# Spatial and length-based models for management of migratory transboundary species: application to Pacific hake (Merluccius productus) 

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## Abstract

This dissertation develops new modeling tools to provide new scientific perspectives on migratory transboundary fish populations. I particularly focus on two main issues: (1) the interaction between age/size based migratory movement, spatial availability, and fisheries exploitation rates, and (2) time-varying fisheries selectivity caused by size based migration and cohort targeting. I use Pacific hake (Merluccius productus) as a case study. Pacific hake occurs off the Pacific coast of the U.S.A. and Canada and is characterized by ontogenetic migratory movement (older fish migrate further north), strong recruitment events, and time-varying selectivity due to targeting of strong cohorts. In this dissertation, I present two new modeling approaches, and explore the effects of spatial structure on management outcomes using a closed-loop evaluation. First, I use a Lagrangian approach to develop a migration model that describes the Pacific hake dynamics including seasonal migrations, fisheries dynamics, and cohort targeting. Second, I introduce a new stock assessment method that bypasses the requirement of estimating selectivity by using catch at length and growth parameters to produce estimates of exploitation rate at age. This method produces mixed results because of low precision in selectivity estimates. Third, I evaluate the impacts of harvest control rules on the outcomes experienced by Canada and the U.S.A while sharing the Pacific hake resource. I use the migration model described above in a closed-loop simulation to evaluate the long-term impact of 61 harvest control rules. The results indicate that there are differences in performance of harvest control rules between the two nations when maximizing potential long-term yield and log yields. This is a result of the reduced availability of the resource in Canadian waters as the overall harvest rate increases. Caps on allowable catch may help to avoid reduced availability issues. I believe that the results and conclusions presented in this dissertation can inform the future management and modeling of Pacific hake. In addition, the methods presented here could be used for management of other resources subject to time-varying selectivity and other transboundary stocks managed under agreements that do not consider spatial management explicitly.

## Lay Summary

When fisheries resources are shared by two or more nations, tracking the spatial range of the fish and avoiding management actions that severely change this range becomes important. I developed models to aid in the management of shared fisheries using Pacific hake as an example. Pacific hake is fished by the U.S.A. and Canada, and the extent of their annual south-north migrations depends on the age/size of the individual fish, with only larger and older fish present in Canadian waters. I present two new modelling tools: a model that imitates annual Pacific hake migrations; and a model that provides consistent estimates of fish abundance regardless of changes in the location of the fish or fishing vessels. I use these models to explore the impacts that fish movement can have on fisheries management. The contributions presented here can inform future management of migratory and shared resources.

## Preface

This thesis is part of a project entitled: "Developing management procedures robust to variability in stock productivity arising through trophic interactions and persistent environmental changes" which was part of a larger collaboration initiative, the Canadian Fisheries Research Network (CFRN), funded by the Natural Sciences and Engineering Research Council of Canada (NSERC). The objective of all projects under the CFRN was to investigate research questions that are relevant to Canadian fisheries while simultaneously fostering collaboration between members of industry, government and academia. The questions examined in this thesis were designed in partnership with the industry representatives of the Canadian Pacific hake fisheries industry: Brian Mose (Deep Sea Trawlers Association) and Bruce Turris (Canadian Groundfish Research and Conservation Society) and the representative from Fisheries and Oceans Canada and who was also a committee member: Nathan Taylor.

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## Chapter 1

## Introduction

Fish species have evolved to optimize reproductive success, feeding rates and to avoid unfavourable conditions, such as high predation and cannibalism (McKeown, 1984). For many species this optimization is achieved with migratory movement away from nursery grounds (for new recruits), and subsequently between feeding and spawning grounds (Harden Jones, 1968; McKeown, 1984). Migratory movement is indeed a common feature in the ecology of fishes, and has been a frequent subject of study over the last centuries (see Morais and Daverat (2016) for a historic review of fish migration literature). For iteroparous species, the migration routes are frequently traced between spawning and feeding grounds, and can occur repeatedly, in a cyclic manner, throughout an individual's life (Secor, 2015; Walters and Martell, 2004). Examples of cyclic migration behavior are found in tunas and tuna-like species (Nakamura, 1969; Merten et al., 2016), sharks (Hammerschlag et al., 2011), sardines (Lo et al., 2011), flatfishes (Hunter et al., 2003) and gadoids (Robichaud and Rose, 2004; Alheit and Pitcher, 1995).

Migration is frequently associated with segregation of subgroups within a population (Harden Jones, 1968). For example, segregation can occur by sex (e.g., Okamura et al., 2014; Mucientes et al., 2009), size or age (e.g., Ressler et al., 2007; Chen et al., 2005). Size segregation is often a result of fish migrating over larger distances; fish tend to migrate further and faster as they get larger leading to segregation of individuals by size/age (Secor, 2015). Fish movement is of particular concern
when the migratory path of the exploited resource crosses political boundaries, so that if the fish stock is exploited, management may require transboundary management agreements (Munro, 2005; Sumaila, 2013). Management of transboundary stocks frequently assumes that the distribution of the resource is stable over time (Liu and Heino, 2013). Whenever changes in distribution occur, management agreements can become unstable and require renegotiations (Bjørndal and Ekerhovd, 2014). One notable example of how changes in fish distribution can impact international management agreements is the case of Atlantic mackerel. The stock was initially managed through an international agreement between Norway, the EU and the Faroe Islands. However, around 2008 the stock started migrating into Icelandic waters which led to the development of a fishery for Atlantic mackerel in that country. The increase in Icelandic catches lead to conflict and consequent failure of the management agreement previously held (Hannesson, 2013; Spijkers and Boonstra, 2017).

Size segregation can further the problem of transboundary management for migratory species. This is because there is a relationship between size composition and fishing mortality in a population. If we assume that recruitment and natural mortality remain constant, populations under higher fishing pressure will have truncated age structures, i.e., much lower proportions of older and larger fish (Beverton and Holt, 1957). For this reason, management quantities, such as target and threshold exploitation rates, will have an effect on the size distribution of the population. This impacts the migration patterns of the exploited population that segregate by size/age; if larger/older fish migrate further, the migration extent will be shortened by a truncated size/age structure. The change in migration extent may affect the nations sharing the resource to different degrees, and could significantly diminish the availability of the resource to one or more of the fishing nations.

In addition to affecting availability, migratory movement and size/age segregation can also lead to cohort targeting behavior by the fishing fleets. Cohort targeting occurs when fish segregate by age and the fishing fleet targets areas of high abundance. This leads to a disproportionate amount of effort being applied to the most abundant cohorts, either because the cohort is the outcome of a strong recruitment event or because the cohort has been recently recruited and has not yet been fished. When cohorts are targeted, the fishery selectivity changes as the cohorts grow older,
resulting in temporal changes in fisheries selectivity. This is an important issue for many of the modern stock assessment methods that rely on estimates of selectivity to produce age specific fishing mortality rates and derived management quantities.

Both migratory movement and size segregation are common for many exploited species around the globe. For many species, size segregation comes as byproduct of the migratory movement with larger individuals migrating further away from spawning grounds. A few examples of important commercial stocks that exhibit this behavior are: tunas (Nakamura, 1969), sharks (Camhi et al., 2009), Lake Erie walleye (Berger et al., 2012), Pacific halibut (Webster et al., 2013), sardines (Lo et al., 2011) and Pacific hake (Bailey et al., 1982).

This dissertation aims at identifying robust management procedures for transboundary fish populations that are subject to size/age segregation associated with migratory movement. Here, I define the term "management procedure" as the series of choices made regarding the management of exploited fisheries resources, including choices about data collection methods, stock assessment models, target harvest rates and harvest control rules. I evaluate two main aspects that relate to the management of transboundary migratory populations: (1) changes in availability of a fisheries resource to a nation due to management outcomes and (2) the issue of time-varying selectivity caused by changes in availability and cohort targeting by fishing fleets. I use the offshore stock of Pacific hake (Merluccius productus) as a case study, and focus the research questions on issues that are relevant for Pacific hake management.

### 1.1 Management of transboundary stocks

Many fisheries around the world exploit stocks that are distributed across waters under the jurisdiction of two or more coastal nations, such stocks are called transboundary stocks (Sumaila, 1999; Miller and Munro, 2004). Several complications arise in the management of transboundary stocks because the optimal harvest strategy from the perspective of an individual nation usually differs from that of a group of nations exploiting a shared fisheries resource (Criddle and Strong, 2014).

Several studies have modeled the management of transboundary stocks under a game theory approach (Bailey et al., 2010). In this approach, nations involved in transboundary fisheries are represented by players who seek to maximize their benefits (utility) (Munro, 1979). The players can adopt cooperative or non-cooperative strategies with examples of both strategies found in fisheries management (Munro, 2005). However, multiple studies show that although the individual gain can be higher under a non-cooperative strategy, the overall utility is greater when all players opt for a cooperative strategy (e.g., Bailey et al., 2013; Ishimura et al., 2013). The adoption of cooperative strategies is also frequently associated with better long-term management of the resource and increased fishery sustainability (Ishimura et al., 2013). Cooperative strategies are usually represented by treaties and agreements signed by two or more countries or by Regional Fisheries Management Organizations. These agreements typically assume that stock distribution remains somewhat constant over time and that catch shares for each nation are proportional to the biomass of the stock occupying that nation's Exclusive Economic Zone (EEZ). This assumption does not always hold as changes in stock distribution often occur and lead to inadequacy of the management agreements (Liu and Heino, 2013).

Variability in the distribution of exploited resources is not uncommon and can be caused by a wide variety of factors, including range contraction, i.e., as a population decreases, individuals concentrate in optimal areas (e.g., Brodie et al., 1998), or changes in habitat characteristics such as temperature or food availability (e.g., Rodríguez-Sánchez et al., 2002). The disparity between actual stock distributions and that assumed by management agreements can lead to ineffective management regulations and sub-optimal outcomes for one or all nations sharing the resource (Miller and Munro, 2004; Bjørndal and Ekerhovd, 2014).

Movement and migration patterns can both affect management outcomes and be affected by changes in management procedures. Therefore, potential shifts in distribution need to be considered when evaluating the performance of management procedures for transboundary stocks. However, very few studies to date have included a spatial dimension when evaluating the effectiveness of fisheries management procedures. This effect is partly because spatial models are rarely used
for fisheries management (Berger et al., 2017a). However, this scenario has been changing in recent years due to increased spatial data availability, increases in computer power, and development of new data collection and modeling techniques (Goethel et al., 2011, 2016). These factors have contributed to a better understanding of movement dynamics and spatial structures of fished populations. The improved understanding has also led to a surge in management related questions associated with movement and spatial distribution of exploited populations (Goethel and Berger, 2017).

### 1.2 Size segregation and fishing selectivity

Selectivity is defined by a combination of two processes: vulnerability and availability. The vulnerability process represents the contact selectivity, i.e., the proportion of individuals at a given age or size retained by a fishing gear. The availability process represents the spatial dimension of the fisheries, i.e., the degree of overlap between the spatial distribution of the population being fished and the spatial distribution of the fishing activity (Lee et al., 2017).

Both vulnerability and availability of an exploited population can vary over time and therefore modify the resulting selectivity. Vulnerability changes are generally associated with changes in the fishing fleet and gear type. Such changes can be identified if there is good knowledge of the history of the fishery. Documentation on technological innovations, changes in target species or population groups, and development of new fleets are often found in stock assessment documents, legal documents, and industry reports. Availability changes as fish and fishers move. Fish movement can be driven by migration and dispersal, and although ecological studies of fish movement are abundant, the inclusion of spatial distribution of fish in stock assessment models is comparatively scarcer (Berger et al., 2017a). For this reason, in many cases, the effects of fish movement and spatial structure is modeled in stock assessment by considering spatial areas as different fishing fleets that are subject to different selectivities. Although this methodology can capture some of the variance caused by migration and spatial structure, it can sometimes also lead to biased assessment results (Hurtado-Ferro et al., 2014).

The spatial distribution of fishing fleets is also non-static and affects availability. Many fishing fleets target a given size range, either for economic or regulatory reasons. For this reason, a fleet tends to optimize its distribution in order to target areas of high abundance of the resource within their preferred size. For fisheries where the preferred size range is broad, fleets tend to target strong cohorts, especially if the fished resource tends to segregate by size or age. The cohort targeting behavior will lead to changes in the fisheries selectivity over time, which in turn can be a difficult characteristic to model in stock assessments. Cohort targeting is a characteristic of the Pacific hake fisheries, which is consequently, a strong indication that the selectivity patterns for that fishery changes as strong cohorts grow.

Time varying selectivity is an important issue for current fisheries stock assessment (Gudmundsson and Gunnlaugsson, 2012). In statistical catch at age models, now a widespread assessment method for many data rich fisheries (Methot and Wetzel, 2013), selectivity is used as a multiplier to fishing mortality, and therefore acts as a scaler to fishing mortality at age and, consequently, for fishing mortality of each cohort. If not appropriately considered in stock assessments, changes in selectivity over time can severely impact the estimates of fishing mortality and derived management quantities.

In 2014, a special issue of the Fisheries Research journal was dedicated to the estimation of selectivity, and the implications for stock assessment and fisheries management (Maunder et al., 2014). This special issue contains articles that evaluate the impacts of misrepresenting selectivity in assessments (e.g., Butterworth et al., 2014; Martell and Stewart, 2014), present methods for treating selectivity estimation (e.g., Nielsen and Berg, 2014; Waterhouse et al., 2014) and review the occurrence of various selectivity patterns in real data (e.g., Sampson, 2014).

### 1.3 Pacific hake - fisheries ecology and management

Pacific hake, also known as Pacific whiting, inhabits the waters off the west coast of North America, living within the California Current system (Lloris et al., 2005). Several stocks are encountered throughout the species distribution range (Chittaro et al., 2013; King et al., 2012), but a single and
offshore transboundary stock supports most of the Pacific hake commercial fisheries off the west coast of the U.S.A. and Canada. This dissertation focuses on the offshore transboundary stock, and all references to Pacific hake are, therefore, referring to that stock.

The recruitment of Pacific hake is highly variable, and very strong recruitment events happen with some regularity (once or twice per decade) although not in a predictable pattern. The population age structure is heavily influenced by strong recruitment events, and the fishing fleets from both U.S.A. and Canada tend to target the strong cohorts. Maximum age is around twenty years and natural mortality is estimated to be around 0.23 year $^{-1}$, but individuals older than fifteen years old are rarely encountered in the fisheries (Methot and Dorn, 1995). The offshore Pacific hake population exhibits seasonal migratory behavior. Spawning occurs in offshore waters off southern California during the winter with fish migrating north between spring and fall to feed (Bailey et al., 1982; Ressler et al., 2007). The extent of the migrations is correlated with individual size. Larger fish, typically older than age four, migrate longer distances and are found to be more abundant than younger age classes in Canadian waters. Fish three years of age and younger tend to remain in U.S. waters off the coast of California and Oregon (Methot and Dorn, 1995; Ressler et al., 2007).

The fishery occurs between May and November off the coast of northern California, Oregon, Washington (U.S.A.) and British Columbia (Canada), and is conducted almost exclusively by midwater trawls. The fishing vessels operate in areas with bottom depth ranging between 100 to 500 m . Until the 1990s, the Pacific hake fishery was strongly dominated by foreign fleets. The large scale fishery was started in 1966 with factory trawlers from the Soviet Union (Forrester et al., 1978) and expanded in the mid-1970s when factory trawlers from Poland, Federal Republic of Germany, the German Democratic Republic and Bulgaria joined the fishery. A joint venture fishery between U.S.A. trawlers and Soviet factory ships acting as motherships started in 1978. The U.S.A. national fishery expanded during the 1980s, and the fleet became entirely domestic by the early 1990s (Methot and Dorn, 1995; Ressler et al., 2007). In Canada, the domestic fleet also expanded after the mid-1980s but joint venture initiatives continued to occur until 2011. In recent years, most

Pacific hake production has been processed into headed and gutted products and surimi (Ressler et al., 2007; Nelson, 2014).

The offshore Pacific hake stock is managed through a bilateral agreement between Canada and the United States, known as the Pacific hake Treaty (United States State Department, 2004). This treaty and was initially ratified by the U.S. in 2006 but an error in the original text delayed its implementation until a new ratification in 2010. The treaty has been considered in force in Canada since 2008. The agreement determines that a stock assessment should be conducted every year by a Joint Technical Committee (JTC). The JTC is composed of scientists appointed by each country and independent members chosen by a private sector advisory panel. The stock assessment results are used in association with a defined harvest control rule (40:10 rule) to generate a recommendation for a coast-wide Total Allowable Catch (TAC), which is evaluated and adjusted by a Joint Management Committee (JMC). The JMC approved TAC is then shared between the U.S.A. and Canada following a fixed proportion: $73.88 \%$ and $26.12 \%$ of the TAC is allocated to the U.S.A. and Canada, respectively (United States State Department, 2004).

Throughout the Pacific hake exploitation history there has been some concern about potential changes in stock distribution and stock biomass associated with gaps in the occurrence of strong recruitment events. Whenever there is a strong cohort hiatus, as occurred between 1999 and 2010, the population age structure tends to become more truncated with most of its biomass being represented by fish of younger age classes. Because the Pacific hake migratory movement is associated with fish size/age, the truncation of the population age composition has an effect on the population range and distribution (Hicks et al., 2016). This variability in stock distribution can particularly impact the northern distribution of the stock, resulting in lower availability of Pacific hake off the coast of Washington and Canada. These changes have generated concern to the Canadian Pacific hake Advisory Panel regarding the efficiency of the current harvest control rule, and the consequent appropriateness of total allowable catch recommendations (Canadian Advisory Panel, 2013).

A few studies have evaluated the performance of current and alternative management procedures considered for Pacific hake. Ishimura et al. (2005) evaluated the performance of the 40:10
harvest control rule and a series of linear harvest control rules for the aggregate Pacific hake stock. They considered performance metrics relating to average yield (magnitude and standard deviation), probability of closures, and total biomass and found that the best results were obtained for low harvest rates and low threshold biomass. They also found that the $40: 10$ harvest control rule performed well in relation to the best linear harvest control rules. Punt et al. (2008) assessed the performance of a set of harvest control rules a for groundfish stocks off the U.S.A. west coast, including Pacific hake. They evaluated the performance of such rules in relation to average catch and conservation metrics. They found that threshold harvest control rules, i.e., rules that progressively adjust harvest rates as the biomass decreases (reach thresholds), tend to perform better in relation to conservation objectives, but results are sensitive to assumed productivity and recruitment variability. An additional evaluation has been carried out by the Pacific hake JTC since 2014 (Taylor et al., 2014). However none of the evaluations listed above considered issues involving the spatial structure of the stock.

### 1.4 Objectives and dissertation structure

This dissertation focuses on questions that are relevant to the management of transboundary stocks. Particularly, those stocks that are subject to migratory movement, ontogenetic segregation, and time-varying selectivity. We use the Pacific hake resource as an example to illustrate the use of the modeling tools developed. The dissertation is organized into three modeling chapters and a conclusion. The three main chapters evaluate the following questions: (1, Chapter 2) How to model cyclic ontogenetic migrations and fleet dynamics associated with cohort targeting? (2, Chapter 3) Is it possible to overcome the requirement of estimating selectivity curves by using catch at length and growth curve information? (3, Chapter 4) How do commonly considered harvest control rules perform for the management of a transboundary fish stock when performance measures are evaluated separately for each fishing nation?

In Chapter 2, I develop and implement a continuous migration model to describe the population dynamics of the Pacific hake resource. The model simulates the cyclic migratory movement that is
characteristic of Pacific hake including cohort segregation. In this model, the population dynamics of the resource are described with an age-structured model that allows for high variability in recruitment and strong recruitment events. This model is also coupled with a fleet dynamics model that simulates the tendency of fishing fleets to target areas of high abundance, which leads to the targeting of strong cohorts and consequent time varying selectivity. Using a simulation-evaluation analysis, I demonstrate how the model's movement parameters can be estimated given commonly available spatial catch at age composition data.

In Chapter 3, I present a novel length based stock reduction analysis (Length-SRA) approach. This assessment model bypasses the requirement of estimating selectivity parameters, generating no constraints on the occurrence of time-varying selectivity, similarly to what is obtained with a Virtual Population Analysis (VPA). I demonstrate the model performance under three exploitation trajectories, and with both time varying and time invariant selectivity patterns. I also use the approach to estimate trends in selectivity and management quantities for two real data examples: Peruvian jack mackerel and Pacific hake.

In Chapter 4, I use the movement model developed in Chapter 2 as an operating model in a closed loop simulation to evaluate the performance of a series of linear harvest control rules and the harvest control rule currently used to manage the Pacific hake resource, the $40: 10$ harvest control rule with a cap on maximum allowable catch. I evaluate five performance metrics that represent my interpretation of three potential fisheries objectives: high catches with limited variability, low probability of closures and maintenance of biomass above a threshold.

The research presented in this dissertation offers opportunities for improving the understanding of the effects of spatial dynamics on fisheries assessment and management. The modeling tools and framework presented here is informative for the future management of Pacific hake and other transboundary migratory stocks.

## Chapter 2

## A Lagrangian approach to model movement of migratory species

### 2.1 Introduction

Two main drivers of cyclic migration in marine fish species are seasonal availability of food and spawning behavior (Walters and Martell, 2004). In many iteroparous species, these drivers are responsible for a continuous migration cycle between feeding and spawning areas (e.g., Hunter et al., 2003; Costa et al., 2012; Merten et al., 2016). Migration modeling is an important component of fisheries science due to the common presence of migratory behavior in exploited species. In this study, I present a novel method for modeling the migration of fisheries resources and the associated fisheries dynamics that can arise from fish movement.

The migration cycle observed in many iteroparous species can vary in extent (i.e., distance or timing) for subgroups within a population, e.g., for different age or size groups (Ressler et al., 2007), sex (Okamura et al., 2014) or sub stocks (Carlson et al., 2014). This variability can lead to spatial segregation of subgroups within a fish population. When spatial segregation is present, subgroups are susceptible to distinct environmental and ecological drivers leading to differences in natural mortality, recruitment and to additional variability in spatial distribution (Ciannelli et al., 2008). In addition, spatial segregation within a population can cause spatial differences in vulner-
ability and fishing effort or mortality that are independent from fishing gear or fishing techniques (Martell and Stewart, 2014). If ignored, migratory movement and spatial segregation can lead to strong bias in surveys and stock assessment which could result in unreliable management advice (McAllister, 1998; Waterhouse et al., 2014). It can also lead to failure of management strategies, particularly when considering space/time closures (Martell et al., 2000; Grüss et al., 2011). The evaluation of impacts of fish movement on fisheries management often requires the use of migration models and simulation studies. See Kerr and Goethel (2014) for a comprehensive review on the application of simulation studies to evaluate the impacts of movement and migration on fish population dynamics and fisheries management.

Migration models are diverse in the fisheries literature (Goethel et al., 2011) and can be grouped based on two numerical methods used to implement them: Eulerian and Lagrangian models. These terms are originally applied to fluid dynamics but have been used to describe migration modeling for aquatic resources (Kerr and Goethel, 2014; Walters and Martell, 2004). The two approaches differ in the way that movement is measured. In the Eulerian approach space is divided in predetermined areas and the movement rate of individuals across such areas is the variable of interest. Eulerian models have been coupled with stock assessment models and tagging studies (Carruthers et al., 2011; Methot and Wetzel, 2013; Sippel et al., 2015) and are useful when there is interest in tracking the net flux of individual across predetermined spatial areas. In the Lagrangian approach, the movement of individuals is tracked through time and space and the movement tracks are the variable of interest (Walters et al., 1999). Lagrangian models rely on the assumption that an underlying force drives movement. For example, this force could be environmental drivers forcing ichthyoplankton dispersal (Lett et al., 2008) or homing behavior driving salmonid runs (Cave and Gazey, 1994; Branch and Hilborn, 2010). Lagrangian models are not commonly applied to iteroparous species, despite the suitability of the approach to model migratory behavior. Migration hypotheses, such as the cyclic movement between feeding and spawning areas, can be used as the underlying pattern that drives the movement of individuals through space in a Lagrangian model.

In this paper, I describe a Lagrangian movement model designed for iteroparous species that perform cyclic migrations throughout their lifetime. The objective of this model is to provide a way of formalizing movement hypotheses into mathematical models. The resulting model can be used to summarize data and test the validity of alternative migration hypotheses and to represent complex movement dynamics as an operating model in closed loop simulation studies. The model is applied to the Pacific hake (Merluccius productus) as a study case. In particular, I focus on the offshore Pacific hake stock that inhabits the California current system. This stock is believed to perform annual migration cycles between the spawning area off southern California and feeding grounds along the West coast of North America, from Oregon to Southeast Alaska (Ressler et al., 2007). The migration cycle of Pacific hake is partially influenced by the age/length of individuals, with older/larger individuals reaching waters further north (Methot and Dorn, 1995; Ressler et al., 2007). The migration cycle is a key component to consider for management strategies for this stock. The agreement between Canada and the US defines an aggregate (i.e., non-spatial) harvest control rule, but, given that prosecution of the fishery itself affects the mean age/size of fish, it also affects the distribution of the stock and hence, the distribution of the fishery's benefits between the parties. In addition to the model description, I provide a description of data requirements to estimate the model movement parameters. I also show how the model can be extended to incorporate covariates representing biological and environmental factors that alter the distribution and migration range of the populations being modeled.

### 2.2 Methods

### 2.3 Movement model framework

I decompose the model into the following sections: population dynamics, movement, and fisheries dynamics. This division is somewhat arbitrary as all three parts are interdependent, but the division is done to ease the description of the model. All three sections are structured by age, time, space (i.e., modeled area, fishing grounds and territories), and group. All model indexes, i.e., variables used to designate the model dimensions, are presented in Table 2.1. The age dimension, denoted as
$a$, aggregates individuals by cohort, and spans from age one to a plus group $A$, which encompasses individuals of age 20 and older. Individuals age is set to increase in the first month of each year, i.e., $t=t_{0}$. The time dimension is denoted at $t$. I assumed monthly time steps, so all quantities within the model were computed twelve times within a year/migrations cycle, but any step length could be used. The indexing of time is cyclic, so that the range $\left\{t_{0}, \ldots, t_{\max }\right\}$ is repeated every year. The first month of the migration cycle is also indexed with the year counters $(y)$, so that $y-1=t_{0}$ in the previous year. The space dimension is considered at three scales: area, fishing ground, and territory. The variable area $(r)$ refer to small and equally sized intervals of space, which are used to discretize the variables of interest (biomass, fishing effort, etc.). The area range denotes the limits of the modeled space. Fishing grounds and territories are larger than areas, but are contained within the area range (i.e., within the limits of the modeled space). The fishing grounds correspond to areas where a fleet is known to operate and territories correspond territorial waters of a nation or state. Each territory may contain one or more fishing grounds, and the biomass within one territory is only accessible to the fleets operating within that territory. Lastly, the group dimension is used to represent parcels within an age cohort that move at different speeds.

In the population dynamics section (Table 2.3) the processes relating to recruitment, survival, aging and growth are described. These processes are modeled for each group in the population through time and space. The spatial section (Table 2.4) encompasses the description of movement of individuals at age and group through time. And finally, the fishing dynamics section (Table 2.5) describes the model effort distribution as a function of spatio-temporal effort scalers and the spatial distribution of fish biomass (summed over all ages and groups). The spatial distribution of fishing effort is used to generate of spatially explicit fishing mortality. In the movement section, groups are modeled in two ways yielding two versions of the model: single group or multiple groups versions. All model variables are defined in Table 2.2.

The population dynamics is composed of survival and recruitment processes (Table 2.3). The model assumes age-specific vulnerability and fecundity as well as Beverton-Holt recruitment occurring at age 1. Recruitment and aging are assumed to happen at the first time step within a

Table 2.1: Indexes and variable definitions

| Symbol | range | Description |
| :--- | :--- | :--- |
| $t$ | $\left\{t=t_{0}, \ldots, t_{\max }\right\}$ | time steps within a migration cycle |
| $y$ | $\left\{y=y_{o}, \ldots, Y\right\}$ | year index |
| $a$ | $\{a=1, \ldots, A\}$ | age index |
| $r$ | $\left\{r=r_{i n i}, \ldots, R\right\}$ | area index |
| $k$ | $\{k=1, \ldots, K\}$ | fishing ground index |
| $n$ | $\{n=1, \ldots, N\}$ | territory index |
| $g$ | $\{g=1, \ldots, G\}$ | group index |
| $R M$ |  | range of modeled area |
| $d r$ |  | interval between two adjacent areas |
| $t_{\max } \cdot Y$ |  | total numbers of time steps modeled |

migration cycle (Equation T3.2 - cases i-iii) and survival due to natural and fishing mortality are calculated at monthly time steps (Equation T3.2-cases ii-iv). Because of the continuous nature of the model, sometimes some portion of the population might be located outside the boundaries of modeled area and therefore outside the fishing grounds. When this happens, we assumed that individuals are subject to natural mortality only (Equation T3.2- second term on cases ii-iv). Spawning biomass is combined over all areas and groups (Equation T3.3).

The movement section (Table 2.4) assumes the individuals in a population are distributed along a unidimensional gradient $X$, and that they perform annual cyclic migrations between spawning and feeding areas. This cyclic migration is modeled with a sine function in which the position of individuals change as a function of time (Figure 2.1). I have developed two alternative versions: single group and multiple groups. In both versions, the cyclic movement of individuals between spawning and feeding areas is modeled with a sine curve (Equation T4.1). The magnitude of the movement is determined by two parameters representing maximum and minimum positions of the migration cycle ( $X_{\max , a, g}$ and $X_{\text {min }}$ ), and the starting time step of the cycle is given by the parameter $t_{0}$. The maximum and minimum positions of the cyclic movement, $X_{\max }$ and $X_{\min }$, can be modeled as a function of covariates, such as age, size or environmental drivers. Here, I model the maximum position as a logistic function of age (Equation T4.2) and fix the minimum position as constant for all ages. Once the maximum and minimum positions are defined, the sine curve is used to calculate the mean position of individuals in each group of age $a$, in time step $t\left(\bar{X}_{a, t}\right)$.

Table 2.2: Variable definitions

| Symbol | Description |
| :---: | :---: |
| Population dynamics |  |
| $N_{a, t, g}$ | Numbers at age, time and group |
| M | Annual natural mortality |
| $v_{a}$ | Vulnerability at age |
| $S_{0}$ | Maximum juvenile survival rate |
| $S B_{t}$ | Spawning biomass at time t |
| $\beta$ | Beverton \& Holt density dependence |
| propg | Proportion of total recruitments that recruits to group g |
| wt | Normally distributed recruitment error |
| $P r_{a, r, t, g}$ | Proportion of population of age a , group g and at time t in area r |
| $w_{a}$ | Weight at age |
| $f_{a}$ | Fecundity at age |
| $f$ | Proportion of females in the population |
| $\Phi(x \mid \mu, \sigma)$ | Cumulative normal distribution with mean $\mu$ and standard deviation $\sigma$, evaluated at $x$ |
| Spatial dynamics |  |
| $\bar{X}_{a, t}$ | mean position at age and at time t |
| $\bar{X}_{\text {min }}$ | minimum average position |
| $\bar{X}_{\text {max }, a}$ | maximum average position at age |
| $t_{0}$ | time step at which individuals are at their minimum average position |
| $a_{50}$ | inflection point for maximum average position logistic function |
| $\sigma_{X_{\text {max }}}$ | standard deviation for maximum average position logistic function |
| $\sigma_{X_{a}}$ | standard deviation for position at age |
| CV | coefficient of variation for position at at age |
| single group version |  |
| $X_{a, t}$ | probability distribution for position at age and time |
| multiple groups version |  |
| $\bar{X}_{a, t, g}$ | mean position at age, time $t$ and for group $g$ |
| $Q_{X_{a, t, g}}$ | quantiles for mean group distribution |
| $\delta$ | distance between quantiles for mean group distribution |
| $\sigma_{X_{a, g}}$ | standard deviation for position at age |
| $\bar{X}_{a, t, g}$ | mean position at age and group |
| $X_{a, t, g}$ | probability distribution for position at age and time for each group |
| Fisheries dynamics |  |
| $E_{r, t}$ | Effort in area r and at time t |
| $E_{y, k}$ | Maximum yearly effort scaler in fishing ground k |
| $E_{t, k}$ | Maximum time step effort scaler in fishing ground k |
| $A_{r, t}$ | Attractiveness of each area $r$ and at time $t$ |
| $\lambda$ | Attractiveness power |
| $V B_{r, t}$ | Vulnerable biomass by area and time |
| $E_{\text {pot, },}$ | Relative effort potential for each arear |
| $F_{r, t}$ | Fishing mortality rate in area $r$ and at time $t$ |
| $q$ | Catchability coefficient |
| $C_{a, r, t}$ | Catch at age for each small area r and time t |

Table 2.3: Population dynamics model
Initial year and time step $-y=y_{o}$

$$
N_{a, t, g}= \begin{cases}\frac{S_{0} \cdot S B_{0}}{1+\beta \cdot S B_{0}} \cdot \exp (w t) \cdot \operatorname{prop}_{g}, & \text { (i) } t=t_{0} \& a=1  \tag{T3.1}\\ N_{a-1, t, g} \cdot \exp \left(-M / t_{\max }\right), & \text { (ii) } t=t_{0} \& 1<a<A \\ \frac{N_{a-1, t, g} \cdot \exp \left(-M / t_{\max }\right)}{1-\exp \left(-M / t_{\max }\right)}, & \text { (iii) } t=t_{0} \& a=A\end{cases}
$$

Age-schedule information

$$
\begin{equation*}
S B_{t}=\sum^{g} \sum^{a} N_{a, t, g} \cdot f_{a} \cdot w_{a} \cdot f \tag{T3.2}
\end{equation*}
$$

$$
\text { prop }_{g}= \begin{cases}1, & \text { single group }  \tag{T3.4}\\ \Phi\left(Q_{X_{g}}+\delta \mid \mu=0, \sigma=1\right)-\Phi\left(Q_{X_{g}}-\delta \mid \mu=0, \sigma=1\right), & \text { multiple groups }\end{cases}
$$

The proportion of individuals in each area, i.e., small intervals of space, is given by the cumulative normal distribution function given the mean position and standard deviation of the cohort (Equation T4.5) or group (Equation T4.11).


Figure 2.1: Diagram illustrating the sine function used to describe the cyclic movement dynamics used in the Lagrangian model. The position (y-axis) of an individual changes in cyclic waves as time (x-axis) progresses. In this diagram, we assume that a cycle lasts 12 time steps and that movement occurs between values of 30 and 60 along the spatial scale.

The differences between single and multiple groups versions are in how the individuals are distributed around the mean position $\left(\bar{X}_{a, t}\right)$. When a single group is present, the individuals are assumed to be normally distributed around the mean with variance $\sigma_{X_{a}}^{2}$ (Equation T4.4). In the multiple groups version, each group's position follows a group specific normal distribution and the mean and variance of each group is a function of the overall mean and variance (Equations T4.6.T4.9). The main difference between the two versions is that in the single group version, the distribution of fish regenerates to a normal distribution at every time step, but with a new average position. Although individual fish might experience different fishing mortality depending on location, the regeneration assumption does not allow localized depletion to occur. Instead, fish are redistributed across their range in each time step following a normal density function. When multiple groups are considered, each group is distributed according to a group specific distribution that is much narrower than the overall distribution of individuals at an age class. This mechanism allows

Table 2.4: Lagrangian movement model

$$
\begin{align*}
& \text { Movement information } \\
& \bar{X}_{a, t}=\bar{X}_{\text {min }}+\left(\bar{X}_{\text {max }, a}-\bar{X}_{\text {min }}\right) \cdot\left(0.5+0.5 * \sin \left(t \cdot \frac{2 \pi}{t_{\max }}-t_{0} \cdot \frac{2 \pi}{t_{\max }}-\frac{\pi}{2}\right)\right)  \tag{T4.1}\\
& \bar{X}_{\text {max }, a}=\frac{1}{1+\exp \left(-\left(a-a_{50}\right) / \sigma_{X_{\text {max }}}\right)} \cdot e^{\left(v t \sim \mathcal{N}\left(0, \sigma_{v t}\right)\right)}  \tag{T4.2}\\
& \sigma_{X_{a}}=\bar{X}_{\text {max }, a} \cdot C V \tag{T4.3}
\end{align*}
$$

Single group version
$X_{a, t} \sim \mathscr{N}\left(\bar{X}_{a, t}, \sigma_{X_{a}}\right)$

$$
\begin{equation*}
P r_{a, r, t}=\Phi\left(\left.x=r+\frac{d r}{2} \right\rvert\, \mu=\bar{X}_{a, t}, \sigma=\sigma_{X_{a}}\right)-\Phi\left(\left.x=r-\frac{d r}{2} \right\rvert\, \mu=\bar{X}_{a, t}, \sigma=\sigma_{X_{a}}\right) \tag{T4.4}
\end{equation*}
$$

$$
\begin{align*}
& \text { Multiple groups version } \\
& \bar{X}_{a, t, g}=Q_{X_{a, t, g}} \cdot \sigma_{X_{a}}+\bar{X}_{a, t}  \tag{T4.6}\\
& Q_{X_{g}}=\delta \cdot(g-G / 2.0)  \tag{T4.7}\\
& \delta=6.0 / G  \tag{T4.8}\\
& \sigma_{X_{a, g}}=\sqrt{\frac{\sigma_{X_{a}}{ }^{2}}{G^{2}}}  \tag{T4.9}\\
& X_{a, t, g} \sim \mathscr{N}\left(\bar{X}_{a, t, g}, \sigma_{X_{a, g}}\right)  \tag{T4.10}\\
& \operatorname{Pr}_{a, r, t, g}=\Phi\left(\left.x=r+\frac{d r}{2} \right\rvert\, \mu=\bar{X}_{a, t, g}, \sigma=\sigma_{X_{a, g}}\right)-\Phi\left(\left.x=r-\frac{d r}{2} \right\rvert\, \mu=\bar{X}_{a, t, g}, \sigma=\sigma_{X_{a, g}}\right) \tag{T4.11}
\end{align*}
$$

certain groups to experience different fishing pressures depending on where the group is located, which might lead to higher or lower fishing pressure over extended periods of time. Because the distribution range of each group is narrower the regeneration only occurs within a narrow range, which allows local depletion to become apparent.

In the fishing dynamics section (Table 2.5), spatial fishing effort allocation is done with a gravity model (Caddy, 1975). These models assume that effort in each area is a function of the latent yearly and monthly effort in a fishing territory and the attractiveness index of that area (Equation T5.3). The effort potential quantities $E_{y, k}$ and $E_{m, k}$ are scaling matrices of dimensions $\mathrm{Y} \times \mathrm{K}$ and $t_{\max } \times \mathrm{K}$ respectively. The values in these matrices range between 0 and 1 . Values of 0 indicate that no effort
is allowed in that particular year or month, conversely, values of 1 indicate that full effort is allowed in that particular year or month. The attractiveness index can include factors such as fishing cost, target fish abundance and bycatch abundance (Caddy, 1975; Walters and Martell, 2004). I make attractiveness (Equation T5.2) a function of vulnerable biomass $V B_{r, t-1}$, the power parameter $\lambda$ and effort potential $E_{p o t, r}$ (Equation T5.1). I use the vulnerable biomass in the previous time step because I assume that effort distribution is guided by the biomass distribution observed in the previous time step. The parameter $\lambda$ is used to indicate if the attractiveness is directly proportional to abundance $(\lambda=1)$, or if the fleet tends to disproportionately aggregate in high abundance areas ( $\lambda>1$ ). One example in which $\lambda>1$, is when there is communication between fishing vessels when a high abundance area is located. In such cases, fishing effort would tend to aggregate in high abundance areas generating a patchy distribution of effort. The effort potential $E_{p o t, r}$ parameter represents the avoidance factors for a given area, e.g., fishing costs and bycatch avoidance. This parameter can be used to represent a range of differences in fishing fleets, such as storage capacity, autonomy at sea, and distance between fishing grounds and home port. The $E_{p o t, r}$ parameter can also be used to represent areas that are avoided due to high bycatch occurrence. Avoidance areas affect the ability to concentrate fishing effort at a given location, and therefore should be considered in the modeling process. Effort is then multiplied by $q$, the effort scaler, resulting in the fishing mortality in that area. Lastly, catches are calculated for each time step using the Baranov catch equation (Equation T5.4).

Process and observation random errors are incorporated in the model. The process random error was represented annual recruitment variability, annual variability in the maximum average position, and annual variability in the effort scaler $q$. All these variability components were modeled with lognormally distributed error. The age composition data, in numbers and aggregated by fishing ground, are generated with multivariate logistic sampling error.

Table 2.5: Fisheries dynamics model

$$
\begin{align*}
& \text { Fisheries dynamics } \\
& V B_{r, t-1}=\sum^{a} \sum^{g} v_{a} \cdot N_{a, t-1, g} \cdot w_{a} \cdot P r_{a, r, t-1, g}  \tag{T5.1}\\
& A_{r, t}=\left(\frac{V B_{r, t-1}}{\left(\frac{r_{1}}{r \in n} V B_{r, t-1}\right.}\right)^{\lambda} \cdot E_{p o t, r}  \tag{T5.2}\\
& E_{r, t}=E_{y, k} \cdot E_{t, k} \cdot \frac{A_{r}}{\sum_{r} A_{r}}  \tag{T5.3}\\
& C_{a, r, t}=\frac{F_{r, t} \cdot v_{a}}{F_{r, t} \cdot v_{a}+M} \cdot N_{a, r, t} \cdot\left(1-\exp \left(-\left(F_{r, t} \cdot v_{a}+M\right)\right)\right)  \tag{T5.4}\\
& F_{r, t}=q \cdot e^{\left(w x \sim \mathscr{N}\left(0, \sigma_{w x}\right)\right)} \cdot E_{r, t} \tag{T5.5}
\end{align*}
$$

### 2.3.1 Application to Pacific hake and simulation-estimation procedure

The offshore Pacific hake stock was used as an example to illustrate the model dynamics. In the Pacific hake case, the fish are known to perform annual migration between the waters off South California and northern British Columbia. Therefore, I model the movement of hake in terms of latitude degrees, from $30^{\circ} \mathrm{N}$ to $60^{\circ} \mathrm{N}$ (Figure 2.2). The driving population dynamics parameters for Pacific hake were obtained from the 2015 stock assessment (Taylor et al., 2015). The parameters for the effort dynamics were set to mimic the fisheries dynamics described in the stock assessment document (Taylor et al., 2015). The parameters used in the simulation-estimation procedure are listed in Table 2.6.

I did a simulation experiment to evaluate the estimability of the movement parameters. I simulated and estimated population movement dynamics using both single group and multiple groups versions (20 groups). I simulated total catch and catch at age data with observation error, and used that data to estimate the models parameters.

The model parameterization is divided into two categories: fixed (extracted from other models), and parameters that could be estimated, given seasonal catch at age data. The fixed parameters include all the population dynamics and fisheries capacity parameters. These parameters were the recruitment function parameters ( $R_{o}$ and $h$ ) and natural mortality $(M)$. These parameters were


Figure 2.2: Map of the study area. The dashed lines indicate the division between fishing grounds.

Table 2.6: Pacific hake model dimensions and parameter values

| Symbol | value or range | Description |
| :---: | :---: | :---: |
|  | Dimensions |  |
| $t$ | 1-12 | Time steps within a migration cycle |
| $y$ | 1-30 | Years |
| $a$ | 1-20 | Age |
| $r$ | 30-60Area |  |
| $k$ | 3 or 5 | Fishing grounds |
|  | 42, 46, 48.5 and 51 | Fishing ground boundaries in latitude degrees |
| $n$ | 2 | Territories |
|  | 48.5 | Territory boundary in latitude degrees |
| \% | 1-20 | Groups |
| $\begin{aligned} & d r \\ & t_{\text {max }} \cdot Y \end{aligned}$ | 1 <br> 360 Total numbers of time steps modeled | Interval between two adjacent areas |
|  |  |  |
|  | Population dynamics parameters |  |
| M | 0.223 | Annual natural mortality |
| $S_{0}$ | 15.331 | Maximum juvenile survival rate |
| $\beta$ | 5.422 | Beverton \& Holt density dependence |
|  | Movement parameters |  |
| $t_{0}$ | 1 | Time step at which individuals are at their minimum average position |
| CV | 0.1 | Coefficient of variation for position at at age |
| $a_{50}$ | 3.0 | Inflection point for maximum average position logistic function |
| $\sigma_{X_{\text {max }}}$ | 1.5 | Standard deviation for maximum average position logistic function |
|  | error levels |  |
| $\tau$ | 0.4 or 1.0 | Standard deviation for the multivariate logistic error around catch at age |
| $\sigma_{w x}$ | 0.08 | Standard deviation for lognormal variation around the maximum average position |
| $\sigma_{v t}$ | 0.1 | Standard deviation for lognormal variation around the effort scaler |
|  | Effort parameters |  |
| $E_{y, k}$ | Constant for all years and equal to ( 1 , $1,1,0.2,0.2$ ) for fishing grounds from 1 to 5 | Yearly effort scaler - fishing grounds 1-2 and 4-5 were combined when only 3 fishing grounds were considered |
| $E_{t, k}$ | (0.0 0.0 0.0 0.0 0.51 .01 .01 .00 .50 .1 0.00 .0 ) for fishing grounds $1-3$ and (0.0 0.0 0.0 0.00 .01 .01 .01 .00 .50 .3 0.00 .0 ) for fishing grounds $4-5$ | Monthly effort scaler - fishing grounds 1-2 and 4-5 were combined when only 3 fishing grounds were considered |
| $q$ | 1 | Effort scaler |

considered as a fixed input to the model and were assumed to be known without error in both simulation and estimation models. The estimable parameters are: $t_{0}, C V, a_{50}, \sigma_{X_{\max }}$ and $q$. These parameters were estimated with a multivariate logistic likelihood function fitted to simulated age composition data.

A total of 12 simulation-evaluation scenarios were considered in this study (Table 2.7). I considered two data aggregation scenarios with data reported from three or five large fishing grounds (aggregated over all areas within fishing ground). These two levels of data aggregation were considered in order to explore the sensitivity of the model to levels of spatial aggregation of the age composition information. I initially considered these two levels of data aggregation for the single and multiple groups version, however I got very low levels of model convergence ( $50 \%$ or less) when three fishing ground were considered using the multiple groups version. This fact lead me to drop the three fishing ground scenarios when the multiple groups version was used. The aggregated catch at age data was assumed to have multivariate logistic error with two levels of observation error, i.e., the standard deviation $(\tau)$ being either ( 0.4 or 1.0 ). These two levels of variability in the age composition data were chosen in order to evaluate the sensitivity of the model to measurement and sampling errors. In addition, I considered two attractiveness scenarios ( $\lambda=1$ and $\lambda=2$ ). The different levels of attractiveness are likely to change the spatial distribution of fishing effort, and would likely impact the degree of depletion experienced by fish in different areas. This is particularly relevant for the multiple group scenarios as the different $\lambda$ values might affect the local depletion patterns.

The estimation model was identical to the simulation model, and parameters were estimated with a multivariate logistic likelihood function fitted to simulated age composition data and a lognormal likelihood fitted to the simulated total catches. A total of 100 simulations were run for each scenario-version combination. Simulation and estimation routines were performed using ADMB (Fournier et al., 2012). The code and simulated data are available for download from https://github.com/catarinawor/Lagrangian

Table 2.7: Simulation-estimation scenarios

| Scenario number | Model Version | catch at age error | Fishing grounds | $\lambda$ value |
| :---: | :---: | :---: | :---: | :---: |
| 1 | single group | low $(\tau=0.4)$ | 3 | 1.0 |
| 2 | single group | $\operatorname{low}(\tau=0.4)$ | 3 | 2.0 |
| 3 | single group | $\operatorname{high}(\tau=1)$ | 3 | 1.0 |
| 4 | single group | $\operatorname{high}(\tau=1)$ | 3 | 2.0 |
| 5 | single group | $\operatorname{low}(\tau=0.4)$ | 5 | 2.0 |
| 6 | single group | $\operatorname{low}(\tau=0.4)$ | 5 | 1.0 |
| 7 | single group | $\operatorname{high}(\tau=1)$ | 5 | 1.0 |
| 8 | single group | $\operatorname{high}(\tau=1)$ | 5 | 2.0 |
| 9 | multiple groups | $\operatorname{low}(\tau=0.4)$ | 5 | 1.0 |
| 10 | multiple groups | $\operatorname{low}(\tau=0.4)$ | 5 | 2.0 |
| 11 | multiple groups | $\operatorname{high}(\tau=1)$ | 5 | 1.0 |
| 12 | multiple groups | $\operatorname{high}(\tau=1)$ | 5 | 2.0 |

### 2.4 Results

### 2.4.1 Model dynamics

Figure 2.3 shows spatial distribution of biomass in the absence of fishing for the single and multiple groups versions. If fishing is absent, the biomass spatial distributions are practically identical. However, the spatial distributions for the two models tend to change if fishing is present and the effort is not homogeneously distributed throughout the unfished distribution of the resource (Figure 2.4). For the multiple groups version, the spatial distribution of fish at each age tends to deviate from the initial normal distribution assumption as the fish grow older. This distortion is caused by the fact that not all groups are subject to the same effort intensity, hence they encounter different fishing mortality, and therefore depletion levels over their lifetime.

In the Pacific hake example, effort is assumed to be concentrated towards the northern areas (bars on Figure 2.4). Therefore, when the multiple groups version of the model is considered (dark line on Figure 2.4), the groups that move to higher latitudes tend to be subject to stronger fishing pressure, and therefore become more depleted than groups that remain in lower latitudes. This effect cannot be detected for the younger ages (Figure 2.4, age 1). However, as cohort ages, the groups that move further (located to the right of the mean distribution for the entire cohort) start exhibiting perceptibly higher depletion levels compared to groups within the same cohort that
do not migrate as far (located to the right of the mean distribution for the entire cohort, Figure 2.4, age 5). The higher depletion levels on the fish that move further also causes the mean in the overall distribution of each cohort to shift to the south, which, over time would tend to diminish the availability of fish to the fishing fleets in the northern areas.

### 2.4.2 Simulation-estimation

The simulation-evaluation analysis showed that the five key parameters of the movement model can be estimated given spatial catch at age data, assuming that the model assumptions are satisfied. When data were simulated using the single group version (scenarios 1-8- Table 2.7), it was possible to predict the main movement parameters with practically no bias, i.e., parameter estimates were within $10 \%$ of true values (Figure 2.5). Variability in parameter estimates was lower when data were reported for five fishing grounds when compared to scenarios where data were reported only for three fishing grounds. When the data reporting was assumed to occur for five fishing grounds, the data was less aggregated and therefore more informative to the estimation of the movement pattern along the latitudinal migration route of the fish. As expected, higher values of $\tau$, the standard deviation for the catch at age error, resulted in higher variability in the parameter estimates. No difference was observed for scenarios with different values for the $\lambda$ parameter. The parameter $\lambda$ allows effort to concentrate in areas of high abundance. It is likely that the effects different values of $\lambda$ were not noticeable because of the regeneration assumption that is inherent to the single group version of the model. In other words, even though effort might have aggregated in certain areas, it did not affect the overall distribution of fish for each cohort.


Figure 2.3: Illustration of the distribution of fish of age 5, in the month of July for the single and multiple groups versions in the absence of fishing. The multiple groups version output is shown for all groups individually and combined. The vertical dashed line represents the border between territories.


Figure 2.4: Monthly representation of differences between spatial distribution of biomass for single and multiple groups versions. Vertical bars indicate relative fishing effort. Continuous and dashed lines represent vulnerable biomass for fish at age 1 and 5 throughout one year migration cycle, one panel for month). Different shades of gray indicate multiple and single group versions. The vertical dashed line represents the border between territories. Both fish biomass and effort were re-scaled from 0 to 1 for plotting.


Figure 2.5: \% Relative error for estimation of key parameters of the movement model. Scenarios are indicate in the upper right corner of each plot and the scenarios composition is indicated in the plot titles. $\mathrm{SG}=$ single group version, $\mathrm{MG}=$ multiple groups version and $\mathrm{FG}=$ fishing grounds.

When data were simulated with the multiple groups version (scenarios 9-12-Table 3.6), bias in the estimated parameters became more prominent (Figure 2.5). The effort scaler parameter, $q$, was underestimated in all scenarios by about $40 \%$. In order to evaluate the impact of the parameter bias on the predicted biomass distribution, I used plotted the median predicted biomass for scenario 12, one of the cases where the bias was most prominent (Figure 2.6). Despite the bias in parameter estimates for the multiple groups version the impact on the distribution of total biomass over time predicted by the model was relatively small (Figure 2.6). Because of the lower effort predictions due to the underestimation of $q$, higher median biomass distributions are predicted by estimation model. However, little impact is seen in the overall proportion of biomass in each area.

### 2.5 Discussion

The Lagrangian movement model described in this paper is an alternative to traditional Eulerian approaches commonly used to model the distribution of adult iteroparous fish (Goethel et al., 2011; Sippel et al., 2015). The Lagrangian approach shown here allows for the explicit consideration of migration hypotheses, such as the cyclic migration between spawning and feeding grounds, and exploration of potential impacts of covariates in shaping migration variability within a population. Traditional Eulerian models are generally represented by spatially discrete box or bulk transfer models (Carruthers et al., 2015; Methot and Dorn, 1995) or continuous advection-diffusion models (Sibert et al., 1999). Box models are simpler but require the predetermination of, usually large, spatial areas from which flow (i.e., movement) is measured. The determination of such areas can be challenging, especially due to the assumption that fishing mortality is homogeneously distributed within each area and that flow in between boxes is mainly caused by migration or diffusive movement (Walters and Martell, 2004; Carruthers et al., 2011). Frequently, these large spatial areas are determined by political or management boundaries or historical division of data, and do not correspond to an ecologically relevant partition of the habitat of the species being studied. Such artificial partitions can lead to violation of the box model assumptions. The Lagrangian model presented here is continuous in space, and therefore does not require the definition of homogeneous


Figure 2.6: Median biomass distribution for simulation and estimation models for each month of the year for scenario 12 - multiple groups, 5 areas, $\tau=2.0$.
spatial areas. However, the model output can be aggregated in larger areas for comparison with historical data or for investigation of management questions relating to political boundaries.

Advection-diffusion models are continuous in space, but are much more data intensive and generally require the availability of tagging and tracking data (Sibert et al., 1999; Costa et al., 2012). Similarly to advection-diffusion models, the Lagrangian model presented in this paper is continuous in space and time, allowing for predictions of biomass at any location in the time-space continuum. However, differently from the diffusion models, the approach shown here does not assume that animals move at random. Instead, the movement is assumed to be directed by an innate migration hypothesis, frequently derived from observed seasonal size or age distribution of the species of interest (e.g., Ressler et al., 2007; Francis and Clark, 1998). The use of a migration assumption replaces the need to directly estimate advective terms to explain fish movement and, therefore, does not rely on tagging data to determine the direction of fish movement. This is an advantage because for many fish species tagging data is not readily available and tagging studies can be difficult to carry out. This is particularly true for deep water species due the complications and high mortality rates resulting from the barotrauma caused by bringing the individuals to the surface for tagging (Nichol and Chilton, 2006; Winter et al., 2007). In addition, tagging studies usually involve high operational costs, which include tag deployment, recapture surveys and/or publicity campaigns to increase voluntary tag reporting rates in the fisheries and, in some cases, high costs associated with the tags themselves (Pine et al. 2003). Despite the high costs and the large effort associated with tagging studies, the data quality is frequently diminished by violation of basic assumptions of tagging experiments, such as changes in reporting rates over time, time-varying catchability and influence of the tag on fish behavior (Pine et al., 2003). These difficulties associated with tagging data frequently result in the lack of enough information in the data, despite extraordinary expense and effort to accurately resolve the movement dynamics of the species of interest without a number of simplifying assumptions. Alternatively, the movement model presented here relies mainly on seasonal catch and age composition data to estimate its movement parameters. Catch and age composition data are conventionally available for many temperate exploited fish species
(Melnychuk et al., 2017) and the collection of such data is already part of the management programs for such species, i.e., used in stock assessments. Therefore, the Lagrangian model presented can be used as an alternative tool to formalize and test the movement hypotheses based on data, even when tagging or movement track data are not available. It is important to note, however, that the approach described here is not meant to be a complete replacement for tagging studies. There are several caveats associated with the present approach, including the assumption of known population and fishing dynamic parameters. Such parameters are seldom known with certainty, and if the assumed values deviate significantly from the reality, the model outputs would likely be severely biased as well.

Appreciable differences between the two versions of the model, i.e., the single group and multiple groups versions, were observed. These differences are associated with the way in which movement of each age class is treated. In the single group version, all individuals within a cohort are considered equal and individuals are assumed to be normally distributed around the mean position at time. In the multiple groups version each cohort is sliced into groups which have a group-specific mean position at time. The single group model is simpler and, for this reason, much more computationally efficient. However, it relies on the assumption of regeneration of spatial distribution at each time step. That is, fish of a given age are assumed to spread spatially following a normal distribution at each time step regardless of possible local depletion due to concentration of fishing effort. This might be a reasonable assumption if the distribution of effort is relatively homogeneous over the distribution of the age group being exploited. However, effort concentration and local depletion is not uncommon, and has been observed for many fish stocks around the world (e.g., Maury and Gascuel, 2001; Bez et al., 2006). Alternatively, if fishing effort is known to be restricted to some areas, or is known to concentrate heavily in some areas, then using the multiple groups version is more appropriate. I found that a minimum of 15 groups is required to appropriately reduce the effects of regeneration of spatial distribution. The multiple groups formulation will allow local depletion to occur and persist through the life of each cohort.

An important feature of the simulation approach presented is that it explicitly accounts for spatial fishing effort with the gravity model (Caddy, 1975). Because the effort dynamics are modeled explicitly, it is possible to use the model to investigate questions relating to active avoidance of specific areas due to high bycatch occurrence or spatial aggregation in fishing effort. In the specific example of Pacific hake, the U.S. fleet has a strong incentive to avoid areas where abundance of bycatch species is high, despite potential high abundances of the target species. This effect can be modeled by linking the $E_{p o t, r}$ to the abundance and distribution of bycatch species. Spatial aggregation of fishing effort is also important because if fishers aggregate in areas of high abundance, it is likely that strong cohorts will be targeted disproportionately causing variation in selectivity across time. Time varying selectivity can be confounded with fishing mortality estimates leading to biases in the estimation of reference points and management targets (Punt et al., 2015; Martell and Stewart, 2014).

I found that it is possible to estimate the driving movement parameters of the model using spatial catch at age information collected throughout the migration cycle of the species being modeled. Data were generated and estimated using both single and multiple groups versions of the model. This procedure resulted in unbiased parameter estimates for the single group simulation scenarios and up to $40 \%$ median relative error in parameter estimates for multiple group scenarios. The causes for biased parameter estimates in the multiple groups version is unclear. However, the higher data requirements of the multiple groups version is understandable given the higher degree of complexity in the model. I have not tested the performance of this model assuming catch at age from more than five fishing grounds, but it is possible that less aggregated data would result in better resolution of the model parameters. However it is also important to consider that less aggregated data will probably have higher observation error levels and that might also impair the estimation of the model parameters.

It is possible that the relative error estimates obtained in the simulation-estimation analysis are over optimistic because the same model structure was used for simulating data and for estimating parameters. This similarity is likely to have improved the realized model fit. In addition, the pa-
rameter estimates obtained in this study are dependent on assumptions regarding the fixed model parameters, i.e., the fisheries and population dynamics parameters. The true values of such parameters are usually not well known, and estimates can change dramatically over time (Brooks et al., 2015). However, when we attempted to jointly estimate the movement and population dynamics parameters, i.e., use the current model as a stock assessment model, there was a great amount of confounding between the estimates of productivity, recruitment deviations and the movement parameters. Therefore, it is unlikely that the movement dynamics presented here could be integrated into stock assessment models.

A promising application of the Lagrangian model described here is its potential to be used as an operating model in closed loop simulations. Such simulations can be used to evaluate the effects of management strategies for exploited fish populations (Giske et al., 2001; Sainsbury et al., 2000). The model can be used to represent the complex population dynamics of migratory species, as well as the variability in distribution of stocks due to intrinsic (e.g., growth, maturity) and extrinsic (e.g., environmental forcing, fishing effort) forces to the population. One advantage is that the mechanics of this model is different from that usually implemented in stock assessment models (e.g., Methot and Wetzel, 2013; Fournier et al., 1998), which would yield significant differences between operating and estimation models in closed loop simulations. Similarities between operating and estimation models lead to improved performance of estimation models, which in turn result in overly favorable performance of management strategies (McClure et al., 2014). In reality it is unlikely that the estimation models capture all the processes that occur in nature.

A couple model extensions were not included in this chapter, but could easily be added to the model dynamics. These extensions are the addition of multidimensional movement and the use of other mathematical functions to represent migration hypotheses. The model illustration presented in this study only describes movement in a unidirectional basis, that is from spawning to feeding grounds. This simplification of movement trajectory stems partly from the knowledge of the species chosen as a case study. A unidimensional model is commonly used to describe the movement dynamics of Pacific hake, and not much is known regarding the population trajectory and habitat use
in other dimensions (Ressler et al., 2007). However for many species, migration routes are more complex and involve simultaneous migration between spawning and feeding grounds, shallow and deep water and between inshore and offshore grounds (e.g., Misund et al., 1998; Barbaro et al., 2009; Merten et al., 2016). The current approach could be easily extended to a multidimensional approach. The addition of new dimensions, however, would require the development of mathematical functions that describe movement in each dimension. The sine function presented here is a good candidate to describe cyclic movements, but linear, logistic or knife-edge functions could also be used if movement in a given dimension is thought to be permanent, as would be true for migration between nursery and rearing grounds.

I believe that the model presented here is a useful approach to model movement of migratory fish species. I anticipate that the model can be used to examine the plausibility of different movement hypotheses and to explore the possible links between fish migration and ecosystem interactions. In addition, we suggest that the model is a good candidate to be used as an operating model in closed loop simulations, especially when there is interest in evaluating the implication of migratory movement on management outcomes.

## Chapter 3

## Stock Reduction Analysis using catch at length data: Length-SRA

### 3.1 Introduction

Modern stock assessments typically attempt to fit population dynamics models to catch at age and/or catch at length data, in hopes of extracting information from these data about age/size selectivity, cohort strength, and fishing mortality patterns (Methot and Wetzel, 2013; Hilborn and Walters, 1992). Some assessment methods attempt to put aside the length frequency data, by converting these data to age compositions using age-from-length tables, perhaps using iterative methods to estimate proportions of fish at age for each length interval (Kimura and Chikuni, 1987). In cases where age data are lacking, models like MULTIFAN-CL attempt to obtain estimates of selectivity, fishing mortality and population dynamics parameters only from size distribution data (Fournier et al., 1998). Combined with a few assumptions regarding the structure and variability in length at age, this procedure can even be used to attempt to recover information about changes in body growth patterns if there is a strong age-class signal in the length frequency data (Fournier et al., 1998). It is typical for assessment results from length-based assessment models to show substantial deviations between predicted and observed length distributions of catches, reflecting both sampling
variation in the length composition data and incorrect assumptions about stability of growth and selectivity patterns (Hilborn and Walters, 1992).

Selectivity to fishing is the combination of two processes: vulnerability to the fishing gear and availability of the fished population in the area being fished (Beverton and Holt, 1957). Both processes can vary over time and therefore modify the resulting selectivity. Although selectivity process can often be directly measured through gear experiments, availability is generally harder to measure as it depends on the size-based distribution of the exploited population and the spatial distribution of the fishing fleet. Fish movement, size-structured changes in fish distribution, and changes in fleet distribution, can all affect availability and consequently lead to selectivity changes. Changes in selectivity are not uncommon (Sampson and Scott, 2012) but are usually difficult to track over time. This difficulty is associated with an inability to distinguish between changes in fishing mortality and changes in selectivity in most age- and length-based stock assessment methods. For this reason, many assessment methods rely on ad hoc parametric selectivity models that may or may not include changes over time (Maunder et al., 2014). If misspecified, such models might lead to severe bias in fishing mortality estimates and other model parameters, which could result in misleading management advice (Martell and Stewart, 2014).

Here, I introduce an alternative approach to assessment modeling that begins by assuming that the assessment model should exactly reproduce the observed catch at length composition. This approach follows the dynamics of an age structured stock reduction analysis (SRA) (Walters et al., 2006; Kimura et al., 1984; Kimura and Tagart, 1982), which follows a "conditioned on catch" format, in which catch composition is assumed to be known without error. The observed catches at age are then subtracted from modeled numbers at age to project numbers at age over time. A good review of SRA-type models is provided in Thorson and Cope (2015). The assumption of known catch composition is analogous to the classical assumption in virtual population analysis that reconstructed numbers at age should exactly match observed catch at age data (Hilborn and Walters, 1992). The suggested approach may have two key advantages over statistical catch at age and/or catch at length models: (1) it does not require estimation of age or size selectivity schedules,
and (2) catch at length data are commonly available for every year, even when age composition sampling has not been conducted.

I have named this approach a Length-SRA assessment model. Here, I present the model formulation, demonstrate its performance with a simulation-evaluation analysis, and apply it to fisheries data from the Peruvian jack mackerel (Trachurus murphyi) and Pacific hake (Merluccius productus) fisheries.

### 3.2 Methods

### 3.2.1 Stock reduction analysis with catch at length data - length-SRA

The stock reduction analysis (SRA) described here proceeds through the following steps: (1) compute numbers at age (based on recruitment estimates and mortality in the previous year); (2) convert numbers at age into numbers at length using the proportions of individuals at length given each age class; (3) calculate the exploitation rate at length using numbers at length and observed catch at length; (4) convert the exploitation rate at length to exploitation rate at age; (5) compute numbers in the following year using the exploitation rate at age, natural mortality, and recruitment estimates.

The model requires data on length composition of catch in numbers (used in step 3), a prior distribution for the recruitment compensation ratio, and a survey index of abundance that is used to tune the model parameters to the most likely stock abundance trajectory. The model also requires good estimates of growth parameters, variability around mean length at age, and natural mortality. The stock assessment and simulation routines were written in ADMB (Fournier et al., 2012) and are available on github.com/catarinawor/length_SRA.

A crucial component of the length-SRA is the calculation of proportions of individuals at length given each age class ( $P_{l \mid a}$ - eqs. T3.1-T3.5). The calculation of such proportions (eq. T3.1) relies on four main assumptions regarding the distribution of length at age: (1) The mean length at age follows a von Bertalanffy growth curve (eq.T3.4), (2) The length at age is normally distributed (eqs. T3.1-T3.3), (3) The standard deviation of the length at age is defined (e.g., eq.T3.5), and (4) $P_{L \mid a}$ is constant for all lengths equal or greater than a maximum length $L$ (eq.T3.3).

The proportions of length at age are used to convert the length-based quantities into age-based quantities, which are used to propagate the age structured population dynamics forward (Table 3.3). I assume that recruitment follows a Beverton-Holt type recruitment curve (eq. T3.6), that harvesting occurs over a short, discrete season in each time step (year or shorter), and that natural survival rate is known and constant over time (Equations T3.6-T3.10). The computation of numbers at age in the initial year (i.e., first year in which data is reported $-t=$ init) is different from that in the remaining years (Equation T3.13). Recruitment in the initial year is set to the unfished recruitment level $R_{o}$ times random recruitment deviates, which are used to indicate that the population was not at equilibrium at the start of the time series.

I used equilibrium spawner per recruit (SPR) quantities to calculate management targets, for illustration purposes I use $40 \%$ as a SPR target and use Yield $d_{S P R=40 \%}$ and $U_{S P R=40 \%}$ as target management benchmarks (Table 3.4 - Equations T4.6 to T4.14). As in all spawner per recruit calculations, the Yield $_{\text {target }}$ and $U_{\text {target }}$ estimates depend on the selectivity curves calculated for each year (Equation T4.9).

To assess how well the model tracked changes in selectivity over time, I calculated the resulting selectivity estimates by normalizing the yearly vectors of exploitation rate at length $\left(U_{l, t}\right)$ by the yearly average exploitation rate at length $\left(\bar{U}_{l}\right)$ (Equation T3.11), which is more stable than the maximum yearly exploitation rate ( $\max U_{l}$ ). This happens because observation errors tend to average out over the length classes, diminishing variability of $\bar{U}_{l}$ in relation to $\max U_{l}$. When calculating the management targets, I used the same method to calculate the mean selectivity at age (Equation T4.7), however I also averaged the selectivity at age curves over the past two years (Equation T4.7) in order to further smooth the curves.

The Length-SRA model estimates two main parameters: average unexploited recruitment $R_{0}$ and the recruitment compensation ratio $\kappa$. In addition, the annual recruitment deviations $w_{t}$ are estimated for all cohorts observed in the model. That is, the number of recruitment deviations is equal to the number of years in the time series plus the number of age classes greater than recruitment age.

Table 3.1: Indexes, variable definition, and values used in simulation-evaluation

| Symbol | Value | Description |
| :---: | :---: | :---: |
| $l$ | $\left\{l_{o}, \ldots, L\right\}$ | Central point of length bin, $L=50 \mathrm{~cm}$ |
| $a$ | $\left\{a_{o}, \ldots, A\right\}$ | Age-class, $A=20$ years |
| $t$ | $\{1, \ldots, T\}$ | Annual time step, $T=50$ years |
| $a_{o}$ | 1 | First age or age of recruitment |
| $l_{\text {bin }}$ | 2 cm | Size of length bin |
| $l_{o}$ | 8 cm | Central point of first length bin |
| init | 21 | Annual time step in which data starts to be reported |
| Distribution of length given age |  |  |
| $L_{\infty}$ | 50 cm | Maximum average length |
| K | 0.3 | Rate of approach to $L_{\infty}$ |
| $t_{o}$ | -0.1 | Theoretical time in which length of individuals is zero |
| $c v_{l}$ | 0.08 | Coefficient of variation for length at age curve |
| $P_{l \mid a}$ |  | Matrix of proportions of length at age |
| $\Phi$ |  | Standard normal distribution |
| $z l_{a, l}$ |  | Normalized $z$ score for lower limit length bins |
| $z u_{a, l}$ |  | Normalized $z$ score for upper limit length bins |
| $b l_{l}$ |  | Lower limit of length bins |
| $b u_{l}$ |  | Upper limit of length bins |
| $\bar{L}_{a}$ |  | Mean length at age |
| $\sigma_{L}$ |  | Standard deviation of length at age |
| Population dynamics |  |  |
| $R_{o}$ | 100 | Average unfished recruitment |
| $\kappa$ | 10 | Goodyear recruitment compensation ratio |
| $S$ | 0.7 | Natural annual survival |
| $\sigma_{R}$ | 0.6 | standard deviation for recruitment deviations |
| $w_{t}$ | $\mathscr{N}\left(0, \sigma_{R}\right)$ | Recruitment deviations for years \{init-A$\left.a_{o}, \ldots, \mathrm{~T}\right\}$ |
| $N_{a, t}$ |  | Numbers of fish at age and time |
| $S B_{t}$ |  | Spawning biomass at time |
| $\mathrm{mat}_{a}$ |  | Proportion of mature individuals at age |
| $a_{\text {rec }}, b_{\text {rec }}$ |  | Beverton \& Holt stock recruitment parameters |
| $V B_{t}$ |  | Biomass that is vulnerable to the survey at time t |
| $v_{a}$ | $\{0,0.5,1, \ldots, 1\}$ | Survey vulnerability at age |
| $U_{a, t}$ |  | Exploitation rate at age and time |
| $U_{l, t}$ |  | Exploitation rate at length and time |
| $C_{l, t}$ |  | Catch at length and time |
| $N_{l, t}$ |  | Numbers at length and time |
| $l x_{a}$ |  | Unfished survivorship at age |
| $\phi_{e}$ |  | Unfished average spawning biomass per recruit |
| $\widehat{s e l_{l, t}}$ |  | Selectivity estimates at length and time |

Table 3.2: Variable definition for operating model, MSY quantities, and values used in simulation-evaluation

| Symbol | Value | Description |
| :---: | :---: | :---: |
| Operating model |  |  |
| sel $_{l, t}$ |  | Fishing selectivity at length and time |
| $g, d, k$ | vary by scenario | Parameters for selectivity function |
| $U_{t}$ | vary by scenario | Annual maximum exploitation rate |
| $I_{t}$ |  | Index of abundance at time |
| $\sigma_{I_{t}}$ | 0.1 | Standard deviation for index of abundance deviates |
| $q$ | 1.0 | Catchability coefficient |
| $\tau$ |  | multivariate logistic error term with $\sigma_{\tau}=0.1$ |
| Management quantities |  |  |
| $l z_{a}$ |  | Fished survivorship at age |
| $F_{z}$ | $\operatorname{seq}(0.0,1.0, \mathrm{by}=0.001)$ | Hypothetical average fishing mortality to calculate management targets |
| $\phi_{z}$ |  | Average spawning biomass per recruit |
| $\phi_{\text {eq }}$ |  | Average exploited biomass per recruit under $U_{z}$ |
| $\widehat{s e_{a, t}}$ |  | Selectivity at age and time t |
| $R_{\text {eq }}$ |  | Average equilibrium recruitment under $U_{z}$ |
| Yieldz |  | Equilibrium yield under $U_{z}$ |
| Yield ${ }_{\text {target }}$ |  | Yield that would reduce spawner per recruit to $40 \%$ of unfished levels |
| $U_{\text {target }}$ |  | Exploitation rate that reduce spawner per recruit to $40 \%$ of unfished levels |

The objective function (Equation T5.8) is composed of a negative log-likelihood component, one penalty, and a prior component for the recruitment compensation ratio $\kappa$. The negative loglikelihood component minimizes the differences between the predicted and observed index of abundance (Equation T5.1). I assume that such differences are lognormally distributed (Equations T5.3T5.4) and use the conditional maximum likelihood estimator described by Walters and Ludwig (1994) to estimate the survey catchability coefficient $q$ (Equation T5.2). A lognormal penalty is added to the negative log-likelihood function to constrain annual recruitment residuals so estimates have mean of zero and fixed standard deviation $\sigma_{R}$ (Maunder and Deriso, 2003) (Equation T5.5). Lastly, informative normal prior for $\log (\kappa)$ and $\log (q)$ were included in the objective function (Equations T5.6 and T5.7).

Table 3.3: population dynamics for Length-SRA and operating model Distribution of length given age

$$
\begin{align*}
P_{l \mid a} & = \begin{cases}\int_{z l_{a, l}}^{z u_{a, l}} \Phi(z) d z, & l<L \\
\int_{z_{l a l}^{\infty}}^{\infty} \Phi(z) d z, & l=L \\
\int_{-\infty}^{z u_{a, l}} \Phi(z) d z, & l=l_{o}\end{cases}  \tag{T3.1}\\
z l_{a, l} & =\frac{b l_{l}-\bar{L}_{a}}{\sigma_{L_{a}}}  \tag{T3.2}\\
z u_{a, l} & = \begin{cases}\frac{b u_{l}-\bar{L}_{a}}{\sigma_{L_{a}}} & l<L \\
1.0 & l=L\end{cases}  \tag{T3.3}\\
\bar{L}_{a} & =L_{\infty} \cdot\left(1-e^{\left(-K \cdot\left(a-t_{o}\right)\right)}\right)  \tag{T3.4}\\
\sigma_{L_{a}} & =\bar{L}_{a} \cdot c v_{l} \tag{T3.5}
\end{align*}
$$

Population dynamics

$$
\begin{array}{rll}
N_{a, t>\text { init }} & = \begin{cases}\frac{a_{r e} \cdot S B_{t-1}}{1+b_{r e c} \cdot S B_{t-1}} \cdot e^{w_{t}}, & a=a_{o} \\
N_{a-1, t-1} \cdot S \cdot\left(1-U_{a-1, t-1}\right), & a_{o}<a<A \\
\frac{N_{a-1, t-1} \cdot \cdot\left(1-U_{a-1, t-1}\right)}{1-S \cdot(1-U a, t)}, & a=A\end{cases} \\
U_{a, t} & =\sum_{l}\left(P_{l \mid a} \cdot U_{l, t}\right) \\
U_{l, t} & =\frac{C_{l, t}}{N_{l, t}} \\
N_{l, t} & =\sum_{a}\left(P_{l \mid a} \cdot N_{a, t}\right) \\
S B_{t} & =\sum_{a}\left(m_{a t} \cdot w_{a} \cdot N_{a, t}\right) \\
\widehat{s e l_{l, t}} & =\frac{U_{l, t}}{\bar{U}_{t}} \\
V B_{t} & =\sum_{a}^{a} N_{a, t} \cdot w_{a}  \tag{T3.12}\\
\hline
\end{array}
$$

Initial year and incidence functions

$$
\begin{align*}
N_{a, t=\text { init }} & =l x_{a} \cdot R_{o} \cdot e^{\left(w_{t=\text { init }} \cdots w_{t=\left(\text { init }-A+a_{o}\right)}\right)}  \tag{T3.13}\\
a_{\text {rec }} & =\frac{\kappa}{\phi_{e}}  \tag{T3.14}\\
b_{r e c} & =\frac{\kappa-1}{R_{o} \cdot \phi_{e}}  \tag{T3.15}\\
\phi_{e} & =\sum_{a} l x_{a} \cdot m a t_{a} \cdot w_{a} \tag{T3.16}
\end{align*}
$$

$$
l x_{a}= \begin{cases}1, & a=1  \tag{T3.17}\\ l x_{a-1} \cdot S, & 1<a<A \\ \frac{x_{a-1} \cdot S}{1-S}, & a=A\end{cases}
$$

Table 3.4: Management quantities and operating model

$$
\begin{align*}
\hline \text { Operating model } \\
\begin{aligned}
N_{a, t=1} & =l x_{a} \cdot R_{o} \\
U_{l, t} & =U_{t} \cdot \operatorname{sel}_{l, t}^{O M} \\
C_{l, t} & =N_{l, t} \cdot U_{l, t} \cdot P_{l \mid a} \cdot \tau \\
\operatorname{sel}_{l, t} & =\frac{1}{1-g} \cdot\left(\frac{1-g}{g}\right)^{g} \cdot \frac{e^{d \cdot g \cdot(k-l)}}{1+e^{d \cdot(k-l)}} \\
I_{t} & =q \cdot V B_{t} \cdot e^{\left(\mathscr{N}\left(0, \sigma_{t}\right)\right)}
\end{aligned} \tag{T4.1}
\end{align*}
$$

Management quantities

$$
\begin{align*}
& l z_{a}= \begin{cases}l z_{a}=1 & a=a_{o} \\
l z_{a-1} \cdot S \cdot \exp \left(-F_{z} \cdot \hat{\operatorname{sel}_{a-1, t}}\right) & a_{o}<a<A \\
\frac{z_{a-1} \cdot \operatorname{sexp}\left(-F_{z} \cdot \cdot \operatorname{sel_{a-1,t}}\right)}{1-S \cdot \exp \left(-F_{z} \cdot \operatorname{sel} A_{A}\right)} & a=A\end{cases}  \tag{T4.6}\\
& \widehat{\operatorname{sel}_{a, t}}=\frac{\frac{U_{a, t-1}}{U_{t-1}}+\frac{U_{a, t}}{U_{t}}}{2}  \tag{T4.7}\\
& \phi_{z}=\sum_{a} l z_{a} \cdot m a t_{a} \cdot w_{a}  \tag{T4.8}\\
& \text { Target }_{\phi}=\left|\frac{\phi_{z}}{\phi_{e}}-0.4\right|  \tag{T4.9}\\
& \phi_{e q}=\sum_{a} l z_{a} \cdot\left(1-\exp \left(-F_{z} * \widehat{\operatorname{sel}_{a, t}}\right)\right) \cdot w_{a}  \tag{T4.10}\\
& R_{e q}=R_{o} \cdot \frac{\kappa-\phi_{e} / \phi_{z}}{\kappa-1}  \tag{T4.11}\\
& \text { Yield }_{z}=R_{e q} \cdot \phi_{e q}  \tag{T4.12}\\
& \text { Yield }_{\text {target }}=\text { Yield }_{z} \rightarrow \min \left(\text { Target }_{\phi}\right)  \tag{T4.13}\\
& U_{\text {target }}=1-\exp \left(-F_{z}\right) \rightarrow \min \left(\text { Target }_{\phi}\right) \tag{T4.14}
\end{align*}
$$

### 3.2.2 Simulation-evaluation

Model performance was evaluated using a simulation-evaluation with the biological parameters of an hypothetical fish species. I used the same model structure described in Table 3.3 for both the simulation and estimation models. However, the operating model was modified to control annual exploitation rate (Equation T4.2), time-varying selectivity (Equation T4.4), and observation and process errors.

The simulation model was initialized at unfished conditions (Equation T4.1) but only started reporting data for the simulation-evaluation procedure after the $t_{\text {init }}$ year. Selectivity in the operating model was computed with the three parameter selectivity function described by Thompson (1994)

Table 3.5: Likelihood functions and penalties

| Conditional Likelihood |  |
| :---: | :---: |
| $Z_{t}=\log \left(I_{t}\right)-\log \left(V B_{t}\right)$ | (T5.1) |
| $q=e^{\bar{Z}}$ | (T5.2) |
| Sstat $_{t}=Z_{t}-\bar{Z}$ | (T5.3) |
| $L L_{1} \sim \mathscr{N}\left(\right.$ Zstat $\left.\mid \mu=0, \sigma=\sigma_{I_{t}}\right)$ | (T5.4) |
| Penalties |  |
| $P_{w_{t}} \sim \begin{cases}\mathscr{N}\left(w_{t} \mid \mu=0, \sigma=\sigma_{R}\right) & \text { phase }<\text { lastphase } \\ \mathscr{N}\left(w_{t} \mid \mu=0, \sigma=\sigma_{R} \cdot 2\right) & \text { phase }=\text { lastphase }\end{cases}$ | (T5.5) |
| Priors |  |
| $\operatorname{prior}(\log (\kappa)) \sim \mathscr{N}(\log (\kappa), \sigma=0.5)$ | (T5.6) |
| $\operatorname{prior}(\log (q)) \sim \mathscr{N}(\log (q), \sigma=0.5)$ | (T5.7) |
| Objective function |  |
| $\operatorname{Obj}=-\log \left(L L_{1}\right)+\left(-\log \left(P_{w_{t}}\right)\right)+\operatorname{prior}(\log (\kappa))+\operatorname{prior}(\log (q))$ | (T5.8) |

(Equation T4.4). I chose to use this three parameter selectivity curve because of its flexibility, which allowed us to switch between logistic and dome-shaped selectivity curves in the scenarios in which time-varying selectivity was considered. The observation error in the operating model included lognormal error in the index of abundance and logistic multivariate error (Schnute and Richards, 1995) in the catch numbers at length (Table 3.2). Recruitment deviations were assumed to be lognormally distributed with constant $\sigma_{R}$ (Table 3.1).

I considered a total of six different scenarios in simulation-evaluation trials, including three historical exploitation rate trajectories (contrast, one-way trip and $U$-ramp) and two selectivity patterns (constant and time-varying). In the contrast scenario the exploitation rate $\left(U_{t}\right)$ starts low and increases beyond $U_{\text {target }}$ and then decreases until $U_{t} \approx U_{\text {target }}$. In the one-way trip scenario $U$ increased through time until $U \approx 2 \cdot U_{\text {target }}$. In the $U$-ramp scenario, $U_{t}$ increases steadily until $U_{t} \approx U_{\text {target }}$ and remains constant thereafter. In the constant selectivity scenario, selectivity was assumed to follow a sigmoid shape. In the time-varying selectivity scenario, the selectivity curve was assumed to vary every year, progressively changing from a dome shaped curve to sigmoid and back to dome shaped. The complete list of scenarios and the acronyms used are presented in in Table 3.6

All simulations had 30 years of data, and 200 simulation trials were performed for each scenario. I evaluated the distribution of the relative proportional error ( $\left.\frac{\text { esimated-simulated }}{\text { simulated }}\right)$ for the main parameter estimates ( $R_{0}$ and $\kappa$ ) and for four derived quantities (Depletion: $\frac{S B_{t}}{S B_{0}}$, Yield $_{\text {target }}, U_{\text {target }}$, and $q$ ).

Table 3.6: Simulation-estimation scenarios

| Scenario Code | Selectivity | $U$ trajectory |
| :---: | :---: | :---: |
| CC | constant | contrast |
| CO | constant | one-way trip |
| CR | constant | $U$-ramp |
| VC | time-varying | contrast |
| VO | time-varying | one-way trip |
| VR | time-varying | $U$-ramp |

### 3.2.3 Misspecification of growth parameters

One important feature of the Length-SRA is that it assumes that growth follows a von Bertalanffy curve and that the growth parameters are known and constant over time. If this assumption is violated, the model outcomes will be impacted as the model will try to explain the deviations from the true growth curve with changes in the selectivity pattern. Here I illustrate how the model outcomes are impacted by the misspecification of the growth parameters by purposefully misreporting the values of $L_{\infty}$ (Table 3.7). I assumed a simple logistic selectivity curve for this exercise and therefore expect the model to produce logistic patterns in the exploitation rate at length $U_{l, t}$.

Table 3.7: Scenarios for testing misspecification of $L_{\infty}$

| Scenario name | version | $L_{\infty}$ value |
| :--- | :---: | :---: |
| true | true | 68 |
| plus10 | $10 \%$ overestimated | 74.8 |
| minus10 | $10 \%$ underestimated | 61.2 |

### 3.2.4 Real data examples

Two case studies were chosen to illustrate the application of the Length-SRA to real datasets: Pacific hake and Peruvian jack mackerel. Both species are believed to be subject to time-varying selectivity.

The Pacific hake fishery is believed to exhibit time-varying selectivity due to cohort targeting and annual changes, fleet spatial distribution (Ruttan, 2003). The population is know to have spasmodic recruitment, with high recruitment events occurring once or twice every decade (Ressler et al., 2007). Pacific hake tends to segregate by size during their annual migration (Ressler et al., 2007), allowing the fishing fleet to target strong cohorts by changing the spatial distribution of fishing effort as the cohort ages. Pacific hake catch at length data was available for the period between 1975 and 2013. The survey index of abundance was available intermittently from 1995 to 2013.

The movement pattern of jack mackerel is not as well known, although fish appear to move between spawning and feeding areas (Gerlotto et al., 2012). Variability in selectivity patterns for the jack mackerel fishery are believed to be associated both with evolution of fleet capacity and gear utilization and with compression and expansion of the species range associated with abundance changes (Gerlotto et al., 2012). Jack mackerel catch at length data was available from 1980 to 2013, and the survey index was available between 1986 and 2013, with the exception of 2010.

### 3.3 Results

### 3.3.1 Simulation-evaluation

I evaluated the performance of the model in relation to the main parameters, and derived management quantities with boxplots of the relative proportional error. Throughout, I use the terms positive and negative median bias to indicate that the median relative proportional error is above or below zero. The median relative proportional error sign indicate if a parameter has been underestimated or overestimated the majority of the time.

The simulation-evaluation of the Length-SRA model resulted in a small positive median bias for the $\kappa$ parameter in all simulations scenarios. Negative median bias was seen in the $R_{0}$ estimates in all but one scenario (Constant selectivity and one-way trip exploitation history). The relative error estimates for $\kappa$ indicate that this parameter was nearly unbiased, an effect of the informative prior considered for that parameter (Figure 3.1 - bottom panel). The estimates for $\kappa$ are also more
precise than the estimates for $R_{0}$, this is a result of the use of the informative prior as well as the likelihood function which lets $\sigma_{R}$ be higher in the last phase of the estimation (Equation T5.5).


Figure 3.1: Relative proportional error for main parameters for all scenarios considered in the simulation-evaluation. Boxplots center lines indicate the median estimate. Lower and upper hinges indicate first and third quartiles. Upper and lower whiskers are given by the maximum and minimum values within the intervals given by the hinge value $+/-1.5$ - inter-quartile range (distance between the first and third quartiles).

The depletion in the last year of data $\left(S B_{T} / S B_{o}\right)$ estimates resulted in negative median relative error for all scenarios (Figure 3.2-top panel). Yield target median relative error were variable being overestimates for the VO and CO scenarios and underestimated for the CR, VC and VR scenarios. The absolute median relative error for Yield $_{\text {target }}$ was relatively low ( $<7.5 \%$ ) (Figure 3.2 - second panel). The $U_{\text {target }}$ and $q$ relative error estimates were positively biased with higher median biases seen for the CR, VO and VR scenarios (Figure 3.2-third and fourth panels).


Figure 3.2: Relative proportional error for main parameters for all scenarios considered in the simulation-evaluation. Boxplots center lines indicate the median estimate. Lower and upper hinges indicate first and third quartiles. Upper and lower whiskers are given by the maximum and minimum values within the intervals given by the hinge value $+/-1.5$ - inter-quartile range (distance between the first and third quartiles).

The simulation-evaluation exercise showed that the Length-SRA model is able to track selectivity changes through time relatively well (Figure 3.3). However, the selectivity estimates are quite variable, which is likely to be a associated with the observation error in the catch at length composition.


Figure 3.3: Simulated and realized selectivity estimates for a set of years within simulation-evaluation time series. The estimated solid lines indicate median, $2.5 \%$ and $97.5 \%$ quantiles for the derived selectivities.

### 3.3.2 Misspecification of growth parameters

I found that misspecification of $L_{\infty}$ has severe implications in the capability of the model to estimate exploitation rate at length $U_{l, t}$ (Figure 3.4). If the value of $L_{\infty}$ was reported to be lower than true, the estimates of $U_{l, t}$ were lower than true for most length and extremely high for high lengths (approaching the true $L_{\infty}$ ). In the scenario where $L_{\infty}$ was reported to be higher than true, $U_{l, t}$ was estimated to follow a dome shaped pattern, with very low exploitation rates for the higher lengths. This patterns occur because the model is trying to adjust the mismatch between proportions of catch at length and the $P_{l \mid a}$ matrix by changing the predicted selectivity pattern. As a result, failure to adequately specify $L_{\infty}$ leads to erroneous estimation of selectivity patterns and, consequently, to failure in estimating management quantities.


Figure 3.4: Simulated and realized exploitation rate at length $U_{l, t}$ when $L_{\infty}$ is misspecified. Results shown for the last four years of simulation-evaluation time series. Boxplots center lines indicate the median estimate. Lower and upper hinges indicate first and third quartiles. Upper and lower whiskers are given by the maximum and minimum values within the intervals given by the hinge value +/- 1.5 - inter-quartile range (distance between the first and third quartiles).

### 3.3.3 Real data examples

The model fit the Pacific hake and jack mackerel indexes of abundance relatively well (Figure 3.5), despite some limitation in the available data. The Pacific hake index of abundance time-series is relatively short and intermittent (survey happens every two or three years). The index of abundance time series for jack mackerel was longer, but it indicates a downward trend in abundance with low contrast in the last ten years of data.

The model fit for both species resulted in time-varying selectivities that lead to variation in Yield $d_{\text {target }}$ and consequent changes in $U_{\text {target }}$ (Figure 3.5). This is because changes in selectivity result in changes to the vulnerable biomass even if total biomass is constant. Variability in selectivity and, consequently in $U_{\text {target }}$, are more pronounced for Pacific hake, if compared to jack mackerel. The relationship between Yield $_{\text {target }}$ and $U_{\text {target }}$ is also more variable for the Pacific hake case, again an indication of temporal changes in selectivity. Whereas for jack mackerel, both Yield target and $U_{\text {target }}$ seem to follow the same trend.

The selectivity curves estimated for Pacific hake and jack mackerel are quite variable and frequently estimated to be dome shaped (Figure 3.6). The resulting selectivity curves presented for the Pacific hake case, differ from those presented in the 2014 Pacific hake stock assessment (Taylor et al., 2014). The selectivities estimates presented in the Taylor et al. (2014) assessment also vary through time but tend to follow an asymptotic shape. In the present study, the selectivity patterns tends to alternate between dome-shaped and asymptotic. For the Peruvian jack mackerel case, the resulting selectivity shapes match those presented in the assessment closely. Both the results presented here and the results presented in the assessment indicate that the Peruvian fleet selectivity for the Peruvian jack mackerel is dome shaped and with peak selectivity at young ages (Figure 3.6 and Anonymous (2013)). It is important to note, however, that the observed variability in selectivity estimates for both examples might indicate real changes in selectivity (e.g., cohort targeting) or might also be caused by misspecification of the growth parameters (see Figure 3.4). At this point it impossible to determine what are the causes for the resulting patterns in selectivity
observed with the Length-SRA fit. Further investigation would be needed if this model is to be used for management purposes.


Figure 3.5: Fit to index of abundance, historical catches, and Yield $d_{\text {target }}$ and $U_{\text {target }}$ estimates for Pacific hake and jack mackerel. Observed indexes of abundance are shown in open circles, closed dots in Yield target and $U_{\text {target }}$ panels indicate model estimates.

### 3.4 Discussion

I present a length-based stock reduction analysis (Length-SRA) that allows monitoring of timevarying selectivity. In the Length-SRA model, catch at length is assumed to be known without error, and exploitation rate at length is calculated directly from estimates of numbers at length. In turn, numbers at length are produced based on numbers at age and on probabilities derived from growth curve parameters and the assumed variability (standard deviation) around mean length at age. This fact is important because it allows the model to bypass the requirement for the estimation of a selectivity ogive, as is required in more traditional age- and length-based models (e.g., Sullivan et al., 1990; Mesnil and Shepherd, 1990) and in more recent length based state-space modeling approaches (White et al., 2016). Estimation of selectivity ogives can be very difficult, especially


Figure 3.6: Realized selectivity at age patterns across years for Pacific hake and jack mackerel.
if selectivity is believed to vary over time unpredictably (Martell and Stewart, 2014; Linton and Bence, 2011).

Nielsen and Berg (2014) presents a stock assessment approach that accounts for time-varying selectivity by treating fishing mortality at age as stochastic processes that are correlated over age and time. The accuracy in the estimates of selectivity obtained with the Length-SRA are comparable with those presented by Nielsen and $\operatorname{Berg}$ (2014), especially for the one-way trip scenarios. The Length-SRA selectivity estimates are less precise than those shown by Nielsen and Berg (2014), likely because the Length-SRA estimates incorporate observation error. Their model seems to perform extremely well, however they only considered one exploitation rate trajectory, with significant contrast in the data. In addition, the changes in selectivity considered in their study are more subtle than the ones considered here.

An important advancement of Length-SRA over conventional stock-assessment models is the indirect calculation of time-varying selectivity. This information alone can be used to characterize the complexity of the fishery system. Length-SRA on its own is reasonably accurate in deriving important management-oriented parameters (depletion and Yield target ), however another option may be to combine findings from this model with another assessment model, such as a statistical catch at age (SCA) model. In this framework, Length-SRA can be used to calculate annual selectivity patterns and provide an indication of possible changes over time. These selectivity estimates can then become an input into an SCA to calculate other important variables and produce management advice. This combination of models has been used in the past (Walters and Punt, 1994); I suggest Length-SRA may be a useful tool in this context.

Accurate estimates of selectivity are particularly important if the fishery management is based on yield per recruit reference points. Fishery yield per recruit depends on the selectivity curve (Beverton and Holt, 1957) and for this reason, changes in selectivity over time will directly affect reference points (Beverton and Holt, 1957; Hilborn and Walters, 1992). I observed selectivity changes for both Pacific hake and jack mackerel, and show how this variability can lead to a not insignificant difference between the maximum and minimum estimates of Yield target ${ }_{\text {tand }} U_{\text {target }}$
calculated along the time series. I believe that tracking these changes is important not only to ensure appropriate management recommendations, but also to illustrate the relationship between selectivity patterns and management targets (Vasilakopoulos et al., 2016).

One potential point of concern that should be considered when using the Length-SRA is that it assumes that the biological parameters used in the growth curve and catch at age relationship are known without error and constant over time. I have tested the Length-SRA under misspecification of the von Bertalanffy growth parameters, and I observed additional bias in the estimates of parameter and management quantities as well as strong distortions in the resulting selectivity parameters. Similarly, Minte-Vera et al. (2017) showed that misspecification in biological parameters, especially in asymptotic length, can have a significant impact in assessment results. Other length models, e.g., MULTIFAN-CL (Fournier et al., 1998), overcome the assumption of known growth parameters by estimating the von Bertalanffy parameters alongside the assessment parameters. Once a selectivity curve is assumed, additional deviations in observed catch at length are explained by adjusting the growth parameters. This assumption can also lead to bias in parameter estimates, as other studies show that variability in selectivity and non-asymptotic patterns are common (Waterhouse et al., 2014). In reality, in most cases it is difficult to know if patterns observed in catch at length are caused by fisheries targeting (i.e., selectivity) or if they would be more appropriately explained by adjusting the growth parameters. Therefore, I recommend that, when using the Length-SRA, the user should perform extensive sensitivity analyses over the possible range of values for the growth parameters, particularly if the predicted selectivity patterns are highly variable.

As mentioned previously, the model and simulation exercise presented here assumes that the growth parameters are known and constant through time. Consequently, time variability in growth patterns could also impacts the results produced by the model. I would not recommend attempting to estimate time-varying growth parameters within the Length-SRA because growth and exploitation rates at length are confounded. However, if estimates of time-varying growth are available, preferably from fishery independent data (empirical age-length keys), those could be used as an
input to the Length-SRA model. Non-stationarity in growth is a relatively easier phenomenon to study, particularly if a fishery independent survey is already established. Changes in growth can be investigated independently by developing empirical age-length keys. In contrast, measuring changes in selectivity directly is much more difficult and data intensive, requiring independent tagging programs.

The approach used in the Length-SRA is analogous to that used in virtual population analysis in that the length composition data is assumed to be known without error. For this reason, the selectivity estimates include extra variability due to observation and sampling error. I attempted to minimize this effect by smoothing the predicted selectivity over two years, however this method is not capable of completely removing the observation error effect from the selectivity estimates. Because of the assumption of known catch at length, it is important that the catch sampling is representative of the total removals from the population (Pope, 1972). As in any other fisheries model, biased sampling and/or low sampling effort will result in bias in parameter and fishery reference point estimates (Coggins and Quinn, 1998; Bunch et al., 2013).

Some management parameters are consistently overestimated (Yield target ) and underestimated (depletion), which may be cause for concern. However, it is important to note that both parameters have low absolute median relative error $(<7 \%)$. The magnitude of the bias in the estimates of Yield $_{\text {target }}$ and $U_{\text {target }}$ observed in this study are comparable (in magnitude) to the results obtained by Martell and Stewart (2014) for $M S Y$ and $F_{M S Y}$ in a simulation study on the impacts of timevarying selectivity on the estimates generated by a statistical catch at age model. Other studies show even higher biases in face of time-varying selectivity (e.g., Linton and Bence, 2011; Henríquez et al., 2016). The estimates of depletion are also comparable to those produced with other SRA type assessments evaluated by Thorson and Cope (2015). Overall, parameter and derived parameters estimates are generally within the range of many other stock assessment models.

The Length-SRA approach presented in this study can be a useful tool for fisheries stock assessment. I believe that this is particularly true when time-varying selectivity is thought to occur, especially if the variability is not easily predictable from historical changes in gear use/fleet com-
position. However, I would like to acknowledge that the selectivity estimates will only be reliable if the growth parameters for the population being assessed are known. In addition, the simple nature of the Length-SRA model makes it a good candidate model for inclusion in closed-loop simulation studies. Further testing of this model in a closed-loop simulation set up would provide more insight on the model performance on achieving management outcomes (Punt et al., 2016). I foresee the application of this model as an investigative tool to evaluate potential time-varying selectivity patterns, as a stock assessment tool and as part of closed loop simulation studies.

## Chapter 4

## Evaluation of harvest control rules for

## transboundary stocks

### 4.1 Introduction

In fisheries management, harvest control rules are previously agreed upon management actions that should be taken in response to stock status indicators (Deroba and Bence, 2008). Despite the long history of harvest control rule evaluations in the literature (Hilborn, 1986; Walters and Parma, 1996), the practice of formally adopting harvest control rules in fisheries management is more recent (Deroba and Bence, 2008). Over the past decade, harvest control rules have been recognized as a mechanism to increase consistency and transparency in fisheries management (Punt, 2010; Kvamsdal et al., 2016). In addition a variety of policy documents have fostered the adoption of harvest control rules in many fisheries around the world (Government of Canada, 2009; Food and Agriculture Organization of the United Nations, 1996; Magnuson-Stevens act, 2007).

Harvest control rules can be generally grouped into three categories: fixed escapement, fixed exploitation rates and threshold harvest control rules (Punt, 2010). Fixed escapement rules imply that fishing should only occur if the biomass is higher than a given reference biomass, i.e., a given amount of exploitable biomass is allowed to "escape" harvest. This kind of harvest control rule is more commonly applied to salmonids (Hawkshaw and Walters, 2015), and it has been
shown to lead to high variability in yields and increased frequency of closures (Deroba and Bence, 2008). The fixed exploitation rate harvest control rules works by adjusting the yield in proportion to the population size. Fixed exploitation rate harvest control rules reduce inter annual fishery variability when compared to fixed escapement harvest control rules (Hilborn, 1986). Finally the threshold harvest control rules are usually designed to produce stepwise changes in exploitation rate as biomass decreases below some threshold; many such control rules also include a minimum escapement threshold i.e., the harvest rate is set to zero if biomass is below a limit level. Threshold harvest control rules are popular among many fisheries management agencies (Punt, 2010) because they tend to maintain higher biomass and allow for faster rebuilding of depleted stocks (Quinn II et al., 1990).

Ideally, the choice of harvest control rule is based on an evaluation process that optimizes a set of performance metrics associated with the objectives of a fishery. Some examples of commonly used performance metrics include average expected yield, annual average variability in yield and minimum biomass threshold (Punt et al., 2016). This process usually also exposes the trade-offs between potentially conflicting objectives (Hall et al., 1988; Punt and Donovan, 2007). The evaluation of harvest control rules is usually done through closed-loop simulations (e.g., Walters, 1998; Ishimura et al., 2005) which are computer models used to simulate the fisheries management system and evaluate the performance of management options given the best available understanding of dynamic of the resource as well as observation and implementation error models.

The performance of a harvest control rule is often evaluated for an entire stock (e.g., Ishimura et al., 2005; Tong et al., 2014; Hawkshaw and Walters, 2015). However, in the case of transboundary stocks the aggregate evaluation of performance metrics may not reflect the outcomes experienced by each nation separately. This is especially true if the distribution of the fished stock varies systematically with abundance. For example, many stocks exhibit range contraction as abundance decreases (e.g., Brodie et al., 1998). This can affect the availability of the resource in a given area even when the biomass is considered to be above the aggregate stock reference points. In other stocks, spatial distribution may be a function of ontogeny, usually with larger individuals perform-
ing more extensive migrations (e.g., Ressler et al., 2007). These populations too can become less available to a given fishing nation if the population age or size structure becomes truncated due to fishing mortality, even if such fishing mortality is equal to target exploitation goals for the aggregate stock. These effects are usually not accounted for in international fisheries management treaties despite the fact that treaties are often designed with the intention of securing equitable benefits of the resource to all the parties. When the application of a harvest control rule results in a change in the distribution of the stock, then it is possible that the benefits of the treaty will not be realized by one or more parties. In such situations, it may be useful to consider the relationship between biomass, age/size composition and spatial distribution of the stock when managing transboundary stocks. This would enable us to address the following questions: Is it possible to optimize a set of performance metrics across all nations that share the resource? If not, what are the trade-offs between the performance metrics for each of the nations sharing the resource? The explicit consideration of these trade-offs can help to design effective management strategies for shared stocks. This could be achieved by using spatially explicit models to identify potential differences in management outcome experienced by nations separately, thus, exposing trade-offs between two nations that would not otherwise have been visible using a spatially aggregate approach.

Pacific hake (Merluccius productus) is an example of a transboundary stock whose spatial distribution is thought to be affected by changes in age structure (Bailey et al., 1982). It exhibits seasonal migratory behavior with spawning occurring off southern California during the winter and fish migrating north between spring and fall to feed (Ressler et al., 2007). Larger fish, typically older than age-4, migrate longer distances and are found to be more abundant in Canadian waters (Methot and Dorn, 1995). Fish age-3 years and younger tend to remain in U.S. waters off the coast of California and Oregon (Methot and Dorn, 1995; Ressler et al., 2007).

Management of the Pacific hake stock follows the regulations determined in an international treaty between Canada and the U.S.A. (United States State Department, 2004). The treaty establishes that the coastwide Total Allowable Catches (TAC) should be calculated following a 40:10 threshold harvest control rule. The treaty also determines that the TAC be split between the two
countries following a fixed allocation, $73.88 \%$ to the U.S.A. and $26.12 \%$ to Canada. Given the spatial dynamics of the resource and location of the spawning grounds, the American fishing fleet has first access to the incoming cohorts. This has the potential to cause conflicts between the two nations because harvest will lead to age truncation, which in turn could lead to limited availability of the resource in Canadian waters. Despite the potential for conflict associated with harvest levels and spatial distribution, the impacts of the current treaty based management procedures have only been evaluated for the aggregate stock (Ishimura et al., 2005; Punt et al., 2008; Taylor et al., 2014; Hicks et al., 2016). However, given the life history of the stock and the fishing practices (Bailey et al., 1982; Ressler et al., 2007), it is important to consider spatial effect of management strategies that are otherwise masked by non-spatial models.

In this chapter, I aim at addressing how the application of a harvest control rule to an aggregate stock affects spatial fishing opportunities. I evaluate the performance of a large set of harvest control rules for the Pacific hake stock using a spatially explicit model in a closed-loop simulation routine. I illustrate some differences in performance between harvest control rules using yield and conservation related metrics, for the whole stock and relative to each individual nation. I map the tradeoffs between alternative harvest policies for the two nations sharing the Pacific hake resource.

### 4.2 Methods

In order to evaluate the performance of various harvest control rules, I performed a series of closedloop simulations. The spatial operating model was used to simulate fishery and scientific data every year. Observations on the stock status were generated with process and observation error. Annual total allowable catch was set each year using alternative harvest control rules and the data generated from the spatial operating model. In the following sections, I describe the simulation model, the harvest control rules, and performance metrics in detail.

### 4.2.1 The simulation model

I used the spatial model described in Chapter 2 as an operating model to describe the population dynamics of the Pacific hake resource. The Lagrangian model used in that study allows the fish to move in a seasonally cyclic manner that is characteristic of the Pacific hake offshore stock (Ressler et al., 2007). This model applies a sine function to model the cyclic the movement of each individual cohort along the coast of U.S.A. and Canada. The mean position of an individual cohort at a given time step $t$ is given by $\bar{X}_{a, t}$, which is a function of the mean minimum position $\bar{X}_{\text {min }}$, the mean maximum cohort specific position $\bar{X}_{\text {max }, a}$, the number of time steps within a migration cycle $t_{\max }$ and the time step at which the migration cycle starts $t_{0}$ (Equation 4.1).

$$
\begin{equation*}
\bar{X}_{a, t}=\bar{X}_{\min }+\left(\bar{X}_{\max , a}-\bar{X}_{\min }\right) \cdot\left(0.5+0.5 * \sin \left(t \cdot \frac{2 \pi}{t_{\max }}-t_{0} \cdot \frac{2 \pi}{t_{\max }}-\frac{\pi}{2}\right)\right) \tag{4.1}
\end{equation*}
$$

As noted above, the mean maximum position $\bar{X}_{\text {max, }, a}$ is specific for each separate cohort. The extent of the migrations is given by a logistic function of age, similar to the one used in Methot and Dorn (1995) (Equation 4.2), which allows older (and larger) fish to move further away from the spawning grounds. In the following function, the parameters $a_{50}$ and $\sigma_{X_{\max }}$ are the logistic function parameters, and $\sigma_{v t}$ is normally distributed random error component.

$$
\begin{equation*}
\bar{X}_{\text {max }, a}=\frac{1}{1+\exp \left(-\left(a-a_{50}\right) / \sigma_{X_{\max }}\right)} \cdot e^{\left(v t \sim \mathcal{N}\left(0, \sigma_{v k}\right)\right)} \tag{4.2}
\end{equation*}
$$

For a more detailed description of the movement model, as well as the population dynamics components and effort dynamics components of the operating model used in this study, I recommend that the reader refer to Chapter 2. In this study, I used the multiple groups version of the model described in Chapter 2. The model parameterization was extracted from the 2017 stock assessment (Berger et al., 2017b), and the movement parameters were set to approximate the movement dynamics of Pacific hake described in the literature (Methot and Dorn, 1995; Ressler et al., 2007). All
parameter values are given in Table 4.2. In order to mimic the historical trends in abundance, I set the historical catch limits for the historical data equal to the realized catches by each nation.

The operating model, therefore has the ability to model Pacific hake movement and effort distribution allowing the characterization of the relationship between fishing mortality, strong recruitment events and cohort targeting on the distribution of the stock, and hence the realized performance in each nation. As the fishing mortality increases, the age structure of the population will tend to become truncated (due to the cumulative effects of fishing mortality), and therefore, in the operating model, the mean biomass distribution of the stock will shift southwards, reducing the availability of the resource in northern waters.

The Pacific hake stock distribution is also affected by the recruitment dynamics. When a strong recruitment event occurs, the mean biomass distribution of the resource will be strongly linked to the age of that strong cohort, i.e., the mean biomass distribution of the stock will tend to shift north as that cohort grows. Strong recruitment events occur recurrently for the Pacific hake offshore stock (Berger et al., 2017b; Ressler et al., 2007). These strong recruitment events usually increase the overall biomass of the stock significantly, and individuals from strong cohorts dominate the fisheries catch for a few years. Despite the intermittent strong recruitment events in the Pacific hake time series, the causes for such strong recruitment events are unknown so predictions of when a strong recruitment will occur in the future are unreliable. In order to model this uncertainty, I opted to simulate three possible recruitment scenarios based on the historical recruitment time series reported by Berger et al. (2017b). I repeated the last 30 years of recruitment deviations reported by Berger et al. (2017b) twice to generate the recruitment for the next 60 projection years. These projection recruitment time series were modified to generate three scenarios: no strong recruitment events, one strong recruitment event per decade, and two strong recruitment events per decade. I opted for the repetition of the historical recruitment time series in order to maintain the historical patterns in recruitment autocorrelation, as well as the cycles in strong recruitment occurrences, i.e., a minimum interval of thee years between strong recruitment events.


Figure 4.1: Logistic functions used in the three movement scenarios considered in this study.

In addition to scenarios that explore the impacts of strong recruitment events, I also explored the sensitivity to the model in relation to the movement parameters. More specifically, I explored changes in the logistic function that describes the maximum average position reached by each cohort (Equation 4.2). The modification to the logistic curve are shown in Figure 4.1. The movement parameter sensitivity analysis was only performed for the no strong recruitment scenario. A list of scenarios evaluated is presented on Table 4.1.

The historical population was reconstructed for the years 1966 to 2016 by simulating the population dynamics using the stock assessment parameters reported in Berger et al. (2017b), and setting the historical catches equal to those extracted by the U.S.A. and Canada fleets during that period. Catches for both nations for the historical period were also reported by Berger et al. (2017b). Then

Table 4.1: List of scenarios for closed loop simulations

| Number | Recruitment | Movement |
| :---: | :---: | :---: |
| 1 | no strong recruitment | Base |
| 2 | one strong recruitment per decade | Base |
| 3 | two strong recruitment per decade | Base |
| m 2 | no strong recruitment | Early movement |
| m 3 | no strong recruitment | Late movement |

the closed loop simulations were carried on for 60 years into the future. For the closed loop simulations, I assumed that the TAC allocation between nations remains constant as determined in the Pacific hake treaty, $\mathbf{7 3 . 8 8 \%}$ to the U.S.A. and $26.12 \%$ to Canada.

In the simulations, the observation model was represented by adding uncertainty around the model predictions of relative spawning biomass, i.e., spawning biomass levels in relation to the unfished average. This study focuses on exploring and comparing the performance of harvest control rules, not on the stock assessment components of the management process. Therefore, I chose to not implement an assessment model in the closed loop simulations. Instead, the observation uncertainty was represented by adding autocorrelated and normally distributed error around the model predictions of true biomass and spawning biomass (Equation 4.3 and 4.4). Walters (2004) shows that estimates of biomass from stock assessments are usually autocorrelated over time; I assumed that the autocorrelation coefficient, $\rho$, was 0.5 . This approach was chosen because of computational convenience, i.e., faster simulation running time than the simulation of the stock assessment methodology. I believe that the high autocorrelation coefficient I use provides a comparable effect to that of using more complicated assessment models.

$$
\begin{array}{r}
\widehat{B_{t}}=B_{t} \cdot e^{\varepsilon_{t}} \\
\frac{\widehat{S B_{t}}}{\widehat{S B_{0}}}=\frac{S B_{t}}{S B_{0}} \cdot e^{\varepsilon_{t}} \\
\varepsilon_{t}=\rho \cdot \varepsilon_{t-1}+v_{t} \\
v_{t} \sim \mathscr{N}(0, \sigma=0.3) \tag{4.6}
\end{array}
$$

Table 4.2: Pacific hake operating model dimensions and parameter values

| Symbo | Value or Range | Description |
| :---: | :---: | :---: |
| Model Dimensions |  |  |
| $t$ | 1-12 | Time steps within a migration cycle |
| $y$ | 50-160 | Years |
| Y | 60 | Total Number of projection years |
| hy | 50-100 | Historical years |
| $a$ | 1-20 | Age |
| $r$ | 30-60 Area |  |
| k | 5 | Fishing grounds |
| kb | 42, 46, 48.5 and 51 | Fishing ground boundaries in latitude degrees |
| $n$ | 2 | Number of nations |
|  | 48.5 | Nation boundary in latitude degrees |
| $g$ | 1-20 | Groups |
| $d r$ | 1 | Interval between two adjacent areas |
| Population dynamics parameters |  |  |
| M | 0.223 | Annual natural mortality |
| $R_{0}$ | 2923 thousand tons | Average unfished recruitment |
| $h$ | 0.814 | Beverton \& Holt recruitment steepness |
| $\sigma_{R}$ | 1.4 | Standard deviation for recruitment deviations - used in bias correction only |
| Movement parameters |  |  |
| $t_{0}$ | 1 | Time step at which individuals are at their minimum average position |
| CV | 0.07 | Coefficient of variation for position at at age |
| $a_{50}$ | 4.0 | Inflection point for maximum average position logistic function |
| $\sigma_{X_{\text {max }}}$ | 2.0 | Standard deviation for maximum average position logistic function |
| error levels |  |  |
| $\sigma_{w x}$ | 0.08 | Standard deviation for lognormal variation around the maximum average position |
| $\sigma_{v t}$ | 0.1 | Standard deviation for lognormal variation around the effort scaler |
|  | Effort parameters |  |
| $E_{y, n}$ | 1 for nation 1 and 0.35 for nation 2 | Yearly effort scaler - constant for all years |
| $E_{t, k}$ | ( $0,0,0,0,0.5,1.0,1.0,1.0,0.5,0.1,0.0,0.0$ ) | Monthly effort scaler |
|  | $\begin{aligned} & \text { for } k=1,2,3 \\ & (0,0,0,0,0,1.0,1.0,1.0,0.5,0.3,0,0) \\ & \text { for } k=4,5 \end{aligned}$ |  |
| $q$ | 3 | Effort scaler |

### 4.2.2 The 40:10 harvest control rule

The Pacific hake treaty determines that the annual quota for the stock should be determined according to a 40:10 threshold harvest control rule (United States State Department, 2004; Hicks et al., 2016). The $40: 10$ harvest control rule used in the Pacific hake agreement determines that the coast wide total allowable catches are calculated using a proxy for the fishing mortality that will produce maximum sustainable yield ( $F_{M S Y}$ - in practice replaced by the proxy $F_{S P R=40 \%}$ ) whenever the spawning biomass is above $40 \%$ of average unfished levels. The $40: 10$ adjustment refers to the reduction in harvest rate when the spawning biomass falls below $40 \%$ of unfished average equilibrium level. The harvest rate adjustment corresponds to a linear decrease in TAC if the spawning biomass is between $40 \%$ and $10 \%$ of unfished spawning biomass and set to zero if spawning biomass is below the $10 \%$ threshold. I used the same formulation as the one described by Hicks et al. (2016).

The 40:10 harvest control rule results in very high quota recommendations when the stock abundance is high, which happens whenever a strong cohort reaches maturity (around age 3). However, in reality the actual quotas recommended by the Pacific hake Joint Management Committee are usually capped and tend not to exceed 600 thousand metric tonnes (Hicks et al., 2016). For this reason, I implemented a cap on the $40: 10$ harvest control rules recommendations to 600 thousand tonnes.

### 4.2.3 Linear harvest control-rules

I evaluate a series of harvest control rules that are given by a linear relationship between relative spawning biomass ( $S B_{t} / S B_{0}$ ) and TAC. I opted for evaluating linear harvest control rules because they encompass a broad range of harvest control rules commonly used in fisheries management (i.e., fixed exploitation rate and fixed escapement). Similar rules are frequently considered in policy optimization studies, (e.g., Reed, 1979; Moxnes, 2003; Hawkshaw and Walters, 2015). In addition, this type of control rule has also been previously evaluated for Pacific hake (Ishimura et al., 2005) but not within a spatially explicit model. The re-evaluation of the linear harvest control rules allow for direct comparison with the Ishimura et al. (2005) study, building up on previous knowledge.

The linear harvest control rule functional form is given in Equation 4.7 and illustrated on Figure 4.2. The slope is the harvest rate at which the stock biomass is harvested. The intercept is the relative spawning biomass threshold (biomass threshold, for short). The biomass threshold is the minimum relative spawning stock biomass level required for harvest to occur. $\widehat{B_{t}}$ is the observed total biomass in the last year of data and $S B_{0}$ is the unfished average spawning biomass. Analogously to what was implemented for the $40: 10$ harvest control rule described in the previous section, I impose a cap on TAC so that it does not exceed 600 thousand tonnes. Figure 4.2 shows an illustration of the resulting TACs as a function of relative spawning biomass for two linear harvest control rules examples and the implementation of $40: 10$ rule.

$$
\begin{equation*}
T A C=\text { slope } \cdot \widehat{B}_{t} \cdot \frac{\left(\widehat{S B}_{t}-S B_{0} \cdot \text { intercept }\right)}{S B_{0}} \tag{4.7}
\end{equation*}
$$

To evaluate and compare the performance of linear harvest control rules, I systematically calculated a series of performance metrics over a range of 10 slopes (to capture alternative harvest rated from 0.05 to 0.5 in 0.05 intervals) and 6 intercepts (representing different relative biomass threshold from 0.0 to 0.5 in 0.1 intervals). I then mapped the performance metrics values over the slope-intercept surface. I computed the performance metrics for 54 combinations of slope and intercept and the $40: 10$ harvest control rule. Each combination is evaluated with 100 simulation runs with the same set of random number seeds for each harvest control rule, which was sufficient to accurately and precisely characterize the distribution for each performance metric for each harvest control rules.

### 4.2.4 Performance metrics

In order to evaluate the harvest control rules, I calculate a set of performance metrics for the aggregate fisheries and for each nation's fleet separately. The performance metrics that were calculated for each nation separately include $\log$ utility (Average of annual $\log$ of yield plus a small value), total yield and annual average variability in yield (AAV) (Table 4.3). Total yield and AAV were


Figure 4.2: Illustration of the relationship between relative spawning biomass and TAC for two example linear harvest control rules and the 40:10 harvest control rule used in this study.
chosen to illustrate potential impacts of the magnitude and variability of yield, respectively. Log utility was included to represent a composite view of these two quantities as it increases as yield increases, but it also strongly penalizes fisheries closures (i.e., yield equal to zero). In addition, I computed the following performance metrics for the stock as an aggregate (both nations combined), $\%$ of times the fishery closed, $\%$ of times the total biomass was below $40 \%$ of average unfished levels (Table 4.3).

This set of performance metrics was chosen based of potential objectives that have been analyzed in other closed loop simulations for hake (Taylor et al., 2014; Hicks et al., 2016) and other

Table 4.3: Equations used to calculate performance metrics for evaluation of harvest control rules. All quantities were averaged across simulation runs.

Average log utility
$\log (U)=\frac{\sum^{y} \log \left(\text { Yield }_{y}+1\right)}{Y}$
Average annual yield
Yield $=\frac{\sum^{y} \text { Yield }_{y}}{Y}$
\% of closures
\%Closure $=\sum^{y} C L / Y$
Mean Annual Average Variability in Yield
$A A V=\operatorname{mean}\left(\frac{\mid \text { Yield }_{i}-\text { Yield }_{i-1} \mid}{\sum_{i=y-1}^{i=y} \text { Yield }_{i}}\right)$
$\%$ of years with of stock spawning biomass below $40 \%$ of $S B_{o}$
$\% B<40 \%=\frac{\sum^{y} B<40 \% S B_{o}}{Y}$
fisheries (Cox et al., 2013; Punt et al., 2008): preference for higher average yield, stability (i.e., low inter annual variation in TAC), avoidance of fisheries closures, and the conservation objective of maintaining the biomass at or above the target level.

The analysis presented in this study include 305 unique simulation configurations (61 harvest control rules, three recruitment scenarios and three movement scenarios). In order to summarize the outputs I chose to compute the average performance over the projection years and the simulation runs for each harvest control rule, recruitment scenario and movement scenario configuration.

For both yield and log utility, I compare the relative performance by nation by using trade-off plots, i.e., by contrasting the relative performance of each metric by nation. The average performance metrics for each nation are rescaled so that the maximum value is set to one. For these tradeoffs plots, I limit the linear harvest control rules to those with intercept (biomass threshold) equal or below 0.3. This threshold was chosen so that the figures would be more easily interpretable.

To compare the performance of the linear and 40:10 harvest control rules in terms of AAV, percentage of times the fishery closed, and percentage of times the total biomass was below $40 \%$, I created surface maps where the x and y axes represent the values for biomass threshold and harvest
rate for the linear harvest control rules, and the z axis (color gradient) represents the values obtained for each performance metric. I also indicated in the surface, which of the linear harvest control rules produced the minimum or maximum (the optimum) performance metric. The performance metric value obtained with the $40: 10$ rule was also mapped to that surface, i.e., the $40: 10$ indicator was placed on the point that more closely matched the performance metric value obtained with the 40:10 rule.

### 4.3 Results

Each combination of harvest control rule and recruitment scenario gives rise to a biomass and yield trajectory. As an example, I show three of these catch trajectories under the scenario with no strong recruitment events (Figure 4.3 ). These trajectories represent median and $95 \%$ intervals for catch trajectories simulated under the 40:10 rule and for two linear harvest control rules with 0.1 biomass threshold and 0.1 and 0.5 harvest rates. The linear harvest control rule with 0.1 harvest rate (red line, Figure 4.3 ) produces lower catches than the $40: 10$ rule for both nations. However, the linear harvest control rule with higher harvest rate ( 0.5 - blue line, Figure 4.3) produces higher median yields than the $40: 10$ rule for nation 1 (U.S.A.) and lower median yield than the $40: 10$ rule for nation 2 (Canada). This result is an indication of how high harvest rates decrease the availability of the resource in northern areas, leading to lower yield to Canada. One interesting fact to notice is that, in Figure 4.3, the yield variability increases as the exploitation rate increases. This result could be considered counterintuitive as one would expect less variability in catches if a stock is lightly fished. This result is likely a byproduct of the simulation design. Here, I assume that the population has exactly the same recruitment deviation trajectories regardless of stock size for all simulation runs. Therefore the variability around biomass and yield becomes directly proportional to the population size. High biomass, will produce higher recruitment variability and higher observation error, consequently producing higher yield variability, while the inverse will occur for low biomass.


Figure 4.3: Historical and median and $95 \%$ intervals for projected catches for three example harvest control rules under the "no strong recruitment" scenario. Harvest control rules include the $40: 10$ rule with cap, and two linear harvest control rules with biomass threshold $\left(S B_{t} / S B_{o}\right)$ of 0.1 and exploitation rates of 0.1 and 0.5 .

Reproducing Figure 4.3 for all harvest control rules evaluated in this study would be a formidable task. For this reason, I chose to summarize the results for all scenarios and harvest control rules by comparing the mean performance across projection years and across simulation runs.

In Figure 4.4, I show the differences in mean performance when it comes to average log utility and average yield for the two nations sharing the resource. If no interaction between harvest levels and spatial distribution of the stock existed the lines shown in Figure 4.4 would be straight, following a 1:1 ratio. However, the lines tend to bend for low biomass threshold and higher harvest rates, indicating that Canada (Nation 2) experiences lower than expected catches. This is a result of decreased availability of the Pacific hake resource in Canadian waters. As the harvest rate (slope) increases, the population age structure will become more truncated, and it becomes harder for the

Canadian fleet to catch its full quota. In general the difference in performance between nations and harvest control rules become more important as the incidence of strong recruitment decreases (4.4). In terms of log utility, the $40: 10$ harvest control rule tends to perform near optimum for both nations across all scenarios (Figure 4.4). However, when it comes to average yield, the $40: 10$ harvest control rule performs relatively better for Canada than the U.S.A. (Figure 4.4). For the U.S.A (Nation 1 - x axis on Figure 4.4), both yield and log utility tend to increase as harvest rate increases and biomass threshold decreases. For Canada (Nation 2 - y axis on Figure 4.4) results for log utility and yield indicate that better performance is obtained at harvest rates between 0.1 and 0.25 for the no strong recruitment scenario and higher harvest rates ( $>0.35$ ) for the other recruitment scenarios (Figure 4.4). In addition, for the no strong recruitment scenario, the relative yield and log utility for Canada declines when harvest rates are greater than 0.35 , while the relative yield and log utility results for the U.S.A. tend to remain constant (Figure 4.4).






harvest rate $0.1-0.25-0.4-40: 10$

$$
0.15-0.3-0.45
$$

Figure 4.4: Comparison of relative performance (normalized to the maximum value by nation) of average log yield (log utility) and average yield between nations (trade-offs). Quantities were normalized by the maximum observation per nation and scenario for comparison. Nation $1=$ U.S.A and Nation $2=$ Canada. Colors indicate harvest rates for linear harvest control rules and point shape indicate biomass threshold relative to unfished spawning biomass ( $S B_{t} / S B_{o}$ ). Text indicates performance of the 40:10 harvest control rule.

The AAV values increased as the incidence of strong recruitment events decreased (see color scale legend on Figure 4.5). Across all recruitment scenarios, the minimum variability occurs at lower values of biomass threshold ( $\leq 0.1$ ), and high harvest rates $(>0.4$ ) (Figure 4.5). The 40:10 rule AAV gets closer to the point where minimum AAV is found as the incidence of high recruitment events increase (Figure 4.5). This results indicate that, for the scenarios considered in this study, minimum variability in catch is obtained when the stock is fished to very low levels and kept near the origin of stock-recruitment relationship. At some point, in reality, the biomass would get so low that it would no longer be economically viable to operate a fishery. Similarly to what happened in Figure 4.3, the results observed in Figure 4.5 could also be influenced by the simulation design. Lower variability in both biomass and yield occur at low population size, because recruitment deviations here were assumed to follow the same trajectory irrespective of population size. This results would likely change, if, for example, strong recruitment events became more likely when abundance is either high or low. To date, there is no evidence of such phenomenon for the Pacific hake stock, as historical strong recruitment events seem to happen at both high and low spawning biomass levels (Berger et al., 2017b).

Fisheries closures were only computed for the aggregate stock, as closures are determined based on the total biomass threshold. As expected, closure rates decrease as biomass threshold decreases (Figure 4.6). Also, the area with very low closure percentage (blue area in the colored surface) increases as the occurrence of strong recruitment events increases. This happens because when strong recruitment events occur the population biomass tends to increase considerably, rendering it unlikely that the biomass levels will fall below the threshold. The $40: 10$ also performed very well in avoiding fisheries closures, with performance comparable to the minimum closure percentage across all scenarios (Figure 4.6).

With reference to the conservation performance metric, the $\%$ of time that biomass is below $40 \%$ of unfished levels, minimum values occurred for high biomass threshold values (Figure 4.7blue area). For the scenario with two strong recruitment events per decade low harvest rates also produced low \% of biomass below $40 \%$. In relation to the $40: 10$ rule performance, the difference
between the $40: 10$ rule and the minimum $\%$ of time that biomass is below $40 \%$ of unfished levels tended to increase as the number of strong recruitments per decade decreased (Figure 4.7). For the scenarios where no strong recruitments occur, biomass was predicted to be below $40 \%$ of unfished levels about $86 \%$ of the time.

The sensitivity analysis for the movement parameters of the migration model indicate that the movement parameter values have less impact on the difference in performance between nations than the occurrence of strong recruitments (Figure 4.8). However, the movement parameters do have an impact. For the Early movement scenario, i.e., where fish migrate farther at younger ages, the differences in performance between the nations are less prominent than in the Base case and Late movement scenarios. In addition, in the Early movement scenario, the $40: 10$ rule performance is closer to that of linear harvest control rules with low harvest rate and low biomass threshold for both nations (Figure 4.8). This result indicates that if a higher percentage of younger fish migrate further north, there will be less of an impact on the long term yield due to reduced availability of the resource in the northern range of the distribution.

Nation 1

one strong recruitment
Nation 1

two strong recruitments


Nation 2


Nation 2


Nation 2


Total


Total



Figure 4.5: Median Average Annual Variability in yield (AAV). Surfaces indicate performance for linear harvest control rules. White circle indicates performance level comparable to the $40: 10$ harvest control rule. Minimum value along the surface is indicated with black square. Recruitment scenarios are indicated on the rows. Nation $1=$ U.S.A and Nation 2 = Canada.Total is aggregate result.


Figure 4.6: \% closures for total fisheries over the 60 years of simulation. Surfaces indicate performance for linear harvest control rules. White circle indicates performance level comparable to the $40: 10$ harvest control rule. Minimum value along the surface is indicated with a black square. Recruitment scenarios are indicated on the columns: A - no strong recruitments, B - one strong recruitment per decade, C - two strong recruitments per decade.


Figure 4.7: \% of time that biomass is above $40 \%$ of average unfished levels. Surfaces indicate performance for linear harvest control rules. White circle indicates performance level comparable to the $40: 10$ harvest control rule. Minimum value along the surface is indicated with a black square. Recruitment scenarios are indicated on the columns: A - no strong recruitments, B - one strong recruitment per decade,C - two strong recruitments per decade.






harvest rate $0.1-0.25 \ominus 0.4-40: 10$

$$
0.15-0.3-0.45
$$

Figure 4.8: Comparison of relative performance of average log yield (log utility) and average yield between nations (trade-offs) for the three alternative movement scenarios. Quantities were normalized by the maximum observation per nation and scenario for comparison. Nation $1=$ U.S.A and Nation $2=$ Canada. Colors indicate harvest rates for linear harvest control rules and point shape indicate biomass threshold relative to unfished spawning biomass ( $S B_{t} / S B_{o}$ ). Text indicates performance of the 40:10 harvest control rule.

### 4.4 Discussion

The results shown in this study corroborate those presented by Ishimura et al. (2005) in that lower values of both biomass thresholds and harvest rates tend to produce higher yields and lower variability in yield for the aggregate stock. The present results are also in agreement with Ishimura et al. (2005) in pointing that the $40: 10$ harvest control rule performs similarly to the low harvest rate and low biomass threshold alternatives in terms of maximizing yield and minimizing yield variability (bottom left are of the heat maps). The results obtained for the $40: 10$ harvest control rule with cap also corroborate with those presented Taylor et al. (2014) and Hicks et al. (2016), indicating that the $40: 10$ harvest control rule, with cap, performs well in the long term; i.e., it secures yield while minimizing fisheries closures and maintaining the biomass above the $10 \%$ of unfished levels threshold.

However, in addition to evaluating the performance of harvest control rules for the stock as an aggregate, I also evaluated the impacts experienced by each nation individually. I show that there is a difference in performance between the two fishing nations when the log utility and sum of yields metrics are considered. In general, after rescaling by the maximum observed values, the U.S.A. has higher relative yield and log utility when fishing at higher harvest rates when compared to Canada. These differences diminish as the frequency of strong recruitment events increase. This result is associated with the migration of the stock because the Pacific hake migration is associated with age and size of the fish (Ressler et al., 2007). As harvest rates increase, the overall age structure of the population will become more truncated, i.e., older and larger fish become less abundant; therefore the resource becomes less abundant in the northern range of the distribution which corresponds to waters off Washington state and Canada. This effect is minimized as the frequency of strong recruitment events increase because of a combination of higher overall abundance and reduced harvest rates induced by the 600 thousand tons cap imposed on all harvest control rules. The differences in long term yield between U.S.A and Canada are also minimized when if fish start migrating further north at younger ages, as was demonstrated on the early movement scenario.

Overall the 40:10 harvest control rule seems to be a good compromise for the two nations, and it performs relatively well across all performance metrics considered in this study. In the scenario where no strong recruitment events occurred, the $40: 10$ rule tended to reduce the biomass below $40 \%$ of unfished biomass about $86 \%$ of the time. However, even when no strong recruitment events were considered, the biomass rarely went below $10 \%$ of unfished levels. Our results are similar to those obtained by Taylor et al. (2014) and Hicks et al. (2016), who considered even lower TAC caps for the aggregate stock; they also found that the value chosen for the TAC cap is inversely related to the conservation metrics, with lower caps resulting in more conservative outcomes. In alignment with other studies, the adoption of a formal TAC cap for the Pacific hake fishery is likely to result in prevention of fishery closures, prevention of severe depletion of the stock (i.e., stock biomass falling below $10-20 \%$ of average unfished levels), and the provision of a more stable distribution of the resource (given limited exploitation rates on strong cohorts).

The present study has two major limitations. These are the limited sensitivity analyses for the key biological parameters, and the simplified representation of measurement and observation error in the analyses. I assume that the biological population parameters for the Pacific hake stock are stable over time (i.e., fixed and subject to random variability only) and equal to those reported in the 2017 stock assessment (Berger et al., 2017b). Punt et al. (2008) shows that uncertainty in stock recruitment parameters, more specifically, productivity and recruitment variability, can have an impact on various performance metrics, including the percentage of time that biomass is above some threshold quantity. I observed similar results regarding changes in productivity when comparing the results across the three recruitment scenarios considered in this study. I also parameterized the movement dynamics of the resource based on literature documentation instead of using a statistical model fit to data. In Chapter 2, I showed that the movement parameters can be estimated if spatial catch at age composition data is available. An expansion of this study should include an evaluation of uncertainties in other key population dynamics parameters, such as the growth rates, (and how they might vary for strong cohorts), as well as an estimation of the
movement parameters, which will affect the difference in performance between the two fishing nations.

In this study, I used an auto-correlated error time series to represent the measurement error, i.e., the error associated with stock assessments. This methodology was suggested by Walters (2004), and employed in other studies of evaluation of harvest control rules (e.g., Punt et al., 2008). However, even though I believe that the results shown here are representative of the overall trends and trade-offs between performance metrics experienced by each nation, the results might change if other levels of autocorrelation and variance are used in the observation model. In a sensitivity analysis (results not shown), I found that if lower observation error variances are considered, the long term yields become higher and the difference in performance of long term yield between the U.S.A. and Canada become more pronounced. (Moxnes, 2003) reviews evidence of this phenomenon when using a policy optimization model to investigate the impacts of measurement error and stock uncertainty in policy outcomes. (Moxnes, 2003) found that if stock measurements are more uncertain, the revenue from a fishery tends to decrease and the optimum policies become more conservative.

In addition to the weaknesses described above, I would like to also emphasize that the performance metrics chosen for this study are somewhat arbitrary and chosen as a potential representation of the fishery objectives. The performance metrics used in this study are equal or similar to the ones used in the management strategy evaluation process carried out by the Pacific hake Joint Technical Committee (Taylor et al., 2014; Hicks et al., 2016). However, if a similar exercise is to be used to evaluate management options in the Pacific hake fishery, the preferred policies in practice will depend on performance measures and objectives defined in the Pacific hake management process.

Other studies have evaluated management options for migratory and transboundary fish stocks, usually accounting for the spatial effect indirectly. For example, Jones et al. (2016) implemented closed-loop simulations for the Lake Erie walleye fisheries with the objective of comparing the performance of alternative harvest control rules, and report trade-offs between the Canadian commercial fisheries and the U.S. recreational fisheries. To account for changes in availability associated
with fish movement, they included time-varying catchability in their non-spatial model. In addition, in recent years there has been increased interest in investigating the effects of spatial structure on stock assessment outcomes and management benchmarks (Berger et al., 2017a). Many simulation evaluation studies have been done to assess the impacts of spatial structure and movement dynamics on stock assessment performance and reference points (e.g., Lee et al., 2017; Goethel and Berger, 2017; Kerr et al., 2017; Carruthers et al., 2015). However the use of spatially explicit models in closed loop simulations remain relatively scarce, in part due to the computational burden and the difficulties in fitting spatially structured models to data (Goethel et al., 2016).

This study focused on Pacific hake as a case study and, for this reason, the model parameterization and structure set to mimic the dynamic of that resource. However, I believe that the framework designed here can be applied to many other transboundary resources that are subject to size segregation and/or migration range variability. The issue of management of transboundary stocks susceptible to changes in migration range has been explored in the literature under a game theory approach (e.g., Bailey et al., 2013; Hannesson, 2013; Liu et al., 2016). These studies generally point out that cooperative approaches to management perform better over the long term. However, Bjørndal and Ekerhovd (2014) point out that changes in migration range and spatial distribution are likely to impact international management agreements. Here, I present a framework that can aid cooperative management agreements to evaluate the impacts of harvest control rules and other management procedures on the distribution of the stock. This tool can be used to detect changes in spatial distribution over time, and search for management procedures that minimize change in stock distribution, helping to ensure equitable access to the resource by the parties sharing the stock.

In summary, the framework and evaluation exercise presented in this study are valuable for the management of the Pacific hake resource and for the management of migratory transboundary species in general. For the Pacific hake resource, I demonstrate the potential implications of population size truncation and change in migration range that can arise from using different harvest control rules. I also demonstrate the effectiveness of the 40:10 harvest control rule and the potential benefits of imposing a TAC cap. For migratory transboundary species in general, I present a frame-
work to aid the identification of effective management procedures, that promote the sustainability of the stock and stable spatial distribution of the resource.

## Chapter 5

## Conclusion

The overarching objective of this dissertation work was to explore questions that relate to the management of migratory transboundary species. I focused on two main topics: (1) the interaction between age/size based migratory movement and the spatial availability of the resource and (2) time-varying fisheries selectivity associated with size segregation, migratory movement and cohort targeting. I have developed two new modeling tools to address research questions related to these two topics. In chapter 2, I present a continuous migration model capable of modeling cyclic migrations that are commonly found in iteroparous fish species. This model is suitable for exploring, testing and demonstrating potential issues of resource availability that arise from migratory movement and age/size segregation. In chapter 3, I present a length based stock assessment tool that attempts to provide better estimates of time-varying fisheries selectivity. Finally, in chapter 4, I use the model developed in chapter 2 in a closed-loop simulation framework to explore the impacts of a large set of harvest control rules on management outcomes experienced by two nations sharing a transboundary resource. In the following section, I summarize the work in chapters 2 through 4, and discuss how these models and findings may contribute to the management of Pacific Hake and other migratory transboundary species around the globe.

### 5.1 Research summary

In chapter 2 , I introduced a migration model that characterizes the cyclic migrations between feeding and spawning grounds that are common in iteroparous migratory species. A Lagrangian approach to model movement is used to track individual cohorts (or sub groups within cohorts) through space and time. I demonstrate how the movement parameters in the model can be estimated from spatial catch at age data, a commonly available data type for many temperate exploited stocks. The Lagrangian movement model I present is continuous in space and time. This is important because in a continuous model it becomes unnecessary to delimit spatial areas from which movement rates are measured, and time steps can vary in size as needed. On the other hand, the Lagrangian model requires an explicit migration hypothesis to generate the movement trajectories. Such hypotheses, however, exist for many exploited species. For example, many migration hypotheses for the ocean phase of Pacific salmon species are described by Groot and Margolis (1991). These generally include northward migrations following the North American coast then returning to re-enter their natal streams as fish mature. Tunas are another example of a group that in which some species perform trans oceanic cyclic migrations between spawning and feeding grounds (Nikolic et al., 2017; Nakamura, 1969). Other species, like pelagic sharks are also believed to perform cyclic migrations, usually between inshore and offshore waters (Campana et al., 2011; Jorgensen et al., 2010). Similar behavior has also been demonstrated for flatfish like plaice (Hunter et al., 2003) and some cod populations (Robichaud and Rose, 2004).

I illustrated the model performance using Pacific hake as a case study, which perform cyclic migrations between the spawning grounds off southern California in the winter and the feeding areas along the North American coast all the way to northern British Columbia, Canada (Ressler et al., 2007). The migration extent is associated with fish age/size with fish moving further away from spawning grounds as they age/grow. Because I used Pacific hake as an example, I made the migration range a function of age. However, the model can be extended to incorporate covariates representing biological and environmental forces that alter the distribution and migration range of exploited populations. I expect that this movement model will be a useful tool to model fish
migration and to illustrate how fisheries dynamics are affected by fish migration. The model could also be used as the basis for an operating model in closed loop simulation exercises to test the robustness of management frameworks that apply to populations and fisheries that are subject to spatial structure.

In chapter 3, I introduce a new length-based stock assessment model: the length-SRA. This method bypasses the requirement of estimating selectivity by calculating exploitation rate at length directly from observed catch at length data. The objective was to come up with a method that would be robust to time-varying selectivity, a phenomenon commonly associated with resources subject to spatial complexities and cohort targeting. I tested the performance of the Length-SRA with a simulation-evaluation framework under three exploitation rate trajectories and under fixed and time-varying selectivity scenarios. The model produced parameter and derived management quantities estimates with precision and accuracy that are comparable to that of other assessment models, especially when considering time-varying selectivity (e.g., Martell and Stewart, 2014; Linton and Bence, 2011). The selectivity estimates produced by the model were accurate over most of the simulation scenarios, except when the exploitation rate time series showed no contrast, i.e., exploitation rate was kept at values near the management target for most of the time series. In general the selectivity estimates were not very precise. The imprecision in selectivity estimates is probably associated with the fact that the model assumes no error in the catch at length data, and therefore incorporates all the observation error in the selectivity estimates.

In addition, I explored the effects of misspecification of growth parameters on the length-SRA results. The model was found to be extremely sensitive to the growth parameters input, particularly when it comes to selectivity estimates. I used the length-SRA model to assess two species: Pacific hake and Peruvian jack mackerel. Both species are believed to be subject to time-varying selectivity associated with fisheries targeting of areas of high abundance and changes in population distribution over time. I found that both species presented time-varying and mainly dome shaped selectivity, which corroborated with the findings by Waterhouse et al. (2014) and Butterworth et al. (2014). However, as I pointed out earlier, the model is extremely sensitive to growth parameters, and it
remains uncertain whether the growth parameter estimates used for both Pacific hake and Peruvian jack mackerel are reliable. I recommend that whenever this model is used, extra caution is exercised when choosing growth parameter estimates and that extensive sensitive analyses are performed on the growth parameter values. Another alternative might be to use a Bayesian approach to integrate over the uncertainty in growth parameters by using distributions for the growth parameters values. This approach likely will not address the potential biases, but it will better capture the uncertainty caused by misspecification of growth parameters.

In chapter 4, I used the movement model described in chapter 2 in a closed loop simulation approach to evaluate the performance of a large set of harvest control rules for the Pacific hake population. I took advantage of the spatial capability of the movement model to explore the differences in performance of each harvest control rule in relation to the outcomes experienced by the U.S.A. and Canada, the nations sharing the Pacific hake resource. I found that when the harvest control rules allow for higher exploitation rates, issues of availability of the resource in Canadian waters become more prominent, resulting in lower average yields for Canada when compared to the lower exploitation rates. In order to assess the impacts of the occurrence of strong recruitment events in the population, I ran the evaluation under three distinct recruitment scenarios: no strong recruitment, one strong recruitment event per decade, and two strong recruitment events per decade. These scenarios were devised based on the historical recruitment of Pacific hake; strong recruitment events are believed to have occurred in 1980, 1985, 1999, 2010 and 2014, and seem to have no apparent relationship with stock size (Berger et al., 2017b). I found that the availability issue became more acute, i.e., larger decreases of average yield for Canada when strong recruitment events are less frequent or absent. I also tested the sensitivity of the results to movement parameter assumptions, and found that the differences in relative average long term yield between nations become less prominent if fish are assumed to migrate farther at younger ages. However, the impact of the movement parameter assumptions over the range of values explored tend to be smaller than that of the occurrence of strong recruitment events. This is because the occurrence of
strong recruitment events tends to inflate the biomass of the stock, eliminating problems related to availability throughout the species range, even if movement rates are diminished.

Among the harvest control rules being tested, I included the 40:10 harvest control rule with a maximum TAC cap. This rule is currently used for the Pacific hake management. The TAC cap is not officially part of the Pacific hake treaty, but a maximum cap has effectively been implemented consistently by the Pacific hake JMC over the past few years (Hicks et al., 2016). I found that this rule performed well in terms of maintaining the resource exploitation at sustainable levels, and in terms of mitigating the potential losses experienced by the Canadian fleet due to availability issues.

In addition to demonstrating the performance of a set of harvest control rules for the management of Pacific hake, the exercise presented in chapter 4 also has broader implications. The approach presented can be used to evaluate harvest control rules for other transboundary stocks that are subject to changes in distribution and migration range.

### 5.2 Future research directions

The material presented in this dissertation has value for future research and for management applications. The modeling tools are ready for management use provided that the necessary data is available. Future research could include further development of the modeling tools, application of the methods to other species, and further use of the tools in closed loop simulations and management strategy evaluations. There are several ways in which the research presented in this dissertation can be continued and enriched; I discuss some of those in the following paragraphs.

Most of the methodology, particularly chapters 2 and 4, were produced with the Pacific hake study case in mind, and therefore, will need to be modified if other fisheries and resources are considered. The Lagrangian movement model can be modified to include alternative (non cyclic) movement functions, to model more than one spatial dimension simultaneously (e.g., centroids of a distribution, longitude, latitude, and depth), and to incorporate other covariates, such as environmental variables. The explicit inclusion of environmental covariates in the Lagrangian movement
model could be used to test hypotheses derived from correlation between environmental variables and fish distribution (e.g., Chen et al., 2005; Agostini et al., 2006; Mourato et al., 2014).

In relation to the length-SRA model presented in chapter 3, an interesting expansion of the model would be to produce a stochastic version of the stock reduction analysis model, similar to what was done by Walters et al. (2006). In that approach the SRA projections are produced based on a range of hypothetical values for the main model parameters: unfished recruitment $\left(R_{0}\right)$ and recruitment compensation ratio ( $\kappa$ ). Then, these projections are "filtered" either by removing those in which the stock was driven into extinction or by using a sampling-importance resampling routine. This expansion would likely lead to a better characterization of uncertainties associated with the model estimates. In addition, further testing of the model could be done using a closedloop simulation approach. Such testing would enhance the understanding of the model, not only in terms of accuracy and precision, but also in terms of achieving management goals, such as sustainable and stable catches as well as conservation of the stock in the long term.

The closed-loop simulation approach described in chapter 4 could be expanded in a variety of ways, for example, to test different stock assessment methods. Testing of alternative allocations methods, such as the fisheries footprint approach, suggested by Martell et al. (2015) could also be considered. The closed loop simulation framework included in this dissertation could also be incorporated into a full management strategy evaluation process, in which the questions explored, as well as the management objectives and performance metrics, would be the result of consultation with managers, fisheries stakeholders, and scientists. In the case of Pacific hake, a management strategy evaluation process has been underway since 2013 (Taylor et al., 2014), and is likely to continue in the coming years with the expansion to a spatially structured operating model (Anonymous, 2017). The work presented in this thesis, particularly the spatial migration model could be a relevant contribution to the future work carried by the Pacific hake Joint Technical Committee.

In conclusion, the research presented here is comprised of two new modeling tools and a closed loop simulation framework. Each of these could be useful in research and management of transboundary fish stocks that are susceptible to age/size based migration. The use of these tools may
thus lead to improvement in understanding of the potential spatial consequences of management actions and, thereby leading to improved resource management.

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