Exploiting Interactions in Multispecies Fisheries to Assess and Avoid Constraining Species

Thesis Proposal

Samuel Johnson

March 23, 2016

Not Done Yet.

Contents

Introduction

Background

Sustainable management of any renewable resource requires understanding the system dynamics in response to exploitation. In a multispecies fisheries context the system is a collection of semi-discrete self-sustaining fish populations or *stocks* (Begg, Friedland, & Pearce (1999)), and the exploitation involves removing individuals by fishing. Fishing effort impacts target species, non-target species and fish habitat, and therefore a major challenge of multispecies fishery management is to balance fishing yield with broader sustainability goals.

Sustainable and scientifically defensible fishery management is built on a foundation of fisheries stock assessment (Hilborn & Walters (1992)). Quantitative stock assessment methods combine elements of data science, applied population ecology, risk assessment and resource management (Figure 1). Analysts use data from multiple sources including scientific surveys and commercial fishery monitoring to infer biological and fishery dynamics and to characterise uncertainties and risks based on these assessments. These inferences include estimates of species abundance and productivity that are used to inform management decisions.

Stock assessments are lacking in most Canadian fisheries (Hutchings et al. (2012)), especially for non-target species. One reason is that non-target species are typically of lower commercial importance, so there is limited interest in assessments. More commonly, data limitations preclude the assessment of certain species, known as data-limited species. Surveys designed for data-moderate target species are often unsuitable for non-target species and leave managers with the choice of conducting a flawed assessment, or no assessment at all.

A lack of assessments for some species within a multispecies fishery threatens sustainable management of the whole fishery in two ways. First, a lack of assessments creates conservation risks by weakening the link between management decisions and stock status. The dynamic nature of a fishery implies that the distribution of possible stock statuses widens as time passes. Second, eco-certifiers typically require up-to-date stock assessments for all species captured, regardless of whether those stocks are targeted or not. A lack of eco-certification reduces the capacity of a fishery for competition in international and domestic markets, because buyers will prefer eco-certified products (Pelc et al. (2015)).

Technical Interactions in Multispecies Fisheries

Stock assessments are traditionally performed for a single species at a time, even though this approach may lead to sub-optimal outcomes for multispecies fisheries (Sugihara et al. (1984); Gulland & Garcia (1984)). Sub-optimal outcomes may arise from not accounting for the effects of interactions between species. Interactions between fishes in multispecies fisheries are one of two types: ecological or technical. Ecological interactions are either non-trophic interactions, such as competition over habitat or food, or trophic interactions between predator and prey. Ecological interactions affect natural mortality of fish and may bias estimates of species productivity (Mueter & Megrey (2006)). Technical interactions occur when multiple species are caught in the same non-selective fishing gear, and are caused by multiple species of fish being potentially available to the fishing gear.

Within the single-species paradigm, major stocks typically comprise several distinct, but interacting, sub-stocks (Walters & Martell (2004); Ashleen J Benson, Cox, & Cleary (2015)), such as Pacfic salmon (*Onchorynchys spp.*) (Simon & Larkin (1972)). Multiple ecologically and technically interacting populations (i.e., stocks) of Chinook (*O. tshawtcha*), Chum (*O. keta*), Coho (*O. kisutch*), Pink (*O. gorbausch*), Sockeye (*O. nerka*) and Steelhead (*O. mykiss*) occur along Canada's Pacific coast. Each species is made up of genetically distinct subpopulations, defined mainly by discrete spawning habitats and run timing that establish quasi-isolated reproductive populations (Ricker (1972)) connected by low straying rates.

Managing hundreds of distinct fisheries is impractical (Walters & Martell (2004)) so salmon stocks are often grouped together into stock complexes for management and assessment. For instance, in the Fraser River, subpopulations of Chinook and Sockeye are grouped into aggregate stock complexes called runs, which are based on similarity in life history, geographical locations of spawning habitat and arrival timing to fisheries (English, Edgell, Bocking, Link, & Raborn (2011); DFO (1999)). Managing Pacific salmon in runs has both advantages and disadvantages. Advantages stem from more efficient management practices: stocks in the same Sockeye run are fished based on an estimate of sustainable yield for the whole run. While such aggregation might lead to underexploitation of some stocks, there is a larger benefit from more reliable and less costly assessments of the run due to data pooling. A major disadvantage is overexploitation of the weakest stocks in the complex if fishing pressure is calibrated to the average productivity of the complex(Ricker (1958); Ricker (1973); Parkinson, Post, & Cox (2004)). Under this paradigm the weaker than average stocks will be overfished (Figure 2) and eventually wiped out, creating a feedback where average productivity of the complex increases, encouraging overfishing of more stocks and fishing all but the most productive stocks out of a complex. An example of this phenomenon occuring is the Late run of Fraser river Sockeye salmon. The weakest stock in the Late run is the Cultus lake stock, which had historic abundances of 700,000 spawners but in 2004 fewer than 100 spawners returned from the marine life phase. The decline of Cultus lake Sockeye is caused in part by harvesting at average productivity for the complex (Team (2009)). The Late run is now harvested according to the productivity of the Cultus lake stock in order to avoid this effect on the declining population.

The aggregate management approach used for Pacific salmon could be extended to other multispecies fisheries. For example, groundfish fisheries on the west coast of North America exploit stocks of sablefish, Pacific halibut (*Hippoglossus stenolopis*), several species of rockfish (*Sebastes spp.*), Pacific cod (*Gadus macrocephalus*), Dover sole (*Microstomus pacificus*) and other demersal species (Fisheries and Oceans, Canada (2015)). Different groundfish genera and species have their own unique life histories and reproductive strategies that respond differently to fishing pressure (S. Jennings, Greenstreet, Reynolds, & others (1999)). For instance, flatfish are fast growing, mature early and have little parental investment in their young, while rockfish are slow growing, mature later and invest heavily in nursing (King & McFarlane (2003)). Different life histories and reproductive strategies among groundfish imply different productivity levels, similar to mixed-stock Pacific salmon fisheries.

Differing productivity levels and technical interactions create profitability constraints in multispecies fisheries managed through quota systems (Hilborn, Punt, & Orensanz (2004);Baudron & Fernandes (2015)). Constraints are caused by weaker low productivity species that cannot be avoided when targeting stronger high productivity species. Weaker species have low quota that is filled faster, so stronger species are under-exploited in order to reduce the fishing pressure on the weakest, or pinch-point, species (Figure 3) (Hilborn et al. (2004)). An example of a pinch-point species is Boccacio rockfish (*S. paucispinis*) in the British Columbia groundfish fishery, which are difficult to avoid when targeting lingcod (*Ophiodon elongatus*). Bocaccio rockfish are listed as Endangered by COSEWIC[1] and have a very low annual quota of around 110 metric tonnes (mt), while lingcod are highly productive with annual quota of around 3600mt. Avoidance of Bocaccio by harvesters led to less than 33% of Bocaccio quota to be utilised between 2006 and 2014 (Figure 4). Technical interactions between Bocaccio and lingcod means that this avoidance behaviour resulted in around 25% of lingcod quota being utilised in that same time period (Figure 4). This underutilisation translates into a reduction of around **DOLLAR AMOUNT**[2] gross revenue to the

[1] Committee on the Status of Endangered Wildlife in Canada.
[2] February, 2016 prices **HEY DUMMY, ADJUST THIS FOR NPV**

BCIGF between 2006 and 2014.

Assess and Avoid

Profitability constraints caused by technical interactions may be alleviated by conducting stock assessments of data-limited species and avoiding pinch-point species. Species that lack up-to-date assessments often have their quota set to a low level for conservation reasons, creating artificial pinch-points. After assessment the quota of a data-limited species can be scaled to a better estimate of stock-status (Food and Agriculture Organization of the United Nations (1995)), which could have 2 effects. Either the status is such that the pinch-point created by the data-limitation can be removed, or the status requires the pinch-point to remain. In the case where assessments show that the pinch-point cannot be removed then an avoidance strategy is required.

One option for overcoming data limitations to assessments is by explicitly acknowledging technical interactions in multispecies fisheries (Mueter & Megrey (2006); A. E. Punt, Smith, & Smith (2011); Zhou et al. (2010)). Technical interactions can be acknowledged by aggregating multiple species into the same assessment complex or assemblage based on co-occurence in fishing events, in a similar way to Pacific salmon (Beverton et al. (1984); Walters & Martell (2004)). Statistical benefits of aggregation may allow previously unassessed species to be assessed, and increase the profitability of the fishery by relieving constraints and enabling eco-certification. While more complicated than the single specie paradigm, the benefit of assessing previously unassessed species may outweigh the costs.

Based on a re-ordering of the diagram Figure 6 shows three possible models of fishery operation and management. Models (a) and (b) are the current options for assessment in multispecies fisheries. Model (a) is the status quo approach of single species stock assessment, where every stock is treated as a separate population (Hilborn & Walters (1992)). Model (b) is the total aggregation approach used for Pacific salmon (English et al. (2011)), where several species or stocks have their data combined and are then assessed and managed as a single unit (Sugihara et al. (1984); Gulland & Garcia (1984); Gaichas et al. (2012)).

The total aggregation approach used by Pacific salmon may not be suitable for assessing assemblages of multiple species with distinct life histories and reproductive strategies. Like in Pacfic salmon, estimates of average productivity for an assemblage may be far from the true value for each member stock, leading to over or under fishing of some species. Model (c) in Figure 5 addresses this by keeping the data separate as in model (a), but performs assessments for groups of stocks using statistical models that link the data during estimation (Zhou et al. (2010); A. E. Punt et al. (2011); Mueter & Megrey (2006)).

In Chapters 1, 2 and 3 I conduct a simulation study of a hierarchical stock assessment model to share data between species as in model(c) of

Figure 5 (Jiao, Hayes, & Corts (2009); Zhou et al. (2010); A. E. Punt et al. (2011)). The statistical model assumes a hierarchical structure of multispecies fisheries as shown in Figure 7, allowing for an an intermediate level of aggregation between models (a) and (b) of Figure 6. Shared parameters in the hierarchical assessment model allow for some of the benefits of aggregation for data-limited stocks, but the separated data streams allows for species specific estimates of abundance and productivity (Jiao et al. (2009)).

The focus of Chapter 1 is to create a simulation-estimation procedure to study hierarchical assessment models for multi-species assemblages with no sub-stock structure. Data generated by a process error population dynamics model and observation model are provided to hierarchical estimators (Zhou et al. (2010); A. E. Punt et al. (2011)). The statistical performance of the estimators is then quantified by comparing the true values of parameters to estimated values.

In Chapter 2, the simulation-estimation procedure is extended to incorporate a sub-stock structure for each species. Including multiple substocks that correspond to possible multi-stock structure increases the resolution of the data and allows for deviations from average life history parameter values within each species (Su, Peterman, & Haeseker (2004)). Bias and precision are estimated and compared to the results of Chapter 1, to analyse the benefits and costs of including increased structure in the model.

In Chapter 3, the operating model and estimators are extended into a closed loop feedback simulator (Figure 8). Closed loop simulation is the tool at the core of management strategy evaluation (de la Mare (1998); Sainsbury, Punt, & Smith (2000)) and it allows assessment models to be tested as part of a management procedure. Management procedures include the assessment model, harvest strategies (Hilborn & Walters (1992), Ch. 15) and decision rules for strategy implementation based on assessment output. This involves creating an operating model that simulates population dynamics of multiple interacting fish species, effort dynamics of multiple fishing fleets with different gear types exploiting those populations and uncertain observations made by scientific surveys (Jones et al. (2009)). The multi-stock structure of Chapter 2 makes realistic effort dynamics possible, such as targeting behaviour for specific species based market forces (Hilborn & Walters (1987); Parkinson et al. (2004); Clark (2010)). Under the uncertainty provided by the operating mode, all three components combine to produce complex emergent properties of the management procedure, and closed loop simulation offers a low-stakes option for analysing those properties and the associated risks.

In Chapter 4, I investigate a new techology for avoiding non-target species and estimate its economic value. Reliable and explicit commercial data is becoming more abundant with increasing observer coverage in modern fisheries. Concurrent with this, machine learning methods are emerging that allow for analysis of data that isn't collected under strict experimental designs (T. Hastie et al. (2009)), like commercial fishing data. Chapter 4 is a feasibility study of using machine learning methods to detect and avoid conditions leading to the capture of non-target species. The economic value of avoiding non-target species is estimated through analysing the value of information provided by the machine learning approach.

Study System

The British Columbia Integrated Groundfish Fishery (BCIGF) (Fisheries and Oceans, Canada (2015)) is a group of 7 fisheries that spatially and temporally overlap on the BC coast. The overlapping fisheries are managed by one integrated individual transferrable quota system, allowing temporary and permanent transfers of quota allocations between licenses in different fleets. Quota is distributed to harvesters across gear types and management areas for every species encountered, and skippers that exceed their quota for a given species must obtain more from quota holders or stop fishing for the season. All catch and discards are deducted from quota allocations, and are therefore monitored on 100% of vessels by at sea observer or electronic monitoring systems.

Integration and technical interactions react in problematic ways when data limited non-target species interact with directed species. Data limited species such as Petrale sole (*Eopsetta jordani*) are not able to be assessed, so stock status is unknown (Driscoll (2014)). If assessments are lacking, quota is often set to a conservative level based on the most recent stock assessment, if it exists. This creates an artificial pinch-point species, that could be alleviated by assessing and avoiding that species.

In Chapters 1, 2 and 3 the simulation study uses an assemblage composed of all flatfish except halibut in the BCIGF as the biological component of the operating model. This assemblage includes English sole (*Parophrys vetulus*), Dover sole (*Microstomus pacificus*), Petrale sole, Rock sole (*Lepidopsetta bilineata*) and Arrowtooth flounder (*Atheresthes stomias*) (Fisheries and Oceans, Canada (2015)). All fishes share evolutionary history as members of the family *Pleuronectidae* of right-eyed flounders, making this assemblage suitable for a hierarchical approach due to similar but distinct life histories. The amount of data available for different species varies, with Rock sole being subject to regular assessments, and Petrale sole having no up to date assessments (Driscoll (2014)). Halibut are excluded from the assemblage as they are part of a separate, trans-boundary directed fishery.

In Chapter 4, the feasibility study uses sub-legal sized sablefish as its study system. Sablefish are at historic low abundances, with only recent evidence of an increase in their abundance. Discard induced mortality of sub-legal sablefish represents potential growth and recruitment overfishing of the sablefish stock. Reducing discard induced mortality may be an alternative to quota reduction for increasing spawning stock biomass (**STOCK ASSESSMENT REFERENCE**). Discarding of legal-sized sablefish (>55cm, good condition) is economically disincentivised by a quota deduction adjusted for discard induced mortality, but no such incentive or mortality rate exists for unmarketable sablefish (<55cm, poor condition). This incentive structure is evident in the distribution of sablefish discarding, with **CONCRETE NUMBERS**% of sablefish discards made up by sub-legal sized fish.

Chapter 1: Estimating Coastwide Abundance and Productivity in a Multispecies Groundfish Fishery via a Hierarchical Stock Assessment Model

Background

Quantitative stock assessment models have 3 main components, outlined in Table 2: the population dynamics model, the observational model and the statistical model (Hilborn & Walters (1992)). Model inputs are candidate parameter values that are confronted by data in the statistical model to produce posterior density or likelihood values as outputs. Statistical model output is optimised or integrated over the input parameters to extend inferences about stock productivity and status in the form of distributional estimates.

Hierarchical statistical models are becoming increasingly popular for analysing complex fisheries data. In Pacific salmon stock and recruitment analyses, both Bayesian and frequentist (mixed effects) hierarchical models are used in meta-analyses of multistock populations (Su et al. (2004); Malick, Cox, Mueter, Peterman, & Bradford (2015)). More related to this thesis, stock assessment models that use hierarchical statistical models are sometimes used to assess multispecies complexes where data limitations are an issue for single species management, such as technical interactions with data-limited species (A. E. Punt et al. (2011)) or difficulties in species identification (Jiao et al. (2009)).

In this chapter I use a simulation-estimation procedure to study hierarchical Bayesian (Zhou et al. (2010)) and frequentist (A. E. Punt et al. (2011)) state space surplus production models for assessment of a multispecies flatfish assemblage with no sub-stock structure. These models would be used to simultaneously assess target and non-target species in Figure 1.3. In a comparison between single species and hierarchical multispeceis models applied to real assemblages containing data-limited species, it has been shown that the hierarchical models qualitatively change parameter estimates for data-limited species (A. E. Punt et al. (2011); Kell & De Bruyn (2012)). However, it remains unclear as to whether or not the change improves estimates of stock status and productivity.

QUESTION: How do estimates of stock status and productivity for data-limited species change when assessed using hierarchical multispecies models?

Simulated fishery independent indices of abundance and fishery dependent catch are used to test the effect of hierarchical assessment models on estimates of parameters. True parameter values used for simulation can be compared to estimated parameters in Monte-Carlo trials to understand bias and precision of both estimators. Estimators are then tested across a range of scenarios representing implications of technical interactions between species, and contrasts in data availability.

Methods

This chapter uses the flatfish study assemblage defined in the introduction. Each species in the flatfish assemblage is simulated independently using the model defined in Table 2. Population dynamics are simulated by a simple biomass dynamics process error-model (Figure 1.1, Eqs T2.2, T2.4), fishery dependent catch is generated by input fishing mortality (Eq T2.3) and fishery independent observations of catch per unit effort (CPUE) are generated by the observational model (Figure 1.2, Eq T2.5).

Multispecies data produced by the simulation model are supplied to both a Bayesian and frequentist version of a hierarchical state-space assessment model (Figure 7). Both assessment models are specified in the same way, shown in Table 3. The difference between the models is in how the inferences are extended. For the Bayesian state space model the posterior density (Eq. T3.8) is integrated over all input parameters producing marginal distributions for each parameter (Gelman, Carlin, Stern, & Rubin (2014)). For the frequentist state space model, also known as a random effects model, the posterior density is integrated over the priors to produce a marginal "true" likelihood, which is then maximised as in traditional likelihood methods (de Valpine & Hastings (2002)).

Both models require a numerical integration method to produce marginal distributions or likelihoods (de Valpine & Hastings (2002); Gelman et al. (2014), Maunder, Deriso, & Hanson (2015)). Integration generally requires numerical methods like Markov-Chain Monte Carlo (MCMC) algorithms for distribution sampling of complex non-linear, non-Gaussian statistical models. To this end, the Bayesian model will be built using the Automatic Differentiation Model Builder (ADMB) (Fournier et al. (2012)) and the random effects model using Template Model Builder (Kristensen, Nielsen, Berg, Skaug, & Bell (2015)).

Model testing proceeds through Monte Carlo simulation trials of four experimental scenarios, each representing either technical interactions or data availability. Parameter estimates from each trial are then compared to their true values generated by the simulator to estimate bias and precision of the models in each scenario.

The first two parameters tested by experimental scenarios are process error deviations $\epsilon_{s,t}$ and species catchability coefficients q_s, representing effects of technical interactions between species in the assemblage (A. E.

Punt et al. (2011)). For example, species that share the same habitat will encounter the same environmental variation and this may introduce correlations in process error deviations. Similarly, species that are in the same fishing habitat may have similar interactions with fishing gear leading to correlations in catchability.

Parameters representing the effects of technical interactions are modeled hierarchically as shared parameters in the assessment model. For example, equation T3.7 shows a shared prior on process error deviations. In the first two experimental scenarios modifying correlations in shared parameters, bias and precision are measured for different fixed values of the prior variance (eg σ^2) in $(0, \infty)$ (Gelman et al. (2014), Ch 5.5).

The remaining two parameters tested by experiments are contrasts in observation error $\delta_{s,t}$ and fishery development histories F_t, representing data or information available to fishery managers. Observation error is a direct measurment of the quality of data obtained by scientific surveys, so contrasts in observation error variance τ_s^2 simulate differing levels of data availability between species in an assemblage. Fishery development histories are also a source of information, due to the way a fish population will respond to differing levels of exploitation (@hilborn1992quantitative, Ch 2).

Expected Results

I expect this chapter to result in a working knowledge of how hierarchical stock assessment models change the estimates of abundance and productivity when applied to multispecies assemblages. Estimates of model bias and precision as functions of correlation strengths, observation error variance and historical fishing are produced. This will result in a paper about the statistical properties of hierarchical multispecies assessment models.

Assumptions about the strength of correlations in shared parameters are likely to introduce bias through shrinkage towards a mean (Mueter, Peterman, & Pyper (2002)). The extent of the shrinkage introduced can be understood by producing bias and precision estimates under a range of fixed values of shared prior variance.

The extent to which limitations on data and species specific information can be overcome (A. E. Punt et al. (2011)), if at all, can be quantified through bias and precision estimates resulting from scenarios contrasting data-availability and fishing histories. This is especially helpful for fisheries in which there are limited historical fishing and scientific data available, or limited resources for improving existing scientific surveys.

Chapter 2: Adding Multistock Structure to Multispecies Hierarchical Stock Assessment Models

Background

A high degree of spatial variation in genetics, morphology, life-history and behaviour is apparent in many exploited fish populations (Hilborn, Quinn, Schindler, & Rogers (2003); Schindler et al. (2010)). Management of exploited fishes without acknowledgement of this variation risks eroding biodiversity and increasing species vulnerability to environmental variation (Hilborn et al. (2003); Cope & Punt (2011)).

The approach most often used to manage species with high spatial variation is to aggregate sub-stocks into a single management unit and apply management procedures over large spatial scales (Cope & Punt (2011)). The assumption in the aggregation approach is that despite spatial disaggregation of the stock, sub-stocks are connected by migration creating a rescue effect (Dulvy, Sadovy, & Reynolds (2003)). Rescue effects are then believed to reduce the risks of managing spatially complex species in a single aggregate (Cope & Punt (2011)).

However, when stock structure is easily identified, as with Pacific salmon, there are advantages to managing a species at the level of individual stocks, called multistocks. For example, by estimating productivity levels for 43 individual stocks of Pink salmon the effects of local variation in sea surface temperature could be discovered (Su et al. (2004)). Furthermore, estimating individual productivity levels within a management complex reduces the risk of overfishing weak stocks due to an averaging effect (Figure 2).

Managing multistocks also has its challenges. When the exact nature and connectedness of the spatial stock structure is unknown, it is unclear whether or not aggregation is the more precautionary management approach (Ashleen Julia Benson (2011)). Furthermore, for a data-limited species further disaggregation of the data will only raise further barriers to stock assessment by reducing the amount of data available for each sub-stock.

As in Chapter 1, a hierarchical stock assessment model may help overcome data limitations when managing for multiple stocks in a multispecies fishery (A. E. Punt et al. (2011)). Life histories within species are likely to be more similar than between species, reducing variance in prior distributions shared between stocks. Similarly, sub-stocks of multiple species share habitat and experience shared environmental variation allowing for the definition of sub-assemblages with shared priors on process error (Kallianiotis, Vidoris, & Sylaios (2004)).

QUESTION: How do estimates of abundance and productivity change when including sub-stock structure assessments of data-limited species in a hierarchical assessment model?

The BCIGF non-halibut flatfish assemblage exhibits evidence of substock structure. For example, there is evidence that the species population of English sole on the British Columbia coast is made up of multiple segregated major stocks with limited migration (Hart, Clemens, & others (1973)). The simulation experiments of Chapter 1 will be repeated after the addition of stock structure to the assemblage, to investigate the effects of the hierarchical estimators under data limitations.

Methods

The methods for this chapter require small structural changes to the simulation and estimation procedures from Chapter 1 in order to increase data resolution. The simulation model now simulates individual stocks j of each species s (Table 5). Migration can now occur between stocks within each species, making stock dynamics interdependent (T5.4).

The estimation procedure includes another layer of hierarchical structure to include multiple substocks (Figure 8). The multiple stocks within a species now share parameters through prior distributions at the species level. The hyperparameters of shared priors at the species level then share hyperpriors with other species at the assemblage level.

Six experimental scenarios evaluated by estimating bias and precision extend the four outlined in Chapter 1. The original four will be extended to account for the increased depth in the assemblage structure. The first additional scenario models increased data-limitation introduced by disaggregating an already data-limited species into multiple stocks. Disaggregation could lead to increased observation error variance or entirely missing observations for some stocks. The final additional experiment introduces spatial covariation in the state dynamics simulation for each stock (**FIGREF??**) and tests the benefit of including spatial variation in the estimator.

Expected Results

I expect this chapter to deepen understanding of hierarchical estimators and their application in a multistock context. Adding stock structure involves increased model complexity and reduced data availability due to disaggregation, introducing a tradeoff. This tradeoff is then evaluated by varying data availability and model complexity and examining how model bias and precision change. A publication detailing the tradeoffs between bias and precision under different model structures is expected to result from this analysis.

Chapter 3: Performance of a Management Procedure Using an Hierarchical Stock Assessment Model for a Multispecies Groundfish Fishery

Background

The fisheries management procedure extends beyond the stock assessment model (Figure 1). Stock assessment output (Figure 1.3) informs a decision rule (Figure 1.4) that determines the amount of fishing effort expended to collect the harvest quota (Figure 1.5). This effort dynamically impacts fish populations and their habitat (Figure 1.1), providing new data (Figure 1.2) that is used for assessment.

An important test for an assessment model is how it performs as part of a management procedure. Management procedures include harvest strategies, which are input or output controls on the fishery (Hilborn & Walters (1992), Ch. 15) and decision rules that scale controls to stock status. Management procedures made up of decision rules, harvest strategies and assessment models represent the full management cycle of a fishery.

In this chapter, I use closed loop simulation to test management procedures based on a hierarchical multispecies stock assessment model. Closed loop simulation modeling explicitly quantifies feedback in a dynamic system (de la Mare (1998); Sainsbury et al. (2000)). In a fisheries management context, the closed loop includes the management procedure, fish stocks and commercial and scientific data in a feedback loop (Figure 9). The fishery, population dynamics and scientific survey are part an operating model (Jones et al. (2009)) that provide data to the assessment model and harvest control rule as part of a management procedure. Management procedure evaluation then proceeds by experimentally adjusting model parameters and observing the emergent behaviour. In this way, potential risks of management can be quantified under a given set of assumptions.

Simulating a multistock, multispecies fishery requires a more sophisticated simulator than in Chapters 1 and 2. For example, harvesters expend fishing effort based on expected costs and benefits of fishing, including expected catch composition and personal risk.

QUESTION: How can realistic targeting behaviour be included in the operating model?

Targeting behaviour comes down to when and where harvesters expend their effort. That is, targeting behaviour can be simulated by including fishing effort dynamics for multiple fishing fleets (gear types) in the operating model (Hilborn & Walters (1987)). These dynamics are based on estimates of fishery dependent catchability $q_{f,s,t}$ (Table 7) can be empirically drawn from commercial data or simulated parametrically.

Once realistic effort dynamics are included in the operating model, inherent risks of assessment model assumptions can be assessed across multiple experimental scenarios. Experiments include contrast in data-quality, taking into account spatial covariation due to environmental forcing (Dichmont, Deng, Punt, Venables, & Haddon (2006)) .

QUESTION: How do multispecies hierarchical assessment models perform when managing multispecies assemblages containing data limited stocks, with performance measured by probability of overfishing, underfishing and variation in annual catch?

I answer this question by running experimental scenarios that measure the relationship between management risks and data quality. For example, risk countour plots (**FIGURE**) could help inform policy for the application of hierarchical assessment models or communication with stakeholders when providing harvest advice.

Methods

The closed loop simulation extends the simulation model of Chapter 2 into an operating model including effort dynamics (Tables 7, 8 **8 not done yet**). At each time step t, the current state of each fish population is estimated by the assessment model. Asessment models then forecast abundance at time $t + 1$, which is passed through a harvest control rule (HCR) to generate a total allowable catch (TAC) or each species. The TAC for each species is then supplied to the operating model, which distributes fishing effort (Hilborn & Walters (1987)) across space in order to maximise some objective, such as fishing profit, subject to the constraints of the TAC.

Fishing effort dynamics are simulated by through a 2 stage procedure at each time step (Hilborn & Walters (1987)). First, some test fishing is conducted by expending a unit of effort in each fleet and fishing location (statistical area). Then, based on fleet objectives and observed fishery dependent catch rates, the operating model will distribute effort to maximise the objective subject to the TAC for every species. It is possible that these dynamics will lead to underutilised quota for some species, effectively simulating pinch-points.

Management procedures featuring assessment models from Chapters 1 and 2 areused in experimental scenarios. Experiments test a range of observation error variances, process error variances, fishery development history and correlations in catchability $q_{s,j,t}$. Each simulation measures quota utilisation, species depletion, probability of exceeding optimal instantaneous fishing mortality and annual average variation. Simulation output is then used to compare between scenarios and management procedures, quantifying performance and risks of each procedure.

Expected Results

For each experiment a plot of overfishing risk as a function of contrast like Figure (**FIGURE**) will be produced. This plot will show contours of probability that the actual fishing mortality rate F_t is greater than the fishing mortality rate giving MSY F_{MSY}. The y-axis will show target fishing mortality F_t or effort E_t, and the x-axis will show the parameter driving the contrast.

- Contour plot
- Operating model
- Paper

Chapter 4: Avoiding non-target species.

Introduction

Quota on directed species in the BCIGF is constrained by restrictive quotas on pinch-point species and size limits on directed species, both of which are caught as bycatch. For example, an average of 160 tonnes per year of Sablefish below 55cm in length were discarded by trap and trawl fishing vessels between 2007 and 2015 in the BCIGF **SOURCE: GFFOS**. Those discards are due to a size regulation intended to reduce catch of juvenile fish, and so the mortality induced represents growth and recruitment overfishing of Sablefish. This is made particularly challenging by the migratory behaviour of juvenile Sablefish **(FIGURE)**.

- The BCIGF has 100% coverage ASOP/EM providing a reliable and complete data set
  - Unique, reliable data set in BC - GFFOS
  - 106k+ records between 2007 and 2015

  - Could be used to forecast hot spots (Vilela & Bellido (2015)), inform a DOM approach

A quantitative model-based approach to forecasting bycatch could be combined with a fleet communication approach as a form of small-scale dynamic ocean management (Vilela & Bellido (2015); Sims, Cox, & Lewison (2008); Dunn, Maxwell, Boustany, & Halpin (2016)). Most approaches to dynamic management and fleet communication in other fisheries are based on ad-hoc data-based methods, possibly due to reluctance of harvesters to communicate and issues with data quality (Gilman, Dalzell, & Martin (2006)). The unique, reliable GFFOS data set and the infrastructure used to create it could provide an easy route to the implementation of small scale management processes.

In this chapter I test the feasibility of a model-based approach to forecasting bycatch of juvenile Sablefish using commercial data from BC fisheries. Due to the non-random nature of fishing efforts traditional statistical methods that rely on the central limit theorem are unsuitable. Instead, machine learning methods, known as *learners*, will be used to sidestep statistical assumptions and search for correlations in the data (C. M. Bishop (2006); T. Hastie et al. (2009)).

Several learners will be developed and tested individually and as part of a combined model called an *ensemble* learner. Initially, learners will be calibrated for forecasting presence or absence of juvenile Sablefish. This will involve testing a range of possible environmental, temporal and spatial variables for their predictive importance.

QUESTION: What are the important predictors for the presence of juvenile Sablefish in commercial catch in the trawl and trap sectors?

Learners that predict categorical variables such as presence and absence are known as *classifiers*. Possible predictor variables include spatial and temporal variables from the GFFOS database and environmental and oceanographic variables taken from external sources. Importance can be measured through several means, all of which involve some measure of classifier performance when the predictor is included or excluded.

Classifiers often return a probabilistic output similar to a logistic regression. To turn this probabilistic output into a categorical prediction a classification probability threshold is required. Typically a threshold of 0.5 is used as an objective default, but this is an arbitrary choice. Threshold probabilities can be tuned to optimise different performance criteria, and the sensitivity of the threshold to the criteria is an important feature of a classifier model (Freeman & Moisen (2008)).

QUESTION: What is the sensitivity of classification threshold to performance criteria?

High sensitivity of a classification threshold to the choice of performance criteria can indicate low discriminatory power of a learner (Freeman & Moisen (2008)). Testing thresholds and criteria will allow for calibration of the model, and help determine if a model is suitable for forecasting.

Given a feasible model with high discriminatory ability, I next want to test its ability to predict the biomass of juvenile Sablefish caught. This prediction could be important from a dynamic ocean management perspective, where small scale closures can be enacted based on the predicted value. It could also be directly valuable to harvesters from a cost-benefit perspective, where the expected cost of a small amount of non-target species at low probability is worth the expected benefit of a large amount of target species.

QUESTION: What are the important predictors for (a) fishery dependent CPUE and (b) biomass of juvenile Sablefish in commercial catch in BC trawl and trap fisheries?

Again, possible predictor variables include spatial and temporal variables from the GFFOS database and environmental and oceanographic variables taken from external sources. Prediction may be performed either by regression or classification into ordinal categories, and this will dictate how learner peformance and predictor performance are quantified.

Methods

Predictive capacity of machine learning for detecting juvenile Sablefish will be tested across several learner algorithms and multiple ensemble structures. Ensembles are used to avoid overfitting by single learners through model averaging of different forms (Rokach (2010)). Some learners, such as the Random Forest algorithm (Breiman (2001)) are made up of many models and are themselves ensembles.

Learners will be tested first by their capacity to predict presence or absence of juvenile Sablefish in data taken from the GFFOS. Three sets of data will be used: commerical trawl data, commercial trap data, and both sectors combined. Each data set will will go through the same process of model selection and calibration at two levels: the individual learners and the ensemble structures. At all stages, Monte-Carlo trials of cross-validation will be used to produce distributions of model performance.

Model selection for the learners will be performed by testing the importance of various predictor variables. I'll test two ways to assess predictor importance. First, through a sensitivity analysis that measures decreases in accuracy from random perturbations of predictor variable values, as is performed by the Random Forest (Breiman (2001)). Second, through the effect of variable selection on performance of the model.

Performance of individual learners will be calibrated by optimising their classification thresholds to different criteria including κ, percentage correctly classified, and true negative and true positive rates (Freeman & Moisen (2008)). True positive and true negative rates could have asymmetric costs if a predictor like this is used in management decisions, so asymmetric loss functions will be tested.

Model selection at the ensemble level requires selection of the individual learners, and a method to combine them. Individual learners will be selected based on the sensitivity of thresholds to performance criteria, which is a proxy for discrimanatory power (Freeman & Moisen (2008)). Learners with low discriminatory power may be unsuitable to prediction of bycatch when expanded to true forecasts in practice, and will therefore be excluded from ensembles.Ensemble structures range from simple weighted model averaging to more complicated Bayesian Model Combination technique (Monteith, Carroll, Seppi, & Martinez (2011)). Ensemble calibration will depend on the choice of ensemble structure.

Finally, I'll attempt to predict the amount of juvenile Sablefish caught if classification of presence and absence is feasible. Both absolute catch and fishery-dependent catch per unit effort will be used as possible response variables. Prediction of both responses could be done through regression or an extension of the classification method to multiple ordinal classes. For regression, new calibration and model selection techniques are possible, such as the lasso method for variable selection (Tibshirani (1996)). Regression and classification could also be combined in a "hurdle" model. Hurdle models predict an amount by regression only if a presence is predicted by the classifier, and are often used in zero-inflated data sets such as commercial bycatch data (Sims et al. (2008)).

Expected Results

- A conclusion on the feasibility of avoidance based on commercial data retained by monitoring.
- Maps of encounter probability for ease of communication to har-

vesters

- The basis of a fleet communication system for avoidance of non-target species and possible DOM
- Performance of a range of learners for
  - classification
  - regression

Conclusions

This thesis will undertake a study of stock assessment methods for assemblages of multiple interacting species. The focus is on the Robin Hood (RH) method, which contains a hierarchical statistical model linking the data of multiple species. The RH method could prove valuable for data-variable fisheries that are unable to produce stock assessments for all species that they contain. Those species that were previously unable to be assessed could potentially fall inside the stable risk region of the RH method allowing scientifically defensible TACs to be set. This would help some fisheries obtain eco-certification (MSC, Seafood Watch, seaChoice), helping to improve biological sustainability of market share.

Further to contributions to the field of fisheries science, this thesis also satisfies the interdisciplinary spirit of REM in two chapters. First, assessing multiple species simultaneously using the RH approach brings possible advantages, such as an efficient allocation of survey resources. Such advantages are to be tested in Chapter 2 through management strategy evaluation, synthesising ecological drivers of population dynamics and economic drivers of fishing effort. The other methods - single species (SS) and total aggregation (TA) - are analysed as alternatives to the RH method in a risk assessment in Chapter 3. The risk assessment is intended to recommend data-requirements and harvest control rules for stable social and biological risk, synthesising economics, ecology and policy.

Resource allocation improvement (taken from intro)

Efficient allocation of resources is therefore an important part of the sustainable management of multispecies fisheries. This para needs refs, better ideas and structure. Does it even go here? Maybe combine it with the following paragraph on multispecies assessments. Also, include information here about "good enough" mechanisms for resource distribution SARA, PA state that at a given level of biological risk, a recovery process has to be implemented. Are expensive, model based assessments required for every species? What constitutes "good enough" management? There are two parts to resource allocation 1. Identification of need - pinch-point species are an externality on directed species 2. Mechanisms for resource distribution - good enough MPs: Swept-area, total Agg, RH... A paralysis of choice is common in situations like this.

I propose a practical, stake-holder driven management approach that seeks to to satisfy conservation concerns while increasing economic welfare in multispecies fisheries. Assessment techniques should be *practical* in that they achieve conservation and management goals efficiently, such as reserving the most technologically advanced and resource intensive management procedures for those stocks that absolutely need it. Management decisions should be *stake-holder driven*, where priority is given to actions that increase the economic welfare of the fishery. This will allow for positive economic feedback and increase the pool of resources available for future management of the fishery. The goal of a practical, stake-holder driven management approach is to simultaneously improve the sustainability (intergenerational equity) and profitability of multispecies fisheries.

Biblography

Baudron, A. R., & Fernandes, P. G. (2015). Adverse consequences of stock recovery: European hake, a new "choke" species under a discard ban? *Fish and Fisheries*, *16*(4), 563–575.

Begg, G. A., Friedland, K. D., & Pearce, J. B. (1999). Stock identification and its role in stock assessment and fisheries management: An overview. *Fisheries Research*, *43*(1), 1–8.

Benson, A. J. (2011). *An evaluation of the opportunities and impediments in managing quota fisheries for biodiversity* (PhD thesis). Environment: School of Resource; Environmental Management.

Benson, A. J., Cox, S. P., & Cleary, J. S. (2015). Evaluating the conservation risks of aggregate harvest management in a spatially-structured herring fishery. *Fisheries Research*, *167*, 101–113.

Beverton, R., Cooke, J., Policansky, D., Csirke, J., Roughgarden, J., Doyle, R., … others. (1984). Dynamics of single species. In *Exploitation of marine communities* (pp. 13–58). Springer.

Bishop, C. M. (2006). *Pattern recognition and machine learning* (Vol. 4). springer New York.

Breiman, L. (2001). Random forests. *Machine Learning*, *45*(1), 5–32.

Clark, C. W. (2010). *Mathematical bioeconomics: The mathematics of conservation* (Vol. 91). John Wiley & Sons.

Cope, J. M., & Punt, A. E. (2011). Reconciling stock assessment and management scales under conditions of spatially varying catch histories. *Fisheries Research*, *107*(1), 22–38.

de la Mare, W. K. (1998). Tidier fisheries management requires a new mOP (management-oriented paradigm). *Reviews in Fish Biology and Fisheries*, *8*(3), 349–356.

de Valpine, P., & Hastings, A. (2002). Fitting population models incorporating process noise and observation error. *Ecological Monographs*, *72*(1), 57–76.

DFO. (1999). *Fraser river chinook salmon* (No. D6-11). DFO Science

Stock Status Report.

Dichmont, C. M., Deng, A. R., Punt, A. E., Venables, W., & Haddon, M. (2006). Management strategies for short lived species: The case of australia's northern prawn fishery: 2. choosing appropriate management strategies using input controls. *Fisheries Research*, *82*(1), 221–234.

Driscoll, J. (2014). *Groundfish complex, british columbia*. Seafood Watch, Monterey Bay Aquarium.

Dulvy, N. K., Sadovy, Y., & Reynolds, J. D. (2003). Extinction vulnerability in marine populations. *Fish and Fisheries*, *4*(1), 25–64.

Dunn, D. C., Maxwell, S. M., Boustany, A. M., & Halpin, P. N. (2016). Dynamic ocean management increases the efficiency and efficacy of fisheries management. *Proceedings of the National Academy of Sciences*, 201513626.

English, K. K., Edgell, T. C., Bocking, R. C., Link, M. R., & Raborn, S. W. (2011). Fraser river sockeye fisheries and fisheries management and comparison with bristol bay sockeye fisheries. *The Cohen Commission of Inquiry into the Decline of Sockeye Salmon in the Fraser River*.

Fisheries and Oceans, Canada. (2015). Pacific Region Integrated Fisheries Management Plan: Groundfish.

Food and Agriculture Organization of the United Nations. (1995). Code of conduct for responsible fisheries.

Fournier, D. A., Skaug, H. J., Ancheta, J., Ianelli, J., Magnusson, A., Maunder, M. N., … Sibert, J. (2012). AD model builder: Using automatic differentiation for statistical inference of highly parameterized complex nonlinear models. *Optimization Methods and Software*, *27*(2), 233–249.

Freeman, E. A., & Moisen, G. G. (2008). A comparison of the performance of threshold criteria for binary classification in terms of predicted prevalence and kappa. *Ecological Modelling*, *217*(1), 48–58.

Gaichas, S., Gamble, R., Fogarty, M., Benot, H., Essington, T., Fu, C., ... Link, J. (2012). Assembly rules for aggregate-species production models: Simulations in support of management strategy evaluation. *Marine Ecology Progress Series*, *459*, 275–292.

Gelman, A., Carlin, J. B., Stern, H. S., & Rubin, D. B. (2014). *Bayesian data analysis* (Vol. 2). Taylor & Francis.

Gilman, E. L., Dalzell, P., & Martin, S. (2006). Fleet communication to abate fisheries bycatch. *Marine Policy*, *30*(4), 360–366.

Gulland, J., & Garcia, S. (1984). Observed patterns in multispecies fisheries. In *Exploitation of marine communities* (pp. 155–190). Springer.

Hart, J. L., Clemens, W. A., & others. (1973). *Pacific fishes of canada*. Fisheries Research Board of Canada.

Hastie, T., Tibshirani, R., Friedman, J., Hastie, T., Friedman, J., & Tibshirani, R. (2009). *The elements of statistical learning* (Vol. 2). Springer.

Hilborn, R., & Walters, C. J. (1987). A general model for simulation of stock and fleet dynamics in spatially heterogeneous fisheries. *Canadian*

Journal of Fisheries and Aquatic Sciences, *44*(7), 1366–1369.

Hilborn, R., & Walters, C. J. (1992). *Quantitative fisheries stock assessment: Choice, dynamics and uncertainty/Book and disk*. Springer Science & Business Media.

Hilborn, R., Punt, A. E., & Orensanz, J. (2004). Beyond band-aids in fisheries management: Fixing world fisheries. *Bulletin of Marine Science*, *74*(3), 493–507.

Hilborn, R., Quinn, T. P., Schindler, D. E., & Rogers, D. E. (2003). Biocomplexity and fisheries sustainability. *Proceedings of the National Academy of Sciences*, *100*(11), 6564–6568.

Hutchings, J. A., Ct, I. M., Dodson, J. J., Fleming, I. A., Jennings, S., Mantua, N. J., … VanderZwaag, D. L. (2012). Is canada fulfilling its obligations to sustain marine biodiversity? A summary review, conclusions, and recommendations 1 1 this manuscript is a companion paper to hutchings et al.(doi: 10.1139/a2012-011) and vanderZwaag et al.(doi: 10.1139/a2012-013) also appearing in this issue. these three papers comprise an edited version of a february 2012 royal society of canada expert panel report. *Environmental Reviews*, *20*(4), 353–361.

Jennings, S., Greenstreet, S., Reynolds, J., & others. (1999). Structural change in an exploited fish community: A consequence of differential fishing effects on species with contrasting life histories. *Journal of Animal Ecology*, *68*(3), 617–627.

Jiao, Y., Hayes, C., & Corts, E. (2009). Hierarchical bayesian approach for population dynamics modelling of fish complexes without species-specific data. *ICES Journal of Marine Science: Journal Du Conseil*, *66*(2), 367–377.

Jones, M. L., Irwin, B. J., Hansen, G. J., Dawson, H. A., Treble, A. J., Liu, W., ... Bence, J. R. (2009). An operating model for the integrated pest management of great lakes sea lampreys. *The Open Fish Science Journal*, *2*, 59–73.

Kallianiotis, A., Vidoris, P., & Sylaios, G. (2004). Fish species assemblages and geographical sub-areas in the north aegean sea, greece. *Fisheries Research*, *68*(1), 171–187.

Kell, L. T., & De Bruyn, P. (2012). THE rOBIN hOOD aPPROACH fOR dATA pOOR sTOCKS: AN eXAMPLE bASED oN aLBACORE. *Collect. Vol. Sci. Pap. ICCAT*, *68*(1), 379–386.

King, J., & McFarlane, G. (2003). Marine fish life history strategies: Applications to fishery management. *Fisheries Management and Ecology*, *10*(4), 249–264.

Kristensen, K., Nielsen, A., Berg, C. W., Skaug, H., & Bell, B. (2015). TMB: Automatic differentiation and laplace approximation. *ArXiv Preprint ArXiv:1509.00660*.

Malick, M. J., Cox, S. P., Mueter, F. J., Peterman, R. M., & Bradford, M. (2015). Linking phytoplankton phenology to salmon productivity along a north–south gradient in the northeast pacific ocean. *Canadian*

Journal of Fisheries and Aquatic Sciences, *72*(5), 697–708.

Maunder, M. N., Deriso, R. B., & Hanson, C. H. (2015). Use of state-space population dynamics models in hypothesis testing: Advantages over simple log-linear regressions for modeling survival, illustrated with application to longfin smelt (spirinchus thaleichthys). *Fisheries Research*, *164*, 102–111.

Monteith, K., Carroll, J. L., Seppi, K., & Martinez, T. (2011). Turning bayesian model averaging into bayesian model combination. In *Neural networks (iJCNN), the 2011 international joint conference on* (pp. 2657–2663). IEEE.

Mueter, F. J., & Megrey, B. A. (2006). Using multi-species surplus production models to estimate ecosystem-level maximum sustainable yields. *Fisheries Research*, *81*(2), 189–201.

Mueter, F. J., Peterman, R. M., & Pyper, B. J. (2002). Opposite effects of ocean temperature on survival rates of 120 stocks of pacific salmon (oncorhynchus spp.) in northern and southern areas. *Canadian Journal of Fisheries and Aquatic Sciences*, *59*(3), 456–463.

Parkinson, E. A., Post, J. R., & Cox, S. P. (2004). Linking the dynamics of harvest effort to recruitment dynamics in a multistock, spatially structured fishery. *Canadian Journal of Fisheries and Aquatic Sciences*, *61*(9), 1658–1670.

Pelc, R. A., Max, L. M., Norden, W., Roberts, S., Silverstein, R., & Wilding, S. R. (2015). Further action on bycatch could boost united states fisheries performance. *Marine Policy*, *56*(0), 56–60. http://doi.org/http://dx.doi.org/10.1016/j.marpol.2015.02.002

Punt, A. E., Smith, D. C., & Smith, A. D. (2011). Among-stock comparisons for improving stock assessments of data-poor stocks: The "robin hood" approach. *ICES Journal of Marine Science: Journal Du Conseil*, *68*(5), 972–981.

Ricker, W. (1958). Maximum sustained yields from fluctuating environments and mixed stocks. *Journal of the Fisheries Board of Canada*, *15*(5), 991–1006.

Ricker, W. (1972). Hereditary and environmental factors affecting certain salmonid populations. *The Stock Concept in Pacific Salmon*, 19–160.

Ricker, W. (1973). Two mechanisms that make it impossible to maintain peak-period yields from stocks of pacific salmon and other fishes. *Journal of the Fisheries Board of Canada*, *30*(9), 1275–1286.

Rokach, L. (2010). Ensemble-based classifiers. *Artificial Intelligence Review*, *33*(1-2), 1–39.

Sainsbury, K. J., Punt, A. E., & Smith, A. D. (2000). Design of operational management strategies for achieving fishery ecosystem objectives. *ICES Journal of Marine Science: Journal Du Conseil*, *57*(3), 731–741.

Schindler, D. E., Hilborn, R., Chasco, B., Boatright, C. P., Quinn, T. P., Rogers, L. A., & Webster, M. S. (2010). Population diversity and the portfolio effect in an exploited species. *Nature*, *465*(7298), 609–612.

Simon, R. C., & Larkin, P. A. (1972). *The stock concept in pacific* *salmon*. University of British Columbia.

Sims, M., Cox, T., & Lewison, R. (2008). Modeling spatial patterns in fisheries bycatch: Improving bycatch maps to aid fisheries management. *Ecological Applications*, *18*(3), 649–661.

Su, Z., Peterman, R. M., & Haeseker, S. L. (2004). Spatial hierarchical bayesian models for stock-recruitment analysis of pink salmon (oncorhynchus gorbuscha). *Canadian Journal of Fisheries and Aquatic Sciences*, *61*(12), 2471–2486.

Sugihara, G., Garcia, S., Platt, T., Gulland, J., Rachor, E., Lawton, J., ... others. (1984). Ecosystems dynamics. In *Exploitation of marine communities* (pp. 131–153). Springer.

Team, C. S. R. (2009). *National conservation strategy for cultus lake sockeye salmon (oncorhynchus nerka)*. Fisheries; Oceans Canada.

Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society. Series B (Methodological)*, 267–288.

Vilela, R., & Bellido, J. M. (2015). Fishing suitability maps: Helping fishermen reduce discards. *Canadian Journal of Fisheries and Aquatic Sciences*, (ja).

Walters, C. J., & Martell, S. J. (2004). *Fisheries ecology and management*. Princeton University Press.

Zhou, S., Punt, A. E., Deng, R., Dichmont, C. M., Ye, Y., & Bishop, J. (2010). Modified hierarchical bayesian biomass dynamics models for assessment of short-lived invertebrates: A comparison for tropical tiger prawns. *Marine and Freshwater Research*, *60*(12), 1298–1308.