Behavioural biases in multispecies commercial fisheries and their impacts on stock assessments

by

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Abstract

Accurate population estimates are a central aspect in the management of any species, but especially for fish stocks subjected to harvest pressures. Commercial fisheries catch landings provide an abundant source of data, but are inherently biased due to the behaviour of the fishers. Unlike scientifically collected data, commercial landings are a product of fishers actively targeting or avoiding certain species and areas. I investigated how biases in the behaviour of the fishers may impact the overall abundance index through generalized additive mixed models with subsets of data that were selected based on the inferred behaviour of the fishers for two commercially valuable species on the east coast of Canada. For both haddock (*Melanogrammus aeglefinus*) and redfish *(Sebastes* spp), fishing sets targeting the species and sets where the species were caught as bycatch produced different relative abundance indices despite being drawn from the same underlying population. When these indices were used in a virtual population analysis stock assessment for haddock, the resulting spawning stock biomass estimates reflected the biases in the estimates. The bycatch index was more similar to the survey index than was the target index was. When targeting behaviour is constant, changes in the underlying population may not be detected, but when targeting behaviour is changing, then false trends may be produced. Indices produced from bycatch data provided a more robust population estimate than target data, and may be a suitable alternative for when survey data are unavailable.

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Chapter One: General Introduction

1.1 Background

Sustainable harvest of any animal is reliant upon accurate population estimates. Although fish stocks were at one point considered to be inexhaustible, improvements in fishing power have allowed for the depletion and overfishing of many fish stocks (Garstang 1900, FAO 2016). Early advances in fishing power, such as the introduction of steam trawlers in the late 1800's, were thought to have increased fishing power from three to six times that of fishing under sail (Garstang 1900). The continued advancement of fishing vessels and gear since the late 1800's has allowed for fishing in previously inaccessible areas, and for longer periods of time resulting in the overall increased fishing power of vessels (Kerby et al. 2012). Combined with technological advances, such as GPS and navigational equipment, this allowed fishers to locate aggregations of fish, be more precise and efficient in their net placements, and return to specific fishing locations (Kerby et al. 2012, Robins et al. 1998). These improvements in fishing power have contributed to an increasing amount of fish stocks being overexploited and a global decline in fish biomass (Butchart et al. 2010,FAO 2016) . Myers and Worm (2003) suggest that the ocean has lost 90% of its large predatory fishes since the industrialization of fishing. The loss of large predatory fish species has resulted in "fishing down the food web", a global trend where the mean trophic level of landed catch has been in decline since the 1950's (Pauly et al. 1998). Continued exploitation at the current rates will likely lead to widespread fisheries collapses (Pauly et al. 1998), but with drastic reductions in exploitation rates and changes to current fishing practices recovery of fish stocks is still attainable (Pauly et al. 2002, Worm et al. 2009).

To ensure the recovery of overexploited fish stocks and prevent irreparable damage to future stocks, responsible management of our fisheries resources is increasingly important.

Producing stock assessments which are sensitive to changes in the underlying fish availability is a key factor in the management of commercial fisheries (Hilborn and Walters 1992). We are reliant upon our ability to infer population size from samples because fish populations cannot be directly estimated. Behavioural biases inherent to the data set used to produce stock size estimates have the potential to produce inaccurate population estimates which could result in the implementation of ineffective management strategies.

The data used for abundance indices comes from two main sources, fishery independent data or fishery dependent data. Fishery independent data, such as scientific surveys, are designed to minimize bias in how the catch is obtained so that the catch rates can accurately reflect the underlying fish population. Survey data are preferable to fishery dependent data, but are not available for all fisheries. The cost of survey data relative to the amount of data being produced is very high and for this reason not always available. When survey data are unavailable, abundance indices are often based upon the landings of commercial fisheries (Maunder and Punt 2004). Unlike surveys which are designed to minimize bias in how the catch was obtained, commercial fishers are actively targeting valuable species, resulting in non-random effort. Skilled fishers can sustain high catch rates of target species through moderate declines in underlying fish numbers.

Targeting is the application of specific fishing techniques, gear selection or temporal/spatial gear placement with the goal of capturing a certain species or size class of fish within a multispecies fishery. Targeting of valuable species, by weight or market price, is beneficial to fishers. When fishing effort is limited, targeting may not impair the fish stocks ability to persist. Katsukawa and Matsuda (2003) have shown that switching between target species could potentially keep the overall productivity of the fishery high by reducing the fishing pressure on both stocks. However, most economically important fish stocks are currently considered to be either fully fished or overfished (FAO 2016) .Globally in 2013, 58.1% of assessed stocks were considered to be fully fished, and 31.4% being fished at biologically unsustainable levels (FAO 2016).

The issue arising with using data from fishers demonstrating targeting behaviour stems from the relationship between catch-per-unit-effort (CPUE) and the underlying abundance. The current standard in fisheries research is using CPUE to look at changes in abundance assuming that a change in catch, with constant effort, reflects a change in the underlying abundance (Biseau 1998). The relationship between CPUE and abundance is assumed to be proportional (Figure 1-1). Hyperstabiltiy occurs when the abundance rate declines at a greater rate than CPUE, while the opposite pattern, known as hyperdepletion, occurs when catch rates decline at a greater rate than the underlying abundance (Clark 1982, Hilborn and Walters 1992, Harley et al. 2001, Figure 1-1). Effective targeting behaviour can result in a hyperstable relationship by selectively fishing high density areas. This results in a catch rate that remains high even when facing a decline in the underlying abundance. In order to detect overfishing of vulnerable stocks, which at the extreme could cause a crash in the fishery (cod; DFO 2011, anchovy; Glantz and Thompson 1981), it is important that the data we use to derive abundance estimates is representative of the underlying population.

Differences in raw catch, or even CPUE, are unlikely to be solely impacted by the underlying abundance. Variables such as vessel characteristics, fishing location, and the time of year can all contribute to the amount of fish captured in a fishing set. In order to use catch data as an index of abundance, catch is “standardized” to remove the variability associated with changes in catch due to factors beyond changes in abundance. Year is often included as a variable when standardizing catch regardless of significance, to explicitly represent underlying changes in the population (Maunder and Punt 2004). Before advancements in computing technologies allowed us to routinely fit complex statistical models, catch was standardized based on simpler methods focused on relative fishing power (Gulland 1956, Beverton and Holt 1957). The development of generalized linear models (GLM) allowed for linear models to be extended to data that was not described with a normal distribution (Nelder and Wedderburn 1972). For fisheries data this often means using a Poisson, or negative binomial distribution for count data, or a gamma distribution to account for the skew and heteroscedasticity common in continuous catch data (McCullagh and Nelder 1989, p30). Since their development, GLMs have been the common practice when standardizing catch and can be extended to include both fixed and random effects through generalized linear mixed models (GLMM; Helser et al. 2004, Venables and Dichmont 2004). Factors, such as the unique vessel, can be specified in GLMMs as a random effect which incorporates the variability associated with different fishing vessels, without having to quantify specific differences. In more recent years, GLMs and GLMMs have been extended into additive models. These account for trends through the use of smoothing functions that can fit non-linear trends while reducing the number of estimated parameters in the model (Wood 2006). Generalized additive models (GAM) have been used since the late 1990's to standardize catch in the Black Sea, as well as much more recently applied to dogfish in the Gulf of Alaska (Daskalov 1999, Gasper and Kruse 2013). For this study, I chose to use generalized additive mixed models (GAMM), which allows for both fixed and random effects to be used along with smoothing functions.

Because the commercial data we have available is often the result of targeting behaviour by the fishers, there have been many studies which try to account for the variability in catch associated with targeting behaviour. As a broad scale approach, fishing activities can be partitioned based on fishing tactic, a.k.a. fishing métiers (Pelletier and Ferraris 2000, Deporte et al. 2012). In a multispecies fishery, individual fishers are not all fishing in the same way or targeting the same species, so classifying fishing tactics can be useful in accounting for this source of variability in catch rates. Fishing tactics identified from performing clustering analyses, such as described in Pelletier and Ferraris (2000) can be used directly in GLM models as an explanatory variable. Carvalho et al. (2010) used GLMs to model blue shark catch from a Brazilian tuna fishery, accounting for targeting behaviour by including the fishing tactic as a multilevel factor. They found that fishing tactic accounted for up to 73% of the explained deviance. This agreed with Wiff et al. (2008) who also found that fishing tactic played an important role when standardizing catch for a demersal trawl fishery off central Chile. An alternative to using the overall fishing métier to account for targeting was proposed by Winker et al. (2013). Winker et al. (2013) produced a targeting variable based on principal component analysis (PCA) of catch composition and compared it to models where the target variable was based upon clustering methods. They found that the models using the PCA had the best fit to the data based on Akaike's information criterion model selection (AIC; Burnham and Anderson 2004) and greater predictive power based on bootstrap cross-validation of the models. Previous studies have also used simpler incorporation of targeting by including the natural logarithm of catch for an alternate target species (Marriott et al. 2013), or the proportion of catch of an alternative species (Chang et al. 2011) as a proxy for targeting.

Even in studies where targeting behaviour was not accounted for directly in the model variables, consideration of the effects of targeting could be taken into account through data selection. Helle et al. (2015) compared CPUE standardizations between all fishing sets, fishing sets presumed to be targeting ling (*Molva molva*), and fishing sets from vessels that often targeted ling. Tascheri et al. (2010) chose to account for possible changing of targeting behaviour by only selecting fishing sets where the species was identified as target sets through a logistic regression. All of the possible methods outlined above account for changes in targeting behaviour and how they may be influencing the catch rates. Although this in an important aspect of fishing effort, accounting for changes in targeting behaviour may not be accounting for the inherent hyperstabilty of directed fishing effort in general.

When there is no commercial data from target fisheries, bycatch may be used as an alternative. Ortiz and Arocha (2004) used standardized bycatch of billfish species from a longline tuna fishery, while Zhang and Chen (2015) used bycatch of Atlantic cod and cusk from lobster traps in the Gulf of Maine. Bycatch is generally only used when target data are not available, but due to the more random nature of bycatch in relation to the distribution of fish it may be more proportionate to the underlying abundance than target data. This would make indices produced from bycatch data a more appropriate relative index than target data in stock assessments.

In general, stock assessments aim to characterize stock dynamics and uncertainty, with the end goal being able to use the information about the stock dynamics to set management objectives (Haddon 2011). Not all stock assessment models are age-structured, i.e. biomass (or number) of fish are separated each year into separate ages or stages. Surplus production models, a.k.a. biomass dynamics models are considered to be one of the simplest stock assessment models used, and are not age-structured (Hilborn and Walters 1992). In general, surplus production refers to the production of a fish stock above and beyond the amount of fish needed to replace what is lost due to mortality. Rarely are there direct measurements of the biomass of a fish stock, so an index of abundance is incorporated into these assessment models instead (e.g. CPUE). If there is an independent measure of the relationship between the index and the true abundance, then the biomass can be reconstructed directly. However, when this information is not available the production function of the stock and the link between the index and actual abundance must be specified.

The most common production functions used are the Schaefer model and the Pella-Tomlinson model (Schaefer 1954, Pella and Tomlinson 1969). The Schaefer model describes a symmetrical arch shaped function, with the highest production observed when the population is at half of the carrying capacity. The Pella-Tomlinson model incorporates an exponent to the Schaefer model which allows for an asymmetrical production function. In general, surplus production models assume that any amount of fish harvested at or below the surplus production is a sustainable yield, with a single maximum sustainable yield (MSY). Surplus production models treat the biomass of a fish stock as a single entity, whereas in reality the age-structure of the fish stock influences the dynamics of the population.

Age-structured models refer to any stock assessment model which incorporates catch-at-age data, and can be broadly split into virtual population analysis methods (VPA) and statistical catch-at-age methods (SCA) (Hilborn and Walters 1992). Statistical catch-at-age uses a maximum likelihood approach to optimize parameters in the population dynamics model for the first year and youngest age class of fish, then projects the population estimates forwards (Hilborn and Walters 1992). SCA is a purely statistical approach to stock assessment, whereas traditional VPA (Gulland 1965) is calculated using the basic assumption that at an old enough age class, no individuals from a cohort will survive to the following year. Cohorts are projected backwards, instead of forwards as in SCA, by adding back individuals lost through natural and fishing mortality.

The traditional VPA method uses commercial catch-at-age data to reconstruct cohorts which have no surviving members in the current fishery. Auxiliary information is required to “tune” the VPA so that cohorts within the current fishery can be estimated. The auxiliary information is an index of the underlying abundance and may be in the form of a scientific survey, or CPUE trends from commercial fisheries. In general, the index of abundance is used to minimize the error between the estimated abundance from the VPA and the observed index. Depending on the data available and the assumptions made, methods such as extended survivor analysis (XSA; Shepherd 1999), ADAPT (Gavaris 1988) or CAGEAN (Deriso et al. 1985) methods can be used, each with their own strengths and weaknesses (Megrey 1989). These methods all rely upon a relative index of abundance to ‘tune’ the VPA, but the error minimization routine varies depending on the method. For example, XSA uses the estimated abundance of survivors while the ADAPT method uses catchability in the minimization routine. The ADAPT and CAGEAN methods are more of an integrated statistical approach. The population is still projected backwards through time, but the terminal year/age are estimated using statistical techniques. The ADAPT-VPA is used as the main stock assessment model for haddock on the Atlantic coast (Stone and Hansen 2015), and as such was chosen as the model to examine in this study.

1.2 The Study Fishery and Species

For this study the Northwest Atlantic Fisheries Organization (NAFO) division 4X groundfish fishery was used as a representative fishery to examine the effect of targeting behaviour on abundance indices (Figure 1-2). The Maritimes region of Canada supports a diverse range of fisheries, including groundfish, shellfish, and pelagics, with an estimated value of $757 million in 2012. Division 4X encompasses both the western part of the Scotian Shelf and the Bay of Fundy and a small portion of George's Bank, although the commercial records used in this study include only landings from the Scotian Shelf. The term groundfish collectively refers to species that are found near the bottom, as opposed to pelagic species, such as herring and mackerel, which are found in the middle of the water column or near the surface. In the Maritimes region, haddock (*Melanogrammus aeglefinus*) and redfish (*Sebastes sp*.) are considered to be the main target species of the groundfish fishery, with other species such as pollock (*Pollachius pollachius*), hake *(Merluccius sp*.) and Atlantic cod (*Gadus morhua*) caught as well. The groundfish fishery in 4X is comprised of fishers using both fixed (longline and gillnets) and mobile gear (trawls). This study used only records from otter trawl landings, which is the dominant gear type in recent years (Stone and Hansen 2015). Fisheries and Oceans Canada employs at-sea observers on commercial fishing vessel to monitor the accuracy of reported catch and discards. For the 4X groundfish trawl fishery, observer coverage was approximately 2.5% in 2008, increasing to about 10.7% in 2011 (Clark et al. 2015). The data available for the 4X commercial fishery is recorded at the level of a single fishing set. A fishing trip is defined as the time between leaving and returning to a homeport, with each trip made up of several fishing sets. A single fishing set refers to the actual activity of fishing, where the net is deployed, trawling occurs, and the catch is then sorted and stored. For each fishing set, information on species composition, fishing effort, location and vessel characteristics are recorded. The amount of data available, along with the relatively detailed information for each fishing set made the 4X division a good representative fishery for this study. Detailed information of the total landed catch by species and the average catch per set for the data used in this study can be found in Appendix A.

1.3 Aims and Objectives

My thesis investigated the quantification of targeting behaviour, and how fisher behaviour may influence abundance estimates. This was accomplished with data from the NAFO 4X groundfish fishery, but this thesis is not intended as an in-depth study of this particular fishery. The NAFO 4X fishery is being used as a representative fishery and thus the results are intended to represent overall concepts, not specific stock estimates.

Chapter two modeled standardized catch per set with generalized additive mixed models to incorporate the underlying behaviour of the fishers, while chapter three used these models as a relative index of abundance in an age structured stock assessment. Overall, these two chapters investigated both how fisher behaviour may influence catch on a set-by-set level, and how this may affect the estimate of the underlying fish stock. Understanding the effects that biased commercial data may have on population estimates may help in the future with better management of fisheries where survey data may be unavailable.

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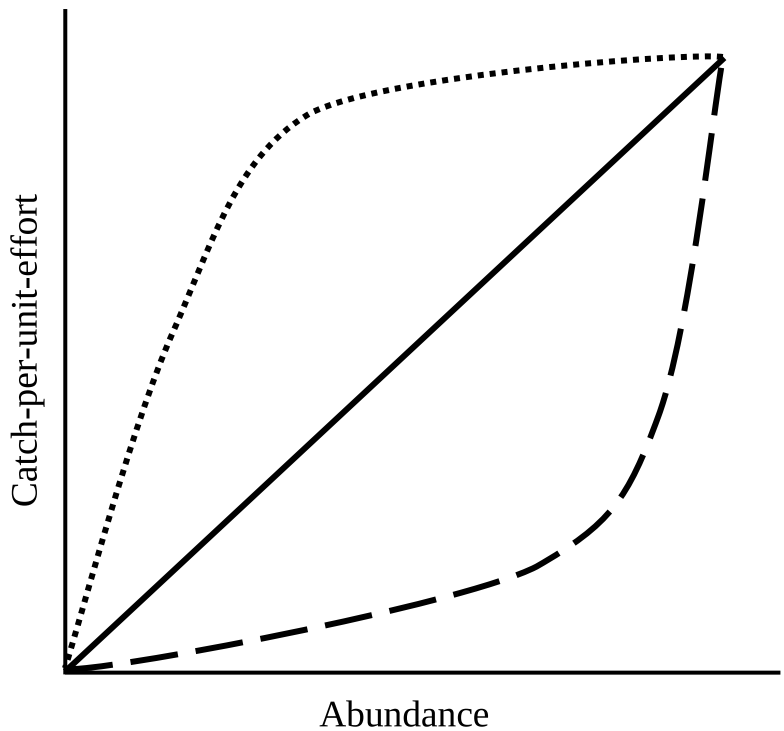

Figure 1- 1 Relationship between catch-per-unit-effort and abundance for hyperstability (••••), proportional (——) and hyperdepletion (- - - -) trends

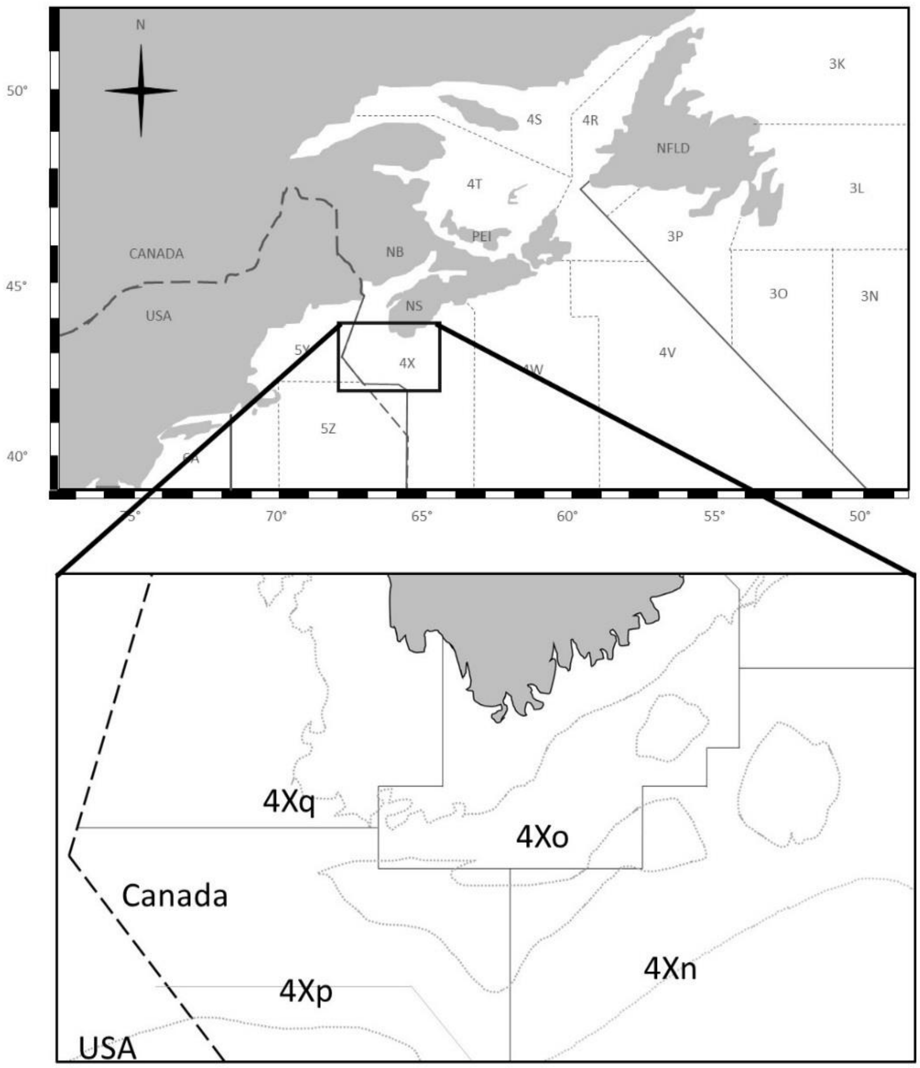

Figure 1- 2 Map of Northwest Atlantic Fisheries Organization (NAFO) designated fishing areas. Data from NAFO 4X was used for this study. Dashed black lines are the border between the Canada and the USA. Grey dashed lines (top) are division areas. Solid grey lines (bottom) are unit area divisions. Grey dotted lines (bottom) are shelf contours.

Chapter Two: The Effect of Behavioural Bias When Standardizing Commercial Catch

2.0 Abstract

Management of fish stocks relies upon accurate abundance estimates. Commercial fishing records are often used as a relative index of abundance, either on their own or as part of a more in-depth stock assessment method. Standardizing catch aims to remove the uncertainty associated with how catch is obtained so that the remaining variability can be attributed to a change in the underlying abundance. Generalized additive mixed models (GAMM) were used to standardize behavioural subsets of data for haddock and redfish in the NAFO 4X division groundfish fishery to examine how fisher behaviour and data selection influence relative abundance indices. Target sets were selected using a 90% threshold of catch by weight, bycatch sets were selected as the remaining catch from target sets, and mixed sets included all sets that did not meet the criteria for target or bycatch classification. For both haddock and redfish species, the patterns in relative abundance differed across the behavioural subsets of data. Comparatively, target and bycatch indices varied in both amplitude and overall pattern. Additionally, patterns in nominal fishing effort (hours trawled) and number of sets per trip were variable between behaviours. Target sets were influenced by the number of fishing sets within a trip, whereas bycatch sets were more influenced by the length of each set within a trip. CPUE effort as a response variable relies upon the assumption that catch and effort are proportional. This assumption was not met by any of the models. The underlying fishing tactic of commercial data influences not only the patterns in relative abundance indices but how we incorporate and interpret fishing effort.

2.1 Introduction

Overexploitation of marine fisheries resources has been an ongoing issue for the past several decades (FAO 2016). Globally, large marine predatory fish stocks have shown drastic declines resulting in increased fishing pressure on stocks at lower trophic levels (Pauly et al. 2008, Myers and Worm 2003). As both fishing power and fishing effort has increased through the latter part of the 20th century, so has the proportion of global fish stocks considered to be overexploited (Butchart et al. 2010). Although many fish stocks have been fished down to critical levels, there may still be potential for recovery with the implementation of more aggressive management strategies (Pauly et al. 2002, Worm et al. 2009). It is both unlikely and unreasonable to expect a repression of all fishing activities, but a reduction in fishing pressure is necessary for many fish stocks to begin recovery (Worm et al. 2009). Having an index of abundance that is sensitive to changes in the underlying population is an important aspect in the implementation of management decisions, along with monitoring their effectiveness. This chapter focuses on exploring how targeting behaviour of fishers, and the bias it introduces into commercial catch data, may influence standardized catch rates and their corresponding abundance indices.

Changes in fishery catch rates are often used as an indicator of changes in underlying fish abundance. Raw catch, or catch-per-unit-effort, is unlikely to be representative of the underlying population size due to spatial and temporal trends in the fish distribution (Hilborn and Walters 1992, Maunder and Punt 2004). The fishing efficiency of individual vessels also influences catch rates (Maunder and Punt 2004). Standardizing catch instead of using raw catch data reduces the effect that unknown factors have on the relative abundance index by removing the variability in catch not associated with changes in population size (Chen et al. 2004, Maunder and Punt 2004).

Nominal effort is often treated as if it were random in catch standardizations, but effort is usually directed towards valuable species, either by weight or market price (Maunder and Punt 2004). Fishers aim to maximize yield by directing their fishing activities towards a certain species, such as fishing select areas or times, and thus introducing bias into the data set (Hilborn and Walters 1992, Pelletier and Ferraris 2000). This directed effort, or "targeting" behaviour, may result in abundance estimates that do not reflect changes in underlying abundance (Hilborn and Walters 1992, Biseau 1998). Effective targeting behaviour can mask changes in underlying abundance when the relationship between catch and effort is assumed to be proportional (Clark 1982, Harley et al. 2001). The lack of change in catch rates may be interpreted as a stable underlying population even if it is in decline. If fishing pressure remains high there could be a crash in the fishery such as the one seen in Grand Banks Atlantic cod (*Gadus morhua*) in the early 1990's (DFO 2011). Therefore, accounting for targeting behaviour is important when developing an unbiased index of relative abundance.

Many methods have been used to incorporate aspects of targeting behaviour when standardizing catch. Studies may only select data targeting the species of interest (Tascheri et al. 2010, Stephens and MacCall 2004) or use data from fisheries targeting a single species (Cosgrove et al. 2014). When data from target fisheries is non-existent or unavailable, catches may be standardized from data where the species of interest is caught as bycatch (Gasper and Kruse 2013, Ortiz and Arocha 2004). Additionally, targeting behaviour may not be consistent and fishers may choose to switch between multiple target species to keep productivity high (Katsukawa and Matsuda 2003). This fishing practice reduces fishing pressure on both stocks; however, an undetected change in target species could bias catch standardizations. Including covariates for gear type (Li et al 2015), amount of other species caught (Marriott et al. 2013), proportion of other species in the catch (Chang et al. 2011), or principal component analysis scores (Winker et al. 2014) along with many others have been used as ways to account for changes in targeting behaviour in a fishery.

In this study, “fishing tactics” refer to the short-term objectives of the fishing vessel, with regard to their realized catch (Sampson 1991, Pelletier and Ferraris 2000). Some studies use “fishing strategy” in place of “fishing tactic” (e.g. Rogers and Pikitch 1992, Babcock and Pikitch 2000) when discussing short-term fishing choices. For this study the term “strategy” will be reserved for reference to long-term objectives. This may be at the vessel level (intended target species is considered the overall strategy) or referring to management strategies of entire fisheries (e.g. Mace 1994, Smith et al. 2009). Some fisheries require the logbook data to indicate the target species, corresponding to the intended fishing strategy (long-term objective), but the tactics used to achieve this may vary between sets.

Previous studies have compared standardized catch rates for target catches vs. all catches (Helle et al. 2015) or catches from different fleets (Chang et al. 2011). However, bycatch trends tend to only be included when no other data sources are available (Zhang and Chen, 2015, Brodziak and Walsh 2013). Using standardized CPUE as an index assumes that CPUE is proportional to the underlying abundance. This relationship also assumes that within the CPUE index, catch is proportional to effort. However, in many studies catch and effort are disproportionate (Aljafary 2016). Having an index of abundance that is both representative of the underlying population size and responds to changes in abundance is crucial to the effective management of fisheries. Consistent targeting behaviour in commercial fisheries has the potential to keep catch rates high, resulting in an insensitive index of abundance (Clark 1982, Harley et al. 2001). In this study, the main objective was to partition commercial fishing records based on targeting behaviour of fishers to compare the effect that behaviour may have on the resulting index of abundance.

2.2 Materials and Methods

2.2.1 Data Selection and Manipulation

The data used for this study spans six years of commercial catch records from the Northwest Atlantic Fisheries Organization (NAFO) 4X division groundfish fishery from 2008 to 2013. Each logbook entry is for one fishing set, which is comprised of a single bottom trawl. For each fishing set, information is recorded about the location, date, length of the trawl and what was caught. Catch information consists of weight in kilograms by species. One fishing trip is made up of multiple fishing sets where the catch is stored onboard between sets. Trips generally last for multiple days, whereas sets are on the scale of hours. Along with spatial and temporal information about the fishing sets, information about the fishing vessels was also recorded. Each vessel was assigned a unique, but anonymous, identifier within the data set so that fishing sets can be attributed to the same vessel across multiple fishing seasons. Vessel characteristics such as length and tonnage were recorded, along with the gear type used. For this study, the gear type was restricted to otter trawls.

The data provided was not used in its raw form, but was sorted and selected based on the requirements of the study in the order described. Incomplete records (at least one required column was missing) were removed and the remaining data was aggregated so that there was only a single weight per set by species, instead of being split by size or market class. Using the latitude and longitude coordinates, fishing sets which fell outside a reasonable fishing area were removed from the data set, i.e. sets that were on land, off the shelf edge or outside of the 4X boundary. Data from 2014 was removed from the analysis as it did not span the entire year and was thus inconsistent with the timeframe of fishing activities from previous years. The original data set contained sets from both inshore and offshore vessels. Inshore vessels are classified as having a length overall (LOA) less than 65’, while offshore vessel can have a LOA greater than 65’ and are regulated separately (Department of Fisheries and Oceans 2010). The original data set was made up primarily of inshore vessels, so to keep records consistent, offshore vessels were dropped from the analysis along with any sets where trawls lasted greater than nine hours. As a final data selection criterion, only vessels with greater than 100 fishing sets per year for all 6 years of data were retained. This provided a data set where fishers were likely to be more experienced, and thus have realized catch that is reflective of their intent, as any fishers who only fished periodically were excluded. Only using vessels with a large number of observations also allowed fishing vessel to be included as a random effect in the standardized catch models. Of the original 277778 records, 126413 records were retained; accounting for 50.1% of the fishing sets and 51.6% of the total catch by weight. Detailed information on the number of fishing sets and associated records removed from the original data set can be found in Table 2-1.

2.2.2 Fishery Catch, Trip and Set Overview

Summary information on fishery catch and effort was calculated for the sixteen fishing vessels across the 6 years of data. Fishery catch, in kg, was aggregated by species across all years and reported as total catch. The proportion of catch was calculated as the total catch of species divided by the total catch of all reported species. Average catch per set was calculated using only sets where the catch was greater than zero, and thus does not reflect the average catch across all sets that occurred.

The length of each fishing trip was calculated in number of days, corresponding to the dates of the first and last fishing set. This ignores initial and final travel to and from port, which could not be determined from the data. The number of fishing sets per trip was calculated before any fishing sets were removed from the analysis during the data manipulation stage.

2.2.3 Target Species ID

Fishery wide targeting was assessed using methods from Biseau (1998) and Gillis et al. (2008). Following the method from Biseau (1998), cumulative distribution functions (c.d.f) of proportion of catch per set were produced for species which had greater than 1000 non-zero records. Biseau (1998) demonstrated that the behaviour of the fishery can be classified based on the overall shape of the c.d.f. Bycatch species have the majority of their landings made up of small catches, whereas target species have the greatest proportion of catches in medium to large landings. The cumulative distribution functions were calculated on a set by set basis, instead of by trip as used in Biseau (1998), with each of the six years of data calculated separately.

In addition to using the cumulative catch distributions, target species were assessed by the skew of the distribution of log transformed non-zero catch following methods developed in Gillis et al. (2008). They show that the distribution of the logarithm of catch is negatively skewed when fishers are targeting a certain species and more symmetrical for bycatch species (Gillis et al. 2008). When fishers are targeting a species, they tend to have a larger proportion of high catches with a long tail of smaller catches. An exception to this is when a target species is fished too intensively, and even smaller aggregations of fish are exploited.

Skews were calculated on a yearly basis for species with greater than 1000 non-zero records. Distributions of catch were made up of the $\log_{10}$ catch (kilograms) on a set by set basis and the degree of skew was calculated using the skewness() function from the moments package (Komsta and Novomestky 2015). To account for the frequency at which species were landed, the proportion of zero catches was calculated for each species per year along with skew. Proportion of zeros in the catch is a measure of frequency of occurrence but does not reflect the total landed weight. It is possible for a species which is landed less frequently to have a larger total landed weight than a species that is landed more often. Proportion of zeros can range from zero, indicating the species was found in all deliveries, to one, indicating the species was not seen in any deliveries.

Proportion of set by weight was used as the criteria to identify targeting behaviour on a set by set basis. To examine the effect of targeting behaviour on abundance indices, catch records were subset by fishing tactic into three categories, “target”, “mixed” or “bycatch”, for haddock and redfish. Target sets were determined by selecting sets where a minimum of 90% of the catch by weight was the species of interest (either haddock or redfish). Using proportion of catch, instead of absolute catch removes the effect of total catch size (Pelletier and Ferraris 2000). Previous studies have used proportion of catch as a way of classifying targeting, such as Chang et al. (2011), which used % of catch to define fishing fleets and account for targeting in longline tuna fisheries, although on a vessel by year basis. Preliminary modeling using catch threshold levels of 80%, 85% and 95% indicated that the patterns in relative abundance remained consistent across threshold levels. Setting the threshold level at 90% of catch by weight allowed for a large enough data subset to estimate model parameters, while minimizing the chance that the catch not the intended target. Bycatch sets were determined by selecting sets where a minimum of 90% of the catch by weight was a single species that was not the species being modeled. Mixed sets were any set where the species of interest was caught, but did not meet the criteria to be classified as either target or bycatch. These three data subsets based upon the fishing tactic; target, mixed or bycatch, will be referred to as behavioural data subsets.

Along with the three behavioural data subsets for each species, catch was modeled for all of the data together with an additional variable to account for targeting. Including models which utilize the full data set allows for the comparison of trends between the behavioural data subsets and a more typical approach to standardizing catch. This behavioural proxy was the calculated proportion of catch by weight for the species of interest. For each of the two species, haddock and redfish, my manipulations resulted in five data sets each, as summarized in Table 2-2.

2.2.4 Standardized Catch Models

Standardizing catch aims to remove as much variability as possible in how the catch was obtained, so that the remaining variability can be attributed to the underlying abundance. Catch per set was standardized for the ten data sets outlined in Table 2-2 using a generalized additive mixed model (GAMM) approach. Generalized models allow for the data to be non-normally distributed, where a general linear model would require transformation (Zuur et al. 2007). Generalized models (generalized linear model (GLM), generalized additive model (GAM) and their mixed effect versions (GLMM, GAMM)) can be described with three main components; the distribution of the response variable, the linear predictor and a link function which provides the relationship between the first two components. GAM's are an extension of GLM's which represent trends in explanatory variables as smoothed functions, such as splines or loess, which better describe nonlinear relationships (Wood 2006, Gasper and Kruse 2013). This also provides the benefit of reducing the degrees of freedom in the model by using a smoothed trend. In this study, smoothed parameters are estimated using thin-plate regression splines as they provide a better representation of the smoothing function relative to traditional regression splines (Wood 2003, Wood 2006). The distribution of the response variable (i.e. catch per set) can be described with a gamma distribution to account for the skew and heteroscedasticity inherent to fisheries data. The probability of y, where y is a value drawn from the Gamma distribution, can be described using μ and ν as in Eq. 2-1 (McCullagh and Nelder 1989, pg. 287).

(2-1) $$P(y) = \frac{1}{\Gamma(\nu)}\left(\frac{\nu y}{\mu}\right)\exp\left(-\frac{\nu y}{\mu}\right)d(\log y)$$

$$where \quad y \geq 0, \nu > 0,\ \mu > 0$$

Using the parameterization from equation 2-1, each observation in the data set, Y, can be described as:

(2-2) $$Y \sim \text{Gamma}(\mu,\nu)$$

$$E(Y) = \mu$$

$$Var(Y) = \mu^2/\nu$$

Where Y is the response variable distributed with a gamma distribution, the expectation of Y is equal to the mean of the response distribution, μ, and ν is a constant that relates the square of the mean to the variance of Y.

In general terms, the linear predictor, η, for a simple (random intercept) additive mixed effect model is described by Eq. 2-3

(2-3) $$\eta = \beta_0 + \beta_1 X_1 + s(X_2)\ldots + \alpha_j$$

$$\alpha_j = \text{normal}(0, \sigma_j)$$

where β represents estimated parameters for fixed effect variables such as area, s() denotes a smoothed fixed effect variable such as year, and α_j represents the random intercept effect, vesselID. The random effect is distributed normally with a mean of 0 and a standard deviation estimated from the data.

The random intercept effect imposes a correlation structure onto the data, in that observations within each group are considered to be more similar than between groups. Because our data are made up of consecutive fishing sets within a trip, autocorrelation was incorporated in the model when necessary to account for the correlation between sets, in order, within each unique fishing trip. A first order autocorrelation parameter, ϕ, was estimated using the corAR1() function from the nlme package(Pinheiro and Bates 2016).

The final component of a generalized model is the link function which relates the mean of the response variable to the linear predictor. For all models a log link (Eq. 2-4) was used.

$$\log(\mu) = \eta \qquad (2\text{-}4)$$

$$\mu = e^{\eta}$$

The log link if often used in fisheries work despite not being the canonical link for the gamma distribution (Venables and Dichmont 2004). The typical equation relating catch and effort (Eq. 2-5) assumes catch is proportional to effort (Gulland 1969, Maunder and Punt 2004).

$$C = q\,f\,N \qquad (2\text{-}5)$$

Where C is catch, q is the catchability coefficient, f is the nominal fishing effort and N is the population size. This represents a relationship where the amount of fish caught is directly related to the underlying population size and nominal fishing effort. By logging the effort variable, f, and using a log link, the resulting model allows for a disproportionate relationship between catch and effort. See Appendix B for detailed equation transformations.

2.2.5 Model Fitting and Selection

Generalized additive mixed models are a fairly recent development and as such, the methods and functions used to fit them in R are not as well developed and documented as generalized linear mixed models. The methods available for fitting a generalized additive mixed model with a defined autocorrelation structure are limited and make variable selection by likelihood or information theoretic methods invalid (Wood 2016).

Model variables were selected using backwards elimination. Starting with a model containing all variables, the least significant variables were removed one at a time until all remaining variables, apart from year, were significant at an α level of 0.05. This was accomplished with the gam() function from the mgcv package (Wood 2016). The gam() function uses a maximum likelihood approach to fit the model and can be used in conjunction with the anova () function from the stats package. When used on a single model object, the anova () function tests the significance of each model term and returns a p-value associated with each. This can be used to obtain a single p-value for multilevel factors to be used as the selection criterion to keep or remove the variable (Zuur 2012). Unfortunately, autocorrelation cannot be directly specified using the gam() function, so alternative methods were used. Using the gamm() function, also from the mgcv package, autocorrelation structures can be directly specified, but models are fit using a penalized quasi-likelihood (PQL). Because the models are fit using PQL methods, the likelihood ratio test needed to return the single p-value for multilevel factors could not be used for backwards elimination (Zuur 2012). Backwards elimination of variables was accomplished using the gam() function, then the model was re-fit using the gamm() function to account for autocorrelation.

Because area is included in the model as an unordered factor, the p-values associated with each area are a comparison to a reference area. In my models, 4XN is the reference area, with areas 4XO, 4XP and 4XQ having p-values indicating if the area is significantly different from 4XN. To obtain a single value for area, indicating the significance of the term as a whole, the anova () function, from the mgcv package was used on the models fit using the gam () function.

An estimated degrees of freedom (edf) is returned for each of the smoothed variables, indicating the number of knots used to describe the trend in the variable (Wood 2006). Knots are the number of connecting points between splines in a smoothed line. An edf of 1 indicates a linear pattern, therefore when this occurred the model was rerun with the variable included as a non-smoothed variable and backwards elimination continued (Wood 2006).

A random effect already imposes a correlation structure on the data, in that values within the random effect levels are more similar than between effect levels but there is no specific structure (Zuur et al. 2013). This is known as compound symmetry (Zuur 2009). Because fishing sets within a trip are ordered temporally, an autocorrelation structure was explicitly specified for each model if the first order autocorrelation of the residuals was greater than 0.2. Autocorrelation was assessed using the acf () function from the stats package and incorporated into the models using the corAR1() function from the nlme package. To improve convergence of the model, the autocorrelation parameter,ϕ, was initially set to the value of the first order autocorrelation indicated by the acf () function to the nearest 0.05.

The possible variables included in our models, which aim to account for variation in the location, time of year, effort and vessel characteristics that may influence the amount of fish which are caught, can be found in Table 2-3. Values ranges and factor levels of each possible model explanatory variable can be found in Table 2-4. Detailed descriptions of the variables follow. The response variable for all models was catch (in kg) per fishing set. For model selection purposes, the full model is considered:

Catch per set ~ s (year) + s (day of season) + s (log (hours)) + s (nsets) + area + VCF + random effect of vessel

Year and day of season are representative of inter and intra-annual variation. Day of season is included to account for changes in catch due to temporal changes in the fish distribution as well as the effect of quota filling. The groundfish fishing season in the NAFO 4X division runs from April 1 to March 31 every year. Accounting for leap years, the day of the fishing season (from 1 to 366) was calculated accordingly from the day of year recorded in the original data set. 'Hours' is the classic measure of nominal fishing effort, recorded as the number of hours trawled. Nsets is the number of fishing sets per trip, area is the sub-area with the 4X division where the fishing set occurred and VCF (Vessel condition factor) represents vessel shape. Details on the calculation of the VCF can be found in section 2.2.10. Finally the random effect, vesselID, is included to account for the inherent variability between fishing vessels. Because vessel effects are included as both random (vesselID) and fixed effects (VCF) in the model, they may compete for variance. VCF accounts for variability in catch per set due to vessel shape, while vessel as a random effect accounts for variability in catch due to any and all vessel characteristics. Along with vessel shape and size, the overall vessel characteristics may include aspects such as a captain's experience level and behaviour which may affect the realized catch. If the random effect accounts for the variability due to fishing vessel, then VCF may be dropped from the model during model selection.

2.2.6 Relative Abundance Index (Year)

In order to produce time series of catch, a covariate which is representative of inter-annual variation must be included. Year was included in all models, regardless of significance, as our indicator of the relative abundance (Maunder and Punt 2004). If the covariate for year was not significant, then the underlying abundance was considered to be unchanged across years.

2.2.7 Nominal Fishing Effort

Often nominal fishing effort is incorporated in the response variable as catch-per-unit-effort (CPUE), but for our models effort was included as an explanatory variable. This allows for the relationship between catch and effort to be estimated instead of assumed proportional as discussed in the introduction. In all GAMMs fit for this study nominal fishing effort was represented as the number of hours trawled.

2.2.8 Sets-per-trip

In addition to fine scale decisions made on a set by set basis, catch per set may also be influenced by fisher decisions at the trip level. Number of sets per trip provided a covariate to represent trip by trip decisions that may affect catch rates. In addition to deciding on which species to direct their fishing effort, fishers may elect to make smaller hauls (by weight) due to factors such as bycatch limits, testing out new areas, or high temperatures which increase spoilage (pers com. Peter Comeau). Although catches may be smaller by weight, the number of fishing sets-per-trip is independent of the number of hours trawled. Number of sets per trip was calculated before any sets were removed from the analysis (incomplete records, duplicate species, location errors, etc.).

2.2.9 Vessel Characteristics

Length and weight are generally highly correlated variables, so often body condition, such as Fulton's K in fish (Fulton 1904, Ricker 1975), is used as a measurement to examine shape independent of size. A fishing vessel's length, measured as LOA, and weight, measured as tonnage, are highly correlated. To account for both aspects of size while avoiding issues stemming from collinearity, a "body condition" of each fishing vessel, which I called vessel condition factor (VCF), was calculated (Eq. 2-6).

(2-6) $$\text{VCF} = a * (\text{W}/\text{L}^{b})$$

where a is a scaling factor to make the VCF values closer to one, W is the tonnage, L is the LOA and b is the slope of the relationship between tonnage and LOA (Eq. 2-7).

(2-7) $$\text{Tonnage} = \beta_0 + b \cdot \text{Length}$$

Fulton's K uses b=3 when calculating body condition, but fitting a linear regression model to the data allows the slope to be directly estimated. Fishing regulations limit vessel length but not tonnage. Allowing for $b > 3$ more closely matches the relationship between length and tonnage observed in the fishery, as ships tend to get proportionally wider as they get longer. The slope of the relationship was calculated using a simple linear regression of the logged values of tonnage and LOA. Both the VCF and tonnage were included in preliminary models to account for both vessel shape and size, but there was no indication of a significant relationship between vessel size (tonnage) and catch per set. Variable selection proceeded with only VCF, as the variability in catch due to vessel size was likely accounted for through the random effect.

2.2.10 Spatial Effects

Spatially, fishing effort tends to be patchy and not consistent across the designated fishing area. To simplify the spatial aspect of the fishery, spatial trends are accounted for in the models by including the fishing unit area as a four level factor. Unit area boundaries can be seen in Figure 1-2. Additionally, using a simplified variable for fishing location provides enough data contrast, as none of the four levels contains less than 30 observations.

2.2.11 Analytical Tools

All data manipulations and analyses were performed using the statistical language R (R Core Team 2015). Custom code was developed to manipulate the data into a form suitable for input into the models. Additional software packages and functions are noted in the description of the methods.

2.3 Results

2.3.1 Data Selection and Manipulation

Comparatively, there were only minor differences between proportion of catch by weight by species between the 16 representative fishers and all fishers from the original data set (Figure 2-1). The top five species by weight were retained in the same order between the two data subsets. In decreasing order, these were redfish, haddock, pollock, cod, winter flounder and all others. The largest difference between all fishers and the 16 representative fishers was an increase in from 30.9% to 37.5% in redfish. Haddock and pollock catch declined slightly between catches from all vessels and the 16 vessels, decreasing from 28.3% to 26.7% for haddock and from 21.2% to 17.9% in pollock. From here on "the fishery" will refer to only the information obtained from the 16 frequently fishing vessels.

The relationship between LOA and tonnage, seen in Figure 2-2, resulted in a slope of 4.36. LOA and tonnage both increased up to a point, where LOA stopped increasing due to licensing regulations but tonnage continued to increase. Preliminary data exploration indicated that when both LOA and tonnage were included in the same model, the variance inflation factors were 5.2 for the haddock model, and 4.5 for the redfish model. Using VCF in place of tonnage and LOA allowed us to retain the information about vessel shape without having to be concerned with issues arising from collinearity. Tonnage and LOA were not considered in addition to VCF during model selection methods due to lack of significance in preliminary models. The variability in catch associated with vessel size was likely accounted for in the random effect (i.e. vesselID).

2.3.2 Fishery Catch, Trip and Set Overview

On average our 16 vessels included in the analysis each made 20.7 trips per year with an average of 13.7 fishing sets per trip (Table 2-5). Each trip lasted an average of three days, with the maximum trip length being 9 days, and the minimum being a single day. Nominal effort (measured as hours trawled per set) averaged 4 hours, but ranged from less than an hour to 9.5 hours. During the data selection process, 58 fishing sets were dropped for having trawl durations greater than 9.5 hours. These were generally data entry errors, i.e. hours fished recorded in 1000's of hours, or "non-typical" sets, with less than 10 data points (often only 1; Table 2-1). Haddock and redfish catches dominated the fishing records, making up 27% and 37% of the total catch by weight respectively (Table 2-6). Comparatively, the other three species that were caught in the top five made up 18% (pollock) and 6% (each cod and winter flounder) of the fishery by weight. Redfish tended to have larger sets by weight, than haddock but were found in a smaller proportion of the fishing sets.

2.3.3 Target Species ID

Collectively, haddock and redfish made up the majority of the fishery by weight (64%) from 2008-2013, but these two main species in our data set were also successfully identified through more objective measures. Figure 2-3 shows the cumulative distribution function (c.d.f) of the proportion of catch by weight per set for the fifteen most commonly caught species. Both haddock and redfish were found in the majority of sets and demonstrated a c.d.f, with a relatively large proportion of catches made up of >50% single species catch, indicative of targeting (Biseau 1998). Winter flounder also demonstrated a "targeting" c.d.f, but unlike haddock and redfish, was found in less than a quarter of the sets.

When all fifteen species with greater than 1000 records were included in the skew-zero plot, most species had negative skews of log-transformed catch (Figure 2-4). Cod, pollock, monkfish and flounder were the only four species who did not show a median negative skew. Most of the species from the c.d.f. plots in Figure 2-3, indicated non-targeted catch, which disagrees with the skew-zero plot in Figure 2-4. When only the top five species (in total catch by weight, representing over 90% of the total weight landed) were considered (Figure 2-5), the indicated target species agreed for both the Biseau (1998) c.d.f. method and Gillis et al. (2008) skew-zero method.

Total fishing effort, as the number of sets per year, remained relatively constant across years with minor changes in the proportion of sets in each of the three fishing tactics (target, bycatch, or mixed). Haddock was landed in an average of 3408 ± 117 (mean ± SE) fishing sets per year, divided on average into 12.7 ± 1.49 % target sets, 72.3 ± 1.33 % mixed sets, and 15.0 ± 1.22 % bycatch sets. Redfish was found on average in fewer fishing sets than haddock, with 2401 ±111 sets per year. The proportion of sets in each data subset was not as consistent across years in redfish as it was with haddock. On average sets were divided annually into 17.0 ±2.52 % target sets, 73.8 ±2.40 % mixed sets, and 9.19 ±1.31% bycatch sets.

2.3.4 Standardized Catch Models and Model Selection

For each of the two target species, haddock and redfish, I was successful in fitting five generalized additive mixed models with autocorrelation to the data. Three of the models were subsets of the non-zero catch records, i.e. target, mixed or bycatch, and the remaining two fit all non-zero catch records with and without accounting for fisher behaviour. All ten models indicated that there was autocorrelation in the residuals, which was then accounted for in the model specification. Autocorrelation of catches within a fishing trip ranged from 0.331 to 0.580 for haddock (Tables 2-7 and 2-8), and 0.216 to 0.494 for redfish (Tables 2-9 and 2-10).

2.3.5 Relative Abundance Index (Year)

Year was included in all models as an indicator of the relative abundance. For both haddock and redfish, the patterns in relative abundance were different depending on the data subset used. Patterns in relative abundance can be examined using the smooths of year from each model. Smooths are plotted on the scale of the linear predictor and centered around zero. Comparisons between the smooths of year can be made by looking at the relative changes from zero when all other covariates are held constant.

For haddock, the target subset indicated a higher starting catch per set, declining across years while the patterns for bycatch was more optimistic (Figure 2-6A). Like the target model, bycatch started high with a decline in catch per set across years, but unlike targeting, indicated increasing catch per set for the last year (Figure 2-6C). The mixed set, which contained the largest portion of the data, was more variable in the pattern of catch per set across years than either target or bycatch. Catch started lower, increasing until 2010, decreasing in 2011 and 2012 with increased catch again for 2013 (Figure 2-6B). When all of the data was included in a single model without accounting for targeting, the relative index of abundance was the same as in the mixed set (Figure 2-7A). Once proportion of catch was included in the model as an indicator of targeting, relative changes in catch were not as extreme between years but indicated an increase from 2008 to 2009 and a decrease from 2009 onwards (Figure 2-7B). Much of the variability in year was accounted for by proportion of catch (Figure 2-8A), as large (by weight) catches tended to also be catches where the species made a large proportion of the landed weight.

The relative index of abundance for redfish was fairly consistent across years for the target subset with a slight downward trend, more variable for the mixed subset and in-between for the bycatch (Figure 2-9). The mixed subset indicated changes in catch per set that cycled between high and low, with a slight downward trend. Bycatch sets indicated a lower starting and ending point with a peak in 2009, but the relationship was not as well defined as targeting and mixed sets. As with the haddock models, the redfish model with all the data was the same as with the mixed set, but once proportion of catch was included in the model (Figure 2-8B), the relative index of abundance was fairly stable with only a slight decrease in catch per set across years (Figure 2-10).

When the models are used to predict catch per set for each year of the study, with all other covariates held at their mean values, target sets have the highest catch for both haddock (Figure 2-11) and redfish (Figure 2-12). With the random vessel effect set to its mean of zero, (the black lines) target sets for haddock are around 2000 kg per set, with mixed and bycatch sets less than 200 kg per set (Figure 2-11). Targeted redfish sets were around 3000 kg per set, with mixed sets under 1000 kg and bycatch sets around 20 kg per set (Figure 2-12). The grey lines in the figures represent the catch per set for each of the individual vessels. For all models, the random effect modifies the intercept and not the slope. Some vessels are inherently better and will have consistently higher catches, as seen in Figures 2-11 and 2-12.

2.3.6 Nominal Fishing Effort

For all models, catch per set was used as the response variable, allowing for nominal fishing effort to be directly estimated as a covariate in the model. This is in contrast to many standardized catch models which use CPUE as the response variable, and assume that the relationship between catch and nominal effort is proportionate. For all models, with the exception of the haddock target model, as nominal effort (hours) increased catch generally increased as well but not proportionally. Doubling effort did not result in double catch, as the relationship is assumed to be when CPUE is the response variable (Tables 2-7, 2-8, 2-9, 2-10). Within the different fishing tactics, (target, mixed, bycatch) for both species the pattern in catch per hours fished was variable. In haddock target sets, the parameter for hours fished was not significantly different from zero. For mixed sets, catch tended to increase with hours fished to a point and then plateaued and finally bycatch sets continued to increase across hours fished (Figure 2-13). Within the redfish behavioural models, target and bycatch sets indicated increasing catch with increasing effort, but the increase was more extreme for bycatch sets. Similar to haddock, mixed sets for redfish increased to a point with increasing effort, but plateaued and slightly declined with increasing hours fished (Figure 2- 13).

2.3.7 Sets-per-trip

Overall trends in the target and mixed sets for both haddock and redfish, indicated decreasing catch per set with increasing number of sets per trip (Figure 2-14). In the bycatch sets for both species, catch per set did not significantly change across the number of fishing sets per trip, and therefore Nsets was dropped as a covariate in the models.

2.3.8 Vessel Characteristics

Vessel condition factor was dropped as a predictor variable in all redfish models, but was retained in the haddock mixed set model and the full model without proportion of catch as a covariate (Tables 2-7 and 2-8). For both models that vessel condition factor was selected for to remain in the model, as VCF increased catch per set tended to decrease.

2.3.9 Spatial Effects

Unit area overall was found to be significant at an alpha of 0.05.For both haddock and redfish, the catch per set varied between unit area locations for all models. For sets targeting haddock, catch tended to be highest in area 4XN, while sets targeting redfish tended to be have the largest catch per set in area 4XO. Because unit area was included in all models as a 4 level factor, the estimated parameter for each of the three areas shown (Tables 2-7, 2-8, 2-9, 2-10) indicated the difference from the baseline unit area,4XN.

2.4 Discussion

My analysis showed that abundance indices based on targeting and bycatch fishing tactics indicated different population trends. I was able to use generalized additive mixed models with autocorrelation to produce relative indices of abundance for fishery catch records that reflected fishing tactics. Fisher behaviour is difficult to quantify but has the potential to both diminish our ability to detect true population trends and to introduce trends that are erroneously attributed to changes in abundance. Selecting only a single method, i.e. data selection vs. variable selection, when standardizing commercial catch may not be sufficient to account for the impacts behaviour has on catch rates. Considering multiple fisher behaviours and methods to incorporate behaviour into models, provides a more complete picture of the underlying fish stock.

Targeting of a widely occurring, abundant species results in fishing sets where the species is caught frequently, caught in relatively large amounts and makes up a large proportion of each fishing set (Biseau 1998, Gillis et al. 2008). Haddock and redfish were found to have patterns consistent with wide-scale targeting behaviour in both the weight of catch and the proportion of catch for the NAFO 4X fishery. The Biseau (1998) method used proportion of catch per set, independent of the absolute catch weight, while the Gillis et al. (2008) method used the distribution of the logarithm of catch to identify targeting behaviour. The cumulative distribution function of proportion of catch, indicated that both redfish and haddock had a large number of landings made up of sets with a high proportion of the species. Additionally, the two species made up the majority of the fishery by weight (>60%) and the distribution of log catch indicated that when all non-zero catch is considered, there is a disproportionate number of large catches (i.e. negative skew). Combined, this is indicative of fishery wide targeting of haddock and redfish.

Winter flounder is likely targeted periodically. Despite being caught in only a small proportion of fishing sets (22%), both the c.d.f. of proportion of catch and the distribution of catch weights were consistent with a target species. When winter flounder is caught, it often makes up a large proportion of the fishing set. When the distribution of catch weight is considered, winter flounder is disproportionately landed in larger amounts (i.e. negative skew). Unlike haddock and redfish which are both found in >50% of fishing sets and each make up >25% of the fishery by weight, winter flounder is found in <25% of sets and makes up <6% of the fishery by weight. Additionally, winter flounder is known to be a bait fish in the lobster fishery (pers com. Peter Comeau). Combined, this provides objective evidence of a species that is not bycatch, but is intermittently targeted for bait.

When all fifteen species found in >1000 sets were included in the skew-zero plot, the majority of the rarely caught species presented distributions of log-transformed catch with negative skews indicative of targeting. This is in contrast to the Biseau (1998) plots where the majority of the species had distribution functions consistent with bycatch species. In general, a more negative skew indicates a more heavily targeted species but the degree of skew is relative to other species and must also be considered with the number of zero catches. Although many of the species had negative skews, the majority of the species each made up less than 1% of the fishery by weight. It is possible that some of the species may be very periodically targeted for bait, but unlike winter flounder, the Biseau (1998) plots did not indicate targeting. On its own, a negative skew does not indicate targeting. Sporadic large catches of a rarely caught species, or close ecological or technological association with a target species, would result in highly negative catch skews, but could still produce the c.d.f observed. In conjunction with the frequency and the total weight at which the species is caught, this gives a broader picture of a bycatch species.

Skew of the logarithm of catch is a useful tool when skews are examined relative to other co-occurring species. When the catch skews from the three main gadidae species (haddock, cod, and pollock) are considered together, haddock has a negative skew consistent with a target species. Cod and pollock are both caught at similar frequencies as haddock, but both have catch skews not significantly different from zero and a c.d.f. of proportion of catch more in line with bycatch than a target species. When the top five species by weight (redfish, haddock, pollock, cod and winter flounder) are considered together, the combined evidence from both the Biseau (1998) and Gillis et al. (2008) methods illustrate the overall strategy of the fishery well. Haddock and redfish are the main, frequent target species, winter flounder is likely an infrequent target species, and cod and pollock are frequently caught bycatch species.

To examine how directed fishing effort affects the index of abundance from the catch records, I needed to identify targeting not just at a fishery wide level, but the finest scale available. Quantifying targeting behaviour becomes more difficult as the scale becomes finer. When all fishing activity in an area is considered, fishing métiers based on gear, vessels characteristic or species group may be used to identify fishing tactics on a broad scale (Deporte et al. 2012). With the data set from this fishery, I was already close to, if not at, the finest métier scale considered in Deporte et al. (2012). Additionally, targeting behaviour for this study was classified on a set by set basis, not at the trip level. The data was fairly uniform relative to many other studies who examined targeting behaviour (e.g. Winker et al. 2013, Stephens and MacCall 2004, Pelletier and Ferraris 2000). The data set used by Winker et al. 2013 contained information from a linefishery in South Africa that targeted pelagic, demersal and reef associated species, unlike my data set which only targeted groundfish. Stephens and MacCall (2004) were able to select target sets based on habitat type to use in CPUE standardization, excluding sets from areas where the species was not expected to be found. Haddock and redfish are both groundfish species but redfish tend to spend more time off the bottom, feeding in more open water. Despite these differences in habitat usage, both haddock and redfish were caught together in many of the fishing sets. It's possible that there were only caught together due to the fishing gear being pulled through multiple habitat types in a single trawl. This had the potential to make the identification of target sets more difficult, but by avoiding methods based on fishing location to ID targeting (e.g. Stephens and MacCall 2004) and by setting the threshold for targeting high enough (90%), I had more confidence in the accurate identification of target sets. In the Senegal fishery described by Pelletier and Ferraris (2000) there were 121 species compared to the 22 in this study. The large number of species allowed for fishing métier classification to describe clusters of related species instead of for individual species, as with my data set. Due to all fishing sets in this study using the same gear type (otter trawls) to target the same type of fish (groundfish), proportion of catch was ultimately used to identify targeting of a single species on a set by set basis.

Selecting 90% of the catch as the criteria for targeting allowed us to have a large enough (>1000 observations) data set in each of the three subsets, while maintaining a high enough threshold that it was unlikely for targeting misspecification. Chang et al. (2011) have previously used proportion of catch to classify fishing fleets on a vessel by year basis, along with using proportion of catch within each standardization model to account for changes in targeting behaviour. Chang et al. (2011) used thresholds as high as >95% annual catch to define fleet types. Landings in the 4X division are considered to be a target sets if >50% of the set is a single species (pers com. Peter Comeau). As the two main target species, it was initially expected that there would be a clear definition between sets catching haddock and sets catching redfish. Preliminary data exploration revealed that there was a continuum in catch proportions from >95% haddock though to >95% redfish and that a 50% threshold would be insufficient to use for data selection. Although larger than the definition of "targeting" from this fishery, a 90% threshold was used to balance the need for sufficient data and confidence in representing trends in catch that existed at the two extremes of fisher behaviour.

As expected, the predicted catch for a "typical" fishing set (all covariates set to their means) was much greater for target sets than either bycatch or mixed, for both species. For redfish, the predicted catch of mixed sets was more similar to the predicted catch of target sets than the same comparison for haddock. Because sets targeting a species result in higher catch weight per set than bycatch sets (Biseau 1998), high redfish catch in mixed sets may indicate the threshold for targeting was set too high for redfish. A lower threshold for targeting classification would reallocate the high redfish catch from the mixed sets to target sets, which may be more appropriate for future models. To maintain consistency between species in this study, the threshold was left at 90% for both haddock and redfish.

Although all data was collected from the same fishery, and thus the same underlying population, the patterns in the relative index of abundance were different between data subsets.

From Biseau (1998), I expected target sets would show the least change between years, and bycatch sets would show the most. The relative index of abundance for redfish targeted sets agreed with the prediction in that it showed the least amount of variation in catch between years, relative to the bycatch and mixed sets. However, the haddock models were most variable in the mixed model and had conflicting patterns of relative abundance between the target and bycatch. Often the concern with using target vs. bycatch data are that the amplitude of the changes in relative abundance are expected to be different, with underestimation in targeting and overestimation in bycatch (Biseau 1998). I have shown that an additional concern is that the relative patterns may also differ depending on the directed effort of the fisher.

In this study, proportion of catch was used as a proxy for targeting behaviour when all sets were considered together. Previous studies have used proportion of catch to represent changes in targeting behaviour as discussed previously (i.e. Chang et al. 2011), but changes in targeting have also been incorporated into standardized catch models through additional means. Catch weight of another species has been used as a covariate in Marriott et al. (2013), while Winker et al. (2014) used principal component analysis scores. Accounting for changes in targeting behaviour, be it through any of the aforementioned methods, is necessary when behaviour of the fishers is not consistent across the dataset. For both haddock and redfish, including proportion of catch as a covariate in the model accounted for much of the variability in the abundance index compared to when all data was modeled together without consideration of targeting. As proportion of catch increased, total catch increased as well. This is in agreement with targeting sets (high proportion) being larger sets by weight than bycatch (low proportion). Although accounting for changes in targeting behaviour when standardizing catch is important to consider, it does not necessarily remove the potential effect of hyperstability in catch records.

Standardization of catch can account for the observed sources of variability in the data, but cannot resolve issues stemming from lack of data contrast (Hilborn and Walters 1992)

The pattern in relative abundance for the model including all data plus the target proxy appeared to include aspects of both the targeting and bycatch indices for both species. Additionally, the pattern in abundance when accounting for targeting behaviour through a model covariate produced an index with less extreme highs and lows than either the target or bycatch alone. Each model is a representation of the same underlying fish population but they resulted in different patterns of relative abundance. This demonstrates how different representations of the system through model covariate or data selection may alter the perception of the underlying abundance. Compared to the abundance index for haddock from the Scotian Shelf summer survey, neither the bycatch nor the target index aligned for all years (DFO 2017, DFO 2016). The survey indicated an increase in biomass between 2008 and 2009, which agreed with the target index and not the bycatch. Conversely between 2012 and 2013 both the survey and bycatch indicated an increase in biomass with the target index declining. For redfish, the trend was more similar between the survey and bycatch then between the target and bycatch. The comparisons between the survey and commercial trends can only be made with some trepidation, as they do not cover the same geographic area. The survey is comprised of both the Bay of Fundy and the Scotian Shelf, while the commercial data is from the Scotian Shelf only. While no single index represents the system perfectly, I would recommend the bycatch index over the target index (if only a single index is used), as it more closely matched the survey for both species. Consideration of the effect that data selection has on relative abundance indices should be taken when using standardized catch rates to make inferences about the true population size.

Of the many methods available, selecting only sets where the species was targeted, such as in Tascheri et al. (2010), may not provide the best representation of the system. Targeting behaviour can result in catch rates that do not reflect changes in population size due to issues arising from hyperstability (as discussed in Hilborn and Walters (1992)). With this study, I have also shown that target data may produce indices that show trends that are not only different in amplitude (i.e. redfish), but may also have contrasting patterns to other representation of the abundance (ie. haddock). Furthermore, target data may be more susceptible to changes in fisher behaviour, as it is directly related to the intent of the fishing vessels.

Spatially, fish are not distributed randomly but tend to be clustered. When commercial fishers target these high density areas, catch rates can remain high even when the overall population size is declining (Harley 2001, Hamilton et al. 2016). This assumes that targeting behaviour remains consistent, but changes in targeting behaviour of the fishers due to market value or quota pressures may produce abundance indices that reflect a change in fishing effort more than a change in population size (Pinnegar et al. 2002, Campbell 2004).

In my study area, the decline in haddock catch in the target subset may be attributed partially to changes in fishing tactics to avoid catching Atlantic cod and may not be representative of an underlying decline in haddock. In 2010 Atlantic cod in the 4X NAFO division was reassigned from special concern to endangered (COSEWIC 2010). In 2011 the total allowable catch for cod in the 4X division was reduced by 45% to alleviate some of the fishing pressure on the stock (DFO 2015). Haddock and cod have a high biological association resulting in them often being caught in the same set (Scott and Scott 1988). Decrease in haddock catch per set for sets targeting haddock are likely due to fishers making smaller sets overall or fishing in suboptimal habitats to reduce the chance of large cod catches.

When a species is not targeted, bycatch data from other directed fisheries has been used instead for catch derived abundance indices. For many shark species, such as spiny dogfish (Gasper and Kruse 2013) and oceanic whitetip shark (Brodziak and Walsh 2013), bycatch from longline fisheries is used in standardized catch models to look at changes in CPUE. Similar to the concerns with only using targeted data sets, using only bycatch sets may not represent the true underlying population size. Zhang and Chen (2015) found that the abundance index from models using bycatch of Atlantic cod from lobster traps did not agree with all indices derived from survey data. Presence or absence of lobster in the traps had a significant effect on the presence of Atlantic cod in the trap, which impacted the overall catch rates. In a multispecies fishery where each species may be considered both a target and a bycatch species, comparison of standardized catch between the two behaviours may provide more insight than either behaviour on its own. Although bycatch sets are expected to be more "random" than target sets, and thus a better representation of the underlying availability, interactions between target and non-target species along with changes in the demand or market value, may influence trends in the bycatch index. While not explored in this thesis, describing potential factors which may influence trends in bycatch indices (outside of fish abundance) would be valuable for the interpretation of bycatch trends and give more confidence in attributing changes in the index to a corresponding change in the fish availability.

In addition to changes in the relative abundance index depending on fishing tactic, the relationship between catch and effort was also variable between behaviours. The pattern of plateauing catch with increasing effort also indicates how one unit of fishing effort may not be equal across all levels of effort. Using catch-per-unit-effort as a response variable assumes that the relationship between catch and effort is proportional and remains consistent across all levels of effort. I found that the relationship between nominal fishing effort (hours trawled) and catch was not proportional. Furthermore, the relationship differed between target, mixed, and bycatch models for each species. Disproportionate relationships may result from the spatial dynamics of the fishery (competition, interference, facilitation; Hilborn 1985) or how the data are aggregated before analysis (Aljafary 2016). For haddock target sets, there was no significant relationship between hours trawled and catch per set. This could reflect fishers targeting haddock that only pulled up their nets once they were full, resulting in no relationship between catch and effort. For sets where haddock was bycatch, longer sets resulted in larger catches which is more in line with the assumptions of using CPUE. For redfish, catch increased with trawl duration for both target and bycatch sets, but at a greater degree for bycatch. Mixed sets indicated increasing catch with hours trawled for the first few hours then plateauing. This is likely an artifact of multiple fishing tactics included in a single model. If all fishers are not fishing to fill their nets with a single species (or are not successful), then catch tends to increase with trawl length, such as with the bycatch models. Because the mixed sets likely included targeting to some degree, at a certain point increasing the trawl length no longer increased the catch, as seen in the target model. The difference between the catch and effort relationship seen in haddock and redfish may reflect different fishing practices between the two species.

For fishing sets targeting the species of interest, number of sets per trip may be more informative than hours trawled, whereas with bycatch fishing effort is a good predictor of catch. In the target models, catch per set decreased with increasing number of sets per trip whereas there was no relationship between number of fishing sets per trip and catch for the bycatch models. Vessels have limited storage space, so if fishers are making large catches, they will fill up the hold faster resulting in fewer sets per trip. Smaller sets would produce the opposite pattern where vessels can make a greater number of sets to fill up the hold. Fishers may elect to make smaller sets for a variety of reasons. For example, during periods of hot weather, fish must be processed quicker so they do not spoil while on deck (pers com. Peter Comeau). A greater number of smaller sets reduces the amount of time it takes to process each individual haul. Number of sets per trip and hours trawled per set are not correlated, so vessels making smaller sets may still be implementing a "filling the net" strategy but with a reduced volume of what is considered full. When a species was caught as bycatch, there was no significant relationship between number of sets per trip and the amount of fish caught, but instead catch size increased the longer a net was in the water. In future studies, this pattern may be used as evidence that a species is caught as bycatch and is not the intended target.

Modeling catch directly instead of using CPUE allows greater insight into the relationship between catch and effort and ultimately a more useful model. Based on results of the models from this study, CPUE would not have been an appropriate way to incorporate fishing effort. The relationship between catch and effort, especially for haddock, was variable depending on the fishing tactic of the data subset. For future studies, if multiple fishing tactics are included in a single model, it may be beneficially to include an interaction effect between fishing effort and fishing tactic.

Although only significant in two of the ten models, vessel condition factor (VCF) allowed us to incorporate aspects of both vessel length and tonnage without the collinearity associated with including both. Because I used mixed effect models to incorporate the inherent differences between fishing vessels, specific vessel characteristics were not required for the majority of the models. The two models that did retain VCF were the haddock mixed set and haddock all data without accounting for targeting. Fisheries data tends to be very "noisy" so the significance of VCF for haddock when fishing tactic was not specified may indicate a weak pattern between vessel shape and fisher behaviour for haddock but not redfish. When fishing tactic was incorporated in some way, either specified using proportion of catch or using data subsets with a single tactic, the VCF was no longer significant.

Through this study I was able to demonstrate that trends in relative abundance indices are influenced by fishing tactic. Along with changes in relative abundance, the relationship between catch and effort also varied depending on fishing tactic, which is further evidence against using CPUE as a direct index of abundance. Consideration of data selection when standardizing catch is imperative to the interpretation of the resulting abundance indices and understanding the fishery is key in selecting the appropriate data to use. Only selecting records where the species of interest was successfully targeted may not only bias the estimate, but can actually produce a different overall pattern in relative abundance then when bycatch sources are used. The best approach is likely to compare multiple indices using different behavioural subsets of data, incorporate predictor variables which account for targeting behaviour, and to avoid using indices that are based solely on data from target sets.

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Table 2- 1 Number of fishing sets and corresponding records (where each record is the weight for one species) excluded from data analysis out of the original 46347 sets and 277778 records. Data comes from the NAFO 4X groundfish fishery from 2008 to 2014. Records were removed in the order listed below.

Selection criteria	**N (sets)**	**Prop (sets)**	**N (records)**	**Prop (records)**
Incomplete data	1785	0.0385	7216	0.0260
Duplicate species	-	-	34722	0.1250
Onshore sets	11	<0.0100	53	<0.0100
Offshelf sets	54	<0.00100	244	<0.0100
Outside 4X	8	<0.0100	50	<0.0100
2014 incomplete	1178	0.0254	6473	0.0233
Offshore vessels (>65ft)	702	0.0152	3593	0.0129
Trawls longer than 9h	58	<0.0010	337	<0.0010
<100 sets per year	19324	0.4169	98677	0.3552

Table 2- 2 Description of data subsets used in fitting standardized catch models for haddock (*Melanogrammus aeglefinus*) and redfish (*Sebastes spp*.) The target, mixed and bycatch data are subsets of the full data set, whereas All + target proxy data consist of all records where the species was caught.

Species	**Data**	**Description**
Haddock	Target sets	Haddock ≥90% of catch by weight
Haddock	Mixed sets	No single species is ≥90% of catch by weight
Haddock	Bycatch sets	Non-haddock species ≥90% of catch by weight
Haddock	All	All data
Haddock	All + target	All data with targeting covariate
Redfish	Target sets	Redfish ≥90% of catch by weight
Redfish	Mixed sets	No single species is ≥90% of catch by weight
Redfish	Bycatch sets	Non-redfish species ≥90% of catch by weight
Redfish	All	All data
Redfish	All + target	All data with targeting covariate

Table 2- 3 Potential variables included in the generalized additive mixed models for haddock *(Melanogrammus aeglefinus*) and redfish (*Sebastes spp*.) to standardize catch rates from the NAFO 4X division multispecies groundfish trawl fishery

Variable	**Type**	**Smoothed**	**Description**
Fixed Effects			
Year	Continuous	Y	Year (indicator of relative abundance)
DayofSeason	Continuous	Y	Day of fishing season Day 1 is April 1
UnitArea	Categorical	N	DFO regulation fishing zone
Hours	Continuous	Y	Length of trawl in hours
Nsets	Continuous	Y	Number of sets per fishing trip
VCF	Continuous	N	Vessel condition factor
Proportion	Continuous	Y	Proportion of catch by weight
Random effect			
Vessel ID	Categorical	N	Unique vessel identifier

Table 2- 4 Summary of numeric and factor variables used in the generalized additive mixed models for haddock (*Melanogrammus aeglefinus)* and redfish (*Sebastes spp.)*. Data are a subset from NAFO 4X division commercial catch records from 2008 to 2013.

Numeric variables					
Variable	**Mean**	**SD**	**Median**	**Max**	**Min**
DayofSeason	161	122	123	366	1
Hours	4.05	1.50	4.5	9.5	0.5
Nsets	15.5	5.10	15	36	1
VCF	1.18	0.239	1.13	1.67	0.836

Factor variables		
Variable	**N. Factor levels**	**Description**
UnitArea	4	“4XN”, “4XO”, “4XP”, “4XQ” *

* Unit areas can be found on NAFO division map (Figure 1-2)

Table 2- 5 Summary of fishery effort from 16 unique fishing vessels selected from NAFO 4X division commercial fishing records. The data set is made up of 1988 fishing trips from 2008-2013.

	Mean	**SD**	**Median**	**Max**	**Min**	**N**
Trips per year	331.3	19.28	333.5	360	304	6
Trips per vessel	124.3	29.88	128	164	80	16
Trips per vessel per year	20.71	6.815	21	37	7	96
Length of trip (days)	3.435	1.297	4	9	1	1988
Nsets per trip	13.72	5.203	14	36	1	1988
Hours/set	4.046	1.504	4.5	9.5	0.5	23227
Sets per vessel	1452	345.0	1384	2126	944	16
Sets per vessel per year	241.9	82.18	241.5	454	101	96

Table 2- 6 Summary of catch weights for top five species from fishing sets made by 16 unique fishing vessels in the NAFO 4X division. The data set consists of 23227 fishing sets from 2008-2013. N is the number of fishing sets where catch was greater than 0. All catches are recorded in kg, with proportion being the proportion of total catch by weight. Mean (set>0) is the average catch per set across sets where the species was landed. Mean (all) is the average catch per set across all sets that occurred including zero catch.

Species	**Total Catch**	**Prop of Total**	**Mean (set>0)**	**Mean (all)**	**SD**	**Median**	**Max**	**Min**	**N**
Redfish	14396181	0.3743	999.4	619.8	1380	492.4	26133	0.001	14405
Haddock	10260974	0.2668	501.8	441.8	1108	157.1	18766	0.001	20450
Pollock	6892133	0.1792	421.0	296.7	1234	62.83	21337	0.001	16371
Cod	2346750	0.0610	120.4	101.0	328.8	33.31	9616	0.001	19496
Winter Flounder	2139781	0.0556	414.6	92.1	527.0	249.9	8117	0.001	5161

Table 2- 7 Parameter estimates from three generalized additive mixed models for haddock (*Melanogrammus aeglefinus)* from the NAFO 4X division commercial fishery. The data set was subset by fishing tactic, one of targeting, mixed or bycatch.

Model	**Term**	**Estimate**	**SE**	**T value**	**Edf**	**F**	**p-value**
	Fixed Effects						
Target	Intercept	7.520	0.089	85.00			<0.001
N=2620	4XO	-0.305	0.136	-2.43			0.021
	4XP	-0.087	0.072	-1.21			0.228
	4XQ	-0.525	0.176	-2.98			0.003
	s(year)				3.26	36.30	<0.001
	s(dayofseason)				6.13	8.08	<0.001
	s(Nsets)				2.48	53.10	<0.001
	Random effect	Sigma					
	vesselID	0.848					
	Autocorrelation	Phi					
		0.331					
	Fixed Effects						
Mixed	Intercept	7.050	0.221	31.9			<0.001
N=14801	4XO	-0.399	0.070	-5.69			<0.001
	4XP	-0.339	0.061	-5.58			<0.001
	4XQ	-0.779	0.065	-11.9			<0.001
	Nsets	-0.024	0.004	-5.56			<0.001
	VCF	-0.545	0.169	-3.22			0.001
	s(year)				3.87	29.3	<0.001
	s(dayofseason)				7.61	108	<0.001
	s(log(hours))				3.22	118	<0.001
	Random effect	Sigma					
	vesselID	1.390					
	Autocorrelation	Phi					
		0.552					
	Fixed Effects						
Bycatch	Intercept	3.180	0.121	26.30			<0.001
N=3029	4XO	-0.554	0.128	-4.33			<0.001
	4XP	0.040	0.105	0.383			0.702
	4XQ	-0.203	0.113	-1.80			0.072
	log(hours)	0.411	0.055	7.47			<0.001
	s(year)				2.94	8.31	<0.001
	s(dayofseason)				6.13	20.2	<0.001
	Random effect	Sigma					
	vesselID	1.30					
	Autocorrelation	Phi					
		0.521					

Table 2- 8 Parameter estimates from two generalized additive mixed models for haddock (*Melanogrammus aeglefinus)* from the NAFO 4X division commercial fishery. Both models used the full data set, but behaviour of the fisher was only accounted for in the second (prop).

Model	**Term**	**Estimate**	**SE**	**T value**	**Edf**	**F**	**p-value**
	Fixed Effects						
All	Intercept	7.600	0.221	34.4			<0.001
N=20450	4XO	-1.220	0.065	-18.8			<0.001
	4XP	-1.070	0.055	-19.5			<0.001
	4XQ	-1.550	0.060	-25.9			<0.001
	VCF	-0.653	0.180	-3.63			<0.001
	s(year)				3.86	39.0	<0.001
	s(dayofseason)				8.30	144	<0.001
	s(log(hours))				3.84	124	<0.001
	s(Nsets)				2.36	28.0	<0.001
	Random effect	Sigma					
	vesselID	1.58					
	Autocorrelation	Phi					
		0.580					
	Fixed Effects						
All+prop	Intercept	4.740	0.070	67.7			<0.001
N=20450	4XO	-0.106	0.034	-3.12			0.002
	4XP	0.019	0.027	0.68			0.498
	4XQ	-0.078	0.031	-2.52			0.012
	log(hours)	0.326	0.015	21.5			<0.001
	s(year)				3.76	74.3	<0.001
	s(dayofseason)				8.31	63.0	<0.001
	s(Nsets)				2.39	93.0	<0.001
	s(prop)				8.97	3163	<0.001
	Random effect	Sigma					
	vesselID	0.811					
	Autocorrelation	Phi					
		0.411					

Table 2- 9 Parameter estimates from three generalized additive mixed models for redfish (*Sebastes spp.)* from the NAFO 4X division commercial fishery. The data set was subset by fishing tactic, one of targeting, mixed or bycatch.

Model	**Term**	**Estimate**	**SE**	**T value**	**Edf**	**F**	**p-value**
	Fixed Effects						
Target	Intercept	7.650	0.093	81.9			<0.001
N=2391	4XO	0.090	0.064	1.40			0.161
	4XP	-0.219	0.048	-4.59			<0.001
	4XQ	-0.194	0.053	-3.66			<0.001
	log(hours)	0.182	0.034	5.35			<0.001
	s(year)				2.88	8.16	<0.001
	s(Nsets)				2.31	55.2	<0.001
	Random effect	Sigma					
	vesselID	0.634					
	Autocorrelation	Phi					
		0.216					
	Fixed Effects						
Mixed	Intercept	5.91	0.252	23.42			<0.001
N=10692	4XO	-0.228	0.0846	-2.693			0.007
	4XP	-0.0937	0.0577	-1.62			0.104
	4XQ	-0.0444	0.0614	-0.724			0.469
	s(year)				3.90	25.0	<0.001
	s(dayofseason)				6.17	10.9	<0.001
	s(log(hours))				3.41	8.91	<0.001
	s(Nsets)				5.49	14.6	<0.001
	Random effect	Sigma					
	vesselID	1.25					
	Autocorrelation	Phi					
		0.486					
	Fixed Effects						
Bycatch	Intercept	2.74	0.247	11.1			<0.001
N=1309	4XO	-0.140	0.282	-0.498			0.619
	4XP	0.774	0.142	5.44			<0.001
	4XQ	0.626	0.199	3.15			0.002
	log(hours)	0.339	0.110	3.09			0.002
	dayofseason	-0.00226	0.000487	-4.65			<0.001
	s(year)				2.89	2.92	0.035
	Random effect	Sigma					
	vesselID	1.37					
	Autocorrelation	Phi					
		0.488					

Table 2- 10 Parameter estimates from two generalized additive mixed models for redfish (*Sebastes spp.)* from the NAFO 4X division commercial fishery. Both models used the full data set, but behaviour of the fisher was only accounted for in the second (prop).

Model	**Term**	**Estimate**	**SE**	**T value**	**Edf**	**F**	**p-value**
	Fixed Effects						
All	Intercept	6.100	0.288	21.2			< 0.001
N=14405	4XO	0.405	0.075	5.37			<0.001
	4XP	-0.210	0.053	-3.96			<0.001
	4XQ	-0.172	0.061	-3.00			<0.001
	s(year)				3.93	36.3	< 0.001
	s(dayofseason)				8.25	18.8	< 0.001
	s(log(hours))				3.53	30.8	<0.001
	s(Nsets)				5.24	20.4	< 0.001
	Random effect	Sigma					
	vesselID	1.35					
	Autocorrelation	Phi					
		0.494					
	Fixed Effects						
All+prop	Intercept	5.780	0.102	56.6			<0.001
N=14405	4XO	-0.007	0.041	-0.17			0.867
	4XP	0.057	0.027	2.12			0.034
	4XQ	0.012	0.030	0.40			0.689
	log(hours)	0.267	0.018	15.1			<0.001
	Nsets	-0.027	0.002	-12.8			<0.001
	s(year)				2.74	27.5	<0.001
	s(dayofseason)				6.48	16.0	< 0.001
	s(prop)				8.97	3747	< 0.001
	Random effect	Sigma					
	vesselID	0.766					
	Autocorrelation	Phi					
		0.331					

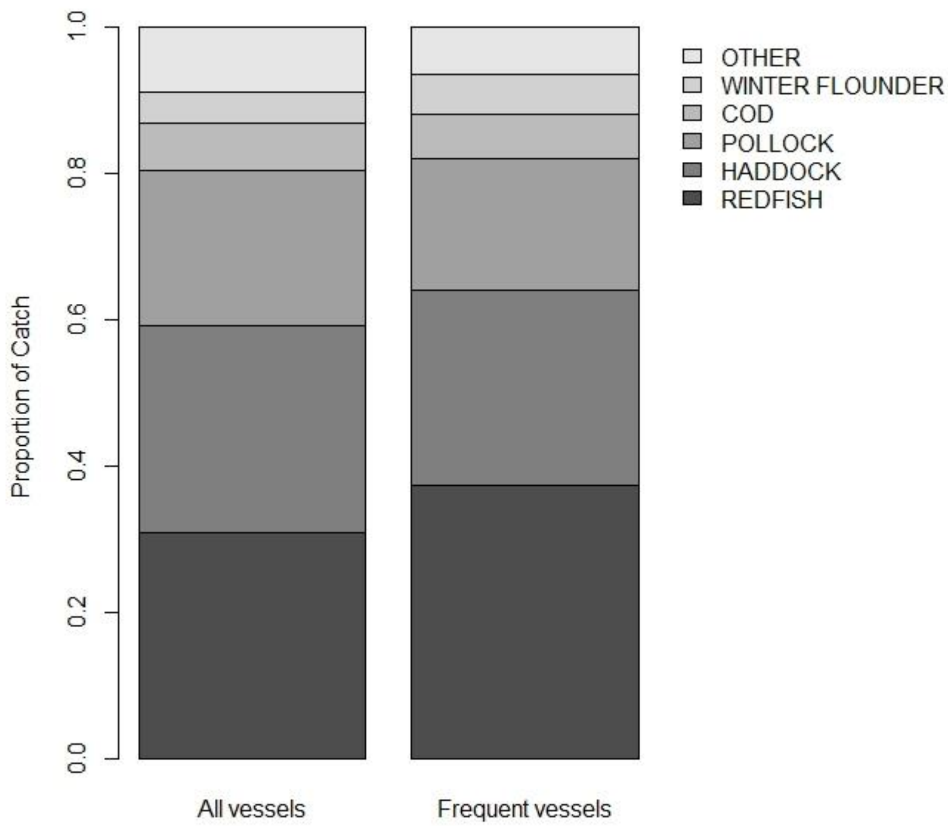

Figure 2- 1 Comparison of the proportion of catch by weight for all vessels in the original data set and the 16 representative fishers from the NAFO 4X division groundfish fishery.

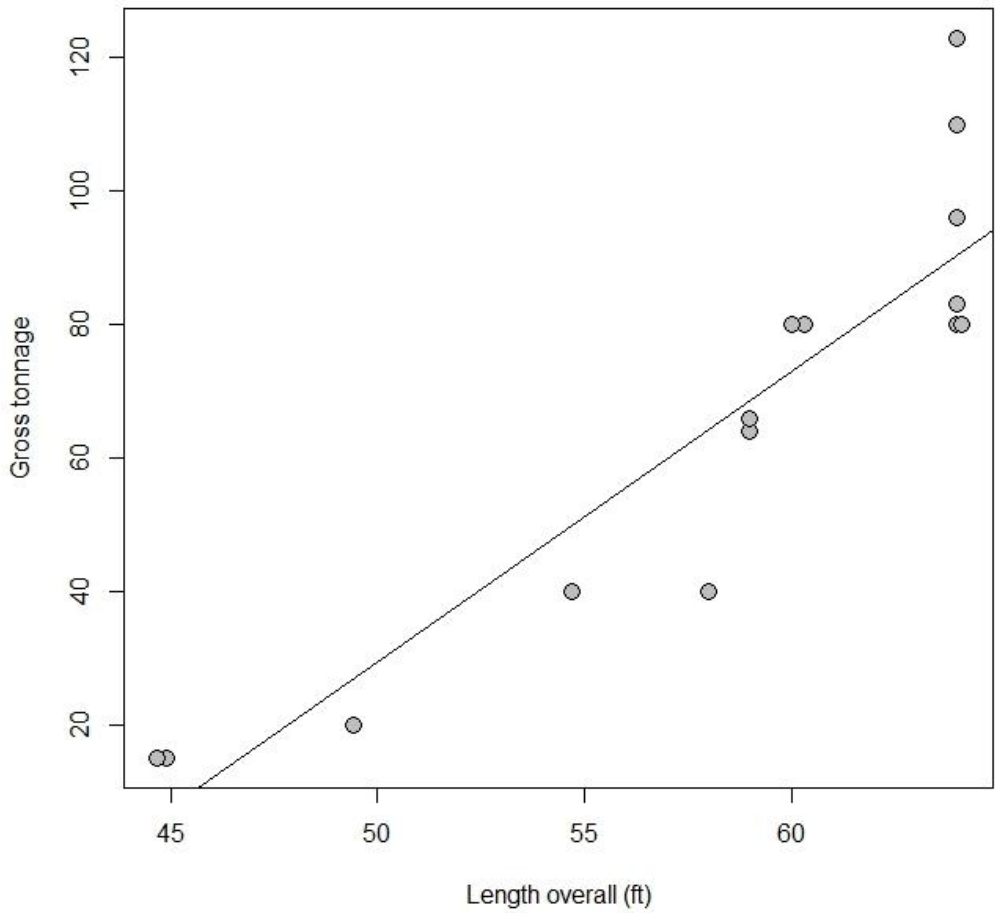

Figure 2- 2 Relationship between length overall and tonnage for 16 vessels from the NAFO 4X division groundfish fishery. Tonnage = 4.36 * Length – 188.4

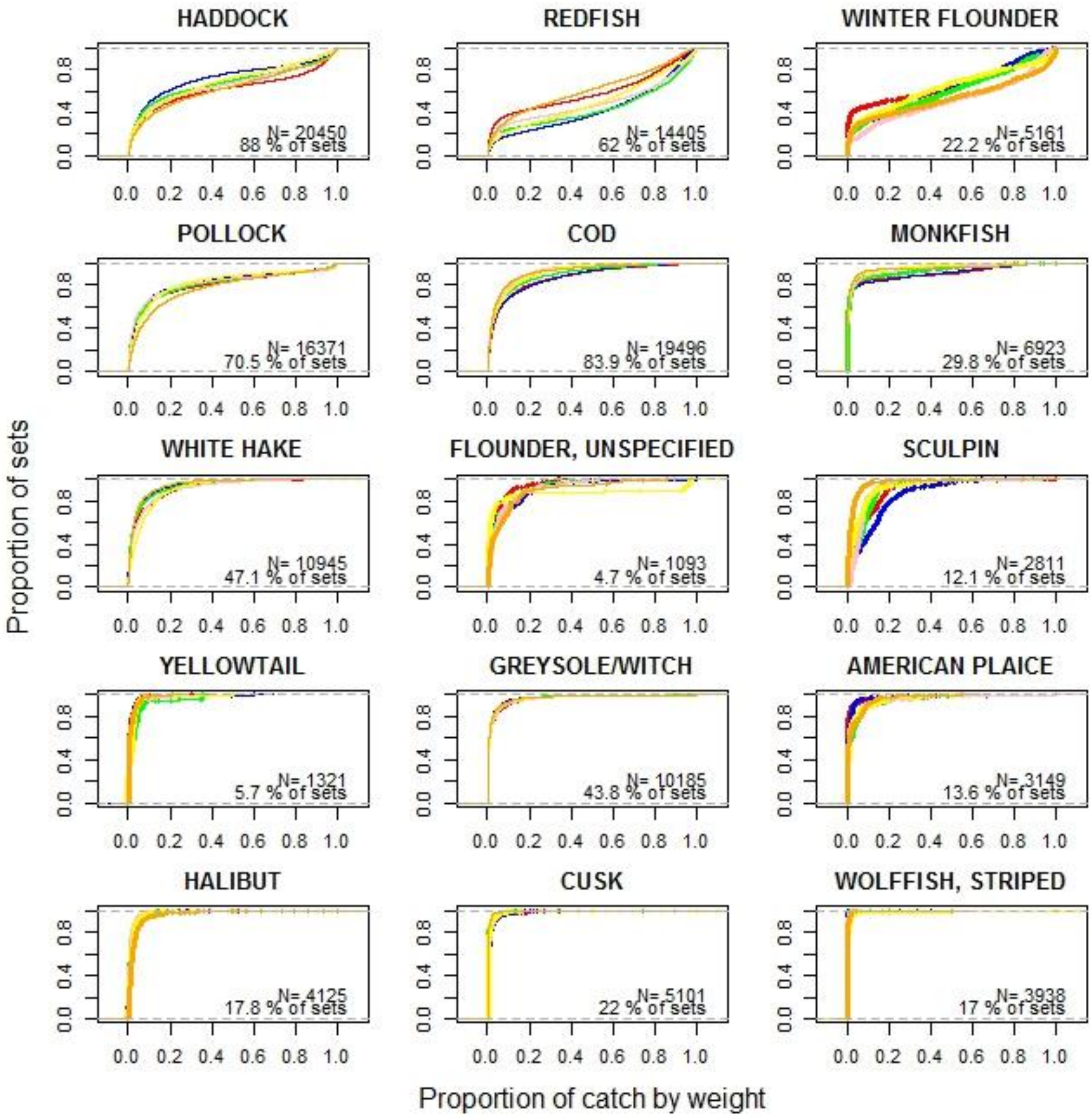

Figure 2- 3 Cumulative distribution functions of proportion of catch by weight per set for 15 species landed in a minimum of 1000 sets from the NAFO 4X division groundfish fishery. Each line represents a single year, with only non-zero catch used.

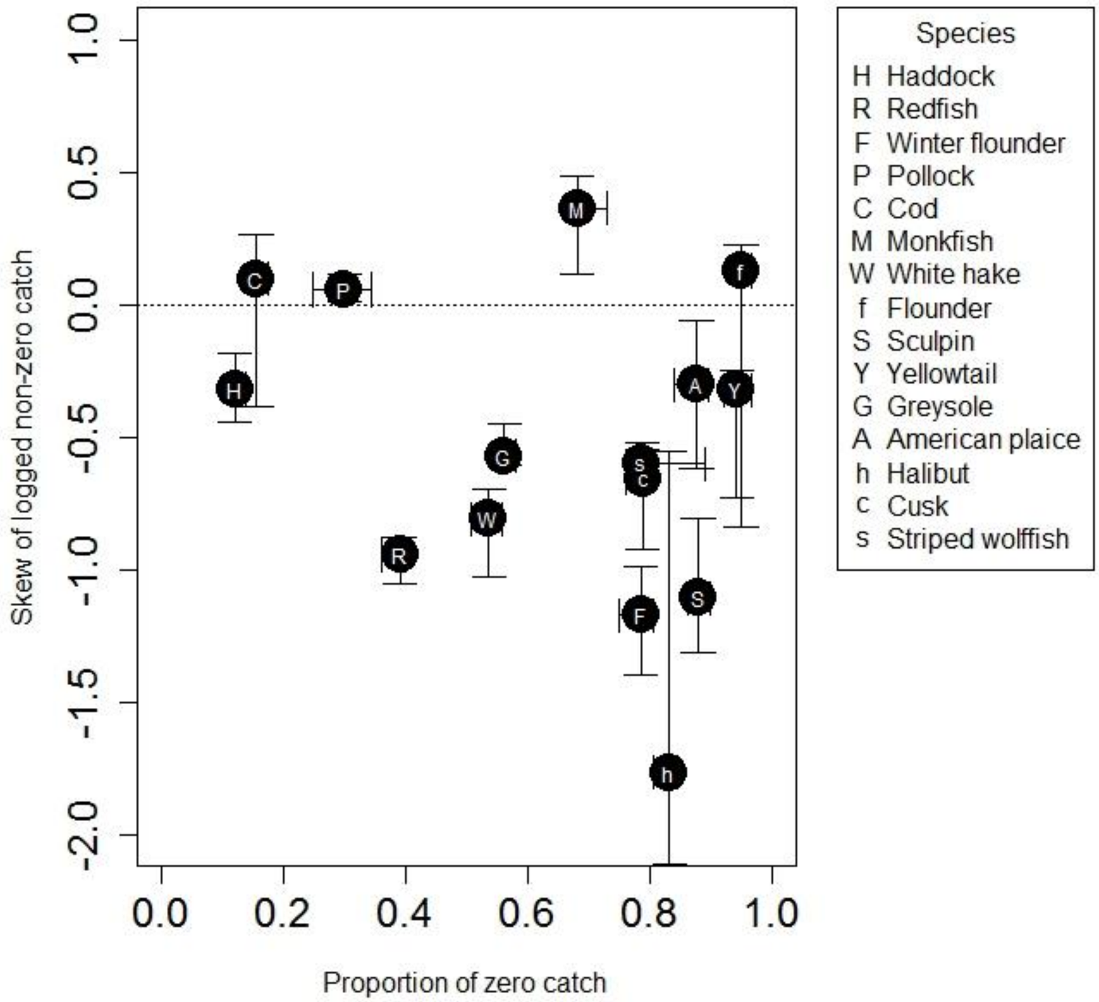

Figure 2- 4 Skew of the logged-non zero catch and how often the species is landed for 15 species landed in a minimum of 1000 sets from the NAFO 4X division groundfish fishery. Skews and zeros were calculated on an annual basis, with the point representing the median value and bars the 25th and 75th percentiles.

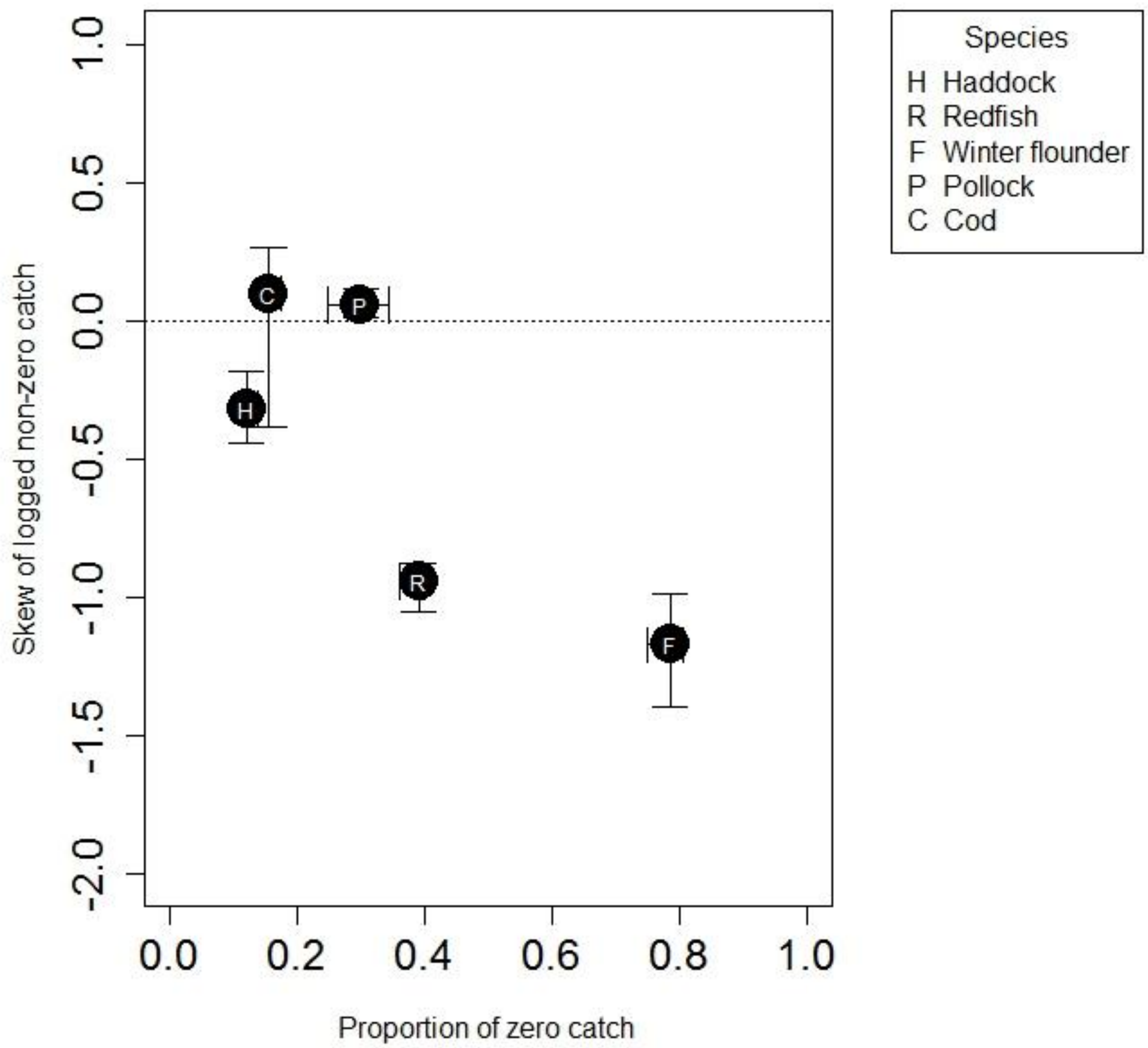

Figure 2- 5 Skew of the logged-non zero catch and how often the species is landed for the five most commonly landed species by weight from the NAFO 4X division groundfish fishery. Skews and zeros were calculated on an annual basis, with the point representing the median value and bars the 25th and 75th percentiles.

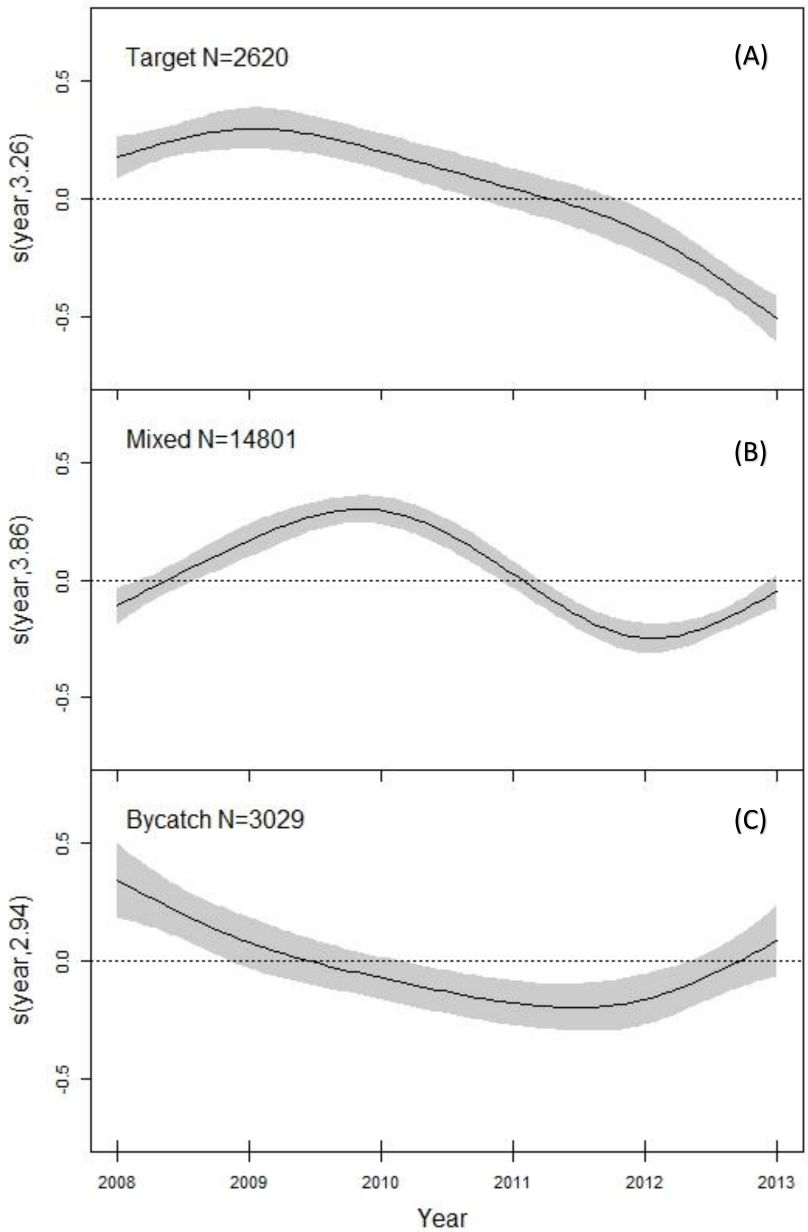

Figure 2- 6 Smoothed trends in year (relative abundance index) from standardized catch GAMMS for target (A), mixed (B), and bycatch (C) data subsets of non-zero haddock catch from the NAFO 4X division fishery. Smooths are plotted on the scale of the linear predictor, with all covariates, other than year, held constant. Black is the relationship with the grey shading the 95% confidence interval around the relationship.

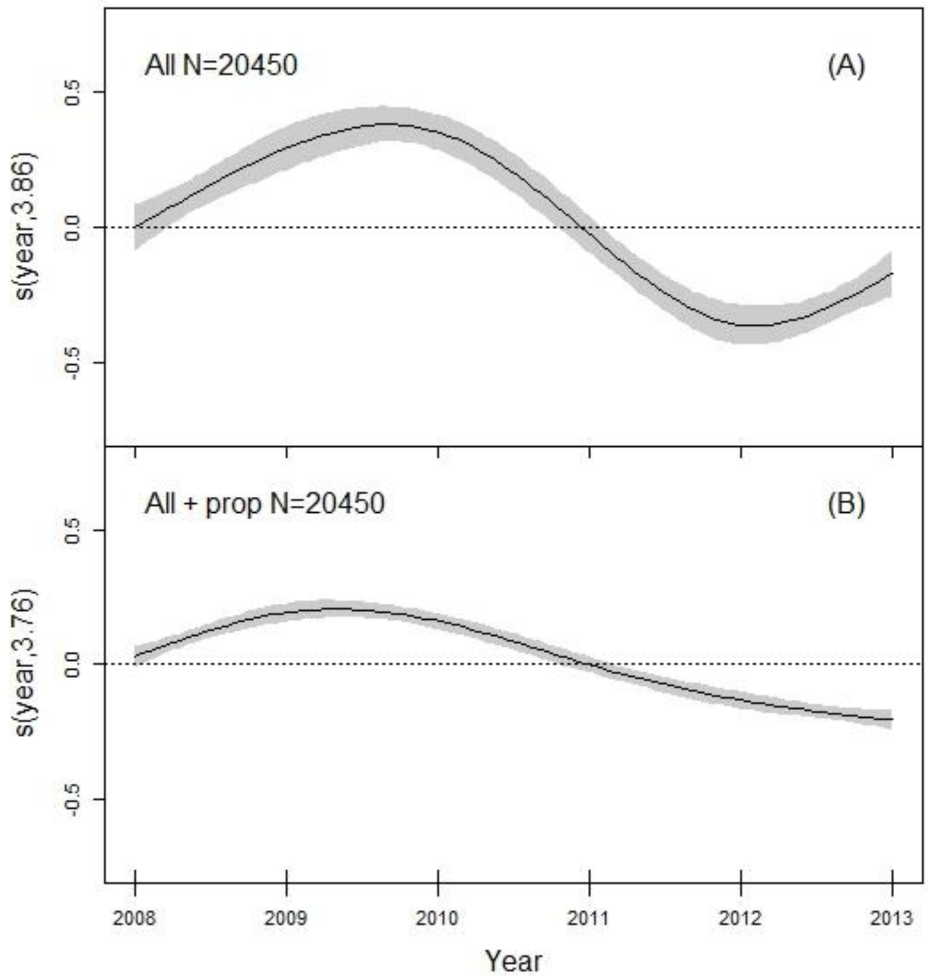

Figure 2- 7 Smoothed trends in year (relative abundance index) from standardized catch GAMMS for all non-zero sets without accounting for targeting behaviour (A), all non-zero sets with proportion of catch included as a covariate to account for targeting behaviour (B) for haddock catch from the NAFO 4X division fishery. Smooths are plotted on the scale of the linear predictor, with all covariates, other than year, held constant. Black is the relationship with the grey shading the 95% confidence interval around the relationship.

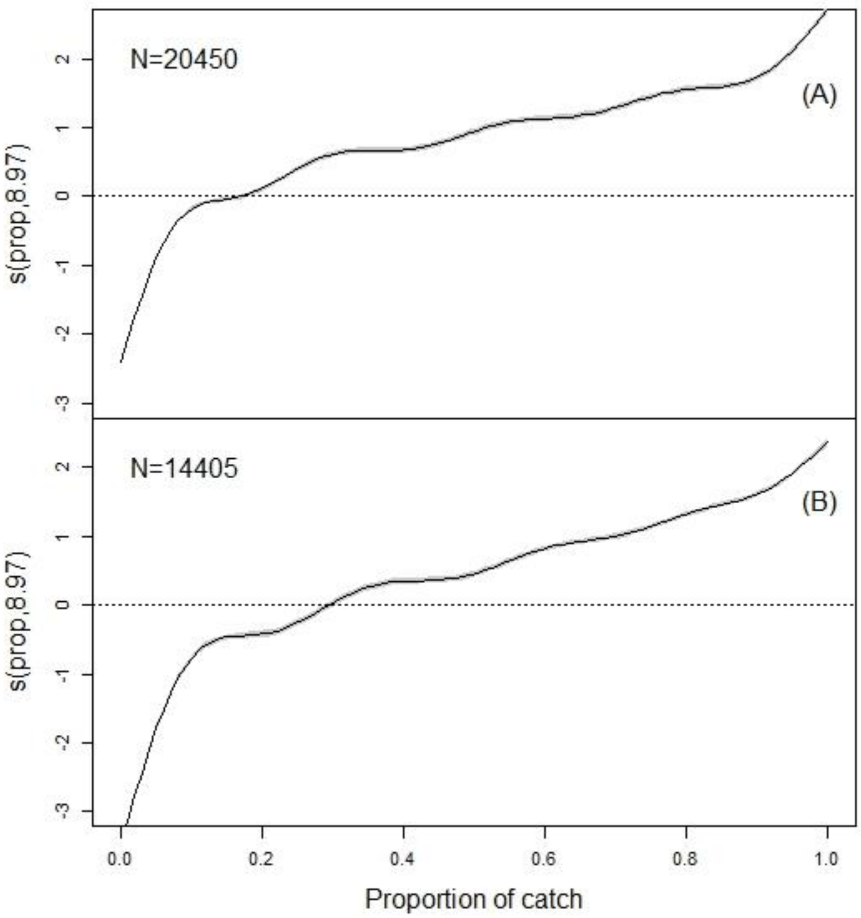

Figure 2- 8 Smoothed trends in proportion of catch from standardized catch GAMMS for haddock (A) and redfish (B) data sets of non-zero catch from the NAFO 4X division fishery. Smooths are plotted on the scale of the linear predictor, with all covariates, other than year, held constant. Black is the relationship with the grey shading the 95% confidence interval around the relationship.

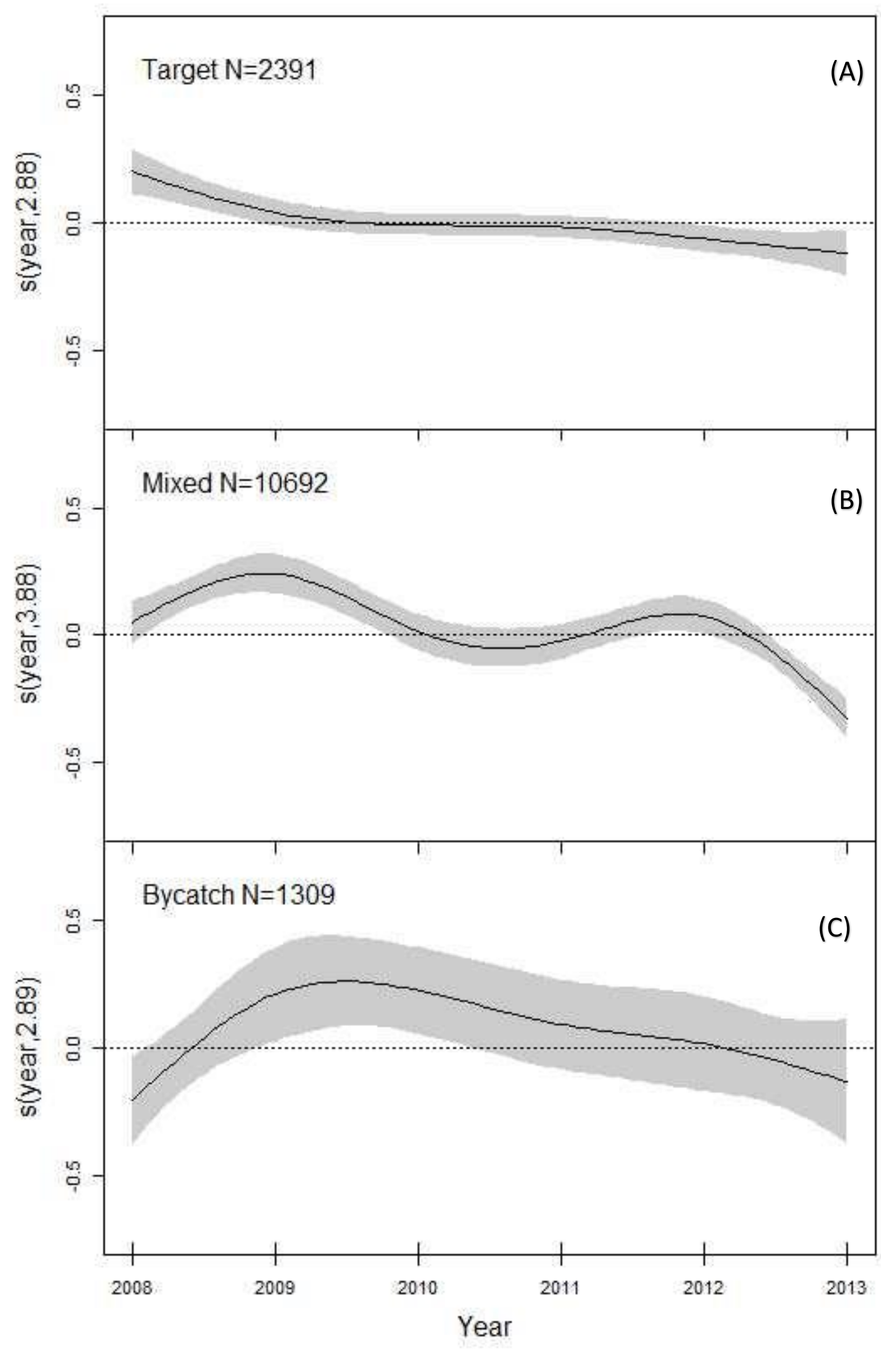

Figure 2- 9 Smoothed trends in year (relative abundance index) from standardized catch GAMMS for target (A), mixed (B), and bycatch (C) data subsets of non-zero redfish catch from the NAFO 4X division fishery. Smooths are plotted on the scale of the linear predictor, with all covariates, other than year, held constant. Black is the relationship with the grey shading the 95% confidence interval around the relationship.

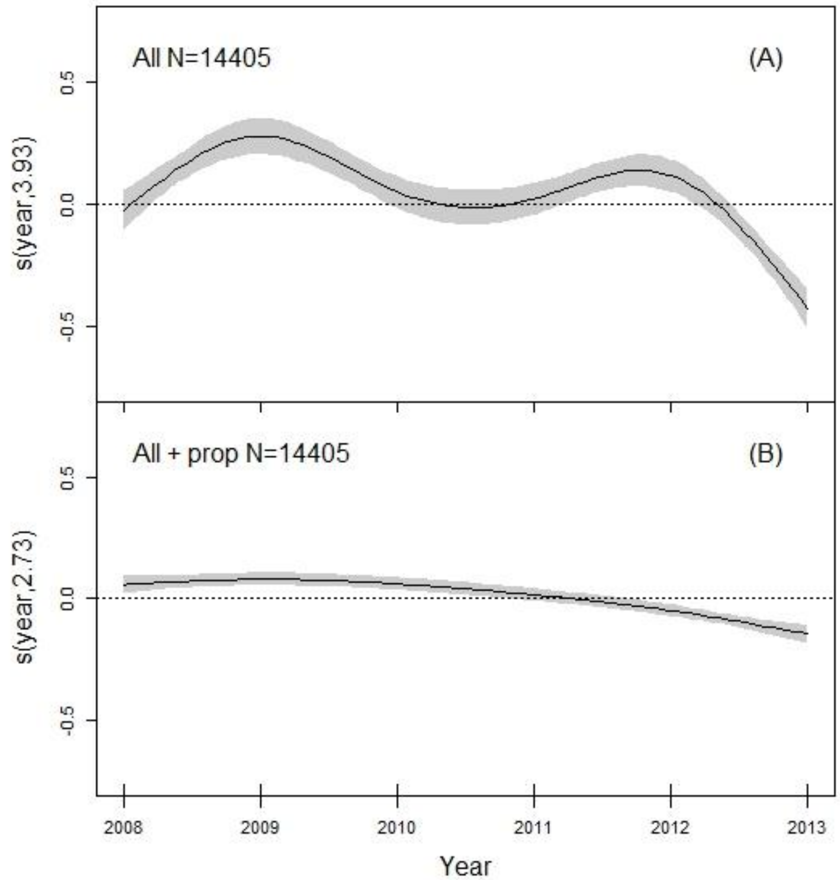

Figure 2- 10 Smoothed trends in year (relative abundance index) from standardized catch GAMMS for all non-zero sets without accounting for targeting behaviour (A), all non-zero sets with proportion of catch included as a covariate to account for targeting behaviour (B) for redfish catch from the NAFO 4X division fishery. Smooths are plotted on the scale of the linear predictor, with all covariates, other than year, held constant. Black is the relationship with the grey shading the 95% confidence interval around the relationship.

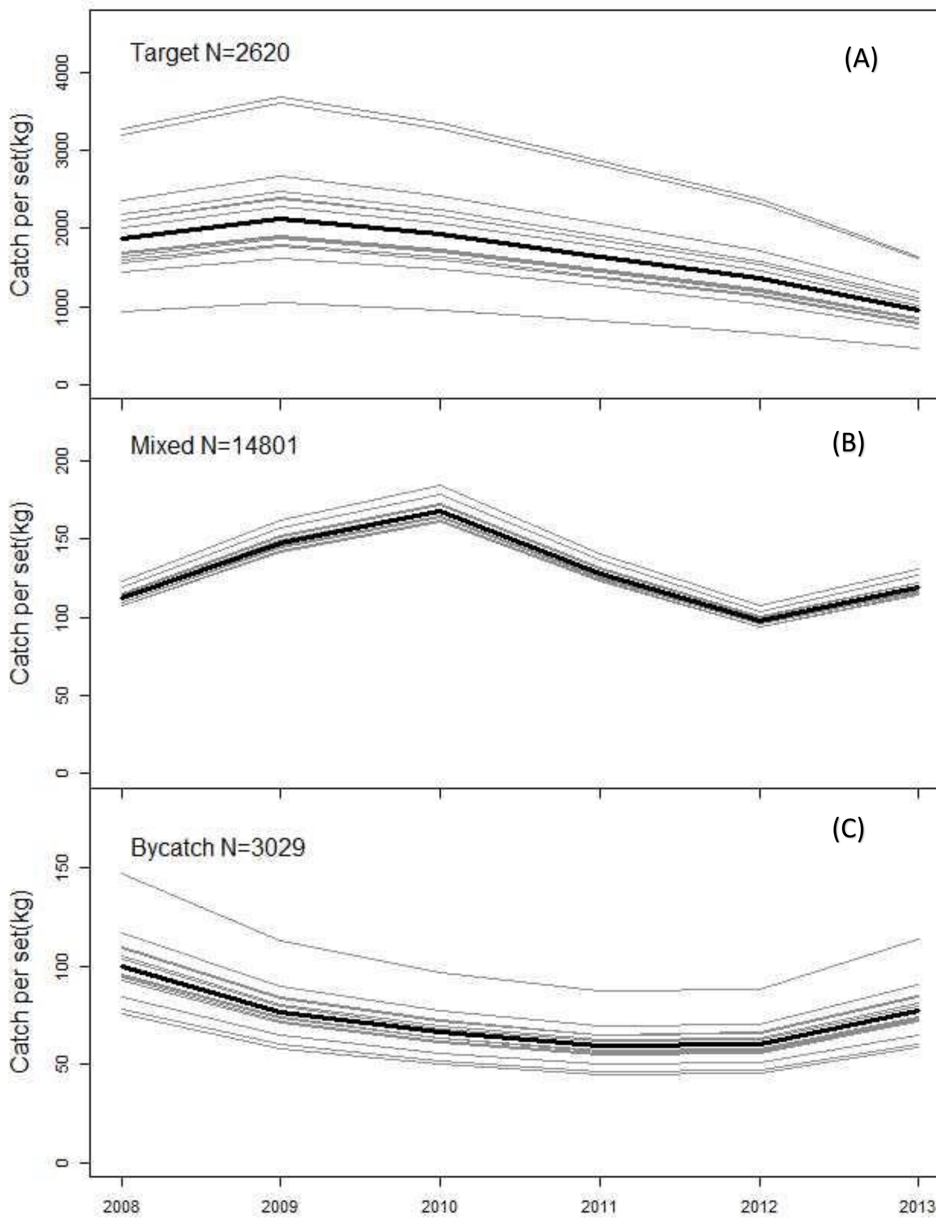

Figure 2- 11 Predicted catch per set from 2008 to 2013 from standardized catch GAMMS for target (A), mixed (B), and bycatch (C) data subsets of non-zero haddock catch from the NAFO 4X division fishery. All continuous covariates were held at their means to represent a “typical” fishing trip. Black is the predicted catch when there is no random effect with the greys lines representing the random intercept effect of the 16 unique vessels used in the study.

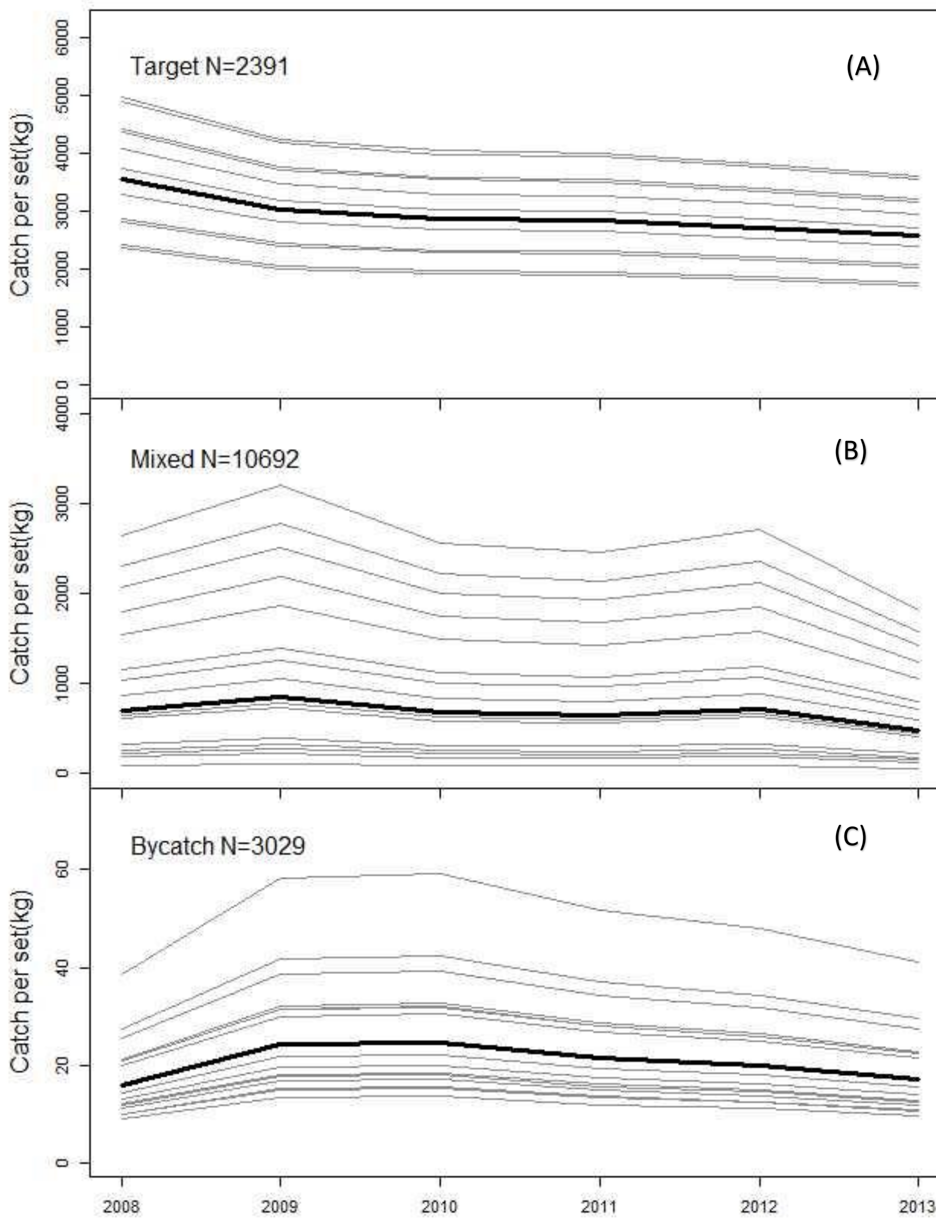

Figure 2- 12 Predicted catch per set from 2008 to 2013 from standardized catch GAMMS for target (A), mixed (B), and bycatch (C) data subsets of non-zero redfish catch from the NAFO 4X division fishery. All continuous covariates were held at their means to represent a “typical” fishing trip. Black is the predicted catch when there is no random effect with the greys lines representing the random intercept effect of the 16 unique vessels used in the study

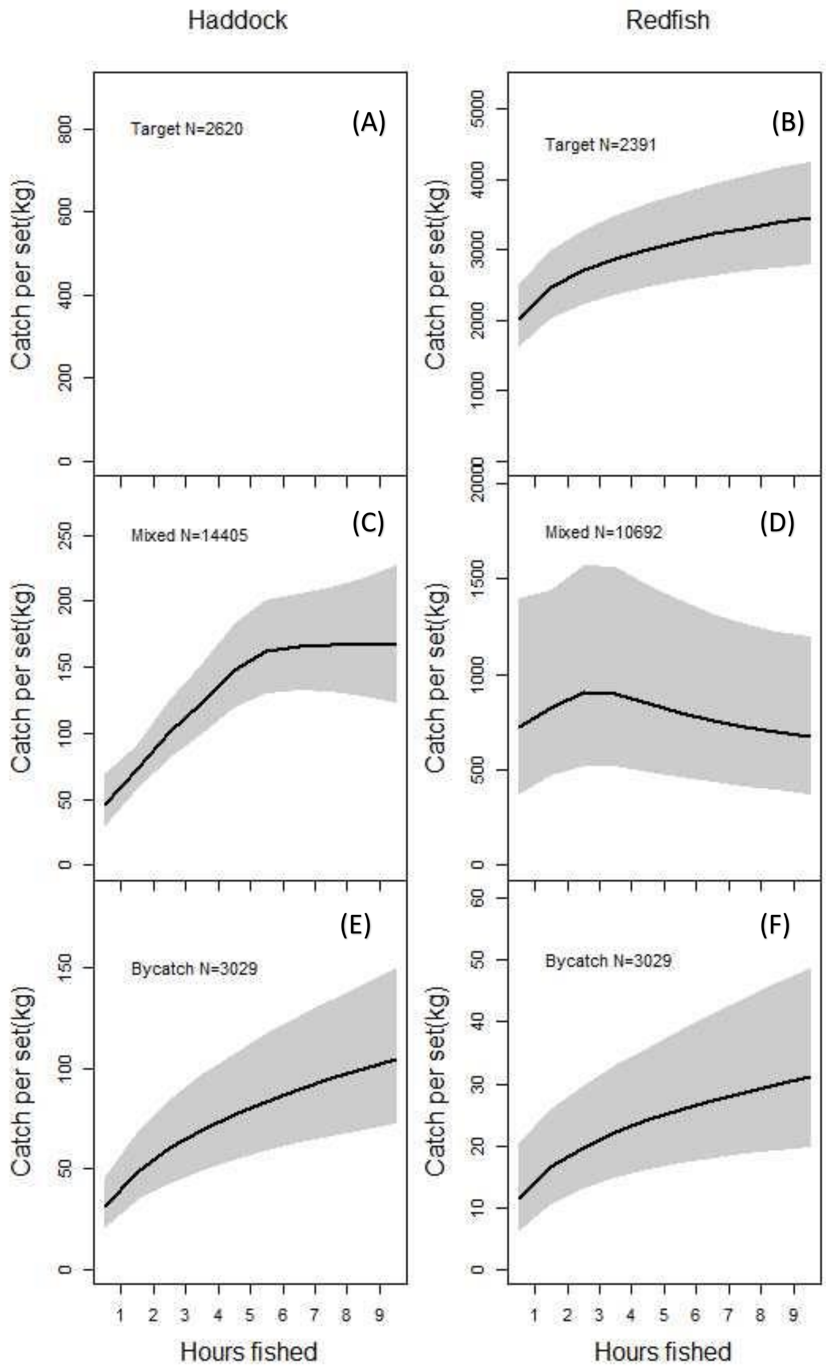

Figure 2- 13 Predicted catch across hours fished (nominal effort) from standardized catch GAMMS for target (A, B), mixed (C,D), and bycatch (E,F) data subsets of non-zero haddock (A,C,E) and redfish (B,D,F) catch from the NAFO 4X division fishery. Grey shading is the 95% confidence interval around the predicted catch. Haddock target model (A) had no significant relationship between catch and hours fished.

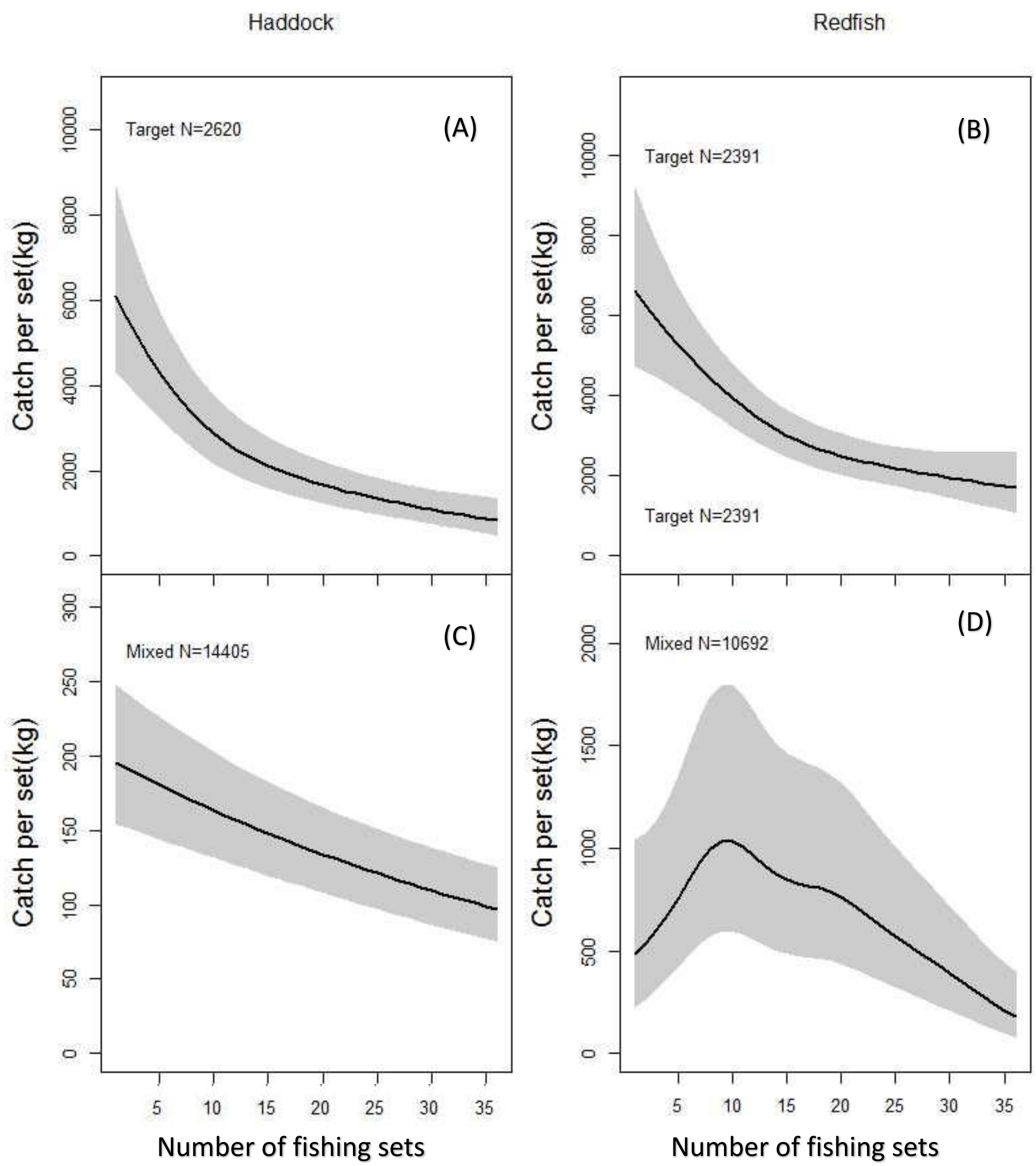

Figure 2- 14 Predicted catch across number of sets per fishing trip from standardized catch GAMMS for target (A, B), and mixed (C,D), data subsets of non-zero haddock (A,C) and redfish (B,D) catch from the NAFO 4X division fishery. Grey shading is the 95% confidence interval around the predicted catch. There was no significant relationship between catch and number of fishing sets for the bycatch models.

Chapter Three: The Effect of Biased Tuning Indices on Virtual Population Analysis Stock Assessment

3.0 Abstract

Using survey data as part of a stock assessment is preferable when estimating population abundance, but for many fisheries only commercial data are available. When using commercial fisheries data as an alternative, fishing records may reflect sets where the species of interest is the main target species, a bycatch species or a combination of both. This study examined how using commercial data as a tuning index in an age-structured stock assessment method (ADAPT-VPA) may influence the spawning stock biomass estimates. An age-structured index was constructed using GAMMs for sets where haddock (*Melanogrammus aeglefinus*) was caught as either a target species or a bycatch species, and compared to a model using survey data as a tuning index. Spawning stock biomass estimates were most similar between the survey and the bycatch index, with the target index indicating a SSB on average 5000 t less than the bycatch. The terminal year (2013) in the index played a large role in the final stock size estimate, indicating how changes in fisher behaviour in more recent years can have a large impact on estimates of stock size. The bycatch model was more robust to manipulation of the terminal year than the target model, and when survey data are unavailable bycatch may be a more reliable choice to use in models that affect the management of fishery resources.

3.1 Introduction

Fishery independent data is widely considered to be the preferred source of data when performing stock assessments, but due to the high cost, or the shortage of time or infrastructure, it is not available for many fisheries worldwide (Maunder and Punt 2004). The alternative to using fishery independent data is to use the abundantly available, but potentially biased, fishery dependent data. To obtain an estimate of abundance, which can then be used as the basis to make management decisions, age-structured stock assessments are employed for many commercially valuable fish species, such as haddock and tuna, (DFO 2012, ICCAT 2012). Comparing how standardized catch indices from fishery dependent sources, based on fisher behaviour, perform against fishery independent data in an age-structured stock assessment framework will help to decide how to better incorporate commercial fishery based indices when fishery dependent data are unavailable.

Age-structured analyses are a common methodology employed by fisheries managers to obtain an estimate of the stock size for commercially valuable fish species (Punt et al. 2013, Hilborn and Walters 1992). The term "age-structured model" refers to any methodology where each year of data is separated by age-class, such as statistical catch-at-age (SCA; Fournier and Archibald 1982) and virtual population analysis (VPA; Gulland 1965). Age-structured data allows for a more in-depth assessment than aggregated data, as individual cohorts can be tracked through time allowing for better estimation of population dynamics. This study focuses on VPA methodology, as it is the currently used method for the assessment of haddock stocks off of Nova Scotia (DFO 2012).

VPA methods work backwards through cohorts, based on the assumption that at an old enough age, a cohort will have no surviving members. By adding back fish that were removed through either fishing mortality or natural mortality, individual cohorts can be reconstructed. While simplistic in concept, accounting for natural mortality is difficult, as estimates are challenging to obtain (Vetter 1988). Natural mortality is often estimated through analysis of catch curves (Ricker 1975), and incorporated into stock assessments as a fixed rate (e.g. Brooks and Legault 2016). Alternatively, it may be more appropriate to let natural mortality vary across age classes and time (Johnson et al. 2015).

Classical VPA, as introduced by Gulland (1965), is unable to estimate cohorts which have not made their way completely through the fishery. Gavaris (1988) developed an adaptive VPA methodology (referred to as ADAPT-VPA) that incorporates a more statistical approach to parameter estimation of incomplete cohorts. ADAPT-VPA uses additional data sources to "tune" the VPA through an iterative process using the sum squared error (SSE) to predict the most likely fishing mortality for the oldest age class and the terminal year. The predicted fishing mortalities can then be used to reconstruct the population in order to estimate all age-classes and years. Alternative methods have been developed to deal with the issue of incomplete cohorts, such as extended survivor analysis (XSA; Shepherd 1999), which has been used for European fisheries, and CAGEAN (Deriso et al. 1985), which is a more statistical approach to VPA. The ADAPT method was selected for this study as it is the current method employed for the haddock stocks on the east coast of Canada.

Many stock assessments and studies integrate survey data and the catch at age data when estimating stock size (Carpi et al. 2015, Stenevik et al. 2015, DFO 2012). This process of using an auxiliary data set to produce a more informed stock estimate is known as "tuning" the model. Tuning may also be completed with catch-per-unit-effort data from the fishery itself (Sweke et al. 2015, Abaunza et al. 2003, Biseau 1998). When survey data are available, it is often the preferred abundance index with CPUE used when survey data are unavailable. Comparing VPA models tuned with survey and catch data from the same fishery will provide valuable information on how commercial data performs relative to survey data.

Scientific surveys are designed to capture fish in an unbiased manner so that the survey index is representative of the underlying population abundance. Alternatively, commercial fishing data contains several sources of bias which could potentially affect the CPUE-abundance relationship. One of the concerns with using commercial data (standardized catch or CPUE) is the issue of targeting behaviour and the ecological or technological association of non-target species with target species. Unlike surveys, commercial fishers can choose where and when to fish, resulting in catch rates that may not reflect the underlying abundance. In the previous chapter, fishing sets were divided based on the behaviour of the fishers into target and bycatch sets. In multispecies fisheries, studies tend to focus on sets where the target species was caught (Helle et al. 2015), and use bycatch data when no target data are available (Zhang and Chen 2015). Using the models from the previous chapter, it is possible to compare survey data to target sets and bycatch sets and evaluate how they each perform in a VPA. These comparisons can be used to determine if bycatch indices are an appropriate alternative when survey data are unavailable.

Many studies compare methodologies (Carpi et al. 2015, Butterworth and Rademeyer 2008, Megrey 1989), but not as much research has been directed at comparing indices within a method. The objective of this chapter is to calculate and compare spawning stock biomass (SSB) estimates calculated using different tuning indices representing targeting behaviour, bycatch behaviour and unbiased survey data. The survey index is assumed to be the best representation of the underlying fish abundance as the survey is designed to minimize bias in how the catch was obtained. Because survey data are not always available, commercial fisher indices of abundance from targeted (deliberately biased) sets and bycatch (potentially unbiased) sets are also examined. Understanding how biases in input data may be influencing the SSB estimates is crucial to making informed management decisions regarding our fishery resources.

3.2 Materials and Methods

3.2.1 Analytical Tools

All data manipulations and analyses were performed using the statistical language R (R Core Team 2015). There are many packaged analytical tools available for performing a VPA, such as the NOAA Fisheries Toolbox, and Fisheries and Oceans ADAPT software, but the underlying details and assumptions are often not documented in detail or the descriptions are incomplete. Custom code was developed to perform the VPA within R, so that underlying assumptions of the method could be directly specified. A summary of abbreviations and terms used in this chapter can be found in Table 3-1.

3.2.2 Adaptive Virtual Population Analysis Methodology

Virtual population analysis (VPA) is an age-structured analysis where cohorts are reconstructed by working backwards through time, adding back fish which were removed from the population due to fishing (F) and natural mortality (M). In general terms this can be expressed as:

(3-1) Population last year = population this year + loss due to last year's total mortality

Total mortality (Z) = fishing mortality (F) + natural mortality (M)

For this study, cohorts were reconstructed using the Baranov catch equation:

(3-2) $C_{ay} = (F_{ay}/ (F_{ay}+M)) * N_{ay} * (1-e^{-(Fay + M)})$

where a = age

y = year

C = commercial catch in numbers

F = instantaneous fishing mortality rate

M = instantaneous natural mortality rate

N = Population size

Virtual population analyses are conducted through the use of matrices with the two dimensions representing age and year. For a more complete explanation see Appendix C. Because cohorts are projected backwards through time, there is an issue with incomplete cohorts from the more recent years. Classic VPA works backwards from the oldest age class, assuming that no individuals of the oldest age survive to the following year. For the cohorts currently in the fishery, the number of fish in the oldest age class is unknown and therefore the cohort cannot be projected back. Given that stock assessments are used to inform population projections and fishing quotas, population estimates are critical for the most recent years.

The ADAPT-VPA method developed by Gavaris (1988) can produce population estimates for all cohorts through the use of auxiliary data to “tune” the population reconstruction. ADAPT-VPA is an iterative process which finds the most likely fishing mortality values for the commercial data, given a certain tuning index, based on catchability. Catchability (q) refers to how many fish are caught in one unit of effort relative to the total population (N). Catchability of an index series (I) can be calculated as:

(3-3) $q_{ay} = I_{ay}/N_{ay}$

The most likely fishing mortalities, given the catch data and index series, are calculated through an iterative process which minimizes the sum squared error (SSE) equation (eq. 3-4).

The SSE calculates the error between the natural log of q (eq. 3-5) and the natural log of the mean q for each age class (eq. 3-6). Catchability is assumed to be constant across years.

(3-4) $SSE = \sum_{ay} (\ln(q) - \ln(q_a))^2$

(3-5) $\ln(q) = \ln(Index_{ay}) - \ln(N_{ay})$

(3-6) $\ln(q_a) = \sum_y (\ln(Index_{ay}) - \ln(N_{ay}))) / n$

Where a = age

y = year

q = catchability

$Index_{ay}$ = Catch-at-age from index series

N_{ay} = population estimate from commercial catch and estimated F using the Baranov catch equation (Eq. 3-2)

n = number of years

A detailed explanation of the methodology and iterative process can be found in Lassen and Medley (2001), chapter 8 and Appendix C of this thesis. The result of the ADAPT-VPA population reconstruction is in number of fish.

3.2.3 Data Sources and Model Inputs

This chapter focuses on producing a spawning stock biomass estimate for haddock (*Melanogrammus aeglefinus*) from the NAFO 4X5Y division fishery, which encompasses both the Bay of Fundy and the Scotian Shelf (Figure 3-1). ADAPT-VPA methods require the following input data;

1. Age-structured catch data from the commercial fishery (C)
2. Estimate of the natural mortality rate (M)
3. Age-structured catch data from an index series (I)

Additionally, to calculate spawning stock biomass, information on the weight-at-age of each age class and an estimate of maturity is required to transform population estimates (numbers) into biomass estimates (weight) of mature fish.

The catch-at-age data (Appendix D), weight-at-age (Appendix D), natural mortality (Table 3-2), and maturity (Table 3-2) from the commercial fishery data was obtained from the Fisheries and Oceans Canada Haddock Stock Assessment Framework meeting (Stone and Hansen 2015). Commercial landings, generally recorded in weight, are sub-sampled for length and weight of the landed fish to produce length distributions and annual length-weight keys for each year of the fishery. Annual age-length keys from the commercial fishery are then applied to obtain estimates for the number of fish in each age class (Wang et al. 2017). The natural mortality rate estimates (M) used in this study were obtained from Wang et al. (2017), which conducted VPAs with mortality estimates that varied by year and age to determine the most appropriate natural mortality estimates to use. M was set at 0.2 for ages 1 to 9 in all years, 0.62 for age 10 and 11+ in 2008 and 2009, and 0.9 for ages 10 and 11+ from 2010 onwards. For this study M was fixed and not allowed to vary during the optimization process.

Weight-at-age is the average weight per age of fish from the commercial fishery with maturity representing the proportion of fish in each age class which are considered mature. To remain consistent with current methods for this stock, recruitment to adulthood is considered to be “knife-edged” where fish from 0 to 3 years of age are considered immature and all fish age 4+ are considered mature (Beverton and Holt 1957). For this fish stock, the terms age 4+ biomass and spawning stock biomass (SSB) are used interchangeably.

To examine how stock estimates are influenced by the tuning index, three different catch-at-age (CAA) tuning indices were used (Figure 3-2);

1. CAA for commercial sets where haddock is targeted
2. CAA for commercial sets where haddock is bycatch
3. CAA from DFO Scotian Shelf summer survey

Detailed information on the input data can be found in Appendix D. The data used for the targeting and bycatch indices came from the GAMMs produced in chapter two. Using the models, catch (in kg) was predicted for each year for a fishing set on January 1, in area 4XN with the other predictor variables set to their means. Because the models produce a single weight per year, the model index was manipulated (see below) to produce an age structured index as is required by VPA methods. For both the target and bycatch indices, one unit of effort is considered to be one fishing trawl.

The CAA data from the DFO Scotian Shelf summer survey was obtained from Stone and Hansen (2015). Unlike the target and bycatch indices, which are on the scale of catch per fishing set (each number in the table represents 1 fish), the summer survey index is on the scale of the entire population size (each number in the table represents 1000 fish). Because it is the relative values that are important when tuning a VPA and not the absolute value, this does not impact the population estimate. It does affect the interpretation of catchability (q), as catchability is proportional to the entire population relative to one unit of effort. Because one unit of effort is the entire survey, catchability can be equal to or greater than one if the population estimate from the survey is greater than or equal to the population estimate from the VPA.

3.2.4 Data Manipulations

The model output from the chapter two GAMMs, was in weight (kg) per fishing set and therefore required some manipulation to obtain age-structured data suitable for tuning the VPA. Using the commercial CAA and WAA data, the proportion of fish in each age class (by weight) was applied to the model output then divided by the WAA to obtain an age structured index with number of fish in each age class.

Although there is a long term data set available for commercial catch-at-age data and the Scotian Shelf summer survey, I used only the years that were available from the chapter two GAMMs (2008 to 2013). Because VPA is based on backwards projection of cohorts, without tuning data from years previous to 2008 the stock estimates would be solely based on assumptions of the terminal age population. Shelton and Morgan (2012) argue that including all available commercial CAA data, even when a tuning index is unavailable, better describes the dynamics between SSB and recruitment than excluding data. Although this may be true when performing a stock assessment with the end goal of setting reference points and quota recommendations, for this study I was focused on investigating the potential impact that biased tuning indices have on SSB estimates. To avoid incorporating additional assumptions into the model, only years where both commercial CAA data and survey data were available were used in the study. In both the commercial catch and summer survey ages ranged from 1 to 16 but ages over 10 were aggregated into an 11 + age class. Age one was dropped from the analysis due to several 0 observations in the commercial catch.

For the bycatch index, the number of age two fish in 2009 and 2010 was calculated as less than one, resulting in convergence issues when estimating the model's parameters. Because VPA indices rely on relative differences, and not absolute values, the index was rescaled so the smallest value was 1.1 to resolve this issue.

3*.2.5 Model Fitting in R*

To produce the VPA models in R, custom functions were created to calculate sum squared errors (SSE) and reconstruct the final population estimate from the estimated fishing mortalities. The SSE function created in R used the Newton-Raphson iteration method to solve the Baranov catch equation (Lassen and Medley 2001). The minimum SSE was calculated by optimizing the fishing mortalities (F) using the optim () function from the default stats package in R. To keep the optimization method from investigating unrealistic F values, upper and lower limits were set at 15 and 0.001 respectively.

Models were fit for each of the three tuning indices using all fishing mortalities (F) set to 0.5 as a starting value. The SSE was calculated for ages 2 to 10, ignoring the plus class. For the population reconstruction, the fishing mortalities (F) for the plus class were considered to be equal to the age 10 fish. From here on, models will be referred to as either target, bycatch or survey, depending on which index was used to tune the VPA. All three models used the same commercial CAA and WAA data, and differed only in the tuning index.

3.2.6 Spawning Stock Biomass

Population estimates, in thousands of fish, were transformed into biomass estimates by multiplying the number of fish in each age class by the average weight-at-age (in kg) and the maturity of each age class (Eq. 3-6). The biomass was then summed across ages for each year, resulting in a single biomass estimate per year.

(3-6) $SSB_y = \Sigma_a (N_{ay} * w_{ay} * m_{ay})$

Where a = age

y = year

N = population size in numbers

w = average weight in kg

m = maturity

3.2.7 Terminal Year Effects

Virtual population analysis methods rely on backwards projection of cohorts and therefore the terminal year (2013) is crucial for accurate population estimates. To evaluate how a change in the index value in the terminal year may affect the overall SSB, I artificially modified the number of fish in each age class. To maintain the proper age structure, the catch per set in kg was modified and the age structure in number of fish was recalculated using the methods described in the previous section. In the raw data, the target index suggests a decrease in population from 2012 to 2013, whereas the raw bycatch index suggests an increase between the two years. To examine how the opposite pattern would affect the SSB estimate, the 2013 value for the target index was increased to the maximum value observed in the raw index (2552 kg seen in 2009). The bycatch index for 2013, was decreased to the lowest value previously observed in the index (87 kg seen in 2011), then rescaled so the smallest value was 1.1.

3.2.8 Retrospective Analysis

The retrospective analysis was completed by iteratively refitting the ADAPT-VPA models, with one less year of data each time. Because there are only six years of data, the retrospective analysis was limited in how many years could be removed. The model was fit with 3, 4, 5 and all 6 years of data, resulting in four SSB patterns for each of the three indices.

3.3 Results

3.3.1 Model Fitting and Output

All three models were successfully fit with no convergence errors, resulting in three separate population estimates based on different tuning indices. For all three VPA models (target, bycatch, and survey) the general pattern in abundance by age per year was consistent across models (Figure 3-3). Overall, the target tuned model tended to have the lowest number of fish in each age class, with the bycatch and survey models having a larger number of fish. The discrepancy between models decreased with increasing age class, with the largest differences observed for the youngest age classes.

Fishing mortality (F) for all models increased with increasing age class for all six years (Figure 3-4). Between the three models, fishing mortality tended to be highest for the target tuned model, with bycatch and survey tuned models having more similar estimates of F. For the oldest single age class (10) and the plus class (11+), fishing mortality in the target model ranged from 2.14 to 12.45, with 4 out of 6 years having an F estimate greater than 5. In contrast, the bycatch tuned model had an F range from 0.62 to 2.12, and the survey tuned model ranged from 0.64 to 6.58, with only a single year having a fishing mortality above 2. Catchability increased across ages, with a greater proportion of older fish caught than younger fish. Detailed information on the estimated population size, fishing mortality, catchability, and error terms can be found in Appendix D.

3.3.2 Spawning Stock Biomass

Spawning stock biomass (SSB) was calculated as the biomass, in metric tons, of age 4+ fish each year. All three models, target, bycatch and survey, showed a general trend of declining biomass throughout the six years (Figure 3-5). The bycatch and survey models both had a slight increase in biomass between 2008 and 2009, which did not appear in the target model. Although the three models indicated the same general declining trend, the different tuning indices did produce slightly different patterns between years, most notably in the terminal year, 2013.

Spawning stock biomass for the target model ranged from a high of 23244 t in 2008, to a low of 7507 t in 2013. Bycatch and survey models tended to have a more similar range in biomass in comparison to the target model. Bycatch ranged from 27722 t in 2009, to 14206 t in 2013, while the survey ranged from 29102 t in 2009 to a low of 10324 t in 2013.

The largest difference in SSB estimates was between the target and bycatch models. The target SSB estimates were consistently lower for each year, with an average of 5680 t less than the bycatch model and 4680 t less than the survey model. Overall, the bycatch and survey SSB estimates were the most similar with only an average 10% difference between the two models. The survey SSB estimate was slightly higher in 2008 and 2009, and lower than the bycatch estimates from 2010 onwards. The SSB estimates for 2013 showed the greatest deviation from the overall patterns described above. Both the survey and target models indicated a decline from 2012 to 2013, with the bycatch model indicating an increase. 2013 was the only year where the SSB estimate from the survey model was closer to the target model estimate than to the bycatch. In 2013 SSB was estimated at 15054 t for the bycatch model, 10323 t for the survey model and 7507 t for the target model.

3.3.3 Probing Terminal Year Effects

When the most recent year of data in the index series was arbitrarily modified, the resulting SSB estimate changed (Figure 3-6). For the target series, the terminal year index was modified so that the catch per set weight (in kg) was equal to the highest catch per set weight observed, and the bycatch was decreased to the lowest catch per set weight. For the target index the 2013 catch per set weight was increased from 1137 kg to 2552 kg, and the bycatch was decreased from 114 kg to 88 kg. These modified indices will be referred to as target increased and bycatch decreased. Although the raw index value, in kg, was equal for two years in the index, the resulting number at age between the two years was different as the fishery data had a different age structure between the two years. The total number of age 2+ fish in 2013 was increased from to 1399 to 3139 for the target index and decreased from 140 to 108 for the bycatch. This corresponded to a percent difference of 77% for the target series and 26% for the bycatch series.

By modifying the index values for 2013, the model tuned with the target index went from the lowest SSB estimates to, on average, the highest. By decreasing 2013 for the bycatch index, the overall SSB estimates from the model also decreased. With the exception of the original target index model, the SSB estimates for 2008 were all within 650 t of each other. The divergence between the original and unmodified indices for both the target and bycatch models increased from 2008 to 2013. The difference in SSB estimates for the original and increased target indices increased from slightly under 4000 t in 2008 to over 9000 t in 2013. The change between the bycatch models was not as drastic, but still noticeable. There was less than a 300 t difference in 2008 through to a 2756 t difference in 2013. As with the original indices, the modified bycatch index was more similar to the survey index than to the modified target index.

3.3.4 Retrospective Analysis

Because of the small number of years available in this study, the retrospective analysis provided only a limited look at how well the models performed (Figure 3-7). For the target index, all retrospective analyses without 2013 indicated a greater SSB. The results of both the bycatch and survey models were more robust to the removal of 2013, with similar SSB estimates to the full models with 2013 included.

3.4 Discussion

Comparing the results of VPAs tuned with both fishery dependent and independent data allowed for the evaluation of how commercial data performs when used as a tuning index relative to a scientific survey. When using a tuning index in any stock assessment method, it is assumed that the amount of fish in the index is proportional to the true abundance (Francis 2011). Deviation from this assumption can bias the stock estimates that are ultimately used to make management decisions. Unfortunately, for many fisheries, survey data are unavailable and commercial data (often as CPUE) is used in its place. With this data I was able to show that three different indices of abundance, all drawn from the same underlying population provided three different estimates of SSB. Because the commercial data and survey data did not produce SSB estimates that were in complete agreement with each other, it is likely at least one index violates the assumption that the index is representative. Francis (2011) states that it is best to omit unrepresentative data sets from being used in a stock assessment, but when only one index is available it is difficult to tell if it is truly representative.

Because of the non-random nature of commercial fishing, I expected the tuning index based on target data to mask some of the variation in the fishery by selectively fishing high density areas. Bycatch has been used previously as an index that is collected in a more random manner, such as using fish bycatch in lobster traps, and therefore considered to be more representative than data from target catches (Zhang and Chen 2015). Comparatively in this study, the bycatch model was in closer agreement with the survey model than the target model. This suggests that the bycatch can provide a more representative index of the underlying abundance than target sets and thus may be an appropriate alternative to survey data.

A representative bycatch index could be the result of fish harvesters exploiting populations with changing distributions. Marshall and Frank (1994) found that as population size of haddock increased, the number of fish in areas surrounding previous high density areas, tended to increase in abundance at a faster rate than in the high density area. This indicates that, as population size increases, fish tend to expand into suboptimal habitats, and retract back into optimal habitats when population size decreases. Fishers tend to distribute themselves non-randomly on the water, aggregating in productive areas where catch rates tend to be higher for their target species (Gillis and van der Lee 2012, Lee et al. 2010, Campbell 2004). This can lead to hyperstability of the fishery and catch rates that are not reflective of the underlying abundance (Harley et. al. 2001). Bycatch of non-target species is likely to be more sensitive to the changes in abundance and range than the target index of that species, due to bycatch being obtained from a larger range of underlying densities. If fishing sets targeting a species are aggregating where fish are found in high densities, they are not being exposed to the changes in density associated with the usage of sub-optimal habitats, as expected from bycatch sets. Brodziak and Walsh (2013) found that their calculated abundance index for shark bycatch in a longline fishery agreed with previous studies indicating an overall decline in shark population (Clarke et al. 2013). This is in agreement with the results of the bycatch tuned VPA being more similar to the fishery independent survey tuned VPA, than the target model. This supports using a bycatch index instead of a target index when survey data are unavailable.

Although I expected the bycatch tuned SSB estimates to be more representative than the target tuned VPA, it was not expected that the target biomass estimates would be much lower than either the survey or bycatch. If targeting behaviour remains consistent, then the index of abundance would be less sensitive to the underlying changes in population size due to the fishers selectively fishing in productive areas only (Harley et al. 2001). For the index series used in this study, this did not seem to be the case. The target index series indicated decline in catch from 2009 to 2013, whereas the bycatch and survey indices indicated relative abundance beginning to increase in 2013. The idea that a target series is less sensitive to underlying population changes than a bycatch series relies on the assumption that targeting behaviour has been consistent across the time frame of the index. Outside factors such as changes in the management of the fishery, or market value may influence how targeting fishers choose to fish (Babcock and Pikitch 2000). During the timeframe of this study (2008-2013), market value of haddock remained relatively stable around $0.70 /lb, and was therefore not likely influential regarding the behaviour of the fishers. Incorporating market value of the target species as well as potentially valuable bycatch species may be informative for future studies regarding this fishery. Changes in targeting behaviour that reduce landed catch, independent of abundance, ultimately result in lowered SSB estimates as were observed in this analysis.

In more recent years in the NAFO 4X division fishery, fishers targeting haddock have been increasingly limited by the amount of cod they can land. Cod total allowable catch (TAC) in the 4X5Y fishery has decreased from 5000 t in 2008 to 3000 t in 2009 and 2010, and finally to the current level of 1650 t (DFO 2015). During the same timeframe, haddock TAC was also reduced from 7000 t in 2008 and 2009, to 6000 t in 2010 and 2011 and finally 5100 t in 2012 and 2013 (Stone and Hansen 2015). Although both species TAC has been reduced since 2008, cod quotas have been reduced by a larger margin. This may limit haddock catches due to a biological association with cod. The two species occupy similar habitat niches resulting in them often caught together (Scott and Scott 1988). Krag et al. (2010) demonstrated that fishers may exclude cod from their haddock sets by fishing slightly above the sea bed, allowing cod to escape underneath the trawl. An alternative tactic, which may better match the data seen in the target index, is for fishers to elect to fish in suboptimal habitats where both cod and haddock population size is lower. This would reduce cod catch, but also haddock catch as observed in the target index. If fishers are limited in the amount of cod they are allowed to land, then it is advantageous to avoid catching cod, even at the expense of the amount of haddock caught per set. If the cod quota is filled then haddock fishing opportunities would end for the season.

The reduced catch per set over time from the target index, which did not match the increase in numbers seen in the bycatch and survey indices, produced SSB estimates that were on average 5576 t less than the estimated SSB from the bycatch tuned model. The average difference between the two indices was greater than the TAC in 2013. Errors in population estimates can propagate through the management process, so a discrepancy of this magnitude is concerning. Although underestimating SSB is not as detrimental to the fish stock as an overestimation of SSB would be, if the stock is considered too low then a fishing moratorium may be introduced. Fishing moratoriums, such as the one introduced in 1992 for Newfoundland cod, have detrimental socio-economic impacts such as unemployment, poor individual health, and a general decline in community well-being (Gien 2000). Both the overestimation and underestimation of fish stocks can have negative consequences, be it for the fish or the fishers.

The terminal year of the tuning index was shown to have a large impact on the SSB estimate from the models. When the target index was modified so that the last year reflected an increase, the SSB estimate was increased for all years. Decreasing the number of fish in 2013 in the bycatch index had the opposite effect, resulting in a lower SSB estimate for all years. Because VPA is a cohort analysis, fish added or removed from the terminal year propagate backwards (Lassen and Medley 2001). Each additional fish added in the terminal year implies that the fish was also present the previous year in the previous age class, as VPA works backwards through time. This is especially true for the oldest age class, as their cohort has been present in a greater number of years, relative to the younger age classes who have not yet moved through the fishery.

The SSB estimate from the modified bycatch model was similar to the effect of removing 2013 altogether, as seen in the retrospective analysis. Retrospective bias can result from changes not taken into account in model assumptions (Mohn 1999). Therefore minimal retrospective bias in a model can be a valuable indicator of how appropriate the model is at representing population trends. A typical retrospective bias results in a pattern which fans out, overestimating the biomass in the terminal year, as each successive year of data is removed. The target model did not have a typical retrospective pattern, but instead biomass estimates were elevated for all years. The target tuned model estimates were more in line with the bycatch and survey, once 2013 was removed. In conjunction with the increased SSB estimate for the modified target model, this highlights the impact that a single year of unrepresentative data may have on the outcome of a stock assessment. Both the bycatch index and survey index SSB estimates were more robust to the removal of 2013, than the target index. Removing more than a single year of data did change the SSB estimates for both the bycatch and survey models, but with such a short time series, the patterns are of limited diagnostic use. The retrospective pattern in the survey and bycatch models were what you would typically expect, with the pattern "fanning" out as each year of data is removed, although estimates decreased for the bycatch model. Although the time series is quite short, the atypical retrospective pattern observed for the target index provides further evidence that target data may not be the best representation of population trends. A longer time series of catch for the commercial catch indices would allow further comparison between the SSB estimates and should be considered before applying this methodology.

The main inconsistency of the bycatch model relative to the survey model was that the number of fish was estimated to be much higher for the terminal year than either the target or survey, especially in the younger age classes. The most recent stock assessment for NAFO 4X5Y haddock indicates the stock has been increasing since 2013 (DFO 2017). It may be possible that the bycatch index was sensitive enough to be an early detector of an increasing population. Updating the model with more recent years of data would allow for a more in-depth evaluation.

In this study the bycatch model SSB estimates were more similar to the survey index SSB, the SSB estimate was robust to the removal of 2013, and in general the fishing mortalities rates in the bycatch model were more similar to the survey model. Changes in fishing tactics and strategies that affect catch rates for target fishing sets may also affect bycatch sets, but overall bycatch estimates may provide the more reliable indicator of changes in relative abundance.

Around the world, many harvested species lack the data that is needed to conduct a full age-structured stock assessment. Smith et al. (2009) have suggested using data-rich fisheries to help with the assessments of data-poor fisheries. By using information from a data-rich fishery, I was able to compare multiple fisher behaviours from commercial data along with survey data and have shown that fisher behaviour in the collection of the data may have a large influence on the relative population estimates. This study can be used to inform data selection of commercial fishing sets when survey data is unavailable, encouraging the use of bycatch sets over target sets to produce abundance estimates. Differences between the tuning indices were enough to impact the SSB estimates of the ADAPT-VPA and as such stresses the importance of tuning indices which account for the underlying behaviour of the fishers.

Stock assessment methods are only as useful as the data given to them, and as such, the quality of the output and subsequent interpretation is heavily reliant upon the quality of the data. Survey indices are considered to be the most useful representation of relative abundance and with the exception of 2013, the bycatch index performed similarly in comparison. When survey data are unavailable, it may be difficult to decide on an alternative source of data. Although both bycatch data and target data have inherent biases, this study has shown that using data from commercial sets that are targeting the species being assessed may be less reliable than data from bycatch sets.

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Table 3- 1 Definitions of abbreviations and terms used in chapter three

Term	**Definition**
VPA	Virtual population analysis
ADAPT	Adaptive virtual population analysis
TAC	Total allowable catch
CAA	Catch-at-age (number of fish)
WAA	Weight-at-age (average kg per fish)
SSB	Spawning stock biomass (weight of age 4+ fish in 000's kg)
M	Natural mortality
F	Fishing mortality
Q	catchability

Table 3- 2 Maturity and natural mortality (M; Wang et al. 2017) for age 2 to 11+ haddock (*Melanogrammus aeglefinus*) in NAFO 4X5Y divison. Maturity is recorded as the proportion of fish. Natural mortality (M) is an instantaneous rate of decline.

		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Maturity	0	0	1	1	1	1	1	1	1	1
M 2008-2009	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.62	0.62
M 2010-2013	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.9	0.9

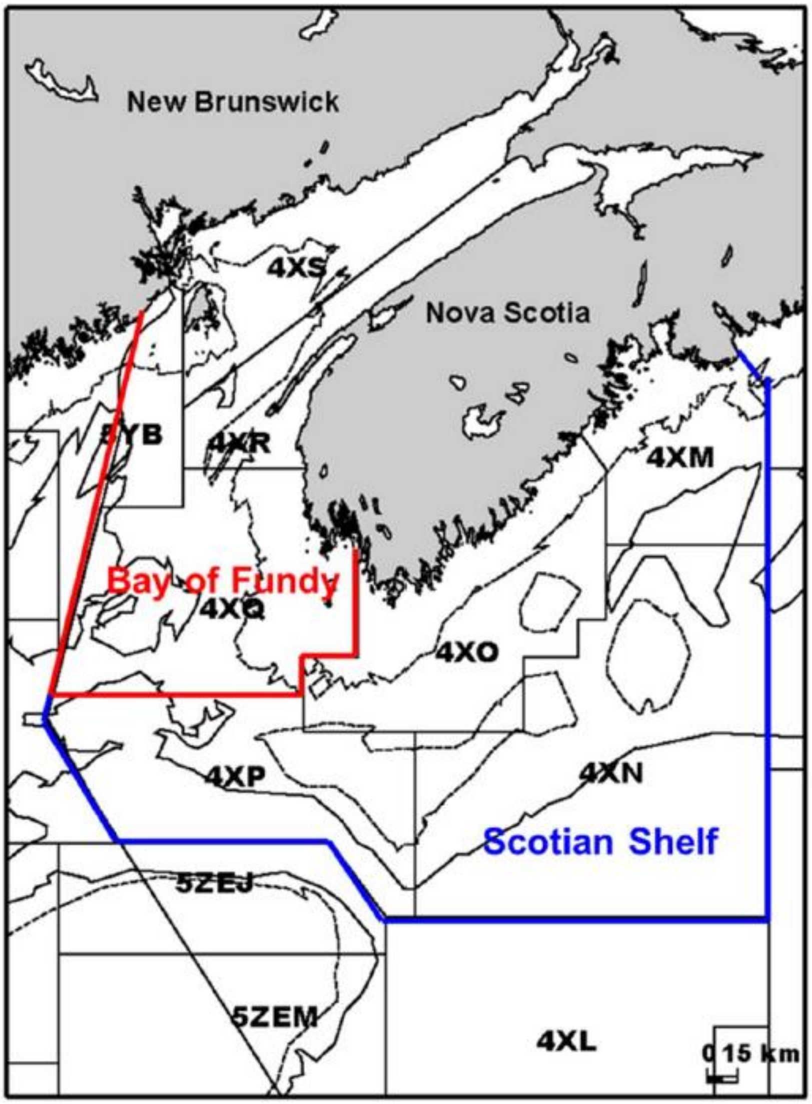

Figure 3- 1 Map of 4X5Y management area. Map is taken from Stone and Hansen 2015

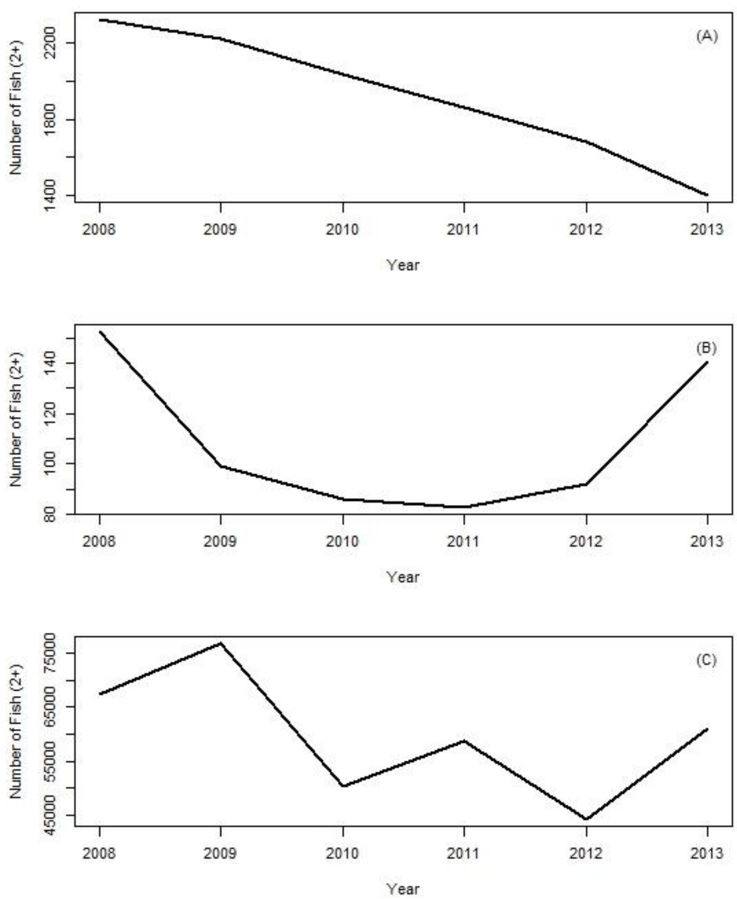

Figure 3- 2 Number of greater than age 2 fish in the (A) target, (B) bycatch, and (C) survey indices used to tune the ADAPT-VPA. The target and bycatch indices are number of fish per fishing set, while the survey index is a population estimate calculated from the Scotian Shelf summer survey.

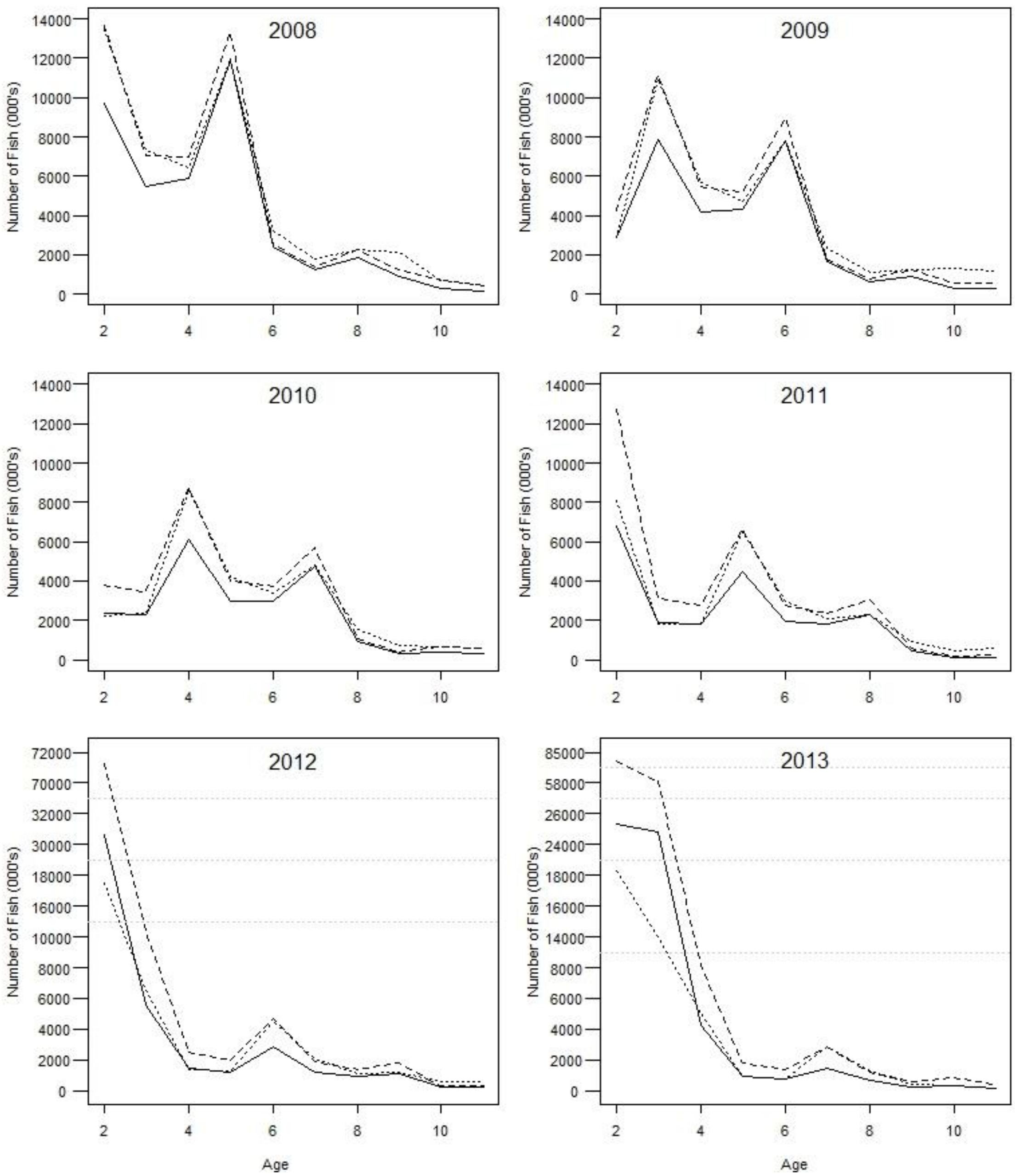

Figure 3- 3 Estimated number of fish in 000's by year and age, for ADAPT-VPA tuned with target (solid line), bycatch (dashed line) or survey (dotted line) data. Grey lines indicate axis break.

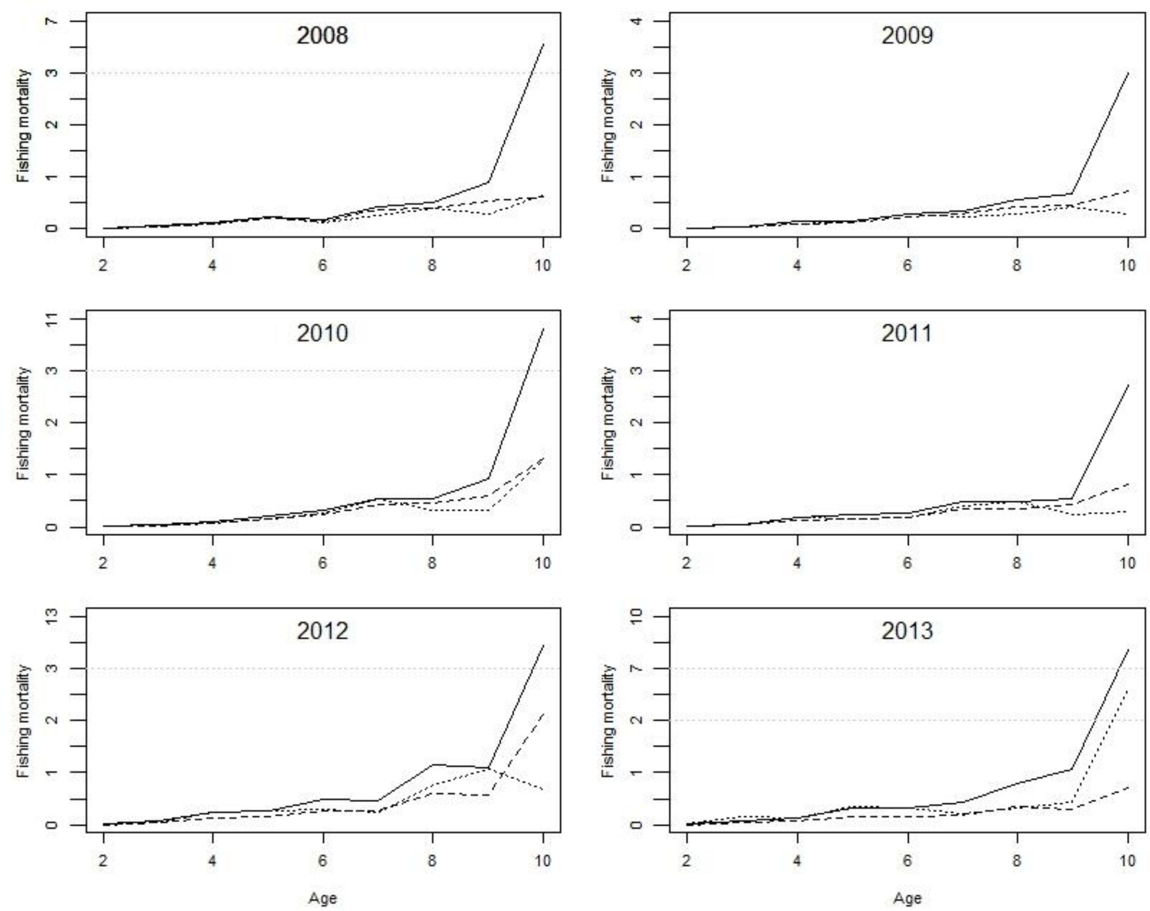

Figure 3- 4 Estimated fishing mortality by year and age, for ADAPT-VPA tuned with target (solid line), bycatch (dashed line) or survey (dotted line) data.

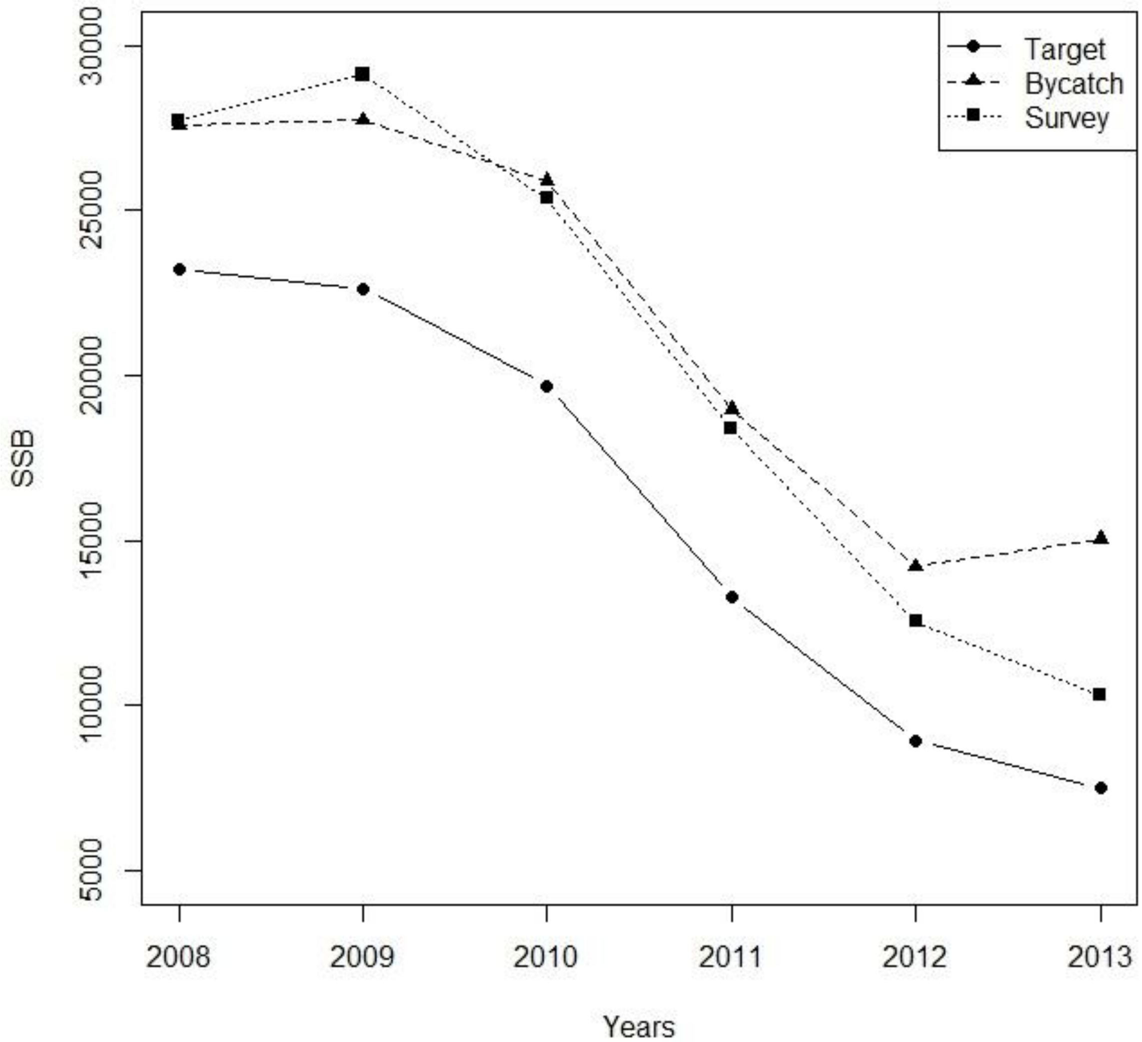

Figure 3- 5 Estimated spawning stock biomass (000’s kg) from the ADAPT-VPA tuned with target, bycatch, or survey data from 2008 to 2013.

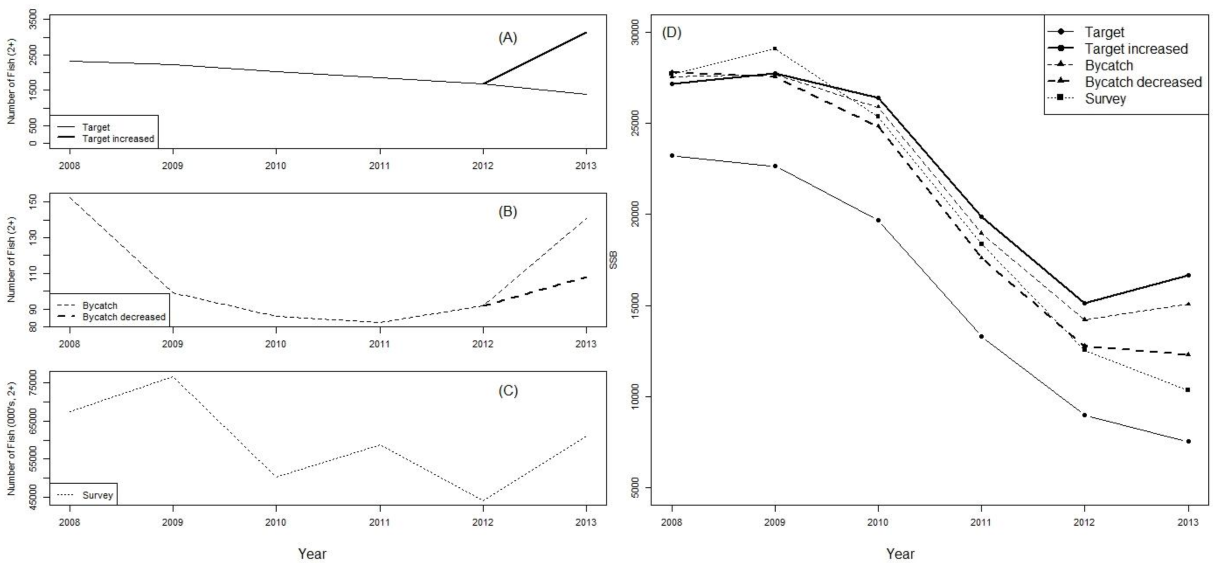

Figure 3- 6 Number of fish age two and greater in the (A) target and artificially increased target indices, (B) bycatch and artificially decreased bycatch indices, and (C) survey index used to tune the ADAPT-VPA. (D) Estimated spawning stock biomass (000's kg, age 4+) from the ADAPT-VPA tuned with the five indices from panels A, B and C.

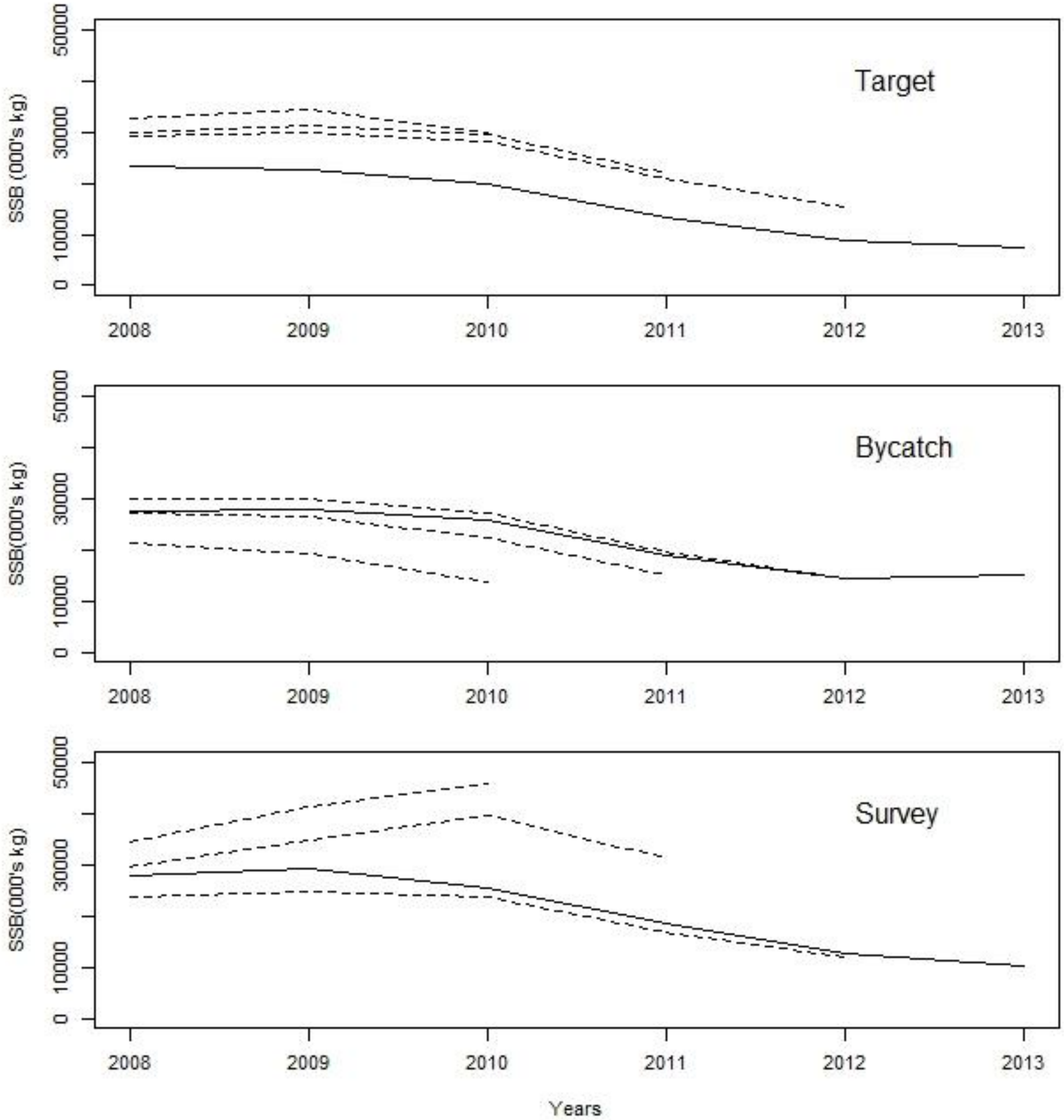

Figure 3- 7 Retrospective analysis of the estimated spawning stock biomass (000's kg) from the ADAPT-VPA tuned with target, bycatch, or survey data from 2008 to 2013. Solid lines represent all years included, with the dashed lines the SSB when a year of data was removed.

Chapter Four: Conclusion

The focus of my thesis has been to evaluate the effect of targeting behaviour on standardized catch rates from commercial fisheries and role that biased indices may play when performing stock assessments. Ultimately, catch data (either commercial or survey) is used for the purpose of estimating population size. As it is impossible to know the true population size, catch-per-unit-effort (CPUE) has become the standard in fisheries research as an index of abundance (Maunder and Punt 2004). Commercial CPUE is widely known to potentially bias population estimates due to non-random fishing effort (Cooke and Beddington 1984, Harley et al. 2001). Fishers can keep catch rate high due to selectively fishing productive areas, even to the extreme of maintaining high rates of catch during drastic decreases in population size (Rose and Kulka 1999). Standardizing catch rates to account for the sources of variability not related to population size is common practice (Maunder and Punt 2004), but can still result in a biased indicator if the standardization model is underfit (Ye and Dennis 2009). With this study I was able to demonstrate the impact that bias in catch rate derived indices has on stock assessments, and the appropriateness of using bycatch indices as an alternative to target data.

Quantification of the effects of targeting behaviour was accomplished through two projects using catch information from fishing vessels in the NAFO 4X division, off the coast of Nova Scotia. Chapter two focused on producing separate relative abundance indices for fishing sets partitioned based on fishing tactic, for haddock (*Melanogrammus aeglefinus*) and redfish (*Sebastes* sp.). Chapter three used the models from chapter two as a tuning index in an ADAPT-virtual population analysis (Garvaris 1988, Lassen and Medley 2001).

Estimating the population size of fish stocks has many challenges and traditional stock assessment methods rely upon the assumption that catch is proportional to abundance (Gulland

1969). Commercial fishing data, although plentiful, is subject to many potential sources of bias, from the actual fishing activity to how the data are selected in analyses. Any of which may violate the assumption that catch is proportional to abundance. Directed fishing effort (i.e. targeting) of a certain species can result in hyperstability where catch rates do not reflect changes in the underlying availability of the fish stock (Clark 1982, Hilborn and Walters 1992, Harley et al. 2001). This can result from fish harvesters who consistently keep catch rates high even in the presence of an overall decline in population due to selectively fishing high density areas.

In chapter two, I classified fishing sets based on catch composition into target, bycatch or mixed sets. By standardizing catch for these three fishing tactics in separate models, I was able to compare patterns among their relative abundance indices. Although more complex ways of defining target and bycatch sets were considered and investigated, such as statistical clustering methods used in previous studies (Pelletier and Ferraris 2000, Holley and Marchal 2004, Deporte et al 2012), they did not effectively distinguish the tactics in this data set. The patterns in the catch composition for the NAFO 4X data set were not easily discernable using statistical clustering methods, and did not readily pull out a haddock or redfish target cluster. Using proportion of catch, based on the species composition, provides a metric for selecting catch records that is simple to define and implement in a variety of fisheries (Biseau 1998). For this study, I choose to use a threshold of 90% to consider a set to be successful targeting. This high threshold allowed there to be enough data in each subset to model, while minimizing the chance of a fishing set being incorrectly classified as targeting. Helle et al. (2015) used a threshold as low as 30% to define targeting but with the catch composition observed in the NAFO 4X data set, I was not confident that a low threshold would be sufficient to model targeting behaviour. A goal of this study was to model trends in fishing sets that were targeting the species of interest and although fishers are highly successful at targeting species fishing is still an inexact practice. Setting the threshold too low runs the risk of including sets where the species of interest was caught incidentally and not truly targeted. Setting a high threshold for targeting when selecting data in a mixed species fishery, may more closely match the successful targeting behaviour observed in other fisheries. Therefore, the trends discussed in this thesis could be applied more readily to target fisheries that rely solely on commercial catch data.

Comparing the catch trends between years for the target, bycatch and mixed subsets of data resulted in the detection of different trends in the perceived underlying abundance for both haddock and redfish. Comparatively, Helle et al. (2015) did not report any major differences in the overall pattern of relative abundance between all fishing sets and target fishing sets with a target threshold of 30%. It may be possible that by setting the threshold for targeting too low, they did not capture the impacts that highly successful targeting may have on the patterns in relative abundance.

Along with comparing the relative index of abundance, I was also able to compare the patterns between catch and nominal effort between the three tactics. The patterns in fishing effort, as the number of hours trawled, varied between fishing tactics, with a smaller increase in catch with an increase in effort for target sets, and a greater increase in catch with effort for bycatch sets. Fishing with the intent to fill the net can result in little to no relationship between catch and effort, as the gear is deployed until it reaches capacity regardless of how long it takes. Depending on the density of the fish in the fishing location, filling the net may take a vessel under an hour to several hours. Furthermore, fishing high density areas and only bringing up the net once it is full contributes to the potential hyperstable relationship between catch and abundance. Accounting for potential interaction effects between hours trawled and fishing tactic may help to improve catch standardizations in future for studies using data sets containing multiple fishing tactics. When only data from fishing sets targeting the species of interest are used for catch standardizations, nominal effort alone may not be useful at describing trends. Additionally, using nominal effort as an offset in the response variable (i.e. CPUE) may bias the abundance index if there is no relationship between catch and hours trawled. Modelling catch directly (instead of CPUE) and including information about the number of fishing sets per trip may be beneficial to improving catch standardizations when only targeting data is used for analysis.

Overall, with this chapter I was able to demonstrate how selecting data based on the underlying fisher behaviour can result in different relative abundance indices, but I could only speculate on if the indices were representative of the true population size. Relative to commercial catch records, scientific survey data are considered to be an unbiased estimate of population size and can provide a benchmark to evaluate the different indices. Population estimates for haddock from the Scotian Shelf scientific survey combined elements from both the target and the bycatch indices produced in chapter two. Unlike the commercial records, the survey data encompasses both the Scotian Shelf and the Bay of Fundy, so a direct comparison between the survey index and the commercial catch indices is done with some reservation. For each of the two species in this chapter, the five models per species each gave a different relative pattern in abundance. Even when all fishing sets were considered together, with behaviour accounted for by using the proportion of catch as a variable in the model, the resulting relative abundance trends were not in alignment with either target or bycatch sets. Campbell (2004) recommends that multiple abundance indices may be preferable to using any single index. Although this recommendation is in the context of the spatial aspects of fishing effort, I have shown that it may also be beneficial to explore multiple indices based on the targeting behaviour of the fishing vessels. Divergent trends between fisher behaviour could then be integrated into stock assessment models through weighted averages of the different indices.

Trends in catch standardizations alone can be used to infer changes in population abundance (Maunder and Punt 2004), but they are also used in conjunction with age-structured methods of abundance estimation (e.g. VPA ; Lassen and Medley 2001). For this study, survey data provided a non-biased index to use as a comparison for target and bycatch data. By using the GAMMs from chapter two, I was able to examine the effect that biased indices may have on stock size estimation, as well as evaluate if bycatch index series provide an appropriate alternative to those based on survey data.

Using trends in standardized catch as an index of abundance, does not account for the age-structure of the underlying population. Age-structured methods are likely to be more representative of fish stock dynamics and thus provide a better representation of the population size than catch (or CPUE) indices alone (Megrey 1989). In general, using an age-structured model, such as a VPA, along with auxiliary information provides a population estimate that incorporates multiple sources of data and thus is more likely to represent the underlying population size. Comparing how the target and bycatch indices performed relative to a scientific survey index when used as the auxiliary information in the age-structured model allowed for the evaluation of each index as a representation of the underlying abundance. Scientific survey data are considered to be less vulnerable to bias introduced by fishing behaviour, as the surveys are designed to minimize this bias, and therefore provide a more reliable index (Maunder and Punt 2004). Overall, I found that using bycatch as a tuning index provided a close estimate to the survey tuned model and a more robust biomass estimates than the target index. The terminal year of the index series played a large role in the overall estimate of spawning stock biomass and was investigated through artificially modifying the index and through a retrospective analysis. The bycatch estimates remained more consistent than the target index did when the terminal year was modified. Using bycatch as auxiliary information may be an appropriate alternative when survey data are unavailable. Although bycatch from another fishery has been used when target information is unavailable (Zhang and Chen 2015), selecting bycatch records from a multispecies fishery may provide a more representative index to use in stock assessment models than all sets or those that target the species of interest.

Extending the time-series used to create the GAMMs in chapter two would provide an opportunity to investigate the effect of limited data on biomass estimates. With this study, the bycatch and tuning indices were relatively short compared to the survey index available, which extended back to 1985. Both the estimated haddock biomass and commercial landings have decreased substantially from a peak in the 1980s (DFO 2012). Comparing the relative performance of bycatch versus target indices over a longer time period where the stock size has been in decline would allow for a more in-depth discussion on the suitability of each index. I would still expect bycatch indices, especially in the context of large declines in abundance, to be a better representation of the true abundance than targeting indices due to the hyperstability issues previously discussed. In the short time-series of catch available for this study, the retrospective analysis was of limited use. A longer index time-series would allow for the biomass estimates to be well anchored in the past and provide a better understanding of how bycatch and target indices perform long term.

Fish populations cannot be directly estimated, so as scientists we rely on models to provide us with the population assessments necessary for the management of commercial harvest and species conservation. The many different types of models discussed in this thesis (CPUE standardization; Maunder and Punt 2004, surplus production, VPA, etc.; Hilborn and Walters 1992) are unified under the assumption that the data we use accurately represents the underlying abundance. The inferences we make about the population size from whichever model is used, are influenced by the data we input into the analysis. The exploration in this thesis of the trends in catch based on fisher behaviour and data selection contribute to a broader knowledge of how biases in fishing behaviour may influence population estimates. Mismanagement of fish stocks can have far reaching detrimental effects, from impacts to the biology of the ecosystem through to the socioeconomic factors affecting people and communities who rely on them. Shifting away from indices which standardize catch based on fishing tactics that may mask underlying trends, and unrepresentative depictions of fishing effort, will help to improve our management of Canada’s traditionally important fishery resources.

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Appendix A: Catch Information for All Species

Table AA- 1 Common and scientific names of species found in the NAFO 4X division otter trawl landings from 2008 to 2013

Common name	**Scientific Name**
Redfish	*Sebastes spp*
Haddock	*Melanogrammus aeglefinus*
Pollock	*Pollachius virens*
Cod	*Gadus morhua*
Winter flounder	*Pseudopleuronectes americanus*
White hake	*Urophycis tenuis*
Monkfish	*Lophius americanus*
Witch flounder	*Glyptocephalus cynoglossus*
Sculpin	Family Cottidae
Halibut	*Hippoglossus hippoglossus*
Skate	Family Rajidae
American plaice	*Hippoglossoides platessoides*
Cusk	*Brosme brosme*
Yellowtail flounder	*Limanda ferruginea*
Red hake	*Urophycis chuss*
Dogfish	Family Squalidae
Stripped wolffish	*Anarhichas minor*
Silver hake	*Merluccius bilinearis*
Greenland halibut	*Reinhardtius hippoglossoides*
Wolffish, unspecified	Family Anarhichadidae
Tilefish	*Lopholatilus chamaeleonticeps*
Northern wolffish	*Anarhichas denticulatus*

Table AA- 2 Total catch in kgs and proportion of total catch by weight for 16 vessels from the NAFO 4X division otter trawl landings from 2008 to 2013

Species	**Total Catch**	**Prop of Total**
Redfish	14396181	0.3743
Haddock	10260974	0.2668
Pollock	6892133	0.1792
Cod	2346750	0.06101
Winter flounder	2139781	0.05563
White hake	947112	0.02462
Monkfish	587272	0.01527
Witch flounder	259356	<0.01
Sculpin	200762	<0.01
Halibut	81276	<0.01
Skate	69809	<0.01
American plaice	67693	<0.01
Flounder, unspecified	62881	<0.01
Cusk	53508	<0.01
Yellowtail flounder	31668	<0.01
Red hake	29480	<0.01
Dogfish	29101	<0.01
Stripped wolfish	7284	<0.01
Silver hake	2231	<0.01
Greenland halibut	401	<0.01
Groundfish, unspecified	318	<0.01
Wolffish, unspecified	185	<0.01
Tilefish	56	<0.01
Northern wolfish	<1	<0.01

Table AA- 3 Mean, median, max and minimum catch in kgs per fishing set for NAFO 4X division otter trawl landings from 2008 to 2013 made by 16 unique vessels. N is the number of sets where the species was found out of a total of 23227

Species	**Mean**	**SD**	**Median**	**Max**	**Min**	**N**
Redfish	999.4	1380.0	492.4	26133	0.001	14405
Haddock	501.8	1108.0	157.1	18766	0.001	20450
Pollock	421.0	1234.0	62.83	21337	0.001	16371
Cod	120.4	328.8	33.31	9616	0.001	19496
Winter flounder	414.6	527.0	249.9	8117	0.001	5161
White hake	86.5	152.6	30.52	2499	0.001	10945
Monkfish	84.8	291.6	7.558	4667	0.001	6923
Witch flounder	25.5	71.8	8.316	3328	0.001	10185
Sculpin	71.4	101.1	42.56	1445	0.001	2811
Halibut	19.7	77.2	11.51	4703	0.001	4125
Skate	176.3	331.1	45.73	3191	0.218	396
American plaice	21.5	55.8	3.519	758.8	0.001	3149
Flounder, unspecified	57.5	142.9	15.79	1654	0.001	1093
Cusk	10.5	21.7	4.082	338.1	0.001	5101
Yellowtail flounder	24.0	67.8	7.288	858.3	0.001	1321
Red hake	842.3	1211.0	11.56	4113	2.678	35
Dogfish	363.8	755.3	38.74	4303	1.063	80
Stripped wolfish	1.9	3.3	0.6740	68.95	0.001	3938
Silver hake	97.0	95.7	75.66	485	6.061	23
Greenland halibut	2.5	8.7	0.3160	94	0.001	159
Groundfish, unspecified	8.0	8.0	6.467	26	0.064	40
Wolffish, unspecified	1.7	2.3	0.7070	12	0.001	111
Tilefish	0.8	2.4	0.2100	13	0.020	67
Northern wolfish	<0.01	<0.01	<0.01	0.001	0	28

Appendix B: Disproportionate Catch and Effort Relationship

When catch-per-unit-effort (CPUE) is used in fisheries research, catch is related to the nominal fishing effort through eq. B-1

(B-1) $C=qfN$

Where C =catch

q = catchability coefficient

f = nominal fishing effort

N = population size

A disproportionate relationship between catch and effort can be included by the addition of an exponent (β) to the effort term (eq. B-2)

(B-2) $C = qf^{\beta}N$

The exponent β can be estimated through the linear predictor (η) from a generalized linear model.

When considered with the log link function (eq. B-3) and linear predictor (η; eq. B-4) from a generalized linear model (μ = the mean of the response variable)

(B-3) $\mu = e^{\eta}$

(B-4) $\eta = \beta_0 + \beta_1 X_1$

If we combine equations B-3 and B-4, and include log(f) in place of the covariate X from eq. B-4, we get eq. B-5

(B-5) $\mu = e^{\beta 0 + \beta 1 \cdot \log(f)}$

This can be rearranged to eq. B-6

(B-6) $\mu = e^{\beta 0} \cdot e^{\log(f)\wedge \beta 1}$

And reduced further to eq. B-7

(B-7) $\mu = e^{\beta 0} \cdot f^{\beta 1}$

Appendix C: VPA Methodology

Virtual population analysis is an age-structured population model, where cohorts are reconstructed backwards through time (Gulland 1965). Simply put, this means that the population last year is equal to the population this year plus the loss due to mortality. This reconstruction is completed using the Baranov catch equation

$$C_{ay} = (F_{ay} / (F_{ay} + M)) * N_{ay} * (1 - e^{-(Fay + M)})$$

Where a = age

y = year

C = commercial catch in numbers

F = instantaneous fishing mortality rate

M = instantaneous natural mortality rate

N = Population size

Population reconstructions are completed using matrices with year increasing horizontally, and ages increasing vertically downward. Based on the assumption that no members of the oldest age class survive into the next year (i.e. N=0), we can calculate the population estimate for the oldest age class in each year and work backwards to reconstruct the population. The oldest age class is known as the terminal age, and is highlighted in Figure AC-1.

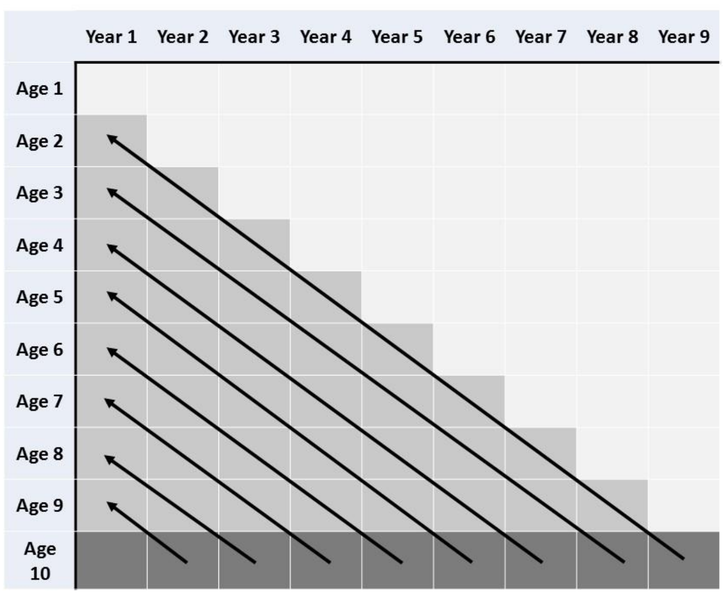

Figure AC - 1. Illustration of an age-year matrix used for a virtual population analysis. Cohorts are backfilled and require an estimate of population size or fishing mortality in the terminal age class (darkest grey). Medium grey indicates an estimated population size, with the lightest grey indicating no estimate.

This method works well for the complete cohorts (i.e. cohorts who have reached the terminal age), but leaves a number of un-estimated values for the incomplete cohorts (lightest grey in Figure AC-1). Because incomplete cohorts make up the current fishery, they are the population estimates that we are most interested in. To fill in the matrix in its entirety, we need an estimate of either population size (N) or fishing mortality (F) for each age class in the terminal year (last column, highlighted below).

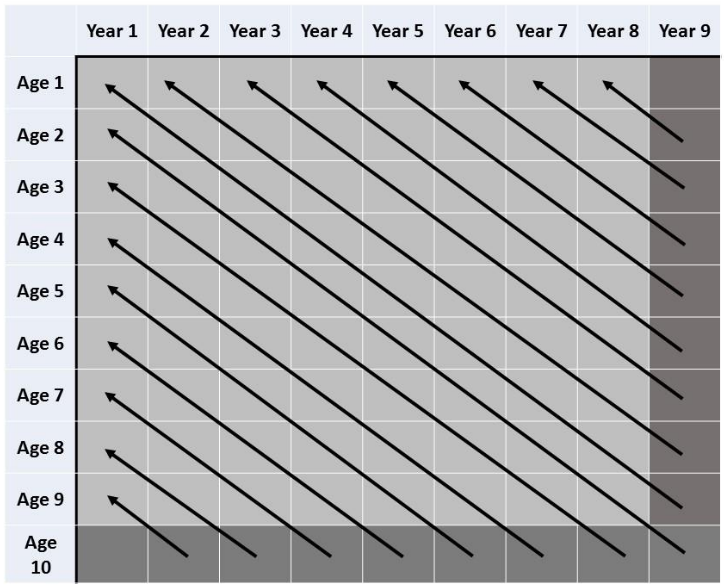

Figure AC - 2 Illustration of an age-year matrix used for a virtual population analysis. Cohorts are backfilled and require an estimate of population size or fishing mortality in the terminal age class (bottom row) and terminal year (rightmost column) to estimate the population size for the previous years of the cohort. Estimated values are highlighted in the dark grey.

To obtain the parameter estimates needed to complete the matrix, auxiliary information, such as a scientific survey or CPUE time-series, is used to “tune” the VPA. The ADAPT-VPA method used in this thesis uses an iterative process to estimate the most likely fishing mortalities given commercial catch-at-age data and a secondary tuning index (Gavaris 1988). The most likely values for fishing mortality (F) are calculated by minimizing the sum- squared error in the calculated catchabilities as described below.

The steps described by Lassen and Medley (2001; in bold) are explained as follows:

(i) Initiate the unknown parameters ln(F), with guessed estimates.

These are the fishing mortalities for the terminal year and age class (dark grey in figure AC-2). Initial values were set to 0.5.

(ii) Perform a VPA to estimate the population (N) for all age groups and years.

The Baranov catch equation can be rearranged to solve for N in the terminal year and age class, given the catch (C), fishing mortality (F) and natural mortality (M). With a value of N for each age in the terminal year, and each year in the terminal age class, the entire matrix can be backfilled.

(iii) Calculate the ln(q) parameters.

Catchability (q) is the link the between the true population size and the index:

Index = catchability * population size

The VPA is "tuned" using the index series through the ln(catchabilities), as logarithmic values are more appropriate than raw values in stock assessments (Lassen and Medley 2001). Using logged values changes the equation for catchability from

$q = \text{Index}/N$; to

$\ln(q) = \ln(\text{Index}) - \ln(N)$

After the N matrix is reconstructed (ii), the catchability of the index series is calculated for each age and year (ln(q)) as well as the average catchability for each age class ($\ln(q_{a)})$.

$\ln(q) = \ln(\text{Index}_{ay}) - \ln(N_{ay})$

$\ln(q_{a)} = \sum_y (\ln(\text{Index}_{ay}) - \ln(N_{ay}))) / n$

(iv) Calculate the sum-of-squares using the VPA solution and the calculated log catchabilities.

The sum-squared error (SSE; simplified from the Lassen and Medley equation) of the catchabilities from the index series are calculated as:

$\text{SSE} = \sum_{ay} [\ln(q) - \ln(q_{a)}]^2$

Steps (ii) to (iv) are imbedded in an iterative optimization routine to find the minimum SSE.

A more detailed descriptions of the methodology can be found in the ADAPT chapter of Lassen and Medley (2001 pg. 55-61).

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Appendix D: ADAPT-VPA Output Tables

Table AD- 1 Commercial catch-at-age (000's) for NAFO 4X5Z haddock (*Melanogrammus aeglefinus*) 2008 to 2013.

Year	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11+**
2008	96	328	597	2179	352	382	689	484	261	159
2009	31	372	505	589	1772	418	256	406	238	216
2010	14	73	585	541	734	1837	369	170	347	302
2011	68	85	284	877	422	625	794	176	73	104
2012	289	307	279	272	1016	410	569	702	200	205
2013	315	1721	512	240	194	468	320	140	288	154

Table AD- 2 Commercial weight-at-age (kg) per fish for NAFO 4X5Z haddock (*Melanogrammus aeglefinus*) 2008 to 2013.

Year	2	3	4	5	6	7	8	9	10
2008	0.626	0.731	0.827	0.971	0.895	0.995	1.047	1.089	1.197
2009	0.612	0.697	0.937	1.06	1.192	1.284	1.352	1.285	1.316
2010	0.61	0.744	0.832	1.006	1.119	1.218	1.209	1.279	1.21
2011	0.626	0.731	0.772	0.91	1.065	1.061	1.27	1.372	1.368
2012	0.582	0.686	0.766	0.885	0.919	1.013	1.089	1.154	1.274
2013	0.473	0.672	0.736	0.876	0.868	0.968	0.998	1.129	1.161
Year	**11**	**12**	**13**	**14**	**15**	**16**			
2008	1.243	1.352	1.29	1.854	0	3.979			
2009	1.322	1.487	1.302	2.177	0	0			
2010	1.407	1.338	1.835	1.427	0	2.191			
2011	1.508	1.465	1.284	1.624	0	4.045			
2012	1.269	1.268	1.319	0.971	1.115	0			
2013	1.32	1.348	1.225	1.124	1.535	0			

Table AD- 3 Catch-at-age index for commercial sets targeting haddock. Values were calculated for a fishing set on January 1 using the GAMM produced in chapter two for sets where haddock made up >90% of the catch. Index is recorded as number of fish per age class

Year	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11+**
2008	40.37	137.92	251.04	916.27	148.02	160.63	289.72	203.52	109.75	66.86
2009	14.38	172.58	234.29	273.26	822.10	193.93	118.77	188.36	110.42	100.21
2010	5.73	29.88	239.47	221.46	300.46	751.97	151.05	69.59	142.04	123.62
2011	36.06	45.08	150.61	465.10	223.80	331.46	421.08	93.34	38.71	55.15
2012	114.68	121.82	110.71	107.93	403.15	162.69	225.78	278.56	79.36	81.34
2013	101.23	553.07	164.54	77.13	62.34	150.40	102.84	44.99	92.55	49.49

Table AD- 4 Catch-at-age index for commercial sets where haddock is caught as bycatch. Values were calculated for a fishing set on January 1 using the GAMM produced in chapter two for sets where a non-haddock species made up >90% of the catch. . Index is recorded as number of fish per age class

Year	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11+**
2008	2.65	9.04	16.45	60.05	9.70	10.53	18.99	13.34	7.19	4.38
2009	0.64	7.69	10.43	12.17	36.61	8.64	5.29	8.39	4.92	4.46
2010	0.24	1.26	10.10	9.34	12.67	31.72	6.37	2.94	5.99	5.21
2011	1.60	2.00	6.69	20.65	9.94	14.72	18.70	4.14	1.72	2.45
2012	6.25	6.64	6.03	5.88	21.97	8.87	12.30	15.18	4.32	4.43
2013	10.18	55.61	16.54	7.75	6.27	15.12	10.34	4.52	9.31	4.98

Table AD- 5 Catch-at-age abundance index for haddock (*Melanogrammus aeglefinus*) from the DFO summer survey. Index is recorded as estimated total stock size in 000's of fish

Year	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11+**
2008	19145	8983	6292	16109	2052	2249	4967	3806	2176	1607
2009	1899	22183	12096	7070	13719	3186	3262	5835	5463	1981
2010	3203	1586	12893	6387	6623	9388	4870	2014	1512	1898
2011	10722	3564	3584	15157	5174	5715	7258	3030	1263	3326
2012	16385	8745	1935	2117	4879	2937	2170	2326	1990	665
2013	20310	23063	6651	910	1900	2943	2758	1147	878	503

Table AD- 6 Population size estimate (000's) for haddock VPA tuned with a) Target, b) Bycatch or c) Survey data.

a) Target Index

Year	2	3	4	5	6	7	8	9	10	11+
2008	9693	5491	5900	11903	2377	1218	1856	887	286	174
2009	2860	7849	4200	4293	7785	1629	655	902	295	268
2010	2342	2313	6091	2983	2984	4781	958	307	376	327
2011	6823	1904	1828	4459	1956	1783	2269	454	100	142
2012	30650	5525	1483	1241	2862	1222	900	1147	214	220
2013	25298	24833	4246	963	771	1433	633	232	316	169

b) Bycatch Index

Year	2	3	4	5	6	7	8	9	10	11+
2008	13689	7029	6991	13318	2568	1381	2275	1255	734	447
2009	4240	11121	5459	5185	8942	1785	788	1244	595	540
2010	3813	3443	8769	4014	3714	5727	1086	415	655	570
2011	12746	3109	2753	6652	2799	2381	3041	558	188	268
2012	71292	10374	2469	1998	4656	1912	1388	1777	299	307
2013	84459	58108	8216	1770	1391	2898	1196	627	826	442

c) Survey Index

Year	2	3	4	5	6	7	8	9	10	11+
2008	13459	7327	6459	11937	3218	1810	2287	2127	715	435
2009	2882	10933	5703	4750	7812	2317	1138	1254	1306	1186
2010	2213	2331	8615	4214	3358	4803	1521	702	662	577
2011	8060	1799	1843	6526	2963	2089	2288	914	422	601
2012	17458	6538	1397	1253	4553	2045	1150	1161	590	604
2013	18246	14032	5076	892	781	2814	1306	434	328	175

Table AD- 7 Estimated fishing mortality F, from the VPA for haddock tuned with a) target, b) bycatch or c) survey data

a) Target Index

Year	2	3	4	5	6	7	8	9	10	11+
2008	0.01	0.07	0.12	0.22	0.18	0.42	0.52	0.90	6.54	6.54
2009	0.01	0.05	0.14	0.16	0.29	0.33	0.56	0.68	3.00	3.00
2010	0.01	0.04	0.11	0.22	0.31	0.55	0.55	0.92	10.80	10.80
2011	0.01	0.05	0.19	0.24	0.27	0.48	0.48	0.55	2.71	2.71
2012	0.01	0.06	0.23	0.28	0.49	0.46	1.15	1.09	12.45	12.45
2013	0.01	0.08	0.14	0.32	0.32	0.44	0.80	1.06	9.37	9.37

b) Bycatch Index

Year	2	3	4	5	6	7	8	9	10	11+
2008	0.01	0.05	0.10	0.20	0.16	0.36	0.40	0.55	0.62	0.62
2009	0.01	0.04	0.11	0.13	0.25	0.30	0.44	0.44	0.73	0.73
2010	0.00	0.02	0.08	0.16	0.24	0.43	0.47	0.59	1.32	1.32
2011	0.01	0.03	0.12	0.16	0.18	0.34	0.34	0.42	0.81	0.81
2012	0.00	0.03	0.13	0.16	0.27	0.27	0.59	0.57	2.12	2.12
2013	0.00	0.03	0.07	0.16	0.17	0.20	0.35	0.28	0.70	0.70

c) Survey Index

Year	2	3	4	5	6	7	8	9	10	11+
2008	0.01	0.05	0.11	0.22	0.13	0.26	0.40	0.29	0.64	0.64
2009	0.01	0.04	0.10	0.15	0.29	0.22	0.28	0.44	0.28	0.28
2010	0.01	0.04	0.08	0.15	0.27	0.54	0.31	0.31	1.29	1.29
2011	0.01	0.05	0.19	0.16	0.17	0.40	0.48	0.24	0.30	0.30
2012	0.02	0.05	0.25	0.27	0.28	0.25	0.77	1.07	0.67	0.67
2013	0.02	0.15	0.12	0.35	0.32	0.20	0.31	0.44	6.58	6.58

Table AD- 8 Estimated log(q) where log(q)=log(Index)-log(N). N is the estimated population size in 000's of fish, with the index recorded as number of fish for the target (a) and bycatch (b) tuned index. For the model tuned with the survey (c) the index is recorded as 000's of fish and is an estimate of the total population size.

a) Target Index

Year	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11+**
2008	-5.48	-3.68	-3.16	-2.56	-2.78	-2.03	-1.86	-1.47	-0.96	-0.96
2009	-5.29	-3.82	-2.89	-2.75	-2.25	-2.13	-1.71	-1.57	-0.98	-0.98
2010	-6.01	-4.35	-3.24	-2.60	-2.30	-1.85	-1.85	-1.48	-0.97	-0.97
2011	-5.24	-3.74	-2.50	-2.26	-2.17	-1.68	-1.68	-1.58	-0.95	-0.95
2012	-5.59	-3.81	-2.59	-2.44	-1.96	-2.02	-1.38	-1.41	-0.99	-0.99
2013	-5.52	-3.80	-3.25	-2.52	-2.52	-2.25	-1.82	-1.64	-1.23	-1.23

b) Bycatch Index

Year	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11+**
2008	-7.12	-5.23	-4.63	-3.98	-4.16	-3.45	-3.36	-3.12	-3.20	-3.20
2009	-7.34	-5.85	-4.84	-4.63	-4.08	-3.91	-3.58	-3.58	-3.37	-3.37
2010	-8.15	-6.47	-5.34	-4.64	-4.26	-3.78	-3.71	-3.52	-3.27	-3.27
2011	-7.55	-5.92	-4.60	-4.35	-4.22	-3.66	-3.67	-3.48	-3.26	-3.27
2012	-7.92	-5.93	-4.59	-4.40	-3.94	-3.95	-3.30	-3.34	-2.81	-2.81
2013	-7.60	-5.53	-4.79	-4.01	-3.98	-3.83	-3.33	-3.51	-3.06	-3.06

c) Survey Index

Year	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11+**
2008	0.35	0.20	-0.03	0.30	-0.45	0.22	0.78	0.58	1.11	1.31
2009	-0.42	0.71	0.75	0.40	0.56	0.32	1.05	1.54	1.43	0.51
2010	0.37	-0.39	0.40	0.42	0.68	0.67	1.16	1.05	0.83	1.19
2011	0.29	0.68	0.67	0.84	0.56	1.01	1.15	1.20	1.10	1.71
2012	-0.06	0.29	0.33	0.52	0.07	0.36	0.64	0.69	1.22	0.10
2013	0.11	0.50	0.27	0.02	0.89	0.04	0.75	0.97	0.99	1.05

Table AD- 9 Error terms from the ADAPT VPA models tuned with a) target, b) bycatch and c) survey data. Error terms were calculated as log(q) – average log(q) by age class, where log(q) = log(Index) – log(N). N is the estimated population size.

a) Target Index

Year	2	3	4	5	6	7	8	9	10	11+
2008	0.04	0.18	-0.22	-0.04	-0.45	-0.04	-0.14	0.05	0.07	0.04
2009	0.23	0.05	0.05	-0.23	0.08	-0.13	0.00	-0.03	0.02	0.23
2010	-0.49	-0.48	-0.30	-0.08	0.03	0.15	-0.13	0.02	0.06	-0.49
2011	0.28	0.13	0.44	0.26	0.15	0.32	0.04	-0.05	0.01	0.28
2012	-0.07	0.05	0.34	0.08	0.36	-0.03	0.34	0.12	0.04	-0.07
2013	0.00	0.06	-0.32	0.00	-0.19	-0.27	-0.11	-0.12	-0.20	0.00

b) Bycatch Index

Year	2	3	4	5	6	7	8	9	10	11+
2008	0.49	0.59	0.17	0.36	-0.05	0.31	0.13	0.30	-0.04	0.49
2009	0.27	-0.03	-0.04	-0.30	0.03	-0.14	-0.09	-0.15	-0.21	0.27
2010	-0.54	-0.65	-0.55	-0.30	-0.15	-0.01	-0.22	-0.10	-0.11	-0.54
2011	0.07	-0.09	0.20	-0.02	-0.11	0.10	-0.18	-0.05	-0.10	0.07
2012	-0.30	-0.11	0.21	-0.07	0.17	-0.19	0.19	0.08	0.35	-0.30
2013	0.01	0.29	0.01	0.33	0.13	-0.07	0.16	-0.08	0.10	0.01

c) Survey Index

Year	2	3	4	5	6	7	8	9	10	11+
2008	0.25	-0.13	-0.42	-0.12	-0.83	-0.22	-0.15	-0.42	0.00	0.25
2009	-0.52	0.37	0.35	-0.02	0.18	-0.12	0.13	0.53	0.32	-0.52
2010	0.26	-0.72	0.00	0.00	0.29	0.23	0.24	0.05	-0.29	0.26
2011	0.18	0.35	0.27	0.43	0.17	0.57	0.23	0.19	-0.01	0.18
2012	-0.17	-0.04	-0.07	0.11	-0.32	-0.07	-0.29	-0.31	0.10	-0.17
2013	0.00	0.16	-0.13	-0.40	0.50	-0.39	-0.17	-0.03	-0.13	0.00

Table AD- 10 Spawning stock biomass (4+, kg) in each age class. Population size in numbers is related to SSB through the commercial weight-at-age. 11+ class weight-at-age is a weighted average of ages 11 to 16.

a) Target Index

Year	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11+**	**4+ biomass**
2008	4880	11558	2128	1212	1943	965	342	217	23244
2009	3935	4550	9279	2092	885	1159	388	354	22643
2010	5067	3001	3339	5823	1159	392	455	460	19697
2011	1411	4058	2083	1892	2882	623	137	215	13301
2012	1136	1098	2630	1238	980	1323	273	279	8957
2013	3125	843	670	1387	631	262	366	223	7508

b) Bycatch Index

Year	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11+**	**4+ biomass**
2008	5781	12931	2298	1374	2382	1367	879	556	27569
2009	5115	5496	10659	2292	1065	1599	782	713	27722
2010	7296	4038	4156	6975	1313	531	792	802	25904
2011	2125	6053	2981	2526	3862	766	257	404	18975
2012	1891	1768	4279	1936	1511	2050	381	389	14206
2013	6047	1550	1207	2805	1194	708	959	583	15055

c) Survey Index

Year	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11+**	**4+ biomass**
2008	5341	11591	2880	1801	2394	2316	856	541	27720
2009	5344	5035	9312	2975	1539	1611	1719	1567	29102
2010	7168	4239	3758	5850	1839	897	802	811	25363
2011	1423	5938	3155	2217	2905	1253	577	906	18374
2012	1070	1109	4184	2072	1252	1340	751	767	12545
2013	3736	782	678	2724	1303	490	380	231	10324