Assessment and Avoidance Management Tools for Multispecies Fisheries Constrained by Technical Interactions

Thesis Proposal

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August 3, 2016

The nature of commercial fishing gear makes it difficult to avoid species with restrictive annual quotas while targeting highly productive profitable species in multispecies fisheries. Exploitation of the high productivity species is then constrained by the low quota species, creating a pinch-point effect on fishery profitability. This thesis proposes 2 management tools for improving profitability in the presence of pinch-point effects. First, quota may be low because of uncertainty about stock status owing to data limitations precluding up-to-date assessments. Hierarchical multispecies assessment models that explicitly acknowledge interactions among species may be used to extend assessments to data-limited species and lift constraints. Second, if assessments are unable to lift restrictive species quota improved avoidance tools may alleviate pinch-point effects. By using machine learning algorithms on commercial monitoring data it may be possible to redirect harvester targeting to avoid restrictive species.

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Introduction

Background

Sustainable management of any renewable resource requires an understanding of 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, as the dynamic nature of a fishery leads to more uncertainty about stock status 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 market share of a fishery both internationally and domestically, as buyers 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 (Gulland & Garcia, 1984; Sugihara et al., 1984). Sub-optimal outcomes may arise from not accounting for the effects of interactions between species. In multispecies fisheries interactions 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 are caused by non-selective fishing gear, and occur when multiple species are caught simultaneously.

Within the single-species management paradigm, a species typically comprises several distinct but interacting sub-stocks (Benson, Cox, & Cleary, 2015; Walters & Martell, 2004). For example multiple ecologically and technically interacting populations (i.e., stocks) of Pacific salmon (*Onchorynchus spp.*) species 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 (Simon & Larkin, 1972). 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 connected by low straying rates (Ricker, 1972).

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 (DFO, 1999; English, Edgell, Bocking, Link, & Raborn, 2011). Managing Pacific salmon in runs has both advantages and disadvantages. Aggregation leads to increased management efficiency and brings statistical benefits from data pooling. However, to avoid overfishing of some stocks complexes must be managed according to the weakest stock's productivity (Figure 2) (Parkinson, Post, & Cox, 2004; Ricker, 1958, 1973), as exemplified by the Cultus lake stock of Late run Fraser river Sockeye salmon. Cultus lake Sockeye have had historic abundances of up to 700,000 spawners but in 2004 fewer than 100 spawners returned from the marine life phase, caused in part by previous over-harvesting at average productivity for the Late run complex (Team, 2009). To avoid continued over-harvesting, the entire Late run is now fished according to the productivity of Cultus lake Sockeye.

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, 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 (Baudron & Fernandes, 2015; Hilborn, Punt, & Orensanz, 2004). 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 species, also known as pinch-point or choke 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 and have a very low annual quota of around 110 metric tonnes (mt)[1], while lingcod are highly productive with annual quota of around 3600mt. Avoidance of Bocaccio by lingcod 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 a maximum of 25% of lingcod quota being utilised in that same time period (Figure 5). This underutilisation of quota translates into a reduction of around $10,000[2] of gross annual revenue to the fishery between 2006 and 2014.

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

[2]Price per pound taken from California *Status of the Fisheries Report*, 2008, assuming a parity conversion on average over the time period.

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 may have two effects. Either the decrease in uncertainty about the stock status allows removal of the pinch-point, or the pinch-point remains. 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 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.

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 (Gaichas et al., 2012; Gulland & Garcia, 1984; Sugihara et al., 1984).

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 6 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 (Mueter & Megrey, 2006; A. E. Punt et al., 2011; Zhou et al., 2010).

In Chapters 1, 2 and 3 I will conduct a simulation study of hierarchical stock assessment models that share data between species as Figure 6(c) (Jiao, Hayes, & Corts, 2009; A. E. Punt et al., 2011; Zhou et al., 2010). The statistical model assumes a hierarchical structure of multispecies fisheries as shown in Figure 7, allowing for an an intermediate level of between models shown in Figures 6(a) and 6(b). Shared parameters in the hierarchical assessment model provide some of the benefits of aggregation, but the separation of 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 (A. E. Punt et al., 2011; Zhou et al., 2010). 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 of Chapter 1 is extended to include a spatial sub-stock structure for each species (Figure 9). Including multiple sub-stocks increases the resolution of the data and allows for multiple stock specific life history parameter values within each species (Su, Peterman, & Haeseker, 2004), however challenges may arise from disaggregation of species data across multiple spatial strata. Bias and precision are estimated and compared to coastwide model bias and precision, to analyse the benefits and costs of including increased structure in the model.

In Chapter 3, a closed loop feedback simulation framework is used to evaluate management procedures using spatially structured multistock and multispecies hierarchical models (Figure 10). This requires an operating model that simulates population dynamics of multiple interacting fish species, uncertain observations made by scientific surveys and effort dynamics of multiple fishing fleets with different gear types exploiting each population (Clark, 2010; Hilborn & Walters, 1987; M. L. Jones et al., 2009; Walters & Bonfil, 1999). Uncertain data provided by the operating model react with the management procedure to produce complex emergent properties. Closed loop simulation offers a low-stakes option for analysing those properties and the associated risks.

In Chapter 4, I will 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, statistical learning methods are emerging that allow for analysis of data that isn't collected under strict experimental designs (Hastie, Tibshirani, & Friedman, 2009; Lennert-Cody & Berk, 2007), such as commercial fishing data.

Study System

British Columbia's Groundfish Fishery (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 across 8 statistical areas (Figure 11) 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 British Columbia groundfish fishery creates pinch-points on quota utilisation, caused by technical interactions between high value target species and data limited non-target species. Many species lack up-to-date assessments creating, to varying degrees, pinch-point effects that may be alleviated by assessing and avoiding those species (Driscoll, 2014).

In Chapters 1, 2 and 3 the simulation study will use a multispecies complex composed of all flatfish except halibut in the British Columbia groundfish fishery 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 and evolutionary histories. Furthermore, Dover sole, Petrale sole and Arrowtooth flounder are subject to technical interactions, as they often co-occur in fishing gear that encounters Sablefish (Figure 12). Halibut are excluded as they are managed by a separate trans-boundary authority.

The amount of data available for DERPA flatfish species varies, and so does the timing of stock status assessments. Rock sole was assessed in 2016 (K. R. Holt, Starr, Haigh, & Krishka, 2016) and 2014 (DFO, 2014), and Arrowtooth flounder in 2015 (DFO, 2015), but before that both species were not assessed for close to a decade (Jeff Fargo & Starr, 2001; Jeff Fargo, Kronlund, Schnute, &

Haigh, 2000).[3] English and Petrale sole were last assessed in 2009 (Starr, 2009a, 2009b). Dover sole was last assessed in 1999 and has never been assessed using a model based assessment (J. Fargo, 1999).

In a departure from the study system in Chapters 1, 2 and 3, in Chapter 4 I will use computational 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 (S. Cox & Kronlund, 2009), and the reduction of discard induced mortality has been identified as a means to increase sablefish spawning stock biomass without necessarily reducing quota (S. Cox, Kronlund, & Lacko, 2011). Discarding of legal-sized sablefish (>55cm, good condition) is disincentivised by a quota deduction adjusted for discard induced mortality, but no incentive structure exists for unmarketable sablefish (<55cm, poor condition). This incentive structure is evident in the distribution of sablefish discarding, with an average of 70% of sablefish discards in the trawl sector between 1997 and 2006 made up by sub-legal sized fish[4].

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) into a statistical model (Figure 1.3) (Hilborn & Walters, 1992). Model inputs are candidate parameter values that

[3]Rock sole were assessed in 2005 in an unpublished working paper, see K. R. Holt et al. (2016).

[4]From the PacHarvTrawl database housed at the Fisheries and Oceans, Canada, Pacific Biological Station, Nanaimo.

are compated to data in the statistical model to produce posterior density or likelihood function values as outputs. Statistical model output is then 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 (Malick, Cox, Mueter, Peterman, & Bradford, 2015; Su et al., 2004). 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 will 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 simulated version 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 (Kell & De Bruyn, 2012; A. E. Punt et al., 2011). However, it is unknown if that change is an increase or decrease in bias. As a result, for this paper I address the following research question.

QUESTION: How do estimates of unfished biomass B_0, growth r and catchability q made by hierarchical multispecies models compare to estimates from single species 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 will be simulated using the model defined in Table 2. Population dynamics are simulated by a simple biomass dynamics process error-model (Figure 1.1, Table 2 equations 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 observation model (Figure 1.2, Eq T2.5).

Multispecies data produced by the simulation model will be 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 (Table 3, Eq T3.8) is integrated over all parameters included in Θ (Eq T3.2) to produce 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 random effects (process errors) and prior distributions to produce a marginal "true" likelihood, which is then maximised as in traditional likelihood methods (de Valpine & Hastings, 2002).

Both models require an 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 models utilising a large number of random effects.

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 ϵ_t, ζ_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 coastwide process error deviations ϵ_t (A. E. Punt et al., 2011). Moreover, interactions between each of the species may cause correlations in their species speficic process errors ζ_t, reflected in the covariane matrix Σ. Similarly, species that are fished by the same gear may have similar interactions with fishing gear leading to correlations in catchability q_s.

Shared priors are defined for process error deviations (Eqs T3.7, T3.8) and catchability parameters (Eq T3.9). Bias and precision are measured for a range of fixed values of the prior variance ($\sigma^2, \kappa^2 \in (0, \infty)$) (Gelman et al., 2014, Ch 5.5) and multiple configurations of the covariance matrix Σ.

The remaining two scenarios contrast information available from survey observations and resource responses to exploitation pressure. Observation error is a direct measurement 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, characterised by fishing mortality $F_{s,t}$ trajectories (Figure 8), are a source of information based on the way a fish population responds to changes in fishing pressure (Hilborn & Walters, 1992, 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. 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 Spatial 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 (Benson et al., 2015; Cope & Punt, 2011; Hilborn et al., 2003).

Aggregation of sub-stocks into a single management unit over large spatial scales relies on migration to mitigate localised depletion of discrete substocks. 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 metapopulation and individual natural mortality rates of sub-stocks (Benson et al., 2015).

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 whose productivity is less than the aggregate's (Figure 2).

Managing multistock populations 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 (Benson et al., 2015). Furthermore, for a data-limited species further disaggregation of the data will only deplete the quantity of data available in each strata at the finer resolution, raising further barriers to assessment.

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). To investigate these effects I ask the following research question.

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?

To answer this question in a simulation study I use the DERPA complex, which 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 will be simulated as individual stocks p of each species s, with stocks corresponding to the discrete populations identified in stock previous stock assessments (DFO, 2015; J. Fargo, 1999; K. R. Holt et al., 2016; Starr, 2009b, 2009a) (Figure 11). The model used for each stock, defined in table 5, is a process error surplus production model with a term representing migration between substocks of the same species. Migration from substock p to substock p' within species s is possible with net migration rate $\phi_{s,p,p'}$, making stock population dynamics interdependent (Tabl 5, Eq T5.4).

Population dynamics are affected by environmental process errors with three components. The first component ϵ_t affects all populations identically. The second component ζ_t affects stocks within species identically, and between species according to the covariance matrix $\Sigma^{(S)}$. Finally, the third component ξ_t is stock specific, with draws correlated according to the covarance matrix $\Sigma^{(P)}$. The stock specific component is meant to capture spatial covariation between stocks of different species that share the same habitat.

The multistock estimation procedure will use three layers of hierarchical structure to include multiple species, each containing multiple stocks (Table 6, Figure 9). The multiple stocks within each species share prior distributions on growth r and catchability q parameters at the species level (Figure 9(b); Eqs T6.7, T6.8). The multistock prior mean catchabilities at the species level then share a multispecies prior (Figure 9(c); Eq T6.10). Additionally, the process error components are shared at the appropriate level (Eqs T6.9, T6.11, T6.12).

Five experimental scenarios are proposed to evaluate bias and precision of the multistock estimator as functions of data quality contrasts, fishery development history and covariation due to shared environment. Four scenarios are extended from Chapter 1 to account for increased depth in the assemblage structure, including covaration between species in $\Sigma^{(S)}$ and covariation between stocks in $\Sigma^{(P)}$. The 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.

Finally, the multistock estimator will be compared to the coastwide estimator in Table 3. The coastwide model uses aggregated data from the multistock simulator, and the 5 scenarios of the previous paragraph are repeated. Bias and precision will be recorded and compared between estimators.

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 for the coastwide and multistock models. 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

Fisheries management procedures extend beyond the stock assessment model in practice (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 influences fish populations and their habitat (Figure 1.1), providing feedback in the form of 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 feedback management procedure. Management procedures include harvest strategies, which are limits on catch or effort in the fishery, and decision rules that scale controls to the health of the stock, such as a harvest rate (Hilborn & Walters, 1992, Ch. 15). Management procedures made up of decision rules, harvest strategies and assessment models represent a season in the management of a fishery.

In this chapter, I will use closed loop simulation to evaluate management procedures based on hierarchical multispecies stock assessment models. 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 provides data to the assessment model and harvest control rule as part of a management procedure. Management procedure evaluation then proceeds by experimentally adjusting operating model and assessment model parameters and observing the emergent behaviour. In this way, potential risks of management can be quantified under a given set of assumptions.

Realistic predictions about management procedure performance require a complex operating model that can accurately reflect fishery history. Historical exploitation patterns are dependent on the spatial distribution of fishing effort, induced by the targeting behaviour of harvesters (Hilborn & Walters, 1987; Walters & Bonfil, 1999; Walters & Martell, 2004 Ch. 9.3). Targeting behaviour is dependent on several factors, including catch composition and expected financial reward, and can be simulated by including a fishing effort dynamics model for multiple fishing fleets (gear types) in the operating model. Effort dynamics are based on fishery dependent catchability parameters $q_{f,s,t}$ (Table 7), which can be empirically estimated from commercial data or parametrically simulated. Using this framework, I address the following research question.

QUESTION: How do multispecies hierarchical assessment models perform when simulaneously managing multiple target and non-target species?

I will answer this question by running closed loop simulations of the DERPA complex under different management and ecological scenarios. A validated operating model that makes use of historical fishery effort and observed population dynamics is used to simulate management procedures forward in time and assess risks of future management decisions. Risks of assessment model errors, harvest control rules and effort dynamics can be tested across multiple experimental operating model scenarios and management. Experiments include contrasts in data-quality between species, spatial aggregation of multistock structure, covariation due to environmental forcing (Dichmont, Deng, Punt, Venables, & Haddon, 2006), and changes in effort dynamics driven by economic forces..

Methods

The closed loop simulator of the DERPA complex requires an operating model that includes effort dynamics (Table 7; M. L. Jones et al., 2009). At each time step t, the current state of each fish stock or species 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) for each species. The TAC for each species is then supplied to the operating model, which distributes fishing effort across the space in order to maximise some objective, such as profit, subject to the constraints of the TAC.

Four classes of model are available for simulating short term distribution of fishing effort (Walters & Martell, 2004, Ch. 9.3). From least to most complex the four classes are: (i) gravity models (Walters & Bonfil, 1999), (ii) ideal free distribution (IFD) models (Benson et al., 2015), (iii) sequential effort allocation models (Hilborn & Walters, 1987) and (iv) individual based models.

For spatial allocation of fishing effort I use a simplified IFD model (Walters & Bonfil, 1999) with a numerical effort response model for fish vulnerability (Cox & Walters, 2002). The IFD model is chosen because of the large spatial scale of discrete stocks in the DERPA complex (Figure 11), allowing for the more complex IFD model over the simplified gravity model more suited to finer resolution. The numerical effort response model allows for the transition of individuals to and from a vulnerable state, reflecting the reality that not all habitat can be fished by all gear.

External economic forces are included in the effort dynamics model. The IFD model ranks the quality of each fishing site by the profitability pr_i of fishing at site i. Profitability is a function of fixed and variable fishing costs, ex-vessel sale price of catch and the cost to acquire the necessary quota for bycatch. Quota prices are subject to market forces, such as scarcity, meaning bycatch quota for pinch-point species can at times exceed the ex-vessel sale price of that species, decreasing the expected profitability of a given site and affecting harvester behaviour.

The closed loop simulation tests future performance of management procedures using single species, coastwide multispecies and multistock multispecies models 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

This chapter is expected to result in an understanding of how hierarchical management procedures perform in multispecies fisheries. Performance of both coastwide and multistock models is compared in closed loop simulation against the status quo management of the DERPA complex, which involves intermittent assessments at best. Furthermore, simulations of the DERPA complex that model status quo management may uncover risks not considered in the current management system.

Results will be published in two articles in the primary literature. The first article will be detail the model linking complex market forces to IFD effort dynamics simulator. The second article will publish the operating model and the pinch-point dynamics that are expected to emerge from the closed loop simulation.

Chapter 4: Avoiding non-target species.

Introduction

Quota on target species in the British Columbia groundfish fishery is increasingly constrained by not only restrictive quotas on pinch-point species, but size limits on target species. 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 fishery[5]. These undersized individuals represent potential growth and recruitment overfishing of the sablefish resource, constraining future TACs by lowering species productivity (S. Cox et al., 2011).

There is general agreement in the literature that incidental catch and discard-

[5]From the Groundfish Fishery Operating System (GFFOS), Pacific Biological Station, Nanaimo.

ing should be reduced as much as possible or practical (Crowder & Murawski, 1998; Pelc et al., 2015; Safina & Lewison, 2008; Saila & Jones, 1983). 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 will 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, novel statistical learning models that may sidestep these restrictions are used to search for correlations in commercial data (C. M. Bishop, 2006; Hastie et al., 2009).

Statistical learning models are trained and optimised on commercial data from the British Columbia groundfish fishery to classify presence and absence of juvenile sablefish for a given fishing event. Event predictions from all models are then combined into a multi-model, or ensemble, classifier (Rokach, 2010; Vrbik & McNicholas, 2015). Ensemble classifiers use weighted model averaging techniques to overcome potential overfitting to the training data. A set of quarantined data is then used to test the performance of the classifiers 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 ensemble classifiers to detect juvenile Sablefish is tested on 4 sets of commercial fishing data from the British Columbia groundfish fishery. The fishery data is contained in the Groundfish Fishery Operating System (GF-FOS) data base that contains spatially and temporally explicit data for every fishing event in the fishery 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, two types of classifiers are developed. First, a finite mixture model will be tested (Frhwirth-Schnatter, 2006). Finite mixture models are weighted combinations of single statistical models, allowing for highly irregular data to be modeled using mixtures of parametric distributions or explanatory or descriptive models. Second, an ensemble classifier using modern machine learning, or big data, techniques will be developed using Random Forest (Breiman, 2001), Naive Bayes (Meyer, Dimitriadou, Hornik, Weingessel, & Leisch, 2015) and Artificial Neural Network (W. N. Venables & Ripley, 2002) classifiers.

Component model configurations for both types are chosen based on average performance over Monte-Carlo trials of a validation procedure (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, with the configurations depending on the type.

Finite mixture models are combined in a prescribed way with weights estimated from the data, but machine learning classifiers have some more flexibility. Methods range from simple weighted 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 each classifier on each data set (Mntyniemi et al., 2009; Pestes, Peterman, Bradford, & Wood, 2008; Peterman & Anderson, 1999). Classifiers are included in the analysis as a form of expert opinion, adjusting the probability of encountering juvenile Sablefish, based querying the expert prior to a fishing event. 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, sorting discards from the catch, as well as the value of landed catch.

Expected Results

It is expected that statistical learning will be economically feasible for the avoidance of non-target species. However, the net benefit is will likely depend on the nature of the species being avoided. For example, pinch-point species with restrictive quota that is costly to acquire, such as Yelloweye rockfish, may result in a greater net benefit, while regulatory discards of juvenile individuals with no quota penalty may result in a lesser net benefit. This could be overcome by including the avoidance technology in larger closed loop simulations of the management system, and seeking predictions of a long term benefit in the form of higher TACs of mature sablefish.

Challenges in this chapter include acquiring spatially and temporally explicit data for bycatch of juvenile sablefish, and estimating the costs and benefits for the decision analysis. For data acquisition, the privacy act creates a limit on the resolution of commercial data, requiring creativity an perspiration in choosing an aggregation scale. Estimates of the costs and benefits of fishing may exist in the literature for other fisheries, but this may be best informed by asking skippers directly.

Conclusion

This thesis is a study of assessment and avoidance tools that may improve management of integrated multispecies fisheries, in which technical interactions cause constraints on fishery profitability. Profitability is constrained when the effort targeting directed, high value species encounters non-target species with restrictive quota. Restrictive species quota may be caused by data limitations precluding regular assessments, or conservation concerns requiring rebuilding strategies. In either case, those species become pinch-points on the efficient management of the fishery.

Hierarchical assessment models studied in Chapters 1, 2 and 3 may overcome data limitations and allow assessments to be extended to species that were previously unassessed. Extending assessments to previously unassessed species may or may not relieve pinch points by reducing uncertainty about stock status, but will always increase scientific defensibilty. Indeed, up-to-date and regular assessments of non-target species allows for improved ratings by eco-certification bodies (Driscoll, 2014). Improved eco-certification can create benefits by improving access to foreign and domestic markets.

Closed loop simulations of hierarchical assessment models studied in Chapter 3 may have further benefits in multispecies fishery management, specifically in improving the allocation of scientific resources. By assessing groups of multiple species with similar life and evolutionary histories, it may be possible to take biological samples more efficiently. For example, age and length sampling may occur only for higher value species in a group, with lower value species sampled for length only. Then length and age can be related through a shared multispecies prior defined in the hierarchical assessment model. If model stability is an issue, low frequency age sampling of the lower value species may be necessary. Closed loop simulation can assess the potential risks associated with these and other survey design modifications.

Avoidance techniques are necessary when assessment methods are unable to relieve pinch-point effects of low quota species. The statistical learning methods to be studied in Chapter 4 are a novel approach to the avoidance problem, combining technological and fleet communication approaches. A centralised communication system can use reported observer data to provide near-real-time information to harvesters, detailing the probability of non-target species encounter under given conditions. The system is not unique to juvenile Sablefish and could be extended to any non-target species encountered, which would change the expected net economic benefit of the product.

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