unfished					
0.0	No Harvest	0	10 | 2	0	103 | 104
CU					
1.1.1	U=0.05	179610 | 195337	18 | 6	0.27 | 0.24	69 | 84
1.1.2	U=0.10	250044 | 317580	33 | 12	0.30 | 0.27	37 | 64
1.1.3	U=0.15	257663 | 375958	46 | 22	0.33 | 0.30	19 | 44
1.1.4	U=0.20	248780 | 373577	58 | 34	0.35 | 0.31	11 | 25
1.1.5	U=0.25	238140 | 355979	66 | 44	0.36 | 0.32	7 | 16
CUT1					
1.2.1	U=0.05, SB_T=20%	180994 | 195673	18 | 6	0.28 | 0.25	72 | 85
1.2.2	U=0.05, SB_T=30%	183038 | 195247	16 | 6	0.29 | 0.25	72 | 85
1.2.3	U=0.05, SB_T=40%	183557 | 194102	16 | 4	0.30 | 0.26	73 | 85
1.2.4	U=0.05, SB_T=50%	181905 | 191941	16 | 4	0.31 | 0.27	74 | 87
1.2.5	U=0.10, SB_T=20%	258631 | 319321	30 | 10	0.32 | 0.28	41 | 67
1.2.6	U=0.10, SB_T=30%	264863 | 322671	28 | 10	0.34 | 0.29	44 | 68
1.2.7	U=0.10, SB_T=40%	267653 | 321487	26 | 10	0.35 | 0.30	47 | 70
1.2.8	U=0.10, SB_T=50%	271273 | 320127	24 | 8	0.36 | 0.30	48 | 71
1.2.9	U=0.15, SB_T=20%	273220 | 381148	42 | 20	0.36 | 0.31	24 | 48
1.2.10	U=0.15, SB_T=30%	286030 | 386772	40 | 18	0.38 | 0.32	27 | 51
1.2.11	U=0.15, SB_T=40%	295870 | 389956	38 | 16	0.39 | 0.33	30 | 53
1.2.12	U=0.15, SB_T=50%	298069 | 389650	36 | 14	0.40 | 0.34	32 | 55
1.2.13	U=0.20, SB_T=20%	269039 | 395099	52 | 30	0.39 | 0.33	17 | 34
1.2.14	U=0.20, SB_T=30%	283014 | 404402	48 | 26	0.41 | 0.35	19 | 39
1.2.15	U=0.20, SB_T=40%	294209 | 414013	46 | 24	0.43 | 0.36	22 | 41

Table 1. (cont'd)

1.2.16	U=0.20, SB_T=50%	303101 | 423362	42 | 22	0.44 | 0.37	24 | 44
1.2.17	U=0.25, SB_T=20%	268231 | 389017	58 | 38	0.41 | 0.35	13 | 25
1.2.18	U=0.25, SB_T=30%	280698 | 403476	55 | 34	0.44 | 0.36	15 | 30
1.2.19	U=0.25, SB_T=40%	292118 | 415541	52 | 30	0.46 | 0.38	18 | 33
1.2.20	U=0.25, SB_T=50%	301277 | 424750	48 | 28	0.47 | 0.40	19 | 36
CUT2					
1.3.1	U=0.10, SB_{UT}=30%, SB_{LT}=20%	273723 | 323895	24 | 8	0.36 | 0.30	49 | 71
1.3.2	U=0.10, SB_{UT}=40%, SB_{LT}=20%	276220 | 321185	23 | 8	0.37 | 0.31	50 | 71
1.3.3	U=0.10, SB_{UT}=50%, SB_{LT}=20%	277347 | 317480	22 | 8	0.38 | 0.32	52 | 72
1.3.4	U=0.10, SB_{UT}=40%, SB_{LT}=30%	279039 | 318711	22 | 8	0.38 | 0.32	52 | 72
1.3.5	U=0.10, SB_{UT}=50%, SB_{LT}=30%	281826 | 316467	20 | 6	0.39 | 0.33	54 | 74
1.3.6	U=0.20, SB_{UT}=30%, SB_{LT}=20%	307403 | 431024	40 | 22	0.46 | 0.38	25 | 43
1.3.7	U=0.20, SB_{UT}=40%, SB_{LT}=20%	320252 | 433642	38 | 20	0.47 | 0.39	28 | 45
1.3.8	U=0.20, SB_{UT}=50%, SB_{LT}=20%	327631 | 436614	36 | 16	0.49 | 0.41	30 | 48
1.3.9	U=0.20, SB_{UT}=40%, SB_{LT}=30%	330235 | 439541	36 | 16	0.49 | 0.41	31 | 48
1.3.10	U=0.20, SB_{UT}=50%, SB_{LT}=30%	331208 | 439614	34 | 14	0.51 | 0.43	33 | 50
CC					
2.1.1	C=100k	99838 | 99999	22 | 4	0 | 0	66 | 83
2.1.2	C=150k	138120 | 149997	30 | 8	0.04 | 0	44 | 73
2.1.3	C=200k	160114 | 198216	41 | 12	0.06 | 0.01	31 | 62
2.1.4	C=250k	176635 | 235566	48 | 19	0.09 | 0.03	20 | 51
2.1.5	C=300k	186973 | 262570	53 | 26	0.11 | 0.05	14 | 37
CCC1					
2.2.1	C=200k, U_T=0.15	155714 | 186374	30 | 10	0.10 | 0.05	44 | 72
2.2.2	C=200k, U_T=0.20	158828 | 190935	35 | 10	0.09 | 0.04	37 | 66
2.2.3	C=200k, U_T=0.25	160393 | 193955	38 | 12	0.08 | 0.03	34 | 65
2.2.4	C=250k, U_T=0.15	173246 | 219183	36 | 12	0.14 | 0.07	36 | 66
2.2.5	C=250k, U_T=0.20	175738 | 225113	40 | 14	0.12 | 0.06	29 | 59
2.2.6	C=250k, U_T=0.25	175358 | 229304	44 | 16	0.11 | 0.05	25 | 57
CCC2					
2.3.1	C=100k, SB_T=20%, C_L=50k	91009 | 97003	18 | 4	0.04 | 0.02	75 | 87

Table 1. (cont'd)

2.3.2	C=100k, SB_T=30%, C_L=50k	86995 | 93998	18 | 4	0.05 | 0.04	77 | 89
2.3.3	C=150k, SB_T=20%, C_L=75k	130166 | 143999	26 | 8	0.06 | 0.02	55 | 77
2.3.4	C=150k, SB_T=30%, C_L=75k	124215 | 139497	24 | 6	0.07 | 0.04	62 | 80
2.3.5	C=200k, SB_T=20%, C_L=100k	158593 | 189925	34 | 10	0.08 | 0.04	37 | 67
2.3.6	C=200k, SB_T=30%, C_L=100k	153871 | 181997	31 | 8	0.09 | 0.05	42 | 71
2.3.7	C=250k, SB_T=20%, C_L=125k	175178 | 227671	42 | 14	0.10 | 0.04	26 | 57
2.3.8	C=250k, SB_T=30%, C_L=125k	172548 | 219998	38 | 12	0.11 | 0.06	30 | 62
2.3.9	C=300k, SB_T=20%, C_L=150k	187017 | 259610	50 | 22	0.12 | 0.06	17 | 46
2.3.10	C=300k, SB_T=30%, C_L=150k	183659 | 253198	46 | 16	0.13 | 0.07	21 | 52

Table 2. Parameters of the SPM, including their treatment over simulations and source.

Parameter Description	**Treatment**	**Source**
Sex-specific abundance at age ($N_{a,y,s}$, to begin SPM)	Drawn from SCAA posterior for each simulation	Fisch et al., (2019)
Sex-specific natural mortality (M_s)	Drawn from SCAA posterior for each simulation	Fisch et al., (2019)
Fishing intensity sex ratios $\left(f_y^r\right)$	Drawn from SCAA posterior for each simulation	Fisch et al., (2019)
Fishery selectivity (s_a)	Drawn from SCAA posterior for each simulation	Fisch et al., (2019)
Weight-at-age of all cisco $(\overline{w}_{a,s})$	Constant over simulations	Fisch et al., (2019)
Weight-at-age of commercially caught cisco $(W_{a,s})$	Constant over simulations	Fisch et al., (2019)
Probability cisco age a is larger than 250mm, $P(Fish_a > 250mm)$	Constant over simulations	Fisch et al., (2019)
Assessment error parameters ρ, σ_e	Constant over simulations	σ_e - CV of 2015 SCAA SB (Fisch et al., 2019). ρ - similar MSEs (Irwin et al. 2008; Punt et al. 2008; Deroba and Bence 2012)
Ricker stock-recruitment parameters α, β	Drawn from posterior distribution of SR function for each simulation	Function derived using SCAA output (Fisch et al., 2019) as data
Ricker stock-recruitment parameter σ_r	Constant over simulations	Thorson et al., (2014)
Bernoulli probability of boom year class, p	Drawn from U(0.15,0.25) and U(0.25,0.40) (4yr and 7yr) for each simulation	Frequency of boom years from (Fisch et al., 2019) and Yule et al., (2006)
Lognormal distribution of bust year recruitments	Recruitment values to derive distribution drawn from SCAA posterior for each simulation	Fisch et al., (2019)

Figures

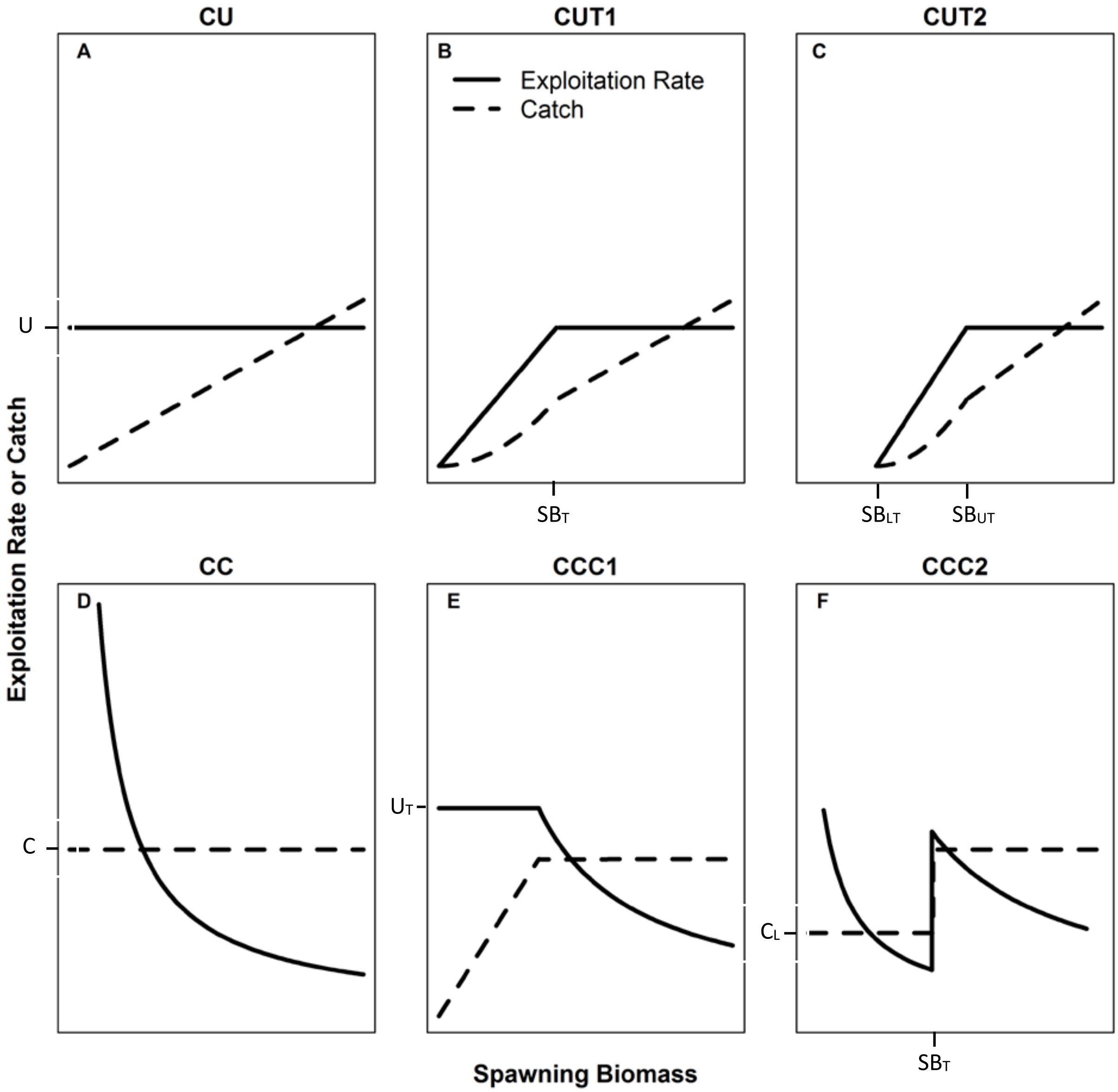

Figure 1. Harvest control rules considered in this analysis and associated policy parameters.

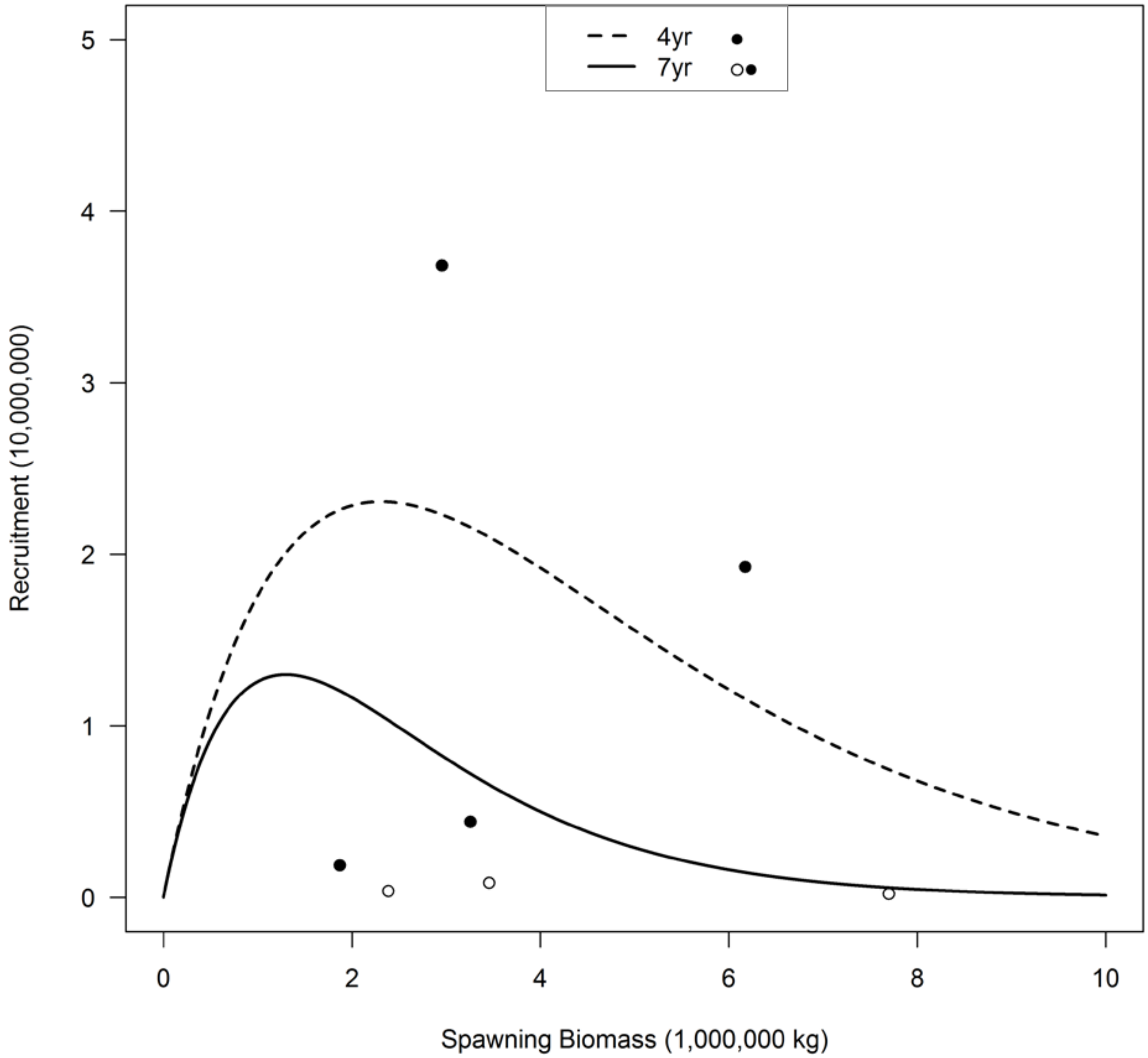

Figure 2. SR curves for each recruitment scenario, which apply to boom years. “Data”, medians of the posterior distribution of the SCAA, are plotted as points. The 7yr scenario SR curve uses all “data” points while the 4yr scenario was solely fit to the filled points. The curves represent the expected recruitment given stock size for the posterior median of the Ricker stock-recruitment parameters, whereas each simulation used a draw of stock-recruitment parameters from that distribution. The dotted line depicts the predicted SR curve for the 4yr scenario and the solid line depicts the predicted SR curve for the 7yr scenario. Spawning Biomass is defined as millions of female kg.

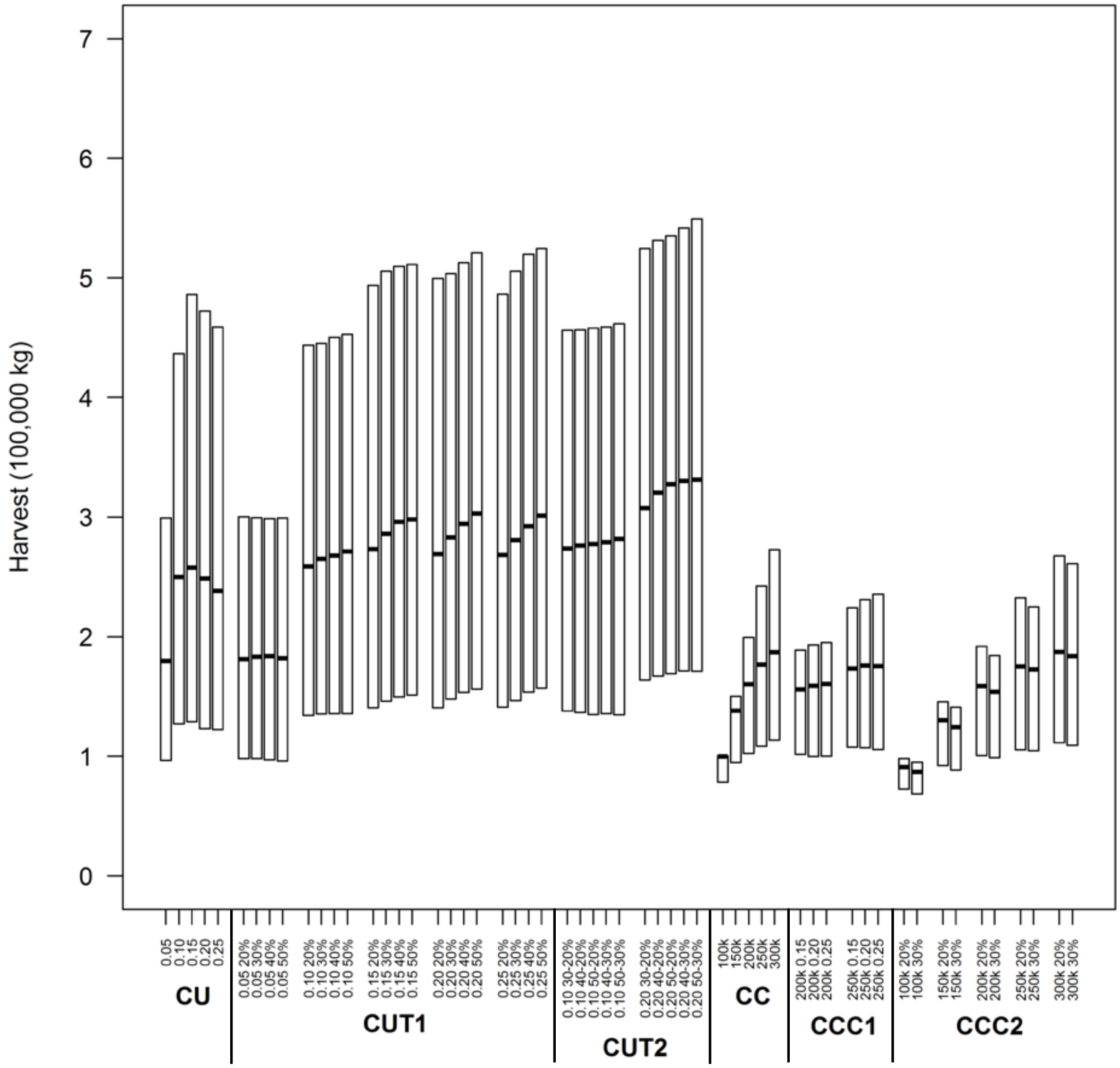

Figure 3. Summary of the distributions of average harvest over the simulation period for each respective control rule. Shown are medians (horizontal bar) and 25-75 quantiles (box). Labels specify policy parameters that make up each control rule (CU = "U"; CUT1 = "U SB_T"; CUT2 = "U SB_{UT}-SB_{LT}"; CC = "C"; CCC1 = "C U_T"; CCC2 = "C SB_T"). Exploitation rates are presented as decimals and biomass thresholds as percentages. For CUT2 control rules, a label of "0.10 50-20%" describes a control rule that has an exploitation rate of 0.10 above 50% of the estimated unfished spawning biomass, while that rate linearly declines below that threshold to 0 at 20% of the estimated unfished spawning biomass. Catch limits are described in 100,000 kg (i.e. 100k = 100,000 kg).

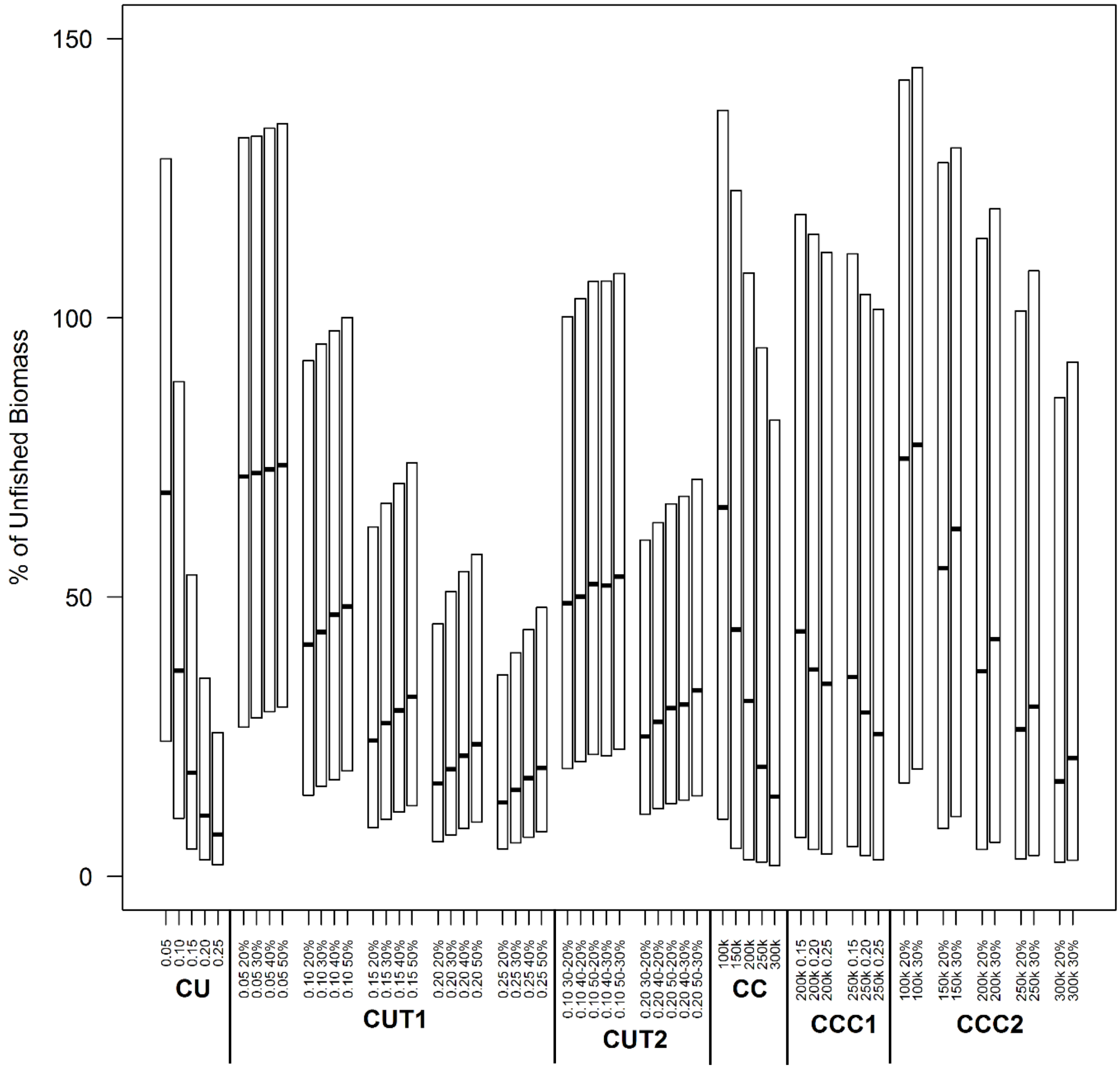

Figure 4. Summary of the distributions of final spawning biomass for each respective control rule, with final spawning biomass defined as the median of the last 5 years spawning biomass in each simulation, characterized as a percentage of the unfished level. Shown are medians (horizontal bar) and 25-75 quantiles (box). Labels specify policy parameters that make up each control rule (CU = "U"; CUT1 = "U SB_T"; CUT2 = "U SB_{UT}-SB_{LT}"; CC = "C"; CCC1 = "C U_T"; CCC2 = "C SB_T"). Exploitation rates are presented as decimals and biomass thresholds as percentages. For CUT2 control rules, a label of "0.10 50-20%" describes a control rule that has an exploitation rate of 0.10 above 50% of the estimated unfished spawning biomass, while that rate linearly declines below that threshold to 0 at 20% of the estimated unfished spawning biomass. Catch limits are described in 100,000 kg (i.e. 100k = 100,000 kg).

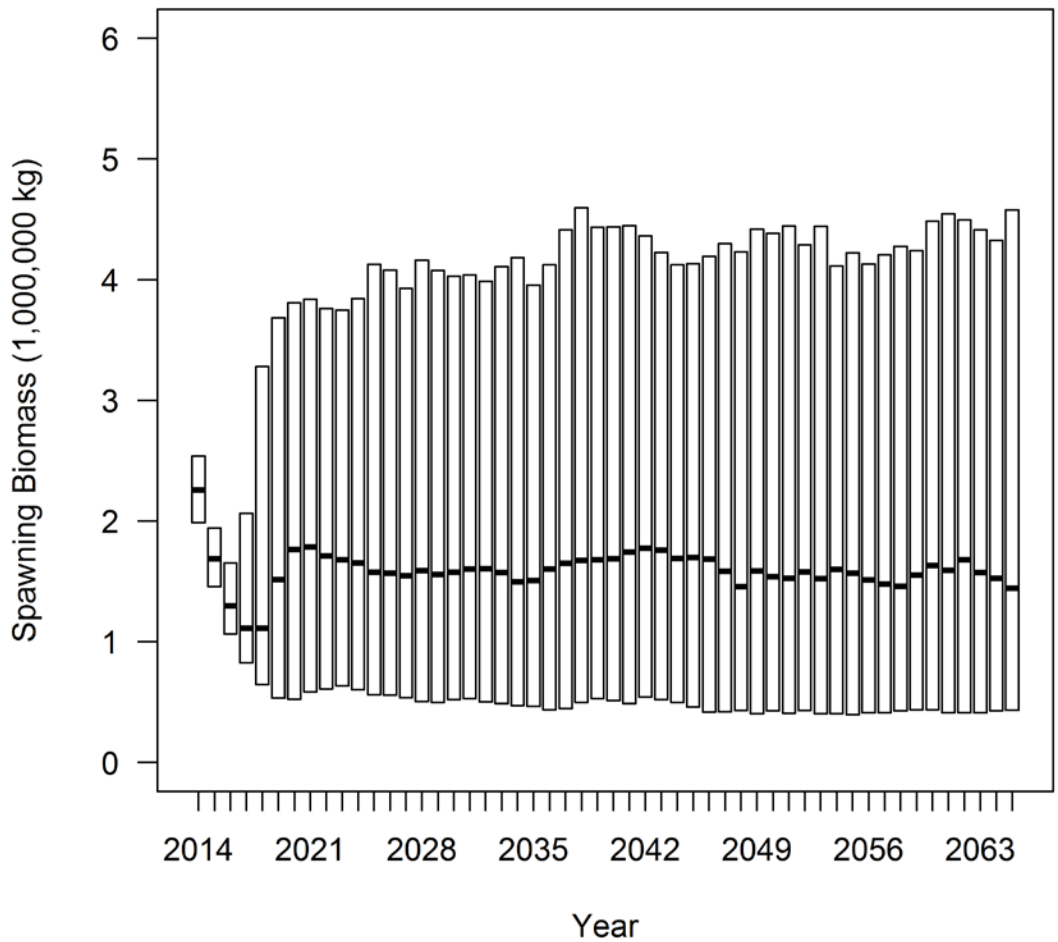

Figure 5. Spawning biomass for the projection of the current harvest control rule, a 10% exploitation rate. Shown are medians (horizontal bar) and 25-75 quantiles (box).