

ON THE ASSESSMENT AND SUSTAINABILITY OF THUNDER BAY CISCO

By

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A THESIS

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Fisheries and Wildlife – Master of Science

2018

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ABSTRACT

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Cisco, *Coregonus artedii*, have been reduced to a small fraction of their historical abundance throughout the Laurentian Great Lakes. Today, remnant spawning stocks that continue to support commercial fisheries are confined to western Lake Superior. Although these fish are of particular economic and ecologic importance in the region, formal stock assessment models have yet to be developed for the species. In addition, effects of current exploitation rates on these remnant stocks have yet to be evaluated using quantitative methods. In this thesis, we first develop and compare multiple state-of-the-art stock assessment models for a spawning stock of cisco in Thunder Bay, Ontario, in an effort to determine an appropriate assessment framework to model the remaining cisco stocks in western Lake Superior. Results strongly suggest statistical catch-at-age assessment (SCAA) methods are most appropriate for modeling cisco in Thunder Bay, and should be applied to stocks in Minnesota and Wisconsin waters of Lake Superior. We then perform a simplified management strategy evaluation of the Thunder Bay cisco stock based on the SCAA in an effort to determine both the sustainability of the current harvest control rule, and the performance of alternate harvest control rules in managing cisco in Thunder Bay. Results suggest current exploitation rates are sustainable in Thunder Bay; however, yield, long-term spawning biomass, and risk of collapse can be improved by implementing control rules involving biomass based thresholds that decrease exploitation rate at low stock sizes.

ACKNOWLEDGEMENTS

First and foremost, I'd like to thank my advisor Dr. James Bence for his patience, guidance, and support throughout the development of this thesis. I would like to thank the Great Lakes Fishery Commission for funding support on this project. I am also indebted to the Ontario Ministry of Natural Resources and Forestry (OMNRF), who were generous enough to lend us their outstanding dataset on cisco. Specifically within OMNRF I'd like to thank Eric Berglund and Anthony Chiodo, who were available to answer any question I had about the dataset. I would like to thank Ian Harding, who lent us his dataset on otolith increments of individual cisco, which was crucial to our project. I would like to thank Dan Yule, who helped me tremendously in understanding and processing hydroacoustic data. I would also like to thank Jared Myers, Sam Truesdell, and Rick Clark who aided in various aspects throughout the project and who, along with Dr. Bence and Dan Yule, developed the proposal that led to the creation and funding of this project. Lastly, I would like to thank all of my colleagues at the Quantitative Fisheries Center at Michigan State University for creating such a great environment to learn about quantitative methods in fisheries science.

The collective work of Jim Bence, Dan Yule, Jared Myers, Sam Truesdell, Rick Clark, and myself on this project is reflected through the use of the plural "we" throughout this thesis.

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INTRODUCTION

Cisco, *Coregonus artedii*, also known as lake herring, are an ecologically and economically important fish species of the Laurentian Great Lakes ecosystem. They historically served as the primary prey for many dominant predators throughout the region prior to the invasion of rainbow smelt, *Osmerus mordax*, and alewife, *Alosa pseudoharengus* (Dryer et al. 1965; Smith 1968; Leach and Nepszy 1976; Christie et al. 1987; Jude et al. 1987; Diana 1990; Wolfert and Bur 1992; Conner et al. 1993; O’Gorman and Stewart 1999; Ray et al. 2007). This has led some to postulate that restoration of a key native predator, lake trout, *Salvelinus namaycush*, in the Great Lakes ecosystem is dependent on the replacement of exotic alewives and rainbow smelt by the native cisco (Bronte et al. 2008; Markham et al. 2008). In addition to their ecological significance, a commercial fishery for cisco has operated in the Great Lakes for over a century primarily targeting spawning females to supply foreign roe markets (Stockwell et al. 2009). During the first half of the 20th century, this fishery accounted for a greater amount of yield taken out of the Great Lakes than that of any other species (Baldwin et al. 2002). However, since that time, cisco fishery yield has drastically decreased, due to the sequential collapse of populations in each of the Great Lakes, largely attributed to overexploitation; Lake Erie in the 1920s (Hartman 1973; Selgeby 1982), Lakes Ontario and Huron in the mid-1950s (Berst and Spangler 1973; Christie 1973), Lake Michigan in 1960 (Wells and McLain 1973), and Lake Superior in the early 1960s (Selgeby 1982). Today the fishery operates on a much smaller scale mostly focusing on stocks in western Lake Superior that have rebounded during the post-collapse period. Due to their importance in the region, rehabilitation and protection of self-sustaining stocks of cisco

to support a stable production of predators and a sustainable commercial fishery has become a priority in Lake Superior (Schreiner et al. 2006).

Current Management

The cisco fishery in Ontario and Minnesota waters of Lake Superior is currently managed based on a fixed exploitation rate control rule. A fixed exploitation rate control rule aims to set catch quotas to some constant proportion of stock size (Walters and Martell 2004). This builds in an inherent feedback system; as the stock declines, the quotas do the same, and vice versa. For this type of control rule to be effective, management agencies need estimates of population abundance each year, or each time period they would like to enact catch quotas (Walters and Martell 2004). In Ontario and Minnesota, this is facilitated by hydroacoustic surveys of spawning cisco abundance, where total allowable catch (TAC) is set at 10% of cisco > 250mm in Ontario, and 10% of cisco > 305mm in Minnesota, both calculated from the hydroacoustic surveys. Management of cisco in the state of Wisconsin does not currently involve setting a TAC; however numerous restrictions on gill net mesh sizes are employed in different areas, in addition to the prohibition of fishing in a number of refuges and restricted-use areas (Stockwell et al 2009). There is currently no targeted fishery for cisco in Michigan waters of Lake Superior as harvest has been restricted to incidental catches in the chub fishery.

Given these current management strategies in western Lake Superior, there are several key concerns related to the long term sustainability of the fishery. Primarily, there is large concern for overfishing in Wisconsin waters of Lake Superior, due to the lack of quota allocations or TAC. This concern stems from the lucrative nature of the

fishery, where catch will largely be determined by market demands. It also stems from the highly efficient nature of the fishery in western Lake Superior, which targets aggregations of fish in November as they congregate to spawn. Under this scenario, fishers can move from dense patch to dense patch of spawning fish maintaining high catch rates, potentially depleting the resource as their catch-per-unit-effort does not necessarily decrease (hyperstability, Hilborn and Walters 1992). Another concern relates to the reliance on hydroacoustic surveys to set a TAC each year, as these surveys are not necessarily done every year due to weather restrictions and budget constraints, or in some years could produce anomalous results due to factors such as fluctuations in spatial distributions. The integration of other sources of data such as fishery catch-at-age into a formal stock assessment model can allow the calculation of abundance even in years when no hydroacoustic survey is performed, in addition to improved estimates in years when surveys are done. Lastly, while fixed 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 Ontario and Minnesota waters has not been evaluated using quantitative methods. In a more formal harvest policy analysis, a stock may be forecasted into the future under a variety of different management strategies using a population model to determine which strategy is optimal in promoting fishery objectives, such as high or consistent yield, and/or sustainability of the stock. These 10% exploitation rates were actually put into place based on exploitation rates seen as sustainable for other Lake Superior fish stocks such as lake trout, lake whitefish, *Coregonus clupeaformis*, and lake sturgeon, *Acipenser fulvescens* (Ebener et al. 2008, Stockwell et al. 2009). Where precautionary approaches to management such as these are an important first step, a harvest policy tailored to what

is known about cisco stocks in western Lake Superior is needed to ensure sustainability of the cisco fishery into the future.

Schreiner et al. (2006) described an objective to rehabilitate and protect Coregonine stocks by exploring “the use of a population model to compliment the use of an acoustics-based model” in determining TAC for cisco. In addition, the fisheries management plan for Minnesota waters of Lake Superior from 2016-2025 (Goldsworthy et al., 2015) states an objective to “Continue to support establishing a lake-wide stock assessment model to complement existing acoustics-based quota calculations”. Ebener et al. (2008) stated that “there is an overwhelming need to develop an overarching research framework to better understand cisco population dynamics and ecology within the context of managing them in a sustainable fashion”. These statements describe a shared view that integrating additional sources of data in characterizing cisco population dynamics is essential in promoting the sustainable management of cisco stocks in Lake Superior.

Contents

The objectives of this thesis were to (1) develop an integrated assessment model that is effective in estimating abundance and characterizing population dynamics of cisco, and (2) to evaluate the sustainability of the current control rule, and the performance of alternate harvest control rules in meeting cisco fishery objectives. Given the superior quality and breadth of data available in Ontario waters of Lake Superior, this thesis focused on the Thunder Bay cisco stock. The assessment and analysis of Thunder Bay cisco can serve as a framework to later model other cisco stocks in Lake Superior (Minnesota, Wisconsin). This thesis consists of two chapters, the first of which

is a comparison of two different stock assessment methods, catch-at-age and catch-at-size, applied to cisco in Thunder Bay in an effort to determine which assessment method best characterizes population dynamics of cisco. The second chapter uses the best assessment model developed in the first chapter to implement a simplified management strategy evaluation of Thunder Bay cisco involving simulations of the stock under multiple sources of uncertainty and harvest control rules to evaluate sustainability and performance of specific harvest control rules in meeting fishery objectives.

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Chapter 1

A Comparison of Age- and Size-Structured Assessment Models Applied to a Stock of Cisco in Thunder Bay, Ontario

Abstract

Stock assessment is a critical component of the fisheries management process, involving the calculation of key variables used in making management decisions. However; there is still considerable uncertainty in assessment science as to which class of models is appropriate to use depending on circumstances. A common class of models used when age data are available are statistical catch-at-age assessment (SCAA) models, which track cohorts through time. When age data are unavailable, as is often the case in invertebrate fisheries where the lack of a bony structure such as otoliths makes aging difficult, statistical catch-at-size assessment (SCSA) models are more often employed, tracking fish or invertebrates through time by size classes rather than ages. Do SCAA models actually perform better than SCSA models when age data are available, or is this just an assumption we make in fisheries research and management? We examined this question as it relates to a specific case study by evaluating the effectiveness of both SCAA and SCSA models in characterizing cisco, *Coregonus artedii*, population dynamics in Thunder Bay, Ontario. Both models were fit using an integrated framework with multiple sources of data including hydroacoustic estimates of spawning stock, commercial and fishery independent age/length compositions, and landings data. Our results suggest that for cisco in Thunder Bay, parameter confounding resulting in the inability to estimate natural mortality hampered the utility of a SCSA model in comparison with a SCAA model when age composition data were available.

Introduction

Stock assessment is a critical aspect of fisheries research and management, supporting the calculation of key quantities such as spawning biomass, abundance, exploitation rate, recruitment, and their associated uncertainties. Most assessments done in the United States are based on age-structured assessment methods (Punt et al., 2017), which, when statistically fit, can be referred to as statistical catch-at-age assessment (SCAA) models. These models track cohorts of fish through time, using observations of catch-at-age and auxiliary information to estimate population parameters (Fournier and Archibald, 1982; Deriso et al., 1985). When catch-at-age data are unavailable for a species of interest, as is the case in many invertebrate fisheries where lack of a bony structure such as an otolith makes aging difficult, size-structured assessment methods are often employed (Punt et al., 2013). Similarly, when statistically fit these types of models can be referred to as statistical catch-at-size assessment (SCSA) models. Sullivan et al. (1990) developed and applied a framework for SCSA, which differ from SCAA in that they utilize observations of catch-at-size and track fish in size bins rather than age classes through time, often making use of a growth model that determines transition probabilities of size bins in subsequent time steps. While age-structured models can be fit using harvest size composition data (and a model to convert predicted age compositions to size compositions; Fournier et al., 1990; Fournier et al., 1998), often together with age composition data (Methot and Wetzel 2013, Punt et al. 2013), contemporarily the use of SCSA is preferred when the sole or primary harvest composition data is for sizes rather than ages (Punt et al., 2013).

Each method offers distinct advantages and disadvantages. For size based methods, the model can directly account for the size structure of removals from a population (Punt et al., 2017), it can more appropriately model some fishery processes such as selectivity as size-based (although in some cases both age and size may be involved), and importantly, size composition data is almost always more abundant and it is both easier and cheaper to collect. SCSA models can considerably decrease the number of fish that need to be aged, as age compositions of the catch are not required. SCSA is not without its challenges. Primary among them, as previously mentioned, an SCSA needs a method, often a growth model, to determine transition probabilities of fish or invertebrates through size bins for each time step, where additional aspects such as time-varying or density dependent growth can add complexity. This is not so in SCAA models which benefit from the fact that a fish **must** be a year older in the next (yearly) time step; A caveat being that our ability to observe ages is not perfect, as there is measurement error involved in aging organisms, and ignoring this error can result in biased assessment output (Coggins and Quinn, 1998; Reeves 2003; Bertignac and Pontual, 2007). Although aging error is generally overlooked in SCAA models, it can be accounted for both within a model (Thompson et al., 2011; Methot and Wetzel, 2013) and using quality control in aging techniques (Campana, 2001).

Most likely due to the ideal transition of fish through age bins (and the properties that come along with it, i.e., recruitment into the model), very seldom are SCSA models developed for species when age data are available. Additionally, few studies have compared the two methods. One such study, Punt et al., (2017), used simulation analysis to compare the performance of age-, size-, and age- and size-structured assessment

methods, concluding that based on an age- and size-structured operating model, size-structured and age- and size-structured assessment methods performed best, while age-structured methods performed poorest. This study was done, as are most simulation studies, based on known population dynamics pre-specified by researchers. The advantage of simulation studies is the ability to compare assessment results to what is pre-specified in the operating model as the true population dynamics of the stock. This specification of the operating model can also be a disadvantage, if the researchers conception on the dynamics of the stock and fishery (e.g. survey selectivity as age-based process in Punt et al., 2017), do not actually reflect underlying processes. Fitting alternative models to real data can be highly useful in helping to better define plausible processes. Thus comparing alternative models fit to real data and simulation studies are not alternative approaches, but rather synergistic ways to advance assessment methods.

In this paper we develop and fit both integrated SCAA and SCSA models for a stock of cisco, *Coregonus artedi*, in Thunder Bay (Lake Superior), Ontario. Our objective was to compare and contrast performance of the different assessment methods when applied to a real stock to provide recommendations on which type of model may be preferred under different scenarios. We were specifically interested in the overall question: “when age data are present, are we, in fisheries research and management, assuming age-structured models will outperform size-structured models because they are more directly intuitive and easier to fit, or can size models be used instead to better model fishery processes and perhaps decrease the burden on natural resource agencies to age so many fish each year?” To our knowledge, only one study has performed a comparison between age- and size-structured models on a real stock with true dynamics

unknown (Akselrud et al. 2017, concluding that age-structured fit data best). In a time of shrinking natural resource agency budgets, it seems these comparisons are overdue, and could provide important information for future simulation studies.

Methods

Study Species

Cisco are a planktivorous species native to the Laurentian Great Lakes. They are largely pelagic, however form annual spawning aggregations during the month of November in nearshore bays and areas of western Lake Superior (remaining stocks are largely confined to western Lake Superior). These aggregations have supported a lucrative commercial roe fishery for decades, as fisherman generally target spawning fish during late November using suspended gillnets. Additionally, since 2005 these aggregations have been surveyed annually using hydroacoustics in Thunder Bay. Current management relies on a fixed exploitation rate control rule where 10% of the spawning fish estimated from the hydroacoustic surveys are allocated as quota among a limited number of fishers. No formal assessment models have been developed for this stock or others in western Lake Superior.

Stock Area

We treated Ontario Ministry of Natural Resources and Forestry (OMNRF) management zones 1-4 (Figure 1.1) as the stock area for Thunder Bay cisco. This stock has been hypothesized to be a discrete spawning stock, primarily on the basis that an adjacent depleted stock in Black Bay has not shown any sign of recovery since a collapse in the 1980s, which would be expected if cisco from Thunder Bay were spilling over into

Black Bay under a non-discrete spawning stock scenario (Ebener et al. 2008).

Additionally this area was chosen based on coverage of the hydroacoustic surveys, which generally sample over zones 1-4 in Thunder Bay.

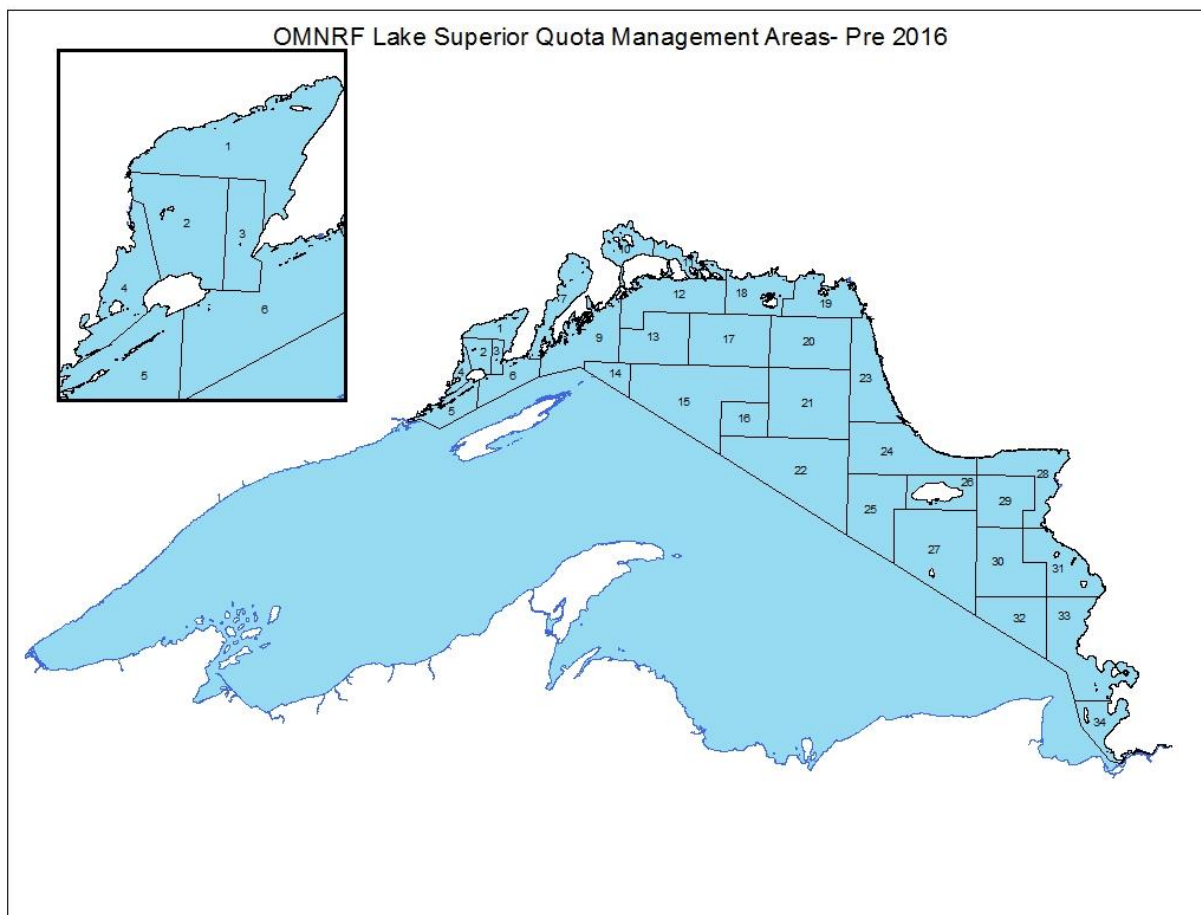


Figure 1.1. OMNRF quota management areas pre-2016. We are characterizing Thunder Bay stock area as zones 1-4.

Data

The SCAA and SCSA models made use of six main sources of observed data in the fitting process (Table 1.1): (1) Number of cisco > 250 mm in Thunder Bay estimated from hydroacoustic surveys (2005, 2007-2015), age or size composition of cisco caught

in (2) mid-water trawls (2005, 2007-2010, 2015) and (3) multi-mesh gillnets (2009, 2013-2015) that accompany the hydroacoustic surveys, (4) age or size composition of the fishery catch subsamples (1999-2015), and (5) male and (6) female biomass in the fishery yield each year (1999-2015). The SCSA made use of one additional source of data; (7) individual growth increments of cisco.

Table 1.1. Data source years for each assessment. Composition refers to age and length composition data.

Year	Hydroacoustic Survey	Fishery Harvest	Fishery Composition	MWT Survey Composition	Gillnet Survey Composition
1999		X	X		
2000		X	X		
2001		X	X		
2002		X	X		
2003		X	X		
2004		X	X		
2005	X	X	X	X	
2006		X	X		
2007	X	X	X	X	
2008	X	X	X	X	
2009	X	X	X	X	X
2010	X	X	X	X	
2011	X	X	X		
2012	X	X	X		
2013	X	X	X		X
2014	X	X	X		X
2015	X	X	X	X	X

Collection & Processing

Fishery Independent Data

The United States Geological Survey (USGS) and the OMNRF collectively sampled spawner abundance in Thunder Bay, Ontario, using acoustics in 2005 and from 2007-2015. Acoustic data was collected and processed using techniques according to the Great Lakes standard operating procedure for fishery acoustic surveys (Rudstam et. al 2009). The USGS performed the acoustic surveys in 2005 and from 2007-2010 while

the OMNRF performed the surveys from 2011-2015. Each year the acoustic gear specifications differed slightly, utilizing different frequency split beam transducers with a half-power beam width varying from 5.3-6.7 degrees. The transducer was generally deployed from 1-5m below the surface depending on the year. The transducer emitted 3-5 pings/s, with pulse duration usually set at around 0.4 ms. Vessel position was measured with a differentially corrected Global Positioning System unit (accurate to 1m), and survey path information was imbedded in the acoustic data files. Acoustic data was processed with Echoview Software (Sonar Data, Tasmania, Australia). Thresholds for the Sv (scattering volume) and single target echograms were set at -65 dB and -60 dB respectively. A line to exclude surface noise was set at 2-7m depth (depending on sea state) and a line to exclude the bottom was set 0.5 m above the bottom signal. Software-defined bottom lines were examined carefully to ensure all bottom echoes were properly excluded, and all segments of echograms containing electrical or other noise (i.e., echoes obviously not from fish) were eliminated before estimating fish densities.

Total fish densities (number/ha) were calculated for 15-m vertical cells over 3km horizontal intervals using echo integration methods described in Yule et al. (2006). To obtain densities of spawning ciscoes (>250 mm TL), we multiplied total fish density in each cell by the proportion of single targets larger than -35.6 dB, a threshold that is consistent with the predicted target strength of a 250 mm cisco (Yule et al. 2006). We summed all the vertical cells down to the lake bed for each 3 km interval. In order to separate density of large cisco from the density of large fish belonging to other species we took the density estimate of large fish (>250 mm) for each interval and matched it up to the nearest mid-water trawl or multi-mesh gillnet sample by Euclidean distance. We

then multiplied the large fish acoustic density estimate for each cell by the proportion of large (>250 mm) cisco caught out of all large fish caught in the nearest bio-data sample (trawl or gillnet). For example, if there was a density estimate of 100 large fish/ha for an interval and the nearest bio data sample caught 80% cisco out of fish caught greater than 250 mm, then the large cisco density estimate would be 80 spawning cisco/ha for that interval. To estimate abundance of spawning cisco in Thunder Bay each year, we averaged the densities of large cisco for all 3 km intervals and multiplied this by the surface area of the bay (77,749 ha, zones 1-4).

As mentioned above, fishery independent bio-data were collected during the acoustic surveys to separate cisco densities from other species densities. Two different types of gear were used in collecting biological samples, mid-water trawls and multi-mesh gillnets. The USGS used mid-water trawls to collect cisco biological samples in 2005 and from 2007-2010, while the OMNRF used multi-mesh gillnets to collect biological samples from 2013-2015. No biological samples were collected in 2011 and 2012, for these years we decided to take the average over the time series of the percentage of large cisco caught out of all large fish caught each year ($\approx 95\%$) to substitute for direct samples of the percentage of large targets attributed to cisco. In 2009 and 2015 each agency collected biological samples using both gears, trawls and gillnets, in order to observe how sampling gear affected spawning cisco density estimates (sampling gear had minimal impact on acoustic density estimates of large cisco). In 2009 we decided to use the acoustic density estimates based on the mid-water trawl apportionment due to the fact that only 4 gillnets were deployed (biological samples from these gillnets were still used for composition data). In 2015 we averaged

the estimates from the mid-water trawl apportioned densities and gillnet apportioned densities to calculate one spawning cisco density estimate for the year. In 2007 the USGS performed two acoustic surveys, one in mid-November and one in late November, to observe if spawner abundance changed as the season progressed (Acoustic densities did not differ significantly between the two surveys). We computed an overall mean acoustic density for 2007 based on a weighted average using the number of 3km intervals that were sampled for each survey to obtain one spawning cisco estimate for 2007.

During the collection of biological samples, cisco were usually subsampled for age although in some years all cisco caught were aged. A complete description of how cisco caught in mid-water trawls and multi-mesh gillnets were subsampled for aging each year can be found in Table 1.2. We applied sex-specific age-length keys (ALK) using 10mm bins to aging data each year to calculate the age composition of male and female cisco caught using mid-water trawls and multi-mesh gillnets in Thunder Bay. For size composition data, we allocated all cisco caught in survey gear each year into sex-specific 10mm length bins.

Table 1.2. Description of survey sampling of cisco in Thunder Bay.

Year	How ages were sampled (Fishery Independent Data)	Number sampled (MWT-Gillnet)	Number Aged (MWT-Gillnet)
2005	Targeted 20 fish per 50mm length bin	794 - 0	196 - 0
2007	Targeted 40 otolith pairs for both males and females per 50mm length bin	1845 - 0	441 - 0
2008	Targeted 40 otolith pairs for both males and females per 50mm length bin	559 - 0	278 - 0
2009	Uncertain for MWT, all gillnet fish were aged	994 - 302	297 - 302
2010	All aged	520 - 0	520 - 0
2011	No bio-data collected with AC survey	0 - 0	0 - 0
2012	No bio-data collected with AC survey	0 - 0	0 - 0
2013	All aged	0 - 678	0 - 677
2014	All aged	0 - 135	0 - 134
2015	All aged except 33 in gillnets	478 - 824	473 - 795

Commercial Data

Licensed operators were required to report daily catch to the Ontario Commercial Fisheries Association, this allowed us to calculate aggregate yield for management zones 1-4 each year. To obtain biological data from the fishery, the OMNRF also collects the first 10 cisco caught in each gillnet on each day. These fish were measured to the nearest millimeter (total length and fork length), sexed, and weighed to the nearest gram. Ages were subsampled in many years based on ALK fixed allocation bin sampling where 10 fish belonging to a 10 mm length bin of each sex and zone were selected at random to be aged. If less than 10 fish were in a 10 mm bin, then all fish in that bin were aged. Some years all cisco sampled from commercial gillnets were aged. Annual subsampling of cisco caught in commercial gillnets for aging is summarized in Table 1.3.

Table 1.3. Description of how the OMNRF sampled commercial fishery data.

Year	Subsampled	Fish sampled – Fish aged
1999	Yes	860 - 402
2000	Yes	3241 - 594
2001	Yes	1221 - 574
2002	Yes	1147 - 676
2003	Yes	1208 - 704
2004	Yes	1091 - 527
2005	Yes	661 - 280
2006	Yes	644 - 378
2007	Yes	839 - 330
2008	No	654 - 654
2009	No	638 - 637
2010	Yes	500 - 219
2011	No	563 - 562
2012	No	478 - 477
2013	No	429 - 427
2014	Yes	733 - 517
2015	Yes	705 - 457

We combined aging data for management zones 1-4 each year and applied sex-specific ALKs using 10mm bins to calculate the age composition of male and female cisco caught in commercial gillnets in Thunder Bay. For size compositions, we allocated

sampled commercial cisco each year to sex-specific 10 mm length bins. If fish had a fork length (FL) but no total length (TL) record, total length was estimated based on a TL-FL linear regression derived from the rest of the commercial data that had both fork length and total length. A sex-specific weight-length power relationship assuming a multiplicative error structure

$$W = aL^b \varepsilon$$

was fit by a linear regression of log weight on log length using the commercial data. This was used to estimate missing weights of harvested fish (through a bias-corrected WL formula)

$$W = aL^b e^{\left(\frac{\sigma^2}{2}\right)}$$

where a is the exponential regression intercept estimate, b is the regression slope estimate, and σ^2 is the regression estimate of the residual error variance. Aggregate yield of management zones 1-4 in Thunder Bay each year was separated into male and female yield by multiplying the total harvest by the proportion of male and female weight in the commercial database each year, respectively (Figure 1.2).

Growth Increments

Sagittal otoliths were removed from cisco collected in the western arm of Lake Superior in both Minnesota and Wisconsin waters during the period 1988-2015 by the Wisconsin Department of Natural Resources. These otoliths were sectioned and data on increments in the radii of these otoliths were collected as part of a Master's thesis (Harding 2017). Additional details on otolith preparation and radii measurement can be

found in appendix 1. We back-calculated growth of individual cisco using the scale proportional hypotheses (Francis 1990), where the length of the cisco at each otolith annuli L_i , is calculated as

$$L_i = \frac{S_i}{S_c} \left(L_c + \frac{a}{b} \right) - \frac{a}{b}$$

where S_i is the radius of the otolith at annuli i , S_c is the radius of the full otolith at capture, and L_c is the length of the fish at capture. a and b are obtained by regressing length of fish on the length of that fish's otolith radius.

$$E(S_c | L_c) = a + bL_c$$

For the final data on individual cisco growth increments, we only used growth during the last full annulus for each fish in an attempt to avoid a substantial Lee's phenomenon, giving us a total of 169 individual cisco growth increments.

Process Model

Predicted quantities needed to compare to the observed data listed above were calculated using a variety of equations describing the stock and fishery. The models ran from 1999 to 2015. The SCAA model ages began at age 2 and ended at a plus group age of 15 (denoting all cisco older than 14) while the SCSA model size bins were divided in 10 mm increments beginning at 170 mm and ending at a plus group of 410 mm (denoting all cisco ≥ 410 mm). Age or size bins are referenced throughout the manuscript with subscript j . Given the fishery operates primarily as a roe fishery, it captures a disproportionate number of females in Thunder Bay each year (Figure 1.2),

we decided to make the assessment models sex specific, essentially tracking the number of male and female fish separately through time. This is presented in subsequent equations with the subscript s , denoting sex.

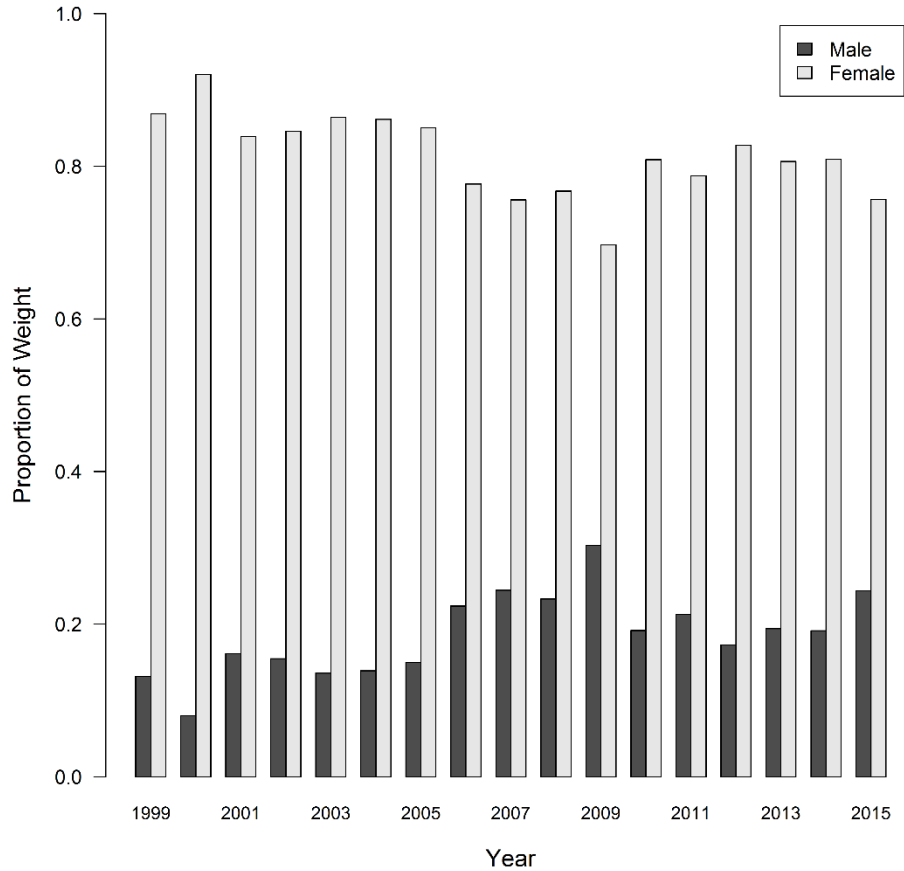


Figure 1.2. Sex-specific proportions of weight in samples of the fishery catch.

To begin, for the SCAA we freely estimated (as parameters) cisco numbers at age for each sex in the first year of the assessment model. For the SCSA, cisco abundance in the first year for each sex was estimated through a combination of size and abundance components; one gamma distribution denoting the initial size composition multiplied by two freely estimated values of abundance, one for each sex.

$$g(x | \alpha, \beta) = \frac{1}{\Gamma(\alpha)\beta^\alpha} x^{\alpha-1} e^{-\frac{x}{\beta}}$$

$$I_j = \int_{j^*-5}^{j^*+5} g(x | \alpha, \beta) dx$$

where α and β are the estimated shape and scale of the gamma distribution, I_j is the initial abundance proportion for size bin j , and j^* is the size bin midpoint. We attempted alternative parameterizations including assuming a separate initial size composition for each sex and estimating one value of abundance, in addition to estimating two size compositions and two abundance values, each of which did not outperform in terms of model comparison criterion PSIS-LOO (Pareto smoothed importance sampling leave-one-out; Vehtari et al., 2017). PSIS-LOO is an efficient approximation of the exact cross-validation model comparison criterion and has been shown to be asymptotically equal to WAIC however more robust in cases with weak priors or influential observations (Vehtari et al., 2017), both of which occur in assessment modeling.

Sex-specific numbers of cisco at each age or size in each year was obtained from the exponential survival equation

$$\text{SCAA} \quad N_{j+1,y+1,s} = N_{j,y,s} e^{-(F_{j,y,s} + M_s)}$$

$$\text{SCSA} \quad N_{j',y+1,s} = \sum_{j=1}^{j'} P_{j,j'} N_{j,y,s} e^{-(F_{j,y,s} + M_s)} + R_{j',y+1,s}$$

where $N_{j,y,s}$ denotes the number of cisco in age or size bin j alive in year y of sex s . $P_{j,j'}$ is the size transition matrix, denoting the probability that a fish in length bin j will grow into length bin j' in the next time step. R_j is the number of fish that recruit into length bin j . $F_{j,y,s}$ represents the sex specific instantaneous fishing mortality in year y for a given age or size bin. M_s is the instantaneous natural mortality for each sex, assumed constant over time and ages or sizes. We decided to allow natural mortality to vary by sex based on information from previous studies which indicated that male cisco may experience higher natural mortality than their female counterparts (TeWinkel et al. 2002, Yule et al. 2008). We evaluated different scenarios where natural mortality was assumed equal for both sexes. Ultimately, and primarily in the interest of numerical stability, we chose to add a prior on each natural mortality variable based on the updated Hoenig linear model surrogate equation from Then et al. (2014).

We calculated the size transition matrix, $P_{j,j'}$, using growth parameters L_∞ and K to model an average growth increment and parameters a and b to model the variance in growth increment as a function of the expected growth increment

$$E(\Delta_j) = (L_\infty - j^*)(1 - e^{-K})$$

$$Var(\Delta_j) = a + b * E(\Delta_j)$$

where j^* is the length bin midpoint. The probability of remaining in the same length bin in the next time step, $P_{j,j}$ (the diagonal of the matrix), was calculated by integrating from 5 mm to 0 (assumes fish are at length bin midpoint). Assuming no negative growth, the

rest of the transition matrix, $P_{j,j'}$, was calculated by plugging in the expected growth increment and variance in growth increment into the cumulative distribution function (CDF) of the gamma distribution, integrating from length bin midpoint +5 mm (j_2') to length bin midpoint -5 mm (j_1').

$$P_{j,j'} = \int_{j_1'}^{j_2'} g(\Delta_j | \alpha_j, \beta_j) d\Delta_j$$

where α_j and β_j can be calculated from $E(\Delta_j)$ and $V(\Delta_j)$. A full description of the gamma likelihood can be found in the likelihood section of this chapter.

For the SCAA, we modeled recruitment in each year as multiplicative deviations about a mean recruitment level:

$$R_y = \mu \delta_y$$

The log of the deviations, $\log(\delta_y)$, assumed a normal distribution with mean 0 and variance σ^2 .

$$\log(\delta_y) \sim N(0, \sigma^2)$$

We assumed equal sex ratios at recruitment, apportioning 50% of the recruitment each year to the model starting age of each sex.

$$N_{2,y,s} = 0.5R_y$$

where $N_{2,y,s}$ denotes the number of cisco age 2 (model starting age) in year y of sex s .

Note that this model does not assume any prior relationship between the magnitude of

recruitment and stock size. We modeled recruitment in the SCSA model with an added length based component p_j , representing the proportion of recruits going into each size class.

$$R_{j,y} = R_y P_j$$

where R_y is modeled in the same fashion as in the SCAA. We calculated the proportion of recruits going into each length class, p_j , using a weighted average of the size transition probabilities of size bins smaller than the model starting bin (i.e. what percentage of fish from bins 15-165 mm would grow into bins > 170 mm in the next time step). To calculate the weights, we used the mean and variance in length at age of cisco ages 0-2 to generate a sample distribution of the size distribution of cisco less than 170 mm (model starting length). To account for depletion in abundance, we weighted different ages using a natural mortality value of 0.3 (i.e. 1 age 0, 0.74 age 1, and 0.55 age 2). These composition weights were then multiplied by the size bin (15 mm-165 mm) transition probabilities into bins greater than 170 mm. Once again we assumed equal sex ratios at recruitment, apportioning 50% of the recruitment each year to the model length bins of each sex, $R_{j,y,s} = 0.5 * R_{j,y}$.

We calculated instantaneous fishing mortality for both models using

$$F_{j,y,s} = s_j f_{y,s}$$

where s_j is the fishery selectivity for cisco over ages or size bins and $f_{y,s}$ is the fishing intensity in a given y year for sex s . During preliminary analysis and in previous work done in Lake Superior (Clark 2012), cisco gill net catch per unit effort (CPUE) displayed

a non-linear relationship with estimates of abundance from hydroacoustic surveys, and over most of the observed range in hydroacoustic densities there was no clear relationship between gill net catch and hydroacoustic density. Due to this, fishery effort was not used when fitting the model. Instead we directly estimated fishing intensity in each year.

We modeled fishery selectivity using a two parameter gamma function as in Deriso et al. (1985)

$$s_j = \frac{j^\alpha e^{-\beta j}}{s_{ref}}$$

where α and β are gear selectivity coefficients and the denominator denotes the value that would be obtained for the numerator for a reference category, made age 7 and size bin 380-390 mm for each respective model. We initially estimated fishery selectivity parameters independently for each sex however, given near identical estimates, in the interest of parsimony decided to assume equal fishery selectivity for each sex.

Observation Model

Predictions of data source 1, the hydroacoustic estimates of the number of cisco greater than 250 mm, \hat{H}_y , were modeled using

$$\text{SCAA} \quad \hat{H}_y = e^\gamma \sum_s \sum_j P(\text{Fish}_j > 250\text{mm}) N_{j,y,s} e^{-Z_{j,y,s} \frac{5}{6}}$$

$$\text{SCSA} \quad \hat{H}_y = e^\gamma \sum_s \sum_{j=250}^L N_{j,y,s} e^{-Z_{j,y,s} \frac{5}{6}}$$

where $P(Fish_j > 250mm)$ is the probability that a cisco in age bin j is greater than 250 mm, L represents the terminal size bin, and γ is the logarithm of the hydroacoustic survey calibration coefficient (Hulson et al., 2008), which when presented as e^γ , can be referred to as hydroacoustic catchability. Given that selectivity of the hydroacoustic survey is assumed to be knife edged at 250 mm, where all fish become fully selected to the gear, hydroacoustic estimates of spawning stock are in theory absolute estimates of spawning stock, so this coefficient was expected to be at or very near 0. We applied mortality to numbers of fish at age or length for the first 10/12ths of the year ($N_{j,y,s} e^{-Z_{j,y,s} \frac{5}{6}}$) given the hydroacoustic surveys are performed during the spawning season in November. The probability that a fish of a given age is greater than 250 mm, $P(Fish_j > 250mm)$, was calculated outside of the model by characterizing the size distribution of each age of cisco. This was done by first obtaining the mean and variance in length of cisco at each age from 0-27 (or model ages, i.e. 2-15), then using the cumulative distribution function of the normal distribution to calculate the probability that a cisco age a chosen at random would be greater than 250 mm. To reduce gear bias we used a multiple gear approach similar to Wilson et al., (2015), combining data from multi-mesh gillnets, mid-water trawls, and commercial gillnets from the assessment model years 1999-2015. Data from both sexes was also combined based on the observation that cisco length at age in Thunder Bay did not appear to differ by sex. To try and reduce bias in mean length at age associated with fixed bin allocation ALK sampling (i.e. 10 fish aged per 10 mm length bin, Quinn and Deriso 1999), we calculated mean length at age by:

$$\bar{L}_j = \frac{\sum_i (n_{i,j} * L_i)}{\sum_i n_{i,j}}$$

Where \bar{L}_j is the mean length at age j , $n_{i,j}$ is the number of fish in length bin i that are age j , and L_i is the midpoint length of length bin i . Variance in length at age was calculated using

$$Var(L_j) = \frac{\sum_i n_{i,j} * (L_i - \bar{L}_j)^2}{\sum_i n_{i,j}}$$

The bias-adjusted mean length at each age and variance in length at each age was then plugged into the cumulative distribution function of the normal distribution to obtain the probability that a cisco age j selected at random would be greater than 250 mm. We then fit a logistic function through these probabilities to obtain the final probability that a cisco age j would be greater than 250 mm, $P(Fish_j > 250mm)$.

Predictions of data sources 2 and 3, the age or size composition of Thunder Bay cisco each year obtained from mid-water trawls and multi-mesh gillnets, was modeled using

$$\hat{P}_{j,y,s}^i = \frac{s_j^i N_{j,y,s} e^{-Z_{j,y,s} \frac{5}{6}}}{\sum_s \sum_j s_j^i N_{j,y,s} e^{-Z_{j,y,s} \frac{5}{6}}}$$

where s_j^i is the survey selectivity of gear i (midwater trawls or multi-mesh gillnets) for age or size j . $\hat{P}_{j,y,s}^i$ is the sex specific predicted proportion at age or size caught from

each survey gear in a given year. Once again we applied mortality to numbers of fish at age or length for the first 10/12ths of the year ($N_{j,y,s} e^{-Z_{j,y,s} \frac{5}{6}}$) given the survey bio-data are collected during the spawning season in November. Survey selectivity was modeled to adequately characterize the selective nature of mid-water trawl surveys and multi-mesh gillnets using a two parameter gamma function identical to the formula described for the fishery, however without a denominator to standardize the selectivity, given we were calculating relative values.

Predictions of data source 4, the age or size composition of the fishery catch, was modeled using the Baranov catch equation

$$\hat{C}_{j,y,s} = \frac{F_{j,y,s}}{F_{j,y,s} + M_s} N_{j,y,s} (1 - e^{-(F_{j,y,s} + M_s)})$$

$$\hat{P}_{j,y,s}^f = \frac{\hat{C}_{j,y,s}}{\sum_s \sum_j \hat{C}_{j,y,s}}$$

where $\hat{C}_{j,y,s}$ is the predicted number of commercially caught cisco age or size j in year y of sex s , and $\hat{P}_{j,y,s}^f$ is the predicted sex specific age or size composition of the fishery catch each year.

Predictions of data sources 5 and 6, the yield of each sex in each year, was modeled using

$$\hat{Y}_{y,s} = \sum_j \hat{C}_{j,y,s} w_{j,s}$$

where $\hat{Y}_{y,s}$ is the predicted sex specific fishery yield each year and $w_{j,s}$ is the mean weight of a commercially caught cisco age or size j . For the SCSA this term was obtained from the weight-length regression previously described. For the SCAA, to account for ALK fixed allocation bin sampling bias in mean weight-at-age (Quinn and Deriso 1999), we calculated the adjusted average weight of a commercially caught cisco similar to $P(\text{Fish}_j > 250\text{mm})$, using

$$\bar{W}_{j,s} = \frac{\sum_i (n_{i,j,s} * W_i)}{\sum_i n_{i,j,s}}$$

Where $\bar{W}_{j,s}$ represents the mean weight of a commercially caught cisco age j of sex s , $n_{i,j,s}$ is the number of fish in bin i that are age j of sex s , and W_i is the average of the length bin endpoints converted to weight using the same weight-length relationship described previously. It should be noted we used 10 mm bins, the same bin sizes used in the ALK sampling procedure. Variance of the mean weight of a commercially caught cisco age j of sex s , $Var(\bar{W}_{j,s})$, was then modeled using

$$Var(\bar{W}_{j,s}) = \sum_i \frac{n_{i,j,s} * (W_i - \bar{W}_{j,s})^2}{(\sum_i n_{i,j,s})^2}$$

A von Bertalanffy growth function (in weight) was then fit using the mean weights of commercially caught cisco, $\bar{W}_{j,s}$, weighted by the inverse of the variance, $\frac{1}{Var(\bar{W}_{j,s})}$, to obtain $w_{j,s}$, the adjusted average weight of a commercially caught cisco age j of sex s .

$$w_{j,s} = W_{\infty,s} (1 - e^{(-K_s(j-t_{0,s}))})^{b_s}$$

The growth function used the beta parameter, b_s , from the weight-length relationship previously described.

Predictions of data source 7, the individual cisco growth increments, which were only used in the SCSA, were calculated using

$$E(\Delta_l) = (L_{\infty} - l)(1 - e^{-K})$$

$$Var(\Delta_l) = a + b * E(\Delta_l)$$

where l represents the starting length of a cisco (length at start of annulus) and $E(\Delta_l)$ denotes the expected growth increment of a cisco given starting length.

Aging Error

Aging error was included in the SCAA model by multiplying the model predicted catch at age (true catch at age) and the predicted relative catch at age from survey gear by an aging error matrix. The aging error matrix was estimated by characterizing the expected coded age (C_j) given true age (T_j) and the coefficient of variation of coded age given true age as linear functions.

$$E(C_j) = a + bT_j$$

$$CV(C_j) = c + dT_j$$

Where a , b , c , and d are estimated parameters. For ease of computation, given preliminary fits suggested a and d were ≈ 0 , further runs of the model assumed both

parameters fixed at zero. The aging error matrix was then computed using the cumulative distribution function of the lognormal distribution, integrating over coded ages $j-0.5$ to $j+0.5$. The plus group was calculated by integrating from $j-0.5$ to infinity. The true catch at age matrix, output by the model, was multiplied by the aging error matrix to obtain the predicted catch at age matrix used in calculations of the predicted age composition of the catch. The same was done for the relative catch at age from the survey, which was multiplied by the aging error matrix prior to calculating predicted survey compositions.

Likelihood

We calculated the log likelihood components, L_i , for data sources 1, 5, and 6 in each model through a lognormal likelihood

$$L_i = -\frac{1}{2\sigma_i^2} \sum_y (\log(x_{i,y}) - \log(\hat{x}_{i,y}))^2 - n \log(\sigma_i)$$

where σ_i is the externally specified standard deviation for likelihood component i , $x_{i,y}$ and $\hat{x}_{i,y}$ are the observed and predicted values for year y , and n is the number of observations.

The log likelihood components for data sources 2, 3, and 4 for the SCAA assumed a robust multivariate normal likelihood equation as in Starr (1999)

$$L_i = \sum_y \sum_j 0.5 \log \left((1 - p_{i,j,y}) p_{i,j,y} + \frac{0.1}{Nb} \right) - \log \left(\exp \left[\frac{-(p_{i,j,y} - \hat{p}_{i,j,y})^2}{2 \left((1 - p_{i,j,y}) p_{i,j,y} + \frac{0.1}{Nb} \right) / \tilde{N}_{i,y}} \right] + 0.01 \right)$$

where $\tilde{N}_{i,y}$ denotes the effective sample size from data source i in year y , $p_{i,j,y}$ and $\hat{p}_{i,j,y}$ are the observed and predicted proportions of cisco in year y that are age j from data source i , and Nb represents the number of age bins. Robust likelihoods aid in keeping a small number of outlier composition data points from unduly influencing model fit (Fournier et al. 1990, Francis 2011). This is especially important given the nature of cisco year classes in Thunder Bay, which exhibit a “boom-or-bust” pattern where there may be a very large cohort moving through the time series followed by many years of almost no recruitment (Figure 1.3). For the SCSA, given we expect less outlier composition data points as disparity in year class strength is reduced due to recruitment into size bins (Figure 1.4), we utilized a regular multinomial likelihood

$$L_i = \sum_y \tilde{N}_{i,y} \sum_j p_{i,j,y} \log(\hat{p}_{i,j,y})$$

where $p_{i,j,y}$ and $\hat{p}_{i,j,y}$ are the observed and predicted proportions of cisco in year y that are in size bin j from data source i . Data sources i for these likelihoods include each composition dataset (age or size; fishery catch, MWT survey, and multi-mesh gillnet survey). It should be noted that both sexes went into one likelihood for each i , meaning only one value of $\tilde{N}_{i,y}$ was used for each data source. This results in double the number of size bins ($Nb * 2$) for each i , to account for both males and females.

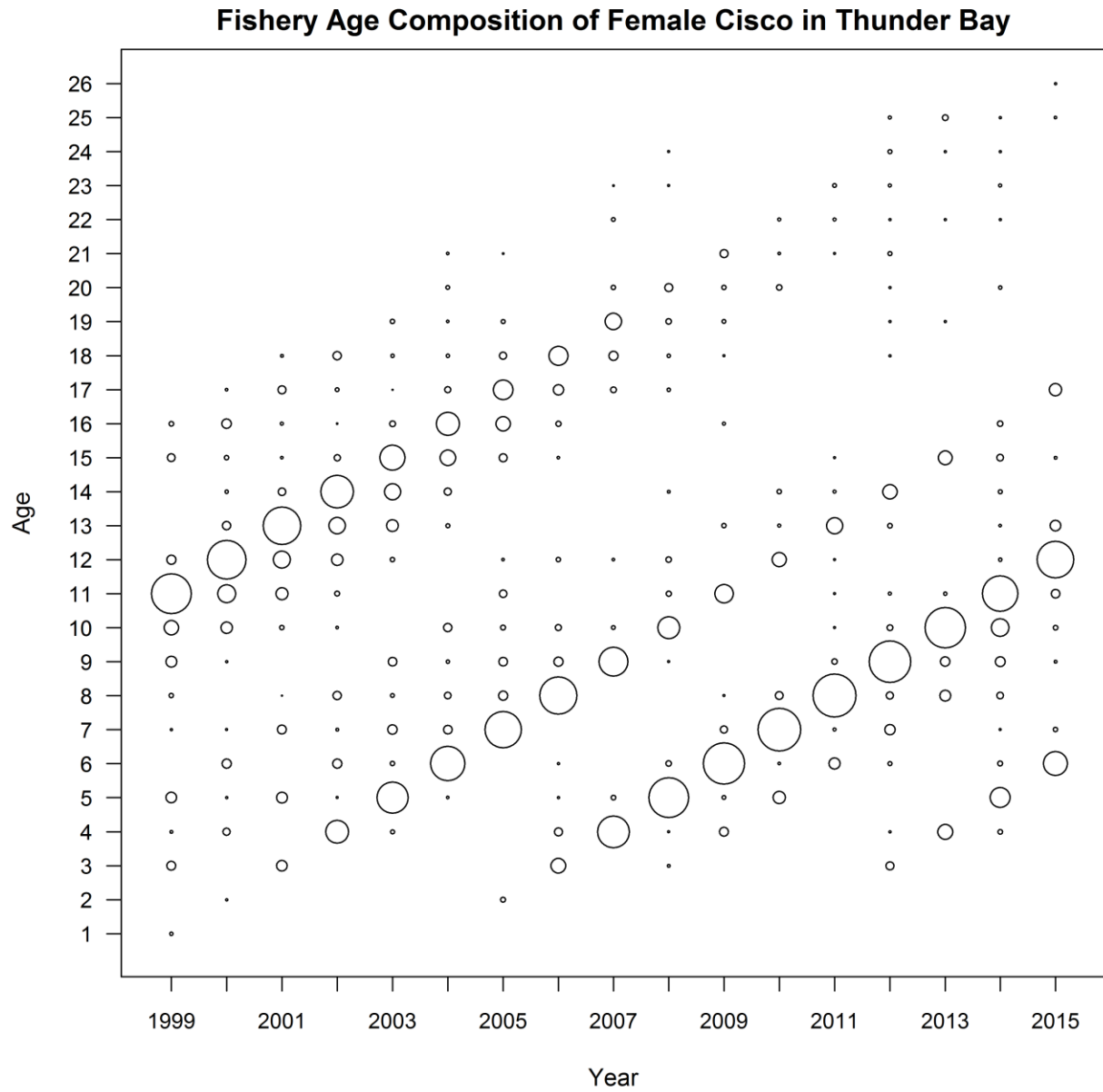


Figure 1.3. Age composition of female cisco caught in Thunder Bay, Ontario, from 1999 to 2015.

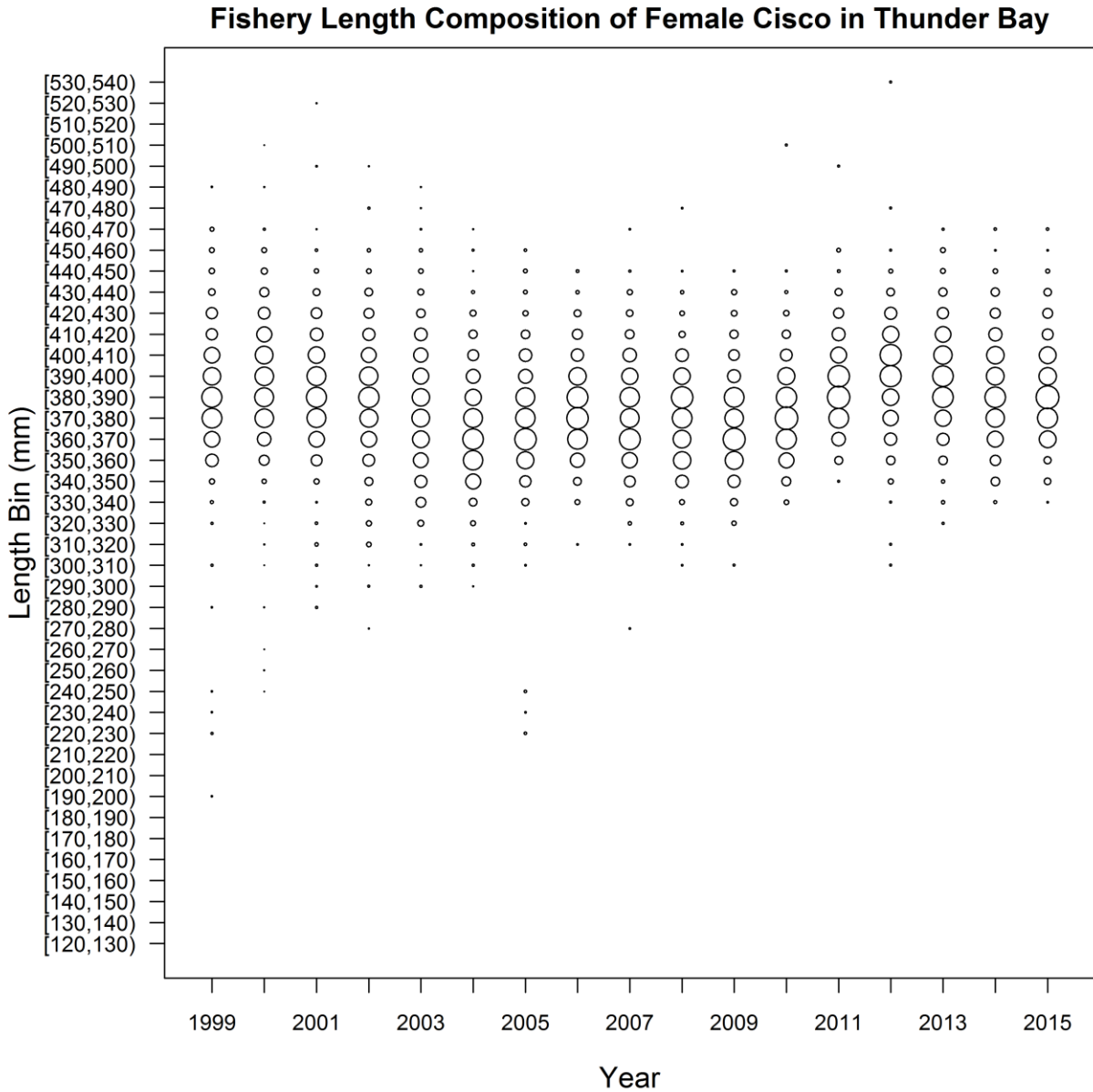


Figure 1.4. Length composition of female cisco caught in Thunder Bay, Ontario, from 1999 to 2015. Y axis labels denote length bin endpoints, i.e. “[150,160)” refers to a length bin starting at 150 mm and ending at 160 mm.

Data source 7, the individual growth increment data, which was only used in the SCSA, assumed a gamma log likelihood

$$L_7 = \sum_l \alpha_l \log(\beta_l) - \log(\Gamma(\alpha_l)) + (\alpha_l - 1) \log(\Delta_l) - \beta_l \Delta_l$$

where α_l and β_l are the shape and rate parameters of the gamma distribution, and Δ_l denotes an observed growth increment of a cisco with starting length l . The expected value is given by $E(\Delta_l) = \frac{\alpha_l}{\beta_l}$ and similarly the variance is defined as $Var(\Delta_l) = \frac{\alpha_l}{\beta_l^2}$.

Log prior components for natural mortality and recruitment deviations that were not compared to data but rather to expectations specified as informative priors also contributed to the objective function through a normal prior distribution

$$L_i = -\frac{1}{2\sigma_i^2} \sum_j (\log(\hat{x}_{i,j}))^2 - n \log(\sigma_i)$$

where $\hat{x}_{i,j}$ represents the model predicted deviations.

The objective function was then the negative sum of the log likelihood and log prior components

$$L = -\sum_i L_i$$

Data Weighting

Standard deviations, σ_i , in likelihood equations for data sources 1, 5 and 6, and for recruitment deviations, were modeled as one estimated parameter and two assumed variance ratios, denoting what we might expect the multiplicative difference in standard

deviations to be. For example, we expected the yield (data sources 5 and 6, sharing a σ) to have the smallest standard deviation, since catch is usually assumed known, followed by hydroacoustic abundance estimates, and finally recruitment deviations, which we expected to vary considerably given the drastic difference in cohort strength between years (Figure 1.3). We estimated the standard deviation for harvest, while assuming variance ratios (Vr) of 0.04 and 0.0004 for hydroacoustic estimates of abundance and recruitment deviations, respectively.

$$\sigma_i = \sqrt{\frac{1}{Vr} \sigma_f^2}$$

where σ_f denotes the standard deviation for fishery harvest.

Effective sample sizes, $\tilde{N}_{i,y}$, for the composition datasets were calculated using iterative reweighting procedure T3.4 of Francis (2011)

$$\tilde{N}_{i,y} = N_{i,y} w_i$$

where $N_{i,y}$ denotes the previous iterations effective sample size. w_i was calculated using TA1.8 of Francis (2011)

$$w_i = \frac{1}{\text{Var} \left[\frac{(\bar{O}_{i,y} - \bar{E}_{i,y})}{(v_{i,y}/N_{i,y})^{0.5}} \right]}$$

where $\bar{O}_{i,y} = \sum_j j * O_{i,j,y}$ with similar formula for $\bar{E}_{i,y}$, and $v_{i,y} = \sum_j (j^2 E_{i,j,y}) - \bar{E}_{i,y}^2$. i in

these formulas denotes a composition data set (age or size; commercial fishery, MWT survey, or multi-mesh gillnet survey) and j denotes age or size bin. The initial effective

sample sizes were a maximum of 200 cisco for the commercial fishery, and a maximum of 100 cisco for each of the survey gears. The iterative process was stopped when the effective sample sizes appeared to converge. This process was robust to starting sample sizes, with the $\tilde{N}_{i,y}$ converging on similar estimates regardless of starting values. We utilized maximum likelihood estimation to obtain effective sample size convergence prior to running the models using Bayesian methods in Automatic Differentiation Model Builder (ADMB). Effective sample sizes converged on 62 for fishery compositions, 45 for MWT compositions, and 50 for multi-mesh gillnet compositions for the SCAA and 58, 22, and 11 for the SCSA.

Model Fitting/Calibration/Troubleshooting

SCAA

The SCAA model was unable to converge on an estimate of γ , which denotes the logarithm of acoustic catchability. Essentially this parameter scales our entire population by representing what proportion of spawning cisco the acoustic survey is actually detecting. Due to this, we decided to assume a conservative scenario where $\gamma = 0$, which assumes the acoustic survey is an absolute index of spawner abundance. Here, by conservative, we mean that actual catchability is likely lower, abundance is likely higher, and thus yield targets set based on the abundance estimates will likely be lower than if the target exploitation rate were applied to an unbiased abundance estimate. The hydroacoustic surveys are generally thought to be a conservative estimate of abundance as all areas of the water column are not detectable with the gear, i.e. surveys are likely missing some fish (Yule et al., 2012). The model was run for 10 million

iterations each saving every 500th, burning in the starting 2500 values from the final chains. Chain burn in was assessed visually and convergence determined using Geweke's convergence diagnostic (Geweke, 1991).

SCSA

It became clear at the beginning of model calibration for the SCSA that the model was going to be unable to output plausible estimates of natural mortality. The model would confound estimates of recruitment, selectivity, and natural mortality. It was unable to converge on plausible estimates of natural mortality even when given assumed known growth parameters at levels previously estimated using fixed natural mortality at prior point estimates. The model would increase natural mortality to an implausibly high value, inflate recruitment, and make larger fish more selected. What the model was doing was creating many fish through recruitment, killing them off at high rates through natural mortality in order to have enough fish at spawning sizes to fit the hydroacoustic data. Few large fish were predicted to survive, but fishery selectivity was highest for the largest fish in order to fit the fishery composition data. Similar to the SCAA, the SCSA was also unable to converge on an estimate of acoustic catchability. Given these issues, we decided to fix natural mortality at its prior point estimates (0.283 for males, 0.256 for females), fix acoustic catchability at 1 ($\gamma = 0$), and estimate growth. We ran the model for double the number of samples (20 million) and also doubled chain burn in (first 5000 iterations).

Comparison

Given different data used in each assessment, it was not possible to compare the final models in terms of predictive accuracy/information theoretic measures such as PSIS-LOO, WAIC, or DIC. Instead, final models were compared using a variety of criteria. First, we considered what assumptions we had to make to fit each model. We also looked at retrospective patterns, parameter/output uncertainty and model fit/residuals. Retrospective analyses primarily focused on spawning biomass and exploitation rate. Mohn's rho (Mohn, 1999) was calculated for spawning biomass and exploitation rate as the mean relative error for the last year of each peel compared to the corresponding year in the full assessment.

$$\rho = \overline{\left(\frac{Y_{F,p} - Y_{F,ref}}{Y_{F,ref}} \right)}$$

Where Y is the assessment output quantity, either spawning biomass or exploitation rate, ref refers to the full assessment, and F refers to the final year of a given assessment peel, p . Five years were removed from the assessment. We also calculated a mean final year absolute bias for the retrospective analyses, as the mean absolute value of the relative error for the last year of each peel compared to the corresponding year in the full assessment. This statistic considers the bias in the final year of each peel as opposed to whether or not there is a consistent pattern.

$$\lambda = \overline{\left(\frac{|Y_{F,p} - Y_{F,ref}|}{Y_{F,ref}} \right)}$$

Both ρ and λ were calculated using medians of the posterior distribution as point estimates.

Residuals for common data sources were compared both visually in addition to using the standard deviation of the normalized residuals (SDNR, Breen et al., 2003; Francis, 2011; Carvalho et al., 2016). These were calculated as the standard deviation of the normalized residual for each data point (formulas in Table B1 in Francis 2011). A relatively good model fit is characterized by smaller residuals and a SDNR near 1 (Carvalho et al., 2016), although Francis (2011) notes that a value much less than 1 is not a cause for concern but rather means that the data set is fitted better than was expected. Due to their correlative nature, composition data points cannot be compared using this metric (Francis, 2011), so these were compared visually.

Results

Point estimates of quantities output from the models are reported as medians of the posterior distribution, with 95% highest posterior density (HPD) intervals reported in parentheses. All parameters in each model indicated convergence based on Geweke's diagnostic at an alpha level of 0.01. The SCAA estimated a total of 89 parameters while the SCSA estimated 67 parameters. Natural mortality estimates within the SCAA for males and females were 0.284 (0.214-0.367) and 0.252 (0.182-0.336) respectively.

Biomass

SCAA biomass fluctuated throughout the time series beginning at 5.92 (2.50-12.48) million kg in 1999, reaching a peak in 2006 of 8.41 (4.94-13.10) million kg, and ending at 1.70 (1.07-2.47) million kg in 2015 (Figure 1.5). Spawning biomass, defined as

the mature female biomass (>250 mm), began at 4.96 (2.10-10.29) million kg, initially declined then rose to an estimate of 4.88 (2.91-7.65) million kg in 2006 and ended the time series at 0.96 (0.59-1.40) million kg.

SCSA biomass exhibited a similar trend to the SCAA, with an increase during the beginning of the time series from 2.62 (1.58-4.54) million kg in 1999 to a peak in 2007 of 5.97 (4.35-7.84) million kg, followed by a decrease to a final year estimate of 2.85 (2.01-3.97) million kg in 2015. Spawning biomass began at 2.04 (1.30-3.48) million kg and ended at 1.44 (0.98-2.05) million kg, with a peak in 2008 of 3.01 (2.17-4.01) million kg.

Exploitation Rate

Exploitation in the SCAA was modest throughout the time series, hovering around 3%, although in 2010 began to increase resulting in a final year estimate of 9% (6%-14%, Figure 1.5). This resulted in fully selected fishing mortality rate estimates of 0.08 (0.04-0.12) and 0.20 (0.11-0.32) for males and females in 2015, respectively. Exploitation rate was defined as yield divided by the biomass of fish larger than 250 mm. This is similar to the control rule allocation in Thunder Bay, where total allowable catch is calculated as 10% of cisco biomass greater than 250 mm estimated from the hydroacoustic survey. For the SCSA, exploitation rate decreased from 8% (4%-13%) at the beginning of the time series to 3% (2%-4%) in 2007 and increased throughout the rest of the time series to a final year estimate of 6% (4%-8%). Final year fully selected fishing mortality rates were 0.05 (0.03-0.07) and 0.17 (0.10-0.25) for males and females.

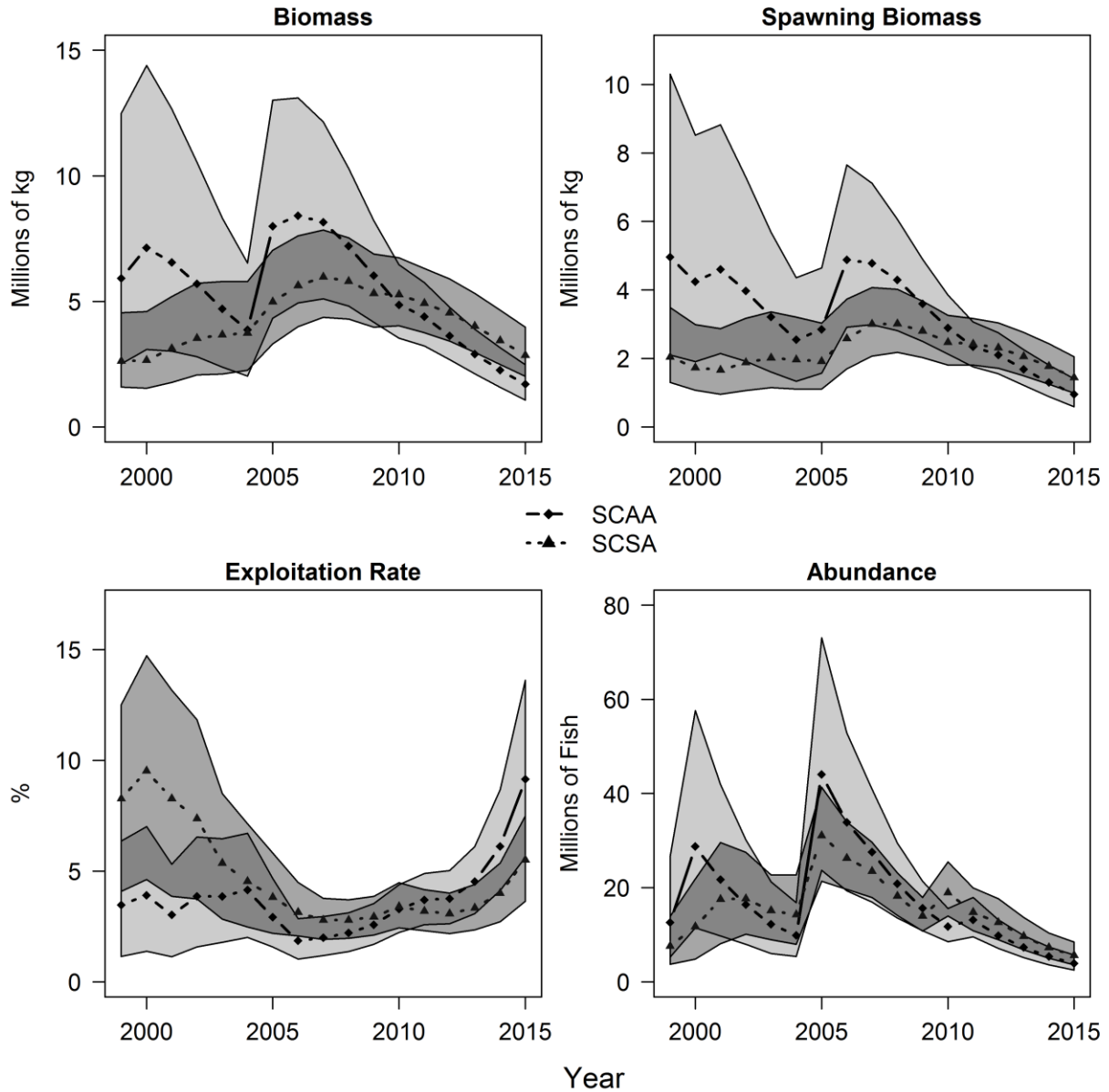


Figure 1.5. Biomass in millions of kg, spawning biomass in millions of kg of mature females (>250 mm), exploitation rate (yield/biomass of fish > 250 mm), and abundance in millions of fish for the SCAA and the SCSA. Shaded regions denote 95% HPD intervals and dashed lines are medians of the posterior distribution. Squares denote SCAA output while triangles denote SCSA output. Light shading denotes the HPD for the SCAA, darker shading denotes the HPD for the SCSA, and the darkest shading is where the two intervals overlap.

Recruitment

As expected, recruitment was highly variable throughout the time series, with evidence of ~4 “boom” recruitment years in the SCAA, belonging to 1998, 2003, 2005, and 2009 year classes (Figure 1.6). Estimates of recruitment (age-2 fish) for these years ($y+2$; 2000, 2005, 2007, and 2011) were 19.19 (7.46-39.43), 36.69 (18.68-61.22), 1.86 (0.91-3.22), and 4.38 (2.30-7.11) million fish, respectively. Recruitment was estimated to be around 15,000 fish in 10 years, and the 3 remaining years were estimated at modestly low values, with estimates ranging from 0.85 (0 -1.78) million in 2004 to 0.21 (0-0.98) million fish in 1999.

Recruitment in the SCSA, where not defined in the same way as the SCAA, in that it describes the number of fish greater than 170 mm that recruit into the model, showed a similar trend to SCAA recruitment with 3-4 clear modes most likely attributed to the 1998, 2003, 2005, and 2009 “boom” year classes (Figure 1.6).



Figure 1.6. Recruitment for the SCAA and SCSA. Where both represent the number of fish entering the model in a given year, they are not defined the same way in that for the SCAA it is the number of age 2s entering the population and in the SCSA it is the number of fish greater than 170 mm that are entering the population. Points denote medians of the posterior distribution and error bars are the 95% HPD intervals.

Abundance

SCAA abundance echoed biomass results, with intermittent spikes due to “boom” recruitment years and an overall declining trend over time. In 1999 the model predicted there were around 12.62 (5.24-26.63) million cisco, a high of 44.07 (23.68-73.08) million estimated in 2005, and in the final year 3.90 (2.46-5.69) million (Figure 1.5).

SCSA predicted abundance began the time series at 7.57 (3.71-13.89) million fish, 31.03 (21.35-41.31) million fish at its peak in 2005, followed by a decrease to around 5.61 (3.63-8.47) million fish in 2015.

Aging Error

Very little aging error was estimated within the SCAA model. Approximately no bias was estimated in aging as true age increased ($b \approx 1.00$), in addition to a very low estimated CV ($c = 0.02$).

Growth

L_{∞} and K were estimated at 428 mm (419-439) and 0.28 (0.25-0.30), respectively (Figure 1.7).

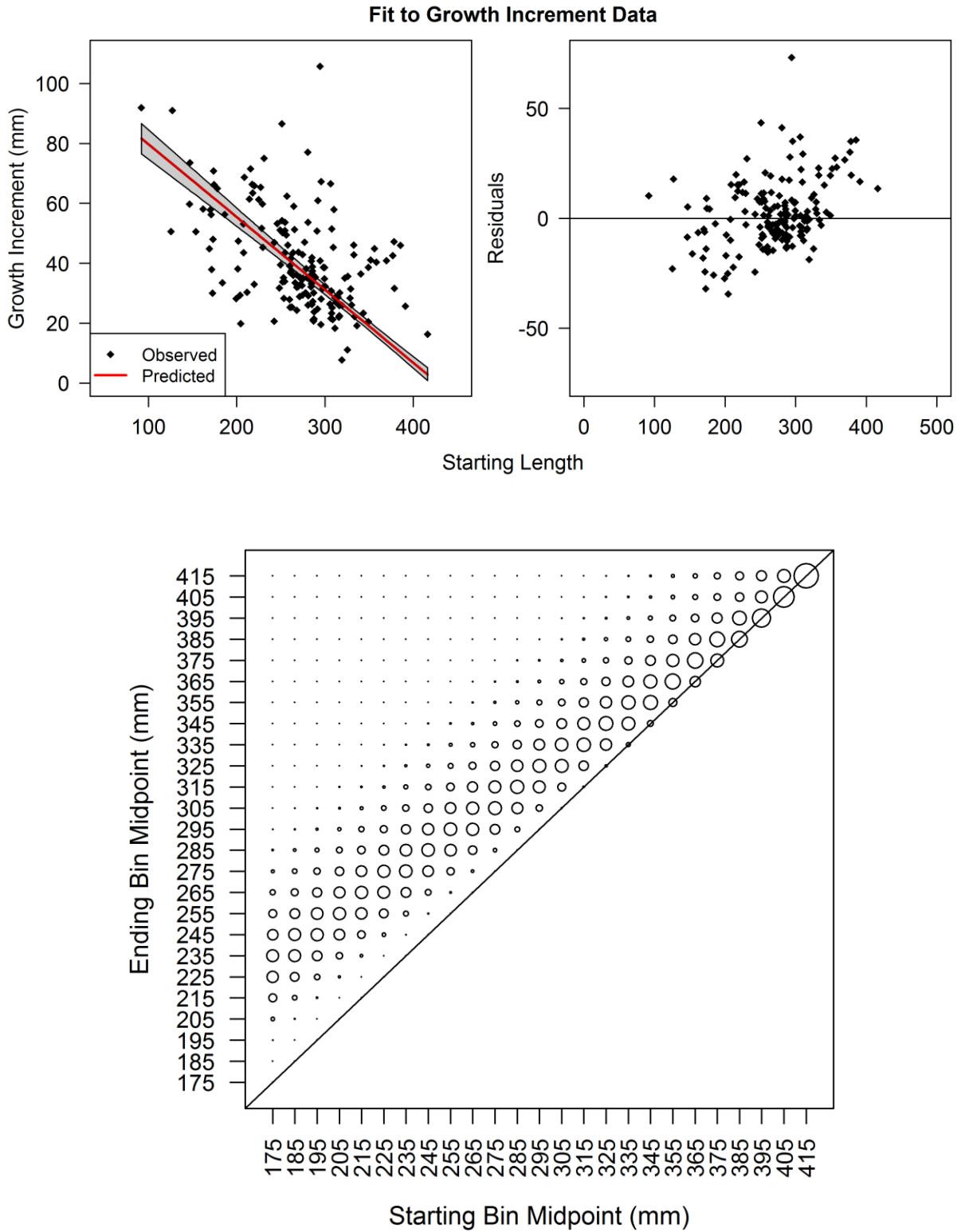


Figure 1.7. Upper left: Fit to growth increment data. Red line depicts the median of the posterior distribution and shaded region represents 95% HPD intervals.

Figure 1.7 (cont'd) Upper right: Residuals, medians of the posterior distribution, from fit to growth increment data. Lower panel: Growth transition matrix at the posterior medians for growth parameters. Note that the area of the circles represent the probability of growing into a length bin given a starting length bin. Length bins are represented on axes as midpoints. Plus group is length bin 410-420 mm.

Retrospective Analyses

Retrospective patterns for each model were very similar (Figure 1.8). Mohn's rho estimates for spawning biomass and exploitation rate were -0.01 and 0.01 for the SCAA and 0.18 and -0.13 for the SCSA, respectively. All of these rho values are within a range of values deemed "not a cause for concern" in retrospective analyses (Hurtado-Ferro et. al, 2015). Absolute bias estimates for spawning biomass and exploitation rate were 0.14 and 0.16 for the SCAA and 0.21 and 0.15 for the SCSA, respectively.

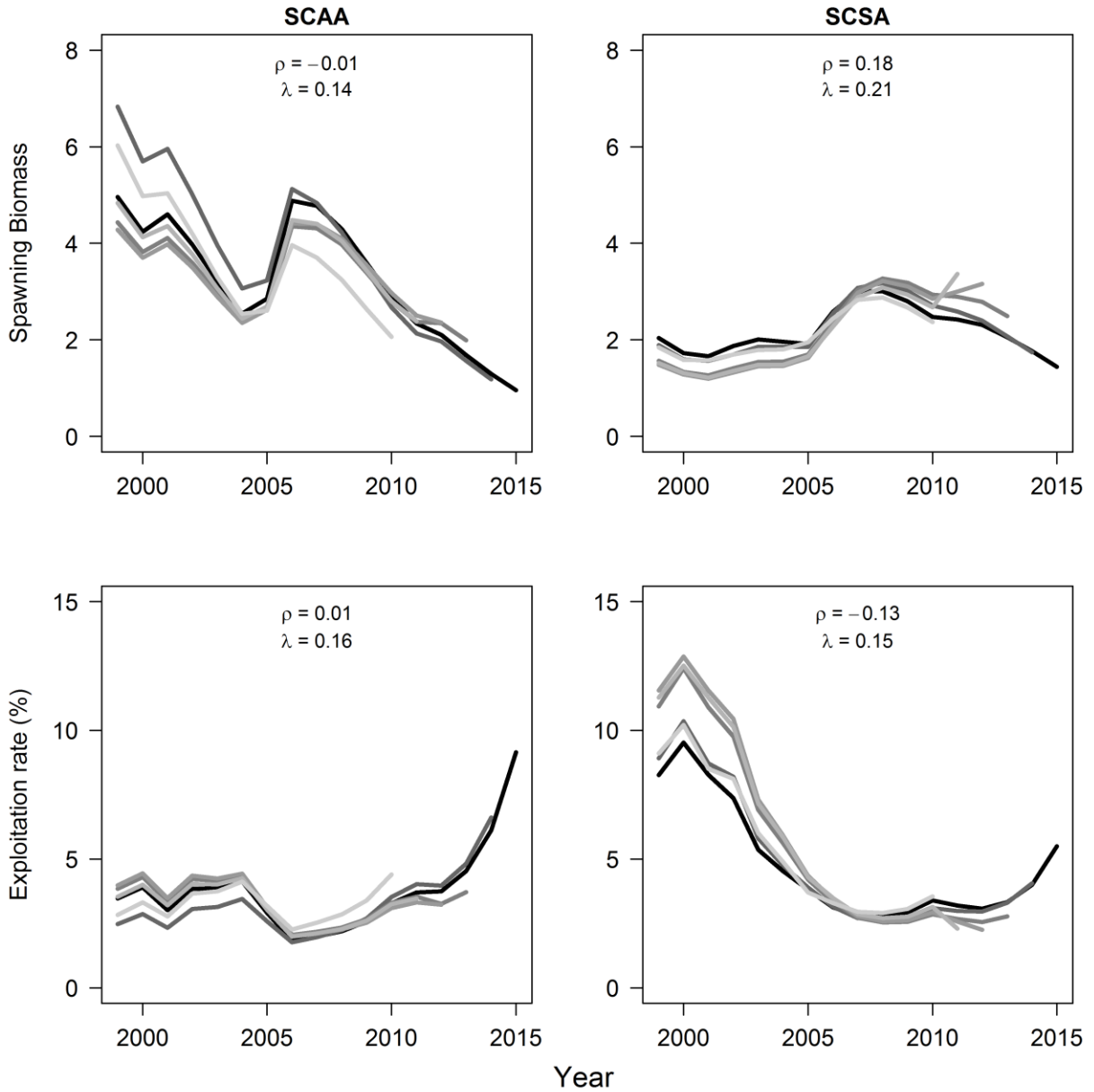


Figure 1.8. Retrospective analyses for spawning biomass and exploitation rate. Shown are times series estimates of spawning biomass and exploitation rate when five terminal years of data are sequentially dropped from each assessment. Spawning biomass in millions of kg of mature females and exploitation rate as yield/biomass of fish > 250 mm.

Model Fit to Data

Assessment model fits to the hydroacoustic data were very similar (Figure 1.9). Both assessments treated the observed hydroacoustic spawning abundance estimate in 2011 as an outlier. Outside of that outlier data point, both models predicted a near linear decline in spawning abundance since 2005, in accordance with the observed data points. The median of the negative log-likelihood for the fit to acoustic data was lower for the SCAA (Table 1.4). SDNR values for the acoustic data were also closer to 1 for the SCAA, indicating better fit.

Fit to harvest data was nearly identical between the assessments (Figure 1.10). In fact both models fit the data so closely that the observed data is no longer visible on Figure 1.10. HPD credible intervals were slightly smaller for the SCSA model. The medians of the negative log-likelihoods for male and female harvest were lower for the SCSA (Table 1.4), and the SDNR values were smaller for the SCSA. Both model SDNR yield values were well below 1, indicating better model fit than expected.

Both models fit the fishery composition data points well (see Supplemental Figures 1.1-1.8). These two fits cannot be directly compared as they used different data.

Table 1.4. Negative log-likelihood and SDNR values for common data sources.

	Male Yield	Female Yield	Hydroacoustic Data
SCAA – NLL	-32.97	-32.94	0.31
SCSA – NLL	-35.30	-35.32	1.94
SCAA – SDNR	0.09	0.12	1.26
SCSA – SDNR	0.06	0.04	1.50

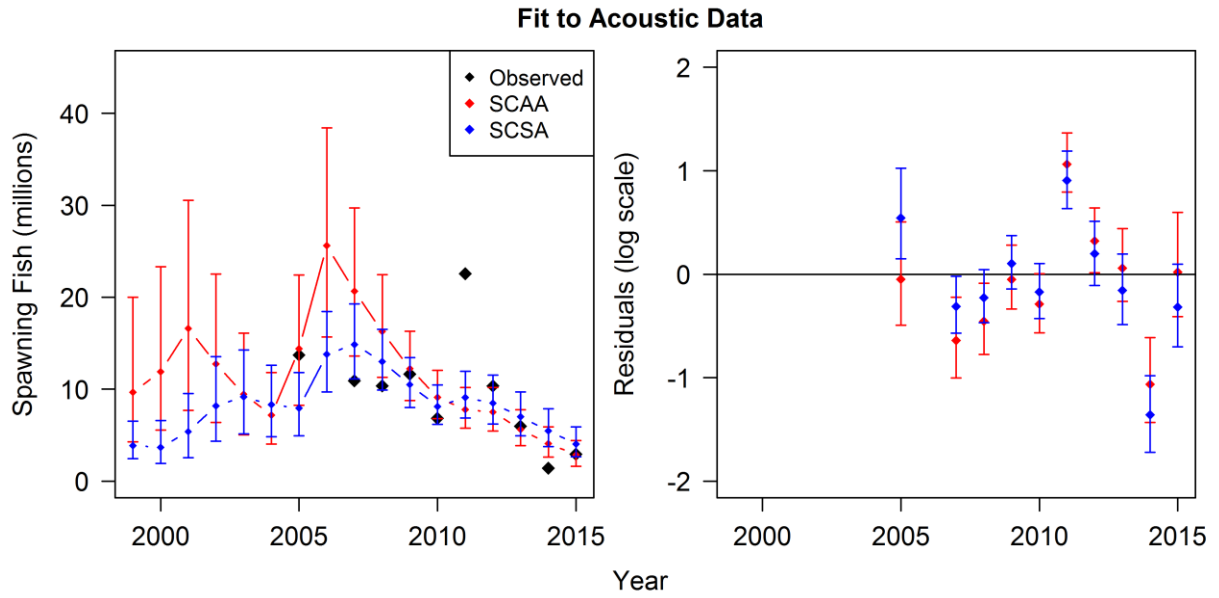


Figure 1.9. Fit to hydroacoustic estimates of spawning abundance. No data from 1999-2004 and in 2006. Spawning fish in millions of fish. Points denote medians of the posterior distribution and error bars are 95% HPD intervals.

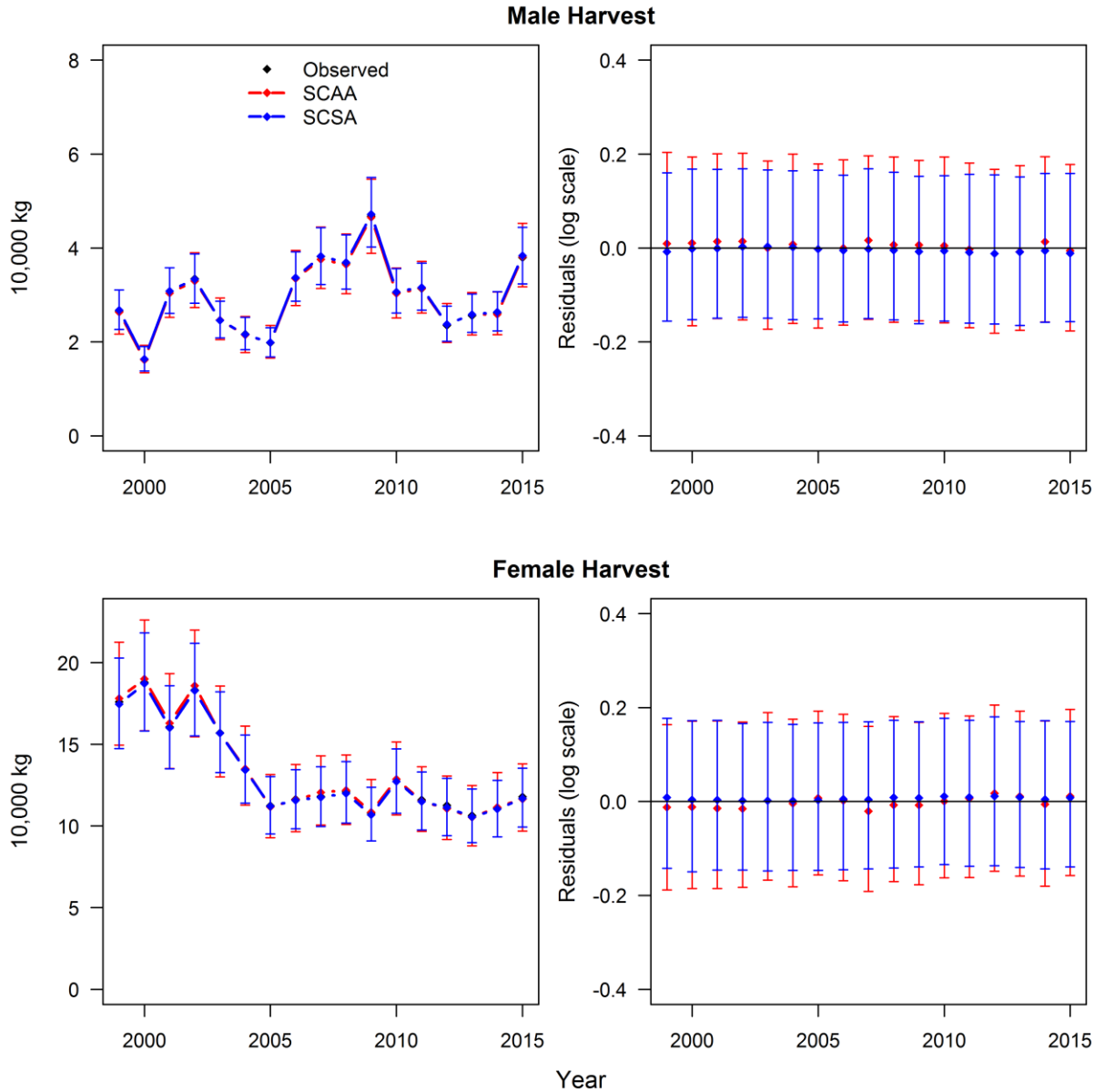


Figure 1.10. Fit to landings data. Harvest (first column) is in 10,000 kg. Note observed data points in the first column cannot be seen as they are covered by model point estimates.

Computational Intensity

The SCSA was considerably more computationally intensive than the SCAA, necessitating about 3x the run time for the same number of iterations (where the SCAA took ~5 hours for 10 million, SCSA took ~15 hours).

Discussion

Overall both models showed similar trends in outputs and modest differences in final year estimates (Table 1.5, Figure 1.5). However, the SCAA model showed a larger degree of uncertainty during the first half of the time series, which decreased throughout the second half of the time series to actually end up being less than SCSA uncertainty in the final year (Figure 1.5). This disparity in uncertainty at the beginning of the time series is likely due to differences in the initial parameterization of each model, where much more flexibility was afforded to the SCAA by estimating 26 initial abundance parameters (1 for each age-sex combination above recruitment age).

Conversely the SCSA estimated only 4 initial abundance parameters; 2 for the initial size composition, and 1 for each sex as abundance multipliers. Increased certainty in the SCSA during most of the time series may also be driven by the assumption of known natural mortality values. In fact, when we re-ran the SCAA with assumed known natural mortalities at their prior point estimates, uncertainty in model output decreased significantly (Figure 1.11), indicating that the certainty in output expressed by the SCSA is likely in some part due to assuming known natural mortality values. In terms of uncertainty in the final year of each assessment, one aspect that might be driving the smaller credible interval for abundance outputs (biomass, spawning biomass, abundance) in the final year for the SCAA is lack of a recent “boom” year class. The last

large recruitment year was in 2009 (Figure 1.6 left panel, and by boom standards it was pretty weak), so effectively, without replenishment the model is consistently decreasing the uncertainty in biomass and abundance from 2009-2015 through depletion of fish.

Table 1.5. Final year (2015) relative differences $[(SCAA-SCSA)/SCAA]$.

Output	Relative Difference
Abundance	-44%
Biomass	-68%
Spawning Biomass	-51%
Exploitation rate	40%

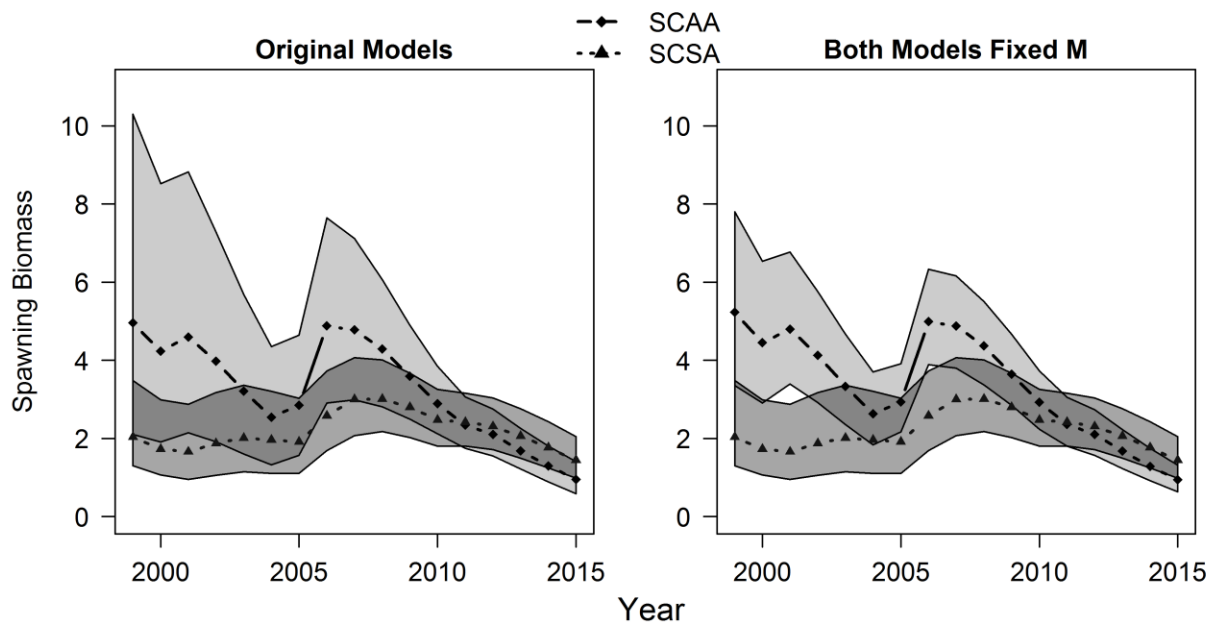


Figure 1.11. Comparison of models when natural mortality is estimated within SCAA and when it is assumed known. First column are the original models, while the second column natural mortality is assumed known for SCAA. Shaded regions denote 95% HPD intervals and dashed lines are medians of the posterior distribution. Squares denote SCAA output while triangles denote SCSA output. Light shading denotes the HPD for the SCAA, darker shading denotes the HPD for the SCSA, and the darkest shading is where the two intervals overlap.

In terms of model fit, the SCAA had better fit to the acoustic data while the SCSA had better fit to the landings data [although the slightly better fit of the SCSA to landings may not be all that significant, as all landings SNDRs were well below 1, indicating better fit than expected by each model (Francis 2011)]. For the retrospective analysis, where ρ estimates were larger for the SCSA, upon visual inspection the patterns appear comparable between the two assessments, if not worse for the SCAA (Figure 1.8). This result of smaller ρ estimates for the SCAA even though patterns may appear more severe if not equal to those in the SCSA is driven by equally large bias in the terminal years of peels for the SCAA in opposite directions (i.e. not a consistent pattern but equal numbers of over and under estimates). Given no ρ estimates are at values considered “cause for concern” (Hurtado-Ferro et al., 2015), it may be more prudent to consider λ in comparing retrospective analyses, which was larger for exploitation rate and smaller for spawning biomass for the SCAA compared to the SCSA. Once again it is likely assuming known natural mortality values at their prior point estimates led to both a smaller λ estimate for exploitation rate and the appearance of less severe retrospective patterns within the SCSA. When we re-ran the SCAA retrospective analysis with assumed known natural mortality values at their prior point estimates, absolute bias estimates (λ) decreased. In fact, all retrospective statistics were lower (closer to 0 for rho) for the SCAA with assumed known natural mortality than the SCSA counterparts (Figure 1.12; SCAA fixed M λ : Spawning Biomass – 12%, Exploitation rate – 14%).

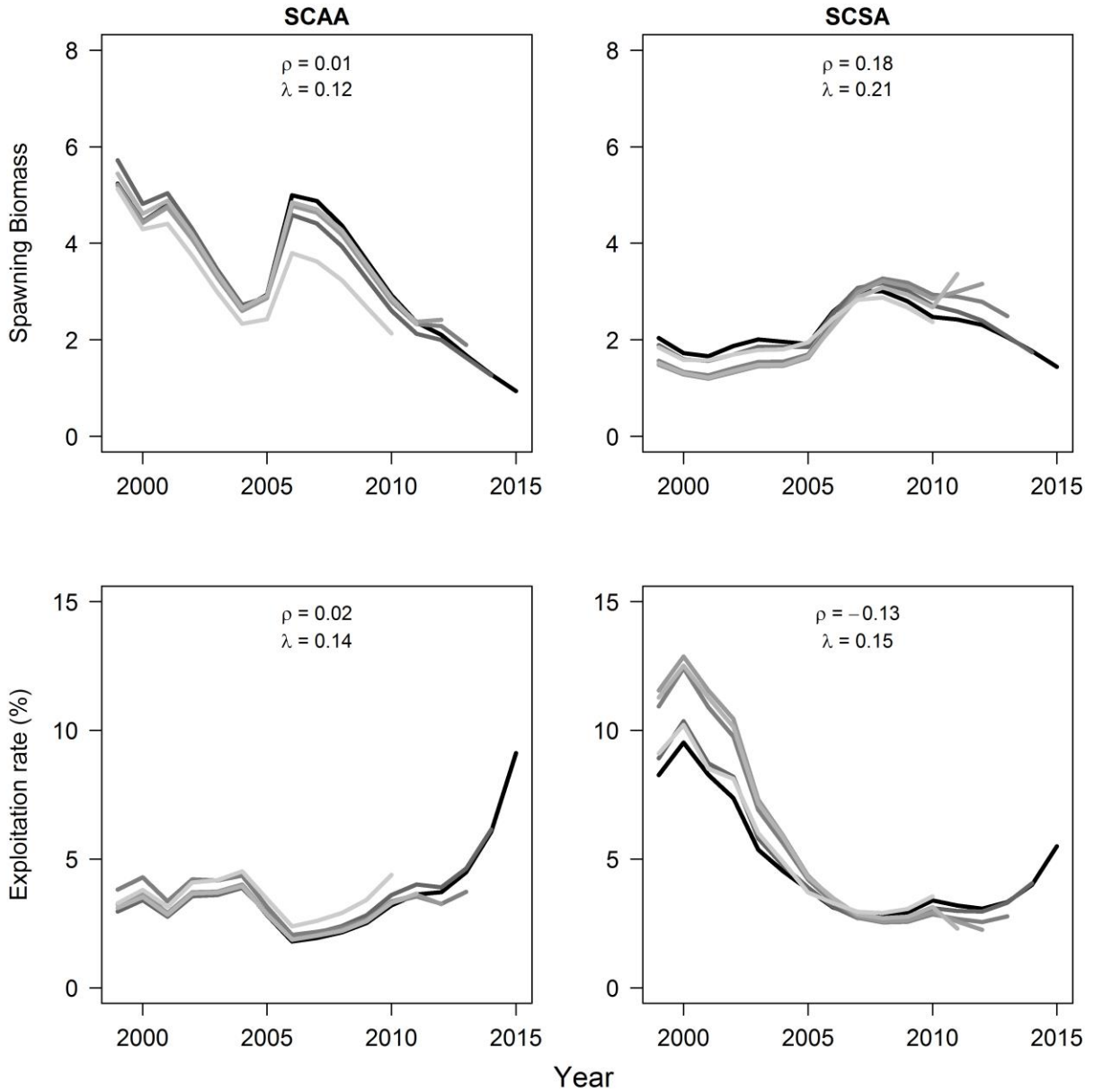


Figure 1.12. Retrospective analyses where both SCAA and SCSA assumed the same known natural mortality values. Shown are times series estimates of spawning biomass and exploitation rate when five terminal years of data are sequentially dropped from each assessment. Spawning biomass in millions of kg of mature females, and exploitation rate as yield/biomass > 250 mm.

Perhaps the most important result of our study is the inability to estimate natural mortality within the SCSA. Given natural mortality is one of the most influential quantities in stock assessment and its estimation within an assessment can be difficult (Lee et al., 2011; Brodziak et al., 2011; Sippel et al., 2017), its estimability in the SCAA certainly favors the SCAA as an assessment model choice. An interesting note is the remarkable similarity of the prior natural mortality point estimates (the fixed, assumed known SCSA M values; 0.283 and 0.256) to the estimated natural mortality point estimates for the SCAA. In fact, when we ran the SCAA model without specifying informative priors on natural mortality, a similar result occurred (Male $M = 0.282$, Female $M = 0.250$), indicating this similarity is not due to the specification of an informative prior in the SCAA but rather that the age composition data are providing crucial information on natural mortality. The similarity between assumed known natural mortality in the SCSA and estimated natural mortality in the SCAA in addition to the utilization of the same hydroacoustic and landings data likely led to similar output between the two assessments.

The inability to estimate natural mortality within the SCSA due to its confounding with estimates of recruitment and selectivity is not a new finding, as parameter confounding has been noted to be potentially more serious in size-structured assessments (Punt et al., 2013). Where parameter confounding did not change growth parameters much (mainly influenced selectivity, recruitment, and natural mortality), its underlying cause may have been variation in growth, such that variation in size-at-age makes it hard for size-structured models to discern cohorts from length composition data (Punt et al., 2013). In fact, even if we assumed growth was known within the SCSA,

the model still confounded selectivity, recruitment, and natural mortality. Another aspect that may have led to the inability to estimate natural mortality within the SCSA is the range of vulnerability to the fishery for cisco in Thunder Bay, where by the time cisco start to show up in the fishery length compositions they are at or very near asymptotic size, by this time having substantially slowed their somatic growth (Figure 1.4). This results in similarity in fishery size composition data between years making it difficult to observe strong year classes pulse through the fishery composition data (Figure 1.4). Where the fishery independent survey gear does select smaller fish and is, to some extent, able to discern cohorts from its length composition data (likely why recruitment in SCSA for 2003 and 2009 cohorts were approximated well), our survey composition data was limited, only having started in 2005 and missing critical years in 2006 and 2011-2012. The missing survey data pre-2005 likely resulted in recruitment of the 1998 cohort being spread over ~5 years in the SCSA (Figure 1.6). Fishery independent survey size composition data throughout the full time series would have likely resulted in a better approximation of year-class strength and possibly allowed estimation of natural mortality within the SCSA. Alternatively in the SCAA model, likely due to the boom-or-bust recruitment pattern, the model was clearly able to distinguish 3-4 large year classes moving through the fishery and estimate their associated depletion. Estimation of natural mortality within the SCAA may also have been made possible by relatively light exploitation, effectively making the major source of mortality and transition through the population-age matrix one of natural depletion.

Estimation of natural mortality within size structured assessments is possible, as within Punt et al. (2013), a review of integrated size-structured assessment methods,

three out of nine assessments that were reviewed in depth estimated natural mortality. Two of these three assessments modeled selectivity as logistic, the other modeled it as a double normal, while all three modeled recruitment as lognormal deviates entering the population through a specified size distribution. These selectivity functions are less flexible than a gamma function, which may indicate a reason they did not experience parameter confounding to the extent we did with regard to natural mortality, selectivity and recruitment. Although interesting to note that in our study even if we fixed selectivity and growth at values estimated using assumed known natural mortalities, and then tried to estimate natural mortality, the SCSA model would still inflate recruitment and estimate implausibly high natural mortalities. Where some size-structured models may indeed be able to estimate natural mortality, our study indicates that this may be an even taller task than it is in SCAA models, and is dependent on a multitude of factors from variability/patterns in recruitment, variability in growth and size at age, and vulnerability range of organisms within size composition data.

Conclusions and Recommendations

Although more uncertain, primarily due to the estimability of natural mortality, we conclude that the SCAA is more appropriate for modeling population dynamics of cisco in the Laurentian Great Lakes. Where size based assessment models can considerably decrease the amount of fish that need to be aged, as this study shows, age composition data can be crucial to the ability to estimate natural mortality within a model. We prefer to avoid reliance on assumed known scale parameters (acoustic catchability) and natural mortalities, if this can be avoided. Where the assessments both resulted in similar natural mortality estimates, in other case studies this may not occur,

and bias in using a surrogate equation for natural mortality may result in biased assessment output. In addition, assuming known natural mortality may artificially decrease model uncertainty. We do not necessarily expect this conclusion to apply for all, or even most species. In fact, this result is likely largely driven both by the unique life history of cisco in exhibiting boom-or-bust recruitment, and the fact that most growth occurs before cisco are vulnerable to the fishery, allowing for the estimation of natural mortality within the SCAA and not within the SCSA. For species with less variable recruitment, less variable growth, and size composition data throughout the growth period of their life span, size based assessment methods may perform equally well, or better, than age-structured methods.

Our conclusion, that the SCAA was more appropriate than the SCSA when applied to cisco, is largely driven by our desire to estimate natural mortality. While it is tempting to contrast our conclusion with other comparisons of size- and age-based assessment models (Akselrud et al., 2017; Punt et al., 2017), those studies did not attempt to estimate natural mortality within the assessment models. Where Punt et al., (2017) concluded that age-structured methods performed poorest and Akselrud et al., (2017) concluded that age-structured methods fit the data best, we believe that the conclusions of these studies might depend on their assumption that natural mortality was known. Akselrud et al., (2017) and Punt et al., (2017) also considered assessment models that take into account both age- and size-based processes in their analyses. Where these models may improve assessment accuracy (Gilbert et al., 2006; McGarvey et al., 2007; Punt et al., 2017), they are also very data- and computationally intensive. We did not consider them in our analyses. It is possible that an age- and size-structured

model could outperform both SCAA and SCSA in application to cisco in Thunder Bay. Additionally, while we believe the comparisons we made and conclusion we reached in preferring the age-based model is valid, we cannot be sure that the estimated population sizes and mortality rates are closer to true values than those generated by a size-based model, given the truth is not known. Further, our analysis cannot define the conditions under which the natural mortality is estimable and produces useable assessment results, as we had only one data set resulting from one set of conditions. This is a potential advantage of simulations like those of Punt et al. (2017) over empirical comparisons of alternative models as shown here. Our empirical comparisons highlighted some aspects of the performance of size- and age-based models contrast in real world applications and thus can point the way for future simulations. More work is needed that directly investigates the estimability of natural mortality and catchability within size-structured assessment models both from a simulation perspective and in real world assessments.

APPENDIX

Excerpt from Harding (2017) on preparation, aging, and measurement of otolith radii: “Transverse sections of the sagittal otoliths were taken as per Schreiner and Schram (2001), and otolith sections were briefly etched in 1% acetic acid solution for 15 minutes to improve the visibility of annuli. Fish were aged using transmitted light at 10X magnification on a Nikon SMZ 1500 stereoscope. All fish were aged twice by the same reader with greater than two weeks between readings. Fish with discrepancies between the first and second readings were excluded from further analyses.... Digital images of otoliths were captured at 4X magnification using a Nikon SMZ 1500 stereoscope and a Nikon DXM 1200 scope mounted camera. All images were calibrated using a stage micrometer. The origin of the otolith was identified as the centroid of the age-one annulus, and the measurement axis was defined as a 30-degree angle from the longest axis of the age-one annulus through the origin to the otolith margin in the ventral-medial direction (Figure 1-2). Measurements were made using ImageJ imaging software (version 1.48, Research Services Branch, National Institute of Health). Measurements were made along the measurement axis from the origin to the outer edge of the discontinuous zone.”

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Chapter 2

Evaluating the Sustainability of a Cisco Fishery in Thunder Bay, Ontario under Alternate Harvest Control Rules

Abstract

Sustainable management of fish stocks is promoted through the application of Management Strategy Evaluations, providing advice 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 cisco, *Coregonus artedii*, stock in Thunder Bay, Ontario, in an effort to determine both the sustainability of the current harvest control rule, a fixed exploitation rate of 10%, and the performance of alternative harvest control rules in meeting fishery objectives. Our simulations explicitly accounted for uncertainty in the frequency of “boom” year classes being produced by cisco, the shape of the stock-recruit function, stock abundance, and the sex-specific nature of the roe harvest. Assuming future productivity is similar to that observed over the past 30 years, results suggest the current exploitation rate of 10% is sustainable in terms of maintaining spawning biomass above 20% of the unfished level. Alternate control rules involving biomass thresholds defining when exploitation rate is to decrease as a function of spawning stock size increased yield, decreased risk, and increased the magnitude of spawning biomass at the end of the simulation period, while resulting in more inter-annual variation in yield. Constant catch control rules greatly underperformed constant exploitation rate control rules in terms of magnitude in yield; however constant catch control rules did reduce inter-annual variation in yield compared to constant exploitation rate control rules, and use of

conditional versions of constant catch control rules (i.e., threshold stock sizes below which catch was reduced) mitigated risks of staying at low stock size.

Introduction

Rational 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 is often 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 attempting to account for uncertainty in key processes, such as the assessment process, 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 (Quinn and Deriso 1999; Caddy and Mahon 1995) 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 control rules refer to the specific formulae used for a given harvest policy that specify the target amount of harvest given policy parameters and the

estimated state of the system (i.e. spawning stock biomass). Control rules generally fall into three separate categories; constant exploitation rate, constant catch, and constant escapement rules, in addition to derivatives of each aimed to correct perceived weaknesses (Deroba and Bence 2008). Constant exploitation rate rules aim to set catch quotas to a constant proportion of stock size (Walters and Martell 2004). This builds in an inherent feedback system; as the stock declines, the quotas do the same, and vice versa. Constant catch rules set catch quotas at some constant level regardless of stock size, valuing the stability in catch. Constant escapement rules set catch at all biomass over some predetermined level, that level generally being chosen to ensure sufficient levels of spawning stock remain in the population to provide for adequate replacement. Derivatives of these control rules can include the addition of thresholds, either biomass-based or exploitation rate-based, that aim to decrease exploitation rate or catch at low stock sizes. Tuning or policy parameters refer to the specific exploitation rate, catch level, or escapement level used to define a given harvest control rule and dictate the level of harvest given the estimated state of the system. Policy parameters can also include biomass or exploitation rate thresholds involved in derivatives 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 artedii*, currently support a roe fishery in Thunder Bay, Ontario, and are managed via a constant exploitation rate control rule, where the total allowable catch (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 (Deroba and Bence 2008, Walters and Martell 2004), the specific exploitation rate of 10% put into place in Thunder Bay has not been evaluated using MSE, rather it was chosen based on exploitation rates seen as sustainable for other 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 similar species, 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 managers to better achieve objectives.

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 to determine which type of control rule and associated policy parameters performs best in achieving fishery objectives. 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. In this paper we present 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.

Methods

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 the Lake Superior Committee on technical information regarding the status of stocks including management alternatives and guidelines in making and evaluating fisheries management decisions. Specifically at this meeting we inquired which type of harvest control rules the technical committee would like us to consider and also which performance statistics were most important to them (i.e., what are the objectives for the fishery). Based on input from the committee, we considered two main types of harvest control rules and their derivatives; constant exploitation rate and constant catch rules. We explicitly considered two derivatives within each control rule in addition to their standard formulation (Figure 2.1). For constant exploitation rate, we considered 1) Constant U (CU), a simple constant exploitation rate control rule where catch will be proportional to stock size (Figure 2.1A). 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 size until both are zero (Figure 2.1B). 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 size and becomes zero at some lower threshold of spawning stock size (SB_{LT} ; Figure 2.1C). These derivatives of the CU rule aim to produce a compensatory

response by gradually decreasing fishing mortality below a threshold. For constant catch control rules, we considered 1) regular constant catch (CC), where catch is constant regardless of spawning stock size (Figure 2.1D). 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 constant exploitation rate at the predetermined threshold (Figure 2.1E; 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 is reduced to a new lower level of constant catch (C_L , Figure 2.1F). Each of these derivatives of the CC rule aim to keep catch relatively stable while attempting to avoid high fishing mortality rates at low spawning stock sizes.

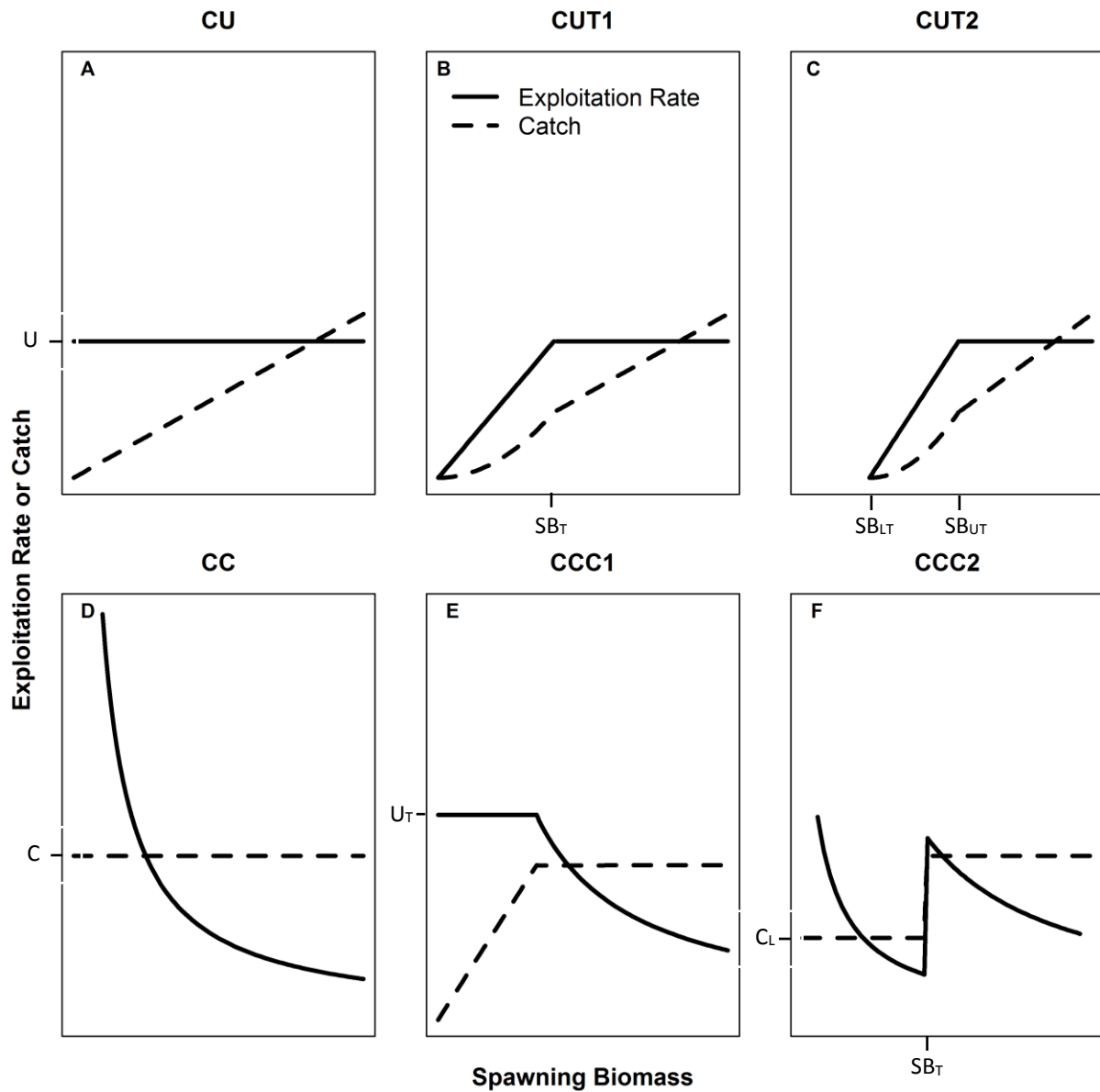


Figure 2.1. Harvest control rules considered in this analysis and associated policy parameters.

Spawning stock biomass thresholds (SB_T , SB_{UT}) were defined as 20, 30, 40, and 50% of unfished spawning stock biomass. Lower spawning stock biomass thresholds for CUT2 (SB_{LT}) were defined as 20 and 30% of unfished spawning stock biomass. We decided to not go lower than 20% of unfished spawning stock biomass as a threshold for

CUT1 and CUT2 as this is a level at which it has been suggested that fishing should stop (Thompson, 1993). In addition, numerous studies have determined spawning biomass should be maintained between 20-50% of unfished spawning biomass (Clark, 1991; Fujioka et al., 1997; Quinn et al., 1990). Exploitation rates for CU, CUT1, and CUT2 were defined as 0.05, 0.10, 0.15, 0.20, and 0.25. Constant catch levels (C) were defined as 100,000 kg, 150,000kg and 200,000kg, 250,000kg, and 300,000kg. Exploitation rates and catch levels were chosen based on their proximity to the current constant exploitation rate (0.10) and to mean harvest levels over the past 17 years (~160,000kg, sd ~ 25,000), respectively. Low catch levels may not be economically viable for fisherman, and very high catch levels may exceed the current fishery capacity, as might high exploitation rates. Threshold exploitation rates at which CCC1 would revert to CU (U_T) were defined as 0.15, 0.20, 0.25. CCC2 lower catch levels (C_L), to be enacted when spawning stock biomass is estimated below thresholds mentioned above, were defined as half of the catch level (e.g. quotas of 100,000kg a year would have a C_L of 50,000kg). In total we compared 51 different harvest control rule combinations (Table 1).

Performance Statistics

Performance statistics the LSTC wanted us to consider included the magnitude of stock size, the magnitude of yield, the variability in yield, and the probability of stock collapse. The committee also noted that they were primarily interested in the performance of these metrics over a 50 year time span. For this reason, performance statistics considered included the percent of years the spawning biomass was below 20% of unfished spawning biomass, hereafter termed “risk” for brevity, the average harvest (per year), the median spawning biomass in the final 5 years (Final SB; as a % of

unfished level), and the absolute annual variation in yield (AAV), as defined in Punt et al. (2008):

$$AAV = \frac{\sum_y |H_y - H_{y-1}|}{\sum_y H_y}$$

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 biomass:

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

where $\bar{w}_{a,s}$ is sex-specific average weight at age of a cisco estimated using a von-Bertalanffy function (Chapter 1), and $P(Fish_a > 250mm)$ is defined as the probability that a cisco of a given age is greater than 250 mm (Chapter 1). We assume that fish greater than 250 mm in length are mature. This definition of spawning biomass was chosen to align with how the current control rule allocates TAC of cisco in Thunder Bay (biomass of cisco > 250 mm). We defined the unfished spawning biomass as the average of the median spawning biomass levels in the final 5 years after running the simulation model with no harvest.

Model

We developed a stochastic projection model (SPM) based on an integrated Statistical Catch-at-Age Assessment (SCAA) model developed in Chapter 1. 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 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 for each simulation), and $F_{y,a,s}$ refers to fishing mortality for a given year, age, and sex combination. Each simulation began by drawing from the posterior distribution of sex-specific 2015 abundance at age from the SCAA.

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 many years of almost no recruitment, until the next big year class is produced (Chapter 1 Figure 1.5; Stockwell et. al, 2009). 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 is characterized as a boom year, a stock-recruit (SR)

function is applied; if characterized as bust, the model draws from a lognormal distribution derived using posterior estimates of bust years from the SCAA model. For boom years, the SR function used was derived 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 are drawn 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 0.711 based on Thorson et al.'s (2014) meta-analysis of recruitment deviation for the family Salmonidae. 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. Specifics on the derivation of the SR function can be found in the appendix.

Given uncertainty in what level of recruitment constitutes a boom or a bust year, and based on the fact that the SR function and bounds of the uniform distribution will be defined by this, we specifically explored 2 different recruitment scenarios. These scenarios are hereafter termed 7yr and 4yr (Figure 2.2), 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 200k 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). The bounds of the uniform distribution for each recruitment scenario were based on the perceived frequency of “boom” year classes over the past 30 years using observations from both the SCAA (Chapter 1) 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 of ~9-11 boom year classes over the last 30 years and $U(0.15,0.25)$ for the 4yr scenario, based on evidence of ~6 boom year classes over the last 30 years. Recruitment values in the SCAA that were not characterized as “boom” recruitment years were placed in the “bust” category and used to derive a lognormal distribution of “bust” recruitments.

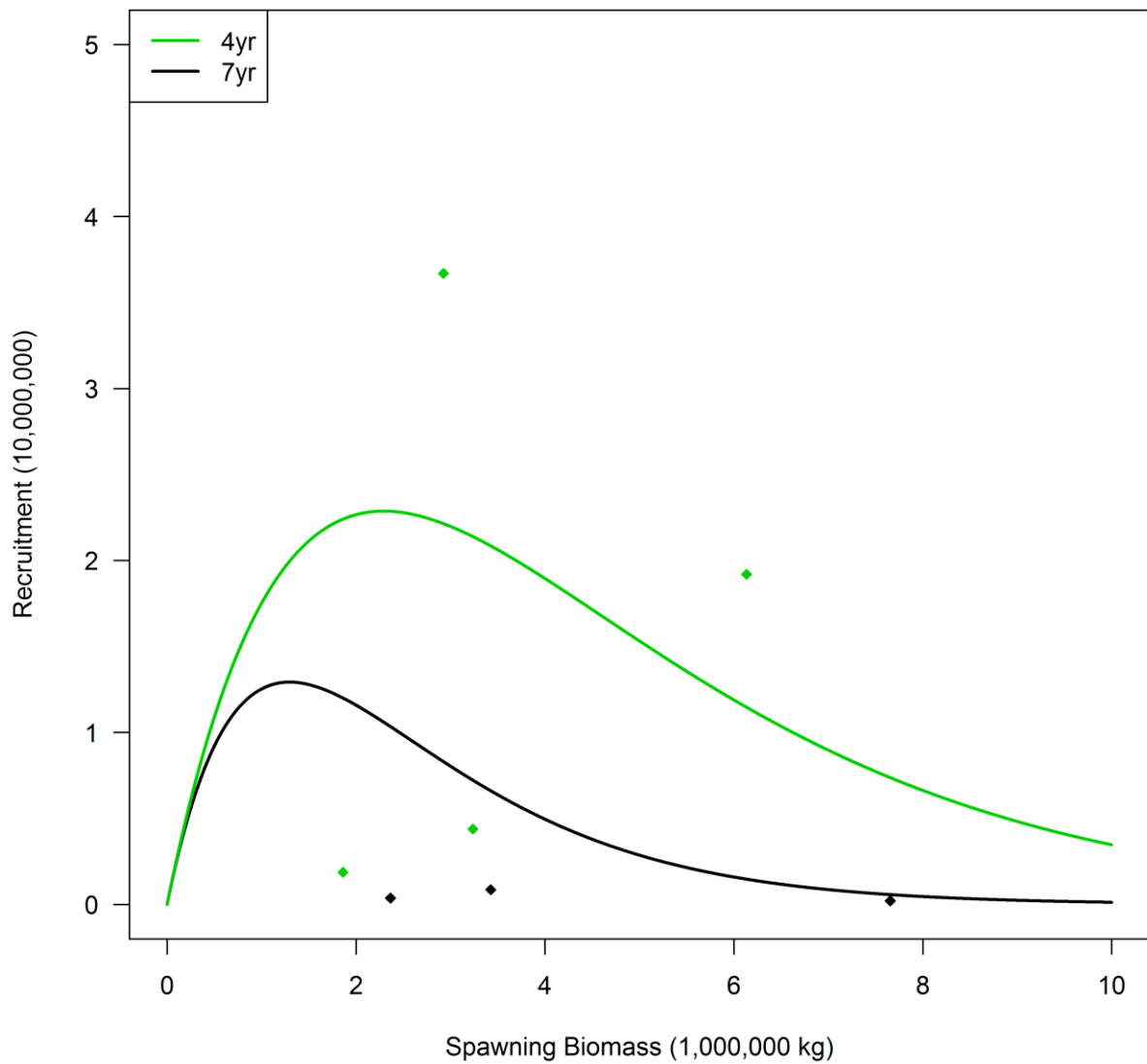


Figure 2.2. SR curves for each recruitment scenario. “Data”, medians of the posterior distribution of the SCAA, are plotted as points. The 7yr scenario SR curve uses all “data” points while the 4yr scenario solely uses the points highlighted in green.

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 ($\approx 80\%$, Chapter 1 - Figure 1.1), there is inter-annual variation. 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. Fishing intensity ratios for all 17 years of the SCAA were drawn for each simulation in the SPM and used to define a beta distribution. Each beta distribution was defined in terms of two shape parameters, here

denoted as p and q which can be written as $p = \mu \left(\frac{\mu(1-\mu)}{\sigma^2} - 1 \right)$ 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. The corresponding beta distribution for each simulation was used to draw fishing intensity ratios for each year within the SPM. Fishing intensity for a given sex/year combination in each simulation was solved for using Newton-Raphson iterations given a harvest control rule:

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

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

where s_a refers to age-specific cisco fishery selectivity (parameters that define selectivity function were drawn from the SCAA posterior distribution) and H_y denotes harvest in a given year and is defined based on a control rule. Female fishing intensity for a given year was solved for and male fishing intensity was calculated 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 fisherman catching every last fish in a given year.

Assessment Error

Assessment estimation error was simulated within the SPM through an autoregressive process

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

Where \hat{SB}_y denotes the assessed spawning biomass and SB_y is the true spawning biomass. ρ and σ_e were specified as 0.7 and 0.16, assuming a lognormal assessment

error with a CV of about 0.22 ($\sqrt{\frac{\sigma_e^2}{1-\rho^2}}$). This was based on the CV of spawning biomass in the final year of the SCAA (≈ 0.22). Alternate values of rho and sigma ($\rho = 0.9$, $\sigma_e = 0.3$) were explored to assess the sensitivity of results to levels of assessment error. Similar procedures have been done in previous harvest policy projections (Deroba and Bence 2012; Irwin et al. 2008, Punt et al. 2008). We did not model implementation error within the SPM given license holders rarely, if ever, go over their TAC. Thus, assuming fishers meet their TAC (unless fishing mortality limit is reached) is likely a conservative assumption.

Sensitivity Analyses

Sensitivity to the bounds of the uniform distribution for the probability of a boom year class was examined by shifting the distribution ± 0.05 for each recruitment scenario. Several of the control rules we considered use unfished spawning stock biomass, and this value, determined based on running the SPM with negligible harvest, depends on the distribution for the probability of boom years. Therefore, we explored two alternate scenarios for setting unfished spawning biomass when shifting the distribution for boom years. First, we assumed unfished spawning biomass at values estimated using the original uniform distribution bounds and second we assumed unfished spawning biomass at new values calculated when the uniform distribution is either shifted up or down by 0.05. The first of these scenarios explores the situation where managers erroneously specify the unfished spawning biomass when the frequency of boom years is shifted, i.e., the shifts represent a situation where system productivity is both different and miss-specified in the control rule. The second

represents a case where the change in system productivity is accounted for in the control rule.

Results

Equilibrium or unfished spawning biomass was calculated as 4,750,000 kg and 4,400,000 kg for the 4yr and 7yr recruitment scenarios, respectively.

Recruitment Scenario

Relative relationships between 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. Results for the 7yr recruitment scenario can be found in Table 1 and supplemental figures 2.1-2.4.

Average Yield

Constant exploitation rate and its derivatives (CU, CUT1, CUT2) outperformed constant catch rules in terms of the maximum (over policy parameters) average yield over the 50yr simulation period (Figure 2.3). 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 around 255,000 kg of yield per year (Table 1, Figure 2.3). While median yields for CU reached an asymptote, the spread of the 25-75 quantile range slightly increased as exploitation rate increased from 0.10-0.25. Derivatives of the CU rule involving thresholds (CUT1 and CUT2) experienced increases in yield (Figure 2.3) over their CU counterparts with similar exploitation rates,

with a CUT2 rule involving an exploitation rate of 0.20 to be linearly reduced at 50% of unfished spawning stock biomass and made 0 at 30% of unfished spawning stock biomass (Policy 1.3.10, Table 1) experiencing the largest average yield over the simulation period at 357,804 kg per year. The constant catch control rules, even at their highest catch levels (300,000 kg per year), were only able to produce average yields of around 180,000 kg per year. In fact, when we increased catch levels above 300,000 kg (up to 550,000 kg) within CC, an asymptote in average yield was reached at around 220,000 kg per year. When thresholds were included in constant catch control rules (CCC1 and CCC2), yield for control rules with similar catch levels did not increase and in fact slightly decreased in almost all cases (Exceptions are policies 2.1.3 vs 2.2.3, 2.1.4 vs 2.2.4, and 2.1.5 vs 2.4.9; Table 1, Figure 2.3).

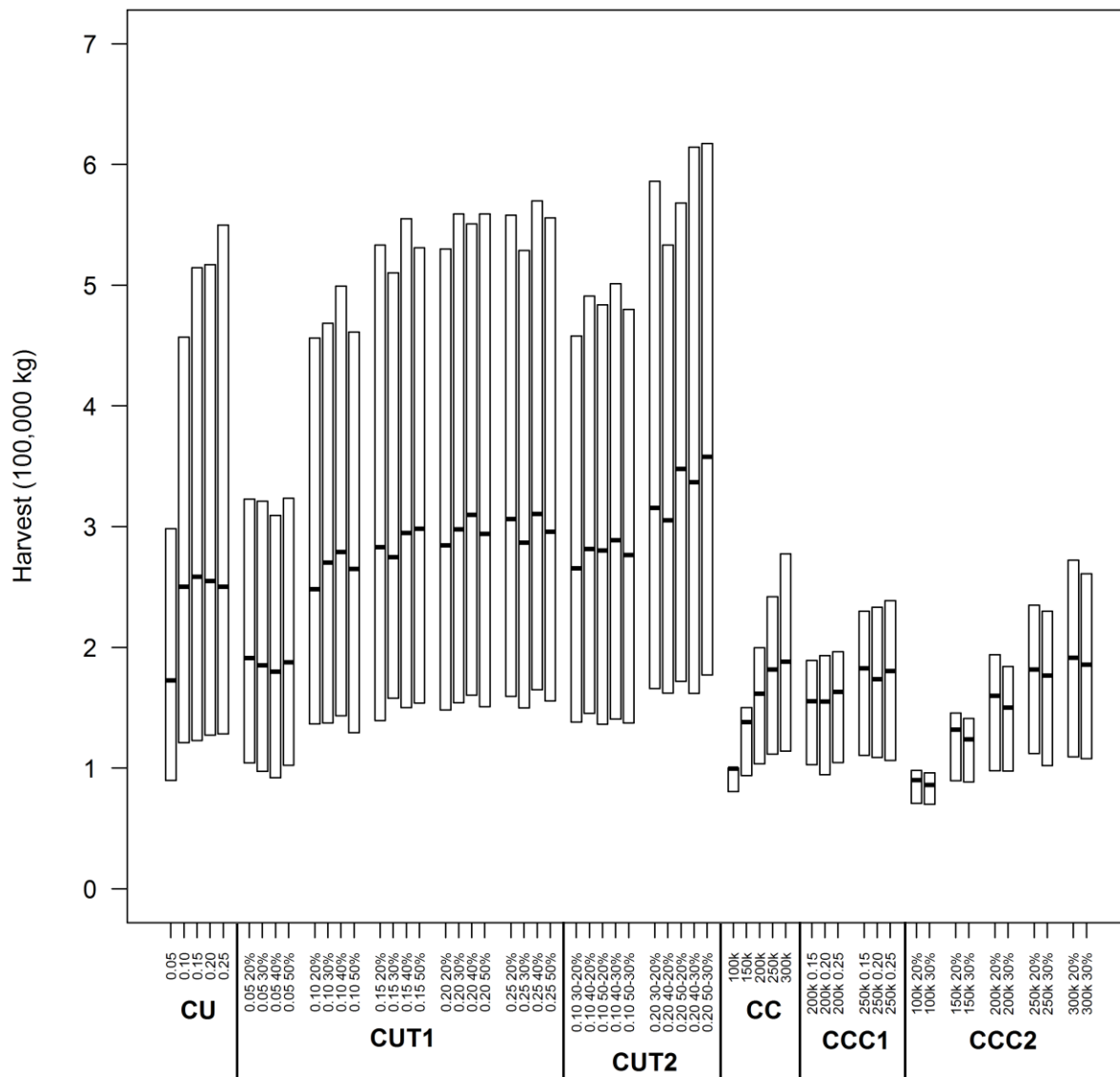


Figure 2.3. Summary of the distributions of average harvest over the simulation period for each respective control rule. Shown are medians (horizontal bar) and 25-75 quantiles (box). Labels specify policy parameters that make up each control rule (CU = “U”; CUT1 = “U SBT”; CUT2 = “U SBT-SBLT”; CC = “C”; CCC1 = “C UT”; CCC2 = “C SBT”). 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 unfished spawning biomass, while that rate linearly declines below that threshold to 0 at 20% of the unfished spawning biomass. Catch levels are described in 100,000 kg (i.e. 100k = 100,000 kg).

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, Figure 2.4). 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 for all exploitation rates. 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 0.10, risk was 34% for CU, 26% at its lowest in CUT1, and 20% at its lowest in CUT2 (Policies 1.1.2, 1.2.7, and 1.3.5; Table 1). A similar result occurred for exploitation rates of 0.20, where under CU risk was 58%, 44% at its lowest under CUT1, and 30% 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 level of 100,000 kg a year to 56% at a catch level of 300,000 kg a year. Risk decreased with the inclusion of exploitation rate thresholds within the CCC1 control rule. Within CCC1, risk increased as the threshold exploitation rate increased (Figure 2.4). For each level of catch, the use of biomass thresholds under the CCC2 rule decreased risk compared to CC control rules. In addition, within CCC2 risk decreased as threshold SB levels increased. For example,

under a catch level of 200,000 kg a year (CC risk=44%), 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 32%. The lowest risk level over all control rules was therefore under a CCC2 rule with the lowest catch level, 100,000 kg, and a threshold of 30% of the unfished spawning biomass at which point the catch level would be cut in half (Policy 2.3.2, risk=16%).

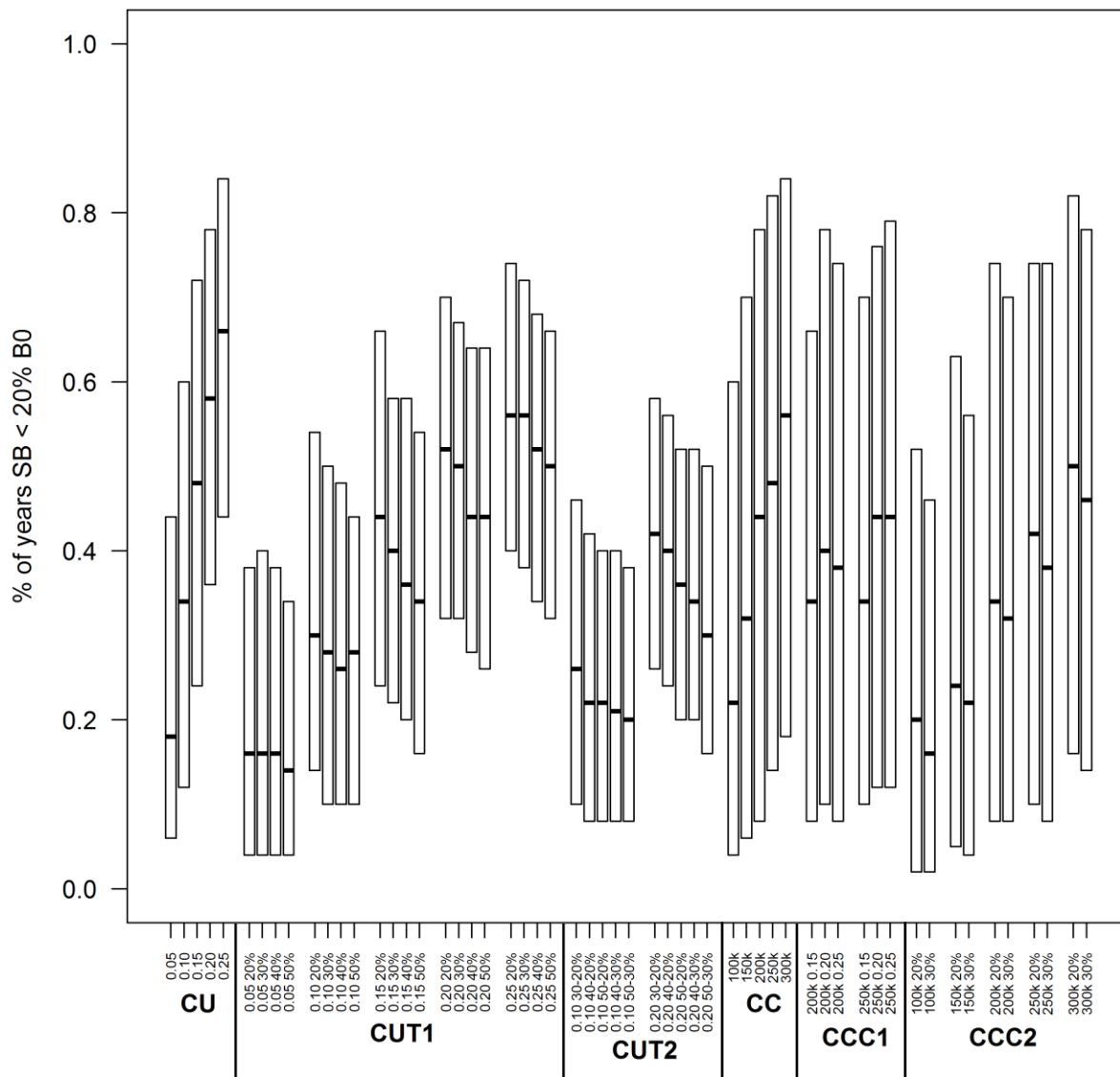


Figure 2.4. Summary of the distributions of risk level for each respective control rule. Risk is defined as the percentage of years in each simulation where SB is below 20% of the unfished level. Shown are medians (horizontal bar) and 25-75 quantiles (box). Labels specify policy parameters that make 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 unfished spawning biomass, while that rate linearly declines below that threshold to 0 at 20% of the unfished spawning biomass. Catch levels are described in 100,000 kg (i.e. 100k = 100,000 kg).

Absolute Annual Variation in Yield (AAV)

Over all control rules, AAV proved considerably smaller for the constant catch control rules (Figure 2.5). For example, a CC rule with a catch level 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 0.32. Also, the inclusion of a threshold within any rule (CUT1 & CUT2 as compared to CU and CCC1 & CCC2 as compared to CC) increased AAV. Within constant exploitation rate control rules, AAV increased as exploitation rate increased. The inclusion a threshold biomass levels for CUT1 rules increased AAV over all exploitation rates, and 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 with similar exploitation rates.

For constant catch control rules, AAV increased as catch level increased, from 0.01 at 100,000 kg a year (Policy 2.1.1) to 0.12 at 300,000 kg a year (Policy 2.1.5). The inclusion of threshold exploitation rates for CCC1 increased AAV as well. For example, a CC rule with a catch level of 200,000 kg a year (Policy 2.1.3) had an AAV of 0.06 while a CCC1 rule with a catch level of 200,000 kg per year and a threshold exploitation rate of 0.15 (Policy 2.2.1) increased AAV to 0.10 . Within CCC1, AAV decreased as the threshold exploitation rate increased for a given catch level. The inclusion of threshold SB levels related to CCC2 also increased AAV compared to CC with similar catch levels, while within CCC2, AAV increased as threshold SB increased for similar catch levels.

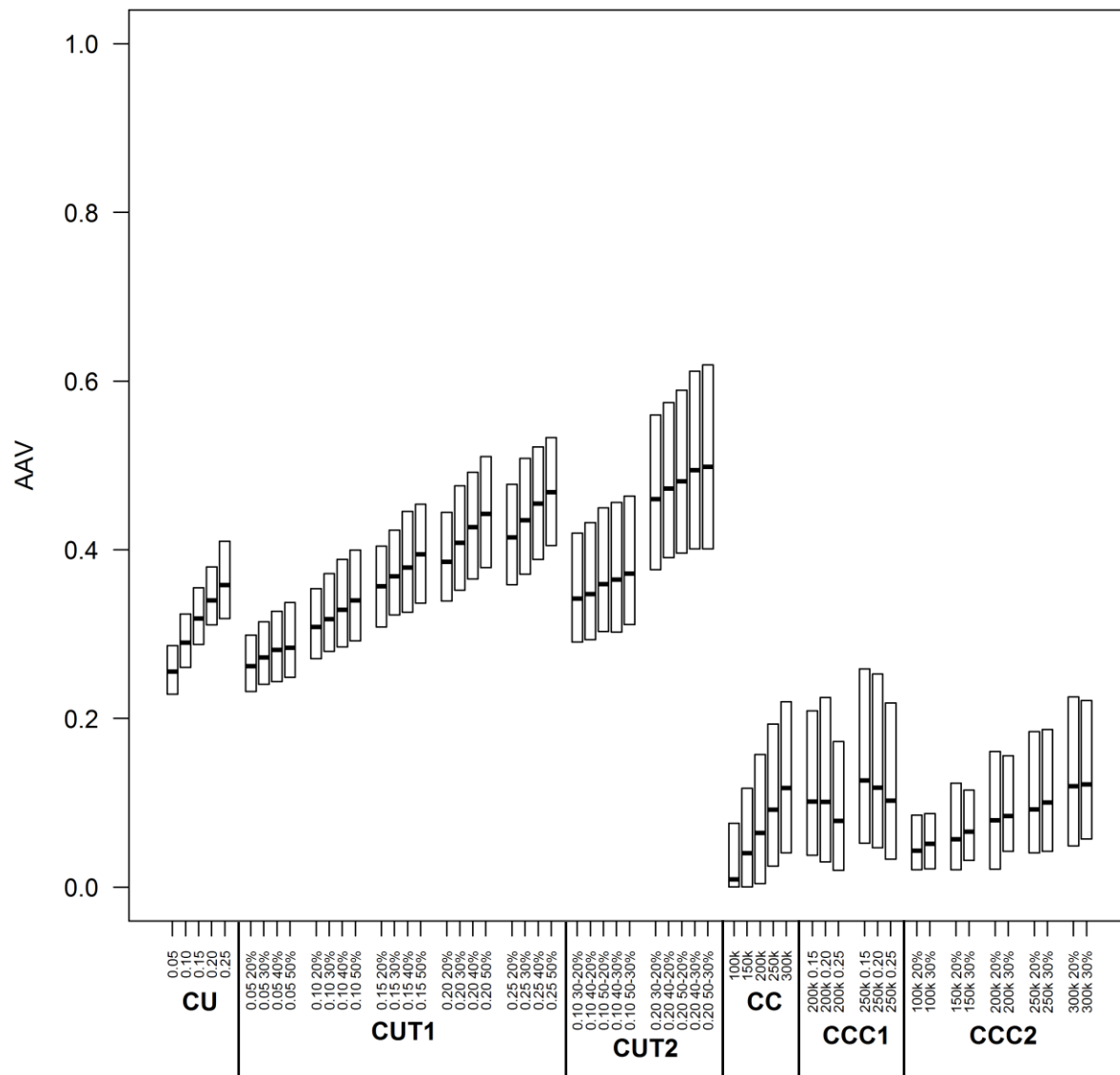


Figure 2.5. Summary of the distributions of absolute annual variation in yield for each respective harvest control rule. Shown are medians (horizontal bar) and 25-75 percentiles (box). Labels specify policy parameters that make up each control rule (CU = “U”; CUT1 = “U SBT”; CUT2 = “U SBT-SBLT”; CC = “C”; CCC1 = “C UT”; CCC2 = “C SBT”). 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 unfished spawning biomass, while that rate linearly declines below that threshold to 0 at 20% of the unfished spawning biomass. Catch levels are described in 100,000 kg (i.e. 100k = 100,000 kg).

Spawning Biomass at the end of the SPM (Final SB)

Spawning biomass at the end of the simulation period, defined as the median SB for the final 5 years of each simulation (Final SB, presented as a percentage of unfished SB), was similar among baseline harvest control rules (CU & CC, Figure 2.6), 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 61% of the unfished level at an exploitation rate of 0.05 (Policy 1.1.1) to 8% at an exploitation rate of 0.25 (Policy 1.1.5). For any given exploitation rate, adding a SB threshold within CUT1 ubiquitously increased Final SB, and CUT2 rules involving an additional lower threshold further increased Final SB, performing best among constant exploitation rate control rules. For example, a CU rule with an exploitation rate of 0.10 produced a Final SB 33% 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 51% of the unfished level (Policy 1.3.5, Table 1). Within CUT1 rules of a given exploitation rate, Final SB increased as threshold biomass increased. Similarly, within CUT2 rules given a level of exploitation rate, Final SB increased as both upper and lower SB thresholds increased.

For constant catch, within the CC control rule Final SB declined as catch levels increased, from 58% of the unfished level at 100,000 kg a year (Policy 2.1.1), to 13% at 300,000 kg a year (Policy 2.1.5). The inclusion of a threshold exploitation rate within CCC1 mostly increased Final SB, and within CCC1 Final SB decreased as threshold exploitation rate increased. For catch levels of 200,000 kg per year, the addition of

threshold exploitation rates increased Final SB for rates of 0.15 and 0.25 and decreased Final SB at a rate of 0.20 (likely an anomalous result due to stochasticity). For catch levels of 250,000 kg, including exploitation rate thresholds increased Final SB (from 18% to 33%, 25%, and 19%, Policy 2.1.4 compared to 2.2.4, 2.2.5, and 2.2.6). For all catch levels, the inclusion of SB thresholds within CCC2 rules increased Final SB levels compared to CC rules with similar catch levels. Final SB also increased as SB threshold increased within CCC2 rules.

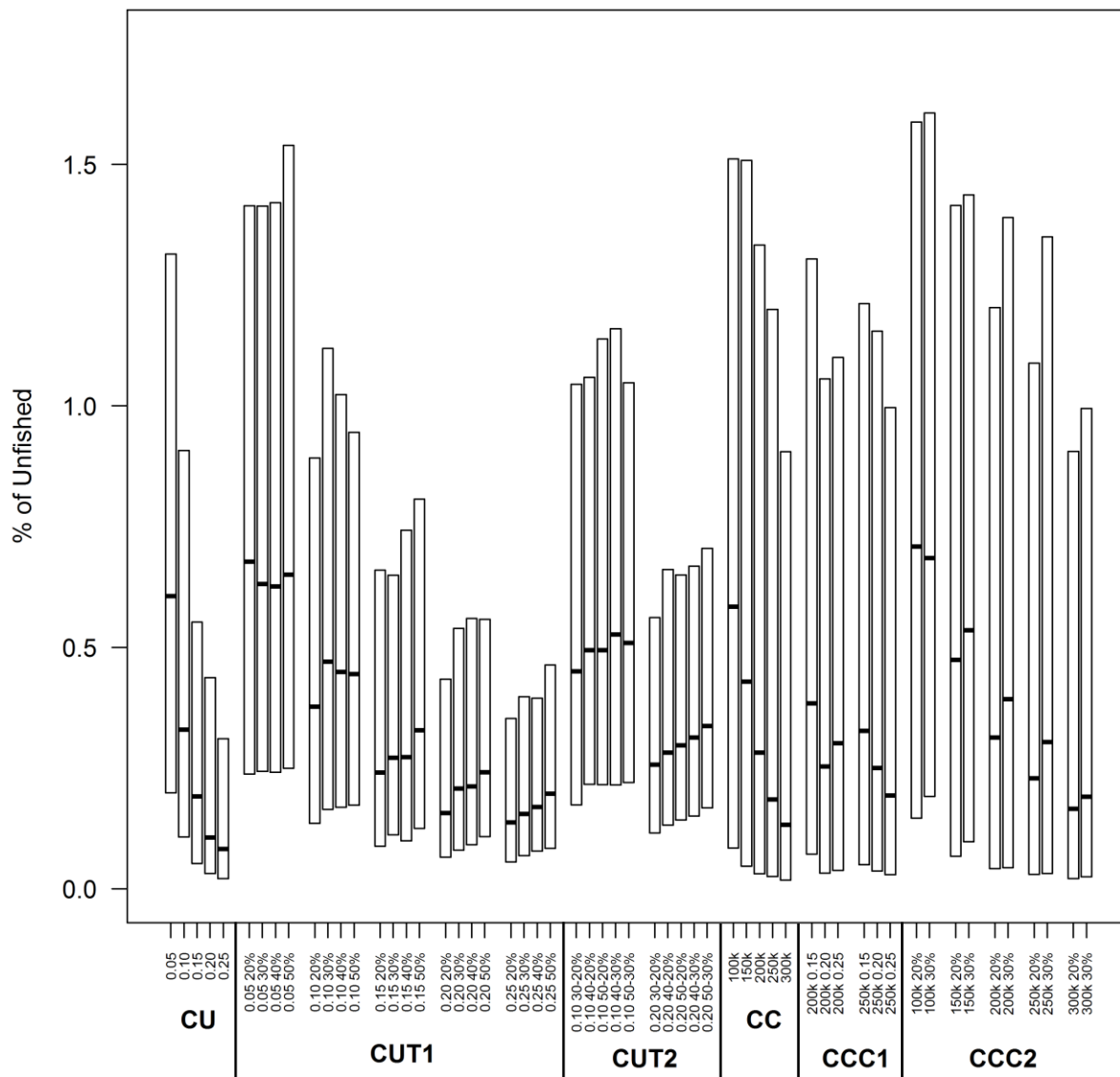


Figure 2.6. Summary of the distributions of final spawning biomass for each respective control rule, with final spawning biomass defined as the median of the last 5 years spawning biomass in each simulation, characterized as a percentage of the unfished level. Shown are medians (horizontal bar) and 25-75 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 unfished spawning biomass, while that rate linearly declines below that threshold to 0 at 20% of the unfished spawning biomass. Catch levels are described in 100,000 kg (i.e. 100k = 100,000 kg).

Performance metrics under similar levels of yield

For CU and CC control rules, an exploitation rate of 0.05 and a catch level of 250k produced similar average yields over the simulation period (Policy 1.1.1 = 172,608 kg/year, Policy 2.1.4 = 181,734 kg/year). For these two specific control rules with similar yield, risk was greater (Figure 2.7 upper panel, Policy 1.1.1 = 18%, Policy 2.1.4 = 48%), and spawning biomass at the end of the time series was lower (Figure 2.7 middle panel, Policy 1.1.1 = 61%, Policy 2.1.4 = 18%) for CC with a catch level of 250k. However AAV was lower for CC with a catch level of 250k compared to CU with an exploitation rate of 0.05 (Figure 2.7 lower panel, Policy 1.1.1 = 0.26, Policy 2.1.4 = 0.09). The inclusion of thresholds in CCC2 did not alter this comparison. For example, while producing a similar amount of yield, CU with an exploitation rate of 0.05 (Policy 1.1.1) produced lower risk, greater Final SB, and greater AAV compared to CCC2 with a catch level of 250,000 kg per year and a threshold SB of 30% (Policy 2.3.8).

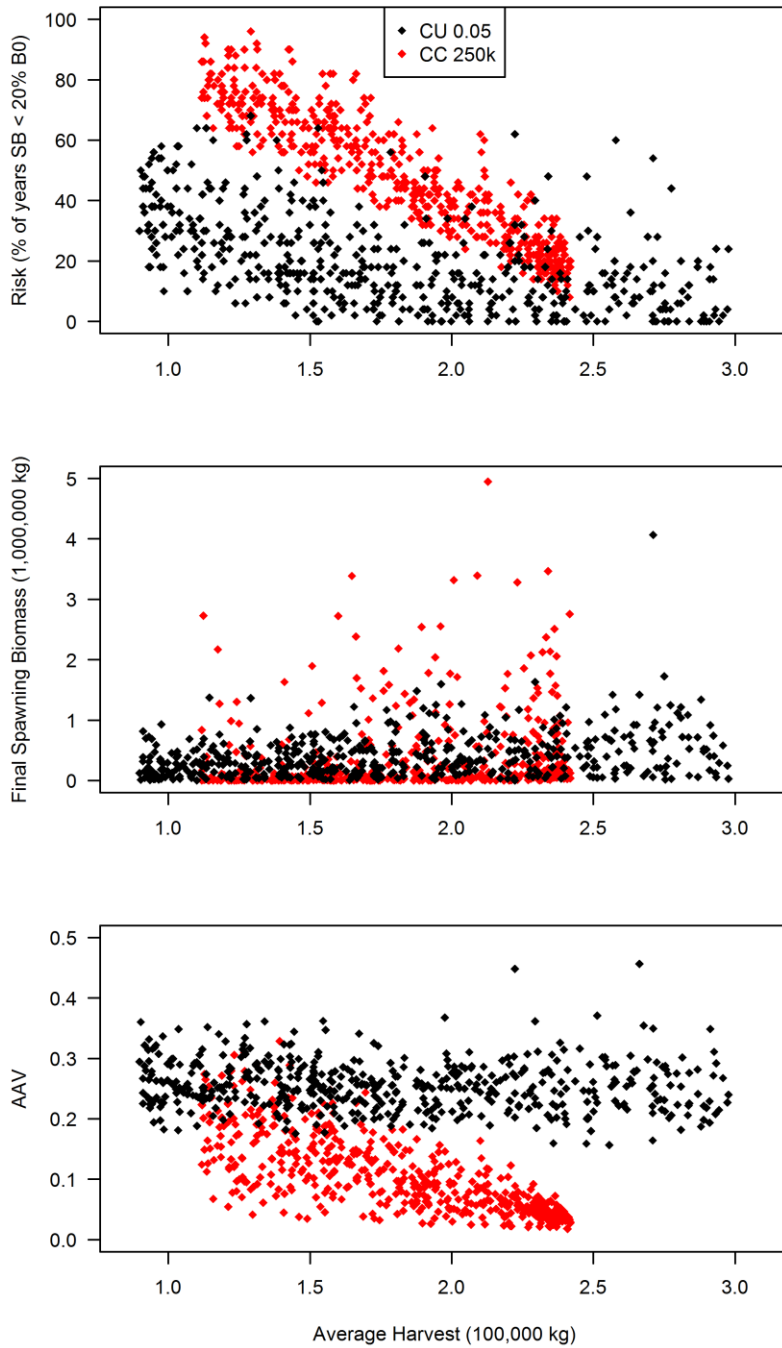


Figure 2.7. Comparison of performance metrics for CU rule with an exploitation rate of 0.05 (black points) and CC rule with a catch level of 250,000 kg (red points). Upper panel plots risk (percentage of years SB < 20% unfished) versus average harvest (in millions of kg) obtained in the same individual simulations. Middle panel compares final spawning biomass (millions of kg) and average harvest. Lower panel compares absolute annual variation in yield and average harvest. Only results from simulations that produced an average harvest within the 25-75% quantiles (i.e., inside the interquartile range) are plotted.

Table 2.1. Performance statistics are presented as results for the 4yr and 7yr recruitment scenarios (4yr | 7yr). Values are presented as medians over simulations. Average yield (kg) is mean yield over years. Risk is calculated as the percentage of years SB is below 20% of the unfished condition. AAV is defined in methods. Final spawning biomass is the median SB of the last 5 years in a simulation. Catch levels for constant catch control rules are presented in 100,000 kg (i.e. 100k=100,000 kg).

Harvest Policy	Policy Parameters	Yield (kg)	Risk	AAV	Final SB
CU					
1.1.1	U=0.05	172608 192664	0.18 0.06	0.26 0.23	0.61 0.84
1.1.2	U=0.10	250215 309911	0.34 0.12	0.29 0.25	0.33 0.61
1.1.3	U=0.15	258561 374726	0.48 0.22	0.32 0.29	0.19 0.47
1.1.4	U=0.20	254988 354457	0.58 0.36	0.34 0.31	0.11 0.25
1.1.5	U=0.25	250156 352739	0.66 0.48	0.36 0.32	0.08 0.15
CUT1					
1.2.1	U=0.05, SB _T =20%	191189 189855	0.16 0.06	0.26 0.23	0.68 0.89
1.2.2	U=0.05, SB _T =30%	185240 196540	0.16 0.06	0.27 0.23	0.63 0.84
1.2.3	U=0.05, SB _T =40%	179941 194120	0.16 0.04	0.28 0.24	0.63 0.85
1.2.4	U=0.05, SB _T =50%	187503 195835	0.14 0.04	0.28 0.25	0.65 0.90
1.2.5	U=0.10, SB _T =20%	248154 309159	0.30 0.12	0.31 0.27	0.38 0.65
1.2.6	U=0.10, SB _T =30%	270291 322572	0.28 0.12	0.32 0.27	0.47 0.68
1.2.7	U=0.10, SB _T =40%	278925 318348	0.26 0.10	0.33 0.28	0.45 0.69
1.2.8	U=0.10, SB _T =50%	264902 325076	0.28 0.10	0.34 0.29	0.44 0.72
1.2.9	U=0.15, SB _T =20%	282876 369314	0.44 0.22	0.36 0.30	0.24 0.46
1.2.10	U=0.15, SB _T =30%	274787 376849	0.40 0.20	0.37 0.31	0.27 0.50
1.2.11	U=0.15, SB _T =40%	294627 400517	0.36 0.16	0.38 0.32	0.27 0.52
1.2.12	U=0.15, SB _T =50%	298119 403222	0.34 0.14	0.39 0.32	0.33 0.57
1.2.13	U=0.20, SB _T =20%	284403 402488	0.52 0.28	0.39 0.32	0.16 0.37
1.2.14	U=0.20, SB _T =30%	297737 393828	0.50 0.28	0.41 0.34	0.21 0.38
1.2.15	U=0.20, SB _T =40%	309875 392536	0.44 0.26	0.43 0.36	0.21 0.40
1.2.16	U=0.20, SB _T =50%	294041 421060	0.44 0.22	0.44 0.36	0.24 0.41
1.2.17	U=0.25, SB _T =20%	306222 386964	0.56 0.40	0.41 0.35	0.14 0.28
1.2.18	U=0.25, SB _T =30%	286845 397990	0.56 0.36	0.43 0.36	0.15 0.28
1.2.19	U=0.25, SB _T =40%	310483 418427	0.52 0.32	0.45 0.38	0.17 0.33

Table 2.1. (cont'd)

1.2.20	U=0.25, SB _T =50%	295778 425424	0.50 0.30	0.47 0.39	0.20 0.35
CUT2					
1.3.1	U=0.10, SB _{UT} =30%, SB _{LT} =20%	265445 309333	0.26 0.10	0.34 0.28	0.45 0.70
1.3.2	U=0.10, SB _{UT} =40%, SB _{LT} =20%	281574 307611	0.22 0.10	0.35 0.30	0.49 0.69
1.3.3	U=0.10, SB _{UT} =50%, SB _{LT} =20%	280217 313174	0.22 0.08	0.36 0.31	0.49 0.75
1.3.4	U=0.10, SB _{UT} =40%, SB _{LT} =30%	288841 319980	0.21 0.08	0.36 0.30	0.53 0.70
1.3.5	U=0.10, SB _{UT} =50%, SB _{LT} =30%	276439 312400	0.20 0.06	0.37 0.31	0.51 0.77
1.3.6	U=0.20, SB _{UT} =30%, SB _{LT} =20%	315477 427299	0.42 0.24	0.46 0.37	0.26 0.44
1.3.7	U=0.20, SB _{UT} =40%, SB _{LT} =20%	305147 424042	0.40 0.20	0.47 0.39	0.28 0.48
1.3.8	U=0.20, SB _{UT} =50%, SB _{LT} =20%	347791 443634	0.36 0.16	0.48 0.39	0.30 0.52
1.3.9	U=0.20, SB _{UT} =40%, SB _{LT} =30%	336807 433390	0.34 0.16	0.49 0.40	0.31 0.51
1.3.10	U=0.20, SB _{UT} =50%, SB _{LT} =30%	357804 413688	0.30 0.16	0.50 0.42	0.34 0.50
CC					
2.1.1	C=100k	99439 99999	0.22 0.06	0.01 0	0.58 0.91
2.1.2	C=150k	138031 149996	0.32 0.08	0.04 0	0.43 0.74
2.1.3	C=200k	161574 197245	0.44 0.14	0.06 0.02	0.28 0.60
2.1.4	C=250k	181734 236464	0.48 0.18	0.09 0.04	0.18 0.49
2.1.5	C=300k	188024 260835	0.56 0.26	0.12 0.06	0.13 0.33
CCC1					
2.2.1	C=200k, U _T =0.15	155451 184377	0.34 0.10	0.10 0.05	0.38 0.75
2.2.2	C=200k, U _T =0.20	155038 191569	0.40 0.10	0.10 0.03	0.25 0.68
2.2.3	C=200k, U _T =0.25	163187 193259	0.38 0.10	0.08 0.03	0.30 0.65
2.2.4	C=250k, U _T =0.15	182654 218018	0.34 0.12	0.13 0.07	0.33 0.65
2.2.5	C=250k, U _T =0.20	173591 225785	0.44 0.14	0.12 0.06	0.25 0.65
2.2.6	C=250k, U _T =0.25	180300 232787	0.44 0.14	0.10 0.04	0.19 0.60
CCC2					
2.3.1	C=100k, SB _T =20%, C _L =50k	90001 97996	0.20 0.04	0.04 0.02	0.71 0.86
2.3.2	C=100k, SB _T =30%, C _L =50k	85999 94000	0.16 0.04	0.05 0.03	0.69 0.92
2.3.3	C=150k, SB _T =20%, C _L =75k	131872 143999	0.24 0.08	0.06 0.02	0.47 0.82
2.3.4	C=150k, SB _T =30%, C _L =75k	123783 139498	0.22 0.06	0.07 0.04	0.54 0.85

Table 2.1. (cont'd)

2.3.5	C=200k, SB _T =20%, C _L =100k	159809 187998	0.34 0.12	0.08 0.04	0.31 0.70
2.3.6	C=200k, SB _T =30%, C _L =100k	149982 181999	0.32 0.08	0.08 0.04	0.39 0.78
2.3.7	C=250k, SB _T =20%, C _L =125k	181532 232018	0.42 0.14	0.09 0.04	0.23 0.61
2.3.8	C=250k, SB _T =30%, C _L =125k	176569 219999	0.38 0.12	0.10 0.06	0.30 0.64
2.4.9	C=300k, SB _T =20%, C _L =150k	191462 256409	0.50 0.23	0.12 0.06	0.17 0.42
2.3.10	C=300k, SB _T =30%, C _L =150k	185590 252969	0.46 0.18	0.12 0.07	0.19 0.50

Sensitivity

Results were largely robust to higher levels of assessment error ($\sigma_e = 0.3$) in addition to increased levels of autocorrelation ($\rho = 0.9$), as relative comparison of harvest control rules based on performance statistics changed little compared to the status quo results (Supplemental figures 2.5-2.12). For AAV, absolute values were higher among all constant exploitation rate control rules for $\sigma_e = 0.3$ compared to status quo scenario (Supplemental figure 2.7). Under scenarios where bounds of the uniform distribution defining the probability of a boom year class are shifted by + or - 0.05 and management correctly specifies unfished spawning biomass (according to runs of the SPM with new uniform bounds), relative comparison of harvest control rules was similar (Supplemental figures 2.13-2.20). However, absolute values of the performance statistics did change significantly, where under a less productive scenario (bounds of the uniform - 0.05), risk and AAV increased and Final SB and yield decreased, and for the more productive counterpart (bounds of the uniform + 0.05), the opposite occurred. Under a scenario where bounds of the uniform distribution defining the probability of a boom year class are shifted by - 0.05 and management **incorrectly** specifies unfished spawning biomass according to status quo scenario (4,750,000 kg), the only perceived

change from that where it correctly calculates unfished SB were increased AAV (Supplemental figure 2.23), decreased risk (Supplemental figure 2.22), and a slight increase in Final SB for control rules with biomass based thresholds (Supplemental figure 2.24). Yield did not change appreciably across all harvest control rules. For a scenario where bounds of the uniform distribution are shifted by + 0.05 and management **incorrectly** specifies unfished spawning biomass according to status quo scenario (4,750,000 kg), changes from that where it correctly calculates unfished SB included a slight decrease in AAV (Supplemental figure 2.27) and an increase in risk (Supplemental figure 2.26) for most control rules with biomass based thresholds. For most harvest control rules changes between scenarios where bounds of the uniform distribution are shifted by + 0.05 and unfished SB is either correctly or incorrectly assumed were imperceptible in terms of yield and Final SB with the exception of decreases in Final SB for most CUT2 control rules at exploitation rates of 0.10 and 0.20 (Supplemental Figure 2.28). It should be noted for both scenarios where unfished biomass is assumed incorrectly that **relative** comparisons of all control rules are largely unchanged.

Discussion

To address the first objective specified—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 might be 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 around 1.5 million kg of SB (Figure 2.8).

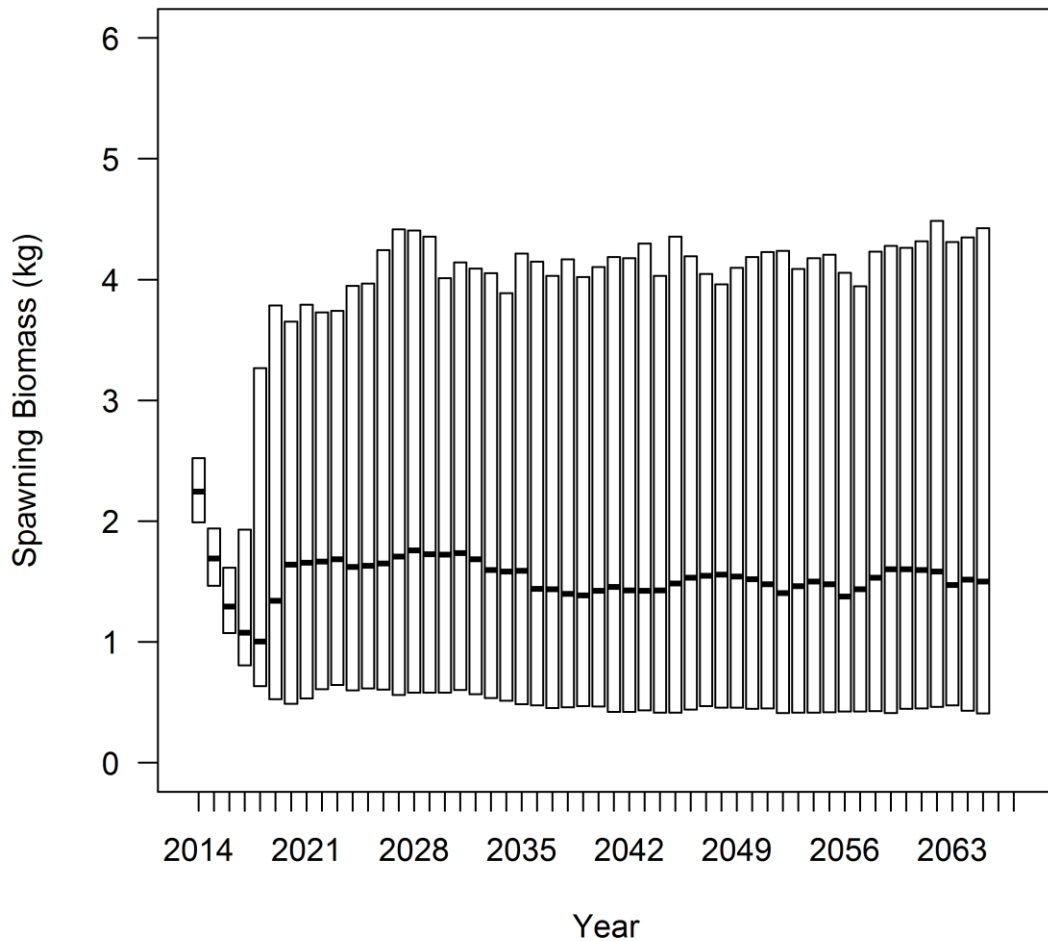


Figure 2.8. Spawning biomass for the projection of the current harvest control rule, a 10% exploitation rate. Shown are medians (horizontal bar) and 25-75 quantiles (box).

A more robust way to explore the sustainability question may to examine it in terms of maintaining SB above a threshold to ensure sufficient replenishment, as many studies have presented arguments for maintaining SB above certain thresholds in fish

populations (Beddington and Cooke, 1983; Caddy and Mahon, 1995; Clark 1991; Francis 1993; Fujioka et al., 1997; Goodyear, 1993; Hollowed and Megrey, 1993; Leaman, 1993; Quinn et al., 1990; Thompson, 1993). What is evident from these analyses is the argument for maintenance of >20% of unfished spawning stock size. If we utilize this criteria, the current 10% exploitation rate is usually “sustainable”, as the SPM projects a median Final SB of 33% and 61% 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 27% and 52% of the new unfished level (estimated using new bounds) under the 4yr and 7yr scenarios.

Alternatively, Mace (1994) and Myers et al. (1994) suggest maintaining spawning biomass at a level that would produce 50% of the maximum recruitment level. If we follow this convention and use the median estimates of our SR functions (Figure 2.2), female SB should not decrease below ~24% of the unfished level for the 4yr scenario and ~15% for the 7yr scenario. Based on this criteria the current 10% rate is also seen as generally sustainable. However, this designation may be risk-prone given the nature of cisco year classes, as the SR function is only applied on average every few years depending on the recruitment scenario. For our specific case study, we recommend against this metric, given a large degree of uncertainty surrounding recruitment of cisco in Thunder Bay.

In terms of our second objective: Can this control rule 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 ~4 unit increase in AAV from CU to CUT1 and a ~7 unit 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. Where we only ran the CUT2 rule for biomass thresholds ranging from 20-50% and exploitation rates of 0.10 and 0.20, one could surmise based on the relationship between the performance statistics, biomass thresholds and exploitation rates, what effect alternate levels would produce. For example had we chosen to include a lower biomass threshold (SB_{LT}) at 10% of the unfished level, this would likely have had the effect of decreasing AAV, Final SB and yield (slightly) while increasing risk.

If low variation in yield is held in a high regard, or a higher regard than all other performance metrics, a more appropriate control rule to adopt may be a constant catch rule. These control rules did not outperform most exploitation rate rules (all but 0.05 rate) in terms of yield and exhibited more risk and smaller Final SB under rules producing similar yield levels (for CC 250k vs CU 0.05, Figure 2.7), however they proved far superior when comparing year-to-year variation in yield. When discussing the efficacy of constant catch rules, it is important to note that if used indefinitely and without a threshold, it has been argued constant catch will eventually lead to extinction due to a stochastic environment (Punt 2010). Theoretically, this can be mitigated through the inclusion of exploitation rate thresholds within CCC1 control rules. In this study, the addition of thresholds within constant catch mostly decreased yield, increased AAV, and usually increased Final SB and decreased risk. Out of the conditional constant catch control rules, CCC2 rules were slightly more effective in decreasing risk, increasing Final SB, while not costing much in yield and AAV compared to CC rules with similar catch levels. Although it is important to note that where CCC2 performed better than CCC1 over the 50yr time horizon in terms of AAV and both decreasing risk and increasing Final SB compared to CC rules, over the long term the theory in Punt (2010) predicts CCC2 will fail. The inclusion of a lower biomass threshold at which point catch level is made zero within CCC2 could potentially mitigate this. It should also be noted that CCC2 rules may perform better at different threshold levels (40-50%) and also different lower catch levels (C_L). We only simulated catch being reduced to half of its original level at biomass thresholds of 20-30%. Similar to CUT2 rules, it is likely the inclusion of higher biomass thresholds within CCC2 would greatly decrease risk and increase Final SB, and the decrease in yield could potentially be mitigated by increasing

the lower catch level to 75% of its original level, although this would likely have the effect of costing more in terms of AAV. If constancy in yield is held in a much higher regard than other performance metrics, adoption of a constant catch control rule with a threshold of the CCC2 type will most appropriately meet fishery objectives. If Punt (2010)'s theory of extinction given a constant catch level and a stochastic environment is considered, the addition of a lower biomass threshold at which point catch level is made zero within CCC2 would be prudent. This would likely have the effect of decreasing risk, increasing Final SB, and increasing AAV. Whether the addition of this threshold would allow CCC2 to continue to outperform CCC1 in terms of AAV is unknown. In addition, it is unclear what effect this lower threshold would have on yield, based on the fact that a lower threshold for constant exploitation rate control rules actually proved to increase yield over base CU rules.

Results comparing the four performance criteria were largely insensitive to changes in the level and correlation of assessment error. This has been noted in similar studies (Irwin et al., 2008; Deroba and Bence, 2012; Punt et al., 2008), 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 ($\sigma_e = 0.3$) 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 to assessment error suggests that results are likely robust to this simplifying assumption. Similarly, our simulations assumed a stock assessment would be performed every year for the stock. Our study could benefit from additional simulations including management strategies where the control rule is applied to hydroacoustic estimates of abundance (how TAC is currently set) to inform the utility of performing stock assessments in each year.

Although relative comparison of the harvest control rules was largely unchanged under different recruitment hypotheses/scenarios, it is important to note that if harvest policy decisions are to be based in some part on the absolute values of certain metrics, such as maintenance of a Final SB above 20% of the unfished level, more liberal exploitation rates or catch levels may be employed under the 7yr scenario. For this reason we recommend primarily comparing the relative performance of control rules when making harvest policy decisions on cisco and when decisions necessitate information on an absolute value, to err in a conservative fashion and use results from the 4yr scenario. This subject is relevant once again when discussing sensitivity to reduced 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 down by -0.05 resulted in the same relative performance across all harvest control rules. Although not surprisingly, absolute values differed, potentially resulting in different conclusions as to which specific control rule meets sustainability criteria. Although it should be noted that under reduced productivity, a CUT2 rule at an exploitation rate of 0.10 can still achieve a Final SB $> 20\%$ of the unfished level.

In analyzing the sensitivity of our results to the probability of a boom year class, the question of whether or not unfished biomass is correctly estimated pertaining to this change in productivity was examined. What we may expect in a scenario where unfished biomass is overestimated is altered performance of control rules utilizing biomass thresholds, as the “true” threshold levels are actually higher than what is thought (i.e. 40% of the unfished level becomes 60% of the unfished level). This should result in an increase in year-to-year variation in yield as catch and exploitation rates are changed more frequently, and a decrease in yield as catch levels and exploitation rates decrease at relatively high stock sizes, when the stock is in no apparent danger. This should also result in decreased risk given more conservative thresholds. Our results indicated no apparent decrease in yield for control rules with biomass-based thresholds however we found increased AAV, decreased risk, and a slight increase in Final SB when unfished biomass is overestimated compared to when it is correctly specified within the lower productivity scenario. This may indicate that for the lower productivity scenario (bounds on the probability of boom - 0.05), increasing biomass-based thresholds on control rules would not cost in terms of reduced yield, however would result in lower risk and higher Final SB at the cost of larger AAV. Alternatively what we might expect in a scenario where unfished spawning biomass is underestimated is increased risk as “true” biomass thresholds are more liberal. This should also result in decreased Final SB, decreased yield, and decreased AAV. Our results corroborated all but decreased Final SB and decreased yield (for most biomass-based control rules) as it pertains to control rules with biomass-based thresholds when unfished biomass is underestimated. This is likely due to the fact that the simulation was of the high-productivity scenario (probability of a boom year class + 0.05), and exploitation rates may not have been high

enough to make a difference. Implications of over and under-estimation of unfished SB on results when the productivity of the stock (bounds of the uniform) is shifted up or down by 0.05 are largely trivial, as CUT1 and CUT2 rules continue to outperform CU rules in terms of risk, Final SB, and yield, however at an increased cost of AAV (if unfished SB is overestimated). In addition, CCC2 rules continued to outperform CC rules in terms of risk and Final SB, at little to no additional cost to yield and AAV over scenarios where unfished spawning biomass is correctly specified. Simulations of over- and under-estimation of unfished spawning biomass on the status quo scenario (regular binomial bounds) are needed to determine effects on the performance of harvest control rules for the most probable recruitment scenario.

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). Our method of estimating unfished biomass most closely relates to the “dynamic B_0 ” method defined in (MacCall et al., 1985) and compared to other methods (calculating the equilibrium point in the SR relationship and average recruitment combined with spawning biomass per-recruit analyses) in Haltuch et al., (2008, 2009). Where Haltuch et al., (2008) and Haltuch et al., (2009) concluded that calculating unfished biomass based on a fitted SR function was generally best (Haltuch et al., 2009 – “if available catch and survey data do not span at least 50 years”), this method was unavailable to us given the boom-or bust dynamics we specified in projecting recruitment (i.e. SR function is only applied for select “boom” years). It should also be noted that 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 unfished biomass based on the SPM is of concern to managers, an alternative to setting biomass thresholds based on an estimated unfished level is to set them based on some low objective value, i.e., no harvest below 500,000kg of spawning biomass. This could have the benefit of retaining 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.

As important as any findings of a study are the associated caveats based on its assumptions and limitations. A critical assumption we make in our study is that the probability of a boom year class, or the productivity of the stock, is static through time. The dominant theory in the literature as it pertains to what is driving these sporadic 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). Of these factors, high wind speeds have been shown to be negatively correlated with cisco year class strength (Myers et al., 2015), the hypothesized mechanism being an increased likelihood of advection of cisco larvae into colder and less productive waters under high wind scenarios. It has also been hypothesized that years with a large degree of ice cover and high temperatures directly after ice out benefit cisco year classes through an increase prey availability and abundance (Myers et al., 2015). Under anthropogenic climate change, surface temperatures are expected to increase, potentially resulting in less ice cover in addition to increased wind speed (Desai et al., 2009), each of which could result in decreasing the probability of a large

cisco year class. Simulations are necessary that take into account changing environmental conditions through time in assessing the relative performance of harvest control rules as they pertain to cisco.

In addition we must mention uncertainties about the process by which we projected recruitment. First and foremost, we used assessment model output as data in deriving the SR model. This has been called "doing statistics on statistics", or a "two-stage analysis" (Link 1999) and potential issues resulting from this have been discussed extensively in the fisheries literature (Brooks and Deroba, 2015; Maunder and Punt, 2013; Thorson et al., 2013). While we would have ideally avoided this, unfortunately existing cisco SR functions that have been developed are inadequate based on known bias in sampling gear (Stockwell et al., 2006), and we were unable to estimate a SR function within the SCAA.

A second issue that applies to our stock-recruit analysis, as it does to many, is that the data were sparse, or more specifically, few data were near the origin. This forced us to rely on a heavily influential prior for the log of the maximum annual reproductive rate parameter within the function, $\log(\tilde{\alpha})$. This prior was developed in Myers (1999) based on stocks of the family Salmonidae, of which 100/106 were stocks of different salmon species (others were 5 brook trout stocks and 1 lake trout). Where this prior relates to the most taxonomically proximal group to cisco available in the meta-analyses, it is safe to say the reproductive strategies of cisco and the species to which the prior was derived are drastically different. Cisco generally aggregate in bays and nearshore areas during the late-fall to spawn. They mate in the upper water column and then let their eggs drop to the bottom showing no apparent preference of bottom substrate (Stockwell

et al. 2009). Cisco also spawn many times throughout their life span, whereas salmon are generally anadromous and semelparous, meaning they travel up rivers to spawn (usually over a preferred rocky substrate) and often die after doing so. What is important in these descriptions of spawning habits is that while the species are relatively close taxonomically, they actually have quite different reproductive habits. Our analyses would greatly benefit from a more appropriate prior on the maximum annual reproductive rate parameter, perhaps one based on species belonging to the subfamily coregoninae, which includes bloater, kiyi, and other ciscoes that share similar reproductive habits. Unfortunately stock-recruitment data for this group are sparse, and a prior based on this subfamily is, to the best of our knowledge, nonexistent. The same can be said for σ_r , the recruitment variability, which was chosen based on a meta-analysis of recruitment variation for the family Salmonidae (Thorson et al., 2014).

Depensation was also not considered in our analyses. The inclusion of depensation at low stock sizes would have likely led to higher risk, lower Final SB, lower yield, and larger AAV over all control rules as simulations that reached a depensatory state may have hit a lower equilibrium point difficult to come out of. It is likely the advantage of threshold control rules would have been increased over baseline CU and CC with the inclusion of depensation.

Lastly, our treatment of “bust” recruitment years (i.e., drawing recruitment from a lognormal distribution derived using recruitment estimates from the SCAA designated “bust” years) may have presented a rescue for very low stock sizes. This treatment presents the opposite effect that depensation would where recruitment under “bust” designated years does not decrease as stock size decreases to very low levels. The effect

this had on our final results however is likely minimal, as bust recruitments are defined at very low values and are highly unlikely to rescue a stock out of a state of very low biomass.

It is important to note that where the current control rule in Thunder Bay is defined as a function of the biomass of fish $> 250\text{mm}$. In Minnesota waters, the control rule is defined in terms of the biomass of fish $> 305\text{mm}$. For this study we followed the Thunder Bay convention in defining spawning biomass as cisco $> 250\text{mm}$ 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.

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 (Chapter 1). 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 7 or 4 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): $\log(\tilde{\alpha}) \sim N(1.43, 0.05)$. 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 unfisher condition, and M is the SCAA median female natural mortality estimate. The Ricker model is then fit as

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

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 $\tilde{\alpha}$

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

Then recruitments for boom years are projected by:

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

Supplemental files containing figures related to the sensitivity to different levels of assessment error, productivity, and incorrectly calculating unfished spawning biomass (Figures 2.5-2.28) solely include the 4yr recruitment scenario.

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