Exploiting Interactions in Multispecies Fisheries to Assess and Avoid Constraining Species

Thesis Proposal

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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)).

Assessments Acknowledging Technical Interactions

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, such as competition, or trophic, between predator and prey. Ecological interactions affect natural mortality of fish and may bias estimates of species productivity when not taken into account (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 sub-populations, 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, sub-populations of Chinook and Sockeye are grouped into aggregate stock complexes called runs 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. Aggregation leads to increased management efficiency and brings adds statistical benefits from data pooling. However, to avoid overfishing due to different productivity levels of member stocks (Figure 2), complexes must be managed according to the weakest stock's productivity (Ricker (1958); Ricker (1973); Parkinson, Post, & Cox (2004)). The Late run of Fraser river Sockeye is managed for the weakest stock: Cultus lake. The Cultus lake stock has historic abundances of up to 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 schema used for Pacific salmon could be modified and adopted in 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)). Different life histories and reproductive strategies among groundfish imply different productivity levels, similar to mixed-stock Pacific salmon fisheries.

Multiple interacting species with different productivity levels 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' quota 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

[1]Committee on the Status of Endangered Wildlife in Canada.

into a reduction of around **DOLLAR AMOUNT**[2] gross revenue to the 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 assessment models (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, similar to Pacific salmon runs (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

[2] February, 2016 prices **HEY DUMMY, ADJUST THIS FOR NPV**

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. 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 incorporates a sub-stock structure for each species. Including multiple sub-stocks 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, a closed loop feedback simulator is used to evaluate management procedures using hierarchical models (Figure 8). 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 (Hilborn & Walters (1987); Walters & Bonfil (1999); M. L. Jones et al. (2009); Clark (2010)). Uncertain data provided by the operating model reacts with the management procedure to produce complex emergent properties and closed loop simulation offers a low-stakes option for analysing those properties and the associated risks.

In Chapter 4, I investigate a data-based approach to avoiding non-target species and estimate its economic value. Reliable, spatially 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)), such as commercial fishing data.

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. 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. Skippers who exceed their quota share must either obtain more from other harvesters, or stop fishing for the season.

Integrated management of the BCIGF creates pinch-points on quota utilisation, caused by technical interactions between directed species and data limited non-target species. Many species lack up-to-date assessments (Driscoll (2014)) creating artificial pinch-points that could be alleviated by assessing and avoiding those species.

In Chapters 1, 2 and 3 the simulation study uses a multispecies complex composed of all flatfish except halibut in the BCIGF as the biological component of the operating model. The complex is made up of **D**over sole (*Microstomus pacificus*), **E**nglish sole (*Parophrys vetulus*), **R**ock sole (*Lepidopsetta bilineata*), **P**etrale sole and **A**rrowtooth flounder (*Atheresthes stomias*) (Fisheries and Oceans, Canada (2015)), and called the **DERPA** complex for brevity. All members of DERPA are from the family *Pleuronectidae* of right-eyed flounders, making DERPA suitable for a hierarchical approach due to similar but distinct life histories. The amount of data available for different DERPA species varies, with Rock sole being subject to regular assessments, and Petrale sole having no up to date assessments (Driscoll (2014)). Halibut are excluded as they are managed by a separate trans-boundary authority.

In Chapter 4, I use machine learning methods to forecast the presence of sub-legal sized sablefish in fishing events. Sablefish are at historic low abundances and are subject to a rebuilding strategy (**REFS**). Reducing discard induced mortality of juvenile sablefish 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 incorporate population dynamics processes (Figure 1.1), observational data (Figure 1.2) and a statistical model (Figure 1.3) (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 between 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 multispecies assessment models. The multispecies models are used to simultaneously assess a simulation of the DERPA complex of flatfish. In a comparison between single species and hierarchical models applied multispecies groups including data-limited species, it has been shown that the hierarchical models induce a change in parameter estimates for data-limited species (A. E. Punt et al. (2011); Kell & De Bruyn (2012)). However, it is unknown if that change is an increase or decrease in bias.

QUESTION: What is the bias in estimates for abundance and productivity produced by hierarchical multispecies models?

Simulated scientific and commercial data are used to test hierarchical assessment models. 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

Each species in the DERPA complex 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 using fishing mortality as an input (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 is coded using the Automatic Differentiation Model Builder (ADMB) suite (Fournier et al. (2012)) and the random effects model using Template Model Builder (Kristensen, Nielsen, Berg, Skaug, & Bell (2015)). Both software packages provide fast numerical integration to produce marginal distributions, with TMB being developed specifically for random effects models.

Model testing proceeds through four experimental scenarios that modify simulation input parameters representing multispecies interactions and data limitations. 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 scenarios investigate model assumptions about process error deviations $\epsilon_{s,t}$ and species catchability coefficients q_s. Both parameters are representive of interactions between species in the complex. For example, species that share the same habitat will encounter the same environmental variation, reflected in process error deviations (A. E. Punt et al. (2011)). Similarly, species that are fished by the same gear may have similar interactions with fishing gear leading to correlations in catchability.

Shared priors are defined for process error deviations (T3.7) and catchability parameters (T3.8). Bias and precision are measured for a range of fixed values of the prior variance (eg $\sigma^2 \in (0, \infty)$) (Gelman et al. (2014), Ch 5.5).

The remaining two scenarios test contrasts in observation error variance τ_s^2 between species and fishery development histories $F_{s,t}$, 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 (Hilborn & Walters (1992), Ch 2). **MAKE FIGURE of Ft trajectories**

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. Results are to be published in a paper about the statistical properties of 2 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); Ashleen J Benson et al. (2015)).

Aggregation of sub-stocks into a single management unit over large spatial scales relies on assumed rescue effects that do not exist in general multistock fisheries. The assumption 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, this rescue effect is highly dependent on dispersal and recruitment patterns in the meta-population and individual natural mortality rates of sub-stocks (Ashleen Julia Benson (2011)).

When stock structure is easily identified, as with Pacific salmon, there are advantages to managing a species at the level of individual stocks. 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 J Benson et al. (2015)). 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.

A hierarchical stock assessment model may overcome data limitations from disaggregation when managing for multiple stocks in a multispecies fishery (A. E. Punt et al. (2011)). Life histories within species are likely to be similar, allowing for prior distributions on life history parameters that are shared between stocks. Similarly, sub-stocks of multiple species share habitat and experience the same environmental variation, allowing for a local spatial effect on process error

(Kallianiotis, Vidoris, & Sylaios (2004)).

QUESTION: How do estimates of abundance and productivity in a multi-stock, multispecies hierarchical model compare to those of a coastwide multi-species hierarchical model?

The DERPA complex exhibits evidence of sub-stock structure. For example, the species population of English sole on the British Columbia coast is managed as two segregated major stocks with limited migration (Hart, Clemens, & others (1973)). Simulated data from a multi-stock model of the DERPA complex is provided to both a coastwide and multistock hierarchical multispecies model. Both models produce parameter estimates, and bias and precision are compared.

Methods

The DERPA complex is simulated as individual stocks j of each species s (Table 5). Migration from stock i to stock j within species s is possible with net migration rate $\phi_{s,i,j}$, making stock dynamics interdependent (T5.4).

The estimation procedure includes a layer of hierarchical structure to include multiple substocks for each species (Figure 8(b)). The multiple stocks within a species share prior distributions on life history parameters 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: Management Performance of Hierarchical Multispecies Assessment Models

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, Punt, & Smith (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 (M. L. 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 incidentally during directed fishing. For example, an average of 160 tonnes per year of Sablefish below 55cm in length were discarded due to size regulations by trap and trawl fishing vessels between 2007 and 2015 in the BCIGF **SOURCE: GFFOS**.

There is general agreement in the literature that incidental catch and discarding should be reduced as much as possible or practical (Saila & Jones (1983); Crowder & Murawski (1998); Safina & Lewison (2008); Pelc et al. (2015)). Mortality of immature individuals caused by unregulated or regulated (i.e. size, quota, trip limits) discarding contributes to both recruitment and growth overfishing of fish stocks (Crowder & Murawski (1998)). Furthermore, bycatch has an impact on the ecosystem containing the target resource, including all non-resource species and habitats that interact with the fishing gear (Safina & Lewison (2008)).

In this chapter I test the feasibility of using a model-based approach to predicting fishing events that encounter and discard juvenile sablefish by analysing commercial fishing data for the purposes of avoiding regulatory discarding. Data generated by commercial fishing is not randomly sampled, so traditional statistical models that rely on the central limit theorem are unsuitable. Instead, machine learning models are used to sidestep statistical assumptions and search for correlations in the data (C. M. Bishop (2006); T. Hastie et al. (2009)).

Three machine learning models are trained and optimised on a subset of commercial data from the BCIGF to classify presence and absence of juvenile sablefish for a given fishing event. Event predictions from all three models are then combined into an ensemble classifier (Rokach (2010)). Ensemble classifiers use weighted model averaging techniques to overcome potential overfitting to the training data. The remaining data is then used to test the performance of the ensemble classifier using multiple metrics (Freeman & Moisen (2008))

The feasibility of a tool to avoid regulatory discarding requires an economic benefit to harvesters. Because juvenile Sablefish are discarded under size regulations, no discard induced mortality is deducted from harvester quota (Fisheries and Oceans, Canada (2015)). No reduction in quota implies a lack of economic incentive for harvesters to avoid conditions that lead to the catch of juvenile fish.

QUESTION: What is the benefit of using a machine learning approach for predicting the presence and absence of juvenile sablefish in commercial fishing events, compared to the status quo?

Economic benefit of the ensemble classifier is measured by estimating the value of information provided by the classifier (Mntyniemi, Kuikka, Rahikainen, Kell, & Kaitala (2009)). Classifier performance is combined with empirical estimates of the probability of encounter in a decision analysis, with utility provided by a dollar value based on the costs and benefits of successful and unsuccessful avoidance.

Methods

Predictive capacity of an ensemble machine learning classifier to detect juvenile Sablefish is tested on 4 sets of commercial fishing data from the BCIGF. The BCIGF data is contained in the Groundfish Fishery Operating System (GFFOS) data base that contains spatially and temporally explicit data for every fishing event in the BCIGF since 2005. The 4 data sets are split by gear type, with data sets containing events using (i) trawl only, (ii) longline trap only, (iii) longline hook only and (iv) all gear types.

For each data set, an ensemble classifier is built from Random Forest (Breiman (2001)), Naive Bayes (ref) and Artificial Neural Network (ref) component classifiers. Component classifier configurations are chosen based on average performance over Monte-Carlo trials of a validation procedure (T. Hastie et al. (2009), Ch 7.2). Performance of classifiers is measured using multiple metrics including percentage correctly classified, area under receiver operating characteristic curves, precision and recall (Freeman & Moisen (2008)). Component classifiers that perform the best are then combined into an ensemble using multiple configurations, ranging from simple model stacking to Bayesian Model combination (Rokach (2010)). Ensemble classifiers are then tested on a reserved portion of the data to estimate the classification error rate of the ensemble.

A formal decision analysis is performed to estimate the value of information provided by using the classifier with the lowest error rate on each data set (Mntyniemi et al. (2009); Peterman & Anderson (1999); Pestes, Peterman, Bradford, & Wood (2008)). Classifiers are included in the analysis as a form of expert opinion, adjusting the probability of encountering juvenile Sablefish given a message from the classifier. The value of information is then the difference in the expected utility of fishing with the classifier's help and the expected utility of fishing without it. The utility is dependent on the costs setting gear and sorting discards from the catch, as well as the value of landed catch.

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 harvesters
- The basis of a fleet communication system for avoidance of non-target species and possible DOM
- Estimates of the economic benefit of a tool for avoiding non-target species.

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 multi-species 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.

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