

Exploiting Interactions in Multispecies Fisheries to Assess and Avoid Constraining Species

Thesis Proposal

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Not Done Yet.

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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); Benson, Cox,

& Cleary (2015)), such as Pacific salmon (*Onchorynchys spp.*) (Simon & Larkin (1972)). Multiple ecologically and technically interacting populations (i.e., stocks) of Chinook (*O. tshawytscha*), Chum (*O. keta*), Coho (*O. kisutch*), Pink (*O. gorbausch*), Sockeye (*O. nerka*) and Steelhead (*O. mykiss*) occur along Canada's Pacific coast. Each species is made up of genetically distinct subpopulations, defined mainly by discrete spawning habitats and run timing that establish quasi-isolated reproductive populations (Ricker (1972)) connected by low straying rates.

Managing hundreds of distinct fisheries is impractical (Walters & Martell (2004)) so salmon stocks are often grouped together into stock complexes for management and assessment. For instance, in the Fraser River, 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 some 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 Bocaccio 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 COSEWIC¹ 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 a maximum of 25% of lingcod quota being utilised in that same time period (Figure 5). This underutilisation translates into a reduction of around **DOLLAR AMOUNT**² gross revenue to the BCIGF between 2006 and 2014.

¹Committee on the Status of Endangered Wildlife in Canada.

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

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-occurrence 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 species 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 (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 6 (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 intermediate level of aggregation between models (a) and (b) of Figure 6. 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 (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 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)). 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 simulator is used to evaluate management procedures using spatially structured multistock and multispecies hierarchical models (Figure 10). 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 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 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 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 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**etrable sole and **A**rowtooth 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 experience technical interactions in trawl 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 decade³ (Jeff Fargo, Kronlund, Schnute, & Haigh (2000); Jeff Fargo & Starr (2001)). English and Petrale sole were last assessed in 2009 (Starr

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

(2009); Starr (070AD)). Dover sole was last assessed in 1999 and has never been assessed using a model based assessment (J. Fargo (1999)). **MAKE THIS PARAGRAPH A FIGURE**

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 function values as outputs. Statistical model output is then optimised or integrated over the input parameters to extend inferences about stock produc-

tivity 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 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 (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: 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 DERPAs complex is simulated 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 observation 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 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 representative 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 specific process errors ζ_t , reflected in the covariance 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 (Hilborn et al. (2003); Cope & Punt (2011); 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 (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 na-

ture 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)).

QUESTION: How do estimates of abundance and productivity in a multi-stock, multispecies hierarchical model compare to those of a coastwide multispecies 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 p of each species s (Table 5), with stocks corresponding to the discrete populations identified in stock previous stock assessments (J. Fargo (1999); Starr (070AD); Starr (2009); DFO (2015); K. R. Holt et al. (2016)) (Figure 11). Migration from stock p to stock p'

within species s is possible with net migration rate $\phi_{s,p,p'}$, making stock population dynamics interdependent (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 covariance 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 has three layers of hierarchical structure to include multiple species, each containing multiple stocks (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 designed 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 covariation 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 is 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 are 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 (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 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 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 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 provide 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 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.

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 closed loop simulations of the DERPA complex under different management and ecological scenarios. A validated operating model that accurately reflects 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 brought about by changing costs and benefits of fishing.

Methods

The closed loop simulator of the DERPA complex requires an operating model including 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. Assessment 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: gravity models (Walters & Bonfil (1999)), ideal free distribution (IFD) models (Benson et al. (2015)), sequential effort allocation models (Hilborn

& Walters (1987)) and 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)) **INCLUDE MATH IN A TABLE**. 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 as part of 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 fishing cost (fuel, deckhands, catch handling), ex-vessel sale price of catch and the price to acquire 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 (**REFERENCE??**), 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 an understanding of how hierarchical management procedures perform in multispecies fisheries. Performance of both coast-wide 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 status quo management may uncover risks unconsidered in the current management system.

Results are to be published in at least one article in the primary literature. The effort dynamics are expected to combine with multispecies catch and quota allocation to produce emergent pinch-point effects within the management system leading to underfishing of some species, forming the basis of one article. Depending on the novelty and complexity of the market forces influencing the IFD effort dynamics simulator, a second article may be warranted.

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)). Mor-

ality 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 (Mn-tyniemi 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

It is expected that machine learning will be economically feasible for the avoidance of non-target species. However, the net benefit is expected to 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.

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 and 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 defensibility. Indeed, up-to-date and regular assessments of non-target species allows for improved ratings by eco-certification bodies (Driscoll (2014)). Improved eco-certification then creates follow on benefits by improving access to foreign and domestic markets, increasing market share of the fishery.

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 machine learning methods 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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