

Appendix F: Modeler's Final Report "*Improving the Stock Assessment of California Red Abalone *Haliotis rufescens* at San Miguel Island*"

Report --- Improving The Stock Assessment of California Red Abalone
(*Haliotis rufescens*) at San Miguel Island

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Prepared for

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To: Scott McCreary, Ph.D. Principal, CONCUR Inc.

From: Yan Jiao, Ph.D. Virginia Tech

Cc: Office of Sponsored Programs, Virginia Polytechnic Institute and State University

Introduction: This report represents the key work product and final deliverable completed for Basic Subcontractor Agreement CONCUR-VT-07-01 between the Office of Sponsored Programs of the Virginia Polytechnic Institute and State University and CONCUR Inc. dated November 16, 2007 in support of tasks undertaken for the project known as *Population modeler to support development of a prospective total allowable catch for red abalone at San Miguel Island.*

Relationship Between This Work and the Charge to the AAG and the TAC: This work is prepared to support the Abalone Advisory Group and an associated Technical Panel. The AAG will provide recommendations to the Department regarding the following four key topics:¹

- A TAC for SMI red abalone
- Alternatives for allocation between recreational and commercial take
- Alternative regulations to achieve the TAC and allocation
- Potential management, enforcement, and monitoring techniques

The role of the overall Technical Panel is to

1. Prepare a draft methodology for determining a TAC that best fits the conditions for red abalone stock at SMI.
2. Identify gaps or further data needs for improving the accuracy of the TAC in the future.
3. Propose alternative methodological approaches for TAC determination.
4. Incorporate input from the review committee and prepare a revised draft for presentation to the AAG.
5. Present and discuss the methodology and alternatives with the full AAG.

Activities and Completion of Tasks by Modeler Yan Jiao

After the proposal was funded, I worked closely with CONCUR, TP, and AAG in the following ways:

- Worked in a dedicated fashion to explore raw data, summarize data and develop models and approaches given available data and other available biological and fisheries information, and present the results (both written and oral).
- Communicated (both written and oral) research progress to the technical panel, review committee, and the AAG at periodic meetings.
- Participated in email exchanges, selected conference calls, and in-person meetings with CONCUR and DFG staff.

¹ AAG Mission Statement: AAG_MissionStatement_Sep2706.pdf

Consistent with both the adopted Terms of Reference for the Technical Panel and the contract, I completed the following tasks:

- Served on a multidisciplinary technical panel as the lead analyst that will oversee a “stock status determination” research project and ultimately, provide recommendations concerning whether the San Miguel Island red abalone population(s) can sustain fishing effort. The contractor will work with the technical panel to objectively evaluate this species’ population dynamics in the context of fishery-related interactions—e.g., implementing an ongoing TAC.
- Worked to spearhead all areas involved in this research endeavor, including the following: summarizing available sources of data (biological, fishery-dependent, and fishery-independent information); developing appropriate model(s) to generate management-related statistics of interest (abundance-related estimates, resiliency to fishing exploitation, spawning stock-recruitment relationships, potential sustainable yields, etc.); and finally, conducting applicable simulation-based modeling efforts to better understand appropriate biological reference points (e.g., “target- and limit-related” thresholds) for this abalone population.
- Conferred regularly with the full technical panel (4-6 individuals) and, when applicable, received guidance, advice, and feedback from the panel.

Please note, the attached analyses are intended for further review and deliberation by the full Technical Panel. As a reference, the essential TOR for the full Technical Panel is excerpted as Appendix 1.

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Executive Summary

In 2007, CONCUR, Inc. released a Request For Proposal for a comprehensive stock assessment of California red abalone (*Haliotis rufescens*) at San Miguel Island (SMI), California as one component of the Technical Panel (TP) organized to support the deliberations of the Abalone Advisory Group (AAG). Yan Jiao, PhD, was selected as a subcontractor to identify and evaluate possible approaches appropriate for a red abalone fishery at SMI and to provide a basis for future fisheries management. In November 2007, a workshop was organized to discuss available data and potential models that might be used based on the proposed stock assessment plan. Many data sets were presented through CONCUR between January and May of 2008, and discussions on which data sets to use continued throughout the summer of 2008. The current stock assessment models and results are based on the datasets identified as most appropriate by the TP and the author.

As an advisory group for the AAG, the TP is charged with preparing draft and alternative methodologies for determining a Total Allowable Catch (TAC) that would best fit the conditions of the red abalone stock at SMI as well as identifying gaps or further data needs for improving future TAC accuracy. The author, lead analyst for the TP, was contracted to oversee all areas of the research endeavor, including: 1) summarizing available sources of data; 2) developing appropriate models to generate statistics of interest; and 3) estimating potential TACs using population abundance and biological reference point estimates. Guiding principles for TAC recommendations include the use of best available science and the balance of a long-term planning approach with sufficient levels of certainty in the modeling process.

Red abalone is an important natural resource at SMI (Hobday and Tegner 2002; Rogers-Bennett et al. 2002). Currently all commercial and recreational abalone fisheries in southern California, including SMI, have been closed for over 10 years. There are public concerns about the stock recovery and the possibility of considering a limited abalone fishery at SMI (CDFG 2005). A systematic stock assessment is needed to better understand the stock status and to better manage this important fishery. Two comprehensive surveys were conducted at SMI in 2006 and 2007. Data on population density, size frequency, and habitat information at survey locations were recorded (CDFG 2006). A study on red abalone fecundity is currently being conducted (Rogers-Bennett personal communication). Limited information is available for the life history and fishery history of this stock. Some information, such as natural mortality estimation, was borrowed from other abalone fisheries for use and comparison in a stock assessment process (Rogers-Bennett et al., 2004; Leaf et al., 2007; Rogers-Bennett et al., 2007). Recruitment of abalone tends to be a limiting factor for population dynamics prediction and decision-based fisheries management because of their broadcast-spawning characteristics. Historical density and abundance indices from miscellaneous fishery-independent and fishery-dependent surveys are synthesized together with length frequency samples and are used to calibrate population dynamics.

The author assessed SMI red abalone using the following methods: 1) yield-per-recruitment analysis with uncertainty modeled through a Monte Carlo simulation approach; 2) statistical catch-at-age model to estimate fishing mortality, population size, and BRPs based on survey abundance, relative abundance indices and length frequency; and 3) population abundance estimation by a geostatistical analysis of fishery-independent surveys in 2006 and 2007 done by the CDFG.

Potential TACs were calculated by combining the above population abundance estimation with the biological reference point estimation. The risk of the population's decline and risk of overfishing was assessed under different TAC management strategies. This work is critical to successful management of SMI red abalone. Our analysis shows that the current red abalone stock at SMI is still low compared with historical levels. The estimates based on multiple models/scenarios have high uncertainty. Precautionary management strategies need to be considered because of the high uncertainty of the data and the stock assessment results.

This analysis enables better understanding of the red abalone dynamics at SMI and helps in developing future studies. The accomplishments of this research will improve this fishery's management by linking it more closely to multi-model approaches and risk-based decision making. This analysis and report should be regarded as a pilot study for this species given the short time period (1 year, with data available after 6 months) and modest funding (\$25,000). A further stock assessment with a longer time period is recommended to follow up for better assessment and management of this fishery.

Some key results are summarized below:

- The hierarchical model captures the temporal variation of individual growth using the tagging data. Red abalone individual growth rate varies largely over time, which needs to be considered in the stock assessment models, such as per recruitment analyses.
- Biological reference points (BRPs) from yield-per-recruitment model tend to be more stable than those from egg-per-recruitment model. However, the F-based BRP (strongly due to the lower L_{∞} from the hierarchical growth model) is much higher than the assumed natural mortality, which indicates problems with using this model. The BRPs from per-recruitment models are sensitive to natural mortality, growth parameters and other biological parameters (Jiao et al 2004; Leaf et al 2008). The current results are based on the agreed biological parameters with TP.
- Statistical catch-at-age modeling results show that recruitment of SMI red abalone is periodic and that the current recruitment regime is low. There is no clear stock recruitment relationship. A precautionary management approach is suggested given the results that spawning stock of this population tends to continue to decline given the low recruitment. The results are based on scenarios that weight catch and length frequency data heavier than the relative abundance

indices. The TP agreed that the data quality of catch and length frequency is much higher than that of relative abundance indices.

- Spawning stock size estimation is a problem. Instead of using the total number of matured abalone, a framework that can incorporate the fertility differences of different size individuals is suggested in a future stock assessment.
- Multiple alternative approaches and criteria were used to estimate the possible TAC and the corresponding risk of overfishing (see Table below). If a criterion of 2000 abalone/ha is used, then current low population density suggests a TAC of no harvest; the recent low recruitment after 2000 suggests that any harvest would increase the trends of further decline of this population.
- Continued fishery independent survey is highly suggested.
- Future stock assessment with consideration of spatial heterogeneity is suggested given the fact that density of the red abalone was highly different in different locations and that time series relative abundance indices were highly different.
- Recruitment is the bottleneck of this species at SMI. Further studies on recruitment dynamics are suggested.

Table 1: Summary of the BRPs from different models and the corresponding potential TACs and risks of population decline (in 1000 abalone).

Model	Biological reference points developed (BRPs)	Potential Total Allowable Catch (TAC)	Risk of population decline $P(SSN_{2008} < SSN_{2007})$	Important Comments or Caveats
Yield-per-recruitment (YPR) model	$F_{0.1}$ and $L_{entry}=197\text{mm}$ $P(F > F_{BRP})=30\%$	174.51	100%	Sensitive biological and fishing parameters - may vary over time due to environmental changes, etc.
Statistical catch-at-age model	$F_{msy}=M=0.15$ $L_{entry}=197\text{mm}$ CV of $F_{msy}=30\%$	22.99	100%	Heavily influenced by the quality of the data. The historical relative abundance indices are short and of low quality.
	$F_{msy}=M=0.15$ $L_{entry}=197\text{mm}$ CV of $F_{msy}=40\%$	22.00	100%	
	$F_{msy}=50\%$ of M $L_{entry}=197\text{mm}$ CV of $F_{msy}=30\%$	11.12	100%	
	$F=0$ (No Fishery)	0	100%	
Minimum abalone density	2000 abalone/ha	0 (Current average abalone density = 1200 abalone/ha)	N/A	Information is not directly from this fishery

$F_{0.1}$ = Fishing mortality reference point (rate at which the increase in yield-per-recruit in weight for an increase in a unit-of-effort is only 10 percent of the yield-per-recruit produced by the first unit of effort on the unexploited stock)

F_{msy} = Fishing Maximum Sustainable Yield

M = Natural Mortality Rate

L_{entry} = Minimum Catch Size

CV = Coefficient of Variation (ratio of standard deviation to the mean)

1 Introduction

1.1 Background

Abalone are a common large herbivorous gastropod along the California coast. There are seven species of abalone in California: red (*Haliotis rufescens*); pink (*H. corrugata*); green (*H. fulgens*); white (*H. sorenseni*); black (*H. cracherodii*); flat (*H. walallensis*); and pinto (*H. kamtschatkana*). California abalones have been harvested by humans for thousands of years, initially by native Californians and then by Chinese immigrants in the 19th century (Cox 1962). The modern fishery for the five most common species (red, pink, green, white, and black abalones) occurred through most of the 20th century. The peak of the commercial fishery occurred in the late 1950s with over 2,000 metric tons landed annually (Karpov et al. 2000). At that time, pink and red abalones were the predominant species harvested. As the fishery continued into the 1970s and 80s and landings declined, green, white, and black abalones became more important in the overall harvest (Karpov et al. 2000). The fishery was eventually closed in 1997 when the state of California enacted an abalone fishing moratorium from San Francisco Bay south to the Mexican border.

The fishery was not sustainable for several reasons including: 1) loss of the original fishing grounds in central California due to the expansion of the sea otter population, which precluded an abalone fishery; 2) an increase in both recreational and commercial fishing effort; and 3) the occurrence of a deadly bacterial disease. The management strategy implemented at that time could not effectively adapt to these negative impacts on the fishery, and therefore the moratorium was enacted.

At the time of the closure, the commercial and recreational fishery was predominantly focused on harvesting red abalone at San Miguel Island (SMI). SMI is the furthest northwest of eight channel islands located in the Southern California Bight south of Point Conception (Figure 1). SMI has always been the center of red abalone abundance in southern California. The constant influx of cold ocean water and upwelling at this location provide optimal conditions for red abalone to thrive. The red abalone population at San Miguel appeared to be stable at the time of the closure (Karpov et al. 2000).

The legislation that created the moratorium also mandated the development of the Abalone Recovery and Management Plan (ARMP). The ARMP is a cohesive document that provides guidance on management of existing abalone fisheries (i.e. the northern California recreational abalone fishery) and all other future fisheries, as well as a plan for recovery of abalone species within the fishery moratorium area. The California Fish and Game Commission (Commission) adopted the ARMP in 2005, approximately eight years after the moratorium was enacted. At the time of adoption the Commission also directed the Department of Fish and Game (Department) to begin exploring the possibility of opening a limited fishery for red abalone at SMI. The Department began a fishery consideration process by utilizing a cooperative planning approach to engage stakeholders in the planning of this potential fishery. A constituent advisory group, the

Abalone Advisory Group (AAG), was developed, and members from various constituencies were appointed. The purpose of the AAG is to provide a suite of potential fishery management recommendations to the Department and the Commission for this limited fishery at SMI. The AAG is charged with providing recommendations in the four following areas:

1. A Total Allowable Catch (TAC) for red abalone at San Miguel Island
2. Alternatives for allocation between recreational and commercial take
3. Alternative regulations to achieve the TAC and allocation
4. Potential management, enforcement, and monitoring techniques

To help fulfill their charge of recommending a TAC, the AAG sought external experts to draft a methodology for determining a scientifically-based TAC. A technical panel (TP) was formed to carry out this task of TAC development and a point person modeler was hired. Over the course of 14 months the technical panel and modeler, with the help of the Department, gathered all available datasets and formulated models for assessing the status of the red abalone stock at the island. This report on the results of the models used forms the basis for the TAC development process.

1.2 Terms of Reference (revised by CONCUR, see Appendix 1)

1.3 TP and AAG participants

The following people were in the TP:

Dr. Laura Rogers-Bennett	California Department of Fish and Game
Dr. John Butler	NOAA Fisheries
Dr. Paul Crone	NOAA Fisheries
Dr. Yan Jiao	Virginia Polytechnic Institute and State University
Robert Leaf	Virginia Polytechnic Institute and State University

The following people were in AAG:

Jessie Altstatt	Science Director, Santa Barbara Channelkeeper
Bill Bernard	Recreational abalone diver
Dr. John Butler	Southwest Fisheries Science Center
Dr. Paul Dayton	Scripps Institution of Oceanography
Dan Richards	Biologist, Channel Islands National Park
Dr. Daniel Geiger	Research Curator of Electron Microscopy, Santa Barbara Museum of Natural History
Jim Marshall	CAA member
Chris Mobley	Director, Channel Islands National Marine Sanctuary
Terry Maas	Recreational abalone diver
Greg Sanders	Minerals Management Service
Chris Voss	CAA President
Sean Hastings (Alt)	Channel Islands National Marine Sanctuary Resource Protection Coordinator Alternate to Chris Mobley

2.1 Hierarchical growth model based on the tagging study: detecting temporal variation of individual growth of red abalone (*Haliotis rufescens*)

Abstract

Many marine species worldwide have shown temporal variation in individual growth. Yearly growth variations have been identified in the California red abalone (*Haliotis rufescens*) off the coast of Santa Rosa Island, but not previously incorporated in growth models. In this study, Bayesian hierarchical models were developed to simulate variability in growth rates of this red abalone population. Von Bertalanffy growth models with Bayesian hierarchical (multi-level) priors were found to fit red abalone growth data considerably better than a non-hierarchical von Bertalanffy model. The hierarchical Bayesian approach represents an intermediate strategy between traditional models that do not include temporal variability and highly parameterized models that assign an estimate of parameters to each period of observation data. By ignoring temporal variability, confidence intervals of the estimates of individual growth can be unrealistically narrow, possibly leading to bias when these models are used for developing biological reference points, such as $F_{0.1}$, F_{max} , or $F_{x\%}$ from per-recruitment models. Use of Bayesian hierarchical approach is suggested for future individual growth modeling and for per-recruitment models that include individual growth.

Introduction

Red abalone (*Haliotis rufescens*) is one of the important abalone species along the Pacific coast. Haaker et al. (1998) developed and supported the hypothesis that individual growth of red abalone significantly varies over time, possibly due to temperature changes during El Niño and La Niña ocean climate oscillations. Although Haaker et al (1998) detected the variations of temporal individual growth, a model that can incorporate this type of variation was not provided in it. Temporal variations of growth may be caused by many reasons, such as environmental changes, prey availability and fishing. Traditional von Bertalanffy models, which assume constant parameters in the models, cannot account for the uncertainties of individual growth even when multi-year data are included in the analysis (Clark 2003).

Incorporating variability in individual growth among years is problematic when using constant growth rate in the von Bertalanffy model. In the present paper, a multi-level prior in a hierarchical approach is used to address the problem of simulating individual growth rates and their associated uncertainty when multiple year data are included and exhibit variability in growth rate. At the same time, the growth rates can be assigned to each time period that we specified. Models with multi-level priors are called hierarchical models (Gelman et al., 2004). Multi-level priors have been used to represent species or group differences when the data are hierarchical (Clark, 2003; Gelman et al., 2004). In contrast to a highly parameterized model that assigns a different parameter value to each time period to capture changes in individual growth rate, hierarchical models accommodate temporal differences but assume these differences derive from an underlying distribution (Gelman et al., 2004).

In this study, a hierarchical growth model was used to model the temporal variation of red abalone growth (Gelman et al. 2004). A hierarchical model provides a coherent mechanism to incorporate variation of individual growth over time and/or space. The estimated hyperparameters capture the temporal and spatial variations and provide more comprehensive characteristics of the growth than these traditional models, which can further be used for

population dynamics and stock assessment. Per recruitment models have been widely used in fisheries stock assessment, including abalone species (Annala and Breen 1989; Hilborn and Walters 1992; FAO 1995; Quinn and Deriso 1999). They were widely used in providing biological reference points (BRPs, e.g., $F_{0.1}$, $F\%$, $F\%_{SSB}$, Caddy and Mahon, 1995). Failure to incorporate or model the temporal variations of growth may result in uncertainty of the BRPs estimation when per recruitment models are used.

To evaluate the model goodness-of-fit, hierarchical models were compared with a non-hierarchical model. More than one hierarchical model were used to fit to different hierarchically structured datasets restructured based on different time periods, such as one year, two years, and so on. Hierarchical models increase the complexity of the model, and it is valuable to look at the model goodness-of-fit, which balances model fit and model complexity. Deviance Information Criterion (DIC) was used to compare model goodness-of-fit. The hierarchically structured models were implemented in a Bayesian framework and analyzed using Markov Chain Monte Carlo (MCMC) simulation. Bayesian methods have previously been used as effective approaches to solving hierarchical models (Gelman et al. 2004). They have been used increasingly in assessing and managing fisheries stocks because of their flexibility in incorporating data from different sources. Specifically, Bayesian methods have the ability to provide results for risk analyses of alternative management strategies and to incorporate prior knowledge of the fisheries into the assessment process.

Materials and methods

Data sources

The only available tagging (mark-recapture) data from 1978 to 1984 at Johnsons Lee (33°54'N, 120°06'W) on the south side of Santa Rosa Island, collected by California Department of Fisheries and Game, were used to measure growth rate (Haaker et al. 1998). SCUBA divers collected red abalone and brought them to the vessel, where they were placed in flowing seawater. Abalones were marked with numbered, stainless steel tags secured with stainless steel wire through two completely formed shell apertures (Haaker et al. 1986). Shell length (maximum shell dimension) was measured to the nearest millimeter with calipers. Records with negative growth of the shell size were deleted in the analysis (Figure 1). Six visits happened from 1978 to 1984, and there was no visit in 1983. In each visit, both tagged and additional untagged abalone were collected and retagged if appropriate. From 1978 to 1979, 158 red abalone were recaptured; from 1979 to 1980, 86 were recaptured; from 1980 to 1981, 210 were recaptured; and from 1982 to 1984, 59 were recaptured.

We determined growth curves from annual increments in length of tagged individuals. We used the nonlinear methodology of Kirkwood and Somers (1984) for mark-recapture data to estimate the parameters and standard errors for the von Bertalanffy growth model.

The von-Bertalanffy growth model can be written as

$$(1) \quad L_t = L_\infty(1 - e^{-kt}), \text{ or}$$

$$dL = L_{t+\Delta t} - L_t = (L_\infty - L_t)(1 - e^{-k\Delta t}),$$

where L_∞ and k are parameters in the von Bertalanffy growth model. L_∞ represents the asymptotic length of red abalone; k is the Brody growth coefficient; t_0 is assumed to be 0 as used in Haaker et al. (1998); L_t is the length at time t ; and $L_{t+\Delta t}$ is the length at time $t + \Delta t$. A hierarchical individual growth model (Gelman et al. 2004) developed in this study can be written as:

$$\begin{aligned}
dL &= L_{s,t+\Delta t} - L_{s,t} = (L_{s,\infty} - L_{s,t})(1 - e^{-k_s \Delta t}) \\
(2) \quad L_{s,\infty} &\sim N(\bar{L}_\infty, \sigma_{\bar{L}_\infty}^2) \\
k_s &\sim N(\bar{k}, \sigma_{\bar{k}}^2)
\end{aligned}$$

where subscript s represents temporal-specific parameters. The hierarchical population structure is implemented in this model through a multi-level prior of temporal-specific parameters in the individual growth model.

The Bayesian approach uses a probability rule (Bayes' theorem) to calculate a "posterior distribution" from the observed data and a "prior distribution", which summarizes the prior knowledge of the parameters (Berger, 1985; McAllister and Kirkwood, 1998; Gelman *et al.*, 2004). This approach was used to estimate the uncertainty in parameter estimates. A nonhierarchical Bayesian model describes a posterior density for parameters ($p(\theta | dL)$) using Bayes' theorem as:

$$(3) \quad p(\theta = L_\infty, k | dL) = \frac{\prod_i f(dL_i | \theta) \pi(\theta)}{\int_{-\infty}^{+\infty} \prod_i f(dL_i | \theta) \pi(\theta) d(\theta)}$$

whereas a hierarchical Bayesian method assign priors of hyperparameters to yield the joint posterior:

$$(4) \quad p(\theta' = L_\infty, k, \bar{L}_\infty, \bar{k}, \sigma_{\bar{L}_\infty}, \sigma_{\bar{k}} | dL) = \frac{\prod_i f(dL_i | L_\infty, k) \pi_1(L_\infty | \bar{L}_\infty, \sigma_{\bar{L}_\infty}) u_1(\bar{L}_\infty) v_1(\sigma_{\bar{L}_\infty}) \pi_2(k | \bar{k}, \sigma_{\bar{k}}) u_2(\bar{k}) v_2(\sigma_{\bar{k}})}{\int_{-\infty}^{+\infty} \prod_i f(dL_i | L_\infty, k) \pi_1(L_\infty | \bar{L}_\infty, \sigma_{\bar{L}_\infty}) u_1(\bar{L}_\infty) v_1(\sigma_{\bar{L}_\infty}) \pi_2(k | \bar{k}, \sigma_{\bar{k}}) u_2(\bar{k}) v_2(\sigma_{\bar{k}}) d(\theta')}$$

In the above equations, $f(dL_i | \theta)$ is the probability density function of dL on parameter vector θ , and $u(\bar{L}_\infty)$ and $v(\sigma_{\bar{L}_\infty})$ are the probability density functions of \bar{L}_∞ and $\sigma_{\bar{L}_\infty}$.

Bayesian implementation of these models requires specification of prior distributions on all unobserved quantities. Non-informative priors (here, wide uniform distributions) were used for variances $\sigma_{\bar{L}_\infty}^2$ and $\sigma_{\bar{k}}^2$.

A critical issue in using MCMC methods is how to determine when random draws have converged to the posterior distribution. Here, three methods were considered: monitoring the trace for key parameters, diagnosing the autocorrelation plot for key parameters, and using the Gelman and Rubin statistic (Gelman and Rubin, 1992; Spiegelhalter *et al.*, 2004). A detailed description of the use of these methods in fisheries can be found in Su *et al.* (2001). In this study, three Markov chains were used. The three chains converged after 50,000 iterations with a thinning interval of five based on the convergence criteria and were discarded. A thinning interval of five was then used to avoid parameter autocorrelation. Another 20,000 iterations were used to generate the posterior distributions. The posterior distributions of the key parameters were obtained through a kernel smooth approach (Bowman and Azzalini, 1997).

To compare the performance of the hierarchically structured model with commonly used non-hierarchical von Bertalanffy growth model, another three hierarchical models were

developed (Table 1). In the first hierarchical model, each year's data (except the year of 1983 because of lack of tagging that year) were assumed to be hierarchically structured:

$$\begin{aligned}
 (5) \quad & L_{t+\Delta t} - L_t = (L_\infty - L_t)(1 - e^{-k\Delta t}) \\
 & L_{\infty 1} \sim N(\bar{L}_\infty, \bar{\sigma}_{L_\infty}^2) \Big|_{1978-1979} I(150, 400) \\
 & \dots \\
 & L_{\infty 5} \sim N(\bar{L}_\infty, \bar{\sigma}_{L_\infty}^2) \Big|_{1982-1984} I(150, 400) \\
 & \bar{L}_\infty \sim U(180, 250) \\
 & \bar{\sigma}_{L_\infty}^2 \sim U(1, 1000) \\
 & \bar{k} \sim U(0.15, 0.35) \\
 & \bar{\sigma}_k^2 \sim U(0.0001, 0.1).
 \end{aligned}$$

In the second hierarchical model, every two year period's data were assumed to be hierarchically structured:

$$\begin{aligned}
 (6) \quad & L_{t+\Delta t} - L_t = (L_\infty - L_t)(1 - e^{-k\Delta t}) \\
 & L_{\infty 1} \sim N(\bar{L}_\infty, \bar{\sigma}_{L_\infty}^2) \Big|_{1978-1980} I(150, 400) \\
 & L_{\infty 2} \sim N(\bar{L}_\infty, \bar{\sigma}_{L_\infty}^2) \Big|_{1980-1982} I(150, 400) \\
 & L_{\infty 3} \sim N(\bar{L}_\infty, \bar{\sigma}_{L_\infty}^2) \Big|_{1982-1984} I(150, 400) \\
 & \bar{L}_\infty \sim U(180, 250) I(150, 400) \\
 & \bar{\sigma}_{L_\infty}^2 \sim U(1, 1000) \\
 & \bar{k} \sim U(0.15, 0.35) \\
 & \bar{\sigma}_k^2 \sim U(0.0001, 0.1).
 \end{aligned}$$

In the third hierarchical model, the model was hierarchically structured, but the data were not assumed to be hierarchical:

$$\begin{aligned}
 (7) \quad & L_{t+\square t} - L_t = (L_\infty - L_t)(1 - e^{-k\Delta t}) \\
 & L_\infty \sim N(\bar{L}_\infty, \bar{\sigma}_{L_\infty}^2) \Big|_{1978-1984} I(150, 400) \\
 & \bar{L}_\infty \sim U(180, 250) \\
 & \bar{\sigma}_{L_\infty}^2 \sim U(1, 1000) \\
 & \bar{k} \sim U(0.15, 0.35) \\
 & \bar{\sigma}_k^2 \sim U(0.0001, 0.1).
 \end{aligned}$$

\bar{L}_∞ , the hyperparameter of the mean of L_∞ , was assumed to follow a uniform distribution between 180 and 250 mm. This range was based on L_∞ estimates from other studies on red abalone populations (Haaker et al 1998; Roger-Bennett 2007). The hyperparameter of the variance of L_∞ , $\bar{\sigma}_{L_\infty}^2$, was modeled as non-informative with a wide uniform distribution between 1 and 1000. The hyperparameter of \bar{k} was assumed to follow a uniform distribution between 0.15 and 0.35, based on k estimates from other studies (Haaker et al 1998; Roger-Bennett 2007). The hyperparameter of the variance of k , $\bar{\sigma}_k^2$, was modeled as non-informative with a wide uniform distribution between 0.0001 and 1.

The non-hierarchical von Bertalanffy growth model is:

$$(8) \quad \begin{aligned} L_{t+\Delta t} - L_t &= (L_\infty - L_t)(1 - e^{-k\Delta t}) \\ L_\infty &\sim U(150, 400) \\ k &\sim U(0.15, 0.40) . \end{aligned}$$

The priors of L_∞ and k in this model are wider than the priors of their mean values in the hierarchical models. The range of L_∞ is as wide as the range of L_t in the hierarchical models to prevent the influence of the informative priors.

Sensitivities of the results to prior assumption of both parameters and hyperparameters were analyzed by changing the lower limits of \bar{L}_∞ and \bar{k} to 50% of the ones used above, and by changing the high limit to 150% of the ones used above.

The goodness-of-fit of the Bayesian hierarchical models was compared with the traditionally used nonhierarchical model based on the estimates of the Deviance Information Criterion (DIC).

$$(9) \quad \begin{aligned} DIC &= 2\bar{D} - \hat{D} \text{ or } \bar{D} + p_D \\ D(y, \theta) &= -2 \log \text{Likelihood}(y|\theta) \\ p_D &= \bar{D} - \hat{D} \end{aligned}$$

where D is deviance, a measurement of prediction of goodness for our models; p_D is the effective number of parameters in a Bayesian model; \bar{D} is the posterior mean of the deviance; and \hat{D} is the deviance of the posterior mean. The DIC is a hierarchical modeling generalization of the AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion, also known as the Schwarz Criterion). It is particularly useful in Bayesian model selection problems where the posterior distributions of the models have been obtained by Markov Chain Monte Carlo (MCMC) simulation. Like AIC and BIC, it is an asymptotic approximation as the sample size becomes large. It is only valid when the posterior distribution is approximately multivariate normal (Spiegelhalter et al. 2002, 2004).

Results

Compared to the non-hierarchical von Bertalanffy model, the hierarchical approaches used here fit the data considerably better (Table 1). Among the four models tested, M1, the model with each year's data treated as hierarchical, performed the best, resulting in the lowest DIC (5891.84). M2 and M3, the other two models with multi-level priors of the von Bertalanffy growth parameters, also resulted in lower DIC values than the non-hierarchical model (M4).

Using a hierarchically structured model generally resulted in parameter estimates with wider credible intervals than that of a non-hierarchical model (Table 1). The credible intervals of L_∞ and k were considerably wider for the hierarchical von Bertalanffy models M1, M2, M3 than for the non-hierarchical model M4, which can be seen from the standard deviation values (Table 1). Because of the size of the table, we showed results of standard deviation values instead of credible interval.

Results from tables 1 and 2 showed that the posteriors of the key parameters in all the hierarchical models were stable when the priors of \bar{L}_∞ widen from $\bar{L}_\infty \sim U(180, 250)I(150, 400)$

to $\bar{L}_\infty \sim U(90, 375)I(50, 400)$ and when \bar{k} widens from $\bar{k} \sim U(0.15, 0.35)$ to $\bar{k} \sim U(0.075, 0.525)$. The posteriors of the key parameters of the non-hierarchical models were also stable when L_∞ widens from $L_\infty \sim U(150, 400)$ to $L_\infty \sim U(50, 400)$, and k widens from $k \sim U(0.15, 0.40)$ to $k \sim U(0.075, 0.575)$ (Tables 1 and 2). It suggested that even though the priors for the key parameters in the hierarchical and non-hierarchical models looked informative, they did not influence the posteriors of the parameters.

Results from the best model, M1, showed that the joint posterior distributions of L_∞ and k differed dramatically between 1978-1979, the highest growth period, and 1982-1984, the lowest growth period, and the three intermediate periods (Table 1 and Figure 2). The posterior von Bertalanffy growth curve also showed that abalone grew much faster and larger in 1978-1979 and much lower in 1982-1984 (Figure 3).

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Table 1: Model comparison among hierarchical and non-hierarchical growth models of San Miguel Island red abalone.

Models	DIC	Parameter estimates L_∞ (mean,median,sd)	k (mean,median,sd)
M1: Hierarchical growth is different each year	5891.84	\bar{L}_∞ (202.1, 201.8,9.335) $\bar{\sigma}_{L_\infty}^2$ (472.4, 437.6, 237.8) L_{∞_1} (223.8,223.5, 5.413) L_{∞_2} (207.5, 207.0, 6.513) L_{∞_3} (200.2, 199.9, 4.5) L_{∞_4} (197.0, 196.9, 2.662) L_{∞_5} (179.5, 179.5, 3.45)	\bar{k} (0.2339, 0.2320,0.0384) $\bar{\sigma}_k^2$ (0.0124,0.0070,0.0148) k_1 (0.2823, 0.282,0.0210) k_2 (0.2155,0.2144,0.0296) k_3 (0.2048,0.2047,0.0172) k_4 (0.2829,0.2827,0.0159) k_5 (0.1671,0.1629,0.0152)
M2: Hierarchical growth is different every 2 years	5958.79	\bar{L}_∞ (199.2, 198.0, 10.91) $\bar{\sigma}_{L_\infty}^2$ (495.7,471.7,254.5) L_{∞_1} (212.7,212.5,3.676) L_{∞_2} (198.1,198.0,2.383) L_{∞_3} (179.4,179.4,3.485)	\bar{k} (0.2443, 0.2426,0.0492) $\bar{\sigma}_k^2$ (0.0260,0.0170,0.0242) k_1 (0.2936,0.2933,0.0185) k_2 (0.2523,0.2521,0.0122) k_3 (0.1669,0.1627,0.0152)
M3: Hierarchical growth is the same throughout the years	6199.78	\bar{L}_∞ (203.1,200.3,15.06) $\bar{\sigma}_{L_\infty}^2$ (466.0,450.0,290.3) L_∞ (196.1, 196.0, 1.586)	\bar{k} (0.2543,0.2565,0.0552) $\bar{\sigma}_k^2$ (0.0397,0.0346,0.0292) k (0.2739,0.2739,0.0098)
M4: Non- hierarchical	10512.2	L_∞ (193.8, 193.80, 1.195)	k (0.269,0.269,0.0076)

Table 2: Model comparison among hierarchical and non-hierarchical growth models of red abalone. Priors of the hierarchical models are $\bar{L}_\infty \sim U(90, 375)I(50, 400)$, $\bar{\sigma}_{L_\infty}^2 \sim U(1, 1000)$, $\bar{k} \sim U(0.075, 0.525)$, $\bar{\sigma}_k^2 \sim U(0.0001, 0.1)$. Priors for the non-hierarchical model are $L_\infty \sim U(50, 400)$, $k \sim U(0.075, 0.525)$. Deviance Information Criterion (DIC), and posterior mean, median and standard deviation (sd) of the parameter estimates were provided.

Models	DIC	Parameter estimates L_∞ (mean, median, sd)	k (mean, median, sd)
M1: Hierarchical growth is different each year	5892.18	\bar{L}_∞ (201.4, 201.5, 10.1) $\bar{\sigma}_{L_\infty}^2$ (483.8, 452.5, 239.1) $L_{\infty 1}$ (223.9, 223.5, 5.3) $L_{\infty 2}$ (207.5, 207.0, 6.7) $L_{\infty 3}$ (200.1, 199.8, 4.5) $L_{\infty 4}$ (197.0, 196.9, 2.7) $L_{\infty 5}$ (179.4, 179.3, 3.5)	\bar{k} (0.2324, 0.2315, 0.0485) $\bar{\sigma}_k^2$ (0.0141, 0.0076, 0.0170) k_1 (0.2820, 0.2816, 0.0203) k_2 (0.2158, 0.2145, 0.0306) k_3 (0.2049, 0.2050, 0.0175) k_4 (0.2829, 0.2826, 0.0161) k_5 (0.1675, 0.1630, 0.0158)
M2: Hierarchical growth is different every 2 years	5959.29	\bar{L}_∞ (197.0, 197.0, 13.2) $\bar{\sigma}_{L_\infty}^2$ (511.3, 488.8, 251.9) $L_{\infty 1}$ (212.6, 212.5, 3.7) $L_{\infty 2}$ (198.2, 198.1, 2.4) $L_{\infty 3}$ (179.4, 179.3, 3.5)	\bar{k} (0.2481, 0.2422, 0.0813) $\bar{\sigma}_k^2$ (0.0297, 0.0209, 0.0258) k_1 (0.2940, 0.2932, 0.0184) k_2 (0.2519, 0.2519, 0.0120) k_3 (0.1669, 0.1629, 0.0149)
M3: Hierarchical growth is the same throughout the years	6200.40	\bar{L}_∞ (196.5, 196.5, 22.6) $\bar{\sigma}_{L_\infty}^2$ (497.9, 500.8, 290.4) L_∞ (196.1, 195.9, 1.6)	\bar{k} (0.2887, 0.2860, 0.1129) $\bar{\sigma}_k^2$ (0.0446, 0.0415, 0.029) k (0.2744, 0.2744, 0.0099)
M4: Non- hierarchical	10512.2	L_∞ (193.9, 193.8, 1.2)	k (0.2688, 0.2688, 0.0076)

Figure 1: Observed abalone length at time t versus length at time $t + \Delta t$.

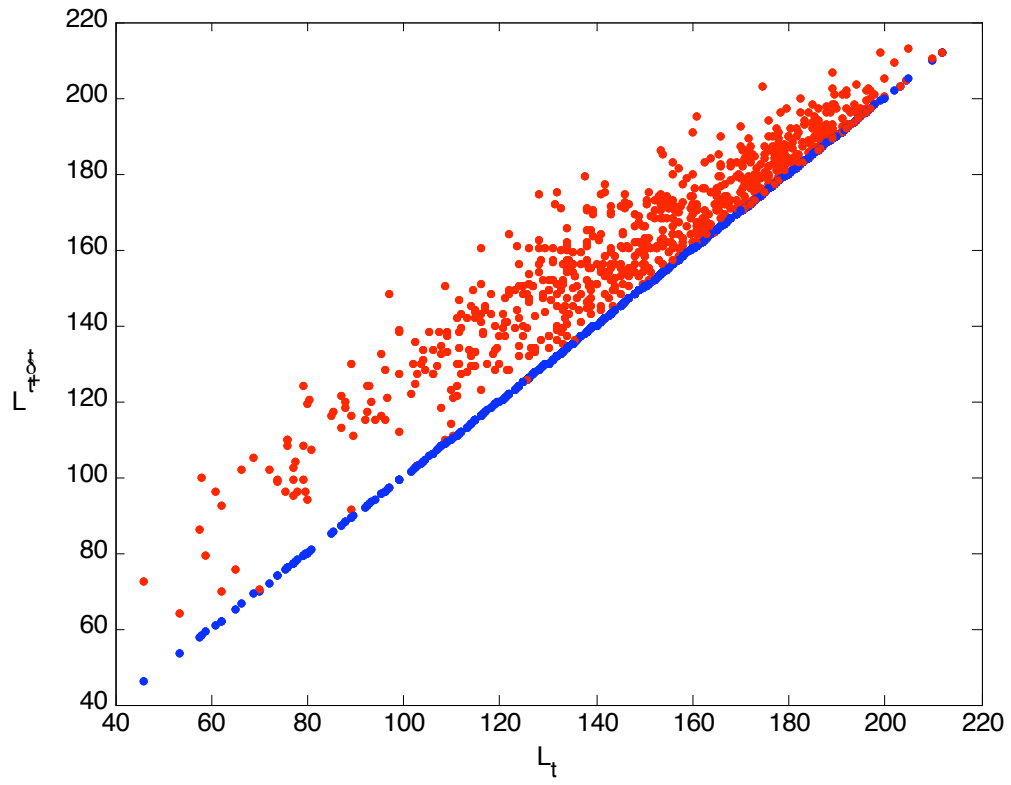


Figure 2: Joint posterior distributions of k and L^∞ from 1978 to 1984 based on the hierarchical individual growth model. Red: 1978-1979; magenta: 1979-1980; yellow: 1980-1981; green: 1981-1982; blue: 1982-1984.

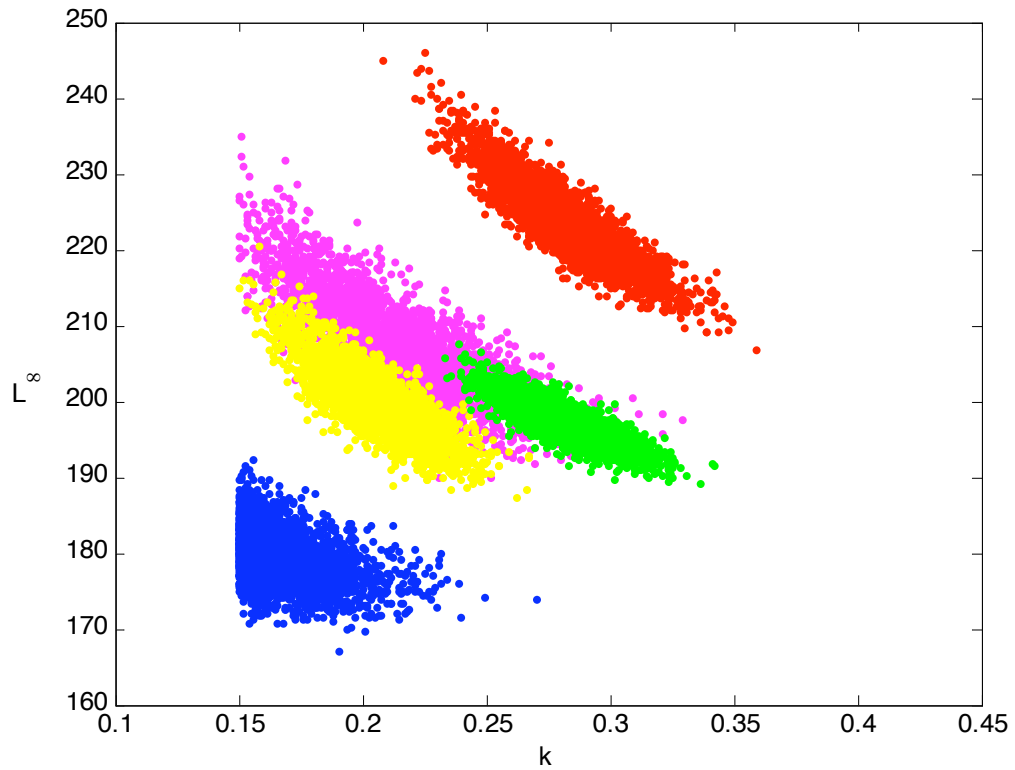


Figure 3: Red abalone individual growth curve based on the posterior distributions of k and L_{∞} .

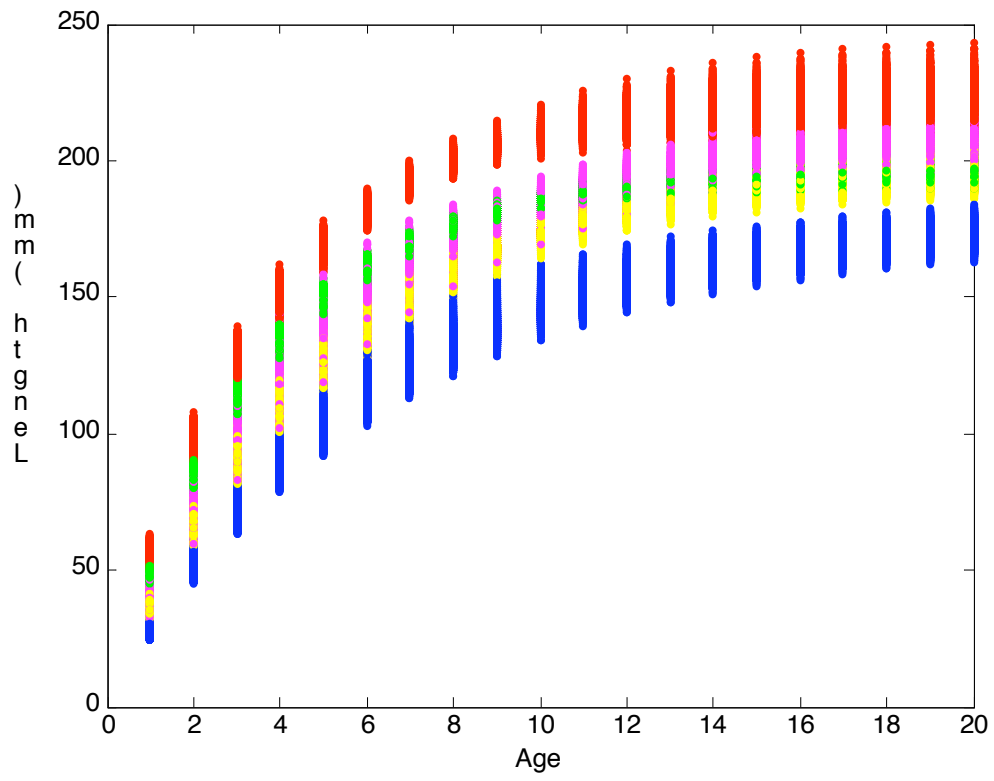
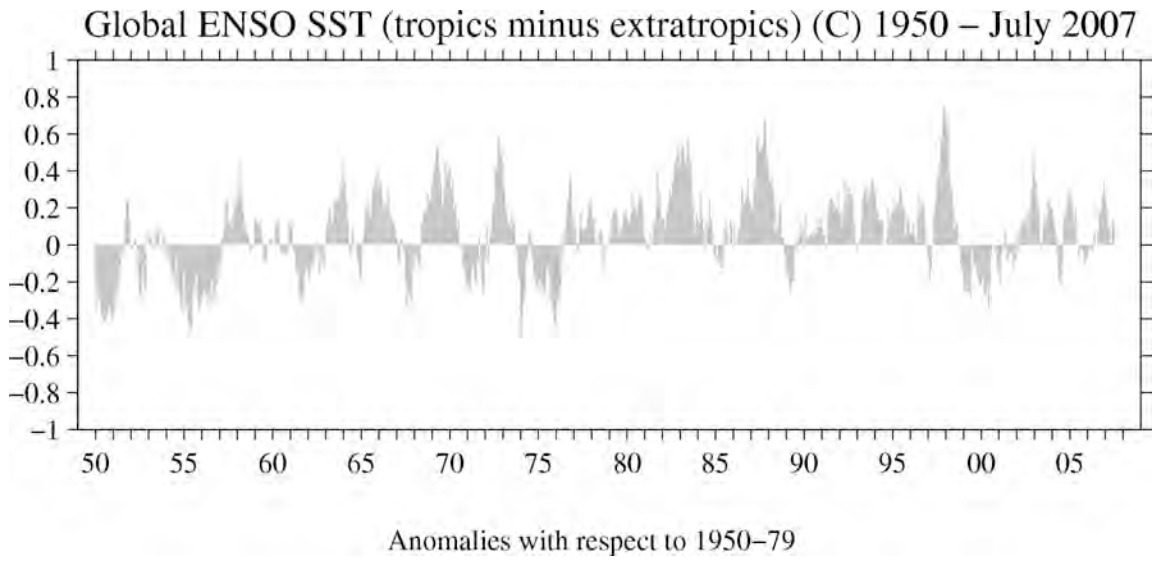


Figure 4: Sea surface temperature (SST) anomalies of El Niño Southern Oscillation (ENSO).



2.2 Per recruitment modeling: probing uncertainty in YPR and EPR analyses of red abalone (*Haliotis rufescens*) at San Miguel Island

Abstract

The red abalone fishery of San Miguel Island (SMI) is one of the major fisheries in southern California. The fishery was assessed based on yield-per-recruitment (YPR) and egg-per-recruitment (EPR) models. Life history information directly collected from the field, from appropriate neighboring populations, and from published literature was collected and used in these models. Because of the temporal variation of individual growth observed based on the tagging data, results of individual growth from a hierarchical growth model were used directly in the uncertainty evaluation of biological reference points (BRPs) in this study. Uncertainties of fecundity, natural mortality, and weight-at-length were also considered in this study. $F_{0.1}$ from the YPR model tends to be more stable and with lower uncertainty among the BRPs. $F_{0.1}$ corresponding to higher minimum catchable size does not suggest that a higher minimum catchable size is recommended for conservation purposes because of the high $F_{0.1}$ s and high uncertainties they exhibit.

Introduction

Per recruitment models have been widely used in fisheries stock assessment (Hilborn and Walters 1992; FAO 1995; Quinn and Deriso 1999). They have also been widely used in providing biological reference points (BRPs, e.g., $F_{0.1}$, $F\%$, $F\%_{SSB}$, Caddy and Mahon, 1995). The declining trend in stock size as well as widely discussed impacts of uncertainty on stock assessment and management calls for a close examination of the role of uncertainty in determining the status of a fishery (Ludwig et al., 1993; Myers and Worm, 2003).

Uncertainty in assessing a fishery may result from various sources such as measurement errors, process errors, model errors, and operating errors (Chen and Paloheimo, 1998; Patterson et al., 2001). An approach commonly used to incorporate uncertainty in assessment is to estimate the empirical probability distribution of indicator reference points using the bootstrap and jackknife methods. In this study, the management reference points are calculated based on fisheries data and life history parameters using per recruitment models.

For many fisheries, knowledge is lacking about the uncertainty in input data, variations in life history, and population dynamics of fish stocks. Thus, it is important to evaluate the impacts of imprecise quantifications of data uncertainty in estimating reference points in the risk assessment and to identify key parameters influencing the determination of a fishery's status. This calls for a sensitivity analysis, which refers to the variation in output of a mathematical model with respect to changes in the values of the model's input.

A sensitivity analysis attempts to provide a ranking of the model's input assumptions with respect to their contribution to model output variability or uncertainty. In a broader sense, sensitivity can refer to how conclusions may change if models, data, or assessment assumptions are changed. A Monte Carlo simulation approach was used in this study for the sensitivity analysis, which allows for the systematic evaluation of model

output with respect to uncertainty in input data. Uncertainty was incorporated into the simulation process in the form of measurement and processing errors. All uncertainties in input data and parameters were examined to determine their effects on the output distributions through numerical experiments (scenarios). By comparing the differences in BRPs calculated under different uncertainty assumptions, the way in which a reference point responds to changes in a particular life history process (growth, selectivity, or mortality) can be evaluated. This helps identify important pathways and parameters for which assumptions about distributional functions contribute significantly to overall uncertainty and aid in focusing data gathering efforts.

The uncertainty analysis and associated sensitivity analysis were applied to the red abalone (*Haliotis rufescens*) in SMI of California. The importance of probing uncertainty in biological reference points is discussed. Key factors that may influence the uncertainty of biological reference points were identified.

Materials and Methods

Growth parameters and their variations are calculated from a hierarchical von Bertalanffy growth model based on the tagging data (Haaker et al 1998; Jiao 2008 submitted). The length at age L_t can be estimated according to the von Bertalanffy growth model

$$(1) \quad L_t = L_\infty(1 - e^{-kt})$$

where L_∞ is the maximum attainable length; k is the Brody growth parameter (Ricker 1975). A model comparison analysis showed that a hierarchical von Bertalanffy model fits the data better and can incorporate the variations of growth among years (Jiao 2008 section 1 in this report). Based on the tagging data analysis, studies (Haaker et al 1998; Jiao 2008 section 1 in this report) have shown temporal variation in growth of the red abalone, calling for the consideration of uncertainty in stock assessment. The joint posterior distribution of all the parameters from the hierarchical growth model is used in estimating the uncertainty of the BRPs in this study.

Weight-at-length relationship was calculated based on the observed length-weight data of red abalone in 2007 (Figure 1). The weight at age W_t can be estimated according to a power relationship and a lognormal distribution error structured:

$$(2) \quad W_t = e^a L_t^b e^{\varepsilon_1},$$

where ε_1 was assumed to follow normal distribution with a mean 0. A Bayesian approach was used to estimate the uncertainty of the parameters.

Fecundity-at-length relationship was calculated based on the observed eggs-length data of red abalone in 2007 (Figure 2). The fecundity at length E_l can be estimated according to this model:

$$(3) \quad E_l = f(L)e^{\varepsilon_2},$$

where ε_2 was assumed to follow a normal distribution with a mean 0.

Three models were compared before one was selected: Gaussian

$$\hat{E}_L = f_1(L) = \frac{1}{\alpha\sqrt{2\pi}} e^{-\frac{(L-L_{\max})^2}{2\alpha^2}}, \text{ power } \hat{E}_L = f_2(L) = aL^b, \text{ and exponential}$$

$\hat{E}_L = f_3(L) = ae^L$. In these three models, L is the length; \hat{E}_L is the estimated number of eggs at length L . In the Gaussian model, a normal distribution curve was used to simulate the fecundity variation over length, with the L_{\max} as the location parameter where fecundity is the highest and α is the shape parameter in the normal distribution curve. A Bayesian approach was used to estimate the uncertainty of the parameters, and the Deviance Information Criterion was used to compare models (Spiegelhalter et al. 2002, 2004; Jiao et al. 2006, 2008).

Because of the high correlation between parameters in these models, the joint posterior distribution of parameters from the hierarchical von Bertalanffy model, the weight-length model, and the fecundity-at-length model were used when estimating the uncertainty of the BRPs.

Length-specific selectivity was modeled as a truncated shape for red abalone according to their management strategy on size limit. That is, selectivity for the commercial fishery is zero if abalone size is under 178 mm and one if not; selectivity for the recreational fishery is zero if abalone size is under 197 mm and one if not (CDFG, Ian et al., 2006).

Natural mortality (M) was assumed to follow a uniform distribution between 0.11 and 0.23 per year, which is from a study based on life histories of northern California red abalone (Rogers-Bennett et al. 2007). A previous study found a natural mortality of 0.15 per year for red abalone in southern California (Tegner et al. 1989). Considering the uncertainty of natural mortality in the previous estimate, the consistency of the mean estimate of 0.15 in the southern area, and the range of 0.11-0.23 in the northern area, the range seems a reasonable approximation of natural mortality with uncertainty. Because of a lack of direct data on natural mortality, a sensitivity analysis using different natural mortality assumptions has been developed in the following uncertainty investigation section.

YPR and EPR models and their BRPs

$F_{0.1}$ was estimated using the yield-per-recruit (YPR) model, which calculates the average yield to be expected under a given pattern of fishing mortality over the life span of a cohort of fish. The YPR model is defined by parameters of life history and fishery processes including individual growth, natural mortality, and gear selectivity.

If we use L_j to represent the size class of j , and the size width $d_j = L_{j+1} - L_j$, then the time interval for the abalone to grow from L_j to L_{j+1} , will be

$$(4) \quad \Delta T_j = \frac{1}{k} \ln \frac{L_{\infty} - L_j}{L_{\infty} - L_j - d_j},$$

where k and L_{∞} are the parameters in the von Bertalanffy growth model. Based on the above equation, natural mortality, fishing mortality, and selectivity coefficients, the commonly used discrete length-based YPR model can be written as

$$(5) \quad C_j = N_j \frac{S_j F}{S_j F + M} (1 - e^{-(S_j F + M) \Delta T_j})$$

$$Y = \sum_j C_j W_j$$

where Y is the attained yield and W_j is the weight of length L_j . N_j is the number of fish at length interval j at the beginning of the year. N_j is estimated from recruitment R as follows:

$$(6) \quad N_j = R e^{-\sum_{g=1}^j (s_g F + M) \Delta T_g}$$

Combining the equation 1, 2 and 3, we get the YPR model as:

$$(7) \quad Y/R = \sum_j \left\{ \frac{W_j S_j F}{S_j F + M} (1 - e^{-(S_j F + M) \Delta T_j}) e^{-\sum_{g=1}^j (s_g F + M) \Delta T_g} \right\}$$

The $F_{0.1}$ was estimated from:

$$(8) \quad \left. \frac{\partial(Y/R)}{\partial F} \right|_{F=F_{0.1}} = 0.1 \left. \frac{\partial(Y/R)}{\partial F} \right|_{F=0}$$

The F_{\max} was calculated from:

$$(9) \quad \frac{\partial(Y/R)}{\partial F} = 0$$

$F_{x\%}$ is estimated using the egg-per-recruit (EPR) model, which calculates the average eggs expected under a given pattern of fishing mortality over the life span of a cohort of fish as a percentage of the eggs expected without fishing. The EPR model is defined by parameters defining life history and fishery processes including individual growth, fecundity, natural mortality, and gear selectivity. Based on the growth, fecundity, natural mortality, fishing mortality, and selectivity coefficients, the commonly used discrete length-based YPR model can be written as

$$(10) \quad Egg = \sum_j E_j N_j$$

where Egg is the attained total eggs and E_j is the fecundity of length L_j . N_j is the number of fish at length interval j at the beginning of the year. N_j is estimated from recruitment R as above (equation 6). Combining the equation 3, 6 and 9, we get the EPR model as:

$$(11) \quad Egg/R = \sum_j E_j e^{-\sum_{g=1}^j (s_g F + M) \Delta T_g}$$

The $F_{x\%}$ was estimated from:

$$(12) \quad \left. \frac{\partial(E/R)}{\partial F} \right|_{F=F_{x\%}} = x\% \left. \frac{\partial(E/R)}{\partial F} \right|_{F=0}$$

We considered estimating $F_{30\%}$ and $F_{40\%}$, making an allowance for applications of these values in other fisheries; we also considered estimating $F_{80\%}$ in this study because of the ten-year moratorium on red abalone fisheries at SMI. L_{entry} is used to represent the minimum catchable size, or the size that enters the fishery.

Uncertainty of BRP estimates from the YPR and EPR models

The uncertainty in estimating $F_{0.1}$ and $F_{x\%}$ using the YPR and EPR models may come from the following sources: uncertainty in the model parameters, which are often estimated from other studies, and natural variability of life history process resulting from variations in biotic and abiotic environments. In this study, some parameters and their variations (e.g., natural mortality) used in estimating $F_{0.1}$ and $F_{x\%}$ were not derived from field data. Therefore, the applicability of these values can be questioned. Thus, we must run a simulation, which involves running a large range of values for the model parameters in deriving the BRPs.

We used the following procedure to estimate the uncertainty considered $F_{0.1}$ and F_{max} : (1) identify the parameters that are likely to have uncertainties in the YPR model; (2) identify the magnitude and nature of errors for each model parameter identified in step 1; (3) randomly sample each parameter from its probability distribution; (4) apply the sampled model parameters to the YPR and EPR model to calculate $F_{0.1}$, F_{max} , and $F_{x\%}$; (5) repeat steps 3 and 4 for N times to yield N estimates of $F_{0.1}$, F_{max} , and $F_{x\%}$; and (6) estimate the probability distribution of $F_{0.1}$ and F_{max} using the results derived in step 5.

Natural mortality is the only parameter that is not estimated based on sound field information. Three simulation scenarios were considered in this study that corresponded to different natural mortality assumptions. Latin hypercube sampling was used to avoid unrealistically large or small values. The first scenario, which was treated as the most reasonable scenario as explained above, used a uniform distribution between 0.11 and 0.23 per year, borrowed from a study on northern red abalone. The second scenario used the estimate from Tegner et al. 1989 with a normal distribution $N(0.15, (0.15 \times 0.3)^2)$, i.e., mean 0.15, and Coefficient of Variation (CV) of 30%. The CV of 30% has been treated as a reasonable assumption for fisheries data (Walters 1998). The difference in estimating $F_{0.1}$, F_{max} , and $F_{x\%}$ between these scenarios illustrated the importance of variability in natural mortality assumptions. Because of the speculations of a higher red abalone natural mortality possibly resulting from climate changes and disease, a high natural mortality scenario was explored to identify possible impacts of increased natural mortality on the BRPs (i.e., Scenario 3; $N(0.30, (0.30 \times 0.3)^2)$). The difference in the estimates of $F_{0.1}$ and F_{max} between the third and first two scenarios reflected the relative importance of natural mortality in estimating uncertainty for $F_{0.1}$, F_{max} , and $F_{x\%}$.

One thousand simulation runs were used to yield stable probability distribution functions (*pdf*) for $F_{0.1}$ and F_{max} . For each simulation run, the same randomly sampled values of model parameters from assumed distributions were used. Boxplots were used to represent the *pdf*s from each scenario under different L_{entry} assumptions.

Because many of the simulated L_{∞} are smaller than the L_{entry} , the minimum size that is catchable to the fishery, which results in F_{BRP} as ∞ , we developed the following equation to address this problem:

$$P_1 = \% \text{ of the } L_{\infty} \geq L_{entry} \text{ in the simulation runs;}$$

$$(13) \quad F_{BRP_{effective}} = F_{BRP} \text{ estimated from the simulated runs with } L_{\infty} \geq L_{entry} ;$$

$$F_{BRP} = F_{BRP_{effective}} / P_1 .$$

Results

The posterior distributions of a and b in the length-weight relationship and their correlation are shown in Figure 3. Among the three models tested in simulating the relationship between fecundity and length of the red abalone, the power model performed the best, which resulted in the lowest Deviance Information Criterion (DIC) (1962.2) compared to the DICs from the Gaussian and exponential models (1963.2, 1965.0). The posterior distributions of α and β in the length-weight relationship and their correlation are shown in Figure 4.

When natural mortality follows a uniform distribution between 0.11-0.23, the most recently used recreational entry value, 178mm, is used as the minimum catchable size; the corresponding median of $F_{0.1}$ is 0.93 and its 90% confidence interval is 0.37-1.24; the corresponding median of $F_{80\%}$ is 0.48 and its 90% confidence interval is 0.16-7.29. If the most recently used commercial entry value, 197mm, is used as the minimum catchable size, the corresponding median of $F_{0.1}$ is 1.53 and its 90% confidence interval is 0.60-2.23; the corresponding median of $F_{80\%}$ is 1.67 and its 90% confidence interval is 0.80-9.52 (Figure 5a).

There are suggestions of increasing the minimum catchable size (John Butler et al. personal communication). From Figures 5 to 7, we can see that the uncertainty of F_{BRPS} increased dramatically if the L_{entry} increases from 198 to higher. The mean values of F_{BRPS} increased dramatically.

F_{max} , $F_{30\%}$, and $F_{40\%}$ have been widely used in many other species. When M follows a uniform distribution between 0.11-0.23, if the most recently used recreational entry value, 178mm, is used as the minimum catchable size, the corresponding median of $F_{30\%}$ is 34.69, and its 90% confidence interval is 8.78-112.24; the corresponding median of $F_{40\%}$ is 6.84 and its 90% confidence interval is 2.93-38.04; and the corresponding median of F_{max} is 1.42 and its 90% confidence interval is 0.39-1.87. If the most recently used commercial entry value, 197mm, is used as the minimum catchable size, the corresponding median of $F_{30\%}$ is infinitive and its 90% confidence interval is infinitive; the corresponding median of $F_{40\%}$ is infinitive and its 90% confidence interval is infinitive; and the corresponding median of F_{max} is 1.99 and its 90% confidence interval is 0.62-3.53 (Figure 5a). In this study only 1,000 Monte Carlo runs were used. Many more runs were needed to calculate the statistics of $F_{30\%}$ and $F_{40\%}$ when the minimum catchable sizes are large. However, considering the fact that these BRPs are not recommended as the management reference points for this fishery (see Discussion), further runs were not added.

The mean estimates of the BRPs increased when the mean of M increased. The uncertainty of the BRP estimated from different M assumptions varies. The uncertainty of the BRPs was lowest when M was assumed to follow a uniform distribution between 0.11 and 0.23; it increased when M was assumed to follow a normal distribution with mean 0.15 and further increased when M increased to 0.30 (Figures 5, 6, and 7).

Comparing the varying minimum entry values of the red abalone and the corresponding yield-per-recruitment, we can see that while F can be high when minimum catchable size is high, the corresponding yield can be much lower after balancing the

population size and the fishing mortality. Compared with the yield per recruit when $F_{0.1}$ was used, the yield per recruit when F_{\max} was used was not more than 5%, but the fishing mortality was much lower (Figure 5b, 6b and 7b).

Discussion

This study suggests that incorporating the uncertainty of BRPs is important when YPR and EPR models are used. The uncertainty of the BRPs must be quantified instead of using a deterministic estimate of BRPs. Ignoring uncertainty may lead to incorrect conclusions regarding management solutions. Further risk assessment is needed based on the uncertainties of BRPs when evaluating management strategies (see 2.4).

The sensitivity analysis suggested that uncertainty in natural mortality was very important in estimating BRPs. This result is consistent with previous studies (Chen and Wilson 2002; Jiao et al. 2004). Parameters used in the YPR and EPR models are usually from biological sampling in the field such as age-length, length-weight, and fecundity-length relationships. While natural mortality estimation is always a challenge with most marine species, reliable estimations of natural mortality and its associated uncertainty is extremely critical in YPR and EPR analyses.

A recent study on red abalone EPR analysis showed that EPR model results were sensitive to growth parameters (Leaf et al. 2007). The estimated high $F_{0.1}$ is strongly because of the low L_{∞} developed from the hierarchical growth model. Higher $F_{0.1}$, compared to the natural mortality assumption in this study, implies problems in this analysis. Further validation of the biological and fisheries parameters is needed. Leaf et al. (2007) provided more sensitivity analysis based on a deterministic EPR model; it may also be considered when developing management strategies based on this type of models.

Quantification of uncertainty in life history and fishery parameters is an essential step for estimating uncertainty of $F_{0.1}$ and F_{cur} . Uncertainties can arise from the variation in the statistical estimation of the parameters and natural variability in the parameters among cohorts and geographic areas. However, it is unlikely that “correct” values can be identified to define the uncertainty for the parameters. In this study, the joint distribution of k and L_{inf} from a hierarchical growth model was used, which incorporated uncertainty varied temporally. Further study on the spatial and temporal variation of these life history parameters will help to develop long and short BRPs.

Between BRPs from YPR and EPR models, we can see that BRPs from YPRs are more stable and precise compared to those from EPRs, which tend to have wider confidence intervals. At the same time, yield per recruit when $F_{0.1}$ is used is close to when F_{\max} is used, but $F_{0.1}$ is considerably lower than F_{\max} . So, $F_{0.1}$ is recommended among all the BRPs from per recruitment analyses.

When L_{entry} increases from 198mm to higher, F_{BRPS} are not recommended for management purposes because of both the high F_{BRPS} values and high uncertainties of them. F_{BRPS} corresponding to L_{entry} of 199mm tend to be much more stable and are recommended even when L_{entry} is increased to avoid extirpating the red abalone population of larger individuals.

The yield per recruit tends to be high when the L_{entry} is lower among all the L_{entry} s studied. We do not recommend decreasing the current commercial and recreational minimum catchable size because of the high uncertainty of the YPR estimates themselves, and because the high uncertainty of the population status and the low mean density of the

population size. At the same time, per recruitment models assume constant recruitment which is obviously not true for red abalone. When reference points are used for management of this species developed from the YPR and EPR models, large variations in recruitment must be considered. Therefore, uncertainty in BRPs derived from the EPR and YPR models may be considered when developing precautionary approaches and managing the fisheries of red abalone, particularly in the San Miguel Island fishery. The high F-based BRPs from YPR and EPR models are much higher than natural mortality assumption, which needs to be considered in a precautionary management framework.

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Figure 1: Length-weight relationship of red abalone.

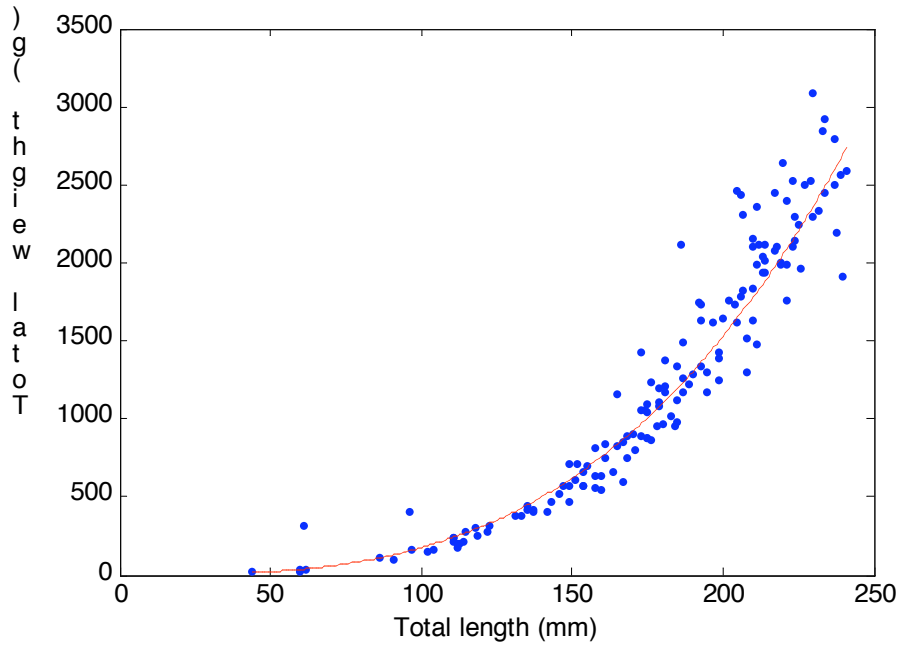


Figure 2: Fecundity analysis of red abalone based on 2007 survey.

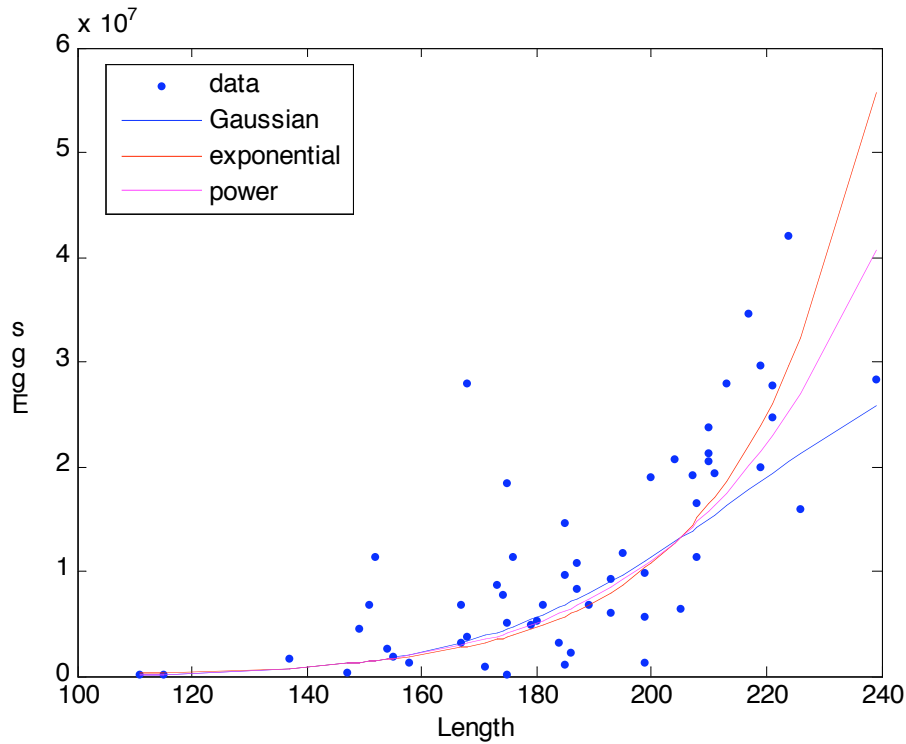


Figure 3: Posterior distributions of a and b in the length-weight relationship and their correlation.

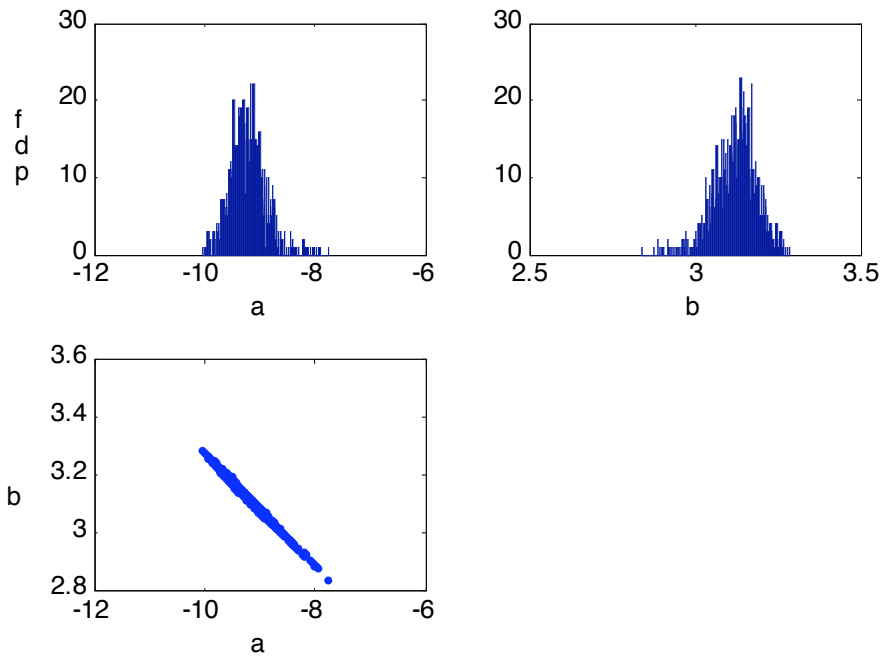


Figure 4: Posterior distributions of α and β on the power fecundity model and their correlation.

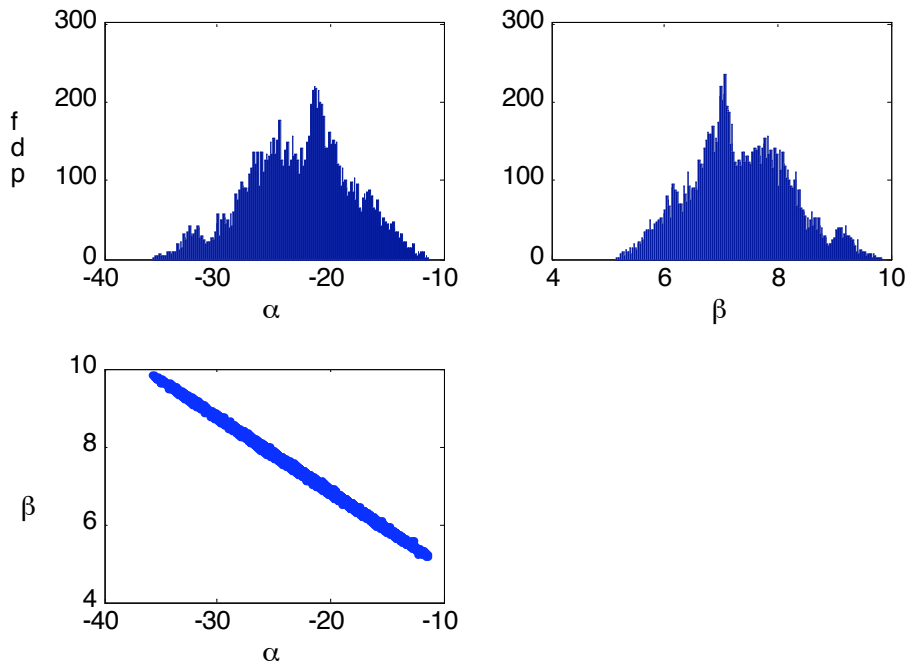


Figure 5a: $F_{0.1}$, F_{\max} , $F_{30\%}$, $F_{40\%}$ and $F_{80\%}$ estimations when M of a uniform distribution between 0.11 and 0.23 was used for all length groups.

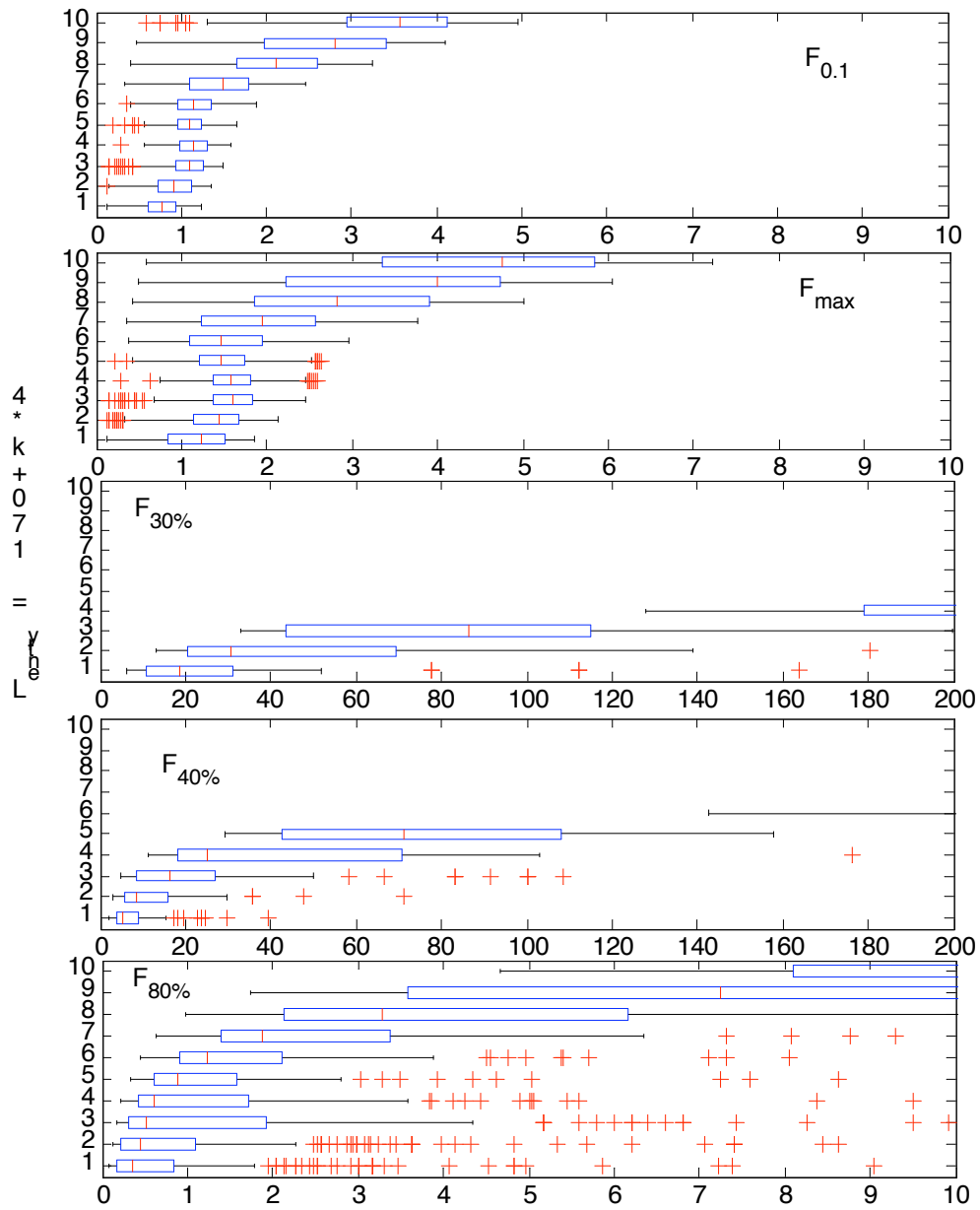


Figure 5b: YPR estimations when M of a uniform distribution between 0.11 and 0.23 was used for all length groups and when F equaled $F_{0.1}$ or F_{max} .

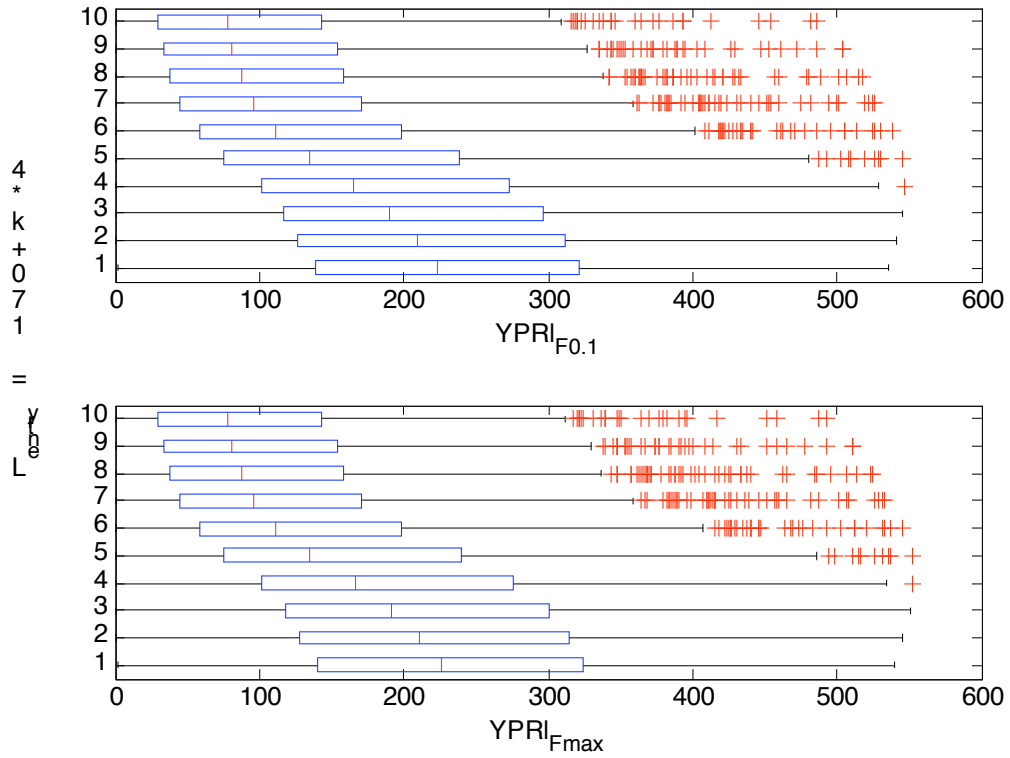


Figure 6a: $F_{0.1}$, F_{\max} , $F_{30\%}$, $F_{40\%}$ and $F_{80\%}$ estimations when mean of $M=0.15$ with $CV=30\%$ was used for all length groups.

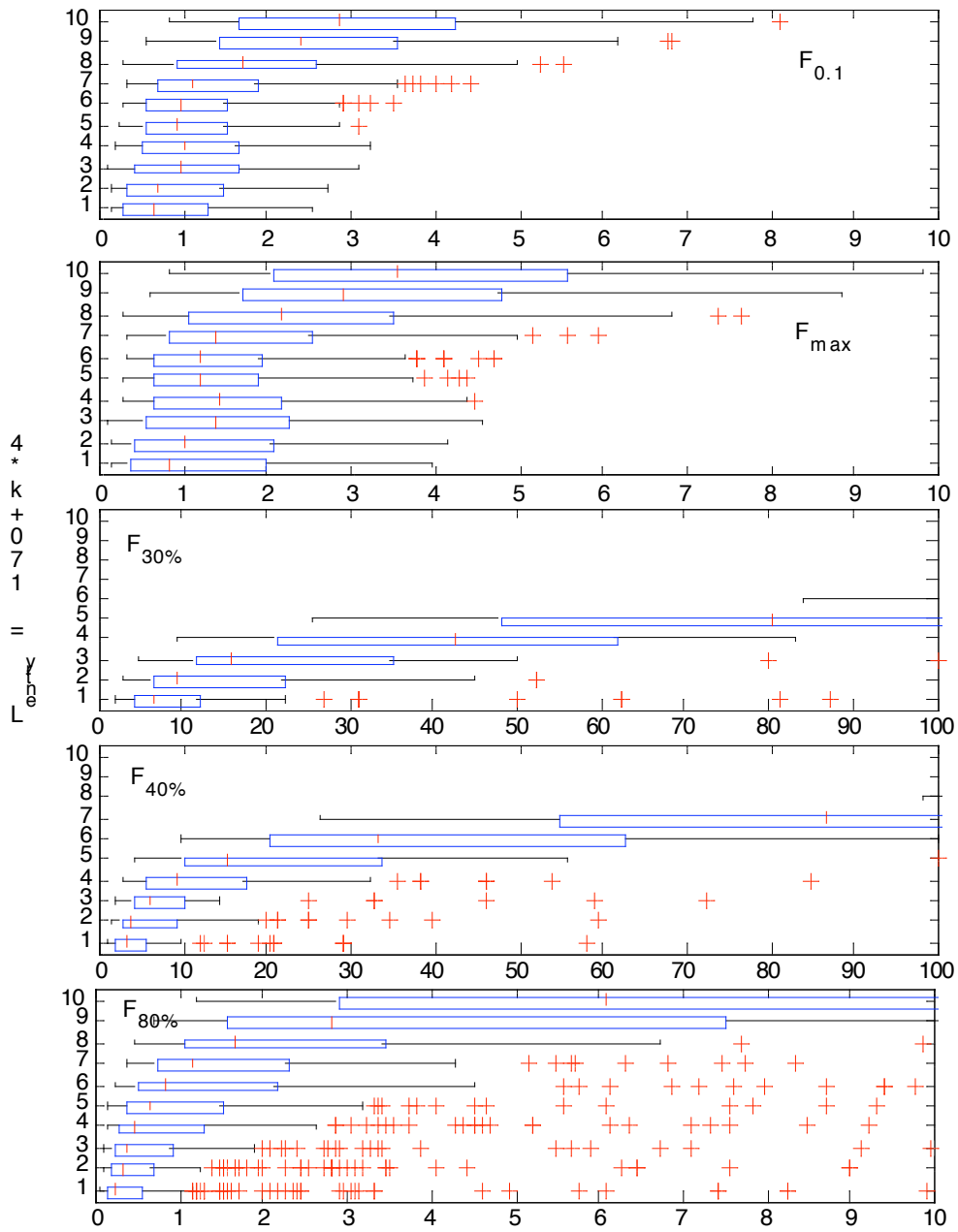


Figure 6b: YPR estimations when mean of $M=0.15$ with $CV=30\%$ was used for all length groups and when F equaled $F_{0.1}$ or F_{max} .

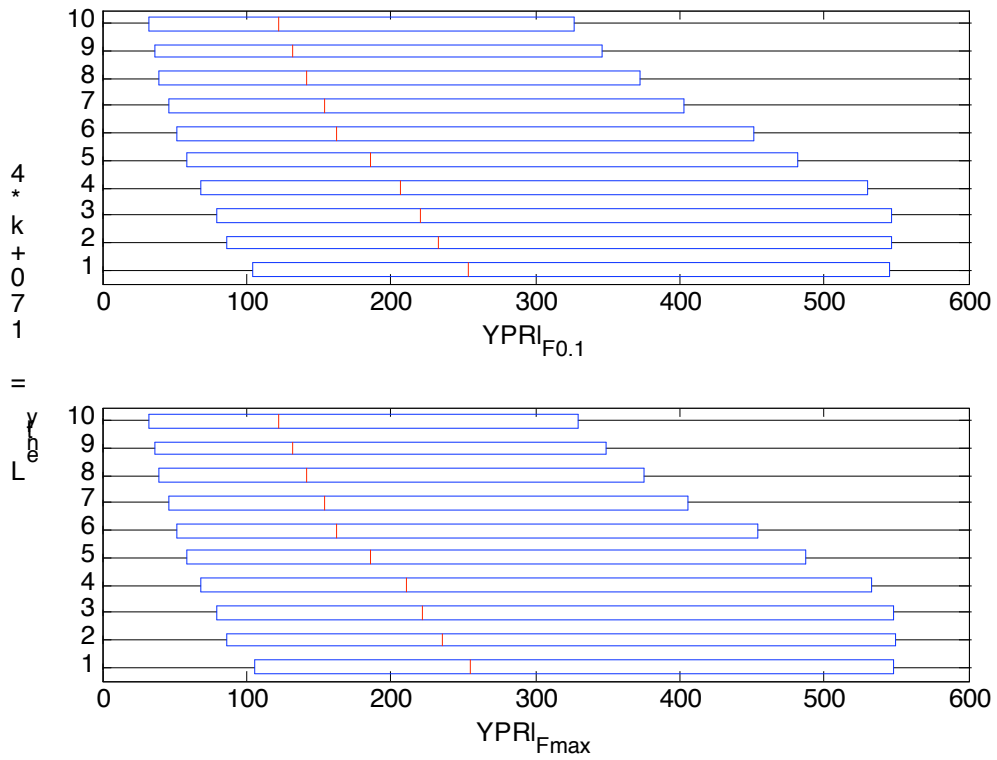


Figure 7a: $F_{0.1}$, F_{max} , $F_{30\%}$, $F_{40\%}$ and $F_{80\%}$ estimations when mean of $M=0.30$ with $CV=30\%$ was used.

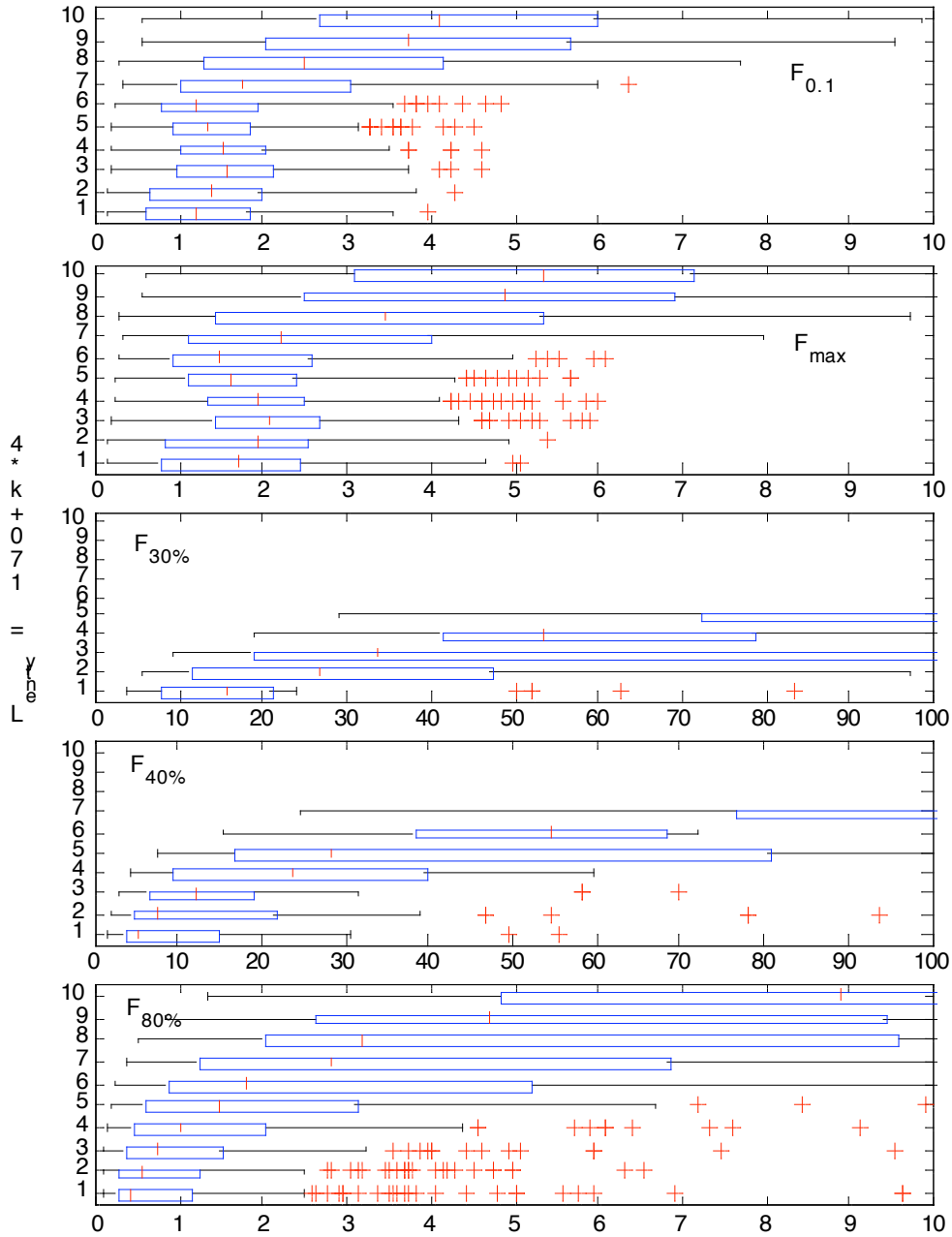
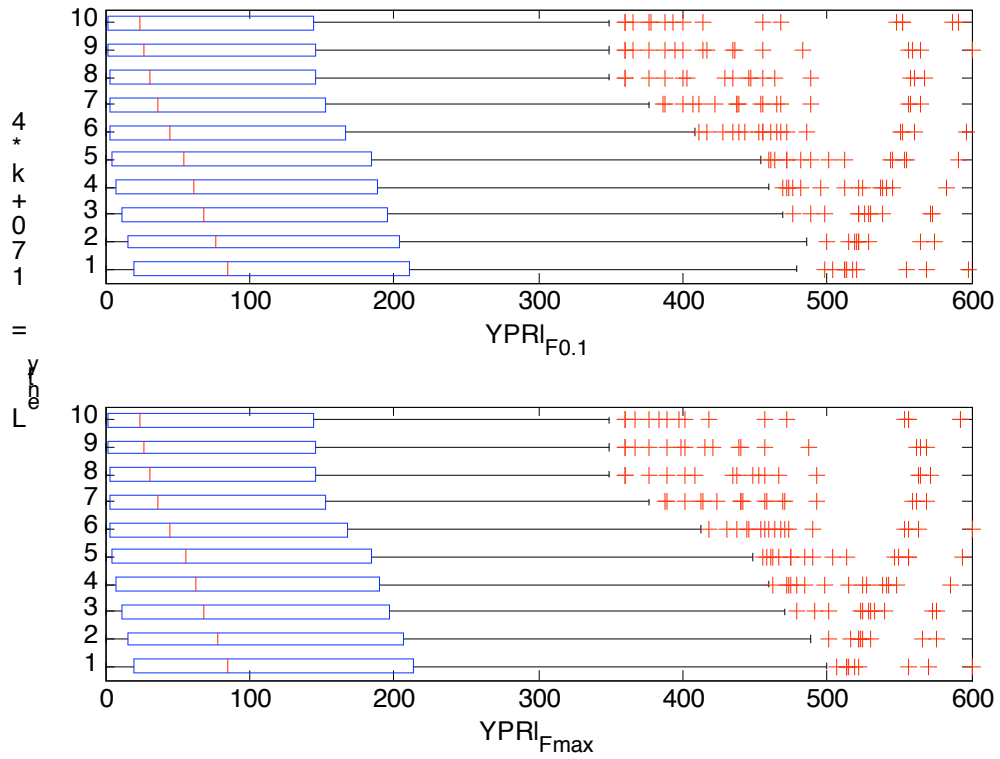


Figure 7b: YPR estimations when mean of $M=0.30$ with $CV=30\%$ was used for all length groups and when F equaled $F_{0.1}$ or F_{max} .



2.3 Modeling San Miguel Island red abalone (*Haliotis rufescens*) population dynamics using catch-at-age/size model

Abstract

In this section we used a statistical catch-at-age model to estimate fishing mortality, population size, and biological reference points for a potential red abalone fishery at San Miguel Island (SMI). Age-aggregated relative abundance and length-frequency indices from the fishery-independent surveys were used in the model. Through this study we found that the population size was still low in 2007 compared to historical population size. The stock recruitment relationship was weak, so biological reference points $F_{0.1}$ from yield-per recruitment (YPR) model were suggested rather than an F_{msy} from the age structured models and the YPR model. However, our estimated $F_{0.1}$ is much higher than the estimated historical fishing mortality, which suggested possible biases when using biological reference points from per-recruitment models. The stock recruitment relationship tends to be weak, and a period of a strong and weak recruitment pattern was observed from the age structured models. The age-aggregated relative abundance indices were of high uncertainty, and the length frequency samplings were very limited considering the years that samples were collected and the spatial coverage of the samples. This study suggested that to better manage this fishery, empirical biological reference points may be used, such as natural mortality as a proxy of F_{msy} .

Introduction

San Miguel Island is one of the islands located in the Southern California Bight. The SMI red abalone fishery, like many other abalone fisheries, was depleted in the early 1990s, and the fishery has been closed since 1997. Recent surveys suggest possible signals of recovery for this important fishery; however, formal assessment on this population is needed.

There are many sources of data for the SMI red abalone fishery including commercial and recreational catches and current and historical (back to 1983) statistics on abalone density and relative abundance: the CDFG recreational survey (RS), CDFG fishery-independent surveys (FIS), the Channel Island National Park (CINP) fishery-independent survey, CDFG fishery-independent swim surveys (FISS), Jack Engle swim survey (JEngle), and the Partnership for Interdisciplinary studies of Coastal Oceans (PISCO) survey data. The FIS surveys also sampled the lengths of abalone observed. A catch-at-age model was then developed for stock assessment and population dynamics modeling of this fishery. F_{msy} was estimated as the biological reference points for management purposes, consistent with the Magnuson-Stevenson Act (Magnuson-Stevenson 1999).

Red abalone populations have shown large variation in recruitment/cohorts. Process error is important to consider in the variability of these situations (De Valpine and Hasting 2002; Jiao et al 2008). We also considered population growth rate variation by using an autoregressive process. A state-space surplus production model was then developed to model the dynamics of this population.

The model was implemented in a Bayesian framework and analyzed using Markov Chain Monte Carlo (MCMC) simulation. A Bayesian method was used to

estimate vital parameters of population dynamics and fisheries management (Chen et al., 2003). Bayesian approaches have been used increasingly in assessing and managing fisheries stocks because of their flexibility in incorporating data from different sources and their ability to provide results for risk analyses of alternative management strategies and incorporate prior knowledge of the fisheries into the assessment process.

Red abalone data are restricted because of limited efforts allocated towards collecting data from both fishery-dependent and fishery-independent sources. Recent survey data have helped us to understand the basis of population size, and are especially useful when time series of abundance indices are lacking. Survey information on population size can be used as prior knowledge in a Bayesian framework to help us better simulate the population dynamics of red abalone.

For many fisheries studies, Bayesian inference may be more appropriate than frequentist inference because it can incorporate prior knowledge on fisheries into parameter estimation (Hilborn and Walters 1992; Walters 1998). Such prior knowledge for most fisheries can be obtained from biological and ecological theories, comparison to other fisheries, fishers' experience, and scientists' insights into the fisheries being studied. The use of likelihood functions in Bayesian inference makes it easy to incorporate data of various sources and uncertainties associated with the data (Taylor et al. 1996). It has been predicted that Bayesian inference will be used in most fish stock assessment studies in the near future (Hilborn and Walters 1992).

Methods

Data sources

Catch. Commercial landings were obtained from the California Department of Fish and Game (CDFG), which collects landing data directly from seafood dealers located in the state of California. Recreational catch estimates were obtained from Commercial Passenger Fishing Vessels (CPFV) logbook data, which are administered by the CDFG. CPFVs are the charter boats that take recreational fishers out fishing. The CDFG has been sampling recreational fishing charter boats operating since 1978 (Figure 1).

Relative abundance. Time series of relative abundance were available from six sources: the CDFG recreational survey (RS), CDFG fishery-independent surveys (FIS), Channel Island National Park (CINP) fishery-independent survey, the CDFG fishery-independent swim surveys (FISS), JEngle swim survey (JEngle), and the PISCO survey data. Because of the short time series and/or low spatial coverage of the FISS, JEngle, and PISCO, these were not used in this study after discussion with scientists John Butler and Paul Crone from SWFSC and Ian Taniguchi and Laura Rogers-Bennett from CDFG. The RS was also not used because the fishery was regulated on a small daily bag limit (two or four abalone per day) causing the CPUE to not truly and directly reflect abundance. The bag limit was furthermore reduced from four abalone per day to two per day during the time frame of the data collection, so the drop in CPUE was artificial. The CINP Kelp Forest Monitoring site, Hare Rock, was eliminated because abalone abundance dropped to zero around 1990. Hare Rock is located in the NE zone of the island where densities of abalone have always been low, and the site is now within a reserve. Channel Island National Park Kelp Forest Monitoring site, Miracle Mile, was eliminated because densities were 100 times larger than other abundance indices. This is

due to the site being placed specifically in a high density abalone area, whereby it is not a randomly sampled location, and not reflective of overall population abundance.

The FIS and CINP Kelp Forest Monitoring site of Wyckoff Ledge (WL) data can be seen from in Figure 2. Because of the heterogeneity of the red abalone distribution around SMI, the FIS surveys were divided into three groups according to their survey locations: NW, SW and SE (Figure 2a). We also considered the FIS without splitting them according to locations (Figure 2b). Different data combinations, shown as scenarios, were used in the sensitivity study (Table 1).

Length frequency. Length-frequency data from the fishery independent surveys (FIS) were used (Figure 3).

The statistical catch-at-age model

A statistical catch-at-age model (Hilborn and Walters 1992; Quinn and Deriso 1999) based on the available red abalone fishery data was written as:

$$\begin{aligned}
 E(N_{a+1,y+1}) &= N_{a,y} e^{-F_{a,y}-M} \\
 C_{i,a,y} &= \frac{F_{i,a,y}}{F_{i,a,y} + M} N_{a,y} (1 - e^{-F_{i,a,y}-M}) \\
 E(C_{i,y}) &= \sum_a C_{i,a,y} \\
 F_{i,a,y} &= F_{i,y} S_{i,a} \\
 N_y &= \sum_a N_{a,y} \\
 E(I_{j,y}) &= q_j N_y \\
 E(P_{i,L,y}) &= \frac{N_{i,L,y}}{\sum_a N_{i,L,y}}
 \end{aligned}$$

An age-length relationship was used to calculate $N_{i,L,y}$ from $N_{i,a,y}$ where a is age, y is year, i is the i^{th} fishery (commercial or recreational; $i = 1$ or 2), j is the j^{th} abundance index (FIS and CINP-ML; $j = 1, 2, 3$ or 4 depend on scenarios, see Table 1 for explanation), $N_{a,y}$ is the population size of age a fish in year y , $C_{i,a,y}$ is the catch of age a in year y by the i^{th} fishery, $F_{i,a,y}$ is the fishing mortality rate of age a in year y by the i^{th} fishery, and $M = 0.15$ is the natural mortality rate (Tegner et al. 1989). We also assumed M is unknown with a prior of uniform distribution between 0.11 and 0.23 when a Bayesian approach was used. $I_{j,y}$ is the j^{th} abundance index observed in year y ; q_j is the catchability coefficient, which calibrates the relationship between the j^{th} abundance index and population abundance.

To quantify the uncertainty in this model, we used an observation-process-error estimator, which considers both the process error in the equation of population size ($E(N_{a+1,y+1})$) and the observation error in the equations of abundance indices ($E(I_{j,a,y})$) and catch ($E(C_{i,a,y})$) (model 1). We assumed lognormal error structures for both process

error and observation errors, which gave the corresponding objective functions for the estimator as follows. For process error:

$$\varepsilon_N \sim N(0, \sigma_N^2); l_N = \frac{1}{2\pi\sigma_N^2} \sum_y \sum_a (\hat{\varepsilon}_N)^2;$$

for measurement error in fishery dependent catch:

$$l_{i,C} = \frac{1}{2\pi\sigma_{i,C}^2} \sum_y [Ln(C_{i,y}) - Ln(\hat{C}_{i,y})]^2 ;$$

for measurement error in the abundance indices:

$$l_{j,I} = \frac{1}{2\pi\sigma_{j,I}^2} \sum_y [Ln(I_{j,y}) - Ln(\hat{I}_{j,y})]^2 ;$$

for measurement error in the LFQ:

$$l_{i,P} = -n_i \sum_y \sum_L P_{i,L,y} \log(\hat{P}_{i,L,y}).$$

The total objective function is the sum of (2), (3), and (4):

$$L = \sum_i l_{i,C} + \sum_j l_{j,I} + \sum_j l_{j,P} + l_N.$$

SMI red abalone abundance indices have fluctuated greatly because of the occurrence of a few very strong year classes. Therefore, it is critically important to consider process errors in the model (Equation 2). Recent research (De Valpine and Hasting 2002) on comparison of observation-error and observation-process-error estimators also suggests the importance of using observation-process-error estimators (Equation 5).

The time series of population size is estimated by projecting the abundance forward from the start of the annual catch series with the initial abundance $N_{a,1978}$, recruitment, and $F_{i,y}$ and $S_{i,a}$ as parameters (Quinn and Deriso 1999). Because annual recruitments of red abalone were observed to fluctuate dramatically over time, recruitment each year was estimated directly from the statistical catch-at-age model instead of using a built-in stock recruitment relationship.

We estimated F_{msy} and N_{msy} by combining YPR and SR models (Shepherd 1982). We also considered the application of $F_{0.1}$ developed from the YPR analysis as the proxy of F_{msy} instead of the F_{msy} because of the weak relationship between spawning stock size and recruitment as shown in the result. Population abundance under $F_{0.1}$ and F_{max} were both considered as proxies of N_{msy} . Only abalone >100mm were considered in both SSN and SSN_{msy} estimations. Because abalone mature at length 100mm, we treated abalones ≥ 100 mm as the spawning stock. However, fecundity at size can vary. We do not have estimates of % mature abalones in different length groups.

Penalized likelihood and Bayesian approaches

We used a penalized likelihood approach to estimate parameters by assuming that $M=0.15$ from 1950 to 2007 or from 1980 to 2007. Assumptions of priors were used as penalties (ref). An automatic differentiation algorithm was used and the program TOMLAB (TOMLAB 2004) was used to estimate parameters.

We also used a Bayesian approach to estimate parameters by assuming that M follows a uniform distribution between 0.11 and 0.23, the same assumption used in the per recruitment analysis. We used data from 1980 to 2007 in this case since no age-length frequency and abundance indices were available before the 1980s. A Bayesian Markov Chain Monte Carlo simulation would require too much time to compute the parameter estimation if data as far back as 1950 were used without calibration information for population size and structure before 1980.

Bayesian implementation requires specification of prior distributions on all unobserved quantities. Non-informative priors (here, wide uniform distribution) were used for precision parameters, defined as the reciprocal of the variance of the error terms in the process and observation equations. Wide non-informative uniform distributions were used for recruitment, age-specific abundance, and fishing mortality.

For the statistical catch-at-age model, selectivity was assumed to be either zero or one for both commercial fisheries and recreational fisheries. If the abalone reaches the minimum harvestable size, the selectivity is one; otherwise, it is zero. The population sizes of 2006 and 2007 were used for the sensitivity analysis as used as informative information.

Determining when random draws have converged to the posterior distribution is a critical issue when using Markov Chain Monte Carlo methods (including Metropolis-Hasting within Gibbs sampling). We used three methods: monitoring the trace for key parameters, diagnosing the autocorrelation plot for key parameters, and Gelman and Rubin statistics (Spiegelhalter et al. 2004). Three chains were used. After several sets of analysis, the first 300,000 iterations with a thinning interval of five were discarded from each chain and another 100,000 iterations with a thinning interval of five were used in the Bayesian analysis. The high number of iterations validates the convergence of the chains, and the thinning interval eliminates autocorrelation.

Sensitivity analysis

To evaluate uncertainty in the various sources of relative abundance data, the sensitivity of model outcomes (i.e., the robustness of results to the data sources) was tested through four different weighting strategies (scenarios) of the data sources (Table 1). We compared results from historical survey data without region-specific differences (Scenario 2 and 3) with region-specific historical survey indices (scenarios 1 and 4); we also compared results from using CIMP WL density surveys (scenarios 1 and 2) with not using CIMP WL surveys (scenarios 3 and 4). The population size surveys in 2006 and 2007 are the most reliable information among all the surveys and were therefore used as informative priors in all of the scenarios (Table 1). Length frequency information from the fishery independent survey was used in all of the sensitivity analyses because it was the only information available to help diagnose the structure of the population.

Likelihoods of catch and length frequency were weighted 10 times higher than relative abundance indices because catch and length frequency data for this species are of higher quality than relative abundance indices. However, in the Bayesian analysis we

used equal weight among likelihoods of catch, length frequency and abundance indices. Extra sensitivity analyses for the weight of different types of datasets were not added, due to the data quality of abundance indices and the time needed to run extra Bayesian analyses.

Results

The relative abundance indices suggested a vague trend of the population from the 1980s to 2000s (Figures 2 and 3). The indices do not agree with each other. These relative abundance indices did not reflect the previous conclusion of decreased population in mid 1990s and did not reflect the need to close the fishery in 1997.

The MLE parameter estimate using data from 1950 to 2007 showed that recruitment was highly periodic and that recruitment could be very low in some years (Figure 4a). The SR relationship was weak, and no clear relationship was found (Figure 4b). Recruitment tended to be high when spawning stock size was high. Population size declined overall from the 1950s to 2000s with some intermittent periods of population increase (Figure 5). The high fishing mortality period occurred from the early 1980s to mid 1990s. After the moratorium, there was no clear increasing trend in population size (Figure 5). The fits of the catch, length frequency, and abundance indices are shown in Figure 6. Catch data and length frequency data were fitted well, but relative abundance indices were not fitted as well. This reflects the quality of these different types of datasets.

The MLE parameter estimate using data from 1980 to 2007 showed that recruitment was highly periodic and that recruitment could be very low in some years (Figure 7a). The SR relationship was weak and no clear relationship was found (Figure 7b). Population size declined overall from the late 1980s to 2000s with some periods of population increase (Figure 8). The high fishing mortality period happened from the late 1980s to the mid 1990s. After the moratorium, there was no clear increasing trend in population size (Figure 8). The fits of the catch, length frequency, and abundance indices are shown in Figure 9. Catch data and length frequency data were fitted well, but relative abundance indices were not fitted as well. This reflects the quality of these different types of datasets.

The MLE parameter estimate using data from 1980 to 2007 with equal weight of different types of data (i.e., catch, relative abundance indices and length frequency) resulted in similar trends as the estimates from the Bayesian approach. Natural mortality estimates tended to be small, and the posterior modes were all close to 0.11 (Fig 10a). The SR relationship was weak, and no clear relationship was found (Figure 10b). Recruitment was high in the early 1990s but could be very low in some years (Figure 10d). Fishing mortalities were high before 1995.

F_{msy} and N_{msy} estimated by combining YPR and SR models (Shepherd 1982) varied largely among scenarios with values between 0.03 and 0.16. Considering that spawning stock size is hard to define and that there was a weak relationship between recruitment (age-1 abalone) and spawning stock size (size of population ≥ 100 mm length), reference points from this approach are not recommended.

Discussion

The stock recruitment relationship of this species is weak, so the biological

reference point $F_{0.1}$ from the yield-per recruitment (YPR) model is usually suggested rather than an F_{msy} from the age structured models and YPR model (Shepherd 1982). However, in this study the estimated BRPs from per-recruitment analyses were much higher than historical F , which suggests a possible bias of using these BRPs. An empirical biological reference point such as natural mortality (Patterson 1992) is therefore suggested as a proxy of F_{msy} based on this study. Population size was highest in 1950 during the time period being assessed and is therefore suggested as the proxy for SSN_{msy} . With more high quality data collected, it may be possible to calculate better BRPs in the future.

The results with catch and length frequency data weighted high and relative abundance indices weighted low matched the historical observations. The results with equal weight on different types of data did not reflect the quality of the data and also did not reflect the observed historic population trends. We therefore recommend that the results with catch and length frequency data weighted higher be used for management purposes.

Age-aggregated relative abundance indices were of high uncertainty, and the length frequency sampling had very limited years of collection and spatial coverage. These results and the high data uncertainty suggest that a precautionary management strategy is needed to better manage this fishery.

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Table 1: Scenarios used in the analysis.

Scenarios	Weight of historical survey without region differences	Weight of region specific historical survey	Weight of WL survey	Weight of length frequency data sets	Weight of survey abundance of 2006 and 2007
1	0	1	1	1	1
2	1	0	1	1	1
3	1	0	0	1	1
4	0	1	0	1	1

Figure 1: Catch (in number of abalone from commercial and recreational fisheries).

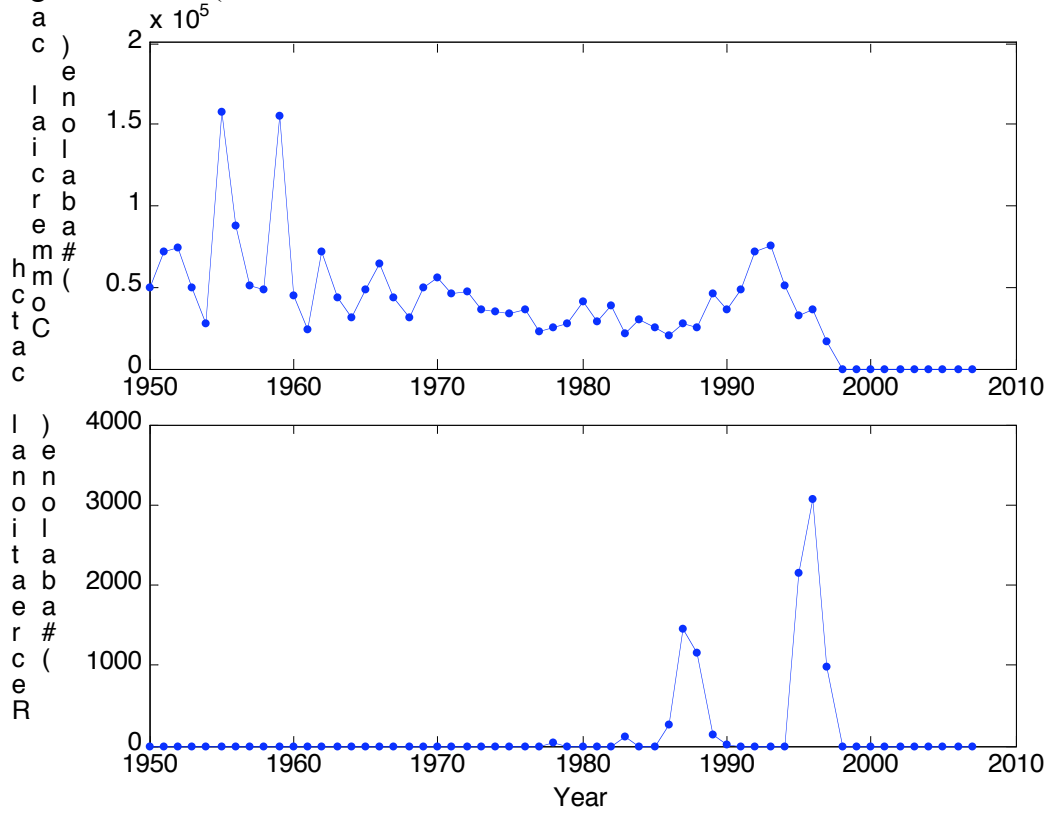
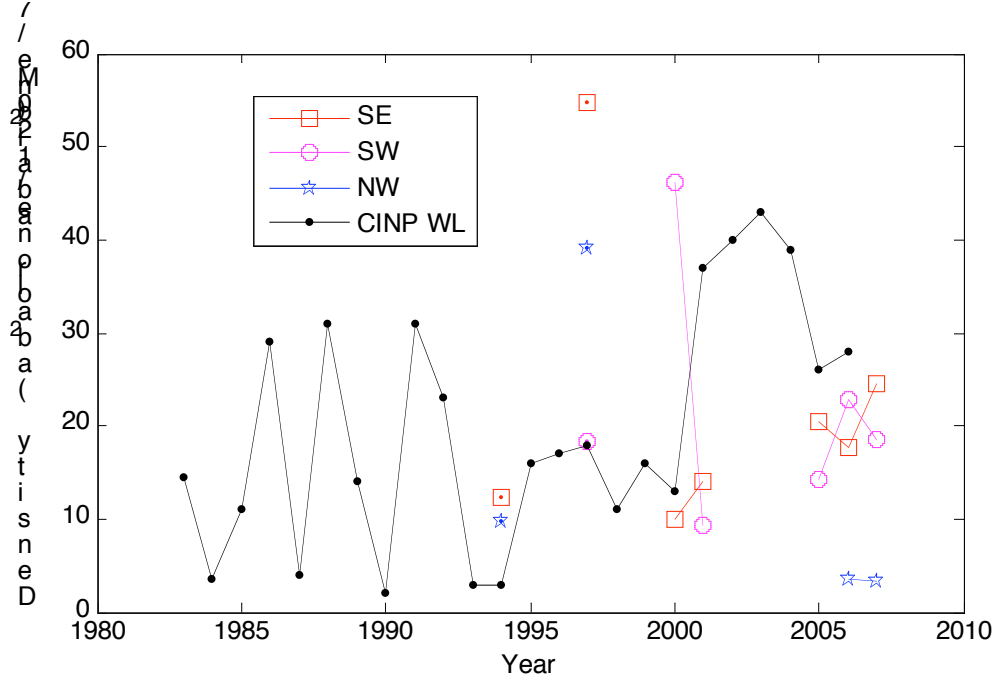


Figure 2: Abundance indices from fishery independent and dependent surveys.
2a



2b

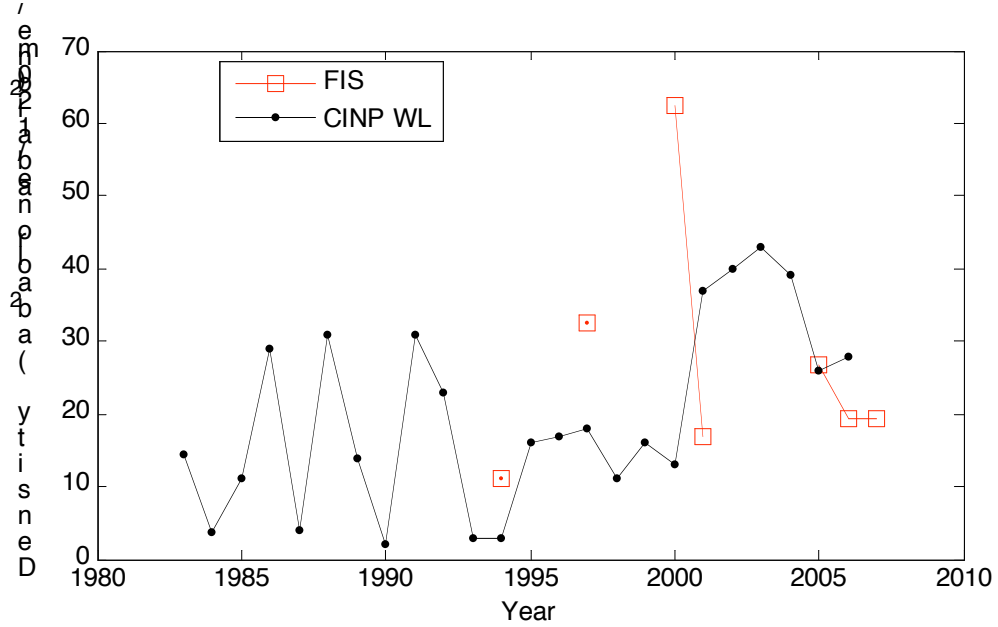


Figure 3: Length frequency from fishery independent surveys on the population.

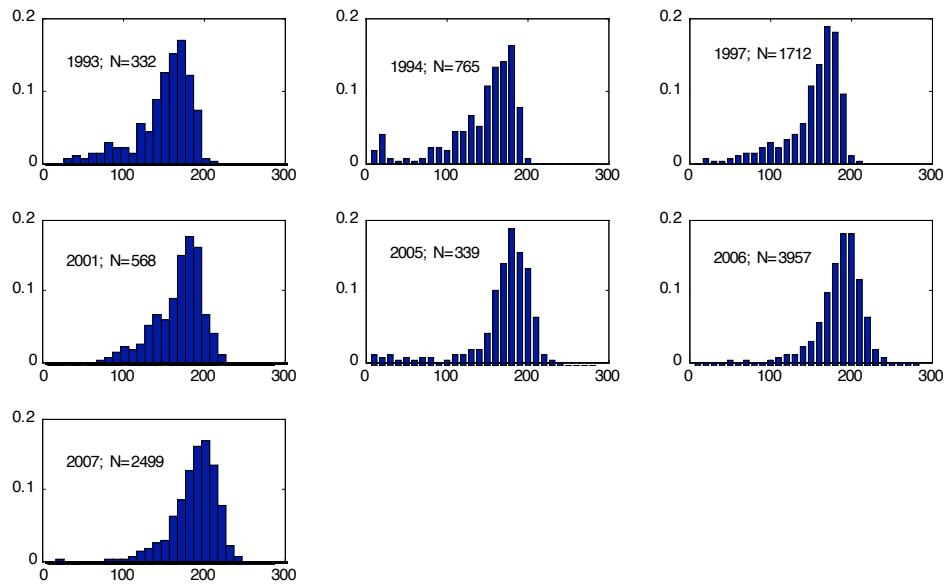
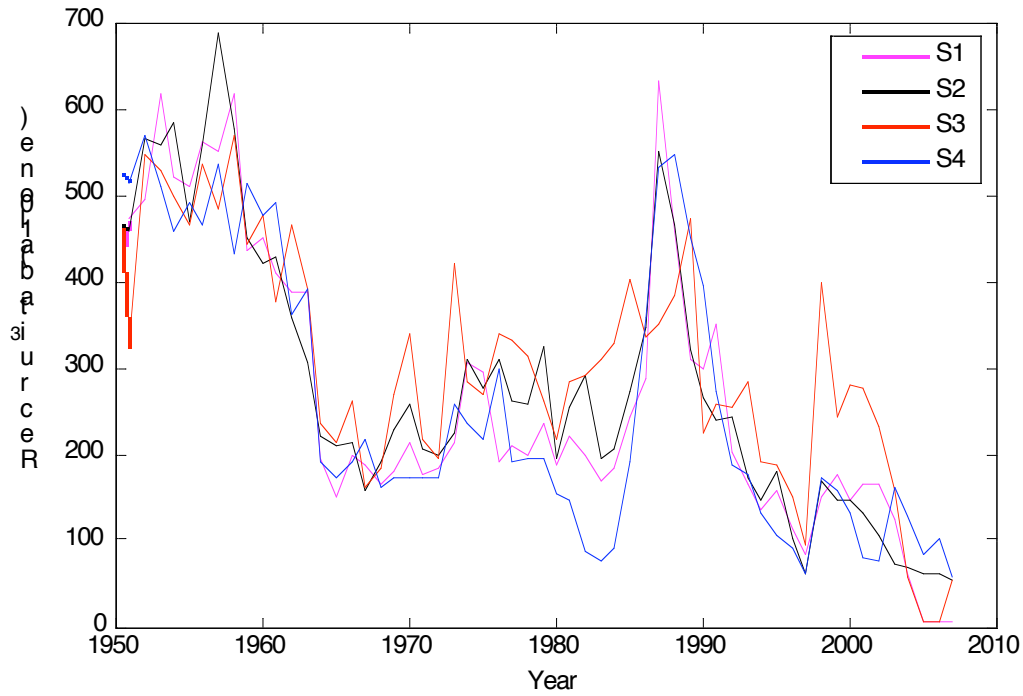


Figure 4: Recruitment estimates.
4a



4b: Stock recruitment relationship.

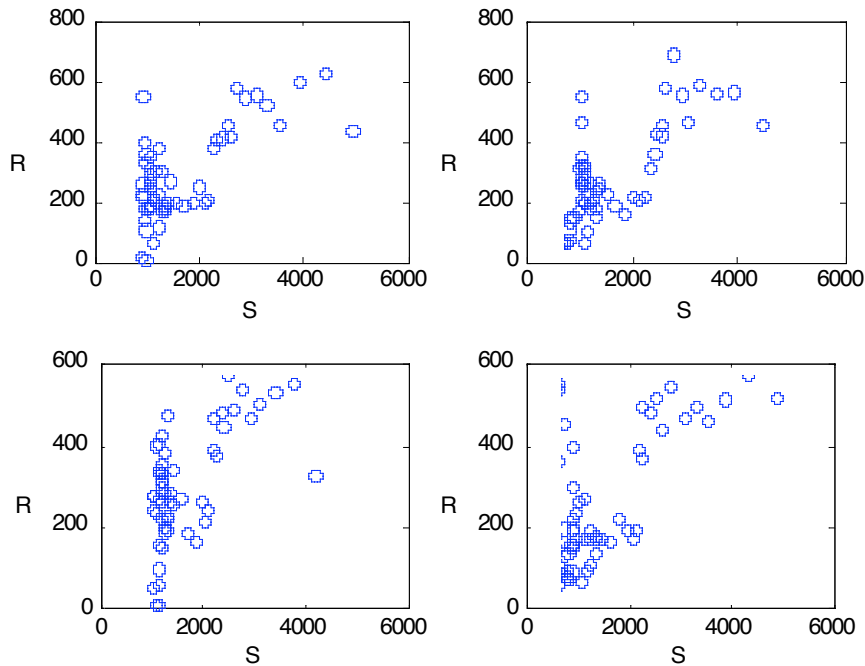


Figure 5: Estimates of population abundance and fishing mortality when data from 1950-2007 were used.

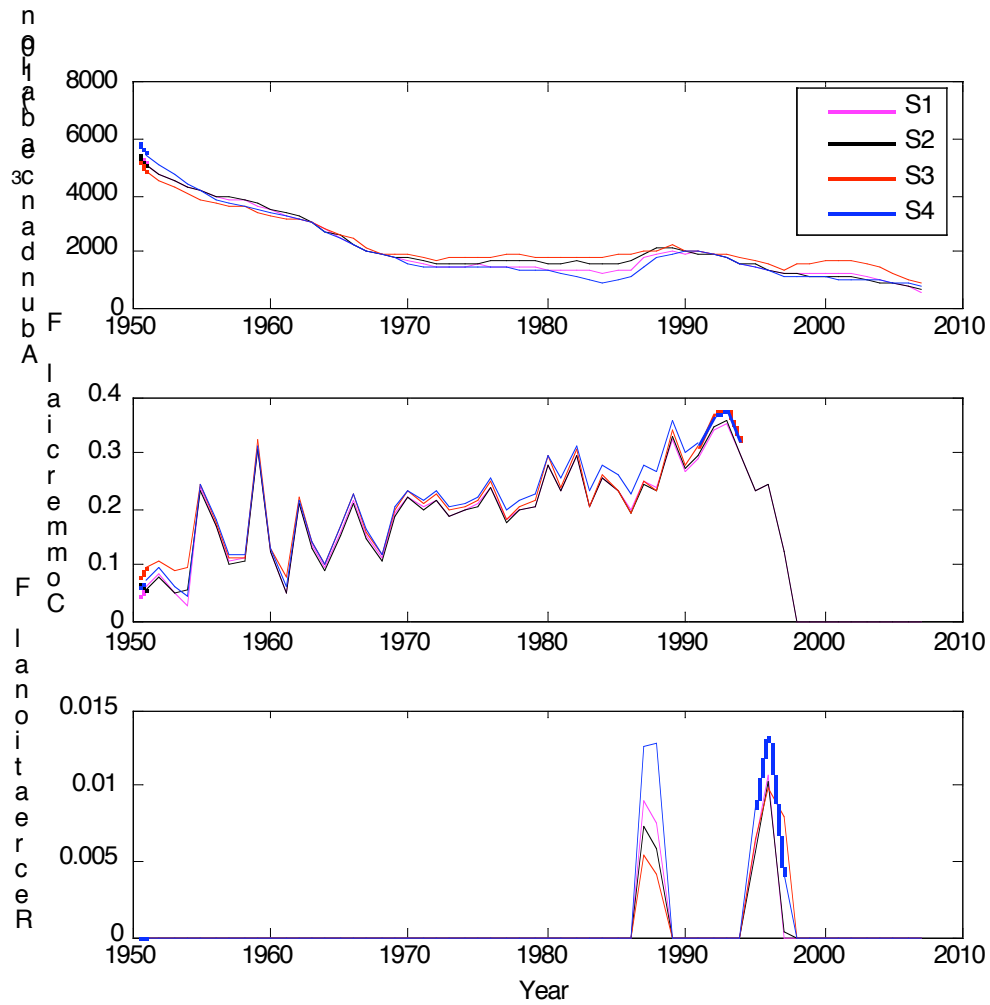
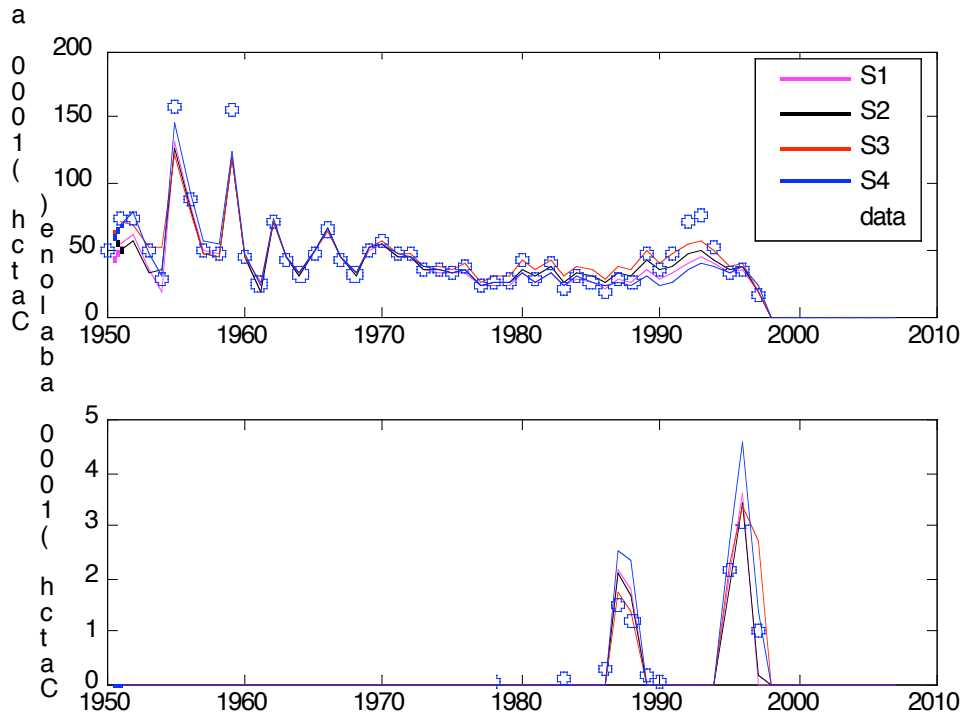
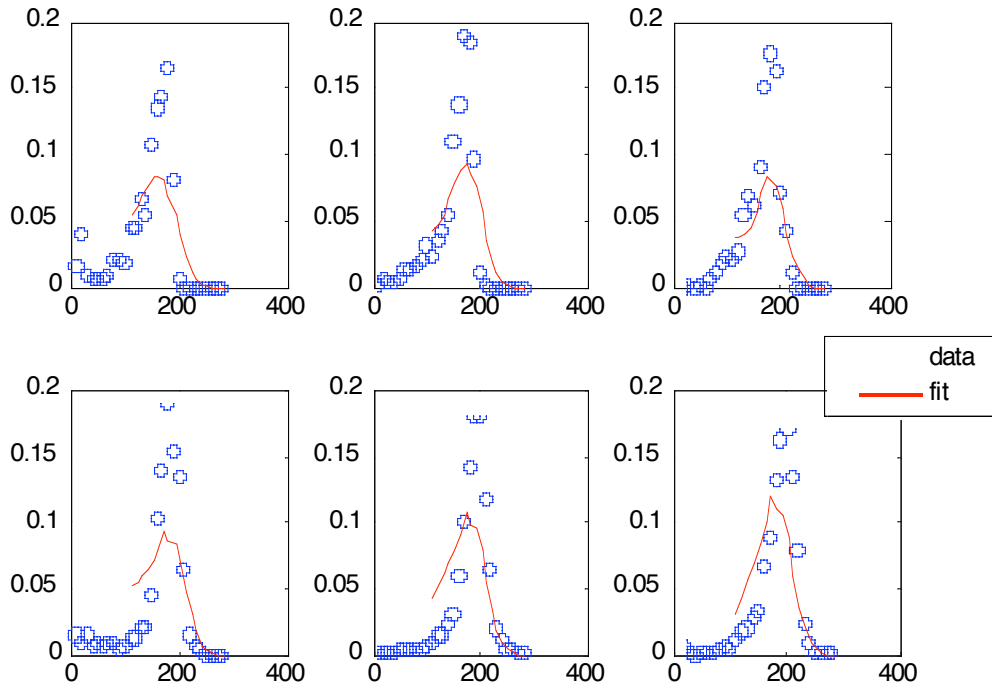


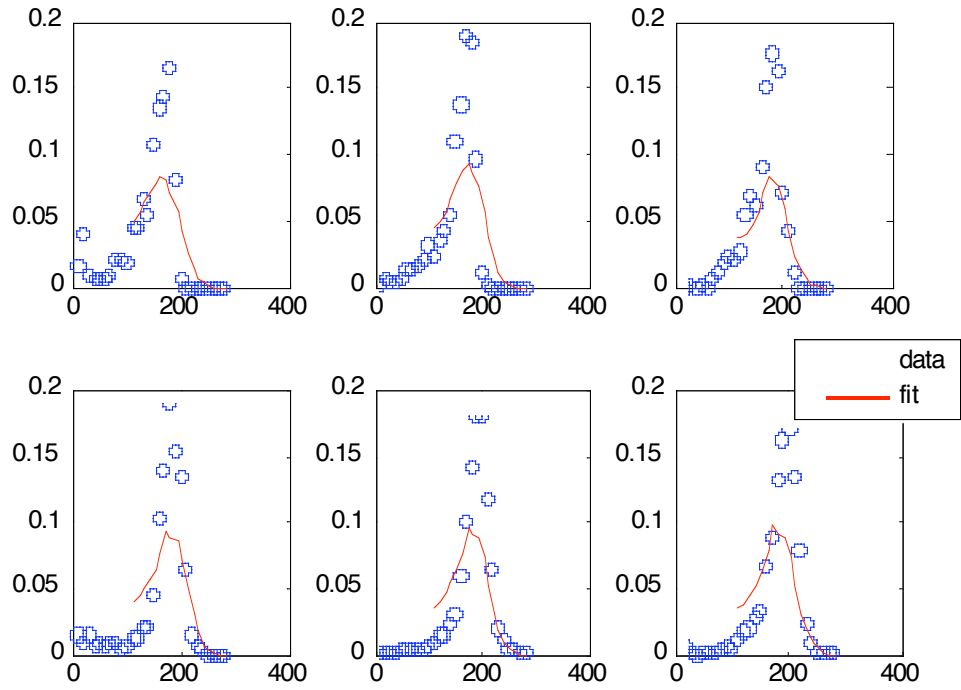
Figure 6: Fit of Catch, LFQ, and relative abundance indices.



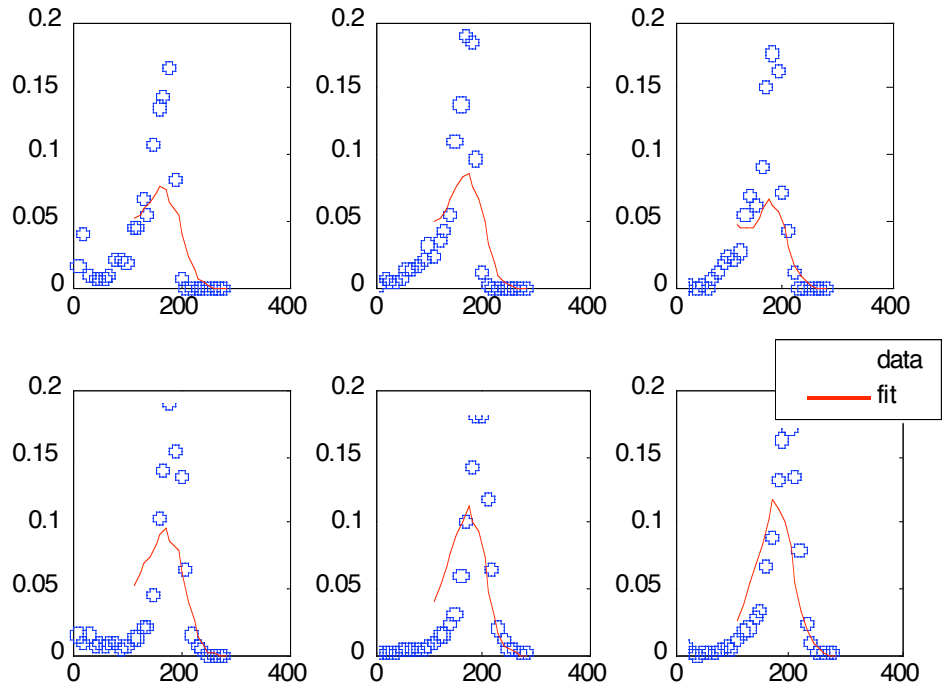
LFQ of S1



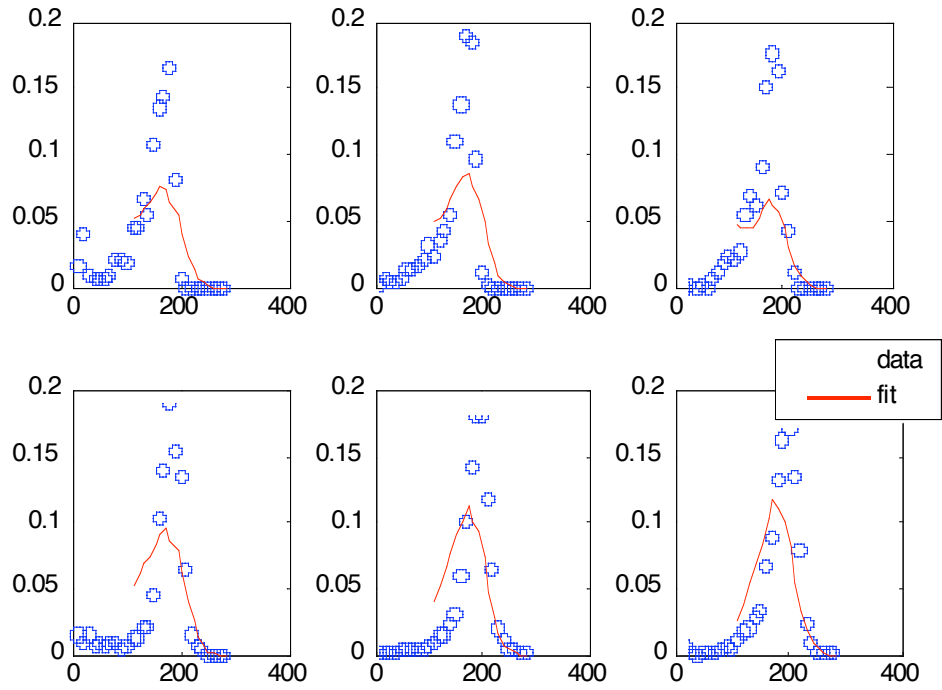
LFQ of S2



LFQ of S3



LFQ of S4



Relative abundance indices

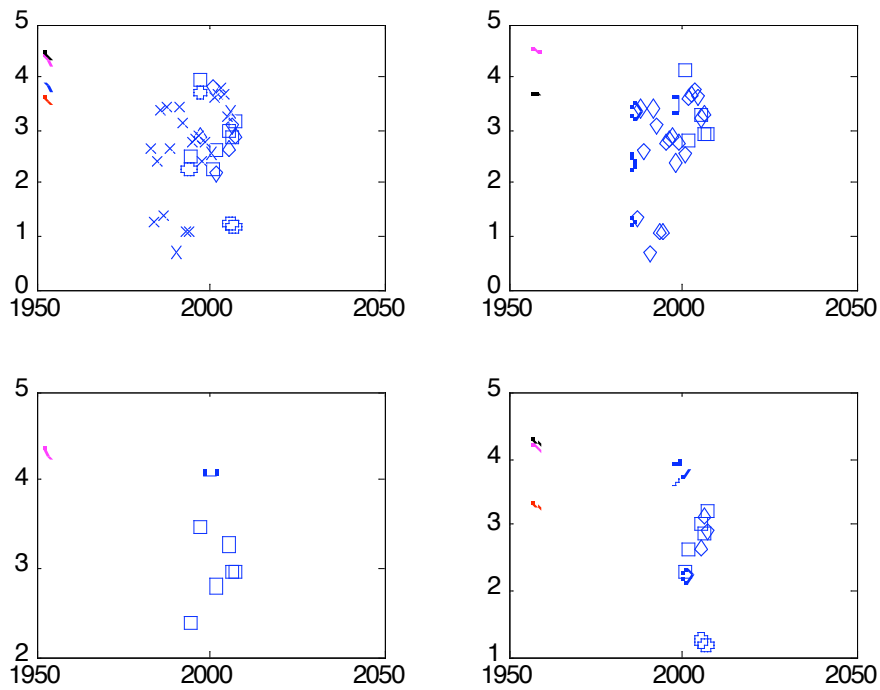
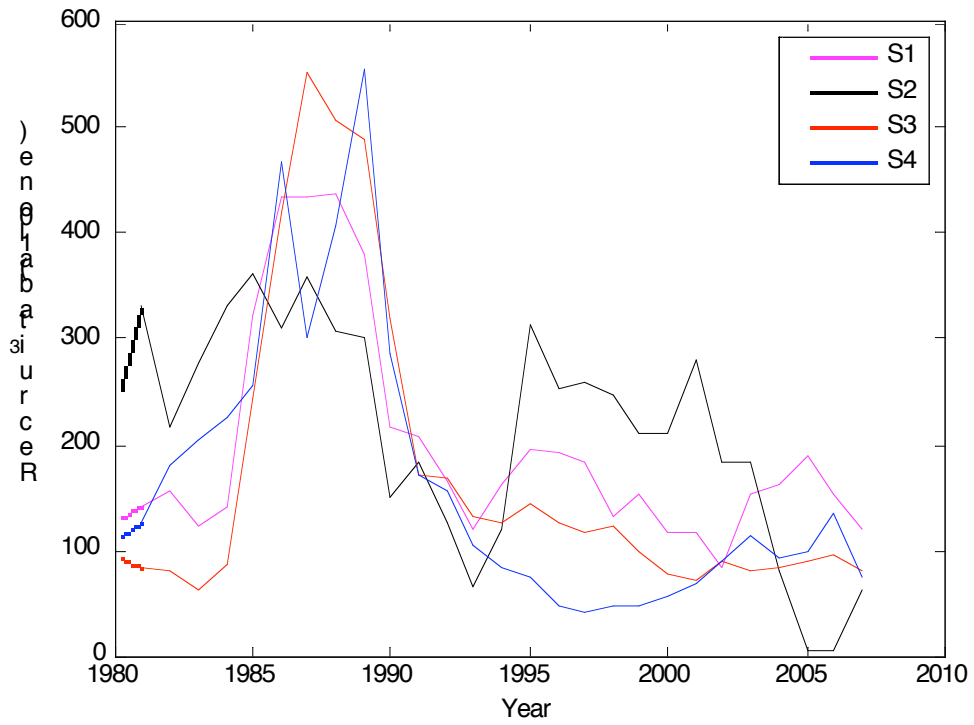


Figure 7: Recruitment.
7a



7b

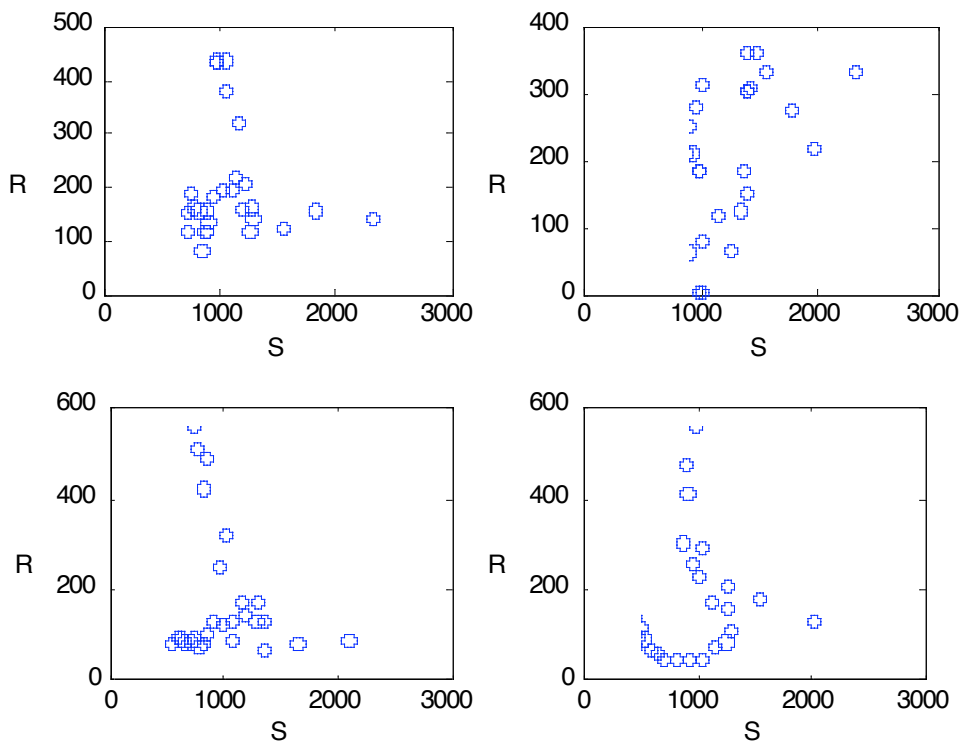


Figure 8: Estimates of population abundance and fishing mortality when data from 1980-2007 were used.

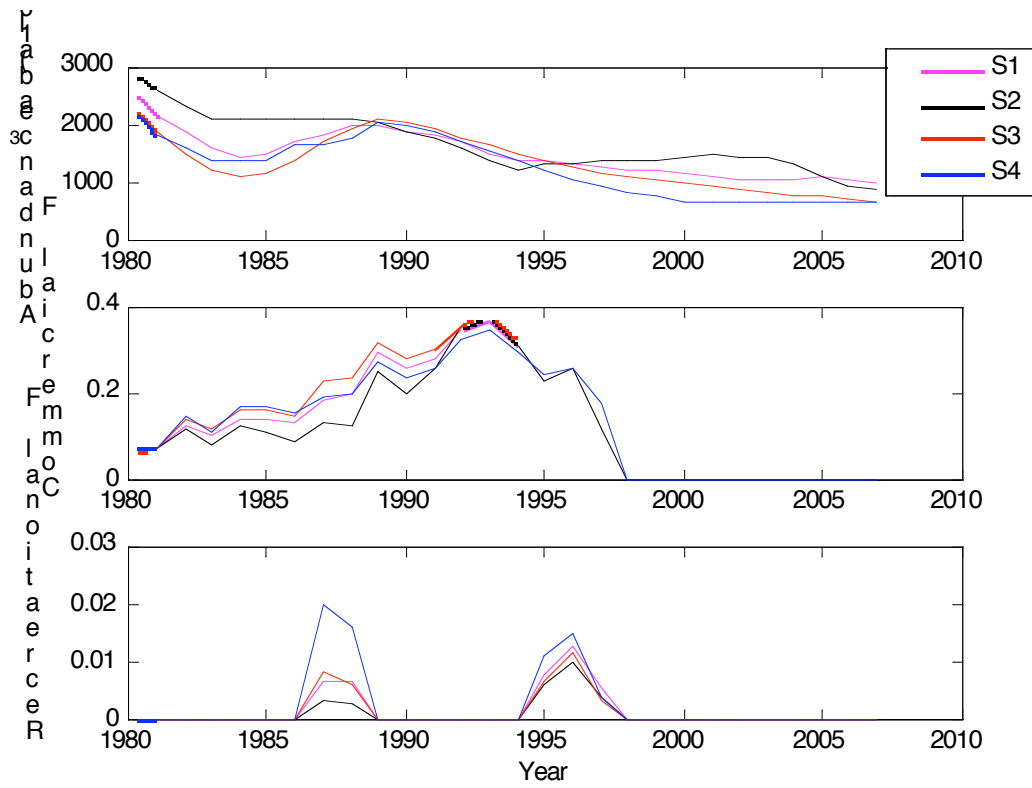
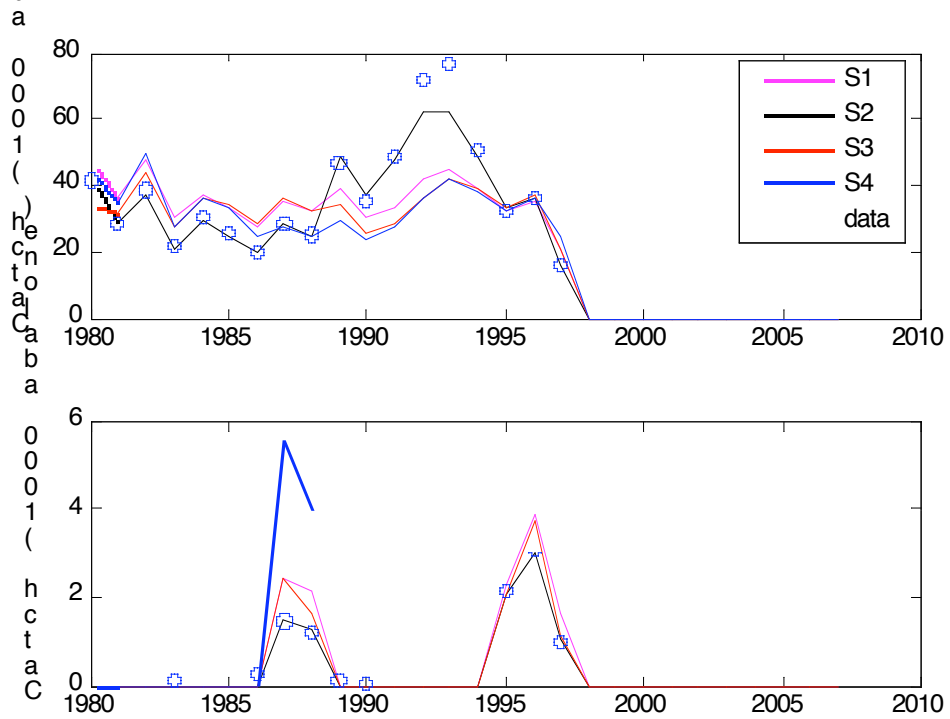
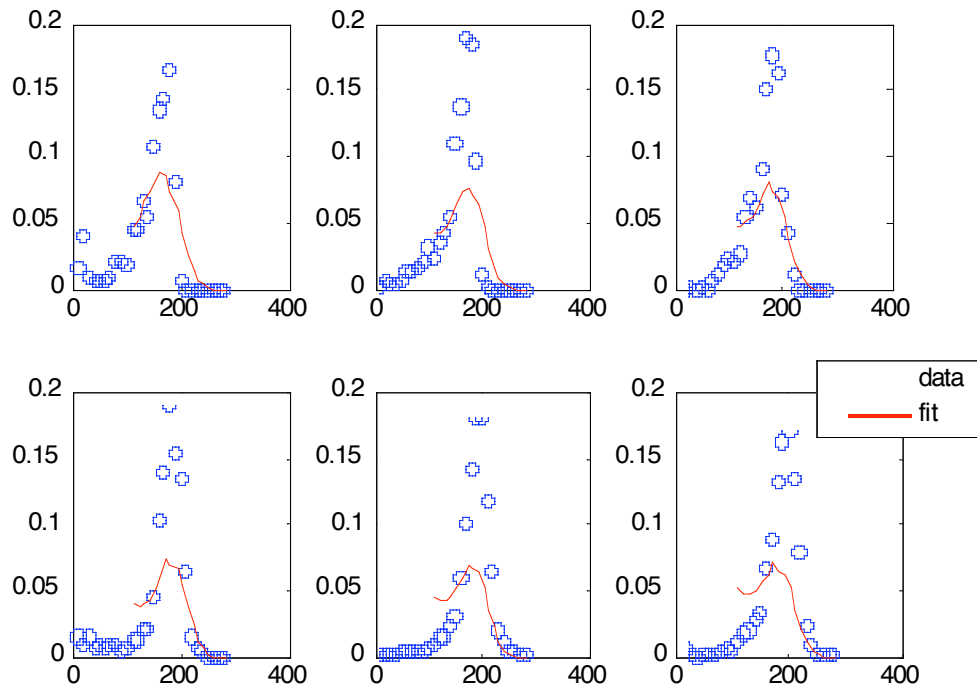


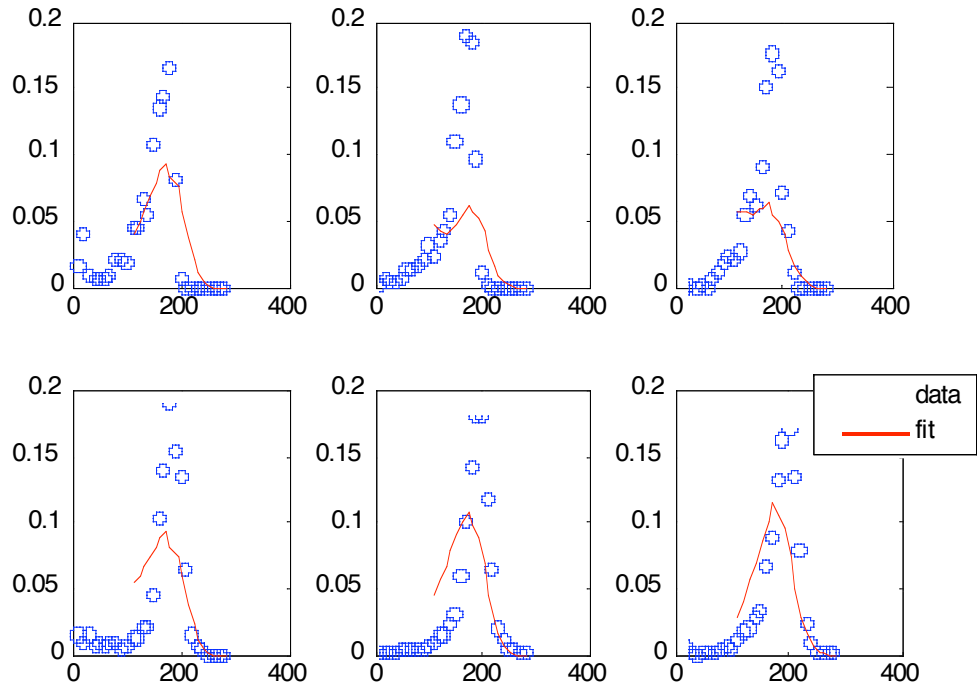
Figure 9: Fit of Catch, LFQ, and relative abundance indices



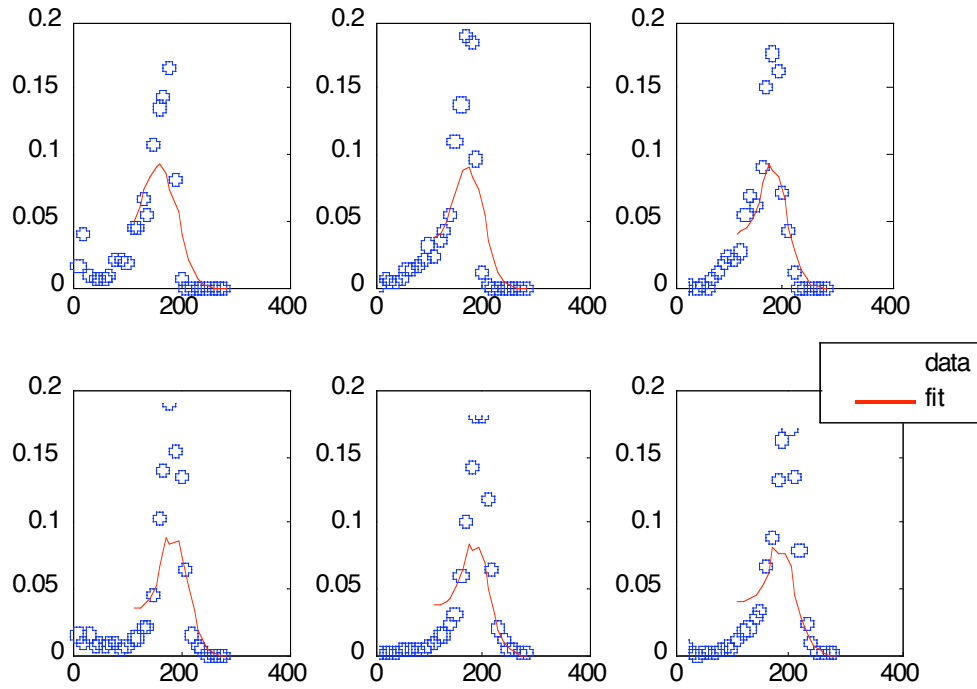
LFQ of S1



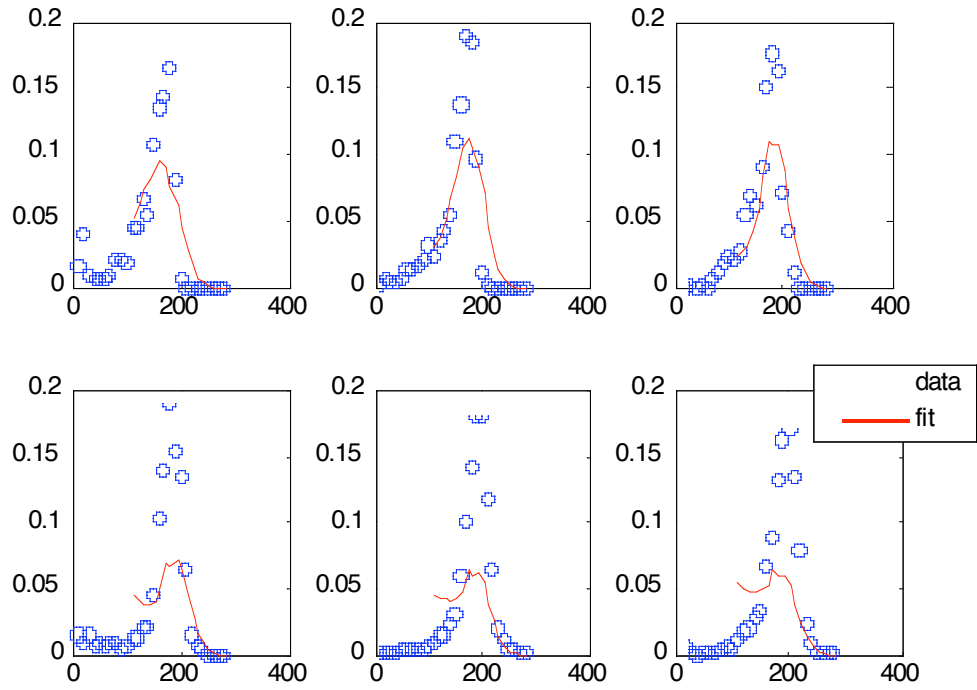
LFQ of S2



LFQ of S3



LFQ of S4



Relative abundance indices

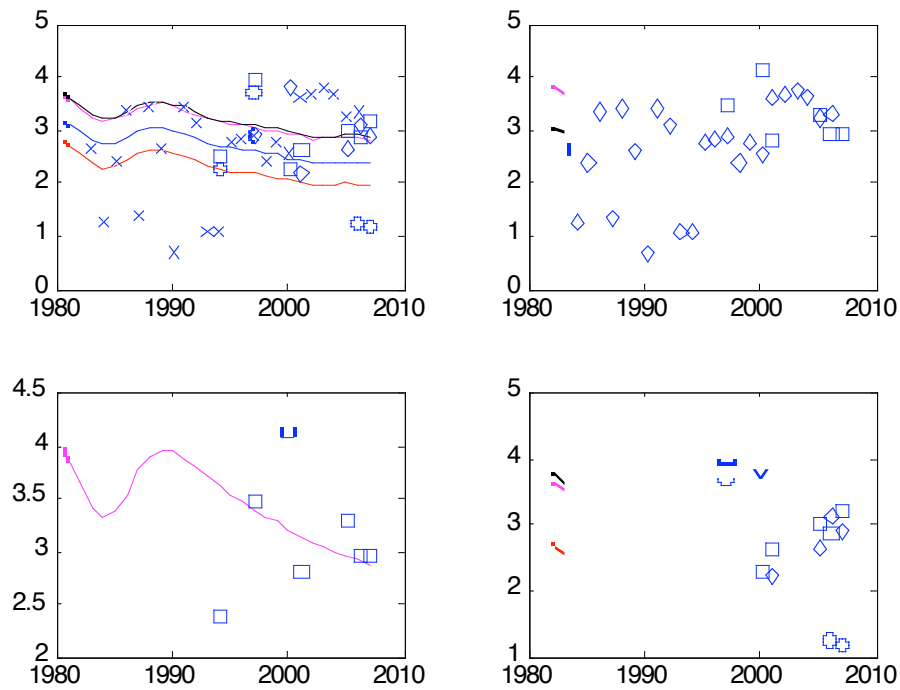
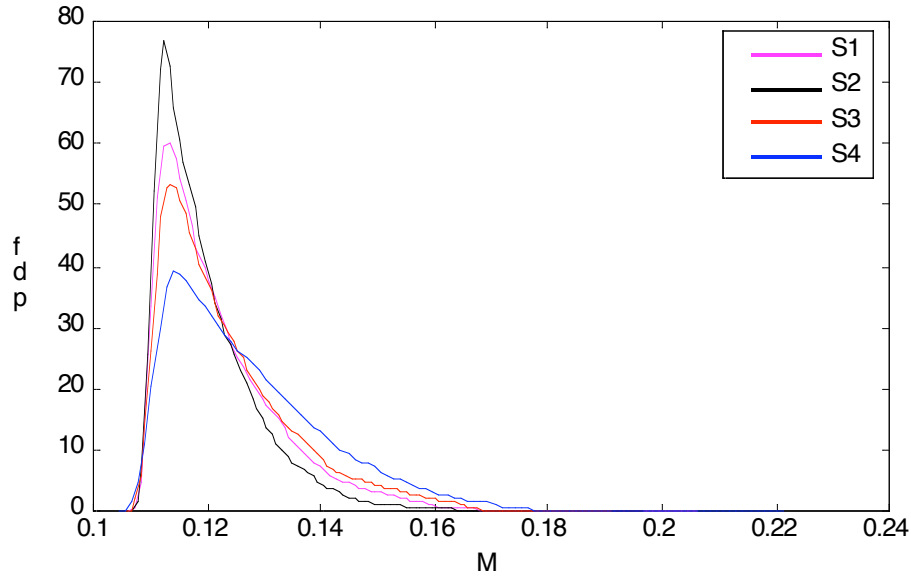
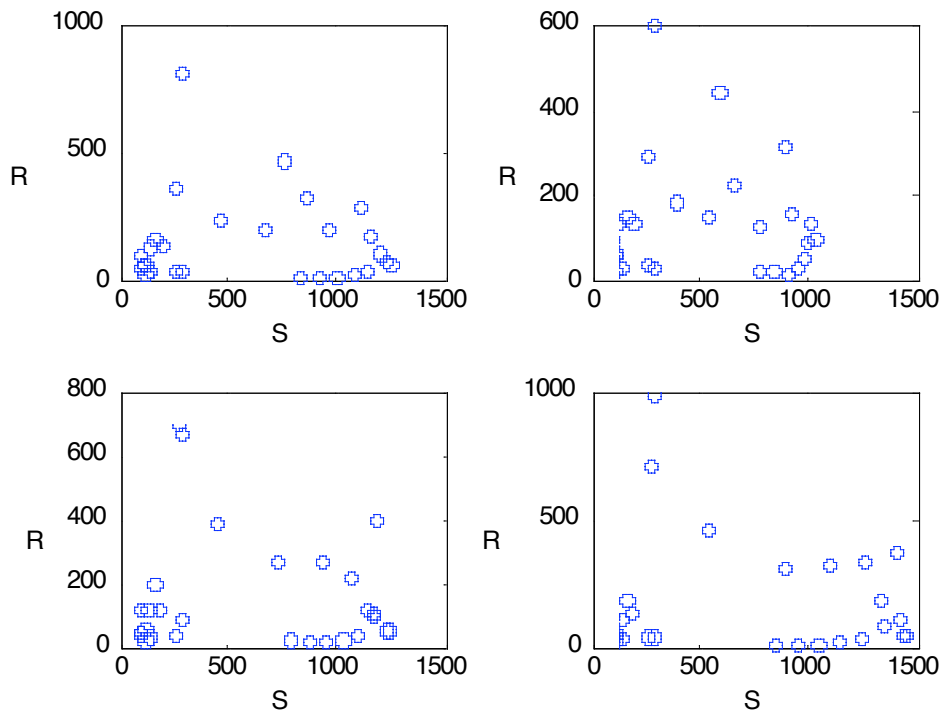


Figure 10: Posterior distributions of key parameters and parameters of management interest from the statistical catch-at-age/size model when M is unknown with uniform prior between 0.11 and 0.23.

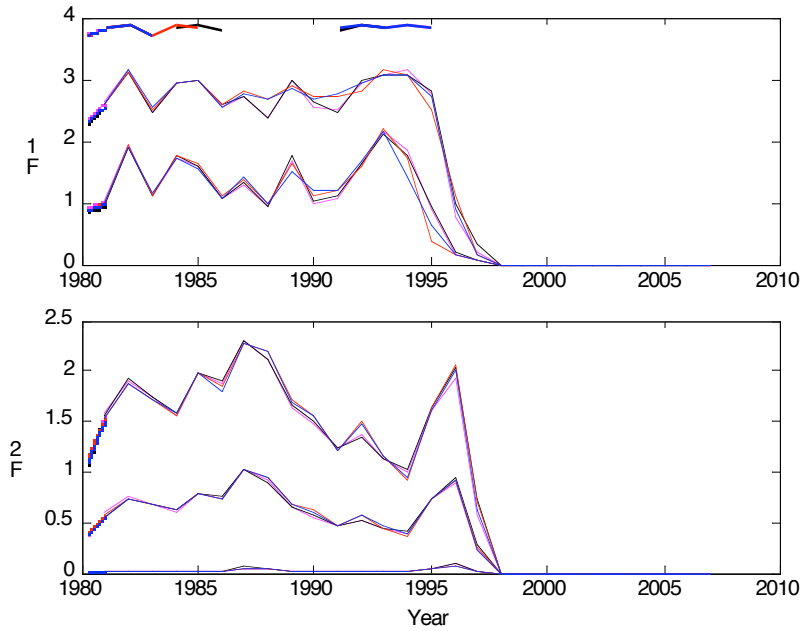
10a: Posterior distribution of M



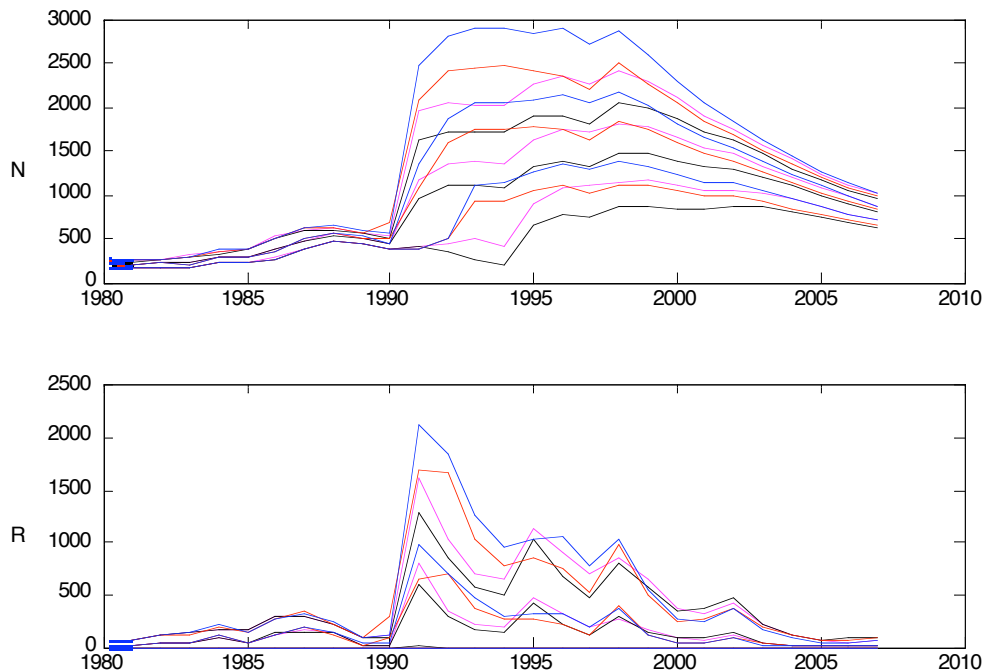
10b: Posterior mean of S and R



10c: Credible interval of fishing mortality estimates. From top to bottom, the corresponding panels are for commercial and recreational F. Continuous lines over years denote the mean; dotted lines denote 95% credible intervals.



10d: Credible interval of population abundance and recruitment estimates. From top to bottom, the corresponding panels are for scenarios 1, 2, 3 and 4. Continuous lines over years denote the mean; dotted lines denote 95% credible intervals.



Risk assessment based on multi-model approaches

Introduction

The status of a fish stock is often determined by comparing an indicator biological reference point (BRP) estimated from stock assessment (e.g., current fishing mortality, current stock biomass) to a management reference point (e.g., $F_{0.1}$, B_{msy} ; Caddy and Mahon, 1995). For species/stocks without good quality BRPs, the management reference point may be set to a deliberately conservative value to offset the uncertainty. This approach has been widely used in fisheries of the United States (Restrepo and Powers 1999). Uncertainty in assessing a fishery may result from various sources such as measurement error, process error, model error, and operating error (FAO, 1996; Chen and Paloheimo, 1998; Patterson et al., 2001). An approach commonly used to incorporate uncertainty in assessment is to estimate the probability of overfishing the fishery, or the probability of the fishery being overfished, after considering uncertainty in both indicator and management reference points (Helser et al., 2001; Jiao et al 2004).

For many fish stocks, there can be more than one approach to assessing the fishery. Thus, there are different approaches for risk assessment given different models. Commonly, in fisheries stock assessment, one specific model is selected and the assessment is conducted as if the selected model had generated the data. That approach ignores the uncertainty in the model selection, leading to over-confident inferences and decisions with higher risk than expected. This section on risk assessment therefore presents an alternative multi-model approach to evaluate the risk of overfishing the fishery and the risk of the fishery being overfished. This section is particularly important for fisheries management, and a final recommendation is made to fully consider model selection uncertainty.

The biological reference points of $F_{0.1}$ from the YPR model, the F_{msy} and B_{msy} proxies from the age structured models, and the minimum population density used as the criterion of minimum population size in other abalone fisheries were all used in this multi-model approach. This study provides a comprehensive risk analysis in determining fisheries stock status and provides a coherent approach for fisheries decision making.

Methods

Risk assessments were done based on multiple stock assessment models and approaches. These models and approaches included: 1) risk of population decline given the hypothesis that any population of abalone will decline if the density of the population is lower than 2000 abalone per hectare; 2) risk of population decline given the BRPs from YPR and EPR analyses; $P(F > F_{0.1})$ was used to develop a TAC; 3) risk of population decline given the BRPs from statistical catch at age model: $P(F > F_{msy})$ and $P(N < N_{msy})$ were used to develop TAC. $M=0.15$ is again used as a proxy for F_{msy} , and SSN1950 is used as a proxy for SSN_{msy} . CVs of 30% and 40% were used for the risk assessment. A CV of 30% is considered a reasonable value for uncertainty of fisheries data (Walters 1993). We were not able to estimate the uncertainty of population size and other parameters from the penalized likelihood approach because of the short time of this

project. A frequentist or Bayesian approach is recommended for future assessments of this fishery.

When BRPs from PR models were used, the stochastic management BRPs were estimated from the models. However, the indicator reference points were estimated separately from different models/approaches. Here, mean population size and population size uncertainty were estimated from the survey (CDFG 2006 and 2007). When density of the abalone was used as an indicator of the population status, mean density and density uncertainty were also estimated from the survey (CDFG 2006 and 2007).

$P(F > F_{msy})$ and $P(SSN < SSN_{msy})$ were estimated as the number of iterations where the posterior value of $F > F_{msy}$ and the number of iterations where the posterior value of $SSN < SSN_{msy}$ in a Bayesian analysis of statistical catch-at-age models. Results of the analysis with datasets weighted equally were not realistic and are not presented here.

The overall mean population density of this fishery was 1200 abalone/hectare in 2006, with standard error ranging from 50 to 170. In high density locations (identified as possible management zones), densities of red abalone ranged from 1500 to 2400/hectare, with standard errors ranging from 200 to 300. A hierarchically structured distribution was used to simulate the density

$$\begin{aligned} D &\sim N(\bar{D}, \bar{\sigma}^2) \\ \bar{D} &\sim U(160, 1600) \\ \bar{\sigma} &\sim U(50, 170) \end{aligned} \quad (1)$$

Considering the high uncertainty of relative abundance data, population size, and other key parameter estimates, a risk level of 10% to 40% depending on the situation was assessed to derive the TAC estimate (Table 1).

Results

The probability of overfishing the SMI red abalone fishery and the probability of this fishery being overfished were considered in the risk assessment. The corresponding TACs given different risk levels and BRPs are listed in Table 1. Given that the current average population density at SMI is 1200/hectare and that the distribution is modeled on a hierarchical structure (equation 1), the probabilities of issuing a TAC with respectively 10% and 20% risk of decreasing the density to <2000 abalone/hectare are both zero.

If $F_{0.1}$ and the current population size from the age-structured model are used, the corresponding mean of the TAC is 174.51, but the probability of the population decreasing is 100%.

If $F_{msy}=M=0.15$ and the current population size from the age-structured model are used, the corresponding mean of the TACs are 22.99 and 22.00 when CV was assumed to be 30% and 40%, but the probabilities of population decreasing are both 100%. If $F=50\%$ of M or $F=0$ and the current population size from the age-structured model are used, the probabilities of population decreasing are still 100%. The low recruitment in recent years created a high probability that the population will keep decreasing even if there is no fishery.

Table 1: TACs given different models/BRPs and different risk levels (in 1000 abalone).

Models and BRPs used	$P(F > F_{BRP}) = 10\%$	$P(F > F_{BRP}) = 30\%$	$P(SSN_{2008} < SSN_{msy} SSN_{1950})$	$P(SSN_{2008} < SSN_{2007})$	*1 $P(\text{density} < 2000 \text{ abalone/ha}) = 10\%$	$P(\text{density} < 2000 \text{ abalone/ha}) = 20\%$
$F_{0.1}$	$C P(C >= F_{BRP} * N) = 10\% =$ 195 $L_{entry} = 178\text{mm}$ 133 $L_{entry} = 197\text{mm}$	$C P(C >= F_{BRP} * N) = 10\% =$ 253 $L_{entry} = 178\text{mm}$ 174 $L_{entry} = 197\text{mm}$	100%	100% TAC $F_{0.1}$ and $L_{entry} = 197\text{mm} = 174.51$	N/A	N/A
$F_{msy} M = 0.15$ in SCA model; and CV of $F_{msy} = 30\%$	N/A	N/A	100%	100% TAC F_{msy} and $L_{entry} = 197\text{mm} = 22.99$	N/A	N/A
$F_{msy} M = 0.15$ in SCA model; and CV of $F_{msy} = 40\%$	N/A	N/A	100%	100% TAC F_{msy} and $L_{entry} = 197\text{mm} = 22.00$	N/A	N/A
$F = 0.5 * M$ with CV = 30%	N/A	N/A	100%	100% TAC F_{msy} and $L_{entry} = 197\text{mm} = 11.12$	N/A	N/A
$F = 0$	N/A	N/A	100%	100% TAC = 0	N/A	N/A
density	N/A	N/A	N/A	N/A	0	0

*1: based on the overall density of SMI red abalone fishery.

Appendix 1: Excerpt from the Revised Terms of Reference

Technical Panel and Review Committee to Support Development of a TAC for Red Abalone at San Miguel Island

Fifth Draft, June 15, 2007

Revised based on:

Email comments received by AAG and Technical Panel members, May 29, 2007

Key Work Considerations and Deliverables:

Key Inputs and Considerations

In developing the TAC methodology and model(s), the technical panel will:

1. Take account of existing SMI red abalone stock data as the basis (e.g., population density, habitat structure) and any fishery dependent data from the past fishery.
2. Consider published data on biological parameters of red abalone in general (fecundity, mortality, survival rates, intrinsic growth rate).
3. Consider associated ecological and anthropogenic parameters that may result in stock fluctuations.
4. Consider continued recovery of SMI stock and surrounding areas.
5. Take into consideration the stock in existing reserves and how it is associated with TAC determination.
6. Utilize information from other similar TAC processes from other fisheries as best as possible.
7. Develop an adaptable methodology that uses the precautionary principle, which is more precautionary at lower levels of data and less precautionary as more data and more accurate stock estimates are available. The methodology should include appropriate statistical models (SD/SE negatively correlated with amount of data available) and error propagation procedures.
8. Incorporate a wide variety of information sources besides peer-reviewed literature. Field observations, working papers, and other materials are considered to be relevant for this assignment. All sources must be cited in a traceable fashion.
9. Provide a best estimate of what the effect of a potential TAC(s) is on the population, e.g., how much recovery of the population is slowed due to a given TAC (e.g. provide a null-model of population development).
10. Consider optimum/minimum densities of the abalone beds in determining a TAC and sustainability of the proposed fishery.

Work Products

The deliverable for the technical panel is a complete methodology for TAC determination with alternative methodological approaches to be used by the AAG. The format of the

intended work product is a concise memorandum, with appropriate graphics and tabular information, presented in a manner that can be well understood by AAG members and other policy bodies. The memorandum will include the following:

1. Fully referenced working assumptions and relevant conceptual models used (i.e., akin to Materials & Methods of a scientific paper, and accessible to AAG members).
2. A fully referenced statement of the data consulted.
3. A list of appropriate stock models to use for abalone and determining TAC along with pros and cons for using them.
4. A risk analysis for various ranges of stock level and corresponding TACs.
5. A comprehensive bibliography of all documents and data sources consulted.
6. A list of data gaps for properly determining stock levels and TAC, with brief discussion of how deviation from the current best guess will affect TAC.
7. A timeframe for periodic revision of the TAC (i.e. 1 year, 2 years ... 10 years etc.)

The deliverable for the review committee is a complete review of the draft methodology with suggested changes and further advice for the technical panel. The review committee will also have the opportunity to review the final recommendation from the AAG on the methodology for TAC determination.