Leveraging what we do not know to quantify uncertainty in fisheries management

Kristin Privitera-Johnson

A thesis

submitted in partial fulfillment of the

requirements for the degree of

Master of Science

University of Washington

2019

Committee:

André E. Punt, Chair

Jason M. Cope

Timothy E. Essington

Program Authorized to Offer Degree:

Aquatic and Fishery Sciences

University of Washington

Abstract

Leveraging what we do not know to quantify uncertainty in fisheries management

Kristin Privitera-Johnson

Chair of the Supervisory Committee:
Director, Dr. André Punt
Aquatic and Fishery Sciences

Stock assessment plays an important role in the broad field of risk management by providing a means to link scientific uncertainty to consequences of management actions, such as overfishing. The first chapter of this thesis reviews the methods and tools used to quantify scientific uncertainty and their relationship to the presentation of uncertainty to fisheries managers. I found that scientific uncertainty is being quantified and included in scientific advice across multiple fishery management systems. The second chapter relates to quantifying the scientific uncertainty used to set catch limits for US west coast groundfish and coastal pelagic species fisheries. This system serves as a good case study because the harvest control rule for reducing the overfishing limit to account for scientific uncertainty is based on the Pacific Fishery Management Council's risk tolerance (*i.e.*, the probability of overfishing) and a measure of scientific uncertainty (*i.e.*, model

specification based on among assessment variation). My approach bases the calculation of this uncertainty on projected overfishing limits, accounting for uncertainty in future recruitment as well as among-assessment variation. Methods for quantifying uncertainty and their incorporation into management advice are quickly advancing and approaches for reviewing progress towards clearly and explicitly communicating the sources, treatment, and impacts of uncertainty in our management processes must keep pace.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGEMENTS

My heartfelt thanks goes to my adviser, Dr. André Punt for years of mentorship and patience. I find your enthusiasm for our projects contagious. Thank you for actively leading an inclusive (and adaptive) classroom and community. The high-quality science I pursue is only possible because I feel welcome and well-incorporated into the UW SAFS community. I look forward to our future projects—let's do our best and learn something new.

I thank Dr. Timothy Essington for the opportunities to grow as a well-rounded scientist. Your commitment to the professional development of the whole student inspires me to push myself in arenas where I feel comfortable and gives me courage to combat the fear of failure in areas where I seek growth. You are an important member of the SAFS community and I look forward to learning more from you during my PhD. And, of course, potentially teaching a course with you as my mentor.

I warmly thank Dr. Jason Cope for always believing in me. Thank you for always answering the call or email. You serve as an integral link between the UW SAFS and NOAA communities. Thank you for your enthusiasm and kindness. I look forward to collaborating with you in the near future.

Completing a graduate degree would have been impossible without the support of the Punt Lab members of the past and present. Many thanks to Kelli Johnson, Felipe Hurtado Ferro, Chantel Wetzel, Caitlin Allen Akselrud, Lee Qi, Lee Cronin-Fine, John Best, Grant Adams, Madi Shipley, and Maia Kapur for your encouragement, mentorship, and moral support.

Many thanks to Melissa Haltuch, Juan Valero, Aaron Berger, Jim Ianelli, Martin Dorn, John Field and many other assessment scientists for your mentorship and networking opportunities.

Finally, I wholeheartedly thank my family for their support throughout the graduate school process. Your sacrifice and patience will not be forgotten. Thank you for your gifts of a debt free education. I look forward to watching you all pursue your dreams and leave your mark upon the world.

This research was funded by the National Science Foundation Graduate Research Fellowship Program and the Usha and S. Rao Varanasi Endowed Fellowship in Environmental and Marine Stewardship. I am grateful for these investments in my career and professional development.

DEDICATION

This thesis is dedicated to my three younger sisters. I hope you find your passion and vocation—and that they inspire you to pursue goals you never believed attainable for yourself.

INTRODUCTION

Our world's fisheries serve as a fascinating, yet enigmatic, example of managing natural resources and ecosystems at the intersection of participants' conservation, economic, traditional, and recreational values. Fisheries managers and scientists are tasked with developing and implementing pragmatic management solutions to honor these values while navigating these "complex, unpredictable, and variable" socio-natural systems (Sethi 2010). Identifying the risk associated with using marine resources is a high priority for stakeholders due to the perception that fisheries management has failed in the past, shifting public attitudes towards risk aversion, and faster computing (Francis and Shotton 1997). To be useful for decision making, risk quantification requires the estimation of an event occurring and the severity of any consequences of that event (Kell et al., 2016). Estimating the probability that an event occurs depends on identifying and quantifying uncertainty, *i.e.*, the notion that the current fishery state and projections about its future cannot ever be fully known (Edwards 2016). The desire to evaluate the consequences of management strategies resulting in unfavorable events drives the development of fisheries stock assessment methodology (Punt and Hilborn 1997). In this thesis, I will a) characterize some of the methods and tools used for quantifying uncertainty and highlighting the consequences of management actions that strive to incorporate the diverse value systems of fisheries participants; and b) present an improved method for quantifying scientific uncertainty.

To highlight the role that stock assessment plays in informing risk of overfishing, it is necessary to describe how uncertainty arises in the fisheries management process. Generally, fisheries management is a feedback loop of data collection, analysis (*e.g.*, stock assessment), review, presentation of scientific advice, decision making, and regulation implementation. First, we must acknowledge the process uncertainty inherent to all natural systems due to the underlying stochasticity in population dynamics, such as unpredictable variation in recruitment, growth and natural mortality, and accept this as an irreducible and uncontrollable uncertainty (Edwards 2016). Observation uncertainty, the variation in measurement of observable quantities such as catch or size-at-age, is associated with the data collection phase (Rosenberg and Restrepo 1994). The analysis phase often leads to model uncertainty, the misspecification of model parameters or structure (*e.g.*, assuming the incorrect form for selectivity as a function of size), and estimation uncertainty, the inaccuracy and imprecision in the estimated model parameters (Francis and Shotton 1997). Process, observation, model, and estimation uncertainties are collectively referred to as scientific uncertainty, and methods for quantifying these within the stock assessment process are well represented across fisheries jurisdictions and taxa.

Stock assessment plays an important role in the broad field of risk management by providing a means for linking scientific uncertainty to consequences of management actions such as overfishing. Best practices for addressing scientific uncertainty encourage efforts to identify and reduce uncertainty, manage fisheries within the context of a changing environment, and manage risk (Cadrin et al., 2015). The repertoire of methods for quantifying and clearly communicating the sources, treatment, and impacts of uncertainty is however vast and varies among management jurisdictions and fish stocks. There are few studies summarizing how this repertoire is used in specific regions (*e.g.*, Dichmont et al., 2016a,b; Marchal 2009; Marchal 2016) but there is opportunity to look at trends in method use on a broader scale. The goals of this thesis are to (a) broadly characterize how uncertainty is quantified and presented to managers, and to identify the factors that influence the methods and tools used, and (b) develop a method for quantifying uncertainty for application in a formal risk management policy.

Stock assessment scientists must carefully communicate uncertainty when providing scientific advice to fisheries managers because both overemphasis and understatement of the magnitude of uncertainty can undermine scientific credibility and, ultimately, progress towards management goals (Dankel et al., 2012). Effectively accounting for uncertainty during the fisheries management process can prevent impediments such as exceeding catch limits, failure to rebuild depleted fish stocks, and missed opportunities to take advantage of sustainable fishing opportunities (Cadrin et al., 2015). Scientific advice may radically differ depending on the assessment modeling framework used (Kell et al., 2016). The first chapter of this thesis reviews the methods and tools used to quantify scientific uncertainty and their relationship to the presentation of uncertainty to fisheries managers. This review was guided by a survey of stock assessment scientists to investigate the following: 1) how are scientific uncertainties presented to fisheries managers?; 2) what methods and tools are used for quantifying uncertainty?; 3) how have methods and tools changed over time?; and 4) what are the most common factors that influence the use of a specific method?

The second chapter relates to quantifying the scientific uncertainty used to set catch limits for US west coast groundfish and coastal pelagic species fisheries. This system serves as a good case study because the harvest control rule for reducing the overfishing limit (OFL) to account for scientific uncertainty is based on the Pacific Fishery Management Council’s risk tolerance (*i.e.*, the probability of overfishing) and a measure of scientific uncertainty (*i.e.*, model specification based on among assessment variation). The current approach used to define the scientific uncertainty component of the harvest control rule quantifies the variation in the historical biomass time series estimated from 81 data-rich assessments of 15 groundfish and 2 coastal pelagic species stocks. A major assumption of this approach is that the uncertainty in historical biomass is a proxy for the uncertainty in the OFL (Ralston et al., 2011). This approach was a good first step in meeting the US Magnuson-Stevens Act and National Standards mandate for harvest control rules that incorporate scientific uncertainty. However, there is room for improvement. Here, I outline a new approach that projects and directly quantifies the variation in OFLs across the following dimensions: a) among assessments of the same stock, b) among assessments across multiple groundfish stocks, c) across multiple projection start years, and d) when assuming deterministic vs. stochastic recruitment. I compare my estimate of scientific uncertainty across all four dimensions to the estimate of uncertainty produced using the historical biomass approach. This work was presented to, reviewed by, and adopted by the Pacific Fishery Management Council.

CHAPTER 1: A REVIEW OF APPROACHES TO QUANTIFYING UNCERTAINTY IN FISHERIES STOCK ASSESSMENTS

1.1 ABSTRACT

Scientific uncertainty affects all parts of the fisheries management process. The goal of this chapter is to summarize methods for quantifying scientific uncertainty for presentation as part of the scientific advice to fisheries managers. Stock assessment scientists were surveyed to a) identify the methods commonly used to quantify uncertainty, b) describe how method use has changed over time, c) investigate the factors that influence which methods are used, and d) characterize how scientific uncertainty is presented to fisheries managers. Scientific uncertainty is being quantified and included in scientific advice across multiple fishery management systems. Frequentist approaches for quantifying uncertainty are used more broadly than Bayesian approaches and the survey did not detect this changing over time. Time restrictions and methodology requests during the scientific review process were commonly reported as factors influencing the use of uncertainty methods. Uncertainty in estimates of management targets (*e.g.*, fishing mortality or biomass), projections, and catch limits were the quantities most frequently included in the scientific advice presented to fisheries managers. Methods for quantifying uncertainty and their incorporation into management advice are quickly advancing, and our approaches for reviewing our progress towards clearly and explicitly communicating the sources, treatment, and impacts of uncertainty in our management processes must keep pace.

1.2 INTRODUCTION

Communicating uncertainty is an inescapable component of providing scientific advice for fisheries management. The efficacy of fisheries management is influenced by at least five types of uncertainty: 1) observation uncertainty, the uncertainty in measurement of observable quantities such as catch or sizes-at-age; 2) process uncertainty, the uncertainty due to underlying stochasticity in stock dynamics such as recruitment or variation in the growth of a fish stock; 3) model uncertainty, the misspecification of model parameters or structure (*e.g.*, assuming the incorrect form for selectivity as a function of size); 4) estimation uncertainty, the inaccuracy and imprecision associated with estimated model parameters; 5) and implementation uncertainty, the variability in the implementation of management strategies (Holland and Herrera, 2009; Rosenberg and Restrepo, 1994). These uncertainties occur in all fishery systems, and affect the interpretation of data, analysis results, ranking of management options, and the efficacy of those options (Peterman, 2004). The resulting impact of uncertainty on scientific advice is critical because both overemphasis and understatement of uncertainty can undermine scientific credibility and ultimately progress towards management goals (Dankel et al., 2012). Failure to effectively account for uncertainty can lead to overshooting management targets, failing to rebuild depleted stocks, and missing opportunities to take advantage of sustainable fishing opportunities (Cadrin et al., 2015). Rosenberg (2007) suggested those who produce scientific advice for fisheries management navigate the pitfalls of blanket generalizations about uncertainty by discerning the "almost certain from the less certain".

It is convenient to consider two classes of uncertainty when discussing the quantification of uncertainty: scientific uncertainty (*i.e.*, observation, process, model, and estimation uncertainties) and management uncertainty (*i.e.*, implementation uncertainty). The focus of this paper is on methods for and applied examples of quantifying scientific uncertainty, as these dominate the literature and are general across jurisdictions and taxa. Identifying the widely used tools and methods for quantifying scientific uncertainty and the frequency of use over time, fish stocks, and regions can contribute to the continued development of best practices. Understanding the factors influencing the use of a tool or method can inform the allocation and development of resources to better quantify uncertainty.

During this exploration of methods and tools for quantifying uncertainty, I will use the following definitions of key concepts. The *fisheries management process* consists of data collection, analysis, scientific review, provision of scientific advice, decision-making, setting of catch limits, and enforcement (FAO 1997). *Jurisdictions* are the organizations (*e.g.*, single governmental, multi-national governmental, and non-governmental) designing and implementing the fisheries management process. A *stock assessment* is a process that includes the activities, analyses, and reports related to the data collection, analysis, and scientific review components of the fishery management process (PFMC 2018). More specifically, the *analysis* process of a stock assessment uses statistical and mathematical models to incorporate different data sources (*e.g.*, survey, fishery, biological) to make quantitative predictions about the abundance and trends of fish stocks and of fishing intensity (Hilborn and Walters 1992). Scientific uncertainty can be quantified using frequentist and Bayesian paradigms of statistical inference (hereby deemed as *uncertainty methods*). *Sensitivity analyses* elucidate how uncertainties propagate through an assessment model and can be apportioned to sources of uncertainty in the model inputs and parameter values (Satelli 2002; Steel et al. 2009). The modeling frameworks designed for stock assessment analysis, the uncertainty methods, and sensitivity analyses can be assembled into *packages* (*i.e.*, well-documented software repositories) to be downloaded and installed on a computer for reproducible analyses.

Dichmont et al. (2016) assert that assembling stock assessment modeling frameworks into packages is integral for increasing access to tools for quantifying uncertainty. The advantages of open access assessment packages facilitates exploration of multiple assessment configurations and strengthens the peer-review process (Dichmont et al., 2016). However, implementing a new model for a stock using packages developed for different, specific stocks presents challenges such as dealing with the “black box” effect when debugging potential errors and the steep learning curve for packages with many options. This meta-analytic approach to characterizing package use in U.S. fisheries management lends itself well to exploration of other analysis components such as methods for quantifying scientific uncertainty.

I apply a similar meta-analytic approach as Dichmont et al. (2016) to summarize the methods that produce model outputs used to communicate scientific uncertainty to fisheries managers. Specifically, I am interested in the methods used for quantifying uncertainty within a given assessment framework and across such frameworks. I surveyed stock assessment scientists to investigate the following: 1) what methods for quantifying uncertainty are used?; 2) how have methods changed over time?; 3) what are the most common factors that influence the use of a specific method?; and 4) how are scientific uncertainties presented to fisheries managers?

1.3 METHODS

The survey addressed each research question through the use of multiple choice and free responses questions (Supplementary Appendix 1.6). Participants were asked to state the assessment tools (*i.e.*, packages) they have used, the approaches used for quantifying scientific uncertainty while conducting assessments, and the quantities of interest used in sensitivity analyses (Supplementary Appendix 1.7-1.9). To characterize how method and tool use has changed over time, participants were asked to provide the tools, analyses, and approaches used in a (subjective) representative sample of the assessments they have conducted (Supplementary Appendix 1.12). To identify factors that may influence method and tool use, analysts were asked which available methods for quantifying uncertainty were not used, which quantities of interest could have been considered for uncertainty evaluation but were not, and why (Supplementary Appendix 1.8-1.9). Finally, participants were asked how they have presented uncertainties to fisheries managers (Supplementary Appendix 1.10).

The survey was distributed to scientists who have conducted stock assessments and provided scientific advice to management. Survey participants (N=59) have provided scientific advice for many organizations around the world. Respondents self-defined the numbers of years worked as a stock assessment scientist and these ranged from 1 to 38 years (Figure 1.1).

Survey respondents were asked to provide information for some representative stock assessments they have conducted over the last 5-10 years. This included the common and scientific names of the stock, the agency for which the assessment was conducted, the year the assessment was conducted, the packages used, the data types used, the sensitivity analyses conducted, and the uncertainty methods used. The resulting time series covered 1997 to 1999 (ranging from 1 to 3 assessments each year) and 2002 to 2018 (ranging from 1 to 57 assessments each year). Originally, information for 335 assessments was reported. However, there were cases of repeat assessments because multiple assessment authors who have worked on the same assessments were surveyed. The information was collated across respondents and resulted in 316 individual assessments. Survey respondents were invited to list the uncertainty methods, sensitivity analyses, and packages listed in the survey and any additional analyses and analysis methods not included in the baseline lists.

1.4 RESULTS

1.4.1 *Representativeness of the survey results*

The survey reviewing methods for quantifying scientific uncertainty has notable limitations. The representation of agencies and regions is not evenly distributed, as ~25 of the 59 respondents were based at NOAA while other organizations like ICES and the Japan Fisheries Research and Education Agency only had one respondent. Also, the patterns in method use presented have low sample sizes (*e.g.*, 1-2 stocks) for assessments in the early part of the time series.

1.4.2 *Software and model framework*

Survey respondents were asked to identify software they use (and have used) in the process of conducting a stock assessment. The provided list of available software featured 23 options (Table 1.2; Supplementary Appendix 1.7) and the survey responses yielded an additional 20 (Table 1.1). Of the original 23 options [Table 1.2], only six options had never been used by any of the 59 respondents: CEDA, FSIM, LFDA, ParFish, SEEPA, and STATCAM (Figure 1.2). Software coded using ADMB was frequently used, with Stock Synthesis being the most frequently used of the packages based on ADMB. The proportion of packages used over time was summarized in terms of the original 23 options [Table 1.2] (Figure 1.4). CEDA, CSA, FiSAT, FiSAT II, FSIM, LFDA, ParFish, PRO-2Box, PRODFIT, SEEPA, and STATCAM were not featured in the specific assessments reported by survey respondents but CSA, FiSAT, FiSAT II, LFDA, PRO-2Box, PRODFIT must have been used at some time.

1.4.3 *Structural models and estimation methods*

Participants were asked if they used sensitivity testing, frequentist (*i.e.*, asymptotic methods, bootstrapping, jackknife, and likelihood profiles) and Bayesian (*i.e.*, AIS, MCMC, SIR) methods to quantify uncertainty. In relation to the use of sensitivity analyses to directly quantify uncertainty, 34 respondents provided a response: 19 respondents reported yes, 13 reported no, and 2 reported sometimes. The participants stated that they used sensitivity analyses to quantify uncertainty qualitatively and as a "2nd tier of uncertainty" to be used in conjunction with other methods (*e.g.*, management strategy evaluation and Bayesian methods) to account for uncertainty when, for example, defining states of nature and bracketing ranges of plausible outcomes when important elements of uncertainty cannot be incorporated into a model (*e.g.*, if one cannot estimate natural mortality, stock-recruitment steepness, or catch uncertainty). These responses also highlighted the strength of sensitivity testing as a qualitative tool useful for representing extremes to demonstrate model behavior and assess the robustness of model results to baseline assumptions and assumed values for model parameters. For the frequentist approaches, asymptotic methods and likelihood profiles were selected most frequently, followed by bootstrapping, and jackknife (Figure 1.2). The dominant Bayesian approach was MCMC and its many variants (N=43) (Figure 1.2). Additional methods for quantifying uncertainty provided by survey respondents were decision tables, ensemble modeling, retrospective analyses, and the Approximate Bayesian Computation.

Respondents referred to assessing the "performance" of models using retrospective analyses of base models and previous assessments of the same stock, and models of various levels of complexity (*e.g.*, fitting a production model as well as a model that includes all the data).

1.4.4 *Model specification and sensitivity analyses*

Respondents were asked if they routinely conduct sensitivity analyses based on alternative catch streams, on assumptions about catchability, growth, maturity, natural mortality, and recruitment (*e.g.*, fixed values for stock-recruitment steepness), selectivity parameterization, and the stock-recruit relationship itself (*e.g.* a Beverton-Holt or Ricker parameterization) and to assumptions about data set choice, and data weighting. They were also asked to provide additional types of sensitivity tests not included in the base list. Of the provided list, data weighting was the most selected option and maturity was the least (Figure 1.2). Additional sensitivities fell into two categories: data processing and changes to structural assumptions. Sensitivities involving data processing included the range of years of data used for specific data sets and how they are used (*e.g.*, a survey using different sampling methods in different years), the binning of length compositions, alternative survey indices (*e.g.*, design- vs. model-based), use of tagging data, how survey data are aggregated over space, area-stratified vs. spatially lumped, and alternative assumptions regarding ageing imprecision. Model structure sensitivity analyses involved comparing results using different stock assessment packages (*e.g.*, personalized ADMB model, Stock Synthesis, and SAM), the number of growth morphs (in a Stock Synthesis assessments), whether the model is single- or two-sex, the number of areas, fleet structure, temporal step, alternative time ranges for the assessment movement/migration assumptions, likelihood distribution assumptions, proportional vs. non-proportional relationships between catch-rate and abundance, amount of fishing prior to the start of the data series, cetacean depredation, time-varying selectivity and IUU trends.

1.4.5 *Presentation of uncertainty to fishery managers*

Survey participants were given eight options for assessment outputs used to communicate scientific uncertainty to fishery managers: estimates of fishing mortality and/or biomass; estimates of fishing mortality and/or biomass relative to reference points; the results of simulation testing; the results of management strategy evaluations; decision tables; values for catch limits (*e.g.*, Total Allowable Catch (TAC), Acceptable Biological Catch (ABC), Overfishing Limit (OFL));

projections under uncertainty; and other (Figure 1.2). Estimates of incoming year class strengths (*i.e.*, recruitment) and the results of ensemble models were suggested as additional ways to communicate uncertainty by the participants. Several respondents reported that while they have presented many of these model outputs to fisheries managers and their scientific review bodies, there are cases when the information (and its associated estimates of uncertainty) have not been used in fisheries management.

1.5 DISCUSSION

Scientific uncertainty is being quantified and included in scientific advice across multiple fisheries management systems. Frequentist approaches for quantifying uncertainty are used more broadly than Bayesian approaches, and the survey did not detect this trend changing over time. This is also reflected in the prolific use of packages using asymptotic methods for estimating uncertainty, which has qualitatively increased over time (*e.g.*, those based on ADMB, although ADMB-based packages can also form the basis for Bayesian approaches for quantifying uncertainty). Similarly, there has been little change in the quantities of interest investigated for sensitivity analyses over time, supporting Maunder and Piner's (2015) statement that successful interpretation of data requires knowledge of growth, recruitment, natural mortality, selectivity, and sampling processes—knowledge that remains incomplete for most stocks and regions. Time restrictions and methodology requests during the scientific review process were commonly reported as factors influencing the use of uncertainty methods (more below). Uncertainty in estimates of management targets (*e.g.*, fishing mortality or biomass), projections, and catch limits were the quantities most frequently presented to managers. Survey respondents also expressed that not all uncertainties that are quantified are presented and not all those presented are used by managers in the decision-making process.

Ultimately, asking assessment scientists what factors influence their use of specific approaches to quantifying scientific uncertainty revealed a common theme: the design of the fisheries management system. The priorities of jurisdictions designing each component of this cycle vary with their respective values, economic structures, and political traditions (Marchal et al. 2016). At the heart of the fisheries management system lies the mission to have a transparent process operating with the utmost integrity to strengthen stakeholder confidence in the decisions being informed by scientific advice. Failure to explicitly define the roles and responsibilities of managers and scientists presents opportunities for certain sources of uncertainty to not be properly identified (Cadrin et al. 2015). The definition and communication of these roles and responsibilities is a dynamic process that changes as the fishery management system encounters new situations and experiences changes in decision-making participants and government structures (Francis and Shotton 1997).

Many jurisdictions create and implement review protocols to meet their goals and avoid the above pitfalls, which directly influence the methods used to quantify uncertainty. This can manifest as specific methodology requests for conducting assessments, quantifying uncertainty, and presentation of scientific advice. The International Council for the Exploration for the Exploration of the Sea (ICES) uses a Generic Terms of Reference for many of its stock assessment working groups. Each stock assessment working group applies an assessment model framework that is either analytical, forecast, or based on trend indicators, and the final report is requested to address the following: input data and data quality; catch misreporting; percent of total catch taken in a regulatory area; if applicable, estimates of maximum sustainable yield proxy reference points; the status of the stock relative to reference points; projected catch scenarios; and historical and analytical performance of the assessment and catch options (ICES 2018). In the U.S., the Pacific

Fishery Management Council has specific requirements for the evaluation of uncertainty in assessment results for U.S. West Coast groundfish and coastal pelagic species stocks: model specification uncertainty; parameter uncertainty (including likelihood profiles); retrospective analysis; historical analysis; probability statements for ranges of model runs; and for groundfish at least three states of nature for model ranges (*i.e.*, most probable, lower biomass trajectory, and high biomass trajectory) (PFMC 2018).

The time allocated to conduct and review a stock assessment varies by jurisdiction, and directly influences the methods used to quantify uncertainty. The amount of time available to conduct and review a stock assessment to prepare scientific advice depends on resource availability (*e.g.*, external reviewers) and the timetable for making short term management decisions (*e.g.*, setting catch limits). In many regions of the U.S., assessments are conducted over the course of a few months and are reviewed over a short time period (*e.g.*, 5 days for U.S. West Coast) and any additional model requests must be performed within this time frame (PFMC 2018). In other systems such as New Zealand and South Africa, assessment groups meet over the course of weeks or months to conduct the assessment and respond to scientific review feedback (Marchal et al. 2009). ICES stock assessment working groups meet for 5-10 days to complete and review assessments (Marchal et al. 2009). The combination of requested methodology and the time available for conducting and reviewing assessments may not leave stock assessment scientists with enough time to run full Bayesian analyses. However, incorporating advances in optimization approaches in software such as ADMB (*e.g.*, Hamiltonian No U-Turn Samplers) may reduce this bottleneck in analysis run time enough to influence the use of uncertainty methods for management advice in the future (Monnahan et al. 2019).

The frequency of assessment for a stock (*i.e.*, stock prioritization) also influences time restrictions and may indirectly impact the use of specific uncertainty methods. Stock prioritization generally relates to the total number of stocks and species assessed by a jurisdiction, relative commercial importance of the stock, and data availability (Marchal et al. 2009; Methot 2015). Depending on the stock, assessment frequency may range from once a year to once every 10 or more years. Jurisdictions with many stocks may have longer gaps between assessments for a single stock because limited resources (*e.g.*, number of available assessment scientists) may restrict the number of assessments that can be conducted annually. The stocks and species assessed may also rotate over time. Stock prioritization procedures (informally and formally defined) decide how this stock rotation occurs and fisheries scientists and managers should collaborate to design procedures that "focus limited resources where they are most needed to reduce uncertainty" (Cadrin et al. 2015). Given these constraints, incorporating major changes to model structure and uncertainty methodology may not be feasible every assessment cycle, especially if there are long gaps since the last assessment for a stock, new data considerations, and requested methodology from scientific review committees.

Summarizing the influence of management design highlights opportunities to expand the options for quantifying uncertainty for use in the development of scientific advice. Survey respondents reported that the uncertainty methods and sensitivity analyses they employ often differ between assessment reports and research publications. Scientists should continue to integrate the latest research into the packages (new and existing) and methods used to inform management. Using packages that have been previously reviewed and approved by the scientific review committees has the potential to alleviate some of the burden of the review process and may promote more effective communication of results (Dichmont et al. 2016a). The expansion of current packages (*e.g.*, Stock Synthesis and CASAL) can include the addition of spatially-structured population dynamics models, incorporation of non-traditional data types (*e.g.*, tagging data, and habitat information), and integration of economic considerations (*e.g.*, Australian fisheries requiring management advice related to maximum economic yield) (Dichmont et al. 2016b). Continued and expanded focus on cooperative research opportunities such as courses (*e.g.*, Advanced School on Multispecies Modelling Approaches for Ecosystem Based Marine Resource Management in the Mediterranean Sea (AMARE-ED), www.echo.inogs.it/amare-med/; ICES training courses, www.ices.dk/news-and-events/Training/) and workshops (*e.g.*, National Stock Assessment Workshops, www.st.nmfs.noaa.gov/stock-assessment/workshops; Center for the Advancement of Population Assessment Methodology (CAPAM), www.capamresearch.org) are integral for developing and disseminating new methods for quantifying scientific uncertainty for use in scientific advice (Cadrin et al. 2015; Dichmont et al 2016b).

Using meta-analytic approaches to characterize how uncertainty permeates through fisheries management systems around the world can also be further developed. The set of methods for quantifying management uncertainty for use in advice for fisheries management has increased in the last decade (*e.g.*, Dichmont et al., 2006; Fulton et al., 2011; Sethi et al., 2005) and exploring how factors such as fisheries management system design influences the development and implementation of these methods is a promising area of future research. Investigating how uncertainties are presented in scientific advice across jurisdictions (*e.g.*, the Kobe framework [Kell et al. 2016]) may provide insight about how to progress effective communication of uncertainty in a field producing increasingly complex and multidimensional management advice to a broad audience of stakeholders. Survey approaches *sensu* Levontin et al. (2017) complement this effort by evaluating the reliability of our visualization of modeling approaches. Methods for quantifying uncertainty and their incorporation into management advice is quickly advancing and the approaches for reviewing our progress towards clearly and explicitly communicating the sources, treatment, and impacts of uncertainty in our management processes must keep pace.

TABLES

Table 1.1. Additional software packages used in the process of conducting a stock assessment; provided by the survey respondents.

Modeling framework	Description	Example reference
Data limited assessment models		
CC-SRA	Catch curve stock reduction analysis	Thorson and Cope (2015)
DCAC	Depletion-corrected average catch	MacCall (2007)
DB-SRA	Depletion-Based Stock Reduction Analysis	Dick and MacCall (2011)
Other assessment models		
ADBAYECOLA	Age structured production model for trawling and longline catches	Payá (2011)
BAM	Statistical catch-at-age model	Williams et al. (2015)
BATOOTHFISH	Age structured production model with trawling and longline catches	Payá (2007)
CALEN	Catch at length model	Davies et al. (2001)
CHOSAM	Age structured production model with trawling and longline catches	Cox et al. (2011)
CHUSmodel	Chilean Humboldt Squid Depletion Model	Payá (2015)
F-ADAPT	A custom statistical catch-at-age spatial model	Brodiak et al. (1998)
Grenadier model	Age structured production model with swept area biomass and length composition	Payá (2009)
iSCAM delay-difference model	Integrated statistical catch age model	Martell (2019)
JibiaModel		
Modified Punt-Walker model	Spatially aggregated age- and sex- structured population dynamics model	De Oliveira et al. (2013) Punt and Walker (1998)
MULTIFAN-CL	Statistical, length-based, age-structured model	Fournier et al. (1998)
SAD	A linked separable ADAPT VPA model	De Oliveira et al. (2010)
SAM	Age-structured state-space model	Nielsen and Berg (2014)
SPiCT	Surplus production in continuous-time	Pedersen and Berg (2017)
Two-stage biomass model (custom)		Roel et al. (2009)
XSA	Extended survivor analysis	Darby and Flatman (1994)

Table 1.2. Software used in the process of conducting a stock assessment; provided to the survey respondents (*i.e.*, the de facto options featured in survey Section 1). All methods can be used to conduct sensitivity analyses.

Software for assessments		
Option	Description	Example reference
ADMB-based model	Auto-differentiation Model Builder	Fournier (2012)
ASPIC	A Stock Production Model Incorporating Covariates	Prager et al. (2006)
AMAK	Age/Age-size Models Assessment Method for	NOAA Toolbox
ASAP	Age-structured assessment program	NOAA Toolbox
BSP	Bayesian surplus production model	McAllister and Babcock (2006)
CASAL	C++ Algorithmic Stock Assessment Laboratory	Bull et al. (2012)
CEDA	Catch Effort Data Analysis	Hoggarth et al. (2006)
Coleraine	A Generalized Age-Structured Stock Assessment	Hilborn et al. (2003)
CSA	Catch-Survey Analysis	Collie et al. (1983)
FiSAT	FAO-ICLARM Stock Assessment Tools	FAO (2013)
FiSAT II	FAO-ICLARM Stock Assessment Tools II	FAO (2013)
FSIM	Forecasting simulator	Goodyear (2004)
LFDA	Length Frequency Distribution Analysis	Hoggarth et al. (2006)
ParFISH	Participatory Fisheries Stock Assessment	Walmsley et al. (2005)
PRO-2Box	Project future abundance and mortality	Porch (2017)
PRODFIT	Surplus production model	Fox (1975)
SCALE	Statistical Catch-At-Length	Northeast Fisheries Science Center (2006)
SEEPA	Simulates longline catch and effort data	Goodyear (2004)
SS	Stock Synthesis	Methot and Wetzel (2013)
STATCAM	Statistical-Catch-At-Age Model	STATCAM (2005); NOAA Toolbox
VPA	Virtual Population Analysis	Pope (1972)
VPA-2BOX	Dual Zone Virtual Population Analysis model	Porch (2004); NOAA Toolbox
Yield	Calculates fishery yields & stock biomasses	Hoggarth et al. (2006)

FIGURES

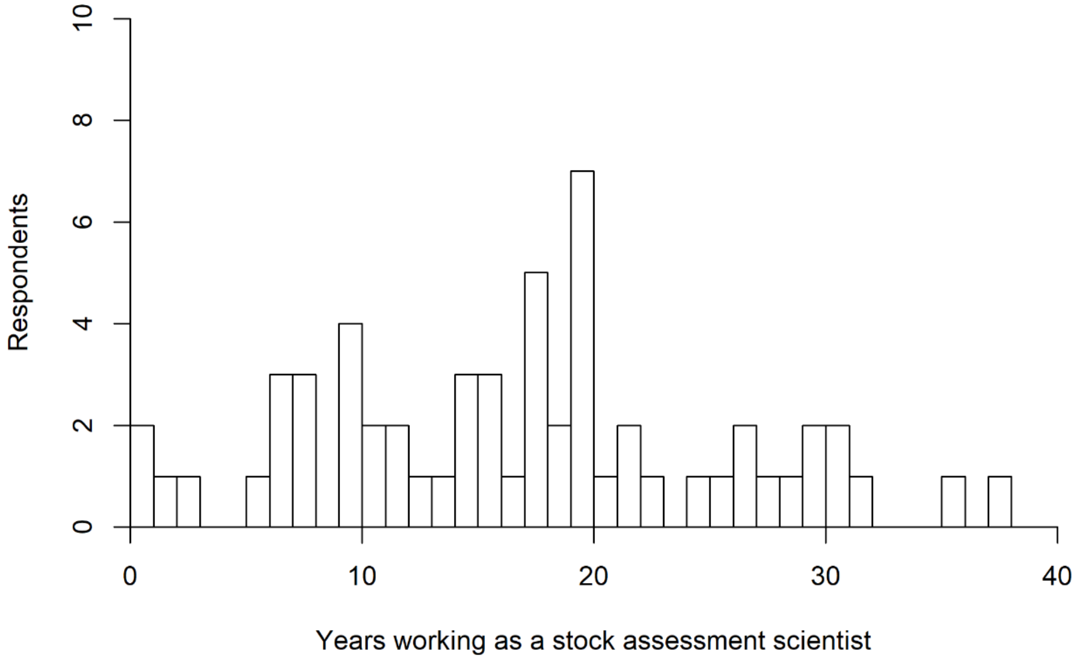
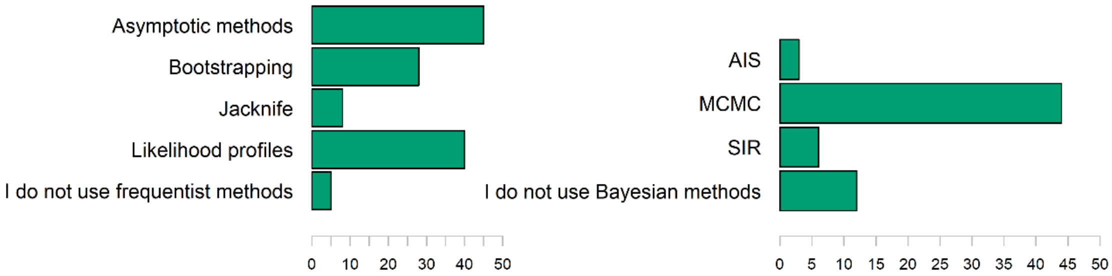
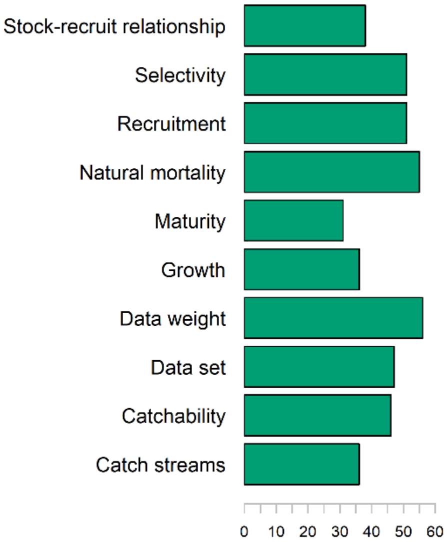
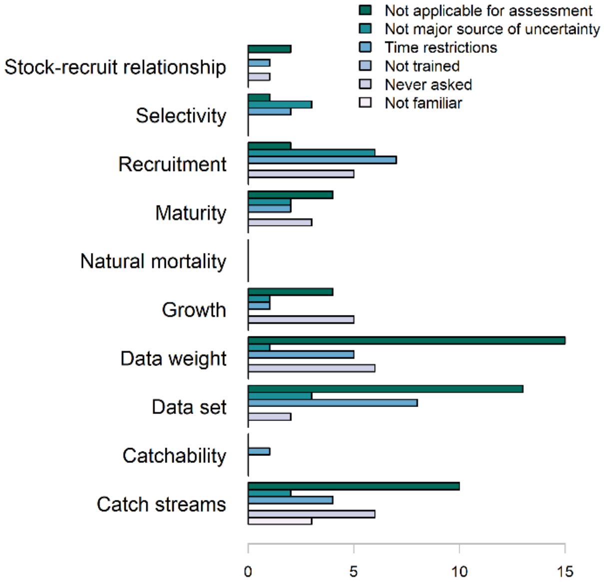
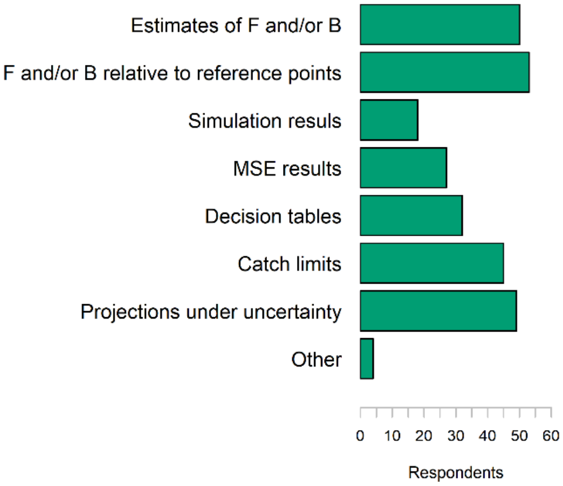


Figure 1.1. A histogram of the number of years each survey respondent has worked as a stock assessment scientist.


Asymptotic methods
Bootstrapping
Jacknife
Likelihood profiles
I do not use frequentist methods
0
10
20
30
40
50
AIS
MCMC
SIR
I do not use Bayesian methods
0
5
10
15
20
25
30
35
40
45
50


Stock-recruit relationship
Selectivity
Recruitment
Natural mortality
Maturity
Growth
Data weight
Data set
Catchability
Catch streams
0
10
20
30
40
50
60


Not applicable for assessment
Not major source of uncertainty
Time restrictions
Not trained
Never asked
Not familiar
Stock-recruit relationship
Selectivity
Recruitment
Maturity
Natural mortality
Growth
Data weight
Data set
Catchability
Catch streams
0
5
10
15


Estimates of F and/or B
F and/or B relative to reference points
Simulation resuls
MSE results
Decision tables
Catch limits
Projections under uncertainty
Other
0
10
20
30
40
50
60
Respondents

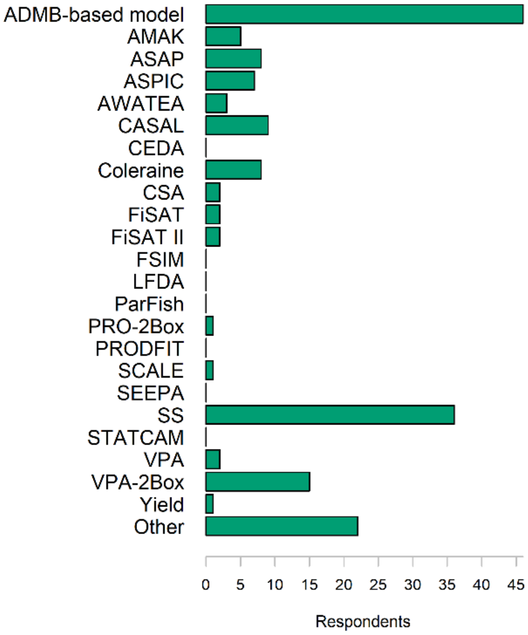

ADMB-based model
AMAK
ASAP
ASPIC
AWATEA
CASAL
CEDA
Coleraine
CSA
FiSAT
FiSAT II
FSIM
LFDA
ParFish
PRO-2Box
PRODFIT
SCALE
SEEPA
SS
STATCAM
VPA
VPA-2Box
Yield
Other
0
5
10
15
20
25
30
35
40
45
Respondents

Figure 1.2. Bar plots of the frequency of use of frequentist and Bayesian approaches for computing measures of uncertainty in assessment model outputs (first row), sensitivity analyses (second row), quantities presented to managers, and software (bottom row). Note that the sum of the responses does not sum to the total number of respondents because some respondents use multiple packages.

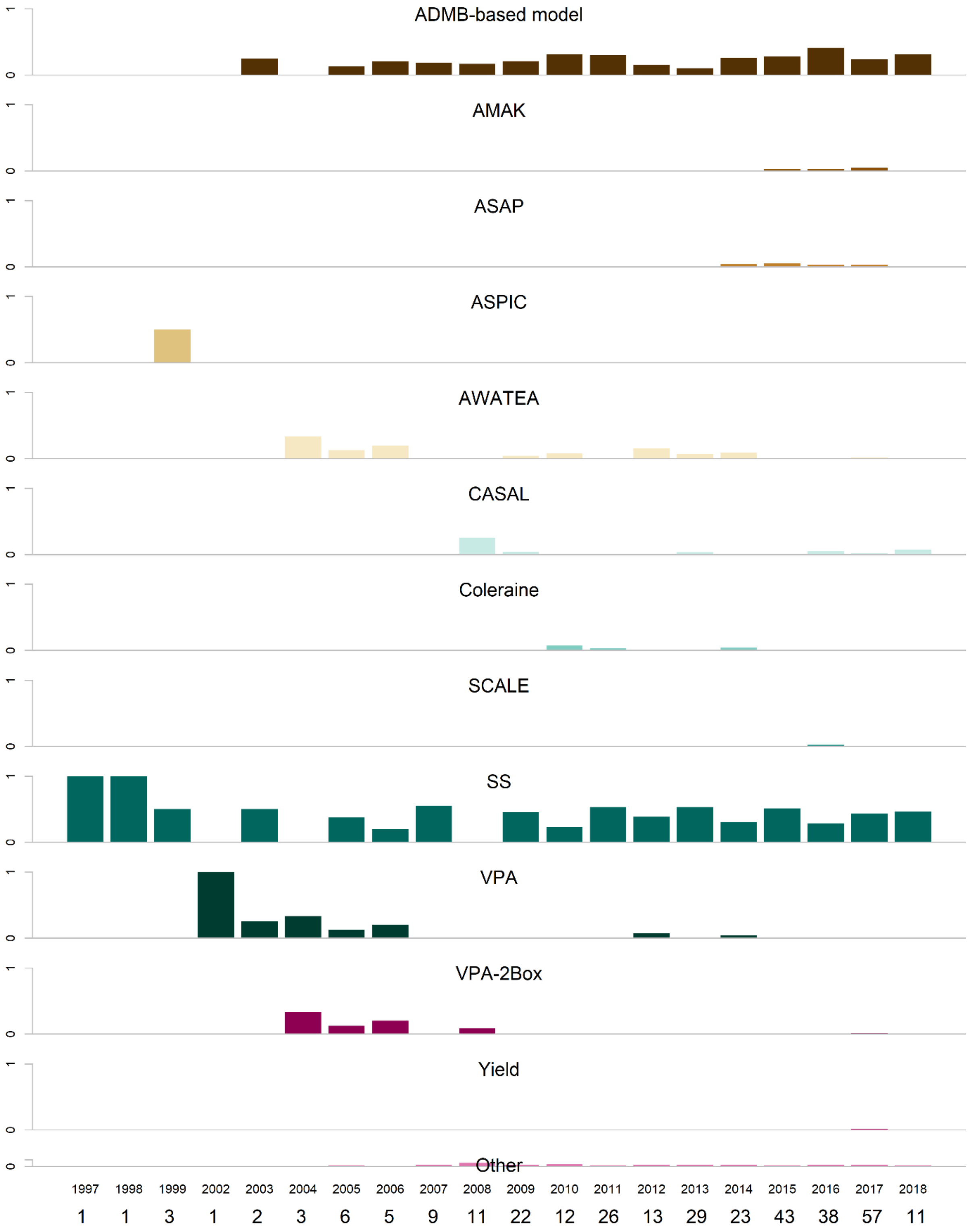


Figure 1.3. Frequencies of package use over time. Numbers below each year indicate the sample size of assessments.

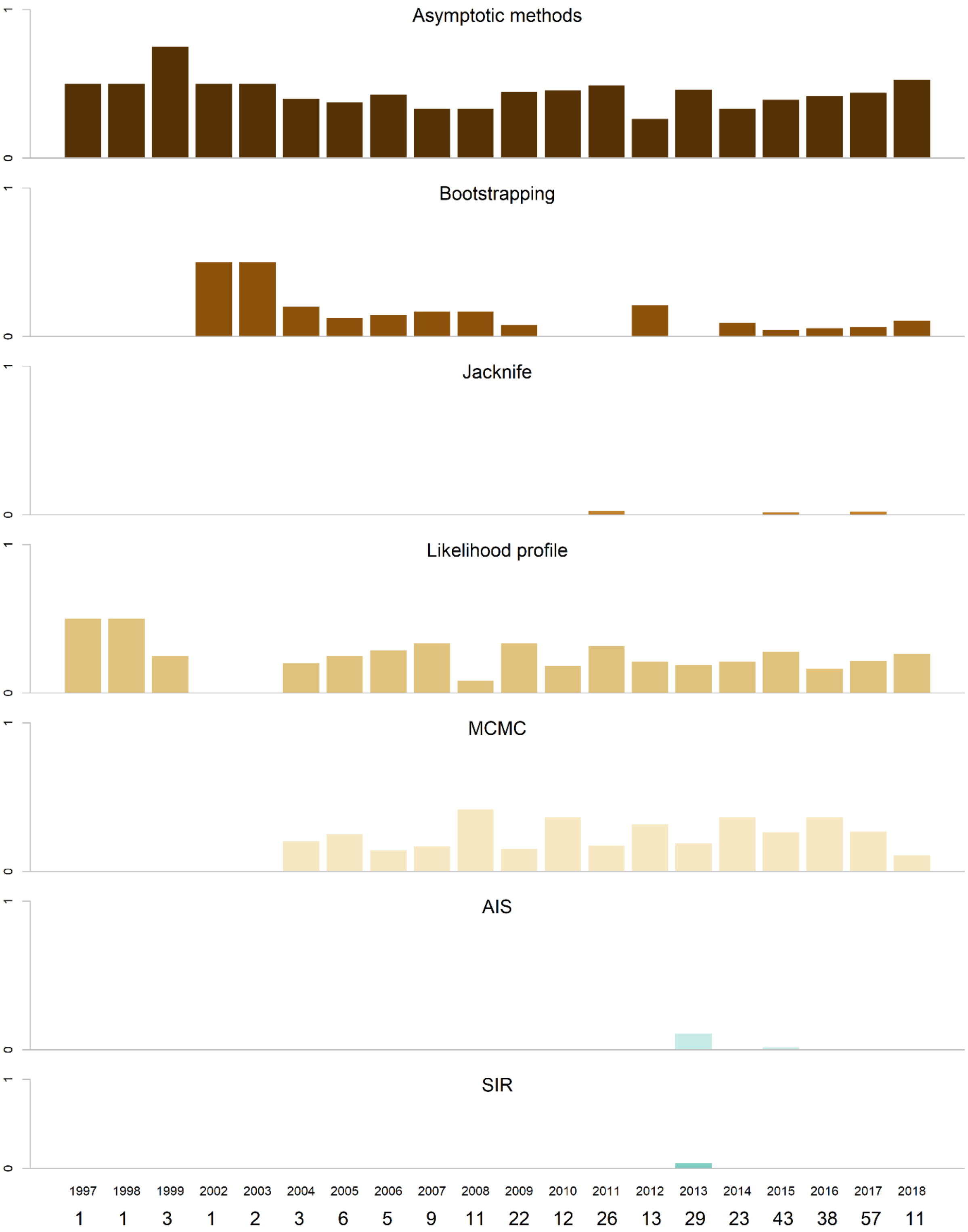
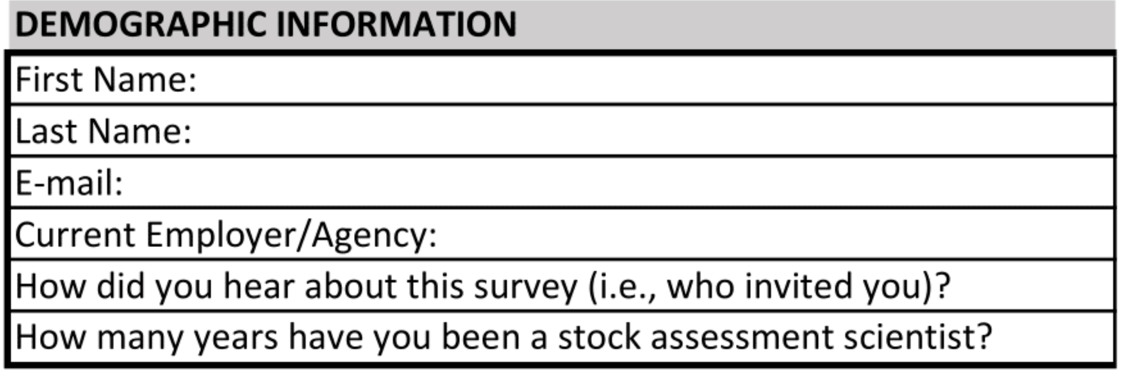


Figure 1.4. Frequencies of uncertainty method use over time. Numbers below each year indicate sample size of assessments.

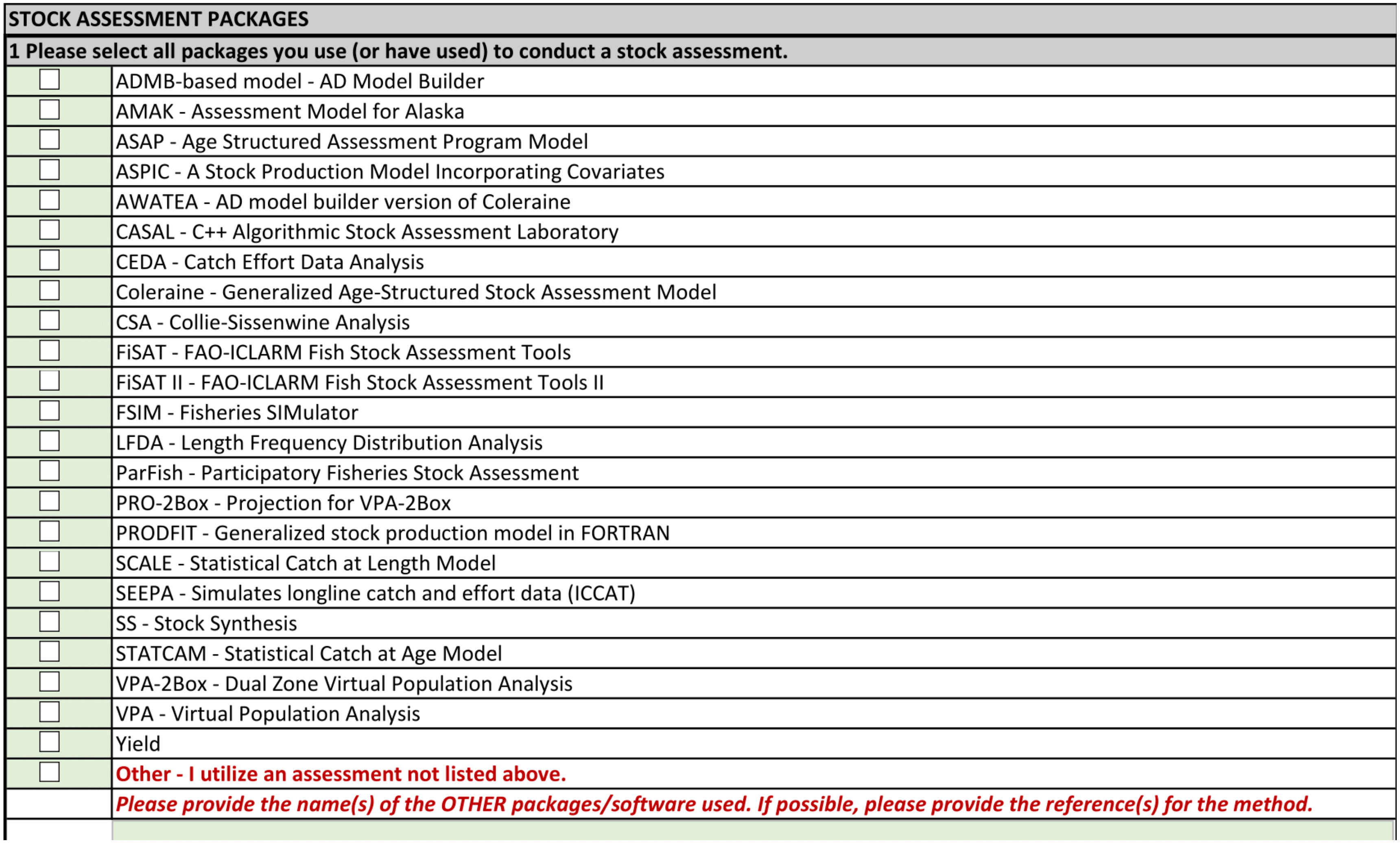
Figure 1.5. Frequencies of sensitivity analyses used over time. Numbers below each year indicate sample size of assessments.

SUPPLEMENTARY APPENDIX



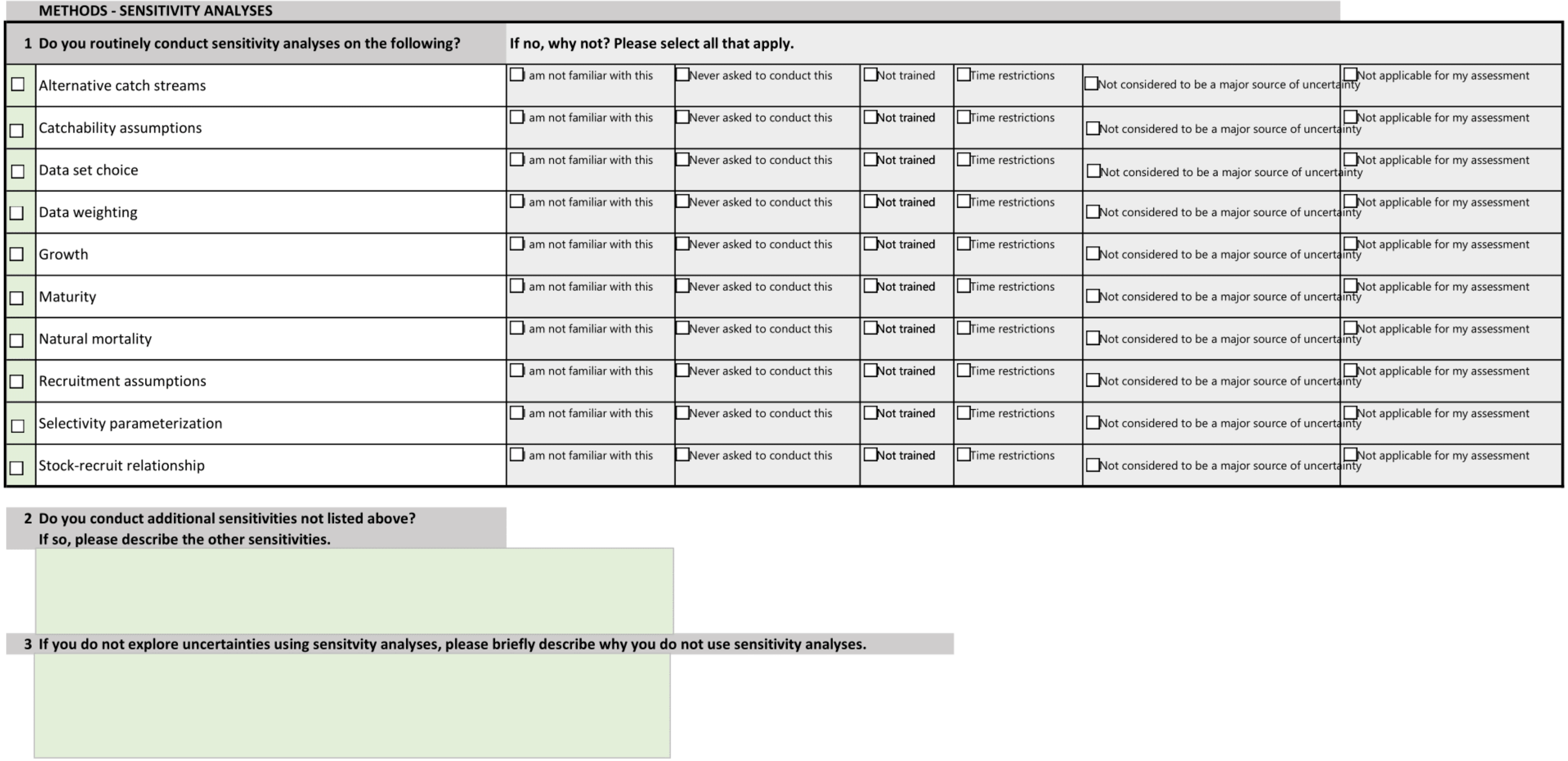
DEMOGRAPHIC INFORMATION
First Name:
Last Name:
E-mail:
Current Employer/Agency:
How did you hear about this survey (i.e., who invited you)?
How many years have you been a stock assessment scientist?

Figure 1.6. Section 1 of the survey.



STOCK ASSESSMENT PACKAGES	
1 Please select all packages you use (or have used) to conduct a stock assessment.	
☐	ADMB-based model - AD Model Builder
☐	AMAK - Assessment Model for Alaska
☐	ASAP - Age Structured Assessment Program Model
☐	ASPIC - A Stock Production Model Incorporating Covariates
☐	AWATEA - AD model builder version of Coleraine
☐	CASAL - C++ Algorithmic Stock Assessment Laboratory
☐	CEDA - Catch Effort Data Analysis
☐	Coleraine - Generalized Age-Structured Stock Assessment Model
☐	CSA - Collie-Sissenwine Analysis
☐	FiSAT - FAO-ICLARM Fish Stock Assessment Tools
☐	FiSAT II - FAO-ICLARM Fish Stock Assessment Tools II
☐	FSIM - Fisheries SIMulator
☐	LFDA - Length Frequency Distribution Analysis
☐	ParFish - Participatory Fisheries Stock Assessment
☐	PRO-2Box - Projection for VPA-2Box
☐	PRODFIT - Generalized stock production model in FORTRAN
☐	SCALE - Statistical Catch at Length Model
☐	SEEPA - Simulates longline catch and effort data (ICCAT)
☐	SS - Stock Synthesis
☐	STATCAM - Statistical Catch at Age Model
☐	VPA-2Box - Dual Zone Virtual Population Analysis
☐	VPA - Virtual Population Analysis
☐	Yield
☐	**Other - I utilize an assessment not listed above.**
	Please provide the name(s) of the OTHER packages/software used. If possible, please provide the reference(s) for the method.

Figure 1.7. Section 2 of the survey.



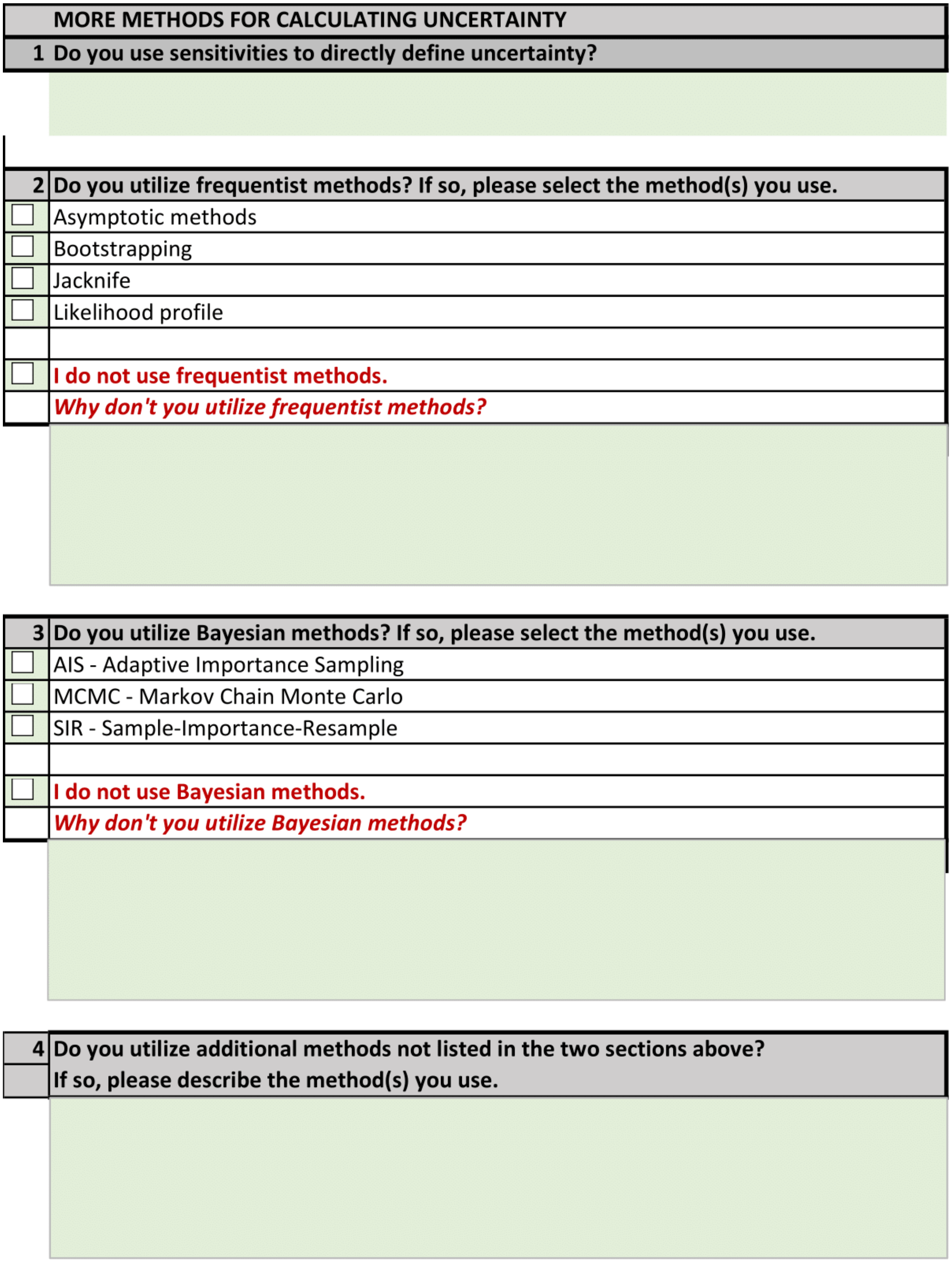
METHODS - SENSITIVITY ANALYSES

	1 Do you routinely conduct sensitivity analyses on the following?	**If no, why not? Please select all that apply.**					
☐	Alternative catch streams	☐ I am not familiar with this	☐ Never asked to conduct this	☐ Not trained	☐ Time restrictions	☐ Not considered to be a major source of uncertainty	☐ Not applicable for my assessment
☐	Catchability assumptions	☐ I am not familiar with this	☐ Never asked to conduct this	☐ Not trained	☐ Time restrictions	☐ Not considered to be a major source of uncertainty	☐ Not applicable for my assessment
☐	Data set choice	☐ I am not familiar with this	☐ Never asked to conduct this	☐ Not trained	☐ Time restrictions	☐ Not considered to be a major source of uncertainty	☐ Not applicable for my assessment
☐	Data weighting	☐ I am not familiar with this	☐ Never asked to conduct this	☐ Not trained	☐ Time restrictions	☐ Not considered to be a major source of uncertainty	☐ Not applicable for my assessment
☐	Growth	☐ I am not familiar with this	☐ Never asked to conduct this	☐ Not trained	☐ Time restrictions	☐ Not considered to be a major source of uncertainty	☐ Not applicable for my assessment
☐	Maturity	☐ I am not familiar with this	☐ Never asked to conduct this	☐ Not trained	☐ Time restrictions	☐ Not considered to be a major source of uncertainty	☐ Not applicable for my assessment
☐	Natural mortality	☐ I am not familiar with this	☐ Never asked to conduct this	☐ Not trained	☐ Time restrictions	☐ Not considered to be a major source of uncertainty	☐ Not applicable for my assessment
☐	Recruitment assumptions	☐ I am not familiar with this	☐ Never asked to conduct this	☐ Not trained	☐ Time restrictions	☐ Not considered to be a major source of uncertainty	☐ Not applicable for my assessment
☐	Selectivity parameterization	☐ I am not familiar with this	☐ Never asked to conduct this	☐ Not trained	☐ Time restrictions	☐ Not considered to be a major source of uncertainty	☐ Not applicable for my assessment
☐	Stock-recruit relationship	☐ I am not familiar with this	☐ Never asked to conduct this	☐ Not trained	☐ Time restrictions	☐ Not considered to be a major source of uncertainty	☐ Not applicable for my assessment

2 Do you conduct additional sensitivities not listed above?
If so, please describe the other sensitivities.

3 If you do not explore uncertainties using sensitvity analyses, please briefly describe why you do not use sensitivity analyses.

Figure 1.8. Section 3 of the survey.



MORE METHODS FOR CALCULATING UNCERTAINTY

1 Do you use sensitivities to directly define uncertainty?

2 Do you utilize frequentist methods? If so, please select the method(s) you use.

☐ Asymptotic methods
☐ Bootstrapping
☐ Jacknife
☐ Likelihood profile

☐ **I do not use frequentist methods.**
Why don't you utilize frequentist methods?

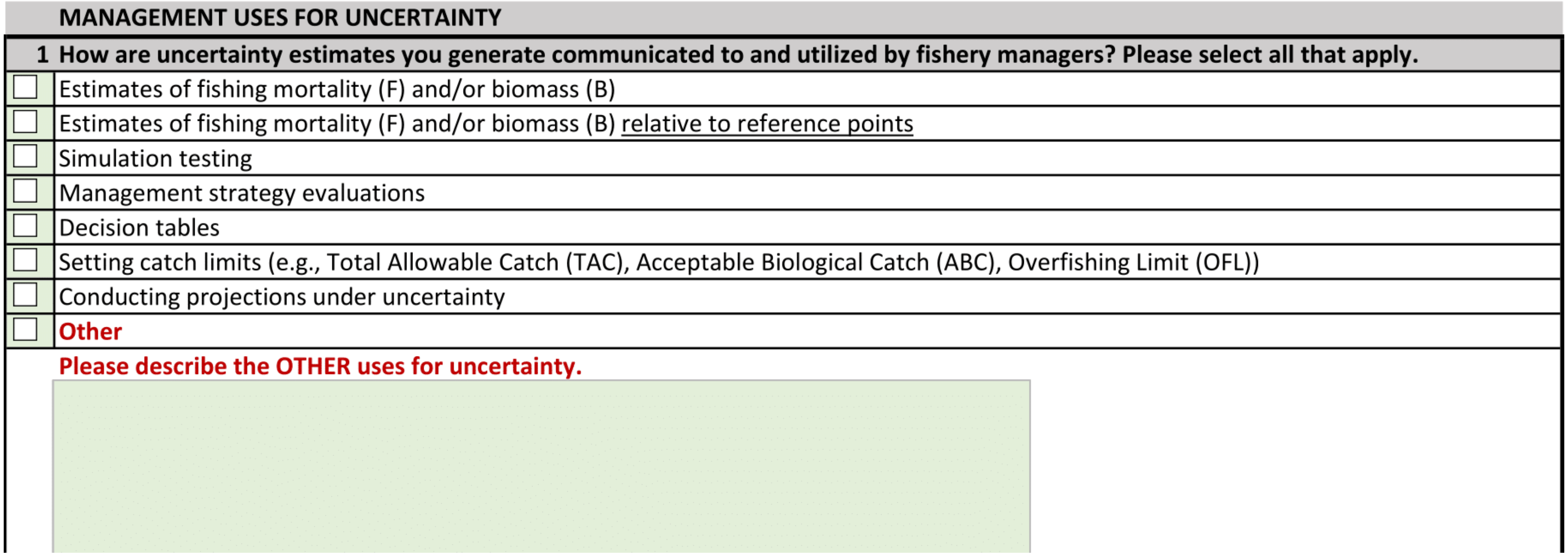
3 Do you utilize Bayesian methods? If so, please select the method(s) you use.

☐ AIS - Adaptive Importance Sampling
☐ MCMC - Markov Chain Monte Carlo
☐ SIR - Sample-Importance-Resample

☐ **I do not use Bayesian methods.**
Why don't you utilize Bayesian methods?

4 Do you utilize additional methods not listed in the two sections above?
If so, please describe the method(s) you use.

Figure 1.9. Section 4 of the survey.



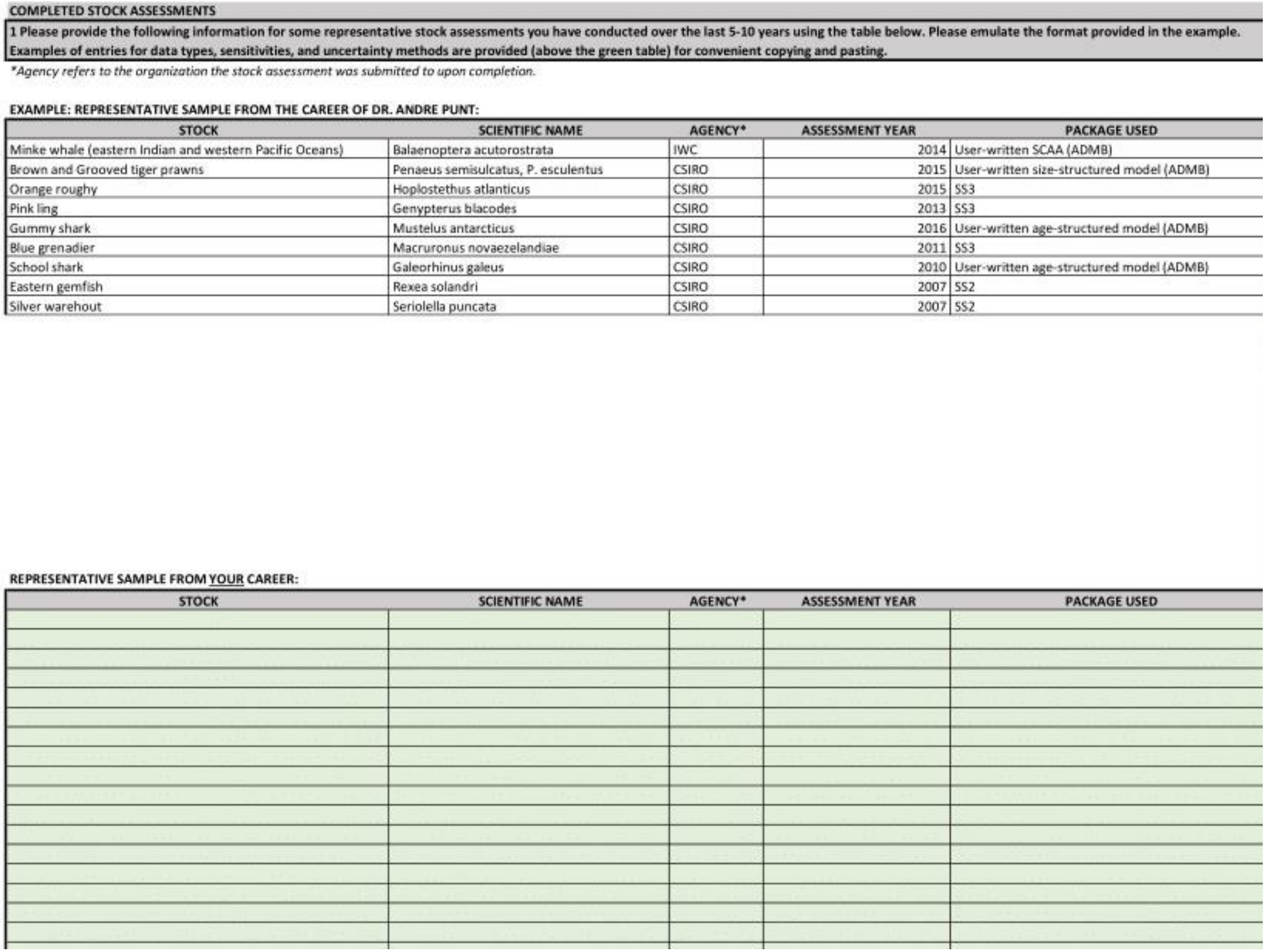
MANAGEMENT USES FOR UNCERTAINTY

1 How are uncertainty estimates you generate communicated to and utilized by fishery managers? Please select all that apply.

☐ Estimates of fishing mortality (F) and/or biomass (B)
☐ Estimates of fishing mortality (F) and/or biomass (B) relative to reference points
☐ Simulation testing
☐ Management strategy evaluations
☐ Decision tables
☐ Setting catch limits (e.g., Total Allowable Catch (TAC), Acceptable Biological Catch (ABC), Overfishing Limit (OFL))
☐ Conducting projections under uncertainty
☐ **Other**

Please describe the OTHER uses for uncertainty.

Figure 1.10. Section 5 of the survey.



COMPLETED STOCK ASSESSMENTS

1 Please provide the following information for some representative stock assessments you have conducted over the last 5-10 years using the table below. Please emulate the format provided in the example. Examples of entries for data types, sensitivities, and uncertainty methods are provided (above the green table) for convenient copying and pasting.

**Agency refers to the organization the stock assessment was submitted to upon completion.*

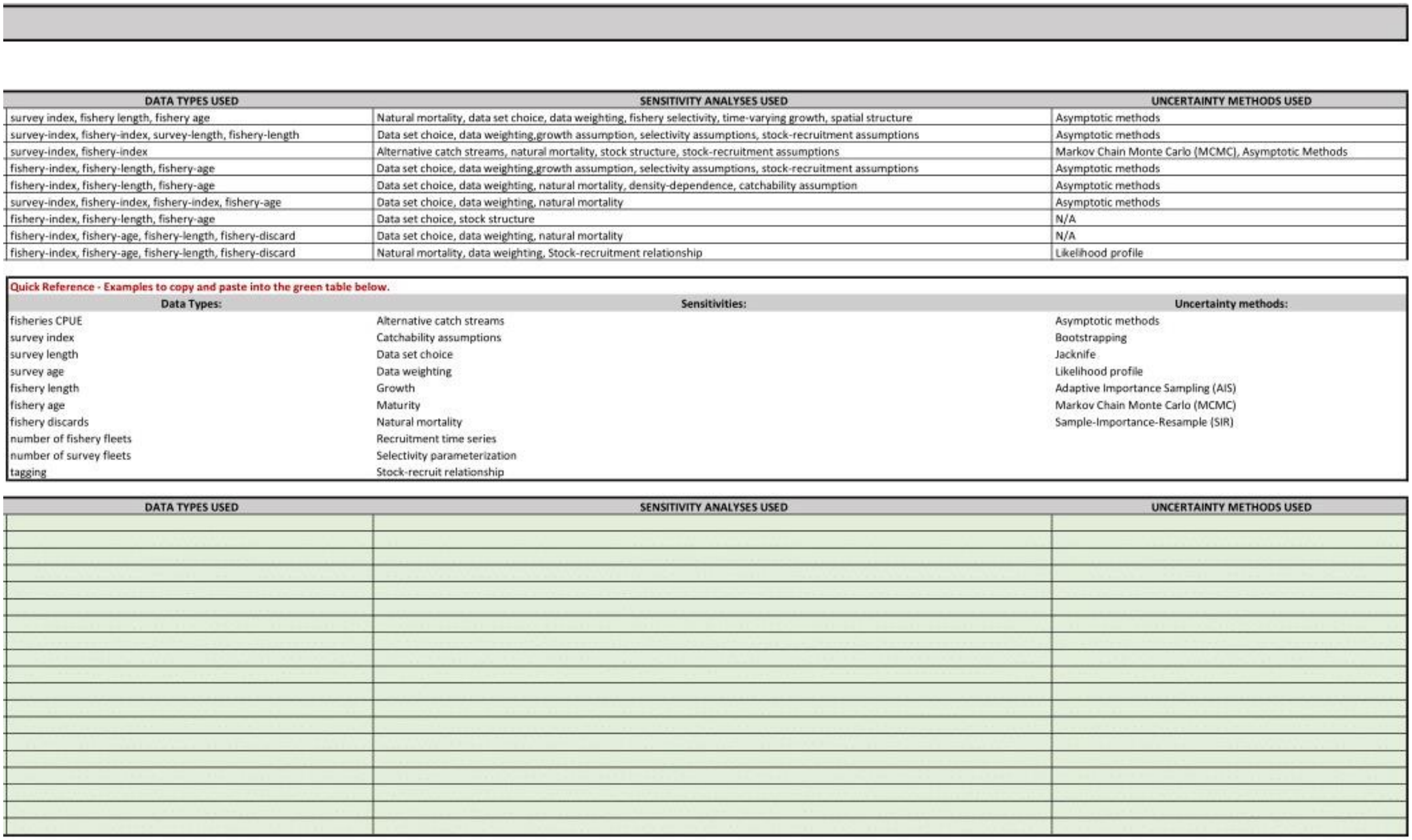
EXAMPLE: REPRESENTATIVE SAMPLE FROM THE CAREER OF DR. ANDRE PUNT:

STOCK	SCIENTIFIC NAME	AGENCY*	ASSESSMENT YEAR	PACKAGE USED
Minke whale (eastern Indian and western Pacific Oceans)	Balaenoptera acutorostrata	IWC	2014	User-written SCAA (ADMB)
Brown and Grooved tiger prawns	Penaeus semisulcatus, P. esculentus	CSIRO	2015	User-written size-structured model (ADMB)
Orange roughy	Hoplostethus atlanticus	CSIRO	2015	SS3
Pink ling	Genypterus blacodes	CSIRO	2013	SS3
Gummy shark	Mustelus antarcticus	CSIRO	2016	User-written age-structured model (ADMB)
Blue grenadier	Macruronus novaezelandiae	CSIRO	2011	SS3
School shark	Galeorhinus galeus	CSIRO	2010	User-written age-structured model (ADMB)
Eastern gemfish	Rexea solandri	CSIRO	2007	SS2
Silver warehout	Seriolella puncata	CSIRO	2007	SS2

REPRESENTATIVE SAMPLE FROM YOUR CAREER:

STOCK	SCIENTIFIC NAME	AGENCY*	ASSESSMENT YEAR	PACKAGE USED

Figure 1.11. Section 6 of the survey.



DATA TYPES USED	SENSITIVITY ANALYSES USED	UNCERTAINTY METHODS USED
survey index, fishery length, fishery age	Natural mortality, data set choice, data weighting, fishery selectivity, time-varying growth, spatial structure	Asymptotic methods
survey-index, fishery-index, survey-length, fishery-length	Data set choice, data weighting,growth assumption, selectivity assumptions, stock-recruitment assumptions	Asymptotic methods
survey-index, fishery-index	Alternative catch streams, natural mortality, stock structure, stock-recruitment assumptions	Markov Chain Monte Carlo (MCMC), Asymptotic Methods
fishery-index, fishery-length, fishery-age	Data set choice, data weighting,growth assumption, selectivity assumptions, stock-recruitment assumptions	Asymptotic methods
fishery-index, fishery-length, fishery-age	Data set choice, data weighting, natural mortality, density-dependence, catchability assumption	Asymptotic methods
survey-index, fishery-index, fishery-index, fishery-age	Data set choice, data weighting, natural mortality	Asymptotic methods
fishery-index, fishery-length, fishery-age	Data set choice, stock structure	N/A
fishery-index, fishery-age, fishery-length, fishery-discard	Data set choice, data weighting, natural mortality	N/A
fishery-index, fishery-age, fishery-length, fishery-discard	Natural mortality, data weighting, Stock-recruitment relationship	Likelihood profile

Quick Reference - Examples to copy and paste into the green table below.

Data Types:	Sensitivities:	Uncertainty methods:
fisheries CPUE	Alternative catch streams	Asymptotic methods
survey index	Catchability assumptions	Bootstrapping
survey length	Data set choice	Jacknife
survey age	Data weighting	Likelihood profile
fishery length	Growth	Adaptive Importance Sampling (AIS)
fishery age	Maturity	Markov Chain Monte Carlo (MCMC)
fishery discards	Natural mortality	Sample-Importance-Resample (SIR)
number of fishery fleets	Recruitment time series	
number of survey fleets	Selectivity parameterization	
tagging	Stock-recruit relationship	

DATA TYPES USED	SENSITIVITY ANALYSES USED	UNCERTAINTY METHODS USED

Figure 1.12. Section 6 of the survey continued.

Chapter 2. ESTIMATING AMONG-ASSESSMENT VARIATION IN OVERFISHING LIMITS

2.1 ABSTRACT

Among-assessment variation in historical spawning biomass trajectories (σ) has formed the basis for setting the buffer for scientific uncertainty for US West Coast groundfish and coastal pelagic stocks management since the analysis of Ralston et al. (2011) was conducted. Past methods have relied on retrospective or historical analysis of assessment ability to predict stock biomass. This "historical biomass" approach may underestimate the true extent of scientific uncertainty, because the overfishing limit is a function of not only estimated biomass, but also estimated target fishing mortality. Moreover, the historical approach does not necessarily equate to the ability of assessment to predict future states. Here, I develop a new approach and applied it to stocks in the US West Coast groundfish fishery. My approach bases the calculation of σ on projected biomass and overfishing limits, accounting for uncertainty in future recruitment as well as among-assessment variation. Including the assessments conducted since 2011 in the historical biomass approach has a small impact on the perceived extent of scientific uncertainty ($\sigma \sim 0.403$ compared to $\sigma=0.360$). Conducting projections rather than using historical estimates of spawning biomass leads to a lower value for σ (0.360), and basing measures of uncertainty on projected overfishing limits rather than spawning biomass leads to a value for σ of 0.393. Allowing for stochasticity in recruitment does not change the values noticeably (the value of σ is 0.433 when it is based on overfishing limits and stochastic recruitment).

2.2 INTRODUCTION

Answering the legislative call to improve US fisheries includes pursuing new ways to characterize and quantify the scientific uncertainty that informs fisheries management (Cadrin et al. 2015). Scientific uncertainty collectively refers to process, observation, model, and estimation uncertainties (Francis and Shotton 1997). Overall goals of the Magnuson-Stevens Fishery Conservation and Management Act (MSA) are to manage US fisheries to ensure that the amount of fish harvested each year will provide the greatest overall benefit, particularly in food production and recreational opportunities, to the nation, and thoroughly account for the conservation and sustainability of marine ecosystems (Federal Register 2009).

One outcome of the pursuit of this goal is the adoption of "precautionary harvest control rules that are designed to reduce 'risk-neutral' point estimates of catch based on the amount of uncertainty in the estimates" (Ralston et al. 2011). Harvest control rules (HCR) are *a priori* guidelines for determining the annual catch limit (ACL) for a fishery and, in the US, are specified in the corresponding fishery management plan. Generally, application of a HCR in the U.S. is a multistep process: 1) a stock assessment calculates the overfishing limit (OFL) for a fishery; 2) the OFL is reduced to account for scientific uncertainty, which establishes the Acceptable Biological Catch (ABC); and 3) managers decide on an ACL that must be less than or equal to the ABC. Establishing an ABC via the application of a multiplier (*i.e.*, buffer) based on uncertainty in exploitable biomass to the OFL utilizes a probability-based HCR referred to as the P^* method (Prager and Shertzer 2010). P^* is hence the percentile of the OFL distribution corresponding to the risk tolerance decided by fisheries managers. The MSA and National Standards mandate that P^* must never exceed 0.5, as this presumes a risk prone view of available biomass (*i.e.*, risk prone to overfishing). The implementation of these federal mandates falls under the jurisdiction of the

National Oceanic and Atmospheric Administration National Marine Fisheries Service and the components of the HCRs (the OFL distribution, including the standard deviation σ) are determined by the Scientific and Statistical Committees (SSCs), which are appointed by the eight regional fisheries management councils established by the MSA (Federal Register 2009).

Groundfish and coastal pelagic species stocks managed in the US northeast Pacific by the Pacific Fishery Management Council (PFMC) are a good example for quantifying the σ for distribution of OFL utilized in the $P*$ HCR. These stocks are classified into three categories based primarily on the quantity and quality of data available for assessments: Category 1 stocks have a catch history, abundance indices, biological data (*e.g.*, length and/or age compositions), or other data that inform a relatively data-rich, quantitative stock assessment; Category 2 stocks have some indices of abundance, and may have a relatively data-limited quantitative stock assessment or non-quantitative assessment; and Category 3 stocks have few available data (*e.g.*, time-series of removals) (PFMC 2014). Each stock category has a different associated minimum scientific uncertainty level, so the ABC control rule ensures the scientific uncertainty (*i.e.*, σ) for each respective stock category increases as data availability decreases.

The initial approach for estimating scientific uncertainty was developed by Ralston et al. (2011) and assumed that scientific uncertainty in the OFL can be characterized using a log-normal distribution on the final year of a time series for historical biomass with a mean of one and a standard error in log-space, σ. This approach also is based on variation in estimates of biomass time-series among the stock assessments. Ralston et al. (2011) thus used the variation in historical biomass as a proxy for model specification uncertainty. The Category 1 stock σ was quantified using the estimated coefficient of variation (CV) of the among-assessment variation in annual estimates of historical spawning biomass based on 81 Category 1 assessments of 15 groundfish and 2 coastal pelagic stocks. Due to the data-limited nature of Category 2 and 3 stocks, the uncertainty associated with estimates of an OFL is difficult to quantify, and the scientific uncertainty is presumed to be higher. The SSC of the PFMC recommended, and the PFMC adopted, setting a minimum CV of 0.36 for Category 1 stocks, doubling the (assumed) uncertainty (CV=0.72) for Category 2 stocks, and quadrupling the assumed uncertainty (CV=1.44) for Category 3 stocks (Ralston et al. 2011).

This approach was a good first step in quantifying scientific uncertainty, but there remains the opportunity to improve on the approach and further understand the errors in quantities more directly related to setting of catch limits (*i.e.*, the OFL). For example, using historical estimates of spawning stock biomass to calculate σ (hereby referenced as the *historical biomass approach*) assumes the uncertainty in the OFL arises only from the uncertainty in terminal-year biomass and this assumption can lead to negatively biased estimates of scientific uncertainty (Ralston et al. 2011). In contrast, estimating σ by quantifying how projections of OFLs (hereby known as the *projection-based approach*) vary among assessments of the same stocks is a direct measure of the management quantity of interest. Projections capture some of the uncertainty in the estimates of current stock abundance and age-structure, and how the abundance and age-/size-structure change over time. As noted by Shertzer et al. (2008), quantifying the variation in OFL projections may also capture some of the uncertainty in the estimation of the target fishing mortality rate (in the case of US fisheries, F_{MSY} or a proxy thereof).

We compare the historical biomass approach for estimating σ to the projection of OFL approach. Further expansions include replicating the historical biomass approach with the addition of new assessments completed after 2011 (*i.e.*, the year the original Ralston et al. analysis was completed) and projecting spawning biomass in addition to OFLs. The projections of OFLs and spawning biomass provide an opportunity to quantify how σ for each stock (*i.e.*, stock-specific σ) and pooled across all stocks (*i.e.*, pooled σ) varies into the future to better inform scientific uncertainty for management.

2.3 MATERIALS AND METHODS

2.3.1 *Sources of uncertainty*

Variation in estimates of OFLs and spawning biomass among multiple assessments of the same stocks can arise from several sources: 1) chosen model structure; 2) fixed parameter values and prior distribution selection for other parameters; 3) data availability; 4) the members of the stock assessment team conducting the assessment; 5) the composition of the group established to review the assessment; and 6) the type and version of the software that was used (Ralston et al. 2011). Accounting for this variation among historical assessments and projected values for OFL is integral for informing management advisory bodies as they review scientific advice for fisheries managers.

Scientific uncertainty is associated with each step of calculating an OFL: 1) estimating the current exploitable biomass; and 2) projecting biomass for a pre-specified number of years while applying an estimate of (or proxy for) F_{MSY} to the forecasts of future biomass (Ralston et al. 2011). The historical biomass approach uses spawning biomass and does not directly use the above biomass inputs used for determining an OFL, whereas the projection-based approach developed in this work directly projects exploitable biomass and applies the F_{MSY} proxy to calculate an OFL.

The projection-based approach directly quantifies the variation in projections of OFL and spawning biomass across the following dimensions: a) among assessments of the same stock, b) among assessments across multiple groundfish stocks, c) across multiple projection start years, and d) when assuming deterministic vs. stochastic recruitment. Projections were based on the best estimates of biomass, age-structure, and selectivity from the stock assessment outputs, and these estimates change over time. Thus, to further characterize uncertainty, projections were started from multiple historical years (*i.e.*, 1998, 2003, and 2008) and involved for 25 future years (*e.g.*, 1998-2023). Assuming a deterministic stock-recruitment relationship does not directly capture projection uncertainty, thus, I also conduct stochastic projections based on a stock-recruitment relationship with log-recruitment deviations with bias correction.

2.3.2 *Data utilized*

US West Coast groundfish and coastal pelagic species stocks were chosen for investigating the projection-based approach to ensure comparability with the historical biomass approach. These stocks were used in the historical biomass approach because there were at the time multiple stock assessments for them (Figure 2 from Ralston et al. 2011). Assessments completed in Stock Synthesis (Method and Wetzel, 2013) post-2007 (v. 3.03a or later) were used in the projection-based approach as they provided the necessary quantities required for projecting spawning biomass and OFLs (Table 2.9 of the supplementary appendix).

Not all assessments reported spawning biomass, but a common metric to compare spawning biomass was needed. Spawning output (usually in number of eggs) based on the non-proportional egg-to-weight relationship described by Dick (2009) was reported in the recent assessments of bocaccio, chilipepper rockfish, darkblotched rockfish, and yelloweye rockfish. Comparing variation across multiple assessments for these stocks required the units of spawning output to be converted into spawning biomass. Thus, spawning biomass in metric tons was calculated for assessments with spawning output reported in eggs:

$$SSB_y = \sum_a^A W_{a,f} N_{y,a} \qquad \text{(Equation 2.1)}$$

where SB_y is spawning biomass in year y, a is age, A is the age plus group, $W_{a,f}$ is mature female weight-at-age, and $N_{y,a}$ is female numbers-at-age. Mature female weight-at-age was calculated as follows:

$$W_{a,f} = \sum_l W_l\, m_l\, \rho_{a,l} \qquad \text{(Equation 2.2)}$$

here W_l is female weight-at-length, m_l is the female proportion mature-at-length, and $\rho_{a,l}$ is the proportion of animals of age a in length-class l.

2.3.3 *Projecting overfishing limits and spawning biomass*

OFLs were computed by applying a target harvest rate, F_{target} (US West Coast groundfish: $F_{50\%}$ for rockfish, $F_{45\%}$ for roundfish, and $F_{30\%}$ for flatfish) to estimates of current exploitable biomass. F_{target} is the target harvest rate that results in an expected decline in spawning biomass-per-recruit equal to 50% (for rockfish), 45% (for roundfish), or 30% (for flatfish) (PFMC 2014).

The estimated natural mortality and projected fishing mortality for the time series covered in the assessment were used to calculate total mortality, Z for projections:

$$Z_{s,a} = M_{s,a} + \sum_f F_{target} S_{s,a,f} \psi_f \qquad \text{(Equation 2.3)}$$

where a is age, s is sex, and f is fleet. S is selectivity by age, sex, and fleet and ψ_f is the fishing mortality rate by fleet f, both at the end of the year before the projections start (*i.e.*, 1998, 2003, and 2008). Z was then used to project the numbers-at-age by sex forward using the following standard age-structured model:

$$N_{y+1,s,a} = N_{y,s,a-1}e^{-Z_{s,a-1}} \qquad \text{if } 1 \le a < A$$

(Equation 2.4)

$$N_{y+1,s,A} = N_{y,s,A-1}e^{-Z_{s,A-1}} + N_{y,s,A}e^{-Z_{s,A}} \qquad \text{if } a = A$$

where *N* is the numbers-at-age by year and sex, and *A* is the plus group. The numbers-at-age for the first year of projection period were set to the estimates from the Stock Synthesis assessment (except as outlined below to account for variation in recruitment prior to the first projection year). The projected numbers-at-age were converted to spawning stock biomass using Equation 2.1.

The projected numbers of fish at age-0 were calculated using the Beverton-Holt stock-recruitment relationship because this relationship formed the basis for the original assessments, and log-recruitment deviations with bias correction were added for stochastic projections (Equations 2.5 and 2.6 respectively):

$$N_{y,s,a=0} = \frac{4hR_0SSB/SSB_0}{(1-h)+(5h-1)SSB/SSB_0} \qquad \text{(Equation 2.5)}$$

$$N_{y,s,a=0} = \frac{4hR_0SSB/SSB_0}{(1-h)+(5h-1)SSB/SSB_0}e^{\varepsilon_y-\sigma_r{}^2/2} \qquad \text{(Equation 2.6)}$$

where R_0 is unfished recruitment, *h* is the steepness parameter, SSB_0 is the unfished spawning stock biomass, and $e^{\varepsilon_y-\sigma_r{}^2/2}$ are-log recruitment deviations with bias correction. The unfished spawning stock biomass was computed using numbers-at-age and fecundity at unfished equilibrium.

The effects of recruitment variation will not immediately manifest in spawning biomass or OFL because several of the stocks are fairly long-lived (*e.g.*, middle panels of Figures 2.1 and 2.2). To better capture uncertainty in the first projection years, Equation 7 was also used to generate recruitment estimates to compute numbers-at-age at the start of the projection start year, with the extent of variation defined by the asymptotic standard errors for the annual recruitment deviations from the last ten years of the assessment. The generated recruitment values are then projected to the start year given the values of Z-at-age estimated in the assessment.

OFLs by year were calculated as follows:

$$OFL_y = \sum_s \sum_f \sum_a W_{s,f,a} F_{target} S_{s,a,f} \psi_f \frac{N_{y,s,a}(1 - e^{-Z_{s,a}})}{Z_{s,a}} \qquad \text{(Equation 2.7)}$$

where W is the selected-weighted retained weight by age, sex and fleet for the end of the year before the projections start.

2.3.4 *Quantifying uncertainty in projections*

The variation (*i.e.*, σ) in projected OFLs and spawning biomass (in log-space) was used to compare the projection-based and historical biomass approaches. The log-space uncertainty assumption (method 2 of three tested by Ralston et al. [2011]) was selected as the preferred method for calculating uncertainty by the PFMC SSC during the review of the historical biomass approach. The projection-based approach calculated σ while accounting for four dimensions: projection year, stock (year and stocks were treated as a sampling unit by Ralston et al. [2011]), projection start-year and the replicate trajectories of spawning biomass and OFL due to sampling of future (and past) recruitment deviations (stochastic projections only). Point estimates of σ were pooled over these dimensions to characterize the corresponding contribution to scientific uncertainty (see Tables 2.1, 2.2 and 2.3 for equations).

2.3.5 *Historical biomass approach*

Since the inception of σ in 2011, 14 of the 17 groundfish and coastal pelagic stocks used to inform σ estimated by the historical biomass approach have new assessments (Table 2.4). I estimated σ based on historical biomass again using these new assessments included. New (*i.e.*, since 2009) assessments for Pacific whiting were not included because the management structure changed with the implementation of an international treaty. Cabezon, chilipepper, and yellowtail rockfishes have not been assessed since 2009 and are also not included in this update (*i.e.*, the information for 13 of the 17 original stocks were updated). For comparison to the projection-based approach proposed in this paper, the Ralston et al. (2011) approach was also applied to: 1) the original 17 stocks, updated with any assessments conducted after 2009 (Table 2.4); 2) the seven stocks featured in the projection-based approach using all available assessments; and 3) the seven stocks based on only the assessments used in the projection-based approach. The updated stock-specific estimate of σ was based on approach 2 of Ralston et al. (2011), *i.e.*:

$$\sigma = \sqrt{\frac{1}{\sum_y (n_y - 1)} \sum_t \sum_i (\ln[B_{i,y}] - \overline{\ln[B_y]})^2} \qquad \text{(Equation 2.8)}$$

where B_y is spawning stock biomass by year, n_y is the number of available assessments for year y ($n_y > 2$) and i is the individual assessment.

2.4 RESULTS

2.4.1 *Estimates of σ based on projections*

2.4.1.1 Example trajectories and results for bocaccio

First, the results for a single stock are summarized to orient the reader before presenting results for pooling across stocks. Figure 2.1 shows spawning biomass trajectories for bocaccio based on three start years (1998, 2003, and 2008) and three stock assessments (conducted in 2009, 2011, and 2015). Identifying multiple assessments for the same stock were simplified as “Oldest (available)”, “Intermediate”, and “Most Recent” and the years the assessments were conducted are reported in Supplementary Table 2.9 for all stocks. Results are shown for deterministic projections (*i.e.*, no variation about the estimated stock-recruitment relationship), when allowance is made for future variation about the stock-recruitment relationship, and when past and future uncertainty in recruitment are included (rows in Figure 2.1). There is variability in future spawning biomass due to differences among assessments in key assumptions (*e.g.*, values of parameters such as initial recruitment size and stock-recruitment steepness). Further, allowing for uncertainty in recruitment leads to a greater spread of results. Implementing stochastic recruitment to capture uncertainty in the first projection year leads to greater variation in spawning biomass for the first years of the projection period. The results for projected overfishing limits are qualitatively identical to those for spawning biomass (Figure 2.2 for bocaccio rockfish; Supplementary Figures 2.14-2.16 for the remaining stocks).

The variation in spawning biomass is quite low for bocaccio when future recruitment variation is ignored and values are pooled over the 25 projection years (0.040 – 0.150 among start years; 0.100 pooled over the three start years; Table 2.5), but is substantially higher when past and future recruitment uncertainties are accounted for (0.291 – 0.319 among start years, 0.302 pooled over start years; Table 2.5a). The uncertainty in OFL projections is greater than that predicted from spawning biomass projections alone (start-year pooled values of 0.100 vs 0.302 for spawning biomass; start-year pooled values of 0.388 vs 0.462 for OFL).

The amount of variation changes through time at rates that depend on model assumptions (Figures 2.3 and 2.4). The values of σ decline over the first five years and increase before declining (deterministic results) or stabilizing (stochastic results).

The within-assessment variation (due to stochastic recruitment) by start year and projection year for bocaccio are shown in Figures 2.5 (spawning biomass) and 2.6 (OFL). There is little within-assessment variation across the start-years. The variation across assessments differs the most during the first five projections years and stabilizes by the end of the 25 year projection period.

2.4.1.2 Estimating σ using all stocks

The values of σ by start-year and stock (and pooled over start-year) are reported in Table 2.5a (spawning biomass) and 2.5b (OFL). Incorporating uncertainty in recruitment leads to higher values for σ based on OFL for bocaccio and lingcod. The values for σ are lower for the remaining stocks because the among-assessment variation is often greater than that due to stochastic recruitment (Supplementary Figures 2.15-2.17). Table 2.6 lists the values of σ due solely to recruitment variation. These range from 0.072 (widow rockfish) to 0.449 (bocaccio).

Variation in OFL being greater than in spawning biomass is not consistent across among stocks. The σ based on spawning biomass is larger than that based on OFL for lingcod, petrale sole and Pacific Ocean perch (Table 2.5).

The stocks-pooled values for $\bar{\sigma}$ are 0.323[1] and 0.393 when the projections are based on spawning biomass, and 0.360 and 0.433 when the projections are based on the OFL.

Figures 2.7 and 2.8 show the time series of stocks-pooled σ by start-year and aggregated over start years. The variation increases with time for spawning biomass (Fig. 2.7), but this is not the case for the OFL, which declines over time (Fig. 2.8).

2.4.2 *Updating σ based on the historical biomass approach*

Consistent with Ralston et al. (2011), the groundfish and coastal pelagic species stock assessments used in the update of σ were data-rich stocks that have multiple benchmark assessments (15 groundfish and two coastal pelagic stocks); “update” assessments, where data are simply refreshed without model parameterization and specification review were not included. With the additional assessments and years included in this study, the number of assessments per stocks used for this meta-analysis ranged from three (chilipepper rockfish and cabezon) to 23 (Pacific whiting). Historical biomass trajectories for the 17 stocks are presented in Supplementary Figure 2.9.

2.4.3 *Stock-specific results*

The distribution of residuals for the 17 stocks is shown in Supplementary Figure 2.10. These distributions are bimodal for the stocks that have few assessments and also have biomass trajectories that do not overlap (*e.g.*, shortspine thornyhead and yelloweye rockfish). For most other stocks, the residual distributions appear unimodal. Some distributions exhibit long tails (*e.g.*, yellowtail rockfish and petrale sole). Darkblotched rockfish and widow rockfish have a more uniform distribution than the original analysis of Ralston et al. (2011) following the addition of recent stock assessments. This may be related to the increased number of assessments, and many

---

[1] Confidence intervals are not provided for these estimates as they are not independent.

biomass trajectories that do not overlap. The number of deviations and the estimated log-scale standard deviation for each of the stocks are presented in Table 2.4. The log-scale standard deviations range from 0.154 (cabezon) to 0.994 (shortspine thornyhead), with an average of 0.403.

2.4.4 *Pooled results*

The unweighted, pooled distributions of residuals for four groupings of stocks are shown in Supplementary Figure 2.11. The distributions are close to normal for all groupings, whereas before roundfish, flatfish, and coastal pelagic stocks exhibited some non-normal features (Fig. 3 of Ralston et al., 2011). The pooled point estimates of σ from this update, the accompanying approximate 95% confidence intervals, and the original pooled point estimates of σ from Ralston et al. (2011) are reported in Table 2.7. Pooling the deviations across all stocks (Supplementary Figure 2.11) leads to a point estimate of σ=0.403. If the residuals are assumed to be independent, an approximate 95% confidence interval based on the chi-squared distribution is $0.387 \leq \sigma \leq 0.421$ (Table 2.7).

2.4.5 *Sensitivities*

The historical biomass approach for updating σ was repeated with the subset of stocks that were used in the projection-based approach (*i.e.*, bocaccio, canary rockfish, darkblotched rockfish, petrale sole, Pacific Ocean perch, widow rockfish, and lingcod). The stock-specific among-assessment variation is shown in Table 2.8. This analysis yielded a pooled point estimate of σ=0.349, with an approximate 95% confidence interval of $0.328 \leq \sigma \leq 0.373$ when all available assessments were included (*i.e.*, those included in Ralston et al. [2011] as well as the new assessments completed post 2009). The point estimate was σ=0.286 with an approximate 95%

confidence interval of 0.0.265≤σ≤0.311 when only the assessments used in the projection-based approach were analyzed using the historical biomass approach (Supplementary Table 2.9).

2.5 DISCUSSION

Our findings confirm Ralston et al.'s (2011) that accounting only for uncertainty in terminal year biomass leads to an under-estimate of the measure of scientific uncertainty is supported by the analyses of this paper. Specifically, the value of σ would be 0.403 based on the updated analyses of this paper compared to 0.358 by Ralston et al. (2011). Both these values are substantially lower than the stock- and start-year-pooled estimates of σ based on projected OFL (0.533 / 0.469 for stochastic and deterministic projections, respectively). The projection-based approach could only be applied to a sub-set of stocks (Tables 2.4 and 2.8), but the estimate of σ, using the historical biomass approach, for the subset of stocks used for the projection-based approach is lower (0.356 if all assessments are included and 0.286 if only the assessments used in the projection-based approach are included) than for the entire set of available stocks (*i.e.*, the updated historical biomass approach value of 0.403), suggesting that the higher value for σ for the projection-based approach is not a consequence of the choice of stocks.

The projection-based approach captures more sources of uncertainty than the biomass-based approach. Notably, it accounts for forecast error, which compounds over time, as well as the difference in variance between projecting spawning biomass and projecting OFLs, with the latter being found to be consequential. Accounting for uncertainty in recruitment, both in the past and in the future, makes the calculations more complete, but does not qualitatively change the results; in fact, in several cases the value for σ was lower when account was taken of stochastic recruitment. The uncertainty estimates based on projected biomass and OFL are nevertheless still likely underestimates owing, for example, to the assumption that quantities such as growth, natural mortality and the stock-recruitment relationship remain constant into the future. There is evidence for several stocks that these parameters are not stationary (Forrest et al., 2018; Lee et al., 2018; Punt et al., 2014).

While it is more complete, the projection-based OFL approach has limited application. Unfortunately, the detailed information needed (*e.g.*, Supplementary Table 2.10) to conduct projections for several of the assessments for which historical biomass trajectories exist is no longer available due to changes in assessment archive structure. In addition, assessments based on a different model structure could not be easily compared. This is not a major concern for the US West Coast groundfish fishery or other regions where assessments use predominantly the same software (*e.g.*, Stock Synthesis or CASAL [Bull et al., 2005; Doonan et al. 2016]). However, this concern could be consequential for regions such as Australia where assessments are often based on bespoke models (Dichmont et al. 2016) and the North Pacific where several assessments packages (including Stock Synthesis and AMAK, Anon, 2015) are used.

Quantifying σ is critical for the determination of catch limits via a probability-based harvest control rule. For the US West Coast, the $P*$ HCR has been adopted and it was considered for adoption off Alaska (Punt et al. 2012). However, the implementation of the $P*$ approach (and whether it used at all) differs regionally within the US. Specifically, the level of scientific uncertainty that determines the OFL buffer varies based on the management plans that utilize the $P*$ HCR and the corresponding SSC. The SSCs for the respective Councils employ various methods for estimating σ in accordance with the corresponding fishery management plans. Generally, the most data-rich stocks use the estimated OFL distribution from the stock assessment and the Council's risk tolerance (*i.e.*, a specified $P*$) to calculate the buffer from OFL to ABC.

Alternative methods (*e.g.*, bootstrapping and Markov Chain Monte Carlo (MCMC) simulations [WPRFMC; Luck and Dalzell 2010], using the mean of a time-series of landings to create an OFL probability distribution [GMFMC 2011], MCMC yield-per-recruit analyses [NEFMC 2010], and Bayesian simulation approaches [NPFMC; Punt et al. 2012]) are listed as viable candidates for stock assessments that do not produce OFL estimates with uncertainty.

The PFMC defines a risk tolerance (*i.e.*, P^*) and the SSC recommends values for the OFL and σ to apply the P^* approach computing a buffer between the OFL and the ABC. The historical biomass approach assumes among-assessment variation in historical biomass is a proxy for the scientific uncertainty associated with OFLs. Quantifying the uncertainty in projections of OFLs as shown here directly captures the impact of more of the uncertainty associated with assessment model assumptions, estimates of current stock abundance and age-structure, how these estimates change over time, and estimates of the proxies for the target fishing mortality rate (F_{MSY} or proxy thereof). The historical biomass approach sensitivity estimate of σ=0.286 is much lower for the assessments used in the projection-based OFL approach (0.433 or 0.393 with or without accounting for recruitment stochasticity). This supports that using variation in historical biomass as a proxy for variation in OFL may underestimate uncertainty. The projection-based OFL approach was presented to and reviewed by the PFMC SSC for potential adoption for estimating the σ for the P^* HCR in the US west coast groundfish and coastal pelagic stocks fisheries.

The projection-based OFL approach addresses additional uncertainty related to changes in assessment model assumptions about natural mortality and productivity, selectivity, and relative year class abundance. However, there are opportunities to extend the approach. For example, it would be useful to know the extent to which variation in key parameters such as growth, natural mortality, and productivity within assessments each contribute to the overall uncertainty. A weakness of the current application is that only assessments that had a relatively simple structure (*e.g.* no seasonal structure) could be projected and several older assessments had to be ignored. If approaches such as the above are to be standard, we recommend that the assessment (whether conducted in Stock Synthesis or not) provide projections from various start values routinely.

TABLES

Table 2.1 Equations for the projection-based approach, where s is stock, y is projection start year (1998, 2003, 2008), p is projection year (measured since the start year), and i is an individual assessment. $X_{s,p,i}$ denotes the estimates of OFL and spawning biomass for year p+y+1 based on assessment i starting in year y, and $n_{s,p}$ is the total number of projection estimates across all assessments for stocks s in projection year p.

	Deterministic recruitment	Stochastic stock-recruitment recruitment	Equation
Stocks-, projection year- and start year-specific mean	$\overline{ln\left[X_{s,p}\right]}_y = \frac{1}{n_{s,p}}\sum_i ln[X_{s,p,i}]_y$	$\overline{ln\left[X_{s,p}\right]}_y = \frac{1}{100n_{s,p}}\sum_j\sum_i ln[X_{s,p,i,j}]$	Tab 2.1.1
Projection year-pooled, stocks-pooled, start-year-specific	$\sigma_y = \sqrt{\frac{1}{\sum_s\sum_p(n_{s,p}-1)}\sum_s\sum_p\sum_i(ln\left[X_{s,p,i}\right]_y - \overline{ln\left[X_{s,p}\right]}_y)^2}$	$\sigma_y = \sqrt{\frac{1}{\sum_s\sum_p(100n_{s,p}-1)}\sum_s\sum_j\sum_i(ln\left[X_{s,p,i,j}\right]_y - \overline{ln\left[X_{s,p}\right]}_y)^2}$	Tab 2.1.2a
Projection year-pooled, stocks-specific, start year-specific	$\sigma_{y,s} = \sqrt{\frac{1}{\sum_p(n_{s,p}-1)}\sum_p\sum_i(ln\left[X_{s,p,i}\right]_y - \overline{ln\left[X_{s,p}\right]}_y)^2}$	$\sigma_{y,s} = \sqrt{\frac{1}{\sum_p(100n_{s,p}-1)}\sum_s\sum_j\sum_i(ln\left[X_{s,p,i,j}\right]_y - \overline{ln\left[X_{s,p}\right]}_y)^2}$	Tab 2.1.2b
Projection year-specific, stocks-pooled, start year-specific	$\sigma_{y,p} = \sqrt{\frac{1}{\sum_s(n_{s,p}-1)}\sum_s\sum_i(ln\left[X_{s,p,i}\right]_y - \overline{ln\left[X_{s,p}\right]}_y)^2}$	$\sigma_{y,p} = \sqrt{\frac{1}{\sum_s(100n_{s,p}-1)}\sum_s\sum_j\sum_i(ln\left[X_{s,p,i,j}\right]_y - \overline{ln\left[X_{s,p}\right]}_y)^2}$	Tab 2.1.2c
Projection year-specific, stocks-specific, start year-specific	$\sigma_{y,s,p} = \sqrt{\frac{1}{n_{s,p}-1}\sum_i(ln\left[X_{s,p,i}\right]_y - \overline{ln\left[X_{s,p}\right]}_y)^2}$	$\sigma_{y,s,p} = \sqrt{\frac{1}{100n_{s,p}-1}\sum_j\sum_i(ln\left[X_{s,p,i,j}\right]_y - \overline{ln\left[X_{s,p}\right]}_y)^2}$	Tab 2.1.2d

Table 2.2 Equations for summarizing the estimates of σ over projection start years.

Start year-pooled among assessment estimate		Equations
Projection year-pooled, stocks-pooled mean	$\overline{\sigma} = \sqrt{\frac{1}{3}\sum_{y}\sigma_{y}^{2}}$	Tab 2.2.1a
Projection year-pooled, stocks-specific mean	$\overline{\sigma_{s}} = \sqrt{\frac{1}{3}\sum_{y}\sigma_{y,s}^{2}}$	Tab 2.2.1b
Projection year-specific, stocks-pooled mean	$\overline{\sigma_{p}} = \sqrt{\frac{1}{3}\sum_{y}\sigma_{y,p}^{2}}$	Tab 2.2.1c
Projection year-specific, stocks-specific mean	$\overline{\sigma_{s,p}} = \sqrt{\frac{1}{3}\sum_{y}\sigma_{y,s,p}^{2}}$	Tab 2.2.1d

Table 2.3 Equations for calculating within-assessment variability, where j indicates a stochastic projection, and the $[X_{s,p,i,j}]_y$ are the stochastic projection estimates of OFL and spawning biomass by stock, projection-year, assessment, stochastic replicate and start-year.

Within assessment estimate	Stochastic stock-recruitment relationship	Equation
Stocks-, projection year- and start year-specific mean	$\overline{ln\left[X_{s,p,i}\right]_y} = \frac{1}{100}\sum_j ln[X_{s,p,i,j}]_y$	Tab 2.3.1
Projection year-pooled, start-year, stocks-, and assessment-specific	$\sigma_{y,s,i} = \sqrt{\frac{1}{\sum_p(100-1)}\sum_j\sum_p\left(ln\left[X_{s,p,i,j}\right]_y - \overline{ln\left[X_{s,p,i}\right]_y}\right)^2}$	Tab 2.3.2a
Projection and start year-, stocks-, and assessment-specific	$\sigma_{y,s,p,i} = \sqrt{\frac{1}{100-1}\sum_j\left(ln\left[X_{s,p,i,j}\right]_y - \overline{ln\left[X_{s,p,i}\right]_y}\right)^2}$	Tab 2.3.2b

Table 2.4 Summary of stock-specific analyses using the historical biomass approach. * indicates stocks with no new assessments since 2009.

			2017 Update			Ralston et al. 2011		
Stocks group	Common name	Scientific name	No. of assessments	Deviations (n)	Log-scale standard deviation	No. of assessments	Deviations (n)	Log-scale standard deviation
Rockfish	bocaccio	*Sebastes paucisipinis*	7	72	0.263	5	61	0.367
	canary rockfish	*Sebastes pinniger*	8	68	0.475	7	85	0.375
	chilipepper*	*Sebastes goodei*	2	22	0.354	2	22	0.354
	darkblotched rockfish	*Sebastes crameri*	6	89	0.274	3	45	0.103
	Pacific Ocean perch	*Sebastes alutus*	5	45	0.502	3	20	0.352
	widow rockfish	*Sebastes entomelas*	7	75	0.418	5	61	0.241
	yelloweye rockfish	*Sebastes ruberrimus*	5	46	0.590	4	58	0.492
	yellowtail rockfish*	*Sebastes flavidus*	6	72	0.258	6	66	0.269
	shortspine thornyhead	*Sebastolobus alascanus*	4	36	0.994	3	39	0.923
Roundfish	cabezon*	*Scorpaenichthys marmoratus*	3	46	0.154	3	46	0.154
	lingcod	*Ophiodon elongatus*	5	45	0.278	4	56	0.263
	Pacific whiting	*Merluccius productus*	23	151	0.286	15	151	0.286
	sablefish	*Anoplopoma fimbria*	8	80	0.329	7	82	0.340
Flatfish	Dover sole	*Microstomus pacificus*	4	42	0.658	3	41	0.360
	petrale sole	*Eopsetta jordani*	5	74	0.197	3	41	0.227
Coastal pelagic	Pacific mackerel	*Scomber japonicus*	6	76	0.484	4	66	0.415
	Pacific sardine	*Sardinops sagax*	6	72	0.347	3	51	0.206

Table 2.5 Estimates of σ by stock and start-year as well as start-year and stocks-pooled values with 95% confidence intervals. Results are shown for analyses based on spawning biomass (a) and the OFL (b).

(a) Spawning biomass

	Deterministic Recruitment							Stochastic Recruitment						
Stocks	1998		2003		2008			1998		2003		2008		
	σ_y	CI	σ_y	CI	σ_y	CI	$\bar{\sigma}$	σ_y	CI	σ_y	CI	σ_y	CI	$\bar{\sigma}$
Pooled	0.342	0.340, 0.344	0.313	0.311, 0.315	0.315	0.313, 0.317	0.323	0.381	0.378, 0.383	0.348	0.346, 0.351	0.351	0.348, 0.353	0.360
	$\sigma_{y,s}$	CI	$\sigma_{y,s}$	CI	$\sigma_{y,s}$	CI	$\bar{\sigma}_s$	$\sigma_{y,s}$	CI	$\sigma_{y,s}$	CI	$\sigma_{y,s}$	CI	$\bar{\sigma}_s$
Bocaccio	0.150	0.148, 0.152	0.079	0.078, 0.080	0.040	0.039, 0.041	0.100	0.319	0.314, 0.324	0.295	0.290, 0.300	0.291	0.287, 0.296	0.302
Canary rockfish	0.475	0.466, 0.485	0.324	0.318, 0.331	0.339	0.333, 0.346	0.386	0.525	0.515, 0.536	0.371	0.364, 0.379	0.373	0.365, 0.380	0.429
Darkblotched rockfish	0.138	0.136, 0.140	0.165	0.163, 0.168	0.163	0.161, 0.165	0.156	0.217	0.214, 0.221	0.240	0.237, 0.244	0.238	0.235, 0.242	0.232
Lingcod	0.137	0.135, 0.140	0.056	0.055, 0.057	0.060	0.059, 0.061	0.092	0.170	0.167, 0.174	0.110	0.108, 0.112	0.119	0.117, 0.122	0.136
Petrale sole	0.633	0.621, 0.645	0.623	0.611, 0.636	0.557	0.546, 0.568	0.605	0.610	0.598, 0.622	0.595	0.583, 0.607	0.537	0.527, 0.548	0.581
Pacific Ocean perch	0.470	0.463, 0.478	0.452	0.445, 0.460	0.488	0.480, 0.496	0.470	0.496	0.488, 0.504	0.459	0.452, 0.467	0.486	0.479, 0.494	0.481
Widow rockfish	0.062	0.061, 0.063	0.113	0.111, 0.115	0.230	0.225, 0.234	0.152	0.121	0.119, 0.123	0.160	0.157, 0.163	0.262	0.257, 0.267	0.191

(b) OFL

	Deterministic Recruitment							Stochastic Recruitment						
Stocks	1998		2003		2008			1998		2003		2008		
	σ_y	CI	σ_y	CI	σ_y	CI	$\bar{\sigma}$	σ_y		σ_y		σ_y		$\bar{\sigma}$
Pooled	0.392	0.389, 0.395	0.355	0.353, 0.357	0.430	0.427, 0.433	0.393	0.425	0.422, 0.427	0.399	0.397, 0.402	0.473	0.470, 0.476	0.433
	$\sigma_{y,s}$	CI	$\sigma_{y,s}$	CI	$\sigma_{y,s}$	CI	$\bar{\sigma}_s$	$\sigma_{y,s}$		$\sigma_{y,s}$		$\sigma_{y,s}$		$\bar{\sigma}_s$
Bocaccio	0.134	0.132, 0.136	0.338	0.333, 0.344	0.412	0.406, 0.419	0.388	0.358	0.352, 0.364	0.475	0.468, 0.483	0.536	0.527, 0.544	0.462
Canary rockfish	0.791	0.776, 0.807	0.596	0.584, 0.608	0.145	0.142, 0.148	0.815	0.755	0.741, 0.770	0.575	0.564, 0.586	0.170	0.167, 0.173	0.557
Darkblotched rockfish	0.422	0.416, 0.428	0.451	0.445, 0.458	0.485	0.478, 0.492	0.523	0.447	0.441, 0.454	0.475	0.468, 0.482	0.509	0.502, 0.516	0.478
Lingcod	0.109	0.107, 0.111	0.042	0.042, 0.043	0.0500	0.049, 0.051	0.104	0.159	0.156, 0.162	0.109	0.107, 0.111	0.122	0.120, 0.124	0.132
Petrale sole	0.105	0.103, 0.107	0.156	0.153, 0.159	0.430	0.422, 0.439	0.382	0.154	0.151, 0.157	0.235	0.231, 0.240	0.491	0.481, 0.500	0.326
Pacific Ocean perch	0.230	0.226, 0.234	0.318	0.313, 0.324	0.399	0.393, 0.406	0.395	0.279	0.274, 0.283	0.367	0.361, 0.373	0.431	0.424, 0.438	0.364
Widow rockfish	0.521	0.511, 0.531	0.143	0.140, 0.146	0.699	0.686, 0.713	0.720	0.543	0.532, 0.554	0.211	0.207, 0.216	0.709	0.695, 0.723	0.530

Table 2.6 Within-assessment variation by stock (projection year-pooled) where A are the assessments based on the stochastic projections.

(a) Spawning biomass:

1998

Stocks	A=1	CI	A=2	CI	A=3	CI	A=4	CI
Bocaccio	0.312	(0.304,0.321)	0.299	(0.291,0.307)	0.281	(0.273,0.289)		
Canary rockfish	0.115	(0.112,0.118)	0.09	(0.087,0.092)				
Darkblotched rockfish	0.162	(0.158,0.167)	0.157	(0.153,0.162)	0.170	(0.165,0.175)	0.118	(0.115,0.122)
Lingcod	0.106	(0.103,0.109)	0.105	(0.102,0.108)				
Petrale sole	0.099	(0.0970,0.102)	0.113	(0.110,0.117)				
Pacific Ocean perch	0.151	(0.147,0.156)	0.159	(0.155,0.164)	0.136	(0.132,0.140)		
Widow rockfish	0.090	(0.087,0.092)	0.123	(0.120,0.127)				

2003

Stocks	A=1	CI	A=2	CI	A=3	CI	A=4	CI
Bocaccio	0.304	(0.295,0.312)	0.307	(0.298,0.316)	0.266	(0.259,0.274)		
Canary rockfish	0.120	(0.116,0.123)	0.084	(0.082,0.087)				
Darkblotched rockfish	0.174	(0.169,0.179)	0.160	(0.155,0.164)	0.158	(0.153,0.162)	0.119	(0.115,0.122)
Lingcod	0.097	(0.095,0.100)	0.088	(0.086,0.091)				
Petrale sole	0.112	(0.109,0.116)	0.114	(0.111,0.117)				
Pacific Ocean perch	0.139	(0.136,0.143)	0.144	(0.140,0.148)	0.140	(0.136,0.144)		
Widow rockfish	0.081	(0.079,0.083)	0.121	(0.118,0.125)				

2008

Stocks	A=1	CI	A=2	CI	A=3	CI	A=4	CI
Bocaccio	0.280	(0.273,0.288)	0.277	(0.270,0.285)	0.309	(0.300,0.317)		
Canary rockfish	0.118	(0.115,0.122)	0.091	(0.088,0.093)				
Darkblotched rockfish	0.187	(0.182,0.192)	0.145	(0.141,0.149)	0.158	(0.153,0.162)	0.120	(0.117,0.124)
Lingcod	0.100	(0.097,0.103)	0.098	(0.095,0.101)				
Petrale sole	0.097	(0.095,0.100)	0.173	(0.169,0.178)				
Pacific Ocean perch	0.131	(0.128,0.135)	0.140	(0.137,0.144)	0.114	(0.111,0.118)		
Widow rockfish	0.072	(0.070,0.074)	0.114	(0.111,0.117)				

(b) OFL

1998

Stocks	A=1	CI	A=2	CI	A=3	CI	A=4	CI
Bocaccio	0.341	(0.332,0.351)	0.358	(0.349,0.368)	0.339	(0.330,0.348)		
Canary rockfish	0.111	(0.108,0.114)	0.118	(0.114,0.121)				
Darkblotched rockfish	0.185	(0.180,0.190)	0.184	(0.179,0.190)	0.193	(0.179,0.190)	0.183	(0.178,0.188)
Lingcod	0.115	(0.112,0.118)	0.115	(0.112,0.118)				
Petrale sole	0.120	(0.117,0.124)	0.134	(0.130,0.138)				
Pacific Ocean perch	0.194	(0.189,0.200)	0.178	(0.174,0.184)	0.144	(0.140,0.148)		
Widow rockfish	0.110	(0.107,0.114)	0.219	(0.213,0.225)				

2003

Stocks	A=1	CI	A=2	CI	A=3	CI	A=4	CI
Bocaccio	0.356	(0.347,0.367)	0.386	(0.376,0.397)	0.398	(0.387,0.409)		
Canary rockfish	0.120	(0.117,0.124)	0.132	(0.129,0.136)				
Darkblotched rockfish	0.187	(0.182,0.192)	0.183	(0.178,0.188)	0.177	(0.172,0.182)	0.172	(0.168,0.177)
Lingcod	0.107	(0.104,0.110)	0.097	(0.095,0.100)				
Petrale sole	0.135	(0.132,0.139)	0.137	(0.133,0.141)				
Pacific Ocean perch	0.196	(0.191,0.202)	0.163	(0.158,0.168)	0.153	(0.149,0.158)		
Widow rockfish	0.102	(0.099,0.105)	0.182	(0.177,0.187)				

2008

Stocks	A=1	CI	A=2	CI	A=3	CI	A=4	CI
Bocaccio	0.324	(0.315,0.333)	0.381	(0.370,0.392)	0.449	(0.436,0.461)		
Canary rockfish	0.121	(0.117,0.124)	0.111	(0.108,0.114)				
Darkblotched rockfish	0.205	(0.200,0.211)	0.163	(0.159,0.168)	0.169	(0.165,0.174)	0.169	(0.165,0.174)
Lingcod	0.110	(0.107,0.113)	0.107	(0.104,0.110)				
Petrale sole	0.117	(0.113,0.120)	0.196	(0.191,0.202)				
Pacific Ocean perch	0.195	(0.190,0.201)	0.157	(0.153,0.161)	0.128	(0.124,0.132)		
Widow rockfish	0.125	(0.122,0.129)	0.179	(0.174,0.184)				

Table 2.7 Summary of pooled and stock group-specific estimates of σ from assessments of groundfish and coastal pelagic stocks using the historical biomass approach.

Group	Number of stocks	σ 2017 estimate	 95% CI	 Ralston 2011
rockfish	9	0.455	0.429, 0.484	0.418
roundfish	4	0.281	0.261, 0.304	0.281
flatfish	2	0.423	0.375, 0.486	0.299
coastal pelagic	2	0.422	0.378, 0.476	0.339
All stocks	17	0.403	0.386, 0.421	0.358

Table 2.8 Summary of stock-specific values for σ based on the historical biomass approach for the subset of stocks with assessments included in the analyses based on the projection-based approach.

		Sensitivity (all assessments) A			Sensitivity (projectable assessments) B		
Common name	Scientific name	No. of stock assessments	Squared deviations (n)	Log-scale standard deviation	No. of stock assessments	Squared deviations (n)	Log-scale standard deviation
Bocaccio	*Sebastes paucisipinis*	7	72	0.263	3	49	0.128
Canary rockfish	*Sebastes pinniger*	8	68	0.475	2	30	0.347
Darkblotched rockfish	*Sebastes crameri*	6	89	0.274	4	55	0.149
Pacific Ocean perch	*Sebastes alutus*	5	45	0.502	2	43	0.513
Widow rockfish	*Sebastes entomelas*	7	75	0.418	3	49	0.387
Lingcod	*Ophiodon elongatus*	5	45	0.278	2	26	0.188
Petrale sole	*Eopsetta jordani*	5	74	0.197	2	55	0.087

FIGURES

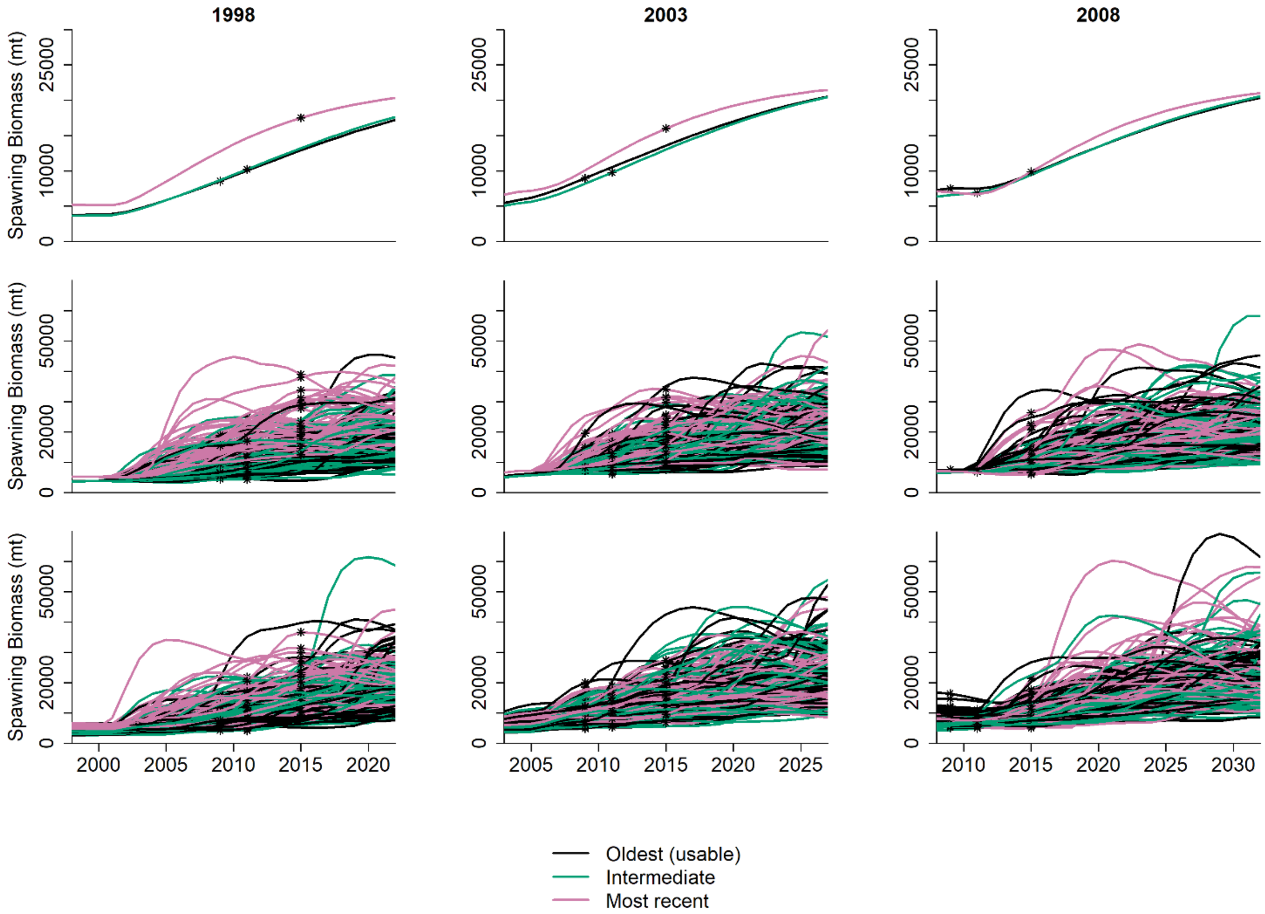


Figure 2.1 Spawning biomass trajectories for bocaccio based on three start years (1998, 2003, and 2008; columns) and three stock assessments (2009, 2011, and 2015; solid dots). Results are shown in the upper panels for the deterministic projections, in the center panels for stochastic projections that only consider uncertainty in future recruitment, and in the lower panels for stochastic projections that account for uncertainty in past and future recruitment.

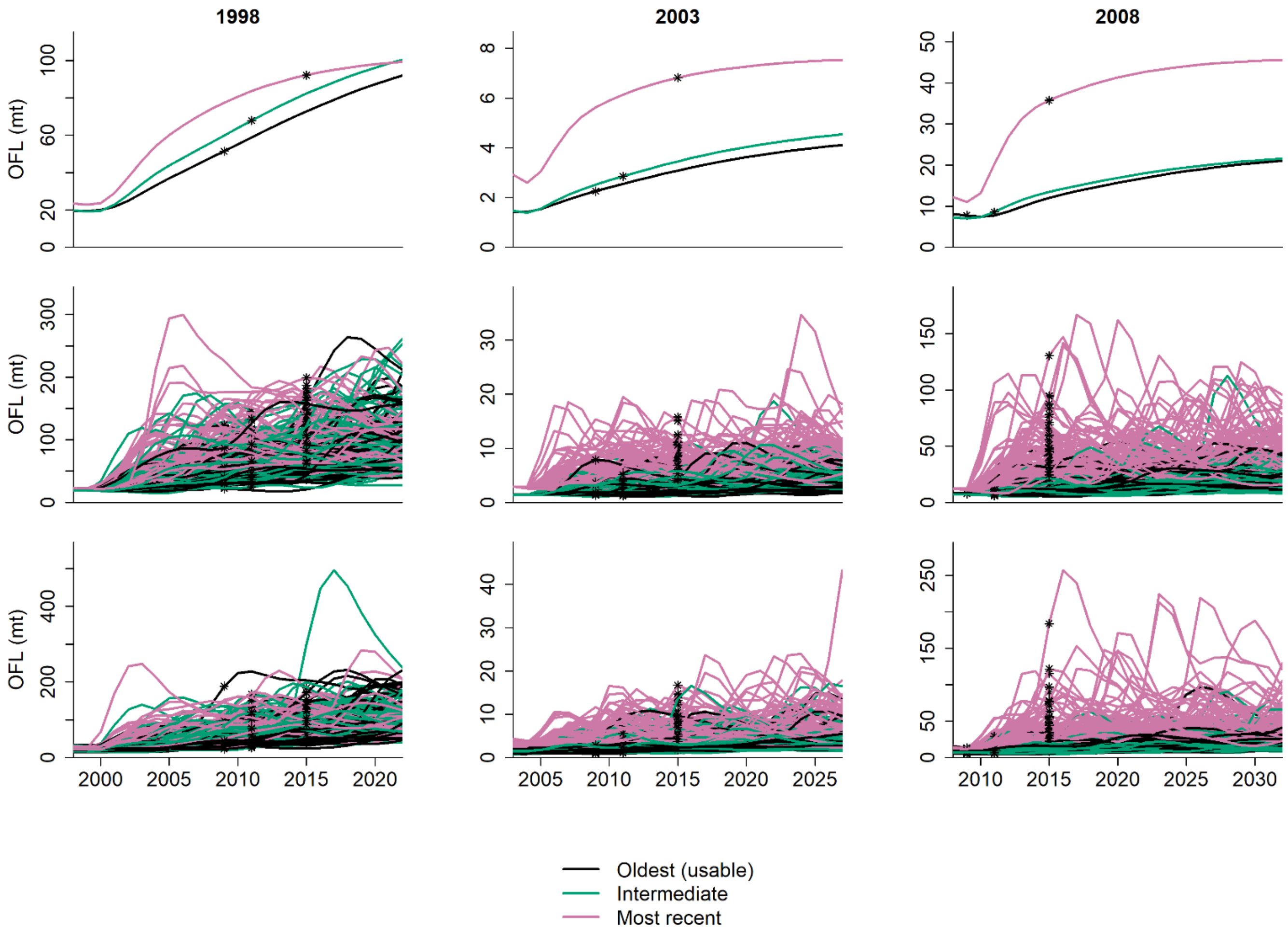


Figure 2.2 As for Figure 2.1, except the results pertain to the OFL.

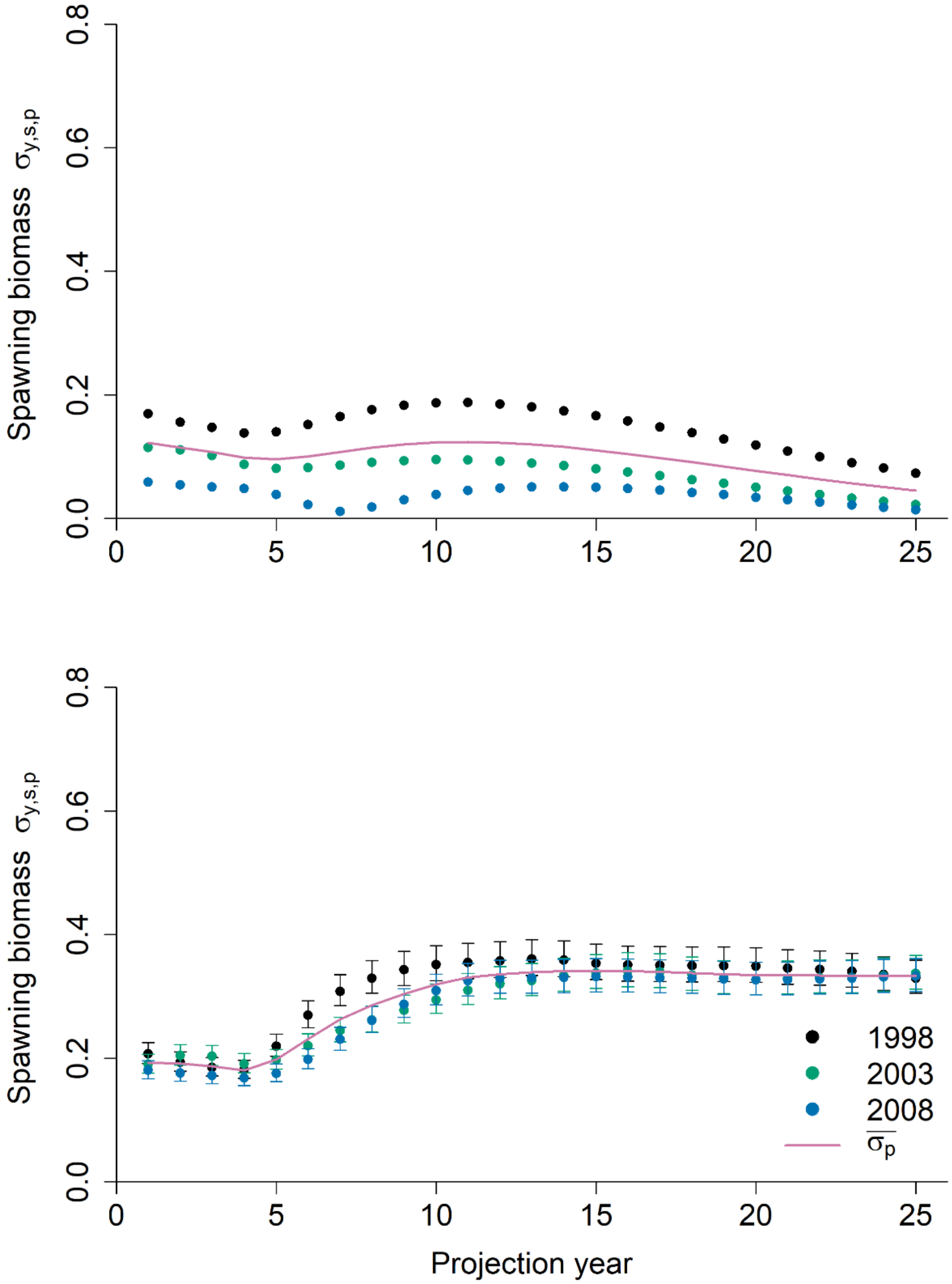


Figure 2.3 Values of σ for bocaccio based on spawning biomass. Results are shown for deterministic (upper panel) and stochastic (lower panel) analyses by start year and pooled over start-years. The whiskers in the lower panel indicate 95% confidence intervals (no 95% confidence intervals are shown in the upper panel owning to small sample size).

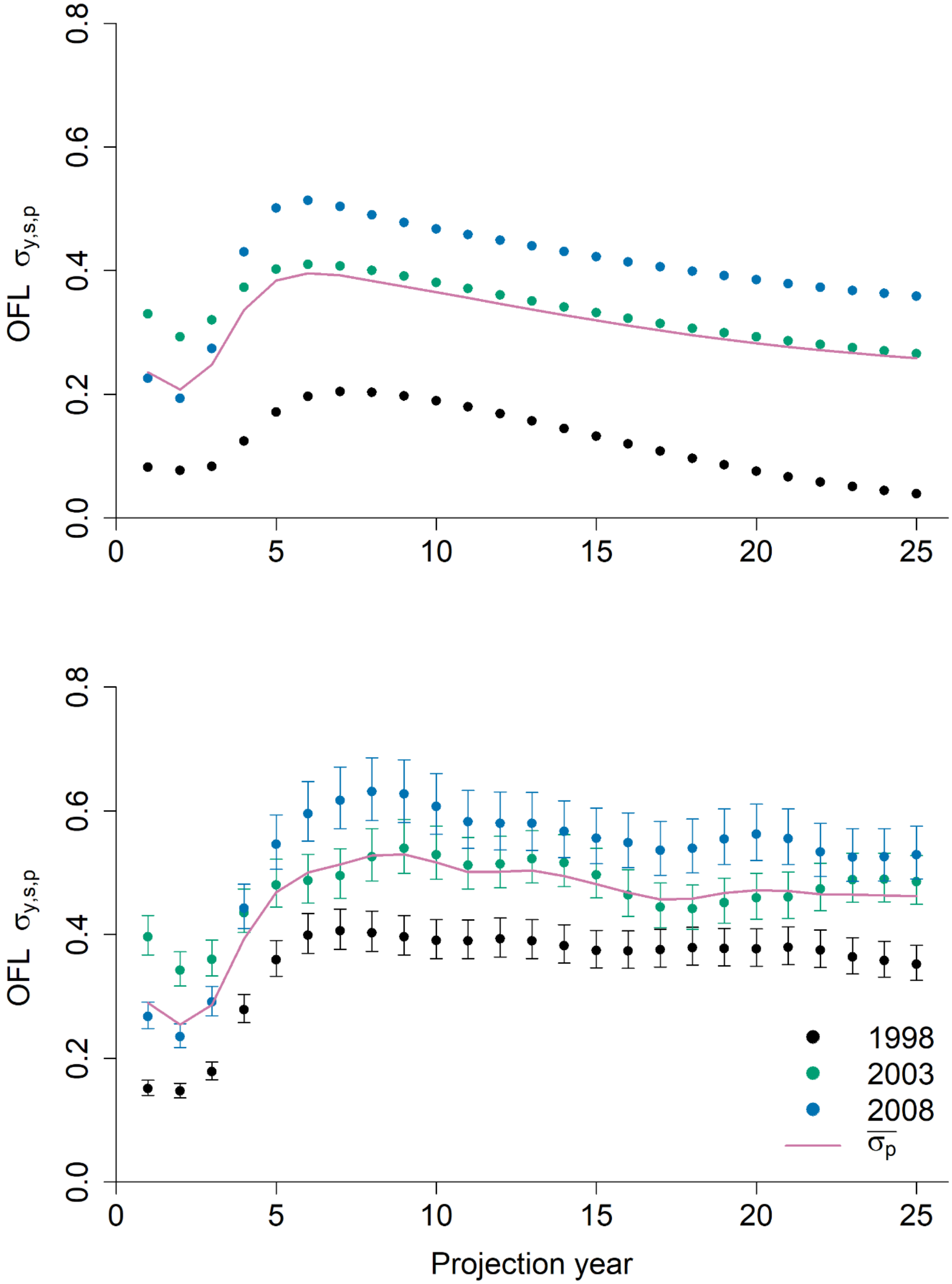


Figure 2.4 As for Figure 2.3, except the results relate to the OFL.

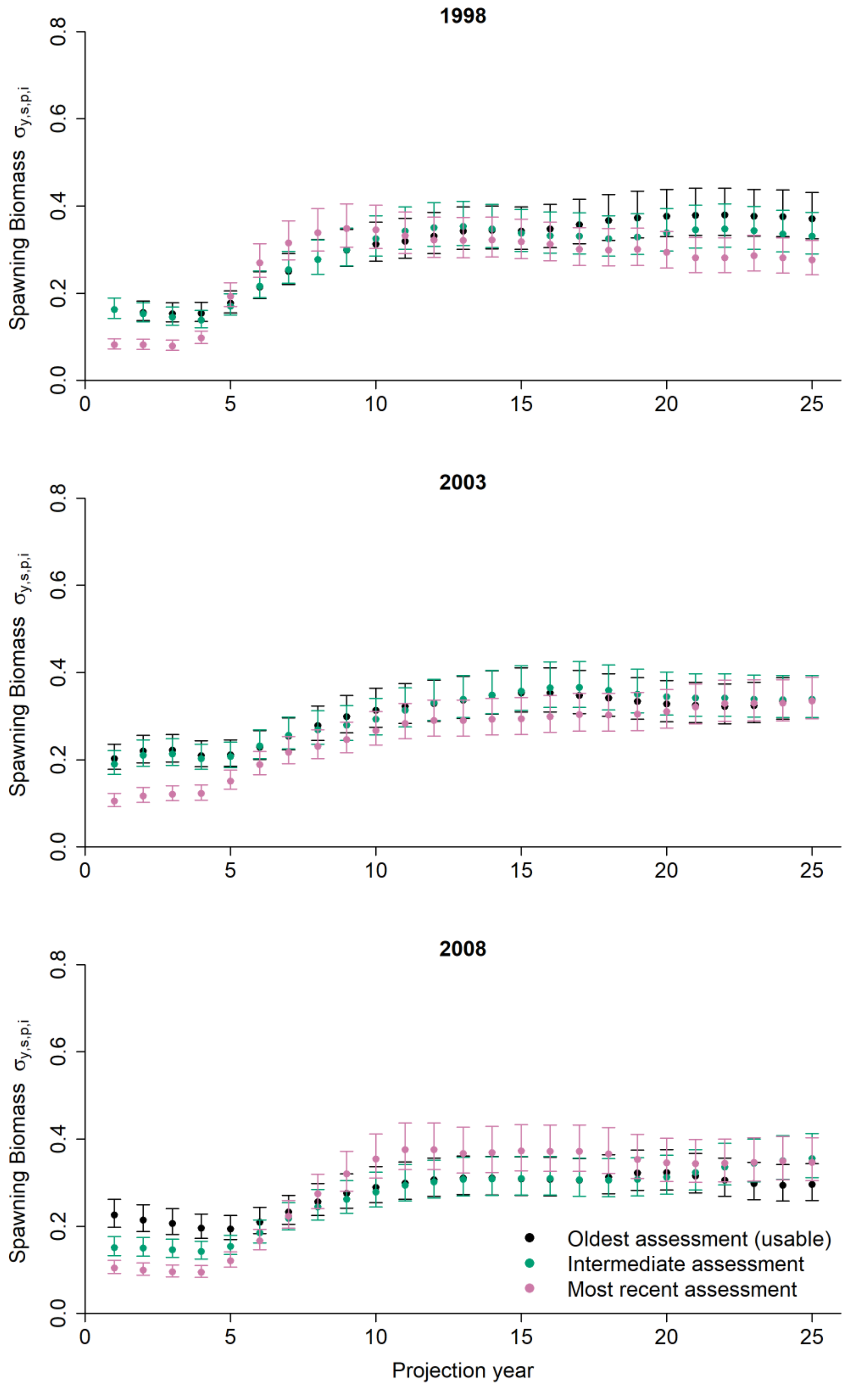


Figure 2.5 Values of within-assessment σ for bocaccio based on spawning biomass. Results are shown for stochastic analyses by start year and by assessment (2009, 2011, and 2015). The whiskers indicate 95% confidence intervals.

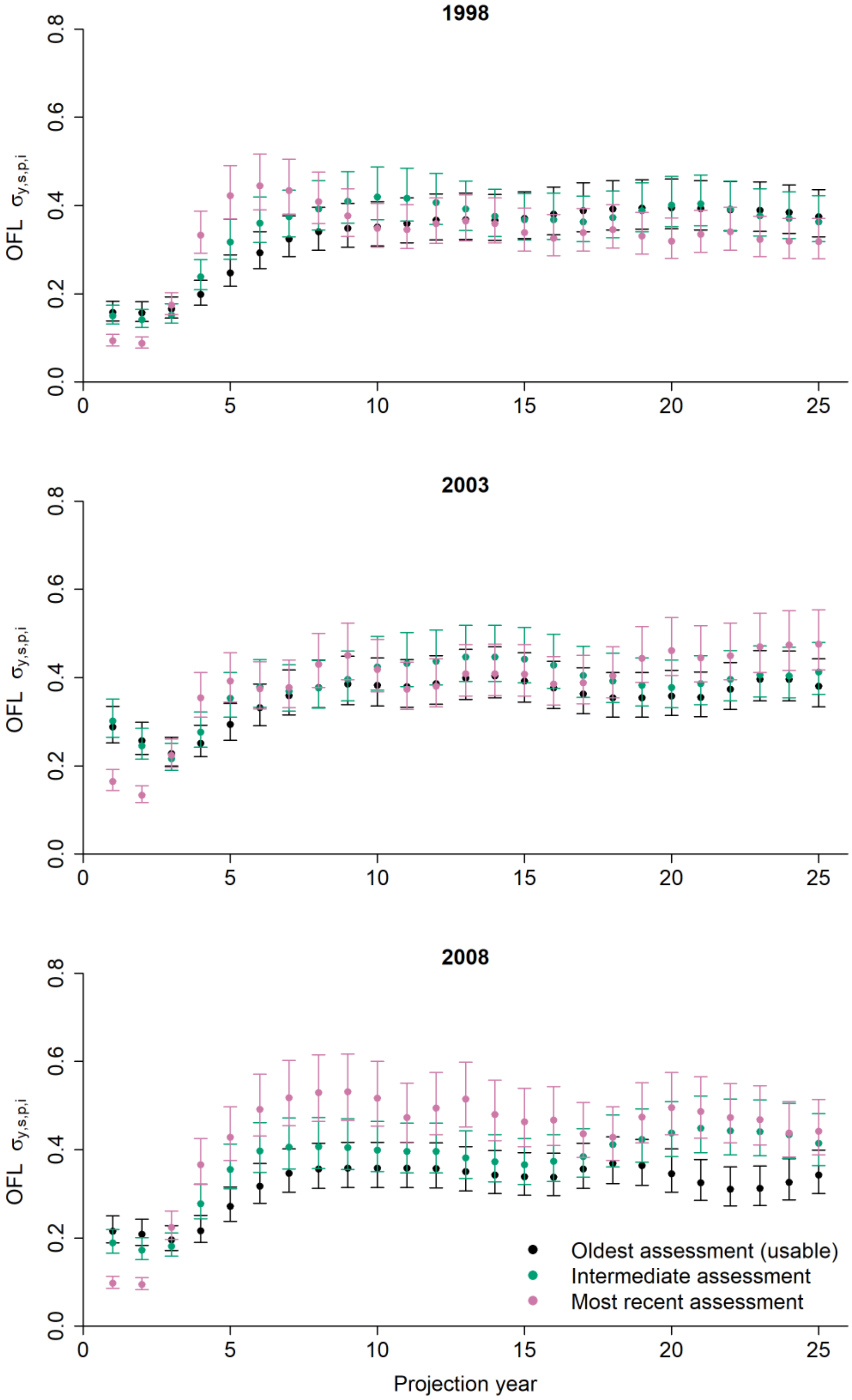


Figure 2.6 As for Figure 2.5, except the results relate to the OFL.

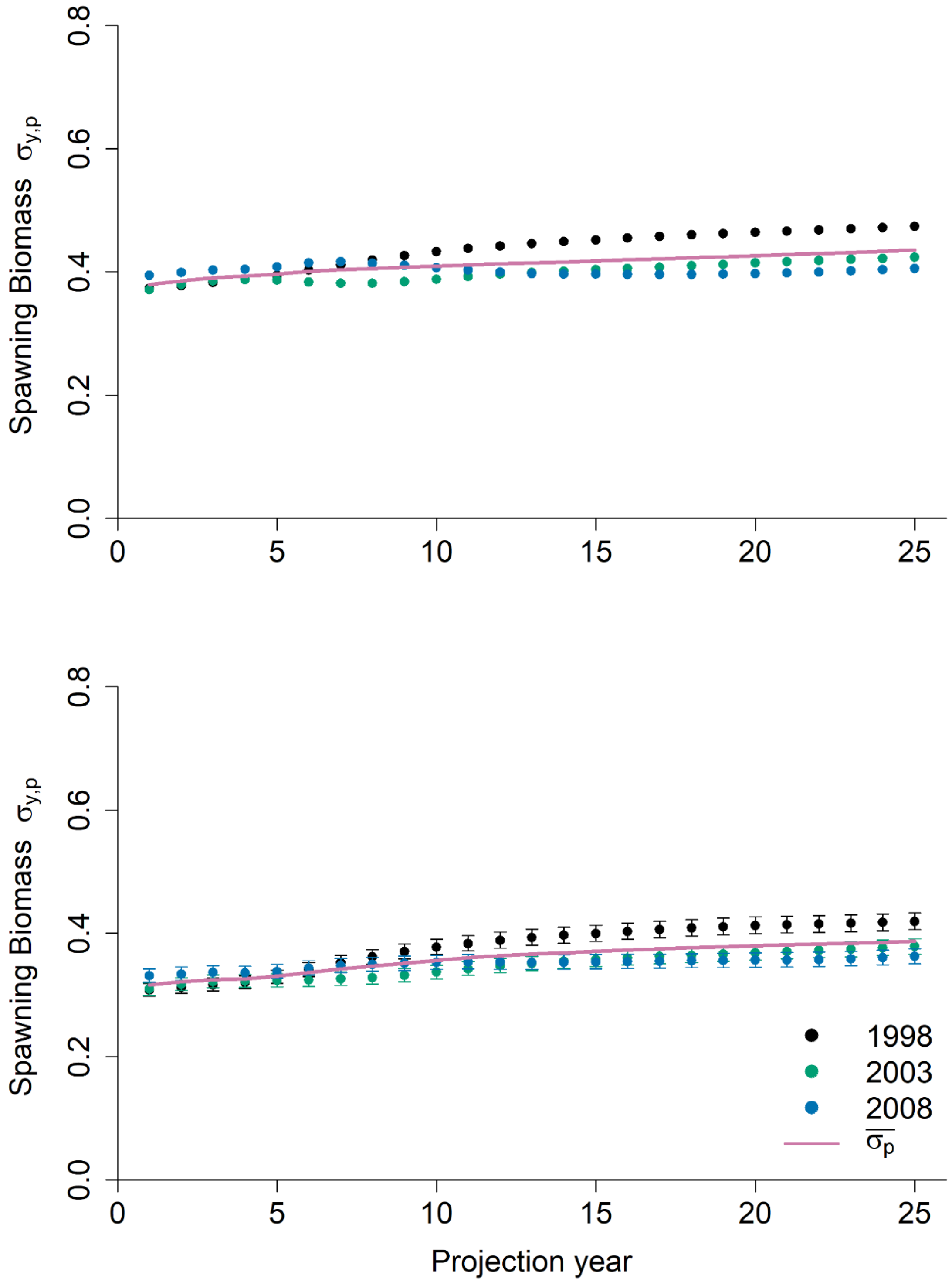


Figure 2.7 Values of σ aggregated over stocks based on spawning biomass. Results are shown for deterministic (upper panel) and stochastic (lower panel) analyses by start year and pooled over start-years. The whiskers in the lower panel indicate 95% confidence intervals (no 95% confidence intervals are shown in the upper panel owning to small sample size).

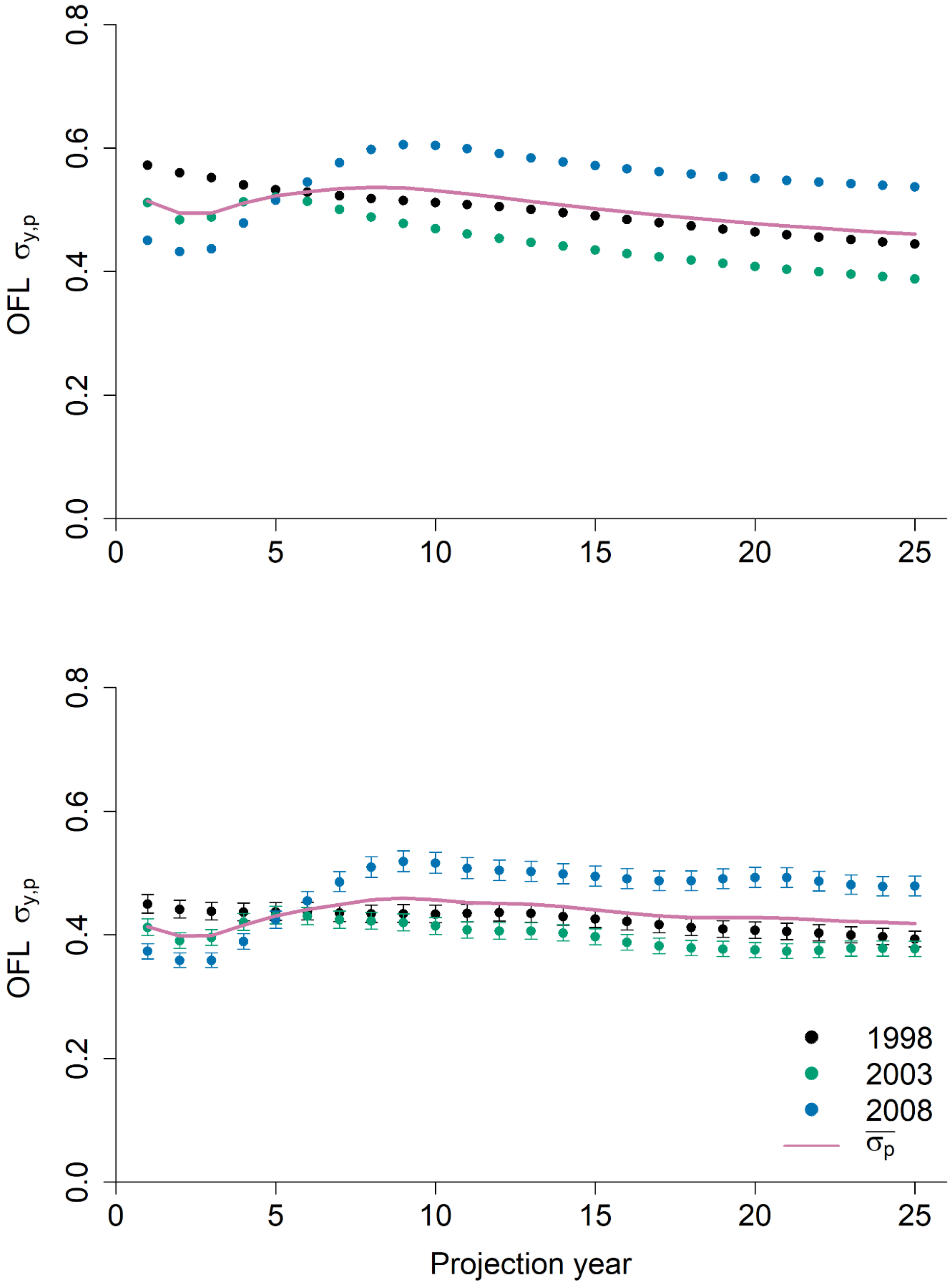


Figure 2.8 As for Figure 2.7, except the results relate to the OFL.

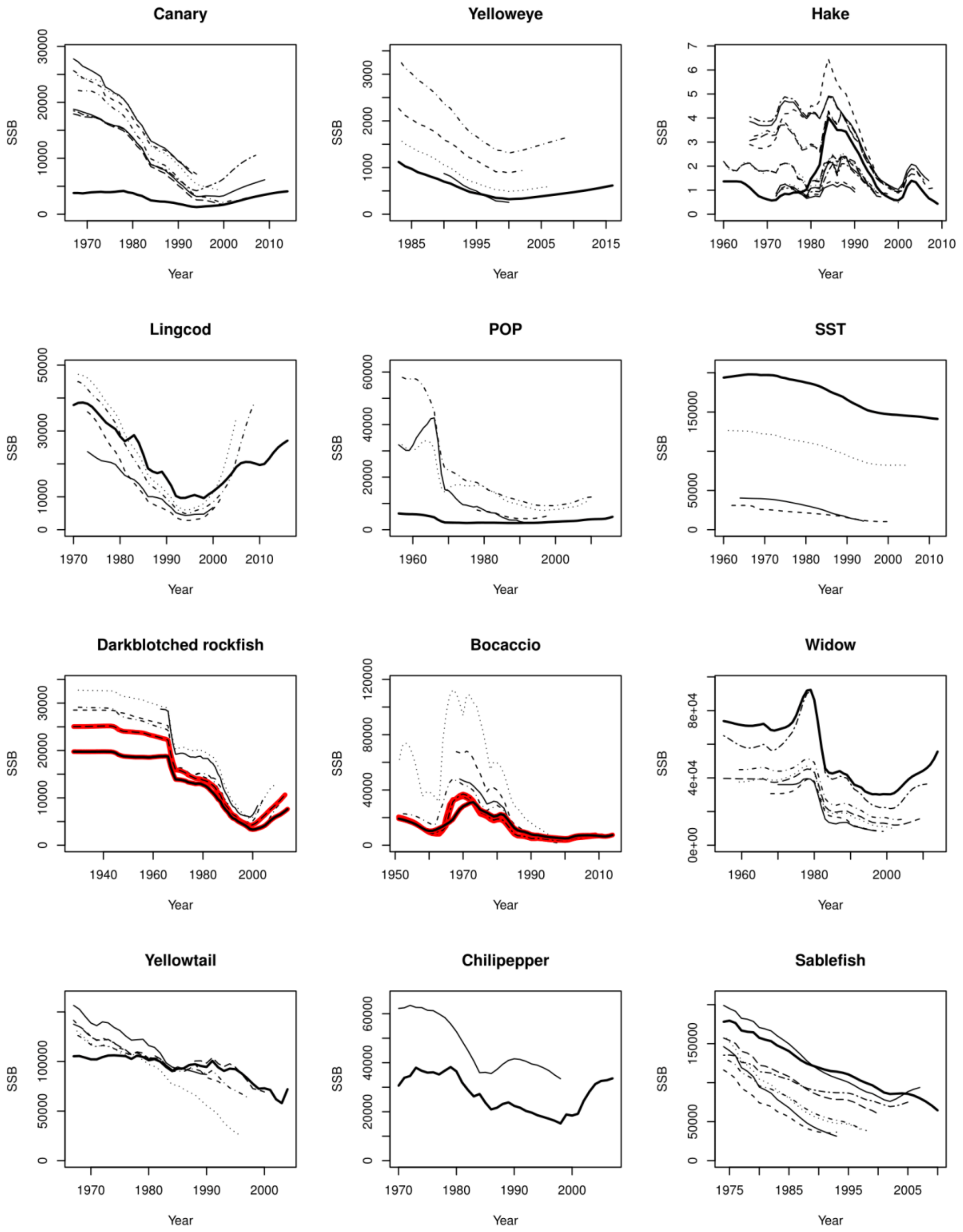
SUPPLEMENTARY APPENDIX

Table 2.9 The US West Coast groundfish benchmark stock assessments used for conducting projections.

Stocks	**Year**	**Authors**
Bocaccio (BOCA)	2009	Field, Dick, Pearson, and MacCall
Sebastes paucispinis	2011	Field
	2015	He, Field, Pearson, Lefebvre, and Lindley
Canary rockfish (CNRY)	2009	Stewart
	2015	Thorson and Wetzel
Darkblotched rockfish (DBRK)	2009	He, Punt, MacCall, and Ralston
Sebastes crameri	2011	He, Pearson, Dick, Field, Ralston, and MacCall
	2013	Gertseva and Thorson
	2015	Hicks and Wetzel
Lingcod (LING)	2009	Hamel, Sethi, and Wadsworth
Ophiodon elongatus	2017	Haltuch, Wallace, Akselrud, Nowlis, Barnett, Valero, Tsou, and Lam
Petrale sole (PETR)	2011	Haltuch, Hicks, and See
Eopsetta jordani	2013	Haltuch, Ono, and Valero
Pacific ocean perch (POP_)	2011	Hamel and Ono
Sebastes alutus	2017	Wetzel, Cronin-Fine, and Johnson
Widow rockfish (WDOW)	2009	He, Pearson, Dick, Field, Talston, and MacCall
Sebastes entomelas	2011	He, Pearson, Dick, Field, Ralston, and MacCall
	2015	Hicks and Wetzel

Table 2.10 The quantities extracted from Stock Synthesis report files to conduct OFL and spawning biomass projections. Reference year of interest refers to the last year of the assessment, as defined by the first year for which spawning biomass and OFL are projected.

Stock Assessment Output
Numbers-at-age for reference year of interest, N
Fecundity (unfished and fished) for reference year of interest, ω
Selectivity at age by fleet, S
Selected-weighted retained weight by age and fleet, W
Natural mortality, M
Relative exploitation rate by fleet, F
Stock-recruit parameters
Unfished recruitment, R_0
Steepness, h


Canary
SSB
0
10000
20000
30000
1970
1980
1990
2000
2010
Year
Yelloweye
SSB
0
1000
2000
3000
1985
1995
2005
2015
Year
Hake
SSB
0
1
2
3
4
5
6
7
1960
1970
1980
1990
2000
2010
Year
Lingcod
SSB
0
10000
30000
50000
1970
1980
1990
2000
2010
Year
POP
SSB
0
20000
40000
60000
1960
1980
2000
Year
SST
SSB
0
50000
150000
1960
1970
1980
1990
2000
2010
Year
Darkblotched rockfish
SSB
0
10000
20000
30000
1940
1960
1980
2000
Year
Bocaccio
SSB
0
40000
80000
120000
1950
1970
1990
2010
Year
Widow
SSB
0e+00
4e+04
8e+04
1960
1980
2000
Year
Yellowtail
SSB
0
50000
100000
1970
1980
1990
2000
Year
Chilipepper
SSB
0
20000
40000
60000
1970
1980
1990
2000
Year
Sablefish
SSB
0
50000
150000
1975
1985
1995
2005
Year

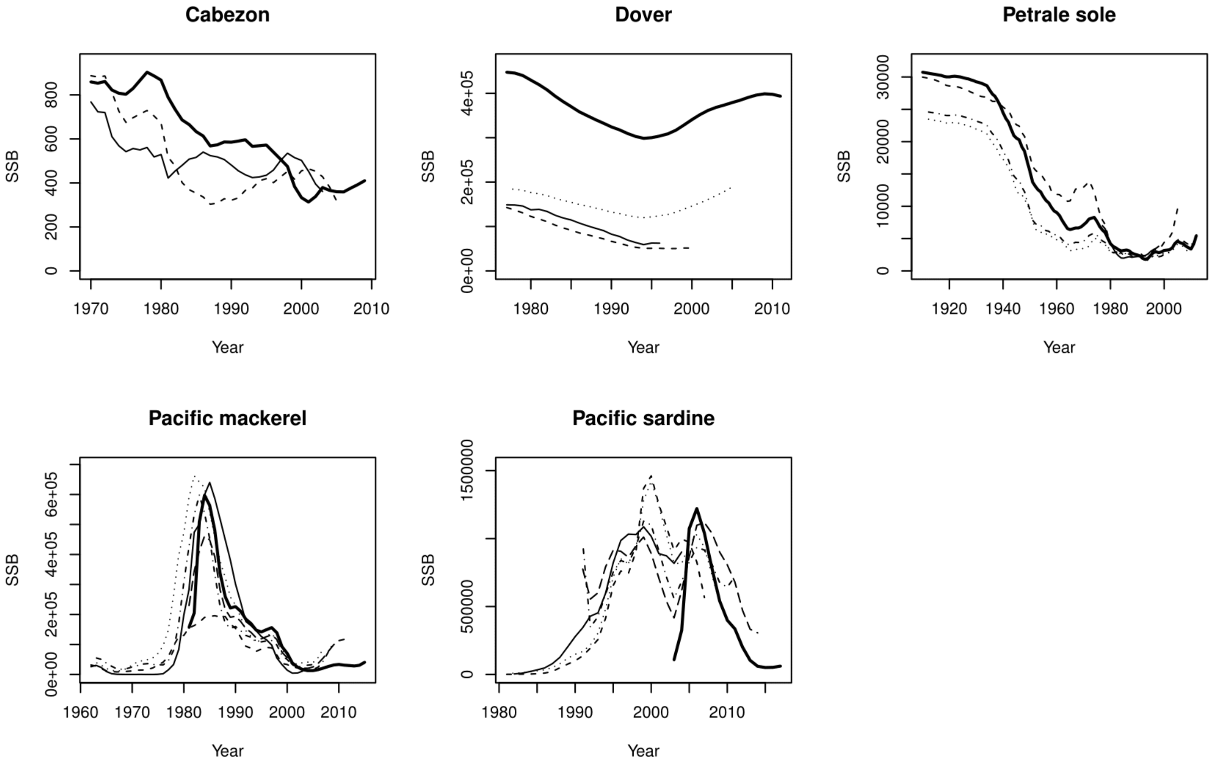
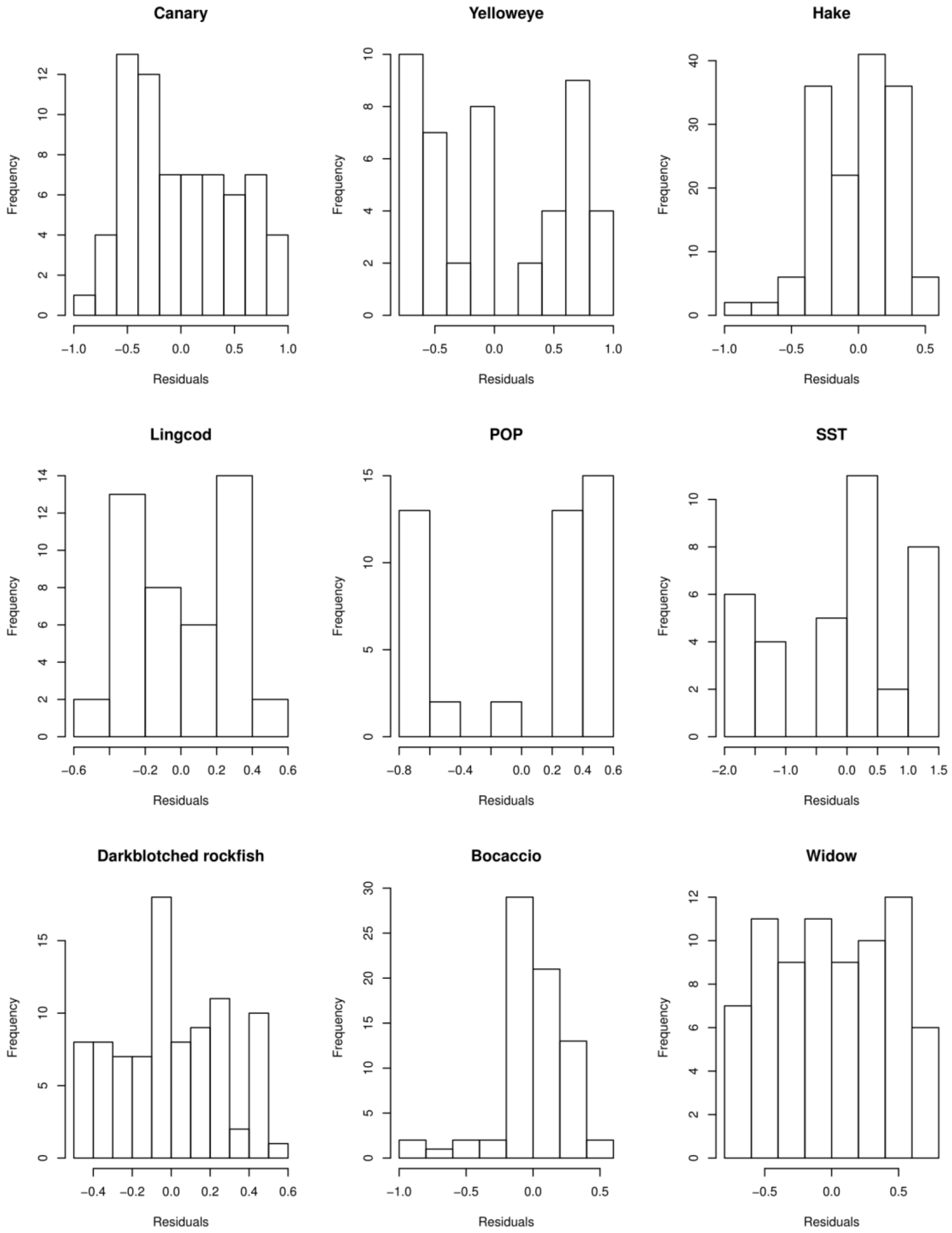
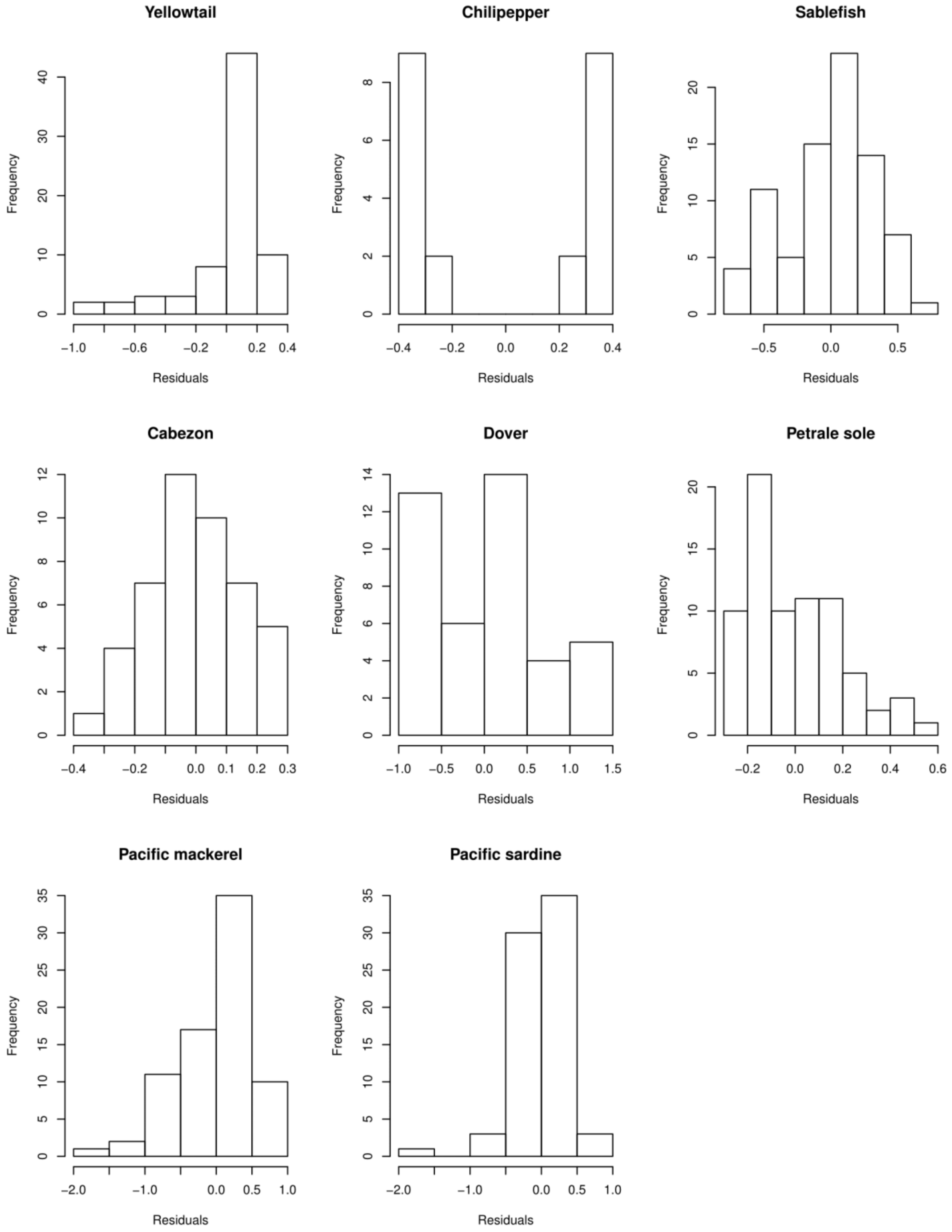


Figure 2.9 Biomass time series for the 17 groundfish and coastal pelagic stocks from stock assessments conducted for the Pacific Fishery Management Council on the west coast of the United States. The thick, solid black line denotes the most recent assessment. The lines highlighted in red are the biomass trajectories that were recalculated to be in metric tons based on outputs from Stock Synthesis in eggs.


Canary
Yelloweye
Hake
Lingcod
POP
SST
Darkblotched rockfish
Bocaccio
Widow



Yellowtail

Chilipepper

Sablefish

Cabezon

Dover

Petrale sole

Pacific mackerel

Pacific sardine

Figure 2.10 Frequency distributions of log-scale biomass deviations for each of the 17 groundfish and coastal pelagic stocks in stock assessments conducted for the Pacific Fishery Management Council. Deviations were calculated from annual means taken from the biomass time series presented in Supplementary Figure 2.9.

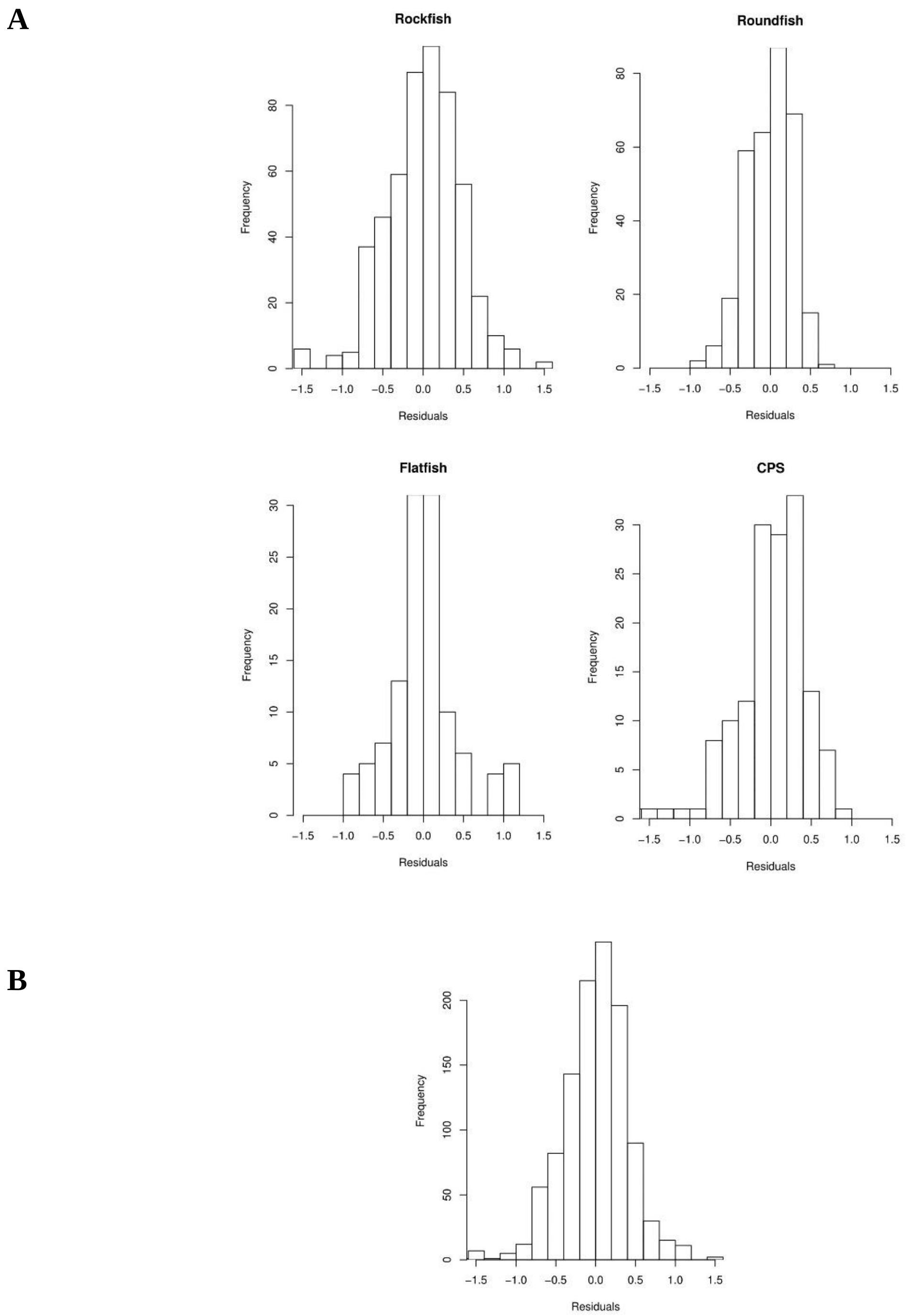


Figure 2.11 Panel A) Composite distributions of log-deviations from the mean, pooled for four meta-analytic groupings (rockfish, roundfish, flatfish, and coastal pelagic stocks). Panel B) Aggregate distribution of log-deviations pooled over all 17 stocks.

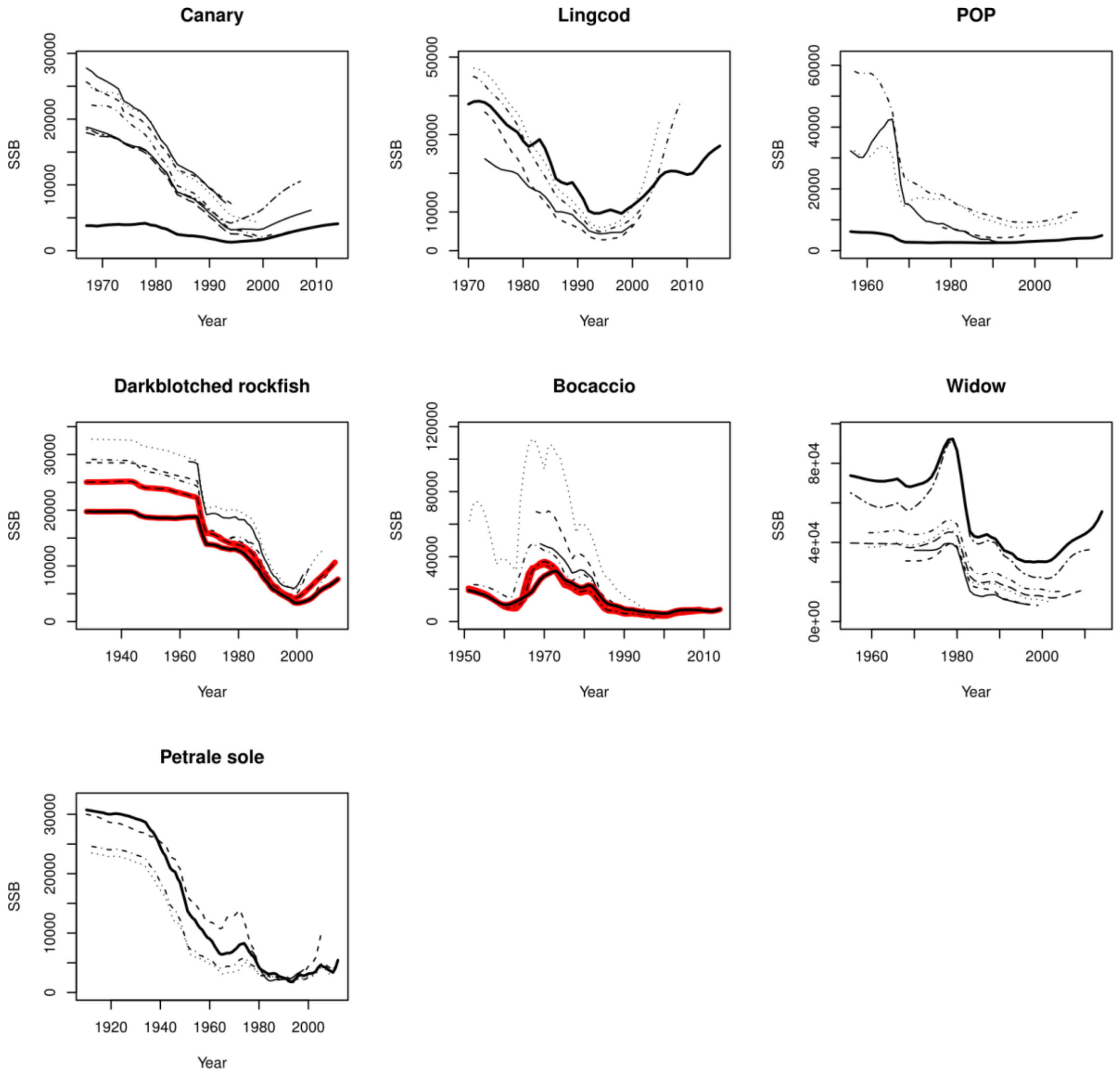


Figure 2.12 Biomass time series for the subset of 7 groundfish stocks from stock assessments conducted for the Pacific Fishery Management Council on the west coast of the United States. The thick, solid black line denotes the most recent assessment.

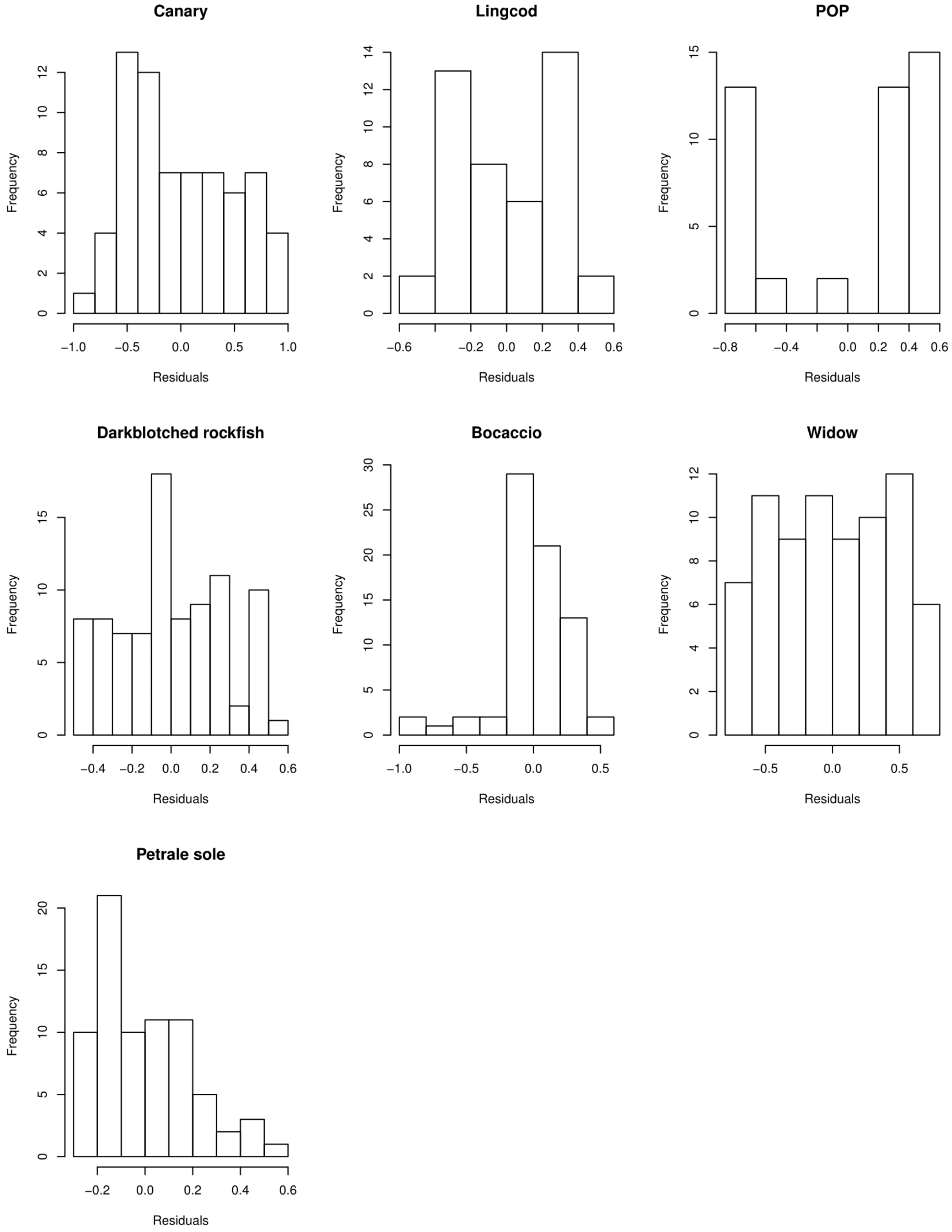
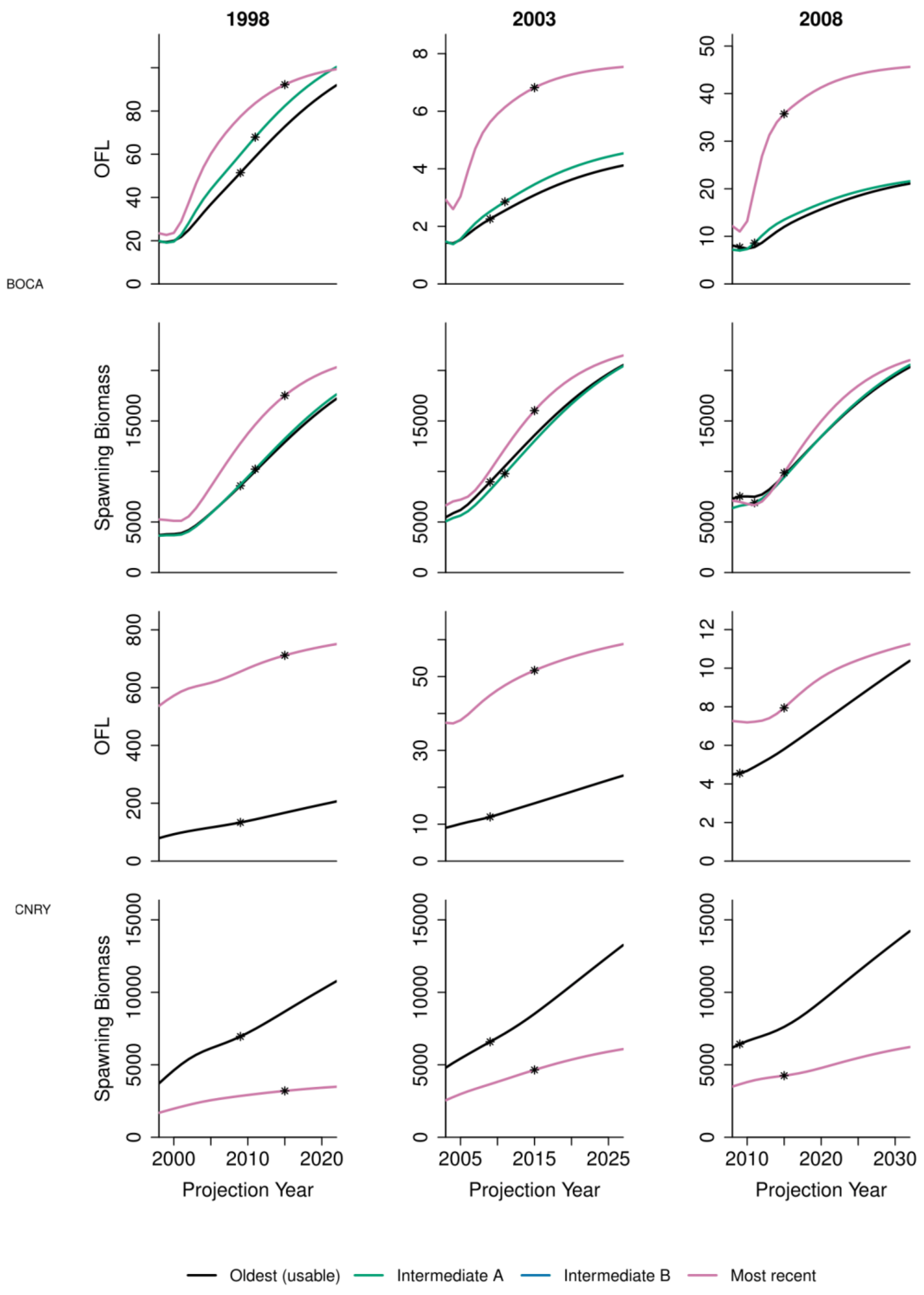
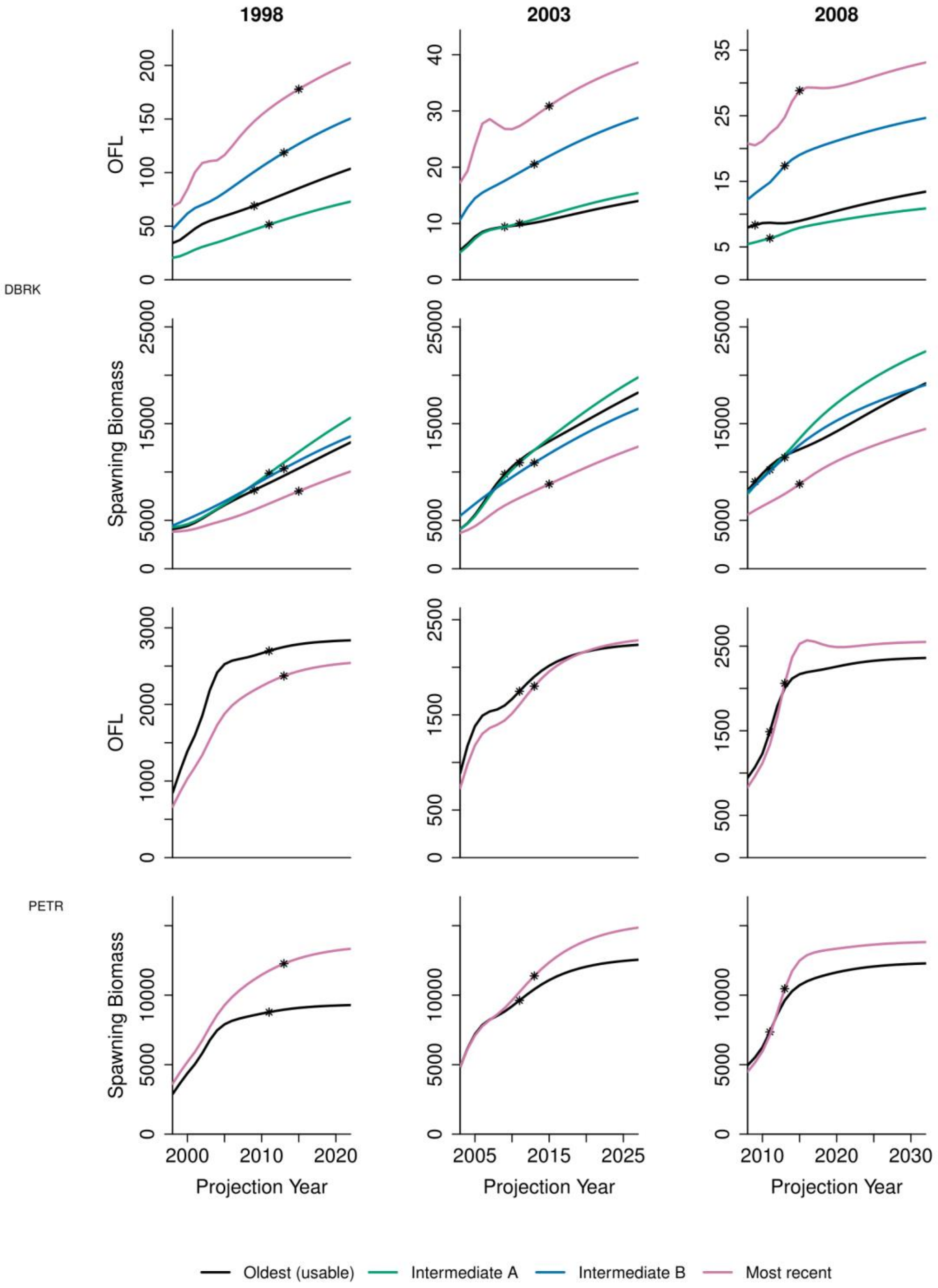
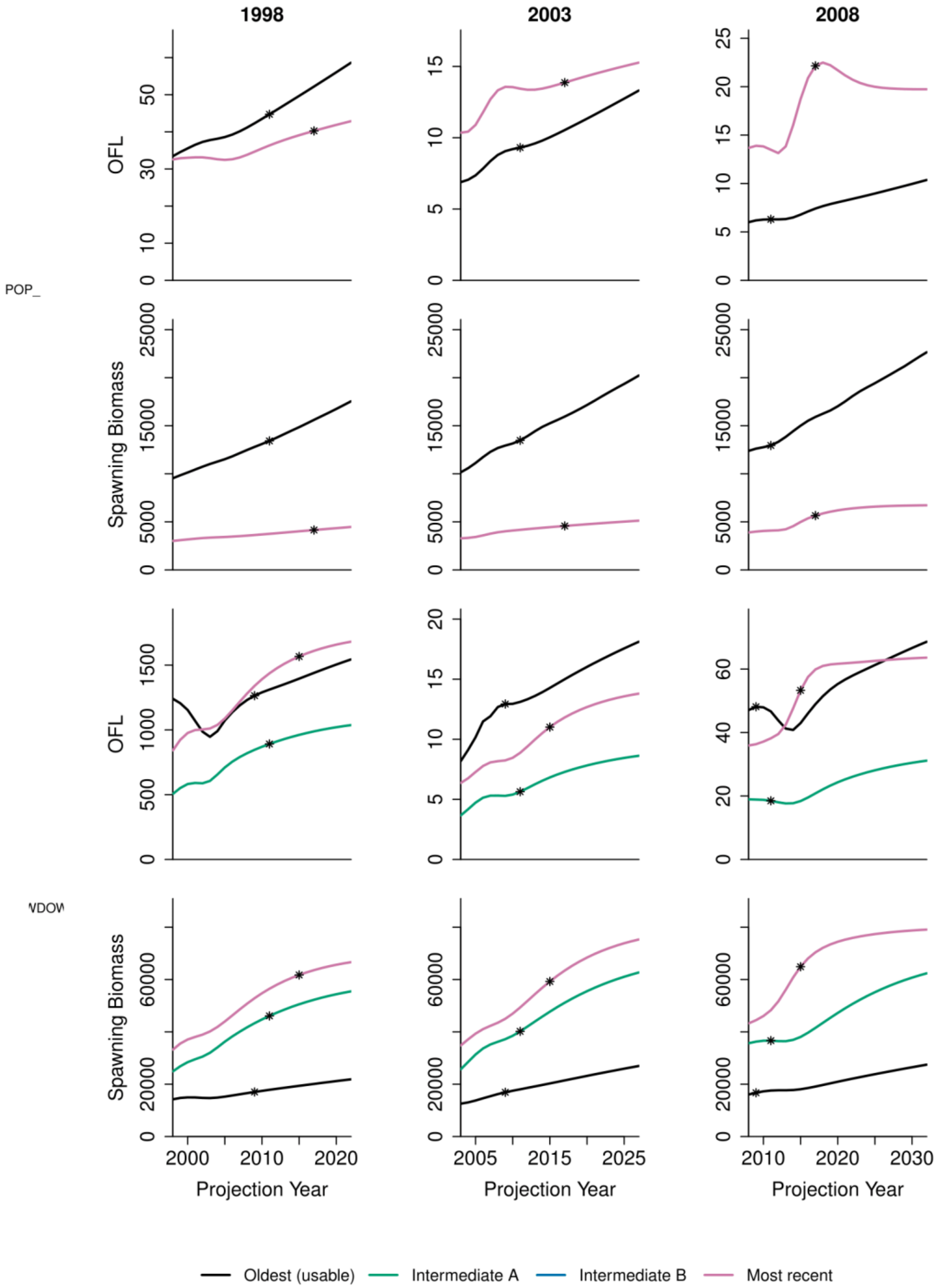


Figure 2.13 As for Supplementary Figure 2.10 for the subset of groundfish.


1998
2003
2008
BOCA
CNRY
OFL
Spawning Biomass
OFL
Spawning Biomass
0
20
40
60
80
0
2
4
6
8
0
10
20
30
40
50
0
5000
15000
0
200
400
600
800
0
10
30
50
0
2
4
6
8
10
12
0
5000
10000
15000
2000
2010
2020
2005
2015
2025
2010
2020
2030
Projection Year
Projection Year
Projection Year
Oldest (usable)
Intermediate A
Intermediate B
Most recent


1998
2003
2008
DBRK
PETR
OFL
Spawning Biomass
OFL
Spawning Biomass
0
50
100
150
200
0
10
20
30
40
0
5
15
25
35
0
5000
15000
25000
0
1000
2000
3000
0
500
1500
2500
0
5000
10000
2000
2010
2020
2005
2015
2025
2010
2020
2030
Projection Year
Projection Year
Projection Year
Oldest (usable)
Intermediate A
Intermediate B
Most recent


1998
2003
2008
POP_
WDOW
OFL
Spawning Biomass
OFL
Spawning Biomass
0
10
30
50
0
5
10
15
0
5
10
15
20
25
0
5000
15000
25000
0
500
1000
1500
0
5
10
15
20
0
20
40
60
0
20000
60000
2000
2010
2020
2005
2015
2025
2010
2020
2030
Projection Year
Projection Year
Projection Year
Oldest (usable)
Intermediate A
Intermediate B
Most recent

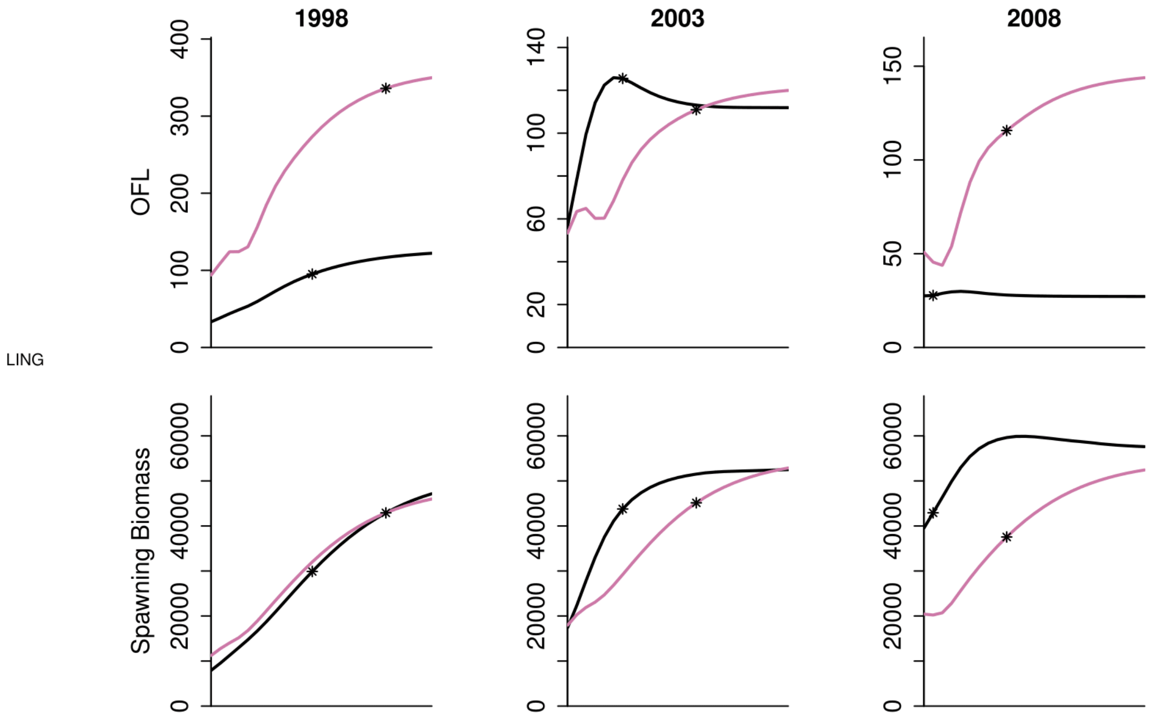
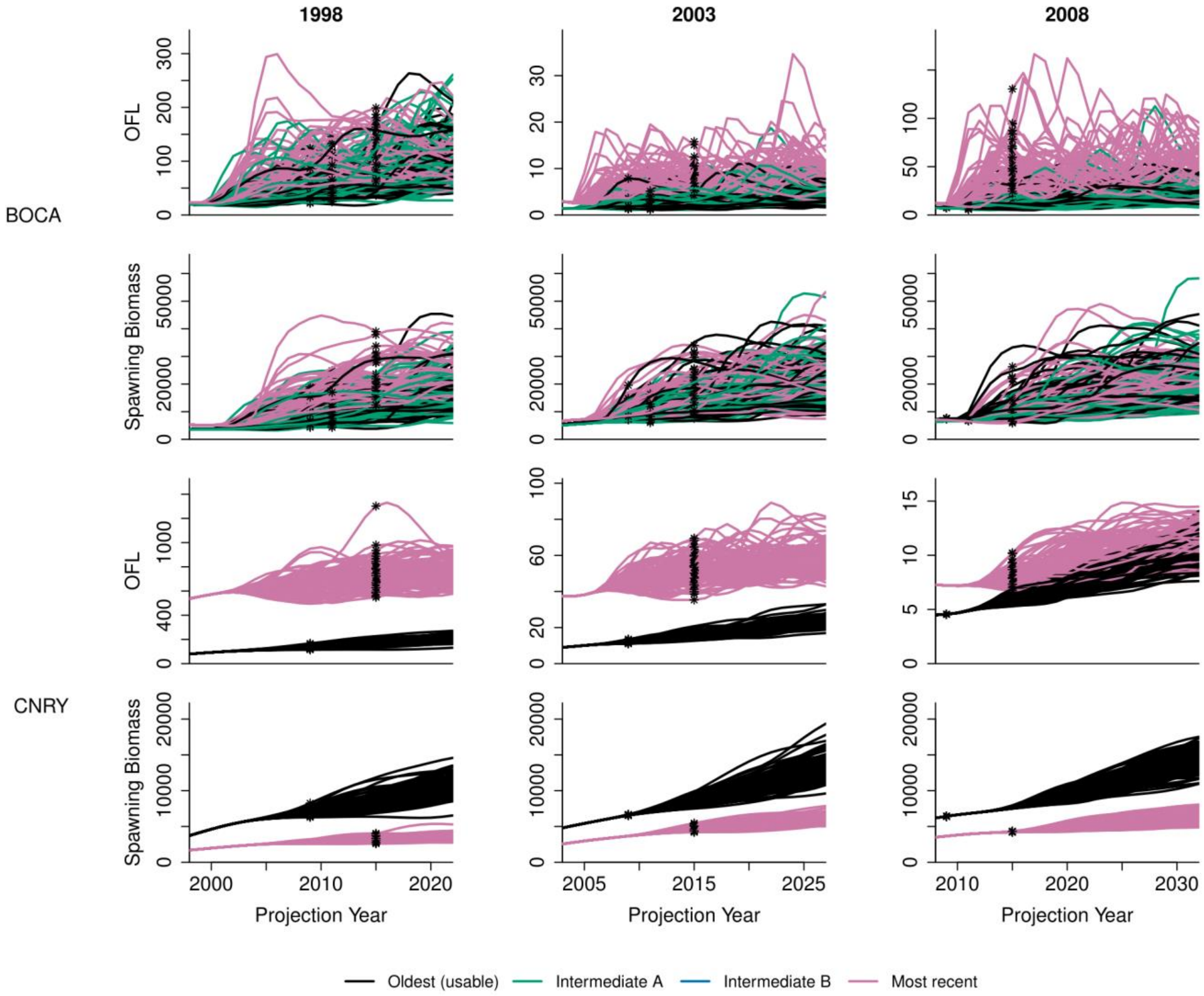
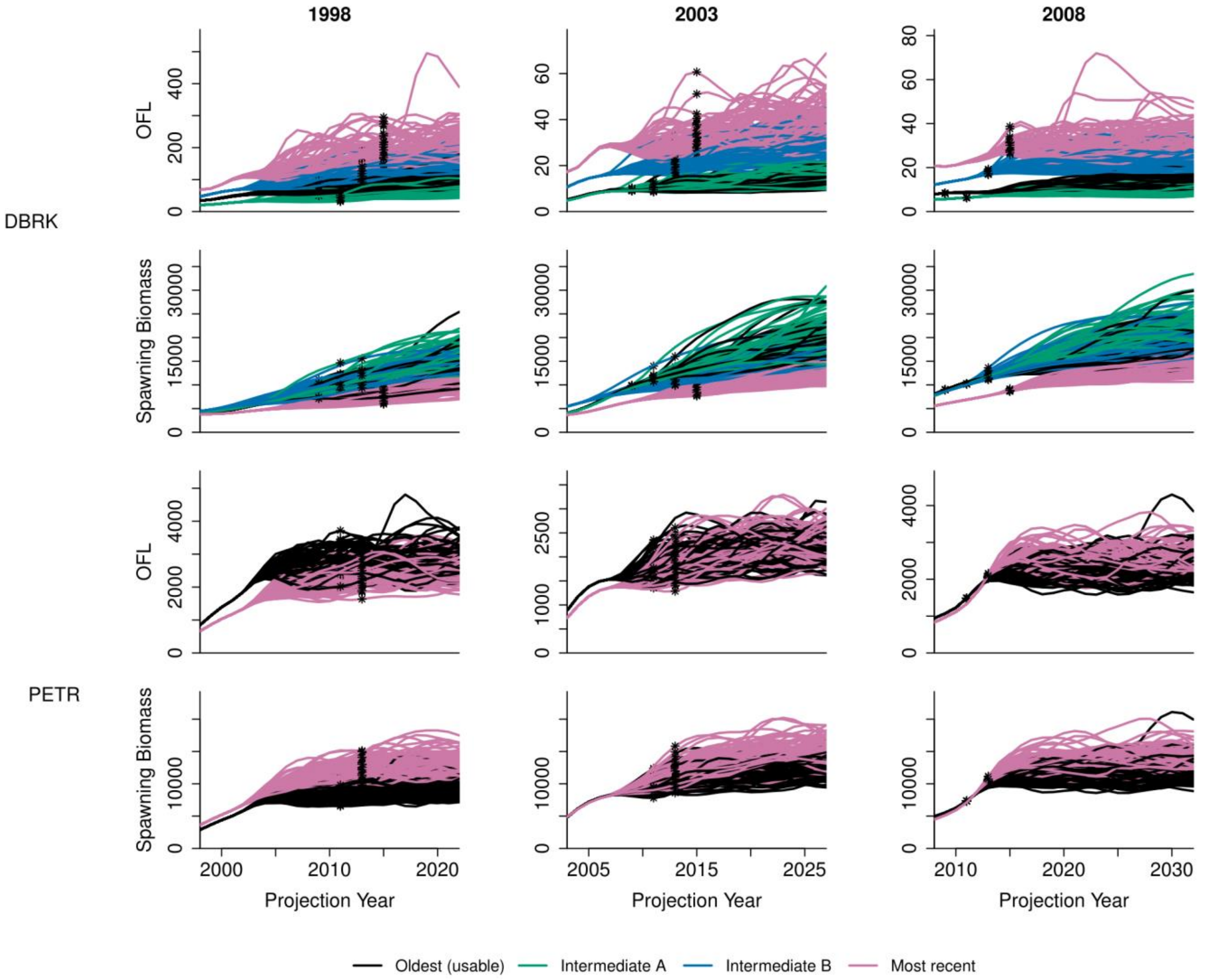
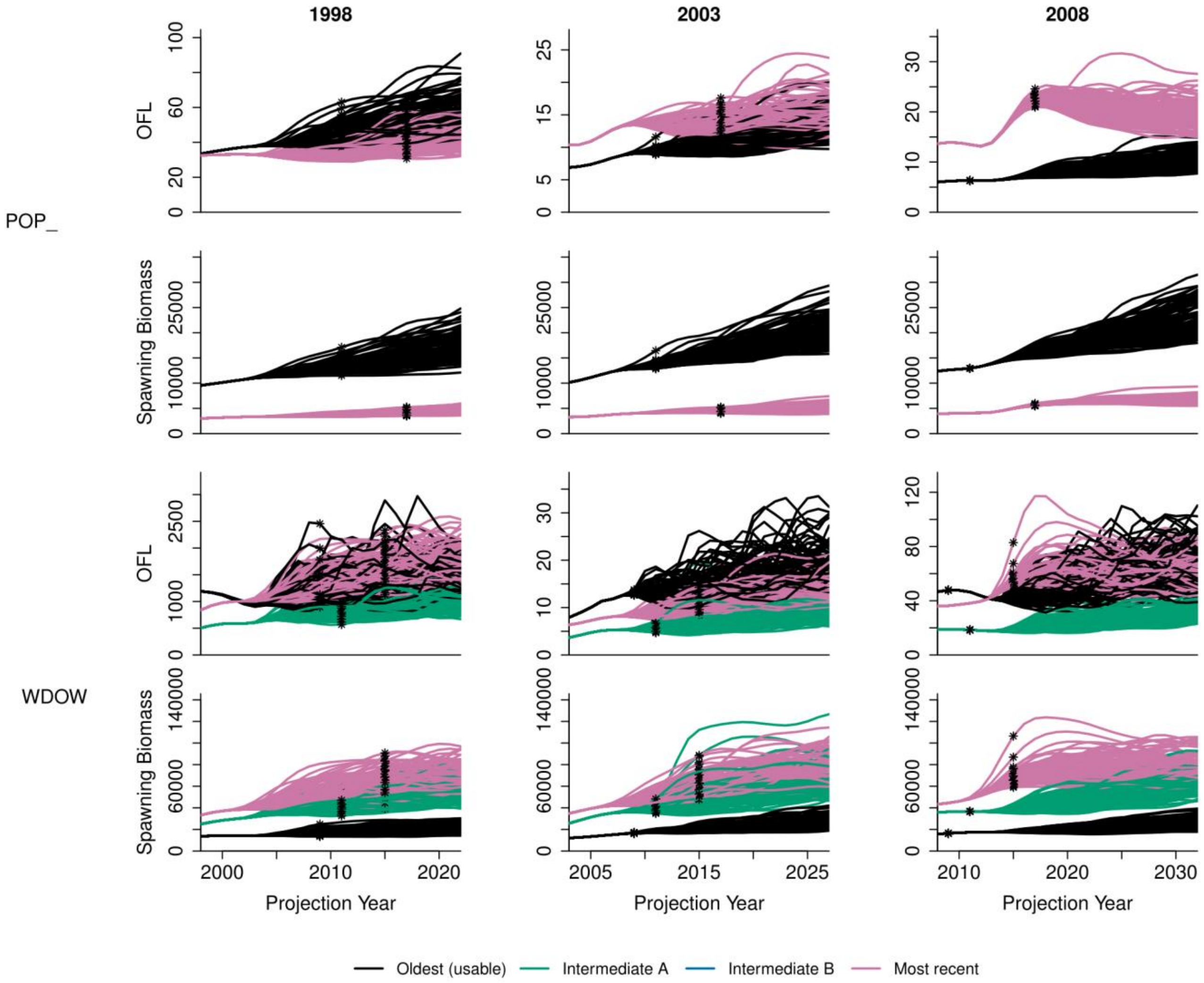


Figure 2.14 Deterministic projections (in metric tons) by stocks, with the upper panels for each stock showing OFL projections and the lower panels spawning biomass projections.


1998
2003
2008
BOCA
CNRY
OFL
Spawning Biomass
OFL
Spawning Biomass
0
100
200
300
0
10
20
30
0
50
100
0
20000
50000
0
400
1000
20
60
100
0
5
10
15
0
10000
20000
2000
2010
2020
2005
2015
2025
2010
2020
2030
Projection Year
Projection Year
Projection Year
Oldest (usable)
Intermediate A
Intermediate B
Most recent


1998
2003
2008
DBRK
PETR
OFL
Spawning Biomass
OFL
Spawning Biomass
0
200
400
0
20
40
60
0
20
40
60
80
0
15000
30000
0
1000
2500
0
2000
4000
0
10000
2000
2010
2020
2005
2015
2025
2010
2020
2030
Projection Year
Projection Year
Projection Year
Oldest (usable)
Intermediate A
Intermediate B
Most recent


1998
2003
2008
POP_
WDOW
OFL
Spawning Biomass
OFL
Spawning Biomass
0
20
60
100
0
5
15
25
0
10
20
30
0
10000
25000
0
1000
2500
0
10
20
30
0
40
80
120
0
60000
140000
2000
2010
2020
2005
2015
2025
2010
2020
2030
Projection Year
Projection Year
Projection Year
Oldest (usable)
Intermediate A
Intermediate B
Most recent

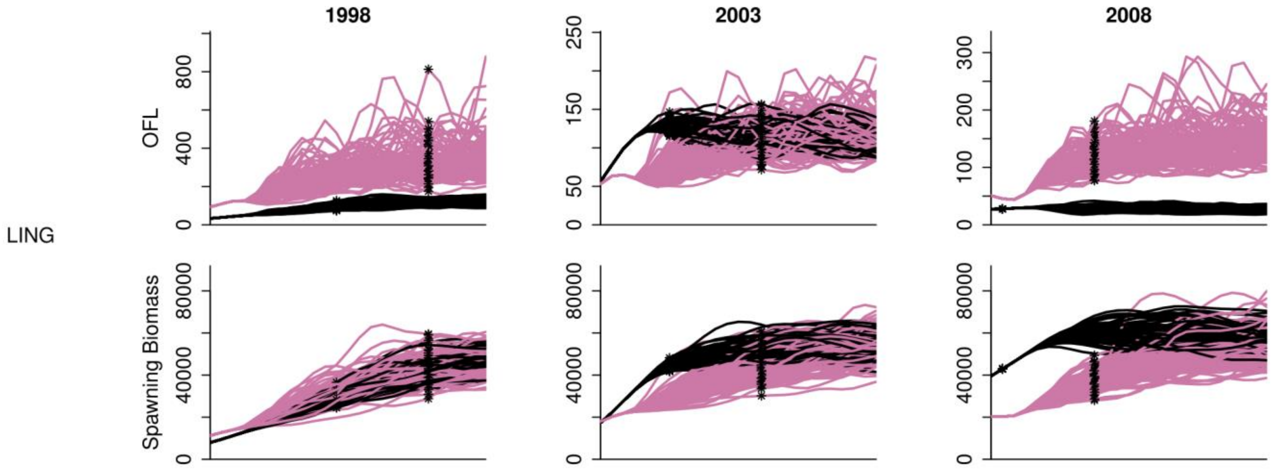
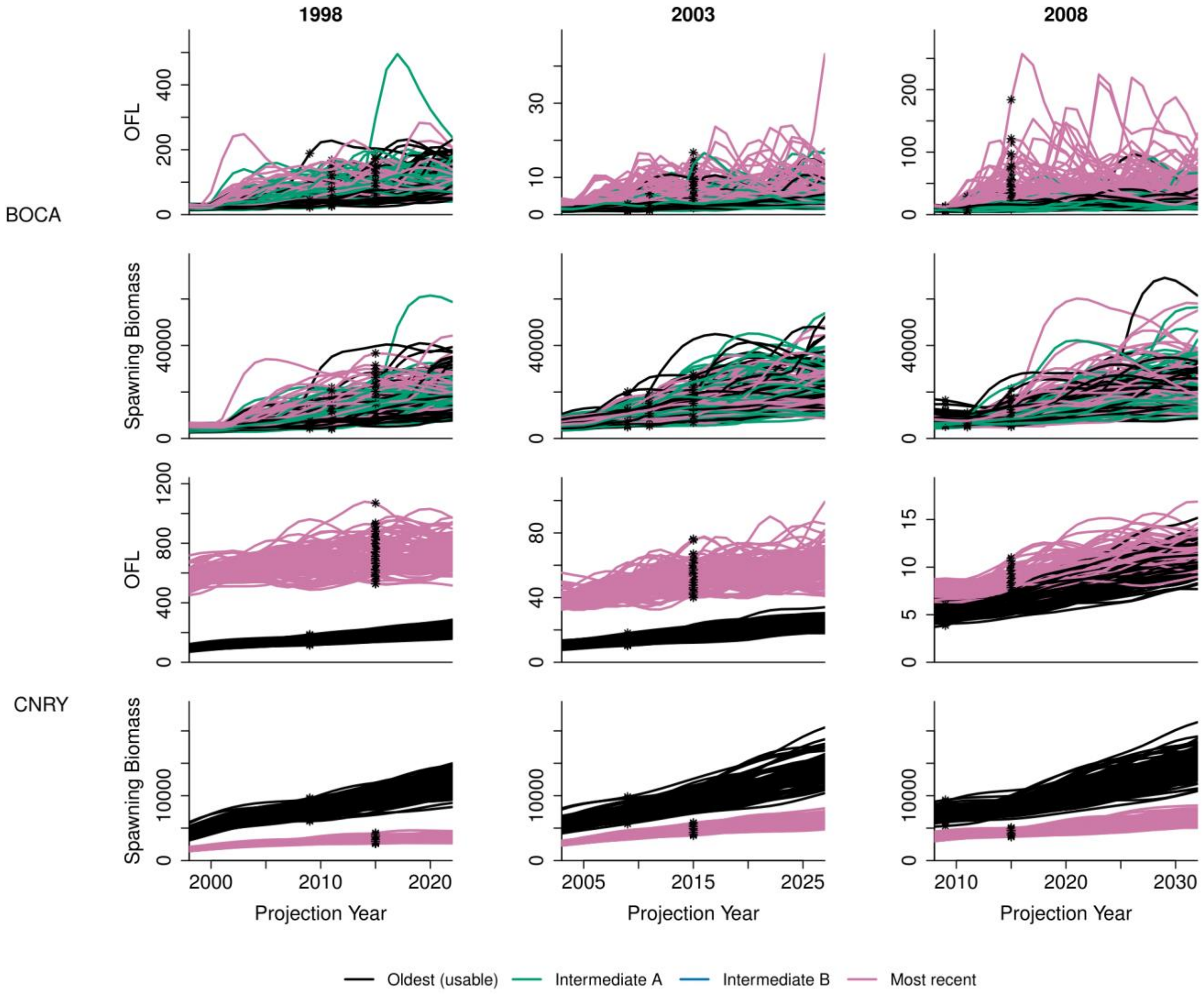
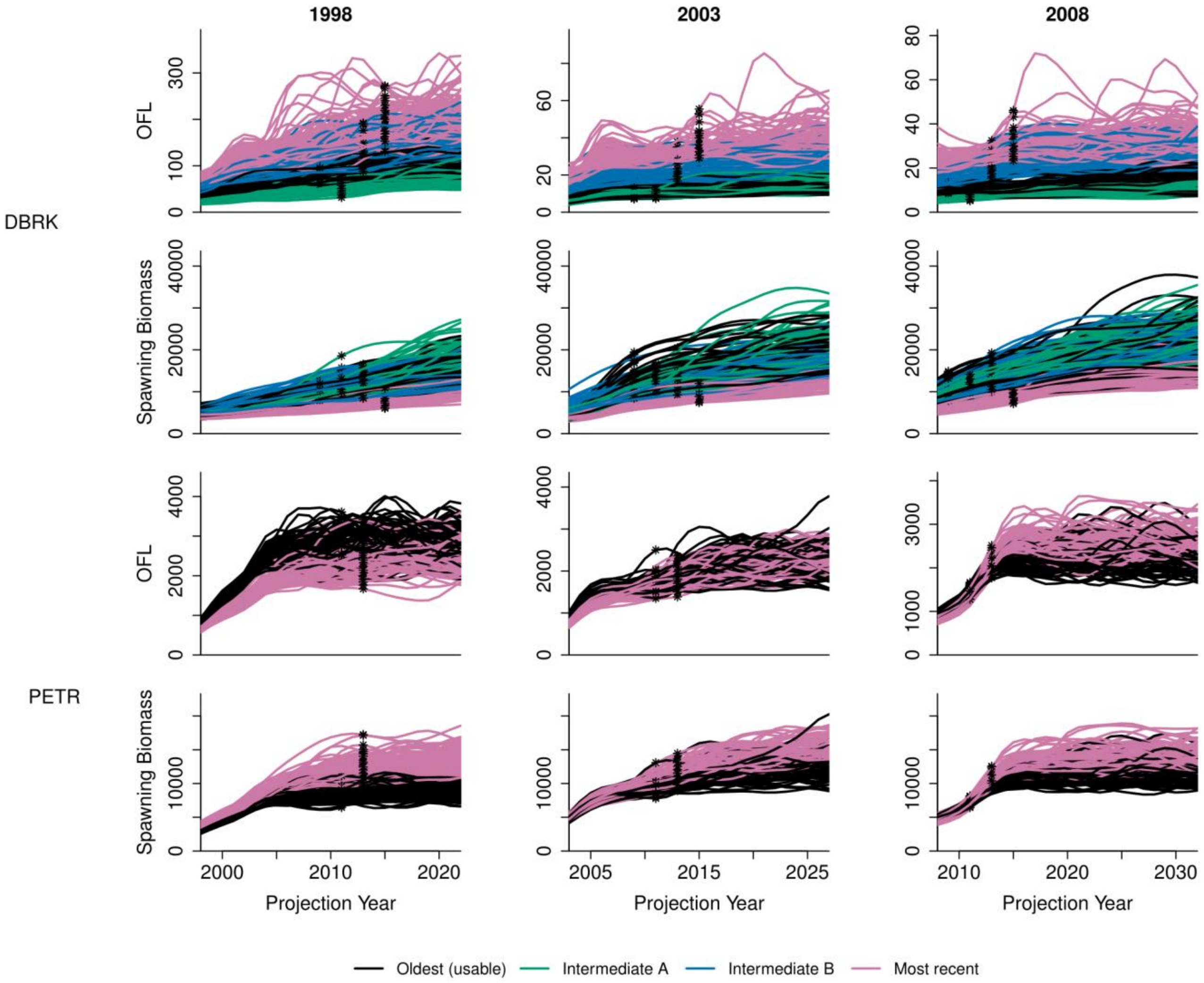
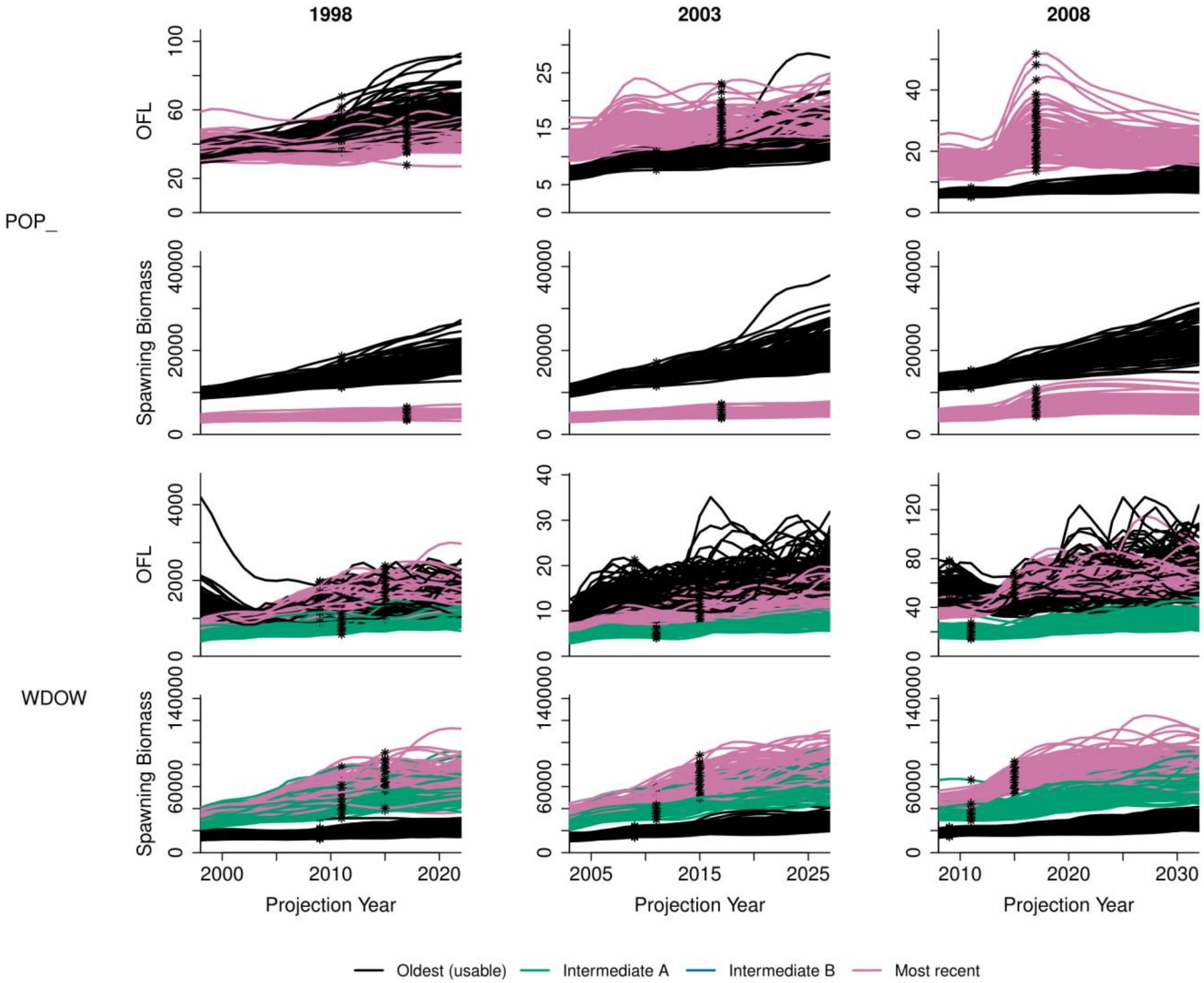


Figure 2.15 OFL (upper rows for each stocks) and spawning biomass (lower rows for each stocks) trajectories (in metric tons) for all stocks based on three start years (1998, 2003, and 2008; columns) and two to three stock assessments (solid dots). Results are shown for stochastic projections that only consider uncertainty in future recruitment.


1998
2003
2008
BOCA
CNRY
OFL
Spawning Biomass
OFL
Spawning Biomass
0
200
400
0
10
30
0
100
200
0
40000
0
40000
0
40000
0
400
800
1200
0
40
80
0
5
10
15
0
10000
0
10000
0
10000
2000
2010
2020
2005
2015
2025
2010
2020
2030
Projection Year
Projection Year
Projection Year
Oldest (usable)
Intermediate A
Intermediate B
Most recent


1998
2003
2008
DBRK
PETR
OFL
Spawning Biomass
OFL
Spawning Biomass
0
100
300
20
60
0
20
40
60
80
40000
20000
0
4000
2000
1000
3000
10000
2000
2010
2020
2005
2015
2025
2030
Projection Year
Projection Year
Projection Year
Oldest (usable)
Intermediate A
Intermediate B
Most recent


1998
2003
2008
POP_
WDOW
OFL
Spawning Biomass
OFL
Spawning Biomass
0
20
60
100
0
5
15
25
0
20
40
0
20000
40000
0
2000
4000
0
10
20
30
40
0
40
80
120
0
60000
140000
2000
2010
2020
2005
2015
2025
2010
2020
2030
Projection Year
Projection Year
Projection Year
Oldest (usable)
Intermediate A
Intermediate B
Most recent

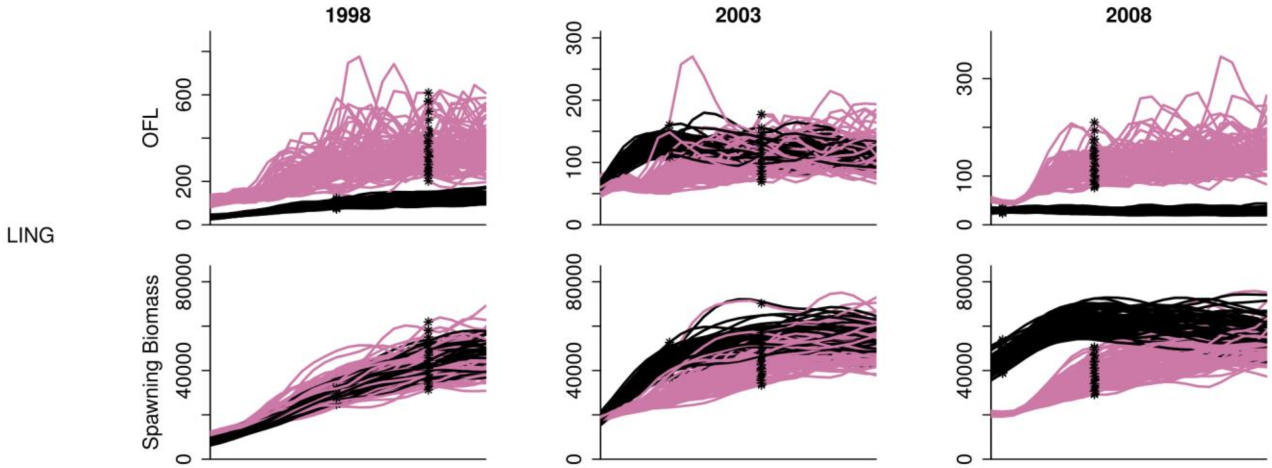
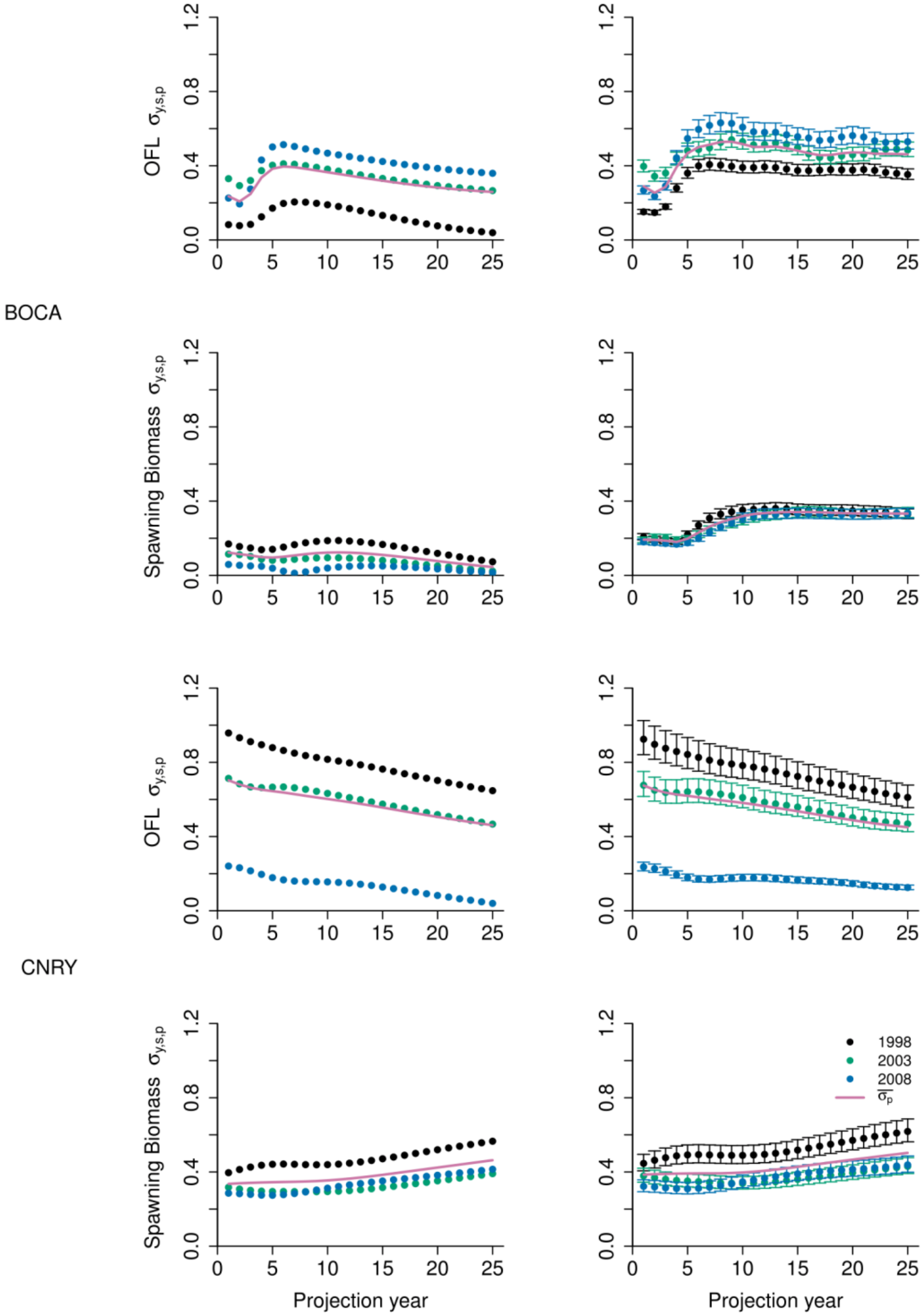
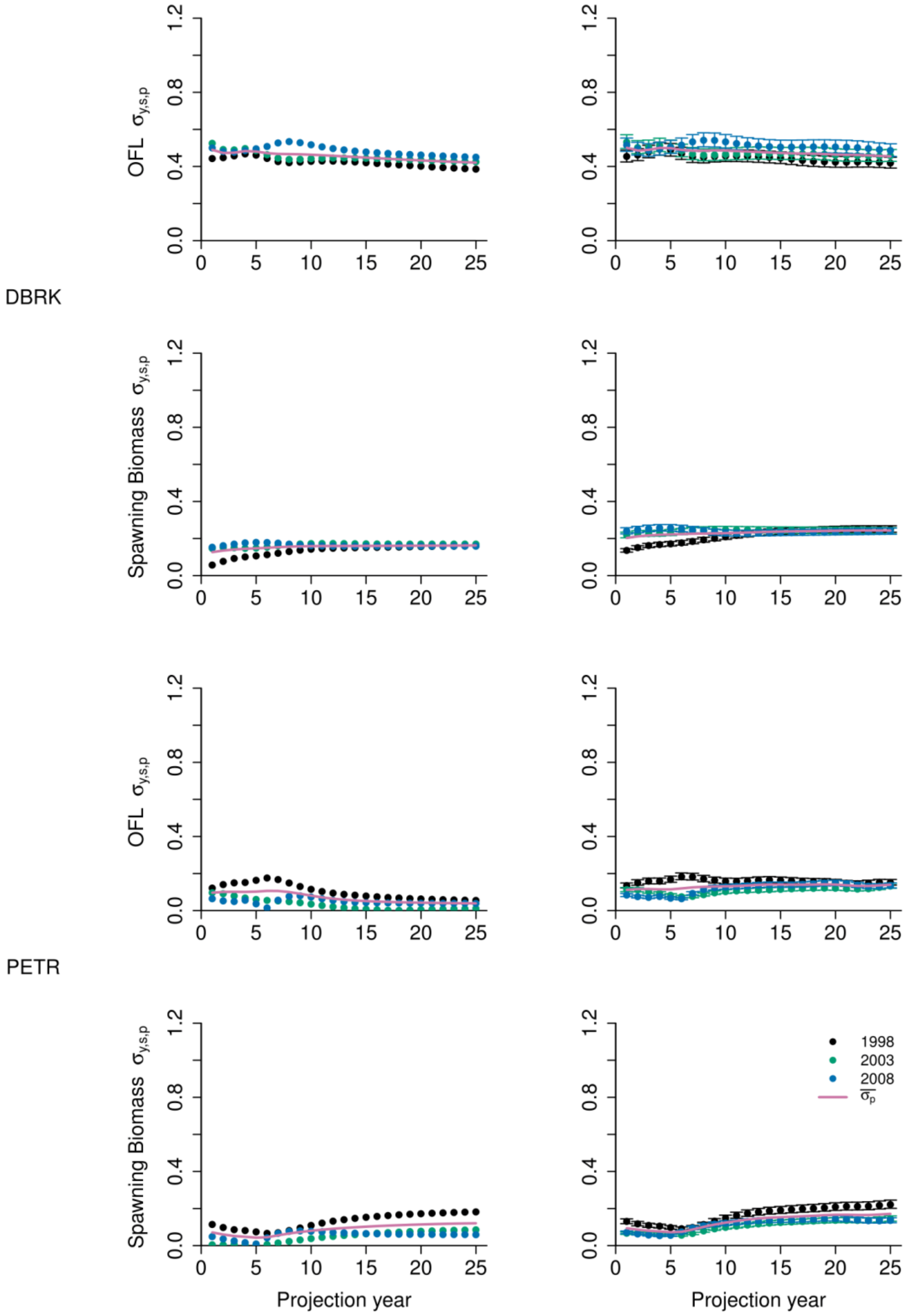
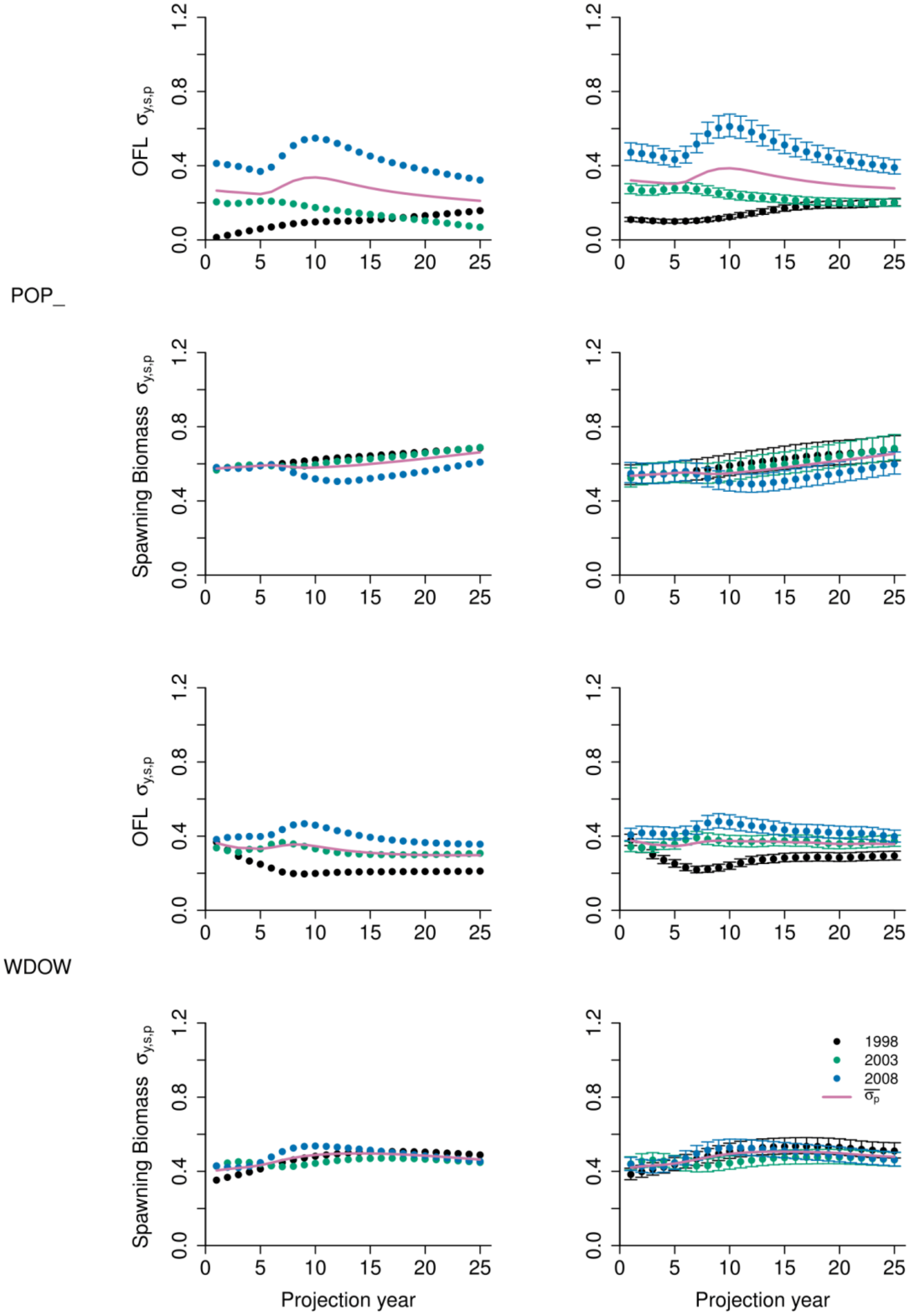


Figure 2.16 Time-trajectories of OFL (upper rows for each stocks) and spawning biomass (lower rows for each stocks) in metric tons for all stocks based on three start years (1998, 2003, and 2008; columns) and two to three stock assessments (solid dots). Results are shown for stochastic projections that account for uncertainty in past and future recruitment.



OFL $\sigma_{y,s,p}$
Spawning Biomass $\sigma_{y,s,p}$
BOCA
CNRY
0.0
0.4
0.8
1.2
0
5
10
15
20
25
Projection year
1998
2003
2008
$\overline{\sigma_p}$


DBRK
PETR
OFL $\sigma_{y,s,p}$
Spawning Biomass $\sigma_{y,s,p}$
0.0
0.4
0.8
1.2
0
5
10
15
20
25
Projection year
● 1998
● 2003
● 2008
$\overline{\sigma_p}$


POP_
WDOW
OFL $\sigma_{y,s,p}$
Spawning Biomass $\sigma_{y,s,p}$
0.0
0.4
0.8
1.2
0
5
10
15
20
25
Projection year
1998
2003
2008
$\overline{\sigma_p}$

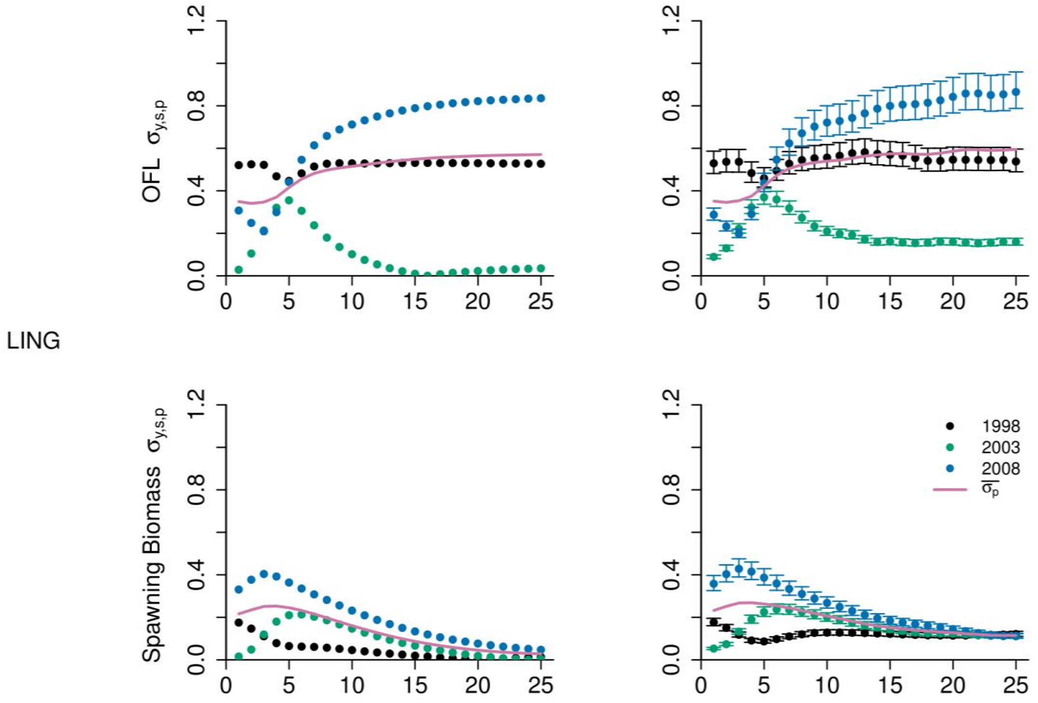
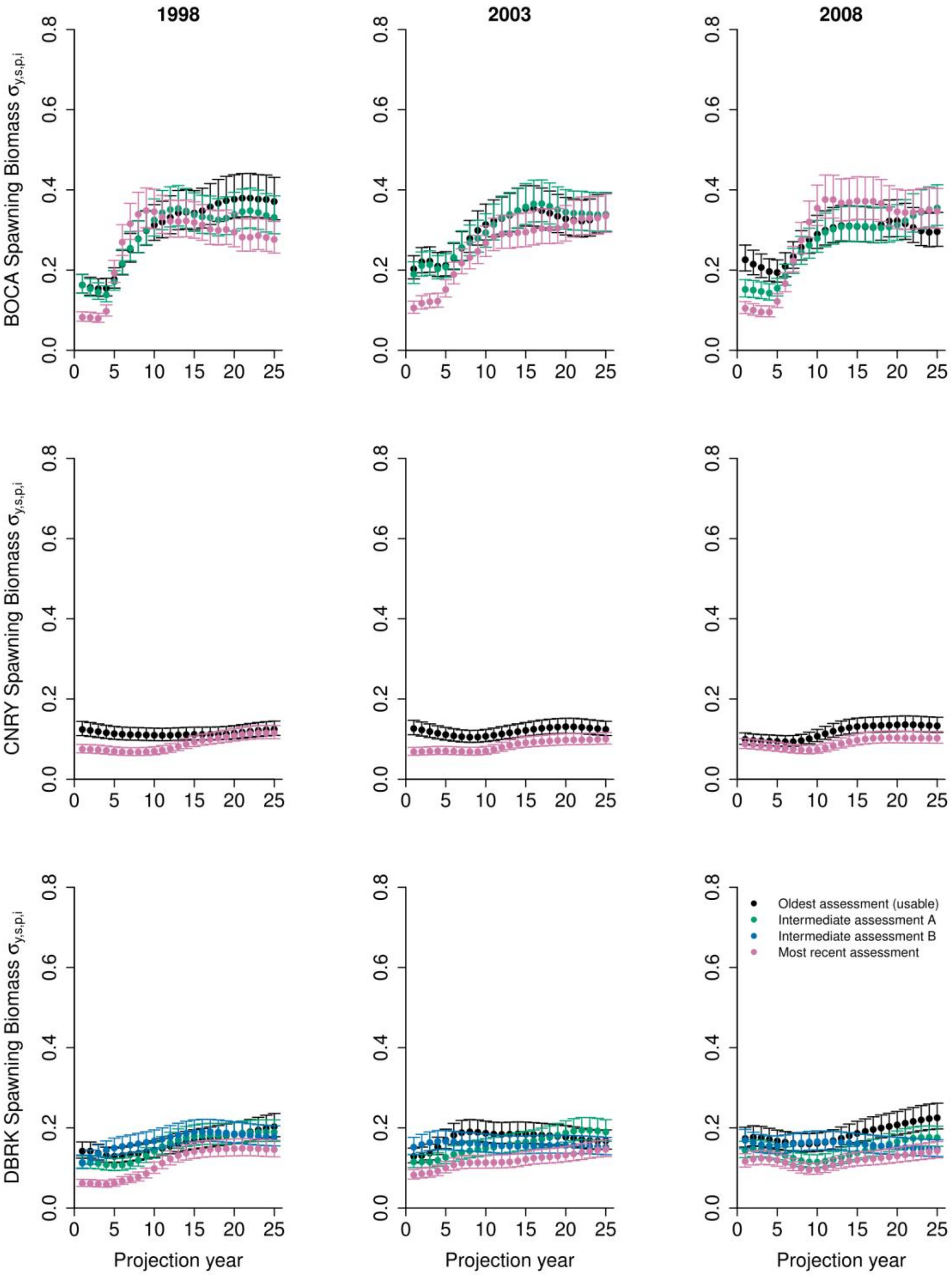
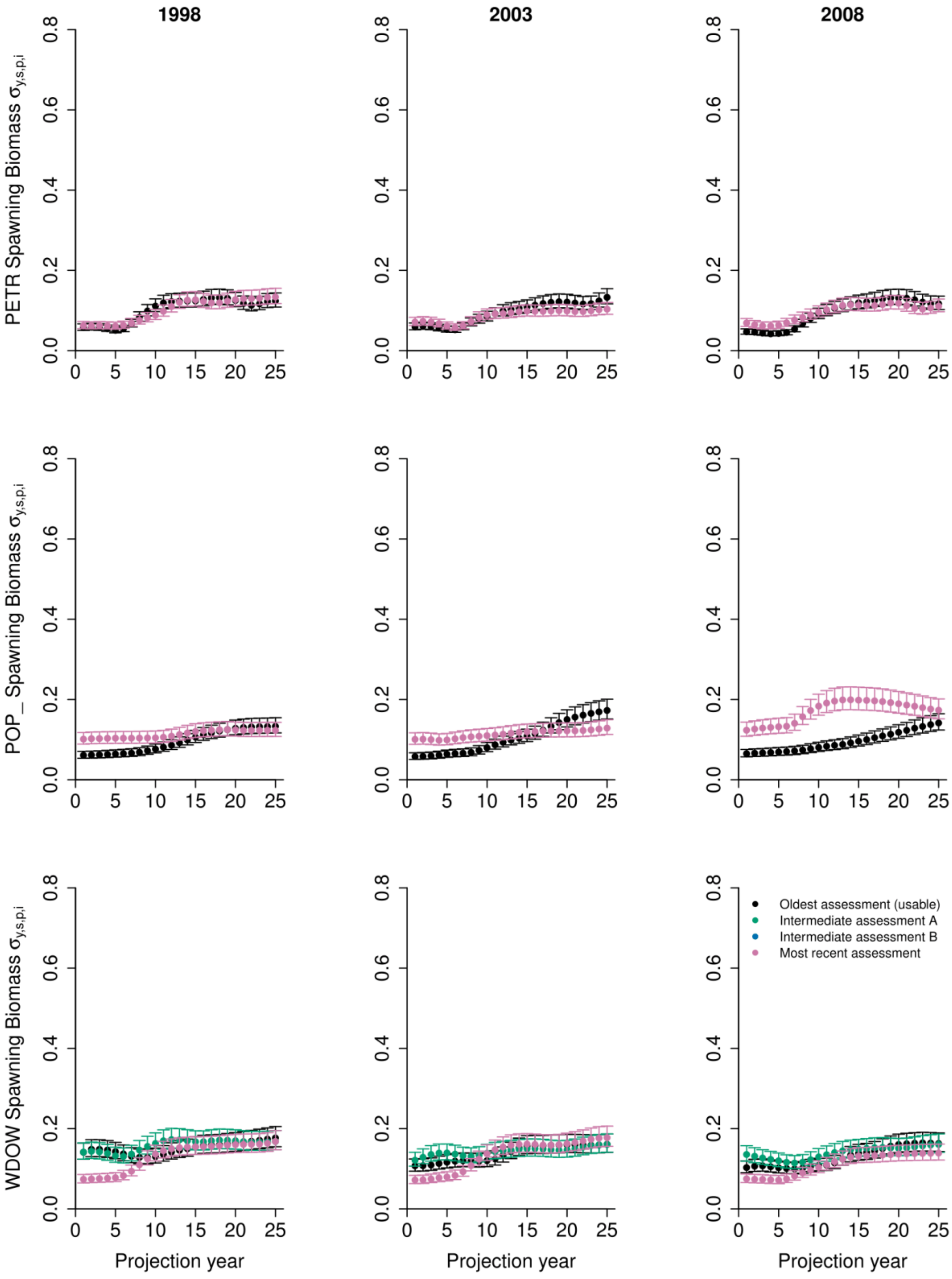


Figure 2.17 Values of stocks-specific σ based on OFL and spawning biomass (upper and lower rows of results for each stocks). Results are shown for deterministic (left column) and stochastic (right column) analyses by start year and pooled over start-years. The whiskers in the right column sindicate 95% confidence intervals (no 95% confidence intervals are shown in the deterministic results owning to small sample size).


1998
2003
2008
BOCA Spawning Biomass σy,s,p,i
CNRY Spawning Biomass σy,s,p,i
DBRK Spawning Biomass σy,s,p,i
0.0
0.2
0.4
0.6
0.8
0
5
10
15
20
25
Projection year
Oldest assessment (usable)
Intermediate assessment A
Intermediate assessment B
Most recent assessment


1998
2003
2008
PETR Spawning Biomass $\sigma_{y,s,p,i}$
POP_ Spawning Biomass $\sigma_{y,s,p,i}$
WDOW Spawning Biomass $\sigma_{y,s,p,i}$
0.0
0.2
0.4
0.6
0.8
0
5
10
15
20
25
Projection year
● Oldest assessment (usable)
● Intermediate assessment A
● Intermediate assessment B
● Most recent assessment

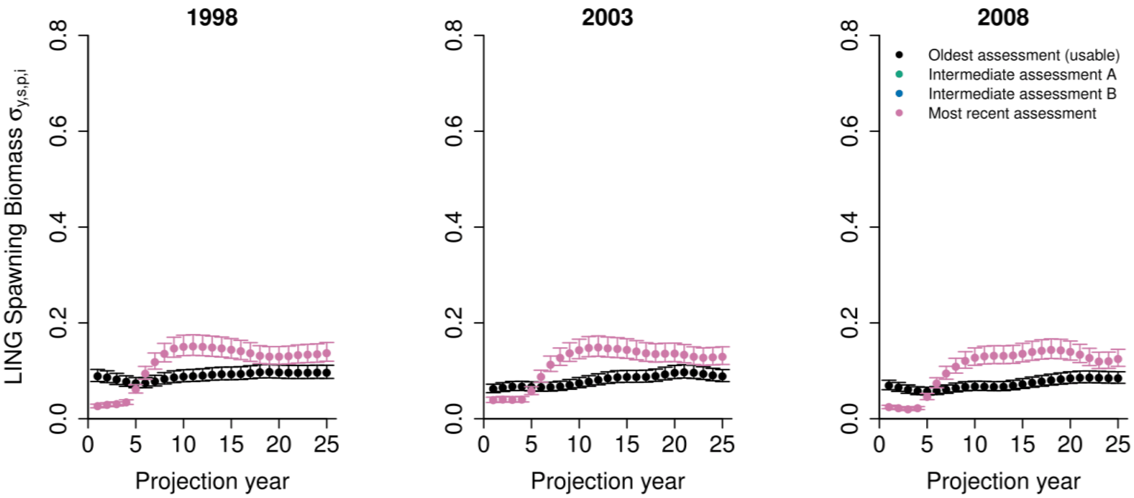
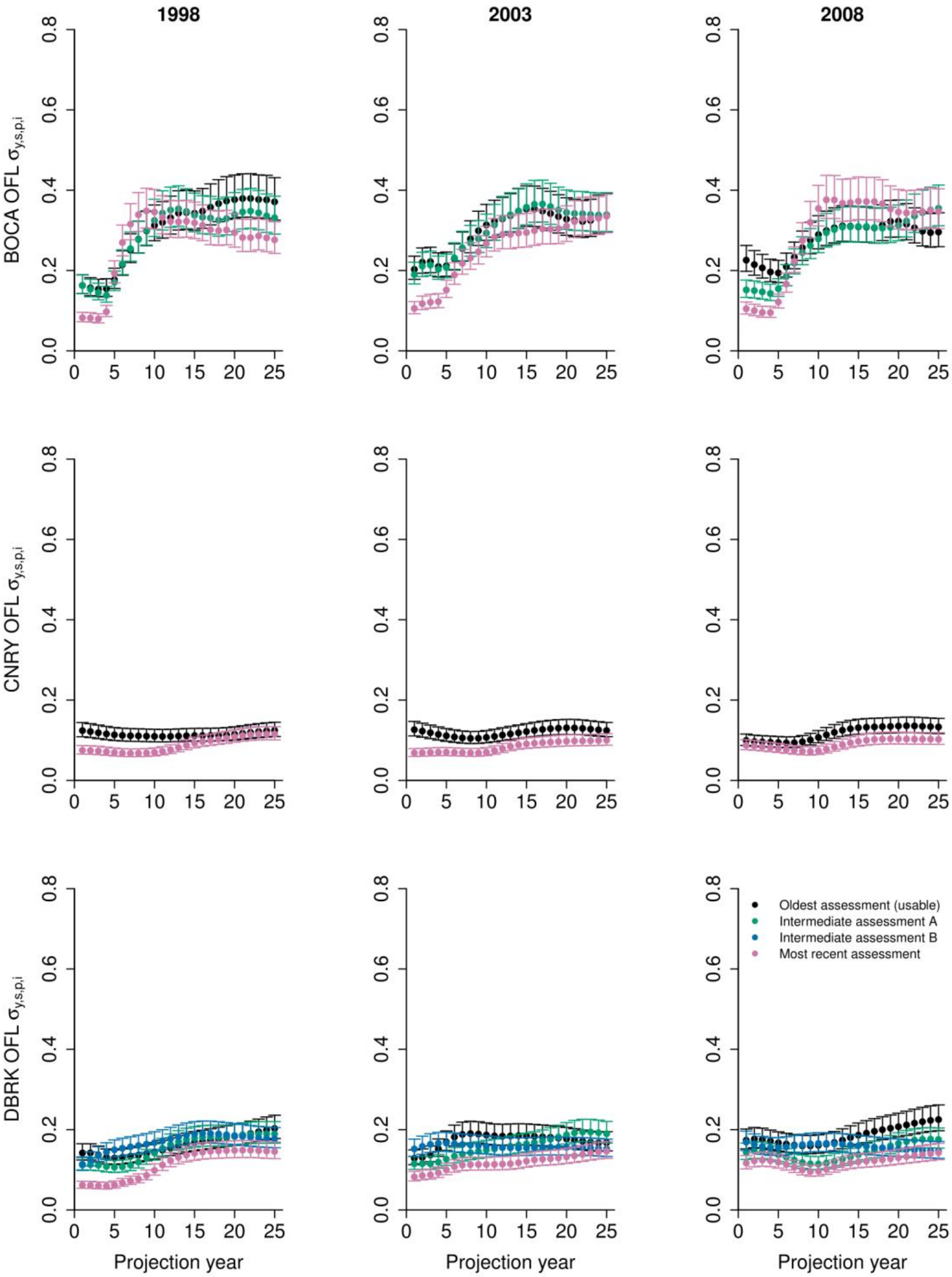
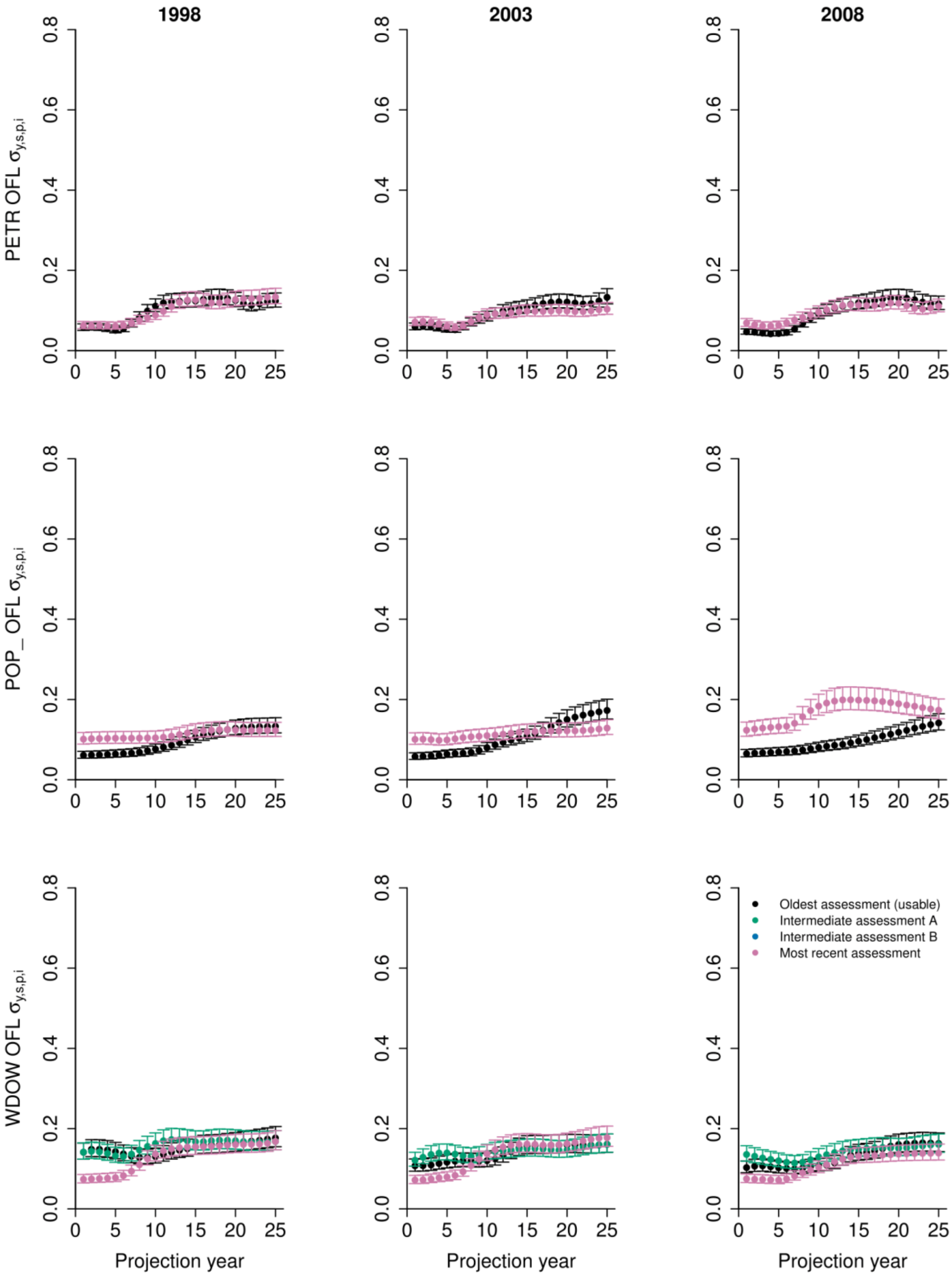


Figure 2.18 Values of stocks-specific within-assessment σ based on spawning biomass. Results are shown for stochastic analyses by start year and by assessment. The whiskers indicate 95% confidence intervals.



1998
2003
2008
BOCA OFL $\sigma_{y,s,p,i}$
CNRY OFL $\sigma_{y,s,p,i}$
DBRK OFL $\sigma_{y,s,p,i}$
0.0
0.2
0.4
0.6
0.8
0
5
10
15
20
25
Projection year
● Oldest assessment (usable)
● Intermediate assessment A
● Intermediate assessment B
● Most recent assessment


1998
2003
2008
PETR OFL σy,s,p,i
POP_ OFL σy,s,p,i
WDOW OFL σy,s,p,i
0.0
0.2
0.4
0.6
0.8
0
5
10
15
20
25
Projection year
Oldest assessment (usable)
Intermediate assessment A
Intermediate assessment B
Most recent assessment

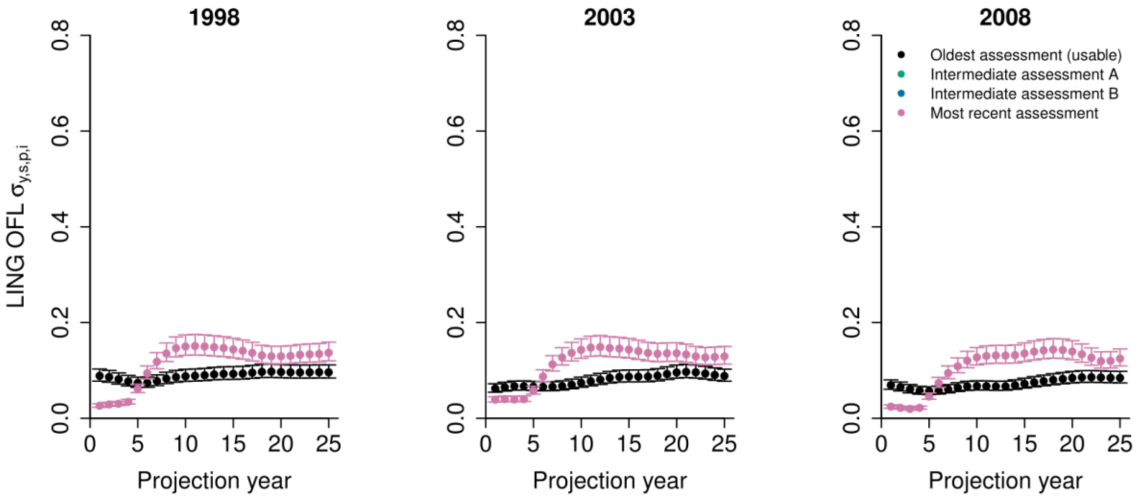


Figure 2.19 Values of stocks-specific within-assessment σ based on OFL. Results are shown for stochastic analyses by start year and by assessment (2009, 2011, and 2015). The whiskers indicate 95% confidence intervals.

CONCLUSIONS

Overview

Stock assessment is just one part of the fisheries management cycle. However, identifying and quantifying scientific uncertainty, starting with data inputs and through how uncertainty propagates through an assessment is necessary to evaluate the consequences of management actions in the broader field of risk management. In this study, I have (a) broadly characterized how uncertainty is quantified and presented to managers, and identified the factors that influence the methods and tools used, and (b) developed a method for quantifying uncertainty for application in a formal risk management policy.

First, I conducted a survey-guided review of the methods and tools used to quantify uncertainty, and their relationship to the presentation of uncertainty to fisheries managers. Overall, I found that scientific uncertainty is being quantified and presented with scientific advice in stock assessments. I also found that frequentist approaches (and packages that use them) are more commonly used than Bayesian approaches for the assessments characterized by the survey. The design of the fishery management system has direct impact on the methods and tools used for quantifying scientific uncertainty in stock assessment. More specifically, the time allocated conducting and reviewing stock assessments, and the methodology requests from scientific review bodies were reported as factors that influence the use of uncertainty methods, and subsequent presentation of uncertainty. Estimates of management targets (*e.g.*, fishing mortality or biomass), projections, and catch limits were the quantities most frequently presented to managers, along with their uncertainty. I also found that not all uncertainties that are quantified are presented and not all those presented are used by managers in the decision-making process.

Second, I developed a method for quantifying scientific uncertainty for use in a probability-based harvest control that directly incorporates managers' risk tolerance. This method is novel because it projects and directly quantifies the variation in overfishing limits across four dimensions: a) among assessments of the same stock, b) among assessments across multiple groundfish stocks, c) across multiple projection start years, and d) when assuming deterministic vs. stochastic recruitment. The previous method used for US West Coast groundfish and coastal pelagic species stocks quantified the variation in historical biomass among assessments of the same stock and among assessments across multiple groundfish stocks as a proxy for uncertainty in overfishing limits. I found that quantifying the uncertainty in projections of overfishing limits directly integrates uncertainty associated with assessment model assumptions, estimates of current stock abundance and age-structure, how these estimates change over time, and estimates of target fishing mortality rate (F_{MSY} or proxy thereof). Ultimately, this method was presented to, reviewed by, and adopted as "best available science" by the Pacific Fishery Management Council Science and Statistical Committee.

Conclusions and future work

This thesis demonstrates that quantifying uncertainty for use in scientific advice for management occurs around the world and the design of a fisheries management system influences the methods used. The set of methods and tools for quantifying uncertainty is vast and continually growing. Current packages can be further expanded to include spatially-structured population dynamics models, non-traditional data types (*e.g.*, tagging data), and economic aspects. Sharing current and new methods should continue through cooperative research opportunities such as coursework (*e.g.*, Advanced School on Multispecies Modelling Approaches for Ecosystem Based

Marine Resource Management in the Mediterranean Sea (AMARE-MED); ICES training courses), and workshops (*e.g.*, National Stock Assessment Workshops; Center for the Advancement of Population Assessment Methodology). Meta-analytic approaches can also be further developed by investigating the development and implementation of methods for quantifying management uncertainty and how uncertainties are presented in scientific advice across jurisdictions (*e.g.*, the Kobe framework [Kell et al. 2016]). Such studies may provide insight about how to progress effective communication of uncertainty in a field producing increasingly complex and multidimensional management advice to a broad audience of stakeholders. Potential future work for the projection-based method outlined in this thesis includes investigating the extent to which variation in key parameters such as growth, natural mortality, and productivity within assessments each contribute to the overall uncertainty.

Methods for quantifying uncertainty and their incorporation into management advice are quickly advancing and our approaches for reviewing progress towards clearly and explicitly communicating the sources, treatment, and impacts of uncertainty in our management processes must keep pace.

BIBLIOGRAPHY

Anon, 2015. Assessment Model for Alaska Description of GUI and Instructions. Available from https://github.com/NMFS-toolbox/AMAK/blob/master/docs/AMAK%20Documentation.pdf (last accessed 16.10.18).

Bull, B., Francis, R.I.C.C., Dunn, A., McKenzie, A., Gilbert, D.J., Smith, M.H., Bian, R., and D. Fu, 2005. CASAL (C++ algorithmic stock assessment laboratory): CASAL user manualv2.30-2012/03/21. NIWA Technical Report 127.

Cadrin, S., Henderschedt, J., Mace, P., Mursalski, S., Powers, J., Punt, A.E., and V. Restrepo. 2015. Addressing Uncertainty in Fisheries Science and Management. National Aquarium.

Dankel, D.J., Aps, R., Padda, G., Röckmann, C., van der Sluijs, J.P., Wilson, D.C., and Degnbol, P. 2012. Advice under uncertainty in the marine system. ICES Journal of Marine Science. 69: 3-7.

Dichmont, C.M., Deng, R.A., Punt, A.E., Venables, W., and Haddon, M. 2006. Management strategies for short-lived species: the case of Australia's northern prawn fishery: 1. Account for multiple species, spatial structure and implementation uncertainty when evaluating risk. Fish. Res. 82: 204-220.

Dichmont, C.M., Deng, R.A., Punt, A.E., Brodziak, J., Chang, Y., Cope, J.M., Ianelli, J.N., Legault, C.M., Methot, R.M., Porch, C.E., Prager, W.H., and K.W. Shertzer. 2016a. A review of stock assessment packages in the United States. Fish. Res. 183: 447-460.

Dichmont, C.M., Deng, R.A., and A.E., Punt. 2016b. How many of Australia's stock assessments can be conducted using stock assessment packages? Marine Policy. 74: 279-287.

Dick, E.J. 2009. Modeling the reproductive potential of rockfish. Ph.D. dissertation, University of California, Santa Cruz.

Doonan, I., Lange, K., Dunn, A., Rasmussen, S., and C. Marsh. 2016. Casal2: New Zealand's integrated population modelling tool. Fisheries Research 183: 408–505.

FAO. 2007. Fisheries management. Technical Guidelines for Responsible Fisheries. 4: 1-82. FAO, Rome.

Federal Register. 2009. Magnuson-Stevens act provisions; annual catch limits; national standard guidelines; final rule. 74: 3178–3213.

Forrest, R.E., Holt, K.R., and A.R. Kronlund. 2018. Performance of alternative harvest control rules for two Pacific groundfish stocks with uncertain natural mortality: bias, robustness and trade-offs. Fisheries Research 206: 259-286.

Francis, R.I.C.C. and R. Shotton. 1997. "Risk" in fisheries management: a review. Can. J. Fish. Aquat. Sci. 54: 1699 – 1715.

Fulton, E.A., Smith, A.D.M., Smith, D.C., van Putten, I.E. 2011. Human behavior: the key source of uncertainty in fisheries management. Fish. Fish. 12: 2-17.

Gulf of Mexico Fishery Management Council. 2011. Generic annual catch limits/accountability measures amendment for the Gulf of Mexico Fishery Management Council's red drum, reef fish, shrimp, coral, and coral reefs fishery management plans. Gulf of Mexico Fishery Management Council, 2203 North Lois Avenue, Suite 1100, Tampa, Florida.

Haddon, M. 2011. Modelling and quantitative methods in fisheries. CRC Press. Boca Raton, FL.

Hilborn, R. and C. Walters. 1992. Quantitative fisheries stock assessment: Choice, dynamics and uncertainty. Chapman and Hall.

Hilborn, R. and M. Mangel. 1997. The ecological detective. Princeton University Press.

Holland, D.S. and Herrera, G.E. 2009. Uncertainty in the management of fisheries: contradictory implications and a new approach. Marine resource economics. 24: 289-299.

Hoeting, J.A., Madigan, D., Raftery, A.E., and C.T. Volinsky. Bayesian model averaging: a tutorial. Statist. Sci. 14: 382-417.

ICES. 2018. 2019 ACOM and ACOM Expert Group Terms of Reference. ICES AC. November 6, 2018.

Lee, Q., Thorson, J.T., Gertseva, V.V., and A.E. Punt. 2018. The benefits and risks of incorporating climate-driven growth variation into stock assessment models, with application to Splitnose Rockfish (Sebastes diploproa). ICES Journal of Marine Science 75: 245-256.

Levontin, P., Baranowski, P., Leach, A.W., Bailey, A., Mumford, J.D., Quetglas, A., and L.T. Kell. 2017. On the role of visualization in fisheries management. Marine Policy. 78: 114-121.

Luck D. and Dalzell, P. 2010. A compendium of ecological and fishery statistics for Reef Fishes in American Samoa, Hawai'i and the Mariana Archipelago, in support of annual catch limit implementation. Western Pacific Regional Fishery Management Council, 1164 Bishop St., Ste. 1400, Honolulu, Hawai'i.

Magnusson, A., Punt, A.E., and R. Hilborn. 2013. Measuring uncertainty in fisheries stock assessment: the delta method, bootstrap, and MCMC. Fish and Fisheries. 14: 325-342.

Majkowski, J. 1982. Usefulness and applicability of sensitivity analysis in a multispecies approach to fisheries management. 149-165. In Pauly, D. and G.I. Murply (eds) Theory and management of tropical fisheries. ICLARM Conference Proceedings 9, 360 p. International Center for Living Aquatic Resource Management, Manila, Philippines and Division of Fisheries Research, Commonwealth Scientific and Industrial Research Organization, Cronulla, Australia.

Marchal, P., Lallemand, P., Stokes, K., and O. Thébaud. 2009. A comparative review of the fisheries resource management systems in New Zealand and in the European Union. Aquatic Living Resources. 22: 463-481.

Marchal, P., Andersen, J.L., Aranda, M., Fitzpatrick, M., Goti, L., Guyader, O., Haraldsson, G., Hatcher, A., Hegland, T.J., Le Floc'h, P., Macher, C., Malvarosa, L., Maravelias, C.D., Mardle, S., Murillas, A., Nielsen, J.R., Sabatella, R., Smith, A.D.M., Stokes, K., Thoegersen, T., and C. Ulrich. 2016. A comparative review of the fisheries management experiences in the European Union and in other countries worldwide: Iceland, Australia, and New Zealand. Fish and Fisheries. 17: 803-824.

Maunder, M.N. and K.R. Piner. 2015. Contemporary fisheries stock assessment: many issues still remain. ICES Journal of Marine Science. 72: 7-18.

Methot, R.D., and Wetzel, C.R. 2013. Stock synthesis: a biological and statistical framework for fish stock assessment and fishery management. Fisheries Research 142: 86-99.

Methot, R.D. 2015. Prioritizing fish stock assessments. U.S. Dep. Commer., NOAA Tech. Memo. NFMS-F/SPO-152, 31 p.

Mohn, R. The retrospective problem in sequential population analysis: an investigation using cod fishery and simulated data. ICES Journal of Marine Science, 56: 473-488.

Monnahan, C.C., T.A. Branch, J.T. Thorson, I.J. Stewart, C.S. Szuwalski. 2019. Overcoming long Bayesian run times in integrated fisheries stock assessments (in review). ICES Journal of Marine Science.

New England Fishery Management Council. 2010. Amendment 15 to the scallop fishery management plan. New England Fishery Management Council, 50 Water Street, Mill 2, Newburyport, Massachusetts.

Pacific Fishery Management Council. 2014a. Pacific Coast Groundfish Fishery Management Plan. Pacific Fishery Management Council, 7700 Ambassador Place NE, Suite 200, Portland, Oregon.

Pacific Fishery Management Council. 2018. Terms of Reference for the groundfish and coastal pelagic species stock assessment review process for 2019-2020. Pacific Fishery Management Council, 7700 Ambassador Place NE, Suite 200, Portland, Oregon.

Patterson, K., Cook, R., Darby, C., Gavaris, S., Kell, L., Lewy, P., Mesnil, B., Punt, A., Restrepo, V., Skagen, D.W., and G. Stefansson. 2001. Estimating uncertainty in fish stock assessment and forecasting. Fish. Fish. 2: 125-157.

Peterman, R.M. 2004. Possible solutions to some challenges facing fisheries scientists and managers. ICES Journal of Marine Science. 61: 1331-1343.

Prager, M.H., and Shertzer, K.W., 2010. Deriving acceptable biological catch from the overfishing limit: implications for assessment models. North American Journal of Fisheries Management 30: 289-294.

Punt, A.E., and R. Hilborn, 1997. Fisheries stock assessment and decision analysis: the Bayesian approach. Reviews in Fish Biology and Fisheries, 7: 35-63.

Punt, A.E., Siddeek, M.S.M., Garber-Yonts, B., Dalton, M., Rugolo, L., Stram, D., Turnock, B.J., and J. Zheng. 2012. Evaluating the impact of buffers to account for scientific uncertainty when setting TACs: Application to red king crab in Bristol Bay, Alaska. ICES Journal of Marine Science 69: 624-634.

Punt, A.E., A'mar, T., Bond, N.A., Butterworth, D.S., de Moor, C.L., De Oliveira, J.A.A., Haltuch, M.A., Hollowed, A.B., and C. Szuwalski. 2014. Fisheries management under climate and environmental uncertainty: control rules and performance simulation. ICES Journal of Marine Science 71: 2208-2220.

Punt, A.E. 2015. Strategic management decision-making in a complex world: quantifying, understanding, and using trade-offs. ICES Journal of Marine Science, 74, 2: 499-510.

Ralston, S., Punt, A.E., Hamel, O.S., Devore, J.D., and R, Conser. 2011. A meta-analytic approach to quantifying scientific uncertainty in stock assessments. Fishery Bulletin 109: 217–231.

Rosenberg, A.A. and Restrepo, V.R. 1994. Uncertainty and risk evaluation in stock assessment advice for U.S. marine fisheries. Can. J. Fish. Aquat. Sci. 51: 2715-2720.

Rosenberg, A.A. 2007. Fishing for certainty. Nature. 449: 989.

Satelli, A. 2002. Sensitivity analysis for importance assessment. Risk Analysis. 22: 1-12.

Sethi, G., Costello, C., Fisher, A., Hanemann, M., Karp, L. 2005. Fishery management under multiple uncertainty. Journal of Environmental Economics and Management. 50: 300-318.

Shertzer, K.W., Prager, M.H., and E.H. Williams. 2008. A probability-based approach to setting annual catch limits. Fishery Bulletin 106: 225-232.

Steel, A.E., McElhany, P., Yoder, N.J., Purser, M.D., Malone, K., Thompson, B.E., Avery, K.A., Jensen, D., Blair, G., Busack, C., Bowen, M.D., Hubble, J., and T. Kantz. 2009. Making the best use of modeled data: Multiple approaches to sensitivity analysis of a fish-habitat model. Fisheries. 34: 330-339.